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City-Level Carbon Emission Abatement in the Subtropics of China: Evaluation and Reallocation for Zhejiang

Dan Hu[1], Yunfei Fang[2], Chenpeng Feng[1] and Junheng Cheng[3]

Abstract

Zhejiang province, one of the classic subtropical regions in China, has promoted the establishment of a carbon trading market in recent years. The appropriate allocation of carbon emission abatement (CEA) quotas is the precondition for constructing a carbon trading market. This article mainly allocates municipal CEA quotas in Zhejiang province during the 12th Five-Year period based on data envelopment analysis approach. The main results reveal that Zhejiang exhibits relatively high environmental efficiency; carbon emission reduction in moderate level would bring gross domestic product growth for certain cities; the actual CEA quotas allocation of Zhejiang during 12th Five-Year period could be further optimized under the precondition of the national requirement of carbon intensity. Possible policy suggestions are provided in terms of the results.

Keywords

data envelopment analysis, carbon emission abatement, environmental evaluation, quota allocation, subtropics, Zhejiang province

Introduction

With dramatic increases in the emission of greenhouse gases (GHGs, mainly as carbon dioxide), climate change and environmental protection have become hot global issues (Intergovernmental Panel on Climate Change, 2006) and draw the common attention of policymakers, private enterprises, and scholars (Li, Emrouznejad, Yang, & Li, 2019; Li, Sun, & Wang, 2019; Song & Cui, 2016; Sun, Wang, & Li, 2018; just to name a few). There are two main methods to deal with the problem of GHGs emission reduction and allocation (Sun, Fu, Ji, & Zhong, 2017; Wu, Zhu, Chu, An, & Liang, 2016): One is allocation for value, take carbon tax (Cui & Song, 2017) as representative; the other is allocation for free, take quotas allocation (Gomes & Lins, 2008) as representative. To combine with both, carbon emission trading scheme (ETS) was creatively proposed in the 1997 Kyoto Protocol and repeatedly emphasized in the 2015 Paris Climate Summit and 2016 Marrakech Climate Summit. Numerous studies have confirmed ETS to be the most effective solution because it introduce market mechanisms to correct the failure caused by negative environmental externality (Stern, 2009). Meanwhile, the efficiency of ETS depends on both emission reduction effects and the economic impact of each participant. Thus, the initial "free allocation" step plays a significant role in determining ETS quality and is our research object.

In view of its particular importance, the free allocation issue of carbon emission rights (also referred to as carbon emission abatements, CEAs) has attracted the continual attention of scholars. In general, current studies classify the related theoretical framework into two views: fairness and efficiency principles. For the fairness principle, the indicator method is the most common approach. Scholars have developed many indicators for carbon quota allocation: grandfathering (Knight, 2013), egalitarianism (Grubb, 1990), and cumulative emission per capita (Yu, Gao, & Ma, 2011), just to name a few.

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For the efficiency principle, many optimization methods have been explored for carbon quota allocation (Wu, Du, Liang, & Zhou, 2013; Wu, Zhu, Chu, An, & Liang, 2016). For both principles, data envelopment analysis (DEA) has been widely accepted and applied.

DEA is a mathematical programming tool for evaluating the relative efficiencies of a set of decision-making units (DMUs). According to the theory of joint production, desirable outputs are always accompanied by undesirable outputs in the process of production (Baumgärtner, Dyckhoff, Faber, Proops, & Schiller, 2001; Zhu, Wu, Li, & Xiong, 2017). It is worth noting that carbon emission is one of these undesirable outputs and cannot be treated like a normal product in the analysis. DEA has both the function of efficiency evaluation and resource allocation and can tackle desirable and undesirable outputs simultaneously (Sun, Li, & Wang, 2019). For instance, many scholars adopt DEA as a tool for fixed cost allocation (Li, Zhu, & Chen, 2019; Li, Zhu, & Liang, 2019). Moreover, DEA does not require the same large sample size as an empirical approach (Cook & Seiford, 2009). Therefore, DEA has a unique advantage of optimizing carbon quota allocation from a production perspective.

Currently, a number of scholars have applied the DEA technique to the allocation of carbon quotas. The following are some represented studies as examples: From the fairness perspective, Gomes and Lins (2008) developed the uniform frontier method to allocate carbon quotas based on the zero sum gains DEA model. In the follow-up studies, series of researches focus on quota allocation (mainly is CEA quota) based on zero sum gains-DEA and the uniform frontier (Wang, Zhang, Wei, & Yu, 2013; Chiu, Lin, Su, & Liu, 2015; Feng, Chu, Zhou, Bi, & Ding, 2019). From the efficiency perspective, Lozano, Villa, and Brännlund (2009) implemented the centralized reallocation of carbon quotas by different objectives. Sun, Wu, Liang, Zhong, and Huang (2014) compared two different CEA quota allocation scheme between decentralized and centralized modes and got the conclusion of centralized mode had better performance. Moreover, Feng, Chu, Ding, Bi, and Liang (2015) proposed a "centralized allocation—compensation scheme" two-step method for allocating the CEAs among 21 Organisation for Economic Co-operation and Development countries, combining the two above-listed perspectives.

Later, a series of relevant empirical studies emerged. Internationally, carbon quota allocation emphasized the mitigation of contradictions between developed and developing countries. Regionally, the allocation of carbon quotas has been investigated within one specific country or region (Wang, Zhang, Wei, & Yu, 2013). In studies focused on China, the majority of studies have been based on a provincial setting (Wang, Zhang, Wei, & Yu, 2013; Wu, Zhu, Chu, An, & Liang, 2016; Wu, Zhu, & Liang, 2016; Zhao, Shi, & Xu, 2018), while studies have only rarely been based on municipal settings (Zhou, Liu, Zeng, Jiang, & Liu, 2018) or factory settings (Sun, Wu, Liang, Zhong, & Huang, 2014; Sun, Fu, Ji, & Zhong, 2017; Li, Emrouznejad, Yang, & Li, 2019).

Generally, the issue of carbon quota allocation has both academic and practical value and warrants further study. In addition, the DEA approach has its own advantages in optimizing allocation, making our research methodology scientific. In particular, DEA can allocate resources in a production system with multiple inputs and multiple outputs and can tackle desirable and undesirable outputs simultaneously. Moreover, DEA is nonparametric which does not require *a priori* information of production technology and does not demand for the same large sample size compared with empirical methodology. Finally, there is a lack of microevidence within one province in every country setting. All these factors provide our research with a foundation in terms of theory, model, and literature and indicate a gap in knowledge.

China has become the second largest economy and the largest carbon emitter, playing a vital role in world economic development and environmental protection. In the past few years, plenty of research works had proposed various attempts in energy saving and emission reductions (Song & Cui, 2016). During the recently concluded 12th Five-Year period (2011–2015), the Chinese government actively implemented its national commitments by launching a series of regulations and policies to promote a low-carbon economy, including the publication of *The 12th Five-Year Plan for National Economic and Social Development of the P.R. China* (in its "Conserving Energy and Reducing Emissions"), which established carbon trading pilot cities and a nationwide market. According to the *12th Five-Year Plan on GHGs Emission Control* introduced by the State Council of the P.R. China (2011a, 2011b), Zhejiang was requested to reduce carbon emissions per unit of gross domestic product (GDP) (also known as carbon intensity) by 19% compared with the 2010 level. The final official statistical results have shown that Zhejiang overfulfilled this task by actually reducing carbon intensity by 20.7% (Zhejiang Provincial Development and Reform Commission, 2016). In addition, as an "economically developed" area chosen for reform and as a pilot for the new policy and as a testing ground for the "lucid waters and lush mountains are invaluable assets" concept, Zhejiang has accomplished much in the arenas of low carbon development and environmental protection. For the recent few years, Zhejiang carried out a series of pilot projects, that is, started the submission, examination, and review of carbon emission reports in order to obtain valuable data and embarked on establishing a regional trading market. Based on the earlier considerations, we choose it as a "representative" region and research setting.

In this study, we focused on the municipal CEA allocation problem in Zhejiang during the 12th Five-Year period. We designed a new CEA allocation plan, specifically by using the centralized-DEA model to reallocate and optimize CEAs in 11 cities. It is worth mentioning that Zhejiang has a relatively typical and comprehensive subtropical climate. This plan would be both efficient and feasible for helping to establish a carbon trading system, as well as guiding future supervision and practice work.

The major contribution of this research is focused on practical field of municipal CEA quotas allocation. Most of the existing research works are based on country-level or provincial-level evidence, while the microperspectives such as city-level or enterprise-level had been relatively little investigated. However, the huge difference among national and provincial conditions would lead to the decline of DMUs' homogeneity, thus leading to the decline of results validation. This research based on DEA methodology to allocate municipal CEA quotas in Zhejiang province for the just finished 12th Five-Year period. The DMUs have relatively high homogeneity in this research. The research results also would provide academic references and possible policy suggestions for the construction of Zhejiang carbon trading market. Therefore, this research also fills the gap of empirical studies in CEA quotas allocation to some extent.

Methods

Study Area

This study was conducted in Zhejiang province. Zhejiang province is located in the eastern coastal and subtropical region of China, with a relatively high economic level (total 2016 GDP of 4,648.498 billion yuan, or 83,923 yuan per capita), rich natural sources (ocean, agriculture and mineral), and thriving commercial, service, and construction industries. In short, it is one of the richest areas in China.

Since it connects the continent and sea and is dotted with rivers, Zhejiang has three kinds of subtropical climates: mountain, continental, and marine. Figure 1 shows a detailed distribution of the three climate types.

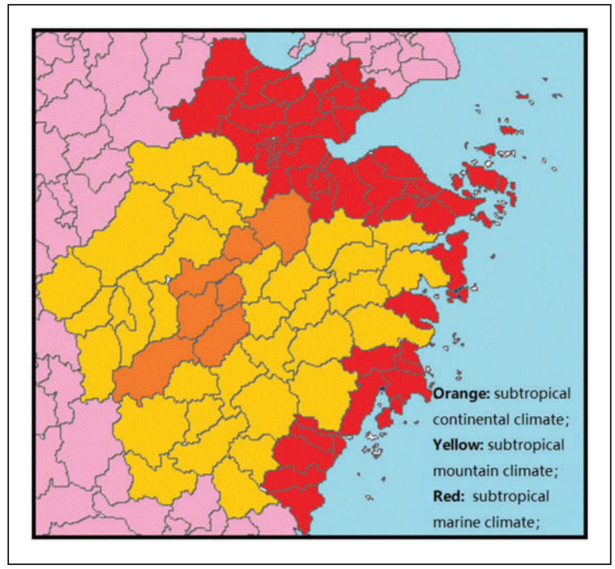

Figure 1. Climate-type map of Zhejiang province.

Environmental Evaluation Methodology

Suppose there are n DMUs in the reference set. Each $\mathrm{DMU_j}$ ($j = 1, \ldots, n$) consumes m inputs and produces s desirable outputs and t undesirable outputs denoted, respectively, as $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$, $Y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$, $U_j = (u_{1j}, u_{2j}, \ldots, u_{tj})^T$. The superscript T represents the transposition. Most current environmental performance studies consider GDP and carbon emission as desirable and undesirable outputs, respectively (Gomes & Lins, 2008; Zhou, Ang, & Poh, 2008b; Zofío & Prieto, 2001). We also follow these classic proxies. For simplicity, $\mathrm{DMU_o}$ denotes the DMU under consideration, (X, Y, U) denotes each DMU's inputs, outputs, and undesirable outputs.

It is one of the academic common sense that both the constant returns-to-scale (CRS) and the variable returns-to-scale (VRS) are classical DEA assumptions. However, CRS assumption usually cannot fit in the practical due to its idealization feature, take ray unboundedness as representative. Yet, VRS assumption relaxes the condition of ray unboundedness and is one of the most commonly used assumption in the previous studies and empirical research field. Therefore, our study is also based on VRS. The output-oriented environmental DEA model (after linearization) proposed by Zhou, Ang, and Poh (2008b) is presented.

$$
\begin{aligned}
&\max \quad \theta_o \\
&s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \sigma_o x_{io} \quad i = 1, \ldots, m && (1)\\
&\sum_{j=1}^{n} \lambda_j y_j \ge \theta_o y_o && (1)\\
&\sum_{j=1}^{n} \lambda_j u_j = u_o && (1)\\
&\sum_{j=1}^{n} \lambda_j = \sigma_o && (1)\\
&\lambda_j \ge 0 \qquad\qquad j = 1, \ldots, n && (1)\\
&\theta_o > 0, \quad \varepsilon \le \sigma_o \le 1 && (1)
\end{aligned}
$$

where σ_o can be deemed as an adjustable variable, which is positive and not larger than 1. Since our study only contains a single desirable output (GDP) and a single undesirable output (carbon emission), we do not give a detailed dimension subscript for both variables in Model (1). Other variables and constraints have the same explanations as Zhou, Ang, and Poh (2008a). We define the optimal objective θ_o^* as $\mathrm{DMU_o}$'s radial technical efficiency, and the related definition can be traced in the literature of Debreu (1951) and Farrell (1957). $\theta_o^* Y_o$ denotes $\mathrm{DMU_o}$'s maximum GDP potential. According to DEA theory, potential outputs can be realized if inefficiency in production can be fully eliminated. Therefore, our study attempts to determine each DMU's potential outputs (i.e., GDP potential) by evaluating relative efficiency. This is the primary reason that Model (1) is output oriented.

It should be noted that, Model (1) satisfies two properties: null joint-ness and weak disposability (Chung, Färe, & Grosskopf, 1997; Färe, Grosskopf, & Hernandez-Sancho, 2004). Null joint-ness means that the only way to eliminate undesirable outputs is to shut down production. Weak disposability shows that no reduction of undesirable outputs is possible without a reduction of desirable outputs given the current production technology.

Centralized CEA allocation methodology

Although Model (1) already considers carbon emission, it cannot analyze the influence of CEA on GDP potential (DMUs' efficiencies). Given this, the environmental evaluation model with a flexible CEA level is provided as follows.

$$
\begin{aligned}
&\max \quad \theta_o \\
&s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \sigma_o x_{io} \quad i = 1, \ldots, m && (2)\\
&\sum_{j=1}^{n} \lambda_j y_j \ge \theta_o y_o && (2)\\
&\sum_{j=1}^{n} \lambda_j u_j = u_o - b_o && (2)\\
&\sum_{j=1}^{n} \lambda_j = \sigma_o && (2)\\
&\lambda_j \ge 0 \quad j = 1, \ldots, n && (2)\\
&\theta_o > 0, \quad \varepsilon \le \sigma_o \le 1 && (2)\\
&u_o - b_o \ge 0 && (2)
\end{aligned}
$$

Compared to Model (1), Model (2) introduces a new decision variable b_o which represents $\mathrm{DMU_o}$'s CEA level, and $u_o - b_o$ represents $\mathrm{DMU_o}$'s expected carbon emission. By introducing this variable, Model (2) can evaluate $\mathrm{DMU_o}$'s environmental efficiency while consider its CEA target. It is worth noting that b_o's upper and lower bounds can be fixed by the third constraint of Model (2), which means a CEA target also should be formulated within a certain range rather than randomly.

In addition, Model (2) can determine the relationship between CEA level and environmental efficiency. Feng, Chu, Ding, Bi, and Liang (2015) concluded that the optimal solution for Model (2) is concave with respect to the CEA level. It means that there exists an optimal CEA level for each $\mathrm{DMU_o}$ to realize maximum GDP potential under the current production technology. If $\mathrm{DMU_o}$'s current CEA level is inconsistent with the optimal level, then it has a motivation to adjust it. (a) If the actual CEA level is lower than the optimal level, then $\mathrm{DMU_o}$ will take the initiative to reduce its carbon emissions. Put another way, the DMU would be "selling" part of its carbon quota to realize "double gains"; (b) If the actual CEA level is higher than the optimal level, then $\mathrm{DMU_o}$ will "buy" more carbon quota (only if the cost is reasonable).

Model (2) shows that CEA level b_j would influence efficiency θ_j, which in turn influences GDP potential. If all DMUs reach optimal CEA levels, then the overall GDP potential would also reach an optimal level. From this theoretical standpoint, all DMUs can use free will to choose their own emission levels. However, this conclusion is clearly not aligned with the current reality because under the current policy of severe restriction of emissions, all DMUs would further reduce emissions as little as possible.

Based on Model (2), the centralized allocation model under the VRS assumption can be constructed. This model allows for a maximum overall GDP potential through allocating CEAs among DMUs.

$$
\begin{aligned}
&\max \sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{kj} y_j \\
&s.t. \quad \sum_{j=1}^{n} \lambda_{kj} x_{ij} \le \sigma_k x_{ik} \quad k = 1, \ldots, n;\ i = 1, \ldots, m && (3)\\
&\sum_{j=1}^{n} \lambda_{kj} u_j = u_k - b_k \quad k = 1, \ldots, n && (3)\\
&\sum_{j=1}^{n} b_k = B && (3)\\
&\sum_{j=1}^{n} \lambda_{kj} = \sigma_k \quad k = 1, \ldots, n && (3)\\
&\lambda_{kj} \ge 0 \quad k = 1, \ldots, n;\ j = 1, \ldots, n && (3)\\
&\varepsilon \le \sigma_k \le 1 \quad k = 1, \ldots, n && (3)\\
&u_k - b_k \ge 0 \quad k = 1, \ldots, n && (3)
\end{aligned}
$$

where subscript k indicates the kth DMU, λ_{kj} represents DMU_j's weights for constituting DMU_k's subpoint. Model (3) aims at maximum overall desirable outputs, that is, the overall GDP potential. The first and second constraints of Model (3) have the same explanations according to Model (2). The third constraint requires that the total CEA should not be lower than the B value, which should be provided *a priori*. The fourth to seventh constraints specify the feasible domains of decision variables $\lambda_{kj}, \sigma_k, b_k$. Let $(\lambda^*, \sigma^*, b^*)$ denote the optimal solution of Model (3). The corresponding CEA vector $b^* = (b_1^*, \ldots, b_k^*, \ldots, b_n^*)$ represents an efficient CEA allocation plan under the VRS assumption.

Results

For the past few years, Zhejiang province vigorously implemented a low-carbon development strategy. On 2014, Zhejiang took steps to start the submission, examination and review work for a carbon emission report. This report was actually a pilot study, including only key enterprises of heavy carbon industries such as electronics, transportation, and chemical engineering. In 2016, this carbon emission data verification had already completely covered all key enterprises. Meanwhile, the General Office of the People's Government of Zhejiang Province (2016) published *Construction and Implement Plan of Constructing Carbon Emission Trading Market in Zhejiang Province*, which clearly proposed future goals for building the foundation for carbon emission rights trading by 2017, and establishing a sophisticated regional carbon trading market by 2020.

One important foundation for a carbon trading market is that all participants accept an allocation plan. Under this foundation, we have applied a centralized DEA method to reallocate and optimize the CEA quotas for 11 cities during the 12th Five-Year period of Zhejiang. As previously mentioned, we regard GDP as a desirable output, carbon emission as an undesirable output, and total employees, fixed asset investment, and energy consumption as inputs. The index chosen follows the work of Feng, Chu, Ding, Bi, and Liang (2015). Our major data source is the *Statistical Yearbook of Zhejiang Province (2012–2016)*,[1] *China Energy Statistical Yearbook (2012–2016)* and the Zhejiang Statistical Database.[2] It is worth noting that energy consumption is calculated as "regional energy consumption per unit of GDP multiplied by the region's GDP"; most importantly, carbon emission is estimated from economic statistics on Zhejiang and the "Zhejiang Provincial Energy Balance Sheet" (in the *China Energy Statistical Yearbook*) from a consumption perspective (for specific estimation criterion, see Note 3)[3]. Table 1 gives the definition of the research indices and descriptive statistics.

Since Zhejiang province only has 11 cities, the DMUs' size is still relatively small, even though it already meets the requirements of DEA's "rule of thumb" in practical use. Hence, we consider 11 cities from 2011 to 2015 as 55 DMUs for environmental evaluation and CEA allocation. A similar method is also applied in the DEA window analysis for two specific reasons: (a) This treatment can greatly increase a DMUs' size; (b) The time window of only 5 years can guarantee no significant technical progress,[4] thereby allowing all the DMUs of different years to be evaluated together with same criteria.

The detailed regional environmental efficiencies based on Model (1) under the VRS assumption are shown in Table 2 and Figure 2. Note that the value of ε in all models was set as 10^{-6} during calculating. The figures in the last column in parentheses represent ranking.

A precondition for the allocation of CEAs is the determination of total CEA quotas, which is the B value in Model (3). Since Zhejiang province already met the emission reduction target set by the central government during the 12th Five-Year period, we set the B value equal to 0 (which means an emission reduction ratio of $R = 0\%$). Table 3 demonstrates efficient allocation of 55 DMUs' CEA quotas obtained with Model (3). Moreover, the figures in the last row represent yearly sum quotas, and the last column represents the sums of 11 cities for 5 years.

Table 1. Research Indices Definition and Description (2011–2015).

Index	Unit	Mean	Standard Deviation
Input			
Employees (X_1)	10 thousand persons	341.67	185.16
Fixed asset investment (X_2)	100 million yuan	1861.41	1,237.39
Energy consumption (X_3)	10 thousand tons SCE	1,906.24	1,172.09
Output			
GDP (Y_1)	100 million yuan	3,487.18	2,411.03
Undesirable output			
Carbon emission (U_1)	10 thousand tons	3,565.12	2,257.34

Note. SCE = standard coal equivalent.

Table 2. Regional Environmental Efficiency of 11 Cities (2011–2015).[a]

Region	2011	2012	2013	2014	2015	Row mean
Hangzhou	1.0725	1.0480	1.0336	1.0048	1.0000	1.0318 (7)
Ningbo	1.0000	1.0429	1.0160	1.0069	1.0000	1.0132 (5)
Jiaxing	1.0000	1.0765	1.1085	1.0000	1.0000	1.0370 (8)
Huzhou	1.1642	1.1319	1.1985	1.0414	1.0033	1.1078 (10)
Shaoxing	1.1694	1.1844	1.1689	1.0684	1.0716	1.1326 (11)
Zhoushan	1.0000	1.0000	1.0000	1.0004	1.0000	1.0001 (1)
Wenzhou	1.1184	1.1669	1.1512	1.0669	1.0000	1.1007 (9)
Jinhua	1.0202	1.0249	1.0108	1.0000	1.0000	1.0112 (4)
Quzhou	1.0000	1.0000	1.0559	1.0406	1.0000	1.0193 (6)
Taizhou	1.0000	1.0096	1.0163	1.0000	1.0000	1.0052 (2)
Lishui	1.0000	1.0166	1.0349	1.0000	1.0000	1.0103 (3)
Column mean	1.0495	1.0638	1.0722	1.0208	1.0068	1.0426

[a]Since we adopted output-oriented measurement, all efficiencies are greater than or equal to one. The smaller the figure, the higher the efficiency.

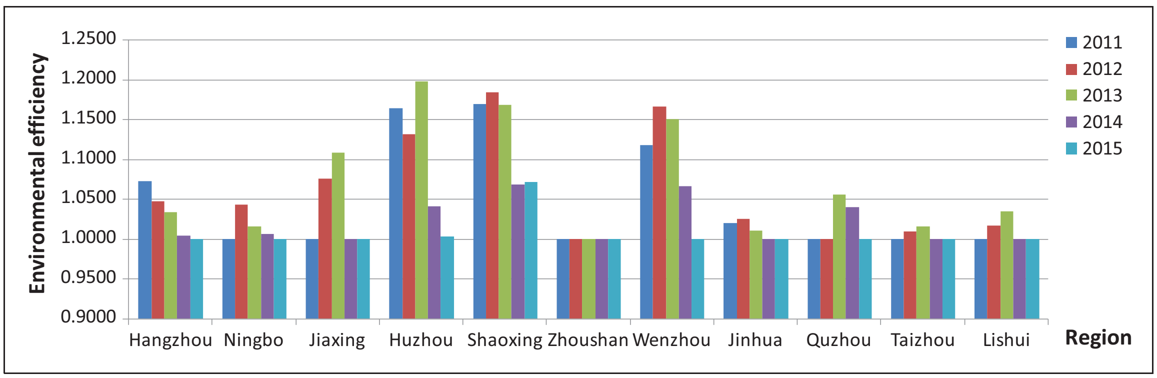

Figure 2. Environmental efficiency tendencies of 11 cities (2011–2015).

Table 3. Regional Efficient CEA Allocation Quotas of 11 Cities (2011–2015, $R = .0\%$)[a] (Unit: 10 Thousand Tons).

Region	2011	2012	2013	2014	2015	Row sum
Hangzhou	−50.97	2.98	33.34	70.47	0.00	55.82
Ningbo	0.00	49.09	−281.30	−162.37	0.00	−394.58
Jiaxing	448.65	453.99	526.10	815.69	927.97	3,172.41
Huzhou	203.25	221.97	87.63	243.49	385.78	1,142.12
Shaoxing	171.11	0.28	−210.42	126.84	57.94	145.75
Zhoushan	0.00	−55.23	−41.33	−8.07	0.00	−104.63
Wenzhou	−173.31	−181.52	−245.05	−234.14	−251.97	−1,086.00
Jinhua	−958.52	−1,109.00	−1,345.59	−1,003.31	−940.49	−5,356.91
Quzhou	0.00	372.49	709.30	704.06	820.57	2,606.42
Taizhou	0.00	−15.40	−85.52	0.00	0.00	−100.92
Lishui	0.00	−16.08	−63.39	0.00	0.00	−79.47
Column sum	−359.80	−276.43	−916.22	552.66	999.79	0.00

[a]Positive values mean "have to reduce emission" and negative means otherwise.

After investigating the most efficient plan given the practical setting, we further consider the theoretically optimal solution by removing the emission constraint.

Figure 3 shows different GDP potential levels corresponding to different carbon emission fluctuation levels ranging from an increase of 10% to a reduction of 10% ($R \in [-10\%, 10\%]$).

Inspired by Figure 3, we calculated the optimal CEA allocation from Model (2) and demonstrated it in Table 4.

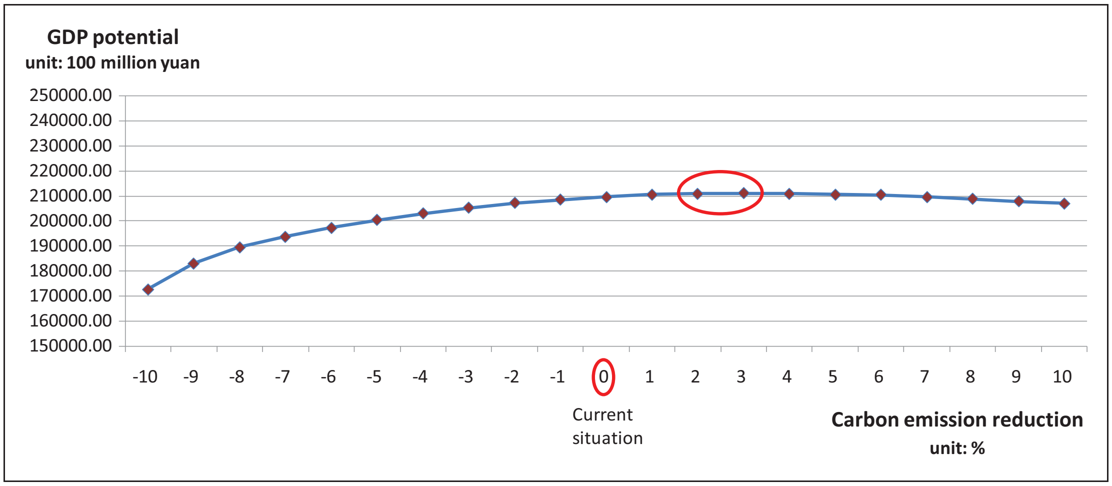

Figure 3. The relations between GDP potential and carbon emission reduction. GDP = gross domestic product.

Table 4. Regional Optimal CEA Allocation Quotas of 11 Cities (2011–2015, $R = 2.6\%$)[a] (Unit: 10 Thousand Tons).

Region	2011	2012	2013	2014	2015	Row sum
Hangzhou	−50.97	2.98	33.34	77.62	0.00	62.97
Ningbo	0.00	63.66	−281.30	−149.21	0.00	−366.85
Jiaxing	623.31	626.20	698.06	974.25	929.14	3,850.96
Huzhou	287.06	334.45	198.74	429.19	490.74	1,740.19
Shaoxing	306.40	179.15	−58.85	432.69	400.93	1,260.33
Zhoushan	0.00	0.00	0.00	−0.02	0.00	−0.01
Wenzhou	−61.69	−89.37	−245.05	−234.14	−251.97	−882.23
Jinhua	−958.52	−1,055.10	−1,214.11	−857.44	−818.79	−4,903.95
Quzhou	1,154.24	1,068.18	709.30	704.06	820.58	4,456.35
Taizhou	0.00	−15.39	−68.32	0.00	0.00	−83.72
Lishui	0.00	−3.82	−24.82	0.00	0.00	−28.64
Column sum	1,299.82	1,110.92	−252.98	1,376.99	1,570.64	5,105.38

Note. CEA = carbon emission abatement.
[a]Positive values mean "have to reduce emission" and negative means otherwise.

Next, we compare the CEA quotas and the corresponding GDP potential change levels of the above two allocation plans, both yearly (Figure 4) and regionally (Figure 5).

In the end, we compare the policy requirements and actual results of carbon intensity reduction rate for 11 cities in Zhejiang province during 12th Five-Year period, as well as the anticipated indicator value under both efficient CEA allocation plan and optimal CEA allocation plan (Table 5).

Discussion

Discussion of the Regional Environmental Evaluation

From Table 2 and Figure 2, the following results can be found. First, the highest row mean (on the last column) is only approximately 1.1, and the overall efficiency mean is less than 1.05. Second, the tendency of yearly average efficiency (on the last row) is relatively stable. These two factors combined indicate that Zhejiang shows a good environmental performance from a statistical perspective. Third, we can categorize 11 cities into three subgroups. The first class includes Zhoushan, Taizhou, and Lishui, which show a relatively high and stable performance level. In particular, Zhoushan needs almost no improvement in performance. The second class includes Hangzhou, Ningbo, Jinhua, and Quzhou. These four cites perform worse than those of the first class but have an overall trend toward continuous progress. The third class, with the poorest performance, includes Jiaxing, Huzhou, Shaoxin, and Wenzhou. They represent high inefficiency and drastic fluctuations in performance. In general, the municipal environmental performances of Zhejiang during the 12th Five-Year period are both encouraging and show a great deal of variation.

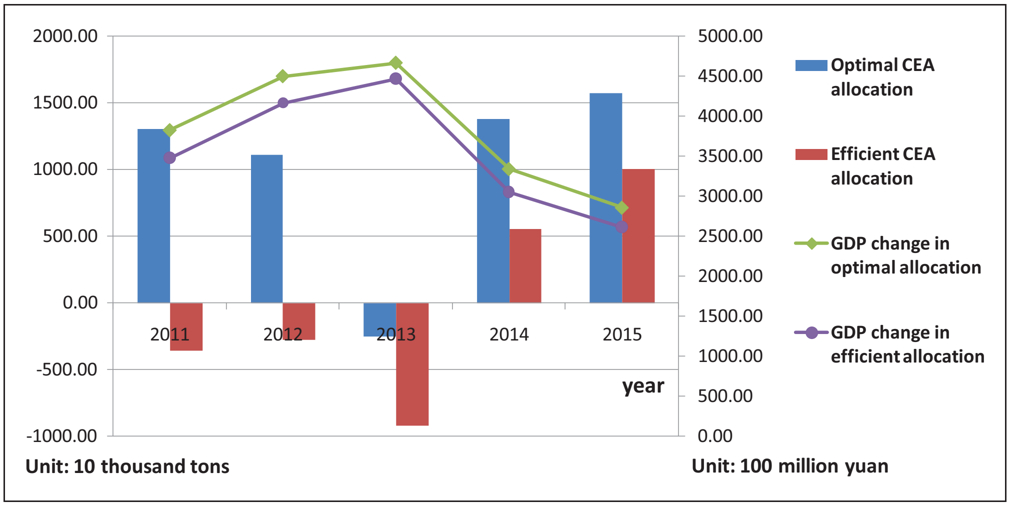

Figure 4. CEA allocation and GDP potential change of Zhejiang during 2011–2015 (yearly). GDP = gross domestic product; CEA = carbon emission abatement.

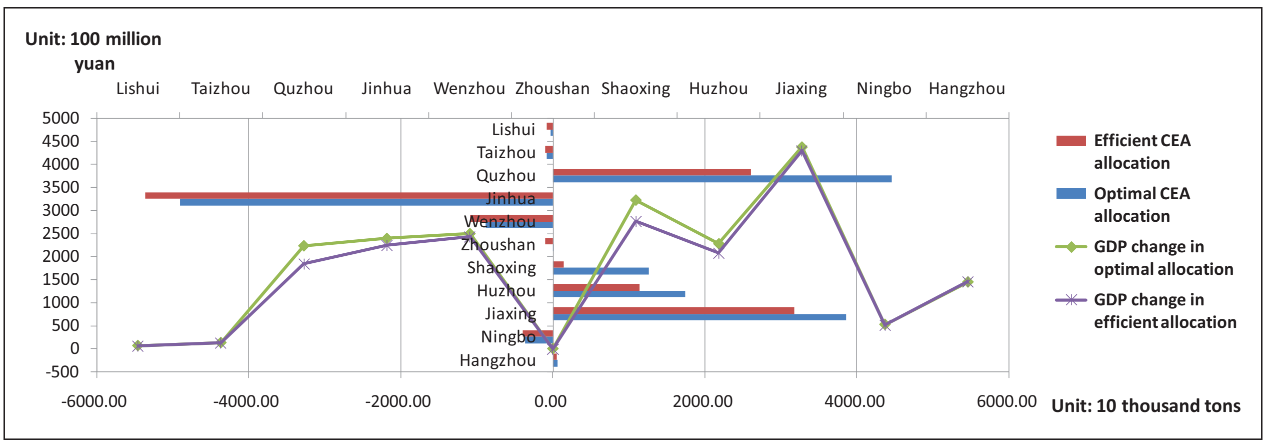

Figure 5. CEA allocation and GDP potential change of 11 cities during 2011–2015 (regionally). GDP = gross domestic product; CEA = carbon emission abatement.

Table 5. The Comparison Within Policy Requirement, Actual Situation, and Allocation Plan of 11 Cities.

Region	Policy requirement	Actual situation	Efficient CEA allocation	Optimal CEA allocation
Carbon intensity reduction rate				
Hangzhou	20.0%	36.9%	36.9%	36.9%
Ningbo	20.0%	25.5%	25.5%	25.5%
Jiaxing	19.5%	24.7%	52.9%	52.9%
Huzhou	20.5%	34.8%	53.4%	56.5%
Shaoxing	20.5%	39.5%	44.6%	50.4%
Zhoushan	16.0%	35.7%	35.7%	35.7%
Wenzhou	19.5%	38.5%	35.7%	35.7%
Jinhua	19.0%	39.8%	26.6%	29.5%
Quzhou	21.0%	31.0%	68.7%	68.7%
Taizhou	13.5%	27.8%	27.8%	27.8%
Lishui	15.5%	38.0%	38.0%	38.0%
Total GDP potential (100 million yuan)				
Zhejiang		191,794.84	209,562.17	210,978.46

Note. CEA = carbon emission abatement.

Discussion of Efficient CEA Allocation

From Table 3, the following may be found. First, the yearly sum of CEA quotas shows an initial 3 years of emission increase and a final 2 years of emission reduction. This may indicate the actual implementation of the 5-year plan as “tight first and loose after.” Second, we can also categorize 11 cities into two types. Ningbo, Zhoushan, Wenzhou, Jinhua, Taizhou, and Lishui belong to the “emission increment class,” demonstrating that they still have space to achieve economic growth (only from a carbon emission rights perspective). While the rest of the cities belong to an “emission reduction class,” this is showing that they have no more “environmental tolerance” for economic growth. Finally, Hangzhou, Ningbo, and Shaoxing show specific data characteristics including “both positive and negative,” while the rest of the cities exhibit data in only one direction.

Discussion of Optimal CEA Allocation

From Figure 3, GDP potential is a concave function of carbon emission reduction (i.e., total CEA quotas), which means that GDP potential will reach a summit point.[5] Under the current situation ($B=0$), the GDP potential would keep declining if emissions rise (on the left side of 0), while GDP potential would exhibit an “increase first decline after” tendency if emissions are reduced (on the right side of 0). More importantly, we can easily and clearly tell from Figure 3 that the maximum level exists in the emission reduction zone between 2% and 3%.

From Table 4, GDP potential would reach its highest level of 21,097.85 billion yuan, at an emission reduction ratio of 2.6%. Meanwhile, after comparing the detail results between Tables 3 and 4, we find that both the overall and individual city’s fluctuation directions are identical, and only specific values change.

The major distinctions, mainly the advantages of optimal allocation compared with efficient allocation are twofolds: (a) The GDP potential obtained from optimal allocation is larger than from the efficient one; (b) This maximum GDP potential would be obtained in the case of an emission reduction of 2.6% over a 5-year period. Normally, GDP growth relies on expanded reproduction and fixed asset investment, and these are the main driving forces behind carbon emission. However, our empirical evidence shows the opposite. This is somehow a “win–win” result for both economic development and environmental protection. From this standpoint, policy-makers may find this theoretical CEA allocation plan both feasible and economically appealing.

Comparison of Efficient and Optimal CEA Allocation

From Figure 4, it the following can be found: First, from the perspective of the direction of emission fluctuation: In the initial 2 years, the optimal and efficient allocation plans are arranged in an opposing scheme, while the remaining 3 years they have the same arrangement. Moreover, Year 2013 is very special for both plans in that it demands an emission increment. Second, from the perspective of emission quantity: The gap between the two allocations gets closer and closer. Finally, from the perspective of GDP potential change conditions: After the first two years’ sustainable growth, marginal growth starts to go down, and this may be reasonably explained by the “law of diminishing marginal utility.”

We can also obtain results from Figure 5 which focuses on the regional comparison issue. First, unlike yearly results, the optimal and efficient allocation plans provide similar optimizing schemes for the 11 cities. Second, the GDP potential change is in the same direction and of a similar extent between the two allocation plans. Third, Jiaxing would experience the highest GDP growth during the optimization process while Zhoushan would experience the least. It is worth mentioning that Zhoushan would even suffer a 1.1 billion yuan loss in efficient allocation, which means this city may need to make sacrifices in order to realize the total maximum benefit.

Comparison of Policy Requirements and Example Results for Carbon Intensity

Table 5 shows the carbon intensity reduction rate for policy requirements and example results. The corresponding total GDP (potential) of Zhejiang province during the 12th Five-Year period is also provided. The State Council demanded Zhejiang to reduce carbon intensity by 19% in 2015 compared with the level of 2010. To accomplish this target, Zhejiang government set different goals for 11 cities according to their economic and natural situations (People’s Government of Zhejiang Province, 2013). It is worth noting that carbon intensity reduction rate set by government is not under principle of total quantity control. Nevertheless, the optimization for carbon intensity reduction target may bring economic beneficial, that is, cost saving (Cui, Fan, Zhu, & Bi, 2014). In this research, we get meaningful and interesting comparison results within policy requirement, actual situation, and two possible CEA allocation plans proposed in this research. The major two findings are as follows: First, the actual situation and all CEA allocation plans meet the policy requirements (substantially exceed expected objectives in great proportion). Second, the CEA allocation plans proposed by the research shows better GDP increment level while still meeting the existing requirements of carbon emissions. To sum up, the two plans proposed by this research are both legitimacy and better than the actual situation.

Implications for Conservation

Environmental issue always is the inevitable negative byproduct of economic development. One of the most effective market mechanisms to solve the greenhouse effect is establishing ETS. Meanwhile, the initial "allocation" step (i.e., the reasonable original allocation of CEA within different regions or enterprise) plays vital role in determining ETS quality. In the past decade, Zhejiang province, as one of the most economic developed region and typical subtropical zone, had carried out a series of pilot projects to establish and implement ETS. Based on this background, and private city-level data, this article evaluates, reallocates, and optimizes the regional allocation of CEAs in Zhejiang province during 12th Five-Year period.

The results reveal Zhejiang exhibits relatively high environmental efficiency. The most important and encouraging finding is that we confirm that, with the "inverse U" shape relations between GDP and emission reduction, this environmental protection task (within a reasonable range) not only is necessary but also has economic benefits in Zhejiang province. This result indicates important steps for further and proper conservation. The optimum solution of convincing companies to fulfill their responsibilities, rather than demanding them to do so, lies in letting them realize that "benefits exceed costs." In addition, the efficient CEA allocation and optimal CEA allocation of Zhejiang province during 12th Five-Year period is obtained in this research. Compared with the actual situation, these new plans receive significant improvement which would increase total provincial GDP potential while reduce (or at least maintain) the current total carbon emission level.

Finally, we proposed two possible suggestions for policy-making in terms of the empirical results. On one hand, it is unlikely that the emission reduction target will be achieved overnight. Hence, we suggest to set yearly target under carbon intensity target to realize "truly" and "effective" reduction. Actually, this research provides feasible reference and solution on "year by year" optimization plan. Similar thoughts may also found in Cui and Huang (2018). On the other hand, we recommend government to adopt CEA allocation target rather than existing carbon intensity target in the long term. The latter one does not have the strong constraint of carbon mission reduction as the first one, and thus may influence the expected reduction effect.

Author Contributions

Dan Hu, Chenpeng Feng, and Yunfei Fang conceived and designed the study. Junheng Cheng collected the raw data. Chenpeng Feng performed the computations and analyses. Dan Hu and Yunfei Fang wrote the first draft of the paper. All authors have read and approved the final manuscript.

Declaration of Conflicting Interests

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Notes

1. We combined Yiwu's data into Jinhua, since Yiwu is a country-level city attach to Jinhua.
2. http://tjjdata.zj.gov.cn/index.do
3. A brief description of the calculation process: The basic principle of statistical specification is from a consumption perspective, rather than an electronic production perspective. Our statistics only cover the electricity consumption carbon emission of the whole society, rather than including carbon emissions from electricity generation. City-level carbon emissions = carbon emissions of primary industry + carbon emissions of industrial enterprises above a designated size + carbon emissions of industrial enterprises below a designated size + carbon emissions of constructing industry + carbon emissions of service industry + carbon emissions of citizens + carbon emissions of total societal electricity consumption.
4. We propose this hypothesis based on two reasons. Charnes, Cooper, Lewin, and Seiford (1994) pointed out that a window width of three or four time periods (Majority of researches interpret "period" as "year") tend to yield the best balance of informativeness and stability of the efficiency results. We believed that treating 5 years as one time-window is not too far from optimal standard. Moreover, since 2011, the beginning year of 12th Five-Year period, majority pollution emitter adopted energy-saving and environmental protective facilities in Zhejiang province.

This is due to Chinese government made environmental protection as national priority, and set concrete standards and targets for different industries and regions.

5. On one hand, it is not the case as "the more reduction the better." Once the reduction is way too much, it will affect the normal economic development. On the other hand, it is neither the case as "the less reduction the better." This can be reasonable explained by "congestion," which means providing emitter with more emission quota may not necessarily bring potential GDP growth. This may due to constrain of existing production technology, there lead too much emission is kind of "waste."

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