Regional efforts to mitigate climate change in China: A multi-criteria assessment approach

Abstract: The task of mitigating climate change is usually allocated through administrative regions in China. In order to put pressure on regions that perform poorly in mitigating climate change and highlight regions with best-practice climate policies, this study explored a method to assess regional efforts on climate change mitigation at the sub-national level. A climate change mitigation index (CCMI) was developed with 15 objective indicators, which were divided into four categories, namely, emissions, efficiency, non-fossil energy, and climate policy. The indicators' current level and recent development were measured for the first three categories. The index was applied to assess China's provincial performance in climate protection based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. Empirical results show that the middle Yangtze River area and southern coastal area perform better than other areas in mitigating climate change. The average performance of the northwest area in China is the worst. In addition, climate change mitigation performance has a negative linear correlation with energy self-sufficiency ratio but does not have a significant linear correlation with social development level. Therefore, regional resource endowments had better be paid much more attention in terms of mitigating climate change, because regions with good resource endowments in China tend to perform poorly.

Keywords: carbon efficiency, climate policy, energy efficiency, mitigation efforts, non-fossil energy, TOPSIS

1. Introduction

Climate change poses a significant potential risk for human society and the natural system (Wei et al. 2014). According to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), human influence on the climate system is clear, and global warming may cause 'severe, pervasive, and irreversible' impacts (IPCC 2014a). To prevent the dangerous anthropogenic interference with the climate system, climate change mitigation has become one of the most important tasks for all countries (Scrieciu et al. 2013). However, great externality exists in tackling climate change which is a typical global issue, and one region has little incentive to reduce emissions while other regions do not take measures to mitigate climate change. Therefore, a tool to assess regional efforts on climate change mitigation is needed to put pressure on regions that perform poorly and highlight regions with best-practice climate policies.

International cooperation is one of key issues on global mitigation strategies, so many tools have been developed to assess national efforts on climate change mitigation. However, few studies have been found to address this issue at the sub-national level. The task of mitigating climate change is usually allocated through administrative regions in many countries, and there is also externality in regional mitigation actions. Therefore, this study explored a method to assess regional efforts to mitigate climate change at the sub-national level.

A climate change mitigation index (CCMI) was developed based on the climate change performance index proposed by Germanwatch (Burck et al. 2014b). CCMI was an index system which integrated 15 objective indicators into a single composite indicator. The 15 indicators were divided into four categories: emissions, efficiency, non-fossil energy, and climate policy. CCMI can be used to assess the performance of climate mitigation strategies. Its goal is to put pressure on regions that perform poorly in mitigating climate change and to highlight regions with best-practice climate policies. In this paper, the index was utilized to assess China's provincial efforts to mitigate climate change based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method.

China was chosen as a case in this study for several reasons. First of all, as the leading energy consumer and the largest carbon-emitting country in the world, China's carbon dioxide (CO_2) emissions from fuel combustion accounted for 25.9% of global emissions in 2012 (IEA 2014). China has occupied more than one half of the global increased CO_2 emissions between 1990 and 2012 (Fig. 1) (Feng et al. 2013; IEA 2014). As a result, China's performance in carbon reduction is critical to the effects of global actions in mitigating climate change.

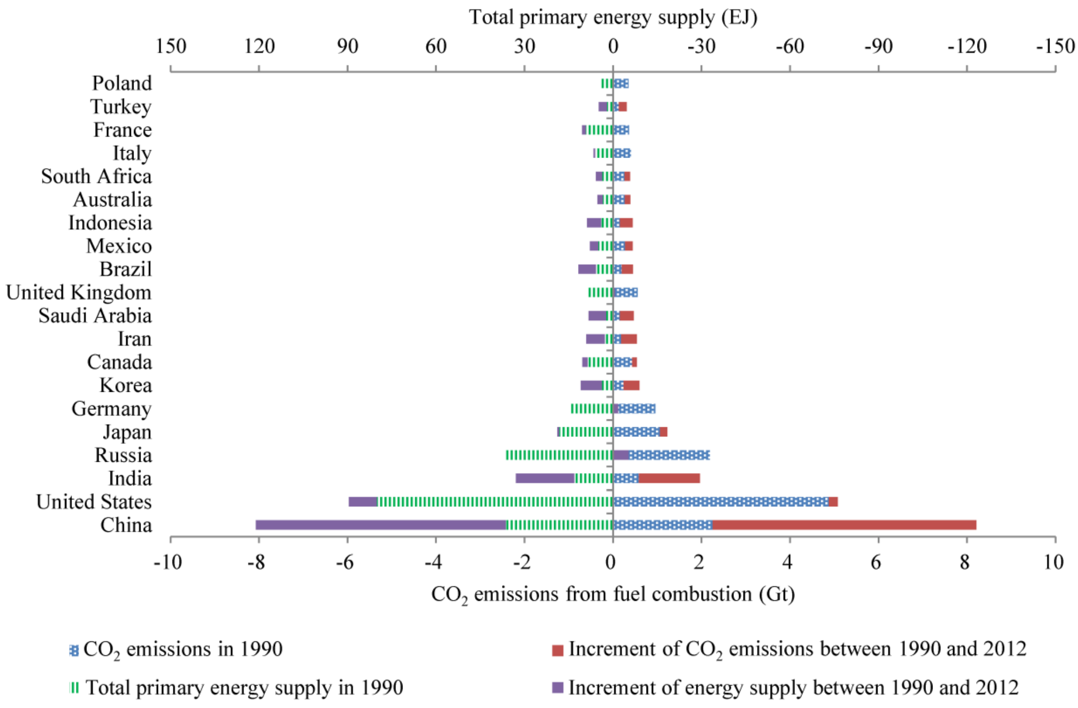

Fig. 1. China occupied more than one half of the global increased CO_2 emissions between 1990 and 2012. EJ refers to 10^{18} joules, and Gt refers to 10^9 tonnes (IEA 2014).

Second, faced with international pressure to reduce its CO_2 emissions as well as limited domestic fossil energy supply and a high level of air pollution, China has set a target to cut carbon intensity [i.e., CO_2 emissions per unit of gross domestic product (GDP)] by 40% to 45% during the period of 2006–2020 (Liu et al. 2013). In the United States (US)–China Joint Announcement on Climate Change released on November 12, 2014, China announced that it aims to achieve the peaking of CO_2 emissions around 2030 and increase the share of non-fossil fuels in primary energy consumption to approximately 20% by 2030 (The White House 2014).

Ultimately, China is a typical country which allocates its task of reducing carbon emissions through administrative regions. To achieve the climate-related targets, the task of reducing carbon emissions is usually allocated through sectors or administrative regions. The Chinese political system requires the country's energy conservation and emission reduction targets to be allocated not through sectors but through administrative regions. The government's Twelfth Five-year Plan (2011–2015) calls for a 16% reduction in energy intensity and a 17% reduction in carbon intensity (State Council 2011b). Each province has been allocated mandatory targets. The target of reducing energy intensity is set to 18% in five provinces, 17% in four provinces, 16% in twelve provinces, 15% in six provinces, and 10% in three provinces (State Council 2011a). Therefore, examining the provincial performance in climate protection in China is significant (Liu et al. 2012).

2. Literature review

National efforts on climate change mitigation have been assessed by many researchers and reports. The IPCC fifth assessment report (2014b) assessed performance of climate policies and measures in developed and developing countries taking into account development level and capacity. These polices are divided into economic instruments, regulatory approaches, information programmes, government provision of public goods and voluntary agreements. Van Sluisveld et al. (2013) used a multi-model comparison to analyze post-2020 mitigation efforts of five major economies, including the United States (US), the European Union (EU), Japan, China and India, in the context of the 2°C target. The results showed that India and the US emphasize on prolonging fossil fuel consumption with carbon storage technologies, whereas China and the EU prefer a rigorously shift to carbon-neutral technologies with renewables. Calvin et al. (2012) assessed national climate policy goals in the Copenhagen Accord using 23 energy and integrated assessment models. They found that the targets outlined by the US, the EU, Japan, and Korea require significant policy action, whereas India's goals are met without any climate policy. Konidari and Mavrakis (2007) used the multi-attribute theory and simple multi-attribute ranking technique to assess the aggregate performances of climate change mitigation policy instruments in eight countries.

Some institutions assessed national efforts on climate change mitigation by developing index system. Germanwatch developed the Climate Change Performance Index to estimate and compare the climate protection performance of 58 countries whose CO_2 releases accounted for more than 90% of global emissions. The index combines thirteen objective indicators and two subjective indicators assessed by more than 200 experts from different countries (Burck et al. 2014b). PricewaterhouseCoopers (PwC) established the Low Carbon Economy Index to examine the rate of decarbonization in the Group of Twenty (G20) economies. The report showed that based on the carbon budget in the fifth assessment report of the IPCC, the global economy needs to reduce carbon intensity by 6.0% yearly until 2100 (PwC 2013). The American Security Project established the Climate Change and Global Security Defense Index to detail how governments around the world plan for and anticipate the strategic threats imposed by climate change. The results showed that more than 70% of the nations in the world view climate change as a serious national security issue (Holland and Vagg 2013). Dual Citizen (2012) introduced the Global Green

Economy Index to rank 27 countries based on their efforts to incorporate environmentally sustainable practices, such as reliance on renewable energy, into their economies. Simultaneously, the index aims to capture how these efforts are regarded internationally.

To the best of our knowledge, only a few studies have estimated regional efforts to mitigate climate change at the sub-national level. Some researchers analyzed China’s regional efforts from the perspective of energy and environmental efficiency using Data Envelopment Analysis (DEA) (Zhou et al. 2008; Sueyoshi and Goto 2012; Zhou et al. 2010). Wang et al. (2013) utilized DEA model to evaluate China’s regional energy and environmental efficiency. The empirical results illustrated that the eastern area of China has the highest energy and environmental efficiency, whereas the efficiency of the western area is the worst. Generally, the energy and environmental efficiency of China increased slightly from 2000 to 2008. Guo et al. (2011) used DEA to evaluate the carbon emission performance of 29 Chinese provincial administrative regions. They found that most of regions have an irrational energy structure and exhibit an overdependence on coal consumption.

Some other studies tried to assess China’s regional performance on climate change mitigation from the perspective of low-carbon or green development by developing index system. Price et al. (2013) developed a low-carbon indicator system at provincial and city levels; the system consists of indicators employed by energy end-use sectors. The indicator system was applied to evaluate the low-carbon performance of 30 provinces, autonomous regions, and cities in China in 2008. Pan et al. (2013) developed a low-carbon development index to examine the comprehensive levels of low-carbon development in China’s 100 cities.

3. Methodology

3.1 Research framework

Fig. 2 shows the framework of this research. First of all, CCMI was developed with objective indicators. Second, it was utilized to assess China's provincial efforts to mitigate climate change based on the TOPSIS method. Third, China's provincial performance was assessed in four fields, namely, emissions, efficiency, non-fossil energy, and climate policy. Fourth, the comprehensive performance of mitigating climate change was estimated. Lastly, several suggestions for mitigation on both national and regional levels were provided.

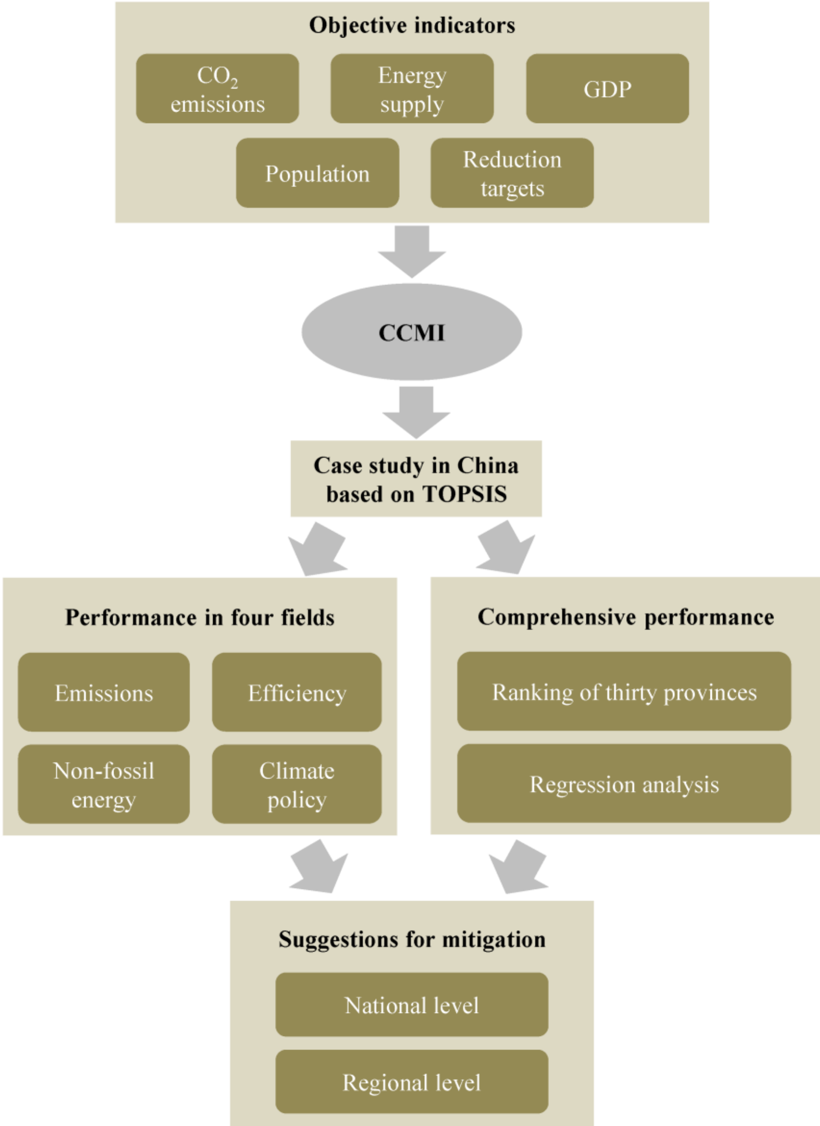

Fig. 2. China's regional efforts to mitigate climate change are assessed using the CCMI.

3.2 Components and weights of CCMI

CCMI was assessed by 15 objective indicators integrated into a single composite indicator. The indicators were divided into four categories: emissions, efficiency, non-fossil energy, and climate policy. The indicators' current level and recent development were measured for the first three categories. Fig. 3 shows all indicators and their corresponding weights in the overall score.

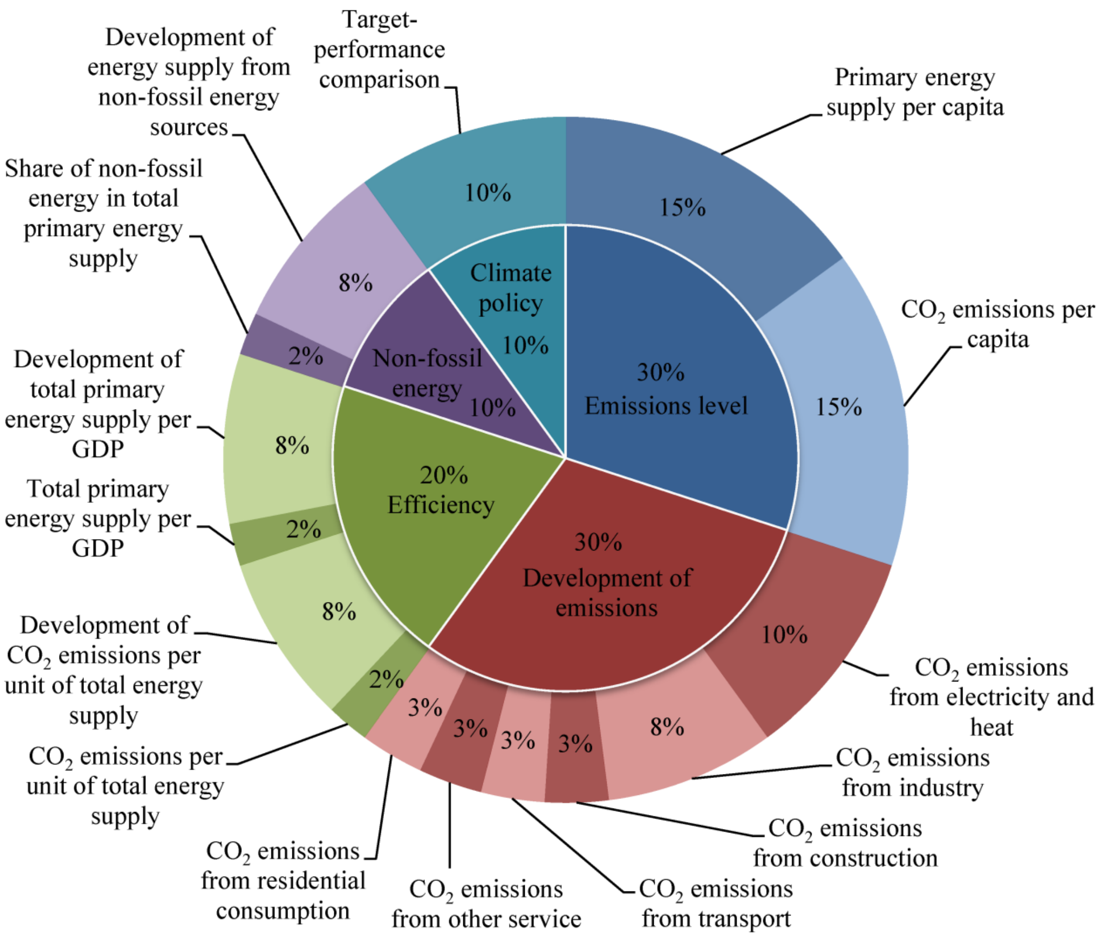

Fig. 3. CCMI is composed of 15 objective indicators.

3.2.1 Emissions

CO_2 emitted from fossil energy is the main cause of human-induced climate change (Sueyoshi and Goto 2012). They are usually regarded as the most important indicator in measuring the effects of climate policies. Therefore, emissions contribute the largest share (60%) in the overall score of a region; the half of this figure is for current emission level, and the other half is for the recent development of emissions.

Two separate indicators, namely, CO_2 emissions per capita and primary energy supply per capita, were utilized to measure the level of current emissions. Egalitarianism is implemented in the index system. In other words, people have equal rights to use atmospheric resources (Baer et al. 2000; Oberheitmann 2010). Hence, the per-capita value rather than total quantity was used.

This study only focused on CO_2 emissions from fossil fuel combustion. The emissions from anthropogenic land use change were not included because of data unavailability (Chen and He 2014; Yu et al. 2014). The CO_2 emissions were calculated by using the algorithm in the *2006 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC 2006; Tang and Nan 2013).

$$T_j = \sum_{i=1}^{m} \left[(A_{ij} - S_{ij}) e_i c_i O_i \cdot 44/12 \right], \tag{1}$$

where T_j is the total CO_2 emissions of region *j*, A_{ij} is the total consumption of fuel *i* in region *j*, S_{ij} is the non-energy use consumption of fuel *i* in region *j*, e_i is the factor for the conversion of fuel *i* into energy units on a net calorific value basis, c_i is the carbon content of fuel *i*, O_i is the fraction of oxidized carbon of fuel *i*, $44/12$ is the molecular weight ratio of CO_2 to C, *m* is the number of fuel types ($m = 27$), and $i = 1, 2, ..., m$; $j = 1, 2, ..., 30$. The sectors which consume energy are divided into two transformation sectors (thermal power and heating supply) and seven final consumption sectors (agriculture, forestry, animal husbandry, fishery and water conservancy; industry; construction; transport, storage and post; wholesale, retail trade and hotel, restaurants; other services; and residential consumption). Fuels which are used as feedstock, reductant or non-energy products do not lead to fuel combustion emissions, so those are excluded from the total energy consumption. There are twenty-seven fuel types, including raw coal, cleaned coal, other washed coal, briquettes, gangue, coke, coke oven gas, blast furnace gas, converter gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, naphtha, lubricants, paraffin waxes, white spirit, bitumen asphalt, petroleum coke, liquefied petroleum gas, refinery gas, other petroleum products, natural gas, and liquefied natural gas.

Primary energy supply per capita is the other emission level indicator, although the CO_2 emission figure is calculated from energy consumption. Under the assumption that energy will never be abundant, this indicator is an important complement to per-capita emissions (Burck et al. 2014a).

The recent development of emissions accounts for 30% of a region's overall score. To rate the overall performance in protecting climate and analyze the strengths and shortcomings in detail, the changes in CO_2 emissions were measured from the electricity and heat production, industry, construction, transport, other service, and residential sectors. According to the categorization in China's statistical data (NBS 2013a), the energy sector contains thermal power and heating supply, and the transport sector includes transport, storage, and post. The weighting of each sector was set according to its proportion in national emissions.

The development of emissions in the agriculture sector was excluded for two main reasons. First, the carbon emissions of the agricultural sector are much lower than those of other sectors. In 2012, the agriculture sector in China emitted 141.07 million tons of CO_2, which only accounted for 1.4% of the national emission figure. Furthermore, agriculture, which provides food, is the fundamental industry of human society. With the growth of the population, it is reasonable to achieve a not very high increase in agricultural emissions.

The recent development of each indicator can be obtained by

$$\alpha_{jk,t} = \left(L_{jk,t} - L_{jk,t-1}\right) / L_{jk,t-1} , \quad (2)$$

where $\alpha_{jk,t}$ is the development of indicator k in region j at year t, $L_{jk,t}$ is the level of indicator k in region j at year t, and $L_{jk,t-1}$ is the level of indicator k in region j at year t-1.

3.2.2 Efficiency

One of the most effective methods to control CO_2 emissions is to improve the energy and carbon efficiency (Streimikiene et al. 2012; Scrieciu et al. 2014), especially for China whose energy consumption is increasing rapidly. Two indicators were considered: CO_2 emissions per unit of total energy supply (10%) and total primary energy supply per GDP (10%). Both the current level (2%) and development (8%) were evaluated for the two indicators. The current development of the efficiency indicators was also calculated with Equation (2).

The first indicator in the measurement of carbon efficiency, the CO_2 emissions per unit of total energy supply, mainly reflects the structure and efficiency of the generation system and the selected fuel mix. The second indicator, total primary energy supply per GDP, is the measurement of energy efficiency; it focuses on the structure of the general economic system and its efficiency (Burck et al. 2014a).

3.2.3 Non-fossil energy

The substitution of fossil fuel by renewable energy is another effective means to reduce carbon emissions (Streimikiene and Balezentis 2013; IPCC 2011). Therefore, the indicator of non-fossil energy contributes 10% to a region's overall score. The largest part of this indicator (80%) is dependent on the development of energy supply from non-fossil energy sources. Considering that several regions have already obtained a high proportion of non-fossil energy in the total energy supply and therefore have less potential to further increase their share of non-fossil energy, the rest (20%) is based on the share of non-fossil energy in the total primary energy supply.

The non-fossil energy of each region contains two parts. The first part is nuclear power and renewable energy (e.g., hydro power, wind power, and solar energy). The second part is imported heat and electricity from other regions or countries. For instance, region 2 imports heat (b_1) and electricity (b_2) from region 1 (see Fig. 4). The total primary energy supply of the two regions is p_1 and p_2, respectively, and the supply of nuclear power and renewable energy is r_1 and r_2, respectively. The two regions' share of non-fossil energy in the total primary energy supply can be obtained by

$$\beta_1 = (r_1 - b_1 - b_2)/P_1 , \tag{3}$$

$$\beta_2 = (r_2 + b_1 + b_2)/P_2 , \tag{4}$$

where β_1 and β_2 are the share of non-fossil energy of regions 1 and 2, respectively. In this manner, the imported heat and electricity are contained in non-fossil energy while the indigenous production of heat and electricity are excluded. Moreover, a certain region's share of non-fossil energy may be negative if its net exports of heat and electricity are larger than the supply of nuclear power and renewable energy (e.g., $b_1 + b_2 > r_1$).

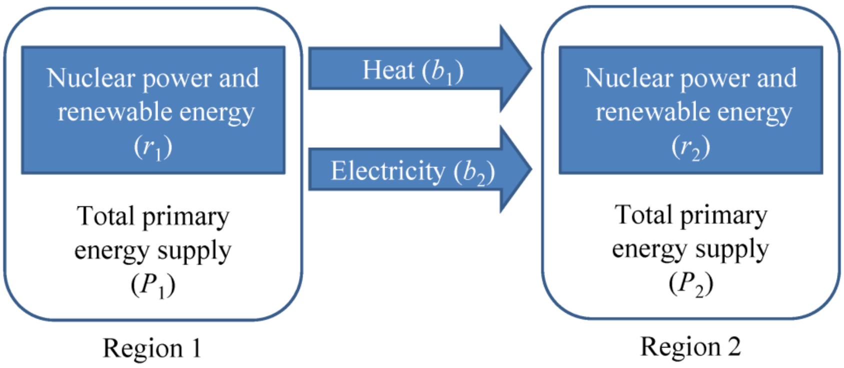

Fig. 4. The non-fossil energy contains imported heat and electricity from other regions.

3.2.4 Climate policy

Climate policy occupies 10% of the overall score of a region. This indicator was evaluated by comparing the target and actual performance. To reduce energy consumption and mitigate climate change, the Chinese government has set the target to reduce energy consumption per unit of GDP by 16% and cut CO_2 emissions per unit of GDP by 17% during the period of 2011–2015 (State Council 2011b). Each region has been allocated mandatory targets. The target of reducing energy intensity is set to 18% in five regions, 17% in four regions, 16% in twelve regions, 15% in six regions, and 10% in three regions (State Council 2011a). In this study, the reduction targets are distributed equally in five years to measure the performance in each year. The indicator of target–actual performance comparison is evaluated by

$$\gamma_j = \left(G_j - \overline{G_j}\right) \Big/ \overline{G_j} \,, \tag{5}$$

where γ_j is the target performance comparison score of region *j*, $\overline{G_j}$ is the target of reducing the energy intensity of region *j*, and G_j is the actual performance of reducing energy intensity.

The comparison indicator of target and actual performance cannot completely reflect the effects of a region's climate policies. Long-term climate policies would generate effects in future years and even decades (Scrieciu and Chalabi 2014). Therefore, a certain year's target performance comparison can only show the effects of short-term policies in that year and partial policies in the past years.

3.3 Combination of indicators based on TOPSIS

The final score of CCMI was combined by the 15 weighted indicators using the TOPSIS method. The TOPSIS, first developed by Hwang and Yoon (1981), is a widely used multi-criteria evaluation technique. It is based on the concept that the positive ideal alternative has the best level for all attributes while the negative ideal is the one with all worst attribute values. According to the method, the optimal alternative should simultaneously have the shortest distance from the positive-ideal solution and the farthest distance from the negative-ideal solution (Ertuğrul and Karakaşoğlu 2009).

All indicators were divided into benefit- and cost-type indicators. The larger the value of a benefit-type indicator is, the better its performance is. The opposite condition applies to the cost-type indicators. For example, the share of non-fossil energy in the total primary energy supply is a benefit-type indicator, whereas CO_2 emission per capita is a cost-type indicator. The benefit-type indicators are normalized by

$$Y_{jk}=100\left(\frac{X_{jk}-X_k^{\min}}{X_k^{\max}-X_k^{\min}}\right), \tag{6}$$

where Y_{jk} is the normalized indicator *k* in region *j*, X_{jk} is the actual value of indicator *k* in region *j*, $X_k^{\min}=\min\limits_j X_{jk}$, and $X_k^{\max}=\max\limits_j X_{jk}$. Accordingly, the cost-type indicators are normalized by

$$Y_{jk}=100\left(\frac{X_k^{\max}-X_{jk}}{X_k^{\max}-X_k^{\min}}\right). \tag{7}$$

In this manner, all normalized indicators are benefit-type indicators, with 100 points as the highest score and zero as the lowest score. The region that performs best in one indicator receives full points in that indicator; the region that performs worst in one indicator receives a score of zero. A score of 100 can be achieved, but this would only mean the best relative performance and not necessarily the optimal effort for climate change mitigation (Burck et al. 2014a). In addition, a score of zero does not mean that the region does nothing to mitigate climate change.

The distance between the region *j* and the worst performance can be obtained by

$$d_j^-=\sqrt{\sum_{k=1}^{n}\omega_k^2\left(Y_{jk}-Y_k^{\min}\right)^2}, \tag{8}$$

and the distance between the region *j* and the best performance can be obtained by

$$d_j^+=\sqrt{\sum_{k=1}^{n}\omega_k^2\left(Y_k^{\max}-Y_{jk}\right)^2}, \tag{9}$$

where d_j^- is the distance between the region *j* and the worst performance, d_j^+ is the distance between the region *j* and the best performance, Y_{jk} is the normalized indicator *k* in region *j*, ω_k is the weighting of indicator *k*, $Y_k^{\min}=\min\limits_j Y_{jk}$, $Y_k^{\max}=\max\limits_j Y_{jk}$, and *n* is the number of indicators (currently $n=15$).

The overall score of CCMI can be determined by

$$I_j = d_j^- \Big/ \left(d_j^- + d_j^+ \right), \tag{10}$$

where I_j is the overall score of region *j*.

3.4 Regression analysis of CCMI's correlation to resource endowments and social development levels

Resource endowments and social development levels have considerable influence on a region's carbon emissions (Mi et al. 2014). Their relationships with CCMI were estimated by linear regression models. The energy self-sufficiency ratio was used as the proxy for resource endowments, and GDP per capita and urbanization rate were selected as the indicators for social development levels. Therefore, the three linear regression functions are

$$I_j = \lambda_f + \mu_f h_{fj} + \varepsilon_j \quad (f = 1,2,3), \tag{11}$$

where I_j is the overall score of region *j*, λ_f and μ_f are regression coefficients, h_{1j}, h_{2j}, and h_{3j} are energy self-sufficiency ratio, GDP per capita, and urbanization rate, respectively, in region *j*, and ε_j is an error term.

4. Data sources

In this paper, we measured China's efforts to mitigate climate change by using regional data, including GDP, population, energy supply and consumption, and CO_2 emissions. The data on GDP and population were obtained from the *China Statistical Yearbook 2013* (NBS 2013b), and the data on energy were from the *China Energy Statistical Yearbook 2012* (NBS 2012) and *China Energy Statistical Yearbook 2013* (NBS 2013a). The CO_2 emissions of each sector were calculated from energy consumption by using the algorithm in the *2006 IPCC Guidelines for National*

Greenhouse Gas Inventories (IPCC 2006). Table 1 provides a summary of the statistics of each region.

Table 1. Key data for each province in China in 2012 are used in the assessment.

	GDP (2005 Billion CNY)		Population (M)		Primary energy supply (Mtce)		CO_2 emissions ($MtCO_2$)		Targets (%)
	Level	Share	Level	Share	Level	Share	Level	Share	
Beijing	1392	3.08%	21	1.54%	60	1.40%	103	1.02%	17
Tianjin	1092	2.41%	14	1.05%	77	1.80%	181	1.80%	18
Hebei	2123	4.69%	73	5.42%	289	6.76%	790	7.86%	17
Shanxi	896	1.98%	36	2.69%	201	4.71%	494	4.91%	16
Inner Mongolia	1119	2.47%	25	1.85%	274	6.42%	699	6.95%	15
Liaoning	1902	4.20%	44	3.26%	238	5.58%	519	5.16%	17
Jilin	924	2.04%	28	2.04%	105	2.47%	250	2.49%	16
Heilongjiang	1200	2.65%	38	2.85%	132	3.10%	282	2.80%	16
Shanghai	1828	4.04%	24	1.77%	105	2.46%	211	2.09%	18
Jiangsu	4284	9.47%	79	5.89%	280	6.57%	671	6.67%	18
Zhejiang	2769	6.12%	55	4.07%	165	3.87%	394	3.91%	18
Anhui	1275	2.82%	60	4.45%	129	3.03%	315	3.13%	16
Fujian	1567	3.46%	37	2.79%	104	2.43%	235	2.34%	16
Jiangxi	940	2.08%	45	3.35%	67	1.56%	156	1.55%	16
Shandong	4134	9.14%	97	7.20%	371	8.69%	926	9.20%	17
Henan	2392	5.29%	94	6.99%	197	4.62%	544	5.41%	16
Hubei	1600	3.54%	58	4.30%	161	3.78%	403	4.00%	16
Hunan	1594	3.52%	66	4.94%	135	3.16%	300	2.98%	16
Guangdong	4821	10.66%	106	7.88%	258	6.03%	546	5.43%	18
Guangxi	955	2.11%	47	3.48%	86	2.01%	199	1.98%	15
Hainan	210	0.46%	9	0.66%	19	0.45%	34	0.34%	10
Chongqing	920	2.03%	29	2.19%	77	1.81%	169	1.68%	16
Sichuan	1818	4.02%	81	6.01%	160	3.75%	331	3.29%	16
Guizhou	474	1.05%	35	2.59%	99	2.31%	233	2.32%	15
Yunnan	776	1.71%	47	3.46%	99	2.32%	213	2.12%	15
Shaanxi	1011	2.23%	38	2.79%	119	2.78%	250	2.49%	16
Gansu	416	0.92%	26	1.92%	66	1.54%	161	1.60%	15
Qinghai	128	0.28%	6	0.43%	26	0.61%	44	0.44%	10
Ningxia	139	0.31%	6	0.48%	56	1.32%	140	1.39%	15
Xinjiang	540	1.19%	22	1.66%	113	2.64%	269	2.67%	10
National Total	45242	100%	1345	100%	4268	100%	10062	100%	16

Note: CNY refers to Chinese Yuan, M refers to million, Mtce refers to million tonnes of standard coal equivalent, and $MtCO_2$ refers to million tonnes of CO_2. Targets are energy intensity reduction targets from 2011 to 2015. The national total data do not contain those of Tibet, Hong Kong, Macao, and Taiwan. 1 US dollar is equal to 6.2628 Chinese Yuan (CNY) according to current exchange rate.

5. Results

5.1 Eight economy-geography areas in Mainland China

The efforts of 30 provinces to mitigate climate change in China were examined. Tibet, Hong Kong, Macao, and Taiwan were excluded because of the absence of relevant energy and emissions data. According to the economic development and geographical feature, Mainland China can be divided into eight economy-geography areas (Wang and Wei 2014): northeast, northern coastal, eastern coastal, southern coastal, middle Yellow River, middle Yangtze River, southwest, and northwest areas (see Fig. 5).

The northeast area consists of three industry-based provinces: Liaoning, Jilin, and Heilongjiang. The natural conditions and resource endowment structures of provinces in this area are almost similar. They face several common problems, such as resource exhaustion and updating of the industrial structure.

The northern coastal area includes two municipalities (China's national capital Beijing and Tianjin) and two provinces (Hebei and Shandong). This area is characterized by an advantageous geographical location and convenient transportation. Educational, scientific, technological, and cultural undertakings are well developed in this area.

Including one municipality (Shanghai) and two provinces (Jiangsu and Zhejiang), the eastern coastal area is the wealthiest area in China. Considering its earlier modernization, this area maintains tighter economic relations with foreign countries than other Chinese regions. It also has a large human capital.

Three provinces (Fujian, Guangdong, and Hainan) are located in the southern coastal area. The degree of opening up in this area is the highest in China, and the area has rich overseas social resources. The economic aggregate of this area is also highly ranked in China, and its industrial sector has developed completely.

The middle Yellow River area consists of three provinces (Shaanxi, Shanxi, and Henan) and one autonomous region (Inner Mongolia). This area is abundant in natural resources, especially coal. Thus, this area exports a large amount of electricity to neighboring regions each year. Given that it is located inland, the degree of opening up to the outside world in this area is insufficient. In addition, the area is overly dependent on resource-intensive industries.

The middle Yangtze River area (including Hubei, Hunan, Jiangxi, and Anhui) has the best natural conditions for agricultural industries and sustains the highest population density in China. Similar to the middle Yellow River area, this area also suffers from insufficient opening up to the outside world and faces the pressure of industrial transformation.

The southwest area, which includes Yunnan, Guizhou, Sichuan, Chongqing, and Guangxi, is located in a mountainous area. This area is inhabited by ethnic minorities, and its poverty level is higher than that of eastern and central areas of China. However, this area is rich in renewable energy resources, such as hydropower and biomass energy, and is in an advanced level of foreign trade with Southeast Asian countries.

The northwest area comprises two provinces (Gansu and Qinghai) and three autonomous regions (Ningxia, Tibet, and Xinjiang). With very poor natural conditions, this area covers a vast territory with a sparse population and a small market. It has become China’s largest energy production base for oil and natural gas. This area also links energy-rich countries in Central Asia to China for further energy cooperation.

Fig. 5. Mainland China is divided into eight economy-geography areas (the map is schematic and does not indicate the definite boundaries).

5.2 Overall scores of CCMI

The CCMI is a tool to estimate national or regional efforts to mitigate climate change. It was applied to examine the performance of China's 30 provinces in this paper. The scores of CCMI are shown in Figs. 6 and 7. The performance of provinces is divided into five categories: the first (ranking the 1^{st} to 6^{th}), second (ranking the 7^{th} to 12^{th}), third (ranking the 13^{th} to 18^{th}), fourth (ranking the 19^{th} to 24^{th}), and fifth (ranking the 25^{th} to 30^{th}) categories. Only three provinces have scores that are higher than 75. These three are Jiangxi (77.86), Hunan (76.14), and Fujian (76.11). On the contrary, the lowest score is gained by Inner Mongolia (36.82).

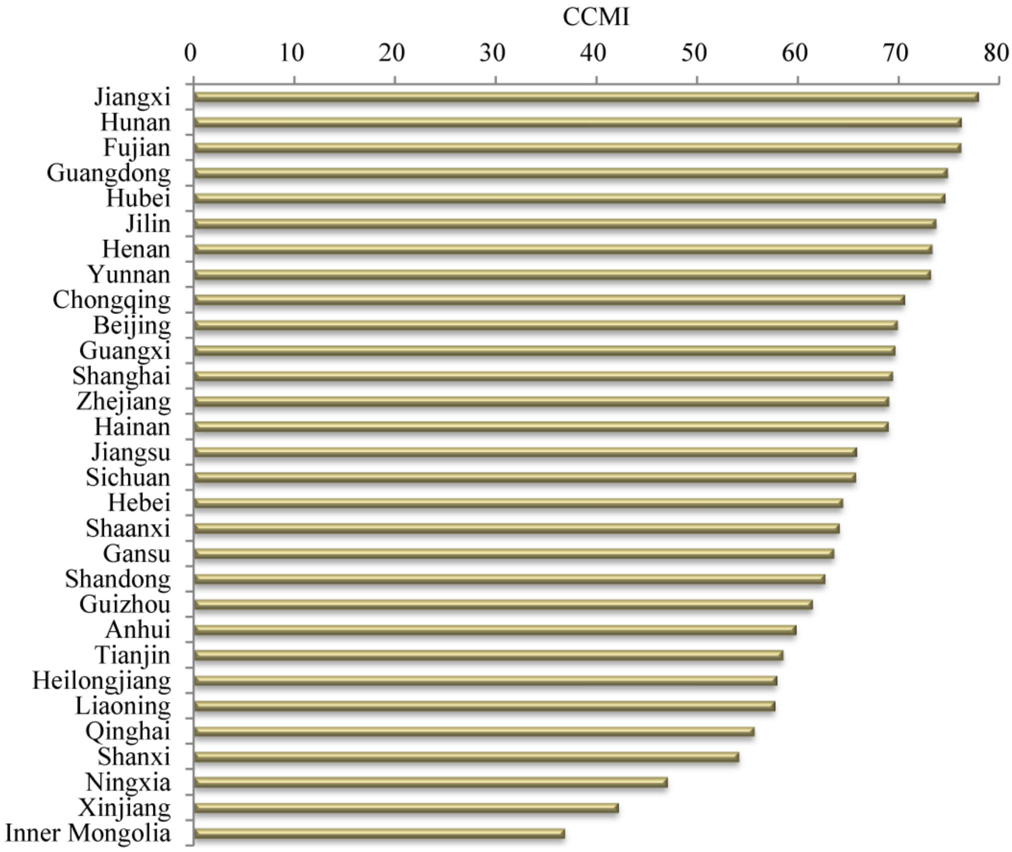

Fig. 6. Overall scores of 30 provinces in China are obtained using CCMI.

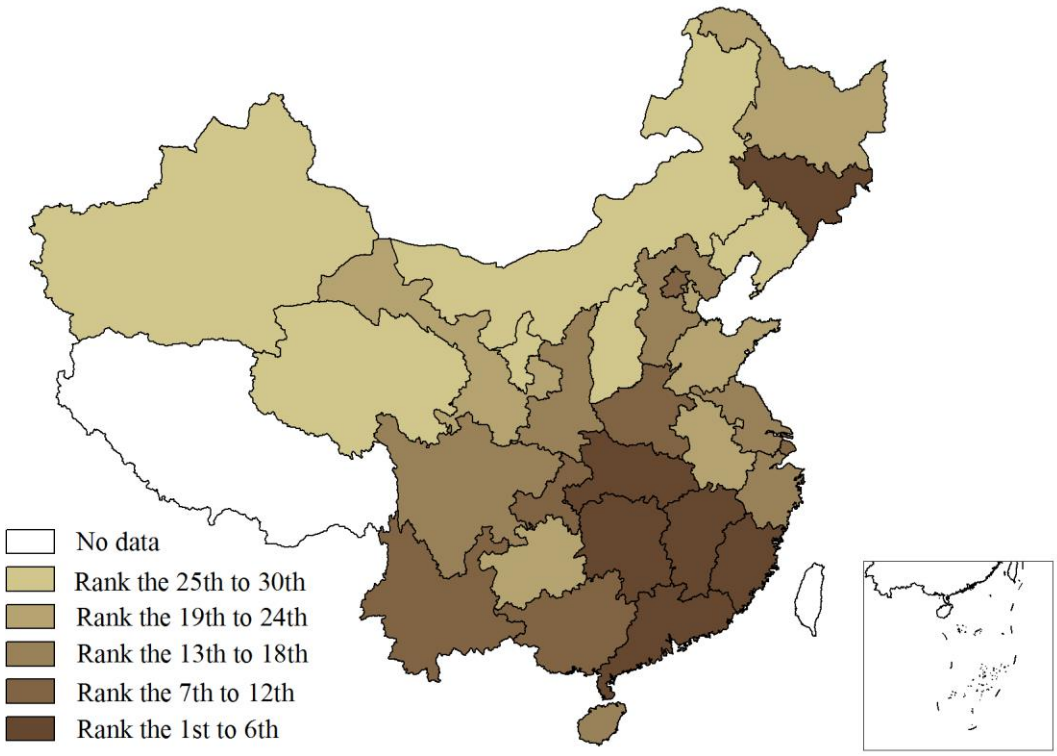

Fig. 7. Regional performance of climate change mitigation in China is assessed using CCMI (the map is schematic and does not indicate the definite boundaries).

5.3 Performance in the four fields

All indicators of CCMI are divided into four categories, including emissions, efficiency, non-fossil energy, and climate policy. So the performance in climate change mitigation can be analyzed from the four fields. Fig. 8 shows regional performance in the four fields of CCMI. Fig. 9 compares CO_2 emissions in six sectors in 2011 and 2012 of China's 30 provinces.

The middle Yangtze River area performs best in the field of emissions. The two highest scores are achieved by Jiangxi (51.54) and Hunan (51.04), which lays the foundation for their good performance in the overall scores. Other provinces in the middle Yangtze River area also have good performance in this field. The provinces that perform worst are generally located in the middle Yellow River area and northwest area. Three provinces have scores that are below 30; these three are Xinjiang (28.61), Ningxia (28.20), and Inner Mongolia (20.79).

The indicator of efficiency accounts for 20% in CCMI. Hubei, Yunnan, and Fujian have the highest scores in this field, whereas Sichuan, Heilongjiang, and Xinjiang have the worst. Hubei has high scores in the development of efficiency because of a significant improvement in energy efficiency and carbon efficiency. To be specific, its CO_2 emissions per unit of total energy supply and total primary energy supply per GDP declined by 6.34% and 6.73%, respectively. Conversely, the two indicators in Xinjiang increased by 1.44% and 9.05%, respectively.

Jilin has a score of 8.55 (the highest score) in the indicator of non-fossil energy. The proportion of non-fossil energy in total energy supply increased from 1.32% in 2011 to 2.94% in 2012 in Jilin. The growth rate was 122.44%, which gives Jilin 100 points in the development of energy supply from non-fossil energy sources. On the contrary, Heilongjiang decreased its non-fossil energy proportion from 1.78% to 0.61% during the same period. As a result, it only has a score of 0.47 in this field. Jilin and Heilongjiang are both located in the northeast area. The two provinces have almost similar natural conditions and resource endowments and face several common problems, such as resource exhaustion and updating of the industrial structure. Therefore, Heilongjiang can refer to Jilin as a model.

For the indicator of climate policy, Henan performs best with full marks. The energy intensity in Henan declined by 18.17% from 2011 to 2012, which was the highest in China. Ningxia also performs well in this field, although it exhibits poor performance in the other three fields. The energy intensity in Ningxia decreased by 12.12% during the same period. As the China’s national capital, Beijing performs poorly in this field. From 2011 to 2012, Beijing reduced its energy intensity by only 3.73%, which was slightly higher than its mandatory target (3.66%).

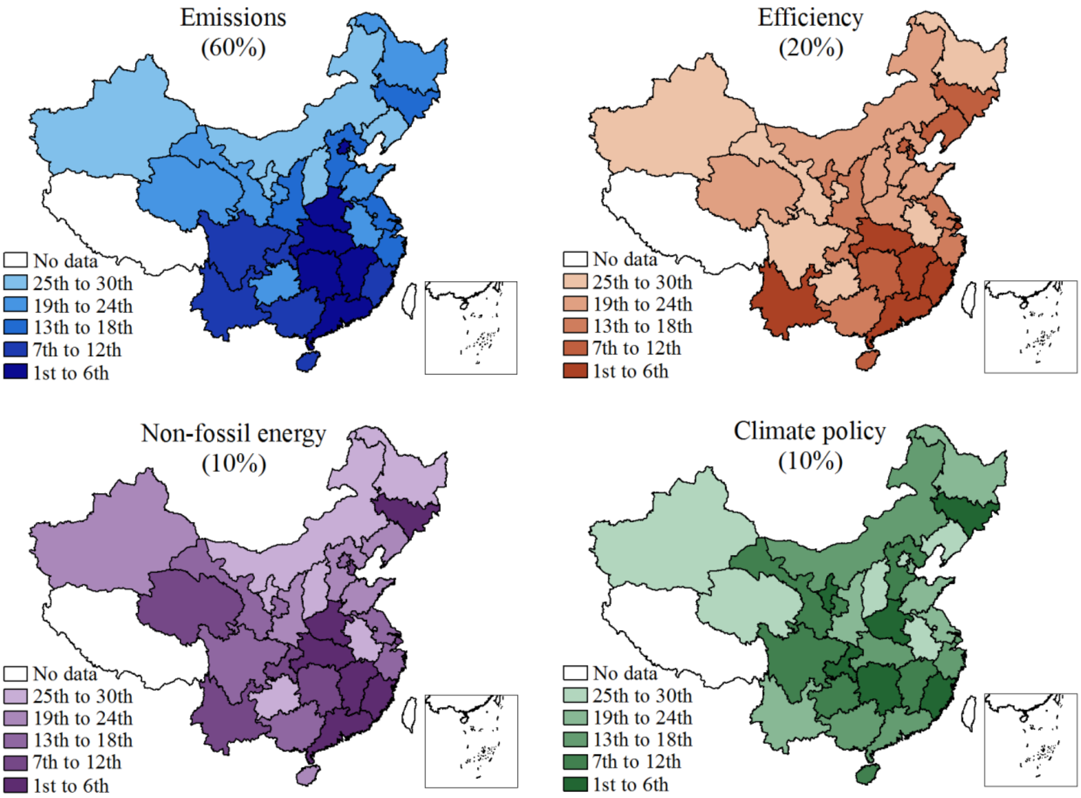

Fig. 8. China’s regional climate change mitigation performance is demonstrated in the four fields (the map is schematic and does not indicate the definite boundaries). The figures in parentheses refer to their corresponding weights in the overall score.

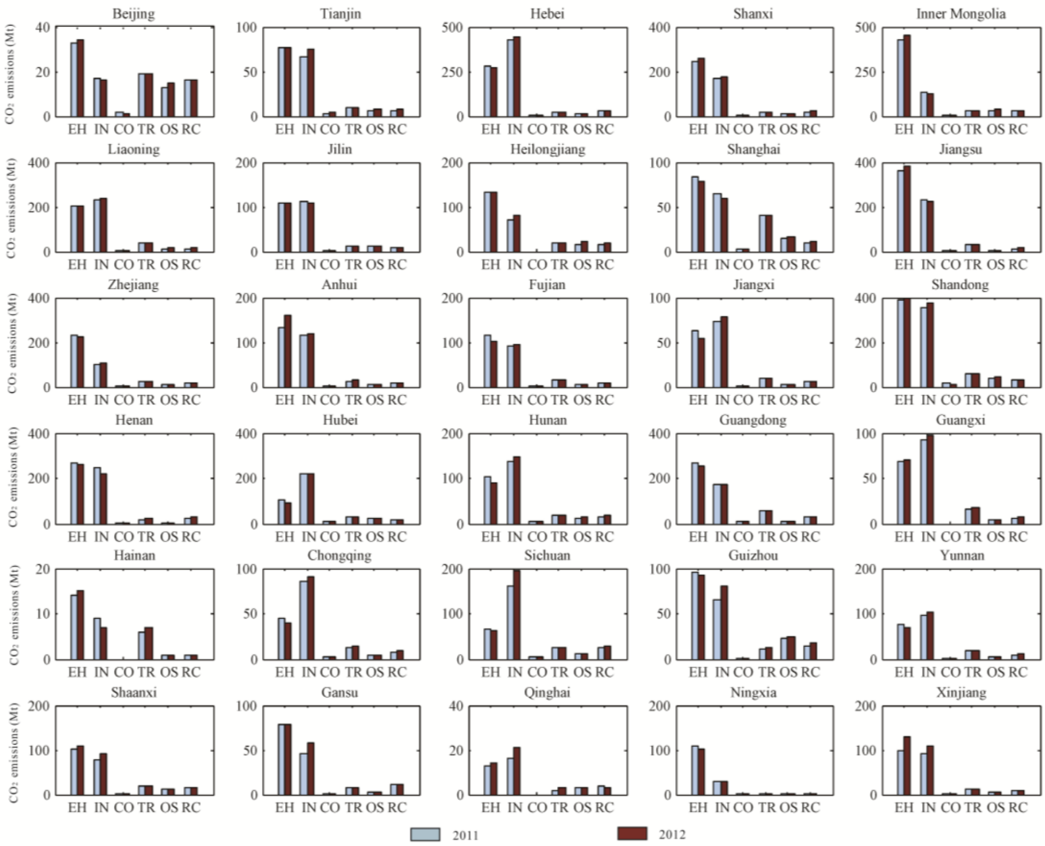

Fig. 9. Most CO_2 emissions are emitted from the electricity and heat production, and industry in China. EH, IN, CO, TR, OS, and RC refer to the electricity and heat production, industry, construction, transport, other service, and residential consumption, respectively.

5.4 Regional performance's correlation to resource endowments and social development levels

The results of CCMI can be used for further analysis. One region's carbon emissions are significantly influenced by resource endowments and social development levels. Their relationships with CCMI were estimated by three linear regression models. The results of the regression models are shown in Table 2. It can be seen that a negative linear correlation exists between CCMI and energy self-sufficiency ratio, and there is no significant linear correlation between CCMI and social development levels.

Table 2. Linear regression models are used to estimate regional performance's correlation to resource endowments and social development levels.

	Model 1	Model 2	Model 3
Constant	69.750***	63.971***	61.854***
	(2.028)	(4.236)	(8.074)
Energy self-sufficiency ratio	-0.065***		
	(0.016)		
GDP per capita		0.014	
		(0.111)	
Urbanization rate			0.048
			(0.144)
R^2	0.595	0.024	0.062

6. Discussions

6.1 Analysis of selected provinces' performance

Jiangxi occupies the first place in CCMI because it performs well in all four fields, especially for the indicator of emissions. In 2012, its primary energy supply per capita and CO_2 emissions per capita were 1.48 tonnes of standard coal equivalent and 3.47 tonnes, respectively, which were both lowest in China. As a result, it achieves 100 points in these two indicators. In addition, its CO_2 emissions from electricity and heat production declined by 12.58% from 2011 to 2012, which causes it to obtain a very high score (97.58) in that indicator.

The lowest score is gained by Inner Mongolia (36.82). Two main factors account for Inner Mongolia's poor performance. First, as one of the largest energy industry regions in China, it is overly dependent on fossil energy. The energy consumption and CO_2 emissions are both rather high because of the high density of heavy industries in this region. In 2012, its primary energy supply per capita and CO_2 emissions per capita were 11.01 tonnes of standard coal equivalent and 28.08 tonnes, respectively, which were both highest in China. Hence, it achieves a score of zero in these two indicators. Second, Inner Mongolia also provides a large amount of electricity to neighboring provinces. The net electricity export was 132.75 billion kilowatt hour (kW·h) in 2012, which resulted in a negative share of non-fossil energy in the total primary energy supply (−4.54%) according to Equation (3). Hence, this region only achieves a score of 0.20 in that indicator.

Jilin can be taken as the benchmark for northeast area. The other two provinces in this area are Liaoning and Heilongjiang. The natural conditions and resources endowments of provinces in this area are close to each other, and resource exhaustion is their common problem. They are China's old industrial bases, and need to upgrade and update the industrial structure for further development. Fig. 10 shows the scores of the CCMI and fifteen indicators in northeast area. It can be seen that Jilin performs better than Liaoning and Heilongjiang in seven indicators, especially in 'CO_2 emissions from residential consumption' (indicator 8) and 'development of energy supply from non-fossil energy sources' (indicator 14). Jilin performs best in these two indicators in China. The CO_2 emissions from residential consumption in Jilin decline by 19.49% from 2011 to 2012. On the contrary, the same indicator in Liaoning and Heilongjiang grows by 15.82% and 2.86%, respectively. The proportion of non-fossil energy in total primary energy supply in Jilin increases from 1.32% in 2011 to 2.94% in 2012, while Liaoning and Heilongjiang both decrease the non-fossil energy share during the same period. Learning from Jilin, the northeast area can reduce the residential CO_2 emissions and increase non-fossil energy proportion to protect the climate.

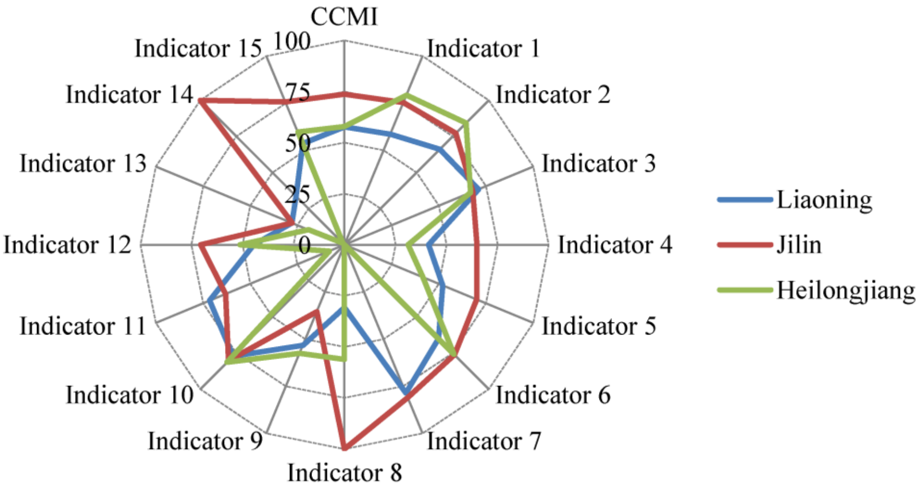

Fig. 10 Jilin performs best in the northeast area. Indicator 1 to 15 refer to the indicator of primary energy supply per capita, CO_2 emissions per capita, CO_2 emissions from electricity and heat, CO_2 emissions from industry, CO_2 emissions from construction, CO_2 emissions from transport, CO_2 emissions from other service, CO_2 emissions from residential consumption, CO_2 emissions per unit of total energy supply, total primary energy supply per GDP, development of CO_2 emissions per unit of total energy supply, development of total primary energy supply per GDP, share of non-fossil energy in total primary energy supply, development of energy supply from non-fossil energy sources, target-performance comparison, respectively.

6.2 Comparison of performance in eight economy-geography areas

The middle Yangtze River area and southern coastal area perform better than other areas in China in terms of mitigating climate change (Fig. 11). The average overall scores of the middle Yangtze River area (72.06) and southern coastal area (73.27) are higher than those of other areas. As shown in Fig. 6, the five highest scores all come from the two areas.

By contrast, the average performance of the northwest area is the worst in China. All provinces in this area belong to the fourth or fifth category (overall scores rank among 19^{th} to 30^{th}) in CCMI. It has the lowest scores in emissions, efficiency, and climate policy. The northwest area is the least developed in China, and its per capita income is much lower than that in the eastern and central parts of China.

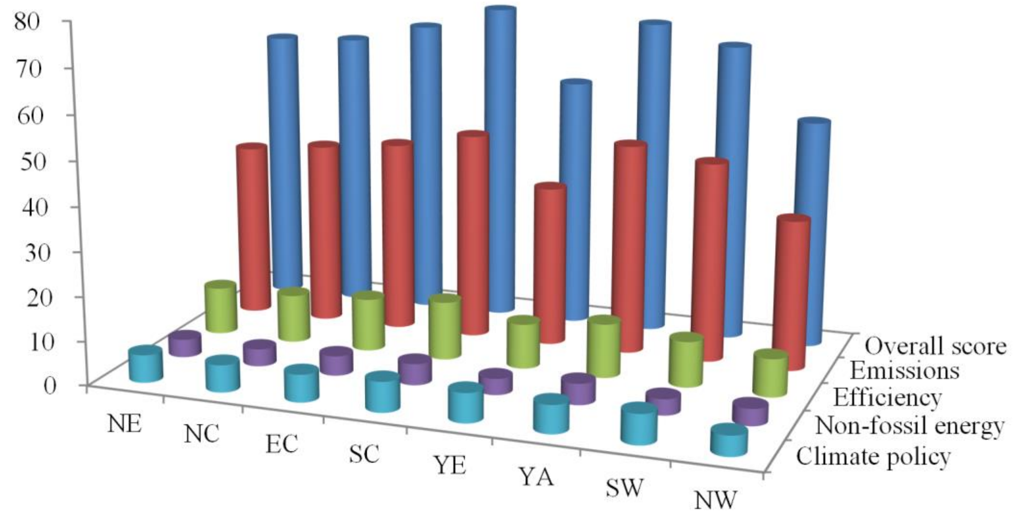

Fig. 11. Average scores of each area in China are calculated from the provincial scores. NE, NC, EC, SC, YE, YA, SW, and NW refer to the northeast, northern coastal, eastern coastal, southern coastal, middle Yellow River, middle Yangtze River, southwest, and northwest areas, respectively.

6.3 Correlation between resource endowments and climate change mitigation performance

Results of regression analysis show that a negative linear correlation exists between CCMI and energy self-sufficiency ratio. In other words, regions with good resource endowments tend to perform poorly in climate change mitigation (Fig. 12). There are two main reasons for this phenomenon in China. First, regions with a high energy self-sufficiency ratio are likely to be dependent on fossil fuel and develop energy-intensive industries. Second, provinces with a high energy-sufficiency ratio export plenty of electricity and heat to other provinces in China. The carbon emissions emitted in the generation of these electricity and heat are accounted to the producer. For example, Inner Mongolia had a very high energy self-sufficiency ratio (286%), and gained the lowest score in CCMI. It was overly dependent on fossil energy, which resulted in highest primary energy supply per capita and CO_2 emissions per capita in China. Moreover, it provided 132.75 kW·h electricity to neighboring provinces in 2012.

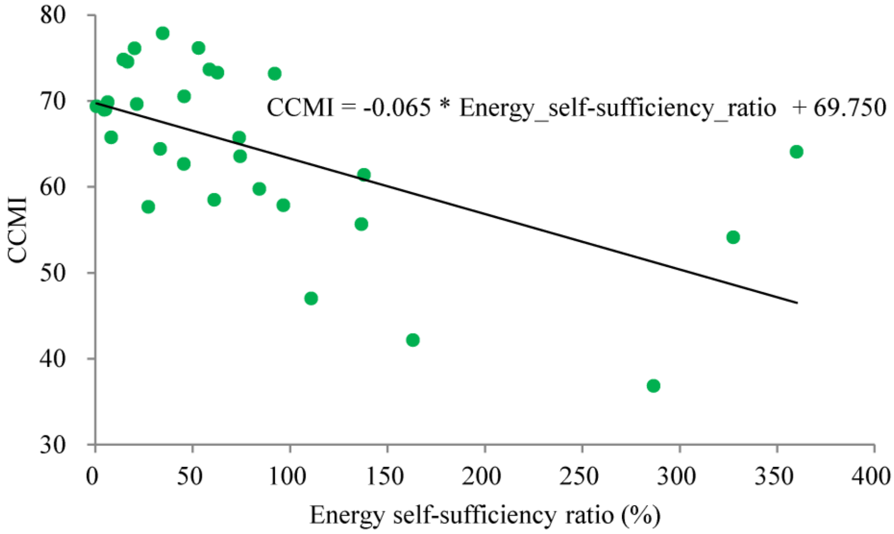

Fig. 12. A negative linear correlation exists between CCMI and energy self-sufficiency ratio.

The phenomenon also exists in international climate change mitigation actions. Energy prices in resource-rich countries are usually lower than those in resource-poor countries. These resource-rich countries are more likely to be dependent on fossil energy and have less incentive to develop non-fossil energy. For instance, in twenty highest CO_2 emitters shown in Fig. 1, Saudi Arabia had the highest energy self-sufficiency ratio with 321% in 2011. Its CO_2 emissions per capita were 154 tonnes in 2011, which were approximately 3.5 times as much as the global average. In 2014, Germanwatch released the Climate Change Performance Index to assess and compare the climate protection performance of 58 countries. In this report, Saudi Arabia gained the last place in the rankings, and needed to 'make a lot more effort to lower their emissions before an improvement could be seen in their positions' (Burck et al. 2014b).

6.4 Correlation between social development levels and climate change mitigation performance

No significant linear correlation exists between CCMI and social development levels. GDP per capita and urbanization rate are indicators for social development levels in this paper. The coefficients of the two indicators are both not significant in the regression models. For example, as one of the less developed provinces in China, Jiangxi gained the first place in CCMI. Its GDP per capita was about 20.87 thousand CNY in 2012 which ranked 26th during thirty provinces. On the contrary, Tianjin's GDP per capita was 77.29 thousand CNY in 2012 which was the highest in China. However, it ranked 22nd in climate change mitigation performance.

Regions at different stages of development all have the capability to perform well in mitigating climate change. During international climate change negotiations, many less developed countries usually claim that they have no ability to reduce CO_2 emissions. However, our results show that no significant linear correlation exists between CCMI and social development levels. In other words, less developed regions also have capability to perform well in climate change mitigation.

The development of indicators had better be taken seriously in assessing international performance in mitigating climate change. The level of indicators usually changes very slowly, and the recent development of indicators is comparatively responsive to effective climate policy. In the structure of CCMI, the changes in levels of emissions, efficiency and non-fossil energy are all taken into account. In this way, regions in differences of social development levels can all be promoted to take actions to mitigate climate change.

7. Conclusions

CCMI was developed in order to assess regional efforts to mitigate climate change at the sub-national level. In this paper, it was utilized to assess the efforts of 30 provinces to mitigate climate change in China based on the TOPSIS method. The classic regression methods were also employed to discuss the correlation of overall performance to resource endowments and social development levels. Several conclusions were obtained.

(1) In China, the middle Yangtze River area and southern coastal area perform better than other areas in mitigating climate change. The average overall scores of the middle Yangtze River area and southern coastal area are higher than those of other areas, and the five highest scores all come from the two areas. On the contrary, the average performance of the northwest area is the worst. All provinces in the northwest area belong to the fourth or fifth category (overall scores rank among 19^{th} to 30^{th}). This area has the lowest scores in emissions, efficiency, and climate policy.

(2) Regions could learn from neighboring regions to improve their performance in climate change mitigation. For instance, Heilongjiang can refer to Jilin as a model. The two provinces are both located in the northeast area with almost similar natural conditions and resource endowments, and face several common problems like resource exhaustion and updating of the industrial structure. However, Jilin performs much better than Heilongjiang.

(3) The index can be used to assess the regional climate change mitigation performance in other countries. CCMI is developed from comprehensive viewpoints of emissions, efficiency, non-fossil energy, and climate policy. All indicators used in CCMI are all objective, and their data are usually available. It can be used for other countries or regions if the weights are adjusted reasonably.

(4) Resource endowments had better be paid much more attention in global mitigation strategies. Our results show that climate change mitigation performance has a negative linear correlation with energy self-sufficiency ratio. In other words, regions with good resource endowments tend to perform poorly in climate change mitigation. The phenomenon also exists in international climate change mitigation actions. The resource-rich regions are likely to be dependent on fossil fuel and develop energy-intensive industries.

(5) The development of indicators had better be taken seriously in assessing international performance in mitigating climate change. The coefficients of GDP per capita and urbanization rate are both not significant in the regression models, which means no significant linear correlation exists between CCMI and social development levels. Therefore, provinces at different stages of development all have the capability to perform well in mitigating climate change. In order to promote regions in different social development levels to mitigate climate change, the changes in levels of emissions, efficiency and non-fossil energy are all taken into account in the structure of CCMI.

However, our method has several limitations. First, several important factors were not considered because of data unavailability. For instance, the CO_2 emission from land use change and the effects of forest carbon sink were not assessed. Second, the weights of the indicators are controversial. This paper develops a climate change mitigation index which is a tool to assess the performance of mitigation strategies. The weights of indicators used in this paper are obtained according to China's current situation. They need to be adjusted reasonably when the tool is used for other countries.

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