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Contrasting patterns in urban energy and emission scaling

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3 **Abstract:** Cities drive most global energy use and emissions of greenhouse gases and other
4 pollutants, yet how these quantities scale with urban population remains debated. Scaling
5 analysis captures this relationship through the exponent β , which defines whether a quantity
6 increases sublinearly ($\beta < 1$), linearly ($\beta = 1$), or superlinearly ($\beta > 1$) with population. Here we
7 conduct a meta-analysis of 27 scaling studies encompassing 362 scaling exponents across cities
8 worldwide. Results show that energy consumption scales near-linearly to superlinearly:
9 electricity, gas, and transportation fuel have median scaling exponents of 1.06 [25th percentile:
10 0.94, 75th percentile: 1.13], 1.18 [1.05, 1.34], and 1.22 [1.19, 1.27], respectively. These results
11 suggest that gas use and congestion-related transportation fuel tend to intensify faster than
12 population growth. In contrast, most pollutant emissions (PM_{2.5}, PM₁₀, NO₂, SO₂, and CO) scale
13 sublinearly. CO₂ emissions are sublinear globally and in China, with median scaling exponent of
14 0.86 [0.80, 1.03] and 0.63 [0.59, 0.99], respectively, although a few countries show superlinear
15 scaling (e.g., U.S., Australia, and Canada), pointing to regional differences in technology and
16 policy. Energy consumption and its associated emissions thus scale in opposite directions, a
17 pattern we attribute to the spatial decoupling of production and consumption. Our analysis
18 reveals that inconsistent city definitions, fragmented energy and emissions data, and limited
19 analyses of temporal evolution introduce variability in reported scaling exponents and constrain
20 the generalization of these findings. Standardized, long-term datasets and mechanistic models
21 linking urban metabolism to emissions are needed to resolve these uncertainties and guide
22 sustainable, low-carbon urban transitions.
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40 **Keywords:** Scaling, urban metabolism, energy, air pollution, greenhouse gases emissions
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1. Introduction

Cities are complex systems that integrate engineered infrastructures, socioeconomic activities, and natural landscapes (Batty 2008, Ramaswami *et al* 2012, Sugar and Kennedy 2021). They now accommodate more than half of the global population, account for over 75% of primary energy consumption and more than 80% of global greenhouse gas (GHG) emissions, and are increasingly responsible for strain on critical natural resources such as water (Wang *et al* 2023, Kontokosta and Jain 2015, Li *et al* 2021b, Ascione *et al* 2021, Shen *et al* 2023, Gudipudi *et al* 2019a, 2019b, Ríos-Ocampo and Gary 2025, Nlend *et al* 2025). This reality complicates the once-prevailing notion that larger cities are generally greener and more efficient for resource consumption compared to smaller or rural settlements (Louf and Barthelemy 2014b, Bettencourt and West 2011, 2010, Bettencourt *et al* 2007, Gudipudi *et al* 2019b, 2019a, 2016, Chen *et al* 2025). For centuries, urban growth and technological innovation have led to an unprecedented increase in energy demand and pollutant emissions (Decker *et al* 2007, Lengyel *et al* 2020, Lu *et al* 2024). As cities continue to expand and concentrate capital, labor, and economic activity (Li *et al* 2021a), energy remains paramount for sustaining productivity and development (Elliott *et al* 2015, Dalgaard and Strulik 2011, Sugar and Kennedy 2021).

Urbanization is both a consequence and a driver of global economic growth, making cities focal points for innovation, opportunity, and environmental pressure (Bettencourt *et al* 2010, Lamsal *et al* 2013, Sugar and Kennedy 2021). The concentration of population and economic activities in cities gives rise to agglomeration effects, which influence patterns of energy consumption and other urban attributes (Riahi *et al* 2017, Güneralp *et al* 2017). A large body of research in urban economics and economic geography has shown that population density plays an important role in shaping urban energy use and emissions, with denser cities often exhibiting lower per-capita infrastructure and transport energy demand due to more efficient land use and shared services, although these relationships remain context-dependent (Güneralp *et al* 2017, Larson and Yezer 2015, Castells-Quintana *et al* 2021, Carozzi and Roth 2023). In fact, the social and economic advantages of spatial concentration and clustering can generate both efficiencies and intensifications in energy consumption and emissions (Facchini *et al* 2017, Gudipudi *et al* 2019a, Chen *et al* 2025, Gudipudi *et al* 2016). On the one hand, these efficiency gains are associated with shared infrastructure and more compact urban form (Chen *et al* 2025, Gudipudi *et al* 2016, Huang and Lu 2025). On the other hand, the concentration of wealth and

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3 economic productivity can amplify consumption, inequality, and pollution, which places cities at
4 the center of global sustainability challenges (Lengyel *et al* 2020, Creutzig *et al* 2015, Pu and
5 Xia 2025).
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8 The concept of urban scaling laws provides a quantitative framework to describe how
9 urban attributes, such as wealth, innovation, energy use, and emissions, vary systematically with
10 population size (Bettencourt *et al* 2007, Batty 2008, Louf and Barthelemy 2014a, Lu *et al* 2024).
11 Originating from analogies to biological allometry, this framework has revealed many scaling
12 relationships across cities despite substantial heterogeneity in their histories, geographies, and
13 socioeconomic structures (West 2017, Conticelli *et al* 2024, Pu and Xia 2025, Wang and Wang
14 2017). Early work emphasized the possibility of universal laws or common underlying
15 principles, whereas subsequent studies have highlighted the influence of context, city definitions,
16 and methodological choices on estimated scaling exponents. Meanwhile, theoretical
17 developments have sought to explain these patterns through underlying mechanisms, particularly
18 the role of human interactions, which scale with population size and generate aggregate
19 socioeconomic outputs, as well as the constraints imposed by spatial structure and infrastructure
20 networks that mediate these interactions (Bettencourt 2013, Ribeiro and Rybski 2023). However,
21 these mechanisms are often inferred rather than explicitly tested in empirical studies.
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32 The scaling relationship is typically expressed as

$$33 \quad Y = Y_0 N^\beta, \quad (1)$$

34 where Y represents an urban property, Y_0 is a normalization constant, N denotes urban
35 population, and β is the scaling exponent. Specifically, sublinear ($\beta < 1$) behavior implies
36 economies of scale, with larger cities requiring less Y per capita. Sublinear relationships are
37 commonly found in urban infrastructure-related quantities, such as electricity networks and roads
38 (Sugar and Kennedy 2020, Fragkias *et al* 2013, West 2017, Bettencourt and West 2010,
39 Bettencourt *et al* 2007, Bettencourt 2013). Linear behavior ($\beta = 1$) indicates proportional growth,
40 which is often associated with individual or household demands insensitive to city size
41 (Bettencourt *et al* 2007, Rao *et al* 2023, West 2017, Bettencourt and West 2010, Bettencourt
42 2013). Superlinear behavior ($\beta > 1$) scaling is often associated with social and economic
43 quantities (e.g., wages, GDP, and patent production) where network effects are at play, which
44 reflect enhanced connections and interactions in larger cities (Sugar and Kennedy 2020, Zhao *et*
45 *al* 2018, Zhou *et al* 2022, West 2017, Bettencourt *et al* 2007).
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3 It should be noted that energy consumption and its associated emissions are tightly
4 coupled (Li *et al* 2021b, Jung *et al* 2024). Carbon dioxide (CO₂), methane (CH₄), nitrogen
5 dioxide (NO₂), and particulate matter (PM) are primarily emitted through anthropogenic
6 activities that require fossil fuels (e.g., transportation and energy production) (Yatzkan *et al*
7 2024, Lamsal *et al* 2013, Liang *et al* 2024, Li *et al* 2020, Leffel *et al* 2025). Consequentially, as
8 urban energy demand increases with population, so do associated pollution emissions. However,
9 whether cities exhibit net gains in efficiency as their populations grow remains an open question
10 (Gudipudi *et al* 2019a). Some studies found that larger cities achieve higher per-capita efficiency
11 through denser infrastructure and innovation (Li *et al* 2021b, Brelsford *et al* 2020, Mohajeri *et al*
12 2015, Louf and Barthelemy 2014b, Bettencourt and West 2010, 2011, Bettencourt *et al* 2007,
13 Huang and Lu 2025), while other studies demonstrate these higher per-capita efficiencies to be
14 dependent on wealth (Lu *et al* 2024, Gudipudi *et al* 2019a, Fragkias *et al* 2013).

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24 Urban scaling relationships can offer a useful high-level perspective for understanding
25 how aggregate urban attributes respond to population growth and may help inform city-level
26 assessments of current and projected future energy use and pollutant emissions (Molinero and
27 Turner 2021). Despite decades of research on scaling laws and urban metabolism, literature
28 remains fragmented in terms of how energy consumption and pollutant emissions scale with city
29 size. To address this gap, this meta-analysis compiles and critically evaluates empirical findings
30 across diverse studies of urban energy use and emissions. We aim to identify recurring scaling
31 patterns, reconcile conflicting interpretations, and highlight the need to address key limitations
32 that would improve the holistic understanding of urban metabolism at scale and eventually
33 inform pathways toward sustainable, low-carbon urban systems.

34 35 36 37 38 39 40 41 42 43 **2. Methods**

44 Guided by the theoretical framework that many facets of urban life can be described with
45 a simple power-law function (Eq. 1), previous reviews have examined the mathematical origins
46 of the scaling law (Ribeiro and Rybski 2023) and energy metabolism in cities (Liu and Wu
47 2024). However, to our knowledge, no prior synthesis has systematically evaluated empirical
48 scaling exponents describing how urban energy consumption and pollutant emissions scale with
49 population size. Here we conducted a meta-analysis to quantify and compare these relationships
50 across 18-years of existing studies. Such a meta-analysis can enable a synthesis of findings
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3 across dozens of studies to reveal patterns and insights that would not otherwise emerge from
4 independently analyzing each study.
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7 Peer-reviewed literature was systematically searched using the Web of Science Core
8 Collection database. The search included all publications prior to July 2025 and used keywords
9 such as “urban”, “city”, “cities”, “energy”, “emission”, and “scaling”. Studies were included if
10 they (1) reported empirical scaling exponent (β) for any form of energy consumption, such as
11 electricity, gas, total, primary, and secondary energy use, or (2) analyzed energy-related pollutant
12 emissions such as CO₂, NO₂, CH₄, PM_{2.5}, and PM₁₀. To ensure comparability across studies, only
13 scaling relationships that used total population (not per capita) as the independent variable were
14 included. Studies that expressed the dependent variable (Y) as concentrations (which are
15 intensive properties) rather than total emissions (extensive properties) were excluded. We also
16 removed cases where the scaling was performed against non-urban or aggregated populations
17 (e.g., national or state-level total populations). Finally, we only retained single-variable
18 regression to maintain consistency in model interpretation. Given the lack of a standardized
19 definition of “city” across studies, we retained the original definitions used in each study and
20 evaluated their implications as part of the synthesis.
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31 For each eligible study, the reported β values were extracted directly from the main text
32 and supplementary materials or derived from the source data repositories. Sample size, 95%
33 confidence intervals, and/or standard deviations were included where possible to help
34 characterize the overall uncertainty across the meta-analysis. Although our literature search was
35 not restricted by publication year, the first study to formally introduce the population-based
36 urban scaling framework was Bettencourt *et al* (2007). Consequently, all eligible publications
37 identified in our search were published in or after 2007. Most identified studies were published
38 after 2019 (figure 1a), underscoring a growing interest in applying the scaling framework to
39 urban energy and environmental systems. Overall, among the 655 studies screened, 92 studies
40 met the general inclusion criteria, and 27 provided extractable scaling exponent values that are
41 used in this meta-analysis. Table S1 summarizes the extracted data and their corresponding
42 references.
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53 3. Results

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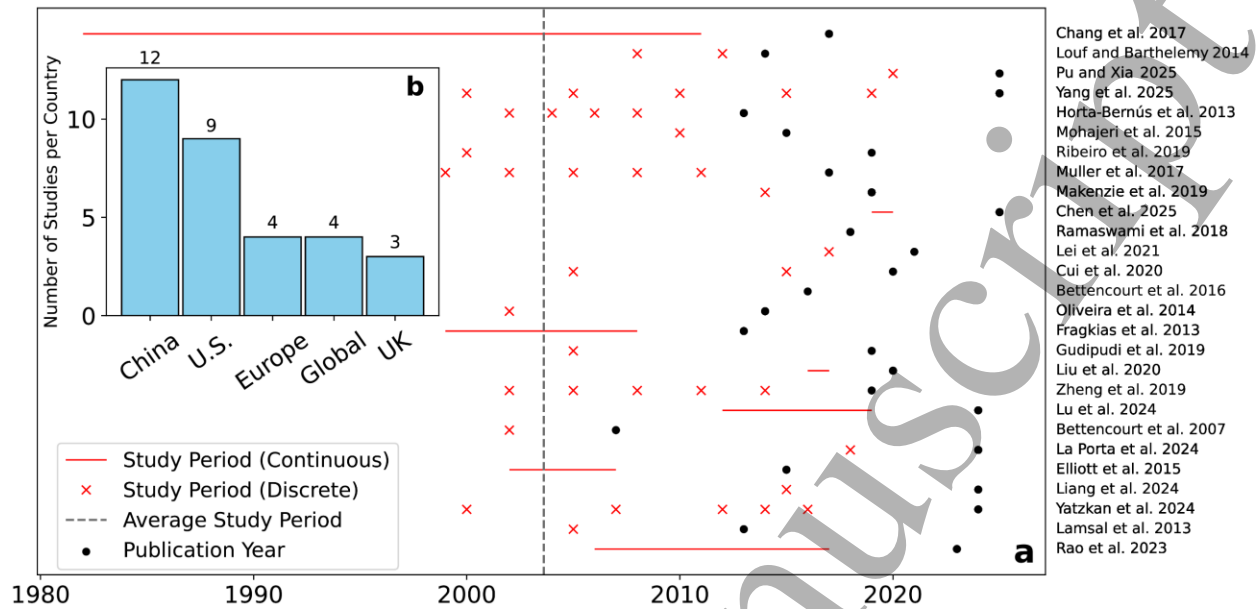


Figure 1. Summary of studies included in the meta-analysis on urban energy consumption and pollutant emission scaling. (a) Temporal distribution of the 27 studies analyzed. The dashed gray line indicates the mean publication year of approximately 2004. Red cross symbols represent studies using discrete years for their scaling analysis, while solid red lines denote continuous study periods. Black dots mark the year of publication. (b) Geographic distribution of studies by country. Countries represented by fewer than three studies are excluded from the figure.

Our meta-analysis includes 362 unique urban scaling exponents (β), including 18 global-scale values, 17 continental-scale values, 312 country-level values, and 15 regional or sub-regional values. Most studies on urban energy and pollution scaling were conducted in China ($n = 12$), the USA ($n = 9$), and Europe ($n = 4$), respectively (figure 1b). The mean and median year used to derive scaling relationships across the 27 studies was 2004 and 2005 respectively (figure 1a)—nearly two decades ago. This temporal gap highlights an important limitation: most urban scaling analyses rely on pre-2020 datasets. This reflects both the lag in availability of consistent city-level energy and emissions data and the relatively slow evolution of key structural features of cities, such as infrastructure networks and urban form. While recent changes in urban energy systems and mobility patterns, including temporary disruptions associated with the COVID-19 pandemic, may have influenced absolute levels of energy use and emissions, the underlying drivers of scaling relationships, particularly interaction dynamics mediated by infrastructure and spatial organization, tend to evolve over longer, often decadal, timescales. Therefore, previously reported scaling relationships still remain informative for understanding long-term urban

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3 dynamics. This also highlights the importance of updated datasets to reassess scaling behavior
4 under contemporary conditions. In terms of methodology, the majority of these studies estimate
5 scaling relationships using cross-sectional analyses across cities, typically by fitting log–log
6 regressions between urban indicators (e.g., energy use, emissions) and population size. In
7 contrast, longitudinal analyses that examine how scaling relationships evolve over time within
8 individual cities remain comparatively limited (see [section 3.3](#)). This imbalance underscores the
9 need for longitudinal analyses to more rigorously evaluate how urban metabolism responds to
10 evolving socioeconomic, infrastructural, and environmental conditions.
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19 *3.1 Scaling of urban energy consumption*

20 Urban energy consumption reflects the aggregation of diverse energy flows that sustain
21 production, transportation, and residential activities. These flows have been studied within the
22 framework of urban metabolism to understand environmental impacts associated with energy
23 consumption, waste production, and material throughput (Kennedy *et al* 2007, 2011). Energy
24 consumption is strongly correlated with economic metrics such as GDP (Kennedy *et al* 2015, Yu
25 *et al* 2024), and often serves as an indicator of a city’s economic advancement (Dalgaard and
26 Strulik 2011, Liu *et al* 2021). This coupling between energy use and economic growth is
27 reflected in urban scaling laws. For example, previous studies reported that residential electricity
28 sales scale linearly with population, while total electricity sales scale superlinearly (Kennedy *et*
29 *al.* 2015; Bettencourt *et al.* 2007; Bettencourt 2013). Superlinear scaling of energy-related
30 indicators has been observed in several countries, particularly for gas consumption and supply
31 (Yatzkan *et al* 2024, Liu and Zou 2020, Lei *et al* 2022, Ramaswami *et al* 2018, Bettencourt *et al*
32 2007).
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43 Indeed, across all studies included in our meta-analysis, the distribution of electricity, gas,
44 and transportation fuel scaling exponents predominantly exhibit superlinear scaling with
45 population ([figure 2a](#)), with 58.3%, 76.9%, and 100% of reported exponents exceeding 1,
46 respectively. The reported median scaling exponent is 1.06 [25th percentile: 0.94, 75th
47 percentile: 1.13] for electricity, 1.18 [1.05, 1.34] for gas, and 1.22 [1.19, 1.27] for congestion-
48 related transportation fuel. Particularly for gas and transportation fuel, our results imply that
49 demand for these urban properties intensify faster than population growth. When aggregated by
50 country, China produced the largest number of energy-related scaling exponents ([figures 2 and](#)
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3), reflecting the country's rapid urbanization, economic development, and the availability of extensive urban data (Lu *et al* 2024, Rao *et al* 2023, Cui *et al* 2020). Our analysis specifically identifies gas as an energy variable exclusively examined in China, where it exhibits a superlinear scaling pattern (figure 2b). In comparison, transportation fuel scaling exponents are largely derived from a single study in the U.S. (figure 2d).

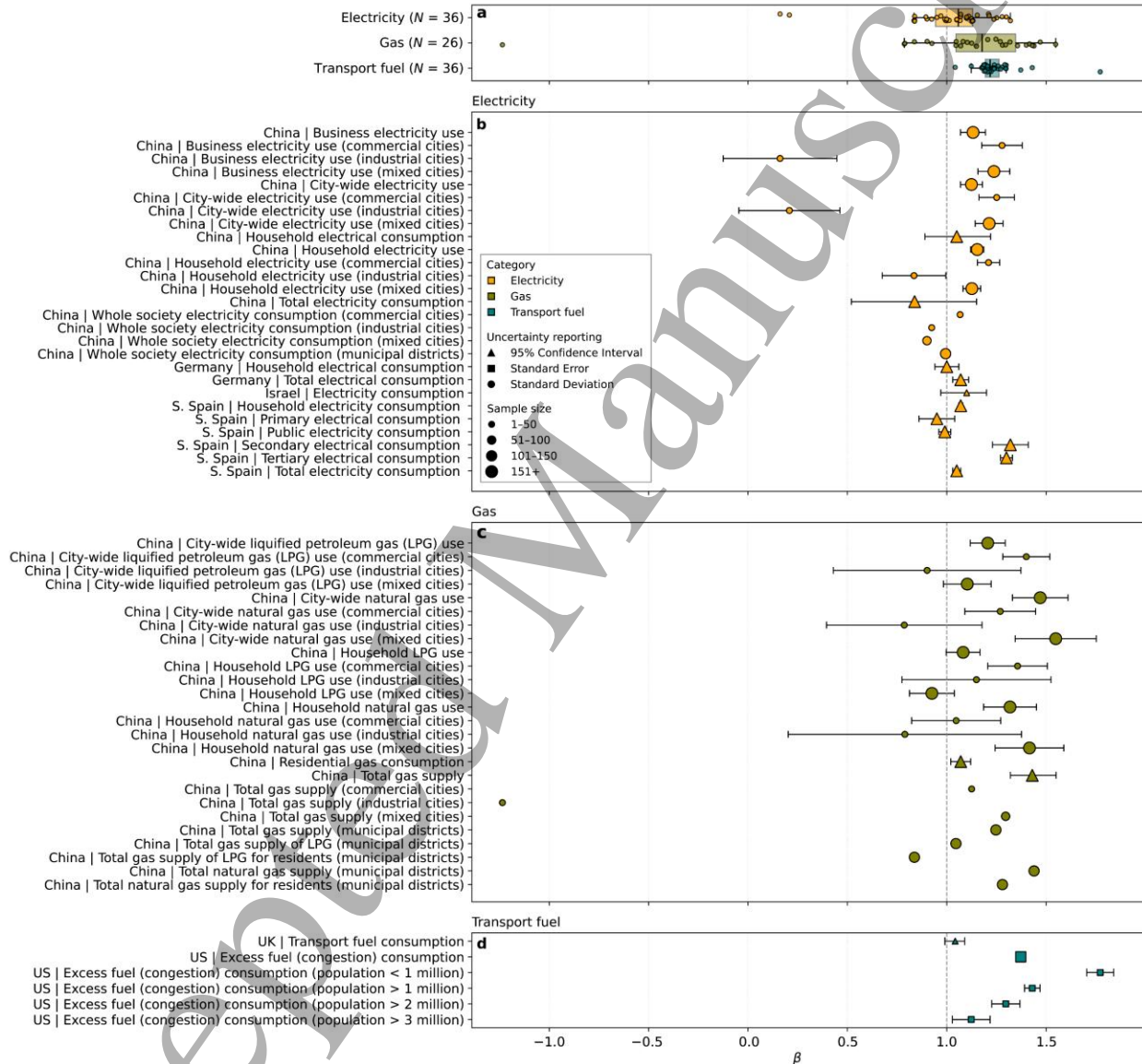


Figure 2. Urban scaling exponents (β) for energy-related attributes. (a) Combined results for all energy-related studies. (b–d) Scaling exponents grouped by energy type: electricity, gas (e.g., natural gas), and transportation fuel, respectively. The dashed vertical line marks $\beta = 1$, indicating linear scaling; values of $\beta > 1$ and $\beta < 1$ correspond to superlinear and sublinear relationships, respectively. Each data point represents an individual scaling exponent. Marker

size denotes the sample size, while solid black horizontal bars indicate the reported uncertainty range. Triangles represent 95% confidence intervals, squares represent standard errors, and circles represent standard deviations. Note that for studies reporting time-series of scaling exponents, only the most recent year or the aggregated exponent is included in panels (b–d).

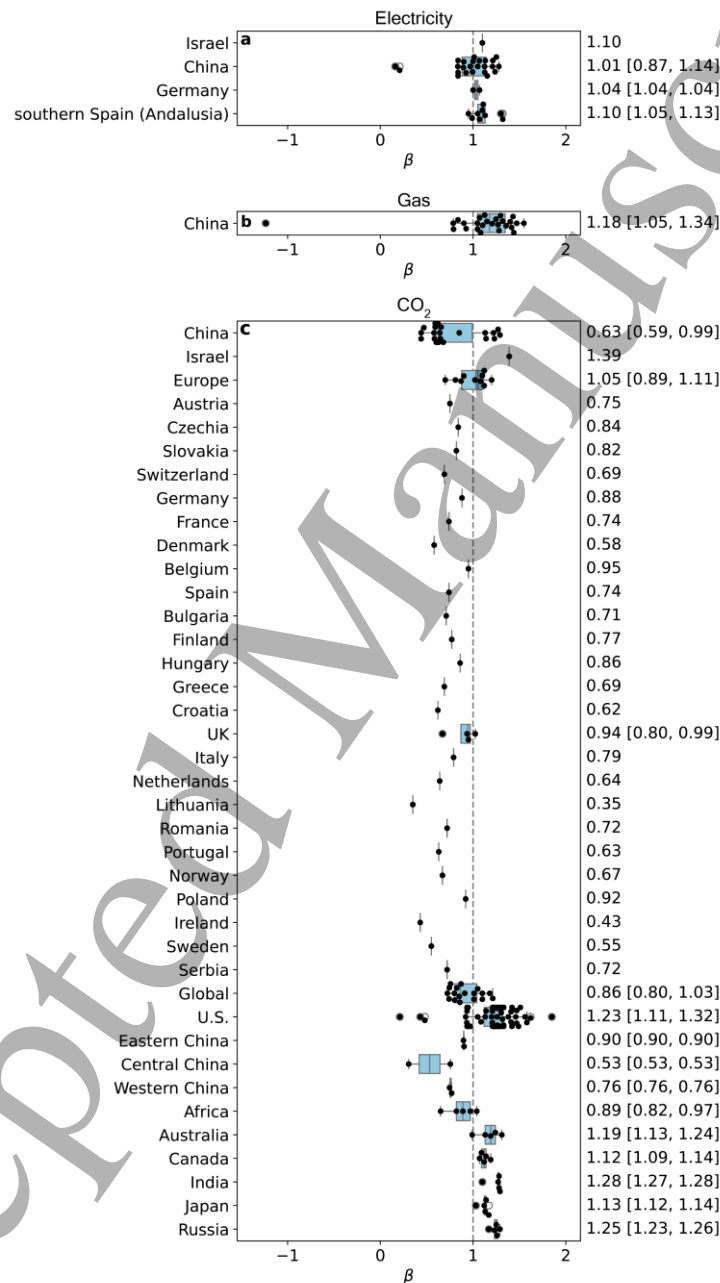


Figure 3. Distribution of urban scaling exponents (β) for electricity, gas, and CO₂ emissions by country. The dashed gray line marks $\beta = 1$, indicating linear scaling; values of $\beta > 1$ and $\beta < 1$ correspond to superlinear and sublinear relationships, respectively. Boxes show the interquartile

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3 range (IQR) of β values between the upper and lower quartiles, whiskers extend to $1.5 \times \text{IQR}$,
4 and points beyond the whiskers denote outliers. Each dot represents an individual β value
5 extracted from the reviewed studies. Numbers on the right show the median [25th percentile,
6 75th percentile] for each country/region; single-exponent cases display the reported value.
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10 Our synthesis here contrasts with earlier individual studies that found sublinear or linear
11 scaling of urban energy use and electricity (Kennedy *et al* 2015, Bettencourt *et al* 2007,
12 Bettencourt 2013, Liu and Zou 2020, Lei *et al* 2022, Ramaswami *et al* 2018, Bristow and
13 Kennedy 2015, Gudipudi *et al* 2019a, Liu and Zou 2020, Dalgaard and Strulik 2011). These
14 discrepancies can be attributed to the different study scales used (e.g., global vs. country-level).
15 Regardless, a universal scaling relationship for urban energy consumption remains elusive, partly
16 due to the challenges of obtaining consistent and comparable energy data across countries and
17 regions (Facchini *et al* 2017).
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25 3.2 Scaling of urban pollutant emissions

26 Pollutant emissions are tightly coupled with urban energy consumption, especially in
27 sectors such as transportation, industry, and construction (Hou *et al* 2024, Bettencourt and West
28 2010, Li *et al* 2024, Keleş *et al* 2022, MacKenzie *et al* 2019, Louf and Barthelemy 2014a).
29 Combustion of fossil fuels is primarily responsible for CO₂, NO₂, and SO₂ emissions, which also
30 contributes substantially to other pollutants such as PM_{2.5} and CO, alongside emissions from
31 industrial activities and agricultural processes (Liang *et al* 2024). Because urbanization and
32 human settlement processes are complex (Batty 2008, Louf and Barthelemy 2014a, Ribeiro *et al*
33 2019), their impacts on pollutant emissions are multifaceted and often spatially heterogeneous
34 (Wang and Komonpipat 2020, Muller 2016).
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43 Like many other urban attributes, pollutant emissions exhibit empirical scaling behavior
44 (Gudipudi *et al* 2019a, Cui *et al* 2020, Li *et al* 2021b, Yatzkan *et al* 2024, Muller 2016,
45 MacKenzie *et al* 2019). While larger, denser cities are often assumed to be less environmentally
46 intense due to shared infrastructures (Bettencourt and West 2010, Bettencourt *et al* 2007, Kumar
47 and Sen 2025), empirical findings remain inconclusive (Fragkias *et al* 2013, Oliveira *et al* 2014,
48 Louf and Barthelemy 2014a). Multiple studies have shown superlinear scaling of pollutant
49 emissions, indicating that larger cities generate disproportionately higher emissions per capita
50 (Lamsal *et al* 2013, Yatzkan *et al* 2024, Liang *et al* 2024, Bettencourt and Lobo 2016, Li *et al*
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2021b, Oliveira *et al* 2014), raising the possibility that larger cities might not have a smaller per-capita environmental footprint. For example, in our meta-analysis, while the median scaling exponent for CO₂ emission at the global scale is 0.86 [0.80, 1.05], that for the U.S. is 1.23 [1.11, 1.32], which tends to be superlinear (figure 3c).

Across all studies compiled in our meta-analysis, pollutant emissions generally scale sublinearly with population. This indicates that most urban air pollutant emissions tend to increase more slowly than population size. Specifically, the median scaling exponents for SO₂, CO₂, NO_x, PM₁₀, PM_{2.5}, and CO are 0.58 [0.32, 0.96], 1.06 [0.78, 1.24], 0.96 [0.60, 1.06], 0.74 [0.74, 0.74], 0.69 [0.59, 0.75], and 0.77 [0.76, 0.85], respectively. Superlinear scaling exponents are reported only for SO₂, CO₂, and NO_x, accounting for 33.3%, 54.3%, and 45.5% of their respective samples. These three pollutants also exhibit broad distributions of reported exponents, suggesting substantial variability across studies. CO₂, in particular, shows a roughly balanced mix of superlinear and sublinear scaling exponents, ranging from markedly sublinear to strongly superlinear across studies and yielding a median slightly above 1. This wide dispersion likely reflects heterogeneity in methodological choices, such as city definitions (see section 4), national contexts, and stages of socioeconomic development. Consequently, the scaling behavior of these pollutant emissions appears not to follow a universal relationship but instead depends on structural, geographic, and developmental differences across study settings.

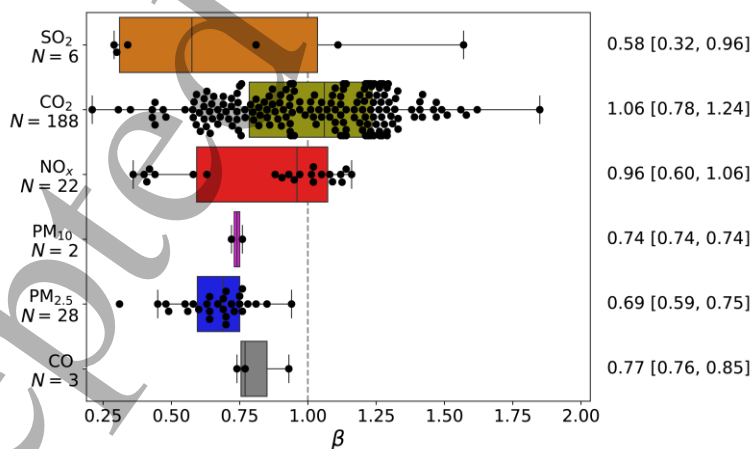


Figure 4. Distribution of urban scaling exponents (β) for pollutant emissions. The dashed gray line marks $\beta = 1$, indicating linear scaling; values of $\beta > 1$ and $\beta < 1$ correspond to superlinear and sublinear relationships, respectively. Boxes show the interquartile range (IQR) of β values between the upper and lower quartiles, whiskers extend to $1.5 \times$ IQR, and points beyond the

whiskers denote outliers. Each dot represents an individual β value extracted from the reviewed studies. Numbers on the right show the median [25th percentile, 75th percentile] for each country/region; single-exponent cases display the reported value.

The geographical variation in pollutant emissions scaling indeed reveals contrasting trajectories (figures 3 and S1). Because of China's rapid urbanization and economic growth over the last two decades, Chinese cities are often viewed as environmentally unfriendly (Cui *et al* 2020, Chen *et al* 2025). However, our meta-analysis suggests that Chinese cities tend to have sublinear scaling of CO₂ emissions, indicating improved emission efficiency with city size (figure 3c). In contrast, urban CO₂ emissions in the U.S., Europe, Australia, Canada, India, Japan, and Russia tend to scale superlinearly, as suggested by the median values, which means larger cities in these regions remain more carbon intensive. This contrast implies that differences in urban infrastructure and energy mix might play a more significant role than city size alone in determining environmental outcomes. Such differences could point toward a quantifiable need to incorporate a higher mix of renewable energy generation to offset the environmental impact of larger city population. Other pollutants, such as PM_{2.5}, NO_x, SO₂, and CO, scale sublinearly across most countries (figure S1), with the notable exception of NO_x emissions in the UK and Israel, which tend to scale linearly or superlinearly.

3.3 Temporal evolution of the urban scaling law

Eight studies in our meta-analysis reported time-varying urban scaling exponents, yielding a total of 18 unique β time series that capture the temporal evolution of scaling relationships (figure S2) (Chang *et al* 2017, Yang *et al* 2025, Horta-Bernús and Rosas-Casals 2015, Muller and Jha 2017, Fragkias *et al* 2013, Lu *et al* 2024, Elliott *et al* 2015, Rao *et al* 2023). These studies represent a small but growing body of work studying whether scaling behavior remains stable or evolves as cities and their energy systems further develop.

From the limited time series available, we find that CO₂ scaling exponents have generally increased over time with regional disparities. However, this apparent upward trend is from a single long-term analysis (Yang *et al* 2025), suggesting the need for caution in generalizing this finding. Nearly all studies examined post-2000 periods, with the exception of Chang *et al* (2017), which analyzed data extending back to 1982. Overall, the lack of time-series analyses in our meta-analysis underscores the short temporal coverage and the limited number of studies

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3 addressing how scaling exponents evolve through time. Moreover, several of the reported β
4 values have substantial uncertainty, as indicated by the wide confidence intervals.
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8 **4. Discussion**

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10 The scaling law provides a coarse-grained framework to quantify how urban systems
11 evolve with size. However, the results synthesized here highlight several fundamental limitations
12 in how these relationships are defined, interpreted, and applied. In particular, variations in city
13 definition, data construction, and study design introduce substantial uncertainty in reported
14 scaling exponents. One of the most important factors is the inconsistent definition of a city/urban
15 area, which remains a major source of variation in reported scaling exponents (Yang *et al* 2025,
16 Louf and Barthelemy 2014a, Decker *et al* 2007, Gudipudi *et al* 2016, 2019a, Kumar and Sen
17 2025, La Porta and Zapperi 2024, Lu *et al* 2024, Cottineau *et al* 2017). As illustrated in [figure 5](#),
18 the same urban attribute can have vastly different scaling behavior depending on how a study's
19 city boundaries are defined. This definitional heterogeneity directly influences whether cities
20 appear to be more or less resource-efficient. Even within the same country, city boundaries are
21 often ambiguous, especially when neighboring metropolitan areas share some functional and
22 socioeconomic characteristics that would otherwise differentiate a city from its surrounding area
23 (Kumar and Sen 2025, Decker *et al* 2007). Intermediate-sized cities may also play an outsized
24 role in shaping national energy flows and emissions but are frequently underrepresented in global
25 analyses (Bahers *et al* 2019).
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38 Furthermore, inconsistencies in urban inventory data, especially for energy consumption
39 in commercial buildings (Kontokosta 2015) and indirect resource flows that occur outside city
40 boundaries (Ramaswami *et al* 2012) can further influence the derived scaling relationships. This
41 issue is particularly important for sectors involving cross-boundary flows, such as electricity and
42 air pollutants, where production and consumption can be spatially decoupled. Such decoupling
43 provides a plausible explanation for the contrasting scaling patterns identified in this study: while
44 energy consumption reflects demand concentrated within cities, emissions (especially CO₂) may
45 be displaced outside city boundaries through regional energy production, industrial relocation, or
46 supply-chain dynamics. As a result, emissions associated with urban consumption may not scale
47 proportionally with population within administrative city boundaries, contributing to the
48 sublinear behavior observed for many pollutants. In such cases, scaling relationships may reflect
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3 differences in accounting conventions (e.g., production-based vs. consumption-based) as much
4 as underlying urban processes. In addition, spatial heterogeneity within cities is often
5 overlooked: studies using finer-resolution spatial data show that intra-urban scaling relationships
6 may differ from city-level aggregates (Li *et al* 2017, Huang and Lu 2025), highlighting the need
7 to consider both boundary definitions and internal spatial structure in scaling analyses.
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12 Another key uncertainty/knowledge gap is the temporal stability and generalizability of
13 the urban scaling law. A key distinction is whether scaling relationships are derived from cross-
14 sectional comparisons across cities or from longitudinal analyses within cities over time, as these
15 approaches may yield different interpretations of scaling behavior (Molinero and Thurner 2021,
16 Keuschnigg 2019). There have been very few comprehensive studies of whether scaling
17 exponents remain constant over time (Burghardt *et al* 2024, Balta-Ozkan *et al* 2015, Liu *et al*
18 2022, Zhao *et al* 2018, Rybski *et al* 2017), despite early formulations of urban scaling often
19 being interpreted as implying universality (Bettencourt 2013, Bettencourt *et al* 2020, West
20 2017). Temporal variations in scaling exponents may arise from heterogeneous growth rates
21 across cities of different sizes, which can systematically shift aggregate scaling relationships over
22 time (Li *et al* 2021a). Though, some studies do suggest that scaling exponents remain stable over
23 time (Lei *et al* 2022, Zünd and Bettencourt 2019, Bettencourt *et al* 2010, Zhao *et al* 2018).
24 However, these studies typically cover short time spans and have small samples of cities and/or
25 small sets of urban attributes (Liu and Zou 2020, Zhao *et al* 2018, Lei *et al* 2022, Zünd and
26 Bettencourt 2019, Pumain 2025). This raises the question of whether observed scaling exponents
27 represent intrinsic, stable properties of urban systems or instead reflect context-dependent
28 outcomes that evolve over time.
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41 The generalization of existing studies is further limited by both spatial and sectoral
42 biases. While disentangling the specific mechanisms underlying these differences is beyond what
43 can be inferred from a synthesis of reported scaling exponents, prior studies suggest that factors
44 such as environmental policy, infrastructure systems, and economic structure can significantly
45 influence observed scaling relationships (e.g., Muller and Jha 2017). For example, while most
46 urban CO₂ scaling studies originate from the U.S. (figure 3), there are surprisingly few analyses
47 of other urban energy consumption and pollutant emissions variables for U.S. cities. This gap is
48 notable given the country's combination of high population, low urban density, and heavy
49 dependence on private vehicles, all of which likely influence the scaling of energy use and
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3 emissions in distinct ways. This gap largely reflects the limited public availability of consistent
4 city-level energy and non-CO₂ emission data. Part of this data unavailability can be attributed to
5 fragmented data governance, as local/regional utility companies and independent authorities
6 often restrict access to energy and emissions data (Gocke 2023, Cao 2024, Kontokosta 2015).
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8 Particularly in the U.S., the decentralized role of utility providers further contributes to reliance
9 on alternative data sources such as the Vulcan Project (Fragkias et al. 2013) and satellite
10 observations (Lamsal et al. 2013), and coarse-resolution governmental datasets such as the
11 Environmental Protection Agency's National Emissions Inventory (Muller and Jha 2017). In
12 addition to data sources, the use of population as the primary scaling variable in existing studies
13 may obscure the influence of urban density, spatial structure, and land-use patterns, which are
14 known to shape energy use and emissions but are not explicitly represented in standard scaling
15 formulations (Ribeiro and Rybski 2023). As a result, widely reported scaling relationships may
16 reflect aggregate effects of population size without fully capturing the underlying heterogeneity,
17 and may not generalize consistently across different socioeconomic and infrastructural contexts.
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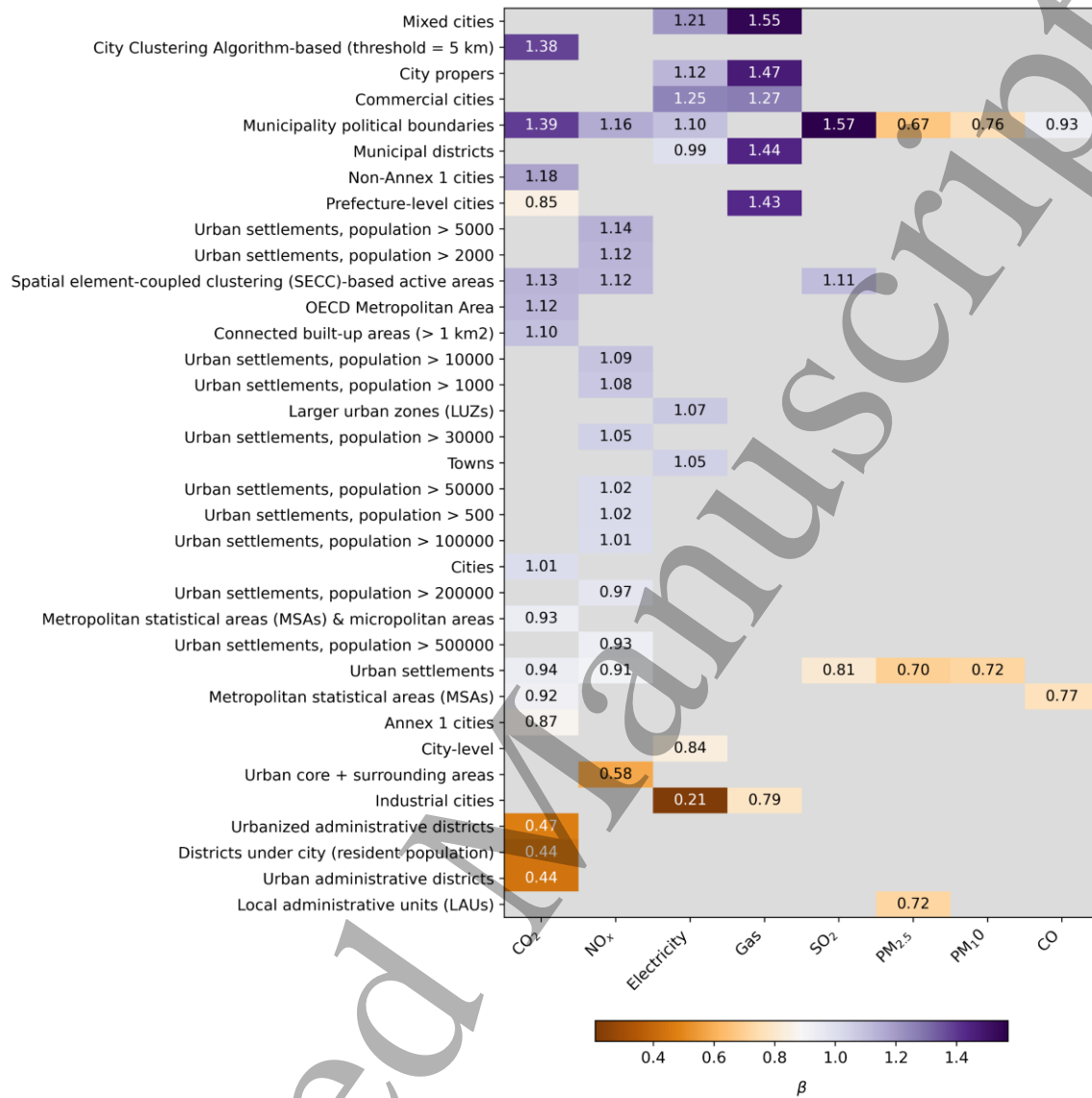


Figure 5. Heat map illustrating how different city definitions influence the calculated urban scaling exponents (β) for total emission/consumption. The color scale is centered over $\beta = 1$, representing linear scaling. Darker shades indicate $\beta > 1$ (superlinear scaling), whereas lighter shades indicate $\beta < 1$ (sublinear scaling). Each filled cell shows a representative β value with the corresponding city definition. When multiple years are reported, only the most recent or aggregated value is used. When both global and regional values are available, only global values are shown. When the same attribute is reported across multiple regions, a single representative value is selected.

All these challenges are closely linked to underlying data limitations. Addressing them will require the development of integrated, gap-free, and long-term datasets suitable for large-

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3 scale and temporally resolved urban scaling analyses (e.g., Wang *et al* 2024, Cao 2024, Xu *et al*
4 2024). Existing datasets often suffer from inconsistent boundary definitions, incomplete sectoral
5 coverage, and temporal gaps due to irregular reporting or changes in administrative delineations.
6 These inconsistencies are especially evident in energy use and emissions, where data are
7 frequently aggregated at coarse regional levels, which can limit their usefulness for city-level
8 scaling analyses. In addition, the inherent lag in many urban energy and emissions datasets
9 further constrain the ability to evaluate how scaling relationships evolve under changing urban
10 conditions, especially for countries undergoing rapid urbanization. At the same time,
11 heterogeneity and incomplete reporting of statistical information across included studies (e.g.,
12 missing uncertainties, inconsistent definitions, and varying estimation methods) also limit the
13 application of formal meta-analysis techniques, such as effect-size weighting or publication bias
14 testing. It is noteworthy that scaling analysis represents only one of several approaches used to
15 examine urban energy use and emissions. Alternative frameworks, including bottom-up
16 inventories, process-based modeling, and high-resolution observational or remote sensing
17 approaches, can provide more mechanistic and spatially explicit insights into urban systems.
18 While model-based reconstructions and downscaling methods can help fill these gaps, they may
19 introduce additional structural uncertainty and may not fully capture local urban dynamics. A
20 promising pathway to improve scaling analyses is to ground them in observationally constrained
21 simulations that integrate models, measurements, and administrative data, leveraging the
22 complementary strengths of these approaches. The integration of such datasets with harmonized
23 definitions of urban boundaries would enable consistent cross-country comparisons and time-
24 series analyses of the urban scaling law.

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These limitations also raise a broader question about the intended role of urban scaling
analyses in advancing understanding of urban systems. Despite extensive empirical evidence
documenting scaling relationships across a wide range of urban indicators, the interpretation and
application of these relationships remain varied. This emerges as a central challenge emerging
from the present synthesis. In the literature, scaling relationships have been used both as
descriptive summaries of cross-city variation and as a framework for generating hypothesis-
informed interpretations about underlying mechanisms, but rarely as rigorously tested
mechanistic or predictive frameworks. For example, sublinear scaling of infrastructure-related
quantities is often interpreted as a consequence of economies of scale in spatially embedded

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3 networks, whereas superlinear scaling of socioeconomic indicators is linked to increased
4 interaction rates, knowledge exchange, and information flow in larger urban populations (West
5 2017, Ribeiro and Rybski 2023). In practice, most studies of urban energy use and emissions,
6 including many included in this synthesis, primarily report cross-sectional scaling exponents. As
7 a result, mechanistic explanations are often invoked, and observed exponents are often
8 interpreted as signatures of efficiency or intensification, even though similar scaling behavior
9 may arise from multiple underlying processes and may be sensitive to city definitions, data
10 construction, and study design. This disconnection limits mechanistic interpretation and partially
11 explains why reported exponents vary across regions and sectors. Future work would benefit
12 from integrating scaling analyses with process-based representations of urban systems, including
13 infrastructure networks, urban form, governance, and energy-system structure, so that scaling
14 exponents can be interpreted not only as empirical summaries but also as tests of hypotheses.
15 Such a shift would be essential if urban scaling is to move from a descriptive framework toward
16 a predictive and explanatory science of cities.
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29 **5. Conclusion**

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31 This meta-analysis synthesizes evidence on how urban energy use and pollutant
32 emissions scale with population across cities. By compiling 362 scaling exponents from 27
33 studies, we show that energy-related quantities such as electricity, gas, and transportation fuel
34 predominantly exhibit superlinear scaling. This result implies that energy demand tends to
35 increase faster than population growth. In contrast, most air pollutants scale sublinearly, which
36 suggests per-capita emission efficiencies tend to improve with city size. A notable exception is
37 superlinear scaling of CO₂ emissions in U.S. cities, which contrasts with the sublinear scaling of
38 CO₂ emissions in Chinese cities and global-scale studies. Such discrepancies are likely a result of
39 differences in energy structure, technology, and policy interventions. More broadly, the
40 contrasting scaling behavior between energy consumption and pollutant emissions may also
41 reflect the spatial decoupling of production and consumption, whereby emissions associated with
42 urban energy demand are often generated outside city boundaries, weakening the direct linkage
43 between population size and locally accounted emissions.
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53 Despite growing use of the urban scaling framework, this synthesis reveals several
54 important limitations in the current literature. The existing literature synthesized here is
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3 geographically uneven, with a strong concentration of studies from China and the U.S. and much
4 more limited coverage of rapidly urbanizing regions such as Africa and Latin America. This
5 imbalance reflects the availability of existing studies. Variations in city definitions and data
6 completeness also continue to produce inconsistent scaling exponents and limit cross-regional
7 and country comparability. In addition, the scarcity of long-term, high-resolution datasets and a
8 lack of temporal analyses limit our understanding of how scaling relationships evolve over time
9 across cities. More fundamentally, the literature remains largely descriptive: many studies report
10 scaling exponents without explicitly examining the mechanisms that give rise to these
11 relationships or testing theoretical predictions. As a result, similar scaling behavior may be
12 interpreted as evidence of efficiency or intensification, even though it may result from various
13 underlying processes and can be sensitive to data construction and study design.

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These limitations have important implications for applications of scaling in practice. Urban planners and decision-makers should interpret scaling relationships with caution, recognizing that inferred trends may depend strongly on data sources, methodological choices, and city definitions. Addressing these challenges will require more geographically diverse, standardized, integrated, and temporally resolved urban energy and emission datasets across sectors, countries, and continents. Expanding urban scaling studies in underrepresented regions will be particularly important for building a more complete empirical basis for comparison. Moreover, improving interpretability requires linking observed scaling relationships to underlying physical, socioeconomic, and infrastructural mechanisms, as well as developing theoretical frameworks that can generate testable predictions. Such efforts would enable more reliable scaling analyses, advance understanding of the dynamics of urban metabolism, and better inform the design of sustainable, low-carbon cities in a rapidly urbanizing world.

Data availability statement

All data that support the findings of this study are included within the article and its supplementary file.

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