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Artificial intelligence applications in urban extreme heat management: A systematic review of forecasting, monitoring, mitigation and decision support

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A R T I C L E I N F O

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A B S T R A C T

Against the backdrop of global warming and rapid urbanization, urban extreme heat is becoming increasingly severe, with profound impacts on public health, infrastructure, and social equity. Advances in artificial intelligence (AI) offer new opportunities to address this challenge. This systematic review examines 102 publications on AI applications in urban extreme heat governance. The findings reveal a "Northern bias," with most studies in the United States, China, and Europe, while gaps exist in sub-Saharan Africa and Latin America. Supervised learning dominates current approaches. AI demonstrates effectiveness across four dimensions of governance. In prediction and early warning, random forests and XGBoost are suitable for short-term forecasting, CNNs and LSTMs excel at spatiotemporal patterns, and hybrid models improve accuracy. In monitoring and assessment, AI overcomes spatiotemporal limits of remote sensing, shifting from static heat mapping to dynamic heat–population risk identification, with social media capturing residents' perceptions. In mitigation and adaptation, AI identifies thresholds of green–blue infrastructure, supports urban form regulation, and expands climate-adaptive design through generative AI. In scenario simulation and decision support, AI-powered digital twins and interactive platforms integrate planning and operations, fostering expert–public collaboration. Yet applications remain constrained by trade-offs between accuracy and efficiency, limited data integration, and insufficient causal inference, particularly in modeling the heat risk chain as a multi-stage system. Future work should build data frameworks integrating physical and social information and advance paradigm shifts toward causal inference and multi-objective optimization. A systematic AI framework can enable closed-loop governance from risk identification to intelligent response.

1. Introduction

The trend of global warming has become increasingly pronounced. Broadly speaking, any high-temperature phenomena that significantly impact human health, infrastructure, or ecosystems (including heat waves, urban heat islands, heat exposure, and human thermal stress) can be considered "extreme heat," with their frequency, duration, and intensity showing significant upward trends over the past decades (Esper et al., 2024). The rapid urbanization process has further amplified this risk, not only exposing more populations to heat threats but also intensifying local thermal environments through urban heat island effects (Q. Cheng et al., 2023a; Yang et al., 2017). This compounding effect not only exacerbates urban residents' heat exposure levels but also profoundly impacts public health (Laaidi et al., 2012), energy systems (L. Jiang et al., 2024a), economic productivity (Fatima et al., 2023), and social equity (Slesinski et al., 2025). The sharp rise in excess mortality during heat waves, grid pressure from surging air conditioning loads, infrastructure failures due to overheating, and disproportionate impacts on vulnerable groups all indicate that urban heat has become a pressing urban environmental challenge requiring global attention (Simpson et al., 2024; Fang et al., 2025).

Urban heat phenomena exhibit highly complex systemic characteristics, posing challenges to traditional research methods (Hochrainer-Stigler et al., 2023; Simpson et al., 2021). From a spatial dimension, urban heat displays significant multi-scale heterogeneous characteristics, from building and neighborhood-scale local microclimates to city-

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wide and regional temperature patterns, with each scale presenting unique thermal environment characteristics and variation patterns (Ye and Yang, 2025). From a temporal dimension, urban heat exhibits complex dynamic change patterns, including diurnal cycles, seasonal fluctuations, and interannual variations (Amnuaylojaroen, 2025; Wang et al., 2024). This spatiotemporal complexity makes accurate prediction and assessment of urban heat extremely difficult. More complex still, urban heat is controlled by the coupling of various natural and anthropogenic factors, including urban morphological characteristics, land use types, transportation and industrial activity intensity, and energy use patterns (Brelsford et al., 2024). The intricate interactions among these factors make comprehensive understanding and precise modeling of urban heat phenomena a significant challenge.

Traditional statistical methods and numerical climate models have obvious limitations in addressing the above complexity. Traditional statistical methods struggle to handle high-dimensional nonlinear relationships, while numerical climate models suffer from high computational costs and limited resolution (H.-C. Zhu et al., 2024a). In recent years, the rapid development of artificial intelligence technology (this paper focuses primarily on AI dominated by machine learning and deep learning) has provided opportunities to address these challenges. Advanced methods such as machine learning and deep learning possess powerful capabilities for processing large-scale, multi-source heterogeneous data, effectively integrating multidimensional information sources including ground monitoring networks, satellite remote sensing imagery, street view data, and building morphology databases, achieving precise modeling of complex nonlinear relationships, and significantly improving prediction accuracy and computational efficiency across multiple spatiotemporal scales (Östh et al., 2025; Rui et al., 2025). In the field of urban heat research, AI technology has been widely applied to various core tasks, including high-resolution land surface temperature or air temperature retrieval, analysis of urban heat island spatiotemporal evolution patterns, prediction of heat wave occurrence and intensity, heat exposure risk assessment, and climate adaptation-oriented urban planning scenario simulation and optimization (Briegel et al., 2023; Fujiwara et al., 2024; Gong et al., 2025).

Although existing review literature has explored AI applications in urban thermal environment research, significant knowledge gaps remain in the research scope and methodological frameworks. On one hand, most existing reviews focus on specific phenomena within urban heat, particularly urban heat island effects, while neglecting the integration of heat wave prediction, exposure assessment, and adaptive design. For example, Ghorbany et al. (2024) reviewed methodological evolution and machine learning applications in urban heat island research, noting that the integration of machine learning significantly expanded capabilities for complex prediction and analysis, but their research context was limited to urban heat island phenomena. In contrast, our review encompasses the full spectrum of urban extreme heat issues, including heat waves, heat exposure, and thermal stress, providing a more comprehensive perspective on AI applications. For instance, Castro and Delina (2025) reviewed research progress in policy-making combined with AI technology for addressing extreme heat, but focused on policy aspects and stakeholder response strategies, with insufficient elaboration on AI methods' technical details. Similarly, Camps-Valls et al. (2025) reviewed AI applications in analyzing various extreme climate events, including floods, droughts, wildfires, and heat waves, emphasizing the importance of building accurate, transparent, and reliable AI models, but lacking in-depth analysis specific to the urban heat domain. Unlike these prior reviews, our study uniquely integrates a four-component governance framework that systematically connects forecasting, monitoring, mitigation, and decision support, enabling a holistic understanding of AI's role across the entire heat risk management chain.

Comprehensively, current AI-enabled urban heat research shows obvious deficiencies in systematic application frameworks, methodological system integration, and practical guidance, particularly lacking holistic modeling of heat risk chains as multi-stage dynamic feedback systems. Existing research often focuses on specific tasks or single contexts, such as improving heat wave prediction accuracy or identifying spatial distributions of heat exposure, lacking collaborative analysis and holistic thinking across different stages, including prediction, assessment, adaptation, and decision-making, and has not fully leveraged AI technology's cross-stage collaborative empowerment potential. Based on this, this review aims to systematically address the shortcomings in existing research. The main contributions of this study are as follows:

- We construct a comprehensive four-component framework (forecasting and early warning, monitoring and assessment, mitigation and adaptation, scenario simulation and decision support) for AI applications in urban extreme heat governance.
- We systematically review 102 publications to document diverse AI methods and identify technical challenges and practical barriers.
- We reveal the “Northern bias” in existing research and highlight knowledge gaps in sub-Saharan Africa and Latin America.
- We propose future directions emphasizing causal inference, multi-objective optimization, and integrated physical-social data frameworks.

Through systematic review and critical analysis, this study provides guidance for AI-driven urban heat research, promoting climate-resilient city construction.

2. Methodology

This study employs a systematic literature review methodology to explore the topic of “artificial intelligence applications in urban extreme heat research,” systematically analyzing the current status, technical challenges, and future development directions of AI technology applications in urban heat forecasting and early warning, monitoring and assessment, mitigation and adaptation, and scenario simulation and decision support. The review process follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure systematicity, transparency, and reproducibility (Page et al., 2021). Based on in-depth analysis of existing literature, we constructed a comprehensive framework for AI-enabled urban extreme heat management.

2.1. Literature search and screening

A comprehensive search was conducted in the Scopus database for English-language peer-reviewed articles and conference papers published from January 2020 to April 21, 2025. The year 2020 was selected as the starting point based on the rapid development and application of deep learning technologies in climate and urban research domains during this period.

The search strategy was structured around three intersecting themes: (1) artificial intelligence methods, (2) urban extreme heat, and (3) application scenarios. The final search query was formulated as: TITLE-ABS-KEY((“deep learning” OR “AI” OR “artificial intelligence”) AND (“urban heat*” OR “extreme heat” OR “heat wave” OR “urban heat island”) AND (predict* OR forecast* OR adapt* OR assess*)) AND PUBYEAR >2019 AND PUBYEAR <2026 AND LANGUAGE(english) AND (DOCTYPE(ar) OR DOCTYPE(cp)) AND (LIMIT-TO (SUBJAREA,”SOCI”) OR LIMIT-TO (SUBJAREA,”ENVI”) OR LIMIT-TO (SUBJAREA,”EART”)).

To ensure high quality and relevance of included literature, rigorous inclusion and exclusion criteria were established. Inclusion criteria comprised: (1) peer-reviewed articles published in SCI/SSCI-indexed journals or high-quality international conferences; (2) empirical studies explicitly applying AI techniques to address urban heat-related problems; (3) research focusing on extreme heat phenomena at urban or metropolitan scales; (4) studies providing clear methodological descriptions and validation results; (5) articles written in English.

Exclusion criteria included: (1) purely theoretical studies or review articles (although relevant reviews were used for supplementary reference); (2) non-peer-reviewed literature (technical reports, preprints, conference abstracts, etc.); (3) studies with scope limited to indoor environments or non-urban areas; (4) research employing only traditional statistical methods without AI technology involvement; (5) articles with insufficient data availability or inadequate methodological descriptions.

2.2. Literature screening and quality assessment

The initial search yielded 145 publications. After removing duplicate entries using EndNote software, we conducted preliminary screening of titles and abstracts of the remaining literature, excluding 27 publications that clearly did not meet the inclusion criteria. Subsequently, we assessed the quality of these articles using the Critical Appraisal Skills Programme (CASP) checklist (Supplementary Note S1), a standardized tool for evaluating the rigor and reliability of systematic review studies

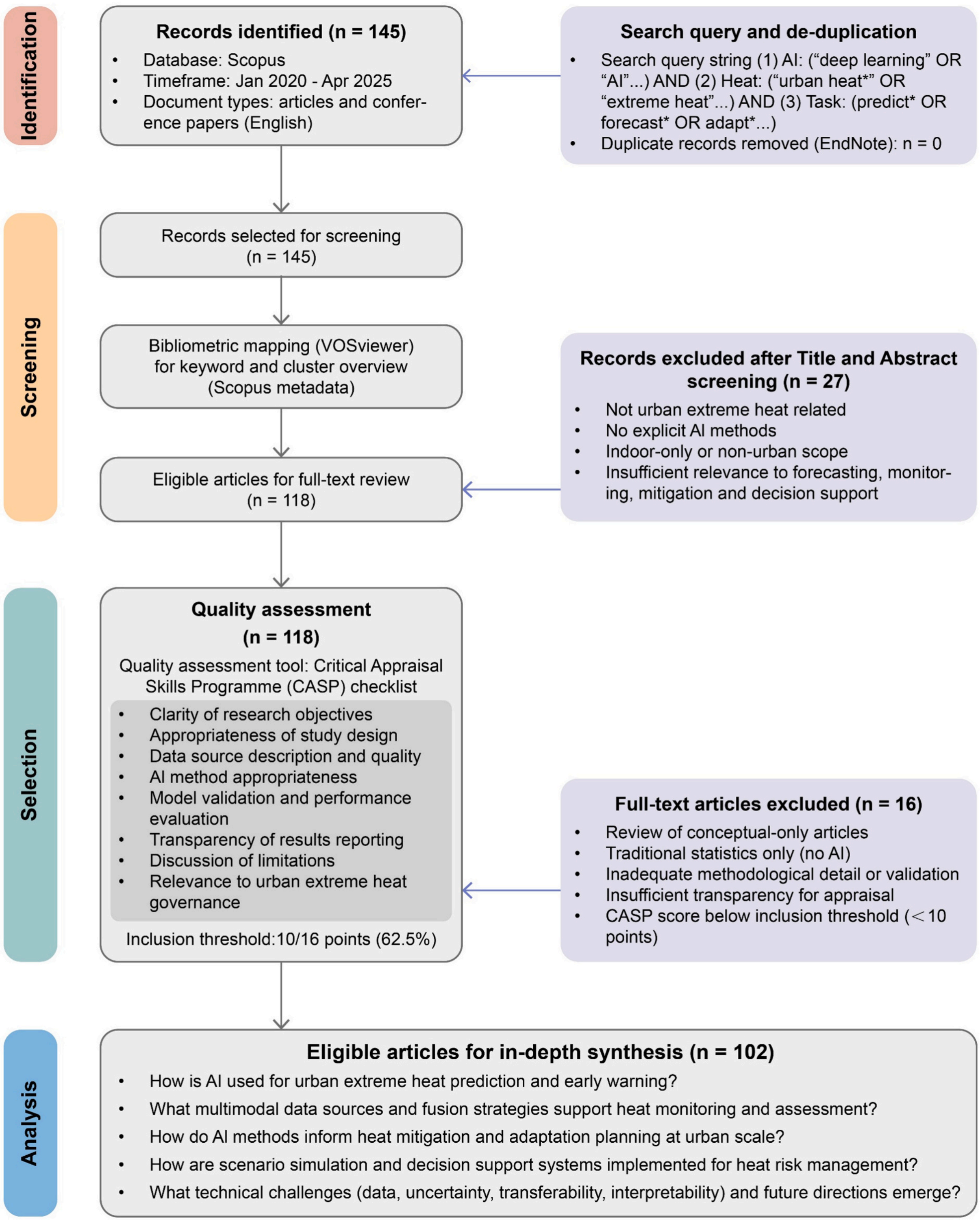

Fig. 1. PRISMA flow diagram illustrating the systematic literature screening and selection process.

(Long et al., 2020). The final quality assessment resulted in a core dataset of 102 publications suitable for in-depth analysis. The complete flow diagram illustrating the systematic literature screening and selection process is presented in Fig. 1.

2.3. Data extraction and analytical framework

We employed a structured data extraction method, systematically recording key information from each study, including: (1) basic research information: publication year, study area, spatial scale; (2) data characteristics: data source types, temporal span, spatial resolution; (3) technical methods: AI model types, algorithm architecture, performance evaluation metrics; (4) application scenarios: specific task types, core problems addressed, practical application effects.

Based on in-depth analysis of existing research, we constructed the comprehensive framework for AI-enabled urban extreme heat management as shown in Fig. 2. This framework is based on multimodal data fusion, integrating multi-source information including meteorological observations, satellite remote sensing, reanalysis data, and socioeconomic data; supported by diverse AI models as core technical infrastructure, encompassing methodological systems including supervised learning, unsupervised learning, semi-supervised learning, and specialized AI; and centered around the complete process of urban heat risk management, categorizing AI applications into four key components: forecasting and early warning (achieving spatiotemporal prediction and proactive response), monitoring and assessment (supporting high-resolution mapping and comprehensive risk assessment), mitigation and adaptation (optimizing intervention effects and generating innovative designs), and scenario simulation and decision support (simulating future scenarios and promoting interactive governance). This framework provides an analytical framework for systematically reviewing current AI applications in urban heat research and establishes a foundation for identifying research gaps and exploring future research directions.

3. Overview of selected literature

3.1. Spatial distribution

To assess the geographical coverage of existing research, we conducted a visualization analysis of the study locations in the included literature. As shown in Fig. 3 (left), the site selection in existing literature exhibits a pronounced "northern bias" pattern: most research sites are densely distributed in economically and scientifically advanced countries in the mid-latitudes of the Northern Hemisphere, particularly concentrated along the east and west coasts of the United States and the Great Lakes region, as well as in Western and Central Europe. However, when using the "Brandt Line" as a reference, we observe a characteristic pattern in the Global South of point-based clustering coexisting with large areas of sparsity: the southern coastal regions of China and the Indian subcontinent, despite being located south of the line, still concentrate a substantial number of sample sites, constituting the most active research hotspots within the Global South. In contrast, sub-Saharan Africa, inland Latin America, and Pacific island nations are virtually uncovered, creating extensive knowledge gaps.

The treemap in Fig. 3 (right) further quantifies this concentration, with numbers representing the total count of urban study locations involved in each country within the reviewed literature. Asia contributes more than half, with China alone accounting for 293 entries, representing over a quarter of the total sample; India, South Korea, Japan, and several Southeast Asian countries form the secondary tier. North America is absolutely dominated by the United States (210 entries), with Canada contributing only a minor portion. Europe displays a multipolar pattern, with research powerhouses including France, Germany, Italy, the United Kingdom, and Russia each forming medium-scale modules. Oceania relies almost entirely on Australia, while South America and Africa contribute only sporadically. This reveals that the current research landscape not only exhibits a North-South divide but also demonstrates regional polarization within the Global South. Future efforts urgently need to strengthen data collection and cross-regional collaboration in underrepresented regions to enhance the global applicability and contextual diversity of research.

3.2. Word cloud

Fig. 4 presents a word cloud visualization of keywords from the reviewed literature. "Urban," "heat," "machine learning," "temperature," "urban heat island," and "climate change" constitute the largest visual weights, indicating that mechanistic research and intelligent prediction of urban heat exposure in the context of climate change represent the current focal points of academic attention. The co-occurring terms "adaptation," "heatwave," "resilience," and

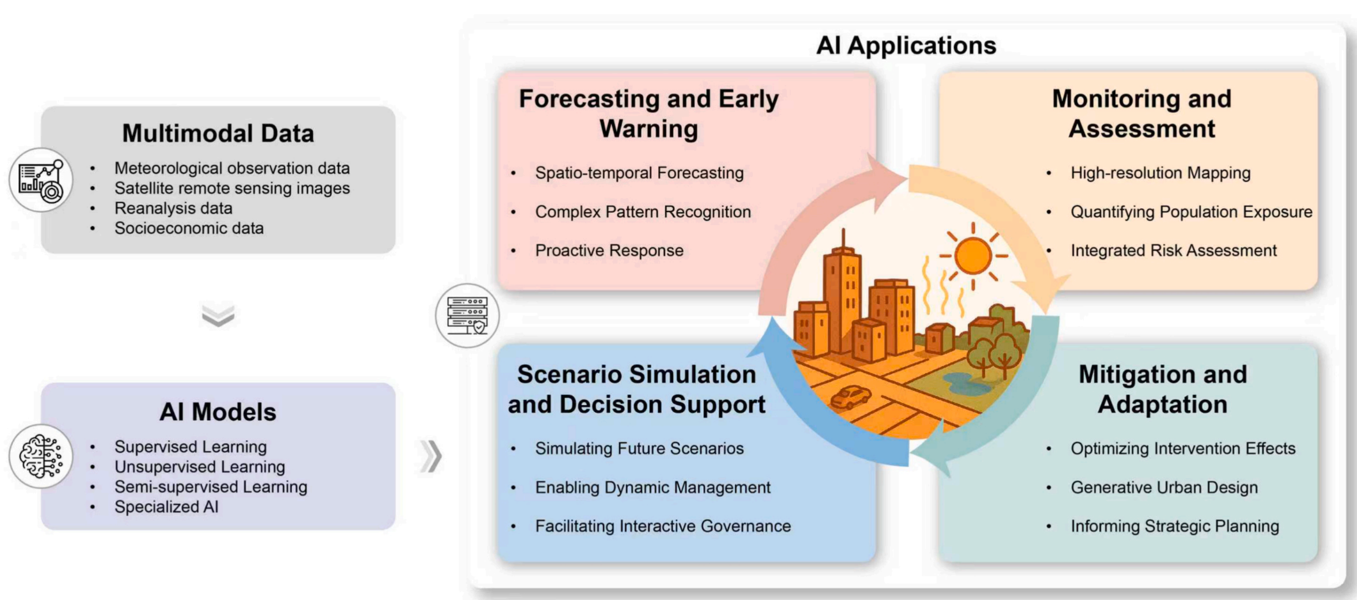

Fig. 2. Integrated framework for AI applications in urban extreme heat management.

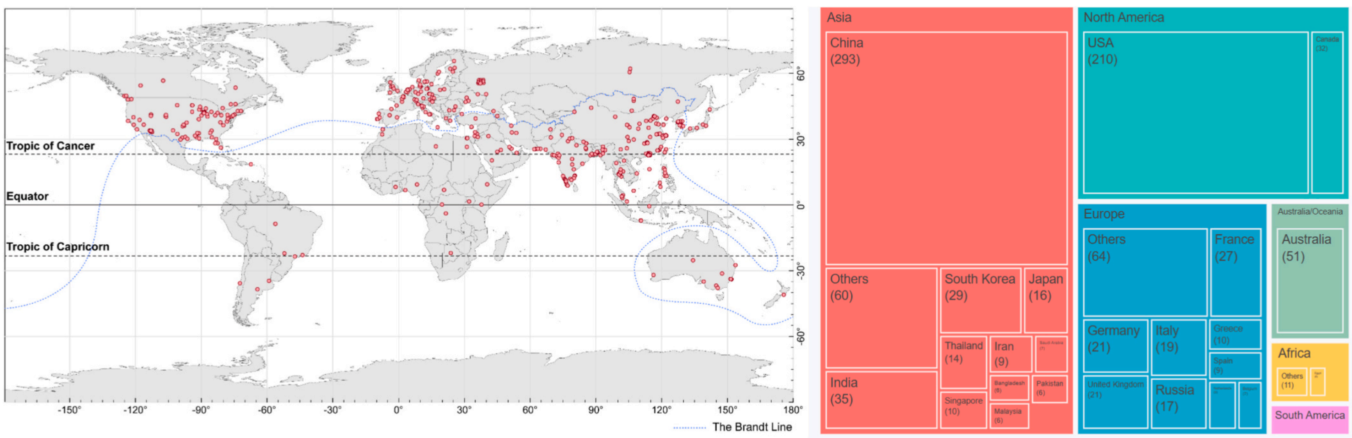

Fig. 3. Spatial distribution of urban extreme heat studies: (Left) global distribution map; (Right) country-wise case study statistics.

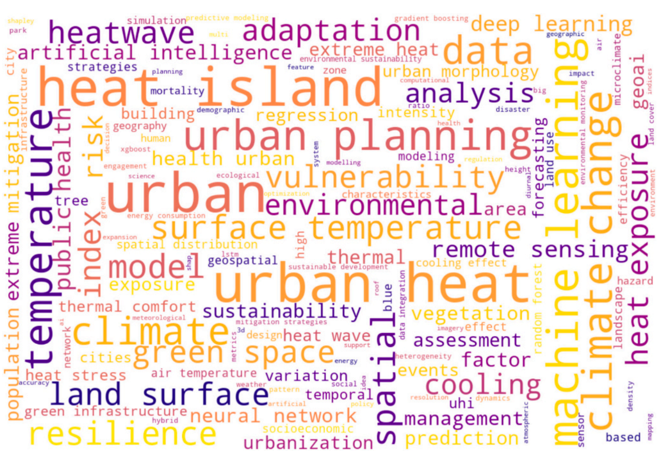

Fig. 4. Word Cloud of keywords.

"vulnerability" reveal that research not only focuses on the thermal environment itself but also emphasizes interdisciplinary exploration of population vulnerability, resilience, and adaptive strategies.

From a methodological dimension, the simultaneous appearance of terms such as "deep learning," "neural network," "regression," "random forest," "xgboost," and "lstm" reflects the coexistence and integration of traditional statistical regression with diverse machine learning models. Terms like "data," "analysis," "model," "prediction," and "simulation" suggest that data-driven prediction-simulation frameworks constitute the technical mainline of research. Spatial information technology characteristics are also prominently featured: keywords including "remote sensing," "spatial," "geospatial," "land surface," as well as "surface temperature" and "spatial distribution" indicate that substantial research relies on satellite or aerial remote sensing to acquire high-resolution thermal environment data and employs spatial modeling to analyze the heterogeneous patterns of urban heat islands.

At the application and practice level, the frequent occurrence of "urban planning," "green space," "cooling," "vegetation," "green infrastructure," and "management" demonstrates that urban planning and green infrastructure are emerging as key pathways for mitigating and adapting to extreme heat. Terms such as "public health," "health risk," "mortality," and "heat exposure" emphasize the direct impacts of heat risk on health, highlighting the close integration between scientific research and public health strategies. Overall, this word cloud reveals an interdisciplinary, multi-scale research landscape: employing artificial intelligence as the core methodology, integrating climate science, urban planning, public health, and remote sensing geographic information systems to achieve monitoring, prediction, assessment, and adaptive management of urban extreme heat risks.

3.3. Data and AI models

3.3.1. Data sources and types

Fig. 5 illustrates the primary data sources for AI applications in urban extreme heat research and their relationship with the geographical locations of study areas. From the perspective of data source composition, National Meteorological Services and Satellite Remote Sensing constitute the most dominant data sources. Academic Research Institutions and Open-Access Databases also provide substantial preprocessed, quality-controlled secondary datasets, thereby reducing the barriers to data preparation. Some studies further integrate data from Commercial Platforms, Public Health Organizations, and International Agencies. Although these represent a relatively small proportion, they demonstrate an expansion toward multidimensional, comprehensive research that incorporates socioeconomic activities and public health impacts.

Different regions also exhibit distinct patterns of data dependency. Urban research in China primarily relies on official meteorological and remote sensing data, emphasizing high-resolution observational data. Research in the United States, while also depending on meteorological and remote sensing data, shows a greater tendency to utilize academic institutions and open databases, reflecting the diversity of data sources. Europe demonstrates a balanced integration of multiple data types, emphasizing multi-source data integration and analysis.

Fig. A1 illustrates that beyond reliance on meteorological and remote sensing data, studies increasingly address social vulnerability, health risks, and the coupling of urban spatial and environmental pressures. It is worth noting that the data fusion approaches employed in the reviewed studies predominantly rely on feature-level concatenation, late fusion, and simple ensemble strategies. More advanced fusion techniques, such as variational data assimilation methods that enforce physical consistency, graph-based fusion models that capture complex spatial dependencies, and knowledge-graph-supported integration that enables semantic interoperability across heterogeneous sources, remain largely underexplored in the current literature despite their demonstrated potential in related domains. Fig. A2 and Fig. A3 illustrate the types of data spans used in the reviewed studies and the availability of code, respectively.

3.3.2. AI models

Fig. 6 presents the distribution of AI methods and models applied in urban extreme heat research. Overall, supervised learning represents the most widely applied paradigm in this field, with traditional machine learning and deep learning constituting the two dominant branches within this category. Traditional machine learning models, such as

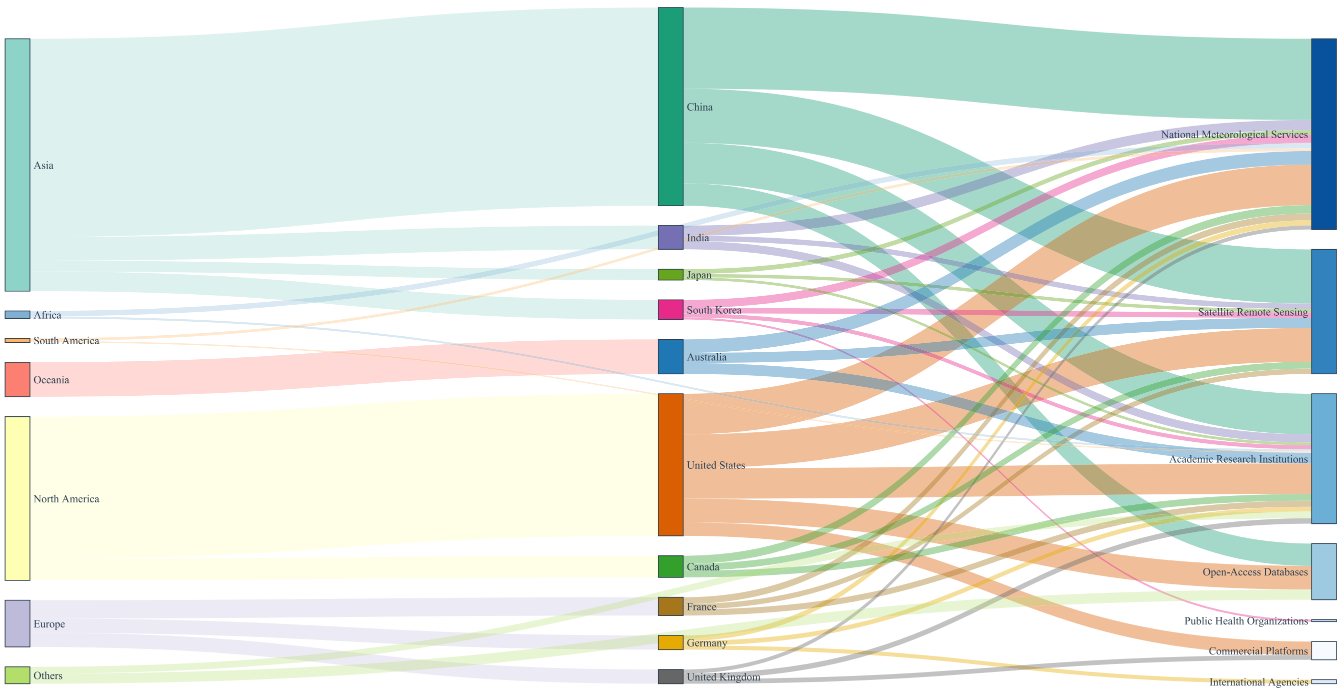

Fig. 5. Sankey diagram of geographic distribution and data sources of reviewed literature.

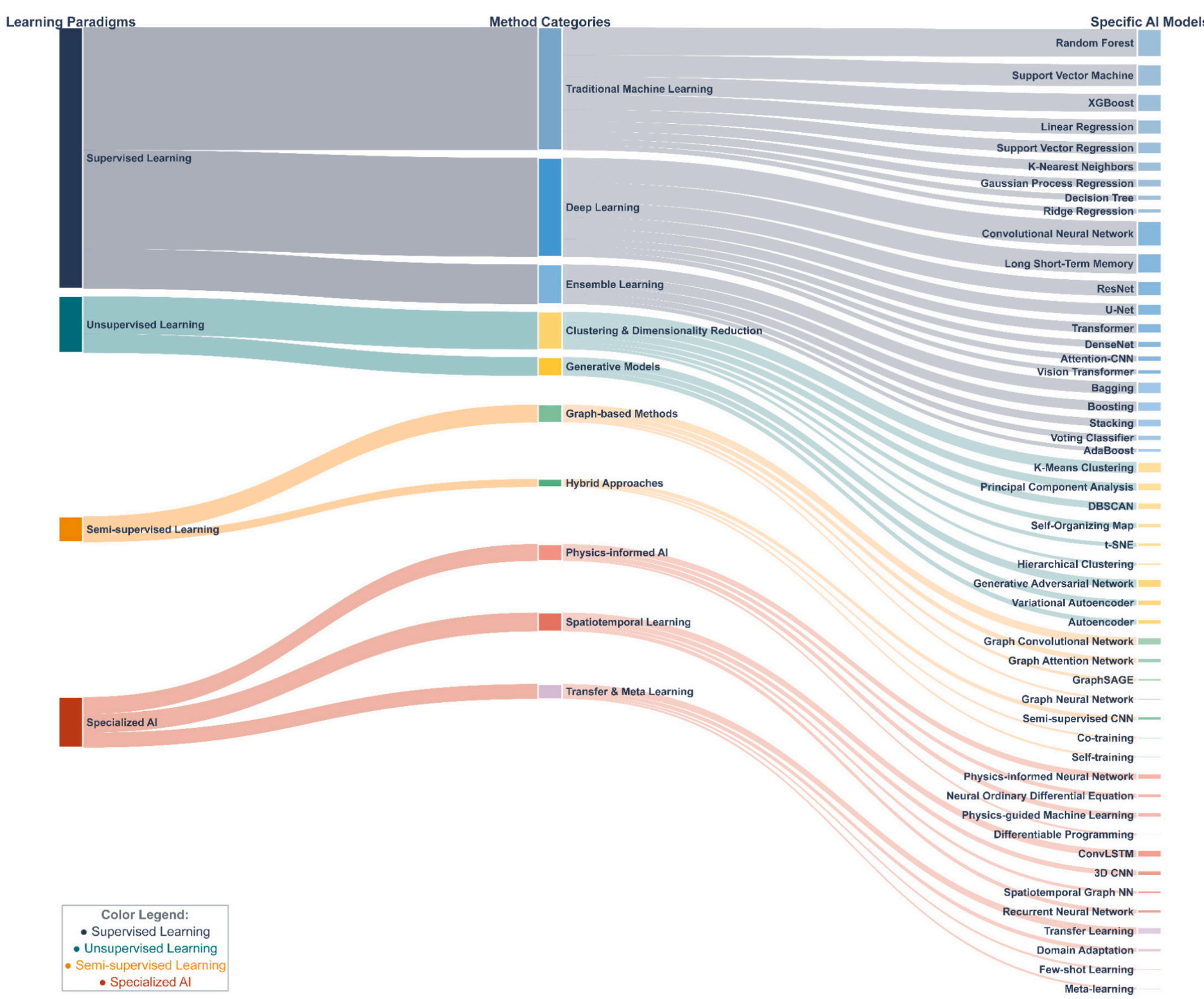

Fig. 6. AI method framework and model distribution in urban extreme heat research.

Random Forest, Support Vector Machine, and XGBoost, maintain a central position in fundamental tasks, including heat risk assessment and driving factor attribution, due to their robustness in handling limited datasets, superior interpretability, and computational efficiency. Deep learning methods are predominantly represented by Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), ResNet, and U-Net. These models can automatically extract multi-scale, high-dimensional spatial and temporal features from data, making them widely applicable in scenarios such as high-resolution thermal field reconstruction, spatiotemporal sequence prediction, and remote sensing image interpretation. Ensemble learning (including Bagging, Boosting, and Stacking) serves as an effective performance enhancement strategy that further improves the generalization capability and robustness of prediction results by integrating the advantages of multiple models.

Unsupervised learning also provides powerful tools for exploring intrinsic data structures, primarily encompassing clustering, dimensionality reduction, and generative models. For instance, methods such as K-means and t-SNE facilitate automatic discovery of latent patterns from large-scale data, providing technical support for tasks including urban functional zone identification and heat island heterogeneity analysis. Generative Adversarial Networks (GANs) and similar models demonstrate potential in data augmentation and scenario simulation. In recent years, to address the challenges of limited labeled data and complex relationships, the application of semi-supervised learning has rapidly developed, particularly models represented by Graph Neural Networks (GCN, GAT, GraphSAGE, etc.), which can effectively model spatial neighborhood relationships and complex network structures, supporting fine-grained characterization of interactions between urban thermal environments and human activities.

Notably, a series of specialized AI methods, deeply integrated with domain-specific problems, are emerging as new research hotspots. Physics-informed AI (such as Physics-informed Neural Networks and Physics-guided Machine Learning) combines physical processes with data-driven approaches, enhancing model generalizability and interpretability. Specifically, these methods embed governing equations such as heat transfer and energy balance constraints as soft constraints in the loss function, enabling models to learn physically consistent representations even with limited training data and to generalize more reliably to unseen climate scenarios. Spatiotemporal learning frameworks, including ConvLSTM and spatial-temporal graph convolutional networks, jointly model the evolution of thermal patterns across space and time, capturing coupled dynamics that conventional approaches cannot represent. Transfer learning enables models pretrained on data-rich cities to be fine-tuned for data-scarce contexts, while meta-learning trains models to rapidly adapt to new urban environments with minimal examples, directly addressing the Northern bias by providing pathways to leverage existing research for global benefit.

4. AI applications in urban extreme heat research

This section will review the current state of AI technology applications in urban extreme heat governance based on the included literature. The content will be organized around four key components: forecasting and early warning, monitoring and assessment, mitigation and adaptation, and scenario simulation and decision support. The analysis will focus on the technical characteristics of different methods and their applicable contexts, while exploring pathways and the practical effectiveness of AI-enabled urban thermal resilience enhancement.

4.1. Forecasting and early warning

Forecasting and early warning refer to the advanced identification of extreme heat events' occurrence timing, intensity, and affected areas by leveraging multi-source data, including meteorological, remote sensing, urban morphological, and social dynamic data, and the timely transmission of risk information to governments and the public through tiered warning mechanisms (Hajat et al., 2010). Against the backdrop of escalating urban extreme heat risks, AI technology has become a core technical approach for establishing efficient urban extreme heat warning systems and enhancing urban climate adaptation capacity, owing to its advantages in multi-source data fusion, complex pattern recognition, and real-time dynamic prediction. Current fusion practices primarily involve feature stacking and model ensembling, while emerging approaches such as physics-informed data assimilation, spatiotemporal graph neural networks, and attention-based cross-modal fusion offer promising directions for improving prediction consistency across heterogeneous data sources (Bi et al., 2023; Lopez-Gomez et al., 2023). Related research exhibits distinct methodological differences in modeling approaches, primarily including modeling methods based on traditional machine learning and explainability techniques, complex feature learning prediction mechanisms based on deep learning, and hybrid modeling frameworks that integrate the advantages of different models to achieve spatiotemporal collaborative prediction (Krishnaraj et al., 2025; Rashtian et al., 2025; Shen et al., 2024). These methods not only demonstrate different characteristics in prediction accuracy and generalization capability but also show differences in functional emphasis, collectively expanding the applicable scenarios and response timeliness of urban heat warning systems.

Methods represented by traditional machine learning models are widely adopted in heat prediction due to their high modeling efficiency and strong feature interpretability, primarily applied in short-term urban heat prediction tasks with low data dimensionality or requiring strong interpretability. Algorithms such as Random Forest (RF), Light Gradient Boosting Model (LGBM), Extreme Gradient Boosting (XGBoost), and CatBoost demonstrate good robustness when processing multidimensional static and dynamic variables, while requiring modest computational resources and moderate labeled datasets, making them feasible for real time applications in resource constrained settings (Chongtaku et al., 2024; Oliveira et al., 2022; Rashtian et al., 2025; Shen et al., 2024; Varentsov et al., 2023). Research typically uses ground observation data, remote sensing temperature data, urban surface and morphological factors as input features to predict target temperature variables such as land surface temperature, 2-m air temperature extremes, or urban heat island intensity. RF was used in one study to downsample numerical weather prediction (NWP) data, successfully improving temperature prediction accuracy from 2.5 km to 250 m, achieving effective identification of local heat hotspots during high-temperature periods and significantly enhancing warning precision at the urban level (Oliveira et al., 2022). Additionally, these models often combine with explainability tools such as SHAP to analyze the marginal contributions and influence mechanisms of variables like vegetation coverage and building density on prediction results, providing decision support for spatial heterogeneity identification and intervention strategies (Lee et al., 2024; Shen et al., 2024).

Compared to machine learning models, deep learning models play an important role in urban heat risk prediction with their stronger nonlinear modeling capabilities and high-dimensional feature learning advantages. Particularly when processing high-frequency time series data and high-resolution image data, deep neural networks possess obvious performance advantages. Convolutional Neural Networks (CNN) are widely used to extract spatial features from remote sensing images, supporting the identification of high-risk areas from urban-scale LST images or downsampling reanalysis data to fine-scale block-level heat exposure maps (Johannsen et al., 2024). Temporal models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are suitable for processing hourly to daily-scale air temperature and heatwave trend prediction tasks, though they require substantial labeled data and GPU-accelerated infrastructure, offering superior accuracy when sufficiently high-resolution dense data are available (Qureshi et al., 2025; Krishnaraj et al., 2025; Tehrani et al., 2024; Zuccarini, 2024). For example, Krishnaraj et al. (2025) integrated LSTM into a multi-technology fusion microclimate management system, utilizing its temporal modeling capability to accurately predict environmental variables such as temperature and humidity, and combined with IoT data collection and blockchain secure transmission to construct an intelligent environmental control framework with real-time response.

As urban data structures become increasingly complex, more research is beginning to explore fusion methods of multiple AI models, forming ensemble modeling systems. Beyond model ensembling, hybrid approaches that couple data-driven AI with process-based physical models are emerging, where numerical weather prediction outputs serve as physics-based constraints or initial conditions for machine learning refinement, enabling the preservation of physical consistency while leveraging AI capabilities for bias correction and downscaling. These models typically embed different types of models through multi-module collaborative approaches, fully utilizing their respective advantages to enhance overall prediction capability, particularly suitable for constructing urban warning systems under multi-source heterogeneous data scenarios. Mukarram et al. (2025) hybridized traditional ML with deep learning, using LSTM to capture trends and cyclical components in temperature time series, then feeding its output as input to XGBoost for final prediction, achieving dual representation of spatial and temporal features. Other research adopts functional division-based hybrid frameworks of multiple deep learning models: a U-Net and ConvLSTM hybrid modeling framework was used to predict marine heatwave intensity and occurrence probability, respectively, in the South China Sea region, achieving comprehensive prediction through dual-model collaboration (Sun et al., 2023).

4.2. Monitoring and assessment

Monitoring and assessment aims to characterize spatiotemporal patterns of thermal environments, quantify population exposure levels, and determine comprehensive risks by integrating social vulnerability through continuous observation and analysis, providing evidence to support subsequent interventions (Reid et al., 2009; Yoo et al., 2023). The application of AI in urban extreme heat monitoring and assessment is progressively evolving from static “thermal environment characterization” toward dynamic “heat-population coupled risk identification.” Core tasks primarily encompass thermal environment monitoring, heat exposure identification, and heat health risk assessment, combined with social vulnerability (Li et al., 2024; Ma et al., 2025). In terms of technical approaches, while traditional statistical models are still applied in some studies, machine learning and deep learning methods represented by RF and U-Net have become the mainstream technical pathways. These methods demonstrate significant advantages in enhancing spatial monitoring accuracy, modeling complex nonlinear relationships, and analyzing social-environmental interaction mechanisms, helping relevant institutions effectively construct high-resolution heat risk monitoring systems.

In thermal environment monitoring and heat exposure identification, AI technology has overcome the limitations of traditional remote sensing in spatiotemporal continuity. Research combines models such as RF and U-Net with multi-temporal Landsat or Sentinel thermal infrared imagery, integrating ground observation data for inversion analysis to achieve continuous spatial reconstruction of LST and urban heat island intensity (Puttanapong et al., 2025; Shaamala et al., 2025). For example, Puttanapong et al. (2025)’s study of the Bangkok metropolitan area demonstrated that models including RF, GTB, and SVM exhibit excellent performance in integrating remote sensing spectral indices with temperature estimation, accurately capturing the contributions of different urban surface types to heat island effects. Meanwhile, the U-Net model showed extremely high efficiency in high-resolution urban heat mapping tasks in the Adelaide metropolitan area of South Australia, completing entire image processing in less than 30 s while maintaining stable prediction accuracy (Shaamala et al., 2025). Comparing these approaches, traditional machine learning models such as RF and XGBoost offer advantages in interpretability, lower computational costs, and robustness with smaller datasets, making them suitable for tabular data analysis and feature importance identification, whereas deep learning architectures like U-Net excel in processing high-dimensional imagery data and capturing complex spatial patterns but require larger training datasets and greater computational resources. Heat exposure identification has further promoted the transition from traditional static indicators toward dynamic and refined approaches. Models such as XGBoost, stacked ensemble learning, and geographically weighted random forest are widely used to construct multidimensional heat exposure assessment systems, achieving separate modeling of daytime and nighttime exposure patterns by integrating dynamic population distribution, meteorological elements, and urban spatial environmental characteristics (Erdem Okumus and Akay, 2025; Ma et al., 2025; Yoo et al., 2023).

In heat health risk and social vulnerability assessment, AI models are widely applied to identify impact mechanisms linking environmental exposure with population sensitivity. One typical approach combines thermal environment variables such as LST and SUHI with socioeconomic data, employing interpretable machine learning or geospatial explainable artificial intelligence models to identify key risk factors affecting heat-related health outcomes. Foroutan et al. (2025) used GeoShapley methods and SHAP value analysis to examine spatial heterogeneity between urban and rural areas, discovering significant differences in high-temperature health risk factors between these two types of regions, providing scientific evidence for regionalized public health intervention strategies. Li et al. (2024) proposed the U-HEAT framework, integrating multiple models, including support vector machines, RF, and CNN, combined with remote sensing and geographic data for classification modeling of urban heat vulnerability, achieving spatial identification of heat-vulnerable populations. Building on this foundation, some studies further introduce high-order spatial relationship modeling approaches to enhance model capability in identifying complex human-environment coupling patterns. A study based on Greater London constructed a Multi-Hypergraph Neural Network (MHGNN) framework, integrating street view images with geospatial multi-source information, effectively capturing structural patterns of urban heat-flood compound vulnerability by mining spatial proximity and high-order dependencies of urban neighborhoods, demonstrating superior performance in urban climate justice analysis (Liu et al., 2025).

Notably, some studies incorporate social media data into monitoring and assessment systems to capture residents' subjective perceptions and behavioral responses to extreme heat events. Natural language processing technologies, particularly deep semantic models based on BERT and RoBERTa, are used to extract sensitivity and emotional information from microblog data. While both models demonstrate strong capabilities in contextual understanding, BERT is more computationally efficient and suitable for standard sentiment classification tasks, whereas RoBERTa offers improved performance on nuanced semantic analysis through its optimized pretraining strategy, though at the cost of increased computational demands and data requirements. For example, Zhi et al. (2021) utilized BERT to analyze urban residents' sensitivity levels to heatwave events and linked this with land surface temperature data obtained from remote sensing, revealing spatial heterogeneity characteristics of heatwave sensitivity. Another study employed RoBERTa models combined with hotspot analysis and Apriori association rule mining methods to identify interaction mechanisms between different urban functional zones and residents' emotional changes, revealing the role of functional spatial structures in shaping emotional health differences during heatwave periods (Y. Zhu et al., 2024b).

4.3. Mitigation and adaptation

Mitigation and adaptation, as core strategies for addressing urban extreme heat, emphasize proactive responses to current and future extreme heat impacts through adjustments to urban systems, infrastructure, and management approaches, aiming to enhance urban thermal resilience and resident welfare (Kumar et al., 2024). In recent years, AI applications have not only achieved precise identification of cooling thresholds for green-blue infrastructure but also promoted fine-tuned regulation of urban structural elements (Feng et al., 2024; Han, 2023). Simultaneously, the deep integration of generative AI with climate models has opened new pathways for climate-adaptive urban design, enabling dynamic assessment of different morphological impacts on thermal environments and optimization of design solutions during the planning phase (Zhou et al., 2025; Aydin et al., 2024; F. Jiang et al., 2024b). Through multi-model collaboration based on machine learning, deep learning, and evolutionary algorithms, AI has further enhanced the capability to characterize cooling elements and their spatial heterogeneity, providing efficient and intelligent solutions for key aspects, including urban planning, green infrastructure layout, and adaptive strategy selection.

AI is widely applied to optimize the planning and design of blue-green infrastructure to maximize its ecosystem service functions. At the macro level, AI models can determine vegetation coverage thresholds required to achieve maximum cooling benefits under different climatic contexts. For example, one study utilized Boosted Regression Trees (BRT) models, which balance predictive accuracy with interpretability and computational efficiency, to precisely calculate that dry-hot cities require ideal vegetation coverage of 30–40% through analysis of urban two-dimensional and three-dimensional landscape indicators, while humid-hot cities need as high as 60–80% to achieve optimal cooling effects (Ren et al., 2024). In specific urban park design, Yang et al. (2025) similarly employed BRT models to reveal that park area, shape, edge density, and internal vegetation and water body proportions are key variables affecting "cool island" intensity through analysis of park landscape patterns along urban-rural gradients. To address regional variations, researchers have also applied geographically weighted random forest models, which, due to their advantages in capturing spatial heterogeneity, can provide differentiated and refined green space configuration recommendations based on specific conditions of different urban functional zones such as commercial and industrial areas (Zhang et al., 2025). AI applications have been refined to the individual tree level, where Das et al. (2022) combined geospatial artificial intelligence with the deep learning model Faster R-CNN to successfully achieve automatic identification and inventorying of urban trees through analysis of high-resolution aerial images, thereby quantifying the cooling contributions of specific tree species. For green roofs as a specific mitigation measure, artificial neural networks (ANN) are used to integrate LiDAR and satellite imagery data to assess their cooling potential under different building heights, sky view factors, and solar radiation conditions, ultimately recommending priority implementation on mid-rise buildings for optimal benefits (Kafy et al., 2024).

Researchers can also identify key heat mitigation factors in built environments through AI and use this guidance for comprehensive renovation of built-up areas and innovative design of future urban forms. Various machine learning models are effectively used to analyze complex nonlinear relationships between urban morphology and thermal environments. Research employing Gradient Boosting Decision Trees (GBDT) successfully identified that vegetation index (NDVI) and green space proximity are important nonlinear factors affecting land surface temperature (Kim, 2024). Similarly, ensemble learning models are used to deconstruct multiple driving factors, clearly indicating that morphological factors such as building density and floor area ratio significantly exacerbate extreme heat, while green spaces and water bodies provide crucial mitigation effects (Liu et al., 2024). Building on this foundation, with the aid of explainable AI tools such as SHAP, researchers can further quantify the specific weights of these urban design elements on urban heat, helping urban planning departments formulate more precise intervention strategies (Li et al., 2025). Furthermore, AI technology is further applied to guide the comprehensive renovation of built-up environments and innovative design of future urban forms. Through analysis of Local Climate Zones (LCZ), AI evolutionary algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) can explore and optimize combinations and spatial layouts of different LCZs to achieve the overall goal of mitigating heat island effects (Mohamed and Zahidi, 2024). More forward-looking research explores how to deeply integrate generative AI with climate models to achieve innovative climate-adaptive urban design. Wang et al. (2025) constructed a hybrid Generative Adversarial Network (GAN) framework combining Pix2pix and CycleGAN, integrating morphology generation with performance assessment to dynamically examine the impacts of different urban designs on heat island intensity, achieving climate-responsive optimization of urban forms during the early planning stage.

4.4. Scenario simulation and decision support

Scenario simulation and decision support refer to constructing urban thermal environment evolution models under different development scenarios, analyzing the potential effects of various intervention measures, and providing scientific decision-making evidence and tool support for policymakers, planners, and managers (D'Ambrosio et al., 2023; Pan et al., 2024). In this field, AI applications are driving a transformation of traditional urban management toward more forward-looking, interactive, and scientific paradigms. AI not only provides key insights for long-term strategic planning through complex scenario simulations but also extends decision support to multiple levels, including real-time operations and public participation through innovative forms such as digital twins and interactive tools, significantly enhancing the intelligence level of urban thermal environment governance (Elnabawi and Raveendran, 2024; Luo et al., 2025; Ye et al., 2025a).

Scenario simulation represents one of the core applications of AI-enabled strategic decision-making. By integrating multidimensional data, including land use, climate change, and socioeconomic factors, machine learning models can simulate and predict future thermal environments under different development pathways. Researchers have successfully predicted the evolution trends of land surface temperature and heat island intensity over the coming decades under different urban expansion and land use change scenarios using models such as Artificial Neural Networks (ANN) and Cellular Automata (CA) (Ashwini et al., 2024). Additionally, Lan et al. (2023) combined Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to conduct spatially explicit predictions of urban heat island risks and population exposure under different climate-socioeconomic policy combinations through ANN models, helping decision-makers formulate more effective macro-level climate adaptation policies.

Urban digital twins, as an advanced decision support platform, are becoming an important vehicle for AI applications, offering advantages over traditional scenario modeling approaches such as ANN-based simulations in terms of real-time responsiveness and interactive visualization capabilities. They can integrate high-precision three-dimensional urban models, real-time sensor data, and climate simulation models to construct a virtual city parallel to the physical world, though their implementation requires significantly higher data infrastructure investments compared to standalone predictive models. Within this virtual environment, managers can test the impacts of different long-term planning scenarios (such as increasing green spaces or changing building layouts) on heat island distribution and intuitively assess their effectiveness through visualization (Vitanova et al., 2025). This technology's application is further deepening toward real-time operational decision-making. A typical example is the application of Smart City Digital Twin (SCDT) systems, which not only contain static urban models but also utilize computer vision algorithms (such as YOLOv3) to analyze real-time pedestrian flow data and combine meteorological data with time series forecasting models (such as SARIMA) to assess and predict short-term collective heat exposure risks in specific areas (Pan et al., 2024). This real-time analysis and prediction capability enables managers to conduct preventive interventions, issuing timely warnings or deploying mobile cooling facilities when high heat exposure risks are predicted, achieving a decision-making closed loop from long-term planning to immediate response.

AI has also spawned a series of intelligent decision support tools covering professional planning to public participation. For professional planners, these tools provide highly specialized solutions. For example, Kumar and Mishra (2025) constructed urban heat vulnerability indices based on fuzzy logic and Analytic Hierarchy Process (AHP) to support priority intervention area ranking under resource-limited conditions. In urban infrastructure management, AI optimization methods such as column generation algorithms are used to enhance public transportation system service resilience under high temperatures by optimizing routes and frequency schedules to provide safer travel options for citizens (Huang et al., 2024). More importantly, AI applications are not limited to the expert level but are also becoming an important bridge for promoting public participation and enhancing community climate resilience. One innovative practice designed interactive workshops combining AI and LEGO blocks, where participants build LEGO cities representing different land uses, and a simplified AI model instantly calculates and visualizes the temperature distribution of their designed cities (Covaci et al., 2024). This educational and entertaining approach significantly lowers the threshold for understanding climate science and stimulates public enthusiasm for participating in urban climate adaptation actions. However, the practical integration of such participatory outputs into formal planning processes remains challenging, as systematic mechanisms for translating public inputs into actionable policy recommendations are still lacking in most urban governance frameworks. This trend aligns with the broader shift toward digital, interactive approaches in environmental impact assessment, where emerging platforms have shown potential to enhance public engagement, though challenges remain in ensuring accessibility across different age groups and digital literacy levels (Northmore and Hudson, 2022).

5. Discussion

5.1. Challenges and gaps in current research

Synthesizing across all four governance components, core bottlenecks emerge at both data and model levels. At the data level, persistent challenges include acquisition constraints (high sensor costs, limited satellite revisit frequencies), quality issues (measurement uncertainties, missing values, inconsistent calibration), and fusion difficulties (reconciling different spatiotemporal resolutions and semantic definitions). At the model level, key challenges include the accuracy-efficiency tradeoff, interpretability limitations of black-box architectures, generalization failures across different urban contexts, and insufficient uncertainty quantification for risk-based decision-making. In forecasting and early warning, AI applications face core challenges, including the balance between prediction accuracy and computational efficiency, insufficient multi-scale prediction capabilities, and difficulties in quantifying uncertainties in extreme event prediction. While deep learning models excel in complex nonlinear relationship modeling, their high computational complexity conflicts with the real-time response requirements of urban heat warning systems. Particularly in high-resolution multi-source data fusion scenarios, models such as LSTM and CNN often require lengthy training times, making it difficult to support rapid warnings for sudden heatwave events (Johannsen et al., 2024; Krishnaraj et al., 2025; Tehrani et al., 2024). Furthermore, urban heat phenomena exhibit significant scale differences from microclimate to macro patterns, but current AI models typically only cover specific scales. Although random forest based on NWP data can downsample spatial resolution to the hundred-meter level, its accuracy and application at street or building scales remain limited (Oliveira et al., 2022). This scale limitation not only affects spatially refined warnings but also constrains differentiated services for different user groups. Notably, existing research focuses primarily on improving prediction accuracy while lacking systematic quantification of prediction uncertainties (Sun et al., 2023; H.-C. Zhu et al., 2024a). AI models often output results with high confidence but lack reliable uncertainty estimates, leading decision-makers to potentially underestimate risks or create imbalanced resource allocation during emergency responses.

AI challenges in monitoring and assessment primarily stem from multi-source data fusion, quantification of socioeconomic dimensions, and the dynamism and precision of assessment results. From a technical perspective, most existing studies adopt relatively straightforward fusion strategies, including early fusion (concatenating raw features), late fusion (combining model outputs), and weighted averaging. However, more sophisticated methodologies, such as variational and ensemble-based data assimilation for enforcing physical constraints, heterogeneous graph neural networks for modeling cross-source relationships, and knowledge-graph-based frameworks for semantic alignment and ontology-driven integration, have been rarely employed in urban heat research. This methodological gap limits the capacity to effectively reconcile discrepancies in spatiotemporal resolution, measurement uncertainty, and semantic granularity across diverse datasets, thereby constraining the accuracy and reliability of integrated risk assessments. Monitoring and assessment heavily rely on remote sensing, ground observations, and statistical data, but these data sources are difficult to fully match in terms of spatiotemporal resolution, accuracy, and coverage, limiting dynamic and precise assessment of heat exposure. While models based on U-Net can efficiently produce maps, their effectiveness is constrained by the availability of high-quality imagery (Shaamala et al., 2025; Briegel et al., 2023). When incorporating social sensing data, such as social media, to assess public heatwave sensitivity, attention must be paid to issues including user group representativeness bias, data noise, and ambiguous emotional expression (Y. Cheng et al., 2023b; Zander et al., 2023; Zhi et al., 2021). Furthermore, heat health risks are influenced by multiple factors, including environmental exposure, individual physiological sensitivity (such as age and underlying diseases), and social adaptive capacity (such as housing conditions, air conditioning rates, and community support). Current AI models have limited capability in quantifying these complex, spatially heterogeneous socioeconomic vulnerabilities, often relying on crude proxy variables such as census data, making it difficult to reveal fine-grained differences at household or individual levels.

In mitigation and adaptation, core AI application challenges include causal inference in intervention effect assessment, the practical feasibility of optimization or automated solution generation, and the complexity of multi-objective trade-offs. While AI models can identify associations between green infrastructure and temperature reduction, such as BRT models precisely calculating vegetation coverage thresholds under different climatic contexts (Ren et al., 2024), establishing strict causal relationships remains difficult, limiting the reliability of AI technology in intervention strategy optimization. Urban morphology or green space layout solutions generated by AI optimization algorithms (such as genetic algorithms) (Mohamed and Zahidi, 2024) may theoretically achieve optimal cooling effects but face practical constraints, including land ownership, construction costs, and conflicts with other planning objectives. The application of generative AI in climate-adaptive urban design is still in the exploratory stage, and the practicality and controllability of generated solutions require extensive validation (Wang et al., 2025; Richards et al., 2024). It cannot be overlooked that urban heat mitigation often requires balancing goals such as improving transportation accessibility and ensuring housing supply, yet most current AI models have limited capability in handling such multi-objective, multi-constraint problems.

AI has driven innovative applications, including digital twins, interactive platforms, and multi-scenario decision tools in urban heat scenario simulation and decision support, but its limitations are primarily reflected in future uncertainties, practical implementation of decision support tools, and fairness in technology application. AI-based scenario simulations heavily depend on input future climate change pathways (RCPs) and socioeconomic development pathways (SSPs) (Lan et al., 2023), and these pathways themselves contain enormous uncertainties that amplify with extended prediction timeframes, thereby affecting simulation result reliability. For decision platforms such as urban digital twins, their high construction costs, large data requirements, and high maintenance demands (Pan et al., 2024; Vitanova et al., 2025) make widespread adoption difficult in small and medium-sized cities. Even well-designed decision support tools depend on effective integration into existing urban governance frameworks for actual application effectiveness. How public opinions can be systematically transformed into legally effective policy recommendations or incorporated into official planning processes remains an open governance challenge (Covaci et al., 2024).

Comprehensively, deeper limitations lie in the current research's lack of holistic modeling that views urban heat risk chains as multi-stage, dynamic feedback complex systems (Brelsford et al., 2024; Westra and Zscheischler, 2023). Most AI-enabled research focuses on single-point optimization of specific segments or tasks, with relatively independent components. This results in high-precision time series predictions from warning models being difficult to directly and dynamically input and update spatial risk assessment models, while high-risk communities identified by assessment models often cannot automatically optimize mitigation and adaptation strategies, hindering translation to actual risk management. It should be emphasized that urban extreme heat phenomena involve complex mechanisms coupling climate, land use, socioeconomic factors, infrastructure, and health elements. Current AI models generally have a shallow theoretical understanding of these multi-scale, cross-domain interactions, often overlooking key cyclical feedback within systems. Similarly, social vulnerability is not static; during sustained heatwaves, community response capacity and resources evolve dynamically, but most assessment models fail to capture this process.

5.2. Opportunities and future research directions

Despite current challenges facing AI applications in urban extreme heat research, the field presents new development opportunities driven by rapid AI technological advancement, continuously enriched multi-source data resources, and growing demands for urban climate adaptation and health resilience. Leveraging cutting-edge AI algorithms and higher-quality, multidimensional data, the future holds promise for achieving deep integration of physical environmental and social vulnerability information, driving research paradigm shifts toward causal inference, multi-objective optimization, and generative design, accelerating the integration of intelligent decision support systems for urban heat, and gradually realizing upgrades from fragmented applications to integrated systems.

First, constructing comprehensive data frameworks that integrate physical environmental and social multidimensional information will help AI models advance from macro thermal effect simulation toward fine-grained risk prediction for communities and individuals. Deepening AI integration with meteorological physical models, combined with multi-source physical data from satellite remote sensing, ground sensor networks, and urban Internet of Things, can significantly enhance the spatial resolution and generalization capabilities of heat prediction (Briegel et al., 2024; Gong et al., 2025). Feasible integration strategies include data assimilation frameworks such as ensemble Kalman filters that optimally combine observational data with physical model forecasts, hybrid sequential architectures where physical models generate initial predictions subsequently refined by neural networks, and physics-informed neural networks that embed energy balance equations directly into loss functions to ensure thermodynamic consistency. Transfer learning and meta learning are particularly critical for global equity as these techniques enable knowledge transfer from well-studied contexts to underrepresented regions without requiring equivalent data investments, systematically addressing the geographic imbalances documented in this review. To fully realize these benefits, future research should systematically explore and compare advanced data fusion paradigms. For instance, 4D-Var and ensemble Kalman filter data assimilation techniques can integrate observational data with numerical models while preserving physical consistency. Graph-based fusion architectures, including heterogeneous graph neural networks and spatial-temporal graph convolutional networks, can effectively capture complex dependencies across multi-modal urban data. Furthermore, knowledge graph frameworks can provide semantic scaffolding that enables ontology-driven integration, facilitating interoperability between datasets with different terminologies and measurement protocols. Systematic benchmarking of these fusion approaches across diverse urban contexts would provide valuable guidance for method selection in practical applications. Further integration with advanced methods, such as Bayesian deep learning to quantify uncertainties in prediction results, will provide more reliable decision support for warning systems (Abdar et al., 2021). Simultaneously, a comprehensive heat risk assessment requires a deep understanding of human social vulnerability. With the proliferation of social media and health monitoring devices, residents' subjective thermal perception, emotional changes, and real-time behaviors have become new critical dimensions. As noted in “Atlas of the Senseable City” (Picon and Ratti, 2023), massive urban real-time data is depicting a new urban map reflecting social dynamics, enabling observation of previously invisible urban pulses. Therefore, future research can utilize AI technologies such as natural language processing and graph neural networks to combine these dynamic social sensing data with environmental exposure data, achieving dynamic tracking and a more refined assessment of human-environment coupled risks (Y. Cheng et al., 2023b; Zhao et al., 2025).

Enhancing AI capabilities in formulating heat mitigation and adaptation strategies requires future research to urgently expand from traditional correlation analysis to deeper causal inference, shift from single-objective assessment to multi-objective collaborative optimization, and efficiently explore innovative cooling design solutions through generative AI. Effective heat mitigation strategies depend not only on understanding correlations between variables but also on revealing underlying causal mechanisms. Integrating algorithms such as causal inference, multi-objective optimization, and reinforcement learning helps dynamically assess comprehensive effects of multiple intervention measures, enhancing intelligent decision-making capabilities (Risser et al., 2025; Li et al., 2022; Li and Cheng, 2025). In practice, attempts can be made to deeply integrate physical process modeling, social-environmental system dynamics, and AI methods to achieve dynamic simulation of multiple elements, including climate, energy, health, and social behavior. Emerging methods such as generative AI and evolutionary algorithms also provide efficient design pathways for collaborative optimization of urban morphology and adaptive infrastructure (Makki et al., 2019; Wang et al., 2025). These technologies can automatically explore innovative design combinations, improving urban cooling effects and spatial utilization efficiency through intelligent iteration. However, practical application of these innovative methods still requires addressing real-world constraints, cost-benefit considerations, and multi-objective conflicts to enhance solution feasibility.

Advancement of intelligent decision support systems and digital twin technologies provides important platforms for AI-enabled heat governance while offering opportunities to break through current research bottlenecks of fragmented segments lacking systematic coordination. This aligns closely with core viewpoints in “Introduction to Urban Science” (Bettencourt, 2021), which views cities as information processing systems forming complex feedback loops between people, physical environments, and infrastructure. Based on this perspective, the future key lies in constructing systematic AI frameworks capable of connecting multi-stage risk management processes with dynamic feedback mechanisms. Through integration of multi-source real-time data, intelligent scenario simulation engines, and interactive visualization tools, organic coordination of forecasting and warning, monitoring and assessment, mitigation and adaptation, and decision support can be achieved, ultimately forming complete closed loops from risk identification to intelligent response (Batty, 2018; Pan et al., 2024). In practical applications, high-precision heatwave warnings can automatically trigger real-time vulnerability assessments for specific communities and dynamically optimize cooling center operations and mobile cooling facility deployment accordingly, achieving effective integration of risk perception and intelligent response. At the technical implementation level, promoting data standardization and model component modularization is necessary to facilitate open sharing of tool chains, establishing technical foundations for multi-departmental collaboration and cross-sectoral governance (Goodchild and Li, 2021; Ye et al., 2025b). Similar calls for methodological standardization and improved study design have been emphasized in environmental monitoring contexts, where inconsistent protocols hinder cross-study comparability and limit the broader utility of collected data (Martins et al., 2023). Decision-makers should also actively explore new models of participatory planning and public empowerment, promoting bottom-up risk consensus building and collaborative governance to enhance social resilience (Evans et al., 2016). Realizing the full potential of these advanced paradigms requires coordinated investment in open data sharing, benchmark dataset development spanning diverse urban contexts, and reproducible model implementations that facilitate systematic comparison of methods across different cities and climatic conditions. Sustainability issues, including ethical responsibility, privacy protection, and carbon footprints in AI governance, should also receive high attention, collectively promoting the construction of inclusive, equitable, and green intelligent heat governance systems (Vinuesa et al., 2020).

5.3. Limitations of this review

This review has certain limitations, and future research can be further improved and expanded in terms of diversifying literature types, in-depth analysis of model mechanisms, and AI ethical and moral assessment. First, the literature search and screening process mainly relied on English databases and mainstream international journals, which may have missed some unpublished works, regional journals, or non-English literature, resulting in certain language and regional biases in research coverage. Additionally, due to the high heterogeneity among different studies in terms of model methods, data types, spatial scales, and evaluation metrics, this paper faces difficulties in conducting in-depth comparisons and quantitative assessments of all technical details and specific cases during the synthesis and summarization process. Finally, although the focus of this paper is not to deeply explore the ethical risks and data privacy protection of AI models, social governance issues such as fairness and sustainability should still receive more attention.

6. Conclusions

This study conducted a comprehensive analysis of the application of artificial intelligence (AI) in urban extreme heat research through a systematic literature review methodology. Following the PRISMA guidelines, we conducted searches in the Scopus database and ultimately included 102 high-quality publications. Based on systematic analysis, we constructed a comprehensive framework for AI-enabled urban extreme heat governance, categorizing applications into four components: prediction and early warning, monitoring and assessment, mitigation and adaptation, and scenario simulation and decision support. We documented the basic information, data characteristics, technical methods, and application scenarios of the research.

The results indicate that AI technologies demonstrate significant advantages across all components. In prediction and early warning, models such as Random Forest and XGBoost are suitable for short-term forecasting due to their efficiency and interpretability, while CNN and LSTM show greater advantages in complex spatiotemporal features and high-resolution prediction. Hybrid modeling further enhances accuracy and generalizability. In monitoring and assessment, AI has overcome the spatiotemporal limitations of traditional remote sensing, achieving a transition from static characterization to dynamic heat-population risk identification, and capturing residents' subjective perceptions through social media data. In mitigation and adaptation, AI identifies optimal thresholds for green-blue infrastructure, promotes urban morphological factor regulation, and generative AI also provides new pathways for adaptive design. In scenario simulation and decision support, digital twins and interactive platforms cover strategic planning and operations, promoting the integration of professional and public engagement. However, applications still face challenges, including the balance between accuracy and efficiency, multi-source data fusion, insufficient causal inference, implementation barriers, and a lack of comprehensive system modeling capabilities.

Future research should focus on constructing a more comprehensive, intelligent, and sustainable AI-driven urban heat governance system. The primary task is to establish a comprehensive data framework that integrates physical environmental and multi-dimensional social information. Through deepening the integration of AI with meteorological physical models and introducing uncertainty quantification, we can achieve a transition from macroscopic thermal effect simulation to fine-grained risk prediction. At the technical level, we need to promote a paradigm shift toward causal inference, multi-objective optimization, and generative design, exploring innovative cooling design solutions. More critically, we must construct a systematic AI framework that links multi-stage risk management processes, forming a complete closed loop from risk identification to intelligent response. This development direction is highly aligned with the United Nations Sustainable Development Goals of Good Health and Well-being (SDG 3), Sustainable Cities and Communities (SDG 11), and Climate Action (SDG 13).

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.

Appendix A. Appendix

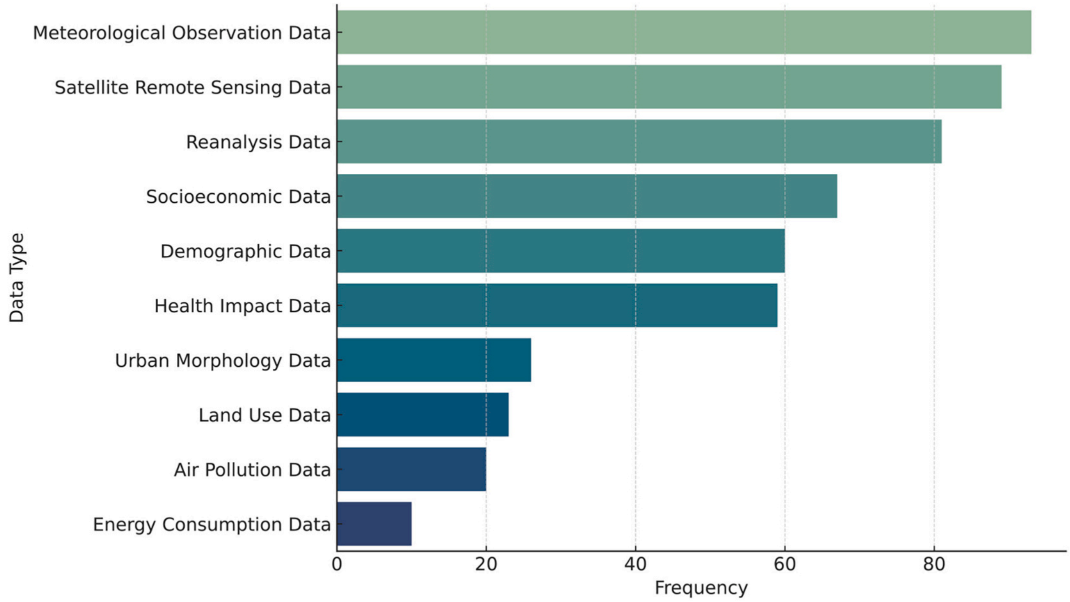

Fig. A1. Data types.

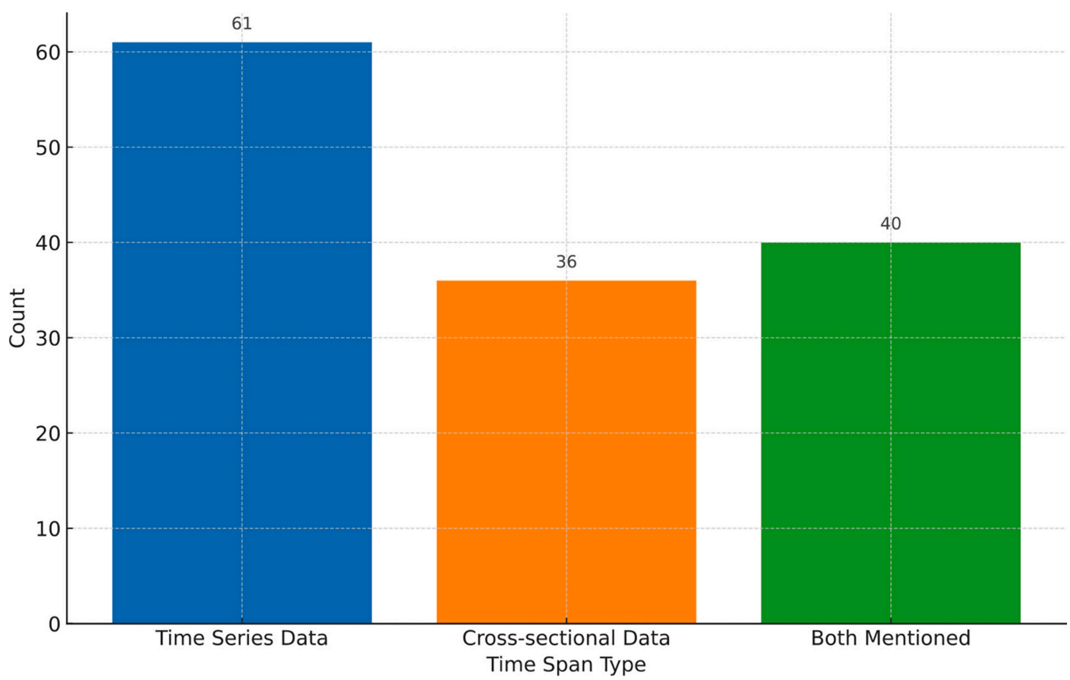

Fig. A2. Time span types.

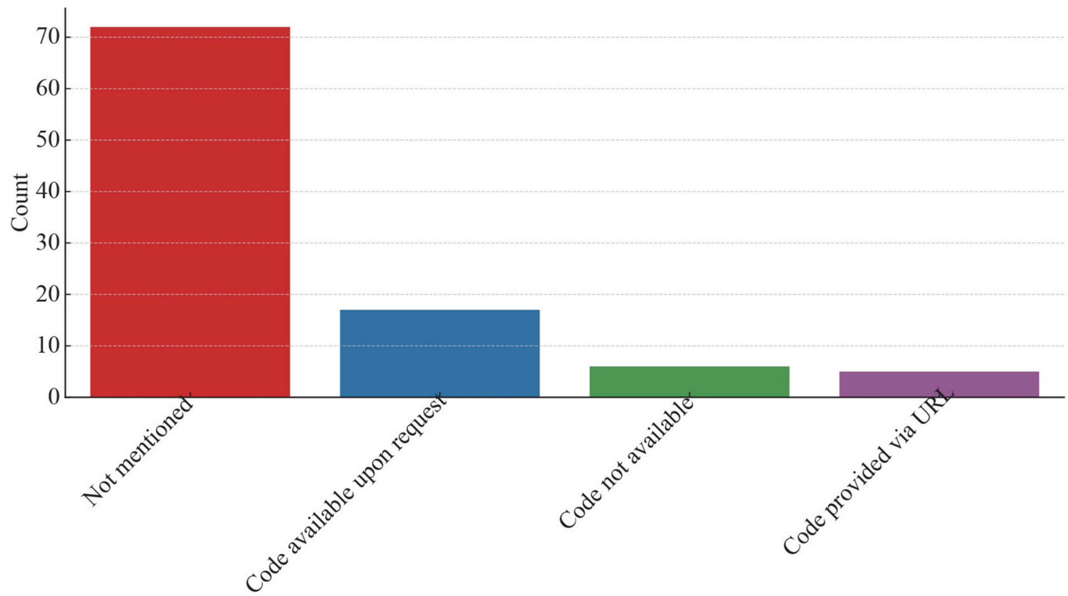

Fig. A3. Code availability.

Appendix B. Supplementary data

Supplementary material to this article can be found online at https://doi.org/10.1016/j.eiar.2026.108363.

Data availability

Data will be made available on request.

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