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Exploring Spatial Patterns of Carbon Dioxide Emission Abatement via Energy Service Companies in China

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Abstract

The disparity of carbon dioxide emission abatement (CDEA) has been impeding more balanced improvement of energy efficiency worldwide. Energy service companies (ESCOs), which are present to varying degrees, have come to play an increasingly key role in reducing CO_2 emission via energy efficiency retrofit projects. China, as the main contributor to carbon dioxide (CO_2) emissions, has been promoting ESCOs for decades. This study aims to identify the factors influencing the spatial differences for CDEA and assess the provincial-level potentials for reducing CO_2 emissions through ESCOs. Data from 3225 ESCO projects in Mainland China spanning from 2011 to 2015 were examined to map out the spatial patterns of CDEA using local Moran's I index and local indicator spatial autocorrelation. Influencing factors were identified through spatial analysis based on Kaya identity and ordinary least squares. The results indicate that the national progress of CDEA can be attributed to the high efficiency of ESCO projects in coastal and northern China. It was observed that population, consumption of coal, and research & development input have a positive influence on CDEA, whereas per-capita GDP, energy industry investment, and industry value added have an inhibitory effect on CDEA.

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Keywords: Energy service companies (ESCOs), Carbon dioxide emissions abatement, Spatial analysis.

1. Introduction

Modern climate change is a worldwide challenge rooted in anthropogenic activities. Greenhouse gases (GHGs), especially carbon dioxide (CO_2), contribute to climate change. Thus CO_2 emission reduction has been an urgent necessity (Zhang and Cheng, 2009). The Kyoto Protocol and the Paris Agreement proposed that involved countries should achieve their individual indicators on GHGs reduction (Robiou du Pont et al., 2017). Li et al. (2016) found that China contributed 10% (± 4%) to global radiative forcing, and the strongest contributions were 0.16 (± 0.02) watts per square meter for CO_2 generated from burning fossil fuels (Li et al., 2016). Due to urbanization and industrialization, China became the dominant contributor to CO_2 emissions as of 2007 ("CO2 emissions (kt) | Data," 2006). China generated one-quarter of CO_2 emissions worldwide in 2011 and accounted for over three-quarters of increased CO_2 emissions since 2008 (Liu et al., 2015, 2013). Thus, CO_2 emissions reduction in China has become a critical priority (Chen et al., 2017). It has been found that CO_2 emissions mainly come from energy use (Zhang and Cheng, 2009), and consequently energy efficiency improvement should be a feasible approach to addressing the CO_2 emissions challenge. The Chinese government has been promoting energy efficiency through the adoption of Energy Performance Contracting (EPC) (Kostka and Shin, 2013). EPC is a market-oriented service provided by Energy Service Companies (ESCOs). ESCOs provide a package of energy services (e.g., energy savings guarantees, associated design, installation services, etc.) that allow customers to improve energy efficiency (Xu et al., 2015; Xu and Chan, 2013). Since the early introduction of EPC into China in 1996 during the first phase of the World Bank/Global Environment Facility Project (WB/GEF project) that aims to foster energy conservation in China (Da-li, 2009), ESCOs have been developing rapidly (Figure 1).

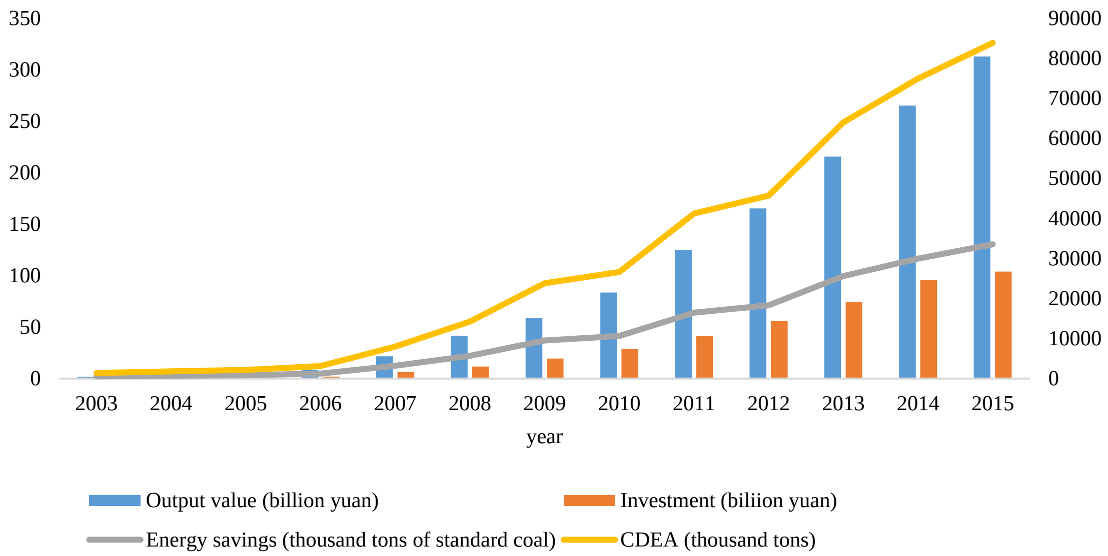

Fig. 1: Output value, investment, energy saving and CDEA of ESCOs in China from 2003 to 2015.

Source: Statistical data from ESCO Committee of China Energy Conservation Association (EMCA)

The energy savings have since drastically increased while CO_2 emissions have rapidly declined, especially after 2010. Likewise, the size of the Energy service company (ESCO) market and the output value generated have also been increasing. In recent years, the Chinese government has supported the ESCO market through subsidies and tax exemptions. This government support through finance and policy has been identified as the main driver for ESCOs industry development (Lee et al., 2003). Goldman et al. (2005) studied the ESCO industry in the United States (US) and found that ESCOs projects are mainly concentrated in regions of high population, active economic production, and abundant policy support. Given its vast territory, China has a notable regional disparity in ESCO presence and carbon dioxide emission abatement (CDEA). However, there is limited literature on the spatial characteristics of CDEA for supporting the ESCO strategy to reduce CO_2 emissions and for policy-making.

In the fields of economics and the natural and social sciences, spatial analysis has been an effective method in quantitative studies involving spatial relations and analyses of complex spatial patterns. The present study examined historical data about CDEA via ESCOs by analyzing 3225 collected projects in 28 provinces in China. The historical data was classified by province, and spatial analysis using ArcGIS was applied to present the spatial distribution of CDEA in China from 2010 to 2015. After identifying the spatial patterns with local Moran's I index and local indicator spatial autocorrelation, the influencing factors were discussed to estimate the ESCO market potential in each province. This paper aimed to contribute to environmental and energy research by (i) demonstrating the importance of ESCOs in reducing CO_2 emissions; (ii) identifying the influencing factors of spatial difference in CDEA; and, (iii) providing evidence to ESCOs in selecting a target market.

2. Literature review

Estimated global CO_2 emissions and their patterns have been widely studied. The results reveal a huge potential for reducing CO_2 emissions in the building, industrial, and transport sectors (Xu et al., 2017). Previous research has long focused on exploring the underpinnings of CDEA, including energy efficiency technology innovation (Wen and Li, 2014; Xiao et al., 2014; Xu et al., 2016), clean energy usage (Murphy and McDonnell, 2017; Nduagu and Gates, 2016), and policy interventions (Murphy and McDonnell, 2017; Standardi et al., 2017). In China, the growing research on CDEA has focused on the driving factors (Ouyang and Lin, 2017; Ren et al., 2014; Zhou et al., 2017), mitigation policies (Jiang et al., 2016; Lu et al., 2016) and technology innovation (Zhang et al., 2017). As for driving factors, CO_2 emissions per capita, energy structure, energy intensity, carbon density, and economy intensity have been found to influence CO_2 emissions in China. To evaluate the effect of mitigation policies on reducing these emissions, various quantitative analyses have been adopted. Regarding technology innovation, most literature emphasizes specific technologies such as heat pump innovation, thermal solar systems, and lighting appliances (Nikolaidis et al., 2009; Sanner et al., 2003). Others evaluated the feasibility of energy saving innovations through economic tools (Nikolaidis et al., 2009).

An avenue blending technology and economic solutions to improve energy efficiency and reduce CO_2 emissions is ESCOs (Li and Colombier, 2009; Steinberger et al., 2009). However, most research has only concentrated on the application, mechanism, barriers, and policies of EPC (Akman et al., 2013; Kostka and Shin, 2013; Vine, 2005). Fang (2013; 2012) developed a dynamic IPAT (I=Human Impact, P=Population, A=Affluence, T=Technology) model with panel data of several countries from 1981 to 2007, and found that the ESCOs significantly reduced CO_2 emissions and energy use. Yet, there are few studies investigating the factors that influence CDEA and evaluating the CO_2 emission reduction by ESCO.

Spatial analysis has been used to show the contribution of ESCOs to CDEA at the regional level

(Fan and Wang, 2016). Koralegedara (2016) studied anthropogenic heat emissions in Taiwan, and surveying distribution over the northern region, central region, southern region, and over Taiwan's main island as a whole. Fan and Wang (2016) analyzed the spatial patterns of China's wind turbine manufacturing industry to provide empirical grounding for policy making and market exploration. Numerous researchers studying China's CO_2 emissions have identified population size, urbanization, income, economic output, industrial structure, and energy consumption as the main contributing factors (Zhang and Da, 2015; Zhou and Liu, 2016). Various methods have been used to generate more precise quantitative measures of proposed relationships. Lin and Lei (2015) used the Logarithmic Mean Divisia Index method to find that energy intensity and industrial activity were the dominant factors affecting CO_2 emissions in the food industry. Jones and Kammen (2011) quantified the CO_2 reduction opportunities for households and communities in 28 cities in the US, utilizing consumption-based life cycle accounting techniques. The results found that the size and composition of CO_2 emissions vary dramatically between regions and that household types and locations affect the CO_2 emissions. Their analysis was based on an independence assumption, ignoring the spatial interaction between regions otherwise deemed to affect the results (Anselin, 1988). However, spatial effects have been proven to be key factors when studying the CDEA. Most air pollutants showed typical regional characteristics due to their high flowability (Hao and Liu, 2016; Xue et al., 2014). The spatial relationship could make the results of conventional econometrics biased or invalid. Spatial analysis has been essential for the quantitative study of problems that need to take dependence on space into consideration. Several factors can affect spatial distribution. Since 1990, researchers have demonstrated increased interest in the spatial dependence associated with other influencing factors. Li et al. (2014) utilized spatial error model (SEM) and spatial lag model

(SLM) to evaluate the effects of economic development, population density and industrial structure on the environment. Burnett et al. (2013), and Auffhammer and Carson (2008) studied factors bearing on CO_2 emissions using spatial panel data models and predicted future trends. The results showed the existence of spatial dependence on CO_2 emissions. Long et al. (2016) utilized spatial regression and stated that industrial energy efficiency, degree of openness, technological progress, and proportion of large and medium-sized enterprises output had a significantly positive impact on industrial carbon productivity, while per-capita GDP, energy consumption structure and industrial ownership exerted a negative effect on industrial carbon productivity.

3. Spatial distribution of CDEA via ESCOs

3.1. Data

In this paper, the data were mainly from the census conducted by the ESCOs Committee of China Energy Conservation Association (EMCA), containing 582, 702, 588, 747, and 606 projects for the years 2011, 2012, 2013, 2014 and 2015, respectively. The ESCO projects took place in 30 provinces of Mainland China (with Taiwan, Hong Kong, and Macao omitted). Data from Tibet and Hainan was missing for some years. Thus, these two provinces were excluded from the analysis. An example of the information drawn upon in this study on each of the 3225 projects is shown in Table 1, which includes investment, energy saving (tons of coal), energy savings profit, and contract period.

Table 1. Example information on the 3225 projects.

Year	Name of ESCO	Region	Area	Name of project	Investment (million yuan/million USD)	Energy savings (tons of coal)	Energy savings profit (million yuan/million USD)	Contract period (year)
2011	Liaoning Nengfaweiye Energy Technology Co., Ltd.	Liaoning	Industry	Renovation of circulating water system	6.78/1.07	7100	8.81/1.33	1

Some ESCO projects were missing from the EMCA's survey. Thus, the Annual China's Energy Service Industry Development Reports was included to supplement the survey data. The amount of CDEA was calculated through the consideration of energy savings from ESCOs in each province per year ($CDEA_{ESCO,i,j}$), as shown in equation (3-1)

$$CDEA_{ESCO,i,j} = 2.46\ \left(\mathrm{kg}\frac{\mathrm{CO_2}}{\mathrm{kg}}\,\text{standard coal}\right) \times \text{Energy saving}_{i.j} \tag{3-1}$$

where 2.46 represents the CO_2 emissions coefficient of standard coal (Yu et al., 2014), i represents the year of the ESCO project, and j is one of the 28 provinces.

Then a ratio (R) that represents the CDEA share of all the ESCO projects per year per province from the total CDEA in China was calculated as shown in equation (3-2).

$$\mathrm{R} = \frac{\sum CDEA_{ESCO,i,j}}{CDEA_{i,TOT\ China}} \tag{3-2}$$

where $CDEA_{i,TOT\ China}$ means the total amount of CDEA in China in year i and was obtained from the China Statistical Yearbook. The total CDEA per year in China also equals to the sum of the total CDEA per year which can be described as equation (3-3)

$$\sum CDEA_{,i,j,TOT} = CDEA_{i,TOT\ China} \tag{3-3}$$

The total amount of CDEA in each province ($CDEA_{i,j,TOT}$) can be shown as equation (3-3).

$$CDEA_{i,j,TOT} = CDEA_{ESCO,i,j}/R \tag{3-4}$$

3.2. Spatial distribution of CDEA from 2011 to 2015

The CDEA calculations provided information for a combination of 28 provinces and three sectors (building, industrial and transport) during the period between 2011 and 2015, for a total of 3225 projects. Figure 2 shows that CDEA has been rapidly increasing all five years, doubling from 41.2 million tons of CO_2 in 2011 to 83.8 million tons in 2015. The industrial sector accounted for the majority of the CDEA with 90.3%, 91.0%, 89.9%, 92.7% and 91.6% for the years 2011, 2012, 2013, 2014, and 2015, respectively. The building sector remained stable in these five years. The transport sector represented the least CDEA among the three sectors, though this sector consumes 20% of the total energy in China. In general, the main cause of energy consumption in the transport sector has been the burning of petroleum. Yet ESCOs in this sector have been limited to road lamp improvement projects.

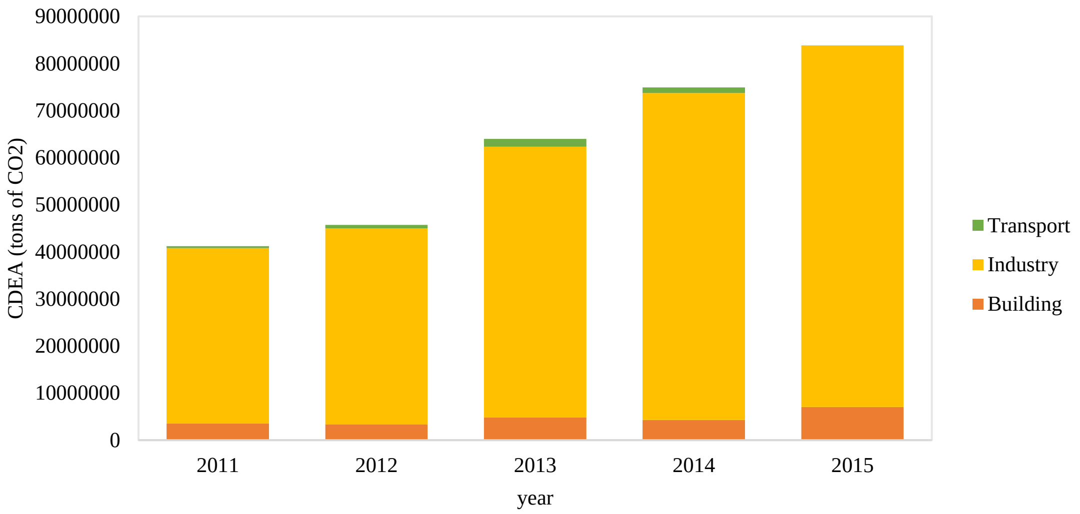

Fig. 2: Total CDEA of China from 2011 to 2015

The Chinese government's 12th five-year plan (2011–15) targeted a 16% reduction in energy intensity (energy consumption per unit of GDP), and a 17% reduction in carbon intensity (amount of carbon emitted per unit of energy consumed). Each region has been assigned mandatory targets (Liu et al., 2013). Thus, all regions are devoting efforts to offset CO_2 emissions. The CDEA breakdown for different provinces from 2011 to 2015 illuminates the diversification of CDEA in the three sectors across China as shown in Figure 3. The industrial sector accounts for the majority of the total CDEA. Guangdong province proved to be a special case, where each of the three sectors consisted of almost the same percentage. There are a variety of road lamp improvement projects which positioned Guangdong province as the most concentrated area for the Light Emitting Diode (LED) lighting industry. In contrast, there is nearly no CDEA in the transport sector in Qinghai, Gansu, Jilin, and Xinjiang.

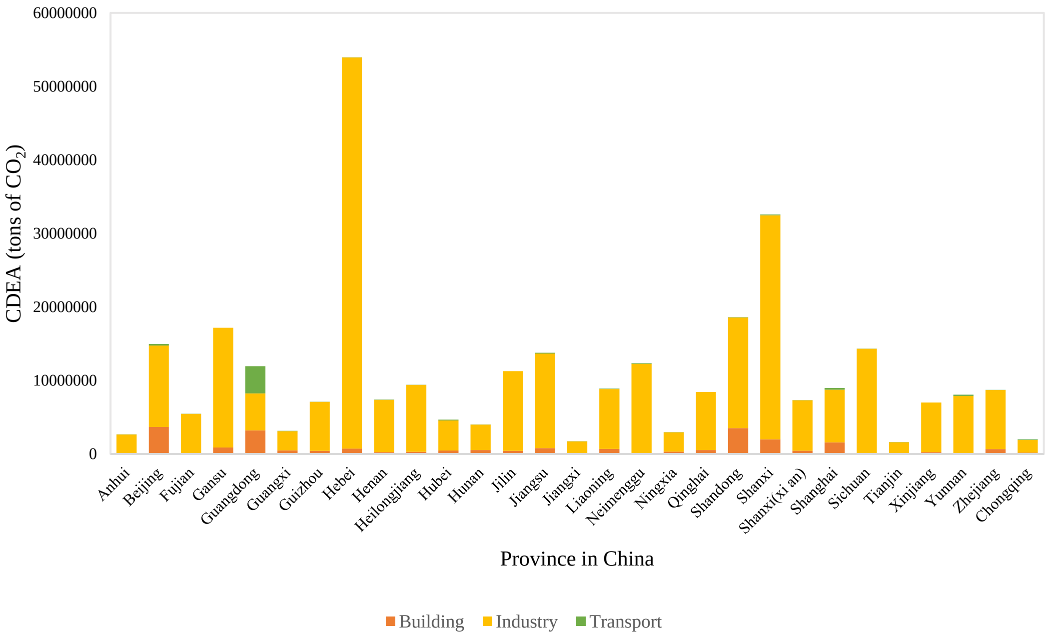

Fig. 3: CDEA of building, industrial and transport sectors in 28 provinces in China.

In terms of CDEA in the building sector, Beijing, Shanghai, Shandong, and Guangdong surpassed all other provinces. During the period between 2011 and 2015, the urbanization rate in Shanghai, Beijing, and Guangdong remained the highest in Mainland China (Table 2). The first round of

ESCOs located in Shandong, Beijing, and Liaoning were established in 1996. Since then, the ESCO industry witnessed a great increase in Shandong province.

Table 2. Urbanization rate of top 10 provinces in China from 2011 to 2015.

	2011	2012	2013	2014	2015
Shanghai	0.89	0.89	0.9	0.9	0.88
Beijing	0.86	0.86	0.86	0.86	0.86
Tianjin	0.8	0.82	0.82	0.82	0.83
Guangdong	0.67	0.67	0.68	0.68	0.69
Liaoning	0.64	0.66	0.66	0.67	0.67
Jiangsu	0.62	0.63	0.64	0.65	0.67
Zhejiang	0.62	0.63	0.64	0.65	0.66
Fujian	0.58	0.6	0.61	0.62	0.63
Chongqing	0.55	0.57	0.58	0.6	0.61

Rapid urbanization has been associated with a dramatic increase in the number of household appliances and urban building areas (Cai et al., 2009). More than 90% of the existing buildings have been reported as having high energy consumption, making China's existing building energy consumption per unit area about two times higher than that found in other developed countries under the same environment conditions (Yong Wu et al., 2007). Retrofitting projects have high potential in the building sector, which has driven increasing energy consumption. These provinces have focused on replacing less efficient energy production systems with more efficient ones in commercial and residential buildings in urban areas and utilizing new forms of energy and advanced technology.

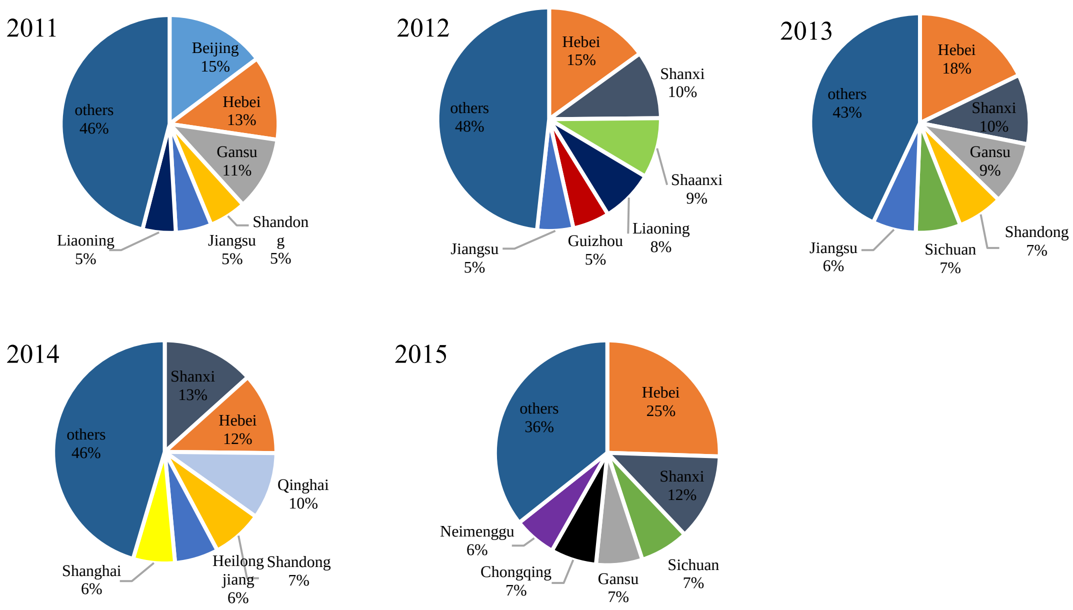

Fig. 4: The contribution to CDEA of each province from 2011 to 2015

The ranking of CDEA in the industrial sector showed Hebei province with the most significant savings followed by Shanxi. Figure 4 supports this finding, suggesting that Hebei and Shanxi contributed the most CDEA during the five years period studied. Hebei is a typical energy-consuming province, recognized as an industrial province in China with energy-intensive and highly polluting industries such as the steel, petrochemical, and building material industries (W. Li et al., 2017). In fact, Hebei contributed 11.62% of the global crude steel production in 2015. Shanxi has been widely known as a resource-based province, dominated by the coal mining industry. The energy consumption and CO_2 emissions in Shanxi have been significantly high. In 2015, investment in coal mining reached 104.7 trillion yuan, accounting for 26.13% of the domestic coal mining investment ("National Data," 2015). The observations above reveal obvious disparities in CO_2 emissions between provinces. ArcGIS software was used to map the geographical distribution of CDEA in China for the period 2011-2015, as shown in Figure 6.

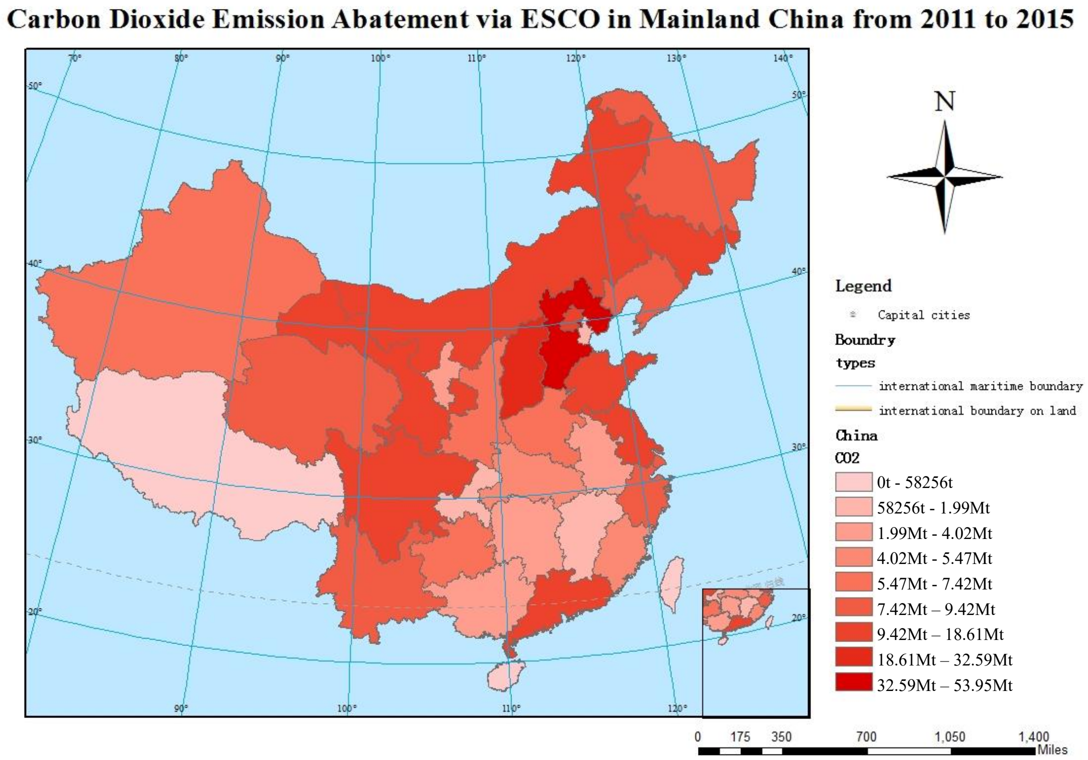

Fig. 5: Spatial distribution of China's CDEA via ESCO in the period of 2011-2015

Figure 6 illustrates that during the 2011-2015 period, the nine provinces with the highest CDEA were, in order, Hebei, Shanxi, Shandong, Gansu, Beijing, Sichuan, Jiangsu, Inner Mongolia, and Guangdong; while Tianjin, Jiangxi, Chongqing, Ningxia, and Guangxi had the least CDEA. Overall, the CDEA of the northern and coastal provinces was higher. CDEA in China can be divided into four clusters: (1) Bohai rim areas, which includes Beijing, Hebei, Shandong, etc.; (2) the Yangtze River Delta region that consists of Shanghai, Jiangsu, Zhejiang, etc.; (3) the western China region, which comprises Sichuan, Inner Mongolia, Xinjiang, Gansu, etc.; and, (4) the middle China region that includes Henan, Jiangxi, etc.

3.3. Analysis of spatial autocorrelation

Previous research has identified population size, urbanization, income, economic output, industrial structure, and energy consumption as the key factors that affect CDEA in China. Yet, spatial patterns can provide further information of CDEA in China. Tobler (1970) proposed that "everything is related to everything else, but near things are more related than distant things," which are principles considered the foundation of spatial dependence and spatial autocorrelation. Spatial autocorrelation refers to the degree of dependency among observations in a geographic space, which has been measured through statistical tools such as Moran's I, Geary's C, Getis's G, and the standard deviational ellipse. The Local Moran's I index identifies pixel clustering. The Getis-Ord Gi index recognizes hot spots, where very high or very low values are concentrated near one another. The Local Geary's C index categorizes areas of high variability between a pixel value and its neighboring pixels. As one of the aims of the present study was to analyze the clustering of CDEA, Moran's I was chosen to show the spatial autocorrelation. Moran's I ranges from approximately +1 to −1 (Moran, 1950). A positive Moran's I value indicates that similar values are likely to occupy locations nearby; while a negative Moran's I value indicates that nearby locations have opposite values. For these two situations, the closer the Moran's I absolute value approaches 1, the stronger the spatial autocorrelation is.

As shown in Table 3, the Moran's I values fluctuated through the period of 2011 to 2015. The spatial autocorrelation in CDEA was statistically significant and showed a clustered pattern for all years, except 2013.

Table 3. Moran's I values from 2011 to 2015.

Year	Moran's I
2011	0.1473
2012	0.1020
2013	0.0014
2014	0.0471
2015	0.1044

Yet, the global Moran's I lacks information regarding the location of the clusters or the type of spatial autocorrelation (Anselin, 1995; Soltani and Askari, 2016). Local indicator spatial autocorrelation (LISA) overcomes this limitation. LISA uncovers similarities or correlations for particular attributes between a spatial unit and its adjacent units; identifies different patterns of spatial clustering; and detects spatial heterogeneity. This study used LISA cluster maps of CDEA to analyze its spatiotemporal features. There are four kinds of clustering on a LISA map, namely High-High (HH) clustering, Low–High (LH) clustering, Low-Low (LL) clustering, and High-Low (HL) clustering.

HH clustering identifies provinces with high (above average) CDEA surrounded by other neighboring provinces with high CDEA. In contrast, LL clustering represents those provinces with low values that are surrounded by neighboring provinces with low values. LH clustering refers to provinces with low values that are surrounded by neighboring provinces with high values, while HL clustering refers to where there are provinces with high values surrounded by neighboring provinces with low values. Both HH and LL clustering indicate positive spatial autocorrelation characteristics, while HL clustering and LH clustering present negative correlating characteristics.

As shown in Figure 7, provinces with HH clustering were found mainly in Bohai Rim Areas, while the few provinces with LL clustering patterns were limited to Xinxiang in 2012 and Guangdong and Hubei in 2014.

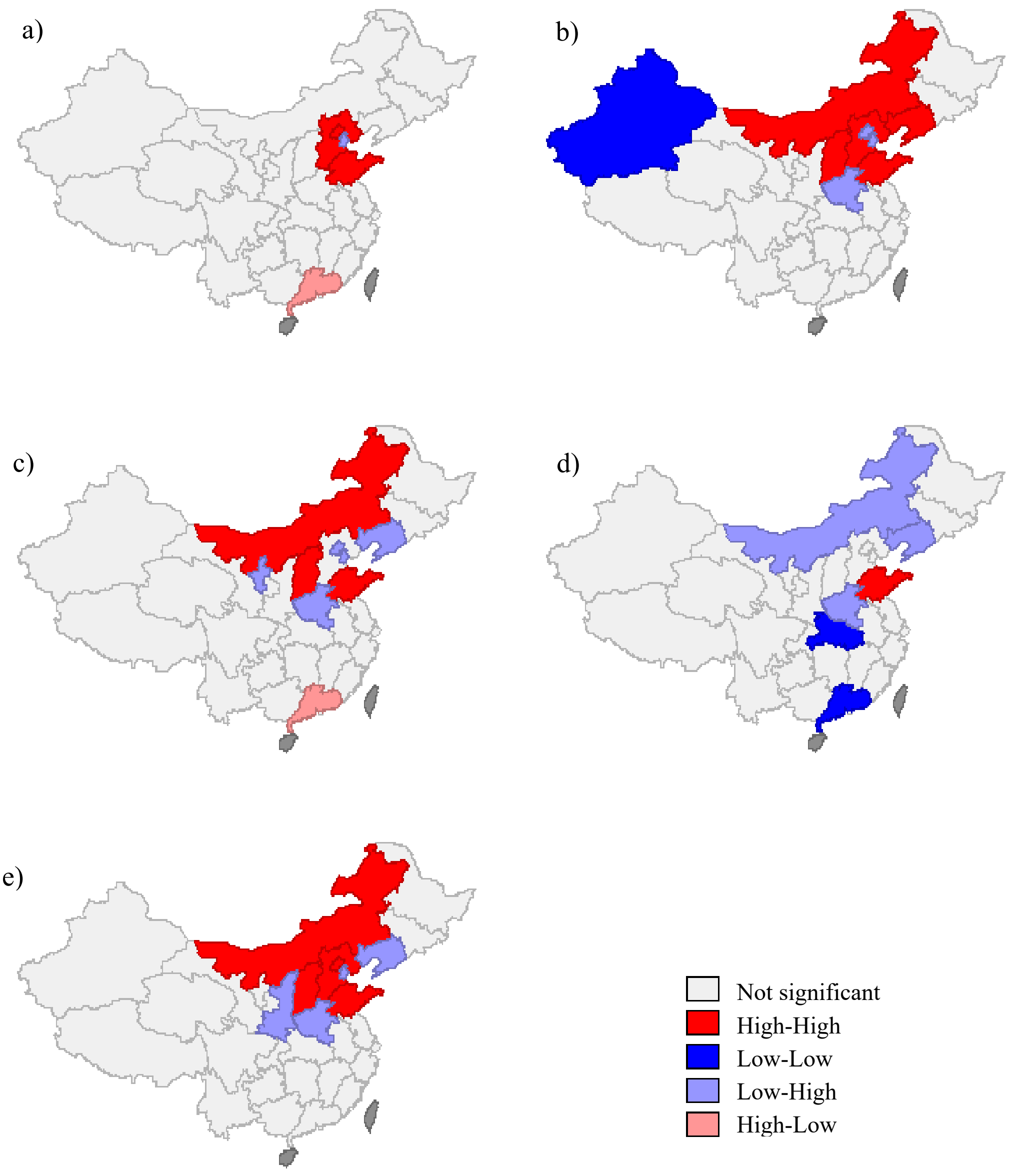

Fig. 6: LISA cluster map of CDEA in China for the years: (a) 2011; (b) 2012; (c) 2013; (d) 2014; and (e) 2015

The HH results for northern China could be explained by government policies promoting initiatives, industrial transfer, and technology innovation (Zhou et al., 2017). Mid-southern Liaoning and

Beijing-Tianjin-Tangshan main industrial activities are focused on the steel and manufacturing industries, which are considered the highest-energy-consuming industries. Awareness of the different climate conditions in China is particularly important. Northern China is considered a “heating zone,” where space heating for urban buildings is mandatory. Nearly 130 million tons of standard coal have been consumed each year, accounting for 45% of total national building energy consumption, 10% of national energy consumption (Berardi, 2016; Zhong et al., 2009). Large amount of CO_2 emissions was produced in these areas, making northern China a hot market for energy savings. In recent years, provinces have been promoting better energy efficiency standards and savings policies.

Figure 7 shows that Henan was an anchor for LH clustering. Hebei, Shanxi, and Shandong as Henan’s neighboring provinces have been mainly high energy-consuming and natural resource-based provinces. In contrast, Henan has been a major agricultural province, one of China’s main production areas for crops. Thus, demand for ESCOs remained low, and ESCOs in Henan have developed slowly. Although the clustering type varied along these five years, the LH spatial autocorrelation trend for these four provinces continued through the period studied.

4. Factors influencing spatial patterns of China's ESCO industry

The research findings described above showed spatial distribution patterns of CDEA with significant differences between provinces. Several factors have been identified as contributors to the different distribution of CO_2 emissions. Kaya and Yokobori (1997) proposed Kaya identity to perform a decomposition analysis of the key drivers that contribute to the total emissions, expressed in Equation (4-1):

$$\mathrm{F} = \mathrm{P} \times \frac{G}{P} \times \frac{E}{G} \times \frac{F}{E} \tag{4-1}$$

where F is global CO_2 emissions from anthropogenic sources, P is the global population, G is the world's GDP, and E is global energy consumption. Kaya identity is an equation that calculates the total emission level as a product of four inputs: human population, GDP per capita, energy intensity (per unit of GDP), and carbon intensity (CO_2 emissions per unit of energy consumed). Data for the human population, GDP per capita, energy intensity can be reached while data for carbon intensity is not available. Provincial Population, Provincial Per Capita Gross Domestic Production, Energy intensity and Consumption of coal were chosen to populate the equation. The data was obtained from the China Statistical Yearbook. In addition to the factors that affect CO_2 emissions, the factors related to an ESCO project's implementation were also considered. The main three factors concerning the ESCO industry include technology, policy, and finance (Da-li, 2009; Goldman et al., 2005; Lee et al., 2003; Vine, 2005). To represent these three factors, Research and development input (R&DI), Energy industry investment (EII) and Industrial value added (IVA) were chosen.

4.1. Definition of variables

Provincial Population (PP). As for "human population," PP was chosen, which has a relatively large impact on CO_2 emissions (S. Wang et al., 2017; Xu et al., 2014, Dong et al., 2018). Provincial Population (PP) in this research was characterized as the permanent population at the year-end. Normally, more people produce more CO_2, and higher PP represented a relatively more developed province.

Provincial Per Capita Gross Domestic Production (PPCGDP). “Per capita GDP” reflects economic growth, which has been associated with increased CO_2 emissions (Xu et al., 2014). The PPCGDP refers to the average final economic value outputs of all residents during a given period, which equals the sum of the added value of each industry. To some degree, more production means more economic activity, which will, in turn, consume more energy. For developing nations like China, rapid economic growth often leads to a sharp increase in CO_2 emissions.

Energy intensity (EI). Previous research has indicated that energy intensity determined CO_2 emissions to some extent (Ouyang and Lin, 2017; Xu et al., 2014). EI represents the energy consumption per unit of GDP, mainly influenced by energy structure and energy efficiency. Energy structure reflects the quality of different coefficients of CO_2 emissions. Different types of energy have different combustion rates, and if a province relies on cleaner energy, then it can produce less CO_2 emissions. Higher EI is associated with provinces endowed with advanced technology for energy efficiency.

*Consumption of coal (CC). “*Carbon intensity” can be difficult to measure at the regional level (Guo et al., 2017). CO_2 emissions are mainly generated from the combustion of fossil fuels (Ouyang and Lin, 2015). The energy consumption of China’s industry has principally derived from coal, which has the highest coefficient of CO_2 emissions among fossil fuels (Ouyang and Lin, 2015). As a result, coal consumption is defined here as the CO_2 emissions per unit of energy consumed.

Research and development input (R&DI). Regarding the technology factor, there are difficulties in measuring the level of technology of a province. R&DI is specified as the creative activities performed to increase professional knowledge and its application in the field of science and technology (i.e., basic research, applied research, and experiment development). In addition, provinces with higher R&D investment have been found to be more likely to develop advanced technology such as clean energy and emission mitigation technologies (Li and Lin, 2016).

Energy industry investment (EII). EII is the money invested in the energy industry, including coal mining and processing industry, petrol and natural gas mining industry, and so on. The ESCO industry is considered as a subindustry of the energy industry. EII was used to describe the importance given to the energy industry in a province. Thus, EII was the variable selected to measure the focus of a province towards the ESCO industry.

Industrial value added (IVA). IVA consists of compensation of employees, taxes on production and imports fewer subsidies, and gross operating surplus. IVA value equals the difference between an industry's gross output and the cost of its intermediate inputs. Rapid economic growth has been identified as a chief factor driving China's energy demand. Similarly, CO_2 emissions caused by energy consumption in China's industrial sector mainly arose from the growth of IVA (Ouyang and Lin, 2015). ESCO projects in the industrial sector accounted for the majority of all ESCO projects. Thus, IVA is used here to represent the development level of the ESCO industry in a province.

4.2. Spatial regression model

Spatial regression models integrate spatial dependency in regression analysis and demonstrate whether variables present in proximate provinces are more important than those variables in distant provinces. Spatial regression analysis was applied to investigate the potential factors affecting CDEA via ESCOs. Spatial regression identified the relationship between CDEA and influencing factors. The spatial error model (SEM) and spatial lag model (SLM) are two common methods for regression analysis that can explicitly take into account spatial effects (Y. Wang et al., 2017). The SEM shows that the error terms across different spatial units are correlated. It evaluates the extent to which clustering of an outcome variable not explained by measured independent variables can be accounted for concerning the clustering of error terms. The SLM means the dependent variable in one place is affected by the independent variables in this place and also another place. It incorporated the influence of unmeasured independent variables and stipulated an additional effect of neighboring attribute values. Anselin (1995) outlined rules for choosing between these two models, and whether spatial dependence should be considered. Firstly, use ordinary least squares (OLS) to estimate the model, checking the Lagrange multiplier lag (LM-LAG) and Lagrange multiplier error (LM-ERR). If both of them are insignificant (LM_LAG/LM-ERR > 0.05), then use OLS for analysis. Otherwise, SLM has to be used when LM-LAG is significant, and SEM when LM-ERR is significant. Table 4 shows the results of OLS estimation for CDEA in 2011 (The data of variable "EI" is available only in the year of 2011. Thus the data for 2011 was chosen for the calculations).

Table 4. OLS estimation of CDEA in 2011.

	P-value
PP	0.47357
PPCGDP	0.59658
EI	0.59709
CC	0.59709
R&DI	0.59709
EII	0.39331
IVA	0.27022
Lagrange Multiplier (lag)	0.11216
Lagrange Multiplier (error)	0.03921
Lagrange Multiplier (SARMA)	0.01844

The LM-ERR was identified as significant, while LM-LAG result was insignificant. According to Anselin's rule, the results indicate that the CDEA distribution was not spatially random. So, spatial dependence inclusion in the modeling is essential for the analysis. This research utilized a SEM to reflect the impact of spatial units on other nearby units in the region. SEM can be described as follows (Anselin, 1988):

$$Y = X\beta + \varepsilon \tag{4-2}$$

$$\varepsilon = \lambda W\varepsilon + \mu \tag{4-3}$$

where Y is the dependent variable (CDEA); X represents the seven independent variables, ε is the regression residual vector, λ and β are the local regression parameters to be estimated, μ is the interference item, and W is a diagonal weighting matrix. The regression analysis was conducted in Geoda software. The binary contiguity matrix - rook contiguity was selected in Geoda software to gain the spatial weight matrix. The spatial results for the seven variables are shown in Table 5.

Table 5. Results of SEM regression of CDEA.

R-square=0.385791

Variable	Coefficient	Z-value	P-value
PP	1.054608	2.740707	0.00613
PPCGDP	-0.2714202	-1.989961	0.04660
EI	-0.2412902	-1.198731	0.23063
CC	1.079549	3.270631	0.00107
R&DI	1.400809	2.532294	0.01133
EII	-0.505915	-2.322865	0.02019
IVA	-2.460822	-2.928725	0.00340

The results indicate that PP, PPCGDP, CC, R&DI, EII, and IVA significantly influence the CDEA in China at α=5% (P-value < 0.05). Among these factors, PP, CC, and IVA were even statistically significant at α=1% (P-value < 0.01). A closer look at the variable coefficient reveals that PP, CC, and R&DI had a positive influence on CDEA, whereas PPCGDP, EII, and IVA had an inhibitory effect on CDEA.

5. Discussion

5.1 Relationship between influencing factors and CDEA

The results of the spatial autocorrelation and spatial regression reveal the existence of uneven CDEA in China's provinces. The positive relationship between provincial population and CDEA indicate that provinces with higher populations have more potential for CDEA. Previous research has found that higher populations result in more CO_2 emissions, and that population growth rate has higher impacts on emissions in developing countries than in developed countries (Cropper and Griffiths, 1994; Shi, 2003). Our results align with these claims to some extent. The market is driven by demand, and ESCOs prefer investing in regions with more CO_2 emissions to be reduced. Thus, increased consumption of coal leads to more CDEA via ESCOs.

These research findings also suggest the existence of a positive relationship between CDEA and IVA. The value of IVA represents the industry level of a province. High IVA value has been associated with higher CO_2 emissions and the prioritization a province gives to the industrial sector compared to lower IVA value provinces (Ouyang and Lin, 2015). In China, industrial cities are usually relatively less-developed cities and ESCOs are in their initial stage. So, the CDEA in industrial cities has not been as high as the developed cities. Thus, these industrial provinces have a huge potential for reducing CO_2 emissions. For example, Qinghai is an industrial city with the highest increasing annual rate of CDEA among the 28 provinces.

As for R&DI, advanced technology can change the energy structure and energy efficiency. For instance, Jiangsu and Guangdong are the top two provinces that invest in R&D experiments. In 2011, renewable electricity in Guangdong province occupied 34% of the total, ranking first in China (Report on the work of Guangdong province, 2011).

Raupach et al. (2007) stated that since 2000 global CO_2 emissions growth has been driven by the continuous increase in population and per-capita GDP. However, the PPCGDP results in this study show a negative relationship to CDEA. Although more CO_2 emissions mean more potential to reduce them, the actual amount of CDEA was also determined by other variables. For instance, economic activities consume larges amount of energy, discharging high quantities of CO_2, which translates into a reduction of the potential of CDEA. Shandong, a typical example, produced 453.6 billion yuan (71.5 billion USD) GDP in 2011, reducing 22.7 billion tons of CO_2 emissions. However, PPCGDP variable needs further research, as there are no other studies that analyzed its relationship with CDEA.

In China, less-developed regions' (i.e., Shanxi and Inner Mongolia) investment to the energy industry has been higher than developed regions (i.e., Beijing). The energy industry is a high-carbon-intensive industry, but less-developed regions are not able to adopt advanced technology to reduce the CO_2 emissions. The negative relationship between EII and CDEA pointed out that those regions with high EII value should be the market of ESCOs since there is a huge potential to reduce CO_2 emissions.

5.2 Spatial dependence in CDEA via ESCOs

In 1998, three pilot ESCOs were created, which were Beijing ESCO, Liaoning ESCO, and Shandong ESCO. Since then, the number of ESCOs has rapidly grown (Kostka and Shin, 2013). ESCOs' investment has been mainly influenced by policy-making, finance investment and technology innovation (Da-li, 2009; Hopper et al., 2007; Stuart et al., 2014; Vine, 2005).

There has been a positive regional effect on policy diffusion (Mooney, 2001; Xu et al., 2018). One region's policy adoptions affected those of its neighbors. The economic practices developed from policy diffusion have been identified as highly clustered, both temporally and spatially, as shown in the spatial clustering of CDEA in China (Simmons and Elkins, 2004). For example, financial incentive policies were first launched in Zhejiang, Shandong, Fujian, Liaoning, and Beijing, which are the most influential cities in the Yangtze River Delta, Middle China, Pearl River Delta, northeast China and northern China (Bohai rim areas), respectively. Adjacent provinces to the most influential cities subsequently adopted similar policies.

The presence of spatial dependence for CDEA has been confirmed in this research, by the association of developed regions of China as major markets for ESCO projects (IFC, 2012). For a country/region, economic activities have been found to benefit from foreign investment via spatial spillovers (Cabrer-Borrás and Serrano-Domingo, 2007). In China, ESCO clients were selected once the three pilot ESCOs were set up. Provinces nearby were then involved, for example, Hebei, Jilin, and Jiangsu, which also became hotspots for ESCO projects. Likewise, technology innovation also shared the same spatial characteristics. Regions whose neighbors were advanced in technology produced more patents, gaining an obvious benefit from spillovers (Jaffe, 1986). Companies without investment in technology development, but located in a high skill intensive region have had high productivity. Hebei, for example, only ranked 15^{th} out of 30 provinces in terms of R&DI in 2011, but still most CO_2 emissions have been mitigated via ESCOs. Hebei is next to Beijing, which has been a major investor in technology development.

6. Conclusions

ESCOs have played a key role in CO_2 emissions mitigation, and the development of ESCOs has varied throughout the different regions of China. Spatial dependence has been identified as an important factor in energy and environmental research (Long et al., 2016). Policy and market optimization can be achieved with consideration of local circumstances. Spatial dependence in CDEA via ESCOs has been verified through the application of spatial analysis. The empirical results show that the CDEA via ESCOs in western China and northern China were higher than in eastern China and southern China, respectively. The Moran's I analysis highlighted a clustering pattern of regional CDEA. As discussed by Dong & Liang (2014), challenges faced by China in emissions-reduction policy come from not only technical constraints but also from China's large regional disparities. This suggests that addressing such regional disparity and balancing regional development should be considered when making policy.

This research complements previous models through the inclusion of spatial dependence. Using the data of 3225 ESCOs projects in 28 provinces of China from 2011 to 2015, this paper utilized spatial regression to analyze the factors that affect CDEA. The results suggest that provincial population size, coal consumption, and research & development input had a positive influence on CDEA; whereas per-capita GDP, energy industry investment, and industry value added had an inhibitory effect on CDEA.

With increasing global concerns about air pollutants and GHG emissions, China, as the biggest developing country and the largest CO_2 emitter in the world, has a commensurate responsibility to reduce CO_2 emissions. Since ESCOs have demonstrated efficient and feasible CO_2 emissions mitigation, this study recommends three main actions for China's central government. Firstly, the policies could be developed to boost the energy service industry not only at the national level but also at the provincial level. The relatively ESCO-undeveloped regions (such as middle China and

western China) can propose more polices to introducing EPC projects adoption, such as reduce tax and provide environmental projects subsidies. For those developed regions including Yangtze River Delta and Bohai Rim Areas, it is advisable to launch stricter environmental regulation, increase energy consumption tax and invent more advanced technology. Secondly, further sharing of information, technology, skills, and other resources across provinces is advised to promote interprovincial cooperation on energy conservation and emissions mitigation. HH provinces should take steps to help LH provinces by teaching advanced technology and sharing experience. Bohai rim areas and Yangtze River Delta region need to lead the direction for western China region and middle China region including invest some ESCO projects in those areas. Thirdly, a compromise between GDP growth and environmental damage is recommended through the establishment of obligatory targets for CO_2 emissions. GDP growth could be encouraged by the development of green technology driven by obligatory CO_2 emissions targets to reduce the impacts on the environment.
The results of the present study provide a basis for two main other recommendations for local governments. Firstly, the increased adoption of ESCO projects in the northeast and northern provinces, areas that have demonstrated high potential for CO_2 emissions, is recommended. Secondly, it is advisable to promote further cooperation on the transfer of advanced technology and experience to the southeast provinces.

There are some limitations in the present study that could be addressed and overcome in future research. The trends in CDEA via ESCOs in each province over time has not yet been analyzed. As mentioned above, the relationship between some variables and CDEA need to be further confirmed, and factors for each sector will be analyzed Based on this study, some questions can be raised for future research, such as: What trends exist for CDEA via ESCOs in China? Are the results valid for other countries? What factor most significantly characterizes ESCO target market potential? Resolving such issues, however, requires comprehensive and reliable time series of ESCO project data combined with geographic data.

This research identified the spatial patterns and factors influencing CDEA, thus guiding ESCOs in choosing their next clients and target markets. Those regions with low per-capita GDP, high consumption of coal, and high energy industry investment (i.e., Shanxi, Qinghai and Inner Mongolia) represent areas with greater opportunities for implementing ESCO projects. Overall, this study contributed innovative and robust spatial analysis on CDEA via ESCOs.

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