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ABSTRACT

Regular patterns of vegetation are considered widespread landscapes, although their global extent has never been estimated. Among them, spotted landscapes are of particular interest in the context of climate change. Indeed, regularly spaced vegetation spots in semi-arid shrublands result from extreme resource depletion and prefigure catastrophic shift of the ecosystem to a homogeneous desert, while termite mounds also producing spotted landscapes were shown to increase robustness to climate change. Yet, their identification at large scale calls for automatic methods, for instance using the popular deep learning framework, able to cope with a vast amount of remote sensing data, e.g., optical satellite imagery. In this paper, we tackle this problem and benchmark some state-of-the-art deep networks on several landscapes and geographical areas. Despite the promising results we obtained, we found that more research is needed to be able to map automatically these earth mounds from space.

Index Terms— Earth mounds, spotted landscapes, raised fields, termite mounds, deep learning

1. INTRODUCTION

Regular patterns of vegetation are considered widespread landscapes, although their global extent has never been estimated. They show a great diversity of shapes, including labyrinths, strips, gaps and spots, the formation of which can be explained by scale-dependent feedbacks between organisms and limiting resources. Water as a limiting resource has received particular attention in cases studied to date [1, 2, 3]. Territorial competition between colonies of social-insect ecosystem engineers (termites in particular) has also been shown to be another mechanism underlying the formation of vegetation spots and gaps [4], with a distinct theoretical framework [5]. Both mechanisms are not mutually exclusive.

Among the diversity of shapes observed in patterned landscapes, spotted landscapes are the most frequent and widespread, and are also the best studied. Regularly spaced vegetation spots in semi-arid shrublands result from extreme resource depletion and prefigure catastrophic shift of the ecosystem to a homogeneous desert [2, 6]. In addition, termite mounds producing spotted landscapes were shown to increase robustness to climate change [7]. Thus, spotted landscapes are of particular interest not only to foresee potential consequences of climate change, but also to buffer the effects of climate change by delaying catastrophic shift.

Although spotted landscapes have been studied mostly in dry environments, they are also widespread in seasonally flooded savannas. Both environments have in common a strong constraint on ecosystem engineers: water is limited in dry environments, well-aerated soil is limited in flooded environments, and low soil fertility often characterizes both. Similar processes may thus drive landscape patterns in both environments and the aforementioned theoretical frameworks may similarly apply. Spotted landscapes are often associated with microtopographic heterogeneity: spots are earthmounds, typically ranging from 1 to 30 m in diameter and 0.2 to 4 m in height. Although present in dry environments, earthmounds are of particular importance in flooded environments, where even slight differences in elevation lead to highly contrasted levels of the constraining resource (well-aerated soils). Thus, understanding the drivers of microtopographic heterogeneity should help to account for the dynamics of most spotted landscapes, in both semi-arid and seasonally flooded landscapes. Various origins have been proposed for the formation of earthmounds, e.g., differential erosion, eolian deposition of sediment, burrowing activity of mammals, nest construction by termites, past or current human agency (raised-field agriculture), leading to a variety of regional names of these landscapes in the literature, e.g., Heuweltjies, Nabkha, Mima mounds, Murundus, termite savannas, raised fields [8]. In many cases, several mechanisms may have been in play successively, or may be in play simultaneously, making it difficult to identify the original cause.

Whatever their origin, earthmound landscapes share common properties that enhance ecosystem functioning and thus make them of particular interest for researchers in ecology in the context of current global changes. The first property is that each mound works as a fertility island [9, 10, 11, 12, 13]. Various mechanisms, not mutually exclusive, may account for

fertility islands. Feedback loops between short-range facilitation and long-range competition for resources between individual plants result in resource concentration under clumps of vegetation [14]. Central-place foragers such as social insects bring food to their nest, leading to the concentration of organic matter in or close to the. As a consequence, large termite nests in termite savannas, for instance, have higher contents of soil nutrients than the surrounding savanna soil, with cascading effects on biodiversity and productivity [10, 15]. Raised-field agriculture is a current practice in some parts of Africa, consisting in piling up topsoil and organic matter to locally increase nutrient availability to crop, the consequence of which is increased yield [16, 17]. Raised-field agriculture has been extensively practiced in South America by pre-Columbian civilizations [18]. Although this practice has been abandoned for several hundred years in the Neotropics, vestiges of raised fields are still visible because the topographic heterogeneity initiated by humans has been beneficial to ecosystem engineers (termites, ants, earthworms, plants) that have maintained resource concentration (and the mounds themselves) through feedbacks ever since the fields were abandoned [19, 12]. Earthmounds, as fertility islands, increase biodiversity and productivity of the ecosystem. The second property common to earthmound landscapes is the regular spacing between earthmounds [10, 20, 21, 22]. The effect of regular spacing on ecosystem functioning has been little investigated, but it was shown that regular spacing of termite mounds increased ecosystem productivity compared to random spacing because it optimizes mound density [10].

The increasing ease of access to satellite images at resolutions high enough to detect meter-scale landscape features opens unprecedented opportunities to study regular patterns of vegetation, and in particular spatial patterns of earthmound landscapes, at the global scale. However, images have to be visually checked and mounds individually labeled for applying point pattern analysis. Thus, characterizing spatial patterns of earthmound landscapes at a global scale requires labor-intensive manual processing. Automatic image processing is thus needed in ecology to reduce manual labor and produce large sets of reliable data, in particular from remote sensing sources. To do so, deep learning has become the reference methodology for identifying patterns in images (including ecological patterns [23]), following the general trend in computer vision and various application fields. Yet, applying deep learning in environmental remote sensing raises some challenges [24], especially the need for large training sets, that can be countered with various strategies [25, 26].

The problem of extracting earth mounds from remote sensing using deep neural networks has been already tackled by a few studies. In [23], termite mounds are identified with a simple CNN as circular shapes clearly visible in a DEM generated from LiDAR data. In [27], the problem is expressed as an object detection task solved with RetinaNet using data acquired with a GoPro camera. More closely related to our
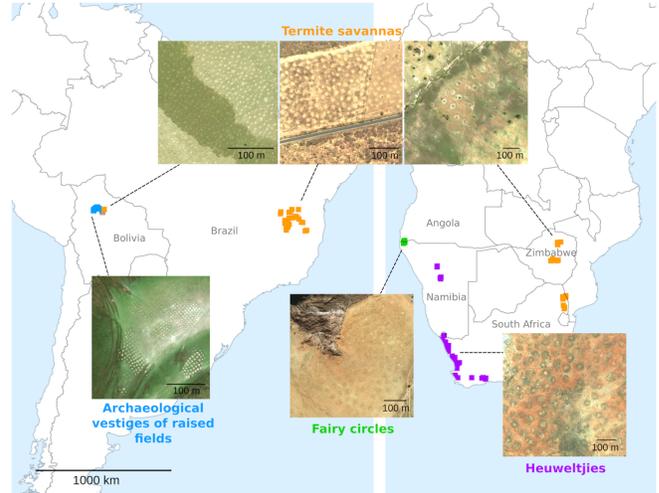
Fig. 1. Sites in South America and Africa from which satellite images were extracted, with illustration of the four categories of spotted landscapes. Images are samples from Maxar WorldView-3 extracted from Microsoft Bing Maps.

work, [28, 29] process very high resolution satellite imagery through CNNs, but no details have been provided on the model and the experimental settings. The problem of automatic earth mound identification from space using optical imagery and deep learning remains still largely unexplored.

We aim here to fill this gap through assessing several state-of-the-art deep networks for this purpose, considering several kinds of landscapes and geographical areas. We show that the problem is complex and requires further research.

2. MATERIAL AND METHODS

2.1. Study sites

The spotted landscapes we studied were located in South America and Africa and were of four commonly recognized categories (Fig. 1).

2.1.1. Termite savannas

Termite savannas feature large termite mounds (about 20 m in diameter and 2 m high) that are regularly spaced and support distinct vegetation compared to the surrounding area. Each mound houses a single termite colony, with the nearest neighbor over 50 m away. We selected sites in Bolivia (28), Brazil (2), South Africa (8), and Zimbabwe (11). Another type of termite savanna, recently discovered in Brazil, spans an area nearly the size of Great Britain [30, 31]. Here, mounds are closer together and result from millennia of soil excavation from underground tunnels. Unlike typical termite nests, these mounds lack a network of tunnels and chambers. We selected 29 sites from this unique landscape. Due to their distinct char-
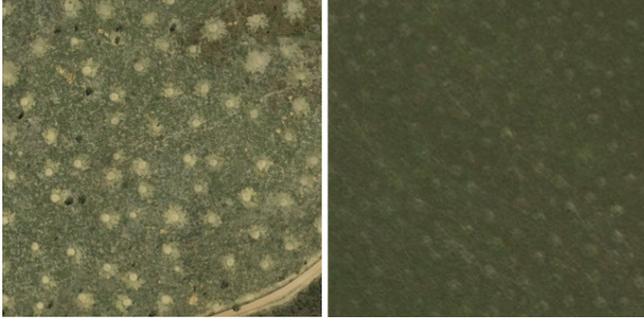
Fig. 2. Examples of satellite images of a termite savanna in Brazil illustrating the two levels of detection difficulty (easy on the left image, difficult on the right image). Same scale for both images. Satellite samples have been taken from Microsoft Bing Maps (Maxar WorldView-3 data).

acteristics, we classified them separately as "supercolony." Fig. 2 illustrates the size variations of termite mounds across Brazil, leading to various levels of difficulty for the detection task. Our study also highlights the significant differences in termite mound structures across continents.

2.1.2. Heuweltjies

Although the origin of Heuweltjies is still debated (eolian deposition of sediments or termite mounds), this type of landscape shares similarities with termite savannas (size and spacing of the mounds in particular) [21]. This landscape type is only known from south-western Africa. We selected sites in South Africa (32) and Namibia (5).

2.1.3. Fairy circles

This landscape type looks like a negative of termite savannas: spots are depressions of bare soil surrounded by vegetation. As for Heuweltjies, their origin is debated. The two best supported hypotheses suggest that fairy circles result either from vegetation-water feedbacks [32] or from the activity of subterranean termite nests [33]. They are known from southwestern Africa and Australia. We selected sites in Namibia (3) and Angola (2).

2.1.4. Archaeological vestiges of raised fields

Raised fields constructed by pre-Columbian civilizations in South America took various forms [18], one of which is circular mounds. The vestiges of circular raised fields have a spatial organization strikingly different from that of termite savannas: mounds are less than a few meters in diameter and usually (today) less than 0.5 m high; the nearest neighbor is within a few meters and in addition to showing regular spacing; they are often oriented in square grids [20]. We selected 93 sites in Bolivia following the map of Rodrigues et al. [34].

For each study site, we extracted a square area of c. 0.58 km2 using Microsoft Bing Maps at the highest resolution (corresponding to Maxar WorldView-3 imagery). Following visual assessment of the study sites, we considered only a subset of the selected sites, ignoring images for which the annotation was questionable.

2.2. Automatic image analysis workflow

2.2.1. Data preparation

We split our data in two parts following the nature of the mounds, i.e. due to human factors or not. The first dataset, called Raised fields dataset in the sequel, includes 67 images with a spatial extent of 2560×2560 pixels. The mounds are small and densely packed, making individual annotation extremely time-consuming. Therefore, we resorted to annotating the group of mounds as a single entity/instance.

The second dataset, called the Termites dataset, contains 76 images featuring four classes: termite savannas (containing only single termite colonies), supercolonies (a more complex kind of termite savannas), fairy circles, and Heuweltjies. Conversely to the first dataset, we annotated each mound individually, given the sparse nature of the mounds.

To prevent memory issues, we resized the images in the Raised fields dataset to 1024×1024 pixels. For the Termites dataset, we split the images into 640×640 tiles. The annotations of the mounds in all the images were carried out using *Make-Sense.ai* annotation tool [35].

2.2.2. Deep learning architectures

We aim to assess the performance of well-established deep architectures for object detection in our specific context. We selected one of the most recent models from the YOLO familly [36], namely YOLOv8 [37] (with the original model, medium size), as well as Faster R-CNN [38], using two different backbones: ResNet50 [39] and MobileNet [40].

The choice of the two backbones was done in order to assess the efficiency of the models in a practical scenario, where both accuracy and deployment time are significant. Let us recall that YOLOv8 comes under the category of one-stage detector models, where the images are processed in a single pass, and the class probability prediction and bounding box estimation happened simultaneously. Such a strategy leads to faster deployment, but the model struggles with highly accurate detection, especially for small objects. On the other hand, we are considering Faster R-CNN, a two-stage detector. In the first stage, the region proposals are generated, while in the second stage, these proposals are fine-tuned and classified. This makes the model highly accurate and more robust for small object detection, but it comes at a higher computational cost and thus a lower processing speed.
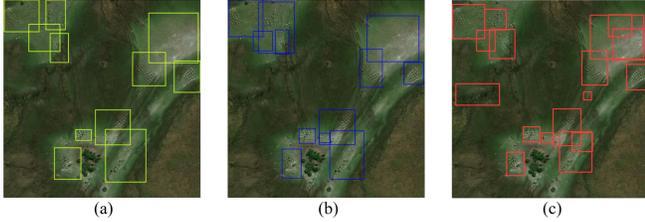
Fig. 3. Visual illustration of results obtained on the Raised fields dataset: (a) Groundtruth, and detection maps generated with (b) Faster R-CNN and (c) YOLOv8.
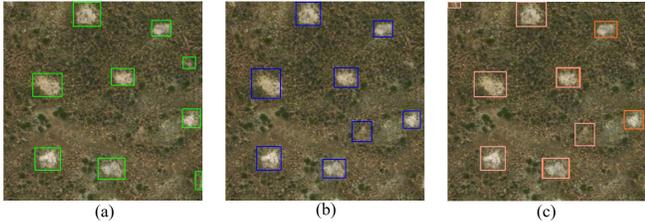
Fig. 4. Visual illustration of results obtained on the Termites dataset (Heuweltjies class): (a) Groundtruth, and detection maps generated with (b) Faster R-CNN and (c) YOLOv8.

2.2.3. Training protocols and evaluation

We rely on a standard evaluation protocol, and split our dataset into a training set (80%) and a testing set (20%). All the models are trained using AdamW [41] optimizer, with a learning rate of 0.001. During training, the batch size has been set to 16. The performance of the models is evaluated using average precision and mean average precision at 0.5 IoU threshold (mAP50).

3. RESULTS AND DISCUSSION

Tables 1 and 2 respectively showcase the detection performance on the Raised fields and Termites datasets. The highest reported values are boldened. Also, for both datasets, the performance of YOLOv8 model is reported with and without augmentation (as YOLOv8 was used as an off-the-shelf method and the code supported automatic data augmentation).

It is observed that in case of the raised fields dataset, the best performance is achieved with Faster R-CNN with the ResNet50 backbone. While older, this method surpasses the YOLOv8 model, even with augmentation. The reason could be that the mounds in the images are relatively small (within a bounding box), and YOLOv8 does not particularly specialises in detecting small objects. On the contrary, YOLOv8 surpasses Faster R-CNN on the Termites dataset, probably due to large size of mounds and lighter architecture.

We also report some qualitative results on the two datasets in Figures 3 and 4. We can see that for the Raised fields dataset, YOLOv8 tended to overpredict the number of mound

Table 1. Quantitative evaluation on the Raised fields dataset.

	Faster R-CNN (ResNet)	Faster R-CNN (MobileNet)	YOLOv8 (No Aug)	YOLOv8 (with Aug)
Overall mAP	**51.4**	44.3	28.8	42.8

Table 2. Quantitative evaluation on the Termites dataset.

Classes	Faster R-CNN (ResNet)	Faster R-CNN (MobileNet)	YOLOv8 (No Aug)	YOLOv8 (with Aug)
Fairy Circles	16.7	29.3	78.8	**85.7**
Heuweltjies	54.8	**55.1**	37.4	37.6
Supercolony	12.5	25.7	23.5	**58.9**
Savannas	43.3	33.0	24.6	**50.4**
Overall mAP	31.8	35.8	42.9	**58.2**

Table 3. Ablation study to assess the impact of the number of samples on the performance of YOLOv8 with augmentation.

Classes	40 Samples	50 Samples	60 Samples
Fairy Circles	77.2	88.7	85.7
Heuweltjies	20.5	36.9	37.6
Supercolony	10.9	20.8	58.9
Savannas	31.2	50.2	50.4
Overall mAP	34.9	49.1	58.2

areas w.r.t. Faster R-CNN, thus generating a lot of false positives. This could be due to difficulty in learning the smaller size of mounds and confusing the 'non-mound' area with those of mounds. For the Termites dataset, we see that both models robustly localise the mounds for the Heuweltjies class, though some smaller mound still go unnoticed. Deep models dedicated to small objects [42, 43] should be considered for such specific settings.

Moreover, we also conducted an ablation study to assess the performance when the number of training samples are decreased. To do so, we considered YOLOv8 model since it is a more efficient model. As observed in Tab. 3, the accuracy decreases for some classes when the number of samples is reduced from 60 to 50. The degradation of the results is more noticeable when the number of training samples is further reduced to 40. But even with only 40 samples, YOLOv8 is competing Faster R-CNN (see Tab. 2).

4. CONCLUSION

In this paper, we aim at detecting mounds from high-resolution remote sensing satellite imagery. We distinguish between artificial farming mounds (a.k.a. raised fields) and natural ones. Using two popular models, namely Faster R-CNN and YOLOv8, we found that YOLOv8 performed better for natural mounds, while Faster R-CNN was superior for the Raised fields. Despite their effectiveness, geographical, spectral, and spatial variability still poses challenges for perfect localization. Future research will explore advanced deep learning techniques and domain-invariant learning to improve model transferability across different geographical locations.

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