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Research article

Who is a good neighbor? Analysis of frontrunner cities with comparative advantages in low-carbon development

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ABSTRACT

A well-developed economy and low-carbon emission intensity are important characteristics of low-carbon cities; they also represent important tasks for achieving global climate change mitigation goals. It is seldom discussed, however, how we should identify frontrunner cities from which low-carbon development experiences can be gleaned and then implemented in neighboring cities. This study, therefore, proposed a simple indicator—the "good neighbor index"—to identify frontrunner cities in low-carbon transformation based on economic and emission performance. Based on this indicator, we identified "good neighbors" in static and dynamic views for China. The results showed that the static good neighbors in 2015 were mostly large cities with higher incomes and better industrial structures whereas the dynamic neighbors achieved better economic growth and emission reductions from 2005 to 2015, though their economic and emissions statuses were generally worse. The good neighbor list is not consistent with the list of national low-carbon pilot cities, which has largely overlooked the experiences of some fast-growing cities. These results have policy implications for the Chinese government in terms of promoting the low-carbon transformation of cities. The study can also provide a reference for other countries in addressing climate change at the city level.

1. Introduction

Mitigating climate change has become a major global task given that rising temperatures are projected to have catastrophic consequences for human populations (Carleton and Hsiang, 2016; Tao et al., 2019). Cities support 60% of the global population, generate 60% of the world's economic output, and contribute to over 70% of global carbon emissions (Moran et al., 2018; Wang et al., 2019a); yet, cities only cover about 3% of the world's land area (Chen et al., 2019). Thus, cities are generally recognized as key to mitigating climate change (Xu et al., 2018). In China, dramatic urbanization processes have been underway for the past 30 years and are expected to continue for a long time. Such urbanization has been the major driver of increases in China's carbon emissions (Wang et al., 2019b). To combat climate change, China pledged to reduce its carbon intensity by 40%–45% by 2020 at the 2009 Copenhagen Climate Change Conference and by 60%–65% by 2030 in the Paris Agreement, compared to the 2005 baseline (Wang et al., 2017a, 2017b). To this end, China established a top-down implementation system for carbon emission reduction. In this system, cities are the most direct and smallest geographical units responsible for reducing and regulating carbon emissions (Cui et al., 2019). To meet national goals, the Chinese government launched an eco-city plan in 2009 and then low-carbon pilot city plans in 2010, 2012, and 2017 (Wang et al., 2019a). The purpose of these plans was to encourage low-carbon development in all cities by having pilot cities set excellent examples for their neighboring cities. The logic behind this is that competition and mutual learning between cities in adjacent regions can promote low-carbon governance in China's cities (Chen et al., 2017; Yu et al.,

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2016). However, it remains ambiguous which cities should be highlighted as excellent examples and what, specifically, other cities can learn from them.

Governance has spatial spillovers that usually positively affect neighboring political entities (Seldadyo et al., 2010). This is particularly true regarding the carbon emission performance of cities, regions, and countries. Evidence has shown that cities tend to learn from their neighbors and become similar to them with regard to carbon emission governance (Qin et al., 2019; Wang et al., 2019c). As a result, agglomerations tend to form that might all have high- or low-carbon emissions simultaneously; these are known as high−high or low−low local Moran's I clusters (Qin et al., 2019). However, the evolution path toward a high- or low-emission agglomeration is determined by multiple socioeconomic factors and spillovers from neighbors (Fang et al., 2019; Su et al., 2018; Wang et al., 2018; Wang et al., 2019c). The process whereby cities become similar to each other and move toward low-carbon agglomeration is called convergence (Mykhnenko and Wolff, 2019). Carbon intensity convergence is useful for establishing evidence-based policies (Li et al., 2017). The convergence of all cities into a low-carbon phase is generally considered preferable—or at least "club convergence" at a regional scale. There is still debate, however, over whether clear convergence trends exist in countries and cities regarding carbon emissions (Ahmed et al., 2017; Li et al., 2017; Zang et al., 2017). Governments have made various efforts to combat climate change by setting positive examples for cities to learn from (Nagorny-Koring, 2019). For instance, Japan and the UK worked together in 2005 to showcase existing low-carbon cities as examples to promote low-carbon transition (Skea and Nishioka, 2008). Moreover, cities in the C40 Cities Climate Leadership Group have served as good examples of ambitious climate change mitigation, using knowledge sharing and capacity building to support low-carbon cooperation with other cities and prompt changes in governance (Gouldson et al., 2015; Lou et al., 2018). Socio-oecological Urban Networks (SEUNs) in Europe have also proven effective for enhancing the sustainability of lagging cities through learning from frontrunners (Mocca, 2017). In addition, more than 300 cities in the US declared to "adopt, honor, and uphold the commitments to the Paris Agreement," despite President Trump's withdrawal from the agreement (Wang et al., 2019a). Unlike most city networks that set high standards for membership (such as C40), China's low-carbon pilot cities were designated using different criteria in 2010, 2012, and 2017, and some failed to meet their targets (Li et al., 2018), thus also failing to set good examples for neighboring cities. Meanwhile, some cities that are not low-carbon pilots have shown outstanding performance. As such, it is necessary to analyze outstanding performers to promote low-carbon convergence and transition at the regional scale and support appropriate policy making in China.

There are several methods for evaluating low-carbon cities in the literature (Su et al., 2013). Macro indicators are most commonly used to assess a city's status and progress toward low-carbon development, including per capita emissions, gross domestic product (GDP), and decoupling status. The independent or combined use of a number of indicators is often reported in the literature. For instance, Tan et al. (2017) developed an entropy weighting factor method to rank the carbon emission performance of 10 cities. The Lawrence Berkeley National Laboratory (in the US) developed a low-carbon evaluation tool called ELITE cities to compare cities' low-carbon performance (Zhou et al., 2015). Other studies have used more complicated methods, such as input–output analysis, to investigate a city's emissions and further analyze contributions by sector. For example, Paloheimo and Salmi (2013) used input–output analysis to assess the production-based and consumption-based carbon emissions of cities in Finland. Lin et al. Lin et al. (2013) proposed a hybrid method combining input–output analysis and lifecycle analysis to evaluate the carbon emissions of Xiamen, China. Zhou et al. (2018) derived a total-factor index using data envelopment analysis to evaluate the carbon emission performance of 71 Chinese cities during 2005–2012. These studies have revealed the emissions performance of various cities and have helped to identify critical factors for low-carbon development. However, all were conducted either on a broad scale to compare cities or in terms of the time series of a single city. As such, they have neglected the important factor whereby distance and spatial adjacency can help showcase good examples and thus inform policy (Yang et al., 2014). Furthermore, geographers often focus on spatial convergence and agglomeration at national or regional scales to reveal spillover effects from a theoretical perspective (Cui et al., 2019); this, however, does not consider the real policy applications whereby cities can set examples for other nearby cities. As a result, a gap exists between research and real-world policy making. How to effectively identify cities with comparative advantages and promote their successful experiences is still unclear, especially in the context of China's low-carbon pilot cities.

In this study, we proposed a new GIS-based simple indicator—namely, the "good neighbor index"—to identify frontrunner low-carbon cities and analyzed how these frontrunners succeed. This study is useful for reevaluating China's low-carbon city strategy, and it can help provincial administrative and local governments absorb advanced development experience to achieve rapid low-carbon transformation.

The rest of this paper is organized as follows. Section 2 presents our new method for identifying frontrunners at the regional scale as well as the data source. Section 3 presents the results, followed by a discussion of the factors contributing to successful cities. Lastly, section 4 presents the conclusions and elaborates on the policy implications.

2. Method and data

2.1. Low-carbon development evaluation

Low-carbon cities are characterized by sustainable economic growth and good carbon emission performance. Thus, we adopted both economic and emissions indicators to identify frontrunners. Because of the availability of statistical data, cities in this study were limited to prefecture-level administrative units, which included all urban and rural administrative areas. Given the large discrepancies between China's cities in terms of area, population, and economy, we used per capita GDP and per capita carbon emissions as the basic indicators rather than the total GDP and emissions. To incorporate the two indicators, we used two-step calculations to rank cities according to their economic and emissions performance. First, to further eliminate the magnitude and dimension inconsistencies in the two indicators, we ranked cities in descending order by per capita carbon emissions (RC); we also obtained another ranking of cities according to their per capita GDP in ascending order (RG). Therefore, a larger RC denotes better performance in carbon emissions, as the city has smaller per capita carbon emissions. The same is true for RG in denoting economic development. Then, based on the Nash social welfare function (Kaneko and Nakamura, 1979), we multiplied the two rankings for each city to obtain a new performance indicator P ($P = \mathrm{RC} \times \mathrm{RG}$) and evaluate the integrated low-carbon performance of the city. Consequently, the larger the value of P, the better the performance in low-carbon development. Furthermore, to identify leading cities from a dynamic perspective, we used the growth rate of the two indicators (growth rate of per capita GDP and growth rate of per capita emissions) to calculate their rankings (RGG and RGC) and dynamic performance indicator, $\mathrm{PG} = \mathrm{RGG} \times \mathrm{RGC}$.

2.2. Definition and identification of a good neighbor

Compared to topological adjacency between cities, spatial closeness in terms of fast transportation connectivity is much more important for cities to exchange goods, services, and information. Drawing on the concept of the "1-h living circle"—an area within a distance of 1 h of traffic access surrounding the city as a core—we extended topological adjacent neighbors to distant close neighbors. To simplify, we defined cities within 100 km of a core city as sufficiently close in distance and

accessible within 1 h. The distance was calculated based on average highway speed (80–120 km/h). In consideration of the size and shape of the core city, the buffer zone was not set from the geometric center but the boundary of the core city. Neighboring cities with an area covered by a buffer zone of less than 1% of its total area were excluded from the neighboring city list. Fig. 1 shows the neighboring cities of Beijing, some of which are not topologically adjacent. This study did not calculate the buffer zone based on high-speed rail since the high-speed rail station is located in the center of the city and has fixed route restrictions. In addition, high-speed rail-based neighboring cities were included in the boundary-started road traffic results from our sampling calculations. Flights were not considered in this study.

To reflect the comparative advantages of neighboring cities in low-carbon development, we only selected the top 10% of well-performing cities in a core city's neighborhood as good neighbors. However, when a core city had fewer than five neighbors, we did not identify good neighbors for the core city. In other cases, the number of a core city's good neighbors was rounded up based on the result for 10% of its total neighbors. We further used a weighted indicator to extend the pairwise good neighbor identification to the regional scale, as follows:

$$good_neighbor_i = \frac{\sum_{j=1}^{n} good_neighbor_{ij}}{n_i}$$

$$\begin{cases} good_neighbor_{ij} = 1, \ city\ i\ is\ a\ good\ neighbor\ of\ city\ j \\ good_neighbor_{ij} = 0, \ city\ i\ is\ not\ a\ good\ neighbor\ of\ city\ j \end{cases} \quad (1)$$

where n_i is the total number of neighboring cities of city i; city j is a neighboring city of city i; $\sum_{j=1}^{n} good_neighbor_{ij}$ indicates the total number of city is identified as good neighbors. Therefore, $good_neighbor_i$ is an indicator evaluating the comparative advantage of the low-carbon development of city i at the regional scale. Specifically, we defined a city selected based on the static performance indicator P ($P = \mathrm{RC} \times \mathrm{RG}$) as a static good neighbor (SGN) and a city selected based on the dynamic performance indicator PG = RGG × RGC as a dynamic good neighbor (DGN).



Fig. 1. Neighboring cities of Beijing.

2.3. Classification of cities

To reveal the characteristics of good neighbors in-depth, we further classified cities according to different criteria. First, we classified the 340 Chinese cities into four categories according to the World Bank's economic classification by income level—namely, high, upper-middle, lower-middle, and low-income economies. The corresponding classification standards of per capita GDP for these four categories are >12475, 4036–12,475, 1026–4035, and <1025 US dollars, respectively. We applied this standard by multiplying the annual exchange rate in 2015 (6.2284 Chinese yuan/US dollar). Second, we set a new three-category classification for the 340 cities according to their industrial structure. Cities with secondary industries contributing to no less than 50% of the GDP were classified as industrial cities whereas cities with tertiary industries accounting for no less than 50% of the GDP were classified as service-oriented cities. The remaining cities were grouped as "other" cities.

2.4. Data sources

The carbon emissions of cities were collected from the Chinese High-Resolution Emission Dataset (CHRED) 1.0 and 3.0 (www.cityghg.com), released by the Chinese Academy of Environmental Planning (Cai et al., 2019, 2018). CHRED is a bottom-up emissions inventory that covers point, line, and nonpoint sources. Currently, CHRED is the most comprehensive bottom-up emissions inventory at the city level in China. CHRED reflects point sources more accurately than EDGAR and FFDAS with bottom-up enterprise-level data (Cai et al., 2018). Compared to the China Emission Accounts and Datasets (CEADs)—the most comprehensive top-down emissions inventory—CHRED covers the emissions of all cities in 2005 and 2015 while CEADs only covers 182 cities (Shan et al., 2018). The emission data of all cities in China are essential for comparing the emission performance of neighborhoods. Therefore, we chose the CHRED dataset for analysis. CHRED provides 1 km × 1 km spatial resolution maps for various greenhouse gas emissions, including CO_2, CH_4, N_2O, and F-gases. We took into account changes in the administrative areas of cities and aggregated carbon emission data for 2005 at the city level according to the administrative areas of cities in 2015. Economic data were collected from the China City Statistical Yearbook 2016 released by the National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/tjcbw/201706/t20170613_1502795.html). The exchange rate of 2015 was collected from the Statistical Communiqué on National Economic and Social Development (http://www.stats.gov.cn/tjsj/tjgb/ndtjgb/). The economic data were also adjusted as far as possible in accordance with changes in the administrative areas of cities. We did not use the GDP deflator to convert 2015 GDP data into the 2005 comparable price because this process was not expected to change the results and would complicate the classification of cities.

3. Results and discussion

3.1. Identification of static good neighbors in 2015

Fig. 2 shows the spatial distribution of SGNs in 2015 identified by our proposed indicator. Of the 340 cities, 105 had a positive good neighbor index (GNI), ranging from 0.06 to 1.00. The identified SGNs were almost evenly distributed across China. This distribution pattern is conducive to each city finding its own low-carbon development example city nearby and subsequently aligning with it and drawing on its experiences.

For brevity, we only focused on the top 20 cities, which are named in Fig. 2. The top 20 SGN cities were mostly distributed on the right side of the Hu Huanyong Line (Hu et al., 2016). Thirteen cities had a GNI of 1, which means those cities outstripped their neighbors in low-carbon performance. For example, Beijing is an SGN of its eight neighboring cities. It has the third-lowest per capita carbon emissions, ranking 164th

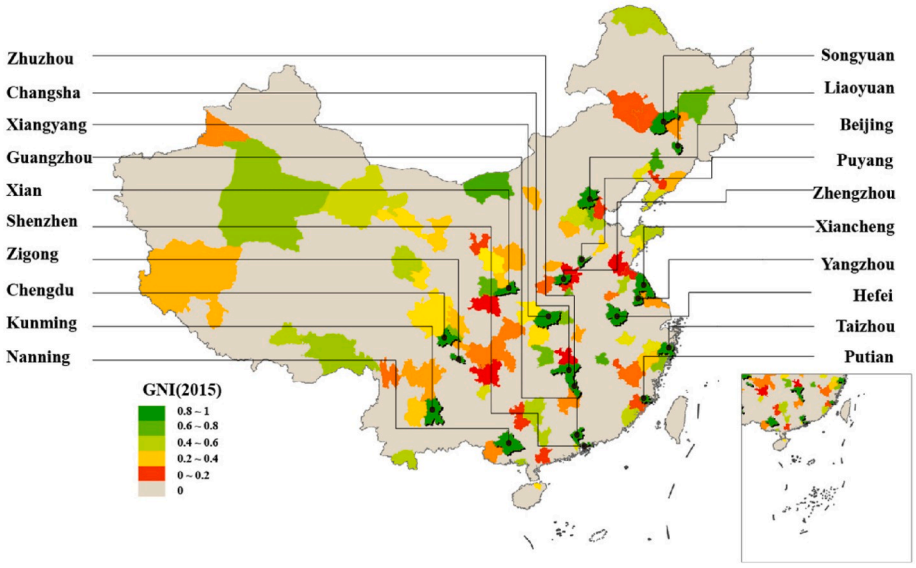


Fig. 2. Spatial distribution and static good neighbor indexes (GNIs) for frontrunner cities.

nationally, below Baoding (233rd) and Cangzhou (194th), while having the highest per capita GDP among its neighbors (320th). By contrast, its best-performing neighbors, Baoding and Cangzhou, showed much worse economic performance, ranking 100th and 180th, respectively. This is in line with the intuitive perception that low-carbon cities should strike a more balanced trade-off between economic status and low-carbon emissions. Deploying renewable energy, improving energy efficiency, and upgrading the industrial structure are feasible approaches that enable cities to meet emission-reduction targets while maintaining rapid economic growth. The same situation can be observed between Zhengzhou and its neighbors.

Fig. 3 shows the rankings in per capita GDP, as well as the per capita emissions of the top 20 SGNs. The figure is divided into four quadrants. Most example cities are located in the first quadrant, with above-average performance in economy and emissions. Only Puyang, a mid-size city in Henan province, was at medium level in terms of economy and emissions. However, it was also identified as an SGN with an index of 0.86. This means the low-carbon performance ($P = RC \times RG$) of Puyang outstripped 12 of its 14 neighbors since its neighbors had either a poor economic status or high emission intensity (e.g., Xingtai, Shangqiu, and Heze with $RG < 100$, in contrast to Handan, Taian, Hebi, and Jining with $RC < 100$). Thus, Puyang had a comparative advantage in the neighborhood. Considering differences in the development stages of cities, it is difficult for a developing city to meet economic and environmental goals at the same level as developed cities. Learning from the experiences of spatially close leading cities—which usually have similar resource endowments, locations, and climate conditions—is the most feasible and realistic path by which a lagging city can achieve low-carbon development. In this sense, a good neighbor does not have to be the best on the national scale. As long as it has comparative advantages on a regional scale, it can still be an example and drive low-carbon development in the entire region. It is worth noting that Nanning, Hefei, Puyang, Guangzhou, Zhuzhou, Zigong, and Zhengzhou have GNIs of less than 1, indicating they do not outperform all neighboring cities. For example, Zigong is an SGN city and is located close to Chengdu, which is also an SGN city and outperforms Zigong in terms of low-carbon development. Cities may have different industrial structures and thus different experiences with developing low-carbon economies.

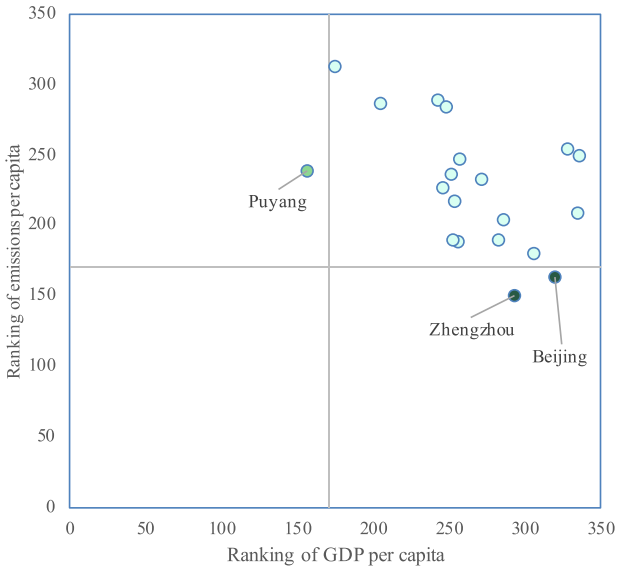


Fig. 3. Performance of the top 20 static good neighbors in economy and emissions in 2015.

3.2. Improvements in low-carbon performance from 2005 to 2015

Static good neighbors in 2015 only reflect one kind of frontrunner that already has superior economic and emissions performance. However, a good neighbor can also be a city that has greatly improved its economic and emissions performance and caught up in the past few years. We used the dynamic performance indicator, PG, to identify DGNs with the above characteristics. Fig. 4 shows the spatial distribution of DGN indicators and highlights the top 20 good neighbors. The dynamic results are considerably different from the static ones in 2015. All cities with GNI >0 are located in the eastern part of China. No cities were identified in Xinjiang and Tibet. Moreover, the list of cities with GNI >0 is considerably different from the list showing the static results. Taking the top 20 cities as an example, only four cities among the top 20 were identified by both methods (Changsha, Yangzhou, Songyuan, and Liaoyuan). This implies that these four cities are developing relatively fast and have achieved a leading position at the regional scale. Other cities in the top 20 list are mostly located in eastern and central China. Unlike the static results for 2014, the top 20 good neighbors in the

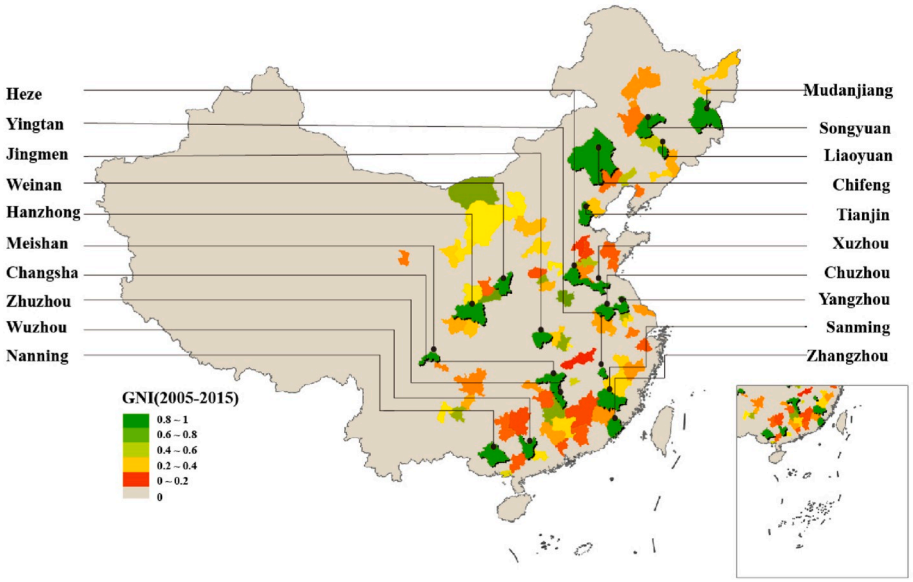


Fig. 4. Spatial distribution and dynamic good neighbor indexes (GNIs) for frontrunner cities.

dynamic view are generally noncapital cities, except Changsha and Tianjin, indicating that noncapital cities progressed faster in low-carbon development during the studied period, possibly due to their lower marginal costs of emission reduction and development.

Fig. 5 shows changes in the economic and emissions performance of the top 20 cities from 2005 to 2015. Almost all DGNs achieved considerable improvements in terms of both economy and emissions, except Chifeng, which declined in per capita GDP ranking from 109th to 79th. The average per capita GDP of these 20 cities increased over fourfold from 12.6 to 55.2 thousand CNY while average per capita emissions increased slightly from 5.75 to 6.68 tons per person. All cities achieved a positive phase change from a worse quadrant to a better one—that is, they moved further from the origin of the coordinates in Fig. 5. Five cities (Mudanjiang, Liaoyuan, Nanning, Jingmen, and Songyuan) changed from the low-low quadrant to the high-high quadrant in the figure, implying a transformative improvement in economy and emissions reduction during the study period. Other cities achieved considerable improvements in only one of the two aspects. For example,

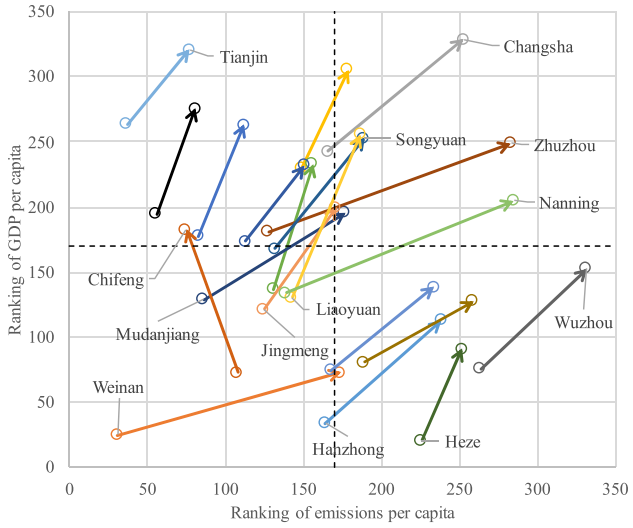


Fig. 5. Improvement of low-carbon performance of the top 20 cities from 2005 to 2015.

Changsha and Yangzhou improved their emissions performance on the basis of high-level economic output since 2005 while Chifeng and Yingtan showed dramatic economic growth. Therefore, these cities provide successful examples of how to balance economic growth and emissions reduction compared to the SGNs in 2015.

3.3. Identification of the success factors for good neighbors

The key factors affecting cities' low-carbon performance are economic level, industrial structure, and policy support. Fig. 6 shows the share of good neighbors in different classifications in 2015 and from 2005 to 2015. In the figure, cities are classified according to the industrial structure and income level. Fig. 6a shows the static results for 2015. Service-oriented cities had the highest possibility (13.3%) of being identified as an SGN, including Beijing, Guangzhou, Shenzhen, Chengdu, Kunming, and Xian. Nine industrial cities were identified as SGNs, with a smaller possibility of 7.6%. The remaining cities had a smaller possibility of 2.8% while the remaining cities represented the largest city type in China, comprising 52.5% of the total cities. All SGNs were high- and middle-high-income cities; however, the high-income cities had a higher possibility (10.9%) of becoming an SGN, compared to 6.3% for middle-high-income cities. No middle-low-income cities were identified as SGNs.

By contrast, the dynamic results show a different distribution pattern (Fig. 6b). Industrial cities had the smallest possibility of becoming a DGN, followed by service-oriented cities. Of the remaining cities, 9.9% were identified as DGNs in comparison to 0% in the static results. In terms of income, middle-low-income cities had the highest possibility of becoming a DGN, followed by low-income cities. These results indicate that cities with a higher position in the industrial chain have better economies and a higher income basis. Thus, they have more financial resources to reduce carbon emissions and therefore lead the low-carbon competition. However, developed cites have higher marginal costs for further improving their performance. By contrast, cities with lower incomes and relatively backward industrial systems have faster economic growth rates and higher emission reduction potential. The better performance in the dynamic results indicates that these cities tend to quickly catch up with developed cities.

Fig. 6a shows that eight of 81 (or 9.9%) low-carbon pilot cities were SGNs in 2015 (Shenzhen, Beijing, Guangzhou, Kunming, Hefei, Changsha, Zhuzhou, and Chengdu). By contrast, 12 of 259 nonpilot cities (4.6%) were SGNs. That is, pilot cities had a higher likelihood than



Fig. 6. Share of good neighbors according to different classifications for (a) static results in 2015 (classifications based on 2015 statistics) and (b) dynamic results from 2005 to 2015 (classifications based on 2005 statistics). The per capita GDP of the "other income" group in (b) is unknown because of a lack of data.

nonpilot cities. For comparison, only four pilot cities (4.9%) were identified as DGNs while eight nonpilot cities (6.2%) were identified. In general, pilot cities face more political pressure to make low-carbon plans, but they also have a stronger economic base (all are high- or middle-high-income cities) to put plans into action. This should lead to better performance in per capita emissions than nonpilot cities, although barriers remain in current policy support and paralleled action programs from different governmental departments (Khanna et al., 2014). Yet, the share of DGNs in pilot cities was unexpectedly lower than that in nonpilot cities, which have less policy support. These results suggest that the government tends to select cities with better economic and emissions foundations as pilot cities. However, relatively underdeveloped cities (industrial and other cities, low- and middle-income cities) account for the majority of cities, and it is impossible for all such cities to follow the same path as the most developed ones. The experiences of DGNs that achieved rapid low-carbon transitions during the past decade may have more relevant implications for most cities.

3.4. Limitations and policy implications

This study has some limitations. First, the CHRED data came from bottom-up estimates, currently only covering city-scale emissions in 2005 and 2015, which are inconsistent with the critical time nodes of the pilot cities in 2010, 2012, and 2017. Therefore, our analysis could only assess the performance of pilot cities during the period 2005–2015. This mismatch in time may lead to a biased assessment of the performance of pilot cities. Second, in 2005, 56 cities did not disclose their demographic data. We excluded these 56 cities, which are mainly located in western China. Third, the jurisdictions of a small number of cities changed during the study period, resulting in changes to the accounting basis for GDP and total emissions. However, the effect of this limitation was minimal because of the small number of such cities and the use of per capita GDP and per capita emissions. These limitations all stem from a lack of essential data. If these data problems can be solved in the future, we can better assess the low-carbon performance of cities within their surrounding regions.

Our study provides some insights that differ from previous studies. One previous study (Cai et al., 2019) found that, in 2012, the most carbon-efficient cities were located along the coast while the worst performers were in the central and western parts. Shenzhen, Changsha, and Songyuan were recognized as better performers in that study as well as in the present study. By contrast, Beijing did not rank at the top due to differences in factor selection. Cai et al. (2019) incorporated more socioeconomic factors (e.g., labor, capital, energy, water) into the evaluation of cities' carbon emission efficiency. Changsha was considered to have a large reduction potential, which is consistent with Zhou et al. (2018). Most studies have found similar carbon performance in neighboring cities. However, previous studies have compared all cities in the country, ignoring differences in natural endowments, infrastructure, and economic development stages. Thus, the ability of underdeveloped cities to learn from developed ones could be overstated. Therefore, regional-level incentive mechanisms might better facilitate the transformation of low-carbon cities.

This study's findings also have several policy implications. First, it is recommended to formulate policies and standard accounting methods for cities to encourage the disclosure of carbon emissions at the city scale. The current top-down accounting database cannot cover all cities because of a lack of essential energy consumption and industrial production data, whereas the bottom-up accounting database is not sufficiently continuous in time because of the high cost of field surveys. Furthermore, all of these databases are nonofficial. Therefore, it is necessary to use administrative power to compel cities to conduct carbon emission accounting and disclosure to help governments evaluate and formulate energy conservation and emission reduction policies more effectively. Second, the low-carbon pilot city program should continue to be implemented, but more attention should be paid to the experience of nonpilot cities that have made good progress. The task of pilot cities is to explore new low-carbon development pathways and provide experiences and lessons for other cities in low-carbon transition. To document the successful experiences of existing nonpilot cities, more trials can be conducted in pilot cities to identify problems in the localization process and provide references for other cities. Third, an incentive mechanism for low-carbon development should be established on a regional scale. Neighboring cities have similar natural conditions and resource endowments. Linking policy and fiscal support with low-carbon performance through a competitive incentive mechanism is conducive to the faster and more equal implementation of low-carbon transformation across the country. Further, our research also provides a reference for low-carbon development at a global scale. Comparing the performances of countries and territories in the neighborhood provides a way for countries and regions to learn from their neighbors' successful experiences. This requires the establishment of more cooperation mechanisms for climate change mitigation between countries and regions.

4. Conclusion

Implementing low-carbon development at the city and regional levels is an important way to achieve global climate change mitigation. This proposed a simple indicator—the "good neighbor index"—to identify frontrunners with better economic and carbon emission performance in a neighboring region, which can provide good examples for neighboring cities in implementing low-carbon transformation. The results showed that most good neighbors were evenly distributed in the eastern and central parts of China. From a static view, well-developed cities with higher economic and emissions performance in 2015 were identified as good neighbors whereas, from a dynamic view, more less-developed cities achieved considerable improvements in economic

growth and emissions reduction from 2005 to 2015. Low-carbon pilot cities are mostly high-income, postindustrial cities, and they did not show substantial economic growth alongside emissions reduction compared to their performance in 2005 and to other cities. These results indicate that the exploration and promotion of low-carbon city development should be adjusted to encompass the near-neighbor experience. We evaluated the low-carbon performance of 340 Chinese cities representing various levels of income, industrialization, and policy support. The static and dynamic analyses may provide insights for other countries aiming to address climate change through adaptation and mitigation at the city level. No city is completely independent of other cities. On the basis of similar natural conditions and resource endowments, learning from the advanced experiences of nearby cities can be an effective mitigation strategy.

Author contribution

Zhen Wang: Writing-original draft, Methodology, Writing-review & editing, Funding acquistion. Xinyu Dou: Methodology, Formal analysis. Pengcheng Wu: Formal analysis, Validation, Resources. Sen Liang: Validation, Resources. Bofeng Cai: Conceptualization, Resources, Softwares, Funding acquistion, Supervision. Linbo Cao: Methdology, Data Curation. Lingyun Pang: Data Curation, Visualization. Xin Bo: Conceptualization, Supervision. Liyuan Wei: Writing-review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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