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REVIEW ARTICLE

Satellite-Based Urban Heat Island Mapping Using Multitemporal Thermal Imagery and AI Models - A Comprehensive Review

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Abstract. Urban Heat Islands (UHIs) are a significant consequence of rapid urbanization, contributing to environmental and health-related challenges in metropolitan regions. With advances in remote sensing and artificial intelligence (AI), satellite-based thermal imagery has become a vital tool for detecting, monitoring, and analyzing UHIs. This review presents an in-depth synthesis of the methodologies, satellite platforms, thermal indices, AI-based modeling techniques, and current trends used in UHI mapping. It explores the potential of multitemporal thermal datasets, discusses the limitations of traditional methods, and highlights the emerging role of machine learning (ML) and deep learning (DL) models in improving UHI analysis accuracy and resolution. Furthermore, the review examines the integration of AI with big data platforms for large-scale urban monitoring and the importance of high-resolution spatiotemporal datasets for climate-responsive urban planning. The findings underscore the growing importance of data-driven approaches in understanding urban thermal dynamics and offer future directions for real-time UHI assessment, policy development, and sustainable urban design.

Keywords: Urban Heat Island (UHI), Thermal Remote Sensing, Multitemporal Satellite Imagery, Land Surface Temperature (LST), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Urban Climate Mapping

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1. Introduction

Urban Heat Islands (UHIs) refer to the phenomenon wherein urban areas experience significantly higher temperatures than their rural counterparts due to the replacement of natural land cover with impervious surfaces like concrete and asphalt. The consequences include increased energy consumption, air pollution, and public health risks. Mapping UHIs is vital for climate resilience and urban sustainability planning.

Remote sensing has proven to be an efficient means to observe surface temperatures at large spatial and temporal scales. In recent years, the integration of multitemporal thermal satellite imagery and AI techniques has led to significant advancements in UHI studies. This review outlines key developments and challenges in this domain, with a focus on AI-enhanced analysis.

The UHI effect has been widely observed in cities across the globe, with increasing intensity over the past few decades due to population growth, industrialization, and declining vegetation cover [1]. These urban thermal anomalies exacerbate heat-related illnesses and mortality rates, particularly during summer heatwaves. Accurate and timely mapping of UHIs is therefore essential for policymakers, urban planners, and public health officials to develop heat mitigation strategies such as green roofing, reflective pavements, and urban greening programs [2].

Traditional field-based temperature measurements, although precise at local scales, are limited in spatial coverage and frequency. In contrast, satellite-based thermal remote sensing provides synoptic and repeatable observations that are essential for capturing the spatial heterogeneity of UHIs across urban landscapes. The advent of machine learning (ML) and deep learning (DL) has further enhanced UHI analysis by enabling predictive modeling and pattern recognition in large and complex geospatial datasets [3]. These advancements are revolutionizing how cities monitor and adapt to heat-related stressors under ongoing climate change.

2. Urban Heat Island concept and importance

2.1. Definition and causes

Urban Heat Islands (UHIs) are localized zones within urban environments that exhibit significantly higher temperatures than surrounding rural areas. This phenomenon arises primarily due to anthropogenic modifications, particularly the transformation of natural land surfaces into urban infrastructures such as concrete, asphalt, and buildings. These surfaces have lower albedo, meaning they absorb more solar radiation and retain heat for longer periods [4].

Additionally, urban areas are characterized by reduced vegetation cover, which diminishes natural cooling through evapotranspiration. Other major contributors include heat emissions from vehicles, industrial activities, and densely packed buildings that trap heat and reduce airflow [5]. The cumulative effect of these changes intensifies surface and atmospheric temperatures in urban zones, thereby creating distinct thermal contrasts between urban and peri-urban areas [6].

2.2. Implications

The presence of UHIs has several critical implications for both environmental sustainability and public health. First, the elevated urban temperatures lead to increased energy demand for air conditioning and refrigeration, placing pressure on local power grids and contributing to greenhouse gas emissions [7]. Second, UHIs are associated with a deterioration in air quality, as higher temperatures accelerate the formation of ground-level ozone and prolong the persistence of airborne pollutants [8]. From a health perspective, vulnerable populations such as the elderly, children, and individuals with pre-existing conditions face elevated risks of heat exhaustion, heat strokes, and even mortality during extreme heat events [9]. Finally, UHIs pose significant challenges for urban planning, requiring adaptive strategies such as increased vegetation, use of reflective building materials, and promotion of sustainable land-use practices to mitigate their adverse effects [10].

3. Satellite-based thermal remote sensing for UHI mapping

3.1. Key satellite sensors used

Thermal remote sensing has become a cornerstone in the monitoring and analysis of Urban Heat Islands, offering wide-scale, repeatable, and cost-effective observations of land surface temperature (LST). Among the most widely used satellite platforms is the Landsat series—specifically Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8/9 (OLI-TIRS). These satellites provide moderate spatial resolution (approximately 30 meters for optical bands and 60–100 meters for thermal bands) and a revisit interval of 16 days, making them suitable for detailed urban-scale studies [11].

The MODIS (Moderate Resolution Imaging Spectroradiometer) sensors aboard NASA's Aqua and Terra satellites are also extensively utilized due to their high temporal resolution. MODIS offers daily LST products with a spatial resolution of approximately 1 km, which is particularly beneficial for regional or global UHI studies requiring frequent observations [12]. Sentinel-3, operated by the European Space Agency, is another valuable platform equipped with the Sea and Land Surface Temperature Radiometer (SLSTR). It provides higher radiometric sensitivity and more accurate LST products with moderate spatial resolution, making it suitable for continental-scale thermal monitoring [13].

In addition, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) onboard NASA's Terra satellite delivers high-resolution (about 90 m in the thermal infrared spectrum) thermal imagery, which is advantageous for mapping UHIs within dense urban landscapes [14]. Each of these satellite systems has specific trade-offs between spatial, temporal, and spectral resolution, and researchers often select or combine sensors based on study objectives and geographic scale.

3.2. Multitemporal Imagery

Multitemporal thermal remote sensing involves the analysis of LST data across multiple timeframes to capture the dynamic nature of UHIs. This includes monitoring diurnal variations, such as differences in temperature between daytime and nighttime, which help identify persistent heat retention zones [15]. For instance, impervious urban surfaces typically cool more slowly than vegetated or water-covered areas, leading to nighttime UHIs.

Seasonal comparisons, such as summer versus winter datasets, provide insights into how land cover and atmospheric conditions affect UHI formation and intensity throughout the year. Moreover, long-term or decadal analyses are used to assess trends associated with urban expansion, land-use change, and the effectiveness of mitigation measures like urban greening [16].

By examining thermal data across these temporal scales, researchers can build a more comprehensive understanding of UHI dynamics, detect hotspots, evaluate vulnerability, and inform climate-adaptive urban planning strategies. The availability of consistent, long-term satellite archives like those from Landsat and MODIS has been instrumental in enabling these multitemporal assessments [17].

4. Thermal Indices and Surface Temperature Derivation

4.1. Land Surface Temperature (LST)

Land Surface Temperature (LST) is the key parameter used in Urban Heat Island (UHI) analysis, as it directly reflects the thermal properties of land surfaces as observed by satellite sensors. LST is typically derived from thermal infrared (TIR) bands of satellite imagery using techniques such as the radiative transfer equation, split-window algorithms, or mono-window algorithms, depending on the sensor characteristics and atmospheric conditions [18]. Accurate LST estimation requires several preprocessing steps, including atmospheric correction, surface emissivity estimation, and radiometric calibration [19]. Emissivity, which depends on land cover type, plays a crucial role in determining the thermal radiation emitted by surfaces. Typically, vegetation, soil, water bodies, and urban materials exhibit different emissivity values, and these variations must be accounted for in LST retrieval models.

LST is often used in combination with auxiliary spatial data, such as land use/land cover (LULC) maps or vegetation indices, to analyze the spatial variability and intensity of UHIs. By comparing LST values across urban, peri-urban, and rural zones, researchers can quantify UHI intensity and detect hotspots. Additionally, temporal LST profiles provide insight into the seasonal or annual progression of heat stress zones in response to climatic or anthropogenic changes [20]. Thus, LST serves as a foundational variable for identifying thermally vulnerable areas and guiding mitigation strategies in urban planning.

4.2. Related Indices

Several remote sensing-derived indices are used alongside LST to better interpret the spatial structure and drivers of UHIs. One of the most widely used is the Normalized Difference Vegetation Index (NDVI), which provides a measure of vegetation density and health. NDVI is negatively correlated with LST in most urban areas—higher NDVI values typically correspond to lower surface temperatures due to the cooling effect of vegetation through evapotranspiration [21].

Another key metric is the Normalized Difference Built-up Index (NDBI), which highlights impervious surfaces such as buildings and roads. NDBI is often positively correlated with LST, as built-up areas retain heat more effectively than vegetated or bare soils [22]. The Normalized Difference Water Index (NDWI) is also relevant, particularly in urban regions with water bodies, which tend to have a cooling influence on nearby land surfaces.

In addition to these, the Urban Thermal Field Variance Index (UTFVI) is a specialized metric used to classify urban areas based on heat stress levels. UTFVI integrates LST with ecological thresholds and is useful for zoning cities into levels of thermal risk or comfort [23]. These indices, when combined with LST data, provide a multi-dimensional view of urban thermal behavior and help identify the landscape features most responsible for UHI formation.

5. AI Models in UHI Mapping

5.1. Machine Learning approaches

Machine Learning (ML) has become a valuable tool in Urban Heat Island (UHI) research due to its capacity to process vast geospatial datasets and uncover complex, non-linear relationships between thermal metrics and urban environmental variables. Popular ML algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Machines (GBM) have been employed to model Land Surface Temperature (LST) based on inputs like NDVI, NDBI, land use/land cover, and elevation [24].

Random Forest is particularly known for its robustness, minimal need for parameter tuning, and high predictive accuracy even in heterogeneous urban landscapes [25]. It has been widely used to classify UHI intensities, detect thermal hotspots, and evaluate the influence of various land surface characteristics on urban heating. SVM is especially effective in classifying complex thermal zones due to its ability to work with high-dimensional feature spaces [26]. These models are typically supervised, requiring well-labeled training data but offering strong performance for predictive UHI modeling.

5.2. Deep Learning approaches

Deep Learning (DL), a subset of AI, brings substantial improvements in feature extraction and pattern recognition, especially from high-dimensional and unstructured data like satellite images. Among DL methods, Convolutional

Neural Networks (CNNs) are the most prominent in geospatial UHI applications. CNNs can automatically learn spatial features from thermal and multispectral imagery, eliminating the need for manual feature engineering [27]. They are used for tasks such as UHI intensity classification, heat vulnerability mapping, and land cover segmentation.

Moreover, Recurrent Neural Networks (RNNs) and their improved versions like Long Short-Term Memory (LSTM) networks are increasingly applied to model temporal dynamics of LST and heat patterns across seasons or years. These networks are capable of capturing sequential dependencies in time-series satellite data, enabling more accurate forecasting of UHI behavior under changing climatic or urban conditions [28].

Despite their capabilities, DL models often require large datasets and significant computational resources for training. Additionally, their "black box" nature makes them less interpretable than traditional models, which is a challenge when communicating results to urban planners and policymakers.

5.3. Hybrid AI models

To overcome the limitations of individual ML or DL models, researchers are increasingly developing hybrid approaches that combine the strengths of both. For example, CNNs may be used for automated feature extraction from imagery, followed by Random Forest or GBM for classification or regression tasks [29]. Similarly, LSTM networks may be integrated with ensemble learning models to predict future temperature trends based on historical thermal and climatic data.

Hybrid AI models offer several advantages, including enhanced accuracy, better generalizability, and the ability to handle both spatial and temporal dimensions of UHI phenomena. These models also support multi-source data fusion, enabling the integration of optical, thermal, LiDAR, and socio-economic data into a unified analytical framework [30].

However, hybrid models require careful tuning and validation to avoid overfitting and to ensure interpretability. As computational power becomes more accessible and datasets grow in volume and diversity, hybrid AI approaches are expected to dominate future UHI research, offering real-time, city-scale insights for climate-resilient urban development.

6. Applications of AI-enhanced UHI mapping

Artificial intelligence-enhanced Urban Heat Island (UHI) mapping has opened new pathways for practical applications in urban climate research, environmental monitoring, and smart city planning. The integration of AI with satellite-based thermal remote sensing facilitates fine-scale, data-driven decision-making for urban resilience and public health.

6.1. Urban planning and sustainable development

AI-driven UHI models help planners identify urban hotspots and design mitigation strategies such as increasing green cover, implementing reflective roofing, and optimizing building orientation [31]. Data from multitemporal thermal imagery, when processed using machine learning, provides valuable insight into how different land-use categories contribute to UHI intensities. Planners use these insights to guide zoning laws, green infrastructure development, and building regulations that improve thermal comfort and reduce energy consumption.

6.2. Public health and heat risk management

The identification of high-temperature zones with dense population through AI-supported thermal mapping enables health authorities to implement targeted interventions during heatwaves [32]. Vulnerable populations—such as the elderly, children, and low-income communities—can be prioritized for cooling centers, early warning systems, and medical assistance. Moreover, AI models can integrate socio-demographic and environmental variables to develop heat vulnerability indices for urban health planning.

6.3. Climate change monitoring and adaptation

Urban areas are central to climate change dynamics. AI models applied to multitemporal satellite data allow for long-term trend analysis of surface temperatures and urban thermal anomalies [33]. This supports policymakers in evaluating the impact of climate mitigation efforts over time and making evidence-based decisions on urban adaptation strategies. Coupled with downscaled climate projections, these models also help forecast future UHI patterns under different emission scenarios.

6.4. Smart City and Real-Time applications

With increasing access to real-time satellite data and IoT-based temperature sensors, AI algorithms are now being employed for real-time UHI monitoring in smart city frameworks [34]. These systems can automatically detect abnormal temperature rises, triggering automated responses such as activating cooling systems or alerting emergency services. AI can also support mobile apps and public dashboards that deliver heat alerts and safety information to citizens.

6.5. Environmental justice and policy design

Disparities in heat exposure due to unequal distribution of green spaces, income, and infrastructure are being highlighted by AI-based UHI mapping. These tools empower advocacy groups and urban stakeholders to push for equitable environmental policies [35]. By visualizing thermal inequalities, governments can allocate resources more fairly and develop inclusive urban resilience policies that serve all socio-economic groups.

7. Challenges and future directions

Despite significant advances in satellite-based UHI mapping using multitemporal thermal imagery and AI models, several challenges persist that limit the full potential of this approach. Addressing these challenges is essential to improve model accuracy, scalability, and practical applicability in diverse urban contexts.

7.1. Limitations in data availability and resolution

One of the primary challenges in UHI mapping is the spatial and temporal resolution of thermal remote sensing data. While sensors like MODIS provide frequent observations, their coarse resolution (~1 km) is often insufficient for detailed urban analysis. In contrast, high-resolution sensors such as Landsat and ASTER offer better spatial detail but suffer from longer revisit periods and limited temporal coverage due to cloud cover or data gaps [36]. Moreover, nighttime thermal data, which is critical for understanding diurnal UHI variation, is less frequently available across satellite platforms.

7.2. Data fusion and integration complexities

Integrating multitemporal data from different sensors (e.g., Landsat, MODIS, Sentinel-3) poses significant challenges due to differences in spatial, spectral, and radiometric properties. Data harmonization techniques—such as statistical downscaling or image fusion—require careful calibration and validation to ensure consistency [37]. Additionally, combining thermal datasets with ancillary data like land use, population density, and socio-economic indicators adds further complexity to preprocessing pipelines.

7.3. AI model generalization and interpretability

While AI models, especially deep learning algorithms, exhibit strong performance in UHI prediction, they often function as "black boxes" with limited interpretability [38]. This lack of transparency can hinder their adoption in policy-making and urban planning. Furthermore, many models trained on data from a specific city or region may not generalize well to different climatic or urban settings without retraining, limiting their scalability.

7.4. Limited ground truth data for validation

High-quality ground-based observations of land surface temperature (LST) are essential for validating satellite-derived UHI models. However, such datasets are often sparse or unavailable, particularly in developing countries [39]. The lack of in-situ measurements reduces confidence in AI model predictions and restricts the development of hybrid models combining satellite and ground data.

7.5. Ethical and equity considerations

AI-driven UHI mapping may inadvertently reinforce existing biases if models are trained on incomplete or unrepresentative datasets. Moreover, unequal access to data and computing resources can create disparities in who benefits from these technologies [40]. Future research must prioritize inclusive data governance and participatory modeling to ensure that UHI mitigation strategies serve all communities equitably.

7.6. Future research directions

To overcome these challenges, future efforts should focus on:

- Developing interpretable AI models: Integrating explainable AI (XAI) techniques can enhance model transparency and trust.
- Enhancing transferability: Designing models that adapt across regions using transfer learning can improve generalizability.
- Integrating real-time IoT data: Combining satellite data with IoT-based temperature sensors can enable continuous, localized UHI monitoring.
- Fostering interdisciplinary collaboration: Collaboration among urban planners, climatologists, data scientists, and policymakers is vital for designing sustainable and actionable UHI solutions.

8. Conclusion

Urban Heat Islands (UHIs) pose a growing threat to the livability and sustainability of cities worldwide, especially in the context of rapid urban expansion and climate change. The integration of satellite-based thermal remote sensing with multitemporal analysis has significantly advanced our understanding of the spatial and temporal dynamics of UHIs. Furthermore, the incorporation of Artificial Intelligence (AI), particularly machine learning and deep learning models, has enhanced the precision and efficiency of UHI mapping and prediction.

This review has highlighted the evolution of thermal remote sensing technologies, the significance of multitemporal datasets, and the capabilities of AI models in capturing the complex patterns of urban thermal environments. While notable progress has been made, challenges such as limited high-resolution data availability, model generalization, lack of ground validation, and ethical concerns still remain. Addressing these limitations requires a multidisciplinary approach that combines technological innovation with inclusive urban planning practices.

Looking forward, future UHI research should prioritize the development of interpretable and transferable AI models, greater integration of real-time ground-based observations, and the use of next-generation satellite platforms. By bridging the gap between remote sensing science, AI advancements, and urban policy, it is possible to design effective, data-driven strategies for mitigating UHI effects and promoting resilient urban development.

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