An easy method for barchan dunes automatic extraction from multispectral satellite data

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Abstract. This work presents an easy method for barchan dunes automatic extraction from multispectral satellite data. The proposed method based on unsupervised classifications of commonly used bands for sand dunes mapping in literature. First, the collected data were atmospherically and spatially enhanced. Moreover, each selected band (band ratio or redness index or crust index) were filtered using low-pass (3x3) filter and transformed with original image (non-filtered) by using principal component analysis (PCA). Additionally, the classifications were achieved for each selected band by using three different algorithms (K-means, Expectation Maximization (EM), and IsoData) after data transformation. Eventually, the obtained maps were segmented and compared with natural colour image. The results indicate that unsupervised classification of crust index selected band, which achieved by IsoData algorithm, presents high performance for barchan dunes detection.

1. Introduction

Studying dunes activity contributes to the understanding sand encroachment evolution and therefore desertification phenomenon [1-3]. Their study can also provide indices about climate evolution [4-7]. Barchans are the most common type of dunes exists within desert areas. The barchan dunes are crescent-shaped dunes that move under roughly unidirectional winds and form under limited supply of sand [8-10]. During its propagation, due to erosion on the windward side of the dune and deposition on the leeward side, they conserved its form without or with minor modifications [11-14]. The magnitude of barchan dunes displacement varies with its size [14-18]. The barchans are classified as the most dangerous form of dunes worldwide due to its continuous mobility and they can affect anything existing in its path. It responsible of one of most dangerous risk, sand encroachment, which inducing various environmental and socio-economical damages (obstructing traffic and causing road hazard, stopping infrastructures development, obstructing cultivated areas, clogging water points such as wadis, etc). Monitoring barchan dunes propagation plays in important role in natural hazard management. In this context, valid mapping of barchan dunes is crucial.

Remote sensing refers to collect information about an object without contact with it by using sensor technologies (aircrafts or satellites or more recently unmanned aerial vehicles). Since the 1970s, the spatial and spectral information from remotely sensed images has been explored to identify, characterize, and extract information on terrestrial and extra-terrestrial sand dunes patterns [19].
Several methods have been proposed to extract barchan dunes using remote sensing mainly from satellite images, that in order to monitor its dynamic movements. Manual tracing of sand dunes shape on aerial photographs and satellite images is the first used method [16, 20, 21]. Manual tracing is a hard work costing time and energy. In contrast, since development of satellites images, automatic and semi-automatic extraction are the most used techniques for sand dunes detection not only from terrestrial landforms but also from planetary landforms such as Mars. For instance, proposed an approach for detecting dune fields on surface of Mars using automatic extraction of local information from Mars Orbiter Camera (MOC) images [22]. The research used Machine Learning (ML) approach to extract barchan dunes from Mars surface using high resolution satellite images (HiRISE) [23]. Others research used offline trained multilayer perceptron (MLP) as a classifier in order to map dunal landform of a part of Rajasthan desert using multi-spectral optical data (LISS III) [24]. The study proposed a new semi-automatic approach for the extraction of sandy bodies of the Cabedelo part of Douro river basin (Portugal) using IKONOS-2 data, based on global thresholding through the Otsu’s method further refined through detected edges (GThE) [25]. The others study also used object extraction based-classification technique to extract barchan dunes shape of the northern part of Laâyoune-Tarfaya basin (Morocco) from panchromatic and multispectral bands of Landsat satellite imagery [18, 26, 27]. The study also extracted barchan dunes form from the middle part of the same basin but using Google Earth images [28].

Generally, the aforementioned studies and others relevant case studies, have been based on supervised classifications of extracted data from satellite imagery. Supervised classifications also costing time due to its needing ground truth data digitalization. Furthermore, so far, no study has been valorised and compared the use of unsupervised classifications for detecting and mapping sand dunes from terrestrial landforms.

Here we present an easy method based on segmentation of unsupervised classified images from Sentinel-2 data. The results were compared for each selected band (band ratio, redness index, and crust index) and each used algorithm (K-means, Expectation Maximization (EM), and IsoData). The current study methodology was applied on a part of the central corridor of sand dunes located in northern part of Laâyoune-Tarfaya basin (Morocco) (figure 1).
2. Material and method

2.1 Material
In this study we collected an online (free of cost) orthorectified Sentinel-2 MSI L1C (MultiSpectral Instrument Level 1C) scene from the Copernicus Open Access Hub site of the European Space Agency (ESA) that was acquired in 18th April 2017. The datasets contained 13 spectral bands in the VISible (VIS), Near InfraRed (NIR) and ShortWave Infrared Spectral Range (SWIR), and list of the detailed specification of each band summarized in table 1. In its downloaded form, these data, are geometrically and radiometrically corrected [29].

Table 1. Characteristics of Sentinel-2A MSI bands.

| Bands | Spectral domain | Spatial resolution (m) | Central Wavelength (nm) | Bandwidth (nm) |
|-------|-----------------|------------------------|-------------------------|----------------|
| B1    | VIS             | 60                     | 443                     | 20             |
| B2    | VIS             | 10                     | 443                     | 65             |
| B3    | VIS             | 10                     | 560                     | 35             |
| B4    | VIS             | 10                     | 665                     | 30             |
| B5    | NIR             | 20                     | 705                     | 15             |
| B6    | NIR             | 20                     | 740                     | 15             |
| B7    | NIR             | 20                     | 783                     | 20             |
| B8    | NIR             | 10                     | 842                     | 115            |
| B8a   | NIR             | 20                     | 865                     | 20             |
| B9    | NIR             | 60                     | 940                     | 20             |
| B10   | SWIR            | 60                     | 1375                    | 20             |
| B11   | SWIR            | 20                     | 1610                    | 90             |
| B12   | SWIR            | 20                     | 2190                    | 180            |

2.2 Method
The proposed methodology flow chart to create the object of this study is shown in figure 2. The method involves four steps: 1) pre-processing, 2) processing, 3) classification, and 4) post-classification.

2.2.1 Pre-processing step
Including atmospheric correction and resolution enhancement. First, the Top-Of- Atmosphere (TOA) Level C1 collected data was atmospherically corrected by using Sen2Cor package that was downloaded from ESA site and installed in SNAP Toolbox to create Bottom-Of-Atmosphere (BOA) Level 2A [30]. The producing Level 2A data contained bands 1–8, 8a, 9, 11 and 12, which are associated to the spectral bands at three different spatial resolutions with a ground sampling distance of 10, 20, and 60m [30]. The spatial resolution of the new data was enhanced by using Sen2Res model imported in SNAP Toolbox. This model consists to unmix low-resolution bands, preserving their reflectance, while propagating band-independent information to preserve the sub-pixel details [31]. For more detail about super-resolution model see the paper of [31]. The obtained sup-resolved bands have same spatial resolution 10m.

2.2.2 Processing step
Including bands selection, data filtering, and data transformation. The study confirmed the potentiality of Sentinel-2A MSI for geological mapping by using band ratios published for Landsat 5 TM and ASTER. For this raison, here, we used the Band Ratio (BR), Redness index (RI) and Crust Index developed for mapping sand dunes respectively [32, 33-36]. Table 2 summary the used bands and its
equivalence for Sentinel-2A MSI (Multi Spectral Instrument). Moreover, each obtained band were filtered using low pass 3x3 filter. The image filtering consists to replace each pixel by the average of the pixels in a small neighbourhood, is a suitable method for classifying each pixel of a textured image and thus for segmenting the scene [37].

![Flow chart of the proposed method.](image)

**Figure 2.** Flow chart of the proposed method.

**Table 2.** Sentinel-2A MSI sand dunes indices as an analogue of developed indices [34–36].

| Index       | Used sensor | Formulation | Sentinel-2A equivalence |
|-------------|-------------|-------------|-------------------------|
| Band ratio  | Landsat ETM*| \( \frac{ETM5}{ETM7} \) \( \frac{b_{11}}{b_{12}} \) | \( \frac{b_{4}}{b_{2} \times b_{3}} \) |
| Redness Index| Landsat TM  | \( \frac{TM2}{TM1 \times TM2} \) | \( \frac{b_{4}}{b_{2} \times b_{3}} \) |
| Crust index | Landsat TM  | \( \frac{TM3 - TM1}{TM3 + TM1} \) \( \frac{b_{4} - b_{2}}{b_{4} + b_{2}} \) |
Eventually, each obtained band from filtering step was transformed with original band (non-filtered). Image transformation consists to reduce the number of features passed to the classifier [37]. We used principal component analysis (PCA), which involves a mathematical transformation of the original data to create new uncorrelated bands (called components or primitives), to reduce the spectral dimensionality of the data and to enhance spectral signatures [38-39].

2.2.3 Classification step
Consists to assign for each pixel or group of pixels a class based on the numerical values in transformed image. There are two common types of image classification: unsupervised and supervised. The unsupervised classification approach is carried out automatically without a need to specify in advance the classes in the image data set, while the supervised classification needs to learn in advance the classes in the image which will be used in the training step in order to achieve the classification. For each approach, the classes’ attribution is performed using special algorithms, also called classifiers. Currently, we used three unsupervised classifiers: K-means, Expectation Maximization (EM), and IsoData. For more detail about these algorithms see a review paper of [40]. All steps cited in top, except classification by IsoData, were executed using GraphBuilder of SNAP Toolbox, while classification by using IsoData algorithm was performed by using ENVI® software. The GraphBuilder model is timely effective, costs few second to execute the whole operation.

2.2.4 Post-classification step
Including image segmentation and results comparison. The images segmentation was executed using ENVI® software package. The images Raster resulting from segmentation step were exported in ArcMap, converted to a polygon, superposed and compared with the natural colour image.

The images segmentation consists to extract the sand dunes classes based on visual comparison with original bands. Before image segmentation, the grey tone in images (derived from K-means and EM classification) imported in ENVI® software was converted using density slicing technique. The density slicing technique consists to convert the continuous gray tone of an image into a series of density intervals, each corresponding to a specific range of digital numbers (DN) [41].

3. Results and discussion
After the images segmentation results obtained (figure 3), a simple vision of these maps indicates that:

a. All unsupervised classifications of crust index bands provide objects in form of barchan dunes, which are the most exist sand dunes in the study area,

b. Band ratio and redness index classifications using Isodata, K-means and EM algorithms, respectively, provide objects without clear shape.

c. The comparison of the natural colour image with the images segmentation providing from crust index bands classifications using Isodata, K-means and EM algorithms reveals that the unsupervised classification, which achieved by IsoData algorithm, presents high performance for barchan dunes detection (figure 4).

Moreover, for all used algorithms and selected bands, we observed that:

a. There are many small barchan dunes haven't detected, maybe the medium resolution (10m) of the used sensor not suitable for detecting the small barchan dunes,

b. There are another barchan dunes with clear colour haven't detected also by IsoData classifier that showing best performance (figure 4), maybe that due to the mineralogical composition of such barchan dunes than other.

c. Eventually, the obtained results lead us to suggest that:

d. Testing the proposed methodology by using high resolution images is necessary and can provide best results,

e. Testing another bands (other rationing and indices) suitable for other mineralogical compositions of sand dunes will be a supplementary study to detect the other sand dunes.
Figure 3. Maps shown images segmentation results of: a, d, g) Crust index bands classification using Isodata, K-means and EM algorithms, respectively, b, e, h) Redness index bands classification using Isodata, K-means and EM algorithms, respectively and c, f, i) Band ratio bands classification using Isodata, K-means and EM algorithms, respectively.

Figure 4. Map comparing images segmentation results from unsupervised classifications of crust index bands with natural colour image.
4. Conclusion
Several studies have been monitoring barchan dunes dynamic by using remote sensing data and GIS technique. Generally, these studies are based on manual tracing of sand dunes shape and on automatic extraction based on supervised classifications using satellite images and aerial photos. The manual tracing and supervised classifications are a hard work costing time and energy. In this work, we present an easy method based on processing of Sentinel 2 data.

The proposed processing techniques include bands selection (band ratio, redness index, and crust index), bands filtering using low pass filter 3x3, data transformation using principal component analysis (PCA), unsupervised classification using K-means, Expectation Maximization (EM) and IsoData algorithms, and images segmentation. The comparison of the obtained results reveals that the unsupervised classification of crust index used bands, which achieved by IsoData algorithm, presents a high performance for barchan dunes automatic extraction. Eventually, this work offering several research axes, such as: methodology validation using high resolution spatial data and investigation of the most suitable spectral bands for sand dunes mapping.

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