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Mapping the distribution and extent of India's semi-arid open natural ecosystems

M. D. Madhusudan[1] | **Abi Tamim Vanak**[2,3,4]

[1]National Centre for Biological Sciences, GKVK Campus, Bangalore, India

[2]Ashoka Trust for Research in Ecology and the Environment, Bengaluru, Karnataka, India

[3]DBT/Wellcome Trust India Alliance Fellow, Hyderabad, India

[4]School of Life Sciences, University of KwaZulu-Natal, Durban, South Africa

Correspondence
Abi Tamim Vanak, Ashoka Trust for Research in Ecology and the Environment, Royal Enclave, Srirampura, Jakkur, Bengaluru, Karnataka 560064, India.
Email: avanak@atree.org

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Abstract

Aim: Non-forested open natural ecosystems (ONEs) support high biodiversity as well as livelihoods of millions of pastoralists, but are highly threatened due to land conversion. To improve the recognition of their value, we generated a high-resolution (30 m) map of ONEs in the low elevation arid and semi-arid regions of India.

Location: Indian subcontinent.

Taxon: Open natural ecosystems, consisting of a range of non-forested habitats.

Methods: We used public datasets in the Google Earth Engine catalogue to identify and mask out pixels with non-ONE land-cover types, and biophysical attributes outside the environmental envelopes of ONEs. We used 181,812 ONE and 116,447 non-ONE training points along with the input composite image to train random forest classifiers to estimate the probability of a pixel being an ONE. We developed a series of local classifiers for each of eight regions of interest and created a mask of pixels with ≥50% probability of being an ONE.

Results: The overall classification accuracy for this map was 85%, with a Kappa statistic of 0.70. We find that ONEs cover approximately 320,000 km^2 (10%) of India's land surface, but <5% of ONEs are covered under the existing protected area network of India. ONE areas vary greatly by region, from 6 km^2 in New Delhi (0.4% area) to 115,069 km^2 in Rajasthan (33% area).

Main Conclusions: A large proportion of India's geographical area represents an ecosystem that is un-recognized and under-protected. This open data source can be used by policy makers and planners to exclude these habitats when considering the location of renewable energy, tree planting for carbon sequestration and other development projects that negatively impact ONEs. We encourage further refinement of ONE maps in India, incorporating vegetation and floristic characteristics, as well as further consideration of these vulnerable neglected ecosystems in other regions of the world.

KEYWORDS
landscape conservation, savanna grasslands, spatial planning, wastelands

1 | INTRODUCTION

Nearly two-thirds of the Earth's terrestrial habitats consist of non-forest open natural ecosystems (ONEs) (Dinerstein et al., 2017). These open ecosystems are diverse in structure and composition, ranging from cold and hot deserts, rock outcrops, boulder and rubble fields (Fitzsimons & Michael, 2017), to highly diverse grasslands and savanna ecosystems (Bond, 2019). ONEs host high levels of endemic and often endangered fauna and flora (Bond, 2019; Bonkoungou, 2001). For example, tropical savannas support the highest densities and diversity of wild mammalian herbivores and carnivores in the world (Sankaran & Ratnam, 2013). ONEs also directly or indirectly support livelihoods for hundreds of millions of people, and provide fodder resources for millions of livestock (McGahey et al., 2014).

Globally, ONEs are highly threatened, as they continue to undergo sustained and rapid change due to anthropogenic pressure (Veldman et al., 2015; White et al., 2000). Continuing human use and modification have resulted in massive losses in the extent of these biomes, at rates exceeding rainforest loss (Parr et al., 2014; Veldman et al., 2015). Paradoxically, among the largest contributors to the loss of ONEs are efforts to mitigate the effects of climate change. For example, ONEs are preferentially targeted for tree-based restoration (Abreu et al., 2017; Kumar et al., 2020; Veldman et al., 2017) and large-scale conversion to grid-scale solar energy farms, as alternatives to fossil-fuel based energy both in India (Vanak et al., 2017) and globally (Rehbein et al., 2020). The unintended consequences of such mitigation efforts is the increased threat to ONEs, even though there is evidence that these ecosystems themselves sequester large amounts of below-ground carbon (e.g., Nerlekar & Veldman, 2020; Veldman et al., 2015). Despite these threats, the conservation of ONEs has not received the attention of most conservationists, policy makers or the general public (Parr et al., 2014; Veldman et al., 2015).

A part of the problem in conserving ONEs lies in the ambiguity in understanding what constitutes such ecosystems. While forested habitats are relatively easier to define, ONEs can range from sandy deserts, rock outcrops, and rubble fields to open grasslands with shrubs and scattered trees in tropical savannas (Ratnam et al., 2011). In several countries, especially where significant tracts of land are managed by foresters, ONEs, especially in semi-arid regions, have historically been regarded as degraded habitats or wastelands, with a consequent push to increase their 'productivity', or to 'develop' them (Baka, 2017; Vanak, 2019; Whitehead, 2010). For example, in India, large tracts of ONEs are officially categorized as wastelands (Government of India, 2019; Vanak, 2019; Vanak et al., 2017). Current vegetation and biogeographic classifications of India do not recognize ONEs and continue to use a 'forest' classification (Champion & Seth, 1968; Puri et al., 1983), even for habitats that fall within the bioclimatic envelope of tropical savanna ecosystems (Ratnam et al., 2019). Much of this misclassification can be attributed to a historical colonial focus on forestry (Ratnam et al., 2011). Such a bias has resulted in the conservation status of these ecosystems being severely compromised. This happens despite ONEs in India harbouring several endemic and endangered species, such as the great Indian bustard (*Ardeotis nigriceps*), the blackbuck antelope (*Antilope cervicapra*), and the superb fan-throated lizard (*Sarada superba*), among others. These ecosystems also support the livelihoods of several million nomadic pastoralists and their indigenous livestock.

A challenge in conserving ONEs has been in representing them as ecosystems of worth, and in mapping their extent and distribution reliably. As noted earlier, most vegetation classifications in India tend to classify the woodier ONEs as 'forest' types, and the more open ONEs as degraded habitats. The exception to this is for ONEs that occur either in montane Western Ghats and Himalayan regions or those in the alluvial floodplains of the Indo-Gangetic and Brahmaputra river systems (Roy et al., 2015). ONEs that occur in the semi-arid and arid biogeographic zones, however, are invariably misclassified. An earlier effort at mapping semi-arid savanna grasslands in India used medium resolution MODIS imagery to produce a probabilistic map of savanna grassland occurrence (Vanak et al., 2015). There was however a problem of misclassification arising from the intermixing of grassland and fallow classes, because that analysis did not use multi-temporal data to generate distinct signatures for historical cultivation to distinguish it from grasslands.

In this paper, we present an open-source, high resolution (30 m) data layer—as an interactive web application and as an analysis-ready dataset on Google Earth Engine (GEE) that may also be downloaded—showing the distribution and extent of ONEs within India's semi-arid zone. This dataset has been prepared from publicly available satellite imagery, and a training dataset derived from publicly available thematic maps of land cover, including 'wastelands', as mapped by the government (Government of India, 2011).

By showing the location and extent of India's ONEs, we believe this map is an essential first step in safeguarding and consolidating the ecological values of India's ONEs. Firstly, this map helps identify key ONEs across the country, to prioritize site appropriate conservation action. Thereafter, by making this dataset public, we hope that it can serve as a spatial filter to improve the siting of projects focused on climate change mitigation through tree-restoration or renewable energy expansion, as well as in siting other development projects in a manner that does not undermine ONEs or the human communities historically dependent on them.

2 | MATERIALS AND METHODS

2.1 | Defining ONEs

In this paper, we treat ONEs as an omnibus class, comprising multiple diverse ecosystems. We define ONEs as those ranging from sparsely treed desert ecosystems, including areas with sand dunes, to semi-arid savanna grasslands, savanna woodlands and some mesic savannas that are normally classified as "open forest", as well as rocky outcrops and other naturally tree-less or sparsely vegetated geological features (Figure S1). We imposed a 1200 mm rainfall cutoff (close to the 1000mm threshold suggested by Ratnam et al., 2016), in most of the study area. Because of this cut-off, some ONEs that might occur in relatively higher rainfall zones, such as the mesic savannas of Chhattisgarh, Jharkhand and Odisha, the plateau grasslands of Meghalaya, the shola-grasslands of the southern Western Ghats and the high-altitude grasslands and deserts of the Himalayas are excluded from this map. We however, made an exception by including the mesic low altitude, lateritic plateaus of the northern Western Ghats that are considered to be an area of high floristic diversity and endemicity (Joshi & Janarthanam, 2004).

2.2 | Analysis platform

We carried out our analyses on the GEE platform (Gorelick et al., 2017). This platform was ideally suited for our purpose given that it not only offered an up-to-date analysis-ready catalogue of publicly available satellite imagery but also contained a variety of value-added thematic data layers that allowed precise masking out of land-cover types that were not of primary interest to us (e.g., forests, built-up areas, or surface water). Further, as a cloud computing platform, GEE allowed us to iterate and evaluate various choices of input data, analysis masks, and classification algorithms before applying them to generate final high resolution outputs over large spatial extents. Figure 1(a)–(e) provides a high-level summary of the steps involved in creating the ONE map in the GEE platform.

2.3 | Data masks and region of interest

Given that our mapping objective was to identify pixels with a high likelihood of being ONEs, we used various public datasets in the GEE catalogue to identify and mask out pixels with land-cover types that were not of direct interest to us, or with biophysical attributes outside the environmental envelopes where ONEs were known to occur (Vanak et al., 2015). Table 1 shows the datasets and the criteria used to develop data masks outside of which we sought to classify pixels as ONEs. In the northern Western Ghats, where grasslands are known to occur on lateritic soils, as an exception, we included pixels westward from the Deccan Plateau up to the main ridge of the Western Ghats mountains, although the rainfall in some areas exceeded 1200mm.

2.4 | Training data

Since no ready training data for ONEs were available across our region of interest, we queried, aggregated and curated training points from publicly available data from the National Remote Sensing Centre's 2018–2019 Land Use Land Cover (LULC) map, and the 2011 Wasteland Atlas of India (Government of India, 2011), both from the Bhuvan Thematic Data Portal (National Remote Sensing Centre, 2020). From the former dataset, we aggregated training points by randomly sampling with land cover types designated as Scrub Land, Degraded Forest, Barren Rocky Area, and Gullied And Ravinous Land; and from the latter dataset, we similarly queried training points coinciding with land cover types designated as Scrub forest-Scrub dominated, Barren rocky area, Scrubland-Land with open scrub, Scrubland-Land with dense scrub, Gullied, Gullied/Ravine land-Medium ravine, Gullied/Ravine land-Deep/very deep ravine, and Dunes. In all, we assembled a training dataset containing 181,812 points corresponding to ONEs, distributed across our entire region of interest. Similarly, based on the NRSC's LULC dataset and from high-resolution basemaps in Google Earth, we also built a training dataset of 116,447 points within our region of interest that were not ONEs but lands under cultivation that

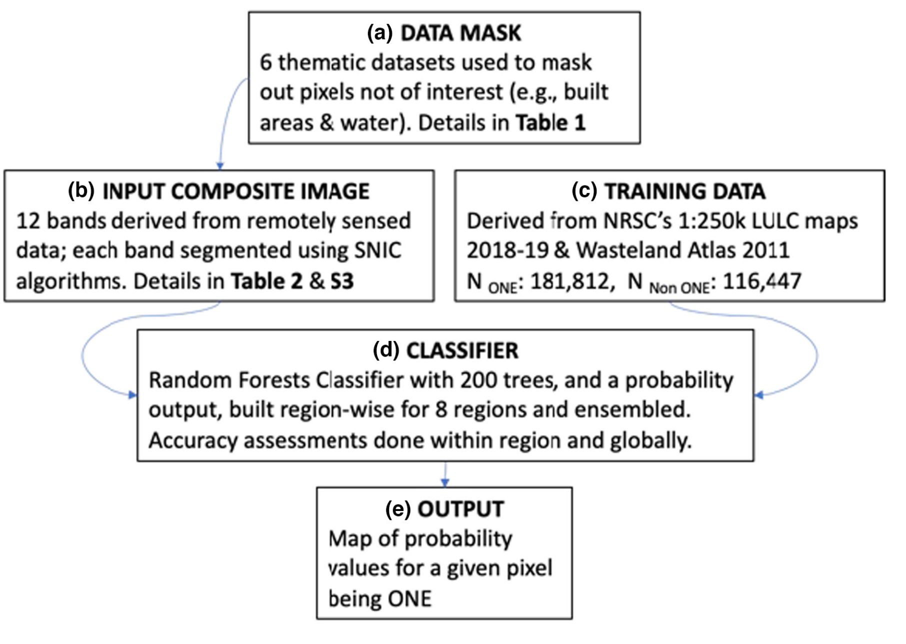

FIGURE 1 A schematic workflow summarizing inputs, process and outputs involved in creation of the Open Natural Ecosystem (ONE) map

TABLE 1 Layers used to develop data mask for analysis

Attribute	Data source	Masking criteria
Rainfall	BIOCLIM (Hijmans et al., 2005)	Total Annual Precipitation <1200 mm
Elevation	SRTM (Farr et al., 2007)	Elevation >500 m, applied to parts of north western Maharashtra to include its high-rainfall lateritic plateaus
Forests	Global PALSAR Forest-NonForest Map (Shimada et al., 2014)	Pixels not classified as forests in any of the yearly images between 2007 and 2018
Surface water	JRC Global Surface Water (Pekel et al., 2016)	Pixels not contained in the maximum extent of surface water between 1984 and 2019
Built-up surfaces	Global Human Settlements Layer (Built Up Grid) (Pesaresi et al., 2016)	Pixels without built-up surfaces in any epoch between 1974 and 2014
Night lights	VIIRS Night Lights (Mills et al., 2013)	Pixels from monthly composites between 2019/11 and 2020/08 where the maximum average radiance was below 4

varied from horticultural crops and irrigated farmlands to marginal rainfed agriculture.

2.5 | Input data layers and creation of input composite

Within our region of interest, we sourced or created data layers (Table 2) and combined them as multiple bands in a single composite image, that was then passed on to a classifier. Most of these input bands were generated using data from the LandSat sensor between the years 2015 and 2019. Most bands were generated by filtering and applying reductions on multi-temporal image collections (see Method of Generation column in Table 2) not only to generate more robust estimates of medians, but also to generate signatures of seasonality and estimates of temporal variability.

Once all bands (except latitude and longitude) above were created, we segmented the pixel data in each input band—a process by which clusters of connected pixels with very similar numerical values are brought together into one spatial unit or segment, and assigned a mean value—by using a simple non-iterative clustering algorithm (Achanta & Susstrunk, 2017) implemented in GEE, with a spacing of 45 pixels and a neighbourhood of 135 pixels. This segmented composite was exported at a 30 m resolution and used as the input for the classifier.

2.6 | Building, applying and validating an ONE classifier

We developed a random forests classifier in GEE with 200 trees using the segmented input composite together with the training points. Hyperparameters were chosen through empirical iterations, rather than through more formal tuning processes. Rather than develop a single, overarching, global classifier, we developed a series of local classifiers with the same hyperparameters for each of eight regions that together constituted our larger region of interest. To begin with, we retained 1% of our overall training data as a holdout validation fraction to assess the overall accuracy of the classification. We used the remainder of the training data as the modelling fraction, where 80% of the labelled points were used as a training fraction, while retaining the remaining 20% in a testing fraction, which was used to assess the accuracy (RMS error) of the classifier. Once we had ensembled the classifications from all eight classifiers, we tested the labels in the known holdout validation fraction against the class labels assigned by binning the probability values into classes, creating a mask of pixels with ≥50% probability of being an ONE. This mask was used to assess the overall accuracy of the ensembled local classifiers.

To understand the size-class distribution of ONEs post-classification, we assessed the frequency and extent of ONE patches (≥1 ha) mapped in our exercise. To determine the current legal conservation status of the mapped ONE, we overlaid the protected areas (PA) map of India (Wildlife Institute of India, 2019) and estimated the proportion ONE area within each PA.

3 | RESULTS

3.1 | ONE distribution and area

Our map reveals that an overall area of 319,675 km^2 (at 30 m pixel), which is approximately 10% of India's geographical area (Figure 2), can be classified as semi-arid ONEs. The overall classification accuracy for this map was 85%, with a Kappa statistic of 0.70 (Table 3; performance of local classifiers are in Table S1). The spatial extent and distribution of ONE are heterogeneous across the country, ranging from 6 km^2 in New Delhi (0.4% of state area) to 115,069 km^2 in Rajasthan (33% of state area; Table 4). Approximately 69% of the ONEs we mapped are shown as one or the other category of 'wasteland' under the Wasteland Atlas. ONEs are mostly distributed in the Deserts and Xeric Shrublands (50%) and Tropical and Subtropical Dry Broadleaf Forests (42%) biomes as classified by Dinerstein et al. (2017), while a small fraction (8%), presumably comprising

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TABLE 2 Layers used in preparation of input composite for ONE classification

	Bands used in final composite	Intermediate bands generated	Source sensor	Method of generation
1	Phase	Phase	Landsat SR, 2015–2019	By fitting an annual harmonic model to 5 year time-series of NDVI data to extract Phase, Amplitude, Constant and Linear Trend terms
2	Amplitude	Amplitude		
3	Spectral distance between tasselled cap images from pre- and post-monsoon periods	Three Tasselled cap bands (brightness, greenness and wetness) for two periods (pre- and post-monsoon)	Landsat SR, 2017–2019	By creating seasonal subsets for pre- and post-mosoon periods, respectively, of TC Brightness, Greenness and Wetness bands using band coefficient values (DeVries et al., 2016) Pre-Monsoon period: 30th to 150th day of year Post-Monsoon period: 245th to 365th day of year
4	Median NDVI	Median NDVI	Landsat SR, 2015–2019	By computing median across entire collection
5	Extent of Browning	Extent of Browning		By computing normalized Difference between NDVI 5th percentile and NDVI 50th percentile
6	Extent of Greening	Extent of Greening		By computing normalized Difference between NDVI 95th percentile and NDVI 50th percentile
7	Relative extent of seasonal vegetation change	Relative difference in the extent of browning and greening		By computing normalized difference between extent of browning and greening in a pixel
8	HV band median as index of vegetation height	HV band median	Global PALSAR-2/PALSAR Yearly Mosaic, 2015–2018	By computing median backscatter coefficients for each pixel across multi-year stack
9	Multiscale Topographic Position	Topographic position index	CSP's SRTM multi-scale Topographic Position Dataset	Raw pixel values resampled to 30 m spatial resolution
10	Elevation	Elevation	SRTM	Raw pixel values
11	Pixel Latitude	Pixel Latitude	-	-
12	Pixel Longitude	Pixel Longitude	-	-

Abbreviation: ONE, open natural ecosystem.

savanna woodlands, falls within Tropical and Subtropical Moist Broadleaf Forests (Table S2).

3.2 | Size class distribution (fragmentation matrix)

Excluding patches <1 ha in size, which accounted for 3009 km^2 or <1% of overall ONE area, an overwhelming fraction (72.7%) of ONE patches mapped were in the range of 1–10 ha, and 94% of the ONE patches were in the 1–100 ha size range (Figure 3, inset). However, these patches together accounted for just about 10% of the overall ONE distribution. Beyond 100 ha, although the number of patches decreased by an order of magnitude with a corresponding one order of magnitude increase in size class, the area represented in each of these size classes was mostly similar. While large expanses of ONE (>1000 km^2) were present across the semi-arid zone (Figure 3), it should be noted that the two largest patches, exceeding 10,000 km^2, were both in the arid regions of Thar and Kutch.

3.3 | Coverage of ONE under PA

Approximately 14,280 km^2 of the ONEs we mapped occur within the PA network of India (Figure 3). This represents less than 5% of the total geographical area of ONEs in India. Furthermore, just five PAs (Desert National Park, Kachch Desert Wildlife Sanctuary, Nagarjunsagar-Srisailam Tiger Reserve, Kailadevi Wildlife Sanctuary and Kaimur Wildlife Sanctuary) accounted for 40% (5,653 km^2) of this coverage.

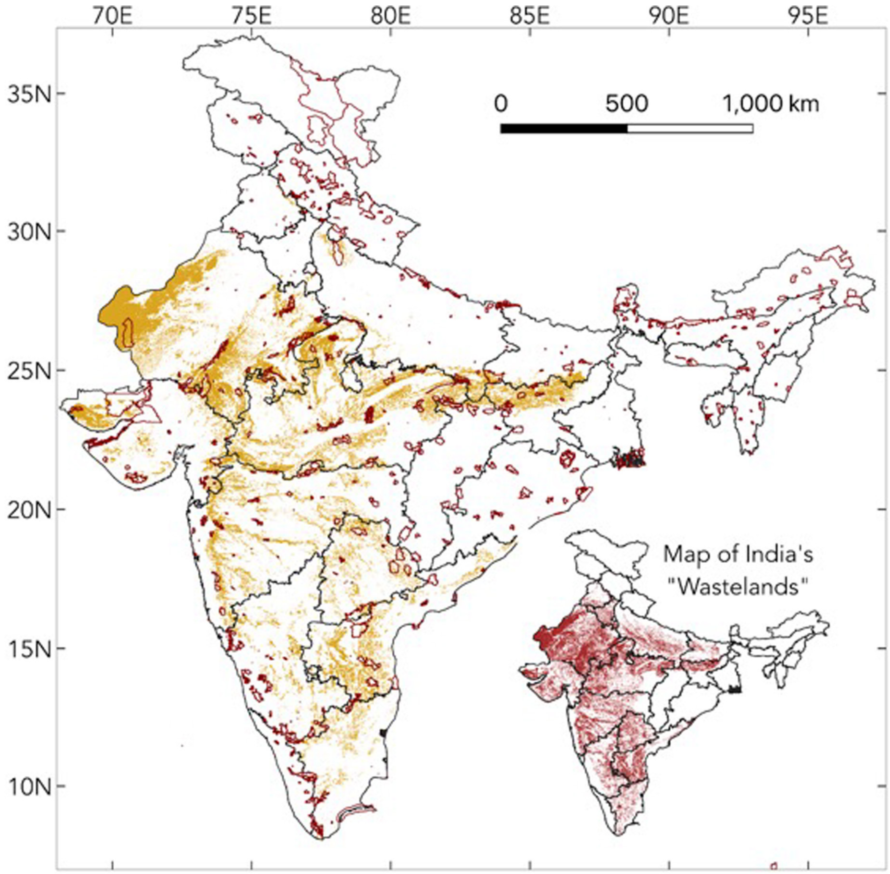

FIGURE 2 Distribution of semi-arid open natural ecosystems (i.e., pixels with a probability ≥50% of being classified as an ONE) in India in relation to protected areas (red outlines), and semi-arid “wastelands”, as designated by the Indian government (inset map).

TABLE 3 Performance metrics of the overall classifier (obtained from ensembling of the eight local classifiers in Table S1) used to classify pixels as semi-arid open natural ecosystems (ONE) in India. The total of the gray boxes equals the class accuracy value presented in the last column. The ratio of gray box totals to overall total provides the Overall Classification Accuracy

	Class label assigned by classifier (based on probability values assigned)				
	0.0–0.35	0.35–0.5	0.51–0.67	0.67–1.0	
Known class label (*N*)	Non-ONE (1952)		ONE (1217)		Class accuracy
Non-ONE (1897)	1544 (81.4%)	151 (8.0%)	121 (6.4%)	81 (4.3%)	89.4%
ONE (1272)	130 (10.2%)	127 (10.0%)	207 (16.3%)	808 (63.5%)	79.8%
Overall classification accuracy					85.5%
Kappa statistic					0.70

4 | DISCUSSION

Open natural ecosystems in India have historically been undervalued and unrecognized, to the extent that contemporary vegetation maps continue to classify grasslands, shrublands and other desert, arid and semi-arid ecosystems either as ‘forests’, ‘degraded lands’ or even as ‘wastelands’. In fact, 68.6% of ONEs that we have mapped are classified as ‘wastelands’ of one sort or another. Here, we have provided an ecologically meaningful high resolution map of ONEs in India, with the aim to better understand their distribution and status as ecosystems in their own right, to be valued and conserved.

We find that ONEs are distributed across the dry sub-humid and semi-arid zones of India and cover ~10% of India's geographical area. The largest swathes of ONE are spread across the states of Rajasthan (~30%) and include the Thar desert and associated sand dunes, thorn scrub and grasslands; and the savanna grasslands and open woody savannas of Madhya Pradesh, Maharashtra and Gujarat (Vanak et al., 2015). Outside of the desert regions in India, nearly half of India's ONEs fall under the broadleaf forest biome category (Dinerstein et al., 2017). This dissonance in global ecoregion classification is striking, because these areas fall well within the bioclimatic envelope of African savannas (Ratnam et al., 2016).

Because of a lack of historical data on the distribution of these ecosystems, we have no estimate of the rates of loss of these habitats. Indeed, the conservation status of these remaining ONEs in India continues to be precarious (Kumar et al., 2020; Vanak

TABLE 4 State-wise estimates of area and proportion of semi-arid open natural ecosystems in India

	State	Estimated ONE area (km^2)	Percent of state's land area
1	Rajasthan	115,069	33.6
2	Madhya Pradesh	58,319	18.9
3	Maharashtra	37,485	12.2
4	Andhra Pradesh	25,084	15.3
5	Gujarat	24,916	13.1
6	Karnataka	14,445	7.5
7	Telangana	12,139	10.8
8	Jharkhand	11,106	13.9
9	Uttar Pradesh	9808	4.1
10	Tamil Nadu	4815	3.7
11	Bihar	4477	4.7
12	Chhattisgarh	1000	0.7
13	Haryana	623	1.4
14	Punjab	383	0.8
15	Delhi	6	0.4
	Overall	319,675	

Note: The areas under ONEs may not include the entire geographic area of a state, and is computed only within the extent of the data mask for each state. These estimates are made at a pixel size of 30 m.

et al., 2017) as the historical bias towards forested ecosystems is also reflected in the PA network of India. Less than 5% of ONEs in India are included in the PA network of India. Indeed, the few that were setup to specifically protect ONEs account for 40% of this coverage. Protected areas established to conserve ONE specialist species such as the great Indian bustard or the blackbuck, are generally small (<50 km^2). Our analysis of the size-class distribution of the remaining patches shows that India's ONEs are still distributed in medium to large patches, which we would consider a considerable advantage for their conservation. Taken together with their significant under-representation in the PA network, there may be opportunities to elevate the conservation status of many of these larger parcels in a manner that acknowledges the adaptation of these ONEs to fire and grazing (Ratnam et al., 2019), and harmonizes these perturbation regimes with local cultural and land-use practices.

Despite the recognition that ONEs such as grasslands, and scrub and thorn forests provide more than 50% of the fodder for India's 500 million livestock (Singh et al., 2006), the continued classification of these landscapes as wastelands (Vanak et al., 2017), render them vulnerable to destructive change led by state policy. Our results show that nearly 70% of ONEs overlap with the Wastelands Atlas of India (Government of India, 2011) across the country. This, in and of itself, is not surprising, since we used many of these 'wasteland' classes (Government of India, 2011) as input training data to train our classifier. The larger issue, however, lies in the normative categorization of these ecosystems as 'wastelands'. The exercise of mapping 'wastelands' in India is conducted every 5 years, and this categorization which actively undervalues the ecological, conservation and livelihood values of these lands, lends a particular policy tilt to India's land-use planning. It becomes almost incontestable and even trivial to replace a 'wasteland' or 'degraded' land with better developmental or commercial uses.

By persisting with such ecologically uninformed definitions of land cover types, policymakers have earmarked large areas of ONEs across the country for conversion. As an unintended consequence, one of the biggest threats to ONE in recent years stems ironically from India's global leadership role in the large-scale deployment of renewable energy technologies, such as grid-scale solar farms. These solar farms have overwhelmingly been deployed in ONE in the semi-arid region (e.g., Besta, 2021; Power Grid Corporation of India, 2013), with large-scale projects continuing to irreversibly damage these ecosystems. Although there have been some efforts to de-prioritize ecologically sensitive landscapes for situating grid-scale solar energy, the lack of spatial data on the distribution of ONEs in India has hampered such initiatives (Kiesecker et al., 2020).

Another important threat to ONEs comes from the mistaken notion that these are degraded forests. Therefore, these landscapes are prioritized for 'afforestation' to meet the target of tree-based greening under India's commitments under the Green India Mission, the Bonn Challenge, and concomitantly, for carbon sequestration as part of India's commitment to the Paris Accord (Government of India, 2015). Such programs ignore the inherent biodiversity value of these ecosystems, as well as their vast potential for below-ground carbon sequestration (Kumar et al., 2020; Veldman et al., 2017). Indeed, several studies have suggested that under certain rainfall regimes and the increasing risk of fires, grasslands may be better at sequestering carbon than tree plantations (Dass et al., 2018).

The United Nations Food and Agriculture Organization has endorsed an application to declare the year 2026 as the International Year of Rangelands and Pastoralists (IYRP, 2021). Implicit in this

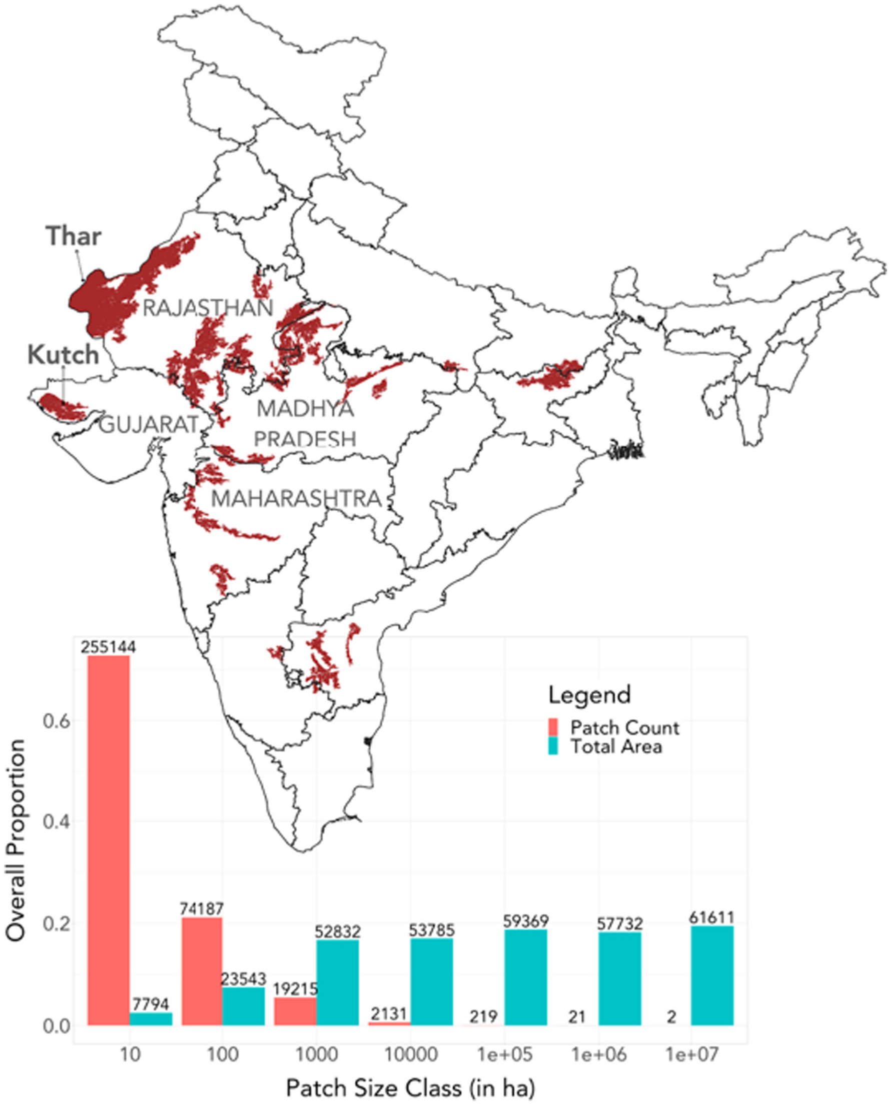

FIGURE 3 Location and area of large tracts (area ≥1000 km^2) of semi-arid open natural ecosystems in India. Inset shows distribution of the count and total area of semi-arid open natural ecosystem patches by patch-size class. Note that only patches of size >1 ha are included in this analysis. Numbers at the top of the columns in the graph indicate frequency (for the patch count column) and area (in km^2 for the total area column).

endorsement is the recognition that most rangelands occur in ONEs, and that the loss of ONEs directly impacts the lives and livelihoods of millions worldwide (Davies & Hatfield, 2007). Our map provides a useful starting point to map rangelands in India and augment efforts to protect traditional movement paths of nomadic pastoralist groups (e.g. https://pastoralism.org.in/initiatives/).

Finally, the lack of a plan to conserve ONEs is at odds with government policy on endangered species that survive in these habitats. For example, there is a conservation breeding program for the critically endangered Great Indian Bustard. Similarly, there are plans afoot to re-introduce the extinct cheetah to India, ostensibly to draw increased conservation attention to the savannas that it once occupied. However, the sites chosen to introduce this species are within an existing 'forest' PA (Jhala et al., 2021). There is an avoidable contradiction between the widespread neglect of ONEs and the conservation priorities of endangered species that they support, and more broadly, between India's global commitments to biodiversity conservation with India's climate change mitigation commitments. Towards reconciling these contradictions, our map thus provides an important layer for planners to incorporate within existing frameworks that prioritize climate change mitigation through tree restoration, or in energy and development planning (Government of India, 2009; MoEFCC, 2013; TNC India, 2020; WRI India, 2018).

Other than the ecological considerations of our dataset, we believe that there is implicit value in making all land cover data open and publicly available. Open peer and public scrutiny can only help improve our classification and mapping of these lands and aid in its conservation. We believe that for lands beyond the pale of conservation management, and as lands undergoing rapid transformation, it is vital to make data about their distribution available openly to raise conservation attention, and to alter narratives about them being wastelands.

Our map is also a necessary first step to characterize ONEs more comprehensively as ecological entities. Going forward, we need vegetation-based classification that separates different constituent habitats within this larger omnibus category of ONEs. The development of such an ecologically and culturally robust classification will also require open data approaches not only towards finished map

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products, but also towards the creation and liberation of open training datasets, and to make the code open-source, which are both goals to which we remain committed and will continue making efforts.

Our map includes the following known limitations: (i) possibility of misclassifying fallow lands, especially in the rain-fed agricultural zone, as open grassland/scrublands; (ii) inclusion of small parcels of rain-fed agriculture or built areas in pixels designated as ONEs; (iii) inclusion of near non-vegetated areas such as dunes and salt-pans along with vegetated areas in the omnibus ONE class; and (iv) potential under-estimation of woodland savanna areas owing to their inclusion as forests in the data mask.

This map builds on earlier efforts to map ONEs in India (Vanak et al., 2015), and we hope that further refinements to this map will result in more ecologically and culturally appropriate definitions of these landscapes. Eventually we hope that the various land cover categories that constitute India's ONEs will find their rightful place in vegetation and landcover maps of the country, and replace ecologically-uninformed and pejorative labels such as 'wastelands' and 'degraded' lands.

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DATA AVAILABILITY STATEMENT

We have made the results of our mapping exercise available in the following formats. First, the dataset is available in an analysis ready form on Google Earth Engine from the following link: https://code.earthengine.google.co.in/?asset=users/mdm/india-one. After loading this dataset, it is possible to export and download these data to a client computer. Second, data are also available to visualize within a zero-code, interactive web application at https://mdm.users.earthengine.app/view/open-natural-ecosystems, through which state and district level-summaries of their area and distribution, and other overlay statistics can be obtained.

ORCID

M. D. Madhusudan https://orcid.org/0000-0003-1652-5242
Abi Tamim Vanak https://orcid.org/0000-0003-2435-4260

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BIOSKETCHES

M. D. Madhusudan studies the interface between people and large wild animals in India, and works with individuals and collectives to mobilize conservation action. He helped establish, grow and manage Nature Conservation Foundation, a nonprofit that strives for knowledge-based and socially-responsible nature conservation across India. He was most recently the Obaid Siddiqi Chair in the History and Culture of Science at the National Centre for Biological Sciences, Bangalore.

Abi Tamim Vanak is a conservation scientist with broad interests in savanna ecosystems, human-domestic animal-wildlife interactions and ecosystem restoration. He is a Professor at the Centre for Biodiversity and Conservation, and leads the Centre for Policy Design at ATREE.

Author contributions: M. D. Madhusudan and Abi Tamim Vanak contributed equally to the conceptualization, design and writing of the manuscript. M. D. Madhusudan performed the analyses.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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