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Spatiotemporal Patterns and Influencing Mechanism of Urban Residential Energy Consumption in China

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Abstract: The residential sector has become the second largest energy consumer in China. Urban residential energy consumption (URE) in China is growing rapidly in the process of urbanization. This paper aims to reveal the spatiotemporal dynamic evolution and influencing mechanism of URE in China. The spatiotemporal heterogeneity of URE during 2007–2018 is explored through Kernel density estimation and inequality measures (i.e., Gini coefficient, Theil index, and mean logarithmic deviation). Then, with several advantages over traditional index decomposition analysis approaches, the Generalized Divisia Index Method (GDIM) decomposition is employed to investigate the impacts of eight driving factors on URE. Furthermore, the national and provincial decoupling relationships between URE and residential income increase are studied. It is found that different provinces' URE present a significant agglomeration effect; the interprovincial inequality in URE increases and then decreases during the study period. The GDIM decomposition results indicate the income effect is the main positive factor driving URE. Besides, urban population, residential area, per capita energy use, and per unit area energy consumption positively influence URE. By contrast, per capita income, energy intensity, and residential density have negative effects on URE. There is evidence that only three decoupling states, i.e., weak decoupling, strong decoupling, and expansive negative decoupling, appear in China during 2007–2018. Specifically, weak decoupling is the dominant state among different regions. Finally, some suggestions are given to speed up the construction of energy-saving cities and promote the decoupling process of residential energy consumption in China. This paper fills some research gaps in urban residential energy research and is important for China's policymakers.

Keywords: spatiotemporal heterogeneity; inequality measures; Generalized Divisia Index Method (GDIM); urban residential energy consumption; decoupling process; China

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1. Introduction

China, as the largest developing country globally, has become the largest energy consumer [1] and energy producer [2]. Energy has been a key factor in evaluating the sustainable development of an economy [3–5]. Residential energy consumption accounts for a large proportion of final energy consumption in China. Following the industrial sector, the residential sector has become China's second largest energy consumer [6], which indicates that achieving energy conservation in the residential sector is an important part of China's sustainable development strategy. China's residential energy consumption per capita is still far smaller than that of some developed countries such as Japan, the United States, and the United Kingdom [7]. According to International Energy Outlook 2019 [8], per capita residential energy consumption in the world displays an annual increase rate of 0.6% during 2018–2050, specially, non-OECD countries that have shown an average annual growth rate of 1.3% from 2018 to 2050. Thus, residential energy consumption in China is expected to have a lot of room for growth.

In fact, 63% of China's residential energy consumption comes from urban areas [9]. A high proportion of residential energy consumption will inevitably bring about a great deal of carbon emissions, which does not conform with China's sustainable development goals. China intends to peak its CO_2 emissions by 2030 and achieve carbon neutrality by 2060 [10]. The residential sector has huge energy-saving potential and plays a critical role in carbon emissions [11]. Under rapid urbanization, China will face tremendous socio-economic pressure as well as environmental pressure brought about by the increase in urban residential energy consumption (URE). Therefore, it is of great importance to comprehensively reveal the spatiotemporal evolution mechanism of China's URE.

In existing research, lots of scholars employ econometric analysis methods to study the influencing factors of residential energy consumption. Many studies focus on the relationship between income and residential energy consumption [1,12,13]. For example, Dong et al. [1] use seemingly unrelated regression to study the driving factors of urban and rural residential energy use in China. The results show income is the main factor increasing residential energy consumption. In the case of EU-28 countries during 1990–2013, the environmental Kuznets curve (EKC) in the residential sector is verified through the panel data model [11]. In addition, urbanization is also a key determinant of residential energy use [6,14,15]. Based on the data of 136 countries, Wang et al. [16] employ panel unit root tests, co-integration test, and Fully Modified Ordinary Least Squares (FMOLS) regression to investigate the impact of urbanization on residential energy use and find the effect of urbanization shows significant heterogeneity across different countries. From the perspective of energy policy, Aydin and Brounen [17] apply different regression models to examine how energy efficiency policies affect residential energy consumption in Europe during 1980–2016. They find that energy labeling policy and building standards negatively influence residential energy consumption. Other factors have also been investigated, such as energy price [18], temperature variations [19], population [16], household characteristics [14], age structure [20], socio-economic status [21], energy efficiency [22], and people's time-use behaviors [23]. On the whole, scholars have utilized various econometric methods to study the relationship between socioeconomic variables and residential energy consumption. Most regression models are established based on the STIRPAT model, considering the impacts of population, affluence, and technology.

Although the decomposition analysis method is commonly seen in energy-related studies, scholars focus on carbon emissions [24], carbon intensity [25], PM2.5 pollution [26], energy use [27], aggregate exergy efficiency [28], thermal power generation [29], etc. Few scholars utilize the Logarithmic Mean Divisia Index (LMDI) approach to investigate the driving factors of residential energy consumption [7,30–32]. For example, using the LMDI method, Zhao et al. [9] investigate the determinants of China's URE during 1998–2007. The results show that population and income are the main factors leading to URE growth, and price deregulation has a negative effect on URE. Nie et al. [33] perform the LMDI method to decompose the variations of residential energy consumption into seven factors. The results specify that climate effect, energy cost share effect, and income effect contribute to increasing residential energy consumption, while the contributions of energy prices and energy expenditure mix are negative; the impacts of expenditure share and population vary in different regions. As an important index decomposition analysis (IDA) approach, the Generalized Divisia Index Method (GDIM) has been increasingly found in energy-related literature [34]. However, this method has not been used in studying residential energy consumption.

This study aims to analyze the spatiotemporal patterns and influencing mechanism of urban residential energy consumption in China. In detail, we intend to address the following issues: (1) What is the temporal and spatial evolution trend of urban residents' energy consumption in China? (2) What are the primary drivers of URE? Further, what are the differences in the factors affecting URE between different regions? (3) How is the decoupling process between URE and residential income growth? The above-mentioned problems have motivated this study. The innovations of this paper lie in the following aspects. (1) This paper reveals the spatiotemporal dynamic patterns of urban residential energy consumption. (2) Most studies employ econometric analysis methods to analyze the driving factors of residential energy consumption. Compared with regression methods, decomposition analysis can provide a complete explanation for the changes in the dependent variable, without residual error. However, the application of decomposition analysis method is rarely seen in the research on residential energy consumption. What is more, the LMDI used in the literature will inevitably miss some important explanatory variables [34]. In this paper, the GDIM decomposition model is adopted to uncover the influencing mechanism of urban residential energy consumption. This paper is able to comprehensively reveal the influence mechanism of URE in contrast to traditional index decomposition methods. While the decomposition analysis method has been widely used in studying driving factors in energy-related research, the GDIM approach provides perfect decomposition of the changes in URE in this paper, thereby obtaining the full understanding of the changing mechanism of URE. This method can be utilized in studying driving factors in any sectors such as the industrial sector, transport sector, agricultural sector, etc.

The data used in this study cover China's 29 provinces spanning 2007–2018. First, this paper adopts Kernel density estimation to uncover the distribution characteristics of URE and measures the regional inequality in URE. When studying the spatiotemporal heterogeneity of URE, the scale effect of total population should be eliminated. Therefore, URE per capita is adopted since such a relative indicator is comparable among different provinces. Then, the GDIM model is utilized to capture the contributions of eight factors on URE changes. Given regional heterogeneity, this paper investigates the determinants of URE at both national and provincial levels. With several advantages over traditional IDA methods, the GDIM decomposition considers more factors in the identification of influencing factors. Furthermore, the application of the decoupling model is to study the dynamic relationship between URE and residential disposable income. This paper is helpful to promote energy conservation in the urban residential sector, thereby contributing to building an energy-saving society in the urbanization process. The study contains sufficient contributions to the new body of knowledge from the international perspective in addition to focusing on the issues of China. While the methodology used in this paper is to study urban residential energy consumption in China, it is expected that the research framework can be applied to other economies and even on a global scale.

The remaining parts of this paper are arranged as follows. The next section describes the methods used in this study. Section 3 shows variables and data sources. Section 4 presents the results and discussion. The final section gives the conclusions and policy implications.

2. Methodology and Data

2.1. Kernel Density Estimation of URE

Kernel density estimation (KDE) is an important tool to describe the unknown distribution of a random variable. In this paper, Kernel density estimation is utilized to obtain the probability density of URE, thereby revealing the distribution characteristics of URE in China.

The Kernel density function of the random variable (i.e., URE per capita) is formulated as:

$$f\left(\overline{EP}\right) = \frac{1}{Nb}\sum_{i=1}^{N} K\left(\frac{EP_i - \overline{EP}}{b}\right) \quad (1)$$

where EP_i is the observation, which is independent and identically distributed, $\overline{EP}$ represents the mean, N is the number of observations, b denotes the bandwidth, and $K(\cdot)$ indicates the Kernel function such that $K(x) \geq 0$, $\int_{-\infty}^{+\infty} K(x)dx = 1$.

In selecting the Kernel function, this paper mainly focuses on the simplicity in the calculation of waveform synthesis. Therefore, the Gaussian kernel is used to depict the distribution characteristics of URE. In addition, according to the thumb rule [35], the optimal bandwidth is obtained as follows:

$$b^* = \left(\frac{4\hat{\sigma}}{3N}\right)^{\frac{1}{5}} \approx 1.06\hat{\sigma}N^{-\frac{1}{5}} \tag{2}$$

where b^* denotes the optimal bandwidth, $\hat{\sigma}$ denotes the standard deviation of observations.

2.2. Regional Inequality of URE

China has a vast territory, and there are huge discrepancies between different regions. Has China's URE inequality eased or worsened? It is necessary to quantify the degree of URE inequality among China's provinces. Three inequality indicators, the Gini coefficient, the Theil index (GE_0), and mean logarithmic deviation (GE_0), are used to quantify the regional inequality of urban residential energy consumption in China. The Theil index and mean logarithmic deviation both belong to the generalized entropy indexes.

$$\text{Gini} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|EP_i - EP_j\right|}{2n^2\overline{EP}} \tag{3}$$

$$GE_1 = \sum_{i=1}^{n}\frac{1}{n}\frac{EP_i}{\overline{EP}}\ln\left(\frac{EP_i}{\overline{EP}}\right) \tag{4}$$

$$GE_0 = \sum_{i=1}^{n}\frac{1}{n}\ln\left(\frac{\overline{EP}}{EP_i}\right) \tag{5}$$

where n denotes the number of provinces in China, and i denotes the i-th province; EP represents urban residential energy consumption per capita, and $\overline{EP}$ is its mean value.

2.3. GDIM Decomposition

Arbitrary and different LMDI decomposition forms may lead to partial decomposition results, which fails to comprehensively reveal the changing mechanism of urban residential energy consumption. Compared with the LMDI method, the GDIM decomposition can consider multiple absolute factors simultaneously. This paper employs the GDIM model to study the influencing factors of URE in China. The procedure of GDIM decomposition can be formulated as followed:

$$\begin{aligned} URE_{it} &= P_{it} \times (URE_{it}/P_{it}) = I_{it} \times (URE_{it}/I_{it}) = A_{it} \times (URE_{it}/A_{it}) \\ &= P_{it} \times EP_{it} = I_{it} \times EI_{it} = A_{it} \times EA_{it} \end{aligned} \tag{6}$$

$$IP_{it} = I_{it}/P_{it} = (URE_{it}/P_{it})/(URE_{it}/I_{it}) = EP_{it}/EI_{it} \tag{7}$$

$$DEN_{it} = P_{it}/A_{it} = (URE_{it}/A_{it})/(URE_{it}/P_{it}) = EA_{it}/EP_{it} \tag{8}$$

where i denotes the i-th province, t is time, P is urban population, I is the disposable income of urban households, A is urban residential area, and EP is energy use per capita. EI is energy use intensity represented by the ratio of urban residential energy consumption to income. EA represents residential energy consumption per unit area. IP indicates disposable income per capita. DEN is residential density, which is denoted by the ratio of urban population to total residential area. Based on Equations (6)–(8), this paper considers the impacts of eight factors on urban residential energy use. Both absolute indicators (i.e., P, I, and A) and relative indicators (EP, EI, EA, IP, and DEN) are included in the GDIM model.

Based on Equations (6)–(8), we have the following formulas:

$$URE_{it} = P_{it} \times EP_{it} \tag{9}$$

$$P_{it} \times EP_{it} - I_{it} \times EI_{it} = 0 \tag{10}$$

$$P_{it} \times EP_{it} - A_{it} \times EA_{it} = 0 \tag{11}$$

$$P_{it} - A_{it} \times DEN_{it} = 0 \tag{12}$$

$$I_{it} - P_{it} \times IP_{it} = 0 \tag{13}$$

The gradient of Equation (9) can be written as:

$$\nabla URE_{it} = (EP_{it}, P_{it}, 0, 0, 0, 0, 0, 0)^T \tag{14}$$

Furthermore, we have the following Jacobian matrix Φ_X:

$$\Phi_x = \begin{pmatrix} EP_{it} & P_{it} & -EI_{it} & -I_{it} & 0 & 0 & 0 & 0 \\ EP_{it} & P_{it} & 0 & 0 & -EA_{it} & -A_{it} & 0 & 0 \\ 1 & 0 & 0 & 0 & -DEN_{it} & 0 & -A_{it} & 0 \\ -IP_{it} & 0 & 1 & 0 & 0 & 0 & 0 & -P_{it} \end{pmatrix}^T \tag{15}$$

Equation (15) is comprised of the first partial derivative of each factor. Under the linearly independent hypothesis, we have $\Phi_X^+ = (\Phi_X^T \Phi_X)^{-1} \Phi_X^T$. Based on the GDIM decomposition, the variation of residential energy consumption is formulated as follows:

$$\Delta URE[X|\Phi] = \int_P \nabla URE^T (I - \Phi_X \Phi_X^+) dX \tag{16}$$

where P denotes the research period, I is an identity matrix, and T denotes the operator of transposed matrix, + indicates generalized inverse matrix. According to Equation (16), the changes in residential energy consumption is decomposed into eight factors, including the population effect (ΔURE_P), income effect (ΔUR_{EI}), residential area effect (ΔURE_A), per capita energy use effect (ΔURE_{EP}), energy intensity effect (ΔURE_{EI}), per unit area energy consumption (ΔURE_{EA}), per capita income effect (ΔURE_{IP}), and residential density effect (ΔURE_{DEN}). The GDIM model provides perfect decomposition results as follows:

$$\begin{aligned} \Delta URE &= \Delta URE_P + \Delta URE_I + \Delta URE_A + \Delta URE_{EP} \\ &+ \Delta URE_{EI} + \Delta URE_{EA} + \Delta URE_{IP} + \Delta URE_{DEN} \end{aligned} \tag{17}$$

2.4. Decoupling Model

Residential energy consumption is closely related to residential income increase. To study the extent to which the urban residential energy consumption is decoupled from income growth, the Tapio decoupling indicator [36] is used to analyze the decoupling of urban residential energy consumption from residential income. The Tapio decoupling index between residential energy consumption and residential income during the period [0, t] can be expressed as:

$$\beta^t_{E-I} = \frac{\Delta URE/URE}{\Delta I/I} = \frac{\frac{URE^t - URE^0}{URE^0}}{\frac{I^t - I^0}{I^0}} \tag{18}$$

where β^t_{E-I} refers to the decoupling indicator of urban residential energy consumption from income growth, URE^{t-1} denotes urban residential energy consumption in the base year $(t-1)$; URE^t represents urban residential energy consumption in the year t; I^{t-1} is the income level of urban residents in the base year $(t-1)$; and I^t denotes residential income level in the year t. Following the decoupling status division in Fang and Yu [26] and Yu et al. [29], Table 1 shows different decoupling states in the Tapio decoupling model.

Table 1. The division of decoupling types.

State	Definition	ΔURE/URE	ΔI/I	β
RD	Recessive decoupling	<0	<0	$\beta > 1$
WD	Weak decoupling	>0	>0	$0 < \beta < 1$
SD	Strong decoupling	<0	>0	$\beta < 0$
END	Expansive negative decoupling	>0	>0	$\beta > 1$
WND	Weak negative decoupling	<0	<0	$0 < \beta < 1$
SND	Strong negative decoupling	>0	<0	$\beta < 0$

3. Variables and Data Sources

This study aims to investigate the spatiotemporal patterns and driving factors of urban residential energy consumption in China during 2007–2018. In doing so, this study employs Kernel density estimation to reveal the distribution dynamic evolution of URE; meanwhile, three inequality indexes are utilized to measure the regional differences in residential energy consumption. Then, the GDIM model is utilized to study the determinants of URE. In addition, we apply the Tapio decoupling index to investigate the decoupling process of URE. The variables and their definitions are shown in Table 2. Due to data availability, 29 provinces are included in this paper. The data of urban residential energy use are derived from China Energy Statistical Yearbook. Residential area data are collected from China Urban Construction Statistical Yearbook, which covers energy use for housing and private transport. In this paper, URE is measured as a coal equivalent. Urban population and residential disposable income come from China Statistical Yearbook.

Table 2. Indicators used in this paper.

Symbols	Indicators	Definitions	Data Source
URE	Absolute indicator	Urban residential energy consumption	China Energy Statistical Yearbook
P	Absolute indicator	Urban population	China Statistical Yearbook
I	Absolute indicator	Urban residential income	China Statistical Yearbook
A	Absolute indicator	Urban residential area	China Urban Construction Statistical Yearbook
EP	Relative indicator	Urban residential energy consumption per capita	China Energy Statistical Yearbook, China Statistical Yearbook
EI	Relative indicator	The ratio of residential energy consumption to income	China Energy Statistical Yearbook, China Statistical Yearbook
EA	Relative indicator	The ratio of residential energy consumption to total residential area	China Energy Statistical Yearbook, China Urban Construction Statistical Yearbook
IP	Relative indicator	Disposable income per capita	China Statistical Yearbook
DEN	Relative indicator	The ratio of urban population to total residential area	China Urban Construction Statistical Yearbook, China Statistical Yearbook

4. Results and Discussion

4.1. Spatiotemporal Patterns of China's Urban Residential Energy Consumption

4.1.1. Distribution Dynamic Evolution

This paper employs the Kernel density estimation to reveal the distribution characteristics of residential energy consumption. The Kernel density curves of URE per capita in 2007, 2013, and 2018 are presented in Figure 1. The kernel density map can be regarded as a probability density map, and its vertical axis can be roughly regarded as the number of times the data appears, and the area enclosed by the horizontal axis is 1. From 2007 to 2018, the Kernel density curve moves to the right, which shows the URE per capita is gradually increasing during the study period. There is evidence that income increase contributes to residential energy consumption [1]. The improvement of living standards promotes each person to consume more residential energy.

In 2007, the Kernel density curve shows a bimodal shape, which shows residential energy consumption has become polarized among China's provinces. Different provinces present an agglomeration effect and can be classified into two groups. From 2007 to 2018, the height of the crest on the left presents little change, and the crest on the right gradually becomes shorter. It shows that more and more provinces gradually gather in a group and the distribution has a tendency towards a more concentrated pattern over time.

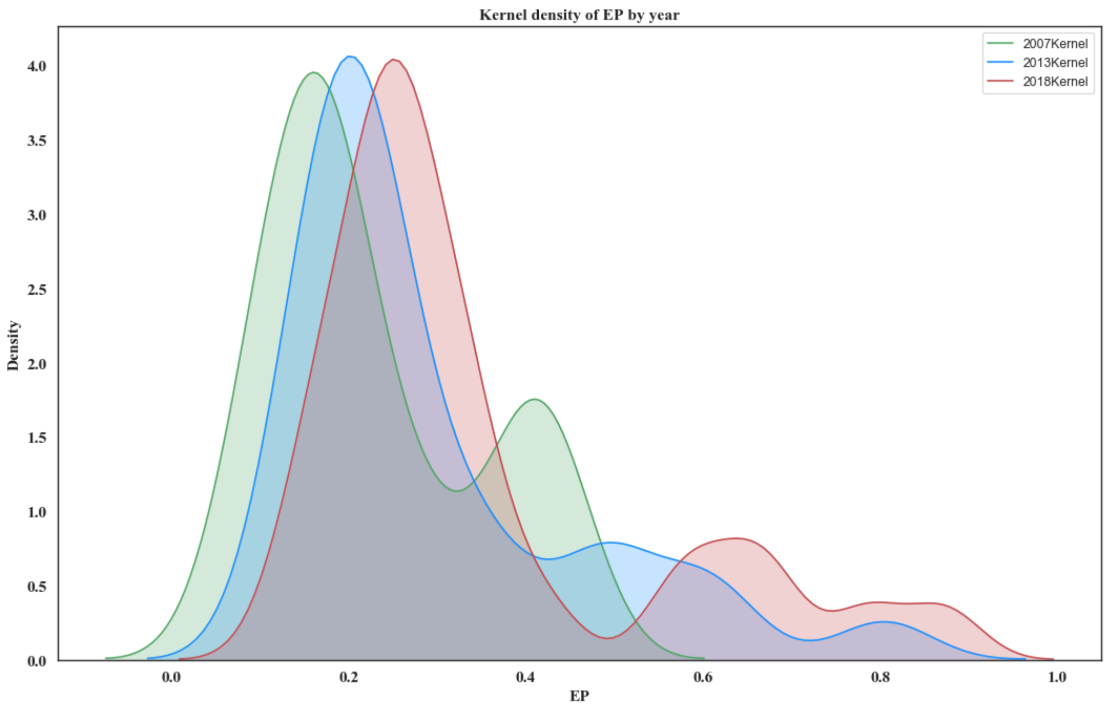

Figure 1. Kernel density estimation of urban residential energy consumption.

4.1.2. Regional Inequalities

Figure 2 shows the geographical distribution of urban residential energy consumption in both aggregate and per capita terms, thereby revealing its inter-provincial differences. For simplification of comparison, URE and Per capita URE are divided into five groups. Figure 2a,b shows the spatial distribution of total URE in China. Guangdong and Shandong remain the largest two consumers in 2007 and 2018. Despite the significant differences between provinces, the spatial distribution pattern of residential energy consumption has not changed much from 2007 and 2018; in other words, most provinces remain in the same cohort.

Figure 2c,d shows URE per capita in 2007 and 2018, respectively. It can be seen that China's provinces display significant differences in per capita URE. Specifically, per capita URE in northern provinces is larger than that of southern provinces. Judging from Figure 2 there are prominent unbalanced distribution characteristics of residential energy consumption in urban China.

Since different provinces show distinct differences in residential energy consumption, it is necessary to quantify the degree of inequality and analyze its changes over time. Given the comparability of different provinces, this paper uses URE per capita to measure the inequality of URE across China's provinces. Based on Equations (3)–(5), we calculate three inequality indicators of EP. The indexes of Gini, GE_1, and GE_0 during 2007–2018 are shown in Figure 3.

As shown in Figure 3, the three inequality indexes display a similar changing trend. They gradually increased from 2007 and 2011 and then decreased during 2011–2018, which suggests the inter-provincial URE inequality increases first and then decreases. The Gini coefficient is almost two times greater than the other two inequality indicators. The largest Gini coefficient of 0.306 was reported in 2011, indicating a 9.3% increase compared with the 2007 level. By contrast, it presents a 10% decline after 2011. Overall, the change rate of the Gini coefficient between 2007 and 2018 is less than 1%, showing that the regional disparities of residential energy consumption in urban China have not been significantly eased.

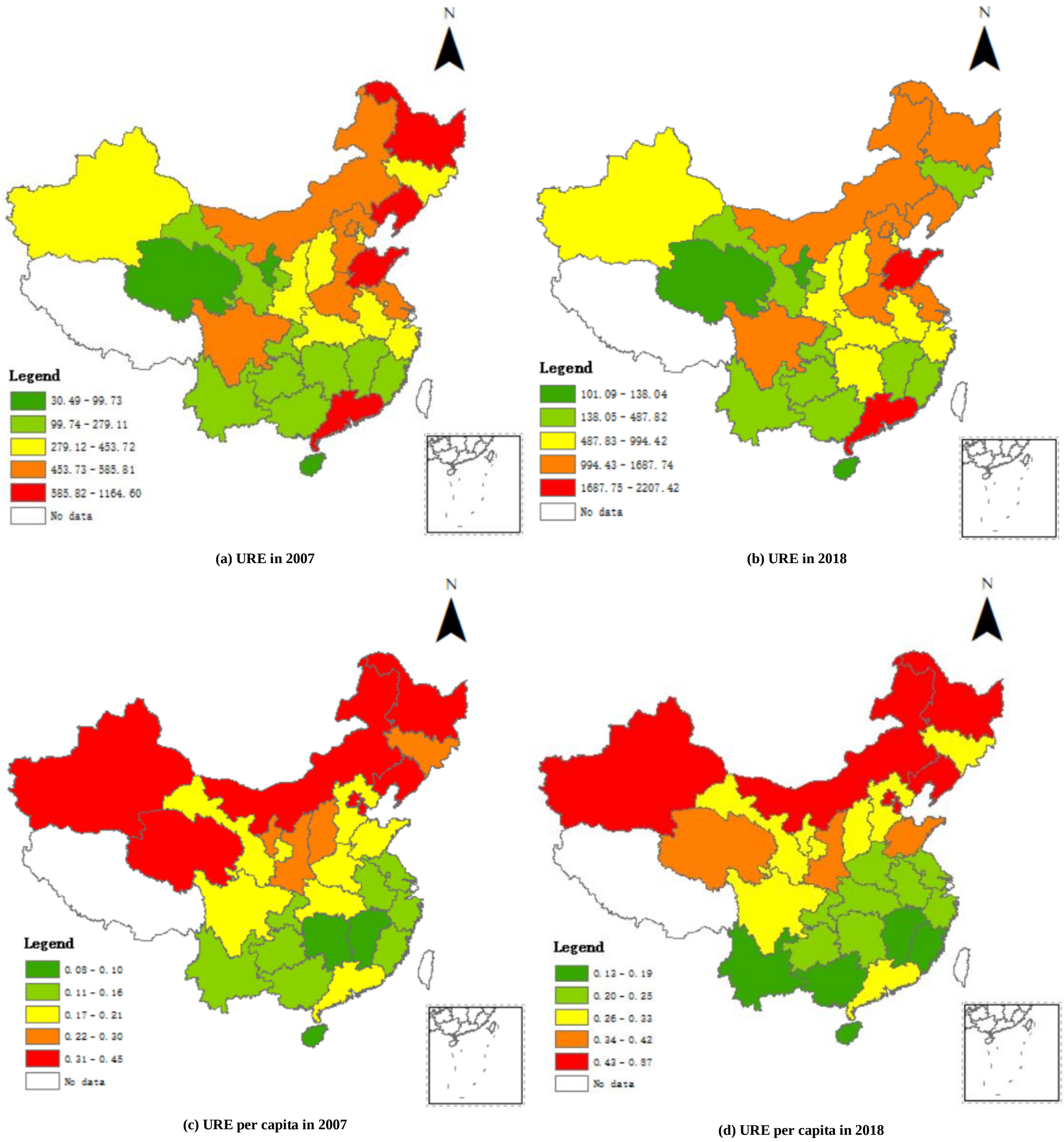

Figure 2. Spatial distribution of URE and Per capita URE in 2007 and 2018.

4.2. Analysis of the Influencing Factors of URE through GDIM Decomposition

4.2.1. National Decomposition Results

Based on Equations (6)–(17), this paper utilizes the GDIM model to examine the factors driving the changes in urban residential energy consumption. The variation of URE is decomposed into the effects of eight factors. Figure 4 shows the national decomposition results in 11 sub-periods. It can be seen that URE increases in 10 sub-periods except for the period 2012–2013. The largest increment of 2.55×10^{-7} tons was reported in 2009–2010, while URE decreased by 1.41×10^{-7} tons during 2012–2013.

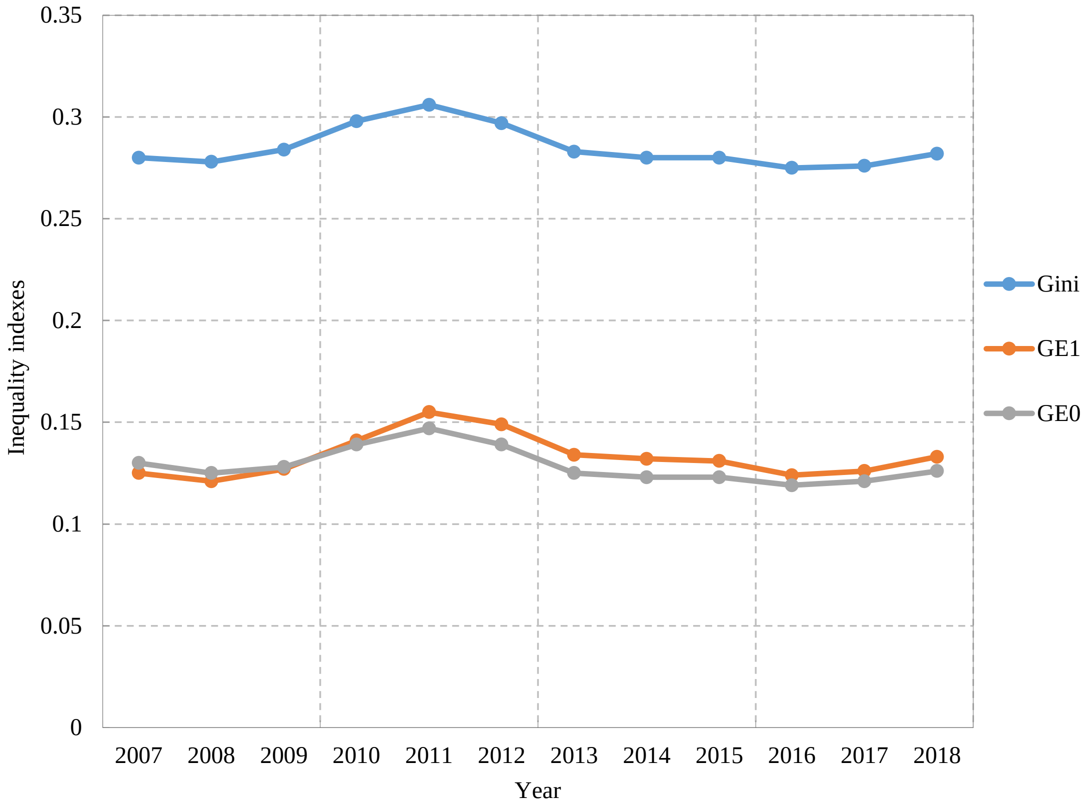

Figure 3. The inequality indexes of urban residential energy consumption among China's provinces.

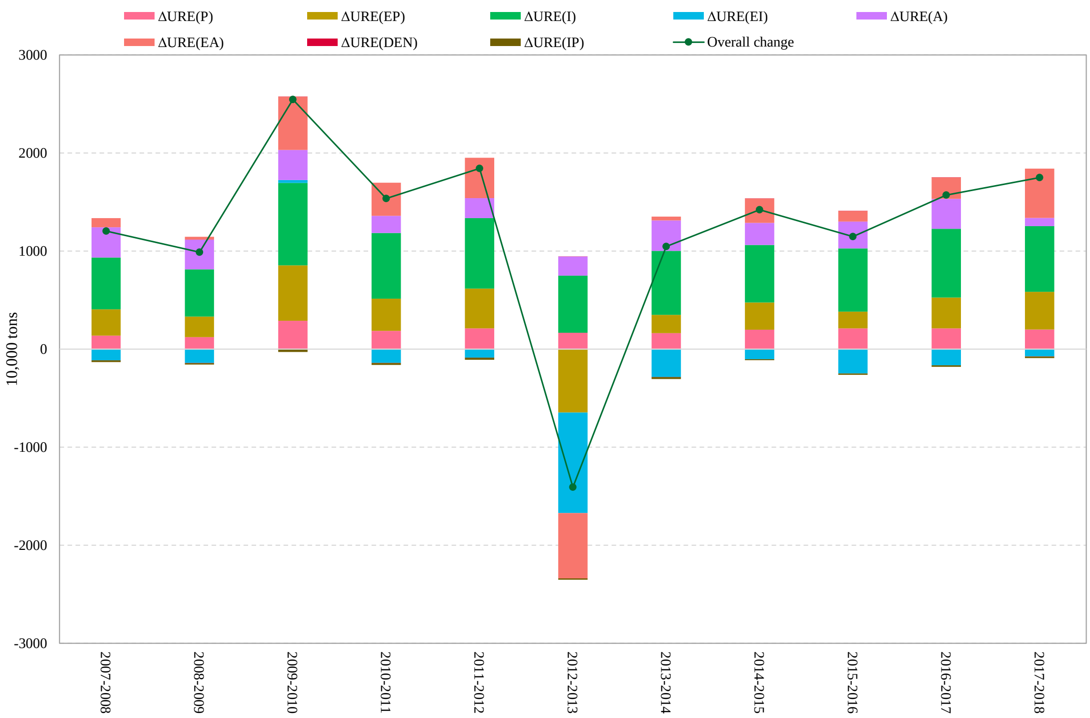

Figure 4. Decomposition results of urban residential energy consumption in China (unit: 10,000 tons). Note: The population effect (ΔURE_P); income effect (ΔUR_{EI}), residential area effect (ΔURE_A), per capita energy use effect (ΔURE_{EP}), energy intensity effect (ΔURE_{EI}), per unit area energy consumption (ΔURE_{EA}), per capita income effect (ΔURE_{IP}), and residential density effect (ΔURE_{DEN}).

As shown in Figure 4, the largest positive influencing factor is the income effect, leading to an average annual increase of 6.43 $\times$ 10^{-6} tons in urban residential energy consumption. That means the increase in urban residential energy consumption is primarily caused by residential income increase. The increase in income will promote more household consumption. In addition, the residential area effect and population effect are also important in explaining the increase of URE in all sub-periods, with an average annual contribution of 2.44 $\times$ 10^{-6} tons and 1.91 $\times$ 10^{-6} tons, respectively. Specially, the per capita energy use effect and per unit area energy consumption effect contribute to increasing URE except for the period 2012–2013.

Figure 4 presents that the energy intensity effect plays a significant role in reducing URE during all sub-periods. Its cumulative emission reduction from 2007 to 2018 was 2.14 $\times$ 10^{-6} tons. In this paper, residential energy intensity is represented by the amount of energy needed to obtain a unit of income. This finding indicates that less residential energy is required to achieve income growth for urban residents. Energy utilization efficiency has been significantly improved.

By contrast, per capita income has a small effect on decreasing URE, with an average annual contribution of 1.7 $\times$ 10^{-5} tons. As people's income increases, their energy-saving awareness is also getting stronger. Energy-saving behaviors are largely publicized in economically developed areas. The cumulative reduction in URE due to the residential density effect is only 4.57 tons, indicating the negative effect of residential density is minor. This is because residential density in China's urban areas shows little change over time; it is around 20 square meters per capita during 2007–2018.

4.2.2. Provincial Decomposition Results

To reveal the provincial differences, we also decompose the variation of URE in different provinces. Figure 5 presents the GDIM decomposition results of URE in 29 provinces. The variations in URE during 2007–2018 in these provinces are depicted on the secondary ordinate axis of Figure 5. It is found that, during 2007–2018, URE increase in all provinces. The biggest increase of 1.33 $\times$ 10^{-7} tons is recorded in Shandong, followed by Guangdong (1.04 $\times$ 10^{-7} tons), Inner Mongolia (8.49 $\times$ 10^{-6} tons), and Jiangsu (8.22 $\times$ 10^{-6} tons). As shown in Figure 5, there are significant regional differences in the effect of each factor on URE changes. On the whole, the income effect is the major contributor to URE growth in most provinces, while energy intensity and per capita income are the main negative contributors.

Among the eight effects, the income effect is the largest negative contributor of URE in all provinces, indicating that income growth has significantly contributed to the increase of URE. The increase in disposable income has largely contributed to consumption growth, thereby leading to increasing URE. The average contribution is 2.78 $\times$ 10^{-6} tons, which is significantly bigger than other provinces. There are great differences in the impact of income on URE in different provinces. Specifically, the group of provinces with the largest contribution values includes Guangdong (7.09 $\times$ 10^{-6} tons), Shandong (6.49 $\times$ 10^{-6} tons), and Liaoning (5.16 $\times$ 10^{-6} tons). Specially, Hainan reports the least contribution of 29 tons from 2007 to 2018. That means income increase leads to little change in URE in Hainan; in other words, URE is minimally affected by disposable income fluctuations.

Figure 5 shows that per capita energy use also has an important impact on increasing URE except for Qinghai and Jilin, with a cumulative increase of 3.34 $\times$ 10^{-7} tons. Specially, during 2007–2018, Shandong has the largest increase in URE caused by the per capita energy use effect. Indeed, Shandong has a large population, and the increase in personal consumption can easily lead to a large increase in total energy consumption. In addition, the contribution of the per capita energy use effect is also large in provinces such as Jiangsu (2.34 $\times$ 10^{-6} tons), Guangdong (2.41 $\times$ 10^{-6} tons), Heilongjiang (2.61 $\times$ 10^{-6} tons), and Inner Mongolia (2.57 $\times$ 10^{-6} tons). By contrast, the contribution is lower than 10 tons in provinces including Yunnan, Ningxia, Guangxi, and Fujian.

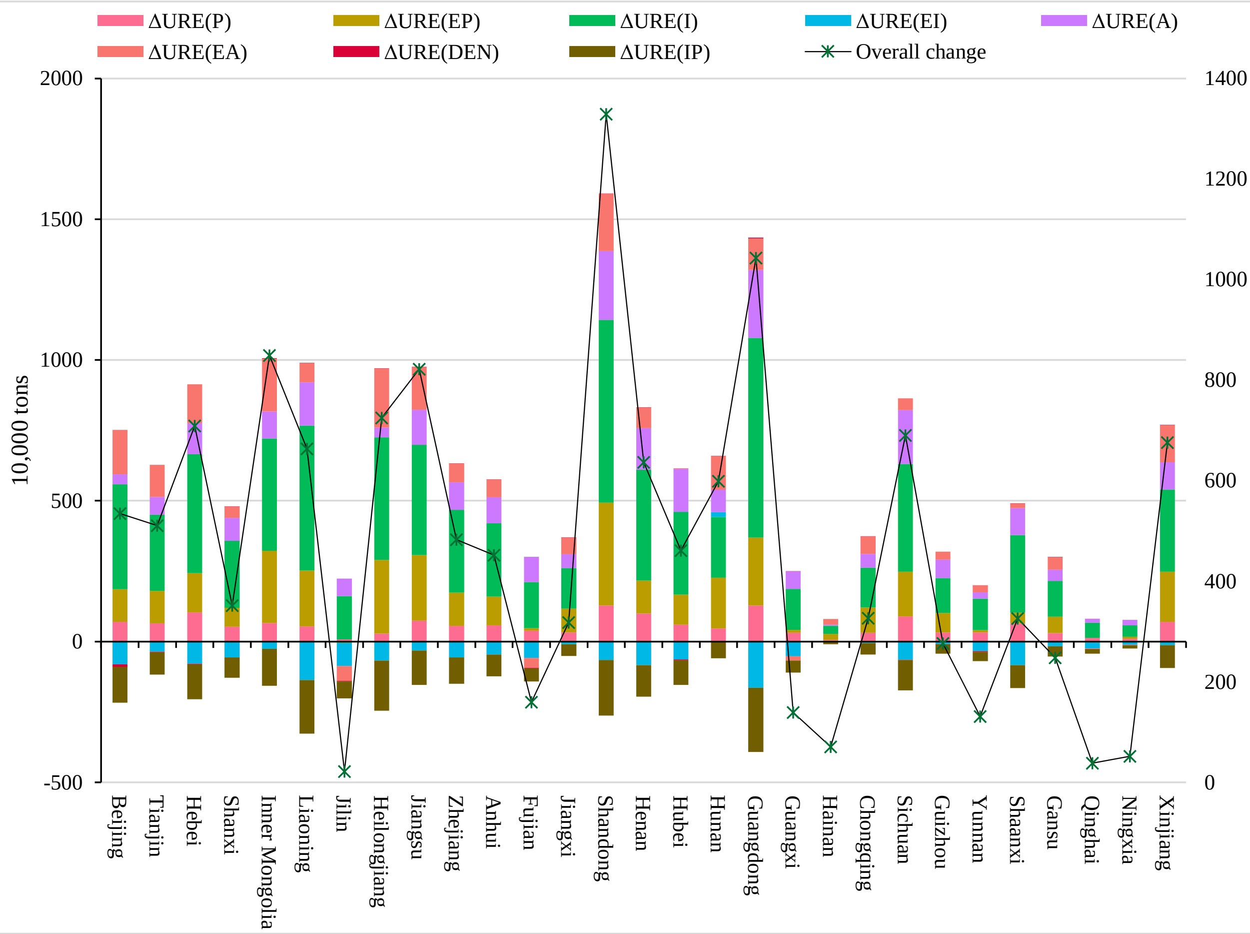

Figure 5. Decomposition results of urban residential energy consumption in 29 provinces (unit: 10,000 tons). Note: The population effect (ΔURE_P); income effect (ΔUR_{EI}), residential area effect (ΔURE_A), per capita energy use effect (ΔURE_{EP}), energy intensity effect (ΔURE_{EI}), per unit area energy consumption (ΔURE_{EA}), per capita income effect (ΔURE_{IP}), and residential density effect (ΔURE_{DEN}).

This paper discusses the impacts of residential area (both in absolute and relative terms) on URE over the period 2007–2018. As shown in Figure 5, the residential area effect leads to increasing URE in all provinces, with an average contribution of 9.0×10^{-5} tons. Obviously, the influences of the residential area effect show distinct differences among individual provinces. The maximum contribution is recorded in Shandong (2.44×10^{-6} tons), while the lowest contribution is reported by Hainan (2.79×10^{-4} tons). In addition, per unit area energy consumption also has a positive influence on URE in most provinces except for five provinces, i.e., Jilin, Fujian, Guangxi, Qinghai, and Ningxia. In most provinces, the increase in per unit area energy consumption results in larger URE. Its average contribution is up to 7.0×10^{-5} tons among 29 provinces. Specifically, the changes in per unit area energy consumption led to the largest increase in URE in Heilongjiang (2.1×10^{-6} tons), followed by Shandong (2.03×10^{-6} tons) and Inner Mongolia (1.88×10^{-6} tons).

The contribution of population is positive in all provinces, with the largest impact recorded in Guangdong (1.28×10^{-6} tons) followed by Shandong (1.27×10^{-6} tons) and Hebei (1.04×10^{-6} tons). The average contribution reaches 5.4×10^{-5} tons among 29 provinces. That means population has a significant positive effect on URE. Previous studies have shown that population is an important determinant of residential energy consumption [1,9,12]. The increase in population leads to more residential energy consumption in China.

Figure 5 shows that compared with other factors, residential density has relatively little impact on URE in different provinces. The average contribution is 3.7×10^{-3} tons among 29 provinces. The effect of residential density in 12 provinces, such as Beijing, Tianjin, Hebei, etc., is negative, and the total reduction reaches 2.6×10^{-5} tons over the period 2007–2018. That indicates that in these provinces, residential density has made a significant contribution to promoting URE reduction. The impact of residential density in the remaining 27 provinces, such as Zhejiang, Jiangsu, and Shandong, is positive, with a cumulative increment of 1.5×10^{-5} tons, which indicates that residential density changes contribute to increasing URE in these provinces.

In all provinces, the decrease in URE is mainly due to the per capita income effect. As income grows, people's awareness of energy saving becomes stronger. Energy-saving behaviors are more widespread among them. Its cumulative contribution is up to -2.5×10^{-7} tons. The largest reduction in URE caused by the per capita income effect is recorded in Guangdong (2.27×10^{-6} tons), followed by Shandong (1.97×10^{-6} tons) and Liaoning (1.9×10^{-6} tons). By contrast, the smallest reduction is reported by Hainan (9.15 tons).

In addition, the energy intensity effect also plays a major role in decreasing URE in all provinces except Hunan and Hainan, with the total reduction in URE of 1.4×10^{-7} tons. That means in most provinces, energy efficiency improvement leads to decreasing URE. Less URE is required to increase per unit of income level. It can be seen that Liaoning and Guangdong have the largest reductions in URE caused by the energy intensity effect, while the contribution is quite small in other provinces.

4.3. Analysis of the Decoupling Relationship between Urban Residential Energy Consumption and Residential Income

4.3.1. National Analysis

The GDIM decomposition results specify that the residential income effect is the main positive factor of urban residential energy consumption, indicating there is an important coupling relationship between urban residential energy consumption and income growth. What is the dynamic evolution of the nexus between URE and residential income over time? It is of vital significance to study the decoupling effect of URE from residential income growth.

Based on the Tapio decoupling model in Equation (18), Table 3 presents the decoupling state between URE and urban residential income in urban China in 11 sub-periods. As shown in Table 3, three decoupling states, i.e., weak decoupling, strong decoupling, and expansive negative decoupling, occur over the study period. Specially, China's URE changes from weak decoupling during 2008–2009 to expansive negative decoupling during 2009–2010, which is due to the economic recession caused by the financial crisis in 2008. The increase rate of URE becomes larger than that of residential income. However, after 2010, URE displays weak decoupling with urban residential income. This is because the growth rate of residential income exceeds that of URE. What is more, they even display a strong decoupling relationship in 2012–2013. This is a favorable signal, indicating a strong decoupling trend. However, from 2013 to 2018, the decoupling relationship between them becomes stable and it remains at weak decoupling.

4.3.2. Provincial Analysis

Different provinces in China show significant differences [37]. When considering spatiotemporal heterogeneity, Table 4 presents the decoupling state of URE in China's 29 provinces in terms of different sub-periods. In detail, given the Five-Year Plan in China, the research period has been divided into three sections (i.e., 2007–2010, 2011–2015, and 2016–2018), which belong to the eleventh, twelfth, and thirteenth Five-Year Plans, respectively. It is found that in most provinces, the decoupling relationship between URE and residential income shows distinct changes over time. However, in three sub-periods, there are always three decoupling states among different regions, i.e., weak decoupling, expansive negative decoupling, and strong decoupling.

Table 3. National decoupling states in different sub-periods.

Period	ΔURE/URE	ΔI/I	β_{E-I}	State
2007–2008	0.100	0.131	0.763	WD
2008–2009	0.075	0.109	0.683	WD
2009–2010	0.179	0.172	1.040	END
2010–2011	0.091	0.119	0.770	WD
2011–2012	0.100	0.116	0.865	WD
2012–2013	−0.070	0.093	−0.753	SD
2013–2014	0.056	0.105	0.532	WD
2014–2015	0.072	0.088	0.814	WD
2015–2016	0.054	0.091	0.590	WD
2016–2017	0.070	0.094	0.749	WD
2017–2018	0.073	0.083	0.881	WD

Notes: WD indicates weak decoupling; SD denotes strong decoupling; END represents expansive negative decoupling.

Table 4. Provincial decoupling states during 2007–2018.

Provinces	2007–2010	2011–2015	2016–2018	2007–2018
Beijing	WD	WD	WD	WD
Tianjin	WD	WD	WD	WD
Hebei	END	WD	WD	WD
Shanxi	END	WD	SD	WD
Inner Mongolia	END	SD	END	WD
Liaoning	WD	WD	WD	WD
Jilin	END	SD	WD	WD
Heilongjiang	END	SD	END	WD
Jiangsu	WD	WD	END	WD
Zhejiang	WD	WD	WD	WD
Anhui	WD	WD	END	WD
Fujian	WD	WD	WD	WD
Jiangxi	WD	WD	END	WD
Shandong	END	SD	END	WD
Henan	WD	WD	END	WD
Hubei	WD	WD	END	WD
Hunan	END	END	WD	END
Guangdong	WD	WD	WD	WD
Guangxi	WD	WD	SD	WD
Hainan	END	WD	WD	END
Chongqing	WD	END	WD	WD
Sichuan	WD	WD	WD	WD
Guizhou	END	WD	WD	WD
Yunnan	WD	WD	WD	WD
Shaanxi	WD	WD	WD	WD
Gansu	WD	WD	END	WD
Qinghai	SD	WD	WD	WD
Ningxia	WD	WD	SD	WD
Xinjiang	END	WD	WD	WD

Notes: WD indicates weak decoupling; SD denotes strong decoupling; END represents expansive negative decoupling.

During 2007–2010, URE shows weak decoupling in 18 provinces. It is worth noting that only Qinghai presents strong decoupling between URE and residential income. However, the remaining 10 provinces including Hebei, Shanxi, and Inner Mongolia have expansive negative decoupling during 2007–2010, indicating the growth rate of URE is higher than that of urban disposable income in these provinces. The development trend is not conducive to decouple income growth from URE.

Weak decoupling is still the dominant state during 2011–2015, which is recorded in 23 provinces. Table 4 indicates that only two provinces (i.e., Hunan and Chongqing) show expansive negative decoupling in 2011–2015, which is a promising development trend. In addition, the number of provinces showing strong decoupling increases to four, including Inner Mongolia, Jilin, Heilongjiang, and Shandong.

As shown in Table 4, 17 provinces present weak decoupling in 2016-2018. In addition, expansive negative decoupling occurs in more provinces, and the decoupling process of URE in these provinces becomes worse relative to the previous period 2011–2015. By contrast, the number of provinces presenting strong decoupling sees little change, which covers Shanxi, Guangxi, and Ningxia.

Over the study period 2007–2018, there are only two decoupling states among different areas. Almost all provinces present weak decoupling except for Hunan and Hainan with expansive negative decoupling, which shows that the decoupling process of URE in Hunan and Hainan lags behind other provinces. There is no province showing strong decoupling. More effort should be made to promote the decoupling between URE and residential income growth in China.

The combined national and provincial analysis has shown some detailed evidence concerning the relationship between URE and residential income during 2007–2018. On the whole, most provinces are in weak decoupling during the study period, and there is only a limited number of provinces showing strong decoupling, but some provinces even present expansive negative decoupling. China is still in the stage of rapid urbanization, and it is necessary to take measures to speed up the construction of energy-saving cities and promote the saving of household energy consumption.

5. Conclusions and Policy Implications

This paper examines the spatiotemporal patterns and influencing mechanism of urban residential energy consumption in China, in the light of Kernel density estimation, inequality measures, GDIM decomposition, and the decoupling model. In detail, Kernel density estimation is employed to reveal the distribution dynamic evolution of URE; meanwhile, three inequality indexes are utilized to measure the regional differences in residential energy consumption. Then, the GDIM model is utilized to study the determinants of URE changes. In addition, we apply the Tapio decoupling index to investigate the decoupling process of URE. The traditional index decomposition analysis (IDA) methods such as the LMDI decomposition have several deficiencies. For example, the decomposition results are overly dependent on the initial factorial identity expressed by the multiplication of all factors. Due to the interdependence of factors, different factorial identities will lead to different results. In addition, it is impossible to consider multiple absolute quantitative variables simultaneously in the decomposition equation, such as income and population. As a novel IDA approach, the GDIM decomposition can overcome the said deficiencies, and it integrates multiple influencing factors and provides a fuller understanding of the influence mechanism of URE. Specifically, URE changes are attributed to the contributions of eight factors, including three absolute indicators and five relative indicators. Specifically, the proposed methodology is a universal approach that can be applied to the urban residential sector in any country.

The empirical results are as follows. First, the Kernel density estimation and inequality indicators are applied to reveal the spatial-temporal heterogeneity of China's urban residential energy consumption during 2007–2018. The results show the inter-provincial URE presents a significant agglomeration effect; the interprovincial inequality in URE increases and then decreases during the study period. Then, using the GDIM decomposition, this paper decomposes the changes in URE into eight factors, including the population effect, income effect, residential area effect, per capita energy use effect, energy intensity effect, per unit area energy consumption, per capita income effect, and residential density effect. The results specify that all three absolute indicators positively influence URE. Among the five relative indicators, only per capita energy use and per unit area energy consumption have positive effects on URE. From the national aspect, the income effect plays a major role in increasing URE. Besides, the effects of per capita energy use and per unit area energy consumption, residential area effect, and population are also important in leading to the increase in URE. By contrast, energy intensity is the main factor decreasing URE, while the negative impacts of residential density and per capita income are relatively small. From the provincial aspect, the residential income effect has the greatest positive influence on URE. The other four factors, including population, per capita energy use effect, residential area, and per unit area energy consumption, also play an important role in increase URE. In addition, per capita income and energy intensity are both important in decreasing URE; however, the negative impact of residential density is negligible. The national and provincial decomposition results are quite consistent. The decoupling model indicates that only three decoupling states, i.e., weak decoupling, strong decoupling, and expansive negative decoupling, appear in China during 2007–2018. Specifically, weak decoupling is the dominant state among different regions. Few provinces show strong decoupling, indicating the decoupling between URE and residential income growth in China.

This study contributes to providing informative implications regarding energy conservation in urban residential sector. The results of this research point to the following policy recommendations. (1) Larger residential area leads to more energy demand for lighting, cooling, and space heating. Population agglomeration can effectively reduce residential energy. As the urban population expands, there is a need to enhance urban compact development, which is helpful to the intensive use of energy. (2) It is supposed to reduce energy use per unit of residential area. In detail, it is important to construct public air-conditioning and heating facilities. Besides, there is a need to improve space-heating efficiency and reduce thermal loss in heating pipes. (3) It is necessary to reduce residential energy consumption per capita. Urban residents' energy-saving awareness should be enhanced. On the one hand, urban residents should choose energy-saving behaviors such as low-carbon travel which helps decrease traffic energy use. On the other hand, measures should be undertaken to decrease housing energy use, such as using more energy-saving household appliances and reducing resource waste. (4) Income growth contributes the most to increasing residential energy consumption, and it is necessary to achieve the decoupling between them by decreasing household energy use required per unit of income growth. Household energy use efficiency should be improved. Natural gas has higher thermal efficiency and fewer pollution emissions compared with other fossil fuels. China's energy revolution will inevitably promote the transformation of the household energy mix. Natural gas is expected to become the major primary energy source of the residential sector.

Due to data availability, this paper does not consider the indirect residential energy consumption, which accounts for a large proportion of energy consumption in the residential sector. Households not only use energy in a direct way (natural gas, electricity, and fuel, etc.), but also in an indirect way (embedded in services and the production, consumption, and disposal of goods), which is highly related with other sectors. Therefore, it is necessary to study indirect residential energy consumption. In addition, this paper only focuses on the urban residential sector. In fact, the rural residential sector deserves further research. The future study can be conducted in other sectors or countries. Besides, it is suggested to address the issue of how to reduce household energy consumption from the perspectives of consumer psychology, consumer behavior, and consumption habits by using micro-level data.

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