Disproportionate Exposure to Urban Heat Island Intensity Across Major Districts of Bangladesh

by

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DECLARATION

I hereby declare that this thesis is my own work and to the best of my knowledge it contains no materials previously published or written by another person or have been accepted for the award of any other degree or diploma at Bangladesh University of Engineering and Technology (BUET) or any other educational institution, except where due acknowledgement is made. I also declare that the intellectual content of this thesis is the product of my own work and any contribution made to the research by others, with whom I have worked at BUET or elsewhere, is explicitly acknowledged.

Muhtamim Haque Tauhid

Dedicated

to

“My Parents”

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ABSTRACT

In recent years, Bangladesh has experienced more frequent heatwaves, which pose a serious risk the health and welfare of people. The urban heat island (UHI) effect intensifies this situation. It emphasizes the urgency of comprehending the impacts among different socio-demographic statuses. The objective of the study is to investigate the disproportionate exposure to UHI intensity across 135 thanas of eight major districts of Bangladesh, specially focusing on the comparison between UHI and different socio-demographic status. The land surface temperature (LST) values calculated within the ArcGIS software were used to identify UHI. Among these 135 thanas, 87 thanas had UHI values higher than 0°C. The relationship between UHI and socio-demographic statuses (extreme poor, poor, literacy, and vulnerable people) was analyzed using Spearman correlation. From the correlation coefficient (r), it was observed that there was a negative relation between UHI and extreme poor (r=-0.36), UHI and poor (r=-0.35), and UHI and vulnerable people (r=-0.47). Additionally, there was a positive correlation between UHI and literacy (r=0.48). To summarize, higher UHI intensity locations tend to have lower poverty rates and fewer vulnerable individuals, but a higher proportion of literate persons.

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CHAPTER 1
INTRODUCTION

1.1 Background and Motivations

The Urbanization in Bangladesh has rapidly transformed its urban landscapes, replacing natural environments with dense built-up areas and concrete structures. This trend has significantly intensified the Urban Heat Island (UHI) effect, where urban regions experience higher temperatures compared to their rural surroundings. This phenomenon occurs due to the absorption and retention of heat by artificial surfaces like concrete and asphalt, coupled with reduced vegetation cover. As a result, urban areas in Bangladesh exhibit elevated temperatures that persist day and night, particularly exacerbated during heatwaves.

In recent years, Bangladesh has experienced an increase in the frequency and intensity of heatwaves, exacerbating the UHI effect and posing substantial challenges to public health. The heightened temperatures associated with the UHI effect increase the risk of heat-related illnesses such as heat exhaustion and heatstroke, especially among vulnerable groups like the elderly, children, and individuals with pre-existing health conditions. Understanding how socio-demographic factors intersect with heat exposure is crucial for developing effective public health strategies and interventions to protect these vulnerable populations during extreme heat events.

Beyond public health concerns, the UHI effect also impacts the environment and exacerbates urban air pollution. Elevated urban temperatures lead to higher energy demands for cooling, resulting in increased greenhouse gas emissions and compromised air quality. This environmental degradation not only affects human health but also contributes to broader environmental challenges. Analyzing the relationship between socio-demographic status and heat exposure provides insights into mitigating these impacts through sustainable urban planning practices. Strategies such as integrating green infrastructure, promoting energy-efficient buildings, and implementing adaptive measures can help reduce heat vulnerability and improve urban environmental quality.

Social equity is a critical consideration in addressing the UHI effect in Bangladesh. Socio-economic disparities influence heat vulnerability within urban populations, with marginalized communities often bearing a disproportionate burden of heat-related risks. Factors such as income levels, housing conditions, and access to healthcare play crucial roles in determining individuals' and communities' ability to cope with extreme heat. Addressing these disparities requires inclusive policies that ensure equitable access to cooling resources, enhance community resilience, and foster social cohesion in urban areas.

Enhancing urban resilience against the UHI effect and heatwaves is essential for sustainable urban development in Bangladesh. This involves strengthening infrastructure, improving emergency response capabilities, and engaging communities to enhance their adaptive capacity. By integrating socio-demographic considerations into urban resilience strategies, policymakers and urban planners can effectively mitigate the impacts of the UHI effect, improve urban livability, and create healthier and more sustainable urban environments for all residents of Bangladesh.

1.2 Research Objectives

The main objective of the current study is to investigate the distribution of urban heat island (UHI) and the relationships between UHI and socio-demographic status in major districts of Bangladesh.

The specific objectives of this study are:

Investigate the distribution of land surface temperature (LST) across 8 districts (Dhaka, Rangpur, Barisal, Rajshahi, Khulna, Chittagong, Mymensingh, and Sylhet) of Bangladesh,

Investigate the distribution of urban heat island (UHI) effect across these districts of Bangladesh,

Analyze relationship between UHI and socio-demographic status (Poverty, Literacy and Vulnerable People).

1.3 Organization of the thesis

Chapter 1: Introduction and Objective. This chapter provides the background and motivations of the research. The overall objectives are also described in this chapter.

Chapter 2: Literature Review. This chapter reviews the related works in the field of urbanization and the Urban Heat Island (UHI) effect, with a special focus on their impact on human health and socio-demographic vulnerability, highlighting global and Bangladesh-specific disparities in heat exposure and methodological approaches.

Chapter 3: Methodology. This chapter describes the methodology adopted to carry out the research.

Chapter 4: Results and Discussion. This chapter describes the results of the distribution of urban heat island (UHI) and the relationship between UHI and socio-demographic status.

Chapter 5: Conclusions and Future Work. This chapter summarizes the conclusions and major contributions of this study and provides recommendations for future studies.

CHAPTER 2

Literature Review

2.1 Introduction

Urbanization and the associated environmental hazards have become a focal point of research, particularly regarding their impact on human health. Among these hazards, Urban Heat Island (UHI) effect is progressively recognized for its significant impact on urban environments. The UHI effect arises from substituting natural landscapes with artificial structures, leading to elevated temperatures in metropolitan areas. This chapter provides a comprehensive review of the existing literature on urbanization, UHI, and their impact on human health and socio-demographic vulnerability. By examining various methodological approaches and spatial analyses, this chapter highlights the global and local (Bangladesh) contexts of UHI impacts, offering insights into the disparities and vulnerabilities associated with urban heat.

2.2 Urbanization and Urban Heat Island (UHI)

2.2.1 Urbanization and Environmental Hazards

The impact of the living environment on health is profound and multifaceted. This relationship between health and the environment is particularly pronounced in urban settings, where social and environmental are closely linked. Interventions aimed at improving health equity through environmental actions are crucial, addressing proximal risk factors such as a safe drinking water supply, reduced air pollution, traffic hazards, noise, and heat stress. While urban environments present health hazards with unequal distribution, they also offer opportunities for targeted interventions. Leveraging the high population density in many urban areas, interventions at small-scale levels can benefit a significant number of people, with existing infrastructure often upgradable to meet health demands (TYAGI et al., 2023).

2.2.2 Urban Heat Island (UHI) Effect

The replacement of native landscapes with artificial structures leads to Urban Heat Island (UHI) formation, primarily in metropolitan regions with high water resistance, non-reflective surfaces, and low vegetation cover (Lee et al., 2017).

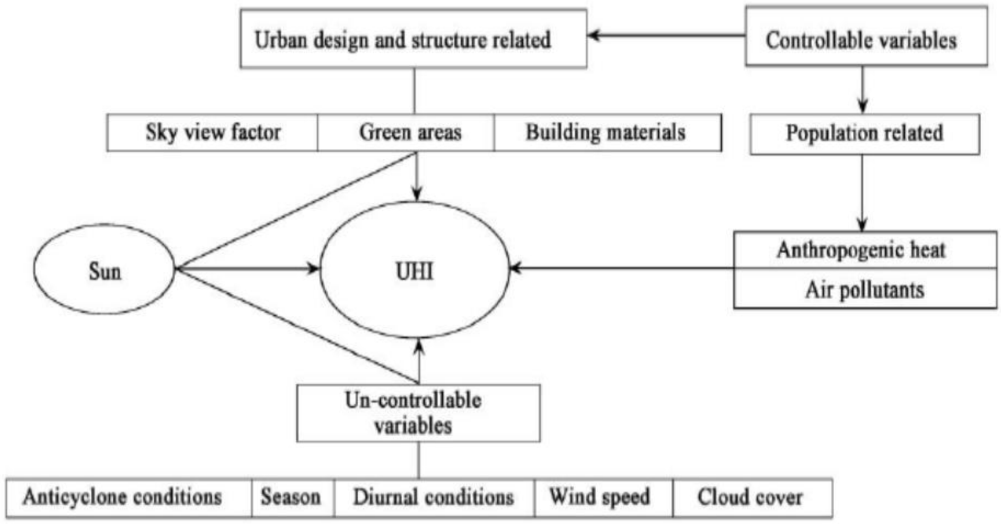


Figure 2.1: Generation of UHI (Ahmed Memon et al., 2008)

Urban heat islands (UHI) are becoming an increasingly significant environmental concern in cities due to changes in land use, population concentration, and urbanization population concentration. UHI can be evaluated using thermal remote sensing (Chudnovsky et al., 2004), fixed-station measurements (Zhou et al., 2011), and numerical models (Montávez et al., 2008) to understand factors contributing to its formation.

UHI intensity varies between seasonal and tropical cities, with different correlations to factors like solar radiation, humidity, and wind speed (Liu et al., 2007). Various research studies have explored UHI in different urban centers, considering seasonal and tropical climate variations.

2.2.2 UHI Impacts

The Urban Heat Island (UHI) effects intensify heat waves, impacting thermal comfort and heat-related mortality, with mortality data reflecting extreme events, suggesting a significant role in predicting morbidity and human well-being.

2.2.2.1 *Human Comfort in Terms of Heat*

Thermal comfort is the range where humans can function in an environment and feel satisfied with the thermal conditions, evaluated by standards like ISO7730 and ASHRAE Std 55 (Nicol & Humphreys, n.d.). Elements influencing thermal comfort encompass heat transfer through conduction, convection, radiation, and evaporation, incorporating factors such as wind speed, moisture content, air temperature, and clothing considered (Cheng et al., 2012). Air temperature and humidity play pivotal roles in determining thermal comfort (Al-Homoud et al., 2009).

Frequent exposure to heated environments can decrease thermal comfort, leading to an increase in heat-related illnesses due to complex physiological and psychological responses in extreme conditions (Lee et al., 2017).

Research on the possible effects of climate change on health, including thermal extremes and air pollution, emphasizes the need for public policy implications to address the risks of continuous heat exposure causing illness and death in humans (Patz et al., 2005).

2.2.2.2 *Illnesses Associated with Heat*

Heat illness is caused by hot weather and physical activity, disrupting body temperature regulation (Wallace et al., 2007). Heat illnesses include stroke, heat exhaustion, rash, and cramps, with heat stroke being life-threatening. Climate change and heat waves are increasing heat-related deaths globally. In the US, there were 8015 deaths from excessive heat exposure from 1979-2003, with a rising trend in heat-related injuries (Lee et al., 2017). Heat waves in different countries like Japan, the US, and Europe have led to numerous heat-related deaths. Saudi Arabia experiences varying incidences of heat stroke and exhaustion per 1,00,000 population. A study in Tokyo assessed heat stroke emergency cases, showing higher rates in males and different age groups (Lee et al., 2017).

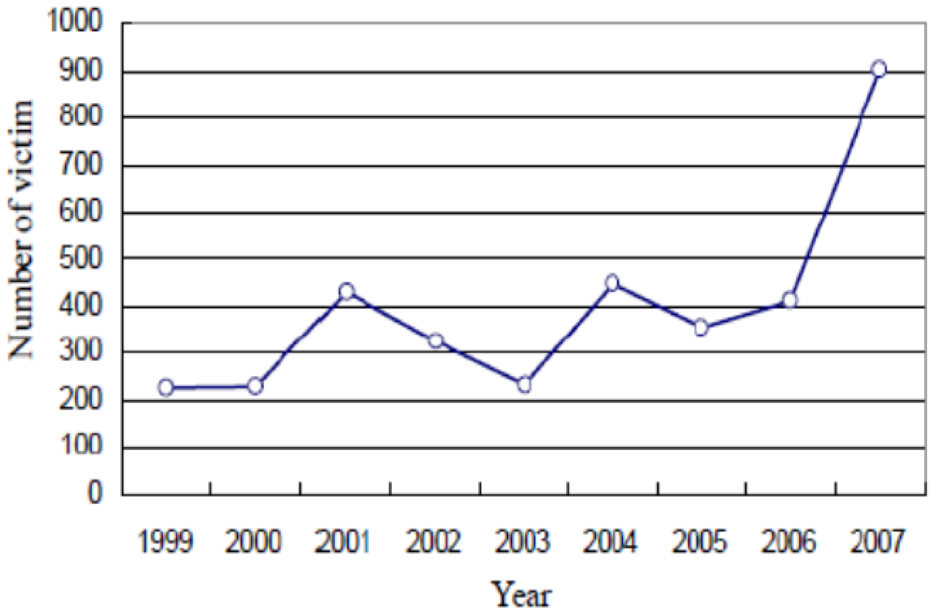


Figure 2.2: The amount of heat stroke deaths that occur in Japan per year (Ohba et al., 2010)

2.3 Urban Heat Islands: Spatial Analysis

Spatial analysis of Urban Heat Islands (UHIs) reveals significant disparities in heat exposure across different areas. (Hsu et al., 2021a) used NASA's MODIS sensor data to analyze how surface urban heat islands (SUHIs) are distributed across major urbanized areas in the continental United States. More localized studies complement this broad geographic analysis, offering detailed insights into the spatial dynamics of urban heat. As an example, (Voelkel et al., 2018a) used vehicle-traverse data to map temperature variations within Portland (Figure 2.3), revealing that certain neighborhoods faced disproportionately high temperatures. This method provided a nuanced understanding of how urban infrastructure and landscape contribute to UHI intensity. The global study by (Chakraborty et al., 2019) further supports these findings, showing that spatial disparities in heat exposure are a common issue in urban environments worldwide. Their research highlights the importance of considering local urban characteristics, such as vegetation cover and building density, when analyzing UHI effects. These spatial analyses are crucial for developing targeted mitigation strategies that address specific local conditions.

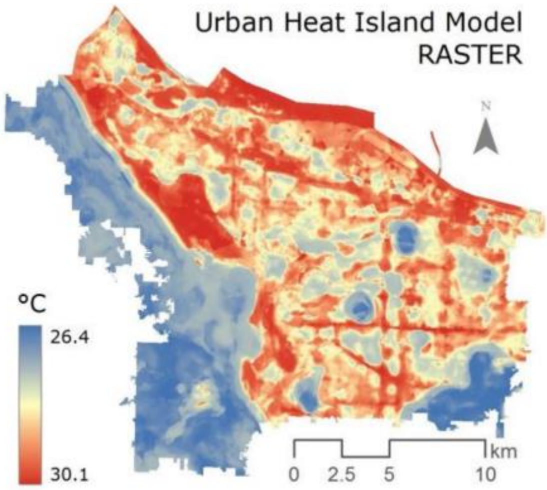
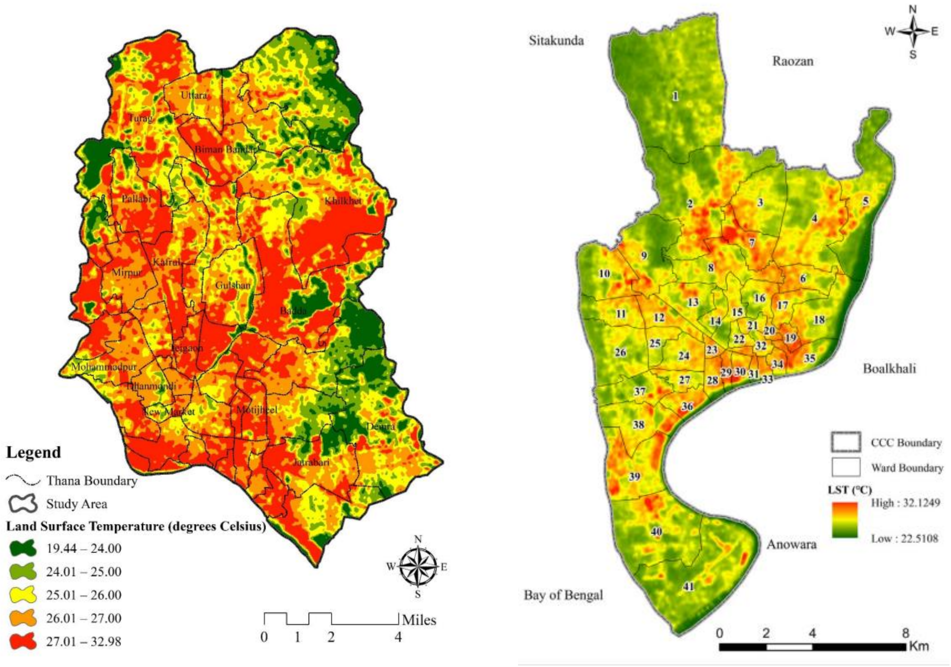


Figure 2.3: The distribution of ambient urban heat in Portland, Oregon (Voelkel et al., 2018a)

In Bangladesh, (Abrar et al., 2022) conducted a detailed spatial mapping of heat vulnerability in Dhaka, highlighting significant disparities in UHI effects across different thanas (Figure 2.4(a)). The study used high-resolution Landsat 8 data to calculate LST, providing a robust basis for analyzing spatial variations in temperature and their correlation with socio-demographic factors. The HVI (Heat Vulnerability Index) analysis revealed high-risk zones predominantly in built-up areas with low vegetation cover. Similarly, (Raja et al., 2021) applied spatial statistical methods, including spatial autocorrelation, cluster analysis, and examination of hot spots, to look into the distribution of heatwave vulnerability in Chattogram. The use of high-resolution satellite data and advanced spatial analysis techniques enabled a comprehensive understanding of how UHI intensity varies across different words in Chattogram (Figure 2.3(b)).



(a) (b)

Figure 2.4: (a) Map of the Dhaka Metropolitan Area's (DMA) land surface temperature (Abrar et al., 2022)**, (b) Land surface temperature (LST) map of Chattogram City Corporation (CCC) based on pixels** (Raja et al., 2021)

2.4 Methodological Approaches in UHI Studies

Different methodological approaches in UHI studies provide varied insights into the phenomenon. Vehicle-traverse surveys, as used by (Voelkel et al., 2018a), offer detailed temperature data at a granular level, capturing local variations that stationary sensors might miss. However, this method can be limited by its coverage and consistency. Satellite data, such as NASA's MODIS sensor used by (Hsu et al., 2021a), provides extensive coverage and a broad overview of UHI intensity across large areas. While this method is beneficial for regional and global analysis, it may lack the detailed local context that ground-based measurements can offer.

In Bangladesh, (Abrar et al., 2022) and (Raja et al., 2021) leveraged advanced methodologies in their studies. (Abrar et al., 2022) employed Principal Component Analysis (PCA) and correlation analysis to construct and validate their HVI, while Raja et al. used spatial statistical methods, including spatial autocorrelation, cluster analysis, and the examination of hot spot, to evaluate heatwave vulnerability's spatial distribution. These diverse methodological approaches highlight the importance of combining various data sources and analytical techniques to gain a comprehensive understanding of UHI effects.

2.5 Socio-Demographic Vulnerability and Thermal Inequity in Urban Heat (Globally)

Research consistently shows that socio-economically disadvantaged populations are more vulnerable to urban heat. (Voelkel et al., 2018) conducted a study in Portland, Oregon, using temperature data collected through vehicle-traverse surveys and census information to determine which socio-demographic populations are most at risk. They found that lower-income and minority populations faced higher exposure to urban heat, highlighting significant socio-economic disparities.

Similarly, (Dialesandro et al., 2021) examined thermal inequities in the Southwestern United States, focusing on how socio-economic factors exacerbate vulnerability to urban heat. Their analysis revealed that lower-income neighborhoods were more susceptible to higher temperatures, exacerbating existing health and socio-economic challenges. These findings are crucial as they align with the socio-demographic factors considered in my study, such as poverty and literacy rates.

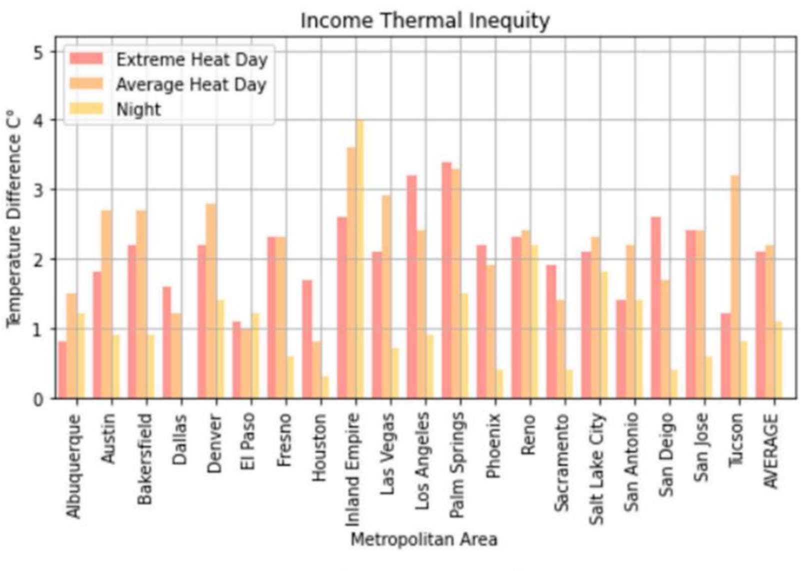


Figure 2.5: Income thermal inequity in the southwestern U.S. (Dialesandro et al., 2021)

These findings align with global research by (Chakraborty et al., 2019), who investigated urban heat exposure across 25 cities worldwide. Their study found that lower-income neighborhoods generally experience higher temperatures due to factors like less vegetation and higher population density. This global perspective underscores the systemic nature of thermal inequity, demonstrating that socio-demographic vulnerability to urban heat is a widespread issue.

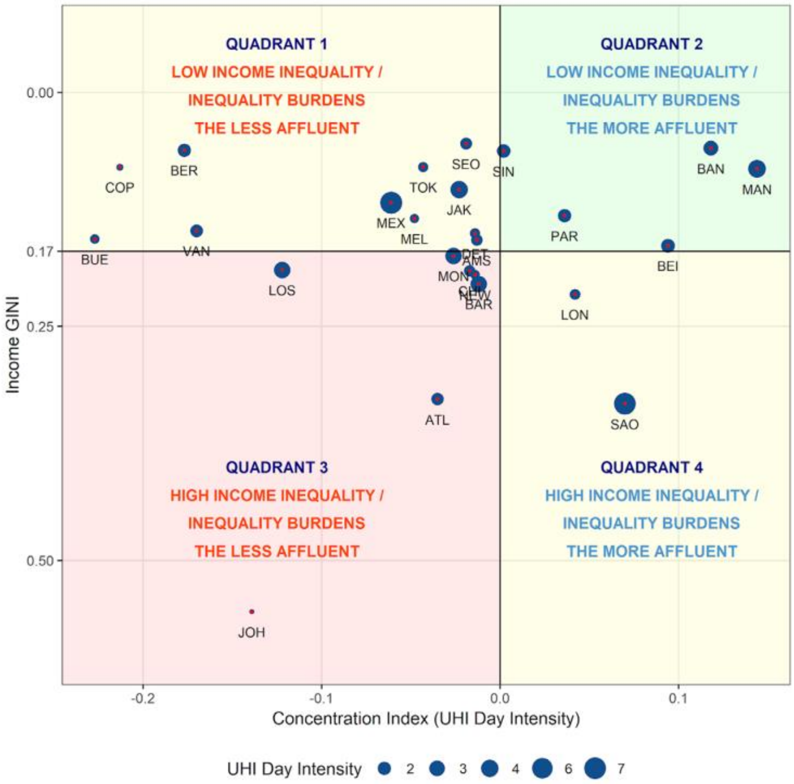


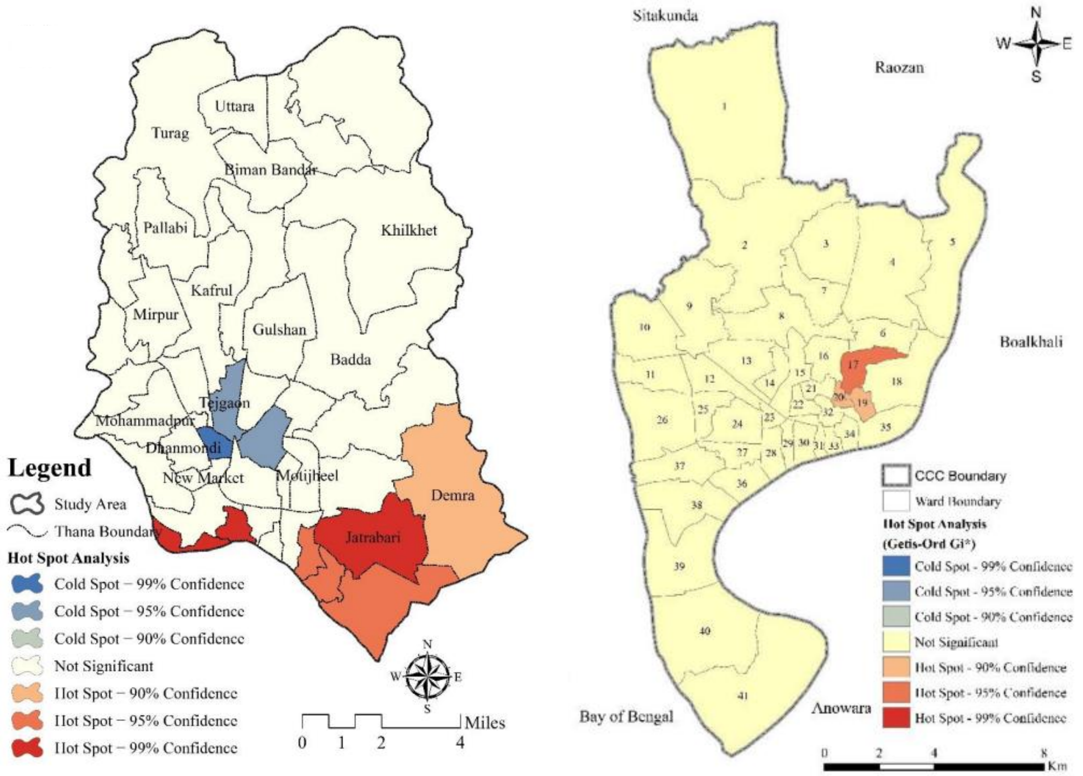
Figure 2.6: A graphical representation showing daytime urban heat island (UHI) concentration and Gini indices for 25 cities arranged in a four-quadrant plot (Chakraborty et al., 2019)

2.6 Urban Heat Islands and Vulnerability in Bangladesh

In Bangladesh, the phenomenon of urban heat islands (UHIs) and associated vulnerabilities have been studied with a focus on socio-demographic factors. Using a Heat Vulnerability Index (HVI), (Abrar et al., 2022) investigated the UHI influence and heatwave vulnerability in Dhaka. At the thana level, this index was created using various kinds of demographic, socioeconomic, and environmental risk indicators. The study utilized Landsat 8 reflectance data to retrieve Land Surface Temperature (LST) and combined this with demographic and socioeconomic statistics from the Bangladesh Bureau of Statistics (BBS), meteorological data from the Bangladesh Meteorological Department (BMD), and nighttime satellite imagery from the National Geophysical

Data Center (NGDC). Principal Component Analysis (PCA) was used to normalize 26 variables across 41 thanas to prepare the HVI. The study found that built-up areas cover more than 60% of Dhaka, resulting in significant UHI effects, with 6 thanas classified as very high-risk and 11 thanas classified as high-risk. The study identified three major hot spots of heatwave vulnerability and emphasized the importance of considering local climatic, socio-economic, physiological, and environmental parameters in assessing UHI impacts.

(Raja et al., 2021) conducted a similar study in Chattogram, developing an HVI that included parameters related to exposure, sensitivity, and adaptive capacity. This study also used Landsat 8 LST data and socio-economic data from the BBS and Chattogram City Corporation (CCC). The variables associated with HVI were evaluated by factor analysis, and the Jenks optimization method in GIS was utilized to classify the normalized HVI values into five groups. The study identified seven wards in CCC as very highly vulnerable to heatwaves, with heatwave vulnerability randomly distributed throughout the city.



(a) (b)

Figure 2.7: Hotspot Analysis of (a) Dhaka Metropolitan Area (DMP), (b) Chattogram City Corporation (CCC)

2.7 Summary

This chapter reviewed the literature of urbanization and Urban Heat Island (UHI) phenomenon, emphasizing its disproportionate impact on socioeconomically disadvantaged populations. Spatial analysis and diverse methodological approaches highlight significant disparities in heat exposure across urban areas globally and in Bangladesh. The results highlight the necessity of focused mitigation strategies to address thermal inequities and improve urban health outcomes.

CHAPTER 3
Methodology

3.1 Introduction

This study's aim is to explore the relationships between Urban Heat Island (UHI) and socio-demographic status in major districts of Bangladesh. This chapter outlines the methodological framework employed to achieve the study's objective. The research is structured around two key approaches: data collection and correlation analysis. It includes a detailed procedure for both data collection and analysis.

3.2 Methodology Overview

The initial phase involved the selection of the study area, necessitating Urban Heat Island (UHI) and socio-demographic data. To acquire UHI data, the first step entailed the downloading of Landsat 8 data from the USGS Earth Explorer. Subsequently, Using ArcGIS, the land surface temperature (LST) was calculated, then, UHI values were derived from the calculated LST. On the other hand, socio-demographic data for the selected study areas were sourced from the Bangladesh Bureau of Statistics (BBS). Three key socio-demographic parameters were considered: poverty, literacy, and vulnerable people based on age distribution. The final step involved the investigation of the relationship between sociodemographic status and UHI.

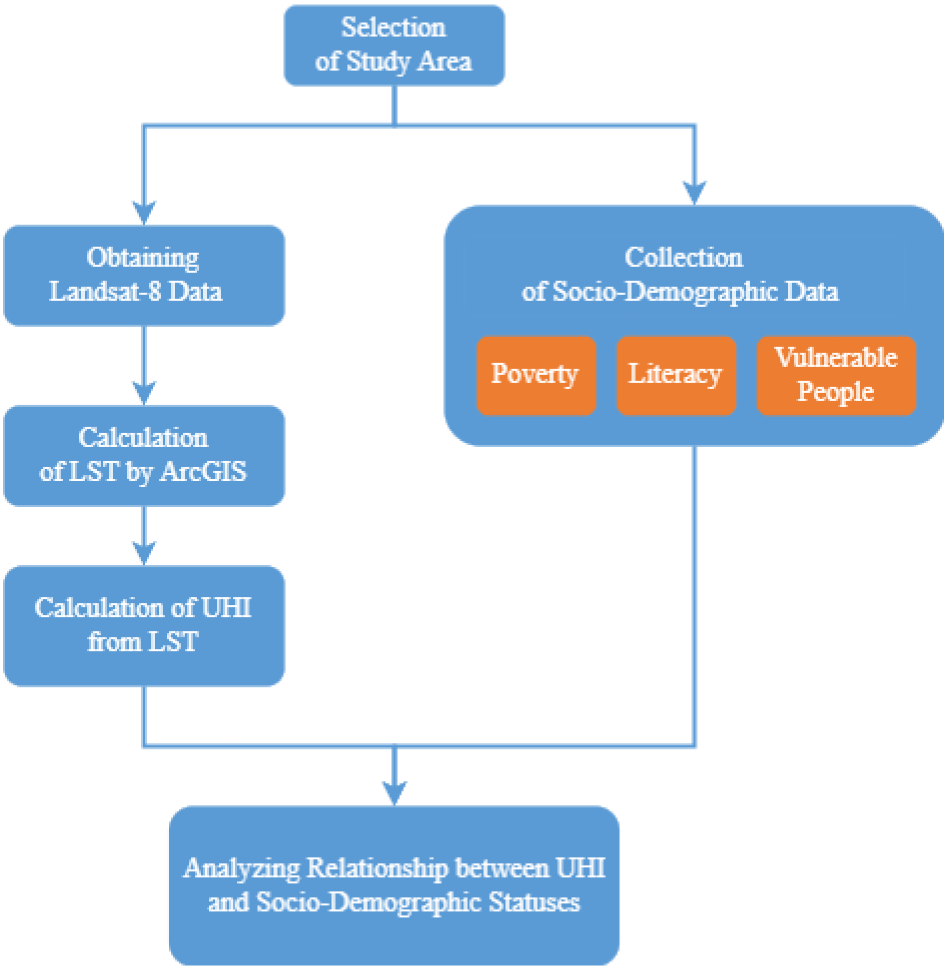


Figure 3.1: Methodology Overview

3.3 Study Area

135 thanas (Table 3.1) in eight important districts (Figure 3.2) of Bangladesh (Dhaka, Rangpur, Barisal, Rajshahi, Khulna, Chittagong, Mymensingh, and Sylhet) were studied for this study. (Rahman et al., 2022a). These districts were selected because of their significance as major urban centers in Bangladesh. The strategic choice of districts from various regions of the country improved the representativeness by capturing both spatial and socio-demographic variations.

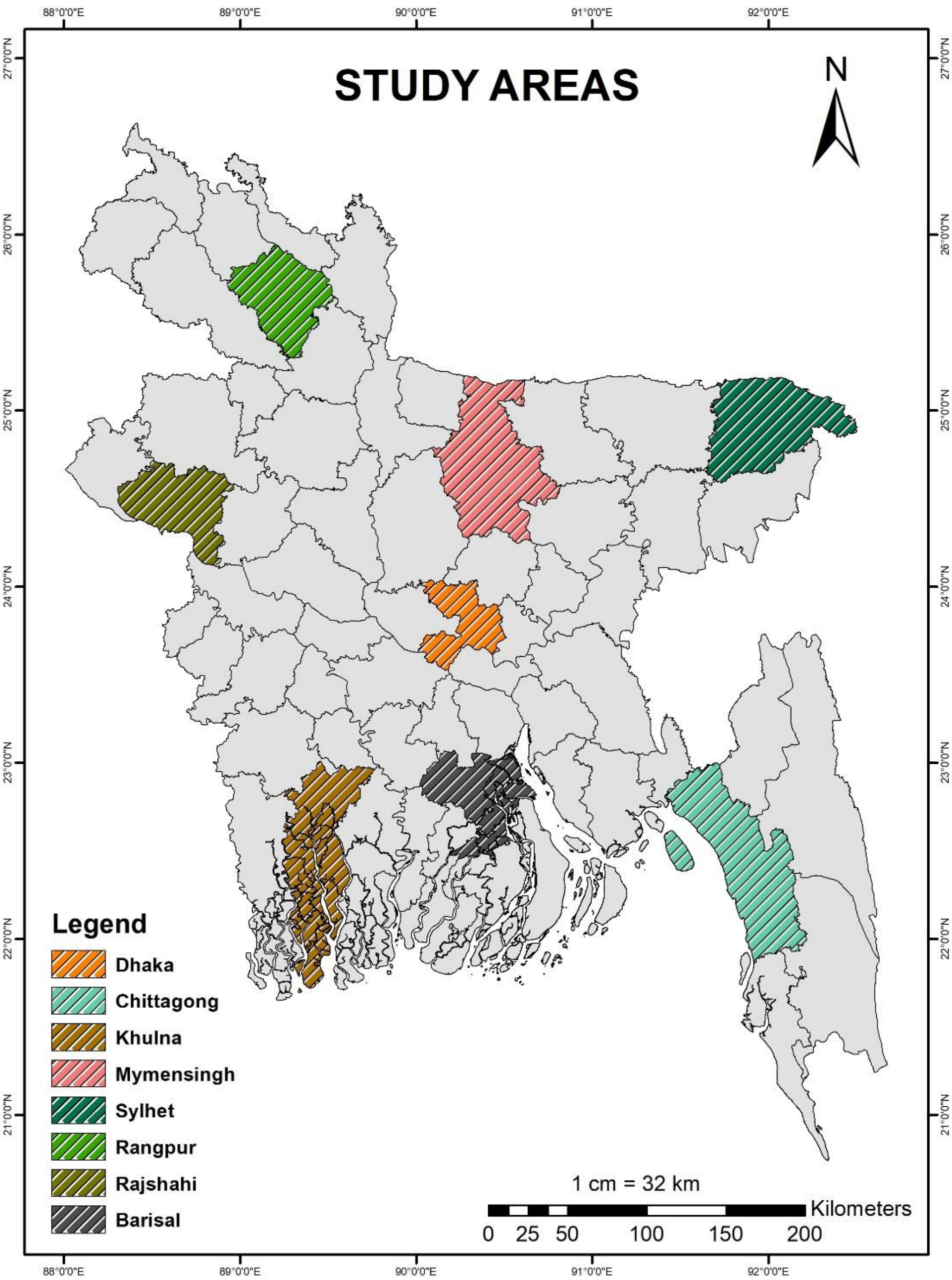


Figure 3.2: Location of Study Areas in Bangladesh

Table 3.1: List of study areas

District	Upazilla/Thana
Barisal	Bakerganj, Agailjhara, Barisal Sadar, Babuganj, Banaripara, Wazirpur, Gaurnadi, Muladi, Hizla, Mehendiganj
Chittagong	Fatikchhari, Hathazari, Patiya, Pahartali, Bakalia, Sitakunda, Chandanaish, Anowara, Boalkhali, Lohagara, Banshkhali, Double Mooring, Khulshi, Mirsharai, Panchlaish, Sandwip, Chandgaon, Satkania, Rangunia, Patenga, Chittagong Port, Kotwali, Raozan, Halishahar
Dhaka	Sher-E-Bangla Nagar, Darus Salam, Shyampur, Lalbagh, Dhanmondi, Gendaria, Mohammadpur, New Market, Badda, Kafrul, Chak Bazar, Gulshan, Demra, Biman Bandar, Tejgaon, Cantonment, Shah ali, Uttara, Khilgaon, Motijheel, Dohar, Ramna, Bangshal, Sutrapur, Dakshinkhan, Shahbagh, Kadamtali, Tejgaon Ind. Area, Paltan, Keraniganj, Jatrabari, Rampura, Pallabi, Adabor, Nawabganj, Uttarkhan, Kotwali, Kamrangir Char, Hazaribagh, Savar, Uttar Khan, Khilkhet, Sabujbagh, Turag
Khulna	Dumuria, Sonadanga, Paikgachha, Khan Jahan Ali, Daulatpur, Terokhada, Rupsa, Dighalia, Phultala, Khalishpur, Koyra, Batiaghata, Khulna Sadar, Dacope
Mymensingh	Gauripur, Nandail, Fulbaria, Haluaghat, Dhobaura, Mymensingh Sadar, Trishal, Ishwarganj, Bhaluka, Muktagachha, Phulpur, Gaffargaon
Rajshahi	Puthia, Boalia, Charghat, Mohanpur, Durgapur, Bagha, Paba, Godagari, Tanore, Baghmara
Rangpur	Gangachara, Pirganj, Pirgachha, Mitha Pukur, Rangpur Sadar, Kaunia, Badarganj, Taraganj
Sylhet	Bishwanath, Gowainghat, Zakiganj, Companiganj, Balaganj, Beani Bazar, Fenchuganj, Golapganj, Jaintiapur, Kanaighat, Sylhet Sadar

3.4 Collection of Landsat 8 Data and Shapefiles

For LST and UHI calculation, the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/; obtained on 2023) provided the Landsat-8 (2023) imagery data (Table 3.2) (Rahman et al., 2022a). A cloud cover of less than 5% images (Rahman et al., 2022a) was chosen from Collection 2 Level 1 categories, OLI/TIRS sensor so that the analysis yielded more accurate results.

Table 3.2: Details of Landsat 8 Data

District	Date of acquisition	Land Cloud Cover (%)	Sensor	Collection/ Level	Path/ Row
Barisal	10 May 2023	2.08	OLI/TIRS	2/1	137/44
Chittagong	28 February 2023	0.01	OLI/TIRS	2/1	136/44
	28 February 2023	0.11	OLI/TIRS	2/1	136/45
Dhaka	10 May 2023	2.08	OLI/TIRS	2/1	137/44
Khulna	2 June 2023	0.02	OLI/TIRS	2/1	137/45
	8 April 2023	4.00	OLI/TIRS	2/1	138/44
Mymensingh	24 April 2023	3.66	OLI/TIRS	2/1	137/43
Rajshahi	2 June 2023	0.30	OLI/TIRS	2/1	138/43
Rangpur	2 June 2023	1.19	OLI/TIRS	2/1	138/42
Sylhet	28 February 2023	0.08	OLI/TIRS	2/1	136/43

And shapefiles for these study areas were downloaded from https://www.arcgis.com/ and https://www.diva-gis.org/gdata.(Hu et al., 2019).

3.5 Socio-Demographic Data

Three sociodemographic parameters were considered: poverty, literacy, and vulnerable people based on age distribution (Hsu et al., 2021b).

1. The poverty data, categorized into 'poor' and 'extreme poor,' were sourced from the ‘Zilla Level Povmap Estimates 2010’. These classifications were expressed as percentages and provided insights into the economic conditions within these study areas.

2. The literacy data was extracted from the Zilla Series "Population and Housing Census 2011”. This parameter served as an essential indicator of educational attainment within the study region.

3. Furthermore, vulnerable people concerning age distribution was examined in two specific age classes: 0-4 years and 65 years and above (Dasgupta & Robinson, 2023). This information, obtained from the Population and Housing Census 2011 (Zilla Series), allowed us to understand the age-related susceptibility within the studied communities.

3.6 Estimation of UHI (Urban Heat Island)

For the computation process, the Raster Calculator tool from Map Algebra within the Spatial Analyst Toolbox was employed.

3.6.1 LST Calculation

There were six processes involved in retrieving the Landsat 8 satellite image's LST.

Step 1: The spectral radiance ($L\lambda$) from band 10 was calculated. (Avdan & Jovanovska, 2016a),

$$\mathrm{L\lambda} = \mathrm{AL} + \mathrm{ML} * \mathrm{Qcal} - \mathrm{Oi}\,,$$

Where, A_L (Band-specific additive rescaling factor) =0.10,

M_L (Band-specific multiplicative rescaling factor) = 0.00034,

Q_{cal} = Band 10 image, and

O_i (Correction for Band 10) = 0.29

Step 2: Following the conversion of the spectral radiance to atmospheric temperature brightness (BT) (Avdan & Jovanovska, 2016b),

$$\mathrm{BT} = \frac{\mathrm{K1}}{\ln\left[(\mathrm{K2}/\mathrm{L\lambda}) + 1\right]} - 273.15$$

Where the metadata's band-specific thermal conversion constants,

K_1 = 1321.1

K_2= 777.9

Absolute zero was added to the radiant temperature to convert the values to degrees Celsius.

Step 3: Determination of the Normalized Difference Vegetation Index (NDVI) (Avdan & Jovanovska, 2016b),

$$\mathrm{NDVI} = \frac{\mathrm{NIR\ (band\ 5)} - \mathrm{R\ (band\ 4)}}{\mathrm{R\ (band\ 4)} + \mathrm{NIR\ (band\ 5)}}$$

Where, R = Red band (Band 4) and

NIR = Near-infrared band (Band 5)

Step 4: Using the minimum and maximum NDVI values, the proportion of vegetation was computed. (Avdan & Jovanovska, 2016b),

$$Pv = \left(\frac{NDVI - NDVImin}{NDVImax - NDVImin}\right)^2$$

Step 5: Using P_v, the land surface emissivity was computed (Rahman et al., 2022b),

$$E = 0.986 + 0.004 \times Pv$$

Step 6: The land surface temperature (LST) was calculated in degrees Celsius (Avdan & Jovanovska, 2016b),

$$LST = \frac{BT}{[1 + (\gamma \times BT/c2)\ln(E)]}$$

Where $c_2 = h \times c/s = 1.4388 \times 10^{-2}$ mK =14,388 μmK,

γ = the wavelength of emitted radiance,

s (Boltzmann constant) =1.38 × 10 − 23 J/K,

h (Planck's constant) = 6.626 × 10 − 34 Js, and

c (velocity of light) = 3×10^8 m/s.

3.6.2 Calculation of UHI

Using the value of the land surface temperature (LST), the UHI was computed (Rahman et al., 2022b),

$$UHI = \frac{T - Tm}{Ts}$$

where, T_m = Mean land surface temperature,

T = Land surface temperature, and

T_s = The standard deviation of land surface temperature.

3.6.3 Masking UHI Raster Data:

By integrating the study area shapefiles into the ArcGIS environment, a spatial overlay operation was conducted to intersect UHI raster data with study area boundaries. This process generated masked layers that exclusively retained UHI information for predefined regions. After outlining and narrowing down Urban Heat Island (UHI) effects in the chosen study areas with ArcGIS 10.7, the subsequent step involved directly extracting the average UHI values. These mean UHI values in the dataset served as precise indicators of the overall UHI in each study area (Voelkel et al., 2018b). Utilizing existing mean values enhanced efficiency and accuracy in depicting UHI intensity across the entire study area.

3.7 Analyzing Correlation between Urban Heat Island (UHI) and Socio-Demographic Status

For analysis of the relationship between Urban Heat Island (UHI) and socio-demographic status, the initial step involved assessing the normality of the dataset. Subsequently, correlation analysis was conducted.

3.7.1 Evaluating Normality of the Dataset

To assess the normality of the dataset, a comprehensive approach was employed, incorporating both graphical and analytical methods. This dual strategy aimed to enhance the robustness of the normality evaluation. Both methods were performed in Python.

3.7.1.1 *The Quantile-Quantile (QQ) Plot*

A QQ plot was used to determine if a dataset matched to a specific theoretical distribution, like the normal distribution. It performed a comparison between the quantiles of the actual data and the quantiles predicted by a certain distribution assumption. The normal distribution was the predicted distribution for the purpose of determining normality. (Hernandez, n.d.).

Interpretation of QQ Plot

A normal distribution of the data seemed to be supported if the dots on the QQ plot roughly followed a straight line that ran from the bottom-left to the top-right. On the other hand, if the points deviated from the straight line, forming an S-shaped or curved pattern, the data distribution departed from a normal distribution.

3.7.1.2 *Shapiro-Wilk (SW) Test*

One statistical technique for determining if a dataset had a normal distribution was the Shapiro-Wilk test. By verifying the null hypothesis that the sample was drawn from a population with a normal distribution, it evaluated how well the data fit the normal distribution (Hernandez, n.d.).

Interpretation of the Shapiro-Wilk Test

1. Null Hypothesis (H0): The null hypothesis stated that the distribution of the data was normal. In the event that the test's p-value exceeded the selected significance level (usually 0.05), there was not enough data to rule out the null hypothesis. It was acceptable to infer that the data in these situations followed a normal distribution.

2. Alternative Hypothesis (H1): According to the alternative theory, there was a deviation from a normal distribution in the data. The researchers provided evidence to reject the null hypothesis based on a p-value lower than the selected significance threshold. This suggested a possible deviation from normalcy and showed that the data deviated from a normal distribution significantly.

3. P-Value Interpretation: High P-Value ($p > 0.05$): The null hypothesis cannot be ruled out. At the selected significance level, there was no discernible difference between the data and a normal distribution.

Low P-Value ($p \leq 0.05$): Rejection of the null hypothesis. The data provided evidence that it deviated from a normal distribution.

3.7.2 Correlations between UHI and Socio-Demographic Status

For determining the correlations between UHI and socio demographic status Spearman Correlation performed. And for visual representation, scatter plots of the data with trend lines were done. The Spearman correlation test, Theil-Sen estimation, Kendall's Tau value and scatter plots with trend line both were done in Python.

3.7.2.1 *Spearman Correlation*

Spearman correlation is a non-parametric statistical method for determining the direction and magnitude of monotonic correlations between two variables. Spearman correlation is robust in scenarios where data may not follow a normal distribution since, in contrast to Pearson correlation, it does not presuppose a certain distribution for the variables (Xiao et al., 2016).

The Calculation of Spearman's Rank Correlation Coefficient (r):

$r<0$: Suggested a negative monotonic connection,

$r>0$: Indicated a positive monotonic connection,

$r=0$: Implied no monotonic connection.

The range of the correlation coefficient (r) was -1 to 1 and the strength of r shows in Table 3.3.

Table 3.3: Strength of Correlation Coefficient

Correlation Coefficient	Strength of Relationship
-1.0 to -0.5 or 1.0 to 0.5	Strong
-0.5 to -0.3 or 0.3 to 0.5	Moderate
-0.3 to -0.1 or 0.1 to 0.3	Weak
-0.1 to 0.1	Very Weak or None

A p-value associated with the correlation coefficient indicates whether the observed correlation was statistically significant. A low p-value (<0.05) suggested a significant association.

3.7.2.2 *Theil-Sen Estimation:*

Theil-Sen Estimation was employed to determine the slope of linear relationships between variables in this study. Unlike traditional linear regression methods, which are sensitive to outliers and assumptions about data distribution, Theil-Sen Estimation calculates the median slope from all possible pairs of data points. This approach is robust against outliers and does not require strict data distribution assumptions, making it suitable for analyzing relationships in datasets that may contain irregularities. The calculated slope using Theil-Sen Estimation provides a reliable measure of the direction and strength of associations between variables, ensuring robust and interpretable results in the context of this research.

By framing it in this way, you explain how you used Theil-Sen Estimation to analyze relationships between variables in this study, highlighting its advantages in handling outliers and flexibility in data distribution assumptions.

3.7.2.3 *Kendall's Tau*

Kendall's Tau was utilized to assess the strength and direction of association between variables in this study. Kendall's Tau is a non-parametric measure that evaluates the ordinal association between two variables. Unlike Pearson's correlation coefficient, which assumes a linear relationship and normal distribution of data, Kendall's Tau does not require such assumptions, making it suitable for datasets where variables are ranked or ordered.

The computation of Kendall's Tau involves:

- Comparing the ranks of paired observations for each variable.
- Calculating the number of concordant and discordant pairs.
- Deriving a correlation coefficient that ranges from -1 (perfect negative association) to +1 (perfect positive association), with 0 indicating no association.

By employing Kendall's Tau, this study ensures analysis of relationships while accommodating non-linear associations and mitigating the influence of outliers. This methodological choice provides reliable insights into the dependencies between variables, contributing to a comprehensive understanding of the research questions addressed in this thesis.

3.7.3 Visual Representation

Scatter plots of data with trend lines and mapping in ArcGIS could complement the quantitative results, providing a visual representation of the correlation between variables.

3.8 Summary

The present study was undertaken across 135 thanas in eight major districts of Bangladesh to examine the unequal exposure to urban heat island (UHI) intensity, with a particular emphasis on contrasting UHI and various socio-demographic factors. The collection of Landsat-8 imagery data was carried out with a cloud cover of less than 5% to ensure accurate analysis. The determination of Land Surface Temperature (LST) involved six steps, includes spectral radiance calculation, brightness conversion to air =temperature, the Normalized Difference Vegetation Index (NDVI) calculation, vegetation proportion calculation, land surface emissivity calculation, and Land Surface Temperature (LST) calculation. UHI was computed using the LST value with respect to the LST mean and standard deviation. The UHI raster data was masked using spatial overlay operations in ArcGIS, and the mean UHI values were extracted from the software to indicate UHI intensity in each study area. The socio-demographic data considered in the study comprised poverty, literacy, and vulnerability based on age distribution. The relationships between UHI and socio-demographic factors were analyzed using Spearman correlation. Additionally, scatter plots with trend lines and ArcGIS mapping were used to create the visual representation.

CHAPTER 4

Results and Discussion

4.1 Introduction

This study focuses on understanding how urban areas in Bangladesh experience different levels of heat, known as Urban Heat Island (UHI) effects, and how this relates to factors like poverty, literacy, and vulnerability to heat-related health problems. By closely examining UHI intensity and its distribution across districts, research uncovers varying temperatures and socio-demographic makeup of different areas. Through detailed analysis and visual tools, the study aims to clarify the connection between UHI and socio-demographic factors, providing valuable insights into the complex factors influencing heat vulnerability in cities.

4.2 Land Surface Temperature (LST) Distribution

The study examined land surface temperatures (LST) across eight major districts of Bangladesh, revealing variations among regions (Figure 4.1). Rajshahi district exhibited the highest LST of 42.8°C, highlighting it as the warmest area studied. Conversely, Mymensingh displayed the lowest LST of 6.45°C, indicating cooler conditions compared to other districts. Barisal experienced a range from 38.26°C as its highest LST to 21.13°C as its lowest, showing significant temperature fluctuations within the region. Dhaka, being the capital, showed a high of 35.97°C and a low of 21.70°C for its LST, underscoring moderate temperature ranges typical of urban environments. Chittagong, a coastal district, registered a maximum LST of 36.06°C and a minimum of 20.57°C, influenced by maritime climatic factors. Khulna displayed LST values between 33.2°C and 17.5°C, indicative of its coastal position and proximity to the Sundarbans. Rajshahi, in addition to its high peak of 42.8°C, maintained a lowest LST of 26.27°C, showcasing significant temperature fluctuations over the study period. Rangpur and Sylhet recorded LSTs ranging from 42.35°C to 26.8°C and from 30.82°C to 17.57°C, respectively, with Sylhet demonstrating milder temperatures consistent with its northeastern location and hilly terrain.

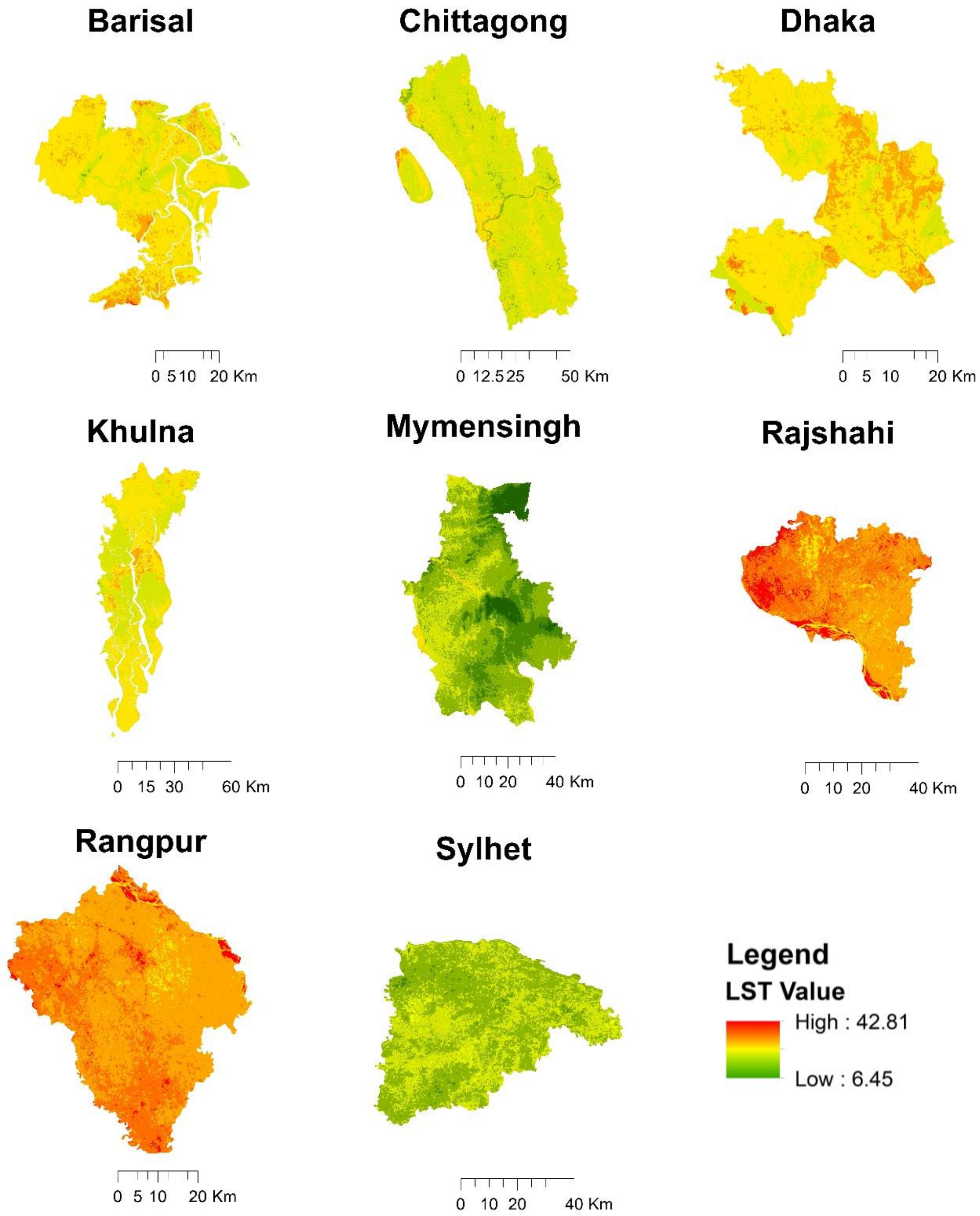


Figure 4.1: Land surface temperature (LST) of Barisal, Dhaka, Chittagong, Mymensingh, Rajshahi, Rangpur, Khulna and Sylhet

4.3 Urban Heat Island (UHI) Distribution

The histograms show the Urban Heat Island (UHI) values for eight major districts in Bangladesh, based on data from various thanas within each district (Figure 4.2). In Barisal, UHI values range from about -0.58 to 0.63, with many values around -0.6, indicating cooler conditions. Chittagong has a wider range of UHI values from -0.31 to 1.57, with peaks at -0.25 and 1.5, showing more variability in heat.

Dhaka has the widest range of UHI values, from -1.46 to 1.83, with significant peaks at -0.25 and 1.0, reflecting its dense urban areas and varied heat levels. In Khulna, UHI values range from -0.15 to 1.51, with peaks at 0.25 and 1.5, indicating both moderate and high heat areas. Mymensingh shows UHI values from -1.81 to 0.98, with a peak at 0.5, suggesting mixed heat distribution.

Rajshahi has UHI values from -0.84 to 0.83, with peaks at both extremes (-0.75 and 0.75), indicating both cooler and warmer areas. Rangpur shows UHI values from -0.82 to 0.69, with peaks at -0.2 and 0.0, suggesting generally cooler conditions. Sylhet has UHI values from -0.63 to 0.47, with peaks at -0.6 and 0.0, indicating a cooler urban environment with some warmer spots.

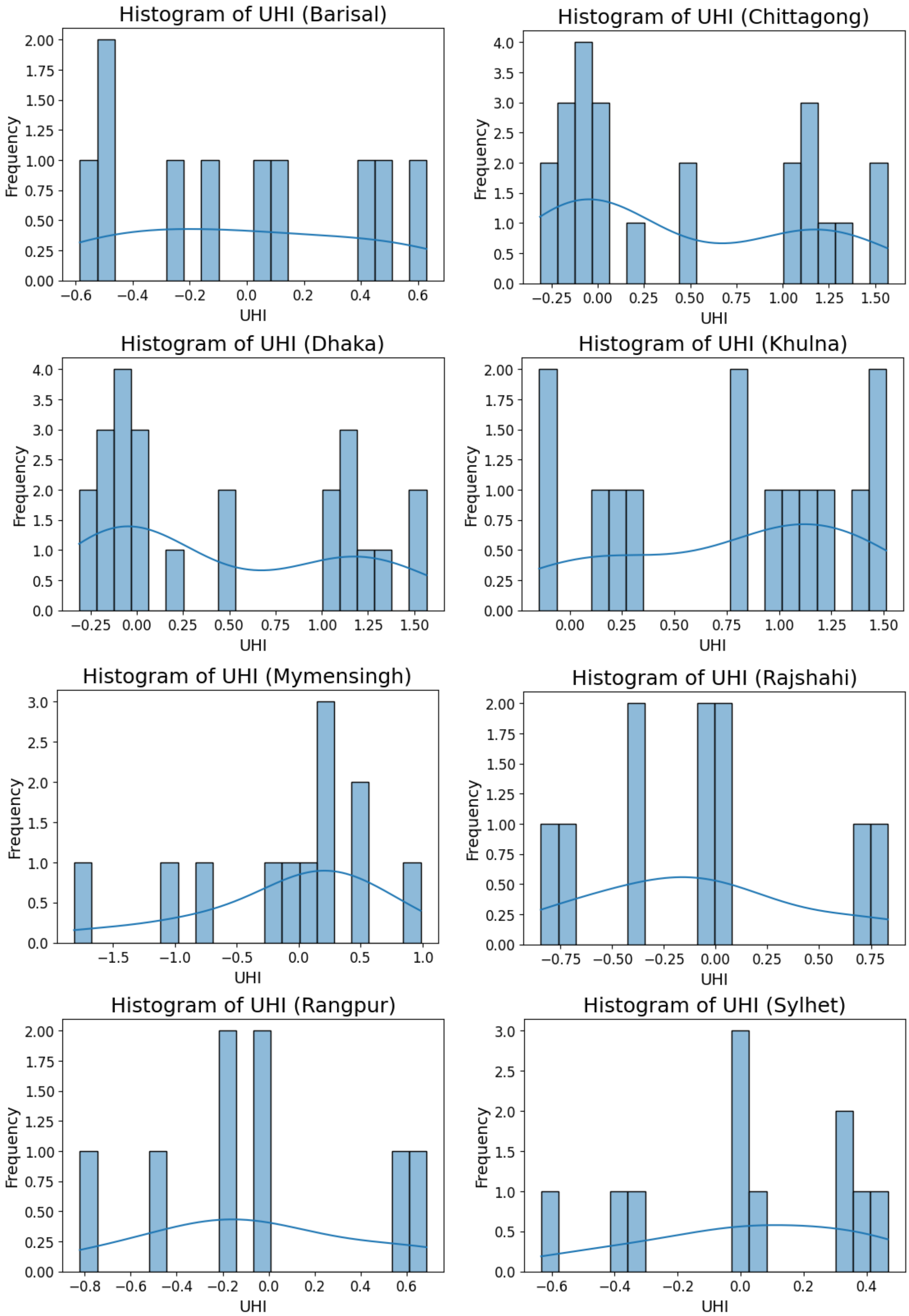
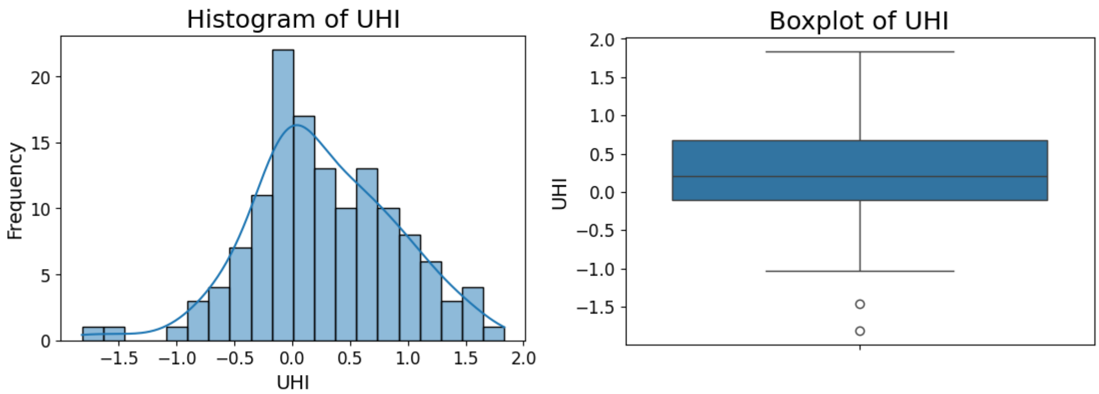


Figure 4.2: Histograms of UHI (Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur and Sylhet)

The analysis of UHI values in the studied districts showed a wide range of temperatures, from -1.81°C to 1.83°C, indicating significant variation in urban heat island effect. The mean UHI value of 0.27°C and a standard deviation of 0.62 suggested that while some areas experienced substantial urban heat island effects, others had cooling effects due to vegetation or water bodies. Among the 135 areas studied, 87 had UHI values higher than 0°C. The present investigation found results consistent with (Rahman et al., 2022c), showing diverse UHI intensity levels across the seven major cities of Bangladesh: Barisal, Chittagong, Dhaka, Mymensingh, Rajshahi, Rangpur, and Sylhet.



(a) (b)

Figure 4.3: (a) Histogram of UHI and (b) Box Plot of UHI for all Districts

The histogram of UHI values demonstrated a normal distribution pattern, which is indicative of a balanced spread of UHI effects across the regions (Figure 4.3 (a)). This pattern helps to understand that the UHI effect is not confined to specific areas but is spread across different regions with varying intensities. The boxplot of UHI values highlighted the median, interquartile range, and the presence of outliers (Figure 4.3(b)). The majority of UHI values fell within the interquartile range, indicating that most thanas had moderate UHI effects. However, the presence of outliers showed that some thanas experienced extreme UHI values, both negative and positive, suggesting unique local conditions or urban planning practices.

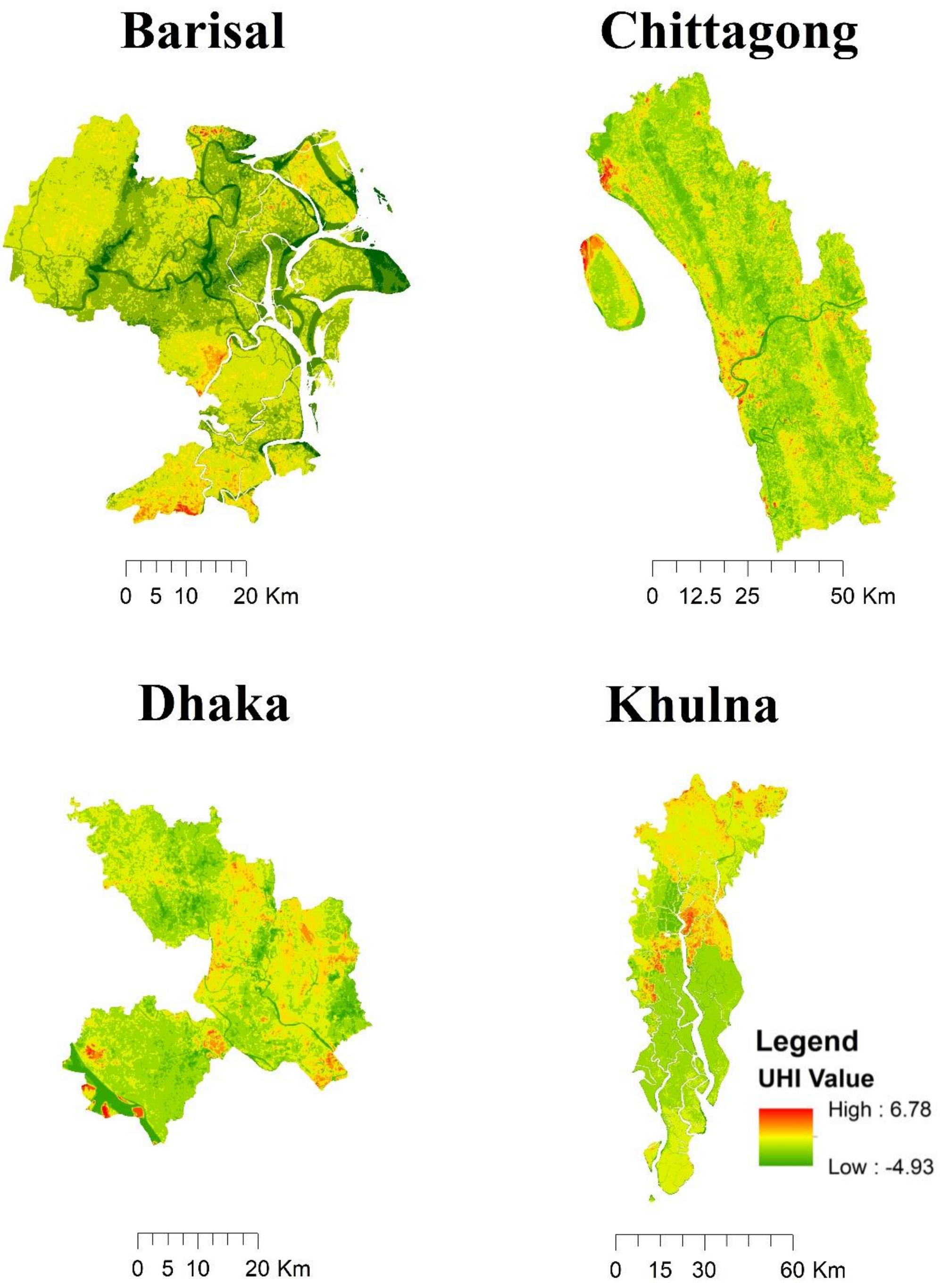


Figure 4.4: UHI of Barisal, Chittagong, Dhaka, and Khulna.

The mean urban heat island (UHI) values for the thanas of Barisal, Chittagong, Dhaka, and Khulna districts exhibited significant variation (Figure 4.4). In Barisal, the range of UHI values from -0.58°C in Mehendigonj to 0.63°C in Bakergonj suggested that differences in land use and urban density played a key role. The negative UHI in Mehendigonj indicated cooling effects due to more vegetation or water bodies, while Bakergonj's higher UHI pointed to more built-up areas with fewer green spaces.

Chittagong's UHI values, ranging from -0.31°C in Boalkhali to 1.57°C in Double Mooring, reflected a diverse urban landscape. Double Mooring's high UHI suggested intense urbanization and industrial activities, whereas Boalkhali's negative UHI could have been due to the presence of parks or water bodies providing cooling effects. Dhaka exhibited the widest range of UHI values, from -1.46°C in Demra to 1.83°C in Boman Bandar. This wide variation could be attributed to Dhaka's large size and varying levels of development, industrial activity, and green space across the city (Byomkesh et al., 2012). Demra's significant negative UHI value might have resulted from less development or more effective urban planning, while Boman Bandar's high UHI value indicated a densely built area with minimal vegetation. In Khulna, UHI values ranged from -0.15°C in Sonadanga to 1.51°C in Paikgachha, showing notable differences across the thanas. Paikgachha's high UHI suggested areas with significant human activity and limited green space, while Sonadanga's negative UHI indicated cooling influences from natural features or better urban planning.

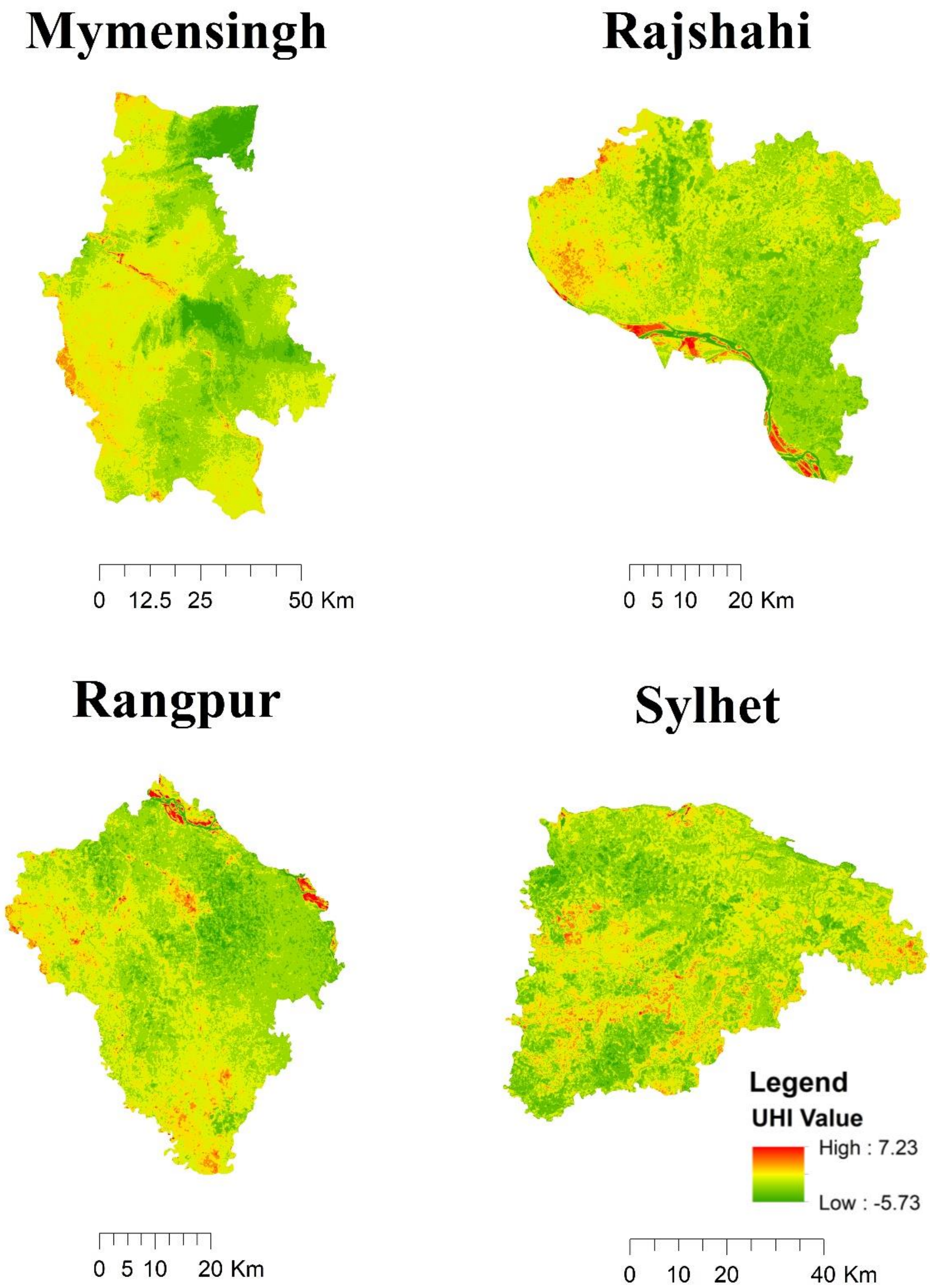


Figure 4.5: UHI of Mymensingh, Rajshahi, Rangpur, and Sylhet.

Similarly, the mean urban heat island (UHI) values for the thanas of Mymensingh, Rajshahi, Rangpur, and Sylhet districts also showed significant variation (Figure 4.5). Mymensingh's UHI values, ranging from -1.81°C in Dhobaura to 0.98°C in Fulbaria, indicated significant differences in land use and urban development. Dhobaura's negative UHI value might have been due to extensive vegetation or water bodies providing cooling effects, while Fulbaria's higher UHI suggested more built-up areas with fewer green spaces. In Rajshahi, UHI values ranged from -0.84°C in Charghat to 0.83°C in Godagari. Charghat's negative UHI value may have resulted from effective urban planning or natural cooling features like parks and rivers, while Godagari's positive UHI value suggested higher temperatures due to dense urbanization and minimal vegetation. Rangpur exhibited UHI values from -0.82°C in Pirgachha to 0.69°C in Badarganj, indicating moderate differences across its thanas. Pirgachha's negative UHI could be attributed to rural characteristics or green spaces, while Badarganj's positive UHI pointed to more developed and urbanized areas. Sylhet's UHI values ranged from -0.63°C in Companiganj to 0.47°C in Golapganj, suggesting less variation in urbanization levels. Companiganj's negative UHI value might have been due to natural features and green spaces that mitigated heat, whereas Golapganj's positive UHI could have been linked to more urban infrastructure and less vegetation.

4.4 Socio-demographic Data

The socio-demographic makeup of the study areas provided crucial insights into key aspects such as poverty, literacy, and vulnerability to heat-related health issues (Table 4.1). On average, approximately 14.5% of individuals were classified as extremely poor, indicating a considerable economic challenge within the studied districts. However, there was a wide range across districts, as evidenced by the substantial standard deviation of 14.3, suggesting significant economic disparity. Similarly, about 25.9% of the population fell under the category of poor, reflecting economic diversity across the regions. The notable standard deviation of 18.4 highlighted the variance in economic status among districts, underlining the complexity of socio-economic dynamics within the study area. The mean literacy rate was recorded at 56.6%, indicating moderate levels of educational attainment. However, the significant standard deviation of 18.65 pointed to considerable variability in educational levels across districts. This diversity in literacy rates underscored the need for tailored interventions to address educational disparities and promote literacy across the region. In terms of vulnerability to heat-related health risks, reflected in the percentage of vulnerable populations in the 0-4 and 65+ age groups, the average stood at 13.4%. This finding suggested a notable proportion of the population susceptible to heat-related health issues. However, there was less variability across districts, as indicated by the standard deviation of 3.07, highlighting a consistent level of vulnerability across the study area. These socio-demographic factors played a pivotal role in shaping the interaction between urban heat island intensity and different demographic backgrounds.

Table 4.1: Socio-demographic Variables

Variables	**Description**	**Mean (%)**	**Standard Deviation**	**Range (%)**
Extreme Poor	Percentage of extreme poor (Lower poverty line)	14.5	14.3	0 to 5
Poor	Percentage of poor (upper poverty line)	25.9	18.4	0 to 64.4
Literacy	Percentage of Literacy (7years and above)	56.6	18.65	21.4 to 95.8
Vulnerable People	Percentage of vulnerable people (0-4 and 65+ age range)	13.4	3.07	5.8 to 20.1

4.5 Investigation of the Relationship between UHI and Socio-Demographic Status

In examining the relationship between Urban Heat Island and socio-demographic status, the first stage consisted of evaluating the normality of the dataset. Following this, a correlation analysis was carried out.

4.5.1 Normality Evaluation of The Dataset

Both graphical and analytical methods were used for evaluating the normality of the datasets.

4.5.1.1 *Quantile-Quantile (QQ) Plot*

In evaluating the distribution characteristics of the variables under study, a Quantile-Quantile (QQ) plot served as a valuable graphical tool. Notably, the UHI dataset exhibited a pattern where the plotted points closely aligned with a straight line on the QQ plot, indicative of adherence to a normal distribution (Figure 4.6(a)). Conversely, the QQ plots for variables such as extreme poor, poor, literacy, and vulnerable people displayed deviations from straight lines, suggesting non-normal distributions (Figure 4.6(b), (c), (d), (e)). This observation highlights how these socio-demographic variables have different distribution patterns compared to the UHI data.

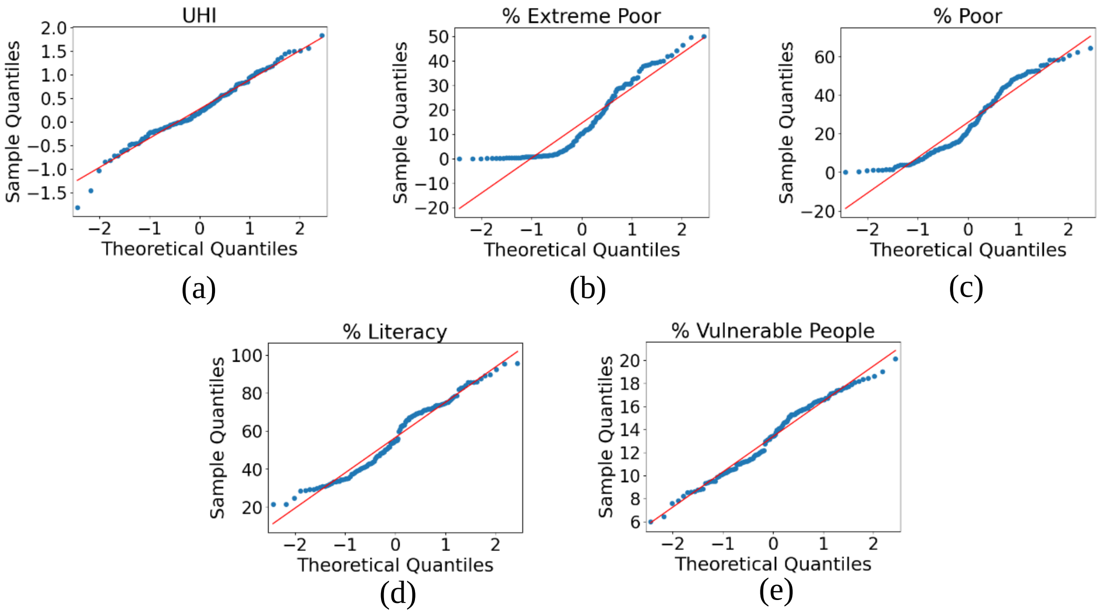


Figure 4.6: Q-Q (Quantile Quantile) plot of variables (a) UHI, (b) % Extreme Poor, (c) %Poor, (d)%Literacy, and (e)%Vulnerable People

4.5.1.2 *Shapiro-Wilk (SW) Test*

The Shapiro-Wilk test was used to check if the data for Urban Heat Island (UHI), extreme poverty, poverty, literacy, and vulnerability followed a normal distribution, as shown in Table 4.2. Results indicated that the UHI data was normally distributed ($p = 0.25$), while the data for extreme poverty, poverty, literacy, and vulnerability did not follow a normal distribution ($p < 0.05$). This consistency between graphical and analytical methods confirmed the reliability of the normality assessment for these variables. These findings highlight the importance of considering the distribution patterns of socio-demographic factors when studying their relationship with UHI in the study area.

Table 4.2: Results of Shapiro-Wilk (SW) Test

Variable	Description	Statistics	P-value	Normally Distributed?
UHI	Mean of Urban Heat Island of study area	0.987	0.25	Yes
Extreme Poor	Percentage of extreme poor (Lower poverty line)	0.868	1.35E-09	No
Poor	Percentage of poor (upper poverty line)	0.93	2.64E-06	No
Literacy	Percentage of Literacy (7years and above)	0.96	0.00055	No
Vulnerable People	Percentage of vulnerable people (0-4 and 65+ age range)	0.976	0.0185	No

The results from both the visual and statistical methods aligned, confirming the reliability of the normality distribution assessment.

4.5.2 Correlation Analysis

Upon assessing normality, it was evident that only the UHI dataset followed a normal distribution, while the others did not. As a result, parametric correlation tests were not applicable, leading to the use of the Spearman correlation, a non-parametric statistical method. To visually represent the data, scatter plots with trend lines were generated using Python, and maps were created using ArcGIS 10.7.

4.5.2.1 *Spearman Correlation*

The Spearman correlation analysis revealed significant associations between Urban Heat Island (UHI) and various socio-demographic variables, as summarized in Table 4.3. Specifically, negative correlations were observed between UHI and extreme poverty (r=-0.36), UHI and poverty (r=-0.35), as well as UHI and vulnerable populations (r=-0.47). Conversely, a positive correlation was identified between UHI and literacy (r=0.48). These correlation coefficients (r), ranging between 0.3 to 0.5, suggest moderate strength of associations (Table 4.3). Importantly, all correlations demonstrated statistical significance based on the corresponding p-values, indicating robustness in the observed relationships.

Table 4.3: Results of Spearman Correlation Analysis

UHI &	Correlation Coefficient, r	P-Value	Conclusion
Extreme Poor	-0.36	1.47E-05	A Significant Correlation
Poor	-0.35	3.25E-05	A Significant Correlation
Literacy	0.48	8.75E-46	A Significant Correlation
Vulnerable People	-0.47	6.46E-09	A Significant Correlation

4.5.2.2 *Theil-Sen Estimation and Kendall's Tau*

The correlation between Urban Heat Island (UHI) intensity and socio-economic parameters was examined using Theil-Sen estimation and Kendall's tau test (Table 4.4). The findings indicated several trends:

1. **UHI vs Extreme Poor and Poor**: Higher UHI intensities showed weak negative correlations with both extreme poor (-0.25) and poor (-0.24) populations. This suggested that areas with higher UHI tended to have lower percentages of economically disadvantaged residents.
2. **UHI vs Literacy**: A moderate positive correlation (0.32) was observed between UHI intensity and literacy rates. Areas with higher literacy rates tended to experience higher UHI intensities, potentially linked to better urban development and educational infrastructure.
3. **UHI vs Vulnerable People**: A moderate negative correlation (-0.31) was found between UHI intensity and the percentage of vulnerable populations. This implied that areas with higher vulnerability indices tended to have lower UHI intensities, possibly influenced by socio-economic factors affecting both vulnerability and heat distribution.

Table 4.4: Theil-Sen Estimation and Kendall's Tau Value

UHI &	Theil-Sen Estimation (Slope)	Kendall's Tau Value
Extreme Poor	-5.45	-0.25
Poor	-9.53	-0.24
Literacy	-15.71	0.32
Vulnerable People	-2.46	-0.31

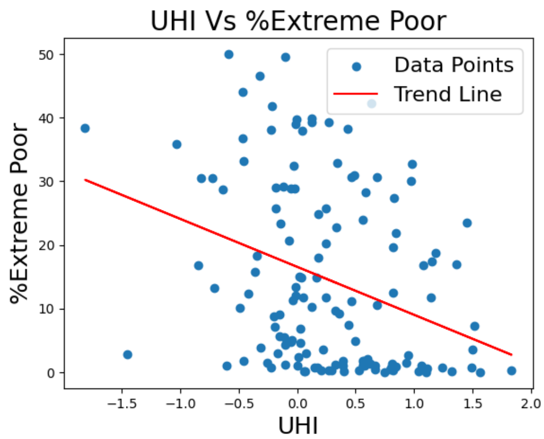
4.5.3 Scatter Plots with Trend Line

The scatter plots generated using Python provided valuable insights into the relationship between Urban Heat Island (UHI) intensity and various socio-demographic factors in Bangladesh. The analysis revealed several key trends:

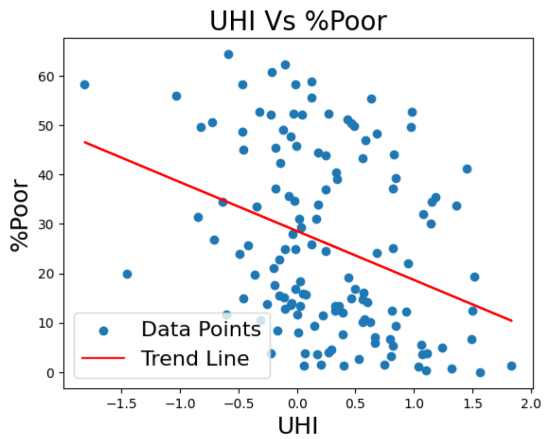
The scatter plots showed negative trends between UHI intensity and both extreme poverty and general poverty levels (Figure 4.7 (a), (b)). This indicates that areas with higher UHI intensity tend to have lower percentages of extremely poor and poor individuals.

Similarly, a negative trend was observed between UHI intensity and the percentage of vulnerable populations, particularly in the 0-4 and 65+ age groups (Figure 4.7 (d)). This suggests that areas with higher UHI intensity have lower percentages of these vulnerable age groups.

Conversely, a positive trend was identified between UHI intensity and literacy rates. This indicates that regions with higher UHI intensity tend to have higher percentages of literate individuals (Figure 4.7 (c)).



(a)



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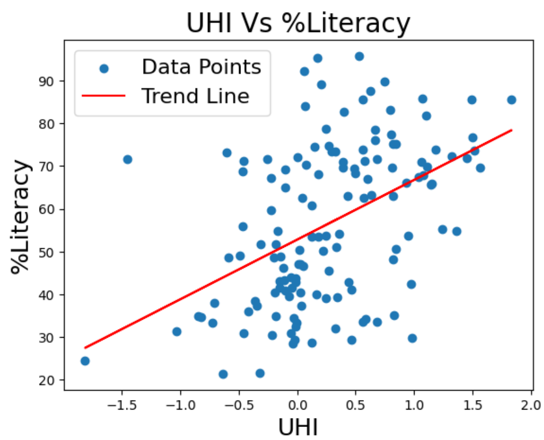

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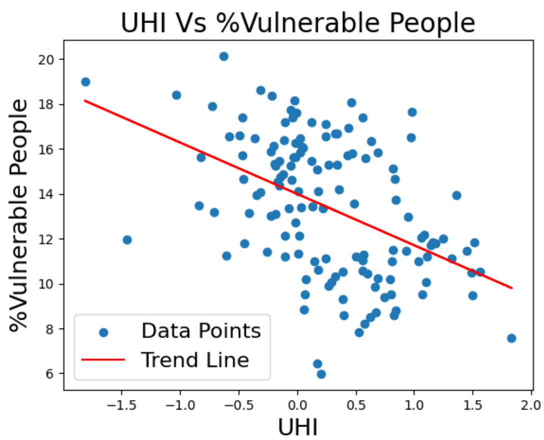

(d)

Figure 4.7: Scatter Plots with Trend Line (a) UHI vs %Extreme Poor, (b) UHI vs %Poor, (c) UHI vs %Literacy and (d) UHI vs %Vulnerable People

4.5.4 Distribution of UHI (Urban Heat Island) by %Extreme Poor, %Poor, %Literacy and %Vulnerable People Maps

The analysis of the data revealed specific patterns within UHI-affected areas. Among the 135 areas studied, 87 had UHI values higher than 0°C, indicating the presence of the urban heat island effect. The average percentage of extremely poor individuals was 17.6%. It was found that 72.4% (63 out of 87 areas) of the UHI-affected areas had percentages of extremely poor individuals below this average (Figure 4.8). Similarly, the average percentage of poor individuals was 31.5%, and 68.97% (60 out of 87 areas) of the UHI-affected areas had percentages of poor individuals below this average (Figure 4.9).

The observed trend in Bangladesh could be attributed to the fact that the poorest populations were less likely to reside in densely urbanized regions with higher UHI effects. Instead, these populations tended to be concentrated in less developed or peri-urban areas where urban infrastructure and economic activities were less intense, resulting in lower UHI effects. These peri-urban areas often had fewer buildings, less pavement, and more green spaces, which helped mitigate the heat accumulation typically seen in urban centers. Additionally, lower-income individuals in Bangladesh might have had limited access to affordable housing in city centers, pushing them to settle in outskirts where land and living costs were lower.

In contrast, in the USA, poor populations were more likely to reside in densely urbanized areas with higher UHI effects. (Voelkel et al., 2018c) found that groups with limited adaptive capacity, including those in poverty, were at higher risk for heat exposure, suggesting an emerging concern of environmental justice in Portland, Oregon. (Hsu et al., 2021c) also found that people living in households below the poverty line experienced higher SUHI (Surface Urban Heat Island) intensity compared to those at more than two times the poverty line across major cities in the USA. This trend could be attributed to several factors. Urban centers in the USA often provided better access to employment opportunities, public services, and transportation, making them more attractive to low-income residents despite the higher living costs and increased heat exposure. Furthermore, historical housing policies and socio-economic segregation might have resulted in poorer communities being situated in more industrialized and built-up areas, where the UHI effect was more pronounced.

This discrepancy between Bangladesh and the USA might have been due to differences in urban development patterns, economic structures, and housing policies. In Bangladesh, rapid urbanization and inadequate urban planning could have led to more affluent populations occupying city centers, while the poor were pushed to less developed outskirts. Conversely, in the USA, historical factors such as redlining, economic disparities, and zoning laws contributed to the concentration of low-income populations in urban centers with significant UHI effects.

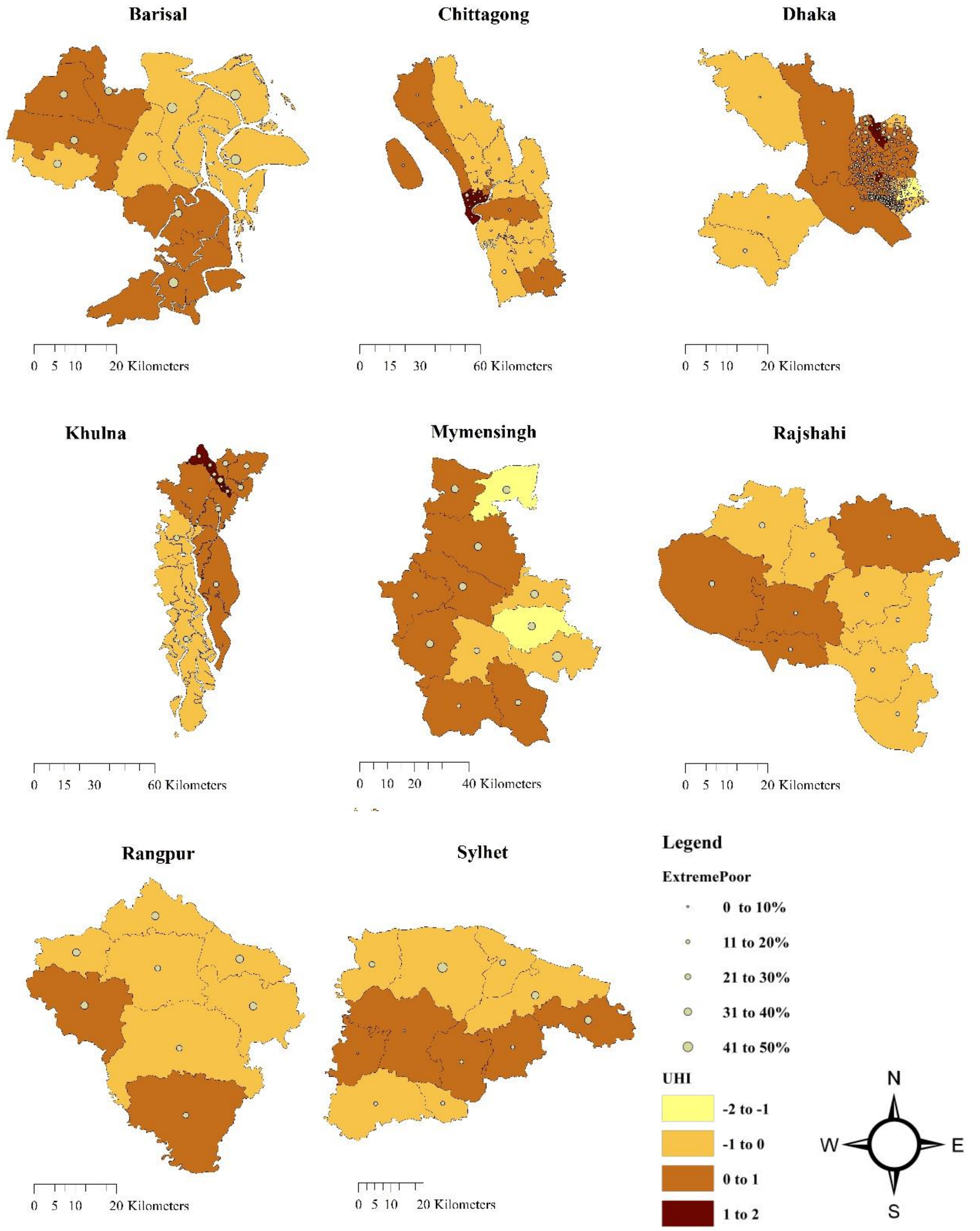

Figure 4.8: Distribution of UHI by %Extreme Poor in Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet

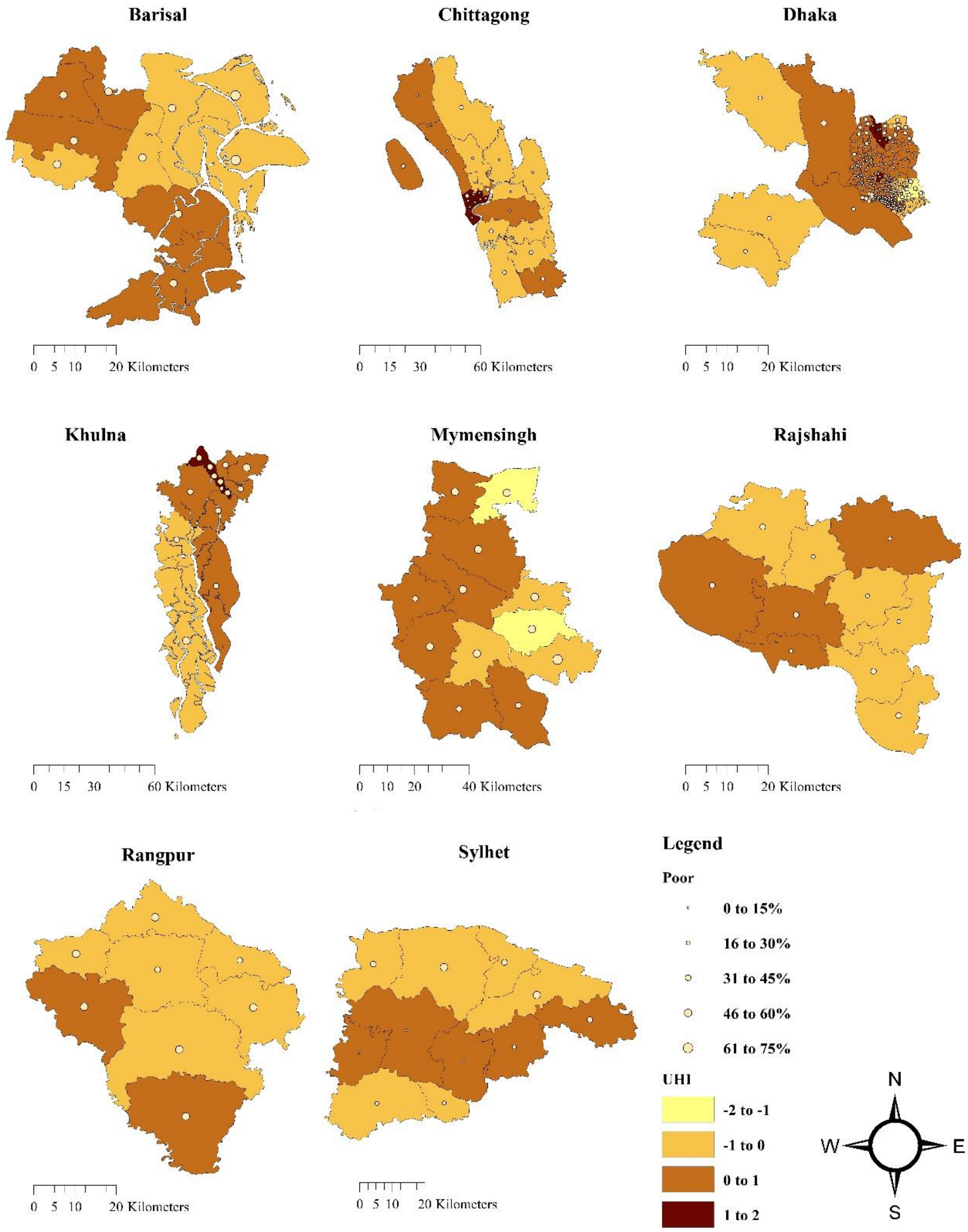

Figure 4.9: Distribution of UHI by %Poor in Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet

On the other hand, despite the average literacy rate being 51.8%, 71.3% (62 out of 87 areas) of UHI-affected areas had literacy rates above this average (Figure 4.10). This meant that most areas with higher temperatures had higher levels of literacy, which contrasted with the trend observed for poverty rates.

This trend in Bangladesh could be attributed to the concentration of educational institutions and resources in more urbanized areas. Urban centers, which typically experienced higher UHI effects due to dense infrastructure and reduced green spaces, often had better access to schools, colleges, and universities. These areas also tended to offer more opportunities for educational attainment and career development, attracting populations with higher literacy levels. Furthermore, urban areas usually had better economic opportunities, attracting individuals and families who prioritized education and could afford better schooling for their children. Higher literacy rates in these regions could also be linked to governmental and non-governmental programs focusing on improving education in cities, where implementation was more feasible due to better infrastructure and accessibility. In contrast, rural or peri-urban areas, which may have had lower UHI effects, often faced challenges such as limited access to quality education, fewer schools, and higher dropout rates. Economic constraints and the need for children to contribute to household income could further hinder educational attainment in these areas. As a result, these regions might have had lower literacy rates despite experiencing less urban heat island effect.

Overall, the higher literacy rates in UHI-affected areas in Bangladesh highlighted the role of urbanization in providing better educational opportunities, even as these areas contended with higher temperatures and associated urban heat island effects.

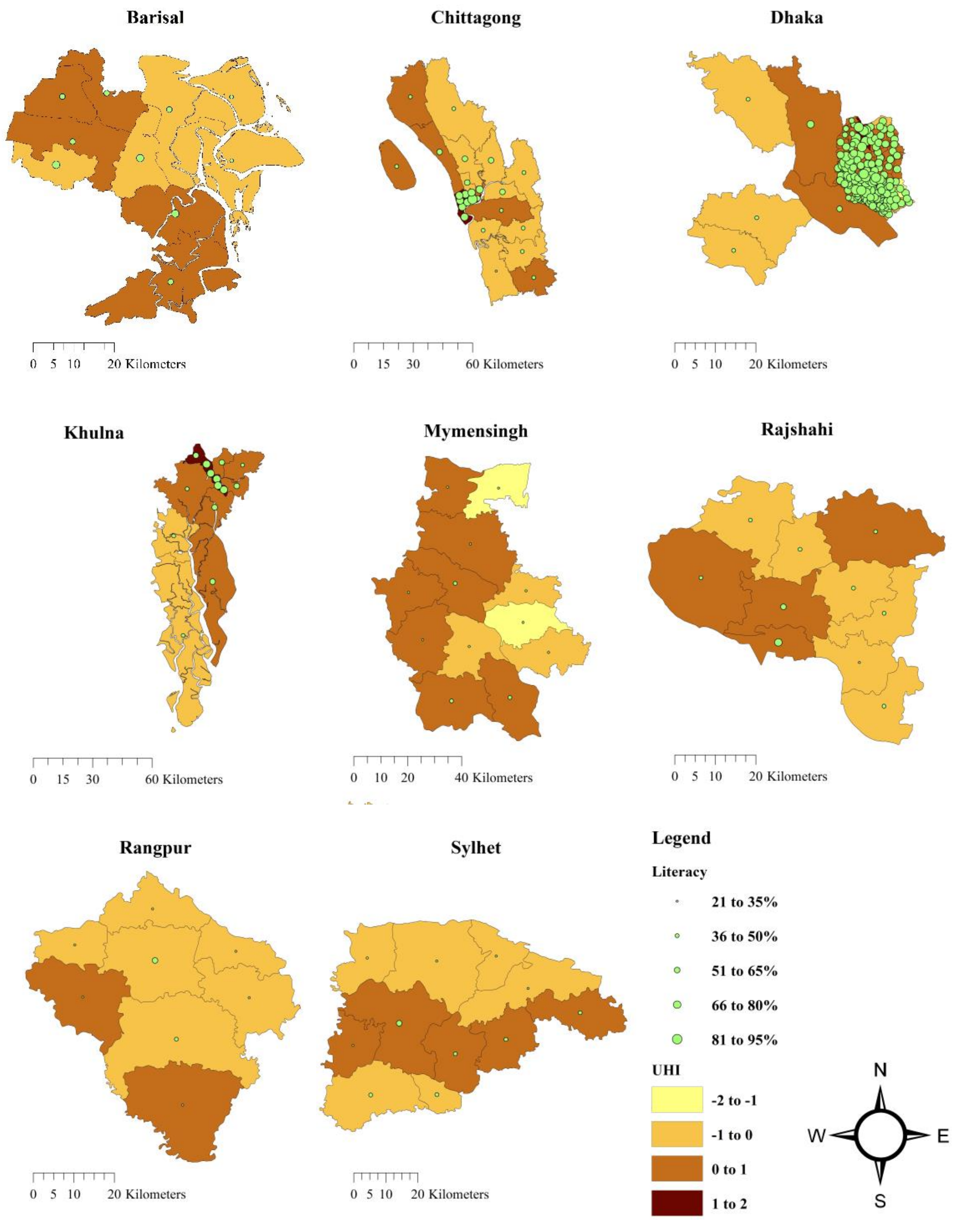

Figure 4.10: Distribution of UHI by %Literacy in Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet

Additionally, the study found that the average percentage of vulnerable people (0-4 and 65+ age range) was 13.73%, with 65.5% (57 out of 87 areas) of UHI-affected areas having percentages of vulnerable people below this average (Figure 4.11).

(Hsu et al., 2021c) had considered vulnerability factors such as age, noting that both very young and older populations are more susceptible to heat-related illness and death due to compromised thermoregulation and other health conditions in major cities of the USA. In the USA, vulnerable populations such as the very young and the elderly tended to reside in densely urbanized areas with higher UHI effects, primarily due to better access to healthcare, social services, and employment opportunities. Additionally, urban areas offered a wide range of amenities and support networks that attracted families, despite the elevated temperatures associated with UHI effects, emphasizing the complex interplay between socio-economic factors and vulnerability to heat-related risks.

However, the result observed in this study for Bangladesh contradicted this. These findings could be understood by several factors. In the context of Bangladesh, vulnerable populations might have been less likely to reside in densely urbanized areas with higher UHI effects. This could be because urban areas in Bangladesh were likely to have had better economic and educational systems. People aged 65+ were not typically involved in economic activities and work, so they might have chosen to move to less dense areas with better greenery and a quieter environment. Similarly, very young people aged 0-4 did not yet require formal education, so their families might have prioritized living in areas with lower population density and better access to natural surroundings.

In urban areas, the focus on economic activities and educational opportunities might not have aligned with the needs and preferences of vulnerable populations, leading them to concentrate in rural or peri-urban areas where they could enjoy a better quality of life despite potential heat-related risks. In such areas, although the UHI effects might be lower, vulnerable populations may face other challenges related to access to healthcare, social services, and infrastructure resilience.

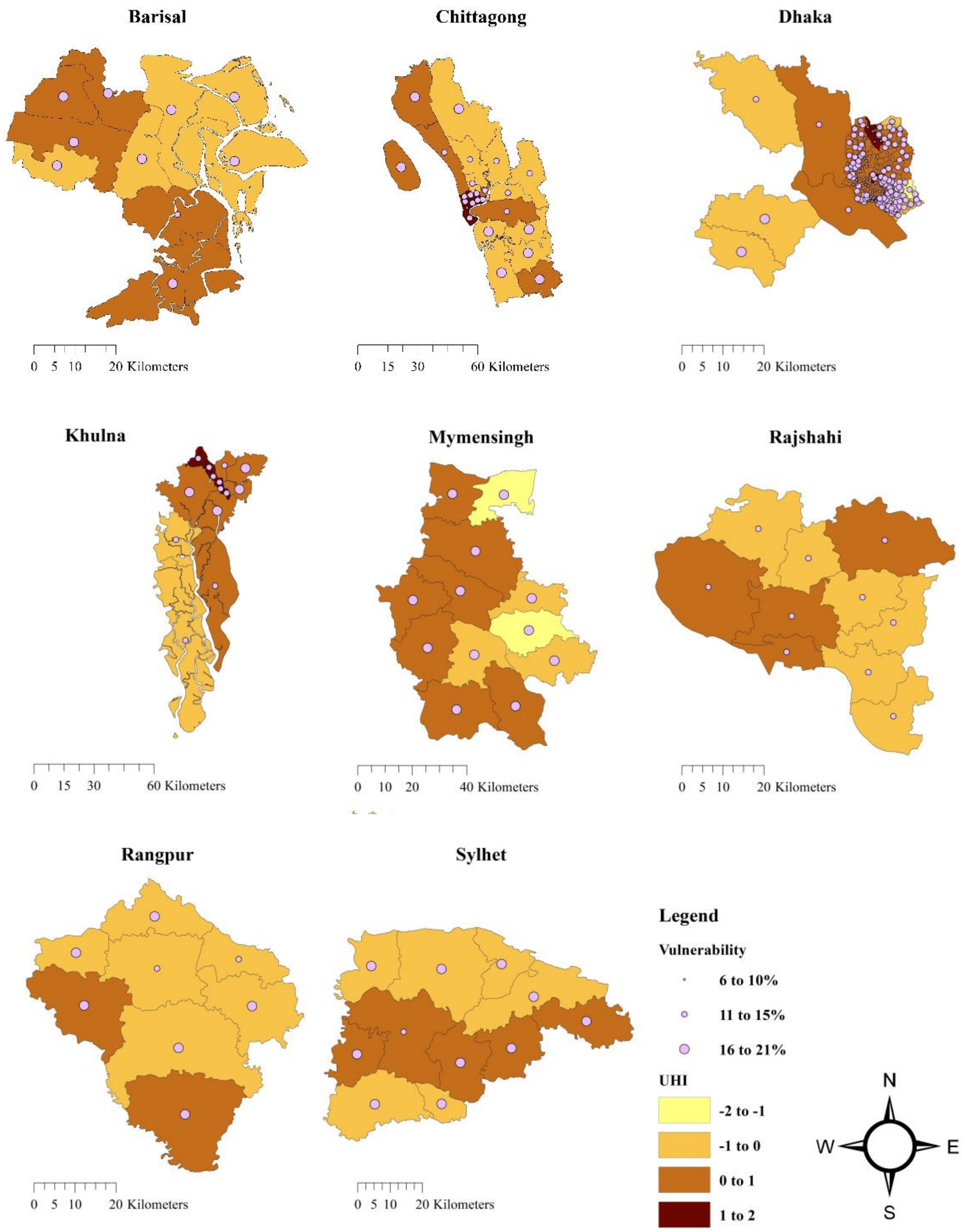

Figure 4.11: Distribution of UHI by %Vulnerable People in Barisal, Chittagong, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet

4.5 Summary

The study explores the distribution of Urban Heat Island (UHI) effects across districts in Bangladesh, uncovering significant variations in UHI and socio-demographic factors such as poverty, literacy, and vulnerability to heat-related health issues. Through thorough statistical analysis and visualization techniques, it reveals the complex relationship between UHI intensity and socio-demographic variables. From the correlation coefficient (r), it was observed that there was a negative relation between UHI and extreme poor (r=-0.36), UHI and poor (r=-0.35), and UHI and vulnerable people (r=-0.47). Additionally, there was a significant positive correlation between UHI and literacy (r=0.4). The higher UHI intensity locations tend to have lower poverty rates and fewer vulnerable individuals, but a higher proportion of literate persons.

CHAPTER 5

Conclusions and Future Works

5.1 Conclusions

This study provides a comprehensive analysis of the Urban Heat Island (UHI) effect in 135 urban areas of Bangladesh, focusing on UHI variations and their correlation with socio-demographic status. The findings reveal:

1. UHI effects are widespread in 87 areas, indicating substantial urban heat concerns.
2. Significant negative correlations were observed between UHI intensity and levels of extreme poverty (r=-0.36), general poverty (r=-0.35), and the percentage of vulnerable populations (r=-0.47), suggesting poorer areas experience less UHI intensity.
3. A positive correlation was observed between UHI intensity and literacy rates (r=0.48), indicating that more educated areas, which are likely more developed, experience higher UHI effects.

5.2 Recommendations for Future Works

Future studies should use data collected over time to understand how UHI (Urban Heat Island) effects change and develop. Researchers should gather more detailed data at smaller levels, like neighborhoods or blocks, to see finer variations in UHI impacts. Primary data collection, such as taking local temperature measurements and conducting detailed surveys, would improve data accuracy and completeness. It is also important to examine how different types of urban features, like parks, water bodies, and building materials, contribute to UHI effects. Including other factors like humidity, wind patterns, and air pollution would provide a more complete picture of urban heat impacts. Overall, future research should aim to create strong, data-driven plans to reduce UHI effects and improve urban resilience.

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APPENDIX

Appendix B

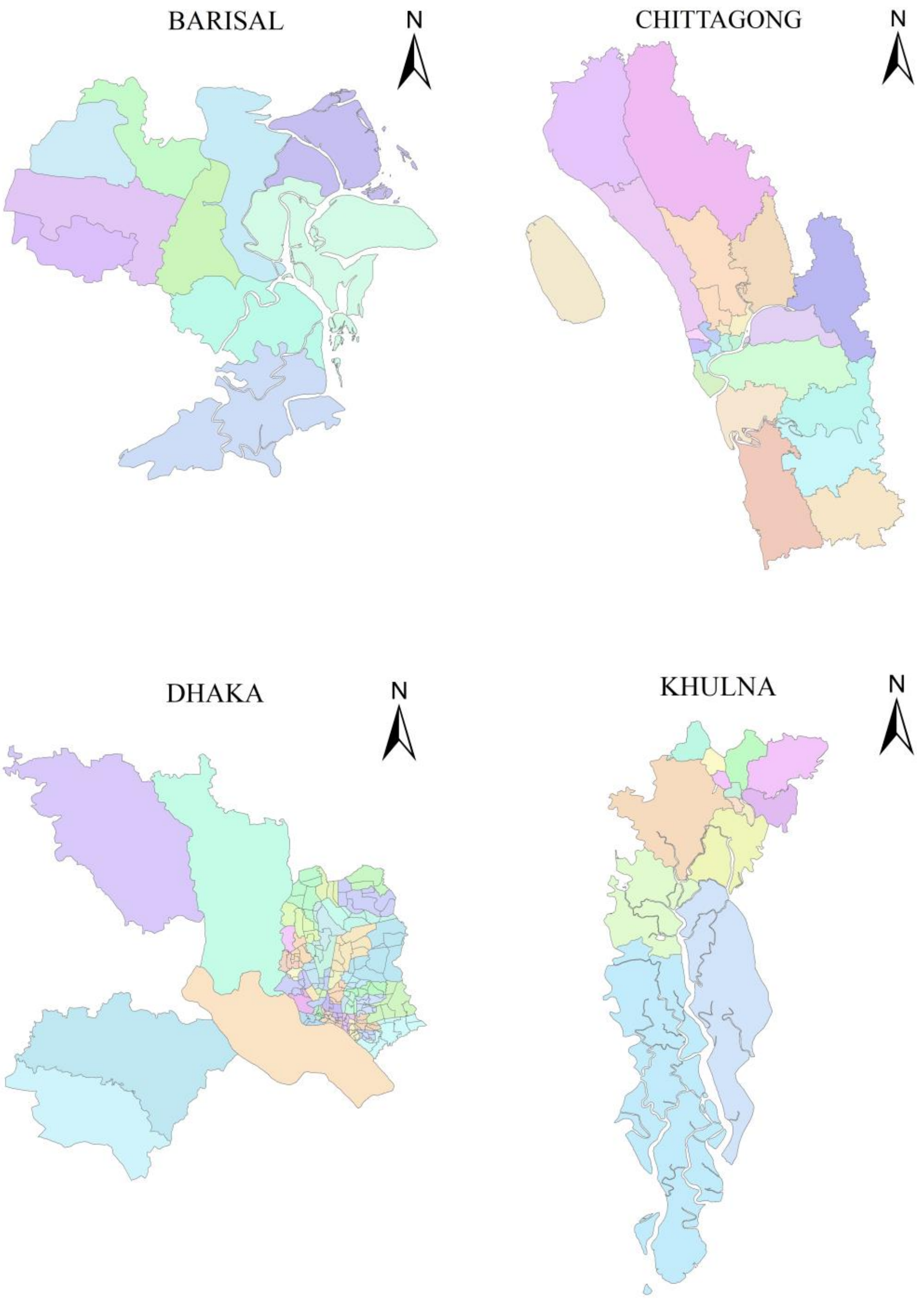


Figure B.1: Administrative boundaries of thanas of Dhaka, Chittagong, Barisal and khulna

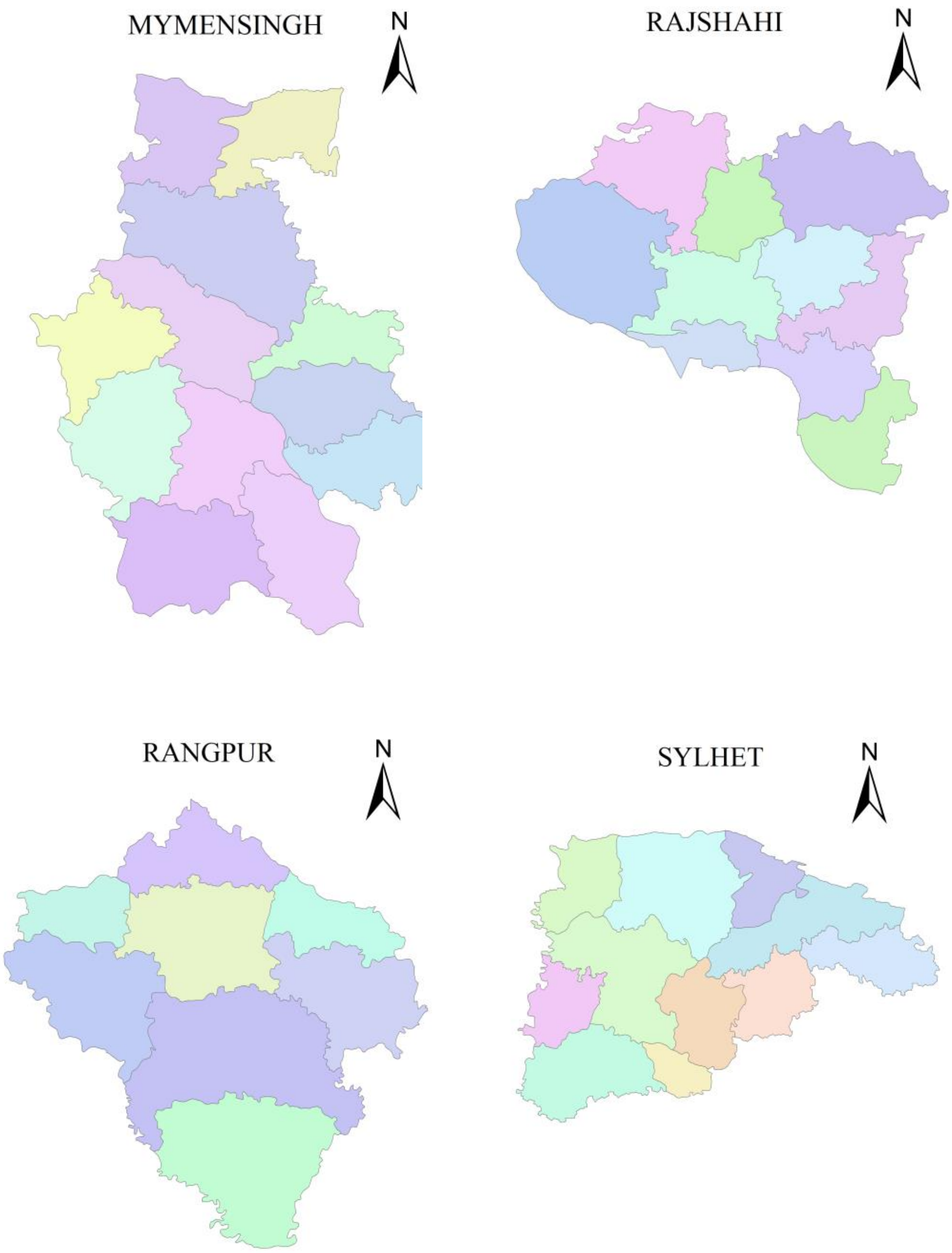


Figure B.2: Administrative boundaries of thanas of Sylhet, Rajshahi, Rangpur and Mymensingh

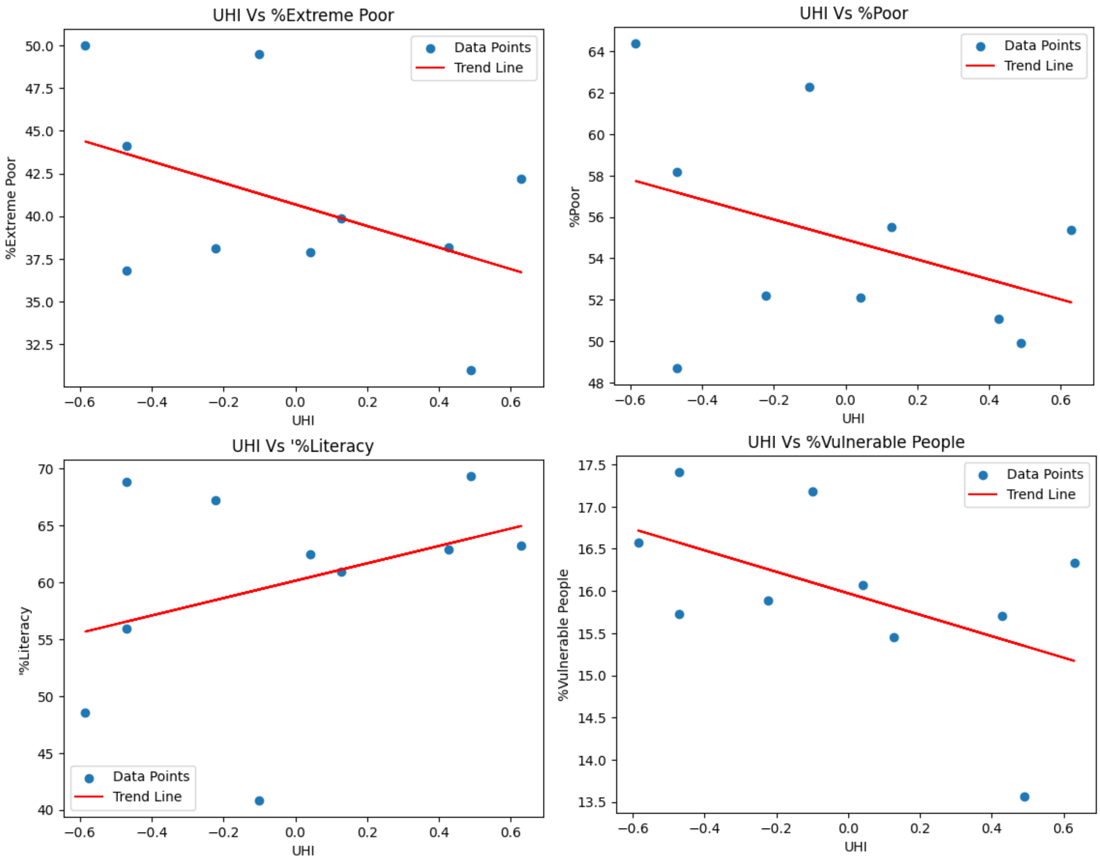
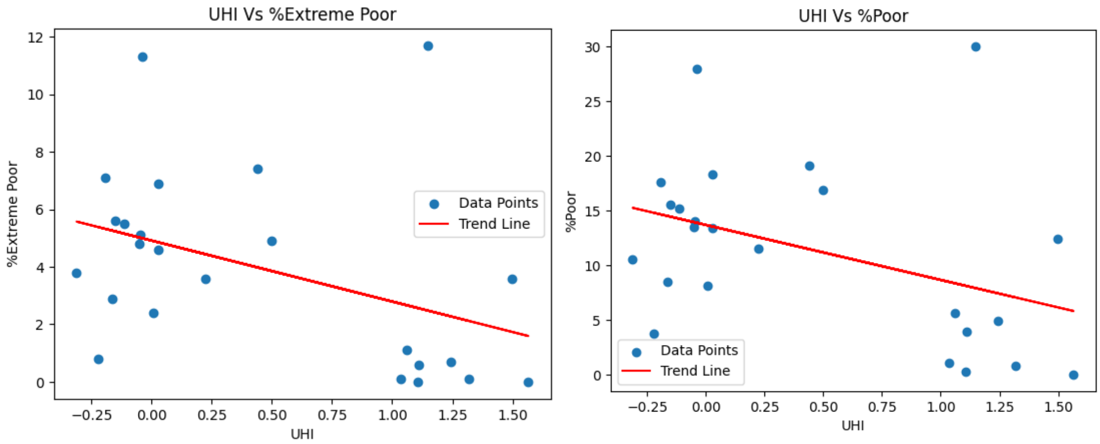


Figure B.3: Scatter Plots with Trend Line of Barisal UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People



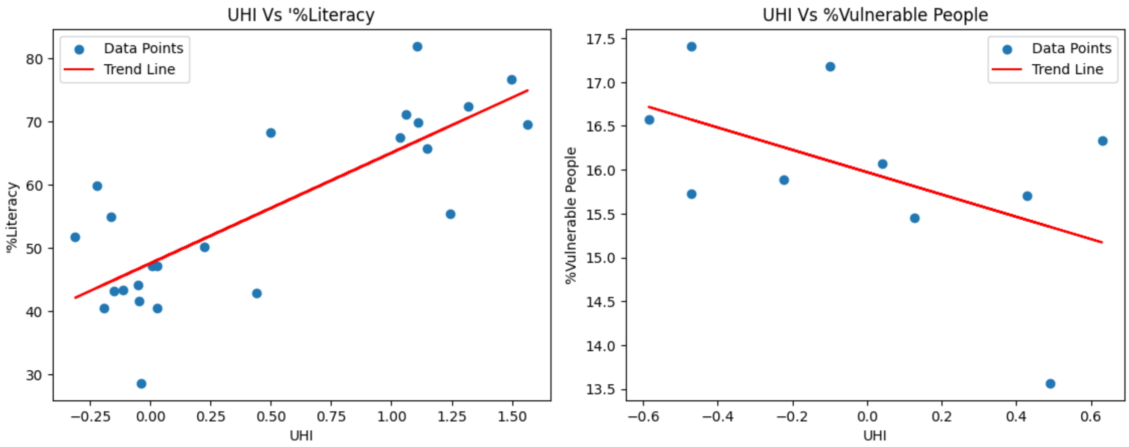


Figure B.4: Scatter Plots with Trend Line of Chittagong UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People

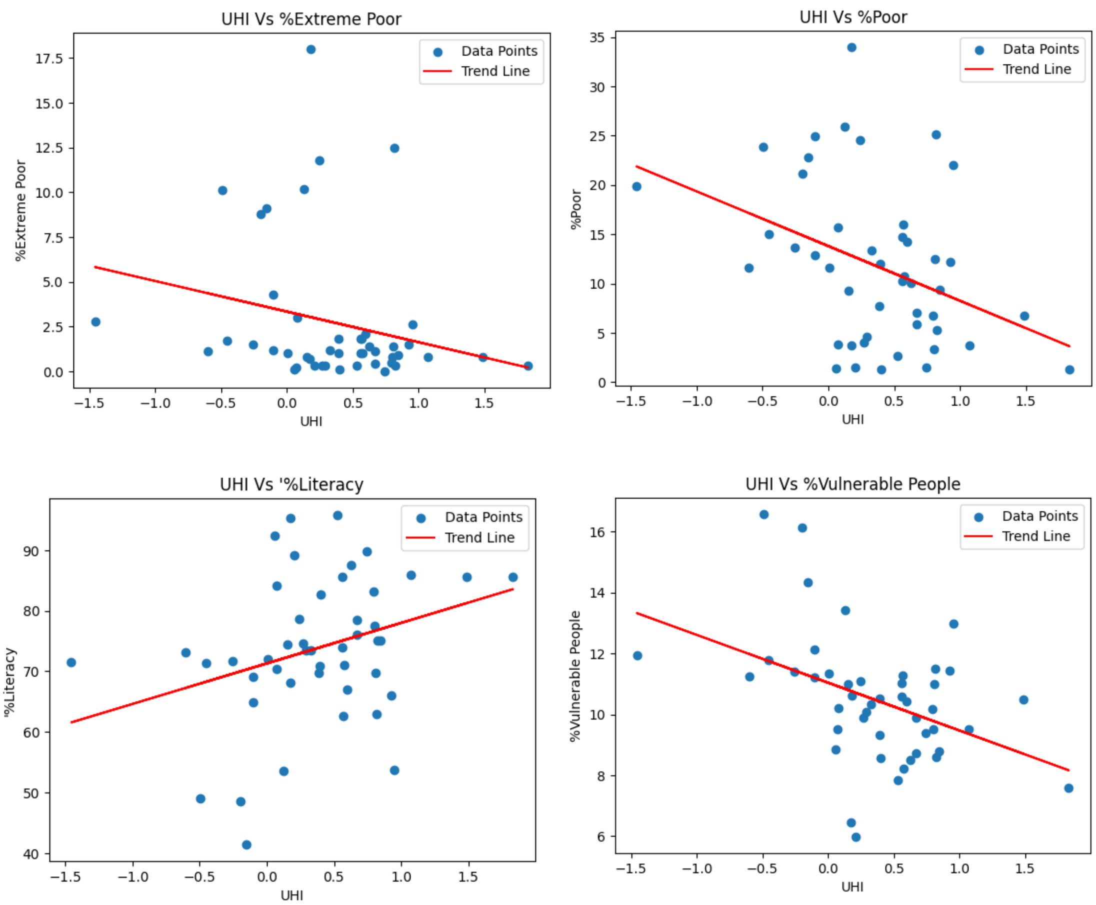


Figure B.5: Scatter Plots with Trend Line of Dhaka UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People

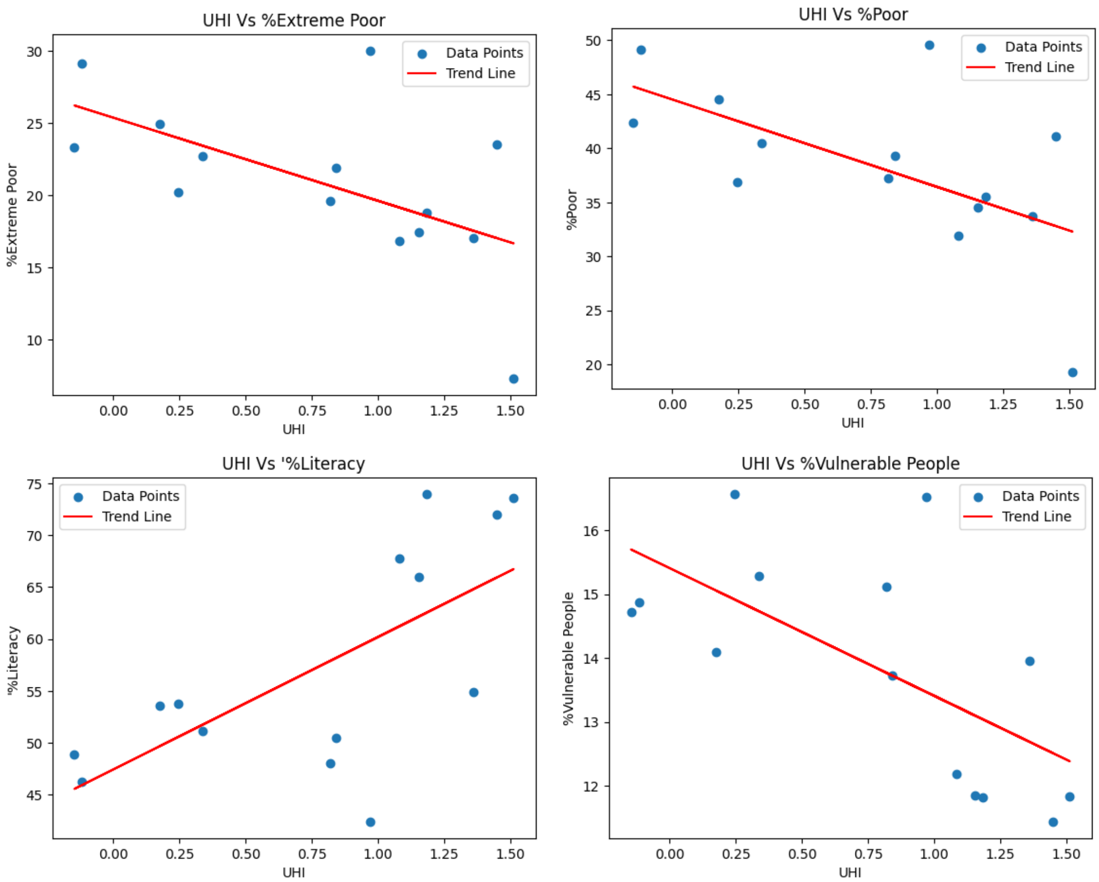
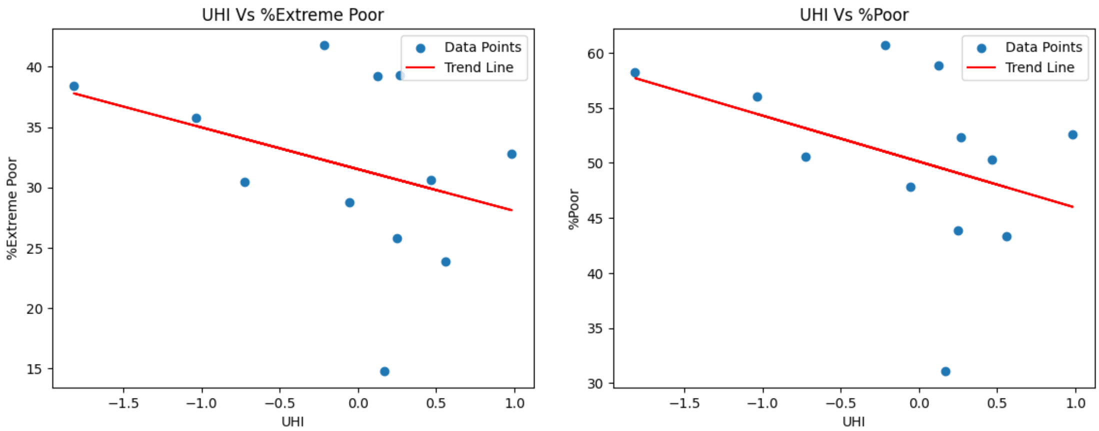


Figure B.6: Scatter Plots with Trend Line of Khulna UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People



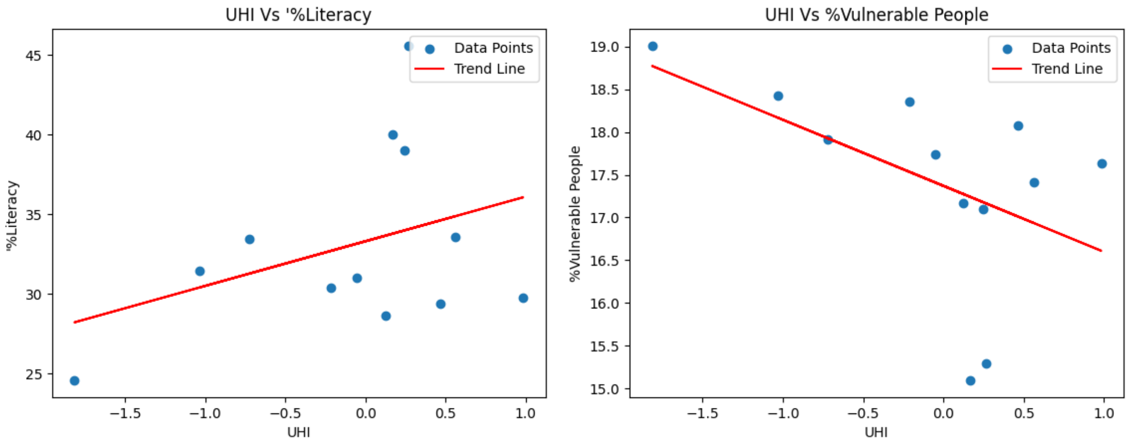


Figure B.7: Scatter Plots with Trend Line of Mymensingh UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People

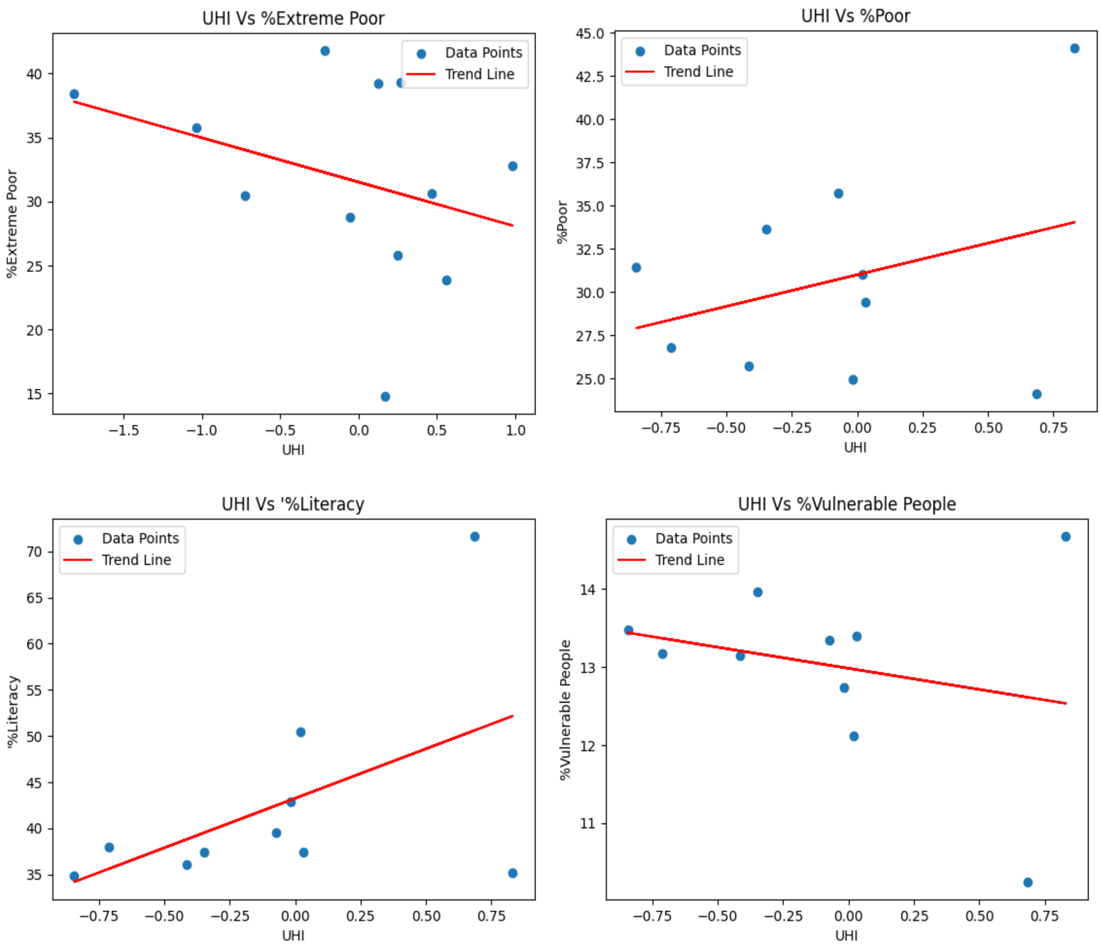


Figure B.8: Scatter Plots with Trend Line of Rajshahi UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People

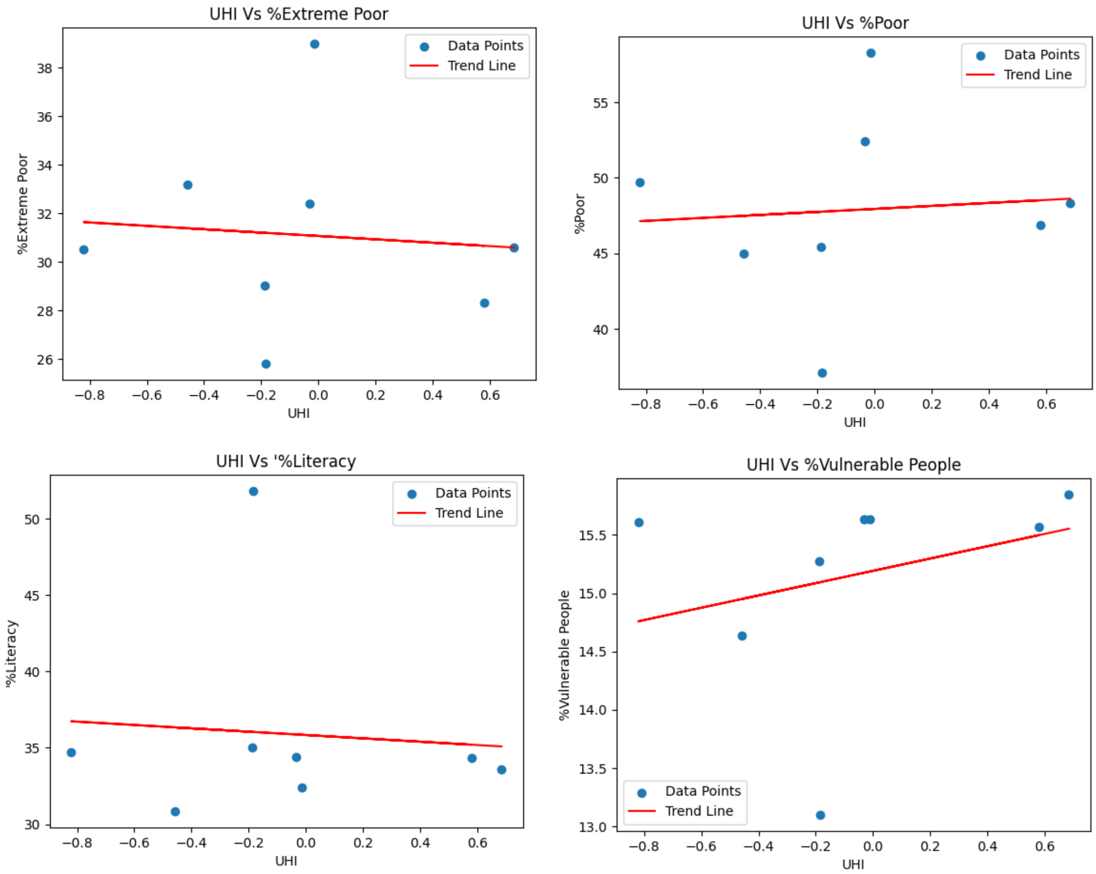
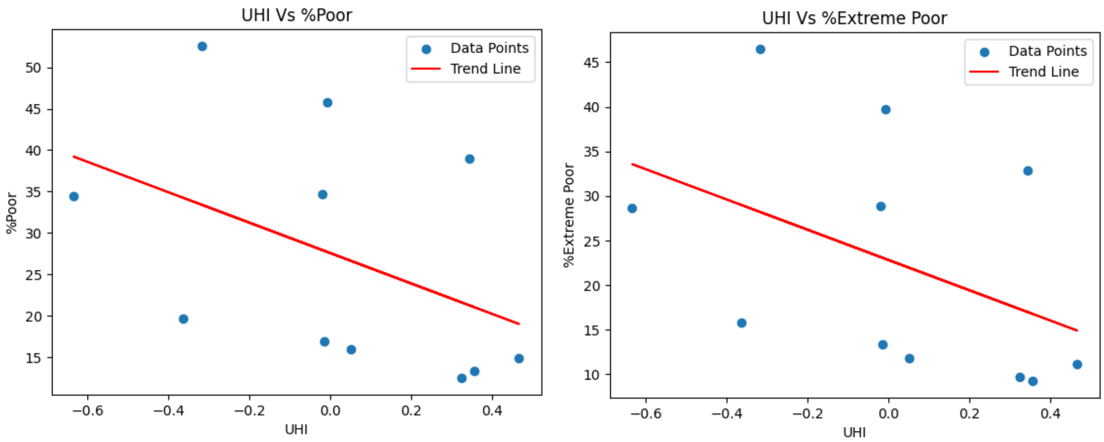


Figure B.9: Scatter Plots with Trend Line of Rangpur UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People



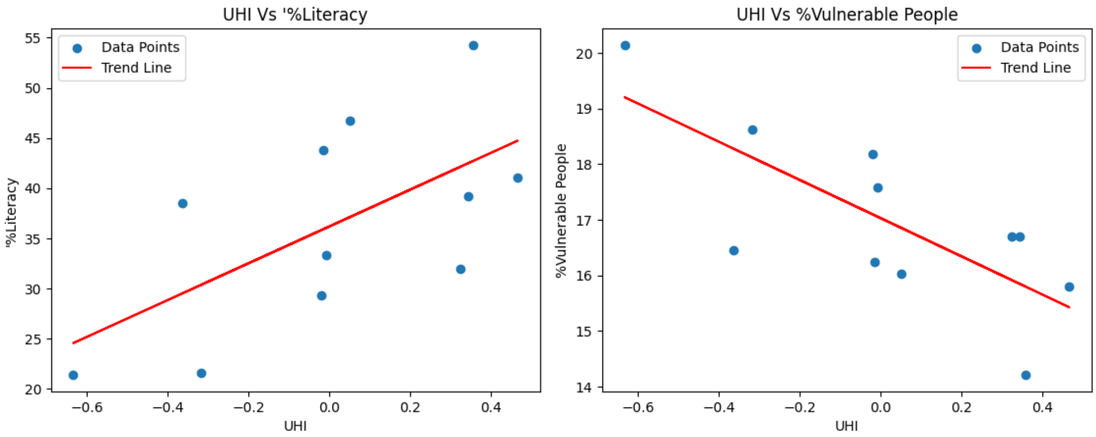


Figure B.10: Scatter Plots with Trend Line of Sylhet UHI vs %Extreme Poor, UHI vs %Poor, UHI vs %Literacy and UHI vs %Vulnerable People