The Structure and Technology of Structuring Marine Areas Using Remote Sensing Data in Semi-Arid Conditions

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Correctly distinguishing urbanized marine areas from bare ground is becoming increasingly important in the context of urbanization and environmental management. This study explores the feasibility of using spectral indices to distinguish urbanized marine areas from bare ground with similar spectral signatures. The Landsat-8 data were analyzed and different spectral indices were calculated and tested for their effectiveness in identifying urban areas. The results show that the Normalized Difference Built-up Index (NDBI) and the Vegetation Blending Unit (VBU) have promising potential for distinguishing urban areas from bare ground. The identification of category boundaries based on the distribution of minimum and maximum values of different spectral indices allows a clear delineation of urbanized areas. This study highlights the usefulness of spectral indices in extracting urbanized marine areas from remote sensing data and has practical implications for urban planners, decision makers, and stakeholders involved in urban planning, land use management, and environmental protection. However, caution is needed to avoid misclassification, and careful selection of appropriate indices is crucial to achieve correct classification results.

KEY WORDS

~ Remote sensing
~ Marine
~ Areas
~ Bare ground
~ Spectral indices
~ Ground cover

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1. INTRODUCTION

The urbanization of the planet, together with its increasing population, is a continuous process that began thousands of years ago (Alphan, 2003; Fu & Weng, 2016). Urbanization is a global phenomenon characterized by the concentration of the human population in cities, leading to the growth of urban areas. The trend towards urbanization is a long-term process that has been increasing at an unprecedented rate in recent decades. The number of people living in urban areas has surpassed the number of people living in rural areas, with 68% of the world's population expected to live in urban areas by 2050 (Akbar et al., 2019; Anand, 2019).

The rapid pace of urbanization has significant implications for economic, social, and environmental sustainability. While urbanization has led to increased economic growth, it has also created significant challenges in terms of poverty, inequality, and environmental degradation (Adnan, 2020). As urban populations continue to grow, the demand for resources such as water, energy, and food will increase, increasing the strain on natural resources (Jirwankar & Prasad, 2021).

The phenomenon of urbanization goes beyond local landscapes and affects global environmental dynamics, especially in marine ecosystems. As urban areas expand, they exert considerable pressure on adjacent marine areas, leading to changes in land use and ecological balance. This global trend is not only a demographic shift, but also an environmental issue, as urban sprawl and infrastructural development often lead to habitat destruction, pollution and ground cover changes that can have a negative impact on the marine environment. Studies such as those by B. Halpern (2008) and F. Holon (2015) have highlighted the intricate link between urban expansion and the degradation of marine ecosystems and emphasized the need for integrated urban and marine spatial planning. This global perspective on urbanization underlines the importance of our study, which aims to accurately identify and manage urbanized marine areas and thus contribute to the sustainable management of the urban and marine environment.

In recent years, the Kerch Peninsula has undergone significant technological change. Just in the last 5-10 years, a major transportation artery, the Tavrida highway, has been built connecting the Russian mainland to the Crimean Peninsula via the Crimean Bridge (Pozachenyuk et al., 2019). These developments have led to significant changes in the landscape and land use patterns of the region, which are of interest to researchers studying the impact of human activities on the environment. Therefore, a study of the changes in the landscape and land use patterns on the Kerch Peninsula is necessary to assess the impact of these changes on the environment and to provide information for future planning and development of the region (Krivoguz, 2021). In addition, the construction and opening of several industrial enterprises has led to the creation of numerous employment opportunities in the region. Nevertheless, statistics show that the population in the region is continuously growing, which is not only due to the increasing number of tourists visiting the peninsula, but also due to the technological advancements in the region (Krivoguz et al., 2018).

The recent technological advances and infrastructural developments on the Kerch Peninsula serve as a microcosm for the broader challenges and changes associated with urbanization. The construction of the Tavrida highway and the establishment of new industrial plants are not only local phenomena, but reflect the global trend of urban sprawl and industrialization. Such developments often have a double impact – while contributing to economic growth and regional development, they also pose a major challenge to environmental integrity and sustainable land use. For example, studies such as that by M. Naikoo (2020) have shown how similar infrastructural projects in other regions have led to significant changes in ground cover and ecosystem services, necessitating a reassessment of urban planning strategies. By analyzing the Kerch Peninsula, this study offers insights into the complex interplay between technological development and environmental sustainability, providing valuable lessons for urban planners and policy makers worldwide.

The study of ground cover in urbanized areas is currently an important task in the context of the development of modern remote sensing technologies as well as the intensification of urbanization processes. This is particularly important considering the continued growth of urban areas and the associated environmental challenges. Therefore, the understanding and accurate characterization of ground cover in urban environments is crucial for urban planning, resource management and environmental monitoring. Research efforts in this area have been intensified in recent years, focusing on the development of accurate and efficient remote sensing techniques for urban ground cover mapping and analysis (Alshari et al., 2021). The process of urbanization often leads to significant changes that can be observed in different areas, resulting in ecosystem changes, reduction of vegetation cover, deforestation, soil degradation and erosion, among others (Joshi et al., 2021).

The advancement of remote sensing methods and tools has addressed the challenge of limited accessibility in conducting comprehensive studies of the Earth's surface in terms of space and time (Borovskaya et al., 2022). This has made possible the acquisition of high-precision data for virtually any location on Earth. The development of these techniques has led to significant advances in the study of urban areas, which is a crucial task in the context of modern remote sensing technologies and the intensification of urbanization processes (Hussain et al., 2022). Remote sensing has played a crucial role in the analysis of urbanization, as it provides a unique perspective on the spatial and temporal dynamics of urban areas (Xia et al., 2019; Karakus, 2019). Remote sensing data can be used to detect and monitor land use and ground cover changes, track urban growth, and assess the impact of urbanization on the environment (Zhang et al., 2019; Ahmad et al., 2017; Cui & Shi, 2012; Patra et al., 2018). Remote sensing is used in many areas, such as mapping the extent of cities, quantifying impervious surface coverage, analyzing the effects of the urban heat island , and monitoring the urban vegetation cover.

Remote sensing has several advantages for the analysis of urbanization, including the ability to collect data at different spatial and temporal scales and giving a comprehensive overview of the urban landscape (Jirwankar & Prasad, 2021; Sultana & Satyanarayana, 2020; Qiao et al., 2020). Remote sensing data can also be used to generate accurate and objective information, avoiding the biases that can arise from subjective assessments. Furthermore, remote sensing data can be easily integrated with other geospatial data, allowing for the development of more complex models and analyses (Krivoguz et al., 2021).

With the increasing availability of high-resolution remote sensing data and advanced analytical techniques, the role of remote sensing in the analysis of urbanization is expected to grow. It has the potential to support evidence-based policy making and urban planning, making possible the better management of urban growth and the protection of natural resources (Yonaba et al., 2021).

Remote sensing has been widely used for land mapping and classification, as well as for monitoring and managing land resources. The spectral reflectance of ground can provide valuable information about ground properties, including texture, organic matter content, and moisture content (Sabaghy et al., 2018; Alexakis et al., 2019; Ben-Dor et al., 2002; Gholizadeh et al., 2019). Remote sensing can detect and quantify these properties over large areas with high spatial and temporal resolution.

Various remote sensing techniques, including optical, thermal and radar technologies, have been used to map and characterize ground. Optical sensors, such as multispectral and hyperspectral sensors, are most commonly used for ground analysis due to their high spatial resolution and ability to capture detailed spectral information. Thermal sensors can be used to estimate ground moisture content, while radar sensors are sensitive to land surface roughness and moisture content (Sabaghy et al., 2018; Yu et al., 2018)

The application of remote sensing techniques in the analysis of urbanization has become increasingly important as it gives a comprehensive overview of the spatial and temporal changes associated with urban growth. These techniques enable the monitoring of land use dynamics, urban sprawl and its impact on the environment with remarkable precision and scale. The research of T. Akbar (2019) and P. Fu and Q. Weng

(2016), for example, show how remote sensing has been helpful in tracking urban expansion and its impact on ground cover in different geographical settings. Their findings highlight the ability of remote sensing to provide not only detailed spatial data but also important insights into urbanization patterns. This is in line with the objectives of our study, which uses remote sensing to analyze the unique landscape changes on the Kerch Peninsula, contributing to a deeper understanding of the impact of urbanization on the environment.

Image processing and analysis techniques such as image classification and spectral mixture analysis were used to extract land information from remote sensing data. These techniques can be used to identify ground types, map ground properties and monitor ground changes over time. Machine learning algorithms such as support vector machines and neural networks have also been used to improve the accuracy and efficiency of ground mapping (Alexakis et al., 2019).

Various studies have dealt with the extraction and analysis of built-up urban areas using remote sensing and geodata. Bouhennache (2019), for example, introduced the built-up land features extraction index (BLFEI) as a new index for this purpose. L. Wang (2018) used qualitative and quantitative analysis methods in combination with land surveys and Google map data to analyze the spatio-temporal characteristics of the extent of built-up areas in cities. S. Sultana (2018; 2020) focused on quantifying the spatial relationship between land use/ground cover changes and land surface temperature in large Indian metropolitan cities using remote sensing and GIS techniques. I. Hidayati (2018) attempted to achieve maximum extraction accuracy by merging several indices including NDBI, NDVI, MNDWI, NDWI and SAVI.

J. Valdiviezo-N (2018) examined the existing build-up indices and discussed their advantages, difficulties and limitations. N. Xia (2019) integrated multiple data sources from remote sensing and geolocation datasets to extract information about urban areas, including nighttime illumination, vegetation cover, land surface temperature, population density, LRD, accessibility, and road networks. C. Karakus (2019) investigated the relationship between land use/ground cover, NDVI and land surface temperature in the city of Sivas and its surroundings using Landsat satellite images from 1989 to 2015, demonstrating the intensity of the urban heat island effect.

Ma (2019) proposed a fusion approach using DMSP-OLS nightlight data, MODIS ground cover product (MCD12Q1), and Landsat 7 ETM+ imagery to accurately extract urban built-up areas. In addition, UHI intensities were estimated for major cities in India during the summer season (Sultana & Satyanarayana, 2020). Li (2020) introduced the POI (point of interest) and LST (land surface temperature) adjusted NTL urban index (PLANUI) to extract urban built-up areas with high accuracy.

On the other hand, various research studies have dealt with determining ground properties using remote sensing data. Jin et al. (2018) provide a comprehensive overview of crop models, remote sensing techniques, and data assimilation methods for monitoring crop growth and estimating yields. Sabaghy (2018) gives an extensive review of current ground moisture downscaling approaches, discussing their capabilities, possibilities, strengths, and limitations. A new hyperspectral remote sensing method for predicting ground properties was developed and validated for the alpine grassland dominated by Stipa purpurea on the Qiangtang Plateau in the northwest of the Qinghai-Tibet Plateau (2018).

Traditionally, vegetation changes have been determined by visual analysis or major destructive sampling during the growing season. However, remote and non-contact detection methods offer an alternative approach to detecting plant changes in near real-time, even before visual symptoms and negative effects become visible (Gholizadeh & Kopačkova, 2019) . Ostivari et al. (2019) developed and evaluated a ground suitability model for rapeseed cultivation on calcareous ground in semi-arid regions in northwestern Iran, incorporating topographic factors, ground data and remote sensing data. Jiang & Wang (2019) give an overview of the role of satellite remote sensing in the simulation of river courses. Innovative methods such as satellite remote sensing, field spectroscopy, soil chemical analysis and GIS have been looked into as methods for monitoring soil organic matter (SOM), calcium carbonate ($CaCO_3$) and ground erodibility (K-factor) at Akrotiri Cape, Crete, Greece (Alexakis et al., 2019). Shang (2020) compares different bare ground extraction methods for the black soil zone and evaluates their applicability to AHSI/GF-5 data. Nguyen (2021) introduces a modified bare-bottom index (MBI) using shortwave infrared (SWIR) and near-infrared (NIR) wavelengths derived from Landsat 8 (OLI – Operational Land Imager).

Evolving remote sensing methods have greatly improved our ability to map and classify ground and analyze built-up urban areas. Pioneering studies such as that of Poggio et al. (2021) have looked at advanced land mapping techniques using remote sensing and demonstrated their effectiveness in distinguishing ground types and conditions. Similarly, the work of Yang et al. (2020) has been instrumental in demonstrating the use of remote sensing for the detailed analysis of urban areas, revealing the intricate patterns of urban sprawl and its impact on surrounding landscapes. These studies emphasize the versatility of remote sensing techniques in both urban and environmental contexts, offering valuable frameworks that our research builds upon. Specifically, our study extends these methods by focusing on the Kerch Peninsula, employing advanced spectral indices to detect the subtle differences between urbanized areas and bare ground. This approach not only contributes to the field of remote sensing but also provides practical insights for urban planning and environmental management.

The main objective of this study is to determine the optimal spectral index for distinguishing urbanized marine areas from bare ground on the Kerch Peninsula, a task that is critical given the rapid expansion of cities and their impact on the environment. Selecting the most effective spectral index is crucial for accurate land use classification, which in turn plays a central role in urban planning and environmental protection strategies. By focusing on the Kerch Peninsula, our research not only addresses a specific regional need, but also contributes to a broader understanding of interactions between cities and the environment. The results of this study aim to provide urban planners and environmental managers with reliable tools and methods to make better decisions in the face of urban growth challenges. As such, it is in line with global efforts to balance urban development and environmental sustainability and offers practical solutions that can be transferred to similar urban contexts worldwide.

2. MATERIALS AND METHODS

2.1. Research area

The Kerch Peninsula region is located in the eastern part of the Crimean Peninsula, bordered by the Sea of Azov to the north, the Black Sea to the south and the Kerch Strait to the east (Fig. 1). One of the special features of this region is the uniqueness of its social, economic and natural conditions, which are determined by the peculiarities of its geographical location, climate, relief and the level of socio-economic and economic development of the area.

Economic activity in this region is primarily focused on the agro-industrial complex, which provides employment for about a third of the entire population of the Kerch Peninsula. The most common agricultural crops grown by farmers on the peninsula are barley, peas and wheat. A total of 84 different farms with different ownership structures are involved in agriculture, the largest of which are "Vostok" and "Zolotoy kolos". In addition to the cultivation of cereals and legumes, animal husbandry and the production of dairy products, as well as the breeding of pigs and sheep have also developed on the peninsula.

Figure 1. Research area map

The development and extraction of gas from the East-Kazantip and North-Bulganaq deposits, as well as oil from the Semenovsk deposit, also play an important role in the economic structure of the peninsula.

The city of Kerch, located in the eastern part of the peninsula, is also an important economic component. Its main activities include shipbuilding, ship repair, fishing, and fish processing. In addition, transportation and logistics companies play an important role, transporting freight and passengers, such as the "Kerch Sea Trade Port" and the "Kerch Ferry Crossing". The largest shipbuilding and ship repair companies are the "Zaliv" plant and the "Fregat" and "Tral" shipyards, which build ships, tugs, ferries, and tankers.

One of the distinctive features of the Kerch Peninsula is the presence of mud volcanoes in the northeast and south. The areas adjacent to the mud volcanoes or mud lakes of the peninsula are characterized by the presence of small hills with white patches, consisting of haloids, boron minerals, and others, as well as oil stains and streams.

Figure 2. Examples of the Kerch Peninsula mud lake surface

2.2. Structural area

The brines of salt lakes (brine) are aqueous solutions saturated with salt (Fig. 2). Salt molecules are present in the form of ions due to electrolytic dissociation: cations (Na^{+}, Ca^{2+}, Mg^{2+}) and anions ($Cl^{-}, SO_4^{2-}, CO_3^{2+}, HCO_3^{-}$). Other ions, some of which may be of industrial importance (bromine, boron, potassium), are also present in the brines of lakes (Table 1).

Name	$T°C$	pH	NO_3	Br	CO_3	HCO_3	Na	Cl
Adjigol	33.3	8.2	0.5	-	0	0.8	2.6	74.5
Chokrak	-	-	1.1	-	0.2	0.9	73.0	98.4
Tobechik	34.6	9.2	0.9	1.9	0	0.9	98.3	159.5
Koyashskoye	34.8	7.9	1.0	2.2	0	0.4	108.0	180.2
Yerofeevskoye	35.3	9.5	0.2	-	0	0.3	19.7	28.4
Achi	31.1	9.8	0.11	0.14	0.05	0.2	11.9	14.2

Table 1. Chemical composition of Kerch Peninsula lake mud according to laboratory analysis

As shown in Table 1, the chemical composition of sludge and brine from different lakes on the Kerch Peninsula can vary considerably. Significant differences are observed not only in NO_3 and Br, but also in Na and Cl concentrations. This leads to the formation of fundamentally different environments whose optical properties differ considerably from each other. The alkaline pH values observed at all six sites indicate that the lakes are dominated by carbonate and bicarbonate species typically associated with alkaline environments. In addition, the presence of sodium and chloride ions at all sites indicates high salinity in the lakes, which is also consistent with the alkaline pH values.

The nitrate content of the lakes is relatively low, with values between 0.11 mg/L and 1.1 mg/L. This indicates that the nitrogen cycle is dominated by anaerobic processes, which convert nitrates to nitrogen gas. The low nitrate content is also consistent with the high salinity of the lakes, as the presence of salt can inhibit the activity of nitrifying bacteria.

Bromide is only present at three sites, which could be attributed to the specific geological or hydrological conditions of these locations. The high bromide concentration in Koyashskoye (2.2 mg/L) may be related to the presence of evaporites or the influence of brine inflows. The carbonate content is also relatively low, with values between 0 and 0.2 mg/L, suggesting that the lakes are not dominated by carbonate mineral precipitation.

Overall, the high salinity and alkaline conditions of these lakes suggest that they are influenced by a complex interplay of geology, hydrology, and biology. The presence of specific chemical types, such as sodium, chloride, and bicarbonate, can be used to understand the geochemical processes occurring in the lakes and their surroundings. However, further research, including more detailed geochemical and hydrological analyses, is needed to fully understand the conditions in these lakes and the factors that influence their chemical composition.

This makes it quite difficult to distinguish urbanized areas from bare ground, which necessitates the search for new extraction methods under the existing natural conditions.

2.3. Data and processing

Data from the Landsat-8 satellite from 2015 and field data for mapping urban areas and ground on the Kerch Peninsula were used for the study. Landsat 8 is a satellite-based remote sensing platform that provides images of the Earth's surface in several spectral bands. It has a total of 11 spectral bands, each with a different wavelength range and resolution (Table 2).

Band	Wavelength range (micrometers)	Resolution (meters)	Application
1	0.43 - 0.45	30	Blue
2	0.45 - 0.51	30	Green
3	0.53 - 0.59	30	Red
4	0.64 - 0.67	30	Near infrared (NIR)
5	0.85 - 0.88	30	Shortwave infrared (SWIR) 1
6	1.57 - 1.65	30	SWIR 2
7	2.11 - 2.29	30	SWIR 3
8	0.50 - 0.68	15	Panchromatic
9	1.36 - 1.38	30	Cirrus
10	10.60 - 11.19	100	Thermal infrared (TIRS) 1
11	11.50 - 12.51	100	TIRS 2

Table 2. Brief overview of the Landsat 8 bands

Bands 1-7 and 9 are referred to as Operational Land Imager (OLI) bands, while bands 10 and 11 are Thermal Infrared Sensor (TIRS) bands. The panchromatic band (band 8) has a higher resolution than the other bands, but it only provides grayscale images. The TIRS bands (10 and 11) are used for Earth surface temperature measurements.

The following indices were used to extract urbanized areas (Table 3):

Index name	Abbreviation	Bands	Equation
Normalized difference buit-up index	NDBI	NIR, SWIR	$\frac{SWIR - NIR}{SWIR + NIR}$
Buit-up index	BU	Red, NIR, SWIR	$NDBI - NDVI$
Built-up area extraction index	BAE	Green, Red, SWIR	$\frac{Red + L}{Green + SWIR}, L = 0.3$
New built-up index	NBU	Red, NIR, SWIR	$\frac{SWIR * Red}{NIR}$
Vegetation built-up index	VBU	Red, NIR, SWIR	$\frac{NDVI}{NDVI + NDBI}$
Urban index	UI	NIR, SWIR	$\left(\frac{SWIR - NIR}{SWIR + NIR} + 1\right) * 100$

Table 3. Spectral indices used in this research to separate urban areas from ground

The use of these indices aims to clearly separate urbanized areas from vegetation, water bodies and bare ground. The main challenge in distinguishing between urbanized areas and bare ground lies in their similar spectral characteristics and the complexity of land features and properties. In general, the spectral signature analysis for urbanized areas and bare ground on the Kerch Peninsula shows significant similarities (Figure 3).

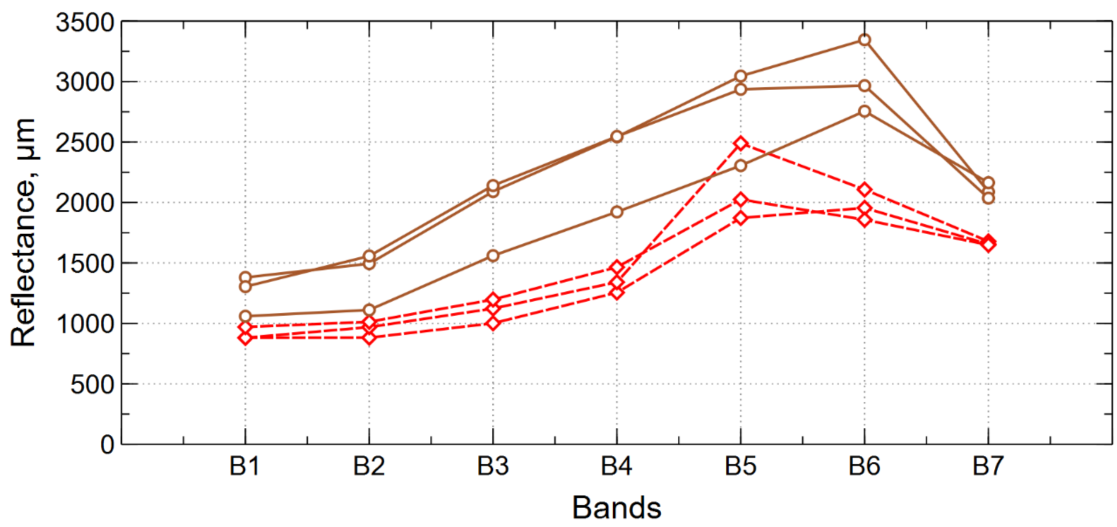

Figure 3. Comparison of the spectral signatures of urban areas (red) and ground (brown)

Overall, the spectral curves are similar for both bare ground and urbanized areas. The reflectance maximum for them falls on the fifth and sixth channels with wavelength ranges of 0.85-0.88 μm and 1.57-1.65 μm, respectively; the minimum - on the first 0.43-0.45 μm.

3. RESULTS

A series of spectral indices were calculated to analyze the possibilities for extracting urbanized areas from the Landsat 8 remote sensing data and distinguishing them from bare ground with similar spectral signatures, as shown in Figure 4, Table 3.

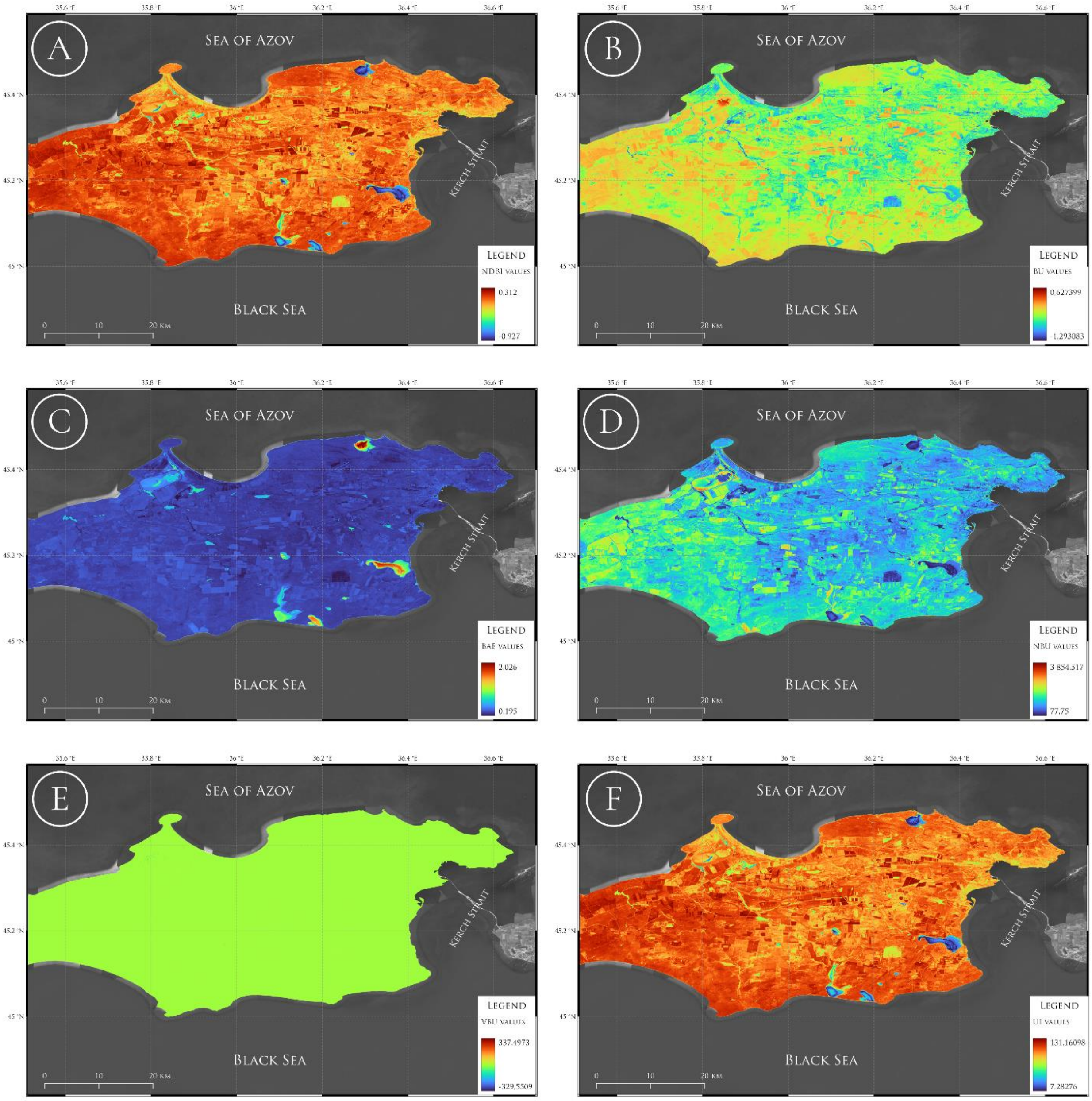

Figure 4. Calculating different spectral indices to extract urban areas from Landsat-8 data: A -- NDBI; B -- BU; C -- BAE; D -- NBU; E -- VBU; F -- UI.

Figure 5 shows that the VBU index is the least suited for the visual identification and differentiation of urbanized areas from ground. In fact, values around zero were assigned for the entire peninsula, except for some areas in the vicinity of the city of Kerch and the village of Schelkino. The BAE index is slightly better, allowing for the clear distinction of different ground cover types, but urbanized areas and ground are almost uniformly shown in the same color, making it difficult to clearly separate the two classes. The other indices, on the other hand, provide acceptable possibilities for such separation, especially in areas with the concentration of mud lakes (in NBU and BU indices, ground is marked with darker orange, while urbanized areas are shown in lighter shades of orange).

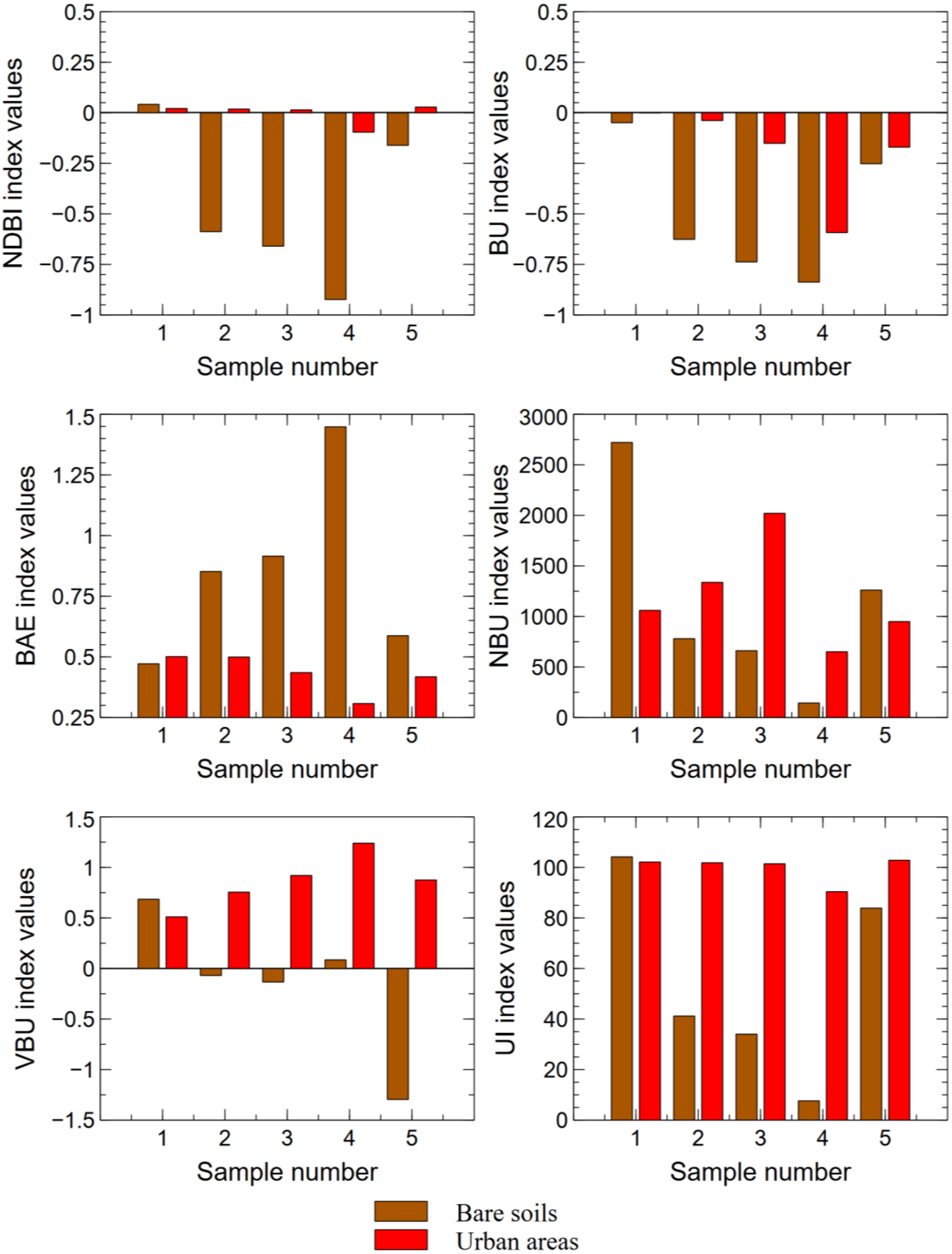

Figure 5. Calculated values of spectral indices for urban area extraction for each sample point

Figure 5 shows that the values of UI in urban areas range from 90.39944 to 102.82609, with a mean of 99.18045. VBU values range from 0.51083 to 1.23963, with a mean of 0.97511. NBU values range from 650.77368 to 2020.27209, with a mean of 1236.61479. BAE values range from 0.3076 to 0.50113, with a mean of 0.44658. BU values range from -0.59266 to -0.00094, with a mean of -0.26101. NDBI values range from -0.09601 to 0.02826, with a mean of -0.02099.

For bare ground, UI values range from 7.62445 to 104.17863, with a mean of 54.31198. VBU values range from -1.29562 to 0.68525, with a mean of -0.25152. NBU values range from 143.82869 to 2721.3042, with a mean of 1066.96614. BAE values range from 0.47152 to 1.44824, with a mean value of 0.94575. BU values range from -0.83755 to -0.04919, with a mean value of -0.42224. NDBI values range from -0.92376 to 0.04179, with a mean value of -0.30116.

Overall, the values of the individual spectral indices tend to be higher for urban areas than for bare ground, with some exceptions. For example, VBU values tend to be higher in urban areas, but there are also a few cases where bare ground had higher values. Conversely, BU values tend to be lower in urban areas, but there are a few cases where bare ground had lower values. These results suggest that spectral indices can be useful for distinguishing urban areas from bare ground, but careful analysis is necessary to avoid misclassification.

Furthermore, the greatest difference between the index values for urban areas and bare ground was observed for the NDBI and VBU indices. Potentially, these two indices may be used to accurately distinguish ground from man-made structures. Other indices show fairly similar results for each point, which leads to subsequent misinterpretation of the results and reduces the accuracy of satellite data classification using machine learning.

The distribution of minimum and maximum values of different spectral indices shown in Table 4 allows clear identification of class boundaries for some indices, and consequently an almost unambiguous differentiation of urbanized areas and bare ground.

	Minimum value	Maximum value
UI_{urban}	90.39944	102.82609
UI_{soil}	7.62445	104.17863
VBU_{urban}	0.51083	1.23963
VBU_{soil}	-1.29562	0.68525
NBU_{urban}	650.77368	2020.27209
NBU_{soil}	143.82869	2721.3042
BAE_{urban}	0.3076	0.50113
BAE_{soil}	0.47152	1.44824
BU_{urban}	-0.59266	-0.00094
BU_{soil}	-0.83755	-0.04919
$NDBI_{urban}$	-0.09601	0.02826
$NDBI_{soil}$	-0.92376	0.04179

Table 4. Distribution of minimum and maximum values of each index for urbanized areas and bare ground

The minimum and maximum values for each index were determined separately for urban areas and ground. The UI values for urban areas ranged from 90.39944 to 102.82609, while for bare ground they ranged from 7.62445 to 104.17863. The VBU index values for urban areas ranged from 0.51083 to 1.23963, while for bare ground they ranged from -1.29562 to 0.68525. NBU index values for urban areas ranged from 650.77368 to 2020.27209, while for land areas they ranged from 143.82869 to 2721.3042. BAE index values for urban areas ranged from 0.3076 to 0.50113, while for bare ground they ranged from 0.47152 to 1.44824. BU index values for urban areas ranged from -0.59266 to -0.00094, while for bare ground they ranged from -0.83755 to -0.04919. Finally, the NDBI index values for urban areas ranged from -0.09601 to 0.02826, while they ranged from -0.92376 to 0.04179 for bare ground.

The analysis of the values presented in Table 3 shows a clear distinction between urban areas and bare ground, as indicated by the different ranges of indices for each type of surface. The highest values for urban surfaces were observed for NBU and UI indices, while the VBU index showed a more moderate range. For bare ground, on the other hand, the NBU index had the largest range and the VBU index had a clearly negative minimum value. BAE index showed values closer to 1 for bare ground, indicating the presence of vegetation, while the values for urban areas were closer to 0. Finally, the NDBI index showed negative values for urban surfaces and positive values for bare ground, reflecting the higher presence of built-up areas in the former and the absence of these areas in the latter.

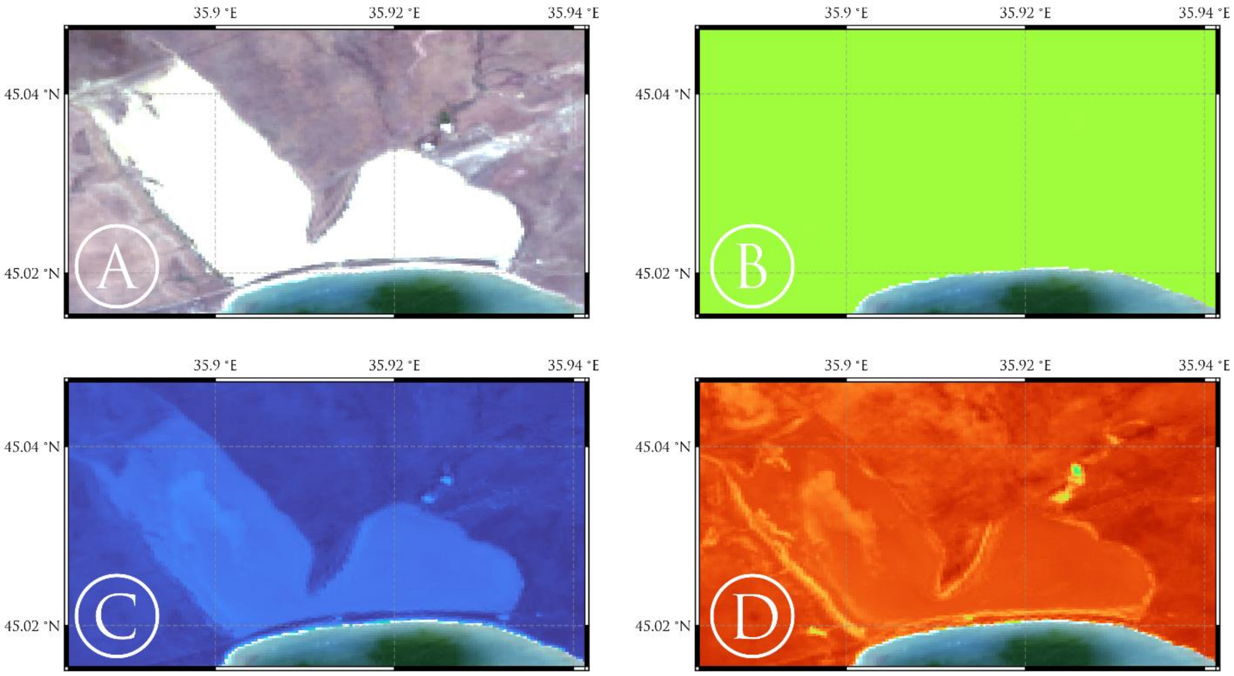

Figure 6. Visual representation of the areas occupied by the class "bare ground" on the example of Lake Kachik (A - RGB Composite; B - VBU; C - BAE; D - NDBI)

The area covered by the "bare ground" category in the vicinity of Lake Kachik on the Kerch Peninsula is presented in Figure 6. The RBG composite image shows that in reality, the lake surface is completely covered by solid matter, i.e. dried mud.

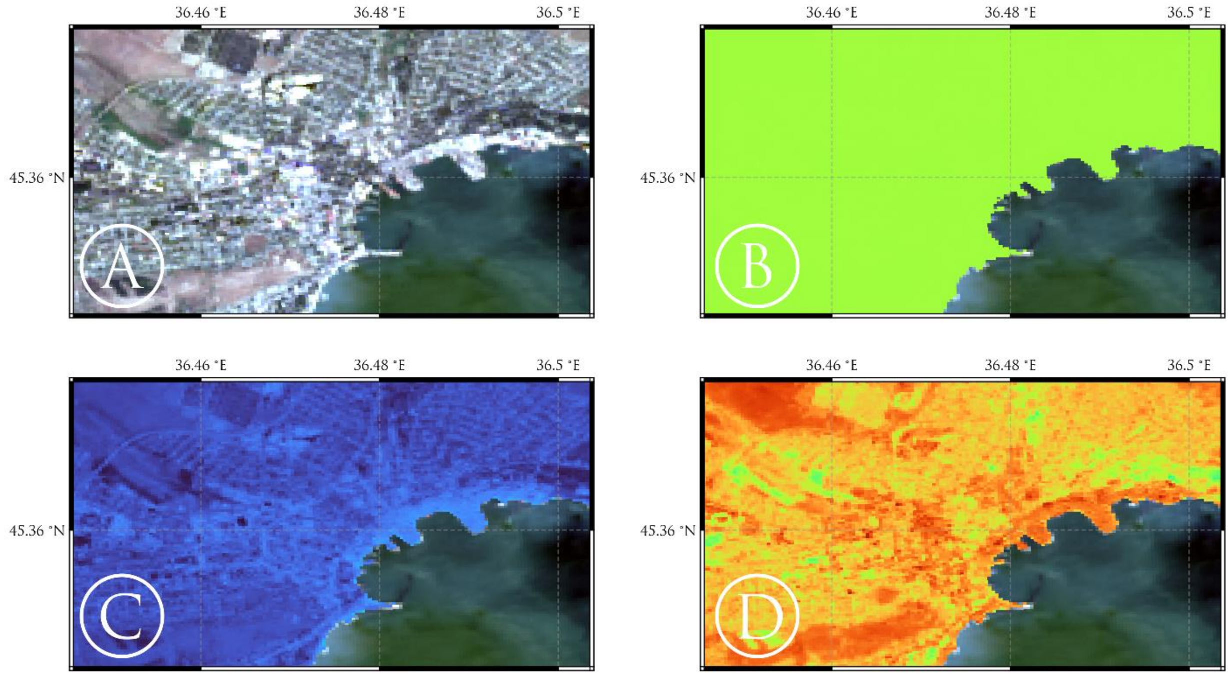

Figure 7. Visual representation of the areas occupied by the "urban area" category on the example of the city of Kerch (A - RGB Composite; B - VBU; C - BAE; D - NDBI)

Visually and by their spectral characteristics, the given area resembles urbanized areas, which are depicted in Figure 7 in white color. The urbanized areas in Figure 7 are not evenly distributed, but rather interspersed with woody and shrubby vegetation, which is typical of urban development. Analyzing the obtained spectral indices, it is noticeable that VBU and BAE indices give practically identical images of "urban area" and "bare ground", which is unsuitable for a clear cut identification of the categories. The NDBI index, on the other hand, allows a clearer distinction between them.

Here, urbanized areas are represented by lighter shades of orange, while ground is shown in a darker red hue. A small problem, perhaps, could be the western part of the lake, where the shoreline visually resembles manmade structures. It is worth noting the BAE index separately. Despite seemingly different ranges of index distribution, there are no visual differences between them.

4. DISCUSSION

The growing application of spectral indices for urbanized area classification emphasizes their critical role in addressing the challenges posed by rapid urbanization. This is evident in the body of research that has emerged in recent years, exploring various indices for urban area mapping and analysis.

For example, Santra (2020) focused on the automated extraction of impervious built-up areas using Resourcesat LISS-III imagery, highlighting the Impervious Built-up Index (IBUI) as the most accurate for this purpose. This finding corresponds to the broader remote sensing trend where the quest for precision in urban area extraction has led to the development and refinement of various spectral indices. By contrast, this study emphasizes the effectiveness of NDBI and VBU indices, contributing to the understanding of their specific applications in distinguishing urbanized marine territories from bare ground. Similarly, Prasomsup et al. (2020) studied the Modified Built-Up Index using Landsat 8 data, finding it more accurate than the original Built-Up

Index for classifying built-up areas. This points to a significant development in spectral index refinement, underscoring the evolving nature of these tools to meet specific environmental and urban demands. The presented research, in its focus on NDBI and VBU, complements this trend by offering a nuanced understanding of how these indices can be applied to distinguish specific land covers, particularly in coastal urban settings.

The study by Son et al. (2020) in San Salvador gives a crucial insight into the relationship between land surface temperature and urban growth using NDBI. These findings, showing a significant correlation between temperature and NDBI, resonate with this research, suggesting that NDBI is not only effective for urban area classification but also for understanding the environmental impacts of urbanization, such as changes in local temperature regimes. Finally, Ezimand et al. (2021) further expanded on this by studying the effects of urban structures on land surface temperature changes in Tartu, Estonia. Their observation that NDBI has a higher correlation with temperature than fractional vegetation cover offers an interesting perspective on the multifaceted nature of the impact of urbanization. It emphasizes the potential of NDBI to characterize urban environmental changes, a topic that is central to this study as well.

The findings of this study, which demonstrate the effectiveness of NDBI and VBU indices in classifying urbanized areas, have significant implications for urban planning, land use management, and environmental protection . The correct identification and delineation of urbanized areas using these spectral indices can greatly enhance the accuracy of urban planning strategies. This accuracy is crucial to meet the growing demands of urban populations, while balancing the preservation of the environment and bare ground. In the realm of land use management, the study's results give planners and decision-makers reliable tools to better understand urban growth patterns. The ability to effectively distinguish urbanized areas from bare ground using spectral indices like NDBI and VBU is particularly valuable for monitoring and managing urban sprawl. This capability is essential for sustainable development, as it facilitates the optimal allocation of land resources, ensuring that urban expansion does not encroach upon ecologically sensitive areas or agricultural land. Moreover, the findings have profound implications for environmental protection. By correctly classifying urbanized areas, the study contributes to a deeper understanding of the environmental impacts of urbanization, such as changes in land surface temperature and the urban heat island effect. This understanding is critical for developing strategies to mitigate the environmental impacts of urban growth, including the design of green areas, urban forests, and other ecological interventions. Furthermore, these insights can inform policy and affect practice in urban and environmental management. Policymakers can leverage these findings to develop more informed and effective urban policies that prioritize both development and environmental sustainability. For instance, urban zoning regulations, land use planning, and urban design can all benefit from the correct classification of urban areas using NDBI and VBU indices.

However, the findings of the study can be interpreted in several ways. First, these results support the hypothesis that specific spectral indices can accurately differentiate between urbanized and bare ground. This is significant in the context of urban sprawl, where precise demarcation of urbanized areas is crucial for effective urban management and policymaking. Second, the research illuminates the intricate relationship between urban expansion and ground cover changes. The ability of NDBI and VBU indices to distinctly classify urban areas highlights the dynamic nature of urban landscapes and the potential of remote sensing technologies in monitoring these changes. Moreover, the findings have implications for environmental management. The clear demarcation of urbanized areas helps understand the environmental impacts of urbanization, such as habitat disruption, changes in local climate, and increased pressure on natural resources. This understanding is vital for developing strategies aimed at mitigating the adverse effects of urban growth and promoting sustainable urban development. Furthermore, the study's outcomes suggest that the use of spectral indices like NDBI and VBU could be integrated into land use planning and environmental conservation frameworks. By providing a more nuanced understanding of urban land cover, these indices can inform the development of more targeted and effective urban policies and strategies. Lastly, the research underscores the need for ongoing refinement of remote sensing techniques in urban studies. As urban environments continue to evolve, the continuous improvement of classification indices will be essential for staying abreast of these changes and providing accurate, up to date information.

Study results open several avenues for future research. One key area is the further refinement of these indices. Future studies could explore the development of more nuanced indices or modifications of NDBI and VBU to enhance accuracy, especially in diverse geographical contexts or under varying environmental conditions. Additionally, integrating these indices with other data sources, such as socio-economic data, demographic information, and climate models, could provide a more comprehensive understanding of the urban ecosystem. Such integrations could be particularly useful in developing predictive urban planning models, where anticipating future urban growth and its environmental impacts become crucial. Another promising direction is the application of these spectral indices to monitoring and managing urban green areas. As urban areas expand, maintaining and increasing urban vegetation is vital for environmental sustainability and urban climate regulation. Research into how NDBI and VBU can assist with the management and optimization of urban green areas could provide valuable insights into sustainable urban development. Moreover, there is a significant opportunity to apply these indices in studies focused on urban heat island effects. Understanding the relationship between urbanization, as indicated by NDBI and VBU, and local temperature variations could inform strategies to mitigate the urban heat island effect, contributing to more livable urban environments. Finally, considering the rapid advancement of remote sensing technologies and data processing algorithms, future research can also explore the application of machine learning and artificial intelligence to improve the efficiency and accuracy of urban area classification using spectral indices.

5. CONCLUSION

The study of the use of spectral indices to extract urbanized areas from Landsat-8 remote sensing data has provided important insights. It was found that while the VBU and BAE indices showed limited effectiveness in distinguishing urbanized areas from ground, they were not completely effective in distinguishing urban areas from ground. However, other indices, particularly the NDBI, showed considerable potential for this purpose, especially in regions characterized by muddy lakes.

The study found that spectral index values were generally higher for urban areas than for bare ground, with NDBI and VBU indices showing the most significant differences between urban areas and bare ground. This suggests their potential utility in accurately segmenting these two land cover types. The distribution of minimum and maximum values of different spectral indices facilitated the identification of clear category boundaries in some instances, enabling the precise differentiation of urbanized areas from bare ground.

It was emphasized that while spectral indices are valuable tools for distinguishing between urban areas and bare ground, caution is needed to avoid misclassification. Choosing the appropriate indices is crucial for ensuring accurate classification results. Inaccurate interpretation and reduced accuracy in the classification of satellite data can occur when indices with overlapping results are used, especially in machine learning applications.

In conclusion, the study highlights the effectiveness of spectral indices such as NDBI and VBU in extracting urban areas from remote sensing data. The results are of practical importance for urban planners and decision makers as they provide important insights for informed urban planning, land use management and environmental protection. The study advocates careful analysis and selection of appropriate spectral indices to avoid misclassification and ensure the correct identification of category boundaries, which is critical for accurate land classification. These insights not only contribute to the field of remote sensing but also provide valuable tools and methodologies for urban planning and environmental management professionals. The research underscores the importance of nuanced analysis in the application of spectral indices, paving the way for more informed and effective decision-making in urban and environmental planning.

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CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship and publication of this article.

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