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Urban household carbon intensity across the Yangtze River Economic Belt: spatial inequality, state persistence and regional factors

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Abstract

Household energy use contributes to urban carbon emissions, but its carbon intensity and persistence vary across cities with different socioeconomic conditions, energy structures and climates. This study estimates household carbon emission intensity (HCEI) for 108 cities in the Yangtze River Economic Belt from 2010 to 2024 and examines spatial inequality, state persistence and regional factors. The analysis uses the Dagum Gini coefficient, global Moran's I , Markov transition matrices and the geographic detector. HCEI changed non-monotonically over the study period, while emissions from electricity use remained the largest component of household carbon emissions. Overall inequality declined, although heterogeneity within regions remained pronounced, particularly in the downstream region. The low and high states were highly persistent, with persistence probabilities of 82.08% and 83.82% for the full YREB, whereas the two intermediate states were more mobile. Per capita disposable income, energy structure and urbanization level had the highest explanatory power for HCEI, and their interactions varied across regions. The results identify distinct patterns of household carbon intensity and transition across cities and provide evidence for regionally differentiated mitigation measures.

Keywords: Household carbon emissions, Carbon emission intensity, Residential energy consumption, Spatial inequality, State persistence, Yangtze River Economic Belt

1 Introduction

Household energy use contributes to carbon emissions through residential electricity, gas and space heating. Demand for these energy services changes with urbanization, income, housing conditions and living standards [1, 2]. The resulting emissions depend not only on household demand but also on local energy systems and climatic conditions. Household carbon emissions therefore vary considerably across cities with different development and energy profiles.

Several approaches are used to account for household carbon emissions, including emission factor accounting, input–output analysis, life cycle assessment and consumption carbon footprint analysis. Their main differences concern system boundaries and the treatment of direct and indirect emissions. Emission factor methods estimate emissions associated with observed household energy use, whereas input–output and life cycle methods can trace emissions embodied in goods and services [3, 4]. Survey evidence also shows that household energy use and carbon burdens vary across socioeconomic groups and locations [5]. The choice of accounting boundary and spatial scale therefore affects both emission estimates and their interpretation.

Most household carbon studies examine total emissions, carbon footprints or emissions per capita. These measures describe emission scale or average individual burden, but they provide limited information on how household emissions change relative to local economic activity. Household carbon emission intensity (HCEI), defined in this study as CO₂ emissions from household energy use relative to city economic output, provides a complementary measure. Two cities can experience similar changes in household emissions but follow different HCEI trajectories when their economic growth differs. HCEI is therefore used here to compare household carbon performance across cities rather than to replace total or per capita emission measures.

Socioeconomic and energy conditions are closely associated with household carbon emissions. Income and consumption affect residential energy demand [6–8], while urbanization changes housing conditions, infrastructure and access to energy services [9, 10]. Demographic composition and human capital can further alter household consumption patterns [11]. Energy structure and technological conditions influence the carbon consequences of residential energy demand [12, 13]. Climate also matters because temperature and humidity affect heating and cooling requirements. The relative importance of these factors can differ across cities and regions.

China provides a useful setting for examining this heterogeneity. Urbanization, income growth and higher living standards have increased residential energy demand, while cities continue to differ in energy structure, climate and economic development [7, 14, 15]. The Yangtze River Economic Belt (YREB) spans eastern, central and western China and includes cities with markedly different socioeconomic and climatic

conditions [16–18]. The study covers 108 prefecture level cities and groups them into upstream, midstream and downstream regions (Fig. 1).

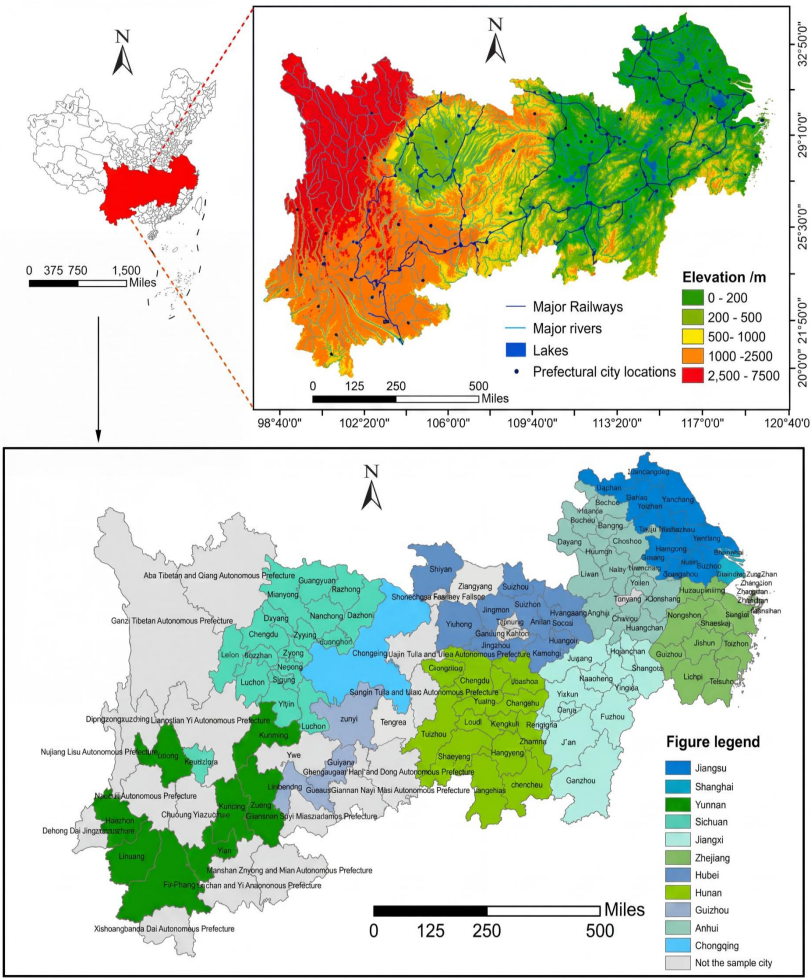


Fig. 1 Study area and regional division of the Yangtze River Economic Belt. The 108 cities are grouped into upstream, midstream and downstream regions.

Recent work has extended household carbon analysis to the city scale. Jiang and Xie [19], for example, examined 337 Chinese prefecture level cities using interpretable machine learning and spatial transition analysis to study household emissions and urban and rural disparities. Their results provide broad evidence on the spatial distribution and nonlinear correlates of absolute household emissions. Less is known about the evolution of household emissions relative to local economic activity and the persistence of cities in different intensity states. Annual spatial patterns alone cannot

distinguish cities that remain in high HCEI states from those experiencing temporary increases. The factors associated with HCEI may also differ across regions and may have greater explanatory power when considered jointly.

We examine these issues using a balanced panel of 108 YREB cities from 2010 to 2024. CO₂ emissions from residential electricity, gas and centralized heating are first estimated and expressed relative to city economic output. The Dagum Gini coefficient and global Moran's I describe regional inequality and spatial dependence. Markov transition matrices measure persistence and movement among HCEI states, while the geographic detector evaluates the spatial explanatory power of socioeconomic, energy, climatic and institutional factors. This framework links changes in average HCEI with inequality, state mobility and regional factor combinations. It therefore distinguishes persistent high intensity conditions from short term fluctuations and shows how the factors associated with HCEI differ among the upstream, midstream and downstream regions.

The study makes three contributions. First, it provides a long-term city-level assessment of direct household energy-related carbon intensity and distinguishes the evolution of absolute household emissions from emission pressure relative to local economic development. Second, it extends static spatial analysis by identifying persistence and mobility across HCEI states, allowing persistent high-intensity conditions to be distinguished from temporary fluctuations. Third, it shows that HCEI differentiation is associated with different combinations of socioeconomic development, energy structure, urbanization and climatic conditions across subregions. These results provide a basis for understanding why household carbon mitigation challenges differ substantially among cities within the same large river-basin region.

2 Results

2.1 Temporal evolution and emission structure

HCEI followed a non-monotonic trajectory across the YREB from 2010 to 2024 (Fig. 2a). For the full YREB, HCEI decreased from approximately 0.79 in 2010 to 0.77 in 2012, rose temporarily in 2014 and then declined with fluctuations to a local minimum around 2020. It rebounded in 2021 and remained close to 0.79 during the final years of the study period. HCEI therefore did not continue the decline observed before 2020.

The regional ordering changed little over time. The downstream region consistently had the highest HCEI, generally between 0.80 and 0.84, while the upstream region remained lowest at approximately 0.71 to 0.75. The midstream region remained between these two levels and broadly followed the YREB trend.

Absolute CO₂ emissions from household energy use followed a different trajectory (Fig. 2b). Emissions from electricity use were the largest component throughout the study period, followed by centralized heating and gas. Emissions from all three sources increased over time, although their annual growth rates varied. Electricity recorded the largest increase and the strongest fluctuations in annual growth during the middle of the study period.

The rise in absolute emissions alongside the relatively narrow variation in HCEI shows that emission scale and emissions relative to economic output evolved differently. Regional differences in HCEI also remained visible throughout the study period.

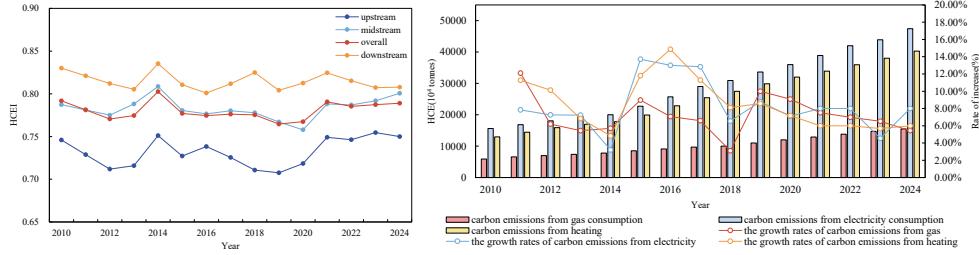


Fig. 2 Evolution and source composition of household carbon emissions in the YREB from 2010 to 2024. **a**, Household carbon emission intensity across the whole region and three subregions. **b**, Household carbon emissions by energy source and their annual growth rates.

2.2 Spatial dependence and geographical distribution

Global Moran's I was positive in every year from 2010 to 2024 (Table 1). The statistic was significant at the 5% level in all years except 2021, when $p = 0.060$. The 2021 value was significant at the 10% level.

Moran's I increased from 0.1131 in 2010 to 0.1465 in 2012 and declined to 0.0677 by 2018. It fell to 0.0658 in 2021 before rising to 0.0885 in 2022, 0.1348 in 2023 and 0.1454 in 2024. Spatial clustering therefore weakened during part of the study period and strengthened again in the final years.

The maps show a similar regional pattern (Fig. 3). In 2010, cities with relatively high HCEI were concentrated mainly in the downstream region, while lower values were more common upstream and midstream. The downstream region remained an important high HCEI area in 2024, although several upstream and midstream cities also recorded relatively high values.

The spatial change between 2010 and 2024 was therefore not a simple shift from east to west. Cities with different HCEI levels increasingly coexisted within the upstream and midstream regions, while the broader pattern of higher downstream and lower upstream values remained visible.

2.3 Regional inequality and decomposition

The overall Gini coefficient increased from 2010 to 2012 and then declined with fluctuations, reaching its lowest value of approximately 0.10 in 2020 (Fig. 4a). It rose again after 2020 but remained below its early period level. Across the full study period, overall inequality declined at an average annual rate of 1.53%.

The downstream region consistently had the largest internal disparity, followed by the upstream region, while the midstream region generally had the lowest. Despite these differences, intra-regional Gini coefficients declined cumulatively by 12.06%, 23.59% and 17.95% in the upstream, midstream and downstream regions, respectively.

Table 1 Global Moran's I of household carbon emission intensity in the YREB.

Year	Moran's I	Z-value	P-value
2010	0.1131	3.8582	<0.001
2011	0.1232	4.9349	<0.001
2012	0.1465	4.3430	<0.001
2013	0.1071	4.1440	<0.001
2014	0.1030	3.6764	<0.001
2015	0.1050	4.1612	<0.001
2016	0.0939	3.9632	<0.001
2017	0.0828	3.4593	0.001
2018	0.0677	2.8785	0.004
2019	0.0737	2.5351	0.012
2020	0.0995	4.0622	<0.001
2021	0.0658	1.8968	0.060
2022	0.0885	3.7112	<0.001
2023	0.1348	4.6389	<0.001
2024	0.1454	4.7712	<0.001

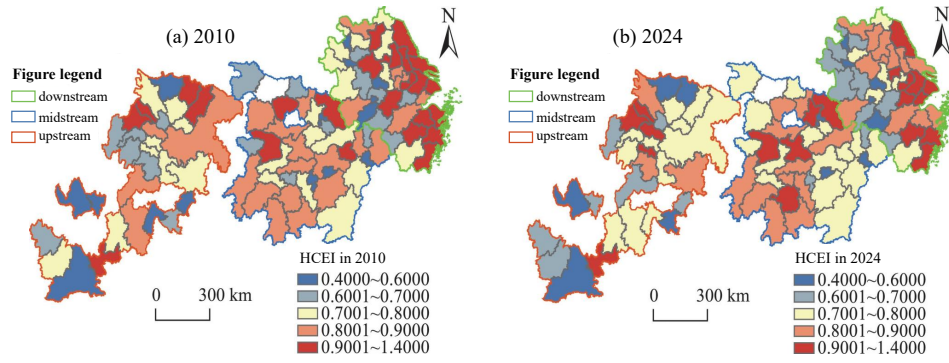


Fig. 3 Spatial distribution of household carbon emission intensity across 108 YREB cities in 2010 and 2024.

The upstream and downstream regions had the largest pairwise disparity during most of the study period (Fig. 4b). Differences between the upstream and midstream regions and between the midstream and downstream regions were smaller and generally declined.

Transvariation intensity accounted for the largest component of overall inequality in the Dagum decomposition (Fig. 4c), reflecting overlap among the HCEI distributions of the three regions. Variation within regions also remained important. The downstream component alone accounted for an average of 16.34% of overall inequality. The decline in aggregate inequality therefore coexisted with marked differences among cities within the same region.

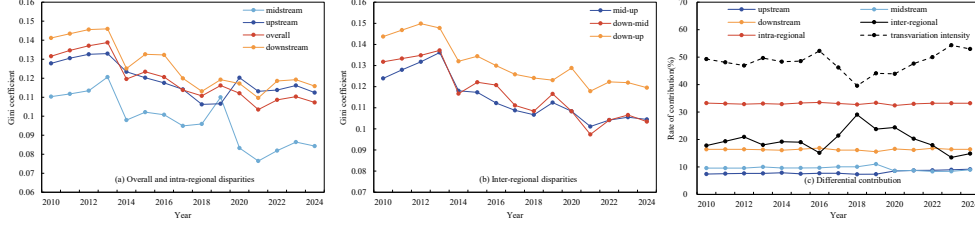


Fig. 4 Regional inequality and decomposition of household carbon emission intensity in the YREB from 2010 to 2024. **a**, Overall and intra-regional disparities. **b**, Inter-regional disparities. **c**, Decomposition of overall inequality.

2.4 Persistence and mobility of HCEI states

The Markov matrices show strong persistence at the two ends of the HCEI distribution (Table 2). For the full YREB, the probabilities of remaining in the low, medium-low, medium-high and high states were 0.8208, 0.6153, 0.6067 and 0.8382, respectively. The low and high states were therefore more stable than the two intermediate states.

The same pattern appeared within the three regions. The probability of remaining in the low state was 76.11% upstream, 79.59% midstream and 78.35% downstream. Persistence in the high state reached 86.97% upstream, compared with 74.52% midstream and 77.55% downstream. The upstream region consequently had the strongest persistence among cities already in the high state despite having the lowest average HCEI.

Cities in the two intermediate states moved more frequently. Across the YREB, 21.47% of medium-low observations moved to the medium-high state and 4.28% moved directly to the high state. Among medium-high observations, 18.23% moved to the high state, while 21.10% moved to either of the two lower states.

Transition direction differed across regions. In the midstream region, 30.15% of medium-high observations moved to the high state in the following period. Downstream, 20.82% moved from medium-high to high, while 15.64% moved to medium-low and 11.39% moved directly to low. Non-adjacent transitions were less common than persistence or adjacent transitions but occurred more often in the midstream and downstream regions.

2.5 Regional factors associated with HCEI differentiation

The explanatory power of the 18 factors differed across the YREB and its three regions (Table 3). For the full YREB, per capita disposable income (PCI) had the highest q -value at 0.4101, followed by energy structure (ES) at 0.3705 and urbanization level (UL) at 0.3289. Low carbon policy (LCP) also had a relatively high q -value of 0.2923.

The ordering differed upstream. UL had the highest q -value at 0.3542, followed by temperature (TEM) at 0.3173, ES at 0.2954 and PCI at 0.2573. Temperature had considerably greater explanatory power upstream than in the other two regions.

In the midstream region, PCI had the highest q -value at 0.4344, followed by ES at 0.3522 and UL at 0.3481. Downstream, UL ranked first at 0.3553, followed by LCP at

Table 2 Markov transition matrices of household carbon emission intensity in the YREB and its subregions.

Region	$t/t + 1$	Low	Medium-low	Medium-high	High
Whole region	Low	0.8208	0.1725	0.0067	0.0000
	Medium-low	0.1272	0.6153	0.2147	0.0428
	Medium-high	0.0493	0.1617	0.6067	0.1823
	High	0.0027	0.0285	0.1306	0.8382
Upstream	Low	0.7611	0.2133	0.0256	0.0000
	Medium-low	0.1940	0.5967	0.2006	0.0087
	Medium-high	0.0449	0.1269	0.6747	0.1536
	High	0.0000	0.0282	0.1021	0.8697
Midstream	Low	0.7959	0.2041	0.0000	0.0000
	Medium-low	0.1409	0.5326	0.2396	0.0869
	Medium-high	0.0632	0.1741	0.4613	0.3015
	High	0.0000	0.0513	0.2035	0.7452
Downstream	Low	0.7835	0.2057	0.0108	0.0000
	Medium-low	0.1026	0.6271	0.2249	0.0455
	Medium-high	0.1139	0.1564	0.5215	0.2082
	High	0.0000	0.0330	0.1915	0.7755

0.2953, per capita consumption expenditure (PC) at 0.2614 and human capital (HC) at 0.2238.

Factor interactions generally had higher q -values than the corresponding individual factors (Fig. 5). For the full YREB, PCI-UL had the highest interaction value at 0.6861, followed by PCI-ES at 0.6049 and ES-UL at 0.5471.

The leading interactions also varied across regions. Upstream, UL-PCI reached 0.6912 and TEM-UL reached 0.5801. Midstream, PCI-ES reached 0.6750. Downstream, the stronger interactions involved urbanization, consumption, human capital and low carbon policy. The regional results show that the factors associated with HCEI do not follow a common ordering across the YREB.

3 Discussion

HCEI in the YREB did not follow a continuous decline from 2010 to 2024. The reduction observed before 2020 was followed by a rebound, after which HCEI remained relatively stable. Absolute CO₂ emissions from household energy use nevertheless continued to increase. The two indicators therefore describe different aspects of household carbon performance. Absolute emissions measure the scale of residential carbon output, whereas HCEI relates those emissions to the economic activity of each city.

Electricity accounted for the largest share of the measured household emissions throughout the period. Growth in residential electrification alone does not imply lower carbon emissions because its effect also depends on electricity demand and the

Table 3 Geographic detector results for factors associated with the spatial differentiation of HCEI.

Variable	Whole region	Upstream	Midstream	Downstream
TEM	0.1289***	0.3173***	0.1411***	0.1188***
RH	0.0406***	0.0305***	0.0396***	0.0436***
GL	0.1096***	0.0944***	0.1147***	0.1045***
HC	0.1035***	0.0964***	0.1137***	0.2238***
GT	0.0305***	0.0233***	0.0294***	0.0325***
LCP	0.2923***	0.1416***	0.2761***	0.2953***
CRP	0.0152***	0.0112***	0.0132***	0.0142***
EI	0.1167***	0.1177***	0.1218***	0.1106***
PI	0.0690***	0.0639***	0.0761***	0.0619***
FI	0.0173***	0.0183***	0.0223***	0.0142***
PD	0.0030***	0.0041***	0.0041***	0.0030***
POP	0.1056***	0.0802***	0.1106***	0.0873***
UL	0.3289***	0.3542***	0.3481***	0.3553***
ES	0.3705***	0.2954***	0.3522***	0.1742***
IE	0.0741***	0.0599***	0.0619***	0.0426***
PC	0.1421***	0.1340***	0.1472***	0.2614***
CP	0.1492***	0.1431***	0.1573***	0.1391***
PCI	0.4101***	0.2573***	0.4344***	0.2030***

*** $p < 0.01$.

emissions associated with electricity supply. The relatively high q -value of energy structure is consistent with this relationship. Reducing emissions from household energy use consequently depends on changes in residential demand as well as continued decarbonization of electricity supply.

The spatial analysis shows that similar HCEI values remained geographically clustered, although the strength of this clustering varied over time. The broad pattern of higher HCEI downstream and lower HCEI upstream remained visible, but differences within each region became more evident. The Dagum decomposition leads to a similar interpretation. Overall inequality declined over the study period, while transvariation remained the largest component and the downstream region retained substantial internal variation. A decline in aggregate inequality therefore did not imply uniform carbon performance across cities. Comparable differences across spatial scales have also been reported in recent carbon studies [19, 20].

The Markov results show that persistence was strongest at the low and high ends of the distribution. More than 80% of observations in both states remained in the same state in the following period, whereas cities in the two intermediate states moved more frequently. This distinction is not captured by average HCEI alone. The upstream region, for example, had the lowest average HCEI but the highest persistence among observations already classified in the high state. A low regional mean can therefore coexist with a smaller group of cities that remain at high intensity.

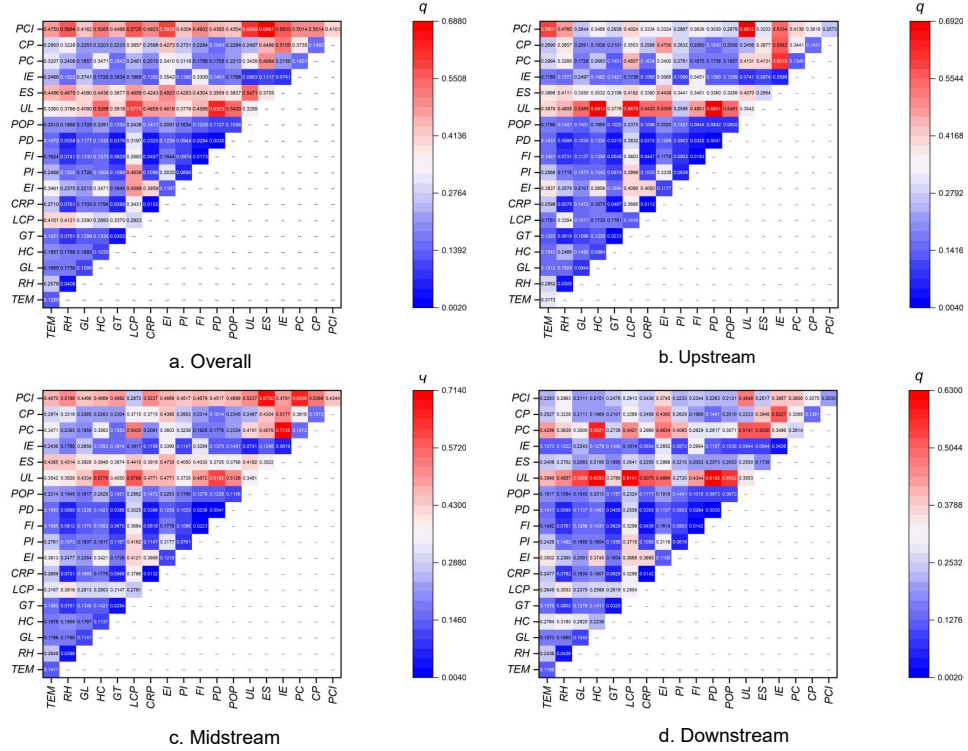


Fig. 5 Interaction detection results for factors associated with household carbon emission intensity in the YREB.

The direction of movement also differed by region. Medium-high observations in the midstream region were more likely to move to the high state than their counterparts in the other regions. Downstream observations in the same starting state moved in both directions more frequently. Cities with similar current HCEI can therefore follow different subsequent paths. This result supports the use of transition information alongside static spatial classifications when considering differentiated carbon reduction measures [21].

The geographic detector results further show that HCEI was associated with different combinations of socioeconomic, energy and climatic conditions. For the full YREB, disposable income, energy structure and urbanization had the largest individual q -values. Their pairwise interactions were stronger, particularly PCI-UL, PCI-ES and ES-UL. These results are consistent with household carbon intensity being jointly associated with development and energy conditions rather than with any single factor.

Regional results provide additional detail. Temperature had greater explanatory power upstream than in the other regions, and the TEM-UL interaction reached $q = 0.5801$. This association is consistent with greater sensitivity of household energy demand to climate where urban development changes the scale and form of residential energy use. In the midstream region, the interaction between income and energy

structure was more prominent. Downstream, urbanization, consumption, human capital and low carbon policy contributed to a more dispersed set of associations. The same factor hierarchy therefore does not apply across all YREB cities.

The transition results also help distinguish different mitigation priorities. Persistent high HCEI states identify cities where short term variation has not been sufficient to change relative carbon performance. The greater mobility of the intermediate states suggests more scope for movement in either direction. Upstream cities may benefit from measures that reduce heating demand and improve building energy performance where climate and urbanization coincide. In the midstream region, residential energy demand accompanying income growth and changes in energy structure warrants closer attention. Downstream cities face a broader combination of consumption, urbanization and policy conditions, which may require a wider mix of demand management and energy efficiency measures.

Several limitations affect the interpretation of the results. The accounting boundary includes electricity, gas and centralized heating but excludes indirect emissions embodied in food, transport services and manufactured goods. The electricity calculation uses benchmark emission factors for each province because a consistent annual historical series was unavailable for the full period. The geographic detector identifies spatial explanatory associations and does not estimate causal effects. The Markov matrices describe observed historical transitions rather than future movement under alternative demographic, economic or energy scenarios. Future research could incorporate annual electricity emission factors, broader consumption accounting, causal designs and scenario analysis where suitable data become available.

Taken together, the results show that declining inequality in HCEI did not eliminate state persistence or regional heterogeneity. Low and high states remained comparatively stable, intermediate states were more mobile, and the factors associated with HCEI differed across regions. Considering inequality, transition and regional associations together provides information that is not available from absolute household emissions or annual spatial distributions alone.

4 Methods

4.1 Study area and data

The study covers 108 prefecture level cities in the Yangtze River Economic Belt from 2010 to 2024. The YREB comprises 11 provincial administrative units, including Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou and Yunnan. Chongqing, Sichuan, Guizhou and Yunnan form the upstream region. Jiangxi, Hubei and Hunan form the midstream region, while Shanghai, Jiangsu, Zhejiang and Anhui form the downstream region (Fig. 1).

Data on household LPG consumption, natural gas consumption and centralized heating floor area were obtained from the *China Urban Construction Statistical Yearbook*. Household electricity consumption and socioeconomic variables were obtained mainly from the *China Urban Statistical Yearbook* and supplemented with provincial and municipal statistical yearbooks and official statistical bulletins. The final sample

507 is a balanced panel covering 2010–2024. Isolated missing observations were interpo-
 508 lated linearly from adjacent years and checked against official statistical bulletins when
 509 comparable values were available.

510 Net calorific values were taken from GB/T 2589–2020, *General Principles for Cal-*
 511 *culatation of the Comprehensive Energy Consumption*. Carbon content per unit calorific
 512 value and oxidation rates were obtained from the *Guidelines for the Compilation of*
 513 *Provincial Greenhouse Gas Inventories*. Electricity emission factors for 2010, 2012 and
 514 2018 were obtained from documents issued by the National Development and Reform
 515 Commission and the Ministry of Ecology and Environment. The arithmetic mean of
 516 the three available values was calculated for each province and applied throughout the
 517 study period.

518 Centralized heating emissions were estimated from reported heating floor area and
 519 the energy consumption quota per unit area specified in the *Energy Consumption*
 520 *Standard for Civil Buildings*.

521

522 4.2 Household carbon emission accounting

523 CO₂ emissions from household energy use were calculated for residential gas, electricity
 524 and centralized heating. Total emissions for city i in year t were defined as
 525

$$526 \quad C_{it} = C_{1,it} + C_{2,it} + C_{3,it}, \quad (1)$$

528 where $C_{1,it}$, $C_{2,it}$ and $C_{3,it}$ represent emissions from household gas use, electricity
 529 use and centralized heating, respectively.

530 Gas-related emissions were calculated as

531

$$532 \quad C_{1,it} = \sum_{m=1}^2 Q_{mit} \times NCV_m \times F_m \times COF_m \times \frac{44}{12}, \quad (2)$$

534 where m denotes natural gas or LPG, Q_{mit} is household consumption of fuel m ,
 535 NCV_m is its average net calorific value, F_m is carbon content per unit calorific value,
 536 COF_m is the oxidation factor and $44/12$ converts elemental carbon to CO₂.

537 Electricity-related emissions were calculated as

538

$$539 \quad C_{2,it} = Q_{eit} \times EF_i \times 10^{-3}, \quad (3)$$

541 where Q_{eit} is household electricity consumption and EF_i is the benchmark electric-
 542 ity emission factor for the province containing city i . For each province, the benchmark
 543 was calculated as the arithmetic mean of the available factors for 2010, 2012 and 2018
 544 and was applied throughout the study period.

545 Centralized-heating emissions were estimated as

546

$$547 \quad C_{3,it} = S_{it} \times Q_{hit} \times EC, \quad (4)$$

548 where S_{it} is centralized heating floor area, Q_{hit} is energy consumption per unit
 549 heating area and EC is the carbon emission coefficient of standard coal, set at 2.46 kg
 550 CO₂ per kg of standard coal.

551 Household carbon emission intensity was defined as

552

$$HCEI_{it} = \frac{C_{it}}{GDP_{it}}, \quad (5)$$

where GDP_{it} is real gross domestic product for city i expressed in constant prices. A higher HCEI denotes more CO₂ emissions from household energy use relative to local economic output.

4.3 Regional inequality

The Dagum Gini coefficient [22] was used to measure HCEI inequality and decompose it into variation within regions, net variation between regions and transvariation intensity. The overall coefficient was calculated as

$$G = \frac{\sum_{j=1}^I \sum_{h=1}^I \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2n^2 \bar{y}}, \quad (6)$$

where I is the number of subregions, n is the total number of cities, n_j and n_h are the numbers of cities in subregions j and h , y_{ji} and y_{hr} are their HCEI values and $\bar{y}$ is mean HCEI.

The overall coefficient was decomposed as

$$G = G_w + G_{nb} + G_t, \quad (7)$$

with

$$G_w = \sum_{j=1}^I G_{jj} p_j s_j, \quad (8)$$

$$G_{nb} = \sum_{j=2}^I \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh}, \quad (9)$$

$$G_t = \sum_{j=2}^I \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}), \quad (10)$$

where G_{jj} is the within-subregion Gini coefficient, G_{jh} is the between-subregion coefficient, $p_j = n_j/n$, $s_j = n_j \bar{y}_j / (n \bar{y})$ and D_{jh} represents the relative influence between the HCEI distributions of subregions j and h .

4.4 Spatial autocorrelation

Global Moran's I was used to test whether cities with similar HCEI values were spatially clustered. For year t ,

$$I_t = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (HCEI_{it} - \overline{HCEI_t}) (HCEI_{jt} - \overline{HCEI_t})}{\left(\sum_{i=1}^n \sum_{j=1}^n W_{ij} \right) \sum_{i=1}^n (HCEI_{it} - \overline{HCEI_t})^2}, \quad (11)$$

where W_{ij} denotes the spatial weight between cities i and j and $\overline{HCEI}_t$ is the mean HCEI in year t . Positive values indicate clustering of similar HCEI values, while negative values indicate spatial dispersion.

4.5 Markov transition analysis

A discrete Markov chain was used to describe persistence and movement among HCEI states. Observations were divided into four ordered states, low, medium-low, medium-high and high, using natural breaks. Thresholds were calculated from the pooled 2010–2024 distribution and then held constant across years. Changes in state therefore reflected changes in HCEI rather than changes in annual classification thresholds.

Let n_{rs} denote the number of observed transitions from state r in year t to state s in year $t + 1$. The transition probability was

$$p_{rs} = \frac{n_{rs}}{\sum_{\ell=1}^K n_{r\ell}}, \quad \sum_{s=1}^K p_{rs} = 1, \quad (12)$$

where $K = 4$. The transition matrix was

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1K} \\ p_{21} & p_{22} & \cdots & p_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ p_{K1} & p_{K2} & \cdots & p_{KK} \end{bmatrix}. \quad (13)$$

Diagonal elements measure state persistence, while off-diagonal elements record movement to higher or lower HCEI states. A transition across more than one category was treated as a non-adjacent transition. Separate matrices were estimated for the full YREB and for the upstream, midstream and downstream regions.

4.6 Geographic detector

The geographic detector [23, 24] was used to measure the spatial explanatory power of candidate factors and their interactions. For factor X , the factor detector statistic was

$$q(X) = 1 - \frac{\sum_{p=1}^L N_p \sigma_p^2}{N \sigma^2}, \quad (14)$$

where L is the number of strata of factor X , N is the total number of observations, N_p is the number of observations in stratum p , σ^2 is the variance of HCEI in the full sample and σ_p^2 is the within-stratum variance. The q -statistic ranges from 0 to 1, with larger values indicating greater explanatory power for the spatial differentiation of HCEI.

Continuous variables were discretized using natural breaks before the geographic detector analysis. The analysis included 18 variables in seven dimensions. Environmental factors were annual mean temperature (TEM), relative humidity (RH) and green coverage level (GL). Technological factors were human capital (HC) and technological innovation (GT). Policy variables recorded participation in the low carbon city pilot program (LCP) and the carbon trading pilot program (CRP). Social factors

included per capita energy consumption (EI), environmental protection investment (PI) and fixed asset investment (FI). Population factors were population density (PD), population size (POP) and urbanization level (UL). Energy factors included energy structure (ES) and energy intensity (IE). Economic factors were per capita consumption expenditure (PC), the common prosperity index (CP) and per capita disposable income (PCI).

The interaction detector compares $q(X_1 \cap X_2)$ with the q -values of the two individual factors. Nonlinear enhancement occurs when

$$q(X_1 \cap X_2) > q(X_1) + q(X_2), \quad (15)$$

whereas bivariate enhancement occurs when

$$\max\{q(X_1), q(X_2)\} < q(X_1 \cap X_2) \leq q(X_1) + q(X_2). \quad (16)$$

The geographic detector results were interpreted as spatial explanatory associations rather than causal effects.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author, Zeyu He (2410591@tongji.edu.cn), on reasonable request.

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