Assessing the role of AI in Heat Mitigation and Adaptation

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Abstract

Climate change, a critical global challenge addressed by the United Nations Sustainable Development Goal 13 (SDG 13), is driving a significant rise in global temperatures. Since the pre-industrial era, the Earth's average surface temperature has increased by approximately 1.1°C, with the past decade being the warmest on record. This warming trend, primarily caused by human activities such as greenhouse gas emissions, has far-reaching consequences, including the intensification of heat, especially in cities. Urban areas are particularly vulnerable to rising temperatures due to dense infrastructure, limited vegetation, and heat-retaining surfaces that exacerbate warming. As climate change amplifies extreme heat events, cities face growing challenges in maintaining livability and resilience. This study therefore provides a comprehensive review of Artificial Intelligence (AI) applications in urban heat mitigation and adaptation, analyzing 65 peer-reviewed studies published between 2014 and 2024. The findings reveal a significant increase in research since 2019, with most studies focusing on North America, Europe, and China. AI is primarily used for heatwave and UHI prediction (46%), data analysis to identify key heat drivers and impacts (25%), and data generation for creating new datasets (12%). Machine Learning (ML) techniques, particularly neural networks and decision trees are widely applied to analyze remote sensing and weather data for urban heat mapping and forecasting. Despite AI's potential to enhance urban heat management—through decision-making frameworks and optimized urban layouts—several research gaps remain. Most studies prioritize heat mitigation (58%) over adaptation (40%), with limited focus on integrating both approaches. Additionally, there is a lack of research on AI applications in tropical regions and on the practical implementation of AI-driven strategies. These findings underscore the need for further research on translating AI-driven insights into actionable solutions, particularly in the Global South, where rising urban temperatures pose increasing risks to public health and infrastructure.

Keywords: Artificial Intelligence, Machine Learning, Heat Mitigation, Heat Adaptation, Urban Heat

Introduction

Temperatures, Atmospheric Heat and Climate Change

Imbalances in the Earth's energy budget due to increasing greenhouse gas emissions have resulted in increased temperatures. Since 1982, the overall temperatures on Earth's surface have increased at a rate of 0.36^0C per decade, with the last ten years being the warmest ten years on record. These increases in atmospheric temperatures and GHG emissions, primarily caused by anthropogenic activities, are the leading causes of climate change. In the year 2015, along with the Paris Agreement on climate change, the Sustainable Development Goals (SDGs) were adopted to address a range of global challenges including climate change and environmental degradation. While there are several overlaps and interconnections among these SDGs, the SDG most pertinent to increasing atmospheric heat is SDG 13: Climate Action. The primary objective of this SDG is to implement measures to address climate change by enhancing resilience and adaptive capacities, incorporating climate action into policies and regulations, developing competencies, facilitating and financing climate-change mitigation initiatives, and augmenting capacity.

Climate change and increasing temperatures are observable phenomena in both natural and human-modified built environments. While the impacts in natural environments primarily affect flora and fauna, the effects are most pronounced in built environments such as urban areas. This is primarily attributable to the biophysical and demographic characteristics of cities, which influence the magnitude of heat and the number of individuals affected by this thermal stress. As of 2024, more than 50% of the global population resides in urban areas, a figure projected to increase to approximately 70% by 2050. Urban areas worldwide are simultaneously contributing to and experiencing the effects of climate change, forming a self-perpetuating cycle. A recent study (Wei, Wu, & Chen, 2021) demonstrated that, out of 167 cities studied, 25 megacities accounted for 52% of the total greenhouse gas emissions through stationary energy use (buildings) and transportation. Urbanization, in conjunction with a changing climate, such as frequent heatwave events (Arias, P.A., N. Bellouin, E. Coppola, R.G. Jones, G. Krinner, J. Marotzke, V.Naik, M.D. Palmer, G.-K. Plattner et al., 2021; Mandal et al., 2019) exacerbates the impacts of increasing heat. This phenomenon of elevated temperatures in urban areas compared to rural surroundings is referred to as the Urban Heat Island (UHI) phenomenon. Numerous studies and existing knowledge have demonstrated that the predominant cause of this increased heat in urban areas is urbanization factors such as increased sensible heat due to expanded impervious areas, increased infrared radiation due to decreased sky view factor, decreased latent heat energy due to reduced vegetation, and increased anthropogenic heat due to increased heat sources such as people, buildings, and vehicles. However, it is essential to recognize that conventional understanding of UHIs is evolving with the advent of new concepts such as local climate zones and urban heat archipelagoes that demonstrate microclimatic variations due to the built environment, leading to multiple hotspots and heat sinks within cities. This work therefore examines this issue of increased atmospheric heat, particularly in urban areas, using the Driver, Pressure, State, Impact, Response (DPSIR) framework, as illustrated in Figure 1. As depicted in the figure, while the primary drivers or root causes remain broadly consistent for various environmental impacts, the pressures differ. In the case of increased atmospheric heat, especially in the built environments, the biophysical characteristics of cities, which can be improved through human intervention, constitute the pressures. Therefore, this study focuses on understanding how Artificial Intelligence is specifically being utilized to address these pressures of urban heat by improving the state, reducing the impact, and enhancing the response to heat within built environments.

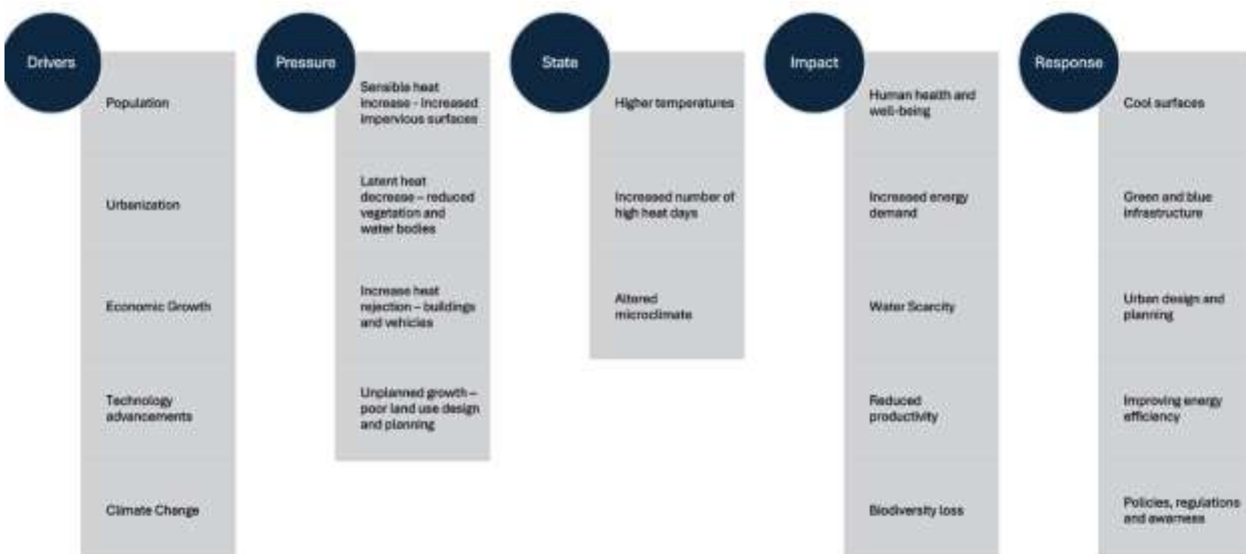

Figure 1: The DPSIR framework for Urban Heat

Artificial Intelligence and Climate Change

As observed in Figure 1, the majority are anthropogenic causes, impacts, and responses that can be analyzed and improved with human intervention. This presents an opportunity for the application of cutting-edge technology, specifically Artificial Intelligence, which has significant potential to contribute to this field. The rapid proliferation of Artificial Intelligence (AI) across diverse sectors necessitates a rigorous and comprehensive examination of its impact on various domains. AI replicates human cognitive functions by executing tasks traditionally associated with human intelligence, such as facial recognition and personalized recommendations based on user behavior (Alhafizh et al., 2023; Seshia et al., 2022). A substantial portion of AI's functionality is driven by Machine Learning (ML), a subset of AI that identifies patterns and relationships within large, complex datasets. Alongside ML, other key techniques contributing to AI advancements include Deep Learning (DL), Natural Language Processing (NLP), and Computer Vision. These technologies enable AI to process and interpret vast amounts of unstructured data, facilitating its application across sectors such as healthcare, finance, and urban development.

One robust framework for understanding artificial intelligence's role in these sectors is through its contribution to the United Nations' Sustainable Development Goals (SDGs). A recent study (Vinuesa et al., 2020) revealed that AI positively impacts 134 SDG targets while potentially impeding progress on 59 others. The positive effects are predominantly observed in areas related to environmental sustainability, whereas negative impacts are noted in social and economic sustainability domains. Furthermore, the study highlights geographic disparities in AI research, which contribute to the uneven distribution of its benefits and challenges across different regions and sectors.

In the domain of environmental sustainability, artificial intelligence (AI) plays a crucial role in various areas, including renewable energy generation (short-term, long-term, and real-time predictions), energy efficiency (smart grids, energy management systems), biodiversity monitoring (wildlife and plant health), building optimization to reduce energy consumption, and urban land-use monitoring to improve microclimates. These technologies also contribute to precision agriculture and the circular economy. Rolnick et al. (2023) comprehensively outline the role of machine learning (ML) in these domains, particularly in addressing climate change. The primary focus of these technologies is either carbon emission reduction or enhanced carbon sequestration, both of which are essential to limiting global temperature rise and mitigating climate change. Estimates suggest that AI could reduce global greenhouse gas emissions by 4% by 2030 (Microsoft and PWC, 2019). AI also demonstrates potential in climate change adaptation, including flood prediction, crop management, and disaster management (Leal Filho et al., 2022).

The near-linear correlation between carbon emissions and global temperatures underscores the critical need to leverage AI for emission reduction to mitigate temperature increases. As temperatures continue to impact various environments—urban, rural, industrial, and natural—the role of AI in heat mitigation and adaptation becomes increasingly significant in the context of climate change. A comprehensive assessment of AI's role in these areas is crucial to harnessing its capabilities in addressing the complex challenges posed by climate change and aligning with the long-term goals of SDG 13 (Climate Action). AI's capacity to process large datasets, model interdependencies, predict climate impacts, and support decision-making positions it as a vital tool in meeting SDG targets related to climate action.

Proposed study

This study presents a systematic review of the literature examining AI's role in heat mitigation and adaptation, specifically in the context of urban areas. Using, the DPSIR framework for urban heat, this study analyzes the role of AI in each of those categories, and shall precisely address the following questions:

1. How has research and tool development in AI-driven heat mitigation evolved over time and across regions?
2. Which aspects of the DPSIR framework for urban heat are most effectively addressed by AI-driven solutions?
3. How is AI most used in this area of heat mitigation and adaptation?
4. Which sectors (e.g., urban planning, energy, transportation, agriculture) benefit the most from AI-driven heat mitigation strategies?
5. What are the current gaps and limitations in AI applications for urban heat mitigation and adaptation?
6. What is the future scope of AI in urban heat mitigation and adaptation, and what research directions should be prioritized?

Methodology

This review primarily focused on peer-reviewed journal articles sourced from databases such as the Web of Science and Scopus. To maintain a clear focus on the role of AI in heat mitigation and adaptation within the broader context of climate action, only studies that directly addressed urban heat and outdoor microclimates were included. Research from related sectors, such as building management and transportation, were referenced selectively for discussion. The search strategy employed specific keywords and their combinations to identify relevant literature. The key search terms included: AI and Air Temperature Reduction, AI and Heat Adaptation, AI and Heat Mitigation, AI and Heat Reduction, AI and Heatwave Mitigation, AI and Urban Heat Island Mitigation, AI and Urban Heat Management, Heat Mitigation and AI Technologies, ML and Air Temperature Reduction, ML and Heat Adaptation, ML and Heat Mitigation, ML and Heat Reduction in Climate Change, ML and Heatwave Prediction, and ML and Urban Heat Island Mitigation.

In addition to peer-reviewed articles, this review examined existing AI-based applications and tools for their effectiveness in mitigating heat and reducing air temperatures. While both "heat" and "temperature" are related concepts, heat encompasses more than temperature alone, also accounting for factors such as humidity (as measured by the heat index). Therefore, this study primarily focused on heat while considering the literature that emphasizes the direct impact on temperature, given that heat is more sensitive to temperature variations than relative humidity (Rachid & Qureshi, 2023; Simpson et al., 2023). This approach ensures that the review focuses on the aspects most critical for understanding the role of AI in addressing heat and temperature-related challenges in the context of climate change.

Inclusion and Exclusion Criteria

This study focused on peer-reviewed journal articles published in English within the last decade (2014–2024). Only the studies relevant to the research questions posed in this review were included. For instance, articles discussing the impact of AI on heat exchanger performance or applications in healthcare were excluded as they fell outside the scope of this review. The inclusion criteria were centered on studies that demonstrated the role of AI in addressing either heat or temperature-related challenges. Special emphasis was placed on heat mitigation within the framework of Sustainable Development Goal (SDG) 13, Climate Action.

In refining the article search on the Web of Science, an additional focus was placed on SDG 11: Sustainable Cities and Communities. Articles that did not provide substantial evidence of the application of AI in these areas were excluded. Furthermore, opinion pieces and editorials were omitted from the analysis in order to maintain the empirical focus of the review.

After applying the inclusion and exclusion criteria, 65 studies were selected for detailed review. This literature review is thus specifically tailored to understand the evolution of AI research in the domains of "heat" and "heatwave" mitigation and adaptation, within the broader context of climate change and sustainability, especially in urban areas.

Categorization of studies

The 65 peer-reviewed journal articles were categorized into three key dimensions.

1. Mitigation vs. Adaptation: Each study was classified based on its primary focus on either heat mitigation, adaptation, or both. Mitigation studies have focused on reducing heat-related emissions or enhancing sequestration, whereas adaptation studies have addressed strategies for coping with rising temperature and heat.
2. Role of AI: The studies were further categorized by the functional role of AI, as follows:
    a. Data Analysis: AI was used to process large datasets to identify patterns in heat-related phenomena.
    b. Data Generation: AI for generating synthetic data and new datasets from existing data.
    c. Optimization: AI was applied to enhance energy efficiency, urban planning, or systems management.
    d. Decision-Making Support: AI aiding policymakers and planners with actionable insights.
    e. Prediction and Forecasting: AI-enabled predictive models for heat waves and urban heat.
3. Impacts and Responses: Studies were also classified based on whether AI helped address the impacts of heat – to mitigate them, or in responding to the impacts of heat – adapting to the impacts.
    a. Impact of heat or heat waves: Examining the consequences of heat events.

b. Factors contributing to heat waves or UHIs: Exploring the causes of heat intensification.
c. Prediction of heat waves or UHIs: AI models predicting future heat-related phenomena.
d. Heat or heat wave management: Strategies for managing or reducing heat exposure.

This structured classification highlights varied roles of AI in addressing heat challenges and helps to identify gaps for future research.

Results and Analysis

AI and Urban Heat Research: Spatio-temporal variations

The collected literature was systematically analyzed to address the research questions posed in this study. As illustrated in Figure 2, the volume of published research in the field of AI applications for heat mitigation and adaptation exhibited a steady upward trend. Notably, the number of peer-reviewed articles published before 2019 was relatively limited, indicating that this is an emerging area of inquiry. However, there has been a marked increase in publications since 2019, with the number of articles nearly doubling every two years, suggesting a growing interest in and recognition of potential of AI in this domain. This trend shows the nascent yet rapidly expanding nature of the field.

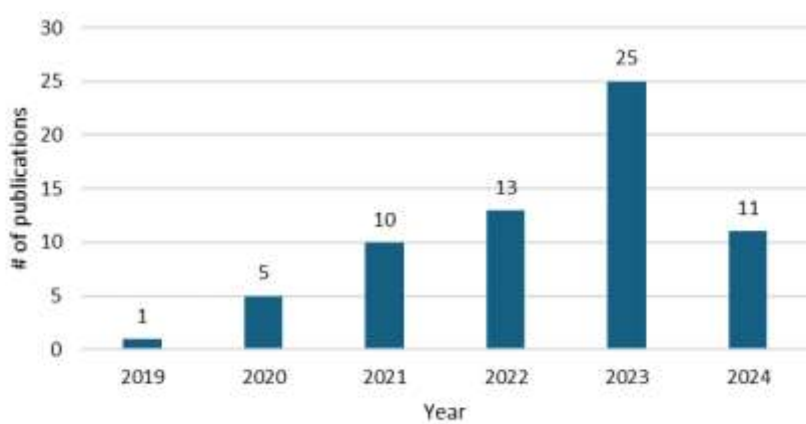

Figure 2: Temporal trend of the reviewed literature

Figure 3 illustrates the geographic distribution of the studies on AI applications for heat mitigation and adaptation. Similar to broader research on urban heat, China, the United States, and Australia have emerged as the leading contributors to this field. By contrast, research output from the Global South, particularly in regions such as South America and Africa, remains limited. This disparity is notable given that tropical regions, which are predominantly located in the Global South, are among the most vulnerable to heat-related impacts. Despite their susceptibility, research activities in these critical areas have remained disproportionately low.

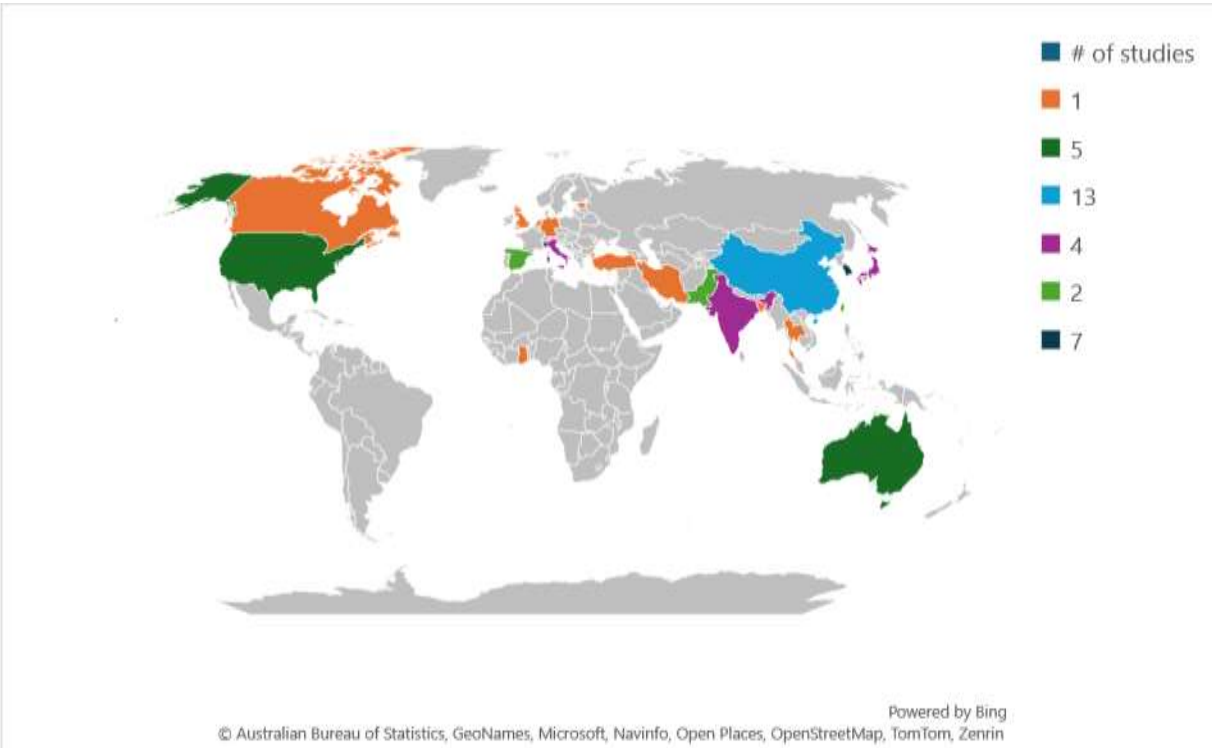

Figure 3: Geographic Distribution of Reviewed Studies on AI Applications in Heat Mitigation and Adaptation

Functional role of AI in Heat Mitigation and Adapation

One of the predominant themes identified in the reviewed literature is the prediction and forecasting of heatwaves and urban heat islands (UHIs) through historical data and machine learning (ML) algorithms, including Neural Networks and Decision Trees. As illustrated in Figure 4, 46% (30/65) of the studies are dedicated to this aspect. Integration of physics-based models with ML algorithms has been demonstrated to enhance both the speed and accuracy of predictions (Zhu et al., 2024). Additionally, 25% of the studies employ ML algorithms such as Convolutional Neural Networks (Vulova et al., 2021), Random Forest (Tepanosyan et al., 2021), and XGBoost(McCarty et al., 2021) for the analysis of remote sensing and weather data, which aids in decision-making processes. Furthermore, 12% (8/65) of the studies focus on utilizing AI and ML for data generation, which supports the development of decision-making frameworks or the evaluation of urban heat mitigation strategies (Buo et al., 2023; Côté et al., 2024). A smaller segment, 8% (5/65) of the studies, is concerned with the creation of decision-making frameworks using AI, addressing various environmental and social factors to identify suitable urban heat mitigation strategies (Côté et al., 2024; Qi et al., 2023). Lastly, while this theme is more prominent in the context of built environments, there is also research focused on optimizing urban layouts to improve micro-climates and reduce urban heat (Lin et al., 2023). This constitutes 9% (6/65) of the reviewed studies.

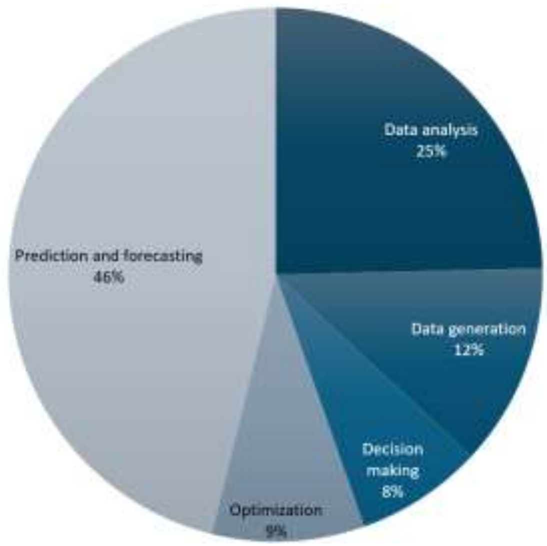

Figure 4: AI related theme across the reviewed literature

AI Interventions across the DPSIR Framework for Urban Heat

Figure 5 illustrates the distribution of studies across various thematic areas within the domain of urban heat mitigation and adaptation. Notably, 46% (30/65) of the studies are dedicated to analyzing the drivers and pressures - both natural and anthropogenic on urban heat and urban heat islands (UHIs). This is followed by research focused on understanding the impacts of heat waves and UHIs, which comprises 23% of the reviewed literature. Additionally, 16% of the studies are concerned with quantifying current state of urban heat and UHI magnitudes, while 15% focus on predicting future trends. Overall, the domain of AI applications for heat adaptation and response is underrepresented, particularly in urban heat management (see Figure 6). Specifically, 58% of the studies pertain to urban heat mitigation, 40% to adaptation, and only 2% address both mitigation and adaptation comprehensively.

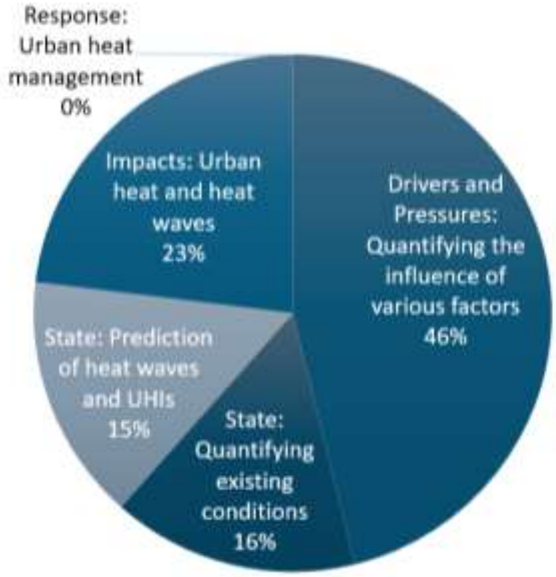

Figure 5: Domain related themes across the review literature

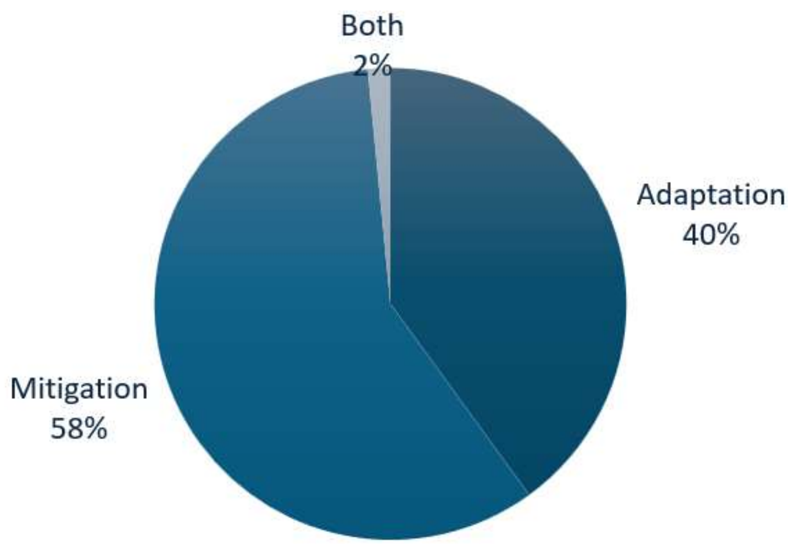

Figure 6: Studies across Heat mitigation and adaptation categories

AI Applications in Heat Mitigation

AI, particularly its subset Machine Learning (ML), has increasingly been employed to understand heat dynamics, heatwave occurrences, and contributing factors within urban environments. Heat mitigation efforts aim to reduce overheating by addressing the following:

- Minimizing heat rejection from various sources.
- Reducing factors that contribute to heat entrapment.
- Creating heat sinks to absorb excess heat.
- Enhancing heat dissipation mechanisms.

These challenges are particularly complex in urban settings due to the phenomenon of Urban Heat Island (UHI), where urban areas experience higher temperatures compared to their rural surroundings. This effect is compounded by intra-urban temperature variations, where certain areas overheat while others act as heat sinks, driven by differences in land use and urban morphology. Key factors influencing UHI formation include:

- Increased absorption of radiation by non-pervious urban surfaces.
- Enhanced trapping of longwave radiation (heat) within urban areas.
- Higher sensible heat storage in urban surfaces.
- Elevated anthropogenic heat release from human activities.
- Reduced latent heat fraction due to decreased vegetation and lower evapotranspiration.
- Decreased heat transfer caused by urban structures impeding wind flow.

Notable trends in the literature highlight the application of AI for:

- **Developing Decision-Making Frameworks:** AI and ML have been utilized to create innovative decision-making frameworks aimed to enhance the efficiency and effectiveness of urban heat mitigation efforts, highlighting the importance of interdisciplinary collaboration to ensure practical applicability across diverse urban environments. (Qi et al., 2022, 2023). These frameworks incorporate AI techniques to automate and optimize decision-making processes for local governments. Essential components include:
    - Ontology-based knowledge representation: Systematically organizes UHMSs.
    - Urban context identification: Tailors strategies to specific urban settings.
    - Sensitivity Analysis: Identifies critical variables influencing heat mitigation.

- Genetic Algorithm-based multi-objective optimization: Balances multiple performance objectives.
- Evidence-based knowledge base: Supports automated queries and informed decision-making.

- **Pressures of Heat Formation within an Urban Environment:** Machine Learning (ML) techniques, including genetic algorithms and optimization methods, as well as Random Forest models, are effectively utilized to quantify the influence of various natural and anthropogenic factors on urban heat (Hou et al., 2023; Wei et al., 2023). These methods enhance the understanding of UHI dynamics and inform targeted mitigation strategies.
- **Reducing Heat Rejection through Buildings:** Optimizing heating, ventilation, and air conditioning (HVAC) systems in buildings is crucial for reducing energy consumption, which not only improves micro-climates but also contributes to lowering global CO_2 emissions. Advances in AI have significantly impacted building design and layout optimization to enhance energy efficiency and micro-climate regulation (Lee & Lee, 2023; Zhou & Liu, 2024).
- **Reducing heat rejection through road transportation:** AI-driven traffic management systems and optimization of electric vehicles play a key role in improving energy efficiency and reducing tailpipe emissions. These advancements indirectly influence urban heat by mitigating the heat generated from transportation activities (Kour et al., 2022).

AI Application in Heat Adaptation

AI is increasingly being leveraged to tackle heat adaptation challenges across diverse domains. Key areas of application relevant to this study include urban heat management, where the capabilities of AI are harnessed to enhance various aspects of heat adaptation. The utilization of multiple datasets and comprehensive spatial and temporal data allows for advanced heatwave predictions and precise mapping of heat hotspots, which in turn supports localized policy and decision-making processes. The primary advantages of AI in heat adaptation include:

- **Enhanced Prediction Accuracy:** AI algorithms, particularly machine learning models, can analyze vast datasets to improve the accuracy of heatwave predictions, enabling proactive measures and timely interventions (Zhu et al., 2024).

- **Localized Hotspot Mapping:** By integrating and analyzing spatial and temporal data, AI can create detailed maps of heat hotspots, which are crucial for targeted and effective urban planning and policy formulation (Lee et al., 2020).
- **Optimized Resource Allocation:** AI facilitates more efficient allocation of resources by identifying critical areas in need of intervention, thereby improving the effectiveness of heat adaptation strategies (Park et al., 2020).
- **Improved Decision-Making:** AI-driven models and decision-support systems provide valuable insights and recommendations, aiding policymakers in designing and implementing adaptive measures tailored to specific urban contexts(Lee et al., 2020; Park et al., 2020).
- **Real-Time Monitoring and Response:** AI technologies enable continuous monitoring of heat conditions and rapid response to emerging heat-related issues, enhancing the resilience of urban environments (Narkhede et al., 2022).
- **Integration of Multiple Data Sources:** The ability of AI to synthesize and analyze diverse data sources—ranging from meteorological data to urban infrastructure information—supports a comprehensive approach to managing and adapting to heat challenges.

AI Applications in Heat Waves

A 2023 study (Barriopedro et al., 2023), examined the application of machine learning (ML) techniques, particularly deep learning models, in climate science with a focus on predicting heat waves. The study underscores the ability of advanced ML algorithms to analyze complex, high-dimensional climate data and uncover patterns and relationships that traditional statistical methods might miss. These sophisticated ML models can generate data-driven ensemble predictions by running multiple simulations to address uncertainties in climate forecasts. By integrating both historical data and real-time observations, these models enhance the precision of heat wave predictions and offer valuable insights into their likelihood and intensity.

Despite these advancements, the study identifies several challenges in applying ML to climate science. These include the limited availability of high-quality observational data, the high dimensionality of climate variables, and the non-stationarity of climate systems, all of which can impact model performance. The authors advocate for the integration of ML with a robust physical understanding of climate processes to develop hybrid modeling frameworks. Such approaches are expected to improve prediction accuracy and deepen the understanding of the factors driving heat waves. Potential applications of these ML techniques encompass refining heat wave definitions, identifying key drivers, developing early warning systems, and managing uncertainty in regional climate projections. These advancements aim to enhance climate adaptation and risk management strategies.

Existing AI Tools for Heat mitigation and Adaptation

Table 2 lists existing AI-based tools designed for heat mitigation and adaptation activities. As illustrated in the table, these tools represent valuable resources in the ongoing effort to manage and adapt to heat-related challenges. By leveraging artificial intelligence, these tools contribute to more effective heat management and adaptation strategies, enhancing our ability to address the impacts of heat through innovative technological solutions.

Table 2: List of AI tools for heat mitigation and adaptation

Tool	**Geographical Applicability**	**Characteristics**	**Category**
Gramener	Canada	Assists in heat adaptation activities by providing advanced data visualization and analytics.	Adaptation
Harmonia IRAP	Europe	Functions as a Decision Support System (DSS) to aid in policy-making and strategic planning for heat mitigation.	Mitigation
ARIES	Global	Integrated modeling and analysis for environmental sustainability; supports decision-making; leverages diverse data sources and AI techniques for comprehensive environmental insights	Environmental modeling

Conclusion

This comprehensive review of AI applications in urban heat mitigation and adaptation reveals significant progress and potential in addressing the growing challenges of urban heat. The analysis of 65 peer-reviewed studies from 2014 to 2024 demonstrates a rapid increase in research since 2019, particularly in North America, Europe, and China. AI is predominantly utilized for prediction and forecasting of heatwaves and urban heat islands, data analysis to identify patterns and drivers of heat, and data generation for decision-making frameworks. Machine learning techniques, especially neural networks and decision trees, are frequently employed to analyze remote sensing and weather data for urban heat mapping and prediction. Most studies focus on heat mitigation rather than adaptation, with limited research addressing both aspects comprehensively. While AI shows promise in enhancing urban heat management through improved decision-making frameworks and urban layout optimization, several research gaps remain. These gaps include insufficient studies in tropical regions and limited focus on practical implementation of AI-driven strategies, particularly in the Global South. The findings underscore the need for additional research on translating AI insights into practice and addressing heat challenges in vulnerable regions. Future research should prioritize bridging the gap between theoretical advancements and practical applications, expanding studies to underrepresented areas, and developing integrated approaches that address both mitigation and adaptation strategies. As increasing heat continues to pose significant challenges worldwide, the role of AI in developing effective solutions becomes increasingly critical. By addressing the identified research gaps and leveraging AI's capabilities, cities can enhance their resilience to heat-related impacts and contribute to broader climate action goals.

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