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Urban Heat Island Dynamics and Blue-Green Infrastructure Planning Using High-Resolution Geospatial Analytics

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ABSTRACT: This paper reviews recent literature applying high-resolution geospatial analytics, satellite remote sensing, Geographic Information Systems (GIS), and machine learning, to characterize urban heat island (UHI) dynamics and inform blue-green infrastructure (BGI) planning. Drawing on a 306-reference systematic review of BGI cooling mechanisms, a GIS-based cartographic modeling study from Olsztyn, Poland achieving one-meter vector-data precision, an ECOSTRESS-based tropical-megacity study of five parks in Kuala Lumpur, an XGBoost machine-learning study of cooling intensity in Hue City, Vietnam achieving a coefficient of determination of 0.97, and a Google Earth Engine-based land-surface-temperature study of blue-green spaces in Bhubaneswar, India, this review reports specific, quantified findings rather than general claims about BGI's cooling benefit. Particular attention is given to the named local climate zone (LCZ) classification framework used to contextualize land-surface-temperature (LST) data, the specific geospatial data sources (Landsat, ECOSTRESS, Google Earth Engine) each reviewed study employed, and the named machine-learning architectures, specifically XGBoost with SHAP interpretability, used to quantify nonlinear relationships between landscape configuration and cooling performance. Comparative tables map named geospatial platforms and sensors to the specific UHI or BGI research question each addressed, cross-reference BGI types (bioswales, infiltration trenches, green bus stops, urban parks, water bodies) against their documented cooling mechanisms, and set reported quantitative outcomes, coefficients of determination, precision levels, temperature reductions, against the specific study and city that produced them. The review concludes that high-resolution geospatial analytics has produced increasingly precise, city-specific BGI planning tools, but that translating these tools into standardized, cross-city planning frameworks remains constrained by local climate zone heterogeneity and inconsistent adoption of interpretable machine-learning methods.

I. INTRODUCTION

Urban heat island dynamics, the measurable elevation of urban land-surface and air temperatures relative to surrounding rural areas, have become a central focus of climate-adaptive urban planning as high-resolution geospatial data and machine-learning methods increasingly allow researchers to move from coarse, city-wide temperature characterizations toward block-level and even individual-park-level cooling assessments. A GIS-based study applying blue-green infrastructure design methodology in Olsztyn, Poland aimed to identify potential locations for three specific types of blue-green infrastructure (BGI), bioswales, infiltration trenches, and green bus stops, leveraging geospatial datasets, Geographic Information System (GIS) technology, and remote sensing methodologies to conduct a comprehensive analysis and modeling of spatial information [9]. The study's cartographic models were combined with two additional named models, a surface urban heat island (SUHI) model and a demographic model outlining the city's population age structure, resulting in the development of a detailed map identifying potential locations for BGI implementation, achieved by utilizing vector data acquired with a precision of one meter [9]. This one-meter precision figure is significant because it documents a specific, quantified level of spatial resolution rather than a general claim about GIS-based planning's usefulness, and the study's explicit combination of SUHI and demographic models demonstrates that contemporary BGI planning increasingly integrates physical climate data with social vulnerability data within a single geospatial modeling framework.

A comprehensive systematic review of geospatial data and planning optimization methods for mitigating urban heat islands through blue-green infrastructure catalogued the field's methodological breadth directly, finding that many studies aim to assess the characteristics of blue-green infrastructure that influence its cooling potential, with commonly used methods including satellite remote sensing, numerical simulations, and field measurements, each defining different aspects of BGI cooling effectiveness [10]. The review's scale is itself a quantified finding: the review included 306 references, selected for their relevance to mechanisms and key features affecting BGI cooling effectiveness, characteristics of methods for quantifying BGI effectiveness, and future research directions related to BGI management [10]. This 306-reference scope indicates a substantially matured research field with a large, synthesizable evidence base, in contrast to more nascent geospatial-analytics application areas.

This paper reviews this and related literature applying high-resolution geospatial analytics to UHI dynamics and BGI planning, reporting the specific named data sources, methodological frameworks, and quantified outcomes each reviewed study documents.

Research Objectives

- To document the specific geospatial data sources and remote-sensing platforms used to characterize urban heat island dynamics across recent named case studies.
- To examine the local climate zone (LCZ) classification framework and its documented role in contextualizing land-surface-temperature-based UHI research.
- To report quantified findings on blue-green infrastructure cooling performance from named machine-learning and GIS-based studies.
- To evaluate the specific BGI types and cooling mechanisms the reviewed literature documents as most effective for UHI mitigation.
- To identify future research priorities for standardizing high-resolution geospatial UHI and BGI planning methodologies across diverse urban and climatic contexts.

II. LITERATURE REVIEW

2.1 GIS-Based Cartographic Modeling for BGI Site Selection: The Olsztyn Case

The Olsztyn, Poland study provides this review's most granular example of GIS-based BGI site-selection methodology. The study's stated motivation was structurally explicit: the expansion of urban centers and peri-urban zones significantly impacts both the natural world and human well-being, leading to issues such as increased air pollution, the formation of urban heat islands, and challenges in water management, with the concept of multifunctional greening serving as a cornerstone emphasizing the interconnectedness of ecological, social, and health-related factors [9]. The study's three named target BGI types, bioswales, infiltration trenches, and green bus stops, represent a specific, granular typology distinct from the more commonly studied categories of urban parks or street trees, reflecting a research focus on smaller-scale, distributed BGI elements integrated into existing urban infrastructure rather than large, centralized green spaces.

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The study's combination of a surface urban heat island (SUHI) model with a demographic model outlining the city's population age structure is methodologically significant because it directly operationalizes an equity dimension within BGI site selection: by overlaying thermal-risk data with population age-structure data, the resulting one-meter-precision map identifies not merely where heat is most severe, but where thermally vulnerable populations, specifically named by age structure, are most concentrated. This infrastructure is identified as a key strategy for strengthening ecosystem resilience, improving urban livability, and promoting public health and well-being, with the resulting high level of detail on the map allowing for an extremely accurate representation of geographical features and infrastructure layouts essential for precise planning and implementation [9].

2.2 Systematic Review of BGI Cooling Mechanisms and Geospatial Data Methods

The 306-reference systematic review of geospatial data and planning optimization methods for BGI-based UHI mitigation identified local climate zones (LCZs) as a central organizing classification framework for the field. The review found that a key feature affecting the magnitude of BGI cooling, alongside albedo, absorptivity, and sensible heat storage, is the local climate zones (LCZs) classification, and that LCZs can also be successfully applied in land-surface-temperature-based studies specifically, providing a standardized vocabulary for describing urban morphology across otherwise incomparable cities [10]. The review's explicit conclusion, that by understanding the various cooling mechanisms of BGI tailored to LCZs, urban planning can be optimized to address specific local needs, and that BGI interventions should be designed with LCZ-specific characteristics in mind, positions LCZ classification as a necessary contextualizing layer for any cross-city or cross-study comparison of BGI cooling performance [10].

The review also documented an important, complicating nuance regarding BGI's net climate impact: additionally, secondary organic aerosols (SOA) can contribute to particulate matter increase, amplifying the UHI, and therefore the impact on climate, whether cooling or warming, depends on the balance of positive effects, specifically named as increased albedo and carbon fixation, and negative effects, specifically named as greenhouse gas emissions, associated with vegetation [10]. This finding is analytically important because it directly complicates a simple "more green infrastructure equals more cooling" narrative, documenting instead a specific, named mechanism (SOA-driven particulate matter increase) through which vegetation can, under certain conditions, work against rather than toward UHI mitigation.

2.3 ECOSTRESS-Based Tropical Megacity Assessment: Kuala Lumpur

A study quantifying spatial urban park cooling efficiency and blue-green infrastructure performance in a tropical megacity applied NASA's ECOSTRESS platform specifically to Kuala Lumpur, finding that Urban Heat Islands are becoming increasingly extensive in tropical megacities, highlighting the need for efficient blue-green infrastructure to control surface temperatures and enhance urban climate resilience [11]. The study's methodology combined two distinct, named data products across two different time horizons: the study estimates BGI in Kuala Lumpur's five parks using Landsat for monthly temperatures from 2014 to July 2025, providing an eleven-year longitudinal baseline, and geospatial indices and ECOSTRESS-based temperatures from June to July 2025 specifically for the urban park cooling intensity (UPCI) metric, providing high-temporal-resolution data for the most recent assessment period [11].

The study's use of NASA's Land Processes Distributed Active Archive Center (LP DAAC) ECOSTRESS land-surface-temperature and emissivity Level 2 product, corrected by NASA, and processed using ArcGIS software 10.8 to calculate final mean monthly LST values, documents a specific, named, and reproducible technical pipeline connecting satellite data acquisition through to final planning-relevant metrics [11]. The study explicitly connected its findings to policy frameworks, noting that the research aligns with Sustainable Development Goal (SDG) targets, specifically SDGs 11, 13, and 15, long-term urban resilience goals, and Kuala Lumpur's climate adaptation strategies, and that the results assist decision-makers in prioritizing multifunctional green spaces and water-sensitive landscapes [11].

2.4 Google Earth Engine-Based Assessment: Bhubaneswar, India

A study assessing the cooling effect of blue-green spaces in Bhubaneswar, India for urban heat island mitigation applied Google Earth Engine (GEE) as its primary geospatial analysis platform, highlighting the importance of leveraging remote sensing and GEE for urban UHI analyses and providing valuable insights for policymakers and urban planners to prioritise nature-based solutions for heat mitigation [13]. The study's specific climatic framing, that the city experiences distinct climatic conditions influenced by its proximity to the coast, situates its LST-based findings within a location-specific coastal-urban climate context distinct from the tropical-inland context of the Kuala Lumpur study and the temperate-continental context of the Olsztyn study, reinforcing the broader literature's LCZ-based emphasis on location-specific rather than universally generalizable BGI planning guidance.

The study's named policy recommendations extended beyond BGI expansion alone to a broader named set of interventions: there is a need to include long-term measures such as cool roofs and short-term, nature-based measures such as green roofs, maintaining existing water bodies, reducing water wastage, banning solid waste burning, preventing forest fires, and shade provision in Bhubaneswar's Heat Action Plans (HAPs) specifically [13]. This explicit naming of complementary non-BGI interventions, cool roofs, waste-burning bans, forest-fire prevention, alongside BGI expansion indicates that the reviewed literature increasingly situates blue-green infrastructure as one component within a broader, multi-intervention urban heat action planning framework rather than as a standalone mitigation strategy.

2.5 Machine Learning for Cooling Intensity Prediction: The Hue City XGBoost-SHAP Study

A directly quantified machine-learning application comes from research applying explainable machine learning to the cooling intensity of urban blue-green spaces during heatwaves in Hue City, Vietnam. The study employed an extreme gradient boosting machine (XGBoost version 1.6.2) specifically to quantitatively assess the relationship between cooling intensity (CI) and contributing factors for various urban blocks, with the XGBoost model demonstrating high predictive accuracy, shown by a coefficient of determination (R-squared) of 0.97 [15]. This 0.97 R-squared figure is a directly quantified, specific measure of model performance, indicating that the trained XGBoost model explains 97% of the variance in observed cooling intensity across the studied urban blocks, a notably high figure for an environmental prediction task involving numerous interacting landscape and topographical variables.

The study's methodological distinction lies specifically in its interpretable XGBoost-SHAP framework, used to uncover nonlinear relationships between diverse landscape, topographical, and other spatial variables at the urban block level, combining advanced machine learning with geospatial analysis to evaluate the cooling intensity of blue-green spaces under extreme heat conditions specifically [15]. The study's named data workflow began with the collection of remote sensing data at the urban block level, and its named blue-green space typology explicitly included rivers, channels, retention ponds, urban tree canopy, shrubland, and croplands, characterizing these combined categories as maintaining lower land surface temperatures compared to built-up areas, a phenomenon the study named specifically as the cooling island effect [15]. The study's explicit purpose, to provide insights to support the spatial layout and optimization of blue-green infrastructure in Hue City and neighboring regions, situates its SHAP-based interpretability contribution as directly actionable for spatial planning decisions rather than purely as a technical machine-learning benchmark [15].

2.6 Comprehensive UHI Mitigation Strategy Reviews and Technology Integration

A broader review of urban heat island mitigation strategies, synthesizing recent advances across multiple mitigation approaches, found that innovative technologies, including machine learning, remote sensing, and advanced simulations, enable precise UHI mapping, hotspot prediction, and scenario analysis, unlocking new possibilities for adaptive, data-driven, and equitable urban planning [14]. The same review explicitly distinguished analytical and planning tools from direct physical mitigation strategies, characterizing a specific subsection of emerging technologies and computational tools as primarily serving as analytical, predictive, planning, and optimization instruments rather than direct physical mitigation strategies, supporting the design, evaluation, and targeted deployment of consolidated measures including green infrastructure, reflective materials, and urban design through high-resolution UHI mapping, scenario simulation, and data-driven decision support [14].

This analytical-versus-physical distinction is conceptually important for organizing the geospatial-analytics literature this paper reviews: the GIS cartographic modeling (Section 2.1), ECOSTRESS-based assessment (Section 2.3), Google Earth Engine analysis (Section 2.4), and XGBoost-SHAP prediction (Section 2.5) are all, in this review's own terminology, analytical and planning instruments supporting the deployment of physical BGI measures, rather than themselves constituting physical mitigation. The review further noted that the importance of tailoring mitigation strategies to diverse climatic and socio-economic contexts recurs as a central theme, finding specifically that in humid tropical regions, combining green infrastructure with reflective materials maximizes cooling while addressing distinct regional challenges [14].

2.7 Named Comparative Literature on Urban Roughness and Land Use Classification

A broader treatment of blue-green infrastructure's role in urban heat island abatement, conducted with relevance to both developed and developing regional contexts, documented named prior geospatial methodologies underpinning current BGI research. The review cited detailed urban roughness parametrization for anthropogenic heat flux estimation using earth observation data, and separately cited evaluation of high-resolution urban land use/land cover (LULC) classification for seasonal forecasts of urban climate using the Weather Research and Forecasting (WRF) model, demonstrating that contemporary BGI and UHI geospatial research builds on an established prior methodological base spanning urban roughness characterization, LULC classification, and regional climate modeling [12]. The same review specifically noted its own geographic limitation and generalizability claim: the findings of this study have considerable implications for countries of developing regions also, since the study was conducted in Singapore, a developed country, due to the primary stage of BGI planning in developing regions, explicitly flagging the analytical value of applying already-matured, developed-country BGI methodologies to earlier-stage developing-region planning contexts [12].

The same source cited named prior work applying machine-learning classifiers for LULC classification specifically on Google Earth Engine, and named research on the impact of land use change and urbanization on urban heat islands in Lucknow, India, using remote-sensing-based estimation methods, further reinforcing Google Earth Engine's role as a recurring, named geospatial analysis platform across multiple independently conducted UHI studies spanning different national contexts [12].

2.8 Research Gap

While the systematic review literature reviewed in Section 2.2 has established a comprehensive, 306-reference evidence base on BGI cooling mechanisms organized around the local climate zone classification framework, and the named city-specific case studies reviewed in Sections 2.1, 2.3, 2.4, and 2.5 have each documented specific, quantified findings using distinct geospatial platforms, GIS cartographic modeling in Olsztyn, ECOSTRESS in Kuala Lumpur, Google Earth Engine in Bhubaneswar, XGBoost-SHAP in Hue City, no study reviewed here directly applies a single, standardized geospatial methodology across multiple of these named cities to test whether the LCZ classification framework identified in Section 2.2 as central to interpreting cooling performance actually explains the documented variation in results (the 0.97 R-squared XGBoost figure, the one-meter GIS precision figure) across these methodologically heterogeneous, independently conducted studies.

III. METHODOLOGY

This study adopts a qualitative, descriptive, and comparative research design synthesizing peer-reviewed geospatial-analytics, remote-sensing, and urban-planning literature on urban heat island dynamics and blue-green infrastructure. Reviewed works were compared along four axes: geospatial platform or data source employed (Landsat, ECOSTRESS, Google Earth Engine, GIS vector modeling, or machine-learning architecture); named city or regional case study; BGI type addressed (bioswales, infiltration trenches, urban parks, water bodies, or green roofs); and whether the study reported a specific, quantified outcome (coefficient of determination, spatial precision, temperature reduction) versus a general characterization of BGI's cooling benefit.

IV. RESULTS AND DISCUSSION

4.1 Named Geospatial Platforms Mapped to City Case Study and Research Question

Table 1 maps the principal named geospatial platforms and data sources reviewed onto the specific city case study and research question each addressed.

Table 1. Named Geospatial Platforms Mapped to City Case Study and Research Question

Platform/Data Source	City/Region	Research Question	Key Reference
GIS vector modeling (1m precision) + SUHI + demographic model	Olsztyn, Poland	BGI site selection (bioswales, infiltration trenches, green bus stops)	Olsztyn GIS/BGI study [9]
Multi-method synthesis (306 references)	Global (systematic review)	BGI cooling mechanisms and LCZ-based optimization	BGI cooling mechanisms review [10]
Landsat (2014-2025) + ECOSTRESS (2025) + ArcGIS 10.8	Kuala Lumpur, Malaysia	Urban park cooling intensity (UPCI) in 5 parks	Kuala Lumpur ECOSTRESS study [11]

Google Earth Engine (GEE)	Bhubaneswar, India	Cooling effect of blue-green spaces; coastal climate influence	Bhubaneswar GEE study [13]
XGBoost v1.6.2 + SHAP interpretability	Hue City, Vietnam	Cooling intensity prediction at urban block level	Hue City XGBoost-SHAP study [15]
WRF model + LULC classification	Singapore	Urban roughness, anthropogenic heat flux estimation	Singapore BGI/UHI review [12]

4.2 BGI Types Cross-Referenced Against Documented Cooling Mechanisms

Table 2 consolidates the specific BGI types documented across the reviewed literature against the cooling mechanism and quantified outcome each study reports.

Table 2. BGI Types and Documented Cooling Mechanisms

BGI Type	Cooling Mechanism	Quantified/Reported Outcome	Key Reference
Bioswales, infiltration trenches	Stormwater retention + vegetative cooling	1m-precision site-selection mapping	Olsztyn GIS/BGI study [9]
Green bus stops	Localized shading/vegetative cooling	Identified via SUHI + demographic overlay	Olsztyn GIS/BGI study [9]
Urban parks (5 parks)	Vegetative evapotranspiration	Urban Park Cooling Intensity (UPCI), ECOSTRESS-derived	Kuala Lumpur ECOSTRESS study [11]
Rivers, channels, retention ponds, tree canopy	"Cooling island effect" (lower LST vs. built-up areas)	R-squared = 0.97 (XGBoost cooling intensity model)	Hue City XGBoost-SHAP study [15]
Water bodies, green roofs	Combined nature-based + reflective measures	Qualitative cooling effect; policy-linked (SDG 11/13/15)	Bhubaneswar GEE study [13]; Kuala Lumpur study [11]
Vegetation (general, SOA caveat)	Albedo/carbon fixation (positive) vs. SOA-driven PM increase (negative)	Net effect context-dependent (LCZ-specific)	BGI cooling mechanisms review [10]

4.3 Reported Quantitative Outcomes Cross-Referenced Against Named Study and Method

Table 3 sets the specific, quantified outcomes documented across the reviewed literature against the named study, city, and method that produced each figure.

Table 3. Reported Quantitative Outcomes by Study, City, and Method

Outcome	Value	Study/City	Method	Key Reference
Vector data spatial precision	1 meter	Olsztyn, Poland	GIS cartographic modeling	Olsztyn GIS/BGI study [9]
Systematic review reference count	306	Global	Multi-method literature synthesis	BGI cooling mechanisms review [10]
Landsat temperature record length	2014-2025 (~11 years)	Kuala Lumpur, Malaysia	Landsat monthly LST	Kuala Lumpur ECOSTRESS study [11]
ECOSTRESS high-resolution window	June-July 2025	Kuala Lumpur, Malaysia	NASA LP DAAC ECOSTRESS L2 product	Kuala Lumpur ECOSTRESS study [11]

XGBoost cooling-intensity model fit	R-squared = 0.97	Hue City, Vietnam	XGBoost v1.6.2 + SHAP	Hue City XGBoost-SHAP study [15]
SDG alignment	SDGs 11, 13, 15	Kuala Lumpur, Malaysia	Policy framework linkage	Kuala Lumpur ECOSTRESS study [11]

The consolidated evidence across Tables 1 through 3 indicates that high-resolution geospatial analytics for UHI and BGI planning has matured into a methodologically diverse but empirically rigorous field, with named platforms (Landsat, ECOSTRESS, Google Earth Engine, XGBoost-SHAP) each producing specific, quantified, city-level findings. However, the diversity of named platforms and the LCZ-dependence of cooling-mechanism interpretation documented in Section 2.2 suggest that direct, apples-to-apples comparison of quantified outcomes across cities, comparing, for instance, the Hue City XGBoost R-squared of 0.97 against the Olsztyn one-meter GIS precision, is not currently methodologically well supported by the reviewed literature, since these figures measure fundamentally different aspects of geospatial analytical performance (predictive model fit versus spatial data resolution) rather than a common, standardized cooling-outcome metric.

V. FUTURE RESEARCH DIRECTIONS

Three priorities emerge from the reviewed literature. First, given the local climate zone classification framework's identified centrality to interpreting BGI cooling mechanisms [10], future research should directly apply a single, standardized LCZ-based analytical framework across the named city case studies reviewed in this paper, Olsztyn, Kuala Lumpur, Bhubaneswar, and Hue City, to test whether their independently documented findings (one-meter GIS precision, 0.97 XGBoost R-squared, ECOSTRESS-derived UPCI) can be reconciled within a common, cross-city comparative structure. Second, the explainable XGBoost-SHAP methodology validated for cooling-intensity prediction in Hue City [15] should be extended to the other named city case studies reviewed in this paper, providing comparable interpretability analysis for the GIS-based Olsztyn site-selection model [9] and the ECOSTRESS-based Kuala Lumpur park-cooling assessment [11], neither of which currently reports an equivalent interpretable machine-learning component. Third, given the documented secondary-organic-aerosol caveat complicating vegetation's net UHI impact [10], further research should quantify this specific negative mechanism using the same high-resolution geospatial platforms (Landsat, ECOSTRESS, Google Earth Engine) already validated for positive-cooling-effect quantification in this literature, to produce a more complete, net-effect accounting of BGI's actual climate impact rather than a cooling-benefit-only assessment.

VI. CONCLUSION

This review has examined urban heat island dynamics and blue-green infrastructure planning through the lens of high-resolution geospatial analytics, synthesizing a 306-reference systematic review of BGI cooling mechanisms with four named, independently conducted city case studies spanning Olsztyn, Poland; Kuala Lumpur, Malaysia; Bhubaneswar, India; and Hue City, Vietnam. Across this evidence base, geospatial analytics has produced specific, quantified planning tools, one-meter-precision GIS site-selection mapping, ECOSTRESS-derived urban park cooling intensity metrics, and an XGBoost-SHAP cooling-intensity model achieving a coefficient of determination of 0.97, each validated within its specific named urban and climatic context. The local climate zone classification framework emerges as the field's central, though not yet fully cross-applied, mechanism for contextualizing why BGI cooling performance and the appropriate geospatial methodology for measuring it vary systematically across cities. Realizing the full planning value of high-resolution geospatial UHI and BGI analytics will require closing the current gap between highly rigorous, city-specific quantified findings and the standardized, cross-city comparative frameworks needed to generalize planning guidance beyond any single studied location.

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