Deep Learning: A new tool for mapping and analysis dunes (e.g. Rub'Al Khali sand sea)

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ABSTRACT: Aeolian dunes are bedforms of great scientific interest because their morphological characteristics (e.g. shape, size, spatial organization) depend on the physical characteristics of i) the moving fluid (e.g. velocity, direction of movement, viscosity), ii) the available sedimentary stock (e.g. density, shape, grain size). Mapping and morphometric analysis of these bedforms can provide elements to understand their formation processes. We developed a mapping protocol based on a Deep Learning approach and automatic tools to digitize their outline and mean crestline. The protocol shows the ability to produce a large numerical database of a dune field (e.g. Rub'Al Khali) that can be used to analyse several form parameters.

1 INTRODUCTION

The surface of some planet's present abundant periodic topographic forms at different scales (mm- km) in different environments called bedforms. These bedforms develop at the interface between the moving fluid and a deformable and/or erodible material. The aeolian bedforms result from wind action mainly in deserts, coastal areas (Pye and Tsoar, 2009; Zheng et al., 2022). Sand dunes correspond to a major bedforms type in aeolian systems and play an important role in understanding how aeolian environments evolve. They are described as aeolian sand mounds or ridges that exist independently of surrounding topography whether slipfaces are visible or not (Bagnold, 1974).

Generally, the dunes are grouped in field and sand seas. Their morphological characteristics (e.g. shape, size, spatial organization) play a critical role in understanding how aeolian environments evolve and interact with global changes (Thomas and Wiggs, 2008; Zheng et al., 2022).

The wide spatio-temporal coverage of satellite imagery and high-resolution digital terrain models are used to estimate and map the evolution of dunes on large-scale investigations. A large-scale dune mapping would provide a digital atlas to characterize variable sand dune morphologies that are crucial indicators of complex and evolving wind processes. In this work, we propose an automatic method of aeolian dunes mapping from DEM based on a Deep Learning approach which allows an instantaneous, massive and integrated extraction of several geometrical properties of each dune - from metric to regional scale.

The prevailing strategy is to extract the Residual Relief (RR, Hillier and Smith, 2008) in order to delete the regional topographic trend and map the different dune generations. Secondly, an unsupervised pixel-based classificator (Deep Learning – U-Net (Shumack et al., 2020)) trained with RR samples of different dune forms is used to detect and map dunes independently of the bedrock. Finally, the crestline of the sand dunes is skeletonized from the identification of high inflection point of the dunes with a Volumetric Obscurance approach (Rolland et al., 2022). The complex morphologies with various forms are individualized according to the neighborhood relationships of the dune forms and crest.

To illustrate the method performance, the protocol is applied on a part of the Rub'Al Khali (660,000 km²) sand sea to map the various dune forms and extracts their crestlines. Then, we use this large digital database to illustrate an example of morphometric application by calculating basic geometrical properties (length, width, height of dunes and crestlines orientation).

2 NUMERICAL DUNE DEFINITION

Sand seas are the fullest expression of aeolians landscapes, being defined by a variety of shapes in which sand grains have accumulated by wind to make sand mounds called "dunes" (Livingstone and Warren, 2019; Lorenz and Zimbelman, 2014). The overall forms of dunes depends on the wind speed in the area, the duration of sand-transporting winds, the direction of the wind speed, the duration of sand-transporting winds, the direction of the winds and their variability (Blumberg, 2006; McKee, 1979).

Many freely available land surface remote sensing data provide a large dataset of high-resolution imagery and digital elevation models (DEMs). These latter are widely used for aeolian systems investigation because of : i) their large spatial coverage (covering all major dune fields in the world) and ii) their always increasing spatial resolution (Hugenholtz and Barchyn, 2010). Dunes can be interpreted on DEMs as three-dimensional bedforms characterized by high inflection points (dune crests) and low inflection points (dune base – dune shape) whether their slipfaces are visible or not (Fig.1).

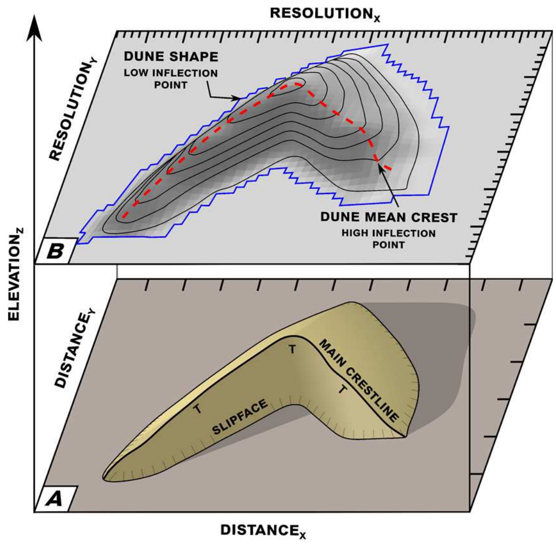

Figure 1. Dune definition. A. Naturalist representation of dune based on Bagnold (1974) descriptions. B. Numerical representation of a dune on a DEM as a 3D bedforms defined as high (dune crest) and low (dune shape) inflection points.

3 MAPPING PROTOCOL

3.1 Extracting and sampling Residual Relief

Dune fields and sand seas show superimposed generations of dunes (m to km-scale) producing complex topographic signal on DEMs (Fig.2). Each dune scale patterns can be examined independently if the topographic signal is disentangled (Hugenholtz and Barchyn, 2010).

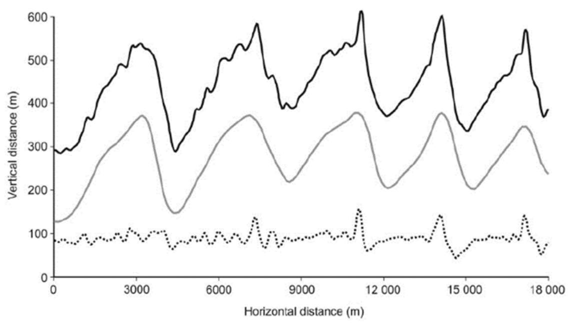

Figure 2. An example of Residual Relief separation showing discrimination of different dune generations. The original surface (black line), the Residual Relief of the medium-scale dunes (dotted black line), and the Residual Relief of small-scale dunes (grey line) (Hugenholtz and Barchyn, 2010).

Our strategy is to separate and isolate the different dune scales in order to highlight the aeolian dune patterns in dune field. For this, we calculated the Residual Relief (Hiller and Smith, 2008) on 100 training samples that are then used as learning data to map the dune shapes. Each sample represent a DEM on which dunes are identified (Fig.3A). These samples are selected from four arid regions and cover a large range of dune types (barchanoid, star, dome, linear and complex dunes). For this first development, we have avoided dune classifications to simplify mapping and interpretation. Dunes outlines were digitized manually on a GIS software and labelled as "ground truth" for the next step (Fig.3B).

3.2 Forms dunes recognition with Deep Learning

In this step, we used a Deep Learning algorithm as an unsupervised pixel-based classificator to form a mapping model of the aeolian dunes shape (Shumack et al., 2020).

All 100 residual relief samples from the DEMs were used by the algorithm as training data. First, the pixels DEM are convolved. At each convolution, for each DEM pixel that is located in a sliding matrix or kernel, the pixel values are multiplied by the kernel values. The sum of the matrices products generates an image of smaller dimension for which the maximum pixel values contained in the ground truth mask labelled are considered as "dune".

After the convolution, a max-pooling operation is used to retain the maximum values associated with the pixel labeled as "dune". All max pooling operations are subsequently reversed by a series of transposed convolutions, ending with an image matching the original input size (Ronneberger et al., 2015; Shumack et al., 2020). Lastly, the different convolutional steps are concatened and subject to more convolutions. The last step consists to use an activation function allowing to create a mapping model in which, each pixel corresponding to the dunes on an analyzed DEM is predicted and assigned by a "dune" class (Fig.3C).

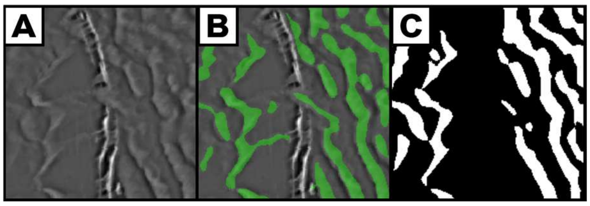

Figure 3. An example of mapping after the unsupervised classificator training on a DEM sample. A. Residual Relief. B. "Dune" ground truth mask manually digitised and used for the unsupervised classificator training. C. Output map after model calculation. The white area corresponds to automatically mapped dunes.

The accuracy assessment of our mapping model is performed on 20% of the training samples randomly selected as a validation subset. After the learning, the mapping model is evaluated with the classical metric: precision, recall and quality (Bianchi et al., 2021; Lewington et al., 2019; Telfer et al., 2015). These metric equations are based on the overlap prediction of the validation subset compared to the training manual map used like "ground truth".

3.3 Crest dunes skeletonization

The crestlines extraction is based on the Volumetric Obscurance algorithm (Rolland et al., 2022). The tool calculates for each pixel on a DEM the ratio between the volume below and above the topography in a sphere of a given radius centred at a given point of the topographic surface (Rolland et al., 2022). This process amplifies the pixel values on a DEM. Thus, the high inflection point pixels as being associated at the crestlines are accentuated favoring their recognition.

The output raster is reduced to a branched skeleton from the identification and digitization of high inflection points corresponding at the crests. The main crestline of the dunes is obtained from an automated analysis of branches connectivity of each bedforms crestlines. The algorithm assigns a connection type and length class to the segments and by iteration, removes the loops and keeps the longest segment to digitize the longest crestline pathway, here considered as the main crestline.

Finally, we used the mapped crestlines to refine dune contours where dunes are adjacent to one another. First, we consider each main crestline as belonging to a morphology. Then, we used a seed region growing algorithm which from the dune crestlines, generates borders and individualizes the dunes.

4 RUB’AL KHALI APPLICATION

The unsupervised classificator is trained on a set of 100 DEM samples with dunes. After the training, the mapping model is assessed from 20% of the samples and reaches 92% of precision, 87% of recall and 70% of mapping quality. The mapping model of the dunes outline reveals a good performance and allows us to apply the protocol on eastern part of the Rub’Al Khali desert. This area is chosen because of its sand dunes diversity whose distribution and spatial variability (Fig.4A, B) at different scales of observation (Fig.4C) illustrate a variation of the wind regimes and the sand availability.

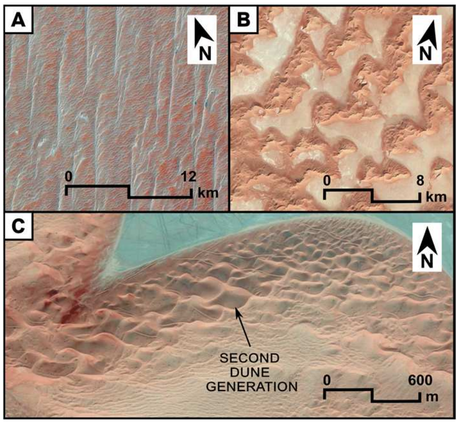

Figure 4. The spatial variability and the different dune scales on the Rub’Al Khali desert (Abdallah and Kumar, 2011; McKee, 1979). A. Linear dunes defined as a “compound dunes”. B. Barchanoid dunes. C. An example of the second dune generation superimposed on the larger dunes.

The different automated steps are applied on the DEM of the Rub’Al Khali and a map of the different dune forms and generation is produced (Fig.5A). More than 78,000 dunes and crestlines are mapped in 6 hours of processing. The aeolian morphologies automatically mapped represents a covered sand surface of 58,000 km² (Fig.5B).

To demonstrate the model performance and applicability of the protocol in the analysis of the pattern’s geometry at a field scale, we calculated for each dune their length, width, height and the median orientation of their main crestline (Fig.5C).

The morphometric analysis reveals a spatial variability of these parameters that quantify the diversity of the shapes at the field scale. This tool also provides an orientation estimate of the main crestlines which is related to the degree of dune organization.

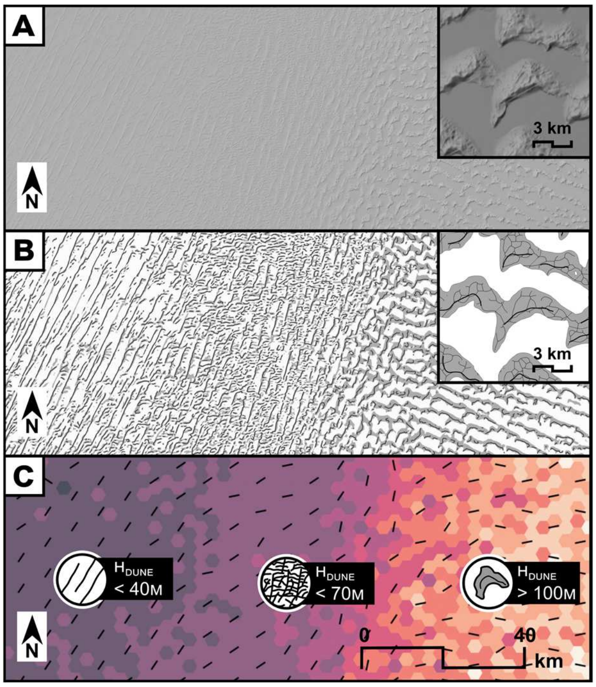

Figure 5. Part of the Rub’Al Khali dunes map produced by the automated protocol. A. Rub’Al Khali DEM and a barchan dune focus (on the right). B. Example of the automated mapping. The grey shapes are individualized dunes. The black lines are their mean crest. C. Spatial variability of the dune height (color gradient) and the crest orientation (black line).

5 CONCLUSION

This work presents a semi-automatic protocol to extract the aeolian dunes and their morphological characteristics from a DEM. The different numerical steps allow to separate the dune scales, digitize the dunes shape and skeletonize the mean crestline by using the Residual Relief extraction, the training and using of an unsupervised classificator (Deep Learning – U-Net) and the Volumetric Obscurance approach respectively.

This protocol reveals good performance to map various and complex dune forms. This work is an original production that completes atlases of this region present in the literature which illustrate the morphological boundaries defined by the aerial and satellite images interpretation (Abdallah and Kumar, 2011; Barth, 2001; Glennie, 1970; McKee, 1979).

Finally, this work demonstrates the ability to produce quickly and accurately a large numerical database that can be used to study the dune geometry on a field scale that reflects spatial variations in wind dynamics and sediment routing.

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