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A global assessment of the impact of individual protected areas on preventing forest loss

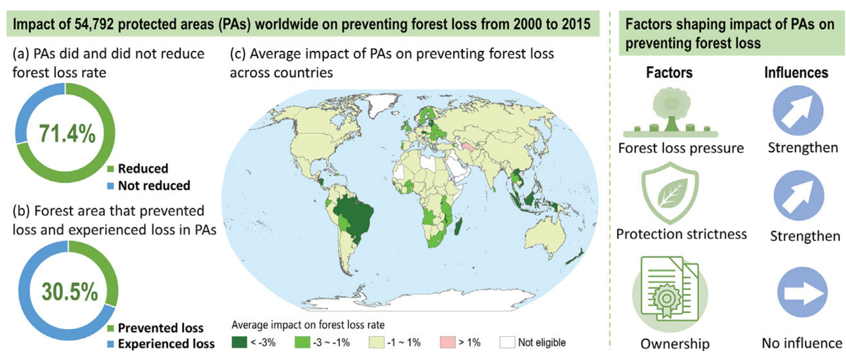
Hongbo Yang [a,b,c], Andrés Viña [a,d], Julie Ann Winkler [e], Min Gon Chung [a], Qiongyu Huang [b], Yue Dou [f], William J. McShea [b], Melissa Songer [b], Jindong Zhang [g,*], Jianguo Liu [a,h,**]

[a] Center for Systems Integration and Sustainability, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48823, USA
[b] Conservation Biology Institute, National Zoological Park, Smithsonian Institution, Front Royal, VA 22630, USA
[c] Global Development Policy Center, Boston University, Boston, MA 02215, USA
[d] Department of Geography, University of North Carolina, Chapel Hill, NC 27599, USA
[e] Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, MI 48823, USA
[f] Environmental Geography Group, Institute for Environmental Studies, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV, Amsterdam, The Netherlands
[g] Key Laboratory of Southwest China Wildlife Resources Conservation, China West Normal University, Ministry of Education, Nanchong, Sichuan Province 637009, China
[h] Ecology, Evolution, and Behavior Program, Michigan State University, East Lansing, MI 48823, USA

HIGHLIGHTS

- About 71% of the protected areas worldwide contributed to preventing forest loss.
- Only 30% of forest loss in protected areas have been prevented.
- PAs situated in regions with higher pressure of forest loss prevented more forest loss.
- PAs allow fewer uses of forest resources performed better than PAs allow more uses.
- Private PAs performed similarly to public PAs in preventing forest loss.

GRAPHICAL ABSTRACT



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ABSTRACT

Globally, the number and extent of terrestrial protected areas (PAs) are expanding rapidly. Nonetheless, their impacts on preventing forest loss and the factors influencing the impacts are not well understood, despite the critical roles of forests in biodiversity conservation, provision of ecosystem services, and achievement of the United Nations' Sustainable Development Goals. To address this important knowledge gap, we quantified the impacts of 54,792 PAs worldwide on preventing forest loss from 2000 to 2015, and assessed important landscape and management factors affecting the impacts of PAs. Although the majority (71.4%) of the PAs contributed to preventing forest loss, only 30.5% of forest loss in the PAs have been prevented. PAs with higher rates of forest loss in their surrounding regions, located at lower elevations, within a few hours of travel from the nearest city, with higher agricultural productivity, and permission for fewer human uses were better able to prevent forest loss. Impacts on preventing forest loss were similar regardless of whether the PAs were privately or publicly owned. Our findings highlight

* Correspondence to: J. Zhang, Key Laboratory of Southwest China Wildlife Resources Conservation, China West Normal University, Ministry of Education, Nanchong, Sichuan Province 637009, China.
** Correspondence to: J. Liu, Center for Systems Integration and Sustainability, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48823, USA.
E-mail addresses: yanghon8@msu.edu (H. Yang), vina@msu.edu (A. Viña), winkler@msu.edu (J.A. Winkler), chungm13@msu.edu (M.G. Chung), huangq@si.edu (Q. Huang), yue.dou@vu.nl (Y. Dou), Mcsheaw@si.edu (W.J. McShea), songerm@si.edu (M. Songer), zhangjd224@163.com (J. Zhang), liuji@msu.edu (J. Liu).

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Deforestation
Matching

the potential benefits of strict protections, involving private entities in the establishment of PAs, and situating PAs in areas exposed to high risks of forest loss to enhance the capacity to combat global forest loss.

1. Introduction

Under the auspices of the Convention of Biological Diversity (CBD), the international community has designated >4 million km^2 – an area larger than India – of new land as PAs over the past decade (UNEP-WCMC and IUCN, 2020). While PA coverage has increased rapidly, there is little evidence of significant transformations that PAs have made to conservation outcomes. Moreover, growing evidence from around the globe points to a widespread degradation and under-resourcing of existing PAs (Mascia and Pailler, 2011; Watson et al., 2014). Even some globally renowned PAs have experienced significant wildlife habitat loss (Geldmann et al., 2019; Liu et al., 2001) and collapse of species populations (Brodie and Waterhouse, 2012).

These concerns highlight the urgency for a comprehensive global evaluation of the impacts of PAs on desired conservation outcomes, such as preventing forest loss (IUCN World Park Congress, 2014). Curbing global forest loss is essential for biodiversity conservation (Betts et al., 2017; Pimm et al., 2014), provision of ecosystem services (Curran and Trigg, 2006; Watson et al., 2018), as well as achieving a number of United Nations' Sustainable Development Goals (Gregersen et al., 2017; United Nations, 2015). Establishing PAs is one of the most common approaches used to prevent forest loss (Andam et al., 2008). Given that current PAs cover >15% of global land surface (UNEP-WCMC and IUCN, 2020), an important question is "Have PAs reduced forest loss around the world?" However, previous global-scale analyses of the performance of PAs have often focused on their spatial overlaps with biodiversity hotspots (Rodrigues et al., 2004; Runge et al., 2015; Venter et al., 2014), management capabilities (Geldmann et al., 2018; Leverington et al., 2010), and the changes in land cover (Heino et al., 2015) or human disturbances (Jones et al., 2018) within PAs, while the impacts of PAs on forest loss worldwide are less well quantified. Existing studies about the impact of PAs on forest loss were mostly conducted at local or regional scales and did not provide a global perspective (Andam et al., 2008; Bowker et al., 2017; Yang et al., 2019) (see Table S1 in Supplementary Information for a list of publications on PAs' impacts on preventing forest loss). In addition, previous evaluations were conducted primarily using parametric regression (e.g., Armenteras et al., 2006; Gaveau et al., 2007) or direct comparison of forest loss inside and outside PAs (e.g., Bruner et al., 2001; Songer et al., 2009) (Table S1). These methods are often biased due to misspecification of functional form or poor comparability between forest inside and outside PAs (Andam et al., 2008; Coetzee, 2017). There have been some meta-analyses (e.g., Geldmann et al., 2013; Oldekop et al., 2016) concerning the impacts of PAs on forest loss at the global scale (Table S1), however, they considered a relatively small number of PAs (<5000 PAs, Table S1) and the case studies included in the meta-analysis primarily rely on regressions or direct inside-outside comparisons to evaluate the impacts. These limitations restricted the ability of meta-analyses to reliably assess the impact of PAs worldwide on preventing forest loss.

To date, there has been only one global empirical analysis about the impacts of PAs on vegetation loss (Joppa and Pfaff, 2011). This study evaluated PAs' impacts by comparing land cover change of protected land pixels to unprotected counterparts with similar characteristics (e.g., elevation and slope) using the matching approach (Ferraro and Hanauer, 2014; Rubin, 1973), and thereby addressing the limitations associated with direct inside-outside comparison or regression. Despite the methodological merit of this study, high uncertainty remained because the land cover maps used in the study had a coarse resolution (1 km/pixel) and inconsistent classification schemes, which might have failed to capture many small-scale forest changes occurred during the short evaluation period (2000 to 2005). Furthermore, this analysis treated the entire network of PAs in one country, instead of each individual PA, as the evaluation unit. Important questions that require a global analysis at the individual PA level remain unanswered. For example, what proportion of the world's PAs reduced forest loss and where were these PAs located relative to human pressure and landscape features?

Furthermore, previous studies evaluating the impacts of PAs primarily focus on quantifying PAs' impacts while factors influencing PAs' impacts are less well investigated, especially at the global scale. For example, previous studies show that the establishment of PAs is primarily driven by land availability and acquisition cost (Baldi et al., 2017). As a result, the distribution of PAs worldwide is biased toward remote areas with low population density and potential for agriculture production, where PAs may least prevent land conversion (Joppa and Pfaff, 2009). In addition to location-associated factors, there are debates over the effectiveness of PAs which allow some human uses of the natural resources and PAs that are owned by private entities. As compared to strictly protected PAs which exclude local inhabitants from access to natural resources, multiple-use PAs aim to achieve both social and conservation goals through allowing some sustainable uses by humans to meet their livelihood demands (Pfaff et al., 2014; Roe and Elliott, 2006). Although strictly protected areas legally permit fewer human uses, the social conflicts associated with strict protection and inadequate management capacity of PAs may comprise their effectiveness. A few regional studies (Ferraro et al., 2013; Nelson and Chomitz, 2011) also show that more strictly protected PAs are not necessarily more effective in reducing human disturbances. Land tenure is known to have a profound impact on land cover change (Hora et al., 2018; Yang et al., 2015) and a growing number of private PAs are recognized and reported to national and international databases (Bingham et al., 2017). Private PAs can complement the state-owned PAs to increase the coverage and connectivity of PAs but they are often believed to have less capacity than PAs owned by governments (Bingham et al., 2017). The performance of private PAs in achieving conservation goals remains unclear and requires empirical evaluations. Understanding the influences of these landscape and management factors on the performance of PAs is critical for effective planning and management of PAs. Armed with this knowledge, conservation practitioners can design strategies accordingly to regulate the factors and enhance the ability of PAs to achieve conservation goals. However, quantitative studies on the influences of those factors on PAs' performance in reducing forest loss at the global scale are rare.

Here we addressed those and other related questions by evaluating the 16-year impacts (2000 to 2015) of 54,792 forested PAs worldwide on forest loss rate using a matching approach. To understand the location-associated factors influencing a PA's ability to prevent forest loss, we assessed the relationships of PAs' impact on forest loss rate with four landscape features, including surrounding forest loss rate, travel time to the nearest urban area, elevation, and agricultural productivity. We also addressed the debates about the performance of PAs that allow some human uses or are owned by private entities by evaluating the influence of protection level (strictly protected versus multi-use) and ownership (public versus private) of PAs on their impacts on preventing forest loss.

2. Methods and materials

2.1. Selection of protected areas

We obtained information on protected areas (PAs) around the world in shapefile format from the World Database on Protected Areas (WDPA) in June 2018 (IUCN and UNEP-WCMC, 2018), with a total of 233,886 PAs included in the inventory. PAs that lacked boundary information in the dataset ($n = 18{,}581$) were excluded from further analysis. Since we aimed to evaluate the impacts of PAs in reducing forest loss from 2000 to 2015, PAs designated after 2000 ($n = 90{,}700$) were also excluded. Marine PAs ($n = 1491$) and PAs not containing forest within their boundaries ($n = 60{,}811$) were excluded. Furthermore, 7511 PAs for which the matching method, discussed below, could not find forest in their buffer zone to serve as controls (e.g., a protected oasis surrounded by desert) for impact evaluation were excluded. These exclusions left a final set of 54,792 PAs across 145 countries in our analysis. The total area of forests within our final set of PAs is 5,851,027 km^2, which accounts for 99.2% of the total forest within PAs that have boundary information and were established before 2000.

2.2. Estimating impact of each protected area on forest loss

We quantified the impact of each of the 54,792 PAs worldwide on forest loss rate using the matching approach (Rubin, 1973). As compared with regression and direct inside-outside comparison, the matching method is more robust to model misspecification, has less strict assumptions, and is more reliable for evaluating the impacts of PAs (Ferraro and Hanauer, 2014). The purpose for using the matching method was to control for observable differences between protected forest pixels within each PA and unprotected forest pixels within each PA's buffer to ensure an "apple-to-apple" comparison for reliable impact evaluation.

Using a 300-m resolution binary forest map (see Section 2.3), we drew a random sample of forest pixels within each PA as well as within its 50-km buffer zone (Fig. S1). To ensure that the sample of forest pixels was representative of the entire population of forest pixels inside each PA or its 50-km buffer zone, we calculated the required sample size using the following equation (Krejcie and Morgan, 1970):

$$Sample\ Size = \frac{N \times X^2 \times p(1-p)}{e^2(N-1) + X^2 \times p(1-p)} \tag{1}$$

where N is the size of the population from which the sample will be collected; X^2 is the Chi-square for the specified confidence level (95% was used here) at 1 degree of freedom; e is the margin of error (2.5% was used here), measuring the desired level of accuracy; and p is the proportion of the population, which was set to 0.5 to ensure the estimated sample size is large enough to achieve the desired level of accuracy as suggested by Krejcie and Morgan (1970). When evaluating the impact of a PA on forest loss, pixels in its 50-km buffer but protected by other PAs were excluded.

For each protected forest pixel within a PA, the matching method found a control within the PA's 50-km buffer zone that is similar in terms of 15 attribute variables, including tree cover in 2000, distance to forest edge, elevation, slope, terrain roughness, topographic wetness index, human influence index, travel time to the nearest city, precipitation, temperature, soil carbon, soil depth, soil acidity, density of bulk in soil, and density of clay in soil (Table 1). Those attribute variables on initial forest status, topography, climate, and soil properties were selected because they shape the distribution of humans, forests, and the interactions between them (e.g., agricultural expansion) (Liu, 2014; Viña et al., 2016; Linderman et al., 2005), potentially with confounding effects on the impact evaluation. This one-to-one matching method was performed based on a propensity score which measures the probability of a pixel being located inside a PA given its values on the 15 attribute variables and was used to determine the similarity between protected forest pixels within PA and unprotected forest pixels in the buffer. To calculate the propensity scores, we constructed an empirical logistic model that links the pixels' 15 attributes to their protection status (i.e., being protected or not) using the sample of pixels from each PA and its 50-km buffer zone. The model was then used to estimate the propensity score for each pixel. To improve the matching quality, a caliper was used to constrain the difference in propensity score between protected and unprotected forest pixels within the 0.5 standard deviation of their propensity scores. The matching was done with replacement. In other words, every time we selected a pixel from the pool of unprotected pixels for matching, we returned it back to the pool so that other protected pixels could be matched to it. Using the matched protected and unprotected forest pixels, the impact of a given PA on forest loss rate was estimated using a bias-adjustment estimator (Abadie and Imbens, 2006). The estimator addresses the potential bias in the impact estimation due to the remaining differences in the 15 contextual biophysical and socioeconomic attribute variables between forest pixels within a PA and the matched pixels in its buffer zone.

Table 1
Description of spatial data layers depicting the socioeconomic and biophysical conditions used in this study.

Data layer	Unit	Description	Data source/resolution
Initial tree cover	%	Percentage of area covered by tree crown in 2000.	(Hansen et al., 2013)/30 m
Forest loss	Dimensionless	Whether the pixel experienced forest loss between 2000 and 2015: 0, No; 1, Yes.	
Distance to forest edge	m	Straight-line distance to forest edge in 2000.	
Elevation	m	Elevation of GDEM pixels.	Aster Global Digital Elevation
Slope	radian	Slope calculated using GDEM elevation.	Map (GDEM)/30 m
Terrain roughness	m	Standard deviation of GDEM elevation.	
Wetness	m	Compound topographic index, a function of both the slope and the upstream contributing area per unit width orthogonal to the flow direction (Moore et al., 1993).	(Marthews et al., 2015)/500 m
Human influence	Dimensionless	Human influence index, a function of land use, population and other features for describing human influence on the environment in 2000.	(WCS and CIESIN, 2005)/1 km
Travel time to city	min	The travel time to the nearest city with >50,000 people in 2000.	(Nelson, 2008)/ 1 km
Precipitation	mm	Average annual mean precipitation from 1970 to 2000.	(Fick and Hijmans,
Temperature	°C	Average annual mean temperature from 1970 to 2000.	2017)/1 km
Soil carbon	ton/ha	Soil organic carbon stock for a depth interval from 0 to 2 m.	(Hengl et al., 2007)/250 m
Soil depth	cm	Absolute depth to bedrock.	
Soil bulk	kg/m^3	Bulk density at a 1 m depth.	
Soil acid	Dimensionless	Degree of soil acidity ranging from 0 to 5. A higher value indicates more acid soils.	
Soil clay	%	Clay content of mass fraction at 0.15 m depth.	

One concern over the estimation procedure above is that the impact of a PA may spillover onto nearby unprotected lands (Ewers and Rodrigues, 2008) and bias the impact estimations. To test for potential spillovers, we used the matching method to compare the forest loss rates of forest pixels within a zone of 0 to 10 km from the PA boundaries to that of pixels in a zone of 10 to 50 km from the PA boundaries. We chose 10 km as the threshold distance because a previous study (Fuller et al., 2019) suggests that the spillover effect of PAs can reach up to 10 km from the boundary of PAs. A statistically significant difference ($p < 0.1$) between the forest loss rates in the two zones was viewed as a sign of spillover effect as suggested by Ewers and Rodrigues (2008). For PAs exhibiting signs of spillover effect, we reran the matching evaluation procedure and mitigated the spillover effects by only using the pixels within the zone 20–50 km from the PA boundaries, rather than all pixels within the 50-km buffer, to estimate PAs' impact on forest loss rate, based on the recommendation by Ewers and Rodrigues (2008). We chose 20 km as the threshold distance here to balance the needs to minimize the spillover effects and the number of forest pixels dropped from the analysis. This distance is twice the distance (10 km) that Fuller et al. (2019) suggests spillover effects can reach and thus should be large enough to mitigate the spillover effects. Meanwhile, regardless of the size of the PA, >75% of forest pixels in the 50-km buffer would be retained for the impact evaluation.

The evaluation procedure above was applied to estimate the impact of each of the 54,792 PAs on forest loss rate. After matching, the differences between protected and unprotected forest pixels along the 15 controlled attribute variables were substantially decreased (Fig. S2), suggesting a good matching quality (Stuart, 2010). The value of the impact on forest loss rate ranges from −100% to 100%. A negative sign of a PA's impact value indicates that the PA reduced the rate of forest loss while a positive sign indicates that the PA did not reduce the rate of forest loss. We performed the matching analyses in R (R Development Core Team, 2020) on computing clusters maintained by Michigan State University (https://icer.msu.edu/) using the 'Matching' package (Sekhon, 2011).

2.3. Spatial data on forest change, socioeconomic and biophysical conditions

We derived forest information from a 30-m resolution global forest dataset developed by Hansen et al. (2013). We aggregated the forest dataset from 30-m resolution to 300-m resolution to reduce the number of pixels for impact evaluation and make the evaluation computationally feasible.

The global forest dataset includes a tree-cover percentage map in 2000. We aggregated this tree cover map from 30 m to 300 m using the mean algorithm in ArcGIS 10.5 (ESRI, 2016). We then partitioned the aggregated tree cover map into a binary forest and non-forest map using the threshold of 10% tree cover. We chose this threshold based on the forest definition by the Global Forest Resource Assessment (The Forest Resources Assessment Programme, 2015), acknowledging that our forest classification is an approximation to the definition because it does not take into account canopy height and land use information. This binary forest cover map was used to generate random samples of forest pixels for estimating the impact of each PA on forest loss rate.

We defined forest loss rate as the proportion of forest that experienced complete removal of tree cover between 2000 and 2015. We obtained the forest loss rate of each 300 m resolution forest pixel from a 30 m resolution binary map of forest loss included in the forest change dataset which measures whether the land experienced forest loss between 2000 and 2015 (Hansen et al., 2013). We aggregated this binary forest loss map from its original size of 30 m to 300 m using the mean algorithm in ArcGIS 10.5 (ESRI, 2016). Each aggregated forest pixel had an average forest loss rate value ranging from 0% to 100%, measuring the proportion of forest experienced forest loss between 2000 and 2015.

When comparing the forest loss rate in each PA with that in its 50-km buffer zone, we controlled for differences between the protected and unprotected forest pixels along with 15 variables that may affect forest loss (Table 1). We obtained the tree cover information for each forest pixel in 2000 by aggregating the tree cover map in the forest dataset provided by Hansen et al. (2013) from 30 m to 300 m. Using the 300-m resolution binary forest cover map mentioned above, we calculated the distance to forest edge by measuring the distance from the center of each forest pixel to the edge of the forest patch where the pixel was located within using ArcGIS 10.5 (ESRI, 2016). We derived elevation, slope, and terrain roughness from the 30-m resolution ASTER Global Digital Elevation Map, and then resampled and coregistered it to the 300-m resolution binary forest map to obtain those terrain attributes for each forest pixel. Similarly, for other metrics derived from sources other than the forest dataset provided by Hansen et al. (2013), we resampled and coregistered the data to the 300-m resolution binary forest cover map using ArcGIS 10.5 (ESRI, 2016) to obtain the attributes for each forest pixel included in our impact evaluation.

2.4. Estimating the amount of forest in protected areas that prevented loss

To estimate the total impact of PAs on forest loss within PAs worldwide, we calculated the amount of forest in PAs that prevented forest loss due to PA protection in each country. To avert the potential bias due to the spatial overlaps among PAs that resulted from boundary inaccuracies or overlapping designation (Deguignet et al., 2017), we calculated the prevented forest loss area using a two-step procedure. We first calculated the average impact of PAs in each country weighted by each PA's forest area. We then multiplied the weighted average impact by the total forest area in PAs of that country to calculate the area that prevented forest loss in PAs. When calculating the total forest area in PAs in each country, all PA polygons were dissolved into a single PA layer to avoid overestimation due to overlapping boundaries. The spatial overlaps among PAs can make forest lands covered by two or more PAs have a disproportional influence on the weighted average impact. However, this uncertainty is unlikely to generate a major effect on the result of the prevented forest loss area because the overlapped forest area only accounts for 2.7% of the total forest in PAs.

We can formally represent the calculation process using:

$$\textit{Prevented forest loss}_j = \sum\nolimits_{i=1}^{n} \left(I_i \times F_i / \sum\nolimits_{i=1}^{n} F_i \right) \times FA_j \tag{2}$$

where, *Prevented forest loss*$_j$ represents the prevented forest loss area in country j; n represents the number of PAs within the target country j; I_i and F_i represent the impact of the ith PA on forest loss rate and forest area in it respectively; FA_j represents the total forest area within PAs in country j.

We estimated the percentage of forest loss prevented by PAs on a global scale using the following equation:

$$\textit{Percentage of forest loss} = \frac{\sum_{j=1}^{m} \textit{Prevented forest loss}_j}{\sum_{j=1}^{m} \left(\textit{Prevented forest loss}_j + \textit{Observed forest loss}_j \right)} \times 100\% \tag{3}$$

where, m is the number of countries globally; *Prevented forest loss*$_j$ is the prevented forest loss area in country j estimated using Eq. (2); *Observed forest loss*$_j$ is the total forest loss area in all PAs in country j between 2000 and 2015 captured by the global forest dataset (Hansen et al., 2013).

2.5. Relationships of PAs' impacts on forest loss with landscape characteristics and management attributes

To examine how the impact of PAs on forest loss changes across landscape, we assessed the relationships of PAs' impact on forest loss rate with four landscape variables using bivariate loess regression (Cleveland, 1979), including surrounding forest loss rate (average rate of forest loss in the 50-km buffer zone of a PA), travel time to the nearest urban area, elevation, and agricultural productivity. We used soil carbon content as a surrogate for agriculture productivity because soil carbon plays a key role in the stability and fertility of soils (Milne et al., 2015). These landscape variables were all measured at the PA level. Definitions and sources of the landscape variables were presented in Table 1.

Using the matching approach, we compared the impacts on forest loss rate of PAs with different levels of protection (strictly protected versus multi-use) and ownership (public versus private). As it is impossible to observe the actual enforcement of protections in PAs worldwide, we followed previous studies (Ferraro et al., 2013; Gray et al., 2016; Joppa and Pfaff, 2011; Naidoo et al., 2019; Soares-Filho et al., 2010) and defined the protection level of a PA based on the IUCN management categories it falls into. Strictly protected PAs are the ones in the IUCN categories I–IV and legally permit few human uses in them. Multi-use PAs are the ones in the IUCN categories V–VI and legally permit a wider range of uses. Public PAs in our analysis refer to PAs owned by state or local governments, while private PAs refer to PAs owned by local communities, NGOs, corporations, or individual landowners.

The WDPA has data gaps and PAs without attributes that are necessary to make those comparisons were excluded in our comparison analyses. After the exclusion, 27,935 strictly protected PAs and 11,819 multi-use PAs were included in our comparison of PAs with different protection levels, while 2296 privately owned PAs and 4504 publicly owned PAs were included in our comparison of PAs with different ownership. Similar to estimating the impact of individual PAs on forest loss rate, the goal of the matching method in the PA comparison analyses is to control for observable differences between PAs that may work as confounding factors and affect the reliability of the comparison results. The attributes we controlled for in each comparison included PA size, forest loss rate within the 50-km buffer zone, initial tree cover, elevation, slope, roughness, wetness, human influence, travel time to the nearest city, precipitation, and temperature, as well as soil carbon, depth, bulk, acid, and clay (Table 1). These attributes were all measured at the PA level and attributes derived from raster data layers were the mean values of a sample of random pixels of the corresponding data layers within each PA. The sample size (i.e., the number of pixels) for each PA was determined using Eq. (1). After matching, the standardized covariate differences moved substantially toward zero (Tables S2 and S3), indicating good matching quality for reliable impact evaluation (Stuart, 2010).

2.6. Robustness checks

We conducted eight robustness analyses to examine the potential impacts of a series of uncertainties on our findings (see Robustness Checks, Supplementary Information). Those uncertainties include: (1) different forest cover change trends inside and outside PAs before the establishment of PAs; (2) changes in PA boundaries during our study period from 2000 to 2015; (3) possible inaccuracy of PA boundary data from the WDPA; (4) presence of plantation forest; (5) the selection of the threshold distance to define the size of buffer zone for impact evaluation; (6) information loss due to aggregation of the forest dataset from 30 m to 300 m; (7) exclusion of PAs that did not report their IUCN management categories and ownership in the comparisons of PAs with contrasting attributes; and (8) selection of study design in the comparisons of PAs with contrasting attributes. We presented how each of those uncertainties might affect our findings and the results of the robustness checks in the Supplementary Information. The results (Fig. S3–S9) show that none of those uncertainties are likely to generate major impacts on the findings of this study.

3. Results

3.1. Impact of PAs on forest loss

Results show that 71.4% (or 39,121) of the PAs reduced forest loss in them (impact on forest loss rate < 0) (Fig. 1). Without their establishment, an additional 77,857 km^2 forest within their boundaries would have been lost between 2000 and 2015. Nevertheless, the forest loss rate in many PAs remains high. The PAs in our assessment only prevented 30.5% of forest loss in them. Forest loss rates in 11.2% of the PAs were higher than the global average between 2000 and 2015 (5.6%). An area of 177,528 km^2 (similar to the size of Cambodia) within our sample of PAs experienced forest loss between 2000 and 2015.

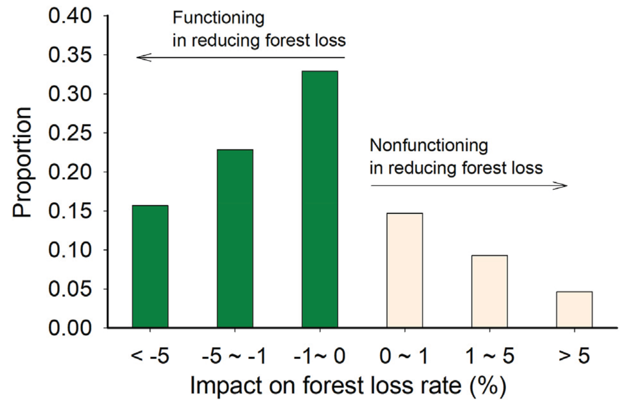

Fig. 1. Proportion of protected areas with different levels of impact on forest loss rate. A negative sign of the impact values indicates that the protected areas reduced the rate of forest loss while a positive sign of the impact values indicates that the protected areas did not reduce the rate of forest loss.

The average impact of PAs on forest loss varied across countries. Most of the countries with high-performing PAs (national average impact on rate of forest loss <−1%) are located in the tropics, such as Brazil, Malaysia, and Madagascar (Fig. 2A). PAs within a group of northern European countries, such as Estonia and Latvia, also had high success in reducing forest loss (Fig. 2A). Countries where the PAs had high average impact in preventing forest loss were often countries experienced with high rates of forest loss (Fig. 2B). The national average rate of forest loss for these countries with high-performing PAs was 6.2% which was more than double that in the other countries (2.8%). Half of the top 30 countries with the highest average PA impacts (Fig. 2C) were also in the top 30 countries with highest average rates of forest loss (Fig. 2D). Major drivers behind the large rates of forest loss in these countries likely included agricultural expansion (e.g., forest clearing for cattle ranching in Brazil (Barona et al., 2010)) and intensive forestry land uses (e.g., tree harvesting in Estonia (Naudts et al., 2016)).

3.2. Associations between PAs' impacts on preventing forest loss and landscape characteristics

We found that PAs with larger rates of forest loss outside the PAs tended to prevent more forest loss within the PAs (Fig. 3A). This is partly a reflection of our definition of PA impact on forest loss rate. Only when a PA is exposed to high pressure of forest loss does it have the chance to significantly reduce the forest loss within its boundary, which also points to the potential benefits of situating PAs in areas with large pressure of forest loss. Elevation, soil organic carbon, and travel time to the nearest city were also important predictors of PA's ability to prevent forest loss. In general, the potential for reducing forest loss is low for PAs located at high elevations, or with low soil carbon stocks (Fig. 3B, C), perhaps because of the low demand for forest land in those areas to establish alternative land uses, such as farming (Rudel et al., 2009). As a result, the establishment of PAs in such regions did not exhibit large impacts on preventing forest loss. The relationship between travel time to the nearest city and PA impact is nonlinear with a maximum value of reducing forest loss rate when a PA is around 3 h of travel from the

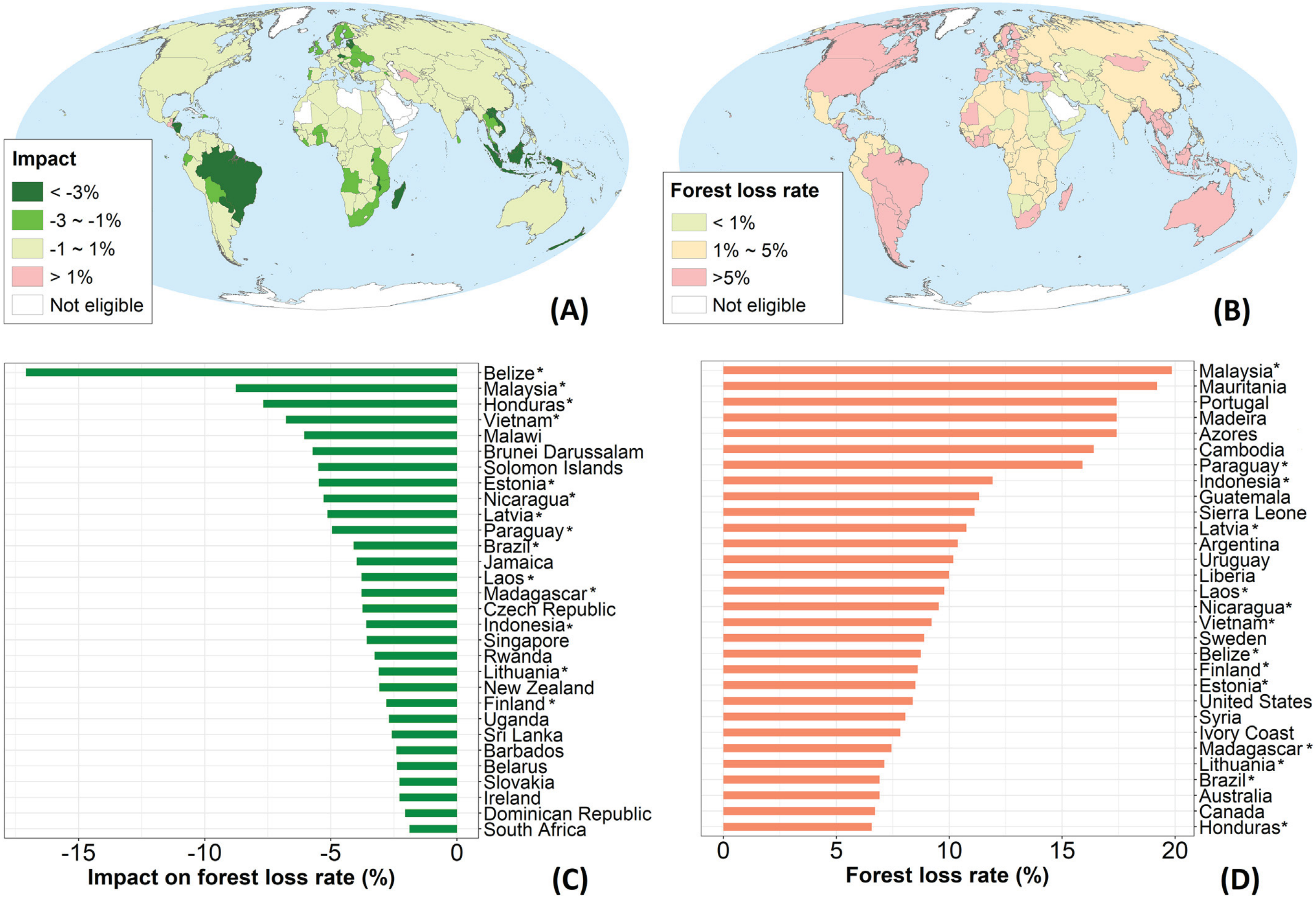

Fig. 2. Average impact of protected areas on forest loss rate (A) and average rate of forest loss (B) at the country level. Of the top 30 countries by impact on forest loss rate (C), 14 are also among the top 30 countries by rate of forest loss (D) and were marked with asterisks. The average impact of a country is calculated by averaging individual protected areas' impacts in that country, weighted by the protected areas' forest areas in 2000. Of the world's 195 countries, 14 do not have sufficient forest to be included in our map of forest loss and 50 do not have protected areas eligible for inclusion in our map of the average impact of PAs on forest loss rate (see Table S4 in Supplementary Information).

nearest city (Fig. 3D). One explanation for this pattern is that the pressure of forest loss is often low in urban areas and in remote areas while high in the transition areas between them. Factors driving the high pressure of forest loss in these transition areas may include urban sprawl, ex-urbanization, and/or high demand for agricultural land uses to meet consumption needs in cities. In addition, travel costs, thus regulation enforcement costs, in the transition regions are lower than remote areas, potentially contributing to a larger impact of PAs in reducing forest loss.

3.3. Effect of protection level and ownership on PA's impact on preventing forest loss

Although PAs that allow some human uses of natural resources can provide socioeconomic benefits (Naidoo et al., 2019), we found that the ability of PAs to prevent forest loss was 1.34% lower than that of the strictly protected PAs (IUCN categories I–IV) ($p < 0.001$) (Fig. 4A). This result indicates that at the global scale there is a trade-off between human uses of natural resources and the prevention of forest loss under current PA management regimes, rather than the synergy hypothesized in some previous studies (e.g., Oldekop et al., 2016). Although concerns have been raised about the performance of private PAs (e.g., Hora et al., 2018; Langholz and Lassoie, 2001), our results show that their impacts on forest loss rate did not differ significantly ($p > 0.1$) from that of public PAs (Fig. 4B). In other words, private PAs included in our assessment performed similarly to public PAs in preventing forest loss.

4. Discussion

Our results show that the establishment of PAs has reduced forest loss across the world. However, it is important to recognize that the establishment of PAs has prevented less than one-third of forest loss inside PAs. Appropriate interventions are urgently needed to enhance the ability of PAs to combat forest loss. Current conservation plans focus overwhelmingly on adding new sites to existing PA estates (Fuller et al., 2010). Our results highlight that the expansion of PA coverage alone is not sufficient to curb the global forest loss. While increasing the quantity of PAs is important, future conservation planning, such as the post-2020 Global Biodiversity Framework, should focus more on improving the quality of PAs to minimize the forest loss in PAs.

The associations between PAs' impact and landscape characteristics show that PAs can better prevent forest loss in areas with high pressure of forest loss. Previous studies (Baldi et al., 2017; Joppa and Pfaff, 2009) have reported that the distribution of PAs worldwide is biased toward remote areas, high elevations, and regions with poor potential for agricultural production because the cost of land acquisition in these areas is often low. Our results show that this distribution pattern of PAs could constrain their performance in reducing global forest loss. We are not arguing that it is useless to protect the land currently under low pressure of forest loss because the pressure might increase in the future. It is important to get those lands under protection to prevent possible future losses. However, situating PAs in regions with high pressure of

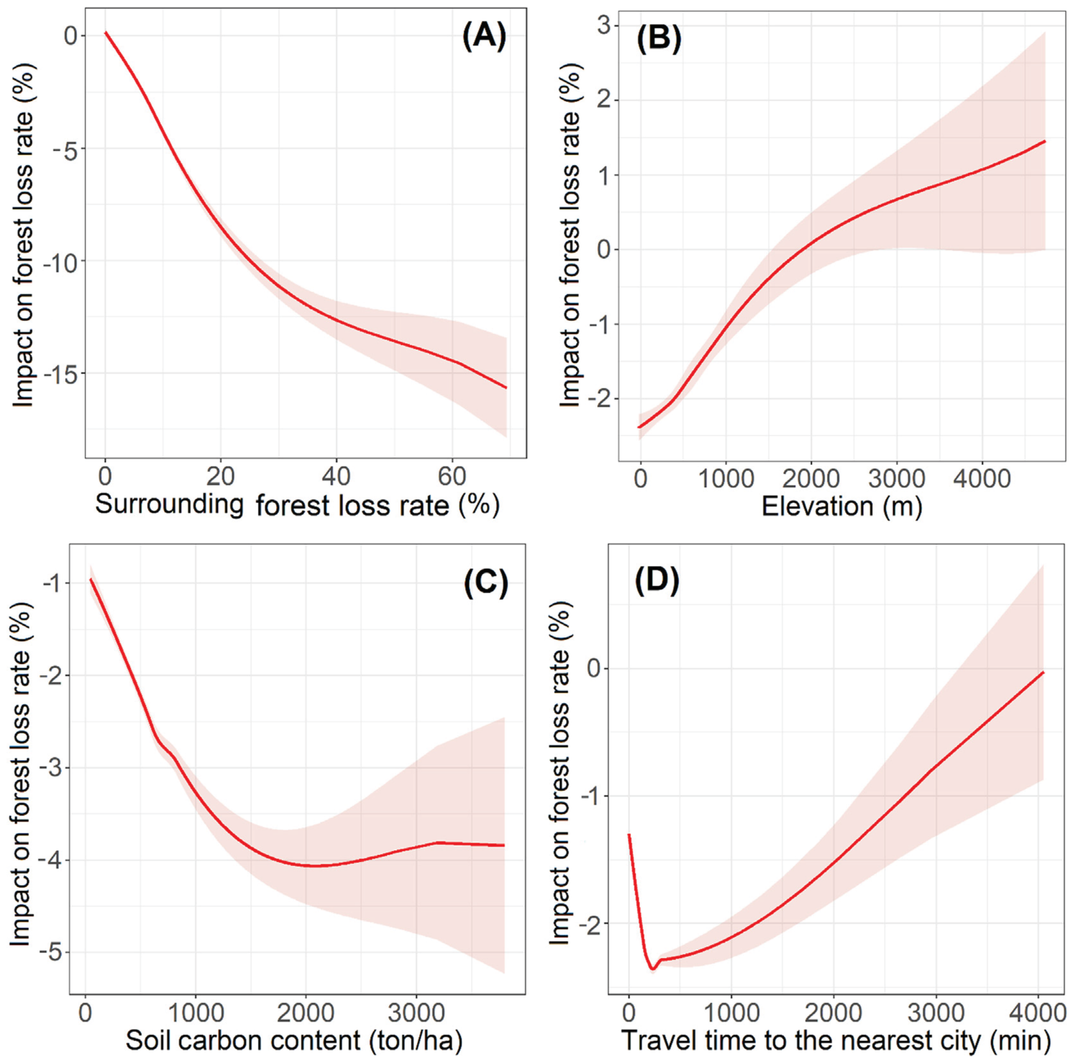

Fig. 3. The relationships between the impact of protected area on forest loss rate and forest loss rate in the surrounding area (A), elevation (B), soil carbon content (C), and travel time to the nearest city (D). The relationship curves were generated using loess regression (degree=1, α=0.9). The light red ribbons show the 95% confidence intervals.

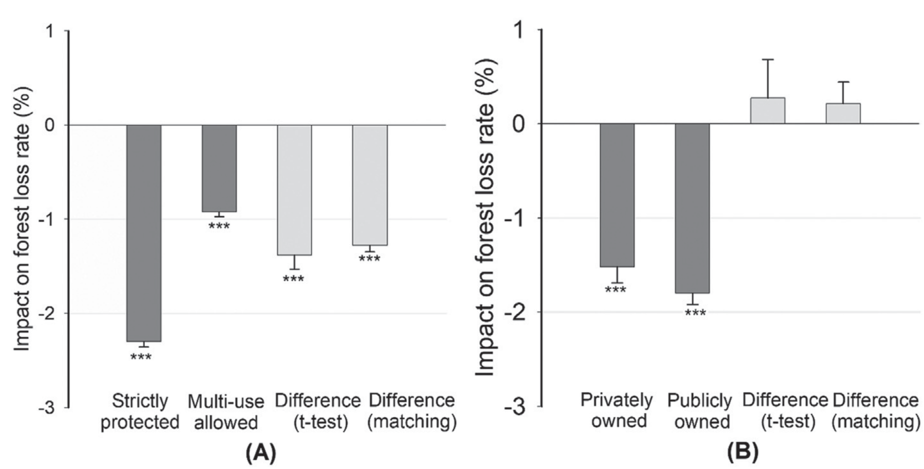

Fig. 4. Comparisons of the impacts of protected areas with contrasting protection levels (A) and ownership (B). The dark bars show the average impacts of protected areas in different comparison categories. The light bars show the differences in the impact on rate of forest loss between different types of PAs estimated using two-sample *t*-test and matching methods respectively. A negative impact difference indicates that the first category of protected areas in comparison has higher impact in preventing forest loss than the second category of protected areas. The error bars refer to standard errors. Asterisks refer to tests of the null hypothesis of non-significant difference from 0 ($^{***}p < 0.001$). The number of strictly protected, multi-use, privately owned, and publicly owned PAs in the comparisons are 27,935, 11,819, 2296, and 4504 respectively.

forest loss can help prevent forest loss that would happen rapidly if no conservation actions are taken.

Our finding that private PAs can perform similarly to public PAs in reducing forest loss suggests that private entities may be able to take on more responsibilities for PA establishment and management, although safeguards would be needed to ensure that conservation objectives are met by private PAs (Bingham et al., 2017). We note that our evaluation only included private PAs that were reported to the WDPA. Many private PAs might have not been included in the reports because of the lack of infrastructure and incentives for the reporting of private PAs (Bingham et al., 2017). Despite this limitation, our results provide strong evidence that private PAs have the potential to perform as well as public PAs in preventing forest loss. Private PAs can help bring private land and other private stakeholders into the conservation movement, fostering new partnerships for conservation targets. Private PAs also open up funding opportunities that are not always applicable to public PAs, such as tax breaks, easements, grants, and subsidies open to private owners who set aside land as private PAs (Stolton et al., 2014). Therefore, the involvement of private entities in PA establishment and management may help address the funding shortages that plague many PAs worldwide (McCarthy et al., 2012). While having some unique strengths for conservation, private PAs are known to have disadvantages, such as the lack of permanence and management capacity. Unlike public PAs, private PAs are more vulnerable and may stop being a PA when the owners change their mind or when ownership changes. Furthermore, many private PAs exist without effective monitoring and effectiveness assessment (Stolton et al., 2014). It is important for conservation organizations and government agencies to work in collaboration with owners of private PA to ensure the private PAs are managed in alignment with the regional, national, and global conservation goals.

Mechanisms that improve the flow of conservation resources within and across countries to areas where PAs can prevent more forest loss are critical for the success of PAs in combating forest loss (Lindsey et al., 2017). The information at the global scale about individual PAs' impact on preventing forest loss and the underlying determinants presented here can assist with this prioritization. For example, special attention should be paid to PAs that failed to prevent the high forest loss rate in them. Increasing the level of protection of PAs also needs to be considered to prevent forest overuse within PAs (Di Minin and Toivonen, 2015; Hilborn et al., 2006) and thus enhance the ability of PAs to protect forests (Pringle, 2017). This includes better enforcement of the impressive body of government policies and regulations for PAs that have already been approved. Better policy enforcement may have similar benefits such as increasing the protection level of PAs, and our results show that increased protection levels can improve the ability of PAs to prevent forest loss. We note that further analyses may be required to complement the findings of our global analyses before management actions are taken, including assessments of a wider range of the costs and benefits that PAs bring to local human and natural systems (Naidoo et al., 2019; Ricketts et al., 2016) as well as impacts of external factors on PAs' performance, such as tourism (Chung et al., 2018; Yang et al., 2021), labor migration (Yang et al., 2018), and trade (Liu, 2020).

5. Conclusion

Although many nations report being on track in meeting their CBD commitments to expand PA networks (Protected Planet, 2018), our analyses suggest that this progress may be partly undermined by the modest impacts of many PAs in delivering desired conservation outcomes, such as preventing forest loss. Although the majority of the PAs contributed to preventing forest loss, less than one third of forest loss in the PAs have been prevented. Our analyses on the impact of PAs on forest loss and its relationships to contextual variables and management practices revealed potential pathways to improve the performance of PAs. We found PAs with higher rates of forest loss in their surrounding regions, located at lower elevations, within a few hours of travel from the nearest city, with higher agricultural productivity are better able to prevent forest loss. PAs that allow fewer human uses tend to prevent more forest loss than PAs that allow more uses. Private PAs show good potential to complement public PAs because the impacts on preventing forest loss were similar regardless of whether the PAs were privately or publicly owned. These findings highlight the potential benefits of strict protections, involving private entities in the establishment of PAs, and situating PAs in areas exposed to high risks of forest loss to enhance the capacity to combat global forest loss. Future conservation planning, such as the post-2020 Global Biodiversity Framework that the CBD is preparing to guide global conservation efforts in the next decade (United Nations, 2019), should highlight the importance of PAs' impacts on conservation outcomes and incorporate PAs' impacts and the underlying factors into the design and management of PAs.

CRediT authorship contribution statement

Hongbo Yang: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Andrés Viña:** Investigation, Writing – review & editing, Project administration. **Julie Ann Winkler:** Investigation, Writing – review & editing, Project administration. **Min Gon Chung:** Investigation, Writing – review & editing, Project administration. **Qiongyu Huang:** Data curation, Writing – review & editing. **Yue Dou:** Data curation, Writing – review & editing. **William J. McShea:** Writing – review & editing. **Melissa Songer:** Writing – review & editing. **Jindong Zhang:** Data curation, Writing – review & editing. **Jianguo Liu:** Conceptualization, Data curation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors have no conflict of interest to declare.

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Appendix A. Supplementary information

Supplementary information to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145995.

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