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ENVIRONMENTAL GEOLOGY

Monitoring Land Surface Temperature and Vegetation Dynamics in Response to Land Use Changes using Spatiotemporal Analysis in District Chiniot, Punjab Pakistan

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ABSTRACT

Understanding the impact of land use and cover changes (LULC) on vegetation and built-up areas is crucial for local governments and communities in rapidly developing countries. The study was conducted in district Chiniot, Punjab, Pakistan. The present study aims to explore the relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI). This study aims to investigate the relationship between land surface temperature (LST) patterns and changes in LULC due to urbanization in District Chiniot. Using Landsat 5 and 8 data, LST was computed and correlated with NDVI to assess vegetation changes. The results indicate a decrease in NDVI over the years, suggesting declining vegetation, and an increase in LST, indicating rising temperatures. Supervised classification revealed an increase in built-up areas and a decrease in vegetation, contributing to the rise in LST. These findings highlight the importance of effective land management strategies to mitigate the adverse impacts of urbanization on local environments.

Keywords: Land Surface Temperature, Normalized Differentiated Vegetative Index, Land Use Land Cover, Normalized Differentiated Built-up Index, Land Satellite, Remote Sensing Data.

Monitoreo de la temperatura superficial terrestre y las dinámicas de vegetación en respuesta a los cambios en el uso del suelo a través del análisis espacio-temporal, en el distrito de Chiniot, Punjab, Pakistán

RESUMEN

El conocimiento del impacto del uso del suelo y los cambios en la cubierta de vegetación en las áreas urbanizadas es determinante para los gobiernos locales y para las comunidades de los países en desarrollo acelerado. Este estudio se realizó en el distrito de Chiniot, Punjab, Pakistan. El presente estudio busca explorar la relación entre la temperatura de la superficie terrestre y el índice de vegetación de diferencia normalizada. El trabajo se enfoca en investigar la relación entre los patrones de temperatura de la superficie terrestre y los cambios en la cubierta vegetal y en el uso del suelo debido a la urbanización del distrito de Chiniot. Con el uso de las bases de información Landsat 5 y Landsat 8, se computó y se correlacionó la temperatura de la superficie terrestre con el índice de vegetación de diferencia normalizada. Los resultados indican un decrecimiento en el índice de vegetación a través de los años, lo que sugiere una caída de la vegetación, un incremento en la temperatura de la superficie y por ende un proceso de aumento de las temperaturas. Una clasificación supervisada reveló un incremento de las áreas urbanizadas y un crecimiento de la vegetación, lo que contribuye al aumento de la temperatura de la superficie. Estos hallazgos resaltan la importancia de las estrategias de manejo efectivo de los suelos para mitigar los impactos adversos de la urbanización en los ambientes locales.

Palabras clave: Temperatura de la superficie terrestre; índice de vegetación de diferencia normalizada; uso del suelo/cobertura del suelo; índice de urbanización de diferencia normalizada; satélites terrestres; información de detección remota.

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1. Introduction

Measured within the range of the remote device, the Land Surface Temperature (LST) is the radiative skin temperature of the land surface. It is most likely derived from Top-of-Atmosphere brightness temperatures from the infrared spectral channels of a constellation of stationary satellites. Its estimate is also influenced by the plant cover, ratio, and soil moisture content. Temperatures of the bare soil and plants may combine to form LST. The LST exhibits quick fluctuations as well because of how quickly each reacts to changes in incoming radiation caused by implementers, aerosol load alterations, and illumination variations. The LST therefore affects how energy is distributed between plants and the ground, which in turn affects the temperature of the surface air (Yaseen , 2022).

The phenomenon of Land Surface Temperature (LST) holds considerable importance within the context of global climate change. As greenhouse gas levels escalate in the atmosphere, LST tends to increase correspondingly. Consequently, this elevation in temperature contributes to the melting of glaciers and ice sheets, thereby affecting local vegetation. Given the fluctuating patterns of rainfall and the possibility of monsoon disruptions, the repercussions are anticipated to be particularly pronounced in regions reliant on monsoons (Rajeshwari & Mani, 2014).

The thermal environment and microclimate in regions experiencing rapid economic growth and established industries, particularly urban areas with dense populations and significant waste discharge into the environment, have undergone notable transformations (Yang et al., 2021). These changes have led to the emergence of urban heat island effects, disrupting the energy equilibrium and negatively impacting the quality of life for residents. The term "urban heat island" denotes widespread alterations in microclimates due to urbanization, with land surface temperature serving as an indicator of the severity of global warming (Yang et al., 2021).

There are various natural and industrial sources of environmental contamination such as an increase in cadmium which is found in various biota. Increasing temperature increases the uptake and toxic impact of cadmium on microorganisms, land plants, and aquatic organisms (World Health Organization, 1992).

Consequently, there is growing interest in developing strategies to mitigate the escalation of land surface temperature and prevent further deterioration of urban thermal environments (Yang et al., 2021).

The expansion of infrastructure and the conversion of grasslands and forests into urban areas are exacerbating this problem. The reduction in grass and forest land, crucial for carbon sequestration, is leading to increased anthropogenic carbon emissions. The extensive conversion of land for urban infrastructure is a major factor contributing to this issue (Waseem & Khayyam, 2019).

The estimation of Land Surface Temperature (LST) is essential for diverse applications as it provides valuable information about the temporal and spatial variations in surface thermal equilibrium (Li et al., 2014). According to Benelli et al.,(2012), LST finds utility across various domains such as evapotranspiration, climate change analysis, hydrological processes, vegetation surveillance, urban climate assessment, and environmental research(Yaseen & Khan, 2022).

NASA and the United States Geological Survey (USGS) collaborate on this initiative, formerly referred to as the Landsat Data Continuity Mission. Pakistan, a developing nation, is experiencing a rapid surge in urbanization, bringing significant advantages to its citizens. However, if left unchecked, this process can also have adverse impacts on the environment (Elsayed, 2012). As highlighted by Amanollahi et al.,(2016), a primary concern associated with urbanization is the elevation of ambient temperature, resulting in the Urban Heat Island (UHI) effect and deterioration of the urban environmental quality. Consequently, scholars have suggested in numerous studies the incorporation of urban climate considerations into development and planning efforts (Raghavan et al., 2015).

This study delves into the evolving landscape of urbanization over time and its potential implications for the human lifecycle. Population growth has exacerbated global warming, with Pakistan being especially susceptible to extreme weather events. Consequently, this research elucidates the noteworthy transformations occurring over time (Saleem et al., 2020).

Methods for measuring the urban thermal environment include remote radiant temperature measurement from airborne and spaceborne platforms, mobile sampling of air and surface kinetic temperature from ground and airborne vehicles, and sampling of air and surface kinetic temperature at fixed locations. To estimate radiant temperature, at least, remote sensing has the greatest synoptic capabilities due to its nearly immediate collection of several samples over a large area. Remote sensing has the most synoptic capabilities, at least for radiant temperature measurement. For obtaining a general understanding of thermal fluctuations in an urban ecosystem, it can still be a helpful. It can still be a helpful tool for understanding how temperatures vary in an urban setting (W. Yue, 2007).

In the recent past various studies have been done to evaluate the importance of Land Surface Temperature (LST) in understanding global energy and water balance processes has been recognized by the remote sensing industry according to Yaseen & Khan (2022). According to Jiménez-Muñoz et al.,(2014) Monitoring LST and its correlation with the Normalized Difference Vegetation Index (NDVI) is crucial for understanding land cover changes and their environmental impacts. LST, a key indicator in physics, affects various fields such as hydrology, ecology, agriculture, and global change studies (Jiménez-Muñoz et al., 2014). Its rise can lead to significant environmental imbalances, including melting ice caps and disruptions to crop calendars and climatic conditions, particularly in monsoon regions. Thermal infrared remote sensing technology has become vital for studying land surface thermal characteristics. Landsat satellites have provided valuable thermal data since 1978, allowing for the computation of LST using different sensors (Zhang et al., 2023).

Rajeshwari & Mani (2014) conducted a study that integrated ASTER and MODIS data, specifically bands 31 and 32, to generate Land Surface Temperature (LST). Emissivity computation involved the use of NDVI and a supervised classification method for land use and land cover. The comparison with in situ data revealed a positive correlation between LST and NDVI, as well as the land use/land cover technique.

The research conducted by Strahler & Strahler (2013) suggested that the forward model utilized a representative sample of natural materials sourced from the MODIS UCSB emissivity database, containing 113 distinct spectral emissivity values between 8 and 14 µm. This dataset encompasses various materials, including soils, minerals, plant species, and water types. Notably, man-made materials were excluded due to the TIRS instrument's spatial resolution and focus on environmental applications. Remote sensing imagery enables the creation of vegetation indices, with NDVI being a commonly used metric for monitoring vegetation and estimating soil moisture in semi-arid regions. However, it responds predominantly to the red band with significant absorption (Strahler &Strahler, 2013).

Simulation data suggests a potential temperature increase of up to 0.21°C per year by 2041, as observed by Rousta et al.,(2018). Over the past 27 years, LST has shown an average increase of 1.74°C. These rising temperatures, attributed to global climate change, have implications for land use, vegetation cover, and water resources, contributing to various environmental challenges (Solangi et al., 2019).

Attri et al., (2015) emphasizes the significance of land in sustaining human life. Changes in land utilization patterns over time can lead to diverse environmental consequences, impacting energy distribution and temperature fluctuations. Land use pertains to the utilization of land for various purposes such as agriculture or urban development, while land cover encompasses the physical attributes of the area, including forests or water bodies.

The study conducted by Gur et al., (2024) aimed to assess the potential impact of global climate change on the highland areas of Kastamonu, a significant province in Turkey known for its numerous and varied highlands. The investigation focused on 59 selected highland locations within the region. Using the De Martonne climate classification, projections were made for four future periods (2040, 2060, 2080, and 2100) under two scenarios: SSPs 245 and SSPs 585.

The study conducted by Schwaab et al., (2021) suggest that the urban trees play a significant role in influencing city temperatures, yet their effectiveness in mitigating urban heat remains understudied, especially in comparison to green spaces lacking trees. High-resolution satellite data from 293 European cities suggest that urban trees contribute to cooler summer temperatures and alleviate heat stress, particularly in severe weather conditions (Schwaab et al., 2021). Amidst global climate change challenges, including the rise in average surface temperature known as global warming, understanding LST variations is paramount for numerous hydrological, meteorological, and climatological applications. Utilizing Geographic Information Systems (GIS) and remote sensing (RS), sensors like Landsat-8, MODIS, and AVHRR provide valuable data for LST modeling and climate analysis (Solanky et al., 2018). The impact of climatic and environmental changes on crop health is evident in variations in rainfall, increased heat stress, shifts in LST, and population migration from rural to urban areas (Hussain & Karuppannan, 2023). The surge in LST, attributed to global climate change, has transformed land usage, vegetated areas, and water resources, posing significant environmental challenges (Solangi et al., 2019).

The present study aims to explore the relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI). The study also focused to identify abrupt temperature fluctuations attributed to escalated urbanization in the Chiniot district, located in Punjab, Pakistan. This study also aims to analyze the impact of rising land surface temperatures on vegetation, addressing challenges such as ecosystem loss and declining biodiversity amid global climate warming. Understanding the causes and effects of temperature shifts is crucial for devising effective land management strategies. Exploring Land Surface Temperature dynamics is essential for understanding spatial and temporal variations in surface equilibrium, influencing heat and water exchange in the weather and climate system. Developing reliable methodologies and technologies for monitoring LST data is vital for various applications including weather prediction, climate research, urban planning, agriculture, and natural resource management.

2. Study Area

The study area is situated in the northwest region of the Chenab channel and is connected to several cities in Punjab, including Faisalabad, Sargodha, and Jhang, via road networks. It is approximately 160 km east of the city center, around 30 km southwest of the city, 56 km west of Sargodha, and 86 km southwest of Jhang. The coordinates of the study area range from 31°43′ to 31°44′ N latitude and 72°58′ to 73°0′ E longitude.

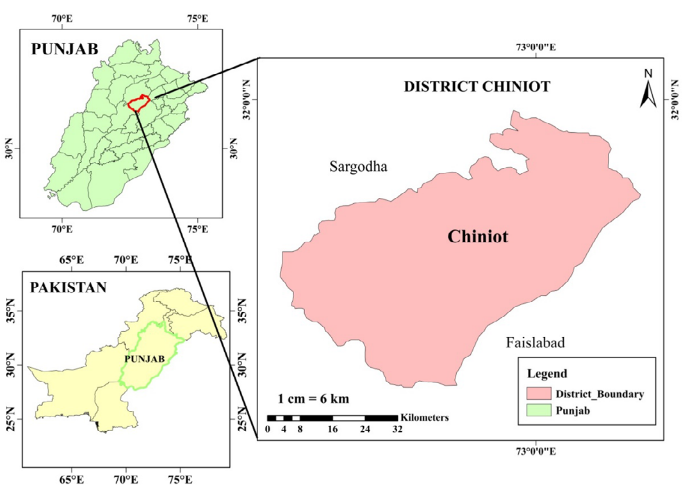

Figure 1. Map of the study area.

3. Materials and Methods

Data Sets

The main source of data for this study is Landsat 5, which was in operation from March 1, 1984, to January 15, 2013, and played a significant role in surface monitoring (Egorov, 2022). Particularly chosen for its thermal infrared band was Landsat 8 OLI/TIRS data from March 9, 2020, with a spatial resolution of 30 x 30 m (Acharya & Yang, 2015). The research region, which included Chiniot, made use of Landsat data from 1990, 2000, and 2009. Important information for the correlation study was obtained by processing the Landsat 8 data for Land Surface Temperature (LST) inversion (Acharya & Yang, 2015). To further improve the comprehension of LST patterns in March 2020, meteorological data from the digital weather station operated by the Pakistan Meteorological Department at Nusrat Jahan College Rabwah was also included.

Table 1 Data sets showing sensors utilized in the study.

Sensors	Date	Bands	Resolution (m)	Source	Purpose
Landsat 5	7 March 1990 2 March 2000 11 March 2009	1, 2,3, 4,5,6	30x30m	Earthexplorer. usgs.gov	To calculate LST
Landsat 8	9 March 2020	1,2,3,4,5,6, 7,8,9,10,11	30x30m	Earthexplorer. usgs.gov	To calculate NDVI and NDBI

Data Collection

Thematic mappers, enhanced thematic mapper plus, and OLI/TIRS sensors were used in this study's data collecting process, which was complemented by satellite data and other information sources. Two steps were involved in the conversion of thermal bands into land surface temperature (LST) and top-of-atmospheric spectral radiation (ToAr). Spectral radiance (L) was calculated using equations and converted to centigrade scale using ArcGIS 10.5 software.

Data Assessment

The assessment of vegetation greenness, density, and health was achieved through the normalized difference vegetation index (NDVI). NDVI computation involved a ratio between red (R) and near-infrared (NIR) measurements (Li et al., 2013). The NDVI equation determined vegetation amount (Pv) and emissivity (ε). The LST equation facilitated the creation of a surface temperature map, and NDVI and LST data were integrated into ArcMap for further analysis.

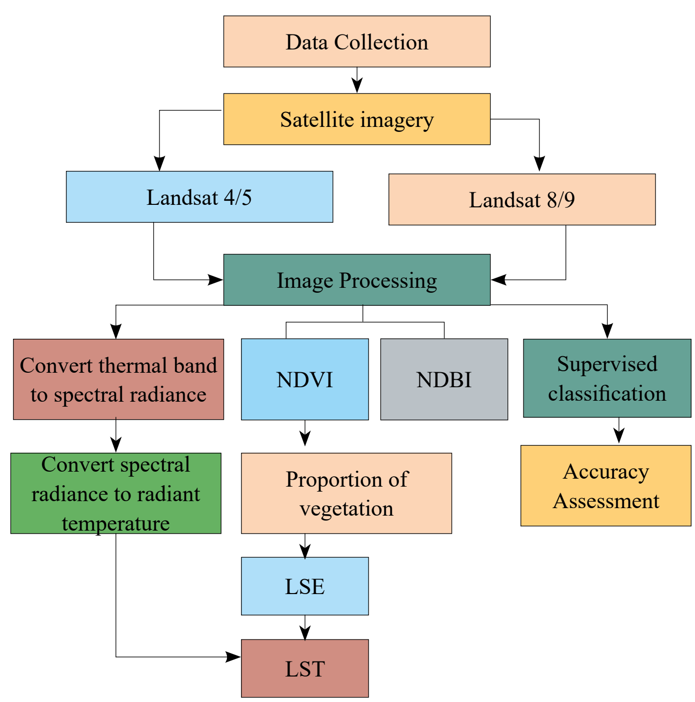

Figure 2. Research methodology of the study performed.

Methodology

Using the methods described by Chen et al. (2002), bands 3, 4, and 5 of Landsat 5 were used to determine the land surface temperature. The following formula was first used to translate the digital numbers (DNs) of these bands into radiation luminance: QCALMIN and Qcalmax stand for 1 and 255, respectively, QCAL is an acronym for DN, and LMAX and LMIN are comparable to 1 and 255, respectively (Chen et al., 2002).

$$OA = L\lambda = \frac{(Lmax\lambda - Lmin\lambda)}{Qcalmax - Qcalmin \times (DN - Qcalmin) + Lmin\lambda} \tag{1}$$

Where *TOA* is top of atmosphere, *Lλ*, denotes the spectral at sensor radiance to top of atmosphere, *Lmin λ*, refers to spectral radiance scaled to *Qcalmin*, while *Lmax λ*, refers to spectral radiance scaled to *Qcalmax*, while *Qcal* is the quantized calibrated pixel value.

Land surface temperature was also calculated in Kelvin using the following equation, where *BT* is the satellite brightness temperature in Celsius and K1 and K2 represent thermal conversion from the metadata, DN=255, K1=607.76, K2=1260.56.

$$BT = T = \frac{K2}{Ln\left(\left(\frac{K1}{\lambda 1}\right) + 1\right)} - 273.15 \tag{2}$$

The thermal bands of Landsat 8 are used to determine the land surface temperature (LST), and the research region, Chiniot, is then extracted for analysis in ArcMap 10.8. The relationship between LST and NDVI and LST and NDBI is then established. Land surface temperature is calculated using Bands 10 and 11 of Landsat-8. The following formula is used in the raster calculator when importing Bands 10 and 11 into ArcMap (Ghouri et al., 2022).

$$L\lambda = ML \times Qcal + Al \tag{3}$$

ML, extracted from the metadata, represents the specific-band multiplicative rescaling factor, whereas *Qcal* denotes the Thermal band (B10, B11), and *AL*, also derived from the metadata, signifies the specific-band additive rescaling factor.

Land surface emissivity refers to the proportion of radiation emitted from a material surface relative to a blackbody under identical conditions at the same temperature. The provided equation can be utilized for emissivity calculation (Ghouri et al., 2022).

$$\mathcal{E} = 0.004 \times Pv + 0.986 \tag{4}$$

In the Land Use Land Cover (LULC) categorization system, which has four main indexes—the built-up index being the most important—the Built-up Index is used to derive ground-based built-up area information from satellite data. Greater intensity of built-up regions with less vegetation is indicated by elevated NDBI readings, and vice versa. According to the above equation, NDBI computation uses the Short-Wave Infrared (SWIR) and Near-Infrared (NIR) bands (Ghouri et al., 2022).

$$Built\ up\ Index = \frac{(SWIR - NIR)}{(SWIR + NIR)} \tag{5}$$

Accuracy assessment in this research work was implied to verify the results of supervised classifications as either accurate or not, using the formula given below:

$$Overall\ accuracy = \frac{Total\ number\ of\ correctly\ classified\ pixels\ (diagonal)}{Total\ number\ of\ reference\ pixels} \times 100 \tag{6}$$

4. Result Analysis

A mean of 0.124726, a low of -0.511111, and a high of 0.760563 are shown in the NDVI values for March 7, 1990 (Fig. 4a). The NDVI image for March 2, 2000 (Fig. 4b) shows a mean of 0.156615, a low of -0.438596, and a high of 0.751825. Additionally, (Fig. 4c), the NDVI image for March 11, 2009, shows a mean of 0.256689, a minimum of -0.217391, and a high of 0.730769. Finally, the NDVI image for March 9, 2020 (Fig. 4d) shows a mean of 0.207287, a minimum value of -0.154056, and a maximum value of 0.568629. According to these results, the NDVI showed a downward trend between 1990 and 2020, indicating a decrease in vegetation over time.

Table 2. Normalized difference vegetation index of the data collected on year basis.

NORMALIZED DIFFERENCE VEGETATION INDEX			
YEAR	MAX	MIN	MEAN
1990	0.760563	-0.511111	0.124726
2000	0.751825	-0.438596	0.156615
2009	0.730769	-0.217391	0.256689
2020	0.568629	-0.154056	0.207287

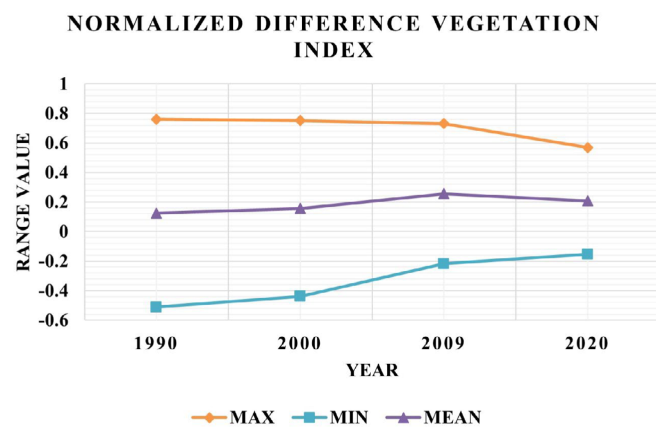

Figure 3. Graphical representation for NDVI, showing max, min and mean value for the studied year.

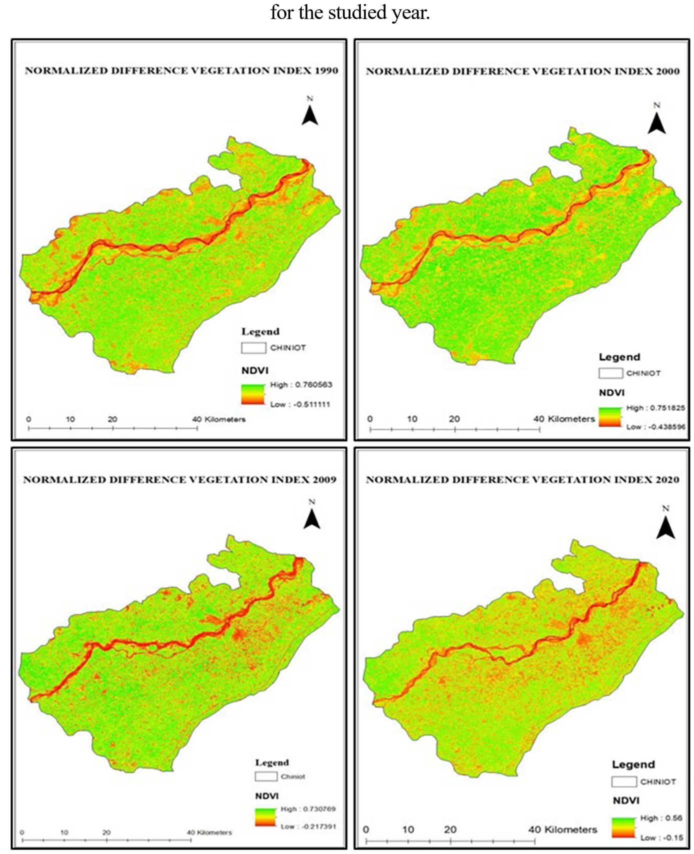

Figure 4. Normalized difference vegetation index (a) for year 1990 (b) for year 2000 (c) for year 2009 (d) for year 2020.

The Land Surface Temperature (LST) readings for March 7, 1990 (Fig. 6a) show a mean of 22.77°C, a low of 14.71°C, and a high of 30.83°C. In the same way, the LST picture for March 2, 2000 (Fig. 6b) shows a mean value of 22.85°C, a minimum value of 16.1°C, and a high value of 29.6°C. Additionally, the March 11, 2009 LST image (Fig. 6c) shows a mean value of 29.46°C, a minimum value of 15.18°C, and a high value of 43.73°C. Lastly, the March 9, 2020 LST image (Fig. 6d) shows a mean temperature of 17.08°C, a minimum temperature of 9.13°C, and a high temperature of 25.02°C.

Table 3. Land Surface Temperature of the data collected on year basis.

LAND SURFACE TEMPERATURE (°C)			
YEAR	**MAX**	**MIN**	**MEAN**
1990	30.83	14.71	22.77
2000	29.6	16.1	22.85
2009	43.73	15.18	29.46
2020	25.02	9.13	17.08

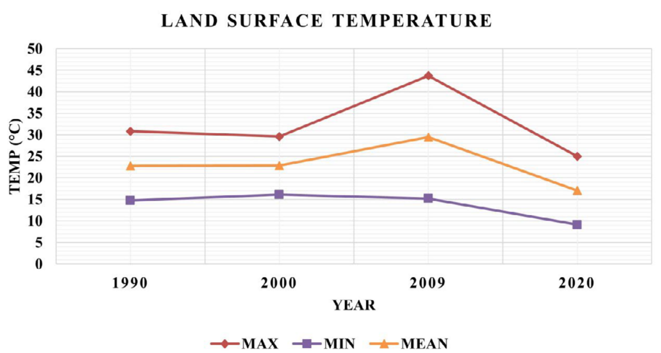

Figure 5. Graphical representation for LST, showing max, min and mean value for the studied year.

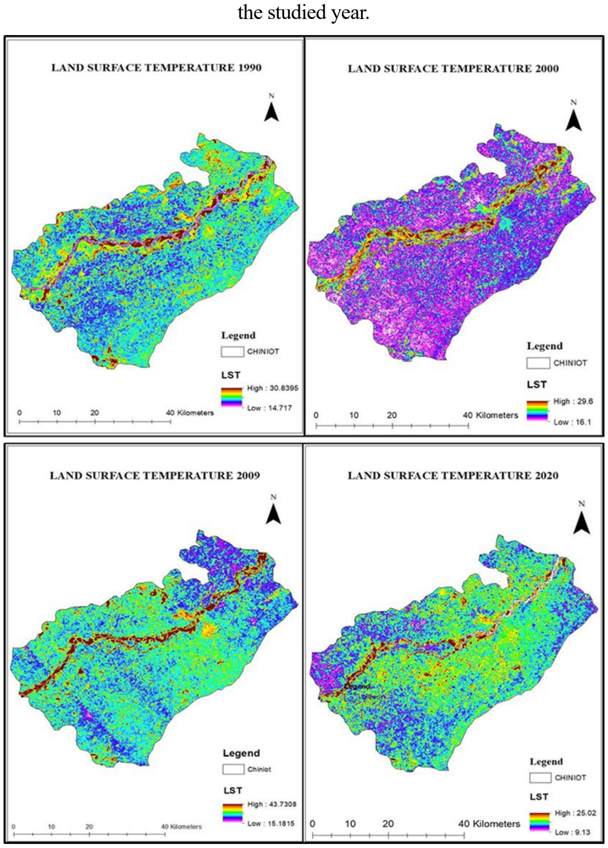

Figure 6. Land surface temperature (a) for year 1990 (b) for year 2000 (c) for year 2009 (d) for year 2020.

The analysis of these values suggests a notable increase in land surface temperature in district Chiniot from 14.71°C in March 1990 to 25.02°C in March 2020. According to Yaseen & Khan (2022), the higher temperature observed near the riverbed covered with sand can be attributed to the sand's low specific heat energy, causing it to rapidly heat up in sunlight and cool down quickly when sunlight is absent. This phenomenon is consistent with our findings.

Table 4. Supervised classifications based upon different parameters studied.

SUPERVISED CLASSIFICATION				
Parameters	**1990**	**2000**	**2009**	**2020**
Built up	20%	28%	28%	40%
Vegetation	56%	63%	61%	51%
Water Body	1%	1%	0%	1%
Sand	1%	3%	2%	5%
Barren Land	21%	6%	8%	3%

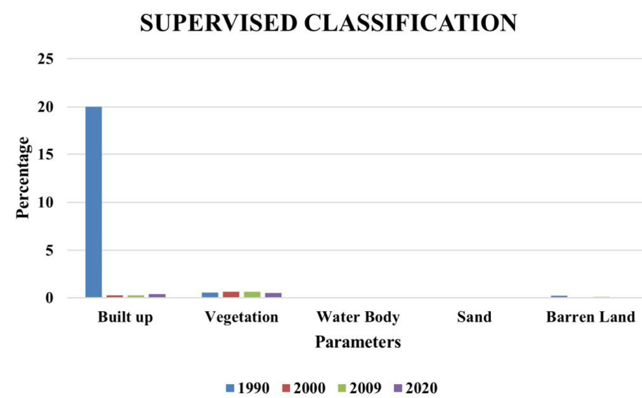

Figure 7. Graphical representation for supervised classification, showing percentages for each parameter.

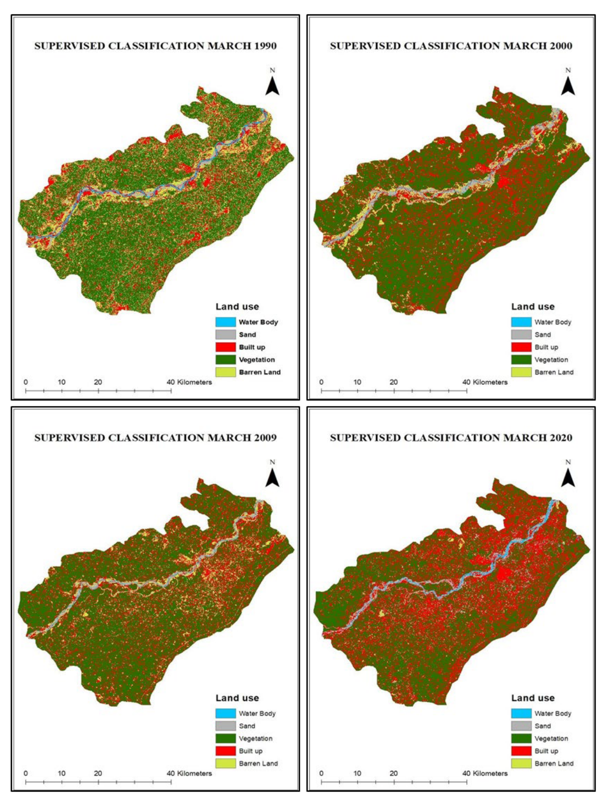

Figure 8. Supervised classification (a) for year 1990 (b) for year 2000 (c) for year 2009 (d) for year 2020.

According to the March 1990 supervised categorization findings (Fig. 8a), the Chiniot district is mostly composed of low-built-up regions and high vegetation cover. In contrast to 1990, there is discernible evidence of growing built-up areas and a commensurate decline in vegetation by March 2000 (Fig. 8b). In comparison to 1990 and 2000, this tendency is also present in March 2009 (Fig. 8c), with significant increases in built-up areas and losses in vegetation. Additionally, the March 2020 data (Fig. 8d) show a persistent pattern of declining vegetation and growing built-up regions over time.

These findings suggest a consistent pattern of urbanization and land transformation, with built-up areas expanding at the expense of vegetation cover. This phenomenon is closely associated with changes in land surface temperature over time. Table 4 provides a detailed breakdown of the supervised classification values for the specified years.

The March 7, 1990, NDBI study findings (Fig. 10a) show a mean value of 0.05, a minimum value of -0.72, and a high value of 0.825137. Likewise, on March 2, 2000 (Fig. 10b), the mean is zero, the lowest is -0.818182, and the highest is 0.789474. The NDBI value drops to 0.48659 by March 11, 2009 (Fig. 10c), with a mean of 0.01 and a minimum of -0.478261. The highest NDBI value drops even further to 0.210882 by March 9, 2020 (Fig. 10d), with a mean of -0.1 and a minimum of -0.415411. These results point to a pattern of declining vegetation cover over time, with NDBI values showing a steady rise from 1990 to 2020.

This trend is associated with an increase in land surface temperature (LST) over the same period. Table 5 provides a comprehensive overview of the NDBI values for the specified years.

The accuracy assessment represents the final stage in the classification process of satellite images. For March 1990, 2000, 2009, and 2020, the supervised classification accuracy was evaluated using 30 ground samples for each year. This assessment involved determining the user accuracy, producer accuracy, and overall accuracy for each year. The resulting overall accuracies for the respective years, as calculated above, were 53.3%, 56.6%, 63.3%, and 63.3%.

Table 5. Normalized difference built up index of the data collected on year basis.

NORMALIZED DIFFERENCE BUILT UP INDEX			
YEAR	MAX	MIN	MEAN
1990	0.82	-0.72	0.05
2000	0.78	-0.81	0
2009	0.48	-0.47	0.01
2020	0.21	-0.41	-0.1

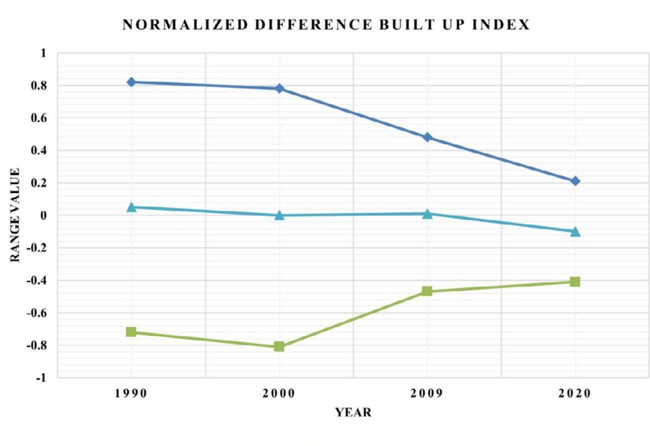

Figure 9. Graphical representation for NDBI, showing max, min and mean value for the studied year.

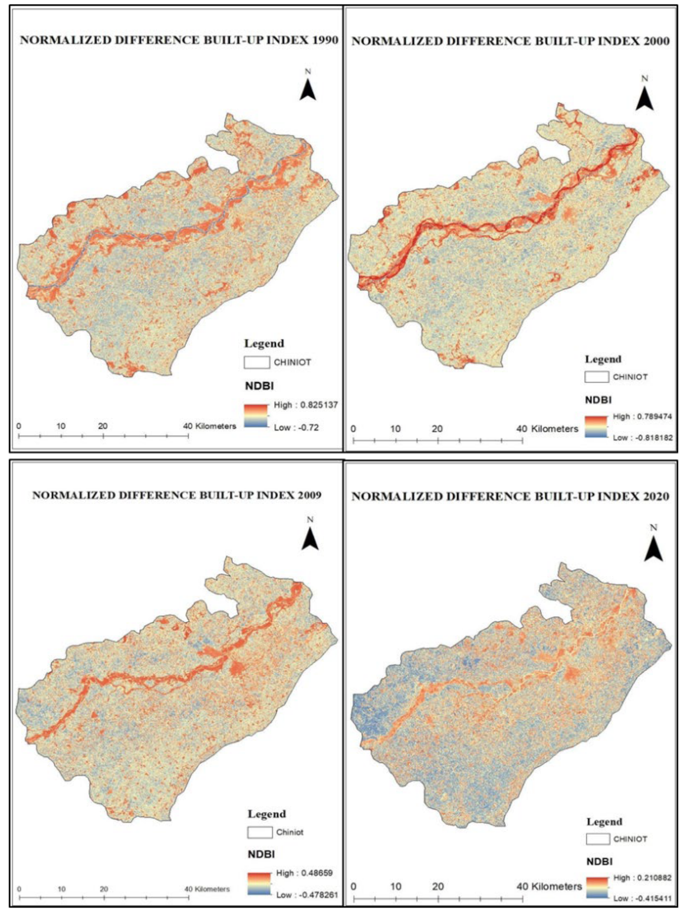

Figure 10. Normalized difference built up index (a) for year 1990 (b) for year 2000 (c) for year 2009 (d) for year 2020.

Discussion

An investigation of land surface temperature (LST) connections with vegetation cover (NDVI) and built-up areas (NDBI) in Chiniot district, Punjab, Pakistan was conducted through Landsat imagery evaluation from 1990 to 2000 to 2009 to 2020. Analysis shows that local environmental transformation has involved both vegetation reduction and built-up area expansion while LST values rose substantially over 30 years.

Vegetation greenness and density show reduced NDVI measurements throughout the 1990s until 2020. The growing built-up area supports the transformation of vegetated land into urban development since this pattern remains consistent across time. The reduction in vegetation creates severe impacts on environmental services by diminishing carbon uptake and air quality improvement and failing to control temperatures. When vegetation covers decreases it facilitates more surface runoff and more soil erosion occurs.

An analysis of LST shows that ground temperatures in the area have significantly increased throughout the research timeframe. Analysis shows that temperature increased from 14.71ºC during 1990 to 25.02ºC at 2020 indicating an upward temperature pattern in this area. An increase in temperature results from multiple factors such as built-up area spread that maintains heat better than vegetated landscapes (Oke, 1982). The measurements of rising LST match the NDVI reduction because vegetation dramatically affects evaporative cooling which controls surface temperature. The research notes how riverbed sands might affect surface temperatures and confirms the same finding as Yaseen & Khan (2022), highlighting the importance of considering local geographical features.

The supervised classification method verifies the assessment findings obtained throughout the study. The results show an unbroken upward pattern of built-up areas alongside a downward pattern of vegetation cover which indicates the urbanization trend in Chiniot district. The transformation of land cover structure generates direct effects on both the LST observation and NDVI assessment. Built-up areas that gain more impervious surfaces produce elevated LST and simultaneously reduced NDVI values result from losing vegetated surfaces. The factor was in correlation with the study conducted by (Ullah et al., 2024) addressing the impact of the supervised classification using advanced deep learning algorithms.

The NDBI assessment validates the classification output results previously discovered. Data shows NDBI increasing steadily throughout the years 1990 to 2020 which demonstrates expanding built-up areas and disappearing vegetation. Thermal environmental effects result from a mixture of NDVI and NDBI alongside LST according to their mutual correlations.

Accuracy assessment of supervised classification provides essential information about the reliability of the land cover classification results. Although the range of accuracy between 53.3% to 63.3% is moderate it offers essential information about land cover transformations in the studied area. The classification accuracy might benefit from improved classification approaches together with imagery resolution improvements.

Overall, the research shows how remote sensing methods serve effectively for detecting land use modification effects on vegetation cover and LST distributions. This research shows that cities need sustainable land management strategies for urban planning since these approaches will counteract the adverse effects of urban growth such as overheating heat islands and service ecosystem depletion. Future studies need to identify particular drivers of land cover modifications in Chiniot district while assessing related local climate and water resource effects. Socio-economic information would create a thorough understanding of urbanization patterns within the region and their wider consequences.

Conclusion and Recommendations

This study investigates the relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) using Landsat 8 OLI/TIRS and Landsat 5 data. The findings highlight that built-up areas and bare soil contribute significantly to LST elevation, whereas vegetation tends to lower LST levels. The study aims to evaluate changes in Land Use and Land Cover (LULC) and LST in Chiniot district, Punjab, Pakistan, from 1990 to 2020. Results indicate an expansion of urban areas at the expense of water bodies and vegetation, accompanied by a rise in average LST over the decades. Furthermore, GIS analysis reveals a strong positive correlation between LULC changes and LST increase, particularly due to the conversion of cultivated land to built-up areas. Notably, the temperature distribution across different LULC classes shows the highest temperatures in built-up areas and the lowest in water bodies. The study also projects a reduction in vegetation and water bodies by 2020 compared to 1990. Additionally, analysis of LST data from March 1990 to March 2020 indicates a steady increase in temperature over time. The presence of sand near riverbeds is identified as a significant factor contributing to high temperatures due to its low specific heat energy compared to water. Supervised classification of Chiniot district highlights a shift in vegetation patterns over the years, with a noticeable increase in built-up areas and a corresponding decrease in vegetation. This trend underscores the influence of land use changes on LST variations. Overall, the decline in NDVI and the increase in NDBI from 1990 to 2020 signify a decrease in vegetation and an expansion of built-up areas, contributing to the observed rise in LST.

The analysis shows an alarming pattern of growing Land Surface Temperature (LST) in Chiniot district because of both urban development and changes in ground cover. Integration of the following strategic policies presents a solution to reverse this trend while promoting urban sustainability in the area such as targeted tree planting in which national efforts should establish tree planting initiatives which use local climate-adapted native species for all plantations. Placing trees in roadside areas and parks and residential spaces promotes maximum shade and cooling effects from evapotranspiration. Green roofs and walls strategies that includes policy that should offer economic benefits for building owners who construct green roofs together with vertical green walls on large structures. The implementation of these features successfully lowers surface temperatures for buildings as they function to reduce localized heating in these areas. Several organizations should establish community gardens together with urban farming initiatives. The programs create additional green areas in addition to strengthening food availability for local communities and encouraging public involvement. Policy measures should exist to safeguard present green areas from being transformed into built structures. The implementation of improved management practices will enable maximum utilization of cooling capabilities from urban areas. The development of dense and combined living and working areas will prevent city expansion through urban sprawl while trimming down demands on big transportation systems. Neighborhood layout which promotes walking and biking helps people avoid using private vehicles for everyday needs. Roads together with parking lots and sidewalks should use permeable pavements as their primary choice. Water permeates through these surfaces which helps groundwater absorption while also decreasing flooding and heat from the environment. Installing public transportation systems and building cycling networks with pedestrian paths will decrease private car use on roads. Support the adoption of electric vehicles along with other vehicles with low emission levels. The city should adopt water-sensitive urban design principles to both save water and effectively manage its water resources. Guam should deploy three water conservation methods through rainwater harvesting along with greywater recycling programs and the establishment of urban wetlands systems. Urban green spaces and agricultural land should adopt suitable irrigation technology to reduce water losses and enhance evapotranspiration-based cooling. A series of public information initiatives should reach residents to demonstrate the consequences of LST rise alongside the advantages of implementing urban green spaces and sustainable management. Workers from the community need to participate in both environmental heat monitoring and data collection activities across cities. The program enables the collection of awareness data that advances decision-making through valuable evidence. The implementation of a new policy and regulatory system must use incentives to promote sustainable practices and enforce limitations on operations which cause LST increase. Different public agencies must partner with urban planners along with developers and community organizations for implementing collaborative LST reduction strategies. Financial support for scientific investigations should maintain focus on studying the multi-factor relationships between land use modification and LST heat flux and climatic change patterns in the Chiniot district. A plan must be created for continuous LST monitoring as part of long-term evaluations that measure outcome success from implemented mitigation approaches. These actionable strategies will help the Chiniot district develop a sustainable urban atmosphere which combats LST increases to create higher quality living conditions for its citizens. The achievement of extended success requires implementing a combined approach between green infrastructure and sustainable urban planning and community engagement methods.

Research Outcomes

The research outcomes reveal several discrepancies in the processing of the data. Firstly, inaccuracies were detected in the processed images of the year 2000, where the land surface temperature appeared low despite a high built-up area, leading to misleading interpretations. This discrepancy may stem from geographical or climatic fluctuations in the year 2000, or it could be attributed to errors in the bands of the images used during processing. Furthermore, the Normalized Difference Vegetation Index (NDVI) for the year 2020 yielded invalid results showing increased vegetation, contrary to expectations. Additionally, the Land Surface Temperature (LST) values for the year 2020 were unexpectedly low, suggesting a difference in band values of the image used for processing. Moreover, the Normalized Difference Built-up Index exhibited high values in 2000 instead of low values, and lower values in the year 2020, indicating potential errors in the image processing methodology. These discrepancies highlight the need for a thorough review of the image processing techniques and data used in the thesis to ensure the accuracy and reliability of the research findings.

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