

Review of road selection methods for the purpose of multiscale mapping

Abstract

Cartographic generalization reduces map detail to ensure clarity and accuracy at smaller scales. This study reviews road selection methods for multiscale mapping, covering scales from 1:10,000 to 1:1,000,000. The applied methodology was inspired by the PRISMA search model and based on searches in the Web of Science and Scopus databases, supported by the ResearchRabbit platform. As a result, five categories of approaches: semantic-based, stroke-based, mesh-based, graph-based, and machine learning-based, were identified and analyzed in terms of their strengths and limitations. Emphasis was placed on automation and the importance of selecting appropriate generalization techniques based on map scale and purpose. The literature review also revealed a variety of quality evaluation metrics used in the analyzed approaches, with a predominance of quantitative measures such as accuracy and F1-score, complemented by qualitative expert visual assessments.

Keywords

Cartographic generalization • road selection • artificial intelligence • GeoAI • multiscale mapping

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Introduction

Cartographic generalization is the process of reducing map details to present information on a map at a smaller scale. The map should present the relevant details and omit unimportant ones, according to its scale and purpose (Stanislawski et al. 2014). While designing the map, we simplify and synthesize reality, as generalization intentionally serves to remove details to suit the map's purpose, level of detail necessary, and user requirements (Kraak et al. 2020). Previously, generalization was a manual process that required experienced cartographers to decide which objects to keep and which to eliminate by considering their characteristics. This process was then seen as both an art and a science (Eckert 1908), offering space for creativity due to its subjectivity (Pawlak 1971). Technological advancements helped to make generalization more cost-efficient and faster, however, the cartographer's role still remained crucial. Conceptual models and general rules were introduced alongside technology development to deliver coherent results, with models for digital mapping emerging in the 1960s. These models used so-called operators to manipulate objects on a map. The operators could be of quantitative and qualitative nature (Ratajski 1967). Depending on the target scale, representation could change from many points to one area, or maintain the original distribution with fewer points, while preserving spatial relations (Bertin 1983; Sarjakoski 2007). It warrants mentioning that the development of efficient methods of cartographic generalization is of interest not only to research groups, but also commercial companies as well as national mapping agencies (NMAs). NMAs are still among the main end users of the research concerning automated generalization, as it is transferred into their map production lines (Stanislawski et al. 2012; Brewer et al. 2013; Duchêne et al. 2014).

One of the most important objects presented on various maps are road networks. Many methods have been developed

for this purpose (Mackaness 1995; Mustière 2005). Mackaness (1995) emphasized abstracting road network patterns and representing them at appropriate scales, using a pattern analysis algorithm to derive meaningful hierarchies. Mustière (2005) focused on road coalescence issues at large-scale maps, and adaptive generalization through machine learning (ML) algorithms, dividing roads into segments for the efficient adaptation. In the stroke-based methods road segments are connected based on the good continuation principle, optimizing segment connections at intersections (Thomson & Brooks 2000; Weiss & Weibel 2014). Mesh-based methods, proposed by Chen et al. (2009) and further enhanced by Wu et al. (2022), consolidate less significant road segments within specified areas based on density thresholds, efficiently eliminating redundant road segments. In graph-based methods, the road network is converted into graph structures, allowing for the calculation of topological metrics to select important segments. Graph structure also constitutes a good baseline for AI implementations (Zheng et al. 2021; Lyu et al. 2022; Karsznia et al. 2024a).

In this research, we focus on methods applicable to topographic and general geographic maps, with particular emphasis on multiscale map design. We investigate road network selection strategies across a broad range of cartographic scales, including large and medium scales (from 1:10 000 to 1:250 000) as well as medium to small scales (from 1:200 000 to 1:1 000 000). The primary objective of this study is to critically assess existing approaches to road network generalization, with a specific focus on medium and small-scale map products, which remain relatively underserved by current automated solutions (Benz & Weibel 2014; Han et al. 2020). Selection associated with these scale ranges focuses on overall network patterns and connectivity maintenance unlike large-scale selection, which emphasizes individual road segments. Previous studies by

Weiss and Weibel (2014) and Benz and Weibel (2014) highlight scale-dependent generalization, with different approaches required for varying scales. This paper examines road selection in vector databases and, specifically, approaches to cartographic generalization of road networks that are automated as well as conducted with the use of artificial intelligence (Kang et al. 2024; Harrie et al. 2024). Through this work, we aim to identify research gaps and stimulate discussion on practices in the field of road network selection.

The main contributions of this paper are as follows. First, we aim to describe the workflow and effectiveness of key generalization techniques, such as stroke-based, mesh-based, and graph-based methods across different scale transitions. Second, we explore the potential of artificial intelligence (AI), including both traditional machine learning and its subfield, namely deep learning models, to enhance the automation, adaptability, and quality of theselection process. Third, building on the findings of our literature screening, we analyze the evaluation strategies commonly employed in the field. Finally, we emphasize the role of visual assessment and advocate for the development of more advanced visualization techniques that can improve the interpretation and comparative analysis of generalization outcomes.

Artificial intelligence in cartographic generalization

Artificial intelligence (AI) is a branch of computer science. It involves developing computer programs to complete tasks which would otherwise require human intelligence. AI assumes the automation of activities that we usually associate with human thinking, specifically decision-making, problem solving, learning (Bellman 1978). AI algorithms can accomplish task solving, communication, interaction, including taking decisions and making predictions (Gil de Zúñiga et al. 2023). These algorithms should behave according to certain conventions related to human interactions in order to make themselves understood and useful. The underlying representation and reasoning in such an algorithm or AI-based system can, but is not limited to, be based on a human model (Russell & Norvig 1995). AI can be used in a broad range of tasks such as automating complex processes, generating text or images, classifying objects, and making predictions about data.

The use of artificial intelligence (AI) applications in cartography has increased significantly in recent years, primarily due to achievements in ML and deep learning (DL) (Kang et al. 2024; Harrie et al. 2024). Geospatial Artificial Intelligence (GeoAI) is an emerging domain that integrates AI technologies, such as ML, DL, and other computational models, with geospatial science to address complex geographic and cartographic challenges. GeoAI leverages geographic knowledge and spatially-explicit data to support applications ranging from map generalization and design to map analysis and feature recognition.

Elements of AI have been applied to map generalization already in the 1980s and 1990s (Weibel 1995; Weibel et al. 1995), with DL being used for automation since 2018 (Sester et al. 2018; Feng et al. 2019). Examples of AI elements applied in cartographic generalization include using (DT) to select representative features such as settlements, based on population or other attributes (Karsznia & Weibel 2018; Lisiewicz & Karsznia 2021; Karsznia et al. 2022). More complex polyline-based generalization solutions employ deep convolutional neural networks (DCNN), graph convolutional networks (GCN), generative adversarial networks (GAN), and DT for the selection and simplification of road networks (Karsznia et al. 2022), mountain roads (Courtial et al. 2020), river networks (Yan et al. 2022), and coastlines (Du et al. 2022). DTs (Xu et al. 2019; Karsznia et al. 2022) and GCNs (Zheng et al. 2021) have also been used to select roads based on their characteristics. Additionally, DCNN

and GAN approaches have been trained end-to-end on raster maps to perform polyline generalization (Courtial et al. 2020; Courtial et al. 2023).

Despite the advanced research in this area, challenges remain in integrating multiple algorithms to generalize all map features, as current deep models face limitations due to the raster nature of input and output data (Courtial et al. 2023). To overcome these limitations, researchers are exploring various encoding methods for model inputs, such as multi-dimensional tensors, graphs (Zhou et al. 2022), and vectors processed by autoencoders (Yu & Chen 2022).

Map generalization is typically an iterative process, requiring the evaluation of intermediate results to assess improvements (Courtial et al. 2022; Yang et al. 2022). Recent studies propose further advancements in DL models for map generalization. Fu et al. (2023) utilize a multi-dimensional tensor input for a U-Net architecture to improve building generalization across scale transitions. Yan and Yang (2023) model lines and polygons as graphs, processed by a self-supervised graph autoencoder to enhance shape preservation, area balance, and angle characteristics. Xiao et al. (2024) combine data-driven approaches and domain knowledge for point cluster generalization, maintaining both local and overall characteristics. Addressing the orchestration of multiple deep models, Courtial et al. (2023) propose a framework where different models generalize separate map layers, with a final GAN assembling the layers. This approach has shown promise in generalizing building, water, and road data on scales from detailed to medium. Karsznia (2023) demonstrate that ML techniques such as random forests (RF), support vector machines (SVM), decision trees DT, and neural networks (NN) can effectively select roads for smaller scale maps. These results indicate that these ML models produce outputs that are more similar to atlas products than those produced using non-AI-based methods.

Literature search

The goal of this research was to study the available methods of road selection for the purpose of multiscale map design. We considered the selection process as a preprocess of cartographic generalization where the selected road segments were kept as geographic objects in a vector database. We did not consider any form of object manipulation other than road segment elimination (selection). Thus we excluded any further road generalization operators such as: smoothing, simplification etc. We decided to search for publications that tackle the issue of road network selection in two most popular and most widely used scientific databases:

- Web of Science,
- Scopus.

The initial search of both databases resulted in 797 (before duplication merging) research articles, book chapters and conference proceedings. Due to multiple databases being used, duplication removal was carried out. As a result, 55 publications were removed. To narrow down the number of publications, we conducted two screening rounds. The first round focused on the titles and the abstract content to select only relevant papers. The second screening round concentrated on full-text reading. Moreover, we used additional criteria for both the first and second screening. We decided that publications need to fulfil the following conditions:

- concern cartographic generalization,
- regard road selection,
- focus on vector data (raster based methods were excluded),
- apply multiscale solutions,
- utilize vector databases as input,
- be written in english.

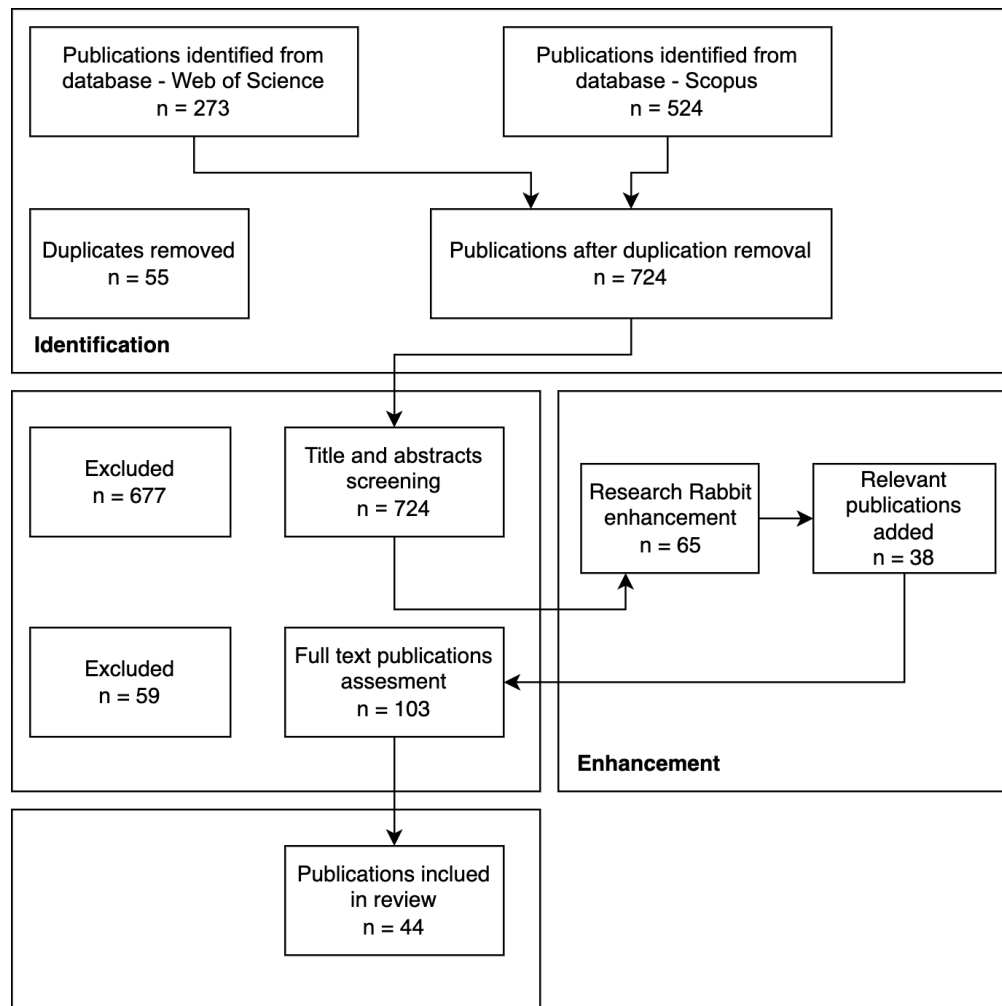


Figure 1. Literature search scheme (inspired by the Prisma searching model)
Source: own elaboration

The search query used was constructed as follows:
road network OR roads OR road networks OR generali* (Title) and select* OR omiss* OR filter* OR thin* OR eliminat* OR prun* OR extract* OR reduc* OR exclud* (All Fields) and cartograph* (All Fields) and English (Languages)

To compile a comprehensive and relevant corpus of articles, proceedings, and book chapters using only search query proved to be very challenging. After removing duplicates (55) and conducting an initial screening based on titles and abstracts, a total of 65 out of 724 publications were identified.

To make the obtained dataset more comprehensive, the ResearchRabbit platform was additionally used. By leveraging features such as "Earlier Work," "Later Work," and "Similar Work," in the ResearchRabbit platform, an additional 38 relevant publications were incorporated into the list which then was screened second time and that summed up to 103 papers for the second screening round.

Last screening round was full-text reading where we narrowed down the number of 103 publications to 44 that fell within the scope of our research. The publications that comprised the final selection were published by the 27th of November, 2024. The two stages screening methodology is presented in figure 1.

The adopted methodology resulted in distinguishing five groups of road selection methods.

Groups of methods

According to the screened literature and currently used methods, we have distinguished five main groups of approaches for road selection (fig. 2). Depending on how road networks are constructed, and the way in which they are processed, the methods can be categorized as semantic-, stroke-, mesh-, graph- and ML-based methods. This does not mean that they always exist separately. Various approaches can be merged, or used in a sequence, as will be elaborated in further sections of this paper.

Notably, ML and stroke-based representations are the most prevalent approaches, with each appearing 12 times suggesting a dominant preference for or the higher relevance of this method among the research community. Mesh-based representations, with 9 occurrences, represent a substantial but slightly lesser preference compared to the dominant methods. Graph-based representations, appearing 8 times, show moderate interest and usage. Semantic representations account for only 4 occurrences, reflecting relatively lower adoption, possibly due to niche applications and overall pursuit to use more automated

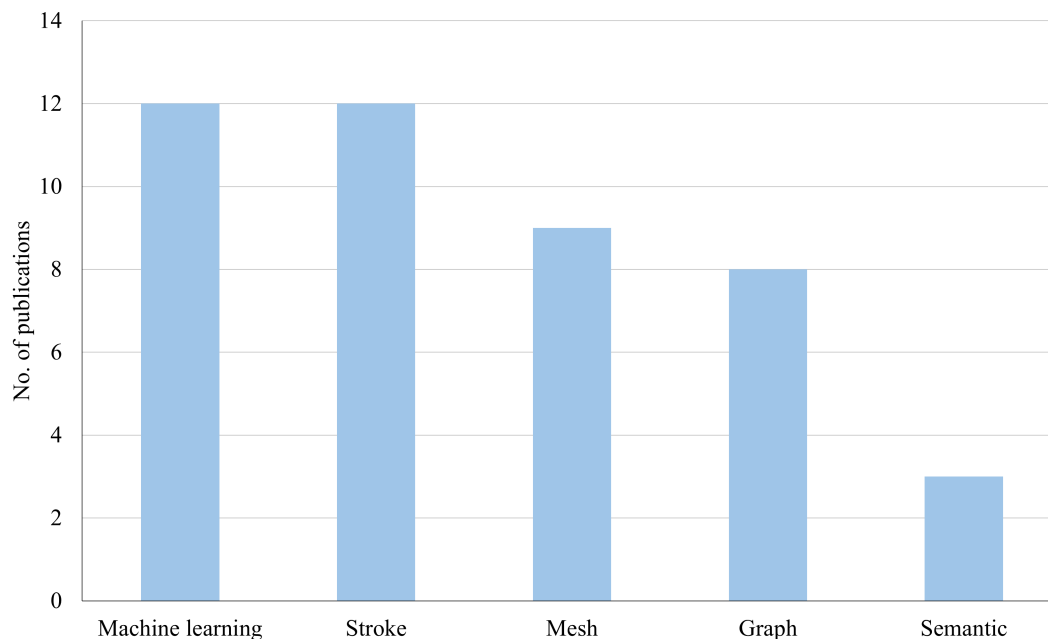


Figure 2. Distribution of types of methods appearing in selected publications

Source: own elaboration

methods for line object selection. This distribution emphasizes the dominance of ML and stroke-based methods, with mesh and graph-based approaches also holding significant relevance in the research landscape.

Semantic-based methods

These methods use the importance of roads based on attribute information, such as road class and road type, road category or any other attribute which can hierarchize this thematic layer. The semantic information of roads is often employed as auxiliary features in conjunction with geometric and topological road features for road network selection (Tang et al, 2024). The implementation of this method relies only on what the map designer needs to achieve.

The road selection process usually utilizes input data from the vector database. Selection is based on attributes and their values. An example of the semantic-based generalization was presented by Sielicka and Karsznia (2019) where General Geographic Object Database (GGOD), which includes detailed attributes of roads, such as class, number of lanes, management category, existence status, and surface material was used as a source database. The methodology applied a combination of attribute-based selection and network connectivity analysis to identify roads to be retained for small-scale maps. Higher-class roads, such as highways and expressways, were prioritized based on their attributes, while lower-class roads were included only if they ensured overall network connectivity, such as linking to settlements or forming junctions with higher-class roads. The selection process was implemented in ArcGIS using various tools and algorithms to analyze connectivity as well as to evaluate road importance. The output was a simplified and symbolized road network that retained essential connectivity and functionality, designed for scales of 1:500,000 and 1:1,000,000. The results were evaluated according to the visual and functional consistency, ensuring the generalized road network aligns with the requirements of small-scale cartographic representation (Sielicka & Karsznia 2019).

Stroke-based methods

The line type approach (more commonly known as stroke-based) assumes the connection between individual road segments using the conceptual grouping principle of good continuation (Thomson & Brooks 2000). At each intersection, a decision is made regarding which segment to connect to the next one. This decision is typically based on the deflection angle between the considered segments (Weiss & Weibel 2014). Generally, a smaller angle is preferred; however, this is not always the case. The attributes stored in the database, such as road class or road name, can supplement this decision-making process. The creation of strokes allows the combination of the road segments into longer sections, which are then selected to be displayed on the map, while shorter segments are omitted.

Due to significant differences in the principles of generalization between rural and urban road networks, different methods are often employed for each. Such an approach was adopted by Touya (2010). In rural areas, the author relied on enriched data describing road strokes when deciding on road selection. The preliminary processes such as data enrichment (Brassel & Weibel 1988) and the proper detection of complex junctions, highway interchanges, and crossroads were crucial for appropriate stroke creation. The selection was based on the shortest paths between attraction points (e.g., residential areas to commercial areas). Attraction points came from facility data, weighted by the importance. If facility points are not available, random points can be used (Ruas & Morisset 1997). Travel time estimation, not just road length, was used for path computation. Factors such as road class, sinuosity, and town crossing influenced travel time. Roads were selected based on road use estimation, stroke length, T-node crossings, and dead-end characteristics.

Another interesting example of stroke type data application for the purpose of map generalization was proposed by Yang et al. (2011). The authors presented a method of generating hierarchical strokes in urban street networks to ensure good continuity. The method addressed such challenges as detecting and tracking dual carriageways, especially when auxiliary streets connect

them, and identifying complex street junctions to maintain stroke continuity during stroke generation. Then, the network was used as a source for stroke ranking. Strokes were ranked based on length and centrality measures. These measures were integrated into a comprehensive indicator for hierarchical selection. Last but not the least, the task was to maintain the connectivity of the source urban street network. The minimum spanning tree (MST) method was thus employed to connect disjointed strokes and regain overall road network connectivity.

Further methodological solution, proposed by Kim et al. (2019), focused on on-demand road generalization to create sketch maps. This consisted of four main steps: (1) identifying input facilities, selected by the user, to be surrounded by a road network; (2) creating suitable road networks; (3) rearranging selected objects; and (4) generating a final map. The emphasis was on road generalization, specifically on generating global and local stroke networks structures. The system took the strokes from a database within a given map area and created a global stroke network by selecting suitable strokes based on predetermined conditions. This network partitioned the map into sub-areas, within which a local stroke network was created for areas containing the facility. Both stroke networks were represented using GeoJSON format; the resulting map with road generalization was illustrated using OpenStreetMap and displayed using Leaflet. The algorithm selected the minimum number of necessary strokes from the local stroke network based on the reachability to facilities and average angles with other selected strokes, ensuring high reachability and avoiding redundant detours.

Liu and Li (2019) proposed an algorithm for stroke generation in road networks that incorporates geometric and structural properties using a feature-based information entropy model. The method addresses limitations of traditional stroke generation techniques, which rely on fixed angle thresholds and disregard road network diversity and structural variability. The proposed approach used an entropy-based model to calculate road network information at the road segment and neighborhood levels, reflecting geometric characteristics and topological connections under varying angle thresholds. The algorithm thus improved stroke generation technique by introducing steps to compute connectivity, identify merging candidates based on deflection thresholds, and optimize computational efficiency. Although it still employs deflection angles to merge road segments into strokes. Furthermore, the Douglas-Peucker algorithm was used to simplify the information volume curve, enabling the determination of optimal angle thresholds for stroke generation across different road network morphologies. The authors determined optimal angle threshold ranges for stroke generation in each test network of different morphology (e.g., 45°–48° for Monaco, 54°–63° for Chicago, and 61°–63° for Moscow). Results demonstrated that these thresholds led to improved connectivity and reduced suspension of strokes compared to fixed-threshold methods. Authors highlighted the importance of adapting thresholds to specific road network structures for effective stroke generation.

An interesting and recently used road selection approach is an analytical hierarchy process (AHP). AHP constitutes one of the multicriteria decision-making methods. It helps to find optimal decisions by considering multiple values as well as taking into consideration the user preferences. This approach was recently used for road selection by Han et al. (2020). The authors used points of interest (POIs) to build indicators of contextual characteristics and calculate stroke importance with the use of the AHP model. Roads were selected according to the stroke importance, as well as on further criteria of density and overall road network connectivity maintenance. The scope of this research covered road selection from 1:5 000 to 1:200 000 and based on the resulting map the authors concluded that using the AHP method

helps to preserve the structure and characteristics of the source road network.

Mesh-based methods

The mesh- or block-based approach indirectly enables to select the most relevant roads by consolidating less significant road segments within a specified area. In this method, adjacent road segments form a mesh cell or block. The retained road count is determined by a density threshold, which can be either fixed or dynamic, based on neighboring mesh information. One of the first examples of this approach was proposed by Chen et al. (2009). Their approach involved an iterative process, in which the mesh with the highest density was identified, and its least important road segment was removed. The remaining mesh parts are then merged with the closest mesh to form a larger one. The elimination of road segments follows a priority order based on parameters such as road class, length, or stroke degree.

A similar block-based approach was suggested by Gülsen and Gökgöz (2011). In this method, only roads from the lower classes (less significant than highways, for example) are considered. Blocks are created in a cycle involving two stages (Gülen & Gökgöz 2011). Here, the primary objective is to maintain the space allocated for individual buildings, which varies based on the target scale. Blocks are then categorized based on “minimum block space” and “minimum block area.” Problematic blocks undergo generalization, starting from the smallest, using algorithms such as the smallest neighbor block algorithm (which merges the two smallest blocks) and the minimum-weighted common boundary algorithm (which removes the least important boundary between blocks).

Recently, some new enhancements to the original mesh method have been introduced. Initially, the starting mesh is selected based on its density and boundary characteristics. Further, instead of a single mesh, a pair of meshes with the highest density is considered as the starting mesh (Wu et al. 2022). Each iteration of mesh elimination then follows the stroke connection order rather than descending mesh density. This iterative method processes all small meshes within the aggregated areas until the densities of the newly formed meshes exceed the assumed threshold (Wu et al. 2022).

Graph-based methods

Graph theory can be applied to road networks by initially converting the network into a graph structure, which is a straightforward task: road segments connecting intersections become edges, while intersections represent nodes. Graphs can articulate topological relationships between objects, allowing for calculations of measurements such as shortest path, betweenness, closeness, degree and minimum spanning tree. These calculations can be later used as a importance metrics for road selection (Mackaness & Beard 1993; Jiang & Claramunt 2004). Such workflow was followed by Jiang and Claramunt (2004). The authors proposed the methodology of generalizing urban street networks based on structural properties. This work aimed to simplify representations while preserving the fundamental characteristics of the network. The input to this approach was a detailed representation of the street network where vertices represented named streets and edges represented street intersections (Jiang & Claramunt 2004), encompassing geometric, topological, and semantic properties of streets. Streets were then ranked based on their structural importance using measures like connectivity, centrality, and hierarchy. The generalization process iteratively removed less significant streets while maintaining network connectivity and topological integrity. The output was a generalized network suitable for various scales, retaining the core structure and functionality of the urban street network.

Another approach which utilized graph structure for road selection was proposed by Chmiani et al. (2014). This method focused on generating consistent and connected representations of road networks across multiple scales for continuous zoomable maps. Road networks were represented as weighted graphs, with edge weights reflecting road importance based on attributes like road class or centrality measures. The methodology revolved around formulating the problem as an optimization task, aiming to identify an optimal sequence of edge removals that maximizes the aggregated weights of retained edges across all scales while maintaining network connectivity at every step. The input constituted a connected weighted graph that represented a road network at the largest scale. The output was a sequence of road network generalizations that progressively simplified the network while preserving its overall structure and connectivity.

Lyu et al. (2022) proposed a slightly different method, which aimed at generalizing road networks based on residential areas to maintain spatial distribution consistency and spatial relations between roads and residential areas. The proposed method involved six steps: clustering of residential areas, classification of roads and settlements, evaluating settlement importance, building a geographic network, removing redundant paths, and ensuring visual and topological connectivity. Settlement importance was determined based on area, residential density, Voronoi area, and road index. Direct and indirect paths between the most important settlements were identified using Dijkstra's least-cost algorithm based on travel time. The final stage involved removing redundant roads either by simplifying adjacent settlement pairs or by evaluating and potentially replacing paths between adjacent settlements based on their costs and connectivity.

ML-based methods

These methods incorporate the artificial intelligence elements to make the selection process more efficient. The implementation of advanced methods can be conducted in various ways. From self-organizing NN (Jiang & Harrie 2004) through supervised ML models such as DT, RF, SVM and finally the use of the most advanced DL models. A compelling example of ML utilization is the road selection research proposed by Karsznia et al. (2022), where models are compared with the official regulations of road selection provided by the Polish National Mapping Agency. The traditional approach, involving simple attribute selection, was compared with a novel approach that utilizes data enrichment and ML models for binary classification of road segments. The training data were collected with the assistance of experienced cartographers. The study employed DT, decision trees optimized with genetic algorithms (DTGA) and RF models.

Zheng et al. (2021) employed GCNs for road network selection, abstracting the road network into a graph structure. The dual graph representation of the road network was adopted, switching the roles of nodes and edges to better capture the network's topology. This representation aligns with the tendency of GCNs to aggregate node characteristics. The authors considered only three attributes concerning roads: road type, length, and coordinates. The model structure comprised three main components: a graph-convolution block for extracting local spatial features, a fusion block for integrating global and local features, and a prediction block for forecasting the selected roads. Multiple model architectures were tested, including JK-Nets, ResNet, and DenseNet.

Combinations of methods

All methods mentioned in figure 2 and described in previous sections can be combined to exploit the advantages of various solutions. Examples of such applications are briefly explained in the following sections.

Stroke–mesh combination

This involves the combination of the stroke or graph approach with meshes. By combining linear and areal structures, it is possible to keep both long road segments and road network density. Stroke generation allows for the creation of real-world long road segments, while graphs can supplement the information about networks using centrality measures. The mesh approach, on the other hand, allows for the tuning of the desired network density. Such a combination was proposed by Li and Zhou (2012), where two types of road network are formed. Meshes, strokes, and bridges between them were identified. In the first step, the areal hierarchies were traversed until the desired number of areal segments was selected or omitted (Weiss & Weibel 2014). In the second step, the linear segments were traversed in a top-down manner. When constructing linear networks, the search for the shortest path linking them to areal or linear networks was carried out.

To improve this novel method, Benz and Weibel (2014) decided to change the approach for linear transversion to bottom-up. They proposed a set of constraints that helped the final selection be more cartographically appropriate. The constraints indicated the fraction of source road segments to be retained (70% of source), which segments must be retained (most important ones, such as highways), and that the roads must not be disconnected locally. The stage of long stroke reconnection, roundabout recognition, and POI accessibility was introduced to keep the road network connected. To keep the road network density in urban areas higher than in rural areas, meshes were formed only in areas labeled as settlement areas.

Another interesting solution was presented by Zhang et al. (2017), where the authors proposed an improvement to the hybrid method, combining linear and areal representation. The approach enhances the traditional stroke generation algorithm by introducing stroke evaluation indicators and using a weighted Voronoi diagram for global control of road selection. First, the stroke generation algorithm was applied in a linear representation mode by using an ordinary least squares (OLS) model to consider overall information for the roads to be connected. Simplified indicators, such as road length and the number of connected roads, were then used to calculate road segment importance. Second, in the areal representation mode, the proposed method partitioned road networks and calculated road density based on weighted Voronoi diagrams. Three parameters – stroke importance (SI), stroke density threshold (DS), and selected network length (LS) – were considered for road selection. Strokes were generated and sorted based on their importance. A weighted Voronoi diagram was used to partition the road network and calculate density. Finally roads were selected based on stroke importance and density threshold, ensuring a reasonable spatial structure.

Stroke–graph combination

A combination of stroke and graph allows for the creation of long, connected road segments that resemble those appearing on paper maps. The graph approach enables measures to be used such as the “shortest path between random points,” or centrality measures such as betweenness, closeness, and degree. Additional information about the geometric characteristics of roads can enhance the selection process.

A prime example of incorporating the line approach with additional information, gathered from stroke and graph road structure, was presented by Weiss and Weibel (2014). The authors improved the selection algorithm based on betweenness centrality. The main contribution of this paper consisted of proposing four extensions that addressed the deficiencies of the basic centrality-based algorithm and led to a significant improvement of the results. The first extension ensured that

roundabouts were properly detected and collapsed. The second added more semantic information to the stroke generation process, allowing longer and more plausible strokes to be built (Weiss & Weibel 2014). The third extension, using density-based clustering, detected areas of higher road density. As a result, the local threshold in these areas have been increased, leading to more road segments being eliminated from urban areas. The final extension addresses inappropriate dead ends by reconnecting roads that should be part of the network but were not included after the selection process. The first two extensions greatly improved the stroke creation process, while the third and fourth were implemented to maintain road density at a reasonable level and to avoid discontinuities in the road network.

Mesh-stroke-ML combination

One of the first methods which used such a combination was a GCN framework combined with mesh-line structure unit (MLSU) data structure (Xiao et al. 2024). The MLSU integrated the characteristics of both mesh and line structures, capturing road and polygonal mesh features within a unified framework. By combining roads and their adjacent meshes into MLSUs, the method facilitated the comprehensive feature extraction for both interconnected road networks and isolated roads. The implementation uses topology adaptive graph convolutional networks (TAGCN) to process the complex relationships within the MLSUs. TAGCN enhances the ability to extract higher-order neighborhood information, enabling the model to learn spatial and topological generalization rules directly from the data. The model was trained on a dataset of roads from the southern area of the United States, mapped at scales of 1:1,000,000 and 1:2,000,000, with MLSUs characterized by road-specific, mesh-specific, and interaction-based features. These features included road hierarchy, mesh density, geometric properties, and relationships between roads and meshes. The adoption of GCN reduced the reliance on manually defined rules and thresholds, allowing the system to derive generalization decisions autonomously.

Graph-ML combination

A study of the structure of a benchmark proposed by Zhou and Li (2017) lets us see how capable of correct road selection the different supervised learning algorithms are. In this research, digital road networks from three study areas were considered. The source scales were 1:20 000 and 1:50 000, whereas the target scales for selection and benchmark were 1:50 000, 1:100 000, 1:200 000, and 1:250 000. The authors decided to compare nine different algorithms – namely: ID3, C4.5, CRT, RF, SVM, naive bayes (NB), k-nearest neighbor (KNN), multilayer perception (MP), and binary logistic regression (BLR). Information about the strokes was encoded in the following attributes: length, degree, closeness, betweenness, road class, and number of lanes. However, it is important to note that not all databases contained complete information; for example, some were missing the road class attribute. The output of the applied algorithm was the binary classification of roads. Overall, the experiment aimed to evaluate the effectiveness of various supervised learning approaches regarding the selective omission of road segments based on different input attributes and output classes.

Discussion

A direct comparison of various road selection or elimination methods is challenging and, in some cases, may not even be feasible. In appendix 1, we have synthesized the most important information from the literature, which was identified during our review. This consolidation required balancing the quantity, quality, and relevance of the information to ensure its usefulness for such a comparison.

Despite these challenges, we have identified and highlighted the most important metrics discussed by the authors in the analyzed papers. While many metrics overlap thematically, particularly in the context of ML approaches (Zhou & Li 2017; Zheng et al. 2021; Karsznia et al. 2022; Guo et al. 2023; Karsznia et al. 2024a), there is considerable variation in the qualitative evaluation methods used in studies that do not incorporate elements of artificial intelligence. This diversity reflects the range of approaches and metrics used across different research to assess the effectiveness of road network generalization methods. The comparison of the selected solutions and improvements has been summed up in appendix 1.

Assessment

Visual examination of the results is essential in research on cartographic generalization. The perceived correctness of outputs often relies on the expertise and subjective judgment of experienced cartographers. In the majority of the referenced works, the authors examined visual results of automatic selection based on their own judgements. Although there were cases where researchers enrolled other cartographers to consult or assess the quality of the results (Benz & Weibel 2014; Weiss & Weibel 2014; Sielicka & Karsznia 2019; Han et al. 2020). At times, the differences among various approaches are so subtle that they cannot be identified through visual inspection alone (Karsznia et al. 2024b). Although numerous methods of effective road thinning networks exist, the primary roads are generally retained, while the inclusion or exclusion of minor roads varies widely between the screened approaches. This situation also arises in manual generalization, where a map designer decides which roads to preserve based on the surrounding area characteristics, the presence of important nearby features, and personal expertise. To ensure consistent evaluation and facilitate direct comparison, most studies rely on a single target map as a standardized reference. Adopting a common dataset allows for systematic assessments of different methods under the same conditions, thereby supporting more objective and comparative analyses. This brings us to the most commonly used metrics, which align with adopting a single baseline for selection assessment to maintain simplicity.

Major metrics

Among the variety of metrics reported in the literature as F1 score, maximum similarity, mean improvement over baseline approaches, correlation coefficients, shape similarity, and others, the accuracy emerges as the most consistently and frequently employed performance indicator. Approximately 35% of the referenced works contained in appendix 1 point out the accuracy as the primary or “major metric,” making it a base for benchmarking performance across different approaches and scale transitions. The popularity of this metric can be attributed to its ease of application and straightforward interpretation. Accuracy reflects how often a particular method successfully selects or retains the “correct” features (e.g., roads, strokes, or mesh elements) relative to a ground truth or a reference dataset or map. In a field where the output (a generalized road network) needs to closely resemble an accepted standard, accuracy provides a clear, binary measure of right vs. wrong selections.

The second and yet most frequent metric appears to be F1 score and maximum similarity. F1 score combines the concepts of precision and recall into a single number, making it especially useful when one needs a balance between these two measures. Apart from accuracy, precision and recall are the basic metrics calculated for automatic classification tasks. As the F1 score constitutes the harmonic mean of precision and recall, it penalizes extreme differences between them. If precision is very high but recall is low (or vice versa), the F1 score will be lower. This ensures that the model is performing well both in detecting

as many positive cases as possible (high recall) and ensuring that its positive predictions are correct (high precision). Other measures, like common stroke ratio, matching ratio, number of road segments, selected road length change, mean similarity with the target, road length overlap, average number of identical strokes, and mean consistency with the existing map, all yield percentage-based values derived from comparing selected road segments against a reference. Although these metrics emphasize slightly different aspects, such as the proportion of shared strokes, the extent of length overlap, or the consistency of selected features, they are fundamentally similar as they quantify how closely the resulting generalization aligns with a known standard, which can be ground truths defined by authors or target map that they used in the research.

During the earliest works, traditional ML classifiers such as SVM, DT, RF (Zhou & Li 2017; Karsznia et al. 2022; Karsznia et al. 2024a), back-propagation neural networks (BPNN) (Zhou & Li 2014), and logistic regression (Park & Huh 2019) were employed to guide the selection of features for map generalization. Within these frameworks, accuracy emerged as a major measure to determine how closely the generated output approximated a trusted reference dataset. These initial studies often relied on well-defined training samples and labeled data, enabling accuracy to serve as a simple and efficient indicator of the proportion of correctly retained or omitted objects. As the research concerning GeoAI and ML evolved, the attention shifted toward more complex, graph-based, and network related methods. GCN, graph attention networks (GAT), graphSAGE (Zheng et al. 2021; Xiao et al. 2024; Tang et al. 2024), and other hierarchical frameworks appeared, reflecting a growing recognition of the importance of topological relationships in generalization process. Although these models introduced greater sophistication, complex network structures and advanced feature embeddings, they continued to report accuracy as a core measure of quality.

In parallel, integrated neural architectures and approaches enriched with semantic features were further developing. In these approaches, the inclusion of domain-specific heuristics, semantic constraints, and specialized indicators such as satisfaction of hard constraints or maximum similarity scores offered more nuanced insights into a model's performance.

Map purpose

Within the reviewed studies and proposed methods the major purpose of the generalization and specifically road selection is identified as "database generalization", accounting for 64% of the studies reviewed. This category, spanning from the earliest contributions (e.g., Liu et al. 2010; Touya 2010) to the most recent investigations (e.g., Xiao et al. 2024; Tang et al. 2024), consistently highlights the emphasis on producing generalized, datasets capable of supporting a wide range of subsequent applications.

By focusing on database-oriented outcomes, these methods are intended for scalability and reproducibility, ensuring that the designed maps can be readily integrated into mapping workflows regardless of the map use. In contrast, other purposes appear less frequently and exhibit a more specialized focus. Topographic maps, for instance, comprise 12% of the studies, reflecting a dedicated interest in maintaining thematic integrity and spatial accuracy within distinct geographical contexts. "Map updates" and "navigation," each accounting for 8%, point to more targeted or dynamic needs, such as ensuring temporal relevance or route optimization. Meanwhile, "general geographic map" and "urban road generalization," each at 4%, highlight niche demands arising from particular environments or user scenarios (appendix 1). This distribution of thematic purposes suggests that while specialized interests occasionally shape

methodological decisions, they do not overshadow the prevalent goal of database generalization.

Results

In some studies, the improvements across multiple areas were presented (Weiss & Weibel 2014). In such cases, the accuracy values were included in appendix 1. Other measures indicate how well the described methods function as improvements over previously implemented ones (Wu et al. 2022; Yang et al. 2011; Touya 2010; Chen et al. 2009), how accurately they mimic existing map products or manual selections (Gülgen & Gökgöz 2011), or if the proposed improvements satisfy the specified constraints (Benz & Weibel 2014), making them more comparable to the rest of the metrics gathered in appendix 1. The comparison of different road network generalization approaches reveals their varying effectiveness as well as their applicability to multiple scales. While many publications tackled the problem of selection for 1:200 000 target scale (Li et al. 2012; Zhou & Li 2014; Weiss & Weibel 2014; Zhou & Li 2017; Han et al. 2020; Tang et al. 2024; Xiao et al. 2024) there are only a few publications which focus on small-scales (Karsznia et al. 2022; Karsznia et al. 2024a; Zheng et al. 2024). ML-based approaches, such as those presented by Karsznia et al. (2024) and Guo et al. (2023), generally demonstrate high accuracy across various scales. For instance, the GNN model achieved an F1 score of 92.1% (appendix 1; Guo et al. (2023), indicating its effectiveness for large-scale to medium-scale generalization (1:10,000 to 1: 50,000). Similarly, Karsznia et al. (2024a) reported high accuracy rates with various ML models, including DTGA achieving 90% accuracy (appendix 1; Karsznia et al. 2024a) for smaller scale map design.

Stroke-based approaches have also shown good results, particularly when applied to medium and small-scale generalization. For example, Weiss and Weibel (2014) demonstrated a mean improvement of 67.88% over basic methods in multiple research areas using enhanced stroke generation techniques (appendix 1; Weiss & Weibel 2014). This approach proved to be effective for the target scale of 1:200 000. In a similar way the AHP implementation to stroke generation proposed by Han et al. (2020) allowed to achieve rather high common stroke ratio of 89% for the same target scale. Stroke generation was also effective both in the research conducted by Li et al. (2020) and Zhang et al. (2017) for road generalization up to 1:50 000 scale. The proposed methods achieved 91.64% and 88.80% maximum similarity respectively.

Mesh-based approaches, such as those employed by Benz and Weibel (2014), are particularly helpful at maintaining structural integrity and satisfying so-called hard constraints. Their extended stroke-mesh combination method enabled to achieve 100% satisfaction concerning hard constraints which included: percentage of roads to be kept, necessary segments that cannot be removed, keeping complete road connectivity, not creating new dead ends, not collapsing the roundabouts, and keeping important POIs accessible (appendix 1; Benz & Weibel 2014). Satisfying these hard constraints makes the approach suitable for medium-scale applications, that is, from 1:10 000 to 1:50 000. Moreover, this method requires minimal manual corrections, which is a significant advantage in practical applications. Similarly, Chen et al. (2009) demonstrated a mean consistency for all test areas at the level of 89.50% with existing maps using mesh density-based selection for scales from 1:10 000 to 1:50 000 (appendix 1; Chen et al. 2009).

Graph-based approaches build on the notion that roads and intersections can be represented as nodes and edges, thereby focusing on topological relationships. For example, Lyu et al. (2022) reported an accuracy of 86% in road-path selection, demonstrating that these methods can perform competitively at scales transitioning from 1:50 000 to 1:100 000 (appendix 1; Lyu

et al. 2022). Similarly, Pung et al. (2022) introduced correlation-based measures such as Pearson ($p = 0.964$) and Spearman ($R = 0.911$) to evaluate how closely the generalized network structure aligns with the source configuration at large scales (appendix 1; Pung et al. 2022). Earlier work by Zhang et al. (2011) highlights the potential of graph-based reasoning employing ego network and weighted ego network analyses. Ego networks consist of a single actor (ego) together with the actors that they are connected to (alters) and all the links among those alters (Evert & Borgatti 2005). Use of such a method allowed to maintain high retention rates (above 90%) of critical road segments in scale-free contexts (Zhang et al. 2011). Compared to older stroke- or mesh-based methods, these graph-centric techniques not only sustain or improve the established accuracy standards, but also enrich the evaluative framework by capturing topological, structural, and relational qualities.

The hybrid approaches that combine stroke and mesh methods have also shown high usefulness. In this scope Touya (2010) proposed an enriched structural selection method that allowed to achieve a road length overlap of 97%, showing the method's ability to maintain consistency and structural integrity (appendix 1; Touya 2010). This hybrid approach is particularly effective for medium- to small-scale transitions, such as from 1:50 000 to 1:100 000. However, the author pointed out that in urban road networks the road length overlap could be falsely high because many segments in more dense areas have identical lengths. The work of Zhou and Li (2017) supports the application of ML and elements dedicated to graph type solutions (enriching information about roads with centrality measures). In this research high accuracy rates were achieved across multiple target scales, such as 91.55% for 1:200 000 using the MP method (appendix 1; Zhou & Li 2017).

Conclusions

This literature screening revealed a range of automated road network selection methods, each accompanied by a diverse set of evaluation metrics, purposes and detail levels application. While numerous metrics have been employed, accuracy constitutes as the most commonly reported measure. Its popularity can be attributed to its straightforward interpretation, ease of implementation, and the simplicity that it brings to comparisons across various approaches. However, high accuracy scores do not necessarily guarantee visually satisfactory results; indeed, an approach can achieve high accuracy value, even if the result seems poor to the experienced map designers. As such, although accuracy remains a convenient and widely recognized baseline, it should not be regarded as a sole quality indicator. Therefore

visual assessment remains a crucial component of overall evaluation, but the methods employed to present and interpret visual results can be limited. Authors generally rely on a single target map or display all selected segments at once, leaving room for improvement in how results are visually communicated and understood. At the same time, more sophisticated visualization techniques could provide deeper insights, helping to clarify subtle differences between the implemented approaches that may be obscured by metrics. Implementing more advanced visualization strategies would not only enhance the interpretability of results but also better align quantitative metrics with the practical concerns of map users and map designers (Adolf & Karsznia 2024).

In addition to accuracy, other metrics which were included in some of referenced papers such as the F1 score, maximum similarity, correlation coefficients, and specialized measures reflecting topological or semantic properties should enrich the evaluation toolbox. These metrics often align with more nuanced priorities, such as maintaining network connectivity, reflecting user-specific constraints, or emulating established map products. In summary, while accuracy provides a convenient baseline for evaluation, it should be complemented by other metrics and improved visualization techniques to foster a more holistic understanding of the selection quality performance.

The recurring trend of use of stroke generation and mesh approaches indicates that the field is far from being fully explored. The development of ML models and other classifiers, from traditional ML techniques to more sophisticated DL, also indicates that this research area is promising and fast-growing.

Finally, considering the intended purpose of proposed methods there is clear emphasis on generalization of databases. This definitely leaves room for the development of effective solutions also for cartographic and graphic generalization as it is necessary to take those stages into account simultaneously. This can lead to the conclusion that specialized tasks such as topographic mapping or navigation-based applications are important but the majority of methods regarding road network selection focus rather on creating broadly applicable solutions.

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Appendix 1. Information about most important characteristics of the research undertaken concerning road network selection. Selected references considered in this paper are included, as many of the works lack quantitative results' evaluation

Author	Year	Approach	Source scale	Target scale	Method	Major metric	Major purpose
Xiao et al.	2024	ML	1:100 000	1:200 000		Accuracy	database generalization
					MLSU-TAGCN	81.40%	
					MLSU-GCN	74.80%	
					MLSU-GAT	75.51%	
					MLSU-GraphSAGE	80.80%	
					Selection-4Fs	71.20%	
					Selection-22Fs	78.40%	
Tang et al.	2024	ML	1:10 000			F1-score	database generalization
				1:50 000	GCN with functional semantic features	89.74%	
				1:200 000		82.70%	
Zheng et al.	2024	ML	1:250 000	1:1 000 000		Accuracy	database generalization
					HAN	75.35%	
Karsznia et al.	2024a	ML	1:250 000	1:500 000		Accuracy	general geographic map
					DT	81.25%	
					RF	84.38%	
					SVM	84.38%	
					DTGA	90.00%	
					NN	81.88%	
Guo et al.	2023	ML	1:10 000	1:50 000		F1 Score	database generalization
					GNN	92.10%	
					AHP	88.00%	
Lyu et al.	2022	Graph	1:50 000	1:100 000		Accuracy	database generalization
					Road-path selection constrained by settlements	86.00%	
Pung et al.	2022	Graph	1:10 000	„Large-scale”		Selected-Source Correlation	urban road generalization
					Functional node elimination	Pearson (p) = 0.964	
						Spearman (R) = 0.911	
Karsznia et al.	2022	ML	1:250 000			Accuracy	database generalization
				1:500 000	DT	84.46%	
					DTGA	83.33%	
					RF	84.96%	
				1:1 000 000	DT	99.18%	
					DTGA	99.44%	
					RF	99.34%	
Wu et al.	2022	Mesh	1:10 000	1:50 000		Shape similarity overlap	topographic map
					Direct pair merging	100%	
					Iterative area elimination	100%	

Continued Appendix 1. Information about most important characteristics of the research undertaken concerning road network selection.
Selected references considered in this paper are included, as many of the works lack quantitative results' evaluation

Author	Year	Approach	Source scale	Target scale	Method	Major metric	Major purpose
Zheng et al.	2021	ML	1:10 000	1:100 000		Accuracy	database generalization
					MLP	85.83%	
					JK-GAT	88.12%	
					Res-GAT	87.88%	
					Dense-GAT	87.41%	
Han et al.	2020	Stroke	1:5 000	1:200 000		Common stroke ratio	database generalization
					AHP	89%	
Yu et al.	2020	Stroke	Unknown			Maximum similarity	navigation
				1:5 000	Traffic Flow Radical Law Strokes	61.15%	
				1:25 000		65.86%	
				1:50 000		90.95%	
				1:5 000	Traffic Flow Pair Strokes	61.61%	
				1:25 000		65.58%	
				1:50 000		90.95%	
Li et al.	2020	Mesh, Stroke	1:10 000	1:50 000		Maximum similarity	topographic map
					Mesh elimination	89.52%	
					Stroke-edge elimination	91.64%	
Park, Huh	2019	ML	1:5 000	1:25 000		Matching ratio	topographic map
					Logistic Regression	81.66%	
Zhang et al.	2017	Stroke	1:10 000	1:50 000		Accuracy	database generalization
					Stroke generation with weighted Voronoi diagrams	88.80%	
Zhou, Li	2017	ML				Accuracy	database generalization
			1:20 000	1:50 000	MP	80.45%	
					SVM	77.05%	
					BLR	80.90%	
				1:100 000	MP	79.90%	
					SVM	81.10%	
					BLR	80.65%	
				1:200 000	MP	91.55%	
					SVM	92.90%	
					BLR	92.35%	
			1:50 000	1:250 000	MP	83.20%	
					SVM	82.70%	
					BLR	83.10%	
Weiss, Weibel	2014	Stroke	1:10 000	1:200 000		Mean improvement (vs. Basic)	database generalization
					Enhanced stroke generation	67.88%	

Continued **Appendix 1. Information about most important characteristics of the research undertaken concerning road network selection.**
Selected references considered in this paper are included, as many of the works lack quantitative results' evaluation

Author	Year	Approach	Source scale	Target scale	Method	Major metric	Major purpose
Benz, Weibel	2014	Stroke, Mesh	1:10 000	1:50 000		Satisfaction of hard constraints	database generalization
					Extended stroke–mesh combination	100%	
Zhou, Li	2014	ML	1:20 000			Accuracy	map updates
				1:50 000	BPNN	82.4%	
				1:100 000		87%	
				1: 200 000		98.6%	
Li et al.	2012	Stroke, Mesh				Accuracy	database generalization
			1:20 000	1:50 000	Stroke generation	84.7%	
				1:100 000		76.7%	
				1:200 000		68.5%	
			1:50 000	1:250 000		77.3%	
			1:20 000	1:50 000	Mesh density	67.7%	
				1:100 000		63.7%	
				1:200 000		61.6%	
			1:50 000	1:250 000		71.4%	
Zhang, Li	2011	Graph				No. of road segments	navigation
			Scale free	Top 2% strokes	Ego network	82.1%	
				Top 10% strokes		89.9%	
				Top 15% strokes		92.5%	
				Top 20% strokes		92.6%	
				Top 2% strokes	Weighted ego network	87.1%	
				Top 10% strokes		95.8%	
				Top 15% strokes		94%	
				Top 20% strokes		94.6%	
Gülgen, Gökgöz	2011	Mesh				Selected road length change	database generalization
			1:25 000	1:50 000	Urban block amalgamation	14.10%	
				1:100 000		-17.30%	
Yang et al.	2011	Stroke	1:1 000	Not specified		Mean similarity with target	database generalization
					Hierarchical stroke generation	40.75%	
Touya	2010	Stroke, Mesh	1:50 000	1:100 000		Road length overlap	database generalization
					Enriched structural selection	97%	

Continued **Appendix 1. Information about most important characteristics of the research undertaken concerning road network selection.**
Selected references considered in this paper are included, as many of the works lack quantitative results' evaluation

Author	Year	Approach	Source scale	Target scale	Method	Major metric	Major purpose
Liu et al.	2010	Stroke	1:10 000	1:50 000		Avg no of identical strokes	database generalization
					Stroke generation with seed extension	91.84%	
Chen et al.	2009	Mesh	1:10 000	1:50 000		Mean consistency with existing map	map updates
					Mesh density-based selection	89.50%	

Source: own elaboration