Masters Program in **Geospatial Technologies**

Temporal Analysis of Land Surface Temperature for Urban Heat Island Detection in Thimphu, Bhutan

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TEMPORAL ANALYSIS OF LAND SURFACE TEMPERATURE FOR URBAN HEAT ISLAND DETECTION IN THIMPHU, BHUTAN

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TEMPORAL ANALYSIS OF LST FOR URBAN HEAT ISLAND DETECTION IN THIMPHU, BHUTAN

ABSTRACT

Climate change is a matter of considerable global importance, as evidenced by the increased urban surface temperatures in developed and undeveloped areas. Hence, this study aims to analyze the threshold and index of the urban heat island (UHI) phenomenon within the urban region of Thimphu, Bhutan. This study conducts a temporal analysis of the Normalized Difference Vegetation Index (NDVI), Normalized Different Buildup Index (NDBI) and Land Surface Temperature (LST) to detect Urban Heat Islands (UHIs) in Thimphu, Bhutan. The research focuses on assessing changes in vegetation cover and surface temperatures over time to identify and understand the patterns of UHI development in urban areas. This has potential benefits for urban planners involved in urban planning and management, as well as for increasing public awareness regarding the urban heat island effect.

Advancements in thermal remote sensing, GIS, and statistical techniques have facilitated the monitoring of LST and its association with Land Use and Land Cover (LULC). To investigate this connection, supervised classification, and change detection were conducted to ascertain the spatial trends in LULC changes. Subsequently, the spatial distribution of LST was acquired using the thermal band of Landsat imagery. Regression analysis was then applied to investigate the link between surface temperature and various land surface characteristics, including both types of land use and land cover, as well as associated indices.

In summary, this analysis contributes to the broader understanding of urbanization impacts on the local climate and provides valuable insights for sustainable urban planning and climate mitigation strategies in Thimphu, Bhutan.

KEYWORDS

1. Land use land cover.
2. Land Surface Temperature
3. Landsat
4. Regression analysis
5. Thermal Remote Sensing
6. Urban Growth
7. Urban Heat Island

ACRONYMS

1. GIS Geographic Information System
2. LST Land Surface Temperature
3. LULC Land use land cover
4. NDBI Normalized Difference Built-up Index
5. NDVI Normalized Difference Vegetation Index
6. NDWI Normalized Difference Water Index
7. UHI Urban Heat Island
8. WGS 84 World Geodetic System 84
9. GEO SAM Geo Segment Anything Model

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INTRODUCTION

1.1. BACKGROUND AND MOTIVATION

Urbanization is currently a prominent worldwide phenomenon, particularly accelerating at a concerning pace in developing nations. This surge leads to an increase in cities in terms of both quantity and scale across the globe. Urban expansion is a developmental progression that unfolds gradually, as cities and their surrounding areas extend into adjacent rural landscapes. This expansion is predominantly driven by population growth, reflecting a global trend of thousands of individuals relocating to urban centers each year(Cohen 2004).

Urban expansion involves the conversion of natural land covers into developed areas(Radwan et al. 2019). Urban expansion leads to a reduction in green spaces within cities, resulting in a rise in impermeable surfaces. This transformation induces significant alterations in the patterns of land use and land cover in urban areas. With the continuous progression of urban growth, research focused on understanding the mutual effects of these changes is becoming increasingly crucial(Amin and Graham 1997). The expansion of urban areas negatively affects land surface attributes, particularly its thermal properties. This heightened thermal storage capacity gives rise to the phenomenon known as the urban heat island (UHI) effect. This effect manifests as higher temperatures in urban regions compared to rural areas, making it a significant area of investigation within urban climate and environmental research (Abulibdeh 2021). The Urban Heat Island (UHI) arises from alterations to the land surface that promote heat retention and confinement, such as a decrease in vegetation cover. Additionally, it is influenced by the release of Human-caused heat from sources like vehicles, industries, and buildings (Phelan et al. 2015). This is a critical environmental concern that can have detrimental effects on both humans and the environment (Brtnicky et al. 2021). It leads to air quality deterioration, impacts the local climate, enhances the production of ground-level ozone, and ultimately has an impact on our overall well-being (Almetwally, Bin-Jumah, and Allam 2020). Hence, the topic of urban expansion and the Urban Heat Island (UHI) phenomenon has garnered interest from ecologists, urban planners, sociologists, administrators, policymakers, and ultimately, the inhabitants of urban areas (Masson et al. 2020). Many investigations encompass a diverse array of UHI-related subjects, including the impact of urban landscapes and land use and land cover changes on the UHI phenomenon, the spatiotemporal variation of UHI, the correlation between UHI and LULC indices, UHI modeling and simulation, the influence of UHI on heat waves and human well-being, and potential strategies to alleviate its effects. These studies offer a significant contribution to researchers and policymakers engaged with the UHI phenomenon (Yang et al. 2017).

Bhutan is experiencing rapid urbanization, marked by a growth rate of 5.7% from 2000-2010, the highest in South Asia(Ellis, Peter and Roberts, Mark 2015). This urbanization is driven significantly by rural-urban migration, resulting in challenges to meet the increasing demand for livable spaces and demanding changes in land morphology and infrastructure development. Despite being the only carbon-negative country with substantial forest coverage (71.7%), maintaining this status is becoming challenging due to the imperative for economic growth(Yangka, Dorji and Newman, Peter and Rauland, Vanessa and Devereux, Peter 2018). Balancing sustainable built environment planning with socio-economic growth is crucial for achieving long-term goals such as carbon neutrality and understanding the environmental impacts of planning solutions.

Thimphu, the capital city, hosts the largest share of the public sector and constitutes 19.1% of the total population, making it the most populous city in the country. The city experienced a notable 45% population increase in 2017 compared to 2005(National Statistics Bureau of Bhutan 2018). This rapid urbanization is reshaping land use dynamics, leading to city expansion and the development of socio-economic infrastructure. The construction sector's growth resulted in a more than 50% decrease in open green spaces in 2017, and the built-up area expanded by 12.77% in 2018 compared to 2005(Wang, Lamchin, and Lee 2022). Recognizing the importance of green and blue infrastructure, the introduction of such elements is viewed as a crucial opportunity for sustainable urban development planning, offering strategic guidance in urban planning initiatives(Royal Government of Bhutan 2022).

While urban green spaces provide recreational areas for the public, there is a pressing need to enhance accessibility and distribution, as travel time to these spaces remains unequal. Moreover, public preference leans towards green spaces with abundant tree coverage, emphasizing the importance of incorporating more trees into urban green spaces(Rai, C.M., Dorji, Y. and Zangmo, S. 2022).

Land Surface Temperature (LST) is a critical component in the study of the Urban Heat Island (UHI) phenomenon. It refers to the temperature of the Earth's surface, specifically the topmost layer of soil, vegetation, and other natural or artificial features. Understanding LST is essential in comprehending the dynamics of urban areas and their impact on local climates. In urban environments, various factors contribute to fluctuations in LST. The prevalence of concrete, asphalt, and other heat-absorbing materials, coupled with limited vegetation, leads to higher temperatures. Additionally, anthropogenic activities such as industrial processes, transportation, and building energy use release heat into the environment, further elevating LST levels. The significance of monitoring LST lies in its implications for urban planning, environmental management, and public health. High LST can exacerbate heat-related health issues, increase energy consumption for cooling, and alter the overall livability of urban areas. Consequently, comprehending and mitigating the effects of elevated LST is of paramount importance in creating sustainable and resilient cities.

Researchers and policymakers frequently employ advanced technologies like thermal remote sensing and Geographic Information Systems (GIS) to measure and analyze LST patterns. By doing so, they can develop informed strategies to mitigate the Urban Heat Island effect and create urban spaces that are more conducive to the well-being of both residents and the environment (Taylor and Hochuli 2015). LST can be obtained from openly accessible data sources like Landsat, MODIS, and ASTER. The thermal band in these sensors facilitates the acquisition of data regarding the thermal characteristics of the Earth's surface, determined by the emitted energy levels. Furthermore, this data can serve the purpose of tracking changes in Land Use and Land Cover (LULC) over extended periods. Consequently, these dual capabilities empower researchers to investigate the correlation between alterations in LULC and corresponding shifts in LST over time. This development has facilitated the monitoring of the UHI effect attributable to LULC changes (Dissanayake et al. 2019).

The study highlights various algorithms used to derive LST from thermal images, including Single Channel, Split window, Mono window, and Radiative transfer equation methods. However, certain limitations apply to some of these methods. For instance, Split window relies on two adjacent thermal bands, which are not available in

Landsat 4, 5, and ETM+ images, rendering it unsuitable for these datasets. Similarly, the Radiative transfer equation method requires in-situ radio sounding, which can be logistically challenging. The Mono window method also necessitates in-situ measurements to determine parameters like effective mean atmospheric temperature, emissivity, and transmittance. The Single Channel method, while effective, demands high-quality atmospheric transmittance data, making it a complex choice. Consequently, this study opts for an image-based approach that relies solely on surface emissivity to represent brightness temperature, eliminating the need for sophisticated atmospheric profile parameters.

This study examines the expansion of urban areas within Thimphu city and investigates the variations in LST among different land use and land cover types in the region. Similar to many developing countries, Bhutan is undergoing significant urbanization, particularly in Thimphu, which stands as the most densely populated urban center experiencing rapid urban growth. Various factors contribute to this phenomenon, including the physical characteristics of the city, accessibility to public services, employment opportunities, the real estate market, population growth, political conditions, and governmental plans and policies. The physical features of the city, characterized by suitable topography for residential purposes, play a role in the escalating urbanization. Thimphu, serving as the primary economic hub of the country, offers employment opportunities and convenient access to public services. The central area of the city houses major commercial and government establishments, fostering real estate market growth. However, the effectiveness of government plans and policies related to land use is perceived to be limited, emphasizing the significance of urban growth as a crucial process in the city.

This research seeks to analyze the repercussions of urban expansion on land surface temperature within the city. Considering that LST is a pivotal factor influencing urban climate, understanding its variations is essential. Additionally, the study aims to quantify changes in LULC, providing insights into the spatial-temporal dynamics of urban growth and its environmental impacts in Thimphu.

Of all, Bhutan's unique position as a rapidly growing economy undergoing rural-to-urban migration, emphasizing its commitment to carbon neutrality and Gross National Happiness (GNH) objectives. Thus, this study would create foundational step in developing holistic and sustainable urban development strategies that align with the country's commitment to carbon neutrality and Gross National Happiness objectives.

1.2. AIM & OBJECTIVES

This research aims to analyze the impact of urban expansion on land surface temperature for the Three years: 2000. 2013 and 2020, using GIS and Remote Sensing techniques on Landsat imagery. The objectives are:

- To Assess Urban Heat Island
- To Estimate the highly heated spots in the urban centers
- To Quantify Changes in Land Surface (LULC)
- To Derive Land Surface Temperature (LST), NDBI and NDVI, and Examine Temporal Trends
- To access relationship between LST, indices and LULC
- To Provide Recommendations on procedure and outline on how to mitigate UHI

1.3 REARCH QUESTIONS

A. What is the connection between LULC changes, land-surface temperatures, NDBI and NDVI values in Thimphu, Bhutan, and their impact on Urban Heat Islands?

B. How does urbanization contribute to the Urban Heat Island (UHI) effect in Thimphu, Bhutan?

1.4. RESEARCH WORK FLOW

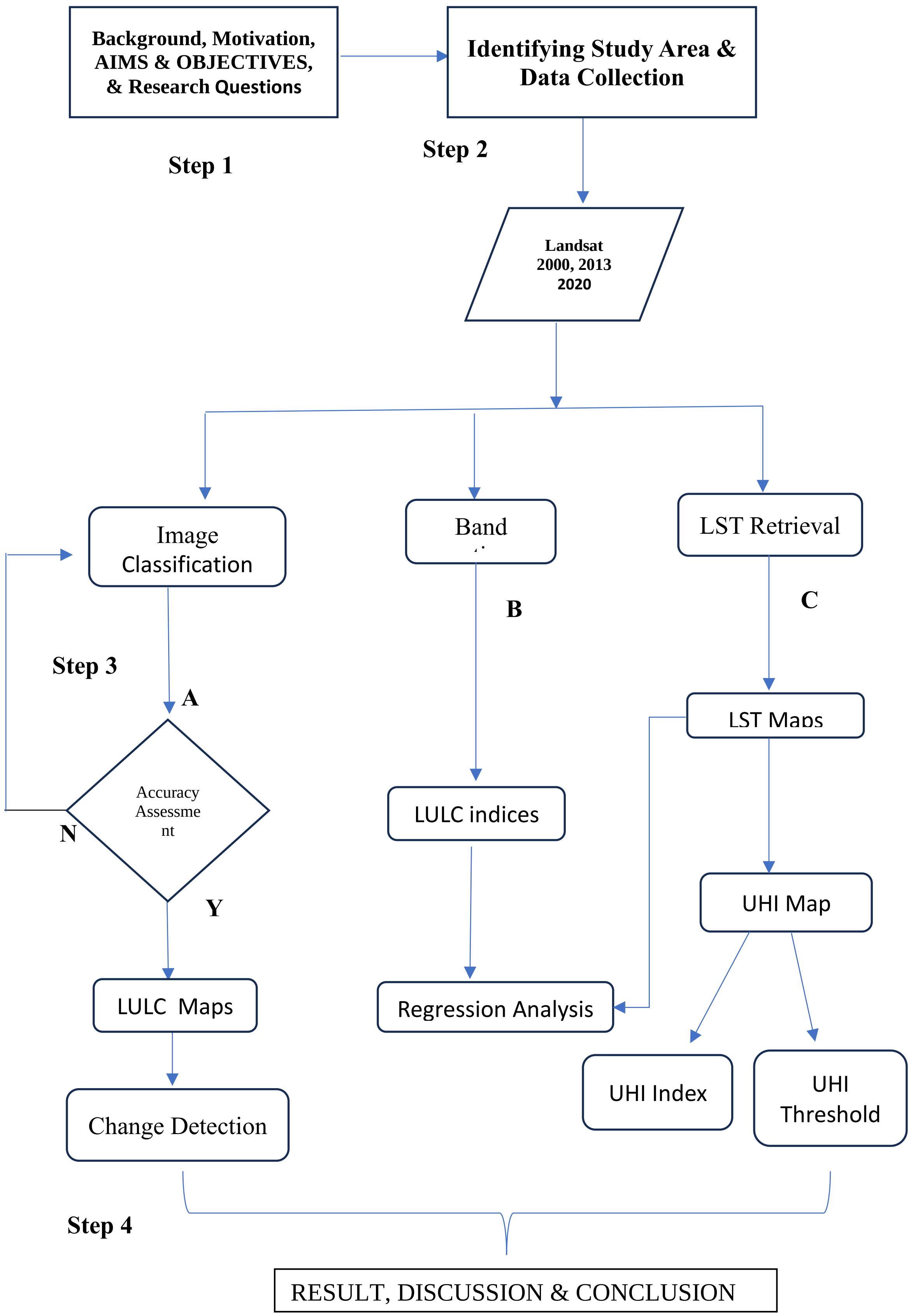

Figure 1: Research workflow

Figure 1 illustrates the overall framework of the thesis, outlining the interconnectedness among its various chapters. Step 1 introduces the research background, motivation, objectives, and research questions. Step 2 provides a concise overview of the data, software, and the study area. In Step 3, a comprehensive discussion is presented on the detailed methodology employed in the research. The findings and corresponding discussions are outlined and finally conclusion summarizing the research accomplishments, acknowledging limitations, and suggesting avenues for future work in Step 4.

2. LETERATURE REVIEW

2.1 UHI

Research on urban climate has been conducted globally, focusing on various scales such as regional, micro, local, and street levels. This exploration has become crucial due to the escalating risk and vulnerability of urban areas to climate change. Among the various facets of urban climate, the UHI phenomenon stands out as the most extensively studied field (Rasul et. al. 2017).

The rapid pace of urbanization and the absence of climate-sensitive urban planning have exposed people to the adverse impacts of climate change. The recent 6th Assessment Report from the IPCC emphasizes that the persistent threats of UHI contribute to increasing vulnerability among urban populations (IPCC, 2023). As urban areas expand through the construction of buildings, roads, and socio-economic structures, the energy balance within these areas undergoes significant alterations (Hong, Je-Woo, Hong, Jinkyu, Kwon, Eilhann E, Yoon, DongKeun, 2019). The UHI effect is influenced by the thermal environment in urban areas, leading to temperature differences of up to 10 degrees Celsius between urban and rural areas (Santamouris, M, 2001).

The inaugural investigation into UHI occurred in 1818 when Luke Howard conducted a study in London city. Howard's daily temperature measurements across the study area revealed that the temperature difference between the city and its surrounding rural areas was more pronounced in winter. This difference was attributed to the heat generated from buildings and the lack of green cover (Heisler, Gordon M, Brazel, Anthony J, 2010). Subsequently, numerous scholars have extensively explored the UHI phenomenon, establishing its close association with anthropogenic heat, surface characteristics and structure, vegetation cover, population density, and meteorological conditions (Feng, Rundong, Wang, Fuyuan, Wang, Kaiyong, Li, Li, 2021).

A UHI study in Vancouver, Canada, conducted by Ho, Hung Chak, Knudby, Anders, Walker, Blake Byron, and Henderson, Sarah B (2017), revealed a surface temperature difference of 9-12 K between urban and rural areas. This disparity was primarily attributed to the higher impervious surface presence in the urban area.

There are four distinct types of Urban Heat Island (UHI): Surface UHI (SUHI/UHIsurf), Canopy-level UHI (CUHI/UHIucl), Boundary Layer UHI (UHIubl), and Substrate UHI (UHIsub). Among these, SUHI and CUHI are the most extensively studied UHI types (Wang, Jing and Zhou, Weiqi and Zhao, Wenhui 2023). UHIubl corresponds to the air temperature above building heights, while UHIsub corresponds to the soil temperature below the ground surface. SUHI is based on the temperature of urban surfaces such as the ground, walls, and rooftops. On the other hand, CUHI is based on near-surface air temperature below the building roof height(Ghosh, Sukanya and Kumar, Deepak and Kumari, Rina 2022). The extent of CUHI is closely tied to urban surface properties, including the thermal characteristics of the urban fabric, the presence of vegetation, sky view factor, and heat generated from buildings(Azevedo, Juliana Antunes and Chapman, Lee and Muller, Catherine L 2016). Figure 1 provides a visual representation of the various types of UHI.

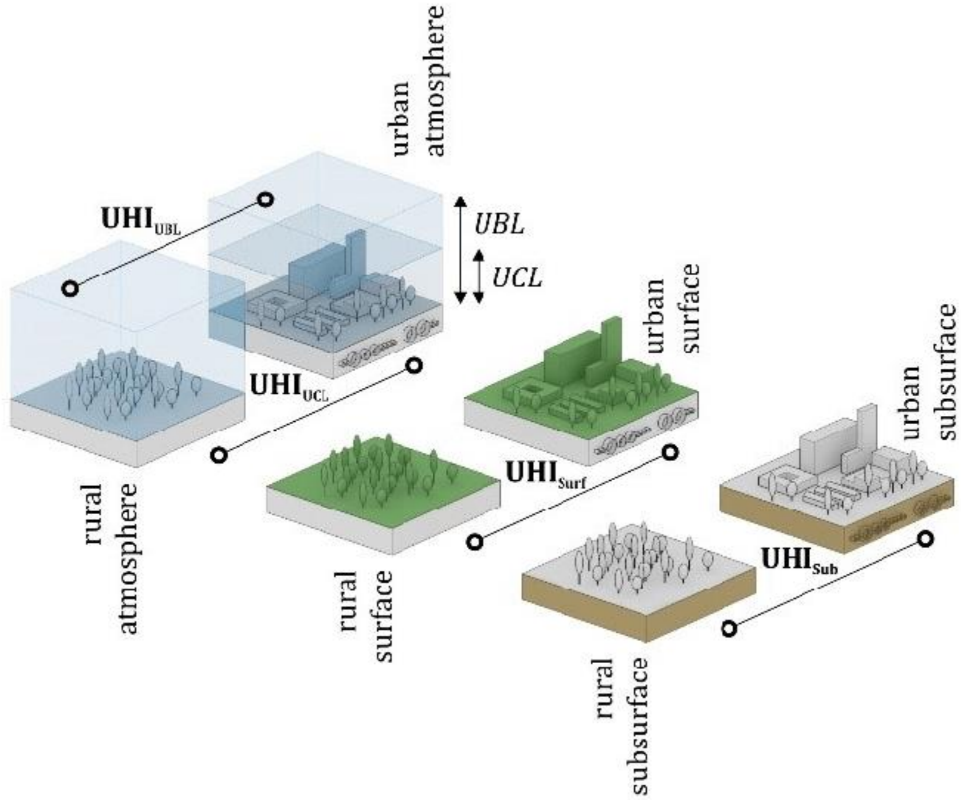

Figure 2: UHI types (Source: Authors, with modifications based on Oke, 2017 (Oke, Mills, Christen, Voogt, 2017))

The typical way to identify Surface Urban Heat Island (SUHI) is through remote sensing, while Canopy-level Urban Heat Island (CUHI) is usually determined using direct measurements from field weather stations or traverse measurements. Studies on CUHI, conducted with both fixed and mobile stations, have indicated that its intensity is higher in rural areas compared to urban areas, particularly during calm nights with clear skies(Ramakreshnan al- 2018 n.d.). SUHI is primarily examined using satellite platforms to measure Land Surface Temperature (LST), which exhibits significant spatial variation with higher magnitudes during daytime(Sismanidis, Panagiotis and Bechtel 2022). Remote sensing offers spatial extents to SUHI at city or regional scales (Zhou, Decheng and Xiao Al 2018) using imagery from satellites like Landsat, Sentinel, MODIS, etc. Landsat's thermal imagery sensors, with a spatial resolution of 30m pixels, are particularly well-suited for studying the daytime urban thermal environment(Chen, Yang and Yang Al 2022 n.d.).

2.2 SURFACE UHI

In the realm of urban climate studies, thermal infrared (TIR) remote sensing techniques have been predominantly utilized for analyzing Land Surface Temperature (LST) and its fluctuations across different surface types, evaluating Urban Heat Island (UHI), and underscoring LST as a crucial indicator of Surface Urban Heat Island (SUHI) (Bechtel et al., 2019; Ferreira and Duarte, 2019; Weng, 2009). Voogt and Oke (2003) concentrated on the fundamental principles of thermal remote sensing and concluded that LST holds the potential to be a significant parameter for urban climate studies. Beyond urban climate research, LST finds applications in agriculture, disaster risk studies, and UHI investigations (U.S. Geological Survey, 2023).

LST is defined as the radiative skin temperature of the land surface, measured in Kelvin by sensors, and is typically associated with LULC characteristics (Weng, 2009; Bokaie et al., 2016), including the composition of vegetation, water, and built-up patterns (Tian et al., 2019; Zeng et al., 2015). Chen et al. (2006) explored the UHI intensity with temporal and spatial variations in LST in the Pearl River Delta in Guangdong Province, southern China. Their findings indicated a reduced UHI attributed to vegetation intensity, moisture content, and vegetation cover, in contrast to higher UHI observed in built-up areas.

3 DATA & STUDY AREA

3.1 STUDY AREA

Thimphu, the capital of Bhutan is located in the Northwest at an altitude of 2320 meters above sea level. The urban area of Thimphu lies in the city surrounded by forests. River Wang Chhu flows through the Thimphu city. The river originates in the north from snow and glaciers, and it flows south-easterly through west-central Bhutan. The study area is shown in Figure 1. Befitting its role as the capital of a small Himalayan country, Thimphu stretches along the banks of the Wangchu river ("chu" means "river" in the national language, Dzongkha) at an average elevation of 7700 to 8000 feet with average temperature in peak -1.1 and maximum of 28 C and in summer minimum is 16 C to

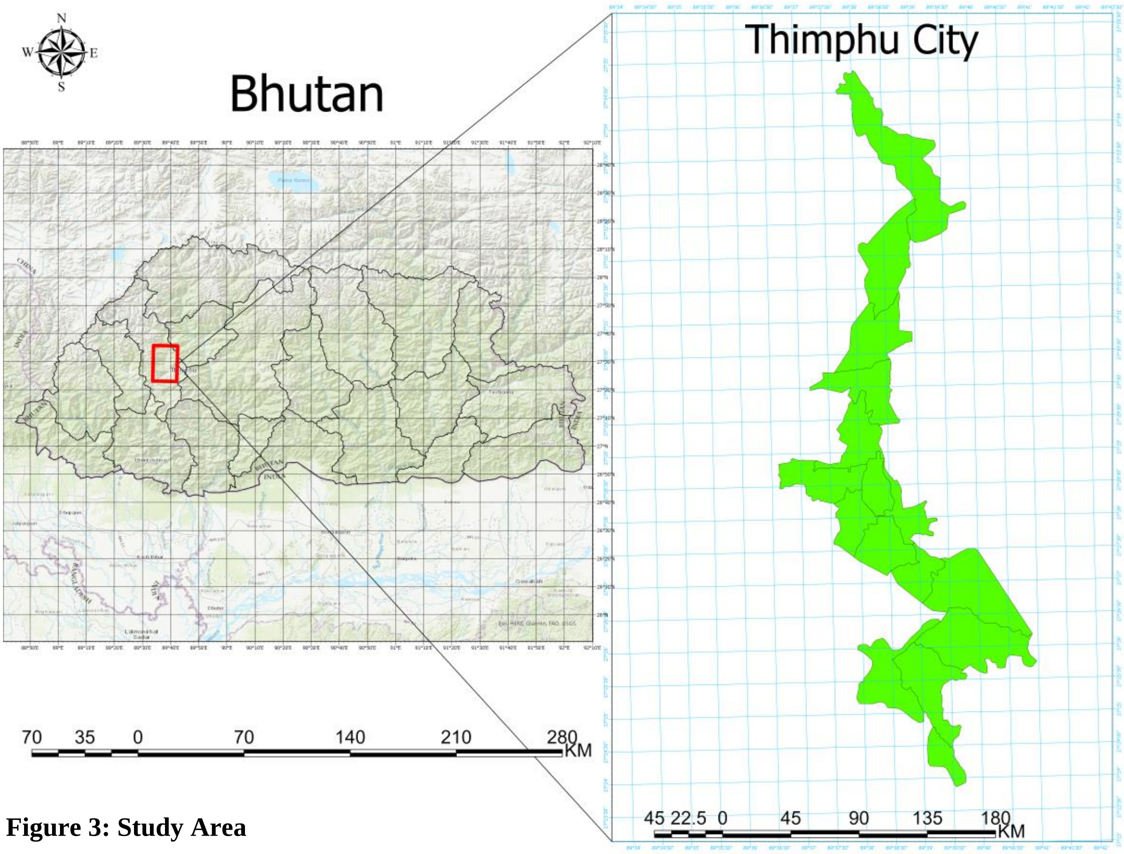

Figure 3: Study Area

maximum of 30 C. The city is generally located at 27 29N latitude and 89 36E longitude. Most of the city occupies the left side of the Wangchu, with the main market and some small industries such as woodworking shops on the right side.

3.2 DATA

The primary data utilized in this study consists of Landsat satellite imagery, specifically Landsat 7 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI),

Table 1: Details of Images used.

Data	Resolution (M)	Bands	Bands Name	Source
Landsat 8 OLI_TIRS	30	1	Ultra-blue	USGS
	30	2	Blue	
	30	3	Green	
	30	4	Red	
	30	5	NIR	
	30	6	SWIR 1	
	30	7	SWIR 2	
	30	10	TIRS	
Landsat 7 TM	30	1	Blue	
	30	2	Green	
	30	3	Red	
	30	4	NIR	
	30	5	SWIR	
	30	6	Thermal	
	30	7	SWIR	
Data on (Roads, buildings & rivers)	30			Open street map

obtained on 2000-12-19 for 2000; 2013-12-31 for 2013; and 2020-11-16 for 2020. These Landsat datasets are accessible at no cost through the USGS portal and have been processed by NASA to create radiometric calibration and atmospheric correction algorithms, resulting in Level-1 products (http://earthexplorer.usgs.gov/). In order to ensure a more accurate comparison of surface temperature and Urban Heat Island (UHI) effects without cloud cover, satellite images from the month of November and December were selected for all three years. Additional details regarding the Landsat imagery are presented in the table below, and their respective band designations can be found in the appendices section.

Landsat images are extensively employed in satellite remote sensing due to their broad application in mapping and planning projects, facilitated by their advantageous spatial, spectral, and temporal resolutions (Wulder et al. 2008). Landsat images were used to classify land use land cover classes, retrieve LST and calculate NDVI, NDBI and NDWI indices. Besides Landsat images, the secondary data used in this research different layers of Thimphu city such as road networks, water bodies and building footprints which are prepared by the National Land Commission Secretariat of Bhutan. Road network data includes information about the layout, type, and connectivity of roads within Thimphu city and it can influence UHI by affecting surface albedo, heat absorption and creating urban heat island along the paved surfaces. Studying the road networks helps us to understand the role of impervious surfaces in UHI formation and its impact on local temperature patterns. Water bodies represent the spatial distribution of water bodies such as ponds, rivers, and lakes around the city. Water bodies act as cooling elements in urban areas. Studying water patterns can help us access their moderating effect on temperature as the area with water bodies experiences lower temperature by its nature of evaporation and causing cooling effect in the area. Building footprints represents spatial extents of individual buildings within Thimphu city. Building density and height can impact UHI by influencing by absorbing and re-emission of heat. Areas with high building density and tall buildings can contribute to increase of UHI and studying the building footprints can help us identify potential areas with UHI hotspots in the city.

3.3 SOFTWARE & TOOLS

Several software tools were employed for image processing, spatial analysis, and map generation. These tools include as show in the Table 2 below.

Table 2: Tools used for the analysis.

Sl	Tools/ Software	Remarks
1	Excel and word	Documentation and reporting
2	ArcGIS Pro/ QGIS	Analysis, mapping and visualization
3	SankeyMATIC	Statistical analysis and data visualization
4	GEO SAM	Segmentation tool to label Landforms

Most of the spatial analyses such as change detection, Urban Heat Island, determination of LST, deriving indices were conducted using ArcGIS Pro and QGIS, while Geo SAM was specifically used for the data preparation – annotation for training samples and validation samples for image classification to generate LULC of the study area. The Landsat images, and digital image classification. Linear regression was performed with ARCGIS Pro, MS Office packages (Word, Excel) were used for documentation, tabulation and graphical representation of the results.

3.4 DATA PREPARATION

The process entails carefully examining and understanding data, followed by the application of remote sensing techniques for analysis. In this specific study, Landsat 7 TM and Landsat 8 OLI/TIR images from 2000, 2013, and 2020, sourced from the United States Geological Survey (USGS), are utilized. The research focuses on Thimphu City, Bhutan, and the data processing incorporates Geographic Information System (GIS) methods in conjunction with remote sensing methodologies. All datasets use the WGS 1984, UTM zone 45 N spatial reference system. Consequently, any data not originally in this system, especially vector layers and other Thimphu city layers, were transformed to align with this system and finally, Landsat images were clipped to obtain the area of interest.

4. RESEARCH METHODS

This section addresses the strategies employed to achieve the previously mentioned aim and objectives. These strategies demonstrate the practical applications of GIS and Remote Sensing, specifically in utilizing spatial-temporal datasets to tackle real-world issues, with a focus on the Urban Heat Island (UHI) phenomenon in our study. The primary techniques employed in our research encompass supervised maximum likelihood classification, change detection analysis, urban heat island assessment and regression analysis.

4.1 SUPERVISED MAXIMUM LIKELIHOOD CLASSIFICATION

Supervised Maximum Likelihood Classification was employed for categorizing the study area based on land use and land cover classes. This method involved defining the spectral characteristics of the classes by identifying training samples, with crucial input from knowledge about the area of interest. Following the collection of training samples, the application of the Maximum Likelihood Classification algorithm facilitated image classification. In this algorithm, each cell is assigned to the class with the highest probability, where the probability value is determined by the statistical distance using mean values and covariance matrix information of the clusters(Otukei and Blaschke 2010).

The classification result included three land use land cover classes: Build Up, Vegetation and Bare soil. In this way the final land use land cover maps were produced for all three years 2000, 2013 and 2020 respectively. These maps enabled spatial-temporal change analysis.

4.2 ACCURACY ASSESSMENT

Accuracy assessment is a fundamental step in evaluating the reliability of land cover classification methods, such as Maximum Likelihood Classification (MLC), in remote sensing studies. The process involves comparing the results obtained from the MLC algorithm with ground truth data, collected through field surveys or other reliable sources. To conduct accuracy assessment for MLC, a representative set of reference data is collected, covering various land cover types in the study area. Random sampling ensures a statistically significant selection of pixels for assessment. The construction of a confusion matrix facilitates the calculation of accuracy metrics, including overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient. Visual interpretation and error analysis are crucial components of accuracy assessment, providing qualitative insights into misclassifications and guiding improvements to the classification model or parameters. Accuracy assessment ensures that remote sensing-based land cover maps accurately represent the true conditions on the ground, enhancing the reliability of information for decision-making in diverse applications.

Table 3: LULC Accuracy Assessment (Confusion Matrix)

	2000		**2013**		**2020**	
LULC	User Ac.	Pro Ac,	User Ac.	Pro Ac,	User Ac.	Pro Ac,
Built Up	0.93	0.78	0.73	0.81	0.88	0.83
Vegetation	0.82	0.98	0.87	0.96	0.89	0.9
Bare Land	0.65	0.87	0.84	0.64	0.82	0.86
Over All	0.76		0.81		0.87	
Kappa	0.64		0.71		0.8	

4.3 LAND SURFACE TEMPERATURE RETRIEVAL

The Land surface temperature was retrieved from the thermal infrared band of Landsat images (band 6 of Landsat 7 TM and band 10 of Landsat 8). The basic steps for the retrieval of LST given below are based on the guidelines provided in Landsat Data Users Handbook published by USGS (Landsat 7, 2011; Landsat 8, 2015). Besides, one of the methods discussed in the research article by (Nicholas E. Young 2017) has been also taken as reference.

I. Conversion of pixel values to radiance

The pixel values from digital number units were converted into radiance using the header files parameters of Landsat images as follows:

For Landsat 7 TM:

$$L\lambda = \frac{(LMAX\lambda - LMIN\lambda)}{(\mathrm{QCALMAX} - \mathrm{QCALMIN})} * (\mathrm{QCAL - QCALMIN} + \mathrm{LMIN}\lambda \quad (1)$$

For Landsat 8:

$$L\lambda = ML * QCAL + AL \qquad (2)$$

II. Correction for Atmospheric Effects Eliminating atmospheric influences from the thermal bands is crucial for the transformation of radiance into reflectance measurements. Consequently, this study adopts a specific atmospheric correction model known as DOS-1. The DOS-1 model is specifically designed for multispectral image data and operates as an image-based procedure, eliminating the need for in-situ measurements. Notably, DOS-1 corrects for both the atmospheric additive scattering component, associated with path radiance, and solar effects, encompassing solar irradiance and solar zenith(Richter, R and Schl 2011).

III. Conversion of spectral radiance to at-sensor brightness temperature

$$Tb = \frac{K2}{Ln\left(\frac{K1}{L\lambda}+1\right)} \qquad (3)$$

IV. Surface Emissivity Determination

Achieving precise surface temperature determination relies on an accurate understanding of surface emissivity. Surface emissivity is identified by considering the contributions of various components within pixels in proportion (Mitraka et al. 2012). In this investigation, the determination of emissivity was executed using the NDVI threshold method, as proposed by (Petitcolin and Vermote 2002). Notably, the NDVI is computed from the reflectance values of the visible and near-infrared bands in the following manner:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \qquad (4)$$

where, NIR and RED are the reflectance obtained by applying the DOS-1 method as mentioned above, at the Near Infrared band and Red band, for atmospheric effect correction.

V. Land Surface Temperature retrieval

The land surface temperature corrected for spectral emissivity is computed as follows(P. Dash and Fischer 2002)

$$\text{LST (K)} = \frac{Tb}{(1+\left(\Lambda\frac{TB}{\rho}\right)*Ln\epsilon)} \qquad (5)$$

where,

λ is the central band wavelength of emitted radiance (11.45 μm)

ρ = h * c/ σ (1.438*10-2m*K) with: h is the Planck's constant

(6.62* 10-34J*s),

c is the velocity of the light (2.998*108 m/s) and

σ is the Boltzmann constant (1.38*10-23 J/K)

VI. Convert land surface temperature value from Kelvin unit to degree Celsius

LST (° Celsius) = LST (Kelvin) – 273.15 (6)

Table 4 provided below outlines all the previously introduced parameters.

Table 4: Parameters in LST Retrieval

Parameter	Description
Lλ	Spectral radiance values
Grescale	Spectral radiance values
Brescale	Bias offset for radiometric calibration
QCAL	Quantized calibrated pixel values
LMINλ	Minimum spectral radiance for a given band
LMAXλ	Maximum spectral radiance for a given band
QCALMIN	Minimum quantized calibrated pixel value
QCALMAX	Maximum quantized calibrated pixel value
ML	Multiplicative rescaling factor for calibration
AL	Additive rescaling factor for calibration
K1,K2	the calibration constants
ϵ	Emissivity of the surface

4.4 LAND USE LAND COVER INDICES

The study utilized NDVI (Normalized Difference Vegetation Index), and NDBI (Normalized Difference Built-up Index) to investigate the correlation between Land Use Land Cover (LULC) and Land Surface Temperature (LST). These indices proved valuable in evaluating and monitoring the thermal characteristics of urban areas. In certain instances, these indices were employed to delineate specific LULC types by applying appropriate threshold values. In addition to LULC indices, official vector data on LULC are used which are downloaded from open street maps to further quantify correlation between LST and the indices. The LULC indices were extracted from the satellite images using the following expression:

For Landsat 7 (ETM+): 2000

NDVI:

- Band 4 (NIR): Near-Infrared
- Band 3 (Red): Red

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \qquad \text{(Putra and Soni 2017)} \qquad (7)$$

NDBI:

- Band 5 (SWIR2): Shortwave Infrared 2
- Band 4 (NIR): Near-Infrared

$$NDBI = \frac{(\mathrm{SWIR2}-NIR)}{(\mathrm{SWIR2}+NIR)} \qquad \text{(Mukherjee, Al. 2021)} \qquad (8)$$

For Landsat 8 OLI/ TIRS: 2013 and 2020

NDVI:

- Band 5 (NIR): Near-Infrared
- Band 4 (Red): Red

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \qquad \text{(Ding et al. 2014)} \qquad (9)$$

NDBI:

- Band 6 (SWIR2): Shortwave Infrared 2

- Band 5 (NIR): Near-Infrared

$$NDBI = \frac{(\text{SWIR2}-NIR)}{(\text{SWIR2}+NIR)} \quad \text{(Mahdi Hasanlou 2015)} \qquad (10)$$

4.5 URBAN HEAT ISLAND ANALYSIS

Urban heat islands (UHI) were identified through the utilization of Land Surface Temperature (LST) acquired from preceding analyses. The procedural steps were as outlined below:

- Establish a minimum surface temperature threshold designating an area as an urban heat island. This threshold value was determined to be 3 °C, guided by expert opinion.
- Calculate the UHI threshold, representing the temperature value indicative of the occurrence of the urban heat island phenomenon, using the provided equation (Mas'uddin1, Lina Karlinasari1,2*, Setyo Pertiwi3, Erizal 2023):

$$\text{UHI} = \mu + \frac{\sigma}{2} \qquad (11)$$

$$\text{LST} > \mu + \frac{\sigma}{2} \qquad (12)$$

Regions are exclusively concentrated on areas experiencing the Urban Heat Island (UHI) phenomenon, while non-UHI regions are restricted to occurrences defined by the subsequent relationships(Liu et al. 2021).

$$0 < \text{LST} \leq \mu + 0.5\sigma \qquad (13)$$

- Calculates the UHI (Map) index using the following formula (Fawzi 2017)

$$UHIindex = Tmean - (\mu + \frac{\sigma}{2}) \qquad (14)$$

Where: μ is the mean surface temperature derived from the obtained Land Surface Temperature (LST) values, σ denotes the standard deviation of surface temperature derived from the obtained LST values, and Tmean signifies the median value within the obtained LST class.

5. RESULT AND DISCUSSION

5.1 SPATIAL PATTERN OF LST AND LULC INDICES

Determination of Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Built-up Index (NDBI) in Thimphu City was conducted for the years 2000, 2013, and 2020. Table 1 and Figure 7, Figure 8, and Figure 9 displays LST Area changes and visual representation of LST, NDVI, NDBI and LULC respectively for the study area. In 2000, Thimphu City experienced the highest recorded LST at 28.06 °C, covering 4 KM2 (13% of the total area), while the lowest LST was 1.95 °C, encompassing 0.041 KM2 (0.12% of the total area). In 2013, the lowest recorded LST was 3.1 °C, and the highest was 29.01 °C, with an average LST of 7.75 °C. NDVI analysis in 2000 showed values ranging from -0.26 to 0.50, covering 18% of the total area. The NDBI map indicated values between -0.37 (vegetated built-up area) and 0.39 (built-up area), with the largest NDBI area in 2000 measuring 10 KM2 (29% of the total area) and increasing to 14 KM2 (40% of the total area) by 2020.

Table 5: LST Area changes in Thimphu City for 2000, 2013, and 2020

LST Class °C			Area (KM2)						LST change 2000-2013		LST change 2000-2020	
2000	2013	2020	2000	%	2013	%	2020	%	Δ	Δ %	Δ	Δ %
1.95 - 8.41	3.10 - 8.69	9.81 - 15.45	0.04	0.12	10	29	6	17	10	28	6	17
8.4 - 11.88	8.69 - 11.84	15.45 - 18.54	4	11	12	34	7	20	8	23	3	9
11.88 - 14.65	11.85 - 14.69	18.54 - 21.27	11	30	4	11	9	26	-7	-19	-2	-5
14.65 - 18.95	14.69 - 18.15	21.27 - 24.63	16	45	4	11	5	14	-12	-34	-11	-31
18.95 - 28.06	18.15 - 29.02	24.63 - 32.99	4	12.8	5	14.29	8	22.9	1	1	4	10

Over the years, there was a slight increase in LST from 28.06 °C in 2000 to 29.01 °C in 2013, and the LST area expanded from 4 KM2 (13%) in 2000 to 5.2 KM2 (14.29%) in 2013. The NDVI maximum value declined from 0.50 to 0.38, and it is anticipated that LST values will experience a slight rise of 0.97 °C in 2013. In 2020, LST values ranged from 9.81 to 32.99 over 8 KM2 (22.9% of the total area).

The relationship between LST and NDVI indicates a robust negative correlation, suggesting that a decrease in NDVI corresponds to increased LST. There is a notable decline in the extent of dense vegetation land, reducing from 10 KM2 in 2000 to 5 KM2 in 2020, with a density value of 0.49 in 2020. The NDBI analysis in 2020 revealed values between -0.29 and 0.39, covering 6.5 KM2 (18.4% of the overall study area). This change may be attributed to Land Cover Change, where alterations in the area's land cover over time influence the observed NDBI values.

The data presented distinct temperature ranges within each LST class, organized into intervals. The temperature intervals for the years 2000, 2013, and 2020 exhibit an upward trend. The provided information includes the spatial distribution of areas corresponding to each LST class for the respective years, showcasing how different temperature ranges are distributed across the study area. The calculated LST changes (Δ) for each class during the periods 2000-2013 and 2000-2020 reveal that positive values signify an increase in temperature, while negative values indicate a decrease. The percentage change (%), offering a relative measure, indicates the magnitude of LST change for each period. Notably, positive changes in LST are noticeable, especially in the higher temperature classes, whereas lower temperature classes generally display smaller changes or occasional decreases. The data implies temporal trends in LST changes, suggesting potential shifts in temperature patterns over the examined years.

5.2 RELATIONSHIP BETWEEN LST, NDVI AND NDBI

Figure 4: Correlation LST with Indices

Correlation coefficient between LST and NDVI was calculated and for 2000 is -0.41

in 2013 is 0.05 and in 2020 is -0.10. For 2000, the negative correlation coefficient of -0.41 between LST and NDVI in 2000 suggests a moderate negative correlation. This indicates that as vegetation (NDVI) increases, there is a moderate tendency for land surface temperature to decrease. Negative correlations between LST and NDVI are common, as vegetation tends to have a cooling effect on the environment through evapotranspiration and shading. While for 2013, the correlation coefficient of 0.05 between LST and NDVI in 2013 indicates a very weak positive correlation. This suggests a minimal association between vegetation and land surface temperature in 2013. The positive correlation implies that as vegetation increases, there is a weak tendency for land surface temperature to increase. The weak positive correlation may indicate that other factors play a more dominant role in influencing LST during this year. Finally for 2020, the negative correlation coefficient of -0.10 between LST and NDVI in 2020 suggests a very weak negative correlation. This indicates a very weak tendency for land surface temperature to decrease as vegetation increases in 2020. The weak negative correlation implies that the influence of vegetation on land surface temperature is minimal during this year, and other factors may have a more significant impact. The overall finding is the varying correlation coefficients suggest changes in the relationship between land surface temperature and vegetation over the years. The negative correlations in 2000 and 2020 indicate a general trend where increased vegetation is associated with lower land surface temperatures. The weak or very weak correlations in 2013 suggest that other factors, such as urban development or specific local conditions, may be influencing the relationship during that year.

Regarding LST and NDBI, the correlation coefficient between LST and NDBI in 2000 is 0.033, for 2013 is 0.49 and for 2020 is 0.54. The correlation coefficient of 0.033 between LST and NDBI in 2000 indicates an extremely weak positive correlation. The weak positive correlation suggests that there is a minimal association between land surface temperature and built-up index in the year 2000. The practical significance of this correlation may be limited, as changes in one variable are barely associated with changes in the other.

Whereas for 2013, the correlation coefficient of 0.498 between LST and NDBI in 2013 indicates a moderate positive correlation. This suggests a stronger association compared to the correlation in 2000. Changes in land surface temperature are moderately associated with changes in the built-up index in 2013. The positive correlation implies that as built-up areas increase, there is a moderate tendency for land surface temperature to increase. Finally for 2020, the correlation coefficient of 0.541 between LST and NDBI in 2020 indicates a moderate positive correlation similar to 2013. This suggests a consistent relationship between land surface temperature and built-up index over time. The positive correlation implies that as built-up areas increase, there is a moderate tendency for land surface temperature to increase.

The overall findings on LST and NDBI reveals that the correlation coefficients show a variation in the strength of the relationship between LST and NDBI over the years. The consistent positive correlation in 2013 and 2020 indicates a moderate association between urban development (as indicated by NDBI) and land surface temperature. The factors contributing to this relationship could include heat retention in built-up areas, changes in land use patterns, and urban heat island effects.

Table 6: The changes in area of NDVI density

Vegetation Density	Area (KM2)						NDVI Area Change			
							2000-2013		2000-2020	
	2000	%	2013	%	2020	%	Δ	Δ%	Δ	Δ%
Not Vegetated	6	18	5	14	6	17	-1	-4	0	-1
Low Greenness	6	17	10	29	7	20	4	11	1	3
Low Green	8	22	7	20	8	23	-1	-2	0	1
Medium	5	15	6	17	9	26	1	3	4	11
High	10	28.6	7	20	5.0	14	-3	-9	-5	-14

Tables 5, 6, and 7 provide insights into the variations observed in LST, NDVI, and NDBI for the years 2000, 2013, and 2020. The study reveals a statistically significant moderate positive correlation between LST and NDVI. The NDBI indicates that the expansion of built-up areas is positively correlated with an increase in LST values, suggesting a rise in LST over time. Specifically, the LST values for built-up areas expanded from 1.95 to 28.06 °C in 2000 to 3.1 to 29.06 °C in 2013, covering 5 KM2 (14.29% of the total area). In 2020, the LST range will be extended from 9.81 to 32.99 °C, covering 8 KM2 (22.9% of the total area).

Table 7: The changes in area of NDBI

Building Density	Area (KM2)						NDBI Area Change			
							2000-2013		2013-2020	
	2000	%	2013	%	2020	%	∆	∆%	∆	∆%
Non Building	5	15	8	23	6.0	17	3	8	1	3
Very Low	5	15	7	20	7.0	20	2	5	2	5
Low	8	23	7	20	8.0	23	-1	-3	0	0
Medium	11	31	6	17	5.0	14	-5	-14	-6	-17
High	5	14	7	20.0	8.0	22.9	2	6	3	9

5.3 LAND COVER CLASSIFICATION (2000, 2013, AND 2020)

The land cover classification of Thimphu City encompasses three distinct categories, namely vegetation, built-up, and Bare land. Area in square kilometers, and percentages for each class are summarized in Table 7 and Figure 4. Table 3 displays the result of LULC accuracy test for the study. The findings point out that the Built-Up area has experienced significant growth over the years, increasing from 10 KM2 in 2000 to 19 KM2 in 2020. This substantial rise indicates urban expansion and development, encompassing an expansive area of 19 KM2, accounting for approximately 54% of the total land area. While Vegetation remains the dominant class, its percentage has decreased from 44% in 2000 to 27% in 2020, suggesting potential changes in land use, deforestation, or urbanization affecting green spaces. The percentage of Bare Land has decreased from 27% in 2000 to 18% in 2020, indicating a reduction in open, non-vegetated areas. The data suggests a dynamic shift in land cover, with urbanization leading to increased Built-Up areas at the expense of Vegetation and Bare Land. This transformation has implications for ecological balance, biodiversity, and urban planning. Figure 4 depicts the graphical representation of the each LULC class changes from 2000 to 2020.

As the Figure 5 depicts that there was reduce by -3 KM2 and -6 Km2 from 2000 to 2020 from the total area. Conversely, there is a significant increase of 9 KM2 in Build up from 2000 to 2020 of the total area.

Table 8: The LULC Classification 2000, 2013, and 2020

Year	LULC	%	Area KM2
2000	Built Up	28	10
	Vegetation	45	16
	Bare Land	27	10
2013	Built Up	40	14
	Vegetation	36	12
	Bare Land	24	8
2020	Built Up	54	19
	Vegetation	27	10
	Bare Land	19	6

Figure 6 visualizes the LULC cover changes over the year 2000 to 2020 and the changes is shown in KM2. As the study focuses on Build up and Vegetation to find out the relation with LST to determine which and classes do contribute to UHI by increasing temperature. The diagram show increase in Built up area from 0.1224 to 0.05 KM2 and similarly vegetation too from 5.571 to 11.24 KM2 from bare land built up.

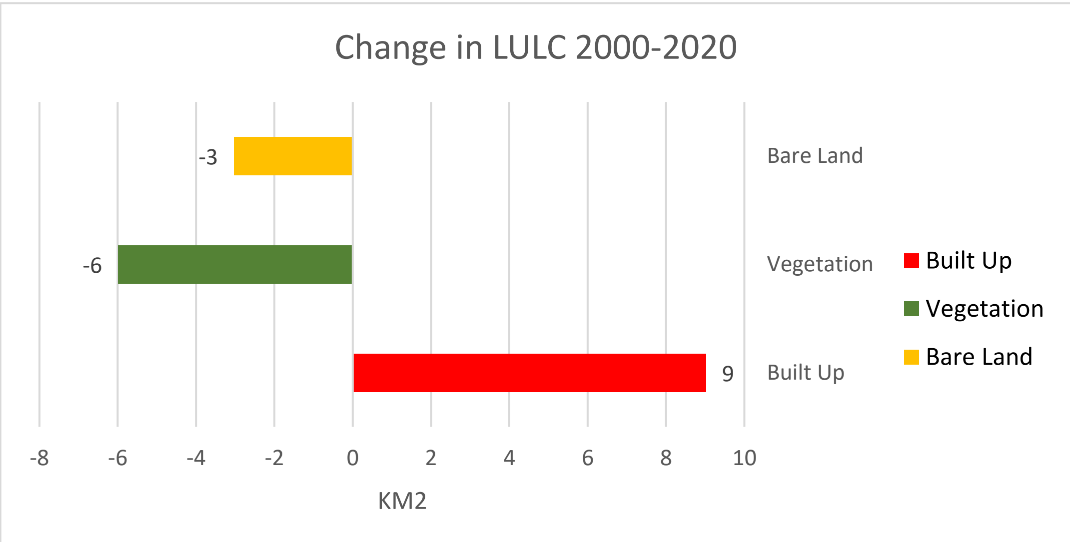

Figure 5: LULC changes from 2000 to 2020 in graph

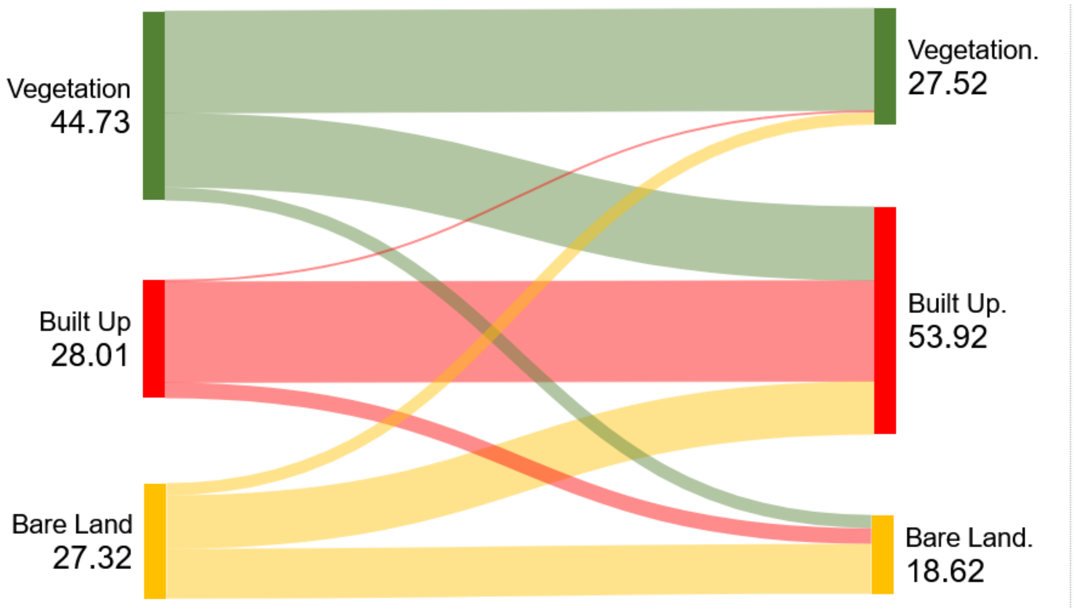

Figure 6: LULC changes from 2000 to 2020 in detail with Sankey diagram

5.4 LAND SURFACE TEMPERATURE DISTRIBUTION AND LAND COVER CLASS

The temporal variations in Thimphu City's land surface temperature (LST) across the years 2000, 2013, and 2020 are evident in the spatial distribution. As per satellite image analysis, the LST displayed a spectrum of temperatures, ranging from around 1.95 °C to 28.06 °C in 2000, approximately 3.10 °C to 29.0 °C in 2013, and about 9.81 to 32.99 °C in 2020, as illustrated in table 5. This study investigates the distribution of Land Surface Temperature (LST) and analyzes the spatial extent and location of temperature changes within each land cover class in Thimphu City for the years 2000, 2013, and 2020. Table 9 displays the changes in LST for Thimphu City in 2000, 2013 and 2020 and figure 10 displays the LST over three LULC classes.

Table 9:LST distribution over LULC and Area in KM2

LULC Class	2000		2013		2020	
	LST °C	% KM2	LST °C	% KM2	LST °C	% KM2
Built Up	14	29	8	42	16	55
Vegetation	9	45	5	35	13	27
Bare Land	15	28	11	24	18	19

The information provided in Table 9 indicates that in 2000, Built-Up Areas experienced an LST of 14°C, covering approximately 29% of the total area (KM2). By 2013, the LST decreased to 8°C, encompassing 42% (KM2) of the total area. However, in 2020, there was a notable increase in LST to 16°C, expanding the coverage to 55% (KM2) of the total area. The Built-Up Areas showed a substantial decrease in LST from 2000 to 2013, suggesting a potential cooling effect. However, a significant increase in LST was observed in 2020, indicating possible urban heat island effects or changes in land use patterns. The percentage of the total area covered by built-up areas consistently increased, indicating urban expansion.

In 2000, the LST for Vegetation Areas shows 9°C, covering 45% (KM2) and representing 35% of the total area and, in 2013, the LST decreased to 5°C, covering 35% (KM2) of the total area. However, in 2020, LST significantly increased to 13°C, covering 27% (KM2) of the total area. Overall, Vegetation Areas consistently show a decrease in LST, indicative of a cooling effect. The percentage of the total area covered by vegetation remains relatively stable, with a slight decrease.

According to (Senevirathne et al. 2021) which use low albedo materials leading to high heat absorption in urban centers. In addition, removal of vegetation cover and emissions of waste heat from various sources contribute to the accumulation of heat energy, leading to formation of urban heat islands. Overall, Built-Up Areas show a notable fluctuation in LST, possibly influenced by urbanization trends. Conversely, Vegetation Areas consistently exhibit a cooling effect, contributing to temperature reduction.

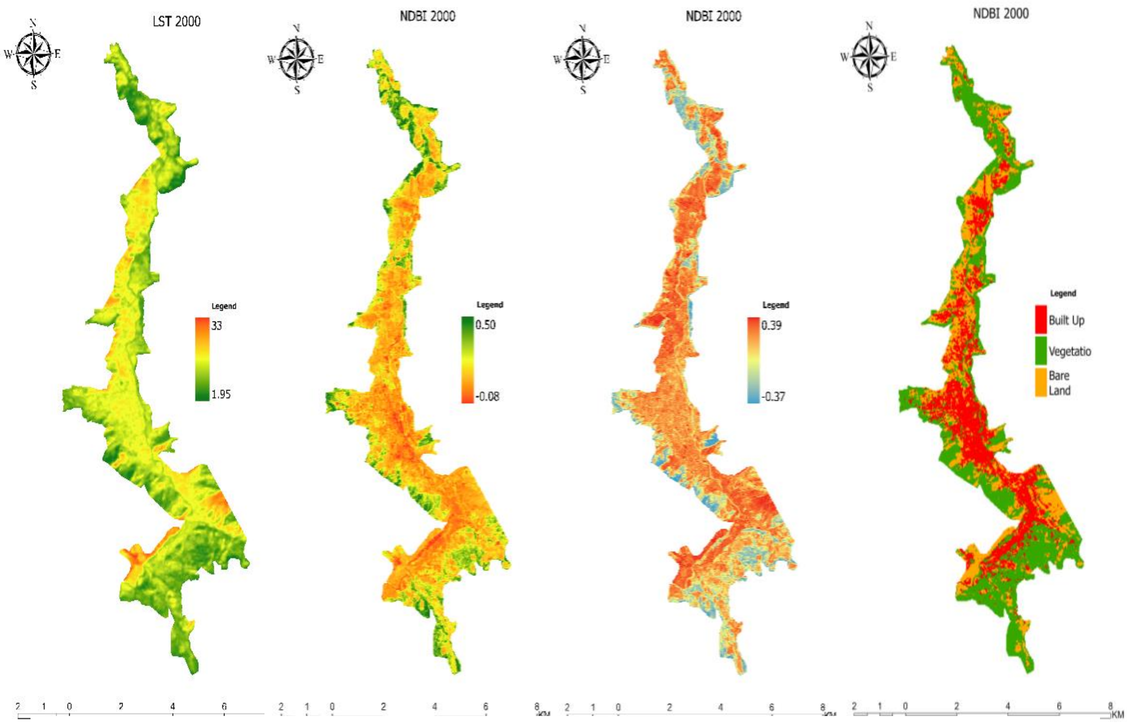

Figure 7: The results of LST, NDVI, NDBI, and land cover for 2000

Similarly, Bare Land Areas follow a cooling trend, reflecting changes in land cover and use in the study area.

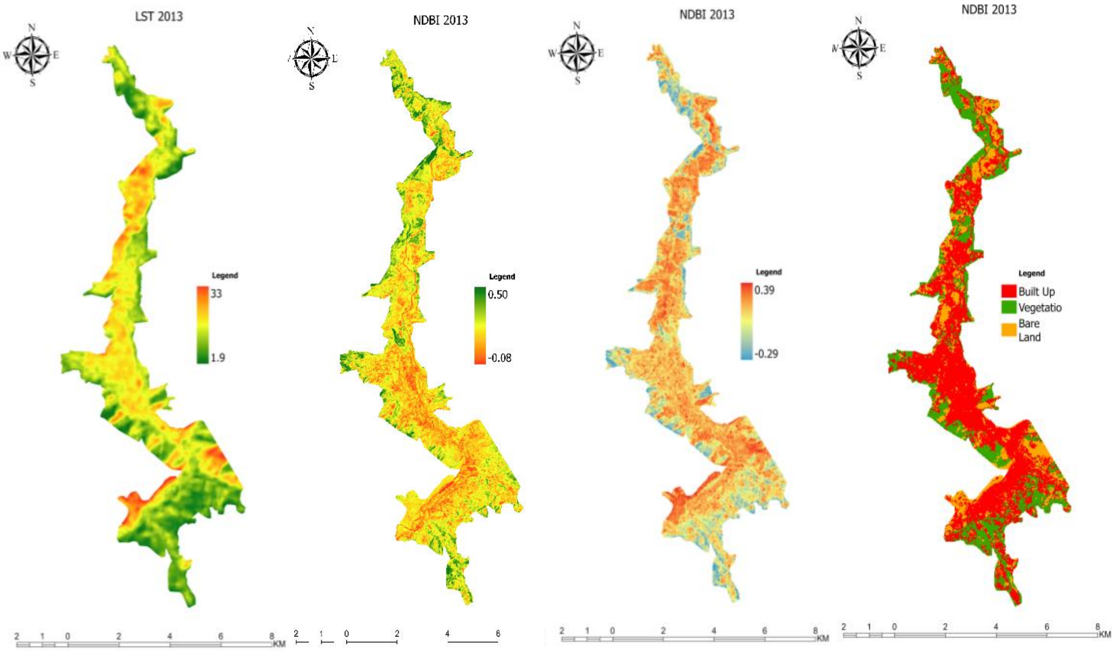

Figure 9: The results of LST, NDVI, NDBI, and land cover for 2013

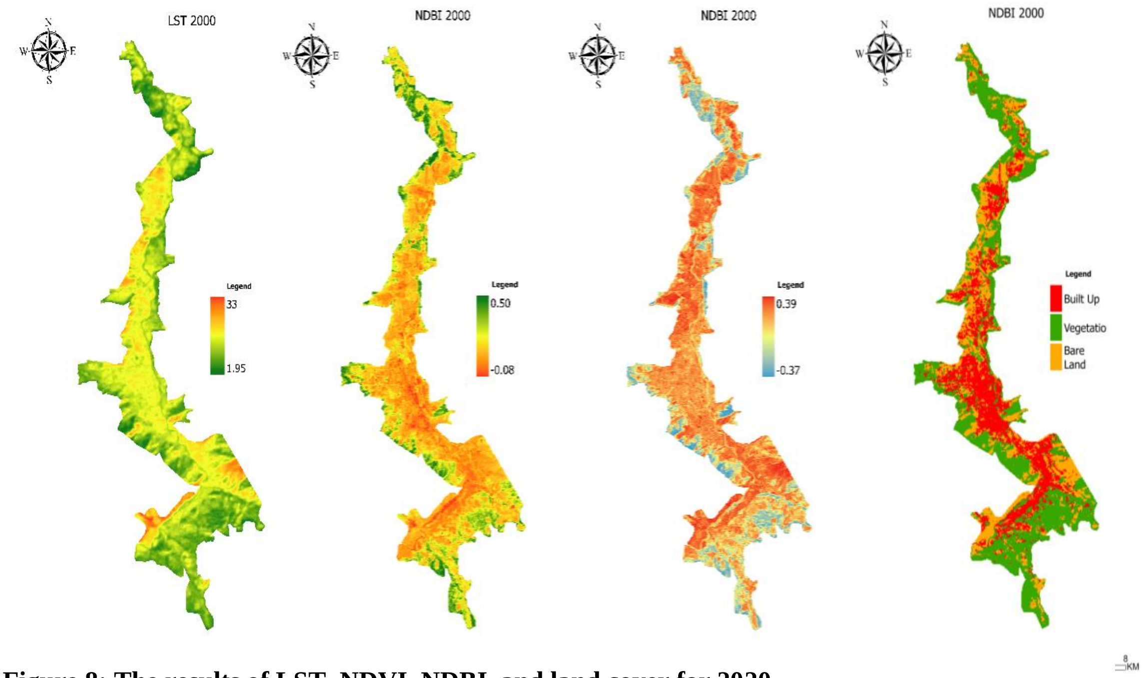

Figure 8: The results of LST, NDVI, NDBI, and land cover for 2020

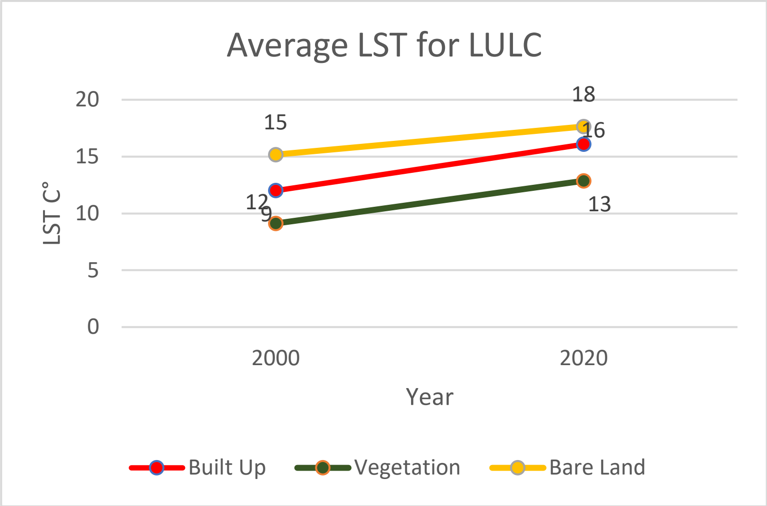

Figure 10: LST distribution on LULC classes

5.5 URBAN HEAT ISLAND DETECTION

Detecting the existence of the urban heat island (UHI) in Thimphu City involves employing equations (11), (12), and (13) to determine the atmospheric conditions. temperature threshold for UHI occurrence. Additionally, UHI threshold calculations facilitate the spatial mapping of UHI phenomena distribution within Thimphu City. Furthermore, equation (14) is utilized for UHI Index analysis, enabling an assessment

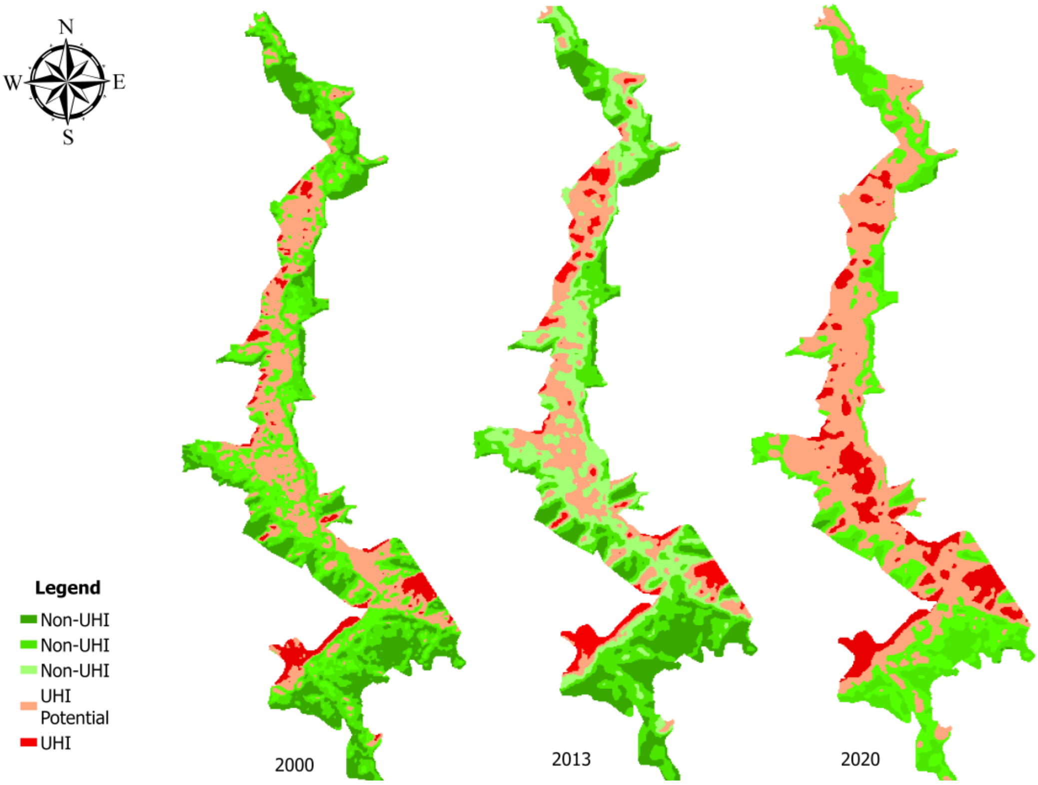

Figure 11: UHI maps for 2000, 2013 and 2020

of the extent of UHI phenomenon potential. The UHI index is categorized into three distinct classes: non-UHI, potential UHI, and UHI.Thimphu City functions as a central hub for services, playing a pivotal role as the primary economic center for the regions. It supports diverse community activities, encompassing trade hospital and education. The continuous development and growth of Thimphu City over time underscore the imperative acknowledgment of the inevitable presence of the urban heat island phenomenon in the area.

The examination of the temperature threshold triggering the Urban Heat Island (UHI) phenomenon in Thimphu City reveals that the region is indeed undergoing the effects of UHI. The identified threshold temperature for the UHI phenomenon in 2000 was documented as 14.21%. When the land surface temperature surpasses this threshold, it indicates the manifestation of the urban heat island phenomenon in the corresponding area. The outcomes of the analysis pertaining to the urban heat island phenomenon in Thimphu City for the year 2000, 2013 and 2020 are detailed in Table 10. As illustrated in Figure 11, the findings align with the determined threshold temperature, the UHI phenomenon exhibits a notable concentration within the city's central region, subsequently extending to the surrounding areas.

Table 10: UHI threshold for 2000,2013 and 2020

Year	Tmax	Tmin	Median (µ)	Std	UHI Threshold
2000	28.06	1.95	12.12	4.19	14.55
2013	30	3.10	7.75	3.89	14.38
2020	33	9.81	15.44	3.65	20.79

The urban heat island phenomenon's prevalence in Thimphu City is 11.43% of its total area. Additionally, 45.71% of the city's area exhibits potential for experiencing the UHI phenomenon, while the remaining 42.86% of Thimphu City's total area remains unaffected by the UHI phenomenon. The production of a map illustrating the distribution of UHI phenomena in Thimphu City in 2000 can be facilitated by utilizing the UHI index, as depicted in Figures 11 and Figure 12.

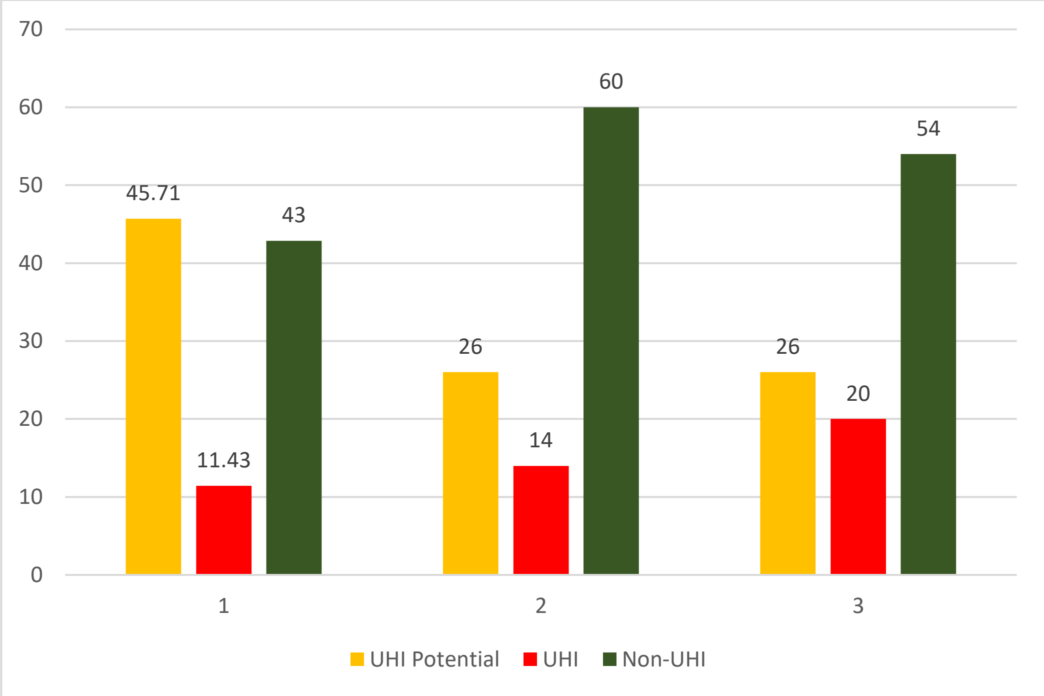

Figure 12: The comparison of UHI condition in Thimphu city for 2000, 2013, and 2020

Regions with land LST exceeding 17.08 indicate UHI areas, whereas regions with LST ranging from 1.95 °C to 14.65 °C indicate non-UHI regions. The UHI conditions in Thimphu City during the year 2013 were examined Table 12.

Regions with LST exceeding 9.57 ℃ indicate UHI areas, whereas regions with LST ranging from -0.39 ℃ to 9.98 ℃ indicate non-UHI regions. The UHI conditions in Thimphu City during the year 2013 were examined by employing the UHI index.

Table 11: UHI phenomenon of 2000 based on LST

LST Class (°C)	Median	UHI Index	LST Class	Area KM2	%
1.94 - 7.92	4.94	-9.62	Non-UHI	0.400	1.14
7.92 - 11.34	9.64	-4.92	Non-UHI	4	11.43
11.35 - 14.67	14.00	-0.55		11	30.29
14.67 - 18.95	16.81	2.26	UHI Potential	16	45.71
18.95 - 28.06	23.51	8.95	UHI	4	11.43

The UHI conditions in Thimphu City experienced a temperature increase of 4.93 °C (from 28.06 °C in 2000 to 32.99 °C) in 2020. The UHI category refers to a specific geographical region with a UHI index of 7.70 ℃. This region spans an area of 1 KM2, which accounts for approximately 3% of the total area of Thimphu City. Table 13 presents the UHI phenomenon observed in Thimphu City. Figure 10 depicts the spatial distribution of the UHI phenomenon in Thimphu City in the year 2020 is depicted.

Based on the analysis, it is evident that the UHI phenomenon exhibits a comparable pattern to that of the preceding year, disseminating across the adjacent region.

Table 12: UHI phenomenon of 2013 based on LST

Class LST (°C)	Median	UHI Index	LST Class	Area KM2	%
3.10 - 8.69	5.90	-8.48	Non-UHI	10	29
8.69 - 11.84	10.27	-4.11	Non-UHI	7	20
11.85 - 14.69	13.27	-1.11		4	11
14.69 - 18.15	16.42	2.05	UHI Potential	9	26
18.15 - 29.02	23.59	9.21	UHI	5.00	14.29

The data was sourced from the USGS data portal. The data indicate that Thimphu City witnessed a rise in the UHI coverage from 9.29% in 2000 to 14 % in 2013 and further to 20% in 2020, relative to the total area of the city affected by this phenomenon. The stakeholders in Thimphu City can adopt various strategies to mitigate the effects of Urban Heat Island (UHI). One key approach involves effective vegetation management in land development, which plays a vital role in establishing a favorable microclimate that supports cool and healthy urban environments. Enhancing the control system for more ecologically sustainable use of urban space is essential. This includes increasing the presence of green open spaces within the city, integrating green elements into government infrastructure and residential building environments. The development of comprehensive regulatory frameworks for green infrastructure in buildings is imperative. Successful implementation of development control relies on adhering to

Table 13: UHI phenomenon of 2020 based on LST

Class LST (°C)	Median	UHI Index	LST Class	Area KM2	%
9.81 - 15.45	12.63	-8.16	Non-UHI	7	20
15.45 - 18.54	17.00	-3.79	Non-UHI	8	23
18.54 - 21.27	19.91	-0.88		4	11
21.27 - 24.63	22.95	2.17	UHI Potential	9	26
24.63 - 32.99	28.81	8.03	UHI	7	20.0

designated land use, employing appropriate building materials and construction techniques, and establishing sustainable urban space infrastructure.

Further exploration is needed to understand the impact of urban built-up land cover configuration on the escalation of the UHI phenomenon. Research, such as that conducted by (Moyer and Hawkins 2017), indicates that the presence of vegetation and water bodies in land cover significantly reduces the UHI effect.

6. CONCLUSIONS

The research uncovered a significant increase in urban expansion within Thimphu City. The primary factors contributing to this expansion are the substantial influx of population and inadequate land use planning. Consequently, valuable agricultural land and open spaces are being replaced by concrete structures. This pattern is anticipated to worsen in the future unless effective land use plans and policies are put into practice.

Based on our analysis of thermal pattern of the study area over the given period, we found gradual increase in temperature in the study areas. There was the formation of urban heat island in the central urban area of the city. The study proved that the surface temperature is influenced by urban growth. Urban growth not only increases the UHI effect but also affects quality of life of the people residing in the urban area.

In our study, regression analysis was conducted, revealing a noteworthy positive correlation between Land Surface Temperature (LST) and Normalized Difference Built-up Index (NDBI). Conversely, the correlation between LST and Normalized Difference Vegetation Index (NDVI) was observed to be weak, suggesting that the increase in temperature is influenced by NDBI and not by NDVI. Similarly, the regression analysis conducted on LST and Land Use Land Cover (LULC) exhibited a consistent pattern. Built-up areas and bare land were identified as contributors to the elevation of LST, while vegetation did not exhibit a similar effect.

However, the study encountered several limitations. The image resolution proved to be only moderate, posing challenges for classification and change detection purposes. Despite the extensive Landsat imagery repository, obtaining suitable images that met our specific requirements proved challenging at times. Additionally, due various land cover within pixels and the complex landscape of the study area, pixel-based classification did not yield higher accuracy. Furthermore, the focus of our study was on the pattern of Land Surface Temperature (LST) rather than its absolute values across the area of interest. Moreover, the study specifically concentrated on daytime LST during the winter season, encompassing only three years and excluding cloudy conditions.

We would like to propose that, given the critical state of urban growth in Thimphu City, it is imperative for relevant authorities to initiate necessary measures, and urban residents should build resilience against the impacts of urban growth and the Urban Heat Island (UHI) effect. Reducing Urban Heat Islands (UHIs) requires a multifaceted approach that combines urban planning, green infrastructure development, and sustainable design strategies. Implementing cool roof technologies, increasing green spaces, and promoting reflective surfaces can mitigate the heat absorption of urban surfaces. Additionally, integrating urban forestry and promoting energy-efficient building practices contribute to temperature moderation. Public awareness and community engagement are crucial for the success of UHI reduction initiatives. By adopting these strategies, cities can enhance overall livability, environmental sustainability, and resilience to climate change.

We also suggest the utilization of high-resolution images and alternative classification methods to enhance the accuracy in obtaining multiple Land Use Land Cover (LULC) classes. For a robust examination of the LULC-LST relationship, incorporating both daytime and nighttime temperature data over an extended period is advisable. Furthermore, if prioritizing absolute temperature, the application of atmospheric correction parameters considering local climatic conditions becomes essential. Finally, a comprehensive exploration of alternative regression methods is crucial to gain a deeper understanding of the LULC-LST relationship.

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