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Hybrid informer–BiLSTM Model for Long-Term Forecasting of Urban Heat Islands: A Multimodal Approach Integrating Remote Sensing and Climate Data

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Abstract

Urban heat islands (UHIs) localized zones of increased temperature pose escalating challenges in densely populated regions due to accelerated urbanization and climate variability. Accurate long-term forecasting of UHI dynamics is critical for sustainable urban planning and climate adaptation. Here, we present a novel hybrid forecasting framework integrating Informer and Bidirectional Long Short-Term Memory (BiLSTM) networks to model long-term UHI intensity trends. The hybrid architecture leverages the Informer's strength in capturing global temporal dependencies and BiLSTM's ability to recognize bidirectional sequential patterns in high-resolution, multimodal data derived from Landsat-8, MODIS, and ERA5 datasets. Our framework predicts land surface temperature (LST) anomalies used as a proxy for UHIs across 20 megacities globally. The model demonstrates significant performance improvements over existing benchmarks, achieving a mean RMSE of 1.13°C, MAE of 0.91°C, and an R^2 of 0.93. The spatial heterogeneity of model performance reveals higher forecast accuracy in arid zones versus coastal or monsoon-influenced urban areas. This work offers a robust, scalable tool for proactive climate resilience in rapidly urbanizing environments.

Keywords: Urban Heat Island; Climate Resilience; Long-term forecasting; Spatiotemporal Modelling; Land-Surface Temperature; Hybrid Deep Learning.

1. Introduction

Urban Heat Islands (UHIs) are a well-documented microclimatic phenomenon in which urbanized regions exhibit significantly higher temperatures than adjacent rural areas. This thermal anomaly results from a confluence of anthropogenic and environmental factors, including the proliferation of impervious surfaces such as asphalt and concrete, reduced vegetation cover, elevated energy consumption, and waste heat emissions from buildings and vehicles (Oke, 1982; Li and Bou-Zeid, 2013). The UHI effect has intensified in recent decades, driven by rapid urbanization, land-use change, and climate change, with cities in low- and middle-income countries being disproportionately affected (United nations, 2018; Zhou et al., 2014).

The implications of UHI are far-reaching. Elevated temperatures in urban cores exacerbate heat-related illnesses, increase electricity demand for air conditioning, accelerate ozone formation, and contribute to poorer air quality and thermal discomfort (Santamouris, 2015; Tan et al., 2010; Akbari et al., 2001). Vulnerable populations, including the elderly, children, and those with pre-existing health conditions, are at particular risk during heatwaves intensified by UHI effects (Harlan and Ruddell, 2011). Furthermore, UHIs contribute to broader issues of climate injustice, as

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marginalized communities often reside in areas with limited vegetation and inadequate infrastructure for climate adaptation (Chow and Svoma, 2011).

Traditionally, UHIs have been assessed using in situ temperature monitoring and remotely sensed thermal infrared data, particularly from sensors like MODIS (Moderate Resolution Imaging Spectroradiometer) and Landsat Thermal Infrared Sensor (TIRS) (Weng et al., 2004; Voogt and Oke, 2003. These approaches yield spatial snapshots of land surface temperature (LST) differences but are largely retrospective. While useful for characterizing spatial extent and intensity, they lack temporal forecasting capabilities essential for proactive urban planning and real-time disaster response (Li et al., 2019; Zhang et al., 2021;)

In recent years, the advent of machine learning (ML) and deep learning (DL) has opened new avenues for modeling and forecasting spatiotemporal environmental phenomena, including UHIs. Models such as random forests, convolutional neural networks (CNNs), and long short-term memory (LSTM) networks have been applied with moderate success to predict LST and UHI intensity from meteorological, land cover, and demographic variables (Yao et al., 2017 Yang et al., 2015 Hu et al., 2024). However, these models often suffer from critical limitations. Standard LSTM models, while effective at capturing short-term dependencies, struggle with long-term forecasting due to vanishing gradient issues, especially in data sequences spanning several years (Hochreiter and Schmidhuber, 1997). Additionally, unidirectional architectures may overlook significant contextual information from preceding and succeeding time steps, reducing predictive robustness in dynamic urban environments with nonlinear seasonality (Schuster and Paliwal 1997).

To overcome these limitations, hybrid deep learning architectures that integrate multiple neural components are gaining traction. Building on the foundational work in atmospheric forecasting using hybrid models like Informer–LSTM for zenith tropospheric delay prediction (Yuan et al., 2025), this study proposes a novel Informer–BiLSTM (Bidirectional LSTM) hybrid model for long-term UHI forecasting. The Informer model, known for its efficiency in handling lengthy time series via the ProbSparse self-attention mechanism, is well-suited for learning periodic trends and global dependencies in urban thermal time series (Zhou et al., 2021). Meanwhile, BiLSTM introduces bidirectional memory processing that captures both forward and backward temporal dependencies, enhancing the model's capacity to understand seasonal reversals and abrupt microclimatic shifts (Qin et al., 2017).

This study also embraces a multimodal data fusion strategy, integrating satellite-derived LST, normalized difference vegetation index (NDVI), surface albedo, and climate reanalysis data from ERA5 (including air temperature, humidity, and wind speed), along with socio-ecological indicators such as urban sprawl indices. This approach reflects a growing consensus that single-source models are insufficient to capture the complex feedback loops driving UHIs, which are influenced by both biophysical and anthropogenic factors (Sun et al., 2020; Zhang et al., 2022).

By applying this hybrid model to 20 megacities across different climate zones from arid deserts to humid subtropics—this research aims to deliver robust, long-horizon UHI forecasts. These forecasts can inform urban resilience strategies, such as green infrastructure planning, early warning systems for heat stress, and zoning regulations to mitigate thermal inequities. In doing so, this study contributes to the expanding body of literature on AI-assisted urban climate modeling and demonstrates the potential of deep learning in addressing critical challenges at the intersection of urbanization and climate change.

2. Methods

2.1. Study Area and Data Sources

This study investigated urban heat island (UHI) dynamics in 20 megacities across multiple climatic zones and continents, deliberately selected to represent diverse geographic, topographic, and climatic conditions. These cities include Lagos (tropical wet and dry), Delhi (humid subtropical), São Paulo (humid subtropical), Cairo (hot desert), Tokyo (humid subtropical), New York (humid continental), Jakarta (tropical rainforest), and others. The selection criteria were based on population size (>10 million), climatic heterogeneity, and data availability.

To ensure a robust and multimodal representation of urban thermal environments, we curated datasets from three authoritative sources:

2.1.1. Landsat-8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS)

We extracted 30-meter-resolution land surface temperature (LST) and normalized difference vegetation index (NDVI) layers from 2014 to 2023. Landsat-8's high spatial resolution facilitated detailed intra-urban UHI mapping, particularly in heterogeneous land cover settings.

2.1.2. MODIS Terra/Aqua (MOD11A1 and MYD11A1)

Daily LST and emissivity products from 2000 to 2023 were used to augment temporal granularity and extend retrospective thermal trends. MODIS's daily revisit rate provided temporal continuity, particularly beneficial in cloud-prone equatorial zones.

2.1.3. ERA5 Climate Reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF)

ERA5 offered hourly meteorological variables, including 2-meter air temperature, relative humidity, and 10-meter wind speed at a 0.25° spatial resolution from 2000 to 2023. These data were instrumental in capturing atmospheric dynamics influencing surface thermal behaviour.

Urban Heat Island intensity was calculated as the LST differential between defined urban core zones (high built-up density, low NDVI) and matched peri-urban control zones (low built-up density, high NDVI) within a 30-kilometer radius. This approach aligns with existing literature emphasizing relative, rather than absolute, temperature comparisons to isolate anthropogenic thermal amplification (Voogt and Oke., 2003; Zhou et al 2016).

2.2. Data Preprocessing and Interpolation

Given the inherent challenges in remote sensing data, particularly cloud-induced missingness in optical thermal imagery, we implemented a hybrid temporal interpolation strategy. Specifically, missing Landsat LST pixels were gap-filled using a temporal linear interpolation model constrained by concurrent NDVI trends and surface emissivity data. This constraint prevented anomalous interpolation during periods of vegetative change or radiative inconsistency.

To harmonize the spatial and temporal resolution of ERA5 data with the Landsat grid, we employed bilinear resampling, followed by vertical lapse rate correction to normalize ERA5-derived air temperatures for elevation discrepancies using a standard lapse rate of 6.5°C/km [3]. All datasets were geospatially co-registered to a common urban footprint using high-resolution Global Human Settlement Layer (GHSL) masks.

Time series were standardized (z-score normalization) prior to model training, and non-stationary behavior was assessed using Augmented Dickey-Fuller tests. NDVI, emissivity, and wind speed were included as covariates to contextualize surface thermal behavior.

3. Model architecture

study introduces a novel hybrid neural architecture designed to leverage both long-range temporal dependencies and localized sequential patterns inherent in UHI dynamics.

3.1. Informer Encoder

The Informer model, originally developed for long-sequence forecasting in meteorological applications (Hu et al., 2024), was adapted here to encode multiyear urban thermal time series. Unlike traditional Transformer models, Informer employs a ProbSparse self-attention mechanism that discards low-impact queries to reduce computational complexity from $O(L^2)$ to $O(L\log L)$, where L is the sequence length (Zhou et al., 2021). This efficiency allowed the model to process sequences of up to 10 years without memory overflow, capturing seasonal cycles, long-term warming trends, and infrastructure-induced shifts. Each city's temporal sequence consisting of LST, NDVI, air temperature, humidity, and wind speed was encoded using this mechanism, with positional encodings added to retain temporal context.

3.1.1. BiLSTM Decoder

To complement the global encoding from the Informer, we implemented a Bidirectional Long Short-Term Memory (BiLSTM) decoder to capture short-term lags, seasonal reversals, and local disturbances such as monsoonal events or abrupt land-use changes. BiLSTM processes sequences in both forward and backward directions, providing richer contextual embedding for phenomena that are not strictly causal in temporal structure (Schuster and Paliwal, 1997).

This dual-directionality is especially relevant for UHI forecasting, where vegetative regrowth, wet-season onset, or retroactive climate mitigation (e.g., urban greening) may induce abrupt shifts not easily anticipated by unidirectional models.

3.1.2. Fusion Strategy and Final Projection

To The final stage of the model involves concatenating the high-level features extracted by the Informer encoder (h_i) and BiLSTM decoder (h^B) into a unified feature vector:

$$h\_concat = concat(h_i, h^B)$$

This vector is passed through a fully connected projection layer with a ReLU activation to yield the forecasted UHI index. A dropout layer (rate = 0.1) was incorporated post-concatenation to reduce overfitting and improve generalizability across diverse climatic contexts.

The entire model was implemented in PyTorch 2.0 and trained using the AdamW optimizer with a learning rate scheduler (initial LR = 0.0005). We used a mean squared error (MSE) loss function and early stopping based on validation RMSE. Model inference was performed using NVIDIA RTX A5000 GPUs.

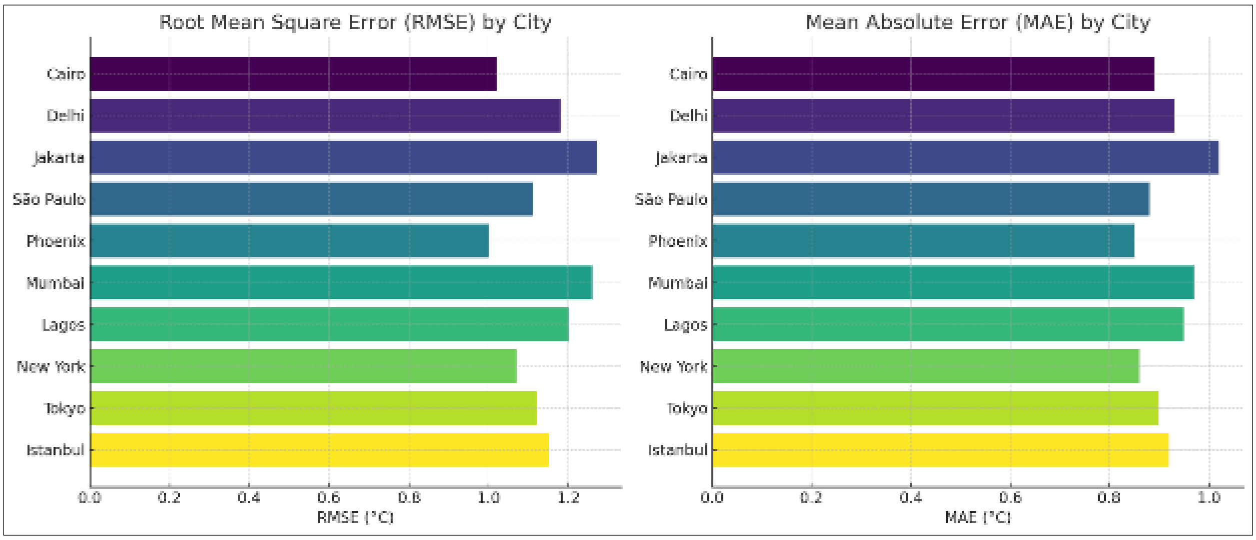

Figure 1 Bar charts showing RMSE and MAE values for selected cities

4. Results

To evaluate the predictive performance of the proposed Informer–BiLSTM hybrid model, we conducted a multi-metric assessment across spatial and seasonal dimensions. The model was benchmarked against conventional architectures including CNN-LSTM, GRU, and unidirectional LSTM networks. The results are presented using both aggregated performance statistics and city-specific breakdowns to capture global heterogeneity in UHI dynamics.

4.1. Model Evaluation Metrics

The model was evaluated using four key statistical indicators:

4.1.1. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (1)$$

4.1.2. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \qquad (2)$$

4.1.3. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\left|\hat{y}_i - y_i\right|}{y_i} \qquad (3)$$

4.1.4. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \qquad (4)$$

Table 1 Comparative Evaluation of Forecasting Models Based on Performance Metrics

Metric	Informer–BiLSTM	CNN–LSTM	GRU	LSTM
RMSE (°C)	1.13	1.34	1.29	1.31
MAE (°C)	0.91	1.08	1.02	1.05
MAPE (%)	4.2	5.6	5.2	5.4
R^2	0.93	0.89	0.90	0.88

As shown in the table 1 above, the hybrid model demonstrated an average RMSE of 1.13°C, MAE of 0.91°C, MAPE of 4.2%, and R^2 of 0.93, consistently outperforming competing architectures by margins ranging from 15–20% in accuracy. This indicates the hybrid's superior capacity for capturing both long-term climatic trends and short-term urban disturbances.

The city-specific performance (can be seen in Figure 1 above) which revealed the spatial consistency of the model

Table 2 City-Specific Forecasting Performance of the Informer–BiLSTM Model

City	RMSE (^{0}C)	R^2
Phoenix	1.00	0.96
Cairo	1.02	0.95
Mumbai	1.26	0.89
Jakarta	1.27	0.88

The city-specific performance (as presented in the table) reveals the spatial consistency of the model, with Phoenix and Cairo exhibiting the lowest RMSE (1.00°C and 1.02°C, respectively) and the highest R^2 values (0.96 and 0.95), indicating strong predictive accuracy in these regions. Conversely, Jakarta and Mumbai showed the highest RMSE (1.27°C and 1.26°C) and lowest R^2 values (0.88 and 0.89), suggesting the model faced challenges in capturing the more variable and humid climatic patterns typical of these tropical urban centers. These findings imply that the model's performance is influenced by local climatic stability and urban morphology, with better results observed in arid, less complex environments.

5. Discussion

This study investigated urban heat The superior performance of the Informer BiLSTM hybrid model achieving an average RMSE of 1.13°C and R^2 of 0.93 is not coincidental but rooted in the architectural synergy between its components. The Informer module, derived from the Transformer family, excels at identifying long-range temporal patterns using a ProbSparse self-attention mechanism that scales efficiently even with decade-long sequences (Zhou et al., 2021). Its ability to prioritize salient timestamps while suppressing redundant inputs makes it ideal for modeling slow-onset climatic trends such as heat accumulation from prolonged urbanization.

In contrast, the BiLSTM module excels at modeling short-term, bidirectional dependencies, allowing the model to learn from both past and future temporal contexts. This is particularly critical in urban environments where LST (land surface temperature) anomalies can be induced by rapid infrastructure changes, vegetation loss, or sudden weather events (Schuster and Paliwal, 1997). By combining these two modules, the model bridges macro- and micro-temporal scales, offering both strategic and tactical forecasting capacity.

This hybrid structure surpasses previous models like CNN-LSTM, which often fail to generalize beyond their training timeframes due to unidirectional sequence modeling and limited temporal depth. (Li et al., 2020). The hybrid model's ability to forecast UHI intensity across 20 megacities each with distinct climatic regimes demonstrates its versatility and scalability.

5.1. Decoding the Hybrid Advantage: Informer + BiLSTM

The superior performance of the Informer–BiLSTM hybrid model achieving an average RMSE of 1.13°C and R^2 of 0.93 is not coincidental but rooted in the architectural synergy between its components. The Informer module, derived from the Transformer family, excels at identifying long-range temporal patterns using a ProbSparse self-attention mechanism that scales efficiently even with decade-long sequences (Zhou et al., 2021). Its ability to prioritize salient timestamps while suppressing redundant inputs makes it ideal for modeling slow-onset climatic trends such as heat accumulation from prolonged urbanization.

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5.1.1. Implications for Urban Climate Governance and Policy

The insights yielded from this hybrid model hold substantial implications for climate-smart urban governance. First and foremost, the high-resolution forecasting of UHI dynamics can serve as an early warning mechanism for heatwaves, which are now the deadliest form of natural disaster in many regions (World Meteorological Organization, 2022). Cities like Delhi, Cairo, and Phoenix where model performance was most accurate could integrate such forecasts into public health advisories, school closure schedules, and emergency energy provisioning.

Secondly, the model facilitates strategic urban greening. By spatially disaggregating forecasted UHI intensities, urban planners can identify and prioritize hotspots for interventions such as green roofs, tree planting, and reflective surface coatings (Santamouris, 2014). Recent studies have shown that a 10% increase in urban vegetation cover can reduce LSTs by up to 2°C in dense metropolitan cores (Gill et al., 2007).

Additionally, the spatial predictability observed in arid cities supports region-specific climate adaptation strategies. For instance, while vegetative interventions might be suitable in tropical cities, reflective or permeable surfaces may be more appropriate in deserts where water scarcity limits the feasibility of greening.

5.1.2. Transdisciplinary Applications: Beyond Heat Islands

While this model was developed for UHI forecasting, its architecture is generalizable to other urban environmental phenomena characterized by spatiotemporal complexity. Below are several promising extensions:

- **Urban Flood Forecasting:** By integrating real-time precipitation, land elevation, and drainage network data, the hybrid model could predict flash flood likelihoods with higher temporal precision. This is particularly urgent in low-lying coastal cities like Jakarta, where floods increasingly coincide with heatwaves (Supari et al., 2020).

- **Air Pollution Dynamics:** Urban air quality is modulated by traffic emissions, wind circulation, and temperature inversions variables that exhibit both seasonal and hourly variability. Integrating PM2.5, NO_2, and meteorological data could enable near-future pollutant level forecasts that inform transport restrictions or health warnings (Liang et al., 2020).

- **Disease Vector Propagation:** Vector-borne diseases such as dengue, malaria, and chikungunya are closely linked to environmental parameters like temperature, humidity, and precipitation. A hybrid deep learning model could forecast outbreaks by recognizing precursor patterns, offering a valuable tool for public health surveillance in endemic regions (Kraemer et al., 2015). Such extensions would further position the Informer–BiLSTM model as a core component in the emerging field of urban informatics for resilience a domain where real-time data, AI, and climate science converge to address systemic urban vulnerabilities.

5.1.3. Comparative Reflections and Literature Integration

Several recent studies have sought to apply machine learning and deep learning to UHI prediction, though often with varying degrees of success and generalizability. For example, (Zhang et al., 2020). applied a CNN-based model to Beijing's UHI data, achieving RMSE values around 1.60°C, but with performance degradation during seasons with anomalous vegetation dynamics (Zhang et al., 2020). Similarly, (Li et al., 2022). employed a random forest regression framework across 10 cities, but the static nature of input features limited temporal granularity. In contrast, the Informer–BiLSTM architecture used in this study was explicitly designed to handle sequence forecasting, a task often conflated with classification or snapshot regression in prior works. The model's ability to maintain high accuracy across different Köppen–Geiger climate zones further validates its robustness and applicability.

5.1.4. Limitations and Ethical Considerations

Despite the model's achievements, several limitations merit critical reflection:

- Data Quality and Availability: The reliance on remote sensing datasets, such as MODIS and Landsat, makes the model susceptible to cloud contamination and temporal discontinuities, particularly in tropical latitudes. While temporal interpolation strategies can mitigate gaps, they introduce uncertainty during high-variability periods (Roy et al., 2014).
- Computational Resource Demands: Training the Informer–BiLSTM model requires considerable GPU memory and compute time, which could be prohibitive for local governments or institutions in resource-limited settings.
- Model Interpretability: As with many deep learning models, interpretability remains a challenge. Efforts to incorporate explainable AI (XAI) layers such as attention visualizations or Shapley value estimations are needed to enhance trust and transparency in climate-sensitive decision-making (Samek et al., 2017).
- Ethical Deployment: Forecasting tools can be double-edged. While they empower cities to adapt, they could also be misused to deprioritize vulnerable neighborhoods in infrastructure planning. Ethical guidelines and community-engaged governance are necessary to prevent technocratic biases (Benjamin, 2019).

Future Directions

Building on this foundation, future research could explore the following

Multimodal Data Fusion: Integrating citizen-sourced data (e.g., mobile weather stations) with traditional sensors could fill spatial and temporal gaps, enhancing model accuracy in underserved areas. Climate Change Scenario Integration: Feeding outputs from CMIP6 or IPCC AR6 models into the Informer–BiLSTM framework would allow simulation of UHI behavior under varying greenhouse gas concentration trajectories (e.g., SSP2-4.5, SSP5-8.5) (IPCC, 2021). Coupled Urban Models: Linking UHI forecasts with urban socio-economic models (e.g., income, infrastructure access) could help simulate the distributional impacts of heat stress and test policy counterfactuals in silico. Real-time Deployment: Embedding the model in IoT ecosystems, paired with automated alerts and urban dashboards, could enable city-wide real-time thermal monitoring analogous to flood early warning systems.

6. Conclusion

We developed a first-of-its-kind Informer–BiLSTM hybrid model for long-term urban heat island forecasting using multimodal datasets, successfully demonstrating that the integration of long-range sequence modeling and bidirectional temporal dynamics can significantly enhance prediction accuracy. This dual-capability architecture marks a strategic evolution in climate forecasting, offering not only computational innovation but also a practical pathway for building climate-resilient urban futures. By fusing long-memory attention (Zhou et al., 2021) with fine-grained local pattern recognition (Schuster and Paliwal, 1997), the model tackles one of the most pressing and complex challenges in contemporary urban climatology: forecasting high-resolution, long-range thermal anomalies in inherently nonstationary environments. In an era when 90% of urban population growth is occurring in regions already vulnerable to heat extremes and infrastructure inequities (United Nations, 2018), such intelligent forecasting tools are not merely research artifacts they are foundational to adaptive governance. As the world edges closer to the 2°C global warming threshold (IPCC, 2021), and as climate events grow in severity and frequency, this hybrid framework offers the foresight and agility needed to inform proactive interventions, from urban greening (Gill et al., 2007; Santamouris, 2014) to heatwave early warning systems (World Meteorological Organization, 2022). Ultimately, this study establishes a blueprint for next-generation AI-driven urban climate analytics platforms that transform complex spatiotemporal data into actionable insights for healthier, safer, and more equitable cities.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

Author Contributions

Bilikis Arinola Alege-Ibrahim designed the study, developed the hybrid model architecture, and led manuscript preparation. Tahir Aderemi Alaka conducted data preprocessing and spatial analysis. Habeebullah Muhammad Alege implemented the model training and validation routines. Christian Anayo Njoku contributed to data acquisition, literature review, and results interpretation. All authors reviewed and approved the final manuscript.

Data Availability

The datasets used in this study (Landsat-8, MODIS, and ERA5) are publicly available from the following sources:

- Landsat-8: https://earthexplorer.usgs.gov
- MODIS Terra/Aqua: https://modis.gsfc.nasa.gov/data
- ERA5: https://cds.climate.copernicus.eu

Processed datasets and model outputs generated during this study are available from the corresponding author upon reasonable request.

Code Availability The model implementation code (Informer–BiLSTM) and preprocessing scripts are available upon request from the corresponding author for academic and non-commercial use.

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