Comparative Remote Sensing Analysis of Urban Heat Islands in Contrasting Climates

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ABSTRACT:

The formation and intensity of Urban Heat Islands (UHIs) are significantly influenced by the climatic conditions of different regions, making comparative studies across varying climates essential for understanding urban thermal behavior. The objective is to assess Land Surface Temperature (LST) dynamics and UHI patterns using multi-source remote sensing data. Landsat 8 OLI/TIRS imagery from July 2022 was used to derive LST using the Single Channel method and spectral indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), Normalized Difference Infrared Index (NDII), and Normalized Difference Impervious Surface Index (NDISI), while MODIS LST products (MOD11A2) provided diurnal and nocturnal LST as well as long-term trends (2000–2020). The findings indicated that the UHI phenomenon in both cities predominantly occurs at night, with the highest and lowest LST in Hamadan being 23.31°C and 15.61°C, respectively, while in Mashhad the maximum and minimum temperatures were 26.35°C and 19.21°C, respectively, with no appreciable thermal variations observed during the day. LST-derived thermal hotspots were primarily in desert regions, industrial zones, and newly urbanized regions with little vegetation cover. The 20-year MODIS time series indicated a warming trend consistent with urban expansion in the northwestern part of Mashhad and the eastern to southeastern areas of Hamadan. Regression analyses demonstrated a strong correlation between satellite-derived LST and meteorological data, with R^2 values of 0.90 for Mashhad and 0.94 for Hamadan. Multiple regression analysis showed that in Mashhad, LST was negatively correlated with NDVI (-0.25) and positively correlated with NDBI (+0.25), and in Hamadan, NDISI had the maximum positive correlation (+0.48). These results highlight the role of urban form and land cover in shaping thermal behavior across varying climates, providing insights for climate-responsive urban planning.

1. INTRODUCTION

UHI effect describes the process through which urban areas are warmer than their rural counterparts. The thermal contrast is generally a result of the urbanization processes such as modifications in land cover, increased anthropogenic heat emissions, vegetation cover loss, and the heat-absorbing properties of construction materials (Almeida et al., 2021).

Understanding and monitoring UHI is crucial, especially in densely populated cities where heat-related risks and energy demands are significantly higher. In this context, satellite remote sensing provides an efficient and essential tool for observing LST across various spatial and temporal scales. According to Li et al. (2013), remote sensing data allow for continuous, extensive, and systematic recording of LST. Their wide spatial coverage and high temporal resolution make them particularly valuable for examining UHI phenomena and analyzing long-term thermal trends as well as the influence of surface parameters such as land cover, land use, and urban morphology (Li et al., 2023). Studies have shown that urban morphological characteristics such as building density, building height, street width, surface cover ratio, and the spatial configuration of urban elements play a significant role in the intensity and extent of urban heat islands. In particular, areas with high construction density, extensive impervious surfaces, and limited green spaces are more prone to UHI formation. Analyzing these variables through remote sensing data and spatial analysis provides a more precise understanding of how the physical structure of cities contributes to the emergence or intensification of the UHI phenomenon (Taheri Otaghsara & Arefi, 2019) Furthermore, recent studies have shown that NDVI, as one of the most widely used tools for assessing vegetation cover in urban environments, is highly sensitive to both the type and amount of vegetation. Findings indicate that in areas with low vegetation cover, NDVI variations are mostly influenced by shrubs and bushes, whereas in areas with dense vegetation, lawns and trees have a greater impact. Therefore, analyzing NDVI without considering the specific vegetation types may lead to misleading interpretations (De La Iglesia Martinez & Labib, 2023). A global study of 49 cities in the Northern Hemisphere using an urban ecohydrological model and remote sensing data found that UHI intensity and patterns are strongly influenced by climate. In humid areas, UHI is driven by evapotranspiration differences, while in arid climates, heat transfer plays a larger role. Nighttime UHI is more intense in dry climates due to heat retention in urban materials, highlighting the importance of climate context in UHI analysis (Zhang et al., 2022).

A study conducted in Tehran further emphasized the significance of combining spectral and morphological parameters in urban heat assessments. It demonstrated that spectral indices such as

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NDVI and NDBI, along with morphological variables like building and road density, play a key role in influencing LST variations. The results revealed that LST tends to be higher in densely populated areas, barren lands, and industrial zones, with the strongest correlation observed between LST and NDBI. These findings highlight the importance of integrating urban structure analysis with spectral indicators to better understand the urban heat island phenomenon (Ghanbari et al., 2023). In a study conducted in Mashhad, the relationship between vegetation index and land surface temperature was examined, revealing an inverse correlation where increased vegetation cover led to lower temperatures, highlighting the importance of green space in managing UHI in dry regions, with lower NDVI areas, like barren lands, exhibiting higher temperatures (Gorgani et al., 2013), similarly, another study over three decades showed that increased construction and barren land expansion raised land surface temperatures, with indices like NDVI and NDBI showing less sensitivity to temperature, emphasizing the need to focus on barren lands in UHI analysis (Naserikia et al., 2019), Similarly, in Hamedan, land use patterns and landscape structure had a significant impact on land surface temperature; the increase in built-up areas and the decrease in vegetation cover were directly associated with higher temperatures, while the spatial distribution of barren and industrial areas played an important role in the intensity and expansion of the urban heat island (Shojaei et al., 2019).

The aim of this study is to compare and analyze land surface temperature and the intensity of the urban heat island phenomenon in two cities with different climatic conditions, Hamedan with a mountainous climate and Mashhad with a semi-arid climate. Using remote sensing data and spectral indices, this comparison seeks to examine the impact of climatic characteristics and urban morphology on the distribution and intensity of land surface temperature and urban heat islands.

2. MATERIALS AND METHODS

In this study, Landsat 8 imagery from July 2022 was used to extract LST and spectral indices. In addition, MODIS day and night data for the same period were employed to analyze diurnal and nocturnal temperature behavior. To examine long-term temperature changes, a 20-year MODIS time series (2000 to 2020) was utilized. Data processing and index calculations were conducted in Google Earth Engine (GEE) and GIS environments. Hotspot identification, long-term temperature trend analysis, and two types of regression, comparison of satellite-derived and ground-based temperatures, and multivariate regression between LST and spectral indices, were performed. Finally, the results were interpreted, and recommendations for managing urban heat impacts were provided.

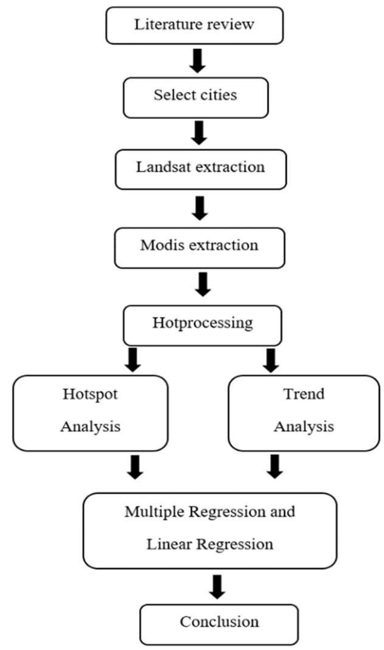

Figure 1. Flowchart of the method used in this study

2.1 Study area

In this study, the cities of Hamadan and Mashhad were selected as the study areas. Hamadan, with a cold mountainous climate, is located in western Iran, while Mashhad, characterized by a hot semi-arid climate, lies in the northeast. The climatic, geographic, and urban development differences between the two cities provide a suitable basis for comparing the intensity and distribution of urban heat islands.

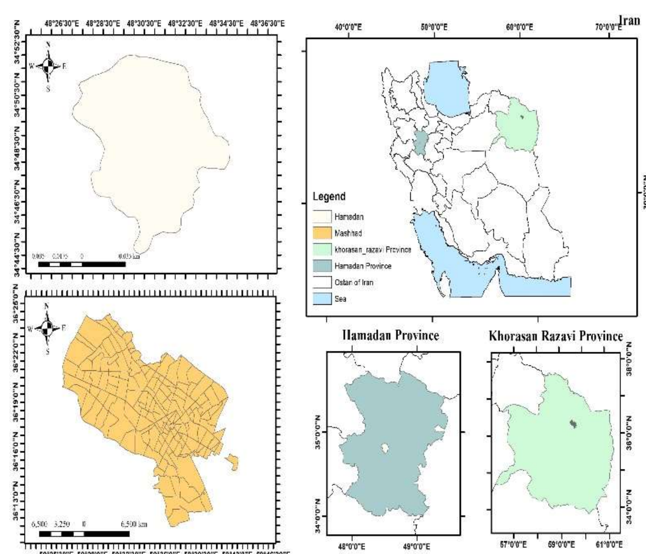

Figure 2. Study area

2.2 Data set

Landsat 8 OLI/TIRS data of July 2022 were utilized in the current research to extract LST and calculate spectral indices such as NDVI, NDBI, NDWI, NDII, and NDISI. MODIS daytime- and nighttime LST products for the same duration were utilized, and a 20-year (2000–2020) MODIS series facilitated the detection of long-term trends. Satellite-derived LST validation also utilized synoptic weather station data. Two climatologically distinct cities, Hamadan and Mashhad, were investigated.

Sensor	Use	Time	Period
Landsat 8	LST, Indices	Morning	July 2022
MODIS (Monthly)	Diurnal UHI	Day & Night	July 2022
MODIS (Time Series)	Trend	Night	2000–2020
Synoptic Stations	LST Validation	Daily	Oct 2018 – Dec 2022
LST & Indices	Regression	Morning	July 2022

Table 1. Datasets used in this study

2.3 Data processing

2.3.1 Data Processing and LST Calculation

For LST estimation, the thermal band (Band 10) of the TIRS sensor was used. Single-channel method was the method that was used and involved brightness temperature, surface emissivity, and atmospheric transmittance to estimate more accurate LST (Jiménez-Muñoz & Sobrino, 2003).

$$\text{LST} = \frac{B_T}{(1 + (\lambda * B_T)/\rho * Ln(LSE))} \tag{1}$$

In Equation 1, the value of $\rho = \frac{hc}{K}(1.438 * 10^{-2}\, mK)$ where λ is the wavelength emitted (m), h is Planck's constant, and K is the Boltzmann constant. Both parameters, BT and LSE, represent the brightness temperature and the emissivity of the land surface, respectively. From Equation (2), brightness temperature can be determined.

$$\text{B}_T = \frac{K_2}{\text{L}_n\left(\frac{\text{K}_1}{\text{K}_\lambda} + 1\right)} \tag{2}$$

In Equation 2, BT is the effective brightness temperature in terms of Kelvin, Lλ is the spectral radiance of the sensor in units of 2 (w/ (M^2.sr. μ m)) and the values $K1$ and $K2$ are the constants for the first and second calibrations (wm−2), where the images of different Landsat satellite series extracted from the Header file of images are different (Ghanbari et al., 2023).

2.3.2 Spectral indices

In order to study land surface characteristics and their relationship with LST, the following spectral indices were calculated:

NDVI: Normalized Difference Vegetation Index

NDBI: Normalized Difference Built-up Index

NDWI: Normalized Difference Water Index

NDII: Normalized Difference Infrared Index

NDISI: Normalized Difference Impervious Surface Index

EMISSIVITY: Land surface emissivity coefficient

$$\text{NDVI} = \frac{(\text{NIR}-\text{R} \quad)}{(\text{NIR}+\text{RED})} \tag{3}$$

$$\text{NDBI} = \frac{\text{SWIR 1}-\text{NIR}}{\text{SWIR 1}+\text{NIR}} \tag{4}$$

$$\text{NDWI} = \frac{\text{GREEN} - \text{SWIR 1}}{\text{GREE} \quad \text{SWIR 1}} \tag{5}$$

$$\text{NDII} = \frac{(NIR-TIR)}{(NIR+TIR)} \tag{6}$$

$$\text{NDISI} = \frac{TIR - (MNDWI+NIR+SWIR\ 1)}{TIR + (MNDWI+NIR+SWI \quad 1)} \tag{7}$$

EMISSIVITY = (FV * 0.99) + ((FV - 1) * 0.97) (8)

where, NIR is the Near Infrared band, SWIR is the Short-Wave Infrared band, TIR is the Thermal Infrared band, MNDWI is the Modified Normalized Difference Water Index, FV represents the Fractional Vegetation, and 1 is a correction factor ranging between 0 and 1.

2.3.3 Landsat satellite data

Satellite images from Landsat were used to investigate temperature and identify urban LST-derived thermal hotspots in the two Hamadan and Mashhad cities, which are imaged daily and during morning hours, to measure Landsat spectral indices.
Data were utilized. These data were relevant to temperature analysis and heat island identification due to their high spatial resolution, such as NDVI, NDBI, NDII, NDISI, LST, NDWI, and Emissivity. These data were used to identify urban hot spots and study day and night temperature differences in the cities of Hamadan and Mashhad. Landsat satellite data, which are widely utilized in land cover and land use transformation studies, were utilized in this research. Potapov et al, (2022) dataset shows the capability of Landsat imagery to track long-term surface variations across the globe (Potapov et al., 2022).

2.3.4 MODIS satellite data

MODIS satellite data that provide daytime and nighttime temperature information at the large scale were utilized to investigate 20-year temperature variations in the cities of Hamedan and Mashhad. These data were particularly beneficial in comparing the day and nighttime urban heat islands of the two cities. Based on a linear regression on 20 years (2000–2020) of MODIS land surface temperature satellite data, this study analyzed the long-term surface urban heat island trends over megacities. The MODIS data, as a good data source with high

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temporal resolution, provide the capability to assess daytime and nighttime temperature changes at a large scale. These findings can be of significant value in urban planning and mitigating the adverse effects of urban heat (Nayak et al., 2023).

2.3.5 Synoptic station data

For linear regression analysis, synoptic station temperature data of Hamedan and Mashhad were collected. These data were used to examine correlation and perform regression with satellite temperature data.

2.3.6 Regression analysis

In the current research, regression analyses were carried out to compare satellite and synoptic station temperature observations. Furthermore, multivariate regression between spectral indices and temperature was also carried out to investigate the complex relationship between indices and land surface temperature.

2.3.7 Data validation

LST values obtained from LANDSAT satellite images were used to test the accuracy of surface temperature measurement with a comparison between the derived values and the values measured by meteorological stations. The Single Channel satellite and synoptic station data technique confirmed that Hamedan city's LST model is of high accuracy, the correlation coefficient being approximately 0.94. In Mashhad city, the R^2 was about 0.90, indicating good consistency between the temperature values taken from satellites and on-ground measurements.

2.3.8 Multivariate regression analysis between spectral indices and LST

To investigate the relationship between land surface temperature and land surface characteristics, multivariate regression analysis was performed between LST and spectral indicators NDII, NDISI, NDVI, NDBI, and NDWI for Iranian cities Hamedan and Mashhad. The results of the corresponding analyses adequately depict the climatic and spatial differences between the two cities: Hamedan City: For Hamedan, NDISI index yielded the highest positive correlation coefficient with land surface temperature (0.48) and accounted for the contribution of impermeable surfaces to increasing temperatures. NDII also yielded a negative correlation coefficient of -0.42 and suggests that areas with higher relative moisture have lower surface temperatures. NDVI also yielded a weak positive correlation coefficient (0.17) with temperature, and this is due to vegetation cover conditions in the mountainous climate of the region

Mashhad city: In Mashhad, relative to Hamedan, NDVI had a relatively low negative correlation (-0.25) with temperature, whereas NDBI had an identical positive correlation (0.25). These findings confirm that with enhanced urbanization, surface temperature rises, whereas vegetation cover reduces temperature. The indices NDII, NDWI, and NDISI also had weak correlations with land surface temperature.

3. RESULTS

3.1 Surface Temperature Distribution, Urban Heat Islands, and LST-derived thermal hotspots Analysis Using Landsat Data

Landsat satellite images taken in July 2022 (corresponding to Iranian calendar's Tir 1401) were used to obtain LST maps, which illustrated temperature spatial variations between the cities of Hamedan and Mashhad. On the maps, red, brown, and pale-colored areas indicate hot urban heat pockets and elevated temperatures. In Mashhad, the LST-derived thermal hotspots are located in the city center, southeastern parts, and newly urbanized industrial areas. These areas are characterized by high development, impermeable surfaces, and low vegetation cover, which enhance the amount of daytime solar thermal energy absorption and storage, In Hamedan city, hot areas are mostly observed in the southern and southeastern parts of the city. These areas include wastelands, industrial, and underdeveloped ones, which, due to having an open structure and lacking any surface cover, indicate greater temperature compared to other areas of the city.

In contrast, areas in both cities with dense vegetation cover, urban vegetation, or low-density regions are readily identifiable as cold spots on the maps represented by light green and blue symbols. It must be mentioned that the analysis of LST-derived thermal hotspots was performed based on Landsat morning data and LST, as day- and night-time MODIS data were also available for the same timeframe in order to analyze the temporal dynamics of the UHI phenomenon. Daytime urban heat islands are week or absent in semi-arid regions due to intense atmospheric attenuation by aerosols and dust, reducing incoming solar radiation and surface heating. Atmospheric turbidity changes the daytime temperature regime by smoothing peak land surface temperatures and decelerating morning warming. Thermal contrast between the urban and rural settings decreases during the day (Göttsche & Olesen, 2009).

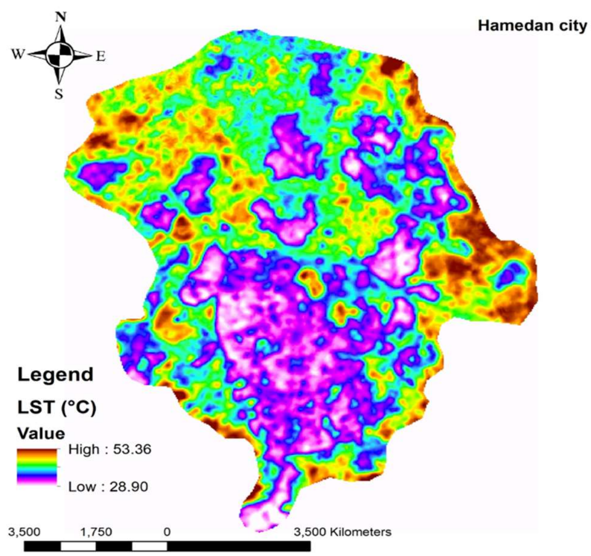

Figure 3. Average LST in the Hamedan City Area Based on Landsat Data

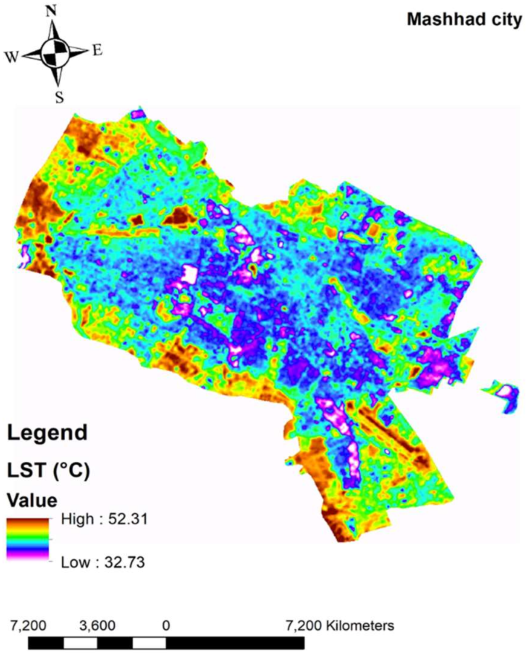

Figure 4. Average LST in the Mashhad City Area Based on Landsat Data

3.2 Spatial distribution of Spectral indices

Analysis of spectral index maps indicates that southern and industrial parts of Mashhad, i.e., Elahieh and Tous, possess high values of NDBI and NDISI coupled with low NDVI and NDWI reflecting dense urban areas with sparse vegetation and high heat island formation potential.
Conversely, NDVI and NDWI values for the northern and north-western areas of Hamadan indicate more existence of vegetation and more humid regions than other urban regions.
Central regions in both cities contain high NDISI and low NDII values, which align with concentrated construction and impervious surface.
In addition, NDII values in Hamadan indicate that there are larger areas of low surface moisture than in Mashhad, especially interior regions.
Generally, the spatial distribution of spectral indices reveals the evident impact of urban sprawl, loss of vegetation cover, and increased imperviousness on UHI intensification in both cities.

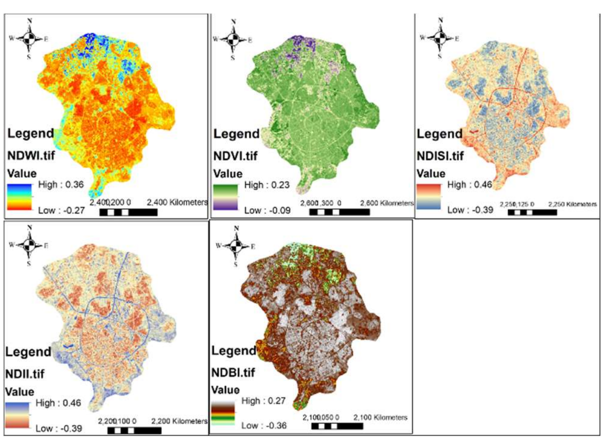

Figure 5. Spectral indices map of Hamadan

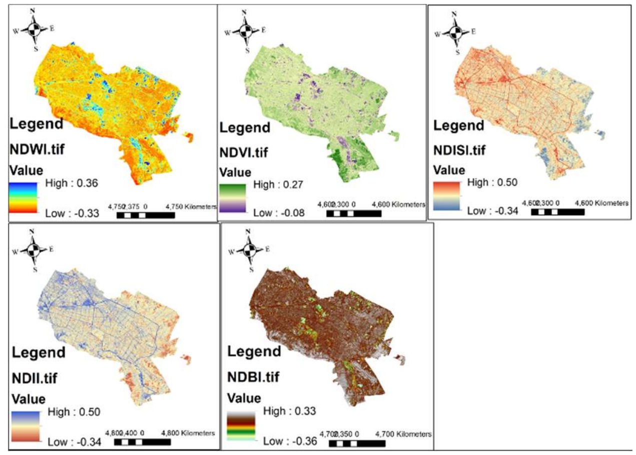

Figure 6. Spectral indices map of Mashhad

3.3 Analysis of Daytime and Nighttime LST and UHI, and 20-Year LST Trend Using MODIS Satellite Data

To gain a better insight into temperature trends and investigate the temporal behavior of the UHI effect, daytime and nighttime MODIS satellite observations for the one-month period July 2022 for both Hamadan and Mashhad have been used. Statistical analysis revealed that the UHI effect was predominantly realized during nighttime in both cities, while at daytime, no significant temperature difference between urban and rural locations could be established. This action is consistent with climatic patterns in arid and semi-arid regions, where building materials and impervious surfaces store heat in the daytime and emit it bit by bit during the nighttime(Space considerations are evident in Figures 5 and 6).

For a complementary short-term perspective, the long-term analysis was performed by looking at nighttime MODIS LST from January 1, 2000, through January 1, 2020, for both cities. The 20-year trend showed a decrease in temperature at central, western, southwestern, and southern areas of Hamadam, and a significant increase in northern areas, such as newly developed areas of Qasemabad, Bouali Industrial Town, petrochemical complex, and airport region. All of these changes are mainly caused by urban expansion, increase in imperviousness, and vegetation removal, which have increased the UHI effect in such areas. Within Mashhad, the findings indicated a definite temperature increase in recently urbanized areas such as Elahieh (which contains very little vegetation), and the Tous Industrial Area. These zones had the greatest LST increase of all over the two decades, with other city districts, particularly those that have green belt lands or farms, having more stable or even decreasing temperature trends.

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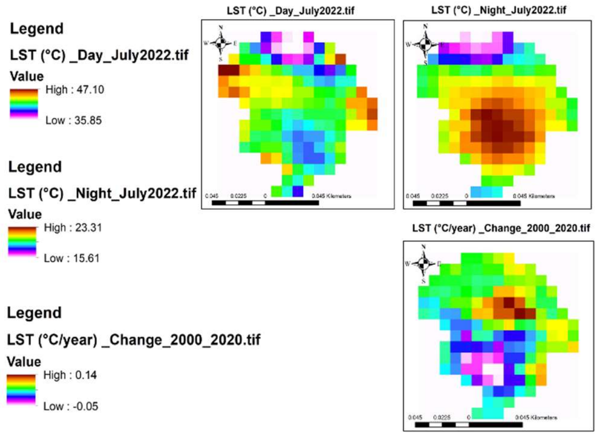

Figure 7. MODIS-based maps of LST for Hamadan, including daytime LST, nighttime LST, and long-term nighttime trend

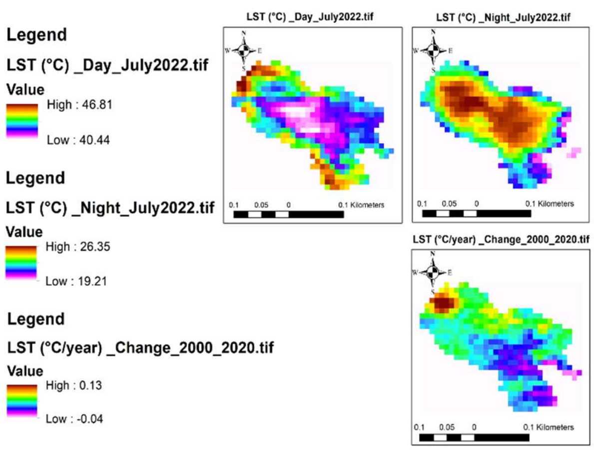

Figure 8. MODIS-based maps of LST for Mashhad, including daytime LST, nighttime LST, and long-term nighttime trend

3.4 Validation of Satellite Derived LST Using Synoptic Station Data

To evaluate the appropriateness of satellite-retrieved LST from Landsat imagery, satellite data were also contrasted with synoptic weather station air temperature records for the Hamadan and Mashhad cities. A linear regression of station-based data from October 27, 2018 to December 31, 2024 was computed.

Hamadan:
The ground station temperature regression model of satellite LST showed highly accurate results in Hamadan with an R^2 of 0.94. Such high correlation confirms that Landsat data are highly trustworthy for analyzing urban heat in this city.

Mashhad:
The relationship between station temperature and LST obtained from satellites was also robust and satisfactory in Mashhad, with $R^2 = 0.90$. Although the model error was somewhat greater than in Hamadan, the Landsat data accuracy in Mashhad for surface temperature estimation remained at a very high satisfactory level.

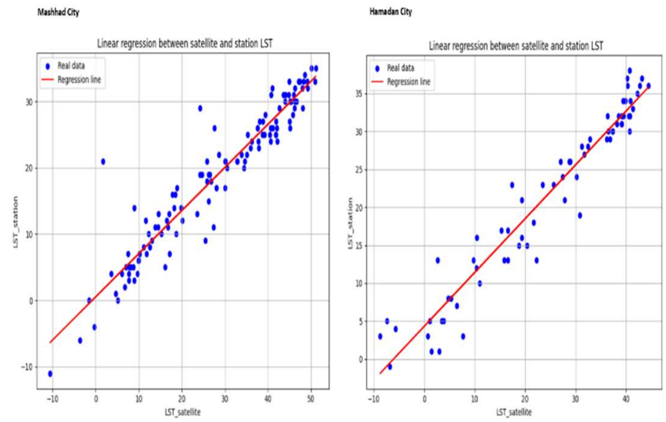

Figure 9. Linear regression of satellite and synoptic land surface temperature

3.5 Multiple Regression Analysis Between Spectral Indices and LST

In order to quantify the relationship between LST and ground characteristics, multivariate regression analysis was conducted between LST and important spectral indices, namely NDVI, NDBI, NDWI, NDII, and NDISI for Hamadan city and Mashhad city. The results clearly indicate spatial and climatic differences between the two cities.

Hamadan:
The highest positive regression coefficient with LST in Hamadan was NDISI (coefficient = 0.48), which indicates the significant role of urban areas and impervious surfaces in increasing the temperature. NDII had a negative coefficient of -0.42, indicating that the areas with higher surface wetness have lower temperatures. NDVI had a very low positive coefficient (0.17) that can perhaps be related to vegetation response under mountain climate of the area.

Mashhad:
In Mashhad, unlike Hamadan, NDVI had a moderate negative coefficient (-0.25) with LST, and NDBI had a coefficient of 0.25. The results confirm that land development and construction activities are the causes of higher surface temperature. NDWI, NDII, and NDISI also had weak coefficients with LST but with the positive direction as expected by the physical nature of each index.
More broadly, these findings suggest that spectral index effects on LST are sensitive to local climate and urban form, underlining the necessity of regional considerations in climate-resilient urban planning.

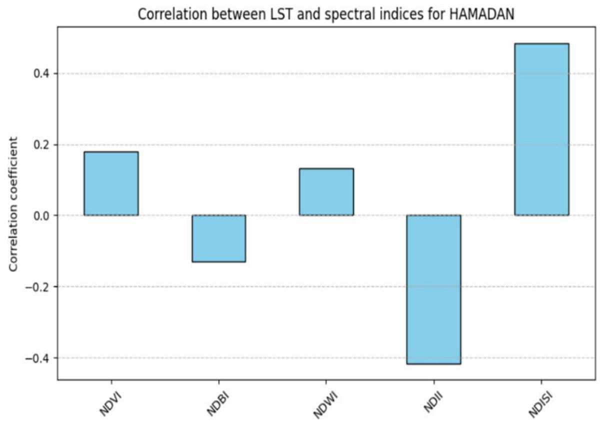

Figure 10. Multiple regression of indices on land surface temperature in Hamadan

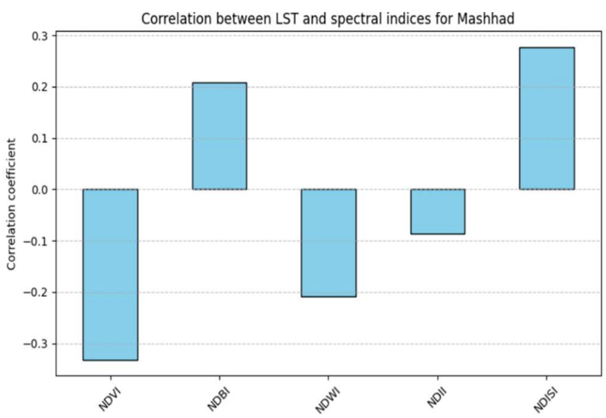

Figure 11. Multiple regression of indices on land surface temperature in Mashhad

4. CONCLUSIONS

The findings from this study revealed that the UHI effect in Mashhad and Hamadan primarily occurs during nighttime, while no significant difference was observed between urban and non-urban areas during daytime. The 20-year MODIS time series also showed a clear temperature increase in newly developed, industrial, and vegetation-free urban zones.

Ground synoptic stations validation of satellite-derived LST ensured the reliability of Landsat data, with $R^2 > 0.90$ in both the cities.

Multivariate regression analysis between LST and spectral indices showed indices' impact varies based on climate and urban geometry; in Hamadan, NDISI contributed most with the highest positive coefficient for LST, while in Mashhad NDBI contributed most to surface temperature.

Overall, the results indicate that land cover change, urban expansion, and local climate conditions all significantly affect the intensity and pattern of urban heat islands. Therefore, integration of remote sensing information in city planning and heat management policy is important for climate-resilient urban development.

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