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Supplementary information

A forest loss report card for the world's protected areas

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Supplementary Information

Supplementary Methods

In the following subsections, we provide additional methodological details related to our analyses.

IUCN protected area management categories

Protected areas have been categorized in a number of ways. For convenience and to avoid confusion, here we provide the IUCN's definitions used in the World Database on Protected Areas.

The (management) categories are given in Dudley[1] as:

Ia Strict nature reserve: Strictly protected for biodiversity and also possibly geological/ geomorphological features, where human visitation, use and impacts are controlled and limited to ensure protection of the conservation values

Ib Wilderness area: Usually large unmodified or slightly modified areas, retaining their natural character and influence, without permanent or significant human habitation, protected and managed to preserve their natural condition

II National park: Large natural or near-natural areas protecting large-scale ecological processes with characteristic species and ecosystems, which also have environmentally and culturally compatible spiritual, scientific, educational, recreational and visitor opportunities

III Natural monument or feature: Areas set aside to protect a specific natural monument, which can be a landform, sea mount, marine cavern, geological feature such as a cave, or a living feature such as an ancient grove

IV Habitat/species management area: Areas to protect particular species or habitats, where management reflects this priority. Many will need regular, active interventions to meet the needs of particular species or habitats, but this is not a requirement of the category

V Protected landscape or seascape: Where the interaction of people and nature over time has produced a distinct character with significant ecological, biological, cultural and scenic value: and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values

VI Protected areas with sustainable use of natural resources: Areas which conserve ecosystems, together with associated cultural values and traditional natural resource management systems. Generally large, mainly in a natural condition, with a proportion under sustainable natural resource management and where low-level non-industrial natural resource use compatible with nature conservation is seen as one of the main aims

When presenting our results by category, we generally omit the Unknown category since unknown category PAs could be either Strict or Nonstrict, which complicates direct comparisons.

Forest raster processing and protected area filtering

We used the following layers from version 1.6 of Hansen et al.[2]: tree cover in the year 2000 (percentage of each pixel); forest loss between 2001 and 2018 (binary raster) forest gain between 2000 and 2012 (also binary); and primary year associated with forest loss event. Tree cover is the extent of canopy closure for vegetation with height greater than 5 m, forest loss is defined as a change from a forest to non-forest state, and forest gain is defined as the inverse of loss[2]. Forest loss and gain have different timespans because the annual forest loss data continue to be updated. To simplify the analysis by reducing computational requirements, we re-projected each raster to 1-km resolution in Behrmann Equal Area cylindrical projection using nearest neighbor resampling. Since the actual amount of forest loss in a pixel depends on the initial forest cover, we multiplied forest loss by tree cover, so that our final forest loss map ranges from 0 (no loss) to 100 (loss within a pixel that had 100% forest cover).

We excluded PAs from our primary analysis that: [1] had point (centroid) information only, [2] were exclusively marine, [3] were established after 2000 since the forest loss data range from 2001 to 2018, [4] had area less than 1 km^2 since forest change in small PAs can be hard to estimate accurately, [5] were entirely outside of the forest change maps' common extent, [6] had no land with forest change data within their boundaries, [7] were entirely outside of forest biome(s), [8] had less than 30% forest cover across their entire extents, or [9] could not be matched with appropriate control areas (see next section). To determine the extent of forest biomes, we used a terrestrial map of biomes[3]. We considered the following biomes to have been historically forested: *Tropical & Subtropical Moist Broadleaf Forests*, *Tropical & Subtropical Dry Broadleaf Forests*, *Tropical & Subtropical Coniferous Forests*, *Temperate Broadleaf & Mixed Forests*, *Temperate Conifer Forests*, *Boreal Forests/Taiga*, and *Mangroves*.

When summarizing results for lower and higher GDP per capita regions, we determined the groupings using the United Nations M49 standard[4]. These groups were originally defined as developing and developed countries respectively. However, they generally align with GDP per capita, so we opted to use the more neutral terms: lower and higher GDP (per capita).

Protected area matching

To match protected areas with unprotected areas that have similar characteristics, we used a version of 1-k coarsened exact matching (CEM)[5], with the following matching covariates (inspired by Nelson & Chomitz[6]):

1. Elevation (U.S. Geological Survey's global 30 arc-second digital elevation model)
2. Slope (Calculated from elevation using the 'terrain' function in the 'raster' R package)
3. Tree cover[2]
4. Travel time (by land) to nearest densely-populated area[7]

5. Population density[8] smoothed using 20-km circular mean filter (i.e., average population density within 20 km)
6. Country
7. Ecoregion[3]
8. Primary driver of forest cover loss[9] (Commodity Driven Deforestation, Shifting Agriculture, Forestry, Wildfire, Urbanization, Zero or Minor Loss)

These covariates include geographic, environmental, and anthropogenic variables that may related to deforestation rates. By pairing PAs with unprotected sites having similar values of these covariates, we can better estimate the effects of protection on deforestation rates.

We derived our dataset used for matching by resampling these covariates to 1-km resolution. We retained all pixels with at least 30% tree cover located in a forest-type biome. We then partitioned the dataset into treatment (inside PA) and control (outside PA) datasets. We removed all pixels from the control dataset that were within 10-km of a PA to avoid bias due to local scale leakage[10]. We averaged values within protected areas to obtain one observation per protected area. To quantify the extent to which treatment (PA) and control (other pixel) datasets differed with respect to the matching covariates, we first discretized each continuous variables using 10 uniformly spaced breakpoints and then calculated the global L1 imbalance measure[11].

For the 1-k matching of PAs with control areas, we coarsened each continuous matching covariate by dividing it into five roughly equal-sized groups using the 0%, 20%, …, 100% quantiles as breakpoints. For each PA, the matched control pixels were then taken to be those with the same covariate values (after coarsening). We removed unmatched PAs, i.e., those for which no control pixels shared identical (coarsened) covariates. As a sensitivity analysis, we also considered matching based on 0%, 10%, …, 100% quantile breakpoints. This resulted in 10 classes per continuous variable, except for travel time where the 0% and 10% quantiles were both zero (so we omitted the first class).

Deforestation rates

To estimate the annual deforestation rate over an area (e.g., PA, control area, or country), we used the FAO formula as given in Puyravaud[12]:

$$q = \left(\frac{A_2}{A_1}\right)^{\frac{1}{t_2 - t_1}} - 1,$$

where A_1 is the initial forest cover, A_2 is the final forest cover, t_1 is the initial time, and t_2 is the final time. We used this formula (with $t_1 = 2001$ and $t_2 = 2018$) rather than the one based on continuous compounding because that rate is not defined when 100% forest loss occurs, which can is occasionally the case for small areas[12]. For A_1, we used the sum of tree cover in 2000 across the area, and for A_2, we used A_1 minus the sum of tree cover across pixels with tree cover loss. In our results, we refer to $-q$, because our focus is on deforestation rates. We generally report differences between percentage deforestation rates in additive, rather than multiplicative, terms. For example, an increase from 1%/year to 1.1%/year would be described as an increase of 0.1%/year rather than an increase of 10%.

In addition to considering deforestation rates in and around PAs, we assessed the change in the deforestation rate associated with PA establishment for PAs established between 2002 and 2017. We used this time range because it allows for the spatial estimation of deforestation rates before and after PA establishment since the forest loss maps span 2001-2018. For each of these PAs and its associated control area, we computed the annual deforestation rate (as described above) before and after the PA was established. We used these data to compute change in deforestation rate (after – before) in each PA and in its associated control area.

Net forest loss

Due to differences between the forest loss and gain variables, we used a different approach to calculate net forest loss. Specifically, we defined net forest loss as (loss/18 – gain/13)/cover. Because the change in forest cover associated with forest gain is not readily estimable, we used forest loss (binary) rather than the product of forest loss and cover in this calculation. In order to put loss and gain on the same scale, we divided 2001-2018 loss by 18 and 2000-2012 gain by 13.

The primary analysis did not include forest gain since this variable can be difficult to estimate using remote sensing, the change in forest cover associated with gain is not known, and forest gain was not designed to be directly comparable to forest loss[2,13].

Species ranges – mapping and modeling

We derived species richness variables from IUCN Red List species range maps[14]. We used only data for terrestrial vertebrates (classes Mammalia, Amphibia, Aves, and Reptilia) that were coded in the Red List as using forest habitat exclusively. We defined threatened species as those with endangerment category VU (Vulnerable), EN (Endangered), or CR (Critically Endangered). We rasterized each species' range map at 1-km resolution, with only polygons where the species was coded as Native and either Extant or Probably Extant retained. When data were available, we removed areas in the resulting rasterized range that were outside of the species' altitude limits coded in the Red List. For this step, we used the U.S. Geological Survey's Global 30 Arc-Second Elevation map (re-projected to 1-km). We added the resulting range maps (for non-threatened and threatened species separately) together to form the species richness maps. We computed the averages of threatened and non-threatened forest species richness to use as predictor variables in our models.

Country analysis data processing

Part of this analysis involved calculating the averages of several variables at the scale of countries. Details are given in the following subsections.

Species richness

We calculated the number of terrestrial forest obligate vertebrate species (mammals, amphibians, reptiles, and birds) present within each country using the country information in the IUCN Red List species fact sheets[14]. Within each country, we only considered species that the IUCN Red List categorized as Native and Present. Although threatened species may stand to benefit the most from PAs, we included non-threatened species here because adequate protection is important to ensure that they do not become threatened in the future.

Forest carbon

To estimate forest carbon by country, we used the Oak Ridge National Laboratory 1 degree resolution global forest area, carbon stocks, and biomass map set[15]. We used the map of aboveground forest tree biomass for 2000, which has units of tonnes carbon per 1-degree grid cell. We converted this map to tonnes carbon per km^2, resampled to 1-km resolution and added up the grid cell values within each country.

Forested area protected

To determine the percentage of forested land within each country that is protected, we used a 30% tree cover threshold (in 2000) for forest. This parallels our selection of forested PAs based on those that are have at least 30% tree cover in one of their associated 1-km pixels. For each country, we calculated the percentage of forested land that falls with a PA of any category.

Subsetting

Because the primary focus of our country-level analysis was on protected areas, biodiversity, and forest change, we restricted our countries dataset to only those with at least 15 PAs included in our analysis, at least 5 forest obligate vertebrates, and at least 10,000 km^2 forest. This prevents the results from being dominated by, for example, countries with relatively little forested area.

Model fitting

We modeled deforestation rates in PAs using spatially and non-spatially varying coefficient (SNVC) models fit with the "besf_vc" function in the "spmoran" R package with the default exponential covariance model[16–18]. This modeling approach tests whether spatial variations occur for each coefficient, and is robust to multicollinearity[18]. The effects of each predictor variable are classified as either spatially varying or not spatially varying based on minimizing AIC or BIC. For our analysis we used BIC minimization. For each non-spatially varying coefficient, a single estimate, standard error, and p-value are obtained. For the spatially varying coefficients, estimates, standard errors, and p-values all vary spatially and can be obtained for any location. In the SVNC framework, spatial dependence is modeled using Moran eigenvectors, which are the eigenvectors of a particular spatial proximity matrix[16]. The "besf_vc" function that we used is based on a memory-free implementation of the SVNC model, and is suitable for large datasets. Because spatial dependence is explicitly modeled with this approach, residual autocorrelation does not indicate a violation of model assumptions – a potential concern with some spatial matching methods[19].

For coefficients that were found to vary spatially, we obtained point estimates, standard errors, and false discovery rate (FDR) adjusted p-values[20] at the PA centroid locations. For our primary PA deforestation model, we used the following covariates (all linear terms, no interactions):

1. Deforestation rate in the associated control area
2. Population density
3. Travel time (by land) to nearest densely-populated area
4. PA age (years since establishment)
5. GDP/capita of the country in which the PA is located
6. Strict (IUCN category I-IV) versus nonstrict (category V-VI) protection
7. PA area (in square kilometers)

Because the distributions of PA and control deforestation rates had a few extreme outliers, we $\log(10^{-7} + x)$ transformed these variables, to prevent them from dominating the results. Similarly, we log transformed GDP/capita, and PA area, and we $\log(1 + x)$ transformed population density and travel time.

As a secondary analysis that was exploratory in nature, we fit two additional models: one with control area deforestation and threatened forest vertebrate species richness as predictors and the other with control area deforestation and non-threatened forest vertebrate species richness as predictors.

Software

We carried out the GIS analysis using Google Earth Engine[21] to download most datasets, R[22] and Python with GDAL for general raster processing, Julia[23] for coarsened exact matching, and R (with ‘ggplot2’) for statistical modeling and data visualization.

Supplementary Discussion

Limitations and future work

The combination of a very large PA dataset and high resolution remotely sensed forest change maps allowed us to explore factors associated with deforestation in and around the world's protected areas in search of overall relationships. The price of this generality is that it precluded detailed investigation into each PA's unique circumstances. For example, our analysis generally treated forest loss as the same everywhere, but different types of deforestation (e.g., natural fires, slash-and-burn agriculture) may have different ecological consequences. This limitation should be kept in mind, especially when considering comparisons between very different regions. Additionally, while remotely sensed forest fire data are available, distinguishing between natural and anthropogenic fires can be challenging. This distinction is important, however, because natural fires in PAs do not necessarily indicate ineffective management. We attempted to mitigate this issue by accounting for control area deforestation rates, which may be similarly affected by fire, as a predictor in our models and by using "primary driver of forest loss" as a matching covariate. This does not, however, completely address the issue of geographic variation given that, for example, different types of tree plantations may be common in different regions.

In our analysis, we assessed PA effectiveness both in terms of spatial and temporal comparisons. However, the timespans of these analyses were constrained by the availability of forest change data. Specifically, the spatial comparison comprised PAs established in 2000 or earlier, while the temporal comparison used those established between 2002 and 2017. These analyses are not directly comparable since they reflect different time periods.

We treated forest habitat-using vertebrates as interchangeable and focused solely on total and threatened species richness. In reality, the composition of species within each protected area, their levels of endemicity, and the status of individual subspecies and populations occurring in PAs have major conservation significance. The lack of detailed biodiversity data within the more than 18,000 PAs in our analysis made it impractical to address these subtler issues. On a related note, we assumed that species geographic range maps (masked according to altitude limits) are reasonably accurate. In summary, our approach to defining the effectiveness of forested protected areas in terms of their deforestation rates relative to control areas represents one of many ways to define "effectiveness," and other, methods tied more closely to species populations may be more appropriate when data are available. This is important because forest degradation (e.g., due to selective logging) may have major impacts on ecological communities, but often cannot be readily detected using global remotely-sensed forest change maps.

Current remotely sensed global-scale forest change data do not distinguish between different forest types. At smaller scales, airborne laser-guided imaging spectroscopy has been used to map forest canopy traits include leaf mass per unit area and solar insolation[24]. Such maps could be used to obtain a more complete picture of forest change in PAs. They could also be used to link forest change with its effects on forest obligate species through species distribution models. When considering the effects of deforestation in PAs on species, it may help to incorporate information on nearby habitat quality and the spatial relationships among PAs. Although our analysis treated each PA separately, many are close to each other and networks of PAs can have beneficial effects on species by improving connectivity between populations and creating opportunities for successful dispersal[25]. Another possibility for future work is to consider the various indices we developed jointly in the framework of multi-objective optimization[26].

Lastly, it is important to note that most countries created their own PA categorization systems before the IUCN standard was established and that national designations may be more predictive of PA policy and outcomes given possible mismatches between country-specific and IUCN management categories, which are not always interpreted consistently[27,28]. This apparent inconsistency may be partly explained by IUCN categories being defined primarily in terms of management objectives rather than quantifiable targets related to biodiversity and habitat availability[27,29]. Our analysis suggests a criterion (deforestation in PAs relative to matched control areas) that could be refined to form one of a set of quantitative metrics on PA effectiveness. Remotely sensed global datasets coupled with careful ground-truthing and local assessments have the potential to produce spatially consistent estimates of PA deforestation rates. Compared to a 'management objectives' framework, such estimates can more effectively differentiate between current and desired PA effectiveness.

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Supplementary Table

Supplementary Table 1. Country indices that scale species richness, deforestation rate, and forest carbon by area protected adjusted to account for PA effectiveness in limiting deforestation. The columns are Country, Species (number of terrestrial forest obligate vertebrates), Prot. (proportion of forested area protected), Score (total forest loss in matched control areas divided by toal forest loss within PAs), Prot. × Score (adjusted level of protection: proportion protected times score), Loss (annual deforestation rate as a percentage of forest cover in 2000), Carbon (above ground forest biomass in units of gt Carbon), $I_{species}$ [species threat index: Species/(Prot. × Score)], I_{loss} [forest loss threat index: Loss/(Prot. × Score)], I_{carbon} [forest carbon threat index: log10(carbon)/(Prot. × Score)]. Only countries with at least 10,000 km^2 forest, 15 protected areas included in our analysis, and 5 forest obligate vertebrates were considered.

Country	Species	Prot.	Score	Prot. × Score	Loss	Carbon	$I_{species}$	I_{loss}	I_{carbon}
New Zealand	11	0.31	7.53	2.36	0.01	0.62	4.66	0.00	3.73
Bulgaria	9	0.41	4.25	1.72	0.00	0.38	5.23	0.00	4.98
Germany	11	0.37	3.27	1.22	0.00	2.50	9.03	0.00	7.72
Spain	9	0.28	4.32	1.22	0.01	0.80	7.40	0.01	7.32
South Africa	20	0.15	8.10	1.21	0.01	0.46	16.52	0.01	7.16
Latvia	11	0.18	3.87	0.70	0.02	0.41	15.71	0.03	12.30
Costa Rica	346	0.24	2.86	0.69	0.00	0.11	503.76	0.01	11.70
Panama	429	0.27	2.45	0.66	0.00	0.30	646.90	0.01	12.77
Thailand	335	0.18	3.60	0.65	0.01	0.85	516.61	0.01	13.77
Czechia	10	0.22	2.87	0.64	0.01	0.56	15.65	0.01	13.69
Guatemala	268	0.31	1.87	0.58	0.02	0.42	459.59	0.03	14.80
Lithuania	10	0.17	3.37	0.57	0.01	0.36	17.46	0.02	14.94
Romania	9	0.23	2.39	0.55	0.00	1.00	16.43	0.01	16.43
Tanzania	172	0.38	1.41	0.54	0.00	1.47	319.32	0.01	17.02
Poland	9	0.40	1.27	0.50	0.01	1.54	17.84	0.02	18.21
Hungary	6	0.23	1.91	0.43	0.01	0.30	13.96	0.02	19.71
Zambia	28	0.39	1.09	0.42	0.00	2.13	66.14	0.01	22.04
Honduras	267	0.23	1.76	0.41	0.01	0.33	656.41	0.03	20.95
Laos	209	0.17	2.30	0.38	0.01	0.75	548.72	0.04	23.31
Brazil	1000	0.19	2.00	0.37	0.01	47.68	2702.24	0.02	28.86
Australia	192	0.20	1.88	0.37	0.01	6.55	521.09	0.02	26.64
Sweden	11	0.14	2.54	0.36	0.01	1.96	30.47	0.04	25.74
Mexico	547	0.15	2.48	0.36	0.01	3.55	1515.71	0.01	26.46
Kenya	83	0.16	2.30	0.36	0.00	0.36	230.71	0.01	23.80
Austria	9	0.28	1.17	0.33	0.00	0.84	27.20	0.02	26.97
Venezuela	616	0.41	0.80	0.33	0.00	4.36	1882.94	0.01	29.47
Colombia	1082	0.14	2.25	0.32	0.00	3.83	3362.45	0.01	29.78
Nicaragua	211	0.37	0.87	0.32	0.02	0.29	660.32	0.05	26.46
Cambodia	117	0.26	1.22	0.31	0.02	0.56	372.42	0.06	27.83
Ecuador	904	0.22	1.44	0.31	0.00	0.89	2892.23	0.01	28.63
United Kingdom	5	0.29	0.96	0.27	0.01	0.20	18.30	0.03	30.40
Finland	12	0.13	1.99	0.26	0.02	1.24	45.87	0.06	34.76

Vietnam	353	0.15	1.80	0.26	0.01	0.67	1351.54	0.05	33.79
Côte d'Ivoire	104	0.22	1.16	0.26	0.01	1.59	403.63	0.05	35.71
Guinea	83	0.22	1.13	0.25	0.01	0.41	326.13	0.04	33.85
Japan	48	0.18	1.36	0.25	0.00	1.63	191.70	0.01	36.79
Ghana	87	0.14	1.71	0.24	0.01	0.30	359.81	0.04	35.06
Madagascar	431	0.05	4.26	0.23	0.02	0.72	1875.64	0.07	38.55
Philippines	317	0.15	1.45	0.22	0.00	0.41	1428.95	0.02	38.81
Argentina	201	0.10	2.14	0.22	0.01	1.59	927.69	0.05	42.47
United States of America	151	0.13	1.41	0.18	0.01	26.31	831.89	0.06	57.41
Italy	9	0.22	0.83	0.18	0.00	0.73	50.00	0.01	49.24
Canada	56	0.11	1.62	0.18	0.01	19.96	317.21	0.04	58.35
Peru	1008	0.19	0.91	0.17	0.00	7.04	5986.51	0.02	58.49
South Korea	17	0.17	0.92	0.16	0.00	0.33	108.30	0.02	54.29
Indonesia	1000	0.12	1.20	0.14	0.01	4.23	6913.02	0.08	66.55
Malaysia	499	0.06	2.20	0.14	0.02	1.26	3610.38	0.16	65.84
Uganda	128	0.15	0.87	0.13	0.01	0.25	989.04	0.04	64.88
India	323	0.05	2.60	0.12	0.00	3.03	2616.69	0.02	76.81
Sri Lanka	59	0.28	0.41	0.12	0.00	0.06	512.58	0.02	67.57
Dem. Rep. Congo	228	0.13	0.81	0.11	0.01	19.10	2142.35	0.06	96.60
Papua New Guinea	497	0.04	2.64	0.10	0.00	0.94	4976.09	0.02	89.83
Russia	34	0.09	1.05	0.10	0.01	52.89	344.53	0.06	108.66
Myanmar	276	0.06	1.53	0.10	0.01	1.27	2838.47	0.06	93.62
Nepal	104	0.23	0.43	0.10	0.00	0.25	1074.47	0.00	86.74
Serbia	9	0.08	1.08	0.09	0.00	0.22	100.72	0.01	93.44
Chile	19	0.23	0.34	0.08	0.01	1.16	244.99	0.10	116.87
Iran	8	0.08	0.89	0.07	0.00	0.46	112.01	0.00	121.22
Nigeria	98	0.13	0.54	0.07	0.00	0.76	1418.35	0.06	128.53
Switzerland	10	0.10	0.58	0.06	0.00	0.30	163.89	0.02	138.95
Ukraine	9	0.03	1.82	0.06	0.01	1.50	149.74	0.12	152.65
Sierra Leone	72	0.06	0.71	0.04	0.02	0.13	1806.42	0.60	203.95
China	338	0.02	1.80	0.03	0.00	10.16	10742.46	0.14	318.04