Impact of Urbanization on Land Use Land Cover and Urban Climate, Using Spatio-Temporal Techniques: A Case Study of Islamabad, Pakistan

Novera Azka[1], Dr. Muhammad Hamid Chaudhary[2], Qudsia Gulzar[3], Dr. Sajid Mahmood[4], Tibra Ishaq[5]
[1]Center for Geographic Information System, University of the Punjab, Lahore, 54000, Pakistan.
[2]Assistant Professor, Center for Geographic Information System, University of the Punjab, Lahore, 54000, Pakistan.
[3]Assistant Professor, Center for Geographic Information System, University of the Punjab, Lahore, 54000, Pakistan.
[4]Associate Professor, Department of Civil Engineering, NUST Campus, Risalpur.
[5]Center for Excellence in Solid State Physics, University of the Punjab, Lahore, 54000, Pakistan.
***Correspondence:** Novera Azka azkanovera43@gmail.com,
Citation | Azka. N, Chaudhary. M. H, Gulzar. Q, Mahmood. S, Ishaq. T, "Impact of Urbanization on Land Use Land Cover and Urban Climate, Using Spatio-Temporal Techniques: A Case Study of Islamabad, Pakistan", IJIST, Vol. 6 Special Issue, pp 8-23, June 2024
Received | May 18, 2024 **Revised |** May 24, 2024 **Accepted |** May 28, 2024 **Published |** June 02, 2024.

A major environmental challenge faced by Pakistan with the rapid expansion of urban areas, leading to a reduction in vegetation. This shift directly influences Land Surface Temperature (LST), causing substantial changes in the urban climate. This paper explores the relationship between changing land use, land cover (LULC), and rising temperatures in Islamabad, focusing on LULC, LST, and Normalized Difference Vegetation Index (NDVI) as key parameters. Unlike previous research, this study emphasizes the crucial role of vegetation in mitigating the impact of rising temperatures, compared to the effects of built-up areas. The study spans four years, from 2019 to 2022, utilizing LULC maps obtained from the ESRI Sentinel 2 Land Use Land Cover Explorer. LST maps were derived from the Level 2 Sentinel 2B Sea and Land Surface Temperature Radiometer (SLSTR) sensor LST product, while NDVI was calculated using Sentinel 2B bands 4 and 8. The results indicate a 7% decrease in vegetation area and an 8% increase in built-up areas over the study period. NDVI maps show a dramatic decline in dense vegetation, from 6.01% in 2019 to just 0.17% in 2022. The study further reveals that built-up areas consistently exhibit higher LST throughout the studied years, with temperatures ranging from 18.09 °C in 2019 to 13.62 °C in 2022. In contrast, water and vegetation areas display the lowest LST, recorded at 13.4 °C and 13.5 °C, respectively. This inverse relationship between LST and vegetation is validated by Pearson's Correlation Coefficient, which shows a negative correlation of -0.41 between LST and NDVI, indicating that as vegetation decreases, LST increases. The paper concludes that the increase in built-up areas and rangeland, coupled with the decrease in vegetation and bare ground, is directly influencing LST and altering the climate of Islamabad. To mitigate these effects, the study advocates for the adoption of sustainable urban management plans that incorporate green alternatives to reduce the environmental impact of urban expansion.
Keywords: Land use Land Cover (LULC); Land Surface Temperature (LST); Normalized Difference Vegetative Index (NDVI); Pearson's Correlation Coefficient; GIS and Remote Sensing.

Introduction:

Earth, the only known habitable planet in the universe, is enveloped by a protective shield of gases that shield it from harmful radiation and regulate global temperatures [1]. However, Earth's well-being is currently under threat due to a combination of natural phenomena, such as changes in atmospheric composition, alterations in land and sea geography, shifts in topography and bathymetry, and human activities like the concentration of greenhouse gases, modifications in ozone levels, the proliferation of aerosols, and transformations in land surfaces. These factors collectively contribute to the accelerated warming of our planet [2]. Anthropogenic activities, in particular, have played a substantial role in altering Earth's climate. The burning of fossil fuels, such as gas, oil, and coal, releases carbon dioxide (CO2) and other greenhouse gases into the atmosphere. These gases trap heat from the sun, leading to a rise in temperature and global warming. Deforestation, which involves the clearing of trees for various purposes, further exacerbates global warming. Trees play a vital role in absorbing carbon dioxide during photosynthesis and releasing oxygen into the atmosphere. However, deforestation reduces the number of trees available to perform this essential function, thereby decreasing the capacity to absorb carbon dioxide [3].

The escalating growth of the human population has emerged as a significant challenge in developing nations, leading to the pressing issue of unplanned urbanization [4]. This phenomenon, coupled with changes in Land Use Land Cover (LULC), stands as one of the most influential catalysts of global transformation, particularly within urban regions [5]. As urbanization continues to advance, the spatial patterns of cities are rapidly evolving, resulting in significant alterations to the urban environment [6]. LULC is closely related, as human activities often bring about modifications to the Earth's physical and biological features [7]. According to the United Nations, 56% of the world's population lives in urban areas, amounting to nearly 4.4 billion people. This trend is expected to continue, with the urban population likely to double by 2050 [8].

Land Surface Temperature (LST) is an important parameter for studying Earth's climate system, as it affects the exchange of energy and moisture between the land surface and the atmosphere [9]. LST is a critical factor that directly influences the urban thermal environment. It refers to the surface-climate cooperation and energy exchanges between the air and the ground, playing a significant role in studying thermal environmental impacts [10]. The relationship between LST and vegetation is complex and influenced by various factors. LST measures surface temperature from space, while vegetation represents the plant cover on the land surface [11]. Climate change is causing significant alterations in global temperatures and precipitation patterns, which can profoundly impact vegetation cover and ecosystem health [12]. Changes in vegetation cover due to deforestation or other factors can significantly affect the global carbon cycle and climate [13]. LST can also be used to monitor and model the impacts of climate change on vegetation cover and ecosystems. By employing remote sensing techniques and other tools, researchers can improve their understanding of this relationship and develop new methods for utilizing this valuable information [14].

Vegetation plays a crucial role in lowering the temperature of an area. The cooling effect provided by trees through evapotranspiration and shading is substantial. For example, a single fully grown tree with a 30-foot crown diameter can evaporate 40 gallons of water each day, which is comparable to counteracting the heat produced by a modest electric heater operating for 4 hours. The increase in LST can have several negative consequences. It can exacerbate heat-related illnesses and discomfort for urban residents, particularly during heatwaves. High temperatures also lead to increased energy consumption for cooling purposes, placing a burden on electrical grids. Moreover, elevated LST can negatively impact air quality by intensifying the formation of air pollutants such as ozone. To mitigate the rise in LST and its impacts, urban planners and policymakers have implemented various strategies. These include promoting green infrastructure, such as parks, green roofs, and urban forests, to increase vegetation cover in urban areas [15]. Additionally, adopting sustainable urban design practices, such as using reflective materials for buildings and incorporating water bodies into the urban landscape, can help mitigate the urban heat island effect and reduce LST [16].

In Pakistan, almost one-third of the population currently resides in urban areas, a figure that is continually rising [17]. The rapid growth of cities in Pakistan has become a major issue, driven by both natural population increases and internal migration. As a result, the population of the country's largest cities has surged into the millions. Economic activities and urbanization are widely recognized as interlinked processes. Over the past 20 years, Pakistan has experienced significant urbanization, with a rapidly growing urban population and increasing urbanization rates. According to the 2023 census, Pakistan's population has reached 241.4 million, with an annual growth rate of 2.55%. This makes Pakistan the 5th most populous country in the world, with 34.7% of its population living in urban areas [18].

Urbanization has had significant environmental impacts in Pakistan, including air pollution, water pollution, and deforestation. The growing number of vehicles on the roads, the use of fossil fuels, and inadequate waste management systems in cities are major contributors to environmental degradation [19]. Rapid urbanization has also led to an increase in air pollution in Pakistani cities [20]. Urban areas are the primary sources of air pollution due to vehicular emissions, industrial activities, and domestic energy use. This has led to serious health issues, such as respiratory diseases, and has also contributed to climate change by increasing greenhouse gas emissions. Urbanization has led to the development of the urban heat island effect in Pakistani cities, and a reduction in green spaces, which has impacted the local climate. Additionally, urbanization has increased the demand for water in Pakistani cities [21].

Changes in LULC and LST can be studied using ground surveys and satellite-based Remote Sensing (RS) techniques. Ground surveys include air temperature and rainfall measurements taken using weather stations, while remote sensing data consists of satellite images analyzed through Geographic Information Systems (GIS) techniques. The integration of remotely sensed data with GIS is an increasingly popular method for characterizing LULC, NDVI, and LST changes at both temporal and spatial levels [22].

Objectives:

Land Surface Temperature (LST) is increasing at an unusual rate worldwide, particularly in developing countries like Pakistan, leading to rapid and intense changes in global climate. The primary cause appears to be a rapid increase in built-up areas and a decrease in vegetation due to urbanization. Urban expansion causes LULC changes that increase LST and contribute to urban warming. This research has the following objectives:

To identify variations in Land Surface Temperature during a specific period using GIS and remote sensing.

To examine the relationship between Land Surface Temperature (LST), urban expansion, and vegetation.

To spatially analyze the impact of urbanization on Land Surface Temperature (LST).

Novelty Statement:

This paper investigates the evolving urban landscape of Islamabad using geospatial techniques, revealing the critical relationship between changing land use and land cover, rising temperatures, and the mitigating role of vegetation. Unlike previous research, which primarily used LST data from Landsat satellites, this study employs Sentinel data for LST, LULC, and vegetation analysis. Additionally, this study emphasizes the importance of vegetation in comparison to built-up areas in combating increasing temperatures. The research contributes to understanding urbanization's impact on climate and underscores the need for sustainable and resilient urban planning that incorporates green infrastructure.

Material and Methods:

Study Area:

Islamabad, the capital city of Pakistan, is located in the northwestern part of the country on the Pothohar Plateau, a region characterized by rolling hills and fertile plains. The city, purposefully constructed to replace Karachi as the capital in 1960, is known for its wide avenues, green spaces, and modern architecture. Geographically, Islamabad is nestled at the foothills of the picturesque Margalla Hills, offering breathtaking natural scenery. The city's topography includes a mix of flat plains and hilly terrain, with a subtropical climate characterized by hot summers and cool winters. Average temperatures range from 16°C in January to 38°C in June. The city's climate is influenced by the region's monsoon season and the surrounding hills, with northern slopes receiving higher rainfall compared to southern slopes and the plain. Islamabad is vulnerable to extreme weather events, such as floods, landslides, and earthquakes [23]. The temperature during winter can drop to freezing levels in higher areas, while summer months can be extremely hot and humid [24]. The region's topography also influences the distribution of rainfall, with the northern slopes of the hills receiving more precipitation than the southern slopes and plains [25].

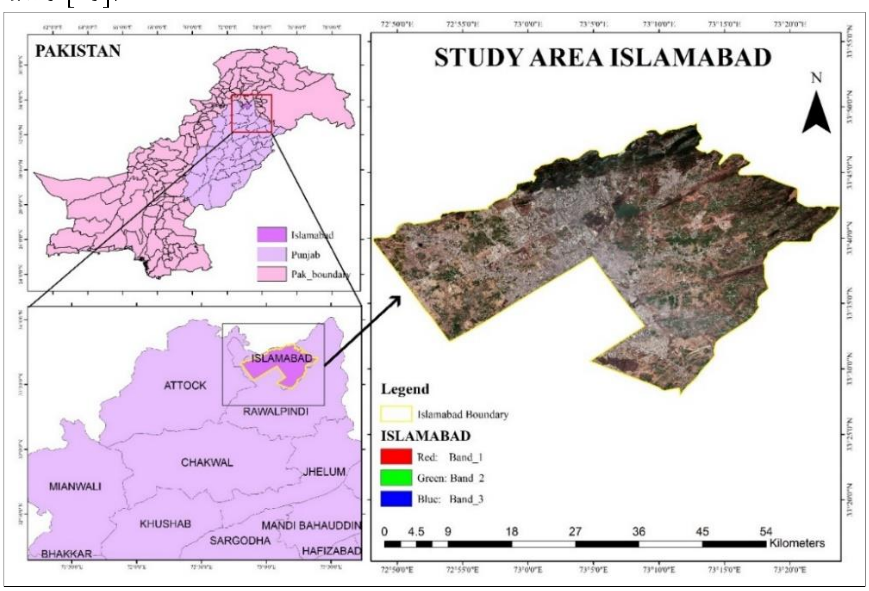

Figure 1: Study Area Map

Datasets:

In this study, two types of datasets are utilized to estimate the three key research parameters: Land Use Land Cover (LULC), Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) across the studied region. The primary data source for the analysis is remotely sensed satellite data from Sentinel-2B and Sentinel-3B, which provides high-resolution imagery essential for accurate assessments [26]. This satellite data, acquired from the Copernicus Open Access Hub, offers a spatial resolution of 10 meters, ensuring detailed analysis of the region (Table 1, 2). For the Sentinel-2B data, two tiles were downloaded for each date to cover the entire study area comprehensively. The LST measurements were obtained using the SL_2_LST product from the Sentinel-3B SLSTR sensor, which is specifically designed for surface temperature monitoring [27]. Additionally, ground survey data from the Pakistan Meteorological Department Office in Lahore is incorporated to validate the satellite-derived results (Table 3). This complementary data ensures the accuracy and reliability of the remote sensing analysis, providing a robust foundation for the study's conclusions.

Table 1: Sentinel 3B SL_2_LST information

Satellite	Date of Acquisition
SENTINEL 3B	43493
SENTINEL 3B	43856
SENTINEL 3B	44226
SENTINEL 3B	44588

Table 2: Sentinel 2B data information

SCENE ID	PATH/ROW
L1C_T43SCT_A010084_20190110T055542	207/37
L1C_T43SBT_A010084_20190110T055542	207/37
L2A_T43SCT_A015089_20200126T055113	213/48
L2A_T43SBT_A015089_20200126T055113	213/48
L2A_T43SBT_A020380_20210130T055057	214/48
L2A_T43SCT_A020380_20210130T055057	214/48
L2A_T43SBT_A025528_20220125T055118	400/48
L2A_T43SCT_A025528_20220125T055118	400/48

Table 3: Islamabad Zero Point January Data Source: PMD Lahore

Year	Rainfall (mm)	Mean Temperature ('C)	Min Temperature ('C)	Max Temperature ('C)
2019	126.11	9.2	2.5	15.9
2020	131.72	9.05	2.3	15.8
2021	99.06	10.85	2.2	19.5
2022	100.09	13.09	2.4	16.11

Methodology:

The data from sentinel 2B and 3B is then used for analysis using ArcMap 10.8 as shown in figure 2.

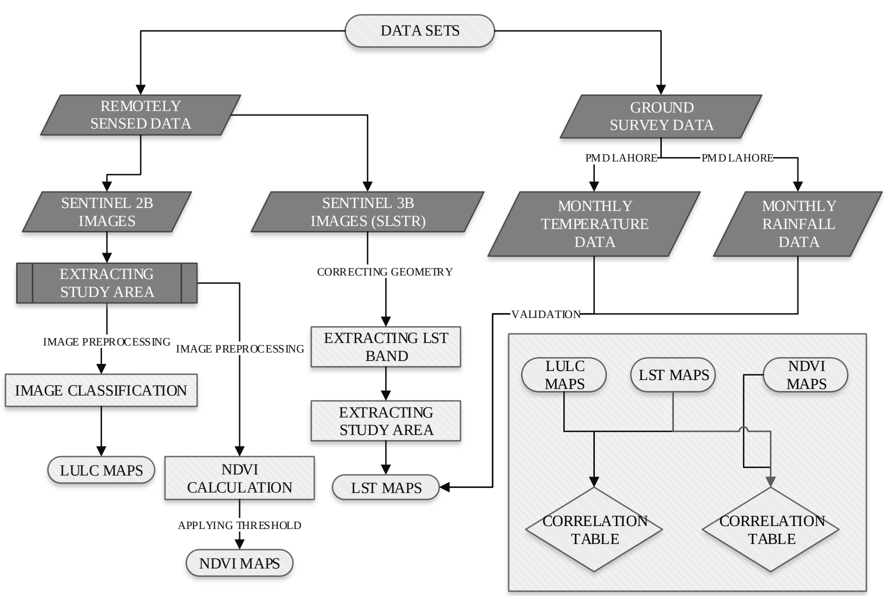

Figure 2: Methodology Flowchart

Image Pre Processing:

Sentinel-2B and 3B images were pre-processed by applying atmospheric and radiometric corrections. This step is crucial to ensure the accuracy of the satellite data, which was accomplished by processing the metadata.xml file using the Snap Desktop software.

Image Classification:

Classified images of the study area from 2019 to 2022 were obtained from the ESRI Sentinel-2 Land Cover Explorer. These images come with a Universal Transverse Mercator (UTM) WGS84 data projection, and the source image has a cell size of 10 meters [28]. The downloaded data, provided in TIFF format, was extracted according to the specific boundaries of the study area using ArcMap 10.8. The resulting raster images were then reclassified into distinct categories, labeled as built-up area, vegetation, rangeland, bare ground, and water [29].

Normalized Difference Vegetative Index (NDVI):

NDVI a major parameter for evaluating urban climate change, can be calculated using the following formula

$$\mathbf{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$$

Where NIR is the Near Infrared Band which is Band 8 and RED band is Band 4 in the case of Sentinel 2B [30]. After calculating NDVI in ArcMap, it is then classified into five classes based on the amount of vegetation (Table 4).

Table 4: NDVI Classes Source: USGS

Sr no.	Class label	Value	Re-Class Value	Type of Vegetation
1	No vegetation	Less than 0.1	1	Barren rock, sand, snow
2	Less sparse vegetation	0.1 – <0.2	2	Sparse shrubs and grasslands
3	Sparse vegetation	0.2 – <0.5	3	Shrubs, grasslands, senescing crops
4	Less dense vegetation	0.5 – <0.6	4	Sparse trees and crops at the start of their growth
5	Dense vegetation	0.6 and above	5	Forests, crops at their peak growth age

Land Surface Temperature:

For this research, the Land Surface Temperature (LST) product from the SLSTR sensor of Sentinel-3A, generated at a wide 1 km raster resolution, was used. This data, covering the years 2019 to 2022, was downloaded from the Copernicus Open Access Hub. The downloaded raster images were first processed in Snap Desktop software, where radiometric corrections were applied. Following this, the images were extracted to match the study area using ArcMap 10.8. The extracted images were then reclassified into specific temperature classes, labeled as very low, low, moderate, high, and very high, based on the LST values for each studied year from 2019 to 2022 [31]. After computing the three key parameters—LULC, NDVI, and LST—the reclassified images were analyzed to determine the area covered by each class, along with their percentage relative to the total area. Statistical graphs were then generated to visually represent these findings.

Pearson's Correlation Coefficient:

The Pearson correlation coefficient was used to statistically assess the degree and direction of the linear relationship between two variables, NDVI and LST. This coefficient ranges from -1 to +1, where 0 indicates no correlation, +1 indicates a perfect positive correlation, and -1 indicates a perfect negative correlation [32]. By analyzing this correlation, we can gain valuable insights into the health and productivity of vegetation, as well as identify potential environmental factors influencing vegetation growth [33].

Results and Discussion:

Land Use Land Cover (LULC):

The quantification of LULC classes for the years 2019 to 2022 is detailed in Table 5 and visually represented in Figure 3, showing both area and percentage distribution. The results indicate that vegetation is the dominant class in the study area throughout the four years, though it exhibits a decreasing trend. In 2019, vegetation covered approximately 42% of the area, but this decreased to 35% by 2022. The vegetation class includes irrigated land, grasslands, forests, and some flooded crops. On the other hand, the built-up area emerges as the second dominant class, displaying an increasing trend—rising from 44% in 2019 to 52% in 2022. This shift suggests significant urban expansion at the expense of natural vegetation cover in the study area.

Table 5: Statistics of LULC Classes 2019 - 2022

Classes/ Years	2019		2020		2021		2022	
	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
Water	964.09	0.98	1019.82	1.03	877	0.89	888.14	0.9
Vegetation	42290.09	42.98	43255.69	43.97	38318.14	38.95	35131.98	35.71
Built Area	44014.19	44.74	46032.4	46.79	48097.09	48.89	51162.04	52
Bare Ground	134.93	0.13	114.54	0.11	132.29	0.13	29.97	0.03
Rangeland	10971.78	11.15	7952.63	8.08	10950.56	11.13	11162.69	11.34
Total	**98375.08**	**100**	**98375.08**	**100**	**98375.08**	**100**	**98375.08**	**100**

The Rangeland class, which includes bare soil, shrubs, and very sparse vegetation, is the third most dominant land cover category in the study area. This class remains relatively stable over the years, with a notable decrease from 11% in 2019 to 8% in 2020. However, it subsequently increases to 11% in 2021 and 2022. The fourth dominant class is water, which shows a slight increase from 0.9% in 2019 to 1.0% in 2020, but then decreases to 0.8% in 2021 and 0.9% in 2022. The bare-ground class is the least dominant, consistently occupying the smallest proportion of the study area throughout the years.

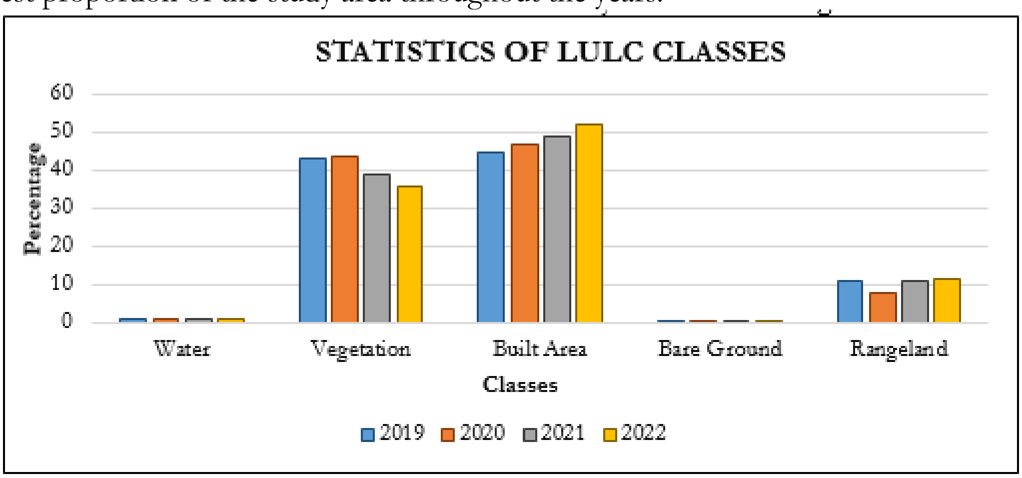

Figure 3: Graph showing statistics of LULC classes

The spatial distribution of LULC classes for the years 2019 to 2022 is illustrated in Figure 4. The built-up area is predominantly concentrated in the central and western parts of the study area, encompassing the residential sectors of Islamabad. In contrast, the vegetation class, which includes crops, flooded vegetation, grass, and forests, is distributed across various parts of the study area, both in sparse and dense forms. Notably, the northeastern part of the study area features dense vegetation, including the lush forests of Margalla Hills and the Margalla Hills National Park.

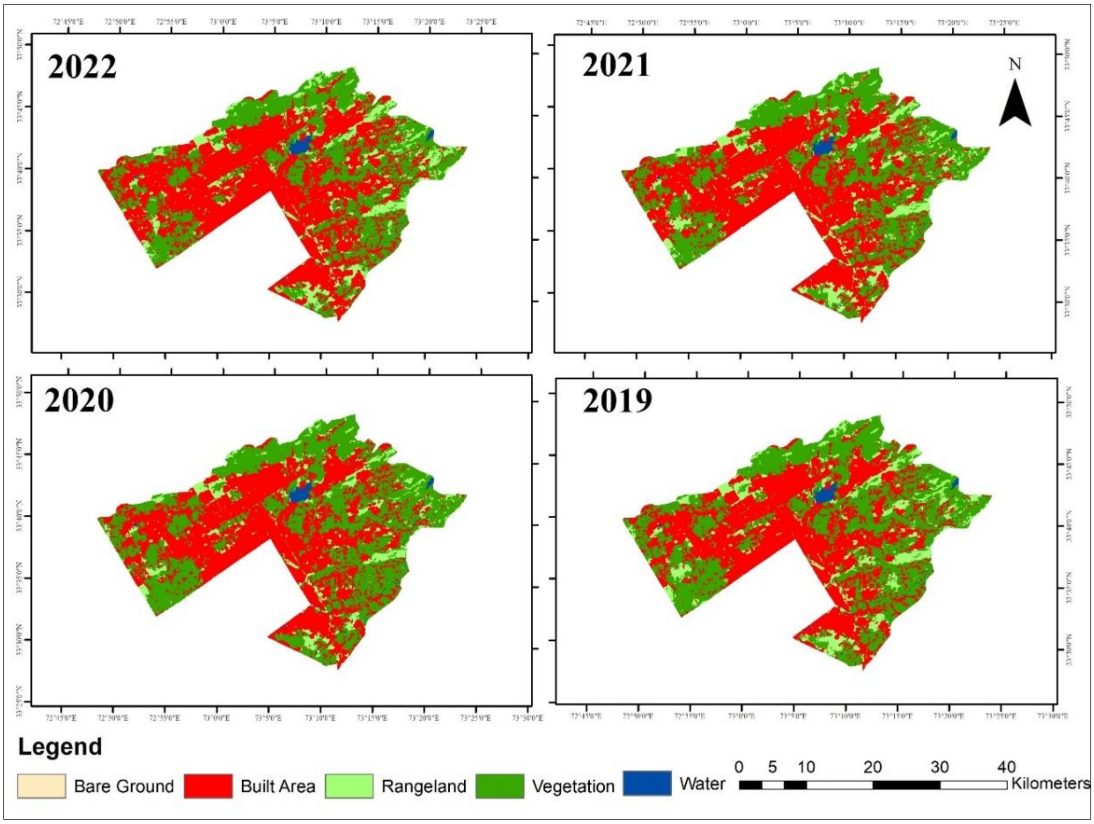

Figure 4: LULC Maps 2019-2022

There are several dense forest patches within the study area designated as reserved forests. The results indicate that the city has only two major lakes: Rawal Lake, located centrally, and Simly Dam Lake, situated on the northeastern side. Vegetation in the southern and southwestern parts of the city is showing a declining trend, largely due to increased built-up areas.

Normalized Difference Vegetation Index (NDVI):

The quantification of NDVI classes for the years 2019 to 2022 is detailed in Table 6 and Figure 4, showing the area and percentage of each class. Typically, urban areas exhibit lower NDVI values compared to non-urban areas. This is accompanied by a consistent decrease in the mean NDVI and a corresponding increase in the mean LST. As urban development intensifies, there is a noticeable decline in NDVI values.

Table 6: Statistics of NDVI classes 2019 – 2022

Re-Class Value	Class Label	2019		2020		2021		2022	
		Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
1	No vegetation	18135.65	18.43	10814.65	10.99	9644.21	9.8	23730.36	24.12
2	Less sparse vegetation	24469.47	24.87	18257.16	18.55	19440.46	19.76	31451.08	31.97
3	Sparse vegetation	39736.34	40.39	39509.91	40.16	41505.76	42.19	41097.69	41.77

4	Less dense vegetation	9325.8	9.47	8670.21	8.81	9810.64	9.97	1919.72	1.95
5	Dense vegetation	6707.56	6.81	21122.89	21.47	17973.64	18.27	175.97	0.17
	Total	**98374.8**	**100**	**98374.8**	**100**	**98374.8**	**100**	**98374.8**	**100**

The statistical analysis of NDVI values for the years 2019 to 2022 reveals notable variations in vegetation health over the study period. In 2019, the mean NDVI was 0.27, with a standard deviation of 0.19, indicating moderate vegetation cover. The NDVI values ranged from a minimum of -0.44 to a maximum of 0.80. By 2020, there was a slight increase in the mean NDVI to 0.36, accompanied by a standard deviation of 0.23, reflecting a broader spread in vegetation conditions. The NDVI values for this year ranged from -0.70 to 0.99. In 2021, the mean NDVI further increased to 0.35 with a standard deviation of 0.22, and the range of values expanded from -1.00 to 1.00. However, by 2022, the mean NDVI decreased to 0.20, with a standard deviation of 0.13, suggesting a decline in overall vegetation health. The values for this year ranged from a minimum of -0.26 to a maximum of 0.72. These variations indicate significant changes in vegetation cover and health across the years, reflecting broader trends in land use and environmental conditions.

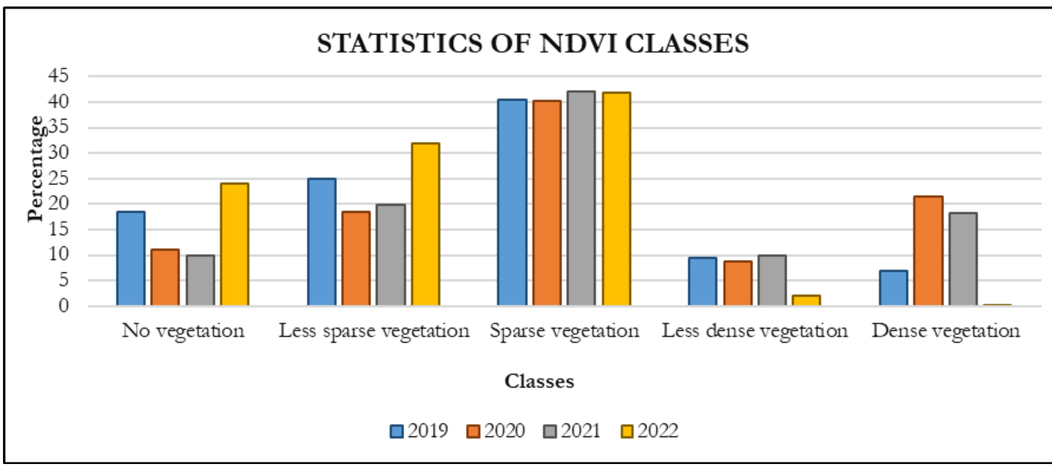

Figure 5: Graph showing statistics of NDVI classes

Figure 6 shows the spatial distribution of NDVI classes in percentage, having five classes labeled as < 0.1 (no vegetation), 0.1 - <0.2 (less sparse vegetation), 0.2 - <0.5 (sparse vegetation), 0.5 – <0.6 (less dense vegetation) and >= 0.6 (dense vegetation).

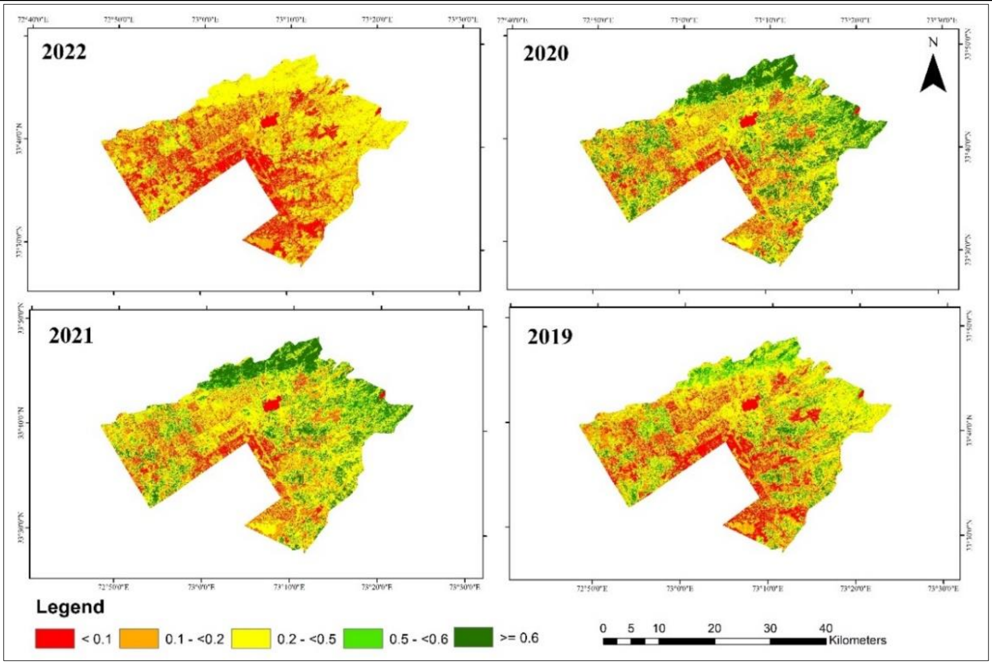

Figure 6: NDVI maps 2019 – 2022

Geographically, dense vegetation is predominantly located in the northern part of Islamabad, encompassing the Margalla Hills forests and several other reserved forest areas. In contrast, the urban core and southern parts of the city exhibit minimal vegetation, with only sparse patches and a few trees scattered along streets and roads. Sparse vegetation, which is the most prevalent class, is distributed across all parts of the city. The quantification of Land Surface Temperature (LST) for Islamabad from 2019 to 2022 reveals distinct trends. In 2019, LST values ranged from a minimum of 13.7°C to a maximum of 20.85°C, with a mean temperature of 17.96°C and a standard deviation of 0.82°C. By 2020, both the minimum and maximum LST values decreased, with a minimum of 10.49°C and a maximum of 12.07°C. The mean temperature in 2020 was 6.52°C, and the standard deviation increased to 1.38°C, indicating a broader range of temperature variability. In 2021, LST values rose again, reaching a minimum of 12.02°C and a maximum of 19.83°C. The mean temperature for this year was 15.6°C, with a standard deviation of 1.17°C. However, in 2022, LST values showed a decrease, with a minimum of 9.9°C, a maximum of 16.3°C, and a mean of 13.5°C. The standard deviation for 2022 was 0.76°C, reflecting a return to lower temperature variability compared to the previous year.

Table 7: Statistics of LST classes 2019 to 2022

Value	Class Label	2019		2020		2021		2022	
		Area (Ha)	%	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
1	Very Low	339.81	0.34	10490.19	10.66	2624.08	2.66	538.03	0.54
2	Low	3642.68	3.7	50771.48	51.61	35242.55	35.82	6449.12	6.55
3	Moderate	49693.83	50.51	27653.57	28.11	41647.66	42.33	58069.92	59.02
4	High	40986.4	41.66	8403.5	8.54	17690.15	17.98	31756.6	32.28
5	Very High	3711.91	3.77	1056.1	1.07	1170.13	1.18	1561.03	1.58
	Total	**98374.8**	**100**	**98374.8**	**100**	**98374.8**	**100**	**98374.8**	**100**

Based on the quantification of Land Surface Temperature (LST) classes, as illustrated in Figure 7, the moderate temperature class emerges as the most dominant category. This class exhibits notable fluctuations over the years: it initially decreased from 50% in 2019 to 28% in 2020, subsequently rose to 42% in 2021, and further increased to 59% in 2022. Despite these fluctuations, the overall coverage of the moderate temperature class shows an upward trend from 2019 to 2022. In contrast, the high-temperature class, which is the second most prevalent, displays a different trend. This class initially decreased from 41% in 2019 to 32% in 2020, but then showed an increasing trend in 2021 and 2022. The low-temperature class, which started at a modest 3.7% coverage in 2019, decreased slightly to 6.5% by 2022. The very low and very high-temperature classes are the least dominant categories throughout the study period from 2019 to 2022.

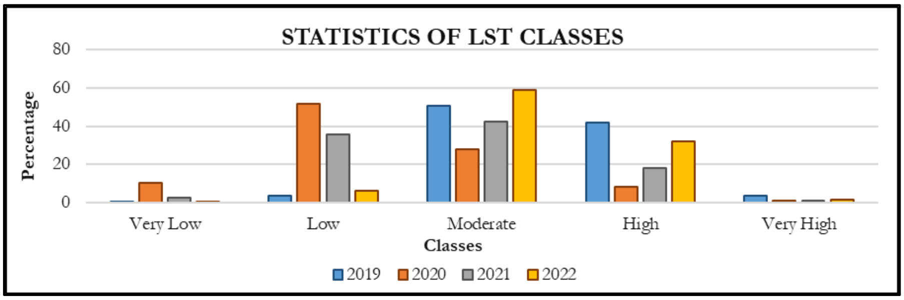

Figure 7: Graph showing statistics of LST classes

The spatial distribution of Land Use Land Cover (LULC) classes from 2019 to 2022, as depicted in Figure 8, highlights distinct patterns across the study area. In both 2019 and 2022, the high-temperature class is the most prominent, primarily concentrated in the central and residential zones of the study area. This class is highly visible and dominates these two years. The moderate temperature class, which is the second most prevalent, predominantly covers the southern and northeastern parts of the study area. In 2020, the spatial distribution of temperature classes is more evenly spread across the entire area, with all classes being distinctly visible throughout the region. This variation reflects the shifting thermal landscape over the years and emphasizes the spatial dynamics of temperature changes in the study area.

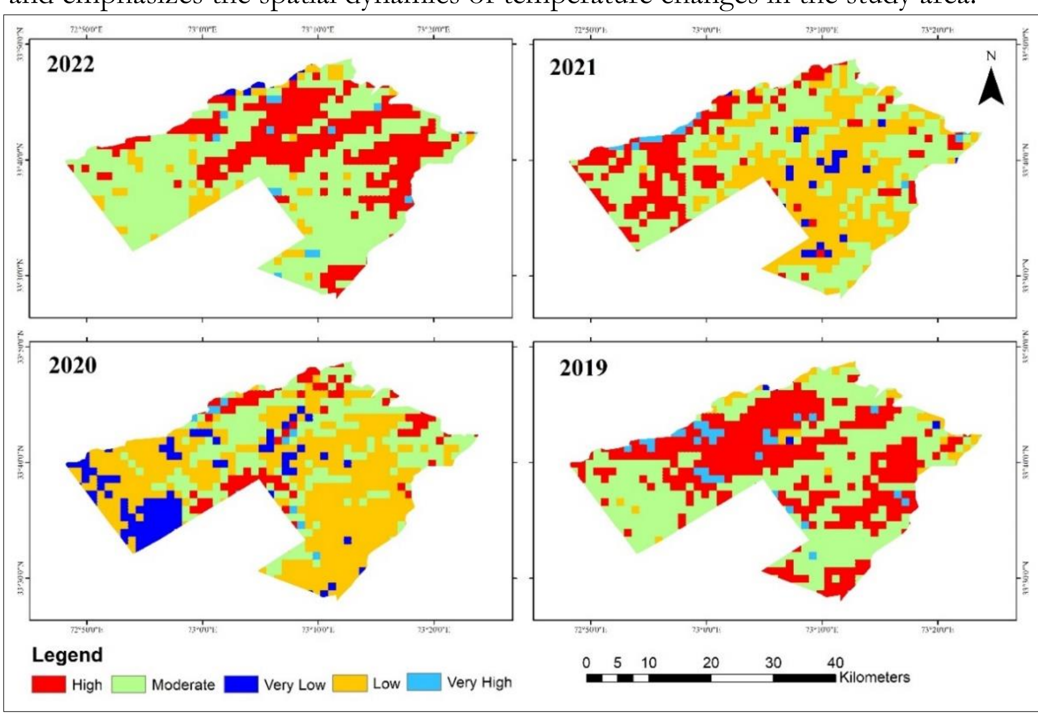

Figure 8: LST Maps 2019 - 2022

In 2021, the study area exhibited notable variations in temperature distribution. The urban regions on the southern and western sides experienced high-temperature values, while the central area displayed moderate temperatures. Conversely, the eastern side of the study area primarily showed low and very low temperatures, highlighting the cooler conditions in that part of the city. By 2022, high and very high temperatures were observed in the central urban areas and parts of the northern region. Meanwhile, the southeastern and southwestern parts of the region showed moderate temperatures, indicating a mix of thermal conditions across different parts of the city.

Correlation of LST with Air Temperature

The relationship between land surface temperature (LST) and air temperature is intricate and influenced by several factors, including urban land cover, vegetation density, and climatic conditions. The analysis reveals that while the maximum values of LST and air temperature are closely aligned, the minimum values differ, as illustrated in Table 8. Figure 9 presents the trend of LST and air temperature from 2019 to 2022. The trends for both LST and air temperature are initially similar: from 2019 to 2020, LST decreased from 17.9°C to 6.5°C, and air temperature decreased slightly from 9.2°C to 9.1°C. In 2021, both LST and air temperature increased, with LST reaching 15.6°C and air temperature rising to 10.8°C. However, in 2022, a divergence occurred; LST decreased from 15.6°C to 13.5°C, while air temperature continued to rise from 10.8°C to 13.1°C. This divergence indicates the complex interaction between surface and atmospheric temperatures, particularly in response to varying environmental factors.

Table 8: Correlation between LST and Air Temperature

	LST			Air Temperature		
Years	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
2019	13.7	20.8	17.9	2.5	15.9	9.2
2020	3.2	12.1	6.5	2.3	15.8	9.1
2021	12.0	19.8	15.6	2.2	19.5	10.8
2022	9.9	16.3	13.5	2.4	16.1	13.1

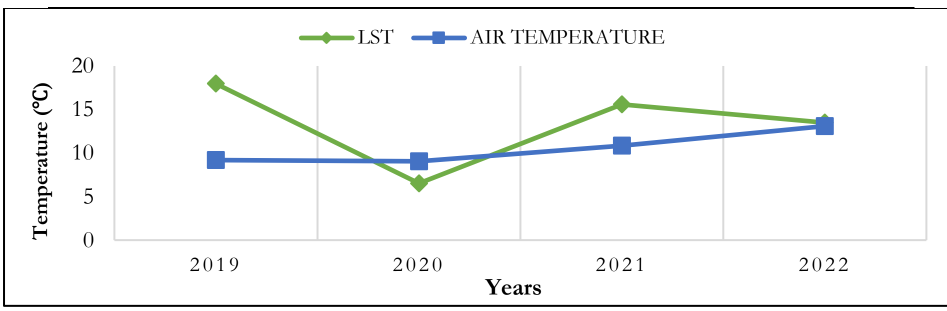

Figure 9: Graph showing the correlation between LST and Air temperature

Correlation of LST with NDVI:

Pearson's correlation coefficient reveals a negative relationship between land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI), with a correlation value of -0.416, as indicated in Table 9. This negative correlation signifies an inverse relationship between LST and NDVI. Specifically, areas with higher NDVI values tend to have lower LST, while areas with lower NDVI values exhibit higher LST. This inverse relationship underscores the impact of vegetation on surface temperatures, where increased vegetation generally correlates with cooler land surface temperatures.

Table 9: Correlation between LST & NDVI

YEARS	LST	NDVI	CORRELATION
2019	17.974401	0.271265	-0.416282736
2020	6.558604	0.365335	
2021	15.586561	0.356983	
2022	13.516875	0.205925	

Urbanization Impact on Land Surface Temperature:

From the perspective of Land Use Land Cover (LULC) classes, the vegetation class exhibited land surface temperature (LST) values of 17.8°C, 6.36°C, 15.76°C, and 13.58°C for the years 2019, 2020, 2021, and 2022, respectively. In comparison, the built-up area class recorded LST values of 18.09°C, 6.62°C, 15.79°C, and 13.6°C for the same years, as detailed in Table 10.

Table 10: LULC Classes with their LST

LULC Class	2019 (LST °C)			2020 (LST °C)			2021 (LST °C)			2022 (LST °C)		
	Min	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
Water	13.73	19.78	16.75	4.86	12.02	7.97	12.03	18.82	14.19	12.32	15.27	13.44
Vegetation	15.20	20.09	17.87	3.21	10.77	6.36	12.10	19.83	15.76	10.50	15.68	13.5
Built Area	15.07	20.85	18.09	3.29	12.05	6.62	12.93	19.73	15.79	10.61	16.30	13.62
Bare Ground	16.59	19.55	17.63	4.44	9.271	5.60	14.10	17.47	15.76	12.58	15.48	13.62
Rangeland	14.99	20.21	18.05	3.71	10.470	6.61	12.10	19.83	15.97	10.67	16.29	13.69

The built-up area class and rangeland class exhibit higher LST as compared to other classes as shown in Table 10 and Figure 10. The water class exhibits lower LST as compared to others as it shows 16.75°C, 7.97°C, 14.19°C and 13.44°C in 2019, 2020, 2021, and 2022.

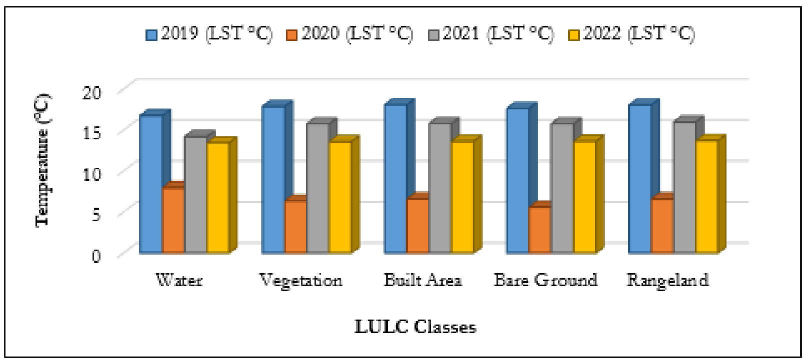

Figure 10: Graph showing LULC Classes with their LST 2019-2022

The negative correlation between LST and NDVI confirms that the vegetation decrease in an area leads to an increase in LST in that area as shown in Table 11.

Table 11: Pearson's Correlation coefficient

Variable	Pearson's Correlation Coefficient	LST
LST	N=4	1
NDVI	N=4	-0.4162827

Discussions:

The results indicate a significant and troubling decline in vegetative cover over the four years studied. In 2019, vegetation covered 42% of the area, but this decreased to just 35% by 2022. Conversely, the built-up area expanded rapidly, from 44% in 2019 to 52% in 2022. This increase in urbanization corresponds with a reduction in the city's vegetative cover. Dense vegetation, particularly in the northern part of Islamabad, has diminished to nearly negligible levels by 2022, largely due to deforestation. Sparse vegetation along streets and roads is the only category that has shown an increase, though it is insufficient to counterbalance the rising temperatures in the city. The rise in built-up areas due to anthropogenic activities is a major driver of the decline in vegetative cover and subsequent increase in city temperatures. The expanded urban areas contribute significantly to the urban heat island effect, exacerbating climate change. Vegetation in Islamabad includes not only flooded areas, grasslands, and crops but also forests like those in Margalla Hills National Park. However, even with the world largely on lockdown in 2020, vegetation cover only marginally increased from 42% to 43%. During the same period, built-up areas grew from 44% to 46%, as shown in Graph 2. The mean LST decreased in 2020, likely due to reduced human activity such as lower traffic. By 2022, the built-up area had risen to 52%, while vegetation had dwindled to 35%, predominantly consisting of sparse vegetation. This drastic reduction in dense vegetation aligns with the negative correlation between land surface temperature and NDVI, confirming that decreasing vegetation correlates with rising temperatures. Additionally, an increase in land surface temperature from 2020 to 2021 can partly be attributed to the increased rainfall in 2020, which measured 131.72 mm as per Table 3. This higher rainfall contributed to increased humidity, which in turn elevated surface temperatures. The rising land surface temperature exacerbates climate change, impacting both human and environmental systems and disrupting ecological balance.

Conclusion:

The results indicate a significant and troubling decline in vegetative cover over the four years studied. In 2019, vegetation covered 42% of the area, but this decreased to just 35% by 2022. Conversely, the built-up area expanded rapidly, from 44% in 2019 to 52% in 2022. This increase in urbanization corresponds with a reduction in the city's vegetative cover. Dense vegetation, particularly in the northern part of Islamabad, has diminished to nearly negligible levels by 2022, largely due to deforestation. Sparse vegetation along streets and roads is the only category that has shown an increase, though it is insufficient to counterbalance the rising temperatures in the city. The rise in built-up areas due to anthropogenic activities is a major driver of the decline in vegetative cover and subsequent increase in city temperatures. The expanded urban areas contribute significantly to the urban heat island effect, exacerbating climate change. Vegetation in Islamabad includes not only flooded areas, grasslands, and crops but also forests like those in Margalla Hills National Park. However, even with the world largely on lockdown in 2020, vegetation cover only marginally increased from 42% to 43%. During the same period, built-up areas grew from 44% to 46%, as shown in Graph 2. The mean LST decreased in 2020, likely due to reduced human activity such as lower traffic. By 2022, the built-up area had risen to 52%, while vegetation had dwindled to 35%, predominantly consisting of sparse vegetation. This drastic reduction in dense vegetation aligns with the negative correlation between land surface temperature and NDVI, confirming that decreasing vegetation correlates with rising temperatures. Additionally, an increase in land surface temperature from 2020 to 2021 can partly be attributed to the increased rainfall in 2020, which measured 131.72 mm as per Table 3. This higher rainfall contributed to increased humidity, which in turn elevated surface temperatures. The rising land surface temperature exacerbates climate change, impacting both human and environmental systems and disrupting ecological balance.

Recommendations:

Following are some recommendations for further analysis;

- Town planners and policymakers should make sustainable urban plans that include building eco-friendly urban infrastructures.
- The amount of vegetation should be more than the area of the built-up area as it will help reduce the impact of the increase in temperature. Thus, the town planners should make such policies that involve an increase in vegetation along with an increase in urban area to compensate increasing population.
- For better and more efficient implementation, analysts, technicians, and other specialists who work with geospatial data processing and analysis should adopt a precise methodology. This involves the use of a model builder or Google Earth Engine.
- Based on the current analysis, future predictions of the percentage of urban areas and LST can also be made.

Acknowledgment: Authors are grateful to Almighty Allah who gave them the strength to complete this research work. Moreover, they are grateful to the University of the Punjab, Lahore for providing us with a platform as well as financial support for the completion of this work.

Author's Contribution: Novera Azka is the researcher of the research paper, Dr. Hamid Chaudhary supervised the work, Qudsia Gulzar helped with the write-up, and Dr Sajid Mahmood and Tibra Ishaq helped in the analysis of the work.

Conflict of Interest: This research paper is part of Novera Azka's MPhil thesis submitted to the Center for Geographic Information System, University of the Punjab, Lahore so there is no conflict to publish this work in this journal.

References:

[1] A. Younes, A. Ahmad, A. D. Hanjagi, and A. M. Nair, "Understanding Dynamics of Land Use & Land Cover Change Using GIS & Change Detection Techniques in Tartous, Syria," Eur. J. Geogr., vol. 14, no. 3 SE-Research Article, pp. 20–41, Jul. 2023, doi: 10.48088/ejg.a.you.14.3.020.041.

[2] S. Tariq, S. Mehmood, A. Nisa, Z. Ul-Haq, and U. Mehmood, "Remote sensing of aerosol properties during intense smog events over Lahore (Pakistan)," Kuwait J. Sci., vol. 48, no. 4, 2021, doi: 10.48129/KJS.V48I4.10407.

[3] H. Antal and S. Bhutani, "Identifying Linkages Between Climate Change, Urbanisation, and Population Ageing for Understanding Vulnerability and Risk to Older People: A Review," Ageing Int., vol. 48, no. 3, pp. 816–839, 2023, doi: 10.1007/s12126-022-09504-7.

[4] I. P. Senanayake, W. D. D. P. Welivitiya, and P. M. Nadeeka, "Remote sensing based analysis of urban heat islands with vegetation cover in Colombo city, Sri Lanka using Landsat-7 ETM+ data," Urban Clim., vol. 5, pp. 19–35, 2013, doi: 10.1016/j.uclim.2013.07.004.

[5] H. A. Ahmed, S. K. Singh, M. Kumar, M. S. Maina, R. Dzwairo, and D. Lal, "Impact of urbanization and land cover change on urban climate: Case study of Nigeria," Urban Clim., vol. 32, no. August 2019, p. 100600, 2020, doi: 10.1016/j.uclim.2020.100600.

[6] T. Azevedo and L. F. Matias, "Urban land use and land cover mapping: proposal of a classification system with remote sensing," Agua y Territ., no. 23, pp. 73–82, 2024, doi: 10.17561/at.23.7251.

[7] Z. Hassan et al., "Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan," Springerplus, vol. 5, no. 1, 2016, doi: 10.1186/s40064-016-2414-z.

[8] P. D. Department of Economic and Social Affairs UN, World Population Prospects 2022, no. 9. 2022. [Online]. Available: www.un.org/development/ desa/pd/.

[9] S. Hussain and S. Karuppannan, "Land use/land cover changes and their impact on land surface temperature using remote sensing technique in district Khanewal, Punjab Pakistan," Geol. Ecol. Landscapes, vol. 7, no. 1, pp. 46–58, 2021, doi: 10.1080/24749508.2021.1923272.

[10] X. Zhang et al., "Evaluating the Reconstructed All-Weather Land Surface Temperature for Urban Heat Island Analysis," Remote Sens., vol. 16, no. 2, pp. 1–17, 2024, doi: 10.3390/rs16020373.

[11] C. J. Tomlinson, L. Chapman, J. E. Thornes, and C. Baker, "Remote sensing land surface temperature for meteorology and climatology: A review," Meteorol. Appl., vol. 18, no. 3, pp. 296–306, 2011, doi: 10.1002/met.287.

[12] Y. Qian et al., "Urbanization Impact on Regional Climate and Extreme Weather: Current Understanding, Uncertainties, and Future Research Directions," Adv. Atmos. Sci., vol. 39, no. 6, pp. 819–860, 2022, doi: 10.1007/s00376-021-1371-9.

[13] A. I. Almulhim and P. B. Cobbinah, "Can rapid urbanization be sustainable? The case of Saudi Arabian cities," Habitat Int., vol. 139, p. 102884, 2023, doi: https://doi.org/10.1016/j.habitatint.2023.102884.

[14] M. Ahmad, "Assessing the Impact of Urbanization on Land Use and Land Temperature in Lahore : An Empirical Analysis Using GIS Mapping," IUB J. Soc. Sci., vol. 5, no. 2, pp. 381–397, 2023, doi: 10.52461/ijoss.v5i2.2394.

[15] M. Fatemi and M. Narangifard, "Monitoring LULC changes and its impact on the LST and NDVI in District 1 of Shiraz City," Arab. J. Geosci., vol. 12, no. 4, 2019, doi: 10.1007/s12517-019-4259-6.

[16] W. Liu, B. Jia, T. Li, Q. Zhang, and J. Ma, "Correlation Analysis between Urban Green Space

and Land Surface Temperature from the Perspective of Spatial Heterogeneity: A Case Study within the Sixth Ring Road of Beijing," Sustain., vol. 14, no. 20, 2022, doi: 10.3390/su142013492.
[17] M. Kugelman, "NOREF Expert Analysis Urbanisation in Pakistan : causes and consequences," NOREF, no. January, 2013.
[18] Pakistan Bureau of Statistics, "Announcement of Results of 7th Population and Housing Census-2023," no. CCI, 2023, [Online]. Available: https://www.pbs.gov.pk/sites/default/files/population/2023/Press Release.pdf
[19] B. Roy and E. Bari, "Examining the relationship between land surface temperature and landscape features using spectral indices with Google Earth Engine," Heliyon, vol. 8, no. 9, p. e10668, 2022, doi: 10.1016/j.heliyon.2022.e10668.
[20] K. Javid, M. A. N. Akram, M. Mumtaz, and R. Siddiqui, "Modeling and mapping of climatic classification of Pakistan by using remote sensing climate compound index (2000 to 2018)," Appl. Water Sci., vol. 9, no. 7, pp. 1–9, 2019, doi: 10.1007/s13201-019-1028-3.
[21] A. Rehman et al., "Modelling of Land Use/Cover and LST Variations by Using GIS and Remote Sensing: A Case Study of the Northern Pakhtunkhwa Mountainous Region, Pakistan," Sensors, vol. 22, no. 13, 2022, doi: 10.3390/s22134965.
[22] W. E. Stoney, "Asprs Guide To Land Imaging Satellites," Http://Www.Asprs.Org/News/Satellites/, 2008.
[23] Punjab Information Technology Board, "Rawalpindi," Punjab Portal, 2016. https://www.punjab.gov.pk/rawalpindi
[24] "Geography of Islamabad," Wikepedia. 2021. [Online]. Available: https://en.wikipedia.org/wiki/Geography_of_Islamabad
[25] M. T. Sohail et al., "Impacts of urbanization, LULC, LST, and NDVI changes on the static water table with possible solutions and water policy discussions: A case from Islamabad, Pakistan," Front. Environ. Sci., vol. 11, no. February, pp. 1–13, 2023, doi: 10.3389/fenvs.2023.1018500.
[26] A. Amazirh, O. Merlin, and S. Er-Raki, "Including Sentinel-1 radar data to improve the disaggregation of MODIS land surface temperature data," ISPRS J. Photogramm. Remote Sens., vol. 150, pp. 11–26, 2019, doi: https://doi.org/10.1016/j.isprsjprs.2019.02.004.
[27] D. Ghent, J. Remedios, and E. Dodd, "Sentinel 3 Land surface temperature," Compr. Remote Sens., vol. 1–9, pp. 264–283, 2021, doi: 10.1016/B978-0-12-409548-9.10375-6.
[28] Esri, "What is image classification?," ArcGIS Desktop, 2021. https://desktop.arcgis.com/en/arcmap/latest/extensions/spatial-analyst/image-classification/what-is-image-classification-.htm
[29] IEE, "Sentinel 2 10m Land Use/ Land cover Time series," ESRI, 2021. https://www.arcgis.com/home/item.html?id=d3da5dd386d140cf93fc9ecbf8da5e31#
[30] M. Ranagalage, R. C. Estoque, and Y. Murayama, "An urban heat island study of the Colombo Metropolitan Area, Sri Lanka, based on Landsat data (1997-2017)," ISPRS Int. J. Geo-Information, vol. 6, no. 7, 2017, doi: 10.3390/ijgi6070189.
[31] S. Ullah, "Simulating Land Use Land Cover Changes and their Impacts on Land Surface Temperature in Northern Pakistan," COMSATS University, Islamabad, 2021.
[32] D. Khamchiangta and S. Dhakal, "Time series analysis of land use and land cover changes related to urban heat island intensity: Case of Bangkok Metropolitan Area in Thailand," J. Urban Manag., vol. 9, no. 4, pp. 383–395, 2020, doi: 10.1016/j.jum.2020.09.001.
[33] I. Amrulloh and V. N. Fikriyah, "Time series analysis of landsat data for urban heat island monitoring in Semarang City," IOP Conf. Ser. Earth Environ. Sci., vol. 1314, no. 1, 2024, doi: 10.1088/1755-1315/1314/1/012086.