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LETTER

Retrospect driving forces and forecasting reduction potentials of energy-related industrial carbon emissions from China's manufacturing at city level

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Abstract

Lack of either spatial or temporal coverage in city-level carbon emissions analysis might curb our understanding of historical drivers and make future forecasting uncertain. To fill these gaps, we analyzed time-series energy-related industrial carbon emissions (EICEs) from manufacturing in over 99 cities nationwide in China during the period 2000–2015. We estimated these cities' EICEs reduction potential up until 2030 by improving scenario design, which imposed constraints separately on different city groups based on historical drivers. Results indicated distinct changes of EICEs around 2013 for the heavy manufacturing [HM], light manufacturing [LM] and high-tech development [HD] city groups and of emissions intensity for the energy production [EP] city group. The slowing economic growth would partly explain these transformations since 2013. Energy efficiency and industrial structure contributed most to these switches for the EP and HD city groups, respectively, while energy mix and energy efficiency were also major contributors for the HM and LM city groups. Given economic growth at a normal speed, EICEs will increase by 59%, 78%, 90% and 95% for the EP, HM, LM and HD city groups, respectively, from 2015–2030. Our scenarios show that energy efficiency improvement and industrial structure optimization will spur the EICEs to peak before 2030 and limit future EICEs increase by 6.4% and 33.4% in 2030 for the EP and HD city groups, respectively. This implies that energy efficiency improvement and industrial structure optimization are key emissions mitigation factors for the EP and HD cities. Equally important, our study found more unclean fuel structure with higher coal share in the HM and LM city groups than in the other groups. It is therefore imperative to improve their energy efficiency and optimize energy and industrial structures in the HM and LM cities. Results highlight the need to impose different constraints in scenario design and provide mitigation strategies at city level.

1. Introduction

1.1. Overview

With its booming economy and industrialization, China has become the world's top energy consumer and CO_2 emitter since 2007 (Netherlands Environmental Assessment Agency (2007)), contributing nearly one third (29.5%) of the global total fossil fuel and cement emissions in 2015 (European Commission 2016, Boden *et al* 2016). Specifically, the manufacturing industry as the engine of industrialization and pillar of the national economy is responsible for over 57% of China's total energy consumption (Zhang and Zhang 2018) and 73% of its carbon emissions (Ren *et al* 2014). It was pledged in the Paris Agreement on Climate IPCC (2018) that the national CO_2 emissions of China are targeted to peak by 2030, with carbon intensity (per GDP of CO_2 emissions) decreasing by 60% to 65% compared to that of 2005 (The Chinese Government (2015)). Given the fact that China is still in a trajectory of rapid industrialization and regarded as the world's factory, manufacturing will continue to play a key role in China's economy (Tian *et al* 2018) in the long term. Therefore, it is important to investigate this field and put in place appropriate measures to reduce CO_2 emissions from manufacturing.

Furthermore, some cities in China are developing local climate action plans, but their aggregate impact on emissions is uncertain (Seto *et al* 2014). Given the resource endowments, industrial structures, economic development levels and energy consumption patterns as well as other characteristics associated with manufacturing are diverse among cities nationwide (Segal and Thun 2001, Cole *et al* 2011, Wang 2014, Zheng *et al* 2018), this uncertainty is due, in part, to the low accountability and lack of baseline data on city-level emissions as well as the strategies adopted, which may not be the most effective at lowering emissions for a particular type of city (Su *et al* 2014, Zheng *et al* 2018). Thus, it is of major importance to provide policy-makers with more information about what strategies are effective for different types of cities and what the magnitude is of the total mitigation potential of future manufacturing in different city groups.

The investigation of city-level CO_2 emissions makes it possible to implement the national carbon reduction targets on the unit of cities—the basic administrative unit of urbanization and industrialization in China (Su *et al* 2014, Zheng *et al* 2018). But, unlike the extensive data accumulated at the national (Liu *et al* 2015b, Zhang *et al* 2017, Mi *et al* 2017) and provincial levels (Dong *et al* 2017, Wang *et al* 2017a), information to support the provision of city-level emissions inventories is generally less available and of lower quality (Su *et al* 2014, Zheng *et al* 2018). Some researchers have started to focus on the time series of city-level studies in China's provincial cities (Kennedy *et al* 2014), but mainly in cities like Beijing (Wei *et al* 2017), Shanghai (Shao *et al* 2016), Tianjin (Mi *et al* 2016) and capital cities (Wang *et al* 2012). Other studies have focused on the number of cities nationwide, but just based on one-year inventories (Zheng *et al* 2018, Shan *et al* 2018a). These previous studies have generated in-depth knowledge for dozens of cities.

1.2. Our motivation

However, significant knowledge gaps, i.e. lack of either spatial or temporal coverage in city-level carbon emissions analysis, could be a cause for uncertainty in forecasting future reduction potentials. Investigating cities nationwide would allow us to identify effective mitigation strategies across different types of cities, while retrospective time-series emissions inventories would help to forecast the reduction potential of energy-related industrial carbon emissions (EICEs) for mitigating climate change.

In this study, we conducted a nationwide time-series investigation at city level on the EICEs from manufacturing using historical inventories of city-level emissions based on physical energy flows, including the disaggregation of fossil fuel types and socioeconomic sectors within city boundaries. We expect that such an investigation with both large spatial and long temporal coverage will help deepen our understanding of the historical underlying drivers for different cities at different growth periods and provide useful information for forecasting the emissions reduction potential of cities in the future. The scientific questions that the study seeks to resolve are: (1) what are the underlying drivers for different cities at different periods of growth and (2) how will the emissions reduction potential of different cities perform under different scenarios? For the latter, it is worth noting that we made improvements in scenario design, which imposed several and separate constraints on each different city group based on an investigation of the historical underlying drivers. This allowed us to compare carbon emissions reductions yielding different constraints and then provide a city-level strategy for mitigating carbon emissions, unlike the scenario that sets one constraint nationwide.

The technical routing map for the analytical framework of this study is illustrated in figure 1. The cities' statistics books were required to contain a complete set of standard information from 2000–2015, including energy consumption of 17 fossil fuels from 39 manufacturing sectors, industrial outputs of these manufacturing sectors, population and other socioeconomic data sets. Based on this criterion (method S1 (https://stacks.iop.org/ERL/15/074020/mmedia)), 99 cities nationwide were selected for the analysis in our study. We first estimated the city-level EICEs (equation S1, method S2) and combined the corresponding socioeconomic data set to build the analysis inventories. Second, we classified the 99 cities into four city groups (energy production [EP], heavy manufacturing [HM], light manufacturing [LM] and high-tech development [HD]) using Shan's clustering method (Shan *et al* 2018a, method S3). We then decomposed the major EICEs driving forces in each city group using the conventional logarithmic mean division index (LMDI) method (Ang 2004, method S4), which has already been

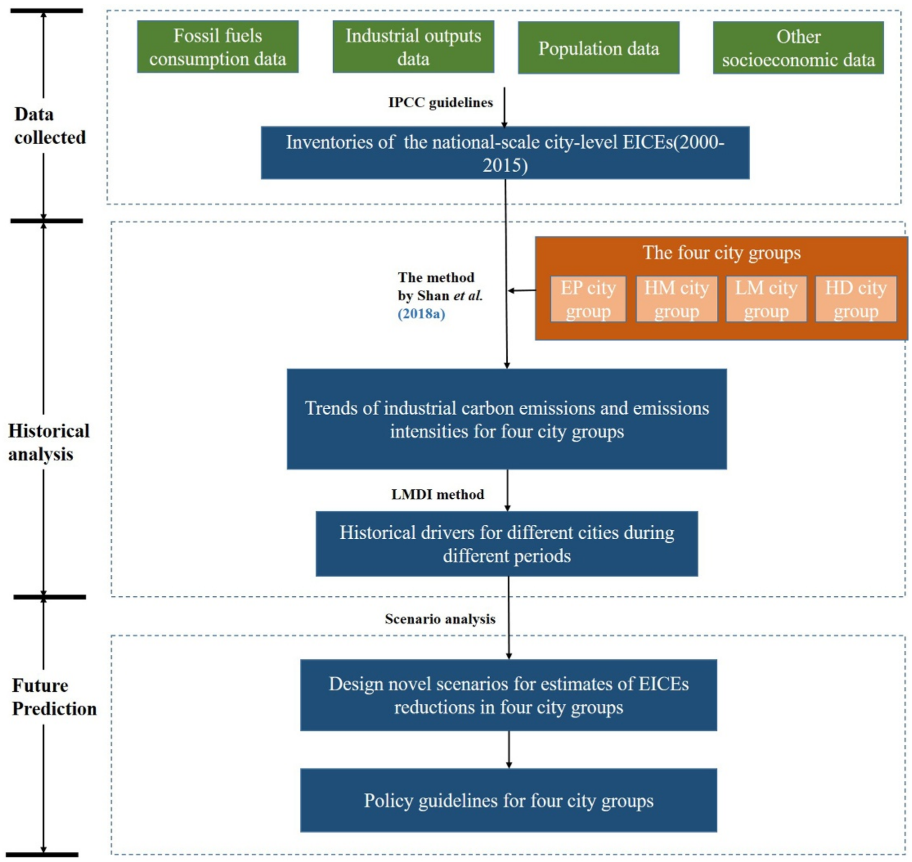

Figure 1. Technical routing map of the study's analytical framework.

extensively leveraged for investigating the driving forces of long-term air-pollution-related variations (Zhang *et al* 2019). Subsequently, we designed five scenarios by imposing different constraints, which are based on the investigation of underlying historical drivers for different city groups (method S6). Last, we estimated the EICEs reduction potential for 2030 for each city group in each scenario and analyzed the impacts of economic growth on historical EICEs before 2015 and on future EICEs after 2015 in scenario 5 (method S7, table S1); the details are presented in supplementary methodologies.

2. Results

2.1. Trends of industrial carbon emissions and emissions intensities of the four city groups

To quantify the temporal variation trends of China's city-level EICEs from 2000–2015 and overall increasing trends of the cities' EICEs, the SLOPE index method was used (Su *et al* 2014) (figure 2). In general, during 2000–2015, 33% of cities recorded a slow growth rate and 27% recorded a relatively slow growth rate. The slow and relatively slow growth-rate-type cities together accounted for 10% of the EP cities (13 in total, largely concentrated in northwestern China), 48% of the HM cities (27 in total, distributed randomly), 81% of the LM cities (29 in total, mainly located in southern and central China) and 52% of the HD cities (30 in total, mainly distributed over the eastern coastal regions), respectively (figure 2). Meanwhile, 11% of the 99 cities belonged to the rapid growth type and, 12% of the cities belonged to the relatively rapid growth type. The rapid and relatively rapid growth-rate-type cities together covered 80% of the LM cities, 31% of the HM cities, 8% of the LM cities and 30% of the HD cities, respectively.

Specifically, 2007 and 2013 are two key time frames referring to the temporal variations of the four city groups' EICEs (figure 3(a)), which accounted for about 69% of national EICEs estimated by Shan *et al* (2018b) and 56% of China's total carbon emissions estimated by Guan *et al* (2018) (figure 3(a)). During the period from 2000–2007, the EICEs of the EP, HM, LM and HD city groups increased by 16.4%, 15.2%, 15.8% and 14.1% per year, respectively (figure 3(a)). From 2007–2013, the pace of growth began to slow down, with average annual rates of 9.4%, 5.8%, 4.1% and 5.7% for the EP, HM, LM and HD city groups, respectively. An EICEs peak was detected in 2013 for the HM, LM and HD city groups. Subsequently, the EICEs slightly dropped by 1.7%, 1.8% and 5.9% per year, respectively, except for the EP city group, which reported an annual EICEs increase of 5.9%. A reverse pattern in 2013 was also detected in the emissions intensity (EICEs per industrial output) for the EP

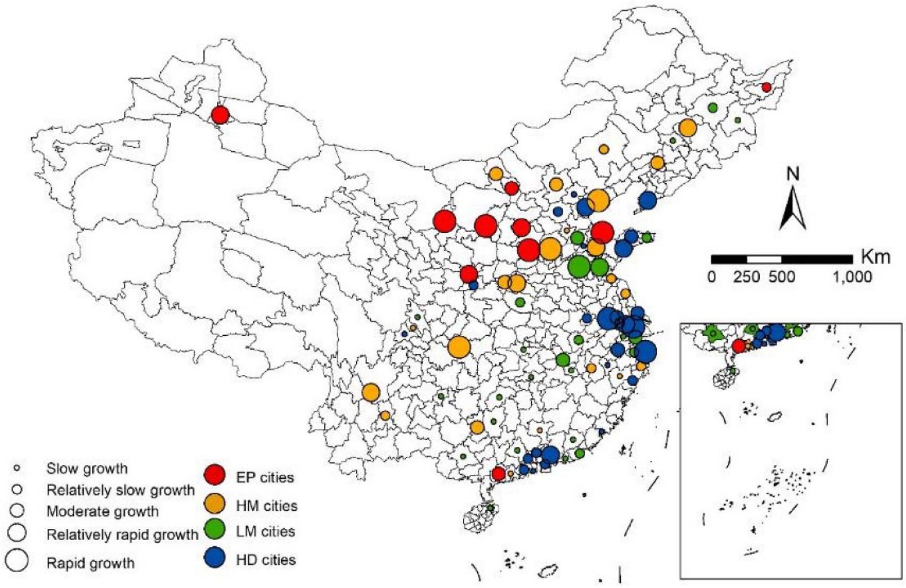

Figure 2. Overview of location and incremental rates in EICEs of the 99 Chinese cities that were classified by a K-means cluster analysis: 13 energy production [EP] cities (red), 27 heavy manufacturing [HM] cities (orange), 29 light manufacturing [LM] cities (green) and 30 high-tech development [HD] cities (blue). Size of the circles indicates EICEs growth trends from 2000–2015.

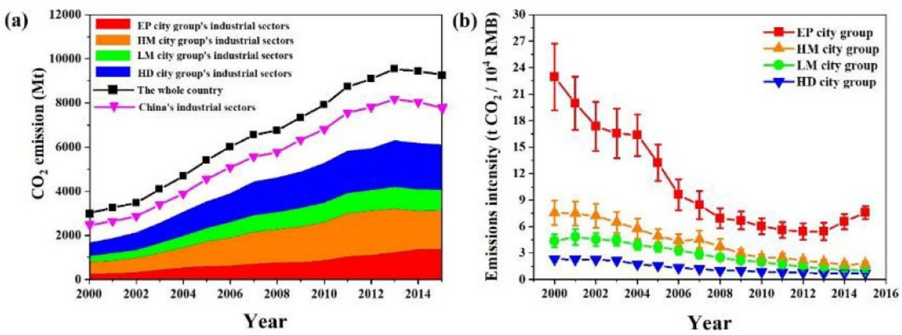

Figure 3. Time-series EICEs and carbon emissions intensity from 2000–2015. (a) China's EICEs from different sources: the energy production [EP] city group (red block), heavy manufacturing [HM] city group (orange block), light manufacturing [LM] city group (green block) and high-tech development [HD] city group (blue block), total carbon emissions in China (black line) and total industrial carbon emissions in China (pink line). (b) Emissions intensities of the four city groups from 2000–2015.

city group, while the emissions intensity of the HM, LM and HD city groups continuously declined from 2000–2015 figure (3(b)).

Notwithstanding the distinct transitions in both EICEs and emissions intensity before and after 2013 for all city groups, the cumulative sum test (method S4) suggests that EICEs changes were structurally significant only in the HM city group at the 90% confidence interval (around 2013) as shown in figure (4). The abrupt changes in the HM city group were probably due to a reduction of the heavy industry sector around 2013/2014 (Zhao *et al* 2015, Liu *et al* 2016). Our findings indicate that for most of the city groups, the decreasing trends did not represent a sudden fluctuation, but a stable change resulting from recent policies and socioeconomic growth. Hence, a reliable approach would be to program the future trajectory of EICEs based on their historical dynamics.

2.2. Comparison of energy intensities, industrial structures and energy mix structures among the four city groups

Given the smallest standard deviations in 2015 and the significant discrepancy in emissions intensity among the four city groups (figure 2(b)), we further investigated their industrial structures, energy intensities and energy mix in 2015 to better understand the differences in emissions intensity.

The HD sectors revealed the highest energy efficiency followed by the LM and HM sectors, while the EP sectors showed the lowest (figure 5(a)). For each sector category, the energy intensities followed the order: EP > HM > LM > HD city groups (figure 5(a)). The results showed more high-tech sectors with higher efficiency energy utilization technologies in the HD city group, but more energy-insensitive sectors with lower efficiency

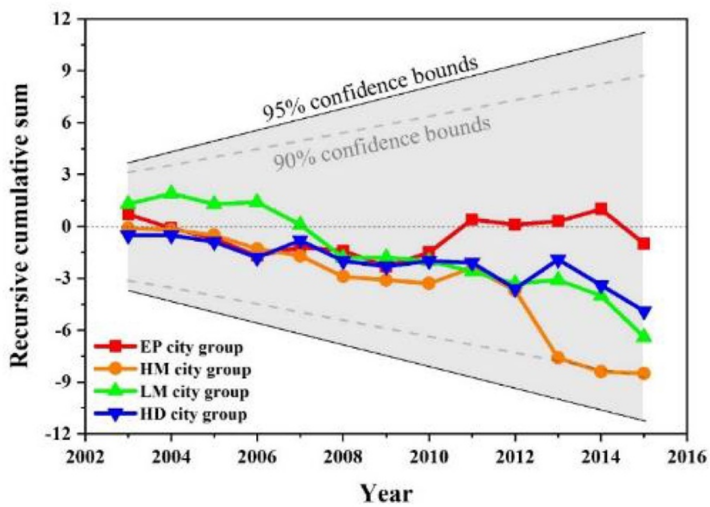

Figure 4. Recursive cumulative sum curve of EICEs of the four city groups. Cumulative sum curve will have a structural break once crossed with the confidence band of 90% or 95%. EP, energy production; HM, heavy manufacturing; LM, light manufacturing; HD, high-tech development.

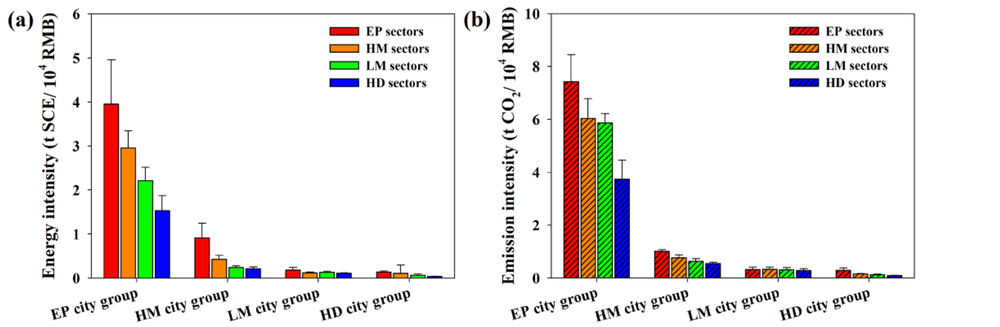

Figure 5. Energy intensities (a) and emissions intensities (b) of four sectors in the four city groups in 2015. Note: tSCE/¥10 000 (unit of energy intensities in [a]) is ton of standard coal equivalent per 10^4 RMB. EP, energy production; HM, heavy manufacturing; LM, light manufacturing; HD, high-tech development.

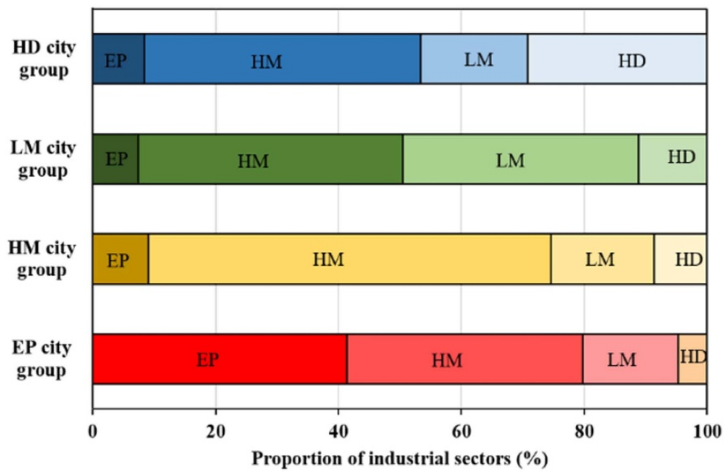

Figure 6. Industrial structures of the four city groups in 2015. For each city group, the dark to light colors represent the energy production (EP), heavy manufacturing (HM), light manufacturing (LM) and high-tech development (HD) sectors, respectively.

energy utilization technologies in the EP city group (figure 6). It is thus clear that such differences in energy intensity between city groups were determined by both the economic structures and technology levels (Zhang *et al* 2017). Previous studies have maintained that energy-intense cities in the central and western regions rely more on coal than do the southeast coastal zones and developed northern areas (Zhang *et al* 2011). However, our results show that the sum share of oil and gas used in industrial

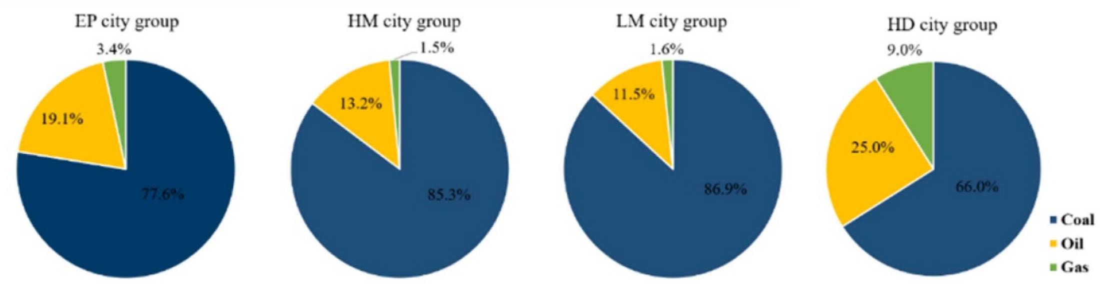

Figure 7. Fuel mix structures used in industrial output of the four city groups in 2015. EP, energy production; HM, heavy manufacturing; LM, light manufacturing; HD, high-tech development.

production of the EP cities located in northwestern China was 22.5%, which is much higher than that in the HM (14.7%) and LM cities (13.1%) located in southern and central China (figure 7). As a result, the higher emissions intensity associated with low energy efficiency in the EP city group could be partly compensated by its cleaner energy structure, leading to a smaller difference in emissions intensities between the EP and HM/LM city groups than the difference in energy intensities (figures 5(a) and (b), table S2). The reason why both the EP and HD city groups showed higher percentages of clean energy is probably related to the national long-term projects 'West to East Natural Gas Transmission' and 'West to East Electricity Transmission', of which western or northwestern China are the main sources of clean energy supply while the coastal region is the recipient (Chen *et al* 2010).

2.3. Decomposing the driving forces of historical EICEs in the four city groups

Based on the results of our previous study (Su *et al* 2014) and in sections 2.1 and 2.2 in this study, we found that population variation, economic variation, industrial structure, energy intensity, energy structure and emissions coefficient all have an important influence on changing carbon emissions. However, we were still unaware of how together these factors affect the change in carbon emissions. Therefore, we conducted a further in-depth investigation by decomposing the driving forces of EICEs dynamics; i.e. identified major drivers and quantified their contributions to support the accurate prediction of future trends (see section 2.4). Due to the relative and more obvious change of carbon emissions and carbon emissions intensity around 2007 and 2013, we subdivided the 2000–2015 historical period into three time periods (2000–2007, 2007–2013 and 2013–2015) to facilitate this presentation and the discussion (figure 8).

In the first (2000–2007) and second periods (2007–2013), the growth of industrial output was the dominant contributor boosting EICEs for the EP city group (135.6% and 185.6%), HM city group (151.6% and 313.4%), LM city group (137.5% and 400.2%) and HD city group (158.5% and 189.7%). Population growth played the second most important role in influencing the EICEs increment of the city groups, but its contribution was much smaller than that of the growth of industrial output. In contrast, energy intensity served as the dominant negative driver of EICEs growth in all four city groups, contributing −43.5% and −84.1% in the EP city group, −59.9% and −178% in the HM city group, −46.9% and −255.6% in the LM city group and −68.9% and −119.8% in the HD city group in the 2000–2007 and 2007–2013 time periods, respectively. Worth noting is the role of industrial structure in EICEs reduction, which was remarkable in the second period (2007–2013) contributing −13.7%, −28.2% and −60.2% to EICEs growth for the EP, HM and LM city groups, respectively, except for the HD city group (+18.8%). By comparing the periods between 2000–2007 and 2007–2013, we found that despite the rapid increase in industrial output, the growth of EICEs slowed down for all city groups. This indicated that industrial structure optimization, energy intensity improvement or energy structure optimization could exert significant effects on emissions reduction.

The distinct changes in EICEs or emissions intensity around 2013 for the four city groups allowed us to determine the most effective driving factors for emissions mitigation by comparing the contributions of influencing factors between the periods 2007–2013 and 2013–2015.

For the EP city group, the economic downturn (−41.3%) and industrial structure optimization (−51.7%) contributed the most to restrain EICEs in the period of 2013–2015 (figure 8(a)). However, the reduction associated with these two factors could not offset the carbon increase caused by the decrease of energy efficiency (+185.4%) on the whole, inducing an increase of total EICEs (figure 3(a)) and a rebound of carbon intensity (figure 3(b)) during the period of 2013–2015. This probably suggests that energy efficiency acted as the dominant driver of EICEs mitigation in the EP city group. For the HD city group, the decline of carbon emissions in the 2013–2015 period was mainly due to the switch in roles of the industrial structure from a promoter (+18.8%) to a suppressor (−162.8%), while

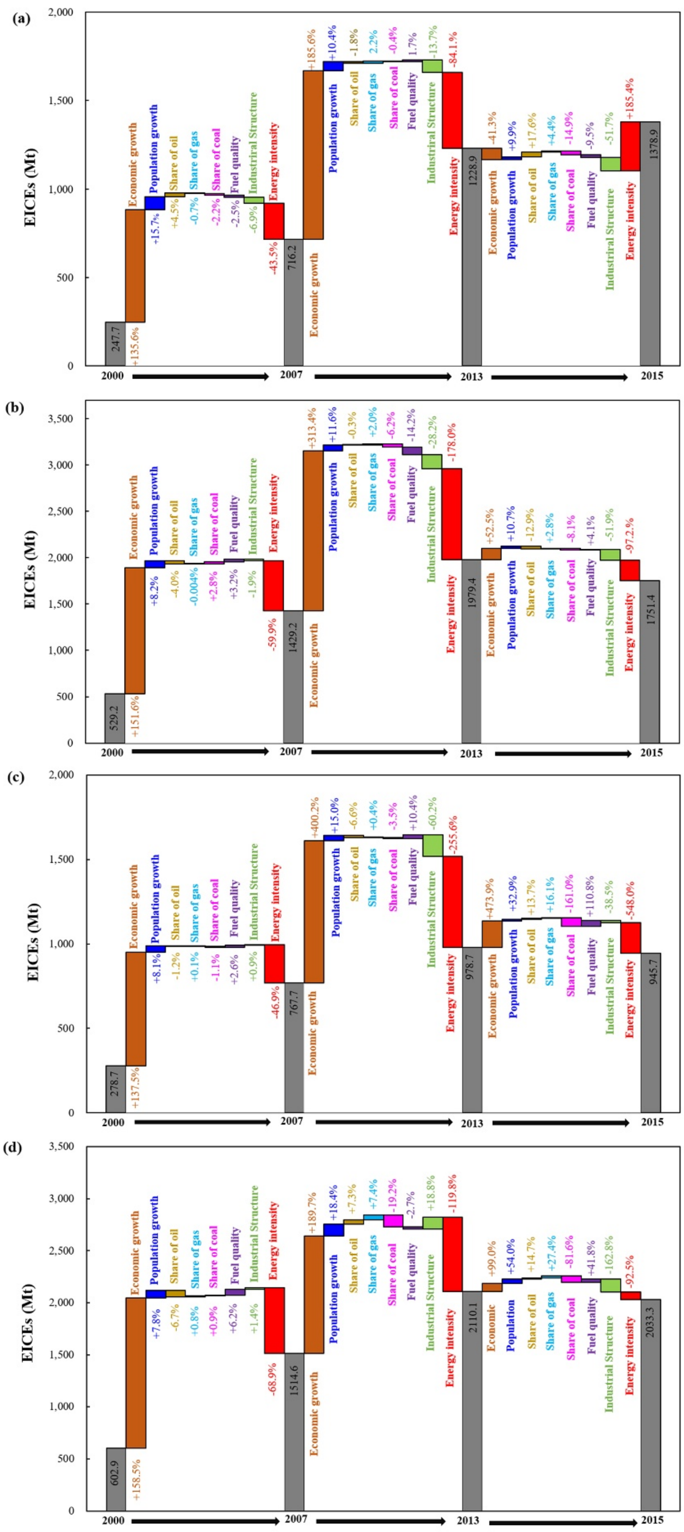

Figure 8. Contribution of socioeconomic drivers toEICEs dynamics in the 2000–2007, 2007–2013 and 2013–2015 time periods. (a) Energy production city group;(b) Heavy manufacturing city group; (c) Light manufacturing city group; (d) High-tech development city group. Length of each bar reflects the contribution of each factor per time period.

economic growth (+99.0%) and energy intensity (−92.5%) still played important positive and negative roles, respectively, as in the previous periods (2000–2007 and 2007–2013) (figure 8(d)). For the HM and LM city groups, the situations are very different. Besides the decrease of the economic growth rate and improvement of energy efficiency, the adjustment of energy structure (the decreasing share of coal and oil) also contributed importantly to restrain EICEs, with −8.1% and −12.9% in the share of coal and oil,

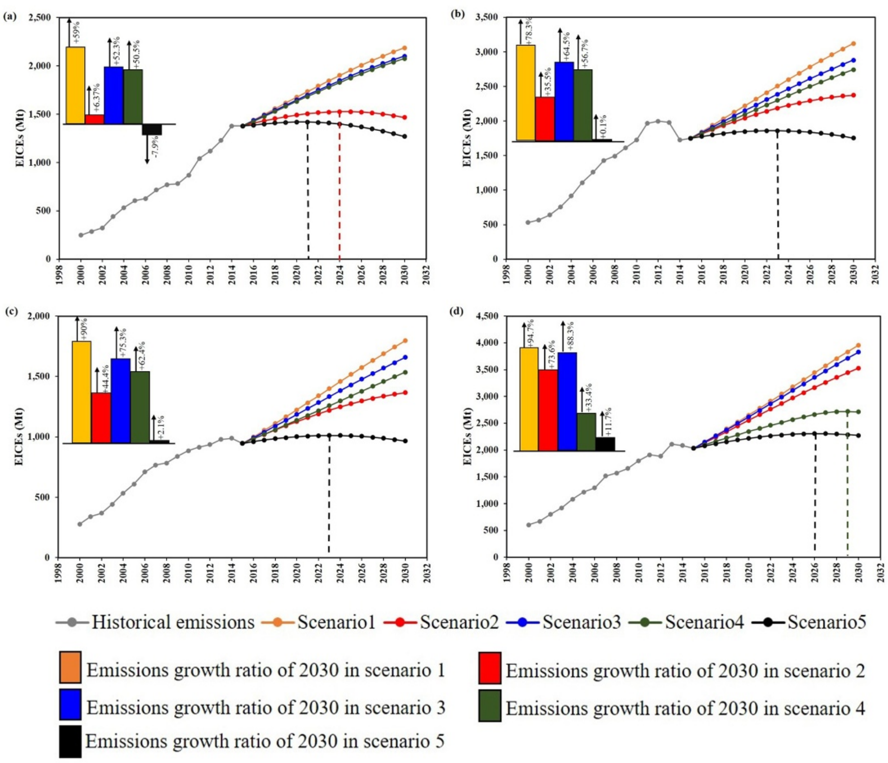

Figure 9. Historical and prospective EICEs dynamics of the four city groups under four scenarios during the period of 2000–2030. (a) Energy production city group; (b) Heavy manufacturing city group; (c) Light manufacturing city group; (d) High-tech development city group.

respectively, for the HM city group (figure 8(b)) and −161.0% in share of coal for the LM city group (figure 8(c)).

2.4. Estimating EICEs reduction capacities in the four city groups

Unlike previous studies that set a uniform constraint to each factor for all cities (e.g. Steckel *et al* 2011, Wang and Liang 2013, Yi *et al* 2016), we improved the scenario design to estimate the EICEs reduction potential in 2030 (figure 9) by optimizing the different major drivers for each city group (e.g. industrial output growth, energy efficiency improvement, energy mix and industrial structure, see method S6).

Under scenario 1 (figure 9), which only follows the industrial output growth without changes in other drivers, EICEs are predicted to increase by 807.5 Mt (59%), 1371.0 (78%), 1925.0 (90%) and 1925.0 Mt (95%) in the EP, HM, LM and HD city groups, respectively, from 2015–2030. Clearly, the EICEs of all four city groups will rapidly increase provided that China's economy increases at the normal growth rate. Under scenario 2 (figure 9), driven by industrial output growth and energy efficiency improvement, the EICEs of the four city groups will be reduced by 52.2%, 42.8%, 45.6% and 21.1%, respectively, in 2030 in comparison with the estimates of scenario 1. The EICEs of the EP city group is likely to reach the maximum in 2024. Under scenario 3 (figure 9), driven by industrial output growth and improvements in energy mix structure, the reduction potentials of EICEs for the EP, HM, LM and HD city groups will increase by 6.3%, 13.8%, 14.7% and 6.4%, respectively, in comparison with the estimates of scenario 1. The predicted EICEs in 2030 under scenario 4 (figure 9), which adds the industrial structure optimization driver based on scenario 1, will be reduced by 8.0%, 21.6%, 27.6% and 54.5% for the EP, HM, LM and HD city groups, respectively, in comparison with scenario 1. What should be noted is that for these three situations with a single constraint measure, only the EICEs of the EP city group under scenario 2 (2024) and the HD city group under scenario 4 (2029) are likely to reach the maximum before 2030. Under scenario 5, by combining the constraints of industrial output growth, optimization of industrial structure, improvement of energy efficiency and adjustment of energy mix, the EICEs for the EP, HM, LM and HD city groups are forecast to rise by −7.9%, 0.1%, 2.1% and 11.7% in comparison with the EICEs of 2015. In addition, the EICEs in the HM and LM city groups will peak before 2030 (HM: 2023; LM: 2023) only under scenario 5.

The uncertainty underlying these scenarios is considerable. Structural uncertainty is based on uncertainties in economic growth, how energy use (including energy structure and intensity) changes with economic growth and industrial structure

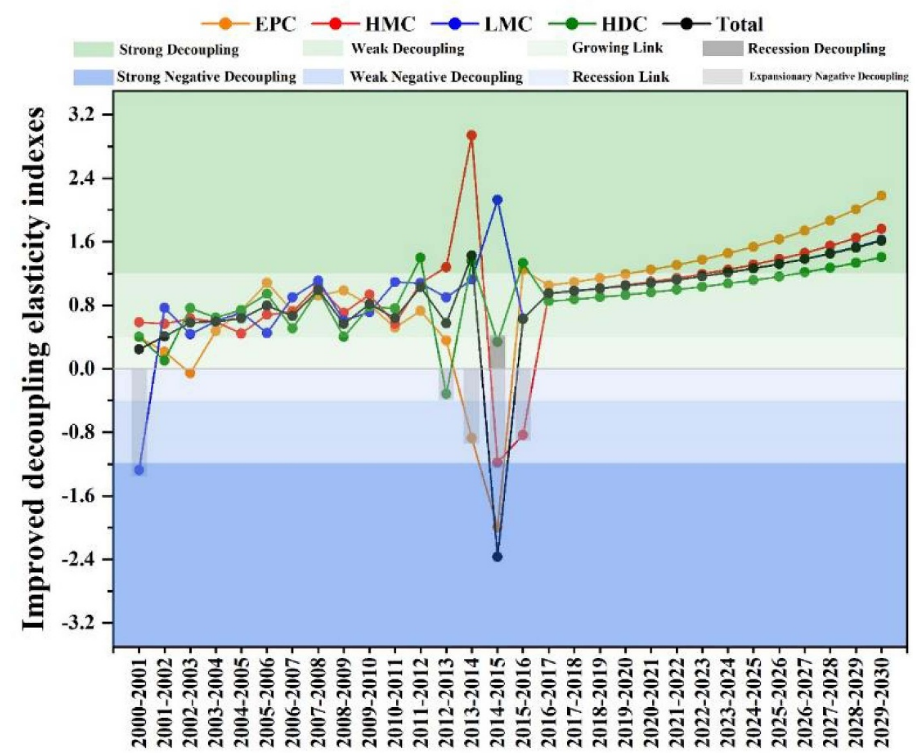

Figure 10. Dynamics of the improved decoupling index in the past (2000–2015) and in the future (2015–2030) under scenario 5. EPC, Energy production city group; HMC, Heavy manufacturing city group; LMC, Light manufacturing city group; HDC, High-tech development city group.

changes. We utilized Matlab7.10.0 to report the uncertainty of EICEs with the Monte Carlo simulation analysis for scenario 1 and scenario 5 (figure S2). Despite the uncertainties, the scenarios illustrate the enormous potential for a mitigation wedge in the four city groups. The uncertainties change the magnitude of potential, but the underlying reasons for the mitigation wedge remain.

Furthermore, decoupling relationships between economic growth and EICEs changes will become robust and reach strong levels before 2030 under scenario 5 compared with the fluctuating and weak decoupling relationships prior to 2015 (figure 10, method S6). This indicates that industrial structure optimization, energy efficiency improvement and the clean transformation of energy structure are able to give rise to a trade-off of economic growth and EICEs reduction in the four city groups without obstructing their economic growth.

3. Discussion and policy guidelines

Lacking either spatial or temporal coverage in city-level carbon emissions analysis might lead to insufficient understanding of historical drivers and to uncertainty in forecasting future reduction potentials. Our study is the first attempt to investigate the nationwide long-term inventories of city-level emissions based on physical energy flows. The results show that economic development (industrial economic growth) is always a positive dominant contributor to boost the EICEs for all city groups, similar to previous findings (Ren *et al* 2014, Xu *et al* 2016, Zhou *et al* 2017, Guan *et al* 2018), but its impact decreased in the 2013–2015 period compared with prior periods (figure 8). In addition, the relationship between economic growth and EICEs fluctuated between strong decoupling and expansionary negative decoupling from 2013–2015, compared to the stable weak decoupling in the earlier years (figure 10). These results raise three important points. First, the EICEs reduction after 2013/2014 was partly due to the slowing economic growth induced by China's active adjustments to avoid excess manufacturing capacity, restructured government debt, strengthened capital constraints (Lardy 2010, 2016) and passive responses to the global financial crisis (Liu 2009). This implies that economic recovery can still increase carbon emissions. Second, is that other factors such as energy efficiency, energy structure and industrial structure have been playing an increasingly important role in EICEs, with absolute contributions even exceeding economic contributions in some city groups in the period of 2013–2015 (figure 8). Third, the effect of energy efficiency, energy structure and industrial structure on EICEs were not stable yet, perhaps due to the lack of long-term effective policies (Wang 2010, Creutzig *et al* 2015). Importantly, our study further found that the key factors among these three indexes that contributed to the transformation of the carbon emissions trends between the periods of 2013–2015 and 2007–2013 were entirely different among the four city groups. Specifically, energy efficiency and industrial structure contributed most to the switch in emissions intensity, or EICEs, for the EP and HD city groups, respectively, while energy mix and energy efficiency were also strong contributors for both the HM and LM city groups.

With the long-term implementation of policies involving territorialization, e.g. the national development priority zoning strategy (Fan and Li 2009) and socioeconomic imbalance among different cities are becoming serious issues (Wang *et al* 2017b) in China. Scholars and administrators have realized the drawbacks caused by national unification policies for carbon emissions reduction (Long *et al* 2009, Su *et al* 2014, Creutzig *et al* 2015) and strongly call for differentiated city-level policies (Su *et al* 2014, Ramaswami *et al* 2017, Zhou *et al* 2018) that are more efficient and targeted. Unlike most previous studies that applied a uniform constraint to each factor for all cities (e.g. Steckel *et al* 2011, Wang and Liang 2013, Yi *et al* 2016) or discussed different effects of one factor on carbon emissions for different city groups (Zheng *et al* 2018, Shan *et al* 2018a), this study is the first to predict the emissions reduction potential for each city group, separately, using different constraints that are decomposed as major driving factors based on the widely employed LMDI method. This approach allows each city group to implement differentiated constraints and make more reasonable and feasible plans to achieve the emissions mitigation target. We expect that this sector-based, city-level perspective of China's industrial CO_2 emissions could offer relevant insight concerning city-level mitigation strategies for attaining the national emissions target.

In practice, there are three major ways for governments to influence the behavior of enterprises in relation to carbon mitigation (Zhang and Xu 2013). (1) Draft guidance documents on the carbon emissions quota (Zhang *et al* 2014, Zhang and Hao 2017), carbon trading system (Lohmann 2008, Lo 2012, Liu *et al* 2015a, Zhao *et al* 2017) or other carbon reduction targets (Bows and Anderson 2007, Hao *et al* 2015); (2) Propose financial measures (Galinato and Yoder 2010, He *et al* 2015, Zhang *et al* 2017) such as subsidies, taxes, incentives and fines; (3) Enforce policies related to the regulation and control of resources (i.e. labor force, land and water resources), which largely affect the long-term survival and growth of enterprises (Liedholm and Mead 2013). Referring to our results, policy-makers are suggested to take the following actions.

(a) For the EP city group, policy-makers should consider implementing strategies to improve energy efficiency. For example, a lower carbon emissions quota should be assigned to low-energy efficiency city sectors (method S6.2), especially those in the EP city group. We also suggest providing more financial subsidies aimed to trigger their actions (e.g. increasing R&D expenditure and fixed asset investment in developing energy-saving transformation, utilization and recycling processes as well as emissions reduction technologies) on emissions mitigation in the early stage and stronger incentives for keeping their enthusiasm on emissions mitigation in the late stage.
(b) For the HD city group, policy-makers should consider developing more strategies on energy efficiency improvement rather than the traditional industrial transfer policies to adjust industrial structure in manufacturing sectors, which only shifts carbon emissions from highly developed cities to less-developed energy-producing and heavy-manufacturing cities (Shan *et al* 2018a). Governments should implement strategies to attract investments in high-tech industries for modern industrial growth. Preferential policies on water use, land-use quota and introducing highly qualified talent will be greatly beneficial in reaching this goal. In addition, industrial structure adjustment means shifting the demand for industrial products (Zhang *et al* 2017). Therefore, market-oriented methods are also plausible and effective besides government interventions, which have been evidenced by some developed countries (Lin and Moubarak 2013).
(c) It is imperative for the HM and LM city groups to promote mitigation potential through energy structural adjustments (e.g. develop new energy) besides energy-efficiency improvement and industrial structure optimization, given their lower percentage of new energy and higher coal share at the present stage (figure 7). However, what should be noted is the inherent relative shortage of clean energy sources (e.g. inadequate solar radiation energy) in central China (Dan 2011), where most cities are of the HM and LM type. Therefore, for the HM and LM city groups governments must urgently resort to building a large-scale and intensive renewable energy production base and enforce policies that inspire the utilization of new and clean energy, such as accelerating energy pricing and increasing subsidies for renewable energy.

In the end, this study proposes one potential mitigation strategy rather than the only way to reduce carbon emissions for each city group. More studies are warranted to further investigate this issue.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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