

## YSSP Report Young Scientists Summer Program

---

# Trade-offs and synergies between ecosystem benefits from forest restoration in India

Trisha Gopalakrishna, trisha.gopalakrishna@ouce.ox.ac.uk

## Approved by

---

**Supervisor:** Ping Yowargana

**Program:** Biodiversity and Natural Resources

September 24<sup>th</sup> 2021

This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

It was finished by Trisha Gopalakrishna and has not been altered or revised since.

This research was funded by IIASA and its National Member Organizations in Africa, the Americas, Asia, and Europe.



This work is licensed under a [Creative Commons Attribution-NonCommercial 4.0 International License](https://creativecommons.org/licenses/by-nc/4.0/).  
For any commercial use please contact [repository@iiasa.ac.at](mailto:repository@iiasa.ac.at)

*YSSP Reports* on work of the International Institute for Applied Systems Analysis receive only limited review. Views or opinions expressed herein do not necessarily represent those of the institute, its National Member Organizations, or other organizations supporting the work.

# Table of Contents

Abstract	iii
Keywords	iii
Acknowledgments	iv
About the authors	iv
1. Introduction	5
2. Methods	6
2.1. Additional land area where natural forests can be sustained _____	6
2.1.1. Mapping the bioclimatic envelope of natural forests _____	6
2.1.2. Spatial exclusion of current land uses and covers that cannot be restored to forest ____	6
2.2. Assessment of climate change mitigation benefit _____	10
2.3. Assessment of biodiversity benefit _____	13
2.4. Landscape variation metrics for feasible and successful natural regeneration of forests _____	14
2.5. Prioritization Analyses _____	16
3. Results	16
4. Discussion	26
4.1. Restoration Opportunity and Climate Change Mitigation Benefits _____	26
4.2. Biodiversity benefits from forest restoration _____	26
4.3. Spatial prioritization of restoration opportunity for natural regeneration of forests _____	26
4.4. Policy implications and furthering global dialogues _____	27
5. Conclusion	27
6. References	28

## Abstract

Forest restoration pledges and targets are often one dimensional focusing on land area to be restored and the resulting climate change mitigation benefits. However, forest restoration can lead to contrasting outcomes between ecosystem services. Here, we used two spatial prioritization techniques to estimate the trade-offs and synergies between climate change mitigation and biodiversity, across 7.6 Mha of additional land area suitable for natural regeneration of forests, in all Indian states. In the first technique, we developed a Forest Restoration Opportunity score indicating combination of benefits, feasibility and success of forest restoration, resulting in 38.5% of the additional land area being prioritized for synergies of benefits. In the second technique, we used a spatial conservation planning framework, optimized for a sole target of India's biodiversity pledge and minimization of the population density affected. We estimated that 13.5% of the additional land area could deliver an optimum combination of benefits considering feasibility and success. In the UN Decade of Restoration, we recommend forest restoration policies to include the nuances of multiple ecosystem benefit leading to more impactful, wholistic on-the-ground forest restoration strategies.

## Keywords

forest restoration; ecosystem benefits; spatial prioritization; nature-based solutions; biodiversity; reforestation

## Acknowledgments

I sincerely thank my main supervisor Ping Yowargana for his continued interest, input and encouragement, right from when I contacted him about the YSSP program in 2019. I also am grateful for the support and enthusiasm of my co-supervisors Piero Visconti and Esther Boere. Their challenging questions always set me on the right track. I would also like to thank the entire YSSP family: Tanja Huber, Aleks Cofala and all my fellow YSSPers for making this remote fellowship the best it could be. Lastly, I would like to thank my partner Guy Lomax for helping me with everything, from troubleshooting silly errors to feeding me amazing food over the summer.

## About the author

**Trisha Gopalakrishna** is a DPhil candidate at the School of Geography and the Environment and the Oxford-Indira Gandhi 2019 scholar at the Oxford India Center for Sustainable Development, University of Oxford (UK). Her doctorate research investigates the opportunities and realities of forest restoration for climate change mitigation in India. She previously worked as an Applied Scientist at an international environmental non-profit, The Nature Conservancy (Washington DC), conducting scientific research to support international and national climate policy. She holds a Master's in Environmental Management, focusing on Ecosystem Science and Conservation from the Nicholas School of the Environment, Duke University, (USA).

## 1. Introduction

Forest restoration is considered to be a promising land-based carbon sequestration strategy to mitigate rising global temperatures because of its relative low costs, scalability and multiple co-benefits (Busch et al., 2019; Cook-Patton, Gopalakrishna, et al., 2020; Griscom et al., 2017). And there are numerous international efforts that are recognizing the need for increased removals of greenhouse gases from the atmosphere, to achieve the 1.5-2°C temperature targets of the Paris Climate Agreement with varying success (Coleman et al., 2021; Fleischman et al., 2020). Similarly, commitments under the Convention on Biological Diversity have not been delivered fully, with decline in biodiversity indicators and the Aichi target 11 of protecting 17% of the global terrestrial area by 2020 not being met (Cunningham et al., 2021). With the increased importance of the natural environment during the COVID-19 pandemic, the post 2020 Global Biodiversity Framework and the United Nations Climate Change Conference (COP26), this is an important policy window to recognize the mutually beneficial outcomes of limiting global warming and conserving biodiversity for the sustainable production of benefits to people (Pörtner et al., 2021).

Implementation of forest restoration is inherently complex and can lead to multiple contrasting outcomes, especially ecosystem benefits, when considering different forest restoration techniques (Brancalion & Holl, 2020; Holl & Brancalion, 2020). Brancalion et al., (2019) considered socioeconomic benefits and feasibility of restoration and mapped restoration hotspots globally, defined as areas with high potential return on benefits and feasibility. They concluded 88% of these areas are in conservation hotspots and 73% of these areas are in countries committed to the Bonn Challenge. Similarly, Strassburg et al., (2020), used a systematic conservation planning framework based on multiple criteria of benefits and costs and estimated that restoring 15% of the restoration opportunity could avoid 60% of expected extinctions, while sequestering 299 GtCO<sub>2e</sub>. Soto-Navarro et al., (2020) mapped terrestrial 'hotspots' of carbon stocks and biodiversity globally (highest 20% scores), recommending restoration and conservation of ecosystems particularly in the Neotropics and Indo-Malayan regions. And Jung et al., (2021), concluded that conservation and restoration of the highest scored terrestrial areas considering carbon stocks, biodiversity and water benefits, could help spatially operationalize multiple global targets and pledges of climate change, biodiversity and water.

Similarly, at the regional scale, there are various synergies and trade-offs between ecosystem benefits from forest restoration. Forest restoration via monoculture plantations could rapidly sequester carbon, but with limited long-term storage (Conti & Díaz, 2013; Hulvey et al., 2013). Also, monoculture plantations may provide habitat to generalists, wildlife with more specialized habitat require forests with a diversity of foliage, flowering, and fruiting resources (Lugo et al., 2012) aligned with the biodiversity and ecosystem function theory (Cardinale et al., 2012). Newmark et al., (2017) concluded that targeted restoration between forest fragments in the Eastern Arc of Tanzania and Atlantic Forest of Brazil could increase bird species persistence. Barnett et al., (2016) concluded that opportunistic hardwood reforestation in the Mississippi Valley, when considering biodiversity, water and climate change mitigation benefits, resulted in 85%-94% less efficiency of obtaining combination of benefits when compared to targeted reforestation. Similarly, reforestation of 'climate corridors' could facilitate faunal movement and tracking of climate envelopes with changing climates (McGuire et al., 2016). In central India, Dutta et al., (2018) determined that targeted reforestation in habitat corridors would increase connectivity for tigers.

Like many countries, India has ambitious goals as part of its Nationally Determined Contribution (NDC) to the Paris agreement, which includes "Additional (cumulative) carbon sink of 2.5-3 GtCO<sub>2e</sub> by 2030" in the Land Use Land Use Change and Forestry (LULUCF) category, with the goal of increasing forest cover area from 23% to 33% of its land area, by 2030 (Pandve, 2009). Also, it has pledged 21 Mha to be restored to forests by 2030, as part of the Bonn Challenge. India's National Biodiversity Targets to the Convention on Biological Diversity are wide ranging, including "integrating values of biodiversity into national and state planning and development programmes"

and “effective, participatory and updated national biodiversity action plans made operational at multiple levels of governance”. However, there is no information or guidance for selection of areas for forest restoration, that will provide an optimum combination of climate change and biodiversity benefits, crucial to achieve India’s global pledges and targets.

Here, I use a spatial optimization and conservation planning framework to map priority areas for forest restoration for multiple ecosystem benefits in each of the 28 Indian states and six out of eight Indian union territories (Table 1), hereby referred to as jurisdictions. First, we map additional land area where natural forests can be biophysically sustained at appropriate forest canopy densities considering current land use and land cover constraints, following methodology in Gopalakrishna et al., 2021. We calculate the climate change mitigation benefits as the cumulative carbon stocks that could naturally regenerate in the additional land area. I then determine two metrics of biodiversity (1) additional forest habitat that will be created from natural regeneration of forests in the additional land area and (2) rarity weighted richness index of species considered in the additional land area. Lastly, I completed two spatial prioritization analyses to estimate priority areas of the additional land area that could deliver an optimum combination of ecosystem benefits, considering two additional criteria of landscape variation for feasible and successful forest restoration.

**Table 1** Details of the state to which Indian union territories were included as part of for the analyses after estimation of maximum biophysical potential of forest restoration; Andaman and Nicobar and Lakshadweep islands have been excluded from the analyses

Chandigarh	Punjab
Dadra and Nagar Haveli and Daman and Diu	Gujarat
Puducherry	Tamil Nadu

## 2. Methods

### 2.1. Additional land area where natural forests can be sustained

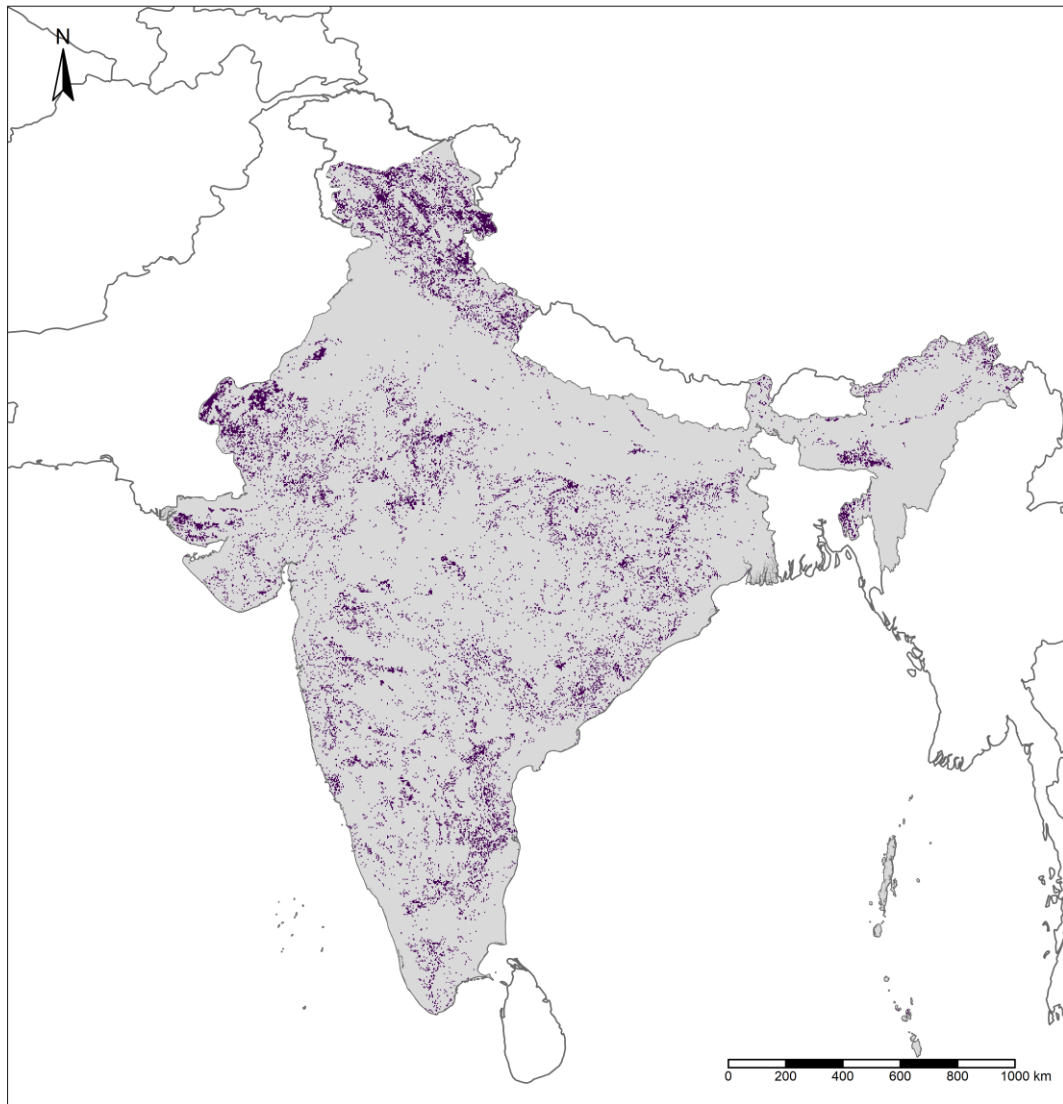
#### 2.1.1. Mapping the bioclimatic envelope of natural forests

We modelled the bioclimatic envelope of natural forests by using 10,756 ground truth collected points of different forest types across India and 22,453 pseudoabsence points (Fig 1 and Fig 2) from land areas where forests could be sustained biophysically, but currently do not have natural forests, as training data (Fig 3). I used the random forest classification algorithm trained against 11 predictor climatic, topographic and edaphic variables (Table 2 and Fig 4), using spatial cross validation (5 partitions of the data with 100 repetitions to reduce variance caused by data partitioning (Schratz et al., 2018)), to account for spatial autocorrelation structure of both training and environmental predictor information (Ploton et al., 2020). I tuned the algorithm to use 537 trees, 9 terminals nodes and 3 predictors in each tree that resulted in the highest Area Under Curve (AUC) metric of 0.72 (Fig 5). Lastly, I applied a threshold of 0.41 to develop the bioclimatic envelope because this threshold resulted in the least mean misclassification error or 0.07. All analyses was completed using the *mlr* R package (Bischl et al., 2016). I validated the predicted bioclimatic envelope against the potential natural vegetation classes from Hengl et al., (2018).

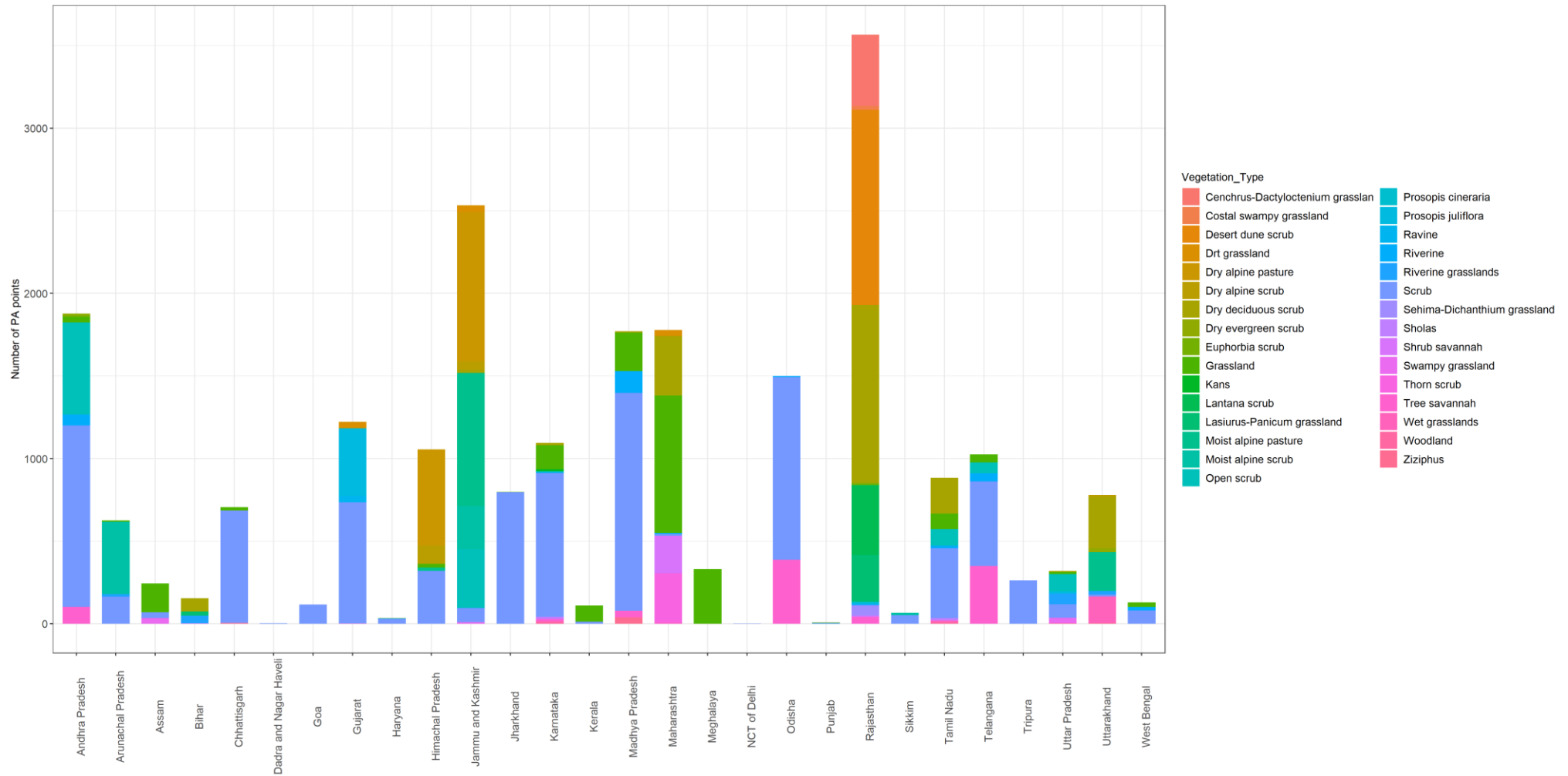
#### 2.1.2. Spatial exclusion of current land uses and covers that cannot be restored to forest

From the bioclimatic envelope, I excluded water bodies, areas under aquaculture, salt pans and snow because these land covers cannot be restored to natural forests. I excluded mangroves, permanent wetlands and built-up areas due to separate carbon accounting methodologies following Fargione et al., (2018) and Griscom et al., (2017). I excluded all grasslands to protect native and endemic non-forest ecosystems. I excluded all-natural forests- deciduous broadleaf, mixed, evergreen broadleaf, deciduous needleleaf and evergreen needleleaf because these areas are already forested and would continue to provide climate change mitigation benefits with no additional land conversion i.e. considering additionality benchmark. I excluded all cropland to protect food security, resulting in a

spatially explicit map of additional land area available for natural regeneration of forests (100mx100m spatial resolution). Lastly, I extracted the current land use and land cover of the estimated additional land area to estimate what is current land use and land cover that will revert back to natural forests.

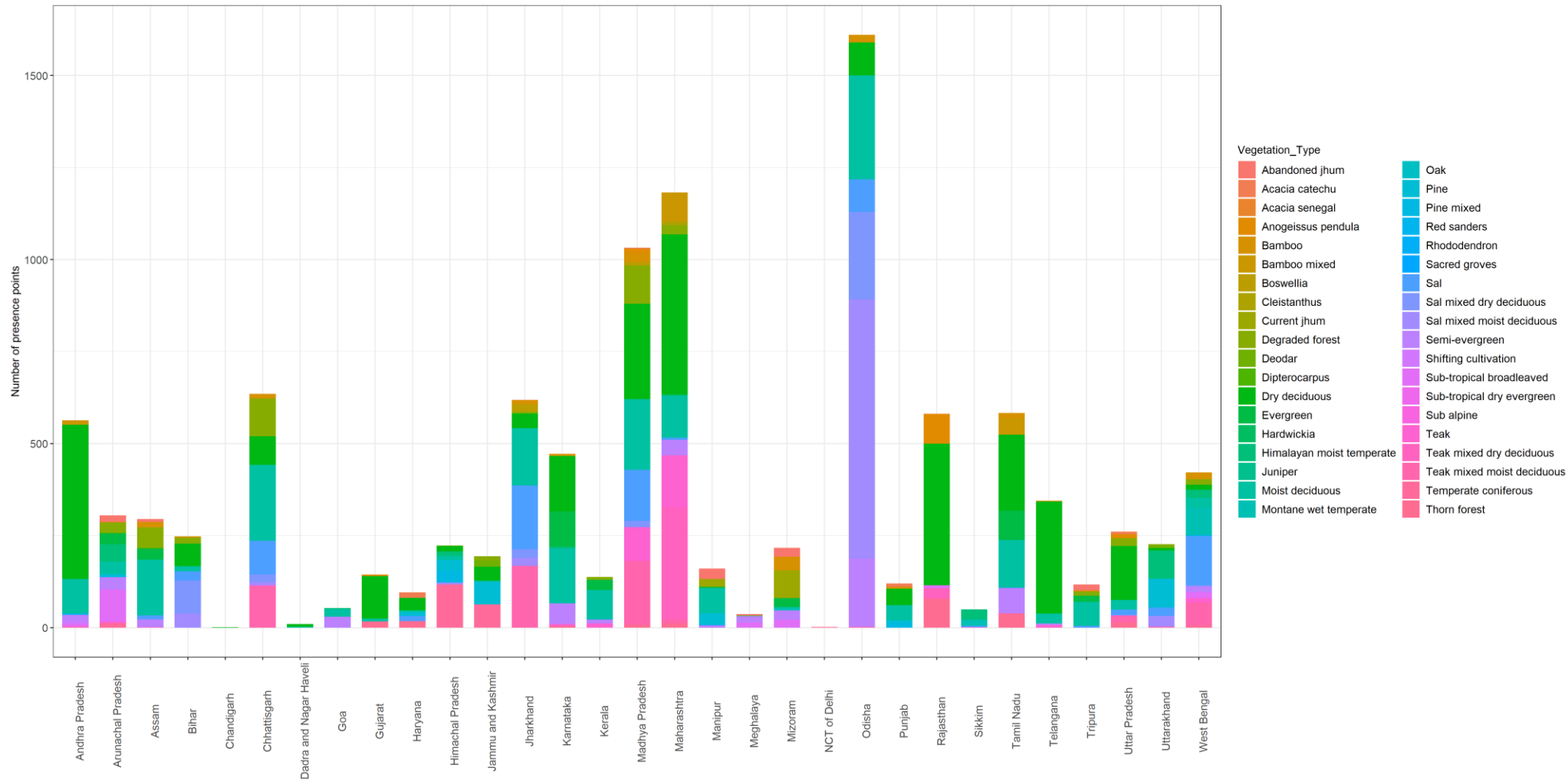


**Figure 1** Distribution of pixels from which 23000 pseudoabsence points were drawn. Pseudoabsences were extracted randomly from land use and land cover categories that could sustain forests based on biophysical conditions, but currently do not have forests such as scrub/shrub, grasslands and woodlands, riverine vegetation and locale specific vegetation as per Roy et al., 2015 following Gopalakrishna et al., 2021.



**Figure 2** Distribution of pseudoabsences across different vegetation classes across India. 3566 points were selected from Rajasthan and 7 points were selected from Punjab and a maximum of 8810 points were selected from scrub vegetation class and the least of 3 points were selected from Prosopis Cineria vegetation class as per Roy et al., 2015 following Gopalakrishna et al., 2021





**Figure 3** Distribution of 10943 GPS collected points across different vegetation classes in India was used as training data to develop the bioclimatic envelope of forests, with the highest number of points of 1182 in Maharashtra and the least number of points of 37 in Meghalaya. The highest number of points of 2850 were in dry deciduous forest type while the least number of points of 1 was in Acacia Senegal forest type. Points with duplicate environmental predictors information were excluded resulting in 10756 presence points being used as training points.

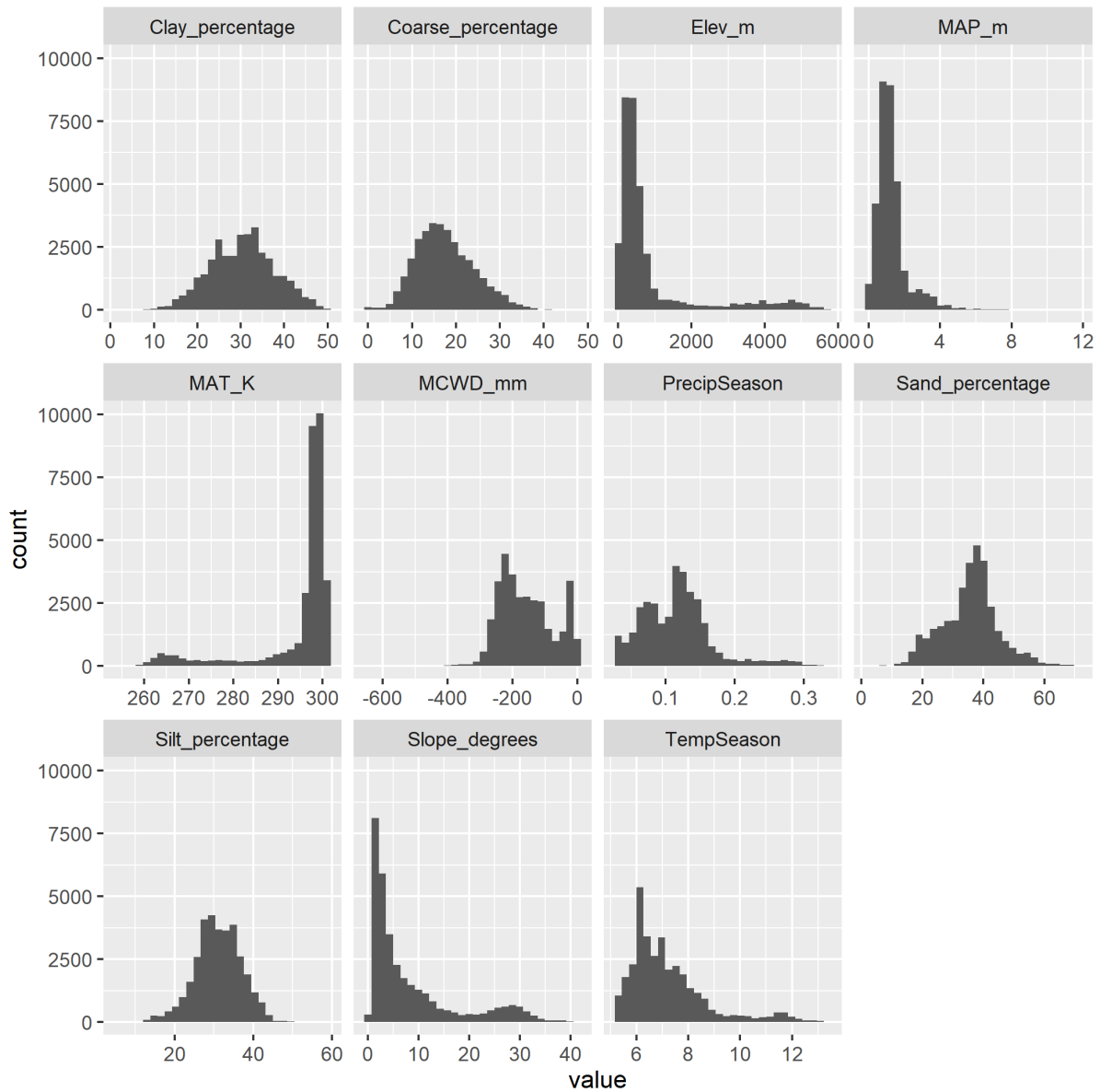
**Table 2** Brief description and details (source, reference, spatial and temporal resolution) of environmental predictors used

Environmental variable	Source and Reference	Description of preparation	Spatial and temporal resolution
Mean Annual Precipitation	CHIRPS (Funk et al., 2015)	As described in (O'donnell & Ignizio, n.d.)	0.0089° 1981-2019
Precipitation Seasonality			
Mean Annual temperature	ERA5 Land Reanalyses Product (Hersbach et al., 2020)	Data processed in Google Earth Engine(Gorelick et al., 2017)	
Temperature seasonality			
Maximum Climate Water Deficit	TerraClimate (Abatzoglou et al., 2018)	As described in and R code published by (Aragão et al., 2007) using total monthly precipitation and monthly potential evapotranspiration	0.0089° 1981-2019
Elevation	SRTM (Jarvis et al. 2008)	Data extracted and processed in Google Earth Engine (Gorelick et al., 2017) at 90m resolution and resampled to 0.0089° using bilinear method	90m
Slope			
Soil texture- sand %	ISRIC World SoilGrids (0-30cm depth) (Hengl et al., 2017)	Apart from extracting these data to India and resampling to 0.0089° using bilinear method, no processing done	0.0020°
Soil texture- silt %			
Soil texture- clay %			
Coarse fragments %			

## 2.2. Assessment of climate change mitigation benefit

We completed a cross tabular area analyses of the additional land area where natural forests can be sustained, the potential natural vegetation spatial estimates from Hengl et al., (2018) and the dominant forest types of India from Reddy et al., (2015), in each Indian biogeographic zone (Rodgers & Panwar, 1988) and in each jurisdiction. I assigned mean carbon stocks for above ground and below ground biomass, deadwood and litter across three canopy cover densities as per Forest Survey of India (2011), to the additional land area, based on the highest additional land area in each potential natural vegetation spatial estimate against the dominant forest type. I used carbon stock data for montane moist temperate forests for montane wet forests, semi evergreen forests for dry evergreen forests and the average of tropical evergreen forests in the North Eastern and Western Ghats biogeographic zones for tropical evergreen forests in the Deccan Plateau.

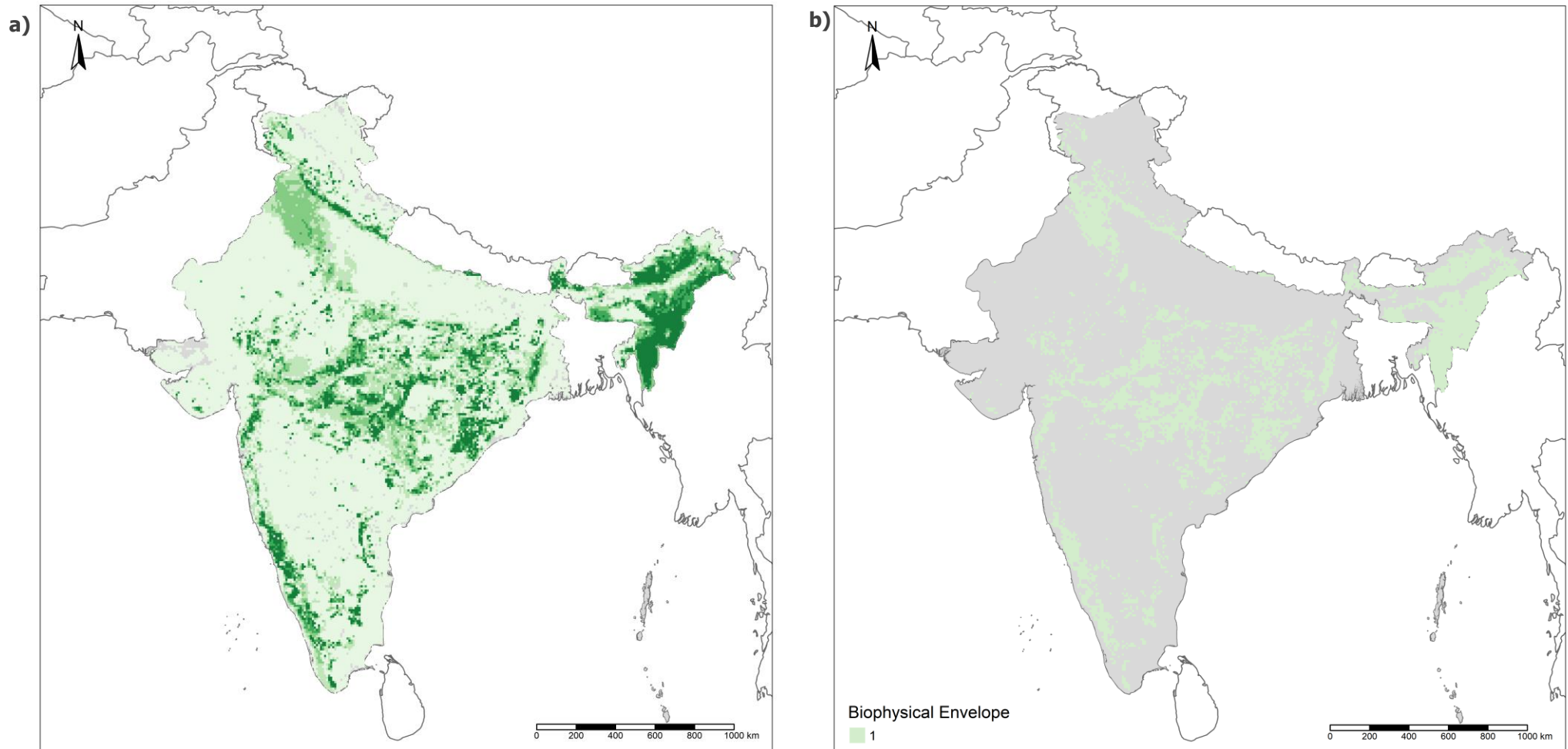
Considering that the assigned carbon stock values was based on the potential natural vegetation and dominant forest type cross tabular analyses, there was limited variation in the climate change mitigation potential on a pixel-by-pixel basis in the additional land area. Consequently, there was limited variation in the trade-offs and synergies between climate change mitigation benefits and the remaining benefits and indicators, described in the next sections. To overcome this limitation, I extracted the aboveground and belowground biomass sequestration rates in the additional land area from Cook-Patton et al., (2020) as the climate change mitigation benefit to be used in prioritization analyses. All analyses were completed for each state and the results are reported for six regions of India (Table 3).



**Figure 1** Distribution of 11 environmental predictors considered across the 10756 presence points and 22453 pseudoabsence points, as training data. Clay\_percentage, Coarse\_percentage, Sand\_percentage and Silt\_percentage are edaphic factors of the percentage of different size fractions in soils.

**Table 3** List of regions and states assigned to each of the regions

Northern India	Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Punjab, Rajasthan, Uttarakhand, Uttar Pradesh
Northeastern India	Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Tripura, Sikkim
Eastern India	Odisha, Bihar, Jharkhand, West Bengal
Central India	Madhya Pradesh, Chhattisgarh
Southern India	Karnataka, Tamil Nadu, Kerala, Andhra Pradesh, Telangana
Western India	Maharashtra, Gujarat, Goa



**Figure 2** a) Distribution of the biophysical envelope of natural forests. Using the random forest classification algorithm accounting for spatial autocorrelation structure of training and environmental predictor information. Shades of dark green indicate high probability of natural forests being sustainable while light shades of green indicate low probability of natural forests being sustainable based on biophysical conditions. b) Estimated 67.4 Mha biophysical envelope of natural forests in India indicated by the shade of green (100m x 100m spatial resolution). This map was obtained after thresholding the probability map of where natural forests can be sustained using a threshold of 0.41 because of the least mean misclassification error of 0.07.

### 2.3. Assessment of biodiversity benefit

We considered 44 forest dependent mammals and reptiles that are listed as endangered and critically endangered by the International Union for the Conservation of Nature and Natural Resources (IUCN) (Table 4). For each of the selected species, I developed the area of habitat considering the species specific range and its habitat preferences (elevation and forest type) following Brooks et al., (2019), using the information provided by the IUCN and an extensive literature review for each species with missing information about preferred forest type and elevation. I determined the preferred forest type within the range of each species, by creating a look up table between the IUCN forest type habitat preferences and dominant forest types from Reddy et al., (2015), as per IUCN forest type definitions (IUCN, 2020) (Table 5).

We calculated the rarity weighted richness index defined as the inverse of the number of sites in which the species occurs followed by the sum of the rarity scores for all species present at a given site (Albuquerque & Beier, 2016; Usher, 1986; Williams et al., 1996), where sites included both area of habitat and the additional land area where natural forests can be sustained. I used this index in the prioritization analyses described in the following sections.

**Table 4** Details of the 44 species considered to estimate biodiversity benefits, with percentage increase in the area of habitat from natural regeneration of forests in restoration opportunity. Species are arranged in decreasing order of percentage increase in area of habitat

Scientific Name	Common Name	Percentage increase in area of habitat
Barkudia_insularis	Madras Spotted Skink	0
Batagur_baska	Northern River Terrapin	0
Biswamoyopterus_biswasi	Namdapha Flying Squirrel	0
Cremnomys_elvira	Large rock rat	0
Dasia_subcaerulea	Boulenger's Dasia	0
Eurylepis_poonaensis	Poona Skink	0
Millardia_kondana	Kondana rat	0
Moschus_cupreus	Kashmir muskdeer	0
Otocryptis_beddonii	India kangaroo lizard	0
Platyplectrurus_madurensis	Travancore hills thorn-tail snake	0
Suncus_dayi	Day's shrew	0
Vandeleuria_nilagirica	Nilgiri long-tailed tree mouse	0.374
Cnemaspis_wynadensis	Wynad day gecko	0.392
Moschus_leucogaster	Himalayan muskdeer	0.449
Bubalus_arnee	Wild water buffalo	0.471
Mus_famulus	Bonhote's mouse	0.685
Ailurus_fulgens	Red panda	0.904
Semnopithecus_ajax	Kashmir gray langur	1.263
Feroculus_feroculus	Kelaart's long-clawed shrew	1.577
Trachypithecus_geei	Gee's golden langur	2.098
Hadromys_humei	Hume's rat	2.768
Indotestudo_elongata	Elongated tortoise	2.989
Manis_crassicaudata	Indian pangolin	4.675
Cuon_alpinus	Dhole	5.112
Manouria_emys	Asian giant tortoise	5.347
Panthera_tigris	Bengal tiger	5.542

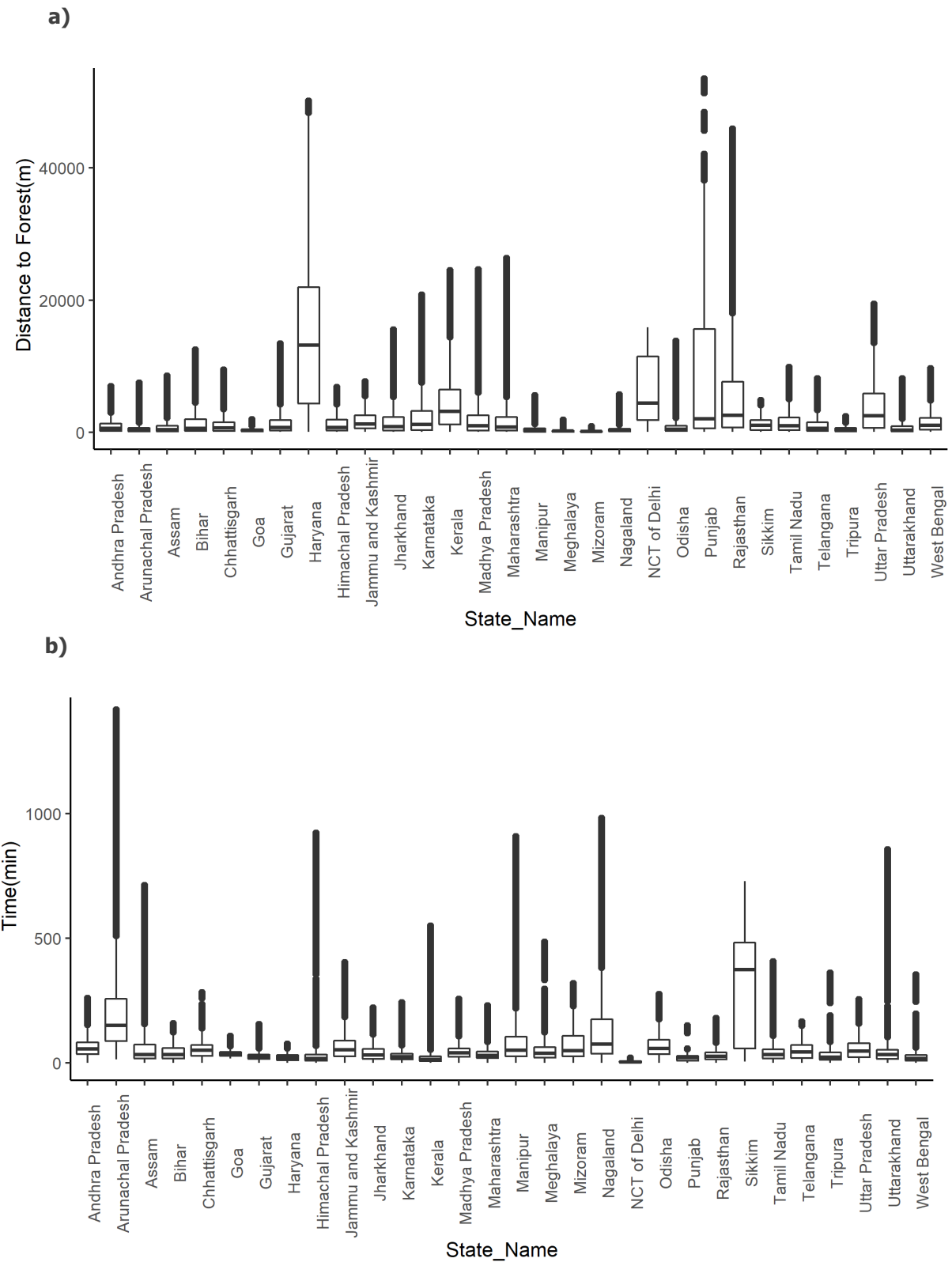
Manis_pentadactyla	Chinese pangolin	5.953
Nycticebus_bengalensis	Bengal slow loris	5.976
Melanochelys_tricarinata	Tricarinate hill turtle	6.560
Hoolock_hoolock	Western hoolock gibbon	6.586
Cuora_mouhotii	Keeled box turtle	6.856
Cnemaspis_goaensis	Goan day gecko	7.212
Cuora_amboinensis	Southeast asian box turtle	7.808
Elephas_maximus	Asian elephant	8.026
Macaca_munzala	Arunachal macaque	8.3109
Vijayachelys_silvatica	Cochin forest cane turtle	12.709
Macaca_silenus	Lion tailed macaque	22.293
Hipposideros_pomona	Andersen's roundleaf bat	24.329
Eutropis_clivicola	Inger's mabuya	31.075
Latidens_salimalii	Salim Ali's fruit bat	39.333
Viverra_civettina	Malabar civet	50.248

**Table 5** Crosswalk of dominant forest types from reddy et al., 2015 with the IUCN Forest Classification as per IUCN (2020)

<b>Dominant Forest Type from Reddy et al., 2015</b>	<b>IUCN Forest Classification</b>
Tropical Wet Evergreen	Subtropical/tropical moist lowland
Tropical Semi Evergreen	Subtropical/tropical moist lowland
Tropical Moist Deciduous	Subtropical/tropical moist lowland
Tropical Dry Deciduous	Subtropical/tropical dry
Tropical Dry Evergreen	Subtropical/tropical dry
Tropical Thorn	Subtropical/tropical dry
Littoral and Swamp/Mangrove	Subtropical/tropical mangrove vegetation above high tide level
Subtropical broadleaved	Temperate
Subtropical Pine	Temperate
Subtropical Dry Evergreen	Subtropical/tropical dry
Montane Wet Temperate	Subtropical/tropical moist montane
Montane Moist Temperate	Subtropical/tropical moist montane
Montane Dry Temperate	Subtropical/tropical moist montane
Subalpine	Subantarctic

## **2.4. Landscape variation metrics for feasible and successful natural regeneration of forests**

For all additional land area where natural forests can be sustained, I calculated the distance to the closest natural forest (100m-53421m), such that additional land area close to natural forests will have higher chances of successful natural regeneration, than additional land area far away from natural forest. The underlying assumption here is that there is improved seed dispersal when close to natural forests (Crouzeilles et al., 2020) (Fig 6). I also calculated the time taken to reach the closest city from the additional land area as per definitions in Weiss et al., (2018), as an indicator of feasibility for natural regeneration (0min-1416.41min) (Fig 6). I assumed that the more time it takes to travel to the estimated additional land area from the closest city, the lower the opportunity costs to convert it to a production-based land use and hence more feasible for forest restoration.



**Figure 6** Landscape variation metrics for feasible and successful natural regeneration of forests. Distance of each opportunity pixel to the closest natural forest pixel(100m-53421m) in a) and time taken (min) to travel from each opportunity pixel to the closest city, defined as per Weiss et al., 2018 (0-1416.41 min) in b), for each jurisdiction considered in the study.

## 2.5. Prioritization Analyses

We completed two prioritization analyses to estimate restoration opportunity that is to be prioritized to deliver both carbon sequestration rates and habitat for rare species, considering feasibility and success of natural forest regeneration, hereby termed as four criteria for prioritization. In the first analyses, I rescaled each of the four criteria within each region, such that all values close to one would indicate optimum conditions for prioritization. Within each region, I calculated the mean value of the rescaled criteria, for the estimated additional land area, called 'Forest Restoration Opportunity Score', where scores close to one indicate a synergy between the four criteria, while scores close to zero indicate a trade-off between the four criteria. I evaluated one scenario of prioritization in which I estimated all estimated land area with a better than average Forest Restoration Opportunity Score, within each region.

In the second prioritization analyses, I used the spatial conservation prioritization approach to determine prioritized land area, having an optimum combination of the four criteria, using the *prioritizr* R package (Hanson et al., 2021). Here, I specifically used an integer linear programming approach which is advantageous over other prioritization algorithms such as heuristic algorithms and simulated annealing, commonly used in protected area network planning because it provides exact solutions (Ball et al., 2009). In this approach, each 100mx100m additional land area pixel was a planning unit. I considered the cost of natural regeneration in the restoration opportunity as the population density (based on national censuses and population registers as of 2020) that would be affected (Doxsey-Whitfield et al., 2015). I chose a sole target, across all criteria, to be '17% of the terrestrial and inland water....' that needs to be effectively conserved as per India's National Biodiversity Action Plan, with the objective of minimizing the population density impacted from natural regeneration.

All analyses were completed in R (R Core Team, 2020).

## 3. Results

The area of the biophysical envelope of forests was 67.4 Mha (Fig 5 (b)) and 64.9 Mha after excluding areas under aquaculture, salt pans, snow, mangroves, permanent wetlands and grasslands. The final additional land area for natural regeneration, after excluding current forests and croplands was 7.6 Mha (state wise estimates in Table 6). The highest estimated land area of 2.9 Mha was present in southern India with the state of Kerala having the most additional land area, while the least of 0.6 Mha was present in western India with the least additional land area in Goa (Fig 7). Of the 7.6 Mha, 44.6% is classified as shrublands and 29% is classified as plantations, while the remaining restoration opportunity is classified as fallow land, waste land and barren land (Fig 8).

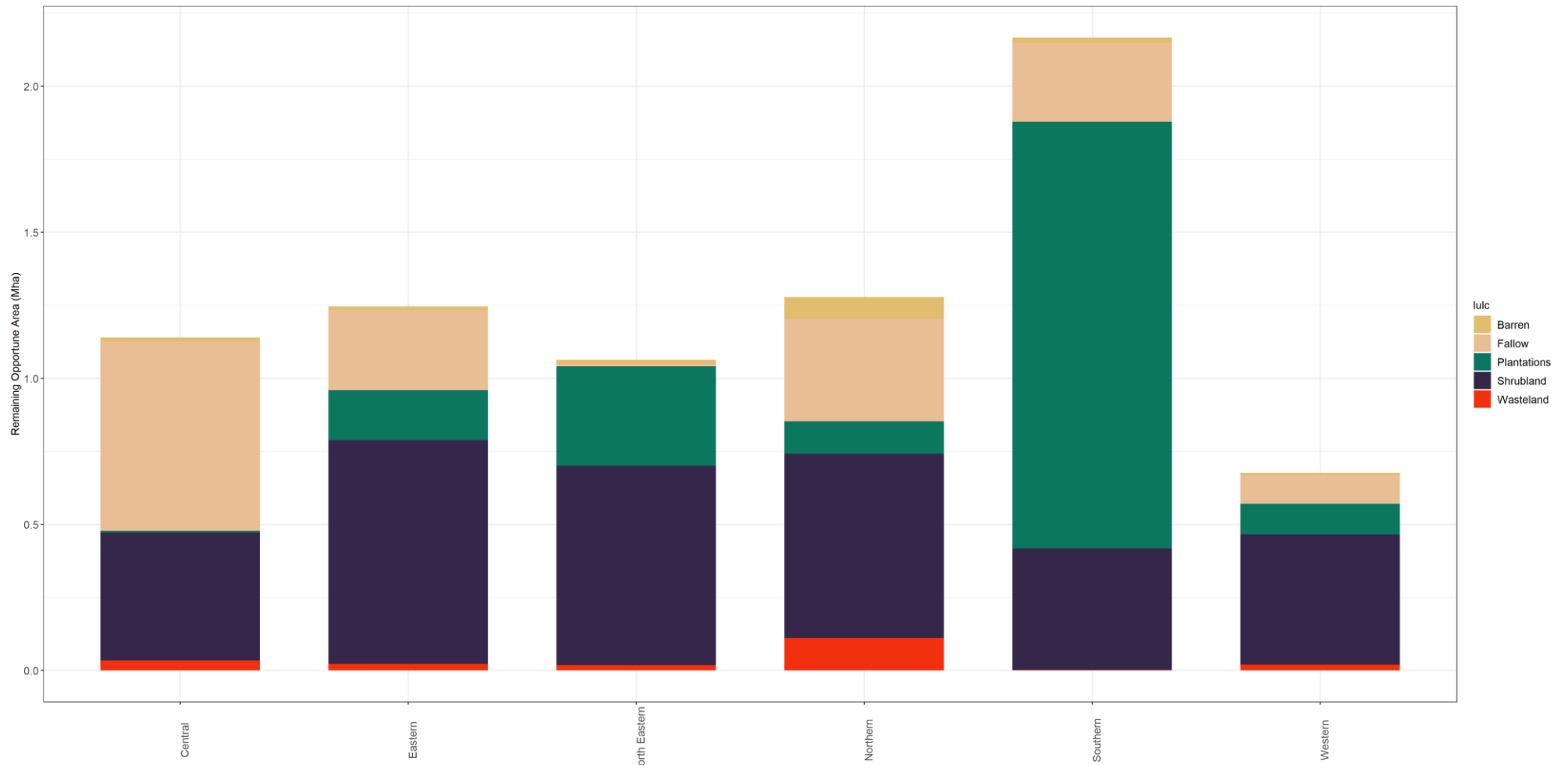
At the national scale, I estimated the cumulative carbon stocks that could naturally regenerate in the restoration opportunity to be 388.5 MtC, with the highest mitigation potential of 119.2 MtC in southern India and the least mitigation potential of 37.9 MtC in western India (Fig 9). The range of the aboveground and belowground biomass accumulation rates was 0.59-4.42 MtCha<sup>-1</sup>yr<sup>-1</sup> and 0.19-2.40 MtCha<sup>-1</sup>yr<sup>-1</sup> respectively.

The mean additional habitat area created for the 44 species considered was 6.7% (Fig 10). The highest increase in habitat from natural regeneration of forests in the restoration opportunity was by 50.2% for the Malabar long-tailed civet (*Viverra civettina*) and the lowest increase in habitat was by 0.37% for Nilgiri long-tailed tree mouse (*Vandeleuria nilagirica*). There was no increase in habitat, if forests were to naturally regenerate in the restoration opportunity, for 11 species (Table 4). The rarity weighted richness index across the restoration opportunity varied from 9.8e-09 to 0.003.

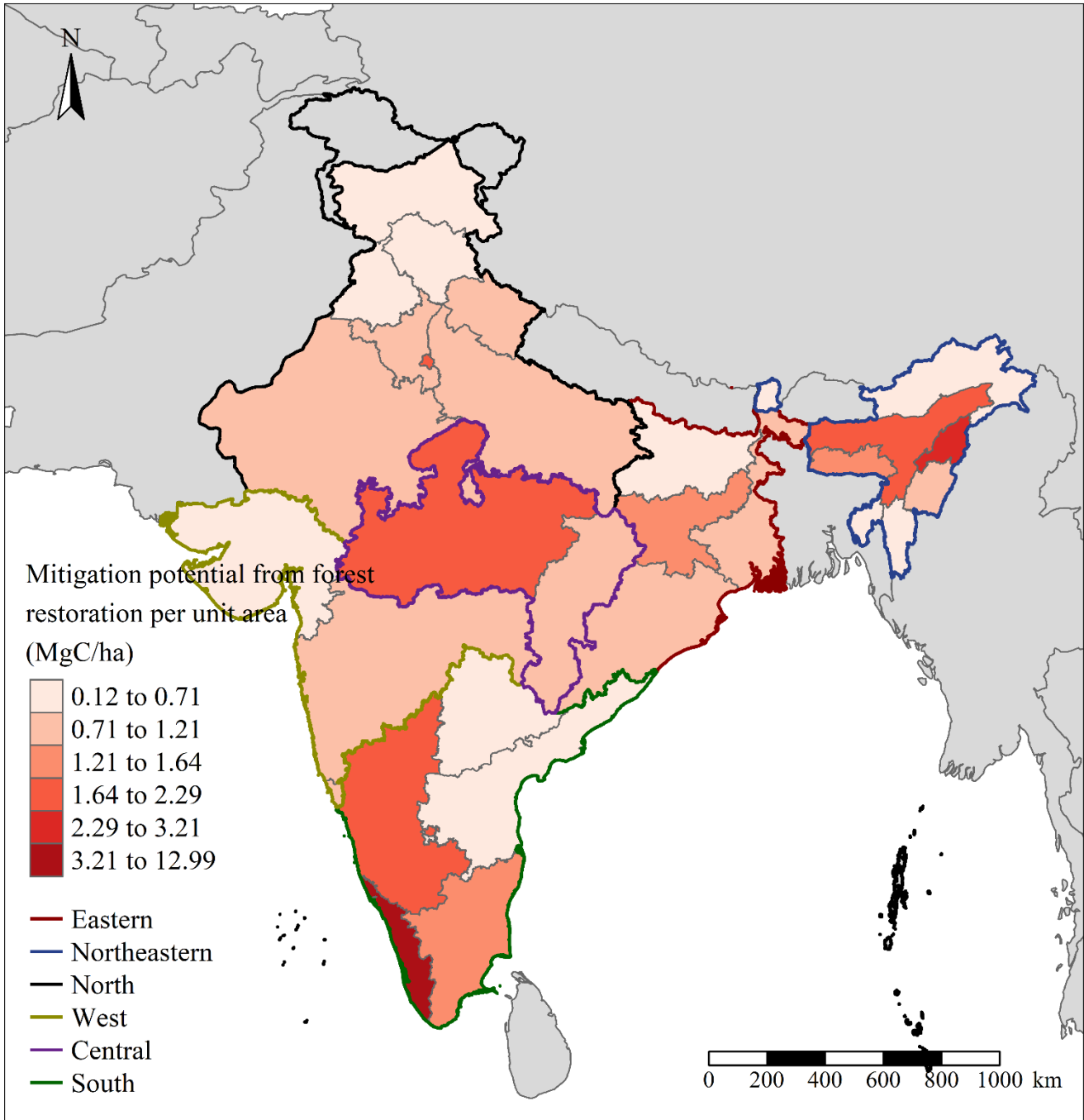




**Figure 7** Additional land area where natural forests can regenerate (Mha), considering all LULCs that cannot be restored, by region (indicated in Fig 2 and listed in Table 3) arranged in decreasing order of total opportunity from left to right. Southern states have the highest total opportunity of 2.17 Mha and western states have the least opportunity of 0.676 Mha. Within each plot, states are arranged in decreasing order of opportunity. Madhya Pradesh has the highest opportunity of 0.92 Mha while Mizoram has the least opportunity of 0.006 Mha overall. The size of each bar is the bioclimatic envelope of forest cover in that state (Mha) while the remaining colours indicate the area of different LULCs that cannot be restored. See Table S6 for opportunity for all jurisdictions.

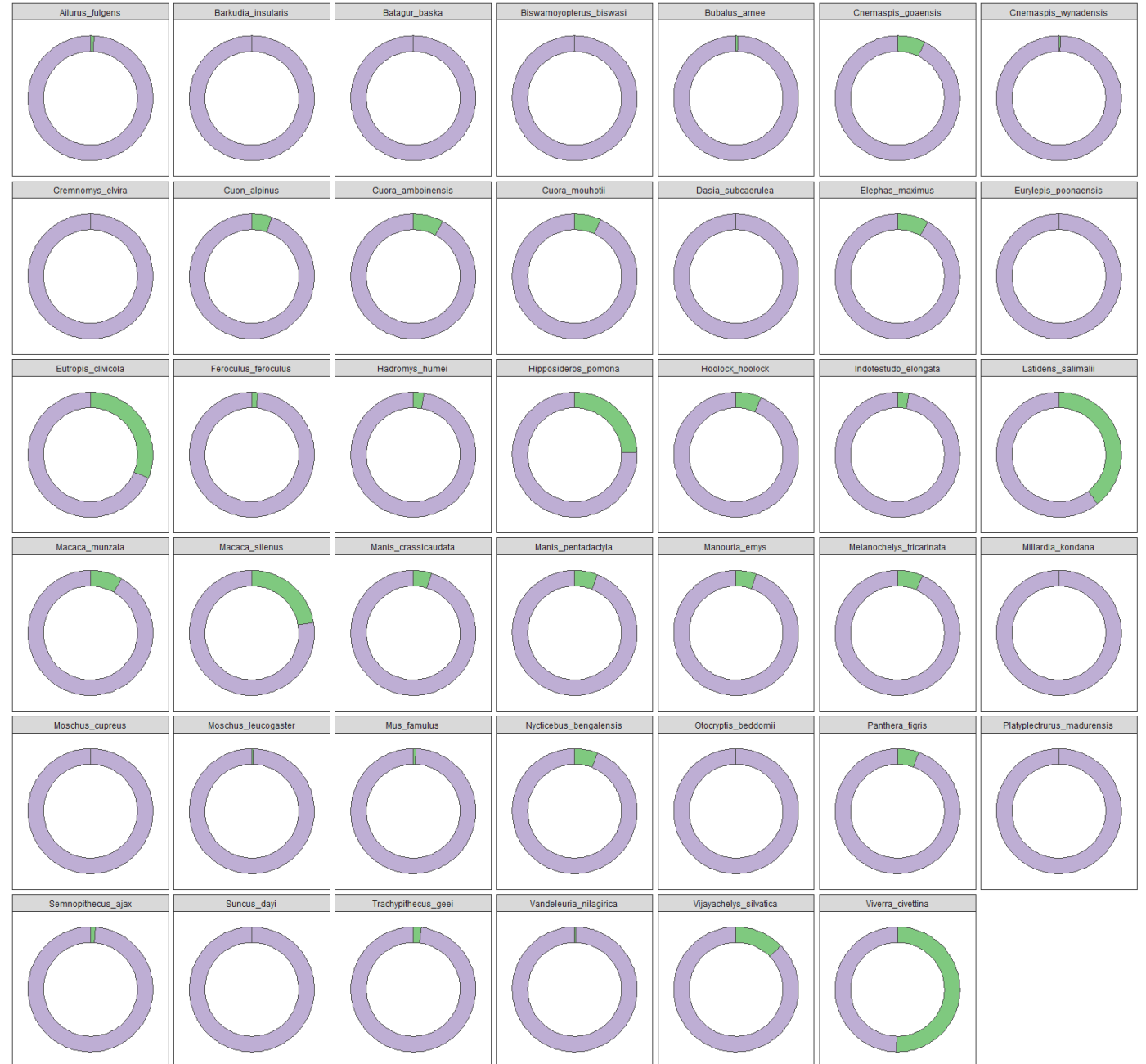


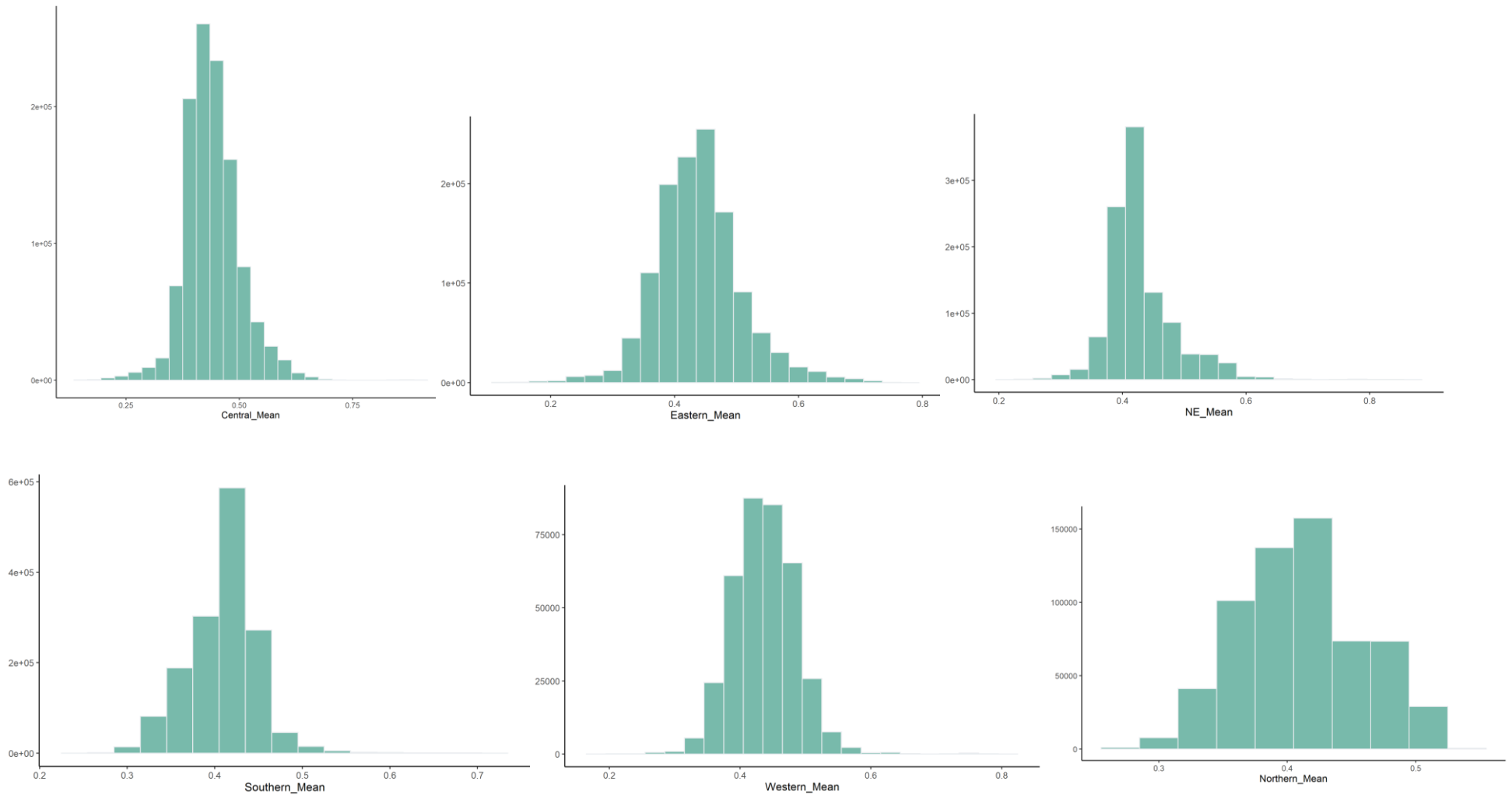
**Figure 8** Distribution of current LULCs in restoration opportunity across regions. In the central region, 56.9% is classified as fallow and 0.57% is classified as plantations, in the eastern region 61.4% is classified as shrubland and 0.84% is classified as barren, in the north eastern region 64.2% is classified as shrubland and 0.73% is classified as fallow, in the north 49.4% is shrublands and 5.9% is barren, in the south 67.5% is classified as plantations and 0.06% is wastelands and finally in the western region 65.9% is shrubland and 1.1% is barren,



**Figure 3** Climate change mitigation potential normalized by total land area in each jurisdiction. At the national scale, 388.5 TgC can be cumulatively generated from natural regeneration of forests in the restoration opportunity. The highest mitigation potential of 119.2 TgC is in southern India and the least mitigation potential of 37.3 TgC in the north east. Madhya Pradesh has the highest mitigation potential of 59.4 TgC and Mizoram has the least mitigation potential of 0.27 TgC.

**Figure 4** Distribution of additional habitat area created from natural regeneration in restoration opportunity. Each donut represents a species, in which the additional habitat area created is indicated by green, while the remaining habitat area is indicated by purple. There was an increase in habitat area by 50.2% for the Malabar long-tailed civet (*Viverra civettina*) and the lowest increase in habitat was by 0.37% for Nilgiri long-tailed tree mouse (*Vandeleuria nilagirica*). There was no increase in habitat for 11 species ( See Table S6 for details)





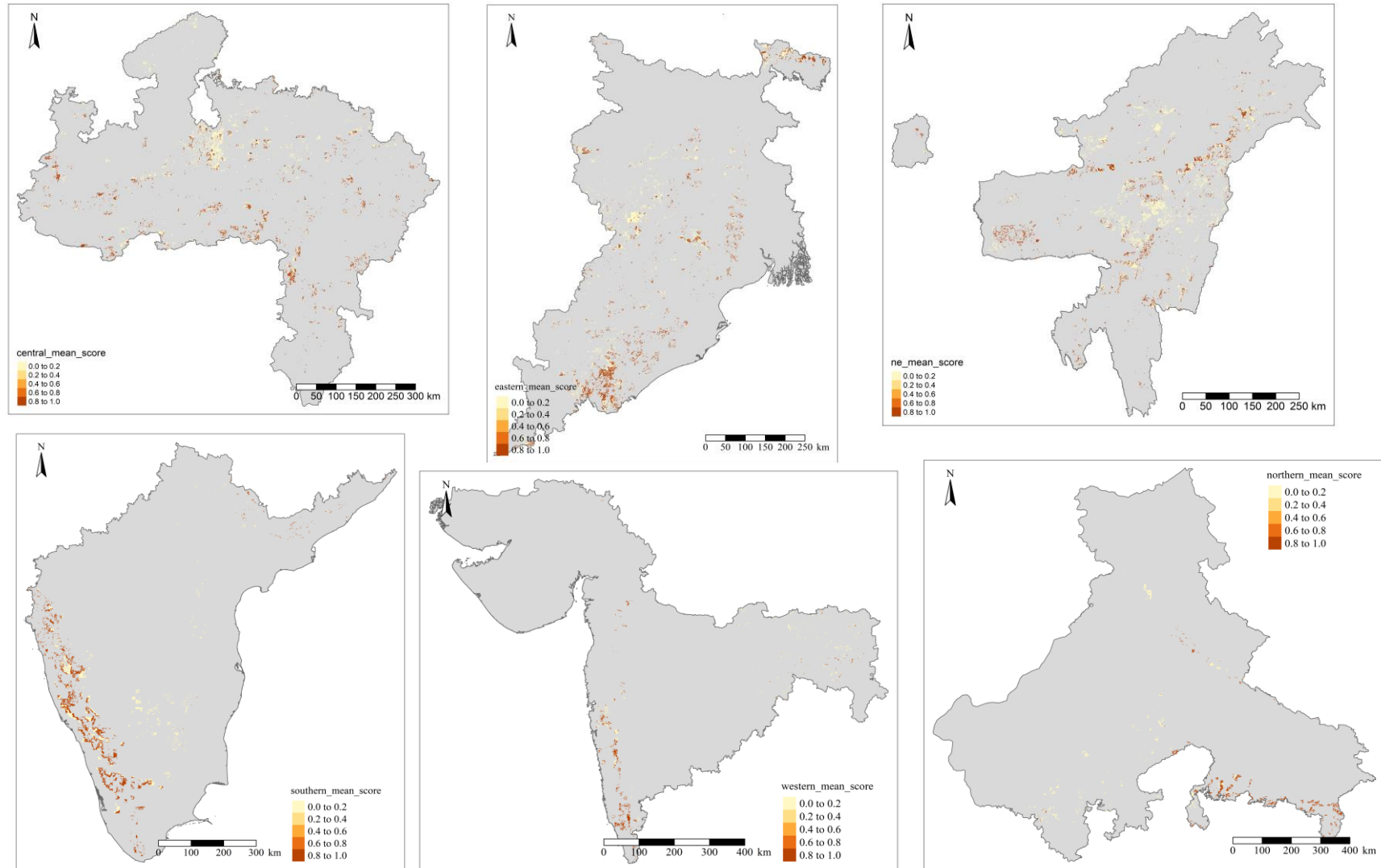
**Figure 5** Distribution of Forest Restoration Opportunity Score in each region. We estimated the range of the Forest Restoration Scores to be 0.15-0.90 with a threshold of 0.44 in the central region, 0.22-0.85 with a threshold of 0.42 in the north east, 0.27-0.55 with a threshold of 0.41 in the north, 0.23-0.73 with a threshold of 0.41 in the south and finally 0.17-0.80 with a threshold of 0.43 in the western region.

**Table 6** Area estimates in different jurisdictions including bioclimatic envelope area of forests, area remaining after excluding certain LULCs and final restoration opportunity after excluding croplands and current natural forests (Mha). Jurisdictions are arranged in decreasing order of restoration opportunity.

<b>State Name</b>	<b>Bioclimatic Envelope Area (Mha)</b>	<b>Area remaining after exclusion of certain LULCs (See Supplementary Methods)(Mha)</b>	<b>Restoration Opportunity remaining after exclusion of croplands and natural forests (Mha)</b>
NCT of Delhi	0.03781	0.032946	0.004942
Mizoram	2.143642	2.082105	0.00642
Goa	0.095353	0.092966	0.006909
Sikkim	0.236005	0.215968	0.006947
Tripura	0.320233	0.309109	0.013115
Punjab	3.022112	2.822431	0.017654
Telangana	0.849909	0.834121	0.0525
Haryana	2.114491	2.036752	0.065975
Manipur	2.270895	2.185252	0.077411
Meghalaya	0.957928	0.928639	0.078427
Himachal Pradesh	0.789598	0.720806	0.090515
Jammu and Kashmir	0.585634	0.51593	0.097004
Bihar	0.707806	0.68469	0.10161
Andhra Pradesh	1.473553	1.43923	0.101998
Uttarakhand	0.900791	0.845484	0.129049
Arunachal Pradesh	4.452945	4.303717	0.154863
Gujarat	1.462066	1.39562	0.157216
Nagaland	1.710731	1.661698	0.167331
West Bengal	1.636401	1.488981	0.184347
Chhattisgarh	4.270999	4.19693	0.218512
Tamil Nadu	1.558676	1.532999	0.335785
Jharkhand	3.042589	2.96496	0.39457
Uttar Pradesh	1.766223	1.655091	0.434298
Rajasthan	2.018244	1.93506	0.438715
Maharashtra	6.617766	6.485117	0.511888
Assam	3.685986	3.471183	0.558561
Odisha	5.117907	5.003952	0.565973
Karnataka	3.279796	3.129875	0.773009
Kerala	1.501324	1.447255	0.903053
Madhya Pradesh	8.762968	8.568623	0.920814
<b>Total</b>	<b>67.39038</b>	<b>64.98749</b>	<b>7.569411</b>

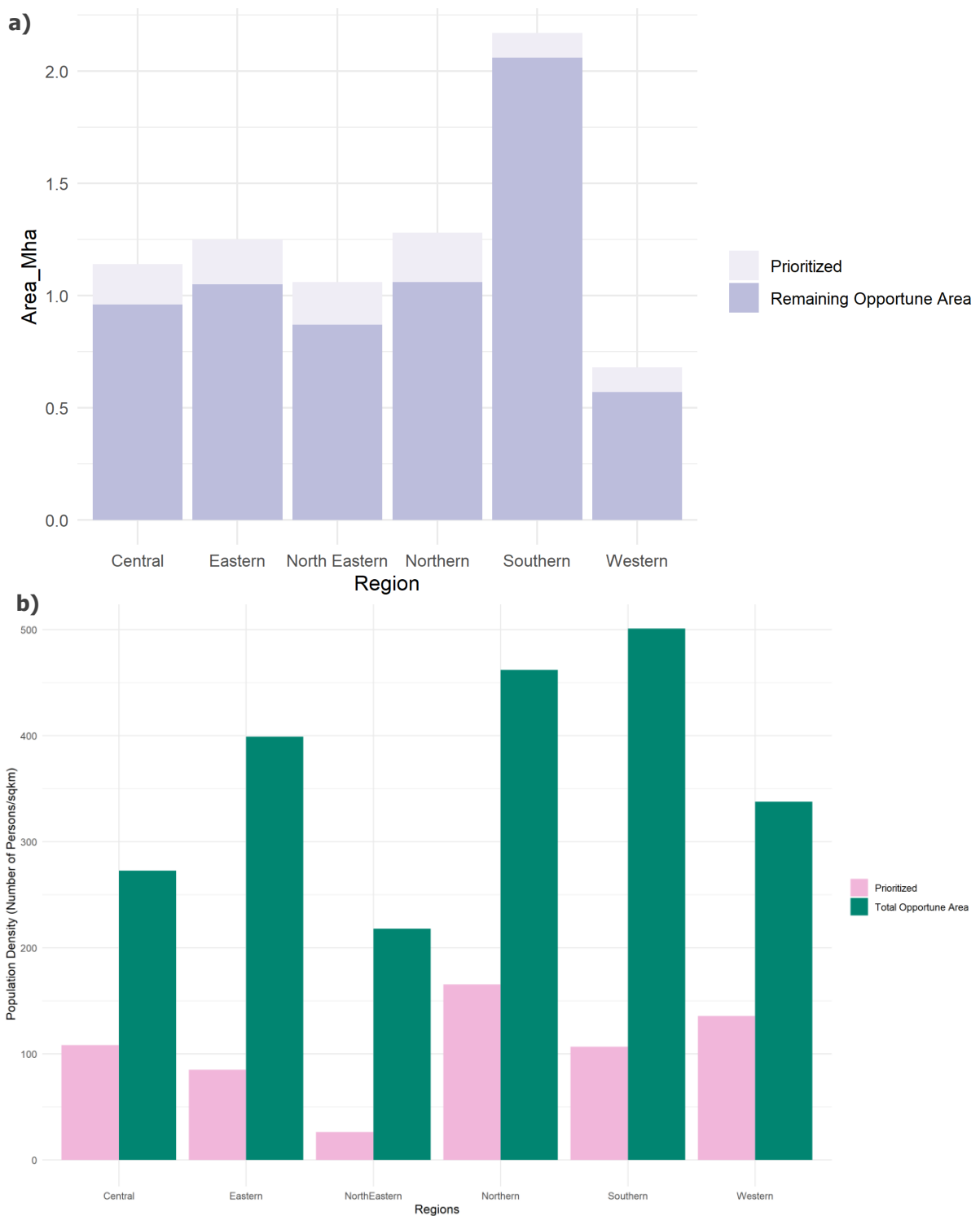
We estimated the range of the Forest Restoration Scores to be 0.15-0.90 with a threshold of 0.44 in the central region, 0.22-0.85 with a threshold of 0.42 in the north east, 0.27-0.55 with a threshold of 0.41 in the north, 0.23-0.73 with a threshold of 0.41 in the south and finally 0.17-0.80 with a threshold of 0.43 in the western region (Fig 11). 38.5% of the restoration opportunity was prioritized, with regional variation of a maximum of 48% of the restoration opportunity in the eastern region being prioritized and the least of 23% of the opportunity in northern India being prioritized for forest restoration (Fig 12). By using the spatial prioritization framework, I estimated 13.5% of the

total restoration opportunity as priority that would minimize the population density being impacted by forest restoration (mean across all regions of 104.5 people/sqkm in prioritized opportunity versus national mean of the total restoration opportunity of 365.1 people/sqkm) (Fig 13).



**Figure 6** Priority areas for natural regeneration in restoration opportunity across all regions. Priority areas that deliver better than average combination of benefits and are feasible and would be successful indicated in orange, while the remaining restoration opportunity that is not priority is indicated in yellow. Scores close to 1 indicate a synergy between the four criteria used and scores close to zero indicate a trade-off between the criteria. Regions are not comparable with each other, but priority opportunity within a region are comparable.





**Figure 7** Distribution of prioritized areas and the remaining opportunity across regions shown in which 13.5% of restoration opportunity was prioritized, with limited variation across regions because of the sole target of 17% optimized in (a). With the objective being minimization of population cost affected, nationally mean population density affected within the prioritized areas was 104 people/sqkm versus 365 people/sqkm in all the total restoration opportunity in (b)

## 4. Discussion

### 4.1. Restoration Opportunity and Climate Change Mitigation Benefits

This proof-of-concept study is the first nationally comprehensive analyses of climate change mitigation and biodiversity benefits, from forest restoration in India. The findings are important considering India's ambitious carbon centric goals, which are starkly different to its earlier environmental reform that focused on wildlife and biodiversity conservation. The highest restoration opportunity and mitigation potential in the southern Indian states can be attributed to steady expansion of exotic timber plantations of *Eucalyptus* and *Pinus* species, to name a few (Arasumani et al., 2018). Considering the possible negative consequences to biodiversity and limited long term carbon storage benefits, I recommend additional opportunity cost and cost benefit based analyses to estimate the feasibility of conversion of the additional estimated land area to naturally regenerating forests (Lewis et al., 2019). The western Indian states have the least restoration opportunity and mitigation potential due to less carbon stocks of the dominant forest types (tropical thorn and dry deciduous forests as per (Roy et al., 2015)) that could naturally regenerate coupled with the already reduced available area due to biophysical conditions of high mean annual temperature, long dry seasons and low annual precipitation. With 44% of the available estimated land area currently shrublands, restoration could include natural regeneration and controlling grazing pressure, bearing in mind the open forest canopy density and structure of forests that would regenerate (Allen et al., 2018).

### 4.2. Biodiversity benefits from forest restoration

For the 44 forest dependent endangered and critically endangered mammals and reptiles considered, I estimated 0.37%-50.2% increase in habitat area from forest restoration. Large terrestrial mammals like the Asian elephant, Bengal tiger and the Indian dhole, considered in this study are susceptible to increased pressures and risks, especially considering India's complex socio-political landscapes (Srivathsa et al., 2020), highlighting the importance of this study. With 81.8% of the species considered are threatened by land use and land cover conversion to "annual and perennial non-timber crops", I highlight the contextual significance of our results of additional habitat created from forest restoration. However, the 11 endemic species for which there is no benefit from forest restoration in opportunity is due to the already restricted habitat ranges of these threatened species. In the future, I aim to complete similar analyses for all 1760 forest dependent mammals, amphibians, reptiles and additionally approximately 700 bird species, for which IUCN provides range maps, thereby providing a complete analyses of biodiversity benefits quantified as the total additional habitat created from forest restoration. Additionally, I recognize that the concept of biodiversity and hence its benefits do not have a simple and comparable definition relative to carbon stocks, carbon sequestration rates or climate change mitigation because of its multiple facets (Soto-Navarro et al., 2021). Hence, to complete this study, I aim to use a multi-dimensional biodiversity metric in the additional land area estimates, that is more wholistic in the sense that the metric uses a variety of indices such as rarity weighted richness index calculated here, species richness, species abundance and intactness metrics as per Soto-Navarro et al., (2020).

### 4.3. Spatial prioritization of restoration opportunity for natural regeneration of forests

The differing amounts of additional land area prioritized by the two prioritization techniques is mainly due to the differing objectives used. Though simplistic, the non-spatial prioritization exercise is a flexible approach that can be easily communicated to stakeholders with varying degrees of expertise in spatial prioritization approaches. Additionally, stakeholder preferences can be easily incorporated by weighting the different benefits and feasibility metrics. However, the spatial optimization using the spatial conservation planning framework is a more nuanced, robust and equally flexible interface that finds optimal solutions based on a broad range of user defined objectives, constraints and penalties (Hanson et al., 2021). Here, I completed a trial analyses by focusing on one target and with the objective of minimizing the population density i.e. the cost of the

analyses. I believe that the use of population density addresses the caveat of not incorporating opportunity costs and cost benefit analyses of forest restoration in this study. Our future steps would include using multiple targets of India's climate change and biodiversity pledges and targets, multiple scenarios in which objectives of climate change mitigation and biodiversity benefits are maximized and the use of different constraints such as selection of neighbouring and contiguous restoration opportunity that would address species movements and dispersal and forest restoration in animal corridors.

#### **4.4. Policy implications and furthering global dialogues**

The current narrative of forest restoration and associated policies, pledges, goals and targets are one dimensional, mostly addressing only the climate change mitigation benefits. However, forest restoration is not only about the carbon stocks that will regenerate, but a multitude of other ecosystem benefits that might be delivered synergistically or in a contrasting manner (Bonnesoeur et al., 2019; Lamb, 2018; Lamb et al., 2005). And by incorporating the nuances of the trade-offs and synergies between different ecosystem benefits from forest restoration will not only move forward the field of restoration science in the tropical biome but also move towards coordinated development of policies that address multiple challenges of biodiversity conservation and climate change mitigation. This synergistic framework or lens of estimating multiple benefits from forest restoration is especially important in India, whose ambitious and recent carbon centric goals and pledges is starkly different to its earlier environmental reform that focused on wildlife and biodiversity conservation (Dubash et al., 2018; Lele, 2019).

The results of this proof-of-concept study and the full project has direct implications for national and subnational policy design and delivery in India. Firstly, the spatial maps of restoration opportunity of 7.6 Mha, of which only 7.7% is classified to be protected under the various IUCN protection categories, can support expansion of current protected areas, thereby contributing to the targets of the post 2020 Global Biodiversity Framework and target 11 and 15 of India's current National Biodiversity Action Plan. The spatial maps of prioritized areas that are feasible and will successfully naturally regenerate and provide an optimum combination of ecosystem benefits can support India's Tax Revenue Distribution reform that encourages state governments to protect and restore forests, using ecological fiscal transfers, the first reform of its kind in world (Busch & Mukherjee, 2018). Lastly, the multi spatial scale analyses and results from this study can support multiscale levels of policy design and delivery, with feasible targets.

## **5. Conclusion**

In this proof-of-concept study, I proposed to push the one-dimensional narrative of climate change mitigation benefits from forest restoration that is currently driving forest restoration policy at multiple scales, to include multiple ecosystem benefits and the inherent contrasting outcomes of forest restoration. At the national scale, I estimated a total of 7.5 Mha of restoration opportunity delivering 388.5 TgC of climate change mitigation benefits. Of the 44 species considered, natural regeneration of forests in the restoration opportunity could result in an average increase of habitat area of 6.7%. Using two prioritization techniques, I exhibited the utility of estimating priority areas for multiple objectives, a new facet to the area-based agenda of forest restoration.

## 6. References

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. *Scientific Data*, 5(1), 1–12. <https://doi.org/10.1038/sdata.2017.191>
- Albuquerque, F., & Beier, P. (2016). Predicted rarity-weighted richness, a new tool to prioritize sites for species representation. *Ecology and Evolution*, 6(22), 8107–8114. <https://doi.org/10.1002/ece3.2544>
- Allen, E. B., Williams, K., Beyers, J. L., Phillips, M., Ma, S., & D’Antonio, C. M. (2018). Chaparral Restoration. In E. C. Underwood, H. D. Safford, N. A. Molinari, & J. E. Keeley (Eds.), *Valuing Chaparral: Ecological, Socio-Economic, and Management Perspectives* (pp. 347–384). Springer International Publishing. [https://doi.org/10.1007/978-3-319-68303-4\\_13](https://doi.org/10.1007/978-3-319-68303-4_13)
- Aragão, L. E. O. C., Malhi, Y., Roman-Cuesta, R. M., Saatchi, S., Anderson, L. O., & Shimabukuro, Y. E. (2007). Spatial patterns and fire response of recent Amazonian droughts. *Geophysical Research Letters*, 34(7), 1–5. <https://doi.org/10.1029/2006GL028946>
- Arasumani, M., Khan, D., Das, A., Lockwood, I., Stewart, R., Kiran, R. A., Muthukumar, M., Bunyan, M., & Robin, V. V. (2018). Not seeing the grass for the trees: Timber plantations and agriculture shrink tropical montane grassland by two-thirds over four decades in the Palani Hills, a Western Ghats Sky Island. *PLOS ONE*, 13(1), 1–18. <https://doi.org/10.1371/journal.pone.0190003>
- Ball, Ian, Possingham, Hugh, Watts, M., Ball, I. R., Possingham, H. P., & Watts, M. (2009). Marxan and relatives: software for spatial conservation prioritisation. *Spatial Conservation Prioritisation: Quantitative Methods and Computational Tools*, 14, 185–196.
- Barnett, A., Fargione, J., & Smith, M. P. (2016). Mapping Trade-Offs in Ecosystem Services from Reforestation in the Mississippi Alluvial Valley. *BioScience*, 66(3), 223–237. <https://doi.org/10.1093/biosci/biv181>
- Bischi, B., Lang, M., Kotthoff, L., Schiffner, J., Richter, J., Studerus, E., Casalicchio, G., & Jones, Z. M. (2016). {mlr}: Machine Learning in R. *Journal of Machine Learning Research*, 17(170), 1–5. <https://jmlr.org/papers/v17/15-066.html>
- Bonnesoeur, V., Locatelli, B., Guariguata, M. R., Ochoa-Tocachi, B. F., Vanacker, V., Mao, Z., Stokes, A., & Mathez-Stiefel, S. L. (2019). Impacts of forests and forestation on hydrological services in the Andes: A systematic review. *Forest Ecology and Management*, 433(February), 569–584. <https://doi.org/10.1016/j.foreco.2018.11.033>
- Brancalion, P. H. S., & Holl, K. D. (2020). Guidance for Successful Tree Planting Initiatives. *Journal of Applied Ecology*, July, 1–13. <https://doi.org/10.1111/1365-2664.13725>
- Brancalion, P. H. S., Niamir, A., Broadbent, E., Crouzeilles, R., Barros, F. S. M., Almeyda Zambrano, A. M., Baccini, A., Aronson, J., Goetz, S., Leighton Reid, J., Strassburg, B. B. N., Wilson, S., & Chazdon, R. L. (2019). Global restoration opportunities in tropical rainforest landscapes. *Science Advances*, 5(7), eaav3223. <https://doi.org/10.1126/sciadv.aav3223>
- Brooks, T. M., Pimm, S. L., Akçakaya, H. R., Buchanan, G. M., Butchart, S. H. M., Foden, W., Hilton-Taylor, C., Hoffmann, M., Jenkins, C. N., Joppa, L., Li, B. V., Menon, V., Ocampo-Peñuela, N., & Rondinini, C. (2019). Measuring Terrestrial Area of Habitat (AOH) and Its Utility for the IUCN Red List. *Trends in Ecology and Evolution*, 34(11), 977–986. <https://doi.org/10.1016/j.tree.2019.06.009>
- Busch, J., Engelmann, J., Cook-Patton, S. C., Griscom, B. W., Kroeger, T., Possingham, H., & Shyamsundar, P. (2019). Potential for low-cost carbon dioxide removal through tropical

- reforestation. *Nature Climate Change*, 9(6), 463–466. <https://doi.org/10.1038/s41558-019-0485-x>
- Busch, J., & Mukherjee, A. (2018). Encouraging State Governments to Protect and Restore Forests Using Ecological Fiscal Transfers: India's Tax Revenue Distribution Reform. *Conservation Letters*, 11(2), 1–10. <https://doi.org/10.1111/conl.12416>
- Cardinale, B. J., Duffy, J. E., Gonzalez, A., Hooper, D. U., Perrings, C., Venail, P., Narwani, A., MacE, G. M., Tilman, D., Wardle, D. A., Kinzig, A. P., Daily, G. C., Loreau, M., Grace, J. B., Larigauderie, A., Srivastava, D. S., & Naeem, S. (2012). Biodiversity loss and its impact on humanity. In *Nature* (Vol. 486, Issue 7401, pp. 59–67). Nature Publishing Group. <https://doi.org/10.1038/nature11148>
- Coleman, E. A., Schultz, B., Ramprasad, V., Fischer, H., Rana, P., Filippi, A. M., Güneralp, B., Ma, A., Rodriguez Solorzano, C., Guleria, V., Rana, R., & Fleischman, F. (2021). Limited effects of tree planting on forest canopy cover and rural livelihoods in Northern India. *Nature Sustainability*. <https://doi.org/10.1038/s41893-021-00761-z>
- Conti, G., & Díaz, S. (2013). Plant functional diversity and carbon storage – an empirical test in semi-arid forest ecosystems. *Journal of Ecology*, 101(1), 18–28. [https://doi.org/10.1111/1365-2745.12012@10.1111/\(ISSN\)1365-2435.SOUTHAMERICA](https://doi.org/10.1111/1365-2745.12012@10.1111/(ISSN)1365-2435.SOUTHAMERICA)
- Cook-Patton, S. C., Gopalakrishna, T., Daigneault, A., Leavitt, S. M., Platt, J., Scull, S. M., Amarjargal, O., Ellis, P. W., Griscom, B. W., McGuire, J. L., Yeo, S. M., & Fargione, J. E. (2020). Lower cost and more feasible options to restore forest cover in the contiguous United States for climate mitigation. *One Earth*, 3(6), 739–752. <https://doi.org/10.1016/j.oneear.2020.11.013>
- Cook-Patton, S. C., Leavitt, S. M., Gibbs, D., Harris, N. L., Lister, K., Anderson-Teixeira, K. J., Briggs, R. D., Chazdon, R. L., Crowther, T. W., Ellis, P. W., Griscom, H. P., Herrmann, V., Holl, K. D., Houghton, R. A., Larrosa, C., Lomax, G., Lucas, R., Madsen, P., Malhi, Y., ... Griscom, B. W. (2020). Mapping carbon accumulation potential from global natural forest regrowth. *Nature*, 585(7826), 545–550. <https://doi.org/10.1038/s41586-020-2686-x>
- Crouzeilles, R., Beyer, H. L., Monteiro, L. M., Feltran-Barbieri, R., Pessôa, A. C. M., Barros, F. S. M., Lindenmayer, D. B., Lino, E. D. S. M., Grelle, C. E. V., Chazdon, R. L., Matsumoto, M., Rosa, M., Latawiec, A. E., & Strassburg, B. B. N. (2020). Achieving cost-effective landscape-scale forest restoration through targeted natural regeneration. In *Conservation Letters*. Wiley-Blackwell. <https://doi.org/10.1111/conl.12709>
- Cunningham, C. A., Crick, H. Q. P., Morecroft, M. D., Thomas, C. D., & Beale, C. M. (2021). Translating area-based conservation pledges into efficient biodiversity protection outcomes. *Communications Biology*, 4(1), 1–5. <https://doi.org/10.1038/s42003-021-02590-4>
- Doxsey-Whitfield, E., MacManus, K., Adamo, S. B., Pistolesi, L., Squires, J., Borkovska, O., & Baptista, S. R. (2015). Taking advantage of the improved availability of census data: a first look at the gridded population of the world, version 4. *Papers in Applied Geography*, 1(3), 226–234.
- Dubash, N. K., Khosla, R., Kelkar, U., & Lele, S. (2018). India and climate change: Evolving ideas and increasing policy engagement. *Annual Review of Environment and Resources*, 43, 395–424. <https://doi.org/10.1146/annurev-enviro-102017-025809>
- Dutta, T., Sharma, S., & DeFries, R. (2018). Targeting restoration sites to improve connectivity in a tiger conservation landscape in India. *PeerJ*, 2018(10), e5587. <https://doi.org/10.7717/peerj.5587>
- Fargione, J. E., Bassett, S., Boucher, T., Bridgham, S. D., Conant, R. T., Cook-Patton, S. C., Ellis, P. W.,

- Falcucci, A., Fourqurean, J. W., Gopalakrishna, T., Gu, H., Henderson, B., Hurteau, M. D., Kroeger, K. D., Kroeger, T., Lark, T. J., Leavitt, S. M., Lomax, G., McDonald, R. I., ... Griscom, B. W. (2018). Natural climate solutions for the United States. *Science Advances*, 4(11). <https://doi.org/10.1126/sciadv.aat1869>
- Fleischman, F., Basant, S., Chhatre, A., Coleman, E. A., Fischer, H. W., Gupta, D., Güneralp, B., Kashwan, P., Khatri, D., Muscarella, R., Powers, J. S., Ramprasad, V., Rana, P., Solorzano, C. R., & Veldman, J. W. (2020). Pitfalls of Tree Planting Show Why We Need People-Centered Natural Climate Solutions. *BioScience*, 70(11), 947–950. <https://doi.org/10.1093/biosci/biaa094>
- Forest Survey of India. (2011). Methodology used by FSI in Carbon Stock Accounting. In *Carbon Stock in India's Forests* (p. 10).
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data*, 2(1), 1–21. <https://doi.org/10.1038/sdata.2015.66>
- 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*. <https://doi.org/10.1016/j.rse.2017.06.031>
- Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., Schlesinger, W. H., Shoch, D., Siikamäki, J. V., Smith, P., Woodbury, P., Zganjar, C., Blackman, A., Campari, J., Conant, R. T., Delgado, C., Elias, P., Gopalakrishna, T., Hamsik, M. R., ... Fargione, J. (2017). Natural climate solutions. *Proceedings of the National Academy of Sciences of the United States of America*, 114(44). <https://doi.org/10.1073/pnas.1710465114>
- Hanson JO, Schuster R, Morrell N, Strimas-Mackey M, Watts ME, Arcese P, Bennett J, P. H. (2021). *priorizr: Systematic Conservation Prioritization in R* (R package version 7.0.1.).
- Hengl, T., De Jesus, J. M., Heuvelink, G. B. M., Gonzalez, M. R., Kilibarda, M., Blagotić, A., Shangquan, W., Wright, M. N., Geng, X., Bauer-Marschallinger, B., Guevara, M. A., Vargas, R., MacMillan, R. A., Batjes, N. H., Leenaars, J. G. B., Ribeiro, E., Wheeler, I., Mantel, S., & Kempen, B. (2017). SoilGrids250m: Global gridded soil information based on machine learning. *PLoS ONE*, 12(2). <https://doi.org/10.1371/journal.pone.0169748>
- Hengl, T., Walsh, M. G., Sanderman, J., Wheeler, I., Harrison, S. P., & Prentice, I. C. (2018). Global mapping of potential natural vegetation: an assessment of machine learning algorithms for estimating land potential. *PeerJ*, 6, e5457. <https://doi.org/10.7717/peerj.5457>
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., & others. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049.
- Holl, K. D., & Brancalion, P. H. S. (2020). Tree planting is not a simple solution. *Science*, 368(6491), 580–581. <https://doi.org/10.1126/science.aba8232>
- Hulvey, K. B., Hobbs, R. J., Standish, R. J., Lindenmayer, D. B., Lach, L., & Perring, M. P. (2013). Benefits of tree mixes in carbon plantings. *Nature Climate Change*, 3(10), 869–874. <https://doi.org/10.1038/nclimate1862>
- IUCN. (2020). *The IUCN Red List of Threatened Species*. <https://www.iucnredlist.org>
- Jarvis, A., Reuter, H.I., Nelson, A. and Guevara, E. (2008). *Hole-filled SRTM for the globe Version 4*. 15, 25–54.



- Jung, M., Arnell, A., de Lamo, X., García-Rangel, S., Lewis, M., Mark, J., Merow, C., Miles, L., Ondo, I., Pironon, S., Ravilious, C., Rivers, M., Schepashenko, D., Tallowin, O., van Soesbergen, A., Govaerts, R., Boyle, B. L., Enquist, B. J., Feng, X., ... Visconti, P. (2021). Areas of global importance for conserving terrestrial biodiversity, carbon and water. *Nature Ecology & Evolution*. <https://doi.org/10.1038/s41559-021-01528-7>
- Lamb, D. (2018). Undertaking large-scale forest restoration to generate ecosystem services. *Restoration Ecology*, 26(4), 657–666. <https://doi.org/10.1111/rec.12706>
- Lamb, D., Erskine, P. D., & Parrotta, J. A. (2005). Restoration of degraded tropical forest landscapes. *Science*, 310(5754), 1628–1632. <https://doi.org/10.1126/science.1111773>
- Lele, S. (2019). *15 Climate change and the Indian environmental movement*. 2011.
- Lewis, S. L., Wheeler, C. E., Mitchard, E. T. A., & Koch, A. (2019). Restoring natural forests is the best way to remove atmospheric carbon. *Nature*, 568(7750), 25–28. <https://doi.org/10.1038/d41586-019-01026-8>
- Lugo, A. E., Carlo, T. A., & Wunderle, J. M. (2012). Natural mixing of species: Novel plant-animal communities on Caribbean Islands. In N. Pettorelli & R. Ewers (Eds.), *Animal Conservation* (Vol. 15, Issue 3, pp. 233–241). John Wiley & Sons, Ltd. <https://doi.org/10.1111/j.1469-1795.2012.00523.x>
- McGuire, J. L., Lawler, J. J., McRae, B. H., Nuñez, T. A., & Theobald, D. M. (2016). Achieving climate connectivity in a fragmented landscape. *Proceedings of the National Academy of Sciences of the United States of America*, 113(26), 7195–7200. <https://doi.org/10.1073/pnas.1602817113>
- Newmark, W. D., Jenkins, C. N., Pimm, S. L., McNeally, P. B., & Halley, J. M. (2017). Targeted habitat restoration can reduce extinction rates in fragmented forests. *Proceedings of the National Academy of Sciences of the United States of America*, 114(36), 9635–9640. <https://doi.org/10.1073/pnas.1705834114>
- O'donnell, M. S., & Ignizio, D. A. (n.d.). *Bioclimatic Predictors for Supporting Ecological Applications in the Conterminous United States Data Series 691*. <http://www.usgs.gov/pubprod>
- Pandve, H. (2009). India's national action plan on climate change. In *Indian Journal of Occupational and Environmental Medicine* (Vol. 13, Issue 1, pp. 17–19). Wolters Kluwer -- Medknow Publications. <https://doi.org/10.4103/0019-5278.50718>
- Ploton, P., Mortier, F., Réjou-Méchain, M., Barbier, N., Picard, N., Rossi, V., Dormann, C., Cornu, G., Viennois, G., Bayol, N., Lyapustin, A., Gourlet-Fleury, S., & Pélissier, R. (2020). Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications*, 11(1), 1–11. <https://doi.org/10.1038/s41467-020-18321-y>
- Pörtner, H.O., Scholes, R.J., Agard, J., Archer, E., Arneeth, A., Bai, X., Barnes, D., Burrows, M., Chan, L., Cheung, W. L., Diamond, S., Donatti, C., Duarte, C., Eisenhauer, N., Foden, W., Gasalla, M. A., Handa, C., Hickler, T., Hoegh-Guldberg, O., Ichii, K., Jacob, U., Insarov, G., Kiessling, W., Leadley, P., Leemans, R., Levin, L., Lim, M., Maharaj, S., Managi, S., Marquet, P. A., McElwee, P., Midgley, G., Oberdorff, T., Obura, D., Osman, E., Pandit, R., Pascual, U., Pires, A. P. F., Popp, A., R., García, V., Sankaran, M., Settele, J., Shin, Y. J., Sintayehu, D. W., Smith, P., Steiner, N., Strassburg, B., Sukumar, R., Trisos, C., Val, A.L., Wu, J., Aldrian, E., Parmesan, C., Pichs-Madruga, R., Roberts, D.C., Rogers, A.D., Díaz, S., Fischer, M., & Hashimoto, S., Lavorel, S., Wu, N., Ngo, H. T. (2021). *IPBES-IPCC CO-Sponsored Workshop Biodiversity and climate change*. <https://doi.org/10.5281/zenodo.4782538>
- R Core Team. (2020). *R: A Language and Environment for Statistical Computing*. <https://www.r->

project.org/

- Reddy, C. S., Jha, C. S., Diwakar, P. G., & Dadhwal, V. K. (2015). Nationwide classification of forest types of India using remote sensing and GIS. *Environmental Monitoring and Assessment*, 187(12), 1–30. <https://doi.org/10.1007/s10661-015-4990-8>
- Rodgers, W. A., Panwar, H. S. (1988). Planning a wildlife protected area network for India: an exercise in applied biogeography. *Tropical Ecosystems: Ecology and Management*, 93–107.
- Roy, P. S., Behera, M. D., Murthy, M. S. R., Roy, A., Singh, S., Kushwaha, S. P. S., Jha, C. S., Sudhakar, S., Joshi, P. K., Reddy, C. S., Gupta, S., Pujar, G., Dutt, C. B. S., Srivastava, V. K., Porwal, M. C., Tripathi, P., Singh, J. S., Chitale, V., Skidmore, A. K., ... Ramachandran, R. M. (2015). New vegetation type map of India prepared using satellite remote sensing: Comparison with global vegetation maps and utilities. *International Journal of Applied Earth Observation and Geoinformation*, 39, 142–159. <https://doi.org/10.1016/j.jag.2015.03.003>
- Schratz, P., Muenchow, J., Iturrutxa, E., Richter, J., & Brenning, A. (2018). *Performance evaluation and hyperparameter tuning of statistical and machine-learning models using spatial data*. <https://doi.org/10.1016/j.ecolmodel.2019.06.002>
- Soto-Navarro, C. A., Harfoot, M., Hill, S. L. L., Campbell, J., Mora, F., Campos, C., Pretorius, C., Pascual, U., Kapos, V., Allison, H., & Burgess, N. D. (2021). Towards a multidimensional biodiversity index for national application. *Nature Sustainability*. <https://doi.org/10.1038/s41893-021-00753-z>
- Soto-Navarro, C., Ravilious, C., Arnell, A., De Lamo, X., Harfoot, M., Hill, S. L. L., Wearn, O. R., Santoro, M., Bouvet, A., Mermoz, S., Le Toan, T., Xia, J., Liu, S., Yuan, W., Spawn, S. A., Gibbs, H. K., Ferrier, S., Harwood, T., Alkemade, R., ... Kapos, V. (2020). Mapping co-benefits for carbon storage and biodiversity to inform conservation policy and action. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375(1794). <https://doi.org/10.1098/rstb.2019.0128>
- Srivathsa, A., Sharma, S., Singh, P., Punjabi, G. A., & Oli, M. K. (2020). A strategic road map for conserving the Endangered dhole *Cuon alpinus* in India. *Mammal Review*, 50(4), 399–412. <https://doi.org/10.1111/mam.12209>
- Strassburg, B. B. N., Iribarrem, A., & Beyer, H. L. (2020). *Global priority areas for ecosystem restoration. August 2019*. <https://doi.org/10.1038/s41586-020-2784-9>
- Usher, M. B. (1986). Wildlife conservation evaluation: attributes, criteria and values. In *Wildlife conservation evaluation* (pp. 3–44). Springer.
- Weiss, D. J., Nelson, A., Gibson, H. S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T. C. D., Howes, R. E., Tusting, L. S., Kang, S. Y., Cameron, E., Bisanzio, D., ... Gething, P. W. (2018). A global map of travel time to cities to assess inequalities in accessibility in 2015. *Nature*, 553(7688), 333–336. <https://doi.org/10.1038/nature25181>
- Williams, P., Gibbons, D., Margules, C., Rebelo, A., Humphries, C., & Pressey, R. (1996). A comparison of richness hotspots, rarity hotspots, and complementary areas for conserving diversity of British birds. *Conservation Biology*, 10(1), 155–174.