From Linear Trends to Geospatial Foundation Models: A Baseline Thermal Justice Index for the Barind Tract and a Proposed ConvLSTM2D Architecture

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Abstract. Urban Heat Island (UHI) intensification in the Global South is measurable from satellites yet rarely actionable. This paper presents two contributions. First, a completed baseline study in the Barind Tract, Bangladesh, using Google Earth Engine's *ee.Reducer.linearFit()* on 24 years of Landsat imagery (2000–2024) to project a persistent, spatially clustered thermal anomaly over Rajshahi by 2035, proposing a Thermal Justice Index (TJI) framework. Second, it proposes a ConvLSTM2D spatiotemporal architecture as the next step towards a scalable Geospatial Foundation Model (GeoFM) for climate-aware urban digital twins—continuously updated virtual replicas of a city's microclimate used for planning simulation.

Keywords: Urban Heat Island · Thermal Justice Index · ConvLSTM2D · Geospatial Foundation Model

1 Introduction

Secondary cities at South Asia's semi-arid margins face dramatic thermal transformations; two decades of satellite observation in Bangladesh's Barind Tract reveal wetland erasure, impervious surface expansion, and Urban Heat Island (UHI) intensification threatening marginalised communities. Cloud-native linear trend modelling via Google Earth Engine (GEE) [2] documents historical Land Surface Temperature (LST) increases but cannot model the non-linear land-cover/atmosphere feedbacks needed for block-level heat prediction. Spatiotemporal deep learning, and ultimately Geospatial Foundation Models (GeoFMs) pre-trained on multimodal satellite archives for minimal-retraining transfer [4], are needed to bridge this gap and to power climate-aware *urban digital twins*—continuously updated microclimate replicas for planning simulation. This paper moves from a completed linear baseline (Section 2) and TJI metric (Section 3) to a deep learning upgrade (Section 4).

2 Baseline Study: Linear Trend Analysis & Spectral Disambiguation

When wetlands and vegetation are replaced by impervious surfaces, more solar radiation is absorbed and re-emitted as heat rather than used for evapotranspiration or reflected by open water, driving a measurable, spatially clustered LST rise over time — the physical basis of UHI quantified below. We processed the entire available Landsat 5/7/8/9 surface reflectance archive for the Barind Tract (2000–2024) via the GEE Python API [2], using the QA_PIXEL bitmask (Fmask) algorithm with a strict cloud filtering threshold of $< 10\%$ to build pristine composite median images.

A key challenge is "spectral hallucination": dry riverine sandbars and laterite soils exhibit SWIR reflectance nearly identical to impervious concrete, inflating built-up estimates under simple indices like NDBI. We instead used an XGBoost classifier with SHAP explainability to isolate true impervious surfaces via non-linear multi-spectral interactions, producing the land-cover mask used for LST and MNDWI computation. LST was retrieved via the Statistical Mono-Window (SMW) algorithm [1] and blue infrastructure tracked via MNDWI [5]. The *ee.Reducer.linearFit()* OLS regression was applied to the 2013–2024 sub-period, capturing the most aggressive recent densification phase and aligning with the ConvLSTM2D training window (Section 4).

Results (Fig. 1) document a 68% contraction in water body area and an accelerated LST increase of 0.10–0.15°C/year, indicating a persistent, spatially concentrated thermal anomaly over the Rajshahi urban fringe by 2035. The strong negative correlation between ΔMNDWI and ΔLST ($r = -0.71$, $p < 0.001$, 95% CI $[-0.75, -0.66]$) confirms blue infrastructure loss as the dominant driver, while a Global Moran's I test yielding an Index of 0.9789 ($z = 2268.29$, $p < 0.001$) confirms near-perfect spatial clustering, ruling out a random-noise explanation.

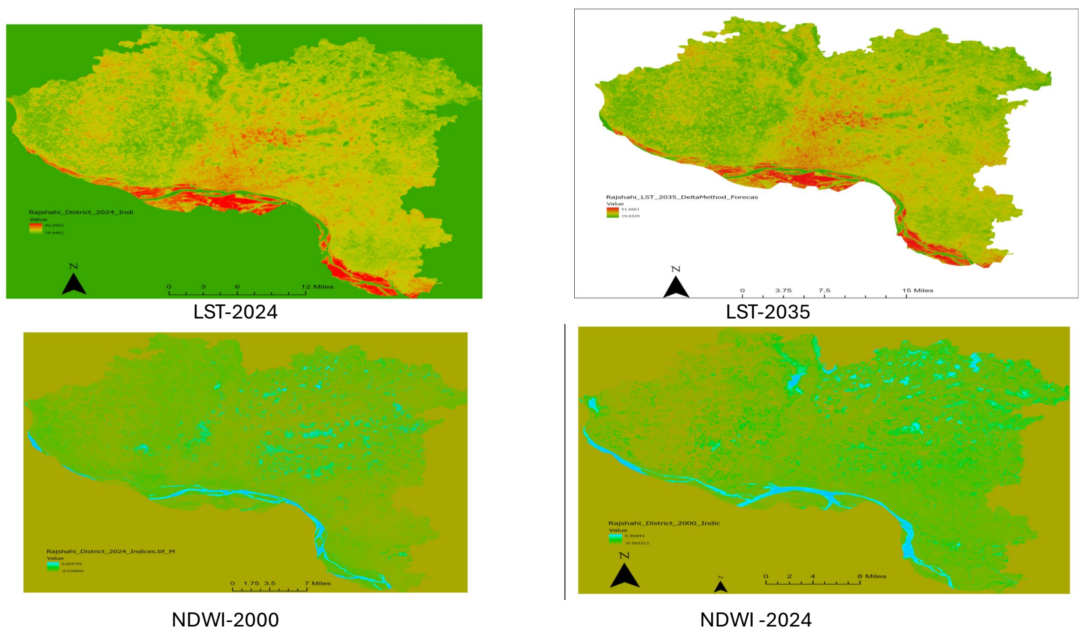

Fig. 1. Baseline results: (a) 2024 LST, (b) 2035 projected LST, (c) 2000 MNDWI, (d) 2024 MNDWI.

3 Thermal Justice Index (TJI): Proposed Framework

To translate this warming into an actionable planning metric, we propose the Thermal Justice Index (TJI). Formally, for a spatial unit i:

$$TJI_i = 0.5 \cdot \delta LST_i + 0.3 \cdot PopDens_i + 0.2 \cdot GreenDeficit_i \tag{1}$$

where δLST_i is the projected LST increase (normalized to $[0, 1]$), $PopDens_i$ is normalized population density, and $GreenDeficit_i$ is the normalized per-capita green-space deficit. The weights (0.5, 0.3, 0.2) are heuristic baselines, not empirically fitted: they prioritize thermal exposure, then population density, then adaptive green capacity, reflecting the intuition that exposure severity should dominate while still weighting how many people are affected and how much vegetation can buffer heat. A sensitivity analysis across alternative weightings is left for future work, as is incorporating explicit socioeconomic indicators (e.g., income, housing quality) alongside the current physical-environmental formulation. Mapping the TJI across Rajshahi is the immediate next step toward a deployable planning tool.

4 Proposed Architecture: ConvLSTM2D to GeoFM

Linear extrapolation has three limitations motivating a nonlinear architecture: it cannot capture non-linear land-cover/atmosphere feedbacks, since vegetation loss does not raise LST by a fixed increment; Multi-Layer Perceptrons flatten the 2D grid and discard the near-total spatial autocorrelation just demonstrated (Moran's I = 0.9789); and the process is inherently spatiotemporal, depending on cumulative land-cover trajectories rather than only the present state. We therefore propose a Convolutional Long Short-Term Memory (ConvLSTM2D) encoder-decoder network, preserving 2D spatial structure via convolutional filters at every time step while propagating temporal dependencies through recurrent gates.

Architecture: input is a 5D tensor (batch, 10 years, H, W, 4 channels), with $H = 128$, $W = 128$, and channels [LST, MNDWI, NDVI, NDBI]. The encoder uses three ConvLSTM2D layers (128, 64, 32 filters, 3×3 kernel), mirrored by a transposed convolutional decoder with two continuous regression heads (LST, MNDWI). Training: Adam optimizer (learning rate = 0.001), Mean Squared Error (MSE) loss, evaluated via RMSE/MAE; data split temporally into 2013–2020 (training), 2021–2022 (validation), 2023–2024 (test).

GeoFM Vision: A city-specific ConvLSTM2D pipeline is locally accurate but requires full retraining elsewhere. The long-term vision (Fig. 2) is a GeoFM replacing the site-specific encoder with a transformer backbone pre-trained on multi-petabyte, multimodal satellite archives—in the spirit of SatMAE [3]—decoupling global pre-training from lightweight per-city fine-tuning, with the TJI layer exposed as a REST API for near-real-time climate policy interventions within urban digital twins.

5 Conclusion

This paper establishes a linear LST baseline and TJI metric, and outlines a deployable ConvLSTM2D/GeoFM architecture for climate-aware digital twins. Immediate next steps are end-to-end ConvLSTM2D training and operational TJI mapping across Rajshahi.

Acknowledgments. Declaration: Generative AI tools were used solely to improve readability and grammatical structuring. The author takes full responsibility for the content.

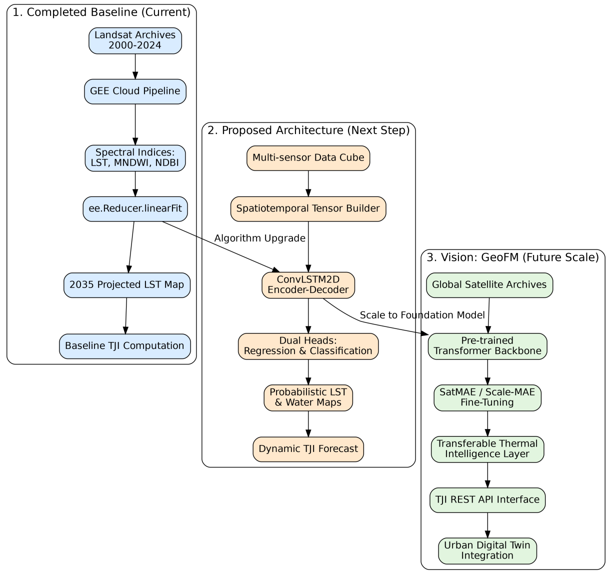

Fig. 2. Proposed architectural progression from baseline to GeoFM.

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