Article
Method for Identifying the Traffic Congestion Situation of the Main Road in Cold-Climate Cities Based on the Clustering Analysis Algorithm

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Abstract: Congestion has become a common urban disease in countries worldwide, with the acceleration of urbanization. The connotation of the congestion situation is expanded to describe, in detail, the traffic operation status and change characteristics of the main road in cold-climate cities and to provide more comprehensive identification methods and theoretical basis for cold-climate cities. It includes two aspects: the state and trend. A method to distinguish the traffic congestion state level and trend type of the main road in cold-climate cities is proposed on the basis of density clustering, hierarchical clustering, and fuzzy C-means clustering, and the temporal and spatial congestion characteristics of the main roads of cold-climate cities are explored. Research results show that we can divide the traffic congestion state into three levels: unblocked, slow, and congested. We can also divide the congestion trend into three types: aggravation, relief, and stability. This method is suitable for the identification of the main road’s congestion situation in cold-climate cities and can satisfy the spatiotemporal self-correlation and difference test. The temporal and spatial distribution rules of congestion are different under different road conditions, the volatility of the congestion degree and change speed on snowy and icy pavements, and the instability of congestion spatial aggregation are more serious than that on non-snowy and non-icy pavements. The research results are more comprehensive and objective than the existing methods.

Keywords: cold-climate cities; congestion situation; density clustering; hierarchical clustering; fuzzy C-means clustering

1. Introduction
With rapid economic development and the accelerating urbanization process, the traffic demands of countries around the world have increased sharply. The contradiction between the development of urban traffic and the limited carrying capacity of urban resources and the ecological environment has become increasingly prominent, and the problem of urban traffic congestion has become increasingly serious. Traffic congestion not only brings inconvenience to travel and life but also causes additional fuel consumption, exhaust emissions, and noise pollution, as well as serious economic losses. According to the latest data released by the traffic information analysis company INRIX, the cost of traffic congestion was approximately $87 billion in the United States in 2018 [1]. The data updated by the European Commission on August 2020 show that traffic congestion in European Union countries causes economic losses of nearly 100 billion euros every year, accounting for approximately 1% of Gross Domestic Product (GDP). At the same time, carbon dioxide emissions from urban transportation account for 40% of the total emissions from the transportation industry, and other pollutants account for 70% of the total emissions from the transportation industry. According to a study by the Sustainable Development Strategy Group of the Chinese Academy of Sciences, the economic cost of...
traffic congestion in China is equivalent to 5–8% of GDP, and residents of 15 major cities spend 28.8 billion more minutes, or 480 million hours, commuting to work each day than those in the European Union [2]. It should be noted that, because of the impact of the COVID-19 pandemic, the human mobility and travel mode choice of most countries around the world has changed. Especially in the early stage of the epidemic, the traffic flow has been significantly reduced and the traffic congestion has been reduced because of the lockdown and sanitary regime [3,4]. As the epidemic eased, traffic has gradually recovered, but people are starting to shift from public transport to private cars and non-motorized vehicles to avoid contact with others. Passenger car sales are increasing, and congestion is estimated to be more severe than before the outbreak of the COVID-19 pandemic [5]. Traffic congestion is a worldwide problem and a major “urban disease” under the industrial civilization. It not only hinders the sustainable development of urban traffic but also restraints the sustainable development of cities.

Cold-climate cities refers to a special urban group distributed in the Northern Hemisphere. 171 «Thermal design code for civil buildings» (GB 50176-2016) issued by the National Standardization Management Committee divides regions into five categories, including severe cold, cold, hot in summer and cold in winter, hot in summer and warm in winter, and mild [6]. The cold-climate cities refer to the severe cold regions and cold regions with evident climatic characteristics. The definition standards are shown in Table 1:

| Annual Coldest Monthly Average Temperature (°C) OR Days with Daily Average Temperature Below 5 °C (D) |
|-----------------|-----------------|
| Severe cold areas: (−∞, −10] OR (−10, 0) | Cold areas: (145, +∞) OR (90, 145) |

Cold-climate cities have low temperatures and long duration of winters, and the wind speed is basically 3–5 m/s [7]. Under the action of cold wind, the comfort of outdoor activities is low. Snowfall is very frequent, which will not only affect the line of sight but also form ice and snow pavements and reduce the pavement friction coefficient. Under such climate conditions, the travel volume and the choice of travel mode of residents in winter will change significantly compared with other seasons. According to the investigation on the traffic flow data of the Iowa Interstate, New York, Wisconsin, Canada, and other countries and regions, some scholars found that the travel volume in cold-climate cities in winter is reduced by 16–47% compared with that in other seasons, with the greater intensity of snowfall indicating a greater reduction degree [8,9]. Among all travel modes, the share rate of cycling and walking decreases the most (the decline range is 45–85%) [10,11], whereas the share rate of motor vehicles, such as cars, taxis, and public transportation, increases (the increased range is 30–70%) [12,13]. The climate conditions of cold-climate cities are also not conducive to economic development, which will lead to the failure to promote emerging transportation modes such as the subway and BRT. Conventional public transport is the main body of public transport. Therefore, the ground traffic pressure of cold-climate cities is much greater than that of non-cold-climate cities, the congestion degree is more serious, and the congestion characteristics are more complex [14]. Figure 1 shows the relationship among urban economic development, the average temperature in winter, and the congestion level of some cities in the United States, Canada, Japan, and China. In order to avoid the presence of COVID-19 affecting the analysis results, for the economic development and congestion level, the Gross Domestic Product (GDP) in 2019, and the average congestion level evaluation data of cities around the world in 2019 (calculated by the ratio of actual travel time and free-flow travel Times) the TomTom companies were selected for analysis. It can be seen from the figure that the cold-climate cities represented by Harbin, Moscow, and Dalian have backward economic development and serious congestion degrees.
When congestion occurs initially, it is generally distributed at intersections because intersections are the decisive factor for the smoothness of the road network [15,16]. When the congested vehicles cannot be relieved by themselves or cannot be effectively dredged by traffic managers, the congestion will intensify and spread to the associated roads. At this time, if it cannot be effectively controlled, the congestion will further deteriorate. Finally, closed-loop congestion will be formed between multiple associated sections in the road network, and the whole road network will be paralyzed in a large area [17]. If the congestion can be relieved and it is only located at an intersection or a partial road section, the congestion can be restored to normal in a short time. As time goes by, the congestion is controllable until it forms a closed loop. Under the command of the traffic manager, the congestion may still return to normal after a long period of time. However, once the congestion forms a closed loop, not only are the command and coordination of traffic managers required, but also some traffic control measures, such as the prohibition of turning and temporary traffic restrictions, etc., this will take longer to restore the entire road network to normal. Therefore, the accurate identification of traffic congestion situations is very important.

A good urban road network structure is an important factor for the smooth operation of urban traffic, which is composed of the expressway, primary and secondary main roads, and branch roads with a reasonable gradation proportion [18]. Roads at all levels are organically connected and coordinated with each other, and each performs its own duties. Among them, main roads, as the framework of the urban road network, play a role in connecting the main areas of the urban area. They are not only the traffic link between different groups in the city, but also the main corridor of medium and long-distance traffic, which bears most of the travel volume of the city, and the congestion is mainly distributed along them too [19,20]. Although more abundant and comprehensive congestion data can be obtained through the evaluation and analysis of the whole road network, due to the limited ecological environmental carrying capacity and shrinking resource reserves of cold-climate cities, it is necessary to scientifically plan the short and long-term construction time sequence according to the priority and urgency of the project and promote the construction step by step to avoid a financial deficit. Therefore, it is necessary to put forward a method to identify the congestion situation of main roads in cold-climate cities, so as to provide support for the rational management of traffic congestion on main roads.

As for the method of identifying traffic congestion, research has been started in the world since the 1950s [21]. From traditional traffic flow theory to emerging machine learning methods that intersect with computers and other disciplines, scholars

![Figure 1](image-url)
from all over the world have carried out many explorations. The traditional traffic flow theory is mainly based on the index, macroscopic fundamental diagram, two-fluid theory, and cellular automata model. Among them, index-based methods are the most widely studied and applied. In the early stage of research, scientific research institutions in various countries put forward nearly a hundred indicators for identifying congestion and determined the congestion threshold of each index based on the results of experimental results [22]. When identifying congestion, it is obtained by comparing the actual operation result with the threshold. With the urban road traffic system becoming increasingly complex and multi-dimensional, it is more and more difficult for a single traffic flow parameter to comprehensively express the complex traffic conditions, so some comprehensive indicators converted from single traffic flow parameters and traffic characteristics have been widely used. In recent years, the development of big data, cloud computing, satellite positioning, and mobile internet technology has made it possible to obtain and identify real-time urban road dynamic traffic data [23,24]. Some map navigation software makes extensive use of mobile phone signaling data and vehicle GPS data, borrows or proposes a variety of indicators to identify and rank traffic congestion in major cities around the world, and publishes real-time road traffic operation information, which greatly facilitates the residents’ travel and route selection. Commonly used identification indicators and their identification standard are shown in Table 2.

Table 2. Commonly used identification indicators and their identification standard.

| Indicator                  | Calculation Formula | Source                                                                 | Identification Standard                                                                 |
|----------------------------|---------------------|------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|
| Speed                      | —                   | Japan Highway Public Corporation [25]                                 | When the speed is lower than 40 km/h, it is identified as congestion                    |
|                            |                     | China Standardization Administration «Road traffic information service traffic condition description» (GB/T 29107-2012) [26] | For main roads, when the speed range is \((+\infty, 30 \text{ km/h})\), it is unblocked, \((15 \text{ km/h}, 30 \text{ km/h})\] is slow, and \((-\infty, 15 \text{ km/h})\] is congestion |
|                            |                     | American Road Capacity Manual (HCM2000) [27]                         | When the road service level reaches F level (the actual speed is \(1/3~1/4\) of the free-flow speed, and the traffic volume may exceed the road capacity), it is identified as congestion |
| Road service level         | —                   | American Road Capacity Manual (HCM2016) [28]                        | When the road service level reaches F level (when the free-flow speed is 55 km/h, the actual speed is \(\leq 17 \text{ km/h}\), or the free-flow speed is 50 km/h, the actual speed is \(\leq 15 \text{ km/h}\), and the volume capacity ratio is \(\leq 1\)), it is identified as congestion |
| Occupancy                  | \(\sum \frac{\text{Vehiclelength}}{\text{Roadlength}}\) | Chicago Transit Authority [29]                                       | When the occupancy rate \(>30\%\), and the duration exceeds 5 min, it is identified as congested |
| Travel Time Index (TTI)    | \(\frac{\text{Actualtraveltime}}{\text{Traveltimeinfreeflowstate}}\) | American «Urban Mobility Report» [30]                                | No congestion level set                                                                  |
|                            |                     | AutoNavi Map [31]                                                    | \((0, 1.5]\) is unblocked, \((1.5, 1.8]\) is slow, \((1.8, 2]\) is congestion, \((2, 10]\] is very congestion |
| Traffic State Index (TSI)  | \(\frac{\text{Desiredspeed} – \text{Actualspeed}}{\text{Desiredspeed}}\) | China Standardization Administration «Evaluation index system for urban road traffic state» (DB31/T 997-2016) [32] | \([0, 30]\) is unblocked, \((30, 50]\) is relatively unblocked, \((50, 70]\) is congestion, \((70, 100]\] is severe congestion |
| Degree of Congestion (DC)  | \(\frac{\text{Actualtrafficvolume}}{\text{24h}}\) | Japan Highway Public Corporation [25]                                | Taking 12 h as an example, \([0, 1]\) is congestion, \([1, 1.75]\) is gradual congestion, and \([1.75, +\infty]\) is chronic congestion |
| Inrix Congestion Index (ICI)| \(\frac{\text{Freeflowspeed}}{\text{Actualspeed}}\) | INRIX [1]                                                            | No congestion level set                                                                  |
Traffic congestion identification methods based on the macroscopic fundamental diagram, two-fluid theory, and cellular automata model are also widely studied. The macroscopic characteristics of traffic flow can be obtained by statistically analyzing the relationship between different traffic flow parameters and simulating the microscopic characteristics of each vehicle, so as to identify traffic congestion. For example, Buisson et al. [33] obtained the traffic flow operation data based on the coil detector and obtained the relationship between traffic volume and density through the macroscopic fundamental diagram. Xiao, Z. et al. [34] established the main road traffic model based on the two-fluid theory and proposed a scoring function to evaluate the service level. In addition, there is much research on traffic congestion identification and congestion characteristic analysis based on machine learning methods such as the Bayesian network and Markov chain. For example, Emmanuel Kidando et al. [35] proposed a Bayesian statistical method for random road capacity analysis, congestion duration statistics, dynamic evolution of repeated traffic conditions, and clustering different traffic conditions. Sakib Mahmud Khan et al. [36] used vehicle interconnection technology to evaluate traffic congestion with traffic density as an indicator and established a simulation network to study the effectiveness of this indicator. Munajat et al. [37] proposed a method to identify the degree of road congestion by simultaneously using the speed and traffic flow density and tested this method through the fuzzy model. Yuta Sone [38] proposed a system traffic flow model based on mixed logic dynamics to clarify the mechanism of traffic congestion, revealing that traffic congestion is the evolution process of spreading from the lane to the overtaking lane.

Based on the above content, it is easy to deduce that the existing research “focuses on the state, but ignores the trend”, lacks the identification of traffic congestion trends, cannot reflect the future direction of congestion, and cannot determine the timing of congestion control. The existing congestion grade identification standards “have common, no difference”, and use uniform and fixed standards for different cities. These standards are usually determined by experiments on the congestion level of typical days in non-cold-climate cities, without taking into account the large difference in the congestion level of cold-climate cities under the influence of special climate, which is one-sided and cannot accurately reflect the real congestion level of cold-climate cities when applied to them. Some of the identification methods are “partial to theory, but underapplied”, which cannot realize automatic application and cannot allow travelers and city managers to obtain road condition information in a timely manner and take control measures. Clustering is also one of the common unsupervised machine learning algorithms, which can process large and complex data sets and obtain data distribution, and the association rules, classification, and other preprocessing steps of the algorithm can be used to obtain data of the basic situation, thereby leading to a more accurate and efficient feature extraction or classification. At present, scholars have used the clustering analysis algorithm to analyze the degree and characteristics of congestion. For example, Nguyen et al. [39] proposed a method of extracting highway congestion features based on the cluster analysis algorithm. Mohanty et al. [40] analyzed clustering techniques in Vehicular Ad-hoc Networks to detect congestion on roads with minimal infrastructural support. Mondal et al. [41] used the traffic density and average speed of vehicles, and the k-means clustering algorithm classified the different road segments. At present, thanks to the rapid development of information technology, real-time traffic flow indicators are widely collected, which makes it possible to use clustering algorithms to achieve faster processing and more accurate identification.

Therefore, the purpose of this paper is to use the clustering algorithm to propose a method for identifying the congestion level of main roads in cold-climate cities, which should not only identify the congestion state, but also identify the congestion trend. This will allow the ability to comprehensively, quickly, and accurately grasp the traffic congestion situation of main roads in cold-climate cities, determine the congestion control opportunity, and formulate scientific and reasonable treatment schemes, so as to reduce the congestion time and alleviate the adverse impact of congestion on the economy and environment. In order to make the identification standard applicable to cold-climate cities
and reflect the congestion difference of cold-climate cities under different climate conditions, the congestion data under different climate conditions are used to put forward the identification method of the congestion state identification standard for the main roads in cold-climate cities. For the identification of the congestion trend, in order to reflect the varying regularity of congestion under different climatic conditions, a method for determining the type of congestion trend and its distinguishing criteria in cold-climate cities under different climatic conditions is proposed. The rest of the paper is organized as follows: Section 2 introduces the methods of congestion state and trend identification. Section 3 tests the proposed method through case city. Section 4 discusses the identification results and compares and analyzes them with other cities. Finally, Section 5 introduces the research conclusions and future research directions.

2. Materials and Methodologies

2.1. Research Area and Data Sources

2.1.1. Overview of the Case City

Harbin, a cold city in China, is selected as the case city. Harbin is located in the northeastern part of China’s Northeast Plain, 125°42′~130°10′ E and 44°04′~46°40′ N. It is the largest city at the same latitude and a famous ice and snow city in the world. The winter temperature in Harbin is low and long, often accompanied by snowfall, and the road surface is slippery and easily freezes. The frost-free period of the year is only 100~140 days, and the icing period is 190 days, mainly from November to February of the following year. Table 3 shows the average temperature, precipitation, and precipitation days of each month in Harbin in the five years from 2015 to 2019. The form of precipitation from November to February is mainly snowfall, and the value is converted from snowfall.

| Month     | January | February | March | April | May | June |
|-----------|---------|----------|-------|-------|-----|------|
| Average temperature (°C) | −16.9   | −11.9   | −1.3   | 8.6  | 15.8 | 20.6 |
| Precipitation (mL)       | 3.1     | 6.1     | 8.1    | 12.7 | 67.3 | 129.7 |
| Precipitation days (D)   | 5.8     | 5.7     | 5.7    | 6.7  | 10.3 | 13.5 |

| Month     | July | August | September | October | November | December |
|-----------|------|--------|-----------|---------|----------|----------|
| Average temperature (°C) | 24.2 | 22.0   | 16.1      | 6.8     | −5.5     | −14.6    |
| Precipitation (mL)       | 96.2 | 127.3  | 55.7      | 15.0    | 13.5     | 8.9      |
| Precipitation days (D)   | 14.2 | 12.3   | 9.9       | 7.1     | 6.0      | 7.2      |

Source: National Bureau of Statistics of China.

At present, Harbin City has formed a road network structure of “two-axis, four-ring, 10-radiation, and circular radial”. The road network density is 6.5 km/km² and the road land use rate is 10.6%. Furthermore, the main road is 435 km, and the density is 1.18 km/km², which satisfies the requirement of 0.8~1.2 km/km² width recommended by the specification. The length of conventional bus operation lines is 5664.9 km; 292 bus lines and 7031 bus operation vehicles are available, and the annual passenger volume is 1.27 billion. The transfer coefficient and average walking distance of bus trips are the smallest among cities of the same level. However, problems, such as the unreasonable design of the bus network, low bus trip rate, and low bus punctuality, also exist. Harbin Rail Transit has built and put into operation the Metro Line 1 and Line 3, with a line length of 21.8 km, a coverage rate of 10% for 1 km, and an annual passenger volume of 83 million. Problems include extremely small operating mileage, not yet networked, and slow construction progress; some rail transit stations are not closely connected with conventional bus stations, and the advantageous role of urban rail transit in sharing residents’ travel has not been played out [42]. The layout of Harbin’s main road network can be seen in the spatial difference graph in Section 3.3.2.
Harbin is significantly affected by the geographical climate, rail transit has little effect, and conventional public transportation is the main public transportation mode. In winter, the road friction coefficient is reduced, road capacity is decreased, traffic delay is increased, and traffic congestion is prominent, indicating the typical traffic characteristics of cold urban climate conditions.

2.1.2. Data Sources

In order to realize the purpose of real-time and rapid identification of the congestion situation, considering that the service level, occupancy, and other identification indicators are not easy to obtain in real-time, even if they can be obtained, the existing collection technology and collection equipment are easily affected by factors such as weather and signals, and are not very stable [43,44]. The speed, flow, and travel time, as well as TTI, TIS, ICI, and other identification indicators collection methods are relatively mature and have been widely collected by many maps navigation software. Among these, TTI is the most widely used. It can not only accurately explain the overall level of traffic flow from a single indicator such as speed, but also judge whether travel can be expected to be completed based on the travel time, which can better reflect the reliability of the travel [45–47]. Besides the American «Urban Mobility Report» and AutoNavi Map mentioned in Table 2, the Baidu Map, Didi Chuxing and other software, as well as literature [48–52], etc., all used TTI to identify the congestion level and study congestion probability estimation methods, dynamic traffic flow–dispersion model, etc. Therefore, TTI is selected as the identification indicator in this paper, and the 24-h TTI data (time granularity is 30 min) of Harbin main road in 2019 is obtained by AutoNavi Map.

Compared with cities in non-cold-climate cities, the unique snow and ice climate in cold-climate cities is the main factor that causes the deterioration of the traffic environment, among which, snowy and icy pavements is the most direct cause of the aggravation of congestion, which will not only reduce the speed but also increase the time headway [53,54]. Therefore, in order to solve the problem that the existing identification standards do not fully consider the differences of cities in cold regions affected by climatic conditions, TTI data under snowy and icy pavement conditions and TTI data under non-snowy and non-icy pavement conditions are selected in this paper to conduct experiments, so as to obtain the congestion identification standard suitable for the main roads in cold-climate cities.

The formation of snowy and icy pavements is closely related to climatic conditions, and changes in real-time with climatic conditions such as snowfall and temperature [55]. Due to the lack of real-time data on whether the pavement is in the form of snow and ice, this paper makes a determination based on weather information. Literature [56] analyzes the formation process of snowy and icy pavements by rain, sleet, and snow in China’s cold-climate cities Baicheng, Changchun, Baishan, and Yanji during the 30 years from 1986 to 2015, and obtains the formation conditions of snowy and icy pavements, which can be used for daily forecast, as shown in Table 4. This paper uses this as the basis for determining snowy and icy pavements.

| Table 4. The discrimination basis of snowy and icy pavements proposed in literature [56]. |
|-----------------------------------------------|-------------------------------|-----------------------------|
| **Rain or Sleet**                             | **Snow**                      |
| Daytime temperature                           | ≤ −3 °C                       | ≤ −3 °C                   |
| Night temperature                             | ≤ −3 °C                       | ≤ 0 °C                    |

Cities in cold regions generally set strict regulations on the completion time of snow cleaning. The main roads are generally priority roads, and the snow cleaning operation time is generally 2–6 h. For example, Canada requires 2–4 h after the snow stops, Finland requires 6 h to clean up, and China requires “clear immediately” [57,58]. Therefore, in this paper, only the TTI data of the day that meets the conditions for the formation of snowy and icy pavements are used as experimental data under snowy and icy pavements. After collecting the actual weather information, it is determined that there are 12 days in January,
February, November, and December of 2019 in Harbin that meet the conditions of snowy and icy pavement formation. Considering that extreme weather in winter also often occurs in April to May in cold-climate cities, and the sharing rate of walking and cycling is high from June to August, while the sharing rate of motorized traffic is low [12,59], the TTI data of September and October are selected as the experimental data under the condition of non-snowy and non-icy pavement.

The difference in traffic congestion levels between weekdays and rest days has been confirmed by a large amount of literature [60–62]. In order to further understand the congestion characteristics of main roads on weekdays and rest days under the conditions of snowy and icy pavement and non-snowy and non-icy pavement in cold-climate cities, the collected TTI data were split and integrated according to weekdays and rest days. A total of 48 pieces of data were collected throughout the day (24 h a day, collected once every 30 min). Therefore, a total of 196 pieces of data were obtained on weekdays and rest days under the conditions of snowy and icy pavements and non-snowy and non-icy pavements. In addition, in order to obtain the real congestion data of Harbin to verify the rationality of the proposed method, we distributed survey questionnaires about Harbin’s frequently congested roads and congestion time (according to what they know) to Harbin citizens, and used various methods such as surveys of traffic management departments, traffic broadcast information collection, and on-site surveys to obtain the frequently congested main roads in Harbin and their congestion time in the snow and ice periods and non-snow and non-ice periods.

### 2.2. Conceptual Background

The connotation of the traffic congestion situation is defined as follows: the sum of traffic congestion state and change trend, as shown in Figure 2.

![Figure 2. Schematic of traffic congestion state and trend.](image)

What is traffic congestion? At present, although scholars from all over the world have conducted considerable research on traffic congestion from different perspectives, they have not yet formed a consensus on the definition of the connotation of traffic congestion.

Traffic congestion arises along with the road traffic system, which is a complex system composed of people, vehicles, and roads [63,64]. During the operation of the transportation system, the various components are coordinated with each other, but congestion occurs when the dynamic changes in various components, their interactions are unbalanced, and their work is not coordinated.

The traffic state is an objective reflection of the traffic flow, that is, the traffic state and the traffic flow characteristic index are essentially a mapping relationship [65–67]. As the existing congestion identification methods are all based on the movement regularity of traffic flow as the breakthrough point, through the statistical characteristics of traffic flow
indicators, induction, and abstraction, and then establish the corresponding discrimination formula and conditions for identification. Therefore, it can be said that traffic congestion is a state variable, which represents a state of traffic flow operation. When we say that a certain road is congested, it means that the road is in a congested state. In view of this, the connotation of defining the state of traffic congestion is as follows: at a certain time, the traffic operation condition of a road or area, such as the congestion state at the time when the congestion occurs, the peak time, or the end time.

Corresponding to congestion is non-congestion. In the current practical application, since the traffic operation state cannot be described only by congestion or non-congestion, scholars further divide congestion into many levels according to the similarity of the state, such as very smooth, smooth, mild congestion, comparative congestion, and severe congestion, so as to take corresponding measures to control congestion according to different congestion levels. When there are too many levels of the congestion state, the calculation process is often very complicated, and the difference between adjacent levels of traffic congestion state is not significant. However, when it is too small, the characteristics of congestion cannot be reflected in detail. Therefore, most countries or scholars set the number of congestion levels to 3–6. As shown in Table 2, the China Standardization Administration divides the congestion state into four levels: unblocked, relatively unblocked, congested, and severe congestion and the Japan Highway Public Corporation divides the congestion state into three levels: congestion, gradual congestion, and chronic congestion. These classification methods can reflect the congestion state from a single road to the entire road network and are basically domestic or international standards, or domestic or internationally recognized standards. Although the congestion state of main roads in cold-climate cities is more serious and complex under the conditions of snowy and icy pavements, there are certain regularity and periodicity, which can also be divided into 3–6 levels and accurately describe the characteristics of congestion. Therefore, this paper proposes Hypothesis 1:

**Hypothesis 1 (H1).** There are certain rules in the congestion of main roads in cold-climate cities, which can be divided into 3–6 levels.

It is worth noting that the numerical value of the congestion identification index and the level of the congestion state are only relative to certain identification methods, which are relative and have no significance by themselves. Only grasping the congestion state, it is impossible to determine the timing of congestion control. This is similar to the stock market. The meaning of stock price can only be reflected through the impact on the overall state [68–70]. A high stock price does not mean that it can be bought, and a low stock price does not mean that it can be sold. It is necessary to grasp the trend of price changes in order to adopt the corresponding trading strategy (the concept of trend originated from the stock market). Therefore, the concept of trend is extended to the road traffic system, the connotation of the traffic congestion trend is defined as follows: over time, the evolution of congested roads or congested areas. For example, the traffic system changes from the time of congestion generation to the time of congestion peak and then to the time of congestion end, which has a trend.

The stock price changes in real-time, seemingly chaotic, but its changing trend is always constantly transforming among the three trends of rising, falling, and seesawing [71,72]. Traffic flow is also a complex and constantly changing continuous process, and its traffic congestion trend will also show several forms of change. Therefore, this paper proposes Hypothesis 2:

**Hypothesis 2 (H2).** The congestion trend of main roads in cold-climate cities has certain changing rules and can be divided into several types.

Based on the above analysis of the congestion state and congestion trend, it can be seen that the traffic congestion state and trend are closely related, and the two rely on each
other. The congestion trend contains a congestion formation mechanism and evolution law and finally appears as the congestion state. The traffic congestion state is a momentary characteristic of the congestion trend, and the congestion trend is the continuous change process of the congestion state at different times. The traffic congestion situation realizes the collaborative description of the traffic congestion state and trend.

2.3. Methodologies

Research was undertaken on the following premises (Figure 3). For the identification of the congestion state, TTI data are initially collected. Then, to reflect the differences in snowy and icy pavement and non-snowy and non-icy pavement, the data recording method of the congestion density distribution curve is proposed to obtain the congestion density distribution curve diagram of the case city in cold-climate conditions; we obtain the location sparse matrix through transformation. On this basis, the Density-based Spatial Clustering of Applications with Noise (DBSCAN) calculates the congestion state classification number and boundary of the main road congestion state in the cold-climate cities. Subsequently, the spatio-temporal autocorrelation of the congestion state is calculated on the basis of the identification results and compared with the real data to test Hypothesis 1 and verify the effectiveness of the identification method.

For the identification of the congestion trend, first, the congestion change speed index is proposed to identify the congestion trend, and it is used as the basis to identify the type of congestion evolution trend. Second, the Hierarchical Cluster Method (HCM) is used to classify the congestion trend change types in snowy and icy pavements and non-snowy and non-icy pavements in cold-climate cities. Third, the Fuzzy C-means (FCM) is used to measure the degree to which each data sample belongs to each clustering type through the membership degree matrix, and then the fuzzy division is carried out to obtain the fuzzy division range of each type. Fourth, the effectiveness of the method is tested based on the difference in the mean of the sample data. Finally, through these methods, the temporal and spatial characteristics of the main road congestion situation in the cold-climate cities of the case city are obtained, and compared and discussed with other cold-climate cities and non-cold-climate cities.
2.3.1. Identification Method of Traffic Congestion State of the Main Road in Cold-Climate Cities

Considering that the classification standard of the traffic congestion state of the main roads in cold-climate cities should reflect the differences in congestion under different climatic conditions, a data-recording method of congestion density distribution curve is proposed. Considering that the DBSCAN is the most representative density-based clustering algorithm, a new method for identifying the congestion state of the main road in cold-climate cities combined with the DBSCAN is proposed to use TTI data under snowy and icy pavements and non-snowy and non-icy pavements in cold regions for congestion classification. Thus, the one-sidedness and mechanization of the discrimination results is avoided. The specific calculation process is as follows: Step 1, arrange the TTI data at all times of the day on snowy and icy pavements and non-snowy and non-icy pavements in descending order, taking the time point as the abscissa and the TTI value as the ordinate to form a preliminary congestion density distribution curve, and any point is marked as \( p_i(s, z, d) \). In this case, \( i \) represents the time point, \( s \) represents the season, \( z \) represents the working day or the rest day, and \( d \) represents the TTI value. Step 2, based on the congestion density distribution curve, record the position of each time on the abscissa and its corresponding TTI value, and convert the distribution position of each time into a \((48 \times s \times z) \times 1\) column position matrix \( N_i \). When the time, \( i \), coincides with the time of the congestion density distribution curve, it is recorded as 1; otherwise, it is recorded as 0.

Step 3, use the DBSCAN to cluster each position matrix \( N_i \) and describe the tightness of the neighborhood sample distribution based on neighborhood parameters (neighborhood distance \( \Delta r \), the minimum number of neighborhood samples MinPts) [73]. Among these, for any sample \( x_m \), a subset \( N^\Delta r(x_m) = \{ \text{distance}(x_m, x_n) \leq \Delta r \} \) exists within its neighborhood distance \( \Delta r \); if \( |N^\Delta r(x_m)| \geq \text{MinPts} \), then \( x_m \) is the core object. The sample traverses to find all the core objects, and then the class about the neighborhood parameters is obtained, forming the density distribution interval of each time \( i \).

Step 4, find the maximum density that connects the distribution interval of each time \( i \), integrate them together, and find the position of the time that minimizes the overlap rate of the maximum density distribution interval.

Step 5, based on the time and location, correspondingly find the dividing limit value and the number of the congestion density distribution curve, that is, the number of congestion levels and the dividing standard.

2.3.2. Identification Method of Traffic Congestion Trend of the Main Road in Cold-Climate Cities

Considering the quantification of traffic congestion trends is the prerequisite for analyzing congestion evolution trends, this paper proposes congestion change speed indicators as the basis for judging the types of congestion evolution trends, that is, the ratio of the difference between the next congestion state and the previous congestion state and the congestion duration, as shown in Equation (1).

\[
\nu_t = \frac{I^m - I^n}{t^m - t^n}
\]

where, \( \nu_t \) is the congestion change speed, \( I^m, I^n \) is the value of TTI at the next moment and the previous moment, \( t^m, t^n \) is the congestion time.

Considering that there are differences and dynamic changes in the travel behavior of residents in different cities, and the cold-climate cities are affected by severe climatic conditions, the formation and propagation of traffic congestion on snowy and icy pavements are more special and complex than those on non-snowy and non-icy pavements. Therefore, for the purpose of exploring the types and numbers of traffic congestion trends on main roads in cold-climate cities, the types of congestion trends in cold-climate cities on snowy and icy pavements, and those on non-snowy and non-icy pavements are divided. HCM is the most commonly used clustering method at home and abroad, and it does not
need to know the classification structure in advance. By taking the sample data without any association as a class, all sample data can be classified based on the similarity statistics between classes [74,75]. The commonly used system clustering method is based on distance as the similarity statistic. Distance calculation methods include intergroup connections, intragroup connections, and the Ward method. The Ward method is selected to classify the main road traffic congestion trends in cold-climate cities, to classify the types of congestion trends, and achieve the effect of large differences between classes and small differences within classes.

For real-time and accurate determination of the traffic congestion trend type and to address the previous problem, congestion data should be collected over a longer period of time to determine congestion trends. In addition, adding a “label” to the mutation range of each trend type is necessary to determine the mutation threshold of the congestion change speed index among different types. Thus, the congestion trend type can be identified by two congestion state indexes, and then the congestion control strategy or travel route can be rapidly adopted. The mutation thresholds of the congestion change speed indicators among different types should be determined to identify the types of traffic congestion trends in real-time accurately and to provide a basis for the decision-making work of urban residents and city managers on traffic congestion control in cold regions. FCM is a fuzzy clustering algorithm, which takes the minimum weighted sum of the distance between the data sample and the cluster center (the center point of a certain category of data) as the objective function, and by analyzing the membership function between each data sample and different cluster centers, the degree of membership of each data sample to a certain category is measured, and then divides the data without strict or clear boundaries [76].

Considering that the operation of the transportation system is a complex and constantly changing continuous process, the traffic conditions and trends at different times, which are vague and uncertain, affect each other. Therefore, the FCM is selected to determine the sudden change threshold of each type of traffic congestion trend. The specific calculation process is as follows:

Step 1, given a set of data samples \(X = \{x_1, x_2, \cdots, x_n\}\), \(n\) is the sample size.

Step 2, determine the number of clustering types \(s\), the iterative stop threshold \(\lambda\), the fuzzy weighting index \(\varphi\), and other parameters.

Step 3, calculate the initial cluster center \(S^{(0)} = \{s_1^{(0)}, s_2^{(0)}, \cdots, s_s^{(0)}\}\), set the number of iterations \(\mu = 0\). The selection of the initial cluster center will directly affect the final cluster results. In this paper, the initial cluster center is obtained through the following process: calculate the distance \(d\) between any two data samples, select the two closest samples to be classified into one category, and take the center value of these two samples as the cluster center of the category. Set the distance threshold \(\alpha = d_{\text{max}}/s\), where \(d_{\text{max}}\) as the maximum distance, find all data samples whose distances from the two samples in the first category are greater than the threshold \(\alpha\), and select the two closest samples from these samples as the second category, and take the center value of the two samples as the cluster center of the second category. And so on, until the cluster centers of \(s\) classes are found.

Step 4, obtain the membership degree of each sample data to the cluster type based on \(S^{(0)}\), and establish the fuzzy membership matrix \(U = \{u_{ij}\}\), as shown in Equation (2), and the conditions to be satisfied as shown in Equation (3).

\[
u_{ij} = \left \{ \frac{1}{s} \sum_{k=1}^{s} \left( \frac{d_{kj}}{d_{ij}} \right)^{\frac{1}{\varphi}} \right \}
\]

(2)
where $d_{ij}$ is the Euclidean distance from the $j$-th sample data to the $i$-th cluster center, and its calculation equation is shown in Equation (4). $u_{ij}$ is the membership of the $j$-th sample data to the $i$-th cluster category.

$$d_{ij} = \|x_j - S_i\|, s_i = \frac{\sum_{j=1}^{n} u_{ij}^q x_j}{\sum_{j=1}^{n} u_{ij}^q}$$

where $x_j$ is the $j$-th sample data, and $S_i$ is the $i$-th cluster center.

Step 5, according to the fuzzy membership matrix $U$, recalculate the new cluster center $S_1^{(1)}$,

$$S_1^{(1)} = \sum_{i=1}^{n} \frac{(u_{ij})^q}{\sum_{j=1}^{n} (u_{ij})^q} x_i / \sum_{j=1}^{n} (u_{ij})^q.$$

Step 6, calculate whether the iterative stop condition is satisfied, that is, when $\|S_1^{(1)} - S_1^{(0)}\| < \lambda$ the clustering stops, output the cluster center $S_1^{(0)}$ and the fuzzy membership matrix $U$, and then obtain the fuzzy range of the sample data under different categories.

### 2.3.3. Effectiveness Verification Method

#### 1. Effectiveness Verification Method of Traffic Congestion State

In the actual road traffic operation process, the traffic state at the next moment is affected by the previous moment, and the upstream section is affected by the downstream section, which has evident characteristics of temporal and spatial self-correlation. Considering that the traffic congestion data are obtained from the observation results of the actual traffic system, the premise of the cluster analysis is that the spatio-temporal objects have self-correlation. If no self-correlation exists or the self-correlation is weak, no evident clustering phenomenon occurs. Therefore, to test hypothesis 1 and verify the effectiveness of the traffic congestion state identification method, the spatio-temporal self-correlation of the discriminant results is necessary.

The temporal self-correlation of the traffic congestion state refers to the correlation of the traffic congestion state discrimination index at adjacent moments; it represents the time dependence of the congestion state. The calculation equation is shown in Equation (5).

$$AC_\tau = \frac{\sum_{t=1}^{T-\tau} (I_t - \bar{T})(I_{t+\tau} - \bar{T})}{\sum_{t=1}^{T} (I_t - \bar{T})^2}$$

where, $AC_\tau$ is the temporal self-correlation coefficient of the congestion state of the $\tau$-period delay and the value range is $[-1, 1]$. $\tau$ is the number of time delay periods; $T$ is the total number of periods; $I_t$ is the congestion discrimination index value at time $t$; $\bar{T}$ is the mean value of the congestion indicator of the total number of periods $T$; $I_{t+\tau}$ is the congestion discrimination index value at the time $t + \tau$. When $AC_\tau$ is closer to 1, the temporal self-correlation of the congestion state is higher.

Similar to the temporal self-correlation of the congestion state, the spatial self-correlation of the congestion state refers to the degree of interdependence between the congestion state of a certain spatial location and the congestion state of the surrounding spatial location. The closer state indicates a higher correlation. The Moran index, which is widely used in...
global self-correlation, is selected for the spatial self-correlation analysis. The equation is shown in Equation (6) [77].

\[
M = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (D_i - \overline{D}) (D_j - \overline{D})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \times \sum_{i=1}^{n} (D_i - \overline{D})^2}
\] 

(6)

where \(M\) is the Moran index of the entire region, that is, the spatial self-correlation of the congestion state of the entire region, and the value range is \([-1, 1]\). \(n\) is the number of roads in the entire region. \(D_i, D_j\) is the congestion level of roads \(i\) and \(j\), and \(w_{ij}\) is the adjacency relationship of roads \(i\) and \(j\). \(\overline{D}\) is the average congestion level of the entire region. The Moran index is a type of inferential statistics; thus, its analysis results should be explained under the null hypothesis, and the expected index value should be calculated, compared, and analyzed. The null hypothesis is as follows, whether to reject the null hypothesis by calculating the score of probability \(p\) and standard deviation multiple \(z\) should be judged. The calculation equation of \(z\) score is shown in Equation (7).

**Hypothesis 3 (H3).** The analyzed metrics are randomly distributed among the elements in the study area.

\[
z = \frac{M - E(M)}{\sqrt{v(M)}}
\]

\[
E(M) = \frac{-1}{n-1}
\]

\[
v(M) = E(M^2) - [E(M)]^2
\]

(7)

When the calculation result is significant, the hypothesis is rejected, and the measurement index is related to space. On this basis, the Moran index is positive, which indicates that the space is positively correlated. The larger index indicates a more concentrated spatial distribution. A negative Moran index indicates that the space is negatively correlated; the smaller index has a more discrete spatial distribution. If the Moran index is zero, then it indicates that the space is uncorrelated and randomly distributed.

2. Effectiveness Verification Method of Traffic Congestion Trend

To test Hypothesis 2 and to verify the rationality of the classification, first, each level is assumed to obey a normal distribution, the variance of each level is equal, and the samples are independent of each other. If the hypothesis is true, then it indicates no significant difference between the levels, otherwise, a significant difference is found. Second, the hypothesis is tested by calculating the sum of squared deviations and establishing a test statistic (F statistic). The total sum of square deviations \(S_T\) and degrees of freedom \(df_T\), the sum of square deviations between groups \(S_A\) and degrees of freedom \(df_A\), the sum of square deviations within groups \(S_E\), and degrees of freedom \(df_E\) are calculated, and the calculation equations are shown in Equations (8)–(10), as follows:

\[
S_T = \sum_{i=1}^{r} \sum_{j=1}^{m} (y_{ij} - \overline{y})^2, df_T = n - 1
\]

(8)

\[
S_A = m \sum_{i=1}^{r} (\overline{y}_i - \overline{y})^2, df_A = r - 1
\]

(9)

\[
S_E = \sum_{i=1}^{r} \sum_{j=1}^{m} (y_{ij} - \overline{y}_i)^2, df_E = n - r
\]

(10)

where, \(i\) is the number of levels, \(l = 1,2,...,r\). \(j\) is the number of samples at each level, and \(j = 1,2,...,m\). \(n\) is the total number of samples.
Third, the mean square is calculated between groups and within groups. The equation is \( MS = S/df \). Fourth, the ratio \( F \) of the mean square of the sum of squares of deviations between groups to the mean square of the sum of squares of deviations within groups is used as the statistic for testing the hypothesis, and the equation is shown in Equation (11).

\[
F = \frac{MS_A}{MS_E} = \frac{S_A/df_A}{S_E/df_E}
\]  

(11)

Fifth, the test value \( p \) is obtained based on the density function corresponding to the F distribution, \( p = P(F) \). The significance level is 0.05. When \( p < 0.05 \), the hypothesis is rejected; otherwise, the hypothesis is accepted.

3. Results

3.1. Identification Standard

3.1.1. Identification Standard of Traffic Congestion State

On the basis of the monitoring data of AutoNavi Map, with time point as the abscissa and TTI as the ordinate, we draw the congestion density distribution map in descending order, as shown in Figure 4.

![Figure 4. Distribution of congestion density in Harbin.](image)

The congestion density distribution curve at each time \( i (I = 0:00, 0:30, 1:00, ..., 23:30) \) is decomposed and integrated every 6 h to form Figure 5. The figure shows that the distribution of congestion density is different in different time periods, and the congestion index value fluctuates greatly in the same time period. This finding shows that the congestion degree changes remarkably on snowy and icy pavements and non-snowy and non-icy pavements, as well as on weekdays and rest days, which explains that the degree of congestion and the characteristics of congestion change with time and space, and are unstable in different time and space positions.

We can obtain a sparse matrix of \( 192 \times 1 \) positions at each time based on the distribution of congestion density at each time by using the congestion data of snowy and icy pavements and non-snowy and non-icy pavements monitored every 30 min, as well as workdays and rest days. Through the DBSCAN, the maximum density distribution interval at each moment is obtained, as shown in Figure 6. The figure shows that when the abscissa is divided into three segments, the overlap rate of the maximum density distribution interval can be minimized, and the positions at this time are the 45th and 136th positions. On this basis, the congestion density distribution curve should also be divided into three parts, that is, the congestion state level should be divided into three levels. The classification standard is as follows: TTI \( \leq 1.22 \) is unobstructed, \( 1.22 < TTI < 1.6 \) is slow, and \( TTI \geq 1.6 \) is congestion.
Figure 5. Distribution of congestion density in different periods in Harbin. (a) 0:00–5:30, (b) 6:00–12:00, (c) 12:30–18:00, (d) 18:30–23:30.

Figure 6. Maximum congestion density interval of Harbin at each time.
3.1.2. Identification Standard of Traffic Congestion Trend

We obtained the cluster analysis gravel map through the HCM, as shown in Figure 7, by using the monitoring data of the AutoNavi map. Figure 7 shows that the clustering results on snowy and icy pavements and non-snowy and non-icy pavements in Harbin are similar, and the aggregation coefficients gradually decrease with the increasing number of types. The three points are significant turning points. Therefore, the traffic congestion trend of the urban main road in cold-climate cities is divided into three types.

![Figure 7. Cluster analysis of congestion trend types of the main road in Harbin under snowy and icy pavement and non-snowy and non-icy pavement.](image)

In addition, based on the dendrogram of the clustering results, the congestion change speed of each congestion trend type in Harbin on snowy and icy pavements and non-snowy and non-icy pavements shows the characteristics of positive increase, negative decrease, and insignificant change between positive and negative values. Therefore, the three types of traffic congestion trends are described as aggravating, alleviating, and stable. Among these, the aggravating type indicates that the congestion state is gradually becoming more serious, the alleviating type indicates that the congestion state is gradually improving, and the stable type indicates that the congestion state remains unchanged.

The MATLAB fuzzy logic toolbox is used to calculate the monitoring data of the congestion state of Harbin on snowy and icy pavements and non-snowy and non-icy pavements through the FCM. When using the FCM, the number of clustering types \( s \), the iterative stop threshold \( \lambda \), and the fuzzy weighting index \( \phi \) should be calibrated in advance. This study is based on the HCM to obtain traffic congestion trends that can be divided into three types; therefore, \( s \) is set to 3. The iterative stop threshold \( \lambda \) is an important parameter to measure the clustering accuracy; generally, the value is small. This study ensures the accuracy requirements; \( \lambda \) is set to \( 10^{-5} \). The fuzzy weighting index \( \phi \) represents the degree of fuzziness of the clustering results, the value range is \((1.5, 2.5)\); the larger value indicates a higher degree of fuzziness. In practical applications, the best value range is \((1.5, 2.5)\), then \( \phi \) is set to 2 in this study. The cluster centers of the congestion change speed in the two seasons are obtained, \((-2.42 \times 10^{-5}, 0.0033, -0.0021)\) and \((1.86 \times 10^{-5}, 0.0029, -0.0019)\), and the clustering results are shown in Figure 8.
Figure 8. Clustering results of traffic congestion trend types of the main road in Harbin under snowy and icy pavement and non-snowy and non-icy pavement.

Figure 8 shows the fuzzy classification range of the congestion change speed under the three trend types, and the rounded result is shown in Table 5.

Table 5. Fuzzy classification range of various traffic congestion trend types of Harbin’s main road under snowy and icy pavement and non-snowy and non-icy pavement.

|                        | Aggravating Type | Alleviating Type | Stable Type   |
|------------------------|------------------|------------------|---------------|
| Non-snowy and non-icy  | (0.001, +∞)     | (−∞, −0.001)    | [−0.001, 0.001] |
| Snowy and icy pavement | (0.002, +∞)     | (−∞, −0.002)    | [−0.002, 0.002] |

3.2. Verification Results

3.2.1. Verification Results of Traffic Congestion State

The temporal self-correlation function graph of congestion (the time delay step is 30 min) is obtained on the basis of the results and the temporal self-correlation calculation equation, as shown in Figure 9.

Figure 9. Changes in the temporal self-correlation of the congestion state in Harbin on snowy and icy pavements and non-snowy and non-icy pavements in the number of delay periods.
Figure 9 shows that the temporal self-correlation of congestion based on the TTI is correlated regardless of climate conditions, working days, and rest days. The accumulation of temporal self-correlation coefficients over time shows a clear downward trend, which can reflect the temporal characteristics of the main road’s congestion state in cold-climate cities. From the perspective of the climate condition, the temporal self-correlation of congestion of working days on snowy and icy pavements and non-snowy and non-icy pavements is insignificantly affected by the climate condition. The self-correlation coefficient is large before the delay period number 12 (5:30), showing that the congestion state at the current moment has a great correlation with the congestion state at the subsequent moment; however, it drops sharply after, at approximately 0.6. Subsequently, at the delay period of 32 (15:30), a sudden drop occurs again. The temporal self-correlation of congestion on rest days is higher than that on working days, and it changes slightly under the influence of climate conditions. This finding may be due to the high volume and regularity of weekday travel, the rest days are mainly for entertainment, and the travel modes are more diversified because of the climate. At the same time, with the increase in time delay, the road section is not only affected by the traffic flow transmission at the previous moment but also gradually by the traffic flow backtracking at the next moment. Thus, the self-correlation gradually decreases.

Based on the spatial location and congestion level of each main road in Harbin from 6:30 to 19:00 under the conditions of snowy and icy pavements, the spatial self-correlation of the congestion state at each time node can be obtained through ArcGIS software, as shown in Figure 10. Among them, the time granularity was 30 min, and the confidence was 95% ($z$-score $< -1.96$ or $> +1.96$, $p < 0.05$ showed significant).

Figure 10 shows that the traffic congestion state level of the Harbin main road under the conditions of snowy and icy pavements obtained by the proposed congestion state identification method is basically related to the space. Furthermore, a positive correlation exists between 7:00 and 14:00, and in the morning peak period, the spatial distribution clustering degree is the largest, and the level of congestion is also the highest. As time progresses, the correlation between the level of congestion and space continues to decrease, and the spatial distribution is slightly dispersed. From 16:30 to 19:00, the correlation fluctuates and presents a random distribution, which may be because Harbin, as an
internationally famous city of ice and snow culture, has an increasing number of tourists traveling in winter, especially in the afternoon and evening, and the travel rules change. In summary, the traffic congestion state of the main road in cold-climate cities can be divided into three levels, and Hypothesis 1 is valid. This identification method of the traffic congestion state can satisfy the requirements of describing and studying the traffic congestion state of the urban main roads in cold-climate cities.

3.2.2. Verification Results of Traffic Congestion Trend

The analysis results were tested for mean difference, and the results are shown in Table 6. The table shows a significant difference between snowy and icy pavements and non-snowy and non-icy pavements, indicating that the classification results are reasonable and effective and can better reflect the differences between different types.

| Variable                                         | Sum of Deviationsquares | df | Mean Square | F     | Significance |
|--------------------------------------------------|-------------------------|----|-------------|-------|--------------|
| Under the condition of non-snowy and non-icy pavement | Interblock | 0.000 | 2 | 0.000 | 65.048 | 0.000 |
| Speed of congestion change                        | Intraclass  | 0.000 | | 85 | 0.000 |
| Speed of congestion change                        | Total        | 0.001 | 88 |
| Under the condition of snowy and icy pavement     | Interblock | 0.001 | 2 | 0.000 | 126.314 | 0.000 |
| Speed of congestion change                        | Intraclass  | 0.000 | | 89 | 0.000 |
| Speed of congestion change                        | Total        | 0.001 | 92 |

3.3. Traffic Congestion Situation Characteristics of the Main Road in Cold-Climate Cities

The discriminant results of the new and old methods are compared, the temporal and spatial characteristics of the congestion situation are analyzed, as well as the severity of the main road traffic congestion in cold-climate cities, the scope of influence, and the law of occurrence and change.

3.3.1. Temporal Characteristics

The frequency of each level in the new identification standard at each time and the frequency of each level in the existing identification standard of the AutoNavi map are counted on the basis of the monitoring data of the AutoNavi map, as shown in Figure 11. It is compared with the statistics on the frequency of congestion in each time period obtained from the field survey (Figure 12). The comparison indicates that the identification results based on the new identification criteria can better reflect the actual congestion characteristics of the main road in cold-climate cities. Thus, the cold-climate cities can comprehensively and accurately grasp the congestion characteristics, thereby improving the accuracy of congestion control and improving the efficiency of congestion control.

The congestion time distribution of cold-climate cities on snowy and icy pavements and non-snowy and non-icy pavements, working days and rest days are obtained, as shown in Figure 13, on the basis of new criteria for the congestion state and the method of the congestion trend.

The figure shows that whether it is the congestion state or the congestion trend, the congestion characteristics of Harbin weekdays differ significantly from those of rest days. The congestion characteristics under different road conditions are also different due to the weather conditions. Furthermore, the start time, peak time, and end time of the morning peak of congestion in Harbin weekdays are similar regardless of road conditions, at 7:00, 8:00, and 10:30, respectively. In this process, the degree of congestion on snowy and icy pavements is more serious than on non-snowy and non-icy pavements. Regardless of road conditions, the traffic operation level shows a stable change before 6 o’clock, and then it begins to show an aggravating change; the aggravating speed under the condition
of snowy and icy pavements is higher than that under the condition of non-snowy and non-icy pavements. After the peak time of congestion, the change trend of congestion alleviates until 10:30, and the alleviating speed under the condition of snowy and icy pavements is faster than that under the condition of non-snowy and non-icy pavements. From 10:30 to 16:00, the state of congestion is slow, the trend of congestion starts to transform from the stable type to intensified type at approximately 16:00 under the condition of snowy and icy pavements, and approximately 16:30 under the condition of non-snowy and non-icy pavements. For the evening peak, Harbin’s main road starts to be congested at 16:00 when the pavement is snowy and icy, and approximately half an hour later when the pavement is non-snowy and non-icy; both of them reach their peak at 17:30. Regardless of the road conditions, the congestion ends at approximately 19:30. In this process, the congestion trend first shows an aggravating change from 15:30 to 16:00. At the peak of congestion, the aggravating speed is the fastest, and then the congestion trend shows an easing type. The easing speed under the condition of snowy and icy pavements is faster than that under the condition of non-snowy and non-icy pavements, and the congestion trend shows a stable change until 20:30. For rest days, the start time of congestion is later than weekdays, in which the start time of congestion is approximately 10:30 under the condition of snowy and icy pavements and 10:00 under the condition of non-snowy and non-icy pavements. Subsequently, the traffic state fluctuates between congestion and slow traffic without evident peak time, and the end time of congestion is less regular and less evident. The evening peak under the condition of snowy and icy pavements starts earlier than that under the condition of non-snowy and non-icy pavements, at 16:00 and 16:30, respectively. The evening peak congestion under the condition of snowy and icy pavements is more severe than that under the condition of non-snowy and non-icy pavements, and then the congestion ends at approximately 19:00 regardless of road conditions. The trend of congestion on rest days is stable, but the fluctuation under the condition of snowy and icy pavements is greater than that under non-snowy and non-icy pavements.

![Figure 11](image1.png)

**Figure 11.** Frequency of congestion in Harbin at different times based on the new and old criteria. (a) Statistical results based on new criteria (b) Statistical results based on existing criteria.

### 3.3.2. Spatial Characteristics

The data at this time are selected, considering that the congestion is the most severe at 8:00 on weekdays under the condition of snowy and icy pavements, and the spatial difference graph is made by the local Moran index (Equation (12)) to obtain the local spatial variation characteristics of each main road at this time, as shown in Figure 14, based on the new and existing identification criteria of the congestion level, respectively. Through field investigations on 20 major main roads in Harbin, the frequency of congestion in the morning peak in the snow and ice period was obtained, as shown in Figure 15.
The comparison of Figure 14 with Figure 15 indicates that the identification result based on the new identification standard is more consistent with the actual situation.

\[
M_i = \frac{n \sum_{j=1}^{n} w_{ij} (D_i - \overline{D}) (D_j - \overline{D})}{\sum_{j=1}^{n} w_{ij} \times \sum_{i=1}^{n} (D_i - \overline{D})^2}
\]

(12)

Figure 12. Frequency of congestion at different times in Harbin based on field survey.

Figure 13. Time characteristics of congestion state and trend in Harbin. (a) Congest state (b) Congest trend.

Figure 14. Spatial congestion characteristics of the main road in Harbin at 8:00 on weekdays under the condition of snowy and icy pavement based on old and new criteria. (a) Statistical results based on new criteria (b) Statistical results based on existing criteria.
Figure 15. Congestion frequency of 20 main arterial roads in Harbin during the morning peak in snow and ice period based on field investigation.

A spatial difference map was made for the congestion aggravation and mitigation process in the morning peak under the condition of snowy and icy pavements and non-snowy and non-icy pavements to find the congested hotspots, based on the new identification method, and the congestion aggregation or dispersion characteristics of a small area centered on each main road, and the evolution characteristics of spatial equilibrium or heterogeneity were obtained, as shown in Figure 16. The redder the road, the higher the local Moran index value and the more concentrated the congestion.

Figure 16 shows that with the aggravation of congestion, its clustering becomes increasingly evident, with the highest degree of clustering, the widest range of congest-
tion, and the strongest spatial heterogeneity at peak time. Under the condition of snowy and icy pavements, Kangning Road, Hongqi Street, and Xuefu Road take the lead in gathering. Under the condition of non-snowy and non-icy pavements, the degree of gathering is smaller than that under snowy and icy pavements, and we mainly distributed it on Huagong Road and Kangning Road. In the aggravation process, the traffic congestion is distributed radially along the main road with the intersections as the core, mostly distributed around the residential communities, schools, and other sizeable areas. The congestion around the school is particularly severe given that the morning peak time on weekdays is also the peak time for school. At the same time, as a traffic attraction source with a high attraction effect, shopping malls have high congestion aggregation. In addition, the spatial distribution range of congestion under the condition of snowy and icy pavements and non-snowy and non-icy pavements is compared, and the results show that congestion under the condition of snowy and icy pavements is more likely to occur on steep slopes or undulating road sections. In the congestion alleviation process, the road section to be congested first under the condition of snowy and icy pavements also dissipates behind time, and the spatial heterogeneity is still relatively serious. However, with the continuous easing of congestion under the condition of non-snowy and non-icy pavements, the space presents certain stability.

4. Discussion

On the basis of the congestion density distribution curve and density clustering algorithm, the congestion states of the main road in cold-climate cities can be divided into three levels. The classification criteria are as follows: $TTI \leq 1.22$ is unblocked, $1.22 < TTI < 1.6$ is slow, and $TTI \geq 1.6$ is congestion. In addition, on the basis of the systematic clustering algorithm, the congestion trend of the urban main road in cold-climate cities can be divided into three types, namely, the aggravating type, the alleviating type, and the stable type regardless of the road conditions. The Fuzzy C-means algorithm is used to calculate the mutation threshold range of each type under different pavement conditions to determine the traffic congestion trend type in real-time and accurately.

On the basis of these methods, the start time, peak time, and end time of the morning peak congestion in Harbin on weekdays are relatively similar regardless of the road conditions. The congestion aggravation and alleviation duration are also relatively similar. However, the start of evening peaks on snowy and icy pavements are earlier than those on non-snowy and icy pavements, and the congestion aggravation lasts longer than that under non-snowy and icy pavements. The degree and speed of congestion change fluctuate greatly in the morning and evening peak period, and the fluctuation under the condition of snowy and icy pavements is slightly greater than that under the condition of non-snowy and non-icy pavements. This finding may be because the working time of most units is the same, and the leaving time is slightly loose. In winter, the solar altitude angle becomes smaller in cold-climate cities, and the sunshine duration becomes shorter. People prefer to travel in advance to avoid driving at night and avoiding the evening peak hours. In addition, the start time of the morning peak in Harbin on rest days is later than that on weekdays, and the duration of the congestion aggravation is longer than that on weekdays. The start time and aggravation of congestion in the morning peak under snowy and icy pavements are later than non-snowy and non-icy pavements, the start of the evening peak under snowy and icy pavements is earlier than non-snowy and non-icy pavements, and the congestion trend under non-snowy and non-icy pavements is more volatile than that of the condition of snowy and non-icy pavements. This finding is mainly because people travel more casually on rest days, and people tend to travel later than work hours; thus, the start time is delayed, and entertainment and leisure activities generally take half a day, resulting in a longer aggravation time. At the same time, due to the poor regularity of travel on rest days and the formation of snow and ice pavements in the cold climate in winter, travel is easily disturbed. Therefore, the change trend of congestion is relatively fluctuating. In terms of space, although the spatial adjacency relationship between sections is similar, the local
Moran index varies greatly, indicating that sections are affected by adjacent spaces and the influence degree is unbalanced. The spatial evolution of congestion presents significant instability in the degree and location of the congestion aggregation. Moreover, the peak time of congestion is the most unbalanced, and snowy and icy pavements are more serious than non-snowy and non-icy pavements. This finding is mainly due to the instability of the road traffic environment due to the unique ice and snow weather in winter. As the spatial location changes, the closer it is to commercial areas and schools, the higher the degree of spatial aggregation, and the congestion on snowy and icy pavements also gathers on the ramp. This change process reflects that the main roads in different spatial locations bear different traffic demands. The closer they are to the attraction point, the stronger the congestion aggregation effect caused by the spatial aggregation of travel behavior. The farther they are from the attraction point, the more scattered and random the travel behavior becomes in space.

Due to the limitation of snowfall data sample collection and data quality, previous studies on the influence of snow and ice conditions on traffic congestion characteristics are few, and the research perspectives are quite diverse, and the research results are also different to some extent. The literature [78] believes that the snowfall time has a greater impact on traffic congestion, and separately studied the impact of snowfall before and after the trip in Beijing. Beijing also belongs to a cold-climate city, but the winter cold degree is not as high as Harbin, the average winter temperature is $-4.6\, ^\circ C$. According to the study, some travelers may change their travel mode on the second day when it snows the night before the trip. Before the morning peak, the speed is lower than normal days, and the congestion is more serious than normal days. After 8:30, the speed of snowy days began to increase. Although the speed decreased during the evening peak period, the speed of snowy days was higher than normal days and the congestion level was lower than normal days until 24:00 at night. The main road speed increased by 12–21%. The reason may be that the snowfall has damped some of the demand for traffic, resulting in less traffic on the roads and less congestion. When there is snow on the day of travel, that is, the snow occurs in the process of travel, the snow on the day of travel will not cause much reduction in traffic demand. Therefore, the speed of the entire day on snow days is lower than that on normal days, and the congestion index is also higher than that on normal days. The main road speed will be reduced by 3% to 9%. In addition, research shows that when snow falls on the day before travel, the morning peak on the snowy days is earlier than that on normal days. Both the start time and peak time of congestion are 30 min earlier than that on normal days, but the evening peak time is similar. The morning peak and evening peak start time of the snowfall day is about 1 h earlier than that of the normal days.

In the literature [79] taking Xi’an as the research city, the influence of snowfall conditions on congestion characteristics was studied. Xi’an is not a cold-climate city. The average temperature in winter is above 0 $^\circ C$, and there is very little snow in winter. According to the study, in Xi’an, from 7:00 to 19:00, the average delay during most of the snowy weather is higher than that of normal weather conditions. As precipitation continues to increase, so does the increase in delays. Precipitation decreases, and the gap between the speed of snowfall and the speed of normal weather decreases. Around 18:00-19:00, snow was still falling, but the delay was reduced due to reduced traffic volume and increased speed.

The literature in [80] takes Beijing as a case city and analyzes the congestion characteristics on weekdays and holidays under snow and ice conditions. Studies have shown that whether it is weekdays or holidays, the severely congested periods under normal weather are more affected by severe weather. On weekdays, the impact of snowfall on the traffic operation in the evening rush hour is greater than that on the morning rush hour, and after the evening rush hour, its influence on the traffic operation in the evening hours is reduced. During holidays, the impact of snowfall on traffic operations is mainly concentrated before lunch and in the afternoon. In addition, the snowy weather expands the congested space, and the congested space expands more obviously on weekdays than on holidays. Furthermore, the United States’ national traffic survey also found that regardless of climatic
conditions, entertainment areas, major shopping centers or stadiums, and some restricted roads (such as bridges) have become the main locations of congestion [81].

Research on the time and space distribution law of main road congestion in cold-climate cities, as well as the law of change, provides a basis for determining the timing of congestion management and formulating scientific and reasonable governance plans. In order to avoid spending more time and resources to manage congestion when congestion forms a closed loop, traffic diversion should be carried out when the congestion trend is aggravating. Combining the international development situation and the characteristics of congestion, the following congestion management strategies are proposed: (1) Considering that the epidemic virus may exist on the earth for a long time in the future, working from home can not only reduce the risk of virus transmission, but also reduce the amount of commuting, and due to the arrival of the COVID-19 pandemic, the mode of working from home has been recognized by some companies, therefore, more companies can adopt the home office model. (2) Considering the impact of the COVID-19 pandemic, residents’ travel modes are gradually shifting to cars, walking, and bicycles. In order to encourage residents to make more choices about walking and cycling, cold-climate cities should pay attention to the construction of walking and cycling transportation facilities. The severe climatic conditions in winter in cold-climate cities make it more difficult to install walking and bicycle facilities than in other cities. It is necessary to fully consider climate factors such as temperature, wind, and sunshine so that the natural environment and the traffic environment depend on each other and provide residents with a comfortable travel environment. (3) Considering that congestion in cold-climate cities is concentrated in time and space during morning and evening rush hours, in order to avoid the excessive concentration of travel demand during rush hours, it is suggested that companies stagger work shifts. Especially when it snows, companies should be flexible in adjusting commute times. (4) In view of the traffic congestion caused by the excessive concentration of traffic attracting sources and insufficient regional traffic carrying capacity, the following measures can be taken to alleviate and improve through the construction of pedestrian bridges, underground passages, and other 3D pedestrian crossing facilities to realize the separation of pedestrians and vehicles, the resistance of pedestrians to traffic is reduced, and regional accessibility is improved. For areas where attracting sources are concentrated, implementing measures, such as number restriction and traffic restriction, is recommended to reduce the total traffic volume in the area and alleviate the pressure on the roads in the area. (5) Build an intelligent traffic management system with real-time collection of weather and road conditions, traffic flow statistics, congestion state, and trend calculation and release, and optimization of intersection signal timing and other functions to improve management and operation efficiency. For ice and snow weather, traffic organization and management plans are formulated to ensure normal traffic order in ice and snow weather, the efficiency and effectiveness of plan execution are improved, traffic accidents are reduced, and road traffic capacity is improved. For ice and snow weather, advanced technical methods are adopted to rapidly and efficiently clean up ice and snow sections in time. For sections that are congested due to untimely snow removal, the management department should conduct traffic guidance or take control measures according to the real-time road conditions to reduce the frequent occurrence of traffic accidents and congestion in ice and snow weather. On the basis of summarizing the current situation of winter traffic problems, the characteristics of traffic flow are analyzed, and the slope signal and some main road signal control schemes are adjusted appropriately to address the problems of slippery roads in winter and long braking distances, such as extending the yellow light time to reduce rear-end collisions caused by braking distance. (6) In ramps, intersections, and other road bottlenecks, adopt advanced methods such as increasing the width of ramps and constructing interactive interchanges to improve traffic capacity.
5. Conclusions

In order to comprehensively and accurately analyze the congestion characteristics of cold-climate cities under severe climatic conditions, grasp the time and spatial distribution of congestion, and provide a basis for the treatment of traffic problems in cold-climate cities, the corresponding cluster analysis algorithm is selected to put forward a traffic congestion situation identification method suitable for the use of the urban main road in cold-climate cities to realize the transition from qualitative analysis to quantitative analysis in the traffic operation level of cold-climate cities, considering the advantages and disadvantages of different cluster analysis algorithms and applicable conditions. The congestion situation identification results based on these methods have passed the spatio-temporal self-correlation and mean difference test, which can reflect the spatiotemporal characteristics of congestion. In addition, compared with the existing methods, it can better reflect the actual congestion characteristics of the main road in cold-climate cities and solve the problem of “focuses on the state, but ignores the trend; partial theory, but lack of application; common, but no difference” in the past. The method proposed in this paper is not only suitable for severe cold cities, but also for cold cities. The congestion state and trend identification standard obtained in this paper are based on the congestion data of Harbin, which can fully reflect the congestion characteristics of Harbin. Because the congestion characteristics of cities in the cold regions are similar to some extent, if other cold-climate cities lack relevant experimental data, the situation identification standard calculated in this paper can be used, which is certainly more accurate than the existing standards that do not consider the climate characteristics of cold-climate cities. However, due to differences in residents’ travel behaviors and dynamic changes between different cities, for example, a certain cold city may often hold large-scale events during the ice and snow period. The degree of congestion, congestion time, and space, etc. are different from those of other cold cities. If you want to identify the congestion characteristics of this city more accurately, you need to use the relevant data of this city to determine the congestion situation identification standard of this city based on the method proposed in this paper.

By comparing the congestion characteristics of Harbin with other cold-climate cities and non-cold-climate cities, it can be seen that the traffic problem in cold-climate cities is more serious and complex than that in other cities. Congestion will not only lead to an increase in fuel consumption and exhaust emissions but also a decrease in productivity. If people spend too much time on the road, they feel nervous or frustrated when they are working, which affects work efficiency, and if emergency medical personnel, firefighters, and policemen are delayed on the road, medical treatment and rescue services will also be delayed. In addition to the impact on work, congestion also has an impact on travel such as shopping, traveling, and seeing a doctor. Before traveling, people always make plans based on questions such as “How long do I need to stay in the car or bus?” “Is it worth it?” To be honest, such a city is not suitable for living. People may move to areas with warmer climates, the vitality of the city will be reduced, and the city will not be able to achieve sustainable development. Therefore, it is important to solve the problem of congestion in cold-climate cities. Large-scale expansion of urban traffic infrastructure is an effective approach for solving the problem of traffic congestion in the main roads of cold-climate cities, but it cannot expand road facilities on a large scale endlessly, whether from the perspective of urban space resources or construction funds. In addition to the construction or reconstruction of road traffic infrastructure of an appropriate scale, innovating and exploring the potential on the basis of existing facilities according to the congestion characteristics under different weather conditions, formulating special management strategies in view of severe climate conditions, and realizing the coordinated development of the natural environment and traffic are necessary to ensure the sustainable development of cities in cold regions.

In the future, in order to further optimize the congestion situation identification method of main roads in cold-climate cities, it is necessary to increase the amount of data, including the congestion data of other cold-climate cities and the congestion data of
different years, so as to improve the accuracy of the identification standard. Considering the influence of cold climates on congestion in this paper, only the conditions of snowy and icy pavements and non-snowy and non-icy pavements are considered. In fact, the forms of snowy and icy pavements, such as a thin ice surface, snow melting surface, visibility, and vehicle performance during snowfall all have an impact, so further consideration is needed. In addition, considering that congestion occurs not only on the main road, but also on other roads, and that the roads affect each other, how to extend the method proposed in this paper to the whole road network to distinguish the overall operation level of the city is also worth further study.

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