Overall environmental impacts of industrial agglomeration: An energy consumption-based agglomeration accounting for Chinese cities

Abstract: This study addresses the limitation of conventional monetary-based approaches in assessing industrial agglomeration (IA). From a perspective of how energy consumption, agglomeration can be quantified to better demonstrates the relationship between IA and environmental impacts. Drawing on China Emission Accounts and Datasets (CEADs) and the China Statistical Yearbook, we employs the multi-regional input-output (MRIO) method to calculate both local and non-local (embodied) energy consumption across 313 Chinese cities and 42 sectors, and measures agglomeration patterns using the Gini coefficient and location quotient index. This study innovatively utilizes the thermodynamic concept of energy as a metric, thereby distinguishing between output-based and energy-based agglomeration patterns. Our findings reveal that embodied energy consumption is highly concentrated in East China (approximately 4 times that of Northeast China), with Extraction of petroleum and natural gas (I3) exhibiting the highest agglomeration (Gini coefficient: 0.92) and Agriculture, forestry, animal husbandry and fisher (I1) the lowest. Importantly, significant sectoral variations exist between output-based and energy-based agglomeration: increased agglomeration alleviates overall environmental impacts in Manufacturing of communication equipment, computers and other electronic equipment (I20) but exacerbates them in Scientific research and polytechnic services (I36). The findings can serve as a supplement to conventional approaches for assessing IA and offer additional implications for industrial structure adjustments in China.

Keywords: Industrial agglomeration; energy consumption; embodied energy; input-output analysis; Gini index; location quotient

1. Introduction

Industrial agglomeration (IA) refers to the phenomenon where similar industries and their supporting industries cluster in specific geographic areas (Marshall, 1890). Due to variations in natural endowments and government policies across regions, industries tend to concentrate in areas with compatible resources and supportive policy environments. This phenomenon contributes to the emergence of regional IA (Tang et al., 2020). Regional IA further facilitates the concentration of advanced production technologies, specialized labor force, and integrated supply chain networks, thereby enhancing the competitive advantages of the industries in this region. Practical experiences from various countries and regions have shown that industries with competitive advantages often exhibit strong agglomeration characteristics, making IA an important way for countries and regions to enhance their international competitiveness (Guo et al., 2025; Luo and Cao, 2005; Wang et al., 2020; Zheng and Du, 2020). For China, a country experiencing rapid economic development, the evolution of IA has garnered significant attention. A substantial body of research on manufacturing agglomeration (Chen et al., 2022; Chen et al., 2020; Cheng, 2016; Li et al., 2021), service agglomeration (Shao et al., 2017; Wu et al., 2024; Xie and Wang, 2024) and agglomeration of high-tech industries (Ren and Tang, 2024; Song et al., 2023b) has provided significant insights into the trajectory of China's industrial development.

However, the relationship between IA and the environment remains unclear, and it has emerged as a substantial concern, considering the escalating severity of environmental problems in China (Guo et al., 2020). Some studies suggest that IA contributes to mitigating local environmental issues. Wu et al. (2020) empirically confirmed that agglomeration of agricultural activities yields positive externalities on energy efficiency, holding significant implications for reducing agricultural energy consumption and carbon emissions. Yu and Liu (2017) found that the agglomeration of producer services mitigate water and air pollution through industrial structure upgrading, technological innovation, and efficiency improvement. Wen et al. (2024) showed that regional IA improves energy efficiency through its spatial effects on labor pooling, knowledge spillovers, and input sharing. In contrast, there are also some studies that present different perspectives. Wang and Nie (2016) examined the influence of IA within the development zones established in China in 2006 on the water quality of rivers, and found a significant short-term deterioration in water quality around these zones. Shen and Peng (2021) employed a spatial panel model to evaluate environmental efficiency under the influence of IA, revealing a U-shaped relationship between them. Li et al. (2021) discovered that unrelated diversification agglomeration had a significant negative impact on industrial ecological efficiency, and this negative influence would decrease once the agglomeration reached a certain level. These studies have yielded substantial outcomes related to the impacts of IA on local resources and the environment. However, limited attention has been devoted to the impacts of IA on non-local resources and the environment.

In today's increasingly specialized division of labor, the production of one industrial sector often relies on the intermediate inputs provided by both local and non-local industrial sectors. These non-local inputs necessitate resources consumption and generate environmental pollution during their production process. For example, the manufacturing of a car not only entails significant electricity consumption in the local area but also necessitates the procurement of automotive glass from upstream suppliers, whether local or non-local. Similarly, the manufacturing process of automotive glass not only entails significant consumption of energy resources but also requires the input of quartz sand from upstream suppliers. As a result, the entire supply chain of the automotive industry records the total resources consumption and environmental pollution in both local and non-local areas. The agglomeration of the automotive industry in a specific region generates not only localized effects on resources and the environment, but also extended impacts on other regions involved in the production of intermediate goods, such as glass and quartz sand. Consequently, the sole reliance on local assessment fails to elucidate the system-wide impacts. China's industries are currently undergoing a transformation to adopt an efficient and sustainable development model. A thorough evaluation of the overall resources and environmental impacts of IA is highly significant for achieving this transformation in China.

In order to track both local and non-local impacts, the concept of embodied energy is employed. Embodied energy refers to the total amount of energy consumed throughout the entire life cycle of a product, including processing, manufacturing and transportation (Chen and Wu, 2017; Chen and Chen, 2015). On one hand, energy resources are not only important natural resources in the environmental system but also basic production materials in the economic system. The limited availability of energy reserves and their high carbon content render energy resources critical factors in resolving the contradiction between economic development and environmental protection. Thus, the consumption of energy resources reflects the pressure of economic production activities on the natural environment and is selected in this study as the benchmark for evaluating the pressure exerted by regional IA on resources and the environment. On the other hand, compared with direct energy consumption, embodied energy consumption represents a virtual energy flow that measures the total energy input over the entire production history of a product and provides a system-wide modeling framework for overall environmental impact assessment. Extensive studies have been conducted on embodied energy accounting for China at the national or international (Chen et al., 2018; Cui et al., 2015), provincial (Lindner et al., 2013; Zhang and Tang, 2015) and sectoral (Liu et al., 2012; Tian et al., 2013) levels. However, the city-scale embodied energy accounting is limited due to the data unavailability. Recently, Zheng et al. (2021) built the input-output table of Chinese cities based on the entropy framework for the first time. This table has since been utilized to assess urban carbon footprints, virtual water flows, and pollution emissions (Du et al., 2022; Pang et al., 2024; Qian et al., 2022; Wang et al., 2025; Wang et al., 2023; Wei et al., 2023; Xia et al., 2022; Xing et al., 2022; Yang et al., 2024; Zhang et al., 2024; Zhu et al., 2022). Based on the city-level input-output table, this study provides a systems accounting of embodied energy for 313 administrative units and 42 sectors in China in 2017, and then develops an energy consumption-based agglomeration accounting model, in order to clarify relationship between IA and embodied energy consumption. By employing the Gini coefficient and location quotient methods, the energy consumption agglomeration across various regions and industrial sectors in China is measured. The characteristics and causes of energy consumption agglomeration in China are also examined, with the aim of offering recommendations for formulating targeted industrial energy-saving policies and regional resource allocation strategies.

The main contribution of this study lies in two aspects. Firstly, the thermodynamic concept of energy is employed as the metric, and the agglomeration of industrial activities is measured based on their embodied energy consumption for the first time. Through this approach, the total energy consumption and the overall resources and environmental impacts of IA can be disclosed. Secondly, a city-level accounting of embodied energy is carried out for China. The relationship between embodied energy intensity and the degree of IA is innovatively explored across various sectors, which reveals how environmental impacts vary with changes in IA from a dynamic perspective. The subsequent sections of this paper are structured as follows: Section 2 details the methodologies, indices, and data sources, while Section 3 provides a comprehensive presentation of the primary findings. In Section 4, the discussions focus on the distinctions between the methodologies employed in this study and traditional approaches, along with their policy implications. Finally, a conclusion is provided in Section 5.

2. Methods and data

2.1. Multi-regional input-output (MRIO) analysis method

Multi-regional input-output (MRIO) analysis has been widely applied to embodied energy accounting (Dong et al., 2022; Ling et al., 2019; Wang et al., 2022). This study integrates the city-level input-output table with sectoral direct energy consumption data to build an MRIO model that links final consumption activities to total energy consumption across the supply chain. Based on the sectoral biophysical balance, direct and indirect energy consumption associated with the economic activities can be calculated, as shown in Equation (1).

$$e_i^r + \sum_{s=1}^{n}\sum_{j=1}^{m}(\varepsilon_j^s z_{ji}^{sr}) = \varepsilon_i^r (\sum_{s=1}^{n}\sum_{j=1}^{m} z_{ij}^{rs} + \sum_{s=1}^{n} f_i^{rs}) = \varepsilon_i^r x_i^r \tag{1}$$

where the superscripts r and s denote cities, while the subscripts i and j represent sectors. n represents the total number of cities, and m denotes the total number of sectors. e_i^r signifies the direct energy consumption of sector i in city r. ε_i^r represents the embodied energy intensity of sector i in city r, which indicates the sector's total energy consumption to produce per unit of output. z_{ij}^{rs} represents intermediate goods provided by sector i of city r to sector j of city s. f_i^{rs} means the final product provided by sector i of city r to city s. x_i^r represents the total output of sector i in city r, which is calculated as the sum of intermediate output and final output.

The embodied energy in the total output (*EET*) of each sector in each city can therefore be calculated, as shown in Equation (2). EET_i^r represents the total amount of energy resources required to support the production activities of sector i in city r, including both the direct energy consumption of the sector and the indirect energy consumption caused by the intermediate inputs from other sectors.

$$EET_i^r = \varepsilon_i^r x_i^r \tag{2}$$

It is important to note that the calculation of EET_i^r takes the energy consumption of intermediate products into account. Because these intermediate products will be further consumed by other sectors to produce final products, this calculation may lead to the issue of double counting. However, when a sector produces goods, it is not possible to completely differentiate whether the products are intended for intermediate production or final consumption. Each product consumes energy during its production processes. Hence, each product exerts an impact on resources and the environment, necessitating a detailed accounting of its embodied energy. Moreover, the production activities of intermediate products in one sector and their subsequent consumption activities in another sector occur in distinct time periods. It implies that the environmental pressure initially occurs in the production sector and then shifts to the consumption sector. Therefore, EET_i^r is used here to denote the total impacts of this sector on natural resources and the environment, as well as the overall pressure it exerts on them.

2.2. Measurement of industrial agglomeration (IA)

The level of IA essentially reflects the degree of evenness in the distribution of industries. The higher the level of agglomeration, the greater the degree of unevenness in the industrial layout. There are various methods to measure the level of IA, such as location quotient (Dennison, 1939), industry concentration index (Keil, 2017), Gini coefficient (Fedderke and Szalontai, 2009), Herfindahl-Hirschman Index (HHI) (Hamburg et al., 2005), Ellison-Glaeser (E-G) index (Ellison et al., 1994), and the industrial regional agglomeration degrees index (Kvålseth, 2018). This paper selects the Gini coefficient and location quotient as the indicators, which serve distinct yet complementary roles in analyzing IA across Chinese cities. The former quantifies the inequality of geographic distribution for specific industries (ranging from 0 to 1), which facilitates cross-industry comparisons of spatial agglomeration patterns at the national level. While the latter measures the relative specialization of an industry within individual cities, with a value exceeding 1 signals above-average local concentration compared to national benchmarks, thereby highlighting a city's competitive positioning in regional economic divisions. The combined application enables both macro-scale analysis of industrial spatial dynamics and micro-level identification of urban industrial advantages, thereby providing multidimensional insights into China's urban industrial structure patterns. The *EET* indicator, as defined in Equation (2), modifies the approach used in prior research by replacing the total output of industrial sectors measured by monetary units with the total energy consumption of those sectors. The Gini coefficient is commonly used to measure income inequality and the geographical concentration of production. Here, the Gini coefficient is employed to indicate the concentration of energy consumption in industrial sectors. The Gini coefficient based on energy consumption for each industry can be calculated as follows.

$$GE_i = \frac{1}{2n^2 \overline{S_i}} \sum_{r=1}^{n} \sum_{s=1}^{n} | S_i^r - S_i^s | \tag{3}$$

In this equation, $S_i^r = EET_i^r \Big/ \sum_{r=1}^{n} EET_i^r$, representing the proportion of energy consumption in sector *i* of city *r* relative to sector *i* across all cities. $\overline{S_i} = (\sum_{r=1}^{n} S_i^r) \Big/ n$, indicating the average value of S_i^r . The more evenly energy consumption is distributed across cities within an industry, the lower the corresponding Gini coefficient tends to be. The Gini coefficient for an industry is 0 when its energy consumption is uniformly distributed across all cities. Conversely, if an industry's energy consumption is entirely concentrated within a single city, the corresponding Gini coefficient approaches 1.

The location quotient is a specialization index used to measure the spatial distribution of regional factors and indicate the level of industrial specialization. The location quotient based on energy consumption is presented as follows.

$$LQE_i^r = \frac{EET_i^r \Big/ \sum_{i=1}^{m} EET_i^r}{\sum_{r=1}^{n} EET_i^r \Big/ \sum_{r=1}^{n}\sum_{i=1}^{m} EET_i^r} \tag{4}$$

LQE_i^r represents the location quotient of energy consumption of sector *i* in city *r*. The higher the value, the greater the degree of energy consumption agglomeration of the industry in the city. When $LQE_i^r > 1$, it indicates that sector *i* in city *r* has a higher level of energy consumption concentration compared to the national average. When $LQE_i^r = 1$, it suggests that the degree of energy consumption agglomeration for sector *i* in city *r* is at the national average level. When $LQE_i^r < 1$, it implies that sector *i* in city *r* exhibits a lower degree of energy consumption agglomeration compared to the national average.

2.3. Data sources

The 2017 China city-level MRIO table is sourced from China Emission Accounts and Datasets (CEADs). This table covers 42 specific sectors across China's three major industries, as presented in Table S1 in the Appendix. Moreover, 313 administrative units in China, which consist of 309 prefecture-level cities and 4 provinces, and cover over 95 % of the national population and more than 97% of the national gross domestic product (GDP), as depicted in Table S2 in the Appendix. Additionally, sector-specific direct energy consumption, including the direct utilization of crude oil, raw coal, natural gas, hydroelectricity, nuclear power, and other renewable energy sources, is retrieved from the China Statistical Yearbook and CEADs.

2.4. Limitations

This paper initially employs the spatial Gini coefficient to measure the degree of IA, thereby identifying industries with high agglomeration levels in China. Subsequently, it calculates the location quotient of these highly agglomerated industries to determine the cities where these industries are primarily concentrated. However, both the spatial Gini coefficient and the location quotient consider only the variation in industry distribution across regions, without accounting for the internal organizational structure within each industry, such as firm size (Kvålseth, 2018). Consequently, a number of enhanced measurement methods have been successively proposed, such as the HHI (Hamburg et al., 2005) and the E-G index (Ellison et al., 1994). However, due to limitations in data availability for Chinese industries, the input-output table employed in this study to calculate the embodied energy consumption of industrial sectors does not include micro-level firm-level data. Therefore, the Gini coefficient and location quotient methods, which are consistent with the precision level of the available data, were selected for this study. Future research may consider integrating additional methodologies that capture the impact of firm-level characteristics on agglomeration dynamics. In addition, this study is limited by the relatively narrow temporal scope of the data employed, which originates from an earlier period. Future research should prioritize the use of up-to-date data and extend the time frame to facilitate a more comprehensive and dynamic analysis.

3. Results

3.1. Geographical distribution of energy consumption

Figure 1 illustrates the spatial patterns of embodied energy consumption in China. The indicator of *EET*, calculated using Equation (2), denotes the embodied energy consumption for each sector and each city in the figure. For clarity, the 42 sectors considered in this study are grouped into three major industries. The primary industry encompasses sectors that directly extract resources from nature, such as agriculture and mining. The secondary industry involves the processing and manufacturing of raw materials, including activities related to manufacturing and construction. The tertiary industry delivers non-material-based services, such as distribution, technology, finance, and education. The details can be found in Table S1 in the Supplementary materials. The sectoral embodied energy consumption in seven regions, namely Northwest China, Southwest China, South China, Central China, East China, Northeast China, and North China, the details of which can be found in Table S2 in the Supplementary materials, is also presented. The results indicate a significantly higher concentration of energy consumption in East China, whereas the level in Northeast China is the lowest. The total energy consumption in East China is 195.62 TJ, which is nearly 4 times that of the Northeast China (57.16 TJ). East China, Northwest China and North China are three major energy-consuming regions, collectively accounting for 58.73% of China's total energy consumption. Advanced manufacturing, heavy chemical industries, and rapid urbanization have collectively contributed to a substantial increase in energy demand in the eastern region of China. This demand is met through cross-regional energy transfers facilitated by national infrastructure projects, such as the West-to-East Power Transmission and North-to-South Coal Transportation Initiatives. As a result, a model characterized by high economic density and high energy dependency has emerged in East China. In contrast, Central and Northeast China face multiple challenges, such as industrial decline in traditional manufacturing bases, resource depletion, low energy efficiency, population outflows, and delayed realization of policy benefits, all of which jointly constrain the expansion of energy demand.

It can be seen from Figure 1 that the secondary industry takes up a significantly higher proportion of energy consumption compared to the primary and tertiary industries. The energy consumption of China's secondary industry accounts for 76.67% of the total, which is 2.29 times higher than the combined energy consumption of the primary and tertiary industries. In East China, this proportion is even more pronounced, with the secondary industry's energy consumption being 5.28 times that of the primary and tertiary industries combined.

From a city-specific perspective, in the primary sector, only Yulin, Wuzhong, and Qingyang surpass the 1 TJ threshold of energy consumption, with *EET* of 4.63 TJ, 1.28 TJ, and 1.19 TJ, respectively. All three cities are located in Northwestern China, at the core of the Shaanxi-Gansu-Ningxia Energy Golden Triangle. Their positioning as national-level energy and chemical industry bases is fundamentally underpinned by abundant reserves of coal, oil, and natural gas, with the sectors of *Mining and washing of coal* (I2) and *Extraction of petroleum and natural gas* (I3) serving as the primary consumption sectors.

The secondary industry in Shenzhen in Guangdong province records an *EET* of 5.79 TJ, ranking ninth among the cities under consideration. Meanwhile, its tertiary industry ranks fifth with an *EET* of 2.41 TJ. As a pivotal center for electronic information manufacturing, it clearly demonstrates a strong demand-pull effect. Although the ranking of the secondary industry is slightly lower than that of the tertiary industry, its absolute value is still approximately 1.4 times higher. This highlights the energy-consumption characteristics of the secondary industry. The *EET* of secondary and tertiary industries in Shanghai both surpass 6 TJ. The secondary industry ranks eighth, and the tertiary industry leads the nation. As the core city of the Yangtze River Delta, Shanghai maintains substantial demand for both high-end manufacturing and large-scale service consumption. Chongqing's secondary industry exhibits an *EET* of 10.29 TJ, ranking first across the nation. It highlights the distinctive position of Chongqing as a manufacturing center in Southwest China.

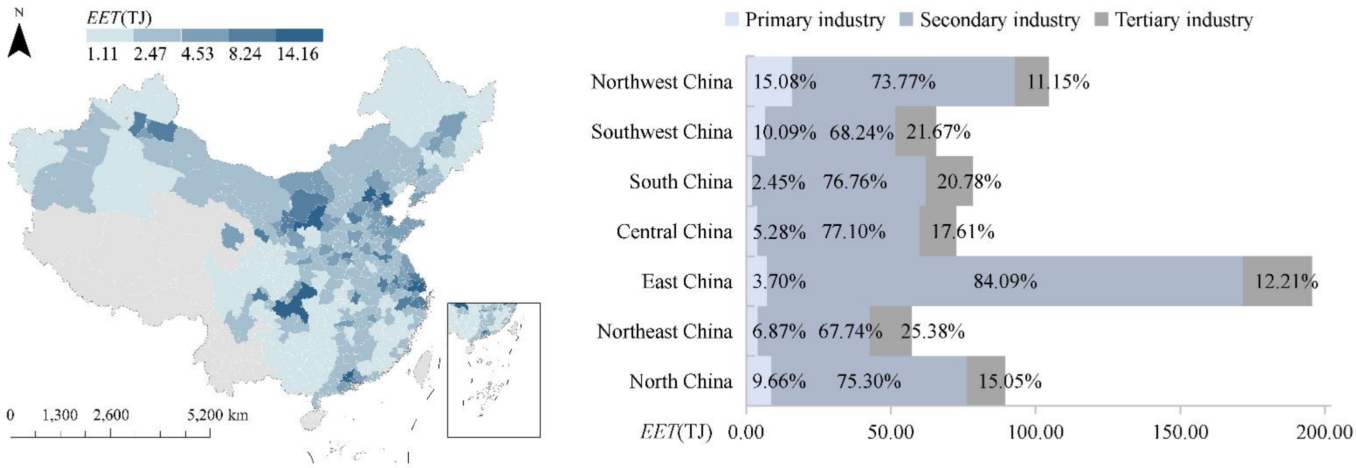

Figure 1 Geographical distribution of embodied energy consumption for China (Cities that are not included in the analysis are assigned a value of 0; *EET* records the embodied energy consumption in the total output of the sector in the city or region.)

3.2. Agglomeration of sectoral energy consumption at national scale

Table 1 presents the Gini coefficients of embodied energy consumption (*GE*) across sectors, which are employed to measure the degree of agglomeration of energy consumption. The sectors are categorized into five groups according to their varying levels of agglomeration, as determined by their respective *GE*. Group 1 comprises sectors exhibiting the highest degree of agglomeration, all of which belong to the primary and secondary industries. The sector of *Extraction of petroleum and natural gas* (I3) exhibits the highest level of agglomeration in terms of energy consumption, with a *GE* of 0.92. Specifically, the top ten cities with the highest energy consumption account for 62.22% of the total energy consumption in this sector. Similarly, the sectors of *Mining and processing of metal ores* (I4) and *Mining and washing of coal* (I2) are also categorized into Group 1, characterized by a high level of agglomeration, with Gini coefficients of 0.84 and 0.83, respectively.

As resource extraction sectors, their concentration characteristics are largely due to the uneven geographical distribution of natural resources across China. Among the secondary industries, the sector of *Comprehensive use of waste resources* (I23) emerges as the most concentrated in terms of energy consumption, with a Gini coefficient of 0.85 calculated based on energy consumption. Notably, the Gini coefficient of this sector based on total output measured in monetary units is also relatively high, reaching 0.82. This uneven distribution is associated with the high-level pollution of waste resources and diverse government policies regarding the waste recycling industry across different cities. There are also two high-tech equipment manufacturing sectors in Group 1, namely *Manufacture of communication equipment, computers and other electronic equipment* (I20) and *Manufacture of measuring instruments* (I21), of which the energy consumption mainly concentrated in Guangdong and Jiangsu provinces, respectively.

Most sectors in Group 2 fall under the category of secondary industries. In this group, *Production and distribution of gas* (I26) is the sole sector of which the Gini coefficient calculated based on energy consumption exceeds that calculated based on total output. It indicates that this sector is embodied energy-intensive, with relatively high energy demand throughout its supply chain. Among the tertiary industries, the sector of *Scientific research and polytechnic services* (I36) ranks first in terms of the agglomeration of energy consumption and is located in Group 2. This sector, which relies heavily on infrastructure such as high-performance computing systems, laboratory equipment, and data centers, is geographically concentrated in major cities and developed economic zones. Its rapid growth is driven by policy incentives and the demand for innovation, which in turn further increases energy consumption both locally and non-locally. The majority of sectors within Groups 3 and 4 fall under the category of the tertiary industry. The sector of *Education* (I39) shows an equal Gini coefficient of 0.57, as calculated based on both energy consumption and total output. The sector of *Agriculture, forestry, animal husbandry and fisher* (I1) belongs to Group 5. This sector has the lowest degree of energy consumption agglomeration, as indicated by a *GE* of 0.39. As a foundational industry, *Agriculture, forestry, animal husbandry and fisher* (I1) is widely distributed across nearly all cities of China. This widespread distribution reduces the spatial agglomeration of energy consumption. Furthermore, the promotion of technologies such as mechanized farming and standardized breeding can also help narrow urban disparities in energy consumption intensity. Additionally, policies supporting agricultural and rural development, such as power grid modernization and subsidies for agricultural machinery, have improved the distribution of energy infrastructure and mitigated regional imbalances in energy usage.

Table 1 Gini coefficient based on energy consumption for the sectors

Group	Sector	*GE*	*GE* / *G*	Group	Sector	*GE*	*GE* / *G*
1 (*GE*≥0.80)	I3	0.92	0.98	3 (0.60≤*GE* ＜0.70)	I32	0.68	0.92
	I23	0.85	1.04		I14	0.67	1.02
	I4	0.84	1.02		I9	0.67	0.95
	I20	0.84	0.95		I41	0.66	0.96
	I2	0.83	0.98		I34	0.66	1.02
	I21	0.81	0.96		I28	0.65	1.02
2 (0.70≤*GE* ＜0.80)	I36	0.79	0.97		I24	0.64	0.71
	I7	0.78	1.00		I37	0.63	0.95
	I18	0.78	0.95		I33	0.63	0.90
	I11	0.78	0.95	4 (0.50≤*GE* ＜0.60)	I12	0.59	0.92
	I22	0.77	0.97		I40	0.58	0.97
	I35	0.77	1.00		I29	0.58	0.91
	I8	0.76	0.97		I42	0.58	1.07
	I19	0.75	0.97		I25	0.57	0.96
	I26	0.75	1.03		I39	0.57	1.00
	I16	0.73	0.96		I30	0.56	0.92
	I27	0.71	1.00		I38	0.56	1.00
	I10	0.71	0.98		I6	0.51	0.87
	I17	0.71	0.95	5 (*GE*＜ 0.50)	I13	0.48	0.81
	I15	0.70	0.99		I31	0.46	0.78
	I5	0.70	0.98		I1	0.39	0.96

Notes: GE and *G* respectively denote the Gini coefficient of embodied energy consumption and total output.

3.3. Agglomeration of sectoral energy consumption at the city scale

To systematically investigate the agglomeration patterns of sectoral energy consumption among Chinese cities, this study selects three representative sectors from primary, secondary, and tertiary industries, respectively. As a typical primary sector, *Agriculture, forestry, animal husbandry and fisher* (I1) belongs to Group 5 in Table 1 and has the lowest Gini coefficient based on energy consumption. In contrast, *Manufacturing of communication equipment, computers and other electronic equipment* (I20) and *Scientific research and polytechnic services* (I36) belong to Group 1 and Group 2 respectively, both of which have high Gini coefficients based on energy consumption. The location quotient method is employed to analyze the spatial concentration of energy consumption across cities for the three sectors, and it is compared with the spatial concentration of total output, as depicted in Figure 2. The left-hand map displays the two indicators for the cities: the blue shading denotes the magnitude of the location quotient value of energy consumption, as represented by the indicator of *LQE*; whereas the red scatter points is proportional to location quotient value of total output, as represented by *LQX*.

As the sector with the lowest Gini coefficient, *Agriculture, forestry, animal husbandry and fisher* (I1) exhibits the lowest degree of agglomeration of energy consumption among the three selected sectors, illustrated in Figure 2(a). For the sector of *Agriculture, forestry, animal husbandry and fisher* (I1), cities such as Kashi, Suihua, Shuangyashan and Boertalamenggu lead the rank in terms of agglomeration of energy consumption indicated by the indicator of *LQE*. When viewed in conjunction with total output, however, the *LQX* values of these cities are not as prominent as their *LQE* values, which indicates low energy-input-output ratios. These cities mainly located in Xinjian and Heilongjiang provinces, which function as national commodity grain bases and timber reserves. In these cities, the rich resource endowments and the inefficient utilization patterns jointly lead to an increase in energy consumption both locally and non-locally, as well as the increased pressure on the environment.

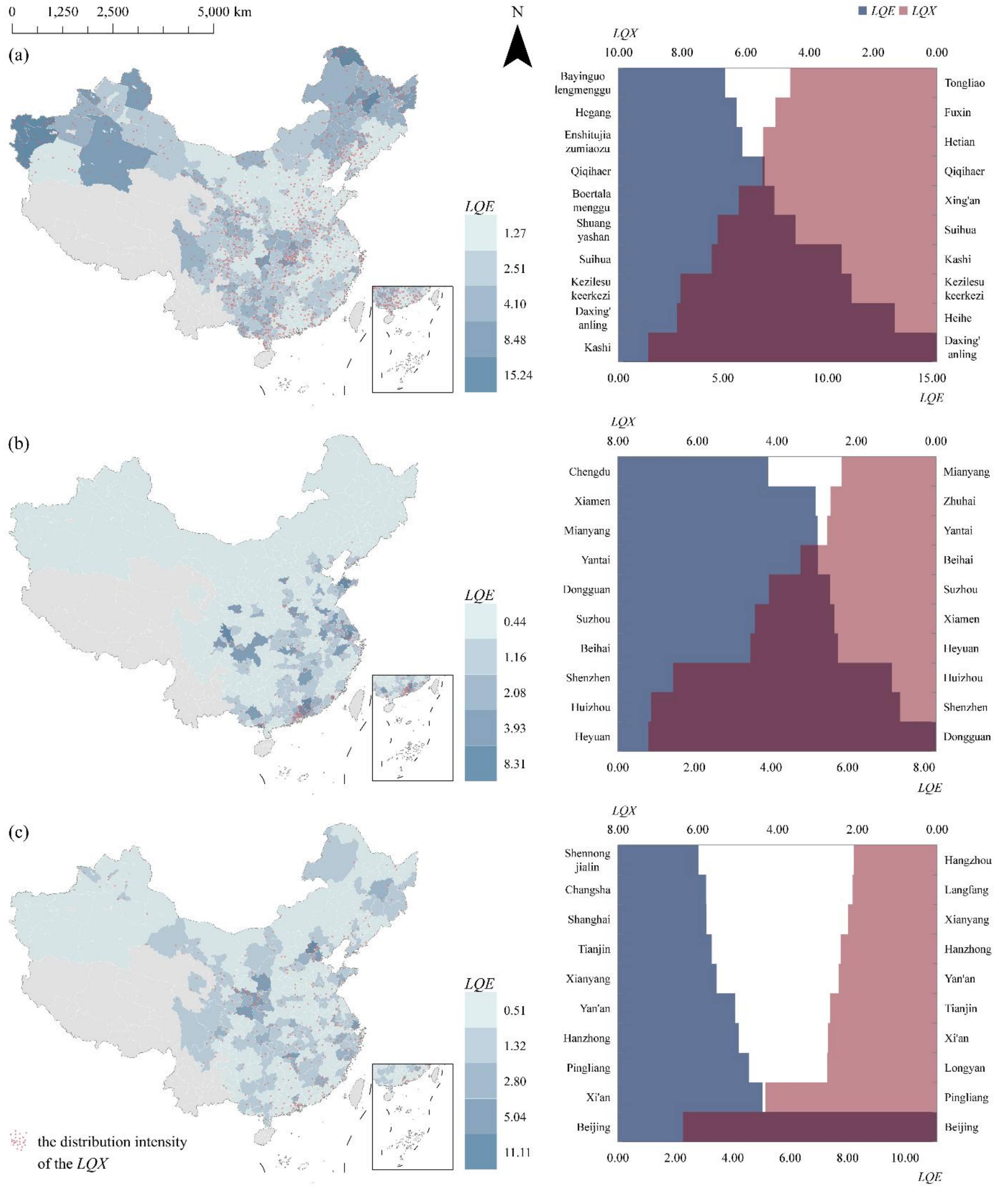

Figure 2 Agglomeration of energy consumption for representative sectors at the city scale: (a) *Agriculture,*

***forestry, animal husbandry and fisher* (I1); (b) *Manufacturing of communication equipment, computers and other electronic equipment* (I20); (c) *Scientific research and polytechnic services* (I36) (Cities that are not included in the analysis are assigned a value of 0; *LQE* and *LQX* respectively denote the location quotient values of energy consumption and total output.)**

The energy consumption of *Manufacturing of communication equipment, computers and other electronic equipment* (I20) is mainly concentrated in Guangdong province, the Jiangsu-Zhejiang-Shanghai region, and Sichuan province. The three cities with the highest *LQE* are all located in Guangdong province, namely Heyuan (8.31), Huizhou (7.37), and Shenzhen (7.16). As a representative sector of secondary industry, *Manufacturing of communication equipment, computers and other electronic equipment* (I20) encompasses end-products including telecommunications base stations, smartphones, laptops, servers, wearables, and integrated circuits. It supplies both capital goods and the infrastructure indispensable to the city's digital and smart upgrade, and its production is highly energy-intensive. The energy consumption related to this sector in Shenzhen is calculated to be 1.03 TJ, positioning Shenzhen as the sole city surpassing the 1 TJ threshold. Shenzhen hosts a complete 3C-electronics ecosystem and is home to global brands such as Huawei, Zhongxing Telecom Equipment, BYD and Dajiang. The local manufacturing and sales activities of these brands give rise to a significant energy demand throughout the supply chain.

As illustrated in Figure 2(c), the energy consumption in the sector of *Scientific research and polytechnic services* (I36) is primarily concentrated in Beijing, with the highest *LQE* reaching 11.11. It is noteworthy that total energy consumption associated with this tertiary sector in Beijing (1.41 TJ) surpasses that associated with certain secondary sectors, such as *Manufacturing of communication equipment, computers and other electronic equipment* (I20) (0.23 TJ). Since 2014, as Beijing has gradually eliminated non-capital functions and relocated energy-intensive industries, a notable transformation has occurred in the city's direct energy utilization. Sectors characterized by high energy consumption, high water usage, and high pollution levels have been relocated, and modern service sectors have witnessed expansion in Beijing. Nevertheless, it is important to emphasize that despite the fact that service sectors generally rely on cleaner fuels like electricity and natural gas, their full-life-cycle energy footprint cannot be overlooked. Overall, the embodied energy of the tertiary industry accounts for 42.11% of the total embodied energy in Beijing.

4. Discussions

4.1. Comparison with the traditional measurement method

Energy consumption-based accounting for IA can be considered as an input-oriented approach, contrasting with the output-oriented methods based on total output used in previous studies. Total output-based accounting for IA emphasizes the ultimate outcomes of the industry, reflecting its economic scale and market competitiveness across various regions. It is widely regarded that a high gross output of an industry serves as a strong indicator of substantial economic activity within that industry in a given region, as well as its notable contribution to overall economic growth. In contrast, energy consumption-based accounting for IA places greater emphasis on the efficiency of production processes and resource utilization within industries. By measuring IA through energy consumption, it provides a more intuitive reflection of regional variations in resource dependency and industrial production structure. Consequently, this approach enables a more comprehensive assessment of the environmental impacts associated with industrial activities.

The indicator of GE/G presented in Table 1 compares the degree of IA based on embodied energy consumption with that based on total output, which is the traditional measurement method. The results indicate that, among the 42 sectors investigated, 7 sectors exhibit a higher Gini coefficient in energy consumption than that in total output. It suggests that these 7 sectors have undergone a development process characterized by disproportionately high energy consumption relative to the economic value generated. The sector of *Public administration, social insurance, and social organizations* (I42) holds the highest GE/G value of 1.07. Unlike the primary and secondary sectors, the production activities of the sector of *Public administration, social insurance, and social organizations* (I42) are largely influenced by government regulation. Through centrally directed transfers as a fiscal irrigation system, fiscal funds are reallocated across provinces and then redistributed to needy ones (Dai and Zhang, 2018; Yin and Xu, 2011; Zhou, 2016). This second-round distribution equalizes budgetary revenues and, in statistical terms to a certain degree, produces a markedly even spatial pattern of reported output (Yin et al., 2007). Energy consumption, however, is governed by production structure and technical levels, which vary across different cities (Li, 2015). For this sector, total energy consumption of the top 10 cities, as reflected by the indicator of *EET*, account for 29.46% of national total. As a result, the energy consumption of this sector exhibits a relatively uneven distribution. In contrast, the indicator of GE/G for the sector of *Accommodation and Catering* (I31) is calculated to be 0.78, indicating the degree of IA based on the energy consumption is significantly lower than that based on the total output. From the perspective of total output, the sector of *Accommodation and Catering* (I31) in cities such as Shanghai, Beijing, Chongqing, Guangzhou, and Shenzhen exhibits a high degree of agglomeration. However, when energy consumption in this sector is taken into account, several less-developed cities, including Langfang, Shijiazhuang, and Handan, also show significant levels of agglomeration. Although high-end hotels and chain restaurants in large cities consume a greater overall amount of energy, they can improve energy efficiency through economies of scale, such as centralized energy supply systems, and through technological advancements (Fan et al., 2021). Consequently, they can reduce the gap in total energy consumption when compared to small cities (Jiang et al., 2011). For instance, the top 6 cities in terms of total output within the sector of *Accommodation and Catering* (I31) contribute 17.50% of national total output, while their energy consumption represents only 12.23% of the national total.

In addition to total output, other indicators, such as the added value, number of enterprises, and employment data have been used to analyze IA in previous studies, as shown in Table 2. Song et al. (2023a) utilized the sectoral total output across 284 prefecture-level cities in China in 2017 to assess the degree of IA. Their findings indicated a distinct spatial distribution pattern, characterized by relatively lower levels in western regions and higher levels in eastern regions. In contrast, from the perspective of energy consumption, our study reveals that northern cities such as Tangshan and Eerduosi exhibit substantial upward shifts in their rankings. This is attributed to their inefficient energy utilization, which is characterized by a high level of energy input relative to the low output level. Cheng (2016) utilized the quantity of employment to compute the degree of manufacturing agglomeration, and explored the interaction between manufacturing agglomeration and environmental pollution. They pointed out that provinces such as Hebei, Shanxi, and Shandong demonstrated a feature of a high level of manufacturing agglomeration accompanied by high pollution levels. In our study, both local and non-local energy consumption are taken into consideration. It is found that among the top 20 cities in the secondary industry which is mostly characterized by manufacturing, only Tangshan and Shijiazhuang are situated in Hebei province. Guangdong and Jiangsu provinces, where a larger share of their final demand is satisfied by non-local production activities, lead to a significant transfer of energy consumption to production areas, and therefore exhibit a higher level of agglomeration when non-local energy consumption is considered.

Table 2 Comparison with previous studies on IA

	IA type	Methods	Main result
Liu and He (2024)	Added value of the industry	Location entropy; E-G index	The synergistic agglomeration of manufacturing and modern service industries significantly promotes the high-quality development of the manufacturing industry in China.
Yu et al. (2022)	Number of the enterprises	Kernal density function	The agglomerations of manufacturing industries are distributed in the central and south-eastern regions within the Greater Bay Area of China.
Song et al. (2023a)	Total industrial output	Location entropy	The agglomeration of industrial activities exerts a positive influence on the total industrial wastewater discharge and a negative influence on the total industrial smoke and dust discharge.
Cheng (2016)	Number of employees	Location quotient	Manufacturing agglomeration aggravates environmental pollution, while environmental pollution restrains manufacturing agglomeration.
This study	Energy consumption of sectors	Gini; Location quotient	The agglomeration of certain industries can improve energy efficiency, and alleviate environmental pressures.

4.2. Overall environmental impact of IA

The agglomeration of production activities in a particular region promotes intensive energy resource utilization locally, thereby generating increased direct environmental pressures within that area. Simultaneously, the local demand for intermediate inputs drives energy resource consumption in other regions, thereby expanding the region's indirect environmental impacts beyond its geographical boundaries. In this section, the correlation between IA and overall environmental impacts is examined for the three respective sectors, as depicted in Figure 3. The bubbles in the figure represent the cities, and their radii are proportional to the cities' total energy consumption, as indicted by the index of *EET*.

In Figure 3 (a), the agglomeration of agricultural activities within the city is denoted by the city's index of *LQX* of *Agriculture, Forestry, Animal Husbandry and Fisher* (I1), which is presented on the horizontal axis. The overall environmental impacts of such agglomeration are represented by the index of ε that records the total energy consumption per unit of output associated with the sector in the city, and is shown on the vertical axis. As can be observed from the plot, the distribution of the bubbles approximates a straight line, and there are no discernible downward or upward trends. This indicates that the degree of agglomeration of agricultural activities does not directly affect the level of their environmental impacts. In particular, the Daxing'anling region exhibits a higher degree of agglomeration in agricultural activities, with an *LQX* of 9.07, in contrast to Akesu, which has a lower agglomeration degree with an *LQX* of 4.20. However, ε of the Daxing'anling region and Akesu are 2.05E+04 J/yuan and 1.98E+04 J/yuan, respectively, indicating that the overall environmental impacts of the agricultural activities in the Daxing'anling region are comparable to those in Akesu.

For the sector of *Manufacturing of communication equipment, computers and other electronic equipment* (I20) depicted in Figure 3 (b), the distribution of the bubbles forms a line with a negative slope. It suggests that the higher the degree of agglomeration of manufacturing activities, the lower the environmental impacts they impose. The manufacturing activities are primarily concentrated in cities belongs to Guangdong province, with relatively lower environmental impacts. As one of the leading manufacturing provinces, Guangdong has a comprehensive industrial chain covering operating systems, semiconductor chip design, component manufacturing, end-product assembly, and application development. Consequently, the majority of high-energy-consuming processes are located within its provincial boundaries, creating a significant spatial synergy. Dongguan, a representative city in Guangdong Province, exhibits the highest level of manufacturing agglomeration with an *LQX* of 7.23. However, ε of Dongguan is only 0.73 J/yuan, indicating a relatively low level of environmental impacts. Dongguan is characterized by a diverse array of industrial categories and a relatively well - established industrial system. It clusters high-tech enterprises in fields such as electronic materials, critical components, intelligent components, and end-product manufacturing, which serves as an impetus for the expansion of its industrial economic scale and the high-quality development of its manufacturing economy. When the sectors within this city achieve a high degree of agglomeration, the operation of the entire industrial chain leads to the growth rate of upstream energy consumption being slower than that of local added value, and the energy consumption per unit of total output has decreased.

It is worth noting that the sector of *Scientific research and technical services* (I36) shows a different result. In Figure 3 (c), a slight upward trend is observable, suggesting a positive correlation between the degree of IA and the level of environmental impacts. Beijing, the capital of China, plays a leading role in terms of *LQX*, and its ε is 1.12 J/yuan. In contrast, for Tianjin, a neighboring city of Beijing, its *LQX* is 2.68, 57.93% lower than that of Beijing, and its ε is also lower, at 0.89 J/yuan. Distinguished from the secondary sector, the tertiary sector exhibits relatively few energy-intensive production activities in local regions. Nevertheless, there exists substantial energy consumption in non-local areas to underpin the development of the local tertiary sector via the supply chains. For instance, the scientific research in Beijing necessitates computers that are produced in other cities and result in energy consumption in those production areas. In fact, this phenomenon can also be observed from Figure 3 (d), which provides an overall view of the three representative sectors. As reflected by the size of the bubbles, *EET* of the sector of *Scientific research and technical services* (I36) is particularly prominent among the three sectors. This is because the longer the production chain or the more the intermediate inputs of a sector, the higher the energy consumption it has to account for, which is manifested as a higher *EET*. As a knowledge-intensive service sector, *Scientific research and technical services* (I36) is highly reliant on intermediate inputs from other industries and thus has a longer production chain. The value of ε represents the amount of both local and non-local energy consumption per unit of output of the sectors. The proportion of non-local energy consumption intensity to ε is therefore greater in the tertiary sector than in the secondary sector.

Moreover, regional IA has direct impacts on the production technology and energy efficiency in the local area, whereas it has indirect, relatively weaker, and even distinct impacts on those in non-local areas. Therefore, compared to the sector of *Manufacturing of communication equipment, computers and other electronic equipment* (I20), the agglomeration of the sector of *Scientific research and technical services* (I36) present a different impact on the value of ε, owing to the different non-local contributions to ε in the two sectors.

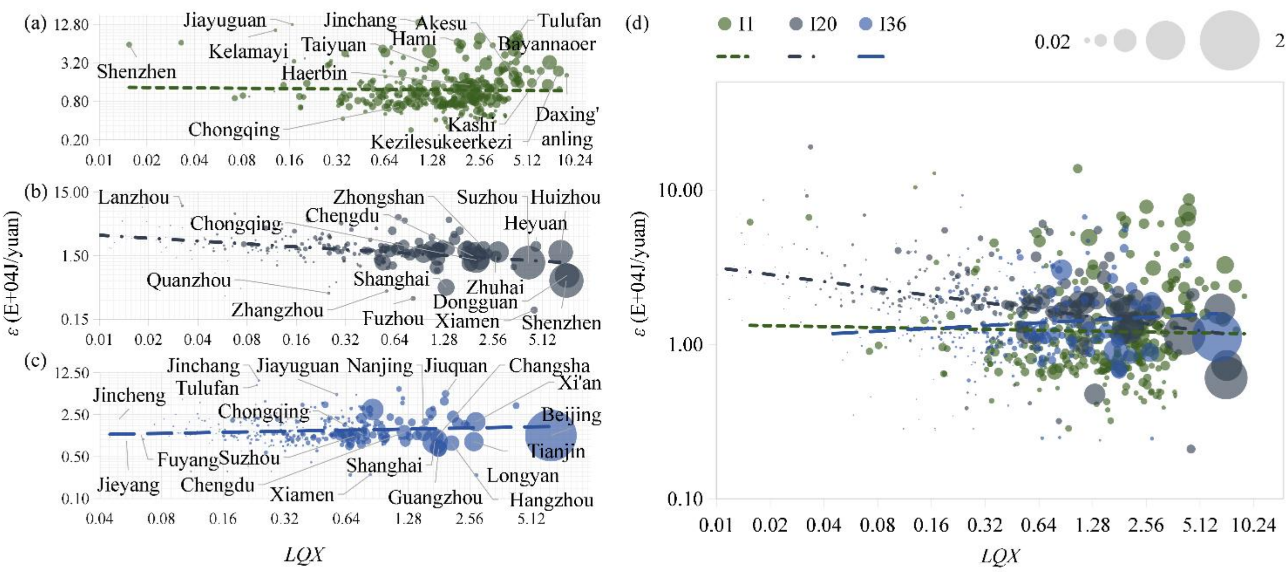

Figure 3 Overall environmental impacts of IA for: (a) ***Agriculture, forestry, animal husbandry and fisher*** **(I1), (b)** ***Manufacturing of communication equipment, computers and other electronic equipment (I20)*****, (c)** ***Scientific research and polytechnic services*** **(I36), (d) the three representative sectors. (Bubbles are used to denote cities, and**

the radius of each bubble corresponds to the city's *EET* value; *LQX* denotes the location quotient value of total output and ε measures the embodied energy intensity.)

4.3. Policy implications

This study offers a supplementary instrument to conventional approaches for evaluating IA by utilizing the concept of embodied energy. As a result, the findings have further implications for the adjustment of the industrial structure in China, from the perspective of the energy demand throughout the entire supply chain. Two primary policy recommendations targeting the enhancement of the effectiveness of industrial structural adjustment in China are presented herein. First, the correlation between energy consumption agglomeration and total output agglomeration across sectors reflects the substantial local and non-local environmental impacts of IA. Local environmental impacts have been recognized in current research and policy frameworks; however, non-local environmental impacts remain largely overlooked. The concentration of industrial production activities in a given region necessitates substantial intermediate inputs, thereby imposing environmental pressures on the regions responsible for producing these inputs. Especially, the agglomeration of the tertiary industry, such as the sector of *Scientific research and polytechnic services* (I36), primarily occurs in developed cities. Although it does not result in substantial direct environmental impacts, it may produce significant indirect environmental effects on other regions, the majority of which are economically and technologically underdeveloped areas characterized by low energy efficiency. Therefore, the environmental management in both the region experiencing the process of IA and the regions producing intermediate inputs should be considered in a coordinated manner. For sectors with significant non-local environmental impacts, the incorporation of environmental compensation mechanisms should be considered during policy design.

Second, for the typical secondary sector, *Manufacturing of communication equipment, computers and other electronic equipment* (I20), it is observed that as the degree of agglomeration increases, the embodied energy consumption intensity and the overall environmental impacts decrease. On the one hand, the concentration of production activities in a given region reduces local energy consumption intensity associated with these activities due to economies of scale. On the other hand, such concentration creates substantial demand for intermediate inputs from other regions, thereby lowering the energy consumption intensity of both the production and transportation of these inputs in other regions, driven by the combined effects of scale economies and technology spillovers. Consequently, the phenomenon of IA has the potential to improve energy consumption efficiency both at the local level and across distant segments throughout the entire supply chain. In contrast, for the tertiary sector, specifically *Scientific research and technical services* (I36), a distinct result is observed. As the degree of agglomeration increases, both the embodied energy intensity and the overall environmental impacts also increase. Because the development of tertiary sector requires few local production activities, the local energy intensity is extremely low compared to the non-local energy intensity in this sector. The impacts of the IA on non-local production technology and energy efficiency are not significant, due to geographic distance. Therefore, non-local energy efficiency does not improve along with the agglomeration of *Scientific research and technical services* (I36). It is crucial to promote industrial restructuring and environmental governance strategies that are specifically adapted to the unique characteristics of each sector.

5. Conclusions

In this study, industrial agglomeration (IA) is measured by utilizing sectoral total energy consumption, which differs from conventional evaluation methods that depend on monetary benchmarks. The concept of embodied energy is employed in this study to quantify both direct and indirect, that is, total energy demands across the supply chains, which enables the measurement of overall impacts of sectoral production activities on natural resources and the environment. The multi-regional input-output (MRIO) method is used for embodied energy accounting, and the Gini coefficient and location quotient index are utilized to assess the degree of agglomeration of energy consumption among 313 cities and 42 sectors in China.

The spatial distribution of embodied energy consumption varies among different sectors across the nation. East China is demonstrated to be the largest consumer of embodied energy, and the embodied energy consumption of the secondary industry in this region is more than five times that of the combined primary and tertiary industries. The embodied energy consumption in Northeast China is the lowest, accounting for only one-quarter of that in East China. Resource extraction sectors, such as the sector of *Extraction of petroleum and natural gas* (I3) exhibit a high degree of agglomeration in terms of energy consumption because of the unbalanced distribution of resource reserves in China. Agricultural sectors, represented by the sector of *Agriculture, forestry, animal husbandry and fisher* (I1) show a low degree of energy consumption agglomeration. The sectors of *Comprehensive use of waste resources* (I23) and *Scientific research and polytechnic services* (I36) exhibit the highest degree of agglomeration in terms of energy consumption among the secondary and tertiary sectors, respectively, and their energy consumption mainly concentrated in Fuyang and Beijing. Notable disparities are observed between the agglomeration of energy consumption and that of total output, which indicates the varying energy efficiency across different cities. For the sector of *Agriculture, forestry, animal husbandry and fisher* (I1), Daxing'anling shows the highest degree of agglomeration from the conventional perspective of total output. Meanwhile, Kashi ranks first in terms of energy consumption agglomeration, owing to the relatively lower energy efficiency in the supply chain. Hence, the utilization of both local and non-local resources and their environmental impacts should be equally considered in the process of IA. The relationship between IA and overall environmental impacts is investigated, and varying results are observed across the sectors. For the sector of *Manufacturing of communication equipment, computers and other electronic equipment* (I20), of which the energy consumption is primarily concentrated in Guangdong province, an obvious trend is observed: as the degree of IA increases, overall environmental impacts decrease. However, an inverse trend is observed in the sector of *Scientific research and polytechnic services* (I36). Beijing is the leading energy consumer in this sector, but the majority of its energy consumption takes place outside Beijing. The non-local energy consumption accounts for a larger proportion in the total energy consumption of this tertiary sector than in that of the secondary sector. Regional IA impose distinct impacts on local and non-local energy consumption owing to geographical distance and administrative division. Consequently, this leads to the different trends observed in the two sectors. These differences have implications for the formulation of targeted policies related to the industrial adjustment in different cities.

The findings of this study are compared with those in previous IA studies that rely on conventional indicators, such as economic output and employment data. This study presents an innovative accounting framework for IA grounded in the thermodynamic concept, thereby enhancing conventional methodologies for the evaluation of IA. Non-local environmental impacts of IA that were overlooked in previous studies are highlighted in this study by taking into account the entire supply chain. The findings of this study offer supplementary implications for the nationwide structural transformation and sustainable development at the city and sectoral levels.

Acknowledgement

This study was supported by the National Natural Science Foundation of China (No. 72474227).

References

Chen B, Li J S, Wu X F, Han M Y, Zeng L, Li Z and Chen G Q. 2018. Global energy flows embodied in international trade: A combination of environmentally extended input-output analysis and complex network analysis. Applied Energy 210: 98–107.
Chen G Q and Wu X F. 2017. Energy overview for globalized world economy: Source, supply chain and sink. Renewable & Sustainable Energy Reviews 69: 735–749.
Chen S Q and Chen B. 2015. Urban energy consumption: Different insights from energy flow analysis, input-output analysis and ecological network analysis. Applied Energy 138: 99–107.
Chen Y F, Xu Y and Wang F Y. 2022. Air pollution effects of industrial transformation in the Yangtze River Delta from the perspective of spatial spillover. Journal of Geographical Sciences 32(1): 156–176.
Chen Y N, Ma J H, Miao C H and Ruan X L. 2020. Occurrence and environmental impact of industrial agglomeration on regional soil heavy metalloid accumulation: A case study of the Zhengzhou Economic and Technological Development Zone (ZETZ), China. Journal of Cleaner Production 245.
Cheng Z H. 2016. The spatial correlation and interaction between manufacturing agglomeration and environmental pollution. Ecological Indicators 61: 1024–1032.
Cui L B, Peng P and Zhu L. 2015. Embodied energy, export policy adjustment and China's sustainable development: A multi-regional input-output analysis. Energy 82: 457–467.
Dai H and Zhang S. 2018. Spatial Spillover of Public Expenditure and Effects on City Efficiency:Based on Regions of Jing-Jin-Ji-Meng. Journal of Central University of Finance & Economics(06): 119–128.
Dennison S R. 1939. Report on the Location of Industry in Great Britain. by Political and Economic Planning. The Economic Journal 49: 331–335.
Dong K Y, Wang J D and Taghizadeh-Hesary F. 2022. Assessing the embodied CO2 emissions of ICT industry and its mitigation pathways under sustainable development: A global case. Applied Soft Computing 131.
Du H B, Liu H W and Zhang Z K. 2022. The unequal exchange of air pollution and economic benefits embodied in Beijing-Tianjin-Hebei's consumption. Ecological Economics 195.
Ellison G, Glaeser E L, Ellison G and National Bureau of Economic R. 1994. Geographic Concentration in U.S. Manufacturing Industries : a Dartboard Approach. Cambridge, Mass, National Bureau of Economic Research.
Fedderke J and Szalontai G. 2009. Industry concentration in South African manufacturing industry: Trends and consequences, 1972-96. Economic Modelling 26(1): 241–250.
Guo L, Tang M, Wu Y, Bao S and Wu Q. 2025. Government-led regional integration and economic growth: Evidence from a quasi-natural experiment of urban agglomeration development planning policies in China. Cities 156: 105482.
Guo Y H, Tong L J and Mei L. 2020. The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization. Journal of Cleaner Production 258.

Hamburg B, Hoffmann M and Keller J (2005). Consumption, Wealth and Business Cycles in Germany, CESifo.
Jiang H, Xiao H, Li G and yuan F. 2011. Research on the spatial layout of five-star hotels in the Yangtze River Delta. Commercial Research(07): 79–83.
Keil J. 2017. The trouble with approximating industry concentration from Compustat. Journal of Corporate Finance 45: 467–479.
Kvålseth T O. 2018. Relationship between concentration ratio and Herfindahl-Hirschman index: A re-examination based on majorization theory. Heliyon 4(10): e00846.
Li L. 2015. Dynamic evolution, regional disparity and cause identification of China's energy performance: Based on a new total-factor energy productivity change indicator. Journal of Management World(11): 40–52.
Li X H, Zhu X G, Li J S and Gu C. 2021. Influence of Different Industrial Agglomeration Modes on Eco-Efficiency in China. International Journal of Environmental Research and Public Health 18(24).
Lindner S, Liu Z, Guan D B, Geng Y and Li X. 2013. CO2 emissions from China's power sector at the provincial level: Consumption versus production perspectives. Renewable & Sustainable Energy Reviews 19: 164–172.
Ling Z L, Huang T, Li J X, Zhou S, Lian L L, Wang J X, Zhao Y, Mao X X, Gao H and Ma J M. 2019. Sulfur dioxide pollution and energy justice in Northwestern China embodied in West-East Energy Transmission of China. Applied Energy 238: 547–560.
Liu Y and He Z. 2024. Synergistic industrial agglomeration, new quality productive forces and high-quality development of the manufacturing industry. International Review of Economics & Finance 94: 103373.
Liu Z, Geng Y, Lindner S, Zhao H Y, Fujita T and Guan D B. 2012. Embodied energy use in China's industrial sectors. Energy Policy 49: 751–758.
Luo Y and Cao L. 2005. A Positive Research on Fluctuation Trend of China's Manufacturing Industrial Agglomeration Degree. Economic Research Journal(08): 106–115+127.
Marshall A. 1890. Principles of Economics, Palgrave Macmillan London.
Pang Q H, Liu X, Zhang L N and Chiu Y H. 2024. Temporal-spatial evolution of environmental inequality of embodied energy transfer within inter-provincial trade of China. Energy 299.
Qian Y K, Zheng H R, Meng J, Shan Y L, Zhou Y and Guan D B. 2022. Large inter-city inequality in consumption-based CO
emissions for China's pearl river basin cities. Resources Conservation and Recycling 176.
Ren F and Tang G. 2024. Agglomeration effects of high-tech industries: Is government intervention justified? Economic Analysis and Policy 83: 685–700.
Shao S, Tian Z H and Yang L L. 2017. High speed rail and urban service industry agglomeration: Evidence from China's Yangtze River Delta region. Journal of Transport Geography 64: 174–183.
Shen N and Peng H. 2021. Can industrial agglomeration achieve the emission-reduction effect? Socio-Economic Planning Sciences: 100867.
Song C Z, Chen Y B, Yin G W and Hou Y M. 2023a. Spatial correlation and influencing factors of industrial agglomeration and pollution discharges: a case study of 284 cities in China. Environmental Science and Pollution Research 30(1): 434–450.
Song Y, Yang L, Sindakis S, Aggarwal S and Chen C. 2023b. Analyzing the Role of High-Tech Industrial Agglomeration in Green Transformation and Upgrading of Manufacturing Industry: the Case of China. Journal of the Knowledge Economy 14(4): 3847–3877.

Tang C, Chen W, Wu J, Zhou G, Wang M and Guo X. 2020. Spatial distribution and industrial agglomeration characteristics of development zones in the Yangtze River Economic Belt. Scientia Geographica Sinica 40(4): 657–664.
Tian Y H, Zhu Q H and Geng Y. 2013. An analysis of energy-related greenhouse gas emissions in the Chinese iron and steel industry. Energy Policy 56: 352–361.
Wang B and Nie X. 2016. Industrial Agglomeration and Environmental Governance:The Power or Resistance——Evidence from a Quasi-natural Experiment of Establishment of the Development Zone. China Industrial Economics(12): 75–89.
Wang L, Xue Y, Chang M and Xie C. 2020. Macroeconomic determinants of high-tech migration in China: The case of Yangtze River Delta Urban Agglomeration. Cities 107: 102888.
Wang Q, Jiang F, Li R and Wang X. 2022. Does protectionism improve environment of developing countries? A perspective of environmental efficiency assessment. Sustainable Production and Consumption 30: 851–869.
Wang X, Long R, Chen H, Na J and Wang Y. 2025. Invisible chains: Tracking urban carbon-economic inequality in China. Cities 164: 106075.
Wang Y, Guo J, Yue Q, Chen W-Q, Du T and Wang H. 2023. Total CO2 emissions associated with buildings in 266 Chinese cities: characteristics and influencing factors. Resources, Conservation and Recycling 188.
Wei J, Lei Y, Liu L and Yao H. 2023. Water scarcity risk through trade of the Yellow River Basin in China. Ecological Indicators 154.
Wen Y Y, Yu Z L, Xue J J and Liu Y. 2024. How heterogeneous industrial agglomeration impacts energy efficiency subject to technological innovation:Evidence from the spatial threshold model. Energy Economics 136.
Wu J Z, Ge Z M, Han S Q, Xing L W, Zhu M S, Zhang J and Liu J F. 2020. Impacts of agricultural industrial agglomeration on China's agricultural energy efficiency: A spatial econometrics analysis. Journal of Cleaner Production 260.
Wu X L, Zhu M J, Pan A and Wang X L. 2024. Industrial agglomeration, FDI, and carbon emissions: new evidence from China's service industry. Environmental Science and Pollution Research 31(3): 4946–4969.
Xia C Q, Zheng H R, Meng J, Li S P, Du P F and Shan Y L. 2022. The evolution of carbon footprint in the yangtze river delta city cluster during economic transition 2012-2015 (vol 181, 106266, 2022). Resources Conservation and Recycling 184.
Xie X and Wang C. 2024. Productive services agglomeration: An accelerator of manufacturing servitization output? Finance Research Letters 62.
Xing Z, Jiao Z and Wang H. 2022. Carbon footprint and embodied carbon transfer at city level: A nested MRIO analysis of Central Plain urban agglomeration in China. Sustainable Cities and Society 83.
Yang Y, Yu H, Su M R, Chen Q H, Wen J and Hu Y C. 2024. Urban water resources accounting based on industrial interaction perspective: Data preparation, accounting framework, and case study. Journal of Environmental Management 349.
Yin H, Kang L and Wang L. 2007. The equalization effect of intergovernmental transfers on fiscal capacity: Evidence from Chinese county-level data. Journal of Management World(01): 48–55.
Yin H and Xu Y. 2011. On the Interactions of Local Public Infrastructure Expenditure in China. Economic Research Journal 46(07): 55–64.
Yu Y and Liu F. 2017. The Impact of Spatial Agglomeration of Productive Service Industries on Environmental Pollution. Research on Financial and Economic Issues(08): 23–29.

Yu Z D, Zu J Y, Xu Y, Chen Y M and Liu X T. 2022. Spatial and functional organizations of industrial agglomerations in China's Greater Bay Area. Environment and Planning B-Urban Analytics and City Science 49(7): 1995–2010.
Zhang S, Yang D W, Ji Y J, Meng H S, Zhou T, Zhang J M and Yang H. 2024. Spatio-temporal patterns and cascading risks of embodied energy flows in China. Energy 298(2024).
Zhang Y and Tang Z. 2015. Driving factors of carbon embodied in China's provincial exports. Energy Economics 51: 445–454.
Zheng H, Többen J, Dietzenbacher E, Moran D, Meng J, Wang D and Guan D. 2021. Entropy-based Chinese city-level MRIO table framework. Economic Systems Research 34(4): 519–544.
Zheng S and Du R. 2020. How does urban agglomeration integration promote entrepreneurship in China? Evidence from regional human capital spillovers and market integration. Cities 97: 102529.
Zhou W. 2016. The Spatial Spillover Effect of Economic Development in Beijing-Tianjin-Hebei Region. Journal of University of Chinese Academy of Social Sciences(02): 45–52.
Zhu M M, Wang J G, Zhang J and Xing Z C. 2022. Urban Low-Carbon Consumption Performance Assessment: A Case Study of Yangtze River Delta Cities, China. Sustainability 14(16).

Supplementary Information

Table S1 and Table S2 present the 42 industrial sectors and 313 cities included in China's multi-regional input-output tables, respectively.

Table S1 The industrial sectors in the multi-regional input-output table of China

Number	Industrial sector	Classification	Number	Industrial sector	Classification
I1	Agriculture, forestry, animal husbandry and fisher		I22	Other manufacturing	
I2	Mining and washing of coal		I23	Comprehensive use of waste resources	
I3	Extraction of petroleum and natural gas	Primary industry	I24	Repair of metal products, machinery and equipment	
I4	Mining and processing of metal ores		I25	Production and distribution of electric power and heat power	Secondary industry
I5	Mining and processing of nonmetal and other ores		I26	Production and distribution of gas	
I6	Food and tobacco processing		I27	Production and distribution of tap water	
I7	Textile industry		I28	Construction	
I8	Manufacture of leather, fur, feather and related products		I29	Wholesale and retail trade	
I9	Processing of timber and furniture		I30	Transport, storage, and postal services	
I10	Manufacture of paper, printing and articles for culture, education and sport activity	Secondary industry	I31	Accommodation and catering	Tertiary industry
I11	Processing of petroleum, coking, processing of nuclear fuel		I32	Information transfer, software and information technology services	
I12	Manufacture of chemical products		I33	Finance	

I13	Manuf. of non -metallic mineral products	I34	Real estate
I14	Smelting and processing of metals	I35	Leasing and commercial services
I15	Manufacture of metal products	I36	Scientific research and polytechnic services
I16	Manufacture of general purpose machinery	I37	Administration of water, environment, and public facilities
I17	Manufacture of special purpose machinery	I38	Resident, repair and other services
I18	Manufacture of transport equipment	I39	Education
I19	Manufacture of electrical machinery and equipment	I40	Health care and social work
I20	Manufacture of communication equipment, computers and other electronic equipment	I41	Culture, sports, and entertainment
I21	Manufacture of measuring instruments	I42	Public administration, social insurance, and social organizations

Table S2 The cities in the multi-regional input-output table of China

Region	City	Province
Northeast China	Haerbin, Qiqihar, Jixi, Hegang, Shuangyashan, Daqing, Yiichun, Jiamusi, Qitaihe, Mudanjiang, Heihe, Suihua, Daxing’anling	Heilongjiang
	Changchun, Jilin, Siping, Liaoyuan, Tonghua, Baishan, Songyuan, Baicheng, Yanbian	Jilin
	Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Jinzhou, Yingkou	Liaoning
	Hulunbeier, Xing’an, Tongliao, Chifeng, Xilinguole	Neimenggu
North China	Huhehaote, Baotou, Wulanchabu, Eerduosi, Bayannaoer, Wuhai, Alashanmeng	Neimenggu
	Beijing	
	Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui	Hebei

	Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Lvliang	Shanxi
	Tianjin	
Northwest China	Lanzhou, Jiayuguan, Jinchang, Baiyin, Tianshui, Wuwei, Zhangye, Pingliang, Jiuquan, Qingyang, Dingxi, Longnan, Linxiahuizu, Gannanzangzu	Gansu
	Yinchuan, Shizuishan, Wuzhong, Zhongwei, Guyuan	Ningxia
	Qinghai	Qinghai
	Xi'an, Tongchuan, Baoji, Xianyang, Weinan, Yan'an, Hanzhong, Yulin, Ankang, Shangluo	Shaanxi
	Wulumuqi, Kelamayi, Tulufan, Hami, Changjihuizu, Yili, Aletai, Boertalamenggu, Bayinguolengmenggu, Akesu, Kashi, Hetian, Shihezi, Kezilesukeer, Tacheng	Xinjiang
East China	Hefei, Wuhu, Bengbu, Huainan, Ma'anshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Lu'an, Bozhou, Chizhou, Xuancheng	Anhui
	Fuzhou, Xiamen, Sanming, Quanzhou, Zhangzhou, Nanping, Longyan, Putian, Ningde	Fujian
	Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yancheng, Yangzhou, Zhenjiang, Taizhou, Suqian	Jiangsu
	Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ganzhou, Ji'an, Yiichun, Fuuzhou, Shangrao	Jiangxi
	Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Jining, Tai'an, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Binzhou, Heze, Weifang, Liaocheng	Shandong
	Shanghai	
	Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou, Lishui, Wenzhou	Zhejiang
Central China	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhumadian, Jiyuan shi, Xuchang, Zhoukou	Henan
	Wuhan, Huangshi, Shiyan, Yichang, Xiangfan, Ezhou, Jingmen, Huanggang, Xianning, Suizhou Shi, Enshitujiazumiaozu, Xiantao, Xiaogan, Jingzhou, Shennongjia, Tianmen, Qianjiang	Hubei
	Changsha, Zhuzhou, Xiangtan, Hengyang, Yueyang, Changde, Yiyang, Chenzhou, Yongzhou, Huaihua, Xiangxitujiazumiaozu, Loudi, Zhangjiajie, Shaoyang	Hunan
South China	Guangzhou, Shaoguan, Shenzhen, Zhuhai, Shantou, Foshan, Jiangmen, Zhanjiang, Zhaoqing, Huizhou, Meizhou, Shanwei, Heyuan, Yangjiang, Qingyuan, Dongguan, Zhongshan, Chaozhou, Jieyang, Yunfu, Maoming	Guangdong
	Nanning, Liuzhou, Guilin, Wuzhou, Fangchenggang, Qinzhou, Guigang, Yuulin, Baise, Hezhou, Hechi, Laibin, Chongzuo, Beihai	Guangxi
		Hainan
Southwest China	Chongqing	
	Guiyang, Liupanshui, Zunyi, Anshun, Bijie, Tongren, Qiandongnanmiaozudongzu, Qiannanbuyizumiaozu, Qianxinanbuyizumiaozu	Guizhou

Chengdu, Zigong, Panzhihua, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Meishan, Guang'an, Yaan, Ziyang, Ganzizangzu, Yibin, Dazhou, Bazhong, Abazangzuqiangzu, Liangshanyizu	Sichuan
	Xizang
	Yunnan