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Extraction of Urban Areas Using Spectral Indices Combination and Google Earth Engine in Algerian Highlands (Case Study: Cities of Djelfa, Messaad, Ain Oussera)

Extração de Áreas Urbanas Usando Combinação de Índices Espectrais e Google Earth Engine em Terras Altas da Argélia (Estudo de Caso: Cidades de Djelfa, Messaad, Ain Oussera)

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Abstract

The fundamental difficulty in mapping urban areas, especially in semi-arid and arid environments, is the separation of built-up areas from bare lands, owing to their similar spectral characteristics. Accordingly, this study aims to identify the suitable spectral index that can provide high differentiation, between urban areas and bare lands, in semi-arid areas of three cities of the province of Djelfa, namely, Djelfa, Messaad, and Ain Oussera (Algerian central highlands), through a selection of four spectral indices including Urban Index (BUI), Band ratio for built-up area (BRBA), Normalized Difference Tillage Index (NDTI) and Dry Bare-soil Index (DBSI). In order to increase the mapping accuracy of the built-up in studied areas, a multi-index approach has been applied focusing on identifying an adequate combination of spectral indices of remote sensing that provides the highest performance compared to the images of sentinel 2A. The multi-index approach was developed using three spectral indices combinations and was created using a layer stack process. For forming bare land layer stacking data, both NDTI and DBSI indices were used, while the built-up area layer stacking data was made with both BUI and BRBA indices. The main process was carried out on the Cloud Computing Platform based on geospatial data of Google Earth Engine (GEE) and using machine learning classification by the Support Vector Machine (SVM) algorithm, based on imagery from sentinel 2A acquired during the dry season. The results indicated that the thresholds of the built-up areas are difficult to delineate and distinguish from bare land efficiently with a single index. The obtained results also revealed that the use of multi-index including BUI index provided the best results as they showed the highest effects with NDTI index and DBSI index compared to BRBA index, where the overall accuracies of the multi-index (DBSI/ NDTI/ BUI) were 98.7% in Djelfa, 96.5% in Messaad, and 97.87 % in Ain Oussera, and the kappa coefficients were 97.3%, 85.4%, and 95.3% respectively. These results show that this multi-index is effective and reliable and can be considered for use in other areas with similar characteristics.

Keywords: Built-up area; Multi-index approach; SVM algorithm

Resumo

A dificuldade fundamental no mapeamento de áreas urbanas, especialmente em ambientes semi-áridos e áridos, é a separação de áreas construídas de terras nuas, devido às suas características espectrais semelhantes. Assim sendo, este estudo procura identificar o índice espectral adequado que pode proporcionar uma alta diferenciação entre áreas urbanas e terras nuas, em regiões semiáridas de três cidades da província de Djelfa, a saber: Djelfa, Messaad e Ain Oussera (planaltos centrais argelinos), apesar de uma seleção de quatro índices espectrais, incluindo Urban Index (BUI), Band ratio for built-up area (BRBA), Normalized Difference Tillage Index (NDTI) e Dry Bare-soil Index (DBSI). Com o propósito de aumentar a precisão do mapeamento das da área urbana, aplicamos uma

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abordagem multi-índice com foco na identificação de uma combinação adequada de índices espectrais de sensoriamento remoto que fornece o maior desempenho em comparação com as imagens de sentinela 2A, a abordagem multi-índice foi desenvolvida usando três combinações de índices espectrais, e foi criada por meio de um processo de pilha de camadas. Para a formação de dados de empilhamento de camadas de terra nua, os dois índices NDTI e DBSI foram usados, enquanto os dados de empilhamento de camadas de área construída foram feitos de índices BUI e BRBA. O processamento principal foi realizado na Cloud Computing Platform com base em dados geoespaciais do Google Earth Engine (GEE) e usando classificação de machine learning pelo algoritmo Support Vector Machine (SVM), baseado em imagens do sentinel2A adquiridas durante a estação seca. Os resultados indicaram que, com um único índice, os limiares das áreas construídas são difíceis de delinear e distinguir de forma eficiente dos terrenos nus, revelando também que o uso de multiíndice incluindo índice BUI forneceu melhores resultados, uma vez que apresentaram os maiores efeitos com índice NDTI e índice DBSI em comparação com o índice BRBA, onde as precisões gerais do multi índice (DBSI/ NDTI/ BUI) foram 98,7% em Djelfa, 96. 5% em Messaad e 97,87% em Ain Oussera, e os coeficientes kappa foram 97,3%, 85,4% e 95,3%, respectivamente. Estes resultados mostram que este índice multi é eficaz e confiável e pode ser considerado para uso em outras áreas com características semelhantes.

Palavras-chave: Área construída; Abordagem multi-index; Algoritmo SVM

1 Introduction

Over the last 60 years, urbanisation has expanded widely more than ever in the human history (Scott & Storper 2015) and it has changed boundaries, morphologies and scales of human settlements (Viganò et al. 2017). Urban areas are one of the fastest-growing and continuously changing land use/covers on earth (Suliman & Zhang 2018). Urban growth leads to the change in land use /cover in both developed and developing countries. However, unlike developed countries where urban growth is under control, cities in developing countries are marked by a considerable expansion of their urban territories, where control is a major challenge for urban policies. At the present, the data obtained from remote sensing platforms provide up-to-date information and a general view of landscape characteristics and changes in urban areas, constituting a more effective manner of detecting and monitoring urban growth on various scales with useful results. However, the differentiation of urban areas from other land use/ cover has often been proven difficult, especially in semi-arid and arid environments, where the most challenging task is the correct differentiation between bare lands and urban areas due to the spectral similarity. In this context, various studies have been proposed, using remote sensing data, and one of the most significant research topics in geographical information technologies is the processing of those sources to come up with these data (Linares & Picone 2018). However, the precise extraction of urban areas represents a challenging task due to different issues involved in the classification process (Valdiviezo-N et al. 2018). Different research has been proposed to extract the urban areas from satellite data, in which the results can vary depending on the study areas and the imagery used. These methods include: spectral unmixing (Dennison & Roberts 2003; Lu & Weng 2006; Ward et al. 2000), multiple regression (Xiao et al. 2007), artificial neural networks (Flanagan & Civco 2001; Hu & Weng 2009), object-oriented and knowledge-based classification methods (Goetz et al. 2003; Grippa et al. 2017; Zhang & Foody 2001), and the use of built-up indices. The latter, according to the results of Valdiviezo-N et al. (2018) has often been seen as an effective technique for urban extraction, because of its simplicity, easy implementation, and speed. However, the performances of built-up indices used in his study are sensitive to the location of the area under study and Seasonal Variation, especially in the dry season, where most of them confuse urban surfaces with bare soils because of their spectral similarity. In conclusion, no method of the abovementioned is considered the best to determine urban areas from various types of urban landscapes that vary geographically and exhibit various material compositions (Cabral 2007).

Currently, several spectral indices have been proposed to work suitably with medium to coarse spatial resolution data such as Sentinel 2 (Osgouei et al. 2019) and High-Resolution Satellite Imagery such as Quick bird (Chen et al. 2018), World View (Kumar et al. 2012). The spectral behaviour of the built-up area and different features related to the electromagnetic spectrum's wavelengths are the basis for the development of these indices, as far as absorption or reflection is concerned (Firozjaei et al. 2019). The studies undertaken by Bourcier (1994), proposed the cuirass index (IC) for distinguishing between built-up areas and bare soils, using green and red spectral bands of Landsat TM imagery. Kawamura et al. (1996) proposed the urban index (UI) for mapping built-up area, by using Landsat TM imagery, the (UI) computed by band 7 and 4, and the modified Soil adjusted Vegetation index (MSAVI), In the City of Colombo in Sri Lanka, it is assumed that high pixel value indicates built-up area intensively. The Normalized Difference Built-Up Index (NDBI), first introduced by Zha et al. (2003) for mapping the built-up areas successfully, concluded arithmetical management from Landsat TM imagery in the city of Nanjing in eastern China. The subtraction of the NDVI channel from the NDBI image delineates built-up and barren areas with positives values, while other land covers are marked with values from 0 to – 1. The mapped results at an accuracy of 92.6% indicate that they can be used to fulfil the mapping objective reliably. Later, in 2010, an improvement of the NDBI that utilizes a threshold algorithm to identify built-up regions was proposed by He et al. (2010). The index-based Built-Up Index (IBI) was proposed by (Xu 2008) using the Landsat ETM+ image of Fuzhou City in south-eastern China, based on three thematic indices, It enhances built-up land pixels by subtracting the Modified Normalized Difference Water Index (MNDWI) and the Soil Adjusted Vegetation Index (SAVI) from the Normalized Difference Built-Up Index (NDBI). Jieli et al. (2010) proposed the new Built- Up Index (NBI) by manipulating the Red, NIR, and MIR spectral bands, of TM imagery of Changzhou city, China. The main concept behind this built-up index is that the R band's spectral response of barren land is higher than the built-up regions, which is one of the best land use land cover classes compared to others (Waqar et al. 2012) developed the Band Ratio for Built-Up Area (BRBA) and the Normalized Built-Up Area Index (NBAI). Both indices were employed to extract the built-up areas of Islamabad city, Pakistan from Landsat TM images through; NBAI using the bands 7, 5 and 2, BRBA by using the ratio of bands 5 and 3. As-syakur et al. (2012) developed the Enhanced Built-Up and Bareness Index (EBBI). They suggested, from Landsat TM imagery of Denpasar, Indonesia, the extraction of built-up and bare land areas using a single calculation that utilizes Near Infrared (NIR), Short Wave Infrared (SWIR), and Thermal Infrared (TIR) bands at the same time. Rasul et al. (2018) proposed the Dry Built-Up Index (DBI) and Dry Bare-Soil Index (DBSI) to map built-up and bare areas in arid and semi-arid climates from Landsat 8. In Erbil city of Iraq, the results showed an overall classification accuracy of 93% and 92% for DBI and DBSI, respectively.

Another category of the dataset was also developed by combining various spectral indices to improve the separation of built-up areas from bare lands (Bramhe et al. 2018; Hidayati et al. 2018; Lynch & Blesius 2019; Osgouei et al. 2019; Patel & Mukherjee 2015), in view of using a spectral indices as bands is more efficient than using initial bands. However; the carried out study by Osgouei et al. (2019) applied the Normalized Difference Tillage Index (NDTI) proposed by Deventer et al. (1997), for the first time, as an element to differentiate between built-up areas and bare land, it was previously applied by (Eskandari et al. 2016; Quemada & Daughtry 2016; Sharma et al. 2020; Sonmez & Slater 2016) for soil management and agricultural practices. The research used the NDTI index with SWIR bands of the Sentinel-2 images and achieved success in distinguishing between built-up area and bare land classes better than the other spectral indices applied. In addition, the classification of the multi-index based NDTI was carried out using the SVM algorithm, which increased the precision and accuracy of the mapping of heterogeneous urban areas.

Most of these spectral indices have been designed primarily for Landsat imagery; however, it may not be feasible for other satellites due to band discrepancies. Likewise, Sentinel-2 satellites, compared to Landsat, are capable of acquiring images with a spatial resolution of 10–60 m, providing for precise mapping of urban areas. Xi et al. (2019) investigated for the first time a comparative study on built-up land derived from various built-up indices namely Urban Index (UI), Normalized Difference Built-up Index (NDBI), Index-based Built-up Index (IBI), and two visible based indices, i.e., VgNIR-BI and VrNIR-BI) between Landsat-8 and Sentinel-2A satellite imageries, and concluded that in terms of built-up land mapping capacity, S2A outperforms L8 because of differences in spectral response functions and spatial resolution.

However, the optical satellite data at a spatial resolution of Landsat (30m×30m) is higher than the building's size, can also reveal some issues which obstruct the precise mapping of urban areas and increased the spectral confusion between urban areas and bare lands, due to the spectral responses of component materials of urban areas with asphalt, concrete, metal, glass, and plastic (Herold et al. 2002; Thapa & Murayama 2009), that shows similarities to spectra of other materials, for example, barren land, sand and fallow land (Heiden et al. 2007; Lu et al. 2011). Besides, Liu et al. (2018) and Sun et al. (2019) reported in their studies that Spectral confusion between urban land and bare soils, in arid and semi-arid areas which are characterized by large areas of bare soils, appeared unaddressed issue in optical imagery, due to the components of built-up including rock material which coming from bare soil, produce errors in classification.

The above results led us to try improving the mapping of urban features during the dry season by the use of spectral indices, and the application of the multi-index method, including the BUI (Built-Up Index) (improved NDBI), where the procedure of extracting urban areas using this index according to the studies of (Kaimaris & Patias 2016; Lee, Lee & Chi 2010) is the optimized and reasonable method. The BRBA index was applied in different researches, such as (Hazaymeh et al. 2019; Kaşıkçı et al. 2020; Kayman & Sunar 2015; Pandey & Tiwari 2020; Qiu et al. 2018; Sariyilmaz et al. 2017), as well as the Dry Bare-Soil Index (DBSI) which have been assessed in several previous studies for example: (Fakhri & Gkanatsios 2021; Kimwatu et al. 2021; Lynch & Blesius 2019; Sultana & Satyanarayana 2020; Vermeulen et al. 2021), due to the semi-arid climate in our study area, and NDTI index which was applied so far in the studies of (Osgouei et al. 2019; Rouibah & Belabbas 2020) to increase the contrast between built-up areas and bare land, by employing index combination technique, where the Multi-Index, which includes the NDTI index as well as an appropriate spectral index, can improve the mapping of urban areas. Osgouei et al. (2019) have succeeded in separating built-up surfaces from bare lands in Sentinel-2A imagery using the multi-index combination-based approach, with the indices of NDTI (normalized difference tillage), NDVI (normalized difference vegetation) and MNDWI index (modified normalized difference water). The algorithm used in the study was the machine learning-based SVM. The multi-index combination showed an outstanding overall performance with a 93% accuracy and a 0.91 kappa value, while the study of (Rouibah & Belabbas 2020) was proposed to use the multi-index included NDTI, BSI, and NDVI, in Sentinel-2A imagery, for mapping cities in dry climates, and discriminating between built-up and barren (bare soil) with the k-means as an unsupervised classifier which provided an automatic and rapid detection of urban areas. The overall accuracy for this multi-index was 92% and the kappa coefficient was 83.91%.

In this study, we are attempting to put the process of separating urban areas and bare land into a test, in order to achieve the best and most effective multi-index dataset including the NDTI index, and to achieve the maximum accuracy of extraction through the combination of three spectral indices among the BRBA, BUI, NDTI, and DBSI. For this purpose, we explored a rapid and accurate mapping of built-up of semi-arid regions via Google Earth Engine (GEE) which provides a cloud platform to access and seamlessly process a large amount of freely available satellite imagery including those acquired by the sentinel 2A remote sensing satellite, as well as processing power to analyse data at planetary scale. GEE consists of a multi-petabyte of geospatial and tabular data, with a JavaScript, Python-based API (GEE API), and algorithms for supervised image classification, which we selected among them for our study the SVM algorithm.

In this regard, we selected three cities of Djelfa province to be our research area, since they are located in a semi-arid region (Algerian steppe) and characterized by vast bare soil and a sparse vegetation density, especially during dry season. With the aims to (i) identify the suitable index that can clearly distinguish the built-up area, where the main challenge is the similar spectral response of bare soil and built surfaces due to the natural materials used in the buildings' roofs of cities in our study area. (ii) examine a new approach that combines several spectral indices to achieve the best performance and provide a multi-index combination dataset that can separate built-up areas from other types of land cover, particularly, barren soil cover, and produce high accuracy.

2 Study Area

The study area located, in the central part of Algerian highlands between the Tel Atlas and the Saharan Atlas. The area includes 3 cities of Djelfa province as shown in (Figure 1) namely Djelfa, Messaad, and Ain Oussera. Djelfa province is located 300 Km from the South of Algiers, at an average altitude of 1180m above sea level. The climate of the study area regions is semi-arid, and arid, with rainy cold winters, dry and warm summers with an average annual precipitation of 200 - 400 mm, and most of it falls between November to March. The annual air temperature is generally above 20°C in the coldest months, the minimum temperature is -4°C, while it can exceed 37°C in the warmest months. The residential land use type is the most dominant land use in urban area, comprising buildings constructed with locally available materials such as gravel, stone, compacted soil, sand, and quarry sand, also it is characterized by vast bare soils and a sparse vegetation density, due to the irregularity and scarcity of precipitations, which is characteristic of the steppe regions. Djelfa is the principle district of Djelfa province, It is located between 34°40' 13" of latitude North and 03°15' 01" of longitude East, with a surface of 24.47 km^2. Messaad, located at 76 km from the South-East of Djelfa city, between 34° 8′ 31″ - 34° 10′ 52″ of latitude North and 3° 27′ 58″ - 3° 31′ 48″ of longitude East, its covers approximately 7.90 km^2. Ain Oussera is located 100 km from the North of Djelfa city, extended between 35° 26´ 56″ of latitude North and 2° 55´ 16″ of longitude East, with a surface of 13.76 km^2. The selection of these cities, includes several criteria such as the geographical settings, climatic conditions, land cover/use characteristics, and various physical sizes.

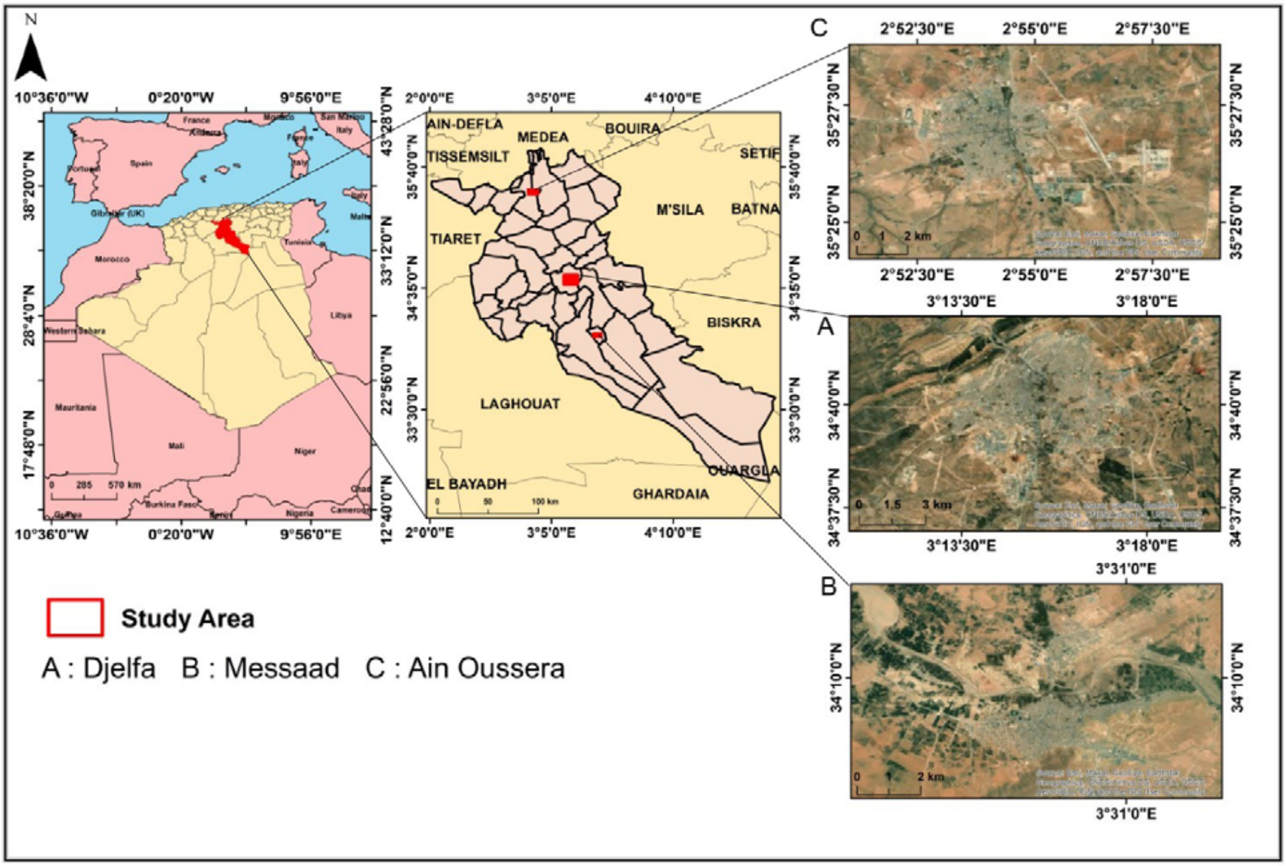

Figure 1 Location map of the study area.

3 Methodology

Three customized GEE Code Editor Scripts were used according to (2020), to avoid confusion and assist in processing time. The custom scripts developed in this study combine several components from official Google resources. Each of the three scripts in each city of the study area consists of six main components. As shown in Figure 2 including:

a. Acquiring Sentinel 2A image; **b**. clipping as the area of study; **c**. pan sharping bands to10 m; **d.** application of spectral indices formulas; **e**. classification with SVM algorithm; **f.** validation and accuracy assessment.

a. Acquiring Sentinel 2A Image Collection: the first steps in accessing and acquiring data started with a function to call and make a composite image by calling a stack or series of images from the Image Collections, each one has its own Image Collection and ID in GEE. In this case, the sentinel 2A collection was called and composed. An image collection from individual images or image merging from existing collections can also be derived in the GEE.

A filter function was scripted to limit the acquired image only to its chosen location (Djelfa, Messaad, Ain Oussera) and date of interest (on June 13th,2020) the image's date is primarily during the summer. In order to guarantee the quality of data, we used the minimum cloud cover synthesis algorithm provided by GEE to Pre-process and generate the images required. The downloaded images were processed at Level-1C, which included radiometric and geometric correction, ortho rectification, and spatial registration on a global reference system, namely the WGS84 datum and Universal Transverse Mercator (UTM), Projection with zone 31 North.

b. Clipping as the area of study: Clipping reduces the file size by eliminating areas of the scene that are not used, thus speeding up the processes which are carried out on the imager (Firman et al. 2018). The images then were clipped to the user's preference of designated shape (vector). This study imported vector data from the Google Fusion Table into GEE platform, the false color (8, 4, 3 band combination). The quality of data in Figure 3 showed its efficiency and that it matches the requirements.

c. Pan-sharpening bands to 10 m. 13 spectral bands of Sentinel-2A range from the Visible (VNIR) and Near Infra-Red (NIR) to the Short Wave Infra-Red (SWIR), with 290 km swath width at different spatial resolutions ranging from 10 to 60 meters on the ground, 10 m (the three classical RGB bands ((Blue (~493 nm), Green (560 nm), and Red (~665 nm)) and a Near Infra-Red (~833 nm) band), 20 m (4 narrow Bands in the VNIR vegetation red edge spectral domain (~704 nm,~740 nm, ~783 nm and ~865 nm) and 2 wider SWIR bands (~1610 nm and ~2190 nm), and 60 m (Bands mainly focused towards cloud screening and atmospheric correction (~443 nm for aerosols and ~945 nm for water vapor) and cirrus detection (~1374 nm). Hence, for unifying the spatial resolution of these bands, the nearest neighbourhood sampling was used for downscaling to a 10 m resolution.

d. Application of spectral indices formulas by creating a function that adds indices bands to clipped images to extract the built-up areas and identify the suitable index where the built-up area is distinguishable.

e. Classification with SVM Algorithm: This study used a SVM algorithm classifier for sentinel 2A images and multi-index images, to separate the dataset into two classes (built-up and non-built-up) and establish a comparison between the results of these classifications. An examination of the composite images was done to identify sets of training and testing points and polygons (based on Google Earth images) for two classes (built-up and non-built-up including bare land, grassland, and forested land) as Feature Collection using the Geometry tools and import. A presence of some sample selection biases existed as these samples' selection is conducted manually based on the available references. The number of good samples was experimentally investigated by running the script repeatedly to gain acceptable visual and statistical results. The samples then were used to train the Classification and Support Vector Machine (SVM) classifier within the Earth Engine platform (API Documentation). Subsequently, a map function was used to display the classification result.

f. Validation and Accuracy Assessment: In this paper, ground truth data or the testing samples was collected by interpreting existing Google Earth images, of the respective year and GIS database acquired from maps of urban master planning. Confusion matrices were used to assess the accuracy of the supervised classifier and to get a true validation accuracy, 'testing' data must be introduced and allocated to the classifier. To simplify and display how convenient is to use GEE, the previously collected samples have been scripted randomly Segregate by 70:30 percent for training and testing. The script was written to hold out data for testing, then apply the classifier to the testing data and assesses the Confusion Matrix for this withheld validation data. The validation results then were printed in the Console on the right side of the Code Editor or can be exported into table properties to Google Drive.

An index is defined as a variable synthetic, digital characterizing the intensity or the extension of an overly complicated phenomenon to be broken down into a manageable number of parameters (Caloz & Collet 2001). For mapping built-up areas, several indices have been

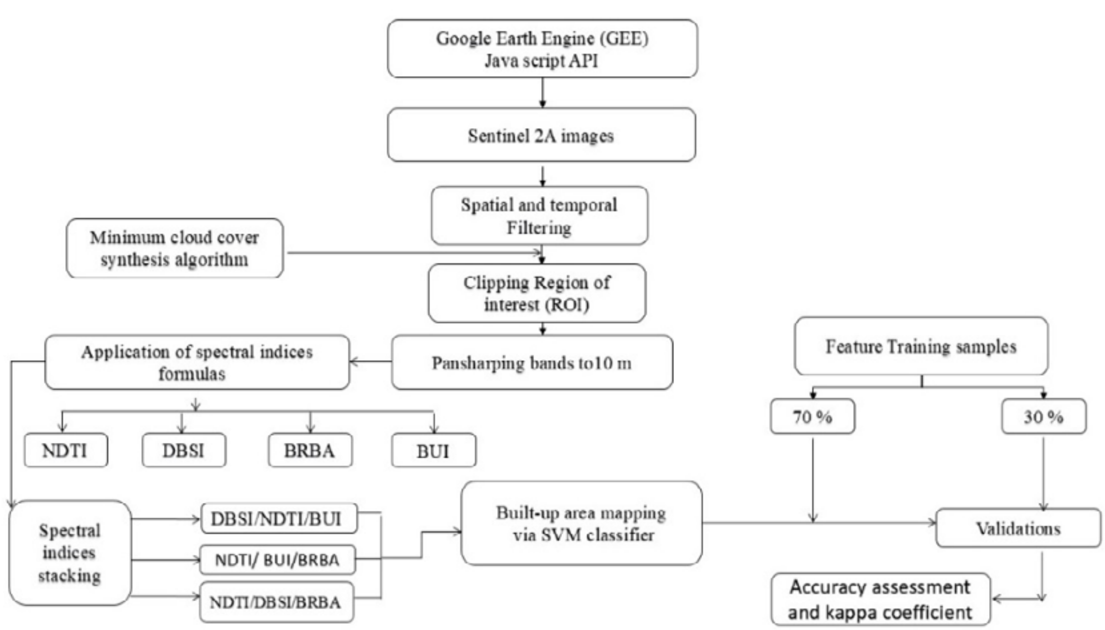

Figure 2 Schematic methodology for the extraction of built-up area with the application of spectral indices and GEE platform with SVM classifier.

proposed utilizing different combinations of spectral bands. Table 1 presents the spectral indices used in this study.

As shown in Figures 3 and 4, the Spectral indices can highlight and separate the built-up areas from forests and grasslands. Nevertheless, in some cases, some indices cannot distinguish the built-up areas from bare lands. In Djelfa city, the BRBA index provided high contrast difference between the urban area with positive values and white, bright grey, light grey tones, and bare land with negative values and dark grey tones, compared to the other indices. On the other hand, the DBSI index was used in arid regions to determine bare soil, highlighted bare land, and built-up area with moderated positive values in the cities of Messaad and Ain Oussera. The results also indicate that the BUI and NDTI provided a low difference between the built-up areas and the bare lands, no significant contrast was observed in index images between these two regions. In addition, Table 2 presents the statistical values of the four spectral indices used, where it is noteworthy that for all indices, the standard deviation values are low.

Table 1 The Spectral indices utilized in this study on Sentinel-2A.

Index name	Index ID	Formula on Sentinel 2A image	Reference
Normalized Difference Tillage Index	NDTI	(B11-B12/ B11+B12)	(Deventer et al. 1997)
Built up index	BUI	NDBI – NDVI Where ; NDBI = B11-B8 / B11+B8	(He et al. 2010)
Band ratio for built-up area	BRBA	(B4 / B11)	(Waqar et al. 2012)
Dry Bare-Soil Index	DBSI	[(B11-B3/ B11+B3) – NDVI] Where ; NDVI = B8-B4/ B8+B4	(Rasul et al. 2018)

Table 2 Statistical values of the four indices used.

Spectral indices		Djelfa	Messaad	Ain Oussera
NDTI	Min	-0.1051	-0.581	-0.0712
	Max	0.2426	0.2658	0.268
	Mean	0.06875	-0.1576	0.0984
	StdDev	0.02918	0.04462	0.02172
	Range value		From -1 to 1	
BUI	Min	-1.03	-1.12	-1.09
	Max	0.441	0.41	0.6415
	Mean	-0.2945	-0.355	-0.22425
	StdDev	0.10546	0.19292	0.07317
	Range value		From -1 to 1	
BRBA	Min	-0.7054	-0.6902	-0.9601
	Max	0.2301	0.1675	0.2195
	Mean	-0.23765	-0.26135	-0.3703
	StdDev	0.08066	0.09315	0.05744
	Range value		From -1 to 1	
DBSI	Min	-0.2436	-0.3708	-0.2464
	Max	0.6559	0.4673	0.6865
	Mean	0.20615	0.04825	0.22005
	StdDev	0.06927	0.09376	0.05598
	Range value		From -2 to 2	

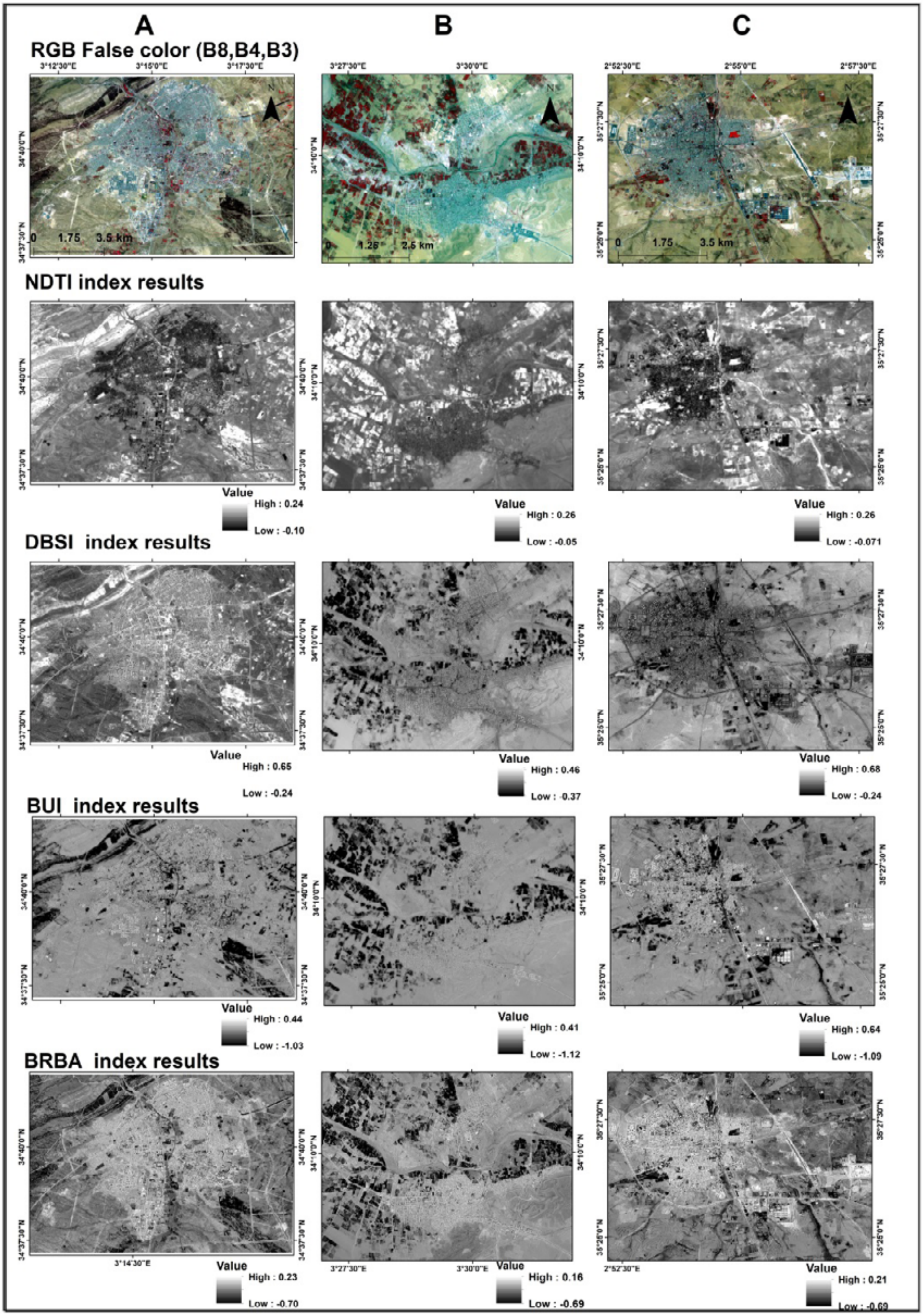

Figure 3 Result of the used Spectral indices, False color composite (RGB 8 - 4 - 3) from Sentinel 2 images: A. Djelfa; B. Messaad; C. Ain Oussera.

Although spectral index calculation is computationally easier, finding the thresholds that can differentiate between classes is extremely difficult, which is one of the major disadvantages of using spectral indices directly in remote sensing applications. For this reason, we opted for the multi-index approach to examine the extent to which this approach is being used in the extraction and calculation of the surfaces of built-up areas.

The correlation between the four spectral indices is shown in Table 3. It is observed that there is a very good correlation between the BUI-NDTI, and the BRBA-NDTI pairs of indices are correlated negatively.

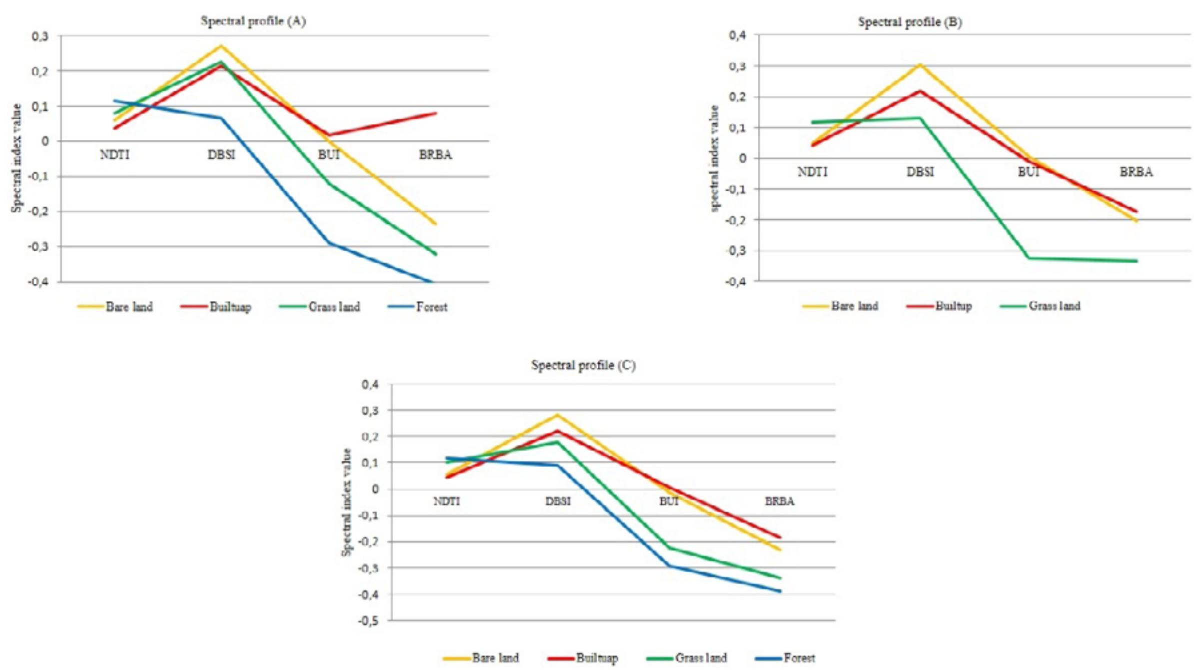

Figure 4 Simplified spectral signatures represented by the mean of major categories of land cover for the spectral indices images: A. Djelfa; B. Messaad; C. Ain Oussera.

Table 3 Correlation between spectral indices.

Cities	Indices	DBSI	NDTI	BRBA	BUI
Djelfa	DBSI	1	-0,301696111	-0,156293369	0,729394789
	NDTI	-0,301696111	1	-0,636356012	-0,742299917
	BRBA	-0,156293369	-0,636356012	1	0,453044291
	BUI	0,729394789	-0,742299917	0,453044291	1
Messaad	indices	DBSI	NDTI	BRBA	BUI
	DBSI	1	-0,757986153	0,583380557	0,897739933
	NDTI	-0,757986153	1	-0,777498001	-0,872437045
	BRBA	0,583380557	-0,777498001	1	0,823940729
	BUI	0,897739933	-0,872437045	0,823940729	1
Ain Oussera	indices	DBSI	NDTI	BRBA	BUI
	DBSI	1	-0,141976289	-0,430458142	0,503217905
	NDTI	-0,141976289	1	-0,523422347	-0,670884372
	BRBA	-0,430458142	-0,523422347	1	0,394480774
	BUI	0,503217905	-0,670884372	0,394480774	1

The multi-index approach was created by three spectral index combinations, formed by the layer stack process, both NDTI and DBSI indices were used to form the bare land layer stacking dataset and both BUI and BRBA indices were used to form the built-up area layer stacking dataset, which can be represented by three cases: Multi index (DBSI/ NDTI/ BUI), Multi index (NDTI/ BUI/ BRBA), and Multi index (NDTI/ DBSI /BRBA).

For the purpose of finding the highest accuracy in extracting built-up areas as the second component, the spectral indices combinations have been compared with the classified Sentinel-2A image.

The classification method of the Support Vector Machine (SVM) has been carried out on three multi-index images, and the sentinel 2A image with the selection of 06 bands; B2, B3, B4, B5, B6, and B7, which has provided the best classification results after several attempts.

In terms of accuracy, speed, and memory requirements, the SVM-based classification methods perform better, and if there are limited training samples, as is frequently the case for satellite image classification problems, it can function efficiently and accurately (Maulik & Chakraborty 2017), and when applied to multi-index images, the SVM classification performed better than the regression trees (CART) and Neural Network (NN) classifier (Shao & Lunetta 2012). Furthermore, the research of (Osgouei et al. 2019) have shown the performance of the algorithm to classify the land cover over multi-index datasets. In this study, the SVM was developed as a binary classifier (built-up and non-built up) and the built-up Class mainly included, roads, residential, military, industrial areas, and impervious surfaces, as well as, bare soil, grassland, and forests are included in the non-built-up class, and the overall accuracies, consumer's accuracy, producer's accuracy, Kappa statics, were acquired from the confusion matrix to examine the accuracy of the results of classification.

The classification results accuracy assessment was carried out with stratified random points, maps of urban master planning, and Google Earth imagery on the same date as the data of reference. In addition, a random distribution point was designed based on the heterogeneity potentials and areal coverage of the classes. The distribution of training and validation of the samples utilized in the accuracy assessment for every city is provided in Table 4.

Table 4 Distribution of training and validation of samples for the area of study.

Cities	Sample	
	Training	Validation
Djelfa	2512	1117
Messaad	2018	838
Ain Oussera	1728	723

4 Result and Discussion

The processed series images in Figure 5 present the results of the built-up area extracted from the sentinel 2A image and the multi-Index dataset. Table 5 also shows the statistics obtained from the SVM classification result.

According to the value of the surface area of the multi-index images and the classified sentinel 2A image in Table 5, the built-up class of the multi-index closest to the same class of the classified sentinel 2A image in the cities of Djelfa, Messaad, and Ain Oussera is resulting from the multi-index (DBSI /NDTI/BUI) with 24.69 km^2, 7.95 km^2, and 13.99 km^2 respectively.

The confusion matrix resulting from the accuracy assessment is shown in Table 6. The results indicated that the built-up area was better mapped using multi-index (DBSI/ NDTI/ BUI); the overall accuracies achieved are 98.7% in Djelfa city, 96.5% in Messaad city, and 97.87 % in Ain Oussera city, the kappa coefficients achieved are 97.3%, 85.4%, and 95.3%, respectively regarding the assessment of the classification quality of each class, which aids in comparing the accuracy of both classes, between the multi-index dataset developed and sentinel 2A image. We note that in terms of the precision of consumers accuracies in built-up areas, the multi-index (DBSI/ NDTI/ BUI) has also proved high percentages in the cities of Djelfa, Messaad, and Ain Oussera, it achieved 99.5%, 96.9%, and 98.1%, respectively. Although it is also noted that the multi-index (NDTI/ BUI/ BRBA) in Ain Oussera city showed a similar value of consumers accuracy to the multi-index (DBSI/ NDTI/ BUI). Additionally, the producer accuracies of built-up class of multi-index (DBSI/ NDTI/ BUI) in the cities of Djelfa, Messaad, and Ain Oussera achieved 98.2%, 79.6%, and 98.5%, respectively, whereas in Messaad city the producer's accuracy of built-up areas resulted from multi-index (DBSI/ NDTI/ BUI) showed a similar value to the multi-index (NDTI/ DBSI /BRBA).

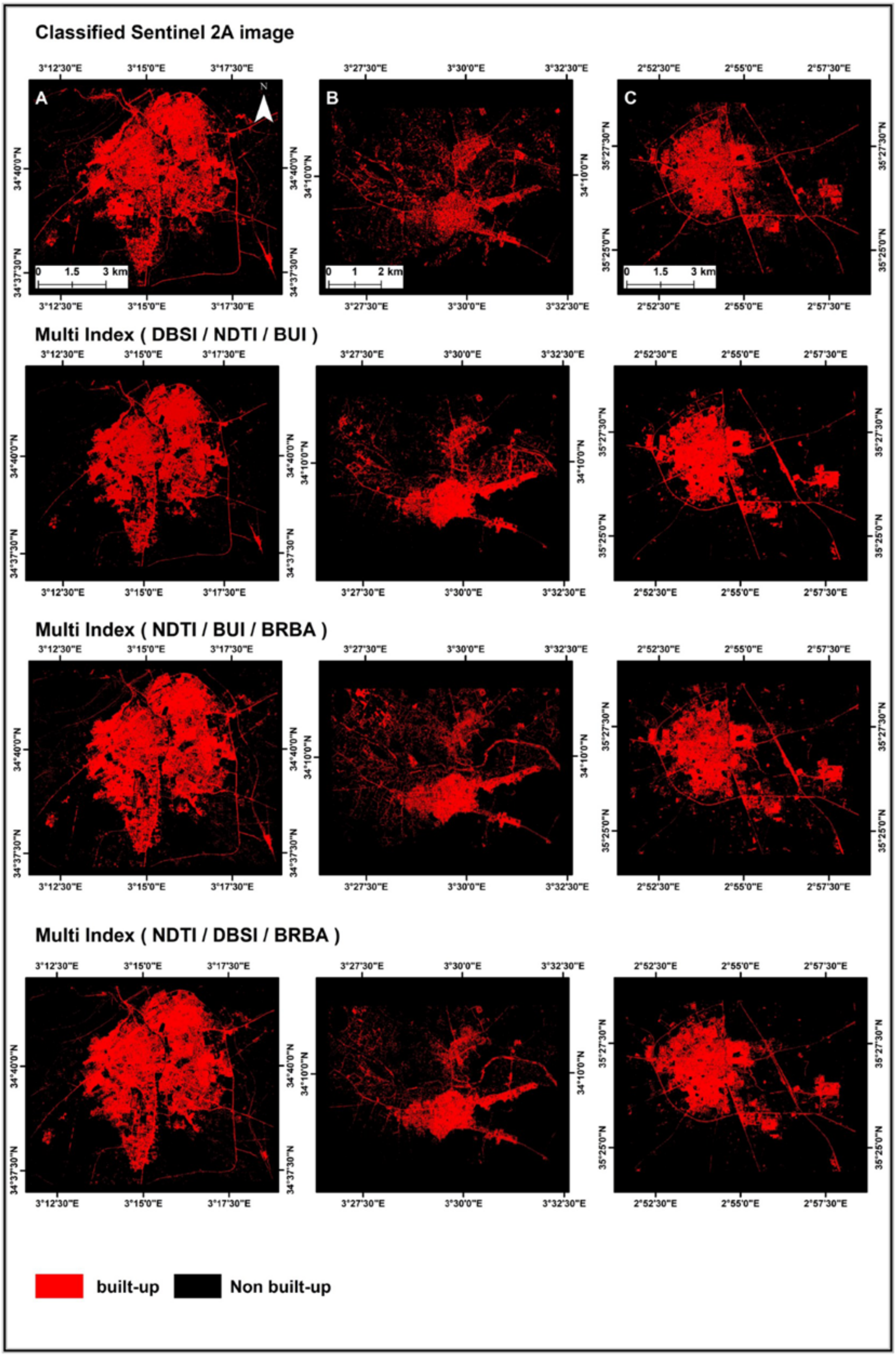

Figure 5 Binary image of SVM classifier in: A. Djelfa city; B. Messaad city; C. Ain Oussera city.

Table 5 The extracted built-up area according to the Support Vector Machine (SVM) classifier over cities of the study area.

	Djelfa		Messaad		Ain Oussera	
	Built-up surface (Km^2)	**Others (Km^2)**	**Built-up surface (Km^2)**	**Others (Km^2)**	**Built-up surface (Km^2)**	**Others (Km^2)**
Multi index (DBSI /NDTI/BUI)	24.69	70.41	7.95	44.61	13.99	63.03
Multi index (NDTI/BUI /BRBA)	25.47	69.64	8.57	43.98	14.15	62.87
Multi index (NDTI/DBSI/BRBA)	23.18	71.93	7.07	45.49	14.13	62.90
Classified Sentinel-2A	24.47	70.48	7.90	44.53	13.76	63.10

Table 6 Accuracy assessment of maps results of the study area.

	Land cover class	(Sentinel-2A Image (6 Bands)		Multi index		Multi index (NDTI/ BUI/ BRBA)		Multi index (NDTI/ DBSI /BRBA)	
		Producers Accuracy	**Consumer's Accuracy**	**(DBSI/ NDTI/ BUI)**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**
Djelfa	Built up	0.992	0.997	0.982	0.995	0.955	0.9907	0.960	0.981
	Non built-up	0.997	0.988	0.993	0.976	0.987	0.941	0.975	0.946
	Over all accuracy	0.994	0.987	0.969	0.966				
	Kappa	0.987	0.973	0.936	0.931				
	Land cover class	**(Sentinel-2A Image (6 Bands))**		**Multi index (DBSI/ NDTI/ BUI)**		**Multi index (NDTI/ BUI/ BRBA**		**Multi index (NDTI/ DBSI /BRBA)**	
		Producers Accuracy	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**
Messaad	Built up	1	1	0.796	0.969	0.727	0.952	0.799	0.945
	Non built-up	1	1	0.995	0.964	0.994	0.953	0.992	0.967
	Over all accuracy	1	0.965	0.953	0.965				
	Kappa	1	0.854	0.798	0.846				
	Land cover class	**(Sentinel-2A Image (6 Bands))**		**Multi index (DBSI/ NDTI/ BUI)**		**Multi index (NDTI/ BUI/ BRBA)**		**Multi index (NDTI/ DBSI /BRBA)**	
		Producers Accuracy	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**	**Producers Accuracy**	**Consumer's Accuracy**
Ain Oussera	Built up	0.994	0.998	0.985	0.981	0.941	0.981	0.962	0.969
	Non built-up	0.996	0.990	0.966	0.973	0.967	0.902	0.944	0.932
	Over all accuracy	0.995	0.9787	0.950	0.956				
	Kappa	0.989	0.953	0.894	0.904				

As the visual analysis of the binaries results illustrated in Figure 5 shows; it is indicated that the multi-indexes developed, a separated built-up area from other land cover classes differently. Although, when compared to the Sentinel 2A images (6 bands), which clearly shows the different land cover/use of the study area's regions, it shows that few pixels of bare soil, are misclassified as built up and vice versa.

The confusion matrix which consists of classified built-up statistics and non-built-up points was generated for every city in Table 7. It is generally observed in regions of the study area that the multi-index (DBSI/NDTI/BUI) had a low misclassification of built-up area compared to other multi-index, which makes it possible to reduce the complexity of mixing the built-up and the bare soil.

Table 7 A classification confusion matrix for the built-up and non built-up classes of the study area.

Multi index	Cities	Djelfa		Messaad		Ain Oussera	
	Classe Name	Built-up	Non Built-up	Built-up	Non Built-up	Built-up	Non Built-up
DBSI/NDTI/BUI	Built-up	1446	7	231	64	1086	26
	Non Built-up	16	1043	13	1710	30	586
NDTI/BUI/BRBA	Built-up	1398	74	222	84	1038	45
	Non Built-up	15	1025	11	1701	20	625
NDT/DBSI/BRBA	Built-up	1399	58	227	57	1068	42
	Non Built-up	26	1029	13	1721	34	584

In this combination, the BUI index provided a better understanding of built-up area patterns than the BRBA index with the same combination, which is NDT and DBSI indices, the DBSI index showed its performance toward bare soil mapping. The NDTI which was determined by dividing the difference of the SWIR bands by their sum exhibited a significant improvement compared to images of spectral index in the previous section, where there was no major contrast between built-up and bare soil. It should be also noted that the developed multi-index did not work with the same performance in the city of Messaad compared to both cities, where the kappa coefficient achieved was 85.4%, and the producer's accuracy of the built-up class was decreased to 79.6%, since it considered as un heterogeneous region where the vegetation has an important part. Likewise, the multi-index has detected more bare soil than the built-up in Messaad, which can be explained by different effects like a decrease in chlorophyllase activity, tree diseases, or the effects of the phenomenon of drought during the period studied, where the multi-index pick it up the vegetation like bare soil because it does not contain plant vigor. These misclassifications could also be due to the "mixed pixel" effect. Since the area is in the arid region, it means that the spectral response is following environmental and climatic conditions. Although multi-index images generated using NDT/DBSI/BRBA, NDTI/BUI/BRBA have showed satisfying results, their accuracies remain lower than the Multi-index DBSI/NDTI/BUI, for built-up and non-built-up classes, due to the influence of BRBA when paired with the other spectral indices (NDTI, DBSI, BUI) reduced the classification accuracy of built up features. Through visual verification on the ground, the highways in the study area which run across different parts of the cities could be determined visually, the dry riverbeds could also be distinctly observed, urban areas such as buildings, factories, roads, were correctly represented but some vegetation patches within cities and in regions near the green areas, were misclassified by the binary images generated from these two combinations NDTI/ BUI/ BRBA, NDTI/DBSI/BRBA. Agricultural land that is not being farmed, particularly those compacted as a result of field operations, tillage implements, and heavy equipment, were frequently misclassified as built-up areas with the multi-index NDTI/ DBSI /BRBA and NDTI/ BUI /BRBA. This observation indicates that the association of BRBA with the other spectral indices resulted in the misclassification of vegetation patches. also, there was a misclassification of the bare lands as built-up regions in the multi-index images. The above analysis revealed that the behaviour of BUI, DBSI, and NDTI indices next to each other helped led to the best binary result in low mixing of built-up area and bare land, compared to the multi-index NDTI/BUI/BRBA and NDT/DBSI/BRBA using SVM method.

Our findings coincided with (Osgouei et al. 2019; Rouibah & Belabbas 2020) research, that pointed out that the multi-index method including the NDTI index, is the most efficient to increase the accuracy of the extraction and the separation between bare land and built-up areas, where The developed dataset that has been tested in this new region showed effectiveness in the mapping of urban areas.

They are also close to those reported in study of (Luo, Peng & Gao 2017) that it was hard to distinguish built-up areas from bare lands using only built-up indices. The study also agrees with the findings of (Bramhe et al. 2018; Lee, Acharya & Lee 2018; Osgouei et al. 2019; Xi et al. 2019) considering the thematic classification focused on the use of layer stacking of spectral indices as a clustered data for the SVM classifier.

The problem of the most urban built-up indexes that have been proposed only for the detection of built-up or impervious surfaces has not been used for extraction of its sub-classes (Pandey & Tiwari 2020). In this study, any sub-categories of built-up classes have not been calculated. i.e. surfaces of main roads, the secondary axes which ensures distribution in urban neighborhoods, branching spaces and the tertiary axes and impasses), pavements, parking lots, and metallic roofs.

Future works are planned to integrate high-resolution LiDAR (Light Detection and Ranging) geospatial data, to characterize the urban areas and to obtain a fine segmentation of urban objects.

5 Conclusion

This study focused on identifying and delineating urban areas in semi-arid and arid environments, which submits a difficult task due to the problems in the classification process. For that, a multi-index approach has been tested by creating combinations with the pre-selection of various spectral indexes to prove the most efficient and highly accurate, multi-Index dataset to reduce the spectral confusion between built-up areas and bare soils, where the stake was its identical spectral responses due to the components of built-up including materials which coming from bare soil. The results show that the classification of built-up areas was highly accurate, quick, automatic and has the best performance achieved by the multi-index, including BUI, with the NDTI and DBSI indices in comparison with the BRBA index, based on the confusion matrix, overall precision, and Kappa coefficient, tested in the new area including three cities of the Algerian steppe, which are Djelfa, Ain Oussera, and Messaad, in the dry season. The multi-index images have been classified by the SVM algorithm, and the results were compared to those of the classification of Sentinel-2A images. Additionally, the problems paired with underestimation of bare land and overestimation of built-up areas can be improved effectively, using this combination (DBSI/ NDTI/ BUI) in similar conditions, also it improves urban growth assessment. Local authorities and decision-makers can use this paper as a basis to quickly identify and estimate built-up areas in semi-arid and arid regions. We also suggest combining other spectral indices that could improve the mapping of built-up area.

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Dib Samira: conceptualization; formal analysis; methodology; validation; writing-original draft; writing – review and editing; visualization. **Nouari Souiher:** methodology; validation; supervision. **Bengusmia Djamal:** writing – original draft.

Conflict of interest
The authors declare no potential conflict of interest.

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