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Study on Risk Prediction Model of Expressway Agglomerate Fog-Related Accidents

Jianyang Song [1], Hua Tian [1,2,*], Xiaoyu Yuan [1], Jingjing Gao [1], Xihui Yin [3], Zhi Wang [1,2], Meichao Qian [1] and Hengtong Zhang [3]

1 Public Meteorological Service Center of China Meteorological Administration, Beijing 100081, China; songjy@cma.gov.cn (J.S.)
2 Key Laboratory of Transportation Meteorology of China Meteorological Administration, Nanjing 210041, China
3 Road Network Monitoring and Emergency Response Center of the Ministry of Transport, Beijing 100029, China
* Correspondence: tianh1@cma.gov.cn

Abstract: Based on meteorological observations, traffic flow data and information of traffic accidents caused by fog or agglomerate fog along the expressways in Jiangsu Province and Anhui Province in China from 2012 to 2021, key impact factors including meteorological conditions, road hidden dangers and traffic flow conditions are integrated to establish the prediction model for risk levels of expressway agglomerate fog-related accidents. This model takes the discrimination of the occurrence conditions of agglomerate fog as the starting term, and determines the hazard levels of agglomerate fog-related accidents by introducing the probability prediction value of meteorological conditions for fog-related accident as the disaster-causing factor. On this basis, the hourly road traffic flow and the location of road sections with a hidden danger of agglomerate fog are taken as traffic and road factors to construct the correction scheme for the hazard levels, and the final predicted risk level of agglomerate fog-related accident is obtained. The results show that for the criteria of disaster-causing factor classification threshold, 72.3% of fog-related accidents correspond to a hazard of a medium level or above, and 86.2% of the road traffic flow conditions are consistent with the levels of the traffic factor defined based on parametric indexes. For risk level prediction, six out of the seven agglomerate fog-related accidents correspond to the level of higher risk or above, which can help provide meteorological support for traffic safety under severe weather conditions. Moreover, the model takes into account the impacts of traffic flow and the road environment, which is conducive to further improving the reliability of the risk assessment results.

Keywords: expressway; agglomerate fog; risk level prediction of fog-related accidents; meteorological conditions; road hidden dangers; traffic flow conditions

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1. Introduction

Fog is one of the most common disastrous weather events on expressways [1,2]. With ab increasing road network density and the changing climate environment, the impacts of fog on expressway traffic safety and traffic efficiency are becoming increasingly serious. In China, the accumulated mileage blocked by fog is 1.78 times the total national expressway mileage per year on average [3,4].

The occurrence, development and dissipation of fog are caused by multiple processes (thermodynamical, radiative, dynamical and microphysical), and these processes interact nonlinearly with each other. The micro-physical characteristics of fog can impact the duration, radiation and visibility of fog. Many studies [5–10] on the micro-physical characteristics of fog are conducted, and present the variation characteristics number, concentration and size of fog droplets, which can provide some reference for the improvement of parameterization schemes in numerical models via a better understanding of the mechanism of fog occurrence. For example, Haeffelin et al. [11] used the ParisFog dataset to investigate the effect of hydrated aerosols on visibility, the role of aerosols' microphysical and chemical properties on supersaturation and droplet activation, and the role of turbulence and sedimentation on fog life cycles. Guo et al. [12] used the data collected in the project Low-Visibility Weather Monitoring and Forecasting in the Beijing–Tianjin region to study the microphysical properties of aerosol, cloud condensation nuclei, the fog droplet spectrum and liquid water content for an unusual fog-haze event that lasted for one week in North China. They presented the physical characteristics of aerosol accumulation, as well as the transition and mixture of aerosol and fog. Using a ground-based counterflow virtual impactor, Duplessis et al. [13] measured the size distributions of fog droplet and aerosol near Halifax on the eastern coast of Canada, as well as the fog droplet residuals. In addition, many studies analyzed the macro characteristics related to the formation, development and dissipation of fog, such as the synoptic pattern and meteorological factors (wind speed, relative humidity and moisture) [14–16].

Since the 21st century, many scholars have gradually applied multi-source traffic monitoring data to propose various real-time accident risk prevention and control techniques by considering the comprehensive effects of road traffic flow, weather conditions and road features [17–20]. Xu et al. [21] took into account the meteorological elements of precipitation and visibility when using logistic regression to assess the impacts of environmental factors and real-time traffic conditions on expressway crash risks, thus improving the prediction accuracy of expressway accident occurrence by 6.8%. Based on the real-time traffic flow data on foggy days, Wu et al. [22] estimated the influences of traffic and weather variables on rear-end collisions using the random logistic regression and negative binomial distribution models.

In China, systematic studies have been conducted on various aspects including the disaster-causing mechanism in the foggy section of expressways, dense fog or visibility monitoring and forecasting as well as road traffic safety and security measures [23–27]. Specifically, the quantitative impact assessment of foggy weather on expressway traffic safety is the key to defending against fog damage. Based on machine learning algorithms, using traffic accident information and meteorological observations, some important accident-related variables are selected, such as time, geolocation and the meteorological environment. Then, the mathematical models of the accident probabilities are built, which can be used to assess the real-time traffic safety state on expressways during foggy days [28,29]. Additionally, the factors indicating accidents under low visibility conditions are selected from the observed or simulated traffic parameters including upstream and downstream traffic volume, speed and occupancy rate, and the road traffic safety status under foggy conditions is quantitatively evaluated by detecting the number of traffic conflicts or safety distance [30]. The occurrence of accidents is linked to drivers, vehicles and roads (environment), but only a few scholars have integrated multi-source information (such as traffic, weather and visual information) into risk prediction due to the complexity and data availability of road traffic systems. For example, Qu et al. [31] introduced the single traffic flow and road environment to establish a risk level prediction model of fog disasters on expressways in Hebei Province. Tian et al. [32] established a weather risk warning index system for expressway traffic safety control by introducing the traffic flow, road alignment and location type. However, in general, the spatio-temporal resolutions of these forecast models are low, and the timeliness is poor. Moreover, the input data of non-meteorological factors in the model are static, and thus the dynamic driving capability of the models is obviously limited.

Agglomerate fog is a low-visibility weather phenomenon with locality, abruptness and spatio-temporal inhomogeneity, and it is also a difficult problem during road traffic weather monitoring, forecasting and early warning services. In China, the rate of traffic accidents caused by agglomerate fog is found to be 2.5 times that caused by other severe weather events, and the number of casualties in agglomerate fog-related accidents accounts for

29.5% of the total number of casualties in traffic accidents [33]. Up to now, many scholars have carried out studies on expressway agglomerate fog, with their focus on fog formation and dissipation [34–36], simulation and diagnosis [37–39], distribution law [40–42] and disaster-causing mechanisms [43–45], while there are few studies on the impact forecasting or risk early warning of agglomerate fog traffic accidents. To this end, taking the Jiangsu and Anhui area (hereinafter referred to as the "test area", as shown in Figure 1) where agglomerate fog accidents occur frequently as an example, this study establishes a risk level prediction model for expressway agglomerate fog accidents by integrating the key impact factors (meteorological environment, road hidden dangers and traffic flow conditions) and proposing the factor classification threshold determination method. This model provides a new approach to predict the agglomerate fog-related accident risk level. It is noteworthy to mention that the introduction of dynamic traffic parameters and the determination of factor classification thresholds in this study is more objective than that in past studies. We hope the results of this study can help improve the fine-resolution meteorological impact prediction and disaster prevention capability for expressway traffic safety under severe weather conditions.

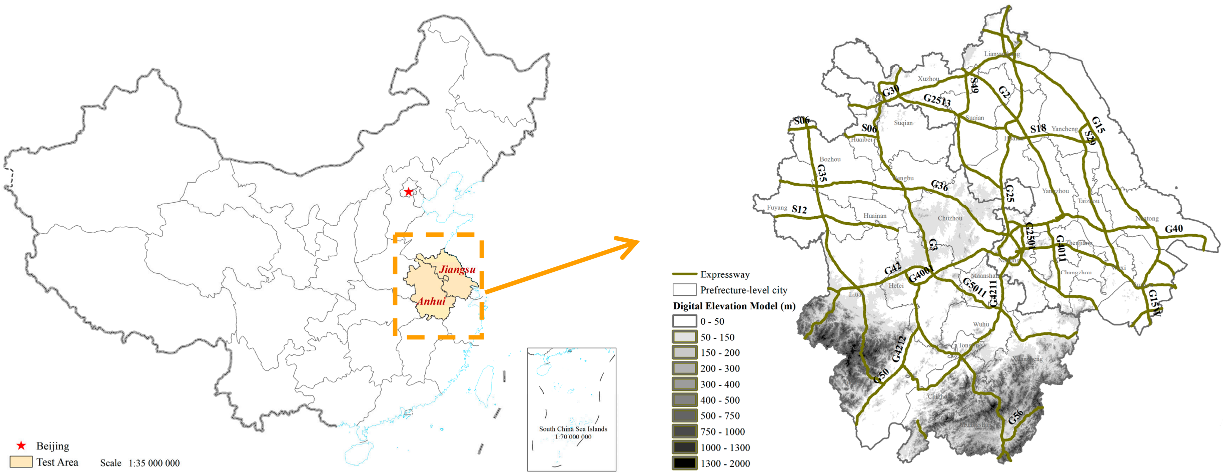

Figure 1. Basic information of the test area.

The remainder of this paper is organized as follows. Section 2 describes the data sources. The modeling method is provided in Section 3. The values and calculation procedures of the disaster-causing factor, traffic factor and road factor are given in Section 4. Section 5 presents the application and validation of the risk level prediction model. Finally, Section 6 gives the conclusions and discussion.

2. Data

In this study, the meteorological observation data are obtained from 616 traffic meteorological stations, 317 regional meteorological stations and 30 national meteorological stations along the expressways in the test area, which are provided by the National Meteorological Information Center of the China Meteorological Administration. The data quality control method refers to the "Quality Control of Meteorological Observation Data-Surface" (QX/T 118-2020) of the meteorological industry standard of the People's Republic of China. The traffic accident data in foggy or agglomerate foggy days are from the traffic control departments and news reports of media. The two kinds of data cover the period from 2012 to 2021. The traffic flow data such as vehicle flow rate and congestion index are calculated via road section estimation and road matching based on the mobile location information from internet navigation and national heavy-load freight, which covers the period from 2018 to 2021. These kinds of data are derived from the National Intelligent Road Network Monitoring Platform, and the website is http://hmrc.palmgo.cn/lwzx2/a1c64c3e6c9b76efcbccb8effd58fcad.html (accessed on 15 May 2023). In terms of the information of road sections with hidden dangers due to agglomerate fog, this study uses the information of road sections with frequent agglomerate fog released by the Traffic Administration Bureau of the Ministry of Public Security of the People's Republic of China in recent years, and the results of expressway traffic meteorological disaster risk survey by the China Meteorological Administration.

3. Modeling Method

3.1. Index Selection

Road traffic accident risk is jointly determined by the driver, vehicle and road environment. Considering the predictability of traffic accident systems, three types of indexes (weather, traffic and road) are selected to construct a risk level prediction model for expressway agglomerate fog-related accidents.

The traffic accidents in foggy days are closely related to the synoptic background. The hazard of meteorological conditions for agglomerate fog-related accidents is selected as the disaster-causing factor and the core index to construct the risk level prediction model. In addition to its low visibility, fog can often cause the reduction in the road friction coefficient through the interaction between fog droplets and dust, or through forming a thin layer of ice on cold road surfaces. By using the random forest and support vector machine algorithms, Song et al. [28,29] established a model depicting the relationship of the probability of fog-related accidents within an hour with the meteorological elements (visibility, relative humidity, wind, air temperature, etc.) and related derived variables, where recursive feature elimination and principal component analysis were used for feature selection. By using the results of the two models, the probability prediction value P of the meteorological conditions for the occurrence of fog-related accidents is obtained by weighting, which is used as the disaster-causing factor. The formula is as follows:

$$P = \sum_{i=1}^{2} p_i \times \alpha_i \tag{1}$$

where p_1 is the probability prediction value output by random forest model, p_2 is the probability prediction value output by the support vector machine model, and α_i is the weight coefficient. Considering risk prevention and control, it is hoped that the events are not missed. Hence, the ratio between the recall rates of the two models in the training set is used as the criterion for weight assignment. For the training sample consisting of the same accident group and control group, the recall rate of the random forest model and support vector machine model is 75.4% and 81.4%, respectively. Therefore, α_1 and α_2 are 0.48 and 0.52, respectively.

The traffic factor is a dynamic correction index of the risk level prediction model for expressway agglomerate fog-related accidents. The traffic operation of road network is closely related to traffic meteorological disasters, and the traffic flow situation should be considered when studying unfavorable weather effects [46]. Taking the sections of the Beijing–Shanghai Expressway, Beijing–Taipei Expressway and Nanjing–Luoyang Expressway in the test area where fog-related traffic accidents frequently occur as an example, the accumulated number of fog-related accidents (Figure 2a) is generally consistent with the annual average foggy days (visibility < 1 km) along the expressways in terms of spatial distribution (Figure 2b). The determination coefficient of the power function fitting curve is 0.106, which passes the confidence test at a 95% confidence level. However, it is also influenced by the operation status of expressway traffic (Figure 2c), and the determination coefficient of the power function fitting curve is 0.078, which passes the confidence test at a 95% confidence level. From the perspective of temporal distribution (figure omitted), dense fog occurs frequently during 03:00–08:00 BST (Beijing standard time, the same below) and peaks during 05:00–07:00 BST, while fog-related accidents occur mainly during 05:00–10:00 BST and peak during 07:00–08:00 BST when the traffic flow increases rapidly. Hence, this study chooses hourly traffic flow prediction as the traffic factor for the dynamic correction of the risk level of the occurrence of expressway agglomerate fog-related accidents.

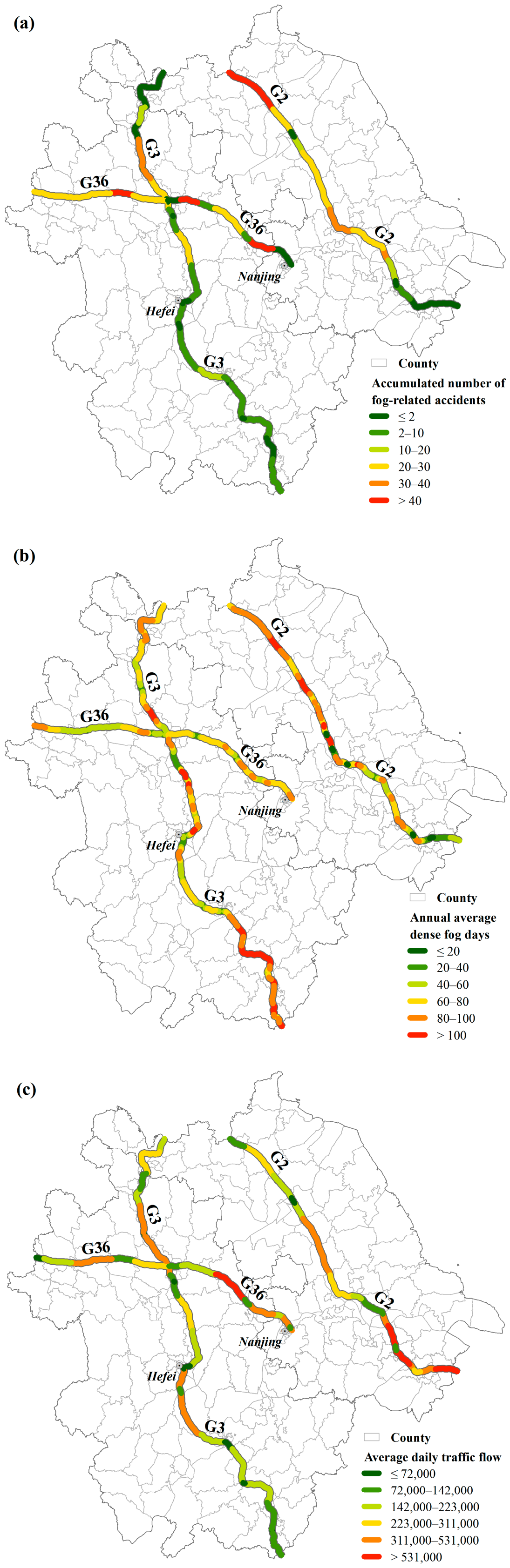

Figure 2. Spatial distributions of (**a**) accumulated number of fog-related accidents from 2013 to 2018, (**b**) annual average dense fog days from 2013 to 2018, and (**c**) average daily traffic flow from 2018 to 2021.

The road factor is a static correction index of the risk level prediction model for expressway agglomerate fog-related accidents. Agglomerate fog is usually formed under the background of meso–micro-scale circulation systems over mountainous areas, river valleys and areas with dense river networks [45], exhibiting specificity in terms of the geographical environment of roads. In this study, the location information of segmented roads in the test area is collected as the road factor, which is used for the static correction of the risk level by identifying the special form of a disaster-pregnant environment with hidden dangers in the risk level prediction model.

3.2. Assessment Procedure

As shown in Figure 3, the assessment procedure consists of three key steps: discrimination of the occurrence of agglomerate fog, risk level initial prediction of agglomerate fog-related accidents based on the disaster-causing factor, and risk level correction of agglomerate fog-related accidents based on traffic and road factors. To achieve the operationalization and visualization of this prediction model, the hierarchical threshold determination method is used to quantify the factors in the model.

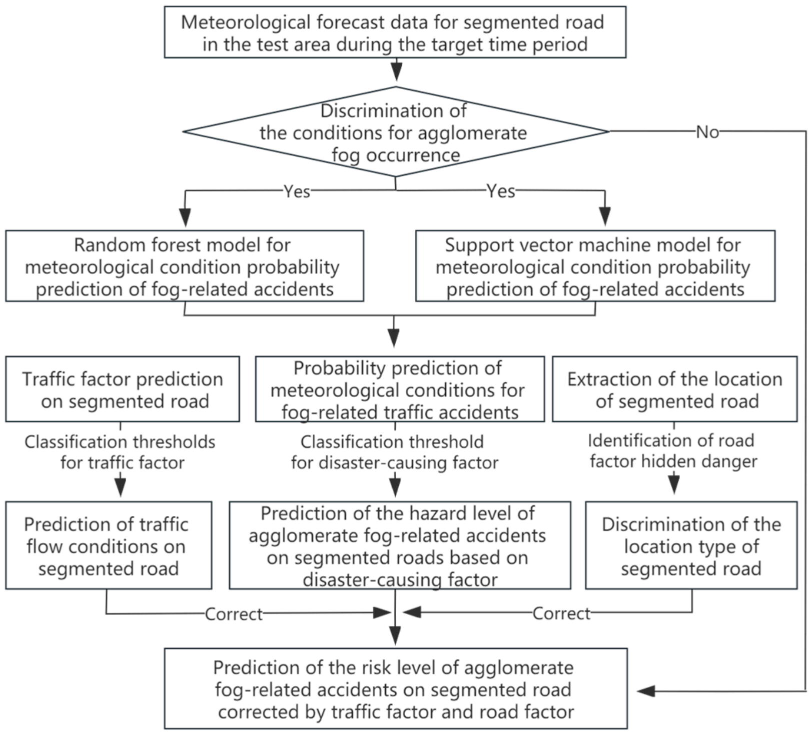

Figure 3. Flow chart for risk assessment of agglomerate fog-related accidents.

In the first step, the occurrence of expressway agglomerate fog is taken as the starting term of the risk level prediction model for expressway agglomerate fog-related accidents. If the meteorological forecast data on segmented road in the test area meet the predetermined conditions for the occurrence of agglomerate fog, the risk level of traffic accident is further calculated; otherwise, the risk is directly determined to be low. The test area consists of two parts: Jiangsu Province and Anhui Province. According to the data of agglomerate fog-related traffic accidents recorded by the traffic department, the variation characteristics of meteorological factors (visibility, relative humidity, temperature and wind) around agglomerate fog occurrence are analyzed to establish the meteorological forecast indexes for agglomerate fog in the two provinces separately (Table 1). Specific details can be found in Tian et al. [35] and Gao et al. [36].

Table 1. Meteorological forecast indexes for agglomerate fog in the test area.

Meteorological Characteristics of Agglomerate Fog	Jiangsu Province	Anhui Province
Background conditions	Fog weather background	Fog weather background
Relative humidity	>92%	>86%
Daily temperature decrease	>7 °C	>8 °C
Wind speed	<2 m s^{-1}	<1 m s^{-1}

In the second step, the pre-trained meteorological probability prediction model for fog-related accidents is utilized to obtain the probability prediction value of meteorological conditions for fog traffic accidents on corresponding road sections. According to the mapping relationship between the configured ranges of the disaster-causing factor at different hazard levels and the risk levels of agglomerate fog-related traffic accidents, five levels are initially determined, which are in the order of the extremely high level (Level 5), high level (Level 4), medium level (Level 3), low level (Level 2) and extremely low level (Level 1).

In the third step, the defined thresholds for grading the traffic factor and road factor are utilized to classify the traffic flow conditions (peak and off-peak periods) and road locations (special and ordinary types). Combined with the emergency handling experience of public security traffic administration departments, the hazard levels of meteorological conditions for agglomerate fog-related accidents are adjusted. On this basis, four risk levels are obtained (Table 2), where Level I (severe risk), Level II (very high risk), Level III (high risk) and Level IV (general risk) indicate the extremely high, very high, high and general possibilities of the occurrence of traffic accidents induced by expressway agglomerate fog, respectively.

Table 2. Classification of the risk levels for the occurrence of expressway agglomerate fog-related accidents.

Hazard Level of Disaster-Causing Factor	Ordinary Location		Special Location	
	Off-Peak	Peak	Off-Peak	Peak
Extremely high (Level 5)	I	I	I	I
High (Level 4)	II	I	I	I
Medium (Level 3)	III	II	II	II
Low (Level 2)	IV	III	III	III
Extremely low (Level 1)	No	IV	IV	IV

4. Factor Values and Calculation

4.1. Classification of Disaster-Causing Factor

According to Equation (1), the probability prediction values of meteorological conditions for fog-related accidents corresponding to 418 fog events [28,29] in the training set are calculated, and then the frequency of disaster occurrence at a probability interval of 0.05 is calculated by using the statistical method of histogram. Figure 4 reveals that a significant negative skewness appears in the distribution of disaster frequency corresponding to the probability of meteorological conditions, with the skewness and kurtosis being −1.36 and 1.21, respectively, and the left side of the peak shows a monotonically increasing trend. Thus, we count the frequency of fog-related events in the left range of the peak at intervals of 0.01 probabilities. Then, the first occurrence of three consecutive intervals with a frequency of more than or equal to 2 is defined as the change point where the accident frequency begins to increase significantly. The average of the meteorological condition probability prediction value corresponding to the continuous interval is calculated and is used to determine the initial probability value of the meteorological conditions that induce traffic accidents on foggy days. It is found that the probability value of disaster-causing meteorological conditions is 0.19, which is taken as the critical threshold for disaster-causing factor at Levels 1–2.

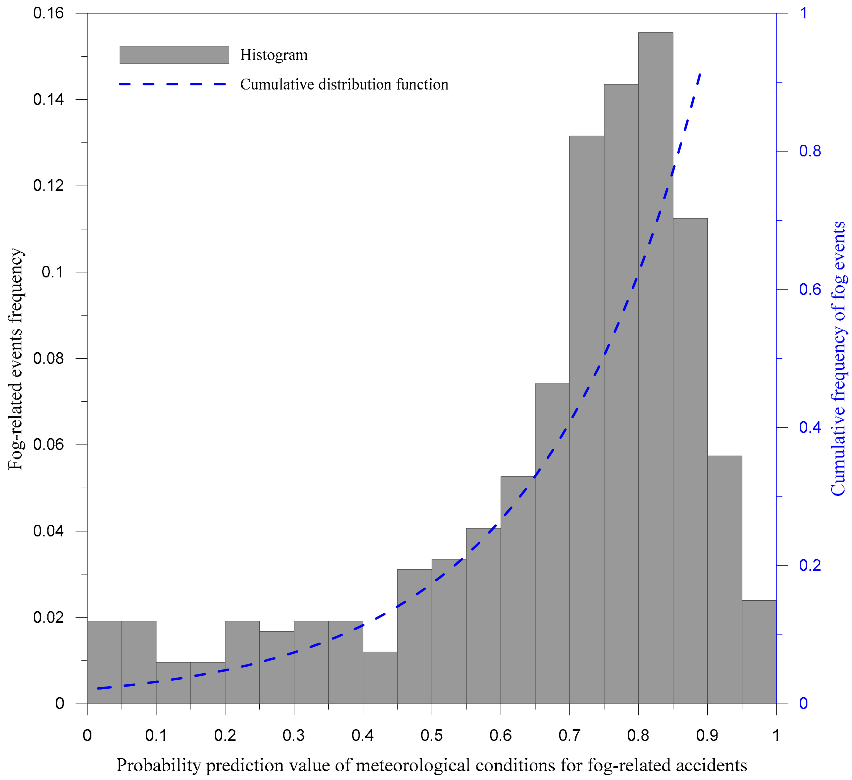

Figure 4. Histogram of disaster frequency of fog events corresponding to disaster-causing factor.

The thresholds for disaster-causing factors at Levels 2–5 are further determined based on the cumulative distribution function. The fitting equation is determined according to the features of the cumulative distribution functions of the probability of meteorological conditions for fog-related accidents and the frequency of fog events, which conforms to the exponential characteristics. On this basis, the predicted values of the probability of meteorological conditions corresponding to the cumulative frequency of 25%, 50% and 75% are used as the critical thresholds for disaster-causing factor at Levels 2–3, Levels 3–4 and Levels 4–5, respectively. Using the samples of 47 fog events and 141 non-fog events from the validation set [28,29], Table 3 validates the rationality of the of hazard of a disaster-causing factor. The results show that the frequency of disasters at the five hazard levels is consistent with the criteria for index classification. Approximately 72.3% of fog-related accidents correspond to a hazard of a medium level or above, while the false alarm rate is about 7.1%.

Table 3. Defined hazard levels for disaster-causing factor and corresponding effect validation.

Hazard	Extremely Low	Low	Medium	High	Extremely High
	[0, 0.19)	[0.19, 0.60)	[0.60, 0.75)	[0.75, 0.84)	[0.84, 1]
Number of accidents	2	11	14	12	8
Number of non-accidents	105	26	7	3	0

4.2. Classification of Traffic Factor

With the increasing traffic flow, the car following distance on the expressway becomes smaller, which makes it prone to causing traffic accidents due to low visibility, slippery road conditions or improper operation. The traffic risk under foggy weather conditions is basically proportional to the traffic volume, and the traffic flow can be divided into off-peak (normal) and peak (risk) periods according to the variations in hourly traffic volume [32]. Considering that each province has different management standards for expressways within its jurisdiction, the classification thresholds for traffic factor are determined in each province.

The hourly traffic flow of the expressways in the test area during 2018 to 2020 is extracted in sections based on the county level, which is further divided into several sections at 5th-percentile interval. Furthermore, the average value of the congestion index in each section is calculated in two provinces. The congestion index is a comprehensive parameter characterizing the operation state of road traffic and the change in traffic flow, which is expressed as follows:

$$I_{A,T} = \sum_{i=1}^{N} l_{\mathrm{i}} \times \beta_{i,T}, i \in A \tag{2}$$

where $I_{A,T}$ is the congestion index in the analysis area, A, during the period, T (unit: km h), l_i is the length of road section i (unit: km), $\beta_{i,T}$ is the cumulative congestion (speed less than 40 km h^{-1}) duration on road section i during the period, T (unit: h), i is the road section number, and N is the total number of road sections within the analysis area.

With the increasing road utilization rate, the mutual interference between vehicles is aggravated, and the growth characteristics of the congestion index with traffic volume also changes significantly. The variations in the average congestion index in the unit percentile section of hourly traffic flow are shown in Figure 5. It is found that the line type usually changes from near-linear growth to near-exponential growth. In this study, split points are set from 15% to 85% at an interval of 5%, and the linear fitting formula and the exponential fitting formula between the mean congestion index and the corresponding percentile before and after split points are calculated separately; the goodness-of-fit values on the two fitting curves are recorded separately. The split point corresponding to the maximum value of the average goodness of fit is determined as the position where the congestion index abruptly changes, and the corresponding percentile value of traffic flow is adopted as the classification threshold for the traffic factor. It is found that the largest value of the average goodness of fit appears at the split point that adopts the 55th percentile of the historical hourly traffic flow dataset, which can be regarded as the cut-off point when the traffic flow becomes saturated with conflict from the free and stable state. Accordingly, the 55th percentile value of the above historical hourly traffic flow dataset is defined as the classification threshold for traffic the factor (9871 vehicles h^{-1} in Jiangsu Province and 5405 vehicles h^{-1} in Anhui Province). If the hourly traffic flow on the segmented road during the target time period is higher than the threshold, it is considered the peak (risk) traffic flow condition; otherwise, it is regarded as the off-peak (normal) condition.

Considering the difficulty of obtaining real-time traffic flow data, this study constructs the parametric index of the traffic factor by calculating the average hourly traffic flow during 2018–2020 based on the spatio-temporal distribution characteristics of traffic flow with the county-level sections, with months and hours as basic statistical units, which is used to simulate the traffic flow conditions on corresponding road sections in similar periods. Additionally, to characterize the distinct features of the sharp increase in traffic flow and peak hours on holidays (such as the New Year's Day and the Spring Festival), the parametric indexes for the traffic factor during holiday periods are constructed differentially. Table 4 validates the rationality of the classification of the traffic factor using the observed traffic flow in 2021. The results show that the parametric index of the traffic factor constructed from historical data has a strong positive correlation with that constructed from the observed data (statistically significant at the 99% confidence level), with which can well-simulate the trend variations of hourly road traffic flow. Furthermore, about 86.2% of the traffic factor levels are consistent with the conditions of road traffic flow defined based on the observed data.

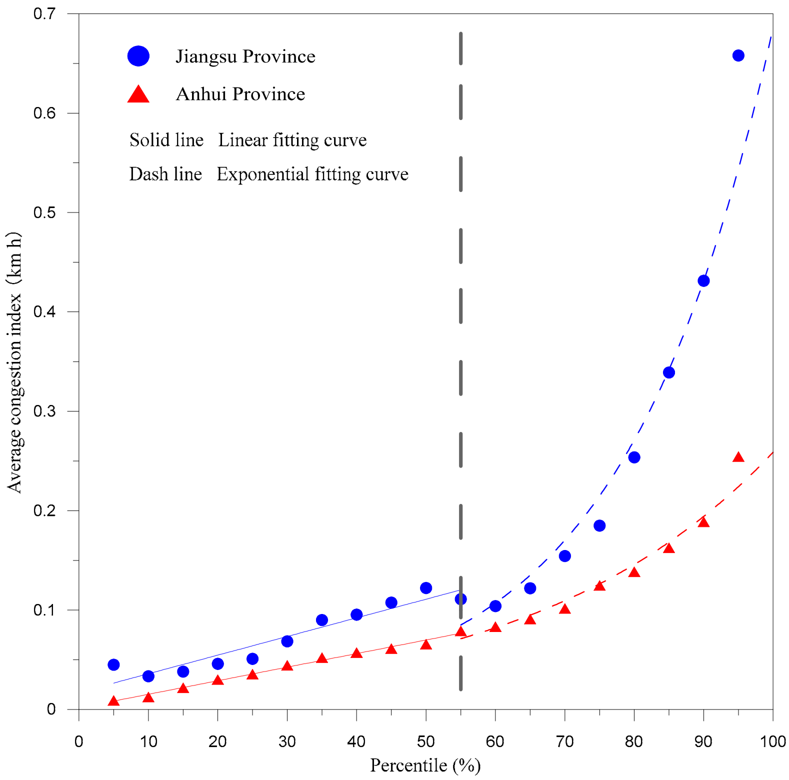

Figure 5. The variation curve of congestion index corresponding to the percentile of hourly traffic flow (taking the split point of 55% as an example).

Table 4. Effect validation of the classification of traffic factor levels.

Validation Scope	Pearson Correlation Coefficient between Parametric Index of Hourly Traffic Flow and Observed Data	Consistency of Traffic Factor Levels Classified Based on Parametric Index and Observed Data	
		Consistent with Traffic Flow Conditions	Inconsistent with Traffic Flow Conditions
Jiangsu Province	0.850	85.6%	14.4%
Anhui Province	0.867	87.0%	13.0%
Test area	0.860	86.2%	13.8%

4.3. Identification of Road Factor Hidden Danger

Using the spatial analysis technique based on the geographic information system, the road within a range of 1 km around the road section with frequent agglomerate fog in the test area are marked as special location, and the rest are marked as ordinary locations. Under similar weather conditions, the topographical features around the special road section are more conducive to the formation and maintenance of agglomerate fog, which help increase the occurrence probability of agglomerate fog-related accidents.

5. Application and Validation

5.1. Overall Situation

Seven agglomerate fog-related accidents in the test area from 2015 to 2021 are selected as the test samples to assess the application of the risk prediction model for expressway agglomerate fog-related accidents. The hindcasts give the risk level of test samples and the classification of each factor, as shown in Table 5. Overall, six out of seven agglomerate fog-related accidents correspond to risk level III or above, where three correspond to the level of severe risk and three are at the level of higher risk. For the No. 4 traffic accident on the Huaibei section of the Sixu Expressway (S06), the risk of agglomerated fog-caused accidents is predicted to be low as the daily temperature decrease fails to reach the conditions for agglomerate fog formation, while the meteorological, traffic and road factors are all conducive to the occurrence of traffic accidents. The introduction of traffic factor and road factor has appropriately raised the risk levels of agglomerate fog-related accidents on local road sections, especially for cases in which a low-visibility condition is not evident around the location of the traffic accident. For example, the visibility at the adjacent traffic weather station I5814 in accident No. 1 is approximately 2.6 km, and the disaster-causing factor corresponds to the level of low hazard. However, considering that it is a special location with frequent agglomerate fog events, the model adjusts the risk of the occurrence of agglomerate fog-related accidents on this road section from level IV to level III. In accident No. 2, the visibility at Station I2858 near the accident location is higher than 3 km before and after the accident. However, affected by the increase in traffic flow on the National Day, the traffic operation on this road section is in a peak condition. Therefore, the model adjusts the risk of agglomerate fog-related accident from level IV to level III. It can be seen that the model is of good indicative significance for the risk of agglomerate fog-related accidents, especially for the identification and warning of road sections and periods of risks under atypical disaster-causing meteorological conditions.

Table 5. Validation of the model application based on agglomerate fog-related accidents.

Number	Accident Occurrence Period		Location	Situation	Distance of Traffic Station from the Accident Location and Corresponding Average/Minimum Visibility	Agglomerate Fog Index	Hazard Factor	Traffic Factor	Road Factor	Risk Level
1	13 February 2021	07:00–08:00 BST	Tongling, Anhui, Shanghai–Chongqi-ng Expressway (G50)	7 accidents of several vehicles scraping each other and rear-end collision	1 km (I5814) 2666/1630 m	matches the conditions	Level 2	Off-peak	Special	III
2	3 October 2019	06:00–07:00 BST	Bengbu, Anhui, Nanjing–Luoyang Expressway (G26)	10 people dead and 7 injured in 4 accidents	8 km (I2858) 3768/3432 m	matches the conditions	Level 2	Peak	Ordinary	III
3	15 November 2017	07:00–08:00 BST	Fuyang, Anhui, Chuzhou–Xincai Expressway (S12)	18 people dead and 21 injured in multi-point and multi-vehicle collisions	1 km (I2754) 80/57 m 71/68 m	matches the conditions	Level 5	Peak	Special	I
		08:00–09:00 BST				matches the conditions	Level 5	Peak	Special	
4	5 February 2017	08:00–09:00 BST	Huaibei, Anhui, Sixian–Xuchang Expressway (S06)	16 vehicles damaged and 6 people injured	3 km (I1358) 226/165 m	mismatch with the conditions	Level 5	Peak	Special	No
5	2 April 2016	12:00–13:00 BST	Changzhou, Jiangsu, Shanghai–Chengdu Expressway (G42)	51 vehicles damaged, 3 people dead and 31 injured	5 km (M9112) 1058/846 m	matches the conditions	Level 2	Peak	Ordinary	III
6	7 December 2015	00:00–01:00 BST	Yancheng, Jiangsu, Shenyang–Haikou Expressway (G15)	3 people dead and 3 injured in multi-vehicle collisions	4 km (M9437) 87/75 m	matches the conditions	Level 5	Peak	Ordinary	I
7	23 May 2015	06:00–07:00 BST	Lianyungang, Jiangsu, Shenyang–Haikou Expressway (G15)	4 people dead and 8 injured in dozens of rear-end collisions	3 km (M9433) 197/115 m	matches the conditions	Level 4	Peak	Ordinary	I

5.2. Typical Cases

From 07:35 BST to 08:57 BST on 15 November 2017, a multi-point and multi-vehicle rear-end collision occurred on the road section from 191 km to 194 km along the downward direction of the Chuzhou–Xincai Expressway (S12) due to sudden agglomerate fog, resulting in 18 deaths, 21 injuries and 70 vehicles damaged.

Figure 6 provides the output of the risk prediction model of the expressway agglomerate fog-related accidents. It can be seen that the risk level in northwestern Anhui is obviously higher than that in other road networks in the test area before and after the occurrence of accidents. Since the early morning of November 15, the coverage of higher-risk or above of agglomerate fog-related accidents has gradually expanded from the northwest to southeast, and rapidly weakened from southeast to northwest after reaching its peak during 06:00–07:00 BST. From 08:00 BST to 09:00 BST, there was generally no risk of agglomerate fog-related accidents along the expressway in the test area, but the accident section still showed the severe risk level, indicating that the simulation results are reasonable and can provide targeted tips for determining the risk of local road traffic safety.

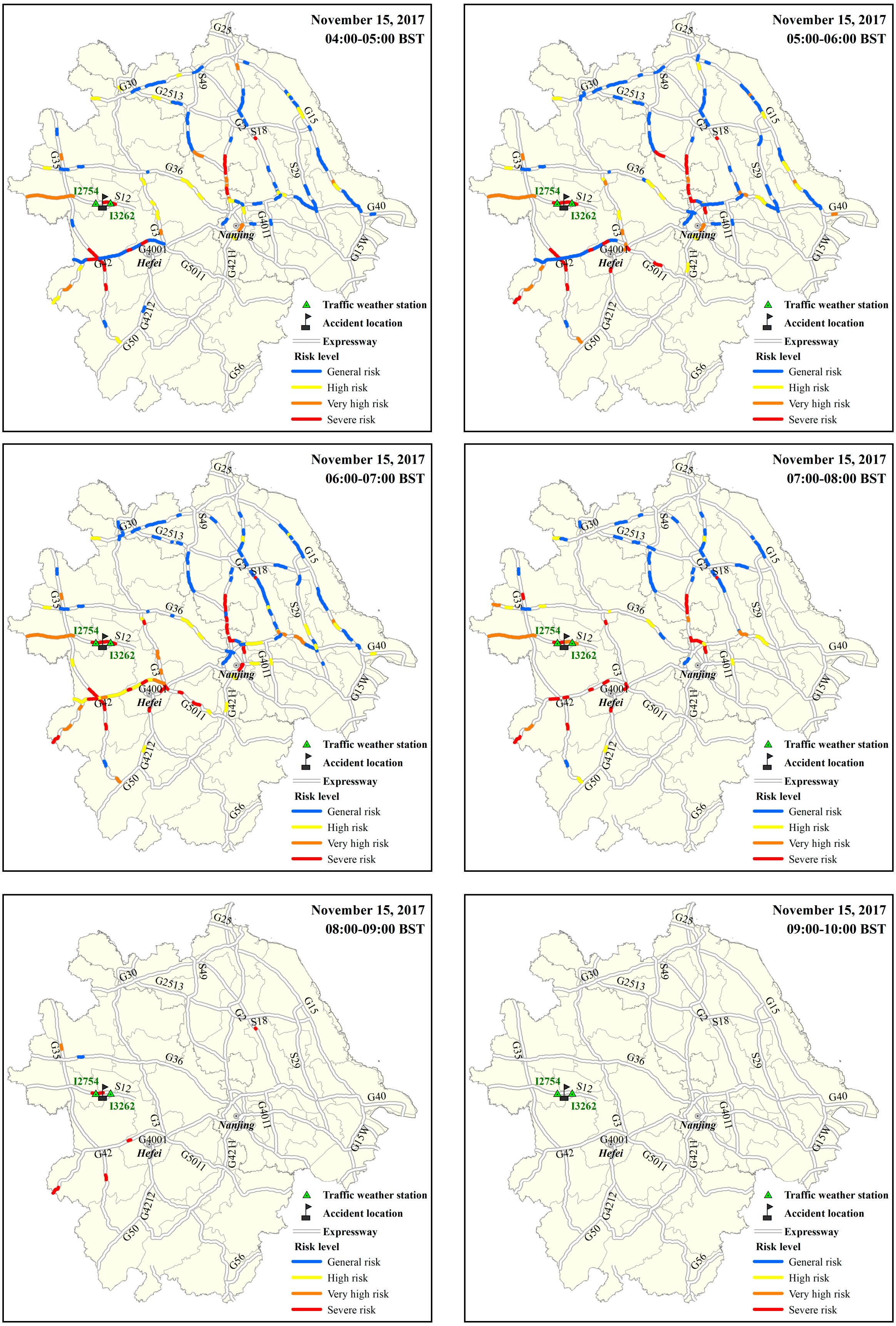

Figure 6. Assessment results of the risk level prediction model of expressway agglomerate fog-related accidents (from 04:00 BST to 10:00 BST on 15 November 2017).

From the evolution of road traffic risks at the accident location (Figure 7), the entire accident section (191–194 km) showed an extremely high risk level of traffic accidents induced by agglomerate fog two hours before the first traffic accident. After 09:00 BST, the entire accident section returned to a no-risk situation, coinciding with the end time of this series of traffic accidents. Particularly, the section east of the accident location (Station I3262) is the section with the earliest occurrence time of severe risk (Level I), and the closer section west of the accident location (Station I2754) is the section where the risk of an event at Level I finally disappears.

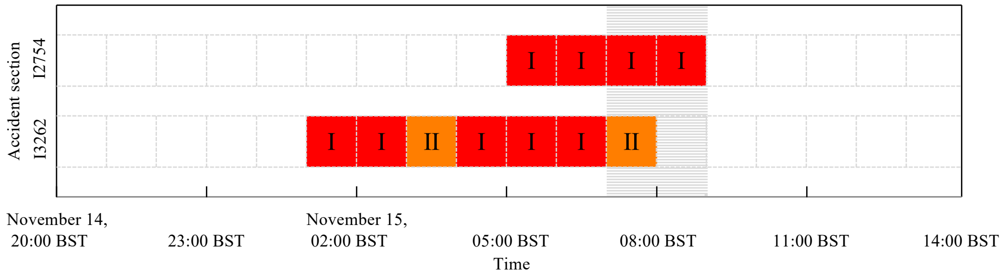

Figure 7. Evolution process of the risk levels of agglomerate fog-related accidents in the accident section (the shading indicates the period when the accident occurred).

6. Conclusions and Discussion

For severe weather-related traffic accidents, the key impact factors including meteorological conditions, road hidden dangers and traffic flow conditions are integrated to establish the risk assessment procedure and risk level prediction model for expressway agglomerate fog-related accidents, which consists of three core steps—discrimination of the conditions for agglomerate fog occurrence, risk level initial prediction of agglomerate fog-related accidents based on disaster-causing factors and risk level correction of agglomerate fog-related accidents based on traffic and road factors.

The probability prediction value of meteorological conditions for fog-related accidents is taken as the disaster-causing factor. The thresholds for five levels of disaster-causing factor are determined according to the statistical relationship between the frequency of historical fog-related events and the probability of meteorological conditions in the corresponding periods. The validation reveals that approximately 72.3% of fog-related accidents correspond to a hazard of the medium level or above.

The predicted value of hourly road traffic flow is taken as the traffic factor, and the thresholds of traffic factor levels are determined in each province based on the variation characteristics of the congestion index increasing with the traffic volume. There is a good consistency between the traffic factor levels defined based on the parametric index of traffic flow and the observed traffic data in 2021, where the traffic flow conditions with the same type account for about 86.2%.

Based on the analysis and validation of seven cases of agglomerate fog-related accidents from 2015 to 2021, it is found that three cases correspond to the level of higher risk and three correspond to the level of severe risk, indicating that the prediction results can support the demand for meteorological support for traffic safety under severe weather conditions. In addition, the comprehensive consideration of traffic flow and road environment impacts can help in the accurate identification of key prevention areas on foggy or agglomerate foggy days and the timely research and judgment of the risk periods, which can improve the quality of prediction of the risk of agglomerate fog-related accidents.

This study proposes a new research idea and methodological exploration for the risk prediction of agglomerate fog-related accidents, especially for the dynamic consideration of the impact of road traffic flow conditions and the objective calculation of the factor classification thresholds. However, the prediction accuracy is restricted by the limited road condition data. In the model prediction, the real-time-measured information of traffic flow parameters is not introduced, and some other factors such as road shape and vehicle type are not considered. In the future, we need to use more fog-accident data and more detailed traffic and meteorological data to conduct studies on the influencing mechanism of unfavorable weather conditions and the associated relationship. On this basis, by introducing the real-time traffic flow parameters and more impact factors such as road characteristics and vehicle types, we may continuously modify and improve the risk prediction model of agglomerate fog-related accidents, which is beneficial to further enhancing the reliability of the assessment results.

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