Influencing Factors Analysis on Provincial Difference of Rural Energy Efficiency in China Employing Super Efficiency SBM Model and Global Malmquist-Luenberger Index

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Research Article

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Influencing factors analysis on provincial difference of rural energy efficiency in China employing super efficiency SBM model and Global Malmquist-Luenberger Index

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Abstract

Given the current circumstance of increasingly severe resource and environmental deterioration, the progress of Chinese rural energy efficiency has a remarkable impression on Chinese future high-quality development. Energy consumption in rural areas accounts for a considerable proportion, so it is imperative to make a specific and accurate assessment of rural energy efficiency. This paper abandons the traditional method of regional division and separates China into eight economic zones. First of all, this paper applies Super-SBM model to calculate the rural energy efficiency and constructs a Global Malmquist-Luenberger (GML) Index based on 2008-2018 panel data. Subsequently, GML is decomposed into technical efficiency change index (GMLEC) and technological progress change index (GMLTC) to analyze green total-factor productivity (GTFP) in rural areas. Eventually, the GML and its decomposition terms of eight economic zones are explained by practicing a cumulative multiplication method from 2008 to 2018. The consequences of employing panel data of

region prove that: (1) There is a severe regional imbalance of Chinese rural energy efficiency. (2) The rural energy efficiency in the northwest and southwest (western region) is higher than the Middle Yangtze River and the Middle Yellow River (central region). (3) GMLTC has a significant impact on GTFP.

Keywords: CO_2 emissions; eight economic zones; rural energy efficiency; regional imbalance; Super-SBM; Global Malmquist-Luenberger Index

1. Introduction

With the advancement of the economy and technology, China has constantly shifted from high-speed development to high-quality development. Policymakers continuously pay attention to the significance of sustainable development and have formulated enforceable carbon reduction tactics and targets. China is not only a developing country but also a predominantly agricultural country in the traditional sense. Rural areas account for a large proportion of the country, so it is imperative to make a specific and accurate assessment of energy efficiency in Chinese rural areas. Some scholars have conducted elaborate studies on the sustainable development of energy in China (Ahmad et al., 2021; Benintendi et al., 2020; Lo and Castán Broto, 2019; Rao, 2020; Ren, 2018; Zha et al., 2020).

In recent years, the accelerated evolution of urbanization has led to numerous rustic residents move to cities in China. Inversely, the population of the countryside continues to decrease. **Fig.1** points that the proportion of rural population has diminished from 53 percent in 2008 to 40 percent in 2018, with an average annual drop speed of 2.16 percent. The total rural inhabitants had diminished from 704 million in 2008 to 564 million in 2018. According to Chinese energy balance table in the China Energy Statistical Yearbook, the coal consumption of China arrives at 3.821 billion tons and coal output reached 3.524 billion tons in 2017. Furthermore, the terminal consumption is 917 million tons and the rural living consumption is 80.386 million tons. Rural living

consumption accounts for 8.77% of the final consumption and 2.1% of the total consumption. The oil products utilized in rural residential energy utilization are principally liquefied petroleum gas (LPG) and diesel oil. The consumption of LPG was 17.9559 million tons in 2017, and the terminal consumption of rural livelihood was 8.0328 million tons, which accounts for 16.7 percent of the terminal consumption. The rural diesel consumption is 3.578 million tons, exceeding the urban diesel consumption 3.1516 million tons. Chinese natural gas consumption is 186.496 billion cubic meters in 2017. Surprisingly, rural terminal consumption is only 268 million cubic meters, but urban terminal consumption is 41.761 billion cubic meters. Overall, rural energy consumption displays the following distinct characteristics: (1) In general, the total amount of rural energy consumption is tremendous. (2) The level and structure of energy consumption is significantly inconsistent with various regions. (3) The proportion of coal consumption is enormous. (4) The utilization of electricity, natural gas, and the renewable energy are limited.

Data Envelopment Analysis (DEA) is a non-parametric method, which has been universally adopted to evaluate carbon emission efficiency (Cova-Alonso et al., 2020; Fancello et al., 2020; Mustafa et al., 2020). However, the traditional DEA model ignores radial direction and angle, which affects the slack problem and efficiency measurement accuracy. Therefore, Tone (2001) introduced a slack-based measure (SBM) to accomplish the specific relaxation of input and output in a single-process efficiency

evaluation. This pattern attracted scholars' attention and was extensively implemented in the empirical investigation of energy efficiency and environmental efficiency (Cecchini et al., 2018; Cheng et al., 2020; Guo et al., 2020). To adequately explain the intricacy ranking of effective DMU, Tone (2002) stated the Super-SBM model. Huang and Liu (2020) propose a sustainable hydrogen production scheme combining coal-based hydrogen production with renewable hydrogen production. Zhou et al. (2019) estimates the construction industry's total factor carbon emission efficiency from 2003 to 2016 by applying Super-SBM DEA.

With the deepening of the research, some scholars are motivated to practice Malmquist-Luenberger Productivity Index for investigation, including the research of estimating the green total-factor productivity (GTFP) of 34 industrial sectors in China (Wang et al., 2020) and the research of evaluating China's total factor productivity (TFP) of 1999-2012 under the situation of unexpected output (Du et al., 2018). Furthermore, diverse researches on the industries, such as the pulp and paper industry (Yu et al., 2016), light manufacturing industries (Emrouznejad and Yang, 2016a), iron and steel industry (X. Zhu et al., 2019), the logistics industry's efficiency (Long et al., 2020), the efficiency of the green industry at the provincial level (Liu et al., 2021), as well as CO_2 emissions on manufacturing industries (Emrouznejad and Yang, 2016b).The following **Table 1** lists some of previous studies on Chinese environmental efficiency.

Most of the previous investigations concentrate on the industry level. There are still

significant gaps in rural energy efficiency research, so this paper probes the rural energy efficiency and provincial differences in China from 2008 to 2018. For this purpose, we employ the super-efficiency SBM model to measure Chinese rural energy efficiency and utilize the GML to interpret the rural modernization from the two perspectives, specifically technical efficiency index and technological progress index.

This paper's composition is as follows: Section 2 introduces the methodology, including the Super-SBM DEA model and Global Malmquist-Luenberger Index. Section 3 introduces the selection of input-output variables and the result of the static and dynamic investigation. Section 4 discusses the energy efficiency and spatial differences in Chinese rural districts. Ultimately, conclusions and strategy suggestions are expressed in Section 5.

2. Methodology

2.1 Super-SBM DEA model

The DEA model is a non-parametric linear programming process based on decision-making units'(DMUs) pertinent efficiency without specific functional relations. There are two conventional DEA patterns, namely the CCR model and the BCC model. These models base on radial and directional measurements, and the effectiveness of DMUs will be overvalued when there are too numerous inputs or insufficient outputs. In order to settle this puzzle, a slacks-based measure (SBM) model with undesirable

outputs was introduced by Tone (2001). Suppose there are n DMUs, m, S_1, and S_2, represent the inputs, desirable outputs, and unexpected outputs, respectively. Can be represented by vectors as $x \in R^m$, $y^d \in R^{s_1}$, $y^u \in R^{s_2}$; x、y^d、y^u are matrices; $X = [x_1 \cdots x_n] \in R^{m\times n}$, $Y^d = [y_1^d \cdots y_n^d] \in R^{s_1\times n}$, $Y^u = [y_1^u \cdots y_n^u] \in R^{s_2\times n}$;

The production possibility set as Eq.(1):

$$P(x) = \left\{ \left(x, y^d, y^u \right) | x > X\lambda, y^d \le Y^d\lambda, y^u \ge Y^u\lambda, \lambda \ge 0 \right\} \tag{1}$$

Where λ is the non-negative weight vector assigned to input and output, and the SBM model is constructed as follows:

$$\min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d} + \sum_{l=1}^{s_2}\frac{s_l^u}{y_{l0}^u} \right)} \tag{2}$$

$$\begin{cases} x_{i0} = \sum_{j=1}^{n} x_{ij} l_j + s_i^- \\ y_{r0}^d = \sum_{j=1}^{n} y_{rj}^d l_j - s_r^d \\ y_{r0}^u = \sum_{j=1}^{n} y_{lj}^u l_j + s_l^u \\ s_i^-, s_r^d, s_l^u, l_j > 0, \sum l_j = 1 \\ i = 1,2,\ldots m; r = 1,2,\ldots S_1; l = 1,2,\ldots S_2 \end{cases} \tag{3}$$

Slack based measure with undesirable outputs divides the DMU into effective DMU and invalid DMU. However, effective DMU cannot be further distinguished. To solve these dilemmas, Tone (2002) offered a Super-SBM DEA model so that the efficiency value of DMU can be more than 1, thus explaining the ranking obstacle of relatively efficient units. In this article, the Super-SBM DEA model with unexpected output is

applied to evaluate rural energy efficiency. The super-SBM model is written as follows:

$$min\sigma = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{ik}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}^d}{y_{rk}^d}+\sum_{l=1}^{s_2}\frac{\bar{y}^u}{y_{lk}^u}\right)} \tag{4}$$

$$\begin{cases} \bar{x} \geq \sum\limits_{\substack{j=1 \\ j\neq k}}^{n} x_{ij}\lambda_j \\ \bar{y}^d \leq \sum\limits_{\substack{j=1 \\ j\neq k}}^{n} y_{rj}^d\lambda_j \\ \bar{y}^u \geq \sum\limits_{\substack{j=1 \\ j\neq k}}^{n} y_{lj}^u\lambda_j \\ \bar{x} \geq x_{ij}, \bar{y}^d \leq y_{rj}^d, \bar{y}^u \geq y_{lj}^u, \lambda_j \geq 0 \\ i=1,2,\ldots m; r=1,2\ldots s_1 \\ l=1,2,\ldots s_2 \end{cases} \tag{5}$$

Where σ represents the objective function, and its efficiency value can be larger than 1, x_{ik}, y_{rk}^d, y_{lk}^u refer to inputs, desirable outputs, and undesirable outputs, respectively. The slackness intricacy can be effectively shunned by utilizing the Super-SBM model with undesirable outputs. Consequently, an authentic evaluation is provided by the model, and DMUs are ordered effective.

2.2 Global Malmquist-Luenberger Index

The Malmquist index is one of the most well-known methods to measure productivity variations. Sten Malmquist (Malmquist, 1953) initially recommended this approach to investigate the fluctuations in consumption over a while. The Malmquist index proposal

had a strong response at that time, but it was unexpected that there was almost no associated investigation for quite an extended time after that. According to (Chung et al., 1997) the ML productivity index from t period to t+1 period can be constructed as Eq.(6):

$$
\begin{aligned}
ML^{t+1} &= \sqrt{\frac{1+\vec{D}_0^{t}(x^t, y^t, b^t; g^t)}{1+\vec{D}_0^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \times \frac{1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; g^t\right)}{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)}} \\
&= \frac{1+\vec{D}_0^{t}\left(x^t, y^t, b^t; g^t\right)}{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \times \sqrt{\frac{1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; g^t\right)}{1+\vec{D}_0^{t}\left(x^t, y^t, b^t; g^t\right)} \times \frac{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)}{1+\vec{D}_0^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)}} \\
&= EC_t^{t+1} \times TC_t^{t+1}
\end{aligned}
\tag{6}
$$

Decompose the ML into Efficiency Change Index (EC) and Technological Progress Index (TC), it makes the Malmquist index method universally utilized in various research domains. The convenience of this method is that it can dodge subjective weighting and has no residual, and it also makes up for the deficiency that the DEA model can only distinguish and scrutinize the efficiency of a particular period through cross-sectional data.

In this essay, employing the GML introduced by Pastor and Lovell (2005) to deliberate rural energy efficiency. Furthermore, Oh (2010) proposed the GML model based on Chung et al. (1997). This investigation constructs a GML index, which can regard GML as the technical efficiency change index (GMLEC) and the technological progress change index (GMLTC). GMLEC refers to the advancement of management systems and resource allocation methods. GMLTC mainly indicates the enhancement of production technologies and manufacturing skills.

The advantage of the GML principally according to the following four circumstances: First of all, GML refers to the equivalent frontier and determines a sole Malmquist index. Furthermore, the computation of efficiency variation still exerts its boundaries, the efficiency values obtained are comparable. Thirdly, the evaluated DMU must be incorporated in the global production possibility set, it does not exist the situation that VRS without solution. Eventually, the reference of each stage is a mutual frontier, which is transitive and multiplicative. According to Oh (2010), the GML index from t to t+1 defined as:

$$
\begin{aligned}
GML_t^{t+1} &= \frac{1+\overset{\mathrm{r}}{S}^{G}\left(x^{t}, y^{dt}, y^{ut}; g_{y^{d}}^{t}, -g_{y^{u}}^{t}\right)}{1+\overset{\mathrm{r}}{S}^{G}\left(x^{t+1}, y^{dt+1}, y^{ut+1}; g_{y^{d}}^{t+1}, -g_{y^{u}}^{t+1}\right)} \\
&= \frac{1+\overset{\mathrm{r}}{S}^{t}\left(x^{t}, y^{dt}, y^{ut}; g_{y^{d}}^{t}, -g_{y^{u}}^{t}\right)}{1+\overset{\mathrm{r}}{S}^{t+1}\left(x^{t+1}, y^{dt+1}, y^{ut+1}; g_{y^{d}}^{t+1}, -g_{y^{u}}^{t+1}\right)} \\
&\times \frac{\left[1+\overset{\mathrm{r}}{S}^{G}\left(x^{t}, y^{dt}, y^{ut}; g_{y^{d}}^{t}, -g_{y^{u}}^{t}\right)\right]/\left[1+\overset{\mathrm{r}}{S}^{t}\left(x^{t}, y^{dt}, y^{ut}; g_{y^{d}}^{t}, -g_{y^{u}}^{t}\right)\right]}{\left[1+\overset{\mathrm{r}}{S}^{G}\left(x^{t+1}, y^{dt+1}, y^{ut+1}; g_{y^{d}}^{t+1}, -g_{y^{u}}^{t+1}\right)\right]/\left[1+\overset{\mathrm{r}}{S}^{t+1}\left(x^{t+1}, y^{dt+1}, y^{ut+1}; g_{y^{d}}^{t+1}, -g_{y^{u}}^{t+1}\right)\right]} \\
&= GMLEC_t^{t+1} \times GMLTC_t^{t+1}
\end{aligned}
\tag{7}
$$

In the Eq.(7), it decomposes GML into GMLEC and GMLTC. If $GMLEC_t^{t+1} > 1$, which signifies that compared with the t period, DMU is closer to the productive frontier in the $t+1$ period; if $GMLTC_t^{t+1} > 1$, it means that DMU has technological progress in the $t+1$ period; if $GML_t^{t+1} > 1$, it implies that the rural energy efficiency is progressing. This article employs the GML productivity index to measure the dynamic efficiency of energy efficiency in rural regions of China and discover the factors that can control energy efficiency.

3. Result

3.1 Indicators and data

The research intention of this article is the rural districts of 30 provinces in China. The input-output data from 2008 to 2018 are elected as the investigation individuals. According to the data's availability and representativeness, the relevant data come from China Statistical Yearbook (2009-2019), China Energy Statistical Yearbook (2009-2018), China Rural Statistical Yearbook (2009-2019), China Environmental Statistical Yearbook (2009-2019), and provincial statistical yearbooks. The missing data is estimated according to its historical data by applying the moving average method. Furthermore, considering the diversity in rural areas in different regions of China, this essay determines the total output value of agriculture, forestry, animal husbandry and fishery (TOV) as the expected output to measure rural economic growth. Powerfully, we select CO_2 emissions as an unexpected output since the CO_2 data at the provincial level in China needs to be assessed. In order to guarantee the consistency of the data, this article employs the IPCC (2006) to determine the rural CO_2 emissions in various provinces of China. The mathematical calculation formula is as Eq.(8):

$$CO_2 = \sum_{i=1}^{8} \mathrm{CO}_{2,i} = \sum_{i=1}^{8} E_i \times NCV_i \times CC_i \times COF_i \times \frac{44}{12} \tag{8}$$

Where CO_2 is the emission of each province, i represents all kinds of fossil energy, including raw coal, coke, petrol, kerosene, diesel oil, fuel oil, liquefied petroleum gas (LPG), and natural gas. E_i is the consumption of type i energy, NCV is average low

calorific value, *CC* denotes the carbon content of energy, *COF* is the carbon oxidation factor of each energy source, 44/12 describes the mass proportion of carbon dioxide molecules to carbon elements.

Because distinct provinces attach different attention to rural advancement, Chinese rural areas have particular limitations and inconsistent resource environments. This article practices the total number of employees in the primary industry (TNE) as an index of labor input. Regarding the total sown area of crops as the index of land input. Each province's annual standard coal consumption is utilized to reveal the energy input. The terminal consumption in the regional energy balance table of China Energy Statistics Yearbook was transformed into standard coal (10,000 tons) by applying IPCC (2006). The total power of agricultural machinery and rural fixed assets investment are selected to estimate the quantity of capital investment in rural zones, and the investment in fixed assets is determined by the perpetual inventory method. The calculation formula is as Eq.(9):

$$K_{i,t} = I_{i,t} + \left(1-\delta_{it}\right)K_{i,t-1} \tag{9}$$

$K_{i,t}$ signifies the annual capital investment of the i region in t year, $I_{i,t}$ denotes the total fixed asset investment in the t year calculated by the i region at the constant price of the base year. δ_{it} describes the depreciation percentage of the economy. Referring to Zhang et al. (2004) research method, this essay sets δ_{it} as 9.6% and regards 2000 as the base period, divides the rural fixed capital investment by 10% in that year, then

calculates the capital investment in rural areas of each province according to Eq.(9). The relevant input and output indicators adopted in the model are illustrated in **Table 2**. **Table 3** presents statistics descriptions of the input and output variables.

3.2 Static analysis of rural energy efficiency

This investigation aims to explore the reasons influencing the diversity in rural energy efficiency among distinct provinces in China on a broader scale. To avoid the customary and rough division of China in the past, such as East, Central, and West (East, Central, West and Northeast). China is subdivided into eight comprehensive economic zones. Expressly, dividing 30 provinces into eight economic zones following the regional partition principle proposed in the 11th Five-Year Plan (Tibet, Hong Kong, Taiwan, and Macao are excluded because of data availability). These areas and their constituent regions are listed in **Table 4**.

Table 5 explicates the rural energy efficiency value of 2008-2018 in each province and the average value of regional energy efficiency in Chinese eight comprehensive economic zones. The energy efficiency value of Sichuan province is less than 1 only in 2014, and the value of Liaoning province shifts invalid after 2015. Heilongjiang presents a skyward trend, and the efficiency value is surpassed 1 since 2013. On the contrary, Jilin displays a noticeable descending trend, and the rural energy efficiency was less than 1 after 2013. In this article, the energy efficiency values are divided into

three degrees. The most excellent level incorporates the eastern coastal and the southern coastal region. The average rural energy efficiency (φ) is 1.333 and 1.285 from 2008 to 2018, respectively. The next degree covers the northern coastal, the northeast, and the northwest. The most outstanding region is the northern coastal, followed by the northeast and northwest. The φ of three economic zones are 0.974, 0.835 and 0.830, respectively. The Middle Yangtze River, the Middle Yellow River, and the southwest belong to the ultimate level. Guangxi and Sichuan are effective among the five provinces in the southwest of China, and the values of φ are eminent in the third degree. The average value of the Middle Yangtze River dropped to a minimum of 0.426 in 2018, and the rural energy efficiency in Hunan province reduced from 0.679 to 0.356, and the proportion of rural energy efficiency diminished 47.6%. Additionally, the rural energy efficiency contracted by 43.1%, 20.7%, and 28.9% in Hubei, Jiangxi, and Anhui. The Middle Yellow River is the weakest because Shanxi rural energy efficiency is the lowest among all provinces in China, although Shanxi has an inevitable upward trend. All DMUs in the southern coastal areas are effective. Likewise, DMUs of the northern coastal and eastern coastal areas are similar to southern coastal, except for Hebei and Zhejiang. Among the provinces in the northern coastal areas, only Hebei revealed a significant downward tendency. The rural energy efficiency of Hebei has decreased by 45.2% from 2008-2018, with an average annual decline rate of 4.1%. Moreover, only Zhejiang has a significant downward inclination in the eastern coastal. The rural energy

efficiency was reduced from 0.7 to 0.459, a total contraction of 34.5% with an average annual drop of 3.1%. Furthermore, the rural energy efficiency in Chinese coastal areas is relatively significant, achieving the slightest energy input while generating the same output. It indicates that the coastal region's economic progression is excellent, and the technological level is superior. The conclusion is consistent with the results of (H. Liu et al., 2020; Qin et al., 2018; W. Zhu et al., 2019). The rural energy efficiency in the northwest and southwest (western region) is higher than the Middle Yangtze River and the Middle Yellow River (central region), which is different from (H. Liu et al., 2020). **Fig.2** displays the spatial distribution of energy efficiency in various levels of rural districts.

Fig.3 manifests the annual average efficiency of Chinese eight comprehensive economic zones. The coastal areas present a decreasing tendency of energy efficiency from the eastern coastal area, the southern coastal to the northern coastal area. Specifically, it can undoubtedly prove that the northern coastal area's average energy efficiency has an upward trend, and the average efficiency value has progressed by 2.3%. On the other hand, the eastern coastal tends first to rise up and then move down. Moreover, energy efficiency reached a peak of 1.422 in 2011 with an average annual growth rate of 0.41%. The southern coastal regards 2014 as the center, showing twice trend of falling first and then rising. The volatility before 2014 is relatively significant, and the lowest points of the two fluctuations are 1.225 (2012) and 1.263 (2016),

respectively. Inversely, the northwest exhibits twice diverse trends, which first rise and then move down. The highest points of the two fluctuations are 0.933 (2013) and 0.875 (2015). The northeast and the Middle Yangtze River tendency are similar, both of which are in a state of consecutive decline. The distinction is that the northeast began to decrease sharply after 2015, while the Middle Yangtze River declined rapidly after 2014. The rural energy efficiency in these two areas contracted by 12.8% and 21.3%, respectively. The average efficiency of the northeast is lower than the southwest in 2017 and 2018. Furthermore, the southwest presents the tendency of declining at the beginning and rising in later. The rural energy efficiency reached the lowest point of 0.558 in 2014. Then, the southwest has been progressed since 2014 and has overtaken the northeast since 2017. The rural energy efficiency in the Middle Yellow River has been steady, and the fluctuation of average efficiency value is less than 0.05.

The energy efficiency values of northern coastal areas are lower than the eastern coastal and southern coastal because rural heating of northern China in winter will generate a large amount of energy expenditure. Contrasted with the southern provinces, this portion of energy input is necessary for daily life and will result in a tremendous quantity of undesirable output (CO_2 emissions), and the effect on increasing the expected output is negligible. In the northern coastal areas, Beijing, Tianjin and Shandong's rural energy efficiency values are more than 1 during the investigation period. Unfortunately, only the rural energy efficiency of Hebei province is less than 1

with an average of 0.460, this phenomenon is related to the rural energy expenditure in Hebei. The consumption of standard coal increased from 4.653 million tons to 16.055 million tons. **Fig.4** exhibits the energy consumption in the northern coastal. It indicates that the proportion of energy expenditure increased from 36.5% to 58.6% in Hebei. On the one hand, Hebei's economic development is at a disadvantage compared with Beijing and Tianjin. On the other hand, the utilization rate of renewable and clean energy is not significant in rural areas, and low-carbon and energy substitution technologies are relatively underdeveloped. Hebei confronts the overuse of fossil energy, which makes the undesirable output exceed the environment's processing capacity. Hence, diminishing the total energy consumption and promoting the technological level is critical to Hebei's low-carbon energy consumption structure (X. Liu et al., 2020; Qin et al., 2018).

The average energy efficiency of rural areas along the southern coastal and eastern coastal is greater than 1 during the research period, it indicates DMUs are perpetually in an effective state. Initially, the temperatures of the two regions are warmer than the northern coast. Hence, these areas consume relatively less energy on heating in winter. Additionally, the economy of the southern coastal and eastern coastal is relatively developed and technical level is comparatively advanced, which promotes the energy efficiency of the local rural areas. On the contrary, the contrast to previous research is Zhejiang province. Preceding researchers have analyzed Zhejiang's energy efficiency

from rural and urban fields. Therefore, the performance of energy efficiency is preeminent in Zhejiang. The reason is that city regions have performed an outstanding contribution to raising energy efficiency. Conversely, we only explore rural areas' aspects, excluding the influence of city on the outcomes, and conclude that the rural energy efficiency of Zhejiang is relatively poor. This conclusion is different from Feng and Wang (2017). We notice that the rural energy efficiency decreases in Zhejiang province, resulting from output and input joint action. From the input perspective, the gap between urban and rural areas is increasingly widening with the economy's development, rural living situations and social welfare are far inferior to those of urban residents, which leads to a large number of rural labor force flow to urban regions. As a result, the productivity in rural areas is insufficient, and population aging is terrible. From the point of output, Zhejiang has more numerous rural coastal areas, and fishing is the leading industry. As an essential component of agriculture, the fishery has a significant industrialization degree and more frequent machinery utilization rate. Simultaneously, the fishery is deeply dependent on energy and resources and significantly impacts the environment. Consumption of massive resources and energy is the principal reason for numerous undesirable outputs. **Fig.5** reveals that diesel oil and LPG account for a considerable proportion of energy expenditure in the rural of Zhejiang. In general, rural energy types and energy structure lead to the inefficiency of Zhejiang. Policymakers should optimize the energy structure, reduce the energy

consumption needed to obtain each unit of expected output, continually stimulate technological innovation, boost clean energy use, narrow the gap between rural and urban areas, and diminish regional imbalances.

3.3 Dynamic analysis of green total factor productivity in rural areas

The GML and its decomposition items of the eight comprehensive economic zones are displayed in **Table 6**. The GMLEC values of the northern coastal, eastern coastal and southern coastal areas fluctuate around 1. Notably, during the entire investigation period (2008-2018), GMLEC=1 indicates that the rural energy efficiency has been in an effective state in the southern coastal. Additionally, GMLTC dramatically influences GML in southern coastal. Therefore, when GMLTC is more massive than 1, GML is more numerous than 1. Likewise, the eastern and northern coastal have a similar nature, which demonstrates that technological progress is the foremost factor affecting rural energy efficiency in Chinese coastal zones (Feng and Wang, 2017; Ouyang et al., 2021). During the entire research phase, the GMLTC of the northeast was higher than 1. Inversely, only the GMLEC was greater than 1 in 2010-2013. Besides, GML reached a maximum of 1.221 in 2010-2011. GML<1 in the Middle Yangtze River occurs only in 2008-2009 and 2016-2017. The Middle Yellow River has three GML<1, which demonstrates that GTFP is progressing. The average GMLEC of the Middle Yangtze River is 0.965, indicating that this area's rural energy efficiency is ineffective, so the

extension of GTFP chiefly depends on technological progress. Diversely, the average GMLEC of the Middle Yellow River is 1.009. Namely, this region is closer to the productive frontier, so the development of GTFP is the combined effect of technical efficiency change and technological progress. GML, GMLEC, GMLTC in the southwest are all less than 1 in 2008-2009, but all greater than 1 in 2017-2018. It proves that the GTFP in the southwest is promoting. The GTFP of northwest declined in 2008-2011 and extended in 2011-2015. The average GML was 1.020, but GMLEC=0.998<1 in the northwest. Consequently, the improvement in GTFP in the northwest is owing to technological progress. **Table 7** exhibits the dynamic decomposition of rural GTFP in eight comprehensive economic zones. According to Oh (2010), we calculated the GML from 2008 to 2018 by cumulatively multiplying the following Eq.(10):

$$GML^{t-1,t} \times GML^{t,t+1} = GML^{t-1,t+1} \tag{10}$$

The decomposition term of GML is calculated similarly. The trend of GML and its decomposition components in each area are exhibited in **Fig.6.**

According to the Eleventh Five-Year Plan's division method, China is divided into eight major economic zones. **Fig.7a** manifests GML changes in four economic zones: the Southern coastal, Middle Yangtze River, Middle Yellow River and Southwest. Similarly, **Fig.7b** exhibits GML changes in the Northern coastal, Northeast, Eastern coastal and Northwest, respectively. The GML of the four regions manifested similar fluctuations in **Fig.7a**. The GTFP progressed in these four regions from 2008 to 2011

with an average annual expansion of 5.34%, 9.09%, 8.87% and 9.93%, respectively. The four regions touched their peak at the end of the Eleventh Five-Year Plan (2010-2011), and they all had an inevitable downward trend later. The other four economic zones also exposed an analogous change in **Fig.7b**, reaching a peak in 2010-2011 and declining after 2010-2011. The eastern coastal GTFP climbed most active, with an average annual expansion of 7.19%. The northwest has the slowest progress, with an average annual augmentation of 2.43%. The expansion of GTFP points out that the Chinese government attaches great significance to rural energy efficiency and puts forward establishing a new socialist countryside. The contemporaneous frontier shifts towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs. Significantly, **Fig.7** revealed that the GTFP of the southern coastal, the Middle Yangtze River, the Middle Yellow River and southwest economic zones escalated to a new peak in the later period of the Twelfth Five-Year Plan, which increased by 24.92%, 7.53%, 13.20% and 8.41% compared with the previous year. Conversely, the GTFP of the northern coastal, northeast, eastern coastal and northwest decreased during Twelfth Five-Year Plan. At the beginning of the Twelfth Five-Year Plan, the eight major economic zones presented a downward tendency, this phenomenon may be due to the inevitable demand for enormous investment in the initial development stage, accompanied by imperfect technology and low output efficiency. Successfully, the effect of strategy implementation was

demonstrated at the end of the Twelfth Five-Year Plan (2015-2016). The phenomenon of GTFP growth proves that the Chinese government has made more tremendous efforts in promoting rural energy efficiency.

4. Discussion

The innovation of this investigation is that we concentrate on the rural areas of China, and we abandon the traditional method of dividing the east, central and west (east, central, west and northeast) in terms of regional distribution. According to the Eleventh Five-Year Plan's division method, we classify China into eight major economic zones. Moreover, we can discover the similarities and contrasts between regions through a more comprehensive investigation, which can also provide novel ideas for policymakers.

We notice that Chinese rural energy efficiency exhibits a decreasing inclination from coastal to inland areas. On the contrary, the changing trend of GTFP manifests a similar fluctuation shape in the southern coastal, the Middle Yangtze River, the Middle Yellow River and southwest economic zones. Another similar fluctuation is presented in the northern coastal, northeast, eastern coastal and northwest economic zones. If we obey the traditional division process, it will lead to incomplete research and then ignore some conclusions, for example, the general judgment that the western region should expose identical features. Nevertheless, from the consequences of our investigation, the

fluctuation trend of GTFP in southwest and northwest regions is discrepant. Likewise, the trends of GTFP in the eastern coastal and southern coastal are not similar. Additionally, we also notice a significant gap between urban and rural areas in Zhejiang province. The research points out that Zhejiang's rural energy efficiency is not excellent in China, and exists excessive energy consumption, this phenomenon is related to the geographical location, sorts of energy consumption and industrial structure of Zhejiang. The conclusion is distinct from preceding research consequences, but Zhejiang performs more satisfying if the input and output of cities are taken into account (Ouyang et al., 2021). Consequently, it is meaningful to subdivide China into eight economic zones to consider the regional energy efficiency discrepancies. In order to promote Chinese energy efficiency, policymakers should concentrate on rural areas in the future. Paying more attention to the optimization of energy structure and upgrading of industrial structure in rural areas, enhancing the level of science and technology in agriculture, improving the utilization rate of resources in rural areas, reducing the waste of resources, breaking the original urban-rural pattern, and establishing a system of urban-rural integration while minimizing regional imbalances.

One limitation of this paper is that our study only reveals the characteristics of imbalance in China's diverse regions. For future research, we suggest further exploration of spatial interaction and interpreting the interaction mechanism among disparate regions.

5. Conclusion

As we all know, the advancement of a low-carbon economy has become the subject of the eras. We calculate the energy efficiency of rural regions using the Super-SBM model. Besides, construct the GML index, and decompose it into GMLEC and GMLTC, then examine the spatial distribution from the dynamic perspective. This essay abandons the traditional and rough dividing method, excluding the influence of cities and building thorough research of rural energy efficiency in China. The conclusion of this article are drawn as follow:

(1) The eastern and southern coastal areas have more outstanding energy efficiency and resource utilization rate in the eight economic zones. As the pioneer of Chinese Economic Reform and open up, the rural industrial economy is stimulated, and energy consumption has transformed from solving essential heating to clean energy expenditure. Consequently, the rural energy efficiency values are exceeding 1.2 from 2008 to 2018.

(2) The coastal area is subdivided into the northern coast, the eastern coast and the southern coast. With the evolution of the economy and technology, the eastern and southern coasts preserve excellent energy efficiency, and the average energy efficiency is between 1.0 and 1.4. The northern coastal is only slightly better than the northwest and northeast. Although they belong to coastal areas, they exhibit diverse characteristics. Likewise, although the northwest and southwest regions belong to the western of China,

there are remarkable discrepancies in rural energy efficiency and GTFP. Contrasted with the previous studies on energy efficiency, the investigation results about regional imbalances are more impressive, which provides a new idea for policymakers. This kind of investigation idea possesses particular research value and significance.

(3) Research on the spatial distribution of rural energy efficiency reveals regional imbalances and urban-rural gaps in China. As a result, rural resources inequality with cities, and numerous laborers and talents flow to cities. Therefore, it is unavoidable to advance the coordinated development of the regional economy, spontaneously support low energy consumption industries, and actively promote cross-regional exchanges and cooperation.

(4) The decomposition term of GML index reveals that GMLTC contributes more significantly to promoting GTFP than GMLEC. Consequently, policymakers should pay more attention to the elevation of technological advancement.

Ethical Approval

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Consent for publication

Not applicable

Funding

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Consent to Participate

Not applicable

Availability of data and materials

The corresponding data required for emergy value estimation chiefly originates from "Shandong Statistical Yearbook", "China Energy Statistical Yearbook", "China Statistical Yearbook" and the national data website

Authors Contributions

LW: Conceptualization, Validation, Investigation, Writing - Review & Editing.

YZ: Methodology, Software, Formal analysis, Data Curation, Writing - Original Draft.

Competing Interests

The authors declare that they have no competing interests

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Figures

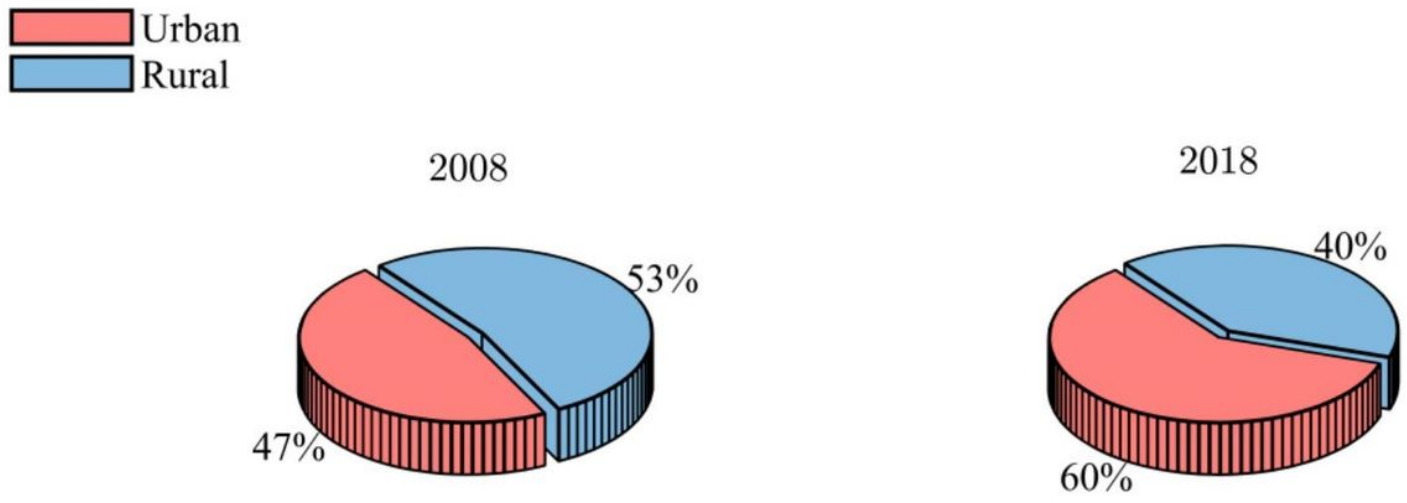

Figure 1

Population changes in urban and rural areas of China.

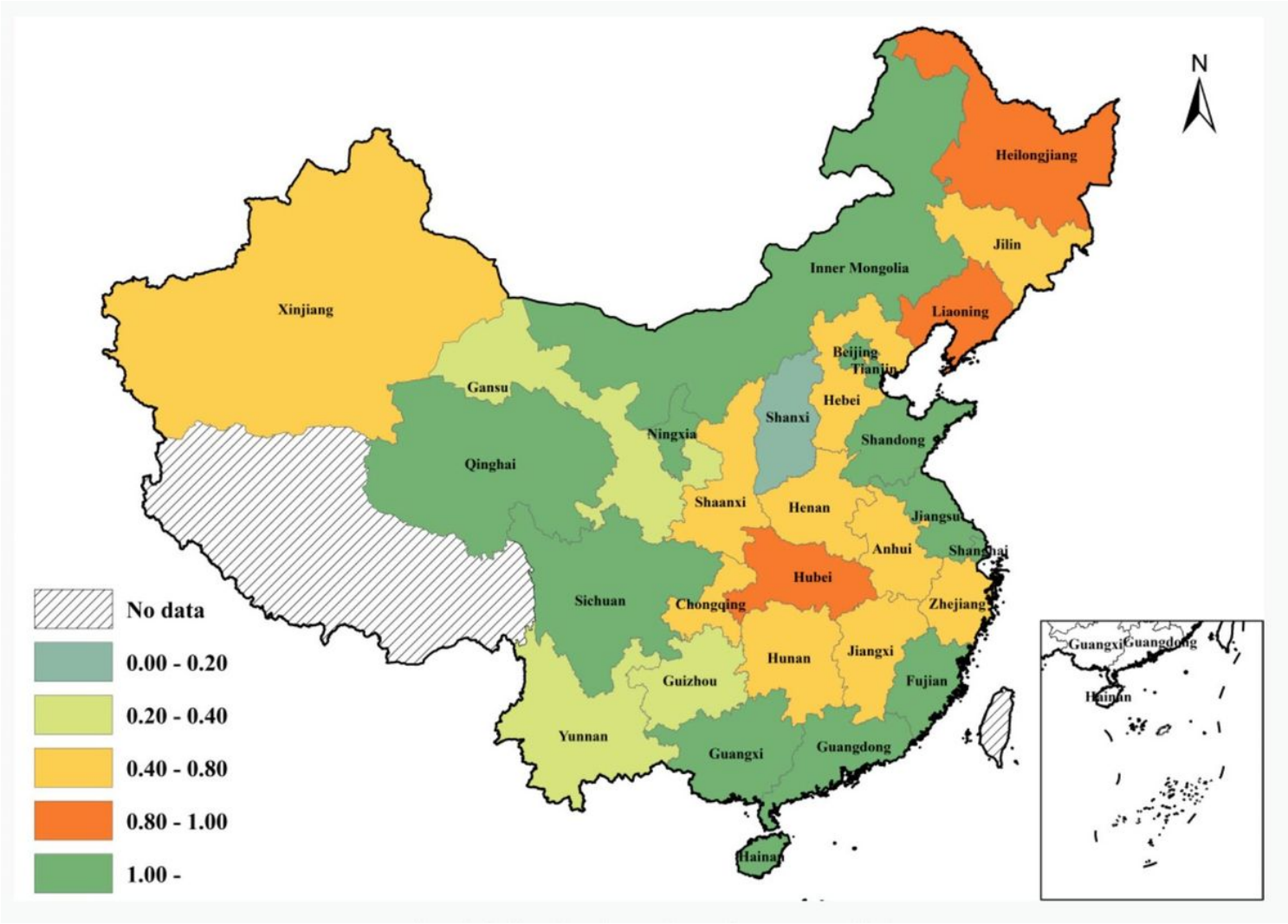

Figure 2

Spatial distribution of rural energy efficiency.

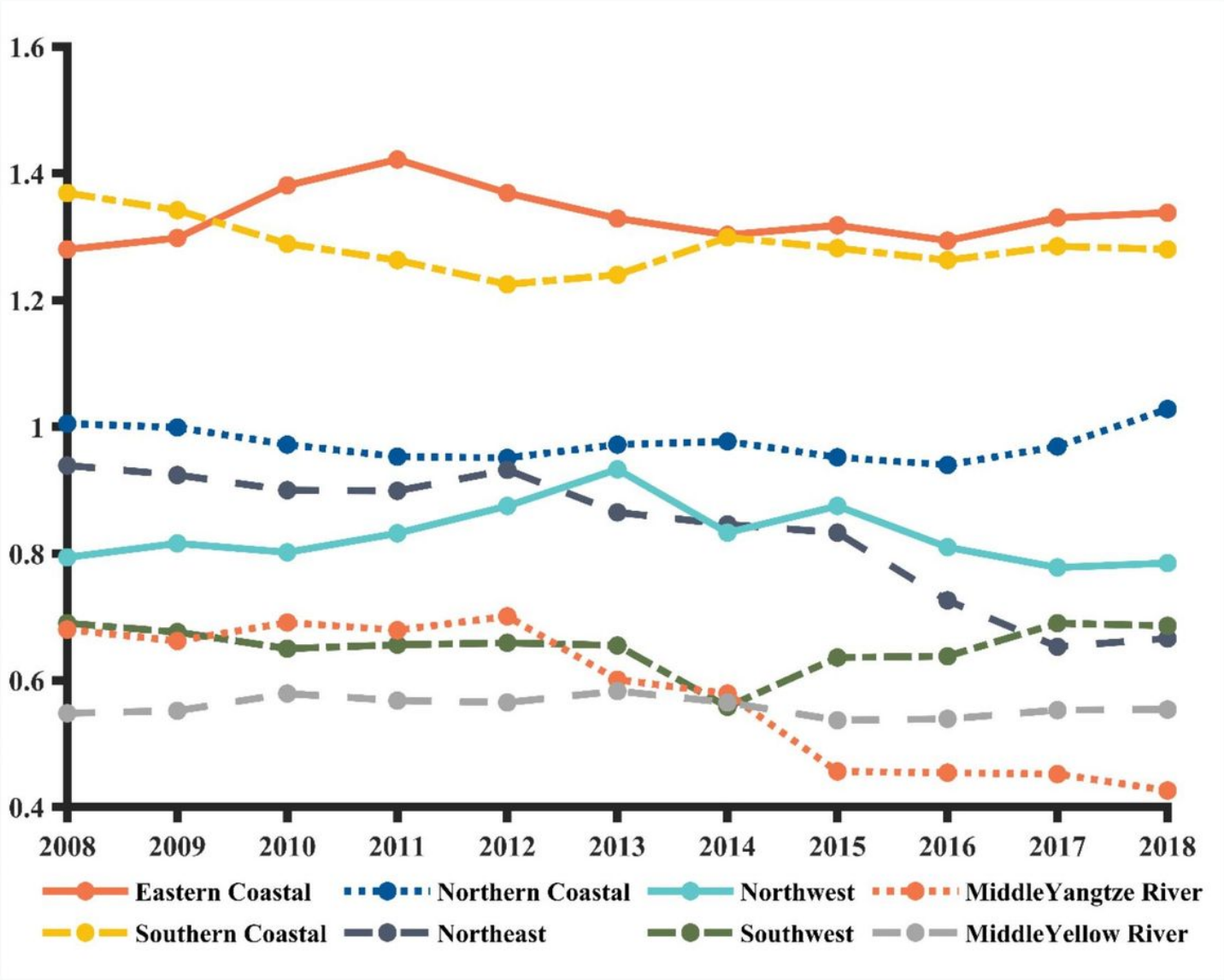

Figure 3

Rural energy efficiency of China's eight comprehensive economic zones from 2008 to 2018.

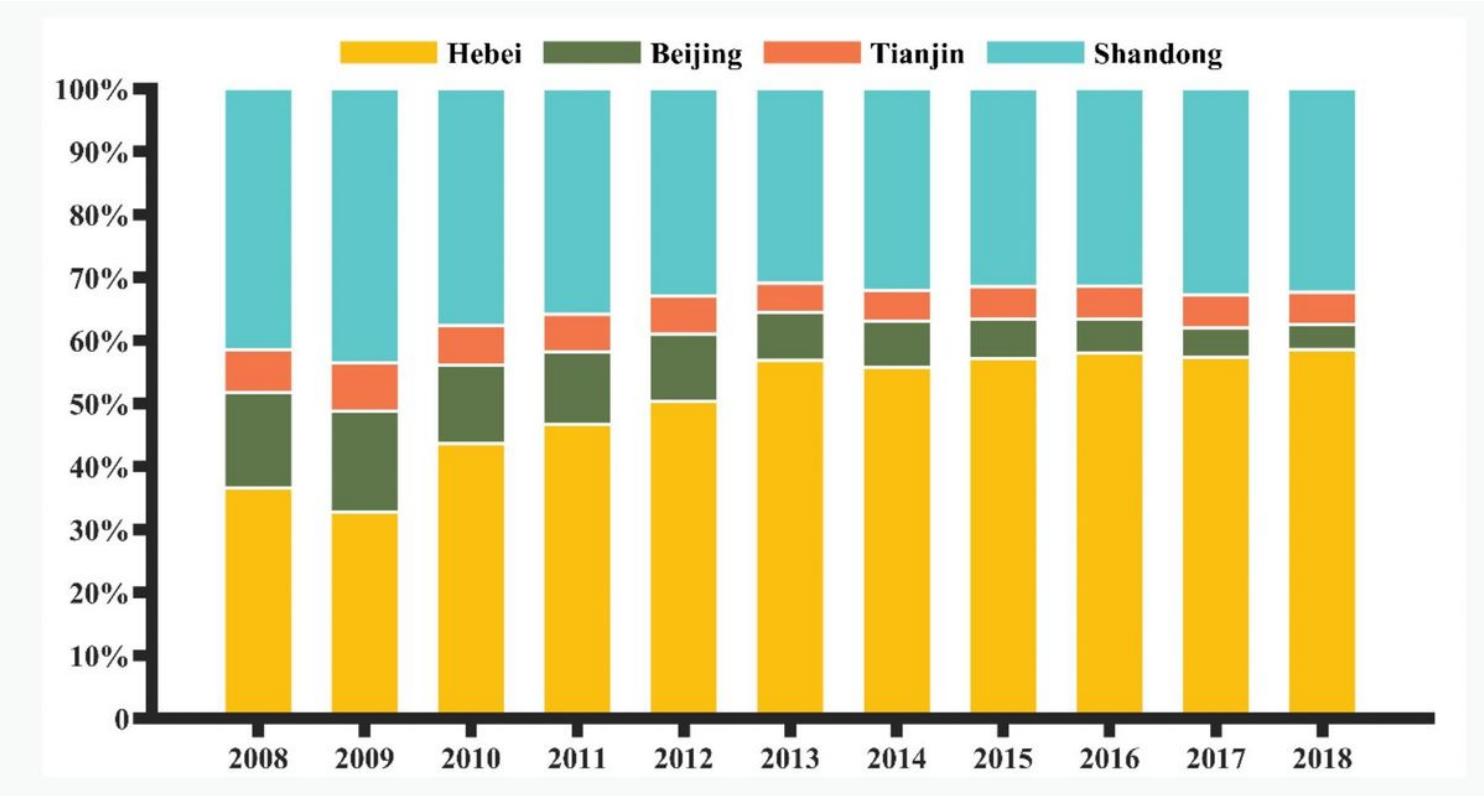

Figure 4

Consumption of standard coal in the northern coastal.

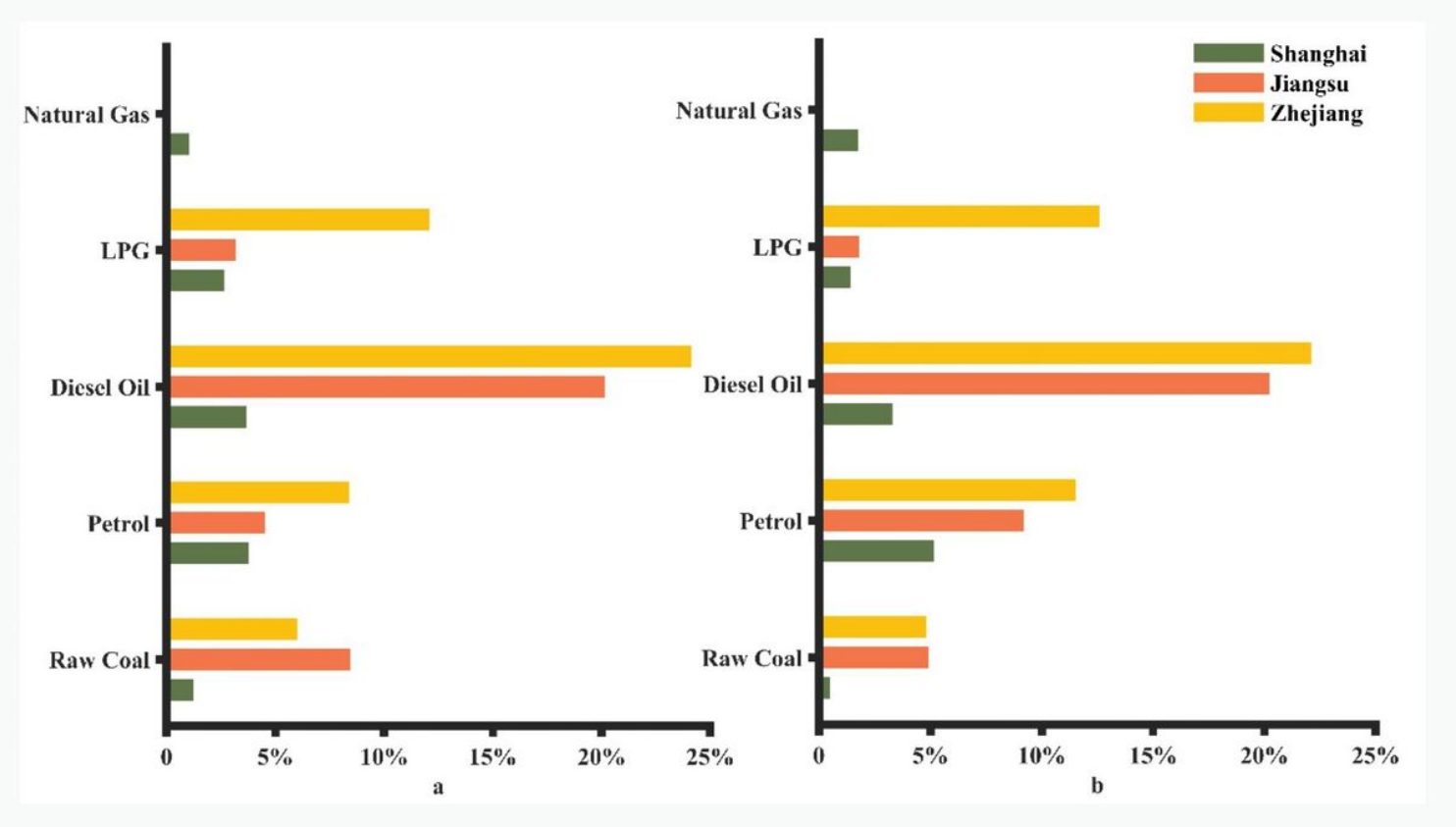

Figure 5

Energy structure of eastern coastal in 2010 and 2016.

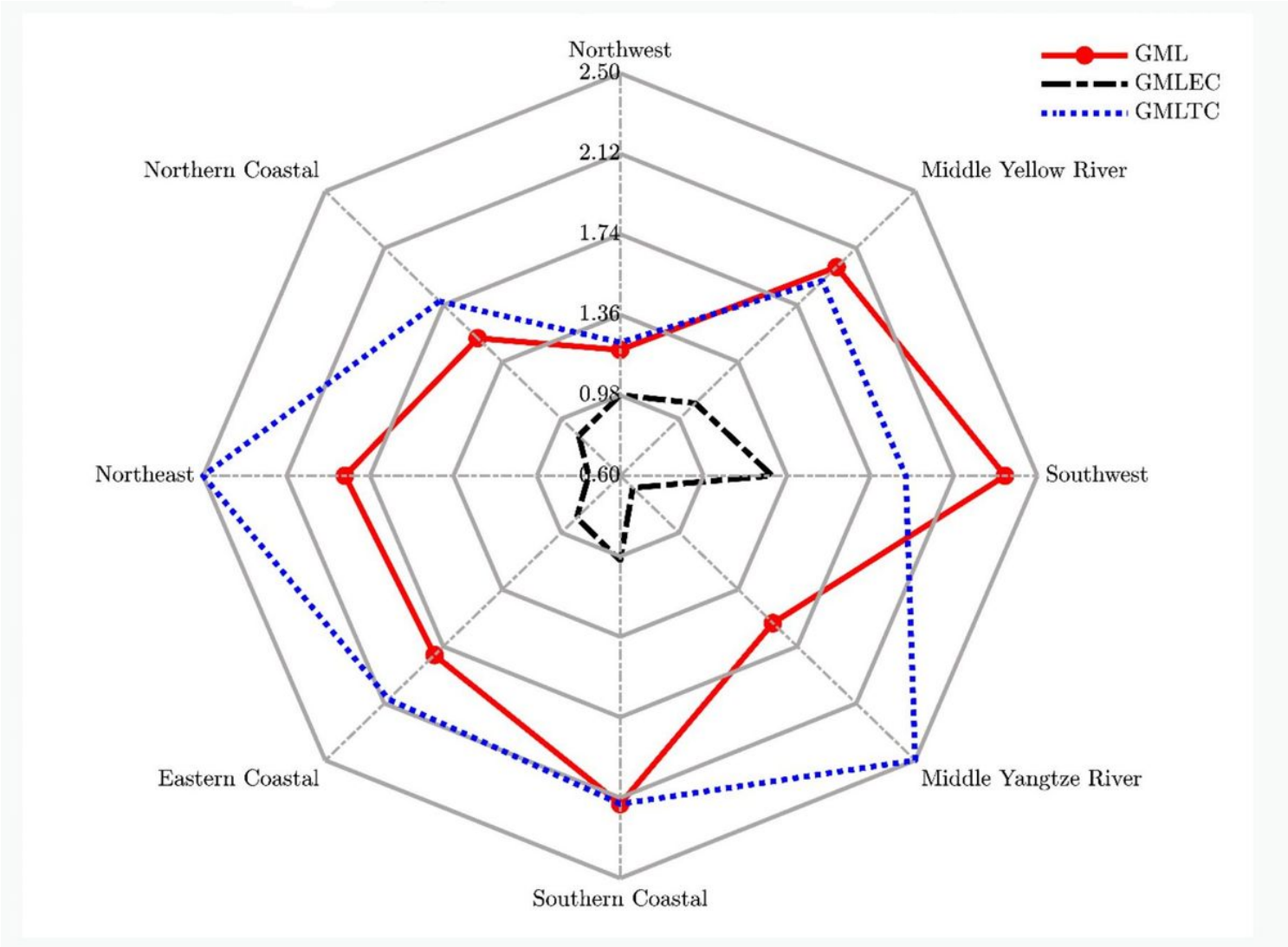

Figure 6

GML GMLEC and GMLTC in eight economic zones from 2008 to 2018.

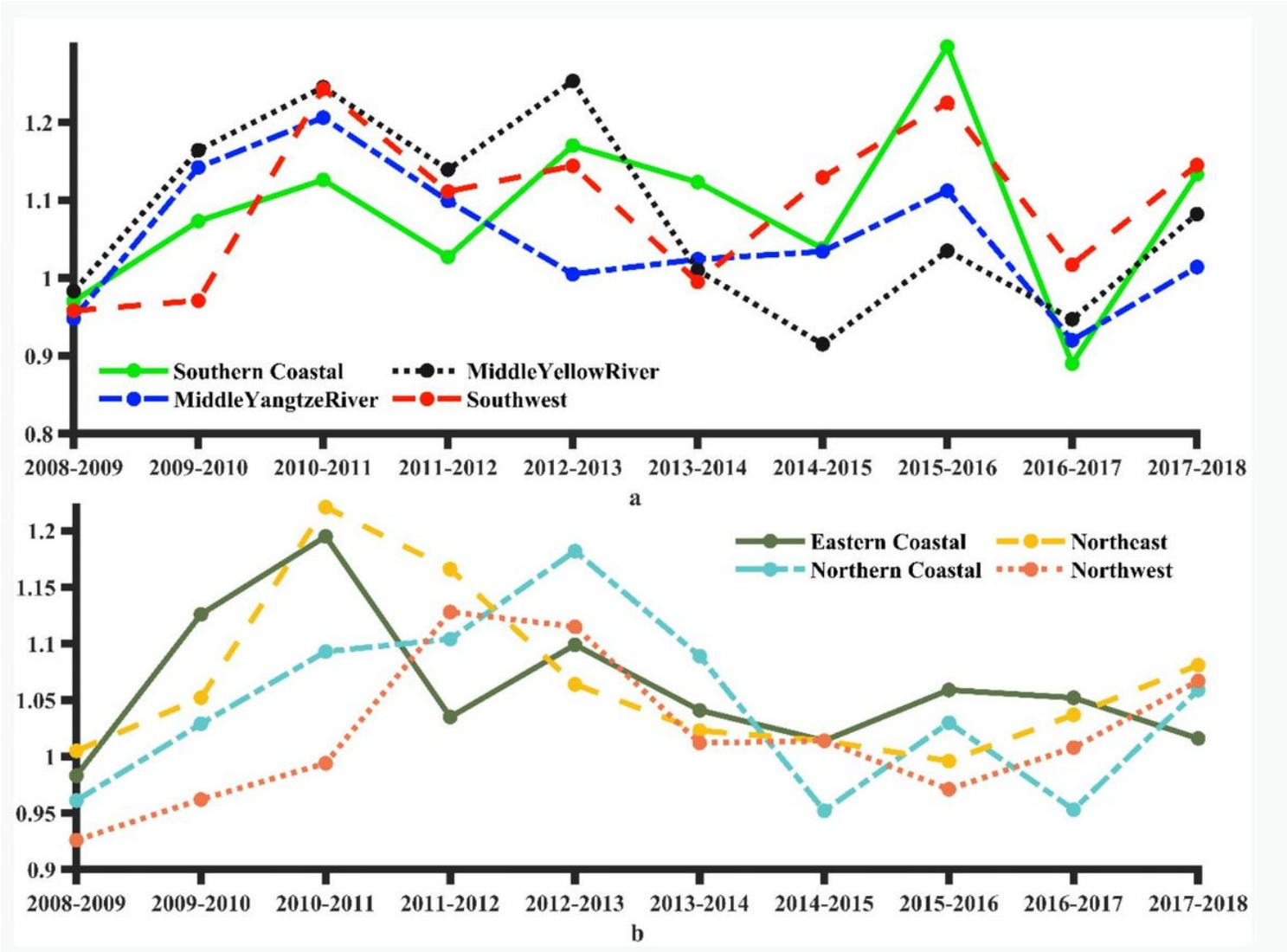

Figure 7

GML of eight economic zones from 2008 to 2018.