Sustainable Cities and Society 134 (2025) 106943

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Recent advances on machine learning techniques for urban heat island applications: a review and new horizons

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ARTICLE INFO

Keywords:
Urban heat island
Machine learning
Mitigation
Sensing
Adaptation
Prediction

ABSTRACT

Urban Heat Islands (UHIs) pose a significant global urban challenge, exacerbating heat stress, increasing energy demand, and negatively impacting public health. This review critically analyzes the application of machine learning (ML) strategies for UHI mitigation through an integrated lens encompassing sensing, prediction, optimization, control, and adaptive management. This review starts with a comprehensive evaluation of various data acquisition techniques, such as remote sensing, mobile surveys, and ground-based sensor networks, along with their respective strengths and limitations. Subsequently, the review explores advanced data processing methodologies leveraging ML algorithms for the analysis and interpretation of complex UHI datasets, enabling accurate forecasting and timely interventions. ML-driven prediction and forecasting techniques for UHI are then presented, underscoring the importance of precise and timely predictions for effective mitigation. Further investigation delves into the optimization of UHI mitigation strategies, examining how ML can enhance the effectiveness of approaches such as green infrastructure, cool materials, urban water bodies, and urban planning and design. Finally, the integration of ML insights into flexible adaptation strategies and urban planning processes is discussed, highlighting the necessity for long-term, climate-responsive urban development. The review concludes by assessing the transformative potential and inherent limitations of ML approaches in this domain, outlining critical challenges and promising future research directions for advancing UHI mitigation within rapidly evolving urban environments and under changing climate conditions.

1. Introduction

The escalating convergence of rapid urbanization and global climate change is intensifying the Urban Heat Island (UHI) effect, presenting a critical and multifaceted challenge for cities worldwide (Leal Filho et al., 2018; Aghamohammadi et al., 2021; Kim & Brown, 2021). The UHI is characterized by significantly higher temperatures in urban areas compared with their rural surroundings, a phenomenon driven by altered land cover and increased anthropogenic heat emissions (Jusuf et al., 2019; Nwakaire et al., 2020; Dijoo, 2021). This temperature disparity, often more pronounced during nighttime, leads to increased energy demand, compromised air quality, adverse human health outcomes, and reduced thermal comfort (Heaviside et al., 2017). Consequently, as cities continue to grow and climate change intensifies, a comprehensive understanding of the UHI effect and the development of effective mitigation approaches are crucial for building sustainable and resilient urban futures (Lee et al., 2014; Larsen, 2015; Irfeey et al., 2023; Han et al., 2023; Rajagopal et al., 2023; Yang et al., 2024).

Historically, UHI research has been predominantly conducted using a combination of experimental measurements, field observations, and computational modeling. These established methodologies have provided valuable insights, with in situ measurements from sensor networks and mobile platforms capturing localized thermal variations (Rodríguez et al., 2020), and high-resolution remote sensing offering synoptic perspectives on urban thermal patterns (Zhou et al., 2018; Almeida et al., 2021). Furthermore, computational fluid dynamics (CFD) models have been instrumental in simulating complex urban airflow and heat transfer, elucidating the drivers of thermal accumulation in dense urban environments (Mirzaei & Haghighat, 2010; Silva et al., 2021). Moreover, experimental wind tunnel studies and laboratory experiments have served to validate these models and deepen the understanding of microclimatic phenomena (Yan et al., 2022; Zhao et al., 2023). However, the increasing availability of large and diverse datasets has spurred the adoption of machine learning (ML) techniques as a transformative paradigm in UHI research (Ngarambe et al., 2025). In the realm of environmental science and urban studies, ML has emerged as a powerful

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https://doi.org/10.1016/j.scs.2025.106943
Received 25 March 2025; Received in revised form 27 October 2025; Accepted 27 October 2025
Available online 28 October 2025
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paradigm for analyzing intricate environmental phenomena and extracting meaningful patterns from large, diverse datasets in urban contexts. The inherent complexity of the UHI effect, influenced by a multitude of interacting factors such as urban morphology, land cover characteristics, and prevailing meteorological conditions, makes it particularly amenable to analysis using advanced computational techniques like ML. These approaches leverage advanced analytical tools to process heterogeneous data from sources like satellite imagery and IoT sensor networks (Pioppi et al., 2020). ML models, including convolutional neural networks (CNNs), random forests (RF), and support vector machines (SVMs), are now being employed to predict urban heat patterns and optimize mitigation strategies, offering potentially faster and more adaptive solutions (Shi et al., 2021b; Zumwald et al., 2021; Du et al., 2024). The integration of these ML methods with established CFD models and experimental protocols holds significant promise for enhancing predictive accuracy, streamlining data processing, and achieving a more nuanced understanding of urban thermal dynamics. This synergy not only builds upon the strengths of conventional techniques but also opens new avenues for real-time monitoring, adaptive control, and informed urban planning, fundamentally reshaping the strategies for UHI mitigation (Milojevic-Dupont & Creutzig, 2021; Wang et al., 2022).

Building upon the increasing interest in ML for UHI research, this review paper presents a comprehensive review of ML strategies across various UHI applications, highlighting both their transformative potential and inherent limitations. Recognizing that robust data acquisition is fundamental to the success of ML approaches, the review first examines diverse data collection techniques, including remote sensing, mobile testing, and ground-based sensor networks, emphasizing their relevance and reliability in capturing urban thermal dynamics. Subsequently, the paper explores advanced data processing using ML techniques and their crucial role in extracting actionable insights from raw data. The application of ML for accurate and timely UHI prediction and forecasting, vital for effective intervention, is then reviewed. This is followed by a critical examination of ML optimization of UHI mitigation strategies, encompassing the strategic deployment of cool roofs, the placement of green infrastructure, improvements in building energy efficiency, and enhancements to urban ventilation. Furthermore, the review discusses the role of ML control and monitoring systems in enabling real-time management and adaptive responses to UHI. Finally, the integration of ML insights into flexible adaptation strategies and urban planning frameworks is explored to support long-term, climate-resilient urban development. By synthesizing existing literature and identifying key challenges and future research directions, this paper aims to advance the development of more effective and sustainable UHI mitigation strategies in the context of a changing climate.

2. Background and methodology

This section provides a concise overview of the UHI phenomenon and its analysis using ML. It reviews UHI origins, mechanisms, and impacts, and briefly outlines ML's role in these studies. The methodology, covering the systematic literature search, selection criteria, and conceptual framework, is also detailed.

2.1. The UHI effect

The UHI effect is broadly characterized by higher temperatures in urban areas compared to their rural surroundings (Oke, 2011). This phenomenon is observed in two primary forms: the canopy-layer UHI, defined as an air-temperature difference between urban and rural sites, and the Surface Urban Heat Island (SUHI), quantified from land-surface temperature (LST) retrieved via thermal infrared remote sensing. The Surface Urban Heat Island Intensity (SUHII) is defined as the urban–rural LST difference, ($SUHII = LST_{urban} - LST_{rural}$) (Santamouris et al., 2015). It is crucial to distinguish their typical diurnal patterns: the canopy-layer UHI is most pronounced at night under calm, clear conditions due to the slow release of stored heat from urban materials, whereas SUHI often reaches its maximum intensity during the daytime when urban surfaces absorb intense solar radiation. Thus, UHI effect is amplified by numerous factors. First, urban landscapes, with prevalent impervious surfaces like roads and buildings, have high solar radiation absorption and thermal storage capacities (Zhao et al., 2018). Second, limited urban vegetation reduces evapotranspiration, decreasing natural cooling (Taha, 1997; Ramakreshnan et al., 2018). Third, anthropogenic heat from dense urban activities, including traffic, industry, and air conditioning, adds substantial heat (Sailor, 2011). Additionally, urban geometry, often involving the formation of deep street canyons, can impede ventilation and trap radiant heat (Rizwan et al., 2008). Finally, urban air pollution exacerbates UHI by absorbing and re-emitting longwave radiation (Wu et al., 2024).

2.2. Impacts of the UHI

The UHI intensifies environmental, health, and economic burdens. On the environmental side, elevated cooling demand increases electricity consumption, driving higher greenhouse-gas emissions and urban air pollution (Li et al., 2019). UHI can exacerbate photochemical smog by promoting ground-level ozone and, through warmer stormwater and baseflow, degrade receiving-water quality (Mathew et al., 2024). Social and health impacts include greater risk of heat exhaustion and heatstroke, with disproportionate effects on older adults, people with pre-existing conditions, and communities with limited access to cooling (Ebi et al., 2021). Thermal discomfort also reduces well-being and labor productivity (Aznarez et al., 2024). Population exposure is increasingly assessed with thermal comfort metrics such as Humidex, Wet-Bulb Globe Temperature (WBGT), Universal Thermal Comfort Index (UTCI), and Temperature–Humidity Index (THI) to quantify heat stress during hot spells (Kim et al., 2024). Economically, UHI-driven energy consumption raises electricity costs for individuals and businesses, and peak demand can strain energy infrastructure. Additionally, extreme heat can damage transportation and energy systems, increasing maintenance costs. The combined effects of heat-related health issues and reduced worker productivity can also negatively impact economic output.

2.3. Background of machine learning

Machine learning (ML), a dynamic branch of artificial intelligence, develops algorithms to learn patterns and make predictions from data (Tyagi & Chahal, 2020; Sarker, 2021). Urban studies has seen a significant transformation with increasing integration of ML techniques in recent decades (You et al., 2021). Initially reliant on traditional statistical methods and simulation models, urban analysis now widely adopts ML algorithms, due to the growing availability of large, diverse datasets and increased computational power (Ghorbany et al., 2024). This shift acknowledges ML's capacity to provide novel insights into urban phenomena that conventional approaches may find difficult to obtain. Specifically, in UHI studies, ML has become a powerful tool to unravel the complex interplay between urban form, land use, and microclimatic processes (Bansal & Quan, 2024). The vast data from satellite imagery, in situ sensors, and simulation outputs enables ML methods to model spatial and temporal variations in urban temperatures with high precision.

ML methodology encompasses a sequential process of data collection, preprocessing, training, evaluation, and hyperparameter tuning. ML model performance depends on input data quality and quantity. In UHI research, high-resolution thermal maps, environmental datasets, and building/surface characteristics are crucial inputs for training algorithms. These trained models predict temperature distributions, identify high-risk areas, and provide insights for urban planning. ML methods are categorized into supervised, unsupervised, semi-supervised, and reinforcement learning (Fig. 1), each offering distinct analytical strategies for contemporary UHI studies.

Supervised learning employs labeled datasets for predictive tasks like regression and classification (Cunningham et al., 2008; Nasteski, 2017). In UHI research, regression models, such as feed-forward and deep neural networks, forecast surface temperature variations (Tran et al., 2024; Zaka et al., 2025). Similarly, classification models like support vector machines (Suthaharan, 2016) and random forests (Breiman, 2001) segment urban areas by thermal characteristics, identifying heat islands and cooler islands (Li et al., 2024b; González-Collazo et al., 2024). Unsupervised learning offers alternatives when labeled datasets are limited (Boccalatte et al., 2023; Naeem et al., 2023). These methods automatically discern data patterns without predefined labels. Clustering algorithms, like k-means (Hartigan & Wong, 1979), group areas by thermal characteristics (Chen et al., 2024a). Furthermore, dimensionality reduction techniques, including principal component analysis (Abdi & Williams, 2010) and autoencoders (Zhai et al., 2018), extract features from high-dimensional urban datasets, simplifying analyses.

Semi-supervised learning combines supervised and unsupervised methods, using a small amount of labeled data with a larger pool of unlabeled data (Van Engelen & Hoos, 2020). This is advantageous in UHI research, where annotating large datasets is challenging. Various techniques fall under this category, including self-training (Amini et al., 2025), where models refine predictions by labeling unlabeled data, and co-training (Zhou & Li, 2005), which uses multiple models to improve label accuracy. Graph-based methods propagate labels across networks of similar data points (Song et al., 2022), while generative models, like variational autoencoders (Kingma & Welling, 2019) and generative adversarial networks (Goodfellow et al., 2020), learn data distributions to create synthetic examples for augmenting labeled data. Reinforcement learning (RL) trains agents to make decisions through environmental interaction, guided by rewards and penalties (Kaelbling et al., 1996; Sutton & Barto, 1998). In urban planning, RL can develop adaptive control strategies for mitigating UHI, such as optimizing green space or reflective surface placement (Vázquez-Canteli & Nagy, 2019). RL methods include model-based approaches (Moerland et al., 2023), which construct environment models for planning future actions, and model-free approaches (Huang, 2020), which learn policies from interaction experiences. These are divided into value-based methods, estimating state rewards (Byeon, 2023); policy-based methods, optimizing actions (Nachum et al., 2017); and actor-critic methods, integrating value and policy learning (Grondman et al., 2012).

2.4. Methodology

This review follows a structured literature-search and evidence-synthesis workflow designed to remain distinct from the background material. Records were retrieved from Scopus, Web of Science, and IEEE Xplore using combinations of urban-heat terms (e.g., urban heat island, surface urban heat island, sensing, prediction/forecasting, optimization, mitigation, control, adaptation) and machine-learning terms (e.g., machine learning, physics-informed machine learning, deep learning, random forest, convolutional neural network), with database-specific syntax. Studies were eligible for the core synthesis if they directly applied ML to a UHI question and reported quantitative results. Papers that were purely conceptual, addressed non-UHI topics, or discussed ML without a relevant application were excluded from the core but could be retained for contextual framing. The search yielded approximately 350 records; after deduplication, titles and abstracts were screened and 280 articles proceeded to full-text assessment. Following full-text review, 187 studies met the inclusion criteria and formed the core evidence set used for the synthesis, with an additional 64 publications retained for background/context, for a total of 251 cited works. Each core study was coded to one of the review's organizing themes, which align with the conceptual framework in Fig. 2 and structure the synthesis that follows.

The resulting distribution is: Sensing & Data Analysis (n = 52),

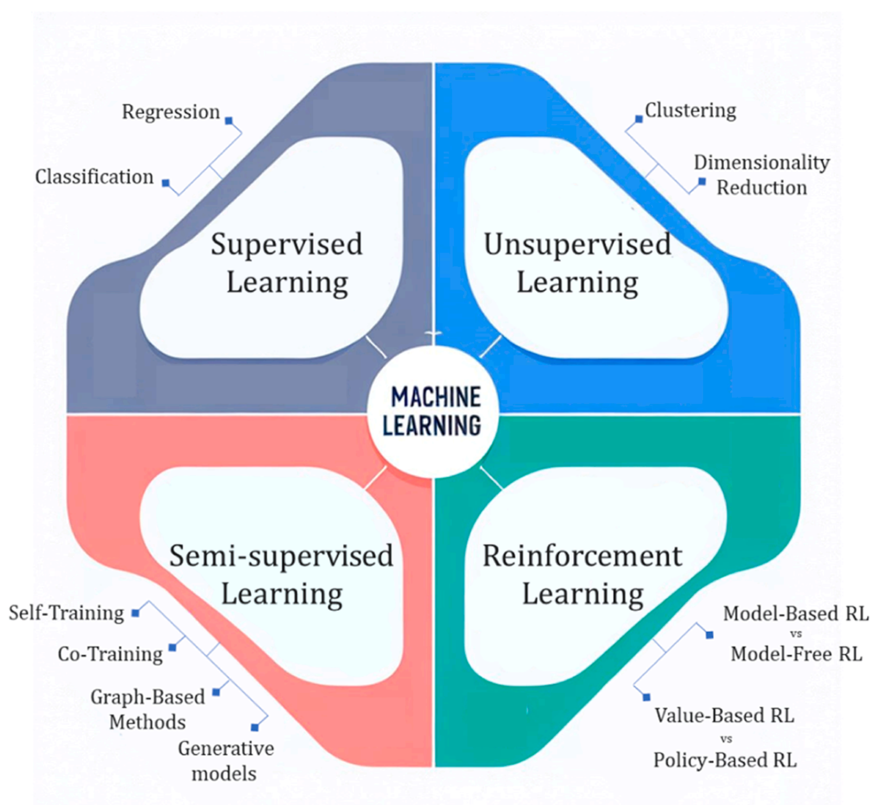

Fig. 1. Machine learning categories.

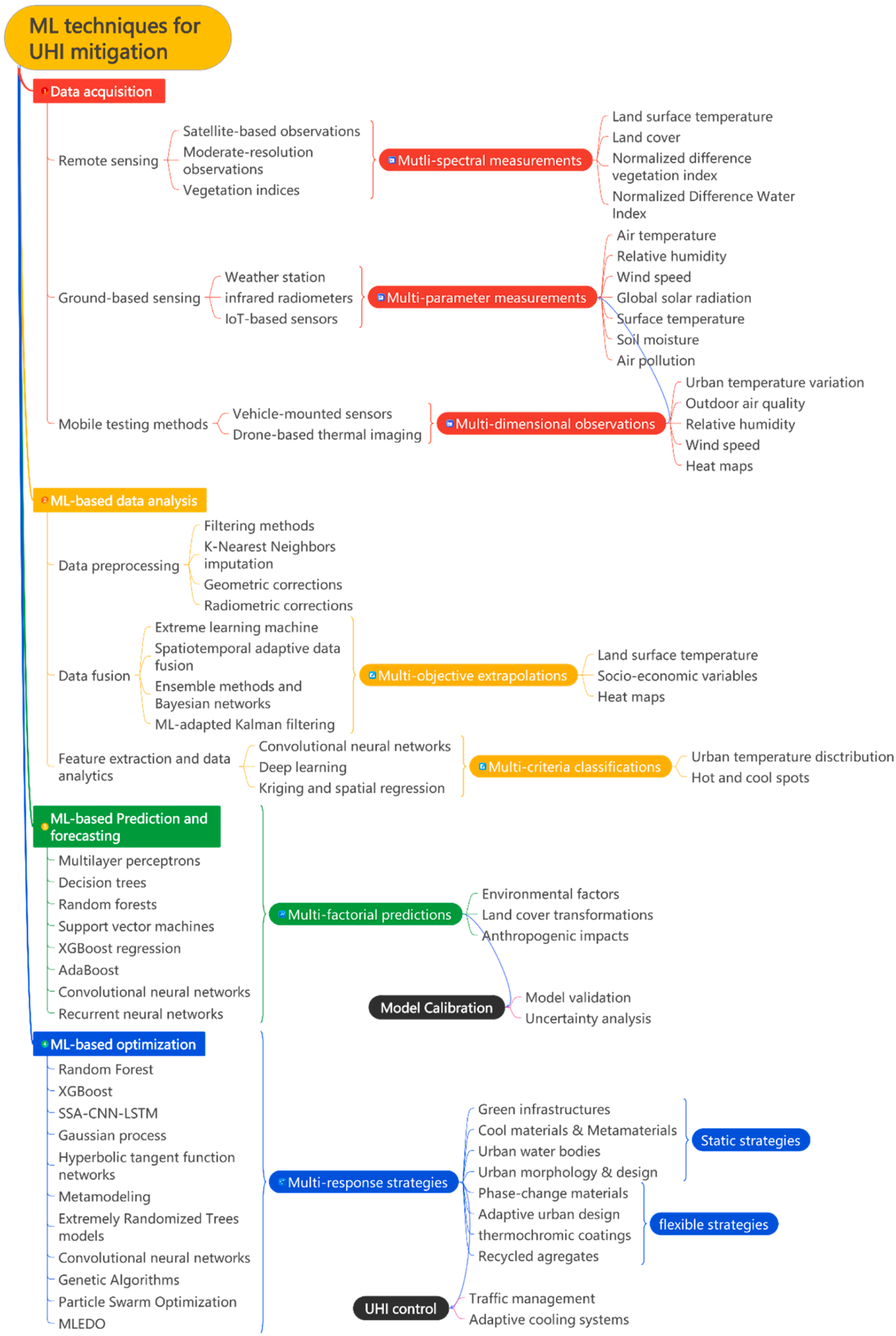

Fig. 2. Conceptual framework of the methodology.

Prediction & Forecasting ($n = 53$), Optimization & Control ($n = 59$), and Flexible Adaptation ($n = 23$). These counts are used descriptively to map research activity across subfields and to guide the narrative emphasis in Sections 3–6, where representative works are synthesized to characterize datasets and methods, compare performance and limitations, and identify gaps that motivate future directions. The thematic distribution is visualized in Fig. 3, which complements the conceptual framework (Fig. 2) and connects the evidence base to the review's structure.

3. Machine learning for sensing and data analysis

3.1. Data acquisition techniques

Effective UHI monitoring requires diverse data sources with unique spatiotemporal resolutions and coverage. A comprehensive understanding of UHI is best achieved by integrating data from remote sensing, mobile measurement campaigns, and ground-based sensor networks. This integration enhances analysis reliability and facilitates calibration and validation across platforms.

3.1.1. Remote sensing

Remote sensing is fundamental to SUHI research, providing consistent observations of urban features, especially land-surface temperature (LST) which serves as a primary proxy for the broader UHI phenomenon (Azevedo et al., 2016; Fernandes et al., 2023). Satellite observations offer a broad view of urban areas, capturing LST, land cover, and vegetation indices. Moderate-resolution sensors (e.g., Landsat) provide long-term data for trend analysis, while higher-resolution sensors (e.g., Sentinel-2) enable detailed mapping (Santra, 2017). For instance, several studies using MODIS LST data show that urban structures and materials significantly influence thermal retention (Zhou et al., 2018; Qiao et al., 2024).

Contemporary satellite platforms also offer multi-spectral capabilities for computing indices like the Normalized Difference Vegetation Index (NDVI) or the Enhanced Vegetation Index (EVI) and the Normalized Difference Water Index (NDWI), which are crucial for assessing factors influencing SUHI intensity (Almeida et al., 2021). Advanced processing algorithms correct for atmospheric distortions, cloud masking, and calibrates thermal infrared data to enhance LST measurement accuracy (Ayanlade & Jegede, 2015). Recent advancements, like geostationary satellites, enable near real-time monitoring of SUHI dynamics, beneficial for understanding diurnal temperature fluctuations (Hurduc et al., 2024). Combining data from multiple missions, such as MODIS and Sentinel-2, overcomes individual sensor limitations, improving spatial detail and temporal frequency in SUHI monitoring. Despite these advancements, trade-offs exist between resolution, revisit times, and sensitivity, necessitating sophisticated data assimilation and ML techniques to refine UHI assessments (Zhou et al., 2018).

3.1.2. Ground-based sensors

Ground-based sensor networks provide continuous, high-resolution measurements of essential meteorological parameters (Pathak et al., 2022; Cheval et al., 2024). Traditional meteorological stations provide essential data like temperature, humidity, wind speed, and solar radiation for long-term analyses. However, their often sparse distribution can limit the capture of fine-scale microclimatic variations (Nguyen & Henebry, 2016). To address this limitation, specialized sensors and recent technological advancements, including infrared radiometers, miniaturized energy-efficient sensors, and low-cost IoT networks, are increasingly deployed (Fauzandi et al., 2021; Xia et al., 2022; Hu & Uejio, 2024). Despite these advancements, challenges persist in sensor calibration, data management, and security (Mendez-Astudillo et al., 2021). Regular recalibration is essential to prevent measurement errors from drift and interference. Additionally, handling large IoT data volumes while ensuring security and privacy requires standardized frameworks and strong cybersecurity measures (Malings et al., 2018).

3.1.3. Mobile testing methods

Mobile testing, including vehicle-mounted sensors and drone-based thermal imaging, dynamically captures urban temperature variations at high spatial and temporal resolution (Rodríguez et al., 2020; Lee & Lee, 2024). Vehicle-mounted sensors in mobile transects record temperature fluctuations to identify thermal hotspots (Sun et al., 2019; Yin et al., 2020). Drones with thermal cameras provide ultra-high-resolution data at the neighborhood scale, enabling detailed analyses of microenvironmental variations (Henn & Peduzzi, 2024; Hu et al., 2024). These platforms may also carry other sensors for humidity, wind speed, and air quality, offering a multidimensional perspective on urban climate dynamics (Hu et al., 2024) and enabling researchers to assess environmental interactions affecting UHI intensity, guiding urban planning and public health strategies (Rickens & Tonekaboni, 2023). To manage and analyze the large volumes of high-resolution imagery from mobile surveys, advanced ML algorithms are increasingly employed (Kim et al., 2021). Despite their advantages, mobile testing methods face limitations like restricted drone flight durations, limited spatial coverage, and intensive computational resources for processing complex datasets (Kaya & Erener, 2024).

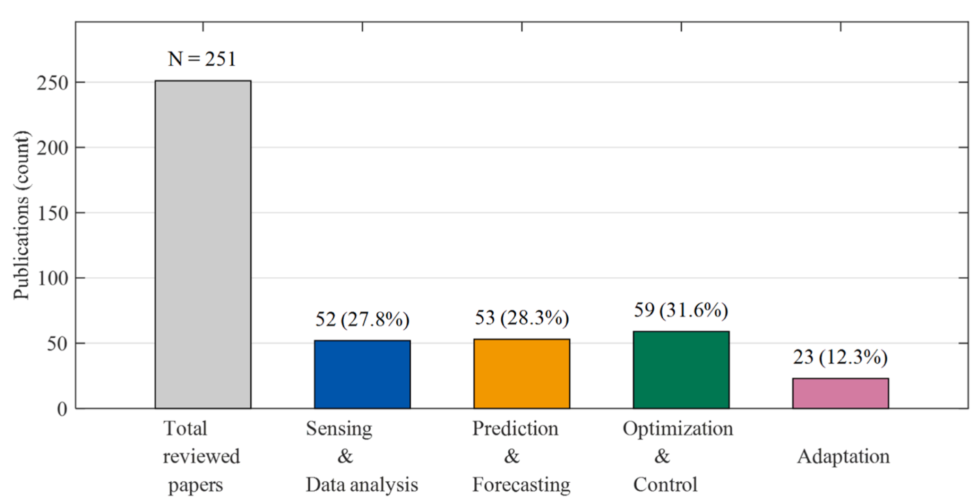

Fig. 3. Thematic distribution of the reviewed papers.

3.2. ML-based data analysis

UHI analysis increasingly uses a multi-step ML approach, integrating and refining diverse datasets like satellite imagery, land cover maps, ground sensor measurements, and socio-economic data. These are merged using a geographic information system (GIS) for detailed UHI maps, capturing macro- and micro-scale temperature variations (Du et al., 2024). Advanced ML techniques, such as neural and Bayesian networks, and ensemble methods, are then applied to identify complex patterns and correlations often missed by traditional statistics (Zhang et al., 2018; Ghorbany et al., 2024). By automating the processing and analysis of large, heterogeneous datasets, these methods improve UHI prediction accuracy and provide insights into relationships between urban morphology, land use, and thermal dynamics (Liu et al., 2024b), supporting better urban planning and targeted heat mitigation (Liu et al., 2021; Eslamirad et al., 2023). ML models also correct bias and downscale temperature predictions, improving urban heat map resolution (Blunn et al., 2024).

3.2.1. Data preprocessing

Raw urban environmental data requires preprocessing for reliable analysis. UHI datasets often have missing values, such as from cloud obstruction or sensor malfunctions. ML techniques, like K-Nearest Neighbors (KNN), can impute these missing values (Shi et al., 2021a; Tanoori et al., 2024). Data cleaning also involves removing noise and outliers using methods like Gaussian or median filters (Sailaja et al., 2024). Normalization, scaling data to a common range, is crucial for many ML algorithms. Specific normalization strategies may be needed for certain data, like remote sensing imagery (Bhamjee et al., 2023). Additionally, geometric corrections use ground control points to rectify spatial distortions in remotely sensed imagery from satellites, Unmanned Aerial Vehicles (UAVs), and ground sensors (Miniandi et al., 2025). Radiometric corrections also normalize sensor outputs across platforms and time, ensuring temperature measurement consistency (Zhou et al., 2018). These steps create a strong foundation for ML models to accurately predict and analyze UHI dynamics (Almeida et al., 2021; Addas, 2023).

3.2.2. Data fusion

Data fusion integrates data from multiple heterogeneous sources for more comprehensive and accurate information. This approach leverages diverse data acquisition techniques to create unified, high-resolution representations of the urban thermal environment by combining data from sources like satellite imagery, UAV surveys, ground sensors, and IoT networks (Shen et al., 2016; Shi et al., 2021a; Ezimand et al., 2021; Miniandi et al., 2025). It addresses challenges related to varying spatial and temporal resolutions, data formats, and uncertainties. For instance, satellite-derived LST data can be fused with more accurate ground-based air temperature measurements.

ML algorithms, including neural and Bayesian networks, are well-suited for data fusion, learning interrelationships between data sources to generate more reliable UHI maps and datasets. Specialized data fusion algorithms, like the extreme learning machine and spatiotemporal adaptive data fusion algorithm for temperature mapping (STAFF), enhance LST retrieval using multi-source data, refining LST maps (Weng et al., 2014; Bai et al., 2015). Similarly, ensemble methods and Bayesian networks integrate socio-economic variables with thermal data to reveal UHI drivers (Addas, 2023). Techniques like ML-adapted Kalman filtering facilitate real-time updates of fused datasets for continuous monitoring of urban heat patterns (Acosta et al., 2021). These strategies improve predictive accuracy and help urban planners design climate-resilient cities (Wang et al., 2017; Pan et al., 2023).

3.2.3. Feature extraction and data analysis

Feature extraction and data analysis convert processed data into model-ready predictors and insights for urban heat studies. Feature extraction creates input variables (features) from raw data and derived layers. Common features include vegetation indices (e.g. NDVI), built-up indices (e.g., NDBI), water indices (e.g., NDWI), land-cover classes, urban density metrics (e.g., impervious fraction, floor-area ratio), building height and morphology (plan/frontal-area indices), sky-view-factor (SVF) proxies, long- and short- wave radiation factors including surface albedo; emissivity and absorptivity and distance-to-water/green space. These capture key characteristics of the urban environment that influence temperature. Beyond hand-crafted variables, ML can learn features automatically: convolutional/attention networks extract hierarchical spatial-spectral representations directly from multispectral and thermal tiles, while dimensionality-reduction models (e.g., PCA or autoencoders) compress inputs into informative latent embeddings that can be used alone or concatenated with tabular features.

Advanced ML models then perform data analytics. CNNs classify urban materials from multispectral and thermal imagery, enabling detailed urban surface maps to predict temperature distributions (Johannsen et al., 2024; Mohamed & Zahidi, 2024). For example, CNNs detect building footprints in satellite imagery to show how urban morphology impacts heat distribution (Ramani et al., 2024; Li & Stouffs, 2024). Deep learning models also automate the identification of urban hotspots and cool zones. Time-series analyses further reveal UHI effects over time (Xiong et al., 2022). Clustering algorithms can also be employed to classify urban thermal environments (Chen et al., 2024a). Additionally, statistical and geostatistical methods, like kriging and spatial regression, interpolate temperature data in areas with sparse measurements (Wang & Zhang, 2023). GIS remains a central tool in these efforts, integrating spatial datasets, from temperature readings to land use patterns, and vegetation indices. By analyzing these layers, researchers visualize correlations between urban features and thermal behavior, generating essential heat maps for decision-making and urban planning (Eslamirad et al., 2023). These analytical processes consider data and model uncertainties to ensure robust conclusions.

4. Prediction and forecasting of UHI

Accurate prediction and forecasting of UHI intensity are of paramount importance for the development and implementation of proactive mitigation and adaptation strategies. The ability to identify the timing and spatial extent of severe UHI effects enables targeted interventions, such as the activation of public cooling centers, optimization of energy consumption, and implementation of adaptive traffic management plans. However, the prediction of UHI phenomena presents inherent complexities due to the intricate interactions between urban morphology, meteorological factors, land cover dynamics, and anthropogenic activities (Oliveira et al., 2022). Contemporary predictive frameworks increasingly leverage ML methodologies that integrate diverse datasets, ranging from satellite-derived LST measurements to socio-economic indicators, to generate detailed and actionable insights (Fig. 4). The efficacy of these models is contingent not only on the sophistication of the algorithms employed but also on the spatial and temporal fidelity of the input data.

4.1. ML predictive frameworks

ML paradigms have become pivotal tools in the accurate forecasting of UHI intensities (Ashtiani et al., 2014; Han et al., 2022; Yin et al., 2023; Wang et al., 2025). These methodologies typically establish functional relationships between urban features, with LST as a primary target variable, and a range of environmental determinants. These determinants encompass meteorological factors such as air temperature, humidity, wind speed, and solar radiation; land cover transformations, including changes in vegetation, impervious surfaces, and water bodies; and anthropogenic impacts, such as urban development metrics like building density, energy consumption, and traffic patterns (Rehman et al., 2022; Suthar et al., 2024; Tanoori et al., 2024).

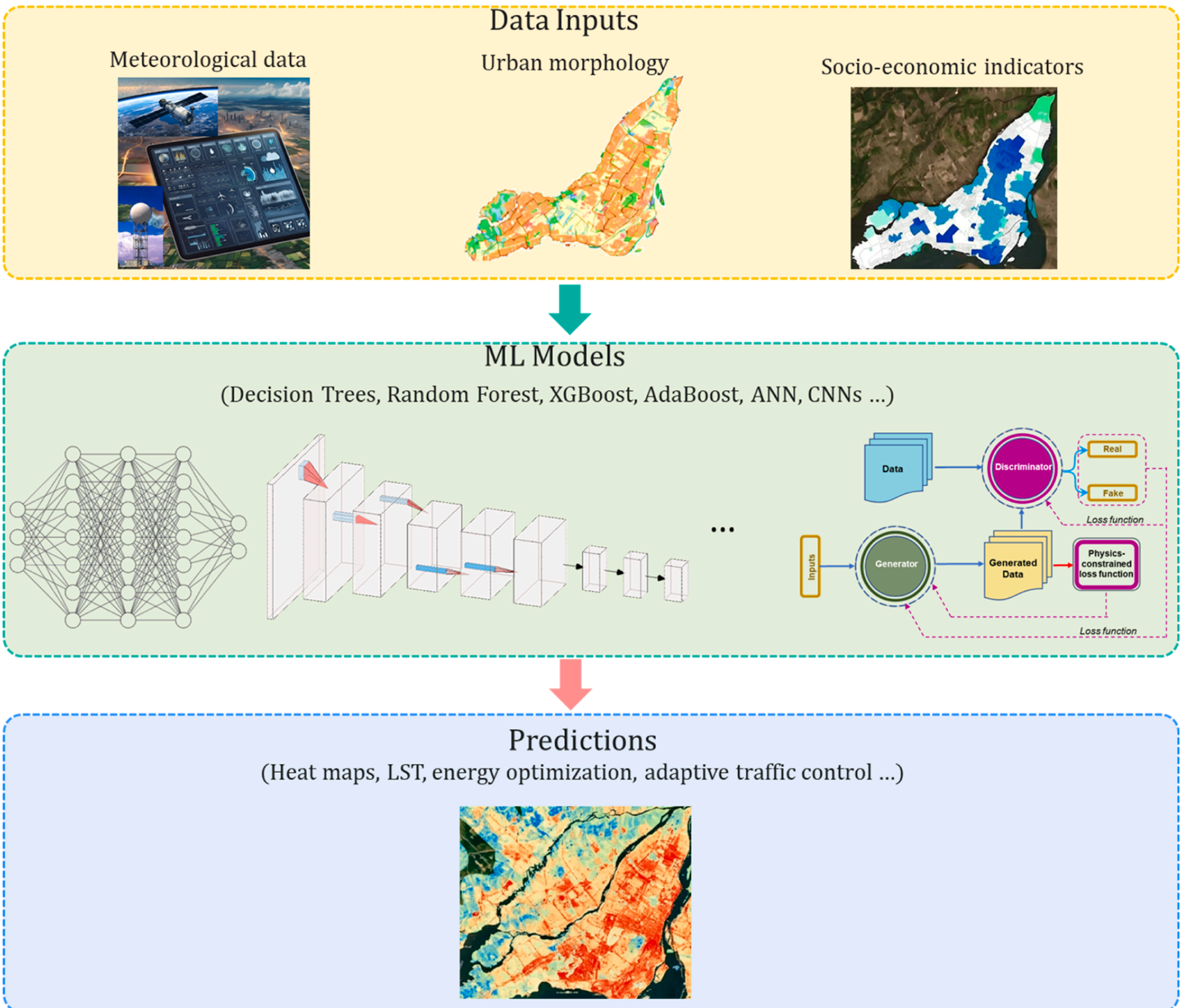

Fig. 4. Machine learning for UHI prediction.

A diverse spectrum of ML and deep learning algorithms has been employed to model these complex relationships. These include multilayer perceptrons (Li et al., 2021), decision trees (DT) (Samardžić-Petrović et al., 2017; Phiri et al., 2020; Karimi et al., 2021), random forests (RF) (Li et al., 2021; Suthar et al., 2024), support vector machines (SVM) (Karimi et al., 2019), XGBoost regression (XGB) (Madaan et al., 2021; Mohammad et al., 2022; Khanifar & Khademalrasoul, 2022), and AdaBoost (Chen et al., 2017). The advent of deep learning has further refined LST prediction by effectively modeling intricate nonlinear relationships and leveraging high-dimensional remote sensing data. CNNs have proven particularly effective in this domain Li et al. (2024a), while ensemble techniques such as adaptive boosting further enhance forecasting accuracy (Bhandari et al., 2022; Li et al., 2022; Pande et al., 2023; Siqi et al., 2023; Tanoori et al., 2024). These advanced methodologies enable the detection of subtle patterns and complex correlations that traditional statistical methods might overlook, ultimately leading to more precise and reliable UHI forecasts.

4.2. Integration of high-resolution data and temporal dynamics

High-resolution remote sensing data (e.g., Landsat, Sentinel, LiDAR) has markedly improved urban-heat prediction at fine spatial scales, enabling observation of temperature variations down to individual buildings (Rodríguez et al., 2020). ML models leverage this detail for more accurate LST and air temperature predictions. For example, LiDAR-derived 3D metrics combined with RF accurately predict temperature variations (Voelkel et al., 2016). Consistent with 3D LiDAR information, recent ML studies show that building height and its variability are among the most influential predictors of (S)UHI when 3D morphology is included. This is because incorporating mean building height (MBH) and height variability (e.g., standard deviation/difference) substantially improves SUHI/LST modeling over 2D-only landscapes (Han, 2023; Yuan et al., 2024; Zhu et al., 2023; He et al., 2025; Zhou et al., 2022b; Chen et al., 2023b). Explainable-ML analyses (partial dependence/SHAP) reveal non-linear, scale-dependent responses; that is, cooling often emerges once low-rise thresholds are exceeded, with strongest predictability at neighborhood scales (hundreds of meters) (Han, 2023; He et al., 2025; Chen et al., 2023b). Empirically, low-rise, high-density blocks tend to warm more, whereas taller or more height-variable blocks can reduce LST via shading and canyon ventilation, with direction and magnitude varying by season and urban context (Zeng et al., 2022; Zhou et al., 2022b; Chen et al., 2023b). In practice, height/morphology descriptors can be ingested as tabular features computed from 3D footprints or learned as embeddings from rasterized 3D/DSM tiles via convolution/attention encoders; ensemble models (e.g., Random Forest, XGBoost) repeatedly rank building height and its variability among dominant SUHI drivers, particularly in dense cores (Han, 2023; He et al., 2023; Ding et al., 2025). Model accuracy increases with data resolution, which enables detection of localized thermal variations crucial for understanding urban structure (Liu et al., 2023; Zhong et al., 2024). Combining high-resolution LST data with urban feature details (e.g., green spaces, building materials, street design) significantly improves prediction accuracy by capturing these fine-scale thermal variations.

Incorporating temporal dynamics is essential for capturing the changing nature of urban heat. UHI intensity varies diurnally, seasonally, and interannually (Das & Ghosh, 2019; Lee et al., 2019; Cureau et al., 2024). Short-term changes driven by weather can be analyzed with time-series methods and RNN/LSTM models, while long-term trends linked to urbanization (Zhou et al., 2024) and climate change (Eunice Lo et al., 2020) are better captured by models that incorporate socio-economic drivers and climate projections. Processing high-resolution spatiotemporal data is computationally intensive (Shi et al., 2021a); efficient algorithms and optimized data pipelines, often leveraging high-performance computing (HPC) systems and GPUs, are therefore critical. Considering both high spatial resolution and temporal dynamics enables spatially precise and temporally robust predictions that support real-time heat responses and long-term urban planning.

4.3. Modeling positive feedbacks

Urban heat can be self-reinforcing: higher outdoor temperatures increase cooling demand, and Air-conditioning systems (AC) waste heat in turn warms the near-surface environment, especially under weak winds. Data-driven studies operationalize this pathway by estimating anthropogenic heat flux (AHF) with ML and embedding it as a dynamic predictor in UHI/SUHI models. Recent work produces fine, spatiotemporal AHF maps, capturing building/energy 'metabolic' heat and mobility signals that scale with AC use (Qian et al., 2022; Ao et al., 2024). ML temperature models that include AHF and related human-activity variables reveal non-linear relations consistent with AC–UHI feedbacks (Kim et al., 2022), while explainable learners (e.g., histogram-based gradient boosting with SHAP) quantify interaction effects between energy/human drivers and urban morphology (Hoang, 2025; Yang et al., 2025). ML models trained on long time series of urban–rural temperature differences (ΔT) can capture temporal persistence pathways through which feedback mechanisms manifest (Varentsov et al., 2023). Although fully closed-loop feedbacks are often simulated with coupled urban-climate and building-energy models, these ML approaches provide operational, data-driven representations of feedback-amplified heating for predictive UHI/SUHI frameworks.

4.4. Model validation and uncertainty analysis

A critical step in UHI prediction is to rigorously validate models and analyze associated uncertainties. Given the complexity of the data and the non-linear dynamics of UHI, robust validation techniques are essential (Vogel & Afshari, 2020). Common methods include splitting data into training and testing sets (Coproski et al., 2024), and cross-validation. Quantifying uncertainty in UHI predictions is also very important (Narock et al., 2025). Uncertainty analysis measures confidence in model outputs and helps understand possible outcomes. Sensitivity analysis identifies how input parameters affect model outputs (Bavarsad et al., 2023), while methods like Monte Carlo simulations and Bayesian inference provide a clear understanding of confidence levels and potential error margins (Maracchini et al., 2022). Some ML techniques, such as Bayesian methods and ensemble models, inherently estimate prediction uncertainty (Shafi et al., 2022). Understanding uncertainty is essential for informed decision-making and risk assessment, especially for extreme heat events (Narock et al., 2025).

Common performance metrics for ML models in UHI prediction include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared. High R-squared values and low MAE and RMSE values indicate better model performance. These practices ensure ML models reliably capture urban thermal dynamics, highlight limitations, and guide improvements. Ultimately, thorough validation and uncertainty analysis ensure credible and actionable predictive insights, informing effective urban planning and heat mitigation strategies.

5. Optimization of UHI mitigation strategies

5.1. UHI mitigation strategies

A range of strategies has been advanced to mitigate the UHI effect (Fig. 5). A cornerstone approach is the expansion of vegetation and green infrastructure through policies that support interconnected green corridors, urban parks, street trees, green roofs and walls, and permeable pavements (Mitra et al., 2024; Karan et al., 2025). Vegetation cools primarily via latent heat flux (evapotranspiration), and it also provides shade, reduces short-wave thermal radiation absorbed by built surfaces, and improves outdoor air quality. Co-benefits include better stormwater management, enhanced biodiversity, and carbon sequestration. Cool materials represent a complementary pathway. High-albedo and other reflective surfaces, implemented as cool roofs, reflective paints, cool pavements, and spectrally selective façade coatings, reduce shortwave solar absorption and sensible heat storage, lowering surface and near-surface temperatures (Li et al., 2025).

Improved urban planning and design approaches are also crucial for achieving better natural ventilation and diminishing the "urban canyon effect" (Chen et al., 2024b). This involves designing building and street layouts to maximize airflow, reducing the trapping of hot air between tall structures. Techniques include orienting buildings to prevailing winds, creating wider streets, and incorporating open spaces to facilitate air circulation. The urban canyon effect, created by tall buildings lining narrow streets, can impede airflow and trap heat, an effect these planning strategies aim to mitigate. Digital twins, which are virtual representations of urban environments, can be used to test the impact of different planning decisions on UHI before physical implementation (Koeva et al., 2024).

Urban waterbodies and blue-green spaces, such as ponds, lakes, rivers, canals, wetlands, and vegetated riparian zones, can cool surrounding areas primarily via evaporative cooling and enhanced heat storage–release cycles (Ramaiah, 2021; Manteghi et al., 2015; Liu & Weng, 2008; Zhao et al., 2017; Kang et al., 2023). Water absorbs heat and releases it more slowly than most built surfaces, moderating local temperatures, while permeable pavements that promote infiltration and evaporation can further aid cooling. Because evaporative cooling adds moisture to the near-surface air, the net benefit depends on background humidity and wind that increase or decrease the absorbed latent heat compared to the sensible heat. In arid and semi-arid climates (or dry summer conditions), large vapor-pressure deficits support stronger evaporation and typically yield larger air-temperature reductions and improved thermal comfort indices; however, in humid climates, the added moisture can offset air-temperature decreases and, under weak winds, may increase heat-stress indices even when air temperature drops. Cooling footprints and magnitudes vary with waterbody size and shape, wind exposure and orientation to prevailing winds (downwind advection), edge shading and adjacent vegetation, and seasonal hydroclimate. Accordingly, evaluations should pair temperature-based indicators with heat-stress metrics (e.g., Heat Index) and report both microclimatic and comfort outcomes to determine when and where waterbodies provide net benefits (He et al., 2023).

Additionally, the use of district cooling systems, which distribute chilled water from a central plant to buildings, can reduce energy

Fig. 5. Illustrative non-exhaustive examples of key UHI mitigation strategies.

consumption and heat emissions compared to individual AC units (Gros et al., 2016; Lake et al., 2017; Eveloy & Ayou, 2019). Furthermore, the implementation of smart monitoring technologies, such as sensors and data analytics, can optimize energy use and urban planning to mitigate UHI effects by monitoring temperature variations and adjusting urban systems accordingly (MacLachlan et al., 2021; Lyu et al., 2022; Jang et al., 2024; Chakrabortty et al., 2025). Other control strategies include the use of irrigation systems (Gao et al., 2020) to cool surfaces through evaporation and the implementation of artificial shading structures (Balany et al., 2020). Finally, reducing anthropogenic heat emissions through energy efficiency measures in buildings and transportation can contribute to overall UHI mitigation.

5.2. ML applications in UHI mitigation and control

ML optimization is reshaping UHI mitigation by enabling targeted and multi-objective interventions (Islam et al., 2024; Guan et al., 2025). Integrations of LST, detailed building attributes, and solar radiation maps within GIS and ML frameworks help identify locations with the highest potential for cool-roof deployment, thereby maximizing reductions in heat exposure. When LST is combined with urban-morphology metrics and microclimate modeling, planners can position parks, green roofs, and street trees to enhance cooling while improving air quality. At the building scale, ML models trained on historical and real-time energy data reveal opportunities for retrofits and operational adjustments that reduce cooling demand. Surrogate models and flow-aware learners further support the design of block layouts and street orientations that strengthen natural ventilation within urban canopies. In practice, multi-objective optimization driven by ML predictions helps balance implementation costs, energy and comfort gains, and environmental co-benefits so that strategies are both effective and feasible at city scale. Table 1 summarizes the principal ML applications for UHI mitigation and control; detailed treatments are provided in Sections 5.2.1–5.2.5

5.2.1. ML applications for green infrastructure

ML provides scalable tools to site, size, and manage green infrastructure for UHI mitigation (Koeva et al., 2024; Zhang et al., 2025b; Ganjirad et al., 2025). Tree-based surrogates such as Random Forest and XGBoost accelerate design exploration when compared with workflows that rely solely on computational fluid dynamics, which reduces computational burdens while preserving fidelity for decision support

Table 1
ML applications in UHI mitigation and control.

Area	ML objectives	Typical inputs	Representative methods	Targets / metrics
Green infrastructure	Site, size, and manage trees/parks/green roofs; accelerate design vs CFD (e.g. Envi-met® tool) only workflows; monitor and operate assets	LST; NDVI/EVI; 3D morphology (height, density, SVF); LCZ; street geometry; meteorology; in-situ/RS time series	RF, XGBoost; CNN/attention surrogates; time-series learners; SHAP for attribution	ΔLST/SUHII; UTCI/WBGT/ Heat Index; mortality risk; and ventilation potential
Cool materials	Infer material properties and siting; evaluate lifecycle performance and cost trade-offs	Albedo/emittance; solar exposure; orientation; building density; pavement type; aging/soiling; and energy demand	Neural net works; RF; meta-models; evolutionary search	ΔLST; building energy; net GHG impact; durability/ cost
Urban water bodies	Design and place blue infrastructure; quantify cooling drivers; monitor performance	NDWI/MNDWI; water area/shape/ dispersion/depth; winds; adjacency vegetation; LST/ET; land-use and hydrologic constraints	RF/ExtraTrees; CNNs for ET with footprint/physics; PSO + microclimate or LST surrogate	ΔLST/SUHII; UTCI; cooling footprint radius; land/cost
Planning and design	Evaluate scenarios and optimize urban form; identify ventilation corridors; and enable morphology-aware comparability	3D morphology (MBH, BHSD, H/W, SVF); LCZ; LST; winds; land use; and socio-economic layers	Surrogates + genetic algorithms; ridge/SVR/GBDT; UVNM; and digital twins	Urban thermal comfort; energy/emissions; ventilation; multi-objective trade-offs
UHI control	Forecast-informed, real-time adaptive operations at building/district/city scales	Dense sensors; short-term forecasts; mobility and load data; and building telemetry	Model predictive control; supervised controllers; hotspot prediction; and traffic flow ML	Peak demand; comfort; congestion heat; and spatial targeting efficacy

(Ahn et al., 2024). Recent applications illustrate these advantages. In Turin, a GIS-integrated ML assessment of urban regeneration documented a 19.46 % increase in vegetation cover accompanied by a measurable reduction in SUHII (Mutani et al., 2024). In Tokyo, ML-based scenario evaluation indicated that ground-surface greening and related measures reduce outdoor temperatures and associated heat-related mortality (Ohashi et al., 2025).

Model choice also informs species and trait selection. ML analyses rank vegetation types by evapotranspiration and shading potential under local climate conditions (Marando et al., 2022) and identify tree traits such as trunk circumference and crown volume that most strongly predict cooling outcomes (Helletsgruber et al., 2020). For green roofs, hybrid deep models such as SSA-CNN-LSTM provide accurate thermal-performance predictions that aid both design and operation (Wang et al., 2024a; J. Wang et al., 2024b). During implementation and maintenance, ML applied to remote-sensing and in-situ data streams supports continuous monitoring of green-infrastructure performance and enables adaptive interventions. Learning-based controllers can also optimize irrigation schedules, improving cooling efficiency while reducing resource consumption.

5.2.2. ML applications for cool materials

ML supports the design and deployment of cool materials by relating spectral and thermal properties, such as albedo and thermal emittance, to surface and air temperature responses under diverse urban conditions. Data-driven models help identify properties and configurations that minimize heat absorption and maximize cooling benefits at building and street scales. Neural-network models have been used to predict urban albedo for reflective coatings with good accuracy, including Gaussian-process and hyperbolic-tangent architectures conditioned on solar radiation and surface orientation (Yuan et al., 2023). Random-forest analyses of surface modifications report that modest albedo increases (about 3.09 %) are associated with measurable SUHII reductions (Mutani et al., 2024). Meta-modeling has been applied to estimate the net greenhouse-gas impact of pavement albedo changes by jointly accounting for air temperature and building energy demand at high resolution (Xu et al., 2020). Evolutionary search has also been used to optimize paving layouts by assigning materials with different albedo levels while considering material costs (Green et al., 2019). Beyond material selection, ML can target deployment by ranking locations where reflective roofs and pavements yield the largest impact given building density, solar exposure, and baseline LST, and it can forecast long-term performance and energy savings to inform cost–benefit and policy decisions (Visvanathan et al., 2024).

A central challenge is balancing multiple objectives. Materials should maximize solar reflectance and thermal emittance, retain performance under aging, soiling, and weathering, and remain cost-effective to install and maintain. ML frameworks are well suited to this trade-space because they can fuse laboratory measurements with field observations, learn degradation trajectories, and drive multi-objective optimization that evaluates cooling, durability, and cost simultaneously. Such workflows support choices that perform well in controlled tests and remain robust in the complex operating conditions of real urban environments.

5.2.3. ML applications for monitoring and managing urban water bodies

Urban blue-green spaces, including water bodies, are recognized as effective elements in mitigating UHI effects by reducing LST (Budzik et al., 2025; Wang et al., 2024c; Zhang et al., 2025a). Cooling efficiency depends on physical characteristics and spatial configuration, with size, shape, depth, and distribution all influencing performance and more complex shapes often enhancing cooling (Liu et al., 2024a). ML supports planning and design by linking water features to observed thermal responses, frequently within GIS and digital-twin environments. Tree-based learners such as Random Forest and Extremely Randomized Trees capture the relationship between water presence and LST with high robustness, enabling city-scale prediction of cooling effects (Wang et al., 2024c). Convolutional models assist mechanistic understanding by estimating urban evapotranspiration (ET); incorporating flux-footprint information and basic physical constraints improves the fidelity of ET simulations and clarifies the role of blue infrastructure in surface cooling (Chen et al., 2023a).

Optimization workflows increasingly pair ML with population-based search to design waterbody layouts that maximize cooling under practical constraints. Particle swarm optimization (PSO) encodes decision variables such as water area share, centroid locations, shape or compactness, and dispersion, and evaluates candidates with a microclimate model or LST-based surrogate subject to land-use and hydrologic limits. At city scale, PSO has been used to allocate land-use classes, explicitly including waterbodies, to reduce LST (Xiao et al., 2025). At microclimate scale, PSO has optimized tree placement to lower UTCI (Shaamala et al., 2024), illustrating a simulation–optimization pattern that extends directly to waterbody layout for UHI and SUHI mitigation. In operation, ML applied to remote-sensing and in-situ networks supports continuous monitoring of waterbody performance, detection of deterioration or anomalies, and adaptive management. Together, these ML-driven approaches enable more informed and efficient use of urban waterbodies as a core element of UHI mitigation.

5.2.4. ML applications for urban planning & design approaches

ML is increasingly central to optimizing planning and design strategies for UHI mitigation (Koomen & Diogo, 2017). Models trained on historical links between urban morphology and observed temperatures enable rapid evaluation of counterfactual layouts and development scenarios (Koomen & Diogo, 2017). Digital twins that integrate three-dimensional city models enriched with synoptic real-time data and ML provide practical platforms to visualize and predict cooling outcomes under alternative plans (Koeva et al., 2024).

Recent applications illustrate the breadth of ML-enabled planning tools. Hao et al. (2023) introduced an ML-Enhanced Design Optimizer that couples a neural-network surrogate with a genetic algorithm to explore cooling strategies efficiently, demonstrating advantages for early-stage decision making in Southern China. López-Guerrero et al. (2024) combined several ML models, including SVR, MLP, and Gradient Boosting with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to optimize building and district-scale designs, yielding notable reductions in energy loads and heat emissions. Okumus and Terzi (2021) used Ridge Regression to quantify the contribution of urban fabric components (e.g., building coverage ratio, vegetation index) to surface UHI formation, providing actionable guidance for climate-sensitive layouts. For wind-driven relief, an Urban Ventilation Network Model (UVNM) identified ventilation corridors by accounting for building height and prevailing winds, subsequently validated with LST patterns (Qiao et al., 2017). At the block scale, a performance-based workflow integrating CFD with evolutionary algorithms improved ventilation potential by ~16 % relative to initial layouts (Lim & Ooka, 2021). Genetic algorithms have also been used to optimize land-use patterns for thermal benefit by exploring scenarios that minimize heat accumulation.

The Local Climate Zones (LCZ) framework provides a standardized, morphology-aware typology that pairs naturally with ML for climate-aware planning and attribution. Global ~100 m LCZ layers produced with Random Forests are now available (Demuzere et al., 2022), while deep-learning benchmarks such as So2Sat LCZ42 have accelerated cross-city LCZ classification using Sentinel-1/2 (Zhu et al., 2019; Zhou et al., 2022a; Liu & Shi, 2020; Cui et al., 2022). In UHI/SUHI modeling, LCZ can function as a categorical feature, a stratification layer for training/evaluation within homogeneous forms, or a bridge integrating morphology with spectral/land-cover indices. LCZ-aware ML has been shown to improve skill and interpretability, including diurnal cycle characterization (Oliveira et al., 2022). Building on this framework, a recent study proposed a multi-scenario optimization method based on local climate zones, employing genetic algorithms to adjust the quantity and structure of these zones, thereby enhancing the overall urban thermal environment (Chen et al., 2024c). More broadly, ML can analyze airflow patterns in urban environments to identify layouts that promote better ventilation, aiding in heat dissipation (Koomen & Diogo, 2017), and can support sustainable urban transformation by analyzing various layers of environmental, social, and economic data to guide the development of urban plans and designs that minimize UHI effects and enhance overall urban resilience.

5.2.5. ML applications for UHI control

ML enables a shift from static mitigation to adaptive control guided by real-time data. Dense sensor networks and short-term weather forecasts feed ML models that anticipate heat intensity and spatial patterns, allowing city services to target interventions where they matter most. Examples include dynamically operating misting systems and deployable shading in public spaces, and prioritizing streets or plazas with the highest projected thermal stress. Such workflows coordinate actions across departments while balancing comfort gains, water use, and operational constraints.

At the building and district scale, ML-based controllers improve the efficiency of cooling systems by learning the relationship between outdoor conditions, UHI amplification, and indoor demand. Studies demonstrate adaptive HVAC control that responds to moment-to-moment conditions to optimize energy use and comfort (Hassan & Abdelaziz, 2022; Gaidhani et al., 2024). Forecast-informed building management systems further adjust setpoints and schedules in anticipation of UHI-driven peaks, reducing electricity demand and costs while maintaining thermal comfort (Attarhay Tehrani et al., 2024). In parallel, mobility analytics use ML to redistribute traffic flows in real time, easing congestion hotspots and associated anthropogenic heat emissions at street level (Vihurskyi, 2024). Together these dynamic control strategies extend the impact of traditional measures by delivering timely, location-aware responses to evolving urban heat conditions.

6. Flexible adaptation for UHI mitigation

Traditional UHI mitigation strategies often rely on static interventions, such as fixed cool roofs, predetermined green spaces, and permanent urban layouts (Chen & You, 2020). However, UHI mitigation necessitates not only immediate interventions but also long-term planning and flexible adaptation strategies that can dynamically adjust and evolve in response to changing climate conditions and urban development patterns (Cakmakli & Rashed-Ali, 2022). Unlike mitigation strategies that aim to reduce the root causes of UHI, adaptation focuses on adjusting to the effects of increased urban heat to minimize negative impacts (He et al., 2023). Adaptive measures offer a dynamic approach, enabling cities to respond in real-time to fluctuating environmental conditions. These measures involve deploying smart materials that dynamically adjust their thermal properties in response to ambient temperature and sunlight intensity (Irfeey et al., 2023; Turhan et al., 2023), alongside sustainable techniques such as incorporating recycled aggregates (Moretti & Loprencipe, 2018; Jeong et al., 2019), phase-change materials (PCMs) (Reyez-Araiza et al., 2021; Marani & Nehdi, 2019; Wong et al., 2021), and thermochromic coatings (Jamei & Tapper, 2019; Hu & Yu, 2020). These materials can modulate surface temperatures by reflecting more solar radiation, storing and releasing latent heat, or even changing color to optimize thermal absorption based on the time of day and season (Irfeey et al., 2023; Andoni & Wonorahardjo, 2018). Such adaptive systems not only reduce surface temperatures and greenhouse gas emissions but also enhance overall energy efficiency by using locally sourced, eco-friendly building components (Santamouris et al., 2019; Irfeey et al., 2023). Moreover, adaptive urban design can integrate modular green spaces that expand or contract based on real-time thermal data, and ventilation corridors that adjust with evolving wind patterns and urban growth (Fadhil et al., 2023). By continuously monitoring and responding to fluctuating urban climate conditions, adaptive strategies provide a more resilient and flexible framework to mitigate the effects of UHI (Qi et al., 2020).

ML plays an increasingly important role in enabling these flexible adaptation strategies for UHI (Ghorbany et al., 2024). One key application lies in the dynamic deployment of resources based on real-time UHI data and heat wave predictions generated by ML models. For example, ML can analyze sensor network data and weather forecasts to predict periods of extreme heat, triggering the activation of cooling centers in vulnerable neighborhoods or the deployment of additional emergency medical services. ML algorithms can analyze the large volumes of real-time data from sensors, satellites, and IoT devices across urban environments to identify emerging heat patterns, predict short-term temperature fluctuations, and determine the optimal timing for activating adaptive cooling systems (Liu et al., 2021; Zumwald et al., 2021). Predictive models can forecast when and where a city might experience a heat surge, allowing automated systems to dynamically deploy smart materials or adjust ventilation pathways. Furthermore, ML can optimize the performance of adaptive infrastructures by learning from historical data and continuously refining intervention strategies (Okumus & Terzi, 2021).

ML-based simulations can also help urban planners develop adaptive urban planning and design solutions (Koomen & Diogo, 2017). By modeling different climate change scenarios and urban growth projections, ML can inform the design of flexible infrastructure and green spaces that can effectively mitigate heat under a range of future conditions. Additionally, ML can be used to identify vulnerable populations within cities based on factors like age, income, and health status, allowing for the tailoring of adaptation strategies to their specific needs. This could include targeted heat alert systems delivered via mobile apps or the provision of cooling assistance programs for low-income households. Community involvement and citizen science initiatives, potentially facilitated by ML-powered data collection and analysis tools, can also contribute to flexible adaptation by empowering local communities to monitor heat conditions and implement localized solutions (Zuccarini, 2024).

Finally, ML can be applied to enhance the resilience of urban infrastructure to extreme heat. By analyzing historical data on infrastructure failures during heat waves and incorporating climate projections, ML models can predict the potential impacts of future heat events on roads, power grids, and other critical systems. This information can then inform the development and deployment of more heat-tolerant materials and proactive maintenance strategies. Developing digital twins of cities that integrate real-time data, urban models, and climate change projections provides a powerful tool for testing and evaluating different urban planning and adaptation scenarios (Du et al., 2024). Moreover, ML models can be trained on urban data to identify effective policy interventions for UHI mitigation, such as assessing the impact of different incentives for cool roof adoption or green infrastructure development. By integrating real-time environmental feedback with adaptive control systems, ML not only enhances the efficiency of UHI mitigation measures but also supports the development of a responsive urban environment capable of evolving with climate challenges.

7. Discussion and synthesis

This review has illuminated the progressively central role of ML methodologies in the comprehension, prediction, mitigation, and adaptation strategies concerning the UHI effect. The synergistic integration of diverse data streams, sophisticated analytical techniques, and advanced modeling tools has unlocked novel avenues for tackling this complex and multifaceted urban challenge. This section synthesizes the key findings of the review, critically evaluates the potential and inherent limitations of ML approaches in this context, and proposes promising directions for future research endeavors.

A significant portion of the current body of research on ML applications in UHI has been dedicated to data analysis, prediction, and forecasting. These efforts have yielded a more granular and nuanced understanding of UHI dynamics by uncovering intricate relationships between urban morphology, land cover characteristics, and meteorological variables. Furthermore, the enhanced accuracy and timeliness of ML-driven forecasts are enabling more proactive and targeted mitigation measures through improved predictions of urban temperature distributions (Ghorbany et al., 2024). However, this review has revealed a notable imbalance in the current research landscape. While predictive capabilities have advanced considerably, there is a comparatively limited focus on leveraging ML for the optimization of UHI mitigation strategies. Even fewer studies have explored flexible, adaptive approaches that can dynamically respond to evolving climate conditions and shifting urban development patterns. Given that effective UHI management necessitates not only precise forecasting but also the capacity to optimize interventions and adjust strategies in real time, this disparity represents a critical area demanding greater scholarly attention in the future.

In light of this identified gap, future research efforts should prioritize the development of ML-based frameworks that extend beyond the realm of prediction. Such frameworks should integrate robust optimization tools to maximize the effectiveness of mitigation measures while carefully considering and minimizing associated costs and potential trade-offs (Turhan et al., 2023). Moreover, these frameworks should actively support adaptive urban planning strategies capable of responding to dynamic environmental and socio-economic changes. By incorporating socio-economic and behavioral data alongside traditional environmental variables, these sophisticated models can inform the development of more equitable and resilient long-term urban policies (Parsaee et al., 2019; Liu & Morawska, 2020).

Overall, while ML methods have undeniably made substantial contributions to the understanding and forecasting of UHI, a greater emphasis on the application of ML for optimizing and flexibly adapting UHI mitigation strategies is urgently needed. Addressing this critical gap will be essential for the development of holistic and sustainable solutions to effectively manage urban heat in the face of a rapidly changing climate. In the subsequent section, and as visually summarized in Fig. 6, a more in-depth discussion of the key challenges and research gaps identified throughout this review will be presented, along with promising prospects and future directions for advancing the impactful application of ML in UHI mitigation.

7.1. Challenges and research gaps

7.1.1. Challenges in UHI data acquisition and quality

UHI research relies on a diverse and often fragmented collection of data sources, including high-resolution remote sensing imagery, ground-based sensor networks, and outputs from numerical models. While these sources provide rich spatial and temporal information, several fundamental challenges persist in acquiring and ensuring the quality of UHI data.

One significant challenge lies in the heterogeneous and sparse nature of observations. Remote sensing platforms, although offering high spatial resolution, often have limitations in temporal frequency and can be affected by factors such as cloud cover and calibration inconsistencies. Ground-based weather stations provide valuable near-surface air temperature data but are frequently spatially sparse, exhibit wide variations in data quality, and can be influenced by sensor placement and maintenance protocols. These disparities across data sources necessitate careful consideration during integration and analysis.

Another critical challenge is multi-scale and multi-format data integration. Urban areas are characterized by complex and highly heterogeneous features arising from variations in land cover, building geometry, and surface materials. This inherent variability leads to significant microclimatic differences that are not easily captured by any single data source. Integrating structured numerical data from simulations, semi-structured remote sensing products, and unstructured metadata presents considerable hurdles in terms of data cleaning, standardization, and effective aggregation to facilitate meaningful analysis.

Temporal limitations and the scarcity of long-term records also pose a substantial challenge. Many currently available datasets have relatively short record periods compared to the extended time scales required to thoroughly assess the impacts of long-term climate change on UHI intensity. This limitation restricts the ability to examine long-term variations and trends. Furthermore, capturing the full spectrum of diurnal, seasonal, and interannual temperature variations, particularly during nighttime when UHI effects are often most pronounced, remains a significant hurdle.

Finally, the density and strategic placement of sensing infrastructure constrain the comprehensive evaluation of the UHI effect. Existing sensor networks may not adequately cover all targeted regions, limiting the understanding of localized variations. A more comprehensive assessment necessitates both an increase in the density of measurement stations and the implementation of strategic placement planning in adjacent areas to enable robust comparative analysis. This enhanced data collection would facilitate a more thorough examination of the various factors influencing UHI.

Collectively, these challenges underscore the pressing need for improved data collection protocols, the establishment of longer-term observational networks, and the development of sophisticated data fusion techniques capable of effectively bridging the existing gaps in the spatial, temporal, and qualitative dimensions of UHI data.

7.1.2. Challenges in ML algorithm application for UHI analysis

While ML offers powerful tools for advancing the understanding and analysis of UHIs, its application presents several significant algorithmic challenges that must be addressed to fully realize its potential in this domain. One major hurdle stems from the complex, nonlinear, and nonstationary dynamics inherent in UHI phenomena. These phenomena arise from intricate and dynamic interactions among urban morphology, land cover, meteorological conditions, and human activities. Many standard ML algorithms, originally developed for fields like image recognition or natural language processing, often struggle to effectively capture these complex, nonlinear, and time-varying relationships.

Another significant challenge lies in the dependence on limited and potentially biased labeled data. Supervised ML techniques typically require substantial amounts of high-quality, labeled data. However, UHI datasets frequently suffer from issues such as sparsity, uneven spatial and temporal distribution, and a lack of comprehensive labeling for specific UHI-related tasks. This scarcity of suitable data can lead to problems like model overfitting, where the model performs well on the training data but poorly on unseen data, or poor generalization in regions or time periods that are underrepresented in the training data. Furthermore, ML models trained on data from one city or climate zone may face limitations in their generalization and transferability across diverse urban environments. Differences in urban morphology, land cover characteristics, and meteorological conditions necessitate region-specific training data.

Furthermore, the interpretability challenges and the ’black box’ nature of many advanced ML models pose a significant obstacle. Complex models, such as deep learning architectures and ensemble methods, often operate as "black boxes," making it difficult to understand the underlying physical mechanisms driving their predictions. In critical applications like urban planning and climate adaptation, the ability to understand and explain predictions is paramount for building trust and gaining scientific insights. Consequently, there is a growing need for more interpretable ML approaches in UHI research (Ang et al., 2024; Wu & Snaiki, 2022).

Beyond these issues, practical challenges also exist in terms of hyperparameter tuning, uncertainty quantification, and computational

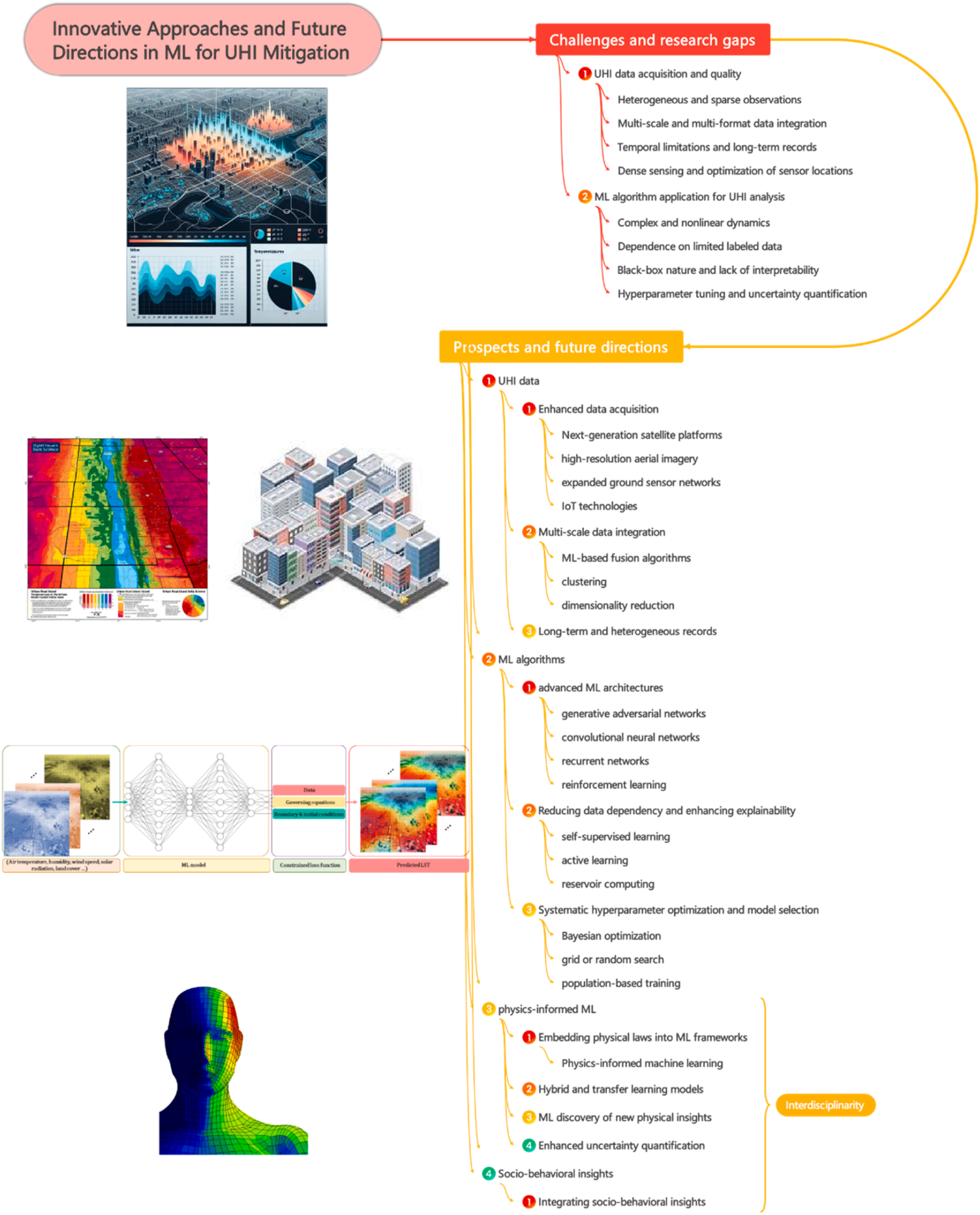

Fig. 6. Mind map of challenges, research gaps and future perspectives.

demands. Choosing the most appropriate model architecture and tuning its hyperparameters often remains a largely trial-and-error process. Moreover, while robust uncertainty quantification is essential, particularly when ML predictions inform policy decisions, systematic approaches for assessing and propagating uncertainty in UHI predictions are still underdeveloped. Additionally, processing and training complex ML models, especially when dealing with high-resolution spatiotemporal data, can be computationally demanding, requiring significant resources (Shi et al., 2021a). Finally, it is important to be mindful of the distinction between correlation and causation when interpreting the results of ML models, as purely data-driven approaches may sometimes identify spurious relationships without capturing the underlying physical processes.

Addressing these multifaceted challenges will necessitate the development of specialized ML frameworks specifically tailored for the complex dynamics of UHIs. These frameworks should not only excel in predictive performance but also incorporate physical principles, provide transparent and robust uncertainty estimates, and be computationally feasible for practical applications.

7.2. Prospects and future directions

While the application of ML to the study of UHIs has yielded considerable progress, many challenges remain that also open up exciting new avenues for research. This section outlines key prospects for advancing the field, focusing on improvements in UHI data acquisition and processing, the enhancement of ML algorithm performance, the integration of physical principles into ML approaches, and the incorporation of socio-behavioral insights through interdisciplinary collaboration.

7.2.1. Prospects for UHI data

The future of UHI research is poised for significant advancements driven by enhanced data acquisition capabilities and a growing emphasis on integrating diverse data sources. To address current limitations in UHI data, future work should prioritize the development and integration of new data sources alongside sophisticated processing techniques. Enhanced data acquisition will play a crucial role, with next-generation satellite platforms and high-resolution aerial imagery providing more detailed and frequent observations of land surface temperature. Innovations in sensor technology and deployment strategies will enable more accurate and continuous monitoring of urban thermal environments, while advanced thermal imaging techniques will further contribute to improved data quality. The deployment of denser networks of low-cost ground-based sensors, including the expansion of community-based monitoring initiatives, offers a practical solution to fill observational gaps and provide near real-time air temperature data at unprecedented spatial resolutions.

Furthermore, future research will increasingly focus on multi-scale data integration to gain a more holistic understanding of UHI. UHI phenomena manifest across a wide range of scales, from building-level variations within neighborhoods to city-wide patterns. Advanced data fusion techniques, such as advanced data assimilation techniques, ML-based fusion algorithms, clustering, and dimensionality reduction, will be essential to effectively integrate high-resolution remote sensing data with in situ measurements and numerical simulation outputs. Beyond these sources, there will be a growing emphasis on integrating diverse data, including meteorological data, detailed urban morphology information like building footprints and land use maps, socioeconomic data to understand vulnerability, and even potentially incorporating social media data to capture human experiences of urban heat. Establishing common data standards and interoperable platforms will be critical to facilitate the seamless aggregation, cleaning, and integration of data from these diverse sources, ultimately improving the robustness and coverage of UHI datasets.

Finally, given the profound impacts of climate change on urban thermal behavior, it is critical to establish long-term and heterogeneous records. Long-term observational networks are necessary to capture diurnal, seasonal, and interannual variations, enabling the study of long-term trends and extreme events. In addition, creating standardized protocols for data collection and processing will be essential to harmonize heterogeneous datasets derived from different instruments and sources, ensuring the consistency and comparability of data over time and across various studies.

7.2.2. Prospects for ML algorithms

The continuous evolution of ML presents promising avenues to address the complex, nonlinear nature of UHI phenomena and significantly benefit future research in this area. It is anticipated that more robust and generalizable ML models will be developed, exhibiting less susceptibility to overfitting and greater applicability across diverse urban environments. One key direction involves adopting advanced ML architectures. Emerging ML algorithms, such as generative adversarial networks (GANs), convolutional neural networks (CNNs), recurrent networks like LSTMs, and reinforcement learning, hold significant potential for capturing the intricate spatiotemporal patterns characteristic of urban thermal environments. These methods can be specifically tailored to efficiently process grid-based data, like high-resolution maps of land cover and temperature, as well as time-series measurements. Furthermore, the continued development and application of advanced deep learning architectures, such as graph neural networks (GNN) and transformer networks, alongside ensemble learning methods, are likely to lead to further improvements in UHI prediction and analysis.

Another crucial area of progress lies in reducing data dependency and enhancing explainability. Given the challenges associated with acquiring densely labeled UHI datasets, unsupervised and semi-supervised learning techniques offer appealing alternatives. Techniques such as self-supervised learning, active learning, and reservoir computing may enable effective model training even when labeled data are scarce. Moreover, there will be a growing focus on explainable AI (XAI) methods (Attarhay Tehrani et al., 2024) to enhance the interpretability of complex ML models used in UHI research. This will allow researchers and practitioners to better understand the factors driving urban heat and to have greater confidence in model predictions. Techniques like sensitivity analysis and layer-wise relevance propagation will be vital in this regard. Additionally, techniques like domain adaptation and meta-learning will likely play a key role in improving model transferability across different urban environments. The integration of physical constraints and knowledge into ML models, through the burgeoning field of physics-informed machine learning (PIML) (Shaeri et al., 2025), holds significant promise for generating more accurate, physically consistent, and interpretable UHI predictions.

Finally, developing robust and generalizable ML models for UHI analysis will necessitate systematic hyperparameter optimization and model selection. The use of automated optimization methods, such as Bayesian optimization, grid or random search, or population-based training, can help identify optimal model configurations that strike a balance between performance and generalizability while mitigating the risk of overfitting. This systematic approach to model development will be crucial for building reliable and trustworthy ML tools for UHI research and urban planning applications.

7.2.3. Prospects for physics-informed ML

Integrating physical principles into ML models represents a promising direction for UHI research, offering a way to bridge the gap between purely data-driven ML models and traditional physics-based models (Shaeri et al., 2025). Embedding physical laws into ML frameworks, known as physics-informed machine learning (PIML), involves incorporating known physical constraints, such as energy conservation, radiative balance, and heat transfer equations, directly into the learning process (Snaiki & Wu, 2019). This can be achieved by adding physics-based regularization terms to the loss function, ensuring that model predictions remain consistent with established thermal dynamics even when observational data are sparse. One such option is illustrated in Fig. 7, where the network takes as input various factors, including meteorological variables (e.g., air temperature, humidity, wind speed, and solar radiation), land cover transformations, and anthropogenic factors. The model predicts the spatial distribution of LST while also minimizing residuals from the corresponding partial differential equations. This approach not only enforces physical consistency, even in data-sparse regions, but also improves extrapolation to unseen urban conditions. By incorporating known physical laws and principles, such as those governing heat transfer and fluid dynamics, into the learning process of neural networks and other ML architectures, PIML can lead to models that are not only accurate in fitting observed data but also respect the underlying physical processes (Shaeri et al., 2025). This integration can significantly improve the interpretability of ML models and enhance their ability to generalize to unseen urban environments and future climate scenarios (Shaeri et al., 2025).

Hybrid and transfer learning models also present a valuable avenue for future research. A hybrid modeling framework that combines physics-based numerical simulations (e.g., a CFD or energy balance simulation) with ML bias-correction techniques can leverage the strengths of both approaches. For example, high-fidelity urban energy balance simulations can be used to pre-train ML models, which are then fine-tuned using observational data with embedded physical constraints. Another approach consists of constructing a two-stage framework where a conventional physics-based urban climate model produces a baseline temperature field. An ML model is then trained to "correct" this output by learning the biases between the simulation and observed data. Such models not only improve prediction accuracy but also enhance interpretability by ensuring that predictions adhere to the underlying physics.

Furthermore, ML discovery of new physical insights is a compelling prospect of PIML. By jointly learning from data and enforcing physical constraints, these models can reveal unexpected interactions between urban morphology, land cover, and meteorological conditions that might be overlooked by traditional analysis methods, thereby advancing the fundamental understanding of UHI dynamics.

Finally, enhanced uncertainty quantification can be achieved by embedding physics into ML models. This approach can constrain the solution space to physically plausible regimes, which improves the reliability of uncertainty estimates. Further research is needed to develop systematic methods for propagating uncertainties from both data and model parameters, a critical requirement for decision making in urban planning. PIML also has the potential for accurate estimation of urban thermal comfort metrics (such as UTCI) by directly embedding physical relationships into the model structure. Furthermore, PIML can be used to downscale coarse-resolution climate model outputs to the urban scale while ensuring that the downscaled data adheres to fundamental physical constraints.

Each of these approaches brings the strengths of both ML and established physical theory, potentially reducing the reliance on large training datasets while also increasing interpretability and extrapolation ability for urban climate predictions.

7.2.4. *Socio-behavioral insights and interdisciplinary collaboration*

Beyond technical advancements in data acquisition and ML algorithms, effective UHI mitigation increasingly recognizes the importance of understanding the human and social dimensions that influence urban climate dynamics. Future research should consider proactive human-centered approaches by integrating socio-behavioral insights. Mitigating UHI is not solely a technical challenge; it also involves understanding human behavior and community dynamics. Incorporating socio-behavioral data, such as patterns of energy use, population exposure, thermal comfort, vulnerability, and community response strategies, into UHI analyses can yield more effective and equitable mitigation measures. By capturing the interplay between built environments and human activity, models can better inform policy decisions that address both physical and social vulnerabilities (Degirmenci et al., 2021). This integration should also include socioeconomic factors, such as income levels, racial demographics, and age distributions, along with behavioral data related to energy consumption patterns and adaptation strategies, to provide a more nuanced understanding of vulnerability and inform more equitable mitigation efforts.

Addressing the complex challenges of UHI effectively requires fostering interdisciplinary collaboration between experts from diverse fields, including urban planning, climate science, computer science, social science, public health, and engineering (Zuccarini, 2024). Promoting interdisciplinary research will be key to developing innovative, robust solutions that are scientifically sound and practically applicable. By bridging disciplinary boundaries, researchers can develop integrated frameworks that leverage state-of-the-art data and ML techniques while also accounting for human and societal factors. Engaging communities and leveraging citizen science initiatives in data collection and the implementation of local mitigation measures will also be crucial (Zuccarini, 2024).

Furthermore, there is a need to develop user-friendly ML-powered tools and platforms that can be used by urban planners, policymakers, and the public to visualize UHI data, explore different mitigation scenarios, and make informed decisions. Finally, as the use of ML in this domain expands, it will be essential to address ethical considerations related to data privacy, algorithmic bias, and ensuring equitable access to information and resources. By embracing these socio-behavioral and collaborative approaches alongside technical advances, future UHI research can achieve a more holistic understanding of urban heat dynamics and support the development of comprehensive adaptation strategies.

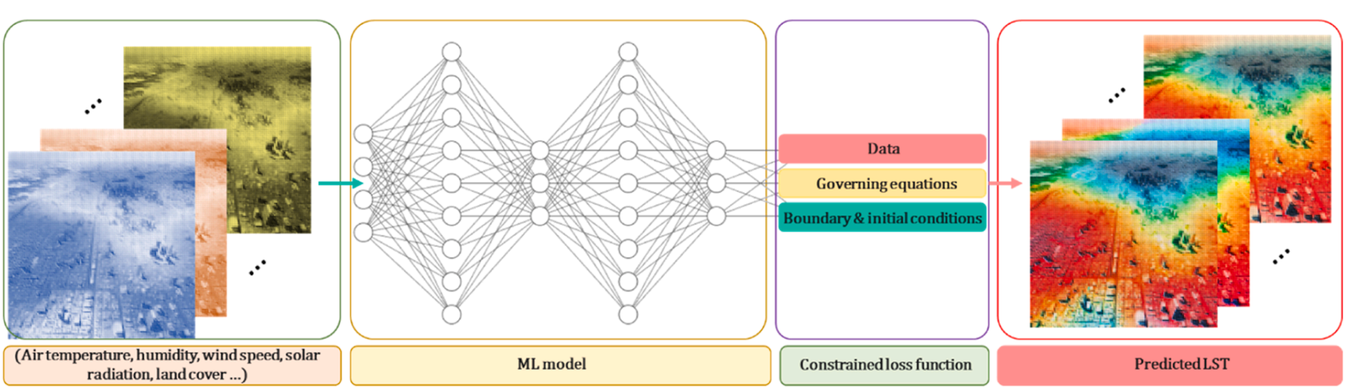

Fig. 7. Schematic of the physics-informed ML model for LST prediction.

8. Conclusion

This review has systematically examined the burgeoning application of ML methodologies within the domain of UHI research. By synthesizing insights across diverse data acquisition modalities, sophisticated processing pipelines, and cutting-edge ML models, this work elucidates the significant potential of these approaches to enhance the understanding of complex urban thermal dynamics and inform the development of more efficacious mitigation strategies. The integration of satellite-derived observations, mobile in-situ measurements, and dense sensor networks, coupled with advanced data fusion and analytics, has underscored the transformative capacity of ML methodologies in accurately forecasting UHI patterns and optimizing targeted interventions.

Despite these considerable advancements, several critical challenges warrant careful consideration. The robustness and reliability of ML-driven insights are intrinsically linked to the quality and consistency of the underlying data. Issues pertaining to sensor calibration, data heterogeneity across sources, and substantial computational resource demands continue to present significant obstacles. Furthermore, the inherent 'black-box' nature of certain ML architectures raises valid concerns regarding the interpretability of their outputs, while ethical and privacy implications associated with the collection and analysis of large-scale urban datasets necessitate rigorous attention and the development of responsible data governance frameworks. These limitations underscore the imperative for ongoing refinement of analytical frameworks and the development of more robust and transparent models capable of effectively capturing the intricate complexities of urban environments.

Looking towards the future, research efforts should prioritize enhancing data quality through improved sensor technologies and rigorous calibration protocols, alongside expanding the spatial and temporal coverage of urban monitoring networks to bolster the generalizability of predictive models. Notably, the integration of physics-informed machine learning (PIML) represents a promising frontier for overcoming current limitations. By embedding fundamental physical principles and constraints directly into ML models, PIML offers the potential to enhance model interpretability, reduce the reliance on extensive datasets, and improve the robustness of predictions, particularly in data-scarce urban settings. This approach ensures that model outputs are not only data-driven but also physically plausible, thereby increasing their reliability for real-world applications. Moreover, the synergistic integration of digital twin technologies, real-time adaptive control systems for urban infrastructure, and interdisciplinary collaborations holds significant promise for translating data-driven insights into tangible urban planning and management strategies. By diligently addressing these challenges and strategically leveraging emerging opportunities, ML methodologies can play a pivotal role in fostering the development of sustainable, resilient, and thermally comfortable urban environments in the face of accelerating urbanization and the pervasive impacts of climate change.

CRediT authorship contribution statement

Reda Snaiki: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Abdelatif Merabtine:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

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

Acknowledgements

This work was partly supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) [grant number CRSNG RGPIN 2022–03492].

Data availability

No data was used for the research described in the article.

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