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Understanding the Dynamics of the Pick-Up and Drop-Off Locations of Taxicabs in the Context of a Subsidy War among E-Hailing Apps

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Abstract: The locations where taxicabs pick up and drop off passengers are crucial to understanding the dynamics of taxi trip demand. Investigating their spatial distribution and derived dynamic features is still a key task in the fields of urban geography and transportation. Such investigations are urgently needed, considering the competition created by new communication technology services, specifically e-hailing apps such as Uber, Didi and Kuaidi. For example, a subsidy war between two e-hailing apps occurred in China in 2014. However, how the pick-up and drop-off locations of taxicabs change during subsidy wars is still an open question. This paper introduces a methodological framework that can be used to derive the pick-up and drop-off dynamics of taxicabs. It also proposes three indexes that can be used to assess the dynamics of the pick-up and drop-off locations at the city and sub-district scales, namely the numbers of daily pick ups and drop offs per taxi, average transfer distance per unit area of weighted mean centers of pick-up and drop-off locations, and degree of dispersion in the spatial distribution of pick-up and drop-off locations. This paper employs data from taxicabs in the city of Shenzhen to uncover the dynamics of their pick-up and drop-off locations. The results show that the methodological framework and the indexes introduced are powerful tools for uncovering the dynamics of the pick-up and drop-off locations of taxicabs in urban environments.

Keywords: taxi trajectory mining; human dynamics; spatial pattern; subsidy war; e-hailing service

1. Introduction

Taxicabs represent a significant transportation mode in urban areas because they offer flexible and uninterrupted door-to-door service [1]. The difficulty of hailing taxis has always been an intractable problem in many Chinese cities (i.e., Beijing, Shanghai). The limited willingness of taxi drivers to serve during shift-operation scheduling, as well as the non-equilibrium and sporadic nature of passenger demand for taxis, make taxi services unacceptable to urban residents. Recently, e-hailing services (i.e., Didi, Kuaidi and Uber) have begun to connect passengers and taxi drivers directly using communication technology. These e-hailing services offer convenient passenger-to-taxi booking services and improve the quality of urban taxi services. Moreover, competition among e-hailing service companies triggered a subsidy war from January to August 2014 in China. The different services gave promotion fees to taxi drivers for serving passengers who use the same app. At the same time, they gave bonuses to passengers to encourage them to use their e-hailing apps. How the pick-up and drop-off locations of taxicabs change in a subsidy war is of interest to taxi regulators and e-hailing service companies. Such insights are helpful in developing future passenger-attraction plans that are intended to improve taxi services in their cities and earn money.

Several factors contribute to the dynamics of pick-up and drop-off locations, or transport demand; for example, demographics, commercial activity, transport options, land use, demand management, and prices [2]. However, consumption is affected by prices, the direct, perceived costs of using a good [2]. The law of demand states that although, individually, decisions on consumption behavior may seem variable, in aggregate people tend to follow a predictable pattern: price reductions usually increase consumption, and when prices increase, consumption declines [3]. Transport activities present this pattern as well; namely, when transport prices decrease, mobility tends to increase, and when prices increase, mobility decreases [2]. Based on this theory, a subsidy war creating a fluctuation in taxi fees which affects transport demand should be recognized as a primary factor. This factor could be validated by the growth rate (559.4%) of the users of the e-hailing service in China in 2014 in the context of the huge subsidy provided by Didi and Kuaidi [4].

To make sustainable future passenger-attraction plans, including e-hailing services, it is essential to understand the change dynamics of taxi trip demand, the stability of taxi trip demand dynamics, and the local effectiveness dynamics under these plans, because the change dynamics and stability dynamics of taxi trip demand influence plans, and the local effectiveness dynamics affect plans at different local spatial units. However, how the pick-up and drop-off locations of taxicabs change to form these three kinds of dynamics during periods of subsidy wars has yet to be investigated in depth. To investigate this question, this paper proposes a methodology that can be used to understand the dynamics of the pick-up and drop-off locations of taxicabs in the context of a subsidy war among e-hailing apps. This paper introduces a methodological framework that can extract taxi pick-up and drop-off locations from the original trajectories, including empty and occupied trips of taxicabs equipped with global positioning systems. It also proposes three indexes that can be used to help assess the dynamics of the pick-up and drop-off locations of taxicabs on the city and sub-district scales, namely the numbers of daily pick ups and drop offs per taxi, average transfer distance per unit area of weighted mean centers of pick-up and drop-off locations, and degree of dispersion in the spatial distribution of pick-up and drop-off locations. Based on these indexes, this paper provides answers to three specific questions about the dynamics of the pick-up and drop-off locations of taxicabs, which are as follows:

(1) Was the spatial pattern of pick-up and drop-off locations significantly influenced by the subsidy war? For example, increases or decreases in the number of pick-up and drop-off locations during different periods of the subsidy war. The answer to this question can help us understand the change dynamics of taxi trip demand for each divided cells and sub-district.
(2) Was the spatial distribution of the pick-up and drop-off locations within the different sub-districts stable or unstable during the subsidy war? The answer to this question can help us estimate the stability of taxi trip demand dynamics by subsidy policies.
(3) To what extent do the pick-up and drop-off locations become disperse or clustered at the sub-district and city scales during the subsidy war? The answer to this question can help us investigate the local effectiveness dynamics of subsidy policies.

The remainder of this paper proceeds as follows: Section 2 reviews the literatures on taxi trajectory mining, policy investigations on taxicabs, and investigations on subsidy wars among e-hailing services. Section 3 presents a methodological framework that can be used to derive and measure the pick-up and drop-off dynamics of taxicabs. Section 4 analyzes the results and discusses the dynamics identified. Lastly, Section 5 concludes the paper and suggests directions for future study.

2. Related Work

2.1. Taxi Trajectory Mining

Many studies have mined massive taxi trajectory data in the context of identifying mobility patterns, models, the dynamics of behavior or activities, and spatial structures and interactions. First, researchers have used taxi trajectories to identify simple, reproducible patterns [5]. For example, the travel displacements of taxis in urban areas tend to follow an exponential distribution instead of a power-law distribution [6–10]. Other distributions that have been identified include power-law distributions of the running time interval [11], the spatial mobility distance [12], a mixed function of an exponential power law and a truncated Pareto distribution of travel time [13], and a distribution describing the directional anisotropy of human mobility in urban settings [6]. In addition to these distributions, Kang and Qin [14] identified a set of high-level statistical features of the spatial operation of taxicabs in Wuhan by using a non-negative matrix factorization method. Zhang et al. [15] investigated intra-urban taxi mobility using taxi trajectory data collected in Harbin and proposed a movement-based kernel density estimation method to estimate the service ranges of taxicabs.

Second, several researchers have used taxi trajectories to understand the behavioral characteristics of residents and the spatiotemporal distributions of human activities, such as the spatiotemporal distribution of taxicab pick ups and drop offs [16–18], the distribution of trajectories and urban dynamics [19–23]. They have also analyzed the factors that influence the pick up and drop off of taxicab passengers using a geographical weighted regression model [18]; identified the spatiotemporal development of urban activity patterns [24]; uncovered the behavior patterns of cabdrivers and the differences in the behavior of top drivers and ordinary drivers, as categorized using their daily income [25]; and identified events in spatiotemporal trajectory data automatically [26].

Third, researchers have used taxicab trajectories to examine land-use types, reflect the spatial structure of urban areas, and examine the interactions between residents and functional zones. Such approaches have been used in, for example, accessibility analysis of urban road networks [27,28], mining alternative space–time path dynamics of travel [29], mining hotspots and points of interest in urban areas [30–32], determining the spatiotemporal attractiveness of specific areas [33,34], detection and analysis of functional regions [35–37], classification of land-use types [38,39], analysis of the structure of urban regions [40–43], observing strong links between public transportation terminals [44], evaluating the effectiveness of urban planning after it has been carried out [45], identifying the spatiotemporal patterns of functionally critical locations in urban transportation networks [46], and locating optimal taxi stands on city maps using pick-up and drop-off locations in Singapore [47].

The taxi trajectory-mining approaches used to investigate the three aspects listed above reveal the spatial dynamic characteristics of urban taxicabs. The existing studies can be extended to investigate the effects of market and regulatory policies on the trip demands or behavior of taxicabs.

2.2. Investigations of Taxicab Policies

Researchers have attempted to investigate the effects of market and regulatory policies on taxicab drivers and their behavior, as well as demand for taxis. In terms of market policies, Wen et al. [48] investigated the effects of subsidy wars among e-hailing services by investigating whether or not it is better to give subsidies (bonuses or promotions) to taxi drivers or passengers in order to alleviate the difficulties associated with hailing taxis. Other researchers compared the degree of capacity utilization of UberX drivers and taxi drivers [49], analyzed the behavior of driver-partners working with Uber based on both survey data and administrative data [50], and explored ride-sourcing services in San Francisco by comparing them with traditional taxi services to analyze their impact on the use of public transit and overall vehicle travel [51].

In terms of regulatory policies, a nested logit model was used to predict the taxi-hailing behavior of customers [52]. This model was then used to analyze potential taxi policies that enhance the utilization rate of taxi stands and introduce additional taxi stands in different districts and regions. The optimal routing policy in Singapore changed taxi queuing and the behavior of cabdrivers simultaneously [53]. In addition, many regulatory policies affecting taxi fares and the wages of taxi drivers have been implemented or investigated. Examples include the incremental discount policy used in Japan [54]; the fare reduction policy of Haifa, Israel [55]; the fare policy of New York [56]; government regulations [57]; the pricing policy used to manage transportation demand in

Tehran [58]; the transport policy act implemented in 1989 in Sweden that deregulated the Swedish taxicab industry [59]; the sustainability-oriented transport policy used in Spain [60] to reduce the supply of transport that increased fares and implemented subsidization and privatization policies on the wages of taxi drivers [61]; taxi licensing policies [62,63]; and the deregulation of the taxi sector in Ireland [64].

The easy collection of massive trajectory data from taxicabs indicates that investigations of taxi policy have considerable prospects of success. Taxi trajectory data-mining approaches can be used to improve the assessment process used in policy-making regarding the taxi industry and services. This paper attempts to investigate the dynamics of the pick-up and drop-off locations of taxicabs during a subsidy war, which is a necessary first step for taxi regulators and e-hailing service companies to assess their market and regulatory policies.

2.3. Investigations of the Subsidy War among E-Hailing Services

Several studies have investigated the effects of subsidy wars among e-hailing services from two perspectives. The first perspective investigates whether it is better to give subsidies (i.e., bonuses or promotions) to taxi drivers or passengers in order to alleviate the problems associated with hailing taxis. Wen et al. [48] found that these problems would not be alleviated if subsidies were given to passengers, whereas they would be alleviated if subsidies were given to taxi drivers. The second perspective investigates the number of trips taken by taxicabs, the distance they travel and their idle time, as well as the distribution of hot spots of pick-up and drop-off locations. Leng et al. [65] came to three conclusions on these subjects. Specifically, (1) the average number of trips increases, and the idle time becomes shorter, when taxi service data collected during a period with subsidies are compared with a period without subsidies; (2) a boom in short-distance trips occurs, whereas the distribution of long-distance trips is unchanged, in the period with subsidies; (3) the distribution of pick-up and drop-off locations does not change significantly in the period with subsidies. However, how the pick-up and drop-off locations of taxicabs change during periods when subsidy wars are conducted has yet to be investigated in depth. Examples of such changes involve increases and decreases in the number of pick-up and drop-off locations and the aggregated patterns of spatial and temporal dispersion features among these locations. These aspects can assist in understanding the spatial dynamics of taxi demand and thus contribute to evaluating the effects of subsidies on the spatial variations in taxi trip demand.

3. Methodology

This section introduces the framework of the proposed method and three indexes for measuring pick-up and drop-off dynamics. These three indexes are the numbers of daily pick-ups and drop-offs per taxi, average transfer distance per unit area of weighted mean centers of pick-up and drop-off locations, and degree of dispersion in the spatial distribution of pick-up and drop-off locations.

3.1. Framework of the Method

Figure 1 shows the framework of the introduced method, which is used to understand the dynamics of the pick-up and drop-off locations of taxicabs in the context of a subsidy war among e-hailing apps. Taxi trajectory data records service status information of each taxicab as vacant or occupied, which can be denoted as 0 and 1 respectively. Here, 0 means the taxicab is not serving a passenger, whereas 1 means the taxicab is serving a passenger. Therefore, the service status information (0 or 1) can be used to identify the pick-up and drop-off locations. When the service status in trajectory data changes from 0 to 1, it represents pick-up behavior; by contrast, when the status changes from 1 to 0, this indicates drop-off behavior. To investigate the entire process of change during the subsidy war, this paper divides the whole affected time period into several periods, according to the varying subsidy policies available to taxi drivers or passengers. Additionally, to investigate the spatial dynamics of pick-up and drop-off locations, this paper divides the whole study area into equally sized 500 m × 500 m grid cells. These cells represent the minimum spatial units that are used to identify the spatial dynamic patterns in sub-districts and cities. According to the temporal and spatial divisions, this paper identifies the increase or decrease in the number of pick ups and drop offs in each cell and for each period. Based on the resulting number of pick ups and drop offs in each cell, this paper uncovers the dynamics of the pick-up and drop-off locations of taxicabs on the city and sub-district scales. Three indexes, including the numbers of daily pick ups and drop offs per taxi, average transfer distance per unit area of weighted mean centers of pick-up and drop-off locations, and degree of dispersion in the spatial distribution of pick-up and drop-off locations, are defined in the following section. The first index, namely the numbers of daily pick ups and drop offs per taxi, is used to uncover the spatial distribution of the locations where taxicabs pick up or drop off passengers. The second and third indexes extend the analysis of spatial distribution in two aspects, that is, the stability of the derived spatial distribution in different neighboring periods, and the pattern of spatial dispersion of the locations of increases or decreases in the number of pick ups and drop offs. The results of these three analyses uncover the dynamics of the pick-up and drop-off locations in the context of a subsidy war among e-hailing apps.

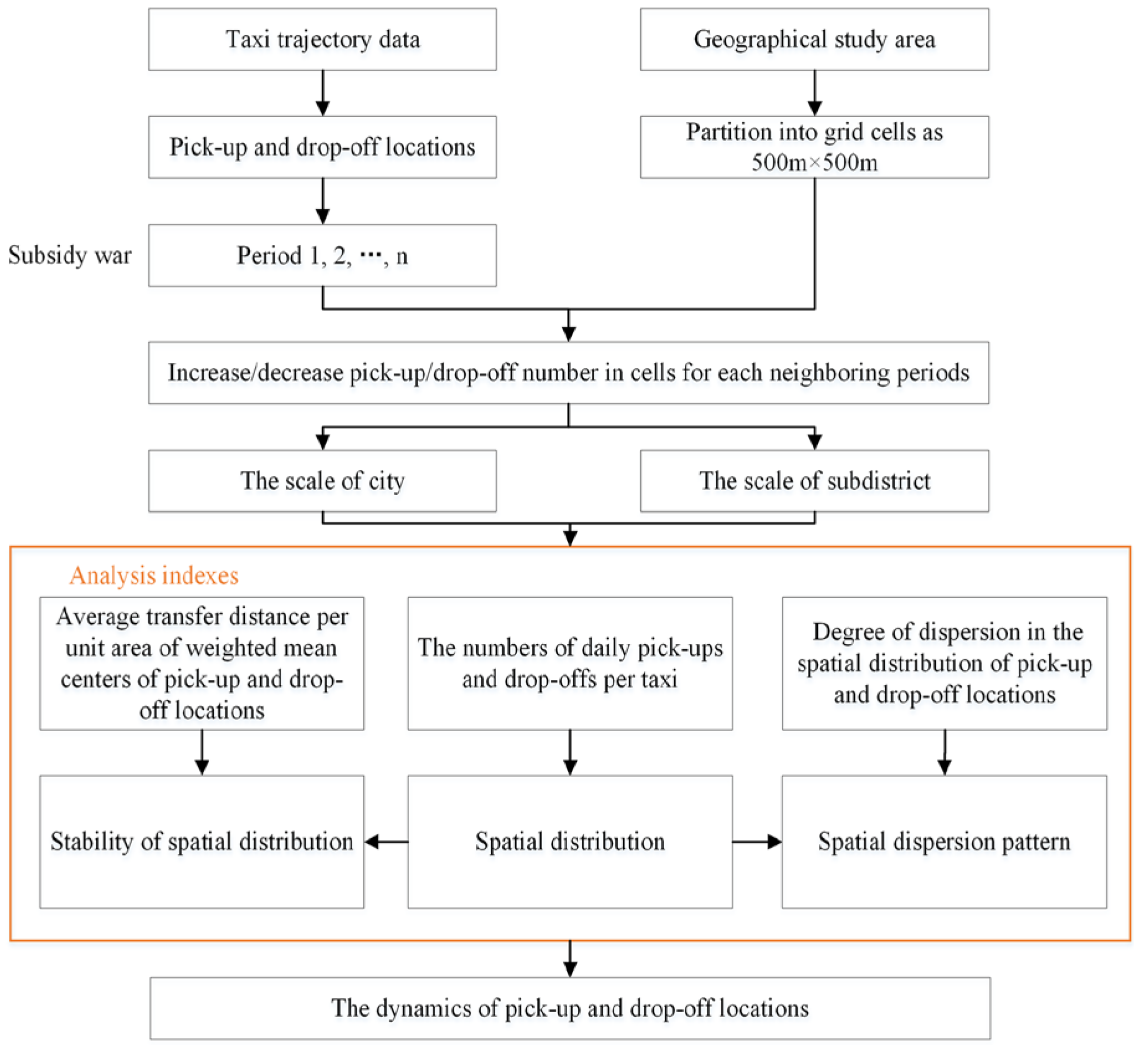


Figure 1. The introduced methodological framework.

3.2. *Spatial Measurements of Taxi Pick-Up and Drop-Off Locations*

This section introduces three indexes that measure the pick-up and drop-off dynamics of taxicabs and introduces the visualization methods of pick-up and drop-off dynamics.

3.2.1. The Number of Daily Pick-Ups and Drop-Offs per Taxi

The first indicator is the number of daily pick ups and drop offs per taxi within a specific spatial unit, such as a cell. This indicator represents the demand for taxi travel in the corresponding urban area. The pick-up location means the origin of a taxicab trip, and the drop-off location means the destination of a taxicab trip. Therefore, the increase or decrease in the number of pick-ups and drop-offs by taxicabs within individual cells indicates the dynamics of the demand for taxi trips among them. It is noteworthy that the numbers of taxicabs in these divided periods are not identical. In order to eliminate the effect of different numbers of taxicabs on the dynamics of pick-up and drop-off locations, this paper uses the numbers of daily pick ups and drop offs per taxi rather than directly using the numbers of pick ups and drop offs. The indicator can be calculated as follows:

$$w = \frac{w_s}{N_{car} N_{day}} \tag{1}$$

where w denotes the numbers of daily pick-ups and drop-offs per taxi, w_s denotes the numbers of pick-ups and drop-offs, N_{car} denotes the number of taxicabs in a specific period of subsidy war, and N_{day} denotes the sampling days of a period in subsidy war.

3.2.2. Average Transfer Distance per Unit Area of Weighted Mean Centers of Pick-Up and Drop-Off Locations

The second indicator is the average transfer distance per unit area of weighted mean centers between each two neighboring periods. This indicator measures the stability of the spatial distribution of cells in terms of the increase or decrease of the numbers of pick ups or drop offs in individual cells. A taxi pick-up or drop-off mean center is the average location of all cells where the taxi has ever picked up or dropped off passengers. Considering that cells with higher visiting frequency should make crucial contributions to the mean center of pick-up or drop-off events, we measure the visiting frequency of each cell as a weight to calculate the weighted mean center:

$$\overline{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

$$\overline{y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{3}$$

where $\overline{x}$ and $\overline{y}$ denote the coordinates of the weighted mean center, x_i and y_i denote the coordinates of the geometric center of a cell which contains an increase or decrease in the number of pick ups or drop offs, n denotes the number of cells within an analysis area, and w_i denotes the weight of the cell, which is assigned according to the increase or decrease in the number of daily pick ups or drop offs per taxi occurring within the cell.

The weighted mean center within an analysis area during any period of a subsidy war is represented as $(\overline{x_t}, \overline{y_t})$. When all of the weighted mean centers $(\overline{x_1}, \overline{y_1}), \ldots, (\overline{x_t}, \overline{y_t})$ are connected among each two neighboring periods, a path of weighted mean centers $P = \{(\overline{x_1}, \overline{y_1}), \ldots, (\overline{x_t}, \overline{y_t})\}$ is created. The mean of the transfer distances per unit area of the weighted mean centers in every analysis area among all of the neighboring periods during the subsidy war can be calculated by:

$$\overline{d} = \frac{1}{A} \cdot \frac{1}{m-1} \cdot \sum_{j=1}^{m-1} d_{j,j+1} \tag{4}$$

$$d_{j,j+1} = \sqrt{(\overline{x}_j - \overline{x}_{j+1})^2 + (\overline{y}_j - \overline{y}_{j+1})^2} \tag{5}$$

where $\overline{d}$ denotes the average transfer distance per unit area of weighted mean centers, $d_{j,j+1}$ represents the transfer distance between the weighted mean centers $(\overline{x}_j, \overline{y}_j)$ of period j and $(\overline{x}_{j+1}, \overline{y}_{j+1})$ of period $j+1$, A denotes the area of the analysis area, and m denotes the count of weighted mean centers within the analysis area. A higher value of the average transfer distance per unit area of weighted mean centers indicates a less stability of the spatial distribution of cells.

3.2.3. Degree of Dispersion in the Spatial Distribution of Pick-Up and Drop-Off Locations

The third indicator is the weighted nearest neighbor index (*WNNI*), which is an extension of the nearest neighbor index (NNI). The NNI was proposed by Clark and Evans [66] and it provides a precise measure of the spatial distribution of a pattern. This index indicates whether a pattern is regularly dispersed, randomly dispersed, or clustered. In NNI, all of the sample points have equal weights. However, cells with higher visiting frequency should make more significant contributions to the degree of dispersion in the spatial distribution of pick-up and drop-off locations. Thus, this paper extends the NNI to the *WNNI* in order to assess the spatial distributions of the patterns of the increases and decreases in pick ups and drop offs. In calculating the *WNNI*, the weight of each sample point represents the count of pick ups or drop offs in the corresponding cell. The *WNNI* is thus defined as:

$$R_{WNNI} = \frac{d_o}{d_r} \tag{6}$$

$$d_o = \frac{\sum_{i=1}^{n} w_i d_i}{\sum_{i=1}^{n} w_i} \tag{7}$$

$$d_r = \frac{1}{2}\sqrt{\frac{a}{n}} \tag{8}$$

where R_{WNNI} is the *WNNI* value, d_o represents the mean observed nearest neighbor distance, d_r denotes the mean expected nearest neighbor distance, d_i is the distance between cell i and its nearest neighbor cell, w_i represents the increase or decrease in the number of pick ups or drop offs in cell i, a is the area of an analysis area, and n is the number of cells within an analysis area. The distance used here is the Euclidean distance between the geometric centers of the cells. When the *WNNI* is equal to 0, the pattern of sample points is totally clustered, which means that all of the points are gathered at one point. When 0 < *WNNI* < 1, the pattern is clustered. When the *WNNI* is equal to 1, the pattern is randomly dispersed. When *WNNI* > 1, the pattern is regularly dispersed. Therefore, the *WNNI* also provides a precise measure of the spatial distribution of patterns, and enables determination of whether these patterns are regularly dispersed, randomly dispersed, or clustered.

3.2.4. Visualization Methods of Pick-Up and Drop-Off Dynamics

In this paper, the study area is partitioned into 500 m $\times$ 500 m grids. For each grid, the number of daily pick ups and drop offs per taxi was computed based on Equation (1). Each grid is rendered according to this value. Finally, a heatmap is drawn to depict the spatial distribution of pick-up and drop-off locations.

In order to visualize the change in spatial distribution of pick-up and drop-off locations between each two neighboring periods in a subsidy war, for each grid this paper subtracts the number of daily pick ups or drop offs per taxi of the last period from the current period value to obtain the difference map. In this way, this paper is able to investigate the change patterns of the number and the spatial distribution of pick-up and drop-off locations.

4. Results

4.1. Subsidy War and Experimental Data

In China, a subsidy war among taxi e-hailing apps (i.e., Didi and Kuaidi) occurred in 2014. Based on the different subsidy policies available to drivers and passengers, this paper divides the whole time period of the subsidy war into six sub-periods, which are listed in Table 1. In the first period, that is, before 9 January, there was no subsidy on cabdrivers or passengers. During the second period (10–16 January), the subsidy war had just begun, and the subsidy for both cabdrivers and passengers was 10 RMB yuan. The third stage extended from 17 February–4 March, which was a peak period in the subsidy war. The e-hailing apps provided the highest subsidies during this period. The subsidy ranged from 10 to 20 yuan for passengers. Moreover, new drivers using Didi could receive an additional 50 RMB yuan. The fourth stage extended from 22 March to 16 May. Cabdrivers still received higher subsidies; however, passengers received lower amounts. During the fifth stage, which extended from 17 May to 8 July, both e-hailing apps canceled the subsidies for passengers; however, cabdrivers still received some subsidies. Finally, neither of these apps provided subsidies for anyone after 10 August.

Table 1. Subsidy policies in different periods during the subsidy war (unit: RMB Yuan).

Period	Duration	Didi		Kuaidi	
		Driver	Passenger	Driver	Passenger
1	Before 9 January	0	0	0	0
2	10 January–16 February	10	10	10	10
3	17 February–4 March	10 (50 for new user)	10–20	5–11	10–13
4	22 March–16 May	10	3–5	5–11	3–5
5	17 May–8 July	10	0	5–11	0
6	After 10 August	0	0	0	0

There is an obvious difference in human travel patterns between holidays and non-holidays. In addition, bad weather also greatly affects the demand for taxi services. In order to reduce the influence of such factors, holidays and bad-weather days are excluded in our datasets. This paper only focuses on working days. It is noteworthy that the third period has only 12 working days after excluding holidays, weekends and bad-weather days. In order to keep the sampling days all equal, 12 working days are filtered out for other periods correspondingly. Eventually, 23–27, 30, 31 December in 2013 and 2, 3, 6, 8 and 9 January in 2014 were selected for the first period; 20, 21, and 23, 24, 27–29 January and 10–14 February were chosen for the second period; 17–21, 24–28 February and 3, 4 March were chosen for the third period; 24–28 March and 4, 9, 10, 16, 17, 21, and 22 April were selected for the fourth period; 26, 27, and 29 May and 3–5, 11–13, and 26, 27, 30 June were chosen for the fifth period; and 11, 15, 18, 21, 25, 26, and 29 August and 2, 3, 9, 10, and 18 September were selected for the sixth period. This paper uses Periods 1, 2, 3, 4, 5, and 6 to represent the six periods, respectively.

To investigate the pick-up and drop-off dynamics of taxicabs, this paper collected the trajectories of taxicabs that operated in the city of Shenzhen, China, during Periods 1, 2, 3, 4, 5, and 6. All of these taxicabs operated continuously, performing pick ups and drop offs during every single day of the study period. Each record includes the spatial location (i.e., longitude and latitude), timestamp, operation status (i.e., vacant or occupied), driving direction and velocity of a taxicab. For this paper, the plate number, start time and end time, and pick-up and drop-off locations of taxi trips that make up these collected trajectories, were collected. This information was used to analyze the pattern of the increases or decreases in pick ups and drop offs and the aggregated patterns of spatial and temporal dispersion features among these locations.

Figure 2 shows the 58 official administrative sub-districts in the city of Shenzhen. Each sub-district is given a unique ID to assist in analyzing the aggregated dynamic patterns. To understand the spatial variations in pick-up and drop-off locations on the scale of the city as a whole, this study partitioned the study area into 8232 cells of 500 m × 500 m. These cells were used as the minimum statistical unit. These patterns were then aggregated into each sub-district unit.

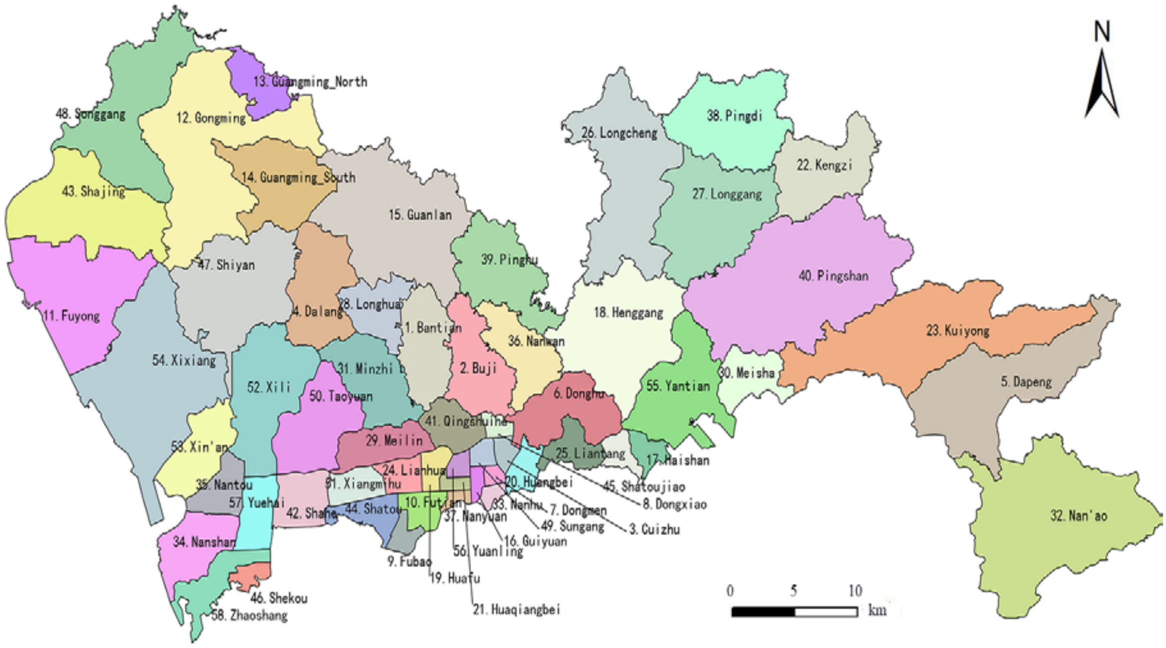
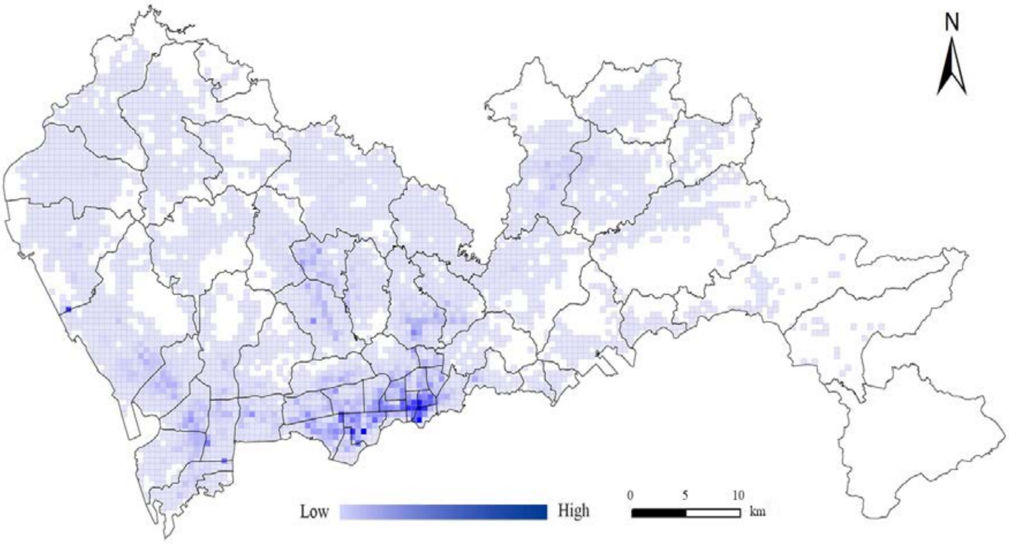


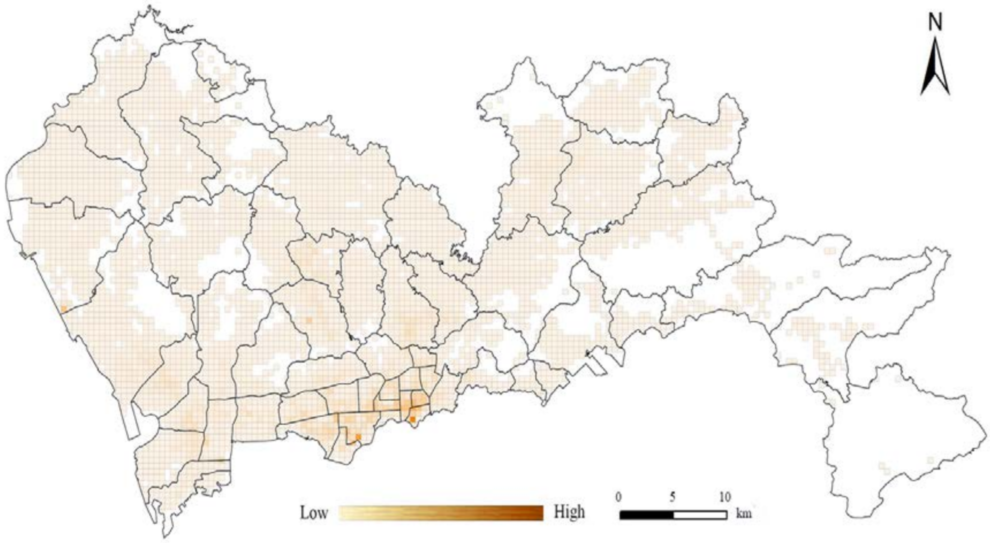
Figure 2. Official administrative sub-districts in the city of Shenzhen, China.

4.2. Spatial Distribution of Pick-Up and Drop-Off Locations

This study analyzed the spatial distribution of pick-up and drop-off locations on the cell and sub-district scales. At the scale of cells, Figure 3a,b illustrate the spatial distribution of pick-up and drop-off locations in Period 1, respectively. Each cell has a value of the numbers of daily pick ups or drop offs per taxi which is derived from Equation (1). The numbers of taxicabs in the six periods are as follows: 12,700, 12,327, 12,188, 12,299, 12,031, and 12,255. Even though the numbers of taxicabs are different in the six periods, the indicator of the numbers of daily pick ups and drop offs per taxi could eliminate the probable influence of this. Since there are no obvious differences among the heatmaps of the six periods, we only present the heatmap of Period 1. The similarity among the heatmaps of the six periods indicate that the pick-up and drop-off areas within the study area do not change significantly during the six periods. These heatmaps represent the taxi trip demand in terms of pick-up and drop-off locations. The spatial distribution patterns shown in the heatmaps indicate that the taxi trip demand was not significantly influenced by the subsidy war.



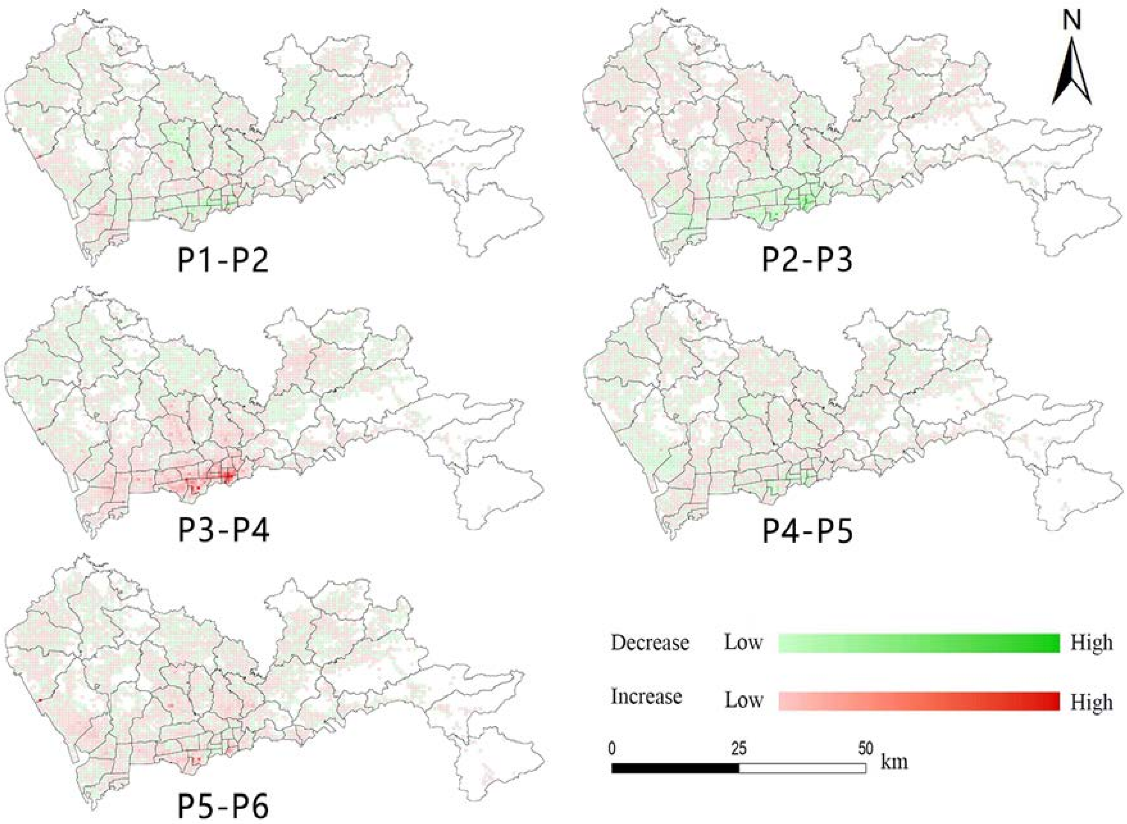
(**a**)



(**b**)

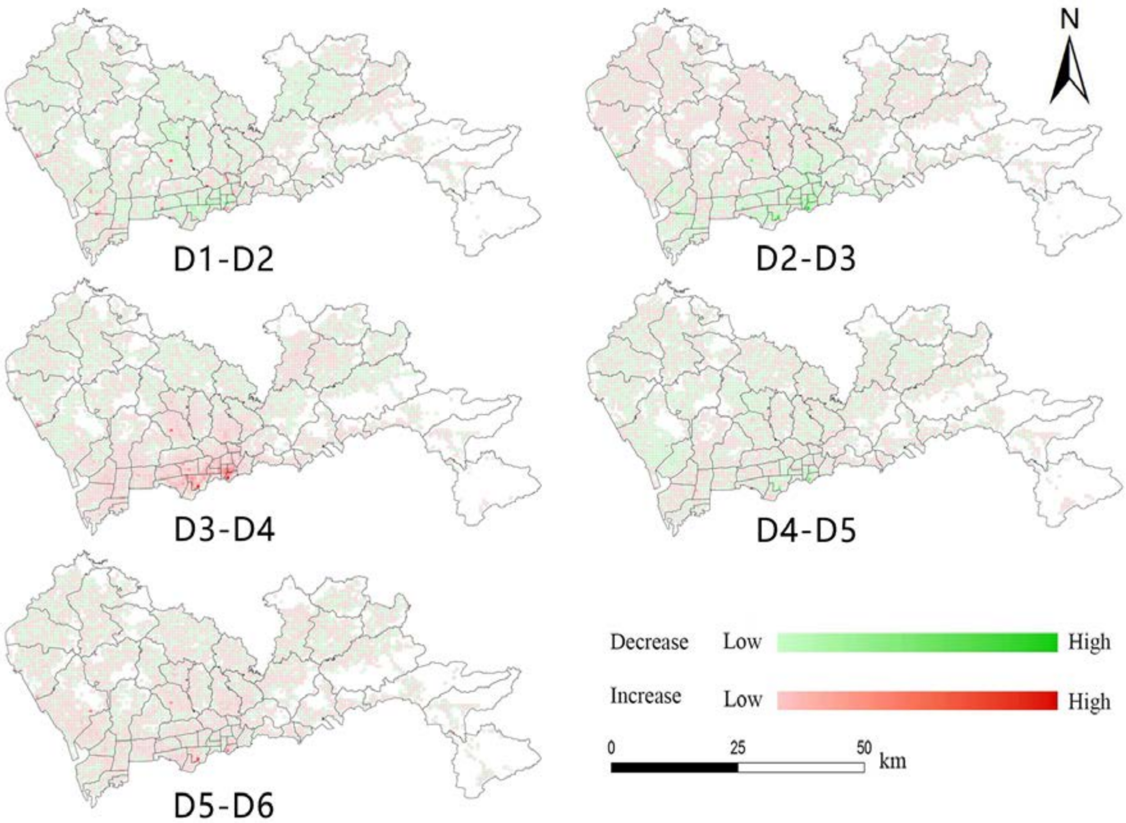
Figure 3. Spatial distributions of pick-up (**a**) and drop-off (**b**) locations in Period 1.

In the maps shown in Figure 4a, P1, P2, P3, P4, P5, and P6 represent aggregated pick ups during the corresponding periods (Period 1, 2, 3, 4, 5, and 6, respectively). In the same figure, P1–P2, P2–P3, P3–P4, P4–P5 and P5–P6 represent the differences in pick ups between these neighboring periods. Similarly, Figure 4b shows the corresponding pattern for drop-offs between neighboring periods (i.e., D1–D2, D2–D3, D3–D4, D4–D5 and D5–D6). Several observations regarding the spatial distribution can be obtained from these figures, specifically: The differential results between neighboring periods in Figure 4 indicate obvious changes in the pattern of the spatial distribution of cells that display increases or decreases in the number of daily pick ups and drop offs per taxi, which were influenced by the subsidy war. In Figure 4, red cells indicate increases in the numbers of pick ups or drop offs, whereas green cells indicate decreases in the numbers of pick ups or drop offs. Table 2 lists the numbers of cells that display increases and decreases in the number of daily pick ups and drop offs per taxi between neighboring periods. Figure 4 and Table 2 show similar spatial patterns in terms of the increases or decreases in the number of daily pick ups and drop offs per taxi. Specifically, the maps of P1–P2 and D1–D2 show that 2171 (26.37%) and 1885 (22.90%) cells display an increased number of daily pick ups and drop offs per taxi, and that 2552 (31.00%) and 3294 (40.01%) cells display a decreased number of daily pick ups and drop offs per taxi. The maps of P2–P3 and D2–D3 show that the proportions of cells displaying increases in the number of daily pick ups and drop offs per taxi increased to 30.79% and 35.40%, respectively, whereas the proportions of cells displaying decreases in the number of daily pick ups and drop offs per taxi decreased to 26.74% and 27.27%, respectively. These results show that the elevated subsidies in Period 3, which were the highest awarded during the subsidy war, did create additional taxicab trip demand. These proportions remain almost constant in P3–P4 and D3–D4. However, the red cells became concentrated in the south area of the city which is the downtown area. This result shows that the policy of reducing subsidies to passengers in Period 4 attracts more trips in downtown area. The maps of P4–P5 and D4–D5 show that the number of cells having increases in the number of daily pick-ups and drop-offs per taxi decreased to 27.49% and 28.33%, and that the number of cells having decreases in the number of daily pick-ups and drop-offs per taxi increased to 29.77% and 34.72%, which both indicate that the policy of awarding no subsidies to passengers in Period 5 actually decreased taxicab trip demand. During the final Period 6, no subsidies were provided to taxi drivers or passengers. The numbers of cells displaying increases in the number of daily pick-ups (32.67%) and drop-offs (36.01%) per taxi show that the taxicab travel demand increased after the end of the subsidy war, which means that the e-hailing services recovered some taxicab travel demand after encouraging passengers to develop the habit of using their services during the subsidy war.



(**a**)

Figure 4. *Cont.*



(**b**)

Figure 4. The changes in spatial distributions of pick-up (**a**) and drop-off (**b**) locations between neighboring periods.

Table 2. The number of cells that display increases and decreases in the number of daily pick ups and drop offs per taxi between neighboring periods.

Pick-up/Drop-off	Increase/Decrease	Neighboring Periods				
		1–2	2–3	3–4	4–5	5–6
Pick-up	Increase	2171 (26.37%)	2535 (30.79%)	2574 (31.27%)	2263 (27.49%)	2689 (32.67%)
	Decrease	2552 (31.00%)	2201 (26.74%)	2146 (26.07%)	2451 (29.77%)	2063 (25.06%)
Drop-off	Increase	1885 (22.90%)	2914 (35.40%)	2898 (35.20%)	2332 (28.33%)	2964 (36.01%)
	Decrease	3294 (40.01%)	2245 (27.27%)	2295 (27.88%)	2858 (34.72%)	2247 (27.30%)

On the sub-district scale, Table 3 shows the sequential patterns of increases or decreases in the number of daily pick ups and drop offs per taxi. The derived patterns contains two aspects, that is, patterns derived from neighboring periods and from comparison between each period with the beginning of the subsidy war (i.e., Period 1). It is noteworthy that patterns with a number of sub-districts of less than four are removed due to their low frequencies. Several conclusions can be drew from Table 3:

(1) When comparing pick-up and drop-off locations between all neighboring periods, this study shows that the predominant patterns displayed by the sub-districts within this study area

are "increase- decrease- increase- increase- increase", "decrease- decrease- increase- decrease- increase", and "decrease- decrease- increase- increase- increase". Nearly half of the subdistricts display these three patterns. Figure 5 displays the spatial distributions of these three predominant patterns. In Figure 5a, the subdistricts displaying Pattern 1 in pick-up number are mainly tourist spots, green areas and recreation spaces. The pick-up numbers of these subdistricts decline only in Period 3 when the subsidy war was white hot. Pattern 2 is distributed mainly over the central business districts which have the two major entry–exit ports in Shenzhen city and an important railway station. Unlike Pattern 1, the pick-up numbers of these sub-districts decline when the subsidy war just began. In addition, when the two companies cancelled the subsidy on passengers, the numbers of pick-ups decline. The sub-districts showing Pattern 3 are mainly industrial parks, hi-tech parks and recreation spaces. The only difference between Pattern 3 and Pattern 1 is that the number of pick-ups declines when the subsidy war had just begun in Pattern 3. As for the patterns of drop-off numbers, as shown in Figure 5b Pattern 1 is distributed mainly over the Luohu and Futian districts which are both central business districts in Shenzhen city. The sub-districts showing Pattern 2 are mainly tourism area, ports and hi-tech parks. In addition, Pattern 3 is distributed mainly over hi-tech parks and the tourism area.

(2) When comparing the pick-up and drop-off locations in Period n with Period 1, this study shows that the first two predominant patterns that accounted for about half of the sub-districts are "decrease- decrease- decrease- decrease- decrease" pattern and "decrease- decrease- increase- increase- increase" patterns. Figure 6 shows the spatial distributions of these two predominant patterns. The southern sub-districts displaying Pattern 1 are the downtown area of Shenzhen city. The northern sub-districts showing Pattern 1 are mainly industrial parks. The numbers of pick ups and drop offs always decrease compared with Period 1 when the subsidy war had not begun. Pattern 2 is distributed over hi-tech parks, green spaces and tourism places. Their numbers of pick ups and drop offs decline in Period 2 and Period 3 when compared with Period 1. However, after Period 3, their numbers always increase.

(3) Figure 7 shows the spatial distributions of the sub-districts with increases or decreases in the number of daily pick ups and drop offs per taxi when comparing pick-up and drop-off locations in Period 6 with Period 1. The sub-districts with an increase in the number of daily pick ups and drop offs per taxi are mainly distributed in the south with the exception of several sub-districts in the Luohu and Futian districts which are both the central business districts (CBDs) of Shenzhen city, and of Xin'an sub-district which is the political, economic, and cultural center of Baoan district. In addition, the sub-districts with a decrease in the number of daily pick ups and drop offs per taxi are mainly distributed in the north. These results indicate that the subsidy war eventually inspired travel demand mainly in the south area of Shenzhen city but does not include some downtown areas.

Table 3. The sequential patterns of increases and decreases in the number of daily pick ups and drop offs per taxi.

Period	Pick up/Drop off	Pattern	Count
n→n + 1	Pick up	increase- decrease- increase- increase- increase	15
		decrease- decrease- increase- decrease- increase	10
		decrease- decrease- increase- increase- increase	7
		decrease- increase- decrease- decrease- increase	5
		decrease- increase- increase- increase- increase	4
		decrease- increase- increase- decrease- increase	4
n→n + 1	Drop off	decrease- decrease- increase- decrease- increase	15
		increase- decrease- increase- increase- increase	9
		decrease- decrease- increase- increase- increase	7
		decrease- increase- decrease- decrease- increase	5
		decrease- increase- increase- decrease- increase	5

Table 3. *Cont.*

Period	Pick up/Drop off	Pattern	Count
1→n	Pick up	decrease- decrease- decrease- decrease- decrease	18
		decrease- decrease- increase- increase- increase	9
		increase- increase- increase- increase- increase	4
		increase- decrease- increase- increase- increase	4
		decrease- increase- decrease- decrease- decrease	4
		decrease- decrease- decrease- decrease- increase	4
1→n	Drop off	decrease- decrease- decrease- decrease- decrease	20
		decrease- decrease- increase- increase- increase	9
		increase- increase- increase- increase- increase	6
		increase- decrease- increase- increase- increase	5

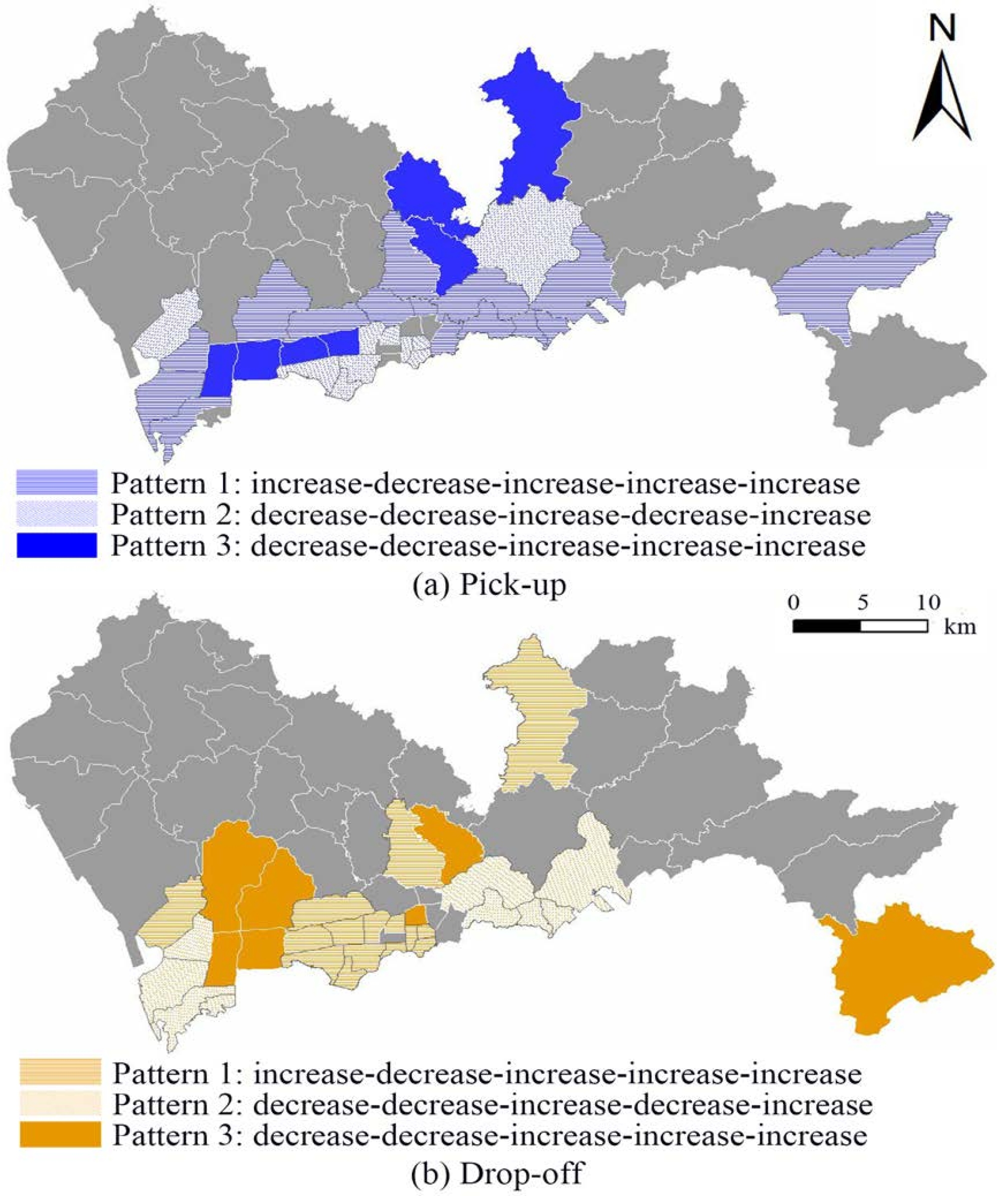


Figure 5. Spatial distributions of the first three predominant patterns displayed by the subdistricts when comparing pick-up (**a**) and drop-off (**b**) locations between all neighboring periods.

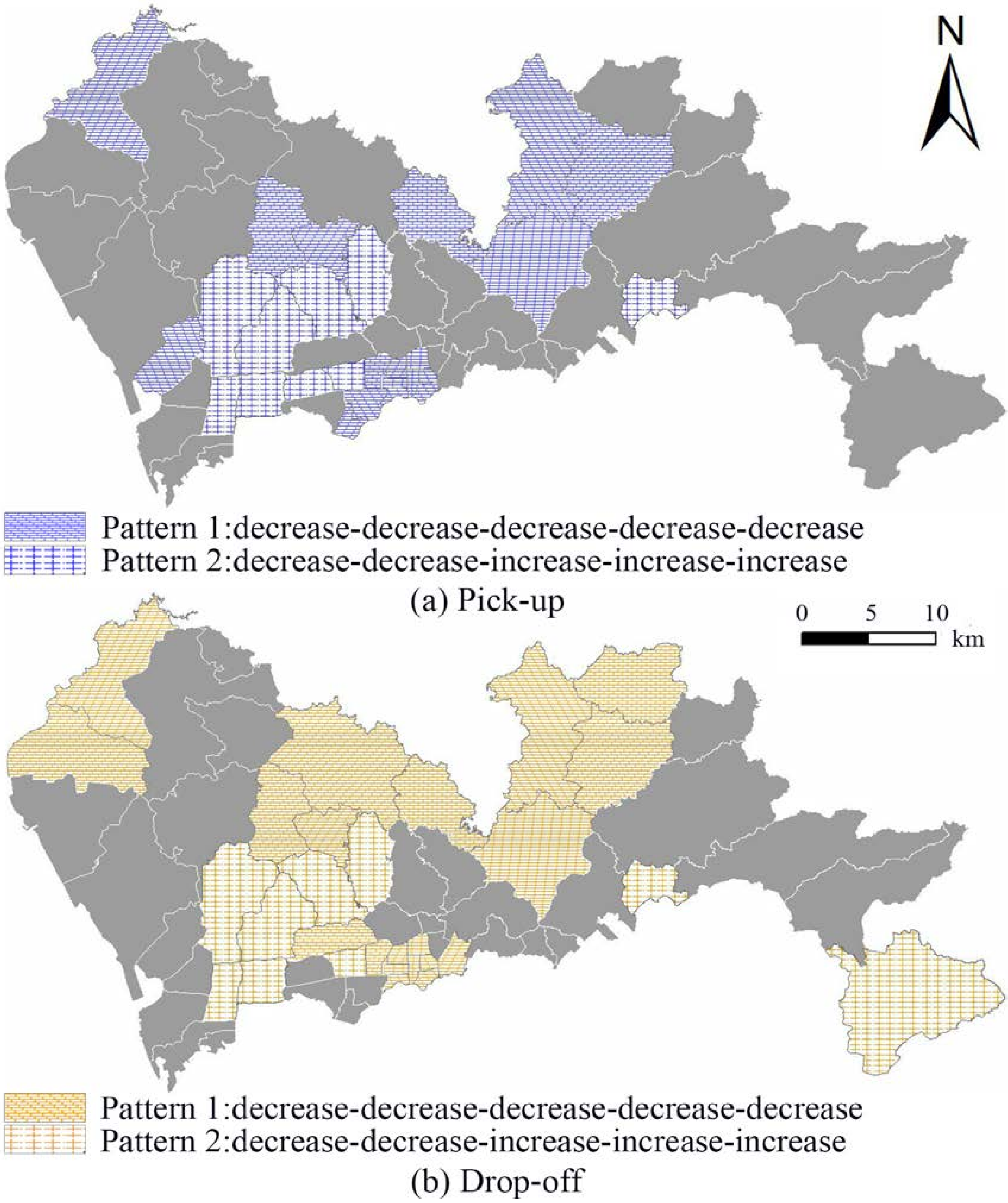


Figure 6. Spatial distributions of the first two predominant patterns displayed by the sub-districts when comparing pick-up (**a**) and drop-off (**b**) locations in Period n with Period 1.

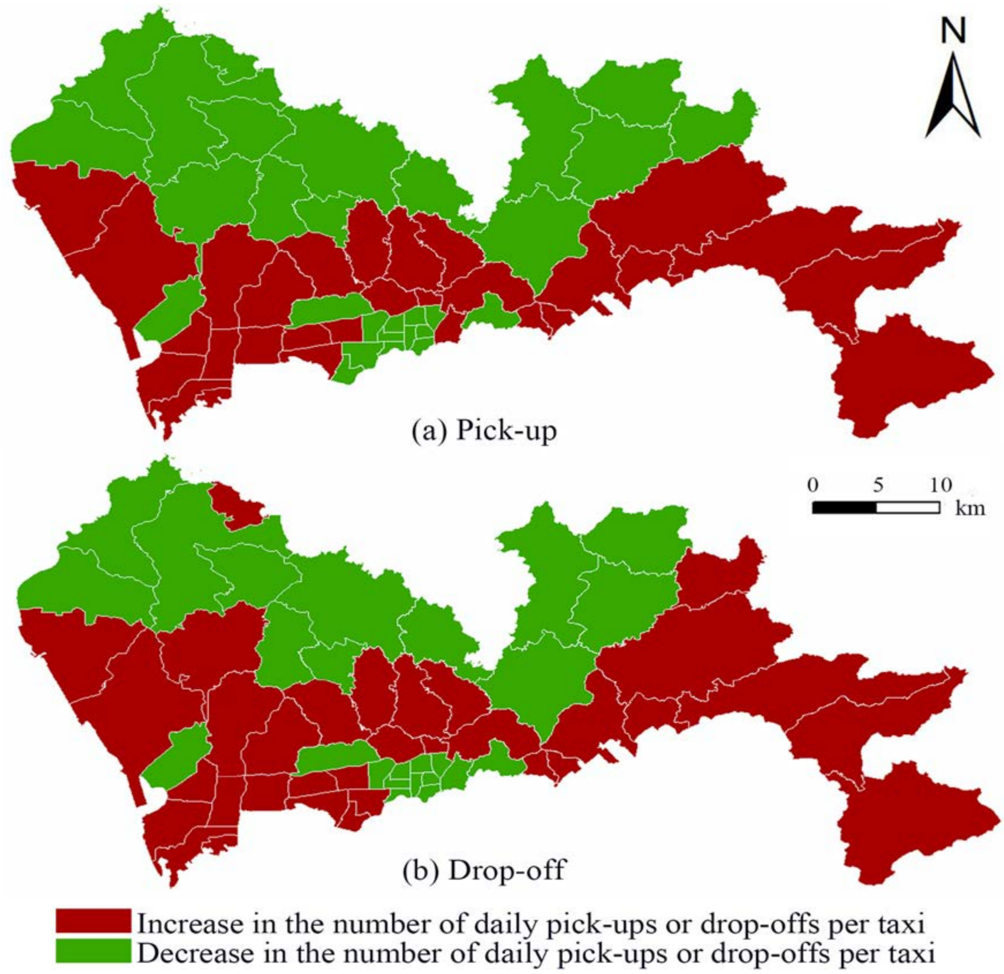


Figure 7. Spatial distribution of the sub-districts with increases or decreases in the number of daily pick ups (**a**) and drop offs (**b**) per taxi when comparing pick-up and drop-off locations in Period 6 with Period 1.

4.3. Stability of Spatial Distribution

This study uses the average transfer distance per unit area of weighted mean centers to investigate the stability of spatially aggregated distribution of cells in the administrative sub-districts. Each cell may display either an increase or decrease in pick ups, as well as an increase or decrease in drop offs. This study calculates the average transfer distance per unit area of weighted mean centers for each type of cells in the sub-districts. The mean and standard deviation of these average values are then calculated; these values are shown in Table 4.

Table 4. The mean and standard deviation of the average transfer distance per unit area of the weighted mean centers.

Type	Mean	Standard Deviation
Increased pick up	79.67	91.13
Decreased pick up	69.47	75.53
Increased drop off	74.52	94.63
Decreased drop off	68.75	75.48

The mean of the average transfer distance per unit area of the weighted mean centers in the sub-districts that display an increase in pick ups and drop offs is 79.67 and 74.52, respectively, which is larger than the values (69.47 and 68.75, respectively) that occur in sub-districts that display decreases in pick ups or drop offs. This result indicates that the distribution of cells that display increases in pick ups or drop offs represents a relatively large spatial change, whereas the distribution of cells that display decreases in pick ups or drop offs represents a relatively small spatial change. In terms of the standard deviation of the average transfer distance per unit area of the weighted mean centers, the sub-districts that display increases in pick ups and drop offs have similar values (approximately 91–94) and, meanwhile, the standard deviation for the sub-districts that display decreases in pick ups and drop offs also have similar values (approximately 75) which is much smaller than those of the other sub-districts. This result indicates that the cells that display increases in pick ups and drop offs in the sub-districts are spatially more variable than the cells that display decreases. In other words, the attracted passengers present a relatively unstable spatial pattern influenced by these subsidy policies.

4.4. Spatial Dispersion Patterns

This study uses the *WNNI* to investigate the changes in the spatial distributions of the increases and decreases in the number of pick ups and drop offs at the city and sub-district scales. Here, the *WNNI* reflects the degree of dispersion of the affected spatial distribution in terms of the differences in the pick-up and drop-off locations caused by the subsidy policies. Lower values of the *WNNI* mean greater clustering of the increased or decreased pick-up and drop-off locations, whereas higher values of the *WNNI* mean that the increased or decreased pick-up and drop-off locations are dispersed in space.

Figure 8 illustrates the *WNNI* values associated with the differences in the number of pick ups and drop offs between different pairs of neighboring periods on the city scale. Figure 8a,b show a similar pattern of change for the differential increase or decrease in the number of pick ups and drop offs. In the original period, that is, P1–P2, the degree of dispersion of the increase in pick-up and drop-off locations is at its lowest level, which means that the area that displays an increase in taxicab trip demand is concentrated within the urban space. When the subsidy was becoming white hot in Period 3, the areas that display increases in pick-up and drop-off locations become very sparse. This phenomenon indicates that a considerable subsidy amount would encourage cabdrivers to pick up and drop off passengers in a wider range. In addition, when the subsidy given to passengers reduced in Period 4, the dispersion trend of increases in pick up and drop off locations begins to alleviate. For pick-up locations, it shows a relatively closed degree of dispersion to the original status. However, for drop-off locations, the degree of dispersion still much higher than the original level. When passengers obtained no subsidy but cabdrivers still received some in Period 5, the degree of dispersion of increases in pick-up and drop-off locations slightly changed. This result suggests that a small amount of subsidy is not able to influence the degree of dispersion of increases in pick-up and drop-off locations. In Period 6 when both passengers and cabdrivers received no subsidy, the spatial distribution of the increase in pick ups and drop offs becomes more dispersed than in the previous period. On the contrary, the decrease in pick ups and drop offs displays the opposite pattern compared to the increased one.

At the sub-district scale, Table 5 lists the sequential patterns of the *WNNI* for increases and decreases in pick ups and drop offs in the sub-districts. Patterns with the numbers of sub-districts less than four which could be treated as a low frequency are removed from this table. Several conclusions can be drawn based on Table 5:

(1) The first two predominant patterns associated with increases in the number of pick ups in the sub-districts are "decrease- increase- decrease- increase" and "decrease- increase- decrease- decrease", whereas the predominant patterns associated with decreases in the number of pick-ups in the sub-districts are "increase- decrease- increase- decrease" and "increase- decrease- increase- increase". Nearly half of the sub-districts show these predominant patterns. The difference of the first two predominant patterns associated with increases or decreases in the number of pick ups lies in the last change. The last change of the first predominant pattern is an increase in *WNNI*,

but the last change of the second predominant pattern is a decrease. Figure 9 shows the spatial distributions of sub-districts displaying predominant patterns for the increase (Figure 9a) and decrease (Figure 9b) in pick ups. Pattern 1 denotes the first predominant pattern and Pattern 2 denotes the second predominant pattern. There are both 16 sub-districts showing Pattern 1 of the *WNNI* in increases and decreases in the number of pick ups and 9 sub-districts showing Pattern 2 of *WNNI* in increases and decreases in the number of pick ups. Pattern 1 is mainly distributed over the downtown area of Shenzhen city and sub-districts with important transportation hubs such as Shenzhen railway station, Shenzhen east railway station, Luohu and Futian entry–exit ports. In addition, the sub-districts showing Pattern 2 are mainly tourism areas, hi-tech parks, and recreational places. In short, in most cases sub-districts showing the first or second predominant pattern of *WNNI* associated with increases in the number of pick ups will also display the first or second predominant pattern of *WNNI* associated with decreases in the number of pick ups.

(2) Similarly, the first two predominant patterns for the increase in drop offs in the sub-districts are "decrease- increase- decrease- increase" and "increase- increase- decrease- increase", whereas the predominant patterns for the decrease in drop offs in the sub-districts are "increase - decrease- increase- decrease" and "decrease- decrease- increase- decrease". The difference of the first two predominant patterns associated with increases or decreases in the number of drop offs lies in the first change. For example, the first change of Pattern 1 of increases in the number of drop offs is a decrease in *WNNI*; however, the first change of Pattern 2 is an increase in *WNNI*. For the predominant patterns of *WNNI* for the decrease in drop offs, the first change of Pattern 1 is an increase in *WNNI*, and of Pattern 2 is a decrease in *WNNI*. Figure 10 shows the spatial distributions of sub-districts showing predominant patterns of *WNNI* for the increase (Figure 10a) and decrease (Figure 10b) in drop offs. This shows that most of the sub-districts displaying Pattern 1 (Pattern 2) in Figure 10a exhibit Pattern 1 (Pattern 2) in Figure 10b correspondingly. Specifically, there are 15 sub-districts both showing Pattern 1 of *WNNI* in increases and decreases in the number of drop offs and 10 sub-districts both showing Pattern 2 of *WNNI* in increases and decreases in the number of drop offs. Pattern 1 is mainly distributed over Luohu district which is one of the main downtown districts of Shenzhen city, sub-districts with important ports and railway stations, and recreational places. In addition, the sub-districts showing Pattern 2 are mainly hi-tech parks, industrial parks and recreational places. Besides, several sub-districts in Futian district, which is one of the main downtown districts, also present Pattern 2. Similarly, in most cases, sub-districts showing the first or second predominant pattern of *WNNI* associated with increases in the number of drop offs will also display the first or second predominant pattern of *WNNI* associated with decreases in the number of drop offs.

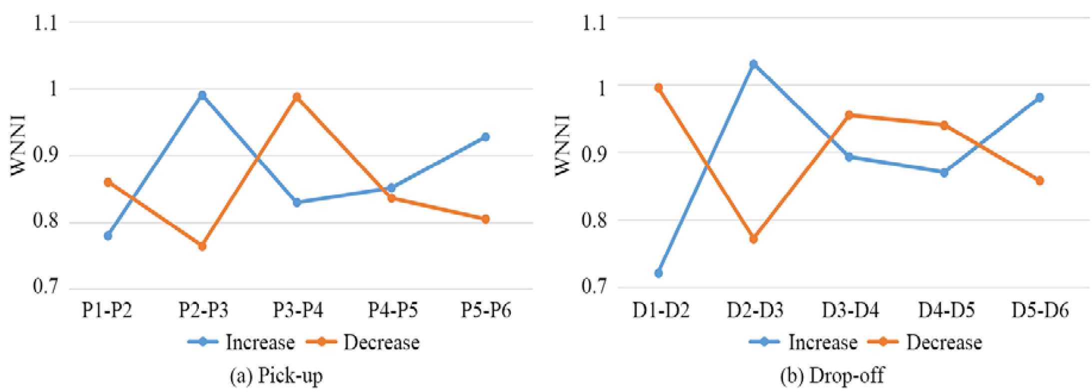


Figure 8. The weighted nearest neighbor index (*WNNI*) values of differential pick ups (**a**) and drop offs (**b**) in pairs of neighboring periods.

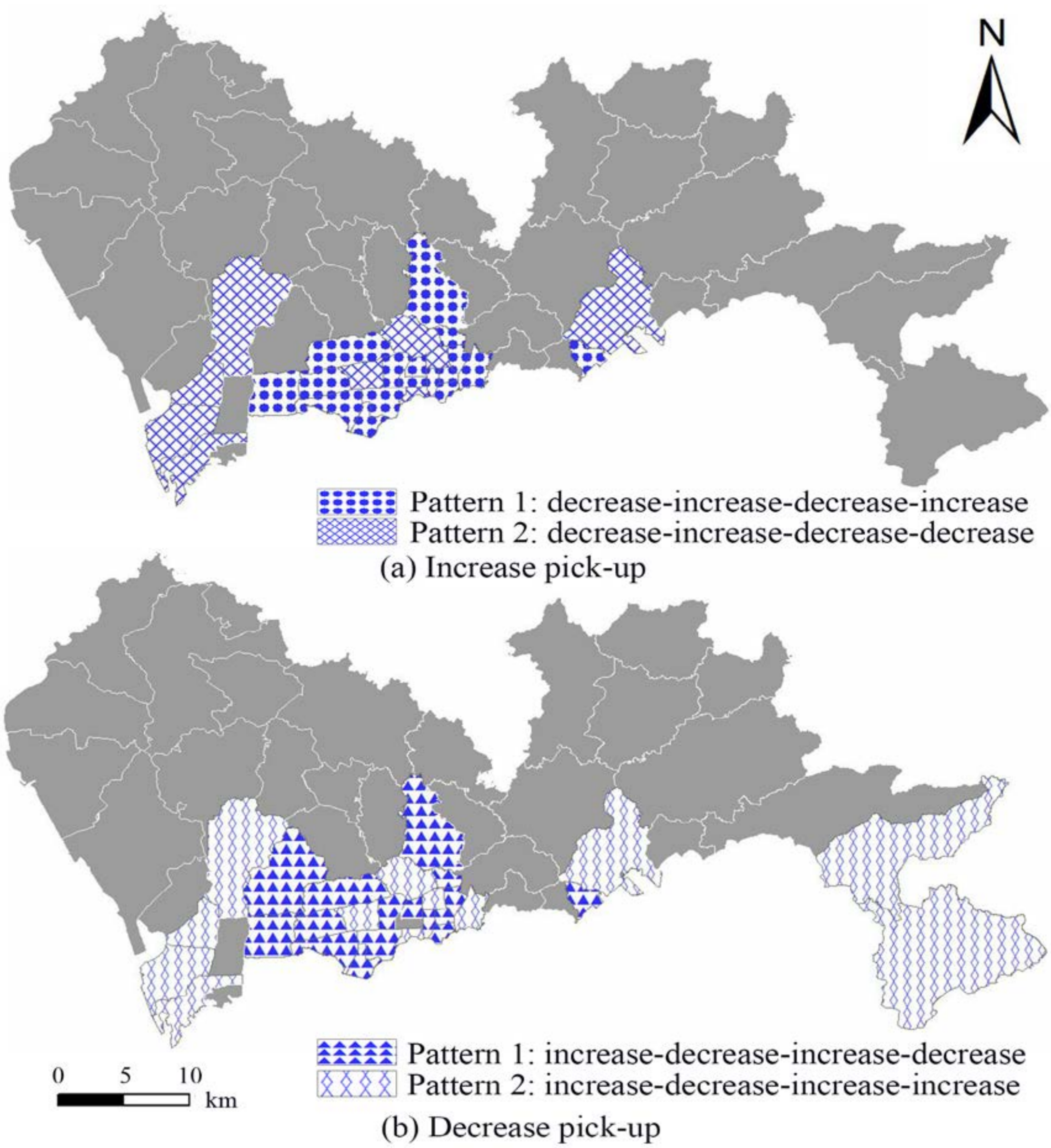


Figure 9. Spatial distributions of sub-districts showing predominant patterns of *WNNI* for the increase (**a**) and decrease (**b**) in pick ups.

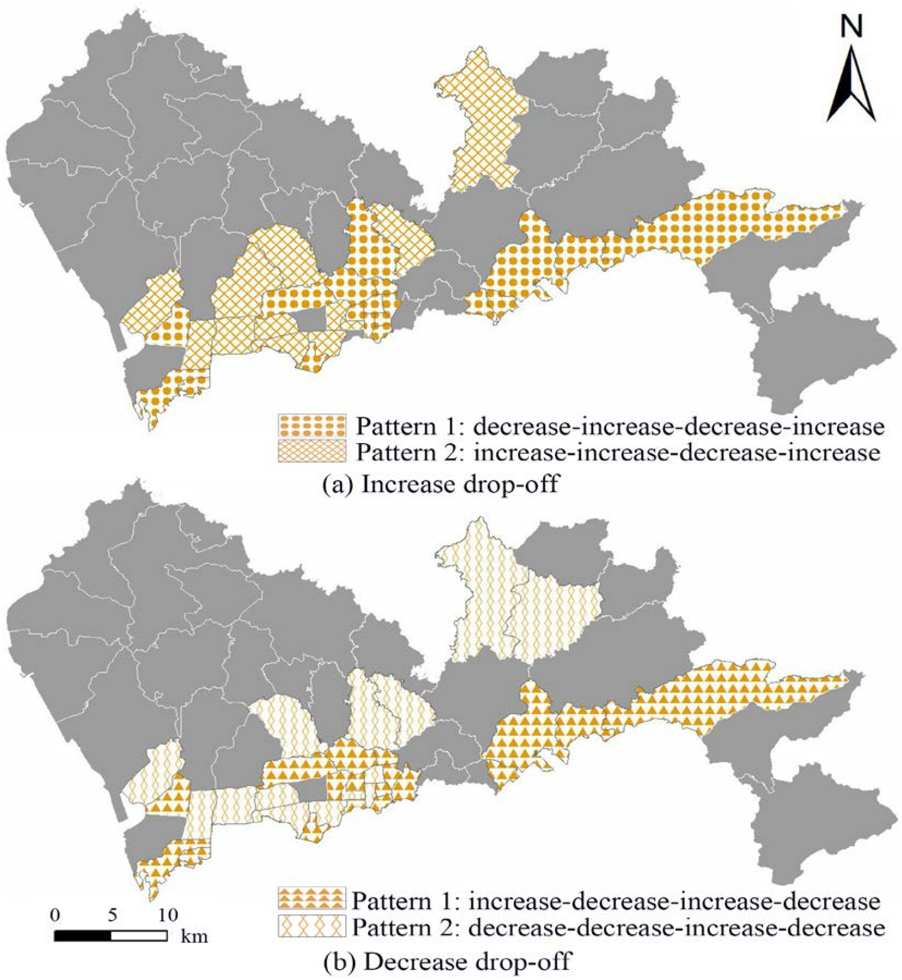


Figure 10. Spatial distributions of sub-districts showing predominant patterns of *WNNI* for the increase (**a**) and decrease (**b**) in drop offs.

Table 5. The sequential patterns of *WNNI* for increase/decrease in pick ups/drop offs in sub-districts.

Type	Pattern	Count
Increased pick ups	decrease- increase- decrease- increase	17
	decrease- increase- decrease- decrease	9
	decrease- increase- increase- decrease	7
	increase- decrease- decrease- increase	6
	increase- increase- decrease- increase	6
	increase- decrease- increase- increase	5
Decreased pick ups	increase- decrease- increase- decrease	16
	increase- decrease- increase- increase	12
	decrease- increase- decrease- decrease	6
	decrease- decrease- increase- decrease	5
Increased drop offs	decrease- increase- decrease- increase	19
	increase- increase- decrease- increase	12
	increase- decrease- decrease- increase	7
	increase- decrease- increase- increase	5
	decrease- increase- decrease- decrease	5
Decreased drop offs	increase- decrease- increase- decrease	18
	decrease- decrease- increase- decrease	14
	decrease- increase- increase- decrease	7

5. Conclusions

This paper has investigated the dynamics of taxi pick-up and drop-off locations in the context of the subsidy war that occurred in the city of Shenzhen, China, in 2014. This paper introduced three indexes to measure the dynamics of the pick-up and drop-off locations at the city and sub-district scales, namely the numbers of daily pick ups and drop offs per taxi, average transfer distance per unit area of weighted mean centers of pick-up and drop-off locations, and degree of dispersion in the spatial distribution of pick-up and drop-off locations, which help to understand the dynamics of the pick-up and drop-off locations in the context of a subsidy war among e-hailing apps, including the change dynamics of taxi trip demand, the stability of taxi trip demand dynamics, and the local effectiveness dynamics by subsidy policies. The main findings of these dynamics can be summarized as follows:

(1) Heatmaps displaying the spatial patterns of the total numbers of pick-up and drop-off locations indicate that the hotspot area of taxi trip demand was not significantly influenced by the subsidy war. However, the subsidy war did cause people to choose to use taxi services in greater numbers, and the increases and decreases in the numbers of drop offs and pick ups varied greatly in spatial distribution among the different periods studied. This finding demonstrates that the subsidy policies did play a role in attracting passengers to take taxi trips. Another significant finding is that the subsidy war eventually inspired travel demand mainly in the south area of Shenzhen city but not some downtown areas.

(2) The spatial distribution of cells in the sub-districts that displayed decreases in the number of pick ups and drop offs appeared to be more stable, whereas the spatial distribution of areas that displayed increases in these numbers appeared to be more unstable. This finding indicates that the attracted passengers present a relatively unstable spatial pattern influenced by these subsidy policies.

(3) At the city scale, the spatial dispersion of cells in the different periods showed opposite tendencies between the cells with increases in drop offs and pick ups compared with the cells with decreases. On the other hand, the pattern of change in the spatial distribution of the increases and decreases in pick ups and drop offs at the sub-district scale was inconsistent with that at the city scale. This finding indicates the local effectiveness dynamics by subsidy policies is opposite between areas with increases in drop offs and pick ups and that with decreases.

Future studies can be carried out with the following aspects. Firstly, this study could be improved by examining the dynamics of pick-up and drop-off locations associated with the time of day, day of the week, and week of the month. This may help enhance the interpretation of the change patterns of pick-up and drop-off locations from the perspective of human behaviour. Secondly, the functional network of pick-up and drop-off locations could be constructed to derive trip purpose dynamics among taxi passengers. This network could help e-hailing companies to plan their future specific taxi-pooling policies and subsidy policies to attract more passengers. Thirdly, it is also vital to investigate changes in empty/occupied trips since the pick-up and drop-off locations are extracted from them. For example, do subsidies influence the number of empty trips towards locations where the chances for passenger pick up after the drop off of previous passengers are higher? Such an investigation could improve our understanding of the changes of taxi services in the context of a subsidy war. Lastly, sophisticated analysis about other related factors which contribute to the dynamics of taxi pick-up and drop-off locations can be carried out. For example, traffic regulations, low-emission rules, road construction, etc. This could help us understand in greater depth the influence of these factors on the dynamics of taxi pick-up and drop-off locations.

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