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EVALUATE THE LEVEL EFFECTIVENESS OF SELECTED BARE SOIL INDICES IN SEMI-ARID LAND USING SENTINEL-2 DATA

Abstract: The Semi-Arid area is a specific climate region, where the accurate mapping of dry soil is a crucial issue and a real challenge. For that reason, this paper investigated this question over a semi-arid land that located in North-East of Algeria, by using Sentinel-2 data with a comparative analysis of selected Index-Based Methods, in addition to apply the Support Vector Machine-SVM method. The finding showed that the Modified Normalized Difference Bare Index (MNDBaI) and the Modified Bare Soil Index (MBSI) which are combining visible bands at 10 m of resolution, worked better than the Bare Soil Index (BSI) and the Dry Bare-Soil Index (DBSI) that are combining VNIR-SWIR bands; the overall accuracy (OA) of the MNDBaI and MBSI are about 92.29 % and 90.86 %, respectively. Meanwhile, the DBSI provided the weakest (OA) that achieved 86%. Based on this, the indices MNDBaI and MBSI are successfully tested in semi-arid land, since they were more discriminative toward dry soil, especially the MNDBaI index that manifested an advanced behavior. Under climate changes and urban expansion impacts in the region, the MNDBaI index can contribute for accurate ecological studies and better spatial management, as it can produce an accurate bare soil information and land cover maps updates; the MNDBaI index is promising to be more adoptable in survey land degradation, indicating soil condition and boosting agriculture management. However, more tests over other areas, are suggested. Additionally, developing new soil indices that are more sensitive to dry soil, is highly needed.

Keywords: Dry Bare-Soil Index (DBSI), Bare Soil Index (BSI), Modified Bare Soil Index (MBSI), Modified Normalized Difference Bare Index (MNDBaI), Support Vector Machine (SVM), dry soil mapping accuracy

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Introduction

The sustainable land use planning required a spatial information using remote sensing technics and data (Kaya & Dervisoglu, 2023). In this context, the bare land class information, is very important as it is a key to understand many geographical topics. Especially, the forest canopy density (Banerjee et al., 2014; Jamalabad, 2004; Rikimaru et al., 2002), the land use changes (W. Chen et al., 2004), estimate soil erosion (Wentzel, 2002) and land degradation (Muna & Walker, 2010) or modeling desertification (Becerril-Piña et al., 2015; Bouzekri et al., 2023). Besides, the bare soil maps and its related information used for agriculture systems observing (Nguyen et al., 2021) or indicating bare soil condition or fallow fields (Tola et al., 2019), in addition to identifying barest pixel composite and bare soil composite (Diek et al., 2017) as well. In this context and according to literature, usually, the detection of the bare soil area and generating soil information, is critical for environment studies, where numerous research adopted the Index-Based Methods to detect soil area.

In last two decade, researchers have developed a several indices for soil discrimination (Capolupo et al., 2020; Javed et al., 2023; Nguyen et al., 2021; Pirowski & Szypuła, 2024), to mention but not limited, the Normalized Difference Bare Land Index (NBLI) (H. Li et al., 2017), the Normalized Difference Bareness Index (NDBaI) (Zhao & Chen, 2005). Additionally, we find the Bare-soil Index (BI) (S. Li & Chen, 2014). but the calculate of previous indices need the introduced of Thermal Infrared band (TIR), the latter is available in Landsat data (Martin, 2024; Yu et al., 2019; Zhou et al., 2014) and not presented in Sentinel-2 data (Vanhellmont & Ruddick, 2016; R. Xu et al., 2018). On another hand, we find other useful bare soil indices that were developed and can be applied within a Sentinel-2 data, such as the Normalized Difference Soil Index (NDSI) (Rogers & Kearney, 2004), the Ratio Normalized Difference Soil Index (RNDSI) which has been proposed by Deng et al. (2015), in addition to the Modified Normalized Difference Bare-land Index (MNDBI) (Faridatul & Wu, 2018) as well. Also, there are other indices which were developed recently mainly: the Modified Bare soil Index (MBI) (Nguyen et al., 2021), the Hyperspectral Bare Soil Index (HBSI) (Salas & Kumaran, 2023), the both Normalized Soil Area Index 1 (NSAI1) and Normalized Soil Area Index 2 (NSAI2) that have been developed by Javed et al. (2023). And additionally, we find the Bare Land Extraction Index (BLEI) (He et al., 2024) and the Modified Normalized Difference Bare soil Index (MNDBSI) (Somanathan et al., 2024).

Regarding the behavior of the bare soil indices within different climate types, it should be noted that in dry-arid and humid regions, the behavior and effectiveness of the bare soil indices differs (Rasul et al., 2018). Moreover, regardless of climate conditions and geographical features, the bare soil indices are relatively sensitive (Nguyen et al., 2021). Also, several barren surface extraction indices provided unsatisfactory outcome, when a low moisture content in vegetated areas surrounding urban in dry climates than in humid regions (Kaur & Pandey, 2022). Another point which is important, is that the wet soil clearly has a lower reflectance than the dry soil, where the dry soil and wet soil are indexed differently (Javed et al., 2023). By referring to the confusion issues regarding spectral signatures similarity between features, we find that the dry bare soil, bright urban impervious surfaces and bare rocks are comparable (Weng & Lu, 2008), where the considerable barren soil causes a higher similarity with built-up reflectance (C. Li et al., 2021; Rouibah, 2025a; Valdiviezo-N et al., 2018). As a result, this type of confusions particularly, is always considered as essential problems, especially for analyzing urban environments (Deng et al., 2015). In same point, and according to literature review, basically, the spectral characteristics of bare ground are between those of vegetation and impervious surfaces. As a result, the potential overlapping and pixel values similarity makes difficult to distinguish the dry soil accurately, as it leads to misclassifying of the dry soil as both built-up and vegetation or vice versa i.e. producing less accurate soil maps. Under this challenge, it should be noted that the misclassification process affects certainly the results accuracy of the studies that rely particularly on the estimation of land and vegetation degradation or agricultural practice survey.

According to the literature review, despite the vast list of bare soil indices, it is still poorly understood which soil index is suitable for a specific study area. In this context, it is important to noted that the studies that carried with soil indices comparison is very limited, especially in dry climate. By focusing on this point, it is concluded that the barest soil indices cannot able to detect bare land accurately regarding the challenge that is clearly stating in semi-arid land. Also, since the selection of the suitable bare soil index for specific area condition is considered as an important issue and a necessary step for different environment studies, identifying the appropriate bare soil index, should be selected based on its effectiveness that correspondent to the study area's climatic conditions (Nguyen et al., 2021). To reach that end, a comparative analysis between soil indices should be carried on, to categorized them regarding climate environment types and land cover conditions as well, focusing on the arid and semi-arid land.

Based on the previous literatures review and analysis, it is stated that, generally, bright buildings and materials cause the main disturbance in dry bare soil with high albedo in summer. Also, the dark vegetated area causes the main disturbance in dry dark soil. Therefore, there is a big challenge related to the dry bare soil detection and its mapping accurately in dry periods, especially that the accurate spatial information support environment studies. In view of these considerations and reasons, identify a reliable soil index is critical. Accordingly, the current research aims to select some bare soil indices to evaluate their level of effectiveness regarding the aforementioned issue, via discussing their behavior (strengths and limitations) based on their structure, bands nature and resolutions, where the main objective, is identifying the reliable index that can detect highly bare soil class with no large misclassification errors in the result i.e. find the bare soil index that is able to suppress maximally the built-up and vegetation pixels. To reach this principal objectives, the Semi- Arid climate of Algeria (Côte, 1996), can be a suitable experiment area, where its sustainable spatial planning, is highly needed.

Methodology

Study area

In this research, we selected a region as an area of study, where is located in the north Est of Algeria and characterized by semi-arid climate according to Amar Rouabhi et al. (2016) and Côte (1996). Also, the study area spread over an area of 27.8573 km2 and contains large amount of the major landcover types mainly the bare soil, impervious surfaces and vegetation; The principal built-up area (Ain Oulmene city), is one of the important urban poles that located at south part in Setif province, as it is been presented in Fig. 1. The city is surrounded by vegetation area with different level of density (green and dry) such as forest area and irrigated agriculture fields, in addition to the presence of different bare soil types and color. Therefore, this area exhibits distinct land use patterns that could have overlapping spectral signatures due to the highly similar features, particularly between buildings, roads and dry soil, presenting a real challenge for dry soil mapping. Accordingly, the region with its specific climate, its spatial heterogeneity with several challenges, is an ideal case study for investigative the effectiveness of the selected bare soil indices, especially when taking in count that according the literature, so far, the region has not known such experiment of bare soil indices comparison.

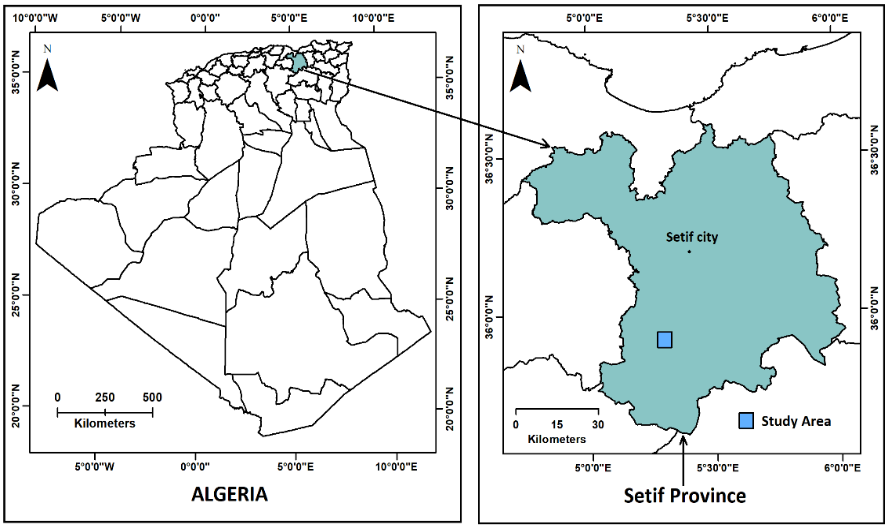

Fig. 1. Geographical Location of the Study Area in North-East of Algeria

Data used in the current research

To reach the objectives of this study, we have employed the Sentinel-2 imagery as remote sensing data, which is a good image quality (Drusch M et al., 2012). Therefore, the images that cover the study area, was acquired from the Copernicus Open Access Hub (https://scihub.copernicus.eu) at level 2, to facilitate processing step. As for the date chosen for discriminating the bare lands, the right time is crucial (Sharma et al., 2016). So that, in order to capture large surface of dry bare soil in the region, the image downloaded, was at 04 august 2022 that represent a dry time. In terms of the Sentinel-2 bands resolution (Suleymanov et al., 2025; Vanhellmont & Ruddick, 2016; Xi et al., 2019), we find that the VNIR bands of Sentinel-2 (Visible + Near-infrared) were produced with distinctive high resolution; the visible bands (Blue, green and red) in addition to NIR band, are at 10 m of resolution. While, the SWIR bands of Sentinel-2 (Short-wave infrared), are at 20 m resolution.

The used software and applications

The processing over Sentinel-2 image, were carried by combining the Quantum Geographic Information System (QGIS), which is a free open-source software obtained from https://www.qgis.org, in addition to the Environment for Visualizing Images (ENVI) software; Semi-Automatic Classification plugin (SCP) (Congedo, 2016) that is integrated in QGIS, was used to clip Sentinel-2 data, the creation of spectral indices grayscale and computing the correlation degree between them. Additionally, QGIS contributed in accuracy assessment step, by generating the stratified random sampling. As for the ENVI software, it was used for stacking bands process, statistical analysis (spectral indices signature), built training sample and then, generating maps via segmentation indices and classification of datasets.

Soil indices selected to dry bare soil detection

In this research we selected four bare soil indices to be applied, which are the Dry Bare-Soil Index (DBSI) (Rasul et al., 2018), the Bare Soil Index (BSI) (Rikimaru & Miyatake, 1997), the Modified Normalized Difference Bare Index (MNDBaI) (Hua et al., 2017), in addition to the Modified Bare Soil Index (MBSI) (S. Zhang et al., 2018) as well. These indices with their structures on Sentinel-2 are presented in Table 1.

Table 1. *Various spectral indices used in this study on Sentinel-2*

Bare soil Index Name and Id	References of index	Formula on Sentinel-2 image
The Modified Normalized Difference Water Index (MNDWI)	(H. Xu, 2006)	(B3 - B11) / (B3 + B11)
Normalized Difference Vegetation Index (NDVI)	(Rouse et al., 1973; Tucker, 1979)	(B08 - B04) / (B08 + B04)
Dry Bare-Soil Index (DBSI)	(Rasul et al., 2018)	((B11 - B03) / (B11 + B03)) - NDVI
Bare Soil Index (BSI)	(Rikimaru & Miyatake, 1997)	((B11 + B4) - (B8 + B2)) / ((B11 + B4) + (B8 + B2))
Modified Bare Soil Index (MBSI)	(S. Zhang et al., 2018)	(B4 - B3)*2 /(B4 + B3 - 2)
Modified Normalized Difference Bare Index (MNDBaI)	(Hua et al., 2017)	(B4 - B2) / (B4+ B2)

Regarding the soil indices that developed specifically for specific climate land, we find among them as an example, the MBI index (Nguyen et al., 2021) that was suggested to be used in tropical climatic regions. In contrast, we find the DBSI index (Rasul et al., 2018) that developed and designed for dry climate such as the semi-arid land. In this context, it should be noted that there is a very high correlation observed between the both bare soil indices BSI and DBSI in semi-arid land (Rouibah, 2025b), which is confirmed over the current test area, as showed in Table 2. According to literature, the BSI index is expansively used, for extracting dust storms in arid areas and bare soil in cities as referred to in the work of Hua et al. (2023). Also, the BSI index was used in semi-arid lands (Al-Quraishi, 2011; Becerril-Piña et al., 2015). Besides, there is the MBSI index that was proposed to develop the Combinational Biophysical Composition Index (CBCI) (S. Zhang et al., 2018) and use only the visible bands which are mainly red and green. As for the MNDBaI index (Hua et al., 2017), it use only the visible bands which are mainly red and blue bands. As far as I know and according to literature review, comparing to the soil indices that combines VNIR-SWIR bands. it should be noted that the both indices MBSI and MNDBaI have not widely applied. So, it is a great opportunity to apply them singly in semi-arid land, to measure their level of effectiveness (strengths and limitations), concerning dry bare soil mapping accuracy using Sentinel-2 bands that are at 10 m of resolution.

It is concluded that the both indices MBSI and MNDBaI uses only the visible bands in their equation. While, the both indices DBSI and BSI, in their formula, they use the Visible, Near-Infrared and the Short-wave infrared. Therefore, the current work tests the indices selected BSI, DBSI, MBSI and MNDBaI, in view of their different band's nature and resolution, in addition to their different structure as well, to make a comparative study between them using Sentinel-2 over an area that located in semi-arid land of Algeria. And then, providing more detailed analysis and perspective with statistical comparison, to verify whether the selected soil indices with only visible bands could enhance the dry soil detection.

Remote sensing technics selected for indices segmentation process and comparison step

Usually, the spectral indices requires finding threshold (Bramhe et al., 2018). In this context, we find the automatic thresholding technic such as the OTSU method (Ng, 2006; Otsu, 1979). However, for the binary process which is an important step in our case, the indices (BSI, DBSI, MBSI and MNDBaI) were subjected to binarisation process via the k-means clustering (MacQueen, 1967), as unsupervised classification method that is available at ENVI software.

Also, for land cover mapping, we selected the Support Vector Machine (SVM) (Vapnik, 1995), which is famous supervised classification method that is available at ENVI 5.6 version; SVM method has known a wide interesting in image classification, since it is a powerful supervised machine-learning algorithm (Bramhe et al., 2018), by maximizing the margin between different classes in addition to its effectiveness with a limited training data (Congcong Li et al., 2014; Shao & Lunetta, 2012). And additionally, it produced the highest accuracy using Sentinel 2 imagery (Thanh Noi & Kappas, 2018). Besides, the False Color Composite FCC (8 -8A-3) of Sentinel-2 image, was selected to be used for visually comparison, selecting training sample and to be adopted as a dataset for SVM method.

All the remote sensing technics used in this study (BSI, DBSI, MBSI, MNDBaI and SVM method) were compared each other visually and statistically, concerning dry bare soil mapping accuracy, using Sentinel-2 over semi-arid land.

Results and Discussion

Results

The results obtained from processing step, can be observed in Fig. 2. The results are mainly the FCC (B8 – B8A – B3), the major Land Cover/Use LCLU (built-up, vegetation and bare soil) that obtained via the SVM method, in addition to the grayscale of the different spectral indices used. Compared to the both grayscale of BSI and DBSI indices, it is observed that the built-up pixels are greatly enhanced with dark grey in both gray scale of both MBSI and MNDBaI indices, where the variance becomes easy visualized between bare soil feature and built-up class.

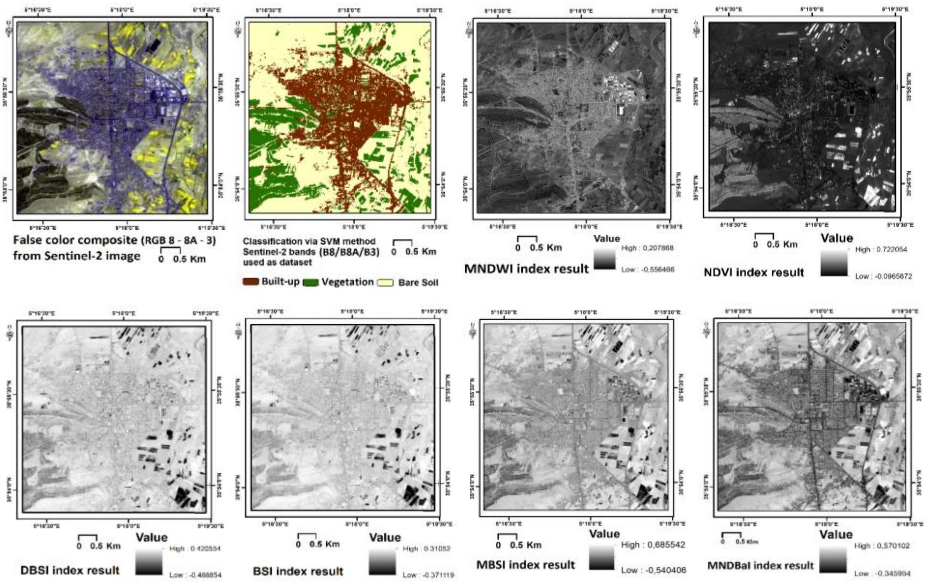

Fig. 2. (a) False Color Composite FCC (RGB B8 – B8A – B3) from Seninel-2 image date 04-08-2022, (b) LCLU classification via the SVM method, (c) MNDWI, (d) NDVI, (e) DBSI, (f) BSI, (g) MBSI, (h) MNDBaI

Statistical Results

The statistical results obtained, are mainly the correlation coefficients between spectral indices selected that are shown in Table 2. Additionally, their spectral signatures are represented in Table 3 and they can be observed in Fig. 3. Meanwhile, the bare soil surface areas were tabulated in Table 4. As for their maps, they can be showed in Fig. 4.

Table 2. Correlation values between four selected bare soil indices and the both NDVI and MNDWI index

Spectral Indices	MNDWI	NDVI	DBSI	BSI	MBSI	MNDBaI
MNDWI	1.000000					
NDVI	-0.486845	1.000000				
DBSI	-0.253435	-0.721408	1.000000			
BSI	-0.246433	-0.706722	0.978016	1.000000		
MBSI	-0.279105	-0.504598	0.779204	0.731069	1.000000	
MNDBaI	-0.396680	-0.231285	0.569714	0.593923	0.869722	1.000000

Focusing on correlation degree between bare soil indices, the results indicated that there is a high correlation between both indices BSI and DBSI. Meanwhile, the MBSI index has a moderate-high positive correlation with them. In contrast, the MBSI and MNDBaI index have a high correlation between them.

Table 3. Statistical values of the various spectral indices from Sentinel-2 used in the study area

Indices used	Mean Built-up	Mean Bare soil	Mean Vegetation	StdDev Built-up	StdDev Bare soil	StdDev Vegetation
MNDWI	-0.185701	-0.298728	-0.301784	0.078389	0.039222	0.050743
NDVI	0.040122	0.073332	0.286535	0.046103	0.017612	0.134657
DBSI	0.145579	0.225474	0.015249	0.061783	0.029429	0.142722
BSI	0.109858	0.163762	0.032171	0.043492	0.017114	0.100672
MBSI	0.133108	0.227295	0.076445	0.064046	0.028383	0.130206
MNDBaI	0.148695	0.233773	0.163421	0.078337	0.022244	0.062645

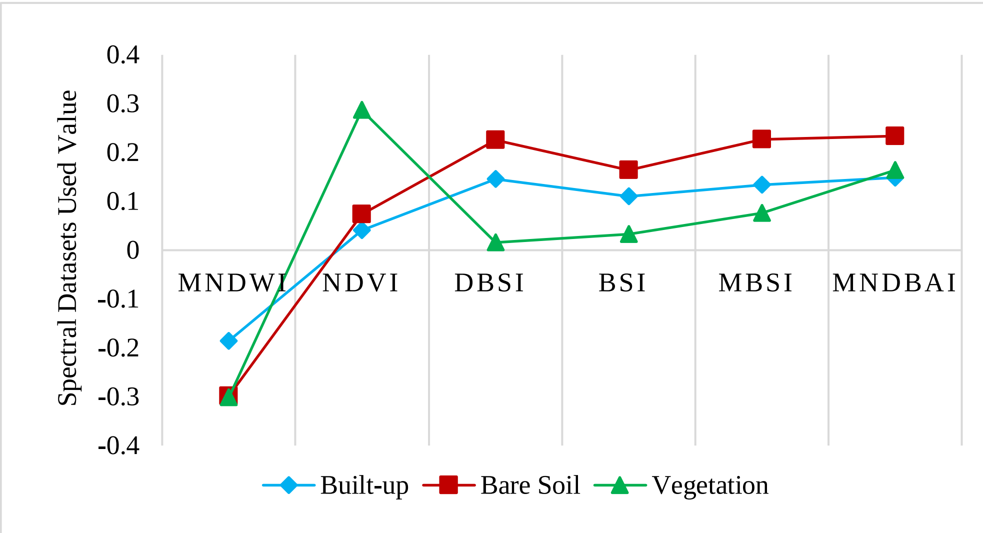

Fig. 3. Simplified spectral signatures of the land cover in the study area for (a) MNDWI, (b) NDVI, (c) DBSI, (d) BSI, (e) MBSI, (f) MNDBaI

The MBSI and MNDBaI index provided a distinctive reflectance of the three major land cover types, as showed in Table 3 and illustrated in Fig. 3; compared to the BSI and DBSI spectral reflectance, the MBSI and MNDBaI index produced a greater variance between bare soil and other major landcover. However, comparatively, in the MNDBaI grayscale, the built-up and vegetation pixels were illustrated very closed, based on their mean value. Accordingly, the behavior of MBSI and MNDBaI index over the study area conduct us to expect a satisfactory results concerning dry soil mapping. Besides, according to the mean value of each landcover types as they tabulated in Table 3, it is well observed that the MNDWI highlight built-up area as showed in Fig. 3, where the pixels value of bare soil and built-up pixels are very closed. While, the NDVI index represent bare soil and built-up pixels very closed. These observations of each index behavior and signatures are interesting and can be exploited in reducing confusion between features.

Table 4. The bare soil area extracted over the study area using the indices DBSI, BSI, MBSI, MNDBaI and SVM

Spectral Indices	Bare soil Surface area		Others (Non-bare soil area)		Total of Study Area	
	Area (km²)	Area %	Area (km²)	Area %	Area (km²)	Area %
DBSI Index	17.2019	61.75006	10.5895	38.2499	27.8573	100
BSI Index	16.9719	60.92442	10.8195	39.0755		
SVM Method	15.5980	55.9925	12.2593	44.0075		
MBSI Index	15.7988	56.7133	12.0585	43.2866		
MNDBaI Index	15.2016	54.5695	12.6557	45.4304		

From Table 4 that permit to compare between the results obtained from the spectral indices used and the SVM method, we found that the MNDBaI index produced the lowest bare soil surface area, which is approximately about of 15.2016 (km2). While, the DBSI detected about 17.2019 km2 of bare soil, which is the highest surface area that is a little over compared to the BSI result. Therefore, the bare soil area that were produced by the indices MBSI and MNDBaI, are less estimated compared to those obtained from the indices BSI and DBSI. This is can be interpreted rapidly through observe Fig. 4, where the maps resulted from MBSI and MNDBaI index manifested more density of built-up area compared to those of BSI and DBSI index.

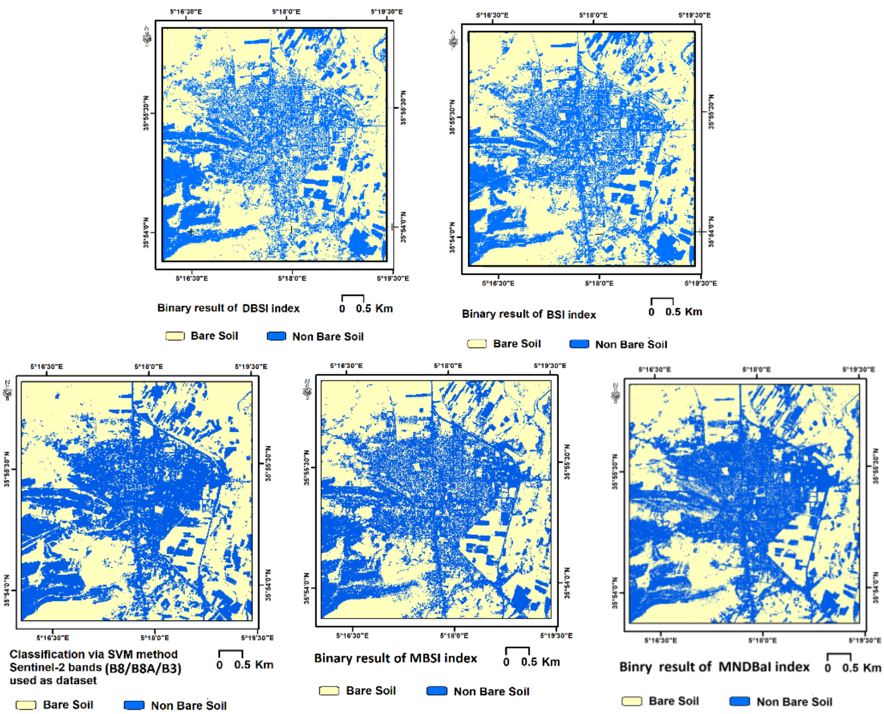

Fig. 4. illustrates the bare soil maps resulting from (a) DBSI, (b) BSI, (c) SVM method, (d) MBSI, (e) MNDBaI

Accuracy Assessment Process

The parameters of the confusion matrix (Foody, 2002) that is presented in Table 5, permitted to evaluate the behavior of each technics used (Index-Based Methods and the supervised classification method), by measuring the accuracy assessment for bare soil classification, and to do that , the stratified random sampling method (Congalton, 1991), was used as it was recommended. Accordingly, 350 points distributed adequately over the study area, by using Qgis software, and to complete this important process, the imagery of google earth was used as reference map that supported by vegetation map using NDVI index, in addition to exploit the FCC (B8 – B8A – B3); the imagery of google earth selected, is characterized by its high quality and resolution, with the closest date to Sentinel-2 data adopted.

Table 5. Accuracy Assessement of Resultant Bare soil Maps for Sentinel-2 Images

Accuracy types	Commission error % User's Accuracies (UA)		Omission error % Producer's Accuracies (PA)		Overall Accuracy Oa %	Kappa Coefficient %
Class types	Bare soil	Non-Bare soil	Bare soil	Non-Bare soil		
DBSI Index	83.17	90.14	92.51	78.53	86.00	71.63
BSI Index	85.78	89.04	91.62	81.76	87.14	73.89
SVM Method	88.38	92.11	93.58	85.89	90.00	79.81
MBSI Index	89.42	92.55	93.37	88.17	90.86	81.66
MNDBaI Index	91.67	92.94	93.22	91.33	92.29	84.56

Discussion

The study area characterized by an environments condition that present certainly a real challenge in terms of dry soil discrimination, because of the very high similar spectral response to those of non-bare land features. Accordingly, the main objective through the current study, is to identify the best index that can provides the accurate bare soil map, focusing on to verify whether the selected soil indices that combine only visible bands could enhance the dry soil detection.

The different bare soil indices (BSI, DBSI, MBSI and MNDBaI) that were used to detect dry bare soil class, they provided different results, where the degree of their effectiveness can be observed rapidly when comparing them to the FCC (RGB 8 -8A-3) that illustrated in Fig. 2. And additionally, they were confirmed by the different accuracy assessment types measured from the confusion matrix (Table 5); the overall accuracy (OA) of the MNDBaI, MBSI index and SVM are about 92.29 %, 90.86 % and 90.00 %, respectively. Meanwhile, their Kappa Coefficient (kc) achieved 84.56%, 81.66% and 79.81% respectively. In contrast, the (OA) of the DBSI and BSI are about 86% and 87.14 % respectively. Meanwhile, their (kc) achieved 71.63% and 73.89% respectively. Based on this, the MNDBaI index with their bands (Red and Blue) provides the highest bare soil map accuracy, following by the MBSI index with their bands (Red and Green). Meanwhile, the DBSI index result provided the weakest result. Visually, from Fig. 2, the soil class can be well-easily distinguished from the grayscale of MNDBaI and MBSI indices that uses only the visible bands from Sentinel-2 which are at 10 m. This result is statistically proved as well as it is presented in Fig. 3 (high variance between soil class and the other major classes). Another point which is important is that, the tested indices DBSI and BSI that integrating, in addition to visible bands, the

NIR and SWIR bands, where these bands are useful for bare soil detection, given that, they have been used for the bare soil indices development (Javed et al., 2023; Nguyen et al., 2021; Salas & Kumaran, 2023; Somanathan et al., 2024). Nevertheless, this study demonstrated that combining only visible bands (Blue, Green and Red) are useful for discriminating between dry bare soil and built-up area in dry environment. This information is interesting and it need making more tests and a large comparative with the aforementioned indices to validate their sensitivity toward dry soil. Besides, it should be noted that the visible bands resolution at 10 m, helped certainly making the difference in bare soil maps results from the MNDBaI and MBSI index compared to those of BSI and DBSI, that were applied within a Sentinel-2 data, combining VNIR bands at 10 m and SWIR band at 20 m. In this context, previously, it is referred to the advantages and utility of Sentinel-2 data in terms of built-up area detection (Kuc & Chormański, 2019; Rouibah, 2025a; R. Xu et al., 2018). focusing on this point which is related to the discrimination capability between bare soil and built-up area, the use of Sentinel-2 imagery at 10 m in the current research, was, also, evidently useful for bare soil surface extraction and exploring its distribution. In conclusion, each soil index provided different level of discriminative between the two major classes (bare soil and non-bare soil area). However, the MNDBaI and MBSI index was more discriminative since their visible bands were more sensitive to dry soil over the region. As for both indices BSI and DBSI, more accurate result could be obtained from if SWIR bands resampled from 20 m to 10 m of resolution.

In the current study, the SVM that was applied over the FCC (8 -8A-3), provided a bare soil map that is better than the results obtained from the both indices (DBSI and BSI) that subjected to the famous segmentation k-means algorithm (MacQueen, 1967); the experimented FCC as input features, provided a clear and excellent landcover visualization in semi-arid land, where the bare soil can be well distinguished from white color to grise. Consequently, it was successfully used via boosting the SVM method to exploring its discrimination capability during the segmentation process. Based on this, The SVM based FCC selected, has overcome the k- means based both indices BSI and DBSI that used singly as input features. In other hand, although the k- means method used for segmentation, does not require using training samples, the finding showed an acceptable performance of the bare soil indices; the both bare soil indices BSI and DBSI provided relatively distinguishable two classes (bare land and non-bare land). Consequently, they permitted easily to classify automatically bare land class during the binary process. However, with less accuracy, relatively. The different level of discriminative between bare soil area and non-bare soil area of each index, affect certainly the performance of the k- means method. Consequently, although the spectral confusion presented in the region, the BSI index was, relatively, more distinctive compared to DBSI index. Meanwhile, the MNDBaI index is more discriminative between highly similar features which are largely presented compared principally to both indices BSI and DBSI in addition to MBSI index as well. The high discrimination ability of the MNDBaI index is clearly evident, especially between the dry soil and buildings, roads and dry vegetation, except some bright pixels of soil with very highly albedo, that were misclassified as non-bare soil class. Thereby, the behavior of both MNDBaI and MBSI reduced the confusion in the study area, it means, they successfully tested in reducing error of misclassifying the dry soil as both built-up and vegetation or vice versa, then, they contributed boosting the performance of the k-means during the segmentation process, producing the best soil maps. However, in view of the irregular variation of the barren lands both spatially and seasonally (Sharma et al., 2016), the estimation of dry soil via both indices MNDBaI and MBSI in dry climate, may be influenced by seasonal changes and different binary methods. In this context, it is important to mention that the MBSI index was introduced to build the CBCI index in subtropical climatic regions (S. Zhang et al., 2018) and has been used within same type of climate as well (Ma et al., 2019; Shaohua Zhang et al., 2021). On the other hand, J. Chen et al. (2020) demonstrated that the MBSI index that was applied singly over the subtropical humid climate, did not have a good enhancement toward information of the bare soil, where its values were mixed with other ground objects. Additionally, the MBSI index provided the weakest result of separation between soil and urban in tropical climate, compared to other bare soil indices used (Javed et al., 2023). Meanwhile, throughout the current study area of semi-arid land, the MBSI index produced a satisfactory result. Besides, although the MNDBaI index that was introduced in tropical climatic regions (Hua et al., 2017) and has been used also within same type of climate (Hua et al., 2020), it has exhibited a distinctive positive behavior in the dry environment as demonstrated in the current study. Accordingly, the behavior of both indices MNDBaI and MBSI, need to be more discussed in future researches, over different climate conditions and using different thresholding methods mainly: manual thresholding or automated thresholding, for example via the famous Otsu method (Ng, 2006; Otsu, 1979), in addition to apply supervised machine learning, given that, they have been successfully used to classify bare soil (Salas & Kumaran, 2023). The applying of different binary method over MNDBaI and MBSI may provide more information and different results given to the high discriminative capability manifested particularly by the MNDBaI index. And additionally, it is important to refer to the applicability of these indices within most satellite imagery, since they use only the visible bands.

The bare soil indices used (BSI) and DBSI misclassified more pixel of built-up as bare soil feature in the study area, in particular the asphalt roads, in contrast to the result of the MBSI index, which classified the road network with high accuracy as it can be observed in Fig. 4. Consequently, the bare soil area detected by the use of DBSI and BSI index is overestimated (Table 4), since that they increase by about 2.0003 (km2) and 1.7703 (km2) respectively, compared to the MNDBaI result which is close to the reality. In other point, it should be noted that the both indices are highly correlated in semi-arid land (Table 2). However, Although the DBSI index was suggested for dry land (Rasul et al., 2018), the BSI index worked a few better than DBSI index in semi-arid land. this result can be justified by the Standard deviation difference between them (Table 3); BSI Index have the lowest Standard Deviation Value (STD) for the three land cover types (Built-up, Bare Soil and Vegetation). Also, it should be noted that the structure of each index as presented in Table 1, they share three spectral bands (Visible, Near-Infrared and the Short-wave infrared) which are mainly the SWIR band (B11) and the both red band (B4) and NIR band (B8) and differs in green band that was integrated in DBSI index. While, the BSI index integrate the blue band (B2). Accordingly, we concluded that the blue band was behind the best binary result of BSI compared to DBSI index. This result support which was demonstrated previously (Rouibah, 2023), where combining B2 with B8 enhanced the separability of built-up from bare lands, because B2 have the lowest correlation with B8 compared to B3, in addition to their sensitivity to dry soil and bright built-up area detection.

Hua et al. (2017) adopted a feature-based approach of decision tree classification in order to extract urban land use and land cover, where the MNDBaI index was introduced and combined with another spectral indices. Based on the results obtained, applying MNDBaI index over the non-vegetation class in the current area of study, to obtain bare land class and non-bare land class, certainly, the result obtained of non-bare land class, is representing only the built-up feature that can be mapped easily with good accuracy, especially that there is no open water body area in the region, in addition to the distinctive result of MNDBaI index that exhibited a significant variance between bare soil and the built-up class. Consequently, the MNDBaI index can be used to extract accurately the built-up in dry land.

In other point that related to the limitations of the soil indices, it is observed in Fig. 4 that the MNDBaI index misclassified a few bare soil pixels with very high albedo as built-up and vegetation. Meanwhile, the MBSI misclassified more built-up pixels as bare soil class. Therefore, the MBSI index overestimated the bare soil class compared to MNDBaI index that produced bare soil map closer to the reality. So, in terms of dry bare soil detection, it concluded that, the red band combined with blue band worked better than combining the red and green band. This is due to the blue band behavior that worked a few better than the green band in terms of separating bare soil from the built-up pixels, as it was proved statistically (Table 5). In other hand, in view of the high correlation between both green and blue band, in addition to the structure of both indices (MBSI and MNDBaI) that exhibited promising results in dry climate, it is possible to combine both bands (Blue and Green) with red band to build a novel index for dry bare soil detection. This new index can be named the Dry Bare Land Index DBLI, where it can be calculated via the equation: (2*Red - (Blue + Green)) / (2*Red + (Blue + Green)); The DBLI index combine the three visible bands. So that, it can be experimented on multiple types of satellite imagery. Besides, it should be noted that the DBLI index can reduce some of the overlapping and misclassification pixels between bare soil and urban area, that were observed and discussed previously principally in MBS index result.

To the fact that an important part of the region is considered as an agriculture area in addition to the urban growth increasing that is observed in the region as well, the current study results, make the MNDBaI and MBSI to be widely applied to estimate bare land area, monitor agriculture practice and estimating urbanization expansion and its impacts. In other hand, considering that the land degradation issue in dry areas is critical (Ebrahimi et al., 2024) and in view of the climate changes in the region (A Rouabhi et al., 2018; Rouibah & Belabbas, 2022), the MNDBaI and MBSI index can be used to estimate the potential land degradation locally, and even in other areas that is characterized by same environment conditions and they marked by runoff variability and soil erosion process. Based on this, we expect, therefore, that these indices can be support decision making regarding land management and local development in dry environments.

In the current work, we focused only on few soil indices mainly BSI, DBSI, MNDBaI and MBSI, where we concluded that the discrimination level between built-up and bare soil, is related to the different behavior of the bands used in each index, in addition to their different resolution as well. Accordingly, it is necessary to think about identifying the effective spectral bands that can be used to build spectral soil indices that are able to separate maximally bare soil class from built-up class in arid and semi-arid land. Additionally, a vast comparative study between the exist soil indices, is highly recommended, especially with applying different thresholding methods, taking in count the seasonal sensitivity in dry land. Another point which is important is that, the literature review demonstrated that the bare soil indices that were developed only with visible bands or whose developed with VNIR bands (Visible + Near-Infrared), are very limited. Therefore, other new soil indices that can be easy to use and reliable over dry land, need to be developed, focusing to integrate only the effective spectral bands i.e. the bands that are more sensitive to dry soil and its divers' patterns. In this context, we expect an increase use of the bare soil indices within the multispectral image of Sentinel-2, given to its VNIR-SWIR bands advantages that are produced with high radiometric and geometric quality (Drusch M et al., 2012). Also, since the combination method of suitable spectral indices has improved the mapping accuracy during classification (Nur Hidayati et al., 2018; Rouibah, 2025b; Samira et al., 2022), the approach can be adopted, expecting a significant contribution for improvement of dry soil mapping accuracy and built-up discrimination as well.

Conclusion

The soil maps and its related information are necessary to understand different environmental topics. Nevertheless, the dry bare soil mapping is difficult and considered as a real issue which is not well addressed. For that reason, the current research aims to identify the best remote sensing technics for dry bare soil detection in semi-arid land. To this end, Ain Oulmene region which is located in semi-arid land (North-East Algeria), was chosen as the area for test. Also, in this paper, Sentinel-2 imagery was chosen as remote sensing data given to its advantages, especially the good resolutions of their bands. Besides, four soil indices have been selected to be applied and segmented with the k-means method, then, making a comparative analysis between them. Additionally, they were compared to the SVM method that use the False Color Composite FCC (B8 - B8A - B3) of Sentinel-2 image, as input dataset. The four indices selected are mainly: the Modified Normalized Difference Bare Index (MNDBaI) and the Modified Bare Soil Index (MBSI) which are combining only visible bands, in addition to the Bare Soil Index (BSI) and the Dry Bare-Soil Index (DBSI) that are combining VNIR-SWIR bands.

The MNDBaI and MBSI index that provided the bare soil maps at 10 m, worked better than the SVM method and the bare soil maps obtained from the both indices (DBSI and BSI); the overall accuracy (OA) of the MNDBaI, MBSI index and SVM are about 92.29 %, 90.86 % and 90.00 %, respectively. Meanwhile, the bare soil area detected by the use of BSI and DBSI index is overestimated, where the DBSI index provided the weakest result since its (OA) is about 86.00 %. Through the current work results in terms of bare soil area maps accuracy, we concluded that the FCC selected as input dataset for classification process, has overcome the both indices BSI and DBSI as input features. Additionally, it is important to refer to the BSI index that worked a few better than DBSI index in semi-arid land. However, the behavior of MNDBaI and MBSI index were more positive, especially the MNDBaI index that achieved the highest (kc) which is about 84.56%. Accordingly, they successfully tested in semi-arid land (i.e. high discriminative capability with a satisfactory performance toward dry soil mapping). These significant results conduct us to considered primarily that both MNDBaI and MBSI index are suitable for arid and semi-arid land. Thereby, they can be classified as reliable dry soil indices in dry climates.

The results obtained in this study via all remote sensing technics and data used, are interesting; the significant result of the MNDBaI and MBSI index make them more adoptable for accurate dry bare land mapping and fallow lands estimation, to support local decision making, because the region is knowing an urban expansion and in the same time, it contains important agriculture areas. Also, the MNDBaI and MBSI index can survey and estimate the potential land degradation in the region, given to the impacts of climate changes. However, it is suggested to discuss the effectiveness level of the technics used over other semi-arid regions in North-East Algeria, focusing to make new comparative studies between vast list of soil indices in addition to involve other advanced remote sensing technics. Moreover, it is necessary to build new indices for dry soil mapping rapidly with high accuracy, by integrating VNIR bands, in addition to base on the combination method of spectral indices that can improve the dry soil maps accuracy, then, they can boost the spatial management and its development, particularly in the context of climate changes threats and urban expansion impacts.

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