# Assessing The Spatial Mapping of Heat in Bangkok Metropolitan Region

## INTRODUCTION

Heat waves have become a global phenomenon and as climate change contributes to severe temperature events, the need to ble due to rapid urbanization, limited greenery, and poor heat

resilience. Among them Bangkok is increasingly becoming a ticking time bomb for heat-related disaskok, Manila, and Jakarta suffer from severe "urban heat island" impacts that make heat stress worse (Arifwidodo & Tanaka, 2015). This study investigates the spatial patterns and drivers of heat intensity across the Bangkok Metropolitan Region (BMR), encompassing 79 districts and 6 provinces.



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#### Abbreviations

LST- Land Surface Temperature

CGI- Green Chlorophyll Index NDBI- Normalized Difference Built-up Index

NDWI- Normalized Difference Water Index

#### Data Source

- 1. Air Quality station data- Thailand pollution Control Dept. (2025)
- 2. Demographic Data- Population Statistics of the Civil Registration Dept. (2024-2025) 3. Remote Sensing Image- United States Geological Survey 4. Shape files- Geographic Information Division Thailand

#### Projection

Projected Coordinate System- WGS 1984 UTM Zone 47N

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# **METHODOLOGICAL FRAMEWORK**

This project used remote sensing data from Landsat 8 imagery along with 36 air quality monitoring station

Accordingtothehotspotanalysis, areas were categorized into three groups: High Risk Zones (significanthot clusters), Safe Zones (cold clusters), and Non Significant Zones (not statishighlighting its vulnerability to extreme urban heat and the urgent need for adaptive planning. Nakhon Pathom stands out with the largest proportion of Safe Zones (20.79%), indicating relatively cooler conditions. Pathum Thani contains not significant clusters. It revealed that extreme heat is highly concentrated in central urban areas such as Bang Plad, Don Muang, and Bung Kum, which recorded the highest LST values. These high-risk zones align with areas showing low GCI, high PM2.5 concentrations, and high NDBI. Targeted mitigation in these districts is essential and should focus on increasing vegetation to enhance GCI, improving air quality to reduce PM2.5, and redesigning urban surfaces to lower NDBI through reflective or permeable materials. By addressing the specific variables driving heat in each location, spatially tailored strategies can promote more effective and equitable urban climate resilience.

### **ANALYSIS & RESULT**

The OLS model explained 84.3% of the variation in LST across 79 districts in Bangkok, with all predictors statistically significant (p < 0.01). GCI and NDWI were negatively associated with LST, while NDBI, PM2.5, and population density showed positive relationships. However, high VIF values for GCI and NDWI indicate multicollinearity. A Global Moran's I analysis of residuals (Index = 0.419, z = 9.13, p < 0.001) revealed significant spatial clustering, suggesting that OLS does not fully account for spatial patterns.



The correlation matrix confirms strong positive relationships between LST and NDBI (r = 0.74), and population density (r = 0.67). GCI showed a moderate negative correlation (r = -0.47). High inter-variable correlations—GCI and NDWI (r = -0.98), GCI and NDBI (r = -0.89) further support the need for Geographically Weighted Regression (GWR) to capture local variations and reduce bias.







High Risk Zone Safe Zone Non Significant Zone





