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Study on Identification and Prevention of Traffic Congestion Zones Considering Resilience-Vulnerability of Urban Transportation Systems

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Abstract: In order to solve the problem of urban short-term traffic congestion and temporal and spatial heterogeneity, it is important to scientifically delineate urban traffic congestion response areas to alleviate regional traffic congestion and improve road network efficiency. Previous urban traffic congestion zoning is mostly divided by urban administrative divisions, which is difficult to reflect the difference of congestion degree within administrative divisions or traffic congestion zoning. In this paper, we introduce the Self-Organizing Feature Mapping (SOFM) model, construct the urban traffic congestion zoning index system based on the resilience and vulnerability of urban traffic systems, and establish the urban traffic congestion zoning model, which is divided into four, five, six, and seven according to the different structures of competition layer topology. The four vulnerability damage capacity indicators of traffic volume, severe congestion mileage, delay time and average operating speed, and two resilience supply capacity indicators of traffic systems, namely, road condition and number of lanes, are used as model input vectors; the data of Guiyang city from January to June 2021 are used as data sets to input four SOFM models for training and testing and the best SOFM model with six competitive topologies is constructed. Finally, the Support Vector Machine (SVM) is used to identify the optimal partition boundary line for traffic congestion. The results show that the four models predict the urban traffic congestion zoning level correctly over 95% on the test set, each traffic congestion zoning evaluation index in the urban area shows different obvious spatial clustering characteristics, the urban traffic congestion area is divided into six categories, and the city is divided into 16 zoning areas considering the urban traffic congestion control types (prevention zone, control zone, closure control zone). The spatial boundary is clear and credible, which helps to improve the spatial accuracy when predicting urban traffic congestion zoning and provides a new methodological approach for urban traffic congestion zoning and zoning boundary delineation.

Keywords: traffic safety; traffic engineering; traffic congestion zoning; SOFM; urban traffic congestion; zoning boundaries; comprehensive traffic evaluation index

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Citation: Zhao, X.; Hu, L.; Wang, X.; Wu, J. Study on Identification and Prevention of Traffic Congestion Zones Considering Resilience-Vulnerability of Urban Transportation Systems. *Sustainability* **2022**, *14*, 16907. https://doi.org/10.3390/su142416907

Academic Editor: Matjaž Šraml

Received: 16 October 2022
Accepted: 13 December 2022
Published: 16 December 2022

1. Introduction

1.1. Background

As China's urbanization continues to accelerate, local traffic congestion is particularly prominent in cities. Urban traffic congestion is universal and widespread and the characteristics of traffic congestion vary in cities with different levels of urbanization and motorization and in different areas of the same city. Traffic congestion in large cities is normalizing and spreading regionally. For example, the traffic congestion index in Beijing has reached 6.7 in part; the congestion index has entered the severe congestion level in some hours; the operating speed of some main roads is lower than 15 km/h in the morning and evening peak hours; and the average daily congestion time of the whole road network exceeds 4 h on weekdays. Some intersections of various urban roads are severely congested and become bottlenecks in the traffic operation of the road network. Traffic congestion mainly occurs in the morning and evening peak hours as commuting demand is concentrated in the traffic corridor, basically causing unidirectional tidal traffic congestion. Precise zoning control of urban traffic congestion is an important part of achieving the "double carbon goal" to curb the degradation of traffic system service capacity, improve the resilience of urban system, and maintain the regional balance of urban traffic congestion. In the view of the regional heterogeneity and nodal homogeneity of urban traffic congestion, such as the prevalence of peak hours, spatial aggregation, and key nodes, detailed zoning control is a key tool to realize urban traffic system management.

1.2. Literature Review

1.2.1. Machine Learning Algorithms Related to Traffic Zoning

At present, scholars at home and abroad have conducted a lot of research on urban traffic congestion partitioning and traffic congestion levels. Some scholars have performed a lot of work by machine learning and improving related algorithms. Using mobile billing data, an integrated traffic zoning method has been proposed [1]. Using the trajectory data of floating cars, a particle swarm optimization algorithm is used to effectively estimate and predict urban traffic congestion [2]. The traffic network is divided into multiple zones, a hybrid approach for traffic assignment is developed, and the scalability of the traffic network is studied [3]. Considering travel patterns in different regions, hidden patterns in the data and user-defined rules are combined to improve the data-driven approach [4]. The decision-making model is used to handle traffic congestion at intersections with adaptive traffic signals [5]. The complete spatiotemporal trajectory information is considered and a clustering-based approach to spatiotemporally integrated traffic partitioning is proposed [6]. A deep prediction model, LSTM-SPRVM, based on the deep learning algorithm, machine learning algorithm, and Spark parallelization technology for predicting future traffic congestion characteristics [7]. An efficient and inexpensive city-wide data collection scheme combined with a hybrid neural network architecture for urban traffic congestion prediction [8]. Based on smart card data and bus trajectory data, self-organizing maps (SOM) are used for clustering to reflect traffic characteristics [9]. A distributed deep learning (DDL) congestion avoidance technique is proposed, borrowing from the idea of "Proactive Congestion Notification" (PCN) [10]. By mining the free-flow speed and free-stream flow to generate the traffic congestion index and considering the association characteristics of each road segment in the road network, a road segment grouping optimization algorithm based on an association subgraph is proposed [11]. Based on historical traffic data, support vector regression is used to solve the joint problem of routing and charging strategies for electric vehicles and urban traffic congestion prevention [12]. A CSD-based data-driven traffic zoning approach is proposed [13]. Based on a model-driven approach, the network is divided into several traffic clusters and the RatioCut algorithm and automatic steering hyperparameters are modified to identify traffic clusters in the road graph [14]. Using a weighted spatio-temporal trajectory big data mining method, the regional traffic velocity estimation (RTVE) algorithm is proposed for urban traffic condition estimation [15].

1.2.2. Research on Traffic Congestion Influencing Factors and Prediction Models

By modeling the nonlinear traffic speed and flow for both non-congested and congested, the work zone capacity model is proposed [16]. A multivariate time series model is used to illustrate the complex interrelationships between congestion performance indicators and socioeconomic factors and to identify the most influential factors affecting system performance [17]. A spatial scale-based approach and panel regression were used to quantify the relationship between urban development patterns and congestion in 98 U.S. metropolitan areas from 2001 to 2011 [18]. The impact of traffic congestion on residential property values was estimated using a dynamic value-preserving price model and a monthly panel dataset [19]. A two-stage least squares panel regression model was used to assess the economic impact of traffic congestion at the regional level [20]. An intelligent traffic prediction system based on the SWARIMA model is developed using three actual operational traffic parameters [21]. A traffic congestion monitoring system is proposed to determine the traffic congestion status of local road sections based on fuzzy rules [22]. An actual urban traffic simulation model (AUTM) for predicting and avoiding traffic congestion is proposed based on map and transport (MT) transformation methods, optimized spatial evolution rules, and congestion-avoiding routing algorithms [23]. The TCN model for short-term city-wide traffic forecasting is proposed [24]. Long Short-Term Memory (LSTM) models are used for congestion prediction using a weighting approach to detect the cause of congestion and the direction of congestion propagation [25]. A hybrid spatio-temporal association rule mining method is used to predict traffic congestion [26]. A hybrid approach is proposed by combining a static traffic assignment model and an agent-based dynamic traffic simulation model [27]. Hidden Markov Models (HMM) are used for congestion pattern prediction in busy traffic areas [28]. The data mining of historical trajectory data to detect and predict traffic congestion and VANET are combined to reduce detected congestion events [29]. The Intelligent Traffic Congestion Prediction System (ITCPS) predicts the traffic congestion status of roads [30]. Multi-modal data are used to simulate traffic congestion events on road networks [31]. After considering the influence of road infrastructure and traffic signal control, a decision tree method based on gradient boosting is proposed [32]. A method for the real-time estimation of traffic conditions and travel time is proposed based on a Gaussian mixture model and a k-means algorithm [33]. A convolutional neural network based on traffic element parameters for supervised congestion prediction is also proposed [34]. Long Short-Term Memory (LSTM) Models are applied to estimate short-term future traffic congestion in LoRa networks [35]. A traffic congestion warning system with point prediction, feature estimation, interval prediction, and comprehensive evaluation is proposed [36].

1.2.3. Distribution Patterns of Spatial and Temporal Characteristics of Traffic Congestion

The congestion avoidance significantly increases the traffic capacity. The congestion-avoiding traffic rules increase the traffic capacity by keeping the emerging congestion and traffic hot spots small, localized, and temporary [37]. The Markov model and back propagation neural network (BPNN) are combined with road occupancy to detect traffic congestion on campus [38]. The analysis of the causes of traffic congestion is based on traffic flow theory [39]. Neural networks and genetic algorithms are used to predict the relationship between vehicle speed and traffic congestion [40]. An improved logistic model is proposed to describe the equilibrium velocity-density relationship around the flyover work area [41]. A vehicle-to-vehicle (V2V)-based road traffic congestion detection method is proposed [42]. The effectiveness of PWSL-KF-based KNN method in monitoring traffic congestion is investigated [43]. The congestion diffusion process in the traffic network is analyzed, the critical value of traffic congestion is obtained, and a coordinated game model of traffic congestion diffusion is proposed [44]. Based on motion wave theory and a Van Aerde single-time flow model, a model was developed to estimate the propagation speed of congestion on the basic roadway [45]. A congestion propagation path estimation method based on the greedy algorithm is proposed [46]. A congestion propagation model (SIS-CP) is proposed to describe congestion propagation patterns in large-scale traffic networks with few parameters [47]. The pattern analysis of recurring traffic congestion based on the raster mapping method is proposed [48]. The spatial spillover effects of traffic congestion on urbanization in China are investigated using a dynamic spatial Durbin model and city-level panel data for 2003-14 [49]. An algorithm is proposed to identify congested road sections and construct a congestion propagation map to simulate congestion propagation in urban road networks [50]. The modeling and analysis of urban traffic congestion in Xi'an, China, using real-time traffic data provided by the Gaode LBS open platform is performed [51]. TomTom Speed Profiles data are used to assess daily changes in traffic congestion and how it varies between time periods and Twitter data are used to capture the spatial patterns of the city's daily pulse [52]. A density-based mobile object clustering method is proposed to extract the spatial and temporal extent of traffic congestion in three steps [53]. By constructing a spatial econometric model, the spatial spillover effect of shared mobility on urban traffic congestion is explored [54]. Using real-time big data to explore the spatial and temporal patterns of traffic congestion performance in 77 major cities in China [55]. This is based on a network analysis of the entire road network from a global perspective [56].

1.2.4. Traffic Congestion Evaluation Index and System Optimization Method

Traffic flow network modeling through cab GPS trajectories to study traffic congestion [57]. Hybrid urban traffic network representation based on directed graphs and Dirgraph convolutional neural network (DGCN)-based learning models to solve congestion identification problems are used [58]. The detection and analysis of the traffic congestion index can be used to estimate the operating conditions of the roads [59]. A nonlinear regression model of road traffic carbon emissions was constructed using the traffic index, GDP, and road passenger volume. The calculation method of road traffic carbon emission intensity in the region is proposed and the equilibrium model of traffic congestion and low carbon economy is constructed [60]. A spatial approach is introduced to identify areas of road traffic congestion within cities [61]. Using the symmetry of potential energy and the mechanism of the action of artificial potential field, a potential energy model of major road traffic congestion in cold climate cities is developed [62]. A new control strategy is proposed to alleviate traffic congestion, using VISSIM to simulate and analyze the urban traffic congestion problem [63]. The strengths and weaknesses of each measure were identified from the data analysis [64]. Based on system dynamics theory, a model of the formation mechanism of traffic congestion in Chinese cities is constructed [65]. A comparison is performed on the effects of traffic zoning on mode choice and travel time using regression analysis [66]. From the perspective of traffic network node capacity, the selection model of congestion evacuation node weights is proposed by combining the transit time of each road [67]. A dynamic memory modulo algorithm is proposed to identify severely congested tasks in distribution routes and transform them into normally congested or even non-congested tasks [68]. The optimization problem of traffic congestion system is studied by the method of a network congestion game [69]. A QL algorithm is proposed to further reduce the congestion at intersections [70]. Traffic congestion forecasting, especially short-term traffic congestion forecasting, is performed by evaluating different traffic parameters. Most studies have focused on historical data for predicting traffic congestion [71]. The congestion identification is performed by obtaining traffic parameters in a small area and the congestion problem is not effectively addressed. There is insufficient research related to urban road network congestion, especially about deep learning [72]. The estimation and prediction of traffic congestion is based on data collected from multiple sources and analysis of traffic congestion indicators with non-uniform evaluation metrics [73].

1.3. Objective

However, at present, the above methods using machine learning prediction methods can only make judgments on urban traffic congestion or not; they cannot display the traffic congestion classification results intuitively and are prone to large errors. The resilience-vulnerability of urban traffic congestion has not been considered, which does not sufficiently reflect the essential characteristics of urban traffic congestion; the traditional traffic congestion zoning is based on administrative divisions, which is not conducive to control according to the characteristics of traffic congestion itself. In recent years, SOFM has been widely used in electric power fault diagnosis, geological evaluation, etc., and has achieved good results; it has the advantages of strong adaptivity, effectiveness, and reliability. The identification and delineation of urban traffic congestion zoning boundaries is an important part of urban traffic management control, but because of the role of urban traffic system heterogeneity, the rationality of boundary conditions needs to be determined in practical work analysis to facilitate multi-scale spatio-temporal traffic congestion analysis.

Therefore, this paper considers the resilience supply capacity and vulnerability damage capacity of urban traffic system to build urban traffic congestion zoning index system and applies SOFM to urban traffic congestion zoning prediction research and expands SOFM model to receive four models based on different competitive layer topologies. Four models were trained and tested with 4000 sets of urban traffic congestion data (traffic volume, severe congestion mileage, delay time, average operating speed, road condition, and number of lanes). The optimal competitive layer topology SOFM model is obtained by combining regional homogeneity and local heterogeneity to construct a comprehensive traffic evaluation index, selecting 1000 sets of data as training samples, dividing the feature vector space by SVM, and allowing different types of traffic congestion units to increase in geographic space intervals to achieve the spatial classification of urban traffic congestion and the accurate distribution of urban traffic congestion in geographic space. This is in order to provide a new method for urban traffic congestion zoning and prevention and control research. Specifically, the study aims to investigate the following three research areas: (1) an urban traffic congestion zoning index system that integrates the resilience-vulnerability of urban transportation system, (2) an urban traffic congestion category zone model based on SOFM, and (3) based on the results of urban traffic congestion category classification obtained using SOFM clustering, the SVM-based urban traffic congestion prevention and control type zoning model is established. This will realize the accurate control of urban traffic congestion zoning.

The rest of the paper is organized as follows: Section 2 describes the study area and the study methodology. Section 3 describes the data sources and processing and the construction of the associated urban congestion zoning model. Section 4 presents the results of the study. The discussion and conclusions are presented in Section 5.

2. Study Area and Research Methodology

2.1. Study Area Overview

In this paper, the traffic data in the main urban area of Guiyang city are used to study the urban traffic congestion zoning boundary problem. In recent years, the urbanization process of Guiyang city has been promoted and, according to the data, the urbanization rate has reached more than 80%; with the number of motor vehicles reaching more than 5 million, the traffic congestion in Guiyang city has been increasing. In 2021, Guiyang city ranked in the middle of the 50 major cities with traffic congestion in China and the traffic has been in a sub-healthy state for a long time, as seen in the traffic congestion data of Guiyang city (see Table 1). Based on the multi-source heterogeneous traffic data of Guiyang city (see Figure 1), the regional functional zoning of Guiyang city and the spatial difference distribution of traffic congestion degree of the regional traffic system are clarified, which help to improve the resilience of the traffic system, reduce the vulnerability, provide a scientific basis for the refined and rational layout of the regional road network of Guiyang city, and solve the problem of contradictory traffic supply and demand faced during the continuous economic development of Guiyang city.

Table 1. Some traffic congestion data in Guiyang.

Rank	Region	Functional Positioning	Peak Congestion Delay Index	Peak Average Travel Speed (km/h)
1	Nanming District	Residential, Commercial Areas	1.77	25.69
2	Yunyan District	Residential, Commercial Areas	1.67	28.46
3	Guanshan Lake District	Technology, Education Area	1.66	27.72
4	Wudang District	Tourism, Industrial Area	1.62	30.27
5	Huaxi District	Tourism, Education Area	1.51	33.03
6	Baiyun District	Industrial Area	1.48	29.96

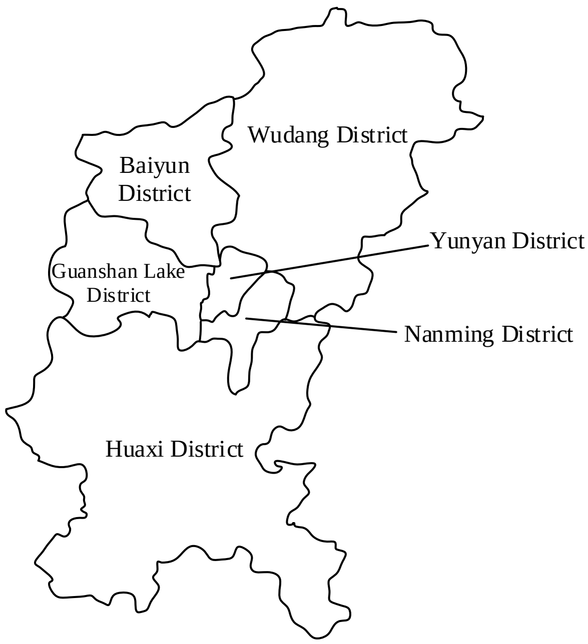


Figure 1. Urban study areas.

2.2. Research Method

The research steps in this paper are divided into three main steps: (1) Considering the resilience and vulnerability of the traffic system, establishing the urban traffic congestion zoning index system, normalizing the multi-source data, and training and testing the model on this basis. (2) The results of different competing layer topologies are analyzed and compared and the optimal model is determined by integrating three aspects: model clustering effect, training results, and testing results. (3) The support vector machine is selected for model training to verify the reliability of the data, find the best urban traffic congestion zoning boundaries, and receive the final zoning results. For the SOFM-SVM-based urban traffic congestion zoning prediction model process, see Figure 2.

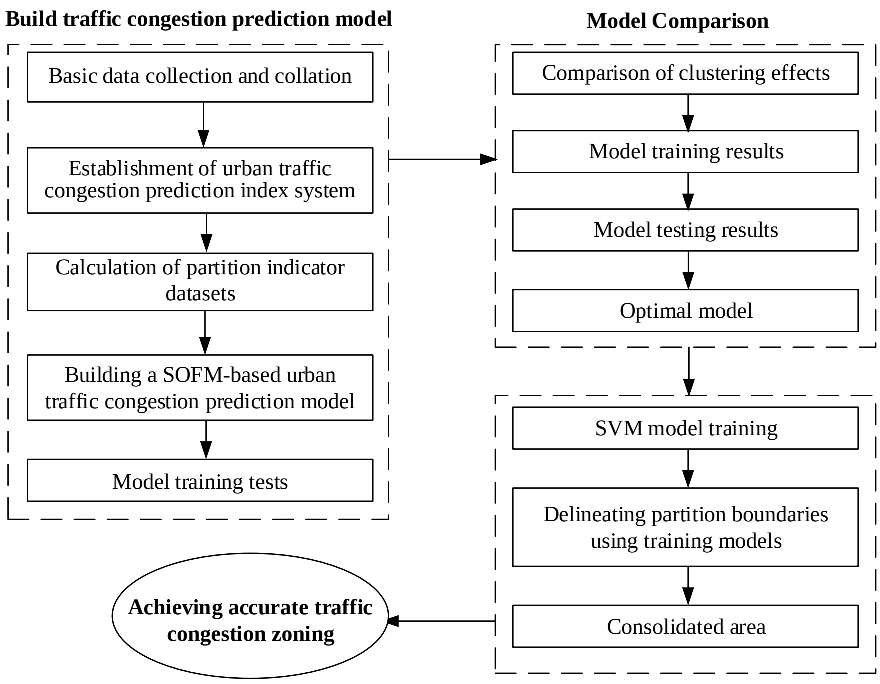


Figure 2. Block diagram of the study model.

3. SOFM-SVM-Based Urban Traffic Congestion Zoning Model

In this paper, the optimal model is determined by model building, comparison, and analysis based on the processing of data from multiple sources.

3.1. Data Source and Processing

The basic data include six categories: (1) district and county administrative boundaries, from Guiyang city basic geographic information data; (2) land use data, from Guiyang City Housing and Urban-Rural Development Bureau, and classifying the land use types into ten categories: residential; (3) public administration and public service facilities, commercial service facilities, industrial, logistics and storage, roads and transportation facilities, public facilities, green areas and squares, construction land, and non-construction land; social economic count data, from Guiyang City Statistical Yearbook 2021; (4) traffic flow data, crawled by Python from January to June 2021 in the main urban area of Guiyang, including traffic volume, operation speed, number of lanes, etc; (5) urban road network data, based on OSM open source vector data; and (6) road surface condition, from field survey data.

3.2. Establishment of Urban Traffic Congestion Zoning Index System

In order to accurately classify the level of urban traffic congestion, it is important to establish a scientific and efficient index system. The zoning should reflect both the irrationality of existing administrative divisions and the resilience and vulnerability of urban traffic congestion problems. Considering the resilience-vulnerability of the study area and the reasonableness of the data, this paper selects six deterministic performance indicators to construct the index system of urban traffic congestion zoning in the main urban area of Guiyang to quantify the resilience and vulnerability of the traffic system.

Transportation system resilience includes the transportation system's own road conditions, environmental conditions, etc. The ability to provide transportation services for drivers or goods, etc. Therefore, from the perspective of the supply capacity of the transportation system, two partition indicators of road conditions and number of lanes are selected in this paper. The traffic system vulnerability refers to the magnitude of traffic system congestion occurring within a certain range and is often characterized by four indicators: traffic volume, severe congestion mileage, delay time, and average operating speed. The zoning range of each indicator (see Table 2).

Table 2. Urban traffic congestion level classification.

Urban Transportation System Division	Traffic Congestion Zoning Level Relationship	Low Value Zone	From Low to Medium Value Zone	Medium Zone	From Medium to High Value Zone	High Value Zone
	Representative Colors	Green	Blue	Yellow	Orange	Red
Transportation System Vulnerability	The relationship between the actual traffic volume q_s and the traffic volume q_f in the free flow case	$q_s \le 0.3q_f$	$0.3q_f < q_s \le 0.6q_f$	$0.6q_f < q_s \le 0.7q_f$	$0.7q_f < q_s \le 0.8q_f$	$0.8q_f < q_s \le 1.0q_f$
	Relationship between the length of road congestion l_f and the actual length of the road l_s	$l_f \le 0.04l_s$	$0.04l_s < l_f \le 0.08l_s$	$0.08l_s < l_f \le 0.12l_s$	$0.12l_s < l_f \le 0.15l_s$	$0.15l_s < l_f$
	The relationship between the actual travel time t_s and the travel time t_f in the free-flow case	$t_s \le 0.3t_f$	$0.3t_f < t_s \le 0.5t_f$	$0.5t_f < t_s \le 0.6t_f$	$0.6t_f < t_s \le 0.7t_f$	$0.7t_f < t_s \le 1.0t_f$
	The relationship between the average travel speed v_s and the free-flowing vehi-cle speed v_f	$v_s \ge 0.7v_f$	$0.6v_f < v_s \le 0.7v_f$	$0.5v_f < v_s \le 0.6v_f$	$0.3v_f < v_s \le 0.5v_f$	$v_s \le 0.3v_f$
Transportation System Resilience	Relationship between pavement mass index p_s and free flow under con-gestion and p_f	$p_s \le 0.6p_f$	$0.6p_f < p_s \le 0.7p_f$	$0.7p_f < p_s \le 0.8p_f$	$0.8p_f < p_s \le 0.9p_f$	$0.9p_f < p_s \le 1.0p_f$
	Relationship between the number of lanes n_s in congestion and the number of lanes n_f in free flow	$n_s \le 0.55n_f$	$0.55n_f < n_s \le 0.65n_f$	$0.65n_f < n_s \le 0.75n_f$	$0.75n_f < n_s \le 0.85n_f$	$0.85n_f < n_s \le 1.00n_f$
Traffic Congestion Rating Index C		$0 \le C < 2.0$	$2.0 \le C < 4.0$	$4.0 \le C < 6.0$	$6.0 \le C < 8.0$	$C \ge 8.0$

C indicates the degree that the urban regional road network system is affected by traffic congestion, which is a quantity with a scale of 1. This paper uses the traffic congestion evaluation index to characterize the degree of urban road traffic congestion. The expression is as follows:

$$\begin{aligned} C &= \frac{q_s}{q_f} + \frac{l_s}{lf} + \frac{t_s}{t_f} + \frac{v_f}{v_s} + \frac{p_s}{p_f} + \frac{n_s}{n_f} \\ t_s &= \frac{l_s}{v_s} = \frac{l_s}{\sum\limits_{i=0}^{n} v_{si}/m} \\ t_f &= \frac{l_s}{v_f} \end{aligned} \tag{1}$$

where: C is the overall traffic congestion evaluation index; q_s is the actual traffic volume; q_f is the traffic volume under free flow; t_s is the actual travel time; t_f is the travel time under free flow; v_s is the actual travel speed of traffic; v_f is the free flow speed of vehicles; v_{si} is the average travel speed of the ith vehicle; l_s is the actual length of the road; l_f is the length of road congestion; m is the number of vehicles in the road section; p_s is the average of the local area of the city where traffic congestion occurs is the overall average road quality index of the area where the traffic congestion occurs under free flow, p_f is the overall average road quality index of the area where the traffic congestion occurs under free flow, n_s is the average number of lanes in the local area of the city where the traffic congestion occurs; and n_f is the overall average number of lanes in the area where the traffic congestion occurs under free flow.

3.3. Establishing SOFM-Based Urban Traffic Congestion Category Zone Model

3.3.1. Building the Model

First, the zonal metrics used (traffic volume, miles of severe congestion, delay time, average operating speed, pavement condition, and number of lanes) were normalized. The data are based on the traffic data of Guiyang from January to June 2021 and can be expressed as Equation (2):

$$x_k = \frac{x'_k - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where: x'_k is the original data of any evaluation index; $x_{\max}$ is the maximum value of the sample data; $x_{\min}$ is the minimum value of the sample data; and the normalized data range is [0, 1].

Second, we determine the best competitive layer network topology in this paper. Based on a large number of model calls, we classify the competitive layer topology into four types: "4, 5, 6, 7". For the four-layer competitive layer topology, see Figure 3.

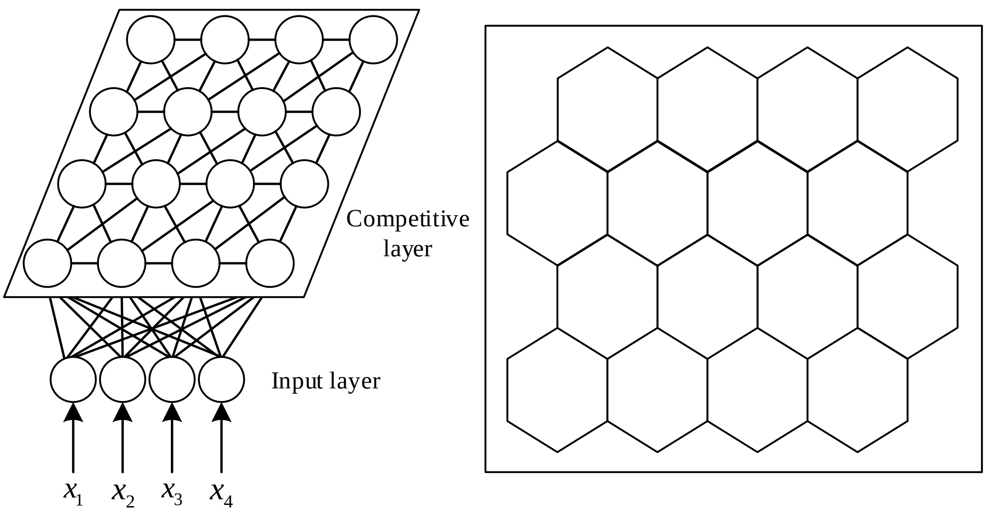


Figure 3. Four-layer competitive layer topology.

The traffic volume, severe congestion mileage, delay time, average operating speed, road condition, and number of lanes are denoted as x_1, x_2, x_3, x_4, x_5, x_6 and each set of data $X = (x_1,\ x_2,\ x_3,\ x_4,\ x_5,\ x_6)^T$ is used as the input variable. By calculating the Euclidean distance between the j-th neuron of the competitive layer and the input vector X, it can be described by Equation (3):

$$d_j = \|X - W_j\| = \left\{\sum_{i=1}^{m} [x_i(t) - w_{ij}(t)]^2\right\}^{1/2} \tag{3}$$

where: d_j is the Euclidean distance between the input sample and the j-th neuron in the competitive layer; t is the network time, $w_{ij}(t)$ is the connection weight between the i-th neuron in the input layer and the j-th neuron in the competitive layer at time t, W_j is the weight vector of the j-th neuron in the competitive layer, m is the number of input neurons, and $x_i(t)$ is the input vector of the i-th neuron of the input layer.

Finally, the model is updated iteratively. It can be described by Equation (4):

$$\Delta w_{ij} = w_{ij}(t+1) - \Delta w_{ij}(t) = \eta(t)[x_i - w_{ij}(t)] \tag{4}$$

where: $\eta(t)$ is the network learning rate at moment t. In this paper, MATLAB is used to call the SOM Toolbox 2.0 toolbox for platform training. The input layer data are constructed according to the partition index system. Two steps of the coarse tuning neighborhood radius and fine-tuning neighborhood radius are used for training and the iteration step is set to 1500 steps. The model is trained until it meets the requirements.

3.3.2. Model Comparison

The clustering effect of the model was evaluated to determine the optimal model. It can be described by Equation (5):

$$y = \sum_{i=1}^{n} (x_i - 80)^2 \tag{5}$$

The traffic congestion partitioning classes corresponding to each neuron of the trained model are examined. Based on the number of traffic congestion partition classes corresponding to each neuron, three categories of neurons, unique neurons, and shared neurons are used to achieve analytical discrimination.

3.4. Establishing an SVM-Based Zoning Model for Urban Traffic Congestion Prevention and Control Types

Based on the SOFM clustering, the urban traffic congestion category classification results are obtained and the optimal classification hyperplane traffic congestion zoning boundary is delineated.

The support vector machine is a machine learning based, supervised learning algorithm for data analysis in classification, regression, and outlier detection. Classification is achieved by constructing the best hyperplane or set of hyperplanes in a high or infinite dimensional space that separates two classes at a maximum interval. Define the parameters: $f(x)$ is the traffic congestion class of the partition; M is the weight vector of each feature parameter; Y is the vector composed of feature parameters; b is the intercept; n is the number of training sets, α is the αth of the sample data y_α is the traffic congestion class corresponding to the feature parameters; and E is the tolerance error. The linear regression function $f(x) = W^T x + \mathrm{b}$ is used to fit the two major categories and six parameters obtained as described before.

Assume that after fitting all the sample data can be represented by a linear function $f(x)$ within $[-E,\ E]$, it can be described by Equation (6):

$$\begin{aligned} & f(X) = \sum_{i=1}^{m} (\phi_i - \varphi_i) K(X_i, X) + b \\ & \min_{W,\ s} = \frac{1}{2}\|W\|^2 + C \sum_{i=1}^{n} \left(S_i + S_i^x\right) \\ & \begin{cases} W^T X_i + b - y_\alpha \le E + S_i \\ y_\alpha - \left(W^T X_i + b\right) \le E + S_i^x \\ S_i,\ S_i^x \ge 0 \quad i = 1,\ 2,\ \cdots n \\ S_i,\ S_i^x = \begin{cases} y_\alpha & (W \cdot X_i + b) \\ & |y_\alpha - (W \cdot X_i + b)|E \\ 0 & |y_\alpha - (W \cdot X_i + b)| \le E \end{cases} \end{cases} \end{aligned} \tag{6}$$

In Equation (6), S_i,S_i^x is the relaxation variable, which is the upper and lower training error of the regression function. The above objective function is transformed into the Lagrangian rows that solve the constrained extremum problem and then the data samples are mapped to the high-dimensional space by the sum function operation; the sample points are nonlinearly transformed k and the urban traffic congestion partitioning level can be achieved by Equation (6). The Gaussian kernel is introduced and the expression is

$$K(X_i, X) = \exp\left(-\frac{\|X - X_i\|^2}{2\lambda^2}\right) \tag{7}$$

where: λ is the Gaussian kernel function.

In this paper, we set the variation range of relevant parameters using the grid search method; use a certain number of samples as the training set and validation set, respectively, use cross-validation to find and rank the classification correct rate, and select the combination with the highest classification correct rate as the model parameters to obtain the most reasonable support vector machine model. The expression is as follows:

$$\begin{aligned} & C = \max(|u + 3\delta|, |u - 3\delta|) \\ & E = 3\varepsilon\sqrt{\frac{\text{In } n}{n}} \\ & \lambda = \frac{1}{2q^2 0.3^{\frac{2}{m}}} \end{aligned} \tag{8}$$

The SVM model parameters selection and training process are based on Python 2.7.13 implementation.

4. Analysis of Results

4.1. Spatial Distribution of Resilience in Urban Transportation Systems

As can be seen from Figure 4a, the pavement condition of Guiyang city shows a spatial pattern of being higher at the lower central edge; the high value areas are concentrated in the northeastern Wudang district, the edge zone of Huaxi district, and the edge zone of Guanshan Lake district. This is consistent with the trend that the average running speed is lower in the middle and higher at the edges. The overall pavement damage and other conditions in Guiyang city are less and the central part has better economic development and higher overall levels of pavement conditions; the urban fringe zone has poor infrastructure construction and poor pavement condition.

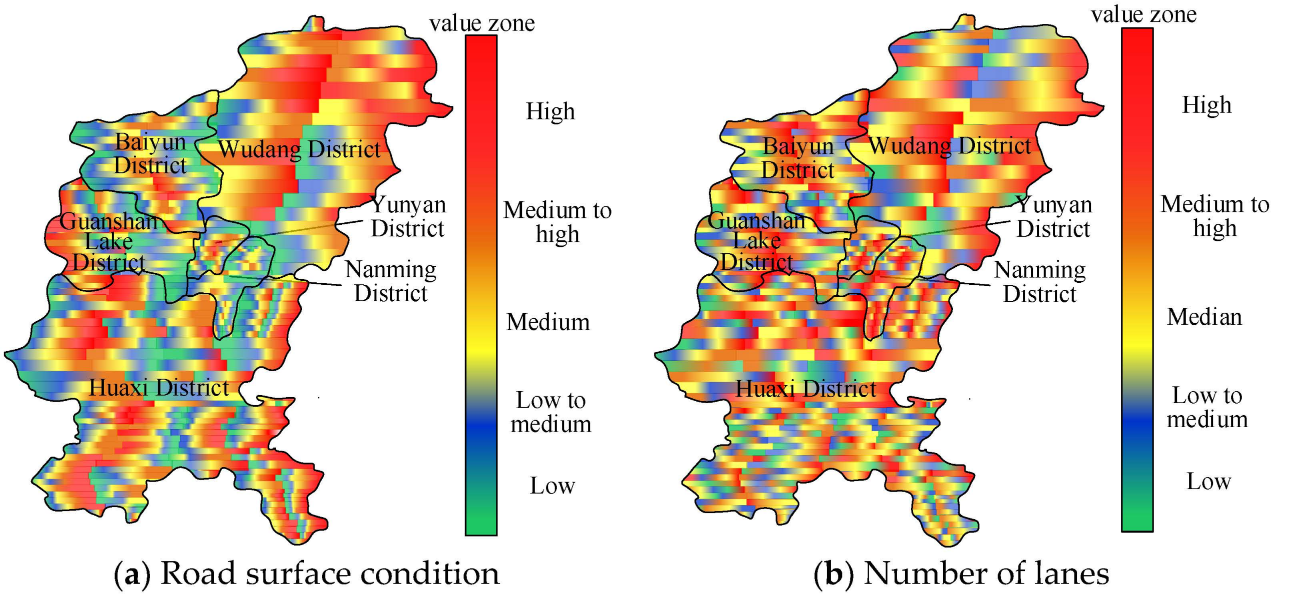


Figure 4. Spatial distribution of resilience supply capacity of the Guiyang city transportation system.

As can be seen from Figure 4b, the number of lanes in Guiyang is unevenly distributed and the high-value areas are mainly concentrated in the new city, Huaxi district, Wudang district, etc. The development of the economic level and the different historical traffic conditions cause the division of urban traffic congestion zoning by the number of lanes, which has a complex and different spatial distribution pattern. The overall distribution is more even, showing the trend of development in the northwest, south, and northeast, which is consistent with the development of urban traffic construction.

4.2. Spatial Distribution of Urban Transportation System Vulnerability

As can be seen from Figure 5a, the traffic volume in Guiyang is influenced by the type of urban land use and the distribution is relatively more fragmented and concentrated. The high value area is mainly in the central and northwestern part, mainly concentrated in Nanming District, Yunyan District, Baiyun District, and the southern part of the Huaxi District. This area is an important area for urban development, with better economic development, more commerce and industry, and more jobs available. The northeastern, southwestern, and partly southeastern regions of Guiyang are more mountainous, with fewer industrial parks and lower traffic volumes.

As can be seen from Figure 5b, the severe congestion course of Guiyang is mainly in the median area, which is dominated by the south and northwest, mainly concentrated in the Huaxi District and the fringe zone of Wudang District. This area is an important area for the development of new cities and an important linkage area to the outside world, with relatively less perfect transportation facilities and a limited level of supply services available. In the central, northwestern, and some southern areas of Guiyang, some short-time traffic demand exceeds supply resulting in high mileage over severe congestion.

As can be seen from Figure 5c, the distribution of delay time in Guiyang is relatively concentrated, mainly in the medium-value areas such as the Huaxi District, Wudang District, and the fringe of the Guanshan Lake District; the Nanming District and Guanshan Lake District are mainly in the high-value areas.

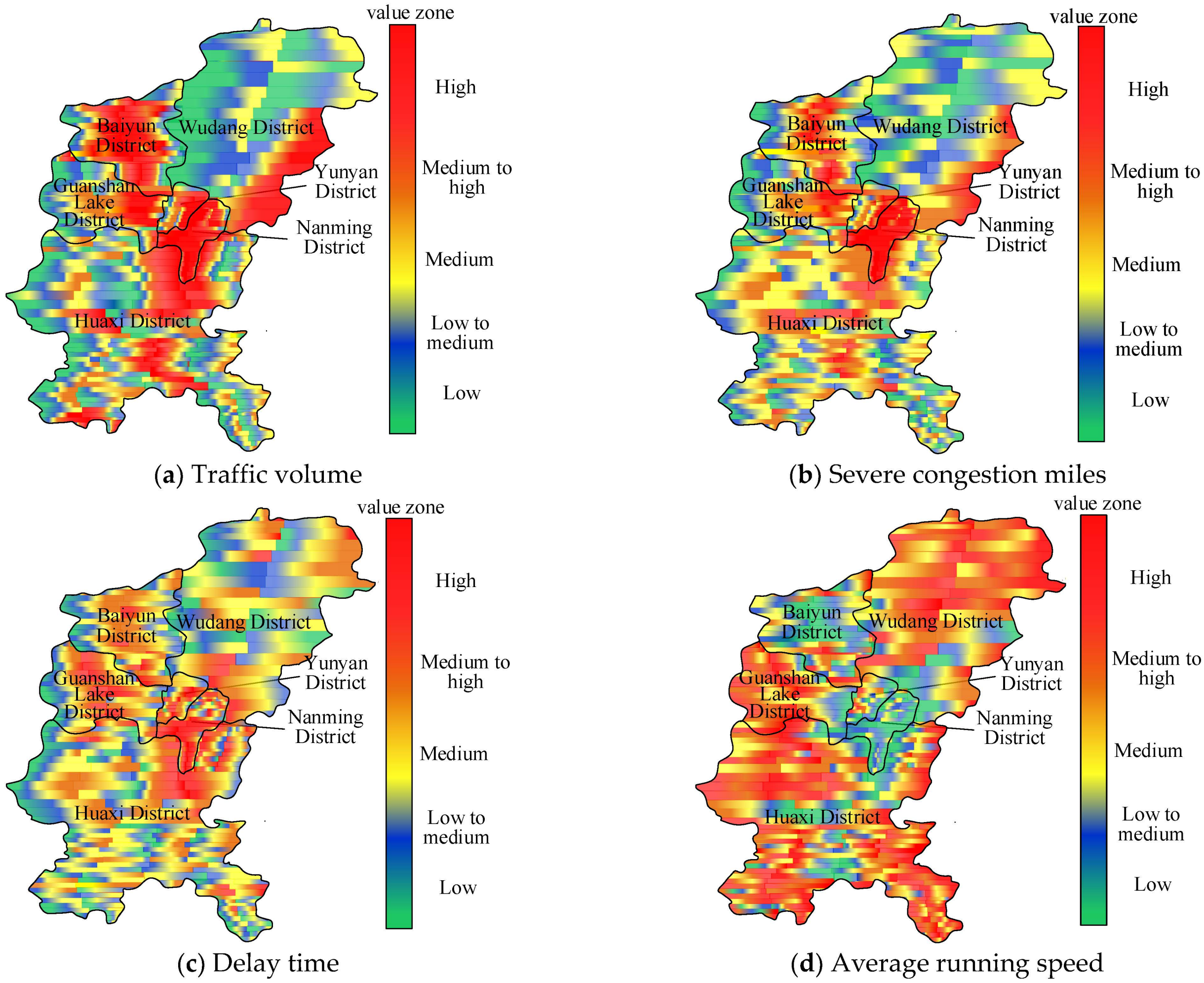


Figure 5. Spatial distribution of vulnerability damage capacity of transportation system in Guiyang city.

As can be seen from Figure 5d, the overall distribution of average running speed in Guiyang is uneven, mainly dominated by medium and high values, with high values mainly distributed in the southeast, northwest, and southwest of the Wudang District, Guanshan Lake District, and Huaxi District. The average running speeds in the central area of the city are mainly low and low-to-medium values and, in the non-central major urban areas such as the Baiyun District, they are also mainly low values, which shows that the city has multi-core and multi-wing coordinated development in the development process.

4.3. Classification of Urban Traffic Congestion Category Zones

4.3.1. Model Testing

To test the effect of the SOFM model urban traffic congestion zoning level classification, 1000 groups in each of the five levels of urban traffic congestion zoning (low value, medium-low value, medium value, medium-high value, and high value) are randomly selected as the test set. Due to the limitation of space, only 20 sets of test sets are shown in this paper. The urban traffic congestion data and the corresponding traffic congestion level test sets are shown in Table 3.

Table 3. Urban traffic congestion test set.

Rank	Traffic Volume q (pcu/h)	Severe Congestion Miles l (km)	Delay Time t (min)	Average Running Speed v (km/h)	Road Quality Index p	Number of Lanes n	Traffic Congestion Zoning Level
1	5260	3.30	6.93	30.56	0.96	3.28	Medium
2	4860	2.91	8.32	31.36	0.97	2.98	From low to medium
3	7862	4.93	13.58	27.23	0.90	4.44	High
4	8926	5.62	16.26	25.89	0.87	4.93	High
5	6842	4.56	9.13	26.31	0.91	4.15	From medium to high
6	5968	3.63	8.16	30.03	0.95	3.48	Medium
7	7986	5.04	13.83	27.46	0.89	4.52	High
8	7536	4.81	12.76	27.85	0.90	4.36	From medium to high
9	6935	4.26	10.62	28.59	0.92	3.98	From medium to high
10	5968	3.76	8.61	29.93	0.94	3.65	Medium
11	4569	2.75	4.59	31.55	0.98	2.86	From low to medium
12	5623	3.12	6.10	30.91	0.96	3.15	Medium
13	4968	2.76	4.26	31.86	0.98	2.89	Low
14	5856	3.59	7.89	30.13	0.95	3.48	Medium
15	4762	2.86	5.31	31.59	0.98	2.96	From low to medium
16	7156	4.53	11.36	28.39	0.91	4.15	From medium to high
17	6423	3.98	9.53	29.42	0.93	3.76	Medium
18	6692	4.19	10.2	28.87	0.92	3.91	From medium to high
19	7569	4.79	14.13	27.53	0.90	4.34	From medium to high
20	8123	5.43	15.87	26.38	0.88	4.76	High

The true levels of the 20 sets of test data and the prediction levels of the four models are shown in Table 4.

Table 4. True level and prediction results of each model.

Rank	Real Level	Competition Layer Topology			
		Four Layers	**Five Layers**	**Six Layers**	**Seven Layers**
1	Medium	From medium-medium to high	From medium-medium to high	Medium	From medium-medium to high
2	From low to medium	From low to medium	From low to medium	From low to medium	From low to medium
3	High	High	From medium to high-high	High	High
4	High	From medium to high-high	High	High	From medium to high-high
5	From medium to high	From medium to high-high	From medium to high-high	From medium to high	From medium to high
6	Medium	From medium-medium to high	Medium	Medium	From medium-medium to high
7	High	High	From medium to high-high	High	High
8	From medium to high	From medium to high-high	From medium to high-high	From medium to high	From medium to high
9	From medium to high	From medium to high-high	From medium to high	From medium to high	From medium to high-high
10	Medium	From medium-medium to high	From medium-medium to high	Medium	From medium-medium to high
11	From low to medium	From low to medium-medium	From low to medium-medium	From low to medium	From low to medium-medium
12	Medium	From medium-medium to high	From medium-medium to high	Medium	Medium
13	Low	From low-low to medium	From low-low to medium	Low	*
14	Medium	From medium-medium to high	From medium-medium to high	Medium	From medium-medium to high
15	From low to medium	From low to medium-medium	From low to medium-medium	From low to medium	From low to medium-medium
16	From medium to high	From medium to high-high	From medium to high-high	From medium to high	From medium to high
17	Medium	Medium	From medium-medium to high	From medium-medium to high	From medium-medium to high
18	From medium to high	From medium to high	From medium to high-high	From medium to high	From medium to high-high
19	From medium to high	From medium to high-high	From medium to high	From medium to high	From medium to high
20	High	High	High	High	From medium to high-high

Note: "*" means there is no corresponding grading result.

The traffic congestion levels in the actual congestion process are sometimes between two levels and the zoning results predicted to be two adjacent levels are also in line with the actual situation; the prediction results of two predicted levels containing less levels than the actual situation are judged to be better.

4.3.2. Model Comparison

The statistical percentages of various types of neurons for the four models using Equation (5) are shown in Figure 6.

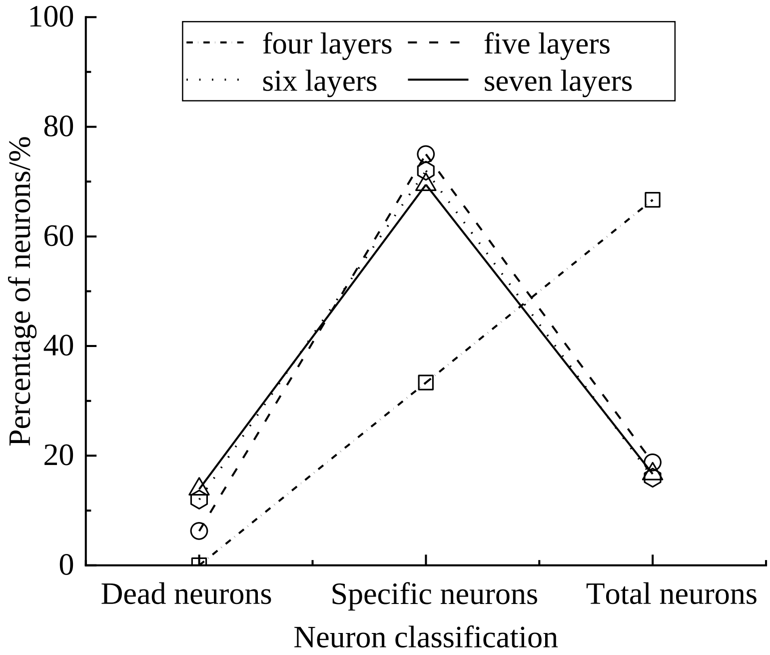


Figure 6. Comparison of the models.

The four-layer competitive topology structure model has the strongest fuzzy hierarchical clustering effect and its common neurons are significantly higher than the other layers of the competitive layer topology structure model; the prediction structure is not accurate enough. The percentage of neurons specific to five, six, and seven is close to or at 70% and the percentage of dead neurons is not very different between the five- and six-layer competitive topology structure models, but the seven-layer competitive topology structure model is smaller, so the clustering ability of the six-layer competitive topology structure model is higher than the clustering ability of the five- and seven-layer competitive topology structure models.

Although the test accuracy of all four models reached more than 95%, the prediction results of the model six-layer competitive topology model did not have dead neurons similar to the seven-layer competitive topology model and the deviation was smaller. In summary, the six-layer competitive topology SOFM model is selected for urban traffic congestion category zone classification in this paper.

4.3.3. Model Division Results

The spatial clustering of partitioning metrics is performed using the six-layer competitive topology SOFM model. It can be significantly seen that the spatial distribution of the traffic congestion of neurons in the same category is relatively fragmented, different categories of neurons exist mixed with each other, the partition of traffic congestion area is not clear, and there is no obvious traffic congestion partition boundary line. It explains that it is difficult to obtain the optimal partition boundary line by directly using the grid data for clustering partitioning and also illustrates the disadvantage that the optimal partitioning scheme cannot be obtained directly by using SVM to improve the six-layer competitive topology SOFM model. The six-layer competitive topology SOFM model can divide the city into six category zones (see Figure 7).

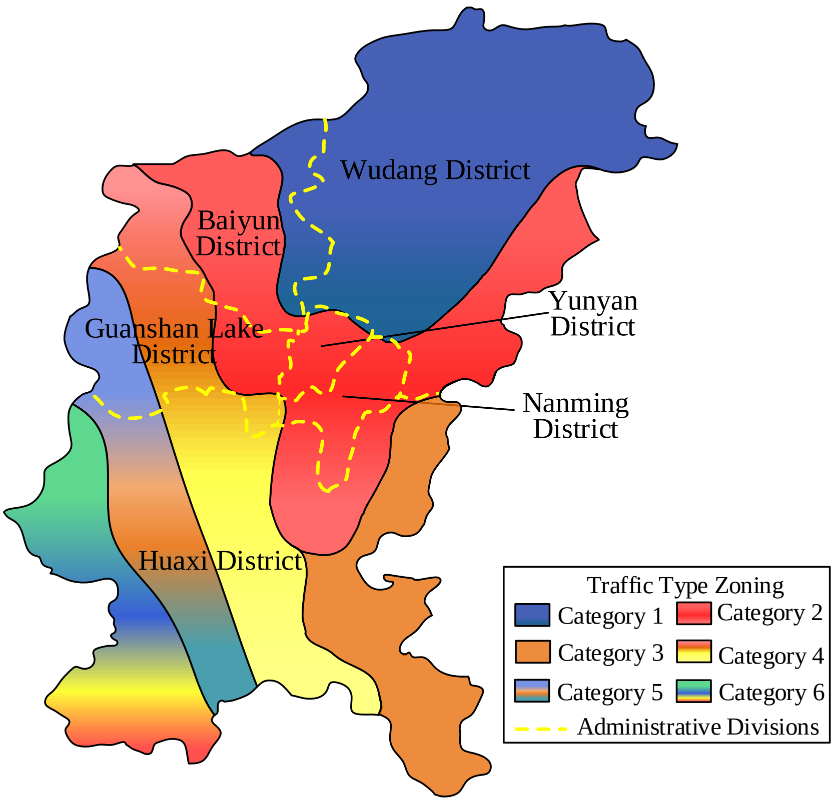
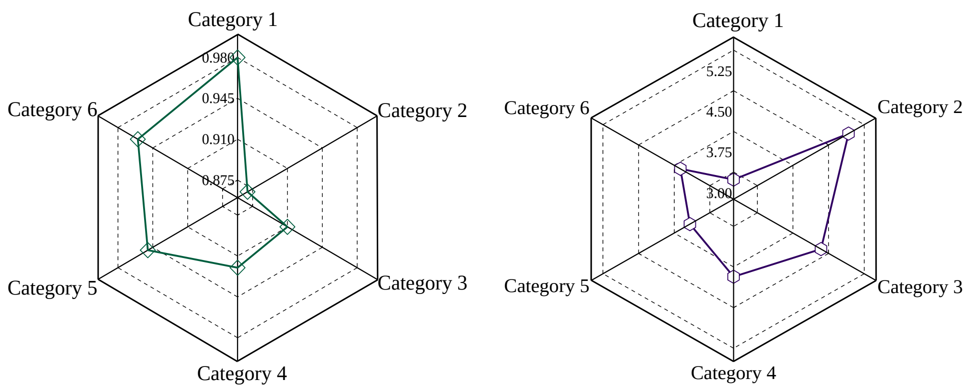


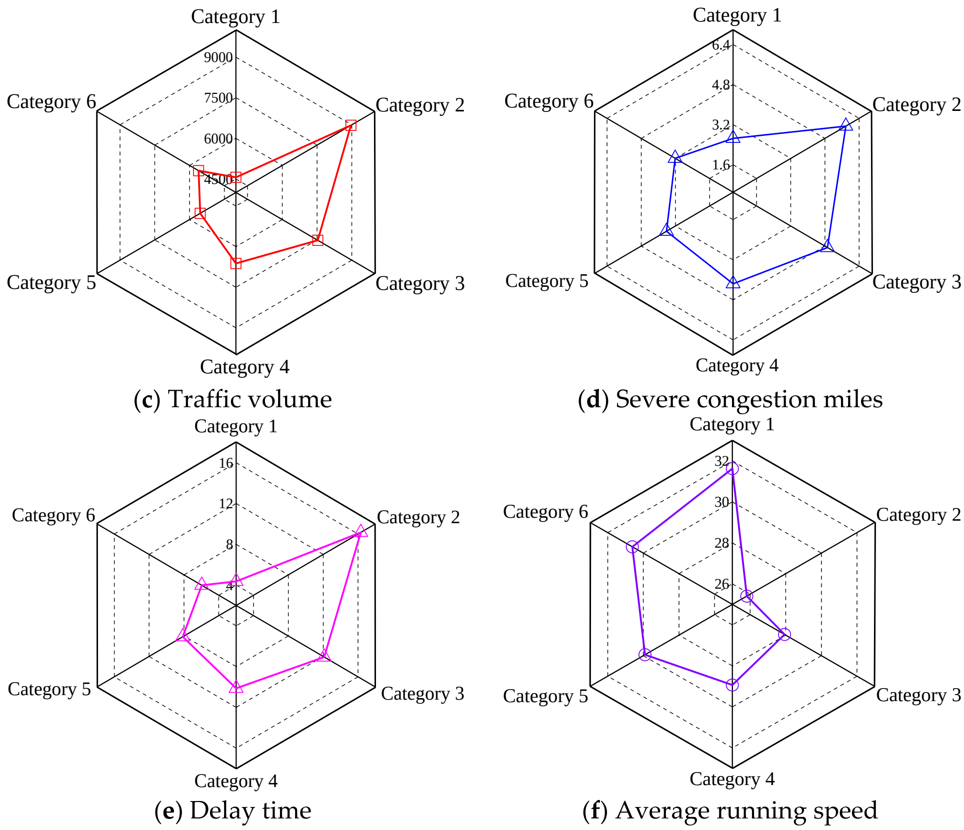
Figure 7. SOFM model division results.

From the statistical analysis of the six category areas, the characteristics of urban transportation system resilience indicators and urban transportation system vulnerability indicators are shown in Figure 8. Category 1 has a good road surface condition, a low number of lanes, and is an underdeveloped area of urban development; category 2 is the core area of urban development, with a good road surface condition, a good number of lanes, and a high traffic system resilience; category 3 is concentrated in the sub-core area of the city, with a high traffic system vulnerability, characterized by severe congestion mileage, high delays, etc.; category 4 has a medium level of traffic system vulnerability and resilience; category 5 has good traffic development but poor road network connectivity; and category 6 has a high level of traffic system resilience.



(**a**) Road surface condition (**b**) Number of lanes

Figure 8. *Cont.*



(**c**) Traffic volume (**d**) Severe congestion miles

(**e**) Delay time (**f**) Average running speed

Figure 8. Distribution of vulnerability and resilience indicators of urban transportation systems in various categories of districts.

4.4. Division of Urban Traffic Congestion Prevention and Control Type Zoning

4.4.1. Model Parameter Selection

Based on the clustering results of the six-layer competitive topology SOFM model, the support vector machine model parameters C, E, and λ are cross-determined using the grid search method, with parameters varying between 0.001 and 10,000. For the optimal combination of parameters in the grid search, C is 1500, E is 0.5, and λ is 0.4. The optimal combination of parameters is used to complete the model training and delineate the partition boundary line.

4.4.2. Model Comparison

The partition results obtained directly by using SVM to delineate the partition boundaries show some relatively small area patches that need to be fine-tuned and smoothed. Using the elimination tool of ArcGIS, this is achieved by programming the Arcpy module to repeat several times and elimination is based on the smallest area spot merged with the neighboring spot with the longest common boundary. The best elimination endpoint is determined based on the coefficient of variation of each classification area until the area size of the partitioned results is relatively balanced.

As shown in Figure 9, the coefficient of variation of each control type partition gradually decreases and the dispersion degree gradually decreases as the number of control type partitions decreases in the microplot merging process. The coefficient of variation decreases from 1.74 to 0.63, which also reflects the effectiveness and accuracy of the merging process. The absolute value of the first-order difference of the coefficient of variation increases and the rate of reduction in the coefficient of variation increases as the merging process proceeds when the number of differential endpoint partitions is greater than 16, while the absolute value of the first-order difference of the coefficient of variation decreases and the rate of reduction in the coefficient of variation gradually decreases when the number of differential endpoint partitions is less than 16. Therefore, a traffic congestion prevention and control partition of 16 is a more desirable endpoint for the merging process.

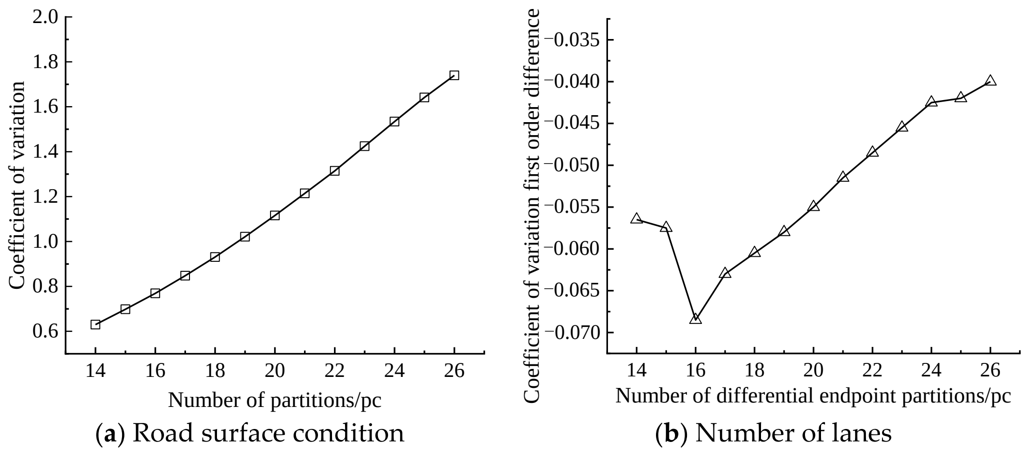


Figure 9. Partition of the prevention and control type of the map spot merging process.

4.4.3. Model Division Results

Finally, Guiyang is divided into 16 traffic congestion control zones and the precise division results are shown in Figure 10.

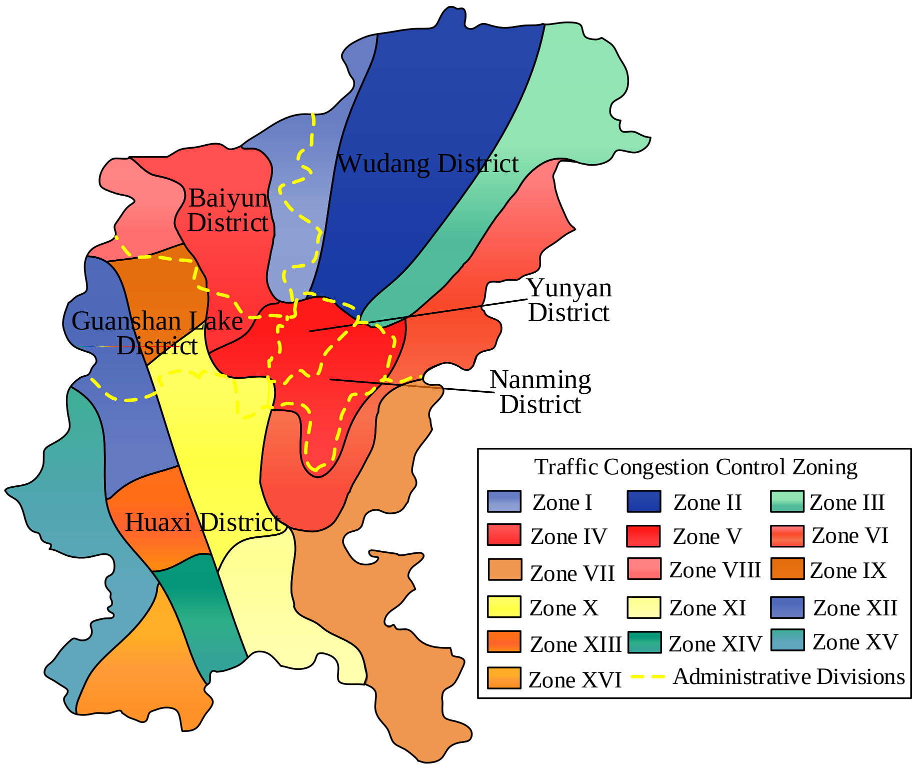


Figure 10. Results of precise congestion control zoning in Guiyang city.

The first, second, and fifth category areas are divided into three control zones, the fourth category area is divided into four control zones, respectively, and the sixth category is divided into two control zones, respectively. In this paper, the traffic congestion partitions are named based on the spatial location and traffic congestion control characteristics considering the characteristics of traffic congestion partition clustering types; the consistency with the actual traffic congestion situation is good.

- I North Important Precautionary Zone (Category 1). The zone is located in the central northeast-southwest area of the Wudang District, which is generally free of congestion and has relatively low traffic volume. It belongs to the medium level of the urban study area. II Northwest General Precautionary Zone (Category 1). The zone is located in the northern core of Guiyang and the regional average delays, severe congestion miles, and other transportation system vulnerabilities are at low levels. III Northeast Secondary Precautionary Zone (Category 1). The zone is located in the northeastern part of Guiyang, with medium-to-high traffic volume, and at the city boundary. This area has good road surface conditions and high potential for traffic development.
- IV Northern Important Control Zone (Category 2). The zone is located in the core area in the north of Guiyang; in the middle and middle east of the Baiyun District, the economic development in the area is better. There are more jobs available, the traffic volume is on the high side, and the construction of transportation infrastructure is more complete, but the contradiction between the transportation supply and demand is more prominent. V Central Special Control Zone (Category 2). The zone is located in the economic, political, and cultural center of Guiyang, with regular traffic congestion, an average operating speed below 25km/h, and a peak congestion delay index above 1.72. It is the most vulnerable area of Guiyang's urban transportation system. VI Central and Central-Eastern Secondary Control Zone (Category 2). The zone is located in the west-central Huaxi District and the east of the Wudang District, with a large volume of external traffic and a decrease in severe congestion miles and delays.
- VII Southeast Special Precautionary Zone (Category 3). The zone is located in the southeastern fringe zone of the city, which mainly consists of the eastern fringe zone of the Huaxi District. There is a lot of transit traffic in the region and the inter-regional connection should be strengthened and the road network should be reasonably laid out. Enhance the stability of the transportation system.
- VIII Northwest Important Control Area (Category 4). It consists of the western area of the Baiyun District and part of the northern area of the Guanshan Lake District. The regional economy is well developed and well connected with the outside region, but the traffic system is more sensitive, with larger traffic volume and delay time. IX Western Secondary Control Area (Category 4). The zone is located in the central area of the Guanshan Lake District, the contradiction between the traffic supply and demand is not prominent and the industrial-type traffic dominance is more prominent. X Central Important Control Area (Category 4). The zone is located in the central core area of the Huaxi District, mainly with educational land and relatively well-constructed transportation. XI Southern Secondary Control Area (Category 4). The zone is located in the southernmost part of the study area, with better traffic infrastructure construction.
- XII Western Secondary Precautionary Zone (Category 5). The zone is located in the western part of the Guanshan Lake District and the central and western part of the Huaxi District, with low volume of external traffic in the region and an average level of economic development. XIII Western Secondary Control Zone (Category 5). The zone is located in the central core of the Huaxi district, with overall low delays and an average running speed of 34 km/h or more. XIV Southern Critical Precautionary Zone (Category 5). The zone is located in the southernmost part of the study area and the overall carrying capacity of the road network is high.
- XV Southwest Secondary Precautionary Area (Category 6). The zone is located in the western core area of the Huaxi District, with good external transportation links and a relatively good road network. XVI Southern Critical Control Area (Category 6). The zone is located in the southernmost part of the study area, with unreasonable signal control at some intersections, low average operating speeds, a high percentage of severely congested miles, and a low level of traffic system vulnerability, which requires further improvement of traffic system stability.

5. Conclusions

The SOFM model is introduced into the study of urban traffic congestion category zone classification by crawling the real-time data of some cities and urban traffic survey data. The SOFM-based urban traffic congestion category zone identification model is established considering the urban traffic system resilience and vulnerability evaluation indexes.

The SVM model is used to find the optimal partition boundary lines for different categories of traffic congestion. The first-order difference of the coefficient of variation and coefficient of variation is used to compare the prevention and control type partition models and finally determine 16 traffic congestion control areas. The distribution of each space is ensured to be relatively consistent and the partition is clearer.

Different from the previous clustering based on administrative districts, the SOFM-SVM model is proposed. This integrates the advantages of spatial clustering and the machine learning algorithm and can meet the actual quantitative demarcation requirements by dividing the broken and mixed parcels into complete blocks after clustering, which can avoid defects such as the long period of single demarcation and the difficulty of repeating the process.

Author Contributions: Conceptualization, X.Z. and L.H.; methodology, X.Z., L.H. and X.W.; formal analysis, X.Z. and X.W.; data curation, X.Z. and J.W.; writing—original draft preparation, X.Z.; funding acquisition, L.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China under Grant 61863019 and 42277476.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available from the corresponding author upon request.

Acknowledgments: The author wants to express his gratitude to all the workmates of the research for their helpful suggestions and patient guidance.

Conflicts of Interest: The authors declare no conflict of interest.

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