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

M.D. Madhusudan[1,2] and A.T. Vanak[2,3,4]

Affiliations:

[1] Independent Researcher

[2] Ashoka Trust for Ecology and the Environment, Royal Enclave, Srirampura, Jakkur, Bengaluru, Karnataka, 560064, India

[3] DBT/Wellcome Trust India Alliance Fellow, Hyderabad, 500034, India

[4] School of Life Sciences, University of KwaZulu-Natal, Durban, 4041, South Africa

Corresponding author email: avanak@atree.org

Abstract

Open Natural Ecosystems (ONEs), consisting of a range of non-forested habitats, are under threat worldwide. These ecosystems range from deserts to savanna grasslands, and host amongst the highest densities and diversity of large mammalian fauna. In addition, this ecosystem supports the lives and livelihoods of millions of pastoralists and their livestock. Yet, ONEs are highly threatened, mainly due to conversion for other land uses. Here, we focus on ONEs in India, where due to historical reasons, this ecosystem has been classified as wastelands. To improve the prospects of recognition of the value of ONEs, we generated a country-wide high-resolution (30m) map of ONEs in the arid and semi-arid regions of India. We find that ONEs cover approximately 300,000 km² (10%) of India's land surface, with the largest extent in states such as Rajasthan, Madhya Pradesh, Maharashtra, Andhra Pradesh and Gujarat. The largest patches (>10,000 km²) occur in the arid parts of Rajasthan and Gujarat. We find that <5% of ONEs are covered under the existing protected area network of India. We hope that this open data source is used by policy makers and planners to exclude these habitats when considering location of renewable energy projects, tree planting projects for

carbon sequestration, and other development projects that negatively impact ONEs. We encourage further refinement of the map taking into account constituent vegetation and floristic characteristics for a more ecologically robust mapping of India's open natural ecosystems.

Introduction

Over a third of the Earth's terrestrial habitats consist of non-forest Open Natural Ecosystems (ONEs). 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. ONEs host high levels of endemic and often endangered fauna and flora (Bonkoungou 2001; Bond 2019). 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. 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; Veldman et al. 2017; Kumar et al. 2020) and large-scale conversion to grid-scale solar energy farms, as alternatives to fossil-fuel based energy (Vanak et al. 2017). 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., Veldman et al. 2015; Nerlekar & Veldman 2020). 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 (Whitehead 2010; Baka 2017; Vanak 2019). For example, in India, large tracts of ONEs are officially categorised as wastelands (Vanak et al. 2017; Government of India 2019; Vanak 2019). Current vegetation and biogeographic classifications of India do not recognise 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 sitana*), 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.

In this paper, we present an open, high resolution (30 m) data layer—as an interactive web application, and as an analysis-ready dataset on Google Earth Engine 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 of India.

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 prioritise 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.

Methods

Defining Open Natural Ecosystems

In this paper we treat Open Natural Ecosystems as an omnibus class, comprising multiple diverse ecosystems. We define ONEs as those ranging from tree-less desert ecosystems, including areas with sand dunes, to semi-arid savanna grasslands, savanna woodlands and mesic savannas that are normally classified as "open forest". Also included as ONEs are the lateritic plateaus of the northern Western Ghats, as well as rocky outcrops and other naturally tree-less or sparsely vegetated geological features. However, because we have imposed a 1200 mm rainfall cutoff, some ONEs, such as mesic savannas in Chhattisgarh, Jharkhand and Odisha, and the plateau grasslands of Meghalaya are not part of our map, and similarly, because we have used a 1000m elevational cutoff, the shola-grasslands of the southern Western Ghats, and the high-altitude grasslands and deserts of the Himalayas are also excluded from this map.

Analysis Platform

We carried out our analyses on the Google Earth Engine (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 it 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.

Data Masks and Region of Interest

Given that our mapping objective was to identify pixels with a high likelihood of being Open Natural Ecosystems, 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 upto the main ridge of the Western Ghats mountains, although the rainfall in them exceeded 1200mm.

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 2018-19 Land Use Land Cover (LULC) map, and the 2019 Wasteland Atlas of India (Government of India 2019), both from the Bhuvan Thematic Data Portal (National Remote Sensing Centre 2020). From the former dataset, we aggregated training points coinciding 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 varied from horticultural crops and irrigated farmlands to marginal rainfed agriculture.

Input Data Layers & 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 to classify ONEs. 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 the latitude and longitude bands) above were created, we segmented the pixel data in each input band 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 30m resolution and used as the input for the classifier.

Building, applying and validating an ONE Classifier

We developed a random forests classifier using the segmented input composite together with the training points. Rather than develop a single, overarching, global classifier, we developed a series of local classifiers for each of 8 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 8 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.

RESULTS

ONE Distribution & Extent

Our map reveals that an overall area of 319,675 km² (at 30 m pixel), which is approximately 10% of India's geographical area (Figure 1), can be classified as semi-arid Open Natural Ecosystems. 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 4). The spatial extent and distribution of ONE are heterogeneous across the country, ranging from 6 km² in Delhi (0.4% of state area) to 115,069 km² in Rajasthan (33% of state area; Table 5).

Size class distribution (fragmentation matrix).

Excluding patches < 1 ha in size, which accounted for 3,009 km² or <1% of overall ONE extent, 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 2). However, these patches together accounted for just about 10% of the overall ONE extent. 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 extent of area represented in each of these size classes was mostly similar. While large expanses of ONE (> 1,000 km²) were present across the semi-arid zone (Figure 3), it should be noted that the largest patches, exceeding 10,000 km², were both in the arid regions of Thar and Kutch.

Coverage of ONE under protected areas

Approximately 14,280 km² of the ONEs we mapped occur within the PA network of India (Figure 1). This represents less than 5% of the total geographical extent 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 km²) of this coverage.

Data availability:

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 visualise 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 extent and distribution, and other overlay statistics can be obtained.

DISCUSSION

Open natural ecosystems in India have historically been undervalued and unrecognised, 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'. 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). 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 (Vanak et al. 2017; Kumar et al. 2020).

We found that the historical bias towards forested ecosystems is also reflected in the Protected Area 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 harmonises 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. A visual examination of the overlap between our ONE map and the Wastelands Atlas of India (Government of India 2019) shows considerable overlap across the country. This, in and of itself, is not surprising, since we used many of these 'wasteland' classes (Government of India 2019) 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 categorisation 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 continuing to persist with such ecologically uninformed definitions of land cover types, policymakers have earmarked large-extents 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., Power Grid Corporation of India 2013; Besta 2021), 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 prioritised 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 (Veldman et al. 2017; Kumar et al. 2020). 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 Organisation (FAO) has endorsed an application to declare the year 2026 as the International Year of Rangelands and Pastoralists (IYRP 2021). Implicit in this 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, the Great Indian Bustard, listed as Critically Endangered under the IUCN Red List, has disappeared from more than 95% of its historic range, mainly due to habitat loss. 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 existing 'forest' protected areas (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 prioritise climate change mitigation through tree restoration, or in energy and development planning (Government of India 2009; MoEFCC 2013; WRI India 2018; TNC India 2020).

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 as 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 characterise 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. Development of such an ecologically and culturally robust classification will also require open data approaches, not only towards finished map 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: a) possibility of misclassifying fallow lands, especially in the rainfed agricultural zone, as open grassland/scrublands; b) inclusion of small parcels of rainfed agriculture or built areas in pixels designated as ONEs; c) inclusion of near non-vegetated areas such as dunes and salt-pans along with vegetated areas in the omnibus ONE class ; and d) 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 eventually 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 eventually replace ecologically-uninformed and pejorative labels such as 'wastelands' and 'degraded' lands.

Acknowledgements: We thank A. Kulkarni for help with map preparation and N. Pandit for useful comments on the manuscript. We thank the AREST program, and Centre for Policy Design, ATREE for funding, and the Nadathur Foundation for support to MDM.

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 < 1200 metres
Forests	Global PALSAR Forest-NonForest Map (Shimada et al. 2014)	Pixels not classified as forests in any of the yearly images between 2007 & 2018
Surface water	JRC Global Surface Water	(Pekel et al. 2016) Pixels not contained in the maximum extent of surface water between 1984 & 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

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 a 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 tasseled cap images from pre- and post-monsoon periods	3 Tasseled cap bands (brightness, greenness & wetness) for 2 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 Normalised Difference between NDVI 5th percentile & NDVI 50th percentile

6	Extent of Greening	Extent of Greening		By computing Normalised Difference between NDVI 95th percentile & NDVI 50th percentile
7	Relative extent of seasonal vegetation change	Relative difference in the extent of browning and greening		By computing Normalised 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	-	-

Table 3. Overall performance metrics of the overall classifier (obtained from ensembling of the 8 local classifiers in Table 4 below) used to classify pixels as semi-arid Open Natural Ecosystems (ONE).

Known Class Label (N)	Class Label Assigned by Classifier (based on Probability Values assigned)				Class Accuracy
	0.0 – 0.35	0.35 – 0.5	0.5 – 0.67	0.67 – 1.0	
	non-ONE (1952)		ONE (1217)		
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*

Table 4. Input and performance characteristics of random-forest-based probabilistic local classifiers developed to classify pixels as ONE and non-ONE

Classification Region	Training Points used to build Local Classifier	RMS Error of Local Classifier
1. Punjab, Haryana, Delhi, Uttar Pradesh, Bihar & Jharkhand	41,439	0.231
2. Rajasthan	60,249	0.309
3. Gujarat	19,506	0.319
4. Maharashtra	29,851	0.306
5. Madhya Pradesh, Chhattisgarh, Odisha	43,438	0.314
6. Andhra Pradesh-Telangana	33,502	0.323
7. Tamil Nadu	12,298	0.302
8. Karnataka	20,701	0.308

Table 5. State-wise estimates of extent and proportion of semi-arid Open Natural Ecosystems. Note that 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 30m.

	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	9,808	4.1
10	Tamil Nadu	4,815	3.7
11	Bihar	4,477	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**	

Figure 1. Distribution of semi-arid Open Natural Ecosystems (i.e., pixels with a probability ≥ 50% of being classified as an ONE) in relation to Protected Areas (red outlines), and semi-arid "Wastelands", as designated by the Indian Government (inset map).

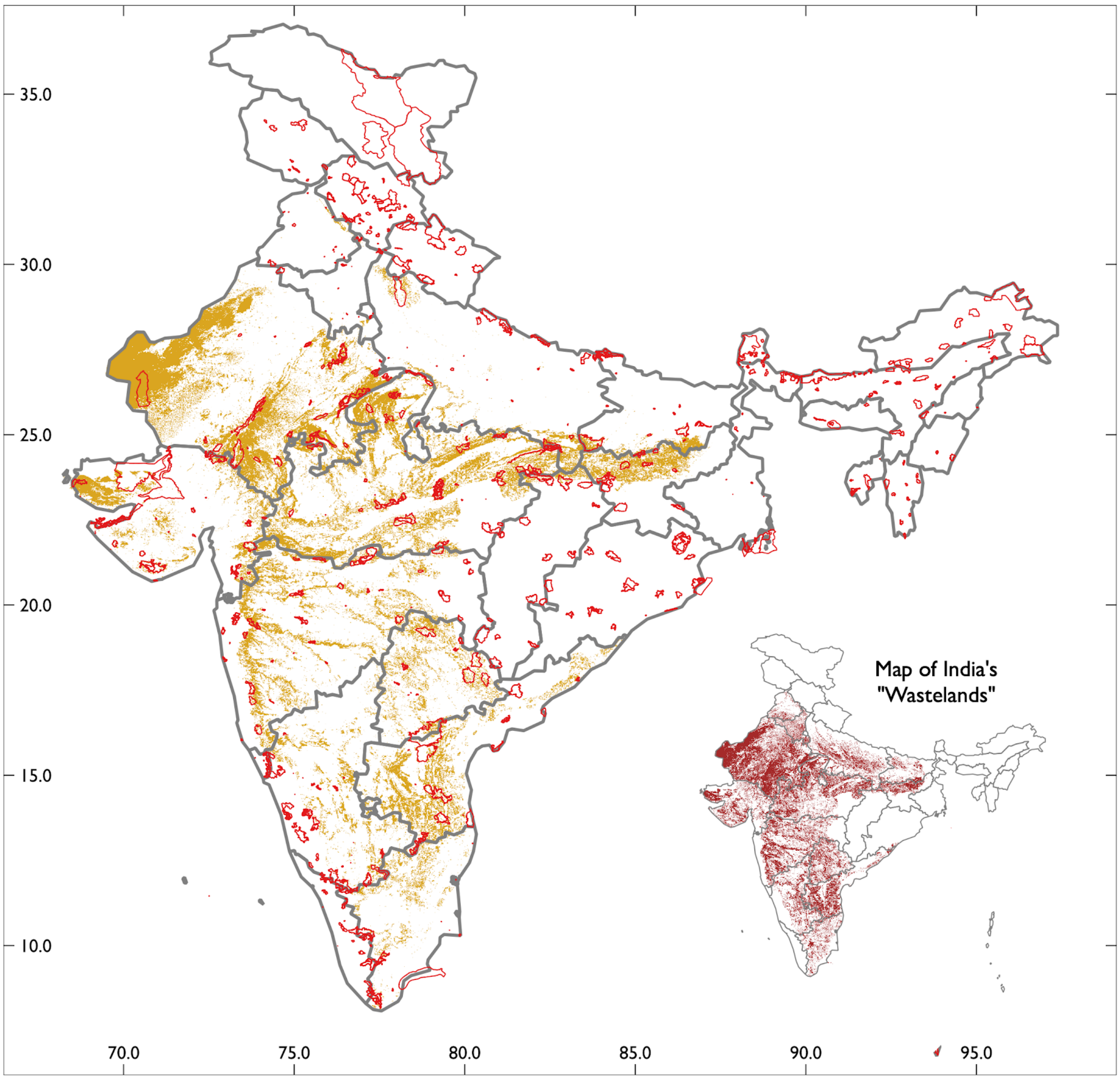


Figure 2. Distribution of the count and total extent of semi-arid Open Natural Ecosystem patches by patch-size class. Note that only patches of size > 1 ha are included in this analysis. Numbers at the top of the columns in the graph indicate frequency (for the Patch Count column) and extent (in km² for the Total Area column).

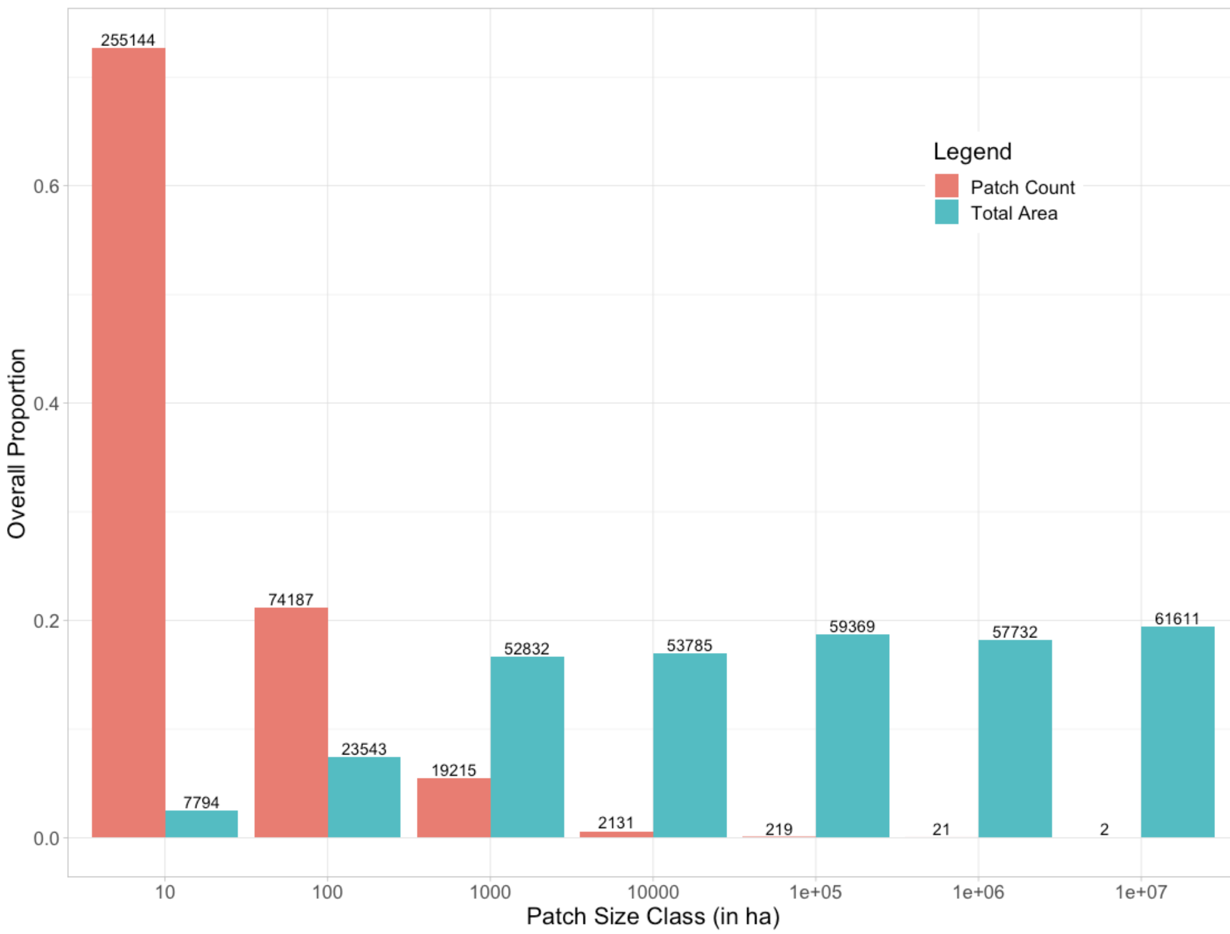
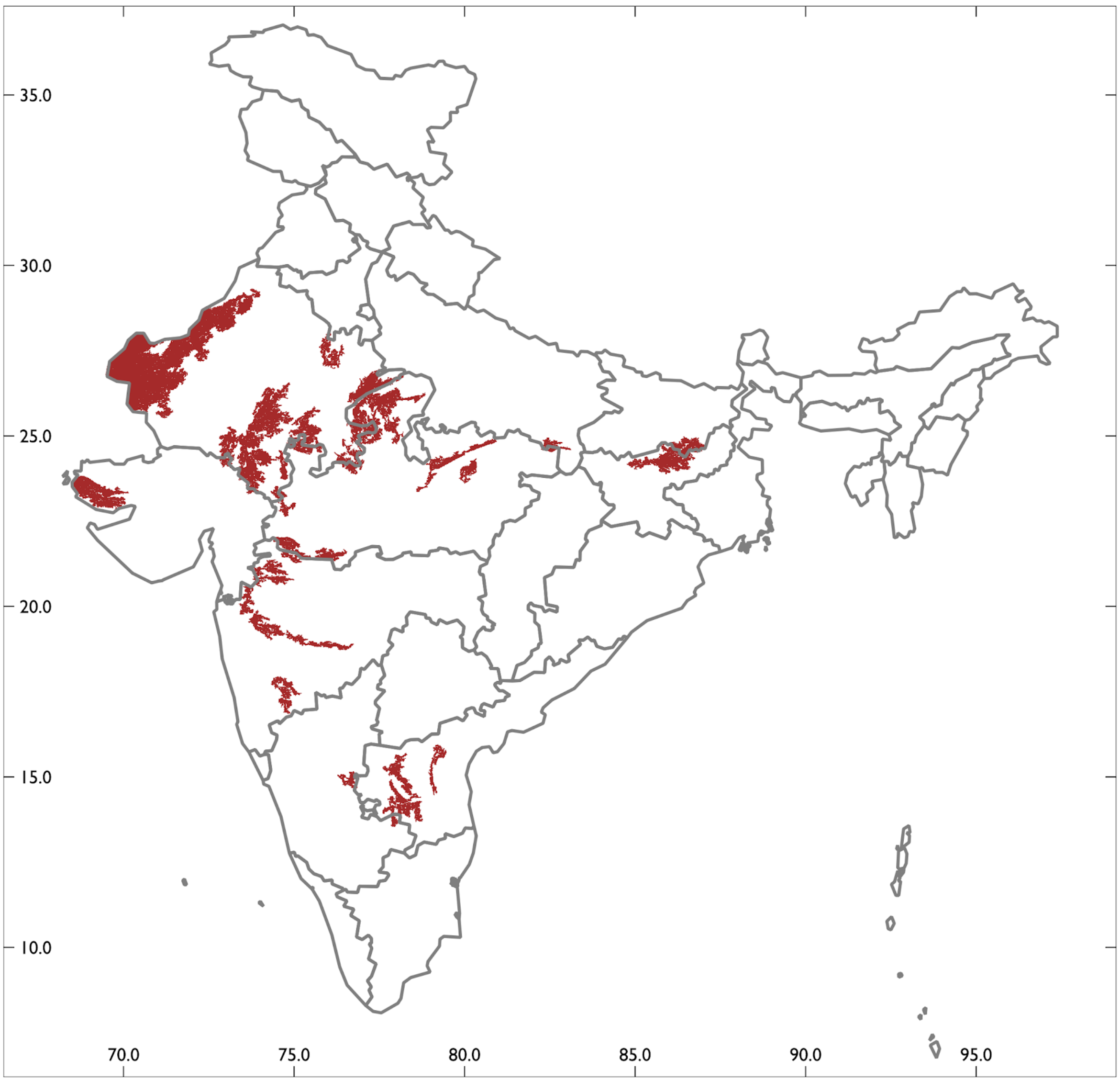


Figure 3. Location and extent of large tracts (area ≥ 1,000 km².) of semi-arid Open Natural Ecosystems in India



References

Abreu RC, Hoffmann WA, Vasconcelos HL, Pilon NA, Rossatto DR, Durigan G. 2017. The biodiversity cost of carbon sequestration in tropical savanna. Science Advances **3**:e1701284.

Achanta R, Susstrunk S. 2017. Superpixels and polygons using simple non-iterative clustering. Pages 4651–4660 Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Baka J. 2017. Making Space for Energy: Wasteland Development, Enclosures, and Energy Dispossessions. Antipode **49**:977–996. Available from https://onlinelibrary.wiley.com/doi/abs/10.1111/anti.12219 (accessed December 26, 2020).

Besta S. 2021, March 19. Profiling the five largest solar power plants in India. Available from https://www.nsenergybusiness.com/features/largest-solar-power-plants-india/ (accessed July 14, 2021).

Bond WJ. 2019. Open Ecosystems: ecology and evolution beyond the forest edge. Oxford University Press, Oxford, New York.

Bonkoungou EG. 2001. Biodiversity in drylands: challenges and opportunities for conservation and sustainable use. Challenge Paper. The Global Drylands Initiative, UNDP Drylands Development Centre, Nairobi, Kenya.

Champion HG, Seth SK. 1968. A revised survey of the forest types of India. Manager of Publications, Government of India.

Dass P, Houlton BZ, Wang Y, Warlind D. 2018. Grasslands may be more reliable carbon sinks than forests in California. Environmental Research Letters **13**:074027.

Davies J, Hatfield R. 2007. The economics of mobile pastoralism: a global summary. Nomadic Peoples **11**:91–116.

DeVries B, Pratihast AK, Verbesselt J, Kooistra L, Herold M. 2016. Characterizing forest change using community-based monitoring data and Landsat time series. PLoS ONE **11**:e0147121.

Farr TG, Rosen PA, Caro E, Crippen R, Duren R, Hensley S, Kobrick M, Paller M, Rodriguez E, Roth L. 2007. The shuttle radar topography mission. Reviews of Geophysics **45**.

Fitzsimons JA, Michael DR. 2017. Rocky outcrops: A hard road in the conservation of critical habitats. Biological Conservation **211**:36–44. Available from http://www.sciencedirect.com/science/article/pii/S0006320716308473 (accessed January 18, 2021).

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment **202**:18–27. Available from http://www.sciencedirect.com/science/article/pii/S0034425717302900 (accessed January 18, 2021).

Government of India. 2009. Jawaharlal Nehru National Solar Mission: Towards Building Solar India. Ministry of New and Renewable Energy. Available from http://164.100.94.214/sites/default/files/uploads/mission_document_JNNSM.pdf (accessed July 14, 2021).

Government of India. 2015. India's intended nationally determined contribution: working towards climate justice. Available from https://www4.unfccc.int/sites/ndcstaging/PublishedDocuments/India%20First/INDIA%20INDC%20TO%20UNFCCC.pdf (accessed December 29, 2020).

Government of India. 2019. Wastelands Atlas of India 2019. Department of Land Resources, Ministry of Rural Development, Govt. of India. Available from https://dolr.gov.in/documents/wasteland-atlas-of-india (accessed December 29, 2020).

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology **25**:1965–1978.

IYRP. 2021. International Year of Rangelands and Pastoralists Initiative. Available from https://iyrp.info/ (accessed July 14, 2021).

Jhala YV, Bipin CM, Jhala HY, Yadav SR, Chauhan JS. 2021. Assessment of cheetah introduction sites and proposed actions. Technical Note. Wildlife Institute of India, Forest Department of Rajasthan and Forest Department of Madhya Pradesh. Available from https://wii.gov.in/images//images/documents/publications/cheetah_introduction_technical_report_2021.pdf.

Kiesecker J, Baruch-Mordo S, Heiner M, Negandhi D, Oakleaf J, Kennedy C, Chauhan P. 2020. Renewable energy and land use in India: A vision to facilitate sustainable development. Sustainability **12**:281.

Kumar D, Pfeiffer M, Gaillard C, Langan L, Martens C, Scheiter S. 2020. Misinterpretation of Asian savannas as degraded forest can mislead management and conservation policy under climate change. Biological Conservation **241**:108293.

McGahey D, Davies J, Hagelberg N, Ouedraogo R. 2014. Pastoralism and the Green Economy–a natural nexus. Nairobi: IUCN and UNEP. x+ 58p.

Mills S, Weiss S, Liang C. 2013. VIIRS day/night band (DNB) stray light characterization and correction. Page 88661P Earth Observing Systems XVIII. International Society for Optics and Photonics.

MoEFCC. 2013. National Mission for a Green India (Under The National Action Plan on Climate Change). Page 48. New Delhi. Available from http://moef.gov.in/wp-content/uploads/2017/08/GIM_Mission-Document-1.pdf (accessed December 29, 2020).

National Remote Sensing Centre. 2020. Bhuvan Portal: Thematic Data Services. Available from https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php (accessed December 29, 2020).

Nerlekar AN, Veldman JW. 2020. High plant diversity and slow assembly of old-growth grasslands. Proceedings of the National Academy of Sciences **117**:18550–18556.

Parr CL, Lehmann CE, Bond WJ, Hoffmann WA, Andersen AN. 2014. Tropical grassy biomes: misunderstood, neglected, and under threat. Trends in Ecology & Evolution **29**:205–213.

Pekel J-F, Cottam A, Gorelick N, Belward AS. 2016. High-resolution mapping of global surface water and its long-term changes. Nature **540**:418–422.

Pesaresi M, Ehrlich D, Florczyk AJ, Freire S, Julea A, Kemper T, Syrris V. 2016. The global human settlement layer from landsat imagery. Pages 7276–7279 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE.

Power Grid Corporation of India. 2013. Desert Power 2050: Integrated Plan for Desert Power Development. Available from https://www.powergrid.in/sites/default/files/footer/smartgrid/desert_power_india.pdf (accessed July 14, 2021).

Puri GS, Meher-Homji VM, Gupta RK, Puri S. 1983. Forest ecology. Volume I. Phytogeography and forest conservation. Oxford & IBH Publishing Co., New Delhi, India.

Ratnam J, Bond WJ, Fensham RJ, Hoffmann WA, Archibald S, Lehmann CE, Anderson MT, Higgins SI, Sankaran M. 2011. When is a 'forest' a savanna, and why does it matter? Global Ecology and Biogeography **20**:653–660.

Ratnam J, Sheth C, Sankaran M. 2019. African and Asian Savannas. Pages 25–49 Savanna Woody Plants and Large Herbivores. John Wiley & Sons, Ltd. Available from https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119081111.ch2.

Roy PS, Roy A, Joshi PK, Kale MP, Srivastava VK, Srivastava SK, Dwevidi RS, Joshi C, Behera MD, Meiyappan P. 2015. Development of decadal (1985–1995–2005) land use and land cover database for India. Remote Sensing **7**:2401–2430.

Sankaran M, Ratnam J. 2013. African and Asian Savannas. Pages 58–74 in S. A. Levin, editor. Encyclopedia of Biodiversity (Second Edition). Academic Press, Waltham. Available from http://www.sciencedirect.com/science/article/pii/B9780123847195003555 (accessed January 18, 2021).

Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R, Lucas R. 2014. New global forest/non-forest maps from ALOS PALSAR data (2007–2010). Remote Sensing of Environment **155**:13–31.

Singh P, Rahmani A, Wangchuk S, Mishra C, Singh K, Narain P, Chundawat R. 2006. Report of the task force on grasslands and deserts. Planning Commission, Government of India, New Delhi.

TNC India. 2020. SiteRight. Available from https://www.tncindia.in/what-we-do/siteright/ (accessed December 30, 2020).

Vanak AT. 2019. Wastelands of the mind: the identity crisis of India's savanna grasslands. Page in M. M. Roy, D. R. Malviya, V. K. Yadav, T. Singh, R. P. Sah, D. Vijay, and A. Radhakrishna, editors. Sustainable use of Grassland Resources for Forage Production, Biodiversity and Environmental Protection. Range Management Society of India, New Delhi, India. Available from https://uknowledge.uky.edu/igc/23/plenary/4/.

Vanak AT, Hiremath AJ, Krishnan S, Ganesh T, Rai ND. 2017. Filling in the (forest) blanks: the past, present and future of India's savanna grasslands. Transcending Boundaries: Reflecting on Twenty Years of Action and Research at ATREE. Ashoka Trust for Research in Ecology and the Environment, Karnataka, 189pp:88–93.

Vanak AT, Kulkarni A, Gode A, Sheth C, Krishnaswamy J. 2015. Extent and Status of Semiarid

Savanna Grasslands in Peninsular India. Pages 192–201 Ecology and Management of Grassland Habitats in India. ENVIS Bulletin 17.

Veldman JW, Overbeck GE, Negreiros D, Mahy G, Le Stradic S, Fernandes GW, Durigan G, Buisson E, Putz FE, Bond WJ. 2015. Where Tree Planting and Forest Expansion are Bad for Biodiversity and Ecosystem Services. BioScience **65**:1011–1018. Available from https://doi.org/10.1093/biosci/biv118 (accessed December 26, 2020).

Veldman JW, Silveira FA, Fleischman FD, Ascarrunz NL, Durigan G. 2017. Grassy biomes: An inconvenient reality for large-scale forest restoration? A comment on the essay by Chazdon and Laestadius. American Journal of Botany **104**:649–651.

Whitehead J. 2010. John Locke and the Governance of India's Landscape: The Category of Wasteland in Colonial Revenue and Forest Legislation. Economic and Political Weekly **45**:83–93.

Wildlife Institute of India. 2019. Protected Areas of India. Available from http://210.212.84.122/erdas-apollo/vector/WII_GEOGRAPHIC_DATA (accessed November 7, 2019).

WRI India. 2018. Overview of the Restoration Opportunities Atlas. WRI India, Mumbai, India. Available from http://wri-sites.s3.amazonaws.com/ifmt/ROAManuals/Overview%2Bof%2Bthe%2BRestoration%2BOpportunities%2BAtlas.pdf (accessed December 24, 2020).