Urban Climate 41 (2022) 101065

Contents lists available at ScienceDirect

Urban Climate

journal homepage: www.elsevier.com/locate/uclim

Data-driven analysis of weather impacts on urban traffic conditions at the city level

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ARTICLE INFO

Keywords:
Traffic condition
Urban climate
Travel time index (TTI)
Interaction effects
Spatial-temporal scales
Urban study

ABSTRACT

Unhealthy traffic conditions have significant adverse implications for environment-friendly, sustainable, and energy-efficient development. As an real-time environmental factor contributing to travel, comparing the effect mechanisms of weather on traffic conditions in multiple cities will provide a deeper understanding of the weather-traffic relationship. This study conducts a contrastive analysis of travel time index (TTI) variations under weather conditions in four cities. Notably, this study will consider the potential benefits of replacing an absolute index of traffic conditions, like traffic volume and travel speed, with TTI, a relative index. The results identified a strong association between complex weather measurements and traffic conditions. Overall, the impact of meteorological variables on TTI on non-weekdays might result in significantly worse traffic conditions. On weekdays, the impact is relatively weak, due to the flexibility for travel mode decision-making, especially during the commute hour. Weather impacts on traffic conditions are not only interrelated, like higher temperature with less rainfall or slower wind speeds, but they also varied with urban spatial layout and geographical condition. Besides, the traffic congestion is certainly related to extreme weather, but not closely. This study could benefit transit agencies by adding meteorological monitoring into traffic condition real-time analysis.

1. Introduction

The urban traffic system, which integrates humans, vehicles, roads, environment and other complex factors, is highly complex, time-dependent, and random. Various external conditions, like policies, economics, and weather, have direct or indirect influences on the operating performance of traffic systems. Weather intrinsically influences the transport sector all the time (Akter et al., 2020; Fu et al., 2014).

Numerous studies that have dealt with weather have focused on travel behavior, traffic safety, traffic signal control and transit operation (Wu and Liao, 2020; Jain and Singh, 2021; Theofilatos and Yannis, 2014; Park et al., 2021; Lu et al., 2019; Tao et al., 2016). Yet, passenger flow or ridership is the final macroscopic expression of the influences of weather on transport systems. There is an emerging scholarly interest in the relationship between weather conditions and passenger flow or ridership (Tao et al., 2016; Wei et al., 2019; Li et al., 2018; Miao et al., 2019; Zhou et al., 2017; Kashfi et al., 2015; Arana et al., 2014; Ngo, 2019). The body of their works

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https://doi.org/10.1016/j.uclim.2021.101065
Received 8 February 2021; Received in revised form 27 September 2021; Accepted 18 December 2021
Available online 26 December 2021

mainly highlight that weather conditions play an important role in intensity fluctuation across various climatic measurements including temperature, precipitation, wind speed, humidity and climate pattern.

Driving on the road actually is an activity that has to be exposed to the outdoor environment, where weather conditions are inevitably considered in each choice throughout the trip. Similar to other travel modes, researchers have been paying more attention to the effect of weather on every aspect of individual travel behavior in micro level, including route and destination choices (Cools et al., 2010; Yoon et al., 2012; Durand et al., 2017) and modal shift (Hyland et al., 2018; Böcker et al., 2013; Heinen et al., 2010). In addition, related research studies have covered different temporal scales and transit modes. Studies have investigated the weather-traffic relationship at hourly levels (Wei et al., 2019; Zhou et al., 2017; Singhal et al., 2014), daily levels (Wei et al., 2019; Singhal et al., 2014; Scott and Ciuro, 2019), with consideration of weekend (Wu and Liao, 2020), during vacation and seasonal periods (Liu et al., 2015b), among bicycles (Scott and Ciuro, 2019), on buses (Miao et al., 2019), and on the subway (Wu and Liao, 2020). It is because of various independent travel behavior choices that result in the ever-changing road conditions by the weather.

On a macroscale road conditions can be regarded as a manifestation of traffic volume on a road network, and the fluctuation of road conditions is also influenced by weather conditions. However, the influence of weather on traffic volume has received relatively less attention. Anta et al. (2016), Zhang and Kabuka (2018), Keay and Simmonds (2005), and Chung (2012) have confirmed the close relationship between weather condition and traffic congestion, especially when there is heavy rain. Other weather elements such as wind speed, temperature and meteorological visibility also affect traffic volume even the impact of the weather that's weak (Lin et al., 2015; Datla and Sharma, 2010). What's even more remarkable is that people pay more attention to their driving experience compared with absolute traffic volume. The research about the effect of weather elements on the extent of traffic congestion is of great significance owing to its practical significance.

At present, scholars have been noticed to the weather effects on travel and traffic, and they have finished some outstand work of this area. However, some problems still remain: 1) little is known of the relationship between weather and real-time road traffic condition; 2) more reasonable congestion indicator, such as travel time index (TTI), is rarely applied in road traffic flow evaluation. Here, this study will focus on analyzing and examining the following research questions:

- Do weather parameters (including temperature, wind speed, rainfall accumulation, and visibility) have a significant impact on real-time road traffic conditions?
- If so, what is the individual impact of each weather parameter on traffic conditions? Whether their impacts on traffic conditions are likely to be interrelated?
- How to capture the weather–traffic relationships at different spatial-temporal scales?
- Is there a specific pattern of weather-traffic among cities with different geographical situation?

Therefore, to address the aforementioned research gaps and extend research on weather-traffic relationships, a series of multivariate regression models at various temporal and spatial levels are proposed to understand the relationship between complete meteorological indicators and traffic conditions. Specifically, this study conducts a contrastive weather-traffic analysis based on four datasets from various Chinese cities with different geographic locations and weather characteristics to discuss their commonalities and their individualities. Interestingly, a newly measurement of traffic condition that are more suitable for comparison between cities is proposed in this study.

The rest of this paper is organized as follows. Section 2 is a literature review of data collection and modeling methods. Section 3 introduces the data source and model design on weather and road conditions. The case study and the obtained results are detailed in Section 4. Section 5 discusses the analysis findings. The final section summarizes the recommendations based on the above findings and points out future research directions.

2. Literature review

The weather-traffic relationship has received substantial research attention. This section will focus on key aspects of in relevant studies, including data collection and modeling details.

2.1. Weather and traffic

A number of existing studies have examined the influences of weather conditions and traffic characteristics. Some research find significant relationship between rainfall and traffic flow, and emphasized that heavy rainfall can lead to reduction in speed, road capacity, traffic flowing, resulting in longer travel time than normal (Yuan-qing and Jing, 2017; Zheng et al., 2019; Sathiaraj et al., 2018). However, in other studies, contrasting relationships are detected that rain may increase the chance of driving to avoid villainous traveling environment (Kent, 2015). These mixed findings could be the result of two factors. One is related to the intensity of the precipitation. In other words, between rainfall and road condition is not necessarily monotonic to the relationship (Kim and Wang, 2016; Dhaliwal et al., 2017; Bartlett et al., 2013). The other pivotal explanation is the differentiating extreme weather thresholds in different cities, where the public perception on rainfall are obvious in some areas but moderate in others (Guo et al., 2018; Sathiaraj et al., 2018). Moreover, wind speed, temperature and visibility also have dual characters. These weather conditions may stimulate the generation of more trips or create hazardous driving environments and lead to decreased traffic volume (Lin et al., 2015; Datla and Sharma, 2010; Pang et al., 2015). Besides, compared to understanding the individual influence of a weather parameter, it's also worth noting that the comprehensive influences of interacting with other meteorological factors on traffic condition. Wei et al. (2019) and Liu et al. (2015a) suggests that the meteorological factors naturally co-occur in reality, which confirms the interrelated climatic impact. However, the research on the interlocking role of meteorological conditions is less comparatively in academic realm, especially for traffic conditions.

In addition, previous studies investigating traffic conditions mainly focus on traffic volume or vehicle speed, which all are crucial factors that influence traffic conditions (Yang et al., 2021; Sathiaraj et al., 2018; Yi et al., 2020). These absolute indexes are able to reflect directly the change of traffic conditions in a specific city, even a specific sub-region. Yet, all these studies challenge similar issues, one of which is how to identify the commonalities and individualities of the weather effects on traffic condition characteristics when transversally comparing multiple cities.

2.2. *Traffic data collection*

There are two common methods for collecting travel behavior data (Arana et al., 2014): one is based on traditional questionnaires to collect individual travel behavior information and characteristics, whether using online surveys (Arroyo et al., 2020; Kroesen and Chorus, 2020; De Oña et al., 2016) or actual surveys (Cools et al., 2010), and the other uses passive data collected by electronic devices and management systems, like a smart card system (Tang et al., 2020; He et al., 2020; Yap et al., 2020). The passive data acquisition methods are both highly efficient and low cost, which has opened new opportunities in transportation research, leading to applications in fields such as bikesharing trip patterns (Bao et al., 2017), individual mobility prediction (Zhao et al., 2018), after-work activities analysis (Wang et al., 2017), and road conditions monitoring. Monitoring equipment like magnetic loop detectors, radar detectors and video detectors (Harrou et al., 2020), can infer the current road conditions based on fixed traffic data, but their weakness is poor precision. Some studies have demonstrated the advantages of introducing GPS data into transport research (Wang et al., 2019; Mattia et al., 2019; Huang et al., 2018), using the floating car data (FCD) method. Compared to fixed traffic monitoring, the FCD method could capture the dynamic and comprehensive characteristics of traffic flow. Moreover, the rapid development of online car-hailing services (Zhang et al., 2020; Sun et al., 2018; Narayan et al., 2020; Javanshour et al., 2019) creates a more convenient source of hardware for applying the FCD method.

When making comparisons of road conditions between different cities, it is important to use a reasonable method. For example, it is difficult to make direct comparisons using absolute indexes like traffic speed or traffic volume. In this study, the extent of traffic congestion is measured by the travel time index (TTI), a frequently used indicator in transit systems. TTI is the ratio of free-flow speed to actual speed. Of note, TTI will be estimated using a new application of FCD with the help of on-demand system.

Given that differences in spatial and temporal scales will inevitably impact the angle and depth of analysis, this research combines the literature mentioned above to understand the relationship between weather and road conditions (TTI) from a different depth and angle, based on the road conditions data estimated from floating car data (on-demand system).

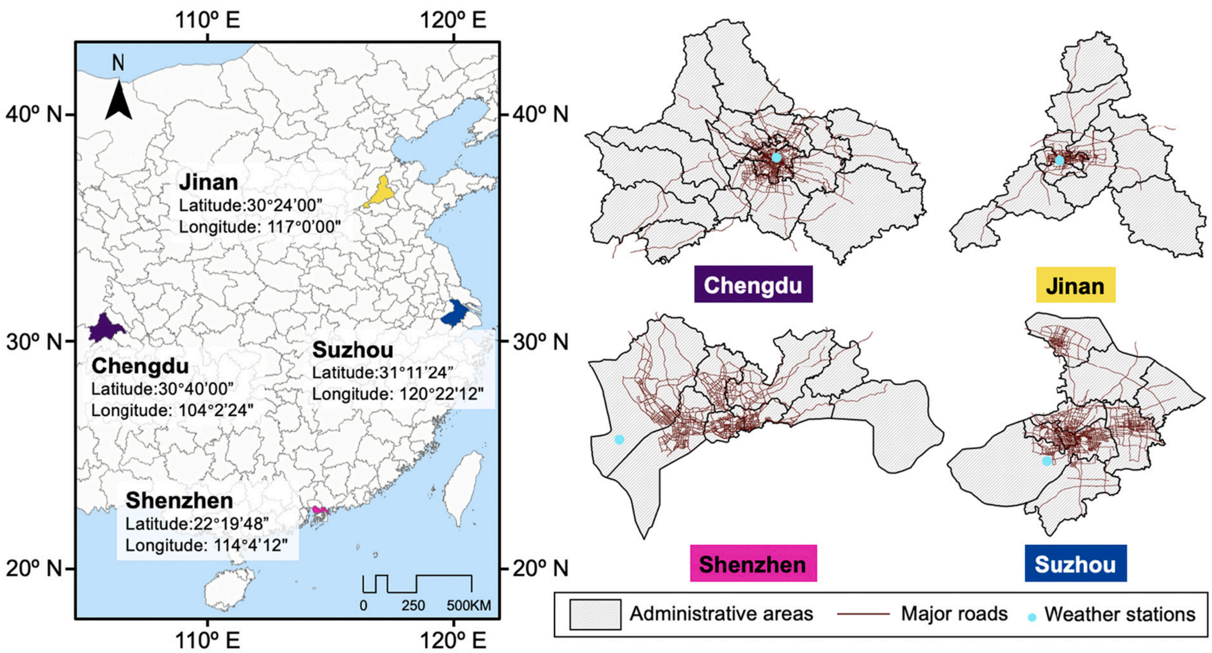

Fig. 1. Location of study area.

3. Empirical context, data and analytical methods

3.1. Geographical areas covered by the study

Geographically, this study focused on four major cities in China located in different locations, including Suzhou, Shenzhen, Jinan and Chengdu, which are located in the Yangtze River Delta region, the Pearl River Delta region, the Bohai Sea region and the Southwestern region, respectively (see Figure 1). With regard to climate type, Shenzhen, Suzhou and Chengdu all are situated in the subtropical monsoon climate region but with different climate characteristics: Shenzhen is rainy and hot at the same time, Suzhou is warm and moist, and Chengdu is foggy and humid. Moreover, Jinan has a typical temperate monsoonal climate with four clearly distinct seasons.

Though, like other major Chinese cities, the above four cities have experienced rapid growth of private car ownership, their road conditions might be quite different due to differences in economic development, travel behavior, and of course, climate characteristics. According to the Traffic analysis report of major Chinese cities in 2019 (*https://report.amap.com/download_city.do*), Suzhou has the most healthy road conditions, Chengdu second, followed by Shenzhen and Jinan.

3.2. Data collection & processing

3.2.1. Background of data collection

Generally, the influence mechanism of urban road conditions caused by varying weather conditions is mainly based on two effects: one occurs when a weather condition directly affects the driving conditions of drivers, and the other occurs when a weather condition affects the traffic volume because the weather conditions have influenced a person's travel mode choice (see Figure 2). For the former, the theory of planned behavior (TPB) (Ajzen, 1991) may be the best suited theory to mine this effect mechanism because the TPB explains the general decision-making process of individual behavior based on expectancy value theory. A large body of researches have shown that the theory is very effective when applied in the field of travel behavior (Jiang et al., 2017; Gao et al., 2020; Lo et al., 2016; Qi et al., 2021). Drawing on TPB this study can think of weather having the potential to influence two elements of a planned behavior, attitude and perceived behavioral control which then has the potential to affect an individual's resultant travel behaviors. With regard to subjective norm, it plays as a constraint in the process of weather influencing travel behavior. For the latter, various weather conditions may trigger a different response by the drivers, affecting the state of vehicle itself (such as velocity and acceleration) (Tan, 2019; Wang et al., 2015) and the car-following state with neighboring vehicles (Hjelkrem and Ryeng, 2016; Chen et al., 2019). This will directly influence the density of traffic flow associated traffic conditions according to the Traffic Flow Theory (Ngoduy, 2015).

In order to obtain reasonable and reliable research results, the weather dataset should encompass sufficient information about the research questions. Given the relationship between types of weather factors and road conditions, this study selected four common

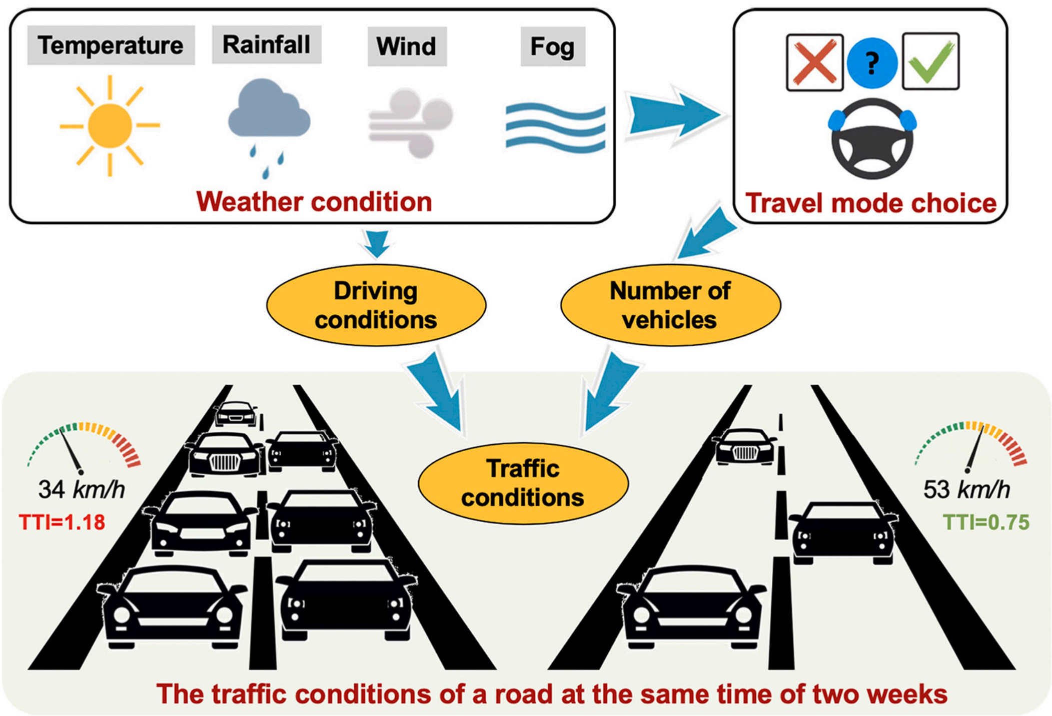

Fig. 2. A conceptual relationship between weather and road conditions.

weather variables to fully describe weather conditions: temperature, wind speed, rainfall accumulation, and visibility. Moreover, road conditions were measured by the travel time index (TTI), a frequently used indicator in transit systems. Hence, urban travel time index (TTI) and weather measurements are used as the two principal data sources in this study to understand the relationship between weather and road condition. Both data were collected for one year (from January 1, 2018 to December 31, 2018). The next section presents the details of the above datasets.

3.2.2. TTI data

TTI data was obtained from Didi company, an international mobile transportation platform, which was calculated in advance based on the trajectory data of operating online car-hailing vehicles (floating car data), collected at 10-min intervals (TTI data, 2021). Generally, the ratio of free-flow speed to actual speed can be regarded as an indicator of urban road conditions. When the value is larger, the road condition is worse, and vice versa. First of all, raw trajectory data are pre-processed to relieve the error caused by the interference problem in data acquisition, including eliminating anomalous floating car, denoising and map-matching. Further the formula for measuring TTI is shown as follows:

(1) The entire road network can be divided into individual road links.

(2) For a link with m time slices, it is assumed that m cars drove on this link. Then the average speed v of the link is:

$$v_{actual} = \frac{ms}{\sum_{i=1}^{m} t_i} \tag{1}$$

where s and t_i are the link's length and travel time of car i, respectively.

(3) If a link is covered with a small number of vehicle track points, it is necessary to optimize the evaluation of the average speed v of the link by combining nearby high-traffic links to improve accuracy. For the link set $L = \{l_1, l_2, l_3, \dots, l_n\}$ near this type of link, the optimized v can be defined as:

$$v_{actual} = \frac{\sum_{j=1}^{n} s_j w_j}{\sum_{j=i}^{n} \frac{s_j}{v_j} w_j} \tag{2}$$

where v_j is the average speed calculated through step 2, then s_j is the length of link l_j. The actual traffic volume is treated as the weight w_j of link l_j for computing the optimized v.

(4) For a link, divide the time into p observing time periods (of less than five minutes each) and make sure that the number of time slices on this link during each observing time period can meet certain quantity requirements. Subsequently, the mean value during observing time period v_l can be calculated. Then, the free-flow speed of a link is defined as the mean value during four consecutive hours (contains q observing time periods) with the highest speed:

$$v_{free} = \frac{\sum_{l=1}^{q} v_l}{q} \tag{3}$$

(5) Finally, TTI can be expressed by the following equation:

$$TTI = \frac{v_{free}}{v_{actual}} \tag{4}$$

Note that the TTI for a city or district is computed by averaging the TTI of all the links within the specified area.

3.2.3. Weather data

Considering the differences of climate features in cities, this study only focuses on the common weather variables and their effects on urban traffic flow, thus revealing the general law in traffic operating under ever-present climate impacts. Therefore, some rare weather events in a particular city will not be considered in this study. Daily weather data used in this study was acquired from the China Meteorological Administration (CMA), based on ground observation stations on 3-h intervals, including four major weather variables: temperature (°F), wind speed (m/s), rainfall accumulation (mm) and visibility (km). It is worth mentioning that rainfall

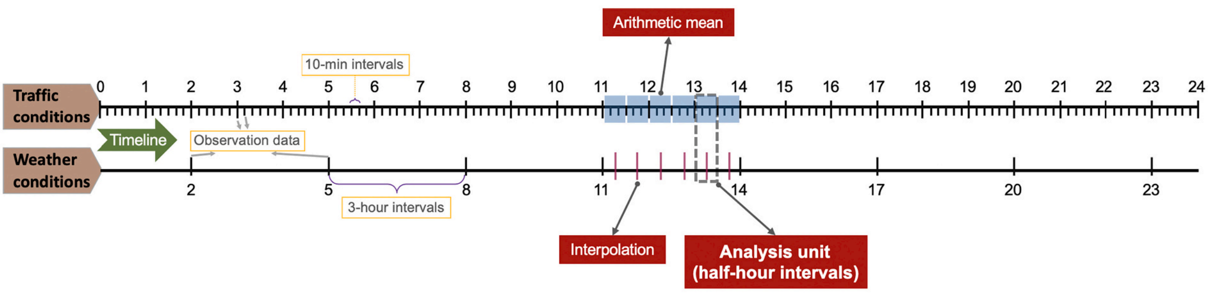

Fig. 3. Schematic diagram of time granularity matching.

accumulation was calculated from average hourly cumulative rainfall data, for the previous six hours.

3.2.4. Time granularity matching

With regard to the initial data format, inconsistency in time granularity of two datasets from multiple sources was discovered, mainly due to differences in observation requirements. Weather and urban road conditions datasets were collected in 3-h and 10-min intervals, respectively. In order to overcome this difference, linear interpolation is introduced to get the processed weather observation data in half-hour intervals, while the interval of raw road conditions datasets is extended from 10-min into 30-min intervals by aggregating and averaging (Fig. 3). For example, the specific weather conditions at 11:00 and 14:00 were observed and recorded by the local weather station; they can be further interpolated to get the estimated weather values at 11:15, 11:45, 12:15, 12:45, 13:15 and 13:45. The values of TTI at 11:00, 11:10 and 11:20 are subsequently summarized as the TTI at 11:15 by aggregating and averaging, and so on. Note that the weather and traffic data of each moment is used to describe the persistent condition totaling 30 min before and after the moment. In this manner, the above datasets can be matched for the following data fusion and analysis.

3.3. Model specifications

This paper applies multivariate regression models to capture the influence of weather on urban road conditions, in which TTI is considered as the dependent variable and the associated weather parameters as the set of independent variables. Specifically, this study controls different spatial fixed effects (city, district) to explore spatial-temporal characteristics of the above relationship.

At the city level, the left-hand is the log daily TTI of city *i*, which is regarded as the dependent variable. Weather variables on temperature (*Temp*), wind speed (*Wind*), rainfall (*Rain*) and visibility (*Visi*) are explicitly considered to impact TTI. Eq.(5) denotes the relationship between them. The formula is shown as:

$$ln(TTI) = \alpha_0 + \beta_1 Temp + \beta_2 Wind + \beta_3 Rain + \beta_4 Visi + \alpha_1 D \tag{5}$$

where *D* is the dummy variable that indicates whether a day is a non-weekday, including weekend, weekend shift and holiday.

At the district level, the four weather parameters are classified into different levels according to their characteristics and occurrence in local areas and the division methods in other cities (Wei et al., 2019; Brodeur and Nield, 2018; Bergel-Hayat et al., 2013). Then, the weather variables in the district-based regression model use the level values given in Table 1, 2, 3, and 4 rather than the original value. In addition, improving the accuracy of weather and road conditions on time scales from day to half-hour is conducted to explore the link between weather parameters and road conditions at a finer level. The multivariate regression model is formulated as follows:

$$ln(TTI) = \alpha_0 + \beta_1 T + \beta_2 W + \beta_3 R + \beta_4 V + \alpha_1 D \tag{6}$$

where *T*, *W*, *R* and *V* refer to the level values of temperature, wind speed, rainfall accumulation and visibility, respectively.

Generally, various weather parameters could be acting together to affect road conditions. As such, another multivariate regression model will be conducted with consideration of the interaction of weather parameters. The improved model is:

$$\begin{aligned} ln(TTI) = {} & \alpha_0 + \beta_1 T + \beta_2 W + \beta_3 R + \beta_4 V + \beta_5 T^*W + \beta_6 T^*R + \beta_7 T^*V + \beta_8 W^*R + \beta_9 W^*V + \beta_{10} R^*V + \beta_{11} T^*W^*R + \beta_{12} T^*W^*V \\ & + \beta_{13} W^*R^*V + \beta_{14} T^*W^*R^*V + \alpha_1 D \end{aligned} \tag{7}$$

All three types of models will be tested in four cities. In addition, researchers will apply the Chi-square test and evaluate model fitness to the final model results before making recommendations on which model is best suited to describing urban road conditions.

4. Data collection & analysis

The study objective was to explore the effect of weather conditions on urban road conditions, which was conducted in two stages. First, researchers studied the statistical characteristics of two datasets corresponding to four cities in different geographical locations. Secondly, the multivariate regression models at different levels were used to quantify the influence of weather parameters and to discover the sensitive weather factors related to road conditions, which included daily-city-based modeling and half-hour-district-based modeling.

4.1. Characteristics of urban traffic and associated weather conditions

This section outlines the meteorological background and road condition characteristics of the four cities.

Table 1
Classification of temperature.

Temperature (*T*)	Level	Description
<32 °F (0 °C)	0	Cold
32–71.6 °F (0–22 °C)	1	Normal
71.6–86 °F (22–30 °C)	2	Hot
>86 °F (30 °C)	3	Torrid

Table 2
Classification of wind speed.

Wind speed (W)	Level	Description
0 m/s	0	Calm
0–5.5 m/s	1	Breeze
5.5–10.8 m/s	2	Strong breeze
>10.8 m/s	3	Gale

Table 3
Classification of rainfall.

Rainfall (W)	Level	Description
0 mm	0	No rain
0–4 mm	1	Light rain
4–13 mm	2	Moderate rain
13–25 mm	3	Heavy rain
>25 mm	4	Storm rain

Table 4
Classification of visibility.

Visibility (V)	Level	Description
>20 km	0	Unlimited
10–20 km	1	Normal
5–10 km	2	Poor
<5 km	3	Bad

Figure 4 reveals that the TTI shows temporal heterogeneity in all the study cities, with features that vary by urban development and across weekdays and non-weekdays. In all four cities, the TTI had some critical periods in common, including a staggered period (7:00–13:00), a differentiated period (13:00–17:00) and a similar period (17:00–21:00). During the staggered period, the rush-hour was found to be delayed for about two hours on non-weekdays compared to weekdays. The TTI on non-weekdays tended to peak at 15:00, while it has an upward trend without any peak on weekdays. The evening peak occurred at about 18:00 on both weekdays and non-weekdays. Specifically, the variation trend of Jinan's TTI was basically consistent with that of Suzhou, and the difference between weekdays and non-weekdays was small. However, in Chengdu and Shenzhen the comparison shows that the road conditions during non-weekdays are worse than during weekdays, particularly in the afternoon in Chengdu and evening peak in Shenzhen. The next section will elaborate on the characteristics of climate of all four cities.

To model the weather aspects of the TTI, weather variations were introduced to the model at both the original and classified levels. It's clear from Figure 5 that the weather measurements, including temperature, wind speed, rainfall and visibility, vary among cities. Temperature varied with high rangeability, but maintained maximum temperature as the latitude increased. The temperature

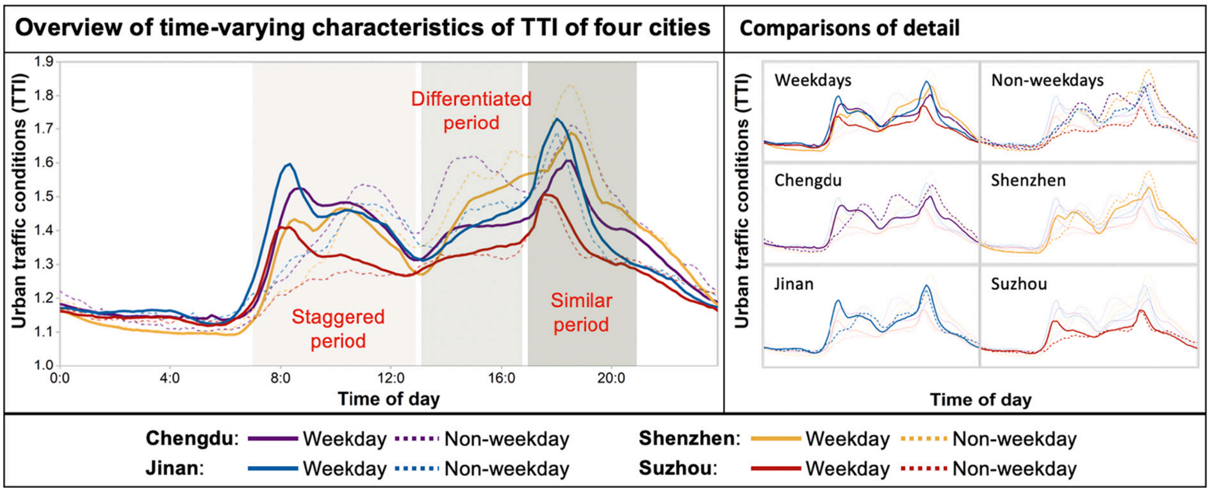

Fig. 4. Temporal trend of TTI of four cities among weekdays and non-weekdays.

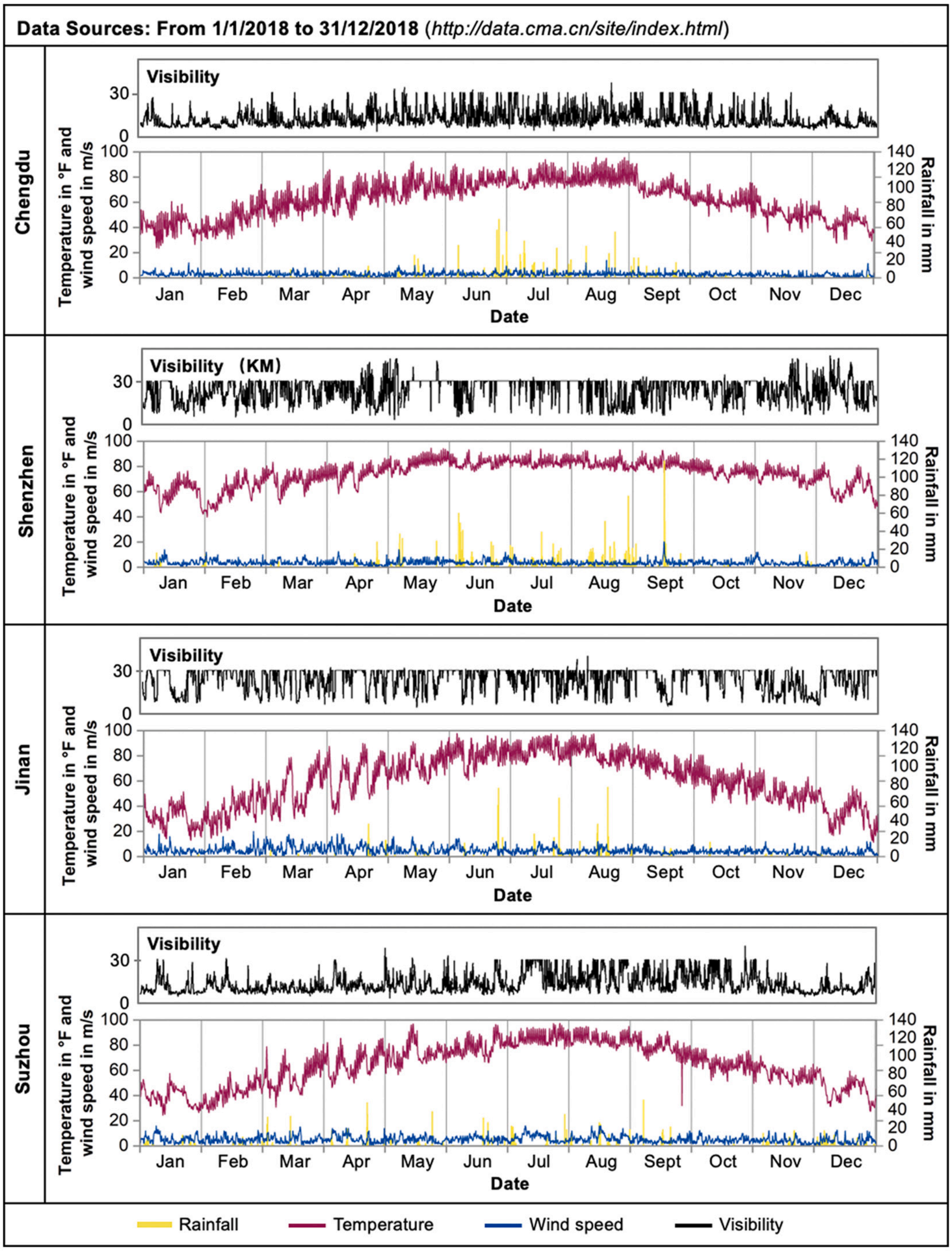

Fig. 5. Weather conditions in four cities from January 2018 to December 2018.

generally stays above freezing all year in Shenzhen, while it can drop to minus ten degrees early in the year in Jinan. Also, Jinan faces strong winds more often than the other cities, especially in the first half of this year. With regard to the accumulative rainfall, it displayed a different uneven characteristic among the four cities. Most of Jinan's and Chengdu's crucial rain occurs in summer (from June to August) but Shenzhen's rain is concentrated in flood season (from April to September). Only the annual rainfall in Suzhou was distributed more evenly throughout the year.

Generally, meteorological visibility was a complex result affected by other weather conditions, like temperature, wind speed, rainfall and humidity. Chengdu is located in central Sichuan basin, which has really low visibility. In comparison, drivers in Shenzhen and Jinan have better visibility all the year round. Of particular interest, the poor visibility in Suzhou only appeared in the first half of this year.

In order to understand people's subjective feelings about weather measurements, Figure 6 shows the level values of them. Overall, the distributions of wind speed and rainfall in four cities showed a similar trend. In addition, the temperature distribution in Shenzhen was warmer for latitude reasons. Much better visibility conditions were found in Shenzhen and Jinan than in Suzhou and Chengdu, and more than half of observation data refer to visibility as an extremely favorable condition.

As a consequence, one can conclude that the weather and road conditions are complex and changing over time. To investigate if there is a significant relationship between the above weather conditions and TTI, this study next conduct models.

4.2. The effect of weather condition on daily TTI at city level

The relationship between weather parameters and road conditions was modeled in this sub-section, and the results are displayed in Table 5 Note that Model 1 was modeled for the whole sample while Models 2–3 were conducted on weekdays and non-weekdays, respectively. On weekdays, the road conditions were found to be most sensitive to meteorological visibility, in all four cities. While the hot weather in Shenzhen seems to have negative effects on the traffic operation conditions, there was little to no impact on TTI. The travelers in Shenzhen have become accustomed to hot weather, so it has little or no impact on travel behavior. The effect of wind was bigger than rainfall, indicating short-lived weather conditions do not directly affect TTI. On non-weekdays, weather does indeed impose a more significant and stronger effect on road conditions than on weekdays, as can be seen from the values of dummy variable *D* (all above 0). Compared with the performance on weekdays, rain was shown to negatively influence running speed across all four weather parameters. This was due mainly to the increasing amount of traffic in the streets as people chose to drive private cars. It is worth noting that Shenzhen was the smallest city influenced by weather, which suggests that people may keep their travel habits unchanged if convenient transportation is available.

As described earlier, there were large differences in the performance of TTI between weekdays and non-weekdays during three divided periods (staggered, differentiated and similar periods), which need concrete analysis and study. Next, the researchers developed the following models to conduct more detailed analysis by spatial unit (from city to district), and to refine time granularity (from daily to half-hour measurements) to explore the interesting phenomenon.

4.3. The effect of weather condition on half-hour TTI at district level

4.3.1. Staggered period

For the staggered period (7:00–13:00), various weather parameters were shown to exert little effect on road conditions across the four cities on weekdays. Only Shenzhen's traffic was found to be influenced by weather conditions in the morning on weekdays. One reasonable explanation for this pattern could be that most of the trips during this time period were work commuting trips. People in Shenzhen have flexible work options, but the work environment might be rigid for the other three. It also reflects the well-developed economy and the modern mentalities about jobs. However, this kind of working trips in four cities experienced a much smaller influence of weather, causing a little variation of TTI. On non-weekdays, people tended to travel by using their private car but with higher flexibility under the influence of weather, causing the effect was limited. Overall, the interaction effects of weather conditions were relatively weak. The results for the regression coefficients of weather parameters are given in Table 6.

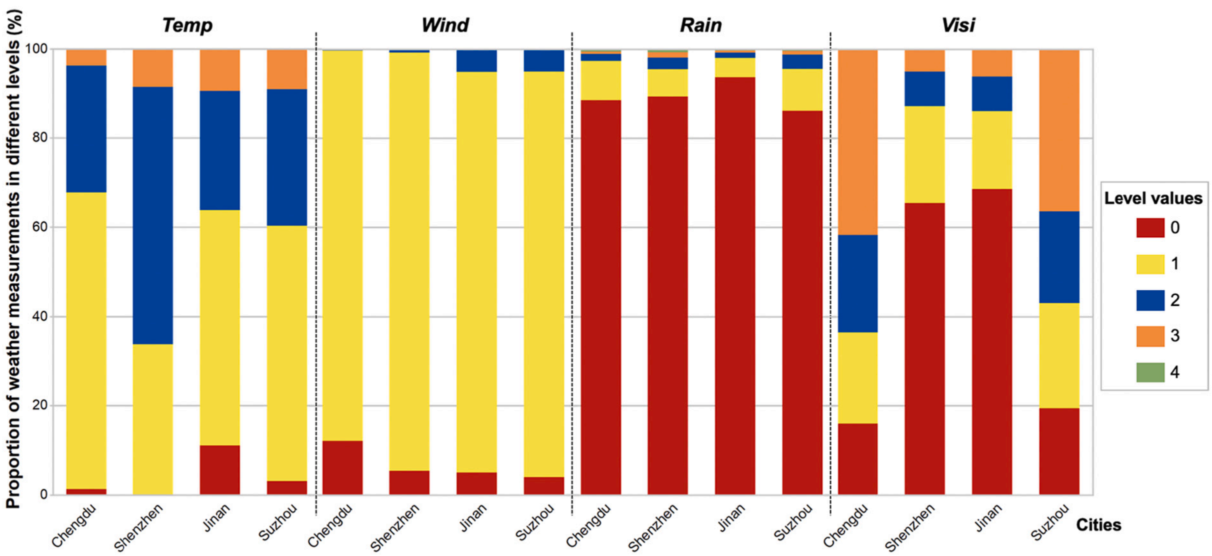

Fig. 6. Percent of temperature, wind speed, rainfall and visibility (according to level values).

Table 5
Daily model results.

	(1)				(2)				(3)			
	All				Weekdays TTI				Non-weekdays TTI			
	Ch	Sh	Ji	Su	Ch	Sh	Ji	Su	Ch	Sh	Ji	Su
Temp	0.015*	0.003**	0.007***	0.014**	0.015**	0.003***	0.004***	0.012***	0.014**	0.009***	0.021*	0.019***
Wind	0.022**	0.009*	0.046***	0.005**	0.014***	0.032*	0.016***	0.002*	0.031***	0.012***	0.019***	0.006**
Rain	0.004***	0.013**	0.016**	0.007***	0.004**	0.006***	0.013**	0.001***	0.035*	0.039*	0.024***	0.038*
Visi	−0.056*	−0.011***	−0.039***	−0.034*	−0.033***	−0.022***	−0.009**	−0.017*	−0.016***	−0.029*	−0.043**	−0.041*
D	0.028***	0.008***	0.005*	0.023*								
N	365				232				133			
AIC	7039	7423	6901	6235	3523	4965	3938	3082	5067	4449	4045	4628

Notes: The dependent variable is the log of TTI. Four TTI datasets obtained from four different cities are analyzed, including Chengdu (Ch), Shenzhen (Sh), Jinan (Ji) and Suzhou (Su).
[*] means significant at 0.05 level.
[**] means significant at 0.01 level.
[***] means significant at 0.001 level.

Table 6
The effects of weather on TTI during staggered period.

	(1)				(2)			
	Weekdays TTI				Non-weekdays TTI			
	Ch	Sh	Ji	Su	Ch	Sh	Ji	Su
Temp	0.029**	0.023*	0.017**	0.008**	0.002**	0.008***	0.009***	0.004*
Wind	0.005***	−0.025**	0.004**	0.012***	0.005*	0.012**	−0.007**	0.014***
Rain	0.011*	0.038**	−0.006**	0.004***	0.009**	0.004**	0.010***	0.005**
Visi	−0.018***	−0.015**	−0.009***	−0.022**	−0.006**	−0.003*	−0.006**	−0.008*
T * *W*	0.004**	–	–	–	–	–	–	–
T * *R*	0.008**	–	–	–	–	0.005**	–	–
T * *V*	–	–	–	–	−0.014***	–	–	0.018**
W * *R*	–	–	0.003**	–	–	–	–	–
W * *V*	–	–	–	–	–	–	–	0.005*
R * *V*	–	0.017**	–	–	–	−0.026**	–	–
T * *W* * *R*	–	–	–	−0.035***	–	–	–	–
T * *W* * *V*	–	–	–	–	–	–	–	–
W * *R* * *V*	−0.007*	0.036***	–	–	–	–	0.003*	–
T * *W* * *R* * *V*	–	–	–	–	0.006**	–	–	–
N	2784				1596			
AIC	14,756	19,832	12,394	21,974	13,849	23,946	19,384	18,234

Notes: The regression coefficients in the above table refer to the average value of all the models conducted on all the counties.
— means the interaction variable isn't chosen according to the results of model fitness and Chi-square test.
* means significant at 0.05 level.
** means significant at 0.01 level.
*** means significant at 0.001 level.

4.3.2. *Differentiated period*

Table 7 presents a non-linear relationship between TTI and weather measurements during the differentiated period (13:00–17:00). The weather conditions play more essential roles in urban traffic in this time period. Temperature has a negligible effect on road conditions on weekdays at a significant level of 1%, but it is significant on non-weekdays, especially in Chengdu and Jinan. This finding implies that the entire running speed will decrease if the perceived temperature rises higher and causes more people in Chengdu and Jinan to choose to drive. Wind speed shows a differentiated effects on TTI by city during this time period, with windy days decreasing travel only in Shenzhen. Both rain and visibility have similar relationships with road conditions in the differentiated period as in the staggered period. Moreover, the results also show that the interaction effect of weather indicators can be crucial in explaining the TTI variations. The extreme weather, especially the muggy or sticky weather, can increase the use of a personal car, thus aggravating road conditions. That is, the higher the temperature with less rainfall or less wind, the more people are likely to choose a car. Further, there

Table 7
The effects of weather on TTI during differentiated period.

	(1)				(2)			
	Weekdays TTI				Non-weekdays TTI			
	Ch	Sh	Ji	Su	Ch	Sh	Ji	Su
Temp	0.017*	0.005*	0.012*	0.011*	0.063**	0.037*	0.074**	0.026*
Wind	−0.021***	0.095*	−0.026*	−0.016**	−0.032***	0.023**	−0.062*	−0.063*
Rain	0.063*	0.073***	−0.039**	0.083**	0.019*	0.097***	0.018***	0.089**
Visi	−0.022*	−0.072**	−0.016***	−0.075*	−0.079***	−0.038*	−0.031**	−0.017**
T * *W*	−0.017**	0.004***	−0.057**	−0.029*	−0.026**	−0.034**	−0.053***	−0.015***
T * *R*	−0.025***	−0.038***	−0.061***	−0.019***	−0.031*	−0.066***	−0.072*	−0.044**
T * *V*	–	–	–	–	–	–	–	–
W * *R*	–	–	–	–	–	0.011***	–	–
W * *V*	–	−0.003**	–	–	–	–	0.009**	–
R * *V*	–	–	–	–	–	–	–	–
T * *W* * *R*	0.021*	0.036***	0.062***	0.027**	0.055**	0.049***	0.063***	0.013**
T * *W* * *V*	–	–	–	–	–	–	–	−0.001**
W * *R* * *V*	–	–	–	−0.014*	–	–	–	–
T * *W* * *R* * *V*	–	0.002***	–	–	–	–	–	–
N	1856				1064			
AIC	14,756	19,832	12,394	21,974	13,849	23,946	19,384	18,234

Notes: The regression coefficients in the above table refer to the average value of all the models conducted on all the counties.
— means the interaction variable isn't chosen according to the results of model fitness and Chi-square test.
* means significant at 0.05 level.
** means significant at 0.01 level.
*** means significant at 0.001 level.

was a positive interaction between the temperature, rainfall and wind, indicating that high temperature, less rain and no wind were unpleasant weather conditions for traffic. Jinan, known as a "furnace" city for its oppressive hot weather, was shown to be most affected by these weather conditions, especially on non-weekdays.

4.3.3. Similar period

Table 8 presents the results of weather impact on road conditions during the similar period (17:00–21:00). As shown in Figure 4, there were no prominent differences of TTI in Chengdu and Shenzhen between weekdays and non-weekdays. The relatively stabilized trend may be less about differences in meteorological parameters than about special time periods, namely evening peak. Certainly, the effects related to rain were bigger than the effects for other weather conditions in this time period, including single variables and some relevant interacted variables. Both these weather variables have positive relationships between TTI on weekdays and non-weekdays. This finding indicated that rainfall can affect the driving conditions during the night, thus decreasing the overall speed of the network. In addition, visibility was found to have similar effects to TTI, especially when people were in no hurry to arrive at their destination on non-weekdays.

4.4. Spatial-temporal overview of weather effects at district level

Given that the road condition in different areas showed a range of sensibility to weather, it's important to understand how weather affects regional traffic at a smaller spatial level. Hence, an exploration about spatial heterogeneity of the effect of meteorological elements was conducted in this sub-section. Notably, this section uses district level aggregation to perform the analysis to reduce the impact of possible low-reliability roads on the mean state evaluation of traffic condition for the whole district. This section will focus on those weather-traffic relationships that show significant spatial difference. One weather-traffic relationship during each period on weekdays or non-weekdays was selected and mapped.

As shown in Figure 7, the standard regression coefficients of weather were mapped for TTI at district level, which revealed some interesting phenomenon. Traffic mode choosing behaviors at the beginning of each weekday were found to be most sensitive to variations of temperature and rainfall, particularly in urban areas. The finding was reasonable because people are more likely to drive instead of using other transit modes when they meet extreme weather, which then leads to increased traffic. The effect of visibility in mountain and hilly area was more significant than in other areas, indicating the poor visibility can have certain space limitations. Coefficients of rainfall reached the highest levels mainly at locations near water. One plausible explanation of this could be that rainfall is often heavier near water than far from water. Wind speed shows a weak effect on TTI. In addition, weather conditions had a more significant and stronger effect in the suburbs on non-weekdays. This may suggest that these places where people can relax are more attractive than other areas, causing a higher sensitivity to weather.

Table 8
The effects of weather on TTI during similar period.

	(1)				(2)			
	Weekdays TTI				Non-weekdays TTI			
	Ch	Sh	Ji	Su	Ch	Sh	Ji	Su
Temp	0.007***	0.001**	−0.023***	0.014***	0.005*	0.015**	0.004***	0.008**
Wind	0.013***	−0.009***	0.005**	0.011***	−0.006*	−0.007**	−0.007**	0.019***
Rain	0.051***	0.034**	0.048***	0.031**	0.062***	0.014**	0.039***	0.065**
Visi	−0.042*	−0.041*	−0.086**	−0.021***	−0.049**	−0.028***	−0.072**	−0.067**
$T * W$	–	–	–	–	–	–	–	–
$T * R$	–	–	–	–	–	–	–	0.006***
$T * V$	–	0.002***	–	–	–	−0.003**	–	–
$W * R$	–	–	–	0.003**	–	–	–	–
$W * V$	–	–	–	–	–	–	–	–
$R * V$	−0.084***	−0.043*	–	−0.015***	−0.009***	−0.017**	−0.024***	−0.027**
$T * W * R$	–	–	–	–	–	–	–	–
$T * W * V$	–	–	–	–	–	–	–	–
$W * R * V$	–	–	–	–	–	–	–	–
$T * W * R * V$	−0.049***	−0.033***	−0.051***	0.015***	−0.048***	−0.004*	0.005**	−0.016***
N	1856				1064			
AIC	14,756	19,832	12,394	21,974	13,849	23,946	19,384	18,234

Notes: The regression coefficients in the above table refer to the average value of all the models conducted on all the counties.
— means the interaction variable isn't chosen according to the results of model fitness and Chi-square test.
* means significant at 0.05 level.
** means significant at 0.01 level.
*** means significant at 0.001 level.

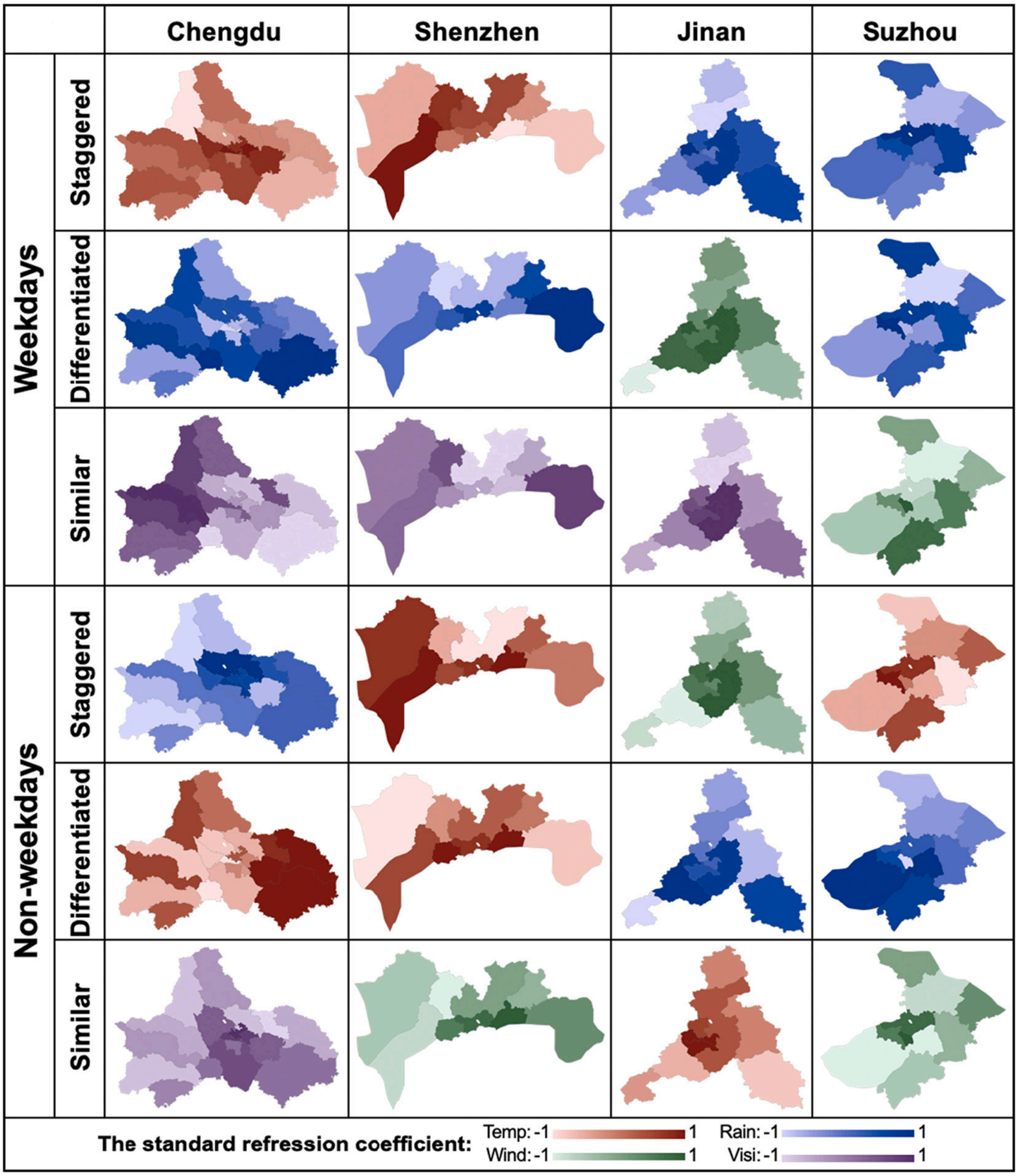

Fig. 7. The spatial distribution of the standard regression coefficients at district level.

5. Discussion

The aim of this paper is to investigate how the influence of weather on traffic time index (TTI), a relative criteria to evaluate road traffic conditions, using 12 months of weather station records and TTI data. Various designed models were computed to capture the weather–traffic relationship at different spatial-temporal scales, as well as the interaction effects of weather parameters were also examined. To this end the proposed conceptual model (see Figure 2) to explain the modeling results and unpack the principal mechanisms underpinning the weather–traffic relationship. Besides, a comparative study of the weather-traffic relationship between four cities with various climatic characteristics across different locations in China was conducted in this paper. Several general insights derived from this study are now discussed as follows:

First, an exploration of the characteristics of TTI was conducted with a focus on the difference between weekdays and non-weekdays. The survey results revealed that three time periods were of concern among four study cities, including a staggered period (7:00–13:00), a differentiated period (13:00–17:00) and a similar period (17:00–21:00). On the one hand, results indicate that the variations of TTI in response to weather change may be quite different at different time periods. On the other hand, traffic flow is shown to be more sensitive to variations in weather on weekends than on weekdays. Drawing on the conceptual model, these dissimilar effects of weather at various stages can be explained by the distinct travel purposes associated with different travel activities.

Second, results revealed that at both the daily and half-hourly temporal scales, weather was found to exert varying influences on TTI. The results for a daily model at city level show that the TTIs in all the study cities were basically most sensitive to meteorological visibility. Local people have adapted to the regional extreme weather, like the drought days in Jinan, the hot days in Shenzhen, and heavy wind in Suzhou. However, the overall running speed would be decreased by increasing the traffic volume, and it would have higher volatility under extreme weather on non-weekdays. This result can be seen from the values of dummy variable D (all above 0), indicating that people have flexibility to control their trips with consideration of weather conditions. Furthermore, from a more detailed spatial-temporal perspective, the half-hour models at district level highlighted that the influence of weather on TTI was not fixed over the course of a day and that it varied by location. Weather was shown to exert little effect on TTI during the commute hour on weekdays, namely during the staggered period; only rainy days have a weak impact, leading to traffic jams and time delays for drivers. When it comes to the differentiated period, the interaction effect of weather indicators can be crucial in explaining the TTI variations. The extreme weather, like muggy or sticky weather, can increase the use of personal cars, thus aggravating road conditions, especially on non-weekdays.

Third, this study subsequently mapped the standard regression coefficients of weather for TTI at district level. As can be seen from the visualization results, the urban area in each city was the most vulnerable area with regard to direct and indirect impacts of climate change on weekdays. Conversely, the sensitivity toward weather started to improve as the traffic volume increased on non-weekdays, indicating that the increased traffic volume would impair the tolerance of weather variations.

6. Conclusion

To this end, temporary fluctuations of weather conditions indeed may affect travel mode choosing behavior and final traffic volume, even though they are less dominant than other factors such as transport policy. Given that an individual's travel behavior was not only determined by travel habit but also weather conditions, it's necessary to provide a new insight for investigating the relationship between weather and final road conditions after the choice of travel mode has been affected by weather. The implications of these findings are presented as follows. Transportation agencies should recognize the positive effects of multi-sectoral collaboration involved in the routine management work of transport to maint stable operation of the transportation system. The real-time weather conditions might also be monitored while monitoring transport data, like traffic volume and ridership. This is not to say that traffic agencies should try to continually adjust traffic facilities and policies during changeable weather conditions, but simply that such a constantly updated multi-source database may be conducive to decision-making in case of a sudden change of weather. On the one hand, climate monitoring can help a transport agency identify the weak links with higher sensitivity to weather among the whole road network system, and then look for the underlying causes such as inefficient transport infrastructure, unbalanced traffic volume distribution and so on. On the other hand, early prediction and precautionary measures under adverse weather conditions might be considered for the specific road or area that is more prone to traffic jams in order to ease the influences of the dramatic changes of traffic volume on traffic flow.

Also, there are two aspects of this study that pave the way for future research. Objectively, an individual's travel behavior is not only determined by travel purpose but also by subjective external conditions, like weather, and weather affects travel behavior differently based on travel purpose. That is, TTI ultimately reflects an individual's travel purpose. Given this, incorporating travel purpose in the modeling of weather conditions influencing TTI will likely provide a deeper understanding of the weather-traffic relationship. In addition, the effect of weather on road conditions might be spatially heterogeneous, taking into account the various built environment around roads. Hence, it would be worthwhile to explore the variation in spatial relationships with consideration of built environment to reveal the indirect effect of it on road conditions. It's hoped that this study will stimulate further research related to this area to promote transport system flexibility and health benefits for urban travelers.

Declaration of competing interest

We declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study has been sponsored by the Scientific Research Foundation of Graduate School of Southeast University (No. YBPY2156) and the National Key R&D Program of China (No. 2018YFB1601000).

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