Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 3215435, 14 pages
https://doi.org/10.1155/2022/3215435

Research Article

How Snowfalls Affect the Operation of Taxi Fleets? A Case Study from Harbin, China

Binliang Li,[1] **Haiming Cai**,[2] **and Dan Xiao**[2]

[1]*Shenzhen Transportation Operation Command Center, Shenzhen 518040, China*
[2]*School of Transportation Science and Engineering, Harbin Institute of Technology, Harbin 150006, China*

Correspondence should be addressed to Haiming Cai; haicai@dtu.dk

Received 29 January 2022; Revised 17 February 2022; Accepted 25 February 2022; Published 20 March 2022

Academic Editor: Qizhou Hu

Taxi network plays an important role in urban passenger transportation. However, its operation is greatly affected by weather, especially by snowfalls in cold region. In this study, we focus on the persistent effect of snowfall on taxi operation and propose an autoregressive distribution lag model (ARDL) to quantitatively analyse it. To support our study, the taxi GPS trajectory data collected in Harbin, China, during 61 days from 1 November to 31 December in 2015 is analysed. First, the daily average order volume (DAOV) is acquired through data sampling and processing. Then, combined with the data of daily snowfall during the 61 days, the ARDL model is constructed. The result shows that the snowfall has a lag effect on taxi operation and it lasts about 3 days. To better interpret the result, visualization of total 6 days before and after a heavy snowfall is conducted. The result also indicates that weekends have a positive effect on operation. These results are expected to assist us to better understand the effect of snowfall on taxi operation and provide some policy suggestions for local municipal and transportation management departments to ensure the normal operation of taxi networks.

1. Introduction

All kinds of public transportation in cities have their own characteristics and are influenced by many factors, such as geographical, economic, social, or cultural factors [1]. The study of these factors can help us better understand the essence of transportation modes and residents' travelling characteristics. Among these factors, weather is considered to be one of the exogenous determinants [2]. Operations of taxis, as an important mode of urban public transport without fixed operating schedule like buses, are more far-reaching and widely affected by extreme weather.

Different from some studies on the influence of climate on transportation [3–6], the impact of weather on public transport is usually short-term [1], which may affect residents' travelling decisions and mode choices [7–10], leading to changes in travellers' trip plans, modes, or routes. Weather may also greatly affect the operation of public transports [11–15], such as decreasing the availability and speed and increasing transit time and trip duration [16], so as to decrease the level of service or operating revenue. In addition, extreme weather may have some significant influence on safety [17–20].

An obvious conclusion that can be drawn is that different weather conditions affect urban public transports in different ways and to different degrees. Some of these meteorological factors have been well studied, including rainfall [9, 17, 18, 21], snowfall [11], temperature [13], wind [22, 23], or combinations of some of these factors [1, 2, 10, 14]. However, no matter what kind of weather factor it is, adverse weather condition has a significant negative impact on taxi operation and service. From the perspective of residents, it brings inconvenience and unsafety and affects their daily trips. From the perspective of transport service providers, it reduces the quality of transport services they provide and decreases their operating revenue [2]. From the perspective of city administrators, adverse weather affects the normal production and living order and increases the financial burden. In view of this, it is of great significance to study the influence mechanism and range of a certain weather factor on the taxi operation.

In the study of these influence mechanisms, an interesting phenomenon is the time lag effect of weather on traffic. The so-called time lag effect refers to that, in a time series, the current value of the explained variable is not only affected by the current value of explanatory variable, but also affected by one or more periods of lag of the explanatory variable or the explained variable itself. This time lag effect is well studied in traffic volume prediction [24–26], travelling time or speed [27], traffic safety [28–30], traffic behaviours [31, 32], logistics [33], and so on. Among the various weather types, snowfall is recognized as the most significant one, because it cannot dissipate quickly after it falls to the roads, which leads to a sustained impact on traffic for hours to days after the snowfall. Many models have been constructed to explain this lag effect. Some of the outstanding works are as follows: Thomas Nosal et al. [25] used regression models with autoregressive and moving average (ARMA) errors to investigate the direct impact and triggered effects of weather variables on hourly and daily cycle counts in Montreal, Ottawa, Vancouver, and Portland as well as on the Green Route in Quebec. In the study of Yannis and Karlaftis [28], an integer autoregressive (INAR) model is used to estimate the effects of weather conditions on different traffic safety categories, and mean daily precipitation height along with its lagged value (1 day) was proved to be the most consistently significant and influential variable. Combining quantile regression with distributed-lag nonlinear models, Zhan et al. [34] examined the nonlinear and lagged effects of hourly precipitation and temperature on ambulance response time (ART) at the 50th and 90th percentiles and found that marginal temperature and precipitation have different degrees of lag effects on ART. Zhang et al. [35] proposed an impulse response function based on the vector autoregression model to provide insight into the cross effects of the traffic parameters and their responses to weather conditions.

However, although many researchers have carried out extensive studies on other aspects of taxis [36–43], very few studies have dealt with the time lag effect of snowfall on normal taxi operations. As an important component of urban transportation system, the service level of taxi needs to be paid enough attention, especially in snowy days, where people's tolerance to low temperature is reduced and buses become unreliable and unpunctual. At the same time, as a means of aboveground transportation, the operation of taxis is inevitably affected by snow, thus affecting the travel of citizens and the income of taxi drivers. Therefore, it is of great significance to study the time lag effect of snowfall on taxis, from the perspectives of improving the service level of taxis and even the whole urban transportation system, facilitating the daily travel of citizens, improving the income of taxi drivers, and giving advice of strengthening the urban road snow removal and deicing work to local municipal department.

In this paper, a large-scale study is presented by sampling and analyzing GPS trajectory data collected from more than 13000 taxis in Harbin, China, for two consecutive months. First, through data sampling and processing, the average daily order volume within 61 days from 1 November to 31 December in 2015 and the pick-up point (PUP) and drop-off point (DOP) of each trip are obtained. Then, based on this, an autoregressive distributed lag (ARDL) model is proposed to study the lag effect of snowfalls on taxi operation. Some visualization methods are applied to help better understand the lag effect. The remainder of the paper is organized as follows. Section 2 describes the study area, data sources, and methodology used in this study. The results of the lag effect are analysed, and visualization of taxi operation conditions is conducted in Section 3 and Section 4. Finally, conclusions and suggestions are presented in Section 5.

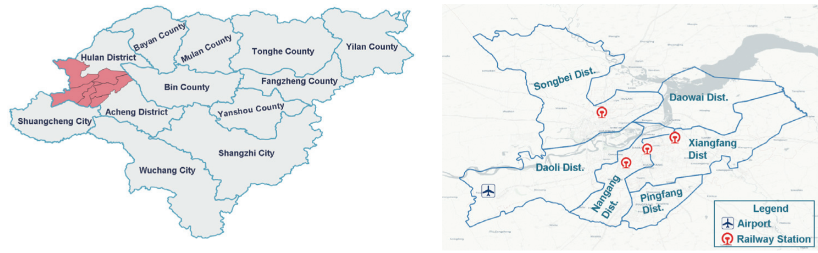
2. Materials and Methods

2.1. Study Area. The case study is carried out in Harbin (125°42′–130°10′E, 44°04′–46°40′N), China, which is located on the Northeast Plain of China. It is the capital of Heilongjiang Province and consists of 9 districts and 9 counties, covering 53100 square kilometres with a population of 9.952 million. In this paper, the study area is focused on the downtown area, including Nangang District, Daoli District, Daowai District, Xiangfang District, Songbei District, and Pingfang District, as shown in Figure 1. The study area covers 4187 square kilometres with a population of 5.4872 million [35]. In 2015, the per capita GNP in Harbin was 59027 CNY [35]. The main public transit system in Harbin includes buses, taxis, and metro.

Harbin is one of the major cities in China with higher latitude and lower temperature. Due to its temperate continental monsoon climate, Harbin has a long and cold winter, lasting for five months (from November to March). Its snowfall period is mainly from November to January, sometimes with heavy snow. The minimum temperature during November and December 2015 can reach −29°C (on December 25). Despite the Harbin metro has been put into use in 2013, there was only one line with 18 stations in 2015, serving 158,600 passengers per day on average [35]. Therefore, the majority of public transportation trips mainly relied on buses and taxis, especially with the reduction of passengers' tolerance of waiting buses due to the snowfall and low temperature in winter, and taxis play an important role in public transportation in Harbin. Therefore, Harbin is a very typical and appropriate city to conduct research on the time lag effect of snowfall on taxi operation.

2.2. Data Source. By 2015, all taxis in Harbin had been equipped and put into use with GPS devices. These GPS devices record taxi location every 30 seconds and play an important role in monitoring the taxi operation and ensuring the safety of drivers and passengers in real time. This study collected the GPS trajectory data of more than 13000 anonymous taxis in Harbin from November 1 to December 31, 2015. The data contains the ID, GPSID, longitude, latitude, speed, status (vacancy or occupied), and other information of each taxi. Table 1 shows a sample of taxi trajectory data.

As Table 1 shows, "DEVID" is a number to distinguish anonymous taxis; "STATE" represents the status of taxis and the different state codes corresponding to different status,



(a) (b)

Figure 1: (a) Location of the study area and (b) the road network of the study area.

Table 1: Taxi GPS data in Harbin city.

DEVID	STATE	LATITUDE	LONGTITUDE	SPEED	GPSTIME
0100324261	0	45.708145	126.59434	0	2015/12/10 0 : 01 : 25
0300020062	0	45.731396	126.69875	0	2015/12/10 0 : 01 : 24
0300061532	0	45.72064	126.67435	0	2015/12/10 0 : 01 : 26
0100323182	1	45.756107	126.61123	342	2015/12/10 0 : 01 : 37
0100304273	1	45.75774	126.58686	176	2015/12/10 0 : 01 : 30
0300017510	1	45.78798	126.640755	0	2015/12/10 0 : 01 : 28

such as “Vacancy” or “Occupied.” “LATITUDE” and “LONGTITUDE” represent locations of taxis; “SPEED” represents the instantaneous speed of taxis, and it is measured in 100 meters per hour. “GPSTIME” represents the real time of data.

Collection. Data of each day is stored in a single file, with 18 to 28 million data items for each day. All the data sets have been cleaned by removing invalid points resulting from device failure or recording errors. In this study, GPS trajectory data of 25% of taxis were sampled as the research object, which accounts to 4 to 7 million items in one day. Theoretically speaking, the 30-second sampling rate and such a large amount of GPS data can basically cover most of the road network in the Harbin downtown. Figure 2 shows the trajectory of 3000 taxis, from which the basic outline of Harbin road network structure is depicted.

From these data, the complete driving trajectory of each taxi in the sample in a day can be extracted. The meanings represented by different state codes are recognized in the study first. Figure 3 depicts a piece of driving trajectory of a taxi. It denotes that the taxi cruises on the road in search of potential passengers (in vacant status); then the driver picks up passengers at pick-up point (PUP) and starts to deliver passengers to their destinations (in occupied status); after the passengers get off the taxi at drop-off point (DOP), the taxi cruises on the road again to search for another potential passengers (in vacant status again). Based on the cleaned data, all the PUPs and DOPs of the taxi sample in the city every day can be extracted, and each PUP corresponds to a specific DOP, which together denote a complete trip. Thus, some other parameters, such as daily average order volume (DAOV), can be calculated to support the follow-up study.

2.3. Methodology

2.3.1. ARDL Model. In this study, an autoregressive distributed lag model was applied to study the lag effect of snowfalls on taxi operation. The ARDL model, originally proposed by Charemz and Deadman to explain economic phenomenon, has been widely used in various fields [44–48]. Compared with the traditional cointegration test method, the ARDL model has the following advantages:

(1) The ARDL method does not need to check in advance whether the time series has first-order single integrity

(2) The ARDL process of boundary test is robust enough to small samples, and the sample length needs to be low

(3) When the explanatory variable is endogenous, the ARDL method can still get unbiased and effective estimates

(4) The ARDL method overcomes many problems caused by nonstationary time series data, such as false regression

Considering the above advantages of the ARDL model, this paper uses the ARDL model to study the impact of snowfalls on taxi operation, which is rarely applied to this topic before.

The ARDL model is a branch of the distributed lag (DL) model. If the current value $Y(t)$ of the explained variable Y not only is affected by the current value $X(t)$ of the explanatory variable X, but also obviously depends on the lag value $X(t-1)$, $X(t-2)$, such a model is a distributed lag

Figure 2: A one-day trajectory map of a sample of 3000 taxis within the study area.

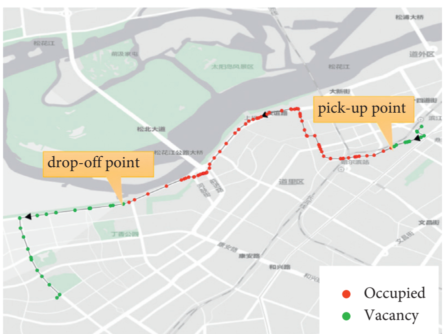


Figure 3: A piece of continuous trajectory of a taxi.

model. The term "autoregressive" indicates that along with getting explained by the current value and the lag value of $X(t)$, $Y(t)$ also gets explained by its own lag value(s), such as $Y(t-1)$. Considering the autoregressive modelling of traffic parameters mentioned in some previous studies [25, 49–51], the lag of $Y(t)$ was also considered in this study. Equation of ARDL (m, n) is as follows:

$$\begin{aligned} Y(t) &= \alpha + \beta_1 Y(t-1) + \cdots\cdots + \beta_m Y(t-m) + \gamma_0 X(t) \\ &\quad + \gamma_1 X(t-1) + \cdots\cdots + \gamma_n X(t-n) + \varepsilon_t. \end{aligned} \tag{1}$$

Here, m and n are the number of lags of Y and X, respectively, β_i is the coefficient for the explained variable Y and its lags, and γ_j is the coefficient for the explanatory variable X and its lags, which is called lag weights, and they collectively comprise the lag distribution. They define the pattern of how X affects Y over time. ε_t is a random disturbance term.

Given the presence of lagged values of the dependent variable as regressors, OLS estimation of an ARDL model will yield biased coefficient estimates. If the disturbance term ε_t is autocorrelated, the OLS will also be an inconsistent estimator, and in this case Instrumental Variables Estimation was generally used.

The distributed lag (DL (q), or ARDL $(0, q)$) models were widely used in the 1960 s and 1970 s. To avoid the adverse effects of the multicollinearity associated with including many lags of X as regressors, it was common to reduce the number of parameters by imposing restrictions on the distribution of values that the γ_i coefficients could take.

The assumptions for ARDL model are as follows:

(1) The primary requirement of ARDL model is the absence of autocorrelation. It is required that the error terms have no autocorrelation with each other.

(2) The time series data should follow normal distribution.

(3) Any heteroscedasticity should not occur in the data. And the mean and variance should be constant throughout the ARDL model.

(4) The time series data should have stationary either on I (0) or I (1), or on both. In addition, the model cannot run if any of the variable in the data has stationary at I (2).

In this study, the daily snowfalls were taken as the explanatory variable. Considering that the number of taxis operating every day is variable and taxi drivers pay more attention to their income, which is positively correlated with the number of orders served by drivers, the study took the daily average orders volume as the explained variable of the model.

2.3.2. Granger Causality Test. Granger Causality Test was proposed by Granger, a famous econometric economist in California in 1969, and further developed by Hendry and Richard. In the case of time series, the causal relationship between two economic variables X and Y can be defined as follows: if the past information of variables X and Y is known, the prediction effect of Y is better than that of Y only based on the past information of Y. That is, variable X helps to explain the future change of variable Y, then variable X causes the change of variable Y, and there is causal relationship between them. For two given time series X and Y in the period of $t = 1, \ldots, T$, to test whether X is the cause of Y, two models can be constructed: one is as (1) shows, and the other is as follows:

$$Y(t) = \alpha + \beta_1 Y(t-1) + \cdots\cdots + \beta_m Y(t-m) + \varepsilon_t. \tag{2}$$

If $\gamma_j = 0$ holds for all $j = 1, 2, \ldots, n$, then variable X will not cause the change of variable Y, which does not constitute a causal relationship, and the choice of lag period can be arbitrary. So we can assume H_0: $\gamma_j = 0, j = 1, 2, \ldots, n$. Then, we regress (1) and (2) to obtain EES_1 and EES_2 of the explanatory square and RSS_1 of the residual square and construct the following statistics: $F = [(\text{EES}_1 - \text{EES}_2)/m]/[\text{RSS}_1/(T - (m + n + 1))]$. F obeys the distribution that the first degree of freedom is m and the second degree of freedom is T-$(m + n + 1)$. Given the significance level a, there is a corresponding critical value F_a. If $F > F_a$, then reject the hypothesis of H_0 with the confidence of $(1 - a)$. In the sense of Granger, X is the cause of Y. Otherwise, accept H_0; that is, the change of Y cannot be attributed to the change of X.

3. Results

3.1. Statistics of DAOV and Snowfall over 61 Days. Figure 4 shows the change of daily average order volume and snowfalls in 61 days. From the figure, we can see that the DAOV is obviously affected by the snowfalls, and the snowfalls still have a continuous impact on the following 2-3 days. In addition, the daily average order volume of every weekend has an increasement in different degrees compared with the working days.

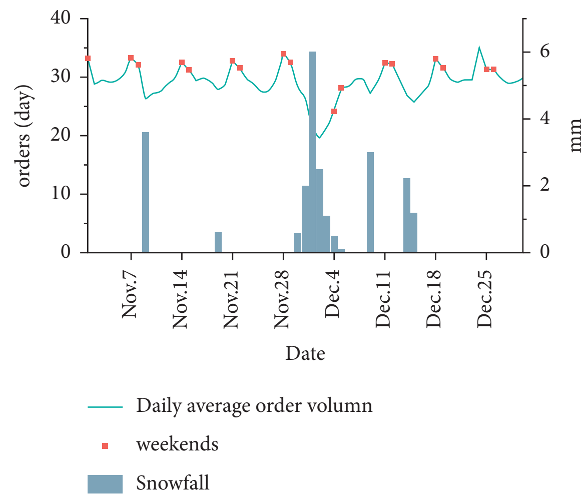


Figure 4: Plot of the DAOV and snowfall over 61 days.

3.2. ARDL Model Analysis. To use the autoregressive distribution lag model to study the time lag effect of snowfalls on taxi operation, a unit root test is implemented first to check whether there is a unit root in the series of daily average order volume and daily snowfall. When there is unit root in the time series, it is regarded as nonstationary, which will lead to the existence of pseudoregression in regression analysis. In this study, the Augmented Dickey-Fuller test (ADF test) was used to perform the unit root test for the stationarity of each series. The original hypothesis of the test is that the time series of the daily average order volume and snowfalls are both nonstationary. Table 2 shows the results of unit root test for the two series.

In the results, Y represents the explained variable, the daily average order volume; X is the explanatory variable, which is snowfalls (in mm). In the test form (C, T, K), C, T, and K represent constant term, trend term, and the order of difference, respectively.

Table 2: Results of the unit root test.

	Test form	ADF value	Critical value 1%	5%	10%	p value	Conclusion
Y	(C, 0, 1)	−4.331	−3.546	−2.912	−2.594	0.001	Stationary
X	(C, 0, 0)	−5.158	−3.544	−2.911	−2.593	0.000	Stationary

As shown in Table 2, both the explained variable Y and the explained variable X reject the original hypothesis at the significance level of 1%; that is, the time series of the daily average order volume and snowfalls are both stationary series; then, the Granger Causality Test can be implemented.

According to the theory of Granger Causality Test, when the snowfall X explains the average daily order volume Y better than the average daily order volume Y explained solely by the lag term of itself, the variable X can be considered as the Granger cause of variable Y. The original hypothesis of the test is that snowfall X is not the Granger cause of daily average order volume Y. Table 3 shows the results of Granger Causality Test under different lag orders of snowfalls.

Table 3: Results of Granger Causality Test.

Original hypothesis: X is not the Granger cause of Y		
Lag order	F-value	p value
1	10.922	0.002
2	4.004	0.024
3	2.853	0.046
4	2.408	0.062
5	2.587	0.039
6	2.402	0.044
7	1.696	0.139

As shown in Table 3, when the lag order is 1 to 6, the original hypothesis is rejected at the significance level of 5% (in which, when the lag order is 1, it is rejected at the significance level of 1%), and when the lag order is 7, the original hypothesis that snowfall X is not the Granger cause of daily average order volume Y cannot be rejected. Therefore, it can be considered that X is the Granger cause of Y. That is, the lag of snowfall X has an impact on the current value of daily average order volume Y.

Based on the above conclusions, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC) were used to determine the lag order of the model. The parameters of the model are shown in Table 4. In ARDL (p, q), p and q represent the maximum order of variable lag in the model.

According to the results of Granger Causality Test, the paper sets the maximum lag order of the model as 6 and determines the model as ARDL (1, 3) according to AIC criterion. Under BIC, HQC, and Adj. R2 criteria, the form of lag model is basically the same. Therefore, the model is preliminarily defined as

$$Y(t) = \alpha + \beta Y(t-1) + \gamma_0 X(t) + \gamma_1 X(t-1) + \gamma_2 X(t-2) + \gamma_3 X(t-3). \quad (3)$$

In (3), $Y(t-1)$ denotes the lag 1 value for the DAOV, while $X(t-1)$, $X(t-2)$, and $X(t-3)$ denote the lag 1, 2, and 3 values of snowfalls, respectively.

Considering the influence of weekend on DAOV, two dummy variables D_1 and D_2 are added into (3) to represent Saturday and Sunday, respectively. Then, the modified model is

Table 4: Selection of model lag order.

Model	LogL	AIC*	BIC	HQC	Adj. R-sq	Specification
39	−87.099	3.422	3.677	3.521	0.821	ARDL (1, 3)
38	−86.555	3.438	3.730	3.551	0.820	ARDL (1, 4)
32	−87.018	3.455	3.747	3.568	0.817	ARDL (2, 3)
31	−86.253	3.464	3.792	3.591	0.818	ARDL (2, 4)
37	−86.522	3.474	3.802	3.601	0.817	ARDL (1, 5)
24	−85.817	3.484	3.849	3.625	0.817	ARDL (3, 4)
25	−86.999	3.491	3.819	3.618	0.813	ARDL (3, 3)
30	−86.155	3.497	3.862	3.638	0.815	ARDL (2, 5)
23	−85.410	3.506	3.907	3.661	0.816	ARDL (3, 5)
36	−86.480	3.508	3.873	3.650	0.813	ARDL (1, 6)
17	−85.710	3.517	3.918	3.672	0.814	ARDL (4, 4)
16	−84.816	3.521	3.959	3.690	0.816	ARDL (4, 5)
15	−83.961	3.526	4.000	3.709	0.817	ARDL (4, 6)
18	−86.984	3.527	3.892	3.668	0.809	ARDL (4, 3)
29	−86.083	3.530	3.932	3.686	0.811	ARDL (2, 6)
22	−85.148	3.533	3.971	3.702	0.813	ARDL (3, 6)
40	−91.205	3.535	3.754	3.619	0.796	ARDL (1, 2)
10	−85.207	3.535	3.973	3.704	0.813	ARDL (5, 4)
9	−84.646	3.551	4.025	3.734	0.812	ARDL (5, 5)
2	−83.835	3.558	4.069	3.755	0.813	ARDL (6, 5)
3	−84.842	3.558	4.032	3.741	0.811	ARDL (6, 4)
11	−86.872	3.559	3.960	3.714	0.806	ARDL (5, 3)
8	−83.949	3.562	4.073	3.759	0.813	ARDL (5, 6)
33	−91.096	3.567	3.823	3.666	0.792	ARDL (2, 2)
1	−83.465	3.581	4.128	3.792	0.811	ARDL (6, 6)
4	−86.513	3.582	4.020	3.752	0.804	ARDL (6, 3)
26	−90.783	3.592	3.884	3.705	0.790	ARDL (3, 2)
41	−94.056	3.602	3.785	3.673	0.778	ARDL (1, 1)
34	−93.569	3.621	3.840	3.705	0.778	ARDL (2, 1)
19	−90.680	3.625	3.953	3.752	0.787	ARDL (4, 2)
27	−93.562	3.657	3.912	3.756	0.773	ARDL (3, 1)
12	−90.592	3.658	4.023	3.799	0.783	ARDL (5, 2)
42	−97.098	3.676	3.822	3.733	0.757	ARDL (1, 0)
5	−90.228	3.681	4.082	3.836	0.781	ARDL (6, 2)
20	−93.506	3.691	3.983	3.804	0.769	ARDL (4, 1)
35	−97.092	3.712	3.895	3.783	0.752	ARDL (2, 0)
13	−93.463	3.726	4.054	3.853	0.764	ARDL (5, 1)
28	−97.092	3.749	3.968	3.833	0.747	ARDL (3, 0)
6	−93.242	3.754	4.119	3.895	0.761	ARDL (6, 1)
21	−97.054	3.784	4.039	3.883	0.742	ARDL (4, 0)
14	−97.053	3.820	4.112	3.933	0.737	ARDL (5, 0)
7	−96.216	3.826	4.155	3.953	0.739	ARDL (6, 0)
39	−87.099	3.422	3.677	3.521	0.821	ARDL (1, 3)
38	−86.555	3.438	3.730	3.551	0.820	ARDL (1, 4)
32	−87.018	3.455	3.747	3.568	0.817	ARDL (2, 3)
31	−86.253	3.464	3.792	3.591	0.818	ARDL (2, 4)
37	−86.522	3.474	3.802	3.601	0.817	ARDL (1, 5)
24	−85.817	3.484	3.849	3.625	0.817	ARDL (3, 4)
25	−86.999	3.491	3.819	3.618	0.813	ARDL (3, 3)
30	−86.155	3.497	3.862	3.638	0.815	ARDL (2, 5)
23	−85.410	3.506	3.907	3.661	0.816	ARDL (3, 5)
36	−86.480	3.508	3.873	3.650	0.813	ARDL (1, 6)
17	−85.710	3.517	3.918	3.672	0.814	ARDL (4, 4)
16	−84.816	3.521	3.959	3.690	0.816	ARDL (4, 5)
15	−83.961	3.526	4.000	3.709	0.817	ARDL (4, 6)
18	−86.984	3.527	3.892	3.668	0.809	ARDL (4, 3)

$$Y(t) = \alpha + \beta Y(t-1) + \gamma_0 X(t) + \gamma_1 X(t-1) + \gamma_2 X(t-2) + \gamma_3 X(t-3) + \eta_1 D_1 + \eta_2 D_2. \quad (4)$$

The least square analysis was conducted on the data, and the regression results obtained are shown in Table 5.

According to Table 5, the model can be represented as

$$Y(t) = 0.127Y(t-1) - 1.105X(t) - 0.689X(t-1) - 0.534X(t-2) - 0.492X(t-3) + 3.112D_1 + 1.925D_2 + 25.886, \quad R^2 = 0.849. \quad (5)$$

As shown in the regression results, the coefficient of the first lag period of variable Y is 0.127, but this coefficient is not significant, indicating that the DAOV of the previous day will not have a significant impact on that of the day. The coefficients of snowfall X and its lags are −1.105, −0.689, −0.534, and −0.492, respectively, which are all valid at the significance level of 5%, indicating that snowfalls have a significant negative impact on the DAOV, and the impact lasts for about three days and decreases with time. The regression coefficients of dummy variables D_1 and D_2 are 3.112 and 1.925, respectively, and are both valid at the significance level of 1%, indicating that the DAOV is significantly higher than that on weekdays due to the weekend effect. DAOVs on Saturday and Sunday are 3.112 and 1.925 more than on weekdays, respectively. The intercept is 25.886, indicating that when there is no snowfall, the DAOV is 25.886 on average. The goodness of fit of the regression equation is 0.849, indicating that the data was well interpreted by the model.

4. Discussion

To support the results more intuitively, this study selects one of the snowy days (December 10, on which the snowfall was 3 mm, classified as heavy snow) and carried out a visual analysis on the taxi operation conditions of the day before the snowfall (December 9), the day of the snowfall (December 10), and the four days after the snowfall (December 11–14).

From Figure 5, we can see that taxi demand follows a stable daily pattern with three peaks, corresponding to morning, noon, and evening peak, respectively. At the same time, the demand getting served by hour on December 10 met a significant decline due to the snowfall starting at the early morning. Note that there is a significant decline on December 11 but not on December 12 and 13. The reason for this is that these two days are weekends, and as the model result shows, there is a positive weekend effect on DAOV during weekends, which offsets the negative effects of the snowfall.

Due to the different nature of land use, the hot spots of pick-up points (PUPs) and dropping-off points (DOPs) in a city are distributed unevenly. At the same time, the heat of both points in the same area in different days will also be affected by weather. Figures 6 and 7, respectively, show the thermal diagram of the PUPs and the DOPs of taxis in Harbin within the 6 days.

As can be seen from Figures 6 and 7, the hot spots of taxi demands are mainly distributed in residential districts of Rongshi, Zhaolin, Nanzhi Road, Renli, Anjing, Aijian, Xinchun, Xincheng, Anbu, Haping Road, Tongda, Hexing Road, Xinhua, Hongqi, Haxi, Jianshe, Wenfu Road and Heilongjiang Province University, Harbin Railway Station, Harbin East Railway Station, Harbin West Railway Station, and Taiping International Airport. And they are all affected by the snowfall to varying degrees. Among the six days, the most significant day is the day of snowfall (as shown in Figures 6(b) and 7(b)), when snowfall happened in the morning and might affect traffic throughout the day. As can be seen from (c), (d), (e), and (f) in Figures 6 and 7, the taxi operation was still continuously affected by the snowfall within 1–3 days after the snowfall, especially within the 1-2 days after, and it gradually returned to the pre-snowfall level by the 4th day after the snowfall.

In the hot spots of the PUPs, the most affected areas by the snowfall are the residential districts of Zhaolin, Renli, Anjing, Aijian, Xinchun, Xincheng, Anbu, Haping Road, Tongda, Hexing Road, Xinhua, Hongqi, Wenfu Road, Haxi, Jianshe, and so on. Among the hot areas at the DOPs, the residential districts of Zhaolin, Renli, Anjing, Xinchun, Tongda, Hexing Road, Wenfu Road, Haxi, and Jianshe are the most vulnerable areas. These areas usually have tourist attractions (such as Anjing Residential District, where Sophia Cathedral is located) or business districts (such as residential districts of Xinchun, Hesheng Road, and Haxi), indicating that the snow mainly has a great impact on residents' entertainment or shopping behaviors. While some residential areas, such as residential districts of Rongshi and Nanzhi Road (which both had a population of more than 100,000), were not significantly affected by the snowfall, indicating that snowfall had less effect on residents' daily commuting behaviors.

As snow reduces the accessibility of the road, the speed of traffic flow will be significantly reduced, which results in longer trip duration than that under normal weather conditions. Figure 8 shows the connection between the PUPs and the DOPs of all the taxi trips. Different colors represent different trip duration levels.

As can be seen from Figure 8, compared with December 9 (Figure 8(a)), the trip duration in December 10 and the following two days (Figures 8(b)–8(d)) has increased significantly, especially for those airport-to-city intervals, because the airport is far away from the city (33 km), and only one expressway connects the two areas. On December 13

Table 5: Regression results.

Variable	Coefficient	Std. error	t-statistic	Prob.*
$Y(t-1)$	0.127	0.114	1.120	0.268
X	−1.105	0.160	−6.895	0.000
$X(t-1)$	−0.689	0.213	−3.236	0.002
$X(t-2)$	−0.534	0.201	−2.651	0.011
$X(t-3)$	−0.492	0.196	−2.513	0.015
D1	3.112	0.500	6.223	0.000
D2	1.925	0.580	3.318	0.002
C	25.886	3.400	7.614	0.000

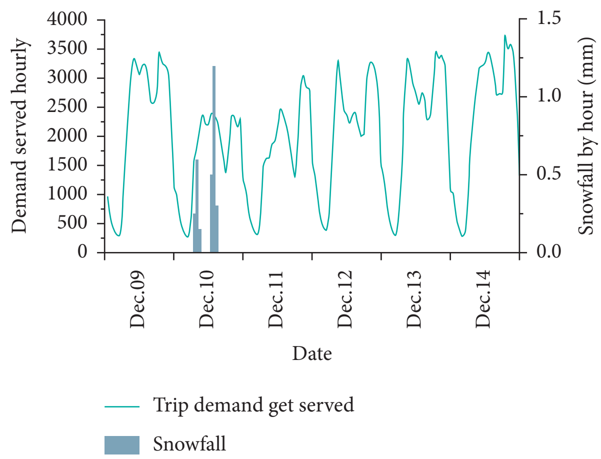


Figure 5: Trip demand getting served in each hour during the 6 days.

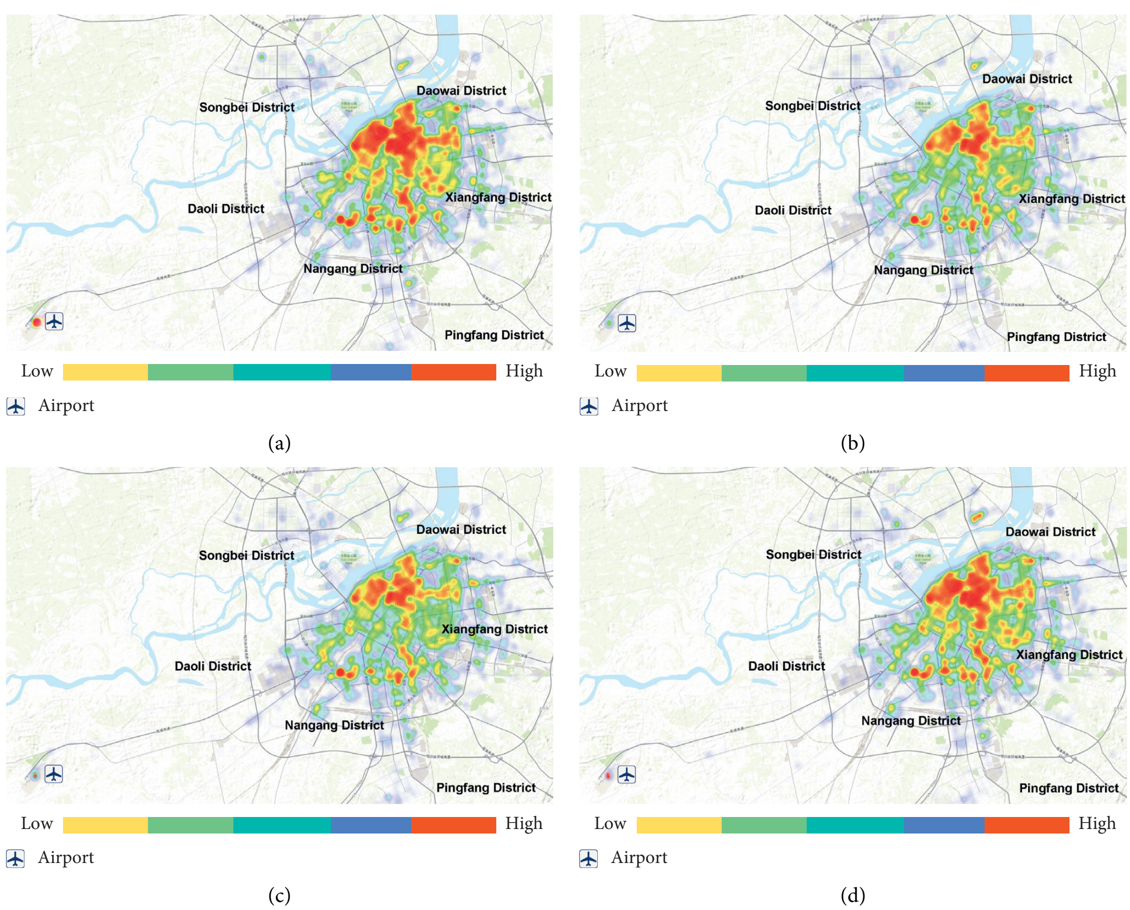
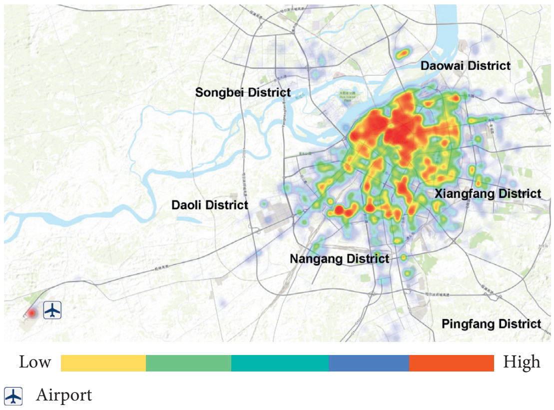
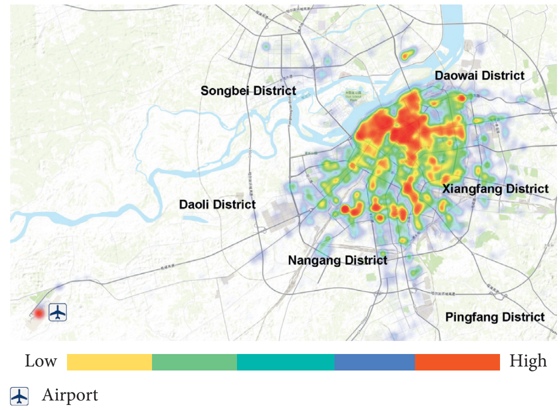


Figure 6: Continued.

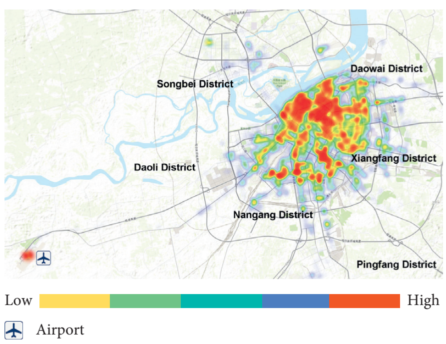


(e)

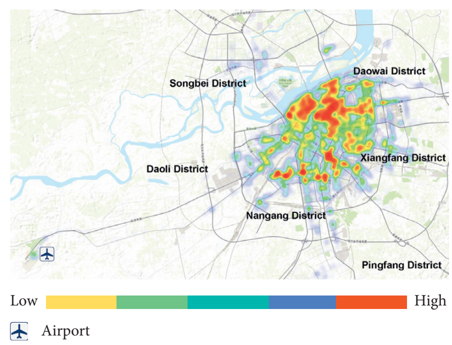


(f)

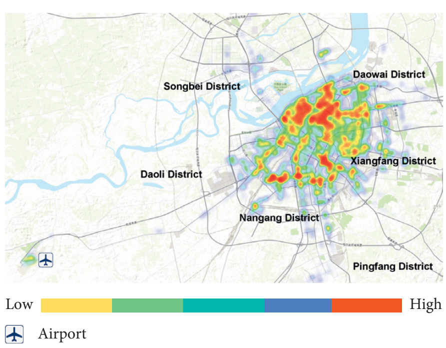
Figure 6: Spatial distribution of PUPs during the 6 days. (a) December 9, (b) December 10, (c) December 11, (d) December 12, (e) December 13, and (f) December 14.



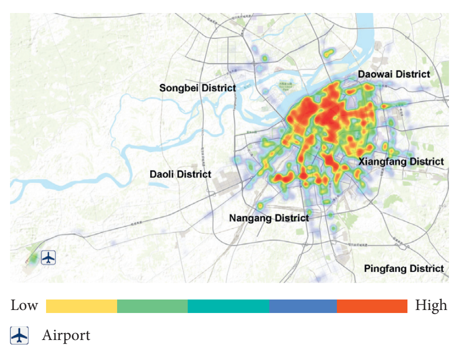
(a)



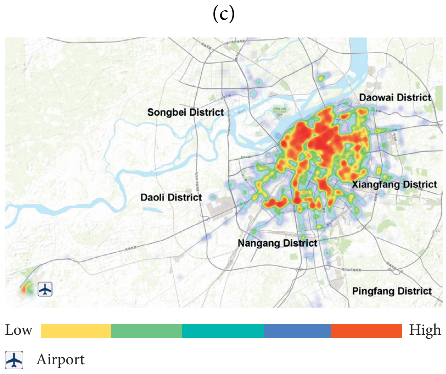
(b)



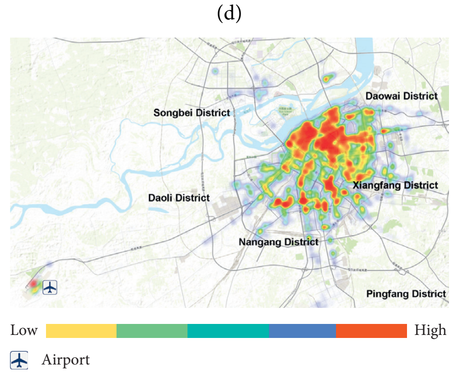
(c)



(d)



(e)



(f)

Figure 7: Spatial distribution of DOPs during the 6 days. (a) December 9, (b) December 10, (c) December 11, (d) December 12, (e) December 13, and (f) December 14.

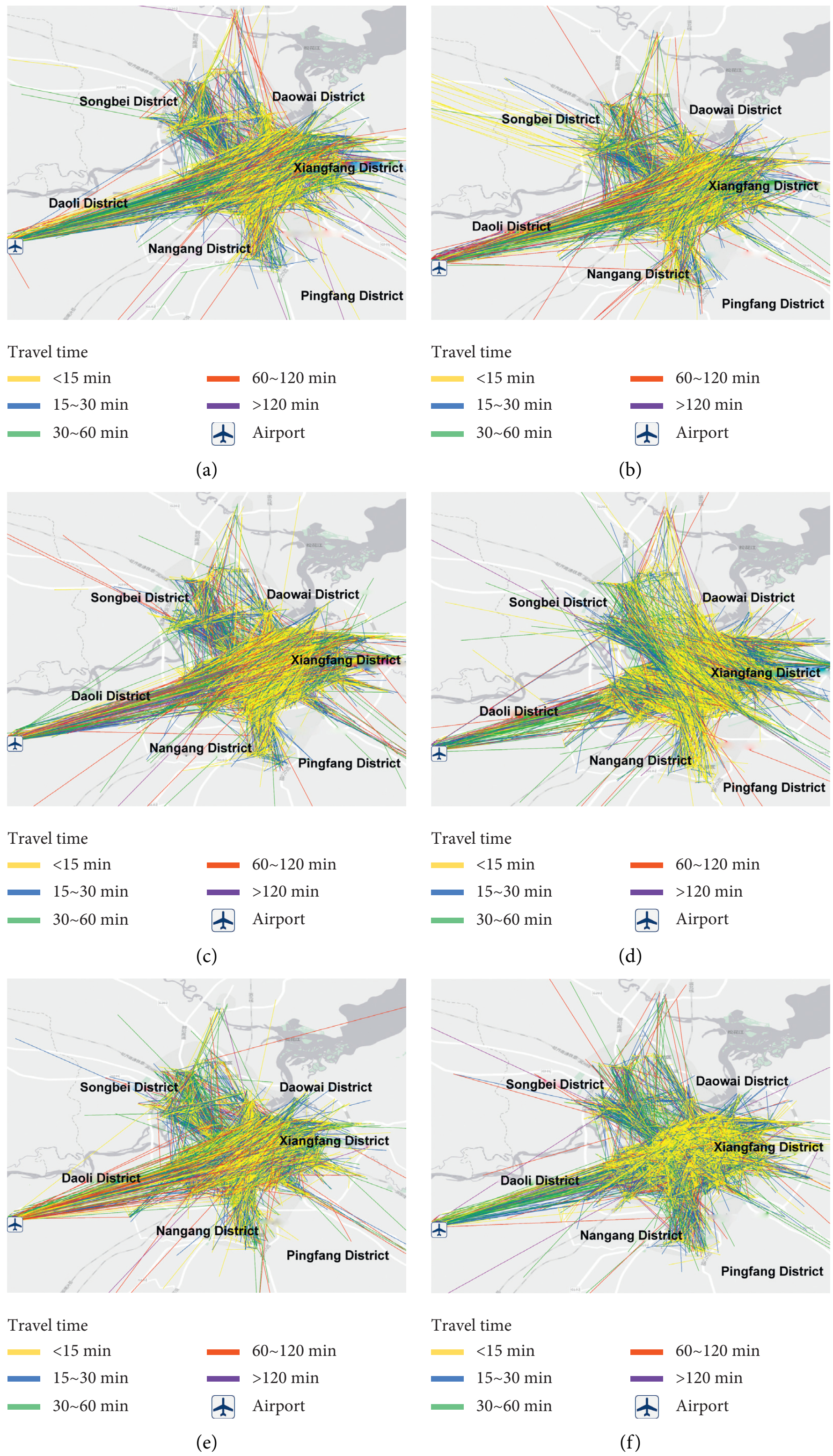


Figure 8: OD distributions with different trip duration levels during the 6 days. (a) December 9, (b) December 10, (c) December 11, (d) December 12, (e) December 13, and (f) December 14.

and 14 (Figures 8(e) and 8(f)), the duration time gradually returned to the level before the snowfall, implying that the snowfall had a significant effect on travel efficiency.

Interval distribution of trip duration reflects taxi trip duration distribution. From Figure 9, we can see that trips within 10 minutes have higher proportions during snowy

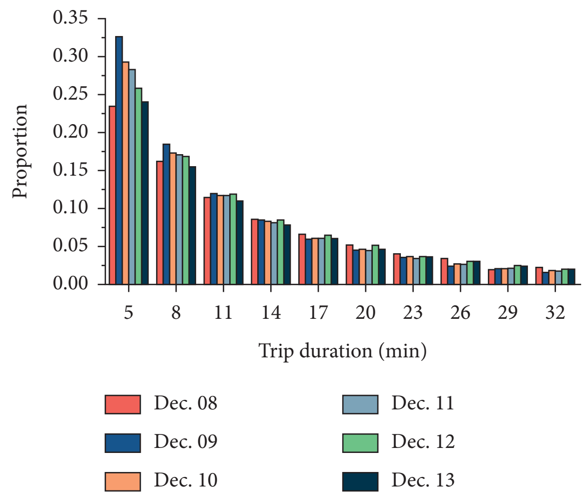


Figure 9: Interval distribution of trip durations during the 6 days.

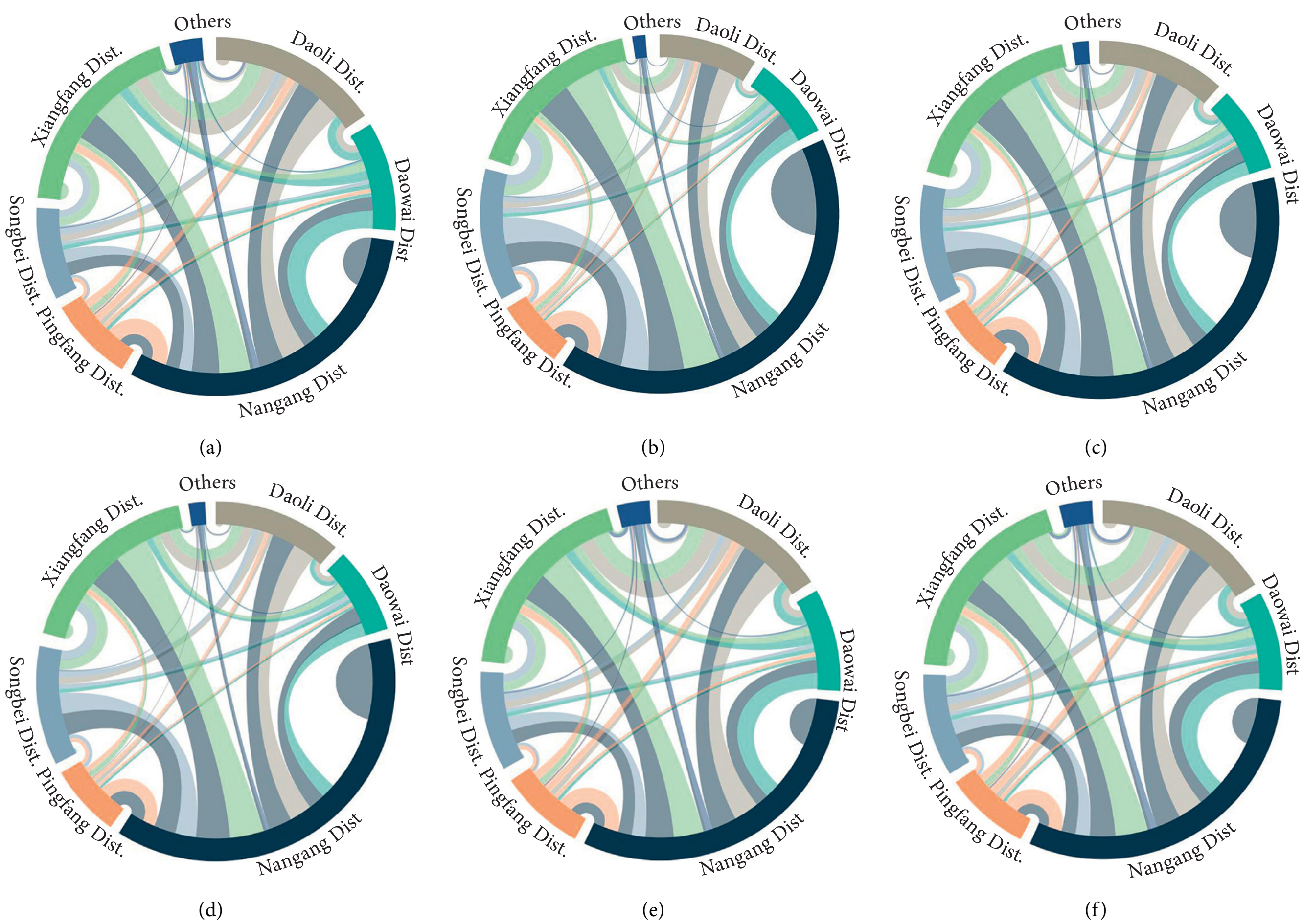


Figure 10: OD flows in different districts of Harbin over 6 days. (a) December 9th. (b) December 10th. (c) December 11th. (d) December 12th. (e) December 13th. (f) December 14th.

days. It can be inferred that during snowy days people would be more likely to take taxis for short distance trips while choosing other transportation modes for middle- or long-distance trips or they even just give up such trips. The reason for this may be that in snowy days the traffic flow speed decreases due to the poor road conditions, which accounts for higher fare, and it is uneconomical to take a taxi to travel far-away.

Different regions in the city are affected by population, geography, economy, land use, and other factors. The taxi travel intensity within and between regions is different and may be affected by snowfall. In order to reflect the OD flow of taxis within and between the districts, a chord diagram was proposed in this study using a circular visualization package, which was well adopted in the study [52].

It can be seen from Figure 10 that Nangang District and Xiangfang District have the highest taxi order intensity among the 6 districts, and the closest travel contact happens between Nangang District and Xiangfang District and between Daoli District and Nangang District. As the residence of Heilongjiang provincial government and more than 20 universities, Nangang District has active economic activities, dense population, and large traffic demand. During the snowy days, the proportion of taxi demands in Nangang met an increase, and the same thing happened to the inner Nangang District. At the same time, as the location of the only airport in Harbin, Daoli District has strong relationships with the other districts. However, the relationships weakened in the snowy days. This can be interpreted that the snowfall accounted for the flight delay or even cancellation, and many passengers cancelled their taxi trips to the airport. This situation returned to normal within the third day after the snowfall.

5. Conclusions

This paper aims to study the lag effect of snowfall on taxi operation through taxi GPS data. First, the paper sampled and cleaned the taxi trajectory data of Harbin for 61 consecutive days, so as to extract all the pick-up points and drop-off points as well as the duration time of each trip from the daily trajectory sample data. Then, combined with the 61 days snowfall data, an ARDL model was built to explain the lag effect. Taxi daily average order volume (DAOV), which is assumed to be directly proportional to taxi drivers' benefits, is constructed as explained variable in the model. In order to better understand and demonstrate the results of the model, some visualization methods are applied to the six days before and after a snowfall. From the results of the model and visualization, the following conclusions can be drawn:

(1) Snow has a significant impact on the benefits of taxi networks and has a significant lag effect with a lag period of 3 days. From the fourth day after the snowfall, the impact of snowfall on taxi benefits was basically eliminated.

(2) The snowfall has a negative impact on taxi benefits in various hot areas of the city, but the impact is different. The impact of snowfall is greater in the areas with business concentration and less in the areas with residential communities. This shows that snowfall has a greater impact on the travel demand for shopping and entertainment.

(3) The DAOV on weekends is significantly higher than that on weekdays; that is, the demand for taxis on weekends is more vigorous, and taxi drivers are expected to have higher benefits on weekends.

(4) Since snowfall will reduce the speed of traffic flow, travel time will increase significantly. Especially for those long-distance trips, the travel efficiency is further reduced.

(5) Snowfalls not only affect the trip demand in different districts to different extents, but they also affect the interaction between different districts.

(6) Although some studies have considered the autoregression phenomenon in traffic parameters, in the study of this paper, the autoregression phenomenon of DAOV is not significant; that is, the DAOV of that day is relatively independent from that of the previous days.

The above conclusions are of great significance, and we give some policy suggestions from three perspectives:

For taxi drivers, they can adjust their operation schedules according to the hot spot distribution and weekend effect, so as to increase the efficiency of finding passengers and increase their benefits. For example, it is advised to relocate their taxis to residential areas after the snowfall since the shopping- and entertainment-related trips decrease. And they are advised to find potential passengers in districts like Nangang, Daoli, and Xiangfang.

For municipal departments, knowing the impact mechanism of snow on taxis, they can adjust their work plan of snow clearing and deicing to minimize the impact of snow on urban traffic. Although the snow clearing work of Harbin municipal department is very timely and efficient, some minor road segments are usually given low priority in the snow clearing schedule. Since these road segments also bear a lot of traffic volume, the snow and ice clearing work of these segments should not be neglected in the 3 days after snowfalls.

For transportation management departments, the results of the study can provide suggestions for developing flexible traffic scheduling schemes to facilitate the daily travel of citizens after snowfalls. Temporary bus routes should be planned to serve the long-distance trips. It is also worth paying attention to ensuring the timely operation of routine buses.

All kinds of urban public transport interrelate and interact with each other, and the traffic demand will transfer among them. To understand the impact of snowfalls on taxi operation and the overall transportation system from a broader perspective, data on other modes of public transport, such as buses and metros, may be obtained for further study in the future.

Data Availability

The experiment data used to support the findings of this study have not been made available because of participant privacy and commercial confidentiality.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

The study has been funded by National Key R&D Program of China (no. 2019YFB2102702).

References

[1] P. Arana, S. Cabezudo, and M. Peñalba, "Influence of weather conditions on transit ridership: a statistical study using data from Smartcards," *Transportation Research Part A: Policy and Practice*, vol. 59, pp. 1–12, 2014.

[2] A. Singhal, C. Kamga, and A. Yazici, "Impact of weather on urban transit ridership," *Transportation Research Part A: Policy and Practice*, vol. 69, pp. 379–391, 2014.

[3] H. Kojo, P. Leviäkangas, R. Molarius, and A. Tuominen, "Extreme Weather Impacts on Transport Systems," *Espoo*, no. 168, pp. 1–136, 2011.

[4] M. J. Koetse and P. Rietveld, "The impact of climate change and weather on transport: an overview of empirical findings," *Transportation Research Part D: Transport and Environment*, vol. 14, no. 3, pp. 205–221, 2009.

[5] A. K. Andersson and L. Chapman, "The impact of climate change on winter road maintenance and traffic accidents in West Midlands, UK," *Accident Analysis & Prevention*, vol. 43, no. 1, pp. 284–289, 2011.

[6] B. Aamaas, J. Borken-Kleefeld, and G. P. Peters, "The climate impact of travel behavior: a German case study with illustrative mitigation options," *Environmental Science & Policy*, vol. 33, pp. 273–282, 2013.

[7] M. Hyland, C. Frei, A. Frei, and H. S. Mahmassani, "Riders on the storm: exploring weather and seasonality effects on commute mode choice in Chicago," *Travel Behaviour and Society*, vol. 13, pp. 44–60, 2018.

[8] L. Böcker, M. Dijst, and J. Prillwitz, "Impact of everyday weather on individual daily travel behaviours in perspective: a literature review," *Transport Reviews*, vol. 33, pp. 71–91, 2013.

[9] S. Najafabadi, A. Hamidi, M. Allahviranloo, and N. Devineni, "Does demand for subway ridership in Manhattan depend on the rainfall events?" *Transport Policy*, vol. 74, pp. 201–213, 2019.

[10] L. Ma, H. Xiong, Z. Wang, and K. Xie, "Impact of weather conditions on middle school students' commute mode choices: empirical findings from Beijing, China," *Transportation Research Part D: Transport and Environment*, vol. 68, pp. 39–51, 2019.

[11] Y. Wang, Y. Bie, and Q. An, "Impacts of winter weather on bus travel time in cold regions: case study of Harbin, China," *Journal of Transportation Engineering, Part A: Systems*, vol. 144, no. 11, Article ID 05018001, 2018.

[12] S. A. Kashfi, J. M. Bunker, and T. Yigitcanlar, "Modelling and analysing effects of complex seasonality and weather on an area's daily transit ridership rate," *Journal of Transport Geography*, vol. 54, pp. 310–324, 2016.

[13] J. Corcoran and S. Tao, "Mapping spatial patterns of bus usage under varying local temperature conditions," *Journal of Maps*, vol. 13, no. 1, pp. 74–81, 2017.

[14] J. Zhao, C. Guo, R. Zhang, D. Guo, and M. Palmer, "Impacts of weather on cycling and walking on twin trails in Seattle," *Transportation Research Part D: Transport and Environment*, vol. 77, pp. 573–588, 2019.

[15] Y. Bie, J. Ji, X. Wang, and X. Qu, "Optimization of electric bus scheduling considering stochastic volatilities in trip travel time and energy consumption," *Computer-Aided Civil and Infrastructure Engineering*, vol. 36, no. 12, pp. 1530–1548, 2021.

[16] M. Hofmann and M. O'Mahony, "The impact of adverse weather conditions on urban bus performance measures," in *Proceedings of the 2005 IEEE Intelligent Transportation Systems*, pp. 84–89, Vienna, Austria, September 2005.

[17] D. Jaroszweski and T. McNamara, "The influence of rainfall on road accidents in urban areas: a weather radar approach," *Travel Behaviour and Society*, vol. 1, no. 1, pp. 15–21, 2014.

[18] E. Chung, O. Ohtani, H. Warita, M. Kuwahara, and H. Morita, "Effect of rain on travel demand and traffic accidents," in *Proceedings of the 2005 IEEE Intelligent Transportation Systems*, pp. 1080–1083, Vienna, Austria, September 2005.

[19] C. Pennelly, G. W. Reuter, and S. Tjandra, "Effects of weather on traffic Collisions in edmonton, Canada," *Atmosphere-Ocean*, vol. 56, no. 5, pp. 362–371, 2018.

[20] K. El-Basyouny, S. Barua, and M. T. Islam, "Investigation of time and weather effects on crash types using full Bayesian multivariate Poisson lognormal models," *Accident Analysis & Prevention*, vol. 73, pp. 91–99, 2014.

[21] D. Chen, Y. Zhang, L. Gao, N. Geng, and X. Li, "The impact of rainfall on the temporal and spatial distribution of taxi passengers," *PloS one*, vol. 12, Article ID e0183574, 2017.

[22] P. Thaker and S. Gokhale, "The impact of traffic-flow patterns on air quality in urban street canyons," *Environmental Pollution*, vol. 208, pp. 161–169, 2016.

[23] H. Budnitz, L. Chapman, and E. Tranos, "Better by bus? Insights into public transport travel behaviour during StormDorisin Reading, UK," *Weather*, vol. 73, no. 2, pp. 54–60, 2018.

[24] H. Xiao, H. Sun, and B. Ran, "Special factor adjustment model using fuzzy-neural network in traffic prediction," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1879, no. 1, pp. 17–23, 2004.

[25] T. Nosal and L. F. Miranda-Moreno, "The effect of weather on the use of North American bicycle facilities: a multi-city analysis using automatic counts," *Transportation Research Part A: Policy and Practice*, vol. 66, pp. 213–225, 2014.

[26] S. Zhang, H. Wang, X. Liu, and W. Quan, "Dynamic impact of meteorological factors on freeway free-flow volume and speed in Yanbian," *Procedia - Social and Behavioral Sciences*, vol. 96, pp. 2667–2675, 2013.

[27] W. Qiao, A. Haghani, and M. Hamedi, "Short-term travel time prediction considering the effects of weather," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2308, no. 1, pp. 61–72, 2012.

[28] G. Yannis and M. G. Karlaftis, "Weather effects on daily traffic accidents and fatalities: a time series count data approach," in *Proceedings of the 89th Annual Meeting of the Transportation Research Board 2004*, p. 14, MD, USA, July 2004.

[29] D. Eisenberg, "The mixed effects of precipitation on traffic crashes," *Accident Analysis & Prevention*, vol. 36, no. 4, pp. 637–647, 2004.

[30] T. Brijs, D. Karlis, and G. Wets, "Studying the effect of weather conditions on daily crash counts using a discrete time-series model," *Accident Analysis & Prevention*, vol. 40, no. 3, pp. 1180–1190, 2008.

[31] R. Billot, N.-E. El Faouzi, and F. De Vuyst, "Multilevel assessment of the impact of rain on drivers' behavior," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2107, no. 1, pp. 134–142, 2009.

[32] T. Nosal and L. F. Miranda-Moreno, "Cycling and Weather: A Multi-City and Multi-Facility Study in North America," in

Proceedings of the Transportation Research Board annual Meeting, Washington DC, USA, January 2012.

[33] N. S. Arunraj and D. Ahrens, "Estimation of non-catastrophic weather impacts for retail industry," *International Journal of Retail Distribution Management*, vol. 44, no. 7, pp. 0959–0552, 2016.

[34] Z.-Y. Zhan, Y.-M. Yu, T.-T. Chen, L.-J. Xu, S.-L. An, and C.-Q. Ou, "Effects of hourly precipitation and temperature on ambulance response time," *Environmental Research*, vol. 181, Article ID 108946, 2020.

[35] H. M. P. S Government, "Harbin statistical yearbook," 2016, http://www.harbin.gov.cn/col/col39/index.html.

[36] N. Takahashi, S. Miyamoto, and M. Asano, "Using taxi GPS to gather high-quality traffic data for winter road management evaluation in Sapporo, Japan," in *Proceedings of Sixth International Symposium on Snow Removal and Ice Control Technology*, pp. 455–469, Transportation Research Board, Washinton DC, USA, June 2004.

[37] S. Zhang, J. Tang, H. Wang, Y. Wang, and S. An, "Revealing intra-urban travel patterns and service ranges from taxi trajectories," *Journal of Transport Geography*, vol. 61, pp. 72–86, 2017.

[38] L. Wu, S. Hu, L. Yin et al., "Optimizing cruising routes for taxi drivers using a spatio-temporal trajectory model," *ISPRS International Journal of Geo-Information*, vol. 6, no. 11, p. 373, 2017.

[39] Y. Wang, K. Qin, Y. Chen, and P. Zhao, "Detecting anomalous trajectories and behavior patterns using hierarchical clustering from taxi GPS data," *ISPRS International Journal of Geo-Information*, vol. 7, no. 1, p. 25, 2018.

[40] L. Tang, F. Sun, Z. Kan, C. Ren, and L. Cheng, "Uncovering distribution patterns of high performance taxis from big trace data," *ISPRS International Journal of Geo-Information*, vol. 6, no. 5, p. 134, 2017.

[41] G. Yang, C. Song, H. Shu, J. Zhang, T. Pei, and C. Zhou, "Assessing patient bypass behavior using taxi trip origin-destination (OD) data," *ISPRS International Journal of Geo-Information*, vol. 5, no. 9, p. 157, 2016.

[42] P. S. Castro, D. Zhang, and S. Li, "Urban traffic modelling and prediction using large scale taxi GPS traces," in *Proceedings of International Conference on Pervasive Computing*, pp. 57–72, CA, USA, May 2012.

[43] C. Yang and E. J. Gonzales, "Modeling taxi demand and supply in New York city using large-scale taxi GPS data," in *Springer Geography Seeing Cities through Big Data*, pp. 405–425, Springer, Berlin, Germnay, 2017.

[44] P. K. Narayan, "Fiji's tourism demand: the ARDL approach to cointegration," *Tourism Economics*, vol. 10, no. 2, pp. 193–206, 2004.

[45] S. A. Hassan and M. Nosheen, "The impact of air transportation on carbon dioxide, methane, and nitrous oxide emissions in Pakistan: evidence from ARDL modelling approach," *International Journal of Innovation and Economic Development*, vol. 3, no. 6, pp. 7–32, 2018.

[46] P. Stamolampros and N. Korfiatis, "Airline service quality and economic factors: an ARDL approach on US airlines," *Journal of Air Transport Management*, vol. 77, pp. 24–31, 2019.

[47] M. K. Khan, J.-Z. Teng, and M. I. Khan, "Effect of energy consumption and economic growth on carbon dioxide emissions in Pakistan with dynamic ARDL simulations approach," *Environmental Science and Pollution Research*, vol. 26, no. 23, Article ID 23490, 2019.

[48] R. P. Pradhan, N. R. Norman, Y. Badir, and B. Samadhan, "Transport infrastructure, foreign direct investment and economic growth interactions in India: the ARDL bounds testing approach," *Procedia - Social and Behavioral Sciences*, vol. 104, pp. 914–921, 2013.

[49] P. Lingras, S. C. Sharma, P. Osborne, and I. Kalyar, "Traffic volume time-series analysis according to the type of road use," *Computer-Aided Civil and Infrastructure Engineering*, vol. 15, no. 5, pp. 365–373, 2000.

[50] Y. Zhang and Y. Zhang, "A comparative study of three multivariate short-term freeway traffic flow forecasting methods with missing data," *Journal of Intelligent Transportation Systems*, vol. 20, no. 3, pp. 205–218, 2016.

[51] W. Wang, H. Zhang, T. Li et al., "An interpretable model for short term traffic flow prediction," *Mathematics and Computers in Simulation*, vol. 171, pp. 264–278, 2020.

[52] H. Wang, H. Huang, X. Ni, and W. Zeng, "Revealing spatial-temporal characteristics and patterns of urban travel: a large-scale analysis and visualization study with taxi GPS data," *ISPRS International Journal of Geo-Information*, vol. 8, no. 6, p. 257, 2019.