Application of Multi-Spectral Index from Sentinel-2 Data for Extracting Build-up Land of Hanoi Area in the Dry Season

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Abstract

A remote sensing index is a simple and effective way to highlight a specific land cover. Therefore, in this study, we try to increase the accuracy of the urban land map developed for Hanoi city by focusing on determining the appropriate combination of spectral indices calculated from satellite image data. To conduct the study, four spectral indices were selected including namely normalized difference tillage index (NDTI), bare soil index (BSI), dry bare soil index (DBSI) and the normalized difference vegetation index (NDVI). All these spectral indices are calculated from Sentinel-2 data acquired in the dry season. The two combinations are created from the superposition of NDTI/BSI/NDVI and NDTI/DBSI/NDVI spectral index layers. The use of the "K-means" algorithm as an unsupervised classifier provides rapid and automatic urban land detection. The results show that the BSI index performs better than using the DBSI index. As a result, the BSI index brings improvements: bare soil types and accumulation processes are better differentiated, with overall accuracy increasing by 5.82% and Kappa coefficient increasing by 11.1%. The results show that the NDTI/BSI/NDVI multi-spectral index dataset is suitable for mapping urban areas with the potential to help better urban management during the dry season.

Keywords: *Sentinel-2 data, K-means algorithm, Bare Soil Index (BSI), Dry Bare Soil Index (DBSI), Normalized Difference Tillage Index (NDTI)*

1. Introduction

Remote sensing imagery constitutes a form of data suitable for monitoring and mapping of changes in built-up within within metropolitan regions, particularly as the effects of population expansion and urbanization escalate [1]. One of the main problems in mapping urban area is determining the change in land use from non-residential to residential [2-5]. Mapping the built-up in urban regions holds significance as the presence of such land type serves as an indicator of urban growth [6]. The techniques for extraction of built-up area from satellite imagery can be grouped into two types: (1) techniques based on conventional multi-spectral image classification such as supervised, unsupervised, object based or deep learning classification (2) techniques based on normalized difference indices such as normalized difference built-up index (NDBI), principal component analysis (PCA) based built-up area index (PCABI), enhanced built-up index (EBI), urban index (UI), etc [7].

Classification methods based on multispectral image classification techniques often fail to achieve reliable accuracy, typically below 80%, due to the spectral confusion of heterogeneous urban built-up land class compared to other land use classes [8]. Instead, many researchers have experimented with normalized difference indices using specific spectral bands for automatic extraction of built-up land from satellite images [9-17]. In practice, the use of spectral indices such as spectral bands perform better than using the original spectral bands [8] and spectral indices play an important role in extraction of built up [18].

With the availability of Landsat satellite archive i.e. the largest series of space-borne earth observation data as well as at good spatial resolution provides huge opportunities for urban mapping [15]. Many studies shown the suitability of Landsat data for urban mapping and monitoring [1-3,6,8,9,15]. However, studies including [5,7,19,20] have leveraged the advantages of Sentinel-2 satellite imagery data to propose various applications of built-up index in urban land classification. Furthermore, some studies such as the work of [19] concluded that Sentinel-2 provides higher accuracy for urban built-up areas compared to Landsat-8 satellite imagery data. Additionally, a study by [20] found that Sentinel-2 data performs better than Landsat-8 data in mapping urban built-up land cover by using a combination of different spectral indices. Valdiviezo-N et al., 2018 [21]suggests that all utilized built-up indices, such as the Normalized Difference Built-Up Index (NDBI), Index-Based Built-Up Index (IBI), New Built-Up Index (NBI), Band Ratio for Built-Up Area (BRBA), Normalized Built-Up Area Index (NBAI), Biophysical Composition Index (BCI), Modified Built-Up Index (MBI), Built-Up Area Extraction Index (BAEI), and Combinational Build-Up

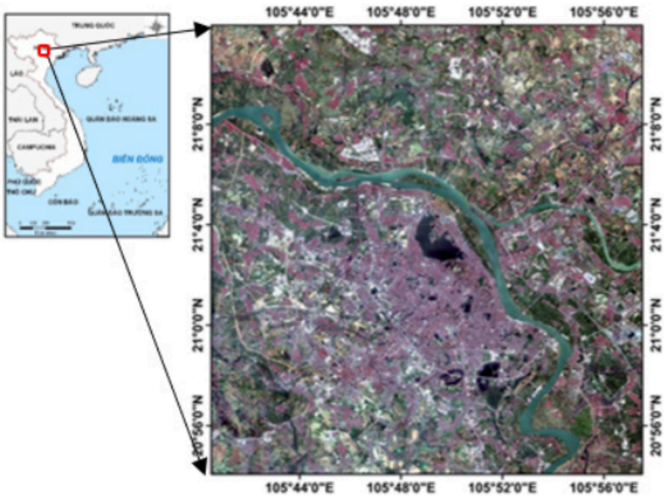


Fig. 1. Location of Study Area
Rys. 1. Lokalizacja obszaru badawczego

Tab. 1. Spectral bands and resolutions of Sentinel-2 MSI sensor
Tab.1 Pasma widmowe i rozdzielczości sensora Sentinel-2 MSI

Band Specification	Wavelength Range (nm)	Resolution (m)
Band 1 - Coastal	433–453	60
B2 - Blue	458–523	10
B3 - Green	543–578	10
B4 - Red	650–680	10
B5 - Red-edge 1	698–713	20
B6 - Red-edge 2	733–748	20
B7 - Red-edge 3	773–793	20
B8 - Near infrared (NIR)	785–900	10
B8A - Near infrared narrow (NIRn)	855–875	20
B9 - Water vapour	935–955	60
B10 - Shortwave infrared/Cirrus	1360–1390	60
B11 - Shortwave infrared 1 (SWIR1)	1565–1655	20
B12 - Shortwave infrared 2 (SWIR2)	2100–2280	20

Tab. 2. Different spectral indices were employed in this study on Sentinel-2 data
Tab. 2. Zastosowane różne wskaźniki widmowe dla danych z Sentinel-2

Index Name	Index Id	References	Formula on Sentinel -2 image
Normalized Difference Tillage Index	NDTI	Deventer, 1997 []	(B11-B12) / (B11+B12)
Bare Soil Index	BSI	Rikimaru and Miyatake, 1997 []	((B11+B4)-(B8+B2))/((B11+B4)+(B8+B2))
Dry Bare-Soil Index	DBSI	Rasul et al., 2018 []	((B11-B03)/(B11+B03)) –NDVI
Normalized Difference Vegetation Index	NDVI	Tucker, 1979 []	(B08-B04)/(B08+B04)

Index (CBI), are influenced by seasonal variations, particularly during dry months when the similarity between the spectra of bare soil and urban areas increases. As a result, these indices led to a less accurate mapping of urban areas during dry periods in the study area.

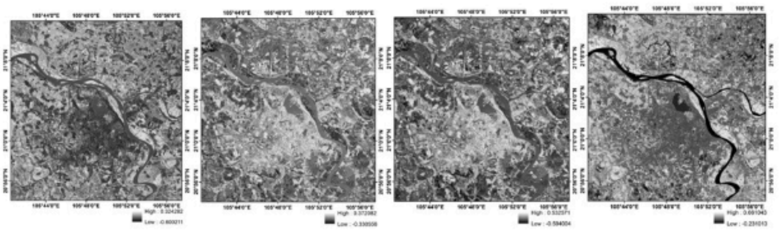
The outcomes discussed previously suggest an enhancement in mapping urbanized regions during dry seasons through the utilization of spectral indices layer stacking technique. Given that semi-arid zones are characterized by sparse vegetation and extensive bare soil, especially during dry periods, two bare soil indices were opted for. The initial one is the Bare Soil Index (BSI) introduced by Rikimaru and Miyatake, 1997 [13], aimed at improving the recognition of bare soil areas and fallow lands, thus distinguishing them from vegetative cover and other land cover types. Recently, the BSI index has seen widespread adoption in various studies, such as [13,23,24], the next index is the Dry Bare-Soil Index (DBSI), a recent creation by Rasul et al., 2018 [6], as an index for detecting bare areas in arid climates.

In recent years, a novel form of dataset emerged through the combination of different spectral indices. The research conducted by Ettehadi Osgouei et al., 2019 [24] employed the Normalized Difference Tillage Index (NDTI) – originally developed by Deventer, 1997 [25] and also utilized in studies by [12,23] – which has used SWIR bands of the Sentinel-2 images and succeeded in differentiating bare land and built-up area classes better than the other spectral indices used in the study. This approach effectively distinguished between bare land and built-up area categories, surpassing the performance of other spectral indices utilized in the investigation. Furthermore, the multi-index NDTI was subjected to classification using the machine-learning-based SVM algorithm [25], resulting in enhanced mapping accuracy of heterogeneous urban areas.

The research article explores the rapid and accurate map-

Fig. 1. Location of Study Area
Rys. 1. Lokalizacja obszaru badawczego

Spectral Indices	BSI	DBSI	NDTI	NDVI
BSI	1.000000	0.952421	0.173467	-0.305834
DBSI	0.952421	1.000000	0.124518	-0.332879
NDTI	0.173467	0.124518	1.000000	0.534376
NDVI	-0.305834	-0.332879	0.534376	1.000000



a) NDTI Index b) BSI Index c) DBSI Index d) NDVI Index

Fig. 2. Spectral indices result used in the study (a) NDTI (b) BSI (c) DBSI (d) NDVI
Rys. 2. Wyniki wskaźników widmowych wykorzystanych w badaniu (a) NDTI (b) BSI (c) DBSI (d) NDVI

Tab. 4. Statistical values of spectral indices were employed in this study on Sentinel-2 data
Tab. 4. Ocena statystyczna wykorzystanych wskaźników spektralnych w oparciu o dane Sentinel-2

Spectral indices	Min	Max	Mean	StdDev	Range value
BSI	-0.445267	0.552146	0.184725	0.052132	From -0.445267 to 0.552146
DBSI	-0.394781	0.573225	0.236719	0.073513	Từ -0.394781 đến 0.573225
NDTI	-0.326284	0.337416	0.071523	0.043426	Từ -0.326284 đến 0.337416
NDVI	-0.384516	0.901425	0.101642	0.072846	Từ -0.384516 đến 0.901425

ping of built-up land during the dry season through testing a new dataset that combines several spectral indices sourced from Sentinel-2 satellite imagery with the aim of identifying multi-spectral combinations for urban built-up land extraction. In this experiment, we leverage the advantages of the new Sentinel-2 satellite imagery data with a spatial resolution of 10 meters, which is widely used and freely available. We chose Hanoi city as the research area to carry out the process of distinguishing between bare land and urban built-up land during the dry season, surrounded by a large area and heterogeneous bare land.

2. Study area and data used

2.1 Study area

Research Area Hanoi is the capital city of Vietnam, covering an area of 3,359.82 square kilometers with a population of 8.4 million people. The terrain of the area includes the central plain region and hilly areas in the northern and western parts of the city. The climate of the Hanoi area is divided into two main seasons: the rainy season (from April to October) and the dry season (from November to March), but the weather is further categorized into four seasons due to transitional months. In 2023, Hanoi established the General Construction Planning for the Capital Hanoi until 2030 and vision until 2050 for a city with 9.1 million inhabitants by 2030 and over 10 million people by 2050. The location of the research area within the city is shown in Figure 1.

2.2 Data used

The Sentinel-2 sensor is a multispectral sensor that was launched in 2015. Sentinel-2 has 13 bands covering the VNIR region with 8 bands and the SWIR region with 2 bands having a spatial resolution of 10, 20, and 60 m. The swath width is 290 km. It consists of two multispectral satellites, Sentinel-2A and Sentinel-2B. The key mission objectives for Sentinel-2 are: (1) to provide systematic global acquisitions of high-resolution multi-spectral imagery with a high revisit frequency, (2) to provide enhanced continuity of multi-spectral imagery provided by the SPOT series of satellites, and (3) to provide observations for the next generation of operational products such as land-cover maps, land change detection maps, and geophysical variables. Consequently, Sentinel-2 will directly contribute to the Land Monitoring, Emergency Response, and Security services [26]. Data Used Sentinel-2 satellite imagery data was chosen for the research area because this satellite imagery data is freely available at https://scihub.copernicus.eu.

The Sentinel-2 satellite imagery data was acquired and processed at level 2A (product name: S2B_MSIL2A_20240212T032849_N0510_R018_T48QWJ_20240212T054533) and has been georeferenced. The dataset was collected on February 12, 2024, corresponding to the driest month of the year covering the research area, including Hanoi city. The selected satellite imagery data from this date provides good observation of both bare land and urban built-up areas, which can be distinguished because there is no mixed vegetation cover within the bare land due to the coincidence with the end of the harvest season in the region.

3. Methodology

3.1 Pre-processing

The data were provided as level L2A data captured under clear atmospheric conditions (cloud coverage = 0.01%) in the dry season. The process of overlayering spectral channels and cutting the research area is conducted using tools within version 8.0 of the SNAP software. The image processing tools for Sentinel-2 satellite imagery can be found at http://step.esa.int/main/download/.

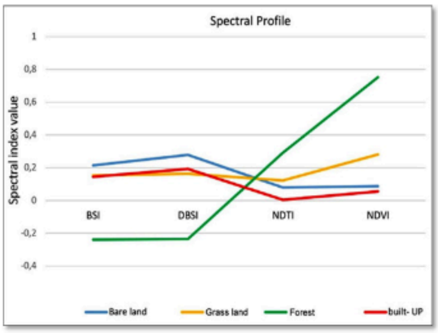


Fig. 3. Simplified spectral signatures represented by the mean of the major categories of Hanoi land cover for the multi-index image
Rys. 3. Uproszczone sygnatury widmowe reprezentowane przez średnią głównych kategorii pokrycia terenu Hanoi dla obrazu wieloindeksowego

Tab. 5 The built-up area extracted using both multi-index of Hanoi city in the Dry Season
Tab. 5. Powierzchnia zabudowana wyodrębniona przy użyciu obu wskaźników miasta Hanoi w porze suchej

Multi Index Used	Built-up area		Others		Total	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
NDTI/BSI/NDVI	593,23	57,29	442,24	42,71	1035,47	100
NDTI/DBSI/NDVI	595,56	57,52	439,91	42,48	1035,47	100
NDTI	531,34	51,31	504,13	48,69	1035,47	100

3.2 Processing

3.2.1. Calculation of spectral indices

1. Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is a remote sensing method that uses the reflectance of light in the visible and near-infrared (NIR) wavelengths to determine the amount and health of vegetation in an area. NDVI is widely used in agriculture, forestry, and ecology to monitor the growth and health of vegetation and to identify areas of stress or damage [27]. NDVI values can also be used to map and classify vegetation types, and to detect changes in vegetation cover over time. Simply put, the Normalized Difference Vegetation Index is an indicator of a plant's health entirely based on how the cell structures reflect the different light waves in visible and near-infrared bands.

NDVI is calculated by subtracting the reflectance of the NIR band from the reflectance of the red band and then dividing that value by the sum of the reflectance of the NIR and red bands. NDVI values range from -1 to 1, with -1 indicating no vegetation, 0 indicating bare soil or water, and values closer to 1 indicating greater amounts and healthier vegetation. The formula below for the evaluation of NDVI:

$$NDVI = (NIR-Red)/(NIR+Red) \quad (1)$$

The values range from -1 to +1. A higher or more positive value indicates greater plant vigor and general health.

2. Normalized Difference Tillage Index (NDTI)

The urban areas had higher blue reflectance than bare soil as a result of the type of building materials, mainly concrete, used for roof surfaces and walls. The NDTI index of van Deventer et al. 1997 [25], which is calculated as:

$$NDTI= (SWIR1-SWIR2) / (SWIR1+SWIR2) \quad (2)$$

3. Dry Bare-Soil Index (DBSI)

Inspection of the Sentinel-2 bands suggested that differentiation of these classes could be done based on spectral values in the SWIR1 and Green bands. In these bands, generally the digital number value (DN) of bare land is slightly higher than the DN of the built-up class [6].

$$DBSI = ((B11-B03)/(B11+B03)) – NDVI \quad (3)$$

The DBSI values can be between –2 to +2, and higher numbers represent more bare soil. An appropriate threshold for the bare soil class can be used for mapping bare soil and non-bare soil areas. Based on a test carried out with a sample of bare soil pixels, a DBSI value 0.26 and higher was delineated as bare soil for the study area, and areas with lower values were delineated as other classes.

4. Bare Soil Index (BSI)

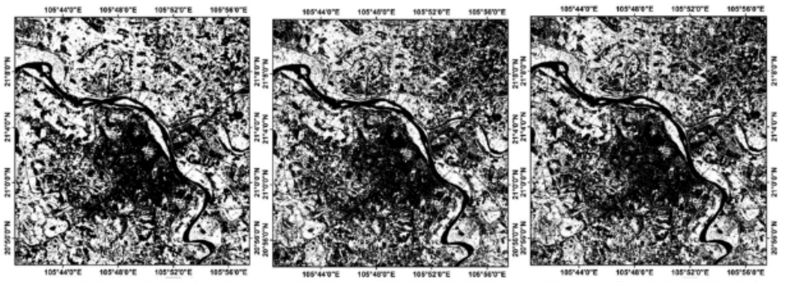
Bare Soil Index (BSI) is a numerical indicator that combines blue, red, near infrared and short wave infrared spectral bands to capture soil variations. These spectral bands are used in a normalized manner. The shortwave infrared and the red spectral bands are used to quantify the soil mineral composition, while the blue and the near infrared spectral bands are used to enhance the presence of vegetation. BSI can be used in numerous remote sensing applications, like soil mapping, crop identification (in combination with NDVI) etc [13]. To calculate the BSI with the following formulas:

$$BSI = ((B11+B4) - (B8+B2))/((B11+B4) + (B8+B2)) \quad (4)$$

All the selected spectral indices are specifically described in (Table 2) and are calculated based on the spectral bands of Sentinel-2 MSI satellite imagery (Table 1).

3.2.2. Multi-Index development

The correlation coefficients between the selected spectral indices are shown in (Table 3). A high correlation is evident between both bare soil indices (BSI and DBSI) within the research area. Conversely, a low correlation is observed be-



a) Binary of NDTI from K-means classifer (Black colour: Built-up area; White colour: Non Built-up area)
b) Binary of NDTI/BSI/NDVI from K- means classifer (Black colour: Built-up area; White colour: Non Built-up area)
c) Binary of NDTI/DBSI/NDVI from K- means classifer (Black colour: Built-up area; White colour: Non Built-up area)

Fig. 4. Binary image resulting from K- means classifer of (a) NDTI (b) Multi-Index (NDTI-BSI-NDVI) (c) Multi-Index (NDTI -DBSI-NDVI
Rys. 4. Obraz binarny wynikający z klasyfikatora K- oznacza (a) NDVI (b) Multiindeks (NDTI-BSI-NDVI) (c) Multiindeks (NDTI -DBSI-NDVI)

Tab. 6. Accuracy Assessment of binary Images resulting
Tab.6. Ocena dokładności uzyskanych obrazów binarnych

	NDTI Index		**Multi-Index NDTI/BSI/NDVI**		**Multi-Index NDTI/DBSI/NDVI**	
Accuracy types	User Accuaracy (UA) %	Producer Accuaracy (PA) %	User Accuaracy (UA) %	Producer Accuaracy (PA) %	User Accuaracy (UA) %	Producer Accuaracy (PA) %
Built-up	79.32	89.32	85.84	92.76	81.38	83.33
Non Built-up	91.22	83.84	95.26	91.22	89.28	88.46
Overall accuracy (%)	86.43		91.96		86.14	
Kappa Coefficient (%)	72.24		82.34		71.24	

tween the built-up area index (NDTI) and both BSI and DBSI. Meanwhile, the BSI index exhibits the lowest correlation with the NDVI index. The correlation between NDVI and NDTI indices is moderate.

Based on the degree of relationship discussed among the four spectral indices, two different combinations are proposed through a layer stacking process to enhance spectral differences between three main land cover classes (built-up area, bare soil, vegetation cover). The combinations are achieved by retaining both NDTI and NDVI indices, with the NDTI/BSI/NDVI trio being the first combination, and the NDTI/DBSI/NDVI trio being the second combination. These composite spectral indices are compared with the NDTI spectral index to determine the most accurate result for extracting built-up areas. Furthermore, to evaluate the impact of the bare soil index on the original NDTI/NDVI combination aimed at reducing misclassification between bare soil and built-up areas.

3.2.3 Extraction of urban built-up land by using the K-means method

Urban built-up land in the study area primarily comprises residential and industrial zones, roads, and other impervious surfaces. However, the non-urban built-up land includes forests, grasslands, and bare land. To achieve high-accuracy separation between these two main classes (built-up and non-built-up areas), binarization was utilized. However, the author Zuur et al., 2007 [28] reported that highlighting a specific land cover type by determining optimal thresholds is a major challenge.

3. Results and Discussion

3.1. Results of spectral indices

In this study, ENVI 5.1 software with the "Band Math" tool was used to calculate the spectral indices provided for further analysis. The calculated results of the spectral indices for the research area are presented in Figure 2.

The spectral profiles presented in Figure 3 show that the NDVI index highlights vegetation areas with large positive values, depicted by shades of gray and white observable in the 3D image (Figure 3). Additionally, the BSI and DBSI emphasize uncultivated and abandoned fields. Average values refer to built-up areas, while low values indicate vegetation cover. Vegetation and bare soil in areas with positive NDTI values and urban built-up land are represented by low positive NDTI values. Conversely, constructed structures yield negative values, depicted by darker pixels in Figure 3. Moreover, the statistical values of the four spectral indices can be found in Table 3, where low standard deviation values are observed for all the spectral indices used.

Based on the analysis of the spectral profiles presented in Figure 4, the process of mapping built-up land from other primary land cover types such as bare soil and vegetation can be easily achieved using the unsupervised classification algorithm K-means developed by [29]. The algorithm is applied for quick and accurate clustering of predefined classes [30]. The K-means algorithm has been successfully utilized to extract a specific land cover class in a region from a single spectral index result [9]. Additionally, the work of [31] has demonstrated the effectiveness of the algorithm for land cover classification based on multi-spectral datasets. The extraction of urban built-up land layers using the K-means algorithm is performed using ENVI 5.1 software.

3.2. Results of urban built-up land by using the K-means method

The results of the urban built-up land layer extraction using the NDTI index and the selected multi-spectral dataset are presented in Figure 4. Statistical data generated from the classification results of spectral indices using the K-means algorithm are shown in Table 5.

Based on the surface area coverage values of each land cover type extracted from the multi-spectral dataset in Table 5, we observe that the area of built-up land classified from the NDTI/BSI/NDVI multi-spectral dataset is 593.23 km^2, accounting for approximately 57.29% of the total study area; this built-up land area is smaller than the corresponding area classified from the NDTI/DBSI/NDVI multi-spectral dataset, which is 2.32 km^2, and larger than the built-up land area when using only the NDTI index, which is 61.89 km^2.

3.3. Accuracy Assessment

The accuracy assessment was conducted using the stratified random sampling method [32], which recommends a minimum of 150 points for each class; 300 random points were distributed among the built-up and non-built-up classes. Additionally, high-resolution images from Google Earth taken on the same day were utilized as reference data. Subsequently, the error matrix [33] was computed as a result of assessing the classification accuracy, including overall accuracy and the Kappa coefficient, producer's accuracy (PA), and user's accuracy (UA). All accuracy metrics are presented in Table 5.

The error matrix presented in Table 5 indicates that the accuracy of the built-up land area is better when comparing the use of the NDTI/BSI/NDVI multi-spectral dataset with the NDTI/DBSI/NDVI multi-spectral dataset. The overall accuracy achieved is 91.96% and 86.14%, with corresponding Kappa coefficients of 82.34% and 71.24%, respectively. Therefore, the improvement in accuracy observed, with an increase of 11.1% in the Kappa coefficient and 5.82% in overall accuracy, is significant. Meanwhile, the NDTI/DBSI/NDVI multi-spectral dataset provides classification results for the built-up land class with similar accuracy in both overall accuracy and Kappa coefficient compared to the classification results using only the NDTI index in the study area. The error matrix shows that the user's accuracy of the built-up land class classified from the NDTI/BSI/NDVI multi-spectral dataset is 85.84%, an increase of 4.44% compared to the user's accuracy when classified from the NDTI/DBSI/NDVI multi-spectral dataset. Similarly, the producer's accuracy of the built-up land class classified from the NDTI/BSI/NDVI multi-spectral dataset is 92.76%, an increase of 9.43% compared to the producer's accuracy when classified from the NDTI/DBSI/NDVI multi-spectral dataset.

3.4 Discussion

Through visual observation of the classification results of built-up land illustrated in Figure 5, it is evident that using the NDTI index and developing multispectral indices has differentiated built-up land from other land types. Observations indicate that some vacant land pixels are misclassified as built-up, especially bright land and vice versa. The DBSI index generates a larger dynamic range compared to the BSI index. Therefore, the DBSI index delineates more built-up land surface than vacant land surface than the BSI index provides. This suggests that the BSI index influences the separation of vacant and built-up land by reducing misclassified pixels through minimizing spectral confusion of both classes. Thus, the BSI index has demonstrated effectiveness in mapping vacant land. As forest class has negative values for both classified vacant land outcomes illustrated in Figure 4, the addition of the NDVI index highlights vegetation with high positive values for the multispectral index, enabling automated classification to distinguish vegetation from vacant land during the classification process.

The analyses above have demonstrated that the BSI index in the multispectral index NDTI/BSI/NDVI yields the most accurate classification results for built-up land due to its enhanced ability to differentiate vacant land from built-up areas. Therefore, using multispectral imagery NDTI with the addition of BSI and NDVI indices proves to be more effective in extracting built-up land from vacant land when employing the K-means classification method.

These results support the method proposed by Ettehadi Osgouei et al., 2019 [24], which advocates a multispectral index-based approach centered on NDTI. Furthermore, the findings also contribute to the developments made by Li et al., 2017 [9] regarding classification methods based on stacking spectral indices as input datasets for K-means clustering. Therefore, the paper re-evaluated both multispectral indices in the classification of built-up and vacant land and compared their impacts since being used in conjunction with the NDTI index. Additionally, the results demonstrate the effective synergy among the three approaches of the aforementioned studies [9; 31] to enhance the discrimination between built-up land and other land types, developed from data tested in urban areas during the dry season.

4. Conclusion

Hanoi city (the capital of Vietnam) is characterized by a climate with distinct dry and rainy seasons, chosen as the research area. The main objective of this study is to find the best solution for combining multispectral indices to accurately extract the built-up land class from other land cover types, primarily vacant land, through experiments using a layer stacking method of various pre-selected spectral indices. Various remote sensing software tools were employed, including SNAP, ENVI, and ArcGIS, to process Sentinel-2 satellite image data.

Separating the built-up land has been the main problem in mapping urbanized areas. In general, both combinations of multispectral indices, NDTI/BSI/NDVI and NDTI/DBSI/NDVI, for Sentinel-2 satellite image data were tested for built-up land mapping through K-mean classification. The results obtained showed a fast classification process for built-up land. However, based on error matrices including overall accuracy and Kappa coefficient, the best results were observed when using multispectral indices comprising BSI in combination with NDTI and NDVI compared to the combination with DBSI.

Competing Interest

All authors declare no conflict of interest.

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Authors' Contributions

Conceptualization, L.T.T.H, N.H.L; data curation, formal analysis, P.T.L; investigation, L.T.T.H, N.H.L; methodology, N.V.T, N.H.L; project administration and supervision, P.T.L, N.H.L; visualization, L.T.T.H, N.H.L; writing original draft, L.T.T.H; writing, reviewing & editing, P.T.L, N.V.T. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Consent for publication

Not applicable.

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Zastosowanie wielospektralnego indeksu z danych Sentinel-2 do ekstrakcji terenów zabudowanych w rejonie Hanoi w sezonie suchym

Wskaźnik zdalnego wykrywania jest prostym i skutecznym sposobem na wyróżnienie określonego pokrycia terenu. Dlatego w tym badaniu staramy się zwiększyć dokładność mapy terenów miejskich opracowanej dla miasta Hanoi, skupiając się na określeniu odpowiedniego połączenia wskaźników spektralnych obliczanych z danych obrazów satelitarnych. Do przeprowadzenia badania wybrano cztery wskaźniki spektralne, a mianowicie znormalizowany wskaźnik różnicy uprawy (NDTI), wskaźnik gołej gleby (BSI), wskaźnik suchej gołej gleby (DBSI) i znormalizowany wskaźnik różnicy wegetacji (NDVI). Wszystkie te wskaźniki spektralne są obliczane z danych Sentinel-2 uzyskanych w sezonie suchym. Dwie kombinacje są tworzone z nakładania się warstw wskaźników spektralnych NDTI/BSI/NDVI i NDTI/DBSI/NDVI. Użycie algorytmu "K-means" jako klasyfikatora nienadzorowanego zapewnia szybkie i automatyczne wykrywanie terenów miejskich. Wyniki pokazują, że wskaźnik BSI działa lepiej niż użycie wskaźnika DBSI. W rezultacie wskaźnik BSI przynosi poprawki: typy gołej gleby i procesy akumulacji są lepiej zróżnicowane, a ogólna dokładność wzrasta o 5,82%, a współczynnik Kappa wzrasta o 11,1%. Wyniki pokazują, że zestaw danych wielospektralnych wskaźników NDTI/BSI/NDVI jest odpowiedni do mapowania obszarów miejskich z potencjałem pomocy w lepszym zarządzaniu miastem podczas sezonu suchego.

Słowa kluczowe: *dane Sentinel-2, algorytm K-means, Bare Soil Index (BSI), Dry Bare Soil Index (DBSI), Normalized Difference Tillage Index (NDTI)*