



Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Factors influencing industrial carbon emissions and strategies for carbon mitigation in the Yangtze River Delta of China

Xibao Xu ^{a,*}, Guishan Yang ^{a,**}, Yan Tan ^b, Qianlai Zhuang ^c, Xuguang Tang ^a, Kaiyan Zhao ^a, Sirui Wang ^c

^a Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing, 210008, China

^b Department of Geography, Environment and Population, The University of Adelaide, Adelaide, 5000, Australia

^c Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, West Lafayette, IN, 47907, USA

ARTICLE INFO

Article history:

Received 31 March 2016

Received in revised form

13 September 2016

Accepted 21 October 2016

Available online xxx

Keywords:

Industrial carbon emissions

Panel model

Carbon mitigation

Yangtze River Delta

ABSTRACT

The Yangtze River Delta is one of the most industrialized regions in China. This study characterizes the spatial and temporal patterns of industrial carbon emissions (ICE) produced by secondary industry sectors in the region from 2000 to 2014. The scale and nature of ICE is measured from five aspects (involving 12 factors): gross industrial output value (GIOV), energy intensity (EI), energy structure (ES), industrial structure (IS) and the structure of industrial enterprises (the number and scale). The study establishes three panel models to analyze the effects of 12 factors on ICE at the county level. The results show that ICE increased dramatically, being 2.1 times the 2000 level (135.94 Mt CO₂) in this region by 2014. The major carbon sources are the consumptions of raw coal and electricity, accounting for more than three quarters of the total ICE during the 2000–2014 period. ICE presents great spatial disparities across 66 counties in the region, being highly coincident with the Z-shaped distribution of the urban clusters in the delta. The GIOV is a major contributor to ICE growth in this region, increasing by 84.1 tC for an increase of one million yuan of GIOV. The adjustment of ES, EI and the structure of industrial enterprises can largely abate ICE. Regulating industrial structure and energy structure, reducing energy intensity and optimizing the structure of industrial enterprises are suggested as imperative measures for carbon mitigation in the region.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

Secondary industry has played a critical role in global energy use and carbon emissions. In 2010, the secondary industry sectors consumed 28% of the global energy and produced 13 gigatonnes (Gt) of CO₂ emissions, which is greater than emissions from the tertiary industry sectors including transportation (IPCC, 2014). As the world's largest carbon emitter, China accounted for 30% of global total emissions in 2014 (10.6 Gt CO₂), increasing by 80% on its 2004 level (Olivier et al., 2015). In China, secondary industry takes the largest share of the national energy consumption (e.g. 70% in 2014) (National Bureau of Statistics of China, 2015). Energy use and

industrial carbon emissions (ICE hereafter) from secondary industry sectors are expected to continue growing due to sustained industrialization and urbanization of China's economy. In order to effectively balance multiple goals between economic development, energy security, environmental quality, and carbon reduction, the Chinese central government has committed to peak its carbon emissions before 2030 and increase the share of non-fossil fuels in its energy production and consumption structure to 20% by 2030 (GCEC, 2014).

Studies on ICE have attracted focal attention around the world due to rising global pressure on climate change mitigation. Recent studies focus on estimating global emissions and patterns (IPCC, 2014; Kim and Kim, 2012; Olivier et al., 2015), analyzing driving forces (Adom et al., 2012; Hocaoglu and Karanfil, 2011), and exploring mitigation pathways and policy interventions (Fujii et al., 2016; Liu et al., 2013; Mishra et al., 2015). In China, growing research in the field focuses on driving forces (Ouyang and Lin, 2015; Ren et al., 2014; Tian et al., 2014; Wang and Wei, 2014; Zhou et al., 2013) and mitigation policies (Cai et al., 2007; Jiang

* Corresponding author.

** Corresponding author.

E-mail addresses: xbxu@niglas.ac.cn (X. Xu), gsyang@niglas.ac.cn (G. Yang), yan.tan@adelaide.edu.au (Y. Tan), qzhuang@purdue.edu (Q. Zhuang), xgtang@niglas.ac.cn (X. Tang), zhaokaiyan13@mails.ucas.ac.cn (K. Zhao), wang2381@purdue.edu (S. Wang).

Abbreviations

ICE	industrial carbon emissions
GIOV	gross industrial output value
EI	energy intensity
ES	energy structure
IS	industrial structure
IES	industrial enterprises' structure
YRD	Yangtze River Delta
SOEs	state-owned enterprises
COEs	collectively-owned enterprises
PEs	private enterprises
FIEs	foreign invested enterprises
LNG	liquefied natural gas
LPG	liquefied petroleum gas
LMDI	Logarithmic Mean Divisia Index
TSC	tons of standard coal

et al., 2015; Zheng et al., 2016). Methodologically, sophisticated approaches to ICE research include Logarithmic Mean Divisia Index (LMDI) (Ouyang and Lin, 2015; Song et al., 2015; Zhao et al., 2010), panel models (Ren et al., 2014; Zhou et al., 2013), data envelopment analysis (DEA) (Sun et al., 2015; Wang and Wei, 2014) and Input-Output models (Mi et al., 2015; Tian et al., 2014). Studies on ICE have been conducted on different scales, from the national (Ouyang and Lin, 2015; Ren et al., 2014; Wang and Wei, 2014; Zhou et al., 2013), regional (Lu et al., 2015; Song et al., 2015; Tian et al., 2014) to city (Mi et al., 2015; Zhao et al., 2010), and further to industry sector (Cai et al., 2016; Lin and Moubarak, 2014; Lu et al., 2015). These studies have not only increased our understanding of the ICE patterns, driving forces and mitigation pathways, but also constructed theoretical frameworks and operational tools for policy makers to work out solutions to mitigate carbon emissions. Previous studies on the driving forces are centered on industrial output, industrial structure, energy intensity, energy structure and industrial sectors. There is little research examining the impact of different types and structures of enterprises on carbon emissions through influencing energy efficiency and government interventions (Cai et al., 2016; Jiang et al., 2015; Lo et al., 2015). A lack of clarity of how these important, but less-studied, factors influence ICE could have a negative effect on mitigation policies for future emission targets and the differentiated responsibilities between stakeholders at all levels.

The Yangtze River Delta (YRD) is one of six megalopolitan regions in the world. Recent research into carbon emissions in the YRD highlights the trends of industrial and total carbon emissions and their driving forces, especially industrial output, energy intensity, energy structure and industrial structure (Lu et al., 2015; Song et al., 2015; Wang et al., 2011; Zhao et al., 2010; Zheng et al., 2016). For example, Zhao et al. (2010) and Lu et al. (2015) suggested that industrial output was the main driving force, and that the decline in energy intensity and the optimization of energy structure, industrial structure and energy efficiency were key determinants for carbon reduction. Zheng et al. (2016) indicated that ICE would increase steadily from 2005 to 2030, at a rate ranging from 61.1% in Jiangsu province, 89.7% in Shanghai to 92.2% in Zhejiang province, based on the GAINS-China model, assuming the current policy remains unchanged. There are remarkable differences across a range of factors that influence carbon emissions between those well-developed counties and those less developed ones in the region. Such factors include industrial output, industrial structure, energy intensity and efficiency, energy structure,

structure of industrial enterprises, available technology, and levels of consumption and emissions. Existing studies on ICE on the provincial and regional scales have provided preliminary explanations of the effects of these factors on a macro scale. However, since many studies did not take into account substantial differences within the region, literature in this field could contain some biased results as they relate to the contributing roles of these factors and policies on carbon mitigation. There is no research disentangling the complex nexus between changing ICE patterns, mechanisms and mitigation policies across industrial enterprises, at the county level, in the YRD. There is a pressing need in research to identify significant factors influencing ICE at both the industrial sector and county levels. Only nuanced understanding can help formulate effective energy-saving and carbon mitigation policies in such rapidly urbanizing regions as the YRD.

This paper seeks to address this pressing need in research by: (1) providing an increased understanding of the magnitude and spatio-temporal pattern of ICE in the YRD at the county level; (2) identifying significant factors contributing to ICE; and (3) drawing out policy implications for ICE mitigation. The study establishes three panel models to explore the impacts of five aspects of secondary industry on ICE: gross industrial output value (GIOV), energy intensity (EI), energy structure (ES), industrial structure (IS) and the structure of industrial enterprises (in terms of the number and scale). Cross-regional panel data for the period of 2000–2014 is used to serve the modeling purposes. Thus this study contributes to understanding the pathway towards industrial carbon mitigation in the YRD, and even China, and offers necessary measures for industrial carbon mitigation based on the findings.

2. Materials and methods

2.1. Study area

The YRD, located on the east coast of China (E118°20'–122°46', N28°2'–33°25'), encompasses two provinces, Jiangsu and Zhejiang, and one municipality, Shanghai, which involve 66 counties/cities (Fig. 1). These counties/cities can be classified into six hierarchical levels in terms of their population size: Level I (over 10 million), Level II (5–10 million), Level III (3–5 million), Level IV (1–3 million), Level V (0.5–1 million) and Level VI (less than 0.5 million) (Xu et al., 2015). The region has 1.2% of the total land area of China but supports 8.1% of the nation's population (1.34 billion) according to the 2010 China census.

The YDR has the largest regional economic capacity in China, contributing 101.4 trillion yuan (or 15.9%) to the national total GDP in 2014 followed a period of remarkable economic development from 2000 to 2014. The GIOV and the number of industrial enterprises above the designated size (i.e. annual prime operating revenue above 20 million yuan) increased substantially, by 4.9 times and 1.2 times above their 2000 levels, respectively. The proportion of GIOV against the gross regional production (GRP) decreased from 46.1% to 41.6% due to upscaling, optimization and transformation in secondary industry, and the development of tertiary industry, over the same time. The YRD consumed 17.5% (or 376.9 million tons (Mt) of standard coal) of the total energy in China and produced 15.5% (or 1228.4 Mt) of total carbon emissions in 2010 (Xu et al., 2015). In particular, rapid industrialization and urbanization in 2000–2014 has dramatically changed the pattern of industrial energy consumption, industrial enterprises and carbon emissions in this region. According to the *National New-Style Urbanization Plan (2014–2020)* and *China's One Belt and One Road Strategy* (started in 2015), the YRD will continue to gain momentum in the process of industrialization and urbanization in the next two decades. This will undoubtedly lead to a trajectory of growing demand for energy

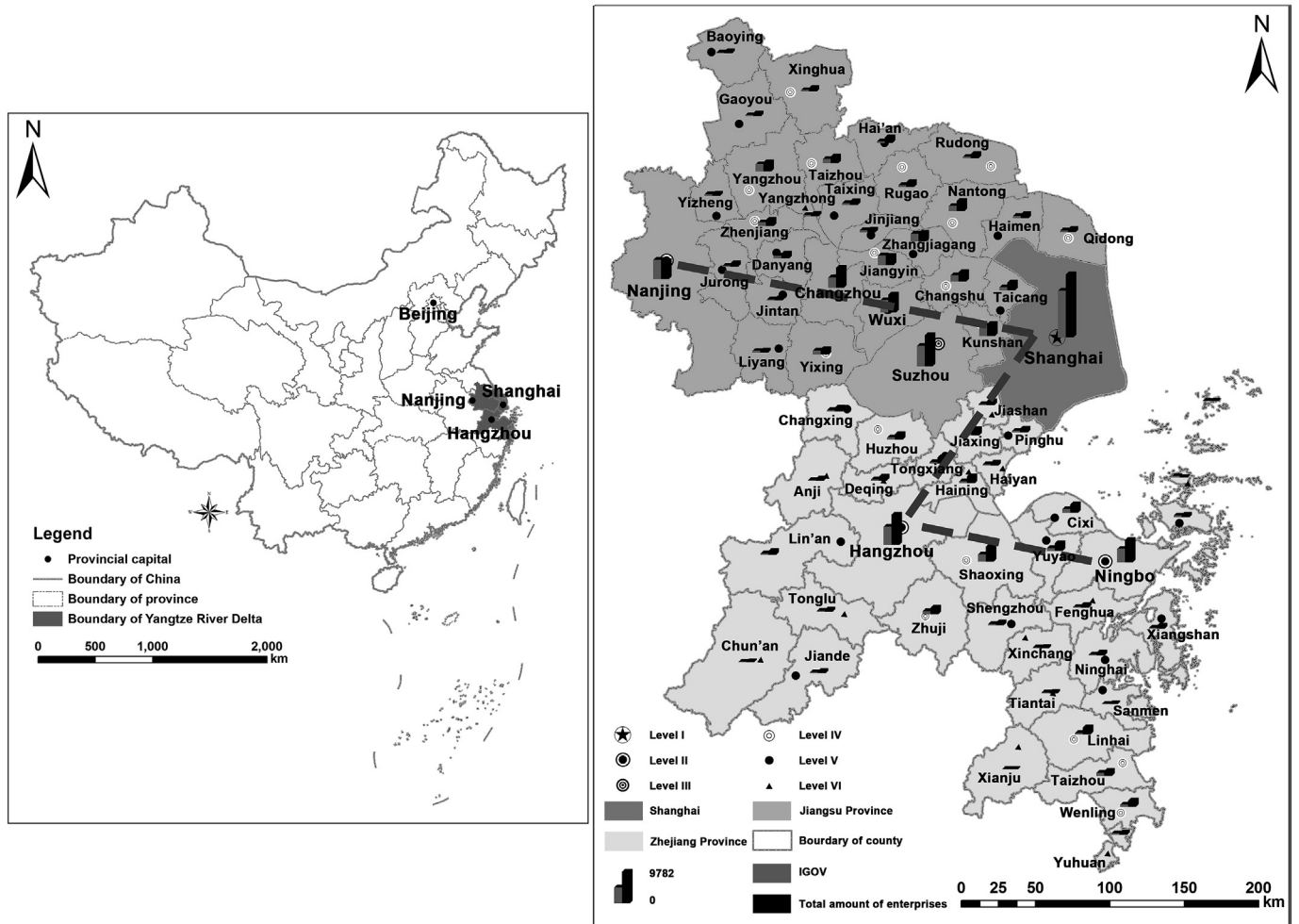


Fig. 1. Location of the Yangtze River Delta, China. Note: Grey bar indicates the GIOV (100 million yuan), and black bar shows the total number of industrial enterprises above the designated size.

consumption and increasing carbon emissions in the coming years if policy initiatives do not target this change.

2.2. Measurement of carbon emissions

According to the IPCC guidelines (IPCC, 2006), carbon emissions can be estimated by multiplying each specific type of energy consumed and its corresponding carbon emission coefficient. This study employs a set of carbon emission coefficients suggested by the *General Guideline of the Greenhouse Gas Emissions Accounting and Reporting for Industrial Enterprises* (GAQSIQ and SAC, 2015). The method used to estimate carbon emission is expressed in Equation (1).

$$C = \sum_{i=1}^{13} F_i * E_i \quad (1)$$

Where C is the annual total amount of ICE; i denotes 13 energy categories, including raw coal, clean coal, coke, natural gas, liquefied natural gas (LNG), gasoline, kerosene, diesel fuel, fuel oil, liquefied petroleum gas (LPG), other gasoline products, heat and electricity; F_i is the total final usage of the i^{th} energy; E_i is the carbon emission coefficient for the i^{th} energy. In this study, the final usage statistics of all energy categories are used to estimate ICE. Coal-based energy and hydropower are the dominant sources of

electricity in China, contributing up to 96.9% of its overall energy consumption in 2014. Unfortunately at the county level, these two sources of electricity cannot be distinguished from available statistics. Thus, the carbon emission coefficients for electricity in this study are set as varying values according to the national composition of coal-based energy and hydropower, with 2.738, 2.531, 2.343 and 2.343 tons C/10000 kwh for 2000, 2005, 2010 and 2014, respectively. Electricity from clean energy sources (wind and solar) is not considered as they emit zero carbon. The carbon emission coefficients for the other 12 energy categories are set as constant values during the period of 2000–2014. In addition, the final usage statistics on consumed fossil energy, such as electricity, gasoline products, and heat, in some industrial subsectors may be contained in data for energy sources such as raw coal, clean coal, coke, natural gas and gasoline. As a result, there is some uncertainty in estimating ICE, and quantifying ICE will need to be improved when end-use energy data from main industrial sectors becomes available in future research.

2.3. Panel model

The scale and nature of ICE are primarily influenced by five aspects of secondary industry: gross industrial output value (GIOV), industrial structure (IS), energy structure (ES), energy intensity (EI), and structure of industrial enterprises (IES) (Adom et al., 2012; Cai

et al., 2016; Hocaoglu and Karanfil, 2011). In this study, the structure of industrial enterprises is measured by the number of state-owned enterprises (SOEs), collectively-owned enterprises (COEs), private enterprises (PEs) and foreign invested enterprises (FIEs) above the designated size and the scale for these four ownership types. PSOEs, PCOEs, PPEs and PFIEs are defined as the proportions of SOEs, COEs, PEs and FIEs, respectively, which are calculated by the corresponding number of specific ownership enterprises against the total number of these four types of industrial enterprises. As statistics of foreign invested enterprises are not distinguished from Hong Kong, Macao and Taiwan invested industrial enterprises in some counties, a proxy of FIEs is defined as the sum of both foreign invested and Hong Kong, Macao or Taiwan invested enterprises. This method may bring about some uncertainty in estimating the effect of FIEs on ICE.

The size of enterprises and type of ownerships influence energy conservation behavior. Large enterprises by their very nature usually have more room for energy efficiency improvement through technical and non-technical advancement than small- and medium-sized enterprises. In addition, ownership type is a key factor influencing government interventions. SOEs are subject to stronger regulatory oversight than that of COEs, PEs and FIEs (Lo et al., 2015). Thus, it is important to investigate the impact of the structure of industrial enterprises (including the number and scale) on ICE.

We build three panel models to better understand how the following 12 factors – GIOV, IS, ES, EI, SOEs, COEs, PEs, FIEs, PSOEs, PCOEs, PPEs, PFIEs – impact ICE. Model 1 only considers GIOV, IS, ES and EI to distinguish the effect of the structure of industrial enterprises on carbon emissions. As expressed in Equation (2), Model 2 involves all 12 factors. Model 3 is a parsimonious means containing only a few independent variables significant at the 10 percent significance level by dropping off those insignificant independent variables (e.g. IS, FIEs, PFIEs) in Model 2. The advantage of Model 3 is that it minimizes the standard errors of the remaining independent variables. The disadvantage of this modeling procedure is that it may suffer from omitted variable bias if any dropped variable is fundamental to explaining the dependent. All the models fit together and can be expressed as:

$$C_{it} = \alpha_i + \beta_1 GIOV_{it} + \beta_2 IS_{it} + \beta_3 ES_{it} + \beta_4 EI_{it} + \beta_5 SOEs_{it} + \beta_6 COEs_{it} + \beta_7 PEs_{it} + \beta_8 FIEs_{it} + \beta_9 PSOEs_{it} + \beta_{10} PCOEs_{it} + \beta_{11} PPEs_{it} + \beta_{12} PFIEs_{it} + \varepsilon_{it} \quad (2)$$

where C_{it} is the ICE for the i^{th} county at time t ; α_i is the drift term, $GIOV_{it}$ indicates gross output value of industrial enterprises above the designated size for the i^{th} county at time t ; IS_{it} denotes the industrial structure for the i^{th} county at time t , measured as the percentage of GIOV against the gross domestic product (GDP); ES_{it} denotes the structure of industrial energy consumption for the i^{th} county at time t , which is measured as the percentage of coal consumption (including raw coal, clean coal, coke) in the total energy consumption; EI_{it} denotes industrial energy intensity for the i^{th} county at time t , estimated by energy consumption per unit of GIOV. $SOEs_{it}$, $PSOEs_{it}$, $COEs_{it}$, $PCOEs_{it}$, PEs_{it} , $PPEs_{it}$, $FIEs_{it}$, and $PFIEs_{it}$ are the number and scale of state-owned, collectively-owned, private and foreign invested industrial enterprises above designated size, respectively. $\beta_1, \beta_2, \dots, \beta_{12}$ are undetermined coefficients, and ε_{it} is the error term.

The panel data was first analyzed with a hypothetical test for heteroscedasticity and cross-sectional dependence. The temporal dependence was not considered due to the four short time periods (2000, 2005, 2010, 2014). The results suggest there exist significant

heteroscedasticity and cross-sectional correlations in the panel data (Table 1). Then, the “Driscoll-Kraay standard errors” ($xtsc$) was applied to build the panel models using Stata 12.0 (Driscoll and Kraay, 1998; Hoechle, 2007). Ignoring cross-sectional correlation in the estimation of panel models can lead to severely biased statistical results for both pooled OLS and fixed effects (FE) regressions. Our estimated “Driscoll-Kraay standard errors” of the models are not only robust for being heteroskedasticity consistent, but also robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007). Thus, the $xtsc$ program is suitable for the panel data with significant heteroscedasticity and cross-sectional and temporal dependence in this study.

2.4. Data sources

The statistics of energy consumption, GDP, GIOV and the number of industrial enterprises (SOEs, COEs, PEs, FIEs) above the designated size at the county level were sourced from the Statistical Yearbooks of each city for various years spanning from 2000 to 2014. Energy consumption involves 13 end-point energy types: raw coal, clean coal, coke, natural gas, liquefied natural gas (LNG), gasoline, kerosene, diesel fuel, fuel oil, liquefied petroleum gas (LPG), other gasoline products, heat and electricity. All statistics were adjusted according to the latest administrative divisions in 2015.

3. Results

3.1. Magnitude of carbon emissions

The total amount of ICE in the YRD has increased dramatically (by 2.1 times the 2000 level) at an annual growth rate of 5.4%, changing from 135.94 Mt CO₂ in 2000, 261.72 Mt CO₂ in 2005, to 386.45 Mt CO₂ in 2010, and further to 421.03 Mt CO₂ in 2014. Strikingly, ICE has started to decrease since 2010 across more than a quarter of counties (17) mainly in Shanghai and Zhejiang Province. Such declines were largely due to the changes in EI and the structure of industrial enterprises under China's policy on saving energy and reducing emissions since 2010. The national policy endeavors to cut CO₂ emissions by 40–45% at the 2005 level per unit of GDP by 2020 (Xinhuanet, 2009). The EI and PEs for the majority of these 17 counties decreased by 25% (Shanghai) and 45% (Zhejiang province) over the 2010–2014 period, larger decreases than for other counties. ICE mainly originated from the consumption of raw coal and electricity, accounting for 48.9–53.5% and 21.5–28.4% of the total ICE in 2000–2014, respectively. The percentages of carbon emissions from raw coal, clean coal, natural gas, liquefied natural gas, heat and electricity increased slightly, compared to marginal growth in the proportions of the other seven energy types. Average carbon emissions per million yuan of GIOV presented a consecutively declining trend, dropping from 183.6 tC per million yuan in 2000 to 86.2 tC per million yuan in 2014 (or by 53.1%).

The total amount of energy consumption rose by 2.2 times (from 154.5 Mt standard coal in 2000 to 492.0 Mt standard coal in 2014). Except for a reduction in the consumption of kerosene, fuel oil and other gasoline (by 75.5%, 43.5% and 6.7%, respectively), the consumption of the other energy types exhibited an upward trend from 2000 to 2014, ranging from 3.4% to 5.3 times (Fig. 2). Although the overall pattern of energy consumption in the YRD was still dominated by raw coal and electricity over the 2000–2014 period, the internal structure of energy consumption experienced interesting changes in three aspects. First, the consumption of raw coal dropped from 45.8% in 2000 to 40.3% in 2010, then increased to 42.9% in 2014. Consumption of electricity increased from 22.5% in

Table 1
Descriptive statistics, heteroscedasticity and cross-sectional dependence of independent variables.

Variable	Obs	Mean	Std. Dev.	Min	Max	XTTEST3		XTCS D	
						chi2	P-value	pesaran	P-value
GIOV	220	44.53	85.39	1.04	723.67	2.5e+5	0.0000	4.339	0.0000
IS	220	47.55	7.92	21.38	65.66				
ES	220	54.98	16.90	8.42	88.52				
EI	220	162.46	113.99	18.73	792.09				
SOEs	220	26.21	95.92	0	1278				
COEs	220	54.72	149.49	0	1678				
PEs	220	678.25	1019.77	1	8065				
FIEs	220	332.02	734.30	5	6128				
PSOEs	220	3.54	5.44	0	30.74				
PCOEs	220	9.54	13.39	0	73.01				
PPEs	220	61.50	22.22	1.52	94.56				
PFIEs	220	25.41	14.20	4.35	84.85				

Note: Stata modules of XTTEST3 (Baum, 2001) and XTCS D (Hoyos and Sarafidis, 2006) are used to test groupwise heteroscedasticity and cross-sectional dependence, respectively. The *P*-values (0.0000) denote that there are significant heteroscedasticity and cross-sectional dependence in the panel data.

2000 to 33.4% in 2010, but fell to 30.6% in 2014. Second, natural gas and liquefied natural gas (LNG) with lower carbon intensity have come into use since 2005. They took a small share in energy consumption, accounting for 3.3% and 0.03% of total energy consumption in 2014. These two sources contributed to total carbon emissions by 1.9% and 0.02%, respectively, in 2014. Third, the proportion of higher carbon-intensive energy consumption, including raw coal, coke, gasoline, kerosene, diesel fuel, fuel oil, liquefied petroleum gas and other gasoline, exhibited a slight decline. These figures suggest that the overall structure of energy consumption in the YRD from 2000 to 2014 tends to be gradually optimized by reducing high carbon-intensive energy consumption. This is a significant movement towards carbon reduction in this region.

3.2. Spatial and temporal pattern of ICE

Fig. 3 depicts increasing spatial disparities of ICE at the county-level from 2000 to 2014. The overall pattern of ICE is consistent with the spatial distribution of the urban cluster in the region. High ICE is concentrated in major cities at high-tier levels (I, II and III), which form a prominent Z-shaped belt encompassing the cities of Nanjing, Zhenjiang, Changzhou, Wuxi, Suzhou, Shanghai, Hangzhou and Ningbo (Fig. 1). The total amount of ICE for each county shows an upward trend during the period of 2000–2010, although over a quarter of counties reduced emissions in 2010–2014. Large reductions appear in counties located within mega- or large cities such as Shanghai, Huzhou, Wuxi, Hangzhou and Cixi. Together, they

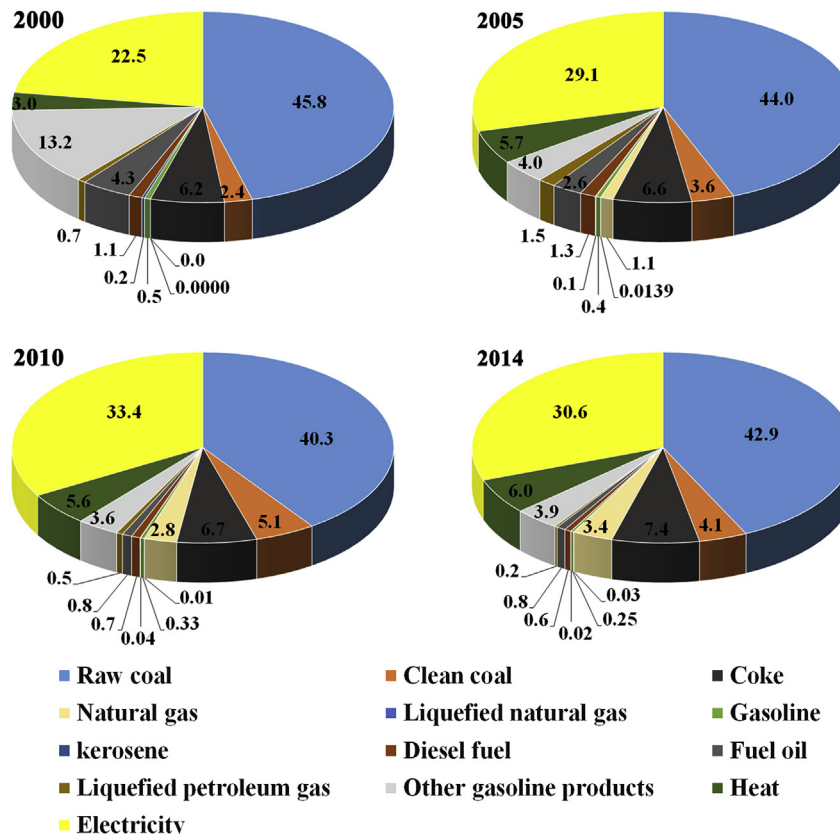


Fig. 2. Proportional composition of energy consumption (%), 2000–2014.

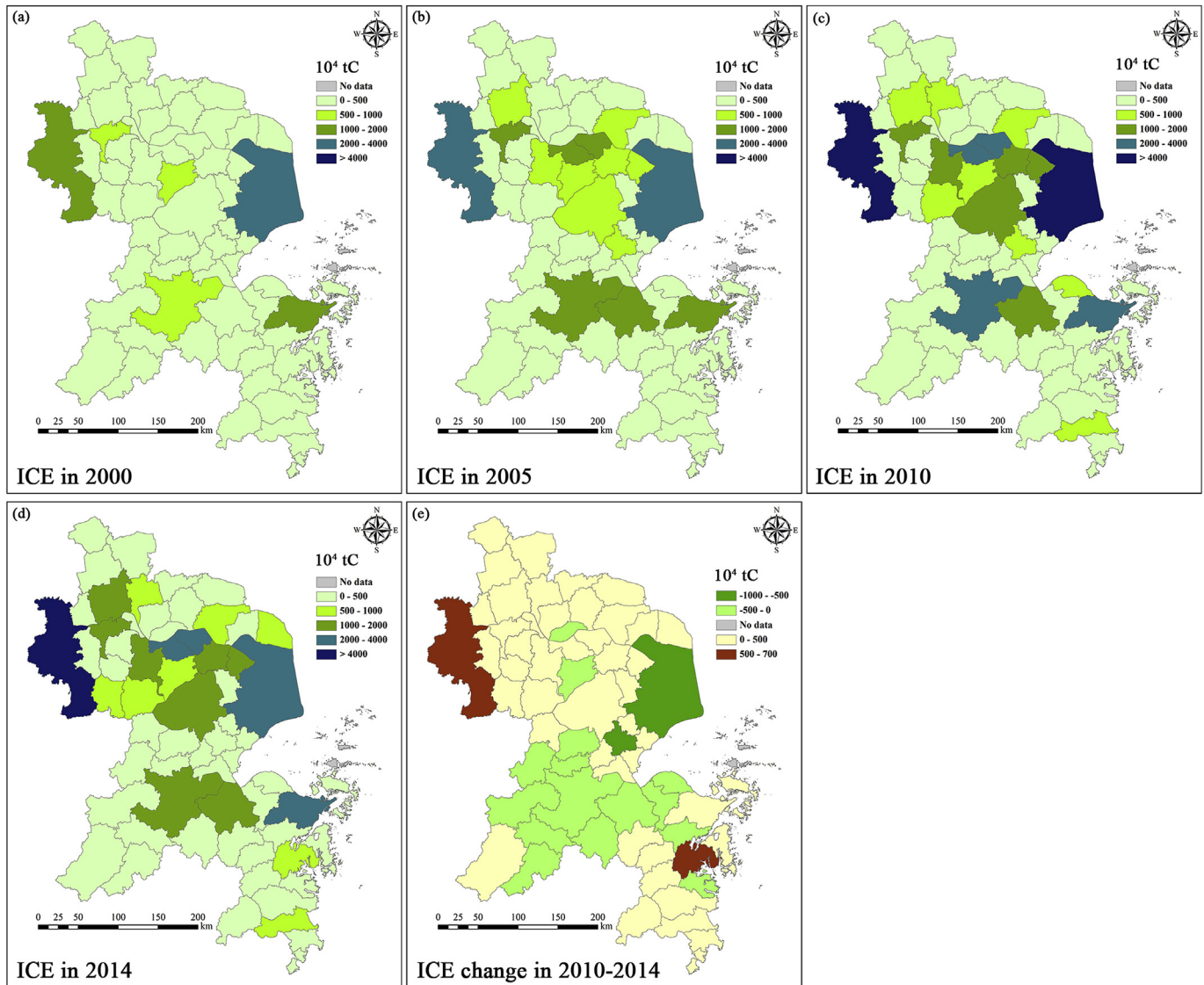


Fig. 3. Spatial and temporal pattern of the total ICE in the YRD, 2000–2014.

contribute 85.6% to the total reduction of ICE (Fig. 3(e)). In contrast, counties where ICE has increased are mainly centered on medium- and small-sized cities (at levels IV and V) such as Ninghai, Zhenjiang, Changshu, Zhangjiagang and Pinghu, with an exception being Nanjing. These medium- and small-sized cities contributed to 54.8% of the overall increase in ICE. These figures point to the fact that the growth rate of ICE in the Delta tends to slow down, with some counties presenting a downward trend in the process of industrial restructuring, upgrading and transformation.

3.3. Determinants

Table 2 presents the results of the three panel models. The differences among these three models show that the structure of industrial enterprises (measured in both the number and scale) has a significant impact on ICE, as reflected by the R^2 (increasing from 0.47 to 0.70). Surprisingly, IS, FIEs and PFIEs are insignificant in Model 2. As demonstrated by the similar high value of R^2 (0.702) and smaller Drisc-Kraay standard errors, Model 3 predicts ICE by dropping the insignificant variables of IS, FIEs and PFIEs which were included in Model 2. Thus, Model 3 can be used as the final model to

Table 2
Coefficients of the panel models.

	Model 1		Model 2		Model 3	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
GIOV	5.802****	0.520	8.134****	0.725	8.410****	0.725
IS	7.314**	3.539	-1.779	3.967		
ES	1.827****	0.502	6.806****	1.211	6.787****	1.239
EI	0.324****	0.094	0.837****	0.059	0.842****	0.066
SOEs			0.704*	0.357	0.722**	0.344
COEs			2.227****	0.388	2.227****	0.292
PEs			0.139***	0.047	0.144****	0.021
FIEs			0.015	0.111		
PSOEs			-15.752****	3.257	-13.566****	2.463
PCOEs			-12.328****	1.208	-10.183****	0.956
PPEs			-4.394*	2.555	-2.450****	0.401
PFIEs			-1.897	2.185		
_cons	-215.477		-189.741	218.492	-283.274**	117.104
N	220		220		220	
R^2_w	0.473		0.703		0.702	

*p < 0.1, **p < 0.05, ***p < 0.01, ****p < 0.001.

analyze how a number of key factors influence and shape change in ICE.

Six factors were positively and significantly correlated with ICE (Table 2). The magnitude of ICE would increase by 84,100 tC for every one unit (i.e. one billion yuan) increase in GIOV, and by 8420 tC for every one unit (i.e. one ton of standard coal per one million yuan) increase in EI. ICE is likely to increase by 6.8% for every 1% increase of ES, assuming other factors remain unchanged. Also, ICE would grow by 7220 tC, 22270 tC and 1440 tC per one unit increase in the number of SOEs, COEs and PEs, respectively. Average GIOV for SOEs, COEs and PEs in 2014 in this region amounted to 1342.1 million yuan, 430.3 million yuan and 284.1 million yuan, respectively. The scale of enterprises, in terms of ownership types (SOEs, COEs, PEs) was negatively, significantly, associated with ICE. ICE produced by SOEs, COEs and PEs was 13.6%, 10.2% and 2.5% less than that produced by the FIEs for every 1% increase in the scale of these three ownership industries, respectively.

The GIOV is the largest contributor to increasing ICE, which is consistent with other studies in this region. However, the effects on ICE were different due to the use of different models (e.g., LMDI), different scales and different data sources (Lu et al., 2015; Song et al., 2015; Wang et al., 2011; Zhao et al., 2010). ICE is a direct byproduct of energy consumption and, as a result, at a certain stage GIOV and ICE will undoubtedly be correlated strongly. The GIOV in the YRD increased from CNY740.4 billion in 2000 to CNY4353.0 billion in 2014, increasing 4.9-fold or at an average annual growth rate of 12.0%. GIOV for all cities increased over time (Fig. 4(a)). Rapid industrial development has led to a sharp increase in ICE, by 2.1 times. Thus the 'pulling' effect of GIOV on ICE can be explained.

EI is an important indicator of energy efficiency. This study shows that EI significantly inhibits ICE, a finding which aligns with other studies in this region (Song et al., 2015; Wang et al., 2011; Zhao et al., 2010). The overall EI decreased by 45.9% on the 2000 level (20.9 tons of standard coal (TSC) per one million yuan), indicating that energy efficiency has been generally improved in this region. EI also presented a great spatial heterogeneity in the region during 2000–2014 (Fig. 4 (b)). For an overwhelming number of counties in the deltaic region, EI presented a downward trend at varying rates (from –6.6% to –85.4%), among which the absolute decreasing rate for over half of the counties was greater than that of the overall EI. However, in one out of five counties, EI shows an increasing trend, by 16.6–330.8%, mainly involving those undeveloped counties including Ninghai, Xiangshan, Pinghu and Chun'an. This is primarily caused by the development of industries characterized by low GIOV and high carbon-intensive emissions. Taking the economic structure of Ninghai as an example, EI increased by 3.3 times, and its secondary industry grew from 32.4% in 2000 to 45.2% in 2014. Energy consumption in Ninghai primarily involves two industrial sectors – coal-based energy production and non-metal minerals production, accounting for 47.5% and 8.9% of its total energy consumption, respectively. This example suggests that rapid industrial development with low GIOV and high carbon-intensive emissions in these undeveloped counties has pushed EI to higher levels. Generally, EI is anticipated to decrease with further adjustments to industrial structure and the promotion of energy-saving technologies in the YRD in the next decade. Moreover, EI will be likely to drop dramatically by designating mandatory energy intensity reduction targets in terms of both production output and output value for high energy-intensity enterprises (Zhao et al., 2016).

ES is another major determinant of ICE reduction. This finding supports the findings of Zhao et al. (2010), but it is contrary to the findings of Song et al. (2015). The disparity may be influenced by three possible reasons. First, the structure of industrial enterprises was considered in the present study and the study by Zhao et al.

(2010), but not considered in the study of Song et al. (2015). The structure of industrial enterprises in this study was measured by the number and scale of SOEs, COEs, PEs and FIEs, while heavy and light industries were considered separately in the study of Zhao et al. (2010). Second, the definitions (or measurements) of ES were different. This study defined ES as the percentage of coal consumption (including raw coal, clean coal, coke) against total energy consumption, whereas it was defined as the proportion of each energy type in primary energy consumption in the study of Song et al. (2015). Finally, the applied models were different between this study (using panel models) and that of Song et al. (using LMDI model). The panel modeling approach used in this study has a more powerful capacity than the LMDI method to capture the complex nexus between ICE patterns, mechanisms and key factors from an industrial enterprises perspective because it allows the investigation of not only the macro-level drivers of ICE (GIOV, ES, EI) but also the intrinsic relationships between the structure of industrial enterprises and ICE at the micro (county/city) level.

Although the overall ES (i.e. coal-intensive energy consumption structure) remained stable in 2000–2014, varying between 54.3% and 55.3%, the ES is shifting to be cleaner. It was characterized by the slightly increasing proportion of low-carbon energy (natural gas and LNG) from zero to 3.4% over the same period. There were great spatial heterogeneities in the change in ES in 2000–2014 (Fig. 4 (c)). The overall ES in 2000–2010 decreased slightly from 54.4% to 52.2%. Fifty-five counties have reduced ES by 0.1–61.3 percentage points, while the other 11 counties increased ES by 0.7–42.9 percentage points. This is especially the case in Ningbo, Zhangjiagang, Taizhou (Jiangsu), Cixi and Xinghua, with an increase of over 10 percentage points. The overall ES in 2010–2014 presented a slight decreasing trend from 52.2% to 54.3%. ES for Gaoyou, Zhenjiang, Nanjing, Hai'an and Zhangjiagang increased by 0.1–17.3 percentage points, while those for other counties showed a downward trend. Generally, the increasing ES in some counties, especially in six counties including Ningbo (42.9%), Zhangjiagang (20.1%), Taizhou (Jiangsu, 16.8%), Cixi (15.7%), Xinghua (12.4%) and Nanjing (10.4%), had offset the overall decreasing ES on the regional scale. This remarkable growth of ES in these cities is mainly due to the development of high energy-intensive and carbon-intensive enterprises, such as petroleum processing and coking, non-metal mineral products, smelting and pressing of ferrous metals, and production and supply of coal-based power. For example, in Ningbo city, coal consumption for petroleum processing and coking, non-metal mineral products, and production and supply of coal-based power increased by 1846 times, 59.2 times and 1.9 times, respectively, from 2000 to 2014. Clearly, ES is deeply influenced by industrial structure and industrial sectors, in addition to the enforcement of national energy restructuring and clean energy strategy. Thus, the decreasing ES for the majority of counties in YRD imposed a remarkable effect on ICE, rising by 1.5% for every 1% increase of ES. High carbon-intensive energy (e.g., coal, coke) must be reduced and low carbon-intensive energy (e.g., natural gas, hydropower, nuclear energy, wind and solar power) should be encouraged.

IS has a positive and significant association with ICE at the 5 percent significance level in Model 1, a finding consistent with some other studies (Mi et al., 2015; Tian et al., 2014; Zhou et al., 2013). However, this association became weak (at the 10 percent significance level) in Model 2 (Table 2), suggesting a relatively small contribution to ICE. This study shows the overall IS in the Delta presented a slightly downward trend, decreasing from 46.2% in 2000 to 41.6% in 2014. There is also a great spatial heterogeneity for IS change in 2000–2014 (Fig. 4 (d)): for over two out of three counties, IS presented a downward trend. High-tier cities (Levels I–III) all show a declining trend, ranging from –0.9% to –9.5%. This is

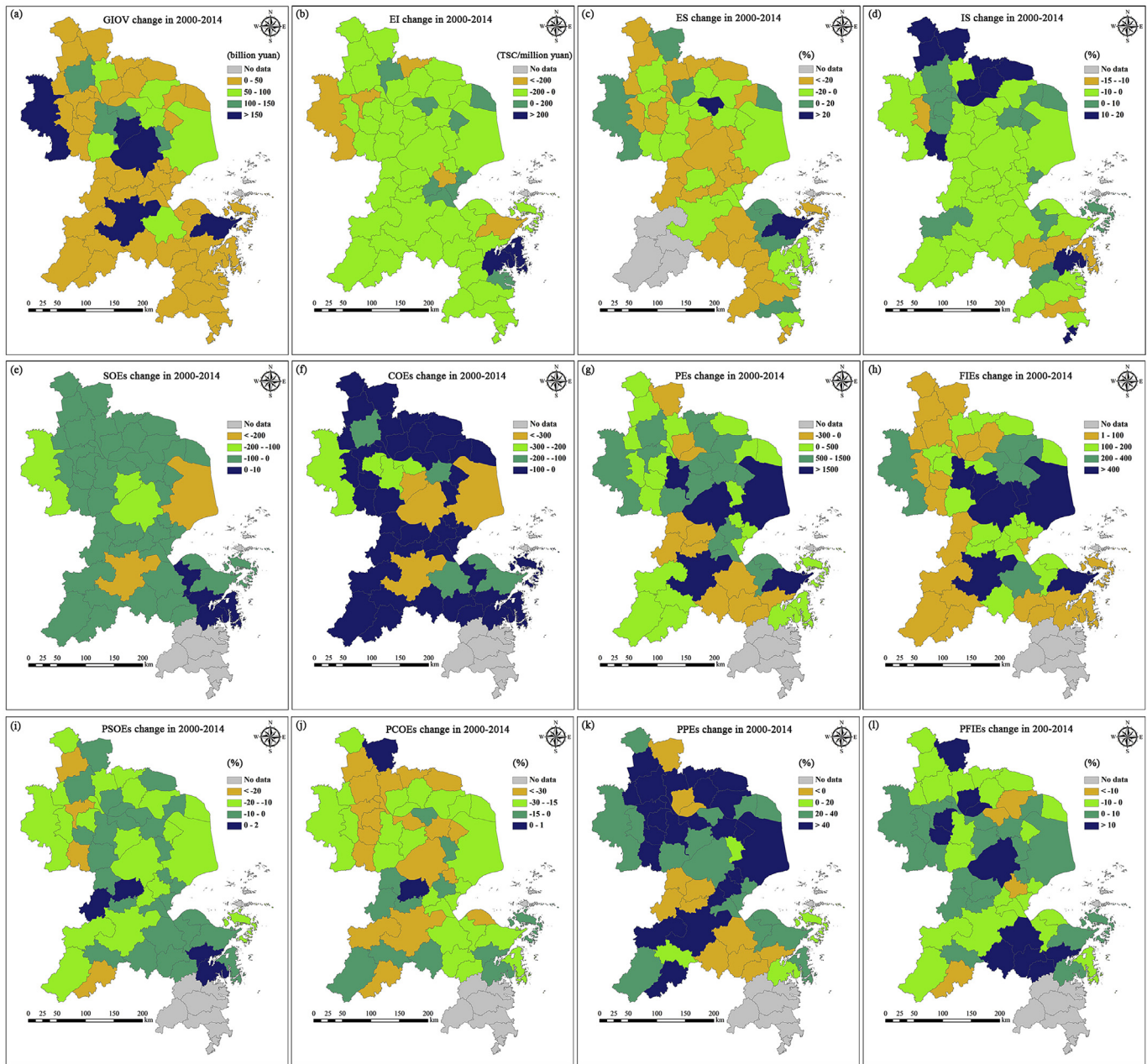


Fig. 4. Spatial and temporal change in 12 factors, by county, 2000–2014.

compared with another one-third of counties (mainly county seats) where IS presented an increasing trend. The increasing IS for these low-tier counties was mainly caused by industrial diffusion of high energy-intensive enterprises from the developed areas (high-tier cities) within this region. Thus, the IS regulated by industrial transfer could reduce ICE in local areas to some extent, but they may not contribute to carbon balance in a wider area, nor from a global perspective. Reducing the proportion of secondary industry is therefore an important countermeasure for carbon mitigation. Close attention should also be paid to industrial symbiotic effects brought by the byproducts, water exchange, and energy graded use between different industries to improve energy efficiency, in order to optimize and update industrial structure (Yu et al., 2015).

The study provides robust new evidence that the structure of industrial enterprises influence ICE significantly. SOEs and COEs mainly involve heavy industry and carbon-intensive productions

(e.g., iron, steel, metal, mining, chemical, petroleum processing, smelting and machinery manufacturing). PEs are mainly involved in light industry and relatively lower carbon-intensive productions (e.g., food production, furniture manufacturing, plastic products). Simultaneously, SOEs generally own more advanced technologies to reduce ICE than COEs. The number of SOEs and COEs monotonically declined from 2000 to 2014 in the study area, by 82.1% and 91.9%, respectively. The number of PEs and FIEs rapidly increased by 5.0 times and 1.5 times over the 2000–2014 period, respectively (Fig. 4(e–h)). Correspondingly, the overall scale of SOEs and COEs dropped from 13.3% and 28.4% in 2000 to 0.7% and 0.9%, respectively; while that of PEs and FIEs increased from 24.8% and 33.5% to 64.4% and 33.9%, respectively (Fig. 4(i–l)). Changes in both the number and scale of these four ownership categories presented great spatial heterogeneities (Fig. 4(e–l)). The sharp reduction of SOEs and COEs was a result of the national policy on dramatic

reforms of state-owned enterprises since 1998. Numerous small- and medium-sized SOEs and COEs were converted into shareholding companies with a mixed state and private ownership, which can be sold, leased, merged or simply allowed to bankrupt (Ouyang and Lin, 2015). These changes suggest that the shrinking SOEs and COEs in 2000–2014 have played an important role in halting ICE in this region. According to the *Guideline to Deepen Reforms of State-Owned Enterprises (SOEs)*, merging and reorganization of SOEs will be further accelerated in this region (Xinhuanet, 2015). This is not only helpful to modernize SOEs by enhancing management of the state-owned assets and promoting mixed ownership to improve efficiency of energy use, but also helpful to eliminate backward production capacity, and optimize and upscale industrial structure by adopting advanced technologies. COEs and PEs also need to be encouraged to improve energy efficiency by merger and reorganization of enterprises.

Despite the statistically insignificant correlation between FIEs, PFIEs and ICE in Model 2, there is a positive relationship between FIEs, PFIEs and ICE (at the 0.001 significance level) based on OLS regression in a bivariate setting to detect the direct effects of FIEs on ICE. The seemingly conflicting results between the two models suggest that the association between FIEs and ICE may be spurious, which is consistent with the study by Lee (2013). One possible reason is that FIEs have played a central role as externalities in economic growth and extended spillover effects by improving energy efficiency and promoting clean energy development (Lee, 2013). The great discrepancies in the effect between FIEs and indigenous enterprises (SOEs, COEs and PEs) could be explained from two aspects. First, FIEs are mostly sourced from developed countries and generally have more advanced technologies, and consequently lower carbon emissions than their indigenous counterparts in developing countries for the same output production (Mielnik and Goldemberg, 2002; Peterson, 2008). Second, the structural differences in output productions between FIEs and indigenous enterprises also bring about a great discrepancy in contribution to ICE (Jiang et al., 2015; Levinson and Taylor, 2008). For example, indigenous enterprises are mainly involved in carbon-intensive production (e.g., steel, mining), whereas FIEs are mainly engaged in “clean” production (e.g., high-tech products), resulting in an overall emission intensity benefiting FIEs. Indigenous enterprises in China experienced relatively faster upgrading in carbon emissions-related technologies across sectors than FIEs did from 1990 to 2010, while FIEs still outperformed indigenous enterprises by 10–110% in terms of sectoral emission intensities in 2010 (Jiang et al., 2015). Thus the lowest contribution of FIEs to ICE is reasonably reflected in Model 2, despite the insignificant correlation between FIEs and ICE. As foreign invested and Hong Kong, Macao and Taiwan invested industrial enterprises cannot be differentiated in this study, the relationship between FIEs and ICE needs to be further studied with separated statistics of industrial enterprises when data becomes available.

4. Conclusion

Secondary industry is a major user of energy and a significant contributor to global carbon emissions. A key contribution of this study lies in its novelty in building three panel models to identify principal factors contributing to ICE in the Yangtze River Delta, at county level, by incorporating the GIOV, IS, ES, EI and the structure of industrial enterprises (measured by the number and scale). This study shows that ICE increased by 2.1 times from 2000 to 2014 in this region. The changing pattern of ICE is coincident with the spatial distribution of the Z-shaped urban cluster in the delta. The GIOV was the largest contributor to ICE growth, at the rate of 84.1 tC for an increase of one million yuan of GIOV, but the adjustment of

ES, EI and the structure of industrial enterprises can largely abate ICE. The trade-off between industry development and carbon mitigation needs further study to capture the dynamic processes of these forces and their effects on ICE.

With the implementation of the *National New-Style Urbanization Plan (2014–2020)* and the *China's One Belt and One Road Strategy* since 2015, industrial development and GIOV in the Yangtze River Delta is expected to accelerate. Continued industrialization will be likely to drive ICE to a growing trajectory under the current policy. To reduce ICE and achieve a dynamic equilibrium between industry development and ICE, four practical measures are suggested:

- Reducing energy intensity by assigning mandatory energy intensity reduction targets in terms of both production output and output value for high energy-intensive enterprises.
- Regulating energy structure by lowering the proportion of high carbon-intensive energy (e.g., coal, coke) and improving the proportion of low carbon-intensive energy (e.g., natural gas, hydropower, nuclear energy, wind and solar power), especially for the cities including Ningbo, Nanjing, Zhangjiagang and Taizhou (Jiangsu), and also for areas where high energy-intensive and carbon-intensive enterprises are rapidly developing.
- Differentiated strategies for industrial restructuring should be encouraged. Optimizing and upgrading industrial structure should be strengthened by industrial symbiosis through effective use of byproducts, water exchange, and energy in high-tier cities (Levels I, II and III). Industrial transformation with low energy-intensive consumption should be particularly encouraged in low-tier cities or county seats (Levels IV, V and VI).
- Optimizing the structure of industrial enterprises by merging and reorganizing the SOEs, COEs and PEs, and facilitating the development of industrial enterprises with low carbon-intensive emissions.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (41371532) and Interdisciplinary Frontier Project of Nanjing Institute of Geography and Limnology, CAS (NIGLAS2012135019).

References

- Adom, P.K., Bekoe, W., Amuakwa-Mensah, F., Mensah, J.T., Botchway, E., 2012. Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: empirical evidence from Ghana, Senegal, and Morocco on the causal dynamics. *Energy* 47, 314–325.
- Baum, C.F., 2001. Residual diagnostics for cross-section time series regression models. *Stata J.* 1, 101–104.
- Cai, B., Wang, J., He, J., Geng, Y., 2016. Evaluating CO2 emission performance in China's cement industry: an enterprise perspective. *Appl. Energy* 166, 191–200.
- Cai, W.J., Wang, C., Wang, K., Zhang, Y., Chen, J., 2007. Scenario analysis on CO2 emissions reduction potential in China's electricity sector. *Energy Policy* 35, 6445–6456.
- Driscoll, J., Kraay, A., 1998. Consistent covariance matrix estimation with spatially dependent panel data. *Rev. Econ. Statistics* 80, 549–560.
- Fujii, M., Fujita, T., Dong, L., Lu, C., Geng, Y., Behera, S.K., Park, H.S., Chiu, A.S.F., 2016. Possibility of developing low-carbon industries through urban symbiosis in Asian cities. *J. Clean. Prod.* 114, 376–386.
- General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China (GAQSIQ), Standardization Administration of the People's Republic of China (SAC), 2015. General Guideline of the Greenhouse Gas Emissions Accounting and Reporting for Industrial Enterprises (GB/T 32150–2015) (in Chinese). <http://www.ccchina.gov.cn/archiver/ccchina.cn/UpFile/Files/Default/20151223100646058345.pdf> (Accessed Dec. 30, 2015).
- Global Commission on the Economy and Climate (GCEC), 2014. China and the New Climate Economy: Executive Summary. Available. <http://2014.newclimateeconomy.report/wp-content/uploads/2014/11/China-and-the-New-Climate-Economy-Exec-Summary-Eng.pdf> (Accessed 14 January 2016).
- Hocaoglu, F.O., Karanfil, F., 2011. Examining the link between carbon dioxide

- emissions and the share of industry in GDP: modeling and testing for the G-7 countries. *Energy Policy* 39, 3612–3620.
- Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. *Stata J.* 7, 281–312.
- Hoyos, R.E., Sarafidis, V., 2006. Testing for cross-sectional dependence in panel-data models. *Stata J.* 6, 482–496.
- IPCC, 2006. Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories, 2006. Available. <http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html>. Accessed 10 July 2013.
- IPCC, 2014. In: Team, C.W., Pachauri, R.K., Meyer, L.A. (Eds.), *Climate Change 2014: Synthesis Report*, pp. 44–54. Geneva, Switzerland.
- Jiang, X., Zhu, K., Wang, S., 2015. The potential for reducing China's carbon dioxide emissions: role of foreign-invested enterprises. *Glob. Environ. Change* 35, 22–30.
- Kim, K., Kim, Y., 2012. International comparison of industrial CO₂ emission trends and the energy efficiency paradox utilizing production-based decomposition. *Energy Econ.* 34, 1724–1741.
- Lee, J.W., 2013. The contribution of foreign direct investment to clean energy use, carbon emissions and economic growth. *Energy Policy* 55, 483–489.
- Levinson, A., Taylor, M.S., 2008. Unmasking the pollution haven effect. *Int. Econ. Rev.* 49, 223–254.
- Lin, B.Q., Moubarak, M., 2014. Mitigation potential of carbon dioxide emissions in the Chinese textile industry. *Appl. Energy* 113, 781–787.
- Liu, Z., Guan, D.B., Crawford-Brown, D., Zhang, Q., He, K.B., Liu, J.G., 2013. A low-carbon road map for China. *Nature* 500, 143–145.
- Lo, K., Li, H., Wang, M., 2015. Energy conservation in China's energy-intensive enterprises: an empirical study of the Ten-Thousand Enterprises Program. *Energy Sustain. Dev.* 27, 105–111.
- Lu, Q.L., Yang, H., Huang, X.J., Chuai, X.W., Wu, C.Y., 2015. Multi-sectoral decomposition in decoupling industrial growth from carbon emissions in the developed Jiangsu Province, China. *Energy* 82, 414–425.
- Mi, Z.F., Pan, S.Y., Yu, H., Wei, Y.M., 2015. Potential impacts of industrial structure on energy consumption and CO₂ emission: a case study of Beijing. *J. Clean. Prod.* 103, 455–462.
- Mielnik, O., Goldemberg, J., 2002. Foreign direct investment and decoupling between energy and gross domestic product in developing countries. *Energy Policy* 30, 87–89.
- Mishra, M.K., Khare, N., Agrawal, A.B., 2015. Scenario analysis of the CO₂ emissions reduction potential through clean coal technology in India's power sector: 2014–2050. *Energy Strategy Rev.* 7, 29–38.
- National Bureau of Statistics of China, 2015. *China Statistical Yearbook 2015*. China Statistical Press, Beijing (in Chinese).
- Olivier, J.G.J., Janssens-Maenhout, G., Muntean, M., Peters, J.A.H.W., 2015. *Trends in Global CO₂ Emissions: 2015 Report*. PBL Publishers, The Hague.
- Ouyang, X.L., Lin, B.Q., 2015. An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. *Renew. Sustain. Energy Rev.* 45, 838–849.
- Peterson, S., 2008. Greenhouse gas mitigation in developing countries through technology transfer?: a survey of empirical evidence. *Mitig. Adapt. Strategies Glob. Change* 13, 283–305.
- Ren, S.G., Yuan, B.L., Ma, X., Chen, X.H., 2014. The impact of international trade on China's industrial carbon emissions since its entry into WTO. *Energy Policy* 69, 624–634.
- Song, M.L., Guo, X., Wu, K.Y., Wang, G.X., 2015. Driving effect analysis of energy-consumption carbon emissions in the Yangtze River Delta region. *J. Clean. Prod.* 103, 620–628.
- Sun, Z., Luo, R., Zhou, D., 2015. Optimal path for controlling sectoral CO₂ emissions among China's regions: a centralized DEA approach. *Sustainability* 8, 28.
- Tian, X., Chang, M., Shi, F., Tanikawa, H., 2014. How does industrial structure change impact carbon dioxide emissions? A comparative analysis focusing on nine provincial regions in China. *Environ. Sci. Policy* 37, 243–254.
- Wang, D., Nie, R., Shi, H.Y., 2011. Analysis of regional differences in energy consumption and energy saving potential for Yangtze River Delta. *Energy Procedia* 5, 690–694.
- Wang, K., Wei, Y.M., 2014. China's regional industrial energy efficiency and carbon emissions abatement costs. *Appl. Energy* 130, 617–631.
- Xinhuanet, 2009. China announces Targets on Carbon Emission Cuts (Accessed 14 January 2016). http://news.xinhuanet.com/english/2009-11/26/content_12544181.htm.
- Xinhuanet, 2015. China issues Guideline to Deepen SOE Reforms (Accessed 14 January 2016). http://news.xinhuanet.com/english/2015-09/13/c_134620039.htm.
- Xu, X.B., Tan, Y., Chen, S., Yang, G.S., Su, W.Z., 2015. Urban household carbon emission and contributing factors in the Yangtze River Delta, China. *Plos One* 10, e0121604.
- Yu, F., Han, F., Cui, Z.J., 2015. Reducing carbon emissions through industrial symbiosis: a case study of a large enterprise group in China. *J. Clean. Prod.* 103, 811–818.
- Zhao, M., Tan, L.R., Zhang, W.G., Ji, M.H., Liu, Y.A., Yu, L.Z., 2010. Decomposing the influencing factors of industrial carbon emissions in Shanghai using the LMDI method. *Energy* 35, 2505–2510.
- Zhao, X.F., Li, H.M., Wu, L., Qi, Y., 2016. Enterprise-level amount of energy saved targets in China: weaknesses and a way forward. *J. Clean. Prod.* 129, 75–87.
- Zheng, J., Jiang, P., Qiao, W., Zhu, Y., Kennedy, E., 2016. Analysis of air pollution reduction and climate change mitigation in the industry sector of Yangtze River Delta in China. *J. Clean. Prod.* 114, 314–322.
- Zhou, X.Y., Zhang, J., Li, J.P., 2013. Industrial structural transformation and carbon dioxide emissions in China. *Energy Policy* 57, 43–51.