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NDVI and NDBI Indexes as Indicators of the Creation of Urban Heat Islands in the Sarajevo Basin

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ABSTRACT

Remote sensing plays a vital role in analyzing urban changes. In this regard, various datasets collected from satellites today serve as a foundation for decision-makers and urban planners. This study compares the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) as indicators for the creation of surface heat islands. Using Landsat 8 OLI/TIRS C2 L2 images, spatial correlations between land surface temperature (LST) were examined for August 2013, 2019 and 2023. Urban heat islands (UHI) are a contemporary phenomenon and increasingly common in large urban areas compared to surrounding, less populated areas. With the advancement in remote sensing, it is possible to adequately determine the spatial differentiation and prevalence of urban heat islands (UHI). The study is based on Landsat 8 satellite image sets for the Sarajevo basin in August 2013, 2019 and 2023, which were used to analyze LST, NDVI, and NDBI indices. This work indicates a relationship between LST and NDVI but varies depending on the analyzed year. Normalized Difference Built-up Index (NDBI) serves as a suitable indicator for surface UHI effects and can be used as an indicator to assess its spatial distribution within a larger urban environment.

Introduction

Urban areas are subjected to continuous surface changes that influence local climatic characteristics. Such areas become warmer compared to the surrounding environment, with temperature differences particularly pronounced at night when vegetated surroundings cool more rapidly than paved urban surfaces. This phenomenon is known in the literature as the Urban Heat Island (UHI) (Voogt & Oke, 2003). The primary factor contributing to the formation of urban heat islands is the increasing replacement of undeveloped or vegetated areas with paved surfaces and buildings. UHI forms in environments with low cloud cover and weak air circulation, specifically in clear-sky and low-wind conditions. Dominantly, the summer months (June, July, August) are periods when the formation of the urban heat island can be observed and its spatial characteristics determined. Numerous scientists and researchers have explored the phenomenon of urban heat islands. Kim (1992) highlighted crucial indicators related to UHI in the capital of the United States based on Landsat TM mission data. He emphasized that temperatures in urban areas during summer can be up to 10°C higher than in nearby forested areas. The entire substrate

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begins to heat up in the mid-morning, driven by the rapid warming of urban surfaces such as buildings, paved areas, surfaces devoid of vegetation, and low vegetation. The effects of urban heat islands are studied at micro (below the surface and on the surface), local (urban canopy layer), and meso (urban boundary layer) scales due to the urban nature and multilayered structure of the atmosphere (Roth, 2013). UHI at the local level has far-reaching consequences for energy use in buildings, water use for irrigation, air quality, and urban ecology, as well as its impact on the thermal comfort of urban residents (Roth, 2013). The adverse effects of UHI are recognized worldwide, leading to increased demand for cooling, higher energy consumption, water demand, and contributing to elevated rates of diseases and mortality from heat stress or poor air quality (Heaviside et al., 2017; Yao et al., 2022).

In the early years of urban heat island research, the focus was on studying the atmospheric urban heat island (AUHI) based on meteorological data from a network of permanent weather stations. To create an accurate thermal map of the city, it was necessary to provide a large number of evenly distributed weather stations for data collection. However, maintaining these stations was expensive, and the reliability and accuracy of the data were questionable on a long-term scale (Wang, 2015). With the development of remote sensing, the research focus shifted to determining surface urban heat islands (SUHI). This method relies on the use of infrared radiation sensing sensors (TIRS), allowing for significantly greater spatial coverage (Fabrizi et al., 2010). Subsequent research has offered improvements over earlier sensor versions, and data from the thermal infrared sensor of the Landsat 8 satellite are widely used to study the state and dynamics of the urban thermal environment (Wang, 2015). Land Surface Temperature (LST) is defined as the temperature at the boundary between the Earth's surface and its atmosphere (Niclòs et al., 2009). Satellite-derived LST is a crucial parameter in studying the Urban Heat Island (UHI) process as it is used to analyze surface radiation and heat energy flow between the surface and the atmosphere (Mulahusić et al., 2018). LST plays a vital role not only in various surface processes but also in regulating sensible and latent heat flux (Sun et al., 2003). Many areas have recognized the significance of this parameter, and it is widely applied in climate and climate change research, hydrological regimes in specific areas, as well as ecological and vegetation changes. Parks and other green spaces in the city usually have lower temperatures than built-up areas, contributing to lowering air temperatures, while densely populated areas directly impact air warming, thus increasing its temperature (Srivanit & Hokao, 2012).

Improvements in high-resolution sensors have aided in the precise monitoring of Land Surface Temperature (LST) and Urban Heat Island (UHI) on large spatial and temporal scales (Naserikia et al., 2019). Numerous studies have indicated that bare soil and impervious surfaces are crucial factors influencing UHI, while vegetation and water surfaces can mitigate UHI formation (Song et al., 2014). Many researchers have explored the relationship between LST and built-up areas (Normalized Difference Built-up Index - NDBI) and vegetation (The Normalized Difference Vegetation Index - NDVI) indices (Chen et al., 2014; Guha et al., 2017; Değerli & Çetin, 2022; Alademomi et al., 2022; Haji et al., 2023). Research has confirmed the exceptional correlation between NDVI and LST, as well as between LST and NDBI. The results of these studies have robustly explained the relationship between urban development and the expansion of UHI in urban areas. The main objective of this study was to examine the values of NDVI and NDBI indices, representing the two main types of land cover. Additionally, based on Landsat 8 satellite imagery, the study aimed to define zones where UHI formation occurs. The specific goal was to explore the application potential of remote sensing products in studying further urban development in the Sarajevo basin. This study is innovative, considering the limited number of studies addressing the UHI phenomenon in Sarajevo during recent years of intensified urbanization (Mulahusić et al., 2018; Drašković et al., 2020). The study results provide a foundation for urban planners and decision-makers at the entity and cantonal levels to plan future urban development in the basin adequately. In this regard, the study attempted to answer two fundamental research questions related to a) the relationship between NDVI, NDBI, and LST and b) defining spatial zones where the intensity of UHI formation is most pronounced. A limitation of the study was the generalization, i.e., the size of the spatial coverage of Landsat 8 satellite images, which were 30x30 m, and the absence of entirely cloud-free satellite imagery, as the 2019 image was somewhat covered by clouds.

The main aim of this study was to compare two fundamental indices, NDVI and NDBI, from the years 2013, 2019, and 2023. The study sought to identify changes occurring during the analyzed years, utilizing Landsat 8 satellite imagery obtained from the United States Geological Survey (USGS) and focusing on the Sarajevo basin as a case study. The specific objective was to highlight the city's expansion and urban development, monitored through the Landsat 8 OLI/TIRS L2 C2 satellite. In line with these goals, the study aimed to address the fundamental research questions – RQ1: Can the urbanization of the Sarajevo basin be tracked based on NDVI and NDBI? RQ2: Is the spatial distribution of Urban Heat Island (UHI) related to land use and land cover?

Data and methods

Study area

Sarajevo basin is situated within the intermontane depression between the massifs of Bjelašnica and Igman to the southwest and the low mountainous and sub-mountainous terrain to the northeast. Its general orientation is approximately Dinaric (NW-SE). Within the basin lies the source area of the Bosna river with its tributaries: Zujevina with Rakovica, Željeznica with Kasindolka, Dobrinja with Tilava, and Miljacka. Based on its geological composition and geomorphological structure, the Sarajevo basin can be differentiated into two morphological units: the first being the mountainous periphery and the second, the basin floor of the Miljacka river with the Sarajevo field (Fig. 1). The average elevation of the Sarajevo basin is around 515 meters above sea level. The lowest elevation is in the north of the basin (in Reljevo, at 493 meters), while slightly higher points are located within the drainage basins and the extensions of the Željeznica, Kasindolka, Tilava, Miljacka, and Zujevina rivers (Hadžić et al., 2015). The area of the mountainous periphery exhibits rather heterogeneous climatic characteristics significantly influenced by the surrounding high mountains of Bjelašnica, Jahorina, and Treskavica (Hadžić & Drešković, 2014). Geographically, the research area is situated between 43° 47' North latitude and 18° 24' East longitude.

Landsat 8 data

For the purpose of this study, enhanced Landsat 8 OLI/TIRS L2 C2 data/images were utilized to measure various bands across the electromagnetic spectrum. Landsat 8 data comprise several bands depending on the wavelength (blue, green, red, infrared, thermal, and panchromatic). Landsat 8 encompasses 11 bands. Band 4 represents the Near-Infrared (NIR), while Band 6 is thermal, detecting heat and providing information about soil temperature, which typically tends to be warmer than the air (NASA Landsat Science, 2023). The Landsat 8 OLI/TIRS L2 C2 images used in this study were obtained from the United States Geological Survey (USGS). It is noted that the images from the year 2019 have a 30 cloud cover percentage, which had a minor impact on the results.

Table 1. Landsat 8 data

Path	Row	Cell size	Date
187	030	30x30	2013-08-16
187	030	30x30	2019-08-17
187	030	30x30	2023-08-28

Source: Processed by authors according to ArcGIS geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science, 2023.

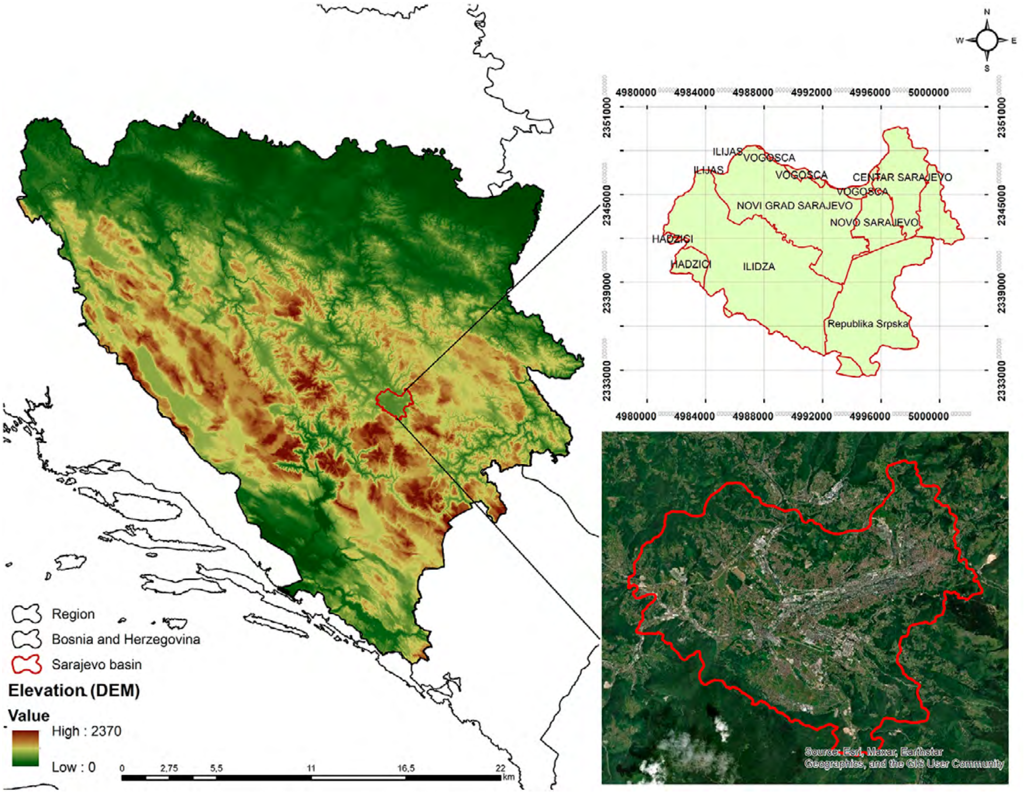

Figure 1. Study area

Source: Geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science adapted by the authors using ArcGIS [GIS software] Version 10.6.1.

Data processing

The NDVI (Normalized Difference Vegetation Index) is calculated as the ratio between the reflectance of the red band around 0.66 µm and the near-infrared (NIR) band around 0.86 µm. NDVI is most easily calculated as the difference between near-infrared (NIR) and red (RED) reflectance divided by their sum. NDVI is represented by the following formula:

$$\mathrm{NDVI} = (\mathrm{NIR}-\mathrm{RED}) / (\mathrm{NIR}+\mathrm{RED})$$

In the study, this index was calculated in ArcGIS 10.6.1 software using the Raster Calculator: Float(Band 5 - Band 4) / Float(Band 5 + Band 4). NIR (Near-infrared) corresponds to the near-infrared spectrum of Landsat 8 images, while RED refers to the red band of satellite images. Areas with dense vegetation in satellite images tend to have positive values, while water bodies and built-up areas tend to have negative values.

The Built-up Index is essentially an image indicating the built-up and non-vegetated nature of areas because it is characterized solely by positive values. It represents one of the main types of land cover (Zha, Gao, and Ni, 2005). Built-up areas and non-vegetated areas reflect more SWIR than NIR rays. The formula for calculating this index (NDBI) is as follows:

$$\mathrm{NDBI} = (\mathrm{SWIR} - \mathrm{NIR}) / (\mathrm{SWIR} + \mathrm{NIR})$$

In the study, this index was calculated using the Raster Calculator as follows: Float(Band 6 - Band 5) / Float (Band 6 + Band 5).

Negative values of the NDBI index indicate water bodies and forests, while higher values (approaching 1) represent built-up areas. The NDBI value for vegetation is low (Macarof, 2017). The month of August was selected as relevant for analysis, considering that the biomass increment is highest during this month. A significant limitation in the research was the use of generalized data obtained from Landsat 8 satellite images with a cell size of 30x30m. Data regarding Land Surface Temperature (LST) were derived from Landsat 8 satellite images and logarithmic operations using ArcGIS tools (Raster Calculator), noting that these data only correspond to the month of August for the observed years.

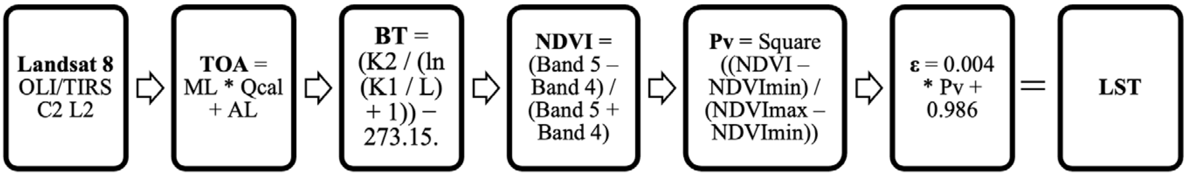

Figure 2. Logarithmic processing of LST data in ArcGIS 10.6 software based on Landsat 8 datasets
Source: Processed by authors, 2023

Results

Landsat 8 OLI/TIRS L2 C2 images were utilized to extract the analyzed parameters in this study. NDVI maps were generated using ArcGIS 10.6.1 software for the years 2013, 2019, and 2023 and are presented in Fig.2. NDVI illustrates significant both temporal and spatial variations between 2013, 2019, and 2023. Green/healthy vegetation absorbs the blue (0.4 - 0.5 µm) and red (0.6 - 0.7 µm) spectra, reflecting the green (0.5 – 0.6 µm) spectrum. Human eyes perceive healthy vegetation as green due to the internal structure of leaves. Healthy plants exhibit high reflectance in the near-infrared radiation (NIR) ranging from 0.7 to 1.3 µm (Fig. 2) (Crippen, 1990). Analyzed statistical parameters (Table 2) demonstrate that the NDVI index mostly varied across the analyzed years. Minimum index values decreased, while maximum values increased. In August 2013, the maximum index value was approximately 0.6, indicating dense vegetation cover, especially in the surrounding mountainous areas. The maximum index value in August 2019 was around 0.7, and in 2023, it increased by 0.01, suggesting a reduced proportion of vegetation cover in favor of built-up areas. NDVI exhibits pronounced annual changes dependent on surface layer temperatures. As expected, a positive correlational relationship (p=0.84) between the NDVI index and LST was confirmed. Statistical analysis of the Pearson linear correlation coefficient affirmed that this correlation (NDVI-LST) lacks statistical significance. In general, changes in surface layer temperatures imply greater plant growth and vice versa. The pronounced annual change in this index is characteristic of densely populated basin centers. Areas with dense vegetation, tending towards positive index values, are mainly at higher altitudes, on the slopes of surrounding mountains and hills (Bjelašnica, Igman, Trebević, Hum, Zuč), which are not under significant anthropogenic pressure. Conversely, areas with negative index values indicate the degree of anthropogenic pressure in the central part of the basin.

To confirm the variations in the indices, an analysis of the NDBI index was conducted for the purposes of this article. The obtained values of the NDBI index, which correlate with the NDVI index (Fig. 2 and 3), confirm a high degree of ur-

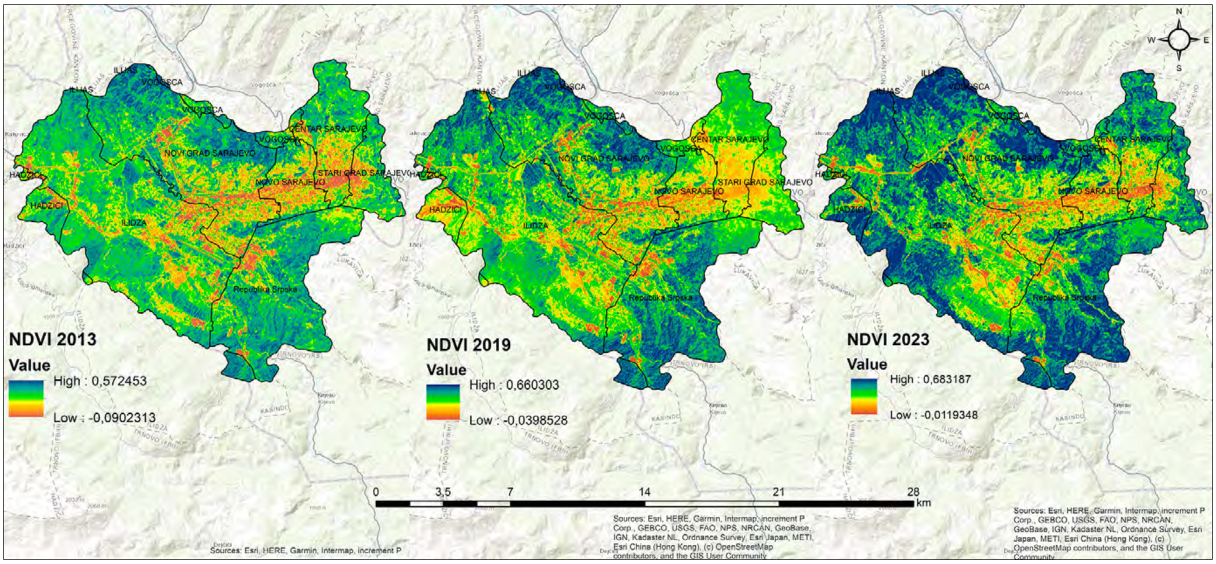

Figure 3. NDVI values for 2013, 2019 and 2023

Source: Geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science adapted by the authors using ArcGIS [GIS software] Version 10.6.1. and Landsat 8 OLI/TIRS L2 C2 images

Table 2. Statistical Data for NDVI Index by Year

Year	Minimum	Maximum	Mean	Standard Deviation
2013	-0,012	0,683	0,305	0,099
2019	-0,040	0,660	0,320	0,103
2023	-0,090	0,573	0,334	0,099

Source: Processed by the authors using data from ArcGIS geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science, 2023

banization in the central part of the Sarajevo basin. Positive values of the NDBI index are concentrated in the central part of the basin, which is highly urbanized, while negative values are observed in its peripheral areas, where dense vegetation predominates, in contrast to the NDVI index. This indicates a negative statistical correlation between the analyzed indices. Urbanization in the Sarajevo basin mostly occurs without proper planning. Thousands of structures have been informally built on the slopes surrounding central Sarajevo (Aquilué & Roca, 2016). The response of cantonal authorities to informal construction and the development of numerous settlements resulted in processes of legalizing informally constructed structures. Despite efforts to implement regulatory plans and provide standard infrastructure for all informally built structures, legalization had limited effectiveness (Martín-Díaz et al., 2018). These settlements remained in the realm of "gray areas," even though they eventually moved away from informality (Legrand, 2013).

In line with this, construction intensified in the peripheral southeastern parts of the Sarajevo basin, and significant changes during the analyzed years were experienced by the settlements of Hrasnica, Ilidža, and Istočno Sarajevo (Drešković & Osmanović, 2024). Over the ten-year analyzed period, the percentage of built-up areas increased. Based on the analysis of Corine Land Cover (CLC) images, data indicate that artificial surfaces covered nearly 29% of the total territory in 2012, and by 2018, their percentage had increased by 10% (Drešković & Osmanović, 2024). This increase was caused by the physical-geographical constraints of settlements, infrastructure, and human activities in a very confined space—basin expansions along watercourses (Hrelja et al., 2021). Urbanization, in this sense, harmed dense vegetation in the peripheral parts of the basin due to land conversion, primarily clearing for various commercial purposes. The percentage of built-up areas increased by approximately 10% in the mentioned six-year period, precisely reducing dense vegetation in favor of construction areas, reflecting progressive urban development and, in certain areas of the basin, unplanned construction.

Table 3. Statistical Data of NDBI Index by Years

Year	Minimum	Maximum	Mean	Standard Deviation
2013	-0,318	0,319	-0,140	0,076
2019	-0,039	0,352	-0,023	0,073
2023	-0,320	0,453	-0,099	0,083

Source: Processed by the authors using data from the ArcGIS geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science, 2023

The surface temperature of built-up layers (LST) was also analyzed to obtain data on areas with the highest heating intensity. The data obtained on the temperature of surface layers indicate the formation of heat islands (UHI) in one of the summer months - August. On the observed

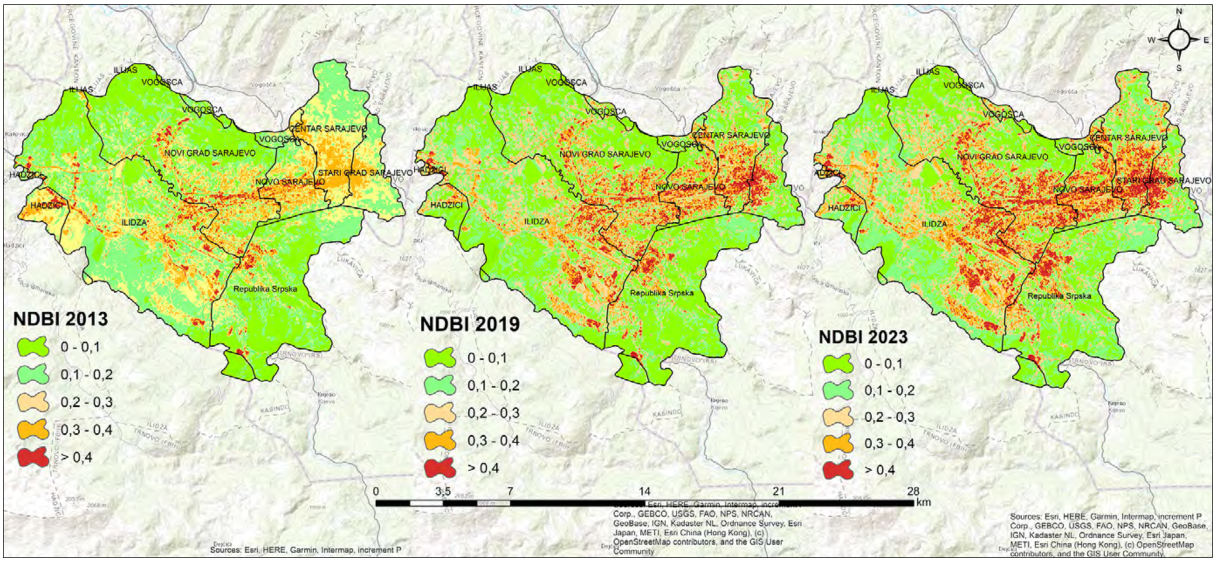

Figure 4. NDBI index for 2013., 2019. and 2023.
Source: Geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science adapted by the authors using ArcGIS [GIS software] Version 10.6.1. and Landsat 8 OLI/TIRS L2 C2 images

day in August 2013, the average daily air temperature was around 34°C, while in 2023, it was 35.2°C. Correlated with the average daily air temperatures is the emission from asphalted, dark surfaces that heat up more intensely compared to the air. Sarajevo is highly urbanized, with large areas covered in concrete, contributing to the creation of a specific microclimate within certain locations, particularly during the summer months (Fig. 5). It is recommended to mitigate UHI effects in the Sarajevo basin by implementing cool roofs and increasing urban greenery.

The highest degree of surface heating is observed in the old part of Sarajevo, as well as in certain areas of the municipalities of Centar, Novi Grad Sarajevo, Ilidža, Vogošća, and Istočno Sarajevo. These areas, due to unplanned construc-

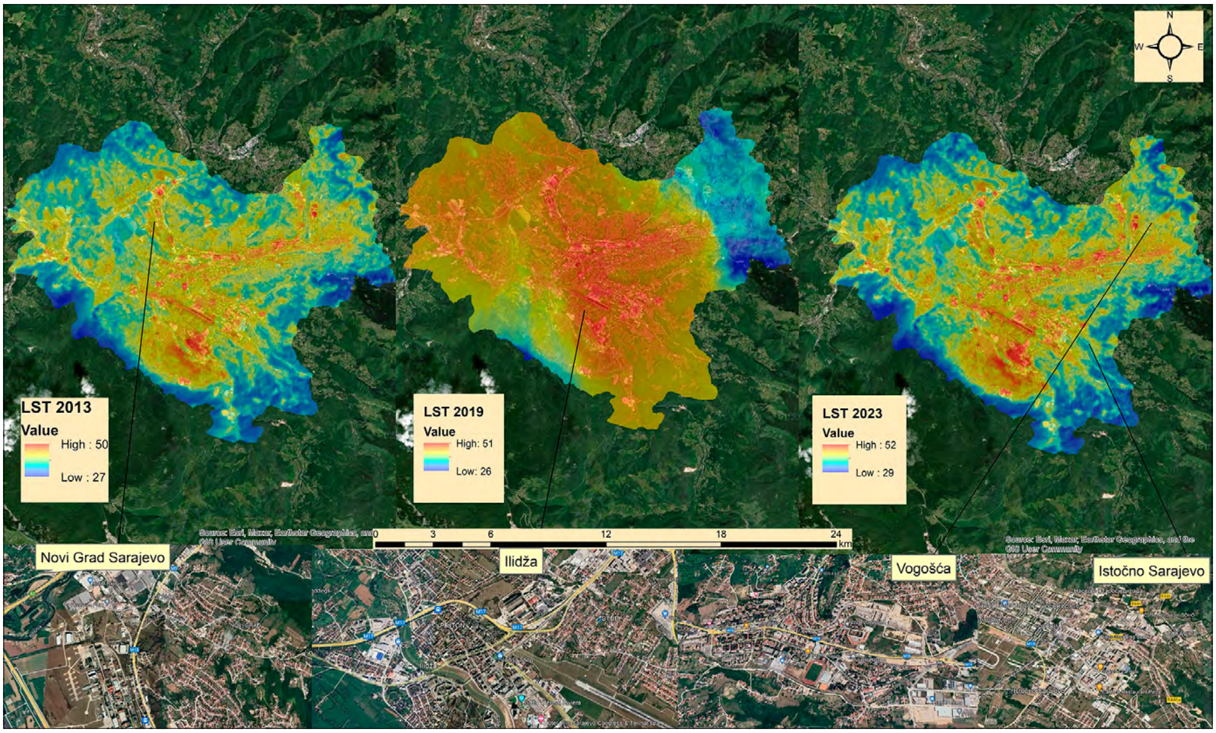

Figure 5. LST in Sarajevo basin in 2013., 2019. and 2023.
Source: Geo-database of GIS Center of Department of Geography, University of Sarajevo – Faculty of Science adapted by the authors using ArcGIS [GIS software] Version 10.6.1. and Landsat 8 OLI/TIRS L2 C2 images

tion and materials used, are predisposed to the formation of urban heat islands (UHI). Extremely high surface layer temperatures in the Sarajevo basin in August during the ten analyzed years (max. 52°C) indicate the predominant spatial representation of concrete and asphalt surfaces that heat up intensively during the summer months, reaching temperatures up to 30°C higher than the surrounding hilly and mountainous areas rich in dense vegetation, which in this case act as cooler air oases. It is essential to note that these areas are mainly residential centers, as well as industrial and commercial areas, predominantly built with materials that have a higher degree of heating and emissions, with sheet metal roofs that intensify heating during the summer months. Mulahusić et al. (2018) found that surface temperatures in 2015 correlated with areas with the highest population density and building density. The images were captured during the hottest summer month because surface heating is most intense during that period, and temperatures remain high for an extended duration. Landsat 8 satellite captures the surface around 10 a.m. local time and only exceptionally at night. Therefore, monitoring urban heat islands during the most intense heat period or analyzing the cooling degree between built-up and non-built-up areas during the night was impossible.

Discussion

Methodology aspect

The widely used methodology has proven successful in identifying the Urban Heat Island (UHI) effect, as numerous studies have established a correlative relationship between NDVI, NDBI, and LST, confirming their significance in monitoring changes and biophysical characteristics of plant communities, as well as the reduction of vegetative cover in favor of built-up areas (Bechtel et al., 2012; Chen et al., 2014; Geletič et al., 2016; Macarof & Statescu, 2017; Guha et al., 2017). Remote sensing products have found broad application in almost all scientific fields and are a good foundation for future studies of these phenomena in the Sarajevo basin, given the limited number of studies on this topic (Mulahusić et al., 2018; Drašković et al., 2020). Typically, only LST has been analyzed as the basic indicator of the spatial distribution of UHI. This study confirms that the degree of urbanization is highest in the city of Sarajevo (municipalities of Stari Grad, Centar, Novo Sarajevo, and Novi Grad), i.e., in the central parts of the basin predisposed to UHI formation due to physical-geographical characteristics and anthropogenic changes. An enhancement of this study could be achieved by investigating the spatial representation and distribution of green areas in the central parts of the basin. The minimum area of urban greenery per capita should be 9 m^2, and the ideal 50 m^2 (World Health Organization, 2012). The number of inhabitants in the Sarajevo Basin according to the last population census from 2013 was 354.030, which means that there should be a minimum of 3.186.000 m^2 of urban greenery in the analyzed area, or 318.6 ha. Of the total area of the city (municipalities of Stari Grad, Centar, Novo Sarajevo, and Novi Grad Sarajevo), which is 14.150 ha, about 25% should be covered by urban greenery, but the Sarajevo basin is far below the average because currently only Veliki Park has an area of about 3 ha and approximately corresponds to the stated criteria. In other areas, green areas were repurposed. This allows urban planners to identify areas with spatial potential for planting trees, which are the best heat absorber (Yaşlı et al., 2023), and find solutions for the future spatial expansion of the basin. A more precise picture could be achieved by selecting and examining specific profiles in different seasons in both central and peripheral parts of the basin to determine temperature differences in micro-locations. Surface temperatures provide important information about the thermal behavior of the annual temperature cycle from thermal infrared images with an accuracy of about 1K. For this reason, urban thermal areas are described by multi-temporal thermal cycles (Bechtel, 2012). A methodological improvement would involve analyzing ASTER satellite images of different spatial resolutions to identify zones with the UHI effect confidently.

Validity of results

One of the main drawbacks is the temporal coverage of Landsat 8 TIRS/OLI L2 C2 satellite images. Landsat 8 captures Earth's surface at 10 AM local solar time, making it impossible to investigate the Urban Heat Island (UHI) effect during the period of most intense surface heating or to determine nighttime temperature differences between built-up and non-built-up areas. This limitation prevents a fully consistent or accurate representation of the actual situation. Satellite image data are processed and validated in ArcGIS software (Imbroane et al., 2014; Gémes et al., 2016) to obtain a more precise depiction of the current state. As remote sensing products are widely applied across scientific disciplines, there is an essential need for an interdisciplinary approach, combining multiple satellite images to detect changes at the local level. Various qualitative approaches, such as Thematic Mapper, Enhanced Thematic Mapper, or Operational Land Imager, could reveal UHI behavior in different parts of the city and establish the interconnection between land cover and surface temperatures in urban and suburban areas. This would provide crucial insights for a more in-depth understanding of the causes and patterns of UHI, as well as in formulating local policies and spatial planning documents.

Conclusion

This study was based on the utilization and processing of multispectral remote sensing products to determine the dynamics of the spatial distribution of NDVI and NDBI indices, as well as their associated Land Surface Temperature (LST) in the urban area of Sarajevo, specifically the Sarajevo basin, during three specific observed years: 2013, 2019, and 2023. The results from the first set of Landsat 8 images indicated significant changes in this area, particularly concerning the NDVI index, whose values varied in August of 2013, 2019, and the same month in 2023. While the urban center itself displayed the highest values across all analyzed parameters, it is notable that even the peripheral parts of the basin experienced significant changes, notably in the clearance of forest communities for land reclamation purposes. Results from the second set of Landsat 8 images confirmed a correlational link between the NDVI and NDBI indices. Specifically, highly urbanized and densely populated areas exhibited predominantly positive NDBI values (up to 1), while areas with various types of vegetation communities and water bodies tended toward negative values. Due to its orographic and topographic position, Sarajevo has historically been densely populated, with intensified urbanization during the post-war period of urban renewal. Novi Grad Sarajevo municipality ranks second in population density in the entire country. Multispectral Landsat 8 imagery and remote sensing, in general, have proven highly effective in studying urban agglomerations and the changes occurring within them. The crucial input parameter for identifying and analyzing urban heat islands in the Sarajevo basin was the data on Land Surface Temperature (LST), specifically the temperature of surface layers in August for 2013, 2019, and 2023. This analysis revealed temperature variations, with extreme values in 2023 representing the highest and lowest values over the analyzed period, attributed partly to increasingly pronounced global climate changes. In the future, more attention should be directed toward urban change patterns, especially urban ecology, through analyzing and comparing satellite imagery from various sources. Such spatial information is invaluable for decision-makers and urban planners to develop appropriate urban and regulatory plans, ensuring sustainable urban expansion.

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