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Burdur Havzası'nda Kara Yüzey Sıcaklığı (LST) ve Spectral İndekslerin (NDVI, NDBI, NDBaI) Mekansal-Zamansal Dinamikleri

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Öz

Son yıllarda iklim değişikliği, artan kentleşme, ormansızlaşma ve arazi kullanım-arazi örtüsü değişikliği gibi çeşitli çevresel parametreler farklı çevresel sorunlara yol açmıştır. Bu etkileri değerlendirmek ve gözlemlemek için, bu çalışma 2014-2025 yılları arasında Burdur Havzası'ndaki Kara Yüzey Sıcaklığı (LST) ve Normalleştirilmiş Fark Bitki Örtüsü İndeksi (NDVI), Normalleştirilmiş Fark Çıplaklık İndeksi (NDBaI) ve Normalleştirilmiş Fark Yapılaşma İndeksi (NDBI) gibi bazı spektral indeksleri incelemiştir. Coğrafi Bilgi Sistemi (GIS) ve Uzaktan Algılama teknolojileri, çok zamanlı Landsat uydularından elde edilen görüntüler kullanılarak Burdur Havzası üzerindeki bu çalışmada kullanılan indekslerin korelasyon analizi, zamansal değişimleri ve mekansal dağılımını hesaplamak için entegre edilmiştir. Bu çalışmanın sonuçlarına göre, LST değerleri özellikle havzanın kuzeydoğu ve orta kesimlerinde 2016 ve 2019 yıllarında artış göstermiştir. Çalışma döneminde NDBI ve NDBaI değerlerinde önemli bir değişiklik görülmemesine rağmen, 2018 yılında kısmen hafif yukarı yönlü değişimler gözlemlenmiştir. NDVI değerleri -0,36 ile 0,68 arasında değişmiş olup, bu değerler yıllar boyunca çoğunlukla istikrarlı kalmıştır. LST ve NDVI arasında çok zayıf pozitif bir korelasyon analizi tespit edilmiştir. Ayrıca, LST ile NDBI ve NDBaI arasındaki ilişki, 2014-2025 yılları arasında orta derecede pozitif bir korelasyon göstermiştir. Sonuçlar, kentsel ve çıplak toprak alanlarının genişlemesinin LST değerlerinde artışa neden olduğunu göstermiştir. Buna karşılık, bitki örtüsünün varlığı yüzey sıcaklığını düşürmeye yardımcı olabilir. Sonuç olarak, bu çalışma, bitki örtüsünün varlığı, kentleşme ve arazi kullanımı ve arazi örtüsü özelliklerinin Burdur Havzası üzerindeki LST değerleri üzerinde etkili olduğunu kanıtlamıştır. Dahası, bu çalışma, CBS ve uzaktan algılama teknolojilerinin entegrasyonunun, zamansal ve mekansal çevresel değişiklikleri değerlendirmek için değerli bir teknik olduğunu göstermiştir.

Anahtar kelimeler: LST, NDVI, NDBI, NDBaI, Uzaktan algılama

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Spatiotemporal Dynamics of Land Surface Temperature (LST) and Spectral Indices (NDVI, NDBI, NDBaI) in the Burdur Basin

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Abstract

In recent decades, several environmental parameters such as climate change, expanding urbanization, deforestation, and land use land cover change resulted in various environmental issues. To evaluate and observe these impacts, this study indicated the Land Surface Temperature (LST), and some spectral indices including Normalized Difference Vegetation Index (NDVI), Normalized Difference Bareness Index (NDBaI), and Normalized Difference Built-Up Index (NDBI) in the Burdur Basin for the years between 2014-2025. Geographical Information System (GIS) and Remote Sensing technologies were integrated by using the images obtained from multi-temporal Landsat satellites to calculate correlation analysis, temporal changes, and spatial distribution of indices used in this study over the Burdur Basin. Based on the results of this study, LST values increased especially in the northeastern and central parts of the basin in 2016 and 2019. Although no significant variation was seen for NDBI and NDBaI values during the studied period, slight upward changes were partly observed in 2018. NDVI values varied between -0.36 and 0.68 while those values were observed mostly stable over years. A very weak positive correlation analysis was indicated between LST and NDVI. Additionally, the relationship between LST and NDBI, and NDBaI produced a moderately positive correlation between 2014-2025. The results indicated that, expanding urban and bare soil areas, resulted in increased LST values. In contrast, presence of vegetation can help to reduce surface temperature. To conclude, this study proved that, the presence of vegetation, urbanization, and land use and land cover properties has an impact on LST values over the Burdur Basin. Furthermore, this study indicated that integrating GIS and Remote Sensing technologies are valuable technique to evaluate temporal and spatial environmental changes.

Keywords: LST, NDVI, NDBI, NDBaI, Remote sensing

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1. Introduction

In recent years, Land Use and Land Cover Change (LULCC) methods and their associated techniques have been extensively utilized in different areas. In addition, numerous mapping techniques have been developed to analyse changes in land properties in a particular region using the LULCC technique [1,2]. Because of this, LULCC in specific basins is very important parameter for monitoring environmental impacts and anthropogenic base changes. With the development of computer technologies in recent years and the consequences of improvements in remote sensing methods and satellite technologies researchers have conducted studies in various regions using different techniques to observe LULCC [3]. Obtaining current and accurate data is necessary to determine the effect of such changes on water resources, surface temperature, and vegetation in the basin. This is because evaluating the environmental impact of the watershed based on a single parameter change may not be sufficient. In addition to traditional land use and land cover classification algorithms, various spectral indices including Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), Normalized Difference Bareness Index (NDBaI), and Land Surface Temperature (LST) are utilized in literature to determine particular land properties. These indices are used for numerous purposes all over the world in many different fields, such as mapping environmental changes in a specific region over time, as well as correlating changes in these indices with each other.

Land Surface Temperature (LST) is a parameter that can be generated using several GIS techniques and collected from many remote sensing data. It is mostly used when defining Urban Heat Island (UHI) zones. Additionally, UHI calculations often use the LST values derived from meteorological stations. However, these estimations may be inadequate due to the stations' limited coverage of most of the region. However, satellite imagery and its integration with remote sensing and GIS tools can overcome these constraints.

Especially in recent decades, the population in most cities is growing [4]. Because of these situations, researchers are investigating how environmental properties and building patterns are changed over time [5,6]. In parallel, the increasing population and urbanization have an adverse effect on environmental factors and have caused changes in LULC over time [7-11]. Therefore, it is essential for researchers to investigate LULCC and related spectral indices to evaluate them in terms of environmental properties in specific regions [12].

In order to determine LULC classification for a particular region, the percentage of different LULC are utilized. Besides, numerous spectral indices are also used to define land properties [13]. At this point, remote sensing techniques and GIS methods have become the most suitable methods to determine LULCC, land surface temperature, and other indices. In order to do that, it requires comprehensive studies integrating scientific methods, remote sensing, and GIS technologies with spatial correlation, regression, and temporal variation models [14]. Observing LST and LULC dynamics over long periods using multi temporal imagery from satellites such as Landsat, Sentinel, and MODIS over a specific area is an effective method for these studies. Integrating this satellite imagery with GIS platforms provides a fundamental environment for the analysis, classification, and interpretation of these datasets, generating spatial outputs that support decision-making processes [9].

The Normalized Difference Vegetation Index (NDVI) is the most common technique that determines the vegetation changes over time, and is particularly integrated with the studies related to surface temperature [15,16,17]. Besides, NDVI is an important part of LST calculations. Several studies related to LST-NDVI correlation have been conducted in the literature to define LST models. Because LST and NDVI indices are closely related and affect each other mutually [5]. In addition, numerous studies have examined the relationship between NDVI and different climate variables over time. But studies show an especially emphasis on the relationship between LST and NDVI [10,18,19]. Researchers assessed the environmental impacts of changes by examining land based modifications and various indicators in addition to key indices like LST and NDVI. For example, in studies related to LULC and LST, the Normalized Difference Water Index (NDWI) is a commonly used index that determines water bodies

[20-23]. Normalized Difference Bareness Index (NDBaI) is another index that is commonly used in the literature. The NDBaI is utilized to define bare areas and generally uses the studies related to LST and LULC indices in different areas [23]. For example, [24] studied the relationship between LST and NDBaI in Raipur City, India. Their results indicate that LST and NDBaI have a positive moderate relationship. Another spectral index, Normalized Difference Built-Up Index (NDBI) is commonly used in literature to detect built up areas, and is mostly used with LST studies [25]. The studies that investigate the relationship between LST and NDBI have produced mostly positive results. However, this relationship can be effected by numerous parameters including vegetation, meteorological parameters, and soil condition [5].

Many researchers have investigated environmental changes in different regions by using several spectral indices and determining their relationship. For example, [26] studied with the indices including LST, NDVI, and LULC as well as the correlation with topographic parameters in Pakistan. Their results indicate that NDVI values increased with altitude, while LST values decreased with altitude. Besides, they found that surface temperature values are higher where built-up and bare soil areas. In addition, the study conducted by [22] determined the seasonal changes in LST and LULC with the indices NDVI, NDBI, NDWI, and NDBaI in Hong Kong. Their findings revealed that LULC types are the primary indicator of LST. Besides, a negative correlation was observed between NDVI and NDWI, while a positive correlation was observed between NDBI and NDBaI. In addition to studies around the world, many researchers have revealed temporal variation in land properties also in different regions in Türkiye by using different indices such as LST, NDVI, NDBI, NDBaI, and NDWI [9,18,27]. For example, [29] investigated spatiotemporal variability in LST for Zonguldak, Türkiye. Their results indicated that the temperature has been steadily increasing, and the expansion of the urban area has resulted in increased LST. [29] used LST and NDVI in Salt Lake Basin Area, Türkiye, to monitor drought. Another study of [30] was used to detect the temporal changes of NDVI and NDBI in Bursa, Türkiye. Their findings showed that NDVI is an effective method for monitoring changes, particularly in urban areas. Besides, details of some of the studies in the literature reviewed for this study, as well as the current study, are given in Table 1.

Table 1. Detailed list of previous studies

Authors	Published Journal	Study Area	Data Used	Method Used
Anbazhagan and Paramasivam (2016)	International Journal of Advanced Earth Science and Engineering	India	Landsat 5, Landsat 7	LST, NDVI
Değerli and Çetin (2022)	Turkish Journal of Agriculture - Food Science and Technology	Samsun, Türkiye	Landsat 7, Landsat 8	NDVI, NDBI
Karakoyun (2024)	MAUN Journal of the Faculty of Engineering and Architecture	Muş, Türkiye	Landsat 8	LST, NDVI
Guha and Govil (2021)	Environment, Development and Sustainability	Raipur City, India	Landsat 5, Landsat 7, Landsat 8	LST, NDVI
Guha et al (2020)	Geomatics, Natural Hazards and Risk	Raipur City, India	Landsat 5, Landsat 7, Landsat 8	LST, NDWI
Siqi and Yuhong (2020)	Urban Climate	Hong Kong	Landsat 8, Sentinel 2	LST, NDBI, NDBaI, NDVI, NDWI
Guha and Govil (2022)	International Journal of Engineering and Geosciences	Raipur City, India	Landsat 5, Landsat 7	LST, NDBaI
Alademomi et al. (2022)	Applied Geomatics	Lagos, Nigeria	Landsat 7, Landsat 8	LST, NDVI, NDBI
Garai et al (2022)	Safety in Extreme Environments	West Bengal, India	MODIS	LST, NDVI
Ullah et al. (2023)	Heliyon	Himalayan Region, Pakistan	Landsat 8	LST, NDVI
Altıner and Bingöl (2025)	Sustainability	Balıkesir, Türkiye	Landsat 4, Landsat 5, Landsat 8, Landsat 9	LST, NDVI, NDBI
This study		Burdur Basin, Türkiye	Landsat 8, Landsat 9	LST, NDVI, NDBI, NDBaI

The integrated application of remote sensing and geographic information systems (GIS) offers robust methodologies for monitoring long-term environmental changes using vegetation indices and land surface temperature (LST) data. This study aims to investigate the spatio-temporal relationship between LST and selected spectral indices, including NDVI, NDWI, NDBI, and NDBaI, within the Burdur Basin over recent decades. To address this aim, remote sensing–based indices derived from multi-temporal satellite imagery are analyzed, and correlation analyses are performed to assess the interactions between LST and other spectral indices. Additionally, the spatial distribution of these indices is mapped to facilitate the interpretation of environmental changes in this semi-arid region.

2. Material and Method

2.1. Study area and data

The Burdur Basin is located in the mid-southwest of Türkiye. The basin covers a total area of 627,378 hectares and constitutes 0.8% of Türkiye's total surface area. Burdur Basin is also called the lakes region. Burdur Lake, Acı Lake, Salda Lake, and Karatas Lake are located within the basin boundaries. The basin location is shown in Figure 1.

In this study, the primary datasets consist of time-series Landsat imagery obtained from the United States Geological Survey website (https://earthexplorer.usgs.gov/), captured by Landsat 8 and Landsat 9 satellites. An image covering the study area and consisting of two different paths for each year was downloaded, and its specifications are given in Table 2. Before proceeding with the calculation of spectral indices, some procedures should be done. ArcGIS Pro software was used for all spectral indices obtained during the study. First, two images covering the study area were combined using the mosaic function in ArcGIS Pro. Then, the resulting image was clipped using the extracted-by-mask function to obtain the necessary bands for the specified study area.

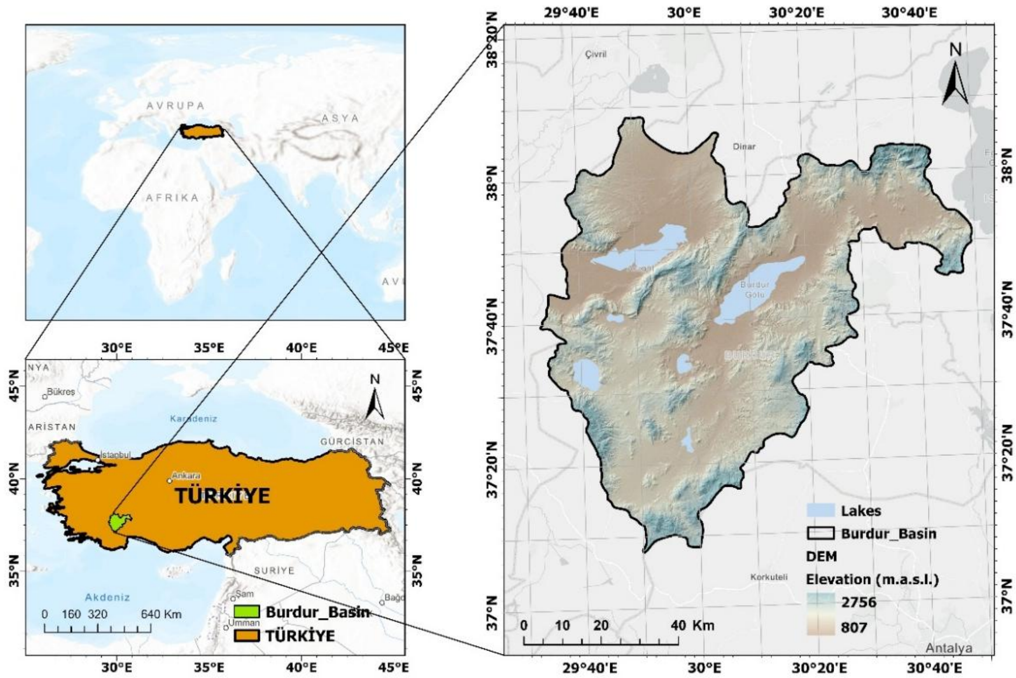

Figure 1. Location of study area

Table 2. Specifications of landsat images

Year	Sensor	Path/Row	Date of acquisition
2014	Landsat 8	178/34	7/3/2014
	Landsat 8	179/34	7/10/2014
2015	Landsat 8	178/34	7/22/2015
	Landsat 8	179/34	7/13/2015
2016	Landsat 8	178/34	7/24/2016
	Landsat 8	179/34	7/15/2016
2017	Landsat 8	178/34	7/11/2017
	Landsat 8	179/34	7/2/2017
2018	Landsat 8	178/34	7/14/2018
	Landsat 8	179/34	7/5/2018
2019	Landsat 8	178/34	7/1/2019
	Landsat 8	179/34	7/8/2019
2020	Landsat 8	178/34	7/19/2020
	Landsat 8	179/34	8/11/2020
2021	Landsat 8	178/34	7/22/2021
	Landsat 8	179/34	7/29/2021
2022	Landsat 8	178/34	7/25/2022
	Landsat 9	179/34	7/24/2022
2023	Landsat 8	178/34	7/12/2023
	Landsat 8	179/34	7/19/2023
2024	Landsat 8	178/34	8/15/2024
	Landsat 9	179/34	8/14/2024
2025	Landsat 8	178/34	8/9/2025
	Landsat 9	179/34	8/10/2025

2.2. Method

2.2.1. Calculation of LST and NDVI

LST represents the surface temperature estimated from thermal-band imagery. The formulas used to compute LST (Eq. 1-6), which rely on satellite-derived inputs, are given below. The initial step in deriving LST for Landsat images involves converting the digital number (DN) to spectral radiance (Lλ), as shown in Equation 1.

$$L_\lambda = RadianceMultiBand * Digital\ Number + Radiance\ Add\ Band \tag{1}$$

where L_λ is spectral radiance.

$$T_b = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda}+1\right)} \tag{2}$$

where T_b is the sensor of brightness temperature, K_2 and K_1 are the calibration constants for Bands 10 and 11.

$$F_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \tag{3}$$

where $NDVI_{min}$ and $NDVI_{max}$ refer to the minimum and maximum values of NDVI.

$$NDVI = \left(\frac{Band5 - Band4}{Band5 + Band4}\right) \tag{4}$$

where Band 4 (red) and Band 5 (Near infrared) are for Landsat 8 and Landsat 9 images.
Next, land surface emissivity is determined using Equation 5.

$$\varepsilon = 0.004 * P_v + 0.986 \quad (5)$$

Subsequently, the LST can be calculated as given in equation 6.

$$LST = \frac{T_b}{1+\left(\lambda * \frac{T_b}{\rho}\right) * \ln(\varepsilon)} \quad (6)$$

Where, λ is the thermal band wavelength, ρ is the value derived from physical constants such as Planck's constant and the speed of light.

2.2.2. Calculation of NDBI and NDBaI

NDBI is calculated by getting the difference between the SWIR and NIR reflectance values and dividing it by their sum. It is commonly used to define built-up areas. Built-up surfaces—such as concrete, asphalt, and roofing materials—generally show strong reflectance in the SWIR bands and comparatively low reflectance in the NIR bands. Urban and built-up areas typically yield positive NDBI values, while vegetation and water surfaces produce negative values. The NDBI formula is given in equation 7.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (7)$$

A bareness index, referred to as NDBaI, distinguishes among bare land, and semi-bare land, and other land-use/land-cover types. NDBaI is obtained by taking the difference between the SWIR and TIR reflectance values and dividing it by their sum. For Landsat 8 and 9 data, SWIR is defined by band 6, and TIR is defined by band 10, and its formula is provided in equation 8.

$$NDBaI = \frac{SWIR - TIR}{SWIR + TIR} \quad (8)$$

3. Results and Discussion

In this study, different spectral indices, including LST, NDVI, NDBI, and NDBaI, were analyzed using a GIS platform over the last decade (2014-2025) in the Burdur Basin. The descriptive statistics, spatial distribution, and correlation analysis of the spectral indices used in this study are given in the following section.

3.1. Descriptive statistics of LST, NDVI, NDBI, and NDBaI

To determine the results of the indices retrieved from the map, some processes were applied. First, fishnet maps were created using a 10x10 grid, resulting in 100 points. Then, the fishnet maps were clipped by the study area, and 41 points remained withinthe study area. The image of these 41 points obtained in the study area is given in Figure 2. Next, all the points were determined for all the spectral indices with the function "extract multi values to points" in the ArcGIS Pro software. The descriptive statistics of the spectral indices used in this study are given in Table 3.

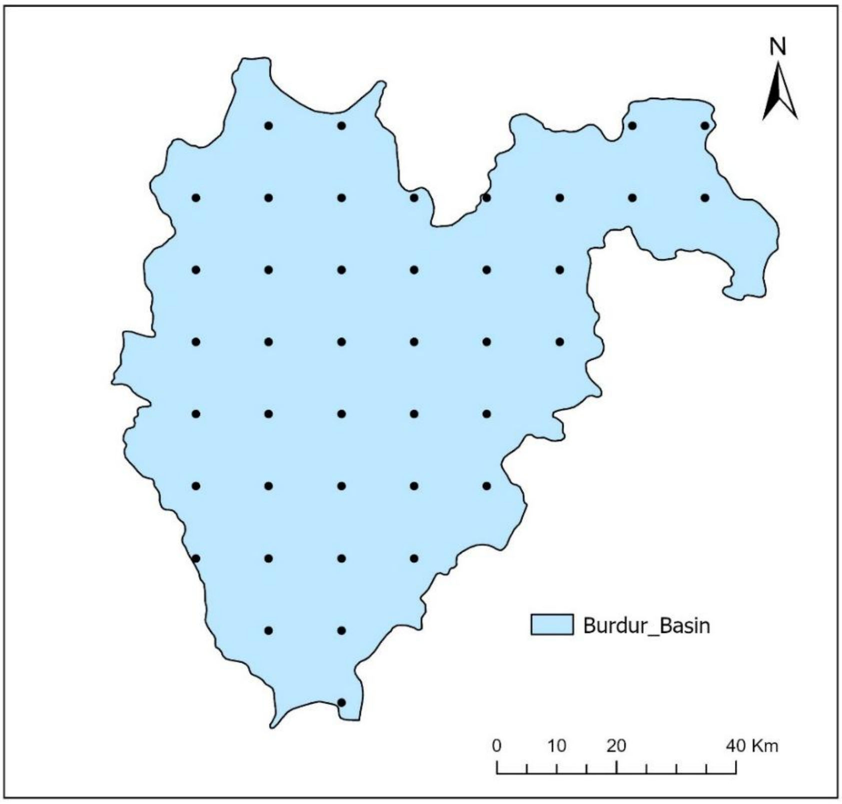

Figure 2. The created fishnet points over the study area

Table 3 shows that the minimum LST values, obtained from 41 points, were observed in 2022 at 11.90 ºC, while the maximum value was observed in 2017 at 48.11 ºC. In addition, the minimum NDBI value in 2019 was -0.34, while the maximum value was observed in 2024 at 0.14. Similarly, the minimum NDVI value was observed in 2020 with -0.26, while the highest value was observed in 2019 with 0.51. Besides, the minimum and maximum values were obtained in 2017 and 2019, respectively, at -0.70 and -0.01.

Table 3. Descriptive statistics of indices used

Year	LST			NDBI			NDVI			NDBal		
	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
2014	22.34	46.08	34.95	-0.16	0.08	-0.01	-0.13	0.35	0.17	-0.67	-0.10	-0.35
2015	20.68	38.74	29.77	-0.18	0.13	-0.02	-0.13	0.39	0.19	-0.66	-0.05	-0.33
2016	22.60	47.86	38.37	-0.19	0.09	0.00	-0.20	0.37	0.16	-0.70	-0.04	-0.36
2017	24.53	48.11	38.71	-0.24	0.08	-0.02	-0.21	0.41	0.18	-0.70	-0.10	-0.37
2018	21.51	39.81	31.38	-0.17	0.10	-0.01	-0.17	0.38	0.18	-0.67	-0.06	-0.33
2019	17.14	41.91	33.42	-0.34	0.07	-0.03	-0.24	0.51	0.19	-0.68	-0.01	-0.35
2020	21.19	44.01	34.14	-0.17	0.09	-0.01	-0.26	0.34	0.16	-0.68	-0.09	-0.33
2021	19.43	40.48	32.54	-0.22	0.10	0.01	-0.15	0.31	0.15	-0.66	-0.08	-0.31
2022	11.90	38.07	26.04	-0.16	0.08	-0.01	-0.13	0.33	0.17	-0.64	-0.06	-0.28
2023	21.38	38.68	32.36	-0.24	0.07	-0.04	-0.22	0.44	0.19	-0.68	-0.09	-0.35
2024	14.69	40.10	29.18	-0.13	0.14	0.02	-0.16	0.55	0.18	-0.65	-0.13	-0.29
2025	15.15	35.61	28.92	-0.24	0.09	-0.01	-0.07	0.43	0.18	-0.69	-0.03	-0.29

3.2. Spatial Distribution of LST, NDVI, NDBI, and NDBaI

LST distributions from 2014 to 2025 reveal notable interannual and spatial variations in surface temperatures within the study area (Figure 3). The maps show that the northern, northeastern, and central parts of the basin consistently have high LST values. On the other hand, wetlands and water surfaces showed lower LST values. The warmest years of the research period were 2016, 2017, 2018, and 2019. In these years, temperatures approached or even exceeded 50°C in many regions. In particular, as shown in the 2018 LST maps, the extent of warming zones reached its peak. A detailed examination of the maps shows a significant warming trend in the basin in 2023, 2024, and 2025. Specifically, it has been defined that higher LST values in the northern and northeastern regions are expected to expand through 2025.

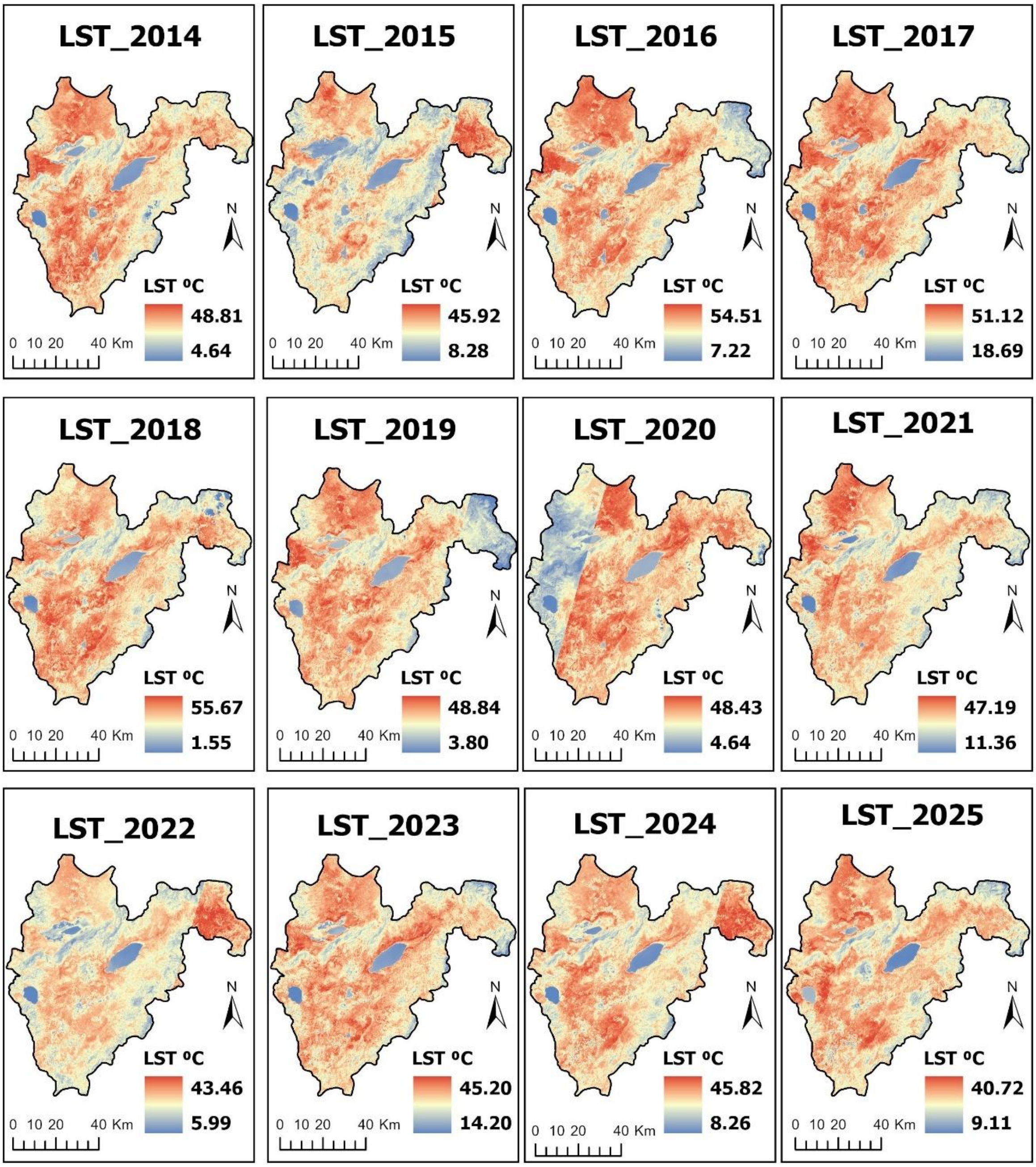

Figure 3. Spatial Distribution of LST over Burdur Basin

The distribution of NDVI values across the basin from 2014 to 2025 shows that vegetation density generally does not change much, but significant fluctuations are observed during specific periods (Figure 4). NDBI shows the size of settlements or urban areas, whereas NDVI shows the density and health of vegetation at the time of measurement. The values of both indices range from −1 to +1. Smaller values represent less vegetation and built-up, while higher values represent more vegetation and built-up [6]. NDVI values broadly indicate moderate to high vegetation cover. However, notable changes have occurred over the years. NDVI values were particularly high in 2017, 2022, and 2025, indicating healthier and denser vegetation during those years. In general, NDVI values did not show a significant deterioration trend during the 2014–2025 period. Still, declines, especially in 2020 and 2024, indicate that the ecosystem's sensitivity in the region persists and remains sensitive to climatic changes.

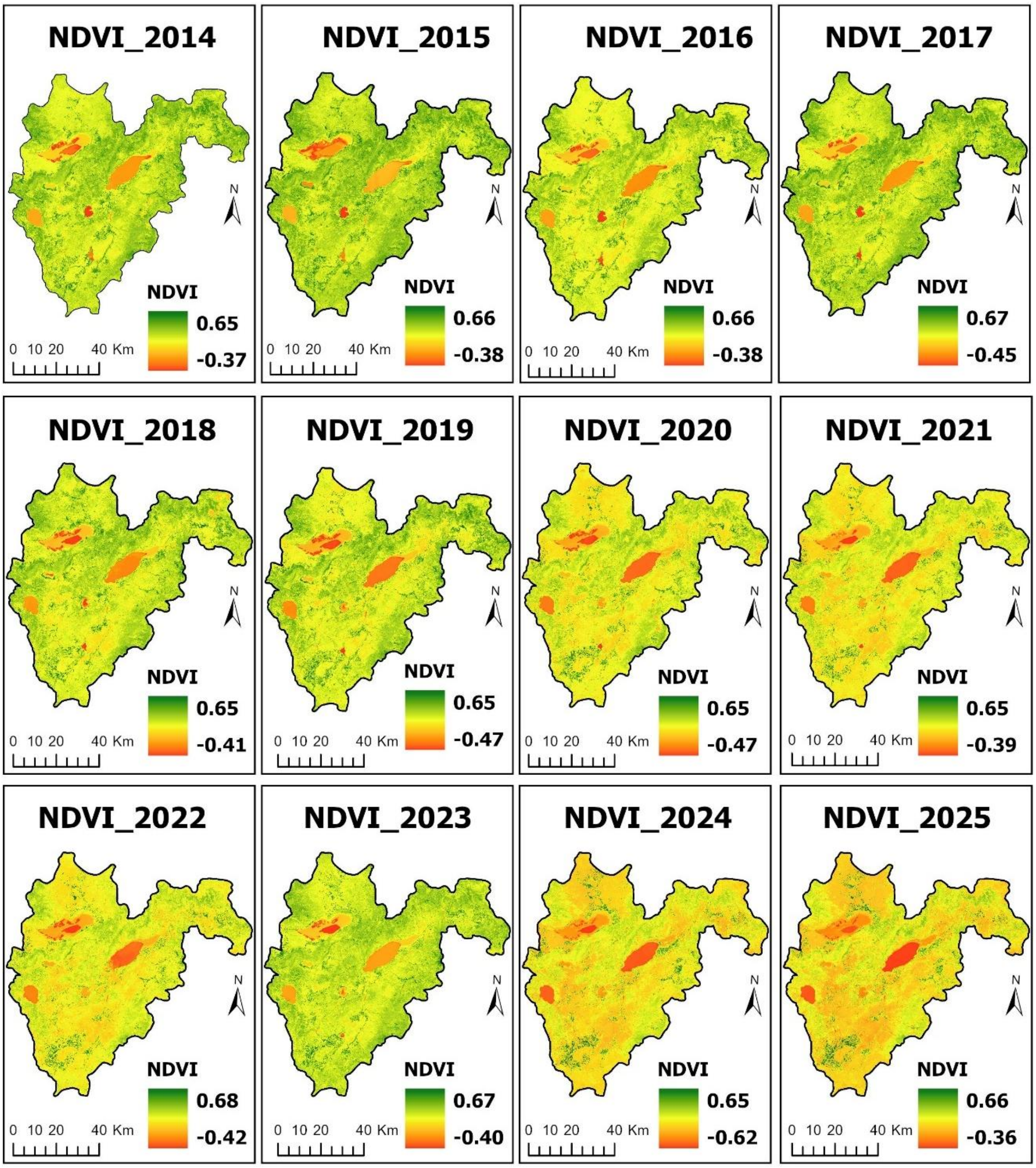

Figure 4. Spatial Distribution of NDVI over Burdur Basin

NDBI distributions from 2014 to 2025 show a similar pattern in the spatial distribution of urban areas and bare-soil surfaces across the study area over the years (Figure 5). However, some specific periods exhibit limited increasing or decreasing trends. In all years, higher NDBI values were observed in the northern and eastern parts of the basin. This indicates a greater density of construction or a higher proportion of bare land in these areas compared to others. Conversely, regions dominated by agricultural lands, water surfaces, and natural vegetation exhibited lower NDBI values. The concentration of NDBI values, mainly within the range 0.35–0.45, suggests a moderate level of construction and bare soil in the study area. It is observed that 2016, 2017, 2018, and 2019 had the highest positive NDBI values. The lower NDBI values in 2020 and 2021 suggest that vegetation cover increased or that bare land areas decreased during this period. In urban areas, NDBI values are consistently positive, which indicates that settlements are either steady or growing modestly over time. Overall, the NDBI values show slight variation between 2014 and 2025, indicating that there hasn't been a significant change in the urban areas in the research region.

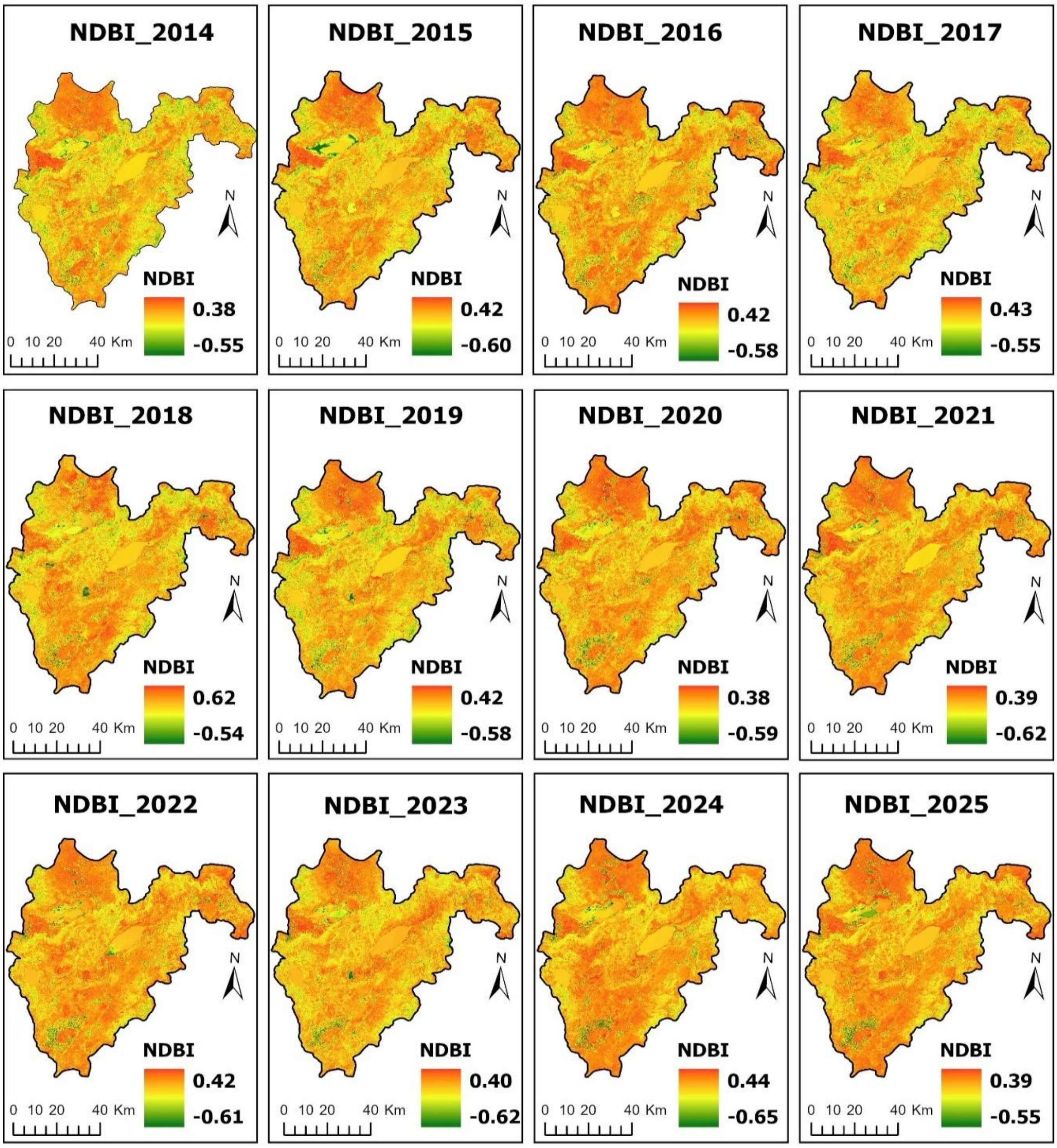

Figure 5. Spatial Distribution of NDBI over Burdur Basin

The NDBaI results from 2014 to 2025 are given in Figure 6. The results indicated that bare soil surface area produces both spatial and temporal variation over the study area. The NDBaI values are mostly moderate across the basin, which means these results are associated with soil moisture and vegetation density. This is because NDBaI values are expected to be lower at water surfaces, while they are expected to be higher in bare soil and sparse vegetation. This trend confirms that NDBaI values increase with decreasing surface moisture and increasing bare soil proportion. The years 2015, 2018, 2022, 2024, and 2025 were periods when relatively higher NDBaI values were observed, indicating that surface moisture decreased or the bare-soil ratio increased in these years. In contrast, NDBal values were relatively low in 2017 and 2019, indicating that those years were either more humid or that vegetation density had increased. The analysis of the NDBal distribution from 2014 to 2025 indicates that seasonal changes driven by climatic conditions have a greater impact on the basin's soil moisture and bare soil conditions than any long-term decline. However, the increasing trend observed after 2022 suggests that water stress and drought pressures are becoming more significant in some regions of the basin.

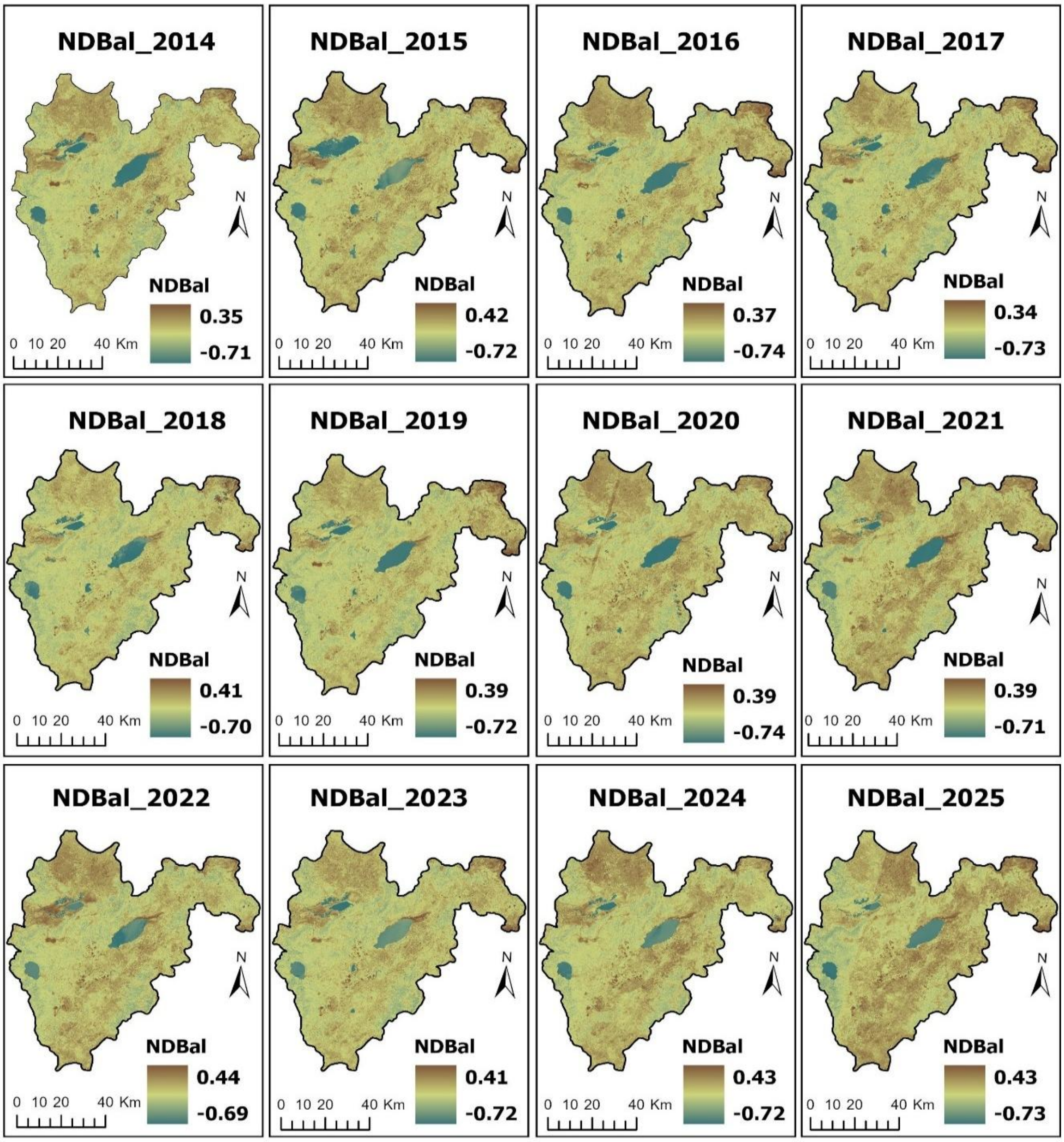

Figure 6. Spatial distribution of NDBaI over Burdur basin

3.3. Correlation analysis of LST, NDVI, NDBI, and NDBaI

The scatter plots of the mean values of LST-NDVI, LST-NDBI, and LST-NDBaI are illustrated in Figure 7. The correlation matrix indicates that LST and NDBaI are negatively associated, whereas LST-NDBI and LST-NDVI have a weak correlation.

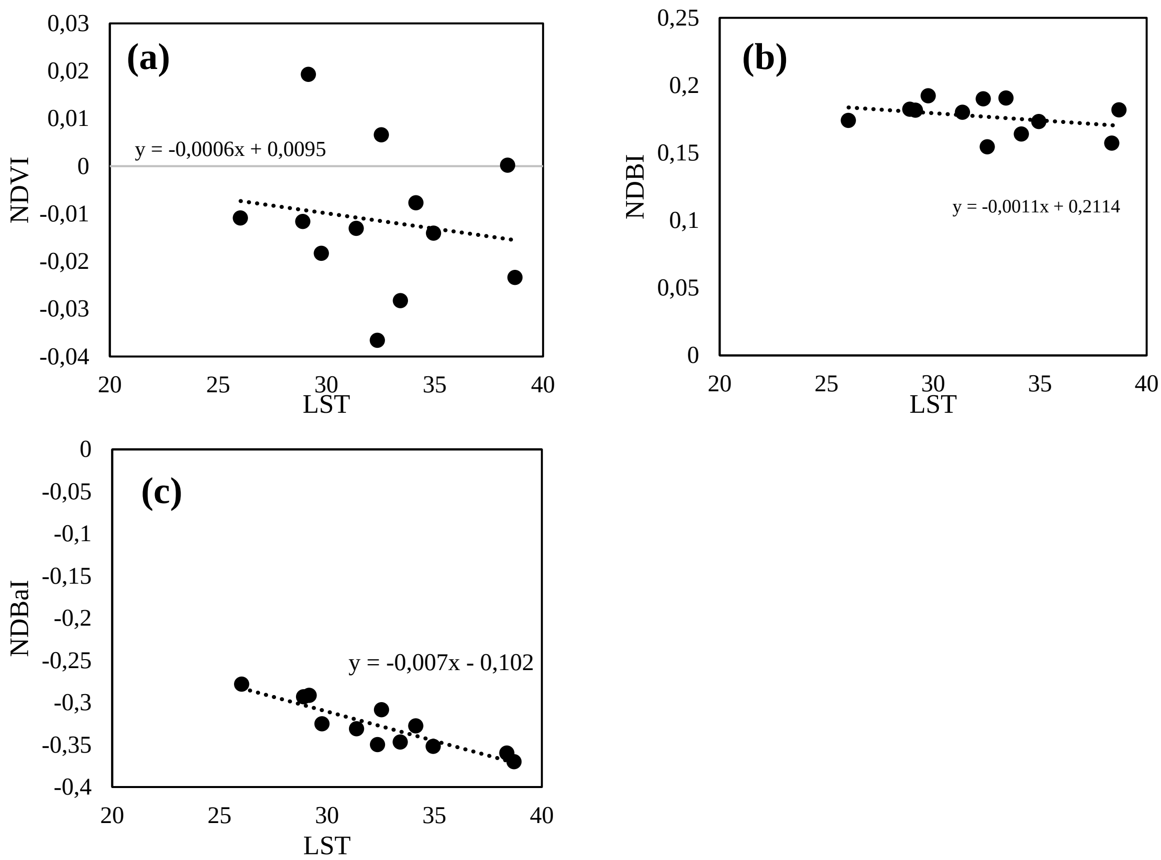

Figure 7. The scatter plot of mean values of (a) LST-NDVI, (b) LST-NDBI, and (c) LST-NDBaI

The results of the annual correlation analysis of LST, NDVI, NDBI, and NDBaI indices between 2014 and 2025 are given in Figure 8. According to these results, a positive correlation is generally observed between LST and NDBaI, and the highest correlation was obtained in 2014 with r=0.63. These results indicate that LST values are higher in dense urban areas. In addition, in terms of the results of annual correlation between LST and NDBI, the highest correlation was observed in 2014 with r = 0.63 while the lowest value was observed in 2025 with r = 0.28. Similarly, it was observed that the correlation between LST and NDBI was positive and moderate between 2014 and 2025, with the highest correlation value in 2021 (r = 0.62) and the lowest value in 2025 (r = 0.25). Similar findings were indicated by [5,9] which also presented positive LST responses to built up and bare soil. According to these results, the effects of the density of urban areas were observed on LST. These results indicate the impact of the density of urban areas on surface temperature. Similar results were also found in the study of [22]. According to their results, LST is positively related to NDBI and NDBaI.

As expected, NDVI, an indicator of vegetation health, showed negative correlations with both building density indices and surface temperature. While the correlation between NDVI and NDBI was -0.48 in 2024, only a very weak positive (0.05) relationship was observed in 2021. The study conducted by [22] also supported the results of this study. Their findings revealed that LST has a positive correlation with NDBI and NDBaI, while a negative correlation with NDVI and NDWI.

A weak but positive correlation has been observed between LST and NDVI. The correlation coefficient ranges from 0.14 in 2019 to 0.41 in 2023. These results may be attributed to several factors, such as seasonal variations in NDVI and LST, or different land use and land cover types. Similar findings have been reported in previous studies. For example, [13] found a similar weak positive correlation in their study conducted in Pakistan. Spatially, higher LST values are particularly observed in urban and sparsely vegetated areas. These results are observed similarly from other studies indicated in Türkiye [18,28] and globally [26] and compared with their findings.

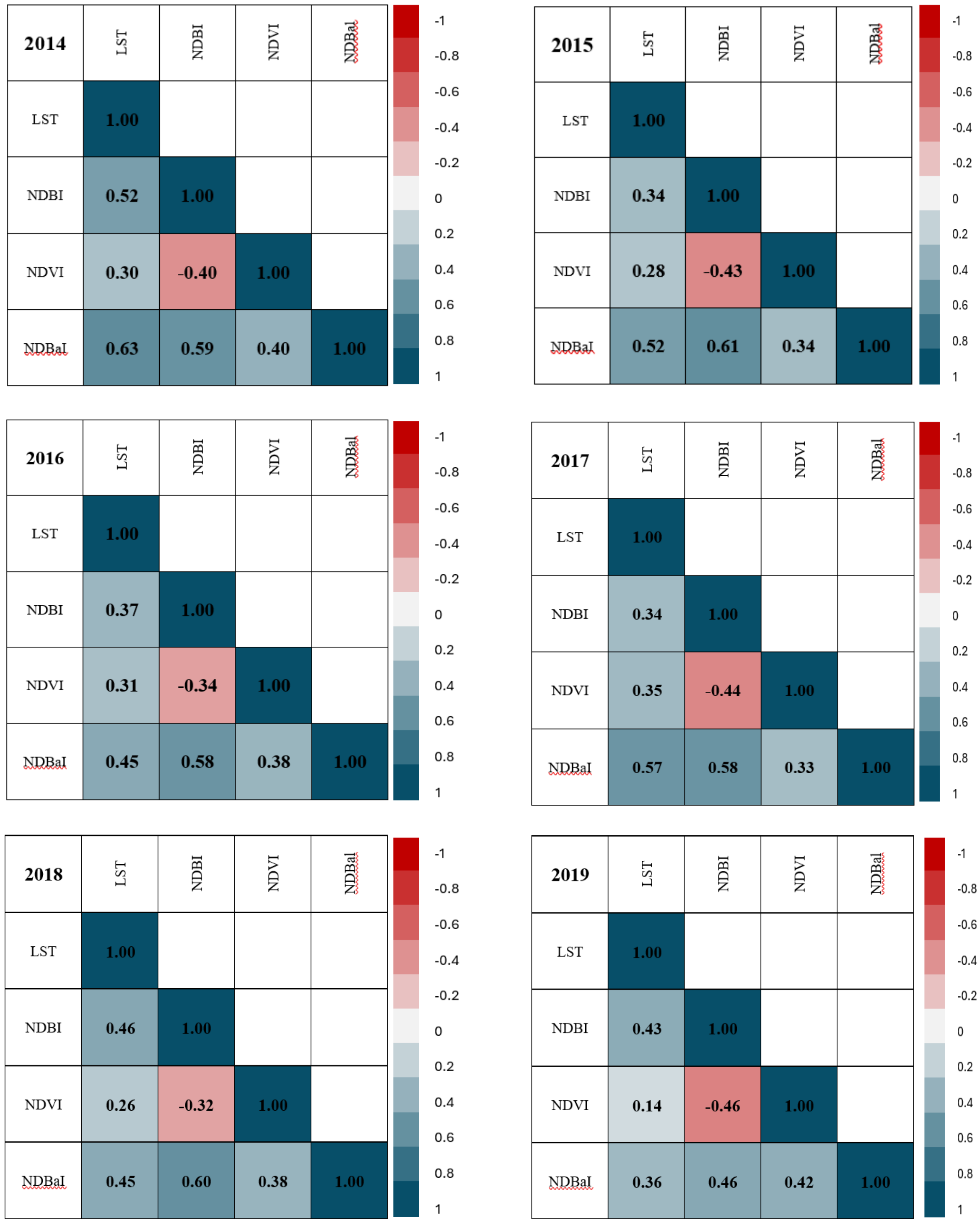

Figure 8. Correlation matrix of spectral indices for the years 2014-2025

2020	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.49	1.00		
NDVI	0.30	-0.19	1.00	
NDBaI	0.53	0.64	0.48	1.00

2021	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.61	1.00		
NDVI	0.34	0.05	1.00	
NDBaI	0.57	0.74	0.46	1.00

2022	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.38	1.00		
NDVI	0.24	-0.40	1.00	
NDBaI	0.48	0.57	0.27	1.00

2023	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.34	1.00		
NDVI	0.41	-0.28	1.00	
NDBaI	0.47	0.56	0.44	1.00

2024	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.46	1.00		
NDVI	0.20	-0.48	1.00	
NDBaI	0.55	0.53	0.25	1.00

2025	LST	NDBI	NDVI	NDBaI
LST	1.00			
NDBI	0.25	1.00		
NDVI	0.19	-0.39	1.00	
NDBaI	0.28	0.64	0.13	1.00

Figure 8. (continued) Correlation matrix of spectral indices for the years 2014-2025

A comprehensive assessment of NDVI, NDBI, NDBaI, and LST changes from 2014 to 2025 clearly reveals the annual dynamics of land cover and surface temperature in the study area (Figure 9). As can be seen in Figure 9, NDVI values remained between 0.15 and 0.20 throughout the period, indicating that vegetation conditions did not change significantly. Although partial decreases in NDVI values were seen, especially in 2015 and 2020, NDVI values generally remained stable during the study period. However, the NDBI values mostly varied between -0.05 and 0.02. This is because the study area has limited urban areas. Although slight increases in urban areas are seen in 2021, these results did not effect the significant variation on the regional scale. Based on the annual NDBaI results, the values ranged between -0.38 and -0.28. It can be concluded from these results that bare soil areas are limited and that the trend of change in these areas during the study period is not upward. The result of LST values has mostly fluctuated between 27 ºC and 36 ºC. between the years 2014-2025. Although LST values decreased significantly in 2022, a partial increase was observed in 2016 and 2023. Besides, an investigation of the relationship between LST and NDVI over the years reveals a negative correlation between these two indices, indicating that surface temperatures tend to decrease over time along with dense vegetation. In contrast, it is expected that LST would increase with less vegetation areas. All these inferences proved that there is a significant effects of vegetation on LST.

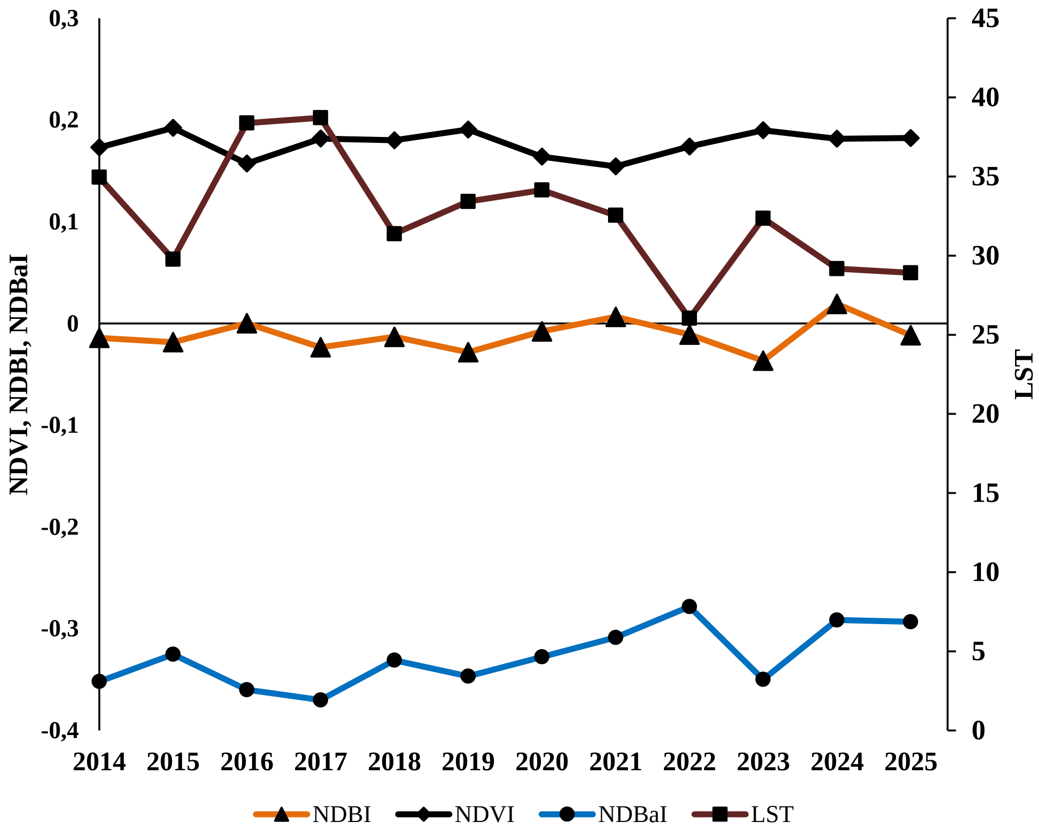

Figure 9. Temporal analysis using the mean values of NDBI, NDVI, NDBaI, and LST

4. Conclusion

This study aimed to investigate the changes and correlations between the spectral indices including LST, NDVI, NDBI, and NDBaI, which are commonly used in literature, in the Burdur Basin using multi temporal Landsat satellite imagery between the years 2014 and 2025. Based on the results, an important variation of LST values was observed in the Burdur Basin during the study period. Spatially, the highest value of LST was seen in the northeastern and central zones of the basin, particularly from 2016 to 2019. In contrast, as expected, the wetland and water surface areas produced the lowest LST values. Besides, during the study period, the NDVI values have not shown any significant changes, but have particularly decreased in the years 2020 and 2024. These could be the reason of the basin can be vulnerable to climate variation. Although NDBI and NDBaI have not shown an important variation during the years, and mostly observed moderate positive correlation with LST, the values were particularly increased in some regions. From these results, it can be concluded that urban and bare soil areas tend to increase LST. The weak and positive relationship between the LST and NDVI in some years can be inferred from seasonal fluctuating and complex land use and land cover change. To conclude, the results of this work revealed that, the climate variables significantly effects the LST values. In order to reduce the adverse effects of climate change, it is crucial to preserve vegetation, mitigate bare land areas, and control the expansion of urban areas in the Burdur Basin. Additionally, this study has shown that GIS and remote sensing methods are dependable and efficient means of tracking long-term environmental changes in semi-arid basins.

5. Author Contribution Statement

The entire work was undertaken solely by the author.

6. Ethics Committee Approval and Conflict of Interest

There is no conflict of interest with any person/institution in the prepared article.

7. Ethical Statement Regarding the Use of Artificial Intelligence

During the writing process of this study, the artificial intelligence tool "ChatGPT," developed by "OpenAI," and “Grammarly” were used only for limited purposes of linguistic editing and translation. The scientific content, analyses, and results belong entirely to the authors.

8. References

[1] R. Thapa *et al*., "Examining the spatio-temporal relationship between LST, NDVI, NDBI and LULC change of Pachhua Dun, Dehradun, Uttarakhand (India)," *J. Geospatial Inf. Sci. Eng.*, vol. 6, no. 2, pp. 136–152, Nov. 2023.

[2] B. Guo, Y. Zhou, S. X. Wang, and H. P. Tao, "The relationship between normalized difference vegetation index (NDVI) and climate factors in the semiarid region: A case study in Yalu Tsangpo River Basin of Qinghai–Tibet Plateau," *J. Mt. Sci.*, vol. 11, no. 4, pp. 926–940, May 2014.

[3] N. You, J. Meng, and L. Zhu, "Sensitivity and resilience of ecosystems to climate variability in the semi-arid to hyper-arid areas of Northern China: A case study in the Heihe River Basin," *Ecol. Res.*, vol. 33, no. 1, pp. 161–174, Dec. 2018.

[4] J. Peng, J. Jia, Y. Liu, H. Li, and J. Wu, "Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas," *Remote Sens. Environ.*, vol. 215, pp. 255–267, Sep. 2018.

[5] S. Guha and H. Govil, "A long-term monthly analytical study on the relationship of LST with normalized difference spectral indices," *Eur. J. Remote Sens.*, vol. 54, no. 1, pp. 487–512, Aug. 2021.

[6] Shahfahad *et al*., "Longitudinal study of land surface temperature (LST) using mono- and split-window algorithms and its relationship with NDVI and NDBI over selected metro cities of India," *Arab. J. Geosci.*, vol. 13, Art. no. 1040, pp. 1–19, Sep. 2020.

[7] D. Sun and R. T. Pinker, "Estimation of land surface temperature from a geostationary operational environmental satellite (GOES-8)," *J. Geophys. Res. Atmos.*, vol. 108, no. D11, Jun. 2003.

[8] K. Deilami, M. Kamruzzaman, and Y. Liu, "Urban heat island effect: A systematic review of spatio-temporal factors, data, methods, and mitigation measures," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 67, pp. 30–42, May 2018.

[9] F. Altıner and F. Bingol, "Spatio-temporal assessment of land surface temperature, vegetation cover, and built-up areas using LST, NDVI, and NDBI in Balıkesir, Türkiye (1985–2025)," *Sustainability*, vol. 17, Art. no. 9245, pp. 1–25, Oct. 2025.

[10] S. Garai *et al*., "Assessing correlation between rainfall, normalized difference vegetation index (NDVI) and land surface temperature (LST) in Eastern India," *Saf. Extrem. Environ.*, vol. 4, pp. 119–127, Jun. 2022.

[11] B. Naga, K. Naidu, and F. Ahmed, "Assessing LULC changes and LST through NDVI and NDBI spatial indicators: A case of Bengaluru, India," *GeoJournal*, vol. 88, pp. 4335–4350, Apr. 2023.

[12] P. E. Zope, T. I. Eldho, and V. Jothiprakash, "Impacts of land use–land cover change and urbanization on flooding: A case study of Oshiwara River Basin in Mumbai, India," *CATENA*, vol. 145, pp. 142–154, Oct. 2016.

[13] A. Ali *et al*., "Examining the landscape transformation and temperature dynamics in Pakistan," *Sci. Rep.*, vol. 15, Art. no. 2575, pp. 1–16, Jan. 2025.

[14] M. S. A. Salan and M. A. H. Bhuiyan, "Estimating impacts of micro-scale land use/land cover change on urban thermal comfort zone in Rajshahi, Bangladesh: A GIS and remote sensing based approach," *Urban Clim.*, vol. 58, Art. no. 102187, Nov. 2024.

[15] X. Yuan *et al*., "Vegetation changes and land surface feedbacks drive shifts in local temperatures over Central Asia," *Sci. Rep.*, vol. 7, no. 1, pp. 3–10, Jun. 2017.

[16] S. Anbazhagan and C. R. Paramasivam, "Statistical correlation between land surface temperature (LST) and vegetation index (NDVI) using multi-temporal Landsat TM data," *Int. J. Adv. Earth Sci. Eng.*, vol. 5, no. 1, pp. 333–346, Apr. 2016

[17] B. Ç. Değerli and M. Çetin, "Evaluation from rural to urban scale for the effect of NDVI-NDBI indices on land surface temperature in Samsun, Türkiye," *Turkish J. Agric. Food Sci. Technol.*, vol. 10, no. 12, pp. 2446–2452, Oct. 2022.

[18] E. Karakoyun, "Evaluating the correlation between land surface temperature (LST) and normalized difference vegetation index (NDVI)," *MAUN J. Fac. Eng. Archit.*, vol. 5, no. 1, pp. 15–25, May 2024.

[19] S. Guha and H. Govil, "An assessment on the relationship between land surface temperature and normalized difference vegetation index," *Environ. Dev. Sustain.*, vol. 23, no. 2, pp. 1944–1963, Jan. 2021.

[20] S. Guha, H. Govil, and M. Besoya, “An investigation on seasonal variability between LST and NDWI in an urban environment using Landsat satellite data,” *Geomatics Nat. Hazards Risk*, vol. 11, no. 1, pp. 1319–1345, Jul. 2020.
[21] M. Jothimani, J. Gunalan, and R. Duraisamy, “Study the relationship between LULC, LST, NDVI, NDWI and NDBI in Greater Arba Minch area, Rift,” in *Proc. 3rd Int. Conf. Integr. Intell. Comput. Commun. Security (ICIIC)*, 2021, pp. 183–193.
[22] J. Siqi and W. Yuhong, “Effects of land use and land cover pattern on urban temperature variations: A case study in Hong Kong,” *Urban Clim.*, vol. 34, p. 100693, Dec. 2020.
[23] H. Zhao and X. Chen, “Use of normalized difference bareness index in quickly mapping bare areas from TM/ETM+,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, vol. 3, pp. 1666–1668, 2005.
[24] S. Guha and H. Govil, “Estimating the seasonal relationship between land surface temperature and normalized difference bareness index using Landsat data series,” *Int. J. Eng. Geosci.*, vol. 7, no. 1, pp. 9–16, Jan. 2022.
[25] A. S. Alademomi *et al*., “The interrelationship between LST, NDVI, NDBI, and land cover change in a section of Lagos metropolis, Nigeria,” *Appl. Geomatics*, vol. 14, pp. 299–314, Apr. 2022.
[26] W. Ullah *et al*., “Analysis of the relationship among land surface temperature (LST), land use land cover (LULC), and normalized difference vegetation index (NDVI) with topographic elements in the lower Himalayan region,” *Heliyon*, vol. 9, no. 2, p. e13322, Feb. 2023.
[27] E. Kilic and S. Arslan, “Uzaktan algılama teknikleri ile altyapı sistemlerinin konumsal analizi: Burdur Havzası örneği,” *Turkish J. For.*, vol. 23, no. 2, pp. 146–155, Jun. 2022.
[28] A. Sekertekin and S. H. Kutoglu, “Evaluation of spatio-temporal variability in land surface temperature: A case study of Zonguldak, Turkey,” *Environ. Monit. Assess.*, vol. 188, no. 30, pp. 1–15, Jan. 2016.
[29] O. Orhan, S. Ekercin, and F. Dadeser-Celik, “Use of Landsat land surface temperature and vegetation indices for monitoring drought in the Salt Lake Basin area, Turkey,” *Sci. World J.*, vol. 2014, pp. 1–11, Jan. 2014.
[30] A. Unver and Z. Baskaya, “NDVI, NDBI ve UI analizleriyle yapılaşma yoğunluğu değişimi analizi (1999–2022): Yıldırım İlçesi (Bursa) örneği,” *J. Geogr.*, vol. 49, pp. 65–81, Oct. 2024.