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

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Protected areas are a key tool in the conservation of global biodiversity and carbon stores. We conducted a global test of the degree to which more than 18,000 terrestrial protected areas (totalling 5,293,217 km^2) reduce deforestation in relation to unprotected areas. We also derived indices that quantify how well countries' forests are protected, both in terms of forested area protected and effectiveness of protected areas at reducing deforestation, in relation to vertebrate species richness, aboveground forest carbon biomass and background deforestation rates. Overall, protected areas did not eliminate deforestation, but reduced deforestation rates by 41%. Protected area deforestation rates were lowest in small reserves with low background deforestation rates. Critically, we found that after adjusting for effectiveness, only 6.5%—rather than 15.7%—of the world's forests are protected, well below the Aichi Convention on Biological Diversity's 2020 Target of 17%. We propose that global targets for protected areas should include quantitative goals for effectiveness in addition to spatial extent.

Current species extinction rates are ~1,000 times higher than pre-human background rates, suggesting that we are in the midst of a sixth mass extinction event[1]. Diverse efforts to conserve biodiversity include captive breeding programmes, legal protections for individual species, restrictions on wildlife trade, control of invasive species and the establishment of protected areas[2] (PAs). PAs are a cornerstone of many conservation programmes and can be effective in reducing overexploitation, habitat loss and many other threats within their boundaries[3]. The percentage of Earth's terrestrial area that is protected has increased substantially over the past decade and is now approaching the Aichi Convention on Biological Diversity's 2020 Target of 17%[4,5]. However, PA coverage alone is an inadequate conservation metric because nearly one-third of protected land is under intense human pressure[6] and 'paper parks' prove ineffective[5]. Moreover, prioritizing area protected over other metrics can indirectly lead to declines in effectiveness[5]. Assessing the effectiveness of PAs is challenging because biodiversity responses to protection are often difficult to measure[7].

One of the most basic functions of PAs is to provide habitat for species. Most of Earth's terrestrial species rely on forest habitat[8]. Consequently, we focus here on deforestation as a form of habitat loss, although other types of habitat loss can be important in non-forest ecosystems. Deforestation increases the extinction risk of forest-associated species[9] and reduces the amount of carbon sequestered into organic biomass[10]. Thus, the extent to which PAs limit deforestation is often a key component of their effectiveness, both in terms of species conservation and carbon storage services. Unlike species populations[7,11,12], forest cover and change can be consistently mapped globally at high resolution using remote sensing, which makes such data well-suited to global analyses[13]. Previous research has demonstrated that PAs conserve forest habitat[7], that mixed-use and indigenous PAs can be more effective than strictly protected PAs[14,15] and that PAs were most effective in preventing deforestation in Australasia and least effective in Asia, with effectiveness positively associated with countries' gross domestic product (GDP) per capita[16]. This parallels the finding that PA effectiveness at limiting human pressure increases was positively associated with human development index[17]. While PA establishment can lead to increased deforestation rates in nearby areas[18] ('leakage'), the opposite outcome ('blockage') is much more common globally[19].

Here, we build on this previous research to conduct the first (to the best of our knowledge) comprehensive, global analysis of the effectiveness of PAs with respect to limiting forest loss. We defined PA effectiveness (with regard to limiting deforestation) based on deforestation rates within PAs compared with rates in matched control areas with similar characteristics. We modelled PA deforestation rates while controlling for background rates in matched control areas using a diverse set of predictors, including: nearby population densities; reserve size, age and management category; and GDP per capita. As geographical variation and local or regional context can affect how these predictors relate to deforestation rates, we adopted a spatially and non-spatially varying coefficient (SNVC) modelling approach, which relaxes the assumption of constant effect sizes. By allowing relationships to vary geographically, our analysis can shed light on differences in results among previous PA effectiveness studies.

From a conservation perspective, regions with high species richness and carbon storage should ideally have high PA cover and effectiveness, because protecting biodiversity and carbon stocks can be important functions of PAs[20]. In addition to our primary modelling effort, we derived a national scale index of effective area protected, which we compared with total forest vertebrate richness and carbon stocks across all countries on the global scale. This allows for the quantification of how well effective protection aligns with biodiversity and carbon sequestration[21], and provides a transparent assessment of which countries are the most under-protected given their biodiversity and carbon stocks, and which countries have excelled at effective forest protection. This comparative, global

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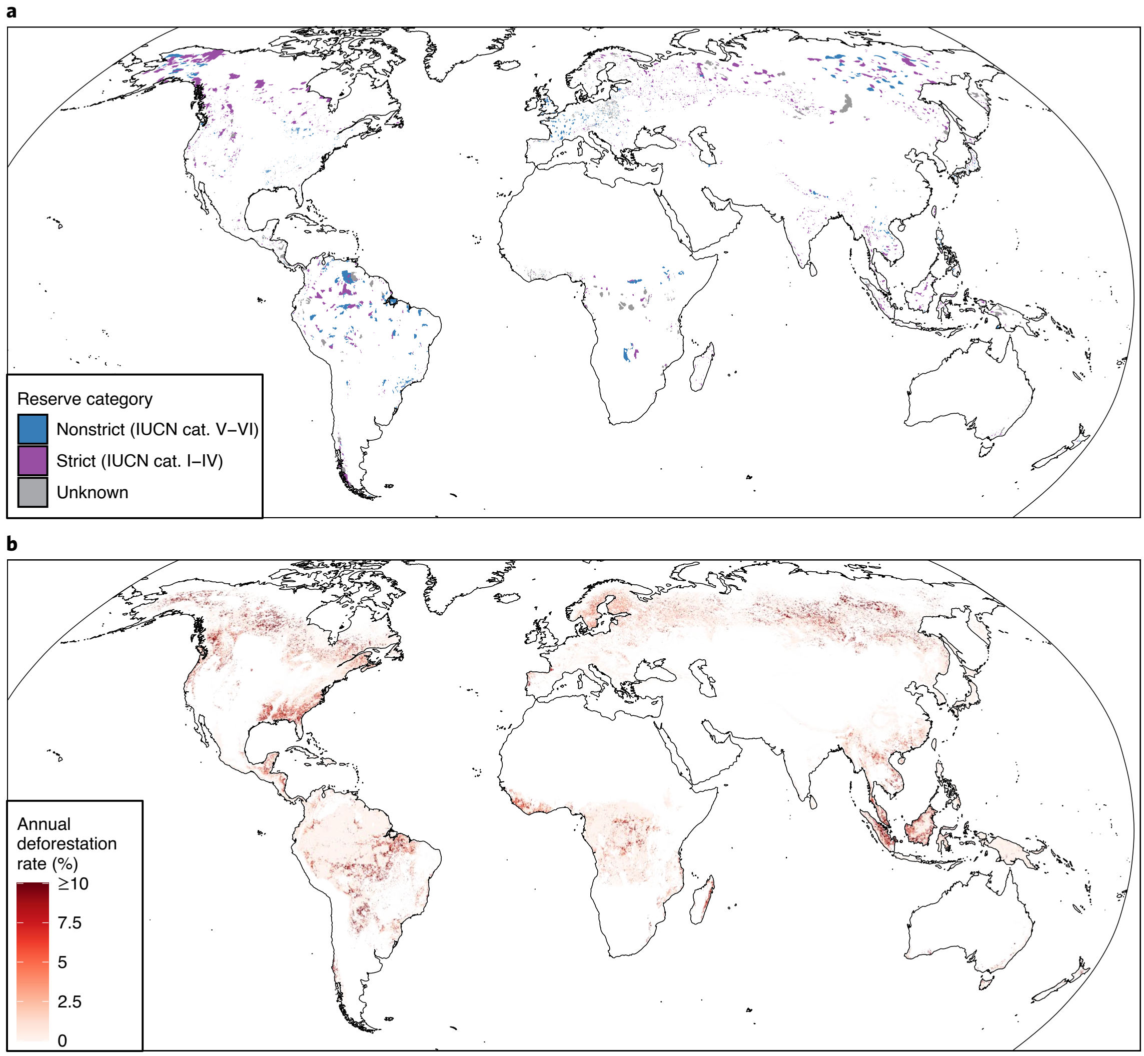

Fig. 1 | Locations of the 18,171 PAs in our main analysis and global deforestation rates. a, PAs are grouped based on their IUCN categories (cat.): Strict (I–IV), Nonstrict (V–VI) and Unknown. Most of the PAs are located within regions of higher GDP per capita, especially the eastern United States and Europe. However, many of these PAs are very small. **b**, Estimated annual deforestation (tree cover loss) rates are for the period 2001 to 2018. Including PAs from all of Earth's forested regions enabled our analysis to assess geographic variation in effectiveness on the global scale.

assessment complements the current coverage target of protection associated with the Aichi Biodiversity Target 11 and other global effectiveness evaluations.

While the subject of PA effectiveness has received considerable attention in the literature, most previous ecological evaluations of PAs have been regional in scope, which precludes testing global hypotheses about political and economic predictors of PA effectiveness. However, there are examples of global studies using either the change in human pressure[6,17] or biodiversity metrics[22–24]. Our use of a global set of PAs and an SNVC modelling framework allowed us to test the relative performance of all forested PAs across the full gradients of latitude, population density, GDP per capita and other important predictor variables, while accounting for regional scale variability. Furthermore, our SNVC modelling approach permits testing of whether the effects of these variables vary geographically or can be treated as constant. Finally, we provide what we believe is the first assessment of the degree to which PA effectiveness and coverage are congruent with areas in greatest need of protection, including those with the highest biodiversity and carbon stocks. We thus provide the first (to the best of our knowledge) global quantitative estimates of the most under-protected countries on Earth.

Results

Prior to matching with control areas, our primary PA dataset contained 25,348 PAs. However, 7,177 (28.3%) of these PAs could not be matched with any unprotected pixels having similar matching-covariate values. Consequently, after applying coarsened exact matching to identify control areas, our final dataset contained 18,171 PAs, with a total area of 5,293,217 km^2 (Fig. 1 and Extended Data Fig. 1). Overall, PAs reduced, but did not eliminate, deforestation; the median annual deforestation rate in control areas (0.54%; s.d. = 2.21%) was 4.97 times higher than within PAs (0.11% per year; s.d. = 2.45%) (Fig. 2). In absolute terms, the 18,171 PAs in our analysis had an average annual forest loss rate of ~1.53 Mha. In our analysis, 28.7% of the PAs did not have any forest loss. Among PAs with known management category, deforestation rates were highest in nonstrict PAs in Africa (0.31% per year), Europe (0.29% per year) and South America (0.19% per year), and lowest in strict PAs in Oceania (0.02% per year) (Fig. 3). General patterns in PA forest

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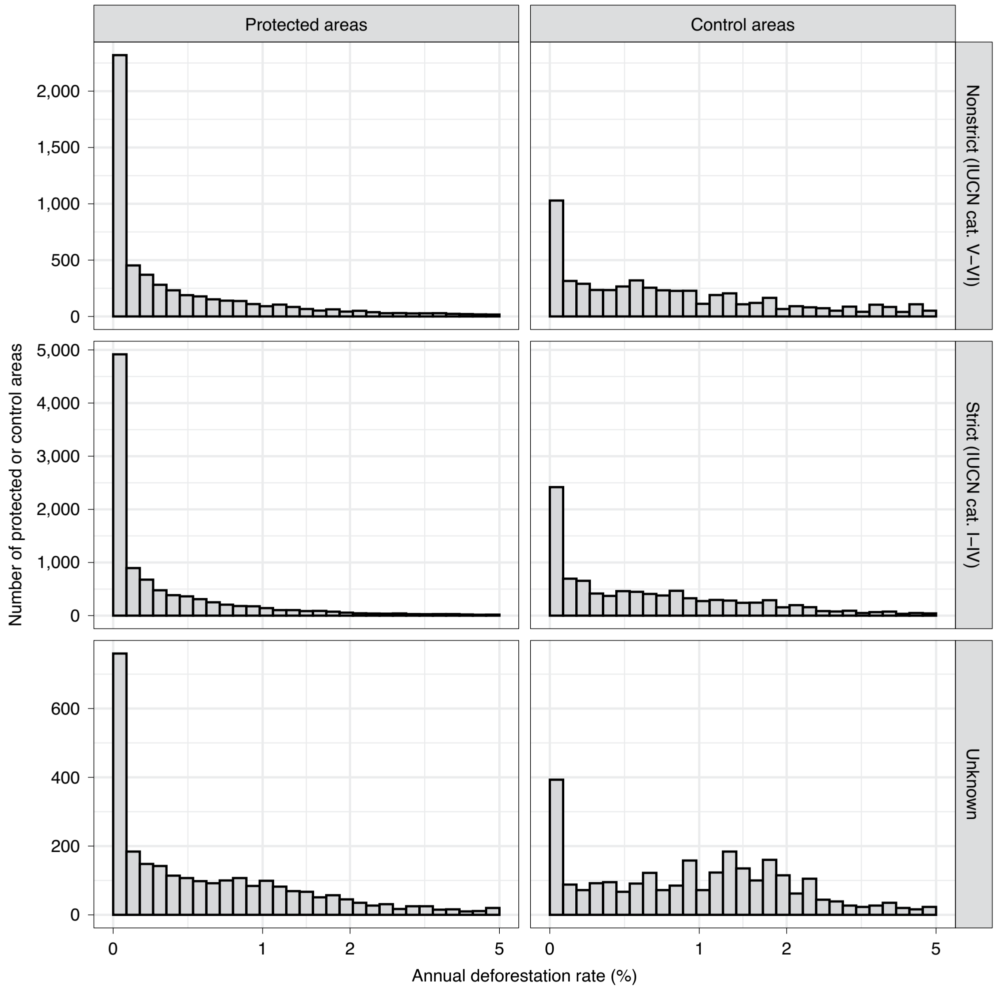

Fig. 2 | Deforestation rate distributions. Histograms of deforestation rates within PAs (left column) and associated control areas (right column) grouped by IUCN category (rows) for the 18,171 PAs in our main analysis. Deforestation rates (2001–2018) are expressed as mean annual rate relative to tree cover in 2000. Deforestation rates tended to be greater in control areas, providing evidence of PA effectiveness. Deforestation rate was truncated at 5% (covering more than 98% of the data) and $\log(1+x)$ transformed for plotting.

loss for the different continents and levels of protection tended to be similar when net forest loss was used instead of total forest loss (Fig. 3 and Extended Data Fig. 2).

We identified 9,875 PAs established between 2002 and 2017 that were suitable for inclusion in our spatiotemporal analysis. The establishment of these PAs was associated with a moderate increase in the deforestation rate (average = 0.19%; s.e.m. = 0.02%), whereas control areas saw a larger increase in the deforestation rate (average = 0.61%; s.e.m. = 0.02%) over the same time span (Extended Data Fig. 3). This overall pattern was observed for both strict and nonstrict PAs in lower and higher GDP countries (Extended Data Fig. 3).

Predictors of PA effectiveness. We found all predictors of PA deforestation rates to be spatially varying with the exceptions of travel time to nearest densely populated area (estimate = 0.066; standard error = 0.071; $P = 0.356$), threatened forest species richness (estimate = 0.080; standard error = 0.037; $P = 0.029$) and non-threatened forest species richness (estimate = 0.018; standard error = 0.004; $P < 0.001$) (Fig. 4 and Extended Data Figs. 4 and 5). Reserve area and background (that is, control area) deforestation rate were both generally positively associated with PA deforestation, although, in both cases, the effects appeared to be stronger in high latitudes and weaker in the tropics (Fig. 4). The effects of the other predictors were often relatively weak or inconsistent (Extended Data Fig. 4).

National level PA effectiveness scoring. Overall, the mean deforestation rate within PAs was 41.1% lower than in control areas (0.62% per year compared with 1.05% per year). This is analogous to deforestation within PAs occurring at background rates over 58.9% of their area and at a rate of 0% over 41.1% of their area, on average ($0.0062 \approx 0.411 \times 0 + 0.589 \times 0.0105$). Thus, the 17% Aichi Target goal (with 0% PA forest loss) is equivalent to 41.3% of land protected after accounting for deforestation within PAs (as $0.413 \times 0.411 \approx 0.17$)—a more than twofold increase.

Globally, 15.7% of forest is formally protected; however, after adjusting for deforestation within reserves, this was reduced to only 6.5%. That is, the 15.7% of forest protected with current deforestation rates would have the same total deforestation rate as 6.5% protected with no deforestation and 9.2% protected with the control area mean deforestation rate ($0.157 \times 0.0062 \approx 0.065 \times 0 + 0.092 \times 0.0105$). Among the 63 countries that we considered, 34 (54%) have at least 17% of their forested area protected (Supplementary Table 1). However, countries varied greatly in terms of area protected after adjusting for effectiveness, where effectiveness is defined as the ratio of control area deforestation to PA deforestation

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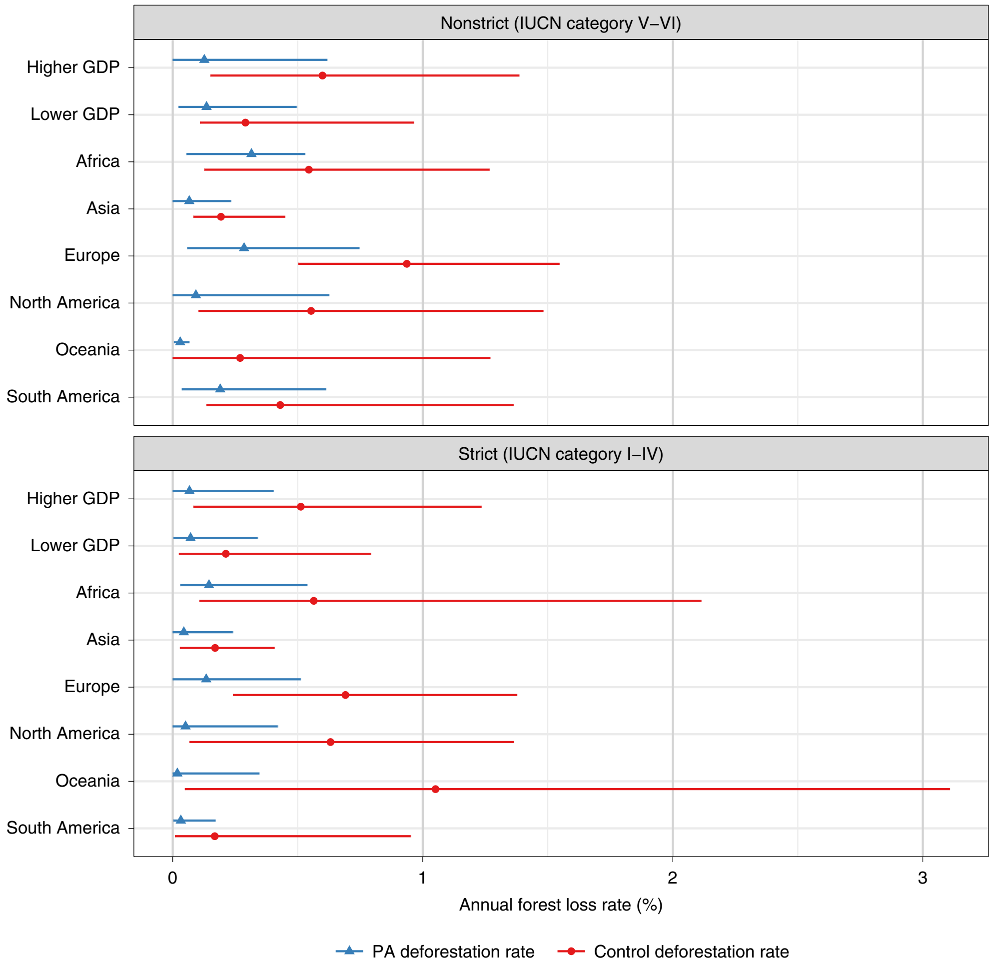

Fig. 3 | Forest loss in and around PAs. Results are grouped by geographic region and PA IUCN category. For each PA, the variables shown are PA and control area forest loss. Forest loss is for the period 2001–2018 and is expressed as the annual deforestation rate relative to forest cover in 2000. Points correspond to median (across PAs) percentage forest loss. Error bar end points are the 1st and 3rd quartiles for this variable. Forest loss within PAs has generally been less than in nearby unprotected areas. The overall pattern of forest loss being lower in PAs than in control areas was generally consistent across both PA type and geographic region.

(Fig. 5 and Supplementary Table 1). These adjusted area protected values ranged from 0.03 (China) to 2.36 (New Zealand) (Fig. 5). South Africa had the highest effectiveness score, 8.10, indicating that PAs there collectively had a greater than eightfold decrease in deforestation rates relative to matched control areas (Supplementary Table 1). Strikingly, there were no countries with both very high PA coverage (adjusted for effectiveness) and high forest species richness (Fig. 5).

There was similarly high variation in the species threat index (ratio of forest vertebrate species richness to level of protection after accounting for effectiveness), with values for the seven countries with at least 500 forest vertebrate species ranging from 1,516 (Mexico) to 6,913 (Indonesia). The continents with the highest mean adjusted threat indices were South America (2,571), Asia (2,196) and Oceania (1,834). The countries with the highest deforestation rates were Sierra Leone (2.40% per year; 5.63% of forested area protected), Malaysia (2.16% per year; 6.29% protected) and Cambodia (1.90% per year; 25.85% protected) (Fig. 6 and Supplementary Table 1). Of the three countries with the greatest amounts of aboveground forest carbon, Russia had the highest threat index for carbon (109), followed by the United States (57) and Brazil (29) (Fig. 6 and Supplementary Table 1). The 11 countries in our analysis with less than 10% of their forested area protected had a total of 72.6 Gt aboveground forest carbon (Supplementary Table 1). Forest carbon and total forest species richness were moderately correlated ($r=0.37$).

Diagnostic and sensitivity analyses. Overall quality of matching was high, with absolute standardized biases ranging from 0.004 for slope to 0.038 for population density. The Rosenbaum bounds excluded zero up to $\Gamma=4$, suggesting that our main result about PA effectiveness relative to control areas is at least moderately robust to hidden biases. When stricter matching criteria were applied (9–10 classes per continuous matching covariate), the resulting dataset size decreased from 18,171 observations to 13,291 observations. For this new dataset, the mean deforestation rate in PAs was estimated to be 42.7% lower than in control areas (compared with 41.1% with our main dataset). Deforestation rate patterns by level of protection and geographic region were generally similar (Extended Data Fig. 6). Overall modelling conclusions about the effects of background rate deforestation and reserve size were also similar, although the effects of strict protection, reserve age and population density (along with travel time) were found to not be spatially varying for the smaller dataset (Extended Data Fig. 7).

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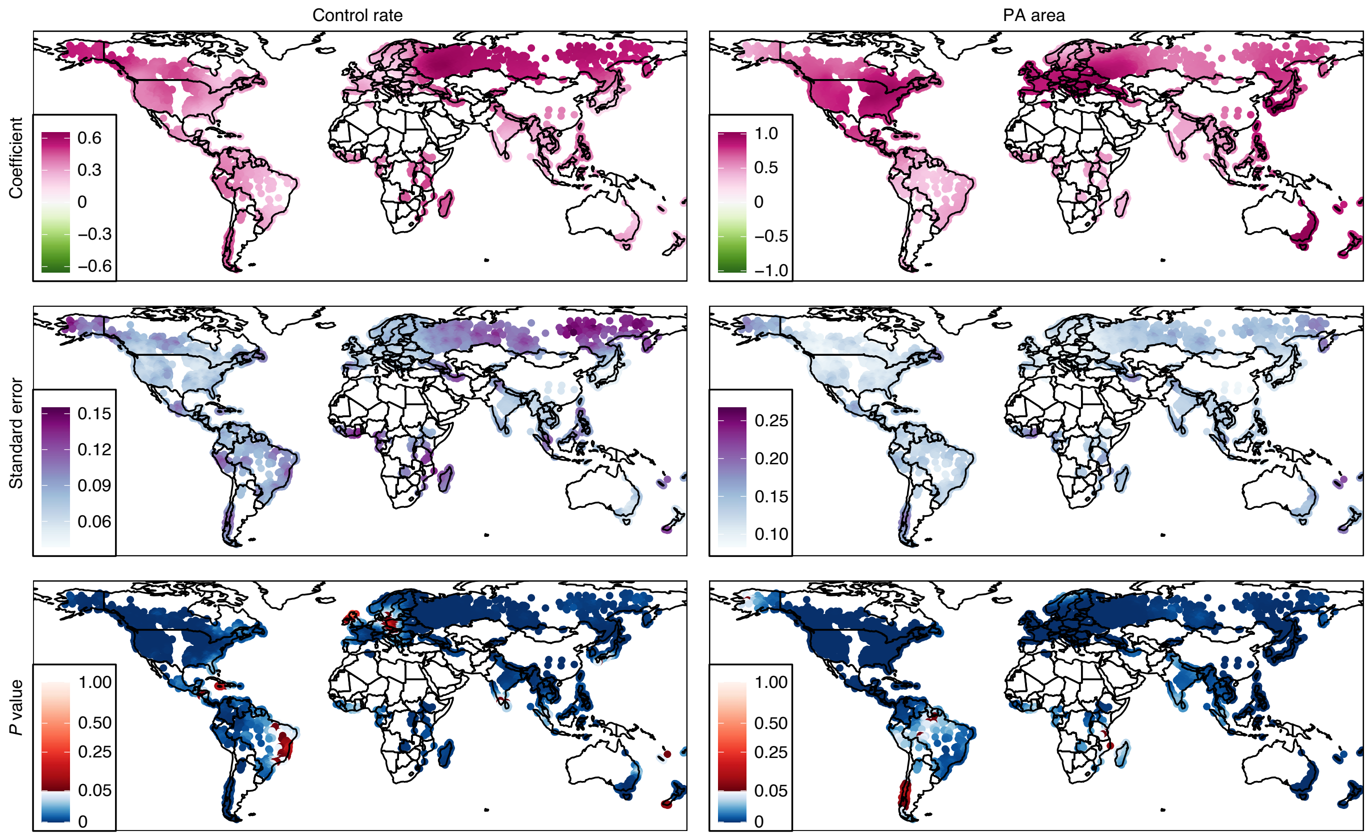

Fig. 4 | Effects of control area deforestation rate and PA area on PA deforestation rates. The maps show spatially varying coefficient model results (coefficient estimates, standard errors and false-discovery-rate-adjusted *P* values) for these predictors of PA deforestation. These results indicate relatively consistent positive relationships for control area (background) deforestation and reserve area. Extended Data Fig. 4 shows results for the complete set of spatially varying predictors. Only coefficients with associated *P* values less than 0.05 are mapped.

Discussion

PAs have been put forth as an important policy tool to ensure global biodiversity conservation and carbon storage in the face of expanding human resource exploitation[3]. However, limitations to enforcement and monitoring can reduce their effectiveness[25–27]. Indeed, our results indicate that PAs are rarely, if ever, strictly 'protected' from deforestation, but rather have the effect of slowing forest loss in relation to matched control areas (Fig. 3). This is consistent with underfunding being common, especially in countries with lower GDP per capita where many reserves may lack the equipment, staff and resources needed for effective management[28–31]. Importantly, while prevention of deforestation is just one of many potential PA management goals, it may be correlated with other metrics of PA management success. For example, forest species are expected to have reduced likelihood of population declines in PAs with lower deforestation rates, either owing to greater forested habitat availability, or other benefits of more effective management, such as effective suppression of illegal hunting. The correlation, albeit moderate, between forest biodiversity and carbon stocks provides further evidence of potential co-benefits, but also suggests there may be important tradeoffs that must be considered when selecting locations for reserves (Supplementary Table 1).

Earth's forests are a major carbon sink, with an estimated uptake of 2.3 $Pg\,C\,yr^{-1}$ between 2000 and 2007[32]. For comparison, the estimated total emissions rate over this period was 8.7 $Pg\,C\,yr^{-1}$, of which roughly 1.1 $Pg\,C\,yr^{-1}$ was due to tropical land use change[32]. As PAs have the potential to limit deforestation, they can be of use in mitigating future climate change as well as protecting biodiversity[21]. Our finding that the effects of PAs on forest loss are highly variable has substantial implications for the implementation of carbon payment systems such as the United Nations' Reducing Emissions from Deforestation and Forest Degradation (REDD+) programme and for future payment for environmental services schemes in that there is a tradeoff between focusing funding on areas where PAs are common and effective (but may have less room for improvement) and areas where PAs are less common and less effective[33]. Although the actual implementation and impact of REDD+ has been hampered by a lack of commitment from the potential funding sources in countries with higher GDP per capita[34], several countries are constructing specific payment for environmental services schemes supported by national funds[35,36]. Such funds could make use of regional threat indices similar to those in our analysis (Supplementary Discussion), allowing them to identify the most vulnerable hotspots within their national PAs and prioritize actions in parks that will have the most effective outcomes. Using these fine-scale indices, internal funding could be directed towards areas with abundant biodiversity, high forest carbon stocks and limited protection.

Larger PAs tended to have higher forest loss rates, even after accounting for loss in paired control areas, although this difference was lower in tropical regions (Extended Data Fig. 4). This is consistent with previous work that has shown that both budgets and staffing on a per-area basis are negatively correlated with reserve size[37], although costs also have been shown to decline rapidly with increasing reserve size[31]. Thus, PA size may be an especially important consideration for biodiverse countries with limited protection, which could benefit from both greater area protected and more effective protection (Fig. 5 and Supplementary Table 1). Our finding on PA size may be partly attributable to controlling for background

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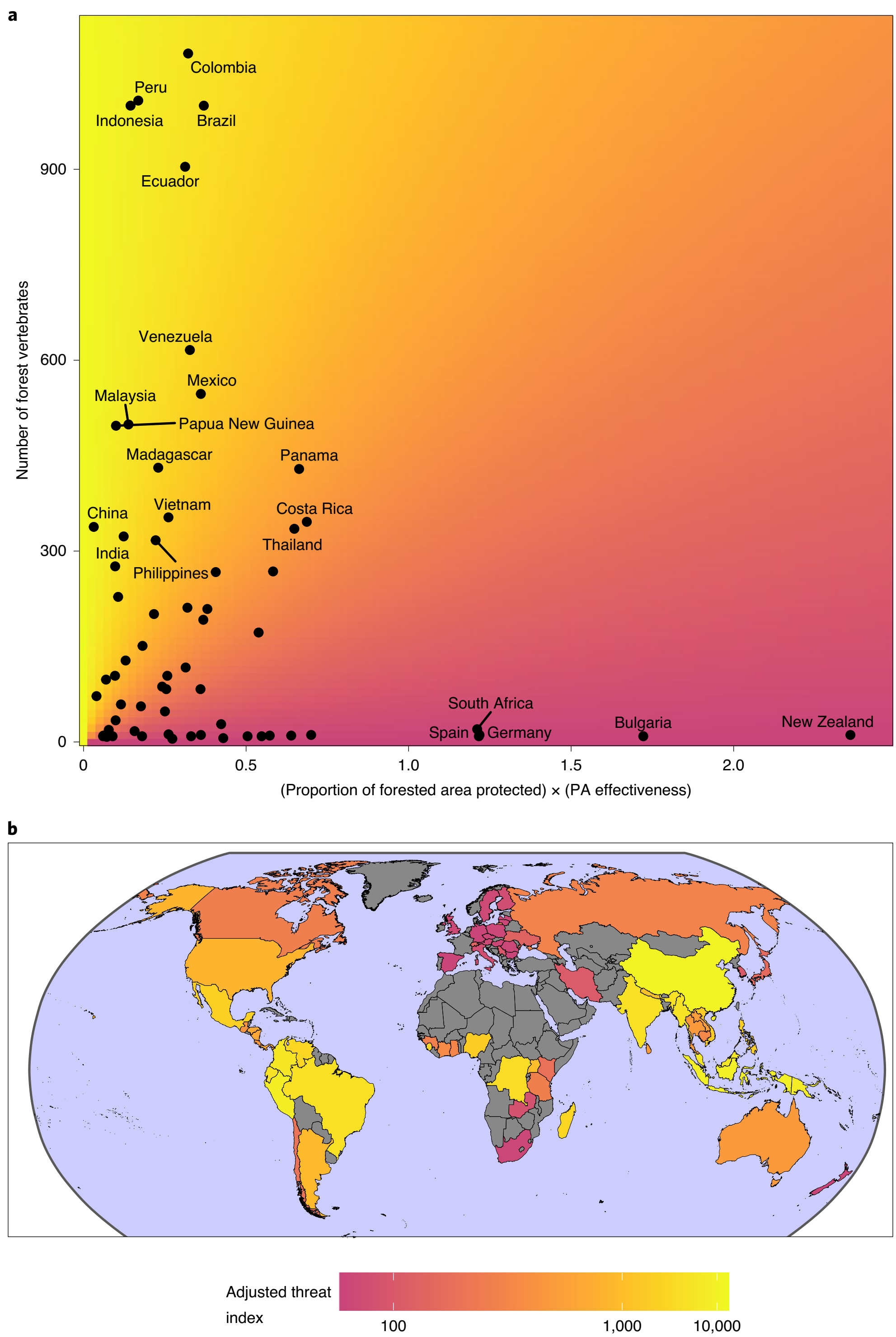

Fig. 5 | Forest biodiversity threat index. a, Number of forest vertebrate species versus area protected adjusted (that is, multiplied) by country-level PA effectiveness (based on forest loss in PAs compared with forest loss in matched control areas). The colours indicate the ratio of these variables, which we term species threat index, and provide insight into which countries have exceptionally high forest species richness relative to their level of protection. **b**, Threat index map showing only countries with at least 15 PAs in our main analysis, at least 5 forest obligate vertebrates and at least 10,000 km^2 forest. The adjusted threat index tended to be greatest in the tropics as expected, given the large number of species in these regions.

deforestation rates given that large reserves may tend to be in areas with relatively little human impact and thus lower deforestation pressure. While strict protection was more effective than nonstrict protection in a few small regions, the effect was not spatially robust (Extended Data Fig. 4). This may be a consequence of differences in levels of use allowed within nonstrict PAs, particularly when they overlap communal lands.

After adjusting for effectiveness at limiting deforestation, New Zealand scored highest for forest protection (Fig. 5 and Supplementary Table 1). In this country, widespread loss of

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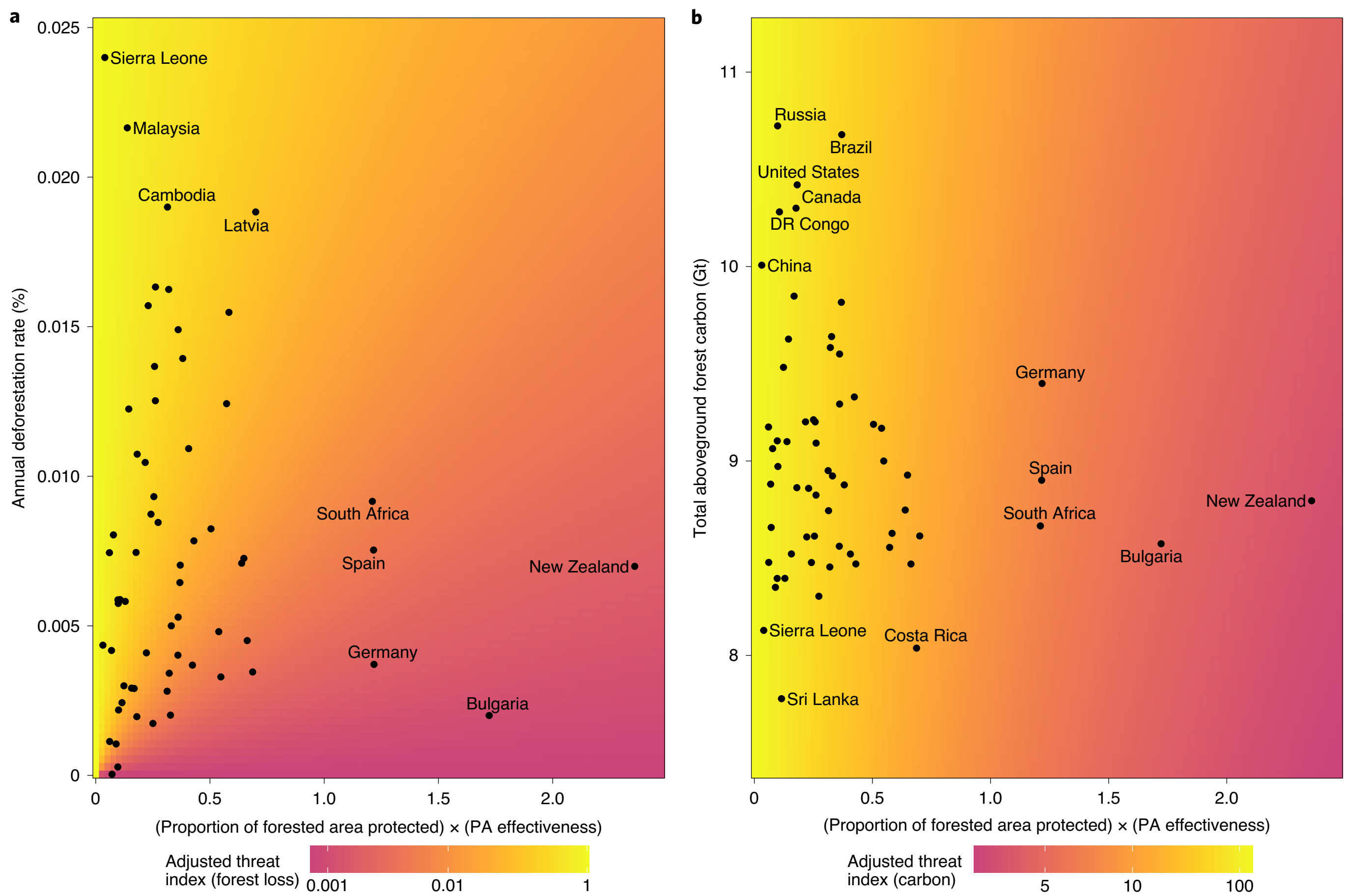

Fig. 6 | Annual deforestation rate and total aboveground forest carbon versus adjusted forested area protected. a,**b**, Annual deforestation rate (**a**) and total aboveground forest carbon (**b**) versus adjusted forested area protected. The adjustment was made by multiplying the proportion of forested area protected by country-level median PA effectiveness (based on forest loss near PAs compared with forest loss within PAs). The colours indicate the ratios of these variables, which we term threat indices (for forest loss and carbon), and provide insight into which countries have exceptionally high deforestation rates or forest carbon stocks relative to their levels of protection. The dataset is provided in Supplementary Table 1. DR Congo, Democratic Republic of the Congo.

indigenous land cover occurred in recent years, but most of this loss (93.9%) occurred outside PAs[38]. This suggests that PAs in New Zealand may be particularly effective at preventing deforestation. New Zealand also had the second highest PA effectiveness score (7.53), after South Africa (8.10). However, these results provide only a partial picture because major forest loss occurred in New Zealand prior to 2000[39]. Conversely, among countries with at least 1,000 forest vertebrate species, Indonesia is notable in that it had both the least amount of forested land protected and the highest species threat index score (Fig. 5). Biodiversity in Indonesia is under threat owing to this country's high rate of deforestation, increasing oil palm production and illegal wildlife trade[40]. Furthermore, Southeast Asia has the greatest proportions of endemic bird and mammal species, and the highest rate of forest loss[40].

Conservation implications. The species-based threat index that we present quantifies countries' forest vertebrate biodiversity relative to their levels of protection (Fig. 5 and Supplementary Table 1). It provides what we believe is the first quantitative measure of the extent to which forest biodiversity and protection align. The finding that many countries with higher GDP per capita are comparatively well protected given their levels of forest biodiversity (Fig. 5) is not surprising considering the financial costs of PAs, and suggests that economic growth could eventually allow for greater protection. Unfortunately, environmental degradation and species loss often occur in the early periods of development[41], and it may be more difficult to reintroduce native species than to increase PA area or effectiveness. Consequently, it should not be assumed that countries with lower GDP per capita can readily restore biodiversity in the long term after income levels increase and forest protection measures are enhanced. Similarly, existing forests store substantial amounts of carbon (Fig. 6), and their loss may not be easily compensated for (for example, through reforestation), especially over short timescales. These timescale differences demonstrate the urgent need to expand and strengthen PA networks where they can be most beneficial.

The Convention on Biological Diversity's global PA target (Aichi Target 11) sets a global, rather than country-specific, percentage goal (17%). While this goal often motivates countries targeting 17% protection, based on our threat index, different goals for individual countries could instead be advocated, with higher targets in countries where biodiversity is most threatened[42]. To achieve these new goals, we therefore see it as vital that countries with higher GDP per capita provide support for the establishment and maintenance of PAs necessary to achieve these higher targets in biodiverse countries with lower GDP per capita, ensuring distributional equity in global conservation targets. It is critical that such support is provided in an equitable way that promotes social justice and sustainable

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development, and is not used to justify ignoring the protection of less biodiverse areas globally[20]. While proximate threats to biodiversity tend to be local, the drivers of these threats are often global[43]. Similarly, many potential benefits and co-benefits associated with biodiversity are accrued on both local and global scales. Thus, the country-specific threat indices reported here highlight humanity's failure to allocate conservation funding, research and other resources where they are most needed.

Many biodiverse countries with substantial forest carbon stocks are unable to achieve effective conservation in isolation—especially given outside demands for their natural resources. One way to reduce these demands is through the establishment of multinational import bans on deforestation-associated commodities[44], which must be coupled with internal enforcement and more efficient use of forest resources (for example, through technological developments). Additionally, strategies such as environmental certification and labelling schemes could be used to give consumers in wealthy countries an opportunity to reward environmentally friendly practices[45]. This may be especially effective in reducing the occurrence of selective illegal logging, which is often difficult to monitor and may be prevalent in large reserves that tend to have high apparent deforestation rates and are more likely to be downsized, downgraded or degazetted[46] (Fig. 4). More research is needed to assess the possible benefits and drawbacks of import bans and certification and labelling schemes—a topic beyond the scope of our present analysis. Although global conservation problems require global solutions, local factors must also be considered, including how conservation programmes can best make use of local knowledge, benefit and empower communities, and contribute to long-term economic development and poverty reduction[47].

As of 2018, 14.9% of land is protected, which is close to the 17% Aichi goal[48]. However, no similar numeric target has been stated for PA quality. This creates a policy incentive to value total PA area above PA effectiveness[49]. Unfortunately, deforestation rates in large PAs (which cover a sizeable area) seem to be relatively high (Fig. 4). To date, more than 40 approaches have been developed to assess reserve context, management inputs and design[50], involving techniques including questionnaires[51], selection of focal conservation targets[52] and engagement with stakeholders[53]. However, such assessments do not directly capture outcomes. Thus, estimates of PA deforestation rates relative to those in matched control areas represent a simple, outcome-focused complement to these methods, acting as a useful starting point for measuring effectiveness given the many co-benefits of reducing deforestation and growing forests to their ecological potential, including increased carbon storage, improved water and air quality, recreation opportunities, and reduced erosion[54]. While we assessed PA deforestation rates relative to matching control areas, it is important to note that absolute deforestation rates can also be of interest. This is especially true in cases where background deforestation rates are exceptionally high, potentially leading to PAs with moderate deforestation rates being identified as highly effective relative to control areas.

By adjusting area protected using a measure of PA effectiveness, we have combined PA quantity (area) and quality (effectiveness) into a single metric (Figs. 5 and 6). This combination represents a small step towards preventing 'perverse outcomes', wherein managers optimize PAs using a single, imperfect metric such as total area protected[5], and can complement existing PA effectiveness assessments[51,55,56]. Taken together, the combination of PA area and PA effectiveness can be used to set more robust targets for PAs—an important consideration for the upcoming Fifteenth meeting of the Conference of the Parties to the Convention on Biological Diversity conference, where new biodiversity conservation targets will be set. Scientists have called for half of Earth's surface to be protected[57,58]. Although such direct statements can attract widespread public support, the success or failure of future protection targets to conserve biodiversity and carbon stores will depend on whether or not they include sub-targets or goals that can be readily measured, connected to species and populations, and achieved in a way that benefits both humans and the environment on which we depend.

Methods

We estimated forest change rates within terrestrial PAs using the World Database on Protected Areas[59] and a set of global forest change maps[13]. We omitted PAs for which forest loss could not be accurately estimated, including recently established PAs, exceptionally small PAs and PAs outside forest biomes, using a series of filtering steps (Supplementary Methods). We resampled the tree cover (year 2000), forest loss (2001–2018) and forest gain (2000–2012) maps from ref. [13] to 1 km × 1 km resolution (Supplementary Methods). We then used forest loss to calculate an approximate annual deforestation rate and used forest loss and gain together to estimate net deforestation (Supplementary Methods).

We identified associated control areas for PAs using a variant of 1-k coarsened exact matching[60–62] and eight 'matching covariates': elevation, slope, tree cover, travel time to nearest densely populated area[63], population density[64], country, ecoregion[65] and primary driver of forest cover loss[66]. Our matched-comparison dataset consisted of one observation for each PA (treatment observations) and one observation for each 1-km raster pixel more than 10 km from all PAs (control observations). We avoided selecting control areas near PAs because these regions may have elevated deforestation rates due to local scale leakage (that is, displacement of deforestation from PAs to nearby areas as a result of protection)[18,67,68] and can differ substantially from adjacent PAs, making them unsuitable for use as counterfactual scenarios[69,70]. We first coarsened the combined dataset by discretizing continuous variables (Supplementary Methods) and then calculated the associated L1 imbalance indicating the extent to which treatment and control observations differ with respect to the matching covariates[71]. We then coarsened the dataset again and paired each PA with the set of control observations that had the same coarsened covariate values. Finally, we estimated forest loss rates within the control areas.

To verify that similar treatment and control units were successful matched, we conducted diagnostic and sensitivity analyses[62]. We first calculated the standardized bias for each covariate, which is defined as $(\overline{X_t} - \overline{X_c})/\sigma_t$, where $\overline{X_t}$ is the treatment mean, $\overline{X_c}$ is the control mean and σ_t is the treatment standard deviation[61]. Absolute standardized biases greater than 0.25 indicate that the quality of matching may be poor[61]. While standardized bias quantifies similarity with respect to observed covariates, there can also be hidden biases owing to unobserved confounding variables[72]. We explored sensitivity with respect to potential hidden biases using Rosenbaum bounds that quantify how results vary with respect to the odds of assignment (treatment or control) depending on unobserved variables[72,73]. We did this by calculating Rosenbaum bounds for the Hodges–Lehmann point estimate using the 'hlsens' function in the 'rbounds' R package[74] where deforestation rates were $\log(x + 10^{-7})$ transformed to parallel subsequent modelling analyses. The odds of differential assignment due to variables not used for matching, Γ, was allowed to vary from 1 to 6 in increments of 1. As a final sensitivity analysis, we recalculated our main results after matching using stricter criteria (Supplementary Methods).

As additional modelling covariates, we determined threatened and non-threatened forest vertebrate species richness using International Union for Conservation of Nature (IUCN) Red List species range maps (Supplementary Methods). We also obtained year of establishment (where available), area and associated GDP per capita (country level; purchasing power parity, current international $) for each PA[75]. For each country, we used the average GDP per capita between 2000 and 2018 (excluding years without data).

The most rigorous test of PA effectiveness is to compare deforestation between pre- and post-PA establishment in relation to associated control areas. Effectively, this is a 'before–after, control–impact' design[76]. Unfortunately, most PAs were established before the origin of global deforestation data, precluding the use of this framework for our primary analysis. Nevertheless, nearly 10,000 PAs meeting our criteria for inclusion were established between 2002 and 2017, which enabled us to adopt this rigorous design for a subset of PAs as a secondary analysis (Supplementary Methods).

Statistical modelling and hypotheses. Because the effects of predictors of PA deforestation may vary spatially due to differences in regional context, we adopted an SNVC modelling approach[77–79] (Supplementary Methods). We used 'PA deforestation rate' as the response variable and statistically controlled for deforestation rates in control areas by including this variable as a covariate. We included six other predictors of deforestation rates: population density, travel time to nearest densely populated area, PA age, GDP per capita, management category (Strict: IUCN category I–IV; Nonstrict: IUCN category V–VI) and PA area (Supplementary Methods). We formed the following set of a priori hypotheses based on the PA literature:

1. Strictly protected PAs have lower deforestation rates than nonstrictly protected PAs because they are more restrictive in terms of allowed activities[7,21,70] and have experienced limited increases in human pressures[6]. However, there

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is also evidence to suggest that Indigenous and other mixed-use PAs can be more effective because they may have greater local support[14,80].

2. Larger PAs, which have had lower increases in human pressures[6], have lower deforestation rates as illegal logging deep inside reserves can be logistically challenging[81]. However, this type of logging is often selective, and thus hard to quantify with remotely sensed imagery. Alternatively, larger PAs could have higher deforestation rates due to potentially having lower budgets per area.
3. GDP per capita is negatively associated with PA deforestation rates because wealthier countries may be better able to fund monitoring and enforcement efforts to ensure PA policies are followed. Alternatively, deforestation rates could initially rise with GDP per capita (as a consequence of increased resource extraction), and then decline (with increasing funding available for conservation)—the environmental Kuznets curve hypothesis[82]. This latter hypothesis would be consistent with the effect of GDP per capita on deforestation rates being positive in poorer regions and negative in wealthier regions.
4. Time since establishment (that is, PA age) is negatively associated with deforestation rates because management infrastructure may (rapidly) increase in the years after establishment[83].

This list of hypotheses is not exhaustive and, in many cases, we have intentionally formed multiple working hypotheses[84]. Both travel time to nearest densely populated area and population density are important measures of potential human impacts. However, we did not form a priori hypotheses for these variables because it is unclear whether they would have differential impacts on deforestation rates in PAs compared with similar unprotected control areas. Similarly, as an exploratory analysis, we also tested whether the numbers of threatened and non-threatened species were associated with deforestation rates within PAs (Supplementary Methods).

Country indices. We used the data on forest loss in and around PAs to explore how area protected and PA effectiveness relate to forest obligate species richness, forest carbon stocks and deforestation rates within countries. For each country, we calculated: (1) forest obligate vertebrate species richness; (2) forest carbon stocks; (3) average forest loss rate; (4) overall PA effectiveness (with respect to limiting deforestation); and (5) percentage of forested area protected (Supplementary Methods). PA effectiveness at the country level was estimated using the ratio of the mean deforestation rate in control areas to the mean deforestation rate of PAs within the country. For each country, we refer to this ratio as its PA effectiveness score. To simplify interpretation, we restricted our scope to countries with at least 15 PAs in our main analysis, 5 forest obligate vertebrate species and 10,000 km^2 of forested land.

We then computed the species threat index, which we defined as the ratio of forest species richness to proportion of forested area protected multiplied by the PA effectiveness score. Countries with high species threat index scores have little protection relative to the number of forest species present. Thus, this analysis identifies countries where improvements in PA quantity or quality (that is, effectiveness at reducing deforestation rates) may have the most beneficial total impact on forest biodiversity. We also calculated variants of the species threat index score using the overall forest loss rate and (log-transformed) aboveground forest carbon biomass in place of species richness.

In summary, we computed the following three threat indices, I, for each country:

$$I_{\mathrm{Species}} = \frac{\mathrm{Species}}{\mathrm{Prot.} \times \mathrm{Score}}; I_{\mathrm{Loss}} = \frac{\mathrm{Loss}}{\mathrm{Prot.} \times \mathrm{Score}}; I_{\mathrm{Carbon}} = \frac{\log_{10}(\mathrm{Carbon})}{\mathrm{Prot.} \times \mathrm{Score}}$$

where 'Species' is the total number of forest vertebrate species in the country, 'Prot.' is the proportion of forested land protected, 'Score' (a measure of effectiveness) is the total forest loss in control areas divided by total forest loss within PAs, 'Loss' is the estimated annual deforestation rate and 'Carbon' is the aboveground forest biomass in units of Gt C. Each index is strictly positive, with higher values indicating potential conservation issues because they suggest that the level of protection in a country is not commensurate with its biodiversity, deforestation pressure, or forest carbon stocks.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data used are publicly available. Sources for the data are given in the Methods section.

Code availability

Analysis code is available at https://github.com/wolfch2/PA_matching.

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Author contributions

C.W. and M.G.B. conceived the project. C.W. conducted the data analysis and wrote the first draft with input from T.L., W.J.R., D.A.Z.-C. and M.G.B. All authors edited the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at https://doi.org/10.1038/s41559-021-01389-0.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41559-021-01389-0.

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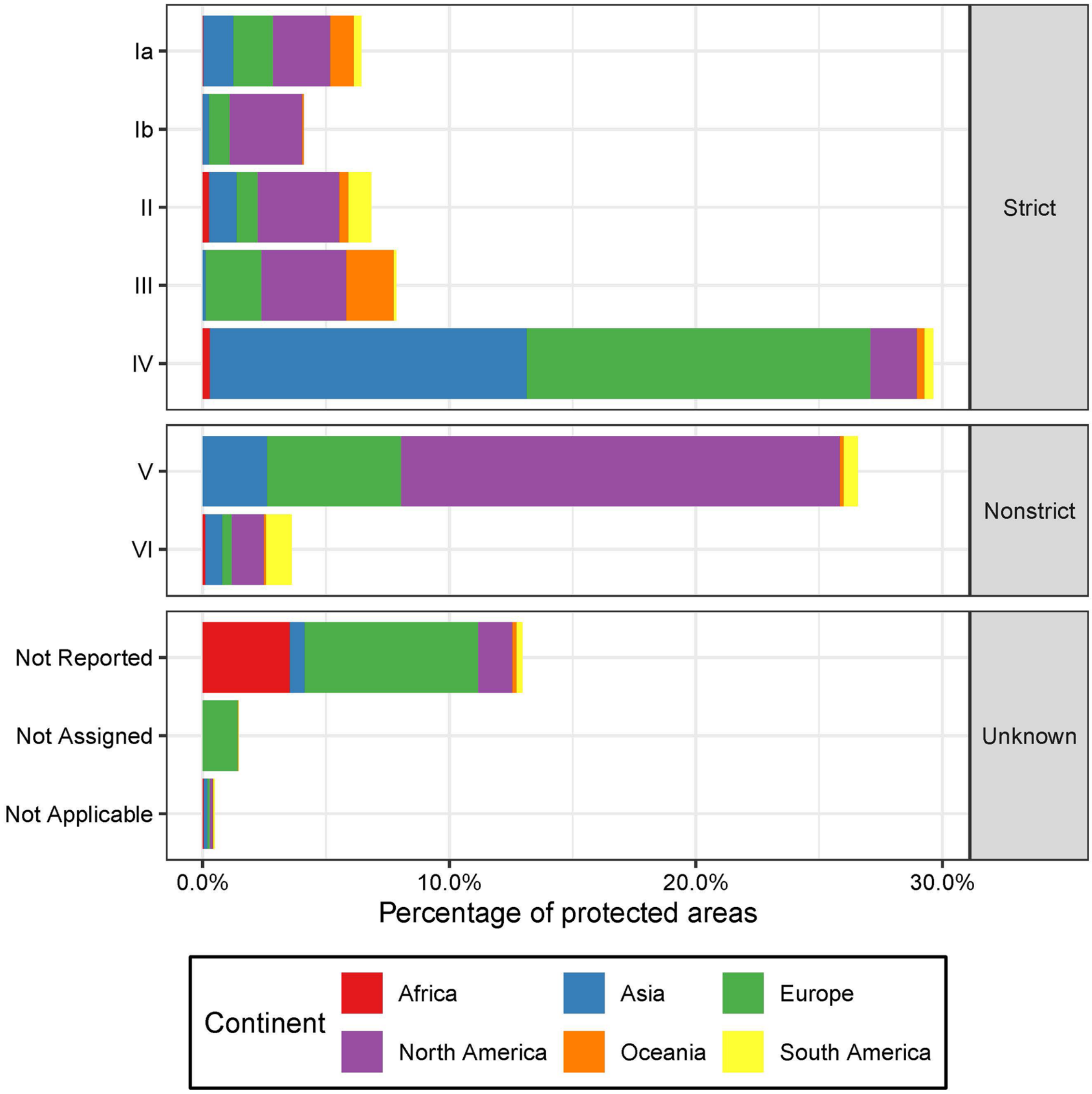

Extended Data Fig. 1 | The distribution of IUCN categories for the 18,171 PAs in our primary spatial analysis. Protected area categories are: Ia – 'Strict Nature Reserve,' Ib – 'Wilderness Area,' II – 'National Park,' III – 'Natural Monument or Feature,' IV – 'Habitat/Species Management Area,' V – 'Protected Landscape/ Seascape,' VI – 'Protected area with sustainable use of natural resources.' The protected areas were split into 'Strict' (categories I-IV), 'Nonstrict' (categories V-VI), and 'Unknown' (any other category).

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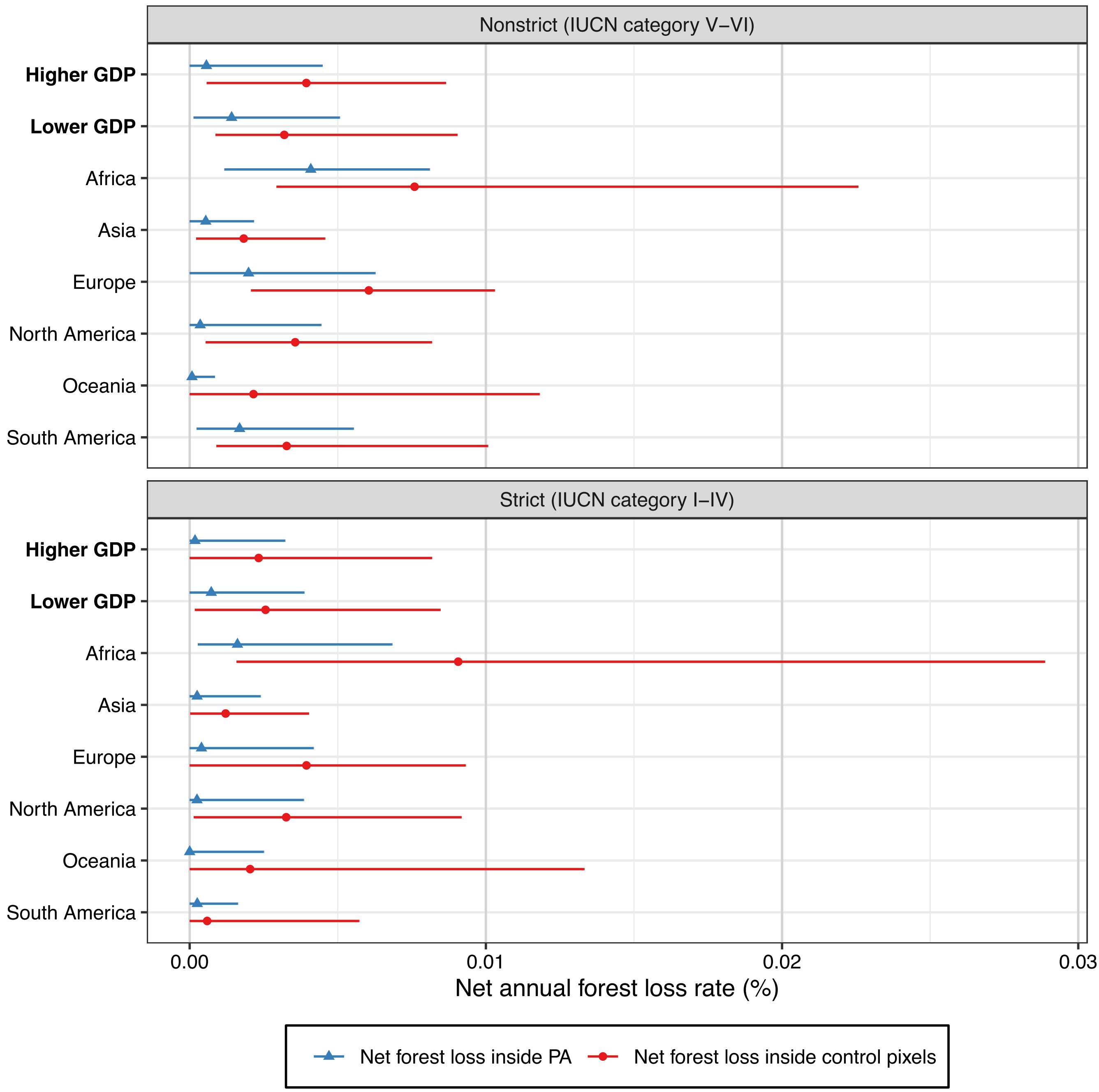

Extended Data Fig. 2 | Net annual forest loss rate within protected areas and in matched control areas. In contrast to the forest loss results, net loss is not a true percentage since loss and gain are binary while cover is continuous (see SI Methods for details). Results are grouped by geographic region and PA category (IUCN category I-IV: 'Strict,' V-VI: 'Nonstrict'). Points correspond to median (across PAs) percentage forest loss. Error bar end points are the 1st and 3rd quartiles for this variable. Forest loss within protected areas has generally been less than in nearby unprotected areas.

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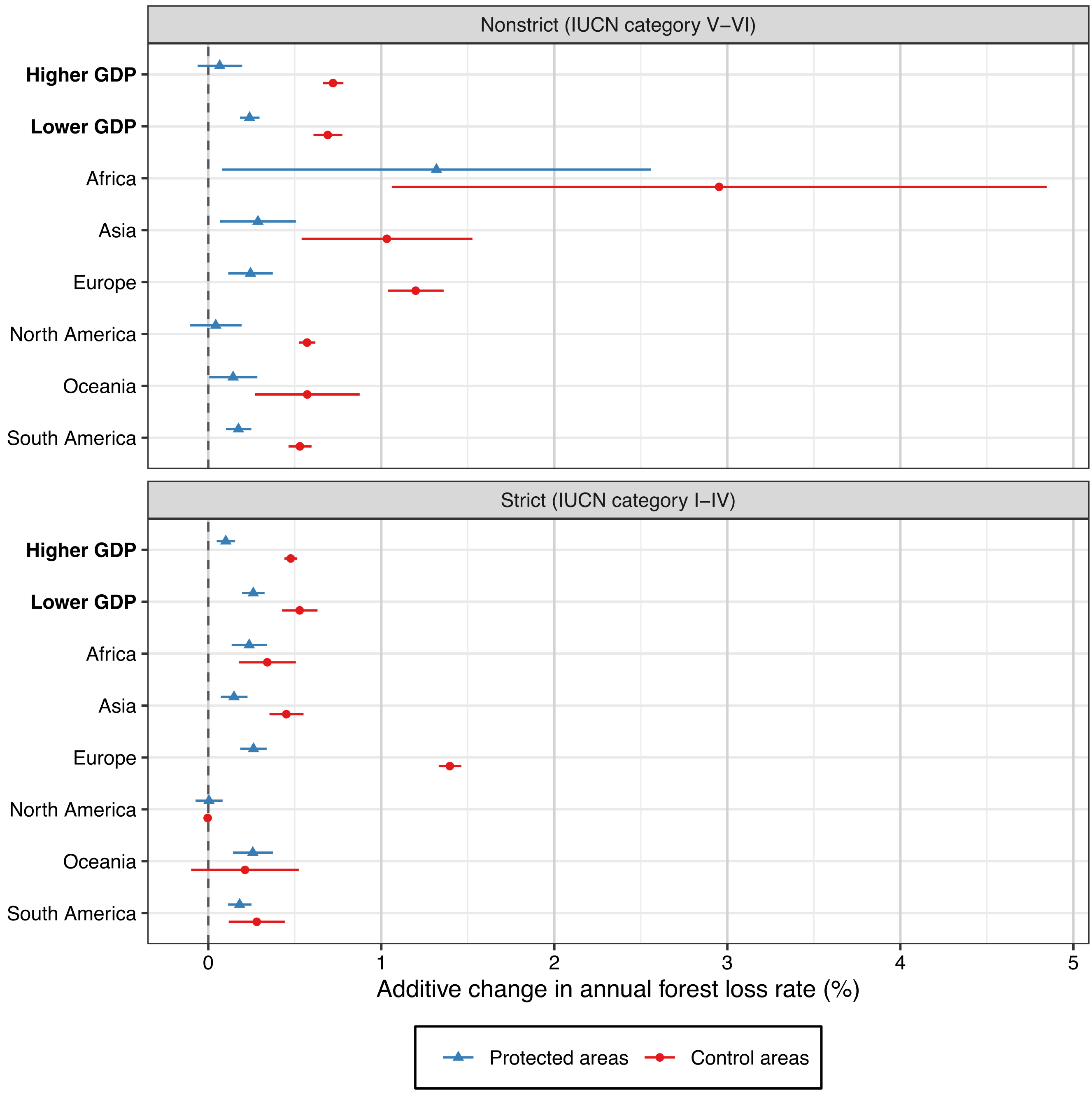

Extended Data Fig. 3 | Change in the annual forest loss rate associated with the creation of PAs. The change variable is the deforestation rate after minus before creation of a PA. Results are grouped by geographic region and PA category (IUCN category I-IV: 'Strict,' V-VI: 'Nonstrict'). Points correspond to means, and error bars show standard errors.

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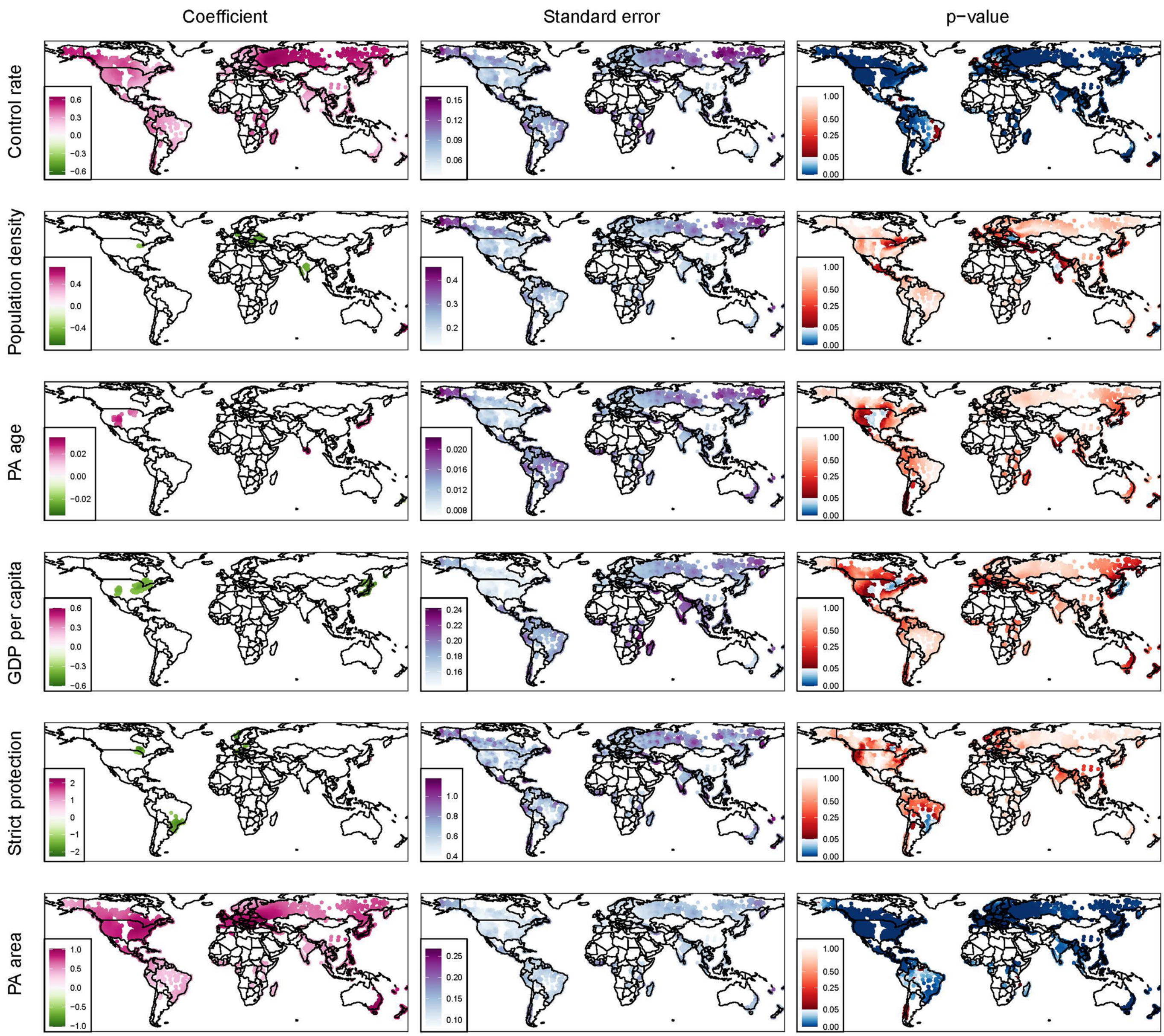

Extended Data Fig. 4 | Predictors of deforestation rates within protected areas. Each row shows a different predictor variable, and the columns show coefficient estimates, standard errors, and FDR-adjusted p-values. Because a spatially varying coefficient model was used, estimates, etc. can all vary geographically. Travel time to nearest densely-populated area was also included as a predictor, but it was found to be non-significant, with no evidence of spatial variability. Only coefficients with associated p-value less than 0.05 are mapped.

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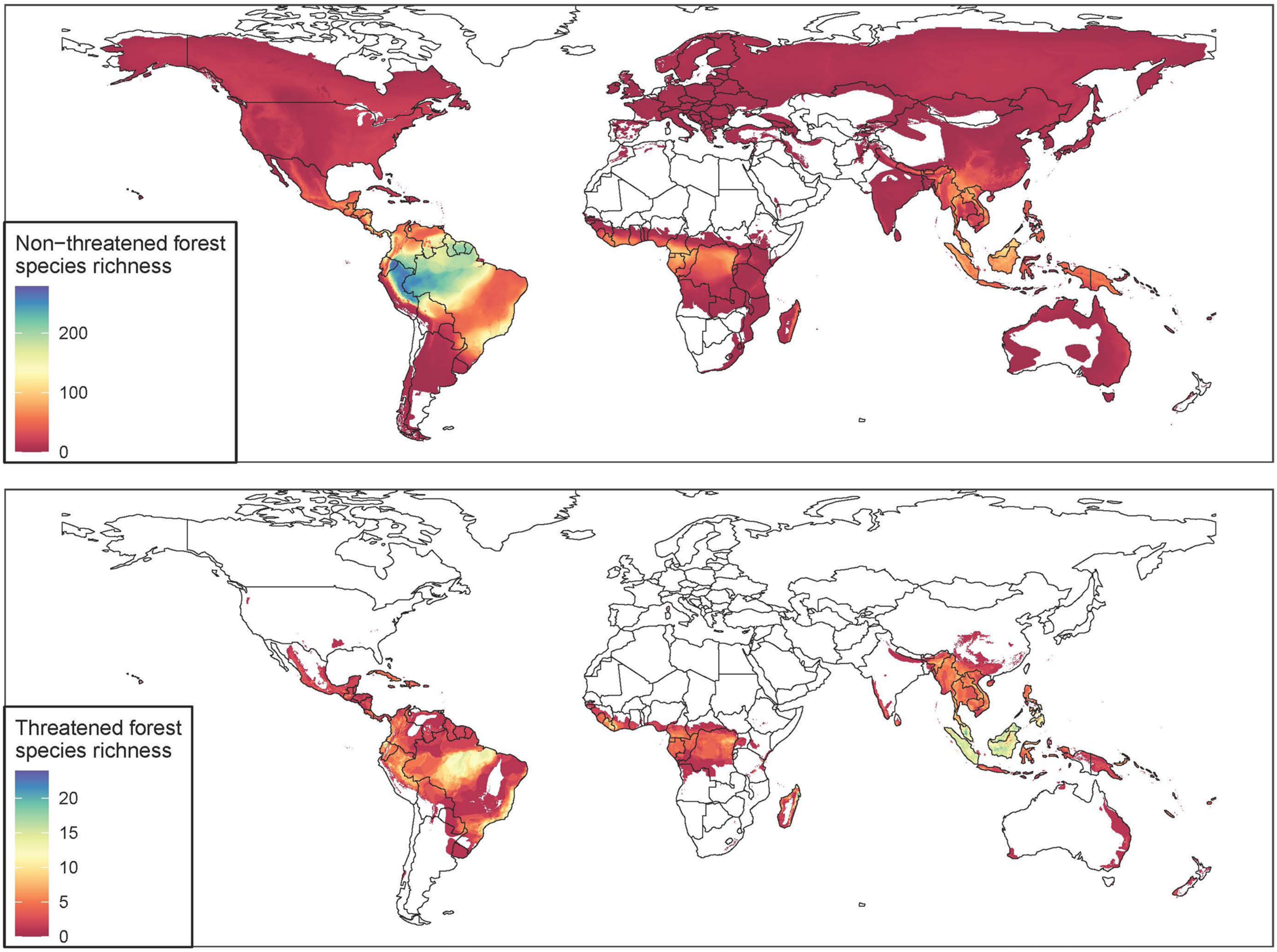

Extended Data Fig. 5 | Threatened and non-threatened forest vertebrate species richness. We considered these spatial variables as predictors of deforestation within protected areas to explore relationships between PA effectiveness (with respect to limiting deforestation) and biodiversity.

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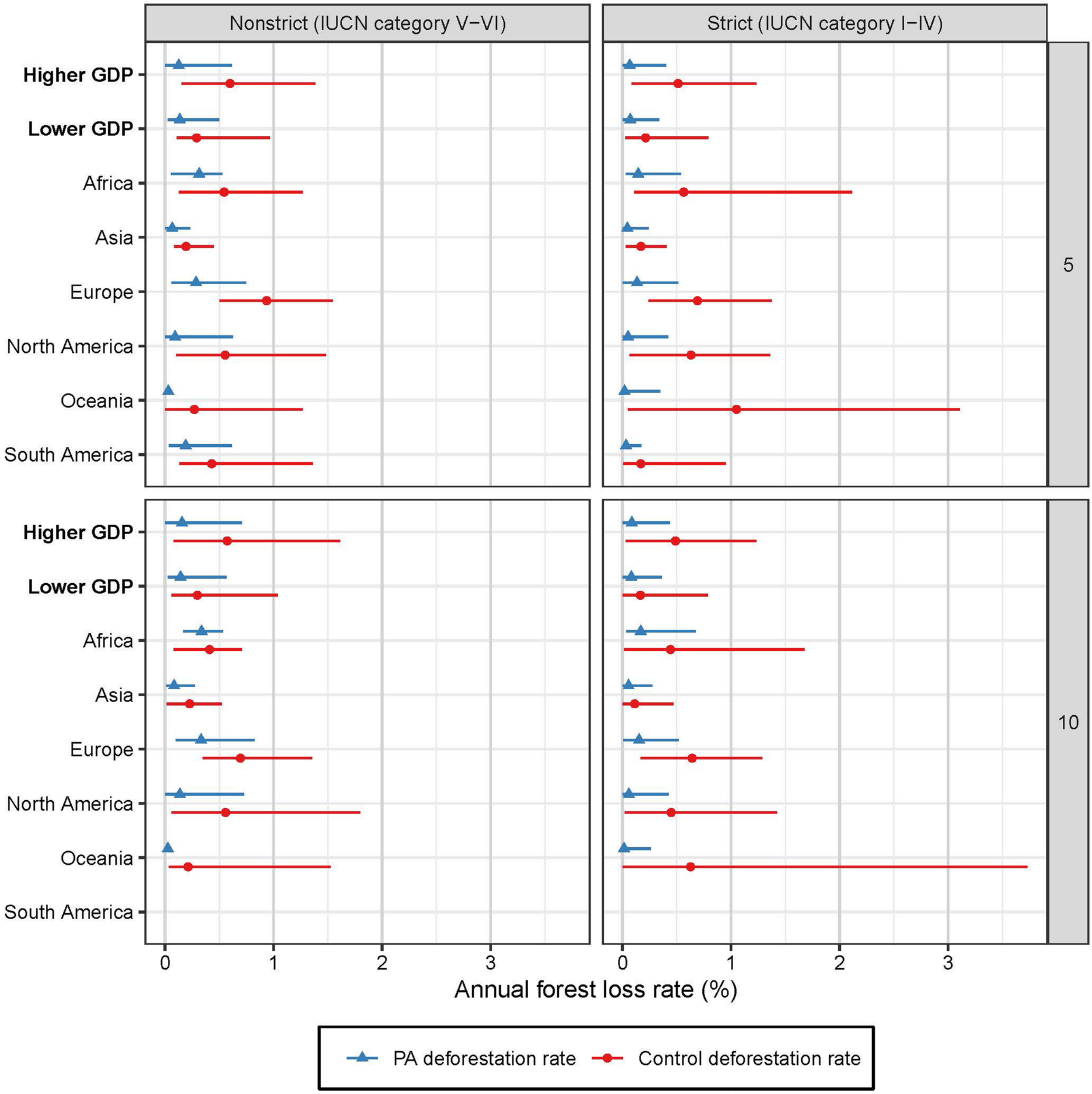

Extended Data Fig. 6 | Sensitivity analysis exploring the effect of stricter matching criteria. Medians (center points) and 1st and 3rd quartiles (ranges) are shown. The first row is for our primary matching dataset (see Fig. 3) based on five classes per continuous matching covariate while the second row shows results based on 10 classes per covariate (only 9 were used for travel time – see Supplementary Methods). Overall, the use of stricter matching criteria did not appear to considerably alter our results.

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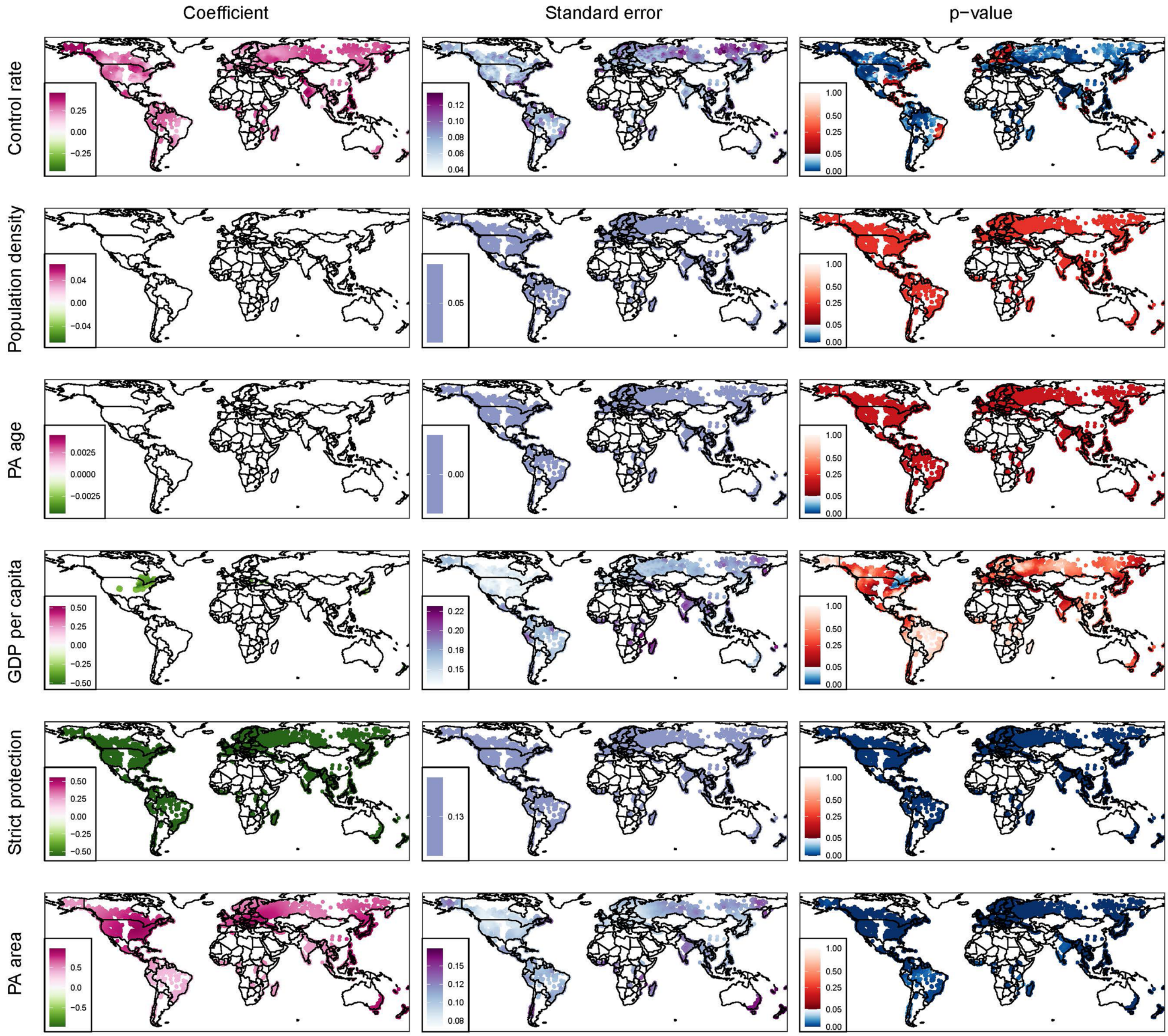

Extended Data Fig. 7 | Predictors of deforestation rates within protected areas for dataset using stricter matching criteria. Travel time to nearest densely-populated area (p=0.20) was not spatially varying and is not shown in order to parallel our main results (Extended Data Fig. 4). Additionally, population density, PA age, and strict protection were all found to be constant spatially for this restricted dataset. Only coefficients with associated p-value less than 0.05 are mapped.

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used (all data are publicly available).
Data analysis	We carried out the GIS analysis using Google Earth Engine to download most datasets, R v4.0.3 and Python v3.7.3 with GDAL v2.4.0 for general raster processing, Julia v1.4.2 for coarsened exact matching, and R v4.0.3 for statistical modeling and data visualization (with 'ggplot2').

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Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This is a global analysis of deforestation rates in protected areas (PAs). The general framework used was a covariate-based matching method where deforestation rates in PAs are compared to deforestation rates in matched control areas that serve as a baseline.
Research sample	Not applicable (we used a database of more than 18,000 protected areas).
Sampling strategy	Not applicable (no sampling was conducted).
Data collection	The primary data source is an existing, public database of protected areas (WDPA). Other data sources are also publicly available.
Timing and spatial scale	We considered protected areas (PAs) established in 2000 or earlier for our main analysis and PAs established between 2002 and 2017 for a before-after comparison. Forest change data range from 2001 to 2018. The PA data are global but restricted to forest biomes.
Data exclusions	We did not collect new data for this project. As noted in the SI, 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 km2 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."
Reproducibility	Not applicable (no experiments were conducted).
Randomization	Not applicable (we used all suitable data in a database of protected areas).
Blinding	Not applicable (this is a global analysis of protected areas).

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

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Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

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