Efficiency assessment of carbon emissions at city level in the Yangtze River Delta Region

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Highlights:

•We formulate carbon emissions reduction targets of prefecture-level cities in YRD region.

•We redistribute carbon emissions reduction targets on basis of 12th Five Year Plan.

•DEA model, entropy weight method and clustering analysis are aggregated in this study.

•Classification of carbon emissions could efficiently achieve reduction targets.

Abstract: The central government of China has only released the detailed distributions of carbon emissions abatement obligations at the provincial level, but lack of specific emissions reduction targets at the city level. Most provincial governments simply allocate carbon emissions reduction tasks to their cities based upon the GDP values of their cities, resulting in inefficient and unfair distribution of resources and obligations for emissions reduction targets. Under such a circumstance, this paper aims to investigate how to allocate carbon emissions reduction targets at the city level by combining a data envelop analysis method (DEA), an entropy weight method and a clustering analysis method. A case study approach is employed in the Yangtze River Delta region (YRD) for the year of 2016. Results show that cities with higher carbon emissions abatement potentials, financial abilities, a large number of above-scaled industrial enterprises and GDP values should take more responsibilities on carbon emissions reduction. In addition, this paper redistributes carbon emissions reduction allocation targets and carbon emissions reduction allocation quotas and increments value of each prefecture-cities in YRD. Finally, corresponding policy implications are provided.

Key words: Carbon emissions reduction allocation target; efficiency assessment; Yangtze River Delta region

1. Introduction

The Fifth Assessment Report of the Inter-governmental Panel on Climate Change (IPCC-AR5) claims that excessive anthropogenic greenhouse gas emission has disturbed the normal conditions of the earth's climate and unforeseen climate change interferes with regular performance of natural and human systems (IPCC, 2014). Resulting changes are recognized as a threat to human survival and development. Numerous measures and policies to relieve and mitigate climate change impacts have been extensively and comprehensively introduced, since the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol were put forward. As the world's biggest energy consumer and largest carbon emitter, China accounted for 29% of total global emissions in 2012 and accounted for 80% of the world's increase in carbon emissions since 2008

(Olivier et al., 2013). The consequence of international negotiations regarding energy conservation and emission mitigation on China is resulted in an ambitious commitment to a mandatory carbon emissions target (Jin et al., 2010; Wei et al., 2015; Xu et al., 2016). However, due to China's rapid process of urbanization and industrialization, the total amount of carbon emissions will continue to increase and is expected to reach the peak in approximately 2030 according to Chinese central government's projections (Xu et al., 2015).

To respond to global climate change challenge, the Chinese government has committed to reduce 40 to 45% carbon intensity by 2020 compared with the level of 2005, and has already implemented many mitigation measures on energy conservation and carbon emissions control during the past few years (Dong et al., 2013). For instance, the initial objective to reduce energy consumption intensity by 20% by 2010 compared with 2005 was set out in the 11th Five Year Plan (from 2006 to 2010), and then further modified to include reduction of carbon emissions intensity and energy consumption by 17% and 16%, respectively, in 2015 compared with 2010 level (Wang et al., 2016). Considering the broad geographic span and disparity of regional economic and social development level in different Chinese provinces (Dong et al., 2015), it is critical to establish a widely acceptable and efficient emissions reduction standard by incorporating disparate carbon emissions characteristics and corresponding driving forces in different regions (Gao et al., 2016). The current carbon emissions reduction targets at the provincial level are based upon historical carbon emissions, economic and social development and energy utilization efficiency in different provinces. Such targets can only be achieved if the targets allocation can be more efficient and equitable. (Xu et al., 2016).

Previous studies have been conducted to establish potential indicators that could generate models of carbon emissions in different countries and regions by employing various methods. Firstly, plentiful methods and analysis tools, such as entropy method, clustering analysis, data envelopment analysis (DEA), Logarithmic Mean Divisia Index (LMDI) model, etc. have been employed to calculate the total emission of a specific region or verify the relevant factors of carbon emissions. Remuzgo et al. (2016), Remuzgo et al. (2016) and Chang and Chang (2016) utilize entropy method to investigate global inequality in greenhouse gases emissions, complexity of global carbon market and China's interprovincial emissions trading. Clustering analysis is employed to explore the convergence of energy-related carbon emissions through panel data of U.S. (Burnett, 2016). DEA was utilized to evaluate the energy-related or environmental efficiency of China's provincial carbon emissions (Fan et al., 2015; Guo et al., 2011; Meng et al., 2016; Zha et al., 2016). LMDI model is deemed as an effective technique to estimate China's provincial or specifically sectoral carbon emissions (Gu et al., 2015; Lin and Long, 2016; Ren et al., 2014; Wang et al., 2011; Xu et al., 2012; Xu et al., 2014; Zhang et al., 2016). Furthermore, past studies investigated carbon emissions of both developed countries such as U.S. and EU, but also the developing countries. Both of Soytas et al. (2007) and Soytas and Sari (2009) demonstrate that income does not Granger cause carbon emissions in the US in the long run. Brink et al. (2016) investigated options to determine the applicable carbon price in EU Emissions Trading System to curb carbon emissions efficiently. Ito (2017) proposed that renewable energy consumption contributes to carbon emission reduction targets of 42 developed countries. Shuai et al. (2017) concluded that higher income generates weak impacts of the affluence on carbon emission in both developed and developing countries. In addition, Narayan and Narayan (2010) probed Environment Kuznets Curve (EKC) hypothesis for 43 developing countries to conclude that the income elasticity in the short period is larger than in the long run only within Middle Eastern and Southern Asia, implying that carbon emissions have fallen with raising revenue (Narayan and Popp, 2012). Ertugrul et al. (2016) investigated the relationship between carbon dioxide emissions, income, trade openness and energy consumption in the top ten carbon emitters among the developing countries. In addition, several significant indicators have been selected for probing whether they would associate with carbon emissions in abundant previous researches. Majority of studies perceived that energy is a relatively more significant parameter than other factors such as labor, capital, urbanization and foreign trade at country level wher diverse economic backgrounds are present (Halicioglu, 2009; Sari and Soytas, 2007), especially in the long run (Ang, 2008). However both for short and long periods there appears to be bidirectional dependency between energy consumption and carbon emissions (Apergis and Payne, 2009, 2010; Lean and Smyth, 2010), implying that energy consumption has a positive effect on carbon emissions (Arouri et al., 2012; Bhattacharyya and Ghoshal, 2009; Kim and Baek, 2011; Seetanah et al., 2012; Yang et al., 2012). Substantial research confirms that urbanization does not contribute to higher emissions (Martínez-Zarzoso and Maruotti, 2011; Sharma, 2011), which is more pronounced in long-term strategies for carbon emissions reduction with comparison to short run elasticity (Dhakal, 2009; Fan et al., 2006; Sadorsky, 2014; Sharif Hossain, 2011). Poumanyvong and Kaneko (2010) found that urbanization mitigates energy utilization within the low-income yet it increases energy utilizing between middle- and high-income groups, which is analogy to study of Liddle and Lung (2010) in essence. What's more, trade, industrialization and technology advancement entirely somewhat dedicate generating alteration of carbon emissions by various approaches (Antweiler and Taylor, 2001; Cole et al., 2001; Ferrantino, 1997; Shahbaz et al., 2012).

The Yangtze River Delta (YRD) is the largest economic center in China, with a total population of 150 million and a total area of 211,700 km^2. Its gross regional product accounted for 18.5% of total national GDP in 2014 (Xu et al. 2015). The corresponding carbon emissions reached 421.03 mega-tons (Mt) and energy consumption reached 492.0 Mt standard coal in 2014 (Xu et al., 2017). Several studies have been conducted in this region, especially focusing on uncovering the key drivers of carbon emissions in YRD through decomposition analysis (Gao et al., 2016; Jian-Feng and Shi-Hui, 2012; Mao et al., 2011; Song et al., 2015; Wang, 2014; Xin-Ming and Gong, 2012; Xu et al., 2015; Zhong-Jie et al., 2013). However, few studies focus on integrating different research methods so that comprehensive and efficient carbon emission reduction allocation targets can be obtained. Acknowledging that alternative methods have inherent limitations, this paper aims to mitigate discrepancies by combining the methods of DEA, entropy weight method and clustering analysis. The drawback of DEA is that the boundary of production function of this method is determined in advance so stochastic disturbance terms are considered as efficiency factors, and that weakly efficient decision making units (DMUs) sometimes could not incur such serious obstructions as the performance of the simulation. Entropy weight method could compensate these drawbacks through multilevel and wide-range coverage of indicators to enhance the comprehensiveness of the studies, whose weakness that established indicators selection systems would be biased towards subjective preference and data availability could offset partially by DEA in reverse. And clustering analysis could employ comprehensive coefficient calculated by entropy weight method to assure accuracy and precision of division categories. Therefore such a combination can lead to more accurate accounting of carbon emissions due to its highlighting of the strengths of different methods. Furthermore, no study has further investigated carbon emissions reduction targets at city level in YRD, so we formulated carbon emissions intensity reduction targets for each prefecture-cities in

YRD through integrating these three methods above.

The remaining part of this paper is structured as follows. The following section provides description of research methods, including detailed flow chart for the proposed integrated method and approach to data collection and processing. Section 3 presents research results. Final section provides a summary of findings and policy implications.

2. Methods and data

2.1 Case study area

The Yangtze River Delta (YRD) region is located within E118º20'-122º46', N28º2'-33º25'.as shown in Fig.1. This region is the first Chinese region to implement reform and embrace opening policy in 1978 and has a strong service industry (Gao et al. 2016). This region is now required to restrict the total amount of carbon emissions to a greater extent than other regions on account of substantial energy consumption and over-reliance on fossil fuels. The economic and social development degree of each prefecture-level city in YRD are unequal, however involving the National New-type Urbanization Plan from 2014 to 2020, relatively undeveloped minor cities within this cluster will be required to play pivotal roles in the new era of urbanization (Xu et al. 2015) and contribute to carbon emission responsibility in YRD (Guan et al., 2014; Zhou et al., 2014). Due to sustained industrialization and urbanization that continually facilitate economic and social development, new balance is needed to mitigate increasing consumption of energy and natural resources, (Xu et al. 2015).

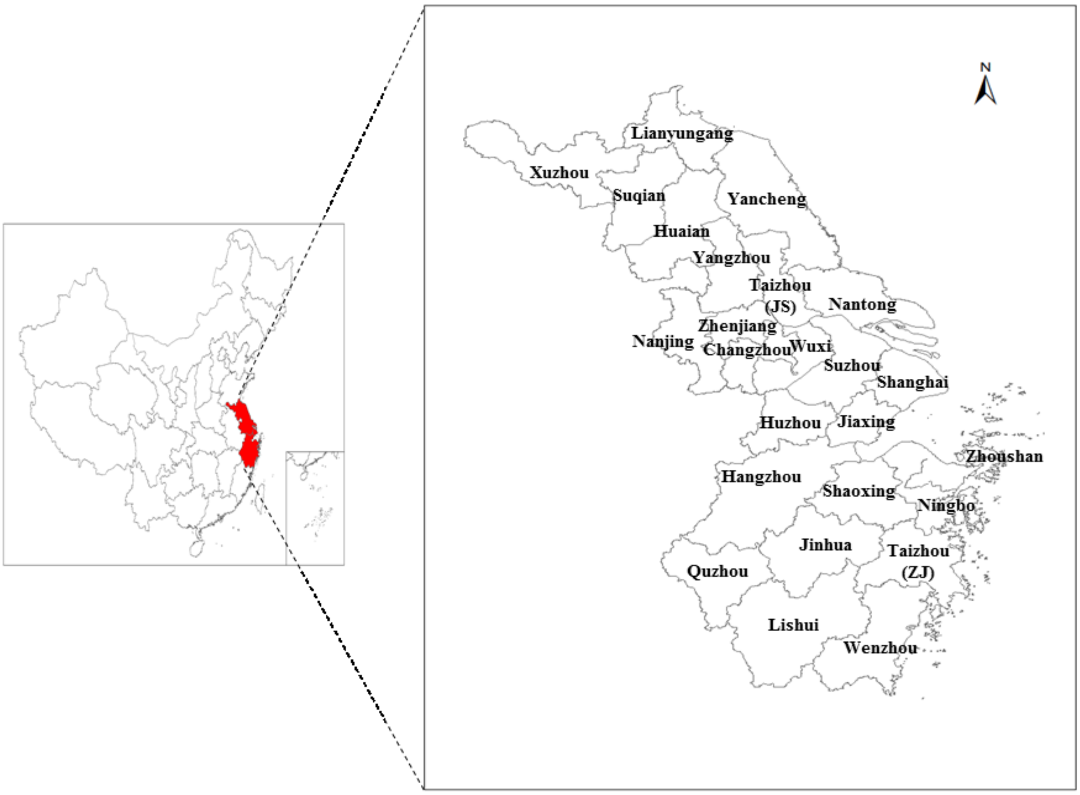

Fig.1 The location of YRD in China

2.2 Detailed flow diagram of integrated methods and data sources

For the integrated method, we firstly define carbon emission abatement space simulated by DEA as a criteria layer for the following entropy weight method. EWM is associated with other four criteria layers to calculate comprehensive coefficients of each prefecture-city in YRD.. Then, we aggregate and regroup the cities through clustering their respective comprehensive coefficients as evaluation criterion to formulate carbon emissions intensity reduction targets for each city. Finally, we calculate carbon emissions reduction quotas for each city, versus their carbon emissions increments. The input, intermediate and output indicators of each method are detailed in Table A1, which will also be further specified in Sections 2.3 to 2.5.

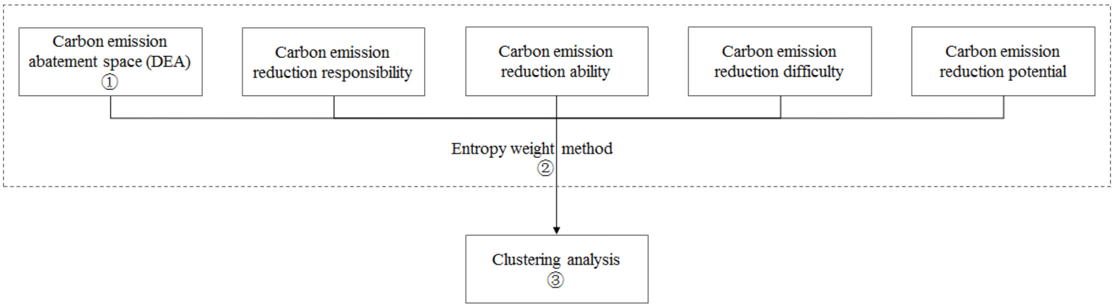

Fig.2 Detailed flow diagram of integrated three methods utilized in this paper (the numbers from ① to ③ represent application sequence of these three methods)

In this paper, provincial GDP data were obtained from Jiangsu, Shanghai and Zhejiang Statistical Yearbooks for the years of 2013, 2014, 2015 and the report of Shanghai Statistics Bureau for the year of 2015. The GDP for prefecture-level cities in 2016 were calculated in the context of their annual average growth rates during years 2012 to 2016, as detailed in Table A2. Carbon emissions in 2012 were calculated by referring to China Energy Statistical Yearbook for the year 2013. In addition, China Energy Statistical Yearbook for the year of 2013 was used.

2.3 DEA method

Data envelopment analysis (DEA) is a nonparametric method in operation research and economics for the estimation of production frontiers and used to empirically measure productive efficiency of decision making units DMUs (Cook et al., 2014). The goal is to identify, from a group of peers, the most effective DMUs to map input data. And the efficient DMUs in the circumstance of benchmarking, as endued definition by DEA, unnecessarily form a "production frontier", but rather generate a "production frontier" (Cook et al., 2014). In the context of the situation that either parametric techniques or non-parametric techniques are common to measure productive efficiency.

Carbon emissions, unavoidably correlated with economic development, are not deemed as a contributor to social progress and climate mitigation, so it should be selected as the undesirable output. In this paper, we employ DEA technique for carbon emissions accounting based on several previous studies, such as Miao et al. (2016) and Zhou and Ang (2008), on assumption that considers fixed assets (K), population (P) and industrial energy consumption (E) of the prefecture-level cities in YRD as input data, GDP (Y) as the desirable output and carbon emissions (C) as the single undesirable output. Environmental production technology (T), could conform to not only weak disposability and null-jointness assumption (Miao et al., 2016), but also the technique which is a closed and bounded set. Then the production procedure could be modelled by following equations:

$$T = (E, K, P, Y, C) = \sum_{h=1}^{H} \lambda_h E_h \le E_g$$

$$\sum_{h=1}^{H}\lambda_h K_h \le K_g$$

$$\sum_{h=1}^{H}\lambda_h P_h \le P_g \qquad (1)$$

$$\sum_{h=1}^{H}\lambda_h Y_h \ge Y_g$$

$$\sum_{h=1}^{H}\lambda_h C_h = t_g C_g$$

$$\lambda_h \ge 0, \qquad h = 1,2,\cdots,H \;\; g = 1,2,3$$

where h denotes the number of prefecture-cities in YRD, g is the number of provincial administrative regions, and λ represents the share of these five investigated indices of each cities accounted for the corresponding province.

All the inputs and desirable output GDP are supposed to be strongly disposable, and the carbon emissions are assumed to be weakly disposable. Then we could calculate efficiency evaluation index (θ) of each DMUs, which investigates whether the carbon emissions of the prefecture-cities are technically efficient and scale efficient or not, through transforming Eq (1) to its dual programming which will be discussed in the following. The range of θ is from 0 to 1, whose validity of appraising a DMU is on basis of relative magnitude to remaining DMUs, to indicate radial optimal between this DMU and efficient frontier or effective envelope. Also, the slack variables of S^- and S^+ are further introduced to figure up this dual programming, which measure the shortage of inputs and surplus of outputs, respectively. So we formulate undesirable output orientation DEA technique to calculate theoretical value of carbon emissions of prefecture-level cities in YRD, and T, as the environmental production technology incorporating these outputs, could be characterized as this dual programming of Eq (1) as follows:

$$\min \theta$$

$$T=(E, K, P, Y, C) = \sum_{h=1}^{H}\lambda_h E_h + S^- \le \theta E_g$$

$$\sum_{h=1}^{H}\lambda_h K_h + S^- \le \theta K_g$$

$$\sum_{h=1}^{H}\lambda_h P_h + S^- \le \theta P_g \qquad (2)$$

$$\sum_{h=1}^{H}\lambda_h Y_h + S^+ \ge \theta Y_g$$

$$\sum_{h=1}^{H}\lambda_h C_h + S^+ = \theta C_g$$

$$\forall\theta,\ S^{+}\geq 0,\ S^{-}\leq 0, h=1,2,\cdots,H, g=1,2,3$$

This model could be operated to determine whether the undesirable output, carbon emission is satisfied with technical efficiency or scale efficiency. Three criteria embracing θ, S^{-}, S^{+} is to impose as follows:

(1) If θ, S^{-}, S^{+} are simultaneously conforming to 1, 0, 0, the DMUs will be in conformity with both technical efficiency and scale efficiency.

(2) If θ=1, jointly at least one of S^{-} and S^{+} is greater than 0, the DMUs will be weakly efficient and not simultaneously accord with both technical efficiency and scale efficiency.

(3) If $\theta < 1$, the DMUs will not satisfy with DEA efficient, in conformity with either technical efficiency or scale efficiency.

Through importing the input side, the final calculation digital of desirable output and undesirable output of 25 prefecture-level cities in YRD would be figured out via functioning Matlab after obtaining intermediate matrixes comprising θ, S^{-}, S^{+} coefficients. Then we could explore the carbon emission abatement space by calculating deviation between actual carbon emission and theoretical carbon emission of each city in the following. In addition, we repute carbon emission abatement space calculated by DEA as a criteria layer for the following entropy weight method which utilizes the indicators presented above.

2.4 Entropy weight method

Entropy weight method can measure the degree of importance of variables, that is associated with uncertainty and disorder degree of the whole system, to reflect significant extent of each indicator. Shannon, who firstly defined the expected value of information to the exclusion of redundancy as information entropy and constructed the mathematical expression in the field of thermodynamics (Griffin, 1989), indicates that information redundancy is common and that the magnitude of redundancy is determined by probability of occurrence and uncertainty.

The regional decomposition and comprehensive evaluation of indices could significantly boost carbon emissions intensity reduction allocation, considering distinct pattern and speed of social and economic development of each city. Thus, the regional characteristics of carbon emissions reduction would be determined by various features, such as industrial structure, configuration of energy sources, development of the economy and demographic composition. As a result, we build a comprehensive evaluation index system from five aspects including carbon emission reduction responsibility, carbon emission reduction ability, carbon emission reduction difficulty, carbon emission reduction potential and carbon emission abatement space, which are shown at Table 1.

Table 1 Comprehensive evaluation index system

Comprehensive evaluation index	Indicators
Carbon emission reduction responsibility	Per capita carbon emission
	Carbon emission accounted for the proportion of YRD
	Regional GDP accounted for the proportion of YRD
Carbon emission reduction ability	Fiscal revenue
	Per capita GDP
	Urbanization rate

Carbon emission reduction difficulty	Above-scaled industrial output value of high energy consuming industries accounted for the proportion of total output value of above-scaled enterprises
	Number of above-scaled enterprises
	Above-scaled high energy consuming industries accounted for the proportion of the number of above-scaled enterprises
Carbon emission reduction potential	Carbon emission per unit of GDP
	Carbon emission per unit of industrial output value
	Carbon emission from industrial energy
	Above-scaled industrial accounted for the proportion of YRD
	Industrial fixed assets investment
	Regional gross output value
Carbon emission abatement space	Theoretical carbon emission

The selection of evaluation indices needs to follow the principles of valid, scientific and applicable purposes, that systematically reflect the social and economic development, energy use and carbon emissions of the prefecture-level cities and present the possibility, feasibility and effectiveness of carbon emissions reduction. The region needs to deliberately screen the evaluation indicators on the basis of current situation for fair allocation of carbon emissions, In addition, some indicators can be considered as criteria at different comprehensive evaluation indices, which illustrates different evaluation methods existing from distinct measurement perspectives. To avoid the over reliance on some factors, the same indicator is only used once to calculate value of criteria index and comprehensive coefficient in the operation.

The paper advocates using normalization processing for indicators, to avert that the dimension of indicators exerts a mathematic influence on allocation. Based on the information entropy method, we present the decision-making matrix $X_{i,j}$ of the original source of data for prefecture-level cities in YRD. These values are collected in the matrix *X*, of dimension *i* × *j*:

$$X = \begin{pmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,j-1} & X_{1,j} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,j-1} & X_{2,j} \\ \vdots & \vdots & & \vdots & \vdots \\ X_{i-1,1} & X_{i-1,2} & \cdots & X_{i-1,j-1} & X_{i-1,j} \\ X_{i,1} & X_{i,2} & \cdots & X_{i,j-1} & X_{i,j} \end{pmatrix} \tag{3}$$

where $X_{i,j}$ represents the value of indicator *j* for prefecture-level city *i* $(i = 1,2,\cdots,m \quad j = 1,2,\cdots,n)$. We need to conduct normalized value $Y_{i,j}$ which are calculated for all the prefecture-level cities *i*.

$$\mathrm{Y_{i,j}} = \frac{\mathrm{X_{i,j}}}{\min(\mathrm{X_{i,j}})} \tag{4}$$

The normalized matrix Y is obtained by normalization processing as above

$$Y=\begin{pmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,j-1} & Y_{1,j} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,j-1} & Y_{2,j} \\ \vdots & \vdots & & \vdots & \vdots \\ Y_{i-1,1} & Y_{i-1,2} & \cdots & Y_{i-1,j-1} & Y_{i-1,j} \\ Y_{i,1} & Y_{i,2} & \cdots & Y_{i,j-1} & Y_{i,j} \end{pmatrix} \tag{5}$$

According to fundamental principle of information entropy, we need to consider the ratio of reality in the certain district and maximum information entropy value. The range of information entropy value for indicator j is from minimum 0 to maximum 1. Consequently, the entropy value H for indicator j is estimated by Eq (6).

$$H_j=-\frac{1}{Inm}\sum_{i=1}^{m}p_{i,j}Inp_{i,j} \tag{6}$$

where $p_{i,j}=\frac{Y_{i,j}}{\sum_{j=1}^{m}Y_{i,j}}$, which denotes proportion $p_{i,j}$ accounted for indicator *j* considering all prefecture-level cities. Especially, when the proportion $p_{i,j}$ is equal to 0, the value for $p_{i,j}Inp_{i,j}$ will be 0.

Meanwhile, the value of criteria indicator SW is defined as follows.

$$SW_j=\frac{1-H_j}{\sum_{j=1}^{q}(1-H_j)} \tag{7}$$

And the final weighting W of indicator *j* is estimated by Eq (8).

$$W_j=ZW_p\bullet SW_j,$$

$$0\le W_j\le 1, \tag{8}$$

$$\sum_{j=1}^{q}W_j=1.$$

Where ZW_p denotes the weighting value given by criteria *p*, SW_j represents rational weight value of indicator *j*, *q* is the number of indicators in criteria *p*.

As a result, the final weighting matrix is defined as follows, which signifies the weight of each indicators, as well as adjustment effect in allocation process of carbon emissions.

$$W = \begin{pmatrix} W_1 \\ W_2 \\ \vdots \\ W_{n-1} \\ W_n \end{pmatrix} \tag{9}$$

Then comprehensive coefficient $Q_{i,j}$ could be deduced by following equation.

$$Q_{i,j} = Y_{i,j} \bullet W_j = \begin{pmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,n-1} & Y_{1,n} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,n-1} & Y_{2,n} \\ \vdots & \vdots & & \vdots & \vdots \\ Y_{m-1,1} & Y_{m-1,2} & \cdots & Y_{m-1,n-1} & Y_{m-1,n} \\ Y_{m,1} & Y_{m,2} & \cdots & Y_{m,n-1} & Y_{m,n} \end{pmatrix} \bullet \begin{pmatrix} W_1 \\ W_2 \\ \vdots \\ W_{n-1} \\ W_n \end{pmatrix} \tag{10}$$

We need to take positive and negative effects of the final weighting W_j into consideration that W_j taking positive number would engender positive effect and W_j taking negative number would engender negative effect. Greater comprehensive coefficient $Q_{i,j}$ exhibits larger regional differences of the indicator which is more significant in emissions reduction allocation target, to undertake more responsibility and direct more attention to reduce carbon emissions. Conversely, smaller comprehensive coefficient $Q_{i,j}$ exhibits weaker regional differences of the indicator which is less significant in emissions reduction allocation target.

2.5 Clustering analysis

Clustering analysis is a statistic method of grouping a set of objects in such a way that objects in the same group are more similar in some sense to each other than to those in other groups. This paper chooses Ward's method as measuring instrument to classify the general evaluation and assessment of all the prefecture-level cities in YRD. Ward's method is a holistic agglomerative hierarchical clustering procedure, which establishes the criterion for selecting the clusters to merge at every steps on account of optimal value of an objective function that reflects purpose of investigators (Varin et al., 2009). To illustrate standard clustering procedures, Ward's minimum variance method is used to minimize total within-cluster variance. In the clustering process each sample is seen as a separate category before merging two samples with the minimum distance variance into an entity. So the distance between sample k and sample j ($D_{k,j}$) could be calculated as follows:

$$D_{k,j} = \frac{(X_k - X_j)^2}{\frac{1}{n_k} + \frac{1}{n_j}} \tag{11}$$

where X denotes the coordinate of the sample and n indicates the sum of the samples totally. Then the distance between sample l and the sample combined with sample k and sample j could be formulated into:

$$D_{l,jk}=\frac{n\times l+n\times j}{n\times l+n\times j+n\times k}D_{l,j}^{2}+\frac{n\times l+n\times k}{n\times l+n\times j+n\times k}D_{l,k}^{2}-\frac{n\times l}{n\times l+n\times j+n\times k}D_{k,j}^{2} \tag{12}$$

To implement this method, the pair of clusters would lead to minimum increase, which is a weighted squared distance between cluster centers, in total within-cluster variance after merging. At the initial step, all clusters are containing a single point. To apply a recursive algorithm under this objective function, the initial distance between individual objects must be proportional to squared Euclidean distance. The initial cluster distances in Ward's minimum variance method are therefore defined to be the squared Euclidean distance between points.

Due to the resolution of the clustering analysis, all the prefecture-level cities in YRD would be divided into different emissions reduction categories after clustering the comprehensive coefficient $Q_{i,j}$ (calculated through Entropy weight method) of each area in SPSS. The four categories will correspond to different carbon emissions abatement obligations. Disparate type of regional division of different carbon emissions intensity reduction targets would be formulated to combine with the total carbon emissions and economic objectives of the region, as well as the future development of area planning.

In addition, we calculate carbon emissions intensity, the ratio of total carbon emission to GDP, for the year 2012, as the foundation of investigation of those of 2016 through redistribution of carbon emissions reduction allocation targets of each prefecture-city. Annual growth rates of GDP of each city are determined by the average increase rate from 2013 to 2015, then the total carbon emissions in 2016 is ascertained by multiplying carbon emissions intensity and GDP. Similarly, carbon emissions reduction allocation quotas of each city could be deduced by deviation between carbon emissions intensity of between year 2016 and 2012 multiplying GDP of 2016. Finally, emission increments values are differentials between total emission of 2012 and 2016.

3. Results

3.1 Carbon emission abatement space

The main purpose of the study is to investigate the disparity between theoretical carbon emission value and actual carbon emission value. We compare the emissions of efficient DMUs and inefficient ones in the context of respective inputs and outputs, which are shown in Table A3. On basis of calculation above, the efficiency of 25 prefecture-level cities in YRD were calculated using the approach set out above to obtain efficiency evaluation index θ, theoretical carbon emission and carbon emission abatement space, that are shown in Table 2.

Table 2 Carbon emission abatement space

Prefecture-level cities	Provinces	θ	Carbon emission abatement space/Mt
Suzhou	Jiangsu	0.84	11.95
Zhenjiang	Jiangsu	0.68	17.19
Changzhou	Jiangsu	0.81	22.41
Xuzhou	Jiangsu	0.59	50.05
Wuxi	Jiangsu	1.00	0.00

Nanjing	Jiangsu	0.65	0.01
Yangzhou	Jiangsu	0.73	0.01
Taizhou	Jiangsu	0.77	0.01
Nantong	Jiangsu	0.85	1.71E-03
Huaian	Jiangsu	0.54	0.01
Yancheng	Jiangsu	0.88	2.25E-04
Suqian	Jiangsu	0.86	4.39
Lianyungang	Jiangsu	0.67	-4.08E-04
Shanghai	Shanghai	1.00	0.00
Quzhou	Zhejiang	0.59	21.83
Huzhou	Zhejiang	0.77	12.80
Ningbo	Zhejiang	0.94	15.21
Shaoxing	Zhejiang	1.00	0.00
Jiaxing	Zhejiang	0.82	14.03
Hangzhou	Zhejiang	0.85	0.01
Jinhua	Zhejiang	1.00	0.00
Lishui	Zhejiang	1.00	0.00
Taizhou	Zhejiang	1.00	0.00
Zhoushan	Zhejiang	1.00	0.00
Wenzhou	Zhejiang	0.97	0.72

As is shown in Table 2, some cities, such as Wuxi, Shanghai and Shaoxing, have higher θ scores reaching 1.00, indicating that these cities have higher carbon emission efficiency and the inputs of these cities have been fully utilized. Thus, carbon emission abatement space in these cities equals to 0. On the contrary, other cities with θ scores lower than 1.00 should reduce their carbon emissions in order to reach DEA frontiers. These cities could not satisfy with DEA efficiency, in conformity with either technical efficiency or scale efficiency. It is explicitly manifested that the θ scores in Huaian, Xuzhou and Quzhou cities are the lowest within YRD, at less than 0.60. Therefore in the subsistent magnitude of capital, population and energy of these three cities, their carbon emissions levels should be reduced to DEA frontier and the carbon emission abatement space is highlighted. Then, they should reduce 0.01, 50.05 and 21.83 million tons of carbon emissions respectively.

Furthermore, the carbon emission abatement space of Xuzhou, Changzhou and Quzhou is reaching the highest level, which is 50.05, 22.41 and 21.83 million tons separately. They should undertake heavier burdens on environmental improvements to achieve technical and scale efficiency. Analyzing these results of θ scores and magnitude of carbon emission abatement space, we could infer that there is no inevitable connection between both of them with the exception of θ scores reaching 1.00.

Distinctively, the carbon emission abatement space of Lianyungang is lower than 0, demonstrating actual carbon emission surpass 400 tons of carbon emission compared with theoretical carbon emission. Due to total industrial energy consumption and carbon emission of Lianyungang are patently less than other cities with equivalent GDP scale, the magnitude of theoretical carbon emission on basis of DEA calculation slightly surpass the actual carbon emission. Namely, under available carbon emission reduction ability, Lianyungang assumes more carbon emission reduction responsibilities.

3.2 Allocation of carbon emissions reduction targets to different cities

The allocation targets of carbon emissions reduction in YRD would conduct an example for regional emissions intensity accounting to implement carbon emissions reduction obligation voluntarily. But just as Chang and Chang (2016) demonstrated to accomplish this ambitious carbon emissions reduction allocation under low carbon economy in China demands numerous practical measures.

We first calculate the value of criteria indicator based on Eq (3) to (7) indicated in Table A4, which demonstrates that the indicators which occupy the maximum entropy weights, such as carbon emission abatement space, fiscal revenue and the number of above-scaled industrial enterprises, exhibit the leading role in redistribution of carbon emission. Conversely, entropy weights of carbon emission per unit of GDP and carbon emission per unit of industrial output value account for the minimum proportions.

On the basis of value of criteria indicator above, we could calculate comprehensive coefficient Q through Eq (10) which is shown in Table 3.

Table 3 Comprehensive coefficient Q

Prefecture-level cities	Provinces	Q
Lianyungang	Jiangsu	2.42
Xuzhou	Jiangsu	11.63
Wuxi	Jiangsu	7.94
Nanjing	Jiangsu	8.20
Yancheng	Jiangsu	4.02
Changzhou	Jiangsu	9.51
Zhenjiang	Jiangsu	7.87
Taizhou	Jiangsu	3.85
Huaian	Jiangsu	2.85
Yangzhou	Jiangsu	3.74
Nantong	Jiangsu	5.92
Suzhou	Jiangsu	16.53
Sujian	Jiangsu	4.51
Shanghai	Shanghai	19.35
Quzhou	Zhejiang	8.34
Lishui	Zhejiang	1.33
Jinhua	Zhejiang	3.74
Huzhou	Zhejiang	6.57
Hangzhou	Zhejiang	8.40
Jiaxing	Zhejiang	8.05
Ningbo	Zhejiang	11.90
Taizhou	Zhejiang	3.69
Zhoushan	Zhejiang	0.97
Shaoxing	Zhejiang	4.53
Wenzhou	Zhejiang	4.66

The comprehensive coefficient Q of each prefecture-level city in YRD reflects the divergence of characteristics of carbon emissions reduction targets allocation, under the influence of entropy weight forcefully. Seen from Table 3, the comprehensive coefficient Q of Shanghai and Suzhou attain the highest level, and those prefecture-level cities such as Zhoushan, Lishui and Lianyungang undertake lest shares of carbon emission burdens. Then, we bring the comprehensive coefficient Q of the prefecture-level city in YRD into SPSS to redistribute the shares of carbon emissions after clustering analysis.

3.3 Redistribution of carbon emissions reduction allocation targets

According to government's 12th Five Year Planning report, Shanghai, Jiangsu Province and Zhejiang Province are required to reduce carbon emissions intensity by 19% during this period. However, how to decompose carbon emissions reduction targets to the subordinate prefecture-level cities is not distinct within the relevant regulatory documents. In this paper, we would calculate carbon emissions intensity, total carbon emissions and carbon emissions reduction targets for every prefecture-level city in YRD in 2016 on the basis of 2012. So, in the context of clustering analysis above, we could formulate separate carbon emissions reduction targets of each prefecture-level city classified on the basis of requirements of two provinces and provincial municipality, that are set out in Table 4.

Table 4 Carbon emissions intensity reduction targets of each prefecture-level cities

Categories	Prefecture-level cities	Carbon emissions intensity reduction targets
First level	Shanghai, Suzhou	21.5%
Second level	Xuzhou, Ningbo	20%
Third level	Zhenjiang, Wuxi, Changzhou, Nanjing, Nantong, Quzhou, Huzhou, Jiaxing, Hangzhou	18.5%
Fourth level	Yangzhou, Taizhou (JS), Huaian, Yancheng, Suqian, Lianyungang, Shaoxing, Jinhua, Lishui, Taizhou (ZJ), Zhoushan, Wenzhou	17%

Due to distinct economic conditions and development stages of prefecture-level cities in YRD, it is not straightforward to propose the reduction targets in accordance with emissions abatement requirements of provincial administrative region. The results shown in Table 4 testify that Shanghai and Suzhou pertain to the first classification of carbon emissions reduction area, that Xuzhou and Ningbo belong to the second classification of carbon emissions reduction area, that those prefecture-level cities such as Nanjing, Wuxi and Hangzhou are incorporated into the third classification of carbon emissions reduction area, that remaining prefecture-level cities are the fourth classification of carbon emissions reduction area.

Shanghai, the most prosperous city in YRD, possesses the highest carbon emission intensity and the highest GDP, industrial carbon emission, fiscal revenue, per capita GDP and urbanization rate. So Shanghai should undertake the heaviest carbon emission reduction responsibility. Suzhou, one of the cities with the highest development stage in YRD, possesses not only the most above-scale enterprises, but also the highest carbon emission, energy consumption, GDP and fiscal revenue except Shanghai. Therefore, when allocating carbon emissions intensity reduction targets from the perspectives of the five criteria layers analyzed above, at the year of 2016 Shanghai and Suzhou should shoulder the largest carbon emissions intensity reduction burdens to achieve the target of reducing 21.5% carbon emissions intensity relative to the year of 2012.

Furthermore, as for the second classification, Ningbo and Xuzhou jointly generate relatively higher carbon emissions, industrial fixed assets investment, stronger carbon emissions intensity and numerous above-scale high energy consuming industries. However, the urban industrial structure and economic composition are not the same level between cities. Ningbo has relatively high GDP, fiscal revenue, per capita GDP and more above-scale enterprises compared with Xuzhou, conversely Xuzhou possesses relatively higher urbanization rate and the highest carbon emission abatement space in YRD on the basis of actual carbon emissions, greatly surpassing theoretical carbon emissions when calculated by DEA mentioned above. Therefore, Ningbo and Xuzhou should shoulder relatively large carbon emissions intensity reduction burdens compared to the reduction targets formulated for provincial administrative region, which should accomplish carbon emissions intensity reduction of 20% in 2016 compared with those of 2012.

Compared with allocated burdens of carbon emissions reduction of Shanghai, Suzhou, Ningbo and Xuzhou, cities of the third classification should undertake relatively lower reduction obligations. Those cities such as Wuxi, Nanjing, and Hangzhou enjoy comparatively wealthy economic conditions and relatively affluent fiscal revenue and industrial fixed assets investment, yet majority of them generate comparatively lower carbon emissions and efficiently transform capital, labor and energy into GDP. Particularly, the GDP, fiscal revenue, industrial fixed assets investment and the number of above-scale enterprises of Quzhou and Huzhou are lower than in the remaining prefecture-level cities of the third classification, but due to their carbon emission abatement space being the highest, they should shoulder heavier carbon emissions intensity burdens compared to the other cities with similar economic development stage. Therefore, those cities of the third classification should assume slightly less emissions intensity reduction obligations than requirement of provincial administration region by 18.5%.

Finally, the prefecture-level cities within fourth classification have being undergoing rapid development and have weaker infrastructure, they should primarily focus on ensuring economic growth and increasing income per capita. If they are to achieve economic prosperity afterwards, they will need to assume more carbon emissions reduction obligations. So now, they simply possess enormous emissions reduction potential, instead of reduction responsibility and reduction ability. They should shoulder the lightest carbon emissions intensity reduction burdens lower than the requirement of provincial administration region, which is formulated to accomplish reduction targets reducing carbon emission intensity by 17%.

Compared with 2012 level, we could calculate carbon emissions intensity of each prefecture-level cities in YRD in 2016, as illustrated in Fig.3.

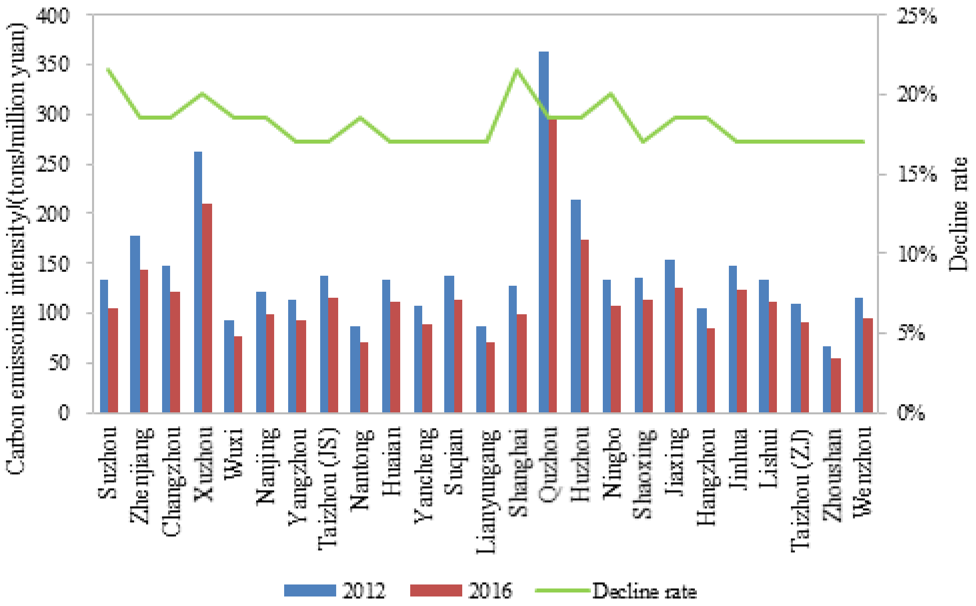

Fig.3 Carbon emissions intensity

The results in Fig.3 specify the carbon emissions intensity of Quzhou, Xuzhou and Huzhou possess the highest level at both 2012 and 2016, of Zhoushan, Lianyungang, Nantong and Wuxi have the lowest level at both 2012 and 2016. Particularly, the emission intensity of Quzhou exceeds 295 tons/million yuan in the year of 2016, significantly surpass other cities, which is 5.4 times more than Zhoushan, the city with the lowest emission intensity. Meanwhile, Quzhou accomplishes the largest absolute value of carbon emissions reduction intensity for the period 2012 to 2016, reaching 67.1 tons/million yuan. Zhoushan assumes the lowest absolute value of carbon emission reduction intensity during this period, only 11.23 tons/million yuan.

On basis of carbon emissions intensity and GDP demonstrated above, we calculate total carbon emissions in the year 2016 and growth rate during this period shown in Fig.4.

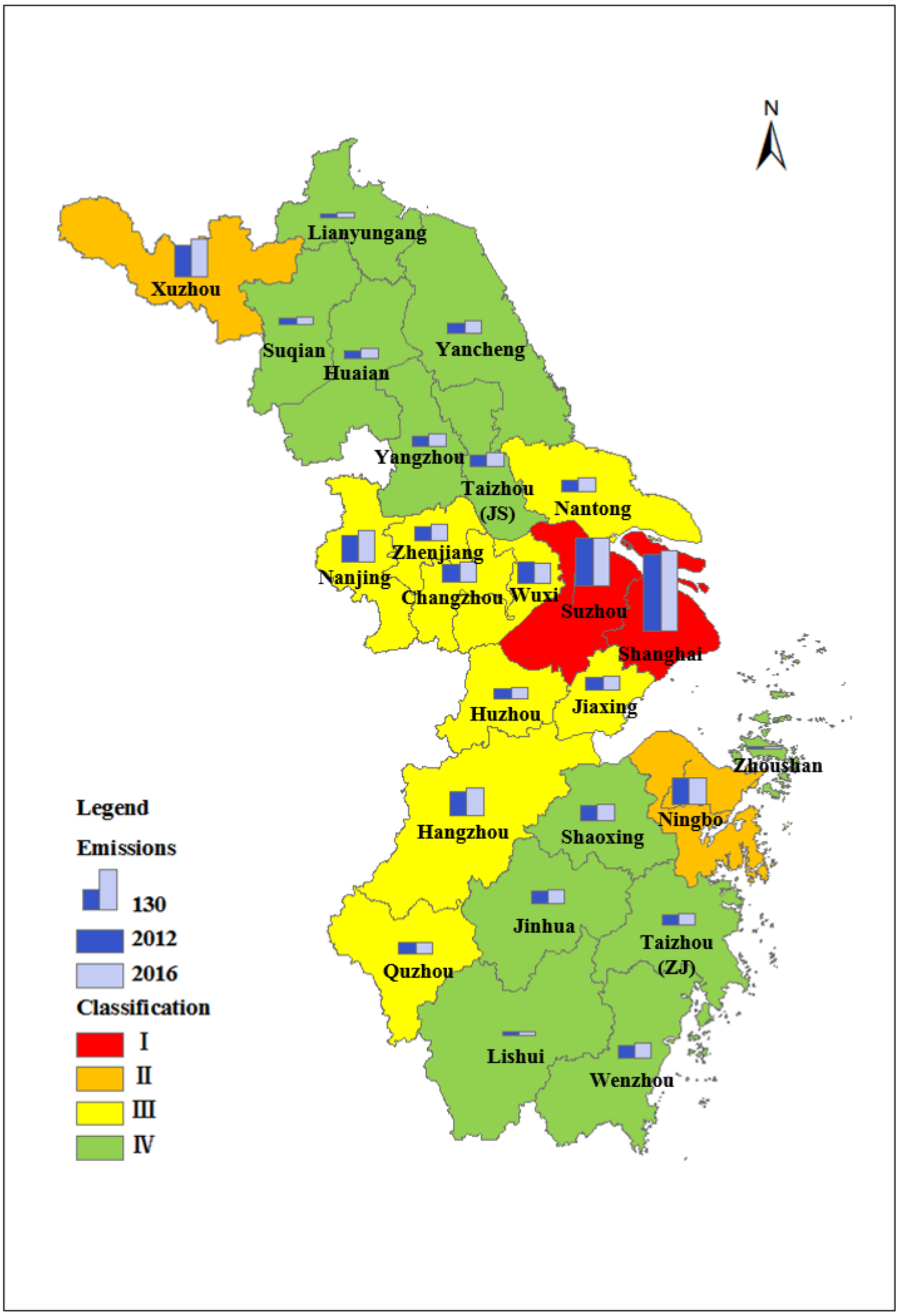

Fig.4 Comparison of total carbon emissions in YRD between 2012 and 2016

As illustrated in Fig.4, Shanghai generates the highest carbon emissions among prefecture-level cities in YRD, already have exceeded 250 million tons. However, Shanghai's growth rate of carbon emissions is remarkably lower than average value, merely 4.24%. Suzhou is another large emissions generator exceeding 150 million tons carbon emissions, prominently surpassing other cities except Shanghai. Conversely, Zhoushan, Lishui and Lianyungang generate the lowest total carbon emissions compared with other cities. Compared to the level for the year of 2012, Huaian, Suqian and Yangzhou possess the highest degree in terms of carbon emissions growth rates, which exceed 25%, and Suzhou, Quzhou have the lowest level of growth rates only slightly surpassing 0. Particularly, Wuxi accomplishes negative growth rate compared with 2012 level, which depends on the situation that reduction target of carbon emission intensity exceeds the growth of GDP, and achieves target of peaking carbon emission during the year of 2012 to 2016. The general circumstance of carbon emissions in YRD is depicted in Fig.4, reflecting the divergence of each prefecture-level city's total emissions between the year of 2012 and 2016.

We calculate total carbon emission in YRD in 2016 by combining every prefecture-level city at 1614.35 million tons, reducing by 1.16 million tons compared to carbon emissions calculated through combining provincial administrations, Shanghai and Jiangsu, Zhejiang Provinces, which equals GDP of three provincial administration regions multiplying carbon emissions intensity that derives from abiding the provincial targets to reduce by 19% compared with the level of 2012. Therefore this redistribution method of carbon emissions reduction allocation is also verified to excessively accomplish the total emissions reduction targets of provincial administrations. Then, when carbon emissions increments of every prefecture-level city are determined, we could make a comparison between carbon emissions reduction allocation quotas of each city and emissions increments value to affirm whether the cities are able to accomplish the reduction targets.

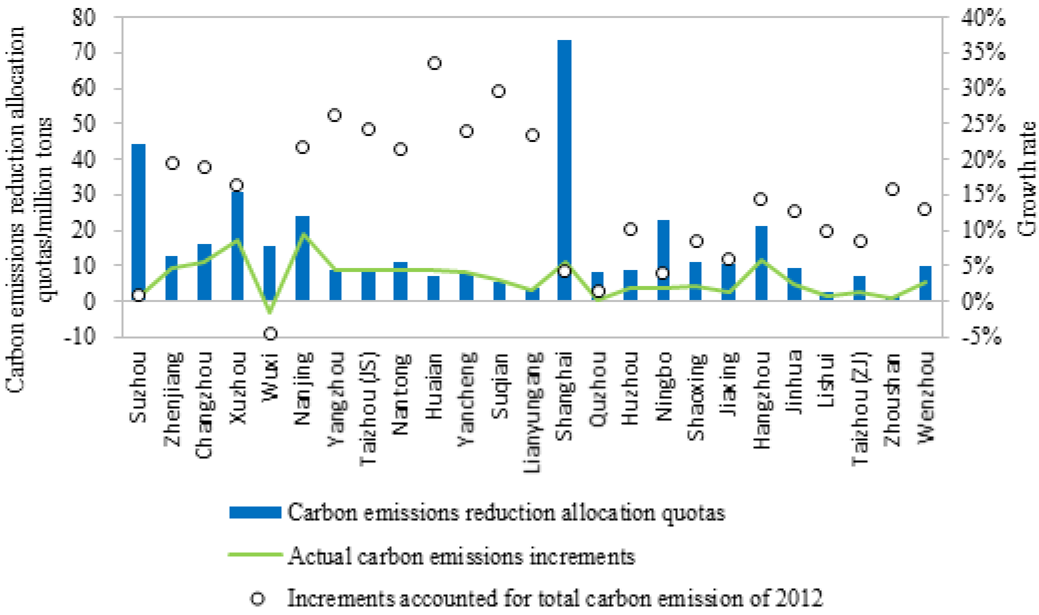

Fig.5 Carbon emissions reduction allocation quotas and increments value

The results exhibited in Fig.5 indicate that entire prefecture-level cities in YRD accomplish respective carbon emissions reduction targets, except Huaian, Suqian and Yangzhou, which exceed 1.60, 0.64 and 0.12 million tons respectively. In addition, the total actual carbon emissions increments are 223.72 million tons lower than emissions reduction allocation quotas generated at 2016, whose value surpass carbon emissions increments themselves that are only 158.77 million tons. The deviation values, which manifest differentials between carbon emissions increments and emissions reduction allocation quotas, of Shanghai and Suzhou possess the highest degree reaching 62.54 and 42.86 million tons, which account for 28.0% and 19.2% of total deviation value of YRD, respectively. The emission deviation value of Wuxi surpasses reduction allocation quota due to particular condition that total carbon emissions for the year of 2012 exceeds the level of 2016. Therefore, redistribution of carbon emissions reduction allocation targets effectively and efficiently contributes to facilitate achieving the government's emissions reduction programming.

Then, majority of cities' emissions increments account for 5% to 30% of total carbon emissions for the year of 2012, however increments of Huaian and Suqian with the highest level among the cities in YRD, account for more than 30% of total carbon emissions in 2012, and of Suzhou and Quzhou simply account for approximately 0. Particularly, due to total carbon emission of Wuxi for the year of 2012 surpassing the level of 2016, the emission increment of Wuxi accounts for -4.58% of total carbon emission at the year of 2016.

4. Conclusion and policy implications

Chinese central government has formulated the carbon emissions intensity reduction targets of provincial administration region of Jiangsu, Shanghai and Zhejiang during 12th Five Year Plan. This paper calculates carbon emissions intensity and total carbon emissions for the year of 2016 in the context of 2012 level and presents carbon emissions allocation quotas of each prefecture-level cities in YRD on basis of government's regulations. Carbon emissions reduction targets of each prefecture-level city should be distributed comprehensively concerning carbon emissions reduction responsibility, ability, difficulty, potential and carbon emission abatement space. Through this redistribution of carbon emissions reduction targets, each city will comprehensively be corresponding to their actual development stages, which are conductive to mobilize their capital, labor, energy and technology to accomplish reduction targets more efficiently. Total carbon emissions of Shanghai and Wuxi possesses the highest level in 2016, with relatively lower emissions intensity and emission growth rate during the year of 2012 to 2016 compared with other prefecture-level cities in YRD. Conversely, Zhoushan, Lishui and Lianyungang generate the lowest total carbon emissions in 2016. Particularly, Wuxi has accomplished peaking carbon emission during the year of 2012 to 2016 which indicates it achieves negative emission growth rate in this period. Moreover, all the prefecture-level cities in YRD can achieve their carbon emissions reduction targets, except Huaian, Suqian and Yangzhou exceeding 1.60 Mt, 0.64 Mt and 0.12 Mt CO_2, respectively. But the total actual carbon emissions increments are greatly lower than emissions reduction allocation quotas generated at 2016, demonstrating this redistribution of emissions reduction share in this paper commendably considers distinct urban development degree in YRD and efficiently achieves carbon emissions reduction targets.

Based on above empirical conclusions, we propose following policy implications on efficient classification and redistribution of carbon emissions intensity and total carbon emissions at prefecture-level cities in YRD for related decision-makers.

Firstly, government should comprehensively consider actual development stage of each city to regulate relative laws and rules to restrict emission intensity degree. Those cities with larger carbon emissions responsibility, ability, potential, difficulty and carbon emission abatement space which refers to GDP, population, revenue, urbanization rate, energy and the scale of above-scale enterprises, should shoulder heavier emission reduction burdens among YRD region. Less-developed cities should take the economic development as the primary targets, then undertake appropriate carbon emissions reduction share to complete emissions reduction target and gradually accomplish transformation from normal economic development mode to low carbon economy.

Secondly, the provincial governments should adjust the energy constitution of the cities and optimize the energy structure to extend cleaner energy utilization including hydropower, nuclear power, wind power and solar power. If the proportion of cleaner energy utilization increases, total energy consumption and carbon emissions will decline by reducing highly-polluted thermal power, especially coal-fired power.

Thirdly, cities in YRD should corporately establish and spread a unified carbon trading market to regulate carbon emissions intensity and total carbon emissions more efficiently. The cities could accomplish carbon trading with each other through this market on basis of their own economic development conditions and emissions efficiencies under carbon emissions reduction targets formulated by government. Meanwhile, the governments could formulate the carbon tax to guide normal operation of the carbon trading market better. The cities that meet the emissions reduction obligation could sell the emissions allocation quota and obtain additional economic revenue which could be utilized to invest in better energy saving technology and renovating conservation equipments to further reduce carbon emissions, the other receives more carbon emissions allocation share so that it could devote more resources to economic development.

Finally, enterprises should enhance economic development efficiency, should mitigate carbon emissions intensity generated by themselves, and should vigorously introduce energy conservation and emissions reduction technology. Through sharing their respectively advanced technique, they could accomplish the complementary advantages of resources and effectively stimulate joint development of the whole YRD region. In addition, residents in YRD should also transform their inherent consumption patterns into cultivating low carbon consumption concept to reduce carbon emissions intensity per capita.

Acknowledgement

This research was supported by Natural Science Foundation of China (71690241, 71461137008, 71603165, 71325006), the Fundamental Research Funds for the Central Universities through Shanghai Jiao Tong University (16JCCS04), the Shanghai Municipal Government (17XD1401800), and Erasmus Mundus programme EMLEADERS.

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