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Understanding the Spatiotemporal Variation of High-Efficiency Ride-Hailing Orders: A Case Study of Haikou, China

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Abstract: Understanding the spatiotemporal variation of high-efficiency ride-hailing orders (HROs) is helpful for transportation network companies (TNCs) to balance the income of drivers through reasonable order dispatch, and to alleviate the imbalance between supply and demand by improving the pricing mechanism, so as to promote the sustainable and healthy development of the ride-hailing industry and urban transportation. From the perspective of TNCs for order management, this study investigates the spatiotemporal variation of HROs and common ride-hailing orders (CROs) for ride-hailing services using the trip data of Didi Chuxing in Haikou, China. Ordinary least squares (OLS) and geographically weighted regression (GWR) models are established to examine the factors that affect the densities of HROs and CROs during different time periods, such as morning, evening, afternoon and night, with considering various built environment variables. The OLS models show that factors including road density, average travel time rate, companies and enterprises and transportation facilities have significant impacts on HROs and CROs for most periods. The results of the GWR models are consistent with the global regression results and show the local effects of the built environment on HROs and CROs in different regions.

Keywords: high-efficiency ride-hailing order; common ride-hailing orders; spatiotemporal variation; ordinary least squares; geographically weighted regression; influential factor

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1. Introduction

With the rapid development of information technology and mobile payment, transportation network companies (TNCs) such as Didi Chuxing, Uber and Lyft have been able to operate ride-hailing services around the world using internet-based platforms [1–5]. Traditional taxis mainly serve passengers on the road based on the drivers' experience, while ride-hailing services can integrate travel information promptly based on smartphone applications and achieve accurate matching between supply (i.e., drivers) and demand (i.e., passengers) [6]. Consequently, this service can effectively reduce the void cruising distance and improve vehicle capacity utilization, which in turn results in less energy consumption and fewer greenhouse gas emissions [7–11]. Due to the convenient service and preferential pricing strategies (such as price subsidies and e-coupons), TNCs have attracted many drivers and users [12]. As of 2020, Uber was operating in 71 countries and in more than 890 cities [13]. As of 2018, Lyft was operating in 200 cities in the United States, and the number of drivers exceeded 310,000 [14]. Didi Chuxing provides travel services to more than 550 million users in more than 400 cities in China, and the daily ride-hailing orders exceed 30 million [15].

High-efficiency ride-hailing orders (HROs) refer to the passengers whose orders can maximize the revenue per unit of travel time for ride-hailing drivers [16]. In actual operation, the distribution of HROs is unbalanced. Some drivers prefer to receive orders in the area where HROs are concentrated, which leads to an imbalance of supply and demand in the ride-hailing market, and resource allocation is not optimal. In addition, during the morning and evening peak hours, affected by road traffic congestion, there are obvious differences in drivers' revenue per unit of travel time in different regions, resulting in an income gap among drivers. For example, it takes a longer time for ride-hailing drivers in the city center to complete an order during the peak periods than usual, although the TNCs increase the fare during these periods. Understanding the spatiotemporal variation of HROs is helpful for TNCs to alleviate the imbalance between supply and demand by improving the pricing mechanism, and to balance the income of drivers through reasonable order dispatch so as to promote the sustainable and healthy development of the ride-hailing industry and urban transportation.

At present, a considerable body of literature has investigated the factors that influence ride-hailing demand. Specifically, factors including users' socio-demographics characteristics such as higher education level and younger as well as built environment attributes such as higher road network density, higher land use mix, lower level of balance between population and employment and higher levels of transit accessibility are associated with higher usage of ride-hailing services [17–19]. However, to the best of our knowledge, there is little research exploring the spatiotemporal variation and influential factors of HROs for ride-hailing services. According to existing studies, passengers with the top 30% of revenue per unit of travel time are defined as HROs, and the remaining 70% of passengers are common ride-hailing orders (CROs) [16,20]. To fill this gap, this study attempts to answer the following questions: (1) What are the spatiotemporal travel characteristics of HROs for ride-hailing service, and what is the difference in the spatiotemporal distributions between HROs and CROs? (2) What factors affect the densities of HROs and CROs, and do the effects of these factors have spatial heterogeneity?

The contributions of this study are mainly in the following two aspects. (1) From the perspective of TNCs for order management, the spatiotemporal travel characteristics of HROs and CROs are compared and analyzed based on the trip data of the city of Haikou in China. (2) In order to reflect the intensity of ride-hailing orders, the densities of HROs and CROs are used as dependent variables, ordinary least squares (OLS) are used to explore the factors affecting their densities during different time periods such as morning, evening, afternoon and night, and geographically weighted regression (GWR) models are also applied to explore the spatial heterogeneity of influential factors, such as secondary roads density, average travel time rate, tourist attractions, and transportation facilities.

2. Literature Review

2.1. Operational Characteristics of Ride-Hailing Services

Exploring the operational characteristics of ride-hailing service is of great significance for understanding the industrial characteristics and the development of ride-hailing services.

Based on the order data of Didi Chuxing in Hangzhou, China, Ke et al. [21] concluded that the passenger demand on weekdays showed a double-peak property (morning peak and evening peak), while the demand on weekends demonstrated a single-peak property (only an evening peak). Based on administrative data and survey data, Hall and Krueger [22] conducted an analysis of the labor market for Uber's drivers. They discovered that the flexibility that the Uber platform offered attracted the drivers. Using the data of the hourly earnings of Uber drivers, Chen et al. [23] documented the ways that the drivers utilized this real-time flexibility and estimated the driver surplus. The results concluded that Uber drivers benefited a lot from this flexibility, and they earned more than twice as much as they did in less flexible arrangements.

Some scholars focused on the impact of ride-hailing trips on the environment. Based on the 1-month GPS trajectory and order data of taxis and Didi Chuxing Express in Chengdu, China, Sui et al. [7] compared and analyzed the fuel consumption and emissions patterns of taxi and ride-hailing trips. They concluded that the fuel consumption, CO, NOx and HC emissions per passenger-on kilometer of taxi trips were about 1.36, 1.45, 1.36 and 1.44 times that of ride-hailing trips, respectively. The results also showed that most of Didi's drivers could perform well in terms of emissions reduction and fuel saving, while only some taxi drivers had the ability to do that. Based on the Didi GPS data, a cross simulation method was proposed by Chen et al. [8] to assess the influence of the user scale on the emission performance of the ride-sourcing system. They identified that under a certain scale of travel demands, the proportion of the void distance gradually decreased with the increasing driver scale. The results also showed that the greater the travel demand of an area, the greater the effect of driver supplement on reducing the proportion of the void distance. Based on the trajectory data of Didi, Sun et al. [24] estimated the NOx emission pattern of road segments and examined the relevant environmental factors that influenced the on-road traffic emissions. They discovered that a short road length with more signal controls, being close to downtown, high bus station density, more ramps nearby and high share of residential or commercial land use could increase the emission rate, while primary roads, longer road segments, road segments far away from ramps and metro stations and the proportion of transportation land use could result in less emissions.

Some scholars also paid attention to the impact of ride-hailing services on other modes of transportation. Using 380 intercept surveys in San Francisco in 2014, Rayle et al. [25] indicated that ride-hailing services and taxis had overlapping but different service markets. More than half of ride-hailing trips replaced travel modes other than the taxi, including private cars and public transport. Nie [26] explored the impact of ride-hailing services on the traditional taxi industry based on taxi GPS data in Shenzhen, China. The results showed that the taxi industry had experienced a huge loss in its ridership due to the competition from ride-hailing services. The taxis could effectively compete with ride-hailing services during peak hours, such as from 6:00 a.m. to 10:00 a.m. and from 5:00 p.m. to 8:00 p.m., and in regions with high population densities. Additionally, ride-hailing services aggravated the traffic congestion in the city, but the impact was mild.

2.2. Factors That Influence Ride-Hailing Demand

Exploring the factors that influence ride-hailing demand can not only identify potential ride-hailing passengers but also improve service quality and user satisfaction. Some scholars utilized questionnaire survey data to conduct such research. For example, Dias et al. [27] applied the ordered probit model to investigate the impacts of socioeconomic and demographic factors on the use of ride-hailing. The results demonstrated that users tended to be well-educated, young and working individuals who lived in higher-density regions. Based on the data of the 2017 National Household Travel Survey, Zhang et al. [28] established zero-inflated negative binomial regression models to explore the relationship between household vehicle ownership and ride-hailing usage. The results revealed that the decrease of one vehicle in households was related to the increase of 7.9% in the frequency of ride-hailing use and the increase of 23.0% in the possibility of ride-hailing use. These effects were greater for individuals who lived in the regions with a higher population density than those who lived in the areas with a lower population density. To investigate the factors influencing the choice among ride-hailing services and traditional travel modes, a multinomial logistic model was established by Du et al. [29] based on valid data from 595 participants. The results showed that the participants were more likely to utilize ride-hailing services for flexible activities, such as business affairs, shopping, entertainment, exercise, especially in suburbs, and the emergency travel (the time is relatively tight for this type of travel). Residents who were not registered permanent residents (it is a special population policy in China called hukou) tended to use this service. Lee et al. [30] adopted discrete choice models to investigate people's willingness to utilize ride-hailing services using the survey data in the US. They found that those who lived in areas with high population densities and had a rural workplace were more likely to use such a service. Based on semi-structured interviews in Denmark, Nielsen et al. [31] discovered that travel cost savings compared with private transport, great flexibility and the opportunity to socialize with other passengers promoted the use of ride-hailing services. Difficulty in finding rides, insecurity and social awkwardness with strangers were the shortcomings of ride-hailing services.

The operation data of ride-hailing services provide an opportunity for analyzing the factors that influence ride-hailing demand from a broader perspective. For example, Yu and Peng [18] established geographically weighted Poisson regression models to investigate the impact of the built environment on ride-hailing demand using the trip data in Austin, Texas. The results indicated that block groups with a higher share of young and well-educated people, higher land use mix, higher road network and sidewalk densities, a lower level of balance between population and employment and higher level of transit accessibility promoted ride-hailing service use. The results also showed the spatial variations of the effects of socioeconomic factors and the built environment on ride-hailing trips. Using trip data from Didi Chuxing in Shanghai, Sun and Ding [32] investigated the effect of the built environment on ride-hailing service demand. The results revealed that commercial and residential land use, rainy weather, higher daytime temperature and transport accessibility had positive effects on ride-hailing service demand. The market share of Express service on rainy days was higher than that of traditional taxi services, which was largely due to the flexibility of operation time and the dynamic pricing mechanisms of Express service [33]. Using the ride-hailing trip data in Chengdu, Zhang et al. [19] focused on the relationship between ride-hailing trips and several types of POIs by establishing ordered logistic regression models. The results revealed that the number of transport facilities had the most impact on the ride-hailing trips, followed by the number of scenic spots. The number of sports facilities and service facilities had impacts on the ride-hailing trips of pick-up locations, while the number of commercial establishments did not influence the ride-hailing trips significantly.

As is evident from the above review of past studies on ride-hailing services, scholars mainly explored the operational characteristics, industrial characteristics and the impact of the service on other transport modes based on survey data and operation data. Regarding the factors that influence ride-hailing demand, past research mainly considered personal attributes, perceptions, built-environment factors and meteorological conditions, and the explorations were performed largely from the perspective of passengers. Very little work has been performed on the spatiotemporal variation and influential factors of HROs from the perspective of TNCs for order management. However, a better understanding of the relationship between the spatiotemporal variation of HROs and built environment factors would help TNCs alleviate the imbalance between supply and demand and balance the income of drivers, which is of great significance to promote the sustainable and healthy development of the ride-hailing industry. Based on this, this study investigates the spatiotemporal variation of HROs and CROs and applies OLS and GWR models to examine the factors that affect the densities of HROs and CROs.

3. Data

3.1. Data Source and Processing

Haikou, located in the south of China, is an important economic center and the transportation hub of Hainan province (Figure 1a). As of 2017, it had an area of 151.6 square kilometers and a permanent resident population of 2.27 million [34]. In 2012, ride-hailing companies such as Didi Chuxing, Shenzhou and Yidao started to operate in Haikou. By the end of 2016, the number of ride-hailing vehicles reached 10,000, and the number of legal ride-hailing drivers was 6000 [35].

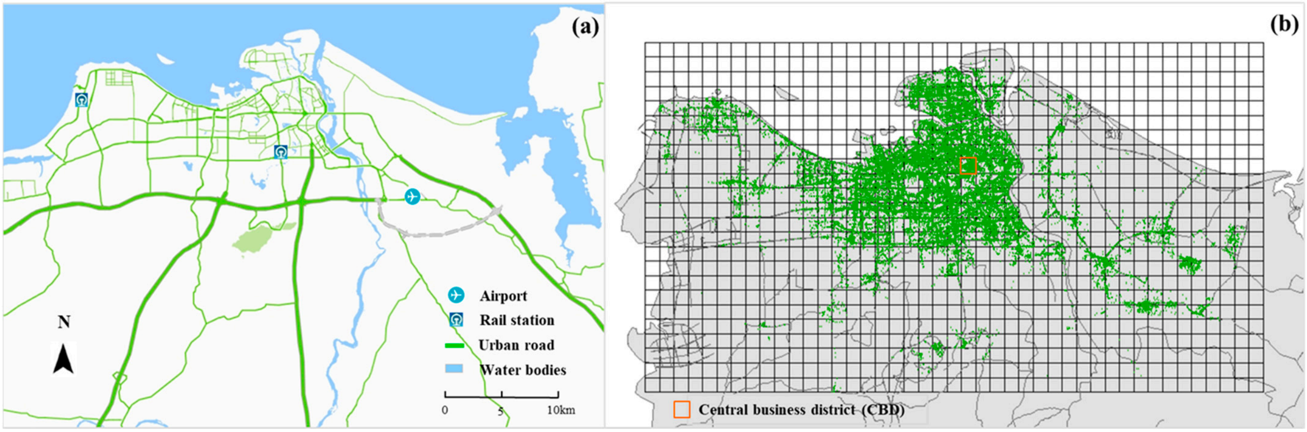

Figure 1. The study area (**a**) and grid cells (**b**).

The data used in this work are the order records of Didi Chuxing in Haikou in September 2017. The records mainly include the order ID, the longitude and the latitude coordinates of pick-up locations, the longitude and the latitude coordinates of drop-off locations, departure and arrival times, travel distances and fares. Past research has indicated that ride-hailing service demand was affected by the built environment [18,19,21]. Based on this, we collected the relevant road information from the OpenStreetMap website (https://www.openstreetmap.org, accessed on 18 August 2020), including the lengths of primary roads, secondary roads and tertiary roads [36]. Based on the Amap Application Program Interface (API), 13 types of POI data were also acquired using Python [37]. These 13 categories were dining facilities, tourist attractions, companies and enterprises (such as construction companies, medical companies, commercial trade and famous enterprises), shopping facilities, transportation facilities, financial and insurance services, science or cultural and educational facilities, commercial residences (residential areas and buildings), daily life services (such as post offices, logistics services, telecom offices and job centers), sports facilities, medical and health service facilities, government offices and accommodation services (hotels and hostels). Detailed information about these POI categories is available on the following website: https://lbs.amap.com/api/webservice/download, accessed on 18 August 2020 [19].

Before the analysis, it was necessary to clean the original order records, since some of them were not appropriate for using in this study. The following records were removed: (1) duplicate order records, (2) order records with incomplete information, such as entries with missing departure and arrival times, (3) pick-up locations or drop-off locations located outside of the study area, (4) records with an average travel speed exceeding 80 km/h and (5) records with travel distances less than 300 m or travel time less than 1 min or longer than 2 h. Using these criteria, the original 2.3559 million order records from 2 September to 29 September (4 weeks) were cleaned, and 2.2747 million order records were finally obtained, accounting for 96.56% of the original records in the dataset.

In order to aggregate the order records in space, we adopted a grid cell structure (1 km $\times$ 1 km) to divide the whole study region into different spatial units [19,21]. A total of 1032 grid cells were created as a result, as shown in Figure 1b. Each ride-hailing order was assigned to a grid cell based on its geographic coordinates. The lengths of different levels of roads and the number of different types of POIs in each grid cell were also obtained based on the Intersect toolbox in ArcGIS.

3.2. Variable Description

In this study, the density of HROs refers to the number of hourly HROs divided by the area of the grid cell, which is 1 km^2. As for each grid cell in Figure 1b, we could obtain the density of HROs for any one hour in a day. The definition of the density of CROs is similar.

To explore the spatial distribution differences of HROs and CROs during different periods, four periods—night (from 12:00 a.m. to 6:00 a.m.), morning (from 6:00 a.m. to 12:00 p.m.), afternoon (from 12:00 p.m. to 5:00 p.m.) and evening (from 5:00 p.m. to 12:00 a.m.)—were selected according to their demand distributions (see Section 5.1) to analyze the spatial variation of two types of orders.

In order to examine the factors that affected the densities of HROs and CROs, some built environment variables were considered in this study, including the primary road density, secondary road density and tertiary road density as well as the number of the 13 types of POIs. To examine the influence of road traffic conditions on the order density, the variable of the travel time rate was adopted. For each order (or trip), the travel time rate equaled the travel time of the trip divided by the travel distance of the trip, which could more directly reflect the seriousness of traffic congestion (i.e., the greater the value, the longer the travel time per unit distance, and thus the more congested the road was) [33]. The average travel time rate of all orders during 1 hour for one grid cell was the average travel time rate of the grid cell, which was used to reflect the road network environment of this grid cell during this period. In addition, the diversity of land use was measured in this study by the variable of POI diversity. The Shannon entropy index was used to calculate the level of land use mix by different types of POIs [38–40]:

$$H = -\sum_{i} P_i \log_n P_i \tag{1}$$

where H is the value of entropy ranging between 0 and 1, P_i is the percentage of the ith category of POI and n is the number of categories.

The daily order number of many grid cells in Figure 1b is zero. After excluding these grid cells, the data of 404 grid cells were utilized in the following analysis. The descriptive statistics of the above variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variables	Variable Description	Mean	Std. Deviation
Dependent variables			
Density of HROs_Morning	The average number of hourly HROs in the morning divided by the area of the grid cell	2.01	3.27
Density of CROs_Morning	The average number of hourly CROs in the morning divided by the area of the grid cell	5.31	10.06
Density of HROs_Evening	The average number of hourly HROs in the evening divided by the area of the grid cell	2.59	4.75
Density of CROs_Evening	The average number of hourly CROs in the evening divided by the area of the grid cell	7.17	14.76
Density of HROs_Afternoon	The average number of hourly HROs in the afternoon divided by the area of the grid cell	3.07	5.40
Density of CROs_Afternoon	The average number of hourly CROs in the afternoon divided by the area of the grid cell	7.46	15.47
Density of HROs_Night	The average number of hourly HROs at night divided by the area of the grid cell	1.13	2.73
Density of CROs_Night	The average number of hourly CROs at night divided by the area of the grid cell	0.52	1.40
Built environment variables			
Primary roads density	Length of primary roads per unit area on grid cell (km/1 km^2)	0.68	1.00
Secondary roads density	Length of secondary roads per unit area on grid cell (km/1 km^2)	0.60	0.95
Tertiary roads density	Length of tertiary roads per unit area on grid cell (km/1 km^2)	0.63	0.98
Average travel time rate	The average travel time rate of grid cell (min/km)	2.04	0.74
POI diversity	POI diversity of grid cell	0.62	0.27
POIs			
Dining facilities	Number of related POI on grid cell	28.40	55.94

Table 1. *Cont.*

Variables	Variable Description	Mean	Std. Deviation
Tourist attractions	Number of related POI on grid cell	0.49	1.07
Daily life services	Number of related POI on grid cell	21.53	41.99
Companies and enterprises	Number of related POI on grid cell	9.20	12.30
Shopping facilities	Number of related POI on grid cell	12.74	30.42
Financial and insurance services	Number of related POI on grid cell	5.03	11.19
Transportation facilities	Number of related POI on grid cell	10.50	16.10
Science or culture and education facilities	Number of related POI on grid cell	8.86	16.36
Commercial residences	Number of related POI on grid cell	7.29	12.07
Sports facilities	Number of related POI on grid cell	8.55	12.84
Medical and health service facilities	Number of related POI on grid cell	2.10	4.23
Government offices	Number of related POI on grid cell	10.63	20.37
Accommodation services	Number of related POI on grid cell	7.31	14.55

4. Method

4.1. Multicollinearity and Spatial Autocorrelation

Multicollinearity refers to the situation where a high correlation between explanatory variables exists. It would render model estimations biased and inaccurate [41,42]. The method of the variance inflation factor (*VIF*) is used to detect multicollinearity between the explanatory variables [43,44]. The formula is as follows:

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

where r^2 is the goodness of model fit. Explanatory variables with *VIF* values higher than 10 are assumed to be multicollinearity variables and should be removed from the model [41].

Spatial autocorrelation refers to the dependence of a given variable's values on the values of the same variable in an adjacent location. Moran's I test is commonly utilized for spatial autocorrelation tests, which can determine whether a variable has spatial autocorrelation and the correlation degree [44,45]. The range of Moran's I statistic is between -1 and +1. A positive value indicates spatial aggregation, a negative value indicates spatial dispersion, and a near-zero value indicates a spatially random distribution. The null hypothesis of Moran's I test is that the explanatory variables are spatially independent, which means that Moran's I statistic is close to zero, and the test statistic provides the confidence level for rejecting the null hypothesis [46].

4.2. Regression Models

(1) Ordinary least squares (OLS)

OLS is a commonly used linear regression model, which is a method to estimate the regression coefficient by minimizing the sum of the squares of the residuals [47]. The model is formulated as follows:

$$Y_i = \beta_0 + \sum_k \beta_k X_{ik} + \varepsilon_i \tag{3}$$

where Y_i is the order density of the ith grid cell, β_0 is the intercept of the linear regression equation, β_k is the regression coefficient of the kth explanatory variable, X_{ik} is the kth explanatory variable of the ith grid cell and ε_i is the random error.

(2) Geographically weighted regression (GWR)

The OLS approach has been criticized for neglecting the spatial variations of the data. GWR is designed to deal with spatial data regression, allowing for coefficients to vary across spaces. It can be viewed as an extension of OLS models by associating explanatory variables with geographical locations [47], and the calculation formula is as follows:

$$Y_i = \beta_{i0}(u_i, v_i) + \sum_k \beta_{ik}(u_i, v_i) X_{ik} + \varepsilon_i \quad (4)$$

where i denotes the ith grid cell, (u_i, v_i) are the geographic coordinates of the centroids of grid cell i, Y_i is the order density of grid cell i, X_{ik} is the kth independent variable, ε_i is the error term of grid cell i, $\beta_{i0}(u_i, v_i)$ represents the intercept and $\beta_{ik}(u_i, v_i)$ is the regression coefficient between the order density and the explanatory variable.

The parameters are calibrated in the way that an observation will have a greater impact on location i (the ith grid cell in this study) if the distance in between is closer, and the degree of this impact can be evaluated by the kernel function, the commonly used Gaussian kernel function is expressed as follows:

$$w_{ij} = \begin{cases} \exp\left[-0.5\left(d_{ij}/b\right)^2\right], d_{ij} < b \\ 0, \text{otherwise} \end{cases} \quad (5)$$

where w_{ij} represents the allocated weight between the centroids of two grid cells, d_{ij} represents the distance between grid cell j and grid cell i and parameter b is the bandwidth, which is used to exclude observations that exceed the distance threshold.

The GWR model will gradually reduce to OLS model as the bandwidth increases, while it will suffer an overfitting problem if the bandwidth goes to 0 [48]. Considering that the grid cells (after excluding the grid cells with a daily order number of 0) were denser in the downtown regions and sparser in the suburban areas, an adaptive bandwidth was selected in this study, that is, the areas with high-density grid cells would have a lower value of bandwidth, while the areas with low-density grid cells had a higher value. The optimal bandwidth was determined by finding the corresponding value that resulted in the minimum corrected Akaike information criterion (AICc), which was used to evaluate the model results and avoid the overfitting phenomenon.

5. Results

5.1. Spatiotemporal Characteristic Analysis

In order to explore the travel characteristics of HROs and CROs at different times of the day, the order data from 2 September to 29 September were utilized to calculate the hourly demands of HROs and CROs. As shown in Figures 2 and 3, they represent the hourly average travel demand of HROs or CROs on weekdays and weekends, respectively.

As shown in the figures, on weekdays, the demand of CROs witnessed a sharp rise from 6:00 a.m. to 9:00 a.m., followed by a steady trend in the next few hours until 12:00 p.m. In the afternoon, the demand of CROs experienced a temporary decline before reaching its peak at 6:00 p.m. This is consistent with the relatively large demand of the residents for ride-hailing services during the peak period [19]. By comparison, the demand of HROs rose steadily in the morning before reaching the first demand peak of the day at 2:00 p.m. The main reason for this is that there were fewer congested roads in the city, and the operational efficiency of ride-hailing vehicles was higher at this time. After the demand of HROs dropped to the lowest at 6:00 p.m., it then reached the second demand peak of the day at 12:00 a.m. At this time, some public transportation services were no longer running, and traffic conditions were generally good. It can be seen that under the influences of the road conditions, residents' travel habits and public transportation, the demand of HROs changed significantly in the course of a day. In addition, the demand of these two types of orders had some similarities between weekdays and weekends, but the level of demand of CROs was lower in the mornings of weekends. The main reason for this is that people tend to rest at home before undertaking entertainment and other activities on weekends, and the departure time is relatively later than that on weekdays [29].

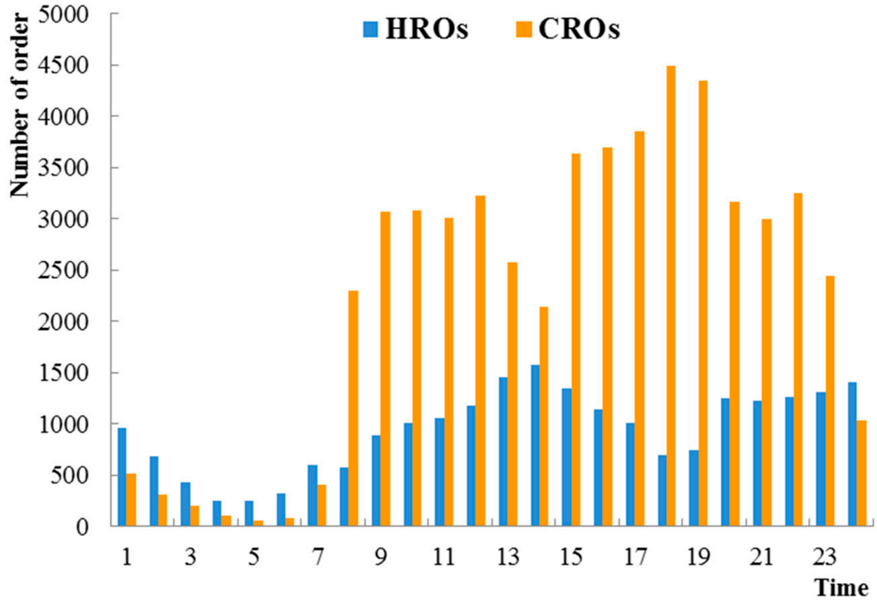

Figure 2. Hourly average travel demand of HROs and CROs (weekdays).

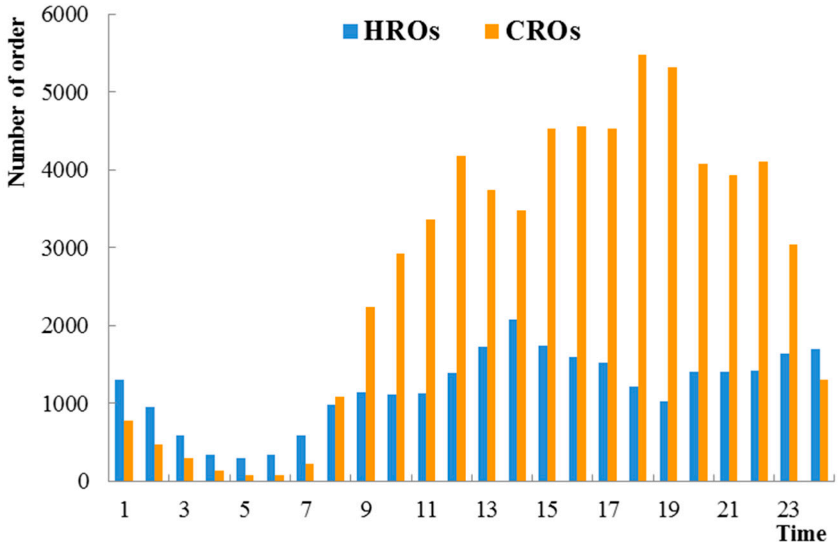

Figure 3. Hourly average travel demand of HROs and CROs (weekends).

To explore the differences in the spatial distribution for these two types of orders, this study selected four periods (from 6:00 a.m. to 7:00 p.m., from 12:00 p.m. to 1:00 p.m., from 5:00 p.m. to 6:00 p.m., and from 11:00 p.m. to 12:00 a.m.) to analyze the spatial variation of HROs and CROs on weekdays and weekends (Figures 4 and 5).

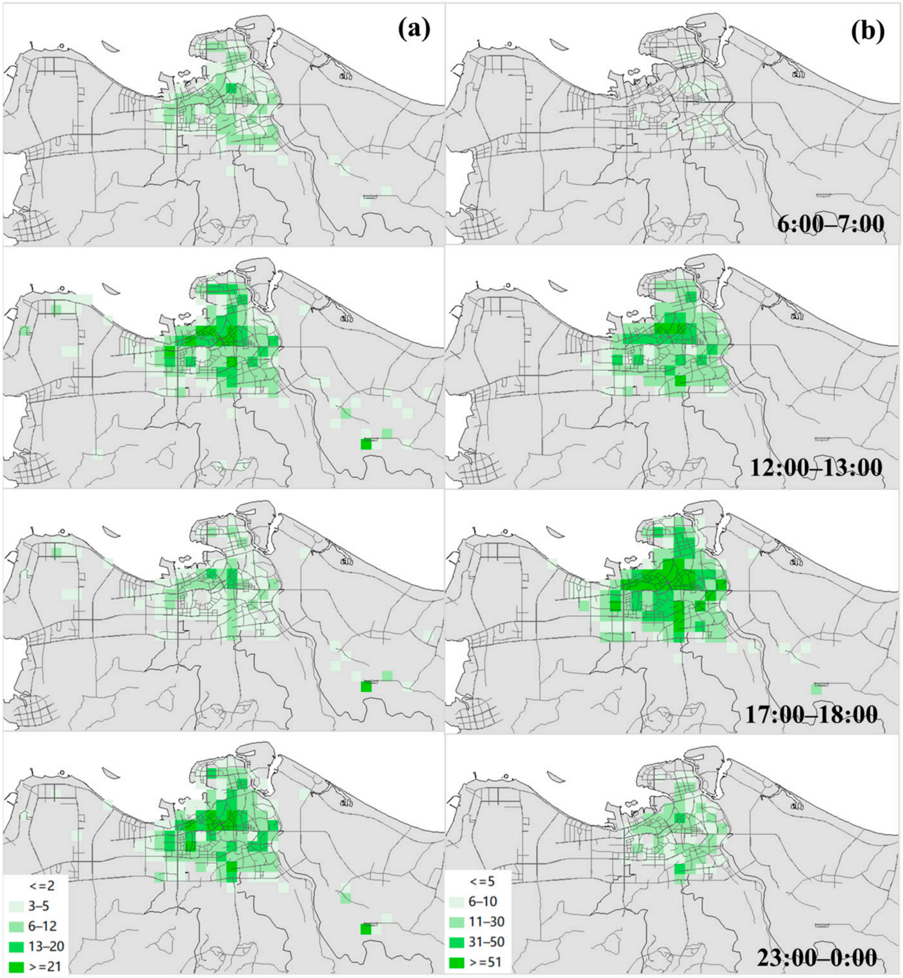

Figure 4. Distribution of HROs (**a**) and CROs (**b**) on weekdays.

As seen from the figures, the demand of CROs was mainly distributed in the core area of the city. The spatial distributions of HROs in different periods indicate their dynamic characteristics, such as intensification, weakening and secondary intensification. By comparison, the distributions of CROs in different periods also presented their characteristics, such as intensification, secondary intensification and weakening. More specifically, from 6:00 a.m. to 7:00 a.m., the density of CROs was low, and the demand density of HROs was relatively low and evenly distributed in the core area of the city. From 12:00 p.m. to 1:00 p.m., the demand density of HROs increased significantly in the core area and showed a certain agglomeration phenomenon. From 5:00 p.m. to 6:00 p.m., the demand density of CROs reached its peak due to the increased demand of returning home, while the demand density of HROs decreased in the core area. The main reason for this is that during this period, the competition among ride-hailing drivers in the core area was fierce, and operational efficiency was low due to traffic congestion. From 11:00 p.m. to 12:00 a.m., the density of HROs in the core area showed a trend of secondary intensification. It is worth noting that some HROs were distributed in the suburb, especially around the Haikou Railway Station in the northwestern region and the Meilan Airport in the southeastern region. In addition, the spatial variation of HROs and CROs had similarities on weekdays and weekends, but the demand on weekends was higher than that on weekdays, especially from 12:00 p.m. to 1:00 p.m. and from 5:00 p.m. to 6:00 p.m.

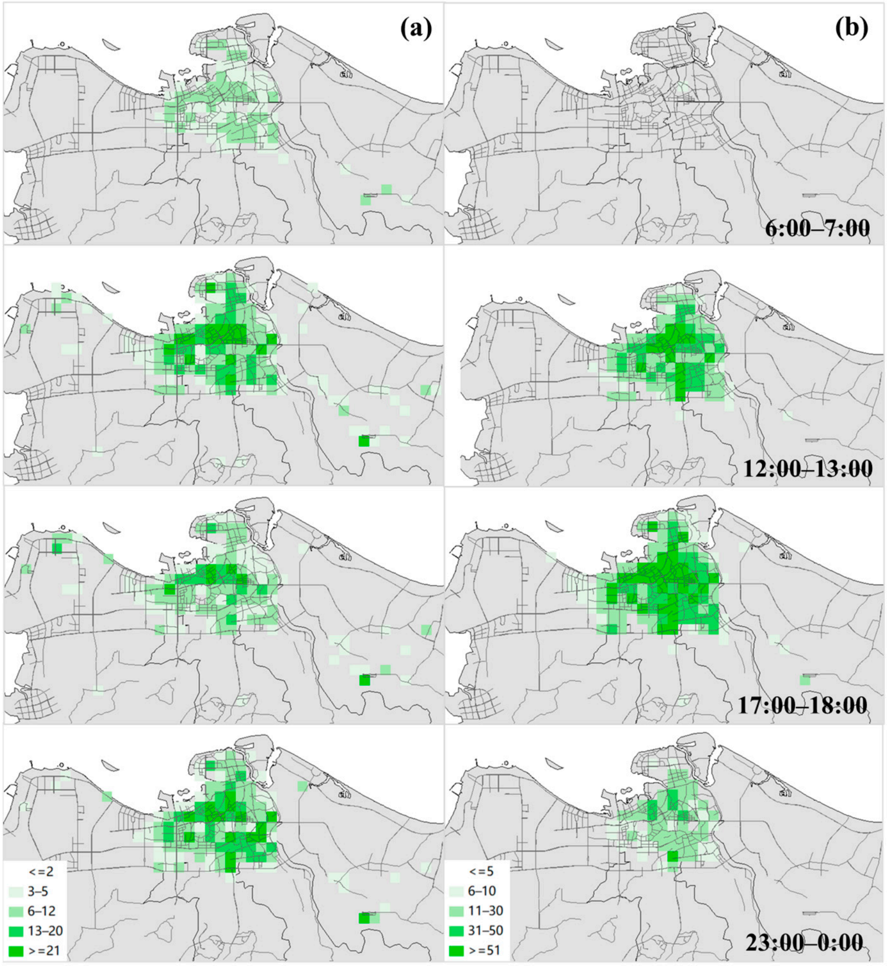

Figure 5. Distribution of HROs (**a**) and CROs (**b**) on weekends.

5.2. Model Results

Considering that the demand characteristics of HROs and CROs were similar on weekdays and weekends but different at different times of the day and in different areas, in this section, we will mainly focus on the factors that influenced the density of these two orders and the spatial heterogeneity of the influential factors during four periods on weekdays—night (from 12:00 a.m. to 6:00 a.m.), morning (from 6:00 a.m. to 12:00 p.m.), afternoon (from 12:00 a.m. to 5:00 p.m.) and evening (from 5:00 p.m. to 12:00 a.m.)—by utilizing global OLS and local GWR models.

To avoid multicollinearity between the independent variables, the VIF values of the explanatory variables were calculated by OLS models, and variables with VIF values greater than 10 were removed from the models. The results of the VIF values of the significant explanatory variables are given in Tables A1–A8 in Appendix A. In addition, Moran's I statistics were carried out to determine if the significant explanatory variables were spatially associated. Table 2 shows the Moran's I test results for each candidate explanatory variable. The p-values were all less than 0.05, implying that the explanatory variables were spatially autocorrelated [48]. Moreover, Moran's I values were positive, which means that the spatial distributions of all candidate variables were more likely to be spatially aggregated. Therefore, it is appropriate to utilize GWR models to examine the spatial variation of the order density.

Table 2. Moran's I test results.

	Moran's I	Z-Score	*p*-Value
Dependent variables			
Density of HROs_Morning	0.608	43.271	0.000
Density of CROs_Morning	0.792	56.239	0.000
Density of HROs_Evening	0.507	36.644	0.000
Density of CROs_Evening	0.742	53.085	0.000
Density of HROs_Afternoon	0.590	42.280	0.000
Density of CROs_Afternoon	0.741	53.065	0.000
Density of HROs_Night	0.457	33.987	0.000
Density of CROs_Night	0.648	47.418	0.000
Built environment variables			
Primary roads density	0.137	9.841	0.000
Secondary roads density	0.202	14.402	0.000
Tertiary roads density	0.226	16.131	0.000
Average travel time rate	0.282	20.027	0.000
POI diversity	0.292	20.686	0.000
POIs			
Tourist attractions	0.216	15.654	0.000
Companies and enterprises	0.505	35.929	0.000
Shopping facilities	0.515	37.703	0.000
Financial and insurance services	0.604	43.483	0.000
Transportation facilities	0.654	46.536	0.000
Commercial residences	0.659	46.778	0.000
Sports facilities	0.596	42.405	0.000
Medical and health service facilities	0.630	44.799	0.000
Government offices	0.581	42.695	0.000

As for the OLS models, we presented the global coefficients, significance results and VIF values. For the GWR models, we showed the statistics of the local coefficients for each explanatory variable, including the minimum, maximum, average and median of the coefficients, as seen in Tables A1–A8 in Appendix A.

With regard to the performance indicators of the models, we showed the values of AIC, AICc, R^2 and adjusted R^2. As seen in Table 3, for the four periods, the GWR models all outperformed the OLS models in terms of model fit. Taking the HROs_ Morning model as an example, the AIC and AICc values of the GWR model (1282.759 and 1288.717) were lower than those of the OLS model (1321.149 and 1322.082), and the R^2 and adjusted R^2 values of the GWR model (0.877 and 0.863) were greater than those of the OLS model (0.851 and 0.847). The improvement in data fitting indicates the superiority of the final models.

Table 3. Comparison results of OLS and GWR models.

	Morning		Evening		Afternoon		Night	
	HROs	CROs	HROs	CROs	HROs	CROs	HROs	CROs
OLS models								
AIC	1321.149	2142.177	1866.377	2506.336	1778.861	2541.740	1505.601	793.363
AICc	1322.082	2142.633	1867.051	2506.701	1779.421	2542.197	1505.884	793.922
R^2	0.851	0.894	0.710	0.852	0.813	0.849	0.623	0.721
R^2 adjusted	0.847	0.892	0.704	0.850	0.809	0.846	0.618	0.715
GWR models								
AIC	1282.759	2059.488	1823.706	2444.141	1739.781	2462.586	1474.197	721.180
AICc	1288.717	2063.222	1828.033	2447.371	1743.801	2466.170	1476.875	726.021
R^2	0.877	0.921	0.760	0.883	0.844	0.885	0.676	0.788
R^2 adjusted	0.863	0.913	0.736	0.873	0.829	0.875	0.651	0.765

6. Discussions

To observe the differences of the effects of various variables on the densities of HROs and CROs during the four periods more conveniently, Table 4 summarizes the results of the OLS models (i.e., HROs_Morning, CROs_Morning, HROs_Evening, CROs_Evening, HROs_Afternoon, CROs_Afternoon, HROs_Night and CROs_Night).

Table 4. Model results of OLS.

	Morning		Evening		Afternoon		Night	
	HROs	CROs	HROs	CROs	HROs	CROs	HROs	CROs
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Built environment variables								
Primary roads density		0.12 *		0.078 *		0.119 *		
Secondary roads density	0.243 ***		0.385 ***		0.423 ***		0.224 ***	0.088 **
Tertiary roads density	0.141 **							0.078 **
Average travel time rate	−0.066 *	0.615 **	−0.111 *	0.997 **		1.209 ***		
POI diversity							−0.852 **	−0.492 ***
POIs								
Tourist attractions	−0.021 *		0.089 *		0.027 *			−0.06 *
Companies and enterprises	−0.004 *	−0.021 *	−0.015 *	−0.048 *	−0.023 *	−0.082 **		
Shopping facilities	−0.007 *			0.094 ***		0.089 ***	0.016 ***	0.013 ***
Financial and insurance services	0.061 ***	0.207 ***	0.107 ***	0.421 ***	0.141 ***	0.386 ***		
Transportation facilities	0.111 ***	0.232 ***	0.173 ***	0.392 ***	0.186 ***	0.387 ***	0.113 ***	0.053 ***
Commercial residences		0.212 ***	−0.051 **		−0.032 *	0.118 ***		
Sports facilities	0.055 ***		0.077 ***		0.082 ***			−0.01 *
Medical and health service facilities	0.079 ***	0.462 ***						−0.001 *
Government offices	−0.02 ***		−0.029 ***		−0.03 ***		−0.01 *	

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

It can be seen that the primary road density had a positive impact on the density of CROs for most periods except at night. By comparison, the secondary road density could significantly promote the density of HROs for the four periods. The main reason for this is that there will be a higher demand for ride-hailing trips near the primary roads [18], while the relatively good road environment of the secondary roads will increase the demand density of HROs.

As expected, an increase in the average travel time rate could promote the density of CROs for most periods, since the periods when traffic congestion occurred were usually also the periods when the demand for ride-hailing was the highest. By contrast, this variable inhibited the density of HROs, especially in the morning and evening periods. The reasons for this are as follows. With an increase in the travel time rate, such as in the peak hours of urban traffic, ride-hailing drivers tend to take a longer time to complete an order than usual, which results in low operating efficiency. At present, although the ride-hailing platform implements multi-time counting fees and will increase the fare accordingly during the peak periods [49], the model results imply that an increase in ride-hailing fares due to the time loss of ride-hailing drivers during the peak periods is not enough to compensate for the normal operational profits of drivers during these periods.

In the OLS models, the POI diversity variable was not significant at the 10% significance level for most periods (except at night). This variable is usually related to more non-motorized travel, such as walking, and therefore this makes sense in theory [50].

For the variable of POIs, the number of tourist attractions was associated with a higher density of HROs, especially in the afternoon and evening. The scenic spots are widely distributed in the entire city of Haikou, which is a tourist city, and tend to increase the travel demand of ride-hailing to some extent. Second, the number of companies and enterprises significantly inhibits the increase of two types of order density for most periods (except at night). The main reason for this is that companies and enterprises are more concentrated in the downtown area, and the overloaded traffic in this area will reduce the operational efficiency of ride-hailing vehicles. The number of shopping facilities will significantly increase the density of CROs for most periods (except in the morning). The number of transportation facilities is associated with higher densities of HROs and CROs for four periods. It may be that the number of transfer activities in the vicinity of traffic facilities, such as airports, railway stations, bus stations and so on, is large [19]. In addition, the number of sports facilities will significantly increase the density of HROs (except at night). However, the number of government offices will significantly inhibit the density of HROs for four periods.

For the GWR models of HROs and CROs during the four periods, the median values of the local coefficients were similar to the global coefficients in the OLS models in terms of the direction and magnitude for those variables that were statistically significant, as seen in Tables A1–A8 in Appendix A. In the following, we will analyze the spatial heterogeneity of the effects of several important variables.

Figure 6 presents the spatial distribution of the coefficient estimates for the secondary roads density during the four periods in the GWR models. It can be seen that the estimates were constantly positive across the region, indicating that a higher secondary roads density was associated with a higher density of HROs. This positive effect was more evident near the core area and the Meilan Airport in the southeastern region. In addition, at night, the positive effect of this variable on the density of HROs was the highest in the area near Meilan Airport. This was related to the high travel demand near this area during this period.

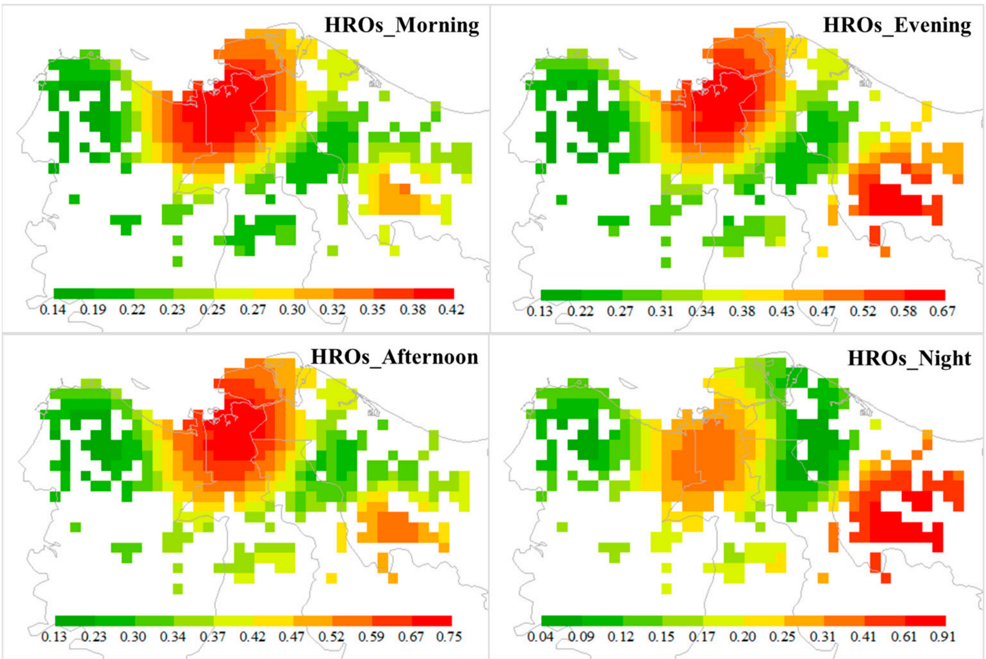

Figure 6. Coefficient estimates of secondary roads density.

Figure 7 shows the spatial distribution of the coefficient estimates for the average travel time rate in the morning and evening periods in the GWR models. It can be seen that the coefficient estimates were constantly positive in the morning and evening across the study region for CROs, and this was mainly because the more congested the area, the higher the demand for ride-hailing services. In addition, for the CROs, the coefficient estimation in the morning was higher in the peripheral area, while the estimation in the evening was greater in the core area. This may be related to the flow direction of commuter travel of residents. For the HROs, most of the coefficient estimates were negative in the study region in the morning, except for few areas in the southwest. In the evening, the coefficient estimates were positive in most areas.

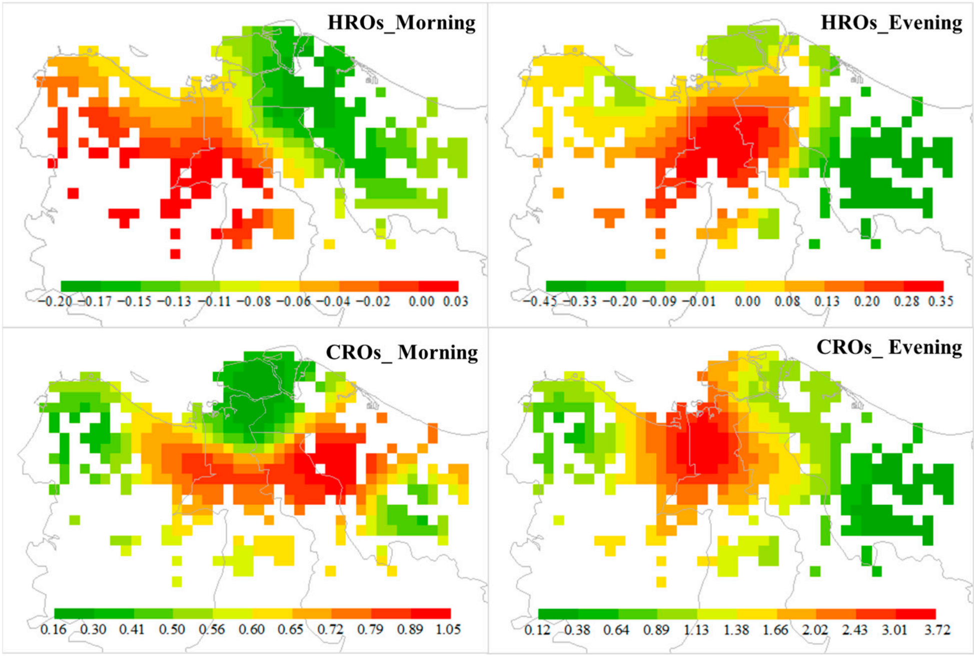

Figure 7. Coefficient estimates of average travel time rate.

Figure 8 presents the spatial distribution of the coefficient estimates for transportation facilities during four periods in the GWR models. It can be seen that the coefficient estimates were constantly positive across the study area during the four periods for both HROs and CROs, implying that a higher number of transportation facilities is correlated with a higher order density. In addition, it can be found that for the HROs, the coefficient estimations had the strongest impact in the area near Meilan Airport, while for the CROs, the coefficient estimations had the greatest effect in the core area.

Figure 9 shows the spatial distribution of the coefficient estimates for tourist attractions in the GWR models. This variable presented mixed estimations, which implies that the impacts of tourist attractions on HROs had significant heterogeneity in different areas. In the morning and afternoon, the influence of this variable was positive in the northwest area and the region near Meilan Airport, and in the evening, the effect of this variable was positive in most regions.

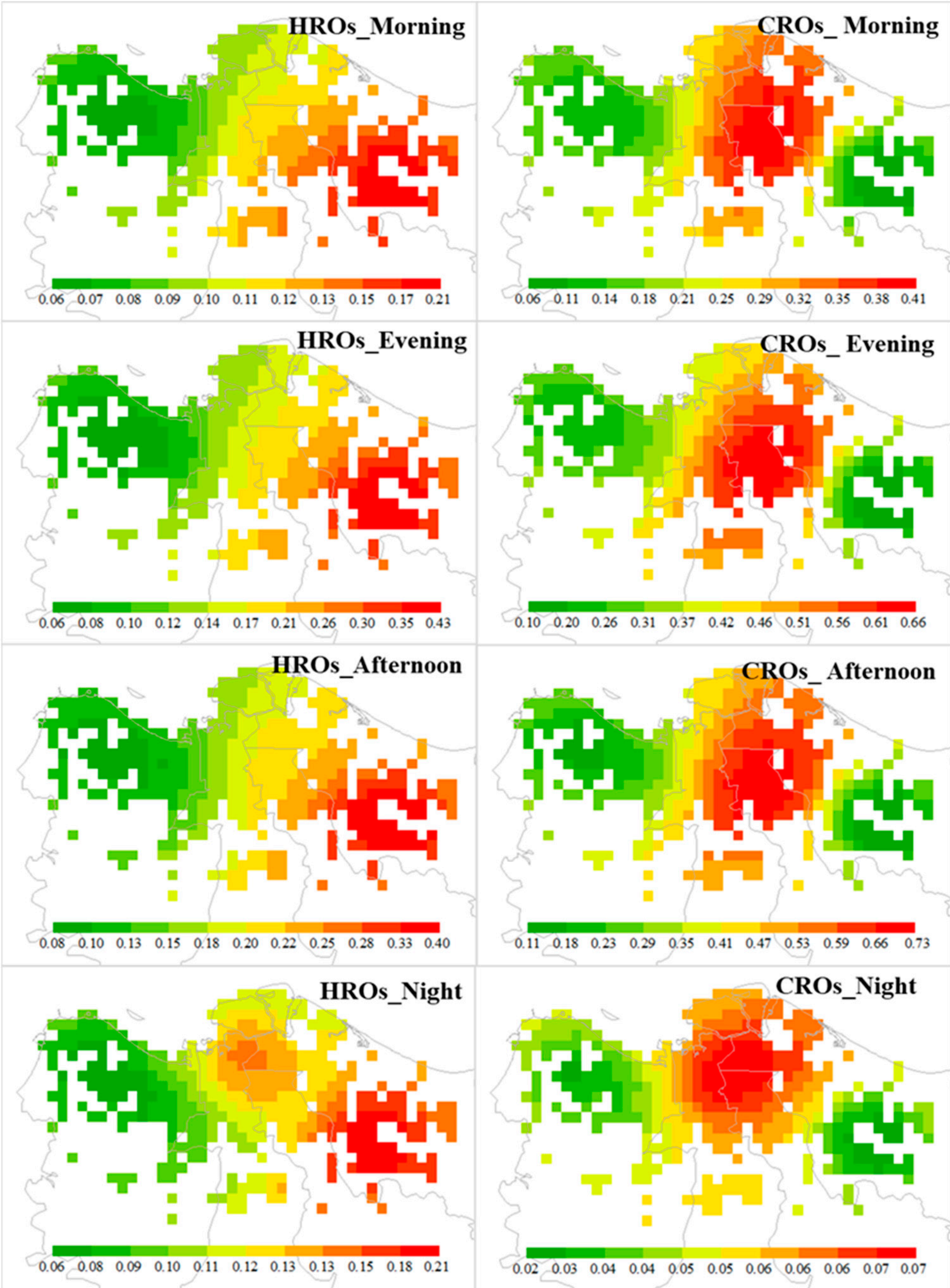

Figure 8. Coefficient estimates of transportation facilities.

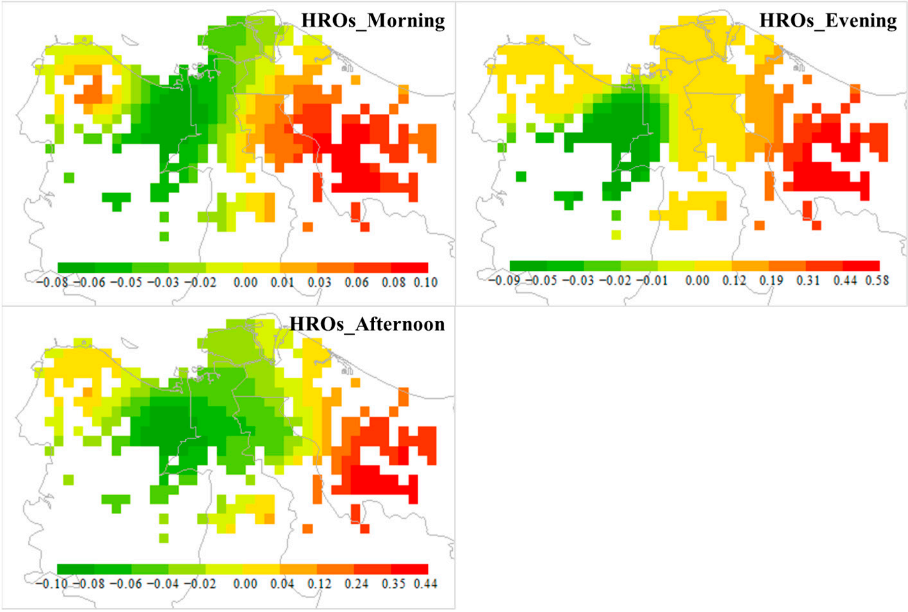

Figure 9. Coefficient estimates of tourist attractions.

7. Conclusions

This study examined the spatiotemporal variation of HROs and CROs for ride-hailing services in Haikou, China using the order data of Didi Chuxing integrated with various built environment variables. OLS and GWR models were established to investigate the factors that affected the densities of HROs and CROs during different time periods, such as morning, evening, afternoon and night. The OLS models show that factors including road density, average travel time rate, companies and enterprises and transportation facilities had significant impacts on HROs and CROs for most periods. The results of the GWR models were consistent with the global regression results and provided detailed information about the spatial variation of the built environment's impact.

The important conclusions are as follows. The primary road density had a positive association with the density of CROs for most periods, while the secondary road density could significantly promote the density of HROs for four periods, and this positive effect was more evident near the core area and Meilan Airport. The increase in the average travel time rate could promote the density of CROs for most periods, and this positive effect was greater in the peripheral area in the morning, while the effect was higher in the core area in the evening, which could be explained by the flow direction of the commuter travel of residents. By contrast, this variable was negatively associated with the density of HROs, especially in the morning period. In addition, the number of transportation facilities was correlated with higher densities of HROs and CROs for four periods, and the coefficient estimations had the greatest effect in the area near Meilan Airport for HROs and had the strongest impact in the core area for CROs.

The current paper is not without limitations. Further research is needed to fill the following gaps. First, the order data of ride-hailing services were used to analyze the travel characteristics of HROs. Future research can further explore this subject combined with GPS trajectory data. Second, this study adopted a grid cell structure (1 km $\times$ 1 km) to divide the study area into different spatial units to aggregate the order records in space. In the future, we can utilize traffic analysis zones (which are usually constructed based on the road network, socioeconomic factors, administrative division and natural barriers, such as railways and rivers) for aggregation if we can obtain them. Third, this study considered some spatial factors that affected the demand density. The influence of other factors such as travel purposes and job–housing balance can also be explored. Finally, multiscale geographically weighted regression (MGWR) can be further applied to examine the implications and interpretation of the spatial scales of the factors affecting HROs and CROs [51].

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Model results of HROs_Morning.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Secondary roads density	0.138	0.421	0.274	0.263	0.243 ***	1.095
Tertiary roads density	−0.001	0.402	0.205	0.196	0.141 **	1.310
Average travel time rate	−0.205	0.035	−0.083	−0.078	−0.066 *	1.245
Tourist attractions	−0.083	0.100	0.002	−0.006	−0.021 *	1.634
Companies and enterprises	−0.015	0.005	−0.002	−0.002	−0.004 *	2.369
Shopping facilities	−0.020	0.009	−0.009	−0.010	−0.007 *	3.447
Financial and insurance services	−0.015	0.100	0.062	0.062	0.061 ***	4.248
Transportation facilities	0.062	0.207	0.112	0.106	0.111 ***	6.997
Sports facilities	−0.056	0.072	0.055	0.065	0.055 ***	5.587
Medical and health service facilities	0.046	0.212	0.087	0.085	0.079 ***	3.937
Government offices	−0.029	−0.001	−0.019	−0.021	−0.02 ***	3.431

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A2. Model results of CROs_Morning.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Primary roads density	−0.133	0.437	0.173	0.162	0.12 *	1.103
Average travel time rate	0.160	1.046	0.594	0.607	0.615 **	1.256
Companies and enterprises	−0.072	0.033	−0.024	−0.027	−0.021 *	2.380
Financial and insurance services	0.066	0.422	0.194	0.179	0.207 ***	3.773
Transportation facilities	0.063	0.414	0.245	0.247	0.232 ***	5.655
Commercial residences	0.082	0.351	0.221	0.226	0.212 ***	3.997
Medical and health service facilities	0.132	0.542	0.415	0.425	0.462 ***	3.365

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A3. Model results of HROs_Evening.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Secondary roads density	0.128	0.667	0.389	0.370	0.385 ***	1.118
Average travel time rate	−0.448	0.354	0.005	0.025	−0.111 *	1.292
Tourist attractions	−0.091	0.576	0.100	0.045	0.089 *	1.539
Companies and enterprises	−0.035	0.010	−0.014	−0.014	−0.015 *	2.473
Financial and insurance services	−0.073	0.157	0.098	0.115	0.107 ***	3.978
Transportation facilities	0.061	0.430	0.176	0.156	0.173 ***	6.997
Commercial residences	−0.091	0.018	−0.046	−0.050	−0.051 **	4.144
Sports facilities	−0.161	0.136	0.077	0.103	0.077 ***	4.923
Government offices	−0.039	−0.007	−0.029	−0.029	−0.029 ***	3.119

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A4. Model results of CROs_Evening.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Primary roads density	−0.474	0.611	0.046	0.045	0.078 *	1.102
Average travel time rate	0.119	3.715	1.385	1.259	0.997 **	1.266
Companies and enterprises	−0.130	0.115	−0.057	−0.083	−0.048 *	2.207
Shopping facilities	0.009	0.116	0.082	0.086	0.094 ***	2.086
Financial and insurance services	0.214	0.657	0.405	0.389	0.421 ***	3.820
Transportation facilities	0.103	0.663	0.409	0.419	0.392 ***	4.398

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A5. Model results of HROs_Afternoon.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Secondary roads density	0.127	0.755	0.427	0.398	0.423 ***	1.116
Tourist attractions	−0.104	0.436	0.024	−0.025	0.027 *	1.539
Companies and enterprises	−0.044	−0.009	−0.020	−0.017	−0.023 *	2.428
Financial and insurance services	−0.044	0.190	0.130	0.141	0.141 ***	3.975
Transportation facilities	0.077	0.398	0.192	0.188	0.186 ***	6.964
Commercial residences	−0.082	0.070	−0.023	−0.028	−0.032 *	4.069
Sports facilities	−0.224	0.127	0.075	0.097	0.082 ***	4.905
Government offices	−0.037	0.027	−0.026	−0.030	−0.03 ***	3.109

Note: *** significance of 1%; * significance of 10%. Coef. stands for coefficient.

Table A6. Model results of CROs_Afternoon.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Primary roads density	−0.349	0.552	0.165	0.171	0.119 *	1.116
Average travel time rate	0.345	4.253	1.500	1.193	1.209 ***	1.301
Companies and enterprises	−0.141	0.006	−0.085	−0.098	−0.082 **	2.439
Shopping facilities	0.008	0.106	0.072	0.073	0.089 ***	2.101
Financial and insurance services	0.170	0.665	0.361	0.336	0.386 ***	3.827
Transportation facilities	0.106	0.725	0.412	0.421	0.387 ***	5.563
Commercial residences	−0.046	0.387	0.134	0.145	0.118 ***	3.613

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A7. Model results of HROs_Night.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Secondary roads density	0.043	0.915	0.238	0.188	0.224 ***	1.095
POI diversity	−1.918	−0.381	−0.946	−0.867	−0.852 **	1.387
Shopping facilities	−0.001	0.033	0.016	0.014	0.016 ***	2.010
Transportation facilities	0.062	0.212	0.118	0.120	0.113 ***	3.069
Government offices	−0.049	0.001	−0.011	−0.009	−0.01 *	2.693

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

Table A8. Model results of CROs_Night.

Variable	GWR				OLS	
	Min	Max	Mean	Median	Coef.	VIF
Secondary roads density	0.019	0.282	0.110	0.091	0.088 **	1.115
Tertiary roads density	−0.040	0.232	0.103	0.124	0.078 **	1.365
POI diversity	−1.284	−0.237	−0.611	−0.534	−0.492 ***	1.535
Tourist attractions	−0.164	0.029	−0.041	−0.025	−0.06 *	1.595
Shopping facilities	0.007	0.016	0.012	0.012	0.013 ***	3.349
Transportation facilities	0.022	0.070	0.052	0.054	0.053 ***	4.791
Sports facilities	−0.018	0.007	−0.007	−0.009	−0.01 *	5.495
Medical and health service facilities	−0.029	0.056	−0.003	−0.010	−0.001 *	3.462

Note: *** significance of 1%; ** significance of 5%; * significance of 10%. Coef. stands for coefficient.

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