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A novel entropy-based method for quantifying urban energy demand aggregation: Implications for urban planning and policy

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ABSTRACT

Urban energy demand aggregation (UEDA) is a key aspect of urban sustainability, as it can help to improve the energy efficiency of urban systems and reduce their environmental impacts. However, UEDA is a challenging task, as it involves aggregating heterogeneous and diverse energy demands of individual buildings into a collective demand at a given spatial scale. This paper proposes a novel entropy-based method for UEDA that quantifies the information loss or distortion resulting from this aggregation process. The method also identifies the optimal spatial scale for UEDA that minimizes information loss or distortion, and evaluates the quality and reliability of UEDA results using entropy-based metrics. We apply the method to a case study of Chicago, where we estimate and analyze the energy demand of buildings at 10 spatial scales, ranging from 1.5 km to 15 km, and for different types of energy sources. We calculate the entropy for each spatial scale and energy source, and compare it with building characteristics and ZIP codes. We also assess the quality and reliability of UEDA results using entropy-based metrics, such as information gain ratio and normalized mutual information. Our results show that different spatial scales reveal different patterns and relationships of energy demand, and that choosing an appropriate scale can enhance the accuracy and efficiency of UEDA. Our results also show that there is an optimal spatial scale for UEDA that balances information preservation and reduction, and that this scale may vary depending on the type of energy source and the urban context. Our findings contribute to the field of UEDA and urban sustainability by developing a novel perspective on urban energy dynamics, revealing the complexity and diversity of urban systems, such as population, land use, transportation, and energy demand.

1. Introduction

Urban energy demand aggregation (UEDA) is a crucial aspect of urban energy planning and management. UEDA involves consolidating individual energy demands of structures into a collective demand at a specific spatial scale, such as a district, city, or region (Zhang et al., 2018). Efficiently executing UEDA can optimize urban energy supply systems by enhancing the alignment of energy supply and demand, reducing transmission and distribution losses, increasing the integration of renewable energy sources, and improving grid reliability and flexibility (Carréon & Worrell, 2018). Moreover, UEDA can help reduce energy losses and emissions by bolstering energy efficiency, encouraging demand-side management, and facilitating community-based and shared business models. Additionally, UEDA contributes to improving urban resilience and sustainability by increasing local control over energy resources, diversifying energy sources, and reinforcing social cohesion and participation. However, UEDA presents challenges, as it encompasses various factors influencing the energy performance of structures and their interaction with the urban environment. A primary challenge in UEDA is selecting an appropriate spatial scale that preserves the most information about the energy demand distribution of structures and its relationship with urban environment factors. The choice of spatial scale can significantly impact the accuracy, feasibility, and cost-effectiveness of UEDA (Nutkiewicz et al., 2018).

Existing methods for UEDA can be classified into two primary categories: top-down and bottom-up approaches. Top-down methods employ statistical data or aggregate indicators to estimate urban energy demand, while bottom-up methods utilize physics-based models or simulation tools to calculate the individual energy demand of each structure and subsequently aggregate them according to a predefined

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spatial hierarchy (Abbasabadi & Ashayeri, 2019). Although both approaches have their merits, they also face inherent limitations that hinder their ability to accurately represent urban energy demand. Top-down methods are often challenged by the heterogeneity and variability of urban environments, such as climate conditions, solar radiation, and wind patterns (Abbasabadi & Ashayeri, 2019). They may not consider the interactions and feedback between energy demand of structures and urban environmental factors, leading to potential inaccuracies in estimating energy efficiency and conservation. Consequently, top-down methods may not provide a realistic and reliable representation of urban energy demand of structures and its spatial distribution (Li et al., 2020). On the other hand, bottom-up methods offer more accurate and detailed representations but often require substantial input data and computational resources (Li et al., 2020). These methods necessitate detailed information on characteristics of structures, occupant behaviors, energy systems, and weather data, which may not be readily available for large-scale urban areas (Li et al., 2020). Moreover, bottom-up methods may encounter difficulties when scaling up from individual structures to urban areas, as they may not account for inter-structure effects and urban micro-climate influences on energy performance (Abbasabadi & Ashayeri, 2019). Additionally, uncertainties and errors in modeling assumptions, parameters, and algorithms can impact the accuracy and reliability of UEDA results obtained from bottom-up methods. Both approaches share some common drawbacks. First, they assume a fixed spatial scale for UEDA, which may not reflect the optimal level of aggregation that preserves the most information about the distribution of energy demand of structures (Unternährer et al., 2017). The choice of spatial scale can significantly impact the accuracy, feasibility, and cost-effectiveness of UEDA. Therefore, a method that can find the optimal balance between information loss and gain by comparing different spatial scales for UEDA is necessary (Lin et al., 2021). Second, they lack a systematic approach to evaluate the quality and reliability of UEDA results, which can be influenced by factors such as data availability, model assumptions, and parameter accuracy (Niu et al., 2021). The quality and reliability of UEDA results can directly affect the validity and usefulness of urban energy planning and management, making it essential to develop a method that assesses the quality and reliability of UEDA results, accounting for uncertainties and variabilities in the data and models (Ghiassi & Mahdavi, 2017). Furthermore, existing methods often neglect other components of urban energy use, such as transportation energy and embodied energy of structures and infrastructure, which significantly contribute to urban energy consumption and emissions (Horak et al., 2022). Consequently, there is a need for a novel UEDA method that addresses these limitations and offers a more comprehensive and robust approach to quantify urban energy demand aggregation at different spatial scales. Such a method would improve urban energy planning and management by identifying the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation, considering the interactions between energy demand of structures and urban environment factors, and evaluating the quality and reliability of UEDA results.

In this paper, we propose a novel entropy-based method for UEDA that addresses the limitations of existing methods and offers a more comprehensive and robust means of quantifying urban energy demand aggregation across various spatial scales. The main contribution of this paper is to propose a novel entropy-based method for quantifying urban energy demand aggregation, which can capture the spatial heterogeneity and diversity of urban energy use patterns. UEDA is a process of estimating and analyzing the collective energy demand of buildings in an urban area at different levels of spatial resolution. UEDA is essential for understanding and managing urban energy systems, such as planning, designing, and operating energy supply and distribution networks, assessing energy efficiency and conservation potential, and evaluating environmental impacts and sustainability. The method can be applied to any urban system with available data on energy consumption and land use, and can be used to compare the energy performance of different urban forms and scenarios. The method can also provide insights into the underlying factors and drivers of urban energy demand, such as population density, land use mix, building characteristics, and socio-economic variables. The method can thus support urban planning and policy decisions that aim to improve the energy efficiency of urban systems and to reduce their environmental impacts. Entropy, a concept originating from mathematics and physics, examines the degree of disorder or uncertainty within a system. It can be employed to measure the complexity and diversity of urban systems, such as population, land use, and transportation. In this study, we utilize entropy theory to assess the degree of disorder or uncertainty in the distribution of urban energy demand at different spatial scales. For instance, if energy demand in buildings is uniformly distributed throughout a city, the entropy will be high, signifying a considerable level of uncertainty or randomness. Conversely, if urban energy demand is concentrated in specific areas or clusters, the entropy will be low, indicating a low level of uncertainty or orderliness.

Our proposed method integrates the strengths of both top-down and bottom-up approaches for UEDA. It leverages entropy theory to measure the information loss or distortion resulting from aggregating individual energy demands of buildings into a collective demand at a particular spatial scale. Furthermore, it can identify the optimal spatial scale for UEDA, which minimizes information loss or distortion caused by aggregation. Our proposed method can be applied to various types of energy demands (e.g., heating, cooling, lighting) and diverse areas (e.g., grid cell, block). It does not necessitate detailed information on individual buildings' characteristics or performance, only requiring their geographical location and aggregated energy demands at a fine spatial resolution. This feature renders the method straightforward, fast to implement, and adaptable to various urban contexts and data sources. The approach also provides a systematic means of evaluating the quality and reliability of UEDA results using entropy-based metrics. These metrics can help determine how well the UEDA results represent the actual distribution of energy demand in the urban context and assess how sensitive they are to different factors (e.g., spatial resolution, aggregation method).

The primary contributions of this paper can be summarized as follows:

- We propose a novel entropy-based approach for UEDA that overcomes the limitations of existing methods and provides a more comprehensive and robust way of quantifying urban energy demand aggregation across various spatial scales.
- We develop a systematic procedure for applying our method to estimate and analyze the energy demand of buildings at different spatial scales, using spatial and energy data of buildings in the urban area of interest.
- We implement a web-based dashboard for the proposed entropy-based model for UEDA for result visualization and user interactions.
- We demonstrate the application and evaluation of our method through a case study of Chicago, where we estimate and analyze the energy demand of buildings for four types of energy: electricity, natural gas, district chilled water and district steam, at 10 spatial scales from 1.5 km to 15 km.
- We show how our method can support urban sustainability by providing insights into the spatial patterns and dynamics of urban energy demand, identifying potential areas for energy saving and optimization, and informing urban planning and policy making.

The remainder of this paper is organized as follows. Section 2 discusses related work. Section 3 describes the data used in this study. Section 4 presents the proposed model. Section 5 describes the implementation details of the system. Section 6 evaluates the proposed model through a case study. Section 7 discusses the related issues of the study. Section 8 concludes the paper and presents the future work.

2. Literature review

UEDA is a process of aggregating individual building energy demands into a collective demand at a certain spatial scale. UEDA is a key issue for urban energy planning and management, as it can help to optimize urban energy supply systems, reduce energy losses and emissions, and improve urban resilience and sustainability. However, UEDA is not a trivial task, as it involves various factors that affect building energy performance and interact with the urban environment. Moreover, UEDA requires choosing an appropriate spatial scale that preserves the most information about building energy demand distribution. In this section, we review the existing methods for UEDA and discuss their limitations.

2.1. Top-down methods

Urban energy demand aggregation, an essential component of urban planning and energy management, relies on top-down methods that use aggregated data like population, income, and climate to estimate energy needs. Regression analysis, a common top-down approach, offers a quantitative estimate of energy demand by relating it to socio-economic and environmental factors. However, this method might not capture complex interactions due to its linear approach. In contrast, simulation-based methods, as elaborated by Abbasabadi and Ashayeri (2019) and Ghiassi and Mahdavi (2017), use mathematical models to simulate individual building energy performance, taking into account diverse factors like building envelope, HVAC systems, and occupant behavior. While providing detailed information, these methods are data-intensive and computationally demanding. Similarly, meter-based methods, highlighted in the works of Liu et al. (2021) and De Cauwer et al. (2017), utilize real energy consumption data from smart meters, offering practical insights with lower computational needs but limited in capturing long-term energy performance trends.

Recent innovations in urban energy analysis have led to more comprehensive methodologies that integrate different sources of data and information. Hedegaard et al. (2019) discuss a bottom-up modeling approach for urban-scale residential space heating demand, complementing traditional top-down methods by focusing on specific residential heating requirements (Sailor & Lu, 2004). Guo et al. (2023) further this by introducing a workflow for generating citywide building energy demand profiles, expanding the scope of urban energy analysis (Hu et al., 2022). The role of data-driven frameworks in energy modeling is underscored by Abbasabadi et al. (2019), emphasizing the importance of leveraging large datasets for accurate modeling. The contribution of smart prosumers in the energy landscape is explored by Arnone et al. (2022), indicating a shift towards more participatory energy models (Arnone et al., 2022). Li et al. (2016) emphasize the significance of real-time data analysis using smart meters, crucial for dynamic and responsive urban energy systems.

In conclusion, the selection of an appropriate top-down method for urban energy demand aggregation hinges on the specific needs and available data of the urban context. Detailed energy infrastructure data might lead to more precise estimates through energy system optimization (Keirstead et al., 2012), while the availability of spatial data could favor GIS-based methods for their spatial analysis capabilities (Lozano-García et al., 2020). The presence of large, diverse datasets is increasingly making machine learning an attractive option for uncovering complex, non-linear relationships in urban energy dynamics (Abbasabadi et al., 2019). Thus, urban energy demand aggregation is evolving, integrating more nuanced and data-rich approaches to meet the demands of modern urban energy management.

2.2. Bottom-up methods

Bottom-up methods for urban energy demand aggregation are pivotal in understanding the energy dynamics at the building level and aggregating them to understand the overall energy consumption at a broader scale. These methods have been explored in various studies, each bringing a unique perspective and methodology.

Simulation-based methods, extensively researched by Ferrando et al. (2020), Siddiqui et al. (2021), and Sathaye and Sanstad (2004), focus on using physics-based models or simulation tools to calculate the energy demand of each building based on its unique characteristics. These methods offer a detailed view of individual building energy demand, taking into account factors such as the building envelope, HVAC systems, and occupant behavior. However, they require detailed input data on building characteristics and are computationally intensive. The complex interactions between different building systems and the urban environment pose a challenge to these methods, making it difficult to accurately capture the nuances of urban energy dynamics. Meter-based methods, on the other hand, utilize actual energy consumption data from smart meters or other devices to estimate the energy demand of individual buildings. Studies by Burleyson et al. (2019) and Ren and Li (2014) highlight the practicality of these methods, which do not require detailed input data on building characteristics and are less computationally expensive compared to simulation-based methods. Despite providing detailed insights into individual building energy demand, meter-based methods have limitations in capturing changes in building energy performance over time and lack detailed information on energy use patterns for different end uses.

In addition to these bottom-up approaches based on physics-based models or simulation tools, some studies have also proposed bottom-up approaches based on data-driven techniques that leverage large datasets from various sources to estimate urban energy demand at different levels (Ferrando et al., 2020; Hedegaard et al., 2019). These approaches include machine learning algorithms that can learn from historical data or real-time data to predict future trends or scenarios (Froemelt et al., 2020), as well as optimization algorithms that can find optimal solutions for complex problems involving multiple objectives (Ciardiello et al., 2020). These approaches have shown promising results in terms of accuracy and applicability, but they also face challenges such as data quality, scalability, interpretability, and validation.

In conclusion, bottom-up methods for urban energy demand aggregation provide critical insights into individual building energy consumption and their collective impact at a larger scale. While each method has its unique advantages, they also share common drawbacks, such as the assumption of a fixed spatial hierarchy and the challenge of integrating other components of urban energy use, such as transportation energy. The evolution of these methods continues to be a vital area of research, contributing significantly to urban energy planning and management.

2.3. Entropy-based methods

Entropy-based methods for urban energy demand aggregation offer a unique approach to understanding the complexity and diversity of urban systems. These methods, grounded in the principles of entropy theory, measure the degree of disorder or uncertainty in the distribution of energy demand among various spatial units at different scales. The application of entropy-based methods in urban energy demand aggregation has been explored in recent research, revealing new insights into the variability and correlation of urban energy demand.

Shannon’s information theory, as explored by Wilson (2010, 2021), employs the logarithm of the probability distribution of a discrete random variable, such as the energy demand of a spatial unit, to measure system disorder. This approach can calculate global entropy, local entropy, joint entropy, and mutual information for each scale. However, it assumes that random variables are independent and identically distributed, a limitation in complex urban systems. Further research by Verwiebe et al. (2021), Li et al. (2020), and Zou et al. (2023) has also contributed to understanding entropy in urban contexts. Additionally, Purvis et al. (2019) extends the understanding of entropy in the broader perspective of urban systems, while Ding et al. (2016) integrates entropy methods with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), offering a novel approach to urban sustainability.

Tsallis' non-extensive statistical mechanics, as discussed by Abe and Okamoto (2001), Gell-Mann and Tsallis (2004), and Ramírez-Reyes et al. (2016), generalizes Shannon's entropy by introducing an entropic index to control non-extensivity. This method captures nonlinear and non-additive interactions between urban energy demand and environmental factors. It considers urban system heterogeneity and hierarchy but requires careful selection of the entropic index for different urban contexts. Additional studies by Wang and Holguín-Veras (2010) and Kontogiannis et al. (2022) have expanded on Tsallis' entropy in urban settings. The work of Gao and Li (2019) and Zhang et al. (2006) further enriches this perspective by applying entropy in understanding the thermodynamics of urban landscapes and the complexity of urban ecosystems, respectively.

Both Shannon's and Tsallis' entropies provide quantitative measures of information loss due to aggregating energy demand at different spatial scales. They can account for interactions between building energy demand and urban environment factors by incorporating these factors into entropy calculations. However, challenges like data availability, computational complexity, and result interpretation persist. Recent studies such as Chen et al. (2018) and Keirstead (2007) offer practical frameworks and insights into urban energy system indicators, which could be pivotal in applying entropy-based methods in urban energy systems. Additionally, Si et al. (2023) and Carréon and Worrell (2018) provide valuable case studies and research agendas focusing on urban energy system transition and urban metabolism within sustainable development frameworks. Therefore, there is a need for innovative UEDA methods that address these challenges, offering a comprehensive and robust approach to quantify urban energy demand at different spatial scales. Such methods would enhance urban energy planning and management by identifying optimal scales for UEDA that minimize information loss, considering the interactions between energy demand and urban factors, and evaluating the quality and reliability of UEDA results. This paper proposes an entropy-based method for UEDA that integrates top-down and bottom-up approaches to address these challenges.

3. Materials

The dataset used in this study is the Chicago Energy Benchmarking dataset, which contains energy performance data for municipal, commercial, and residential buildings in Chicago. The dataset is publicly available on the City of Chicago's website[1] and is updated annually as part of the Chicago Energy Benchmarking Ordinance. The ordinance requires large buildings to report their energy use and efficiency measures, and authorizes the City to share building-specific data with the public.

The dataset includes 14,142 records and 28 variables, covering the years from 2014 to 2019. Table 1 outlines the attributes, data types, and sample values of this dataset. The dataset provides a comprehensive view of energy performance in Chicago's buildings. The dataset features four primary energy sources for our study: Electricity Use, Natural Gas Use, District Steam Use, and District Chilled Water Use. For Electricity Use, the dataset comprises 12,253 records with a mean consumption of approximately 1.23×10^7 kBtu and a median of 4.50×10^6 kBtu. The Natural Gas Use category contains 11,148 records, with a mean and median usage of 1.41×10^7 kBtu and 6.31×10^6 kBtu, respectively. District Steam Use and District Chilled Water Use are considerably less prevalent, with only 364 and 462 records, respectively. The mean District Steam Use is 2.86×10^7 kBtu with a median of 1.38×10^7 kBtu, while District Chilled Water Use has a mean of 1.80×10^7 kBtu and a median of 9.07×10^6 kBtu. These statistics serve as essential indicators of the dataset's utility for modeling urban energy dynamics, albeit with varying degrees of missing data: 13.38% for Electricity Use, 21.19% for Natural Gas Use, 97.43% for District Steam Use, and 96.73% for District Chilled Water Use.

Table 1
Attributes of the Chicago Energy Benchmark Dataset.

Attribute	Data type	Sample data
Data Year	Integer	2019
ID	Integer	12 345
Property Name	String	"John Doe Building"
Address	String	"1234 Elm St"
ZIP Code	String	"60601"
Community Area	String	"Loop"
Primary Property Type	String	"Office"
Gross Floor Area - Buildings (sq ft)	Float	50 000.0
Year Built	Float	1985.0
# of Buildings	Float	2.0
ENERGY STAR Score	Float	75.0
Electricity Use (kBtu)	Float	100 000.0
Natural Gas Use (kBtu)	Float	50 000.0
District Steam Use (kBtu)	Float	0.0
District Chilled Water Use (kBtu)	Float	0.0
Site EUI (kBtu/sq ft)	Float	50.0
Source EUI (kBtu/sq ft)	Float	75.0
Weather Normalized Site EUI (kBtu/sq ft)	Float	52.0
Weather Normalized Source EUI (kBtu/sq ft)	Float	78.0
Total GHG Emissions (Metric Tons CO2e)	Float	100.0
GHG Intensity (kg CO2e/sq ft)	Float	2.0
Latitude	Float	41.8797561
Longitude	Float	−87.63268685
Reporting Status	String	"Complete"
Chicago Energy Rating	Float	4.0
Exempt From Chicago Energy Rating	String	"No"
Water Use (kGal)	Float	2000.0

Chicago is an interesting case study for urban energy dynamics because it is one of the largest and most populous cities in the United States, with more than 2.7 million residents and over 500,000 buildings. The city has a continental climate with four distinct seasons, ranging from hot and humid summers to cold and snowy winters. The city also has a diverse and complex energy system, with multiple sources of electricity generation, transmission, and distribution, as well as natural gas, district heating and cooling, and renewable energy. The city has adopted various energy policies and initiatives to improve its energy efficiency, reduce its greenhouse gas emissions, and increase its resilience to climate change. Some of these policies include the Chicago Climate Action Plan, the Chicago Energy Benchmarking Ordinance, the Retrofit Chicago program, and the Chicago Solar Express program. Therefore, studying the energy performance of Chicago's buildings can provide valuable insights into the challenges and opportunities of urban energy dynamics in a large and dynamic city.

We now use the electricity use of buildings for the year 2019 as an example to illustrate the spatial and quantitative dimensions of the consumption, as shown in Figs. 1 and 2. Firstly, a histogram was generated to depict the frequency distribution of Electricity Use (measured in kBtu) among the buildings. The frequency on the y-axis signifies the count of buildings falling within each bin range of electricity usage, thereby serving as a quantitative proxy for understanding energy consumption trends. Secondly, a geospatial heatmap

[1] Chicago energy benchmarking: https://www.chicago.gov/city/en/depts/mayor/supp_info/chicago-energy-benchmarking/Chicago_Energy_Benchmarking_Reports_Data.html

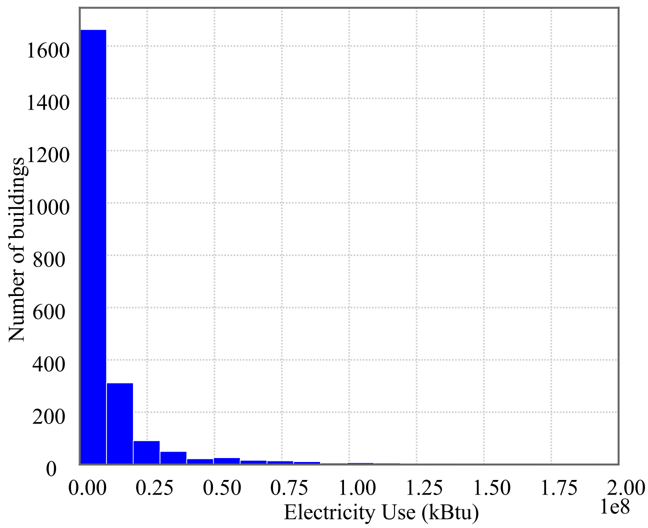


Fig. 1. The distribution of electricity use in 2019.

was created to impart a geographical context to these consumption metrics, which illustrates the intensity of electricity use across various locales in Chicago.

4. Methodology

In this section, we present the proposed entropy-based method for UEDA, which aims to find the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation. We first introduce the concept of entropy and its applications in spatial analysis. Then, we describe the steps of the proposed method in detail, and finally introduce the metrics used for the evaluation.

4.1. Overview

The primary objective of this study is to develop and validate a UEDA model, which is a scalable and computationally efficient method for aggregating energy demand across varying spatial resolutions. This can facilitate urban energy management strategies, such as optimizing urban energy supply systems, reducing energy losses and emissions, and improving urban resilience and sustainability. To achieve this objective, we propose an entropy-based method for UEDA, which is a four-step process that aims to find the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation. Entropy is a concept of information theory that measures the uncertainty or disorder of a system. In spatial analysis, entropy can be used to measure the heterogeneity or diversity of observations across space, while other measures, such as the fractal dimension, can capture the spatial structure or complexity of a system.

Fig. 3 provides an overview of the proposed method, which consists of four steps: data preparation, entropy calculation, optimal scale identification, and result analysis. In the data preparation step, we collect and process the input data for UEDA, which includes building locations and energy demands at fine spatial resolution, and define a set of spatial units at different scales for UEDA. In the entropy calculation step, we calculate two types of entropy for each spatial scale: global entropy, which measures the degree of disorder or uncertainty in the overall distribution of energy demand among different spatial units at a given scale, and local entropy, which measures the degree of disorder or uncertainty in the local distribution of energy demand within each spatial unit at a given scale. In the optimal scale identification step, we use two criteria to identify the optimal spatial scale for UEDA: the global criterion, which maximizes the global entropy, and the local criterion, which minimizes the local entropy. In the result analysis step, we evaluate the proposed method through a use case study, and analyze the results. The proposed method combines the strengths of both top-down and bottom-up methods for UEDA and can help optimize urban energy supply systems, reduce energy losses and emissions, and improve urban resilience and sustainability. The following subsections provide a more detailed explanation of each step of the proposed method.

4.2. Data preparation for UEDA

The first step of this study is the preparation of geospatial and energy demand data for the UEDA model. The UEDA model is a tool that can help design long-term strategies for urban energy planning by analyzing the optimal energy mix, investment needs, energy supply security, resource utilization, technology learning, and environmental constraints. The study area is demarcated based on the geographical extent of the Chicago City, defined by specific longitude and latitude bounds. Following this, the area is divided into uniform grid cells, each having consistent dimensions (see Figs. 5 and 6). For computational efficiency and to facilitate the UEDA experiments, shapefiles for the grid at each scale have been pre-prepared.

The size of these grid cells is determined by a spatial resolution parameter r, which varies from 1.5 km to 15 km, corresponding to scales ranging from 1 to 10. Mathematically, the relationship between r and the scale is defined as $r = 1.5 \times \text{scale}$. The area of each grid cell s is then given by:

$$s = r \times r \tag{1}$$

For each grid cell, or spatial unit j, the energy demand is calculated across various types of energy sources and is represented as $E_j(t,k)$, where t denotes the year (ranging from 2014 to 2019), and k specifies the type of energy source (e.g., Electricity Use, Natural Gas Use, District Steam Use, District Chilled Water Use). The energy demand $E_j(t,k)$ is computed by summing up the energy demands of all buildings falling within spatial unit j for each type of energy source. This is formally expressed as:

$$E_j(t,k) = \sum_{i \in j} E_i(t,k) \tag{2}$$

where $i \in j$ means that building i is part of spatial unit j.

The output of the UEDA model consists of these aggregated energy demands, categorized by spatial unit, year, and type of energy source.

4.3. Entropy calculation

One of the key steps in our method is to calculate the entropy of energy demand at different spatial scales. Entropy is a measure of disorder or uncertainty in a system, and it can help us quantify the degree of aggregation or dispersion of energy demand among and within spatial units. By comparing the entropy values at different scales, we can identify the optimal scale for urban energy planning and management.

We calculate two types of entropy for each spatial scale: global entropy and local entropy. Global entropy measures the degree of disorder or uncertainty in the overall distribution of energy demand among different spatial units at a given scale. Local entropy measures the degree of disorder or uncertainty in the local distribution of energy demand within each spatial unit at a given scale.

Global entropy is calculated by using Shannon's information theory (Shannon, 2001), which defines entropy as:

$$H(E) = -\sum_{i=1}^{N} p_i \log p_i \tag{3}$$

where E is a discrete random variable representing the energy demand of a spatial unit at a certain scale, N is the number of spatial units

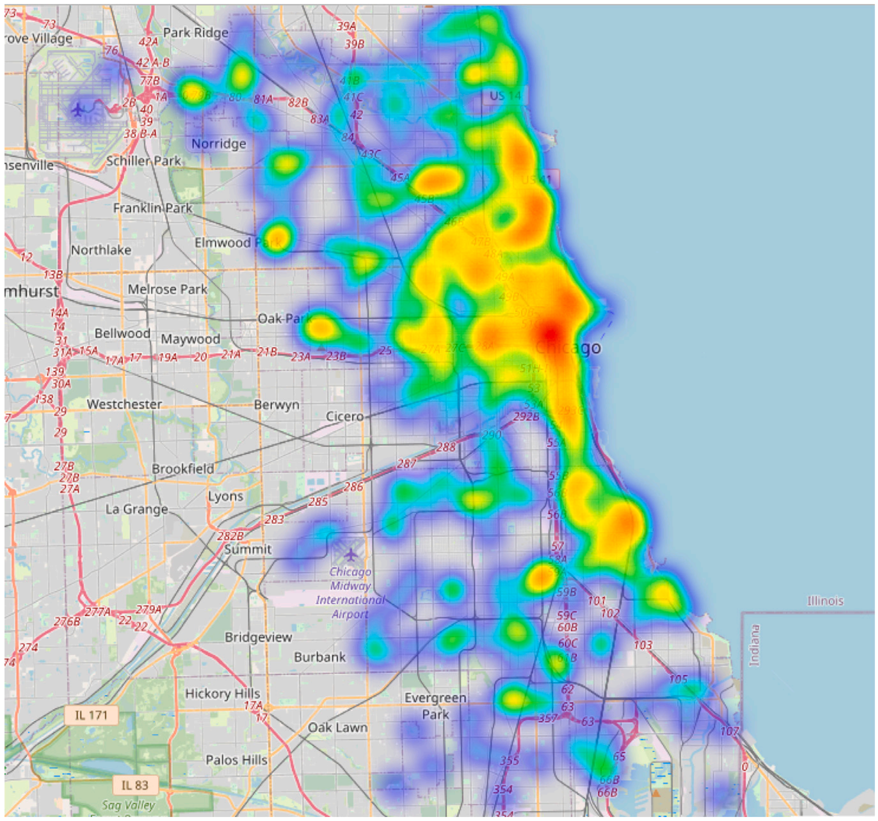


Fig. 2. The spatial distribution of electricity use in 2019.

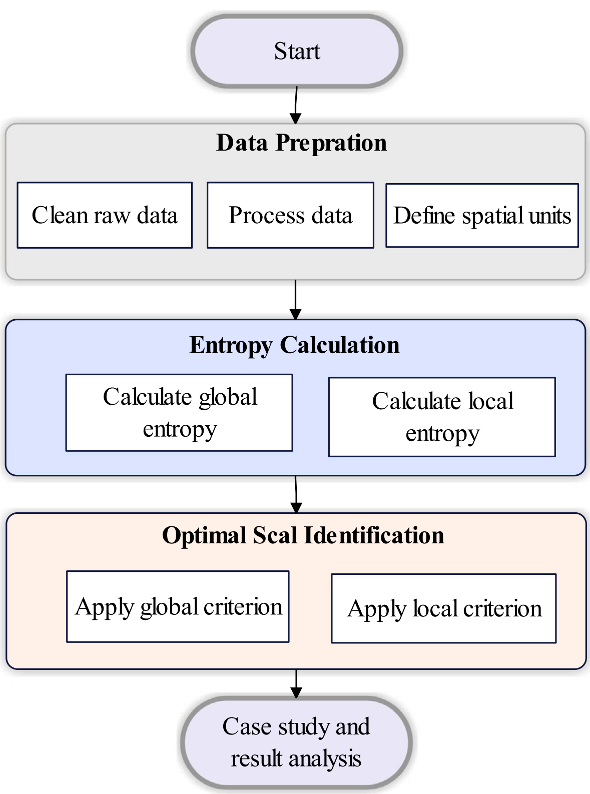


Fig. 3. Flowchart of the entropy-based method for UEDA.

at that scale, p_i is the relative frequency of occurrence of the energy demand of each spatial unit, and log is the logarithm function with base 2. For example, if we consider the city scale, E is the energy demand of a city, N is the number of cities in our study area, and p_i is the proportion of total energy demand that each city consumes. The higher the global entropy, the more evenly distributed the energy demand among different cities.

Local entropy is calculated using Tsallis' non-extensive statistical mechanics (Tsallis, 1988), which generalizes Shannon's entropy as:

$$H_q(E) = \frac{1}{q-1}\left(1 - \sum_{i=1}^{N} p_i^q\right) \tag{4}$$

where q is an entropic index that controls the degree of nonextensivity. When $q = 1$, Tsallis' entropy reduces to Shannon's entropy; when $q > 1$, Tsallis' entropy emphasizes rare events; when $q < 1$, Tsallis' entropy emphasizes frequent events. In our case, we use Tsallis' entropy to capture the local variability of energy demand within each spatial unit at a certain scale. We set $q = 2$ to give more weight to high-energy-demand buildings than low-energy-demand buildings. For example, if we consider the building scale, E is the energy demand of a building, N is the number of buildings in a spatial unit (such as a city or a district), and p_i is the proportion of total energy demand that each building consumes within that unit. The higher the local entropy, the more heterogeneous the energy demand within each spatial unit.

4.4. Optimal scale identification

In this step, we identify the optimal spatial scale for UEDA that maximizes information preservation or minimizes information loss caused by aggregation. This is an important step because different spatial scales may reveal different patterns and relationships of energy demand, and choosing an appropriate scale can enhance the accuracy and efficiency of urban energy planning and management. We use two criteria for optimal scale identification: the global criterion based on Kullback–Leibler divergence and the local criterion based on Tsallis' generalized entropy.

The global criterion is based on the Kullback–Leibler divergence (Van Erven & Harremos, 2014), which measures the relative loss of information between two probability distributions. We define the original distribution as the fine-scale distribution of building-level energy demand, and the aggregated distribution as the coarse-scale distribution of spatial-unit-level energy demand. We calculate the Kullback–Leibler divergence between these two distributions as follows.

$$D_{KL}(P \parallel Q) = \sum_{i=1}^{N} p_i \log \frac{p_i}{q_i} \tag{5}$$

where P and Q are the original and aggregated distributions, respectively, p_i and q_i are their corresponding probability mass functions, and $\log$ is again the logarithm function with base 2. In our case, p_i is proportional to the normalized energy demand of each building, and q_i is proportional to the normalized energy demand of each spatial unit. We normalize both distributions by dividing their values by their respective sums, so that they have equal total probabilities. We calculate the Kullback–Leibler divergence for each spatial scale and plot it as a function of scale. We identify the optimal scale as the one that minimizes the Kullback–Leibler divergence or maximizes information preservation.

The local criterion is based on Tsallis' generalized entropy, which measures the degree of disorder or uncertainty in a system composed of multiple subsystems. We define the system as the entire urban area and the subsystems as spatial units at a certain scale. We calculate the Tsallis' generalized entropy of the system as:

$$H_q(S) = \frac{1}{q-1}\left(1 - \sum_{i=1}^{N} w_i^q H_q(X_i)\right) \tag{6}$$

where S is the system, N is the number of subsystems, w_i is the weight of each subsystem, $H_q(X_i)$ is the local entropy of each subsystem calculated in the previous subsection, and q is again an entropic index that controls the degree of nonextensivity. In our case, we set w_i as proportional to the normalized energy demand of each spatial unit. We choose $q = 2$ for local entropy calculation based on a numerical method that maximizes redundancy and follows the maximum entropy principle. This choice is also consistent with using the variance of the probabilities as a measure of disorder or uncertainty (Tsallis, 1988). We calculate the Tsallis' generalized entropy for each spatial scale and plot it as a function of scale. We identify the optimal scale as the one that maximizes the Tsallis' generalized entropy or minimizes information loss. The complete procedure for identifying the optimal scale is detailed in Algorithm 1, which can be found in Appendix.

4.5. Performance metrics

To ascertain the efficacy and robustness of the proposed method for aggregating urban energy demand, we employ two pivotal performance metrics: Information Gain Ratio (IGR) and Normalized Mutual Information (NMI). These metrics quantify the extent of information preservation or dissipation when the original, granular distribution of energy demand is integrated into a coarser, aggregated distribution.

Information Gain Ratio (IGR) serves as an index for the decrement in entropy or uncertainty affiliated with the original distribution subsequent to its conditioning on the aggregated distribution. Mathematically, it is defined as:

$$IGR(P,Q) = \frac{IG(P,Q)}{H_q(P)} \tag{7}$$

Here, P and Q denote the original and aggregated distributions, while $IG(P,Q)$ stands for the information gain, and $H_q(P)$ represents the Tsallis' generalized entropy of (P). The information gain is expressed as:

$$IG(P,Q) = H_q(P) - H_q(P|Q) \tag{8}$$

In this equation, $H_q(P)$ embodies the global entropy of P, and $H_q(P|Q)$ signifies the conditional entropy of P given Q. The IGR metric ranges between 0 and 1. An IGR close to 1 implies maximum information gain or minimum uncertainty, which indicates that the local entropy contributes significantly to explaining the global entropy. Conversely, an IGR close to 0 suggests no information gain or maximal uncertainty.

Normalized Mutual Information (NMI) quantifies the shared or common information between the original and the aggregated distributions. Its mathematical representation is:

$$NMI(P,Q) = \frac{2I_q(P,Q)}{H_q(P) + H_q(Q)} \tag{9}$$

Here, $I_q(P,Q)$ represents the Tsallis' generalized mutual information between (P) and (Q). The NMI values range between 0 and 1. An NMI close to 1 signifies maximal shared information or identical distributions, whereas an NMI value nearing 0 indicates independent distributions or minimal shared information. Moderate NMI values suggest a complex relationship between local and global energy patterns, requiring different management strategies at different scales.

By applying these metrics, we compare the optimal scale identified by our entropy-based approach with the scales that register the highest values for IGR and NMI. We also examine the sensitivity of these metrics to changes in data inputs and model parameters, such as the entropic index (q) and the spatial unit weight (w_i). We expect that our proposed method will achieve high values for both IGR and NMI, confirming its ability to aggregate urban energy demand while minimizing information loss and maximizing information retention.

5. Implementation

To facilitate the application of our novel entropy-based approach for UEDA, we have developed an interactive visualization dashboard that allows users to explore and analyze urban energy demand data at different spatial scales and dimensions (see Fig. 4). The dashboard integrates both qualitative and quantitative research methodologies and provides a robust and user-friendly platform for data manipulation and visualization.

The dashboard is built using Streamlit, an open-source Python library that enables fast and easy creation of web applications for data science and machine learning. Streamlit allows us to write Python scripts that can run as web apps with minimal code and configuration. Streamlit also provides various widgets and components that enable user interactions, such as sliders, buttons, checkboxes, maps, charts, and tables. The dashboard connects to a PostgreSQL database that stores the urban energy demand data and the spatial data. PostgreSQL is an open-source relational database management system that supports SQL standards and offers high performance and reliability. The spatial data, such as building footprints, administrative boundaries, and geographic coordinates, are managed through PostGIS, an extension for PostgreSQL that enables storage, querying, and manipulation of spatial data. PostGIS allows us to execute complex spatial queries, such as geometric aggregation and spatial joins, using SQL syntax. The dashboard consists of several modules that allow users to perform different tasks related to UEDA. The main modules are:

- **Data Overview:** This module provides a summary of the urban energy demand data, such as the number of records, the range of years, the types of energy sources, and the types of buildings. It also allows users to filter the data based on attributes such as time range, energy type, ZIP code, property type, etc.
- **Data Visualization:** This module allows users to visualize the urban energy demand data using various charts and maps. Users can choose from different types of charts, such as scatter plots, heat maps, bar charts, line charts, etc., to explore the distribution and trends of energy demand across different dimensions. Users can also choose from different types of maps, such as choropleth maps, point maps, hexbin maps, etc., to explore the spatial patterns and variability of energy demand across different scales.

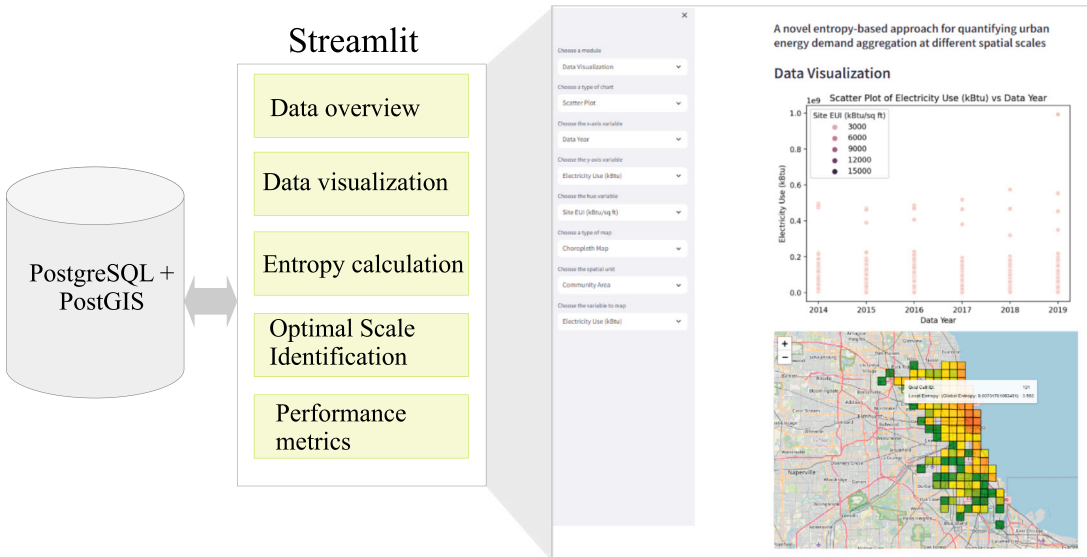


Fig. 4. The urban energy demand aggregation platform and its user interface.

- **Entropy Calculation:** This module allows users to calculate the entropy of energy demand at different spatial scales using Shannon's or Tsallis' entropy. Users can select the type of entropy, the entropic index (for Tsallis' entropy), the type of energy source, and the range of scales to calculate the entropy values. The module also displays the entropy values as a function of scale using a line chart.
- **Optimal Scale Identification**: This module allows users to identify the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation. Users can select the type of entropy, the entropic index (for Tsallis' entropy), the type of energy source, and the range of scales to identify the optimal scale. The module also displays the Kullback–Leibler divergence and Tsallis' generalized entropy values as a function of scale using a line chart.
- **Performance Metrics**: This module allows users to evaluate the quality and reliability of UEDA results using entropy-based metrics, such as information gain ratio and normalized mutual information. Users can select the type of entropy, the entropic index (for Tsallis' entropy), the type of energy source, and the range of scales to calculate the metrics values. The module also displays the metrics values as a function of scale using a line chart.

The dashboard leverages the synergy between PostgreSQL and PostGIS to perform real-time, server-side data processing, which reduces the computational burden on the client-side. Complex SQL and spatial queries are executed on the server, and only the relevant data is sent to the client. This approach ensures scalability and performance, even when dealing with large, multi-dimensional datasets. The dashboard is not merely a data visualization tool but a comprehensive environment for UEDA. It allows users to seamlessly integrate spatial and non-spatial data, offering a multi-dimensional view of urban energy demand. This system serves as a valuable asset for both policy formulation and academic research, facilitating a nuanced understanding of energy consumption patterns in urban settings.

6. Case study

This section will carry out case study to evaluate the proposed model, and present experimental settings, model implementations, data, and results. We use Chicago city as our case study, as we have introduced in the Materials section (see Section 3). Chicago is a major metropolitan area in the United States, with diverse and complex energy consumption patterns. By applying our novel entropy-based method for UEDA to Chicago city, we aim to reveal the spatial and temporal dynamics of urban energy demand and identify the optimal spatial scale for UEDA that minimizes information loss or distortion.

6.1. Entropy calculation based on grid-cell spatial units

We first study the entropy for different types of energy use according to varying grid-cell spatial units from scale 1 to 10 using the shapefiles that we prepared in our data preparation step (see Section 4.2). In this experiment, we showcase the entropies calculated based on the data for 2019, which is the latest available data from the data source. Table 2 presents the detailed analysis result, showing the relationship between spatial scales and various entropy metrics, namely global and average local entropies, IGR and NMI. The local and global entropy values reflect the complexity and diversity of energy consumption patterns across different scales. Specifically, higher local entropy values indicate more variability and heterogeneity in energy use at a finer spatial level, which may require more localized and customized energy-saving measures. Conversely, lower global entropy values imply more uniformity and simplicity in energy use at a coarser spatial level, which may allow for more generalized and standardized energy management strategies. For illustration purpose, we plot the grid cells for a fine scale 1 and a coarse scale 9 in Figs. 5 and 6, respectively. The depth of the color represents the entropy values ranging from 0 to 10. As shown in the figures, the city center area typically has higher entropies than the suburb area. This is because the city center may have more diverse and complex energy consumption patterns than the suburb, due to the influence of various factors such as land use mix, population density, income diversity, and lifestyle variation.

Using the obtained local and global entropies, we also calculate the optimal scale using Algorithm 1, and obtain the results shown at the bottom of Table 2. A notable observation in this table is the emergence of an optimal scale of 5 for District Chilled Water Use, where the local entropy reaches a maximum value of 2.34. The corresponding IGR and NMI values at this scale are 0.68 and 0.42, respectively, suggesting a balanced trade-off between information preservation and information loss due to aggregation. This implies that this scale can capture the most detailed and informative energy consumption patterns for this type of energy use.

For District Steam Use, Electricity Use, and Natural Gas Use, a consistent optimal scale of 9 is observed. At this scale, the IGR values range from 0.85 to 0.93, indicating a high degree of information

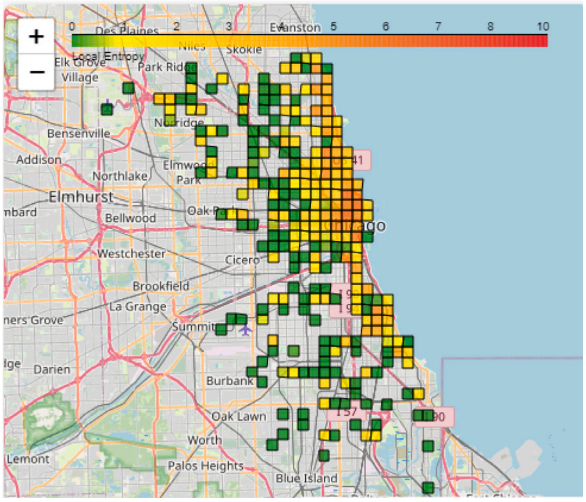


Fig. 5. Local entropy of electricity use on grid cell wiht spatial scale of 1.

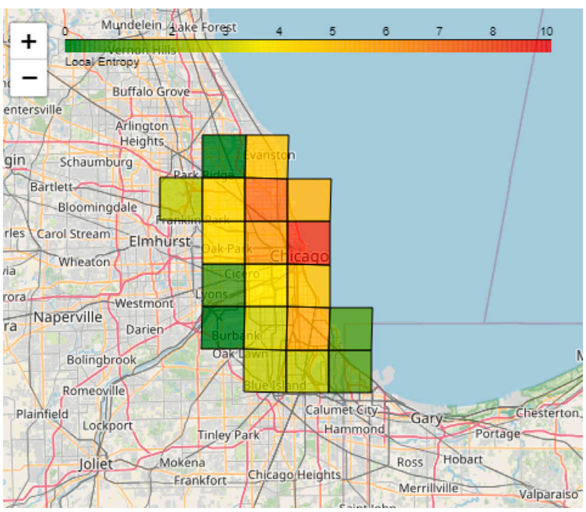


Fig. 6. Local entropy of electricity use on grid cell wiht spatial scale of 9.

preservation or a low degree of information loss due to aggregation. The global entropy values are also significantly high, ranging from 5.48 to 9.65, indicating a high degree of diversity or complexity in energy consumption patterns at this scale. The moderate NMI values (0.31 to 0.58) indicate a nuanced relationship between local and global energy patterns, suggesting that different scales may reveal different aspects of energy consumption behavior.

From an energy management perspective, these results are valuable. The identified optimal scales and associated entropy metrics can guide targeted, scale-specific interventions for maximizing energy efficiency and minimizing costs. Furthermore, the relationship between local and global entropies could inform adaptive strategies that toggle between centralized and decentralized energy systems, thus achieving a harmonized and more efficient energy network.

6.2. Optimal spatial scale analysis

With the calculated global and local entropies at different spatial scales, we could calculate the optimal spatial scale. Fig. 7 presents the optimal scales for different types of energy usage in Chicago from 2014 to 2019, as determined by the Kullback–Leibler divergence and Tsallis generalized entropy (see Algorithm 1). The figure reveals distinct patterns and trends for each energy source, reflecting the complexity and diversity of urban energy consumption. For Electricity Use and Natural Gas Use, the optimal scale is consistently 9 across the years, indicating a high degree of uniformity and stability in the spatial distribution of these energy types. This suggests that the energy infrastructure for these sources is well-established and resilient, and that the energy demand is relatively homogeneous across different spatial units. For District Steam Use, however, the optimal scale varies from 2 to 9, implying a higher degree of variability and uncertainty in the spatial distribution of this energy type. This may be attributed to changes or challenges in district heating systems, such as aging infrastructure, maintenance issues, or demand fluctuations. Further empirical investigation is needed to understand the causes and consequences of this variability. For District Chilled Water Use, the optimal scale oscillates from 0 to 9, with a notable drop to 5 in 2019. This suggests a high degree of heterogeneity and dynamism in the spatial distribution of this energy type, which could be influenced by factors such as climate variations, technological advancements, or policy interventions. The drop in 2019 may indicate a shift in the demand or supply dynamics for chilled water, which could have implications for energy efficiency and conservation. To summarize, the results in Fig. 7 demonstrate the values of using entropy-based methods for identifying the optimal spatial scale for urban energy demand aggregation, which can help optimize urban energy supply systems, reduce energy losses and emissions, and improve urban resilience and sustainability.

6.3. Sensitivity analysis for performance metrics

To rigorously assess the robustness of our proposed method, we conducted a sensitivity analysis, focusing on the IGR and NMI as performance metrics. As delineated in Eq. (6), Tsallis entropy is contingent upon two hyperparameters: the entropic index q and the weight of spatial units w_i. We, therefore, undertook a nuanced evaluation of these hyperparameters under fixed conditions – $w_i = 1$ for varying q and $q = 2$ for varying w_i – with both hyperparameters ranging from 0.5 to 1.5. The data sets employed in this analysis are specific to Electricity Use in Chicago for the year 2019, offering a substantive, real-world context for our evaluation.

The findings, as elaborated in Table 3, exhibit several noteworthy patterns. The IGR values demonstrate a generally ascending yet fluctuating trend across increasing spatial scales, indicative of the complex interactions between spatial granularity and information retention. Such a trend is particularly crucial for policymakers, as it suggests that interventions in electricity use may need to be carefully tailored to specific spatial scales for maximum efficacy. Global Entropy remains notably consistent around 9.6, irrespective of the scale, reinforcing the systemic stability and underlining the potential for scalable interventions based on these entropic measures. The NMI values reveal only modest variations across different w_i settings, underscoring the robustness of the relationships captured and reinforcing the generalizability of our findings. In summary, the insights from Table 3 not only validate the utility of our proposed entropic measures for nuanced spatial analysis of the energy use but also highlight the need for multi-scale, hyperparameter-sensitive approaches in future research and policy planning.

6.4. Entropy calculation based on ZIP code regions

This study uses the spatial division of ZIP code regions as a way to measure the entropy of energy consumption in Chicago. The geographic information comes from the City of Chicago Data Portal, which provides a shapefile with 59 ZIP code regions that cover the whole city area. Using the method described in Section 4, we calculate both the average local and global entropy values for four different types of energy across these ZIP code regions from 2014 to 2019. Fig. 8 shows the entropic change of four energy types across ZIP codes over time. Entropy is a statistical measure of the disorder or complexity in

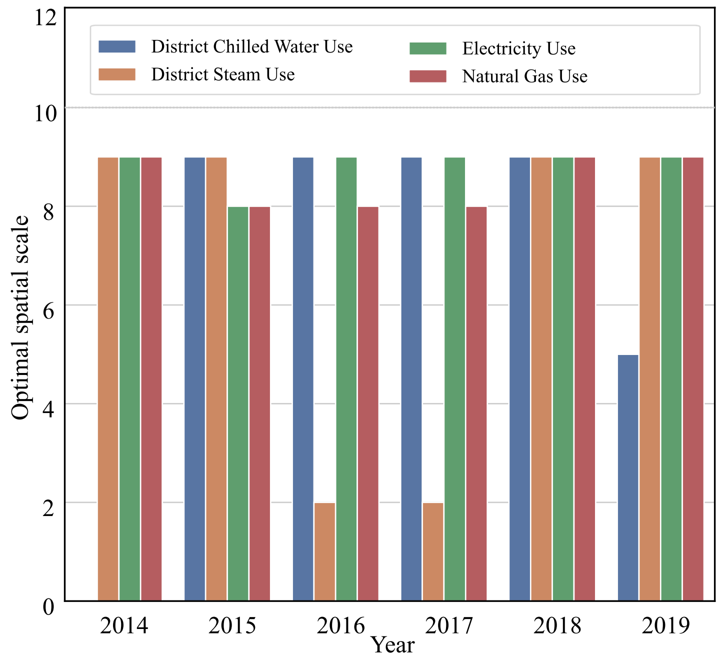


Fig. 7. Optimal spatial scale over the year from 2014 to 2019 by different energy sources.

Table 2
The average local entropy, global entropy, IGR, and NMI of different energy types in 2019.

Scale	District chilled water use				District steam use				Electricity use				Natural gas use			
	Local	Global	IGR	NMI	Local	Global	IGR	NMI	Local	Global	IGR	NMI	Local	Global	IGR	NMI
1	1.41	4.68	0.60	0.50	1.60	5.48	0.65	0.45	1.34	9.61	0.70	0.35	1.29	9.65	0.75	0.40
2	1.71	4.68	0.62	0.48	1.68	5.48	0.68	0.44	1.92	9.61	0.72	0.38	1.87	9.65	0.77	0.42
3	2.68	4.68	0.64	0.46	2.31	5.48	0.70	0.42	2.35	9.61	0.74	0.40	2.38	9.65	0.79	0.44
4	2.19	4.68	0.66	0.44	2.28	5.48	0.73	0.41	2.95	9.61	0.76	0.43	2.94	9.65	0.81	0.46
5	2.34	4.68	0.68	0.42	3.27	5.48	0.75	0.40	3.36	9.61	0.78	0.45	3.38	9.65	0.83	0.48
6	2.76	4.68	0.70	0.40	3.27	5.48	0.77	0.39	3.65	9.61	0.80	0.47	3.56	9.65	0.85	0.50
7	2.01	4.68	0.72	0.38	2.77	5.48	0.79	0.37	3.88	9.61	0.82	0.49	3.85	9.65	0.87	0.52
8	2.56	4.68	0.74	0.36	3.46	5.48	0.81	0.35	3.81	9.61	0.84	0.51	3.68	9.65	0.89	0.54
9	2.60	4.68	0.76	0.34	2.89	5.48	0.83	0.33	4.33	9.61	0.86	0.53	4.28	9.65	0.91	0.56
10	2.70	4.68	0.78	0.32	4.39	5.48	0.85	0.31	4.72	9.61	0.88	0.55	4.69	9.65	0.93	0.58
Optimal Scale	5				9				9				9			

Table 3
Sensitivity analysis of IGR and NMI across different spatial scales, entropic indices q, and spatial unit weights w_i, using Chicago's 2019 Electricity Use data.

Scale	Global_Entropy	Local_Entropy	$IGR_{q=0.5}$	$IGR_{q=1.0}$	$IGR_{q=1.5}$	$NMI_{wi=0.5}$	$NMI_{wi=1.0}$	$NMI_{wi=1.5}$
1	9.70	2.20	0.70	0.75	0.80	0.41	0.38	0.51
2	9.63	2.17	0.72	0.77	0.82	0.39	0.38	0.51
3	9.66	2.15	0.71	0.76	0.83	0.37	0.38	0.50
4	9.72	2.13	0.73	0.79	0.84	0.35	0.39	0.50
5	9.70	2.11	0.74	0.80	0.86	0.33	0.39	0.49
6	9.56	2.08	0.75	0.81	0.85	0.31	0.40	0.49
7	9.66	2.06	0.77	0.83	0.87	0.29	0.40	0.48
8	9.60	2.04	0.76	0.82	0.88	0.27	0.40	0.47
9	9.60	2.01	0.78	0.85	0.90	0.25	0.41	0.47
10	9.63	1.99	0.79	0.84	0.89	0.23	0.41	0.46

a system. Higher entropy scores mean more variability in consumption patterns, while lower entropy values mean more uniformity in energy use. The figure compares local and global entropy values, with the local ones showing the variability within each ZIP code and the global ones showing the variability between all ZIP codes.

Among the four energy types, electricity use has the highest global entropy ranging from 7.33 to 10.06, and the highest average local entropy ranging from 1.37 to 4.01. The analysis shows an increasing trend in local entropy before 2018 and a decreasing trend after. This means that the electricity consumption patterns within each ZIP code became more diverse, while the electricity consumption patterns between ZIP codes became more similar. This suggests that there was a growing difference in energy consumption behaviors at the ZIP code level, but a wider similarity across ZIP codes. The increasing local entropy and decreasing global entropy of electricity consumption imply that there is a growing gap between the energy consumption behaviors of different ZIP code regions in Chicago. This could pose challenges for the city's energy management and planning, as well as its environmental and social sustainability goals. For example, the city may need to consider how to balance the energy supply and demand across different regions, how to reduce the carbon footprint and greenhouse gas emissions

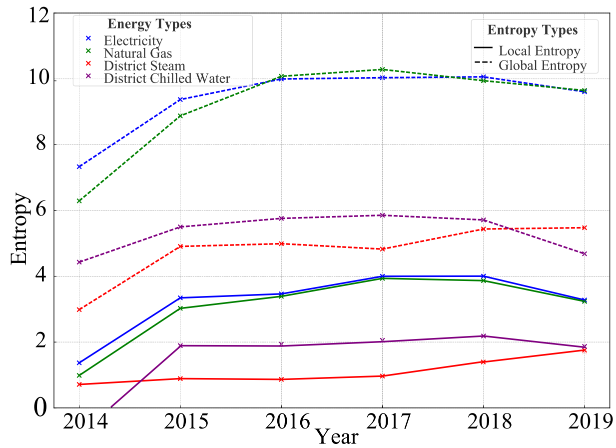


Fig. 8. Local and global entropy of electricity use by ZIP Code in Chicago from 2014 to 2019.

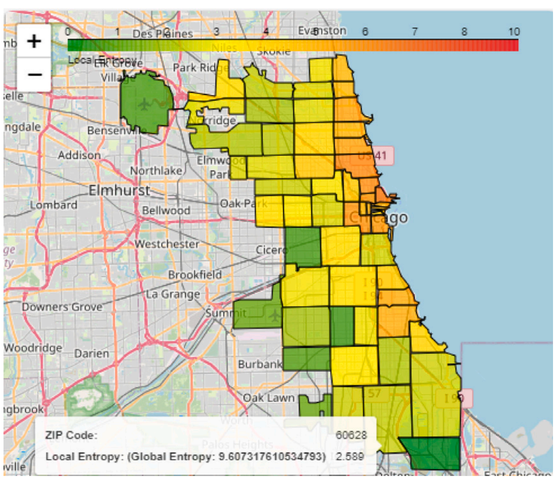


Fig. 9. Local Entropy of electricity use by ZIP Code in Chicago for the Year 2019.

of high-entropy regions, and how to address the energy poverty and inequality issues of low-entropy regions.

Moreover, Fig. 8 explains the role of different energy sources in shaping entropic changes. Electricity, natural gas, district steam, and district chilled water all had positive effects on entropy, meaning that they increased the diversity of consumption patterns. On the other hand, the similarity of energy types within and across ZIP codes makes the electricity consumption patterns less diverse across ZIP codes. The changes in the relative amounts of these energy sources over time also show a dynamic change in energy preferences within Chicago. The role of different energy sources in shaping entropic changes implies that there is a potential for improving the energy efficiency and diversity of Chicago's energy system. For example, the city may explore the possibility of increasing the use of renewable and clean energy sources, such as solar, wind, and hydro power, to reduce the dependence on fossil fuels and lower the environmental impact of energy consumption. The city may also promote the adoption of smart grid technologies and demand response programs, to enable more flexible and responsive energy management and optimization.

In Fig. 9, we illustrate the spatial distribution of local entropy for electricity consumption across ZIP code regions in 2019 as an example to offer compelling insights. The map, included solely for illustrative purposes for one type of energy, reveals a distinct pattern of electricity usage across the city. Areas characterized by higher local entropy values are predominantly situated in central and commercial zones. These elevated entropy levels indicate a pronounced heterogeneity in electricity consumption, likely influenced by a complex interplay of building types, occupancy levels, and disparate utility demands. On the contrary, regions with lower local entropy values are generally residential or less commercially active, suggesting a more uniform pattern of electricity usage within these ZIP codes. This spatial analysis serves as an invaluable tool for understanding the granularity of localized electricity consumption for the year 2019. Though this illustration focuses on electricity, similar analytical frameworks can be extended to other energy types, offering a comprehensive understanding of spatial energy consumption patterns. Such spatially explicit information on local entropy holds significant implications for the design of area-specific energy policies and sustainability interventions.

6.5. Entropy calculation based on property types

In this empirical analysis, we employed entropy as a mathematical metric to investigate the heterogeneity of energy consumption across various property types within an urban context. We focused on the top 13 property types, selected based on the highest number of buildings per category, encompassing a range from 'Multifamily Housing' to 'Strip Malls' for the years 2014 to 2019. Fig. 10 shows the analytic results, which reveal intricate dynamics in energy consumption behaviors, as evidenced by the entropy values computed for four pivotal energy sources: Electricity, Natural Gas, District Steam, and District Chilled Water.

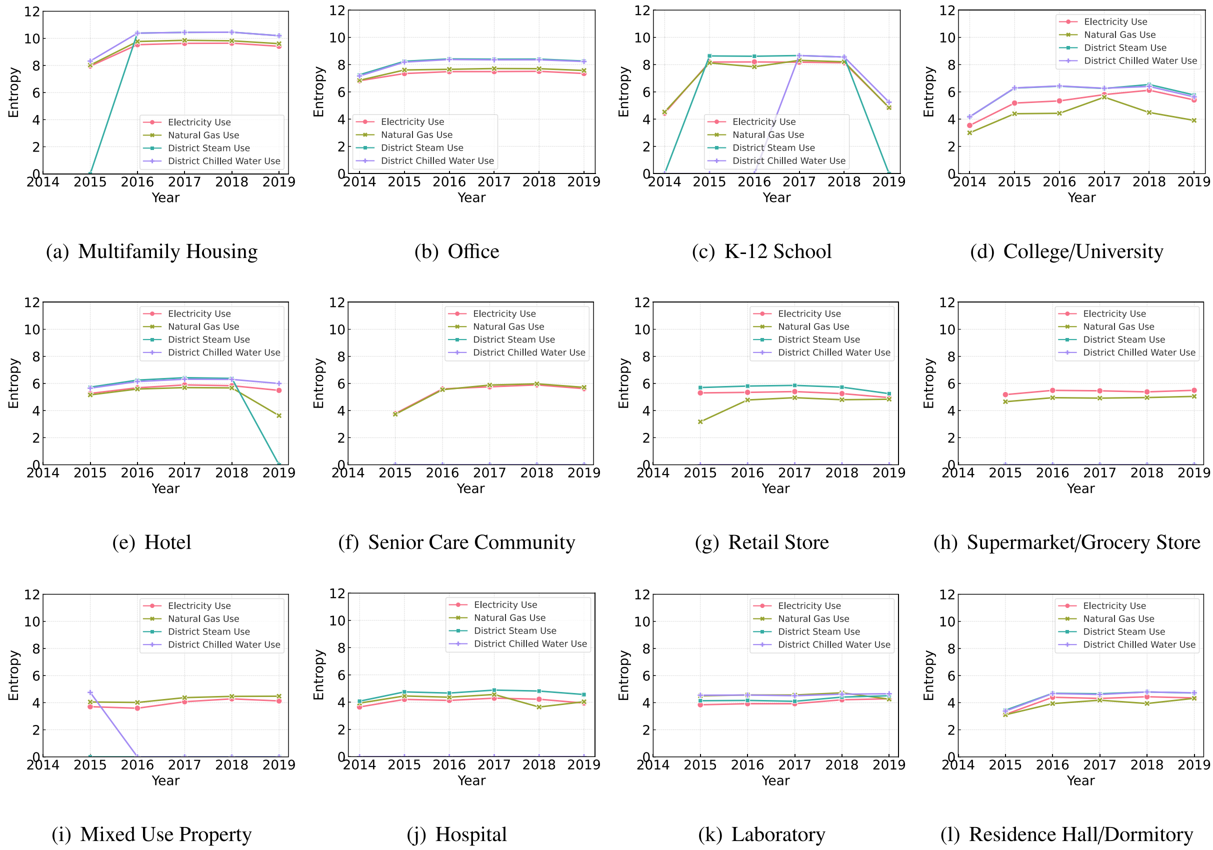
The figure shows that different property types have different entropy values and trends for different energy sources. For example, 'Multifamily Housing' and 'Office' have relatively stable and low entropy values for all energy sources, indicating a homogeneity and consistency in energy consumption patterns, perhaps owing to standardized building functionalities and energy management practices. On the other hand, 'Laboratories' and 'Retail Stores' have relatively variable and high entropy values for some energy sources, such as Electricity and District Steam, suggesting not only temporal shifts but also potential volatility in energy-use practices, possibly influenced by technological upgrades or policy changes. The figure also shows that some property types have missing entropy values for some years and energy sources, indicating data gaps or errors. For example, 'Strip Mall' has no entropy values for District Steam and District Chilled Water for any year, while 'Other - Specialty Hospital' has no entropy values for any energy source for 2014 and 2015. These data gaps or errors underscore the imperative for more exhaustive and reliable energy auditing and reporting mechanisms.

In summary, these nuanced insights offer a robust analytical framework for policymakers and stakeholders, allowing for the design of highly targeted energy conservation measures that can contribute substantially to urban sustainability. By using entropy as a metric to capture the heterogeneity and complexity of energy consumption patterns across different property types, we can identify the key factors and drivers that influence energy consumption behaviors, as well as the potential challenges and opportunities for improving energy efficiency and diversity.

6.6. Entropy analysis across building age

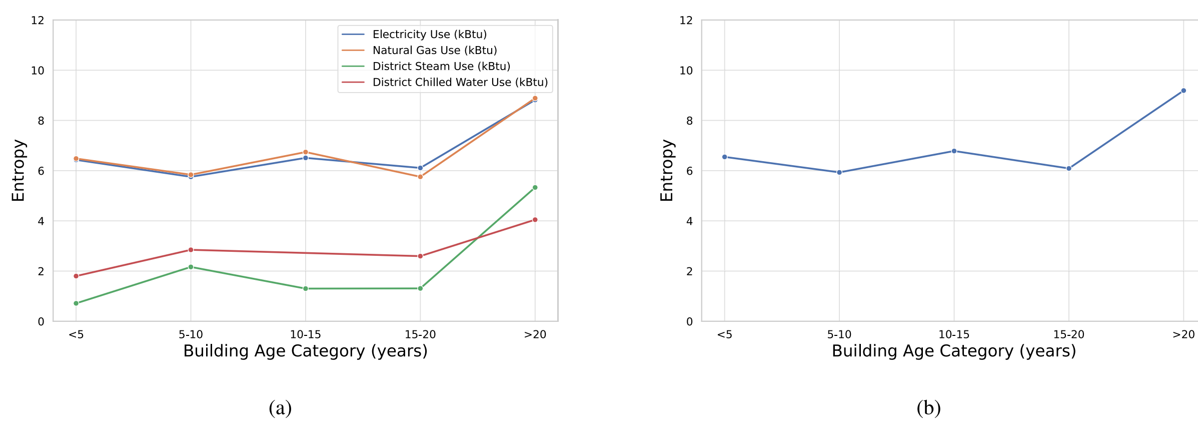
In this subsection, we investigate how building age influences the entropy of energy consumption patterns across different types of energy sources. We use four energy sources: electricity, natural gas, district steam, and district chilled water. We also aggregate the entropy values for all energy sources to obtain a total entropy value for each building age category. We divide the buildings into six age categories: less than 5 years, 5–10 years, 10–15 years, 15–20 years, 20–25 years, and greater than 25 years. We present our results in Figs. 11(a) and 11(b).

Fig. 11(a) shows the entropy values for each individual energy source across different building age categories. The figure reveals that



(a) Multifamily Housing
(b) Office
(c) K-12 School
(d) College/University
(e) Hotel
(f) Senior Care Community
(g) Retail Store
(h) Supermarket/Grocery Store
(i) Mixed Use Property
(j) Hospital
(k) Laboratory
(l) Residence Hall/Dormitory

Fig. 10. Entropy values of the top 13 property types for different energy sources from 2014 to 2019.



(a)
(b)

Fig. 11. Entropy values across different building age categories. (a) Entropy for individual energy sources. (b) Entropy for total energy use.

electricity and district chilled water have higher entropy values in older buildings (greater than 20 years), while natural gas and district steam have lower entropy values in older buildings. This suggests that older buildings have more heterogeneous and complex energy consumption patterns for electricity and district chilled water, while they have more homogeneous and simple energy consumption patterns for natural gas and district steam. This may be due to various factors, such as the type and function of buildings, the occupancy and activity levels of buildings, and the energy efficiency upgrades or retrofitting activities that have been implemented over the years.

Fig. 11(b) shows the total entropy values for all energy sources combined across different building age categories. The figure depicts a pattern where the total entropy values are higher for the buildings in the 5–10 year and greater than 20-year categories, while they are lower for the buildings in the other categories. This implies that these two age categories have a wider range of energy consumption behaviors, while the other categories have a narrower range of energy consumption behaviors. This indicates that building age significantly affects the predictability and uniformity of energy consumption patterns. This may be explained by the fact that buildings in the 5–10 year and greater than 20-year categories may have more diverse and complex energy mixes, while buildings in the other categories may have more similar and simple energy mixes.

Together, these observations emphasize the role of building age as a crucial factor in understanding energy consumption heterogeneity, and they offer valuable insights for the formulation of targeted energy conservation policies. Based on our findings, we suggest some possible implications and recommendations for urban energy planning and management. First, we suggest that older buildings (greater than 20 years) should be prioritized for energy efficiency upgrades or retrofitting activities, as they have higher entropy values for electricity and district chilled water, which are the dominant energy sources in Chicago. These upgrades or activities may help reduce their energy consumption and emissions, as well as improve their energy performance and comfort. Second, we suggest that newer buildings (less than 10 years) should be monitored and evaluated for their energy consumption patterns, as they have higher total entropy values for all energy sources. These buildings may have more potential for energy savings and optimization, as they may have more advanced and innovative energy technologies that can enable more flexible and responsive energy management. Third, we suggest that building age should be considered as an important variable in urban energy modeling and simulation, as it affects the entropy of energy consumption patterns. Building age can provide useful information on the type and function of buildings, the occupancy and activity levels of buildings, and the energy efficiency upgrades or retrofitting activities of buildings. These information can help improve the accuracy and reliability of urban energy models and simulations.

6.7. Entropy analysis across building area categories

In this subsection, we examine how building area affects the entropy of energy consumption patterns across different types of energy sources. We use four energy sources: electricity, natural gas, district steam, and district chilled water. We also aggregate the entropy values for all energy sources to obtain a total entropy value for each building area category. We divide the buildings into five area categories: less than 38k sq ft, 38k-1M sq ft, 1M-2M sq ft, 2M-3M sq ft, and greater than 3M sq ft. We present our results in Figs. 12(a) and 12(b).

Fig. 12(a) shows the entropy values for each individual energy source across different building area categories. The figure reveals that electricity and natural gas have higher entropy values in smaller buildings (38k-1M sq ft), while they have lower entropy values in larger buildings (greater than 3M sq ft). This suggests that smaller buildings have more heterogeneous and complex energy consumption patterns for electricity and natural gas, while larger buildings have more homogeneous and simple energy consumption patterns for these energy sources. This may be due to various factors, such as the type and function of buildings, the occupancy and activity levels of buildings, and the energy efficiency upgrades or retrofitting activities that have been implemented over the years. For example, smaller buildings may have more diverse types and functions, such as residential, commercial, industrial, or mixed-use buildings, which may require different amounts and types of electricity and natural gas for heating, cooling, lighting, or other purposes. Smaller buildings may also have more variable occupancy and activity levels, depending on the time of day or season, which may affect their electricity and natural gas demand. Moreover, smaller buildings may have undergone various energy efficiency upgrades or retrofitting activities over the years, such as installing insulation, replacing windows, upgrading HVAC systems, or adding renewable energy sources. These upgrades or activities may have reduced their electricity and natural gas consumption or changed their consumption patterns. In contrast, larger buildings may have more uniform types and functions, such as office buildings or hotels, which may require similar amounts and types of electricity and natural gas for their operations. Larger buildings may also have more stable occupancy and activity levels, which may result in more consistent electricity and natural gas demand. Furthermore, larger buildings may have newer or more advanced energy technologies, such as smart meters, sensors, or controllers, which may enable more efficient and optimized energy management.

Fig. 12(b) shows the total entropy values for all energy sources combined across different building area categories. The figure depicts a pattern where the total entropy values are higher for smaller buildings (38k-1M sq ft), while they are lower for larger buildings (greater than 3M sq ft). This suggests that smaller buildings display a more complex mix of energy consumption patterns, while larger structures have a simpler mix of energy consumption patterns.

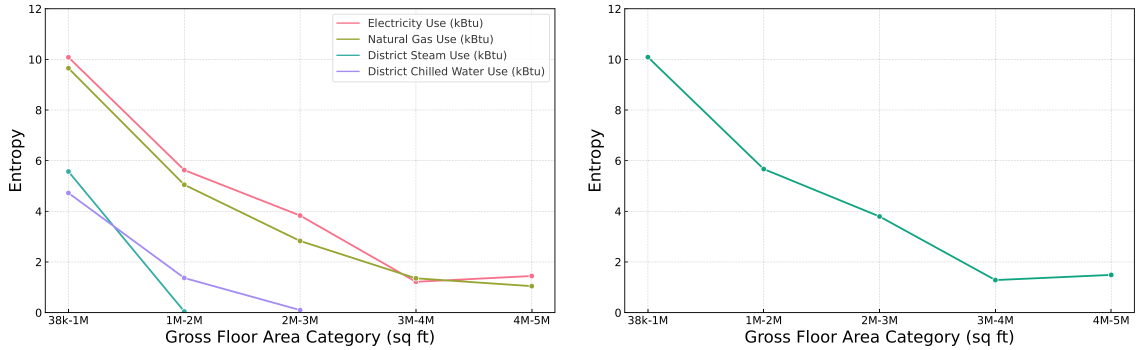
These findings could have significant implications for energy management strategies. For instance, smaller buildings, particularly those in the 38k-1M sq ft range, may benefit from more targeted interventions due to their diverse energy consumption behaviors. Larger buildings, on the other hand, may have more standardized energy uses, allowing for more general approaches in energy conservation efforts. The insights gathered from both figures emphasize the importance of tailoring energy policies and interventions according to building size, given the different complexities in energy consumption patterns observed.

7. Discussion

This study presents a pioneering approach in applying entropy theory to urban energy dynamics analysis (UEDA), with a focus on the city of Chicago. This approach, which diverges significantly from conventional methods, introduces a novel lens through which urban energy consumption patterns can be viewed and analyzed. The rich descriptive analysis of Chicago's urban energy system provides not only a detailed exploration of its spatial and temporal dynamics, but also a basis for broader theoretical and practical implications in the field of urban sustainability.

The study aligns with existing research that emphasizes the heterogeneous and complex nature of urban energy systems (Hong et al., 2020). The use of entropy-based methods for UEDA unveils intricate patterns in energy consumption that vary across different spatial scales and building characteristics (Huang & Chen, 2005). This perspective is crucial for understanding the multifaceted nature of urban energy use and challenges the traditional methodologies that have often overlooked the significance of spatial diversity. By embedding entropy theory into the analysis of urban energy systems, this research contributes to a more nuanced understanding of the distribution and variability of energy usage across urban landscapes. The theoretical implications of these findings are substantial. They underline the necessity of considering spatial heterogeneity in urban energy planning, echoing the interdisciplinary essence of urban sustainability (Ahmad, 2019). This research intersects different disciplines, integrating physical, spatial, and socio-economic dimensions into the analysis of urban energy systems. It thereby contributes to a more holistic understanding of urban sustainability, highlighting the interconnectedness of energy systems with broader urban dynamics.

For practitioners in urban planning and energy management, the findings of this study are particularly relevant. The entropy-based framework facilitates the identification of optimal scales for energy interventions, thereby aiding in the design of effective energy policies and programs (Netto et al., 2020; Purvis et al., 2019). These programs, tailored to the specific characteristics of different urban areas, can lead to more efficient and sustainable energy use. For instance, regions exhibiting higher entropy in energy use might benefit from more localized and customized energy-saving measures. Conversely, areas with lower entropy might be well-suited for broad-scale, standardized energy management strategies (Li, 2022). In the realm of policy development, the insights from this analysis hold significant potential. They can inform the development of targeted policies that focus on energy efficiency and conservation, optimizing energy use across various urban regions (Dall'o', 2020). Understanding the spatial dynamics of energy demand is instrumental for policymakers, enabling them to implement region-specific strategies that are both effective and sustainable (Rondinel-Oviedo & Keena, 2023). This aspect of the research is crucial for urban development that aligns with goals of reducing carbon emissions and enhancing energy security. Furthermore, this study bridges the gap between theoretical concepts in urban planning and practical considerations in energy management. The interdisciplinary approach adopted in this research is vital for urban sustainability, contributing to enhancing the resilience of urban areas.



(a) (b) Entropy by Gross Floor Area for All Energy Sources Combined

Fig. 12. Entropy values across building area categories (a) Entropy for individual energy sources. (b) Entropy for total energy use.

By providing tools to adapt to changing energy demands and environmental challenges, the study equips city planners and decision-makers to address the complexities of urban energy systems effectively.

However, an intriguing aspect to consider is the potential correlation between the urban heat island (UHI) effect and the identified optimal scales of aggregation. The UHI effect, characterized by increased urban temperatures compared to surrounding rural areas, could be intertwined with high entropy processes like extensive energy use and heat generation. It is plausible that areas with higher entropy, indicative of greater energy use and diversity, might also be areas where the UHI effect is more pronounced. Santamouris (2015) provides a comprehensive analysis of the UHI magnitude and characteristics in one hundred Asian and Australian cities, underscoring the widespread impact of UHI on urban climates. This correlation suggests a complex interplay between urban form, energy consumption patterns, and microclimate effects, underscoring the need for multi-dimensional analysis in urban energy planning (Gürsan et al., 2024; Santamouris, 2015). Future research might focus on exploring this relationship, enhancing our entropy-based method to factor in the implications of UHI in determining optimal scales for energy demand aggregation. Such an approach would provide a more comprehensive understanding of urban energy dynamics, accounting for both consumption patterns and environmental impacts.

In the broader scope of urban energy management, our entropy-based approach has significant implications for the integration of various energy systems, including electricity, heating, and cooling. Notably, the method can inform the strategic implementation of district heating and cooling systems, essential for enhancing urban energy efficiency. By identifying regions with high entropy in energy use, our method aids in pinpointing areas where integrated systems, such as the innovative fifth-generation district heating and cooling systems discussed by Dang et al. (2024), could be most beneficial. This approach is particularly relevant for districts exhibiting complex and varied energy usage patterns, where district energy systems can capitalize on synergies across multiple buildings. Moreover, integrating renewable energy solutions, as highlighted by Wilberforce et al. (2024), plays a crucial role in urban energy planning. Thus, our findings contribute to the strategic planning and optimization of integrated energy systems, aligning with the goals of sustainable urban energy management.

Nevertheless, the research presented is not without its limitations. The context-specific analysis, focused on Chicago's urban energy system, provides a valuable case study for applying the entropy-based approach to UEDA. However, urban areas, each with its unique climatic, socio-economic, and infrastructural factors, exhibit distinct energy dynamics. Therefore, further research is needed to explore the applicability of these findings to other urban settings, both within the United States and globally. The integration of IoT technologies, as demonstrated by Raaj et al. (2024), can play a crucial role in the strategic implementation of renewable energy sources within urban energy systems, offering a pathway towards smarter and more efficient energy management. Furthermore, there is an opportunity for future research to extend the entropy-based approach to other urban systems. This approach, integrated with analyses of other critical urban infrastructures such as transportation and water management, could provide a more comprehensive view of urban sustainability. The collaborative efforts in reducing air pollution through digital technologies and clean energy initiatives, as discussed by Shen and Zhang (2024), exemplify the potential of integrating renewable energy sources to enhance urban energy systems' sustainability. Such integrative research could uncover the interdependencies within urban systems, offering insights for more cohesive urban planning and management strategies. Moreover, it is important to acknowledge that the entropy-based approach, while effective in revealing macro-level energy consumption patterns and disparities, does not directly measure specific factors of energy inefficiency within buildings. These factors include heat loss due to poor insulation, inefficient HVAC systems, or energy wastage stemming from inadequate building design. Since the method operates on an aggregated scale, it lacks the granularity required to isolate and evaluate these specific inefficiencies. Lawal et al. (2024) highlight the critical role of energy audits in identifying these inefficiencies within buildings, suggesting that a meticulous assessment of a building's energy consumption, systems, and processes is essential for sustainable energy management. To overcome this limitation, there is a need for integrating detailed building performance data, advanced analytical techniques, and collaborative efforts to enhance the method's capability in identifying and addressing specific energy inefficiency issues. Additionally, a crucial aspect of urban energy dynamics is the integration and management of renewable energy sources, such as solar and wind, characterized by inherent variability. Our proposed entropy-based approach could be further developed to encompass this aspect by incorporating data on the variability of these renewable sources. This enhancement would enable the effective management of renewable energy variability, essential in developing comprehensive urban energy models that encapsulate both demand and supply dynamics. Xiong et al. (2024) emphasize the importance of considering the uncertainty and variability of renewable energy sources in urban energy planning, advocating for statistical analyses that account for market price variations and renewable output power variability. Such variability integration is key to advancing our understanding of sustainable urban energy systems and supports the transition towards more resilient and renewable energy-based urban environments.

In summary, this research makes a significant contribution to the field of urban energy and sustainability. By introducing an entropy-based approach to UEDA, it offers fresh insights into urban energy dynamics, with substantial theoretical and practical implications. It provides a foundation for future research that can build upon its findings to further enhance our understanding of urban energy systems and contribute to the sustainable development of urban areas.

8. Conclusions and future work

The primary motivation of this study was to develop a novel entropy-based approach for UEDA that addresses the limitations of existing methods and offers a more comprehensive and robust means of quantifying urban energy demand aggregation across various spatial scales. In this paper, we presented our approach, which leverages entropy theory to measure the information loss or distortion resulting from aggregating individual energy demands of buildings into a collective demand at a particular spatial scale. Furthermore, our approach can identify the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation. Our approach can also account for building characteristics, such as property types, building ages, and building areas, by incorporating them into the entropy calculation. Additionally, our approach provides a systematic means of evaluating the quality and reliability of UEDA results using entropy-based metrics.

We demonstrated our approach using a case study of Chicago, where we applied our method to estimate and analyze the energy demand of buildings at 10 spatial scales, ranging from 1.5 km to 15 km. We used a dataset of building-level energy consumption and spatial data on building characteristics, ZIP codes, and geographic coordinates. We calculated the global entropy, local entropy, Kullback–Leibler divergence, and Tsallis' generalized entropy for each spatial scale and type of energy source. We identified the optimal spatial scale for UEDA that minimizes information loss or distortion caused by aggregation. To facilitate the applications of the proposed model, we implemented a web-based dashboard for result visualization and user interactions. We also evaluated the quality and reliability of UEDA results using entropy-based metrics, such as information gain ratio and normalized mutual information. Our results showed that different spatial scales reveal different patterns and relationships of energy demand, and that choosing an appropriate scale can enhance the accuracy and efficiency of UEDA. Our results also showed that there exists an optimal spatial scale for UEDA that strikes a balance between information preservation and reduction, and that this scale may vary depending on the type of energy source and the urban context. Our results also showed that urban energy dynamics are influenced by multiple factors at different scales and dimensions, and that entropy theory can provide quantitative measures of variability and correlation of urban energy demand at different scales and dimensions.

Our findings have significant implications and potential impact on the field of UEDA and urban energy planning and management. Our findings contribute to the field by developing a novel perspective on urban energy dynamics, revealing the complexity and diversity of urban systems, such as population, land use, transportation, and energy demand. Our findings also provide a context-specific approach for enhancing building energy efficiency and performance, accounting for building characteristics, such as property types, building ages, and building areas. The entropy-based UEDA approach proposed in this study opens avenues for enhancing urban energy system integration, particularly through the strategic planning of district heating and cooling systems. Our method's ability to identify optimal scales for energy demand aggregation can significantly contribute to developing more efficient and synergistic urban energy systems. This approach underscores the potential of our method in aiding the design and optimization of integrated energy systems, a key aspect in the pursuit of sustainable and efficient urban energy management. Our findings also provide a system-level approach for optimizing urban energy supply systems, reducing energy losses and emissions, and improving urban resilience and sustainability. However, our method's limitation in addressing specific building inefficiencies and the variability of renewable energy sources is a crucial area for future development. Enhancing our methodology to include these aspects would allow for a more holistic understanding and management of urban energy systems, particularly in the context of increasing renewable energy integration.

Our study also suggests several possibilities for further research that can build on our current work. For instance, we could apply our approach to other urban areas with different characteristics and contexts, such as developing countries or megacities, and examine how well it generalizes and applies to them. We could also explore the effects of using different types of entropy or entropic indices for UEDA, such as Shannon's entropy or Renyi's entropy, and evaluate how they influence the sensitivity and specificity of our approach. Moreover, we could enrich the entropy calculation by incorporating other types of data or factors, such as socio-economic data or behavioral data, and investigate how they enhance the understanding of urban energy dynamics. Additionally, developing new entropy-based metrics or indicators for evaluating UEDA results is another promising direction. Extending our methodology to encompass the analysis of renewable energy sources, particularly their variability, is a critical next step. This involves incorporating renewable energy data and developing strategies for managing their variability in urban energy systems.

CRediT authorship contribution statement

Renfang Wang: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Xiufeng Liu:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Xinyu Zhao:** Data curation. **Xu Cheng:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Hong Qiu:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix. Optimal scale identification

Algorithm 1 provides a detailed methodology for determining the optimal scale. This algorithm accepts the global entropy vector $\mathcal{G}$ and the local entropy vector $\mathcal{L}$ corresponding to each spatial scale as inputs. It then identifies and returns the optimal scale S that meets both criteria. In cases where no scale fully satisfies these criteria, the algorithm selects and returns the scale characterized by either the minimum Kullback–Leibler divergence or the maximum Tsallis' generalized entropy.

Algorithm 1 Optimal Scale Identification

function OptimalScaleIdentification($\mathcal{G}, \mathcal{L}$) ▷ *The function takes the global and local entropy vectors as input and returns the optimal scale*
  $\mathcal{D} \leftarrow \{0 \mid g \in \mathcal{G}\}$
  for all $g_i \in \mathcal{G}$ **do**
    for all $g_j \in \mathcal{G}$ **do**
      $d_i \leftarrow d_i + g_j \cdot \log_2(g_j/g_i)$ ▷ *Calculate the Kullback-Leibler divergence for scale using Eq. (5)*
    end for
  end for
  $S_g \leftarrow \arg\min_i d_i$
  $\mathcal{T} \leftarrow \{0 \mid l \in \mathcal{L}\}$
  for all $l_i \in \mathcal{L}$ **do**
    for all $l_j \in \mathcal{L}$ **do**
      $t_i \leftarrow t_i + l_j^2/l_i$ ▷ *Calculate the Tsallis' generalized entropy for scale i using Eq. (6)*
    end for
  end for
  $S_t^* \leftarrow \arg\max_i t_i$
  if $S_t^* = S_g$ **then**
    $S \leftarrow S_t^*$ ▷ *Set the optimal scale as the agreed scale*
  else if $t_{S_t^*} > t_{S_g}$ **then**
    $S \leftarrow S_t^*$ ▷ *Set the optimal scale as the one that maximizes the local criterion*
  else
    $S \leftarrow S_g$ ▷ *Set the optimal scale as the one that minimizes the global criterion*
  end if
  return S
end function

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