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Research on the Evaluation and Spatiotemporal Characteristics of Financial Agglomeration Level of Prefecture-Level Cities in Guizhou Province Based on Multi-Source Data

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Abstract

Scientifically measuring the financial agglomeration level of prefecture-level units in Guizhou can effectively promote the high-quality development of Guizhou's financial industry and give full play to the driving role of finance in surrounding regions. This study incorporated the Baidu search index and introduced the dimension of digital inclusive finance to construct a comprehensive evaluation system containing 30 secondary indicators. Based on the panel data of nine prefecture-level cities and prefectures in Guizhou from 2011 to 2025, this study adopted the entropy-weight-TOPSIS model for quantitative measurement. The time-series results revealed significant regional growth differentiation: Zunyi City achieves the highest provincial growth rate, followed by Tongren City and Qiannan Prefecture with sound growth momentum. Guiyang City maintains a consistently high agglomeration level with an upward overall score and occupies the leading position all the time, while Zunyi City experiences a phased leap after 2017 and develops into a secondary financial growth pole, continuously consolidating the foundation of provincial financial development. From the spatial perspective, hierarchical analysis of the years 2011, 2018 and 2025 with differentiated grading thresholds showed that Guizhou's financial agglomeration pattern has evolved from the single-core dominance of Guiyang and prominent east-west developmental gaps toward a multipolar collaborative development pattern. During the study period, regional disparities have been gradually alleviated, and the overall financial development level of the whole province has steadily improved, but some regions still remain at relatively low agglomeration levels. Overall, the financial agglomeration level of Guizhou Province has been continuously enhanced with an obvious transformation toward multi-polar collaborative development, though regional hierarchical differentiation still remains prominent. Based on the empirical findings, this study puts forward differentiated optimization countermeasures, which can provide a reliable reference for realizing balanced and high-quality financial agglomeration in Guizhou Province.

Keywords

Prefecture-Level Cities in Guizhou Province, Financial Agglomeration Level, Multi-Source Data, Entropy Weight-TOPSIS Method, Comprehensive Evaluation, Spatiotemporal Differentiation

1. Introduction

Financial industrial agglomeration refers to a special industrial spatial structure in which headquarters-based institutions, including national financial regulatory authorities, financial intermediaries, multinational financial enterprises, and domestic financial firms, concentrate in specific regions and maintain close operational connections with international institutions, multinational corporations, and the headquarters of large domestic enterprises (360 Encyclopedia). Under the background of economic and financial globalization, the spatial agglomeration of the financial industry has become increasingly prominent. The interactive development between the financial industry and the real economy has fostered the formation of financial industrial clusters, which accelerate financial innovation, reduce transaction costs, and further drive regional economic growth through agglomeration effects (Zhang, 2013).

Regarding the economic effects, spatial spillover, and micro-impact of financial agglomeration, rich research results have been formed at home and abroad: Zhao et al. (2025) used a spatial panel model of 285 prefecture-level cities in China from 2008 to 2021 to confirm that financial agglomeration has an inverted U-shaped direct effect and positive spatial spillover on urban economic resilience, and the agglomeration pattern shows the characteristics of evolving from point-like to block-like agglomeration (Zhao et al., 2025); Xing (2025) conducted research from the perspective of enterprise sustainable development and found that financial agglomeration can significantly improve the comprehensive ESG performance of enterprises by optimizing resource allocation and upgrading industrial structure. The effect has property rights and regional heterogeneity; Wu et al. (2026) used provincial panel data to verify that financial agglomeration has a positive promoting effect on regional financial resilience, but the central and western regions are constrained by the siphon effect and cannot enjoy the agglomeration dividend. Liu (2026b) focused on 46 prefecture-level cities in Southwest China, confirming that there is a significant spatial correlation in financial agglomeration, and its spillover effect can effectively promote regional urbanization; Liu & Xie (2024) used Guangxi as a research sample and concluded, through location entropy calculation, that the overall level of financial agglomeration in the province is low and the regional resource distribution is unbalanced, and proposed targeted paths for improving the quality and efficiency of finance. Since Guizhou began implementing the "Attracting Finance to Guizhou" strategy in 2012, and in the past two years, the government has focused on building the Guizhou Financial City project. Guizhou's financial industry has gradually entered a golden age, and the gross domestic product of the financial industry has increased year by year. The 2019 Guizhou Provincial Government Work Report emphasized that in order to fully promote high-quality economic development, it is necessary to "strengthen the construction of the local financial system, enhance the linkage between government, finance, and enterprises, strengthen financial product innovation, and focus on alleviating the difficulties and high costs of financing for small and micro enterprises, private enterprises, and agriculture. Increase the cultivation and support for enterprise listing and actively develop regional equity markets." Therefore, accelerating the agglomeration and development of Guizhou's financial industry and giving full play to the agglomeration effect of finance is of great practical significance for Guizhou to accelerate the transformation and upgrading of its industrial economy and fully promote high-quality economic development.

Scientifically evaluating the level of financial agglomeration is a fundamental and crucial issue for accelerating the agglomeration and development of the financial industry. Currently, commonly used methods for evaluating the level of financial agglomeration at home and abroad include (Shen, 2014): Evaluation methods based on regional financial agglomeration level (such as industry concentration, Herfindahl index, location Gini coefficient, industrial cluster index, Halley-White index, etc.), and distance-based evaluation methods (such as K-function, L-function, and SP index). In addition, to cover more information, scholars have also introduced multi-attribute decision-making methods into the evaluation of financial agglomeration level. 1) In terms of the indicator system, the traditional financial agglomeration evaluation framework is mostly limited to the traditional financial industry dimension. Ding et al. (2009) constructed an evaluation indicator system for the degree of financial agglomeration in China from four aspects: the overall scale of finance, banking industry, securities industry and insurance industry (Ding et al., 2009). Ru et al. (2014) constructed a measurement index system for the level of financial agglomeration in central cities from four aspects: financial background, financial scale, financial density, and financial depth. Li & Bai (2014) constructed a regional financial agglomeration level measurement index system, which includes primary indicators such as the insurance market, credit market, trust market, and securities market. Deng et al. (2015) constructed a regional financial agglomeration level evaluation index system with financial scale, financial institutions, and financial talents as primary indicators (Deng et al., 2015). Feng et al. (2016) established a Shandong financial agglomeration degree evaluation index system, which includes primary indicators such as financial resources, financial institutions, and financial output. Liao & Li (2019) established a comprehensive evaluation index system for Guangxi financial agglomeration that includes economic aggregate and financial scale. With the rapid popularization of digital financial business models, digital inclusive finance has become an indispensable core dimension for regional economic and financial evaluation. Guo et al. (2026) empirically found using panel data from 16 cities and prefectures in Yunnan that digital inclusive finance can significantly increase the income of rural residents, and the income increase effect has regional heterogeneity and nonlinear threshold characteristics; Liu (2026a) confirmed based on national provincial panel data that digital inclusive finance can narrow the urban-rural income gap through two paths: industrial upgrading and non-agricultural employment, with significant differences in threshold effects in the sub-dimensions of coverage breadth and usage depth; Su (2025) and Wang & Lv (2023) further demonstrated the key value of digital inclusive finance in narrowing the urban-rural income gap, promoting urban-rural integration, and helping common prosperity, providing sufficient theoretical and empirical support for this paper to add the dimension of digital inclusive finance in addition to traditional financial industry indicators. 2) In terms of evaluation methods, the mainstream measurement tools in existing research include principal component analysis (Ding et al., 2009) Factor analysis method 458 (Li & Bai, 2014; Liao & Li, 2019; Ru et al., 2014) Vertical and horizontal grading method (Deng et al., 2015), and entropy weight TOPSIS method (Feng et al., 2016). The Entropy Weight-TOPSIS model, relying on its advantages of objective weighting, multi-dimensional hierarchical ranking, and dynamic time-series evaluation, has been widely used in various quantitative studies on regional development levels. Duan et al. (2026) built a three-dimensional indicator system and used the model to measure the development level of Xinjiang's land ports, finding that international logistics channels are the core factor restricting the upgrading of land ports (Duan et al., 2026). Jiang (2026a) used the Entropy Weight-TOPSIS method to measure the logistics development level of China-ASEAN countries, confirming the serious imbalance in regional development and proposing differentiated development policies for groups. Jiang (2026b) used the same model to evaluate the standardized development of provinces across the country and identified a pyramid hierarchy pattern of leading in the east and lagging in the west. To sum up, the existing financial agglomeration level evaluation indicator systems have their own characteristics, but they all ignore the use of Internet big data, resulting in insufficient information; In addition, existing methods for evaluating the level of financial agglomeration have their own advantages, but they all lack ambiguity and hesitation, making it difficult to reflect the ambiguity and hesitation of decision-makers in evaluating objective objects.

Baidu Index is a data sharing platform based on Baidu's massive user behavior data. It is one of the most important statistical analysis platforms in the current Internet and even in the entire data era. Since its release in 2006, it has become an important basis for marketing decisions and evaluations for many companies. Through the Baidu Index function module, people can study keyword search trends, understand changes in user demand, monitor media sentiment trends, and locate digital consumer characteristics; they can also analyze market characteristics from an industry perspective (http://index.baidu.com). A large number of existing empirical studies have verified the feasibility and scientific nature of using Baidu Index to quantify public attention and capture market demand: Pan (2026) used Baidu Index as an input variable and combined it with various machine learning models to complete the prediction of tourist volume in scenic spots, proving that there is a close nonlinear correlation between search index and actual economic activities, and there is also a spatial distance attenuation spillover effect; Chen & Wang (2026) based on ten years of Baidu Index data systematically depicted the spatiotemporal differentiation of traditional famous flowers' online attention, confirming that the level of regional economic development, industrial distribution, and seasonal cycle all significantly affect the public search popularity (Chen & Wang, 2026). Chen Zhiyuan et al. empirically found that Baidu Index, as a proxy variable for investor attention, is significantly positively correlated with stock market performance and can improve the accuracy of stock prediction models (Chen et al., 2016). Jiang Wenjie et al. studied and showed that there is a cointegration relationship between Baidu Index and real estate prices, and prediction models incorporating search indexes have higher fitting degrees and advanced predictive capabilities (Jiang et al., 2016). Meng Xuejing et al. combined text mining and Baidu Index to screen keywords and construct an investor sentiment index with leading characteristics, providing a new tool for capital market research (Meng et al., 2016). Liu Jiayi et al. revealed through Baidu Index that there are significant regional and city size differences in tourism public opinion attention, driven by factors such as population, income, and informatization level (Liu et al., 2018). Xiong Lifang et al. used Baidu Index to simulate urban information flow, depict the spatiotemporal evolution characteristics of the Yangtze River Delta city network, and found that the regional network structure is continuously optimized and internal connections are continuously strengthened (Xiong et al., 2013). Currently, the Baidu Index module has been widely used in research on stock market performance, investor sentiment, tourism public opinion, real estate prices, and urban network characteristics. This also provides a reliable reference for this paper to introduce Baidu search indexes for the financial industry, banking industry, securities industry, and insurance industry to measure public and government attention to finance.

In the realm of hesitant fuzzy decision-making research, scholars have continuously optimized models and algorithms centered around the expression and processing of fuzzy uncertainty information. Hu Guanzhong et al. constructed formulas for interval hesitant fuzzy entropy and cross entropy, established a multi-attribute group decision-making method under the condition of unknown attribute weights, and improved the theoretical framework of interval hesitant fuzzy decision-making (Hu & Zhou, 2014). Addressing the shortcomings of the traditional TOPSIS method, Li Chaoqun et al. proposed the hesitant fuzzy vertical distance combined with the orthogonal projection method to optimize the ranking logic of schemes (Li et al., 2018); Liu Jun introduced the Maclaurin symmetric mean operator to construct a group decision-making model, which can adjust parameters based on decision-makers' preferences to enhance model adaptability (Liu, 2018); Wei and Ge proposed the hesitant fuzzy linguistic power mean operator to solve the evaluation fusion problem with unknown expert weights (Wei & Ge, 2016). Based on this, combined models such as hesitant fuzzy linguistic PROMETHEE and DEMATEL-VIKOR have been applied to scenarios such as Sichuan wine brand evaluation, military training assessment, cloud computing service provider selection, local higher education evaluation, and urban-type water disaster risk assessment, confirming the effectiveness of such methods in handling qualitative fuzzy information.

In the practice of multi-attribute comprehensive evaluation, the single subjective weighting method is easily affected by human subjective preferences, and the traditional objective weighting model is difficult to take into account the differences in indicator information and the hierarchical ranking requirements of the schemes, making it difficult to achieve an accurate quantitative assessment of regional development levels. To this end, the entropy weight-TOPSIS fusion model has been proposed and continuously improved by the academic community: the entropy weight method relies on the information entropy of the indicators to achieve purely objective weighting and avoid human scoring bias; the TOPSIS method completes the hierarchical ranking by measuring the Euclidean distance and closeness between the evaluation object and the positive and negative ideal solutions. The combination of the two can fully explore all the information contained in the multi-dimensional indicators. At present, this combined model has been widely used in the field of quantitative measurement of regional development. Duan et al. (2026) used it for dynamic evaluation of the development level of Xinjiang land ports. Jiang (2026a) used this model to calculate the gradient difference in logistics development between China and ASEAN countries. Jiang (2026b) completed the national provincial standardized development echelon division based on entropy weight-TOPSIS, which fully verified the scientificity and applicability of the method in multi-dimensional regional comprehensive evaluation. Brans and Vincke were the first to propose the partial order ranking organization method-PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation), which compares alternative solutions in partial order by constructing preference functions among criteria. It provides a systematic framework for handling multi-attribute and multi-objective ranking problems and has become one of the most widely used methods in the field of multi-criteria decision-making (Brans & Vincke, 1985). However, traditional methods often require decision-makers to express their preferences as precise numerical values, making it difficult to capture the uncertainty that commonly exists in real-world decision-making. To overcome this limitation, Rodríguez et al. introduced the concept of Heterogeneous Fuzzy Linguistic Term Sets (HFLTS), allowing decision-makers to hesitate between multiple linguistic terms. This combines the expressive advantage of linguistic variables with the fuzzy characterization ability of hesitant fuzzy sets, providing a new mathematical tool for handling decision-making hesitancy and uncertainty (Rodríguez et al., 2012). Based on this, Liao et al. defined distance measures and similarity measures for HFLTS, systematically studied their mathematical properties, and applied them to multi-criteria decision-making problems, thereby improving the theoretical system of hesitant fuzzy linguistic decision-making (Liao et al., 2014).

In view of this, this paper addresses the shortcomings of the existing financial agglomeration evaluation system, which has the lack of big data indicators and insufficient information coverage. It introduces Baidu search index to characterize the public and government's financial attention, adds the evaluation dimension of digital inclusive finance, and builds a multi-level secondary indicator evaluation system around the four major sectors of financial industry, banking industry, securities industry and insurance industry. It selects panel data of nine cities and prefectures in Guizhou from 2011 to 2025, uses the entropy weight-TOPSIS method to quantitatively measure the comprehensive level of financial agglomeration in various places, analyzes the gap in financial agglomeration development in the province from the two dimensions of temporal evolution and spatial differentiation, and proposes targeted policy recommendations to promote the quality and efficiency of financial agglomeration in Guizhou based on the current situation of regional financial development.

2. Construction of Evaluation Index System for Financial Agglomeration Level in Guizhou Prefecture-Level Cities

This study is based on the core connotation of financial agglomeration, sorts out and integrates the conclusions of existing relevant research at home and abroad, draws on the construction logic of the China Financial Center Index (CFCI) released by the China (Shenzhen) Development Institute, and combines the actual development characteristics of the financial industry in various prefecture-level cities in Guizhou Province. Following the selection criteria of scientificity, typicality, objectivity and neutrality, regional adaptability, horizontal comparability, and practical feasibility, the article incorporates the Baidu search index to reflect the market and government's attention to finance. Around five dimensions-financial industry, banking industry, securities industry, insurance industry, and digital inclusive finance - a comprehensive evaluation framework for the level of financial agglomeration in prefecture-level cities in Guizhou Province, covering 30 secondary indicators, is constructed. The specific indicator composition is detailed in **Table 1**.

Table 1. Evaluation index system for financial agglomeration level in Guizhou prefecture-level cities.

Target layer	First-level indicators	Second-level indicators	Indicator type	Symbol
	Financial industry	Gross output of financial industry (100 million yuan)	Efficiency	X_1
		The proportion of the gross domestic product of the financial industry to GDP (%)	Efficiency	X_2

Continued

		Number of employees in financial industry at the end of the year (persons)	Efficiency	X_3
		Location entropy of financial industry	Efficiency	X_4
		Public Attention to the Financial Industry	Efficiency	X_5
		Government Attention to the Financial Industry	Efficiency	X_6
	Banking Industry	Year-End Balance of Various Deposits in Financial Institutions (100 Million Yuan)	Efficiency	X_7
		Year-End Balance of Various Deposits in Financial Institutions as a Percentage of the Province's Total (%)	Efficiency	X_8
		Year-End Balance of Various Loans in Financial Institutions (100 Million Yuan)	Efficiency	X_9
		Year-End Balance of Various Loans in Financial Institutions as a Percentage of the Province's Total (%)	Efficiency	X_{10}
		Location Entropy of the Banking Industry	Efficiency	X_{11}
		Public Attention to the Banking Industry	Efficiency	X_{12}
		Government Attention to the Banking Industry	Efficiency	X_{13}
Financial agglomeration level	Securities Industry	Number of Listed Companies	Efficiency	X_{14}
		Total Market Capitalization of Listed Companies (100 Million Yuan)	Efficiency	X_{15}
		Location Entropy of the Securities Industry	Efficiency	X_{16}
		Public Attention to the Securities Industry	Efficiency	X_{17}
		Government Attention to the Securities Industry	Efficiency	X_{18}
	Insurance Industry	Annual Premium Income (100 Million Yuan)	Efficiency	X_{19}
		Life Insurance Premium Income (10,000 Yuan)	Efficiency	X_{20}
		Property Insurance Premium Income (Ten Thousand Yuan) (or Signed Premium)	Efficiency	X_{21}
		Insurance Density (10,000 RMB/person)	Efficiency	X_{22}
		Insurance Penetration (%)	Efficiency	X_{23}
		Location Entropy of the Insurance Industry	Efficiency	X_{24}
		Public Attention to the Insurance Industry	Efficiency	X_{25}
		Government Attention to the Insurance Industry	Efficiency	X_{26}
	Digital Inclusive Finance	Digital Inclusive Finance Index	Efficiency	X_{27}
		Digital Finance Coverage Breadth Index	Efficiency	X_{28}
		Digital Finance Usage Depth Index	Efficiency	X_{29}
		Digitalization Level of Inclusive Finance Index	Efficiency	X_{30}

Indicator Explanation:

1) Location entropy, also known as specialization rate, indicates a higher level of industrial agglomeration in the region. Generally, when the location entropy is greater than 1, the region has an advantage in a certain economic indicator nationwide; when the location entropy is less than 1, it is at a disadvantage. The calculation formula is $LQ_{ij} = \left(q_{ij}/q_j\right)/\left(q_i/q\right)$, where q_{ij} represents j the total output value of the region's i industry, q_j represents j the total output value of all industries in the region; q_i represents the national i industry, q Represents the total output value of all industries nationwide. In Table 1, the location entropy of the financial industry is calculated as follows: (Gross GDP of the financial industry in prefecture-level cities/GDP of prefecture-level cities)/(Gross GDP of the financial industry in Guizhou/GDP of Guizhou); the location entropy of the banking industry is calculated as follows: (Year-end deposit balance of financial institutions in prefecture-level cities/Gross GDP of the financial industry in prefecture-level cities)/(Year-end deposit balance of financial institutions in Guizhou/Gross GDP of the financial industry in Guizhou); the location entropy of the securities industry is calculated as follows: (Total market value of stocks in prefecture-level cities/Gross GDP of the financial industry in prefecture-level cities)/(Total market value of stocks in Guizhou/Gross GDP of the financial industry in Guizhou); the location entropy of the insurance industry is calculated as follows: (Annual premium income of insurance in prefecture-level cities/Gross GDP of the financial industry in prefecture-level cities)/(Annual premium income of insurance in Guizhou/Gross GDP of the financial industry in Guizhou).

2) Baidu Search Index quantifies the weighted sum of keyword search frequencies on Baidu's web search platform, using netizens' search volumes as the data foundation. The index platform restricts the geographic scope to prefecture-level cities in Guizhou Province, incorporating both PC and mobile search traffic, and directly adopts the integrated composite index output by the platform. For data processing, the daily indices are averaged by calendar year to generate annual public attention values for each city. All raw Baidu Index data were batch-exported on July 12, 2026. Missing daily observations within a year are filled via linear interpolation; if a city-year's complete data is unavailable, the sample is assigned a value of 0 following established literature practices. In Table 1, the public attention index for the financial sector is measured by the comprehensive Baidu search index (including PC and mobile trends) using "finance" as the keyword, reflecting the influence of the financial industry in a given region. The public attention index for the banking sector is similarly measured using "bank", indicating the influence of the banking industry in a region. The public attention index for the securities sector is derived from searches for "securities", showcasing the impact of the securities industry. Lastly, the public attention index for the insurance sector is calculated based on searches for "insurance", representing the influence of the insurance industry in a specific area.

3) Government Attention Index refers to the frequency of keywords related to

financial sub-sectors mentioned in the government work reports of prefecture-level cities, serving as a metric to evaluate local governments' policy emphasis, support orientation, and developmental planning for specific financial industries. The corpus for this indicator comprises the full texts of government work reports from nine cities/prefectures in Guizhou Province spanning 2011-2025. In the statistical process, repeated keywords within the same paragraph are counted individually, total keyword frequency is calculated on a per-report basis rather than at the paragraph level, and manual screening is performed to exclude rhetorical expressions and non-financial allusive references, retaining only financially-relevant content concerning local industrial development, policy support, or practical deployment. In Table 1, the government attention indices for finance, banking, securities, and insurance are derived from searches for the keywords "finance", "bank", "securities", "insurance" within the corresponding municipal government reports.

4) The four indicators related to digital inclusive finance selected in this paper are all taken from the prefecture-level city digital inclusive finance index system released by the Digital Finance Research Center of Peking University. The data and complete compilation rules can be viewed and obtained through the official website of the Digital Finance Research Center of Peking University (https://idf.pku.edu.cn/). Among them, the Digital Inclusive Finance Overall Index comprehensively reflects the overall development level of digital finance in various regions; the Digital Finance Coverage Breadth Index measures the popularity of digital financial accounts and the scale of user reach in the region; the Digital Finance Usage Depth Index depicts the actual usage activity of diversified digital financial businesses such as payment, credit, insurance, and wealth management; and the Inclusive Finance Digitalization Degree Index represents the mobile convenience, low-cost advantages, and big data credit application level of digital financial services. These four indicators together depict the complete level of regional digital finance development, making up for the lack of digital business format dimension in traditional financial agglomeration indicators.

3. Entropy Weight-TOPSIS Method

3.1. Basic Knowledge

Given m schemes $A_1, A_2, \cdots, A_m$ and n indicators $C_1, C_2, \cdots, C_n$; X_{ij} is the indicator value of the scheme A_i under indicator C_j ($i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$); W_j As an indicator C_j The weight of $W_j \in [0,1]$, and $\sum_{j=1}^{n} W_j = 1$; then a multi-attribute decision problem can be represented as an initial decision matrix composed of $X = (x_{ij})_{m \times n}$ and W_j.

3.2. Determining Indicator Weights

In information theory, information entropy is defined as

$$H(x) = -\sum_i p(x_i) \ln p(x_i),\ p(x_i) \in [0,1],\ \sum_i p(x_i) = 1 \tag{1}$$

For the original indicator data matrix $X = \left(x_{ij}\right)_{m\times n}$, the steps for calculating indicator weights are as follows:

1) X_{ij} Convert to P_{ij}

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}},\ i = 1,2,\cdots,m;\ j = 1,2,\cdots,n \tag{2}$$

2) Define the entropy of the j indicator as

$$H_j = -k\sum_{i=1}^{m} p_{ij}\ln p_{ij},\ j = 1,2,\cdots,n,\ k = \frac{1}{\ln m} \tag{3}$$

By introducing the constant k, it is guaranteed that $H_j = 1$ when all P_{ij} values of the *j*-th indicator are equal, In this case, the indicator cannot provide any effective information. When $P_{ij} = 0$, let $p_{ij}\ln p_{ij} = 0$, which ensures that $H_j \in [0,1]$.

3) Define the entropy of the j indicators is

$$\omega_j = \frac{1-H_j}{\sum_{j=1}^{n}\left(1-H_j\right)} = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j},\ j = 1,2,\cdots,n,$$
$$\omega_j \in [0,1] \text{ and } \sum_{j=1}^{n}\omega_j = 1 \tag{4}$$

3.3. Entropy Weight-TOPSIS Method Calculation Steps

1) Establish a normalized matrix $Z = \left(z_{ij}\right)_{m\times n}$ (dimensionless)

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}},\ i = 1,2,\cdots,m;\ j = 1,2,\cdots,n \tag{5}$$

2) Calculate the weighted matrix $R = \left(r_{ij}\right)_{m\times n}$

$$r_{ij} = \omega_j \times z_{ij},\ i = 1,2,\cdots,m;\ j = 1,2,\cdots,n \tag{6}$$

3) Determine the positive ideal solution S^+ and the negative ideal solution S^-

$$S^+ = \left\{s_j^+\right\}, j = 1,2,\cdots,n,\ S^- = \left\{s_j^-\right\}, j = 1,2,\cdots,n \tag{7}$$

When C_j is a benefit-type indicator, $s_j^+ = \max\limits_{1\le i\le m}\left\{r_{ij}\right\}$ and $s_j^- = \min\limits_{1\le i\le m}\left\{r_{ij}\right\}$ When C_j is a cost-type indicator, $s_j^+ = \min\limits_{1\le i\le m}\left\{r_{ij}\right\}$ and $s_j^- = \max\limits_{1\le i\le m}\left\{r_{ij}\right\}$.

4) Calculate the Euclidean distance between the positive ideal solution and the negative ideal solution of each scheme

$$sep_i^+ = \sqrt{\sum_{j=1}^{n}\left(s_j^+ - r_{ij}\right)^2},\ sep_i^- = \sqrt{\sum_{j=1}^{n}\left(s_j^- - r_{ij}\right)^2},\ i = 1,2,\cdots,m \tag{8}$$

5) Calculate the similarity between each scheme and the ideal solution

$$c_i = \frac{sep_i^-}{sep_i^+ + sep_i^-},\ i = 1, 2, \cdots, m \tag{9}$$

C_i the larger the value, the A_i the closer the scheme is to the ideal solution, then each scheme can be ranked according to C_i size.

4. Empirical Evaluation of the Financial Agglomeration Level of Prefecture-Level Cities in Guizhou

4.1. Data Source

The data on public attention to the financial industry, banking industry, securities industry and insurance industry in nine prefecture-level cities and prefectures of Guizhou Province from 2011 to 2025 are obtained from the Baidu Index website (http://index.baidu.com). Data on government attention to the financial industry, banking industry, securities industry and insurance industry are derived from government work reports of each prefecture-level city. The raw data for the remaining indicators are sourced from the 2011-2025 Statistical Communiques on National Economic and Social Development, the 2011-2025 Statistical Yearbooks of the nine prefecture-level cities and prefectures in Guizhou Province, the official website of Guizhou Provincial Bureau of Statistics, and the Juhui Database.

4.2. Descriptive Statistics

Descriptive statistics were conducted on the following: gross domestic product of the financial industry, the proportion of gross domestic product of the financial industry to GDP, the number of employees in the financial industry at the end of the year, the location entropy of the financial industry, public attention to the financial industry, government attention to the financial industry, the year-end deposit balance of financial institutions, the year-end deposit balance of financial institutions as a percentage of the province's total, the year-end loan balance of financial institutions, the year-end loan balance of financial institutions as a percentage of the province's total, the location entropy of the banking industry, public attention to the banking industry, government attention to the banking industry, the number of listed companies, the total market capitalization of listed companies, the location entropy of the securities industry, public attention to the securities industry, government attention to the securities industry, annual premium income, life insurance premium income, property insurance premium income, insurance density, insurance penetration, the location entropy of the insurance industry, public attention to the insurance industry, government attention to the insurance industry, the digital inclusive finance index, the digital finance coverage breadth index, the digital finance usage depth index, and the inclusive finance digitalization index. A total of 135 samples were observed. The indicators integrate data from multiple sources, including economic statistics, financial business, capital markets, and digital finance, and can depict the characteristics of financial agglomeration from multiple dimensions, including industry, institutions, markets, and the public. The results are shown in Table 2.

Table 2. Descriptive statistics.

Symbol	Obs	Mean	Std.Dev.	Min	Max
X_1	135	104.7150	143.8850	9.0874	716.6700
X_2	135	5.0836	2.2787	2.5181	13.4000
X_3	135	12470.4145	8653.0614	3112.0000	40930.02
X_4	135	0.8330	0.3831	0.3791	2.1972
X_5	135	36.1778	30.9536	4.0000	136.0000
X_6	135	13.3704	6.7303	0.0000	35.0000
X_7	135	2770.7771	3398.6162	427.9693	15972.93
X_8	135	11.1753	11.7960	3.8100	46.1700
X_9	135	2911.4372	4427.4980	268.6326	23888.23
X_{10}	135	11.1019	13.3567	3.7600	53.0400
X_{11}	135	1.0309	0.1897	0.4983	1.4295
X_{12}	135	48.7556	32.0828	10.0000	143.0000
X_{13}	135	2.5333	2.8855	0.0000	14.0000
X_{14}	135	3.0444	5.6395	0.0000	23.0000
X_{15}	135	1581.5338	4772.4397	0.0000	25802.92
X_{16}	135	0.5149	0.6029	0.0000	2.5423
X_{17}	135	22.2889	26.9831	2.0000	117.0000
X_{18}	135	0.3111	0.6808	0.0000	4.0000
X_{19}	135	42.9236	44.6781	5.5900	222.1000
X_{20}	135	21.8470	25.9344	2.7800	132.0700
X_{21}	135	21.0594	19.1988	2.3900	90.0300
X_{22}	135	9.8162	7.3042	1.2558	37.2149
X_{23}	135	2.2860	0.6656	1.1000	4.3900
X_{24}	135	1.0473	0.3997	0.0134	3.0178
X_{25}	135	45.4963	31.7060	9.0000	170.0000
X_{26}	135	4.6074	3.2367	0.0000	16.0000
X_{27}	135	201.7818	82.8785	21.2600	351.7900
X_{28}	135	206.7368	101.0848	1.8600	412.1800
X_{29}	135	173.5400	64.6668	13.2800	284.9000
X_{30}	135	240.4068	75.1552	25.4300	337.4400

4.3. Empirical Process and Results

1) Calculate attribute weights

To take into account the characteristics of financial development at different stages from 2011 to 2025 and ensure the comparability of cross-year evaluation results (Table 3), this paper adjusts the weight calculation logic based on the entropy weight method in Section 3.2: First, calculate the entropy weight corresponding to the indicators of each city in each year separately (W_{jt}), then take the arithmetic mean of the weights of the same indicator over 15 years ($\overline{w}_j$), and use the average weight as the unified indicator weight ($\sum_{j=1}^{n}\overline{w}_j = 1$).

Table 3. Entropy value and weight (%) of each indicator.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
H_j	86.42	94.07	92.65	94.22	91.94	97.43	86.22	81.59	83.94	78.19
W_j	4.65	3.41	2.32	3	3.31	1.41	4.91	4.88	5.53	5.48
	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}	X_{20}
H_j	78.19	98.58	93.95	86.74	77.12	62.03	85.96	86.99	65.34	89.59
W_j	1.25	2.73	3.05	5.2	6.85	3.22	4.28	7.8	3.57	3.82
	X_{21}	X_{22}	X_{23}	X_{24}	X_{25}	X_{26}	X_{27}	X_{28}	X_{29}	X_{30}
H_j	86.42	94.07	92.65	94.22	91.94	97.43	86.22	81.59	83.94	78.19
W_j	3.38	2.26	1.95	1.37	2.92	1.73	1.4	1.31	1.34	1.67

2) Calculate the Euclidean distance and closeness of the positive and negative ideal solutions of each scheme

Based on the entropy weight-TOPSIS method, the positive and negative ideal distances and proximity degrees corresponding to the financial agglomeration levels of the nine prefecture-level cities in Guizhou Province from 2011 to 2025 are calculated. The results are shown in Table 4. Normalization, entropy-weight calculation, and the determination of positive-negative ideal solutions are uniformly computed based on the full panel dataset, rather than calculated year-by-year. Under this processing strategy, all city-year samples are pooled into a single global evaluation matrix. Global maximum and minimum values are used for indicator normalization, and indicator entropy weights remain fixed across the entire research period. Besides, one unique set of global positive-negative ideal solutions is generated for TOPSIS measurement. This setting ensures that scores obtained in different years are produced under identical evaluation criteria, so the proximity degrees can be directly applied for temporal comparison of financial agglomeration levels.

Table 4. Euclidean distance and closeness of the positive and negative ideal solutions of each prefecture-level city.

The total output value of the region's	Year	D+	D−	Proximity degree C
Guiyang City	2011	0.1579	0.1333	0.4579
	2012	0.1741	0.1102	0.3875
	2013	0.1695	0.1061	0.3850
	2014	0.1774	0.1206	0.4046
	2015	0.1752	0.1225	0.4115
	2016	0.1712	0.1235	0.4191
	2017	0.1692	0.1314	0.4372
	2018	0.1699	0.1354	0.4435
	2019	0.1501	0.1421	0.4863
	2020	0.1473	0.1457	0.4973
	2021	0.1604	0.1471	0.4784
	2022	0.1614	0.1491	0.4801
	2023	0.1635	0.1505	0.4793
	2024	0.1648	0.1529	0.4813
	2025	0.1477	0.1552	0.5122
Liupanshui City	2011	0.2292	0.0235	0.0928
	2012	0.2297	0.0188	0.0755
	2013	0.2098	0.0581	0.2169
	2014	0.2028	0.0853	0.2960
	2015	0.2288	0.0236	0.0937
	2016	0.2178	0.0352	0.1392
	2017	0.2190	0.0322	0.1280
	2018	0.2310	0.0168	0.0679
	2019	0.2304	0.0180	0.0724
	2020	0.2293	0.0198	0.0795
	2021	0.2293	0.0204	0.0817
	2022	0.2294	0.0196	0.0785
	2023	0.2287	0.0207	0.0831
	2024	0.2281	0.0232	0.0922
	2025	0.2269	0.0239	0.0953

Continued

Zunyi City	2011	0.2129	0.0378	0.1509
	2012	0.2143	0.0343	0.1380
	2013	0.2121	0.0557	0.2081
	2014	0.2082	0.0539	0.2056
	2015	0.2052	0.0563	0.2154
	2016	0.1871	0.0655	0.2593
	2017	0.1623	0.0910	0.3593
	2018	0.1922	0.0605	0.2396
	2019	0.1777	0.0872	0.3292
	2020	0.1701	0.1277	0.4288
	2021	0.1694	0.1301	0.4343
	2022	0.1713	0.1131	0.3977
	2023	0.1715	0.1125	0.3962
	2024	0.1725	0.1032	0.3744
	2025	0.1757	0.0953	0.3515
Anshun City	2011	0.2287	0.0381	0.1429
	2012	0.2287	0.0367	0.1383
	2013	0.2291	0.0286	0.1111
	2014	0.2283	0.0304	0.1176
	2015	0.2274	0.0312	0.1206
	2016	0.2287	0.0243	0.0962
	2017	0.2189	0.0330	0.1310
	2018	0.2185	0.0375	0.1466
	2019	0.2294	0.0264	0.1033
	2020	0.2263	0.0361	0.1375
	2021	0.2264	0.0340	0.1306
	2022	0.2253	0.0351	0.1349
	2023	0.2253	0.0351	0.1347
	2024	0.2264	0.0353	0.1349
	2025	0.2264	0.0399	0.1499

Continued

Bijie City	2011	0.2232	0.0291	0.1152
	2012	0.2113	0.0611	0.2244
	2013	0.2316	0.0269	0.1039
	2014	0.2312	0.0288	0.1106
	2015	0.2311	0.0192	0.0768
	2016	0.2162	0.0532	0.1973
	2017	0.2269	0.0283	0.1111
	2018	0.1987	0.1126	0.3618
	2019	0.2293	0.0211	0.0843
	2020	0.2269	0.0243	0.0969
	2021	0.2259	0.0269	0.1064
	2022	0.2271	0.0240	0.0957
	2023	0.2270	0.0255	0.1009
	2024	0.2215	0.0344	0.1344
	2025	0.2216	0.0342	0.1336
Tongren City	2011	0.2361	0.0085	0.0347
	2012	0.2341	0.0227	0.0885
	2013	0.2148	0.0567	0.2088
	2014	0.2324	0.0263	0.1015
	2015	0.2118	0.0578	0.2145
	2016	0.2322	0.0180	0.0719
	2017	0.2296	0.0261	0.1022
	2018	0.2189	0.0346	0.1365
	2019	0.2301	0.0225	0.0890
	2020	0.2268	0.0229	0.0918
	2021	0.2249	0.0241	0.0967
	2022	0.2266	0.0233	0.0931
	2023	0.2263	0.0233	0.0932
	2024	0.2268	0.0245	0.0973
	2025	0.2266	0.0241	0.0961

Continued

Qianxinan Prefecture	2011	0.2341	0.0215	0.0840
	2012	0.2232	0.0329	0.1286
	2013	0.2343	0.0197	0.0777
	2014	0.2243	0.0305	0.1197
	2015	0.2335	0.0167	0.0667
	2016	0.2314	0.0247	0.0964
	2017	0.2323	0.0192	0.0763
	2018	0.2327	0.0171	0.0686
	2019	0.2323	0.0161	0.0647
	2020	0.2318	0.0178	0.0713
	2021	0.2323	0.0167	0.0670
	2022	0.2322	0.0183	0.0730
	2023	0.2311	0.0195	0.0776
	2024	0.2298	0.0227	0.0900
	2025	0.2301	0.0225	0.0892
Qiandongnan Prefecture	2011	0.2334	0.0153	0.0616
	2012	0.2210	0.0373	0.1445
	2013	0.2345	0.0126	0.0508
	2014	0.2322	0.0232	0.0909
	2015	0.2318	0.0166	0.0667
	2016	0.2308	0.0200	0.0798
	2017	0.2023	0.0873	0.3014
	2018	0.2280	0.0277	0.1085
	2019	0.2284	0.0251	0.0989
	2020	0.2298	0.0230	0.0910
	2021	0.2305	0.0206	0.0819
	2022	0.2299	0.0218	0.0868
	2023	0.2184	0.0349	0.1377
	2024	0.2279	0.0259	0.1021
	2025	0.2286	0.0246	0.0970

Continued

Qiannan Prefecture	2011	0.2318	0.0167	0.0673
	2012	0.2323	0.0157	0.0633
	2013	0.2301	0.0349	0.1316
	2014	0.2178	0.0376	0.1473
	2015	0.2163	0.0351	0.1395
	2016	0.2288	0.0197	0.0794
	2017	0.2252	0.0248	0.0990
	2018	0.2259	0.0242	0.0968
	2019	0.2253	0.0245	0.0982
	2020	0.2250	0.0256	0.1021
	2021	0.2238	0.0289	0.1145
	2022	0.2221	0.0304	0.1204
	2023	0.2224	0.0312	0.1230
	2024	0.2226	0.0309	0.1218
	2025	0.2223	0.0328	0.1285

3) Calculate the TOPSIS comprehensive score and ranking

Under the benefit-oriented attribute, the entropy-weight TOPSIS method is adopted to calculate the annual comprehensive score of each prefecture-level city and prefecture. The average score refers to the arithmetic mean of TOPSIS comprehensive scores of the nine prefecture-level cities and prefectures in Guizhou Province from 2011 to 2025, as shown in **Table 5**.

The average scores above show that Guiyang City and Zunyi City rank first and second, respectively, with average scores of 0.4507 and 0.2992, leading the other seven prefecture-level cities and prefectures in the province. This indicates that Guiyang City and Zunyi City are closest to the positive ideal solution, demonstrating strong advantages in financial agglomeration and belonging to the high-agglomeration tier of the province's financial industry. Bijie City and Anshun City follow closely behind, ranking third and fourth. Liupanshui City ranks fifth with an average score of 0.1128. Qiannan Prefecture, Tongren City, Qiandongnan Prefecture and Qianxinan Prefecture show progressively decreasing average scores, with Qianxinan Prefecture ranking last at 0.0834. Most of these remaining prefecture-level regions obtain average scores below 0.11, showing a prominent gap compared with the leading regions and a higher degree of fit with the negative ideal solution. Their financial agglomeration development level is relatively weak, and they belong to the relatively low-agglomeration areas of the province's financial industry. Overall, Guizhou presents a pattern of obvious regional differentiation: Guiyang acts as the absolute core, Zunyi City forms the secondary growth pole, while financial agglomeration capacity declines gradually across subsequent tiers.

Table 5. Average TOPSIS Comprehensive Scores and Rankings of Nine Prefectures and Cities in Guizhou Province (2011-2025).

Prefectures and cities	Average score	Ranking
Guiyang City	0.4507	1
Zunyi City	0.2992	2
Bijie City	0.1369	3
Anshun City	0.1287	4
Liupanshui City	0.1128	5
Qiannan Prefecture	0.1089	6
Tongren City	0.1077	7
Qiandongnan Prefecture	0.1066	8
Qianxinan Prefecture	0.0834	9

5. Spatiotemporal Characteristics Analysis of Financial Agglomeration Development in Guizhou Province

5.1. Time Series Analysis

Figure 1 can intuitively reflect the evolutionary characteristics of the comprehensive scores of financial agglomeration in the nine prefecture-level cities and prefectures of Guizhou Province from 2011 to 2025. Specifically, Zunyi City had a relatively low starting point, with a comprehensive score of 0.1509 in 2011 and 0.3515 in 2025, representing a net increase of 0.2006 over the fifteen-year period and ranking first in the province in terms of growth. Tongren City rose from 0.0347 in 2011 to 0.0961 in 2025, with a net increase of 0.0615, ranking second. Qiannan Prefecture increased from 0.0673 to 0.1285, with a net increase of 0.0612, ranking third. Guiyang City scored 0.4579 in 2011 and 0.5122 in 2025, with a net increase of 0.0544, ranking fourth. Qiandongnan Prefecture rose from 0.0616 to 0.0970, with a net increase of 0.0355, ranking fifth. Bijie City increased from 0.1152 to 0.1336, with a net increase of 0.0184, ranking sixth. Anshun City rose from 0.1429 to 0.1499, with a net increase of 0.0069, ranking seventh. Qianxinan Prefecture increased from 0.0840 to 0.0892, with a net increase of 0.0052, ranking eighth. Liupanshui City recorded 0.0928 in 2011 and 0.0953 in 2025, with a negligible net increase of only 0.0025, ranking last.

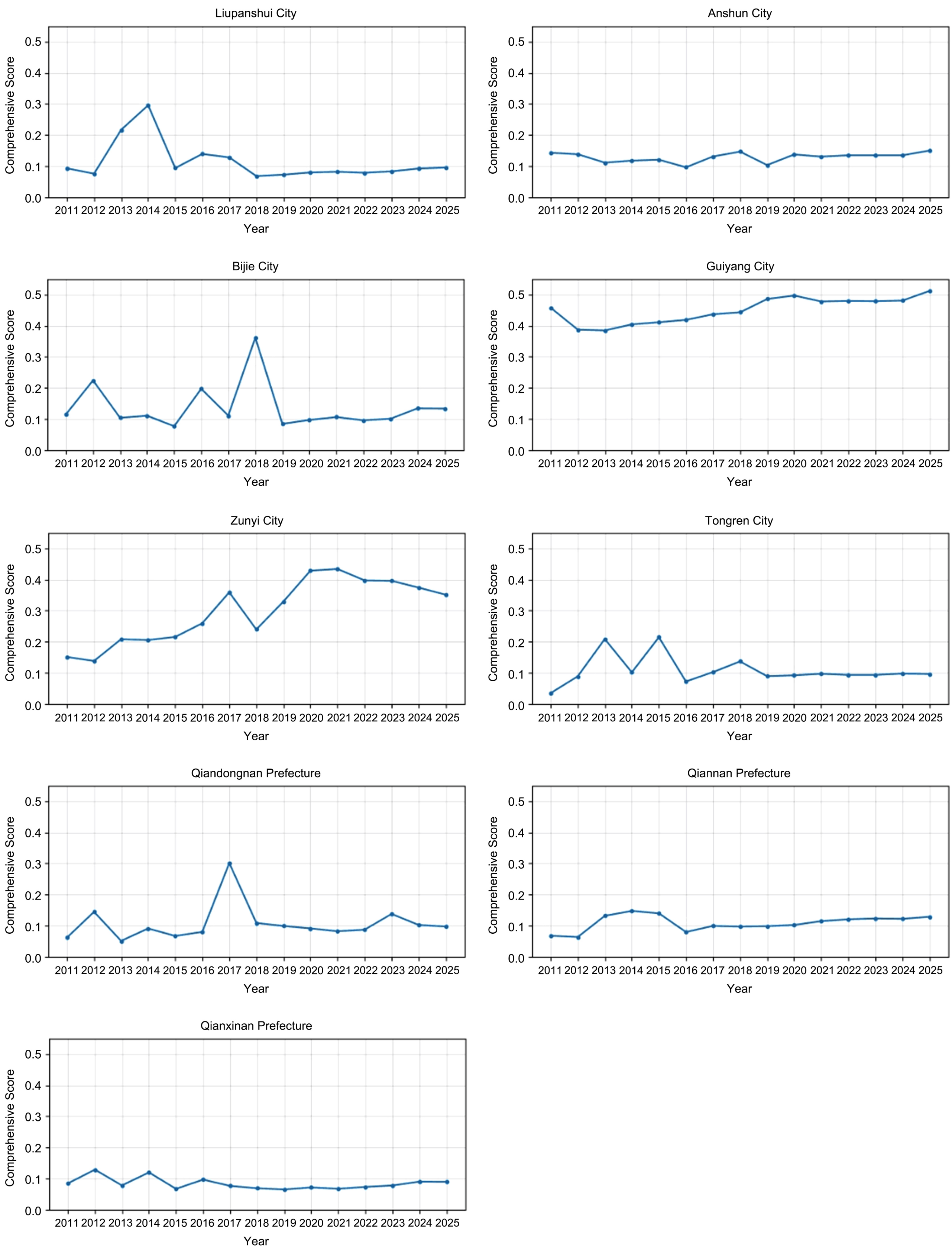


Figure 1. Time trend of nine prefectures and cities in Guizhou Province from 2011 to 2025.

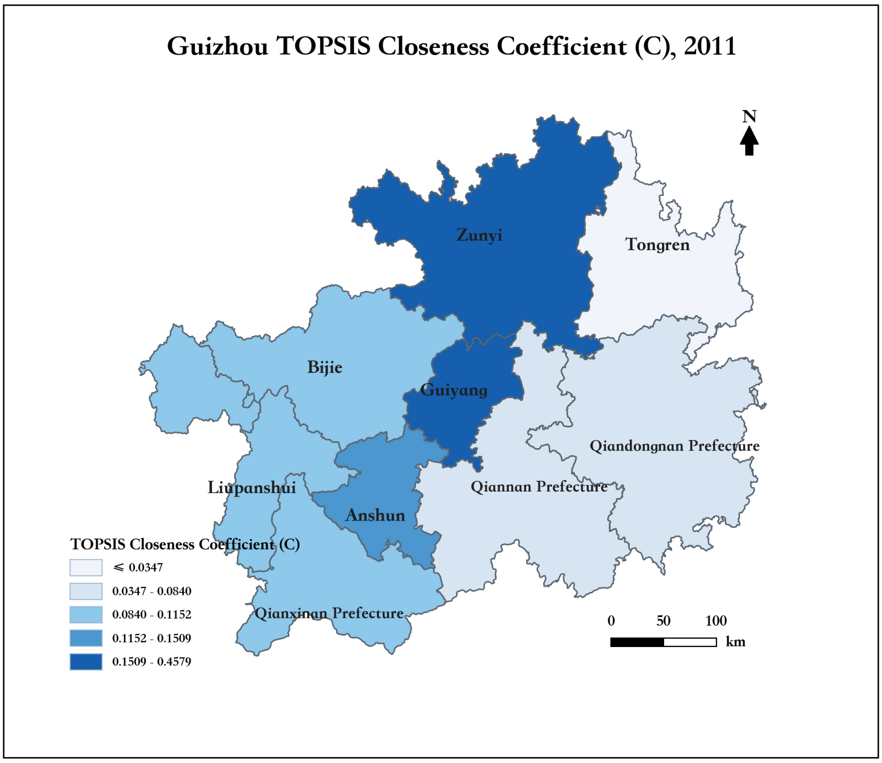
Although Guiyang's growth rate was not the highest, its comprehensive score remained persistently at the top level, fluctuating within the range of 0.38 - 0.51 and ranking first across the province in almost every year (with a fifteen-year average of 0.4507). This demonstrates the first-mover advantage and solid leading position of the provincial capital in the agglomeration of financial resources. Zunyi's curve surged remarkably after 2017, reaching its peak of 0.4343 around 2020-2021, with a fifteen-year average of 0.2992, and has gradually become the secondary growth engine of provincial financial development. Bijie City exhibited a prominent spike in 2018 (0.3618), and Qiandongnan Prefecture showed a clear peak in 2017 (0.3014). Other prefecture-level cities and prefectures displayed divergent growth paces, accompanied by periodic spikes and short-term downward fluctuations. Overall, the comprehensive scores of most regions in 2025 were higher than those in 2011, the provincial bottom level rose year by year, and the overall development level of financial agglomeration kept rising steadily, indicating a gradual enhancement of regional financial development coordination.

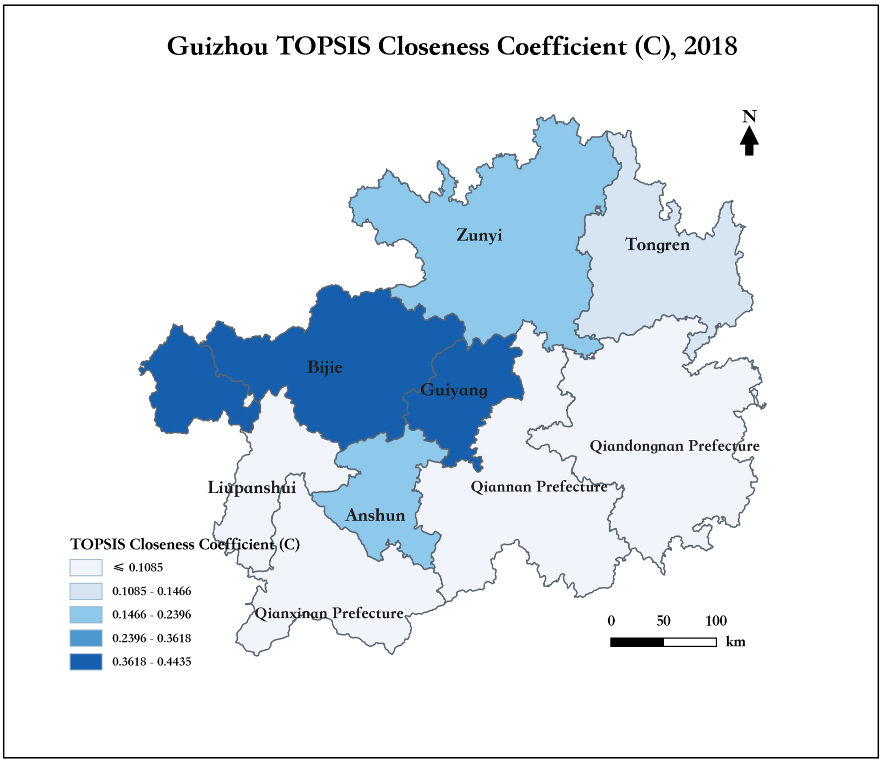
5.2. Spatial Analysis of the Level of Financial Agglomeration in Guizhou

This paper selects three typical years-2011 (base period), 2018 (mid-term policy implementation), and 2025 (final research period)-to draw spatial classification maps instead of generating heat maps for all years. The three time points precisely divide the development process into three major stages: initial foundation, mid-term iteration, and final shaping.

According to the spatial classification maps of TOPSIS scores for financial agglomeration in 2011, 2018 and 2025, over the past fifteen years, the spatial pattern of financial agglomeration across prefecture-level cities and prefectures in Guizhou Province generally exhibited evolutionary characteristics of stable core polarization, growth of secondary high-value areas, partial hierarchical upgrading of low-value units, and gradual alleviation of regional disparities. The spatial differentiation structure and gradient hierarchy underwent phased optimization and adjustment. Color shades in the maps denote TOPSIS comprehensive scores, which increase progressively from white to dark blue, and the classification thresholds vary across years.

In the initial stage of 2011, provincial financial agglomeration presented a pattern of strong single-core polarization and obvious east-west gradient separation. The classification thresholds were ≤0.0347, 0.0347 - 0.0840, 0.0840 - 0.1152, 0.1152 - 0.1509, and 0.1509 - 0.4579. Guiyang City fell within the highest dark-blue range of 0.1509 - 0.4579 and formed the province's sole high-value core area by virtue of its financial resource endowment as the provincial capital. Zunyi City also belonged to the highest-value tier. Bijie City, Liupanshui City and Qianxinan Prefecture were distributed in the medium-value ranges of 0.0840 - 0.1152. Anshun City was classified in the range of 0.1152 - 0.1509. Tongren City, Qiandongnan Prefecture and Qiannan Prefecture fell into the low-value ranges of ≤0.0840. The financial agglomeration foundation of eastern and southern prefecture-level cities and prefectures was weak. Obvious hierarchical gaps existed between the core area in central Guizhou and surrounding regions, highlighting prominent uneven spatial development.





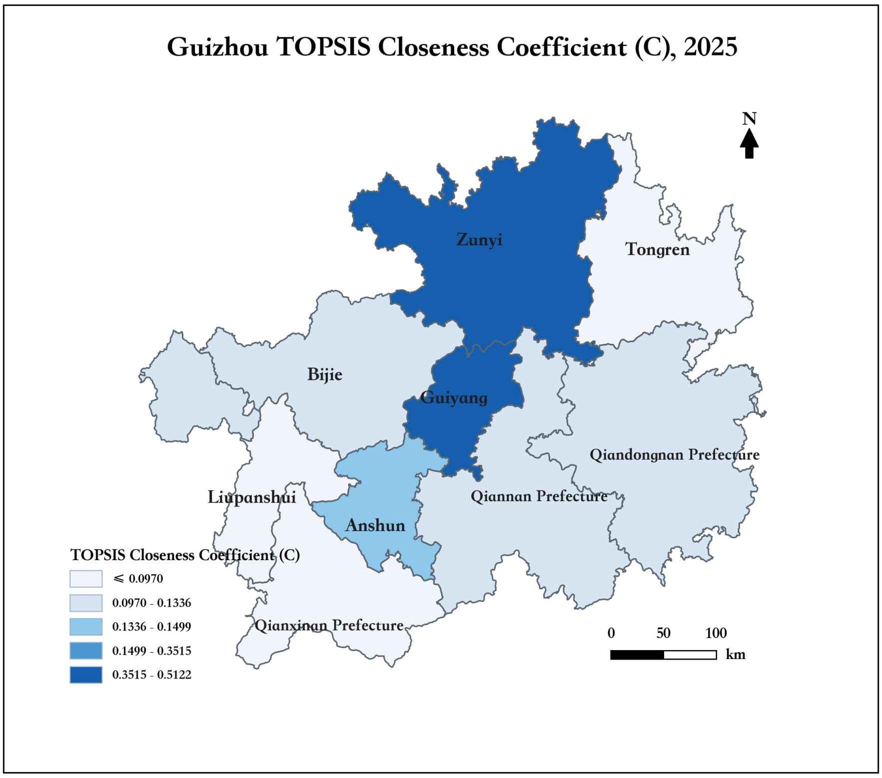


Figure 2. Spatial distribution of financial agglomeration level in Guizhou (note: GS(2024)0650).

By 2018, the spatial pattern experienced phased restructuring rather than a formal dual-core structure, with partial upgrading among peripheral regions. The classification thresholds for that year were ≤0.1085, 0.1085 - 0.1466, 0.1466 - 0.2396, 0.2396 - 0.3618, and 0.3618 - 0.4435. Guiyang City and Bijie City lay in the highest dark-blue tier (0.3618 - 0.4435). Zunyi City dropped to the medium-high range of 0.1466 - 0.2396. Tongren City belonged to the 0.1085 - 0.1466 tier. Anshun City remained at the medium-value level (0.1466 - 0.2396). Qiandongnan Prefecture, Qiannan Prefecture, Liupanshui City and Qianxinan Prefecture fell into the lowest light-colored range (≤0.1085). Large low-value zones were still widely distributed across eastern and southern Guizhou. The radiation-driving effect of the Central Guizhou area had not yet been fully released.

By 2025, the spatial pattern was further optimized: Guiyang and Zunyi constituted the dual high-value poles, while most peripheral units achieved modest improvement, and low-value areas were still present in parts of eastern and southwestern Guizhou. The grading standards for that year were ≤0.0970, 0.0970 - 0.1336, 0.1336 - 0.1499, 0.1499 - 0.3515, and 0.3515 - 0.5122. Guiyang City was located in the highest dark-blue range of 0.3515 - 0.5122, and its status as the provincial core financial hub was further consolidated. Zunyi City also entered the top tier (0.3515 - 0.5122), forming a dual-pole structure together with Guiyang. Bijie City, Qiandongnan Prefecture and Qiannan Prefecture were classified in the 0.0970 - 0.1336 range. Anshun City stepped into the medium-high-score tier of

0.1336 - 0.1499. Tongren City, Liupanshui City and Qianxinan Prefecture still remained in the lowest range (≤0.0970). Although some units saw score improvements, low-value agglomeration units did not disappear completely. Overall, regional hierarchical differentiation persisted, yet the gap between core-pole regions and other areas had narrowed to a certain extent (**Figure 2**).

6. Research Conclusions and Policy Recommendations

Traditional financial agglomeration evaluations often suffer from limitations such as single data sources, insufficient dimensional coverage, and neglect of market and public feedback. This paper integrates multi-source data, including statistical data, financial business data, the digital inclusive finance index, Baidu attention, and government attention, to construct a comprehensive evaluation system comprising 30 secondary indicators across five major sectors: finance, banking, securities, insurance, and digital inclusive finance. Based on panel data from nine prefecture-level cities and prefectures in Guizhou Province from 2011 to 2025, this paper adopts the entropy-weight-TOPSIS model to conduct multi-dimensional and refined quantitative measurement, revealing the evolutionary patterns of regional financial agglomeration from both temporal and spatial perspectives. Specific conclusions are as follows:

1) Time-Series Dimension. According to the multi-source data calculation results, the overall financial agglomeration level of nine prefecture-level cities and prefectures in Guizhou shows a fluctuating upward trend from 2011 to 2025, and the growth differences among prefecture-level units are obvious. Zunyi City ranks first in growth, with a net increase of 0.2006 over 15 years and realizes remarkable phased improvement. Tongren City and Qiannan Prefecture follow with good growth momentum. By contrast, Liupanshui City shows almost stagnant growth with a tiny net increase. Although Guiyang City does not have the highest growth rate, its comprehensive score rises from 0.4579 in 2011 to 0.5122 in 2025, always ranking first in the province and possessing solid core advantages supported by multi-dimensional financial resources. Bijie City and Qiandongnan Prefecture show obvious short-term peaks in individual years (Bijie in 2018, Qiandongnan in 2017), but their long-term growth is limited. Each prefecture-level unit presents phased fluctuations in its development process. Nevertheless, the overall baseline of provincial financial agglomeration rises year by year, and the comprehensive quality and coordination of regional financial development are continuously improved.

2) Spatial Dimension. Based on the TOPSIS scores calculated from multi-source data, this paper conducts spatial hierarchical analysis for 2011, 2018 and 2025 with differentiated grading thresholds. Map colors from light blue to dark blue represent increasing financial agglomeration scores. In 2011, Guizhou presents an obvious single-core polarization pattern dominated by Guiyang; Zunyi also enters the highest-value tier, while most eastern and southern prefecture-level units are in low-value agglomeration areas, and the east-west development gap is promi-

nent. In 2018, the spatial structure underwent phased readjustment. Guiyang and Bijie City form high-value regions, whereas Zunyi drops to the medium-high tier. A large number of low-value agglomeration units are still widely distributed in eastern and southern Guizhou, and the radiation-driving effect of central Guizhou has not been fully exerted. In 2025, Guiyang and Zunyi jointly constitute dual high-value poles. However, some prefecture-level units including Tongren City, Liupanshui City and Qianxinan Prefecture still stay at relatively low agglomeration levels; low-value agglomeration units have not completely disappeared. In general, Guizhou's financial agglomeration pattern gradually evolves toward multi-polar collaborative development, but hierarchical differences among prefecture-level units remain objectively existing.

On the basis of spatiotemporal characteristics and industrial shortcomings identified through multi-source data quantification, this paper proposes differentiated optimization paths to facilitate balanced and high-quality development of financial agglomeration in Guizhou Province.

First, promote a tiered layout according to regional resource endowment differences. Give full play to the radiation-driving function of Guiyang and Zunyi as dual core growth poles, break factor-flow barriers, and advance the cross-prefectural optimal allocation of financial resources. For Tongren City, Qianxinan Prefecture and Liupanshui City which remain at low agglomeration levels, local governments should further improve financial infrastructure, build systems for financial talent introduction and training, and gradually narrow hierarchical gaps in financial agglomeration.

Second, implement targeted governance aiming at industrial structural weaknesses reflected by the evaluation index system. Bijie City and Tongren City suffer from insufficient vitality in the capital market; hence, it is necessary to foster local high-quality enterprises to promote listing work. Anshun City and Tongren City face insufficient vitality in the banking sector, so it is necessary to expand local financial entities and iterate inclusive credit product supply. In view of the underdeveloped insurance industry in Bijie City and Anshun City, insurance services should be extended to grassroots jurisdictions to tap the market potential of county-level insurance business.

Third, explore the practical application value of multi-source data. Integrate sub-dimensions of digital inclusive finance as well as public- and government-oriented financial attention indicators. Considering both realistic development conditions and market demand, authorities can flexibly adjust financial industry support orientations. Meanwhile, consolidate the development foundation of traditional financial institutions, release the driving potential of digital finance, and enhance the overall strength of provincial-wide financial agglomeration.

"Data Availability" Statements

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Availability of Data and Material

Most of the data generated or analyzed during this study are included in the manuscript, and the rest data are promptly available to readers without undue qualifications.

Author Contributions

Conceptualization, Mu Zhang; methodology, Mu Zhang; validation, Mu Zhang and Ya Zhang; formal analysis, Mu Zhang and Ya Zhang; investigation, Ya Zhang; resources, Mu Zhang; data curation, Mu Zhang and Ya Zhang; writing—original draft preparation, Mu Zhang and Ya Zhang; writing—review and editing, Mu Zhang and Ya Zhang; supervision, Mu Zhang; project administration, Mu Zhang; funding acquisition, Mu Zhang. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest/Competing Interests

The authors declare that there is no conflict of interest regarding the publication of this manuscript. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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