# Investigating the Interplay between urban heat island, urban pollution island, and energy demand: a systematic review of modeling approaches and key determinants

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## Abstract

Rapid urbanization, escalating built-up density, and alterations in urban surface characteristics have exacerbated phenomena such as the urban heat island (UHI) and the urban pollution island (UPI). Beyond their documented impacts on air quality, thermal comfort, and public health, these phenomena can substantially influence urban energy demand through elevated cooling loads and modified electricity consumption patterns. Despite the growing body of research, a comprehensive understanding of the interplay among UHI, UPI, and energy demand remains conspicuously absent. To address this gap, the present study undertakes a systematic review of this nexus, with the objective of identifying prevailing modeling methodologies, influential components, and dominant conceptual relationships. Relevant publications were retrieved from Scopus, ScienceDirect, and Google Scholar, and following a rigorous screening process, the content of the selected studies was analyzed using MAXQDA software. A total of 4,060 coded segments were extracted and organized into ten principal codes. Subsequently, frequency analysis, author–code affiliation matrices, and co-occurrence analysis were employed to delineate the conceptual architecture of the extant literature. Findings indicate that scholarly attention has predominantly been directed toward modeling and forecasting, temperature-driven energy demand in relation to UHI, and the physical–thermal properties of urban surfaces. Conversely, indicators pertaining to UPI, urban boundary-layer dynamics, and atmospheric physicochemical processes have received comparatively limited coverage. Co-occurrence results further reveal that energy demand serves as a conceptual mediator between urban heating and air pollution. Accordingly, the development of integrated, multi-scalar frameworks capable of concurrently addressing urban climate, air quality, and energy systems emerges as an imperative direction for future research.

**Keywords:** Air Quality; Energy Demand; Systematic Review; Modeling; Urban Heat Island; Urban Pollution Island;

## 1.Introduction

Rapid urbanization, increasing urban density, the expansion of impervious surfaces, and the reduction of vegetation cover have transformed cities into major hotspots of microclimatic and environmental change. One of the most prominent manifestations of these changes is the Urban Heat Island (UHI) effect, whereby urban areas particularly densely built-up areas characterized by materials with high thermal capacity exhibit higher temperatures than their surrounding environments. This phenomenon has several consequences, including increased heat stress, reduced thermal comfort, heightened vulnerability of public health, and increased energy consumption, particularly for building cooling (Cheval et al., 2024). The physical and morphological characteristics of cities, including building density, urban canyons, material properties, and restrictions on airflow, can simultaneously influence the intensity of urban heating and natural ventilation, thereby affecting the spatial distribution of air pollutants (Ahmed et al., 2025). In this study, the Urban Pollution Island (UPI) refers to the relative concentration of air pollutants in urban environments compared with surrounding areas. It is shaped by emission sources, urban morphology, meteorological conditions, boundary-layer stability, and atmospheric chemical and physical processes. Therefore, UPI is not merely an indicator of air quality; rather, it constitutes part of a complex urban system that can interact with UHI and energy demand. A review of the existing literature indicates that research on UHI has primarily developed along several major lines: modeling and predicting the intensity and spatiotemporal patterns of UHI, investigating the impacts of urban warming and heatwaves on public health and energy consumption, and evaluating mitigation and adaptation strategies for urban heat (Ahmed et al., 2025; Ni et al., 2025; Ventura et al., 2024). Despite considerable advances, several major gaps remain. The predominant emphasis on the thermal dimension of cities has resulted in relatively limited incorporation of the Urban Pollution Island and UPI-related indicators into analyses; many studies have been conducted in a fragmented and non-integrated manner; and the role of energy demand as an intermediary link between urban warming and urban pollution has received comparatively limited conceptual attention. Although numerous studies have conducted systematic reviews or bibliometric analyses of research on the urban heat island, their primary focus has been on scientific trends, knowledge networks, and the factors influencing UHI intensity. In contrast, the present study moves beyond a unidimensional perspective on the urban heat island by examining the interactions among UHI, UPI, and energy demand, thereby seeking to elucidate the existing gap in the simultaneous integration of thermal processes, air pollution, and urban energy dynamics. Using a systematic literature review and qualitative content analysis, the present study extracts the conceptual structure of the existing literature concerning the interactions among UHI, UPI, and energy demand. It further identifies the key components and conceptual relationships while clarifying the research gaps within this field. The main research question is: How does the existing scientific literature conceptualize and model the interactions among UHI, UPI, and energy demand, and what key components and research gaps can be identified within this framework?

## 2. Literature Review

The growth of urbanization and the increasing complexity of urban energy consumption patterns have highlighted the importance of investigating the interactions among the Urban Heat Island (UHI), Urban Pollution Island (UPI), and energy demand. A review of the literature indicates that previous studies have primarily focused on specific dimensions of this relationship, with relatively limited attention given to the simultaneous analysis of these three components (Attarhay Tehrani et al., 2025). Using data from 27,681 buildings in Phoenix, they demonstrated that UHI can increase building cooling energy consumption and that data-driven models, particularly deep neural networks, can predict this effect with high accuracy; however, the interaction with urban pollution was not examined. Delgado-Enales et al. (2025) employed a U-Net architecture to predict street-level surface temperature in Bilbao and demonstrated that deep learning can estimate urban temperatures with high accuracy. However, temperature has not yet been incorporated as a direct variable into analyses of energy consumption or pollution. Zhang et al. (2025) used LSTM and GRU models to predict district-level cooling demand and demonstrated that data partitioning strategies play a decisive role in model accuracy; nevertheless, the effects of UHI or UPI were not simultaneously incorporated into the model. Rezazadeh et al. (2025) developed an integrated energy–emissions–health model that evaluates economic, emission, and health dimensions and highlights the significance of pollution; however, urban warming and UHI intensity were not directly considered in the analysis. Solís-Villarreal et al. (2024) employed Isolation Forest and SHAP to identify energy consumption anomalies in modern cities, demonstrating the potential of artificial intelligence tools for analyzing consumption behavior, although the direct relationship with UHI and UPI was not investigated in this study. Tiwari et al. (2026) compared Prophet, LSTM, GRU, and TCN models across 15 U.S. cities and demonstrated that the performance of energy forecasting models depends on spatial characteristics and the forecasting horizon, indicating that no single model is suitable for all cities; however, the direct effects of urban temperature or air pollution were not incorporated into the analysis.Overall, the review of these studies indicates that the existing literature has developed along three main research pathways: estimation of urban temperature and UHI, prediction of energy demand, and energy–emissions–health optimization or anomaly detection. However, no study to date has simultaneously analyzed UHI and UPI in direct relation to energy demand. By focusing on the integration of these three components, the present study aims to address this gap in the literature and provide a scientific foundation for urban energy policymaking and planning.The present study employs a systematic literature review and qualitative content analysis to extract the conceptual structure of the existing literature concerning the interactions among UHI, UPI, and energy demand. It further identifies the key components and conceptual relationships while clarifying the research gaps within this field. The main research question is: How does the existing scientific literature conceptualize and model the interactions among UHI, UPI, and energy demand, and what components and research gaps can be identified within this framework?

## 3. Theoretical foundations of the research

### *3-1. Urban Heat Island (UHI)*

*Definition and mechanisms of heat island formation*

To assess the intensity of this phenomenon, some studies have adopted an approach similar to that used for Urban Heat Island Intensity and have considered the difference in pollutant concentrations between urban monitoring stations and surrounding reference areas as an indicator for comparing the intensity of pollutant accumulation. However, unlike the Urban Heat Island Intensity (UHII) index, there is still no globally standardized and widely accepted computational method for determining Urban Pollution Island (UPI) intensity. Different studies have therefore employed different approaches depending on the type of pollutant, the spatial scale of the study, and the type of data used (Ulpiani, 2021). Conceptually, the formation of UPI can be considered the result of the interaction of four major factors. First, urban emission sources, including transportation, industry, and energy consumption; second, the morphological and physical characteristics of the city, which influence ventilation and pollutant transport; third, meteorological conditions and the characteristics of the urban boundary layer, which control the mixing and dispersion of pollutants; and fourth, the reciprocal relationship among air pollution, urban heating, and energy consumption, which generates complex feedback mechanisms within the urban system (Fernando, 2010; Santamouris, 2015).

*Effects of Atmospheric Characteristics on Air Quality*

Urban air quality is highly dependent on the atmosphere's capacity to transport, mix, and disperse pollutants. In densely built urban environments, stable atmospheric conditions, reduced wind speeds, a low mixing-layer height, and the occurrence of temperature inversions can restrict the vertical transport of pollutants and increase their concentrations near the ground surface (Fernando, 2010). From a functional perspective, many of the factors influencing the formation of the Urban Heat Island and Urban Pollution Island are shared. For example, tall buildings, high building density, and impervious surfaces, which reduce heat dissipation and intensify UHI, can also restrict airflow and reduce natural ventilation, thereby creating favorable conditions for pollutant accumulation. Therefore, the relationship between UHI and UPI can be understood as the result of the combined influence of urban structure, human activities, and atmospheric processes (Cheval et al., 2024). Furthermore, the interaction between these two phenomena is bidirectional. An increase in urban temperature can raise cooling energy demand, thereby increasing fuel consumption and pollutant emissions; conversely, certain atmospheric pollutants can influence the thermal conditions of cities by modifying radiative processes and atmospheric properties (Santamouris, 2015). Therefore, the simultaneous examination of atmospheric characteristics, urban structure, and emission patterns is essential for developing a comprehensive understanding of the mechanisms underlying UPI formation and its relationship with UHI.

### *3-3. Urban Energy Demand*

*Definition and Components of Building Energy Demand*

Urban energy demand is strongly influenced by the heating and cooling requirements of buildings. In cities characterized by strong UHI effects, outdoor ambient temperatures are higher, and this temperature difference between the outdoor and indoor environments substantially increases cooling requirements (Ahmed et al., 2025). Factors such as building form, envelope permeability, and the overall geometry of the neighborhood, which regulates exposure to wind, are key determinants of cooling loads.

*Energy System Efficiency in the Urban Fabric*

Research evidence indicates that nature-based solutions, such as increasing urban vegetation cover, can reduce cooling energy demand by up to 25% (Ahmed et al., 2025). The efficiency of energy systems does not depend solely on the performance of air-conditioning equipment; rather, it is strongly influenced by the microclimatic conditions of the neighborhood.

Predictive models capable of accurately incorporating the effects of UHI on building energy consumption are critical for optimizing urban energy networks in the future (Ni et al., 2025).

***3-4. Conceptual and Functional Relationship***

The interaction between UHI and UPI is rooted in urban morphological and atmospheric processes. Modern predictive models that employ artificial intelligence, such as deep learning and hybrid models, are transforming the approach from conventional numerical models toward real-time prediction (Ahmed et al., 2025). Urban management in addressing UHI and UPI requires a “smart” approach, whereby physical interventions, such as the design of ventilation corridors, and energy demand reduction strategies are managed in an integrated manner (Lai et al., n.d.). The present study employs a systematic literature review and qualitative content analysis to extract the conceptual structure of the existing literature concerning the interactions among UHI, UPI, and energy demand. It further identifies the key components and conceptual relationships while clarifying the research gaps within this field. The main research question is: How does the existing scientific literature conceptualize and model the interactions among UHI, UPI, and energy demand, and what components and research gaps can be identified within this framework?

## 4. Research Methodology

The present study was conducted with the aim of systematically identifying, classifying, and analyzing studies related to the interactions among the Urban Heat Island (UHI), Urban Pollution Island (UPI), and energy demand. Given the interdisciplinary nature of the subject, a systematic literature review combined with qualitative content analysis was employed. The systematic review was used to identify, screen, and select relevant and reliable studies, while qualitative content analysis was applied to extract key components, methodological approaches, patterns of interaction, conceptual relationships, and predictive models. The qualitative analysis process was conducted using MAXQDA Analytics Pro 2018. The research sources were collected through systematic searches of the scientific databases ScienceDirect, Scopus, and Google Scholar. The search was conducted using keywords related to the main research themes, including Urban Heat Island, Urban Pollution Island, Air Pollution, Urban Air Quality, Energy Demand, Building Energy Consumption, Cooling Energy, Electricity Demand, Urban Climate, Predictive Model, and Machine Learning. The Boolean operators AND and OR were used to combine the keywords. The publication period considered in the review was defined as 2020 to 2026, and only English-language sources were included in the screening process. Specific inclusion and exclusion criteria were established for study selection. Studies were included in the analysis if they were directly or indirectly related to one or more of the following themes: Urban Heat Island, Urban Pollution Island, air pollution, urban air quality, energy demand, building energy consumption, cooling loads, or predictive models. In addition, studies were required to include a clearly defined scientific methodology, empirical data, modeling, statistical analysis, or an evaluable theoretical framework, as well as an accessible full text. In contrast, duplicate sources, studies lacking thematic relevance, sources without accessible full texts, non-scientific publications, and studies without a clear connection to the main research themes were excluded from the analysis. The study screening process was conducted based on the PRISMA framework. In the initial stage, 186 sources were identified from the scientific databases. After removing duplicate records, the number of sources was reduced to 174. In the next stage, the titles and abstracts of the sources were screened, and after excluding irrelevant studies, 96 articles remained for full-text assessment. During the full-text assessment stage, the articles were evaluated in terms of their relevance to the themes of the Urban Heat Island, Urban Pollution Island, energy demand, analytical methods, and predictive models. Ultimately, 55 articles met the inclusion criteria and were selected as the final analytical corpus. The process of identification, screening, and selection of the studies is presented in the PRISMA flow diagram in Figure 1.

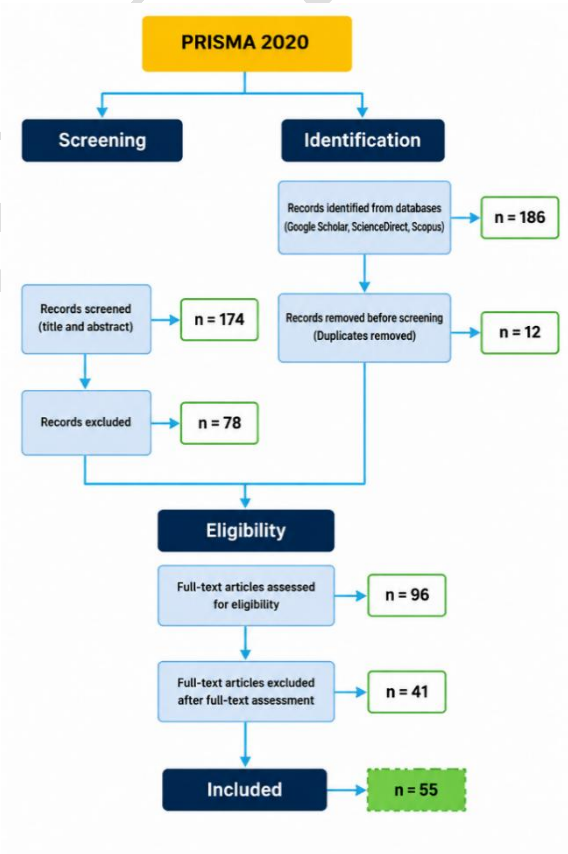


Figure 1: PRISMA2020 Research Chart

Following the selection of the final studies, the full texts of the 55 articles were imported into MAXQDA software. The unit of analysis in this study consisted of sentences, clauses, or paragraphs that referred to one of the main research themes. The coding process was conducted in three stages. In the first stage, initial coding was performed to extract concepts related to physical, climatic, pollutant, energy, and modeling factors. In the second stage, similar and overlapping codes were reviewed and organized into higher-level conceptual categories. In the third stage, the final codes were classified into the main themes of the study. Based on the analysis, the main themes of the study included urban boundary-layer dynamics and atmospheric mixing and transport processes; modeling and forecasting approaches; statistical and correlation analysis methods; interactions and reciprocal feedback between the urban heat island and urban pollution island; atmospheric chemical and physical processes; pollutant concentration and composition indicators; urban energy-demand components; meteorological parameters and atmospheric conditions; physical and thermal characteristics of urban surfaces; and indicators of the intensity and spatiotemporal patterns of the urban heat island. Various outputs from MAXQDA were used to extract and analyze the findings. Code Frequencies was used to examine code frequencies, Code Coverage to assess the extent of content coverage represented by each code, Code Matrix Browser to investigate the distribution of codes across documents, Code Relations Browser to analyze relationships and co-occurrences among codes, and Summary Grid and Summary Tables to synthesize the content of the articles. The use of these outputs enabled the identification of dominant themes, conceptual relationships, recurring patterns, and research gaps. To enhance the validity of the analysis, the coding process was reviewed at several stages. Similar codes were merged, while irrelevant codes were removed. In addition, the final coding structure was compared with the research objectives, the main research question, and the theoretical literature to ensure the conceptual and methodological coherence of the analysis. The use of MAXQDA enabled the systematic management of data, retrieval of coded segments, examination of code distributions, and analysis of relationships among concepts. Finally, the findings were analyzed in terms of the main themes, relationships among the components, and the conceptual framework of interactions among the urban heat island, urban pollution island, and energy demand. The overall research methodology is presented in Figure 2.

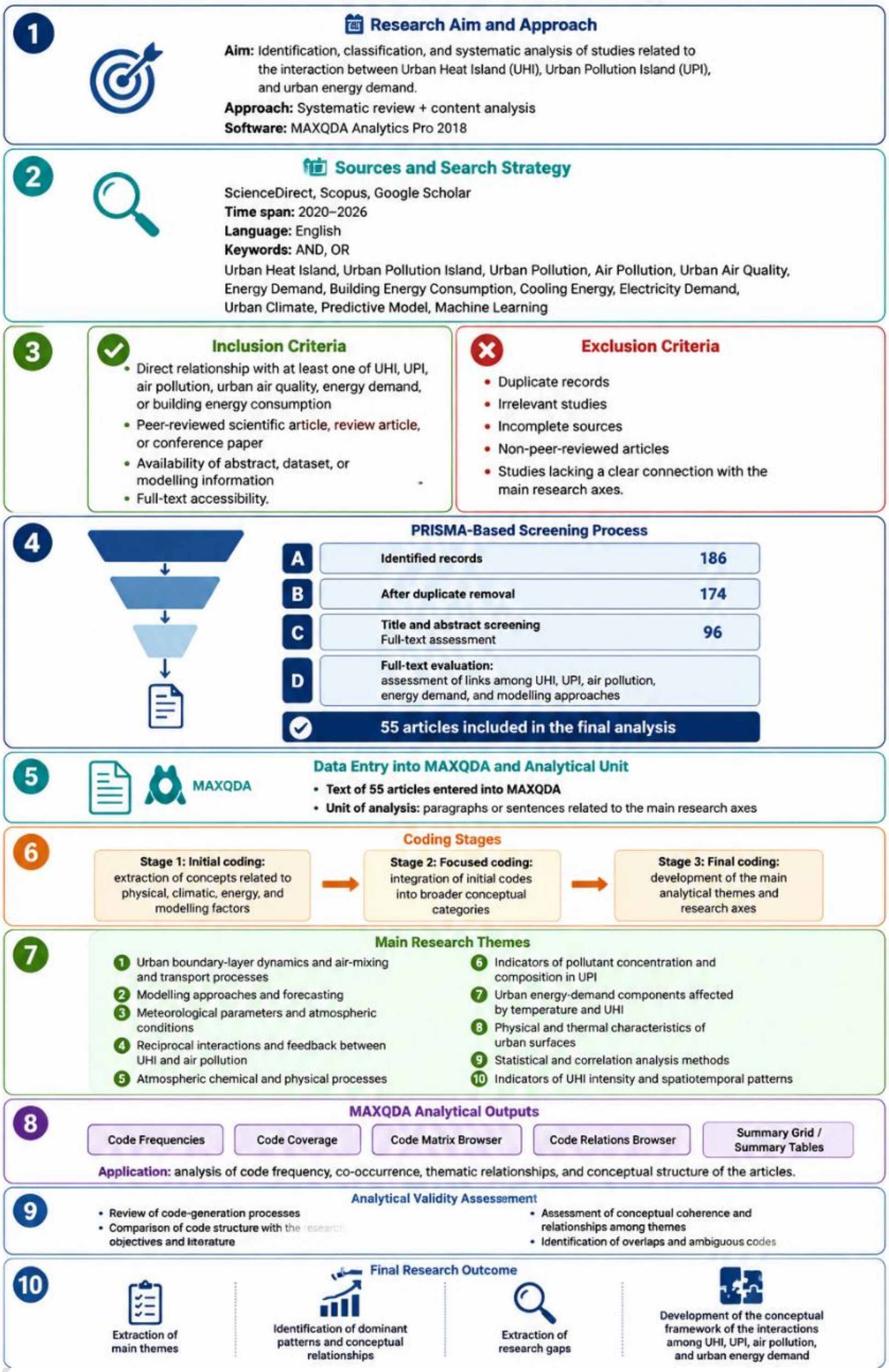


Figure 2: Research method diagram

## 5. Research Findings

This section presents the results obtained from the systematic content analysis of the selected studies. Following the screening and selection of sources related to the interactions among the Urban Heat Island (UHI), Urban Pollution Island (UPI), and energy demand, the key concepts extracted from the articles were coded using MAXQDA software. In total, 4,060 coded segments/coded references were extracted from the selected studies. Following conceptual review, the removal of overlaps, and the consolidation of similar codes, these coded segments were organized into 10 main codes. The findings were analyzed at three levels. First, the frequency distribution of the main codes was examined to identify the dominant themes in the literature. Second, an authors–codes matrix was analyzed to assess the extent to which the selected studies focused on different thematic dimensions. Third, co-occurrence relationships among the main codes were examined to identify the conceptual linkages among UHI, UPI, and energy demand. Accordingly, the findings section comprises the frequency distribution of codes, the pattern of thematic concentration across studies, co-occurrence analysis, and the conceptual synthesis of the findings. Table 1 presents the authors–main codes association matrix extracted from the selected studies and provides the basis for developing the analytical framework of this research. In the first step, a total of 4,060 coded segments were extracted from the selected studies. Since many of these coded segments exhibited conceptual overlap, they were merged through several stages to prevent fragmentation of meaning and maintain analytical coherence. Ultimately, 10 main codes (Parent Codes) were identified. Therefore, the values presented in the table do not merely represent raw frequencies; rather, they reflect the conceptual density of each thematic dimension within the reviewed body of literature. Studies such as Di Bernardino et al. (2026) and Azargoshasbi et al. (2025), owing to their simultaneous coverage of dimensions such as UHI–UPI interactions, meteorological parameters, modeling, and atmospheric processes, play an important role in shaping the conceptual framework of the study. These studies represent examples of multidimensional approaches in the literature, as they attempt to examine the relationships among urban warming, air pollution, atmospheric conditions, and energy-related impacts within a relatively integrated framework. In contrast, studies such as Salhi et al. (2025), Snaiki and Merabtine (2025), and Choi et al. (2026) primarily represent the model-oriented trend in the literature. These studies show higher frequencies of codes associated with modeling, prediction, statistical analysis, and energy, indicating that a substantial body of existing research seeks to simulate, predict, and quantify the effects of UHI on energy consumption and urban climatic conditions. Furthermore, studies such as Maroofiazar et al. (2026), Cheval et al. (2024), and Ventura et al. (2026) focus more strongly on the physical and thermal characteristics of urban surfaces, the intensity and spatiotemporal patterns of UHI, and meteorological parameters. This group of studies is particularly important for explaining the role of materials, albedo, vegetation cover, surface roughness, imperviousness, and local climatic conditions in the formation or intensification of UHI.

Overall, the analysis of the authors–codes matrix indicates that the existing literature is, on the one hand, strongly reliant on modeling and quantitative analysis and, on the other hand, that studies examining the interconnections among the urban surface, local climate, air pollution, and energy demand within an integrated framework remain relatively limited.

Table 1: Relationship matrix of selected studies with main codes extracted from MAXQDA analysis

| | Boundary-layer dynamics | Modelling and forecasting | Statistical and correlation analysis | UHI – UPI interaction | Chemical and physical processes | Pollutant concentration and composition | Energy demand | Meteorological parameters | Urban surface characteristics | UHI intensity and spatiotemporal patterns |
|---|---|---|---|---|---|---|---|---|---|---|
| A. Di Bernardino et al.2026 | 0 | 7 | 7 | 9 | 4 | 9 | 10 | 12 | 6 | 9 |
| A. Lefevre et al.2025 | 4 | 10 | 0 | 0 | 0 | 0 | 8 | 13 | 12 | 5 |
| Abdul Aziz et al.2024 | 0 | 8 | 1 | 0 | 0 | 0 | 11 | 10 | 0 | 0 |
| Abhiraj Tiwari et al.2026 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 7 | 0 | 0 |
| Ahmed Marey et al.2025 | 0 | 20 | 0 | 0 | 0 | 0 | 7 | 7 | 7 | 7 |
| Ali Akbar Rezazadeh et al.2025 | 0 | 13 | 0 | 4 | 0 | 5 | 9 | 5 | 0 | 3 |
| Ali Aslani et al.2025 | 0 | 9 | 4 | 5 | 4 | 2 | 5 | 5 | 22 | 9 |
| Ali Heydari et al. | 2 | 12 | 4 | 4 | 3 | 0 | 5 | 6 | 23 | 9 |
| Ali Majnoon et al.2025 | 0 | 36 | 8 | 4 | 0 | 0 | 11 | 5 | 0 | 6 |
| Ali Najah Ahmed et al.2025 | 0 | 10 | 6 | 4 | 0 | 0 | 6 | 2 | 7 | 3 |
| Alireza Attarhay Tehrani et al.2025 | 0 | 7 | 0 | 2 | 1 | 0 | 8 | 4 | 5 | 3 |
| Alireza Karimi et al.2026 | 0 | 22 | 3 | 4 | 0 | 0 | 11 | 2 | 14 | 12 |
| Amina Salhi et al.2025 | 0 | 75 | 14 | 15 | 0 | 0 | 16 | 0 | 1 | 3 |
| Amnuaylojaroen 2025 | 0 | 44 | 6 | 20 | 0 | 0 | 0 | 11 | 0 | 6 |
| Baoling Gui et al.2025 | 0 | 25 | 18 | 25 | 0 | 0 | 5 | 0 | 26 | 3 |
| Byeongseong Choia et al.2026 | 0 | 51 | 8 | 0 | 0 | 0 | 30 | 1 | 3 | 11 |
| Darvishvand et al.2025 | 0 | 33 | 14 | 2 | 0 | 1 | 44 | 2 | 1 | 1 |
| Delgado-Enales et al.2025 | 1 | 18 | 9 | 10 | 1 | 2 | 14 | 6 | 18 | 12 |
| Elda Cina et al.2025 | 0 | 8 | 2 | 2 | 2 | 1 | 18 | 2 | 8 | 3 |
| Elham Bahadori et al.2025 | 0 | 24 | 2 | 6 | 3 | 1 | 11 | 3 | 14 | 7 |
| Farzad Hashemi et al.2025 | 1 | 25 | 5 | 2 | 1 | 0 | 11 | 8 | 7 | 7 |
| Fei Zhao et al.2025 | 1 | 28 | 4 | 1 | 1 | 0 | 8 | 5 | 11 | 11 |
| Fiona Federer et al.2026 | 3 | 12 | 3 | 13 | 3 | 0 | 0 | 10 | 10 | 11 |
| Forood Azargoshasbi et al.2025 | 1 | 18 | 0 | 36 | 6 | 0 | 12 | 9 | 9 | 14 |
| Gashaw T. Mekonnen et al.2025 | 0 | 9 | 3 | 7 | 0 | 1 | 7 | 0 | 14 | 15 |

| | Boundary-layer dynamics | Modelling and forecasting | Statistical and correlation analysis | UHI – UPI interaction | Chemical and physical processes | Pollutant concentration and composition | Energy demand | Meteorological parameters | Urban surface characteristics | UHI intensity and spatiotemporal patterns |
|---|---|---|---|---|---|---|---|---|---|---|
| Giuseppe Aruta et al.2025 | 0 | 23 | 2 | 2 | 3 | 0 | 15 | 9 | 11 | 11 |
| Hongwei Liu et al.2026 | 0 | 18 | 4 | 3 | 1 | 4 | 8 | 6 | 1 | 5 |
| I˜nigo Delgado-Enale et al.2025 | 2 | 45 | 3 | 3 | 1 | 1 | 13 | 8 | 17 | 13 |
| Ilkim Canli Akyol et al.2025 | 0 | 31 | 2 | 1 | 1 | 1 | 52 | 10 | 2 | 3 |
| J. Litardo et al.2020 | 3 | 5 | 0 | 1 | 2 | 1 | 12 | 8 | 27 | 10 |
| Jia Siqi, Wang Yuhong2020 | 1 | 7 | 4 | 1 | 5 | 0 | 2 | 6 | 18 | 18 |
| Jin Rui et al.2026 | 0 | 26 | 2 | 1 | 0 | 0 | 6 | 6 | 12 | 16 |
| José-Alberto Solís-Villarreal et al.2024 | 0 | 20 | 18 | 3 | 0 | 0 | 28 | 5 | 5 | 3 |
| Lidia Vitanova et al.2025 | 2 | 16 | 6 | 3 | 0 | 0 | 15 | 10 | 25 | 12 |
| Loïc Frayssinet et al.2018 | 5 | 20 | 2 | 4 | 5 | 0 | 41 | 6 | 20 | 7 |
| Manan Singh & Ryan Sharston.2022 | 0 | 5 | 2 | 6 | 0 | 1 | 18 | 11 | 5 | 9 |
| Meng Zhang , Zhihui Li et al.2025 | 0 | 24 | 8 | 0 | 5 | 0 | 0 | 7 | 1 | 2 |
| Muhammad Ehtsham et al.2025 | 0 | 61 | 0 | 2 | 1 | 1 | 19 | 14 | 0 | 4 |
| Muhammad Khalid Anser et al.2025 | 1 | 1 | 1 | 4 | 1 | 2 | 9 | 7 | 31 | 7 |
| Naga Venkata Sai Kumar Manapragada et al.2025 | 0 | 27 | 1 | 3 | 1 | 0 | 8 | 3 | 11 | 3 |
| Pengyuan Shen2025 | 0 | 25 | 2 | 5 | 3 | 0 | 10 | 6 | 10 | 7 |
| Rasool Maroofiazar et al.2026 | 1 | 23 | 8 | 1 | 1 | 1 | 16 | 7 | 33 | 20 |
| Reda Snaiki&, Abdelatif Merabtine.2025 | 1 | 65 | 10 | 7 | 2 | 1 | 4 | 6 | 3 | 11 |
| Sarowar Morshed Shawon et al.2025 | 0 | 36 | 0 | 3 | 1 | 0 | 42 | 10 | 0 | 2 |
| Sergi Ventura et al.2026 | 2 | 15 | 4 | 12 | 1 | 1 | 0 | 20 | 24 | 25 |
| Sheng Liu et al.2025 | 0 | 0 | 6 | 3 | 3 | 0 | 26 | 5 | 25 | 20 |
| Soheil Fathi et al.2020 | 0 | 18 | 2 | 2 | 1 | 0 | 49 | 4 | 3 | 3 |

| | Boundary-layer dynamics | Modelling and forecasting | Statistical and correlation analysis | UHI – UPI interaction | Chemical and physical processes | Pollutant concentration and composition | Energy demand | Meteorological parameters | Urban surface characteristics | UHI intensity and spatiotemporal patterns |
|---|---|---|---|---|---|---|---|---|---|---|
| Sorin Cheva et al.2024 | 3 | 16 | 4 | 2 | 3 | 0 | 1 | 22 | 30 | 24 |
| Xiufeng Liu et al.2026 | 0 | 6 | 4 | 0 | 0 | 0 | 28 | 0 | 0 | 0 |
| Xueli Ni et al.2025 | 1 | 15 | 0 | 3 | 3 | 1 | 1 | 13 | 24 | 22 |
| Yiwen Zhu et al.2026 | 0 | 13 | 4 | 5 | 2 | 0 | 0 | 1 | 40 | 18 |
| Yu Chen et al.2025 | 0 | 42 | 1 | 39 | 0 | 0 | 3 | 0 | 2 | 0 |
| Yuan Lai et al.2024 | 0 | 21 | 0 | 14 | 0 | 0 | 12 | 5 | 5 | 5 |
| Zhiwei Xie et al.2025 | 0 | 28 | 6 | 0 | 0 | 0 | 11 | 0 | 11 | 4 |
| Zhiyuan Zhang et al.2026 | 10 | 27 | 4 | 4 | 0 | 5 | 10 | 3 | 2 | 1 |

Table 2 presents the frequency and percentage distribution of the 10 main research codes. According to the results, the code “Modeling and Prediction Approaches for Climatic Variables and Urban Pollution” has the highest frequency, with 1,205 references, accounting for 29.68% of the total. This is followed by the code “Urban Energy Demand Components Affected by Temperature and UHI”, with 726 references, equivalent to 17.88%, and the code “Physical and Thermal Characteristics of Urban Surfaces Affecting UHI Formation”, with 616 references, representing 15.17%, which rank second and third, respectively. In addition, the codes “Urban Heat Island Intensity Indicators and Spatiotemporal Patterns”, with 455 references (11.21%), and “Meteorological Parameters and Atmospheric Conditions Affecting UHI and Air Pollution”, with 353 references (8.69%), account for a substantial share of the reviewed literature. This pattern indicates that a considerable proportion of studies have focused on modeling, prediction, UHI intensity, urban surface characteristics, and energy-related impacts.
In contrast, codes related to process-based mechanisms and urban pollution account for a smaller share. The code “Interaction and Mutual Feedback between the Urban Heat Island and Air Pollution”, with 312 references (7.68%), and the code “Statistical and Correlation Analysis Methods in UHI and Pollution Studies”, with 231 references (5.69%), occupy an intermediate position. At the lowest frequency level are the codes “Atmospheric Chemical and Physical Processes under Urban Warming Conditions”, with 75 references (1.85%); “Urban Boundary Layer Dynamics and Air Mixing and Transport Processes”, with 45 references (1.11%); and “Indicators of Air Pollutant Concentration and Composition in the Urban Pollution Island”, with 42 references (1.03%). This distribution indicates that the existing literature is predominantly focused on model-based approaches, UHI intensity analysis, urban surface characteristics, and energy-related impacts, whereas atmospheric physicochemical mechanisms, urban boundary-layer dynamics, and specific UPI indicators have received comparatively less attention.

Table 2: Frequency and percentage of frequency of the main research codes

| Main Research Codes | Relative Frequency | Frequency |
|---|---|---|

| | | |
|---|---|---|
| Modelling and forecasting approaches for urban climate and pollution variables | 29.68 | 1205 |
| Urban energy-demand components affected by temperature and UHI | 17.88 | 726 |
| Physical and thermal characteristics of urban surfaces affecting UHI formation | 15.17 | 616 |
| Indicators of urban heat-island intensity and spatiotemporal patterns | 11.21 | 455 |
| Meteorological parameters and atmospheric conditions affecting UHI and air pollution | 8.69 | 353 |
| Reciprocal interactions and feedback between the urban heat island and air pollution | 7.68 | 312 |
| Statistical and correlation analysis methods in UHI and pollution studies | 5.69 | 231 |
| Atmospheric chemical and physical processes under urban warming conditions | 1.85 | 75 |
| Urban boundary-layer dynamics and air-mixing and transport processes | 1.11 | 45 |
| Indicators of air-pollutant concentration and composition in the urban pollution island (UPI) | 1.03 | 42 |
| Total | **100.00** | **4060** |

### *5.1. Co-occurrence Analysis of Main Codes*

Following the code frequency analysis, a co-occurrence analysis was conducted among the main codes to determine how the core concepts extracted from the selected studies appeared alongside one another and what types of conceptual linkages could be identified among them. While frequency analysis indicates the extent to which each code is repeated across the dataset, co-occurrence analysis enables the examination of the relational structure among codes. Accordingly, this analysis was employed to identify the connecting dimensions among the urban heat island, urban pollution island, and energy demand. At this stage, the co-occurrence matrix of the main codes was extracted using the output of the Code Relations Browser in MAXQDA software. Figure 3 presents the colour-coded co-occurrence matrix of the main research codes, based on the output generated by the Code Relations Browser in MAXQDA.

Figure 3: Color co-occurrence matrix of the main research codes based on the output of the Code Relations Browser in MAXQDA

| **Code System** | Boundary Layer | Modelling | Statistical Analysis | UHI–UPI Interaction | Atmospheric Chemistry | UPI Indicators | Energy Demand | Meteorology | Surface Characteristics | UHI Intensity |
|---|---|---|---|---|---|---|---|---|---|---|
| Boundary Layer | 0 | 1 | 0 | 0 | 2 | 0 | 0 | 1 | 2 | 0 |
| Modelling | 1 | 0 | 1 | 0 | 0 | 0 | 2 | 1 | 0 | 2 |
| Statistical Analysis | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| UHI–UPI Interaction | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 1 | 0 | 0 |
| Atmospheric Chemistry | 2 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| UPI Indicators | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Energy Demand | 0 | 2 | 1 | 6 | 1 | 1 | 0 | 0 | 0 | 1 |
| | | | | | | | | | | |
| Meteorology | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 4 |
| Surface Characteristics | 2 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| UHI Intensity | 0 | 2 | 0 | 0 | 0 | 0 | 1 | 4 | 0 | 0 |



As the co-occurrence matrix is symmetrical in nature, duplicated relationships on both sides of the main diagonal were considered only once in the analysis. In addition, the values on the main diagonal, which represent the co-occurrence of each code with itself, were excluded. In this analysis, co-occurrence values were interpreted as indicators of the relative strength of conceptual associations among codes, rather than as evidence of direct causal or statistical relationships. Therefore, the reported values indicate the extent to which two concepts appeared within shared analytical contexts. Table 3 presents ten selected co-occurrence relationships among the main codes.

Table 3: Selected co-occurrence relationships between main codes based on the output of the Code Relations Browser in MAXQDA

| | Co-occurring Code Pairs | Co-occurrence Value | Relationship Level | Analytical Interpretation |
|---|---|---|---|---|
| 1 | Reciprocal interactions and feedback between the urban heat island and air pollution × Urban energy-demand components affected by temperature and UHI | 6 | Strong | This indicates that the linkage between UHI and UPI in the reviewed literature is primarily addressed in the context of energy-related consequences, particularly increased cooling loads, shifts in electricity consumption patterns, |

| | Co-occurring Code Pairs | Co-occurrence Value | Relationship Level | Analytical Interpretation |
|---|---|---|---|---|
| | | | | and the intensification of urban energy demand |
| 2 | Meteorological parameters and atmospheric conditions affecting UHI and air pollution × Indicators of urban heat-island intensity and spatiotemporal patterns | 4 | Relatively strong | This highlights the role of atmospheric conditions—such as temperature, wind speed, humidity, solar radiation, and atmospheric stability—in regulating the intensity and spatiotemporal variability of UHI. |
| 3 | Urban boundary-layer dynamics and air-mixing and transport processes × Atmospheric chemical and physical processes under urban warming conditions | 2 | Moderate | This reflects the connection between vertical mixing, air transport, and the chemical and physical processes influencing pollutant behaviour within urban environments. |
| 4 | Urban boundary-layer dynamics and air-mixing and transport processes × Physical and thermal characteristics of urban surfaces affecting UHI formation | 2 | Moderate | This suggests that the physical structure and thermal properties of urban surfaces contribute to urban thermal and pollution conditions by influencing turbulence, ventilation, and air mixing. |
| 5 | Modelling and forecasting approaches for urban climate and pollution variables × Urban energy-demand components affected by temperature and UHI | 2 | Moderate | This indicates that a subset of studies has utilized modelling and forecasting to estimate the impact of UHI on energy consumption, cooling loads, and urban energy requirements |
| 6 | Modelling and forecasting approaches for urban climate and pollution variables × Indicators of urban heat-island intensity and spatiotemporal patterns | 2 | Moderate | This reflects the role of modelling in simulating, forecasting, and analysing the intensity, spatial distribution, and temporal variations of UHI. |
| 7 | Statistical and correlation analysis methods in UHI and pollution studies × Physical and thermal characteristics of urban surfaces affecting UHI formation | 2 | Moderate | This demonstrates that some studies have employed statistical and correlation analyses to assess the relationship between urban surface characteristics and the formation or intensification of UHI. |
| 8 | Urban boundary-layer dynamics and air-mixing and transport processes × Modelling and forecasting approaches for urban climate and pollution variables | 1 | Weak | This reveals limited but identifiable attention to the application of modelling in investigating mixing processes, air transport, and urban boundary-layer dynamics. |

| | Co-occurring Code Pairs | Co-occurrence Value | Relationship Level | Analytical Interpretation |
|---|---|---|---|---|
| 9 | Indicators of air-pollutant concentration and composition in the urban pollution island × Urban energy-demand components affected by temperature and UHI | 1 | Weak | This suggests that the direct relationship between urban pollution indicators and energy demand remains underdeveloped and limited within the reviewed literature. |
| 10 | Meteorological parameters and atmospheric conditions affecting UHI and air pollution × Reciprocal interactions and feedback between the urban heat island and air pollution | 1 | Weak | This indicates that while some studies have addressed the role of atmospheric conditions in moderating or intensifying the relationship between urban warming and air pollution, this linkage has not yet been extensively developed. |

First, energy demand plays an intermediary role between UHI and UPI in the existing literature. Although the modeling and prediction code had the highest frequency in the coding analysis, the co-occurrence relationships showed that energy demand is one of the most important conceptual links connecting urban heating, air pollution, and the functional consequences of urban systems. This finding indicates that energy has not been considered merely as a consequence of UHI in the reviewed studies; rather, it has served as a link connecting the thermal conditions of the city, energy consumption, and air pollution patterns. Second, the existing literature is more UHI-oriented than UPI-oriented. The higher frequency of UHI intensity indicators and spatiotemporal patterns, together with their relatively strong co-occurrence with meteorological parameters, indicates that the thermal dimension of cities has been well developed in the literature. In contrast, the lower frequency and co-occurrence of indicators related to air pollutant concentrations and composition suggest that the urban pollution dimension has not yet been sufficiently incorporated into integrated analytical frameworks. Third, boundary-layer processes and atmospheric chemistry have still been integrated only to a limited extent into existing studies. Although some relationships were identified among boundary-layer dynamics, air mixing, chemical processes, and urban surface characteristics, the strength of these relationships was lower than that observed for the energy, modeling, and UHI dimensions. This is despite the fundamental importance of mechanisms such as boundary-layer height, atmospheric stability, vertical mixing, urban ventilation, secondary pollutant formation, and photochemical reactions for accurately understanding the interaction between UHI and UPI. Fourth, modeling occupies a dominant position in the literature, but it has often been applied in a fragmented and non-integrated manner. The frequency analysis showed that modeling and prediction approaches accounted for the largest share among the main codes. However, the co-occurrence analysis indicates that these models have predominantly appeared in association with UHI intensity and energy demand, while relatively limited attention has been given to the simultaneous integration of urban surface characteristics, meteorological conditions, boundary-layer dynamics, atmospheric chemistry, UPI indicators, and energy demand. Based on this synthesis, it can be concluded that the existing literature is primarily organized around a dominant pathway: urban surface characteristics and meteorological conditions influence the intensity and spatiotemporal patterns of UHI; UHI is linked to energy demand, particularly cooling loads, through increases in ambient urban temperature; and these changes can be directly or indirectly associated with air pollution patterns. However, pathways related to atmospheric chemistry, boundary-layer dynamics, and specific UPI indicators remain less developed. These findings provide a basis for developing the conceptual framework of the study and for discussing the research gaps in this field.

## 6. Discussion

### *6-1. Comparison of the Research Findings with Other Studies*

The first finding of this study, namely the dominance of model-oriented and energy-oriented approaches in the UHI–UPI–Energy literature, is fully consistent with contemporary research. The study by Song et al. (2024) emphasizes the linkages among urban microclimate, energy systems, and the building sector and identifies the dynamic interactions among these three domains as factors that intensify energy consumption and carbon emissions. Similarly, a comprehensive study that developed an integrated analytical framework combining Structural Equation Modeling (SEM) and machine learning (XGBoost–SHAP) to identify indirect drivers and nonlinear interactions across 269 Chinese cities clearly demonstrates that the existing literature is moving toward integrated and quantitative modeling. Furthermore, the second finding of the present study, namely the relative lack of attention to UPI and pollutant-related indicators, is also reflected in recent research. The study by Cichowicz and Bochenek (2024), published in Anthropocene, indicates that despite the growing body of research on UHI–UPI interactions, the primary focus remains on the thermal dimension of cities. However, recent studies have taken important steps toward addressing this gap. For example, Di Bernardino et al. (2024) assessed Urban Pollution Island Intensity (UPII) in Rome using PM measurements from ground-based monitoring stations, while Niu et al. (2024) investigated the spatiotemporal patterns of the air pollution island across 2,273 cities in China. At the conceptual level, Sinha et al. (2024) conducted a comprehensive review of the linkages between UHI and UPI in tropical countries. The third finding of the present study, concerning the limited integration of boundary-layer processes and atmospheric chemistry, is also supported by some of the most advanced studies published in 2024. A study published in Atmospheric Environment in December 2024, using the WRF-Chem atmospheric chemistry model, explicitly demonstrated that the urban heat island and atmospheric boundary-layer circulation are important factors affecting the transport and spatiotemporal distribution of particulate matter in cities. The study further showed that improving the representation of the urban canopy reduced the daytime simulation error for PM2.5 from 18.24% to 3.28%. In addition, Park et al. (2024), in Scientific Reports, systematically demonstrated that increasing roof albedo, although reducing UHI intensity, can increase surface pollutant concentrations by up to 115% through a reduction in planetary boundary layer (PBL) height. This finding clearly demonstrates that neglecting boundary-layer processes can lead to contradictory and ineffective strategies for the simultaneous management of UHI and UPI.

***6-2. Differences between the Research Findings and Other Studies***

Despite the overall consistency, the findings of this study differ from those of other studies in several important respects, reflecting its methodological and conceptual novelty. First, while most previous studies, such as the comprehensive study covering 269 Chinese cities, have focused on quantitative data and numerical models, the present study employs qualitative content analysis using MAXQDA to reveal latent patterns within the research literature. This approach makes it possible to identify gaps that cannot be readily detected through purely quantitative analyses, including the weak linkage between modeling and UPI, atmospheric chemistry, and boundary-layer dynamics. Second, while studies such as Wu et al. (2024) have focused on simultaneous UHI–UPI control strategies through the use of green infrastructure, the present study adopts a meta-theoretical perspective and demonstrates that, before proposing mitigation strategies, there is a need to redefine the conceptual framework and identify neglected components. This difference in the level of analysis—strategies versus framework—highlights the distinctive position of the present study within the evolutionary trajectory of the literature. Third, recent research, such as the Delhi (2026) study, has introduced the new concept of a combined Urban Heat and Pollution Index (UHPI), which simultaneously considers both thermal and pollution dimensions. However, the present study goes beyond this approach and demonstrates that even such composite indices remain incomplete without considering the dynamic processes of the atmosphere and atmospheric chemistry. In other words, the present study not only emphasizes the need to integrate UHI and UPI but also identifies the boundary layer and atmospheric chemistry as the principal missing links, which have rarely received sufficient attention in previous research.

***6-3. Position of the Findings and Contributions to Future Research***

The findings of this study contribute to enriching the UHI–UPI–Energy literature in several ways and provide directions for future research. First, by identifying three major gaps—the dominance of energy-oriented modeling, insufficient attention to UPI, and limited integration of boundary-layer processes and atmospheric chemistry—the present study provides a clear roadmap for future researchers and demonstrates that the required integration should also incorporate atmospheric and chemical components. Second, the co-occurrence findings of this study indicate that modeling is more strongly associated with UHI and energy demand, while its relationships with UPI, atmospheric chemistry, and boundary-layer dynamics are more limited. This finding, which has received comparatively little attention in previous quantitative studies, represents an important warning for researchers in the field of urban modeling. The RESTART study in Rome (2024–2025), which specifically examined UHI–UPI interactions through an observation-based meteorological approach, provides theoretical support for the direction of such research. Third, by presenting a conceptual model (Figure 4) in which urban surface characteristics, UHI intensity and patterns, meteorological parameters, boundary-layer dynamics, atmospheric chemical processes, UPI indicators, and energy demand are considered simultaneously, the present study provides an operational framework for developing integrated models in future research. As demonstrated by the WRF-Chem study in Liaoning, China, improving the representation of the urban canopy can substantially enhance simulation accuracy. By emphasizing the importance of these components, the present study therefore highlights the need for greater investment in the development of coupled meteorological–chemical models. Fourth, as demonstrated by the Bologna (2025) study, which showed that overlooking private green spaces can lead to an underestimation of their role in mitigating UHI and UPI, the present study indicates that neglecting boundary-layer processes and atmospheric chemistry can likewise result in incomplete and even contradictory strategies for urban air-quality management. Accordingly, future research must adopt integrated and multidimensional approaches. By precisely identifying the neglected dimensions, the present study takes an important step toward defining new research directions in the field of urban climatology. In explaining the root causes of these gaps, particularly the limited attention to the boundary layer and atmospheric chemistry, several fundamental factors should be considered. First, the inherent complexity of atmospheric processes and the difficulty of simultaneously examining dynamic processes such as turbulence, vertical mixing, and urban ventilation and chemical processes such as photochemical reactions and secondary pollutant formation require interdisciplinary expertise in meteorology, atmospheric chemistry, and urban physics, which is less commonly found in highly specialized studies. Second, there are significant limitations in access to specialized data, such as vertical temperature profiles, wind speed, mixing-layer height, and surface heat fluxes. In many cities, such data are unavailable because of limitations in monitoring networks and the high costs associated with measurements (Oke, 1988; Fernando, 2010). Third, the historical focus of urban heat island studies on surface-based and remotely observable variables, such as land surface temperature and land cover, has naturally directed researchers toward variables that can be readily extracted and mapped, whereas atmospheric processes are inherently three-dimensional and dynamic. Fourth, analyzing the relationship between urban structure and air quality requires advanced coupled meteorological–chemical models, such as WRF-Chem, as well as substantial computational infrastructure (Seinfeld & Pandis, 2016). These requirements have encouraged many researchers to adopt simpler and more one-dimensional approaches. Fifth, the indirect and mediating role of the boundary layer and atmospheric chemistry in the UHI–UPI–Energy relationships has caused these processes to be treated as peripheral variables in many analytical frameworks. In reality, these processes act as intermediary mechanisms linking urban structure, thermal conditions, pollutant emissions, and energy consumption, and neglecting them can lead to an incomplete understanding of the feedback mechanisms operating within urban systems. Figure 4 presents the conceptual model of the study.

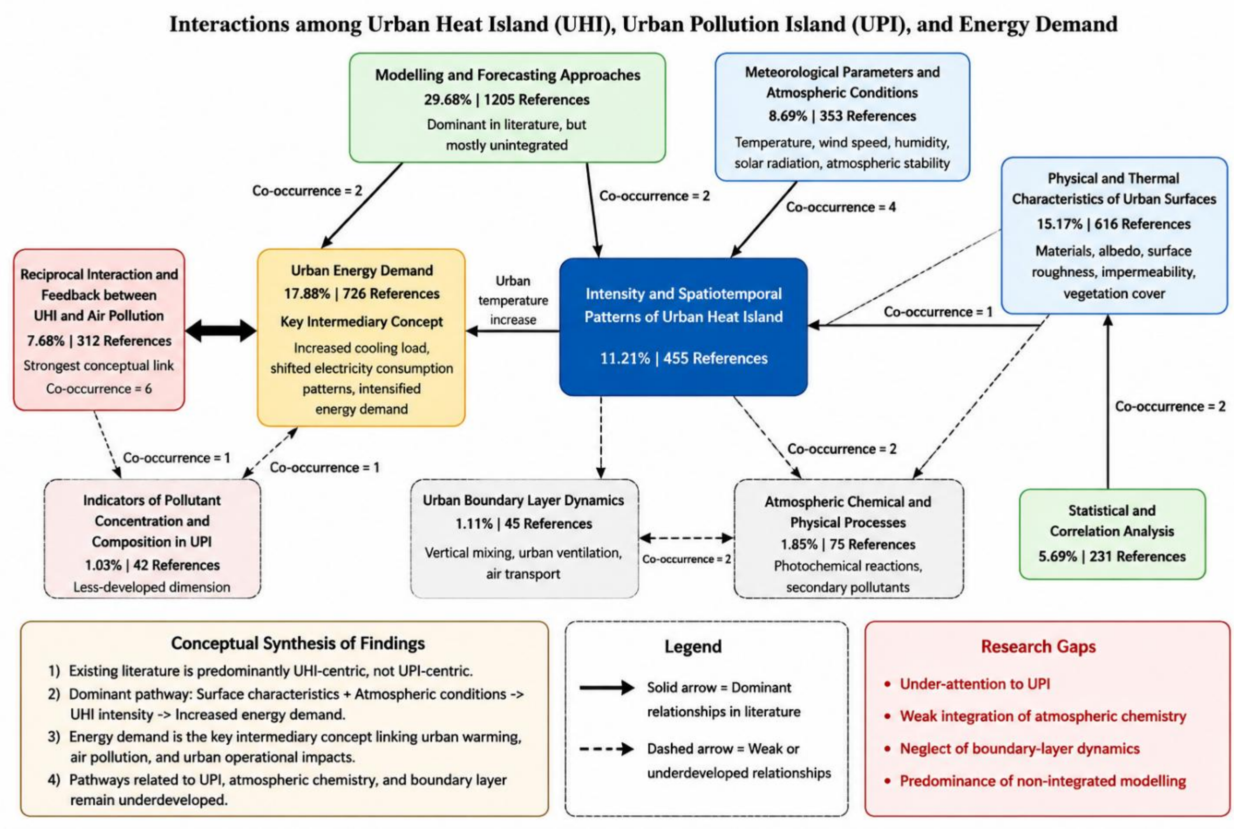


Figure 4: Conceptual research model

## 7. Conclusion

The synthesis of the findings indicates that the predominant pathway in the existing literature begins with urban-scale characteristics and meteorological conditions, progresses to the intensification of the urban heat island (UHI) effect, then leads through increased ambient temperature to higher energy demand, particularly cooling loads, and ultimately may be associated with changes in or intensification of air pollution patterns. However, this dominant pathway does not yet encompass all dimensions of the issue. Feedback loops related to urban particulate pollution (UPI), atmospheric chemistry, and boundary-layer dynamics have been less extensively developed compared with the areas of modelling, energy, and UHI intensity. This limitation indicates that existing frameworks are not sufficient to fully explain the UHI–UPI–Energy relationship and therefore require conceptual and methodological refinement. Based on these findings, the present study emphasizes the need to move towards integrated, multiscale, and multiprocess frameworks that can simultaneously analyse urban climate data, air quality, energy consumption, urban surface characteristics, meteorological conditions, boundary-layer dynamics, and atmospheric chemical processes. Such an approach can move beyond sector-specific perspectives and provide a more comprehensive understanding of the feedbacks among urban warming, air pollution, and energy consumption. The contribution of this type of analysis is not limited to expanding theoretical knowledge; rather, it can provide a practical basis for urban policymaking, reducing UHI intensity, improving air quality, managing energy consumption, and moving towards more sustainable urban management.

## Author Contributions

First author (25%), second author (25%), third author (25%), fourth author (25%).

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## Conflict of Interest

The authors declare that they have no conflict of interest.



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