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Holistic suitability for regional biomass power generation development in China: An application of matter-element extension model

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Abstract

In the context of tremendously promoting bioenergy utilization, regional suitability for industrial development of biomass power generation is a critical factor when deploying region-specific strategies. An integrated framework is developed incorporating resource potential, development demands and development conditions to evaluate the suitability for regional industrial development of power generation utilizing agricultural bioresources. Twelve indicators reflecting local resource, environmental and socioeconomic features are used to measure the suitability of 31 provincial regions in China. An improved matter-element extension model combined with the entropy weight method is adopted to attain holistic and hierarchical suitability ranks. The results reveal that the distribution of holistic suitability ranks among regions is imbalanced with the eastern regions presenting more advantages compared with the western regions. Three regions belonging to Rank I (optimum) are Henan, Shandong and Xinjiang. Hainan, Tibet, Qinghai are classified into Rank V (unsuited). Moreover, there are great differences in the limiting factors of the suitability among regions. Resource potential is a limiting factor for Beijing, Shanghai, Fujian, Hainan and Guizhou; Development demands refrain Fujian, Guangxi and Yunnan; Tianjin and Ningxia are limited by development conditions. Tibet and Qinghai have the worst performance on each criterion. The results and region-targeted policy recommendations can provide insights for bioenergy utilization development in accordance with local conditions closely.

Key words: biomass power generation; agricultural bioresources; suitability; industrial development; matter-element extension model.

Abbreviations

ABRs: agricultural bioresources; **BPG**: biomass power generation; **MCDM**: multi-criteria decision making; **MEEM**: matter-element extension model.

1. Introduction

With rapid economic development, energy consumption-induced climate change and air pollution issues have been gaining increasing attention in China. It has become a sustainable choice to develop clean alternative energy sources in order to reduce the proportion of fossil energy, alleviate environmental problems, and maintain economic growth simultaneously (Mangla et al., 2020; Wang et al., 2019c). Bioenergy as the fourth largest energy source following coal, oil and natural gas keeps increasingly attractive because of its unique advantages (Ramachandra & Hebbale, 2020). Agricultural bioresources (ABRs), including crop straw and residues from agricultural activities, are a kind of typical bioenergy. They are considered as carbon neutral compared with fossil fuels. The energy-oriented utilization of ABRs can effectively moderate air pollutant emissions and the haze phenomenon aggravated by the open burning of discarded straw (Han et al., 2020; Kashif et al., 2020; Lu et al., 2019). Compared with various energy conversion technologies of ABRs, biomass power generation (BPG) has higher technological maturity and promising trend for industrial development (He et al., 2018; Wang et al., 2019b). In recent years, decision makers have promulgated a series of policies on stimulating energy-oriented utilization of ABRs, however, few breakthroughs have been made in terms of the industrialized development. The essential and urgent issue to be solved is "how to achieve industrial development of ABRs utilization in accordance with local conditions closely". This requires stable and long-term supply of resources, mature and feasible technologies and considerable environmental and economic benefits.

In previous studies, the above three aspects have been involved, respectively, primarily with focus on (1) assessment of resource potential and analysis of regional distribution of ABRs; (2) quantitative evaluation of environmental and economic impacts and sustainability performances of bioenergy technologies; (3) polices for industrial development of energy-oriented utilization of ABRs considering various influential factors.

Some studies aiming at quantifying the energy potential and analyzing regional distribution of ABRs have been carried out (Cervi et al., 2019; Jia et al., 2018). For example, Morato et al. (2019) calculated the available agricultural biomass for energy generation and created maps using Geographic Information System (GIS) to show the spatial distribution of residues in Bolivia. Burg et al. (2018) provided regionalized and aggregated estimates of the potentially available resources for bioenergy in Switzerland and defined restrictions for sustainable bioenergy production according to the current state. The results of these studies on national or provincial scales have disclosed local resource conditions and provided suggestions for local industrial development of ABRs utilization.

In terms of energy conversion technologies for ABRs, some researchers have focused on analyzing the economic and environmental impacts of raw materials and scales of technologies (Havukainen et al., 2018; Huang et al., 2019; Xiang et al., 2019; Xu et al., 2016). For example, Maier et al. (2019) assessed the impacts of bioenergy production from residues in British Columbia, Canada by a life cycle assessment model that includes ten impact categories and applied the model to three locations considering four combustion and gasification technologies with different capacities. Malek et al. (2017) quantified the economic and environmental impacts of a 10 MW biomass power plant that utilizes different bioresources in Malaysia, such as sawdust, wood chip, straw, etc. Besides, many scholars' interests lay in comparing the sustainability and development priority of various bioenergy technologies (Strzalka et al., 2017; Wang et al., 2019a). Khishtandar et al. (2017) developed a multi-criteria method integrating the hesitant fuzzy linguistic data and the experts' preferences to deal with the prioritization of existing bioenergy technologies in Iran. Song et al. (2015) applied a dynamic input-output model to evaluate the environmental and economic benefits of five bioenergy technologies in Jilin Province, China. The qualitative or quantitative findings revealed the advantages of different bioenergy technologies in terms of the environmental and socioeconomic performances.

Some policy proposals have been provided by scholars focusing on the influential factors of industrial development of ABRs utilization, such as resource potential, market condition, government support, enterprise operation, technological levels, etc. (Golecha & Gan, 2016; Rincon et al., 2019). For example, Thran et al. (2017) developed a dedicated approach that includes a new modeling framework, an impact assessment, and stakeholder involvement, to provide strategy elements regarding robust bioenergy strategy in Germany. Lantz et al. (2018) compared climate impact and production cost for biogas and ethanol based on wheat grain and straw, respectively, and provided policy suggestions from economic perspective for the technological options in a Swedish context. Zhu et al. (2015) adopted the strategic analysis tools stemming from the SWOT (Strengths, Weaknesses, Opportunities, and Threats) - PEST (Political, Economic, Social and Technological) model to explore the development modes of China's bioenergy industry. To achieve ABRs utilization in accordance with local conditions closely and put forward feasible policy proposals, it calls for clarifying whether and to what extent a region possesses the advantages from several dimensions, especially when plotting layout for industrial development and formulating the targets for BPG in multiple regions. However, no studies have yet been conducted to deal with the suitability for BPG's industrial development.

The evaluation of the suitability for BPG's industrial development is a task pertaining to multi-criteria decision making (MCDM). There have been a series of tools in addressing MCDM such as fuzzy Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR method, grey correlation analysis, etc. (Klein & Whalley, 2015; Ma et al., 2018; Wang et al., 2019a). These MCDM methods yield a ranking sequence of the alternatives, however, without providing explicit classification for them (Ren et al., 2013; Wang et al., 2018a).

Matter-Element Extension Model (MEEM) has been applied in the fields of computer, management, agriculture, ecology, specifically for the assessment of water quality, sustainable development, environmental risk, land suitability etc. (He et al., 2011; Wang et al., 2017). What it deals with are some incompatible and correlated evaluation elements, which can be anagolized as a matter-element consisting of object, attribute and value (termed as the three factors of a matter-element). A matter-element describes the relationships between the values of different attributes and the objects, and converts the relationships from qualitative (incompatible or fuzzy) to quantitative (measurable) (Li et al., 2013; Li & Li, 2017; Li et al., 2017). Compared with other MCDM methods, MEEM can not only help decision-makers/stakeholders determine the priority rankings of the alternatives, but also determine the final “rank/grade” of each alternative. Moreover, it allows users to set the classical domain and joint domain according to the real situations, and attain the results that match well with the preferences of the stakeholders.

In summary, from the perspective of content, scholars have attached emphasis to the estimation of resource potential and evaluation of environmental and economic performances of bioenergy technologies. No policy proposals involving the holistic suitability for BPG’s industrial development have been put forward. From the perspective of method, compared with other MCDM methods, MEEM is more suitable for stratifying the suitability for BPG’s industrial development and the identification of a group of regions with better performances holistically.

China has a vast territory with disparities in ABRs reserve, environmental status and socioeconomic conditions, which play crucial roles in determining whether a region is suitable to propel industrial development of ABRs utilization. This study selects BPG as example to represent energy-oriented utilization of ABRs. An indicator system is developed involving three dimensions as resource potential, development demands and development conditions, which correspond to 12 indicators highlighting local characteristics. The suitability for BPG’s industrial development in China’s 31 provincial regions is evaluated through combining the improved MEEM, entropy weight method and the indicator system. Critical factors and their impacts on the suitability ranks of regions are recognized. We aim at gaining holistic and stratified results of the suitability and finally propose region-targeted suggestions in terms of planning and development of ABRs utilization.

2. Methods

2.1 Research framework

The research framework consists of three stages, as depicted in **Fig. 1**. First, in virtue of existing literature referring to which some indicators are selected and screened, the indicator system is established, which is comprised of a criterion layer and an indicator layer. The weights of the indicators are calculated by the entropy weight method. The national data of China are used in this stage to reflect the national average level. Second, the matter-element, classical domain and joint domain in the MEEM are defined, combining parameters including ranks, attributes and values. After normalization process, the closeness degree and final rank for regions are determined. With analyses of the holistic suitability ranks and the suitability ranks for the criterion layer, policy proposals regarding regional deployment of BPG are provided.

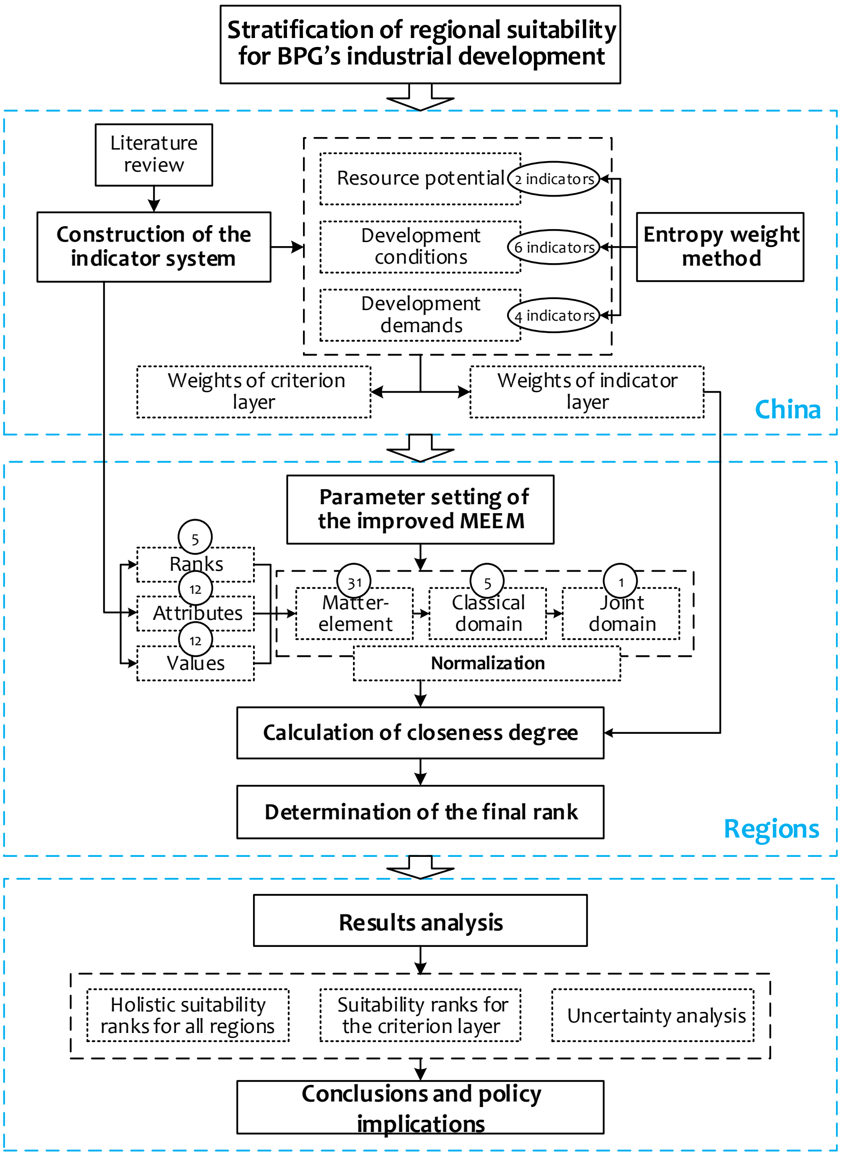

Fig. 1. Research framework of this study (the number in a circle denotes total number of the index)

2.2 Construction of the indicator system

Selection of appropriate evaluation indicators that are capable of collectively measuring the suitability is crucial. Besides the factor "resource potential" commonly considered by existing studies, we further incorporate development demands and development conditions. The former indicates whether it is necessary for a region to facilitate BPG's industrial development. The latter indicates whether there is adequate support for a region to underlie BPG's industrial development from a macro perspective.

As few studies on the suitability for ABRs utilization have ever been conducted, we preliminarily select eighteen indicators in compliance with the above three dimensions respectively through literature review on other relevant fields, such as sustainability assessment of bioenergy alternatives, evaluation of BPG potential, etc. (Hayashi et al., 2014; Kudoh et al., 2015; Martire et al., 2015; Wang et al., 2018b). The preliminarily selected indicators are further replaced, adjusted or improved due to repetitive and incomplete attributes, less relevance to this study and data inaccessibility, in order to make sure the accuracy and comprehensiveness. Based on the preliminary plan, 12 indicators corresponding to three dimensions are finally determined. All the determined indicators with corresponding descriptions are presented in **Table 1**.

Power generation potential (C_1) and *resource density* (C_2) collectively indicate the adequacy and stability of feedstock supply for BPG industry in a region. C_1 is a converted indicator of ABRs reserve that intuitively denotes the power generation capacity of a region from ABRs. C_2 is relevant to both the ABRs reserve and sown area of a region, a larger value of which implies potentially optimal feedstock supply and thus less fuel consumption of transportation.

Considering the potential of BPG in adjusting energy consumption structure, mitigating CO_2 and air pollutant emissions and promoting rural development, we use six indicators to reflect development demands, including *electricity consumption* (C_3), *power generation structure* (C_4), *air pollution* (C_5), *global warming* (C_6), *straw open burning* (C_7) and *rural residents' income* (C_8). C_3 is the average annual growth rate of electricity consumption during the latest years. C_5 is the proportion of the days when the air quality doesn't meet the standards. C_6 is the ratio of energy-related CO_2 emissions to gross domestic product (GDP). C_7 is considered to be a reliable and instant criterion to represent regional situation of discarding and burning of crop straw. As the income level of rural residents is opposed to development demands (lower level of income implies more demand for BPG's industrial development to promote rural development), C_8 is a negative indicator (a smaller value is more positive to the object).

The conditions for *labor* (C_9), *transportation* (C_{10}), *investment* (C_{11}) and *government tendency* (C_{12}) characterize development conditions jointly. Emphatically, road mileage per unit area reflects transport support for feedstock supply; GDP indicates if a region can invest adequately on the development of an emerging industry (as higher GDP implies potentially more government revenue and thus more investment to drive industrial development); Due to the difficulty in quantifying government policies on encouraging and stimulating the development of BPG industry, we use energy conservation and environmental protection expenditure to indirectly denote the tendency of a government in supporting new energy industries. Except C_8, all the other indicators are positive indicators.

Table 1. Evaluation indicators of the suitability for regional BPG's industrial development.

Target layer	**Criterion layer**		**Indicator layer**		**Descriptions of indicators**
Regional suitability for BPG's industrial development	**B_1**	Resource Potential	**C_1**	Power generation potential of ABRs	Installed capacity calculated according to the amounts of nine kinds ABRs
			C_2	Resource density of ABRs	Collectable amounts of ABRs per unit sown area
	B_2	Development demands	**C_3**	Average growth rate of electricity consumption	Average annual growth of recent five years to represent electricity demand
			C_4	Proportion of thermal power in regional total power generation	Representation of regional power generation structure
			C_5	Non-compliance rate of air quality	Proportion of days when the air quality doesn't meet the standards, reflecting the demand for treatment of atmospheric environment
			C_6	Emission intensity of CO_2	Ratio of energy-related CO_2 emissions to GDP, reflecting the demand for global warming mitigation
			C_7	Fire-point intensity of straw burning	Ratio of the number of fire-points to the area of cultivated land, reflecting the severity of straw burning
			C_8	Disposable income of rural residents	Income level to reflect the demand for rural development
	B_3	Development conditions	**C_9**	Rural population	Labor condition for BPG's industrial development
			C_{10}	Road mileage per unit area	Transportation condition for BPG's industrial development
			C_{11}	GDP	Investment condition for BPG's industrial development
			C_{12}	Energy conservation and environmental protection expenditure	Government tendency on BPG's industrial development

2.3 Entropy weight method

The entropy weight method is an objective method to determine weight that has been widely applied to MEEM (Han et al., 2015; Wang et al., 2018a). Entropy is a measure of the disorder of a system that can be evaluated by certain indicators. If the information entropy of an indicator is smaller, the more information it provides, the bigger the role it plays in the comprehensive evaluation, and the higher the weight it has, vice versa. Weight determination by entropy weight method is based on the degree of variation of each indicator, excluding the influence of subjective factors. It requires time sequence data of indicators to build the initial decision matrix (the rows correspond to time and the columns correspond to indicator attributes). As all indicators finally incorporated into the evaluation framework are quantitative and selected allowing for data availability, entropy weight method beseems to this study for obtaining objective weights of indicators.

The specific steps are as follows:

(1) Normalization of data

Positive indicator:

$$C'_{t,i} = \frac{C_{t,i} - \min(C_{t,i})}{\max(C_{t,i}) - \min(C_{t,i})} \tag{1}$$

Negative indicator:

$$C'_{t,i} = \frac{\max(C_{t,i}) - C_{t,i}}{\max(C_{t,i}) - \min(C_{t,i})} \tag{2}$$

$$r_{t,i} = \frac{C'_{t,i}}{\sum_{t=1}^{m} C'_{t,i}} \tag{3}$$

where, $C_{t,i}$ represents the actual value of the i-th indicator in the t-th year (m=5). C_8 is a negative indicator while others are positive. $C'_{t,i}$ represents the value of each indicator after normalization. $r_{t,i}$ represents the proportion of $C'_{t,i}$.

(2) Calculation of entropy

$$H_i = -\frac{1}{\ln m} \sum_{t=1}^{m} r_{t,i} \ln r_{t,i} \tag{4}$$

where, H_i represents the entropy value of each indicator.

(3) Calculation of weight

$$w_i = \frac{1 - H_i}{\sum_{B_i}^{K} (1 - H_i)} \tag{5}$$

$$W_i = w_i \times W(B_k) \quad (6)$$

where, w_i represents weight of indicators pertaining to a criterion. K represents a collection of serial number of indicators under the criterion layer, such as $K(B_1)$=[1,2]; $K(B_2)$=[3,8]; $K(B_3)$=[9,12], $w_1+w_2=1$; $w_3+w_4+\ldots+w_8=1$; $w_9+w_{10}+\ldots+w_{12}=1$. W_i is the final weight of each indicator, $\sum_{i=1}^{n} W_i=1$ (n=12); $W(B_k)$ is the weight of each criterion, k=1,2,3.

2.4 The improved Matter-Element Extension Model

MEEM is based on the framework combining matter-element theory and extension theory to determine the rank of a matter-element. By establishing the classical domain, joint domain and final rank, the correlation of the matter-element to be evaluated with respect to the final rank is calculated. In this work, a provincial region corresponds to a matter-element (R_0) and there are 31 matter-elements in total matching 31 provincial-regions of China. A matter-element consists of object (j), attributes of indicators (c_i, i=1,2,…,12) and values for attributes (v_i, i=1,2,…,12). A rank corresponds to the object in a matter-element and we preliminarily define five ranks for the RS (j=1,2,…,5), as optimum (I), suitable (II), potential (III), limited (IV) and unsuited (V). A classical domain contains a set of ranges for the values of indicators under a rank. A joint domain contains a set of ranges spanning all ranges of classical domains under an indicator. **Table 2** concludes the specific information of the above indices.

Table 2. Descriptions of the indices in the Matter-Element Extension Model.

Index	Notation	Number	Description
Matter-element	R_0	31	The provincial-regions of China.
Attributes	c_i	12	Features of indicators.
Final rank	q	5	Stratified levels of the suitability for BPG's industrial development.
Classical domain	R_j	5	A set of ranges for the values of the indicators under a rank.
Joint domain	R^*	1	A set of ranges spanning all ranges of classical domains under an indicator.

Classical MEEM has several drawbacks. First, the correlation function values are unobtainable if the value of an indicator corresponding to a matter-element exceeds the joint domain. Second, in some cases, the principle of maximum membership degree cannot reflect the fuzziness of the boundary of the matter-element, which may lead to loss of information and deviation of evaluation results. Normalization processing is applied to the classical domain and matter-element to solve the first problem. The improved MEEM adopts the degree of closeness to replace the degree of membership in order to deal with the second problem (Li et al., 2013; Wang et al., 2018a). Furthermore, the entropy weight method is used to determine the weights of indicators, which are embedded into each rank to calculate the degree of closeness. The higher the degree of closeness, the more closely a matter-element pertains to the final rank. The specific steps are as follows:

(1) Determination of matter-element

A matter-element R is a triple of objects P, attributes C, and values V, expressed as R = (P, C, V).

$$R_0 = (P_0, C_i, V_i) = \begin{bmatrix} P & c_1 & v_1 \\ & c_2 & v_2 \\ & \vdots & \vdots \\ & c_n & v_n \end{bmatrix} \tag{7}$$

where, R_0 and P_0 represent matter-element and its rank, respectively; c_i represents the attributes of indicators; v_i represents the actual value of indicator c_i.

(2) Determination of classical domain and joint domain

$$R_j = (P_j, C_i, V_{ij}) = \begin{bmatrix} P_j & c_1 & v_{1j} \\ & c_2 & v_{2j} \\ & \vdots & \vdots \\ & c_n & v_{nj} \end{bmatrix} = \begin{bmatrix} P_j & c_1 & (a_{1j}, b_{1j}) \\ & c_2 & (a_{2j}, b_{2j}) \\ & \vdots & \vdots \\ & c_n & (a_{nj}, b_{nj}) \end{bmatrix} \tag{8}$$

where, R_j represents classical domain corresponding to the i-th attribute and the j-th rank; v_{ij} is the value range of c_i under rank j; a_{ij} and b_{ij} represent the lower limit and upper limit of v_{ij}, respectively.

$$R^* = (P, C_i, V_i^*) = \begin{bmatrix} P & c_1 & v_1^* \\ & c_2 & v_2^* \\ & \vdots & \vdots \\ & c_n & v_n^* \end{bmatrix} = \begin{bmatrix} P & c_1 & (a_1^*, b_1^*) \\ & c_2 & (a_2^*, b_2^*) \\ & \vdots & \vdots \\ & c_n & (a_n^*, b_n^*) \end{bmatrix} \tag{9}$$

where, R^* represents joint domain corresponding to the i-th attribute; a_i^* and b_i^* represent the lower limit and upper limit of v_i^*, respectively.

(3) Normalization processing

For some indicators whose actual value exceeds the range of joint domain, normalization processing provides a valid way to obtain the correlation function value.

$$R_0' = \begin{bmatrix} P & c_1 & v_1' \\ & c_2 & v_2' \\ & \vdots & \vdots \\ & c_n & v_n' \end{bmatrix} = \begin{bmatrix} P & c_1 & \frac{v_1}{b_1^*} \\ & c_2 & \frac{v_1}{b_2^*} \\ & \vdots & \vdots \\ & c_n & \frac{v_1}{b_n^*} \end{bmatrix} \tag{10}$$

$$R_j' = \begin{bmatrix} P_j & c_1 & (a_{1j}', b_{1j}') \\ & c_2 & (a_{2j}', b_{2j}') \\ & \vdots & \vdots \\ & c_n & (a_{nj}', b_{nj}') \end{bmatrix} = \begin{bmatrix} P_j & c_1 & (\frac{a_{1j}}{b_1^*}, \frac{b_{1j}}{b_1^*}) \\ & c_2 & (\frac{a_{2j}}{b_2^*}, \frac{b_{2j}}{b_2^*}) \\ & \vdots & \vdots \\ & c_n & (\frac{a_{nj}}{b_n^*}, \frac{b_{nj}}{b_n^*}) \end{bmatrix} \tag{11}$$

where, R_0' and R_j' represent the matter-element and its classical domain after normalization processing.

(4) Calculation of degree of closeness

$$D_{j(v_i')} = \left| v_i' - \frac{a_{i,j}' + b_{i,j}'}{2} \right| - \frac{a_{i,j}' - b_{i,j}'}{2} \tag{12}$$

$$E_{j(R_0')} = 1 - \frac{1}{n(n+1)} \sum_{i=1}^{n} D_{j(v_i')} W_i \tag{13}$$

where, $D_{j(v_i')}$ represents the distance between matter-element and a classical domain; W_i represents the weight of c_i; $E_{j(R_0')}$ represents the closeness degree of the normalized matter-element to the j-th rank.

(5) Determination of the final rank

$$E_{q(R_0')} = \max\left[E_{j(R_0')}\right] \tag{14}$$

where, $E_{q(R_0')}$ is the maximum of $E_{j(R_0')}$, which can be used to judge whether the matter-element belongs to final rank q.

$$\overline{E}_{j(R_0')} = \frac{E_{j(R_0')} - \min\left[E_{j(R_0')}\right]}{\max\left[E_{j(R_0')}\right] - \min\left[E_{j(R_0')}\right]} \tag{15}$$

$$j^{\#} = \frac{\sum_{j=1}^{J} j^{\#} \overline{E}_{j(R_0')}}{\sum_{j=1}^{J} \overline{E}_{j(R_0')}} \tag{16}$$

where, $\overline{E}_{j(R_0')}$ is calculated to obtain the eigenvalue $j^{\#}$, which is used to determine the closeness of a matter-element towards its adjacent ranks.

3. Data presentation

3.1 Data source

The decision matrix of entropy weight method is built based on the time sequence data of the indicators. The data of 31 regions are difficult to collect because of data insufficiency in some special regions. There are unnoticeable differences of weight results among regions according to a preliminary test (for some regions). We choose the time sequence data of China to build the judgement matrix for the indicator system. The data derive from *China Statistical Yearbook* (CBS, 2013-2017a), *China rural statistical yearbook* (CBS, 2013-2017b), *China Electricity Yearbook* (CBS, 2013-2017c), *Reports on the State of Environment in China* (MEE, 2016a), *China Energy Statistical Yearbook* (CBS, 2013-2017d) and *Monitoring Reports on Straw Burning in China* (MEE, 2016b). In order to ensure that the available data for all regions within the same time range, we designate the period as 2012-2016 (see **Table 3**). C_1 is calculated according to grain yield, straw-grain ratio and collection coefficient of crops (rice, wheat, corn, soybeans, tubers, cotton, peanut, rapeseed and sugarcane), as well as the corresponding low calorific value (Liu et al., 2014; Song et al., 2019; Wang et al., 2018b). C_6 is calculated based on the consumption of fossil fuels referring to the method by Liu et al. (2015). All the values of the economic indicators are converted to the 2010 price level for the comparison across years.

Table 3. Data on the indicators of China (2012-2016).

	Unit	Data source	2012	2013	2014	2015	2016
C_1	10^6 kW	(CBS, 2013-2017b; Liu et al., 2014; Wang et al., 2018b)	59.10	60.32	60.55	61.62	60.88
C_2	t/hm^2	(CBS, 2013-2017a; CBS, 2013-2017b)	3.83	3.88	3.88	3.92	3.87
C_3	%	(CBS, 2013-2017c)	5.46	7.73	4.14	2.33	4.94
C_4	%	(CBS, 2013-2017c)	78.72	78.58	75.43	73.71	71.85
C_5	%	(MEE, 2016a)	39.50	34.00	23.30	21.20	22.00
C_6	t CO_2/10^3 CNY	(CBS, 2013-2017d; Liu et al., 2015)	17.04	16.20	14.89	13.65	12.51
C_7	Number/10^6 hm^2	(MEE, 2016b)	81.29	59.06	37.27	63.70	56.81
C_8	10^3 CNY/people	(CBS, 2013-2017b)	7.30	7.98	8.71	9.37	10.07
C_9	10^6 people	(CBS, 2013-2017a)	642.22	629.61	618.66	603.46	589.73
C_{10}	km/km^2	(CBS, 2013-2017a)	0.44	0.45	0.46	0.48	0.49
C_{11}	10^{12} CNY	(CBS, 2013-2017a)	487.98	525.84	564.19	603.12	643.47
C_{12}	10^9 CNY	(CBS, 2013-2017a)	289.98	333.49	347.09	440.25	443.93

3.2 Provincial data of some individual indicators

In order to explicitly display the difference between the performances on individual indicators and the holistic indicator system, some provincial data in 2016 are depicted in **Fig. 2**. It is obvious that the performances on C_1, C_7 and C_{12} are incompatible. For instance, Beijing has penultimate performance on C_1, but good performance on C_7 (NO. 7) and C_{12} (NO. 1), respectively. Heilongjiang has good performance on C_1 (NO. 2) and C_7 (NO. 1), however poor performance on C_{12} (NO. 22).

More detailed data of the indicators are provided in **Table S-3** in the **Supplementary materials**.

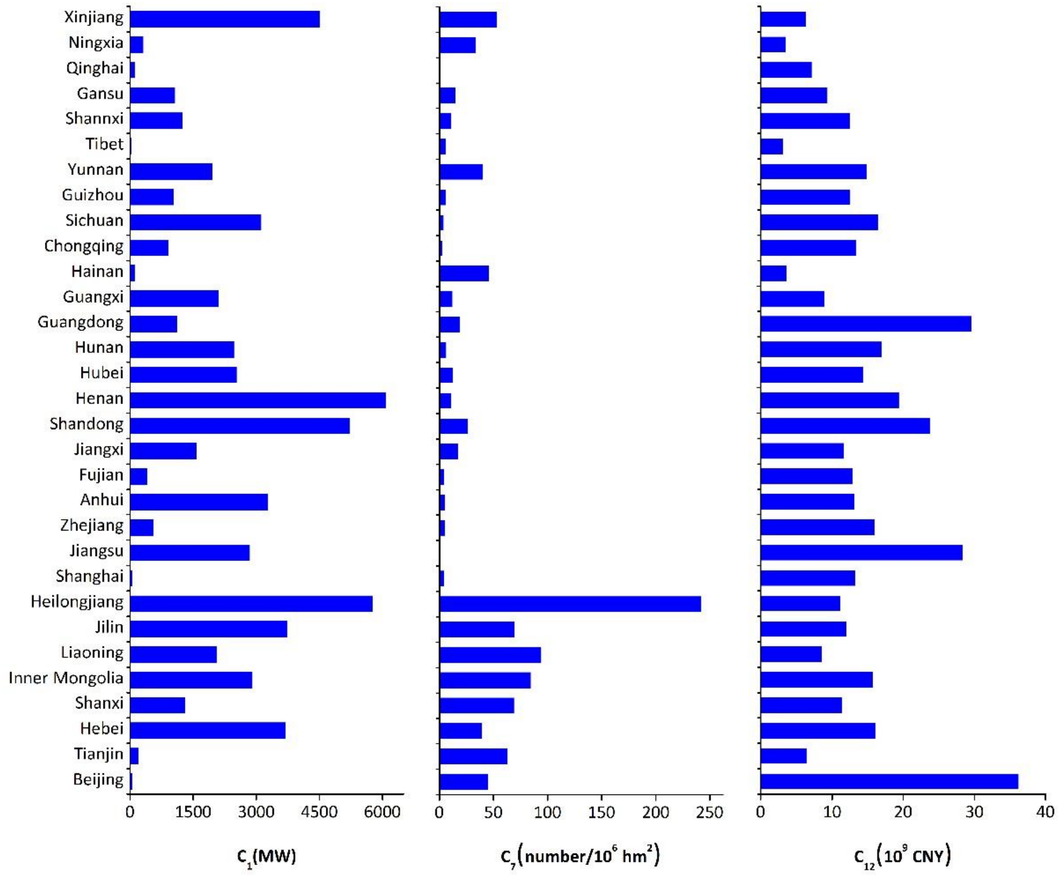

Fig. 2. Provincial data of some individual indicators.

4. Results

4.1 Weights of the indicators

Results of weights calculated according to entropy weight method, are presented in **Table 4**. The weights of the criterion layer are determined according to the suggestions from three groups of experts we invited from universities, government and enterprises. The first group are academics expertized in the theories of energy conversion from biomass; the second group are government administrators focusing on policy formulation and implementation; the last group are managers of BPG plants understanding enterprise operation principles. Most of the experts advise equal weight for resource potential, development demands and development conditions, which is finally determined as $W(B_1)$=0.3333, $W(B_2)$=0.3333, $W(B_3)$=0.3333, respectively. It suggests that the three criteria are mutually influenced and equally important in terms of the current situation of BPG's industrial development in China. Seen overall, C_1 and C_2 have higher weights.

Table 4. Weights of the criteria and indicators.

Criterion layer ($W(B_k)$)	Indicator layer (w_i)	W_i
B_1 (0.3333)	C_1 (0.4769)	0.1590
	C_2 (0.5231)	0.1744
B_2 (0.3333)	C_3 (0.1367)	0.0456
	C_4 (0.1500)	0.0500
	C_5 (0.2920)	0.0973
	C_6 (0.1479)	0.0493
	C_7 (0.1252)	0.0417
	C_8 (0.1483)	0.0494
B_3 (0.3333)	C_9 (0.2370)	0.0790
	C_{10} (0.2424)	0.0808
	C_{11} (0.2550)	0.0850
	C_{12} (0.2656)	0.0885

4.2 Results of the improved MEEM

As described in Formulas (7) and (8), the suitability could be divided into five ranks (j=5), i.e., optimum (I); suitable (II); potential (III); limited (IV); unsuited (V), in this study. **Table S-3** presents the minimum value and maximum value for each indicator in each region. For a certain indicator, we define a value somewhat smaller than the minimum value as the lower limit for the value of this indicator in the joint domain; we define a value somewhat larger than the maximum value as the upper limit for the value of this indicator in the joint domain. Thereout we obtain the range for the value of each indicator in the joint domain. Then, compromising the actual conditions in each region, we further divide each range in the joint domain into five intervals, as Interval 1, Interval 2,…, Interval 5. In total, twelve “Interval 1” form the first classical domain R_1(I); twelve “Interval 2” form the second classical domain R_2(II). In the same way, we obtain five groups of classical domains. The classical domains and joint domain of the improved MEEM are listed in **Table 5**.

Table 5. Classical domains, joint domain and ranks for regional suitability.

Indicators	R_1(I)	R_2(II)	R_3(III)	R_4(IV)	R_5(V)	R^*
C_1	(3500, 6500)	(2200, 3500)	(1000, 2200)	(300, 1000)	(0, 300)	(0, 6500)
C_2	(4.8, 8)	(3.8.4.8)	(3.1, 3.8)	(2.5, 3.1)	(0, 2.5)	(0, 8)
C_3	(8%, 24%)	(5%, 8%)	(4%, 5%)	(2.5%, 4%)	(1%, 2.5%)	(1%, 24%)
C_4	(95%, 100%)	(85%, 95%)	(70%, 85%)	(50%, 70%)	(0, 50%)	(0, 100%)
C_5	(35%, 50%)	(35%, 25%)	(25%, 17%)	(7.5%, 17%)	(0, 7.5%)	(0, 50%)
C_6	(2.2, 6)	(1.3, 2.2)	(0.7, 1.3)	(0.6, 0.7)	(0, 0.6)	(0, 6)
C_7	(50, 100)	(20, 50)	(8, 20)	(6, 8)	(0, 6)	(0, 100)
C_8	(7, 10)	(10, 11.5)	(11.5, 12)	(12, 15)	(15, 30)	(7, 30)
C_9	(28, 50)	(19, 28)	(14, 19)	(4, 14)	(0, 4)	(0, 50)
C_{10}	(1.5, 2.2)	(1.2, 1.5)	(0.8, 1.2)	(0.5, 0.8)	(0, 0.5)	(0, 2.2)
C_{11}	(300, 500)	(200, 300)	(130, 200)	(40, 130)	(0, 40)	(0, 500)
C_{12}	(18, 40)	(14, 18)	(12, 14)	(8, 12)	(0, 8)	(0, 40)

There are in total 31 matter-elements to be evaluated, among which Jilin Province is taken as an example to explicitly present the whole process.

(1) The matter-element R_0 and R_0'

$$R_0 = \begin{bmatrix} & c_1 & 3749 \\ & c_2 & 6.78 \\ & c_3 & 1.16 \\ & c_4 & 79.14 \\ & c_5 & 18.00 \\ P & c_6 & 1.26 \\ & c_7 & 70.64 \\ & c_8 & 12.12 \\ & c_9 & 12.03 \\ & c_{10} & 0.55 \\ & c_{11} & 123.20 \\ & c_{12} & 12.21 \end{bmatrix} \quad R_0' = \begin{bmatrix} & c_1 & 0.58 \\ & c_2 & 0.85 \\ & c_3 & 0.05 \\ & c_4 & 0.79 \\ & c_5 & 0.36 \\ P & c_6 & 0.21 \\ & c_7 & 0.71 \\ & c_8 & 0.40 \\ & c_9 & 0.24 \\ & c_{10} & 0.25 \\ & c_{11} & 0.25 \\ & c_{12} & 0.31 \end{bmatrix}$$

The joint domain ($R*$) has been provided in **Table 5**. The normalized classical domains (R_j') are calculated according to Formula (10). R_3', R_4' and R_5' are obtained in the same way.

$$R_1' = \begin{bmatrix} & c_1 & (0.54,1.00) \\ & c_2 & (0.60,1.00) \\ & c_3 & (0.33,1.00) \\ & c_4 & (0.95,1.00) \\ & c_5 & (0.70,1.00) \\ P & c_6 & (0.37,1.00) \\ & c_7 & (0.50,1.00) \\ & c_8 & (0.23,0.33) \\ & c_9 & (0.56,1.00) \\ & c_{10} & (0.68,1.00) \\ & c_{11} & (0.60,1.00) \\ & c_{12} & (0.45,1.00) \end{bmatrix} \quad R_2' = \begin{bmatrix} & c_1 & (0.34,0.54) \\ & c_2 & (0.48,0.60) \\ & c_3 & (0.21,0.33) \\ & c_4 & (0.85,0.95) \\ & c_5 & (0.50,0.70) \\ P & c_6 & (0.22,0.37) \\ & c_7 & (0.20,0.50) \\ & c_8 & (0.33,0.38) \\ & c_9 & (0.38,0.56) \\ & c_{10} & (0.55,0.68) \\ & c_{11} & (0.40,0.60) \\ & c_{12} & (0.35,0.45) \end{bmatrix}$$

(2) Results of closeness degree

Closeness degree between matter-element (R_0') and classical domains (R_1', R_2',…, R_5') are calculated based on Formulas (12) and (13), with specific results illustrated in **Table 6** and **Table 7**.

Table 6. Distance between matter-element and classical domains.

Indicators	$D_{1(v_i')}$ (I)	$D_{2(v_i')}$ (II)	$D_{3(v_i')}$ (III)	$D_{4(v_i')}$ (IV)	$D_{5(v_i')}$ (V)
C_1	-0.0383	0.0383	0.2383	0.4229	0.5306
C_2	-0.1524	0.2476	0.3726	0.4601	0.5351
C_3	0.2849	0.1599	0.1182	0.0557	-0.0068
C_4	0.1586	0.0586	-0.0586	0.0914	0.2914
C_5	0.3400	0.1400	-0.0200	0.0200	0.2100
C_6	0.1570	0.0070	-0.0070	0.0930	0.1097

C_7	-0.2064	0.2064	0.5064	0.6264	0.6464
C_8	0.0708	0.0208	0.0041	-0.0041	0.0959
C_9	0.3194	0.1394	0.0394	-0.0394	0.1606
C_{10}	0.4332	0.2969	0.1151	-0.0213	0.0213
C_{11}	0.3536	0.1536	0.0136	-0.0136	0.1664
C_{12}	0.1447	0.0447	-0.0054	0.0054	0.1054

Table 7. Closeness degree of matter-element to ranks.

Degrees of closeness	$E_{1(R_0')}$ (I)	$E_{2(R_0')}$ (II)	$E_{3(R_0')}$ (III)	$E_{4(R_0')}$ (IV)	$E_{5(R_0')}$ (V)	Rank	Eigenvalue ($j^{\#}$)
$E_{j(R_0')}$	0.99919	0.99926	0.99924	0.99900	0.99842	II	2.4066

(3) Results of final rank

The final rank for Jilin Province is calculated based on Formula (13), $\max\left[E_{j(R_0')}\right]=E_{2(R_0')}=0.99926$. That is to say the the suitability for Jilin Province belongs to Rank II (suitable). Meanwhile, according to Formulas (15) and (16), the eigenvalue $j^{\#}=2.4066<2.5$ (2.5=(Rank II+Rank III)/2), which indicates that the suitability rank for Jilin Province right belongs to Rank II. If the eigenvalue $j^{\#}>2.5$, the suitability rank has a tendency from Rank II (suitable) to Rank III (potential). Calculation of the final ranks for all other regions follows the above steps.

4.2.1 Holistic suitability ranks for all regions

The holistic suitability ranks for all provincial regions in China are provided in **Fig. 3**. The eastern regions have more advantage compared with the western regions. In detail, three regions belong to Rank I (optimum), including Henan, Shandong and Xinjiang. Jilin, Jiangsu, Anhui and other six regions (in total eight) belong to Rank II (suitable). Seven regions (Beijing, Tianjin, Shanghai, Fujian, Chongqing, Gansu, Ningxia) belong to rank IV (limited). Hainan, Tibet, Qinghai are classified into Rank V (unsuited). The remaining regions are classified into Rank III (potential).

Shandong and Henan are both important agricultural regions of China with high agricultural development level and large crop yields. They are naturally suitable for BPG's industrial development in terms of resource potential and development conditions. Surprisingly, Xinjiang, as a western region in China without outstanding grain yield, has high suitability. Its main crop is cotton with relatively higher straw-gain ratio, which provides abundant feedstocks for the BPG industry. Besides, Xinjiang also has advantage in development demands. In order to unravel the limiting factors of the suitability for each region, the evaluation results of each criterion are further analyzed.

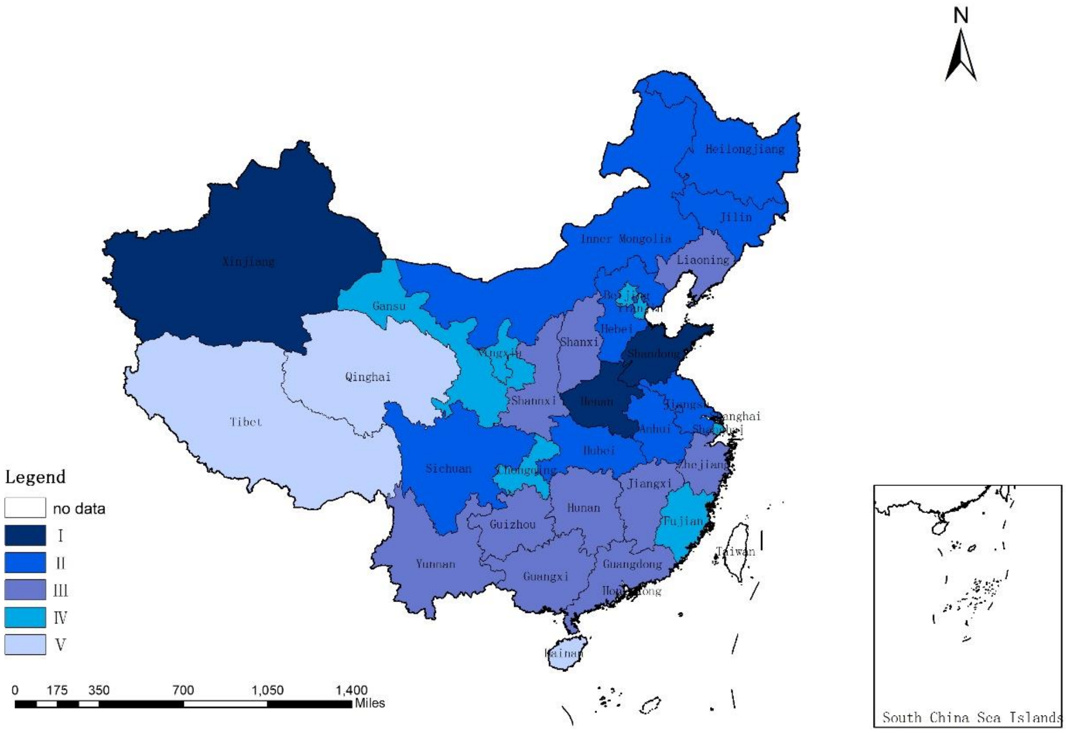

Fig. 3. Spatial distribution of holistic suitability ranks for provincial regions

4.2.2 Suitability ranks for the criterion layer

The above it is an integration of suitability ranks incorporating three perspectives affecting BPG's industrial development. However, seen from the criterion layer, the evaluation results vary greatly across regions. The specific analyses are as follows.

(1) Resource potential (B1)

The evaluation results are overall similar to the holistic suitability ranks. As depicted in **Fig. 4**, ABRs are mainly centralized in the northeast (i.e. Heilongjiang, Jilin), middle-east (i.e. Henan, Shandong), and Xinjiang. These resource-intensive regions are also with high resource density. Nevertheless, the performances are imbalanced on total ABRs and resource density for some inferior regions. Some have smaller amounts of resources (Tianjin, Liaoning etc.), and others have lower resource density (Guizhou, Gansu, etc.), which leads to unsatisfactory evaluation results of resource potential for these regions. The regions (Qinghai, Fujian, Beijing, etc.) that belong to Rank V (unsuited) don't have a good performance on neither of the indicators. Agricultural development in these regions is not prosperous, resulting in additional operating cost and difficulties in feedstock procurement and storage.

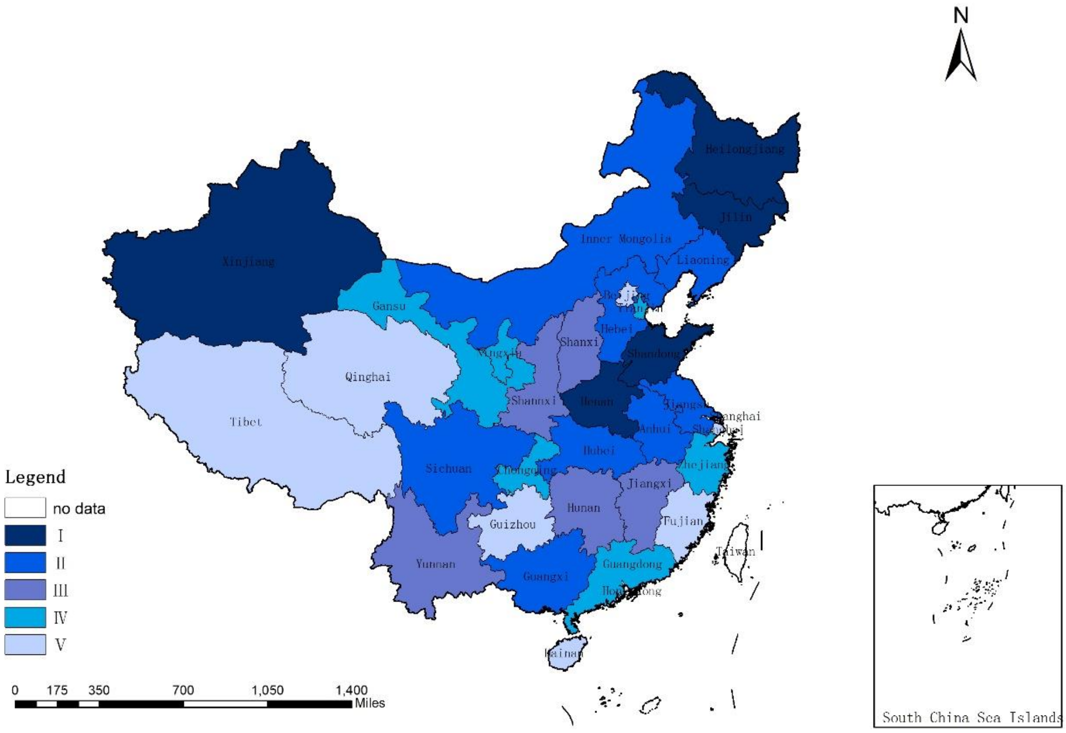

Fig. 4. Spatial distribution of ranks on resource potential.

(2) Development demands (B2)

The results of ranks on development demands are illustrated in **Fig. 5**. The regions belong to Rank I (optimum) mainly gather in the north, such as Beijing, Inner Mongolia, Shanxi, and other regions with poor air quality, serious straw open-burning and high proportion of thermal power generation. The rest regions are mostly classified into Rank IV (limited) and Rank V (unsuited) because of poor performances on most indicators. Most of these regions are in the south, with better air quality and rural economic development. Although the power demand is relatively large, the performances on the other five indicators are all poor, leading to an overall development demand pertaining to Rank V (such as Fujian).

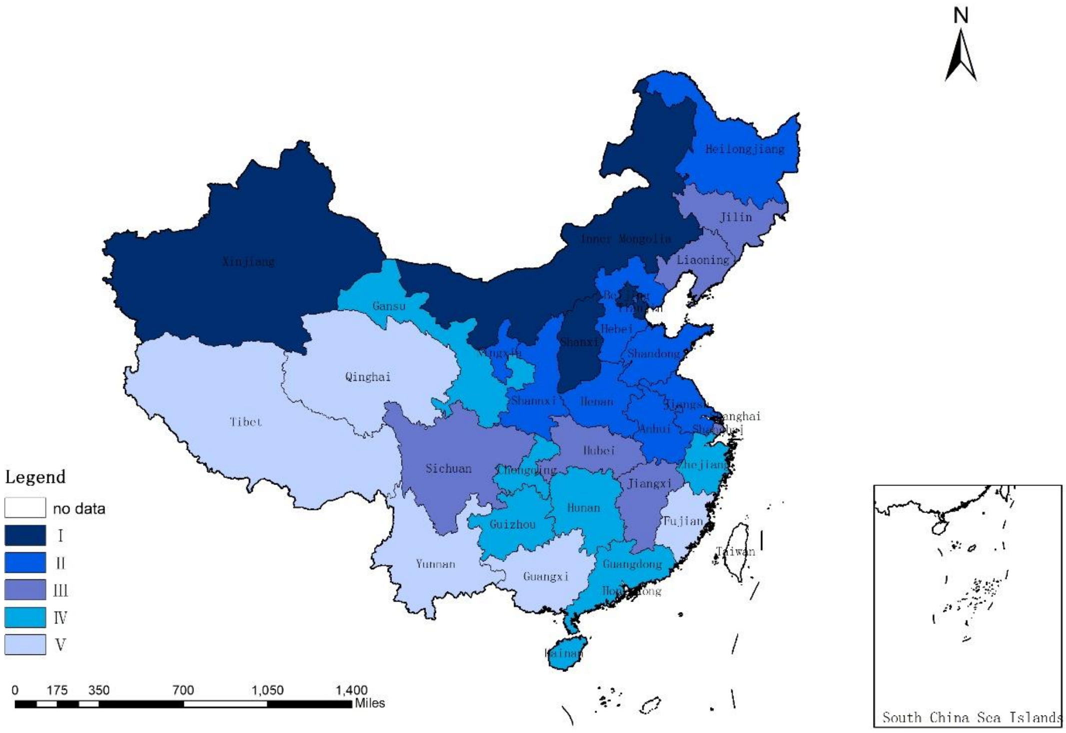

Fig. 5. Spatial distribution of ranks on development demands.

(3) Development conditions (B3)

The results of this part are quite different from the holistic suitability ranks. As in **Fig. 6**, it can be observed that the regions that belong to Rank I (optimum) gather in the middle-east and south, such as Shandong, Henan, Guangdong, Sichuan, etc. There are abundant labors, good traffic conditions, and mighty government support. Four regions belong to Rank V (unsuited), including Tianjin, Qinghai, Ningxia and Tibet. Tianjin has good traffic condition, which still cannot offset the poor performances on other indicators. Most of other regions belong to Rank III (potential), which have divergent performances on the four indicators. Jilin doesn't have a good performance on none of the four indicators.

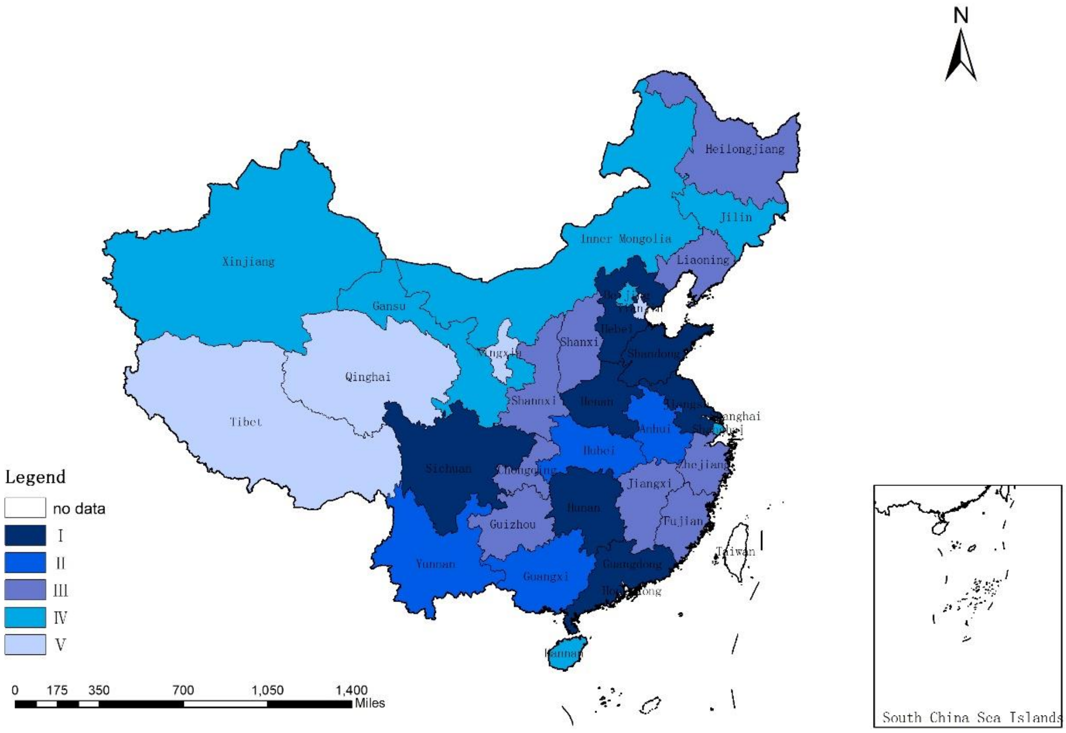

Fig. 6. Spatial distribution of ranks on development conditions.

(4) Summary of ranks for the criterion layer

In summary, most of the regions have incompatible performances on three criteria due to various levels of crop yields, economic development, environmental status, etc. What the limiting factors of the suitability for BPG's industrial development in a region are remains to be further unraveled in detail. Resource potential is a limiting factor for Beijing, Shanghai, Fujian, Hainan, Guizhou, Tibet and Qinghai; Development demand is a limiting factor for Fujian, Guangxi, Yunnan, Tibet and Qinghai; Development condition is a limiting factor for Tianjin, Tibet, Qinghai and Ningxia. The details are provided in **Table S-4** in the **Supplementary materials**.

Shandong and Henan belong to Rank I (optimum) from the holistic perspective with consistent performance on each criterion. However, although Xinjiang belongs to Rank I (optimum), its development conditions are poor (Rank IV), which does not match the good performances on the other two criteria. Beijing, in particular, with a high level of economic development and serious air pollution (such as haze phenomenon), pertains to Rank I in terms of development demands. While good development conditions, such as transport condition and government financial support cannot offset the disadvantages of rural labor. In addition, Liaoning, Jilin and Heilongjiang have unsatisfactory performances on development demands and development conditions which result in a worse holistic rank compared with the rank on resource potential. The ranks on the criterion layer are consistent for Anhui, Tibet, Gansu and Qinghai.

The above evaluation results of the suitability for regional BPG's industrial development are affected by various factors. The established holistic indicator system and assessment model may incur uncertainties, mainly including those induced by changes in weights of the criteria and indicators, and changes in values of some key indicators. The details of the uncertainty analysis are provided in the **Supplementary materials**.

5. Discussion and policy implications

Previous work on regional ABRs utilization is more focused on the types, reserve, distribution, and density of ABRs, whose results reflect if a region has potential in BPG's industrial development from just resource perspective. An indicator system incorporating three dimensions closely relevant to regional BPG's industrial development is constructed, expected to support for achieving a holistic evaluation of RS. Several indicators about the state of fossil energy consumption and CO_2 emissions are introduced into the system to reflect regional demand for reshaping energy consumption structure (such as C_4 and C_6). C_7 is firstly considered to assess BPG's industrial development, identified as one of the best indicators that timely and accurately show the extent to which agricultural residues are discarded.

The core of traditional MEEM is the principle of maximum membership degree. Previous outcomes obtained by using this method is not completely ideal, because almost all maximum membership degree of matter-elements is negative value or even unobtainable. This implies that these results may not really belong to corresponding ranks and the traditional MEEM needs to be adjusted. For this reason, degree of closeness is applied to replace the principle of maximum membership degree to eliminate the inherent limitation of traditional MEEM. The evaluation of the suitability for BPG's industrial development is a MCDM problem. The existing MCDM methods such as the typical TOPSIS method, VIKOR method and grey correlation analysis share similar principles with MEEM, as the degree of correlation, membership or closeness between indicators and evaluation object. The results they provide are a prioritized sequence for the alternatives (possibly with classification, but the number of levels may be indefinite, such as by VIKOR method). While for MEEM, it requires to preliminarily define the number of ranks, as well as ranges within the classical domains and joint domain. This helps to incorporate the practical conditions for the indicators and yield stratified classifications with definitely desired number for the alternatives. Specifically, this study is intent on stratifying the suitability for BPG's industrial development in multiple regions. It hence calls for definite ranks/classifications for the regions corresponding to predefined levels of indicator attributes. Therefore, MEEM is more pertinent and conducive to solving the problem targeted by this study. The employment of the improved MEEM in the field of bioenergy industrial development is deemed as the ***method contribution*** of this study.

The holistic suitability rank for a region represents its overall potential in propelling BPG's industrial development. The suitability ranks for the criterion layer for a region reveal its specific advantages and limiting factors regarding BPG's industrial development. The uncertainty analysis helps to identify the impacts of changes in key indicators on the suitability rank of a region. As stated in literature review, existing studies have focused more on resource accounting, evaluation of environmental-economic performances of bioenergy technologies and policies targeting the influential factors of industrial development of bioenergy utilization. There has been no research engaged in assessing the suitability for BPG's industrial development in China from multiple dimensions so far. The analyses from the above three perspectives can be deemed as the ***content contribution*** of this study.

Based on the results, the following policy implications can be unraveled. (1) Shandong and Henan owing to the best performance on holistic suitability rank (Rank I) should be conferred to priority when deploying BPG development and formulating BPG target. (2) In terms of the regions pertaining to limited development, the BPG projects may be facilitated in several counties with prominent conditions. Decision makers should also strictly control the approval of projects in the regions that belong to unsuited development to prevent blind development. (3) Different from other regions pertaining to Rank I that are well known, Xinjiang does show its extraordinary advantages in the suitability. Its main crop is cotton with much higher straw-gain ratio, which allows abundant ABRs for the region, leading to a high rank on resource potential (Rank I). There are also good performances on the indicators under development demands (Rank I). But the performances on development conditions do not match the optimum performances on the above two aspects (Rank IV). Xinjiang still entails to strengthen its efforts in improving labor conditions, transportation conditions and government support to consolidate its position. (4) Beijing has a high level of economic development and serious air pollution problem (such as haze phenomenon), making it in Rank I on development demands. In terms of development conditions, the performances on C_{10} and C_{12} are also favorable, however failing to offset the disadvantages of rural labor and agricultural development. For this kind of region with high demand for BPG's development, but no advantage in agriculture, it calls for opening up a new way for supporting BPG's industrial development. Operation of small-scale BPG projects and encouragement of more urban labor to engage in BPG are the potential alternatives. (5) The three northeastern provinces in China (Liaoning, Jilin and Heilongjiang), with fertile land and abundant ABRs, do not achieve the expected excellent performance on the holistic suitability rank. The main reason is that they have unsatisfactory performances on development demands and development conditions. In particular, the development conditions in Jilin unexpectedly belong to Rank IV, which largely offsets the advantage on resource potential. This again proves that not all regions with abundant ABRs are suitable for vigorously promoting BPG industry. Development demands and conditions are also indispensable factors.

6. Conclusion

An integrated framework combining resource potential, development demands and development conditions is developed to evaluate the suitability for regional BPG's industrial development in China. The entropy weight method and improved matter-element extension model are employed to attain the suitability ranks (stratified into five ranks) according to the framework. The novelty of this paper lies in two points: the traditional matter-element extension model is improved and applied in the field of bioenergy utilization; this study for the first time provides both holist and stratified results of the suitability for regional BPG's industrial development in China.

Some main conclusions are as follows. The distribution of suitability ranks is highly imbalanced among regions, with the east superior to the west. The regions belonging to Rank I (optimum) assemble in Henan, Shandong and Xinjiang. While Hainan, Qinghai and Tibet belong to Rank V (unsuited). The suitability ranks for regions on three criteria are considerably different. In particular, Beijing belongs to Rank V on resource potential, but pertains to Rank I and Rank IV on development demands and conditions, respectively. The poor performances on development demands are the impediments for Guangxi and Yunnan. Some regions with optimum performances on resource potential are classified into inferior rank due to worse performances on development demands and development conditions, such as Liaoning, Jilin and Heilongjiang. The ranks on the criterion layer verifies the necessity and reasonability of the holistic assessment that includes all aspects of bioresources, society, economy, environment and energy consumption.

There are some other factors in actual development process, which are not concerned in this study due to difficulty in data acquisition and quantification, such as farmers' willingness to sell straw, long-term storage of feedstocks, government taxes and subsidies, feed-in tariff of biomass power, etc., which should be further discussed. Besides the factors that have not been incorporated into the indicator system due to data unavailability, detailed analysis on suitability and development path on the level of sub-regions (cities or counties) considering supply system of feedstocks, scale of power plant, local fiscal and taxation system, etc. will be our future directions of focus. The procedures (indicator system, entropy weight method, matter-element extension model) developed can be transferred to other countries and spatial scales according to the local situation and available data.

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