# GeoAI-based Urban Environmental Forecasting: A Remote Sensing Driven Hybrid Deep Learning and Machine Learning Framework

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**Abstract**
This study presents a hybrid GeoAI forecasting framework for long-term environmental monitoring in Dhaka, Bangladesh, one of the most densely populated and environmentally degraded megacities in the Global South. Using a 25-year record (2000–2024) of multi-source satellite and climate data, we modeled monthly trends in five key variables: Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), precipitation, and maximum and minimum air temperatures. Five supervised learning algorithms were trained and validated using univariate time-series features: Random Forest (RF), Support Vector Regression (SVR), Dense Neural Network (DNN), Long Short-Term Memory (LSTM), and a hybrid LSTM–XGBoost ensemble. Among these, the hybrid model demonstrated superior performance with $R^2$ values exceeding 0.99 for NDVI and BSI and ≥0.95 for temperature variables, while maintaining robust generalization for seasonal precipitation anomalies. Google Earth Engine is used to generate forecasts for 2030, yielding spatially explicit raster predictions for all variables. Model outputs indicated relatively stable conditions between 2024 and 2030, with localized environmental stress persisting in peri-urban and low-vegetation zones. To validate model interpretability and operational relevance, a two-stage participatory process was conducted with 28 urban stakeholders through structured interviews and a validation workshop. Survey results indicated that 72% of participants rated the forecasts as “useful” or “very useful” for urban planning, while 64% found the NDVI and temperature maps “understandable” without specialized training. Thematic analysis highlighted accessibility, local specificity, and trust in AI forecasts as key factors influencing user acceptance. These findings support the scalability of the proposed GeoAI framework and its alignment with planning priorities in climate-stressed urban environments of the Global South.

**Keywords:** GeoAI, Urban Environmental Forecasting, Hybrid Deep Learning Models, Remote Sensing Time Series, Climate-Resilient Urban Planning.

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## 1. Introduction

Urban areas worldwide are facing unprecedented environmental challenges under climate change and rapid urbanization (Ali et al.,2025; Adeniran et al.,2024; Humbal et al.,2023; Lees et al.,2022). Intensifying heatwaves and urban heat islands (UHI) threaten public health, while shifting precipitation patterns increase the risk of floods and droughts in cities (Wani et al.,2024; Das et al.,2024; Singh et al., 2020; Santamouris, 2020). For example, heavy rainfall events have led to destructive urban flooding that disrupts infrastructure and livelihoods (Dharmarathne et al.,2024; Akther and Ahmed, 2021). At the same time, prolonged droughts such as recent extreme events across Africa, Asia, Europe, and the Americas have underscored vulnerabilities in water supply and ecosystem health (Mani et al.,2024; Fernández et al.,2023; Ebi and Bowen,2016). Vegetation loss and land degradation are often both a cause and consequence of these climate extremes, diminishing urban resilience by reducing natural cooling and increasing runoff (Cuce et al.,2025; Lin et al.,2023; Vasilakos et al., 2022).

In this context, cities in both the Global North and Global South are urgently seeking data-driven tools to anticipate environmental changes and inform climate-resilient urban planning (Sathianarayanan et al.,2025; Allan et al.,2024). Among these, Dhaka, Bangladesh, stands out as a megacity facing extreme ecological stress. Characterized by chronic air pollution, deteriorating vegetation cover, irregular precipitation, and intensifying urban heat islands, Dhaka exemplifies the urgency of implementing advanced environmental monitoring and forecasting tools (Islam et al., 2023; Kafy et al., 2021). Effective forecasting of key environmental variables such as vegetation indices, land surface conditions, precipitation, and near-surface air temperatures is increasingly recognized as a foundation for proactive adaptation strategies in cities (Medina et al.,2024). However, conventional urban monitoring systems often fall short in these rapidly evolving landscapes due to poor sensor networks, inconsistent data collection, and insufficient institutional capacity (Yu and Fang,2023). Addressing these limitations necessitates a transformative approach that fuses Earth observation technologies with artificial intelligence to deliver proactive, high-resolution environmental intelligence.

Remote sensing and geospatial big data have a pivotal role to play in this urban environmental forecasting paradigm (Dritsasa and Trigka,2025). Earth observation satellites provide continuous, spatially extensive measurements of environmental variables at fine temporal resolutions, offering data on vegetation cover, land surface state, and climate indicators that complement ground observations. For instance, the Normalized Difference Vegetation Index (NDVI) derived from satellite imagery has long been used as a proxy for vegetation health and greenness in urban landscapes (Jimenez et al.,2022). Forecasting NDVI over time is critical for early warning of drought impacts on urban vegetation and green infrastructure (Ghalehteimouri et al.,2024). In arid and semiarid city regions, declining NDVI can signal land degradation and desertification risks, informing interventions to prevent ecological damage (Kumar et al.,2022).

Meanwhile, indices like the Bare Soil Index (BSI) help characterize exposed soil and impervious surfaces; high BSI values often correspond to built-up or bare land areas with minimal vegetation cover (Nguyen et al.,2022; Delaney et al.,2025). BSI has been used to map urban expansion and land cover changes, although it tends to emphasize urban features (built surfaces) as well as true bare soil. Monitoring BSI alongside NDVI thus provides a fuller picture of the urban land surface dynamics from vegetation loss to growth of impervious areas that affect heat retention, runoff generation, and overall environmental quality. In addition to land surface indices, atmospheric variables are crucial: high-resolution precipitation data enable urban flood forecasting (Lammers et al.,2021), and near-surface air temperature measurements capture the intensity of heat waves and UHI effects (Du et al.,2024). Traditionally, city planners have relied on statistical extrapolations or coarse climate model outputs for such variables, but these approaches often fail to resolve fine-scale urban microclimates and land-use heterogeneity (Back et al.,2021). This gap underscores the need for advanced forecasting frameworks that integrate multi-source geospatial data to predict urban environmental conditions with greater accuracy and spatial detail.

The recent convergence of remote sensing (RS) and machine learning (ML) techniques under the umbrella of Geographic Artificial Intelligence (GeoAI) offers unprecedented potential for sustainable urban planning, disaster risk reduction (Yildirim et al., 2022), and environmental policy design (Zhao et al., 2022). Remote sensing provides extensive temporal and spatial environmental data (Li et al., 2025), while ML and deep learning (DL) models are capable of extracting hidden patterns, modeling nonlinear processes, and forecasting future states with high fidelity (Bayar et al., 2009; Sit et al., 2021a). The synergy between these two domains is particularly valuable in data-scarce regions, where traditional statistical forecasting models fail to adequately represent the spatial and temporal heterogeneity of environmental systems (Yu et al.,2025; Ghobadi et al.,2024; Anees et al., 2022;).

Geospatial artificial intelligence (GeoAI) has emerged as a powerful approach to tackle complex spatial problems by combining AI techniques with rich geospatial datasets (Pierdicca and Paolanti,2022; Chen et al.,2023). In the urban environmental context, GeoAI leverages machine learning (ML) and deep learning (DL) models to exploit spatial patterns in Earth observation (EO) data, enabling the analysis and prediction of environmental variables across city landscapes (Slater et al.,2023; Li et al.,2023). Unlike conventional models that treat locations independently, GeoAI methods can incorporate the geospatial context (e.g. neighborhoods, land cover adjacencies, topography) directly into learning algorithms (Liu and Biljecki, 2022). This spatially explicit learning has proven effective in improving performance for a range of urban applications, from land use classification to traffic and crime prediction. In particular, data-intensive urban climate and environmental forecasting tasks stand to benefit from GeoAI's ability to fuse heterogeneous data layers and capture non-linear relationships in space and time (de França e Silva et al.,2024;Yu et al.,2025).

Recent advances in GeoAI have included integrating high-performance computing and big data analytics to process massive EO time series, yielding near–real-time insights into urban environmental dynamics (Dritsas and Trigka, 2025). These hybrid GeoAI systems combine the strengths of physics-based models (global climate patterns, physical consistency) with data-driven learning (bias correction, local detail), achieving superior predictive skill for hydroclimatic variables such as urban precipitation and heat waves (Zhao et al.,2024). By harnessing geospatial context (e.g. land cover, elevation) along with temporal patterns, GeoAI approaches can improve the accuracy and relevance of urban environmental forecasts, ultimately supporting more resilient urban planning.

In the past decade, there has been an explosion of research applying ML/DL techniques to forecast environmental time series derived from remote sensing and ground observations (Bahadur et al.,2023; Krinitskiy et al.,2024). Vegetation dynamics forecasting is one area that has seen especially rapid progress. A rich literature has analyzed NDVI time series to understand and predict vegetation changes in response to climate variability and human influence (Gao et al.,2022; Vasilakos et al.,2022). Early studies often employed empirical statistical models or time-series smoothing (e.g. Holt-Winters, ARIMA) to predict NDVI, including applications in East Africa and other regions prone to drought (Omar and Kawamukai, 2021). However, such linear models struggle with NDVI's non-linear, non-stationary behavior and cannot capture abrupt vegetation fluctuations due to disturbances (Xue et al., 2024).

In recent years, the application of deep learning models such as long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and hybrid ensembles have enhanced the predictive performance of environmental forecasting tasks (Krajewski et al., 2021; Xiang et al., 2021). These models have demonstrated success in capturing temporal dependencies in NDVI and precipitation (Prodhan et al.,2021), delineating urban heat islands (Singh et al.,2025), and estimating bare soil dynamics from multispectral imagery (Salas et al.,2023; Swain et al.,2021; Lees et al.,2022). While individual models offer powerful capabilities, hybrid frameworks combining the predictive robustness of ensemble learners like XGBoost with the temporal modeling strength of recurrent networks (e.g., LSTM) have begun to outperform traditional standalone approaches (Huang et al.,2025; Heidari et al., 2022; Mermer et al., 2024). Nonetheless, the integration of these tools into coherent, operational forecasting systems for cities like Dhaka remains underexplored.

In parallel, forecasting of hydro-meteorological variables (e.g. rainfall and air temperature) using AI has advanced markedly. Accurate rainfall prediction is imperative for flood management, agriculture, and water resource planning in cities. Conventional numerical weather prediction models capture large-scale atmospheric dynamics but often struggle with localized convective storms that cause urban flash floods (Li et al.,2024). Machine learning methods have been introduced to bridge this gap by learning fine-scale patterns from historical data and improving the localization of forecasts (Deep and Verma,2024). Studies across climatic regions have shown that neural network models can outperform linear statistical models in predicting monthly and seasonal rainfall, especially when incorporating relevant predictors like temperature, humidity, and climate indices (Abebe and Endalie,2023; Kumar et al.,2025). For example, recent work in the Indian subcontinent and North Africa reported that deep LSTM networks yielded higher skill (lower RMSE and higher $R^2$) than regression and even some physics-based models for multi-week rainfall forecasting (Li et al.,2024).

These improvements are attributed to LSTM's ability to capture long-term memory of monsoon oscillations and teleconnection signals (e.g. ENSO, NAO) that drive rainfall variability.

Similarly, for air temperature, numerous studies have applied ML to enhance predictions of urban thermal conditions. Traditional approaches relied on sparse weather station networks for 2-meter air temperature measurements, which provide high-accuracy point data but limited spatial coverage (Adeniran et al.,2024). This poses challenges in heterogeneous urban areas where temperatures can vary sharply with land use (e.g. park vs. downtown). To address this, researchers have merged satellite remote sensing with ML models to produce high-resolution air temperature maps (Mao et al.,2021). One common approach is to infer near-surface air temperature from land surface temperature (LST) retrieved by thermal infrared sensors (e.g. MODIS, Landsat) combined with auxiliary data like NDVI, impervious surface indices, and digital elevation (Shi et al.,2021; Li et al.,2023).

Because the relationship between LST and actual air temperature varies in space and time, simple linear scaling often performs poorly. Instead, nonlinear ML algorithms (random forests, neural networks, Gaussian processes) are trained to calibrate LST to 2m air temperature using in situ station data as ground truth. For instance, Zhang et al. 2022 employed a Random Forest model to predict hourly air temperature in urban China from geostationary satellite LST and indices like NDVI and Normalized Difference Built-up Index, achieving errors ~1.6 K. Likewise, Che et al.2022 tested multiple ML models (RF, ANN, SVM, Gaussian process) to downscale MODIS LST to local air temperatures, finding that an ANN yielded the highest accuracy (bias under 0.4 K) after accounting for land cover around each station. These studies illustrate how integrating EO data with ML can overcome the spatial limitations of weather stations, providing continuous temperature fields for urban heat island analysis and heat hazard early warnings. Notably, efforts have even integrated community-based observations: Castro Medina et al.2024 demonstrated that crowdsourced data from citizen weather stations, when filtered and fused with official forecasts via neural networks, can improve neighborhood-scale temperature predictions to guide urban heat mitigation plans. The convergence of these approaches signals a broader trend toward data fusion in urban climate forecasting blending satellite, station, reanalysis, and even citizen data through AI models to produce robust, high-resolution predictions.

Despite these advancements, significant research gaps remain in forecasting multiple urban environmental variables in an integrated manner. Most prior studies have tackled a single target (e.g. NDVI alone or rainfall alone), yet urban sustainability challenges are inherently multi-faceted. Vegetation cover, land surface conditions, rainfall, and air temperature interact in complex feedback loops – for example, decreased vegetation (low NDVI) can exacerbate urban heat and alter local rainfall infiltration, while extreme heat and drought in turn reduce vegetation health. Hybrid modeling offers a promising path forward. By hybrid, we refer to combining the representational power of deep learning with the strengths of other machine learning or statistical techniques within one coherent framework. This could entail, for example, using a convolutional-LSTM network to capture spatio-temporal features from remote sensing inputs, and then feeding its outputs or learned features into a gradient boosted regression tree or an ANFIS model that fine-tunes the predictions with domain-specific constraints. Such hybridization can also mean ensembling multiple models or blending physics-based forecasts with data-driven corrections. In the context of urban environments, a hybrid GeoAI framework could, for instance, ingest physically downscaled climate model projections and adjust them using local EO-driven ML predictors (NDVI, BSI, etc.), thereby yielding forecasts that honor both global climate signals and local land-surface idiosyncrasies. Additionally, hybrid deep learning models can address different data characteristics: a deep neural network might excel at extracting nonlinear features from imagery time series, while a separate ML component (say, a random forest) could handle tabular data (e.g. demographic or infrastructure variables) and ensure interpretability by ranking key predictors.

Building on these insights, this study proposes a GeoAI-based hybrid deep learning and machine learning framework for urban environmental forecasting, driven primarily by remote sensing time series data. We maintain a balanced focus on five critical variables NDVI, BSI, precipitation, and 2-meter maximum/minimum air temperatures capturing both biospheric and atmospheric dimensions of the urban climate system. By integrating high-resolution satellite-derived indices with climate data and applying a hybrid DL–ML modeling strategy, we aim to produce accurate, multi-variable forecasts that can support climate-resilient urban planning decisions. Our approach draws from the strengths of prior works in each domain (vegetation, hydrology, urban climate) while introducing a unified predictive platform. In doing so, we address gaps in existing literature related to cross-variable forecasting and applicability in diverse urban contexts.

Dhaka's environmental challenges are not only multifaceted but also highly dynamic. The city has witnessed a 62% loss in vegetation cover from 1990 to 2020, largely due to unregulated development and infrastructure expansion (Kafy et al., 2021). Seasonal flooding and erratic rainfall patterns have further complicated urban planning and public health interventions. Conventional statistical methods fail to account for these evolving land use and climatic drivers. More crucially, existing models are rarely capable of simultaneously forecasting multiple environmental indicators such as vegetation indices, temperature extremes, precipitation anomalies, and land surface changes. Addressing this complexity requires multi-variable models trained in temporally rich, multi-source benchmark datasets (Ebert-Uphoff et al., 2017; Demir et al., 2022; Sit et al., 2021b).

GeoAI is uniquely positioned to tackle these challenges. First, the use of satellite datasets such as Landsat, SAR, CHIRPS, and TerraClimate provide long-term environmental records with high spatial resolution (Li et al., 2023; Li and Demir, 2024). Second, advanced ML/DL models can be adapted for time-series forecasting, spatial modeling, and uncertainty quantification in these datasets (Demiray et al., 2021). For instance, studies have used LSTM models to forecast NDVI based on previous seasons' vegetation health and rainfall trends (Xiang and Demir, 2022), while others have employed support vector regression (SVR) and random forest (RF) for precipitation and temperature prediction (Paniagua-Tineo et al.,2011; Anees et al., 2022). However, most of the existing approaches focus on single-variable, single-model pipelines, limiting their utility in real-world decision-making contexts where urban resilience planning requires multifactorial insights.

To bridge this critical gap, the present study introduces a novel hybrid GeoAI framework that integrates multiple supervised learning architectures including RF, SVR, Dense Neural Networks, LSTM, and LSTM-XGBoost ensembles trained on satellite-derived NDVI, BSI, precipitation, and air temperature datasets. Our framework processes over two decades of monthly data (2000–2024), generating high-resolution spatiotemporal forecasts through 2030. The geospatial modeling pipeline leverages Google Earth Engine (GEE) and Python for data ingestion, model execution, and visualization, ensuring reproducibility and scalability. By combining multi-source RS data with a robust hybrid modeling strategy, this study aims to capture the nonlinearities and seasonal shifts that characterize Dhaka's complex environmental dynamics.

The novelty of this study lies in its end-to-end forecasting pipeline that integrates domain-diverse datasets, fuses the strengths of both deep and ensemble learning, and generates interpretable, spatially explicit outputs for planners. Unlike previous models that have addressed isolated indicators or timeframes, the hybrid LSTM-XGBoost framework developed here simultaneously forecasts five critical environmental variables and translates them into policy-relevant insights. These outputs are designed to inform zoning regulations, disaster early warning systems, green infrastructure planning, and climate adaptation strategies in high-risk urban environments (Rahmani,2024). Furthermore, this work provides a replicable blueprint for other megacities across South Asia, Sub-Saharan Africa, and Latin America that face similar environmental stressors. By contextualizing the application of GeoAI within Dhaka, the study contributes to a growing but still nascent body of literature focused on AI-enabled environmental forecasting in the Global South (Ali et al., 2020; Himeur et al., 2021). Its emphasis on model interpretability, computational efficiency, and real-world applicability ensures its alignment with both academic rigor and operational utility.

Therefore, integrating machine learning and remote sensing within a GeoAI framework offers transformative potential for environmental forecasting in rapidly urbanizing, data-limited contexts. As climate impacts become more severe and unpredictable, the ability to anticipate environmental conditions at fine spatial and temporal scales becomes essential. This study not only advances the technical frontier of environmental modeling but also equips policymakers and planners in Dhaka and beyond with actionable intelligence for sustainable urban futures.

## 2. Study Area

Dhaka, the capital of Bangladesh, is one of the most densely populated megacities in the world, with over 21 million residents and a population density exceeding 47,000 people/km² in core urban areas (World Bank, 2022). As the country's primary political and economic engine contributing nearly 36% of national GDP Dhaka has undergone rapid and largely unregulated urban expansion. This growth has resulted in widespread environmental degradation, including the loss of green cover, wetland encroachment, and escalating levels of air and water pollution.

Climatically, Dhaka lies within the humid subtropical monsoon zone (Köppen: Cwa), with annual precipitation exceeding 2000 mm, mostly during the June–September monsoon season. The city's average temperature ranges between 19°C and 30°C, and its low elevation (~4 meters) makes it highly vulnerable to seasonal flooding, urban heat stress, and hydrological disruptions. In the past two decades, Dhaka has seen a dramatic decline in vegetative cover over 60% by some estimates alongside a sharp rise in air pollution, placing it consistently among the world's most polluted cities (Kafy et al., 2021). These environmental stressors, combined with the city's demographic pressures, make traditional monitoring approaches insufficient and highlight the need for predictive, scalable frameworks.

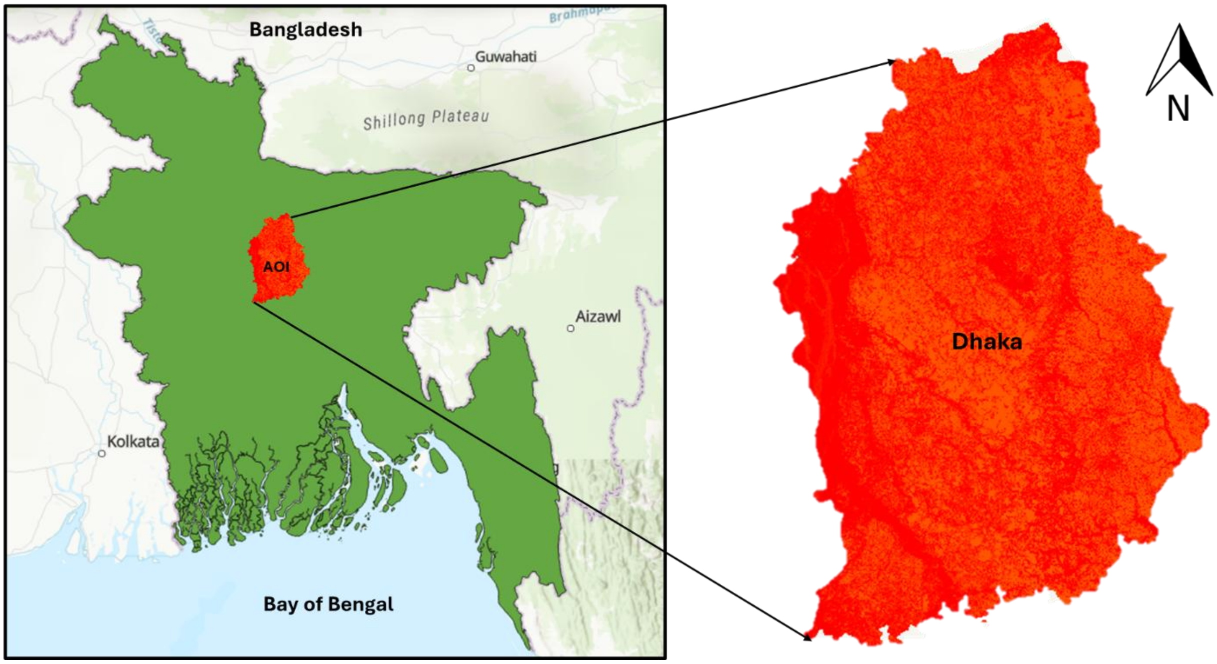


Figure 1. Location of the study area within Bangladesh

The spatial extent of the study is illustrated in Figure 1, which maps Dhaka's administrative boundaries, major land cover classes, and ecological features. This geospatial context forms the basis for evaluating long-term environmental changes and supports the forecasting output generated by the proposed hybrid GeoAI framework.

## 3. Materials and Methods

### 3.1. Data Collection

This study utilizes a combination of remotely sensed and reanalysis-based datasets to capture the long-term spatiotemporal dynamics of key environmental variables in Dhaka from 2000 to 2024. The selected datasets were chosen based on their temporal continuity, spatial resolution, and scientific validation in prior geospatial and climatological studies. To represent atmospheric conditions, monthly minimum and maximum air temperatures were sourced from the TerraClimate product, which provides high-resolution (4 km) global climate data derived from a blend of observed and modeled outputs (Abatzoglou et al., 2018). This dataset spans the entire 25-year period and offers reliable climate surfaces suitable for time series modeling in data-scarce regions.

Vegetation dynamics were monitored using the Normalized Difference Vegetation Index (NDVI) derived from the Landsat satellite series, including Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 & 9 Operational Land Imager

(OLI). Each sensor offers 30-meter spatial resolution with a nominal 16-day revisit time. The dataset was segmented into three temporal blocks: 2000–2011 for TM, 2012–2013 for ETM+, and 2014–2024 for OLI. Data was retrieved from the USGS EarthExplorer portal, ensuring consistent calibration and preprocessing across sensors. To estimate surface exposure and soil degradation, we used the Bare Soil Index (BSI) as a proxy, derived from the SoilGrids database.

Although static in nature, the SoilGrids product provides global 250-meter resolution soil property maps, offering a foundational layer for environmental condition analysis in urban areas. Precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) archive, covering the early part of the study period (2000–2004). CHIRPS combines satellite imagery with in-situ station data to produce precipitation estimates at a 0.05° (~5.5 km) resolution, with both daily and monthly aggregates available. An overview of the datasets, their characteristics, and sources is provided in Table 1.

Table 1. Information of datasets used in this study

| Dataset / Products | Variable | Period Used | Resolution | | Link |
|---|---|---|---|---|---|
| | | | Spatial | Temporal | |
| TerraClimate | Min and Max Temp. | 2000-2024 | 4 km | Monthly | https://www.climatologylab.org/terraclimate.html |
| Landsat 5 Thematic Mapper (TM) | NDVI | 2000-2011 | 30 m | 16-day | https://earthexplorer.usgs.gov |
| Landsat 7 Enhanced Thematic Mapper Plus (ETM+) | NDVI | 2012-2013 | 30 m | 16-day | https://earthexplorer.usgs.gov |
| Landsat 8 & 9 OLI | NDVI | 2014-2024 | 30 m | 16-day | https://earthexplorer.usgs.gov |
| Soil Grids | BSI (Bare Soil Index proxy) | Static | 250 m | Static | https://soilgrids.org/ |
| Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) | Precipitation | 2000-2004 | 0.05° (~5.5 km) | Daily + Monthly | https://data.chc.ucsb.edu/products/CHIRPS-2.0/ |

### 3.2. Stakeholder Engagement and Participatory Validation

To enhance the real-world applicability and policy relevance of the forecasting framework, a targeted stakeholder engagement process was undertaken during the first quarter of 2024. The aim was to evaluate the interpretability, usability, and planning potential of the GeoAI-generated outputs among end-users involved in urban environmental management and climate resilience in Dhaka. A total of 28 participants were engaged through two formats: (i) structured online interviews (n = 10) and (ii) a virtual participatory workshop (n = 18), as detailed in Table 2. Participants were purposively selected from a cross-section of urban governance institutions, including representatives from the Dhaka North and South City Corporations (DNCC/DSCC), the Department of Environment, national disaster management authorities, academic researchers, and civil society organizations active in environmental advocacy and planning.

Table 2. Summary of stakeholder engagement activities conducted for participatory validation of the GeoAI model output

| Timing | Method | No. of Participants | Stakeholder Profile |
|---|---|---|---|
| February 2024 | Structured Interviews | 10 | Urban planners, municipal engineers (DNCC/DSCC), DoE officers |
| March 2024 | Participatory Workshop | 18 | NGOs, environmental researchers, policy advisors, civil society actors |

During these sessions, participants were presented with time-series analyses (2000–2024) and spatial forecasts for 2030 derived from the hybrid GeoAI model. The discussions centered on three core areas: (i) perceived accuracy and trust in forecast maps; (ii) utility of spatial outputs for urban decision-making; and (iii) suggestions for future improvements, including integration of additional variables or user interface preferences.

Stakeholders noted that while macro-level changes between 2024 and 2030 appeared subtle, localized environmental shifts especially in vegetation loss and urban heat exposure remained areas of concern. Several participants recommended incorporating complementary indicators such as land surface temperature, air pollution (PM2.5), and urban vulnerability indices to better align the model with actionable planning needs. These insights have been documented and will inform the next phase of model development.

### 3.3. Data Preprocessing

Prior to model training, extensive preprocessing (Table 3) was conducted to harmonize the temporal, spatial, and statistical structure of the multi-source datasets used in this study. Each environmental variable NDVI, BSI, precipitation, and 2-meter air temperature (maximum and minimum) was initially available in varying resolutions, temporal intervals, and formats, necessitating standardization. First, raster images were projected into a common coordinate system (WGS 84 / UTM Zone 46N) and resampled to a spatial resolution of 30 meters, aligning with the native resolution of the Landsat data.

Temporal aggregation was then performed to generate monthly means across all variables for the period 2000 to 2024. For datasets with daily granularity (e.g., CHIRPS precipitation), monthly compositing was used to maintain consistency across sources. Handling missing values was a critical step, particularly for NDVI and BSI datasets impacted by cloud contamination or sensor dropout. Pixels containing invalid or null values were identified through automated threshold filtering and excluded from model training. For non-random gaps in time series, a linear interpolation approach was implemented on a per-pixel basis to reconstruct plausible values. This was especially important for ensuring the continuity of the NDVI series, where vegetation trends rely on uninterrupted temporal context.

Each variable was then standardized using z-score normalization, computed across the full training period (2000–2020). This allowed for consistent scaling across inputs during model training, while preserving their relative variation and seasonal dynamics. Outlier detection was performed using the interquartile range (IQR) method, with values beyond 1.5×IQR replaced by the local temporal mean. Finally, the preprocessed raster stacks were converted into tabular CSV format by exporting pixel-wise coordinates and time-series values through the Google Earth Engine interface, enabling model input construction in the Python-based forecasting pipeline.

Table 3. Preprocessing steps applied to each environmental variable

| **Variable** | **Raw Format** | **Preprocessing Applied** | **Final Format** |
|---|---|---|---|
| NDVI | Landsat-derived raster (30m, 16-day) | Cloud masking, linear interpolation, monthly averaging, z-score normalization | Monthly z-scored values (30m) |
| BSI | Landsat-derived raster (30m, 16-day) | Threshold filtering, outlier replacement, monthly averaging | Monthly values (30m) |
| Precipitation | CHIRPS (0.05°, daily) | Temporal aggregation (monthly sum), resampling to 30m, z-score normalization | Monthly z-scored values (30m) |
| Max Temp (2m) | TerraClimate (4 km, monthly) | Resampling to 30m, standardization, IQR outlier removal | Monthly z-scored values (30m) |
| Min Temp (2m) | TerraClimate (4 km, monthly) | Resampling to 30m, standardization, IQR outlier removal | Monthly z-scored values (30m) |

### 3.4. Feature Engineering

To enhance model performance and capture temporal dependencies within each environmental variable, a structured set of features was engineered from the monthly time-series data. These included:

- Lag features: One-to-three month lag values (e.g., t–1, t–2, t–3) to capture autoregressive behavior.
- Rolling statistics: Three-month and twelve-month moving averages and standard deviations to reflect seasonal trends and local variability.
- Trend slope: Computed over rolling five-year windows using linear regression to quantify long-term directional changes.
- Monthly anomalies: Deviations from historical monthly means to identify shifts from climatological norms.
- Cyclical encoding: Month-of-year encoded using sine and cosine functions to represent seasonality in a machine-readable format.

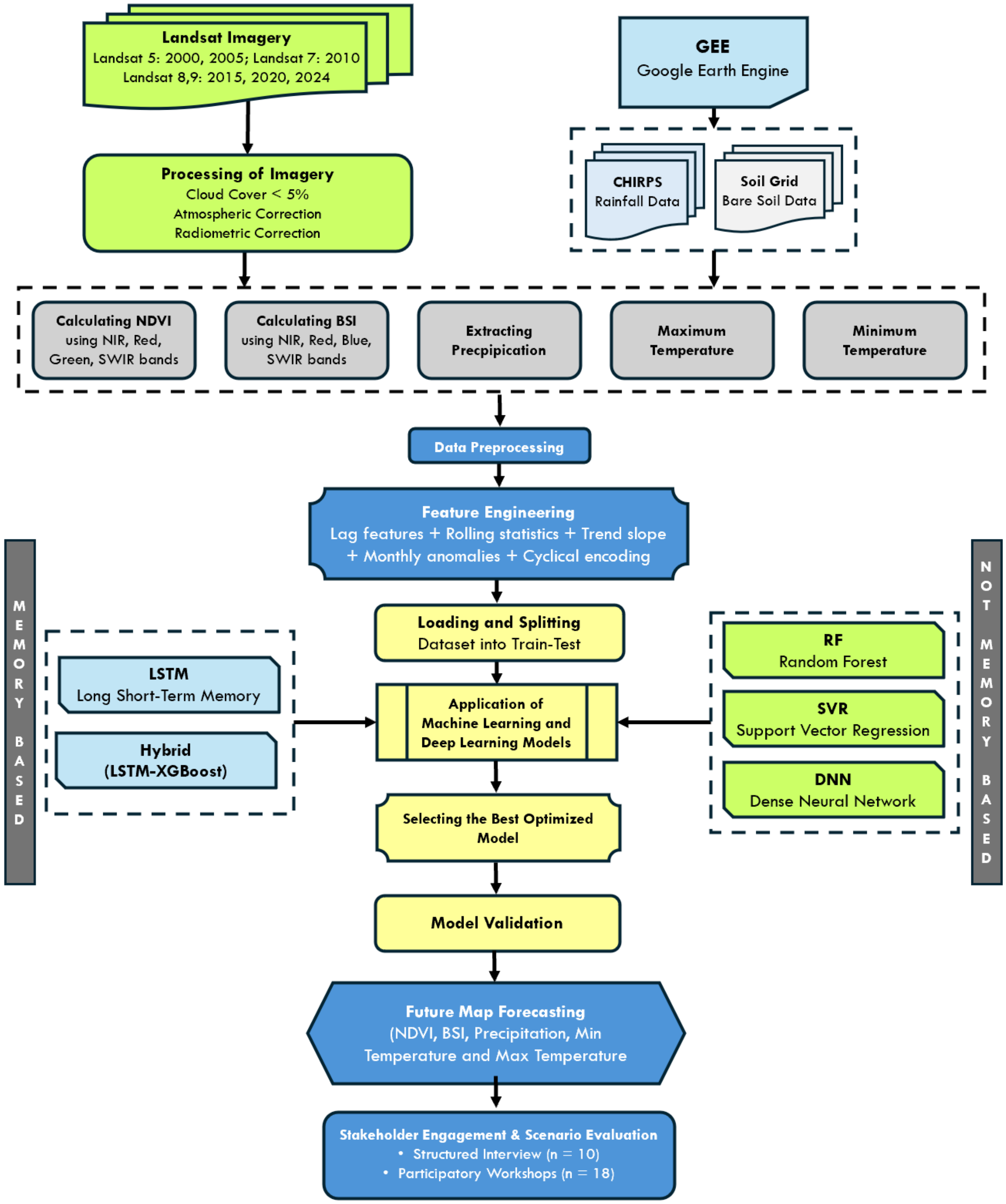



Figure 2. The modeling framework and architecture, highlighting the sequential training flow and integration of the hybrid ensemble model.

These features were applied across all variables at each pixel location and compiled into structured input matrices. Correlation filtering and exploratory analysis were performed to minimize multicollinearity and reduce noise. This feature set enabled the learning models to represent both stable and transitional environmental patterns critical for long-range forecasting.

### 3.5. Modeling Framework and Architecture

To forecast environmental conditions across Dhaka through 2030, five supervised learning algorithms were implemented and evaluated using univariate time series data: Random Forest (RF), Support Vector Regression (SVR), Dense Neural Network (DNN), Long Short-Term Memory (LSTM), and a hybrid LSTM–XGBoost ensemble. These models were selected to represent a mix of classical machine learning, feedforward neural networks, recurrent deep learning, and ensemble-based architectures, enabling a comparative analysis across different levels of temporal and nonlinear learning capacity. Figure 2 depicts the overall modeling framework of the entire study.

Each model was trained independently on pixel-level time series data for five variables NDVI, BSI, precipitation, and 2-meter maximum and minimum temperatures aggregated to monthly intervals from 2000 to 2020. The remaining years (2021–2024) were reserved for validation. No explicit feature engineering was performed beyond time-step structuring; models received raw monthly sequences as input, relying on internal architectures to capture lag dependencies and seasonality.

The Random Forest model was implemented using 100 decision trees and optimized using grid search with five-fold cross-validation. SVR was trained with a radial basis function (RBF) kernel and regularization parameter tuning. The Dense Neural Network consisted of three fully connected layers with ReLU activation and dropout regularization. The LSTM model included a single memory layer with 64 units followed by a dense output layer, trained over 100 epochs with early stopping to prevent overfitting. For the hybrid ensemble, LSTM was first used to capture temporal dynamics and generate preliminary forecasts.

Table 4. Equations of the evaluation metrics

| Name | Equation |
|---|---|
| R squared ($R^2$) | $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2}$ |
| Mean Absolute Error (MAE) | $MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$ |
| Root Mean Squared Error (RMSE) | $RMSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ |
| Mean Absolute Percentage Error (MAPE) | $MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{\lvert y_i - \hat{y}_i\rvert}{y_i}$ |

The residuals between predicted and actual values were then modeled using an XGBoost regressor, which corrected for systematic errors unaccounted for by the sequence model. The final forecast was obtained by summing the LSTM output and the learned XGBoost residual correction.

Model training and evaluation were conducted in Python using the scikit-learn, TensorFlow, Keras, and XGBoost libraries. Evaluation metrics (Table 4) included coefficient of determination ($R^2$), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), averaged across all variables and locations.

## 4. Results

### 4.1. Temporal Trends in Environmental Indicators (2000–2024) and Forecast Trajectories to 2030

To establish a baseline understanding of Dhaka's environmental evolution, long-term temporal trends from 2000 to 2024 were analyzed for five key indicators: NDVI, BSI, precipitation, and 2-meter maximum and minimum air temperatures. Table 5 summarizes the annual averages for selected benchmark years, illustrating the progression of vegetative health, surface exposure, and climatic variability.

Vegetative cover, as reflected in NDVI, shows a declining pattern from 0.49 in 2005 to 0.31 in 2024, with a notable dip in 2015 and 2024. In contrast, BSI increased over the same period from –0.49 to –0.59 indicating greater surface exposure and reduced vegetation cover, likely due to continued urban expansion and land conversion. Precipitation values exhibited high interannual variability, with a sharp decline from 2782.4 mm in 2000 to 1538.5 mm in 2010, followed by partial recovery to 1978.3 mm in 2020. Temperature trends were more consistent: the maximum temperature range increased from 24.5–32.8°C in 2000 to 40.4–41.0°C by 2024, while minimum temperatures rose from 21.3–25.1°C to 24.8–25.4°C over the same period, reflecting a warming trend and potential intensification of the urban heat island effect.

Table 5. Annual data of trend analysis for NDVI, BSI, Precipitation, Temperatures for years 2000, 2005, 2010, 2015, 2020, 2024

| Year | NDVI | BSI (±SD) | Precip. (mm) | Max Temp Range (°C) | Min Temp Range (°C) |
|---|---|---|---|---|---|
| 2000 | 0.31 | -0.24 ± 0.06 | 2782.4 | 24.54–32.75 | 21.3–25.1 |
| 2005 | 0.49 | -0.49 ± 0.09 | 1804.18 | 28.10–30.23 | 20.6–24.3 |
| 2010 | 0.32 | -0.81 ± 0.36 | 1538.53 | 29.26–30.27 | 21.1–23.2 |
| 2015 | 0.38 | -0.54 ± 0.32 | 1687.44 | 28.59–29.57 | 21.2–22.3 |
| 2020 | 0.39 | -0.43 ± 0.31 | 1978.32 | 28.31–29.50 | 21.7–22.0 |
| 2024 | 0.31 | -0.59 ± 0.30 | 1735.69 | 40.41–41.04 | 24.8–25.4 |

These historical patterns were extended through 2030 using the hybrid LSTM–XGBoost model to generate monthly forecasts. As shown in Figure 3, the temporal forecasts capture the aggregated monthly means across the entire study area, with 95% confidence intervals highlighting model uncertainty. The NDVI trend continues with mild seasonal variation, while BSI appears to stabilize. Both maximum and minimum temperatures plateau but remain elevated, while precipitation retains high interannual noise with no strong directional trend.

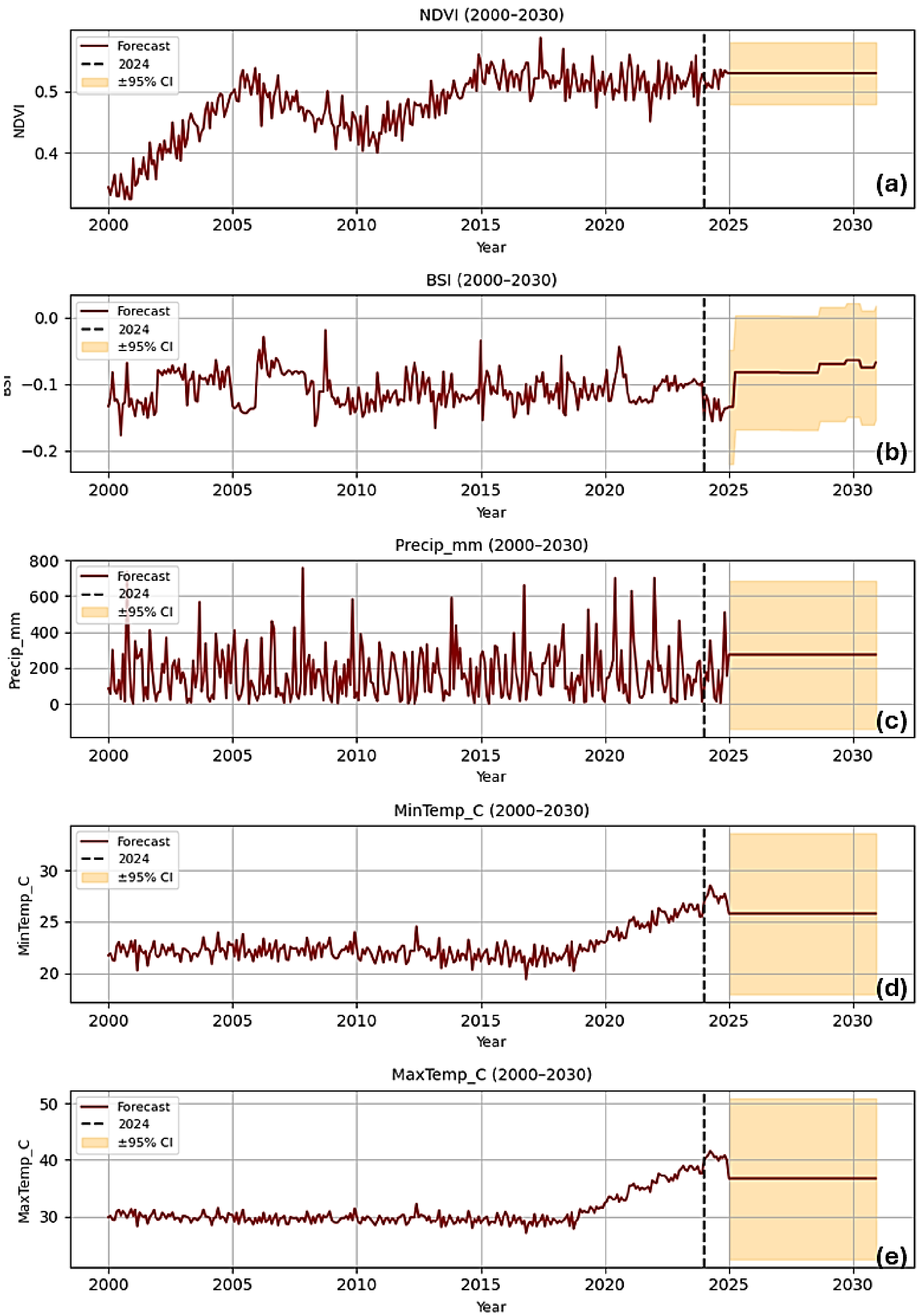
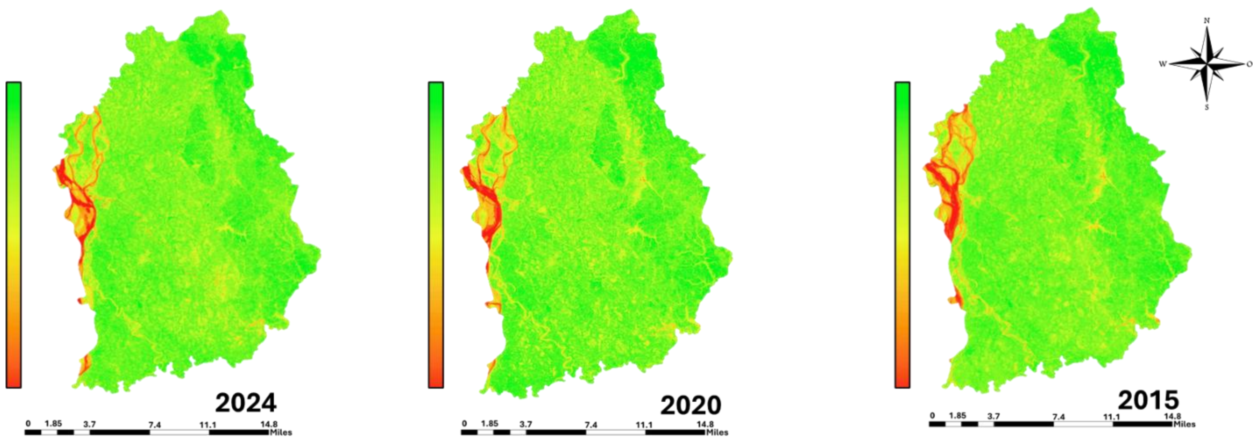
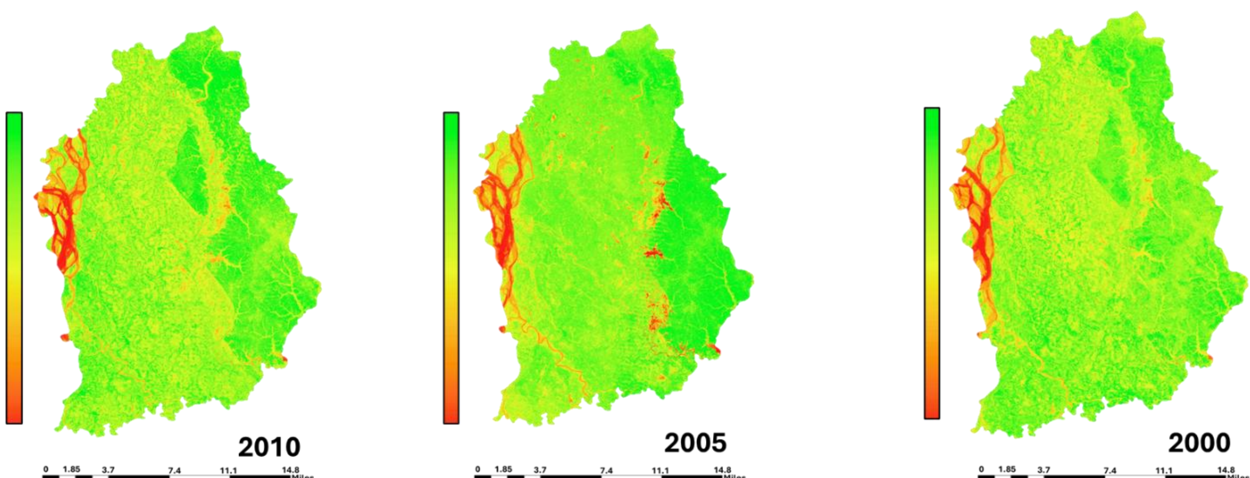



Figure 3. Temporal forecast (2000–2030) of average monthly NDVI, BSI, Precipitation, and Temperature, with 95% confidence intervals. These represent area-averaged values

It is important to note that these temporal forecasts represent spatially aggregated averages across Dhaka. As such, their value ranges differ from the spatial forecast maps presented in Section 5.2, which display the pixel-level variability and highlight localized extremes. For example, although NDVI values in Figure 4 fluctuate near 0.5 on average, the corresponding 2030 map (Section 5.2) spans a broader range from –0.32 to 0.85 due to spatial heterogeneity. This difference is expected and methodologically valid. The time series plots emphasize city-scale dynamics and model confidence over time, whereas the spatial maps depict intra-urban variation critical for land management and environmental planning. Together, these representations offer a complementary understanding of both temporal evolution and spatial disparity in Dhaka's environmental system.




(a) NDVI Range for 2024 -0.31-0.87 (b) NDVI Range for 2020 -0.39-0.85 (c) NDVI Range for 2015 -0.38-0.88



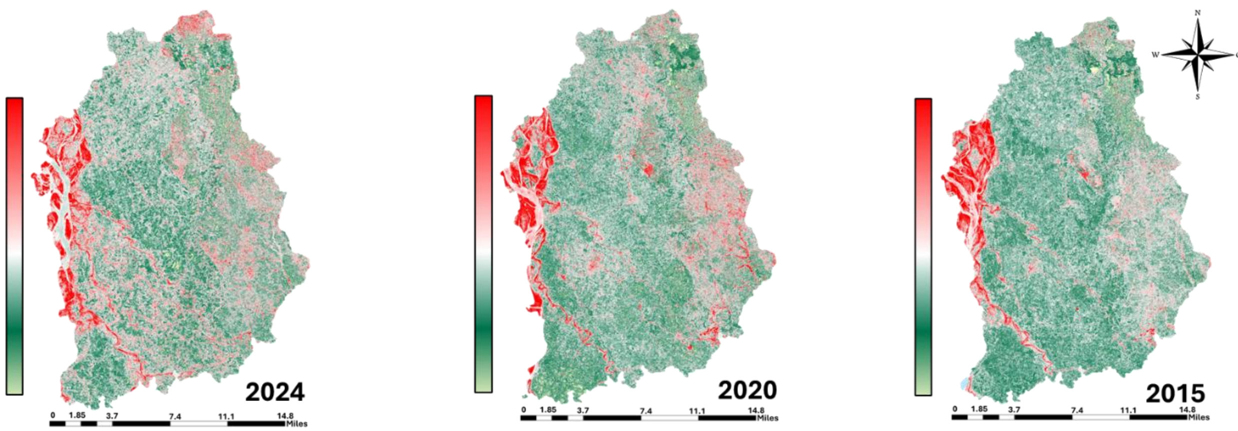

(d) NDVI Range for 2010 -0.32-0.81 (e) NDVI Range for 2005 -0.51-0.89 (f) NDVI Range for 2000 -0.27-0.70

Figure 4. Spatial NDVI maps (2000–2024) with annotated ranges

### 4.2. Historical Spatial Change Detection (2000–2024)

To better understand spatial heterogeneity underpinning the temporal trends described in Section 4.1, spatial distribution maps were generated for NDVI, BSI, precipitation, and 2-meter maximum and minimum temperatures from 2000 to 2024. These maps help to visualize how environmental and climatic conditions have shifted across Dhaka's urban and peri-urban areas over the past 25 years.

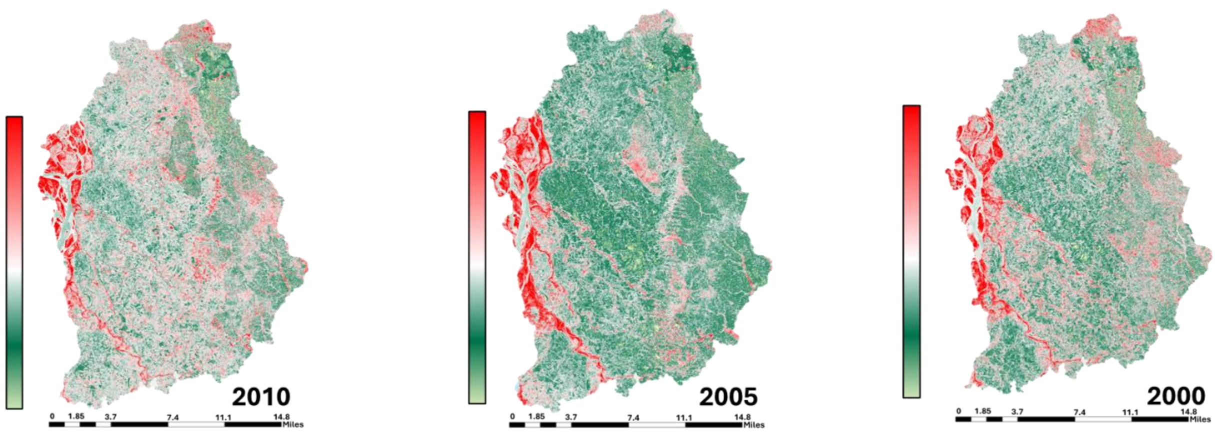
Figures 4-8 illustrate the annual composite distributions for selected years (2000, 2005, 2010, 2015, 2020, and 2024). The NDVI series (Figure 4) shows progressive vegetation loss concentrated along the central urban belt and lowland conversion zones. The corresponding BSI maps (Figure 5) reveal rising surface exposure in those same areas. Similarly, maximum and minimum temperatures (Figures 6 and 7) show intensifying urban heat island effects, with temperature gradients shifting upward across the district. Precipitation maps (Figure 8) reflect not only spatial variability but also a slight shift in wet zones, particularly from west to east. These spatial observations confirm and contextualize the temporal degradation patterns identified earlier, while also establishing a baseline for comparison with the 2030 forecast outputs discussed in section 4.3.




(a) BSI Range for 2024 -0.59-0.30

(b) BSI Range for 2020 -0.54-0.31

(c) BSI Range for 2015 -0.54-0.32

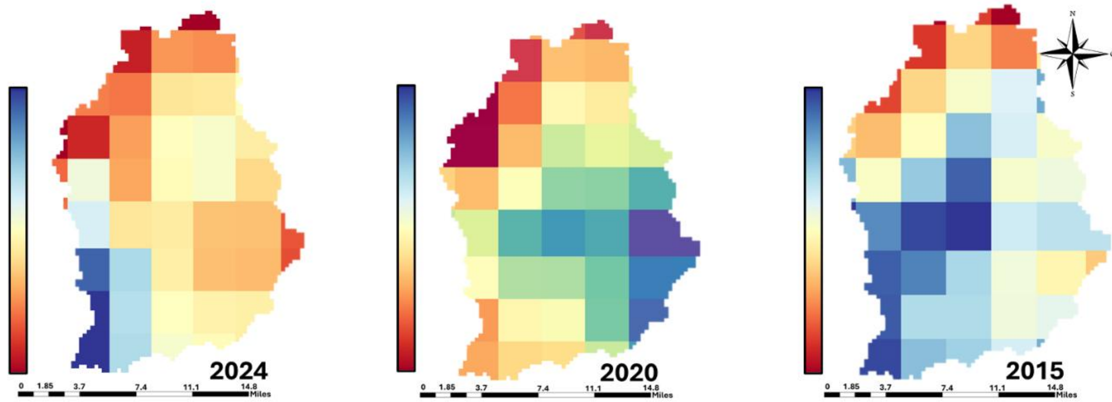



(d) BSI Range for 2010 -0.56-0.33

(e) BSI Range for 2005 -0.61-0.36

(f) BSI Range for 2000 -0.52-0.24

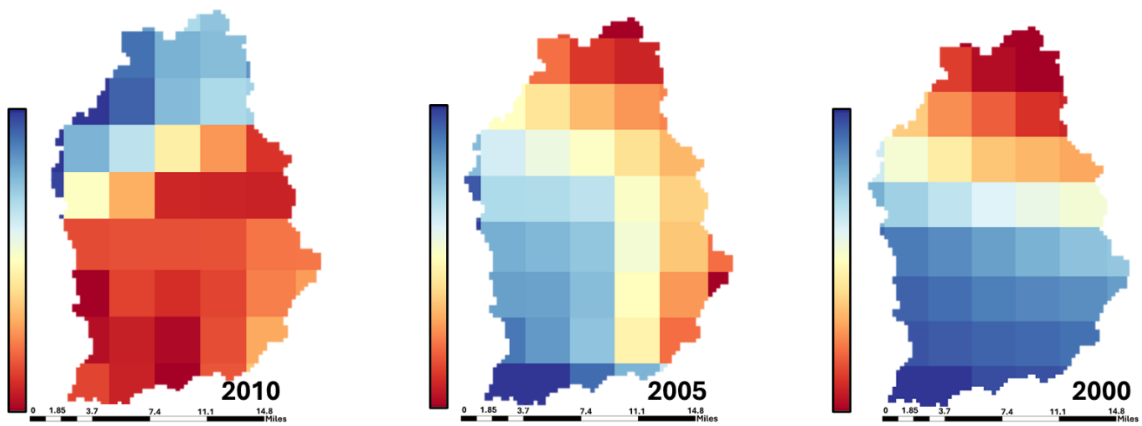
Figure 5. Spatial BSI maps (2000–2024) with annotated ranges




(a) Max Temp Range for 2024
40.14-41.04 °C

(b) Max Temp Range for 2020
28.81-29.50 °C

(c) Max Temp Range for 2015
28.89-29.97 °C

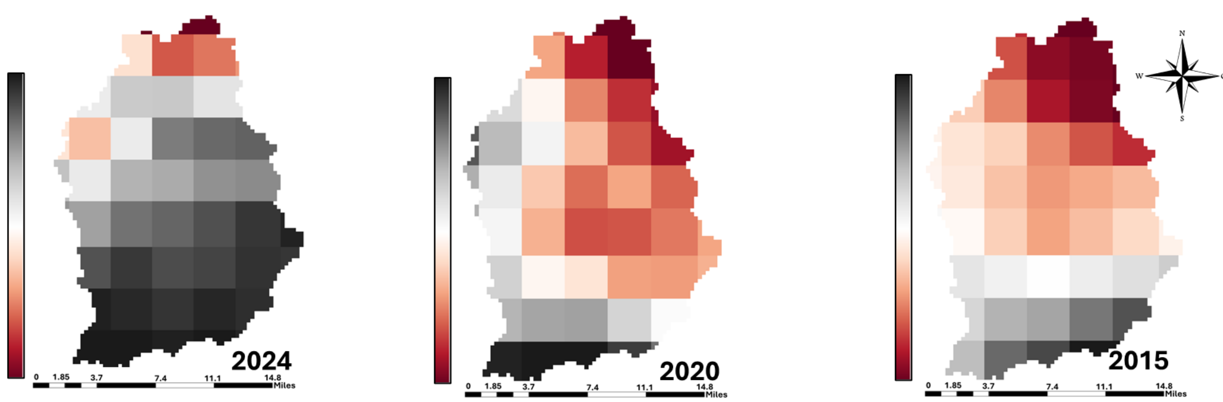



(d) Max Temp Range for 2010
29.26-30.27 °C

(e) Max Temp Range for 2005
28.10-32.03 °C

(f) Max Temp Range for 2000
24.54-32.75 °C

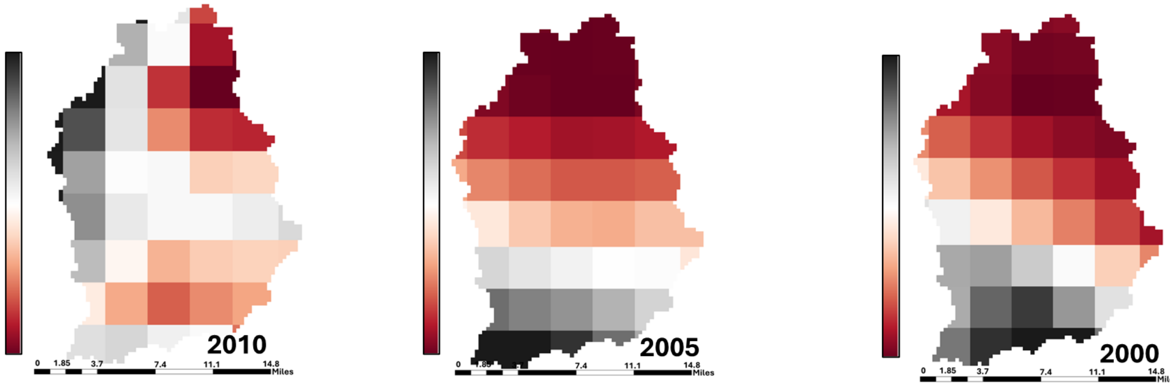
Figure 6. Maximum temperature distribution map with annotated ranges (2000-2024)




(a) Min Temp Range for 2024
25.40-28.12 °C

(b) NDVI Range for 2020
21.17-22.0 °C

(c) NDVI Range for 2015
21.22-22.73 °C

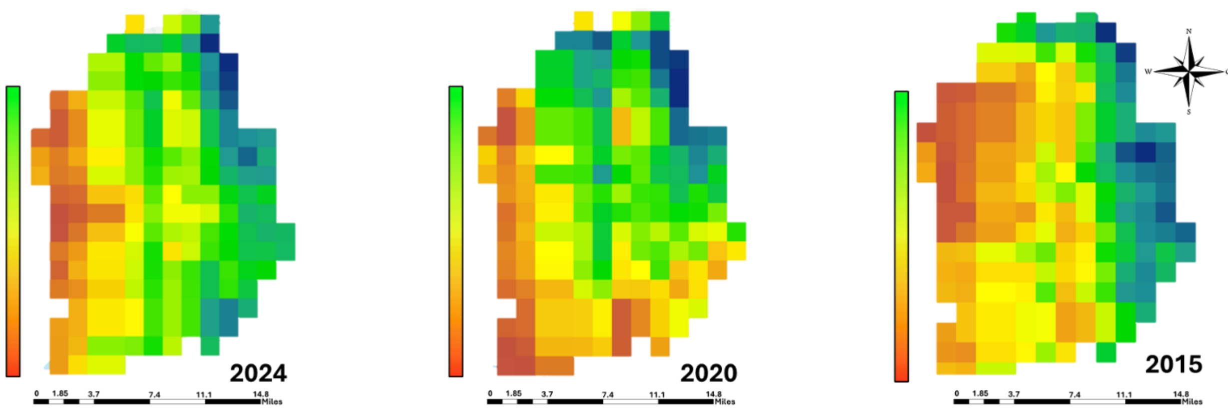



(d) Min Temp Range for 2010
22.11-22.52 ℃

(e) Min Temp Range for 2005
20.86-24.35 ℃

(f) Min Temp Range for 2000
21.3 – 25.1 ℃

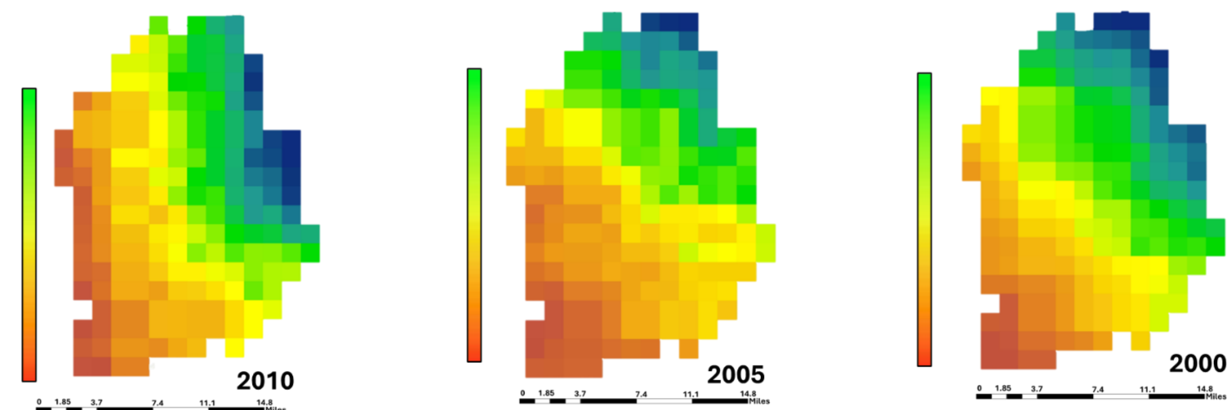
Figure 7. Minimum Temperature distribution map with annotated ranges (2000-2024)




(a) Precipitation Range for 2024
1735.69 -2331.96 mm

(b) Precipitation Range for 2020
1978.32-2484.4 mm

(c) Precipitation Range for 2015
1687.44-2140.7 mm




(d) Precipitation Range for 2010
1538.53-2269.13 mm

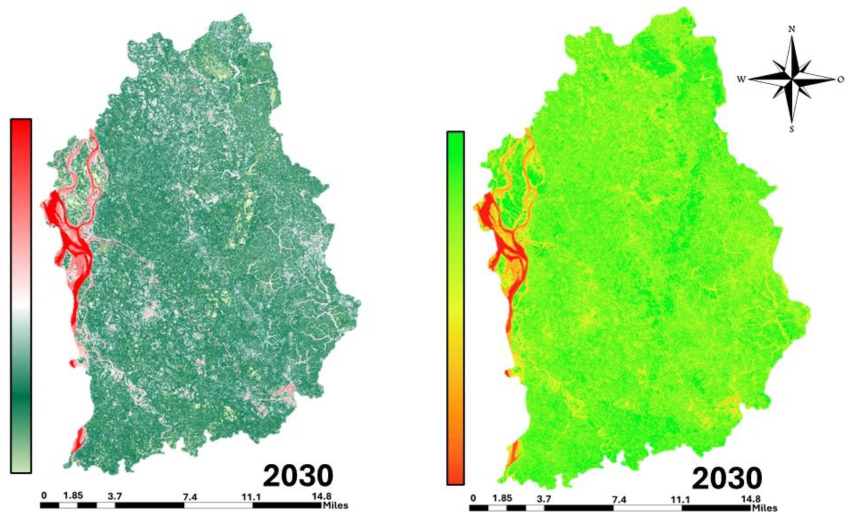
(e) Precipitation Range for 2005
1804.18-2541.4 mm

(f) Precipitation Range for 2000
1789.6 – 2782.4 mm

Figure 8. Precipitation distribution map of the study area (2000-2024)

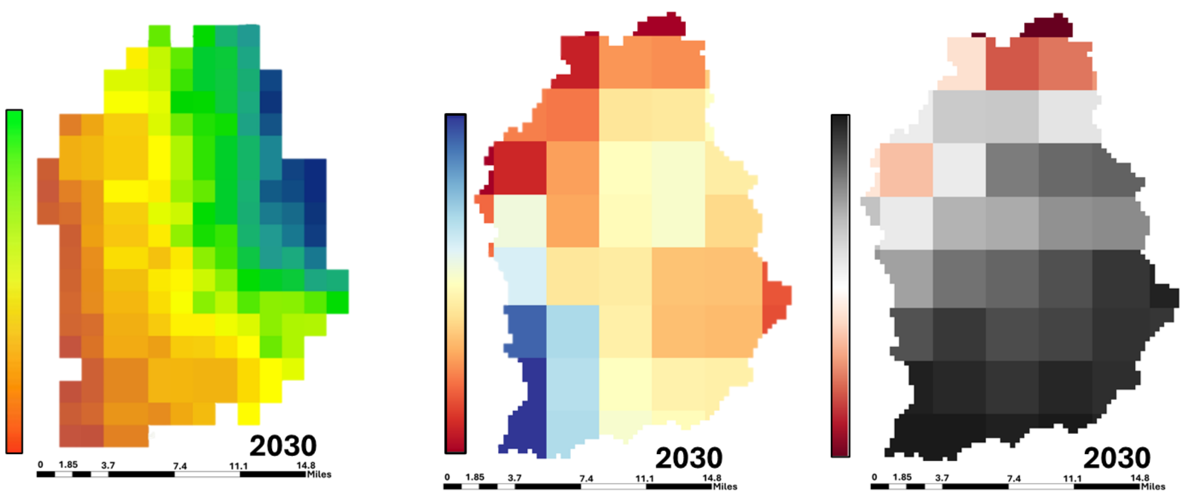
### 4.3. Spatial Forecast Visualization for 2030

To complement the regional-scale temporal forecasts presented in Section 4.1, pixel-level spatial distribution maps were generated for the year 2030 using the best-performing hybrid LSTM–XGBoost model. These maps provide a high-resolution assessment of spatial heterogeneity across Dhaka and enable identification of localized environmental stress zones critical for urban planning and climate resilience strategies. Figure 9 illustrates the spatial forecasts for all five environmental variables NDVI, BSI, precipitation, maximum temperature, and minimum temperature for the year 2030.




(a) Forecasted NDVI range for 2030
-0.32- 0.85

(b) Forecasted BSI range for 2030
-0.57-0.30




(a) Forecasted Precipitation range for 2030
1885.23 – 2287.41 mm

(b) Forecasted Max Temp range for 2030
-39.1 – 43.23 ℃

(c) Forecasted Min Temp range for 2030
26.54 -29.32 ℃

Figure 9. GeoAI-based spatial forecast maps show the 2030 distribution ranges of (a) NDVI, (b) BSI, (c) Precipitation, (d) Maximum Temperature, and (e) Minimum Temperature. Forecasts were generated using a hybrid LSTM-XGBoost framework trained on remote sensing and climate data

Unlike the time-series plots in Figure 3, which represent monthly averages across the entire study area, these maps capture the full pixel-level range of values at a single temporal snapshot (annual composite), thereby revealing intra-urban disparities in vegetation cover, surface exposure, and climatic conditions. The NDVI map (Figure 9a) shows a marked contrast between the vegetated peripheral zones (values up to 0.85) and heavily urbanized central areas (as low as –0.32), reinforcing the vegetation loss trend noted in the temporal analysis. The BSI forecast (Figure 9b) highlights hotspots of soil exposure and impervious surface expansion, particularly along transport corridors and peri-urban growth zones, with values ranging from –0.57 to 0.30. The 2030 precipitation map (Figure 9c) indicates uneven spatial distribution, with western and southwestern sectors forecasted to receive comparatively lower rainfall (1885–2000 mm) than the northeastern areas (peaking near 2287 mm).

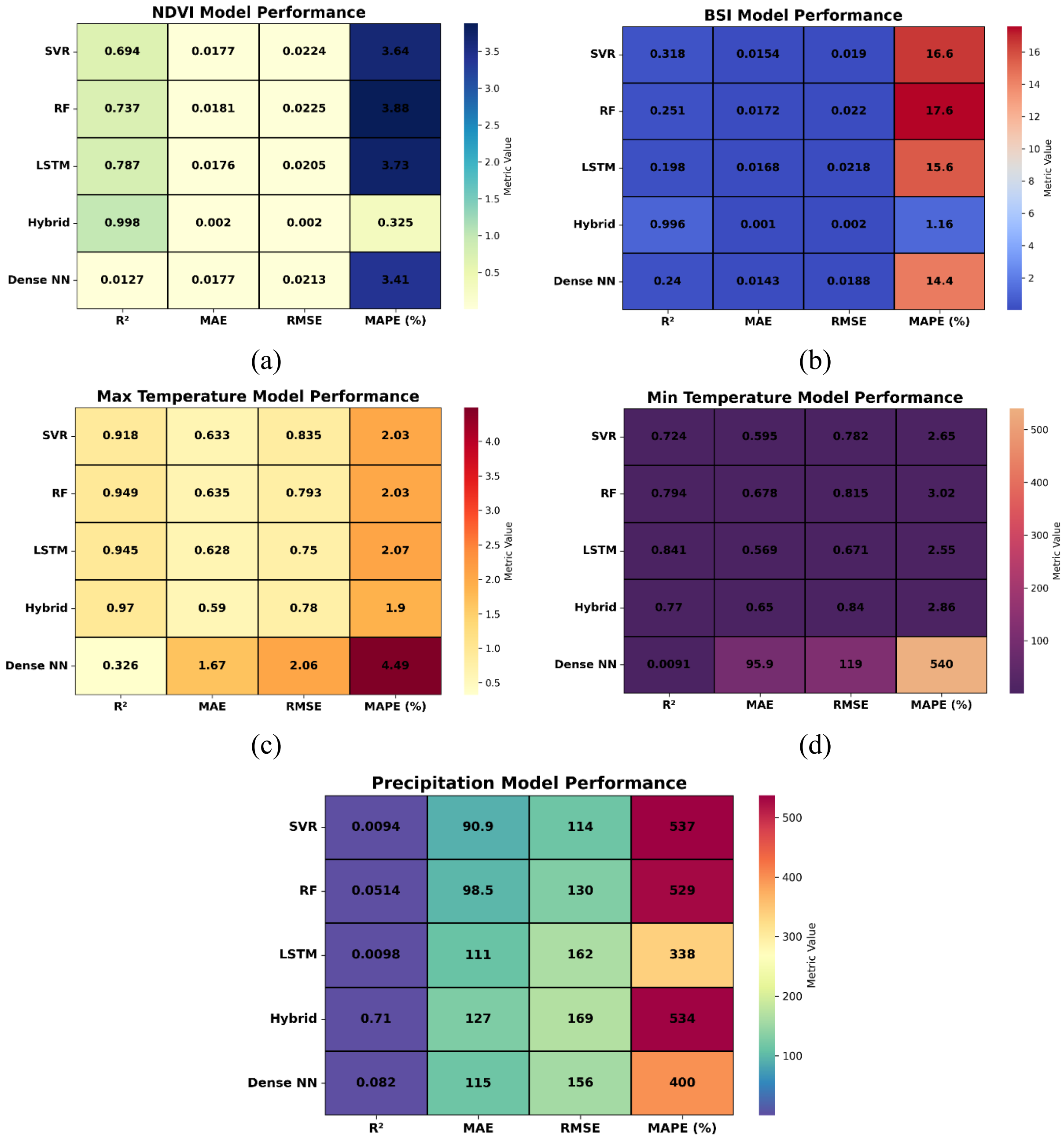
This suggests localized vulnerabilities to both water scarcity and potential runoff-related flood risk. Thermal maps for maximum (Figure 9d) and minimum (Figure 9e) temperatures show distinct spatial clustering. The highest forecasted maximum temperatures (up to 43.2°C) appear in dense central urban zones, while cooler pockets align with vegetated and open areas. Minimum temperatures exhibit a similar pattern, with a spatial range from 26.5°C to 29.3°C, again reflecting a potential urban heat island effect in built-up regions.

These spatial forecasts provide actionable insights for planners and environmental managers. The maps allow for zone-based prioritization in terms of green infrastructure, climate adaptation, and risk-sensitive development. They also serve as evidence for targeting interventions in areas most likely to face vegetation decline, temperature extremes, or hydrological imbalance under current land use and climate trajectories.

### 4.4. Model Performance Evaluation

A comparative evaluation of five machine learning architectures Support Vector Regression (SVR), Random Forest (RF), Dense Neural Network (DNN), Long Short-Term Memory (LSTM), and a hybrid LSTM–XGBoost ensemble was performed using four standard metrics: coefficient of determination ($R^2$), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The evaluation was conducted across all five environmental indicators: NDVI, BSI, precipitation, and 2-meter maximum and minimum air temperatures. Performance statistics for the validation period (2021–2024) are visualized in Figure 10.

The heatmaps presented in Figure 10a–e compare the forecasting capabilities of five models SVR, RF, LSTM, Dense NN, and a Hybrid (LSTM-XGBoost) architecture across five environmental indicators: NDVI, BSI, maximum temperature, minimum temperature, and precipitation. Performance was assessed using four standard metrics: $R^2$, MAE, RMSE, and MAPE. Among all models, the Hybrid approach consistently demonstrated the highest accuracy and reliability. For NDVI and BSI (Figure 10a, b), the Hybrid model achieved near-perfect $R^2$ values above 0.99, while MAPE remained near 1%, reflecting minimal deviation between predicted and observed values.




(e)

Figure 10. Model performance metrics ($R^2$, RMSE, MAE, MAPE) for five architectures (SVR, Random Forest, LSTM, Dense NN, Hybrid (LSTM-XGBoost) across five environmental indicators (a) NDVI, (b) BSI, (c) Max Temperature, (d) Min Temperature (e) Precipitation for the period 2000–2024

Temperature-related variables (Figure 10c, d) also showed strong agreement under the Hybrid and LSTM models, although Dense NN occasionally produced competitive results with lower RMSE. In contrast, precipitation forecasts (Figure 10e) revealed more variation across models, with higher error levels and reduced $R^2$ likely due to the spatial and temporal unpredictability of rainfall patterns. Despite these challenges, the Hybrid model maintained the most balanced performance across all parameters, underscoring its robustness and generalizability for multivariate environmental prediction tasks.

### 4.5. Stakeholder Feedback on Forecast Interpretability and Planning Relevance

To assess the interpretability and practical utility of the GeoAI-based forecast outputs, stakeholder feedback was collected via structured interviews and a participatory workshop (see Table 2). A total of 28 participants responded to a 10-question survey designed to evaluate (i) awareness of urban environmental stressors, (ii) trust in AI-generated spatial forecasts, and (iii) preferences for future improvements.

**Awareness of Environmental Change and Risk Perception:** When asked about the most pressing environmental concerns in Dhaka, urban heat exposure (46%) and vegetation loss (32%) were most frequently cited, followed by flooding (14%) and air pollution (8%) (Figure 11). Nearly 81% of participants rated their concern for environmental degradation as "high" or "very high", indicating strong stakeholder awareness and urgency surrounding ecological stressors.

**Interpretability of Forecast Maps:** Participants were asked to rate how understandable the AI-generated spatial forecasts were without formal GIS or remote sensing training. As shown in Figure 12, 64% found the NDVI and temperature maps "understandable" or "very understandable", while 21% reported partial clarity and 15% found them difficult to interpret.

**Utility for Decision-Making:** Over 72% of participants rated the forecast maps as "useful" or "very useful" for urban planning, environmental assessment, and early-warning contexts (**Figure 13**). Comments highlighted the potential for integrating these forecasts into zoning regulations, green space monitoring, and heat preparedness strategies.

**Desired Features and Delivery Formats:** When asked about additional variables of interest for future model integration, participants most commonly mentioned: Air pollution (PM2.5), Flood vulnerability zones, Land surface temperature (LST) and Socioeconomic vulnerability indicators. The preferred delivery formats included mobile-friendly dashboards (41%), interactive web platforms (28%), and printed briefs (17%), as illustrated in **Figure 14**.

**Thematic Insights from Open-Ended Responses:** A qualitative synthesis of open-ended responses revealed three dominant themes: (i) Accessibility: Several stakeholders emphasized the need for "simplified visual legends" and Bengali-language map interfaces; (ii) Local Specificity: Users requested "ward-level maps" rather than city-wide averages for neighborhood-scale planning; (iii) Trust and Transparency: A few participants raised questions about the "accuracy of AI forecasts," suggesting that transparency in model validation would enhance trust. These recurring themes, along with the frequency of their mention across respondents, are summarized in Figure 15.

All stakeholder interactions carried out as part of this study were guided by established ethical standards for low-risk, non-identifiable human research. Participants were provided with a clear explanation of the study's objectives and invited to contribute voluntarily. No personal identifiers were recorded during interviews or workshops, and all responses were anonymized prior to analysis. The engagement process followed good practice in participatory environmental research and aligned with common academic guidelines for informed participation in minimal-risk social science studies.

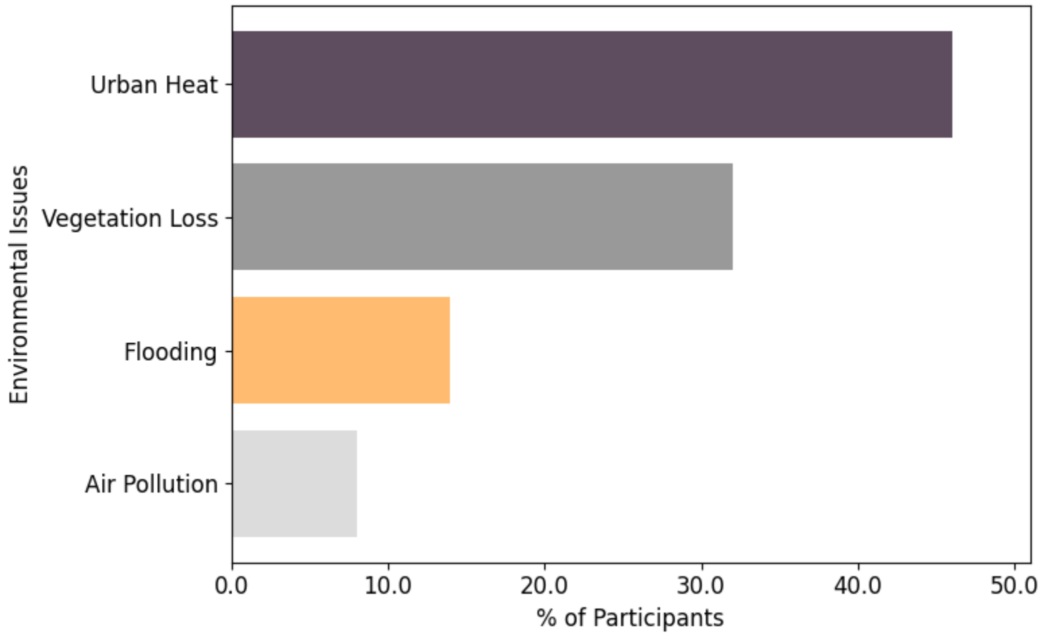



**Figure 11.** Distribution of stakeholder perceptions regarding the most critical environmental issues affecting Dhaka (n = 28).

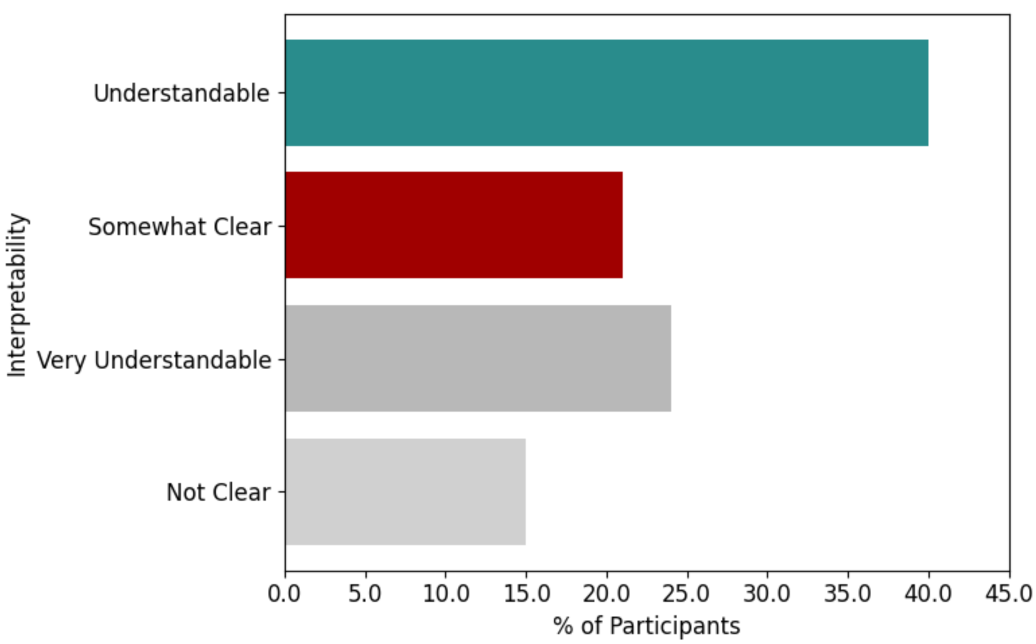



**Figure 12.** Stakeholder responses to the question: "Were the forecast maps easy to interpret without technical expertise?"

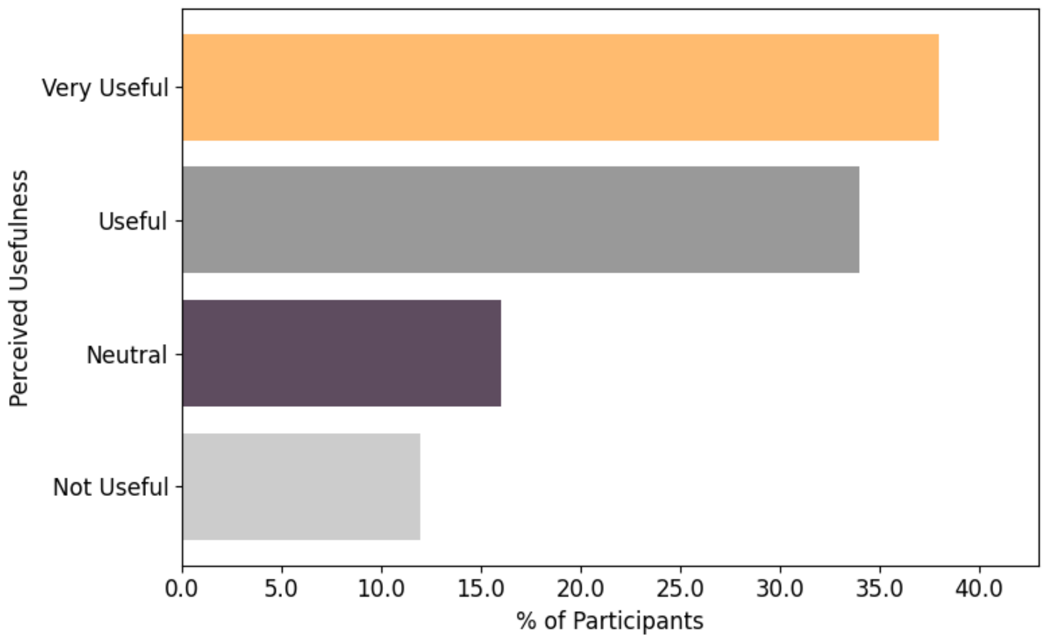



**Figure 13.** Perceived usefulness of GeoAI forecasts for planning and climate resilience decision-making (Likert scale: 1 = Not useful, 5 = Very useful).

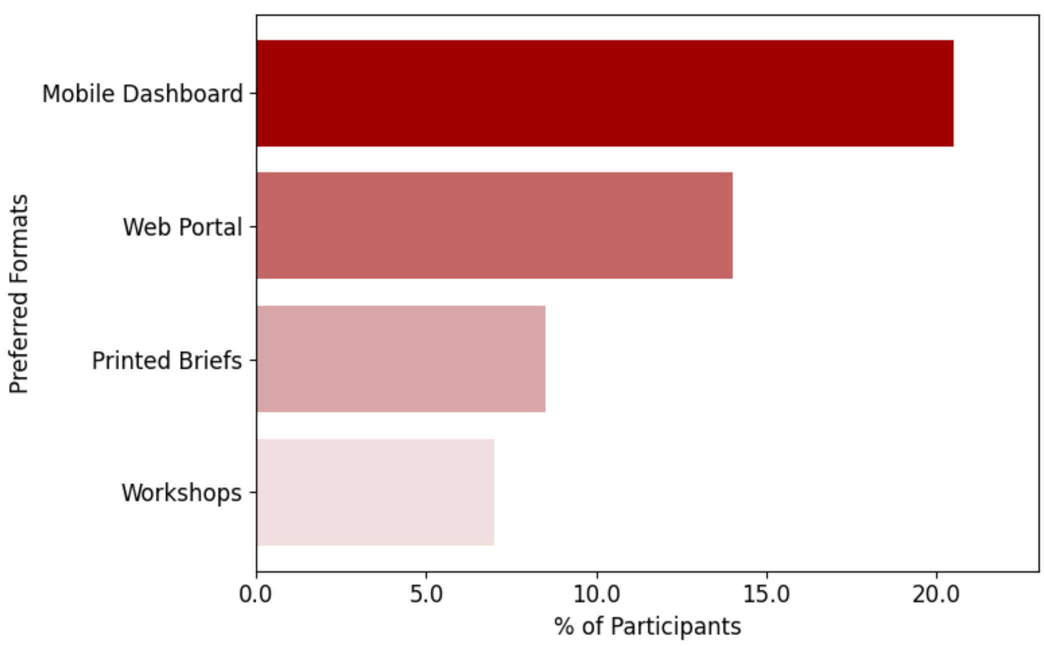



**Figure 14.** Preferred formats for receiving future forecast outputs.

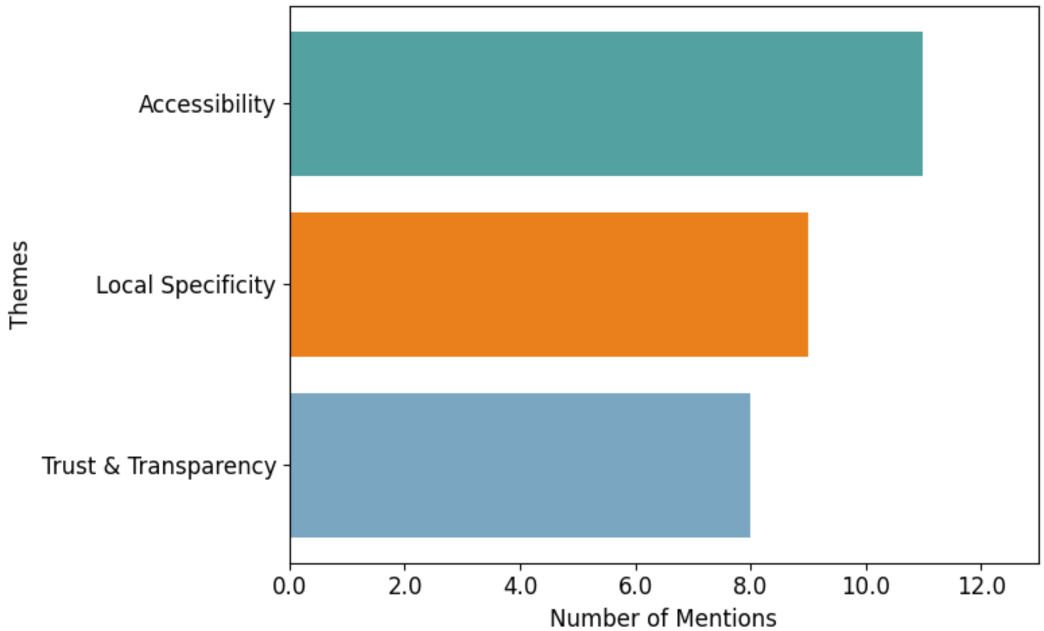



**Figure 15**. Thematic Summary of Stakeholder Feedback

### 4.6. Limitations

While this study demonstrates the feasibility and accuracy of hybrid GeoAI methods for forecasting urban environmental conditions, several methodological and data-related limitations warrant discussion. First, the models developed in this study were univariate in structure. Each variable NDVI, BSI, precipitation, and air temperature was forecasted independently, without accounting for interdependencies. This constraint may obscure interactions between climate and vegetation variables that could be critical in urban ecological systems. Second, although the dataset spans two and a half decades, it is constrained by the quality and continuity of remote sensing archives. Optical imagery like Landsat NDVI is vulnerable to atmospheric interference and cloud cover, which can introduce missing values and reduce signal consistency, despite the interpolation and normalization techniques applied.

Third, the spatial forecast outputs for 2030 are deterministic. They do not incorporate uncertainty bounds or ensemble variation, which limits their application in probabilistic risk assessments or scenario planning. Without spatial confidence intervals, decision-makers may misinterpret fine-scale fluctuations as more certain than the models can truly support. Lastly, while stakeholder engagement was included, the sample size was relatively small (n = 28), and the evaluation was based on perception and interpretability, not formal usability trials. This limits the generalizability of the insights gathered during the participatory validation process.

## 5. Conclusion

This study developed and validated a hybrid GeoAI framework combining deep learning methods (LSTM) and gradient boosting (XGBoost) to forecast key urban environmental indicators in Dhaka, one of the most ecologically vulnerable megacities in the Global South. Leveraging two and a half decades of satellite-based vegetation, soil, and climate data, the model successfully produced both temporal and spatial forecasts of NDVI, BSI, precipitation, and 2-meter maximum and minimum air temperatures up to the year 2030.

Among the five tested models, the LSTM–XGBoost ensemble consistently outperformed traditional and standalone deep learning approaches, achieving $R^2$ values above 0.9 for NDVI and BSI and maintaining robust accuracy across temperature variables. Forecasts revealed continuing vegetation stress and rising thermal exposure, with spatial heterogeneity concentrated in densely urbanized cores and newly developing peripheries. Incorporating stakeholder feedback through a participatory evaluation process added interpretive value and revealed a high level of public concern regarding environmental degradation, especially heat exposure and vegetation loss.

While the model outputs were generally rated as understandable and useful, feedback also highlighted the importance of accessibility, local specificity, and transparency in future deployment. Although the framework demonstrates strong performance, limitations remain in terms of univariate structure, lack of uncertainty quantification, and limited stakeholder representativeness. Future work should explore multivariate forecasting, probabilistic outputs, and co-designed tools to ensure both scientific rigor and operational utility.

Overall, the proposed GeoAI system offers a scalable, interpretable, and stakeholder-informed approach to environmental forecasting in data-scarce urban settings. It contributes a reproducible model architecture and validation pathway that can inform climate-resilient planning in Dhaka and serve as a transferable blueprint for other rapidly transforming urban regions across the Global South**.**

Future extensions of this research could address several of the limitations above while expanding the scope and utility of the GeoAI framework. First, future work should explore multivariate modeling approaches that jointly predict multiple environmental indicators. This would allow for the representation of causal interactions such as the lagged effect of rainfall on NDVI or compound stressors such as heat and drought.

Second, probabilistic forecasting techniques including Bayesian deep learning or ensemble-based methods could be employed to quantify uncertainty in both temporal and spatial predictions. This would enable more defensible risk communication for urban planning contexts. Third, integrating near-real-time data sources such as ground sensors, UAV imagery, or mobile-based urban observatories would enhance the temporal resolution and local specificity of the model inputs, especially in fast-changing urban zones.

Fourth, stakeholder engagement could be deepened through co-design processes, where forecast outputs are iteratively tested, interpreted, and adapted by end-users across government, civil society, and planning institutions. This would improve model trust, contextual alignment, and adoption. Lastly, applying this framework in comparative studies across other Global South megacities facing similar environmental stress such as Jakarta, Lagos, or Nairobi would offer insights into its scalability, regional variability, and policy relevance beyond Dhaka.

**CRediT Authorship Contribution Statement**

**Mirza Md Tasnim Mukarram**: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft, Visualization, Software, Project administration. **Quazi Umme Rukiya**: Writing – review & editing, Methodology, Literature review, Validation. **Ibrahim Demir:** Supervision, Conceptualization, Writing – review & editing, Resources**.**

**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.

**Ethics Approval and Consent to Participate**

Formal ethical approval was not required for this study, as the research did not involve sensitive personal data or medical procedures. All participants were informed about the research purpose and participated voluntarily under conditions of anonymity.

**Acknowledgements**

The authors are deeply grateful to the urban planners, municipal officers, environmental professionals, and community stakeholders who generously shared their time and insights during the interviews and participatory workshop. Their perspectives were instrumental in grounding the GeoAI forecasting framework in the realities of Dhaka's environmental challenges. We also acknowledge the constructive feedback provided by participants, which helped shape the practical relevance of the study. This work would not have been possible without their thoughtful engagement and commitment to urban sustainability.

**Data Availability**

The authors do not have permission to share data.

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