

Article

Evaluating Urban–Rural Disparity of Public Facilities Provision in Chengdu–Chongqing: An Equity Index Approach with Multi-Source Data

Xuan Liu ^{1,*} , Youxin Qian ¹, Guohui Zhou ¹, Guangyu Xu ², Junmin Lyu ³, Legend Zhang ³ and Ergang Wen ¹

¹ School of Public Administration, University of Electronic Science and Technology of China, Chengdu 611731, China; youxinqian@std.uestc.edu.cn (Y.Q.); zhouguohui@std.uestc.edu.cn (G.Z.); ergangwen@uestc.edu.cn (E.W.)

² School of the Environment, The University of Queensland, St. Lucia, Brisbane, QLD 4072, Australia; guangyu.xu@student.uq.edu.au

³ Future Tech Institute, Guangzhou Huashang University, Guangzhou 511300, China; junmin@gzhs.edu.cn (J.L.); lijuan@gzhs.edu.cn (L.Z.)

* Correspondence: liuxuan@uestc.edu.cn

Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- We offer a systemic framework to diagnose inequity beyond administrative boundaries.
- The four-step workflow integrates NTL-based patch delineation, multi-indicator accessibility evaluation, spatial clustering, and group-difference testing.

What are the main findings and/or the implications of the main findings?

- Significant urban–rural spatial inequity exists, with vulnerable groups most disadvantaged.
- Systemic feedback loops between facility investment and population vulnerability perpetuate disparity in the CCEC.

Abstract

Urban–rural public facility disparity is a systemic challenge that reflects dysfunctional feedback loops within and across social and technical subsystems. Traditional administrative-unit-based analyses cannot capture such systemic alignments. This study applies the marker-controlled watershed segmentation (MWS) algorithm, the Two-Step Floating Catchment Area (2SFCA) method, and spatial clustering methods sequentially to dynamically separate urban from rural areas and assess the urban–rural disparity in public facility provisions within the Chengdu–Chongqing economic circle (CCEC). The results indicate: (1) The distribution of public facilities in the CCEC is characterized by significant spatial inequity, predominantly manifested as a substantial disparity between urban and rural areas. (2) A significant misalignment exists between the supply of public facilities and the demands of vulnerable groups. Rural residents, low-income groups, and elderly people are at a disadvantage in accessing public facilities. (3) Rural residents are concentrated in low-income areas and have the most limited ability to obtain public facility services and resources, especially in terms of healthcare facilities. By replacing predefined administrative boundaries with image-derived functional urban–rural patches, the proposed framework enables a more spatially realistic assessment of urban–rural public facility disparities. This approach provides a transferable tool for system-level decision-making in regional planning, particularly for targeting resource allocation in underserved areas.



Academic Editor: Ying Fan

Received: 18 May 2026

Revised: 21 July 2026

Accepted: 23 July 2026

Published: 1 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: public facilities; spatial equity; equity index; urban–rural differences

1. Introduction

Public facilities (PFs) refer to resources provided, managed, or maintained by the government or public institutions aimed at serving and supporting all citizens [1]. The main goal of providing public facilities is spatial equity—ensuring that people of all regions, incomes, social classes, and races have equitable access to diverse services and opportunities [2]. Scholars have been exploring the issue of equitable allocation of public amenities for decades, resulting in the large amount of research literature [3–5]; however, research focusing on the urban–rural scale remains scarce due to the low operability and high difficulty of analyzing spatial equity across urban and rural settings [6]. Particularly in China, which is transitioning from rapid urbanization to integrated urban–rural development, bridging the urban–rural gap in public facility allocation is a complex and necessary measure to achieve regional balanced development, and it is also the cornerstone of social equity [7].

In this study, public facility provision and accessibility are conceptualized as a complex spatial sociotechnical system. This system is operationalized through three coupled subsystems: the geographic subsystem, represented by urban–rural patch delineation; the social demand subsystem, represented by vulnerable-group distributions; and the infrastructure supply subsystem, represented by public facility provision and accessibility. This complexity is often overlooked by studies that use administrative boundaries and annual statistics to separate urban from rural [1,4,8]. The majority of studies on spatial equity still rely on large-scale statistical data, which is often difficult to obtain [9]. The nonlinear dynamics and feedback loops between urban–rural boundary shifts, as well as the vulnerability of specific groups, remain underexplored. Therefore, it is crucial to design methods that can utilize more timely data and effectively distinguish between actual urban and rural spaces.

With the advancement of geographical analysis techniques, new data types, such as points of interest (POIs) and remote sensing data, are increasingly used in public service facility research [10–12]. These data significantly contribute to determining the geographical location and coverage of public facilities. However, their application in rural areas still requires exploration [13]. For the index, common metrics for assessing the spatial inequality of facilities can be measured by the Gini coefficient [4], location entropy [14], and accessibility indicators [15]. However, none of these can reflect the detailed alignment of facility distribution with different population groups. For example, the Gini coefficient lacks consideration of spatial attributes, such as facility supply and demand, spatial distribution, and service coverage. Accessibility is broadly defined as the service-to-population ratio but often neglects distinctions among different population groups, limiting its utility in understanding spatial relationships with socioeconomic patterns [16]. Instead, algorithm-driven analysis based on spatial big data provides an alternative option. The progress in spatial feature extraction [17], spatiotemporal dynamics analysis [18], detection and prediction [19] makes it possible for spatial equity to shift from statistical description to mechanism discovery and actionable diagnosis. Some studies have used spatial clustering methods, such as Moran’s I index and kernel density analysis, to reveal spatial supply–demand matching characteristics under different population needs [20]. Despite these limited studies revealing the spatial characteristics and impacts of public facility provision and accessibility among different population groups, most have focused on urban studies and neglected the value of rural spaces.

In response to the lack of a systemic understanding of urban–rural disparities in public facility provision and the need for evaluation based on geographical analysis and new data, this study frames urban–rural public facility disparities as a system problem rather than an isolated geographical issue. Specifically, the marker-controlled watershed segmentation (MWS) algorithm, a digital image-processing and mathematical morphology method, was first applied to differentiate urban and rural patches with multi-source data. With the Two-Step Floating Catchment Area (2SFCA) method combined with spatial overlay analysis, a public facility provision equity index was then constructed. This index benchmarks the spatial equity of public facilities across municipal and urban–rural boundaries. Spatial clustering methods are used in this study to reveal the correlation between facility equity and socioeconomic characteristics, which provides evidence for reducing urban–rural inequality through integrated planning. The contributions are therefore threefold: (1) to dynamically separate urban and rural areas using a nighttime light (NTL) image-processing and morphology-based classification workflow, capturing systemic nonlinearity; (2) to quantify spatial inequity as an emergent outcome of subsystem interactions; and (3) to provide a transferable system-level decision-support tool for regional coordination.

The subsequent sections of this paper begin with defining urban and rural public facilities and examining spatial equity measurement challenges (Section 2). It then details the data and methodology (Section 3), presents key findings (Section 4), discusses their theoretical and practical implications (Section 5), and provides conclusions, limitations, and future research directions (Section 6).

2. Provision of Public Facilities and Spatial Equity

2.1. Spatial Equity Problem of Public Facility Provision

Urban public facilities are the infrastructure and services provided within cities to support the dense populations and complex needs of urban residents [21]. In contrast, rural public facilities are designed for villages and small towns with sparse populations distributed over large areas, and typically include basic infrastructure, such as local roads and utilities [7]. However, urban and rural areas should be regarded as unified research units in regard to the distribution of various types of infrastructure [22]—regardless of where they live, residents must be treated equally. In theory, spatial equity derives from social equality. It is the principle that service facilities should be distributed fairly [23].

Urban–rural public facilities are fundamental to regional coordinated development and overall social progress [24]. Over recent years, the research focus on spatial equity in public facility distribution has garnered increasing attention from both governments and academia [7,25]. China has launched major national strategies in the 21st century, such as urban–rural integration and rural revitalization [26–28], emphasizing the critical issue of coordinated provision of public facilities in urban and rural settings. Meanwhile, with substantial improvements in living standards, rural residents now demonstrate rising expectations for public service facilities while showing far more diverse needs. However, due to factors such as administrative levels, population size, and economic development, urban–rural integrated development continues to face issues, such as insufficient public facility provision, low resource utilization efficiency, and even facilities that stand idle, giving rise to multiple supply–demand imbalances and social injustices [29]. Scholarly attention has centered on critical aspects of urban public service facilities, including their distribution networks, geographic accessibility, service fairness, and placement efficiency [4,14,30,31], while gradually introducing these research methods to the study of rural public service facility configurations.

Previous research studies have predominantly focused on assessing equity within a delimited set of geographic zones or facility types, primarily located in prosperous urban

and peri-urban regions, which has been a significant contribution [32]. However, a systematic investigation from a holistic urban–rural perspective to identify and determine the equity of the configuration of diverse public facilities across regions and urban–rural areas, as well as its correlation with socioeconomic spatial patterns, requires further enhancement. Despite the persistent disparities in public facilities, reducing such inequalities is crucial for enhancing residents' well-being and promoting regional coordinated development.

2.2. Measurement of Spatial Equity

Spatial equity research covers various fields within the social sciences. For urban planning and management, spatial equity refers to equal spatial proximity or segregation between residents and public facilities [33]. Scholars have broadly classified spatial equity indicators into two categories. The first comprises statistical measures, while the second encompasses spatial metrics that incorporate geographical attributes of public facilities [4]. Before the 21st century, researchers centered predominantly on assessing disparities through economic indicators, like GDP and income distribution, and targeted the statistical characteristics of data distributions. Consequently, various statistical indicators and methods were developed to measure social fairness and equality, such as the Gini coefficient [34], variance [35], coefficient of variation [36], and the Theil entropy index [37]. Notably, these methods initially stemmed from economics to measure data distribution characteristics and differences but have gradually extended to assess equity in various public services [38]. Entering the 21st century, advancements in geographic information technology led to the development and application of diverse methods and indicators for quantifying equity. Accessibility represents a cornerstone for assessing spatial equity, integrating considerations of spatial layout and operational efficiency to understand whether sufficient and equitable public services are provided [39]. Among these, commonly used methods include buffer analysis [40], network analysis [41], kernel density analysis [42], and the 2SFCA method [43,44].

Despite this, notable deficiencies exist in the current spatial equity measurement studies. First, the analytical focus has remained primarily confined to spatial equity assessments of specific public infrastructure types in urban or delimited regional contexts, such as healthcare accessibility [15], school accessibility [45], transportation facilities [46], and green space accessibility [8]. However, whether the proportion and configuration of multiple facility types is appropriate and equitable has been largely overlooked in urban planning efforts, which remains a critical issue. Second, there needs to be a more substantive understanding regarding inequalities in public facilities between different geographical regions, particularly in urban and rural contexts, where spatial inequity in public facility allocation is perpetuated [25]. Meanwhile, most studies have focused solely on the supply side of spatial equity while ignoring demand factors, thereby neglecting fairness evaluations that account for supply–demand disparities and societal characteristics. Tsou et al. [3] developed the integrated service equity index based on weighted facility importance to analyze relative equity across urban facilities, with further insights into the influence of facility scale, yet it overlooked residents' varying demands for different facilities. In recent years, Dadashpoor et al. [47] constructed a comprehensive model for measuring spatial inequality, analyzing facility mismatches based on population needs, distribution, and social deprivation. Additionally, using the 2SFCA method, Ashik et al. [48] computed integrated spatial accessibility metrics for urban public facilities. It subsequently operationalized non-spatial accessibility through population demand indices and social need indicators. However, systematic investigation of the spatial dynamics linking population demand and facility supply continues to be limited.

2.3. The Evaluation of Spatial Equity in Urban–Rural Public Facility Provision

Current resource allocation patterns in many countries often concentrate investments in urban areas at the expense of rural development. This trend has exacerbated interregional inequalities in social welfare, economic vitality, and habitat quality, with particularly pronounced effects in developing contexts [25]. The synergistic development between urban and rural regions heavily depends on improving infrastructure conditions. However, identifying spatial disparities in urban–rural public facilities and understanding the supply–demand dynamics among different demographic groups are pressing issues that urgently need resolution. Currently, several difficulties and challenges exist in this regard.

Firstly, studying urban and rural areas as integrated units presents significant challenges, with data collection and research predominantly focused on urban areas, resulting in a relative scarcity of data from rural areas [49]. Due to limited research resources and biases among researchers, urban studies often dominate, leading to insufficient attention to rural areas where the issues and needs of development are overlooked or less prioritized. Secondly, there needs to be a more systematic analysis of spatial equity disparities in urban–rural areas and their driving mechanisms [50]. Some studies have utilized principal component analysis to construct indicator systems and models, focusing on evaluating the policy effectiveness of specific infrastructure initiatives in achieving urban–rural equilibrium through the dual criteria of efficiency and equity [25]. Xu et al. [38] assessed the equity of nine educational and healthcare facility types using the Gini coefficient and hedonic pricing models, highlighting urban–rural disparities. A comprehensive understanding of urban–rural facility provision and accessibility patterns is hindered by insufficient spatial analysis. Simultaneously, definitional ambiguity in urban–rural spatial boundaries presents a fundamental obstacle to measuring cross-boundary equity, creating a dual challenge for researchers.

With the advancement of geographic information technology, many open-source datasets including POI, NTL data, and population heatmaps have emerged, facilitating research across urban and rural domains. These datasets present opportunities for spatial analysis in urban–rural studies, addressing gaps in rural data availability. Currently, studies utilizing NTL observations for urban mapping and urbanization estimation can be categorized into three main types: threshold-based methods, supervised classification, and statistical relationships between NTL indices and urban area observations [51]. Threshold-based methods, when continuously refined, offer efficient and accurate means to delineate urban areas across different spatial scales, as determined by optimal thresholds derived from varying levels of nighttime light values in different urban regions [52]. POI data provide precise and efficient information on the supply and spatial distribution of public facility points, which has been widely applied in spatial equity research through methods such as kernel density analysis and accessibility analysis [53]. Advances in algorithm-driven spatial intelligence have now made it possible to integrate this multi-source data with image-processing and spatial classification methods for automated urban–rural delineation and equity assessment. However, significant gaps remain in effectively utilizing novel data to study spatial inequalities in urban–rural public facilities and explore differences among various groups in urban and rural settings.

Addressing the above research gaps, this study aims to adopt a holistic urban–rural perspective using multi-source big data and novel methodologies to formulate an analytical framework for spatial facility equity. The scholarly goals underlying this research are: (1) to develop an equity index suitable for evaluating spatial equity of public facilities using new data and methodologies; (2) to delineate urban–rural patches, identify the distribution equity of public facilities among regions and urban–rural areas, and conduct

comparative analyses accordingly; and (3) to examine the mechanisms behind public facility supply–demand between urban areas and among different socioeconomic groups.

3. Data and Methods

3.1. Study Area

This study focuses on the Chengdu–Chongqing economic circle (CCEC) in Western China as the study area, which is one of the four major economic circles in China, covering two provincial administrative regions, Sichuan and Chongqing, and 142 district-level cities (see Figure 1). Since 2011, the Chengdu–Chongqing region has experienced three national plans, progressively deepening cooperation between its cities. As of 2019, the region hosted a resident population of 94.6024 million with an urbanization rate exceeding 60%, contributing a regional GDP of 6.3 trillion yuan (6.9% of national GDP and 30.8% of Western China's GDP). However, compared to the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area, significant disparities persist in public infrastructure provision, urban–rural integration, and regional economic development within the CCEC [54].

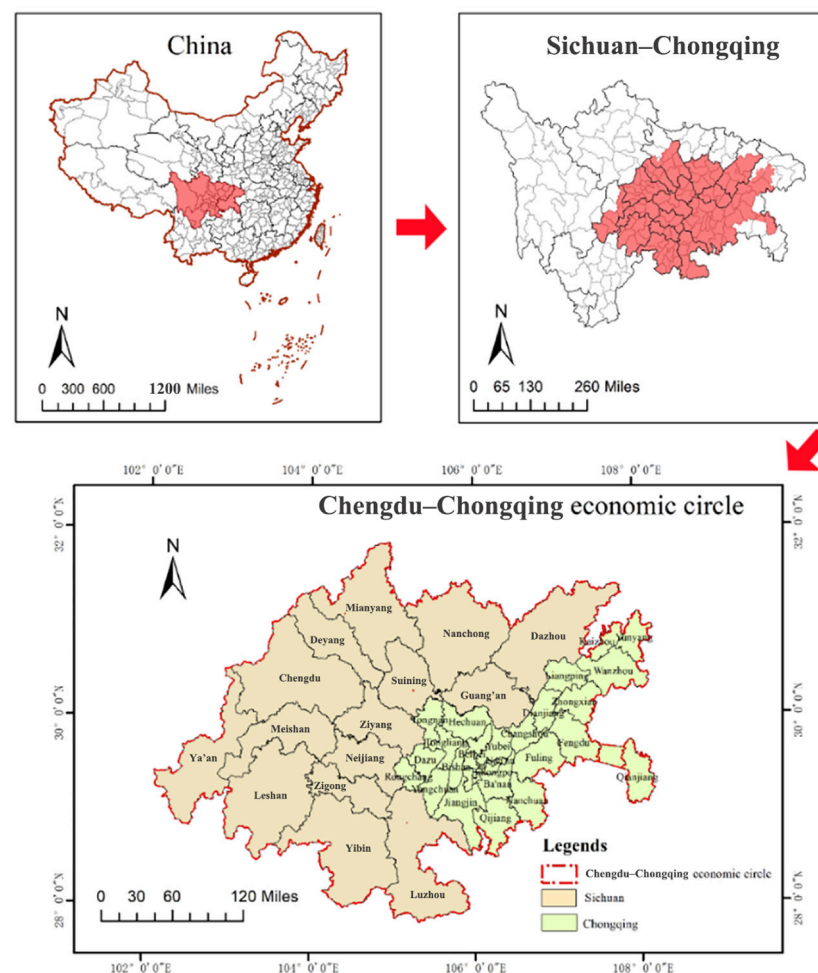


Figure 1. Location of Chengdu–Chongqing economic circle.

Uneven development exists in the CCEC. As of 2020, Chongqing and Chengdu ranked fifth and seventh nationally in terms of GDP, accounting for 62.6% of the economic circle's total. In contrast, other cities' GDPs did not exceed 500 billion yuan, with most falling between 100 and 300 billion yuan. The urban–rural gap in public resource distribution has become increasingly evident. The economic circle boasts 113 urban areas per 10,000 square kilometers, far surpassing the national average of 23 urban areas per 10,000 square kilo-

meters, with an urbanization rate exceeding 60%. Meanwhile, public facilities, such as education, healthcare, and pensions, are predominantly concentrated in core cities, leaving residents in rural areas and smaller cities struggling to access equitable public services. Therefore, investigating the differentiated characteristics of public facility provision within the economic circle and the spatial alignment of resident demands are essential criteria for gauging fairness in citizens' access to public services. This study seeks to establish an evidence-based foundation for policies designed to foster urban–rural integration and regional synergy within the CCEC.

3.2. Data Source

3.2.1. Multi-Source Big Data

- **POI data:** The POI data are sourced from the open API of Baidu Maps, collecting all POI points within the Chengdu–Chongqing region according to its data acquisition guidelines.
- **Urban boundary data:** A global dataset of annual urban maps is available at https://figshare.com/articles/dataset/A_global_dataset_of_annual_urban_extents_1992-2020_from_harmonized_nighttime_lights/16602224/1 (accessed on 1 December 2025). This dataset, developed by Zhao et al. [55], employs consistent nighttime light imagery to facilitate reliable long-term monitoring of urban dynamics at both local and global scales. It provides annual global urban maps covering the period from 1992 to 2020.
- **Population raster data:** The LandScan population dataset, developed by the Oak Ridge National Laboratory (ORNL) of the U.S. Department of Energy, is publicly provided by East View Cartographic at <https://landscan.ornl.gov/> (accessed on 1 December 2025).
- **House price data:** Housing price data, including location, price, and area, were obtained via Python (version 3.14) web scraping from major domestic real-estate platforms, such as Anjuke (version 17.30.0) and 58.com (version 13.21.5). The average housing prices in residential areas reflect the economic level. Due to the lack of detailed household income data, the average housing price in residential areas was used as a regional-level proxy indicator to measure socioeconomic conditions and housing affordability. Existing studies have also employed this proxy indicator to reflect relative socioeconomic disparities among different spatial units [56].

3.2.2. Survey Data

The survey data used in this study include the Seventh Population Census data, and the 2020 editions of the “China County Statistical Yearbook,” “Sichuan Statistical Yearbook,” “Sichuan Health and Family Planning Statistical Yearbook,” “Chongqing Statistical Yearbook,” and “Chongqing Health and Family Planning Statistical Yearbook.” These sources provide accurate population data (children, elderly, urban residents, rural residents), built-up area measurements, and fundamental data on various public infrastructure resources.

3.3. Methodology

3.3.1. System Conceptual Framework

A system-based modeling approach was adopted, consisting of three interacting subsystems: (1) the geographic subsystem, which refers to urban–rural boundaries delineated by a MWS algorithm-assisted classification step using the nighttime-light-derived annual urban extent dataset and administrative boundaries; (2) the social demand subsystem, which includes population density, income distribution, age structure, and so on; and (3) the infrastructure supply subsystem, which mainly refers to the locations and types of public facilities. The overall system output is the spatial equity index of facility accessibility for different social groups.

The urban–rural delineation step was implemented using a NTL image-processing workflow based on MWS [57], cluster screening, and logistic threshold estimation [58]. Subsequently, the coupling relationship between the geographic subsystem, social demand subsystem, and infrastructure supply subsystem is identified by examining whether urban–rural patches, vulnerable-group distributions, and public facility equity show spatial alignment or mismatch.

3.3.2. Workflow

By integrating multi-source big data, this study develops a composite PF equity index to evaluate the accessibility, layout, and equity of urban–rural public facilities, enabling visual identification of disparities. The detailed workflow is shown in Figure 2. First, instead of relying on administrative boundaries, this study adopts a nighttime-light classification procedure to delineate urban and rural patches. Potential urban clusters were first extracted using the MWS algorithm, false luminous clusters were then removed, and cluster-specific optimal NTL thresholds were estimated with a logistic model. Urban and rural areas were finally distinguished according to whether pixel-level values exceeded the corresponding optimal threshold. Second, the 2SFCA and spatial overlay methods were applied to quantify and aggregate public facility provision and accessibility indicators to create a comprehensive evaluation index. Third, Moran’s I method is used to analyze the correspondence of public facilities to socioeconomic characteristics in order to visually identify potential inequity areas. Finally, utilizing the Mann–Whitney U test, this examination then assessed connections between varying social group demands and differential resource allocation patterns of public facilities.

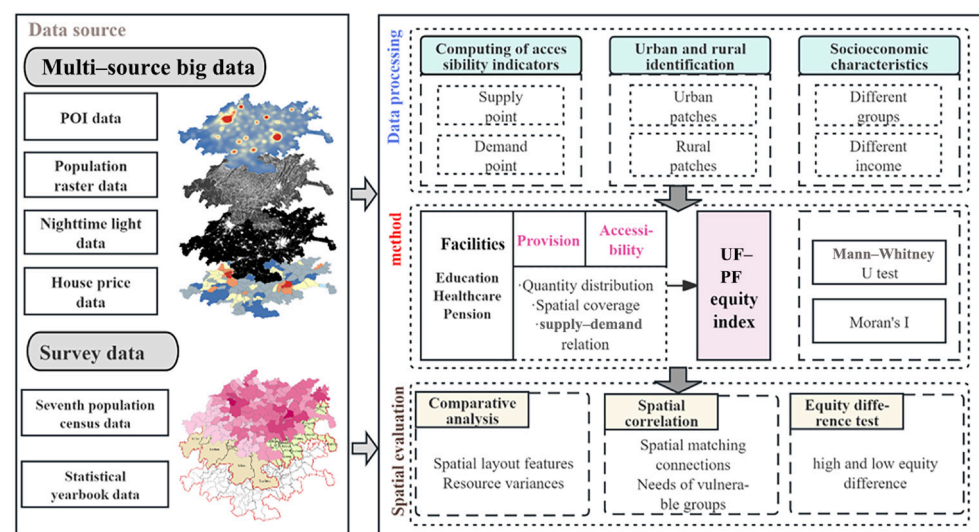


Figure 2. Workflow of public facility equity evaluation.

3.3.3. Data Processing

1. Calculating accessibility indicator

The assessment of accessibility was conducted using the 2SFCA method. Initially proposed by Radke and Mu [59], this method conducts two sequential spatial queries within predetermined distance thresholds between supply and demand locations. The final accessibility score for a demand point is defined as the sum of the supply-to-demand ratios across all service facilities in its catchment area. To implement this approach, the research area was partitioned into a grid system comprising 500 m × 500 m cells ($n = 232,424$), with grid centroids serving as population demand points. To enhance demographic accuracy, county-level population data from the Seventh National Census was used for calibration.

First, zonal statistics in ArcGIS 10.2 were employed to calculate the population of each grid within each county. Next, a population correction factor was calculated based on the ratio of grid-based to census populations within each county. Finally, the grid population was adjusted proportionally based on this correction factor.

The process is divided into the following two steps:

Firstly, taking the public service facility supply point j within the region as the center, and using the spatial distance threshold d_0 as the radius, this study forms a spatial scope. Within this spatial scope, all populations (demand k set) are searched. The weighted population within this area is then summed to obtain the total number of potential users of the public facility point j . The supply–demand ratio R_j for supply point j is calculated accordingly, as shown by Equation (1).

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \quad (1)$$

where R_j represents the supply-to-demand ratio of public facility point j within the region, indicating the service capacity of the supply point. S_j denotes the size of supply of facility j in the region, d_{kj} is the distance from point k to point j , and P_k is the population of point k within the search range d_0 .

Then, using the demand point k as the basis and applying the same spatial distance threshold d_0 as in the first step, another spatial search area is defined. This study sums the supply–demand ratios R_j of the facility points within this spatial search area to obtain the accessibility A_i of each demand point to public service facilities, as shown by Equation (2).

$$A_i = \sum_{j \in \{d_{kj} \leq d_0\}} R_j = \sum_{j \in \{d_{kj} \leq d_0\}} \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \quad (2)$$

where A_i represents the spatial accessibility score of a public service facility point. A higher A_i indicates better accessibility of the public service facility point.

Here, this study determines the service radius for different public facilities with reference to established planning standards (see Table 1).

Table 1. Setting of spatial threshold d_0 for service radii.

Categories	d_0 Value Setting	Travel Time	Reference Standard
Education facilities	Primary school service radius 500 m	Within 10 min walking	“Urban Public Service Facility Planning Standards GB50442 (Revised)” [60]
	Secondary school service radius 1000 m	Within 15 min walking	
Healthcare facilities	County-level and above hospitals 2000 m	Within 10–15 min by public transport or bicycle, or 15–20 min walking	
Pension facilities	Elderly facilities service radius 1000 m	Within 10–15 min walking	“Sichuan Province 14th Five-Year Public Service Plan,” “Chongqing Municipality 14th Five-Year Public Service Plan”

2. Differentiating urban and rural patches

Following Parvati et al. [61], Meyer and Beucher [57], and Zhou et al. [58], this study applies the 2020 global annual dataset in conjunction with administrative boundaries of the CCEC within a GIS environment to delineate urban and rural patches through spatial

masking and extraction techniques. First, potential urban clusters were extracted from the nighttime light (NTL) image using the marker-controlled watershed segmentation (MWS) algorithm, which is rooted in digital image processing and mathematical morphology. In this procedure, the NTL image was treated as a grayscale topographic surface, and contiguous luminous regions were segmented according to morphological characteristics and digital number (DN) gradients. Second, false luminous clusters unrelated to urbanization were removed. Third, following the cluster-based urban mapping method proposed by Zhou et al. [58], a logistic model was used to estimate cluster-specific optimal thresholds. Pixels with DN values higher than the corresponding threshold were classified as urban, whereas the remaining pixels were classified as rural. Previous studies have validated the reliability of this classification by overlaying the derived segments with the spatial distribution of nighttime light intensity, administrative boundaries, and points of interest (POIs) for public facilities [51,58,61]. The derived urban–rural classification results for the CCEC are quantitatively summarized in Table 2, with corresponding visualization presented in Figure 3.

3. Socioeconomic factors

Table 2. Characteristics of urban–rural patches in CCEC.

Provincial Region	Number of Patches	Minimum Area (km ²)	Maximum Area (km ²)	Gross Area (km ²)	Average Area (km ²)	Standard Deviation (km ²)
Sichuan	116	0.730	1485.911	23,182.151	199.846	441.505
Chongqing	53	0.744	723.422	8742.861	164.959	257.041
Summary	169	0.730	1485.911	31,925.012	182.402	349.453

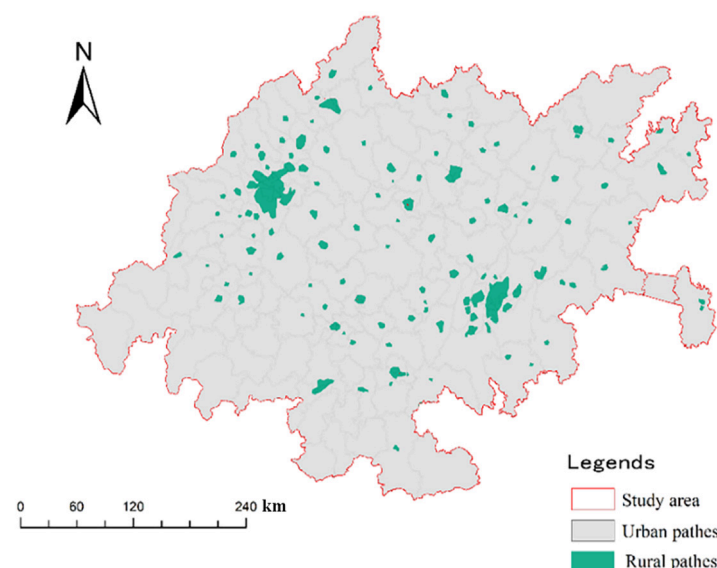


Figure 3. Identification of urban and rural areas in the CCEC.

Six indicators were selected to represent socioeconomic characteristics, as detailed in Table 3.

Table 3. Socioeconomic indicators and measurements.

Factor	Code	Variable	Description
Children	S1	Proportion of children	Percentage of children under 18 to the total population
Elderly	S2	Proportion of old people	Percentage of the elderly over 60 to the total population

Table 3. Cont.

Factor	Code	Variable	Description
Urban residents	S3	% of urban residents	Percentage of urban residents of the total population
Rural residents	S4	% of rural residents	Percentage of rural residents of the total population
Population density	S5	Population density (per hm ²)	Population per hectare
Income	S6	Housing affordability	Housing prices (CNY)

3.3.4. Quantifying and Constructing the Public Facility Equity Index

The indicators are categorized within a dual framework, comprising public facility provision metrics and accessibility measures as shown in Table 4. Provision indicators encompass data on the actual provision of public resources, including quantifiable metrics like facility counts and service radius coverage. Accessibility indicators represent the convenience and likelihood of residents obtaining facility services within the service coverage area of a public facility.

Table 4. Indicators and quantification of the PF equity index.

Index	Category	Variable	Code	Expected Impact
PF equity index	Education facilities	Number of primary and secondary schools	E1	Positive
		500 m service radius coverage rate of primary schools	E2	Positive
		1000 m service radius coverage rate of secondary schools	E3	Positive
		Primary school accessibility	E4	Positive
		Secondary school accessibility	E5	Positive
	Healthcare facilities	Number of healthcare facilities	H1	Positive
		Service radius coverage rate of healthcare facilities	H2	Positive
		Healthcare facility accessibility	H3	Positive
	Pension facilities	Number of elderly care facilities	P1	Positive
		Service radius coverage rate of elderly care facilities	P2	Positive
		Elderly care facility accessibility	P3	Positive

3.3.5. Estimating the Public Facility Equity Index

The spatial location of public facilities determines their supply range and hierarchical affiliation, making it a necessary condition for measuring the equality of facility distribution [47]. By delineating urban and rural patches, this study aggregates all public facility elements within these areas to create an urban–rural public facility equity index, reflecting the equity of urban–rural supply. Similarly, by aggregating all public facility elements within county boundaries, a regional public facility equity index is formed to reflect regional supply equity. Subsequently, urban–rural differences and regional differences are compared to assess the spatial equity of public services and their current characteristics. Following the method proposed by Talen and Anselin [62] and the findings of Zhu et al. [8], all indicators are aggregated using a top-down spatial overlay method in ArcGIS. The research process includes three steps:

1. Extracting elements: The preprocessed data and indicators are clipped and extracted in GIS according to county administrative boundaries and urban–rural patch boundaries, presenting all the elements at regional and urban–rural levels. This process identifies and determines the geographic distribution and locations of public facilities within 142 county-level cities and 169 urban–rural patches.

2. Normalization: The raw scores for each variable are normalized to ensure comparability across variables. Normalized layers for each variable are created sequentially, preserving the corresponding socioeconomic attributes and spatial element attributes to obtain layers at both the county and urban–rural scales. Each variable’s raw value is standardized to a score range from 0 to 1, where “0” represents the weakest and “1” represents the strongest. The standardized scores for all variables are calculated using Equation (3).

$$Z_{ij} = \frac{x_{ij} - \min(x_{1j}, x_{2j}, x_{3j}, \dots, x_{nj})}{\max(x_{1j}, x_{2j}, x_{3j}, \dots, x_{nj}) - \min(x_{1j}, x_{2j}, x_{3j}, \dots, x_{nj})} \quad (3)$$

where Z_{ij} represents the standardized value of the j -th variable in the i -th region.

3. Classification: The normalized results are graphically represented using the natural breaks classification approach, creating the necessary evaluation analysis maps. Each variable is divided into five groups, with similar ranges and numbers of elements within each group, maximizing the differences between classes.
4. Summation of non-geometric means: The PF equity index is obtained by synthesizing all education, healthcare, and pension indicators between regions and urban–rural areas. This process utilizes spatial statistical methods in ArcGIS software to compute the non-weighted geometric mean of various indicators. According to the *National Basic Public Service Standards (2023 Edition)* [63], basic public services cover nine major domains, four of which relate to facility and spatial provision, including transportation, education, healthcare, and pension. Although these facilities differ in function, they are all classified as basic livelihood services that the government must guarantee under China’s basic public service equalization system. Therefore, equal weighting is a policy-normative assumption rather than a data-derived weighting result. It is adopted to avoid imposing a subjective hierarchy among facility types that are institutionally defined as basic public services. The index scores are classified using the natural breaks classification method, ranging from low to high (classes I–V), where higher classes indicate a higher level of equity in the allocation of public facilities, and vice versa.

3.3.6. Spatial Equity Evaluation for Vulnerable Groups

This process consists of two parts. (1) The study uses the equity index as the first variable and socioeconomic indicators as the second variable, deriving bivariate local Moran’s I values for each county-level entity and performing significance assessment through Equation (4). The Local Indicators of Spatial Association (LISA) results roughly reveal four clustering patterns: high–high, low–low, high–low, and low–high. (2) This study divides the equity indexes into high-equity and low-equity groups. The Mann–Whitney U test is then used to examine whether there are significant differences in public resource distribution between high and low equity in various socioeconomic groups using Equations (5) and (6).

$$I_i = \left(\frac{Z_i}{\sum_i Z_i^2} \right) \sum_j W_{ij} Z_j \quad (4)$$

In the equation, Z_i and Z_j represent the average deviation of facility accessibility and social characteristic proportions for units i and j , respectively. W_{ij} denotes the spatial proximity relationship between spatial analysis units i and j .

$$U = n_1 n_2 + \frac{n_2(n_2+1)}{2} - \sum_{i=n_1+1}^{n_2} R_i \quad (5)$$

$$Z = \frac{U - m_U}{\sigma_U} \quad (6)$$

In the equation, n_1 and n_2 represent the number of samples in each specific group; R_i denotes the rank assigned to each sample value, where all sample values are sorted in ascending order; U signifies the disparity in cumulative ranking positions; m_U is the mean of U ; σ_U is the standard deviation of U ; and Z score distinguishes the magnitude of values between the two groups.

4. Results

4.1. Distribution of Public Facilities Under the Urban–Rural Differentiation

Figures 4 and 5 illustrate the public facility equity index distribution between different regions and urban–rural areas in the CCEC. The results reveal pronounced gaps in both the availability and accessibility of public facilities across regional and urban–rural divides, highlighting pronounced spatial inequality. Specifically, the disparities in public facilities distribution are exacerbated under the differentiation of urban–rural patches (see Figure 6).

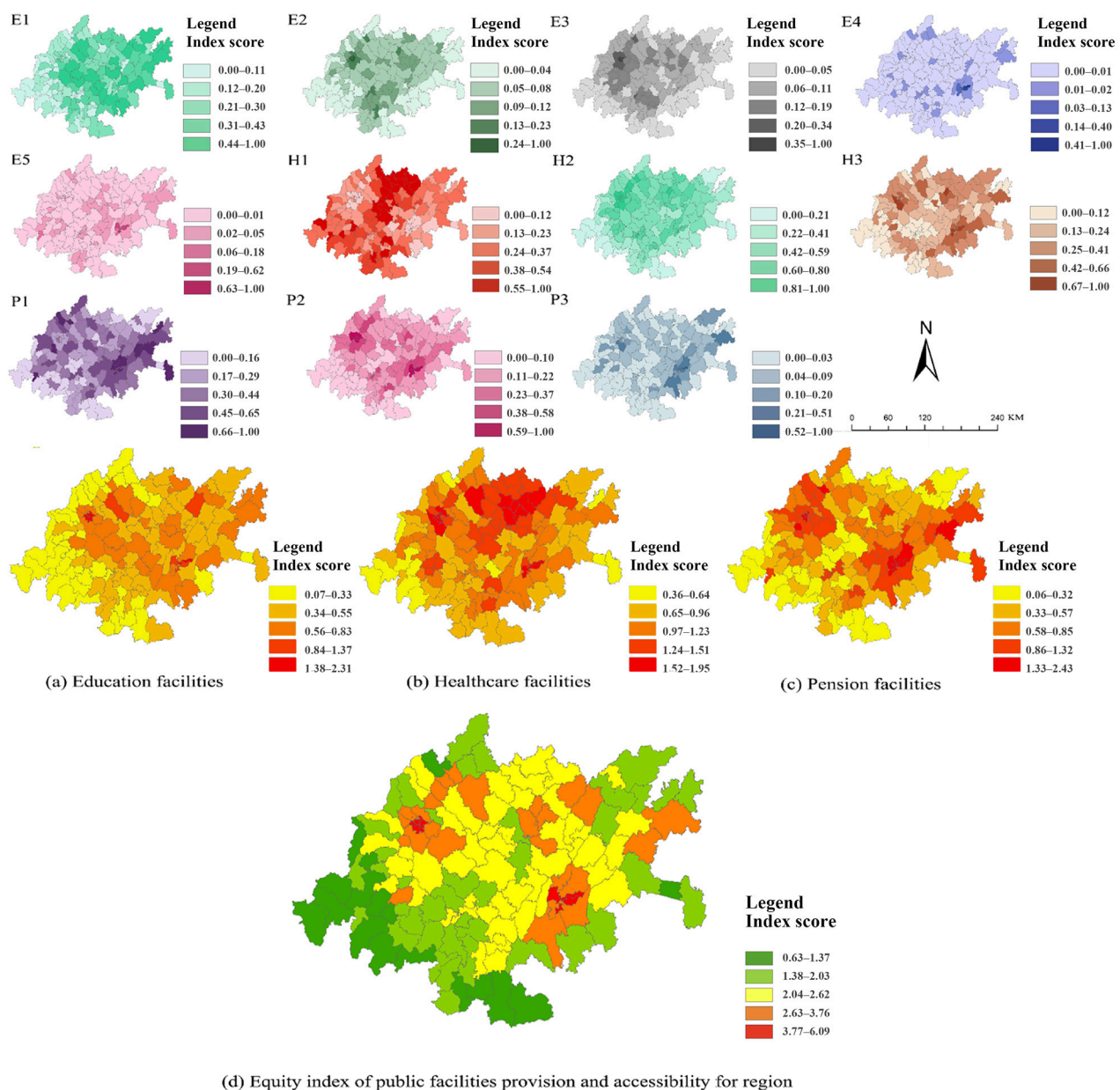


Figure 4. Regional public facility equity index in CCEC.

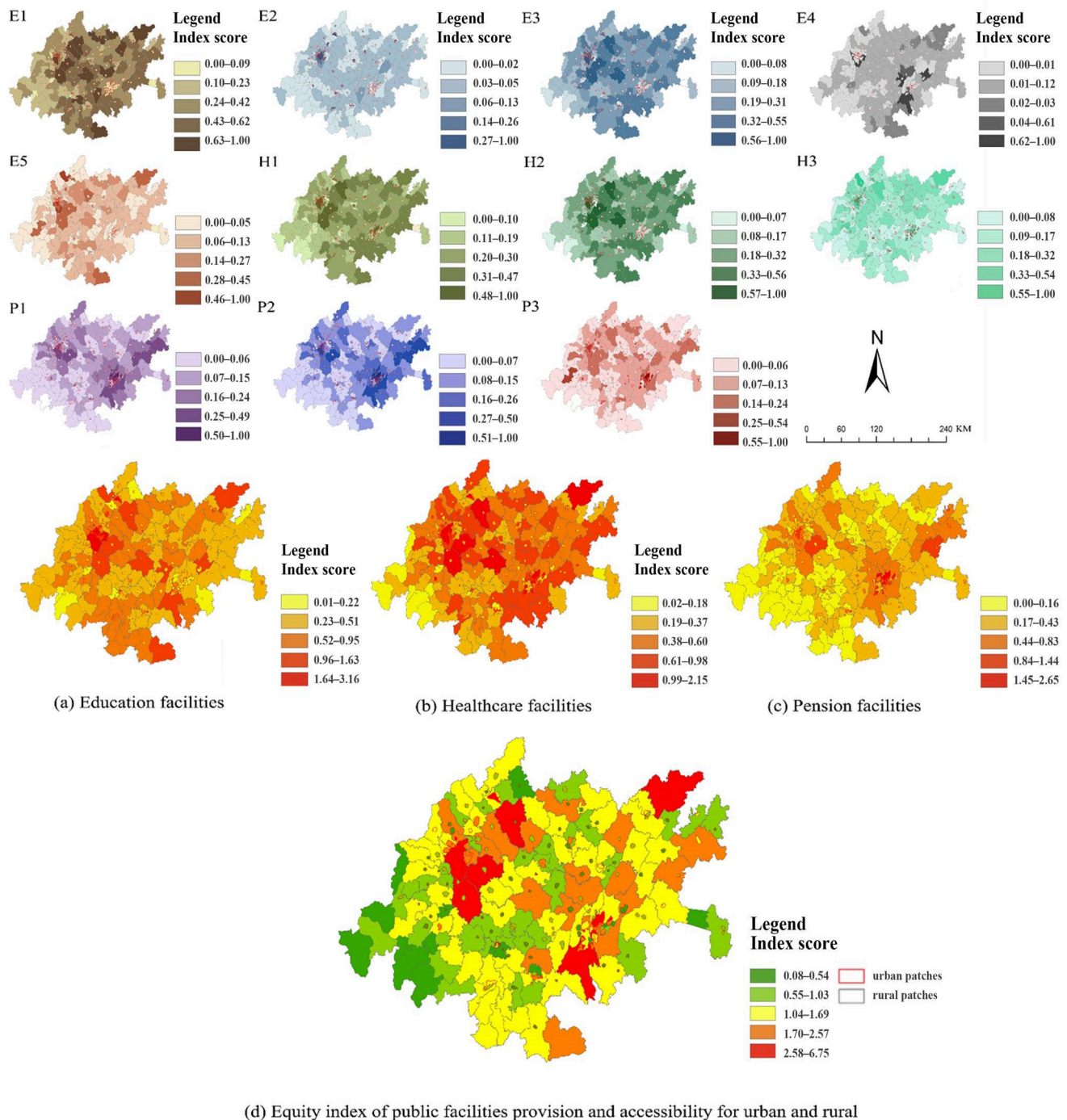


Figure 5. Urban–rural public facility equity index in CCEC.

As shown in Figure 4, the distribution of public facilities demonstrates significant spatial clustering in the urban cores of Chengdu and Chongqing. Most other cities exhibit moderate levels of public facility provision and accessibility, while lower-level cities are heavily concentrated in the southern and southwestern regions. Specifically, the education facilities witness the most severe two-tier differentiation (Figure 4a), with lower-level cities showing distinct spatial prevalence in the western and southern regions of the economic circle, while higher-level facilities are concentrated only within the main urban areas of the two core cities. The overall provision and accessibility levels of healthcare facilities are relatively high, but higher-level facilities are mostly concentrated in cities with relatively lower population densities (Figure 4b), accompanied by resource scarcity in core urban

areas and resource surplus in cities with low population densities. Pension facilities exhibit a concentric distribution pattern that decreases from core urban areas outward. Cities farther from the core urban areas have lower provisions of and accessibility to pension facilities (Figure 4c).

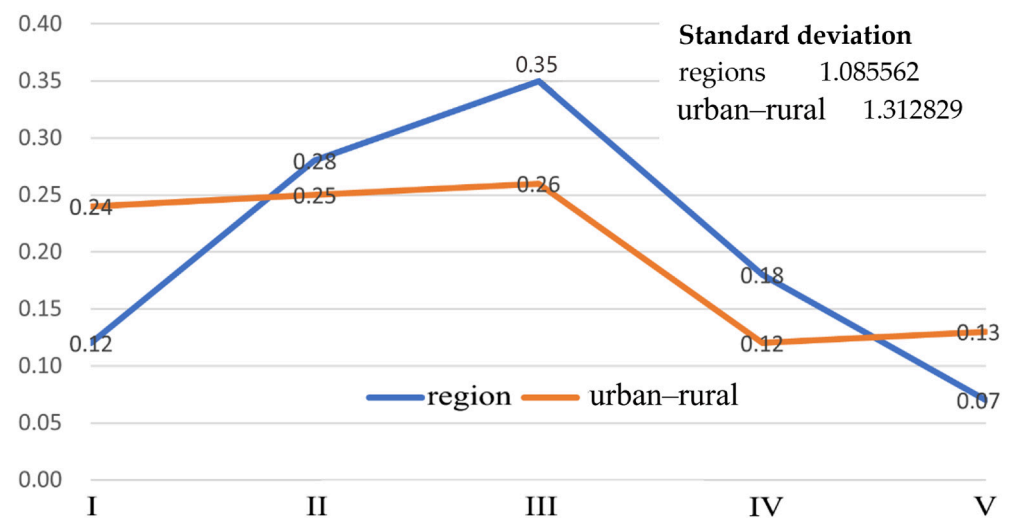


Figure 6. Comparison of the distribution differences in public facilities between regions and urban-rural patches.

The imbalance in public facility provision is exacerbated when taking the differentiation of urban-rural areas into consideration (Figure 5). A small number of districts and counties have rural public facility provision and accessibility levels that are even significantly higher than those in urban areas. However, most rural areas remain suboptimal. The overall levels of education and healthcare facility provision and accessibility are relatively high (Figure 5a,b), except that the educational facilities provision and accessibility levels in the main urban areas of Chongqing are comparatively lower. Regarding the capacity and level of pension facility supply between urban and rural areas, most counties exhibit low levels with no significant differences (Figure 5c).

4.2. Social Equity Differences for Vulnerable Groups

4.2.1. Correspondence Between the Public Facility Equity Index and the Distribution of Vulnerable Groups

As depicted in Figure 7, the overall provision of public facilities exhibits the following characteristics when matching with the distribution of different vulnerable groups: (1) High-high clusters concentrated in the suburban areas of Chengdu's and Chongqing's main urban districts match the spatial distribution of children, elderly, and urban residents and the public facility equity index, with low-low clusters primarily located in the southwest and low-high and high-low clusters exhibit a scattered distribution. The fact that high-high clusters are the most prevalent while low-high and high-low clusters are relatively scarce indicates higher spatial matching, except in Chongqing's main urban area where low-high clusters concentrate, showing severe mismatch between low supply capacity and high demand. (2) In relation to the UR-PF equity index, low-high and high-low clusters dominate for rural residents, indicating the most severe spatial mismatch between rural residents and public facility equity. (3) Population density and income matches in relation to the public facility equity index, with more low-low and high-high clusters, and few low-high and high-low clusters. This indicates that public facilities within the CCEC are relatively equitable and align well with the distribution of populations and their economic levels.

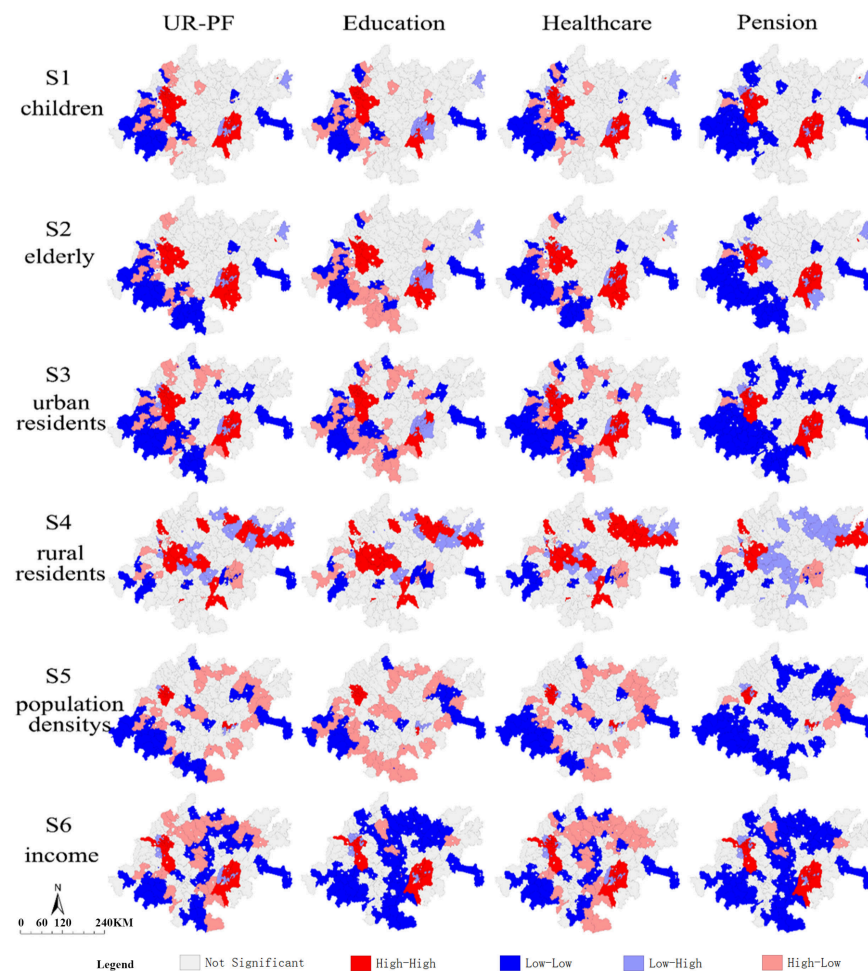


Figure 7. LISA value of UR-PF equity index and social characteristics.

Specifically for the educational facilities, the spatial patterns of designated population cohorts, including children, elderly, and urban inhabitants in Chengdu's main urban area and Chongqing's suburban areas, predominantly show high–high clusters when matching with the public facility equity index. Low–low clusters dominate for matches with rural populations, low-income groups, and the public facility equity index.

Similarly, the provision of healthcare facilities mismatches with the distribution of rural residents and low-income groups, with high–low clusters concentrated in the northern region.

For the pension facilities, low–low clusters dominate most of the CCEC, particularly in the southwest, north, and south. This indicates that the overall supply capacity of pension facilities is relatively low, especially in areas facing dual challenges of low demographic concentration and disproportionate low-income residency. For the elderly population, high–high clusters are concentrated in the suburban areas of Chengdu's and Chongqing's main urban districts.

4.2.2. Mann–Whitney U Test Between High and Low Equity

By dividing the data into high- and low-equity groups, a comparative analysis using Mann–Whitney U tests assessed socioeconomic characteristics across equity-based stratifications. Mean values of high and low equity from the public provision equity index for different groups, along with the results of the related relationship tests, are summarized in Table 5. The study finds that rural residents exhibit significant differences in the high and

low equity of education and pension facilities regarding provisions and accessibility, but not in healthcare facilities.

Table 5. Mann–Whitney U tests for socioeconomic characteristics.

Variable	Dimension	High Median	Low Median	N	Mann–Whitney U Test Z	p-Value
S1	UR-PF	246.04	110.22	289	−12.065	0.000 ***
S2		243.89	110.96		−11.808	0.000 ***
S3		245.70	110.34		−12.024	0.000 ***
S4		149.47	143.46		−0.534	0.593
S5		218.38	119.74		−8.762	0.000 ***
S6		227.97	116.44		−9.907	0.000 ***
S1	UR-Education	325.92	176.46	372	−6.715	0.000 ***
S2		317.80	177.04		−6.324	0.000 ***
S3		319.92	176.89		−6.426	0.000 ***
S4		268.62	180.58		−3.955	0.000 ***
S5		273.08	180.26		−4.170	0.000 ***
S6		308.60	177.70		−5.881	0.000 ***
S1	UR-Healthcare	282.92	132.78	327	−11.660	0.000 ***
S2		280.61	133.38		−11.434	0.000 ***
S3		281.26	133.21		−11.497	0.000 ***
S4		163.35	164.17		−0.064	0.949
S5		246.55	142.33		−8.094	0.000 ***
S6		259.71	138.87		−9.385	0.000 ***
S1	UR-Pension	323.51	154.52	347	−10.025	0.000 ***
S2		322.24	154.69		−9.940	0.000 ***
S3		324.46	154.40		−10.089	0.000 ***
S4		114.94	181.70		−3.960	0.000 ***
S5		280.39	160.14		−7.134	0.000 ***
S6		289.21	158.99		−7.726	0.000 ***

Note: *** indicates statistical significance at $p < 0.001$. Bold p -values indicate non-significant results ($p > 0.05$).

The Z value reflects the degree of difference between the two groups, specifically: (1) The most significant difference in high and low equity was found among children, followed by urban residents, elderly, income, and population density. (2) Among various facilities, the greatest difference in high and low equity for education and healthcare facilities was found for children. But for pension facilities, this was the urban residents. (3) Rural residents enjoyed smaller differences in high and low equity for education and pension facilities.

5. Discussions

Urban–rural public facility disparity is a systemic challenge that emerges from interactions between geographic, social, and infrastructural subsystems. Addressing this systemic issue is crucial for narrowing the urban–rural gap, which strongly aligns with China’s current strategies for urban–rural integration and public service equalization in the CCEC. Similar to previous urban–rural accessibility studies, the results show that rural and peripheral areas tend to experience lower facility provision and weaker accessibility [7]. However, this study differs from conventional spatial equity studies by replacing administrative-unit-only comparison with patch-level urban–rural delineation, and by linking the PF equity index with vulnerable-group distributions. This design makes it possible to identify inequity patterns that may be obscured when counties or districts are treated as homogeneous units.

The system mechanism can be explained through the interaction of three subsystems. In the geographic subsystem, urban–rural boundary delineation determines which popu-

lation and facility points are assigned to urban or rural patches. In the social subsystem, rural residents, elderly residents, and low-income groups are often concentrated in areas with weaker service demand expression and lower market attractiveness. In the infrastructure subsystem, facilities are more likely to be concentrated in high-density urban centers because of economies of scale, administrative priority, and stronger fiscal capacity. The interaction of these three subsystems produces a feedback loop: weaker rural accessibility reinforces population disadvantage, and population disadvantage further reduces the incentive and capacity for facility investment. This mechanism explains why spatial inequity persists even under regional integration policies. Under several rounds of national planning policies and support, the CCEC has adopted a growth-pole strategy, utilizing Chengdu and Chongqing to stimulate surrounding smaller cities. This model has long served as the mechanism for resource allocation and economic development in the CCEC [64], and channeled critical infrastructure and public services toward urban centers. Obviously, the study's findings reveal significant urban–rural disparities in public facility allocation and substantial spatial inequality in service access among vulnerable groups. Enhancing the provision capacity and spatial accessibility of rural public facilities has become crucial for promoting urban–rural integration in the CCEC. Simultaneously, policies and planning efforts should focus more on disadvantaged regions and groups. Targeted interventions are recommended through differentiated policy zones, such as key enhancement areas and optimized coordination areas.

This study adopts a low-cost methodological approach. It allows timely assessment of urban–rural service disparities. The approach is especially suitable for regions that lack infrastructure and face budget constraints. This makes the framework highly transferable to developing regions or localities where conventional data collection remains financially or institutionally unfeasible. Empirically, the findings reveal that, even under policies and plans for urban–rural integration, public facility provision tends to concentrate around subregional centers, resulting in accessibility disadvantages for vulnerable groups residing in peripheral rural patches. Instead of relying on administrative units, this study advocates for patch-level delineation as a more diagnostically precise unit of analysis to allocate resources more equitably.

6. Conclusions

Traditional administrative-unit-based analyses of public facility provision fail to accurately reflect the accessibility of different population groups. This study employed the MWS algorithm to delineate urban and rural patches and matches public facility provision with the social demand subsystem to assess public facility equity in the CCEC. The study's findings indicated the following results: (1) Significant spatial inequality in public facility distribution was found within the CCEC, with most rural areas demonstrating significantly lower levels of provision and accessibility. (2) A significant misalignment exists between the supply of public facilities and the demands of vulnerable groups, aligning with prior studies [8,45,49]. These groups were predominantly clustered in the southern and southwestern parts of the CCEC, including cities like Ya'an, Leshan, and Luzhou. In core urban areas and major suburban regions of cities, such as Chengdu and Chongqing, public facilities demonstrate a high degree of alignment with the needs of diverse population groups. (3) Rural residents are concentrated in low-income areas and have the most limited ability to obtain public facility services and resources, especially in terms of healthcare facilities.

In general, this study was guided by systems thinking, which framed urban–rural public facility equity not as a standalone geographical or statistical issue but as an emergent property of sociotechnical system dynamics. Through the operationalization of three interacting subsystems within an NTL image-processing and morphology-based classification

framework, it was demonstrated how nonlinear system behaviors, such as small boundary shifts, can disproportionately affect the accessibility of public facilities. Furthermore, feedback loops between urban–rural boundary shifts and vulnerability were revealed, representing a systemic mechanism that has rarely been quantified in the spatial equity literature. These insights connect the study’s empirical results to core systems concepts and suggest the value of extending systems thinking into intelligent urban–rural planning. Of course, several limitations should be acknowledged. First, the urban–rural delineation was based on a previously established NTL image-processing workflow and was examined through spatial consistency checks, but independent ground-truth samples were not available. Second, the equal-weighting scheme in the PF equity index was adopted as a policy-normative assumption rather than a data-derived weighting result. Future studies should further test the robustness of the findings using independent validation samples and alternative weighting strategies.

Author Contributions: Conceptualization, X.L.; methodology, X.L., Y.Q. and G.Z.; formal analysis and investigation, Y.Q., G.Z. and L.Z.; writing—original draft preparation, X.L. and G.Z.; writing—review and editing, X.L. and Y.Q.; software, E.W. and J.L.; data curation, Y.Q., G.X. and L.Z.; visualization, G.Z. and E.W.; resources, G.X. and J.L.; supervision and project administration, J.L. All authors contributed to the study design. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Social Science Foundation of China (NSSFC) Key Project [grant number 23AGL037].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are openly available in [urban boundary data] at [https://figshare.com/articles/dataset/A_global_dataset_of_annual_urban_extents_1992-2020_from_harmonized_nighttime_lights/16602224/1] (accessed on 3 July 2026), reference number [55].

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

Abbreviations

The following abbreviations are used in this manuscript:

CCEC	Chengdu–Chongqing Economic Circle
DN	Digital Number
MWS	Marker-Controlled Watershed Segmentation
NTL	Nighttime Light
PF	Public Facility
POI	Point of Interest
2SFCA	Two-Step Floating Catchment Area

References

1. Fu, S.; Liu, Y.; Fang, Y. Measuring the Differences of Public Health Service Facilities and Their Influencing Factors. *Land* **2021**, *10*, 1225. [[CrossRef](#)]
2. Trudeau, D. Integrating Social Equity in Sustainable Development Practice: Institutional Commitments and Patient Capital. *Sustain. Cities Soc.* **2018**, *41*, 601–610. [[CrossRef](#)]
3. Tsou, K.-W.; Hung, Y.-T.; Chang, Y.-L. An Accessibility-Based Integrated Measure of Relative Spatial Equity in Urban Public Facilities. *Cities* **2005**, *22*, 424–435. [[CrossRef](#)]
4. Tahmasbi, B.; Mansourianfar, M.H.; Haghshenas, H.; Kim, I. Multimodal Accessibility-Based Equity Assessment of Urban Public Facilities Distribution. *Sustain. Cities Soc.* **2019**, *49*, 101633. [[CrossRef](#)]

5. Liu, W.; Cao, Y.; Wu, W.; Guo, J. Spatial Impact Analysis of Trans-Yangtze Highway Fixed Links: A Case Study of the Yangtze River Delta, China. *J. Transp. Geogr.* **2020**, *88*, 102822. [\[CrossRef\]](#)
6. Fang, C.; Ma, H.; Bao, C.; Wang, Z.; Li, G.; Sun, S.; Fan, Y. Urban-Rural Human Settlements in China: Objective Evaluation and Subjective Well-Being. *Hum. Soc. Sci. Commun.* **2022**, *9*, 395. [\[CrossRef\]](#)
7. Cui, X.; Ma, L.; Tao, T.; Zhang, W. Do the Supply of and Demand for Rural Public Service Facilities Match? Assessment Based on the Perspective of Rural Residents. *Sustain. Cities Soc.* **2022**, *82*, 103905. [\[CrossRef\]](#)
8. Zhu, Z.; Ren, J.; Liu, X. Green Infrastructure Provision for Environmental Justice: Application of the Equity Index in Guangzhou, China. *Urban For. Urban Green.* **2019**, *46*, 126443. [\[CrossRef\]](#)
9. Neutens, T. Accessibility, Equity and Health Care: Review and Research Directions for Transport Geographers. *J. Transp. Geogr.* **2015**, *43*, 14–27. [\[CrossRef\]](#)
10. Shi, Y.; Yang, J.; Shen, P. Revealing the Correlation between Population Density and the Spatial Distribution of Urban Public Service Facilities with Mobile Phone Data. *IJGI* **2020**, *9*, 38. [\[CrossRef\]](#)
11. Feng, H.; Tang, X.; Zou, C. Optimizing the Layout of Service Facilities for Older People Based on POI Data and Machine Learning: Guangzhou City as an Example. *Land* **2024**, *13*, 700. [\[CrossRef\]](#)
12. Huang, C.; Feng, Y.; Wei, Y.; Sun, D.; Li, X.; Zhong, F. Assessing Regional Public Service Facility Accessibility Using Multisource Geospatial Data: A Case Study of Underdeveloped Areas in China. *Remote Sens.* **2024**, *16*, 409. [\[CrossRef\]](#)
13. Wang, J.; Zhou, J. Spatial Evaluation of the Accessibility of Public Service Facilities in Shanghai: A Community Differentiation Perspective. *PLoS ONE* **2022**, *17*, e0268862. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Rong, P.; Zheng, Z.; Kwan, M.-P.; Qin, Y. Evaluation of the Spatial Equity of Medical Facilities Based on Improved Potential Model and Map Service API: A Case Study in Zhengzhou, China. *Appl. Geogr.* **2020**, *119*, 102192. [\[CrossRef\]](#)
15. Shen, Y.; Tao, Y. Associations between Spatial Access to Medical Facilities and Health-Seeking Behaviors: A Mixed Geographically Weighted Regression Analysis in Shanghai, China. *Appl. Geogr.* **2022**, *139*, 102644. [\[CrossRef\]](#)
16. Lotfi, S.; Koohsari, M.J. Measuring Objective Accessibility to Neighborhood Facilities in the City (A Case Study: Zone 6 in Tehran, Iran). *Cities* **2009**, *26*, 133–140. [\[CrossRef\]](#)
17. Liu, P.; De Sabbata, S. A Graph-Based Semi-Supervised Approach to Classification Learning in Digital Geographies. *Comput. Environ. Urban Syst.* **2021**, *86*, 101583. [\[CrossRef\]](#)
18. Wang, Y.; Liu, Y.; Li, Y.; Li, T. The Spatio-Temporal Patterns of Urban–Rural Development Transformation in China since 1990. *Habitat Int.* **2016**, *53*, 178–187. [\[CrossRef\]](#)
19. Balmer, M.; Weibel, R.; Huang, H. Value of Incorporating Geospatial Information into the Prediction of On-Street Parking Occupancy—A Case Study. *Geo-Spat. Inf. Sci.* **2021**, *24*, 438–457. [\[CrossRef\]](#)
20. Liu, H.; Wang, L.; Wang, J.; Ming, H.; Wu, X.; Xu, G.; Zhang, S. Multidimensional Spatial Inequality in China and Its Relationship with Economic Growth. *Hum. Soc. Sci. Commun.* **2024**, *11*, 1415. [\[CrossRef\]](#)
21. DeVerteuil, G. Reconsidering the Legacy of Urban Public Facility Location Theory in Human Geography. *Prog. Hum. Geogr.* **2000**, *24*, 47–69. [\[CrossRef\]](#)
22. Li, H.; Liu, L.; Cao, Z.; Zhang, L. Scaling and Mismatches of Public Service Accessibility in Rural China: A Comparison of Healthcare and Shopping Facilities. *Habitat Int.* **2026**, *175*, 103895. [\[CrossRef\]](#)
23. Lu, Y.; Chen, R.; Chen, B.; Wu, J. Inclusive Green Environment for All? An Investigation of Spatial Access Equity of Urban Green Space and Associated Socioeconomic Drivers in China. *Landsc. Urban Plan.* **2024**, *241*, 104926. [\[CrossRef\]](#)
24. Yang, X.; Feng, Z.; Chen, Y. Evaluation and Obstacle Analysis of High-Quality Development in Yellow River Basin and Yangtze River Economic Belt, China. *Hum. Soc. Sci. Commun.* **2023**, *10*, 757. [\[CrossRef\]](#)
25. Zhang, X.; Wu, Y.; Skitmore, M.; Jiang, S. Sustainable Infrastructure Projects in Balancing Urban–Rural Development: Towards the Goal of Efficiency and Equity. *J. Clean. Prod.* **2015**, *107*, 445–454. [\[CrossRef\]](#)
26. Mao, Z.; Liu, F.; Zhao, Y. Happy City for Everyone: Generational Differences in Rural Migrant Workers’ Leisure in Urban China. *Urban Stud.* **2023**, *60*, 3252–3271. [\[CrossRef\]](#)
27. Zhang, R.; Yuan, Y.; Li, H.; Hu, X. Improving the Framework for Analyzing Community Resilience to Understand Rural Revitalization Pathways in China. *J. Rural Stud.* **2022**, *94*, 287–294. [\[CrossRef\]](#)
28. Chu, V.H.Y.; Lam, W.-F.; Williams, J.M. Building Robustness for Rural Revitalization: A Social-Ecological System Perspective. *J. Rural Stud.* **2023**, *101*, 103042. [\[CrossRef\]](#)
29. Zhang, R.; Sun, F.; Shen, Y.; Peng, S.; Che, Y. Accessibility of Urban Park Benefits with Different Spatial Coverage: Spatial and Social Inequity. *Appl. Geogr.* **2021**, *135*, 102555. [\[CrossRef\]](#)
30. Setianto, M.A.S.; Gamal, A. Spatial Justice in the Distribution of Public Services. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *673*, 012024. [\[CrossRef\]](#)
31. Szekely, V.; Novotny, J. Public Transport-Disadvantaged Rural Areas in Relation to Daily Accessibility of Regional Centre: Case Study from Slovakia. *J. Rural Stud.* **2022**, *92*, 1–16. [\[CrossRef\]](#)

32. Frenkel, A.; Israel, E. Spatial Inequality in the Context of City-Suburb Cleavages—Enlarging the Framework of Well-Being and Social Inequality. *Landsc. Urban Plan.* **2018**, *177*, 328–339. [[CrossRef](#)]
33. Eiselt, H.A. *Community-Based Operations Research: Decision Modeling for Local Impact and Diverse Populations*; Johnson, M.P., Ed.; International Series in Operations Research & Management Science; Springer: New York, NY, USA, 2012; Volume 167, ISBN 978-1-4614-0805-5.
34. Gini, C. Measurement of Inequality of Incomes. *Econ. J.* **1921**, *31*, 124. [[CrossRef](#)]
35. Fisher, R.A. Statistical Methods for Research Workers. In *Breakthroughs in Statistics: Methodology and Distribution*; Kotz, S., Johnson, N.L., Eds.; Springer: New York, NY, USA, 1992; pp. 66–70, ISBN 978-1-4612-4380-9.
36. Allison, P.D. Measures of Inequality. *Am. Sociol. Rev.* **1978**, *43*, 865. [[CrossRef](#)]
37. Shorrocks, A.F. The Class of Additively Decomposable Inequality Measures. *Econometrica* **1980**, *48*, 613. [[CrossRef](#)]
38. Xu, R.; Yue, W.; Wei, F.; Yang, G.; Chen, Y.; Pan, K. Inequality of Public Facilities between Urban and Rural Areas and Its Driving Factors in Ten Cities of China. *Sci. Rep.* **2022**, *12*, 13244. [[CrossRef](#)]
39. Witten, K.; Exeter, D.; Field, A. The Quality of Urban Environments: Mapping Variation in Access to Community Resources. *Urban Stud.* **2003**, *40*, 161–177. [[CrossRef](#)]
40. Nigg, C.; Fiedler, J.; Burchartz, A.; Reichert, M.; Niessner, C.; Woll, A.; Schipperijn, J. Associations between Green Space Availability and Youth's Physical Activity in Urban and Rural Areas across Germany. *Landsc. Urban Plan.* **2024**, *247*, 105068. [[CrossRef](#)]
41. Park, T.-S.; Lee, M.Y. Accessibility Measure of Cultural Facilities Using Urban Network Analysis. *KSCE J. Civ. Environ. Eng. Res.* **2015**, *35*, 455–464. [[CrossRef](#)]
42. Li, M.; Peng, P.; Ao, Y.; Zhou, Z.; Zuo, J.; Martek, I. Equity in Public Decision-Making: A Dynamic Comparative Study of Urban-Rural Elderly Care Institution Resource Allocation in China. *Hum. Soc. Sci. Commun.* **2024**, *11*, 1526. [[CrossRef](#)]
43. Chen, Y.; Yue, W.; La Rosa, D. Which Communities Have Better Accessibility to Green Space? An Investigation into Environmental Inequality Using Big Data. *Landsc. Urban Plan.* **2020**, *204*, 103919. [[CrossRef](#)]
44. Wu, H.; Liu, L.; Yu, Y.; Peng, Z. Evaluation and Planning of Urban Green Space Distribution Based on Mobile Phone Data and Two-Step Floating Catchment Area Method. *Sustainability* **2018**, *10*, 214. [[CrossRef](#)]
45. Jiang, J.; Wang, Z.; Yong, Z.; He, J.; Yang, Y.; Zhang, Y. Spatial Distribution and Accessibility Analysis of Primary School Facilities in Mega Cities: A Case Study of Chengdu. *Sustainability* **2024**, *16*, 723. [[CrossRef](#)]
46. Coppola, P.; Silvestri, F. Estimating and Visualizing Perceived Accessibility to Transportation and Urban Facilities. *Transp. Res. Procedia* **2018**, *31*, 136–145. [[CrossRef](#)]
47. Dadashpoor, H.; Rostami, F.; Alizadeh, B. Is Inequality in the Distribution of Urban Facilities Inequitable? Exploring a Method for Identifying Spatial Inequity in an Iranian City. *Cities* **2016**, *52*, 159–172. [[CrossRef](#)]
48. Ashik, F.R.; Mim, S.A.; Neema, M.N. Towards Vertical Spatial Equity of Urban Facilities: An Integration of Spatial and Aspatial Accessibility. *J. Urban Manag.* **2020**, *9*, 77–92. [[CrossRef](#)]
49. Chen, X.; Orom, H.; Hay, J.L.; Waters, E.A.; Schofield, E.; Li, Y.; Kiviniemi, M.T. Differences in Rural and Urban Health Information Access and Use. *J. Rural Health* **2019**, *35*, 405–417. [[CrossRef](#)] [[PubMed](#)]
50. Bavnbæk, K.F.; Thuesen, A.A. Navigating Spatial Justice: Exploring Municipal Planners' Logics in Differentiated Village Planning. *J. Rural Stud.* **2025**, *114*, 103496. [[CrossRef](#)]
51. Zhao, M.; Zhou, Y.; Li, X.; Cao, W.; He, C.; Yu, B.; Li, X.; Elvidge, C.D.; Cheng, W.; Zhou, C. Applications of Satellite Remote Sensing of Nighttime Light Observations: Advances, Challenges, and Perspectives. *Remote Sens.* **2019**, *11*, 1971. [[CrossRef](#)]
52. Zhou, Y.; Li, X.; Asrar, G.R.; Smith, S.J.; Imhoff, M. A Global Record of Annual Urban Dynamics (1992–2013) from Nighttime Lights. *Remote Sens. Environ.* **2018**, *219*, 206–220. [[CrossRef](#)]
53. Saghapour, T.; Moridpour, S.; Thompson, R.G. Public Transport Accessibility in Metropolitan Areas: A New Approach Incorporating Population Density. *J. Transp. Geogr.* **2016**, *54*, 273–285. [[CrossRef](#)]
54. Ma, W.; Zhang, W.; Chen, Q.; Jiang, H.; Zhao, K.; Song, C.; Yin, Y. Understanding the Regional Dynamics and Determinants of Urban Cultural Facilities in the Yangtze River Economic Belt, China. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 547. [[CrossRef](#)]
55. Zhao, M.; Cheng, C.; Zhou, Y.; Li, X.; Shen, S.; Song, C. A Global Dataset of Annual Urban Extents (1992–2020) from Harmonized Nighttime Lights. *Earth Syst. Sci. Data Discuss.* **2021**, *2021*, 1–25. [[CrossRef](#)]
56. Chen, Y.; Liu, X.; Li, X.; Liu, Y.; Xu, X. Mapping the Fine-Scale Spatial Pattern of Housing Rent in the Metropolitan Area by Using Online Rental Listings and Ensemble Learning. *Appl. Geogr.* **2016**, *75*, 200–212. [[CrossRef](#)]
57. Meyer, F.; Beucher, S. Morphological Segmentation. *J. Vis. Commun. Image Represent.* **1990**, *1*, 21–46. [[CrossRef](#)]
58. Zhou, Y.; Smith, S.J.; Elvidge, C.D.; Zhao, K.; Thomson, A.; Imhoff, M. A Cluster-Based Method to Map Urban Area from DMSP/OLS Nightlights. *Remote Sens. Environ.* **2014**, *147*, 173–185. [[CrossRef](#)]
59. Radke, J.; Mu, L. Spatial Decompositions, Modeling and Mapping Service Regions to Predict Access to Social Programs. *Ann. GIS* **2000**, *6*, 105–112. [[CrossRef](#)]
60. GB50442; Urban Public Service Facility Planning Standards (Revised). Ministry of Construction: Beijing, China, 2008.

61. Parvati, K.; Prakasa Rao, B.S.; Mariya Das, M. Image Segmentation Using Gray-Scale Morphology and Marker-Controlled Watershed Transformation. *Discret. Dyn. Nat. Soc.* **2008**, *2008*, 384346. [[CrossRef](#)]
62. Talen, E.; Anselin, L. Assessing Spatial Equity: An Evaluation of Measures of Accessibility to Public Playgrounds. *Environ. Plan A Econ. Space* **1998**, *30*, 595–613. [[CrossRef](#)]
63. National Development and Reform Commission of China; Ministry of Education; Ministry of Civil Affairs; Ministry of Finance; Ministry of Human Resources and Social Security; Ministry of Housing and Urban-Rural Development; Ministry of Culture and Tourism; National Health Commission; Ministry of Veterans Affairs; General Administration of Sport of China. *Notice on Issuing the National Basic Public Service Standards, 2023 ed.*; National Development and Reform Commission of China: Beijing, China, 2023.
64. Zhang, X.; Jie, X.; Ning, S.; Wang, K.; Li, X. Coupling and Coordinated Development of Urban Land Use Economic Efficiency and Green Manufacturing Systems in the Chengdu-Chongqing Economic Circle. *Sustain. Cities Soc.* **2022**, *85*, 104012. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.