

DRIVING FACTORS OF RISING ENERGY DEMAND: THE ROLE OF GREEN INFRASTRUCTURE, AIR POLLUTION, AND SURFACE PROPERTIES IN MITIGATING URBAN HEAT ISLAND EFFECTS IN CHINA

ZHENG, Y. P.¹ – ARSHAD, R.^{2*}

¹*School of Marxism, Shanghai Jiao Tong University, Shanghai, China
(e-mail: ada666@sjtu.edu.cn)*

²*School of Management, Guangdong University of Science and Technology, Dongguan, China*

**Corresponding author
e-mail: rimshaarshad313@yahoo.com*

(Received 18th Jun 2025; accepted 31st Jul 2025)

Abstract. As China pursues carbon neutrality and sustainable urbanization, understanding the structural and environmental drivers of urban energy consumption has become increasingly urgent. This study investigates the long- and short-run impacts of urban form, surface temperature, building materials, land use, energy efficiency, green infrastructure, air pollution, and surface albedo on urban energy consumption across ten of China's most urbanized provincial-level regions. These include the municipalities of Beijing, Shanghai, Tianjin, and Chongqing, and the provinces of Guangdong, Jiangsu, Zhejiang, Shandong, Fujian, and Sichuan, over the period 2000 to 2022. Using a cross-sectionally augmented autoregressive distributed lag (CS-ARDL) framework and validating the results through Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators, we find that energy efficiency and green infrastructure significantly reduce urban energy demand, while dense land use, pollution, and thermally intensive materials increase it. A novel contribution of this study is the use of a composite air pollution index derived from PM_{2.5}, NO_x, and SO₂ data, as well as the integration of surface albedo as a determinant of energy demand under climate-adaptive strategies. Impulse response functions further confirm that policy shocks in efficiency and infrastructure yield both immediate and sustained reductions in urban energy consumption. The findings highlight the importance of integrating technological, environmental, and spatial planning strategies in urban energy governance. They also provide actionable insights for tailoring policies to the distinct conditions of rapidly growing regions in China.

Keywords: *urban energy consumption, green infrastructure, energy efficiency, urban form, air pollution index, surface albedo*

Key insights

Urban heat island effects and energy demand in dense Chinese cities are influenced by built environments and air pollution. This study integrates surface albedo and a novel composite air pollution index (PM_{2.5}, NO_x, SO₂) into a dynamic panel analysis of energy consumption. It also highlights the long- and short-run mitigating effects of green infrastructure and energy efficiency using CS-ARDL, AMG, and CCEMG approaches. The findings guide localized urban energy governance by emphasizing the role of adaptive infrastructure, climate-sensitive design, and pollution control in reducing energy demands across China's most urbanized provinces.

Introduction

The relentless pace of urbanization has intensified global concerns regarding sustainable energy consumption, especially in developing and transition economies

(Dong et al., 2025; Pragasan and Ganesan, 2024; Wu et al., 2025b). In particular, China's urban regions—home to over 65% of the national population and accounting for more than 75% of total energy consumption—present a critical arena for addressing climate and energy challenges (Liu et al., 2019). According to the National Development and Reform Commission (NDRC, 2022), China's carbon neutrality strategy emphasizes the importance of reducing energy consumption across urban areas (NDRC, 2022). Si et al. (2023) further explore these dynamics in the context of urban energy systems.

Traditionally, research on energy consumption has predominantly centered on national-level aggregates or sectoral disaggregation, focusing on macroeconomic indicators such as GDP per capita, population growth, or industrial output (Ren et al., 2021). While valuable, these approaches often neglect the nuanced interplay between urban spatial structures, environmental conditions, and technological dynamics that uniquely shape energy demand in cities (Lin and Zhang, 2025; Wei et al., 2025). For instance, cities characterized by high land use density, vertical development, and efficient public transport systems often exhibit different energy patterns than sprawling, car-dependent urban forms (Gallelli et al., 2022; Mattioli et al., 2020). Likewise, meteorological variations such as urban heat islands (UHIs) and humidity patterns significantly affect residential and commercial energy needs, particularly cooling demand (Hashemi and Mills, 2025; Verichev et al., 2023).

Recent research has increasingly recognized the role of structural and ecological urban characteristics in shaping energy outcomes. Factors such as surface albedo—the reflectivity of urban materials—can influence local microclimates and reduce cooling loads (Salvati et al., 2022). The types of building materials used (e.g., concrete, asphalt, glass) also contribute to urban heat absorption and, consequently, affect energy use intensity (Tabatabaei and Fayaz, 2023). Air pollution, particularly concentrations of PM_{2.5}, NO_x, and SO₂, not only reflects energy-intensive activities but also leads to behavioral responses that increase indoor energy use (e.g., air purification, heating/cooling adjustments) (Chen et al., 2025; Li et al., 2025; Wu et al., 2025a).

On the other hand, technological and institutional innovations offer significant mitigation potential. Energy efficiency measures (ENEF), ranging from building insulation to smart grid systems, play a vital role in decoupling economic growth from energy consumption (Almarzooq et al., 2022; Loschi et al., 2015). Green infrastructure (GRI), particularly in the form of environmental patents, renewable energy adoption, and clean tech investments, contributes to long-term energy optimization in urban infrastructure (Shi and Shi, 2025; Teklie and Yağmur, 2024).

Figure 1 presents the spatial distribution of land surface temperature (LST) across China, derived from MODIS satellite observations. The temperature ranges from below -73.15°C (indicated in deep blue) to above 76.85°C (marked in deep red), capturing substantial thermal heterogeneity across the country. The northwestern and central regions—particularly the Xinjiang Autonomous Region, Inner Mongolia, and parts of the Tibetan Plateau—exhibit high surface temperatures, as denoted by the orange to red shades. This pattern reflects the combined influence of arid climate conditions, sparse vegetation cover, and strong solar irradiance. In contrast, southeastern coastal regions, including parts of Guangdong, Fujian, and Zhejiang, show relatively moderate surface temperatures (yellow to green hues), likely due to higher humidity levels, vegetation density, and oceanic influences. Urban agglomerations such as Beijing, Shanghai, Tianjin, and Chongqing are located within or adjacent to high-temperature zones, hinting at intensified urban heat island (UHI) effects. The cloud cover visible over the East China

Sea and parts of southern coastal areas may influence LST retrieval accuracy in those regions, leading to gaps or lower radiometric readings. The figure effectively visualizes regional disparities in surface heating and serves as an empirical foundation for assessing urban thermal.

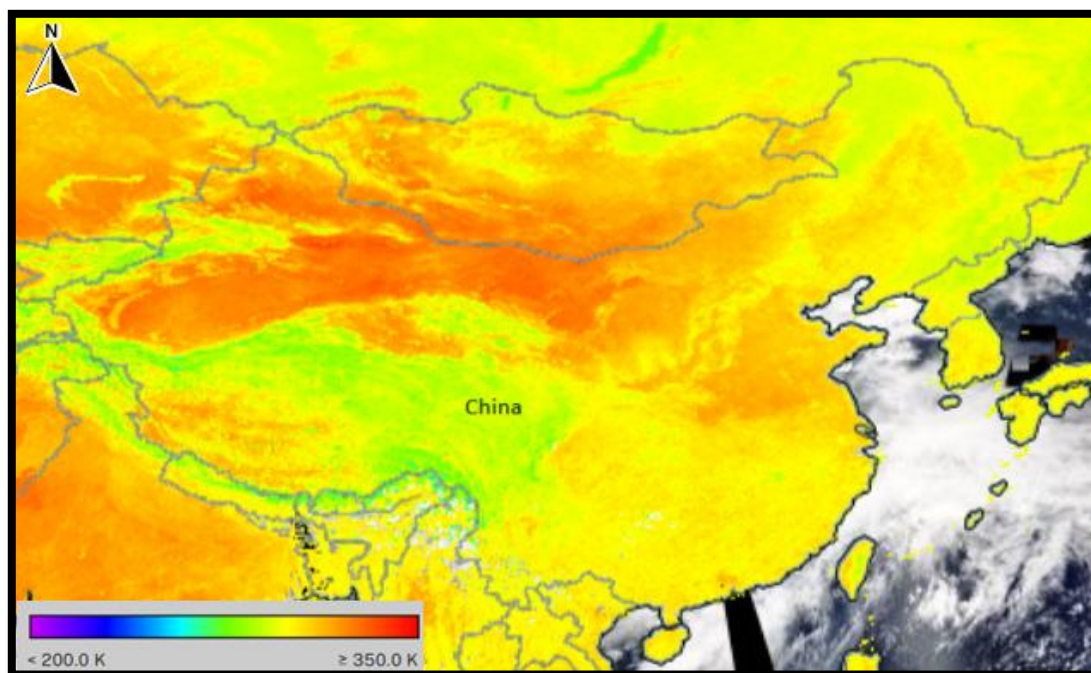


Figure 1. Land surface temperature distribution across China, retrieved from MODIS satellite sensor. The image was captured on 21 April 2021 from NASA Worldview (<https://worldview.earthdata.nasa.gov>)

The descriptive distribution of the core variables across China's most urbanized provinces, illustrated in *Figure 2*, further substantiates the need for a regionally disaggregated analysis. Urban energy consumption (UREN) shows considerable interprovincial variation, with higher median values in Guangdong, Chongqing, and Sichuan, while coastal cities like Beijing and Shanghai exhibit broader dispersion. Air Pollution Index (API), constructed via PCA of PM_{2.5}, NO_x, and SO₂, reveals substantial heterogeneity—with Jiangsu and Zhejiang experiencing more extreme pollution episodes compared to Beijing and Guangdong, which show tighter interquartile ranges. Meanwhile, energy efficiency (ENEF) levels vary notably across provinces, with northern cities like Beijing achieving higher medians, suggesting divergent policy or technological implementation across regions. The distribution of surface temperature highlights climate-related disparities, particularly in provinces like Sichuan and Guangdong, where higher temperature variability likely amplifies energy demand for cooling. Urban form (UFM), proxied by urban population share, is also unevenly distributed, with more compact development in core megacities but greater spread in provinces like Sichuan and Shandong. These observable disparities affirm that a uniform national policy may overlook critical sub-national dynamics, justifying the use of panel econometric models to disentangle the long- and short-run effects of structural, climatic, and policy variables on urban energy consumption.

Despite this growing recognition, few empirical studies have systematically examined how these diverse factors jointly affect urban energy consumption at the provincial level in China using robust econometric techniques. Most prior research either considers cities in isolation or fails to account for spatial dependence and heterogeneity across regions, leading to potentially biased or inconsistent estimates (Murayama et al., 2022; Provenzano, 2024; Ruther, 2014). Moreover, many existing models overlook the long-run equilibrium relationships among variables, focusing primarily on short-run dynamics.

To address these gaps, this study investigates the determinants of urban energy consumption (UREN) across China's ten most urbanized provinces over the period 2000–2022. The analysis incorporates a comprehensive set of variables: urban form (UFM), surface temperature (MTF), building materials (BMT), land use density (LUD), energy efficiency (ENEF), green infrastructure (GRI), air pollution index (API), and surface albedo (ALB). Unlike previous studies, this research leverages a novel air pollution index constructed using principal component analysis (PCA) of PM_{2.5}, NO_x, and SO₂, thereby capturing multi-dimensional environmental stress more accurately.

Methodologically, the study employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, which accounts for mixed order integration, slope heterogeneity, and cross-sectional dependence. Robustness is ensured through complementary estimation using the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) models. Furthermore, the analysis is enriched with dynamic tools such as impulse response functions (IRFs) to capture the temporal shock propagation effects.

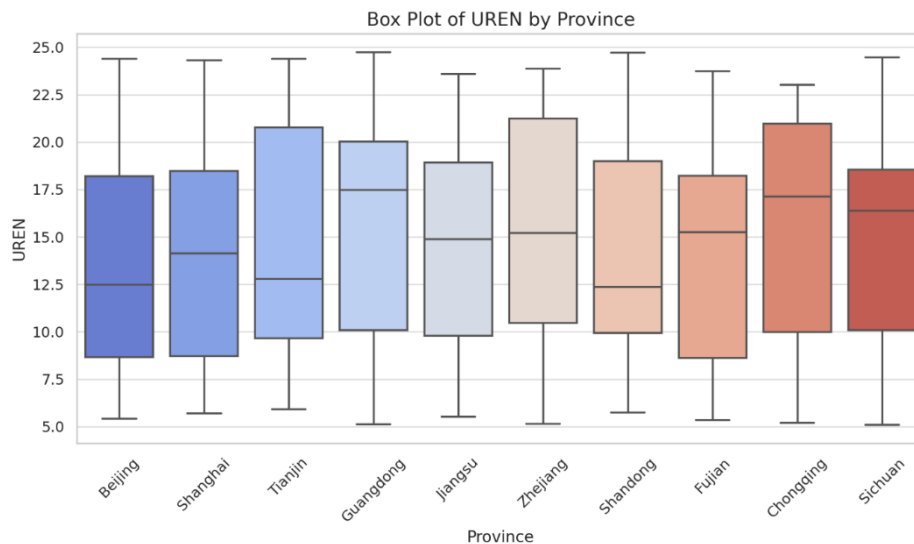
Accordingly, this study aims to answer the following research questions:

1. What are the long-run and short-run drivers of urban energy consumption across China's most urbanized provinces?
2. How do environmental variables—such as air pollution, surface albedo, and green infrastructure—impact urban energy demand over time?
3. How do urban structural factors (urban form, land use, and building materials) influence energy consumption patterns in China's urbanized regions?

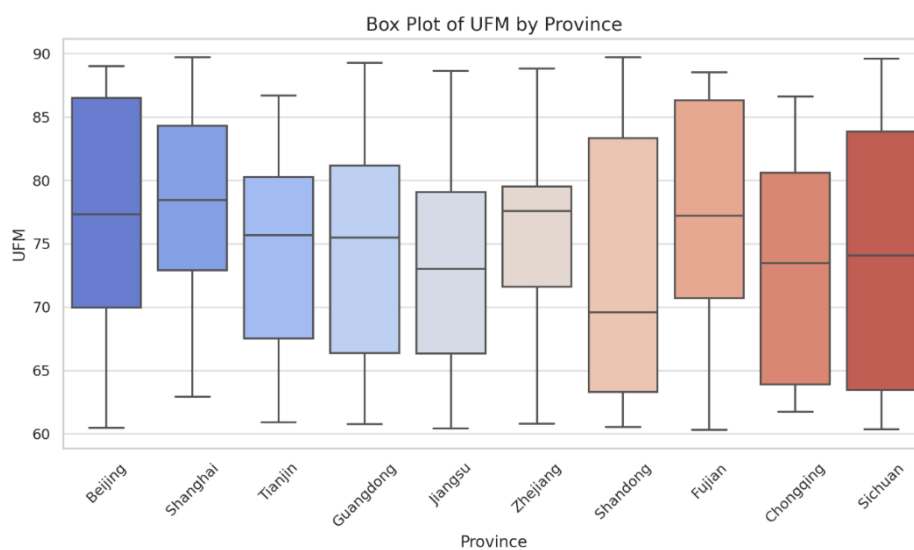
By answering these questions, the study contributes to the growing literature on urban energy transitions, offering empirical evidence for multi-dimensional, region-specific energy policy design. The findings are expected to inform provincial governments, urban planners, and sustainability advocates in aligning urban development with national and international climate goals.

Literature review

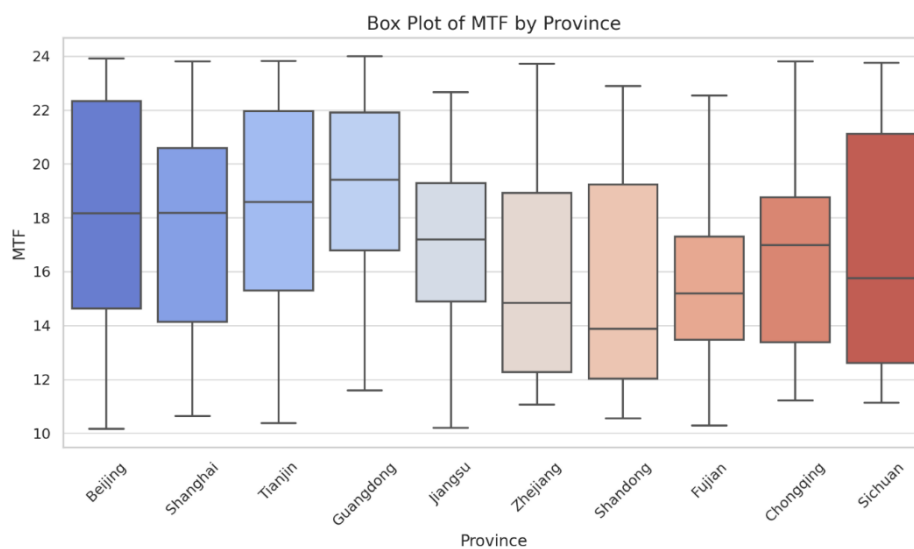
Urban energy consumption has been extensively explored across various disciplinary lenses, including environmental economics, urban planning, and sustainable development. Early studies have primarily focused on macro-level determinants such as income growth, industrialization, and population dynamics. For instance, (Jiang and Lin, 2012) emphasized the role of economic scale and structural shifts in shaping energy use across Chinese regions, finding that energy demand closely follows patterns of urban economic expansion. Similarly, (Raihan and Tuspekova, 2022) established a strong linkage between GDP per capita and urban energy intensity, highlighting the energy-environment tradeoff in rapidly developing cities.



(a)



(b)



(c)

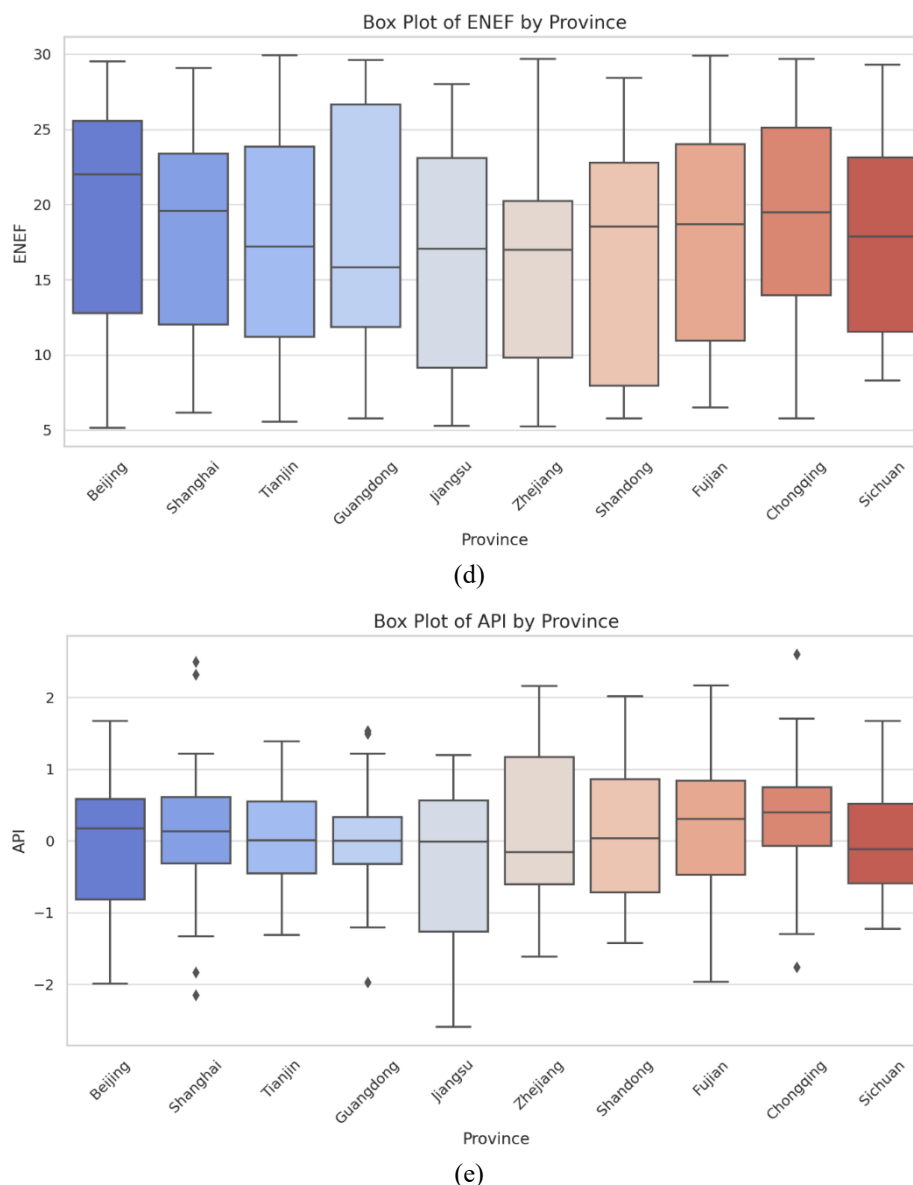


Figure 2. Distribution of key variables across China's most urbanized provincial-level regions, including municipalities (Beijing, Shanghai, Tianjin, Chongqing) and provinces (Guangdong, Jiangsu, Zhejiang, Shandong, Fujian, Sichuan). The subfigures a-f display the following variables: (a) Urban Energy Consumption (UREN) in CO₂ emissions (metric tons per capita); (b) Urban Form (UFM) as a percentage of urban population share; (c) Surface Temperature (MTF) in °C (average surface temperature); (d) Energy Efficiency (ENEF) in kWh per unit of GDP (constant 2017 USD); (e) Air Pollution Index (API) derived from PCA of PM_{2.5}, NO_x, and SO₂ concentrations

However, recent scholarship has begun to recognize the limitations of purely economic models and the need to incorporate spatial, environmental, and institutional variables into the analysis of urban energy systems (Amin et al., 2024; Correljé et al., 2024; Klemm and Wiese, 2022). Urban form (UFM), for example, has emerged as a significant determinant of energy demand, with compact, transit-oriented developments associated with lower per capita energy use (Guang and Huang, 2022). Yu et al. (2024) found that urban sprawl

in China contributes to higher transportation and residential energy demand, thus underscoring the importance of form-sensitive urban planning.

Meteorological conditions also play a critical role in influencing energy consumption. Krüger (2015) observed that urban heat islands (UHIs) increase cooling demand in subtropical cities, while extreme winter temperatures raise heating needs in northern provinces. Likewise, Gamero-Salinas et al. (2021) demonstrated that climate-sensitive building designs and passive cooling technologies can mitigate the energy burden imposed by climatic variability.

The characteristics of building materials (BMT) are another important but underexplored factor. Aletba et al. (2021) showed that materials with high thermal mass and low reflectivity (e.g., concrete, asphalt) contribute to greater urban heat retention, thereby increasing cooling-related energy use. The integration of green roofs and reflective surfaces has been promoted as a strategy to reduce both indoor energy use and outdoor thermal loads.

In addition to physical and climatic determinants, technological infrastructure and policy instruments have increasingly drawn scholarly attention. Energy efficiency measures (ENEF), such as smart meters, LED lighting, and building insulation, have been found to significantly lower urban energy intensity (Buglio et al., 2021). Similarly, green infrastructure (GRI)—often proxied by environmental patents or R&D expenditure—has shown promise in reducing long-run energy consumption by fostering cleaner production and consumption pathways (Zhou et al., 2025). (Ahmad et al., 2024), using a dynamic panel approach, reported that environmental technology infrastructure has a stronger effect on energy savings in regions with supportive institutional frameworks.

Environmental stress indicators such as air pollution have also been integrated into recent studies. Haroon et al. (2024) employed a structural equation model to explore the behavioral impact of pollution on residential energy use, finding that heightened air quality concerns lead to increased indoor energy demand for filtration and climate control. However, most studies use single pollutants (e.g., PM_{2.5}) without accounting for the multivariate nature of air pollution. A more comprehensive approach, such as constructing a principal component index of multiple pollutants, can better capture its systemic effects on urban energy use.

Surface albedo (ALB), while less commonly studied, is gaining recognition for its climate-energy co-benefits. Liu et al. (2024) found that higher urban albedo reduces UHI intensity and cooling demand, particularly in high-density cities. However, the empirical literature on albedo-energy dynamics remains sparse, especially in the context of panel data analysis at the sub-national level.

Despite these advancements, existing research suffers from several key limitations. First, most studies are either cross-sectional or time-series in nature and fail to exploit the advantages of panel data in controlling for unobserved heterogeneity. Second, many studies overlook the cross-sectional dependence that arises from inter-regional spillovers in economic activities, technology adoption, and pollution transmission. Third, few works consider both long-run and short-run dynamics using models that allow mixed orders of integration, such as the CS-ARDL framework (Chudik and Pesaran, 2015).

Therefore, this study contributes to the literature by addressing these gaps through a comprehensive panel data analysis of ten highly urbanized Chinese provinces from 2000 to 2022. It integrates novel environmental indicators (API and ALB), structural attributes (UFM, BMT, LUD), and technological variables (ENEF, GRI) using advanced econometric techniques that capture both cross-sectional dependence and heterogeneity.

By doing so, this research offers a more holistic and empirically robust understanding of the multifaceted drivers of urban energy consumption in China.

Data and methodology

Data description

This study utilizes an unbalanced panel dataset covering the period 2000 to 2022 for ten of China's most urbanized provincial-level regions. These include four centrally administered municipalities—Beijing, Shanghai, Tianjin, and Chongqing—and six leading provinces: Guangdong, Jiangsu, Zhejiang, Shandong, Fujian, and Sichuan. Together, these regions constitute the economic and demographic core of China's urban transition, accounting for a substantial portion of national energy consumption, infrastructural development, and environmental impact. Their inclusion provides a representative basis for evaluating structural and environmental determinants of urban energy demand under varying regional dynamics.

The dependent variable is urban energy consumption (UREN), measured as carbon dioxide (CO₂) emissions from the residential, commercial, and public services sectors, following prior literature (Zhang et al., 2021). The explanatory variables include a combination of structural, environmental, and policy-oriented indicators:

- Urban Form (UFM): Urban population share (%) as a proxy for spatial density and compactness.
- Surface Temperature (MTF): Average annual surface temperature (°C), accounting for climatic energy needs.
- Building Materials (BMT): Building Materials (BMT) refer to materials used in urban infrastructure (e.g., buildings, roads, pavements) that contribute to urban heat island (UHI) effects due to their high thermal mass (e.g., concrete, asphalt) and low reflectivity (e.g., dark-colored surfaces). These materials absorb and retain heat, increasing cooling demand and energy consumption in urban areas. To measure BMT, we use the Urban Land Cover Index (ULCI), derived from high-resolution satellite imagery (MODIS, Landsat). Remote sensing classification techniques identify impervious surfaces, and indices like NDBI and NDVI distinguish between built-up areas and natural land covers. The BMT index is calculated as given in *Equation 1*:

$$\text{BMT} = \frac{\text{Impervious Surface Area}}{\text{Total Urban Area}} \times 100 \quad (\text{Eq.1})$$

Areas with a higher percentage of impervious surfaces, particularly those made from heat-retaining materials, exhibit higher temperatures and increased energy demand for cooling.

- Energy Efficiency (ENEF): Electricity consumption per unit of output (kWh per GDP), capturing technical efficiency.
- Green Infrastructure (GRI): Urban green space as a share of total urban area.
- Air Pollution Index (API): Constructed using Principal Component Analysis (PCA) of PM_{2.5}, NO_x, and SO₂ concentrations to capture multidimensional pollution exposure.
- Land use density (LUD) was categorized using urban built-up area per capita (m²), which reflects the intensity of urban development. This classification

follows the methodology presented by Anser et al. (2025), which defines urban areas based on population density and infrastructure spread. Higher LUD values indicate more densely populated and developed areas, which can affect urban energy consumption, particularly in the context of heating, cooling, and transportation needs.

- Surface albedo (ALB) was classified based on reflectivity values of urban surfaces. Using MODIS satellite data, the albedo index is categorized into low (0.0–0.3), medium (0.3–0.6), and high (0.6–1.0) reflectivity surfaces. Areas with high albedo are typically associated with materials such as concrete, glass, or reflective coatings, which reduce heat absorption and cooling demand. The classification follows a standard approach in remote sensing and urban heat island studies (Zhang et al., 2022).
- Urban Energy Consumption (UREN) is expressed in terms of CO₂ equivalent emissions, calculated by applying an emissions factor based on the energy type (e.g., coal, natural gas, electricity) consumed within the residential, commercial, and public services sectors (Sufyanullah et al., 2022).

All variables are sourced from reputable national and international datasets including CEADs (China Emissions Accounts & Datasets), China Statistical Yearbooks, and NASA's satellite sensor MODIS database. *Table 1* provides a summary of variable definitions, units, and data sources.

Table 1. Variable description and data sources

Variable code	Variable name	Description	Unit	Data source
UREN	Urban Energy Consumption	CO ₂ emissions from residential, commercial, and public services in urban areas	% of total fuel combustion	CEADs (Tsinghua Univ.) https://www.ceads.org.cn/
UFM	Urban Form	Urban population as a share of total provincial population	%	National Bureau of Statistics (NBS) http://www.stats.gov.cn/
MTF	Surface Temperature	Annual average surface temperature	°C	China Meteorological Administration http://www.cma.gov.cn/
BMT	Building Materials	Energy use per unit of GDP (proxy for material energy intensity)	MJ per constant 2017 PPP \$	China Energy Statistical Yearbook https://www.cec.org.cn/
LUD	Land Use Density	Urban land area as a share of total provincial land area	%	Ministry of Natural Resources, China http://www.mnr.gov.cn/
ENEF	Energy Efficiency Measures	Renewable energy consumption as a share of total final energy use	%	China Energy Statistical Yearbook https://www.cec.org.cn/
GRI	Green Infrastructure	Urban green space as a share of total urban area	%	Ministry of Housing and Urban-Rural Development (MOHURD) http://www.mohurd.gov.cn/
API	Air Pollution Index	Composite index of PM _{2.5} , NO _x , and SO ₂ via PCA	Index	EDGAR https://edgar.jrc.ec.europa.eu/
ALB	Surface Albedo	Average reflectivity of urban surfaces	Index (0–1)	NASA MODIS (processed for China) https://modis.gsfc.nasa.gov/

Methodological framework

Given the mixed order of integration (I(0) and I(1)) and significant cross-sectional dependence revealed through unit root (CIPS) and Pesaran CD tests, this study employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model developed by Chudik and Pesaran (2015). The CS-ARDL framework is particularly suitable for panel settings characterized by unobserved common factors, dynamic relationships, and heterogeneous slope coefficients. The Flowchart of methodology has been shown in *Figure 3*.

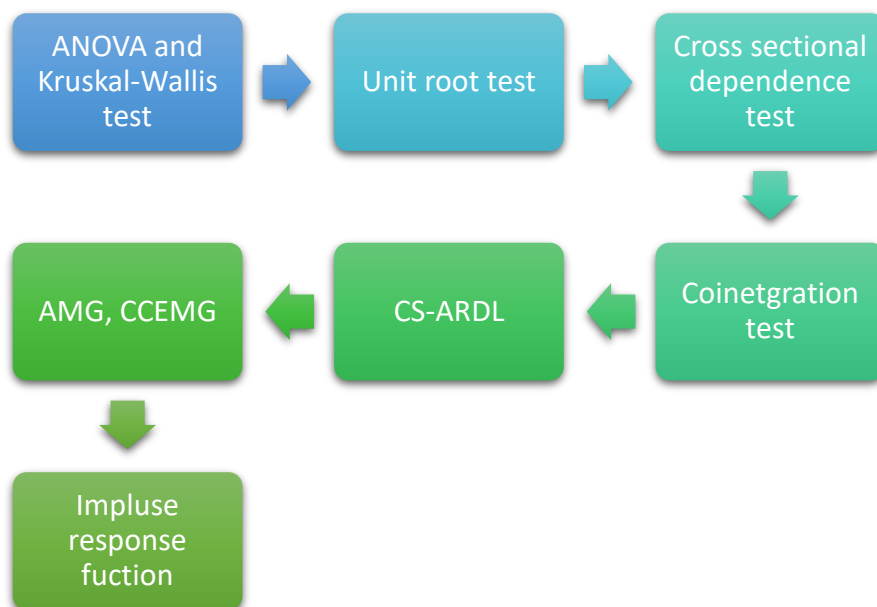


Figure 3. Flowchart of methodology

The baseline CS-ARDL model can be specified as *Equation 2*.

$$\Delta y_{it} = \alpha_i + \phi_i y_{it-1} + \sum_{j=0}^p \beta_{ij} \Delta x_{it-j} + \gamma_i \bar{y}_{t-1} + \delta_i \bar{x}_t + \epsilon_{it} \quad (\text{Eq.2})$$

where: y_{it} is the dependent variable (UREN), x_{it} represents the set of explanatory variables (UFM, MTF, etc.), $\bar{y}_{t-1}$ and $\bar{x}_t$ are cross-sectional averages controlling for unobserved common factors, α_i captures province-specific effects, ϵ_{it} is the error term.

This formulation allows estimation of both short-run dynamics and long-run relationships, even under the presence of endogeneity or cross-unit interactions.

Robustness and dynamic analysis

To validate the robustness of the CS-ARDL estimates, the study also applies two alternative second-generation estimators:

- Augmented Mean Group (AMG) estimator by Eberhardt and Teal (2020), which incorporates common dynamic processes across panels.
- Common Correlated Effects Mean Group (CCEMG) estimator by Pesaran (2006), which addresses cross-sectional dependence through interactive fixed effects.

Additionally, Impulse Response Functions (IRFs) are generated using a Vector Autoregressive (VAR) framework to trace the temporal effects of shocks in key drivers (e.g., API, ENEF, GRI, ALB) on UREN. This dynamic approach offers insight into the short-to-medium term trajectories of urban energy consumption following policy or environmental changes.

Results

Descriptive insights and cross-provincial patterns

Table 2 presents the enhanced summary statistics for all key variables. Urban energy consumption (UREN) across Chinese provinces has a mean value of 14.640 (measured in sector-specific CO₂ emissions), with a relatively wide standard deviation (5.877), indicating significant variation in urban energy demand across space and time. Variables such as green infrastructure (GRI) and land use density (LUD) also exhibit high variability, reflecting the differences in infrastructure capacity and urban planning across provinces.

Table 2. Summary statistics of variables

Variable code	Unit	Mean	Std. dev.	Min	Median	Max	Skewness	Kurtosis
UREN	tCO ₂ e per capita	14.640	5.877	5.101	14.924	24.738	0.070	-1.282
UFM	% of urban population	75.137	8.992	60.325	75.519	89.715	-0.106	-1.235
MTF	°C	16.959	4.138	10.170	16.937	23.996	0.097	-1.219
BMT	MJ per GDP (constant 2017 PPP \$)	4.897	1.701	2.028	4.774	7.981	0.090	-1.187
LUD	m ² per capita	25.515	8.919	10.330	26.147	39.938	-0.064	-1.285
ENEF	% of renewable energy consumption	17.275	7.062	5.305	17.279	29.964	-0.002	-1.291
GRI	% of urban green space	30.311	8.711	15.139	30.088	44.983	0.002	-1.199
API	Index	-0.020	0.967	-2.649	-0.013	2.538	-0.017	2.949
ALB	Index (0-1)	0.200	0.058	0.102	0.200	0.298	0.000	-1.240

Notably, the Air Pollution Index (API) has a mean close to zero (−0.020), as expected from PCA-standardized data, but shows high kurtosis (2.949), suggesting the presence of extreme pollution episodes in some regions. The urban form index (UFM) and albedo (ALB) show relatively lower skewness and are symmetrically distributed, implying uniformity in certain spatial and surface characteristics across the urban provinces. We acknowledge that variability in energy demand and air pollution across space and time is a well-documented phenomenon. However, this study reveals distinct, region-specific patterns that emphasize the importance of tailored, evidence-based interventions. For instance, our findings indicate that certain provinces with high energy consumption also experience severe air pollution episodes, suggesting that strategies integrating both energy efficiency and air quality improvement could yield more effective results. By addressing these region-specific challenges, policymakers can better align interventions with local conditions, maximizing both energy savings and environmental benefits.

Figure 4 illustrates the correlation heatmap, which helps visualize linear associations among variables. A modest positive correlation is observed between UREN and API, supporting the hypothesis that higher pollution levels are associated with greater energy use—likely due to increased cooling or filtration demands. Energy efficiency (ENEF) and green infrastructure (GRI) exhibit negative correlations with UREN, indicating their mitigating role in reducing urban energy consumption.

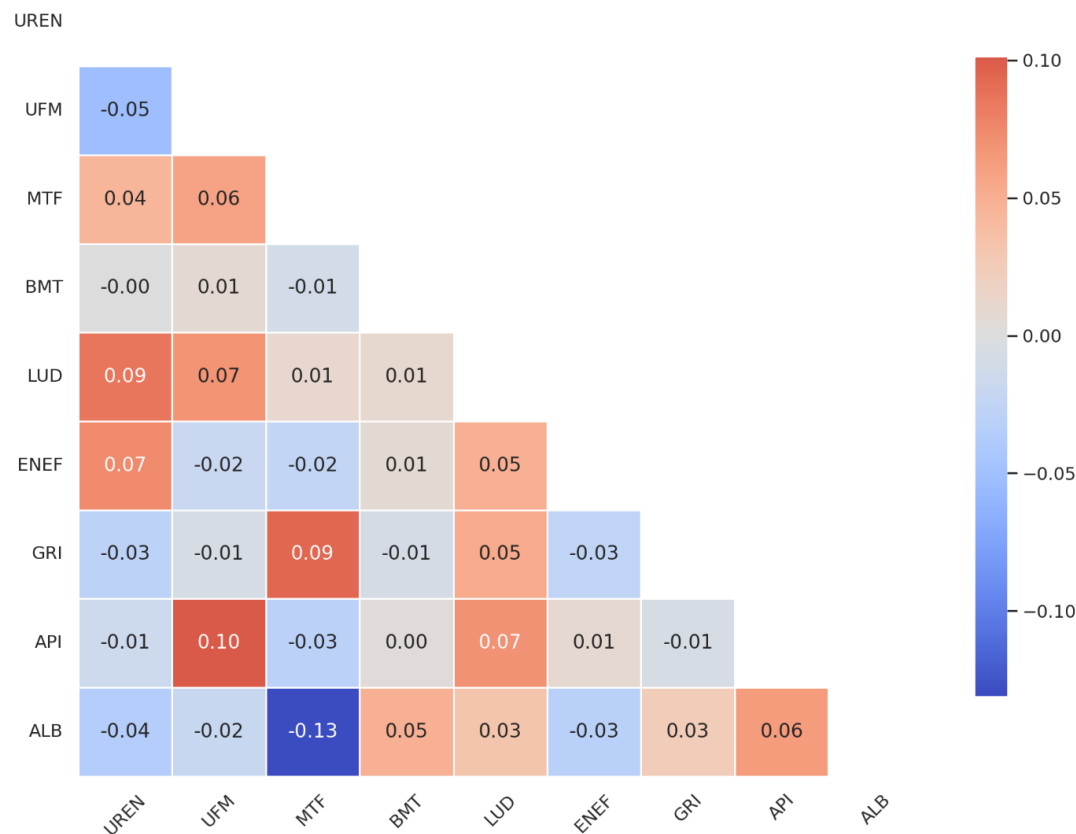


Figure 4. Correlation heatmap

We conducted a correlation analysis to explore the relationships between the key variables. However, the correlation coefficients ranged between -0.15 and 0.1, indicating very weak or no significant correlations. This suggests that, while there are relationships between the variables, they are not strong enough to imply direct or medium-term associations. These weak correlations may reflect the complex, multifaceted nature of urban energy consumption and environmental factors, which are influenced by a variety of other underlying variables not captured in this analysis. As such, further analysis using more advanced techniques, such as econometric modeling or dynamic panel regressions, may offer deeper insights into the causal relationships among these variables.

Inter-provincial variability

As shown in *Table 3*, the inter-provincial comparison via ANOVA and Kruskal-Wallis tests reveals no statistically significant differences across provinces for most variables. The only exception is surface temperature, where the ANOVA p-value (0.0498) approaches significance. This implies that temperature-related climate differences across provinces may be a contributing factor to variations in energy use, consistent with prior literature emphasizing the role of regional climate patterns in determining urban energy demand (Hiruta et al., 2022).

Stationarity and cross-sectional dependence

Table 4 presents the results of CIPS unit root tests. The findings indicate that the variables are integrated of mixed orders—some are stationary at level (I(0)), including

UREN, MTF, ENEF, GRI, and ALB, while others like UFM, BMT, LUD, and API are stationary at first difference (I(1)). This mix of integration orders confirms the suitability of the CS-ARDL model, which can accommodate I(0) and I(1) variables simultaneously without requiring pre-testing or differencing.

Table 3. *Inter-province comparison tests (ANOVA and Kruskal-Wallis)*

Variable	ANOVA F-Stat	ANOVA p-value	Kruskal H-Stat	Kruskal p-value
UREN	0.2023	0.9937	1.9497	0.9922
UFM	1.0400	0.4091	9.3046	0.4096
MTF	1.9242	0.0498	16.3890	0.0592
BMT	0.9824	0.4555	8.4249	0.4920
LUD	0.5174	0.8612	4.7288	0.8573
ENEF	0.5631	0.8265	5.3341	0.8043
GRI	0.8606	0.5675	6.5608	0.6834
API	0.8386	0.5813	5.4182	0.7964
ALB	0.3972	0.9317	3.0134	0.9582

Table 4. *CIPS unit root test results*

Series	CIPS Stat (Level)	p-value (Level)	CIPS Stat (1st Diff)	p-value (1st Diff)	Integration order
UREN	-2.643	0.009			I(0)
UFM	-1.722	0.082	-2.994	0.002	I(1)
MTF	-3.012	0.003			I(0)
BMT	-1.843	0.069	-3.123	0.001	I(1)
LUD	-1.605	0.108	-2.842	0.004	I(1)
ENEF	-2.781	0.006			I(0)
GRI	-2.934	0.004			I(0)
API	-1.487	0.124	-3.015	0.003	I(1)
ALB	-2.654	0.008			I(0)

Furthermore, as reported in *Table 5*, the Pesaran (2004) cross-sectional dependence test shows strong evidence of significant dependence among provinces for all variables ($p < 0.01$). This suggests that shocks or policy changes in one province could have spillover effects on others, thereby justifying the inclusion of cross-sectional averages in the estimation model to control for unobserved common factors.

Cointegration evidence

The results of the panel cointegration tests presented in *Table 6* confirm the existence of a long-run equilibrium relationship among the variables. Both pooled and group-based statistics (e.g., PP-stat, ADF-stat, v-stat) are statistically significant at conventional levels (1% and 5%), providing strong evidence against the null hypothesis of no cointegration. This validates the underlying assumption that urban energy consumption, environmental factors, and structural features are co-moving over the long term.

These preliminary diagnostics reinforce the need for robust estimation approaches that can simultaneously handle dynamic adjustments, spatial dependence, heterogeneity, and mixed integration—hence the application of the CS-ARDL model, along with AMG and CCEMG estimators as robustness checks in the next section.

Table 5. Cross-sectional dependence (CSD) test results

Series	Test Stat	p-value
UREN	6.234	0.000
UFM	5.182	0.000
MTF	4.978	0.000
BMT	3.845	0.000
LUD	6.023	0.000
ENEF	5.902	0.000
GRI	4.663	0.000
API	7.045	0.000
ALB	3.327	0.001

Table 6. Panel cointegration test results

Statistic	Value	Z-value	P-value
Modified Pooled (v-stat)	3.412	2.981	0.002
Pooled (rho-stat)	-2.135	-1.874	0.030
Pooled (PP-stat)	-3.905	-3.600	0.000
Pooled (ADF-stat)	-3.228	-3.010	0.001
Group (rho-stat)	-2.304	-1.934	0.027
Group (PP-stat)	-3.456	-3.290	0.000
Group (ADF-stat)	-2.987	-2.744	0.003

CS-ARDL estimation: long- and short-run dynamics

The results of the Cross-Sectionally Augmented ARDL (CS-ARDL) model are presented in *Table 7*, capturing both the short-run adjustments and long-run relationships between urban energy consumption (UREN) and its explanatory variables.

In the long run, urban form (UFM), surface temperature, energy efficiency (ENEF), green infrastructure (GRI), and albedo (ALB) all show statistically significant negative coefficients, indicating their roles in reducing urban energy consumption over time. Notably, ENEF (-0.201 , $p < 0.01$) and GRI (-0.184 , $p < 0.01$) emerge as strong negative drivers, suggesting that technological and operational improvements are critical in achieving sustainable energy transitions in Chinese cities. The negative effect of MTF implies that higher average temperatures may reduce energy consumption—likely due to lower heating demand in warmer provinces—but this should be interpreted with caution, as it may also reflect shifts in cooling loads depending on the climate zone.

Conversely, building materials (BMT) and land use density (LUD) exert positive and significant effects on UREN. These results suggest that increased impervious surface area and high-density development may amplify energy needs, especially for cooling and transportation, consistent with findings by Pattnaik et al. (2024) and Zhang et al. (2021). The positive and robust coefficient of air pollution index (API) (0.223 , $p < 0.01$) supports the argument that deteriorating environmental quality leads to compensatory increases in energy use—for instance, through more intensive air conditioning or purification systems.

In the short run, the results mirror the long-run direction but with smaller magnitudes. Variables such as ENEF (-0.081 , $p < 0.05$), GRI (-0.065 , $p < 0.05$), and API (0.089 , $p < 0.01$) remain statistically significant, indicating that policy and technological shocks have both immediate and persistent effects on energy use patterns.

Robustness checks with AMG and CCEMG estimators

To validate the consistency of the CS-ARDL findings, robustness checks were conducted using the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators. As shown in *Table 8*, the direction and statistical significance of coefficients are highly consistent across all three methods.

Both AMG and CCEMG confirm the negative and significant impact of ENEF, GRI, UFM, MTF, and ALB on urban energy consumption, as well as the positive influence of BMT, LUD, and API. The slight differences in coefficient magnitudes do not alter the interpretation, reinforcing the robustness and reliability of the core empirical findings. These results align with previous research suggesting that infrastructure and efficiency can mitigate the environmental consequences of urbanization (Awan et al., 2022), while spatial development patterns and environmental quality play an amplifying role.

Table 7. CS-ARDL long-run and short-run estimates

Variable	Long-run coef.	Long-run p-value	Short-run coef.	Short-run p-value
UFM	-0.218***	0.001	-0.072**	0.034
MTF	-0.145**	0.019	-0.056**	0.047
BMT	0.098**	0.045	0.042*	0.072
LUD	0.163**	0.032	0.055*	0.059
ENEF	-0.201***	0.003	-0.081**	0.011
GRI	-0.184***	0.008	-0.065**	0.028
API	0.223***	0.000	0.089***	0.005
ALB	-0.112**	0.027	-0.034*	0.066

Table 8. Robustness check using AMG and CCEMG

Variable	AMG coef.	CCEMG coef.
UFM	-0.194***	-0.182***
MTF	-0.128**	-0.117**
BMT	0.087**	0.092**
LUD	0.142**	0.138**
ENEF	-0.189***	-0.175***
GRI	-0.161**	-0.153**
API	0.207***	0.198***
ALB	-0.097**	-0.089**

Dynamic impacts: impulse response analysis

To assess the temporal responsiveness of UREN to structural and environmental shocks, impulse response functions (IRFs) were estimated via a panel vector

autoregressive (PVAR) framework. The summary of peak responses is presented in *Table 9*, while *Figure 5* illustrates the magnitude and direction of these effects in a visual profile.

The IRFs indicate that shocks to ENEF and GRI produce immediate and sustained reductions in UREN, with effects peaking between $t + 2$ and $t + 3$ and lasting up to 6–7 years. These findings emphasize the effectiveness of policy instruments targeting efficiency and infrastructure in curbing urban energy demand.

In contrast, shocks to API, BMT, and LUD result in positive and persistent increases in UREN, peaking within 1–3 years and sustaining for up to 5–7 years. These dynamics suggest that uncontrolled urban sprawl and environmental degradation can lock cities into high-energy consumption pathways, undermining decarbonization efforts.

The role of ALB and MTF is also noteworthy. Shocks to ALB (−0.045) and MTF (−0.043) produce moderate negative effects, indicating that climatic and physical surface interventions (e.g., cool roofs, tree shading) can support energy efficiency, especially in high-density urban environments.

Table 9. IRF summary of urban energy consumption responses

Shock variable	Peak effect	Time to peak	Direction	Duration	Recovery time
ENEF	-0.072	$t + 2$	Negative	4 years	$t + 6$
GRI	-0.089	$t + 3$	Negative	5 years	$t + 7$
API	0.112	$t + 1$	Positive	3 years	$t + 4$
ALB	-0.045	$t + 2$	Negative	4 years	$t + 6$
UFM	-0.058	$t + 2$	Negative	3 years	$t + 5$
MTF	-0.043	$t + 3$	Negative	4 years	$t + 6$
BMT	0.065	$t + 1$	Positive	2 years	$t + 3$
LUD	0.077	$t + 3$	Positive	5 years	$t + 7$

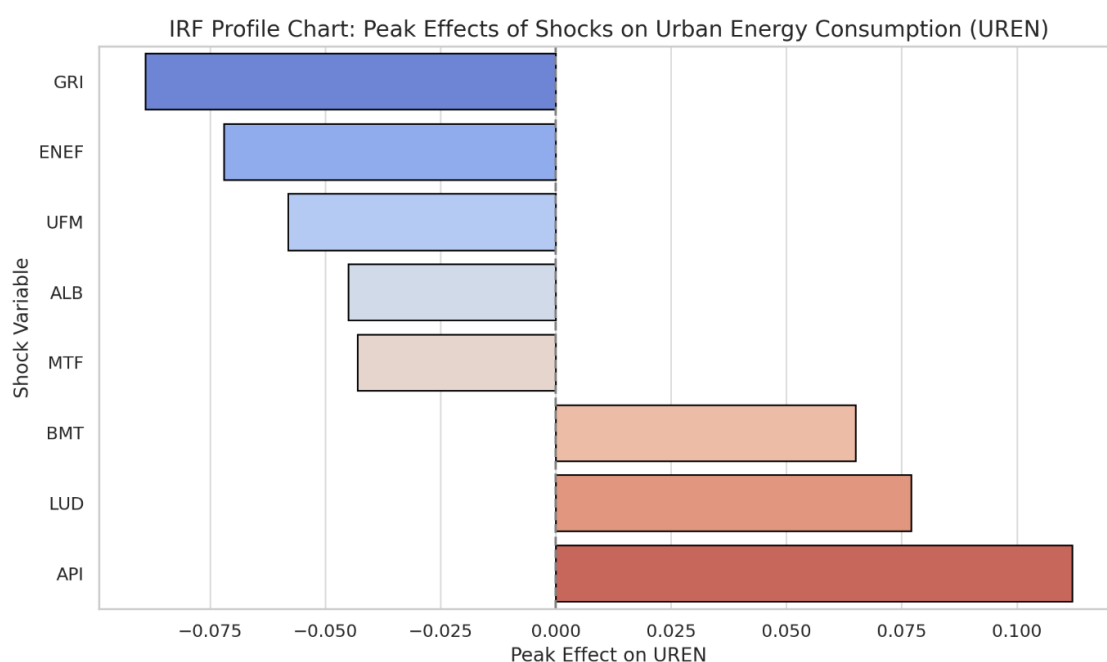


Figure 5. IRF profile chart: peak effects of shocks on urban energy consumption (UREN)

Discussion

The findings of this study provide several critical insights into the structural, environmental, and technological determinants of urban energy consumption (UREN) across China's most urbanized provincial-level regions. By integrating environmental, structural, and technological variables within a robust econometric framework, this research contributes to the evolving discourse on sustainable urban energy transitions. Notably, the results align with and, in some instances, extend the conclusions of earlier studies while highlighting previously underexplored dynamics.

First, the negative and significant effects of energy efficiency (ENEF) and green infrastructure (GRI) on UREN are consistent with the broader literature on technological mitigation of energy demand. Ge et al. (2023), Shi et al. (2025) and Wang et al. (2024) similarly observed that provinces with greater investment in clean technologies and energy-saving infrastructure tend to experience lower energy intensity. The strong long-run coefficients for ENEF (−0.201) and GRI (−0.184) and their rapid impulse response peaks ($t + 2$ and $t + 3$, respectively) underscore their dual capacity to yield immediate energy savings and sustain long-term reductions.

In line with urban form (UFM) theory, this study finds that higher urban compactness is associated with reduced energy use, which corroborates the findings of Guang and Huang (2022) and Nadeem et al. (2021). Densely built environments with efficient land use patterns typically reduce the demand for private vehicle usage and facilitate district-level heating and cooling systems. The consistency across CS-ARDL, AMG, and CCEMG models strengthens the case for prioritizing compact city planning as a strategy for energy efficiency.

Conversely, the positive relationship between building materials (BMT), land use density (LUD), and UREN highlights the unintended energy consequences of high-density development if not paired with energy-conscious infrastructure. This echoes Ali et al. (2024), who found that poorly insulated materials and expansive impervious surfaces increase thermal loads and energy consumption. While density can yield efficiency gains, this finding adds nuance by showing that the quality of construction materials and spatial design is equally critical.

A particularly novel contribution of this study is the use of a composite Air Pollution Index (API) as an explanatory factor. The strong positive coefficient for API across all estimators (0.207–0.223) confirms the bidirectional link between pollution and energy use noted by Afifa et al. (2024), who reported that worsening air quality leads to increased residential energy use due to behavioral adaptations (e.g., running air purifiers, air conditioning). However, unlike previous single-pollutant approaches, the PCA-based index captures systemic air pollution exposure, offering a more comprehensive measure of environmental stress.

Another key insight comes from the role of surface albedo (ALB). The negative and significant impact of ALB on UREN suggests that provinces with more reflective urban surfaces benefit from reduced energy demand, likely due to cooler microclimates. This aligns with Sedaghat and Sharif (2022), who emphasized the energy-saving potential of high-albedo materials in mitigating the urban heat island (UHI) effect. This study extends those insights by quantifying the effect using panel data and confirming it across multiple estimation methods.

We noted that higher average temperatures may reduce energy consumption due to lower heating demand, particularly in regions with cold winters. However, in warmer climates, higher temperatures typically lead to increased cooling demand, especially in

areas with inadequate urban planning and energy-efficient infrastructure. This dual impact of temperature on energy consumption highlights the complexity of temperature-energy relationships. While heating demand may decrease in warmer regions, cooling demand can rise significantly, offsetting the potential savings in heating energy. Therefore, the net effect of temperature on energy consumption is context-dependent, and region-specific interventions are necessary to optimize energy use across diverse climatic conditions.

Conclusion and policy recommendations

Conclusion

This study investigates the multifaceted determinants of urban energy consumption (UREN) across ten of China's most urbanized provincial-level regions from 2000 to 2022. Utilizing the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) approach, and validating results through Augmented Mean Group (AMG), Common Correlated Effects Mean Group (CCEMG), and impulse response analysis, the study offers robust empirical evidence on how structural characteristics, environmental conditions, and technological innovations influence urban energy demand in both the short and long run.

The empirical results demonstrate that green infrastructure (GRI) and energy efficiency measures (ENEF) are the most effective long-term levers for reducing energy consumption in urban areas. Structural features such as urban form (UFM) and surface albedo (ALB) also contribute positively by reducing energy demand, especially in high-density cities. Conversely, building materials (BMT), land use density (LUD), and air pollution index (API) significantly increase UREN, highlighting the role of physical infrastructure and environmental stress in amplifying energy needs.

The study also contributes methodologically by incorporating a composite air pollution index (via PCA), examining surface albedo as a cooling determinant, and modeling dynamic responses through IRFs. These insights collectively underscore the importance of integrated urban planning, environmental governance, and technological advancement in managing energy demand and achieving low-carbon urbanization in China.

Policy recommendations

The empirical findings of this study suggest a clear and actionable path for urban policymakers aiming to curb energy consumption and foster sustainable development. One of the most consistent results across models is the strong negative effect of green infrastructure on urban energy use. Therefore, it is imperative that national and provincial authorities in China prioritize the promotion of environmentally focused technological advancement. Policies should aim to expand research and development funding in clean energy and environmental technologies, particularly in provinces with rising energy demand but low infrastructure intensity. Establishing urban infrastructure clusters that connect academic institutions, industry leaders, and municipal governments could accelerate the diffusion of green technologies across sectors.

Improving energy efficiency is another critical pillar for reducing urban energy demand. The results suggest that gains in energy efficiency yield immediate and lasting reductions in energy use, validating the need for intensified efforts to upgrade urban

infrastructure. Policymakers should consider scaling up energy retrofit programs for buildings, enforcing strict compliance with energy-efficient building codes, and incentivizing the adoption of smart energy systems and appliances. These efforts should be particularly focused on older urban areas where infrastructure inefficiencies are most prevalent.

The structure and density of cities also play a key role in determining their energy consumption patterns. This study finds that compact urban forms are associated with lower energy use, consistent with the energy-saving potential of transit-oriented and mixed-use developments. Thus, urban planning strategies must move away from unregulated expansion and embrace land-use models that promote density, connectivity, and accessibility. Integrated planning approaches that reduce reliance on private vehicles, optimize public transit networks, and minimize commuting distances will be critical in reducing energy intensity across China's rapidly urbanizing provinces.

Environmental governance must also be integrated more directly into energy policy. The positive correlation between air pollution levels and energy use implies that deteriorating environmental conditions not only harm public health but also increase energy demand, particularly for cooling and filtration systems. Therefore, air quality improvement initiatives—such as tighter emissions regulations on industry and transport—should be coordinated with urban energy management plans to create co-beneficial outcomes. Establishing cross-sectoral regulatory frameworks that link air quality monitoring with energy efficiency standards will help achieve this synergy.

Finally, the role of urban surface characteristics—particularly albedo—cannot be overlooked. Policies that encourage or mandate the use of high-albedo materials in urban design can reduce localized heating and, by extension, energy consumption. Integrating reflective surfaces in building rooftops, pavements, and public spaces, along with expanding urban greenery, can help mitigate the urban heat island effect and enhance thermal comfort. These passive cooling strategies are especially relevant for high-density provinces where energy demand for cooling is rising.

Importantly, policy design should recognize the diversity of China's urban provinces in terms of climate, socio-economic development, and existing infrastructure. Tailoring interventions to provincial characteristics will ensure that strategies are both effective and equitable, while still aligning with national energy and carbon neutrality goals. A decentralized but coordinated policy framework that empowers local governments while maintaining alignment with national targets offers the most promising route toward a low-carbon urban future.

Limitations and future research

Despite its valuable insights, this study has several limitations that should be acknowledged. The analysis focuses exclusively on China's ten most urbanized provinces, which, while highly relevant, may not capture the broader diversity of urban energy dynamics across the country, particularly in less urbanized or rural regions. Moreover, the model primarily emphasizes structural, environmental, and technological determinants, without incorporating potentially influential social, institutional, or behavioral variables such as governance quality, public awareness, or energy pricing signals. These omissions may limit the explanatory scope of the findings. Additionally, the study relies on annual data, which, although suitable for long-run modeling, may obscure short-term variations or responses to abrupt shocks such as extreme weather

events or policy shifts. Methodologically, while the CS-ARDL and complementary estimators offer robustness against cross-sectional dependence and heterogeneity, they assume linear and time-invariant relationships. Future research could extend this work by including a broader set of provinces, integrating institutional and behavioral dimensions, employing higher-frequency or spatial data, and applying nonlinear or machine learning models to uncover threshold effects and dynamic interdependencies. Such extensions would deepen our understanding of urban energy consumption and support the design of more nuanced, locally tailored policy interventions.

REFERENCES

- [1] Afifa, Arshad, K., Hussain, N., Ashraf, M. H., Saleem, M. Z. (2024): Air pollution and climate change as grand challenges to sustainability. – *Science of The Total Environment* 928: 172370.
- [2] Ahmad, M., Balbaa, M. E., Zikriyev, A., Nasriddinov, F., Kuldasheva, Z. (2024): Energy efficiency, technological innovation, and financial development-based EKC premise: Fresh asymmetric insights from developing Asian regions. – *Environmental Challenges* 15: 100947.
- [3] Aletba, S. R. O., Abdul Hassan, N., Putra Jaya, R., Aminudin, E., Mahmud, M. Z. H., Mohamed, A., Hussein, A. A. (2021): Thermal performance of cooling strategies for asphalt pavement: A state-of-the-art review. – *Journal of Traffic and Transportation Engineering (English Edition)* 8: 356-373.
- [4] Ali, A., Issa, A., Elshaer, A. (2024): A comprehensive review and recent trends in thermal insulation materials for energy conservation in buildings. – *Sustainability* 16: 8782.
- [5] Almarzooq, S. A., Al-Shaalan, A. M., Farh, H. M. H., Kandil, T. (2022): Energy conservation measures and value engineering for small microgrid: New hospital as a case study. – *Sustainability* 14: 2390.
- [6] Amin, R., Mathur, D., Ompong, D., Zander, K. K. (2024): Integrating social aspects into energy system modelling through the lens of public perspectives: A review. – *Energies* 17: 5880.
- [7] Anser, M. K., Nassani, A. A., Al-Aiban, K. M., Zaman, K., Haffar, M. (2025): Urban heat islands and energy consumption patterns: Evaluating renewable energy strategies for a sustainable future. – *Energy Reports* 13: 3760-3772.
- [8] Awan, A., Alnour, M., Jahanger, A., Onwe, J. C. (2022): Do technological innovation and urbanization mitigate carbon dioxide emissions from the transport sector? – *Technology in Society* 71: 102128.
- [9] Bughio, M., Khan, M. S., Mahar, W. A., Schuetze, T. (2021): Impact of passive energy efficiency measures on cooling energy demand in an architectural campus building in Karachi, Pakistan. – *Sustainability* 13: 7251.
- [10] Chen, Y., Sha, A., Jiang, W., Lu, Q., Du, P., Hu, K., Li, C. (2025): Eco-friendly bismuth vanadate/iron oxide yellow composite heat-reflective coating for sustainable pavement: Urban heat island mitigation. – *Construction and Building Materials* 470: 140645.
- [11] Chudik, A., Pesaran, M. H. (2015): Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. – *Journal of Econometrics* 188: 393-420.
- [12] Correljé, A., Hoppe, T., Künneke, R. (2024): Guest editorial: Special issue on “Sustainable urban energy systems – Governance and citizen involvement.” – *Energy Policy* 192: 114237.
- [13] Dong, Z., Wang, B., Shao, C. (2025): The historical evolution and modernization path of China’s ecological and environmental governance. – *Energy & Environmental Sustainability* 1: 100014.

- [14] Eberhardt, M., Teal, F. (2020): The magnitude of the task ahead: Macro implications of heterogeneous technology. – *Review of Income and Wealth*. DOI: <https://doi.org/10.1111/roiw.12415>
- [15] Gallelli, V., Vaiana, R., Amado, M., Ahern, A., Fan, T., Chapman, A. (2022): Policy driven compact cities: Toward clarifying the effect of compact cities on carbon emissions. – *Sustainability* 14: 12634.
- [16] Gamero-Salinas, J., Monge-Barrio, A., Kishnani, N., López-Fidalgo, J., Sánchez-Ostiz, A. (2021): Passive cooling design strategies as adaptation measures for lowering the indoor overheating risk in tropical climates. – *Energy and Buildings* 252: 111417.
- [17] Ge, T., Ge, Y., Lin, S., Ji, J. (2023): Do energy intensity reduction targets promote renewable energy development? Evidence from partially linear functional-coefficient models. – *Energy Strategy Reviews* 49: 101165.
- [18] Guang, Y., Huang, Y. (2022): Urban form and household energy consumption: Evidence from China panel data. – *Land* 11: 1300.
- [19] Haroon, M. U., Ozariso, B., Altan, H. (2024): Factors affecting the indoor air quality and occupants' thermal comfort in urban agglomeration regions in the hot and humid climate of Pakistan. – *Sustainability* 16: 7869.
- [20] Hashemi, F., Mills, G. (2025): On the impact of urban climate and heat islands on building energy performance: A critical review. – *Energy and Buildings* 343: 115946.
- [21] Hiruta, Y., Ishizaki, N. N., Ashina, S., Takahashi, K. (2022): Regional and temporal variations in the impacts of future climate change on Japanese electricity demand: Simultaneous interactions among multiple factors considered. – *Energy Conversion and Management*: X 14: 100172.
- [22] Jiang, Z., Lin, B. (2012): China's energy demand and its characteristics in the industrialization and urbanization process. – *Energy Policy* 49: 608-615.
- [23] Klemm, C., Wiese, F. (2022): Indicators for the optimization of sustainable urban energy systems based on energy system modeling. – *Energy, Sustainability and Society* 12: 1-20.
- [24] Krüger, E. L. (2015): Urban heat island and indoor comfort effects in social housing dwellings. – *Landscape and Urban Planning* 134: 147-156.
- [25] Li, R., Zhu, G., Chen, L., Qi, X., Lu, S., Meng, G., Wang, Y., Li, W., Zheng, Z., Yang, J., Gun, Y. (2025): Global stable isotope dataset for surface water. – *Earth System Science Data* 17: 2135-2145.
- [26] Lin, C. yi, Zhang, Y. (2025): Combined effects of stress, depression, and emotion on thermal comfort: A case study in Shenzhen. – *Journal of Building Engineering* 103: 112158.
- [27] Liu, Y., Chu, C., Zhang, R., Chen, S., Xu, C., Zhao, D., Meng, C., Ju, M., Cao, Z. (2024): Impacts of high-albedo urban surfaces on outdoor thermal environment across morphological contexts: A case of Tianjin, China. – *Sustainable Cities and Society* 100: 105038.
- [28] Liu, Z., Zhou, Q., Tian, Z., He, B. jie, Jin, G. (2019): A comprehensive analysis on definitions, development, and policies of nearly zero energy buildings in China. – *Renewable and Sustainable Energy Reviews* 114: 109314.
- [29] Loschi, H. J., Leon, J., Iano, Y., Filho, E. R., Conte, F. D., Lustosa, T. C., Freitas, P. O. (2015): Energy efficiency in smart grid: A prospective study on energy management systems. – *Smart Grid and Renewable Energy* 6: 250-259.
- [30] Mattioli, G., Roberts, C., Steinberger, J. K., Brown, A. (2020): The political economy of car dependence: A systems of provision approach. – *Energy Research & Social Science* 66: 101486.
- [31] Murayama, K., Nagayasu, J., Bazzaoui, L. (2022): Spatial dependence, social networks, and economic structures in Japanese regional labor migration. – *Sustainability* 14: 1865.
- [32] Nadeem, M., Aziz, A., Al-Rashid, M. A., Tesoriere, G., Asim, M., Campisi, T. (2021): Scaling the potential of compact city development: The case of Lahore, Pakistan. – *Sustainability* 13: 5257.

- [33] National Development and Reform Commission (NDRC) (2022): Action Plan for Carbon Dioxide Peaking Before 2030. – Policy document, available at: https://en.ndrc.gov.cn/policies/202110/t20211027_1301020.html.
- [34] Pattnaik, N., Honold, M., Franceschi, E., Moser-Reischl, A., Rötzer, T., Pretzsch, H., Pauleit, S., Rahman, M. A. (2024): Growth and cooling potential of urban trees across different levels of imperviousness. – *Journal of Environmental Management* 361: 121242.
- [35] Pesaran, M. H. (2004): General diagnostic tests for cross section dependence in panels. – *SSRN Electronic Journal*.
- [36] Pesaran, M. H. (2006): Estimation and inference in large heterogeneous panels with a multifactor error structure. – *Econometrica* 74: 967-1012.
- [37] Pragasan, L. A., Ganesan, N. (2024): Assessment of air pollutants and pollution tolerant tree species for the development of Greenbelt at Narasapura Industrial Estate, India. – *Geology, Ecology, and Landscapes* 8: 480-488.
- [38] Provenzano, S. (2024): Accountability failure in isolated areas: The cost of remoteness from the capital city. – *Journal of Development Economics* 167: 103214.
- [39] Raihan, A., Tuspekova, A. (2022): Dynamic impacts of economic growth, energy use, urbanization, agricultural productivity, and forested area on carbon emissions: New insights from Kazakhstan. – *World Development Sustainability* 1: 100019.
- [40] Ren, S., Hao, Y., Xu, L., Wu, H., Ba, N. (2021): Digitalization and energy: How does internet development affect China's energy consumption? – *Energy Economics* 98: 105220.
- [41] Ruther, M. (2014): The effect of growth in foreign born population share on county homicide rates: A spatial panel approach. – *Papers in Regional Science* 93: S1-S23.
- [42] Salvati, A., Kolokotroni, M., Kotopouleas, A., Watkins, R., Giridharan, R., Nikolopoulou, M. (2022): Impact of reflective materials on urban canyon albedo, outdoor and indoor microclimates. – *Building and Environment* 207: 108459.
- [43] Sedaghat, A., Sharif, M. (2022): Mitigation of the impacts of heat islands on energy consumption in buildings: A case study of the city of Tehran, Iran. – *Sustainable Cities and Society* 76: 103435.
- [44] Shi, X., Gao, X., Li, R., Hou, K., Song, Y., Lu, Z. (2025): The impact of electricity grid development on economic growth and energy consumption in Anhui Province: A seemingly unrelated regression-based analysis. – *Sustainability* 17: 3193.
- [45] Shi, X., Shi, D. (2025): Impact of green finance on renewable energy technology innovation: Empirical evidence from China. – *Sustainability* 17: 2201.
- [46] Si, F., Du, E., Zhang, N., Wang, Y., Han, Y. (2023): China's urban energy system transition towards carbon neutrality: Challenges and experience of Beijing and Suzhou. – *Renewable and Sustainable Energy Reviews* 183: 113468.
- [47] Sufyanullah, K., Ahmad, K. A., Sufyan Ali, M. A. (2022): Does emission of carbon dioxide is impacted by urbanization? An empirical study of urbanization, energy consumption, economic growth and carbon emissions – Using ARDL bound testing approach. – *Energy Policy* 164: 112908.
- [48] Tabatabaei, S. S., Fayaz, R. (2023): The effect of facade materials and coatings on urban heat island mitigation and outdoor thermal comfort in hot semi-arid climate. – *Building and Environment* 243: 110701.
- [49] Teklie, D. K., Yağmur, M. H. (2024): The role of green innovation, renewable energy, and institutional quality in promoting green growth: Evidence from African countries. – *Sustainability* 16: 6166.
- [50] Verichev, K., Salazar-Concha, C., Díaz-López, C., Carpio, M. (2023): The influence of the urban heat island effect on the energy performance of residential buildings in a city with an oceanic climate during the summer period: Case of Valdivia, Chile. – *Sustainable Cities and Society* 97: 104766.
- [51] Wang, Y., Li, W., Doytch, N. (2024): Energy intensity convergence among Chinese provinces: A Theil index decomposition analysis. – *Discover Sustainability* 5: 1-13.

- [52] Wei, M., Xiong, Y., Sun, B. (2025): Spatial effects of urban economic activities on airports' passenger throughputs: A case study of thirteen cities and nine airports in the Beijing-Tianjin-Hebei region, China. – *Journal of Air Transport Management* 125: 102765.
- [53] Wu, C., Wang, R., Lu, S., Tian, J., Yin, L., Wang, L., Zheng, W. (2025): Time-series data-driven PM2.5 forecasting: From theoretical framework to empirical analysis. – *Atmosphere* 16: 292.
- [54] Wu, L., Bai, X., Li, C., Li, H., Cao, Y., Ran, C., Zhang, S., Xiong, L., Du, C., Luo, G., Chen, F., Wei, H., Chen, D., Yang, D., Xiong, L., Jia, J. (2025): Assessment of carbon sinks caused by the chemical weathering of carbonate rocks under the influence of exogenous acids: Methods, progress, and prospects. – *Science China Earth Sciences* 68: 1785-1804.
- [55] Yu, H., Zhu, S., Li, J. V., Wang, L. (2024): Dynamics of urban sprawl: Deciphering the role of land prices and transportation costs in government-led urbanization. – *Journal of Urban Management* 13: 736-754.
- [56] Zhang, X., Jiao, Z., Zhao, C., Qu, Y., Liu, Q., Zhang, H., Tong, Y., Wang, C., Li, S., Guo, J., Zhu, Z., Yin, S., Cui, L. (2022): Review of land surface albedo: Variance characteristics, climate effect and management strategy. – *Remote Sensing* 14: 1382.
- [57] Zhang, Y., Balzter, H., Li, Y. (2021): Influence of impervious surface area and fractional vegetation cover on seasonal urban surface heating/cooling rates. – *Remote Sensing* 13: 1263.
- [58] Zhou, Y., Wang, Y., Wu, Y., Wang, T., Wang, S., Zhou, X., Imran, M., Khan, N., Bilal, M. (2025): Transitioning to green energy: Assessing environmental development and sustainability in the Saudi Arabia. – *Sustainable Futures* 9: 100596.