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Bigger cities better climate? Results from an analysis of urban areas in China

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ABSTRACT

Continued urban population expansion will be a defining challenge for climate change mitigation, and global sustainability more generally, over the coming decades. In this context, an important but underexplored issue concerns the relationship between the scale of urban areas and their carbon emissions. This paper employs the urban Kaya relation and Reduced Major Axis regression to look at urban emission patterns in China from 2000 to 2016. Our results reveal that larger cities tend to have lower per capita emissions. Thus, population agglomeration may be able to contribute to climate change mitigation and a wider transition to sustainability. The inverse-U shape between carbon emissions and population size is found. In addition, we observe unique scaling patterns in different regions, revealing how the relationship between emissions and population can be influenced by economic geography. City consumption weakens the role of population agglomeration in reducing carbon emissions in the East region, therefore it should be placed top priority in carbon emissions mitigation. These findings are important for China which looks to achieve carbon neutrality by 2060 against the backdrop of intertwined interplay between population agglomeration and city consumption.

1. Introduction

The concentration of individuals in urban areas brings both opportunities and challenges for sustainable development. Although agglomeration makes economies of scale in infrastructure possible and facilitates the provision of services, it can also lead to unprecedented increases in urban greenhouse gases (GHGs) emissions and energy consumption and produces urban challenges related to climate change, such as the urban heat island effect (Bettencourt et al., 2007a, 2007b; Meerow, 2017; Mi et al., 2018). With the rural to urban shift showing no signs of slowing down, nearly 70% of the population is projected to live in urban areas by the middle of this century (United Nations, 2019). Given this inexorable shift, global sustainability and climate change mitigation will depend significantly on our capacity to understand and manage the complexity and dynamism of urban systems (North et al., 2017; Meirelles et al., 2021).

Cities are complex systems with interacting material, social and institutional aspects (Meirelles et al., 2021). Therefore, cities display sophisticated nonlinear changes in elements as they grow in size, giving rise to the development of the science of cities which looks into underlying regularities in urban systems, in cases of distinct geographical constraints and historical trajectories. Urban scaling laws, as a central part of city science, explore how variations in social organization and dynamics caused by expanding urban population sizes impact the interactions between natural and societal systems (Bettencourt et al., 2007a, 2007b). The demographic scale of changes in social organization and patterns of human behavior are unprecedented, which will lead to important, although as of yet poorly understood, impacts on the global environment (Bettencourt et al., 2007a, 2007b; United Nations, 2019). This puzzle is meaningful to explore as the quantitative understanding of human social organization and dynamics in cities is a major piece of the puzzle toward successfully navigating a transition to sustainability (Bettencourt et al., 2007a, 2007b; Rybski et al., 2017). This puzzle especially matters to China, which pledges to achieve carbon neutrality by 2060, against the backdrop of ongoing industrialization and urban population expansion (Mi et al., 2019).

Substantial research on the application of the urban scaling law has been undertaken. This work can be categorized into two streams. The first stream focuses on socioeconomic variables, such as gross domestic product (Bettencourt and Lobo, 2016), number of patents (Bettencourt et al., 2007a, 2007b) and crimes committed (Anand and Luís, 2019). The latter addresses infrastructure performance in urban areas, including

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street networks (Louf and Barthelemy, 2014a; Emanuele et al., 2017), cable networks (Kühnert et al., 2006) and petrol supply networks (Christian et al., 2006). Urban scaling laws postulate a power-law association between urban population and urban variables. A sub-linear scaling (a scaling exponent < 1) indicates economies of scale while a super-linear scaling (a scaling exponent > 1) indicates diseconomies of scale. A linear scaling (a scaling exponent $= 1$) indicates proportionality.

Recent research on urban scaling has been extended to environmental indicators, including carbon emissions. These research shed light on the intricacy of urban emission patterns. Nevertheless, no scientific consensus has yet been reached on urban emission patterns (Louf and Barthelemy, 2014b). For instance, Oliveira et al. (2015) employed a bottom-up approach to find a super-linear association between emissions and population for 2281 clusters in the United States, while Ribeiro et al. (2019) found a sub-linear scaling between CO_2 emissions and urban population size across more than 3000 U.S. urban units. A similar study on German cities depict a sub-linear scaling (Gill and Moeller, 2018). Furthermore, underlying systematic dynamics that govern such scaling properties remain underexplored (Gudipudi et al., 2019a, 2019b). Therefore, Gudipudi et al. (2019a, 2019b) unprecedentedly combined Kaya identity and urban scaling law generating urban Kaya relation and applied it to 61 cities from 12 countries to look at urban emission scaling properties worldwide in 2005. The Kaya identity is an equation that relates the level of carbon emissions to population growth, economic growth, energy intensity and carbon intensity per unit of energy consumed. It is a concrete form of the more general I = PAT equation relating factors that determine the level of human impact on climate. By applying the urban Kaya relation, this paper found a sub-linear scaling for cities in Annex 1 regions and a super-linear scaling for cities in the Non-Annex 1 regions. Problematically, however, a small number of urban agglomerations from different countries are mixed to conduct the scale analysis, which is expected to be performed within a single urban system (Meirelles et al., 2021). In addition, carbon emissions data comes from four diverse sources with varying accounting approaches, leading to comparability issues, particularly around the accounting for electricity emissions and assumptions about urban boundaries (Cottineau et al., 2019). Also, Gudipudi et al. (2019a, 2019b) relied on the cross-sectional data which fails to illustrate the dynamics of emission patterns within and across cities, an issue of particular importance for China, which is experiencing economic development mode shifts and industrial upgrade which may cause changes in urban emission patterns.

To extend the work inaugurated by Gudipudi et al. (2019a, 2019b), this paper applies the urban Kaya relation to 50 Chinese cities to look at the dynamics of urban emission patterns from 2000 to 2016. The urban Kaya relation is utilized respectively among East, Middle and West regions, as well as megalopolis, metropolis, large cities and medium and small cities (further details in section 2) to identify the heterogeneity of urban emission patterns and the impact of city size on GHGs emissions. Results indicate that the larger the cities the lower the per capita emissions. From this, the inverse-U shape between carbon emissions and population size is found. The scaling of emissions with population size depends on the economic geography of the region. Specifically, carbon emissions reductions in the Middle region can primarily be ascribed to energy efficiency improvements, while carbon intensity reductions are the key contributing factor in the West and East regions. Considering that city consumption has offset the role of population agglomeration in reducing carbon emissions in the East region, the East region should be the top priority when it comes to reducing carbon emissions.

2. Method

2.1. The urban Kaya relation

This paper looks into the underlying mechanisms among influencing factors inducing urban emission patterns based on the Kaya identity, which relates carbon emissions per capita to emissions and energy, energy and gross domestic product (GDP), and GDP and population size, as shown in formula (1).

$$C/_P = C/_E \cdot E/_G \cdot G/_P, \tag{1}$$

where C denotes carbon emissions at the city level. This analysis respectively utilizes scope 1 and scope 2 emissions to identify the impact of different emission accounts on urban emission patterns. P and G represent population size and GDP for each corresponding city, and E is energy consumption. According to Kaya identity, carbon emissions per capita acts as a function of carbon intensity per unit of energy consumed (C/E), energy intensity (E/G) and economic activity (G/P).

Urban scaling laws hold that urban indicators scale with urban population. To fully understand the intrinsic factors determining urban emission patterns, we postulate each factor in formula (1) exhibit scaling properties, i.e.

$$C = P^{\varphi} \tag{2}$$

$$C = E^{\partial} \tag{3}$$

$$E = G^{\delta} \tag{4}$$

$$G = P^{\gamma} \tag{5}$$

φ is the value we focused on, as it indicates how carbon emissions scale with population, and whether cities get 'greener' as they get larger. ∂ reflects the carbon intensity of energy sources. The value ofδshows the technological level, especially energy-related technology.γ is a measure of affluence.

Combining the scaling relations in formulas (2)–(5), we obtain.

$$\varphi = \alpha\delta\gamma \tag{6}$$

Therefore, by making adjustments we can identify the chain between urban carbon emissions and population size and reveal an urban Kaya relation with a similar structure to the Kaya identity. In line with formula (6), the exponent of urban emissions and population size can be obtained by the product of exponents of the other factors. Formula (6) allows us to understand the linearity of scaling between emissions and urban population based on the potential scaling of carbon intensity, energy efficiency and economic activity.

2.2. Reduced Major Axis regression

The default method to obtain exponent φ is to transform formula (2) into log-log space, then φ can be computed as a regression coefficient of the linear regression equation. However, the measurement of power-law exponents in urban scaling studies is not as simple as originally thought. While a straightforward regression is thought to be robust and sufficient (Leitão et al., 2016), more rigorous and appropriate regression approaches are required as φ changes with the application of varying regression methods (Gudipudi et al., 2019a, 2019b).

The vast majority of linear regressions are performed using ordinary least squares (OLS) methodology, overlooking assumptions underlying this approach. OLS minimizes the sum of squared errors of the vertical distance between the dependent values and their corresponding predictions, which postulates independent variables are measured without errors. This is an idealized assumption in reality. Reduced Major Axis (RMA) regression is specifically formulated to handle errors in both dependent and independent variables by minimizing both horizontal and vertical distances of data points from the fitting line. Another source of concern about OLS is the asymmetry between the OLS regression of Y on X and of X on Y. The lack of interchangeability between dependent and independent variables is noteworthy for cases where two-way causation exists. For example, energy consumption and economic growth (formula (4)) and affluence and population (formula (5)). The symmetry of X and Y in RMA regression enables the bivariate relationship to hold when variables assigned to X and Y are reversed. This paper therefore employs the RMA regression method to explore urban emission patterns across various urban agglomerations and regions. Then we employ a nonparametric bootstrap method (999 replications) to test the credibility of coefficients obtained from the RMA regression method.

2.3. Limitations in the method

This paper has three main limitations which we leave to be addressed by future research. Firstly, Kaya identity is a widely used equation to determine the level of human impact on carbon emissions by relating the carbon emissions to energy use, economic growth and population growth. However, it fails to consider some factors that can affects the carbon emissions, such as government efficiency, trade and FDI. Future research can address this issue by further enriching the form of Kaya identity. Furthermore, considering the data availability and the representativeness of the 50 cities in population size and carbon emissions, this paper uses the 50 cities as a sample for analysis, which may lead to sample selection bias in the estimation of the parameters. Lastly, this paper uses total population data within the city boundary, does not distinguish between urban population and rural population, and does not deal with the complexity of China's city size.

3. Data

Analysis conducted in this paper is limited to 50 Chinese cities, which ensures consistent demarcation and definition of cities; for these cities, four types of data are available, namely city-level carbon emissions, energy consumption, population size and GDP. To identify the impact of emission accounting inventory scopes on urban emission patterns, this analysis utilizes scope 1 and scope 2 emissions to assess how carbon emissions from fossil fuel combustion and industrial processes occurring within the city boundary or emissions related to electricity and heating change with city size. This paper draws on emissions data from Wang et al. (2019), whose analysis is based on the Intergovernmental Panel on Climate Change (IPCC) territorial emissions (IPCC, 2006). Emissions from agriculture, forestry and other land use, as well as waste, have been excluded due to their high uncertainties and relatively small influence on urban emissions (Wang et al., 2012). Data on national carbon emissions used for prediction comes from CEADS database (CEADS, 2019). Data on GDP and population are collected from the China City Statistical Yearbook (2001–2017). GDP is converted to purchasing power parity (PPP) dollars based on the implied PPP conversion rate using the current international dollar from (EconStats, 2019). We collect energy consumption of industrial enterprises from the corresponding city's statistical yearbooks (2001–2017) and convert these to standard coal equivalents based on conversion factors from China Energy Statistical Yearbook (2017). See Supplementary Table 1 for a statistical description of the variables.

Analysis covers cities in 30 provinces. The contribution of these cities to total population is 30% in 2015, while the combined share of the GDP and cumulative carbon emissions generated from fossil-fuel combustion and industrial production in these cities are 51% and 35% respectively (Wang et al., 2019). Due to distinct geographical constraints, resource endowments, and historical trajectories, there is remarkable divergence among energy mix, city size and affluence across cities. This paper classifies the 50 cities into four city groups according to the standard of city classification published by the China State Council in 2014 in order to explore the impact of city size on urban emission patterns, namely megalopolis, metropolis, large cities and middle and small cities. These represent the cities with residential population living in the urban districts more than 10 million, 5–10 million, 1–5 million and less than 1 million in 2010. The 50 cities are then divided into East, Middle and West regions to look at the heterogeneity of urban emission patterns by region, as shown in Supplementary Table 2.

4. Results

4.1. Carbon emission patterns for all cities

Carbon emissions for 50 cities increased dramatically between 2000 and 2016, with scope 1 emissions increasing from 797 Mt. in 2000 to 1982 Mt. in 2016, and scope 2 emissions reaching 1557 Mt. in 2016 from 435 Mt. in 2000. Scope 1 emissions grew rapidly at an annual growth rate of over 7% before 2008, and stabilized at around 5% for the following four years. Between 2012 and 2016, scope 1 emissions basically achieved zero growth, and even negative growth in 2016. The scope 2 emissions growth rate then started to decline from 18.51% in 2004 to 2.71% in 2008, after reaching a peak of 23.32% in 2003. After that, scope 2 emissions showed slight growth between 2009 and 2011, before bottoming out at −3.23% in 2013 and gradually plateauing (Supplementary Fig. 1). According to the observed time-varying characteristics of the carbon emissions trend, we divide the total trend into four stages: World Trade Organization (WTO) accession (2000−2003), high economic growth (2004–2008), post financial crisis (2009–2011) and the 'new normal' (2012–2016), which is characterized by the economic development mode shifts from extensive growth to intensive growth and the economic growth rate slows down. In order to test whether emissions modes in these stages are statistically significantly different, we perform bootstrapping and a Kolmogorov-Smirnov test. The Kolmogorov-Smirnov test (P-value = 0.000) indicates that emission modes in the four stages show varying characteristics, as shown in Fig. 1.

The rapid growth of export trade after joining the WTO was a key driving force for China's economic development in the first stage, which was characterized by significant increases in industrial outputs, fossil fuel consumption and carbon emissions (Feng and Zou, 2008). The scaling exponent of scope 1 emissions increased from 1.45 to 1.49, while that of scope 2 emissions rose from 1.37 to 1.53. The Chinese government gave top priority to economic development from the 1990s to early 2000s, and as a result China's rapid economic growth was achieved at the cost of significant environmental degradation. Given mounting environmental issues, the 'Scientific Outlook of Development' was proposed in 2003 to seek a balance between economic growth and environmental sustainability. In addition, policy makers have developed a series of binding policies aimed at energy conservation and emission reduction. For example, the Chinese government set an ambitious target of decreasing energy consumption per unit of GDP by 20% during the 11th Five-Year Plan period (from 2006 to 2010), compared with that in

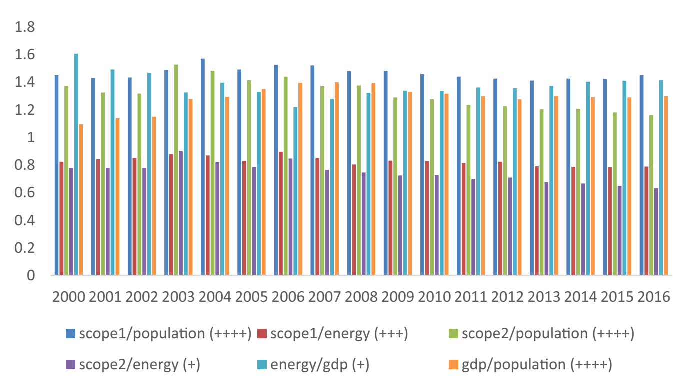

Fig. 1. Scaling exponent and urban Kaya relation for all cities.
Notes: The nonparametric bootstrap method is employed to test the credibility of coefficients obtained from the RMA regression method. For each scaling exponent, we conducted 999 times random sampling with replacement, and then calculated each sample and recorded the results. The results are summarized as follows: ++++ represents at least 90% of the replications lead to exponents larger than 1; +++ represents 60%–90% of the estimates are larger than 1; ++ represents 30%–60% of the estimates are larger than 1; + represents less than 30% are larger than 1.

the tenth five-year plan period (during 2001 and 2005). Thus, in the second and third stages, although GDP still maintained a relatively high growth rate, the scaling exponent of carbon emissions (both scope 1 and scope 2) significantly reduced. Under the constraint of total carbon emission and energy intensity proposed by the Twelfth Five-Year Plan, total carbon emissions and carbon intensity in the 'new normal' stage are well controlled by energy structure adjustment, characterized by emissions shifting from coal-based emissions to gas-based emissions through the progress of clean energy power generation (Zheng et al., 2019).

4.2. Carbon emission patterns for city groups

Do emissions scale the same way for cities of all sizes? Or does the relationship between scaling and population change as cities get larger? To explore this question, the 50 cities in the analysis are divided into four city groups according to the standard of city classification in China, namely megalopolises, metropolises, large cities and middle and small cities, to explore the city size effect on urban emissions, as shown in Supplementary Fig. 3 and Supplementary Tables 3–4. Due to quite limited numbers of cities in the group of middle and small cities, this paper focuses on the analysis of the first three city groups.

Our results indicate that the megalopolis and the metropolis are more energy efficient relative to their population compared to the large city. Although per capita energy consumption in megalopolises is similar to that of metropolises, it is the more advanced power generation technologies employed that typically make its per capita emissions lower than that of metropolis. The scaling of scope 2 emissions with population scale differs across city groups (Supplementary Fig. 3 and Supplementary Tables 3–4). We observe a sub-linear scaling in the megalopolis and the metropolis, and a super-linear scaling in the large city. In order to test whether these slopes are significantly different, we perform bootstrapping and a Kolmogorov-Smirnov test. The Kolmogorov-Smirnov distance between these bootstrapped samples is 1 with a significant P-value (0.000), which confirms that the slopes are drawn from different distributions. Furthermore, the scaling of scope 1 emissions with population scale are smaller for larger cities although super-linear scaling is observed in all city groups. Therefore, we find that larger cities have lower per capita emissions.

The scaling of emissions with population size are smaller for larger cities, and the scaling exponent of the largest cities is on a downward trend over time. These results suggest there may be an inverse-U shape between carbon emissions and population size. Thus, here we predict when China will reach its peak in carbon emissions, as shown in Supplementary Fig. 2. The goodness of fit of up to 97.12% validates the inverse-U shape among carbon emissions and population scale. Applying a quadratic equation between carbon emissions and population size to simulate the peak of carbon emissions based on China's national historical emissions, we project that emissions for China should peak at 9.04 Gt in 2030, realizing its commitment to peak carbon emissions by 2030. Our estimation results coincide with the projection of Yuan et al. (2014). They projected that China's carbon emissions would peak in 2030–2035 at 9.30 Gt or so and may be cut by 0.3 Gt through a cleaner energy path. Also, in view of the progress of energy saving technology, the adjustment of industrial structure and energy mix unconsidered in the fitting equation, it is possible for China to reach its carbon emissions peak earlier.

4.3. The heterogeneity of carbon emission patterns among regions

There is substantial divergence across the 50 cities in geographic location, industrial structure and economic development. For example, from less-developed (e.g. per capita GDP of 3,447 PPP dollars in Linfen in 2016) to more-developed (e.g. per capita GDP of 116,151 PPP dollars in Shenzhen in 2016) in terms of economic development, from heavy-industry dominated (e.g. Tangshan) to service-sector oriented (e.g. Guangzhou and Beijing) in terms of industrial structure. Considering the differences in these city characteristics, this paper divides 50 cities into three groups, namely East, Middle and West, to explore the heterogeneity of carbon emission patterns, as shown in Tables 1-3. The Kolmogorov-Smirnov test (P-value = 0.000) confirms that the scaling of emissions with the population size is different between these subsets. Therefore, the following section will look into the reasons for distinct carbon emission patterns in each region. Tables 1-3 also includes the absolute difference between the prediction (formula (6)) and the measured exponent φ. When using RMA, the deviation of the obtained exponent is extremely small. Thus, we recommend using RMA rather than OLS when analyzing the urban Kaya relation.

Compared to energy efficiency, carbon intensity reduction contribute more to the carbon emissions mitigation in the East region. In specific, the scaling exponent between carbon emissions and energy for the East region decreased by 19.3%, much higher than the improvement of energy efficiency by 3.23% during the period from 2000 to 2016. The improvement of carbon intensity and energy efficiency in the East region may be attributed to the strict implementation of environmental protection and emission reduction policies, including industrial low carbon transformation and rigid emission-limit standards. Shandong and Hebei provinces have made environmental protection a priority as they are primary energy-consuming provinces proximate to capital cities, and have achieved eye-catching emission reductions. Hebei Province has addressed mounting environmental challenges through a steady process of industrial green transformation and energy mix adjustment. This has specifically been achieved by eliminating excess capacity and preventing outdated capacity from resuming production through remote monitoring. In addition, this has been supported through the promotion of industrial restructuring by boosting internet based and cloud computing businesses (Zheng et al., 2019), and by and replacing coal with clean energy in power generation and heating. As a result, carbon emissions have decreased (both carbon emissions and per capita emissions decline for scope 1 and scope 2) for cities in Hebei province in the 'new normal' stage. An exception is for Tangshan, whose economic development relies on heavy industry and abundant coal reserves.

Similarly, Shandong province has taken various measures to promote the low carbon transformation which have contributed to the reduction of emissions in Qingdao and Jinan. A building energy network and regulatory platform based on big data and cloud computing has helped to improve administrative efficiency of both government and enterprises. In addition, apart from eliminating excess capacity in high carbon intensity industries, especially the steel industry and chemical industry, Shandong province also controls approvals of high energy consumption projects and has accelerated emission-reducing projects (Zheng et al., 2019). Further, the active promotion of carbon emissions trading and encouragement of the development of energy saving and low carbon technologies have also contributed.

First-tier cities, such as Guangzhou, have aggressively pursued striking a balance between economic growth and environmental sustainability, achieving a carbon emissions level far lower than other cities while maintaining high economic growth (Qu et al., 2017; Xiong et al., 2020). Beijing and Shenzhen have accelerated emission reduction after the financial crisis, which has led to the rapid development of the service sector in these cities (Mi and Sun, 2021). The worst emission reduction performance is seen in Tianjin, where industries that have shifted from the capital Beijing have led to increases in emissions over the last decade. With advanced science and technology and industrial green transformation, cities in Jiangsu and Zhejiang provinces have performed above average in emissions reduction.

The Middle region has achieved a gain in energy efficiency and carbon intensity that can be attributed to strategic policies. Among them, the improvement of energy efficiency contribute the most to carbon emissions reductions in the Middle region, whose scaling exponent drops from 2.04 to 1.22. While undertaking technical transfer from the East region, the Middle region has actively promoted upgrading of

Table 1
Scaling exponent and urban Kaya relation for the East region.

	$\frac{\text{scope1}_i}{\text{population}_i}\varphi_1$ ++++	$\frac{\text{scope1}_i}{\text{energy}_i}\alpha_1$ +++	$\frac{\text{scope2}_i}{\text{population}_i}\varphi_2$ ++++	$\frac{\text{scope2}_i}{\text{energy}_i}\alpha_2$ +	$\frac{\text{energy}_i}{GDP_i}\delta$ +	$\frac{GDP_i}{\text{population}_i}\gamma$ ++++	$\varphi_1-\partial_1\delta\gamma$ or $\varphi_2-\partial_2\delta\gamma$
2000	1.579	0.841	1.392	0.741	1.762	1.066	0.000
2001	1.604	0.916	1.416	0.809	1.594	1.098	0.000
2002	1.616	0.912	1.448	0.817	1.575	1.126	0.000
2003	1.793	1.002	1.753	0.980	1.335	1.340	0.000
2004	1.946	0.921	1.711	0.810	1.542	1.370	0.000
2005	2.019	0.845	1.790	0.749	1.603	1.490	0.000
2006	2.119	0.926	1.772	0.774	1.468	1.559	0.000
2007	2.094	0.870	1.746	0.725	1.569	1.534	0.000
2008	1.995	0.812	1.734	0.706	1.608	1.527	0.000
2009	1.874	0.829	1.582	0.700	1.626	1.391	0.000
2010	1.879	0.842	1.581	0.708	1.623	1.376	0.000
2011	1.883	0.833	1.509	0.668	1.650	1.369	0.000
2012	1.894	0.841	1.470	0.653	1.654	1.362	0.000
2013	1.872	0.815	1.446	0.629	1.666	1.379	0.000
2014	1.894	0.826	1.425	0.622	1.683	1.362	0.000
2015	1.911	0.822	1.412	0.607	1.689	1.377	0.000
2016	1.903	0.799	1.424	0.598	1.705	1.396	0.000

Notes: a) The nonparametric bootstrap method is employed to test the credibility of coefficients obtained from the RMA regression method. For each scaling exponent, we conducted 999 times random sampling with replacement, and then calculated each sample and recorded the results. The results are summarized as follows: ++++ represents at least 90% of the replications lead to exponents larger than 1; +++ represents 60%–90% of the estimates are larger than 1; ++ represents 30%–60% of the estimates are larger than 1; + represents less than 30% are larger than 1; b) For readability, only three decimal places are reserved for the results in the table. The original results obtained by the RMA regression method are available from the corresponding author upon reasonable request; c) The results in the last column are calculated based on the original results.

Table 2
Scaling exponent and urban Kaya relation for the Middle region.

	$\frac{\text{scope1}_i}{\text{population}_i}\varphi_1$ ++++	$\frac{\text{scope1}_i}{\text{energy}_i}\alpha_1$ +++	$\frac{\text{scope2}_i}{\text{population}_i}\varphi_2$ ++++	$\frac{\text{scope2}_i}{\text{energy}_i}\alpha_2$ +	$\frac{\text{energy}_i}{GDP_i}\delta$ +	$\frac{GDP_i}{\text{population}_i}\gamma$ ++++	$\varphi_1-\partial_1\delta\gamma$ or $\varphi_2-\partial_2\delta\gamma$
2000	2.310	0.717	2.230	0.692	2.045	1.576	0.000
2001	2.051	0.666	2.091	0.679	1.921	1.603	0.000
2002	2.261	0.718	2.061	0.655	1.969	1.599	0.000
2003	1.749	0.574	1.684	0.553	2.174	1.402	0.000
2004	2.008	0.734	1.993	0.728	1.793	1.527	0.000
2005	1.804	0.712	1.533	0.605	2.038	1.243	0.000
2006	1.896	0.774	1.877	0.767	1.705	1.437	0.000
2007	1.819	0.759	1.407	0.587	1.608	1.491	0.000
2008	1.782	0.676	1.404	0.532	1.694	1.557	0.000
2009	2.102	0.824	1.337	0.524	1.562	1.633	0.000
2010	1.860	0.849	1.199	0.548	1.439	1.522	0.000
2011	1.669	0.787	1.114	0.525	1.449	1.464	0.000
2012	1.543	0.747	1.103	0.534	1.417	1.457	0.000
2013	1.633	0.722	1.088	0.481	1.379	1.642	0.000
2014	1.495	0.657	1.116	0.491	1.326	1.716	0.000
2015	1.567	0.659	1.156	0.486	1.260	1.887	0.000
2016	1.974	0.845	1.054	0.451	1.221	1.912	0.000

Notes: a) The nonparametric bootstrap method is employed to test the credibility of coefficients obtained from the RMA regression method. For each scaling exponent, we conducted 999 times random sampling with replacement, and then calculated each sample and recorded the results. The results are summarized as follows: ++++ represents at least 90% of the replications lead to exponents larger than 1; +++ represents 60%–90% of the estimates are larger than 1; ++ represents 30%–60% of the estimates are larger than 1; + represents less than 30% are larger than 1; b) For readability, only three decimal places are reserved for the results in the table. The original results obtained by the RMA regression method are available from the corresponding author upon reasonable request; c) The results in the last column are calculated based on the original results.

characteristic industries (Zheng et al., 2019). Hubei and Hunan provinces, acting as the major energy consumption cities and the transportation hub of the Middle region, have focused on low carbon economic development. This has included eliminating outdated energy-consuming equipment and full monitoring of energy management of major energy consumption equipment and diversified financing support for key energy conservation and emission reduction projects. Hubei has also been one of the seven nationwide pilots for carbon emissions trading markets.

Considering environmental issues caused by industrial structure and outdated technologies, reducing carbon emissions and improving energy efficiency in Changchun and Harbin represent huge opportunities (Dong et al., 2007). However, the challenges faced by state-owned enterprises and the continued dominance of coal in the energy-mix will make this difficult (Zheng et al., 2019). At the forefront of supply-side reform such as de-capacity, Taiyuan has made progress in reducing emissions intensity. Similarly, Zhengzhou has achieved a gain in energy conservation and reductions in emissions through a supervision system aimed at improving the transparency of projects review.

The reduction of carbon intensity is the key contributing factor to carbon emission mitigation in the West region. The scaling exponent between carbon emissions and energy for the West region decreased by 27.7% during the period from 2000 to 2016, which was two times higher than that of energy efficiency improvement (12.9%). The reduction of carbon intensity and energy intensity contribute to emission reductions in the West region that can be primarily attributed to new patterns of sustainable development and the application of environmentally-friendly technologies (Zheng et al., 2019), including a shift from coal

Table 3
Scaling exponent and urban Kaya relation for the West region.

	$\frac{\text{scope1}_i}{\text{population}_i}\varphi_1$ ++++	$\frac{\text{scope1}_i}{\text{energy}_i}\alpha_1$ ++++	$\frac{\text{scope2}_i}{\text{population}_i}\varphi_2$ +	$\frac{\text{scope2}_i}{\text{energy}_i}\alpha_2$ +	$\frac{\text{energy}_i}{GDP_i}\delta$ +	$\frac{GDP_i}{\text{population}_i}\gamma$ ++++	$\varphi_1-\partial_1\delta\gamma$ or $\varphi_2-\partial_2\delta\gamma$
2000	0.916	0.857	0.923	0.863	1.260	0.849	0.000
2001	0.867	0.810	0.766	0.716	1.254	0.853	0.000
2002	0.907	0.798	0.689	0.606	1.357	0.838	0.000
2003	0.906	0.942	0.772	0.803	1.156	0.832	0.000
2004	0.808	0.885	0.695	0.762	1.101	0.829	0.000
2005	0.768	0.911	0.666	0.790	0.963	0.875	0.000
2006	0.721	0.872	0.653	0.789	0.947	0.874	0.000
2007	0.692	0.818	0.647	0.766	0.955	0.886	0.000
2008	0.747	0.878	0.627	0.738	0.964	0.882	0.000
2009	0.758	0.878	0.576	0.667	0.957	0.902	0.000
2010	0.719	0.778	0.583	0.631	1.028	0.899	0.000
2011	0.729	0.771	0.618	0.653	1.047	0.904	0.000
2012	0.716	0.803	0.602	0.676	0.995	0.895	0.000
2013	0.652	0.733	0.627	0.705	0.986	0.903	0.000
2014	0.727	0.749	0.672	0.693	1.070	0.906	0.000
2015	0.740	0.759	0.626	0.642	1.098	0.888	0.000
2016	0.744	0.757	0.613	0.624	1.097	0.896	0.000

Notes: a) The nonparametric bootstrap method is employed to test the credibility of coefficients obtained from the RMA regression method. For each scaling exponent, we conducted 999 times random sampling with replacement, and then calculated each sample and recorded the results. The results are summarized as follows: ++++ represents at least 90% of the replications lead to exponents larger than 1; +++ represents 60%–90% of the estimates are larger than 1; ++ represents 30%–60% of the estimates are larger than 1; + represents less than 30% are larger than 1; b) For readability, only three decimal places are reserved for the results in the table. The original results obtained by the RMA regression method are available from the corresponding author upon reasonable request; c) The results in the last column are calculated based on the original results.

to gas and oil in some industrial processes. Guizhou province has explored new modes of low carbon development to balance economic prosperity and the environment, including the creation of pilot areas for new technologies, low carbon parks and the building of low carbon communities. Tourism in Nanning and Kunming, and cloud computing and big data in Chongqing and Chengdu, have also played a role in reducing the dependence on heavy industry.

4.4. The comparison of emissions scaling among regions

We separately regress logarithmic carbon emissions on logarithmic population size for all cities and three regions (East, Middle and West regions) to look into the complexity of the scaling exponent φ, as shown in Fig. 2. We found that population growth in the East region contributes the most to carbon emissions increase. Specifically, every additional person will bring about another 6.30 tons of scope 1 emissions, which is much higher than that of city-average level (4.98 tons/person) and that of other regions (4.14 tons/person for the West region and 3.36 tons/person for the Middle region) (Fig. 2A), and the marginal effect of population growth on scope 2 emissions in the East region is also above-average (Fig. 2B). This might be attributed to the relatively higher levels of consumption of goods and services for individuals in the East region due to their higher income (e.g. per capita GDP of 29,050 PPP dollars in the East region in 2016 vs per capita GDP of 14,842 PPP dollars in the West region in 2016). Their consumption draws on resources for their fabrication, distribution, sale and use which cause the emission of GHGs (Satterthwaite, 2009; Duan et al., 2018). Furthermore, due to the differences in openness, urban distribution density and natural geographical conditions, China has formed an uneven spatial distribution pattern of population. The densely populated areas are mostly distributed in the East region, whose population accounts for 40% or so of the total population with an average annual growth rate of approximately 1%, higher than the national average (National Bureau of Statistics, 2020). Therefore, the East region should be regarded as the top priority for carbon emission mitigation.

5. Conclusion

If continued urban population growth is a cause of rising GHGs emissions, could it also contribute to a solution? Understanding the impact of urban population expansion on energy consumption and carbon emissions is of great importance for climate change mitigation and sustainable development. This paper applies an urban Kaya relation to explore the role of urban size in contributing to GHGs emissions using an RMA regression method performed within a single urban system and across a 17-year time period. This paper has two main findings. First, population agglomeration may be able to contribute to climate change mitigation and a wider transition to sustainability. China is still in the rapid development phase of urban population expansion. From 1978 to 2013, China's urban population ratio rises from 17.9% to 53.7%, with an average annual growth rate of 1.02%. The traditional extensive city development model has brought about a series of issues, including slow industrial upgrading, environmental deterioration and increased social conflicts, risking the process of sustainable development in the long run. Transferring to a new type of city development path highlighting intensive production and environmental protection with the focus shift to the quality of development is a feasible way to give full play to the role of population agglomeration in reducing emissions. For central cities, it is necessary to accelerate industrial upgrading and set up complete modern industrial systems to exert their scale effects and driving effects, thereby promoting the extension of industrial chains and service chains to the periphery, realizing the joint development of central cities and surrounding cities. Meanwhile, speeding up the population agglomeration of small and medium-sized cities should become the focus in the following city development process: a) small and medium-sized cities should accelerate the construction of comprehensive urban transportation networks and public service facilities so as to enhance their ability to support population gathering; b) it is also necessary to cultivate characteristic urban industrial systems on the basis of urban environmental carrying capacity, factor endowments and comparative advantages; and c) enhancing the undertaking capacity of industrial transfer of small and medium-sized cities is the key to realize specialized division of labor among cities and create an industrial development pattern with complementary advantages.

Second, city consumption will weaken the role of population agglomeration in reducing carbon emissions. In the East region with high population density, population agglomeration has the minimal role on reducing emissions as city consumption has a more significant impact on carbon emissions. Specifically, urban population expansion brings about changes to economic production, lifestyles and land use types,

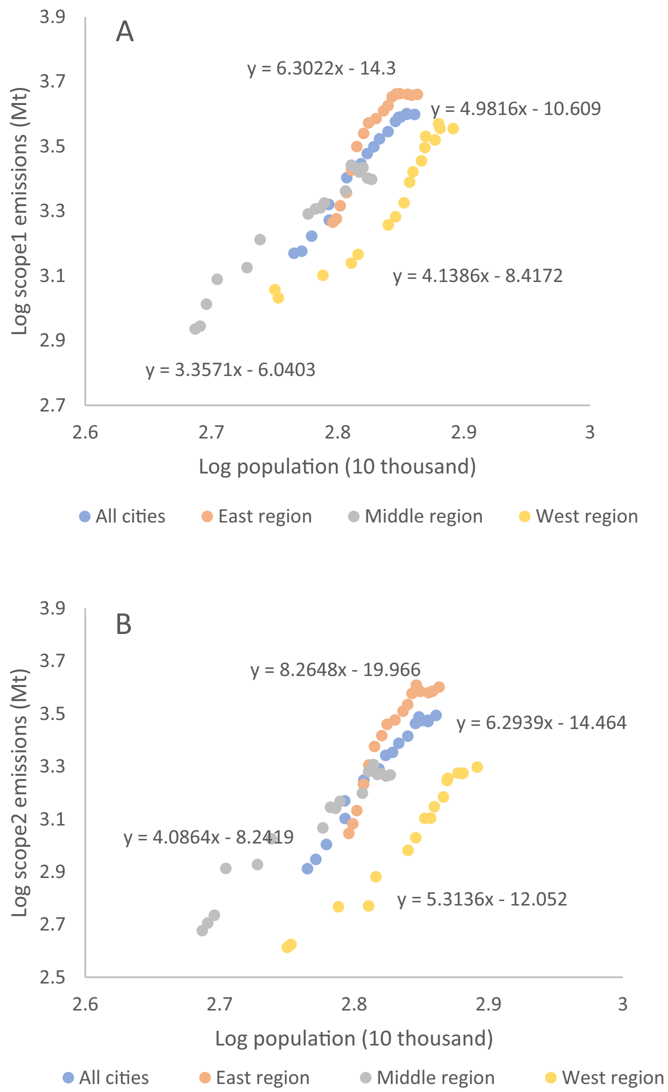

Fig. 2. Comparisons of scaling between carbon emissions and population. (A) Trajectory of scope 1 emissions and population size for all cities and three regions from 2000 to 2016; (B) Trajectory of scope 2 emissions and population size for all cities and three regions from 2000 to 2016.
Notes: The average population and average emissions data for three regions and for all cities are utilized in Fig. 2. Each dot is a year's average data with the horizontal axis represents the average population in logarithmic form for that year and the vertical axis represents the average carbon emissions in logarithmic form.

which affect the carbon emissions in varying extent. Urban population agglomeration involves a process whereby large numbers of people migrate into the urban areas from the countryside and agricultural activities shift to non-agricultural activities. Continuously increased human consumption levels and ongoing industrialization results in increasing energy consumption during urban population expansion, these lead to more carbon emissions. In the process of interactive development of population, economy and society, the proportion of the population in the East region has been continuously increasing from 31.4% in 2000 to 41.8% in 2019, while a downward trend and a U-shaped curve are observed in the Middle and West regions respectively. This dynamic process of population spatial distribution will not only exacerbate the imbalance of regional development, but also increase the pressure on emission mitigation. Therefore, for the East region, the focus should be on improving the ecological environment efficiency of urban development, including improving energy efficiency and optimizing industrial structure. The Middle and West regions will be important growth poles in the future urban development, which need to increase opening up and improve infrastructure on the basis of protecting the ecological environment to undertake industrial and technical transfer from the East region, thereby forming economically vibrant and eco-friendly city clusters.

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CRediT authorship contribution statement

Lu Cheng: Methodology, Formal analysis, Investigation, Writing – original draft. **Zhifu Mi:** Writing – review & editing, Supervision. **Andrew Sudmant:** Conceptualization, Validation, Writing – review & editing, Supervision. **D'Maris Coffman:** Writing – review & editing.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

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