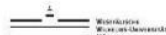




Rawalpindi's Urban Heat Island: Exploring Landscape Dynamics and Thermal Patterns

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Dissertation submitted in partial fulfillment of the requirements for the degree of Master of Science in Geospatial Technologies



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Table of Content

Abstract	9
CHAPTER 1.....	11
Introduction	11
CHAPTER 2.....	14
Research Objectives	14
CHAPTER 3.....	16
LITERATURE REVIEW	16
3.1. Estimation of LST with Remote Sensing & GIS	16
3.2 Landscape Metrics and LST	18
3.3 Diurnal and Seasonal Patterns of LST	19
CHAPTER 4.....	21
MATERIAL AND METHODS	21
4.1 Study area	21
4.1.1 The climate of the Study area	22
4.2 Methodology Flowchart	22
4.3.1 Satellite data	24
4.3.2 Administrative boundary data	25
4.3.3 Land Use & Land Cover data	25
4.4.1 Code Repository.....	27
4.6.1 Data Source and Preprocessing	29
4.6.2 Landscape Metrics Selection	30
4.6.3 Rationale for Metric Selection	32
4.6.4 Study Area and Grid Division.....	33

CHAPTER 5.....	37
RESULTS AND DISCUSSION	37
5.1.2 Nighttime Patterns	42
5.2.2 Metrics Calculation.....	47
5.2.3 Correlation Analysis	49
CHAPTER 6.....	53
CONCLUSION & RECOMMENDATIONS	53
REFERENCES	55

Index of Figures

Figure 1 Comparison of Rawalpindi and Islamabad.....	12
Figure 2 The study area map.....	21
Figure 3 The Methodology Flowchart	24
Figure 4 LULC Map.....	26
Figure 5 The main Code Repository of the Google Earth Engine (code script).....	27
Figure 6 Study area division	33
Figure 7 Day and night Temperature Variations across 8 Grids	35
Figure 8 Day Time Land Surface Temperature (LST) variations over the study area for May...	38
Figure 9 Day Time Land Surface Temperature (LST) variations over the study area for June...	39
Figure 10 Day Time Land Surface Temperature (LST) variations over the study area for July..	40
Figure 11 Day Time Land Surface Temperature (LST) variations over the study area for August	41
Figure 12 Nighttime Land Surface Temperature (LST) variations over the study area for May .	43
Figure 13 Nighttime Land Surface Temperature (LST) variations over the study area for June .	44
Figure 14 Nighttime Land Surface Temperature (LST) variations over the study area for July..	45
Figure 15 Nighttime Land Surface Temperature (LST) variations over the study area for August	46

Index of Tables

Table 1 Datasets	25
Table 2 Summary of the monthly average temperatures for 8 Grids	36
Table 3 Detailed landscape metrics, including PLAND and AI with corresponding day and night LST values for selected grids.	48
Table 4 Detailed landscape metrics, including CA and ENN-CV, with corresponding day and night LST values for selected grids.	48
Table 5 Daytime Correlations	49
Table 6 Nighttime Correlations	51

Abstract

The increasing intensity of the Urban Heat Island (UHI) effect has become a pressing concern for rapidly urbanizing cities, where rising land surface temperatures contribute to environmental and socioeconomic challenges. Addressing this issue requires a deeper understanding of how land cover patterns influence thermal dynamics, particularly in developing urban areas like Rawalpindi, Pakistan.

This study investigates the relationship between landscape composition and thermal patterns in Rawalpindi, hypothesizing that the spatial configuration and diversity of land cover types significantly influence both daytime and nighttime LST variations.

This study examines the spatial and temporal dynamics of Land Surface Temperature (LST) in Rawalpindi, Pakistan, using MODIS satellite imagery. The analysis focuses on both daytime and nighttime LST variations during the summer months of May, June, July, and August capturing the diurnal thermal behavior of the urban and peri-urban landscape. Unlike traditional studies that analyze land use and land cover at the pixel level, this research takes a broader, landscape-based approach. It uses metrics like Proportional Landscape Area (PLAND), Aggregation Index (AI), Class Area (CA), and Euclidean Nearest Neighbor Coefficient of Variation (ENN-CV) to understand how the structure of the landscape affects temperature patterns. These metrics help quantify the relationship between landscape features and thermal behavior.

By combining advanced spatial analysis techniques, the study examines how different landscape patterns influence LST. It connects temperature patterns with landscape characteristics, revealing how heat distribution depends on the diversity and arrangement of land features. This approach highlights the importance of landscape structure in understanding urban heat dynamics.

The findings provide valuable insights into how the fragmentation and aggregation of barren land, crops, and built-up areas influence urban temperatures. These insights are particularly relevant for sustainable urban planning and climate adaptation in fast-growing cities like Rawalpindi. By analyzing the spatial arrangement and composition of these land cover types, the study offers a foundation for developing more effective strategies to reduce urban heat and improve living conditions.

Introduction

Urbanization and industrialization have significantly reshaped natural landscapes, replacing vegetation and open spaces with impervious surfaces such as roads, buildings, and other infrastructure. This transformation has led to the emergence of the Urban Heat Island (UHI) effect, where urban areas exhibit elevated temperatures compared to their rural surroundings. The causes of UHI are multifaceted, including urban geometry, heat emissions from anthropogenic activities, reduced vegetation, increased albedo, and dense infrastructure (Nwakaire et al., 2020). The impacts of UHI are majorly on the health of humans and ecological environments, high consumption of energy, mortality due to heat, and vegetation health (L. Li & Zha, 2019). Pakistan has been ranked as the fifth most affected country by extreme climate change. (IPCC, 2022) According to IPCC report (2021), global warming is projected to exceed 1.5°C by 2050, further intensifying the adverse effects of urban heat.

Previous studies have explored the relationship between land use/land cover (LULC) and LST, often employing pixel-based analyses that focus on individual land cover types, such as vegetation, water, or built-up areas (Voogt & Oke, 2003). While such methods provide valuable insights, they often fail to account for the influence of broader landscape structures. Recent research emphasizes the utility of landscape metrics, such as Aggregation Index (AI) and Proportional Landscape Area (PLAND), to quantify the impact of landscape composition and configuration on LST. These metrics allow researchers to move beyond pixel-level analyses, offering a holistic understanding of how spatial patterns influence thermal dynamics (Turner et al., 2001).

The city of Rawalpindi, Pakistan, exemplifies the challenges of unplanned urbanization. As one of the fastest-growing cities in the country, Rawalpindi has experienced significant landscape transformations, including reduced vegetation, increased impervious surfaces, and poorly managed urban sprawl. Unlike its neighboring city Islamabad, which has more regulated growth and green spaces, Rawalpindi faces pronounced UHI effects, making it an important case study for analyzing Land Surface Temperature (LST) variations. Figure 1 shows the clear difference between the two city layouts where on the right side the capital Islamabad with planned buildup area and a large area with trees and plants. However on the left side Rawalpindi city has a large area of built-up and less area of green cover, that has negative impacts on the environment of the city and result in the increasing of LST.



Figure 1 Comparison of Rawalpindi and Islamabad

Additionally, anomalous temperature patterns observed in other cities, such as Abu Dhabi, where daytime temperatures in downtown areas were cooler than suburban areas (Weng et al., 2014), emphasize the importance of examining diurnal LST variations. Such patterns challenge conventional UHI assumptions and highlight the need for studies that address both daytime and nighttime thermal behaviors.

Urban expansion and land use transformation are known to play a critical role in shaping surface thermal variations. Studies have demonstrated that landscape configuration significantly affects UHI intensity by altering land-atmosphere interactions (Li et al., 2020). Specifically, fragmented green spaces and increased built-up areas contribute to higher LST, whereas larger and more connected vegetation patches can mitigate heat accumulation (Dong et al., 2022).

Understanding these spatial patterns is essential, as traditional pixel-based LST analysis often fails to capture the influence of land cover heterogeneity (Samdrup, 2024). Therefore, this research employs landscape metrics to quantify how land cover composition and spatial arrangement influence thermal behavior in Rawalpindi. The study analyzes both daytime and nighttime LST variations during the summer months of May, June, July and August, utilizing MODIS satellite imagery. Adopting a landscape-based approach, the research investigates how LST is influenced by the spatial configuration and composition of landscapes in Rawalpindi. The findings aim to help with sustainable urban planning and climate adaptation, highlighting the need for comprehensive approaches to tackle urban heat challenges.

Research Objectives

Despite extensive studies on the Urban Heat Island (UHI) effect, most research focuses on the direct relationship between land cover types and Land Surface Temperature (LST). However, spatial configuration and landscape structure play an equally crucial role in shaping urban thermal patterns, which has been largely overlooked. Fragmented urban development, disconnected green spaces, and the spatial arrangement of land cover influence heat retention and dissipation, yet existing studies rarely quantify these effects systematically. In rapidly urbanizing cities like Rawalpindi, where unplanned expansion continues to alter land surface characteristics, it is essential to move beyond conventional land classification and investigate how landscape patterns contribute to urban heating.

This study explores the relationship between landscape composition, and LST variations in Rawalpindi. By analyzing both daytime and nighttime LST using MODIS satellite imagery, it aims to assess how different land cover types that is built-up areas, crops, and barren land affect temperature distribution. Additionally, it incorporates landscape metrics to measure the role of spatial fragmentation, connectivity, and aggregation in intensifying UHI effects. These insights will provide a deeper understanding of how urban form influences thermal dynamics, bridging a gap in existing research.

To achieve this, the study is guided by the following research questions:

1. How do different land cover types influence daytime and nighttime LST patterns in Rawalpindi?
2. To what extent do spatial configuration and connectivity of land cover influence urban heat intensity?
3. Does higher fragmentation in built-up areas lead to increased UHI intensity, while connected green spaces help mitigate it?

CHAPTER 3

LITERATURE REVIEW

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).

3.1. Estimation of LST with Remote Sensing & GIS

Multiple researchers had limited data resources before the invention of GIS in the 1970s. The acquisition of data on urban heat stress at that time of the event was not enough. To map the patterns of the heat over the urban areas required detailed spatial-time series information through the satellite images so that the urban areas and their surroundings could be analyzed. To demonstrate the urban heat stress of Honk Kong at the local scale with detailed information on the urban area was carried out through the ASTER thermal imageries for the summertime. The optical data were gathered from thermal satellite images and GIS data with the ‘in-situ’ ground-based stations. Both day and nighttime images were processed to find the basis for certain climate conditions. The spatial-temporal air temperature analyzed through the satellite images was compared with the ground data. Due to less air pressure and low wind flow, the imagery gathered through sensors during the nighttime was more representative than in the daytime. Also, the night temperature had a strong correlation with the air temperature at the ground level by the distribution of 93% of all the summer night data each year. Therefore, to find the hot areas prone to exceeding temperature, nighttime satellite images were preferred in Hong Kong for analysis. The temperature measured through satellite images for the surrounding areas and nearby towns

had better results when compared with the ground data due to the inferior quality or less specific locations. The extent and magnitude of the UHI calculated through satellite imageries were preferred compared to ground-based GIS data, as it enables the measurement of the hottest and coolest area of Hong Kong and indicated more specific results than climatic stations. (Nichol & Sensing, 2012).

The spatial distribution of LST was strongly linked with the land cover, as the impervious surface has more capacity to store heat radiation compared to green surfaces. The focus of major studies was on the effects of the green cover areas on the LST for the two capitals of Pakistan and China. RS data were analyzed with two satellite sensors, the high-resolution Gaofen-1 (GF-1) and medium-resolution Landsat-8. The increase in the green cover and water bodies fraction and a decreased fraction of impervious areas were the main key factors for minimizing the LST. Contributing to the artificial lakes would be beneficial within the urban vegetation areas. (Naeem et al., 2018).

The analysis of correlation revealed that the rural and suburban zones had more cooling effects due to vegetation than the urban zone. Eco environmental conditions of two capitals were compared and found that the urban zones had the worst condition with a low fraction of vegetation and a high fraction of impervious surfaces. (Naeem et al., 2018).

The Urban Heat Island (UHI) phenomenon, characterized by elevated temperatures in urban areas compared to their rural surroundings, is one of the most pressing environmental challenges associated with urbanization. Factors such as increased impervious surfaces, reduced vegetation cover, urban geometry, and anthropogenic heat emissions are major contributors to the UHI effect (Voogt & Oke, 2003; Nwakaire et al., 2020). With global urbanization accelerating,

particularly in developing countries, understanding the spatial and temporal dynamics of Land Surface Temperature (LST) and its relationship with land use/land cover (LULC) is crucial for sustainable urban development and effective climate adaptation strategies (Weng et al., 2004; Ayanlade et al., 2017).

LST serves as a critical metric in UHI studies, offering insights into surface thermal characteristics over large spatial and temporal scales (Voogt & Oke, 2003). Advances in remote sensing technologies, particularly MODIS and Landsat imagery, have enabled researchers to retrieve LST data efficiently, facilitating the analysis of UHI patterns across diverse landscapes (Weng et al., 2004; Li et al., 2019). The integration of LST with LULC data has consistently revealed that vegetated areas exhibit a cooling effect due to evapotranspiration, whereas built-up areas are strongly associated with elevated LST due to their high heat absorption and low albedo (Ayanlade et al., 2017; Weng et al., 2014).

For instance, Ayanlade et al. (2017) observed a strong positive correlation between built-up areas and LST in Lagos, Nigeria. The study demonstrated that vegetated regions significantly mitigated surface temperatures, emphasizing the importance of green spaces in urban areas.

3.2 Landscape Metrics and LST

Traditional pixel-based approaches to analyze LST and LULC often fail to capture the broader influence of landscape configuration on thermal dynamics. Landscape metrics, such as offer a more comprehensive understanding by quantifying the spatial structure and composition of landscapes. These metrics are essential for understanding how the diversity of landscapes affects temperature patterns.

Li et al. (2019) demonstrated that fragmented landscapes with reduced vegetation were more susceptible to elevated LST, whereas larger, contiguous vegetative patches contributed significantly to cooling effects. The study underscored the importance of both landscape composition and configuration in mitigating UHI impacts. Similarly, Weng et al. (2004) emphasized that integrating landscape metrics with remote sensing provides a nuanced perspective on how urban morphology shapes thermal environments.

3.3 Diurnal and Seasonal Patterns of LST

Understanding diurnal variations in LST is critical for capturing the full extent of UHI effects. Daytime LST is often higher in urban areas due to the dominance of impervious surfaces, while nighttime LST is influenced by heat retention in urban materials (Voogt & Oke, 2003). Ayanlade et al. (2017) found that diurnal variations in LST were significant in Lagos, with urban areas retaining more heat at night than surrounding rural regions. Similarly, studies in Thimphu, Bhutan, revealed that seasonal variations in LST were intricately linked to changes in vegetation and urban density, with summer months exhibiting the highest thermal disparities between urban and rural areas (Li et al., 2019).

Unusual diurnal patterns, such as those observed in Abu Dhabi, where downtown areas were cooler during the day than suburban regions, highlight the importance of studying both daytime and nighttime LST (Weng et al., 2014). These findings challenge conventional UHI assumptions and underscore the need for further research into the drivers of such anomalies.

Most UHI research has been conducted in developed countries, leaving a gap in knowledge regarding rapidly urbanizing regions in the Global South. Furthermore, diurnal variations and thermal anomalies, such as those observed in Abu Dhabi, remain underexplored.

This study aims to address these gaps by analyzing both diurnal and seasonal variations in LST in Rawalpindi, Pakistan, using MODIS imagery and landscape metrics. By adopting a landscape-based approach, the research provides a holistic understanding of the thermal response of urban landscapes, contributing to sustainable urban planning and climate adaptation strategies.

CHAPTER 4

MATERIAL AND METHODS

4.1 Study area

Rawalpindi, a city of Punjab has been selected as the study area. According to the **2023 digital census**, it is one of the largest cities in Punjab, following Lahore and Faisalabad, with a population of approximately **3.1 million** and an area of about **478 km²**. Geographically, it extends from 33.5651° N to 73.0169° E and is 508 m above mean sea level. It is a humid subtropical region with hot summers, and cool to cold winters. The average temperature in summers is recorded as 38°C. The Study area boundary is shown in Figure 2

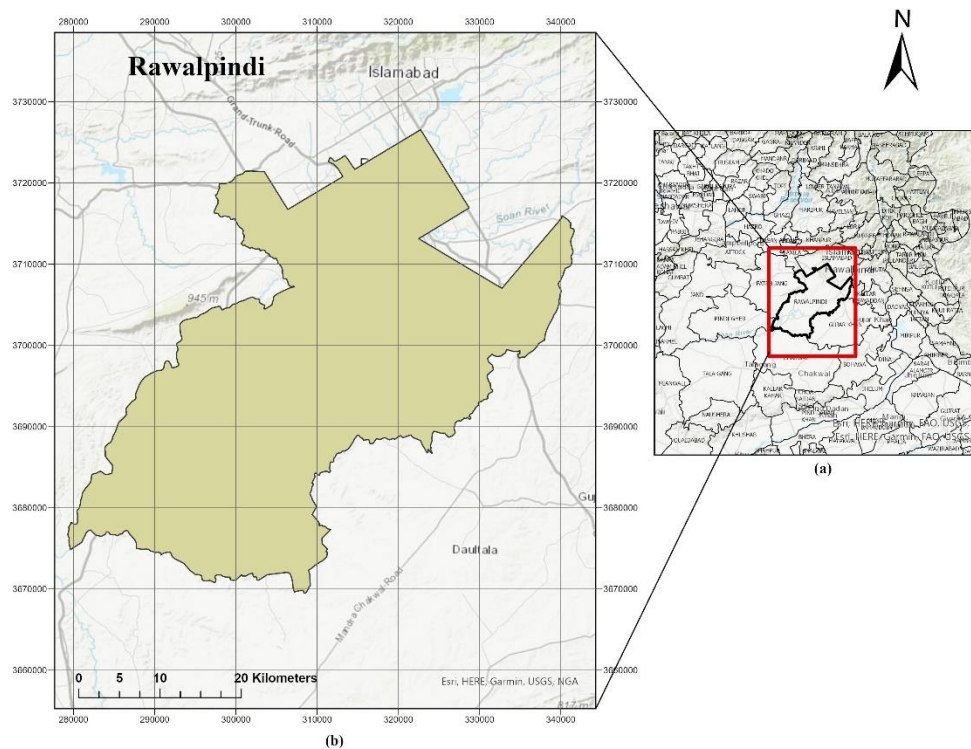


Figure 2 The study area map

4.1.1 The climate of the Study area

The climate conditions of the city are known to have changed historically due to its proximity to the mountainous areas of the Himalayas and the Pir Panjal range. The average temperature varies from 4°C to 38°C on yearly basis and is rarely below 2°C and above 43°C. Pakistan meteorological department (PMD) has recorded an average temperature of 38.11 °C in the summer season (May to August) in 2020. The hottest month of the summer season is June, with an average maximum temperature of 38°C and a minimum temperature of 27 °C. The annual rainfall is 1,346 mm and most of it falls in the monsoon season. It features a humid subtropical region according to the climate classification.

4.2 Methodology Flowchart

The methodology for this study integrates remote sensing data and spatial analysis techniques to investigate the relationship between Land Surface Temperature (LST) and landscape metrics in Rawalpindi, Pakistan. The workflow utilizes Google Earth Engine (GEE) and R programming to handle data retrieval, processing, and analysis.

The process begins in Google Earth Engine, where LST data is retrieved from the MOD11A1 product of the MODIS satellite, which provides a spatial resolution of 1 km for both daytime and nighttime temperatures. These datasets undergo preprocessing steps, including reprojection to ensure compatibility with the LULC raster's reference system. The study area is extracted to focus the analysis specifically on Rawalpindi. The temperature values, originally in Kelvin, are converted to Celsius for easier interpretation. To address potential data gaps, interpolation techniques are applied, generating seamless daytime and nighttime LST maps. These maps serve as a foundation for analyzing diurnal temperature variations and spatial patterns, such as urban heat islands.

In the R programming environment, Land Use and Land Cover (LULC) data for 2023 is utilized to calculate landscape metrics. The LULC map is first reclassified and resampled to standardize the land cover classes and prepare the data for analysis. The reclassified map is divided into grids and within each grid, key landscape metrics are calculated, including Proportional Landscape Area (PLAND), which quantifies the proportion of specific land cover types within each grid cell, and Aggregation Index (AI), which measures the spatial configuration of land cover patches to capture fragmentation or aggregation levels. Additionally, Core Area (CA) calculates the total area of the core (interior) of patches, while Edge-Nearest Neighbor Coefficient of Variation (ENN_CV) assesses patch isolation and connectivity.

Once the LST maps and landscape metrics are prepared, a correlation analysis is performed to examine the statistical relationship between LST and the calculated landscape metrics. This analysis identifies whether and how changes in land cover composition and configuration affect surface temperatures. The results offer insights into the influence of urbanization and land cover patterns on the thermal dynamics of the study area.

This integrated workflow provides a robust framework for understanding urban heat dynamics and offers valuable insights for urban planning and climate adaptation strategies specific to Rawalpindi.

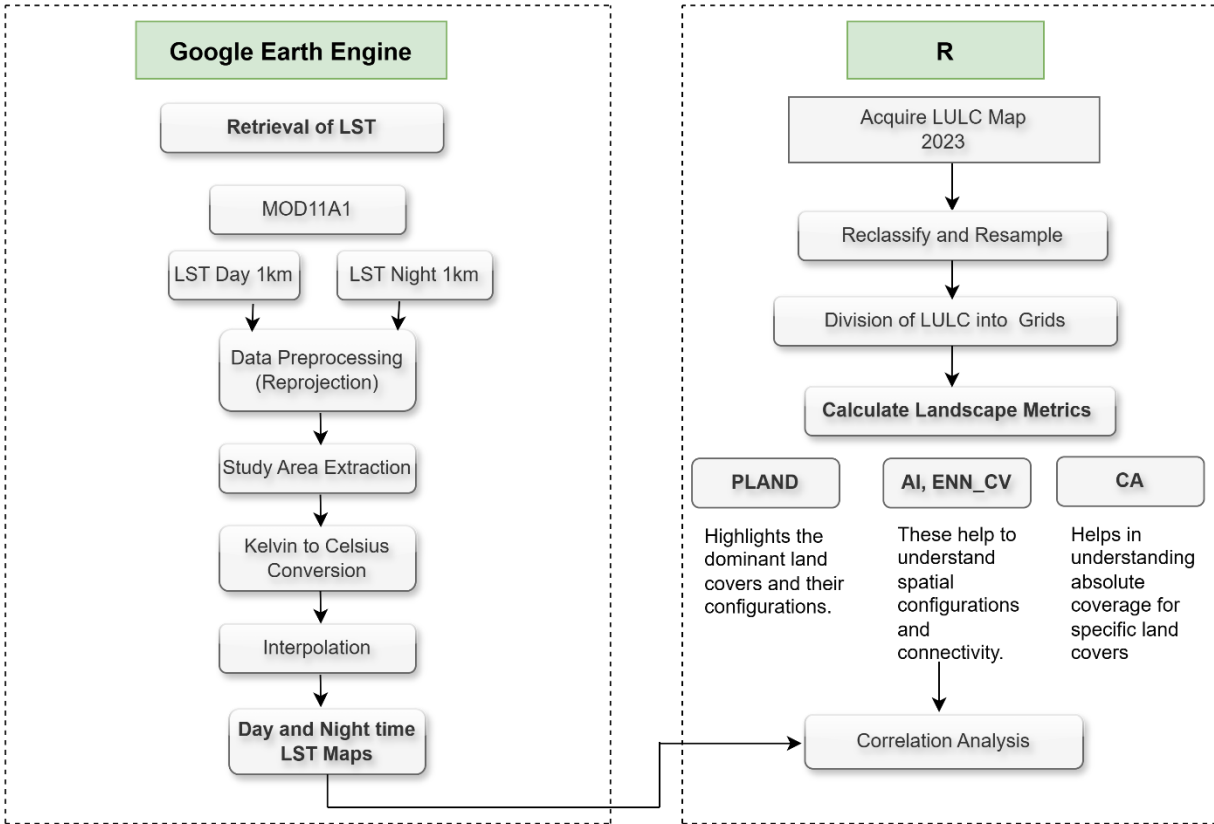


Figure 3 The Methodology Flowchart

4.3 Datasets

4.3.1 Satellite data

Remote sensing data was used to analyze Urban Heat Islands (UHIs) and Land Surface

Temperature (LST) variations. For this study, MODIS data was chosen because it can capture both daytime and nighttime temperature changes, making it ideal for studying daily temperature patterns. Unlike high-resolution data from Landsat or Sentinel, which focus on detailed spatial information, MODIS provides medium resolution (1 km) but with frequent updates over time. This makes it well-suited for tracking temperature changes across larger areas.

The study used the MOD11A1 product, which offers daily and nighttime LST data at a 1 km resolution. The data was processed using Google Earth Engine (GEE), a powerful online

platform for handling large datasets. GEE's cloud-computing capabilities made it easy to access and analyze data without needing local storage, saving time and resources.

Table 1 represents the description of the time-series datasets retrieved from MODIS satellite for this study.

Year	Satellite	Acquisition Date	Source	Time of Day
2023	MODIS	6-May-23	GEE	Day and Night
2023	MODIS	15-May-23	GEE	Day and Night
2023	MODIS	25-May-23	GEE	Day and Night
2023	MODIS	5-Jun-23	GEE	Day and Night
2023	MODIS	15-Jun-23	GEE	Day and Night
2023	MODIS	25-Jun-23	GEE	Day and Night
2023	MODIS	2-Jul-23	GEE	Day and Night
2023	MODIS	14-Jul-23	GEE	Day and Night
2023	MODIS	23-Jul-23	GEE	Day and Night
2023	MODIS	5-Aug-23	GEE	Day and Night
2023	MODIS	22-Aug-23	GEE	Day and Night
2023	MODIS	29-Aug-23	GEE	Day and Night

Table 1 Datasets

4.3.2 Administrative boundary data

The provincial boundary shapefile of the country is publicly available through an online site (Data, 2022).

4.3.3 Land Use & Land Cover data

The land use and land cover (LULC) data used in this study were sourced from the European Space Agency (ESA). ESA provides high-quality global-scale land cover datasets through its Climate Change Initiative (CCI), which are generated using advanced remote sensing techniques. These datasets offer consistent and reliable information on land cover extent and changes, with a spatial resolution of 300 meters. To ensure compatibility for correlation with MODIS LST data, the LULC dataset was reclassified and resampled. The reclassification process standardized the land cover classes, while resampling adjusted the spatial resolution of the LULC data to match

that of the MODIS dataset. These preprocessing steps made it easier to analyze the connection between Land Surface Temperature (LST) and landscape patterns in the study area, ensuring a smooth and insightful process.

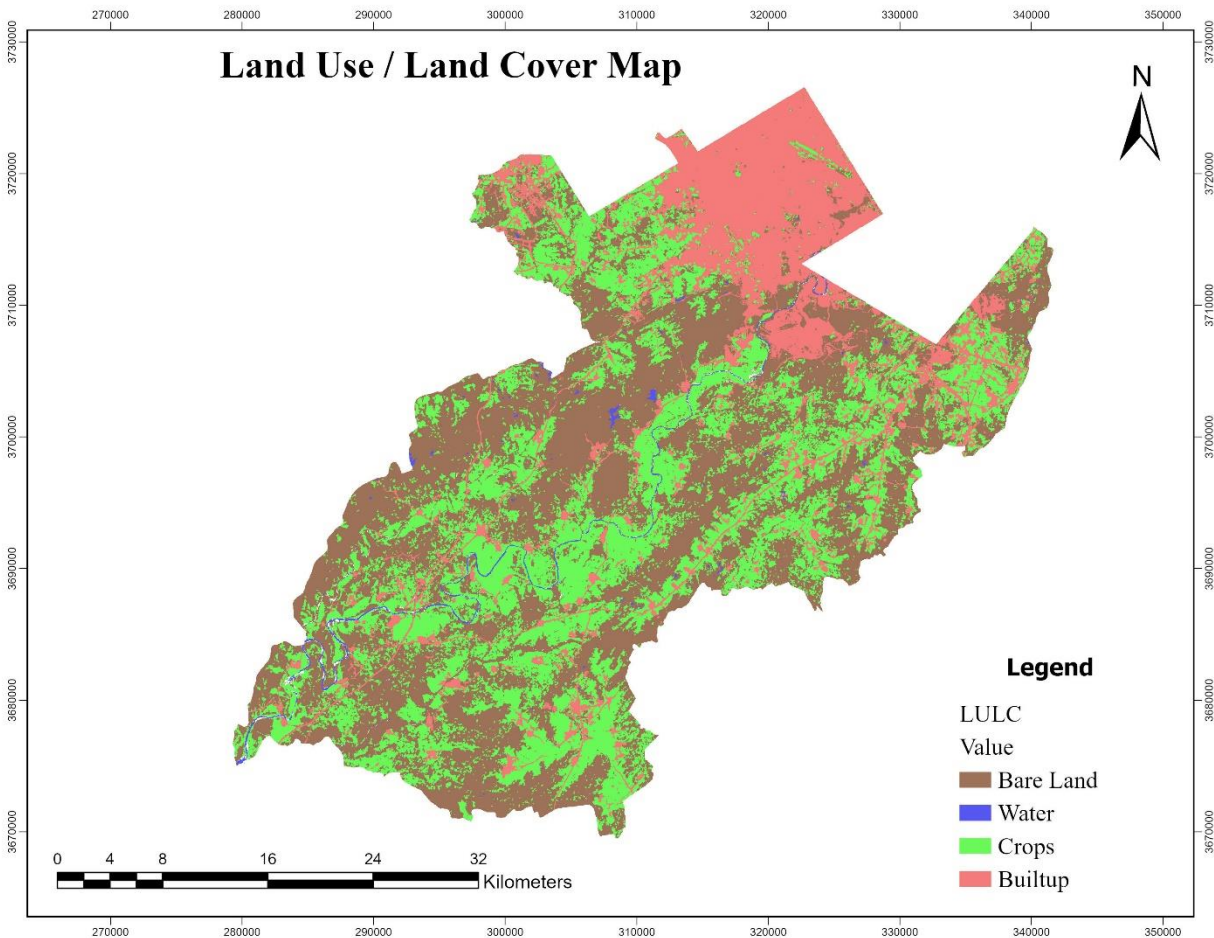


Figure 4 LULC Map

4.4 Google Earth Engine Data Analysis

In the era of cloud computing, geospatial datasets are now visualized and analyzed on the online platform “Earth Engine.” The scientific analysis is carried out by using this platform for non-profit, government, business, academic, and research purposes. Instead of downloading a large amount of data on devices, it has public data archives that store historical satellite imageries of

multiple sensors for the previous forty years. Different data catalogs hosted by Earth Engine are available online for multiple geospatial analyses. Also, it provides the facility to generate different APIs and tools to authorize geospatial analysis on big geospatial data.

4.4.1 Code Repository

GEE provides the Integrated Development Environment (IDE) with an online code editor of JavaScript API. It is easy to modify and calibrate. It has multiple features to make developing workflow easy and fast. It has multiple built-in functions and tools in the code editor including JavaScript code Editor, Map visualization, console, search bar, etc. The framework of the repository Code is shown below in Figure 5, where different options for writing, modifying, and running the code are available.

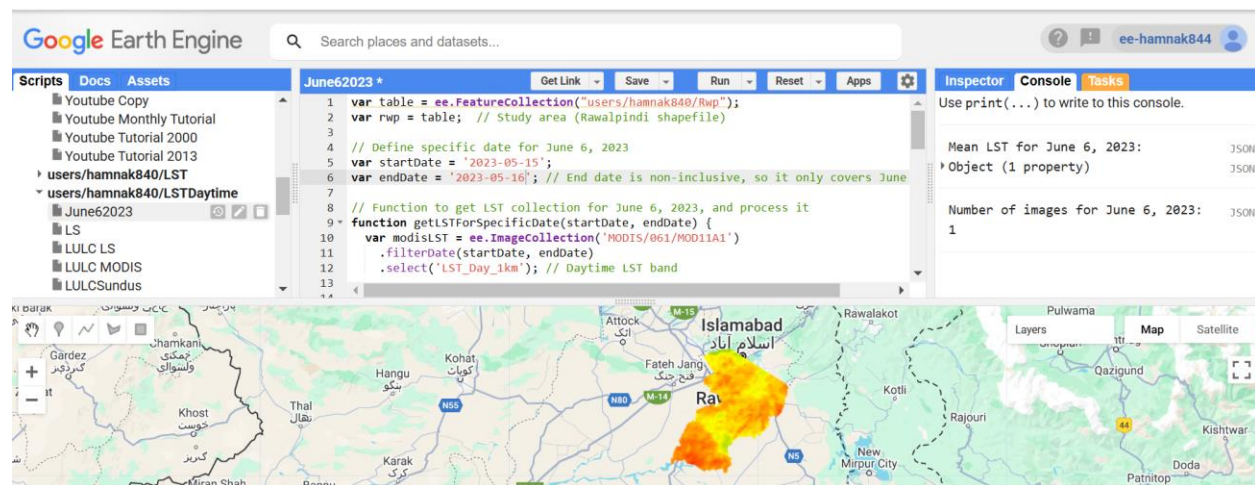


Figure 5 The main Code Repository of the Google Earth Engine (code script)

4.5 Retrieving Land Surface Temperature

The Land Surface Temperature (LST) data for this study were obtained from the MODIS MOD11A1 product through Google Earth Engine (GEE). This data set provides daily measurements of both daytime and nighttime LST at a 1 km spatial resolution, making it well-

suited for analyzing diurnal temperature variations. To achieve comprehensive temporal coverage, LST data was retrieved for specific dates at ten-day intervals during the summer months of May, June, July, and August for the year 2023.

For each selected date, both daytime and nighttime LST data were collected to capture daily temperature changes accurately. This approach provided a clearer picture of thermal patterns, avoiding potential biases from analyzing daytime or nighttime data alone. The study area boundary for Rawalpindi was defined in Google Earth Engine (GEE), and the LST data were clipped to match this boundary, ensuring proper spatial alignment. The data were also reprojected to a consistent coordinate system for uniformity.

To ensure data reliability, the MODIS quality assurance (QA) layer was used to filter out low-quality pixels affected by clouds, sensor errors, or other issues. Only high-quality pixels were kept for analysis. The LST values, originally in Kelvin, were converted to Celsius using standard formulas, making the data easier to interpret and compatible with other datasets. The processed LST data were then organized into separate daytime and nighttime datasets, enabling a clear analysis of daily temperature variations.

By using Google Earth Engine's powerful cloud-computing capabilities, the entire data retrieval and processing workflow was streamlined. This eliminated the need for local storage or heavy computational resources, ensuring efficient handling of large datasets. The result was accurate, high-quality LST data, which served as the foundation for analyzing temperature patterns and their relationship with landscape metrics in Rawalpindi.

4.6 Calculating Landscape Metrics

The calculation of landscape metrics was conducted using R, leveraging its powerful tools for spatial data analysis and visualization. R was selected for this study because of its flexibility, open-source nature, and an extensive ecosystem of packages tailored to geospatial analysis, particularly the landscapemetrics package. This package provided robust methods for calculating a range of landscape metrics, facilitating a detailed understanding of how land cover composition and configuration influence Land Surface Temperature (LST).

To enable a detailed spatial analysis, the study area was divided into 4 grids. This grid size was chosen for several reasons. First, it matched the 1 km resolution of the MODIS LST data, ensuring each grid had enough data points for reliable analysis. Second, it effectively captured local temperature patterns, such as areas that cooled faster at night or retained heat longer during the day. This balance allowed for meaningful insights without oversimplifying or overcomplicating the data. Finally, the grid size was practical for analyzing landscape metrics, providing a suitable scale to explore the relationship between landscape features and temperature patterns.

4.6.1 Data Source and Preprocessing

The land use and land cover (LULC) data were sourced from the European Space Agency (ESA). These high-quality global datasets are derived using advanced remote sensing techniques and are provided at a spatial resolution of 300 meters. The reclassification process grouped land cover types into three main categories: Built-up, Crops, and Barren, focusing on these specific classes due to their relevance in urban heat dynamics. This grouping was designed to highlight the thermal influence of urbanized and agricultural areas, as well as barren lands. The resampling

process adjusted the spatial resolution of the LULC data to match the MODIS LST data, ensuring compatibility for seamless correlation analysis. These preprocessing steps made the ESA datasets highly suitable for understanding the relationship between LST and landscape patterns in the study area.

4.6.2 Landscape Metrics Selection

The landscape metrics selected for this study include Proportional Landscape Area (PLAND), Aggregation Index (AI), Edge-Nearest Neighbor Coefficient of Variation (ENN-CV), and Core Area (CA). These metrics were chosen due to their ability to comprehensively quantify the composition and configuration of landscapes, which are crucial in understanding their influence on Land Surface Temperature (LST). Each metric serves a distinct purpose in characterizing the spatial patterns of land cover, making them highly relevant for examining urban heat dynamics.

For this study, the metrics were calculated separately for each of the three primary land cover classes: barren land, crops, and built-up areas. This approach allows for a detailed analysis of how the spatial characteristics of each land cover type influence thermal behavior. Below is a description of each metric and its relevance to the study.

1. Proportional Landscape Area (PLAND)

PLAND measures the percentage of a specific land cover type within the total landscape area. It helps understand the landscape, showing how dominant or rare certain land covers are. This metric is crucial in urban heat studies because it links directly to surfaces that absorb or release heat, like buildings or vegetation. Many studies have used PLAND to show how the amount of urban or green spaces affects temperature, such as reducing urban heat islands or improving cooling effects.

2. Aggregation Index (AI)

AI measures the degree of aggregation or fragmentation of land cover patches within the landscape. It reflects the spatial configuration by indicating whether land cover types are clustered or dispersed. A higher AI value suggests greater patch aggregation, which has implications for heat retention and dispersion. Urban heat dynamics are particularly sensitive to this metric, as fragmented urban areas tend to have higher LST due to increased edge effects and exposure to solar radiation.

3. Edge-Nearest Neighbor Coefficient of Variation (ENN-CV)

ENN-CV evaluates the spatial isolation and connectivity of patches by measuring the variation in edge-to-edge distances between adjacent patches. This metric is critical for understanding the spatial relationships among different land cover types. Higher ENN-CV values indicate more spatially isolated patches, while lower values suggest a more connected landscape. ENN-CV is particularly relevant for urban heat studies as it helps assess the influence of patch isolation on thermal dynamics, such as the cooling effect of connected vegetation patches or the warming effect of isolated urban patches.

4. Core Area (CA)

CA quantifies the interior area of land cover patches, excluding edge effects. It provides insights into the size and shape of patches. Larger core areas are often associated with greater thermal stability, especially in vegetative or barren patches.

4.6.3 Rationale for Metric Selection

These metrics were chosen among others because they collectively provide a robust framework for analyzing both the composition (PLAND) and configuration (AI, ENN-CV, CA) of landscapes. They offer a balance between quantifying the spatial dominance of specific land cover types and understanding their spatial arrangement and connectivity. This balance is critical for comprehensively assessing the impact of landscape patterns on LST, particularly in urbanized environments.

The selection of these metrics is supported by existing research on urban heat. PLAND shows a strong link to Land Surface Temperature (LST), as impervious surfaces like concrete significantly affect heat. AI (Aggregation Index) and ENN-CV (Coefficient of Variation of Edge-to-Edge Nearest Neighbor Distance) help analyze how land cover is arranged, which is key to understanding heat spread and retention. CA (Core Area) highlights the cooling effect of large green spaces or barren areas, which stabilize temperatures. By combining these metrics, the study aims to better understand how land cover types and their layout influence heat patterns in the area. These metrics are widely used in urban heat research and are backed by evidence, ensuring they are reliable and relevant for this analysis.

Landscape Metrics Analysis

The analysis of landscape metrics was done to examine the influence of landscape characteristics on Land Surface Temperature (LST) dynamics. By integrating Land Use Land Cover (LULC) data and LST data, this approach aimed to capture local-level variations in temperature and assess their relationships with landscape composition and configuration.

4.6.4 Study Area and Grid Division

To better understand the relationship between Land Use Land Cover (LULC) and Land Surface Temperature (LST), the study area was divided into grids. This approach allowed for a detailed, localized analysis of temperature variations and their connections to the surrounding landscape. Figure 6 illustrates the gridded structure applied to the study area.

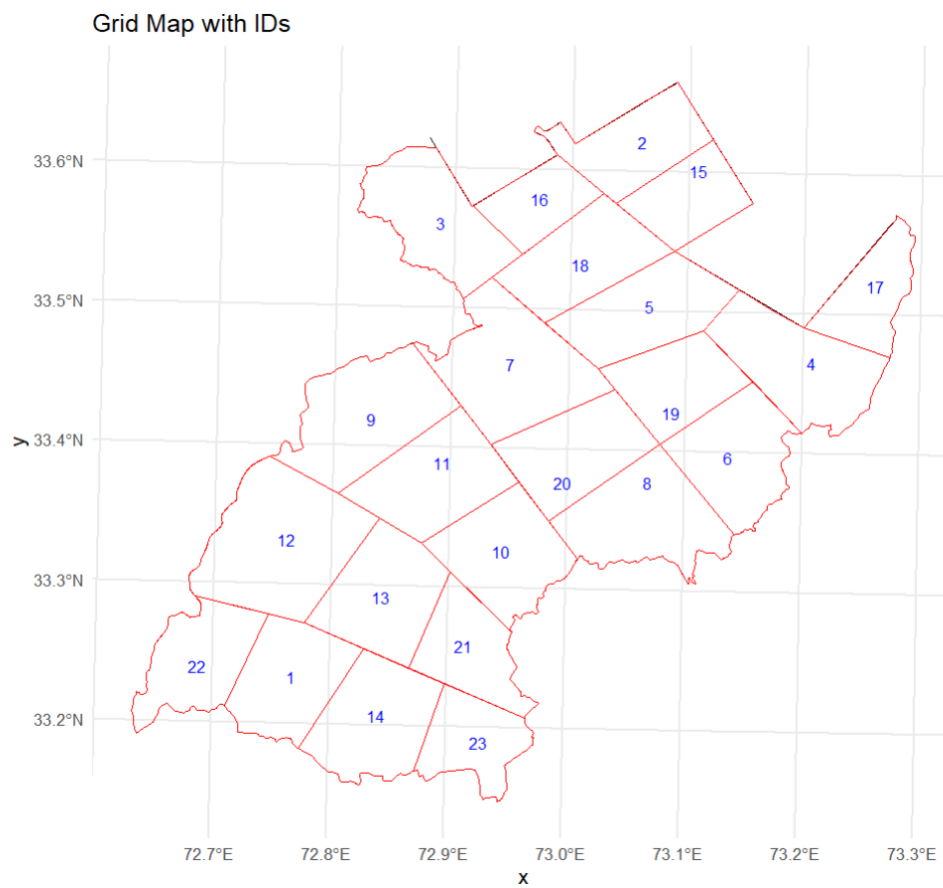
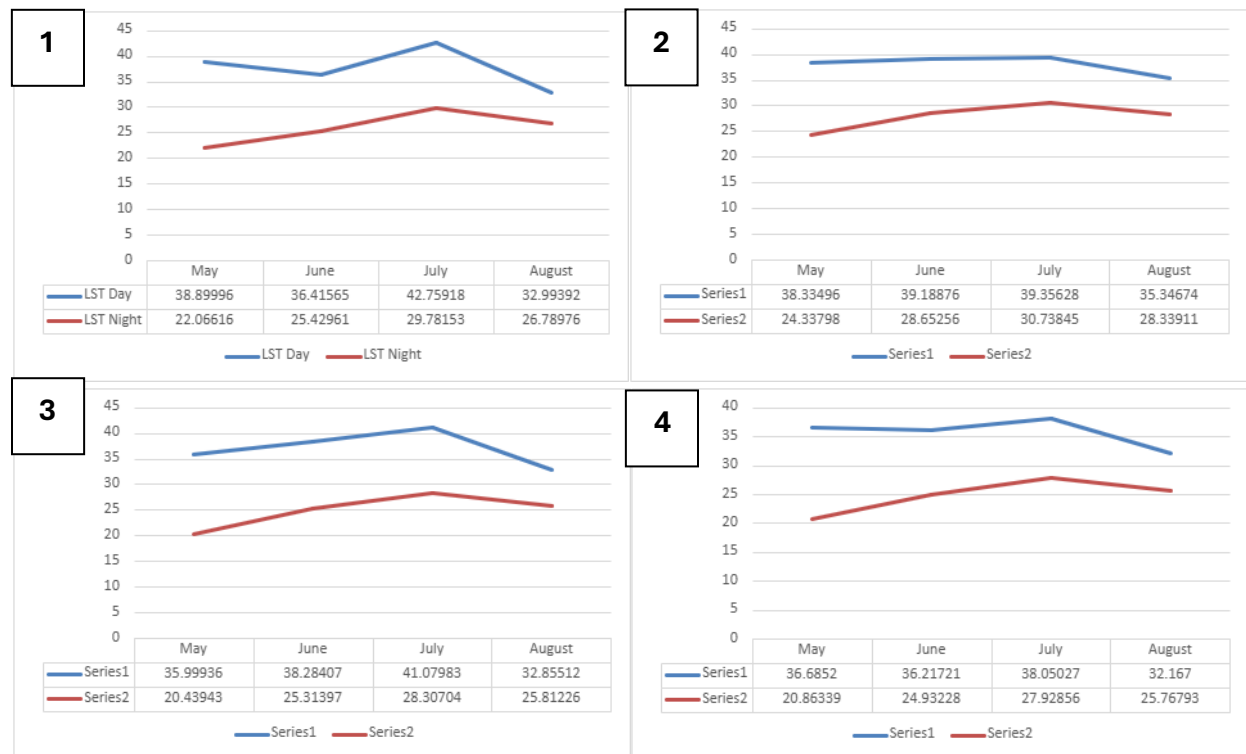


Figure 6 Study area division

The grids were designed to be detailed enough to capture local-level dynamics. This approach created a strong framework for analyzing how diverse and complex landscapes affect thermal behaviour. By dividing the study area into grids, the methodology allowed for a deeper

understanding of how distinct parts of the landscape contribute to temperature variations across the region.

Figure 7 illustrates the changes in day and night temperatures across 8 representative grids from May to August, while Table 2 summarizes the monthly average temperatures and their differences for these grids. Although the study area is divided into 23 grids, these selected grids provide a clear snapshot of the thermal patterns observed across the landscape. The graph highlights how day and night temperatures vary over time for each grid, while the table offers a numerical summary of these trends. Together, these visuals demonstrate the value of combining spatial metrics and temporal data to better understand thermal dynamics across the study area.



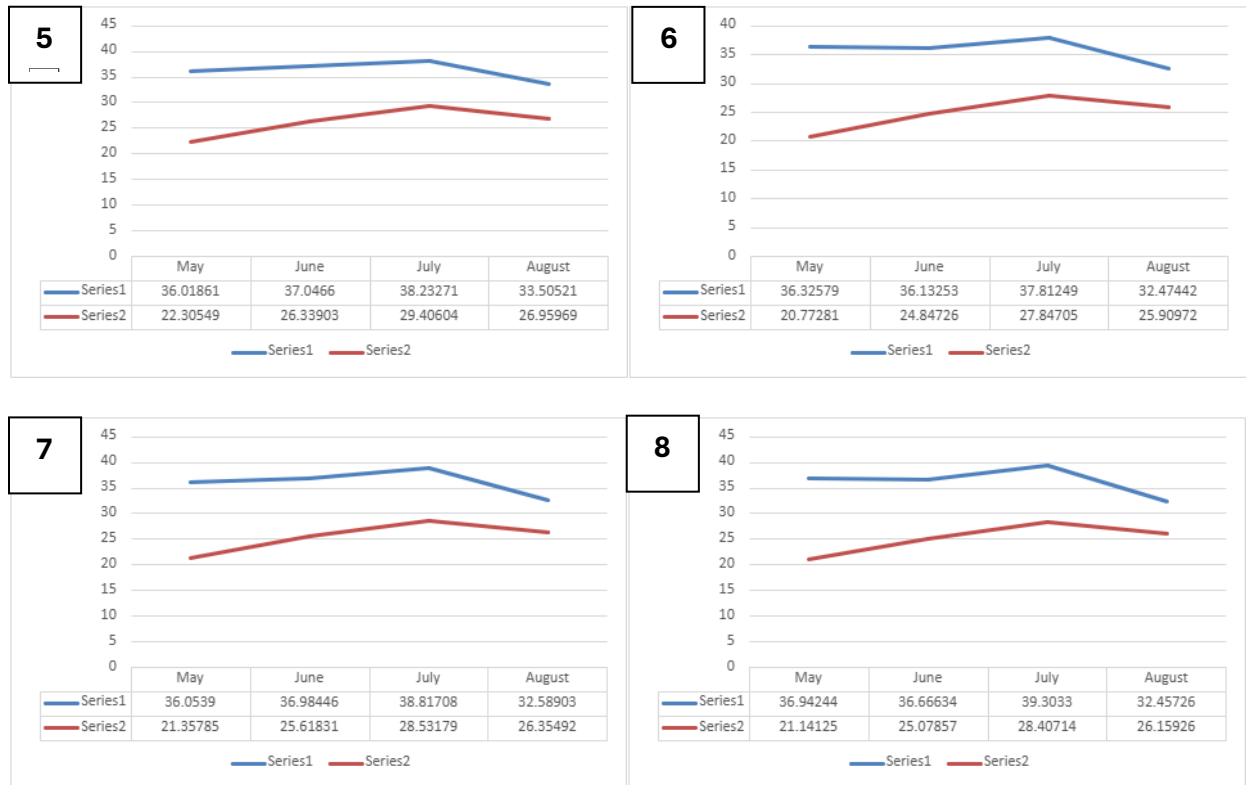


Figure 7 Day and night Temperature Variations across 8 Grids

GRID ID	Month	LST Day	LST Night	Temp Difference
1	May	38.89996	22.06616	16.8338
1	June	36.41565	25.42961	10.98604
1	July	42.75918	29.78153	12.97765
1	August	32.99392	26.78976	6.20416
2	May	38.33496	24.33798	16.8338
2	June	39.18876	28.65256	10.98604
2	July	39.35628	30.73845	12.97765
2	August	35.34674	28.33911	6.20416
3	May	35.99936	20.43943	16.8338
3	June	38.28407	25.31397	10.98604
3	July	41.07983	28.30704	12.97765
3	August	32.85512	25.81226	6.20416
4	May	36.6852	20.86339	16.8338
4	June	36.21721	24.93228	10.98604
4	July	38.05027	27.92856	12.97765
4	August	32.167	25.76793	6.20416

5	May	36.01861	22.30549	16.8338
5	June	37.0466	26.33903	10.98604
5	July	38.23271	29.40604	12.97765
5	August	33.50521	26.95969	6.20416
6	May	36.32579	20.77281	16.8338
6	June	36.13253	24.84726	10.98604
6	July	37.81249	27.84705	12.97765
6	August	32.47442	25.90972	6.20416
7	May	36.0539	21.35785	16.8338
7	June	36.98446	25.61831	10.98604
7	July	38.81708	28.53179	12.97765
7	August	32.58903	26.35492	6.20416
8	May	36.94244	21.14125	16.8338
8	June	36.66634	25.07857	10.98604
8	July	39.3033	28.40714	12.97765
8	August	32.45726	26.15926	6.20416

Table 2 Summary of the monthly average temperatures for 8 Grids

RESULTS AND DISCUSSION

5.1 Spatial and Temporal Patterns of LST

The spatial distribution maps of LST for both daytime and nighttime across May, June, July, and August (Figures 8 to 15) reveal distinct thermal patterns. For each month, three representative dates were selected to capture temporal fluctuations, ensuring that variations within the month were adequately represented. These maps highlight how daytime and nighttime LST patterns evolve with seasonal changes.

5.1.1 Daytime Patterns

The observed variations in daytime land surface temperature (LST) across the study area indicate potential influences of land cover composition and spatial distribution. While factors such as urban density, vegetation coverage, and surface materials contribute to these variations, the precise role of landscape metrics in shaping these thermal patterns requires further investigation. The inclusion of landscape metrics, such as aggregation index and proportional landscape area, will provide deeper insights into how spatial arrangement and land cover configuration affect LST distribution. A more systematic analysis incorporating these metrics will help establish stronger correlations between landscape characteristics and thermal behavior, ensuring that conclusions drawn are based on quantifiable spatial patterns rather than assumptions.

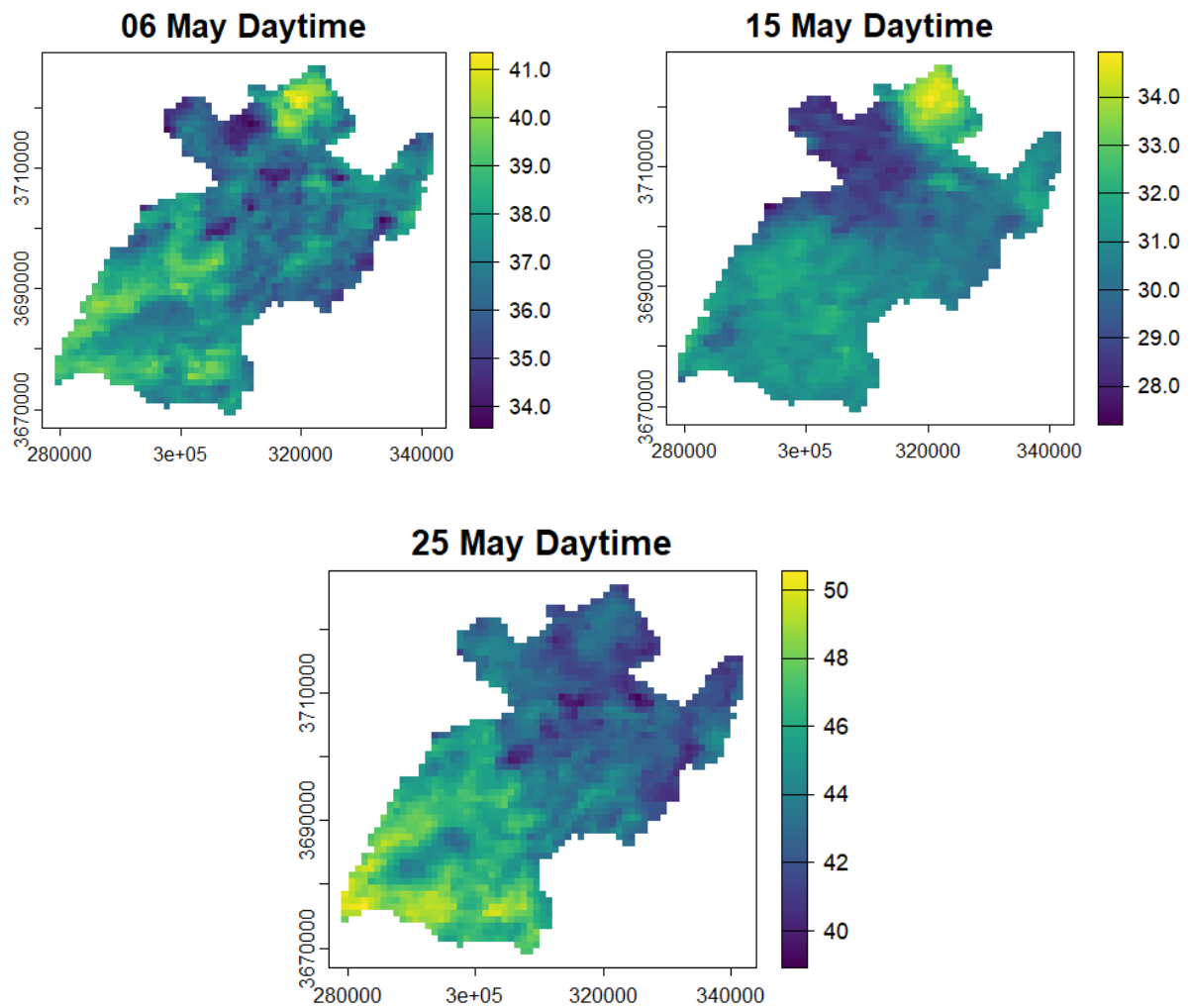


Figure 8 Day Time Land Surface Temperature (LST) variations over the study area for May

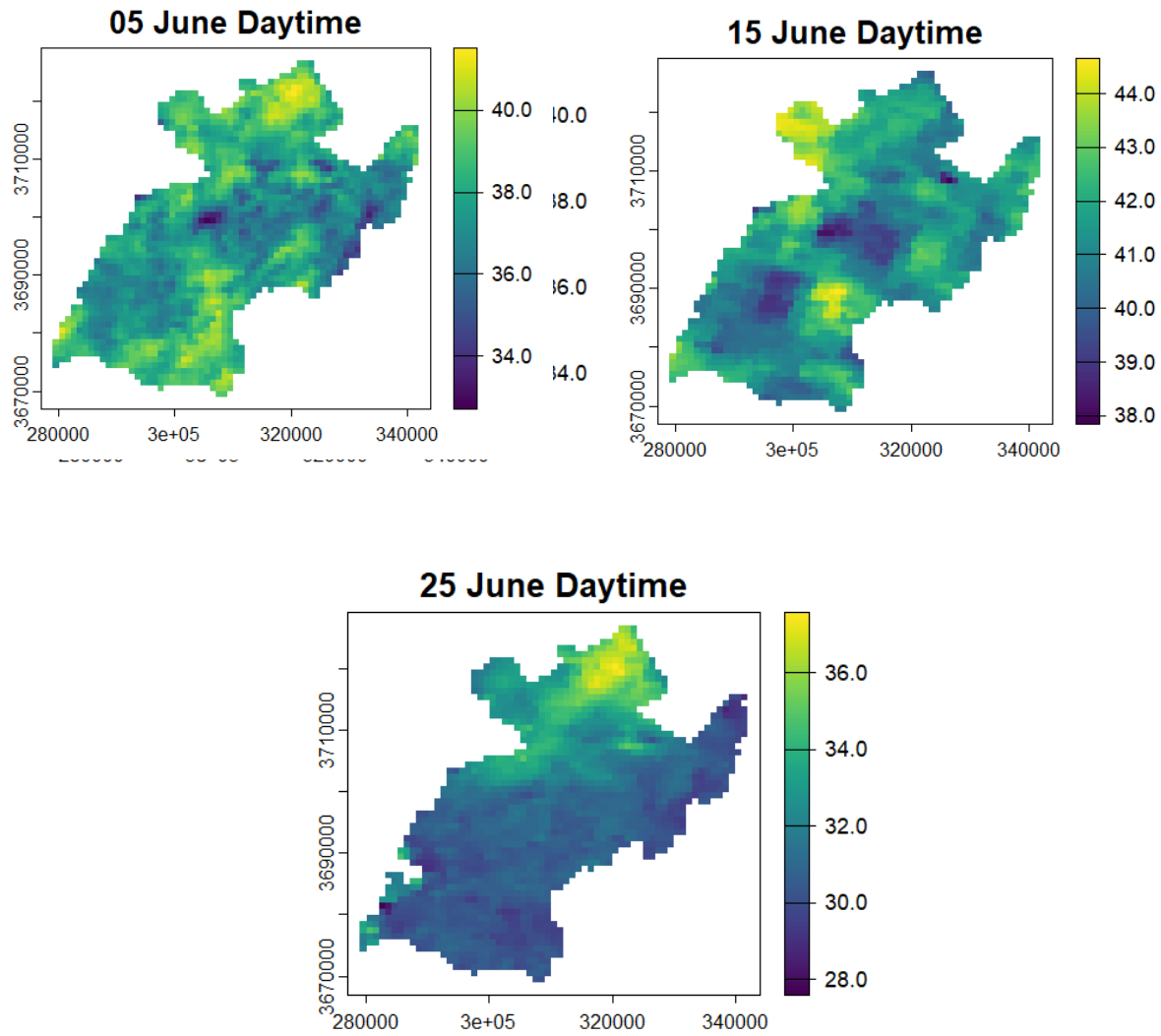


Figure 9 Day Time Land Surface Temperature (LST) variations over the study area for June

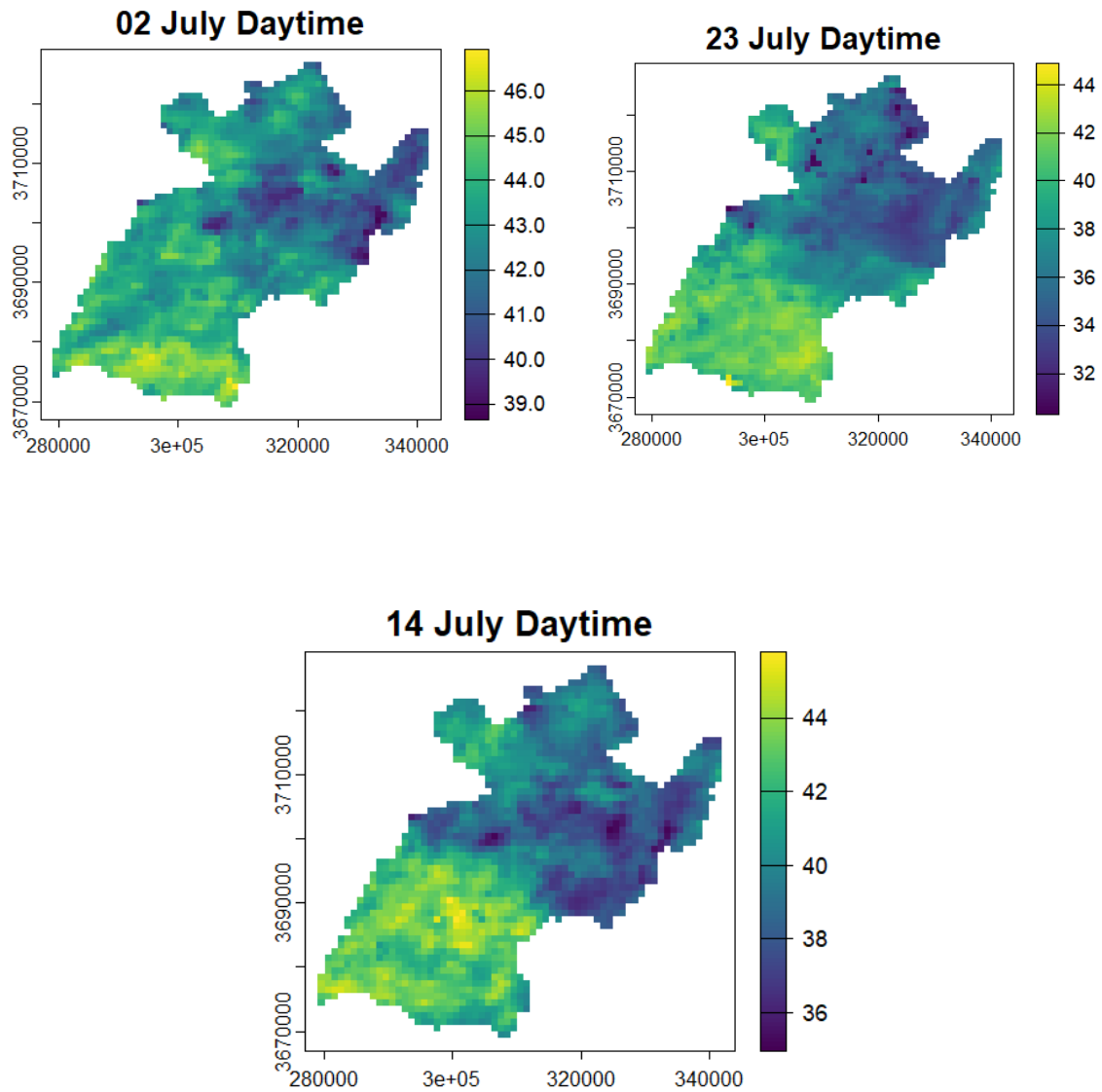


Figure 10 Day Time Land Surface Temperature (LST) variations over the study area for July

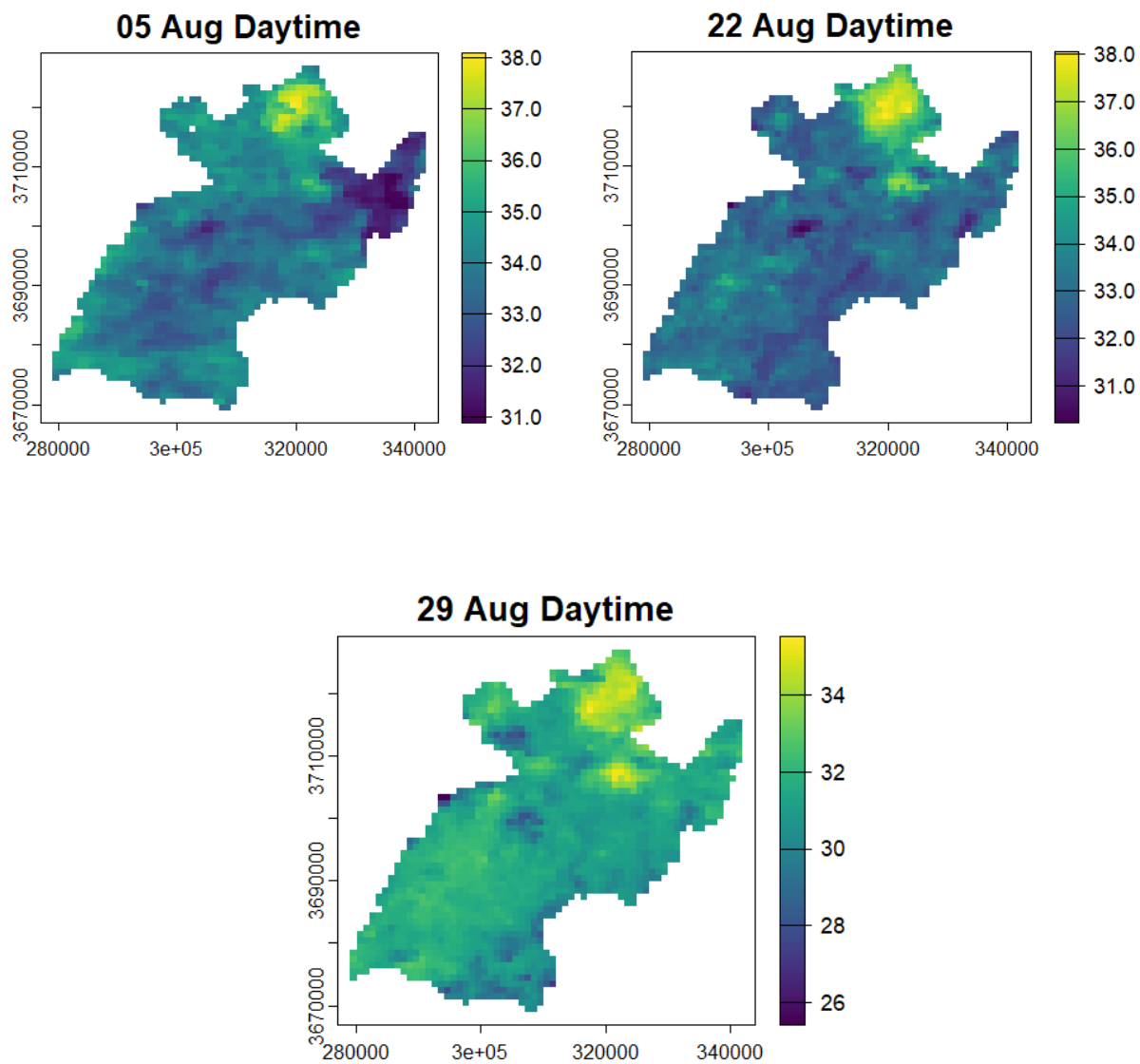


Figure 11 Day Time Land Surface Temperature (LST) variations over the study area for August

5.1.2 Nighttime Patterns

Like daytime LST variations, nighttime temperature distributions reveal significant differences across land cover types. The retention of heat in built-up areas and the cooling effects of vegetative cover are expected to play a role, but without analyzing landscape metrics, the exact influence of spatial configurations remains uncertain. The integration of metrics such as Euclidean Nearest Neighbor and Class Area will allow for a more structured understanding of the extent to which landscape composition affects nighttime heat retention. By incorporating these analyses, the study can provide a more robust explanation of how different land cover patterns impact temperature variations, rather than relying on broad assumptions. This highlights the necessity of studying landscape metrics to accurately interpret urban thermal behavior.

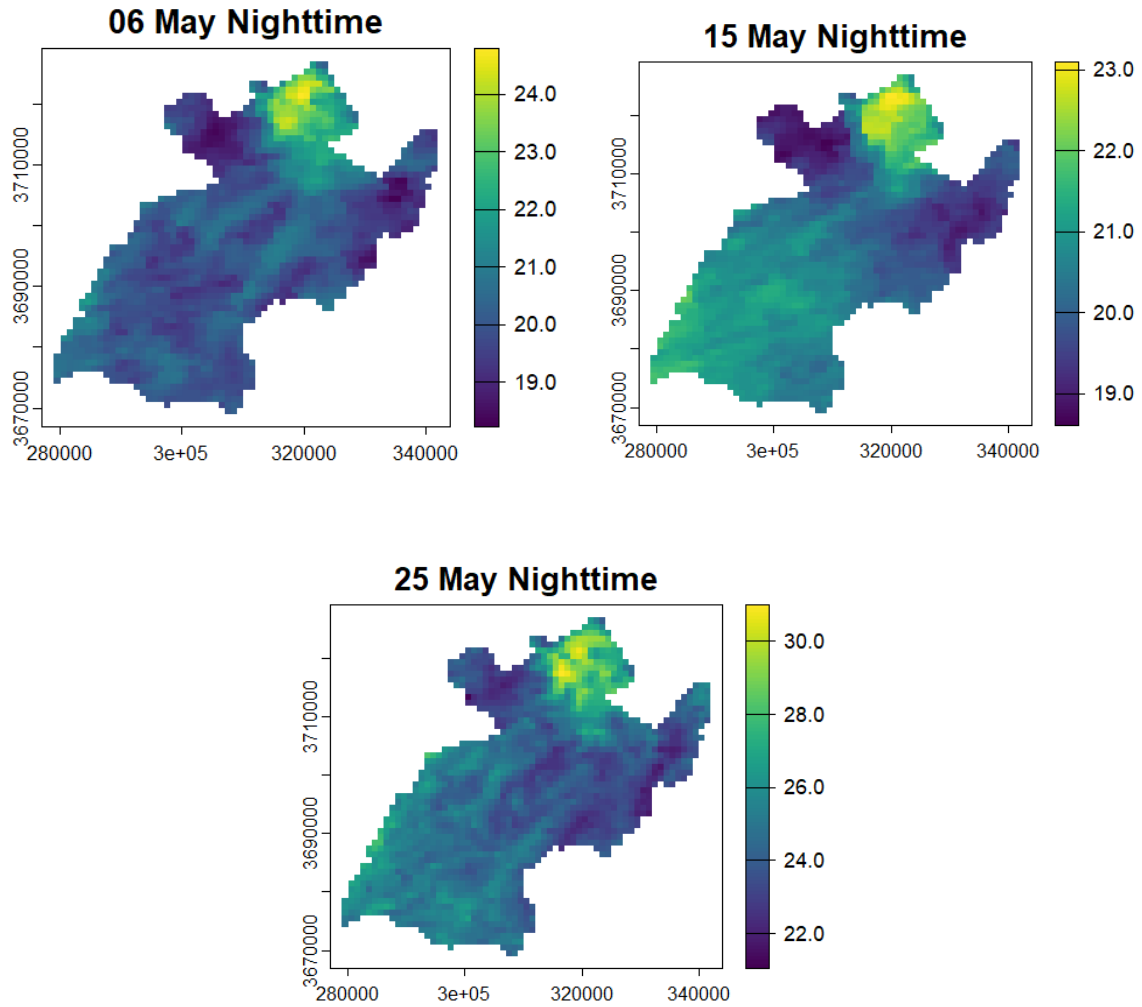


Figure 12 Nighttime Land Surface Temperature (LST) variations over the study area for May

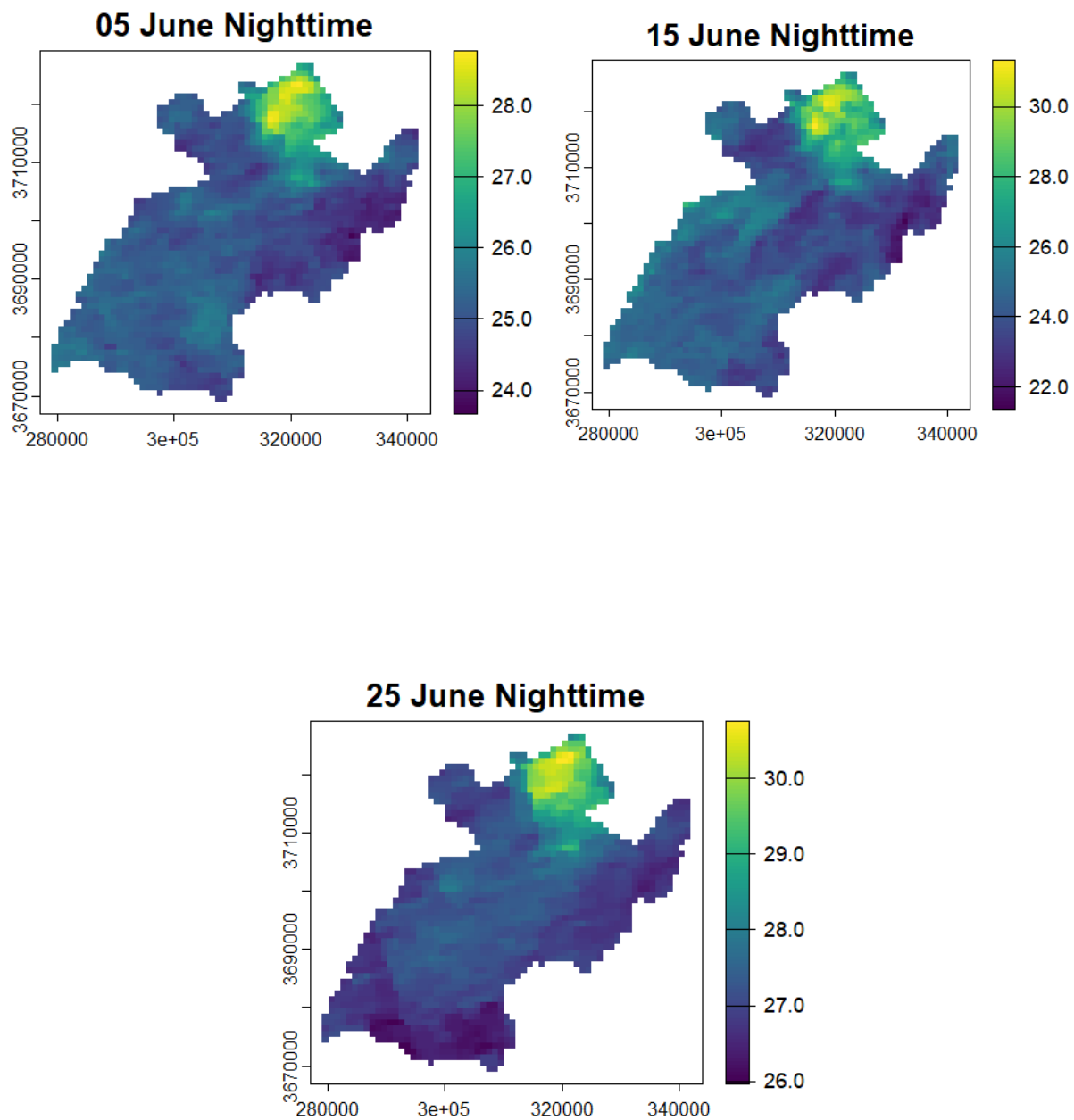


Figure 13 Nighttime Land Surface Temperature (LST) variations over the study area for June

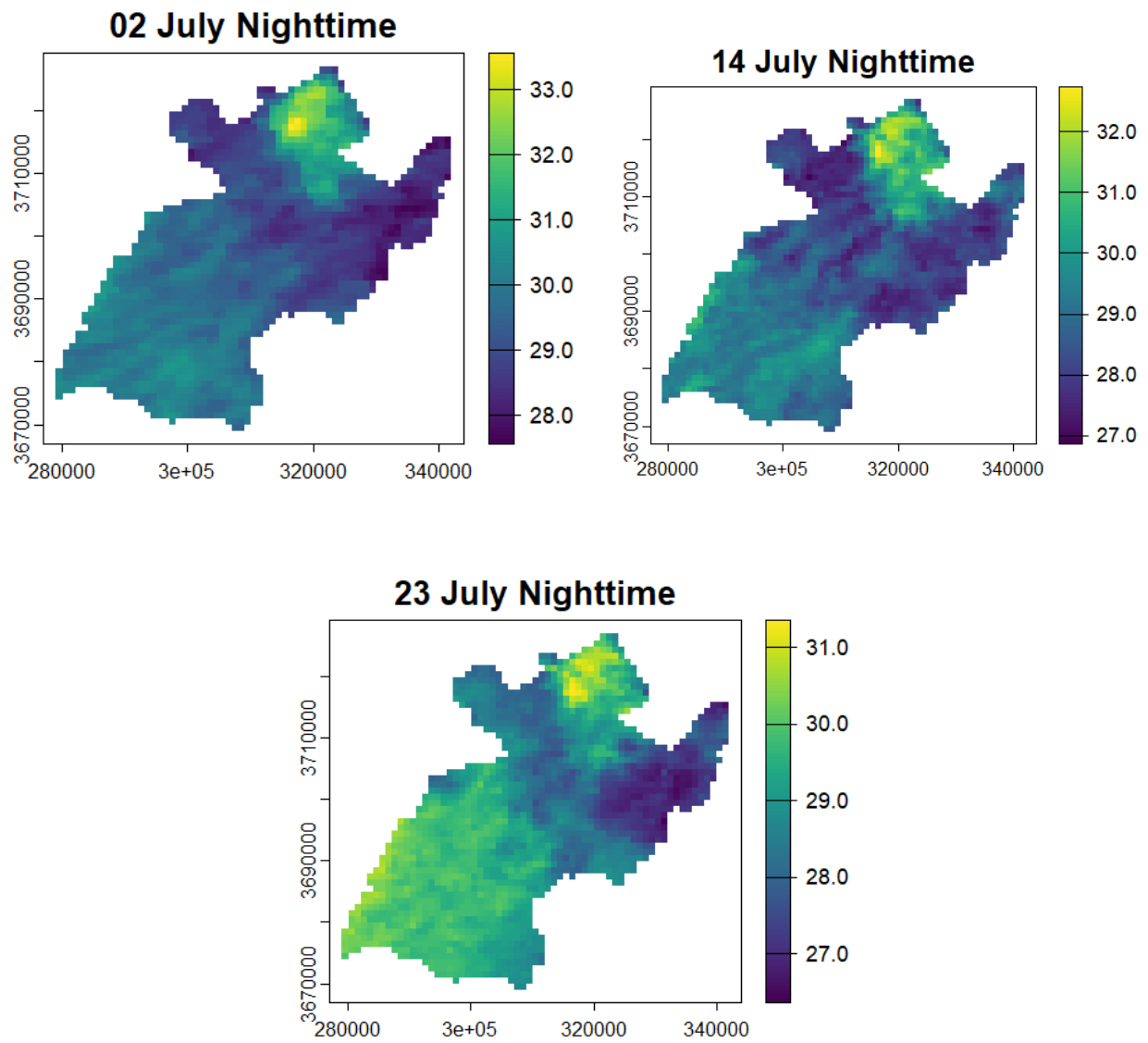


Figure 14 Nighttime Land Surface Temperature (LST) variations over the study area for July

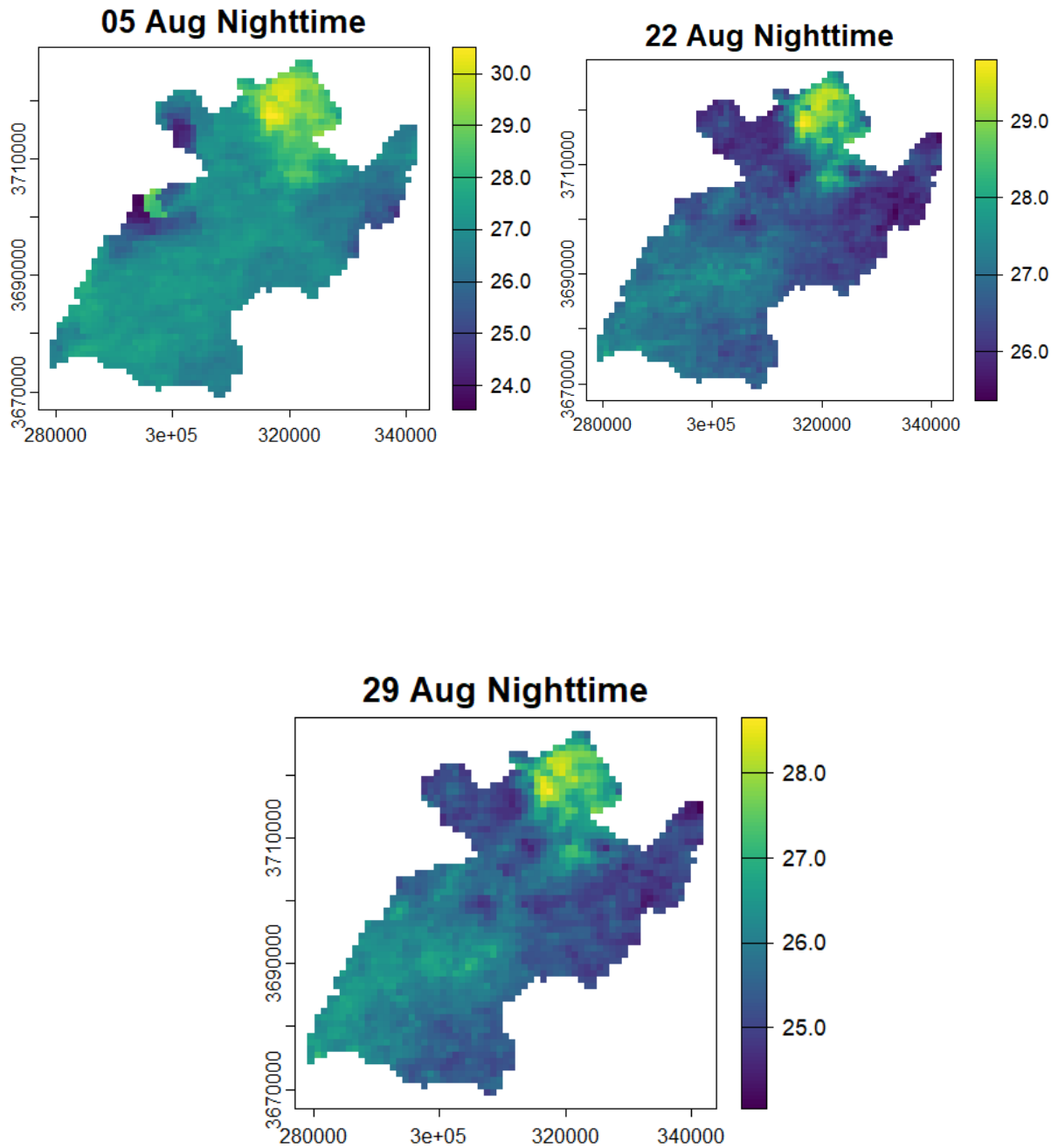


Figure 15 Nighttime Land Surface Temperature (LST) variations over the study area for August

5.2.2 Metrics Calculation

Three primary LULC classes were considered: barren land, crops, and built-up areas, as these were deemed most relevant for studying temperature dynamics. For each grid, landscape metrics were calculated using LULC data. The metrics considered included:

1. **Percentage of Landscape (PLAND):** Quantifies the proportional area of each LULC type within a grid.
2. **Class Area (CA):** Represents the total area covered by a specific LULC class.
3. **Aggregation Index (AI):** Reflects the spatial aggregation of patches within a grid.
4. **Euclidean Nearest Neighbor Coefficient of Variation (ENN-CV):** Indicates the variability in the distances between patches of the same class.

These metrics were computed using the landscapemetrics package in R, and the results were organized in a tabular format. Table 3 present a portion of the computed metrics for Aggregation Index (AI) and Percentage of Landscape (PLAND) across barren land, crops, and built-up areas, alongside LST, date, and time for context. Table 4 shows a similar representation for Class Area (CA) and Euclidean Nearest Neighbor Coefficient of Variation (ENN-CV), further illustrating the relationship between landscape composition and temperature dynamics.

GRID ID	ai_bare	pland_bare	ai_crops	pland_crops	ai_builtup	pland_builtup	LST	Date	Time
1	64.83516	63.855422	26.82927	31.325301	25	4.819277	38.13965	6-May	day
1	64.83516	63.855422	26.82927	31.325301	25	4.819277	20.03471	6-May	night
2	0	2.325581	0	4.651163	90.14085	93.023256	39.16419	6-May	day
2	0	2.325581	0	4.651163	90.14085	93.023256	22.92372	6-May	night
3	35	26.315789	56.94444	45.263158	57.5	26.315789	35.84919	6-May	day
3	35	26.315789	56.94444	45.263158	57.5	26.315789	19.11505	6-May	night
4	59.77011	47.222222	47.69231	36.111111	25.925926	16.666667	37.0127	6-May	day
4	59.77011	47.222222	47.69231	36.111111	25.925926	16.666667	19.58189	6-May	night
5	59.70149	42.105263	48	17.894737	63.333333	37.894737	36.31958	6-May	day
5	59.70149	42.105263	48	17.894737	63.333333	37.894737	21.12188	6-May	night
6	55.07246	45.054945	44.2623	40.659341	5.555556	14.285714	36.51884	6-May	day
6	55.07246	45.054945	44.2623	40.659341	5.555556	14.285714	19.65505	6-May	night
7	70.45455	60.483871	48.33333	29.032258	6.666667	8.870968	36.36323	6-May	day
7	70.45455	60.483871	48.33333	29.032258	6.666667	8.870968	19.94754	6-May	night
8	50.58824	46.728972	58.53659	44.859813	0	8.411215	36.56179	6-May	day
8	50.58824	46.728972	58.53659	44.859813	0	8.411215	20.03429	6-May	night

Table 3 Detailed landscape metrics, including PLAND and AI with corresponding day and night LST values for selected grids.

Grid ID	ca_bare	enn_cv_bare	ca_crops	enn_cv_crops	ca_builtup	enn_cv_builtup	LST	Date	Time
1	5239.6388	0	2570.3888	5.688193	395.4444	52.5985209	38.13965	6-May	day
1	5239.6388	0	2570.3888	5.688193	395.4444	52.5985209	20.03471	6-May	night
2	197.7222	0	395.4444	61.6129	7908.889	0	39.16419	6-May	day
2	197.7222	0	395.4444	61.6129	7908.889	0	22.92372	6-May	night
3	2471.5277	0.16389575	4251.0277	6.712243	2471.528	0.1876363	35.84919	6-May	day
3	2471.5277	0.16389575	4251.0277	6.712243	2471.528	0.1876363	19.11505	6-May	night
4	5041.9165	0.09754606	3855.5832	1.626299	1779.5	16.2467076	37.0127	6-May	day
4	5041.9165	0.09754606	3855.5832	1.626299	1779.5	16.2467076	19.58189	6-May	night
5	3954.4443	15.80253426	1680.6388	6.176311	3559	5.2058796	36.31958	6-May	day
5	3954.4443	15.80253426	1680.6388	6.176311	3559	5.2058796	21.12188	6-May	night
6	4053.3055	21.1159192	3657.861	0.187738	1285.194	16.2102619	36.51884	6-May	day
6	4053.3055	21.1159192	3657.861	0.187738	1285.194	16.2102619	19.65505	6-May	night
7	7414.5831	0	3558.9999	2.585813	1087.472	19.5280691	36.36323	6-May	day
7	7414.5831	0	3558.9999	2.585813	1087.472	19.5280691	19.94754	6-May	night
8	4943.0554	6.15065367	4745.3332	0	889.75	3.4927034	36.56179	6-May	day
8	4943.0554	6.15065367	4745.3332	0	889.75	3.4927034	20.03429	6-May	night

Table 4 Detailed landscape metrics, including CA and ENN-CV, with corresponding day and night LST values for selected grids.

5.2.3 Correlation Analysis

Correlation analysis was performed for both daytime and nighttime temperatures to investigate the relationship between landscape metrics and LST. The analysis considered metric values from all 23 grids in the study area to ensure a comprehensive assessment of spatial variations and their impact on temperature dynamics.

Daytime Correlation Analysis between LST and Landscape Metrics

Metrics	Abbreviation	Correlation with Daytime LST
PLAND_BARE	% of Barren Land	0.45789
PLAND_CROPS	% of Cropland	-0.312345
PLAND_BUILTUP	% of Built-Up	0.256789
AI_BARE	Aggregation of Barren Land	0.1789
AI_CROPS	Aggregation of Cropland	-0.298654
AI_BUILTUP	Aggregation of Built-Up	0.398456
CA_BARE	Area of Barren Land	0.528901
CA_CROPS	Area of Cropland	-0.37289
CA_BUILTUP	Area of Built-Up	0.318765
ENN_CV_BARE	Dispersion of Barren Land	-0.212345
ENN_CV_CROPS	Dispersion of Cropland	-0.419876
ENN_CV_BUILTUP	Dispersion of Built-Up	-0.128943

Table 5 Daytime Correlations

The analysis of daytime Land Surface Temperature (LST) clearly shows that barren land and dense urban development contribute the most to rising temperatures. Among them, the total area of barren land (CA_BARE: 0.5289) has the strongest warming effect, meaning that the more barren land there is, the hotter the area gets. Similarly, the proportion of barren land (PLAND_BARE: 0.4579) also plays a major role, as these surfaces absorb and retain heat due to the lack of vegetation. Even the way barren land is arranged matters, when barren areas are more

clustered (AI_BARE: 0.1789), they tend to hold onto heat, though this effect is not as strong. On the urban side, built-up areas also increase temperatures, especially when they are compactly arranged (AI_BUILTUP: 0.3985). Additionally, PLAND_BUILTUP (0.2568) and CA_BUILTUP (0.3188) confirm that as cities expand, so does their heat signature, reinforcing the well-known urban heat island effect.

On the other hand, croplands help lower temperatures, acting as natural coolers through evapotranspiration and shade. The dispersion of cropland patches (ENN_CV_CROPS: -0.4199) has the strongest cooling effect suggesting that when croplands are spread out rather than concentrated, they provide better relief from heat. Similarly, larger cropland areas (CA_CROPS: -0.3729) play a key role in lowering LST, while the overall proportion of cropland (PLAND_CROPS: -0.3123) also contributes to cooling. Interestingly, even how croplands are arranged matters AI_CROPS (-0.2987) shows that when croplands are more clustered together, they help lower temperatures more effectively. Barren land, despite its general warming effect, shows a small cooling influence when its patches are more dispersed (ENN_CV_BARE: -0.2123), possibly allowing heat to dissipate instead of being trapped in large continuous surfaces.

In short, expanding croplands and keeping them well distributed is key to reducing heat, while limiting the spread of barren land and controlling urban density can help prevent excessive warming. These findings underscore the complex interplay between landscape metrics and LST.

Nighttime Correlation Analysis between LST and Landscape Metrics

Metrics	Abbreviation	Correlation with Nighttime LST
PLAND_BARE	% of Barren Land	0.0642
PLAND_CROPS	% of Cropland	-0.6779
PLAND_BUILTUP	% of Built-Up	0.1919

AI_BARE	Aggregation of Barren Land	0.4173
AI_CROPS	Aggregation of Cropland	-0.2639
AI_BUILTUP	Aggregation of Built-Up	0.3129
CA_BARE	Area of Barren Land	0.1042
CA_CROPS	Area of Cropland	-0.3835
CA_BUILTUP	Area of Built-Up	0.2193
ENN_CV_BARE	Dispersion of Barren Land	-0.1229
ENN_CV_CROPS	Dispersion of Cropland	0.2154
ENN_CV_BUILTUP	Dispersion of Built-Up	0.0555

Table 6 Nighttime Correlations

The nighttime Land Surface Temperature (LST) analysis shows that built-up areas and clustered barren land retain more heat, while croplands have a strong cooling effect. Unlike during the day, barren land has a weaker influence on LST at night, with PLAND_BARE (0.0642) and CA_BARE (0.1042) showing minimal warming. However, the aggregation of barren land (AI_BARE: 0.4713) has a stronger impact, suggesting that when barren patches are clustered, they trap heat more effectively. Built-up areas continue to contribute to heat retention, with PLAND_BUILTUP (0.1919) and CA_BUILTUP (0.2193) indicating moderate warming, while AI_BUILTUP (0.3129) confirms that compact urban structures intensify nighttime heat.

Croplands remain the strongest cooling factor, with PLAND_CROPS (-0.6779) showing the highest negative correlation, meaning areas with more cropland experience significantly lower temperatures. The total cropland area (CA_CROPS: -0.3835) and its aggregation (AI_CROPS: -0.2639) also help in cooling, likely due to moisture retention. Interestingly, ENN_CV_CROPS (0.2154) suggests that more scattered croplands retain slightly more heat, possibly due to fragmentation reducing cooling efficiency.

Overall, clustered barren and urban areas hold onto heat longer, reinforcing the urban heat island effect, while extensive and connected croplands promote cooling. Managing urban density, reducing barren land clustering, and maintaining continuous cropland patches could help regulate nighttime temperatures more effectively.

CONCLUSION & RECOMMENDATIONS

This study provides valuable insights into how land cover patterns influence Land Surface Temperature (LST), reinforcing the importance of spatial configurations in urban heat dynamics. The findings align with the research objectives by demonstrating that barren land and built-up areas contribute to higher LST, particularly when clustered, while croplands have a significant cooling effect. These results directly support the research objectives, which aimed to analyze the relationship between LST and land cover composition, assess spatial patterns of urban heat islands, and evaluate the effectiveness of landscape metrics in explaining temperature variations. A key finding of this study is the identification of the most and least influential landscape metrics for LST variation. During the daytime, CA_BARE (0.5289) had the strongest influence on increasing LST, indicating that the total area of barren land plays the most significant role in temperature rise. Conversely, ENN_CV_CROPS (-0.4199) had the strongest cooling effect, suggesting that widely distributed croplands help lower LST the most. At nighttime, PLAND_CROPS (-0.6779) was the most influential metric, showing that a higher proportion of cropland significantly reduces LST, whereas AI_BARE (0.4713) had the highest warming effect, highlighting that clustered barren land retains heat longer. The least influential metrics were PLAND_BARE (0.0642) for nighttime and ENN_CV_BUILTUP (-0.1289) for daytime, indicating that these factors have a minor impact on temperature variations compared to others. The results have clear implications for urban planning and policymaking. Strategies such as reducing the expansion of barren land, promoting green infrastructure, and encouraging more dispersed cropland distribution could help in temperature regulation. City planners should consider incorporating vegetation within urban structures, ensuring that urban growth

incorporates sufficient green spaces to prevent heat retention. Additionally, limiting the clustering of built-up areas through improved zoning and mixed land-use strategies can mitigate excessive heat accumulation, particularly at night. These findings provide a basis for policies that balance urban expansion with climate resilience by emphasizing the role of land use patterns in mitigating extreme temperature conditions.

While this study offers important insights, it also has some limitations. The dataset may not fully capture seasonal changes, and remotely sensed data has inherent uncertainties in LST estimation. The methods used, though effective, could be improved by incorporating ground-based temperature measurements for better accuracy. Additionally, the study does not account for small-scale weather changes which could influence results. Future research could enhance this work by using more detailed spatial and temporal data, considering additional land cover types, and including socio-economic factors for a more comprehensive approach. Expanding the study with predictive modeling and machine learning could also improve its usefulness for future urban planning.

Despite these limitations, the study provides a robust framework for understanding urban heat dynamics and contributes to the growing body of research on sustainable city planning. The findings emphasize the need for proactive land use management to create climate-resilient urban environments, ensuring that future development prioritizes ecological balance alongside urban expansion. By incorporating these insights into urban planning strategies, policymakers and planners can develop more effective approaches to mitigate the urban heat island effect and enhance environmental sustainability.

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