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The road network similarity calculation based on autoencoders and its application in map generalization quality evaluation

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Abstract

Spatial similarity underpins multi-scale data representation and cartographic quality assessment. However, evaluating the similarity of structurally intricate road networks using conventional approaches often falls short due to inadequate spatial feature extraction and subjective weighting. To address this, we introduce a graph convolutional autoencoder (GCAE) model for road network similarity computation. The model learns deep spatial representations via self-supervised training, combining graph convolutions for feature extraction with autoencoders for graph reconstruction. Similarity is quantified using latent-space cosine similarity and validated against geometric and topological baselines, as well as human perception. Furthermore, we construct a multi-scale road network standard library to mathematically model the relationship between similarity and scale variation, serving as a benchmark for cartographic quality evaluation. Applied to Chengdu and Hefei, the framework assesses map generalization quality via deviation and evaluation-set methods. The results align closely with geographic evolution and human judgment, delivering objective, robust metrics that significantly enhance the intelligence of automated map generalization.

Keywords: Map generalization; road network; similarity relationship; graph convolutional autoencoder; quality evaluation

1 Introduction

Spatial similarity, as a subset of spatial relationships, plays a crucial role in various domains, including spatial data matching, multi-scale spatial data representation, spatial querying and map generalization quality assessment (Du et al., 2015; Li, 1997; H. Yan & Chu, 2009). Judging spatial similarity is closely related to human cognition. Quantifying spatial similarity promotes geographic understanding and refines theories of spatial relationships, while also providing theoretical and technical support for automatic map generalization (Y. Zhang & Yu, 2024). Road networks are critical geographic elements in maps and are among the most dynamic features of geographical data (Guo, 2022; Zhao et al., 2024). Research into their similarity relationships is a key component of similarity theory.

Map generalization is the process of abstracting and generalizing large-scale spatial data to create small-scale representations. It is a fundamental method for the transformation, integration, fusion, analysis and mining of spatial data (Wu et al., 2017). The quality evaluation of map generalization is the final safeguard in the development of multi-scale geographic databases, providing a theoretical foundation for feedback and optimization in the generalization process. It is also essential for enhancing the precision of automated map generalization systems (Wu et al., 2017).

Map generalization is essentially a state transformation process, with similarity transformation at its core. Quantifying spatial similarity is fundamental to controlling the map generalization process and assessing the quality of the resulting maps (H. Liu et al., 2026; Winter, 2000).

At present, numerous methods for calculating road network similarity have been proposed, researchers have approached the similarity of road networks from various angles, including topology (An et al., 2013; Li & Fonseca, 2006; C. Liu et al., 2016), semantics (Liu et al., 2016; Samal et al., 2004; Y. Wang et al., 2023), geometry (An et al., 2015; Chehreghani & Ali Abbaspour, 2017; Chen et al., 2007; Li et al., 2019), and multi-factor combinations (Qin et al., 2021; Ye et al., 2023). For instance, Li proposed a more comprehensive evaluation of micro-map road network quality by integrating shape, direction, distance, topology, and one-dimensional line features (Li & Wang, 2024). Liu established a similarity calculation model based on topology, geometry, direction, and shape, which produced results closely matching real-world conditions, though the weight assignment of feature factors was somewhat subjective (T. Liu et al., 2012). Chu, on the other hand, built a comprehensive quality evaluation framework for road networks, considering spatial distribution, topological relationships, and distance (Chu et al., 2025). Yan, through power function fitting of three typical road networks, developed a formula that describes how spatial similarity changes with map scale. This quantitative method laid the foundation for using spatial similarity as a constraint in road network generalization (H. Yan et al., 2023). Despite these advancements, several challenges remain in current research on road network similarity. Specifically, existing methods emphasize different aspects – geometry, topology, distribution, and partial semantic features – during similarity computation, but a comprehensive, holistic approach to feature measurement has yet to be developed.

With its unique learning capabilities, deep learning enables machines to imitate human learning and cognition (Ai, 2021). Through backpropagation, it can capture high-level features without human intervention in rule definition, excelling in the handling of complex data and tasks (Harrie et al., 2024; LeCun et al., 2015). Graph Convolutional Networks (GCNs) are a type of deep learning model based on graph structures that address the organizational challenges of nonstandard data. They have emerged as the optimal solution for processing map data. GCNs play a crucial role in map applications. They have already achieved notable success in areas such as pattern recognition (M. Wang et al., 2020; X. Yan et al., 2019; M. Yang et al., 2022; Yu et al., 2022), shape retrieval (X. Yan et al., 2021; Y. Yu et al., 2022), urban functional zone recognition (Hu et al., 2021; Xu et al., 2022) and road network matching and selection (Ma et al., 2022; Xiao et al., 2024; K. Zhang, 2020).

However, it is important to distinguish our research from these existing GNN/GCN-based methods. Most current studies on road selection or matching formulate the problem as supervised or semi-supervised classification tasks, which require extensive manually labeled datasets and may inevitably inherit human subjective biases in cartographic decisions. In contrast, road network similarity calculation necessitates an objective, task-independent structural representation. Our proposed GCAE framework addresses this by employing an unsupervised reconstruction mechanism. By forcing the model to reconstruct the original graph from a compressed latent space without relying on human labels, the GCAE captures the intrinsic topological and geometric semantics of road networks. This makes the resulting latent embeddings more robust and objective for quantifying structural similarity than supervised alternatives.

Therefore, this paper applies deep learning techniques to calculate road network similarity, enabling machines to simulate human learning and analysis processes. The aim is to produce similarity measurements that better reflect human cognitive understanding, thereby providing robust theoretical and technical support for evaluating map generalization.

2 Methodology

As shown in Figure 1, the methodology of this paper can be summarized as follows. First, a road network similarity calculation model is constructed using graph convolutional autoencoders in order to compute multi-scale road network similarity relationships. Building on this, a quantitative relationship is established between road network similarity and map scale variation. Based on this quantitative relationship model, the quality of road network generalization is evaluated. To achieve the above research goals, four aspects will be studied.

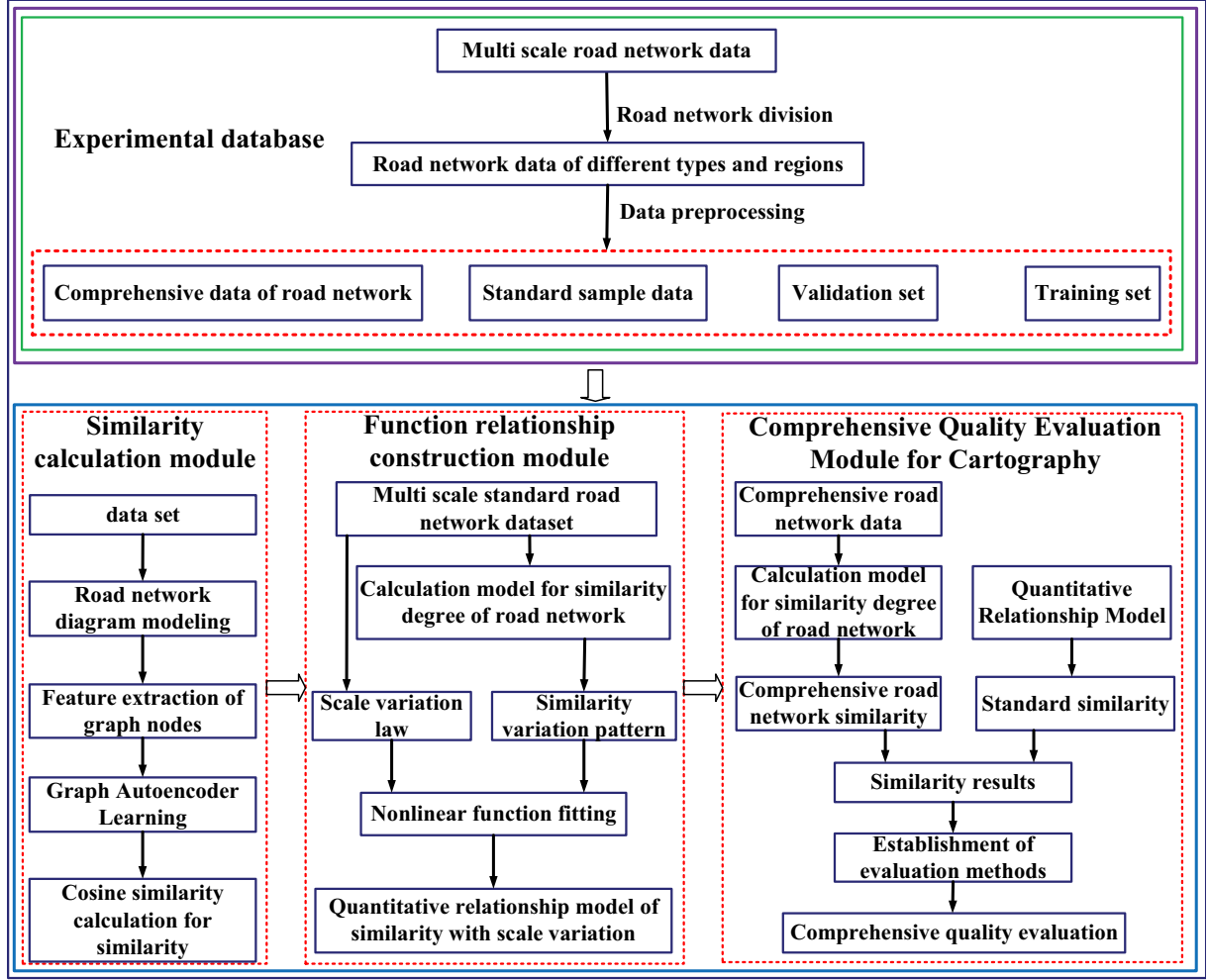


Figure 1: Methodology workflow.

(1) Data preparation and preprocessing: The road network data will be manually divided to create datasets for different regions and types of road. These datasets will then be preprocessed to obtain the necessary training and validation sets, as well as the standard sample map data and comprehensive road network data required for the experiments. The training and validation sets will facilitate the training and learning of the graph convolutional autoencoder model. The standard sample map data will be used to construct a quantitative relationship model between multi-scale road network similarity and scale. The comprehensive road network data will be used to evaluate the quality of generalization.

(2) Development of a road network similarity calculation model based on graph convolutional autoencoders: First, the road network is represented as a graph structure, and its spatial features are assigned to graph nodes from three perspectives: global, local and connectivity. This provides a quantitative representation of the road network graph structure. Next, a graph convolutional autoencoder is used to aggregate and update the node features and structural information of the road network graph. This forms a deep understanding of the road network and encodes the node information. Finally, an average pooling operation is applied to map the complex, high-dimensional feature space into a low-dimensional feature space that is easier to measure, yielding a set of feature vectors. Cosine similarity is then used to calculate the similarity between different road networks.

(3) A quantitative relationship will be established between multi-scale road network similarity and scale variation, based on the similarity calculation model. First, a standard sample map database of multi-scale road networks of different types will be created. Next, the similarity of the multi-scale standard road networks will be computed based on this model, and a set of coordinate pairs representing the similarity

and scale variation of the road networks will be constructed. Finally, six non-linear functions will be used to fit these pairs of coordinates, and the function that best represents the quantitative relationship between multi-scale road network similarity and scale variation will be selected.

Generalization quality evaluation based on the quantitative relationship model: This model can establish the degree of similarity between standard road networks at different scales and can therefore be used as a reference for evaluating the quality of road network generalization. This paper evaluates the quality of road network generalization from two perspectives: deviation and ranking. The deviation-based evaluation method assesses the extent to which features are preserved before and after generalization. The ranking method can assign a quality grade to the generalized road network. First, the ranking evaluation method calculates the standard road network similarity to obtain the standard similarity distribution range. Then, an evaluation set is constructed based on the evaluation set formula and this set is used to assess the quality of the road network’s generalization.

3 Road network similarity calculation based on graph convolutional autoencoders

The road network is an irregular graph data structure, and GCNs are feature extractors that have been specifically designed for graph data. In this paper, we exploit the advantages of GCNs for feature extraction, as well as the ability of autoencoder models to minimize the difference between inputs and outputs. Using an unsupervised approach for end-to-end training enables the model to learn a deep encoding of road network characteristics. Finally, cosine similarity is employed to calculate the similarity between two road networks. This process is illustrated in Figure 2.

3.1 Road network dataset construction and graph modeling

3.1.1 Road network dataset construction

The dataset required for this study was obtained primarily from the OpenStreetMap (OSM) website (www.openstreetmap.org). Road network data from various regions was manually extracted from the downloaded OSM data to form the initial dataset for the experiment. Due to the relatively low level of standardization of OSM road network data, the initial dataset required preprocessing to be cleaned. This includes tasks such as handling pseudo-nodes and isolated roads, to facilitate the subsequent construction of the road network graph structure. In total, 840 road network samples from different regions were extracted. Following preprocessing, 800 standardized datasets were obtained, of which 700 were used to train the model and the remaining 100 to test it.

3.1.2 Road network graph structure construction

In a road network, intersections only reflect the topological connections between roads. However, most important information about the network is concentrated on the edges. The dual graph representation of the road network effectively addresses the problem of representing the spatial features of road segments. In the dual graph, nodes represent road attributes, and edges depict connectivity between roads. Therefore, this study converts the road network into a dual graph and assigns spatial features to its nodes to ensure the data is suitable for deep learning processing.

In the construction of the graph structure for the road network, the first step is to break the roads at the intersection points. A dual graph ($G = \{V, E, W\}$) is then established by converting road segments into nodes and intersections into edges. Let V represent the set of nodes, E represent the set of edges, and W represent the adjacency matrix of the graph. The construction process is illustrated in Figure 3.

It is worth noting that preserving topological connectivity is a critical constraint in map generalization.

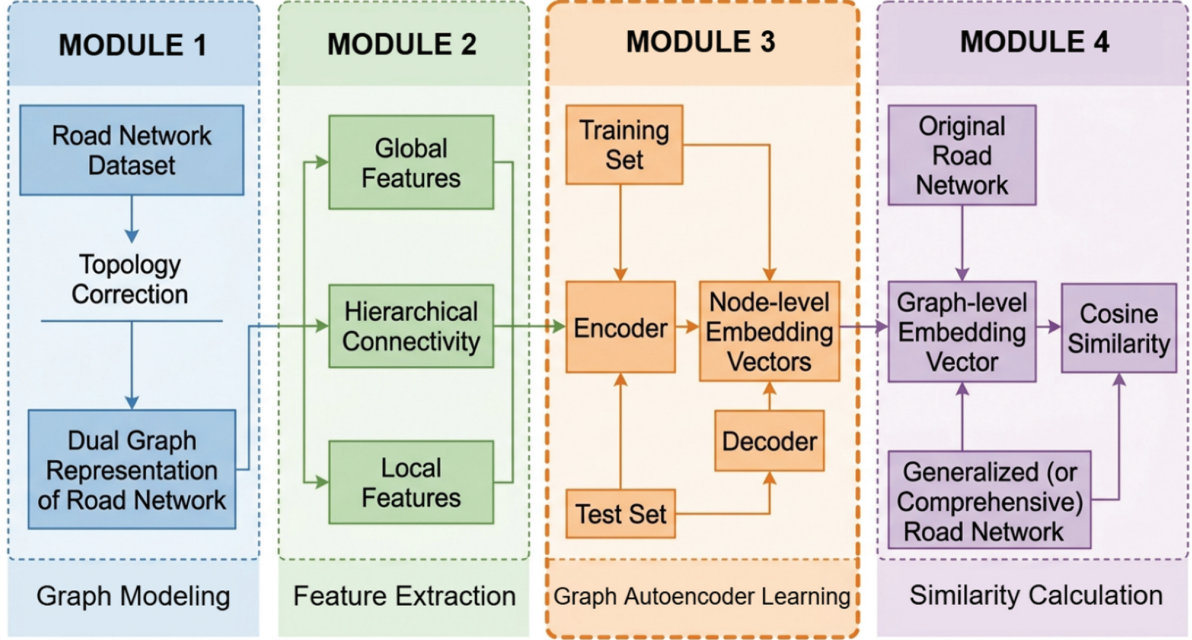


Figure 2: Workflow of road network similarity computation model.

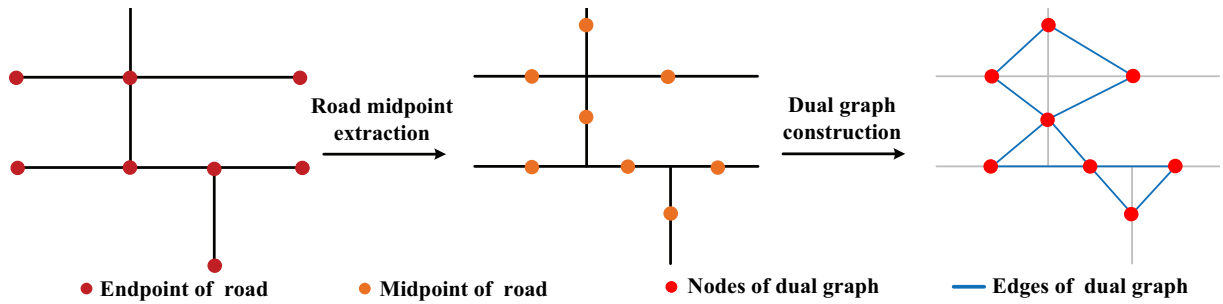


Figure 3: Construction of dual graph.

The dual graph representation natively encodes this topological relationship. In the dual graph, road segments are represented as nodes, and their spatial intersections are explicitly mapped as edges. Consequently, the topological connectivity of the entire road network is directly and rigorously captured by the adjacency matrix. Since our proposed GCAE model utilizes this adjacency matrix as its primary structural input and optimizes for graph reconstruction, the topological connectivity – and its consistency across different generalization scales – is inherently embedded and preserved within the learned latent representations.

3.2 Road network graph node feature extraction

This study employs a Graph Convolutional Autoencoder (GCAE) to learn the features of nodes in a road network. These node features, derived from the dual graph, form a critical foundation for calculating road network similarity. To ensure the selected features effectively capture the characteristics of the road network, three types of feature are considered: connectivity, global distribution, and local.

3.2.1 Connectivity features

The concept of node degree originates from complex network theory, where it represents the number of connections a node has with other nodes (Y. Wang, 2014). Due to the intricate structure of road networks, node degree reflects not only the connectivity of the network, but also the relative importance of road segments. The higher the node degree, the more significant the corresponding road segment is within the network. In this study, therefore, node degree is used as a key metric to capture topological similarity in road networks.

3.2.2 Global distribution features

When observing an object, humans tend to recognize its overall features first before focusing on the details.

A road network consists of multiple road segments. After transforming it into a graph structure, we can obtain connectivity information, but the overall structural characteristics require further description based on the spatial position of each segment.

In this study, the arithmetic mean of the midpoints of all road segments in a road network sample is selected as the reference point. For each road segment, the angle (α) and distance difference (Δl) between the reference point and the two endpoints of the segment are computed. These two features provide a comprehensive description of the global structure of the road network from directional and distance-based perspectives. Using both features ensures the uniqueness of each road segment's spatial position within the network.

As illustrated in Figure 4, let the center point of the road network be denoted as O , for node P , its two corresponding endpoints are A and B . Connect OA , OB , denote the length of OA as L_1 , the length of OB as L_2 , and α as the included angle. The calculation formula for the global feature of node P is as follows:

$$O = (X_0, Y_0) = \frac{1}{N} \sum_{i=1}^N (X_i, Y_i)$$

$$\Delta l = l_1 - l_2 \tag{1}$$

$$\alpha = \arccos \left(\frac{L_{OA}^2 + L_{OB}^2 - L^2}{2 * L_{OA} L_{OB}} \right) \tag{2}$$

3.2.3 Local structural features

The local features of a road network capture the characteristics of individual road segments. The following parameters have been selected to effectively describe the local structural features of the road network and encode each road segment: length, tortuosity, mean direction and the major axis direction of the minimum bounding rectangle (MBR).

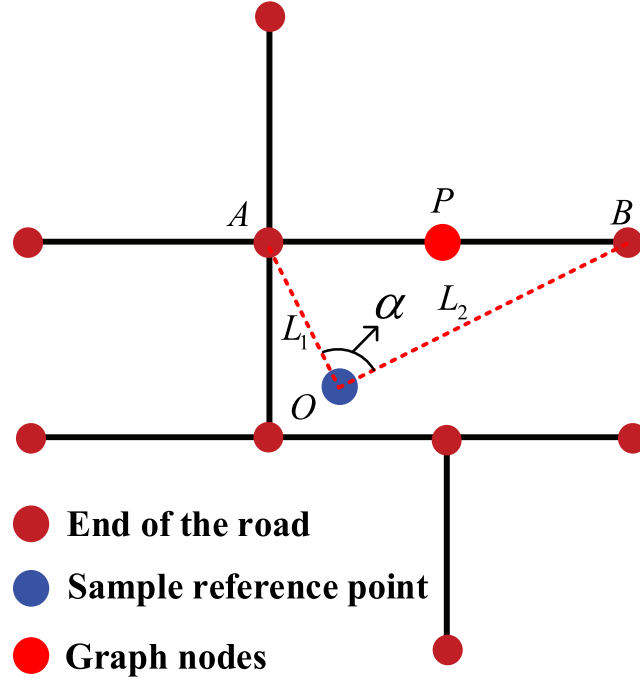


Figure 4: Schematic diagram of global distribution features calculation.

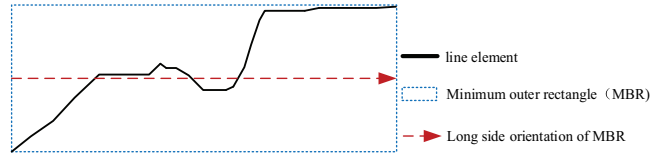


Figure 5: Major axis direction of the MBR.

(1) Length: Length is a fundamental characteristic of linear features and provides a direct measure of the shape of a road segment. The calculation formula is given below:

$$L = \sum_{i=1}^n \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (3)$$

(2) Tortuosity: The tortuosity of a road segment is defined as the ratio of its total length to the Euclidean distance between its two endpoints.

(3) Major Axis Direction of the Minimum Bounding Rectangle (MBR): The direction of a linear feature can be described at local and global levels. In this study, the direction of the major axis of the minimum bounding rectangle (MBR) of a road segment is used to represent its overall orientation, which is described quantitatively using the azimuth angle. As illustrated in Figure 5, this method provides a standardized measurement of road segment orientation.

(4) Mean Direction: The ratio of the length of each polyline segment to the total road length is used as a weighting coefficient. The direction angle of each segment is multiplied by its corresponding weight

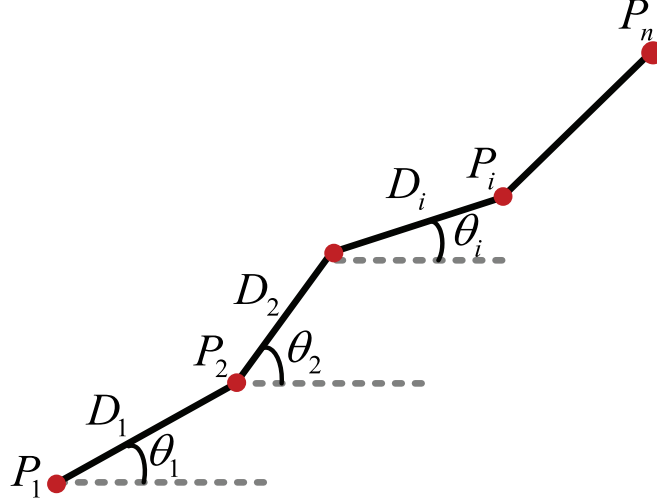


Figure 6: The calculation of mean direction.

to obtain the weighted direction angle of each road segment. Finally, the weighted direction angles are summed to derive the mean direction value. Incorporating segment length as a weighting factor means that the mean direction considers both direction and angle, providing a better representation of local geometric variations in road segments.

As shown in Figure 6, let L denote the total length of a road segment, and let D_i represents the length of the i -th ($i = 1, 2, 3, \dots, n$) sub-segment. The length coefficient (λ_i) is computed as follows:

$$\lambda_i = \frac{D_i}{L} \quad (4)$$

The mean direction of the entire road segment is then calculated using Equation (5):

$$\theta_{avg} = \sum_{i=1}^n \lambda_i \theta_i \quad (5)$$

Where θ_i represents the angle between the i -th sub-segment and the positive x-axis.

3.3 Construction of graph convolutional autoencoder

An autoencoder consists of an encoder and a decoder. It is primarily used for learning representations and the efficient encoding of raw data. Autoencoders are typically trained in an unsupervised manner, with the aim of minimizing the difference between the original and reconstructed samples, without the need for labeled data (Deng & Yu, 2014). The graph convolutional autoencoder (GCAE) combines the feature extraction capabilities of graph convolutional networks (GCNs) with the reconstruction ability of autoencoders. This study adopts Kipf and Welling's (2016) graph autoencoder model, which is trained in an unsupervised manner, to ensure that the extracted features accurately preserve the spatial structure of the original road network. This facilitates the computation of road network similarity.

In the graph autoencoder, the encoder consists of multiple graph convolutional layers that are responsible for mapping the input graph into a vector space. This process obtains a vectorized representation of the road network's spatial characteristics. The decoder then attempts to reconstruct the original input graph. In the encoder's output, each row represents the feature vector of a node in the graph. In deep learning, the inner product is commonly used to quantify cosine similarity between vectors. Therefore, by computing the inner product of each row of the latent variable representation, an output adjacency matrix can be generated. This approach is computationally efficient and effectively captures the spatial topological structure of the road network. This enables the model to learn a richer, more abstract representation of the network and offers new insights into road network analysis.

To derive graph-level embeddings for road networks and facilitate the computation of cosine similarity, this study applies average pooling to the output vectors of the encoder. This transformation converts node-level embeddings into fixed-length, one-dimensional vectors. Figure 7 shows the graph autoencoder model used to compute road network similarity. Here, A represents the input adjacency matrix, A' represents the reconstructed adjacency matrix from the decoder and Z represents the node-level embedding matrix from the encoder. The training objective is to minimize the difference between the input and output. Each row of Z corresponds to a node embedding; the horizontal dimension represents the number of features per node and the vertical dimension represents the number of nodes. The graph-level embedding vector is obtained by computing the mean of the columns of Z , and this graph aggregation approach captures the overall characteristics of the road network while resolving the issue of inconsistent node counts. This enables effective multi-scale road network similarity computation.

The model is trained using an unsupervised, label-free cross-entropy loss function. In machine learning, cross-entropy is commonly employed to quantify the disparity between actual and predicted probability distributions. By minimizing the cross-entropy loss, the model can better approximate reality, thereby improving its performance and accuracy. As the training objective is to minimize the difference between the input and output rather than to reconstruct labeled data, the label-free cross-entropy loss function is used to optimize the model. A smaller cross-entropy value indicates a higher degree of similarity between the two probability distributions, resulting in more accurate model predictions. The cross-entropy loss function is defined as follows: where σ denotes the Sigmoid activation function, N represents the total number of training samples, y_i denotes the ground-truth label of the i -th sample, and z_i represents the encoder's output (logit) for the i -th sample prior to the Sigmoid transformation. The loss function incorporates both positive and negative samples:

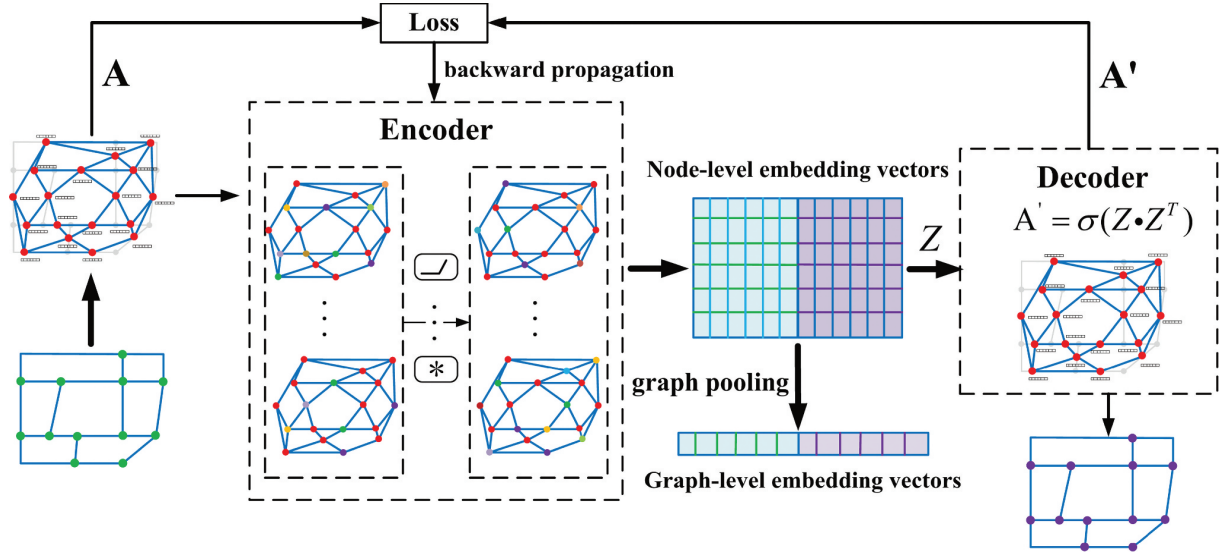


Figure 7: The graph autoencoder model used for computing road network similarity.

$$Loss = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\sigma(z_i)) + (1 - y_i) \log(1 - \sigma(z_i))] \quad (6)$$

- Positive samples correspond to edge indices in the original adjacency matrix.
- Negative sample edge indices are randomly generated, but the number of edges remains the same as that of the positive samples.

3.4 Road network similarity computation

Training the proposed model relies on both the encoder and the decoder. However, only the trained encoder is required for the final road network similarity computation. The encoder's output consists of node-level embedding vectors, which are high-dimensional representations. To facilitate the computation of similarity, these node-level vectors must be aggregated into a single, fixed-size graph-level vector. The similarity between two road networks is then measured by the cosine similarity between their graph-level embedding vectors. The formula for cosine similarity is given below:

$$\text{sim}_{road} = \frac{r^a \cdot r^b}{\|r^a\| \|r^b\|} = \frac{\sum_{i=1}^m r_i^a \times r_i^b}{\sqrt{\sum_{i=1}^m (r_i^a)^2} \times \sqrt{\sum_{i=1}^m (r_i^b)^2}} \quad (7)$$

Where r^a and r^b represent the graph-level embedding vectors of road networks a and b , and m denotes the dimension of the graph-level vector.

It should be clarified that the map scale parameter is not explicitly incorporated as an input feature within the GCAE model itself. The proposed GCAE functions as a pure structural feature extractor, designed to learn spatial representations and compute similarities based solely on the graph's topological and geometric properties. The scale parameter is introduced as an independent variable only in the subsequent analysis stage (as detailed in Section 4.2), where the GCAE-computed similarity values are correlated with their corresponding map scale changes to fit a quantitative mathematical relationship.

3.5 Experimental results and analysis

3.5.1 Data preparation

The validation data used in this study were obtained from national, multi-scale topographic map datasets. The original road network data was at a scale of 1:10,000. Selected areas of this road network underwent data preprocessing to generate the initial datasets for this experiment. These initial datasets covered road networks from three regions: Wuhan, Shenzhen and Kunming.

To ensure the diversity and validity of the sample, the initial road network data was generalized with the involvement of multiple experts with extensive cartographic experience and expertise in similarity theory. This process yielded road networks at five different scales: 1:25,000, 1:50,000, 1:100,000, 1:250,000 and 1:500,000.

A total of three initial road networks were processed, each undergoing five generalization steps. This resulted in 15 road network datasets, which were used for validation in this experiment. Figures 8–10 show visual representations of the three networks.

3.5.2 Parameter sensitivity analysis

During model training, the number of convolutional layers and the kernel size are two parameters that significantly impact the model's performance. Further analyses were conducted to investigate their effects, with the training results illustrated in Figures 11 and 12.

By comparing the loss curves in Figure 11(a) - (d), we can see that, for a fixed number of convolutional layers, the loss generally decreases as the embedding dimension increases. However, in Figure 11(c), the loss at 128 kernels is lower than at 256 kernels. Similarly, Figures 12(a) - (d) show that increasing the number of convolutional layers results in lower loss when the embedding dimension remains constant. However, the difference becomes marginal when the number of convolutional layers exceeds four or five.

Generally, higher embedding dimensions and more convolutional layers lead to lower loss. This is probably because smaller embedding dimensions introduce greater fluctuations in features, making it more difficult for the model to reconstruct them, whereas higher-dimensional embeddings produce smoother feature representations that are better suited to reconstruction. Furthermore, increasing the number of convolutional layers improves the model's ability to capture richer neighborhood feature information, thereby enhancing reconstruction accuracy.

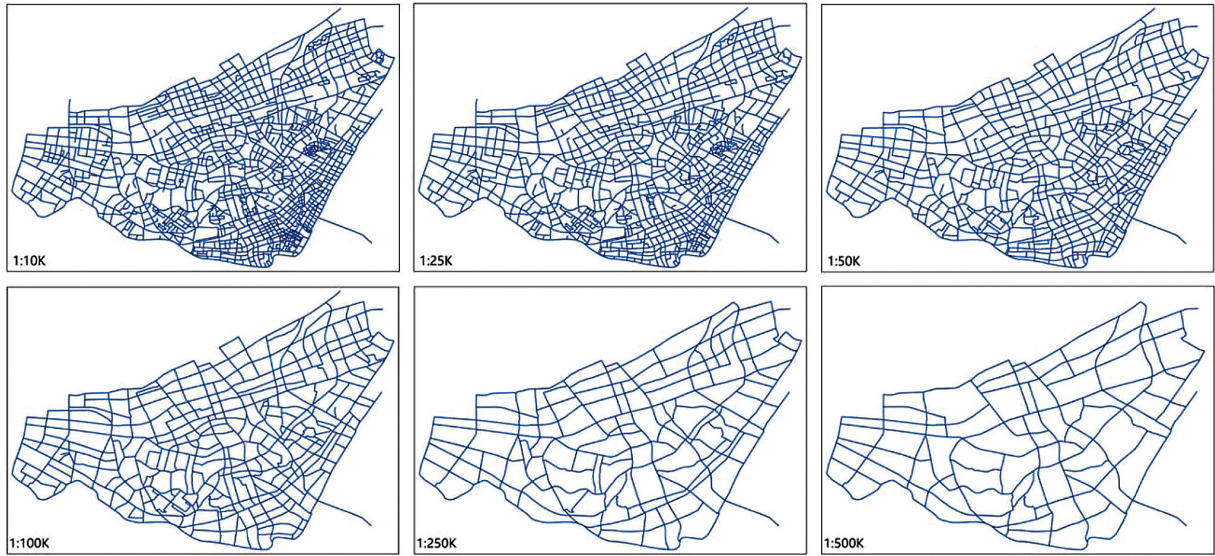


Figure 8: Multi-scale road network in Wuhan.

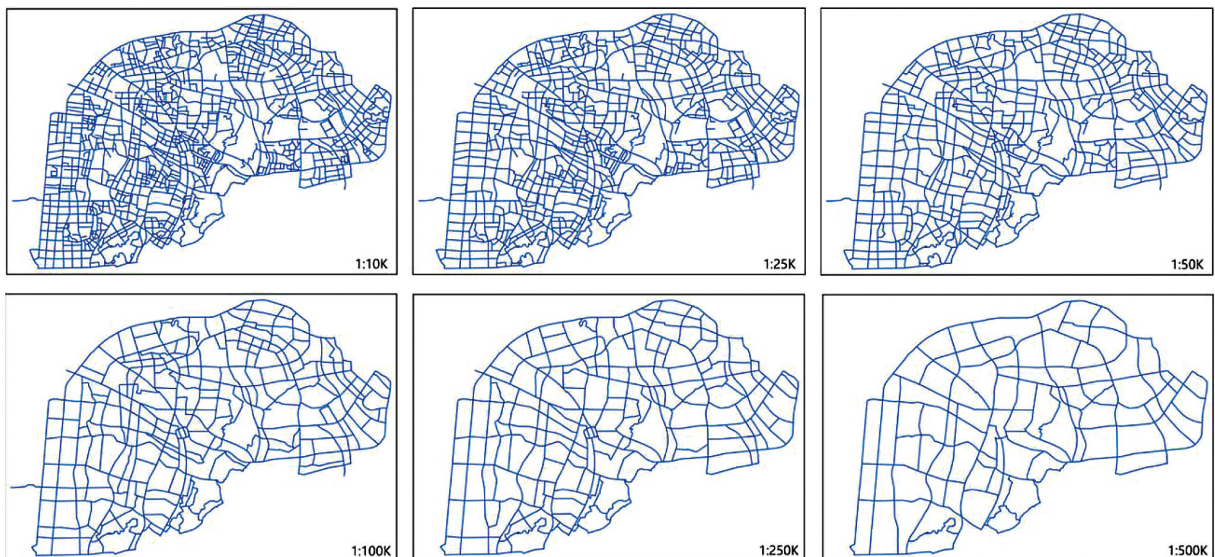


Figure 9: Multi-scale road network in Shenzhen.

Although a lower loss indicates that the reconstructed graph is closer to the original input, it does not necessarily reflect the effectiveness of the encoding process (X. Yan et al., 2022). Furthermore, embedding dimensions that are too high reduce the model’s ability to compress information, enabling it to reconstruct data simply through replication and mapping. Similarly, an excessive number of convolutional layers can impose a heavy computational burden, potentially leading to gradient vanishing or explosion and ultimately degrading model performance.

Based on the above analysis, the final encoder architecture comprises four convolutional layers, each containing 128 convolutional kernels. The first layer serves as the input layer. Here, the input feature vector has a dimension of 7 and the embedded feature vector has a dimension of 128, both using the ReLU activation function. Layer two to four are hidden layers, each with input and embedded feature vectors of dimension 128 and using the ReLU activation function. The decoder reconstructs the original input graph by computing the inner product and applying a sigmoid function to normalize the values within the range (0, 1).

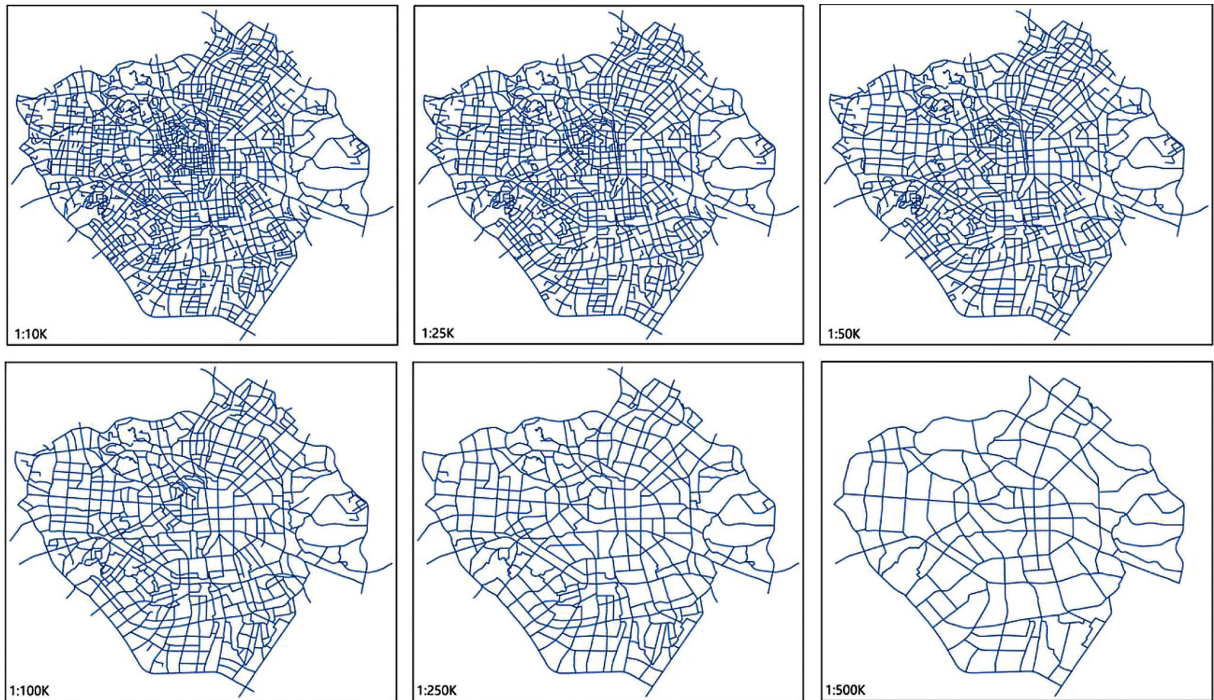


Figure 10: Multi-scale road network in Kunming.

During model training, we used a mini-batch gradient descent approach, dividing the training data into multiple batches of 16 samples each. We also adopted the Adam optimizer to dynamically adjust the model parameters, with the aim of obtaining the optimal solution within 500 iterations. The initial learning rate was set to 0.001 and the weight parameters were initialized accordingly. Using the back-propagation algorithm, we iteratively fine-tuned the model parameters to ensure continuous convergence and performance improvement, thereby laying a solid foundation for subsequent tasks.

Finally, the model was trained and validated using the 700 training samples and 100 validation samples outlined in Section 3.1.1. The model’s reconstruction accuracy was assessed based on precision, and the final training loss, validation loss and validation accuracy are presented in Figure 13.

As shown in Figure 13, after 500 iterations, the model has essentially converged, with the loss value stabilizing at around 0.75. With a validation accuracy exceeding 0.98, the model demonstrates high reconstruction precision for the original input graph, as well as strong generalization performance.

The validation accuracy (>0.98) reflects high reconstruction precision rather than overfitting or task simplicity. First, our dataset of 800 real-world samples from diverse cities (e.g. Wuhan, Shenzhen) encompasses complex grid, radial, and hybrid topologies, ensuring generalized spatial learning. Second,

parameter sensitivity analysis (Figures 11 and 12) led to an optimized 4-layer, 128-kernel architecture that balances representational power with model parsimony. Finally, the stable, non-divergent convergence of training and validation loss curves (Figure 13) empirically confirms model stability and its ability to faithfully capture essential road network structures.

3.5.3 Road network similarity measurement experiment

To validate the proposed method, we conducted experiments to measure the similarity of road networks using the validation dataset described above. Table 1 shows the results of calculating the similarity for the three selected road networks from different regions, as discussed in Section 3.5.1.

As expected, the results in Table 1 show that as the map scale decreases, the similarity values also decrease. Specifically, the similarity values for the three datasets are distributed as follows:

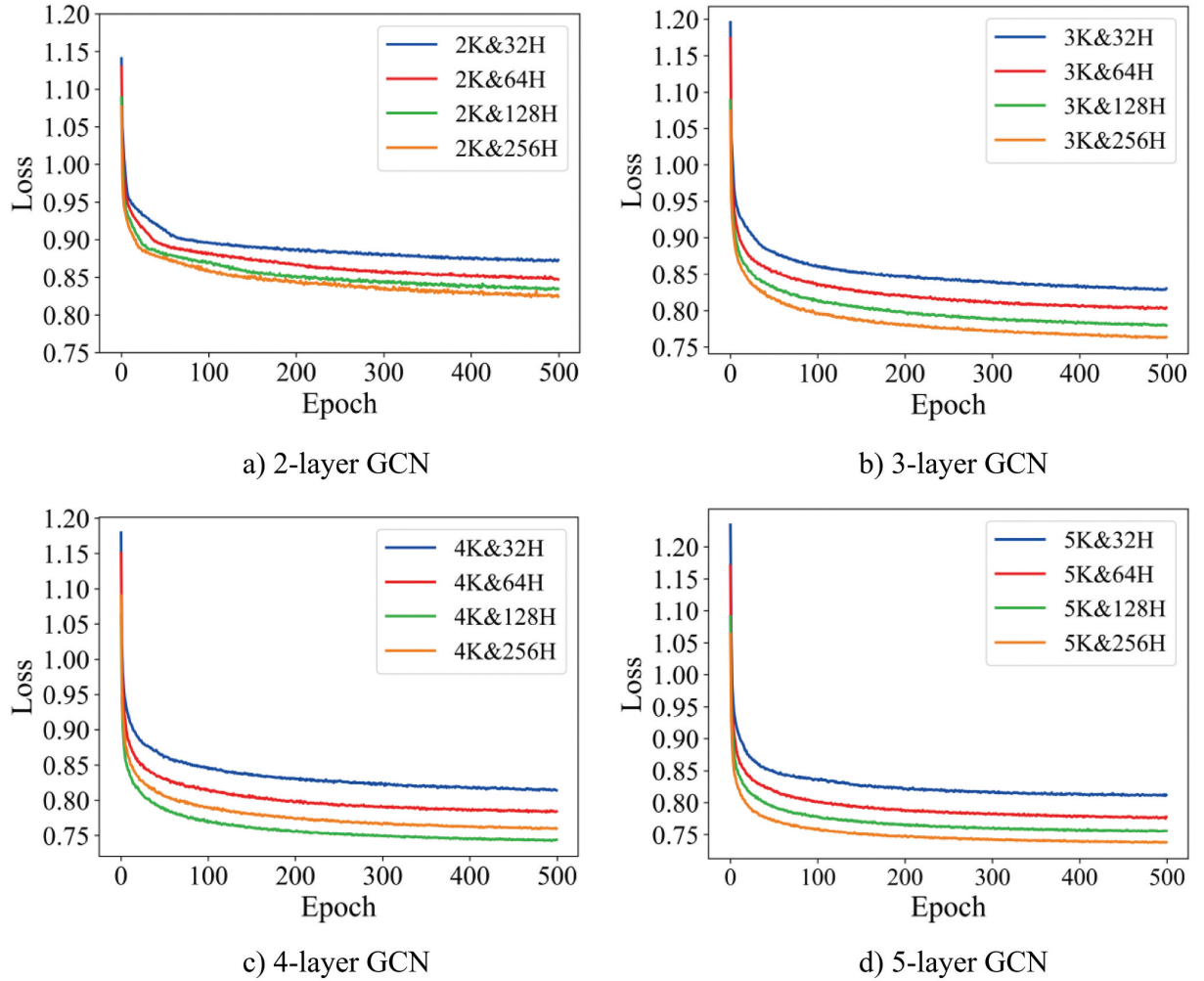


Figure 11: Graph of loss variation with increasing embedding dimension.

1:10,000 – 1:25,000: (0.9121–0.9383)
1:10,000 – 1:50,000: (0.8265–0.8529)
1:10,000 – 1:100,000: (0.7064–0.7431)
1:10,000 – 1:250,000: (0.6279–0.6413)
1:10,000 – 1:500,000: (0.5131–0.5446)

These results demonstrate that the similarity values calculated by our model align with the anticipated scale variations, thereby validating the reliability of our approach. Additionally, the similarity values among the three road networks exhibit relatively small differences for each specific scale. The observed

variations can be attributed to two main reasons: (1) The three datasets originate from different regions, resulting in significant variations in road network types and structures; and (2) the road networks at different scales within the same region were generated through cartographic generalization, meaning that the data does not perfectly correspond to the actual scale variations. Secondly, the road networks at different scales within the same region were generated through cartographic generalization, meaning the data does not perfectly correspond to actual scale variations.

To evaluate the model’s rotation robustness, experiments were conducted on road networks with distinct spatial patterns – grid-based (Chengdu) and organic-radial (Shanghai) – while ensuring topological consistency via network diagnostics (node/edge count error $<0.15\%$). The results reveal that the model’s similarity response is governed by the directional anisotropy of the urban pattern. For grid-based networks with high directional regularity (Avg. Degree 2.95), global rotation significantly shifts the absolute directional features, leading to a lower similarity (≈ 0.2). Conversely, organic-radial networks exhibit higher isotropy (Avg. Degree 1.84), maintaining similarity above 0.8. This differentiation demonstrates that the GCAE model captures intrinsic spatial logic rather than geometric artifacts, effectively distinguishing between direction-dependent and topology-dependent urban structures.

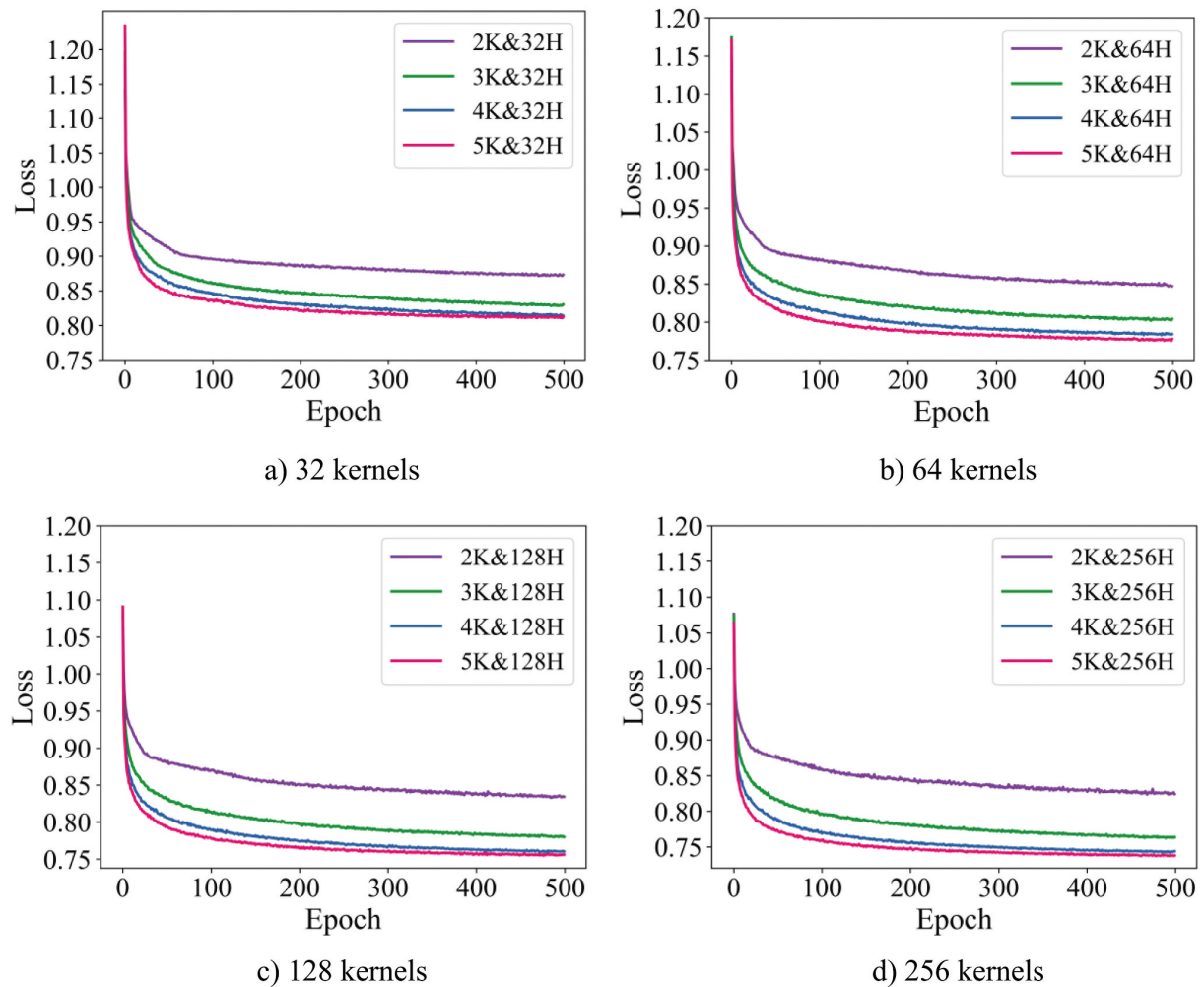


Figure 12: Graph of loss variation with increasing number of convolutional layers.

3.5.4 Similarity perception experiment

Similarity is a subjective human perception. To verify whether the results of the model’s similarity calculation align with human cognitive perception, a psychological perception experiment in the form

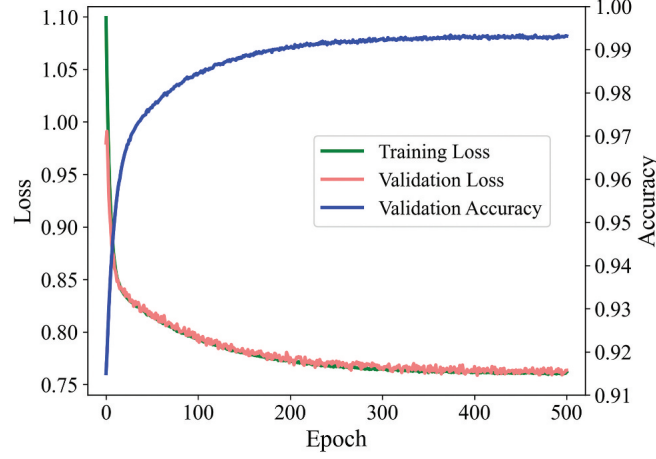


Figure 13: The training loss, validation loss and validation accuracy of the model.

of a questionnaire survey was conducted. Participants evaluated the similarity between generalized road networks and their original samples.

In the similarity perception experiment, participants were recruited through a combination of targeted invitations and random recruitment. The participant pool consisted of professional and nonprofessional groups. Professional participants are defined as individuals with formal academic or professional backgrounds in Cartography, GIS, or related geospatial sciences (e.g. university faculty, graduate students, or industry practitioners), possessing theoretical knowledge of spatial cognition and map generalization. In contrast, nonprofessional participants refer to general map users without specialized training, representing the intuitive public perception of road network similarity.

Table 1: Similarity results for the three selected multi-scale road networks.

similarity	1:1–1:2.5	1:1–1:5	1:1–1:10	1:1–1:25	1:1–1:50
Wuhan	0.9383	0.8529	0.7431	0.6279	0.5131
Shenzhen	0.9253	0.8275	0.7064	0.6413	0.5446
Kunming	0.9121	0.8265	0.7385	0.6329	0.5282

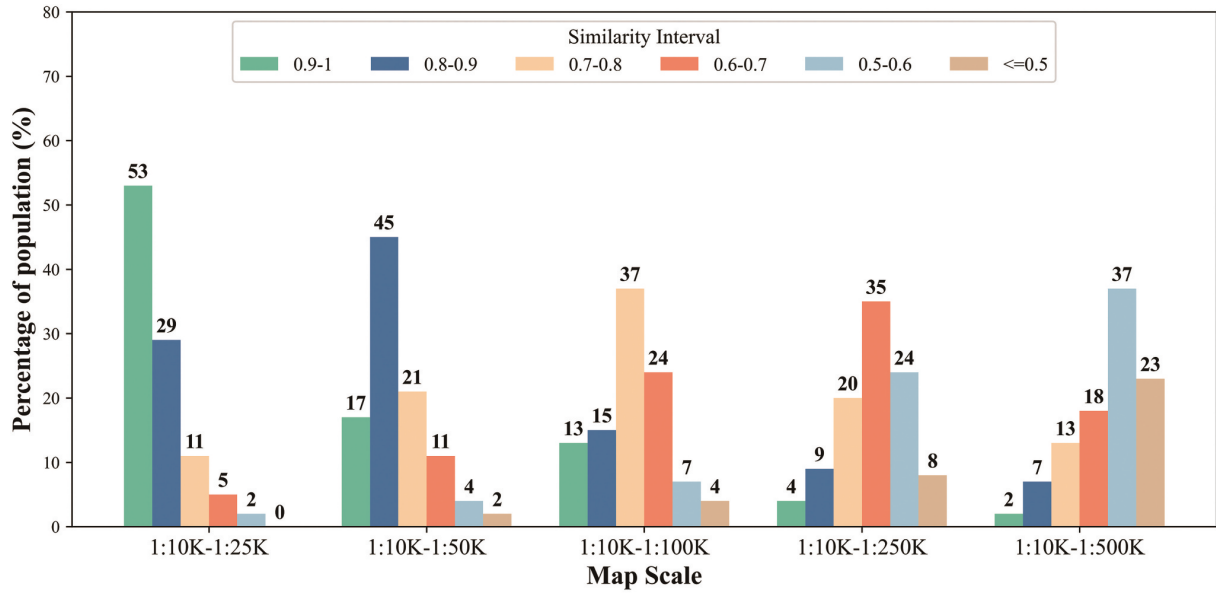
As human perception can be influenced by various contextual factors, the questionnaire divided similarity into six categories: 90–100%, 80–90%, 70–80%, 60–70%, 50–60% and below 50%. Respondents were asked to select the category that best represented their perception. A total of 420 questionnaires were collected for this experiment, 60% of which were completed by professionals and 40% by nonprofessionals. The survey results are illustrated in Figures 14–16.

As can be seen from Figures 14–16, in these three psychological perception experiments both professionals and nonprofessionals tended to rate the similarity of the generalized road networks on five different scales as follows: 0.9–1.0, 0.8–0.9, 0.7–0.8, 0.6–0.7 and below 0.5. Their cognitive results were more in alignment with the model’s calculated results.

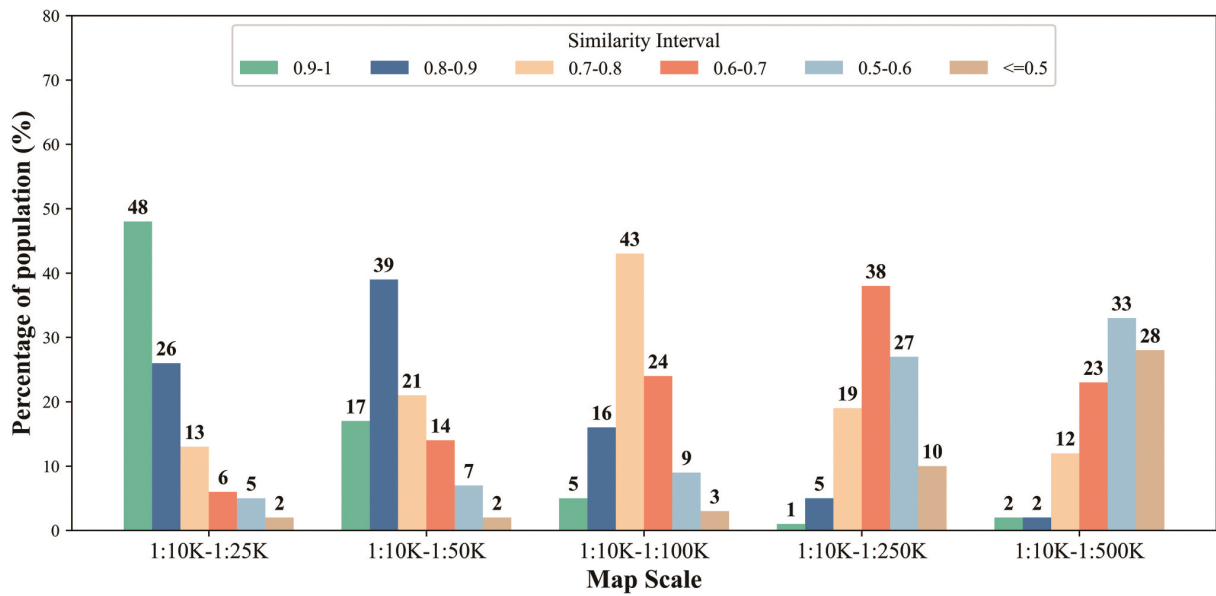
4 Application of road network similarity calculation model in map generalization quality evaluation

4.1 Construction of multi-scale road network sample library

The multi-scale road network sample library presented in this paper comprises two main sections: standard sample data and generalized road network data. Currently, multi-scale urban and national topographic maps provide the data necessary for creating the multi-scale road network sample library. The

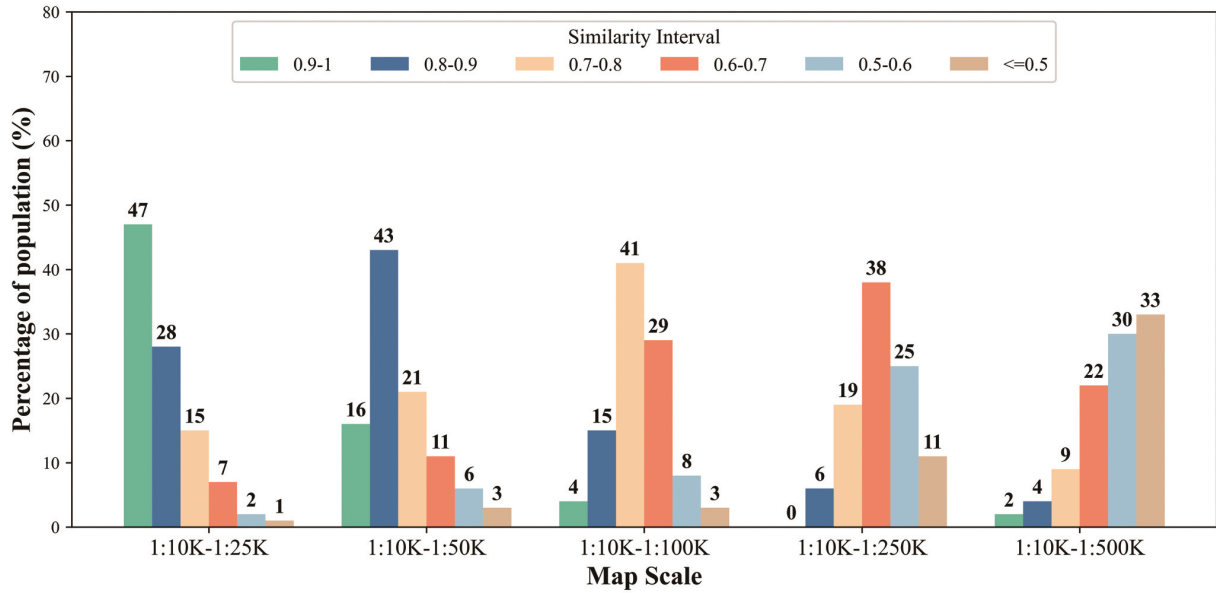


a) Professional

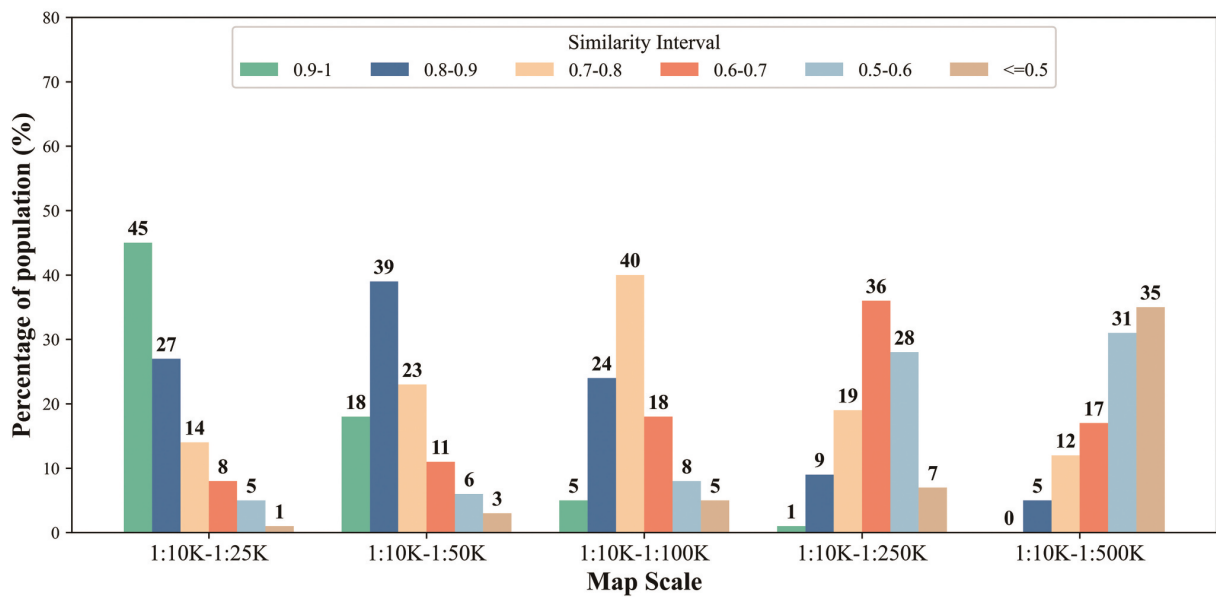


b) Non-professional

Figure 14: Statistical results of multi-scale road network similarity questionnaire survey in Wuhan.

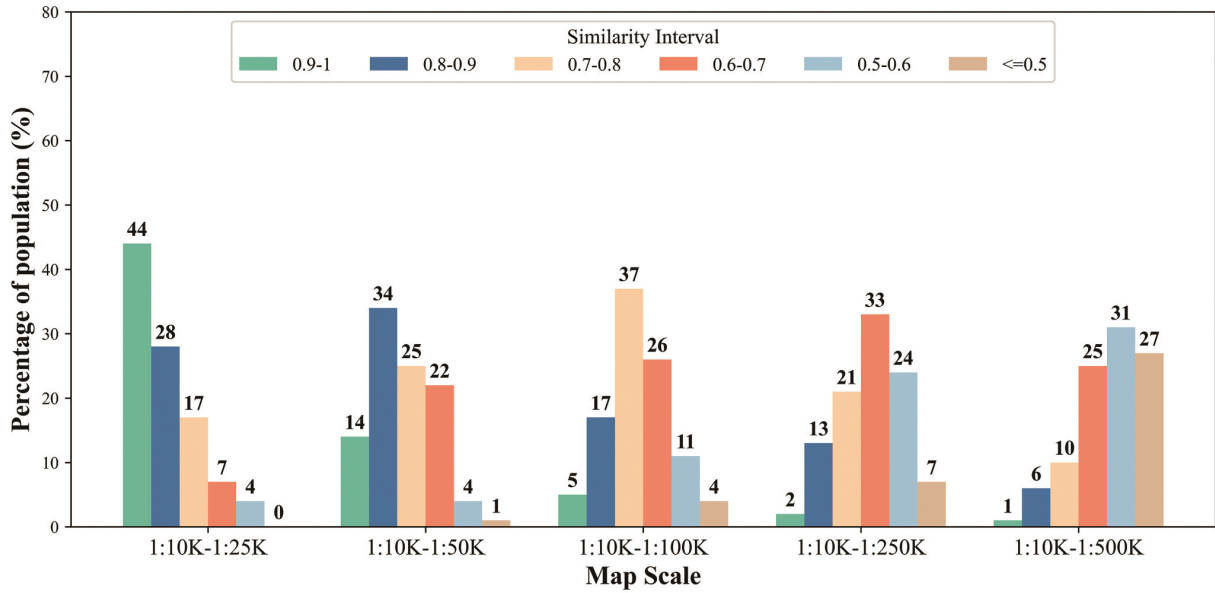


a) Professional

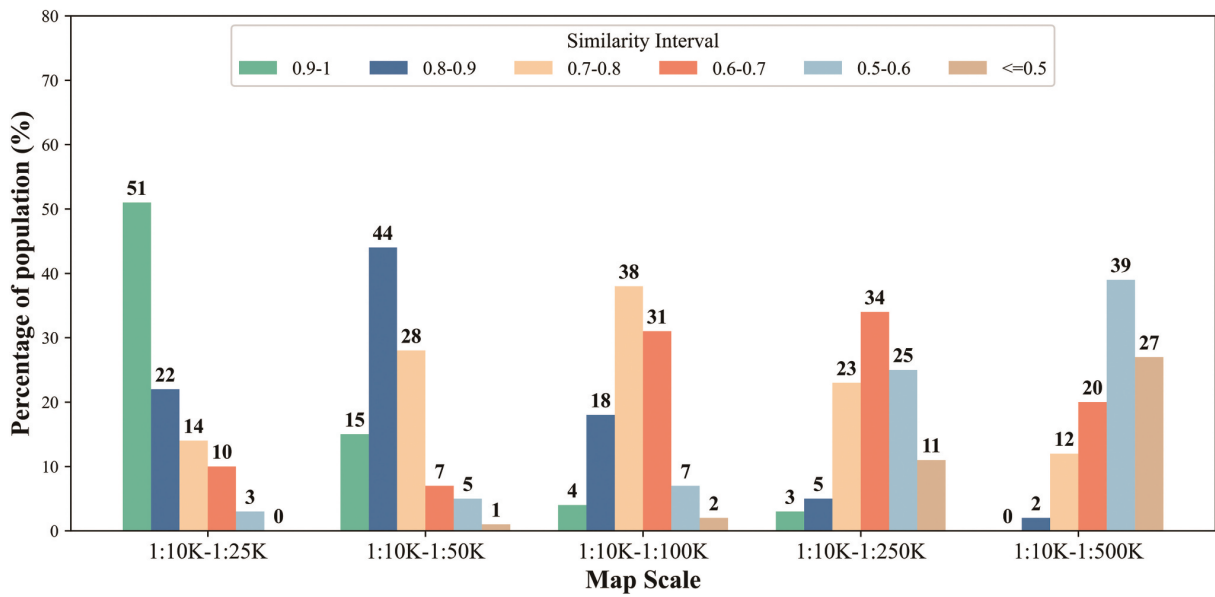


b) Non-professional

Figure 15: Statistical results of multi-scale road network similarity questionnaire survey in Shenzhen.



a) Professional



b) Non-professional

Figure 16: Statistical results of multi-scale road network similarity questionnaire survey in Kunming.

evaluation of cartographic generalization quality is a comprehensive and complex issue. Significant differences exist between elements in terms of topology, geometry, and other characteristics. It is also crucial to verify the consistency of the similarity patterns presented by these elements across different scales. Therefore, a large, general sample library must be constructed to ensure the universality of the experimental results.

4.1.1 Data preprocessing and feature analysis

Data preprocessing is necessary to meet the input requirements of the model. This primarily involves handling abnormal roads, constructing the road network dual graph and extracting segment features. Any road network downloaded directly from sources needs to undergo a topology check. The main purpose of this check is to remove isolated segments. If these are not removed, the constructed dual graph of the road network may become disconnected, which would affect the subsequent experimental results. Once the topology check and correction have been completed, some of the road network's complex intersections need to be simplified to obtain a more standardized network. Next, a road network stroke is constructed and a dual graph of the road network is created. Then, the features of the road network segment nodes are extracted. Finally, the features are normalized to obtain the input data for the model.

After feature extraction, a Pearson correlation analysis was conducted to evaluate the independence of the seven initialized geometric attributes and the diversity of the dataset. As illustrated in Figure 17, the correlation coefficients between most feature pairs are remarkably low (predominantly $|r| < 0.2$). This high degree of orthogonality indicates that the selected features – such as sinuosity, central distance, and MBR direction – provide complementary information with minimal redundancy. Such low correlation ensures that the model can learn robust spatial representations from diverse geometric perspectives. Furthermore, it underscores the non-trivial nature of the road network recognition task, as no single attribute can independently determine the similarity, thereby justifying the necessity of employing a deep learning architecture like GCAE for high-dimensional feature integration.

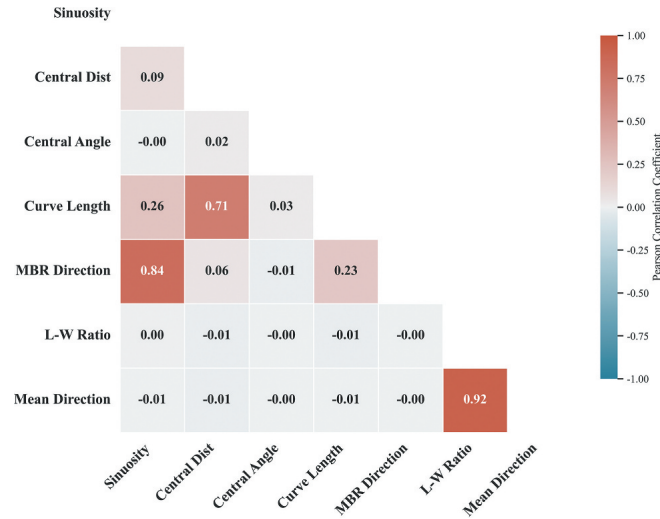


Figure 17: Pearson correlation matrix of the seven initial geometric features.

4.1.2 Construction of standard sample library

A standard sample map is a map that is representative of typical areas and is created according to regulations, mapping specifications or cartographic outlines. A quantitative relationship model for multi-scale road network similarity across scale variations is constructed using data from the standard sample library. A rich and high-quality standard sample library can make the quantitative relationship model

more universal and representative, providing a better basis for evaluating the quality of cartographic generalization.

The cartographic generalization standard sample library must be established in accordance with the “National Basic Scale Map Reduction Specification.” The multi-scale maps in the standard sample library include road network data at the following scales: 1:10,000, 1:25,000, 1:50,000, 1:100,000, 1:250,000 and 1:500,000. To make the data more representative, the standard sample library should encompass various types of road network. Currently, road network distribution patterns can be broadly categorized into four types: grid, freeform, ring-radiating, and hybrid.

Different cities have distinct spatial distribution patterns, which lead to variations in road network types. For instance, Beijing and Chengdu have circular, radiating road networks, whereas Lanzhou has a grid pattern with strip-like features. Road networks of the same type exhibit certain regularities of similarity as the scale changes. For instance, a grid-patterned road network at a large scale should maintain a similar pattern when converted to a smaller scale, which can be considered structural similarity. However, road networks with different patterns exhibit different variations when the scale changes. Therefore, when constructing the standard sample library, it is important to consider the different types of road network. A quantitative similarity relationship model built on such a foundation would be more universal and representative.

4.2 Construction of quantitative relationship model between road network similarity and scale variations

4.2.1 Selection of nonlinear functions

We generally prefer to use functions with multiple parameters when facing fitting problems. However, when addressing specific issues, functions with many parameters may not always produce the best results. As the famous physicist Fermi once said, “Give me four parameters, and I can fit an elephant.” This shows that there is no direct relationship between the number of parameters and the quality of the fit. By establishing a function with an appropriate number of parameters, data can be fitted with arbitrary precision. Similarly, in cartographic generalization, there is a discernible pattern between multi-scale map changes and similarity. The general rule for this relationship is that similarity decreases as scale variation increases. Therefore, a simple functional relationship can be chosen to establish the connection between these variations.

When selecting a non-linear function for data fitting, it is advisable to start with a two-parameter function (with only two free terms, a and b) and then progressively consider multi-parameter functions. After thorough consideration, this paper presents six candidate functions: the linear, power, exponential, logarithmic, quadratic and cubic functions. The functional forms are given as follows:

$$y = ax + b \quad (8)$$

$$y = ax^b \quad (9)$$

$$y = ae^{bx} \quad (10)$$

$$y = a \ln x + b \quad (11)$$

$$y = ax^2 + bx + c \quad (12)$$

$$y = ax^3 + bx^2 + cx \quad (13)$$

After completing the function fitting, it is necessary to evaluate the fitting performance using the coefficient of determination, denoted as R^2 . The closer R^2 is to 1, the better the fitting result.

4.2.2 Construction of the quantitative relationship model

A certain regularity exists between spatial similarity relations and changes in map scale. This section uses the previously selected non-linear functions and data from the standard sample library to identify this pattern by conducting experiments.

First, thirteen different regional standard road networks are selected from the sample library. Then, the similarity calculation model is used to quantify their similarity values. The results are shown in Table 2.

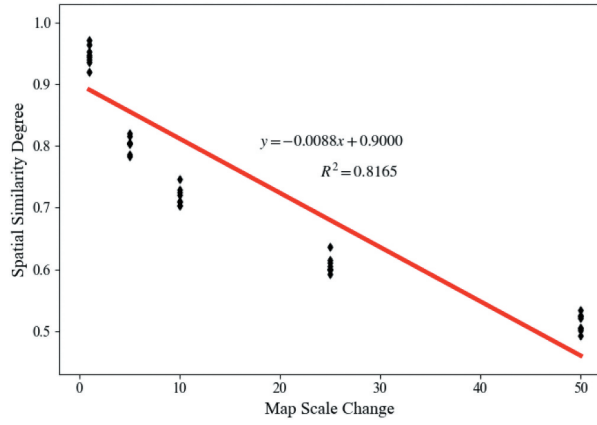
For each road network, the scale change is taken as the horizontal coordinate and the similarity value as the vertical coordinate. Coordinate pairs $(C_s, \text{sim}(M_s, M_r))$ are constructed, where C_s represents the scale change ($C_s = S/S_1$; S_1 is the scale of the original standard map, and S_2 is the scale of the road network being compared) and $\text{sim}(M_s, M_r)$ represents the similarity between the road network at different scales and the original standard road network. The similarity between the original standard road network and itself is denoted as (1, 1). There are six coordinate pairs for each of the 13 regions (1:10,000, 1:25,000, 1:50,000, 1:100,000, 1:250,000 and 1:500,000), resulting in 78 pairs in total. These 78 coordinate pairs are fitted using the six previously established functions. The resulting fitting curves are shown in Figure 18.

The fitting performance of the six functions mentioned above then needs to be evaluated. As can be seen by comparing the six fitting curves in Figure 18, the linear function performed significantly poorly, while the exponential function also performed inadequately. Although the power function fit was relatively good, it was not as effective overall as the logarithmic function. With a value of 0.989, the logarithmic function achieved the highest fitting performance, further demonstrating that it is the optimal function for expressing the relationship between multi-scale road network similarity and scale variation. Although other functions, such as cubic functions, performed better, the logarithmic function was selected as the quantitative model for the relationship between road network scale variation and similarity due to its more complex functional relationship and multiple monotonic intervals. In conclusion, this paper selects the logarithmic function as the quantitative model for the relationship between road network scale variation and similarity. The similarity function is expressed as follows:

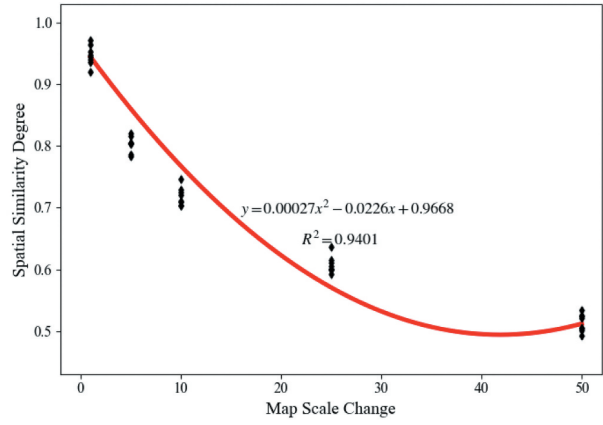
Table 2: The similarity of standard road networks at different scales in 13 different regions.

Region	Type of road network	1:25,000	1:50,000	1:100,000	1:250,000	1:500,000
1	Irregular	0.8973	0.7909	0.7122	0.6080	0.4740
2	Hybrid	0.9223	0.8393	0.7264	0.6312	0.5196
3	Radial	0.9284	0.8169	0.7285	0.5830	0.5162
4	Hybrid	0.9144	0.8063	0.6942	0.5961	0.5073
5	Radial	0.9230	0.8278	0.7432	0.6383	0.5128
6	Grid	0.9018	0.8381	0.7303	0.6102	0.4981
7	Irregular	0.9135	0.8214	0.7146	0.6248	0.5114
8	Hybrid	0.9335	0.8241	0.7196	0.6068	0.5241
9	Hybrid	0.9361	0.8459	0.7310	0.6214	0.5072
10	Irregular	0.8961	0.8038	0.6986	0.6090	0.4944
11	Radial	0.9057	0.8139	0.7285	0.6127	0.5086
12	Grid	0.9204	0.8163	0.7235	0.6190	0.5284
13	Grid	0.8873	0.7890	0.7173	0.6245	0.5568

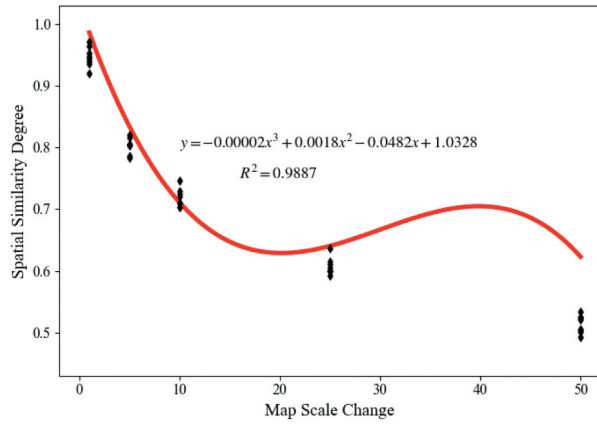
$$S_{\text{sim}} = -0.1261 \ln(x) + 1.0147 \quad (14)$$



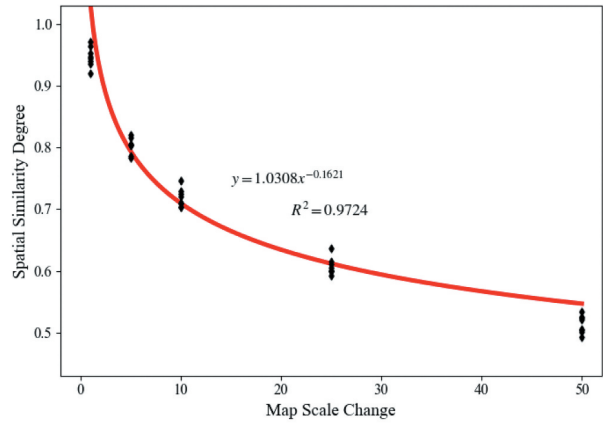
a) Linear function fitting



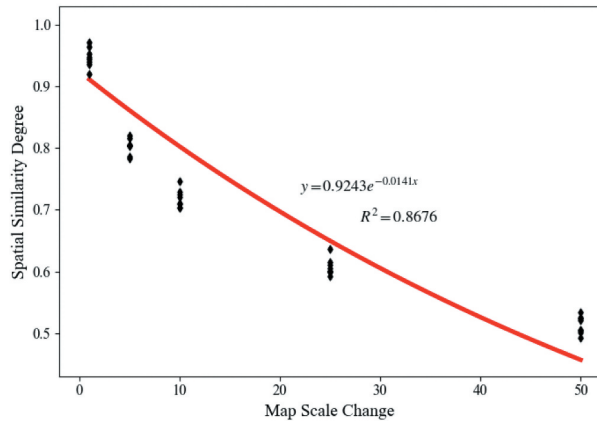
b) Quadratic function fitting



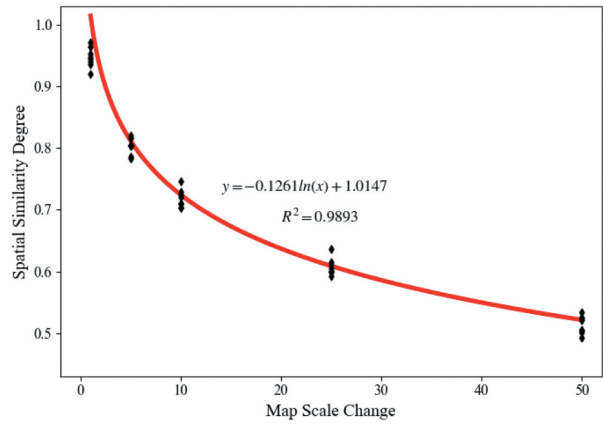
c) Cubic function fitting



d) Power function fitting



e) Exponential function fitting



f) Logarithmic function fitting

Figure 18: Function fitting results.

4.2.3 Visualization and analysis of road network representations

To better interpret the model’s learned representations and validate their discriminative power, we applied t-Distributed Stochastic Neighbor Embedding (t-SNE) to project the high-dimensional graph-level embeddings (128 dimensions) into a 2D latent space. Figure 19 illustrates the distribution of road networks across 13 different geographic areas and 5 distinct map scales.

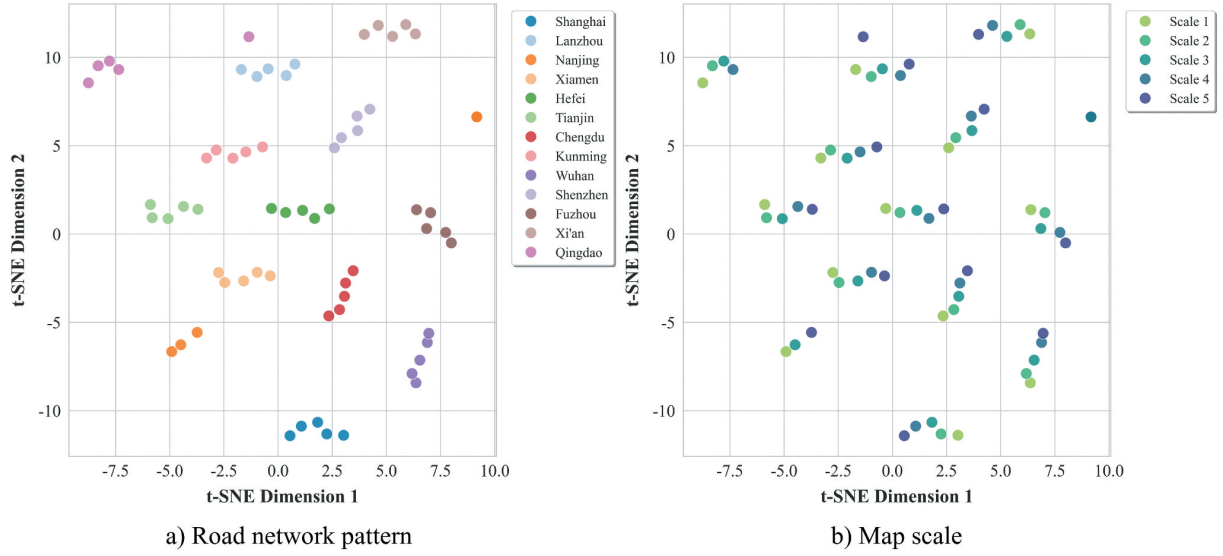


Figure 19: t-SNE visualization of the road network latent space.

As shown in Figure 19a), road networks from the same city naturally form distinct clusters. Since different cities inherently represent varying topological typologies, this clustering confirms that the GCAE effectively captures and encodes the macro-structural semantics of the road networks. Furthermore, Figure 19b) visualizes the embeddings colored by map scale. It demonstrates a discernible spatial gradient and stratified distribution from the largest scale (Scale 1) to the smallest scale (Scale 5). This indicates that the latent space successfully preserves the progressive abstraction and density reduction inherent in the map generalization process. Together, these visualizations validate that the extracted embeddings possess strong discriminative power for both structural typologies and map scales.

4.3 Evaluation of road network generalization quality based on quantitative relationship model

Map generalization is fundamentally a process of similarity transformation. When the content of a map is abstracted and generalized, relatively unimportant elements are removed while key information is preserved. Therefore, map generalization is a contradictory yet unified process. The challenge lies in effectively retaining important map information at a specific scale while determining how to reasonably discard secondary content as the map transitions from larger to smaller scales.

In the context of evaluating the quality of cartographic generalization of road networks in this paper, the similarity between the generalized map and the reference map must strike a balance between closeness and differences. This balance is the fundamental condition for evaluating map generalization quality.

The quantitative relationship model constructed above is used to evaluate the quality of road network cartographic generalization. The process for establishing the method for map generalization quality evaluation is outlined below.

4.3.1 Establishment of the map generalization quality evaluation method

(1) Map Generalization Quality Evaluation Based on Deviation

The quality of map generalization is evaluated by calculating the deviation between the standard and the generalized road networks at a specific scale. This deviation measures how well the characteristics of the road network are preserved during the generalization process. Let this deviation be denoted as E , and the formula for calculating it is as follows:

$$E = \frac{|S - R|}{S} \quad (15)$$

In which S represents the similarity calculated for the standard road network, while R represents the similarity calculated for the generalized road network.

(2) Map Generalization Quality Evaluation Based on Evaluation Set

The basic idea behind establishing the evaluation set is as follows: first, determine the rating levels; then, define the similarity intervals of the standard reference maps; and finally, establish the quality evaluation set for generalization. The principle underlying the quality evaluation is that the closer the similarity of the generalized result is to the similarity interval of the standard reference map, the higher the quality of the generalized result. The specific process for establishing the evaluation set is as follows:

① Determining the Rating Levels

Currently, when evaluating map generalization products, satisfaction with the results is categorized into one of four levels: Excellent, Good, Fair and Poor. The rating levels can therefore be defined as follows: $V = \text{Excellent, Good, Fair, Poor}$.

② Determining the Similarity Interval of Standard Reference Maps

Using the quantitative relationship model, the similarity of the standard reference maps at different scales is obtained, and the similarity intervals for the standard maps at each scale are defined. The obtained similarity intervals are denoted as: $[1, S_1], [S_1, S_2], \dots, [S_{n-1}, S_n]$.

③ Establishing the Evaluation Set

The establishment of the evaluation set is a critical step in the evaluation of the quality of cartographic generalization, as it provides an objective basis for the evaluation. The criterion for evaluation is that the similarity of the generalized result should be as close as possible to that of the standard reference map. The process of establishing the evaluation set in this paper is divided into three steps: (1) defining the rating levels; (2) computing the similarity of standard road networks across scales to determine the similarity distribution intervals of the reference maps using a quantitative relationship model; (3) constructing the quality evaluation set based on the similarity distribution intervals of the standard reference maps; and (4) associating the rating levels with the respective evaluation sets to obtain the map generalization quality evaluation set under different rating levels.

For a map at a scale of n , the corresponding quality evaluation set is E_1, E_2, E_3, E_4 , where each rating level corresponds to a similarity interval calculated by the following formulas:

- For a satisfaction level of “Excellent”:

$$E_1 = [S_n - (S_n - S_{n+1})/4, S_n + (S_n - 1 - S_n)/4] \quad (16)$$

- For a satisfaction level of “Good”:

$$E_2 = [S_n - (S_n - S_{n+1})/4, S_n - (S_n - S_{n+1})/2] \cup [S_n + (S_{n-1} - S_n)/4, S_n - (S_{n-1} - S_n)/2] \quad (17)$$

- For a satisfaction level of “Fair”:

$$E_3 = [S_n - (S_n - S_{n+1})/2, S_n - 3(S_n - S_{n+1})/4] \cup [S_n + (S_{n-1} - S_n)/2, S_n - 3(S_{n-1} - S_n)/4] \quad (18)$$

- For a satisfaction level of “Poor”:

$$E_4 = [S_n - 3(S_n - S_{n+1})/4, 0] \cup [S_n - 3(S_{n-1} - S_n)/4, 1] \quad (19)$$

These two methods evaluate the quality of the road network generalization results from different perspectives: deviation-based evaluation considers the degree of feature preservation, while evaluation set-based considers the rating. The former measures how well features are retained before and after generalization, while the latter assigns a rating to the generalized road network to determine its quality.

4.3.2 Experiment and discussion

This section applies the cartographic generalization quality evaluation method established above to assess the quality of road network generalization. This process consists of three main steps: setting up the evaluation set, selecting the road networks to be generalized, and carrying out the quality evaluation using the proposed method.

Step 1: Establishing the Evaluation Set

The similarity of standard road networks at different scales was calculated based on the previously developed quantitative relationship model between similarity and scale variation. The results are as follows:

- Similarity between 1:10,000 and 1:25,000 standard road networks: 0.8991
- Similarity between 1:10,000 and 1:50,000 standard road networks: 0.8117
- Similarity between 1:10,000 and 1:100,000 standard road networks: 0.7243
- Similarity between 1:10,000 and 1:250,000 standard road networks: 0.6088
- Similarity between 1:10,000 and 1:500,000 standard road networks: 0.5214

Using the similarity interval establishment method from the previous section, the similarity intervals: $[[0,0.5214], [0.5214,0.6088], [0.6088,0.7243], [0.7243,0.8117], [0.8117,0.8991], [0.8991,1]]$

By applying the evaluation set formulas, the evaluation sets for standard road networks at different scales are calculated as follows:

- Evaluation Set for 1:25,000 Road Network
 $P_1 = \{\text{Excellent: } [0.8773, 0.9243], \text{Good: } [0.9243, 0.9455] \cup [0.8554, 0.8773], \text{Fair: } [0.9496, 0.9748] \cup [0.8336, 0.8554], \text{Poor: } [0.9748, 1] \cup [0, 0.8336]\}$
- Evaluation Set for 1:50,000 Road Network
 $P_2 = \{\text{Excellent: } [0.7898, 0.8336], \text{Good: } [0.8336, 0.8554] \cup [0.7680, 0.7898], \text{Fair: } [0.8554, 0.8773] \cup [0.7462, 0.7680], \text{Poor: } [0.8773, 1] \cup [0, 0.7462]\}$
- Evaluation Set for 1:100,000 Road Network
 $P_3 = \{\text{Excellent: } [0.6954, 0.7462], \text{Good: } [0.6665, 0.6954] \cup [0.7462, 0.7680], \text{Fair: } [0.7680, 0.7898] \cup [0.6376, 0.6665], \text{Poor: } [0, 0.6376] \cup [0.7898, 1]\}$
- Evaluation Set for 1:250,000 Road Network
 $P_4 = \{\text{Excellent: } [0.5870, 0.6376], \text{Good: } [0.5651, 0.5869] \cup [0.6376, 0.6665], \text{Fair: } [0.6655, 0.6954] \cup [0.5432, 0.5651], \text{Poor: } [0, 0.5432] \cup [0.6954, 1]\}$
- Evaluation Set for 1:500,000 Road Network
 $P_4 = \{\text{Excellent: } [0.3911, 0.5432], \text{Good: } [0.5432, 0.5651] \cup [0.2607, 0.3911], \text{Fair: } [0.5651, 0.5869] \cup [0.1304, 0.2607], \text{Poor: } [0.5869, 1] \cup [0, 0.1304]\}$

Step 2: Selection of Generalized Road Networks

To validate the reliability of the road network similarity model and the effectiveness of the quality evaluation method more effectively, the study uses road networks from Chengdu (radial-ring pattern) and Hefei (grid-irregular mixed pattern) from the generalized database for quality evaluation experiments.

Step 3: Map Generalization Quality Evaluation

First, the generalized road network in Hefei is evaluated. Figure 20 shows the road networks of Hefei at different scales. Table 3 shows the standard similarity between the generalized road networks and their original networks, as well as the differences and deviations between them.

Analysis of Table 3 shows that the difference between standard similarity and similarity of the generalized road network in Hefei is consistently negative. This suggests that the similarity between the generalized road networks and the original road network at different scales is greater than the standard similarity. This suggests that cartographers may not be simplifying the road network sufficiently, failing to remove less important roads at specific scales.

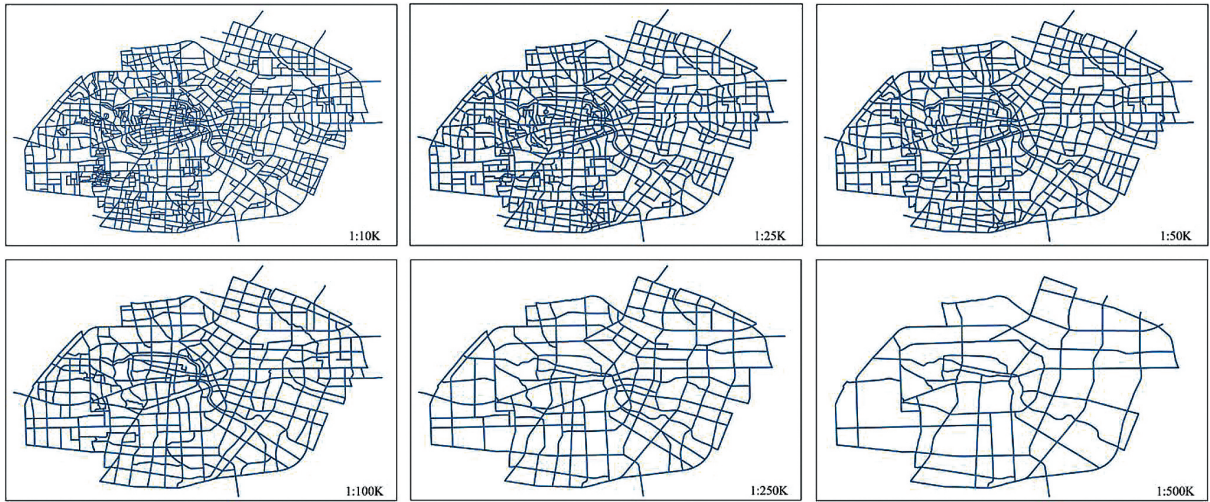


Figure 20: Road networks of Hefei at different scales.

Table 3: The multi-scale road network similarity of Hefei and its statistical deviation from the standard similarity.

	1:1–1:2.5	1:1–1:5	1:1–1:10	1:1–1:25	1:1–1:50
Standard similarity (S)	0.8991	0.8117	0.7243	0.6088	0.5217
Generalized (R)	0.9175	0.8464	0.7844	0.6595	0.5268
$S - R$	-0.0184	-0.0347	-0.0601	-0.0504	-0.0051
deviation	0.0205	0.0427	0.0830	0.0887	0.0098

The deviation values exhibit an initial increase followed by a decrease. Deviation is maximized at the 1:100,000 and 1:250,000 scales, and minimized at 1:500,000. This may be because, as the degree of generalization increases, cartographers find it more difficult to control the level of simplification due to a lack of reference data, resulting in cumulative errors. However, at a scale of 1:500,000, only major roads are retained, enabling cartographers to more effectively determine key features and resulting in a road network that more closely resembles the standard road network at that scale. Finally, the Hefei road network was evaluated using the evaluation set method at different scales: 1:25,000 (“Excellent”), 1:50,000 (“Good”), 1:100,000 (“Fair”), 1:250,000 (“Good”) and 1:500,000 (“Excellent”).

Then, a quality evaluation was performed on Chengdu’s generalized road network. This evaluation used data from two independently generalized road networks (referred to as Generalized Network 1 and Generalized Network 2), which were both derived from Chengdu’s standard 1:10,000 road network

by two professional cartographers. Figures 21 and 22 show visualizations of Chengdu’s original road network and the two generalized results. Table 4 records the standard similarity, the similarity between the two generalized road networks and the original road network, and the deviation between the similarity of the generalized road networks and the standard similarity.

•Evaluation Based on Deviation

As can be seen from Table 4, the smallest deviation for Generalized Road Network 1 occurs at the 1:50,000 scale, indicating that overall feature preservation is best at this scale. Conversely, the largest deviation appears at the 1:500,000 scale, suggesting that excessive generalization has resulted in the loss of essential information and reduced the map’s accuracy. For Generalized Road Network 2, the smallest deviation occurs at 1:25,000 (0.0107), differing by only 0.0096 from the standard similarity. However, at 1:100,000 and 1:250,000, the deviations are significantly larger (0.0654 and 0.0805, respectively). This suggests that cartographers over-generalized the network at these scales, failing to retain key information. Additionally, at 1:25,000 (Generalized Road Network 1) and 1:50,000 (Generalized Road Network 2), the similarity scores are higher than the standard similarity, indicating that insufficient simplification was applied and that some unnecessary details were retained.

Overall, deviation-based evaluation effectively assesses feature preservation, helping to balance over-generalization, which reduces map accuracy, and under-generalization, which retains unnecessary details.

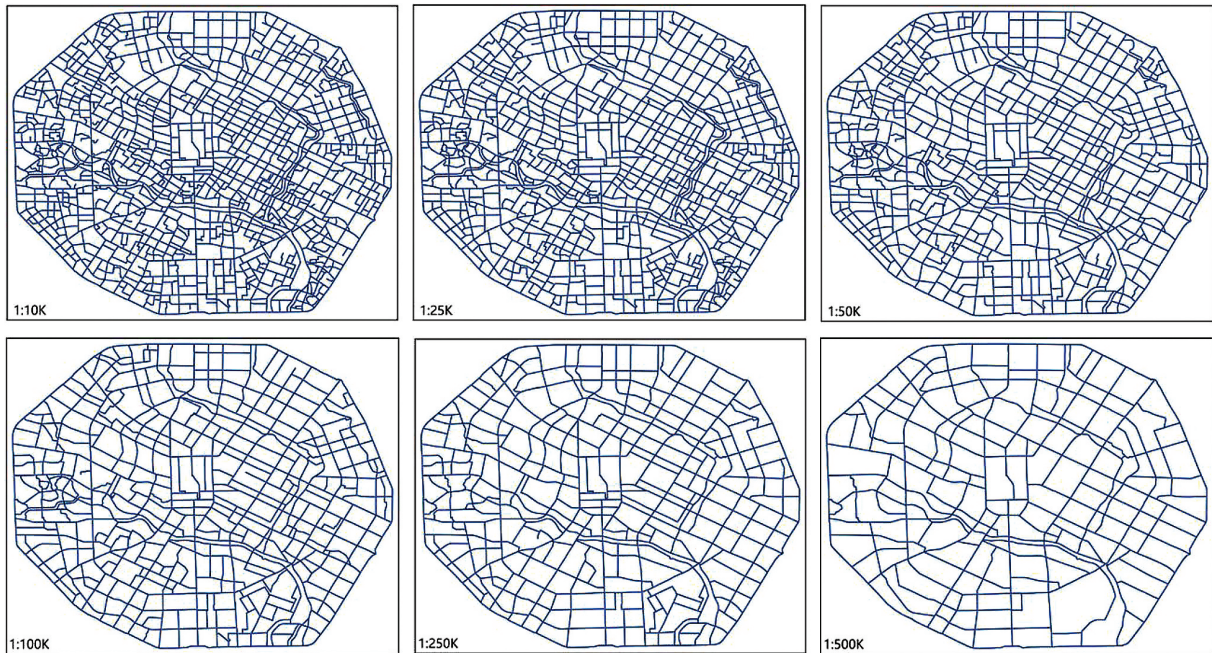


Figure 21: Generalized road network 1 of Chengdu.

Table 4: The multi-scale road network similarity of Chengdu and its statistical deviation from the standard similarity.

	1:1–1:2.5	1:1–1:5	1:1–1:10	1:1–1:25	1:1–1:50
Standard similarity (S)	0.8991	0.8117	0.7243	0.6088	0.5217
Generalized road network 1 (R_1)	0.9253	0.7943	0.6873	0.5792	0.4638
Generalized road network 2 (R_2)	0.9087	0.8388	0.6769	0.5598	0.4920
Deviation of Generalized Network 1	0.0291	0.0214	0.0511	0.0486	0.1110
Deviation of Generalized Network 2	0.0107	0.0334	0.0654	0.0805	0.0534

•Evaluation Based on the Evaluation Set

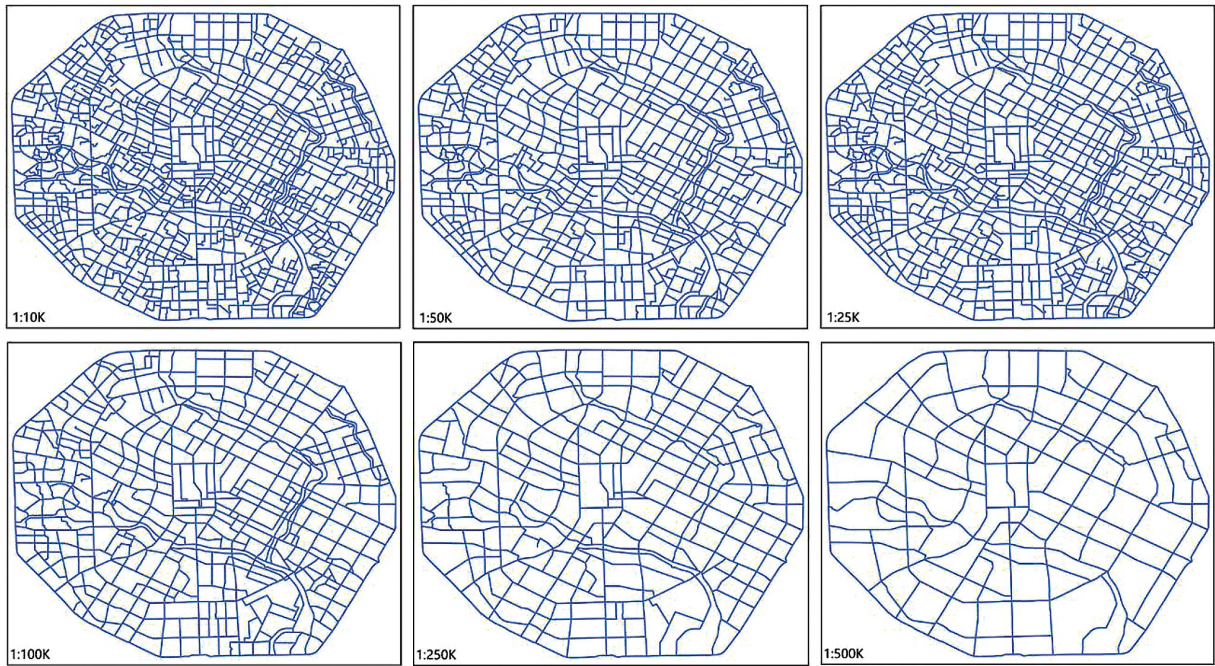


Figure 22: Generalized road network 2 of Chengdu.

Using the evaluation set method, the quality grades of Generalized Road Networks 1 and 2 at different scales are as Table 5:

It can be seen that:

- At 1:25,000, Generalized Road Network 2 performs better than Generalized Road Network 1.
- At 1:50,000, the opposite occurs, with Generalized Road Network 1 performing better.
- At 1:100,000, both networks receive a "Good" rating.
- At 1:250,000, Generalized Road Network 1 is better than Generalized Road Network 2.
- At 1:500,000, both networks receive an "Excellent" rating.
- Overall, maps at 1:10,000 and 1:500,000 generally perform better than those at intermediate scales.

Table 5: The quality grades of generalized road networks 1 and 2.

Scale	Generalized Road Network 1	Generalized Road Network 2
1:25,000	Good	Excellent
1:50,000	Excellent	Good
1:100,000	Good	Good
1:250,000	Good	Fair
1:500,000	Excellent	Excellent

From this, we can infer that Generalized Road Network 1 is slightly superior to Generalized Road Network 2 in terms of overall quality.

The results highlight the subjective nature of the generalization process, in which cartographers tend to focus more on density changes than on preserving key roads. Additionally, generalization at one scale influences subsequent scales, meaning that decisions made early on in the process can have a significant

impact on the final map quality. Both deviation-based and evaluation set-based methods effectively provide objective and reasonable assessments of generalized road networks. Furthermore, the similarity model proposed in this study can provide valuable guidance for cartographic automation.

4.3.3 Comparison with classical similarity measures

To further examine the effectiveness of the proposed similarity model in road network generalization quality evaluation, two classical baseline methods were introduced for comparative analysis, namely a Hausdorff-distance-based geometric similarity and a topology-based similarity index. The purpose of this comparison is not only to examine whether the baselines can reflect the variation of similarity across different generalization levels, but also to evaluate whether they can provide effective support for road network generalization quality assessment.

The comparative analysis was conducted on the same Chengdu and Hefei datasets used in the above quality evaluation experiments. For each city, the original road network “standard” was taken as the reference, and the five generalized road networks at different scales were used as comparison targets.

The Hausdorff-based similarity was adopted from multi-scale point-set similarity research (Cheng et al., 2019). The topology-based baseline was constructed using classical road network connectivity measures. Specifically, four commonly used connectivity indices in road network analysis, namely the alpha index, beta index, gamma index, and cyclomatic number, were adopted (Modak & Sanyal, 2024). Based on these indices, a normalized topology similarity score was further constructed in this study by averaging the four corresponding normalized similarities.

The comparison results between the baseline similarities and the corresponding standard similarity values are shown in Tables 6 and 7. In both Chengdu and Hefei, the Hausdorff similarity decreases monotonically from level 1 to level 5, indicating that geometric deviation gradually increases as the degree of generalization becomes stronger. However, the similarity values remain relatively high overall, suggesting that the Hausdorff-based baseline mainly captures geometric displacement and spatial coverage, while it is less sensitive to internal structural simplification of the road network. This is also related to the normalization form of the Hausdorff-based similarity, in which the Hausdorff distance is normalized by the maximum spatial extent of the original point set. Therefore, when the geometric deviation is relatively small compared with the overall size of the road network, the resulting similarity values remain high. By contrast, the topology-based similarity shows a more pronounced decline across different generalization levels, indicating that it is more sensitive to structural changes such as the reduction of road segments, connectivity variation, and cyclic structure loss.

Although both baseline methods can reflect the variation of similarity across generalization levels, it is still necessary to examine whether they are consistent with the standard similarity values derived from the quantitative similarity–scale relationship model. Therefore, the standard similarity values were further compared with the similarities obtained by the two classical baseline methods. The comparison results show that the Hausdorff-based similarity values are consistently much higher than the corresponding standard similarities in both Chengdu and Hefei. In all scale levels, the relative deviations increase rapidly as the degree of generalization becomes stronger. This indicates that the Hausdorff-based method mainly captures geometric displacement and overall spatial coverage, but is less sensitive to the internal structural simplification of the road network. As a result, it tends to overestimate the similarity between the generalized and original road networks.

By contrast, the topology-based similarity values are much closer to the standard similarities. In Chengdu, the deviations remain relatively small, ranging from

0.0111 to 0.1275, and in Hefei they range from 0.0340 to 0.2438. These results suggest that the topology-based baseline is more sensitive to structural changes, such as the reduction of road segments, changes in connectivity, and the loss of cyclic structure. Compared with the Hausdorff baseline, the topology-based method provides a more reasonable approximation to the standard similarity values derived from the similarity–scale relationship model.

Table 6: Hausdorff-based similarity and deviation results for Chengdu and Hefei.

City	Measure	1:1–1:2.5	1:1–1:5	1:1–1:10	1:1–1:25	1:1–1:50
Chengdu	Hausdorff similarity (R)	0.9804	0.9747	0.9697	0.9564	0.9388
Chengdu	deviation	0.0904	0.2008	0.3388	0.5710	0.7995
Hefei	Hausdorff similarity (R)	0.9831	0.9818	0.9681	0.9364	0.9175
Hefei	deviation	0.0934	0.2096	0.3366	0.5381	0.7587

Table 7: Topology-based similarity and deviation results for Chengdu and Hefei.

City	Measure	1:1–1:2.5	1:1–1:5	1:1–1:10	1:1–1:25	1:1–1:50
Chengdu	Topology similarity (R)	0.8891	0.8204	0.6933	0.5539	0.4552
Chengdu	deviation	0.0111	0.0107	0.0428	0.0902	0.1275
Hefei	Topology similarity (R)	0.8685	0.7792	0.6796	0.5392	0.3945
Hefei	deviation	0.0340	0.0400	0.0617	0.1143	0.2438

5 Conclusion

Spatial similarity relationships are a fundamental reflection of human cognitive synthesis. However, existing multi-feature similarity measurement methods require the importance of different features to be determined manually, which introduces subjectivity and limits the comprehensiveness and cognitive alignment of the results. This study therefore proposes a road network similarity computation model based on a graph convolutional autoencoder to address these limitations and evaluate the quality of generalized road networks. This approach effectively improves the accuracy of road network similarity calculations and enhances the objectivity of map generalization quality assessments. The main contributions of this study are as follows:

(1) construction of multi-scale road network datasets; (2) development of a road network similarity model based on a graph convolutional autoencoder; (3) establishment of a quantitative relationship model between similarity and scale; and (4) development of a road network generalization quality evaluation method. Despite the achievements of this study, several limitations remain, such as:

(2) lack of semantic information in road network features. (2) The selection and design of evaluation metrics directly affect the comprehensiveness and validity of the assessment.

Future research will focus on: (1) Determining the most appropriate evaluation metrics for different applications. (2) Balancing the importance of various metrics in the evaluation framework. (3) designing integrated evaluation functions based on specific application scenarios and requirements.

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Author contributions

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Data availability statement

The data and codes that support the findings of this study are available at: <https://doi.org/10.5281/zenodo.17528074>

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