

Applying Multi-Index Approach from Sentinel-2 Imagery to Extract Urban Areas in Dry Season (Semi-Arid Land in North East Algeria)

Rouibah, K.*, Belabbas, M.

USTHB (Houari Boumediene Sciences and Technology University), FSTGAT, Department of Geography and Territorial Planning, PO Box 32; El Alia, 16111 Bab Ezzouar, Algiers, Algeria.

Abstract: The mapping of urban areas mostly presents a big difficulty, particularly, in arid and semi-arid environments. For that reason, in this research, we expect to increase built up accuracy mapping for Bordj Bou Arreridj city in semi-arid regions (North-East Algeria) by focusing on the identification of appropriate combination of the remotely sensed spectral indices. The study applies the 'k-means' classifier. In this regard, four spectral indexes were selected, namely normalized difference tillage index (NDTI) for built-up, and both bare soil index (BSI) and dry bare-soil index (DBSI), which are related to bare soil, as well as the normalized difference vegetation index (NDVI). All previous spectral indices mentioned were derived from Sentinel-2 data acquired during the dry season. Two combinations of them were generated using layer stack process, keeping both of NDTI and NDVI index constant in both combinations so that the multi-index NDTI/BSI/NDVI was the first single dataset combination, and the multi-index NDTI/DBSI/NDVI as the second component. The results show that BSI index works better with NDTI index compared to the use of DBSI index. Therefore, BSI index provides improvements: bare soil classes and built-up were better discriminated, where the overall accuracy increased by 5.67% and the kappa coefficient increased by 12.05%. The use of k-means as unsupervised classifier provides an automatic and a rapid urban area detection. Therefore, the multi-index dataset NDTI/ BSI / NDVI was suitable for mapping the cities in dry climate, and could provide a better urban management and future remote sensing applications in semi-arid areas particularly.

Key words: Sentinel-2, multi-index dataset, built-up area, bare soil, semi-arid land.

Aplicación del enfoque multi-índice con imágenes Sentinel-2 para obtener áreas urbanas en la estación seca (Zonas semiáridas en el noreste de Argelia)

Resumen: La cartografía de las zonas urbanas presenta una gran dificultad, especialmente en los entornos áridos y semiáridos. Por esa razón, en esta investigación esperamos aumentar la precisión de la cartografía de la ciudad de Bordj Bou Arreridj en las regiones semiáridas (noreste de Argelia) centrándose en la identificación de la combinación adecuada de los índices espectrales obtenidos por teledetección. El estudio aplica el clasificador 'k-means'. A este respecto, se seleccionaron cuatro índices espectrales, a saber, el índice de labranza de diferencia normalizada (NDTI) para el área construida, el índice de suelo desnudo (BSI) y el índice de suelo desnudo seco (DBSI), que están relacionados con el suelo desnudo, así como el índice de vegetación de diferencia normalizada (NDVI). Todos los índices espectrales anteriores mencionados se derivaron de datos Sentinel-2 adquiridos durante

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* Corresponding author: rouibahkld@gmail.com

la estación seca (agosto). Se generaron dos combinaciones de ellas utilizando el proceso de superposición de capas, manteniendo constante tanto el índice NDTI como el índice NDVI en ambas combinaciones, de modo que el multi-índice NDTI/BSI/NDVI fue la primera combinación de conjuntos de datos, y el multi-índice NDTI/DBSI/NDVI fue el segundo componente. Los resultados muestran que el índice BSI funciona mejor con NDTI en comparación con el uso de DBSI. Por lo tanto, BSI proporciona mejoras: las clases de suelo desnudo y la de construcciones fueron mejor discriminadas, aumentando la precisión global en un 5,67%, y el coeficiente kappa un 12,05%. El uso de k-means como clasificador no supervisado proporciona una detección del área urbana automática y rápida. Por lo tanto, el conjunto de datos de varios índices NDTI/ BSI/ NDVI fue adecuado para cartografiar las ciudades en clima seco, y podría proporcionar una mejor gestión urbana y futuras aplicaciones de teledetección en zonas semiáridas en particular.

Palabras clave: Sentinel-2, datos multi-índice, área urbanizada, suelo desnudo, tierra semiárida.

1. Introduction

For a long time, the urban areas detection faces difficulties in arid and semi-arid lands. In this context, recently, numerous research, such as (Pal and Antil, 2017; Valdiviezo-N et al., 2018; Vigneshwaran and Vasantha Kumar, 2018; Ettehadi Osgouei et al., 2019; Xi et al., 2019; Yilmaz et al., 2019), were taking the advantages of the new Sentinel -2 images data, by discussing numerous built-up index applications for urban detection. Nevertheless, based on (Valdiviezo-N et al., 2018) results, the performance of all used built-up indices, namely the Normalized Difference Built-Up Index NDBI (Zha et al., 2003), the Index-Based Built-Up Index IBI (Xu, 2008), the New Built-Up Index NBI (Jieli, 2010), the Band Ratio for Built-Up Area BRBA & the Normalized Built-Up Area Index NBAI (Waqar et al., 2012), the Biophysical Composition Index BCI (Deng and Wu, 2012), the Modified Built-Up Index MBI (Liu et al., 2014), the Built-Up Area Extraction Index BAEI (Bouzekri et al., 2015), and the Combinational Build-Up Index CBI (Sun et al., 2016) are subjected to seasonal changes, particularly, in a dry month, where the similarity between the spectra of bare soil and urban area is increasing. Consequently, they produced a low accurate mapping of urban area in the dry period in the area under study.

In the last few years, a new type of dataset was created by the combination of different spectral indices. In fact, the use of spectral indices as bands work better than using initials bands (Xu, 2007). This option enabled several researchers, for example (Pal and Antil, 2017; Leroux et al.,

2018; Gašparović et al., 2019), to expect a better classification mapping of the land cover/use. Likewise, other researches focused on urban area detection such as the works of (Xu, 2007; Patel and Mukherjee, 2014; Bramhe et al., 2018; Lee et al., 2018; Nur Hidayati et al., 2018; Ettehadi Osgouei et al., 2019; Lynch and Blesius, 2019). However, the study of (Ettehadi Osgouei et al., 2019) applied the Normalized Difference Tillage Index (NDTI) – developed in (Deventer, 1997) and also used in (Daughtry et al., 2010; Eskandari et al., 2016) – 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. Also, the multi-index based NDTI was classified using the machine-learning-based SVM algorithm (Vapnik, 1995) which improved the mapping accuracy of the heterogeneous urban areas.

The results discussed above lead us to expect an improvement in the mapping of built up areas of cities in dry season based on spectral indices layer stacking method, where the Multi- Index including NDTI index along with a suitable spectral index can enhance the built up mapping. Therefore, due to the fact that semi-arid regions are characterized by low vegetation density and large bare soil, particularly in dry season, two bare soil indexes were selected. The first one is Bare Soil Index (BSI) introduced by (Rikimaru and Miyatake, 1997) that enhances the identification of bare soil areas and fallow lands; hence, differentiating it from vegetation cover and other land cover types. Recently, BSI index has been widely selected to be applied in several studies,

such as (Rikimaru et al., 2002; Chen et al., 2004; Jamalabad, 2004; Muna and Walker, 2010; Al-Quraishi, 2011; Gupta et al., 2014; Becerril-Piña et al., 2015; Doumit and Sakr, 2015; Diek et al., 2017; Loi et al., 2017; Ettehadi Osgouei et al., 2019; Tola et al., 2019; Useya et al., 2019). The second one is the Dry Bare-Soil Index (DBSI) which was recently developed by (Rasul et al., 2018) and was referred to in the literature review of (Lynch and Blesius, 2019) as a bare area index detection destined to dry climate.

The paper investigates a rapid and accurate mapping of built-up of semi-arid regions in the dry season via testing of a new type of dataset which combines several spectral indices derived from satellite images with the aim of finding the best Multi -Index combination of the selected built-up and bare soil indices. In this regard, we take the advantage of new Sentinel-2 satellite imageries and its characteristics of 10 m resolution, as well as free open software widely-used in remote sensing. We have selected the city of Bordj Bou Arreridj to be our study area to challenging bare-land and urban area separation process, as it is located in a semi-arid region (North- East Algeria) which is surrounded by extensive and heterogeneity bare land.

2. Methods and Materials

2.1. Study Area

Bordj Bou Arreridj City is located in High plains (North- East Algeria) between the Tellien Atlas and the payments of the Saharian Atlas of semi-arid climate (Côte, 1996). The city placed at 220 km East of the capital Algiers and 65 km West of Setif City at the average altitude of approximately 906 m above sea level. The locations of the study area including the city is presented in Figure 1.

2.2. Data Selection

Sentinel-2 images were selected for working on our study area due to the fact that Sentinel-2 is cost-free satellite imageries available at <https://scihub.copernicus.eu> with. Furthermore, several studies such the work of (Xi et al., 2019) which concluded that Sentinel-2 provided a high accuracy for built-up area compared to Landsat-8 images. In addition, a research of (Pal and Antil, 2017) revealed that Sentinel-2 data, perform better than Landsat 8 data for urban mapping using different indices combination.

Sentinel-2 images were acquired in level 1c tiles (tile id: T 31sfV) which produces the type S2MSI1c, pre-geo referenced (Vanhellemont and

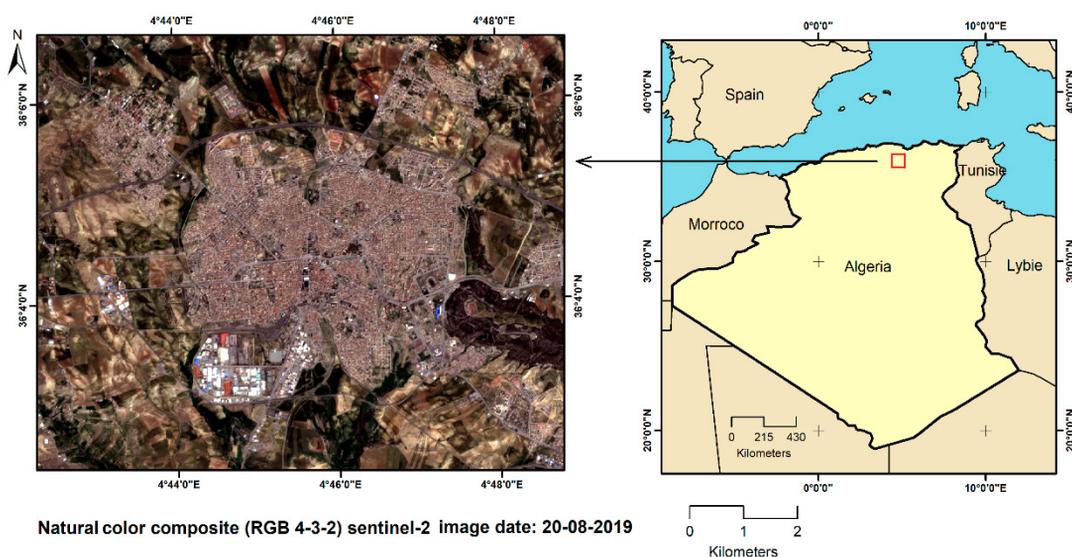


Figure 1. Location of Study Area in high Land (North-East Algeria).

Ruddick,2016). The dataset was acquired on 20 august 2019 which represents the driest month during the year covering the study area including Bordj Bou Arreridj city, entirely. The selected date of dataset provides that bare soil and built-up can be well observed and identified visually, because there is no mixed vegetation grow inside bare soil due to the coincidence with the end of labor and harvesting in the region.

2.3. Method

The overall methods adopted contains three main steps: *preprocessing*, *processing*, and *validation of the results*. which are shown in Figure 2.

2.3.1. Pre-Processing

According to (Drusch et al., 2012), the images of sentinel-2, level 1c, are at TOA (top of atmosphere reflectance).Therefore, in pre-processing step, the

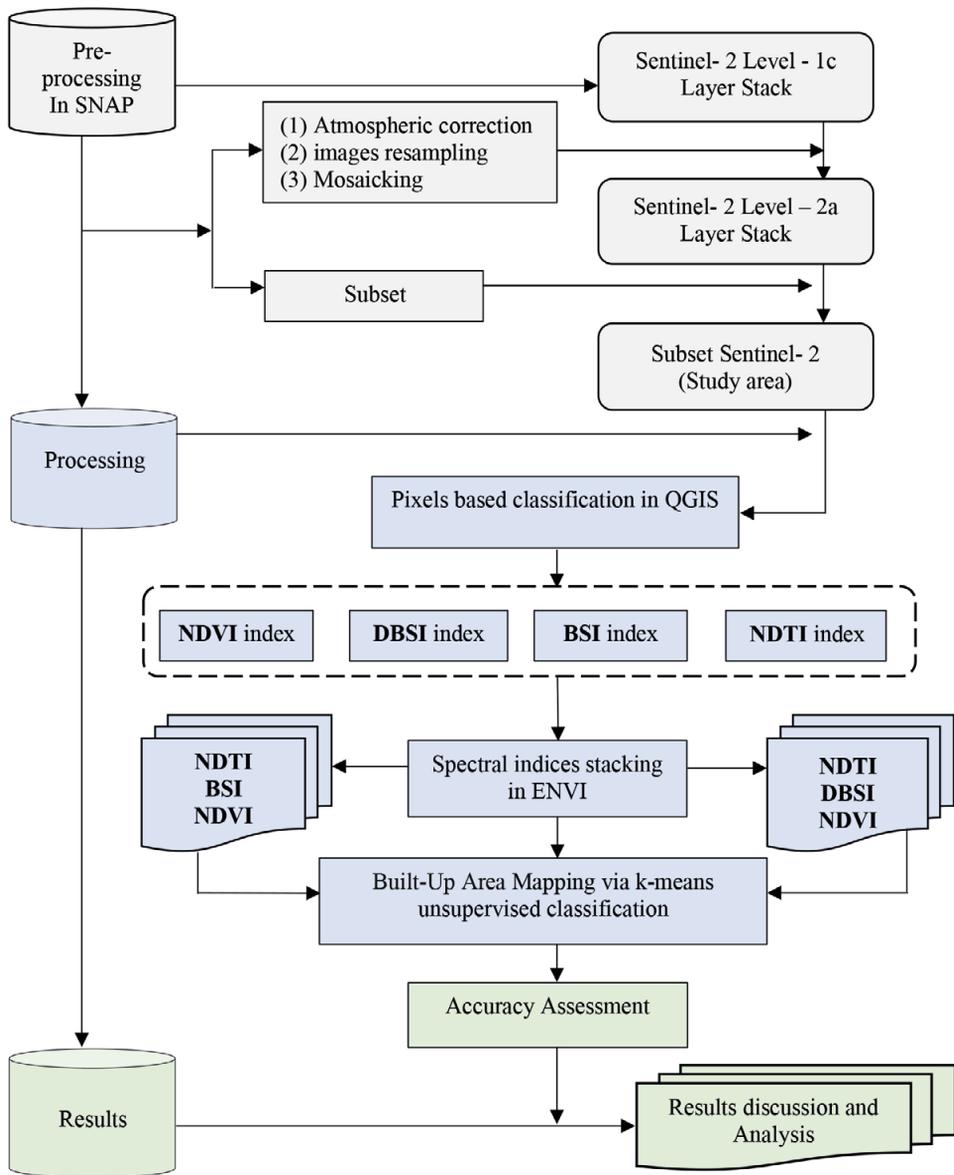


Figure 2. Flowchart methodology of built-up extraction using the multi-index of Sentinel-2 images with k-means classifier.

images were subject to atmospheric corrections to obtain Sentinel-2 level 2a which are at BOA (bottom-of-atmosphere reflectance). The process was performed through the use of Sen2Cor module (Louis et al., 2016). The latter is considered as a plug-in SNAP 6.0 version (Sentinels Application Platform) along with Sentinel-2 toolboxes which can be found at <http://step.esa.int/main/download/>.

The data results were opened in QGIS 3.6.0 version (Quantum Geographic Information System) which is a free open source software obtained from <https://www.qgis.org>. Thus, the processing of mosaicking and clipping of the study area are performed by using a semi-automatic classification plugin (SCP) which is a plugin for QGIS that was created by (Congedo, 2016).

2.3.2. Image Processing

2.3.2.1. Performing spectral indices selected

All spectral indices used in this research are summarized in Table 1.

The Scp plugins in QGIS software was employed for the Creation of Spectral Indices associated with the dataset proposed for classification. The Spectral Indices results illustrated in Figure 3.

2.3.2.2. Multi-Index development

Correlation coefficients between spectral indices selected are shown in Table 2. They indicated a high correlations observed between the both bare soil indices BSI and DBSI. Which means, the

both bare soil index produce almost the same information over the study area. In contrast, low correlations have been noted between the NDTI built-up index and both bare soil indices BSI and DBSI. Whereas, BSI index is the lowest correlated at NDVI index. The correlation between NDVI and NDTI indices is intermediate.

Based on the degree of relationship discussed between the four spectral indices, permit us, to form two different combinations via layer stack process to expect increasing the spectral difference among the three major land cover classes (built –up, bare soil, vegetation). The combinations were performed by keeping NDTI and NDVI index constant, where the spectral indices NDTI, BSI and NDVI formed the first layer stacking dataset, and multi- index NDTI / DBSI / NDVI as the second component. These combinations of spectral indices were compared to NDTI index to find out the one of the highest accuracy toward extracting built-up area. Also, to evaluate the effect of bare soil indices among with the initial combination NDTI / NDVI toward the reduce of misclassification between bare soil and built- up area.

The ENVI 5.3 version (Environment for Visualizing Images) was used to create the spectral layers stacking necessary proposed.

2.3.2.3. Segmentation (Binarization)

The built-up in the area under study includes mainly the residential and industrial area, road and other impervious surfaces. However, the non-built-up

Table 1. Various spectral indices used in this study on 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	(Rouse et al., 1973; Tucker, 1979)	$(B08 - B04) / (B08 + B04)$

Table 2. Correlation values between spectral indices used in the study area.

Spectral Indices	BSI	DBSI	NDTI	NDVI
BSI	1.000000	0.961808	0.164124	-0.316729
DBSI	0.961808	1.000000	0.133774	-0.336952
NDTI	0.164124	0.133774	1.000000	0.531037
NDVI	-0.316729	-0.336952	0.531037	1.000000

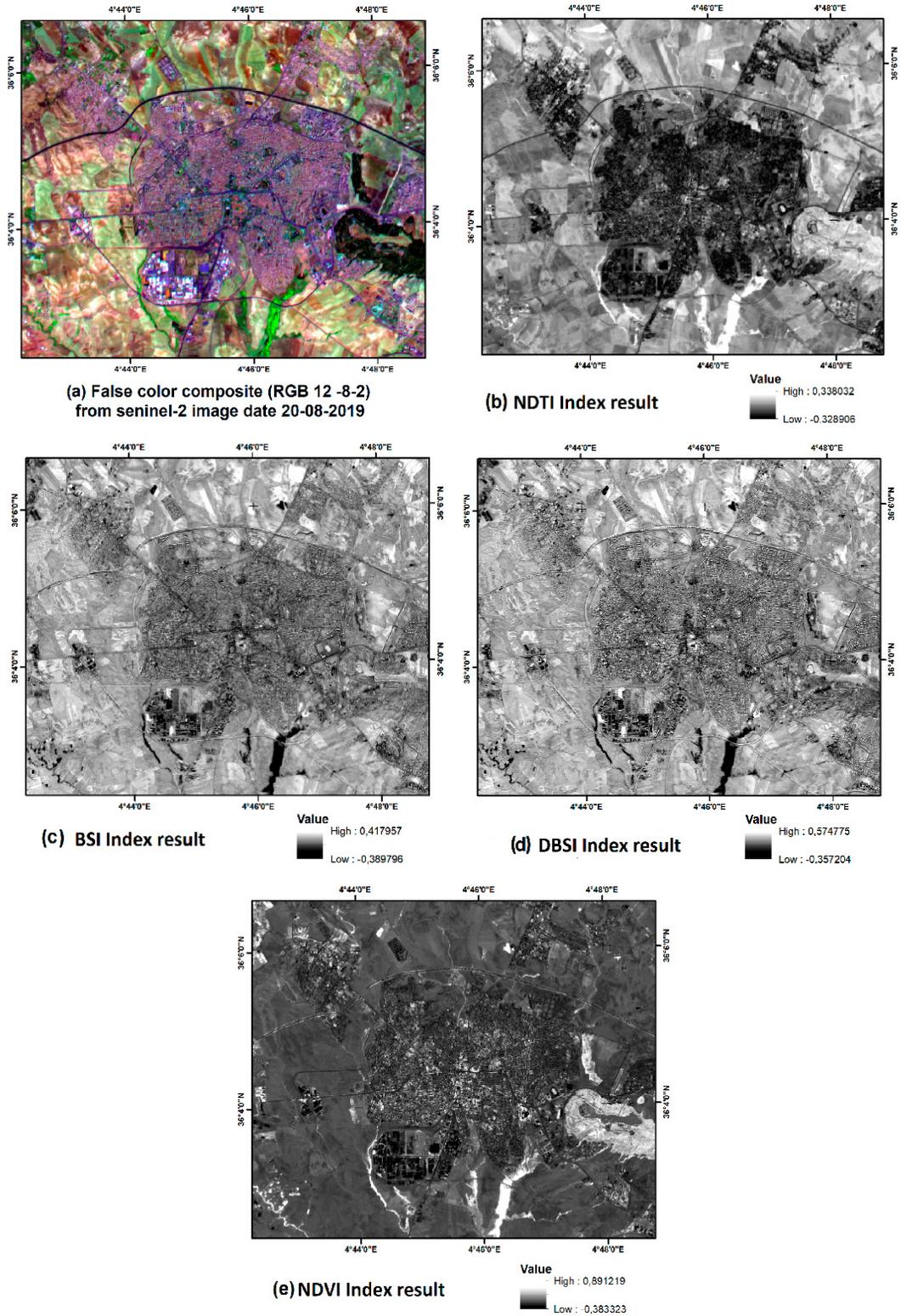


Figure 3. Spectral indices result used in the study (a) False color composite (RGB 12 -8-2) from Seninel-2 image date 20-08-2019 (b) NDTI (c) BSI (d) DBSI (e) NDVI

Table 3. Statistical values of four indices.

Spectral indices	Min	Max	Mean	StdDev	Range value
BSI	-0.447480	0.551865	0.182578	0.052259	From -0.389796 to 0.417957
DBSI	-0.395555	0.776889	0.238394	0.073672	From -0.357204 to 0.574775
NDTI	-0.328906	0.338032	0.070689	0.043218	From -0.328906 to 0.338032
NDVI	-0.383378	0.913799	0.101795	0.072900	From -0.383323 to 0.891219

class includes forest, grass-land, and bare soil. To achieve a high accurate separation between the two major classes (the built-up and non-built-up area), the binarization was adopted. However, the works of (Zuur et al., 2007; Xian et al., 2009) reported that highlighting a specific land cover type via the finding of the optimal thresholds presents a big difficulty.

The spectral profile presented in Figure 4 showed that NDVI index highlighted vegetation in high positive value; it is represented by high gray tones which can be observed in Figure 3. Also, BSI and DBSI highlighted bare soil and fallow fields. Moderate values refer to a built-up and low values present vegetation. The vegetation and bare soil areas having positive NDTI value, and built-up had been highlighted in low positive NDTI value. In the other hand, the bright construction resulted in negative value which represented by dark pixels in Figure 3. In addition, the statistical values of the four spectral indices can be found in Table 3, where the value of standard deviation are low for all spectral indices used.

Based on the above analysis of spectral profile presented in Figure 4, the built-up mapping process from other major land cover types which bare land and vegetation can be done easily, using k-means algorithm which is unsupervised classification that was developed by (MacQueen, 1967). The algorithm adopted to expect a rapid and an accurate segmentation due to the fact that the k-means algorithm is used for dividing data into such number of clusters that is assigned in advance (Gllavata et al., 2004). In addition, the k-means algorithm used successfully to extract a specific land cover area automatically from a single index result (Li et al., 2017). Also, the work of (Gašparović et al., 2019) proved the performance of the algorithm for land cover classification over multi-index dataset as well.

The ENVI software was adopted to apply the k-means unsupervised classification in order to split both the multi -index datasets into two classes (built-up and non-built up).

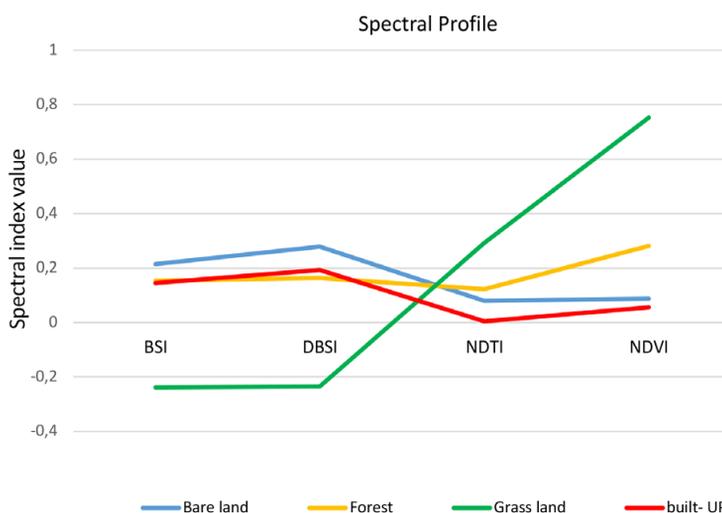


Figure 4. Simplified spectral signatures represented by the mean of the three major categories of land cover for the multi-index image.

3. Results and Discussion

3.1. Results

The results of the built-up area extracted using NDTI index and multi-index dataset developed can be observed from the processed series images in Figure 5. The statistics generated from the result of remote sensing classification are represented in Table 4.

Based on the surface area value of each multi-index class in Table 4, it was found that built up area

resulted from the multi-index NDTI/BSI/NDVI is 31.02 km², which is about 36.17% of the total study area; this built-up surface area is over the same class area resulting from multi-index NDTI / DBSI / NDVI by 1.42 km² and less than the same class area resulting from NDTI index by 6.81 km².

3.2. Accuracy Assessment

The evaluating the performance of the different Multi-Index used for the built-up area extracted is a crucial step. Therefore, accuracy assessment was

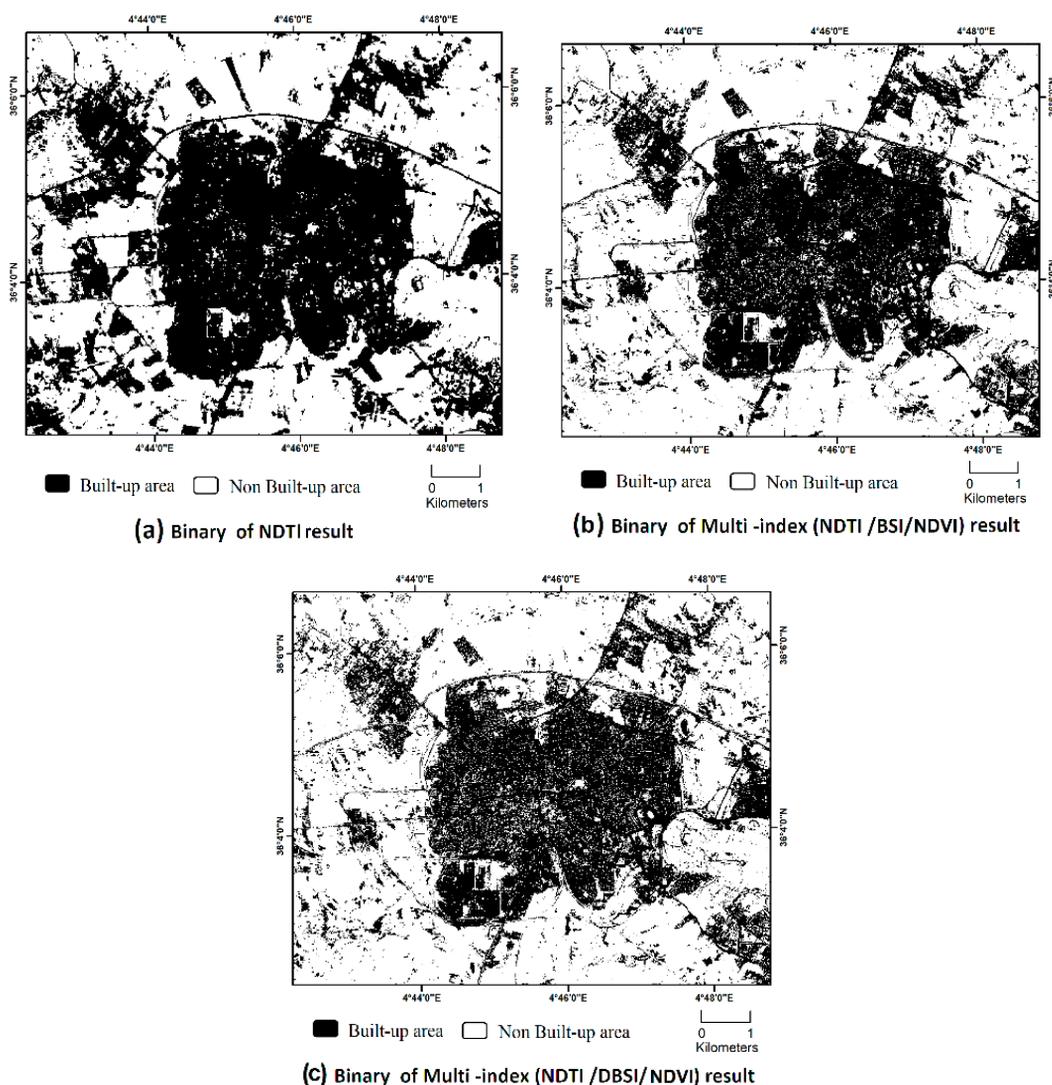


Figure 5. Binary image resulting from K- means classifier of (a) NDTI (b) Multi-Index (NDTI -BSI-NDVI) (c) Multi-Index (NDTI -DBSI-NDVI).

Table 4. The built-up area extracted using both multi-index over Bordj Bou Arreridj City in August Dry Season.

Multi Index Used	built-up Surface area		Others	
	Area (km ²)	Area%	Area(km ²)	Area%
NDTI / BSI / NDVI	31.02	36.17	54.72	68.98
NDTI / DBSI / NDVI	29.60	34.52	56.14	70.397
NDTI	37.83	44.11	41.61	62.17
Total area	85.7472	100	85.7472	100

performed using the stratified random sampling method (Congalton, 1991) which recommended in general at least 50 points devoted from each class; 300 random points distributed among the built-up and non-non built-up classes. Also, free Google Earth software was used to generate a high-resolution aerial images as reference maps that have the same date. Then, confusion matrix (Foody, 2002) resulted from accuracy assessment process that containing the Overall Accuracy, Kappa Coefficient, Producer’s Accuracies (PA), and User’s Accuracies (UA). All accuracy types are shown in Table 5.

The confusion matrix presented in Table 5 showed that the built up area was better mapping using multi-index NDTI/BSI/NDVI compared to multi-index NDTI/DBSI/NDVI; The overall accuracy achieved is 92% and 86.33% respectively, and the kappa coefficient achieved is 83.19% and 71.14%, respectively. Therefore, a significant improvement is noticed in kappa value which is increased by 12.05%, and the overall accuracy is increased by 5.67%. Whereas, the multi-index NDTI/ DBSI /NDVI provides a similar accuracy with respect to overall accuracy and kappa coefficient compared to NDTI index used in the study area.

Concerning the evaluation of the classification quality of each class which help to compare the both classes accuracy between the both multi-index data used. The confusion matrix showed that the user’s accuracies of built-up resulted from multi-index NDTI/BSI/NDVI achieved 86.78% increasing by 4.98 % compared to user’s accuracies of built-up resulted from multi-index NDTI/ DBSI /NDVI. Likewise, the producer accuracy of built-up resulted from multi-index NDTI/ BSI /NDVI achieved 92.92% increasing by 9.59% compared to the producer accuracy of built-up resulting from multi-index NDTI/DBSI/NDVI.

3.3. Discussion

The visual examination of the binaries results illustrated in Figure 5, revealed that the NDTI index and multi-index developed, were distinguishing differently the built-up land from other land cover types. However, in comparison to the false color combination RGB (12-8-2) bands which highlight well the different land cover/use of the study area. It is observed generally that a few pixels of bare soil are misclassified as built up, in particular the bright soil and vice versa. The DBSI index generates a great dynamic range compared to BSI index. Consequently, DBSI index provided bare land surface area more than the bare land surface

Table 5. Accuracy Assesment of Resultant Maps for Sentinel-2 Images.

Dataset used	NDTI index		Multi-Index NDTI/ BSI /NDVI		Multi-Index NDTI/ DBSI /NDVI	
	(UA)	(PA)	(UA)	(PA)	(UA)	(PA)
	Commission error %	Omission error %	Commission error %	Omission error %	Commission error %	Omission error %
Accuracy types						
Urban area	78.46	89.47	86.78	92.92	81.20	83.33
Bare land (fallow)	92.94	84.95	95.53	91.44	89.62	88.17
Overall accuracy Oa %	86.67		92.00		86.33	
Kappa Coefficient %	72.45		83.19		71.14	

provided by BSI index, which proved that BSI index effected the separating bare soil and built-up by decreasing misclassified pixels themselves, this by reducing the maximal confusion spectral of the both classes. So that, the BSI index proved its performance toward bare soil mapping. Also, since the vegetation cover has negative value, particularly, the bright vegetation in the both bare soil indices results illustrated in Figure 4. The adding of NDVI index which highlighted the irrigated vegetation with a high positive value to multi-index developed, that permitted to classify automatically the vegetation cover with bare land cover in the same class during the binary process.

The analysis discussed above demonstrated that The BSI Index behavior was behind the best binary result of multi-index NDTI-BSI-NDVI dataset, where the built-up and the bare land were low mixed. Therefore, using the NDTI-based multi-index image by adding BSI and NDVI index work better concerning built-up and bare soil separating compared to the multi-index NDTI-BSI-NDVI using k-means method.

The results support on one hand the method proposed by (Ettehad Osgouei et al., 2019) toward the NDTI-based multi-index approach. They also support the findings of (Li et al., 2017) and (Gašparović et al., 2019) in terms of automatic classification method that based on the use of spectral indices layer stacking as input dataset to the k-means clustering. Hence, the paper retested the both bare soil indices and comparing its effect since used among with NDTI index. In addition, the results showed the good synergy between the three findings of three works (Li et al., 2017; Ettehad Osgouei et al., 2019; Gašparović et al., 2019) to enhance the built up extraction with the developed dataset tested in this new area, which is semi-arid land.

4. Conclusion

Bordj Bou Arreridj City is located in (North-East Algeria); it is characterized by semi-arid climate, and was chosen to be the area of study. The main purpose of this research work is to find the best multi-index dataset that can produce a high accuracy with respect to separating built up area from other land cover types, mainly, bare soil cover in semi-arid land via testing stacking layers approach

with different spectral index selected previously. Different remote sensing software programs were used, such as: ENVI and ArcGIS and open-source (OS) software, as QGIS in addition SNAP as well, used for the processing of Sentinel -2 as new generation of remote sensing data.

In general, both multi-index datasets developed NDTI/BSI/NDVI and NDTI/DBSI/NDVI, that have been derived from Sentinel-2 and have been tested in semi-arid land for built-up mapping via k-means classifier, showed a high accuracy, rapid and automatic classification of built-up class. However, based on the confusion matrix, mainly, the overall accuracy and Kappa Coefficient, the best result provided by the use of multi-index including BSI index, that exhibited good effects with NDTI index compared to DBSI index. Therefore, the dataset developed has been successfully used in this work over a semi-arid land, via reducing the strong spectral resemblance of the study area features. Hence, contributing to increase the accurate mapping of built-up.

Such results explore the ideal multi-index dataset which could be very helpful to identify the built-up area with accurate information in dry season. Therefore, the planners and decision makers can quickly recognize and making estimation of built-up area states to cities in semi-arid lands. However, further retests of the dataset developed in this study are required in other areas with high land cover heterogeneity in arid and semi-arid lands in both dry or rainy season as well. Also, it is proposed to combine other spectral indices that can improve classification mapping and analysis.

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