Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-025-05855-z OPEN

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Regional differences and dynamic evolution of quality medical resources in Chongqing, China

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Quality medical resources (QMR) play a crucial role in population health, and their spatial distribution disparities remain a significant cause of health inequities. This study constructs the quality medical resources composite index (QMRCI) using panel data from Chongqing (2015–2023), applying the Dagum Gini coefficient, kernel density estimation, Markov chain, and spatial autocorrelation methods to systematically analyze regional disparities, evolutionary trends, and spatial clustering characteristics of QMRCI, combined with overlay analysis of population density and per capita GDP. The results show that while Chongqing's overall CQMRI allocation has improved, significant interregional disparities persist, exhibiting a gradient pattern of "core polarization - new area emergence - peripheral lag" with notable path dependence and neighborhood effects. In spatial terms, QMRCI demonstrates significant positive clustering and spatial dependence characteristics. Although developed areas concentrate QMRCI, they demonstrate mismatches with population and GDP distributions, whereas less developed areas with fewer QMRCI show better matching degrees. The study recommends enhancing medical resource supply efficiency in densely populated (developed) areas while optimizing regional coordination mechanisms to prevent low-level homogenization. It emphasizes aligning GDP growth with medical resource investment increases, particularly improving resource accessibility in peripheral (less developed) regions. To achieve this, Chongqing should establish a comprehensive dynamic balancing mechanism and targeted policy intervention system to strengthen the healthcare system's overall resilience, ultimately realizing coordinated development of structural optimization and equity improvement.

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Introduction

Quality medical resources (QMR), comprising highly skilled healthcare professionals, advanced diagnostic equipment, superior service facilities, robust medical education systems, and integrated information management systems, serve as critical foundations for enhancing public health, achieving health equity, and optimizing healthcare delivery systems. Recent reports from the OECD, particularly the "Health System Balance Report," emphasize that regional imbalances in medical resources constitute a fundamental barrier to global health equity. The WHO's "Global Strategy 2019–2023" explicitly outlines objectives for achieving Universal Health Coverage (UHC), while countries such as the United States, European Union members, and Japan have implemented diverse policies to promote medical resource coordination. These international practices demonstrate the necessity for strengthened global cooperation in policy coordination, technology sharing, and financing mechanisms to address this worldwide challenge. China has prioritized both the expansion and regional balanced distribution of QMR. Since 2015, the government has introduced over ten significant policies, including the "13th Five-Year Plan for Deepening Healthcare System Reform" and the "National Health Plan," to continuously promote the expansion and equitable regional allocation of QMR, with a focus on improving healthcare service equity and accessibility. However, constrained by Chongqing's distinctive mountainous terrain, urban-rural development disparities, and regional imbalances, the distribution of QMR within the municipality continues to face challenges, including insufficient supply, spatial distribution disparities, and significant regional heterogeneity. Global scholars have conducted systematic, multi-scale, and multi-perspective research on the equity and efficiency of medical resource allocation (Alexander et al., 2017; Fylkesnes et al., 2021; Treacy et al., 2018). Existing studies primarily focus on four key dimensions: (1) the relationship between medical services and health outcomes, (2) accessibility of medical facilities, (3) inequities in healthcare provision, and (4) determinants of medical resource distribution (Baba et al., 2014; Evans and Sekkarie, 2017; Glasziou et al., 2017; Gray et al., 2017). Research indicates that the spatial imbalance of QMR represents a global challenge, particularly pronounced in developed countries. Studies have identified significant urban-rural disparities in healthcare access, where urban residents enjoy easier access to QMR. At the same time, remote areas persistently face dual challenges of poor service accessibility and human resource shortages (Winter et al., 2020). European research employing health geography and GIS analysis has revealed the spatial coupling between medical resource supply and population health, emphasizing the fundamental value of spatial justice in achieving health equity (Comber et al., 2011). This spatial inequality exhibits distinct "Matthew Effect" characteristics, where regional economic foundations, government expenditure capacity, infrastructure layout, and historical path dependence collectively contribute to a cumulative cycle: resource-rich areas continue to attract more resources while disadvantaged regions struggle to improve their conditions (Delamater et al., 2012; Jewett et al., 2018).

Chinese scholars have established a multi-scale research system in medical resource allocation, with in-depth explorations spanning national, provincial, and prefectural levels (Huang et al., 2020; Li and Hu, 2022; Qin et al., 2024). By analyzing the three-tier spatial patterns of "eastern-central-western regions," "urban-rural disparities," and "provincial-prefectural distributions," these studies have consistently demonstrated the concentration of QMR in core urban areas of significant cities, forming healthcare hubs centered around provincial capitals. In contrast, peripheral regions in central and western China face chronic resource shortages. However, insufficient attention has been paid to Chongqing as a special case. As the world's largest mountainous city, Chongqing combines provincial-scale administration with megacity characteristics. With 76% of its terrain being mountainous, its urban-rural dual structure and "cluster-based" development model differ significantly from global metropolises like London and Tokyo, as well as from plain cities like Beijing and Shanghai, while showing remarkable similarities to urban development characteristics in middle-income countries such as Indonesia and Peru. Therefore, in-depth research on its medical resource allocation would not only provide a critical case study for developing countries exploring public service governance in provincial-scale cities and validate the feasibility of balanced resource allocation in mountainous terrain but also serve as a valuable reference for healthcare system development in inland cities, demonstrating both regional policy value and international academic significance.

This study offers two main marginal innovations. First, it divides Chongqing into four distinct subregions—Core Urban Area, Metropolitan Expansion Zone, Northeastern Chongqing, and Southeastern Chongqing—rather than treating the study area as a single homogeneous unit, as is common in previous studies. This approach enables a more targeted examination of intra- and inter-regional disparities, thereby enhancing the specificity and policy relevance of the findings. Second, the study adopts an integrated analytical framework combining static and dynamic perspectives. By employing methods such as the Dagum Gini coefficient, kernel density estimation, and spatial Markov chain, it captures both the spatial disparities and temporal dynamics of high-quality healthcare resource allocation in Chongqing, thereby improving the research's explanatory power and practical value.

Methods

Data and regional division. The data used in this study were sourced from *the Chongqing Statistical Yearbook* and *Chongqing Health Statistical Yearbook*. Through systematically organizing medical resource-related indicators in these yearbooks, we constructed a panel dataset of QMR in Chongqing from 2015 to 2023.

Administrative Division. To facilitate analysis of internal disparities in QMR allocation and align with the Chongqing government's regional classification framework, this study divides Chongqing into four regional categories: Core Urban Area, Metropolitan Expansion Area, Northeastern Chongqing, and Southeastern Chongqing (Fig. 1).

Principal component analysis (PCA). Principal component analysis is a widely used dimensionality reduction technique that transforms multiple original variables into a set of linearly uncorrelated composite indicators through a linear transformation while retaining most of the variation in the original data (Jolliffe and Cadima, 2016; Rao, 1964). This study selects seven indicators reflecting QMR: number of Grade III Level A hospitals (units), number of licensed physicians (persons), number of medical equipment valued over 1 million yuan (units), number of hospital beds in general hospitals (units), number of inpatient surgeries in medical institutions (10,000 cases), admission rate per 100 outpatient visits in traditional Chinese medicine hospitals (%), and number of inpatient surgeries in traditional Chinese medicine hospitals (10,000 cases).

Prior to applying PCA, the seven selected indicators reflecting QMR were pre-processed to ensure comparability and analytical stability. Five indicators exhibited skewed distributions and were therefore log-transformed before standardisation, with three indicators (number of licensed physicians, number of hospital beds in general hospitals, and number of medical equipment

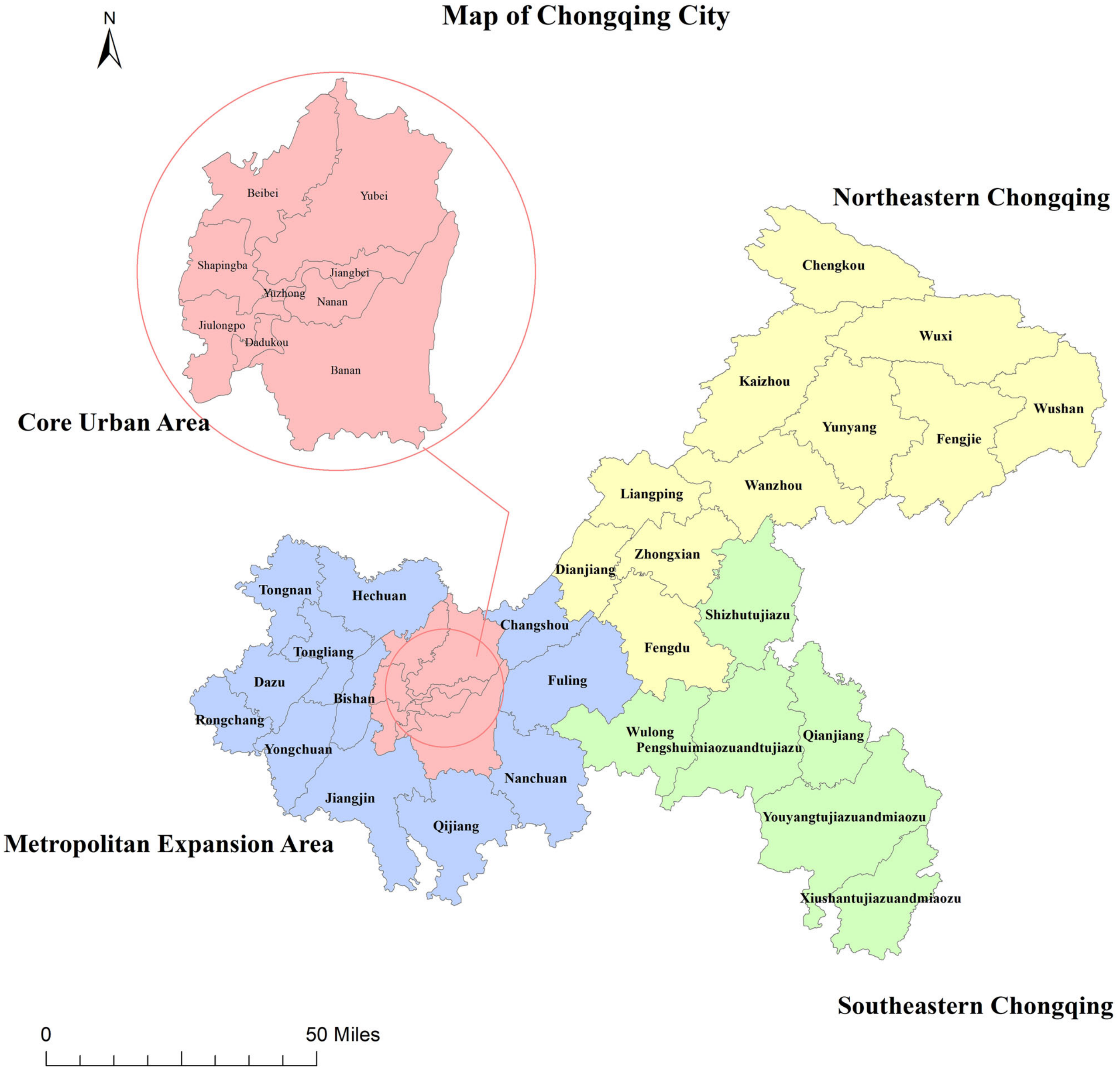

Fig. 1 Administrative divisions of Chongqing Municipality (2015–2023).

valued over 1 million yuan) transformed using ln(x), and two indicators (number of inpatient surgeries in medical institutions and number of inpatient surgeries in traditional Chinese medicine hospitals) transformed using $\ln(x + 1)$ to avoid excessively large negative values due to small data magnitudes. The remaining two indicators—number of Grade III Level A hospitals and admission rate per 100 outpatient visits in traditional Chinese medicine hospitals—were approximately normally distributed or had suitable magnitudes and were directly standardised without log transformation. All indicators, whether log-transformed or not, were standardised using Min-Max normalisation, scaling values to the [0,1] range to ensure comparability across variables for PCA analysis.

PCA was then applied to the pre-processed indicators to construct the Quality Medical Resources Composite Index (QMRCI). This composite index serves as the core variable for subsequent regional disparity analysis and dynamic evolution analysis, providing quantitative evidence for identifying characteristics of unbalanced resource allocation.

Dagum Gini coefficient and its decomposition. This study employs the Dagum Gini coefficient decomposition method to measure the disparities in QMRCI allocation levels across Chongqing. This approach overcomes the limitations of traditional Gini coefficients and Theil indices by effectively analyzing the sources of regional disparities, addressing the issue of subgroup overlap, and enabling precise decomposition of the net contribution of inter-regional gaps to overall regional inequality (Dagum, 1998). The overall Dagum Gini coefficient G is defined as follows:

$$G = \frac{\sum_j^k \sum_h^k \sum_i^{n_j} \sum_r^{n_h} \left| y_{ji} - y_{hr} \right|}{2n^2\bar{y}} \tag{1}$$

Among them, n denotes the number of districts and counties in Chongqing, while k represents the number of regional divisions. n_j and n_h refer to the number of districts and counties within region j and region h, respectively. $\bar{y}$ denotes the average level of QMR allocation across all districts and counties in Chongqing. y_{ji} represents the QMR allocation level of the ith district or county in region j, and y_{hr} denotes the QMR allocation level of the rth district or county in region h. The overall Gini coefficient G is decomposed into three components: the contribution of inter-regional differences (G_{nb}), the contribution of intra-regional differences (G_w), and the contribution of transvariation intensity (G_t), satisfying the relation $G = G_w + G_{nb} + G_t$. This study employs the Dagum Gini coefficient to analyze further the distributional equity of the constructed QMRCI.

Kernel density estimation. To intuitively and vividly reveal the temporal evolution of the QMRCI distribution pattern in Chongqing, this study employs kernel density estimation to depict the dynamic evolution of QMRCI allocation levels. The kernel density estimation method characterizes the distributional state of a variable through a continuous density curve and is now widely used in studies of spatially unbalanced distributions (Zhang et al., 2025). Assuming that the probability density function of a random variable x is $f(x)$, it is expressed as shown in Eq. (2):

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left[\left(x_i - x\right)/h\right] \tag{2}$$

Where n denotes the number of observations, h is the bandwidth, and $K(\cdot)$ is the kernel function, essentially serving as a weighting function. x_i represents independently and identically distributed sample values and x is the sample mean. This study adopts the commonly used Gaussian kernel function, as shown in Eq. (3), with its expression given by:

$$k(x) = (1/\sqrt{2\pi})e^{-x^2/2} \tag{3}$$

Kernel density curves illustrate a given variable's distribution characteristics and polarization trends. The position of the distribution reflects the overall level of QMRCI across regions, while the peaks—representing polarization—indicate the magnitude of absolute disparities through their height and width. Moreover, the number of peaks serves as an indicator of the degree of polarization.

Markov chain. The Markov chain analysis method enables the examination of a variable's internal dynamics and evolutionary process through a transition matrix (Fingleton, 1997). Markov chain approach, emphasizing its unique analytical strength in capturing "path dependence" and "neighborhood effects." This method is particularly well-suited to uncovering the spatio-temporal dynamics of high-quality healthcare resource distribution. A Markov chain is a state space of a discrete-event stochastic process, in which, for any n periods at time t, the probability that the random variable x is in state j at period n depends solely on its state at period n-1 and is independent of all previous states. That is:

$$P\left\{x_n = j | x_{n-1} = i, x_{n-2} = i_{n-2,\dots\dots,} x_1 = i_1\right\} = P\left\{x_{n-1} = j | x_{n-1} = i\right\} = P_{ij} \tag{4}$$

For example, if the QMR allocation levels examined in this study are categorized into N exhaustive and mutually exclusive types, an $N \times N$ transition probability matrix $P = (P_{ij})$ can be constructed, where P_{ij} represents the probability of transitioning from state i to state j, and satisfies $P_{ij} \geq 0$ and $\sum_{j=1}^{N} P_{ij} = 1$. Using the maximum likelihood estimation method, P_{ij} is calculated as $P_{ij} = n_{ij}/n_i$, where n_{ij} denotes the number of observed transitions from state i to state j during the sample period, and n_i is the total number of occurrences of state i.

To extend the basic Markov chain by considering multi-year transition probabilities, let $P_{ij}^{T} = P\left\{X_{t+T} = j | x_t = j\right\}$ denote the d-year transition probability, which reflects the probability that a region in state i will transition to state j after d years. It is calculated as:

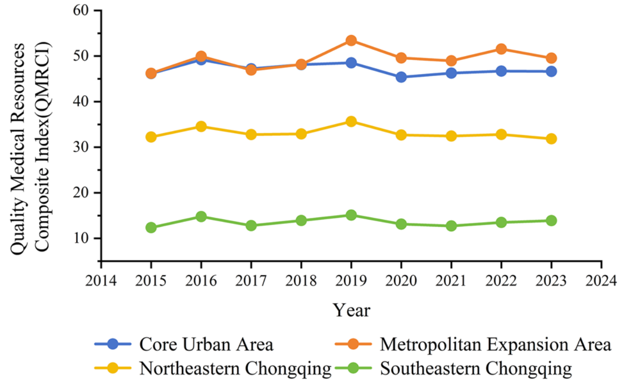

Fig. 2 Temporal evolution of QMRCI in Chongqing's regions (2015–2023).

$$P_{ij}^{T} = n_{ij}^{T}/n_i \tag{5}$$

Where n_{ij}^{T} denote the total number of times that regions in state i during the sample period transition to state j after T years. As a dynamic extension, the spatial Markov chain model characterizes the state transition process between different levels of resource distribution across regions from a time-series perspective.

Spatial autocorrelation and overlay analysis. In Geographic Information Systems (GIS), *Global Moran's I* is used to measure the overall spatial autocorrelation of the QMRCI in Chongqing (Anselin, 1988), while *Anselin Local Moran's I* is employed to reveal local spatial heterogeneity (Anselin, 1995). In addition, data are standardized within the GIS environment, and the Natural Breaks classification method is applied to composite indicators of QMR, population density, and per capita GDP to categorize levels and visually present the spatial distribution pattern of resources (Goodchild et al., 2005).

Results

Dagum Gini coefficient

QMRCI values across different regions of Chongqing. From 2015 to 2023, Chongqing's QMRCI exhibited distinct regional disparities (see Fig. 2). The Core Urban Area and the Metropolitan Expansion Area have consistently maintained the highest levels of QMRCI, with index values steadily ranging between 45 and 55 over the observed period. Northeastern Chongqing remained at a medium-low level (31–36), and Southeastern Chongqing consistently ranked the lowest (12–16), highlighting the "core-periphery" structural differences in QMRCI distribution.

Evolution trend of overall disparities in QMRCI allocation in Chongqing. Figure 3 reveals that Chongqing maintained moderate equity in the overall allocation of QMRCI during the study period. From 2015 to 2023, Chongqing's overall Dagum Gini coefficient fluctuated between 0.24 and 0.26, showing an upward trend. The coefficient experienced a fluctuating decline from 2015 to 2019, reaching its lowest point of 0.24 in 2019, followed by a rebound to peak at 0.26 in 2021. Throughout this period, the Gini coefficient demonstrated periodic fluctuations rather than a consistent downward or upward trend.

Evolution trends of intra-regional disparities in QMRCI allocation in Chongqing. As shown in Fig. 4, from 2015 to 2023, Northeastern Chongqing consistently exhibited the largest intra-regional disparities, with its Gini coefficient remaining around

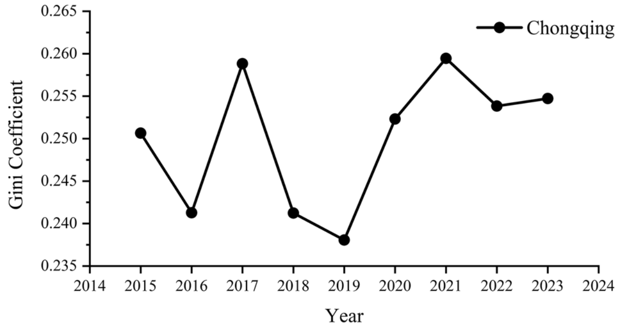

Fig. 3 Temporal evolution of overall disparities in QMRCI allocation across Chongqing (2015–2023).

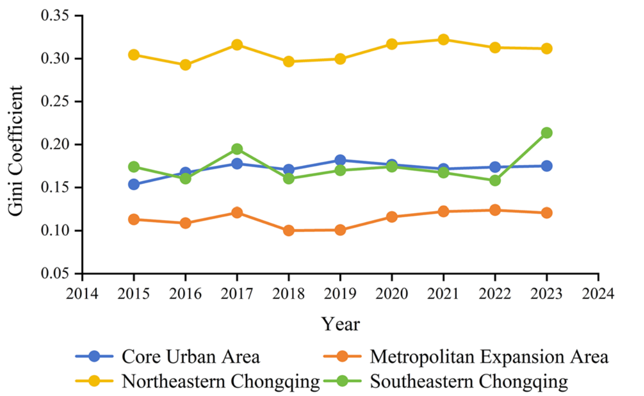

Fig. 4 Intra-regional disparities in QMRCI allocation across Chongqing's functional zones (2015–2023).

0.31, indicating the most unbalanced QMRCI distribution. The Metropolitan Expansion Area maintained long-term low-level coefficients near 0.12. The Core Urban Area and Southeastern Chongqing showed similar Gini coefficients, fluctuating between 0.15 and 0.21.

Evolution of Inter-regional disparities in QMRCI allocation levels in Chongqing. Figure 5 illustrates the evolution of QMRCI allocation disparities among Chongqing's four major regions. The most significant gaps exist between the Core Urban Area and Northeastern Chongqing (1–3) and Southeastern Chongqing (1–4), with Dagum Gini coefficients fluctuating between 0.31 and 0.43. The smallest disparity occurs between the Core Urban Area and Metropolitan Expansion Area (1–2), maintaining a low Gini coefficient of around 0.18, forming a "high-equilibrium development zone." The Metropolitan Expansion Area and Northeastern Chongqing (2–3) show moderate disparities with coefficients ranging from 0.23 to 0.27, while the Metropolitan Expansion Area and Southeastern Chongqing (2–4) exhibit coefficients of 0.26–0.32. The Northeastern Chongqing and Southeastern Chongqing (3–4) pair demonstrate coefficients between 0.27 and 0.33.

Evolution trend of overall disparity sources in QMRCI allocation in Chongqing. Figure 6 demonstrates that inter-regional disparity remains the predominant source of overall differences, with its contribution rate consistently maintained between 59.1% and 65%. In comparison, the contribution rate of intra-regional disparity remains around 20%, exhibiting relatively minor fluctuations and stronger stability. Hypervariable density, an indicator for measuring overlapping cross-regional differences, also shows relatively minor contributions with a limited variation range.

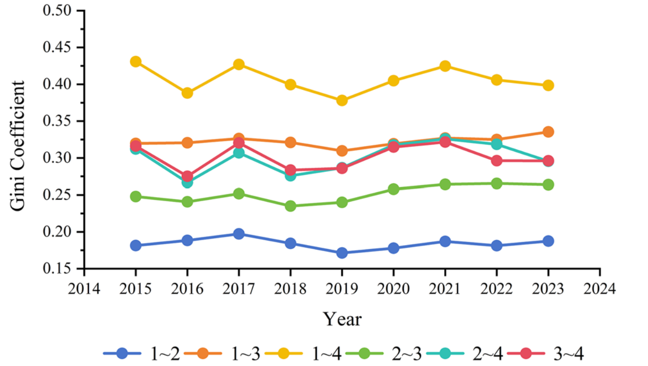

Fig. 5 Inter-regional disparities in QMRCI allocation across Chongqing's functional zones (2015–2023). Note: 1-2: Core Urban Area - Metropolitan Expansion Area; 1-3: Core Urban Area - Northeastern Chongqing; 1-4: Core Urban Area - Southeastern Chongqing; 2-3: Metropolitan Expansion Area - Northeastern Chongqing; 2-4: Metropolitan Expansion Area - Southeastern Chongqing; 3-4: Northeastern Chongqing - Southeastern Chongqing.

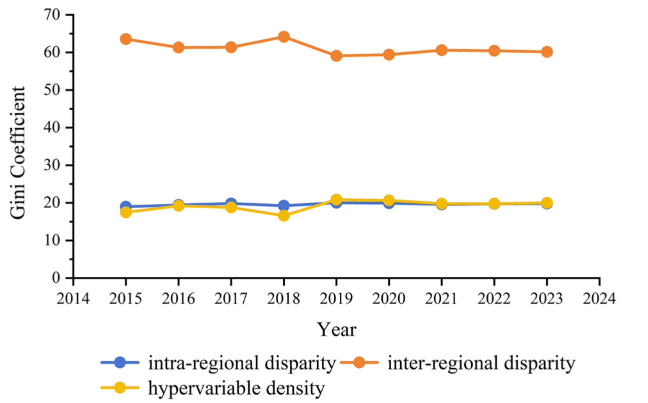

Fig. 6 Evolutionary trends in the sources of overall disparities in Chongqing's QMRCI allocation (2015–2023).

Kernel density estimation. The results indicate that Chongqing's current QMRCI distribution exhibits a gradient pattern characterized by "core polarization, new area emergence, and peripheral lag." The Metropolitan Expansion Area demonstrates rapid growth, while the Core Urban Area shows high resource concentration with internal structural differentiation. Northeastern Chongqing and Southeastern Chongqing remain key target areas for policy intervention (see Table 1).

The kernel density estimation distribution trend of QMRCI across the entire municipality from 2015 to 2023. Figure 7 shows that from 2015 to 2023, the kernel density of QMRCI in Chongqing exhibited a right-skewed unimodal distribution. The main peak was located around 4 and gradually shifted rightward with increasing peak height, indicating overall improvement and a trend toward concentration. In the early period (2015–2017), the dispersed density reflected regional imbalances, while in the later period (2020–2023), the increased peak height and contracted tail suggested a reduction in medium-low value areas. However, the sparse density in the high-value tail (>6) indicates that top-tier QMR remain relatively scarce.

Kernel density estimation distribution trend of QMRCI in the Core Urban Area from 2015 to 2023. Figure 8 presents the kernel density estimation of QMRCI in Chongqing's Core Urban Area from 2015 to 2023, revealing a trimodal distribution. The left peak (QMRCI ≈ 3), emerging during 2020–2023, indicates areas with relatively low resource levels. The central peak (QMRCI ≈ 5),

Table 1 The dynamic evolution characteristics of QMRCI distribution curves in Chongqing municipality and four function regions.

Region	Main peak value	Secondary peak	Distribution structure	Trend summary
Chongqing	4	None	Single peak right shift	Level improvement
Core urban area	5	3、8	Three peak differentiation	Clear stratification
Metropolitan expansion area	4~5	5.5	Double peak distribution	Balanced growth
Northeastern Chongqing	3	None	Left-skewed concentration	Slow improvement
Southeastern Chongqing	2~2.5	3~4	Extreme difference between two peaks	Extreme inequality

This table provides a summary of the key characteristics derived from the distribution curves of QMRCI in Chongqing Municipality and its four functional regions (Figs. 7–11). Features such as peak values should be interpreted in conjunction with the corresponding figures.

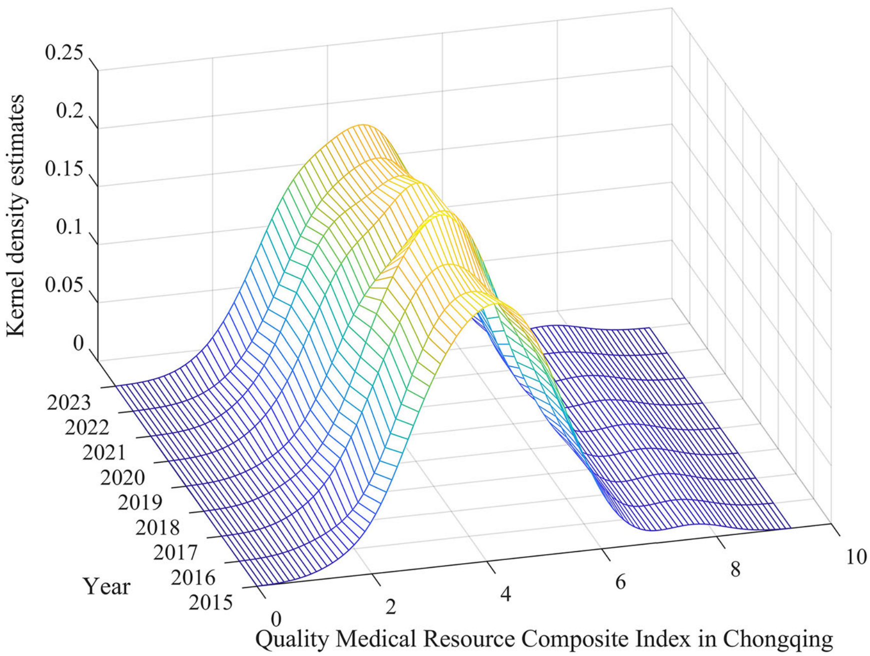

Fig. 7 Kernel density estimation of QMRCI in Chongqing (2015–2023).

also the main peak, spans a broader range, suggesting a moderate level of resource concentration across most areas. Though lower in density, the right peak (QMRCI ≈ 8) reflects a small number of districts with exceptionally high medical resources.

Kernel density estimation distribution trend of QMRCI in the Metropolitan Expansion Area from 2015 to 2023. Figure 9 shows the kernel density estimation distribution of QMRCI in the Metropolitan Expansion Area from 2015 to 2023, exhibiting a medium-high double-peak distribution overall. The main peak at ~4.0 on the resource index represents the balanced development of medical resources in most districts/counties. In contrast, the secondary peak at 5.5 indicates the concentration of high-end medical resources in certain areas. The overall resource distribution demonstrates an "upward shift trend", with a structural balance superior to the Core Urban Area.

Kernel density estimation distribution trend of QMRCI in Northeastern Chongqing from 2015 to 2023. Figure 10 demonstrates that from 2015 to 2023, the kernel density of QMRCI in Northeastern Chongqing exhibited a narrow-peaked left-skewed unimodal structure. The main peak remained stable around 3 with minimal rightward shifting tendency, presenting a concentrated and narrow distribution pattern. This reflects the evident homogeneity of resources in Northeastern Chongqing, where QMRCI has remained consistently low and shown sluggish development over time.

Kernel density estimation distribution trend of QMRCI in Southeastern Chongqing from 2015 to 2023. Figure 11 shows the kernel density estimation distribution of QMRCI in Southeastern Chongqing from 2015 to 2023, exhibiting a bimodal structure. The main peak is high but falls within the QMRCI range of 2–2.5, while the secondary peak shows lower density, with QMRCI values in the 3–4 range. Most districts/counties remain at the resource "bottom plateau," with very few areas advancing to medium-high levels.

Markov

Classical Markov chain transition matrix. The classical Markov chain transition matrix analysis for Chongqing's QMRCI from 2015 to 2023 reveals significant path dependence characteristics (see Table 2). Low- and high-level regions exhibit a "dual-phase lock-in effect," with over 90% probability of maintaining their original states. Medium-level regions show a 79% probability of remaining medium, with an 11% probability of upgrading to a high level and a 10% probability of declining to a low level, making them the most "differentiation-prone" and constituting a "vulnerable transition zone."

Spatial Markov chain transition matrix. With two years setting that aligns with China's policy lag effects, the analysis reveals distinct neighborhood influences (see Table 3): When neighboring areas are "low-level," a "negative lock-in" effect occurs, with low-low structural locking (100% retention) and medium-level areas

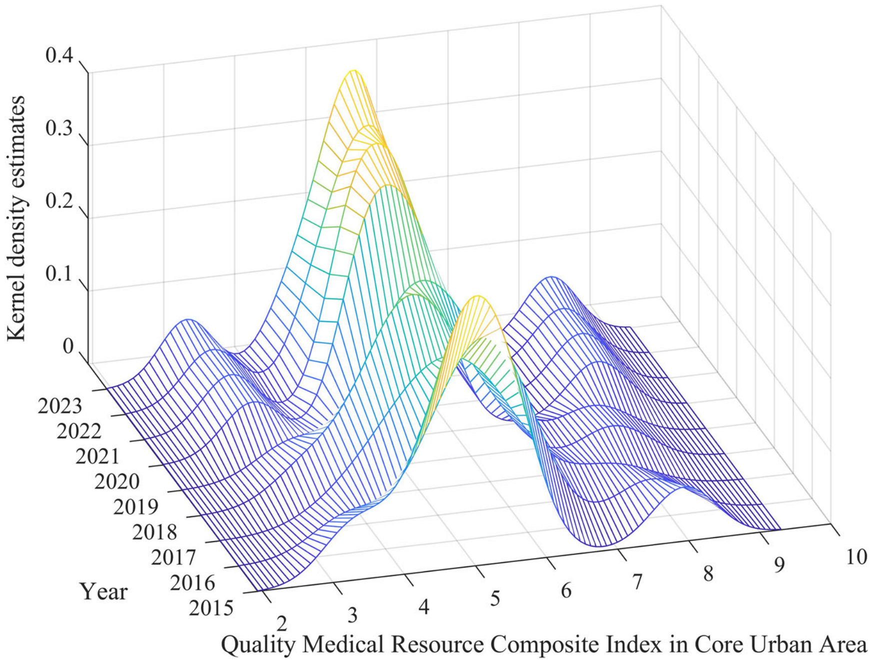

Fig. 8 Kernel density estimation of QMRCI in Chongqing' 's Core Urban Area (2015–2023).

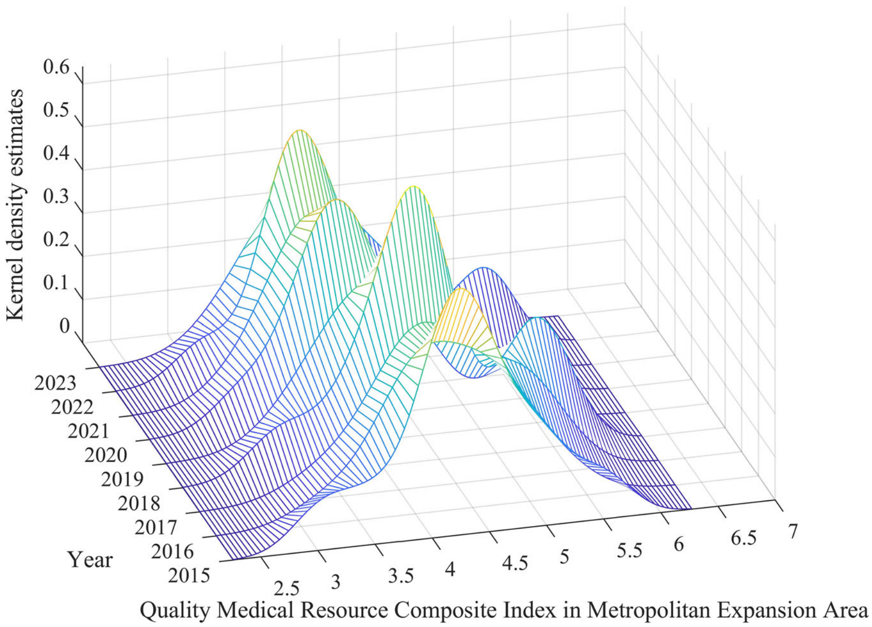

Fig. 9 Kernel density estimation of QMRCI in Chongqing' 's Metropolitan Expansion Zone (2015–2023).

showing no upward transitions but even 18% probability of regression. With "medium-level" neighbors, an "inertial stability" pattern emerges - low-level areas maintain 90% retention, and medium-level areas show 77% stability with minor upward (7%) or downward (16%) mobility. For "high-level" neighbors, "spillover dividends" appear: medium-level areas have a 19% probability of upgrading, while low-level areas remain locked (demonstrating "tiered barriers" in spillover effects), and high-level areas show a 15% probability of downgrading, indicating edge effects.

Spatial Autocorrelation. This study conducts spatial autocorrelation analysis on Chongqing's QMRCI based on three key time nodes: 2016, 2020, and 2023.

Global Moran' 's I. To investigate the spatial clustering characteristics of QMRCI in Chongqing, we conducted a global Moran's I index analysis for three selected years: 2016, 2020, and 2023.

As shown in Table 4, Moran's I values for all three years were positive: 0.35 (2016), 0.33 (2020), and 0.35 (2023), each passing the 1% significance test with significantly positive Z-values. These results indicate that Chongqing's QMR exhibit statistically significant positive spatial autocorrelation, maintaining a relatively stable spatial clustering pattern with evident "high-high" or "low-low" regional agglomeration phenomena.

Anselin Local Moran I. As shown in Fig. 12, the spatial distribution of QMRCI in Chongqing in 2016 exhibits a pronounced

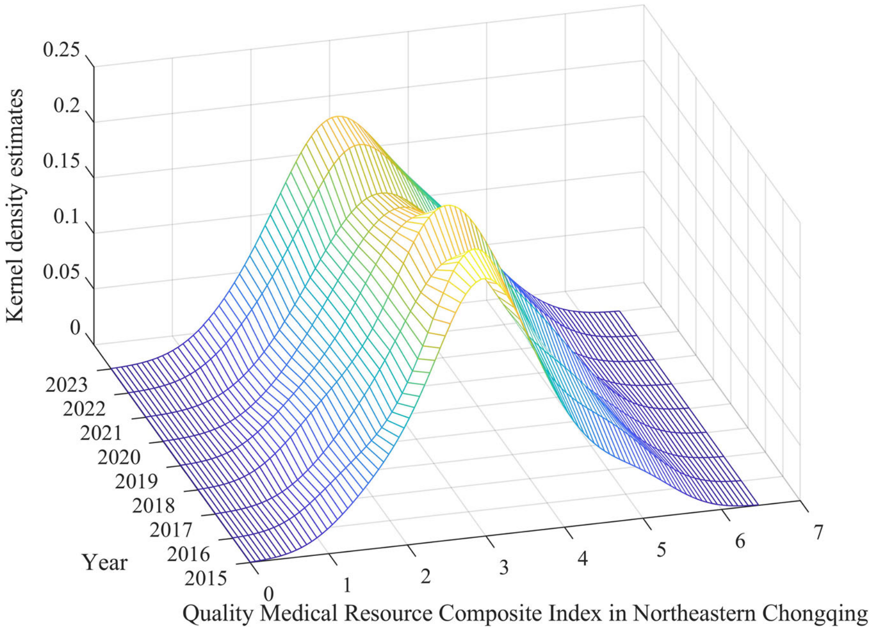

Fig. 10 Kernel density estimation of QMRCI in Northeastern Chongqing (2015–2023).

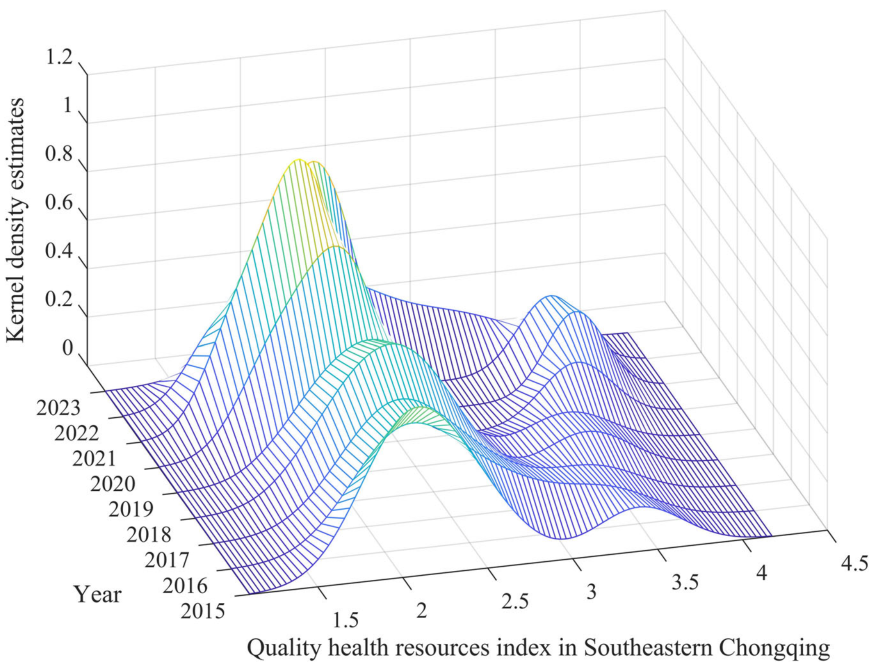

Fig. 11 Kernel density estimation of QMRCI in Southeastern Chongqing (2015–2023).

Table 2 Markov transfer probability matrix for the allocation level of QMRCI in Chongqing, 2015–2023*.

	Quantities	Low level	Medium level	High level
Low level	86	0.94	0.06	0
Medium level	91	0.10	0.79	0.11
High level	89	0	0.09	0.91

*p-value = 0.000001

polarization pattern. A "High-High cluster" is observed in the Core Urban Area, indicating that the local and neighboring districts possess high levels of QMRCI, forming a core zone of medical resource concentration. A "Low-High outlier" is identified in the Metropolitan Expansion Zone, suggesting that while the district has a relatively low QMRCI, adjacent high-resource areas may influence or support it. Additionally, "Low-Low clusters" are found in both Northeastern and Southeastern Chongqing, where the focal districts and surrounding areas are characterized by relatively weak medical resource capacity, highlighting a lag in QMRCI development in these peripheral regions.

In 2020, the spatial pattern of QMRCI changed. The "high-high agglomeration" state in the Core Urban Area still existed, but the coverage was reduced, possibly related to the reallocation of resources that year. The "low-low agglomeration area" in Northeastern Chongqing became smaller, indicating that the resource level had improved. In Southeastern Chongqing, there

Table 3 Spatial Markov chain transfer probability matrix for the allocation level of QMRCI in Chongqing City*.

Neighbor type	Two years	Quantities	Low level	Medium level	High level
Low level	Low level	29	1	0	0
	Medium level	11	0.18	0.82	0
	High level	0	0	0	0
Medium level	Low level	50	0.90	0.10	0
	Medium level	43	0.16	0.77	0.07
	High level	49	0	0.04	0.96
High level	Low level	7	1	0	0
	Medium level	37	0	0.81	0.19
	High level	40	0	0.15	0.85

*p-value = 0.000001

Table 4 Global Moran's I analysis of QMRCI in Chongqing.

Year	Moran's I	Z score	p
2016	0.35	3.47	0.0005
2020	0.33	3.29	0.0010
2023	0.35	3.47	0.0005

were "high-low outliers," indicating that the QMRCI in one area of Southeastern Chongqing had been significantly enhanced, while the resource level in the rest of the areas was low, which may have been the key areas for construction.

By 2023, the "high-high agglomeration area" in the Core Urban Area and its surroundings had expanded to exceed the level of 2016, indicating that resources were more concentrated and the synergy between regions was more obvious. However, no "high-low" or "low-high" anomalies indicated that the differences between regions had narrowed. The situation in Northeastern and Southeastern Chongqing remained the same as in 2016.

Overlay analysis. This study utilizes three key time nodes (2016, 2020, and 2023) to create composite indicators by calculating the QMRCI-to-population density ratio and per capita GDP. Using ArcGIS's Natural Breaks classification method, the results are divided into three tiers, with color gradients from light to dark representing low to high values.

Evolution characteristics of spatial distribution patterns in overlay analysis between QMRCI and population density. Figure 13 and Table 5 show that the distribution of QMRCI-to-population density ratios in Chongqing in 2016 exhibited apparent regional differences. The map demonstrates that red high-value areas predominantly concentrate in Northeastern Chongqing and Southeastern Chongqing, accounting for 11 out of the 12 high-value zones, indicating superior QMRCI-population density matching in these regions. Yellow medium-value areas are widely distributed, with over 50% located in the Metropolitan Expansion Area, reflecting moderate matching levels. Green low-value areas are the least common overall, with approximately 70% situated in the Core Urban Area, showing remarkably stable structural characteristics that suggest relative QMRCI shortages compared to population density in these locations.

In 2020, the spatial distribution pattern of QMRCI-to-population density ratios in Chongqing changed. The map shows that the number of red high-value areas increased from 12 to 15, with primary growth occurring in the Metropolitan Expansion Area (2 additional areas) and Northeastern Chongqing (1 additional area), indicating improved QMRCI-population density matching to 2016. Yellow medium-value areas decreased by 1, while green low-value areas reduced by 2. The quantity and structure remained unchanged in the Core Urban Area and Southeastern Chongqing.

In 2023, the distribution of QMRCI-to-population density ratios exhibited new characteristics. The map reveals that two high-value areas regressed to medium-value status. While the quantity and structure remained unchanged in both the Core Urban Area and Metropolitan Expansion Area, Northeastern Chongqing and Southeastern Chongqing showed modifications from their 2020 baseline - with one fewer high-value area and one additional medium-value area.

Evolution characteristics of spatial distribution patterns in overlay analysis between QMRCI and per capita GDP. Several key findings emerge based on the analysis of the matching degree between the QMRCI and per capita GDP across 38 districts and counties in Chongqing in 2016 (as shown in Fig. 14 and Table 6). The ratio of QMRCI to per capita GDP exhibited significant spatial variation. According to the map, high-value areas (marked in red) accounted for 10 districts, distributed only within the Metropolitan Expansion Zone (4) and Northeastern Chongqing (6), indicating a strong alignment between high-quality medical resources and economic development in these regions. Medium-value areas (marked in yellow) comprised 24 districts, including 7 in the Core Urban Area, 8 in the Metropolitan Expansion Zone, 4 in Northeastern Chongqing, and 5 in Southeastern Chongqing, suggesting that the majority of districts in all four regions exhibited a moderate level of alignment. Low-value areas (marked in green) were limited to just 4 districts—2 in the Core Urban Area, 1 in Northeastern Chongqing, and 1 in Southeastern Chongqing—indicating a relatively low degree of alignment between QMRCI and per capita GDP in these locations.

By 2020, the spatial distribution pattern of QMRCI-to-per capita GDP ratios in Chongqing underwent significant changes. Red high-value areas decreased to 7, yet all four regions contained high-matching districts: the Core Urban Area and Southeastern Chongqing each gained 1 (from zero), while the Metropolitan Expansion Area dropped from 4 in 2016 to 1, and Northeastern Chongqing reduced from 6 to 4. Medium-value areas (yellow) declined substantially from 24 in 2016 to 17 in 2020, with the following distribution: 5 in the Core Urban Area, 6 in the Metropolitan Expansion Area, and 3 each in Northeastern and Southeastern Chongqing. Green low-value areas markedly increased from 4 in 2016 to 14 in 2020, with the Core Urban Area and Southeastern Chongqing each adding 1, the Metropolitan Expansion Area gaining 5, and Northeastern Chongqing increasing by 3, indicating substantially expanded regions with QMRCI shortages relative to per capita GDP.

In 2023, the distribution of QMRCI-to-per capita GDP ratios exhibited new characteristics. Only one red high-value area remained, located in the Metropolitan Expansion Area. Yellow medium-value areas (19 total) nearly equaled green low-value areas (18 total), with medium-value distributions, as follows: Core Urban Area (6), Metropolitan Expansion Area (5), Northeastern Chongqing (5), and Southeastern Chongqing (3). All regions except the Core Urban Area showed increases in low-value areas compared to 2020 - the Metropolitan Expansion Area and Southeastern Chongqing each gained one, while Northeastern Chongqing added two.

Discussion

From 2015 to 2023, Chongqing's QMRCI ranged between 0 and 9.3. Through "policy-driven resource redistribution +

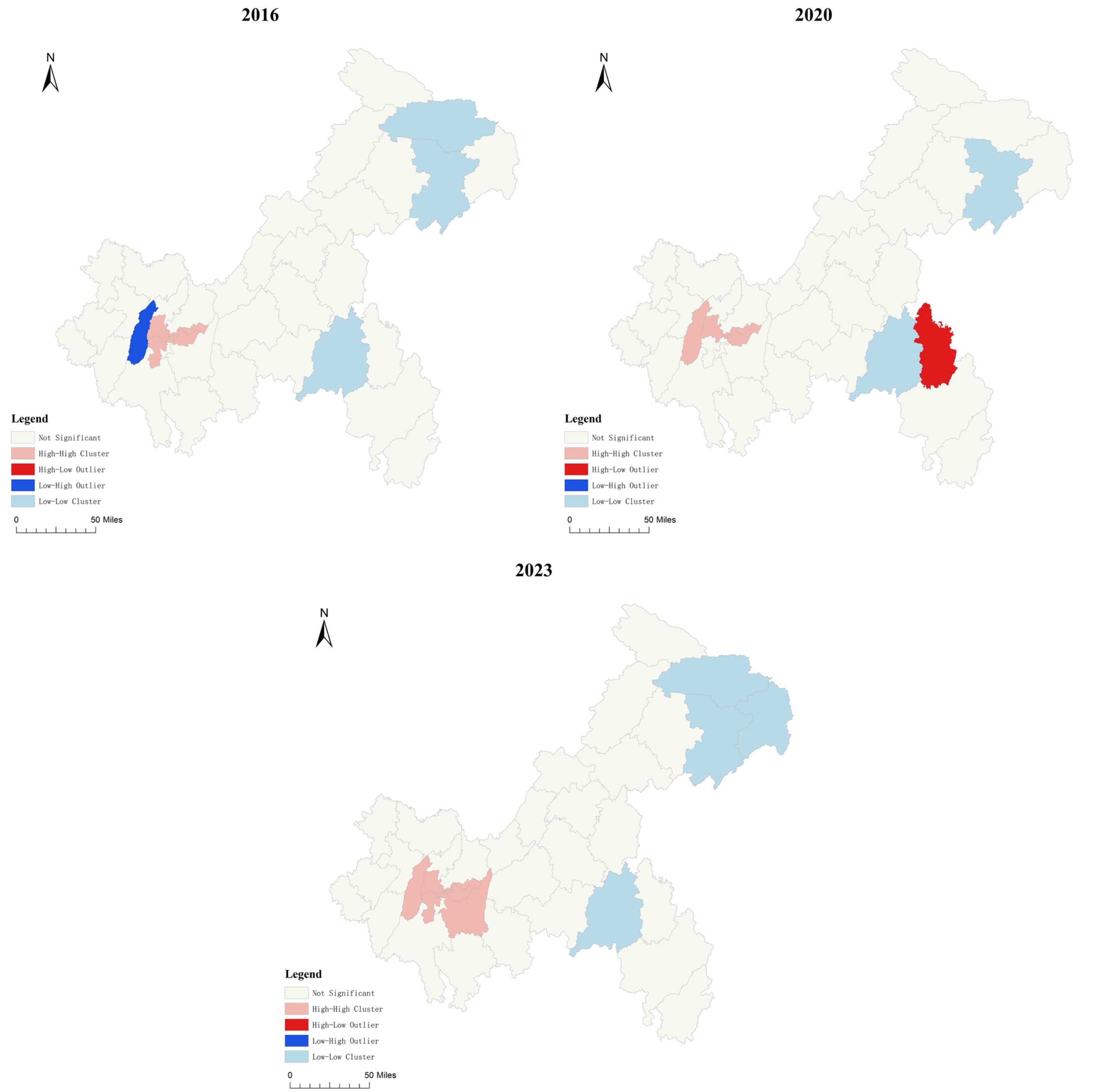

Fig. 12 Spatial clustering patterns of QMRCI in Chongqing (2016–2023): Results from Local Moran's I Analysis.

technology-enabled balanced allocation + regional coordinated development," Chongqing has promoted phased progress in QMR characterized by "enhanced core radiation and addressed peripheral deficiencies," providing a replicable pathway for medical resource equalization in mega-municipalities. However, the following characteristics persist:

Dagum Gini coefficient and its decomposition. Chongqing's overall QMRCI allocation disparities during 2015–2023 were characterized by "general stability with localized polarization," reflecting fundamental tensions in China's healthcare reform between policy-driven grassroots resource redistribution and market-induced concentration and siphoning of high-end resources. The initially declining trend reversed sharply from 2019 through 2022 due to short-term disruptions from the COVID-19 pandemic, when epidemic prevention resources and personnel became concentrated in core urban areas while peripheral regions experienced resource drainage. This caused temporary increases in the Dagum coefficient, revealing regional healthcare system vulnerabilities during public health emergencies - consistent with India's medical resource equity research (Jayaprakash et al., 2024). In the post-pandemic period, continued medical reforms gradually restored resource reallocation and stabilized spatial disparities.

Analysis of Chongqing's overall QMRCI allocation disparities reveals coexisting intra-regional and inter-regional differences, with dominant inter-regional disparities. Regarding intra-regional variations, Northeastern Chongqing showed the most significant differences between 2015 and 2023 (Gini coefficient ≈0.3). Taking Wanzhou District as an example, its QMRCI reached 6.4 as a regional medical center, while Chengkou County's QMRCI was

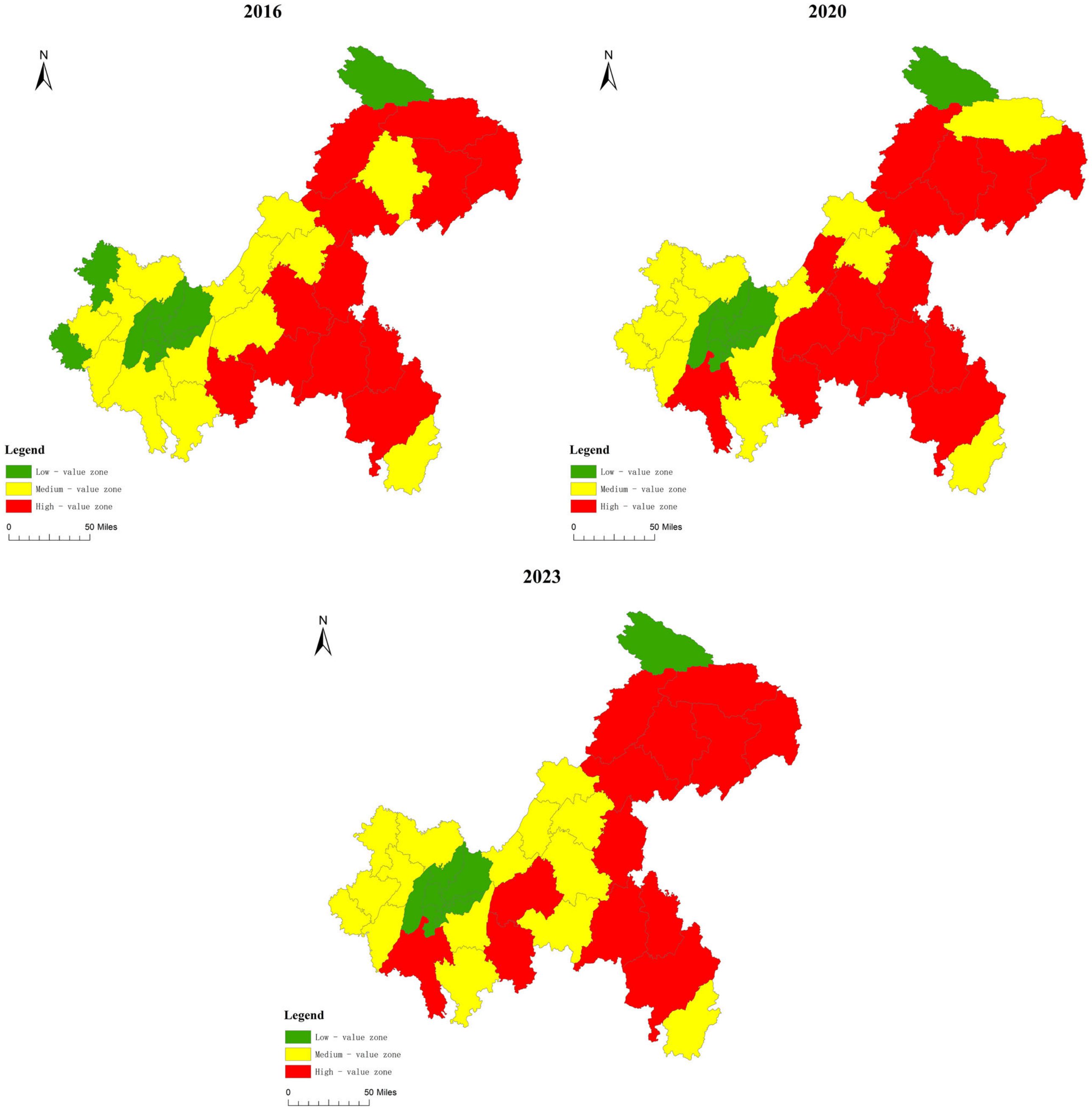

Fig. 13 Spatial stratification of QMRCI-to-population density ratios in Chongqing (2016–2023): Natural Breaks Classification.

Table 5 Distribution of QMRCI-population density ratio across Chongqing's functional zones (2016–2023).

Functional zone	2016			2020			2023		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Core urban area	0	1	8	0	1	8	0	1	8
Metropolitan expansion area	1	8	3	3	8	1	3	8	1
Northeastern Chongqing	6	4	1	7	3	1	6	4	1
Southeastern Chongqing	5	1	0	5	1	0	4	2	0
Total districts ($n = 38$)	12	14	12	15	13	10	13	15	10

merely 0 - the lowest in the municipality. This "cliff-like gap" (6.4 vs 0) vividly reflects the severe imbalance in medical resource distribution in mountainous cities, attributable to the insufficient radiation range of regional medical centers and transportation challenges caused by hilly terrain, creating notable "medical isolation effects" similar to Peru's Andean regions with complex topography. The Metropolitan Expansion Area exhibited minimal intra-regional differences, benefiting from both the "resource

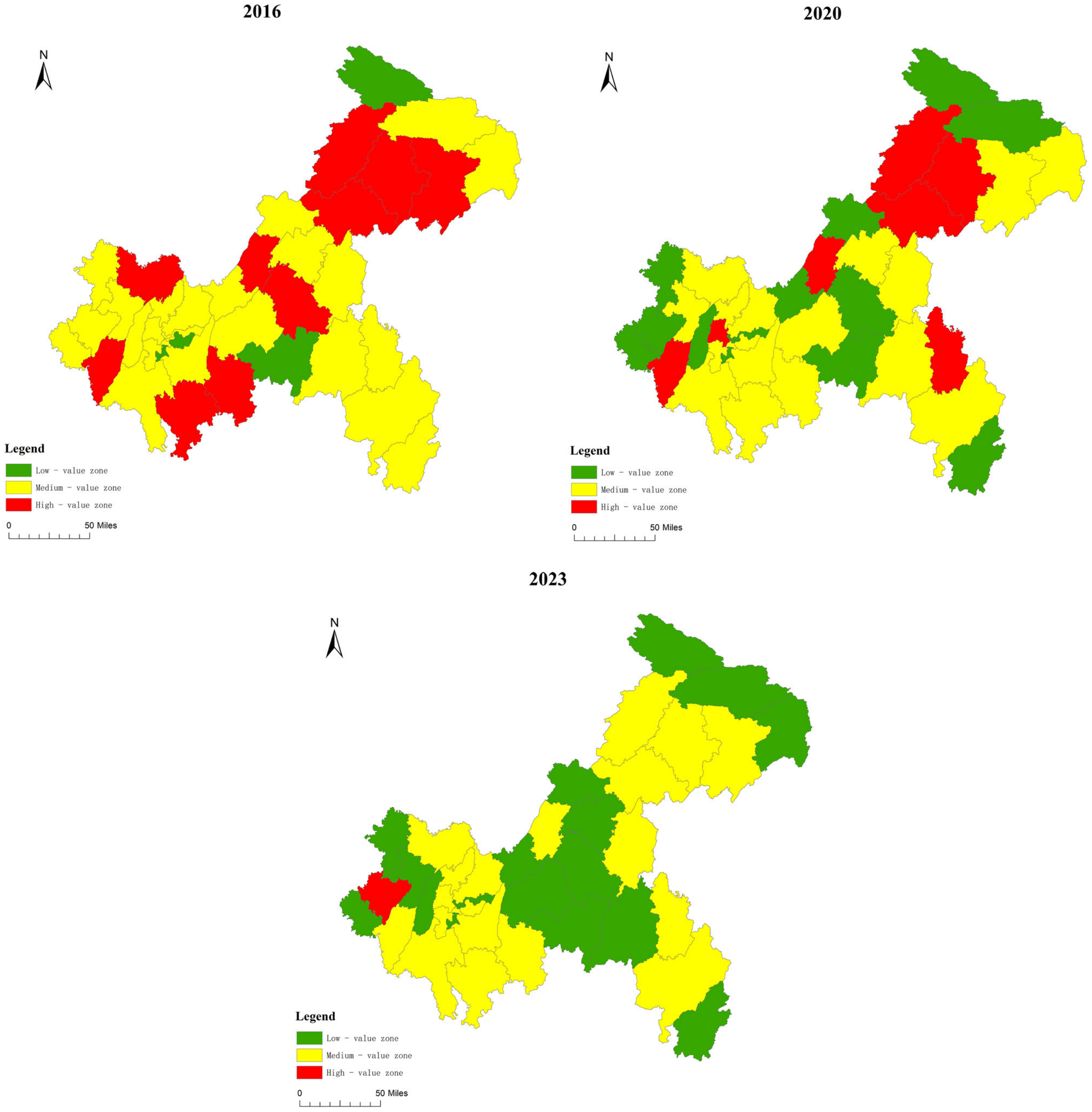

Fig. 14 Spatial Stratification of QMRCI-to-GDP per capita ratios in Chongqing (2016–2023): Natural Breaks Classification.

Table 6 Distribution of QMRCI-GDP per capita ratio across Chongqing's functional zones (2016–2023).

Functional zone	2016			2020			2023		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Core urban area	0	7	2	1	5	3	0	6	3
Metropolitan expansion area	4	8	0	1	6	5	1	5	6
Northeastern Chongqing	6	4	1	4	3	4	0	5	6
Southeastern Chongqing	0	5	1	1	3	2	0	3	3
Total districts ($n = 38$)	10	24	4	7	17	14	1	19	18

spillover effects" from adjacent Core Urban Areas and balanced public service facility planning during initial urban functional zoning, resulting in relatively equitable medical resource distribution among its districts - a pattern also observed in other recently developed Chinese cities like Shenzhen's Bao'an and Longgang districts receiving resource radiation from central Shenzhen (Hu et al., 2019).

The disparities between the Core Urban Area and peripheral regions like Northeastern Chongqing and Southeastern Chongqing are most pronounced at the inter-regional level. The core urban areas maintain dominant positions in resource distribution due to their superior hospital systems, strong fiscal support, and technological accumulation - a pattern consistent with findings from both developing (China) and developed countries (the US), where quality resources tend to concentrate in economically advanced, densely populated urban cores while peripheral areas suffer long-term disadvantages due to weaker fiscal capacity and dispersed medical needs (Horev et al., 2004; Zhou et al., 2022). Meanwhile, the smallest gap exists between the Core Urban Area and the Metropolitan Expansion Area, indicating the preliminary establishment of robust resource-sharing mechanisms under policies promoting "metropolitan integration" and "coordinated development." Notably, asymmetric development trends also exist between Northeastern and Southeastern Chongqing, highlighting divergence paths among peripheral regions - a spatial characteristic requiring particular attention in Chongqing's regional development that remains relatively understudied in existing literature.

Kernel density estimation. The kernel density analysis reveals that Chongqing's QMR exhibited a gradient distribution pattern of "core polarization, new area emergence, and peripheral lag" from 2015 to 2023. This reflects the progressive optimization of spatial allocation under policy guidance and underlying structural contradictions. Such an evolutionary path demonstrates the phased characteristics of resource allocation in China's major cities and aligns with the universal logic of global urban healthcare systems.

From the city's perspective, the kernel density curve of QMRCI shifted to the right, and the peak has increased over the years. This indicated that the distribution of QMR gradually changed from "scattered fluctuations" to "concentrated and stable". This positive change was due to the sinking of primary medical resources in the context of the new medical reform, the promotion of telemedicine, and the construction of county-level medical sub-centers. As the number of low-and medium-level areas decreased, the overall level of resource sharing also improved. However, the lack of high values on the curve indicated that Chongqing lacked top medical resources. In the future, while promoting the balance of resources, it will also be necessary to improve the capacity of high-end medical services in the core urban area to avoid the situation of balanced but low-level medical resources.

Regional differentiation characteristics further reveal the complexity of spatial allocation. The triple-peak structure in the Core Urban Area reflects significant resource density advantages but insufficient internal equity, presenting challenges for redistribution policies. The bimodal distribution in the Metropolitan Expansion Area demonstrates emerging resource clusters under combined policy guidance and new urban development, clearly displaying an evolutionary path of "consolidated middle layer with localized breakthroughs." For instance, Bishan and Yongchuan districts adjacent to the Core Urban Area have formed a "second tier" sub-peak by absorbing central resources like branch hospitals of tertiary institutions, technical collaboration, and scientifically planned urbanization, with significantly lower intra-regional Dagum coefficients than other areas, exemplifying core-new area coordinated development and validating the dual driving effects of locational advantages and policy guidance. As peripheral regions, Northeastern Chongqing and Southeastern Chongqing exhibit transitional characteristics of "dense bottom with single-point breakthroughs," most districts remain in resource allocation "depressions." Such long-term, low-level, homogeneous medical resource distribution in peripheral areas mirrors global challenges - most developed countries still face significant difficulties in achieving comprehensive healthcare services in rural regions (Weinhold and Gurtner, 2014; Wilson et al., 2009).

Compared with typical regions, Chongqing's Core Urban Area has developed an agglomeration effect similar to New York's "core hospital cluster" in the United States. However, Chongqing's distinctiveness lies in the faster development speed of its "second tier" in the Metropolitan Expansion Area than comparable regions - for instance, Shanghai's Pudong New Area took ~15 years to establish a sub-center. Meanwhile, the sub-center development in Northeastern Chongqing and Southeastern Chongqing (e.g., Wanzhou, Qianjiang) remains inadequate in capacity. As health statistics show, each area possesses only one Grade III Level A hospital, falling below developed country standards and resulting in the slow overall improvement in peripheral regions.

Spatial Markov chain. Based on spatial Markov chain analysis from 2015 to 2023, Chongqing's QMR allocation exhibits significant path dependence and neighborhood effects, revealing deep-seated contradictions between resource hierarchy solidification and regional coordination mechanisms.

The classical Markov chain transition matrix demonstrates a "dual-phase lock-in" effect: low-level areas are trapped in "allocation poverty traps" due to geographical isolation and weak economic foundations, while high-level areas reinforce their advantages through "Matthew effects" of resource agglomeration. Medium-level areas constitute the most differentiation-prone "vulnerable transition zones." This structural inertia essentially results from the imbalance between market agglomeration effects and administrative intervention in medical resource allocation - where core areas continuously amplify advantages through historical accumulation and factor siphoning, while peripheral areas struggle to break bottlenecks due to insufficient external driving forces.

The spatial Markov chain further demonstrates significant neighborhood effects on resource allocation. Low-level neighborhoods exhibit pronounced "negative lock-in" effects, where geographical proximity to similarly disadvantaged areas exacerbates resource "collapse," trapping peripheral regions in "collective lock-in" dilemmas. This aligns with existing research showing that low-level areas, due to insufficient fiscal investment, severe brain drain, and weak medical infrastructure, easily fall into a vicious cycle of "resource scarcity-inadequate service capacity-diminished attractiveness," creating locked states that hinder self-driven advancement (Chen and Jin, 2022). Medium-level neighborhoods display "inertial stability" characteristics - while possessing certain resource foundations (as seen in some counties of the Metropolitan Expansion Area), they risk falling into "medium allocation traps" without sustained policy stimuli or core resource inputs, making them susceptible to neighborhood homogenization influences. High-level neighborhoods' "spillover dividends" primarily benefit medium-level areas: when adjacent to high-level zones, medium-level regions show 18.92% upgrade probability (e.g., Bishan and Yongchuan absorbing Core Urban Area spillovers), though peripheral areas remain volatile with low-level zones still "locked," indicating "tiered barriers" in spillover effects. Similarly, studies note that resource spillovers require robust regional coordination mechanisms (Fu et al., 2021); otherwise, "core-periphery" structures intensify, preventing genuine equity. Chongqing's current challenge lies in overly strong market-driven agglomeration coupled with imprecise administrative intervention, creating a "strong-get-stronger, weak-struggle" neighborhood dynamic, warranting reference to Germany's "equalization funding mechanism" to mitigate negative neighborhood effects and Beijing's "compact medical alliances."

Spatial autocorrelation. According to the analysis results of Global Moran's I and Anselin Local Moran's I, from 2016 to 2023, Chongqing's QMRCI showed a development trend of "continuous and stable agglomeration in the Core Urban Area, local improvement in the peripheral areas, and enhancement of overall spatial synergy." This evolution aligned with the general law of resource distribution in large cities worldwide and reflected mountain cities' geographical particularity.

Global Moran's I showed that Chongqing's QMRCI exhibited a significant positive spatial autocorrelation, consistent with the "high-high agglomeration" phenomenon in global urban core areas such as Manhattan and Tokyo's Chiyoda ward, where resources are often concentrated in areas with a good economic foundation and high population density (Giordano et al., 2023; Kusunoki and Yoshikawa, 2024). Anselin Local Moran's I revealed the variation of differences between regions. From 2016 to 2023, the "high-high agglomeration area" in the Core Urban Area first shrank and then expanded, a process that contrasted with New York's core area of resource repatriation after the financial crisis and Beijing's policy-guided resource expansion. There were persistent "low-low clusters" in Northeastern Chongqing and Southeastern Chongqing, similar to those in the mountainous areas of Bavaria in Germany or the underdeveloped areas in western China, reflecting the limitations of topography on the allocation of medical resources. From the trend point of view, with the continuous promotion of policies such as medical alliances, the inter-regional resource coordination mechanism began to play a role. However, the "strong core and weak edge" pattern had not been broken then. The Metropolitan Expansion Area presented the characteristics of a "transition zone". "low-high" anomalies in 2016 gradually disappeared by 2023, indicating that it was transitioning from a resource-receiving area to an equilibrium area. This transformation was somewhat similar to Singapore's "regional medical center" model. However, Chongqing's Metropolitan Expansion Area still mainly relied on the resource spillover of the Core Urban Area, and its independent support capacity still needed to be further improved.

Overlay analysis. This study's overlay analysis of QMRCI with population density and per capita GDP reveals an "initial peripheral advantage - gradual new area improvement - core matching lag" pattern.

The QMRCI-population density matching characteristics evolved from "peripheral priority" to "comprehensive optimization." In 2016, Northeastern Chongqing and Southeastern Chongqing accounted for most high-value areas, indicating better initial medical resource-population density matching in peripheral regions, reflecting early policy support for densely populated but resource-scarce areas. By 2020, the Metropolitan Expansion Area and Northeastern Chongqing showed further improvement, demonstrating enhanced coordination between resource allocation and population distribution during urbanization. However, low-value areas persistently dominated the Core Urban Area, mirroring Manhattan's "core area resource overload coupled with extreme population density causing matching imbalance," highlighting structural contradictions in high-density urban healthcare supply-demand. The 2023 high-value area retreat suggests peripheral regions need more stable resource matching, potentially adopting Tokyo's "multi-center medical circle" model by establishing secondary population-medical matching hubs in Wanzhou (Northeastern Chongqing) and Qianjiang (Southeastern Chongqing) to avoid volatility from "single-point breakthroughs."

The QMRCI-per capita GDP matching characteristics evolved from "economy-driven" to "equilibrium pressure." In 2016, high-value areas were concentrated in the Metropolitan Expansion Area and Northeastern Chongqing, reflecting early-stage economic vitality's attraction of medical resources. By 2020, high-value areas expanded across all regions, with the Core Urban Area and Southeastern Chongqing achieving "zero breakthroughs," while low-value areas surged, revealing the common issue of medical resource expansion lagging behind GDP growth during rapid economic development. In 2023, low-value areas covered 60% of districts/counties, indicating growing imbalance pressure in "economy-medical" matching.

Chongqing's resource-matching evolution demonstrates the superimposed effects of "developing countries' common challenges and mountainous cities' unique constraints." First, the "declining peripheral advantage" in population matching resembles Mumbai's experience where "slum healthcare priority coverage lacks stability" - Chongqing's initial high peripheral matching relied on policy support but later retreated due to insufficient economic foundations, necessitating the establishment of a "population-medical dynamic balance fund" for real-time resource adjustment based on population flows. Second, the "core lag risk" in economic matching: learning from Tokyo Metropolitan Area's planning standard linking "GDP with medical resource density" (adding 500 quality beds per ¥1 trillion GDP increase), Chongqing could implement a "10% QMRCI growth target per ¥10,000 per capita GDP increase" to prevent economic-medical "inversion."

Conclusion

From 2015 to 2023, Chongqing has made phased progress in the development of QMR through policy-driven resource decentralization, technology-enabled equitable allocation, and regional coordinated collaboration, providing a practical pathway for the balanced distribution of medical resources in mega municipalities. However, analysis using the Dagum Gini coefficient reveals that while the overall allocation disparity remains relatively stable, there is a trend of "localized polarization, " with inter-regional disparities being the main contributors to the overall imbalance. Three-dimensional kernel density estimation shows a gradient distribution of resources characterized by " core polarization, the rise of expansion areas, and peripheral lagging. " Although there is an overall evolution toward " stable agglomeration, " the reserve of top-tier resources remains insufficient. The spatial Markov chain analysis uncovers path dependence and neighborhood effects in resource allocation: low-level regions are negatively locked into a " resource poverty trap"; mid-level regions exhibit differentiation potential; and while high-level neighbors exert positive spillover effects on adjacent mid-level areas, "barriers between strata" still exist. Spatial autocorrelation analysis indicates that QMR exhibits "stable core agglomeration, partial improvement in peripheral areas, and enhanced spatial coordination." These patterns align with agglomeration characteristics of international metropolises; however, the independent development capacity of the Metropolitan Expansion Area still requires improvement. Overlay analysis demonstrates a shift in the spatial matching of the QMRCI and population density from a pattern of "peripheral prioritization" toward "holistic optimization."

In contrast, the matching with per capita GDP is transitioning from being "economically driven" to facing "equilibrium pressure," highlighting both the common challenges developing countries face and the unique constraints of mountainous cities. In the future, it is crucial to enhance the efficiency of QMR supply in densely populated (developed) areas while optimizing regional coordination mechanisms to avoid homogenization at lower levels. Medical resource investment should be aligned with GDP growth, with particular attention paid to the accessibility of resources in peripheral (underdeveloped) regions. Drawing from international experience, Chongqing should establish a city-wide dynamic balance mechanism and a targeted policy intervention system to strengthen the overall resilience of its healthcare system, achieve balanced and high-quality development of medical resources, and provide a more universally applicable solution for similar regions.

Limitations and future directions: (1) need for causal methods (e.g., DID) to disentangle policy effects, and (2) absence of micro-level institutional data (e.g., facility-specific budgets) that may drive allocation patterns. Future work should address these gaps.

Data availability

The data used in this study are derived from the *Chongqing Health Statistics Yearbook* and the *Chongqing Statistical Yearbook*. The raw and processed datasets are openly available at [https://doi.org/10.5281/zenodo.16882370].

Received: 7 February 2025; Accepted: 28 August 2025;
Published online: 30 September 2025

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Acknowledgements

We acknowledge funding support from the Chongqing Social Science Planning Project(Grant No: 2023NDYB106); Supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (Grant No. KJQN202200409); the Humanities and Social Sciences Research Planning Project of Chongqing Education Commission in 2022 (Grant No: 22SKGH057).

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Competing interests

The authors declare no competing interests.

Ethical approval

This article does not encompass studies involving human participants conducted by the authors.

Informed consent

This article does not include any studies involving human participants conducted by the authors.

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