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Research on Road Network Partitioning Considering the Coupling of Network Connectivity and Traffic Attributes

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Abstract: The urban road network is a large and complex system characterized by significant heterogeneity arising from different spatial structures and traffic demands. To facilitate effective management and control, it is necessary to partition the road network into homogeneous sub-areas. In this regard, we aim to propose a hybrid method for partitioning sub-areas with intra-area homogeneity, inter-area heterogeneity, and similar sizes, called CSDRA. It is specifically designed for bidirectional road networks with segment weights that encompass traffic flow, speed, or roadside facility evaluation. Based on community detection and spectral clustering, this proposed method comprises four main modules: initial partition, partitioning of large sub-areas, reassignment of small sub-areas, and boundary adjustment. In the preliminary partitioning work, we also design a road network reconstruction method which further helps to enhance the intra-area homogeneity and inter-area heterogeneity of partitioning results. Furthermore, to align with the requirement for comparable work units in practical traffic management and control, we control the similarity in the size of sub-areas by enforcing upper and lower bound constraints on the size of the sub-areas. We verify the outperformance of the proposed method by an experiment on the partitioning of an urban road network in Guangzhou, China, where we employ sidewalk barrier-free score data as segment weights. The results demonstrate the effectiveness of both the road network reconstruction method and the CSDRA proposed in this paper, as they significantly improve the partitioning outcomes compared with other methods using different evaluation indicators corresponding to the partitioning objectives. Finally, we investigate the influence of constraint parameters on the evaluation indicator. Our findings indicate that appropriately configuring these constraint parameters can effectively minimize sub-region size variations while having minimal impact on other aspects.

Keywords: bidirectional road network partitioning; graph reconstruction; multi-objectives; community detection; spectral clustering

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1. Introduction

The urban road network comprises intersections and road segments, which correspond to vertexes and edges in a graph. Due to variations in spatial distribution, population, economy, and traffic, among other factors, there exists both local homogeneity and heterogeneity within the urban road network. Such differences make it impractical to implement a single management or control strategy that can effectively adapt to all areas of a large-scale road network. Therefore, it becomes necessary to partition the large-scale heterogeneous road network into homogeneous sub-networks, enabling fine management of the urban road network. Existing road network partitioning methods can be categorized into two groups: those based on data derived from the road network and those based on the road network itself. The former primarily involves using OD data, occupational and residential population distribution data, and similar data sources to determine the partitioning.

This type of method does not directly consider the topological relationship of the road network and is suitable for macroscopic traffic management and analysis. On the other hand, the latter mainly focuses on partitioning based on the data of intersections [1] or road segments. This method takes into account both the microscopic traffic operation and the topological relationship of the road network. Road segments, as integral components of the road network, carry essential traffic information such as flow, density, speed, and even roadside facility evaluation. Therefore, investigating the partitioning of road networks based on road segments is necessary. For example, by partitioning sub-areas based on traffic flow data, it becomes possible to identify congested and uncongested regions, providing insights for managing traffic congestion effectively. Similarly, partitioning sub-areas based on roadside facility evaluation allows relevant departments to prioritize maintenance and renovation efforts accordingly. Furthermore, it is important to note that actual road segments are bidirectional and exhibit different data characteristics. Thus, in contrast to previous studies that primarily focused on unidirectional road networks [2,3], our research investigates bidirectional road networks with unidirectional road segments as the minimum unit of analysis.

Existing methods for road network partitioning encompass empirical-based partitioning, heuristic algorithms [4,5], clustering algorithms [6,7], and community detection [8]. Empirically-based partitioning relies on administrative districts or physical features such as mountains and rivers to delineate partitions [9]. While simple, this method is restrictive and fails to consider segment attributes. The heuristic algorithm suffers from slow convergence and difficulty in reducing the connection between sub-areas [10]. Other clustering algorithms, such as k-means [11], spectral clustering [12], and related graph partitioning methods such as N-cut [13,14], α-cut [15], and k-way [16] are commonly used in road network partitioning. However, traditional clustering algorithms such as k-means do not account for road network adjacency and are not directly applicable to partitioning. Spectral clustering and its improvement algorithms have been widely used in road network partitioning. For example, Yang et al. [12] utilized spectral clustering to analyze daily traffic state changes based on traffic speed data, extracting traffic change characteristics. Another study by Yang et al. [17] applied Markov chains to enhance the robustness of spectral clustering similarity graphs, combined with genetic algorithms for improved partitioning results. One limitation of clustering algorithms is the need for customizing the number of sub-areas, without a clear connection to the quality of the partitioning results. Compared to the aforementioned algorithms, community detection algorithms are more suitable for large networks and offer potential advantages in road network partitioning studies [2].

Community detection algorithms were initially developed to identify communities within social networks, such as classifying traffic communities based on traffic information in social networks [18]. Although these algorithms are rarely applied directly to road network data partitioning, they are often used in the context of commuting data [19], multi-modal traffic trajectories [8], cell phone signaling [20], POI data [21] and other sources to partition urban road networks or explore urban cluster structures. However, urban road networks possess nonlinear and complex network properties that can be represented as graphs and partitioned using community detection algorithms. The key to applying these algorithms to urban road network partitioning lies in the reconstruction of the road network. There are two main ways to convert the road network into a graph. The first one is a direct conversion [11] where the intersections correspond to vertexes and the road segments correspond to edges. However, this way is not suitable for partitioning based on road segments and may not yield reasonable sub-areas. In complex network theory, vertexes typically represent entities of interest, while edges describe the connections between them. Therefore, some studies take the road segments in the original road network as vertexes and determine the edges base on the connectivity of road segments to create a new graph for partitioning [22,23]. The focus of this conversion is on establishing meaningful connections between road segments to facilitate subsequent partitioning. During the reconstruction of the road network, the selection of partitioning feature parameters is crucial.

Most of the studies primarily focused on the partitioning of individual factors, such as solely considering the topology of the road network [24] or only taking into account a single traffic attribute, such as traffic flow or density. Liu et al. [25] proposed a novel approach that combines methods such as Pearson coefficients and data normalization to incorporate multiple traffic parameters for partitioning. It is important to note that considering only traffic attributes is insufficient for urban road network partitioning, as the adjacency relationship between road segments should also be taken into account. The edges in the graph can be redefined [26] to obtain a more suitable graph for road network partitioning.

Indeed, the existing methods for road network partitioning have their advantages and disadvantages, and they may not be able to simultaneously satisfy multiple objectives and directly achieve the desired partitioning results. To address this, some studies have proposed combined algorithms to improve the partitioning outcomes [27]. For example, Chen et al. [3] proposed a partitioning method that includes initial partition, merging, and boundary adjustment to obtain homogeneous sub-areas. Jiang et al. [28] proposed a six-step partitioning method that aims to achieve intra-area homogeneity and inter-area heterogeneity. These methods primarily focus on obtaining partitioning results with balanced intra-area homogeneity and inter-area heterogeneity [29]. Some studies also consider the balance of sub-area sizes [5], but they may lack control over the size intervals of the sub-areas. Obtaining many smaller sub-areas or a few larger sub-areas achieves a balance of sub-area sizes, but such a partition is meaningless. Hence, it is important to explore approaches that can achieve a reasonable number of sub-areas and similar sub-area sizes while ensuring intra-area homogeneity and inter-area heterogeneity. This requires careful consideration of the objectives and trade-offs involved in road network partitioning.

Previous studies have employed simplistic models of the road network, failing to account for the presence of bidirectional road segments found in real road networks. Moreover, there was insufficient consideration of the connectivity and traffic attributes of the network when determining the basis of partition. Additionally, existing studies primarily focused on achieving intra-area homogeneity and inter-area heterogeneity as partitioning objectives, disregarding the practical need for uniformity among sub-areas. Meanwhile, the majority of existing partitioning methods fail to meet the requirements of multi-objective partitioning. To address these issues, we propose the following approaches.

In this paper, we propose the CSDRA algorithm which aims to accomplish bidirectional weighted road network partitioning by considering the connectivity of the network and the similarity of traffic attributes. Our algorithm considers the objectives of achieving intra-area homogeneity, inter-area heterogeneity, and similar sub-area sizes within controlled intervals. The choice of traffic attributes used in the algorithm depends on the specific application scenario. For instance, traffic flow [30], speed [31], or management facility scores can be considered as potential traffic attributes in different contexts. To improve the partitioning results, we also introduce a road network reconstruction method that incorporates network adjacency relationships and weight similarity between road segments. The output of this road network reconstruction is an edge graph, which serves as the input for the CSDRA algorithm. Initially, the algorithm employs a community detection algorithm to obtain the initial partition result. Then, by controlling constraint parameters, larger sub-areas are partitioned while smaller sub-areas are reassigned to surrounding sub-areas, reducing the variability in sub-area size. This paper differs from previous literature by not only obtaining line sub-areas through road network partitioning [2], but also deriving smooth surface sub-areas. By overlaying spatial data such as population, economy, or points of interest (POI) [26] onto these surface sub-areas, we can provide valuable theoretical support for traffic partition management and control. To assess the effectiveness of our proposed method, we conducted a case study in the downtown area of Guangzhou, China, focusing on the road network of secondary or higher roads. We utilized evaluated data on roadside barrier-free facilities as segment weights for the partitioning process. The performance of our method will be evaluated by comparing the quantitative indicators with those obtained from other existing methods. In summary, we make the following contributions in this paper.

- We propose a road network reconstruction method that considers the adjacency relationship between network segments and their weight similarity. This method uses road segments as vertexes, recalculates the correlation between the road segments, and then obtains new edges and their corresponding weights through threshold screening. Therefore, this method can be seen as a form of data pre-processing that can improve the effectiveness of the road network partition by enhancing the association among similar segments and reducing the association among dissimilar segments.
- We propose a multi-step partitioning method for bidirectional road networks with weights. The method can solve a multi-objective optimization problem and achieves road network partitioning results with intra-area homogeneity, inter-area heterogeneity, and similar size of sub-areas. Through comprehensive evaluations using various indicators, our proposed partitioning method demonstrates superior performance compared to existing algorithms.

The rest of the paper is organized as follows. Section 2 introduces the fundamental theories, defines the problem, and provides an overview of the framework. It also provides an introduction to the road network reconstruction method. In Section 3, we present a comprehensive methodological overview, providing a detailed description of each module comprising the CSDRA approach proposed in this study. Moving on to Section 4, we showcase the results of the road network partitioning case study and compare CSDRA with alternative methods using evaluation indicators. Furthermore, we analyze the impact of constraint parameters on the partitioning results obtained with CSDRA. Finally, in Section 5, we conclude the paper by highlighting potential avenues for future research.

2. Problem Definition and Framework Overview

This section serves to introduce key definitions and concepts pertinent to the methodology presented in this paper. It outlines the problem at hand and provides an overview of the method framework.

2.1. Definition

To make the urban road network in the form of a physical network to be a machine-understandable network, it is necessary to give it a mathematical representation in the form of a graph, as defined in Definition 1 below. In this paper, we take the road segments in the original road network as vertexes and redefine the edges connecting them, so as to construct the Edge Graph as Definition 2.

Definition 1 (Road network)**.** *A real bidirectional urban road network is defined as* $R = (I, S)$*, comprising a set of intersection points* $I = (i_1, i_2, i_3, \ldots, i_n)$ *as nodes, and a set of road segments* $S = (s_1, s_2, s_3, \ldots, s_m)$ *connecting these nodes. Where the road segment* s_i *carries a weight* w_i*, which range is* $(0, 1)$.

The road segment weights can encompass various factors such as traffic flow, speed, pedestrian flow, and roadside facility evaluation. Once the road network is established, it can be transformed into an Edge Graph, which facilitates the partitioning process.

Definition 2 (Edge Graph)**.** *The Edge Graph is an undirected weighted graph, defined as* $G = (V, E)$*. Where the set of vertexes is defined as* $V = (v_1, v_2, v_3, \ldots, v_m)$*, which corresponds to the set S of segments of the road network R;* $e_{i,j}$ *denotes the edge connecting* (v_i, v_j).

During the construction of the edge graph, a crucial step is to calculate the weights assigned to the edges. These weights reflect the similarity between two vertexes, indicating the similarity between two corresponding road segments.

Definition 3 (Weight of the edge)**.** *The edge weight $\omega_{i,j}$ of the Edge Graph is calculated by weighting the Jaccard correlation $J(s_i, s_j)$ and the similarity $Sim(s_i, s_j)$ of the weights of the corresponding segments s_i and s_j in the road network R, as shown in Equations (1)–(3).*

$$\omega_{i,j} = \beta \cdot J(s_i, s_j) + (1 - \beta) \cdot Sim(s_i, s_j) \tag{1}$$

$$J(s_i, s_j) = \frac{|Ns_i \cap Ns_j|}{|Ns_i \cup Ns_j|} \tag{2}$$

$$Sim(s_i, s_j) = 1 - |w_i - w_j| \tag{3}$$

In Equation (1), β is the weight of the Jaccard correlation of the road section in the range of $(0, 1)$. The value can be determined empirically, such as $\beta = 0.5$, or confirmed by an objective weighting method such as the entropy weighting method.

The Jaccard correlation can be used to measure the correlation of edges in the graph [32], but to ensure the continuity of partitioning the resultant sub-areas, a threshold ∂ is needed before calculating the edge weights, such as $J(s_i, s_j) > \partial$, $\partial = 0.3$. It is calculated as the ratio of the number of elements of the intersection of sets Ns_i and Ns_j to the number of elements of their concurrent sets, where the two sets are the vertexes connected to the endpoints of segments s_i and s_j, respectively. The closer the value is to 1 the better the network association of the two road segments. Equation (3) calculates the similarity of segment weights, the closer the value is to 1 means the more similar the weights of two segments are. It is necessary to set a certain threshold γ to ensure intra-area homogeneity and inter-area heterogeneity, and to filter the $e_{i,j}$ worthy of retention according to $\omega_{i,j} > \gamma$.

Once the Edge Graph is constructed, the community detection algorithm can be applied to implement the initial partition that considers the maximum modularity [33,34].

Definition 4 (Modularity)**.** *Modularity is a widely used metric in network analysis to assess the structural properties of a network. It quantifies the level of clustering within different communities of the network [35]. Usually, the higher the modularity value is, the more obvious and tighter the communities exist in the network. Considering that the graph used for partitioning in this paper is an undirected weighted graph, the modularity degree is defined as follows:*

$$Q = \sum_{c=1}^{n} \left[\frac{\varpi^c}{\varpi} - \left(\frac{d^c}{2\varpi}\right)^2\right] \tag{4}$$

The ϖ is the sum of the weights of all edges, while ϖ^c is the sum of the weights of the edges inside sub-area c; d^c is the sum of the strengths of all vertexes inside sub-area c. The concept of strength is similar to the degree of a vertex in a graph and refers to the sum of the weights of the neighboring edges of the vertex [33].

Define a $k \times k$ symmetric matrix $M = (l_{pq})$, where l_{pq} denotes the ratio of the sum of the edge weights connected between sub-areas p and q in the network to the sum of all edge weights. Particularly, l_{pp} represents the ratio of the sum of the edge weights within the sub-area p to the sum of all edge weights. Summing the rows of the matrix M yields $a_p = \sum_q l_{pq}$, which represents the ratio of the strengths of the vertexes connected to the sub-area p to the strengths of all vertexes. Thereby, the modularity expressed in Equation (4) can be further expressed as:

$$Q = \sum_p \left(l_{pp} - {a_p}^2\right) \tag{5}$$

Urban roads typically have bidirectional traffic, and different directions on the same road often carry distinct weights, such as traffic flow, density, or sidewalk barrier-free facilities evaluation. In the real road network, as illustrated in Figure 1a for segment 1a and segment 1b, there is no direct connection between the different directions of the same segment. Without other processing, the graph generated with the initial road network would cause two related road segments (e.g., Figure 1a,b) to lose their close connection in the graph. To avoid this, we establish connections by linking the endpoints of bidirectional segments, as shown in Figure 1b. Subsequently, we convert the road network into an Edge Graph for partitioning, as illustrated in Figure 1c,d. Figure 1c is specifically tailored to consider pedestrian flow or roadside facilities evaluation, while Figure 1d focuses on vehicle flow. The disparity between them primarily lies in the connectivity of road segments. For instance, in Figure 1c, road segments 4a and 3b are directly connected, whereas in Figure 1d, these two road segments lack a direct connection. This indicates that our network reconstruction method is specifically designed to partition the network while considering the aspects of pedestrians, roadside facilities, and vehicles.

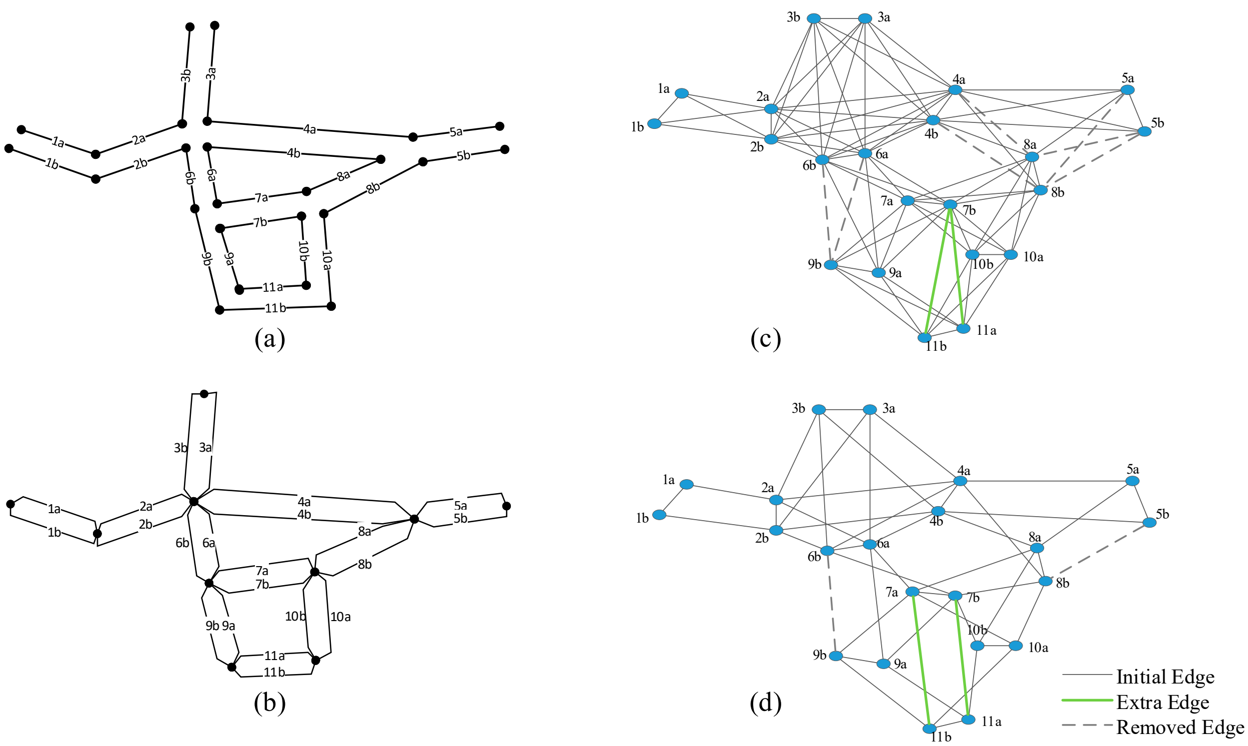


Figure 1. Schematic conversion of the initial road network to an Edge Graph: (**a**) initial road network; (**b**) road network; (**c**) Edge Graph (for pedestrian flow or roadside facilities); (**d**) Edge Graph (for vehicle flow).

In the schematic of the Edge Graph, we have distinguished three types of edges: Initial Edges, Extra Edges and Removed Edges.

Definition 5 (Initial Edges)**.** *The Initial Edges are established based on the adjacency of the road network during the construction of the Edge Graph, which is commonly used in similar studies [22].*

Definition 6 (Extra Edges)**.** *The Extra Edges are obtained by removing the Initial Edges after performing calculations based on Equations (1)–(3) and applying the filtering conditions* $J(s_i, s_j) > \partial$ *and* $\omega_{i,j} > \gamma$*. In other words, the Extra Edge includes connections between segments that were not originally connected in the road network.*

The inclusion of these Extra Edges has somewhat strengthened the internal linkages within the homogeneous group of road segments.

Definition 7 (Removed Edges)**.** *Removed Edges are edges that are filtered out by the threshold constraint $\omega_{i,j} > \gamma$ in Initial Edges.*

The Removed Edges correspond to road segments in the road network that have adjacent relationships but significant differences in weights. These Removed Edges are eliminated from the Edge Graph. Eliminating Removed Edges from the Edge Graph can effectively reduce the linkage between widely differing segments.

This processing enhances the connectivity among homogeneous segments while reducing the connectivity among heterogeneous segments. As a result, it improves the modularity within the sub-areas, leading to more favorable partitioning outcomes.

2.2. Problem Statement

Road network partitioning is an NP-hard problem, and it is difficult to obtain an exact solution directly. To verify the effectiveness of the proposed method, some indicators are needed to evaluate the partitioning results [36]. These indicators include the inverse temperature [37], NMI [38], and GC-measure [39], which have been commonly used in previous studies. In this paper, we summarize the existing literature and propose three evaluation indicators including normalized overall variance (VT), weight cutting (WC), and size variability (LM). These indicators are tailored to the specific partitioning objectives, and smaller values across all three indicators correspond to better partitioning results.

- Normalized overall variance

This indicator measures the degree of intra-area homogeneity within the partition results. It is represented on a scale ranging from 0 to 1, where a smaller value indicates a higher level of intra-area homogeneity. The equation is as follows:

$$VT = \frac{\sum_{c=1}^{N} L_c \cdot Var(w^c)}{L \cdot Var(w)} \tag{6}$$

where, L_c is the sum of the segment lengths of sub-areas c, $Var(w^c)$ denotes the variance of each segment weight of sub-areas c. While L and $Var(w)$ are the sum of the segment lengths of the whole road network and the variance of all segment weights, respectively. Different from similar indicators in the existing literature [14], this paper uses the length of a road segment rather than the number of road segments as the unit of calculation, because the minimum unit of the division method in this paper is road sections of varying lengths.

- Weight cutting

This indicator measures the degree of inter-area heterogeneity within the partition results. It is represented on a scale ranging from 0 to 1, where a smaller value indicates a higher level of inter-area heterogeneity. The equation is as follows:

$$WC = \frac{1}{N}\sum_{c=1}^{N} \rho(R_c) \tag{7}$$

where, $\rho(R_c)$ represents the mean value of the similarity of the weights of the connected sections of the sub-network R_c and its surrounding road network R_{nc}; N represents the total number of sub-areas.

- Size variability

This indicator measures the variability in the size of the sub-areas and is essentially the standard deviation of the normalized length of the road segments in each sub-area. A smaller value of this indicator represents less variability in the size of the sub-areas and the equation is as follows:

$$LM = \left(\frac{1}{N} \sum_{c=1}^{N} (L_c - \overline{L})^2 \right)^{\frac{1}{2}} \tag{8}$$

$\overline{L}$ is the average value of the total length of the segments of all sub-areas, which is the ideal total length of the sub-areas.

Taking the above three evaluation indicators as objective functions, the road network partitioning problem can be formulated as a multi-objective optimization problem. The objectives are to minimize the variability within sub-areas, minimize the similarity between sub-areas, and minimize the variability in the size of all sub-areas. In addition to these objectives, several constraints need to be considered:

$$subject\ to: \quad L = \sum_{c=1}^{N} L_c \tag{9}$$

$$\rho(R_c) = \frac{1}{M} \sum_{w_i \in R_c} \sum_{w_j \in R_{nc}} (1 - |w_i - w_j|), \quad R_c, R_{nc} \in R\ and\ R_c \neq R_{nc}, \quad i \neq j \tag{10}$$

$$L_c \geq L_{\min}, \quad c \in \{1, 2, \cdots, N\} \tag{11}$$

$$Sq_{\min} \leq Sq_c \leq Sq_{\max}, \quad c \in \{1, 2, \cdots, N\} \tag{12}$$

$$N, M > 0, \quad and\ N, M \in N^* \tag{13}$$

where w_i and w_j are the weights of the connected segments between R_c and R_{nc}, respectively, while M denotes the number of connected segments. $L_{\min}$ is the length constraint used in the initial partition to repair the effects of the bottleneck segments, as explained later in 3.1. The $Sq_{\min}$ and $Sq_{\max}$ are the upper and lower bound constraints, respectively, which are essentially the area of the corresponding sub-areas and are used to control the size of the sub-areas.

To solve the above problem, we propose the method shown in the next subsection to obtain the ideal partitioning result by initial partition and dynamic adjustment.

2.3. Framework Overview

Before introducing the methodological framework proposed in this paper, it is important to re-emphasize the objectives of this study. The objectives include achieving intra-area homogeneity, inter-area heterogeneity, and similarity in size. While the first two objectives are commonly considered in relevant studies, the importance of similarity in size is often overlooked. In the partitioning of a heterogeneous road network, it is crucial to not only obtain homogeneous sub-areas but also ensure that the sizes of the sub-areas are similar. This is essential for effective regional coordination control and traffic management. If the sizes of the partitions vary significantly, it becomes challenging to manage and control them in practical application scenarios, despite achieving homogeneity.

The framework of the CSDRA method is illustrated in Figure 2. Unlike most existing road network partitioning methods, our proposed method outputs both line sub-areas and surface sub-areas. The surface sub-areas are intended to be used for overlaying spatially-distributed population, GDP, and other data for analysis. This integration of data can provide valuable insights for urban planning and traffic management.

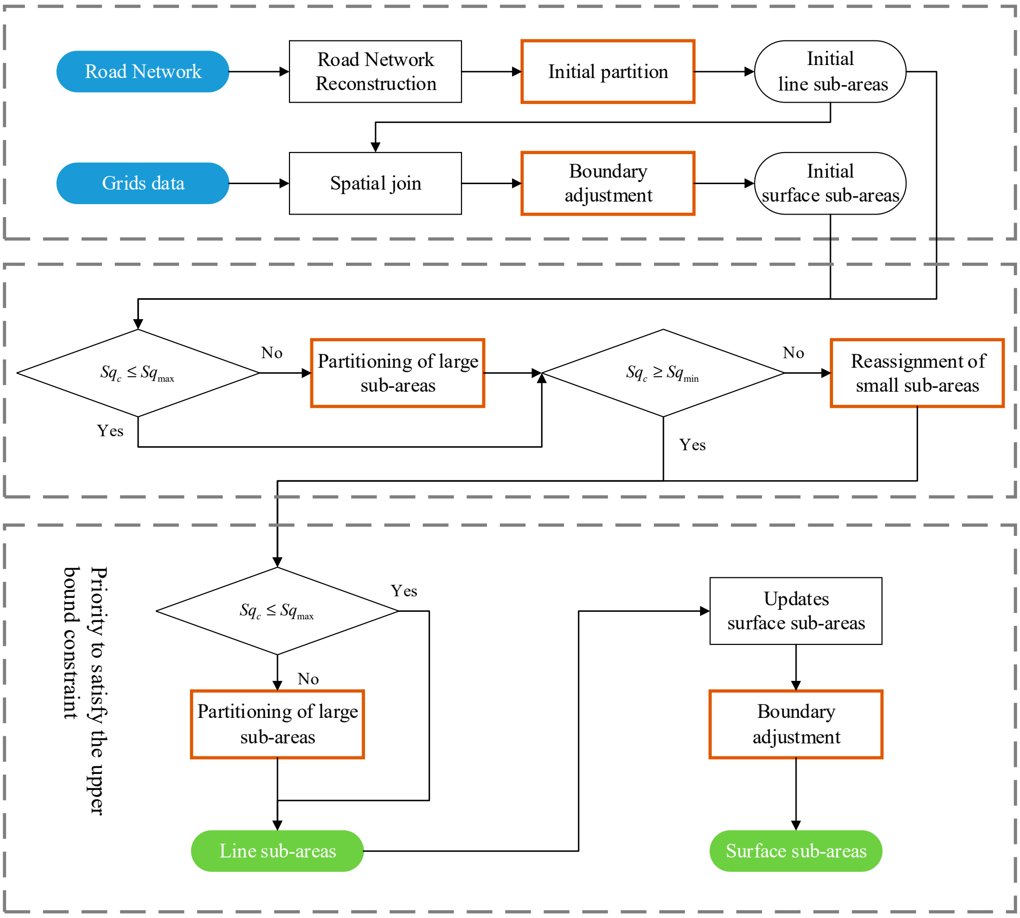


Figure 2. The framework of CSDRA.

In Figure 2, the blue boxes indicate the input data of the method, and the green boxes indicate the final output. In addition, the orange boxes represent important modules within the method, including the initial partition, partitioning of large sub-areas, reassignment of small sub-areas and boundary adjustment. These modules will be discussed in greater detail in Section 3 of the paper. The CSDRA method can be summarized as a process of iteratively adjusting the initial line sub-areas based on the defined constraints, ultimately generating both line and surface sub-areas. The framework of CSDRA can be divided into three main parts:

- Generation of homogeneous sub-areas.

To obtain the initial line sub-areas, we begin by inputting the initial road network and transforming it into an Edge Graph with weighted connections, as outlined in Figure 1. The data input here can be a road network with segment weights as shown in Figure 1a,b. Next, we partition the Edge Graph using the initial partition module (shown in Algorithm 1) and assign sub-area numbers to each road segment, resulting in the initial line sub-areas. We then perform a spatial join between the input grids data and the initial line sub-areas. This process assigns numbers to each grid, resulting in the initial surface sub-areas. The grid data refers to square cells that are uniformly divided based on a specified size, such as square cells with a side length of 500 m, within the defined study area. Then, to ensure the closure and boundary smoothing of each sub-area, the initial surface sub-areas were processed by boundary adjustment.

- Size adjustment and output of the line sub-areas.

To output the final line sub-areas, we need to partition the large sub-areas that exceed the upper bound constraint by Algorithm 2 and reassign the small sub-areas that fall below the lower bound constraint by Algorithm 3. This framework ensures that the output sub-areas satisfy the lower bound constraint, as complete control over sub-area size within the given tighter constraint interval cannot be guaranteed. It is important to emphasize that the adjustments primarily focus on the line sub-areas, with the surface sub-areas being adjusted accordingly after the line sub-areas have been modified.

- The adjustment and output of the surface sub-areas.

The line sub-areas output from the previous process is used as input to adjust the initial surface sub-areas. Finally, the surface sub-areas are processed by Algorithm 4 to ensure their smooth boundaries.

Due to variations in road network density, this method takes into account length constraints during the initial partitioning phase, while area constraints are primarily considered during size control. Moreover, we want to emphasize that the partitioning and adjustment are oriented to the line sub-areas. While the surface sub-areas, derived from the line sub-areas, are mainly used for area calculation to facilitate size control and provide support for the spatial analysis of subsequent partition management.

3. Methodology

In this section, we will describe each module mentioned above in detail.

3.1. Initial Partition

To accommodate the computation of large-scale road networks, this paper adopts the FN algorithm [40] for the initial partitioning process. The FN algorithm employs a greedy approach to search for a partitioning result that maximizes the modularity of the Edge Graph. In real road networks, the weights of road segments may not be uniformly distributed, and bottleneck segments may exist, characterized by significant weight differences compared to their surrounding connected segments. These bottleneck segments can affect the construction of the Edge Graph and may result in smaller and independent sub-graphs. Therefore, to ensure that the initial partition basically aligns the partitioning objective, an adjustment based on the length constraint is necessary. The specific steps for this module are as follows:

1. Initialize the edge graph so that each node is an independent sub-area. By this time, in the matrix $M = (l_{pq})$ discussed in Definition 4, the initial l_{pq} and a_p satisfy:

$$l_{pq} = \begin{cases} \frac{\omega_{p,q}}{2\varpi}, & If\ p\ is\ connected\ to\ q \\ 0, & else \end{cases} \tag{14}$$

$$a_p = \frac{d_p}{2\varpi} \tag{15}$$

2. Merge the sub-areas connected with edges in turn and calculate the increase in modularity after merging:

$$\Delta Q = l_{pq} + l_{qp} - 2a_p a_q = 2(l_{pq} - a_p a_q) \tag{16}$$

   According to the idea of the greedy algorithm, each merger proceeds in the direction where Q increases the most or decreases the least. After each merge, the l_{pq} corresponding to the merged sub-area is updated and the a_p and a_q are recomputed.
3. Repeat step 2 until the entire network is merged into one sub-area, then stop and find the partitioning result corresponding to the largest Q in the merging process and output it.
4. Check whether there are sub-areas that do not satisfy the length constraint by Equation (11). If so, assign these sub-areas according to the principle that are adjacent and have the most similar weights. If not, skip directly to step 5.
5. Output the intra-area homogeneous and inter-area heterogeneous partition results.

Algorithm 1: Initial partition

Input: $G = (V, E)$: Edge Graph to be partitioned.
Output: C_list: List of sub-areas numbers for each road segment s_i.
$C\_list \leftarrow [\{v\}\ for\ v\ in\ G.nodes()]$
$Q \leftarrow \text{modularity}(G, C\_list)$
While True:
  Find $merge\_pair$ that can be merged
  If $merge\_pair$ **is None:**
    EndWhile
  Initial $best\_pair \leftarrow None$, $best\_\Delta Q \leftarrow 0$
  For i, j **in** $merge\_pair$:
    Merge sub-areas and get C_list_new, which is the new list of sub-areas numbers for each road segment.
    $\Delta Q \leftarrow \text{modularity}(G, C\_list\_new)$
    If $\Delta Q > best\_\Delta Q$:
      $best\_pair \leftarrow (i, j)$, $best\_\Delta Q \leftarrow \Delta Q$
      Renew C_list with $best\_pair$, $Q \leftarrow Q + best\_\Delta Q$
    EndIf
  EndFor
If $L_c < L_{\min}$:
 Reassign this sub-area c.
EndIf

3.2. Partitioning of Large Sub-Areas

To address large sub-areas that do not meet the upper bound constraint, we employ spectral clustering, a clustering method derived from complex network theory. Spectral clustering allows us to specify the number of sub-areas to be partitioned, facilitating better control over the partitioning process. The method can be summarized in the following steps:

1. Input the road network R_{up}^c of the sub-area to be partitioned, and obtain the adjacency matrix A according to the segment adjacency relationship.

$$[A(R_{up}^c)]_{ij} = \begin{cases} 1, & If\ s_i\ is\ connected\ to\ s_j \\ 0, & else \end{cases} \tag{17}$$

2. The degree matrix D is first calculated by summing each row of the adjacency matrix A. Then the Laplace matrix is obtained from $Lap = D - A$.
3. Calculate the eigenvalues and eigenvectors of the Laplacian matrix, sort the eigenvalues from smallest to largest, and select the top k eigenvalues and their corresponding eigenvectors f.
4. Combine the selected eigenvectors into a feature matrix, and each row represents the k-dimensional features of the corresponding road segment. Then the feature matrix is used as the input data to obtain the k-class classification results by k-means clustering.
5. Check whether the newly partitioned sub-area all meet the upper bound constraint. If so, output the result directly; if not, extract those unsatisfied sub-areas and return to step 1 for further processing.

Algorithm 2: Partitioning of large sub-areas

Input: R_{up}^c: Road network to be partitioned.
k: The number of sub-areas.
Output: C_list_{up}: List of sub-areas numbers for each road segment s_i in the target area.
$R_{temp} \leftarrow R_{up}^c.copy()$
While True:
  Construct the adjacency matrix A from R_{temp}
  The degree matrix $D \leftarrow \text{diag}(A.\text{sum}(\text{axis} = 1))$

The Laplace matrix $Lap \leftarrow D - A$
Calculate the eigenvectors and eigenvalues of Lap.
Sorting the eigenvalues from smallest to largest
$C\_list_{up} \leftarrow Kmeans([f_1, \cdots, f_k],\ n\_cluster \leftarrow k)$
If $Sq^{i}_{new} < Sq_{\max},\ where\ Sq^{i}_{new} \in [Sq^{1}_{new}, \cdots, Sq^{k}_{new}]$**:**
Renew C_list_{up}
EndWhile
Else:
$R_{temp} \leftarrow R^{i}_{up\_new}$
EndIf

In the partitioning process, determining an optimal value for k is not straightforward. Therefore, we set k = 2 and use an iterative approach in conjunction with the upper bound constraint test to achieve bi-partitioning. This ensures that each new sub-area satisfies the upper bound constraint. Due to the structural characteristics of the road network, the bi-partitioning process may generate smaller sub-areas. These small sub-areas are controlled by the lower bound constraint and eliminated through the reassignment of small sub-areas module.

3.3. Reassignment of Small Sub-Areas

To ensure the similar size of sub-areas, we need to reassign the road segments of small sub-areas to adjacent sub-areas. This reassignment process takes into account both the adjacency and the similarity of the weights of the road segments, following the principle of adjacent and most similar. To achieve this, we propose an inverse search algorithm. The algorithm works by searching for the most similar adjacent road segment in other sub-areas and adopting its sub-area number as the new number for the road segment to be assigned. As shown in Figure 3, the method successfully eliminates the sub-areas to be assigned by sequentially reassigning the road segments of the sub-areas that are adjacent to other sub-areas. The specific steps of the method are as follows:

1. Select the segments of the road network R^{c}_{down} of the sub-areas to be assigned that are adjacent to the road network R_{normal} of other normal sub-areas. These are the road segments to be assigned s_i for each assignment.
2. Calculate $Sim(s_i, s_j)$, where $s_j \in R_{normal}$. Assign s_i to the sub-area where the connected road segment with the highest similarity of road segment weights is located.
3. Check whether there are still road segments of sub-areas to be allocated. If they do not exist, output the final result. If they exist, go back to step 1.

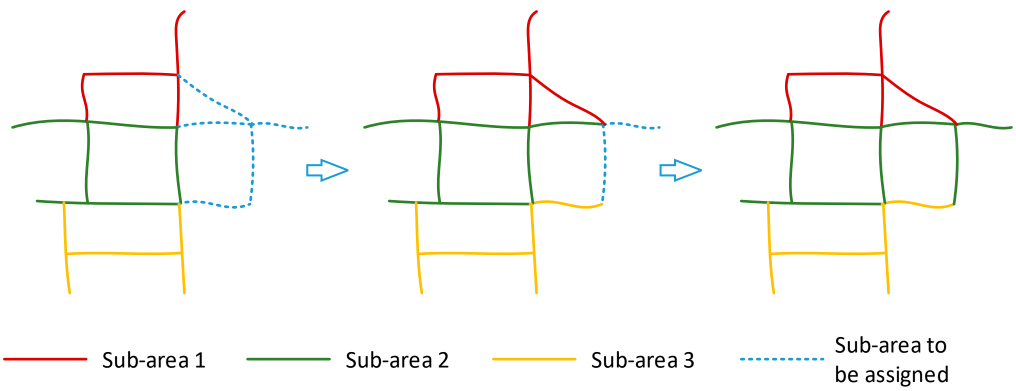


Figure 3. The process of reassignment of small sub-areas.

Algorithm 3: Reassignment of small sub-areas

Input: R^c_{down}: Road network to be assigned.
R_{normal}: Normal road network
Output: Lid: New sub-area number for the segment s_i to be assigned.
While True:
  For $s_i \in R^c_{down}$
    If s_i has connected segment s_j:
      Find the s_j^{target} that is most similar to s_i by $\max\left\{Sim(s_i, s_j)\right\}$
      Update the number of the target road segment, $Lid^{s_i} \leftarrow Lid^{s_j^{target}}$
    EndIf
  EndFor
  Renew R^c_{down} and R_{normal}
  If $R^c_{down} == \varnothing$
    EndWhile
  EndIf

3.4. Boundary Adjustment

To achieve smoother boundaries for the output surface sub-areas, we propose a boundary adjustment method specifically designed for the surface sub-areas. The method follows these steps:

1. The target grid is updated based on the mode of the sub-area numbers in its neighborhood. The neighborhood of the target grid includes other grids that are connected to its points or lines. An example illustrating this step is presented in Figure 4.
2. Check whether there is any change in the sub-area number of each grid in this round compared with the previous round. If there have been changes, continue with the next round of updates. If there have been no changes, conclude the update process and output the final result.

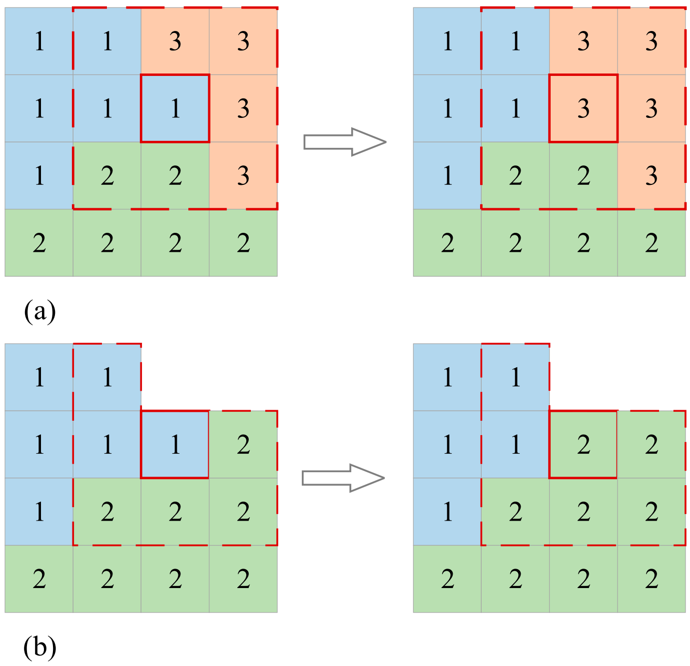


Figure 4. The process of boundary adjustment: (**a**) normal; (**b**) the margin of the study area.

In Figure 4, the sub-areas to which each grid belongs are represented by different colors and numbers. The solid red boxes indicate the target grid that is being updated, and the dashed boxes represent the neighborhoods of the target grid. It is important to mention that this method is also applied to the boundaries of the study area, as depicted in Figure 4b.

Algorithm 4: Boundary adjustment

Input: F: Grid data with sub-areas numbers, $[F_1, F_2, \cdots, F_n]$
Fid: The sub-areas numbers for each grid.
Output: F^{adj}: Adjusted grid data with sub-areas numbers.
1. **While** True:
2. **For** $F_i \leftarrow F_1$ to F_n
3. Find the Fid of all grids in the neighborhood of F_i and get $\left\{Fid_1^i, Fid_2^i, Fid_3^i \cdots\right\}$
4. Update the number of the target grid with the mode of the neighborhood numbers $Fid^i \leftarrow \text{mode}\left\{Fid_1^i, Fid_2^i, Fid_3^i \cdots\right\}$
5. **EndFor**
6. $change \leftarrow Number\ of\ changed\ Fid$
7. **If** $change == 0$
8. **EndWhile**
9. **EndIf**

4. Case Study

This paper uses the survey data of the barrier-free facilities of sidewalks in the downtown area of Guangzhou, China, as a case study. The survey data covers about 963.9 km^2 of land in Guangzhou, including the primary and secondary roads and some expressways with sidewalks in both directions, with a total mileage of about 2076.9 km.

4.1. Weights of Road Segments

In this paper, the survey data were organized into positive evaluation indicators with the value range of (0, 1), and the barrier-free facility level score was calculated by the entropy weight method. The score range is (0, 1), and the higher the score is, the better the comprehensive level of the barrier-free facilities of the road segment, the specific indicators are shown in Table 1. To realize partition management and special upgrade or renovation, we will partition the road network based on the barrier-free facility level score of the road segments.

Table 1. Evaluation indicators system of sidewalk barrier-free facilities.

Category	Content
Pedestrian infrastructure	Spatial validity, facility completion rate
Tactile paving	Tactile paving coverage, tactile paving continuity, Tactile paving conformity rate
Curb ramps	Curb ramps coverage, curb ramps completion rate, Curb ramps conformity rate
Other environmental facilities	Articulation rate of bus stops and tactile paving, coverage of wheelchair access to refuge, sign coverage

4.2. Road Network Processing

Because of the wide coverage of this survey, there are inevitably some missing data. We used the average of the barrier-free facilities scores of the adjacent road segments of the road segments missing data to fill the data of these segments. In addition, we also processed the initial road network to obtain a road network in the form of Figure 1b. As shown in the visualization of the barrier-free facility level score in Figure 5, the green color indicates a high score, while the red color is the opposite.

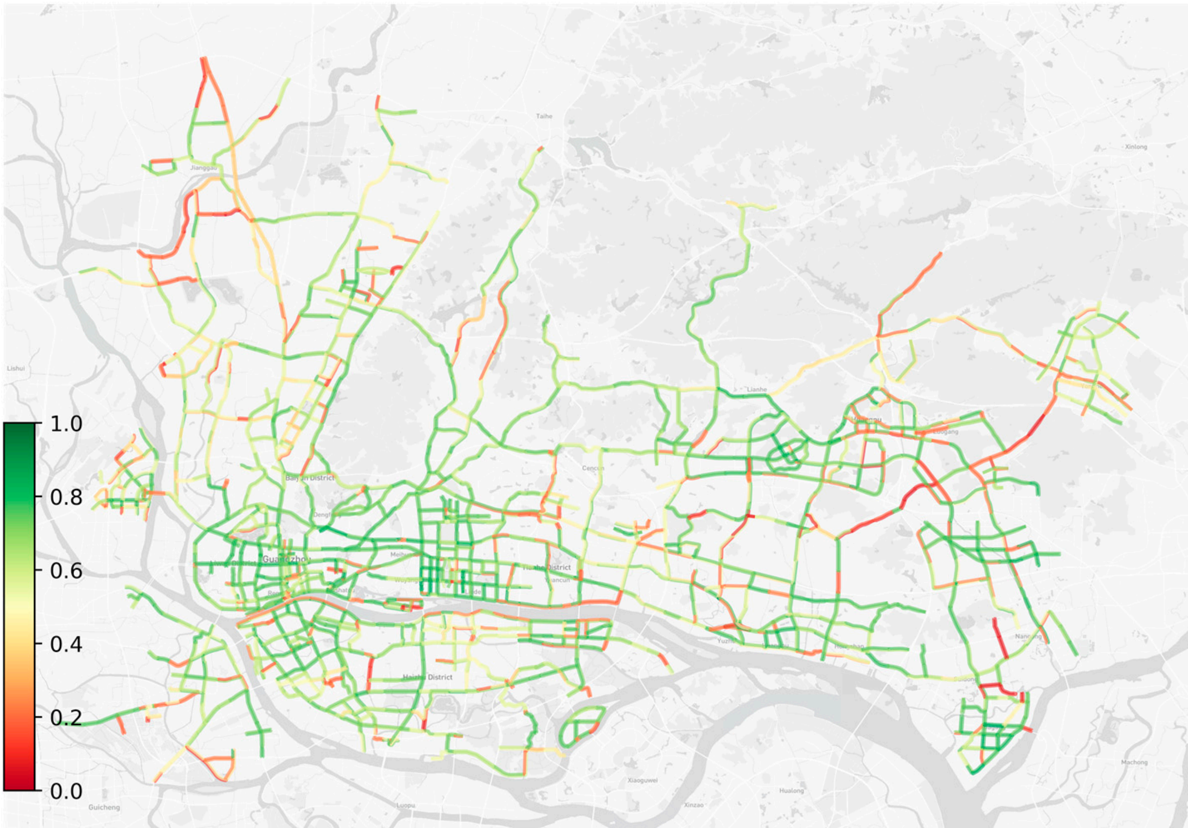


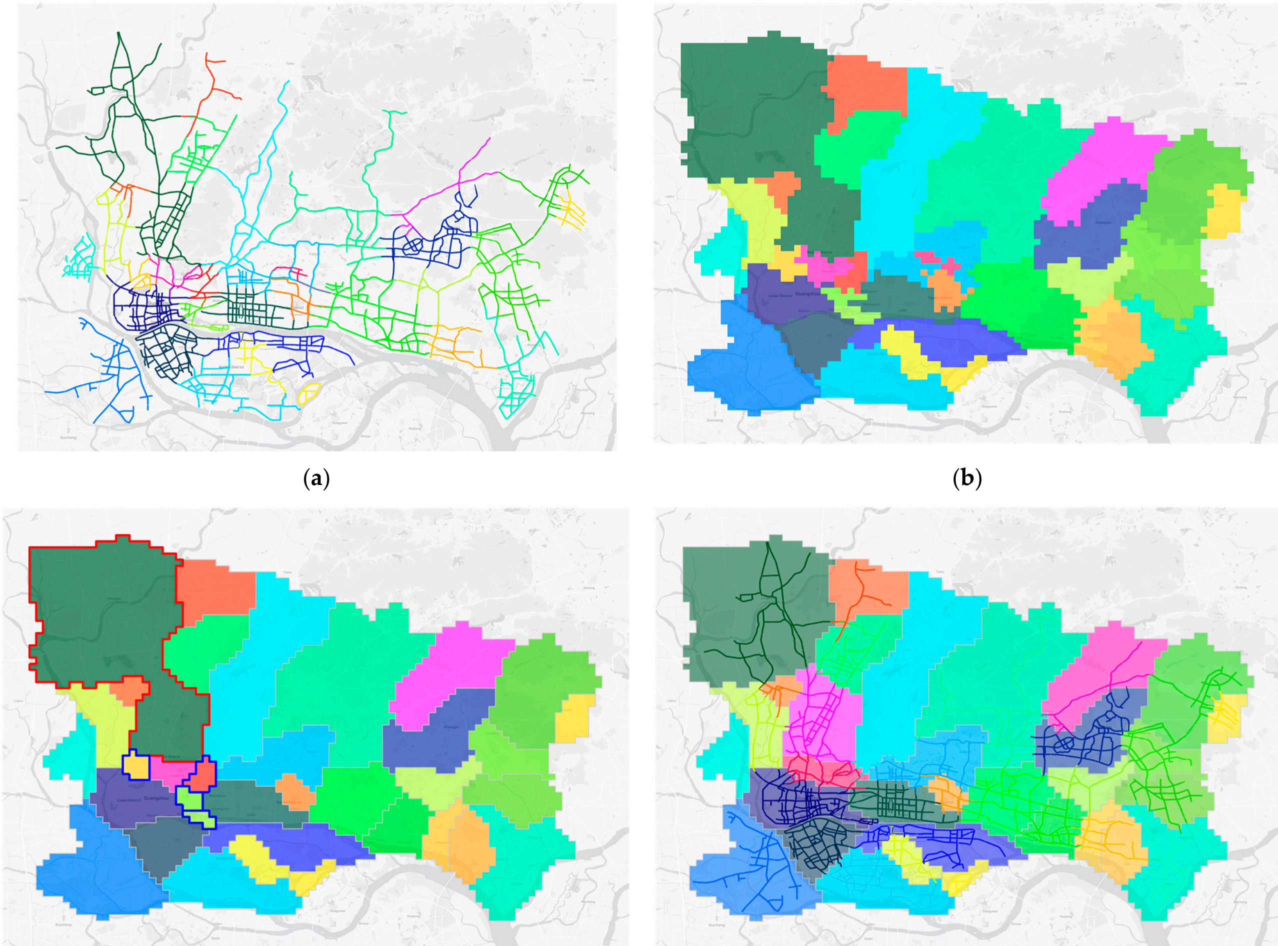
Figure 5. Sidewalk barrier-free facility level score of the case road network.

4.3. Partitioning

By inputting the bi-directional road network with weights, as depicted in Figure 5, we can observe the intermediate and final outputs shown in Figure 6. Each subplot in Figure 6 corresponds to a specific stage of the CSDRA framework. Let us delve into the details of each subplot combined with the framework. In Figure 6a, we can see the initial line sub-areas obtained through the initial partitioning of the Edge Graph. Each color represents a distinct sub-area. Moving on to Figure 6b, the study area is divided into multiple grids at a scale of 500 m. By combining these grids with the initial line sub-areas, we obtain the unadjusted surface sub-areas. Figure 6c shows the surface sub-areas after undergoing the boundary adjustment process. The adjustment ensures smooth boundaries and eliminates any small sub-areas that may have nested relations. Nested relations refer to the possibility of having one sub-area contained within another, which is undesirable in the context of traffic partition management.

The initial line sub-areas obtained from the initial partitioning are not optimal and require further adjustment. To achieve control over the sub-area sizes, we utilize the initial surface sub-areas as a guiding factor. In other words, the upper and lower bound constraints for sub-area sizes are determined based on the surface sub-areas. Referring to Figure 6c, the sub-areas marked with red borders indicate those that do not satisfy the upper bound constraint, while the sub-areas marked with blue borders do not satisfy the lower bound constraint. These sub-areas can be processed using the partitioning of large sub-areas and the reassignment of small sub-area modules, respectively. This ensures that the resulting partition satisfies the constraints to the greatest extent possible.

Finally, after applying the processing steps described above, we obtain the final output shown in Figure 6d. This includes the line sub-areas and the corresponding surface sub-areas.



(a) (b) (c) (d)

Figure 6. Partitioning results of the case road network: (**a**) initial line sub-areas; (**b**) initial surface sub-areas (without adjustment); (**c**) initial surface sub-areas; (**d**) final partitioning result.

4.4. Evaluation and Testing

To validate the effectiveness of the method proposed in this paper (CSDRA), we selected well-established partitioning methods for comparison, including Administrative Division (AD), Spectral Clustering Algorithm (SC), and Ncut, which have been widely used. Meanwhile, to assess the performance of the method proposed in this paper (CSDRA) without constraint adjustment and the effectiveness of constraint adjustment, we include CSDRA-N (with maximum constraint intervals) in the comparison. Furthermore, to validate the effectiveness of the road network reconstruction method, we also applied the Edge Graph obtained by this method to SC and Ncut, resulting in SC-R and Ncut-R for comparison. The performance of each method was evaluated using three evaluation indicators, as shown in Figure 7 and Table 2. The data in Figure 7 represents the relative growth value, which is calculated by comparing each indicator with the corresponding indicator value of the AD method used as a benchmark. A larger value indicates a better partitioning result obtained by the method, corresponding to a smaller original indicator value. The evaluation results of the first two indicators, obtained from CSDRA and CSDRA-N, show better performance compared to other methods. This suggests that the partitioning results achieved by CSDRA exhibit improved intra-area homogeneity and inter-area heterogeneity. Furthermore, the evaluation results based on the LM indicators demonstrate that CSDRA performs the best, while CSDRA-N, without effective partition and assignment, shows poorer performance. This indicates that CSDRA effectively reduces the size variability by adjusting the sub-area sizes within constraints without significantly compromising the intra-area homogeneity and inter-area heterogeneity of the partitioning results. Additionally, a comparison of Ncut with Ncut-R and SC with SC-R reveals that incorporating the Edge Graph obtained through road network reconstruction enhances the performance of the partitioning results in terms of both intra-area homogeneity and inter-area heterogeneity. However, it should be noted that this improvement may come at the minor cost of increased size variability.

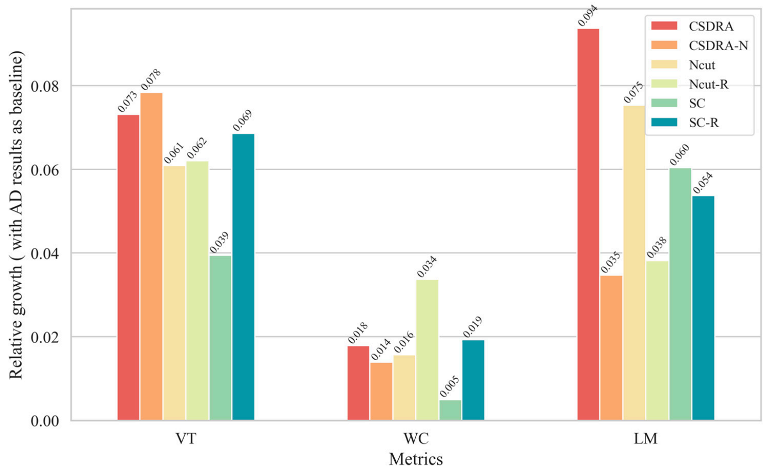


Figure 7. Comparison of evaluation results of case road network partitioning (using the result of AD as a benchmark).

Table 2. Comparison of indicator values of each method.

Method	VT	Relative Growth (VT)	WC	Relative Growth (WC)	LM	Relative Growth (LM)
AD	0.9832	0.0000	0.8513	0.0000	0.3508	0.0000
CSDRA	0.9101	0.0731	0.8334	0.0179	0.2571	0.0937
CSDRA-N	0.9048	0.0784	0.8374	0.0139	0.3161	0.0347
SC	0.9438	0.0394	0.8463	0.0050	0.2904	0.0604
SC-R	0.9146	0.0686	0.832	0.0193	0.2971	0.0537
Ncut	0.9223	0.0609	0.8356	0.0157	0.2755	0.0753
Ncut-R	0.9211	0.0621	0.8176	0.0337	0.3126	0.0382

These findings demonstrate the effectiveness of the CSDRA method in achieving desirable partitioning results that balance intra-area homogeneity, inter-area heterogeneity, and size variability, while the incorporation of the Edge Graph in related algorithms shows promise in improving the overall performance of the partitioning process.

To conduct a thorough analysis of the CSDRA performance and investigate the impact of constraint parameter adjustments on the partitioning results, we conducted multiple experiments with different combinations of upper and lower bound constraints. The results of these experiments are presented in Figure 8. In Figure 8, the vertical axes represent the values of different evaluation indicators, denoted by different colors. Specifically, Figure 8a–c represent VT, WC, and LM indicators, respectively. The horizontal axes represent the upper and lower bound constraints. Each subplot in Figure 8 is a scatter trend plot, where the scatter points are differentiated by color shades and sizes. Each point represents the evaluation result of an indicator under specific constraints. The curve or straight line represents the trend fitting line of all scatter points. To facilitate the following discussion, we must clarify a few concepts. Regarding the upper bound constraint, a larger value indicates a more relaxed constraint, while a smaller value indicates a tighter constraint. The opposite is true for the lower bound constraint. Furthermore, the lower bound constraint should not exceed the upper bound constraint, and the maximum value of the lower bound constraint should not exceed the minimum value of the upper bound constraint.

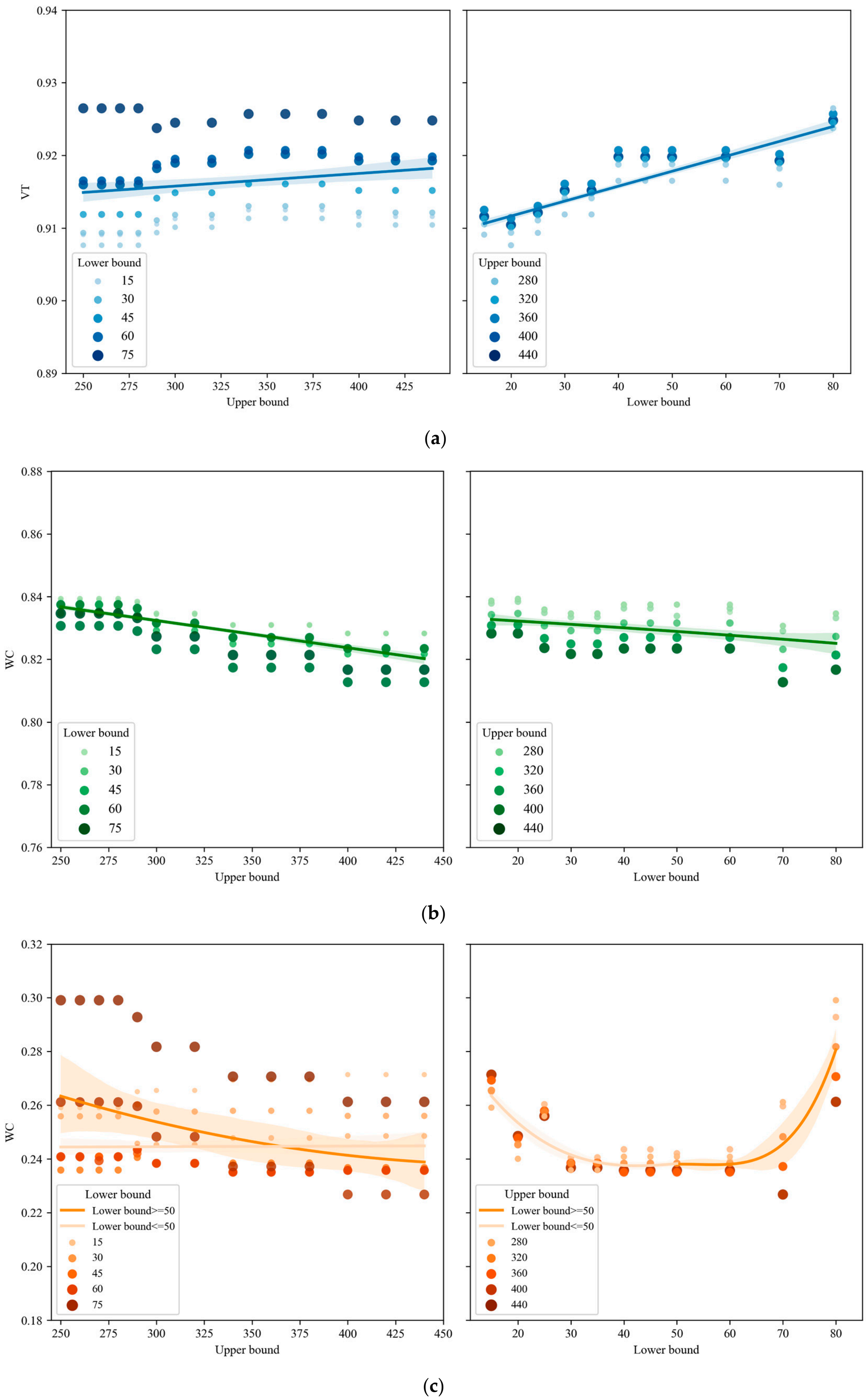


Figure 8. Constraint parameter test results for CSDRA: (**a**) VT; (**b**) WC; (**c**) LM.

In the subsequent analysis, we will interpret each subplot in Figure 8 individually, aiming to explore the impact of size constraints on the partitioning results.

- The intra-area homogeneity of the sub-areas is minimally affected by the upper bound constraint and slightly decreases when the upper bound constraint is relaxed. However, it significantly increases when the lower bound constraint is tightened.

In Figure 8a, the VT indicator is used to measure the intra-area homogeneity of the partitioning results, with a smaller value indicating better homogeneity. The subplot illustrates that changes in the upper bound constraint have minimal impact on the VT value, whereas tightening the lower bound constraint significantly increases the VT value. This phenomenon is easily understandable, as partitioning a homogeneous sub-area results in another homogeneous sub-areas, thus leading to minimal impact. However, the reassignment of smaller sub-areas can significantly reduce the homogeneity of the resulting receiving sub-areas. Additionally, as the lower boundary constraints become tighter, the impact becomes greater with a larger number of sub-areas being assigned.

- The inter-area heterogeneity of the sub-areas increases significantly with the relaxation of the upper bound constraint. However, it is less influenced by the lower bound constraint and shows an overall slightly enhancing trend with the tightening of the lower bound constraint, with local up and down fluctuations.

Figure 8b illustrates the variation in WC, where a smaller value indicates better inter-area heterogeneity of the partitioning results. The plot shows that WC decreases as the upper bound constraint is relaxed. However, the relationship with the lower bound constraint is not clear, as it exhibits a slight decrease with the tightening of the lower bound constraint. The scatter distribution of WC also displays fluctuations. This phenomenon can be easily understood, as a more relaxed upper bound constraint leads to the partitioning of less homogeneous sub-areas, resulting in better inter-area heterogeneity. On the other hand, the impact of the lower bound constraint on inter-area heterogeneity is less significant, with minor fluctuations observed.

- The size variability in the sub-areas demonstrates distinct patterns about the constraint parameters, exhibiting different trends on either side of the lower bound constraint threshold. When the value is below the threshold, the size variability in the sub-areas exhibits a slight increase with the relaxation of the upper bound constraint and a slight decrease with the tightening of the lower bound constraint. On the other hand, when the value is above the threshold, the size variability in the sub-areas experiences a significant decrease with the relaxation of the upper bound constraint and a slight increase with the tightening of the lower bound constraint.

Figure 8c depicts the variation in LM, where a smaller value indicates a smaller size variability in the partitioning results. The variation in this indicator is influenced by a specific threshold value of the lower bound constraint (taking $Lower\ Bound = 50$ as an example). When the value is below the threshold, the LM value exhibits a slight increase with the relaxation of the upper bound constraint and a significant decrease with the tightening of the lower bound constraint. Conversely, when the value is above the threshold, the change pattern is reversed. To better explain this situation, we divide the constraint interval into three cases (1) upper bound constraint relaxation and lower bound constraint tightness, (2) upper bound constraint tightness and lower bound constraint relaxation, and (3) both constraints being tight. Based on the real test results, the size variability does indeed decrease in the first two cases, which aligns with our intuitive understanding. However, in the third case, the change in size variability is unstable and may even increase instead. This is because it may not be possible to maintain the size of each sub-area within a narrow interval when both constraints are tight through multiple partitioning and reassignment, unless we completely disregard the intra-area homogeneity and inter-area heterogeneity of the sub-areas. Therefore, it is important not to set the constraints too tightly simultaneously.

Based on Figure 8 and the related analyses, it is evident that controlling and adjusting the constraints can indeed enhance the partitioning results. While moderate changes in the upper and lower bound constraints may have a slight impact on intra-area homogeneity and inter-area heterogeneity, they can significantly reduce the size variability in the sub-areas. However, it is important to note that setting tighter constraints on both the upper and lower bounds can lead to poorer partitioning results. Therefore, finding an appropriate balance in constraint adjustments is crucial for achieving desirable outcomes.

5. Discussion and Conclusions

In this paper, the road network partitioning objectives encompass intra-area homogeneity, inter-area heterogeneity, and sub-area size similarity, with certain size restrictions. To address these objectives, we propose a network reconstruction method for bidirectional weighted road networks, considering the coupling of network connections and traffic attributes. This method preprocesses the road network by enhancing connectivity among homogeneous road segments and reducing connectivity among heterogeneous road segments, which facilitates subsequent partitioning. Moreover, we introduce the CSDRA algorithm, which consists of several modules. The initial partition module employs a community detection algorithm to generate an initial partitioning result. The partitioning of large sub-areas module utilizes spectral clustering to achieve bi-partitioning. The small sub-area reassignment module applies the inverse search algorithm to reassign smaller sub-areas. Additionally, an edge adjustment module is employed to refine the boundaries of surface sub-areas. By adjusting the sizes of large and small sub-areas in the initial partitioning result based on input constraint parameters, the algorithm aims to achieve a partitioning result that aligns with the desired objectives. Through the verification of evaluation indicators and testing of constraint parameters, we have observed that the proposed algorithm performs well in real cases. The road network reconstruction method effectively improves the performance of partitioning methods in terms of intra-area homogeneity and inter-area heterogeneity, as evident from its application in existing partitioning methods. Through constraint control, the CSDRA method effectively reduces the differences in sub-area sizes while maintaining intra-area homogeneity and inter-area heterogeneity.

However, in networks with bottleneck segments, the road network reconstruction method proposed in this paper may result in the formation of isolated sub-graphs. Consequently, as previously discussed, this can result in the formation of excessively small sub-areas during the initial partitioning process. Bottleneck segments are defined as road segments that have significantly different weights compared to the surrounding segments in the real road network. If these bottleneck segments happen to be critical segments within the road network, they may disrupt the connectivity between different parts of the network. Nevertheless, our method provides a partial solution to this problem by employing the Jaccard coefficient to establish connections between non-adjacent segments, effectively bypassing bottleneck segments. However, it is difficult to avoid the fact that these bottleneck segments may still become isolated sub-graphs and result in the formation of small sub-areas due to their differences from the surrounding segments. In fact, this limitation does not have a significant impact on the improvement of the method because we eliminate these small sub-areas through length constraints in the initial partitioning, and the evaluation results have been promising.

Subsequent research can be conducted on road network reconstruction methods to explore potential improvements. This may involve investigating alternative approaches to redefine the connection relationships between road segments, exploring the integration of network connections with traffic attributes, and addressing other relevant aspects that may improve the overall reconstruction process. Furthermore, future research could investigate methods for determining the constraint parameters in the CSDRA. For example, the constraint parameters can be determined by the size distribution of each sub-area in the initial partitioning result.

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