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Spatio-temporal Dynamic Evolution and Inhibiting Factor Analysis of TFEE in the CCTC Economic Circle

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Abstract: Accounting for 30.8% of the total economic volume of the western region by 2021, the "fourth pole" of China's economic development is progressively being established as the Chengdu-Chongqing twin-city(CCTC) Zone. Therefore, increasing Total Factor Energy Efficiency (TFEE) and reducing the disparities in energy efficiency amongst cities in the area are important for the economic development of the CCTC Economic Zone. Accordingly, this study employs an output-oriented, super-efficient DEA model with constant returns to scale to measure the total factor energy efficiency of 16 prefecture-level cities in the CCTC economic circle from 2006 to 2020. It also examines the spatial distribution and variation patterns of each city's prefecture-level total factor energy efficiency. Then, spatial autocorrelation and random forest were used to explore the interrelationship among the indicators of the drivers, and the variables were screened according to Gini importance, finally, PCA-GWR models and spatial panel regression models were constructed to dissect the key drivers. The empirical findings indicate that: (1) the average energy efficiency of Chongqing and Chengdu is only 0.708 and 0.788, and the overall efficiency shows a steady increase from 2009 to 2018. (2) The spatial distribution is mainly as follows: H-H agglomerations are distributed in the northeastern cities of the CCTC Economic Zone, L-L agglomerations are distributed in the south, H-L agglomerations and L-H agglomerations are distributed in the north-central part of Chengdu-Chongqing Economic Zone. (3) Industrial structure, population structure, and governmental behavior have significant effects on energy efficiency, with a population mortality rate as the inhibiting factor and the proportion of tertiary industry and policy behavior as the contributing factors. Based on the empirical findings, it is recommended to accelerate the industrial structure adjustment, implement the CCTC economic circle's core cities' target of energy-saving, and build a "community" bridge to improve energy efficiency and promote economic development.

Index Terms: Super-Efficient DEA, PCA-GWR Model, Spatial panel regression model, Energy Efficiency, CCTC Economic Zone.

1. Introduction

Economic expansion relies on energy as its "lifeblood." In recent years, environmental concerns and resource constraints have posed significant obstacles to China's long-term economic development [1]. The "13th Five-Year Plan for Energy Development" was released in early 2017, which includes supporting plans for renewable energy and energy technology innovation, with the reduction of coal use and the improvement of its clean utilization rate as one of the most important tasks. The pursuit of energy policy objectives like carbon neutrality and carbon peaking has also increased the strain on China's economic growth. Energy reliance has been a key factor in China's economic growth, and excessive energy consumption will inevitably result in high carbon dioxide emissions, which will harm the environment. Climate change and environmental pollution issues have gained international attention most recently [2], which has gradually improved and optimized China's energy structure. Between 2010 and 2020, coal's share in China's primary energy structure fell from 70.21 percent to 56.56 percent, and the share of fossil fuels decreased from 92.18 percent to 84.33 percent. However, in the course of rapid industrialization and growing urbanization [3], due to China's gradual development as the largest leading consumer, its extensive energy use, and other factors, energy security is under a lot of strain, which is largely fueled by coal, and the current low efficiency of fossil fuels in comparison to developed nations [4]. China's energy shortage issue, which has turned into a bottleneck in its economic development due to the country's increasing energy demand and stagnating energy supply, has significantly deteriorated [5]. In addition, with the rapid development of China's economy, its energy supply is expected to continue to increase, resulting in a shortage of energy, the main cause of which is inefficient energy utilization. Thus, how to efficiently improve energy efficiency has emerged as a crucial concern. Energy demand has substantially increased in China due to changes in energy intensity and geographical disparities [6-7]. With the low level of efficiency in the energy industry mainly caused by low energy efficiency rather than economic inefficiency, China is now focusing on the issue of energy efficiency and maintaining sustainable energy development [8]. Energy security and sustainable development can both be achieved through increased energy efficiency, which is also a prerequisite for structural reform of China's energy supply side.

The Chinese government announced a threshold of energy and emission targets in the 12th Five-Year Plan (2011-2015), including a 16 percent reduction in energy intensity and a 17 percent drop in carbon intensity from 2010 levels. Meantime, to strongly promote energy conservation and emission reduction and hasten the building of a sound economic system of green and low-carbon cyclic growth, the Chinese government has further enhanced the policy mechanism of energy conservation and emission reduction. In the most recent 14th Five-Year Plan, for instance, it is mandated that by 2025, total energy consumption will be reasonably controlled, national energy consumption per unit of GDP will decrease by 13.5 percent compared to 2020, and total chemical oxygen demand, ammonia nitrogen, and volatile organic compound emissions will decrease by about 8 percent to 10 percent compared to 2020.

Nevertheless, it is yet obscure what elements can facilitate or hinder China's efforts to increase its energy efficiency, and the variables that affect these changes are multidimensional. Energy efficiency (EE) is influenced by numerous macroeconomic factors [9], labor input factors, and capital input factors [10]. According to several academics, capital investments are one of the best ways to increase energy efficiency. Improvements in energy efficiency have been primarily attributed to foreign direct investment in China in particular. It has also been suggested that the key drivers of increased productivity and energy efficiency are technological investments. Therefore, it's essential to investigate the motivating aspects that impede energy efficiency from many angles to better define the strategies to increase it. However, the heterogeneity of economic development, energy resource endowment, income inequality, and labor imbalance among different provinces, have a differential impact on the energy efficiency of different provincial regions. it is thus necessary to take into consideration both the heterogeneity of each driver and the characteristics of energy efficiency's geographical and temporal fluctuation. Based on this, to further explore the change characteristics of energy efficiency and its main influencing factors in Chengdu-Chongqing urban agglomeration, this paper selects six indicators, namely, population size, industrial structure, foreign trade, scientific research and development factors, consumption structure, and social regulation, and constructs an index system of total factor energy efficiency driving factors. From the multiple drivers, the main drivers of total factor energy efficiency and their spatial and temporal change characteristics are explored.

Total Factor Energy Efficiency (TFEE) is currently the core indicator of China's energy policy formulation, which is conducive to sound energy policy, rational allocation of energy, and improved energy utilization. Nowadays, less research has been done on the evaluation and monitoring of TFEE drivers in urban agglomerations, particularly in the Chengdu-Chongqing twin-city (CCTC) economic circle, compared to the analysis and measurement of TFEE drivers at the level of inter-provincial cities. Since prefecture-level cities are the foundation of inter-provincial urban development, it is necessary to start from prefecture-level cities to explore the root causes of energy inefficiency in the face of energy security problems and environmental dilemmas. This paper takes the 16 prefecture-level cities in the CCTC economic circle from 2006 to 2020 as the research object, adopts the super-efficiency DEA model and spatial econometric model to evaluate the TFEE of the cities in the CCTC economic circle, and combines with the constructed driving factor index system to find out the fundamental factors of inefficiency and explore how prefecture-level cities should effectively improve energy efficiency, to guide the adjustment of the current policy and to provide a solution to the problem of global warming, environmental dilemma and energy security. Provide ideas and directions for solving the problems of global warming, environmental dilemmas, and energy shortage.

This study contributes to prior literature in the following respects: (1) The fundamental unit of China's provincial cities consists of prefecture-level cities, and the development of counties and cities has a direct impact on the development of the overall provincial region; however, the majority of researchers have focused their attention on cities above the provincial level, and to further explore the underlying factors of low energy efficiency in the Chengdu-Chongqing Twin Cities Economic Circle, indicators of the prefecture-level cities were selected as the object of the study. In order to further explore the underlying factors of low energy efficiency in the Chengdu-Chongqing Twin Cities Economic Circle, prefectural-level cities were selected as the object of research, and the energy efficiency of each city was measured to explore the driving force behind the changes in efficiency. (2) Second, we use the PCA-GWR model to explore the correlation between total factor energy efficiency and multidimensional drivers in the Chengdu-Chongqing Twin Cities Economic Circle, and analyze the characteristics of the correlation in the temporal and spatial dimensions, to focus on the key drivers and spatial/temporal dynamics of the regions with imbalance in the value of energy efficiency, and to clarify the nature of the formation of the regional variability. (3) Finally, the spatial pattern and spatial-temporal dynamics of total factor energy efficiency among cities are explored as a whole, the main factors are screened based on Random Forest Importance, and spatial autocorrelation analysis is used to explore the influencing mechanism of the driving factors in terms of the industrial structure, demographic structure, and governmental behaviors, etc., and targeted policy recommendations with local regional characteristics are put forward from the perspectives of the industrial structure and the urban planning, respectively.

There are six subsections in this paper, and the structure of the remaining parts except the introduction is as follows: the literature review is presented in subsection 2. The third subsection is the indicator selection and the construction of the driver indicator system. Theoretical models and empirical methods are presented in subsection 4, including the super-efficient DEA method, geographically weighted regression (GWR), and spatial autocorrelation. In addition, this subsection presents the main sources of variables and data. The exploratory and analytical results of this study are given in the fifth subsection, including the characteristics of the spatial distribution of total factor energy efficiency (TFE) and the influence mechanisms of the drivers, and the methodology is summarized in the sixth subsection. Finally, based on the main findings, practical recommendations of a policy nature are given in subsection 7.

2. Literature Review

As a result of the advent of climate change and environmental degradation, energy efficiency, eco-efficiency, and environmental efficiency have become key research issues for many academics both domestically and internationally. At present, the research hotspots for this issue are primarily focused on two levels. The first is about measuring energy efficiency, and the second is about analyzing the driving factors of energy efficiency from multiple perspectives. However, regarding the measurement of energy efficiency, scholars have divided it into single-factor energy efficiency and TFEE. The former is frequently defined as the ratio of intended outputs to energy inputs and solely takes into account energy inputs and desired outputs. For example, Dan [11] and Cheng et al. [12] use the inverse of energy intensity, GDP, and energy consumption index to express energy efficiency, which is simple and easy to use but does not accurately estimate energy efficiency, and its energy intensity will be influenced by the structure of the economy and is not the result of the role of energy efficiency alone. In addition, the calculation of single-factor energy efficiency does not take into account the mutual substitution of various production factors or the impact of structural changes to the production process on energy efficiency, leading to low accuracy of direct single-factor energy efficiency estimation. Thus, to enhance the accuracy of energy efficiency estimates, this paper, based on existing studies, considers selecting input measures for labor, capital, energy, and other factors, and output indicators of economic and other elements to build a TFEE assessment index system taking into account various inputs. Reduce the error of measuring energy efficiency as the inverse of energy intensity, and energy consumption index, and facilitate subsequent accurate exploration of drivers. The DEA model has been extensively utilized most recently to measure energy efficiency and CO2 emission efficiency at the macroeconomic level because it disaggregates economic and environmental indicators into a variety of datasets and eliminates the need for model setup and parameter estimation. Estimating the efficiency frontier using convex analysis and linear programming, as well as calculating the efficiency using the distance between the efficiency frontier and the sample points, is the first step in estimating energy efficiency using DEA [13]. Li and HU [14] used a DEA model to assess China's regional ecological total-factor energy efficiency and discovered that the country had a low level of efficiency between 2005 and 2009. Using an empirical investigation of EE in 29 Chinese provinces using a DEA model, Du et al. [15] discovered that China's energy efficiency increased steadily between 1997 and 2011. According to Guo et al. [16], pure technical efficiency and scale efficiency work together to provide low environmental efficiency.

Similarly, other scholars have employed stochastic frontier analysis in the parametric method to measure EE. Lin and Long [17] applied stochastic frontier analysis to estimate the Chinese chemical industry's potential for energy savings and emission reduction. The approach was also applied by Liu et al. [18] and Shen et al. [19] to assess the TFEE of China's industrial and road transportation sectors, respectively. In comparison with DEA, however, SFA requires that efficiency values be measured with known inputs, outputs, and production frontiers, whereas DEA does not, which helps to avoid measurement inefficiencies due to incorrect function estimation. Traditional DEA also has a drawback: it cannot automatically deal with unintended outputs generated in the actual production process. So scholars have proposed a variety of improved methods based on the DEA model to compensate for the model's shortcomings. The super-efficient DEA model is one of them, which can solve the relaxation problem of input-output variables and also avoid radial and angular selection [20]. For instance, Chen et al. [21] used a relaxation-based DEA model to calculate the efficiency of total factor carbon emission. Ratanakuakangwan and Morita [22] combined a multi-objective capacity expansion model and a two-stage SBM approach to measure efficiency for seeking the optimal measure of energy efficiency. Then, additional researchers used the SEU-SBM model to quantify and investigate renewable energy's total factor efficiency [23]. Many scholars consider that super-efficient DEA models and SBM-based DEA models provide more realistic efficiency values [24-26]. Therefore, based on the existing research [27], this study constructs a TFEE evaluation index system considering multiple inputs and adopts the super-efficient DEA model with constant output-oriented returns to scale to measure the TFEE of the 16 prefectural-level cities in the CCTC economic circle. This method is similar to the SEU-SBM model in that each indicator does not require a uniform unit for measurement, and it can maintain the integrity of the original information of the indicators while taking into account the accuracy of the measurement, and overcomes the shortcomings of the single-factor analysis framework. However, this study also incorporates spatial effects and explores the spatial distribution pattern of energy efficiency based on the results of energy efficiency measurement.

Secondly, numerous academics have begun to pay attention to exploring the variables affecting energy efficiency as they search for ways to significantly increase it [28-29]. The approach to the study of its energy efficiency drivers has gradually started to become multi-dimensional. For instance, utilizing the VAR model, Soytas et al. [30] investigated the link between US GDP, energy consumption, and carbon emissions; Applying the LMDI approach, Wen and Li [31] investigated the causes of industrial CO2 emissions in 30 Chinese provinces and suggested carbon reduction plans; Tobit regression modeling was used by Liu et al. [32] and Wu et al. [33] to investigate the variables that affect energy efficiency. Nonetheless, because regional heterogeneity and dependence must be taken into consideration when calculating efficiency values, some researchers, such as Zhao et al. [34], have employed panel regression models to investigate these influences; Using panel data for 30 Chinese provinces from 1997 to 2016, Lv et al. [35] investigated the impact of urbanization on various forms of EE and decoupled energy efficiency measures. To investigate the implications of inter-provincial energy efficiency and identify its spatiotemporal consequences, Yang et al. [36] and Li [37] both used a spatial econometric model; Zhang et al. [38] also applied a GTWR to analyze energy efficiency drivers' spatiotemporal heterogeneity across 30 Chinese provinces. Overall, the majority of researchers have used spatial econometric models to investigate interprovincial city perspectives on the drivers of efficiency values. Nevertheless, fewer studies have utilized spatial regression models and spatial autocorrelation models to analyze the drivers of energy efficiency and their spatial distribution in China, and most applications of regression models tend to ignore the prevailing spatial dependence and heterogeneity. Then, on this basis, this study proposes to apply a combination of principal component analysis, geographically weighted regression, random forest, and spatial autocorrelation models, respectively, to explore the spatial patterns, dynamic change patterns, and their main driving factors of total factor energy efficiency in 16 prefecture-level cities of Chengdu-Chongqing Twin Cities Economic Circle. The spatial heterogeneity of indicator variables and energy efficiency is also taken into account, and the differences are explored based on the model results. The combination of random forest and spatial autocorrelation modeling allows this paper to explore the impact of different drivers on energy efficiency from multiple perspectives without increasing the complexity of the model itself. However, the drawback is that we need to select the appropriate importance threshold to filter out the important factors more accurately according to the random forest importance results.

Finally, synthesizing the findings of existing literature, it is found that population size, industrial structure, and urbanization level are key factors affecting energy efficiency [39-41]. In this study, to more accurately explore the main drivers of energy efficiency in prefecture-level cities, we enriched the indicator dimensions, and selected six levels of indicators, namely, population size, industrial structure, foreign trade, scientific research and development, consumption structure, and social regulation to construct the indicator system of the drivers, and a total of 19 indicators were selected to portray the factors at these six levels respectively. PCA is applied to weight the 19 indicators comprehensively, and the GWR model is constructed by using the integrated principal components and efficiency values to analyze the relationship between each principal component indicator and TFEE, and to study the temporal and spatial distribution characteristics of TFEE and its evolution law, and to put forward effective policy recommendations based on the results of the spatial autocorrelation analysis in a targeted manner.

3. Research Design

3.1. Index selection

The accuracy of EE measurements is directly affected by the performance of the indicators. Therefore, the selection of indicators must be based on the standards of impartiality, thoroughness, and science.

The data from 16 cities in the CCTC economic circle were used as the total factor energy efficiency decision-making unit (DMU) for this study, which covers the years 2006 to 2020. The individual indicators used are listed in Table 1.

Table 1. DEA input-output indicators

Elements	Specific indicators	Measurement Metrics	Unit
Input Indicators	Labor input	Year-end labor force by the municipality	10,000 people
	Capital Investment	All social fixed-asset investments in each city	Billion
	Energy input	Total year-end energy consumption by municipality	Tons of standard coal
Output Indicators	Economic output	Year-end regional GDP by city	Billion
		Year-end local general budget revenue by city	Billion

One of them utilizes capital stock to gauge capital input. The capital stock of each city in the Chengdu-Chongqing economic zone is determined using data from prefecture-level cities from 2006 to 2020. The capital stock was determined as follows using the "Perpetual Inventory Method":

$$K_{i,t} = K_{i,t-1}(1-\delta_{i,t}) + I_{i,t} \tag{1}$$

Equation (1), i indicates a prefecture-level city in the CCTC economic ring, t denotes the year t, $K_{i,t}$ 、 $K_{i,t-1}$ denotes the capital stock in the current and previous periods, respectively, $\delta_{i,t}$ is the depreciation rate(Province-level national economic depreciation rate: 9.6%).

GDP is used as a measurement of desired output and eliminates the effect of price factors across years by using the GDP deflator. Its unit is RMB 100 million.

3.2. Driving factor indicator system

To explore and investigate the effect of TFEE influenced by drivers, the following 19 indicators were selected to construct a driver indicator system.

Table 2. Energy Efficiency Drivers Indicators

Target layer	Guideline layer	Indicator layer	Variable Name
Population size （PS）	Urban and rural population	Population urbanization rate（%）	**PUR**
		Urban and rural population share	**URPS**
	Population Employment	Urban registered employed persons（10,000 people）	**UREP**
	Demographic profile	Population mortality rate（‰）	**PMR**
		Sex ratio of men to women	**SR**
		Population density	**PD**
		Natural population growth rate（%）	**NPGR**
Industry Structure （IS）	Economic output benefits	Gross Domestic Product per capita	**GDPC**
	Industry Structure Benefits	The proportion of secondary industry output value（%）	**PSIOV**
		The proportion of tertiary industry output value（%）	**PTIOV**
Foreign Trade （FT）	Income sufficiency status	Local fiscal general budget revenue（Billion）	**LFGBR**
	Level of the external opening	Total import and export （million dollars）	**TIE**

Research Development （RD）	Science and Technology Innovation Capability	R&D personnel of industrial enterprises above the scale Full-time equivalent （Person-year）	**RD**
Consumption structure （CS）	Living standard	Per capita disposable income of urban residents (Yuan)	**CDIUR**
Social Regulation （SR）	Level of medical services	Number of practicing (assistant) physicians (10,000 people)	**NPP**
		Number of beds in medical institutions（sheet of paper）	**NBMI**
	Education Service Level	Has a public library collection （Thousands of copies）	**PLC**
		Number of full-time teachers in general high schools (10,000 people)	**NFTGHS**
	Social Security Level	Local financial social security and employment expenditure (million yuan)	**LFSSEE**

The names of the cities under investigation are symbolically represented in this article as displayed in Table 3:

Table 3. Symbolic Representation of Chengdu-Chongqing Economic Circle City Cluster

City Name	Symbolic representation	City Name	Symbolic representation
Chongqing City	**CQ**	Chengdu City	**CD**
Yibin City	**YB**	Deyang City	**DY**
Mianyang City	**MY**	Zigong City	**ZG**
Luzhou City	**LZ**	Suining City	**SN**
Neijiang City	**NJ**	Leshan City	**LS**
Dazhou City	**DZ**	Nanchong City	**NC**
Meishan City	**MS**	Guang'an City	**GA**
Ya'an City	**YA**	Ziyang City	**ZY**

The subsequent model analysis process is represented by the simplified notation for the 16 cities.

4. Research Methods

4.1 Super-efficient DEA[i]

DEA model is a research method of multi-indicator input and output evaluation, which calculates and compares the relative efficiency between decision-making units by applying a mathematical planning model and making an evaluation. Generally, there are two types of constant and variable returns to scale respectively. While the super-efficient DEA model is a deformation based on the traditional model, compared with the traditional DEA model, the super-efficient DEA model needs to exclude the decision unit itself from the set of miscellaneous decision units when evaluating a decision unit and use other DMUs as a linear combination of inputs and outputs.

Suppose there are n independent DMUs, each with m inputs and p outputs, X_j denotes the input quantity of the jth DMU, Y_j denotes the output of the jth DMU, then for the first DMU the corresponding super-efficient DEA model takes the following form:

$$\min \theta$$
$$s.t\begin{cases} \sum_{j=1, j\neq k}^{n} \lambda_j X_j = \theta X_k \\ \sum_{j=1, j\neq k}^{n} \lambda_j Y_j = Y_k \end{cases} \tag{2}$$

In Equation (2), where θ is the effective decision unit's efficiency value, the smaller θ is, the less effective it is, and conversely the more effective it is; where $\lambda_j (0 < \lambda_j \leq 1, j = 1, 2, \ldots, n, \sum \lambda_j = 1)$ is the weight factor for the combination of decision units.

4.2. Geographically weighted regression model(GWR)[ii]

The GWR model, which measures the proximity of geographic locations by spatial distance, performs weight calculation by constructing a spatial kernel function and then performs point-by-point parameter estimation by using locally weighted least squares. It is a local linear regression method based on modeling spatially varying relationships. The spatial variation of the estimated parameters by the geographically weighted regression method can reflect the non-stationary characteristics of geographic relationships very intuitively. The model is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{r} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i, i = 1, 2, \ldots, n \tag{3}$$

where (u_i, v_i) represents the ith sample point's coordinate, $\beta_0(u_i, v_i)$ is the intercept term, $\beta_k(u_i, v_i)$ is the ith sample point's kth regression coefficient, which is a result of where something is located, and ε_i is the regression residual.

The weighted least squares method was used to estimate GWR model regression coefficients:

$$\hat{\beta}(u_i, v_i) = [X^T W(u_i, v_i) X]^{-1} X^T W(u_i, v_i) Y \tag{4}$$

where $W(u_i, v_i)$ is the diagonal matrix of spatial weights; X is the independent variable's matrix, while Y is the dependent variable's vector. The Bi-square function is used to determine the spatial weights in the following manner:

$$\begin{cases} w_{ij} = [1 - (d_{ij} / h)^2]^2, d_{ij} < h \\ w_{ij} = 0, d_{ij} \geq h \end{cases} \tag{5}$$

where w_{ij} is the weight when the spatially known point j goes to estimate the unknown point i , d_{ij} is the Euclidean distance between points i j , and h is the bandwidth.

4.3. Global spatial autocorrelation

The global moran statistic is used in this study to examine the spatial autocorrelation of EE (Xu et al., 2022). Its formula is presented in Equation (6).

$$Moran's\ I = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{w_0 s^2} \tag{6}$$

where x_i and x_j denote the observations of the region i and region j, respectively, $\bar{x}$ is the mean of the observations of n regions, w_{ij} and is the element of the binary spatial weight matrix. $w_0 = \sum_{j=1}^{n}\sum_{i=1}^{n} w_{ij}$ is the sum of the elements of the binary spatial weight matrix; $s^2 = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^2}{n}$ denotes the variance of the sample. The index $I \in [-1,1]$, then $I > 0$, indicates the existence of positive spatial correlation; when $I = 0$ indicates no spatial correlation; when $I < 0$ indicates the existence of negative spatial correlation.

Under the assumption that the global Moran's I obeys a normal distribution, the Z-statistic can be constructed to test the derived Moran's I index, and its expression is shown in Equation (7):

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{7}$$

where: $E(I) = -\frac{1}{n-1}$; $Var(I) = \frac{n^2 w_1 - n w_2 + 3 w_0^2}{w_0^2 (n^2 - 1)} - E^2(I)$; $w_2 = \sum_{i=1}^{n} (w_{i*} + w_{*i})^2$; $w_1 = 0.5 \sum_{j=1}^{n}\sum_{i=1}^{n} (w_{ij} + w_{ji})^2$; w_{i*} denote the sum of the elements in row i and w_{*i} denote the sum of the elements in column i of the spatial weight matrix. $E(I)$ and $Var(I)$ are the expectation and variance of Moran's I, respectively.

4.4. Local spatial autocorrelation

Since the global Moran statistic reflects whether energy efficiency has aggregation characteristics in space from an overall perspective, ignoring the instability of spatial processes, it cannot judge the aggregation pattern and degree of aggregation among different cities. Therefore, the local Moran statistic is further used to explore the degree and significance of spatial differences in energy efficiency between a region and its neighboring regions, and its calculation formula is shown in Equation (8):

$$I_i = \frac{n(x_i - \bar{x})\sum_{j=1}^{n} W_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})} = Z_i \sum_{j=1}^{n} W_{ij} Z_j \tag{8}$$

Where Z_i , Z_j denote the deviation between the energy efficiency of the ith city and the jth city and its mean value, respectively, i.e., $Z_i = (x_i - \bar{x})$, $Z_j = (x_j - \bar{x})$, W_{ij} denote the normalized spatial weight matrix with all diagonal elements being zero.

4.5. Data sources

The relevant data in this paper are mainly from the official website of the National Bureau of Statistics published and 2007-2021 China Energy Statistical Yearbook, Sichuan Provincial Statistical Yearbook, Chongqing Municipal Statistical Yearbook, and other materials such as statistical yearbooks and bulletins of cities at various levels in Sichuan Province. Specific data official website information is as follows:

National data: http://www.stats.gov.cn/tjsj/.
National Energy Administration: http://www.nea.gov.cn/.
Chongqing Bureau of Statistics: http://tjj.cq.gov.cn/.
Sichuan Provincial Bureau of Statistics: http://tjj.sc.gov.cn/.

5. Empirical Analysis

5.1. Estimation results and analysis of energy efficiency

With labor, capital stock, and energy consumption as input variables and GDP and local fiscal general budget revenue as expected outputs, the output-oriented super-efficiency DEA model with constant returns to scale is adopted to measure the TFEE and average energy efficiency of cities at each level in the CCTC economic circle from 2006 to 2020, and the trends are shown in Fig.1.

Fig. 1. Time series of energy efficiency in the CCTC economic circle

The CCTC area's TFEE showed a tendency of first declining and then increasing during the research period in terms of average efficiency. From 2006 to 2009, energy efficiency showed a decreasing trend year by year, mainly because with the rapid economic growth, the heavy industrial pattern of each region came to the fore, resulting in a sharply increased fossil energy consumption, serious environmental pollution, and the " high-energy consumption, high-pollution" economic growth model prompted a rapid decline in energy efficiency.

During 2009-2018, the TFEE of CCTC entered a steady climbing period, rising from 1.092 in 2009 to 1.232 in 2018, which shows that the implementation of the Chengdu-Chongqing economic zone has achieved significant results in TFEE improvement, and different impacts exist for prefecture-level cities. Mainly due to 2008~2018, the government has published policies and measures such as "Arrangement on Energy Conservation and Emission Reduction", "Opinions of the State Council on Accelerating the Construction of Ecological Civilization" and "Strategic Action Plan for Energy Development (2014-2020)", and has always aimed at open source, cost reduction, and emission reduction, focusing on transforming energy consumption, ensuring the optimization of energy structure, achieving energy security supply, controlling excessive energy consumption, vigorously promoting Green Sustainable Development, and thus achieving the advancement of total factor energy efficiency.

5.2. Principal component-based geographically weighted regression analysis (PCA-GWR)

5.2.1 Correlation test

TFEE and the drivers were correlated using the Pearson correlation coefficient (Fig. 2).

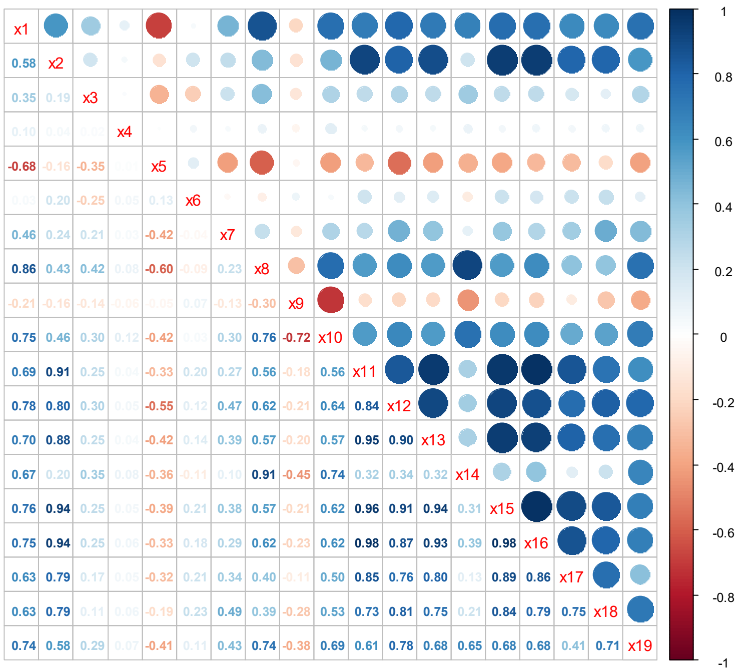


Fig. 2. Heat map of the correlation between energy efficiency and drivers

Correlation analysis of nine drivers of EE with significantly moderate correlation (Fig. 3) revealed that the correlation coefficients among the drivers were large, especially the correlations among socio-economic indicators (labor force, fiscal revenue, and research funding) were strong and prone to the problem of multicollinearity, which led to unreliable regression analysis results. Therefore, using the Kappa test, the result is 2437.052, and there is serious multicollinearity. It is discovered by comparing the variability of the inflation factor findings with the Kappa test results that some indicators have a significant strong association.

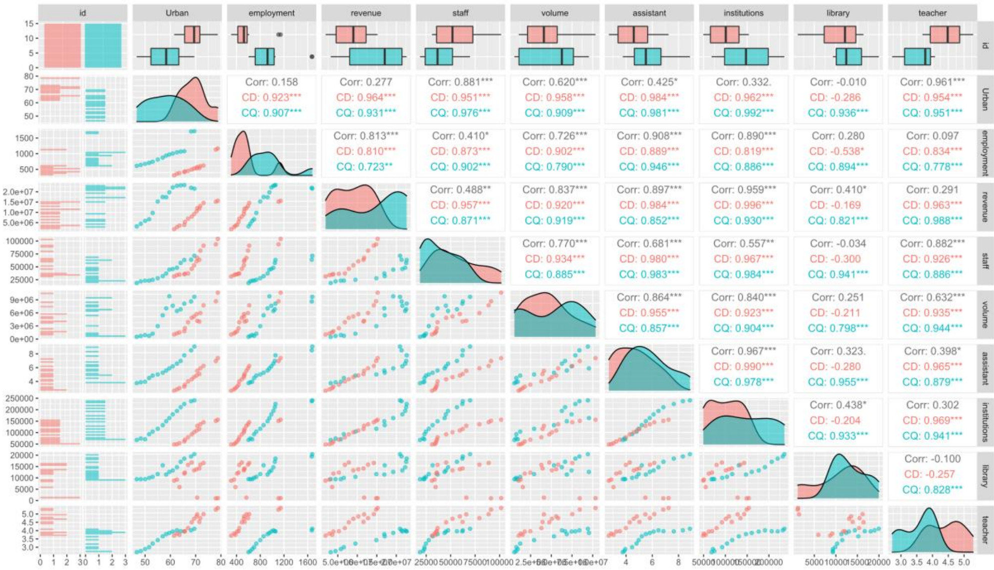


Fig. 3. Correlation chart of the 9 drivers

5.2.2 *Principal component-based factor Synthesis*

Based on the four time periods of 2006, 2010, 2015, and 2020, the 16 independent variable indicators with significant correlation with energy efficiency were subjected to principal component analysis, and the composite factors, i.e., principal components, were determined by dimensionality reduction to replace the original numerous variables, and results are listed in Table 4. The cumulative contribution rates of the first, second, third, fourth, and fifth principal components all reached over 93%, and the amount of information loss was low, so this paper transformed the original 16 drivers with correlation into these five uncorrelated principal components.

Table 4. Contribution of principal components, 2006-2020

year	Cumulative contribution rate				
	First principal component	Second principal component	Third principal component	Fourth Principal Component	Fifth principal component
2006	0.6251	0.7647	0.8652	0.9096	0.9382
2010	0.6463	0.8003	0.8878	0.9230	0.9514
2015	0.6213	0.7538	0.8442	0.9240	0.9470
2020	0.5972	0.7474	0.8505	0.9303	0.9638

The obtained principal component feature matrix was used to construct a linear relationship model between the first, second, third, fourth, and fifth principal components and 19 drivers for 2006-2020, and their scores were used as new composite factors for subsequent modeling analysis with energy efficiency.

5.2.3 Analysis of geographically weighted regression model results

The indicator discretization function gdm function is used to discretize all data of the drivers of energy efficiency in the CCTC economic circle, and the discretization methods are chosen from the natural segment point method (natural), equal method (equal) and quantile method (quantile), considering the time dimension, the indicator interval range is uniformly set between 3-4 according to the data attributes, and the independent classification results of gdm function are shown in Table 5.

Table 5. Results of autonomous classification of geographic detectors

Influencing Factors	2006		2010		2015		2020	
	Discrete Method	interval	Discrete Method	interval	Discrete Method	interval	Discrete Method	interval
C_1	quantile	4	natural	4	natural	3	natural	3
C_2	equal	4	equal	4	quantile	4	quantile	4
C_3	equal	4	equal	4	natural	4	equal	3
C_4	quantile	4	quantile	4	natural	4	natural	4
C_5	quantile	3	quantile	4	quantile	3	quantile	3

Note: C_i denotes the ith principal component, respectively, where i *in* $(1,2,K\ ,5)$.

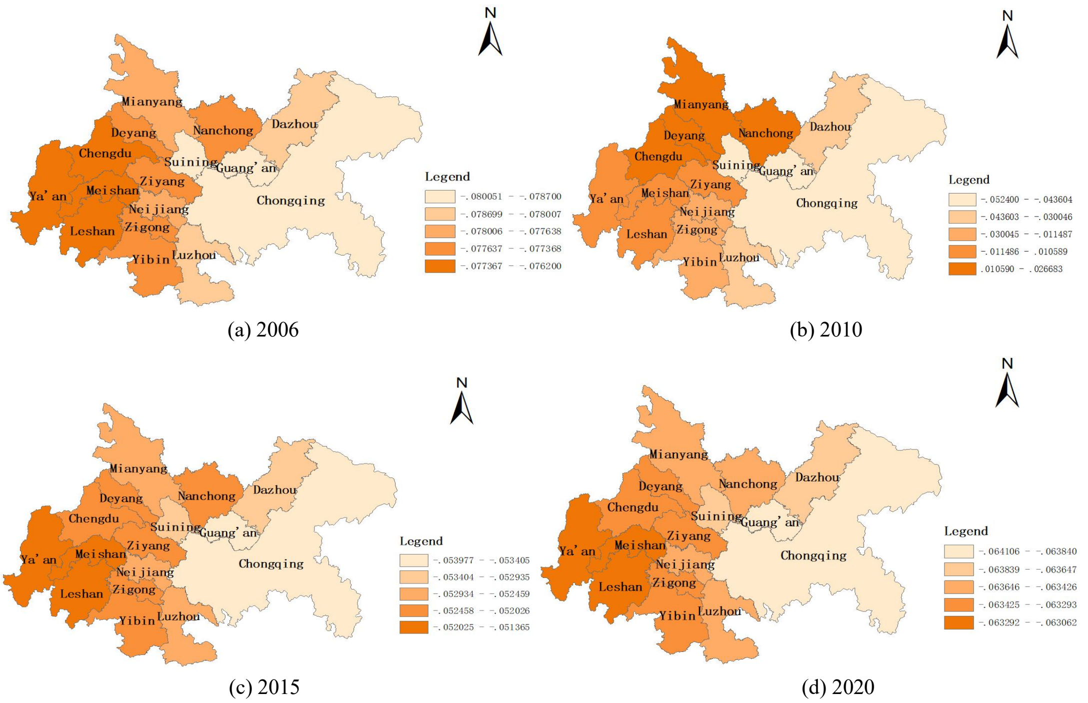
Since the geographic probe can detect and analyze the magnitude of the role of each factor on total factor energy efficiency as a whole, but it cannot show the spatial scope of this influence, this paper further analyzes the factors related to energy efficiency in CCTC economic circle spatially through the GWR analysis model, and Table 6 presents the results that were obtained：

Table 6. GWR model fitting effects for 2006-2020

Time	Sigma value	AICc value	RSS	R^2
2006	0.3059	28.788	0.9235	0.6695
2010	0.1826	62.312	0.2012	0.8180
2015	0.2043	16.010	0.4113	0.5850
2020	0.2085	16.525	0.4291	0.6971

According to Table 6, the residual sum of squares for 2006, 2010, 2015, and 2020 are 0.9235, 0.2012, 0.4113, and 0.4291, respectively, with significant changes over time, indicating that the GWR model was suitable for observed data with certain fluctuations over the years; Sigma value, which is better as the value decreases, is the square root of the total standardized residual variances. The smallest Sigma value was 0.1826 in 2010, followed by 2015 and 2020, and the largest Sigma value was in 2006, indicating that the sum of residual squares divided by the effective degrees of freedom of the residuals was the best in 2010 and the second best in the other years.; Sigma values are consistent with the GWR model fit over time.

Overall, results obtained from the GWR of TFEE and drivers in the CCTC Economic Circle were expressed spatially visualized with Arc GIS10.5 for the estimated coefficients of each component.



(a) 2006 (b) 2010

(c) 2015 (d) 2020

Fig. 4. First principal component regression coefficient analysis

As shown in Fig. 4, the TFEE of the CCTC economic circle from 2006 to 2020 is negatively correlated with the first principal component, but the direction and magnitude of the spatial effects differ, indicating that the first principal component has a suppressive effect on TFEE and the interannual variation of the effect by region is large, and the regression coefficient of this suppressive effect increases spatially roughly from east to west, and the gap between the regression coefficients gradually decreases with the growth of time.

5.3. Spatial distribution characteristics of energy efficiency

5.3.1 Global Spatial Clustering Effect

To effectively measure the phenomenon of high and low aggregation of energy efficiency appearing in the CCTC urban agglomeration, the global Moran's I statistics corresponding to the energy efficiency of 16 cities in the CCTC urban agglomeration from 2015 to 2020 were calculated (Table 7.), and it was easily found that the statistics all passed the significance test of spatial autocorrelation and started to change to negative values in 2016, indicating that from 2016 onward, the energy efficiency of 16 cities had negative spatial correlation in the global context, i.e., the energy efficiency among neighboring cities showed dissimilar aggregation.

Table 7. Global Moran's I statistics for energy efficiency, 2015-2020

year / Variables	2015	2016	2017	2018	2019	2020
Moran's I	0.2573	-0.3842	-0.4941	-0.5001	-0.334	-0.336
P Value	0.0296	0.0458	0.0467	0.0379	0.0278	0.0438

Note: Moran's I statistic passed the significance test for each year at the 0.05 level of significance.

Within the 16 cities in the CCTC Economic Circle, there are large spatial differences in energy efficiency among neighboring cities, and there is no obvious similarity in aggregation characteristics. However, in 2015, there is a certain correlation of space, indicating that the variability of cities within the economic circle has had a strong influence on the changes in EE during recent years. To explore more deeply the aggregation of energy efficiency values in space and their spatial evolution, further spatial statistical analysis of energy efficiency in local areas is needed.

5.3.2 Local Spatial Agglomeration Effect

The global autocorrelation reflects that within the overall 16 Chengdu-Chongqing urban agglomerations, energy efficiency is spatially different among neighboring cities and does not show similarity aggregation. However, to determine whether the surrounding areas of each city also have such a large variability and do not have similar aggregation, analysis of local spatial autocorrelation metrics is needed to analyze the local characteristics of energy efficiency. Firstly, to analyze the influence of the change of time latitude on the local EE characteristics, the energy efficiency values in 2006, 2010, 2015, and 2020 were selected, and locally Moran's I statistics were calculated among 16 cities to plot the local spatial aggregation of energy efficiency in urban clusters at different time points (Fig. 5):

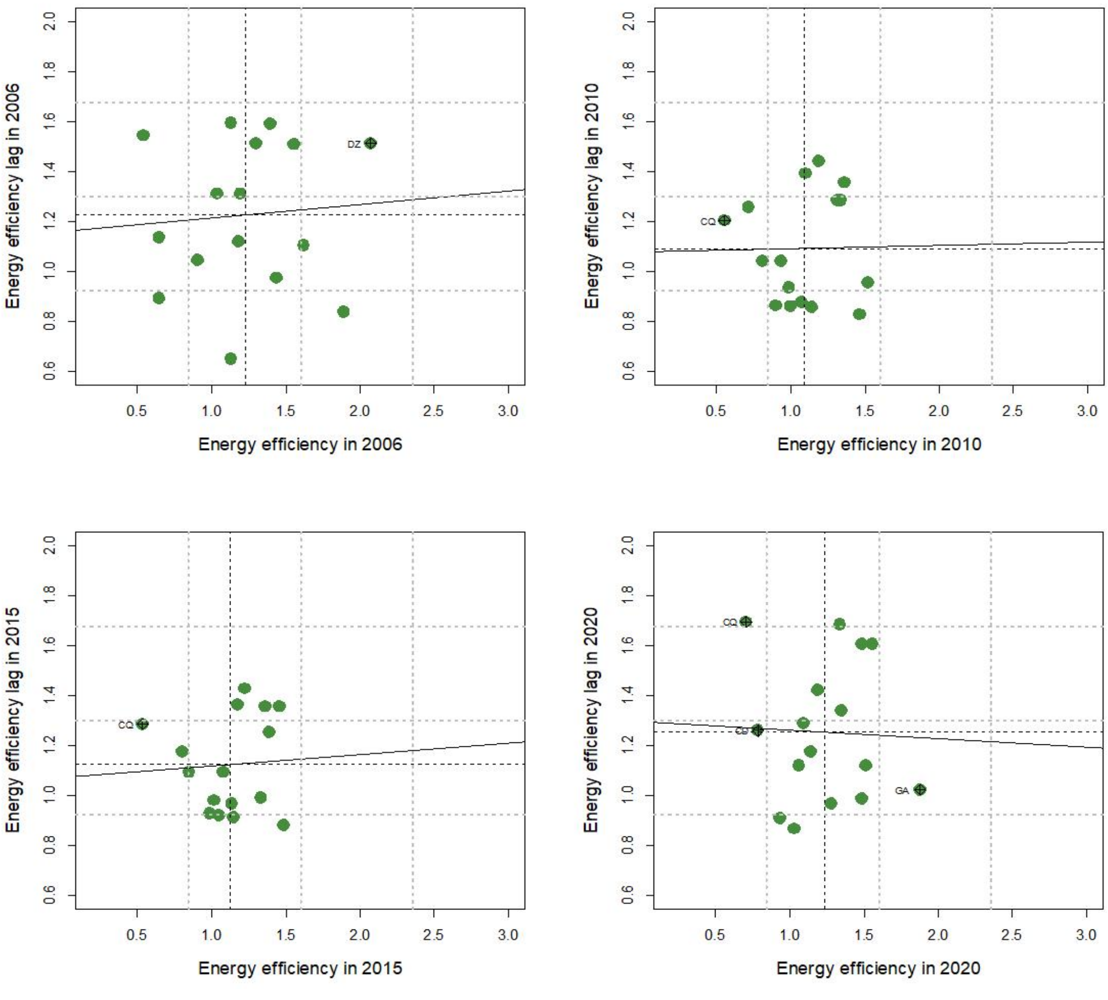


Fig. 5. Local Moran scatter plot of energy efficiency for urban agglomerations

Each scatter distribution in Fig. 5 is the EE distribution of each city, and the 16 scatters are divided into high-high(H-H), low-low(L-L), low-high(L-H), and high-low(H-L) aggregation zones by two dashed lines parallel to the X and Y axes, respectively. With two dashed lines as the new axes, the first quadrant is the H-H aggregation area, the third quadrant is the L-L aggregation area, the second quadrant is the L-H cluster, and the fourth quadrant is the H-L cluster.

Table 8. Local scatter plot of energy efficiency corresponding to the distribution of cities

year	H-H Type	L-L Type	H-L Type	L-H Type
2006	LS YA SN DZ	YB ZY CD DY MY	NJ MS GA	CQ LZ ZG NC
2010	LS YA SN NC DZ	YB LZ ZG NJ ZY DY	MS GA MY	CQ CD
2015	LS YA SN NC DZ	LZ ZG NJ ZY DY	YB MS GA MY	CQ CD
2020	YA SN NC DZ	ZG NJ DY	LZ MS ZY GA	CQ YB LS CD

From the aggregation types of each city in Table 8, we can see that among the cities with high-high aggregation types in 2006, 2010, 2015, and 2020, Dazhou City and Suining City are more fixed, and combined with the geographical location as a reference, it indicates that the highly energy-efficient regions are mainly clustered in the southwestern and northeastern parts of the CCTC Economic Circle. The cities with low energy efficiency are mainly located in the south and north of the CCTC Economic Circle, and the cities with low-low aggregation type are gradually decreasing with the growth of time, indicating that the energy efficiency among cities in the economic circle is driven by the neighboring cities, which subsequently improves the energy efficiency. As a result, the cities with L-H and H-L clusters are changing, but Chongqing City is more fixed and has been in the low-high cluster type.

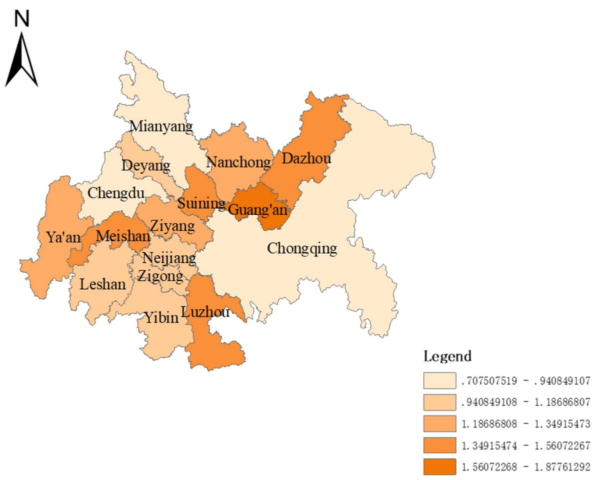


Fig. 6. Spatial pattern distribution of energy efficiency in urban agglomerations in 2020

Since the EE values of each city have gradually increased over time, to further analyze the energy efficiency aggregation of each city in the Chengdu-Chongqing urban agglomeration in recent years and continue to explore the local spatial aggregation of 16 cities from 2017 to 2020, a distribution map of the geographic spatial pattern of the economic circle in 2020 was drawn (Fig. 6).

Table 9. Distribution of cities corresponding to the local scatter plot of energy efficiency

year	H-H Type	L-L Type	H-L Type	L-H Type
2017	LS YA SN NC DZ	ZG NJ ZY DY MY	YB LZ MS GA	CQ CD
2018	YB LS YA SN NC DZ	ZG NJ ZY CD DY MY	LZ MS GA	CQ
2019	YA SN NC DZ	ZG NJ MY DY	LZ MS ZY GA	CQ YB LS CD
2020	YA SN NC DZ	ZG NJ DY	LZ MS ZY GA	CQ YB LS CD

The aggregation of energy efficiency in recent years can be reflected in Table 9, where Leshan City is a city with high-high type of aggregation in 2017-2018, but from 2019, it changed to a city with a low-high type of aggregation, indicating that Leshan City may have a change of aggregation type due to the influence of energy efficiency changes in neighboring cities; combined with the geographical location, the changes of neighboring cities in Leshan City are specifically dissected, where Meishan City, Zigong City, Ya'an City, and Neijiang City all have unchanged energy efficiency aggregation types, which are fixed from 2017 to 2020, but Yibin City has a large change in energy efficiency aggregation types, so it is considered that Leshan City may be influenced by the unstable change in energy efficiency generated by Yibin City. On the whole, Ya'an, Suining, Dazhou, and Nanchong are more fixed in the H-H aggregation area, and Suining, Dazhou, and Nanchong are neighboring cities, which means that the H-H aggregation area is mainly distributed in the northeastern cities of the CCTC Economic Circle; while the cities with more fixed L-L aggregation areas are: Zigong, Neijiang, and Deyang, which are distributed in the southern part of the CCTC Economic Circle; While the central region is mainly H-L aggregation area and L-H aggregation area.

5.4. Random Forest-based Influence Factor Extraction

To investigate the influential mechanism of energy efficiency drivers in the CCTC Economic Circle, this article implements the control variable selection based on random forest. First, low variance filtering and high correlation filtering are used to filter the characteristic variables, and 19 potential control variables are initially integrated. Second, random forest is used to predict the main variables according to the Gini importance. Third, the variables were further screened by testing for multicollinearity to eliminate problems due to uncertainty in parameter estimation and multicollinearity in regression analysis. After eliminating the multicollinearity, the significance histograms of the 19 explanatory variables were plotted (Fig. 7):

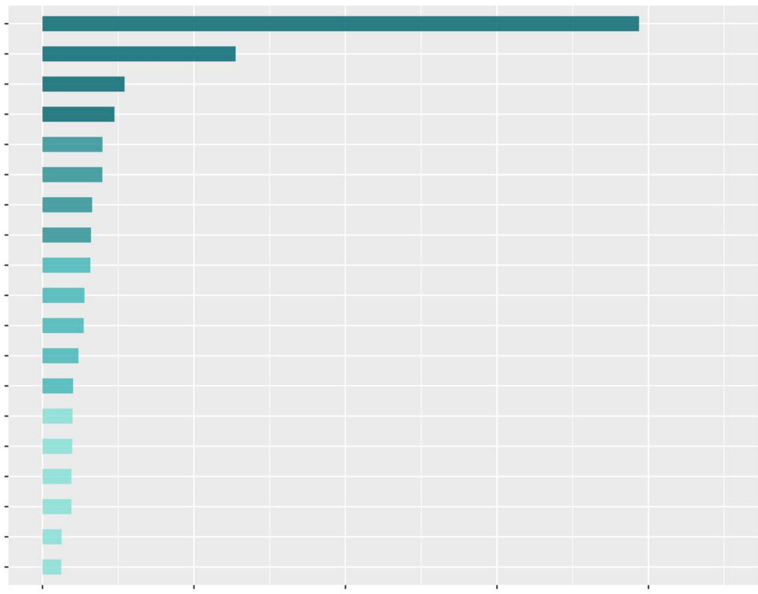


Fig. 7. Histogram of the importance of drivers

The variables were ranked according to Gini importance and the results in Table 10 were screened as the main explanatory variables for the subsequent modeling:

Table 10. Variables in order of importance 1-6

Variables	Importance	Variables	Importance
x_1	0.3938	x_3	0.1275
x_{16}	0.0542	x_{11}	0.0475
x_{19}	0.0396	x_{10}	0.0395

The top 6 variables in order of importance are shown in Table 10: urbanization rate, urban employment, number of beds in medical institutions, general budget revenue of local finance, the share of tertiary industry, and social security and employment expenditure of local finance. The above six indicators were used as explanatory variables for the subsequent panel model.

5.4.1 Estimation Results and Analysis of Spatial Panel Model

For this section, it selected the panel data of 16 cities in the CCTC economic circle from 2017-2020 and the spatial panel model constructed based on the main explanatory variables obtained from the screening in subsection 4.4 (Zhang and Liu, 2022; Wang and Guo, 2022), and Tables 11 display the results of the model estimation:

Table 11. Model estimation results for Chengdu-Chongqing urban agglomeration, 2017-2020

Indicators	SDM (2017)	SDM (2018)	SDM (2019)	SDM (2020)	SAR (2020)	SEM (2020)
Intercept term	2.21*** (17.58)	0.11** (22.29)	2.21*** (19.23)	3.39** (12.99)	0.51 (1.24)	0.86 (0.36)
x_1	2.20*** (-2.73)	0.27*** (-4.49)	2.20*** (-2.63)	0.67* (-1.20)	0.99 (0.01)	0.44 (0.43)
x_3	2.20*** (-0.27)	0.49 (0.21)	2.20*** (-0.35)	4.13** (-0.53)	0.88 (0.03)	0.57 (-0.12)
x_5	2.20*** (-8.71)	0.61** (-13.84)	2.20*** (-9.46)	0.22 (-3.52)	0.11 (2.88)	3.99** (4.11)
x_{10}	2.20*** (-0.58)	0.29 (-0.28)	6.83*** (0.25)	0.68* (0.34)	0.65 (0.14)	0.70 (0.11)
x_{16}	1.03*** (-0.13)	0.47 (-0.10)	2.24*** (-0.24)	0.77* (-0.20)	0.11** (-0.41)	0.80** (-0.36)
x_{19}	2.25** (0.42)	0.12** (0.30)	2.21*** (0.36)	1.23** (0.20)	0.63* (0.24)	0.24 (0.15)
L x_1	2.13*** (-5.62)	1.47** (-3.31)	2.20*** (-3.84)	0.11 (-2.19)	–	–
L x_3	0.64* (-0.15)	1.53** (-1.32)	1.36*** (-0.48)	0.60** (-1.04)	–	–
L x_5	2.13*** (-15.88)	3.66** (-8.23)	6.44*** (-6.02)	0.14* (-5.85)	–	–
L x_{10}	2.20*** (-1.72)	0.99** (-1.12)	0.25** (-0.42)	0.47 (-0.33)	–	–
L x_{16}	2.24*** (0.90)	0.30 (0.21)	0.14 (0.15)	0.16 (0.34)	–	–
L x_{19}	0.14** (0.15)	3.52** (0.42)	1.65*** (0.40)	0.90* (0.02)	–	–
Z-test	0.55*	0.12**	2.30**	4.45**	0.33	0.27
Wald test	0.55*	0.12**	2.31**	4.45**	0.33	0.27
LR test	0.79*	0.16**	0.40**	0.50*	0.49	0.68

Note: ** means significant at the 0.01 level; L x_i all denote lagged terms corresponding to x_i ; SDM(2017) denotes the 2017 energy efficiency and main explanatory variables of the spatial Durbin model.

The SDM suits better than the SAR and SEM, according to the findings of the three major tests. The gender ratio has a more significant significance in its spatial Durbin model for 2017–2020, where the urbanization rate, population mortality rate, and the number of hospital beds are significantly negative at the 1% level, the social security and employment expenditure of local finance is significantly positive at the 5% level, and the proportion of the tertiary industry is significantly positive at the 5% level. The spatial weights are introduced, and the population ratio is not significant. After introducing spatial weights, the population mortality rate, the share of tertiary industry, and local financial social security and employment expenditures pass the test at the 10% level of significance. That is, urbanization rate, population mortality rate, gender ratio, tertiary industry share, number of beds in medical institutions, and local fiscal social security and employment expenditures all have different significant effects on energy efficiency to different degrees, with population mortality rate and urbanization rate showing inhibitory factors. The implementation of energy-related policies and the economic development of each nearby city may be the causes of long-term changes like the other indicators.

6. Conclusion

In this paper, we first measured the TFEE of 16 cities in the CCTC economic circle from 2006 to 2020 using the super-efficiency DEA model and evaluated their sustainable development performance based on spatial evolution characteristics. Then, the link between TFEE and the driving elements is constructed using PCA-GWR. The research's results are as follows. Finally, SDM, SEM, and SAR models are constructed by employing the random forest to choose crucial variables for comparison analysis.

(1) Analyzed by the trend of temporal change, Chengdu-Chongqing urban agglomeration's overall energy efficiency demonstrates an increase in fluctuation, indicating how the 16 cities in the Chengdu-Chongqing region are transitioning to high-quality green development by managing the interaction between the environment, resources, and economic systems. According to the spatial trend, the average energy efficiency of Chongqing and Chengdu, the "twin core" cities in the CCTC Economic Zone, is only 0.708 and 0.788, and Chengdu and Chongqing no longer occupy the core position.

(2) Using PCA analysis, the first five primary components' combined contribution amounts to around 93%., and the GWR model is constructed by using these five principal components and TFEE. The results show that the sigma value keeps changing significantly over time, indicating that the GWR model fits the observed data with certain

fluctuations over the years, and the model fitting sigma value in 2020 is 0.4291, which is good.

(3) From autocorrelation on a global scale analysis and local autocorrelation analysis of energy efficiency, it is found that the H-H and L-L agglomerations of energy efficiency values are not concentrated but are scattered, and the H-H agglomerations are primarily found in the northeastern cities of Chengdu-Chongqing Economic Circle, while L-L agglomerations are spread over the southern portion of the CCTC Economic Circle; combined with the analysis of driving factors, the conclusion is that municipalities with higher energy efficiency values have corresponding urban economies. More advanced cities also have higher EE values, especially the two core cities of Chengdu and Chongqing. Both at once, the population mortality rate in the demographic structure harms energy efficiency; in cities with a higher hierarchical industrial structure and a better economic foundation, and the proportion of tertiary industries keeps increasing, the corresponding energy efficiency values will also be improved accordingly. Increased government investment in energy and environmental management has also facilitated inter-city energy efficiency improvements.

7. Suggestions

The empirical investigation reveals that the EE of core cities differs significantly from that of nearby cities, and it is unclear what driving force the core cities of the CCTC Economic Circle represent. Therefore, to improve the energy efficiency of the CCTC Economic Circle as a whole, the following countermeasures and suggestions are proposed.

(1) Accelerate the restructuring of the manufacturing sector. For the total growth of the regional economy, society, and environment, an optimized and efficient industrial structure and layout are required. Emphasizing technological innovation and improving the success rate of industrial transformation are the boosters of industrial structure adjustment. For cities with low EE, to improve the energy use efficiency of industrial production and lower the output of carbon emissions and environmental pollution products, it is necessary to change their industrial structure, support the city's advantageous industries, introduce energy-saving technologies, and vigorously promote environmentally friendly businesses.

(2) Implementing energy-saving targets for cities by region. The 16 cities that make up the Chengdu-Chongqing urban agglomeration are uniquely unique in terms of their geographic settings, technological advancements, economic foundations, levels of energy use, and population makeup. Setting energy conservation goals for the Chengdu-Chongqing urban agglomeration based on local conditions, paying attention to the division of labor and cooperation among different cities, and scientifically formulating energy conservation and consumption reduction policies with differentiation will help us implement energy saving and emission reduction policies more precisely and advance the improvement of energy efficiency in the economic circle as a whole. The 16 cities can be divided into four regional segments with different aggregation characteristics.

(3) Play the role of core urban areas as a driving force. Maintain the energy efficiency and economic base advantages of Chengdu and Chongqing, pay attention to the development of clean energy industries, spread the growth of beneficial industries and environment-friendly industries to other prefecture-level cities, and jointly drive other prefecture-level cities to introduce new technologies and improve energy efficiency.

Data Availability

The data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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TFEE: The DEA model, or data envelopment analysis method, utilizes input and output indicators and applies a linear programming approach to data analysis.
CCTC: The GWR model, or geographically weighted regression model, is a spatial analysis technique that is widely used in research in geography and related disciplines involving spatial pattern analysis.