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What determines the effectiveness of national protected area networks?

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Abstract

More than 15% of global terrestrial area is under some form of protection and there is a growing impetus to increase this coverage to 30% by 2030. But not all protection is effective and the reasons some countries' protected areas (PAs) are more effective than others' are poorly understood. We evaluate the effectiveness of national PA networks established between 2000 and 2012 globally in avoiding forest loss, taking into account underlying deforestation threats using a combination of matching methods and cross-sectional regressions. We then assess which demographic, agricultural, economic, and governance factors are most strongly associated with national PA effectiveness using machine learning methods. We estimate that national PAs established between 2000 and 2012 reduced deforestation in those areas by 72%, avoiding 86 062 km^2 of forest loss. The effectiveness of national PAs varied by strictness of protection based on International Union for Conservation of Nature category. Strictly PAs reduced forest loss by 81% compared to what would have occurred without protection, while less strictly PAs reduced forest loss by 67%. Thus, the 26% of new PAs that were strictly protected contributed 39% of the total forest loss avoided within PAs between 2000 and 2012. If every country's PAs were as effective as the country with the most effective PAs within the same region, they would have increased the area of deforestation avoided by 38%, saving a further 119 082 km^2 of forest. Part of the variation in PA effectiveness across countries is explained by the placement of PA in areas facing higher deforestation threat. Countries with lower agricultural activity, higher economic growth and better governance are most strongly associated with greater country-level PA effectiveness.

1. Introduction

Species, biodiversity and ecosystem services are declining globally at an unprecedented rate (IPBES Regional Assessments of Biodiversity and Ecosystem Services 2018). A primary response to this threat is to increase the coverage of protected areas (PAs). The global PA network covers more than 17 million km^2 representing almost 15% of the earth's terrestrial area and nearly achieving the goal of the 2010 Aichi Targets of the Convention on Biological Diversity to protect 17% by 2020. Given the severity of the global biodiversity crisis, there is a new and urgent call to protect 30% of the world's ocean and land area by 2030 (Luchansky 2012, Dinerstein *et al* 2019).

PAs vary widely in their effectiveness. Many studies find that PAs help reduce deforestation (e.g. Andam *et al* 2008, Joppa and Pfaff 2011, Shah *et al* 2015). However, studies also show that forest loss and environmental degradation has been widespread within PAs, albeit less than in unprotected areas (Kull 2002, Holmes 2007, Shah *et al* 2015, Wade *et al* 2020). Some PAs have been described as largely 'paper parks' with protection in name only, while other PAs have been made smaller or entirely removed from protected status (Tesfaw *et al* 2018, Naughton-Treves and Holland 2019). Still others may be effective but placed in locations with little deforestation threat, thus increasing the area under protection but adding little to avoid forest loss. Thus, in addition to setting aside more area for protection, there may be large gains from improving the effectiveness of the existing PA network.

The recent availability of high-resolution, global coverage remote sensing data makes it possible to estimate PA effectiveness by comparing observed forest loss to the amount of forest loss that would have occurred in the absence of PAs. Because PAs are not randomly allocated, many recent studies have used matching methods to develop a counterfactual scenario and estimate the effectiveness of PAs in reducing forest loss (Andam *et al* 2008, Sims 2010, Ferraro *et al* 2013, Ferraro and Hanauer 2014, Blackman *et al* 2015, Brandt *et al* 2015, Pfaff *et al* 2015, Shah *et al* 2015, Abman 2018, Yang *et al* 2021) . With the exception of Yang *et al* (2021) and Abman (2018), most of these studies focused on specific PAs or a PA network within individual countries. Other studies that used matching methods for evaluating the effectiveness of cross-national PAs focus on issues other than forest loss, such as natural land cover (Joppa and Pfaff 2011), forest fires (Nelson *et al* 2011), or the PA network's ability to resist anthropogenic pressures (Geldmann *et al* 2019) in deterring forest loss at a global scale.

Several region-specific studies identify determinants of the success or failure of PAs in reducing forest loss (Pfeifer *et al* 2012, Nolte *et al* 2013, Herrera *et al* 2019). Pfeifer *et al* (2012) find that human pressure, forest accessibility, protection status, distance to fires and long-term annual rainfall were significant drivers of forest loss within East African PAs. Herrera *et al* (2019) and Nolte *et al* (2013) find governance of PAs to be an important factor in avoiding deforestation inside PAs in the Brazilian Amazon. While numerous studies focus on determinants of forest cover loss (e.g. Rudel *et al* 2009, DeFries *et al* 2010, Busch and Ferretti-Gallon 2017, Leblois *et al* 2017), understanding why some countries' PAs are more effective than others can help improve the effectiveness of the existing PA network. Abman (2018) uses a sampling of matched pixels to determine PA effectiveness, and then asks how national-level governance and corruption measures are correlated with these different outcomes. A recent study explores the differences in protection levels based on International Union for Conservation of Nature (IUCN) (Leberger *et al* 2020). However, many other factors potentially affect PA effectiveness.

We investigate the determinants of PA effectiveness globally. Here we determine the success of PAs by country and by strictness of protection relative to the counterfactual, accounting for the degree to which they are placed in areas under threat. We estimate the amount of deforestation that could be avoided by improving the effectiveness of PAs to the best results by region and income class. We examine a broad array of agricultural, economic, demographic and governance indicators that are potentially associated with PA effectiveness, enabled by machine learning methods.

2. Materials and methods

We estimate the effectiveness of PAs established between 2000 and 2012 in 81 countries in avoiding forest loss, using high-resolution data on forest cover in 2000 and annual forest cover loss between 2000 and 2012 from Hansen *et al* (2013). We obtained data on PA locations, year of establishment and IUCN category from the World Database on PAs. Our unit of observation for all variables of interest was 6 million 5.5 km by 5.5 km grid cells. We further divide the PAs in each country into strict protection (IUCN category I and II) and less strict protection (IUCN categories III–VI). Across these 81 countries, terrestrial area under protection increased from 9.0 million km^2 in 2000 to 12.2 million km^2 by 2012. Of the 3.2 million km^2 of new terrestrial PA established between 2000 and 2012, 26% were strictly protected. SI table 1 in supplementary information (available online at stacks.iop.org/ERL/16/074017/mmedia) provides more details on (a) the total area under protection circa 2000, (b) the new terrestrial area brought under protection between 2000 and 2012, (c) forest cover in the PAs circa 2000, (d) forest cover in the new PAs as of 2000, (e) forest loss within PAs and (f) forest loss across countries by region and income. Regionally, South America had the largest increase in new PAs, accounting for 49% of the new PAs. Upper-middle income countries accounted for 46% of the new PAs, while low income countries accounted for less than 10% of the new PAs.

In figure 1, we show the percentage of total terrestrial area that was (a) under protection in the year 2000, (b) allocated for protection between 2000 and 2012, and (c) remained unprotected as of 2012, across regions and income categories for the 81 countries used in our analysis. We also show the percentage of terrestrial area in each region that was not included in our analyses.

To control for non-random allocation of PAs, we used spatial matching methods (Honey-Rosés *et al* 2011) to identify a counterfactual group from areas that were not protected but that were similar to PAs based on observable characteristics (Ho *et al* 2007, Sekhon 2007). We included the following covariates in the matching process: forest cover in 2000, slope, spatially weighted slope of neighboring cells, elevation, spatially weighted elevation of neighboring cells, distance to the nearest city with a population larger than 750 000 within the country, distance to the nearest city with a population larger than 750 000, and length of the road network within the cell. To

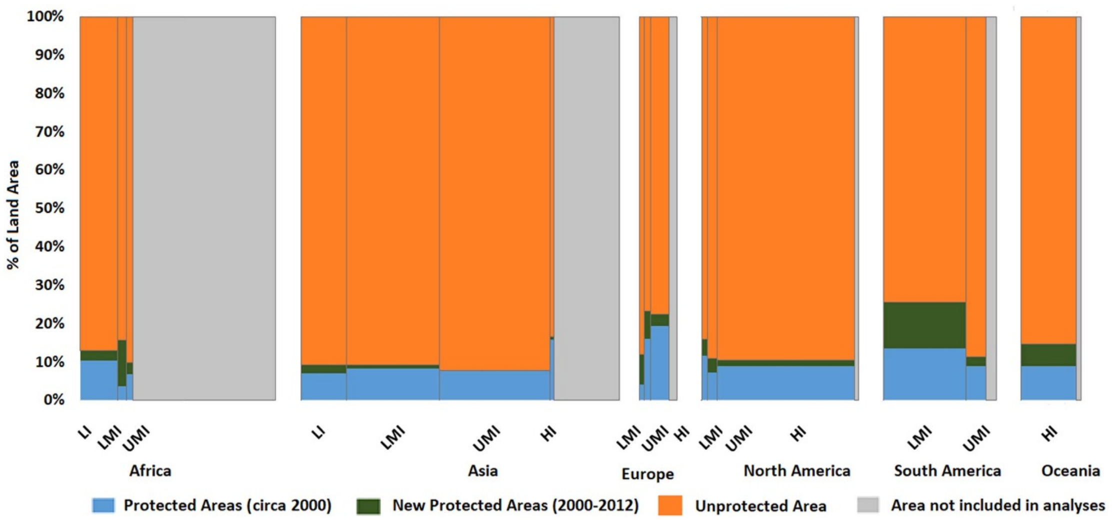

Figure 1. Expansion of PAs from 2000 to 2012, by region and income category.
Notes: In figure 1, we show the existing PAs circa 2000, the new PAs established between 2000 and 2012, the area that remained unprotected in countries used in our analyses within each income and region group. Here, LI = low income countries; LMI = lower middle income countries; UMI = upper middle income countries; HI = high income countries. The width of a column represents land area within a category. Lower income, lower-middle income and upper-middle income countries in Oceania had negligible land area and are not shown. The exact numbers for all other income/region groups are shown in SI table 1 in supplementary information. In our analyses, we excluded 43 countries from Africa, 31 countries from Asia, 26 countries from Europe, 29 countries from North America, 8 countries from Oceania and 4 countries from South America either because these countries had zero forest cover in 2000 within the newly established PAs or countries had less than 20 cells with estimated new PAs covering at least 50% of the cell. We also excluded two countries from Europe and one country from Oceania because the normalized differences in means of covariates post matching was greater than 0.35. More details are shown in the notes for SI table 1 in supplementary information.

control for differences in local policy, we ensured that matched cells were selected from the same country as treatment cells.

To assess the impact of strictness of protection on PA effectiveness, we develop four additional matched datasets following Ferraro *et al* (2013). We match (a) cells that are strictly protected with unprotected cells to estimate the effectiveness of strict PAs by country; (b) cells that are less strictly protected with unprotected cells to estimate the effectiveness of less strict PAs by country; (c) cells that are strictly protected with cells in less strict PAs to estimate the expected change in forest loss on strict PAs had they instead been less strictly protected; and (d) cells that are less strictly protected with cells in strict PAs to estimate the expected change in forest loss had they instead been strictly protected.

Post matching, we performed univariate regressions to estimate the change in forest cover on the change in area under protection between 2000 and 2012. We used the coefficient estimates from these regressions to calculate how much forest loss was avoided (or increased) due to new protection. We also used univariate regressions to estimate how much forest loss was avoided (or increased) due to strict protection and less strict protection, by country. SI table 2 provides details at the country level about the area in new PAs that was forested in 2000 and SI table 3 provides details at the country level for area in new strict and less strict PAs that was forested in 2000. To account for this difference in forested area within new PAs, we divided the estimate of avoided (or increased) forest loss due to new PAs by the forest cover in 2000 within the PAs to arrive at the PA effectiveness for each country.

Next we used our PA effectiveness estimates to determine how much forest loss would have been avoided if each country's PA effectiveness reflected 'best-in-class effectiveness', i.e. if each country's PAs were as effective as the country with the most positive PA effectiveness in a region facing similar types of deforestation threats as identified in Curtis *et al* (2018). Curtis *et al* (2018) disaggregated global deforestation threats into seven regions (North America, South America, Europe, Africa, Russia/China/South Asia, Southeast Asia and Australia/Oceania) based on five key drivers of deforestation. According to their study, the primary drivers of deforestation in North America, Russia/China/South Asia, and Australia/Oceania were forestry and wildfires. In South America and Southeast Asia, the primary drivers of deforestation were commodity-based deforestation and shifting agricultural practices. In Africa, the primary driver of deforestation was shifting agricultural practices. We assume that it is possible for countries within the same region, facing similar types of deforestation threats, to achieve a higher level of PA effectiveness. To do this, we first identified the country with the highest PA effectiveness in each of the seven regions. We then estimated the percentage reduction in forest loss from new PAs in those countries. We used this estimate to calculate the estimated forest loss for each country if their PAs had performed as well as the country with the highest PA effectiveness within the same region. Specifically, we multiplied the coefficient estimate for each country by the area that was established as PA between 2000 and 2012 to obtain the predicted area of forest loss avoided. We limited the potential benefit of PAs to reducing deforestation in their area to zero. We also estimated how much additional forest loss could have been reduced if each countries' PA had been as effective as the most effective PA not only within the same region but also within the same income group.

PA effectiveness estimates are likely to be driven in part by PA placement. PAs placed in locations with a low threat of deforestation will have limited effectiveness (Nolte *et al* 2013). We compared PA effectiveness estimates to deforestation rates between 2000 and 2012 within the country and within the matched counterfactuals areas to assess the role of PA placement on their effectiveness. We further explore whether PA effectiveness estimates shift over time by evaluating the differences in PA effectiveness for the period 2006–2012 between parks established in 2000–2005 and parks established in 2006–2012 (see supplementary information for more details). We use a t-test statistic to determine whether the effectiveness of PAs established between 2000 and 2005 was different than the effectiveness of PAs established between 2006 and 2012.

We used regression trees and bagging trees to determine which of 14 demographic, agricultural, governance and economic indicators were most strongly associated with PA effectiveness. The global scale of analyses requires the use of such non-parametric, non-linear predictive models with no *a priori* assumptions on the nature of the relationship between PA effectiveness and a wide range of predictor variables. The machine learning methods we use can help uncover hidden structures in the data through use of recursion, resampling and averaging techniques that standard parametric regressions cannot capture. We selected variables for inclusion based on the literatures on determinants of deforestation and institutional quality.

Studies have found that corruption, political instability, lack of private property rights, weaker rule of law and governance ineffectiveness can influence deforestation (Meyer *et al* 2003, Koyuncu and Yilmaz 2009, Wendland *et al* 2014, Sommer 2017). Abman (2018) finds that several of the governance and institutional indicators identified in the Worldwide Governance Indicators (WGI) database are directly associated with PA effectiveness; the study specifically shows that low levels of corruption, greater protection of property rights and more democratic institutions are associated with greater PA effectiveness. WGI reports aggregate and individual governance indicators for over 200 countries for six dimensions of governance: corruption perceptions, governance effectiveness, regulatory effectiveness, voice and accountability, rule of law, and political stability. Combined, these six WGI indicators include the process by which governments are selected; the government's effectiveness in establishing and implementing policy decisions; and the respect of citizens and the state for the institutions that govern economic and social interactions among them. We used an index based on the average of these six indicators as a measure of the governance quality for each country.

Countries with a larger reliance on agricultural activity have experienced greater deforestation pressures (DeFries *et al* 2010, Leblois *et al* 2017); thus, we included four agriculture related indicators in our analyses: the percentage of total land that is arable, percentage of land that is forested, agriculture value added to Gross Domestic Product (GDP), and net agriculture trade per capita (World Bank 2000–2012). We also include the percentage of land that was set aside for protection before 2000 to understand whether the extent of existing protection impacts the effectiveness of new protection. Increasing population in rural areas can have mixed effects on deforestation and in turn on PA effectiveness. Porter-Bolland *et al* (2012) show that population growth increased pressure on protected forests. DeFries *et al* (2010) find that urbanization is an important determinant of deforestation in the tropics likely owing to both indirect and direct pressures on forested lands. The relationship between population and PA effectiveness may be further complicated by the inherent endogeneity between population growth and deforestation (Busch and Ferretti-Gallon 2017). Thus, we included three demographic indicators in our analysis: growth rate of urban population, growth rate of rural population and percentage of population living in urban areas (World Bank 2000–2012). Several studies find a strong relationship between economic indicators and deforestation. We included two economic indicators, GDP growth rate and GDP per capita growth (World Bank 2000–2012), in our analyses. We also included categorical variables for countries' region and income group and a dummy variable for whether the country is tropical. In SI table 4, we provide the average and standard deviation for the 11 continuous variables. We applied two methods, regression trees and bagging trees, to identify the most important factors associated with PA effectiveness. We dropped three countries for which not all data were available (Equatorial New Guinea, French Guiana and South Sudan); thus we used 78 countries in the regression and bagging tree analyses.

3. Results

PAs established between 2000 and 2012 reduced forest loss in those areas by 72% over the 12 year period, to 34 024 km^2 from an estimated 120 086 km^2 that would have occurred without protection. Strict PAs

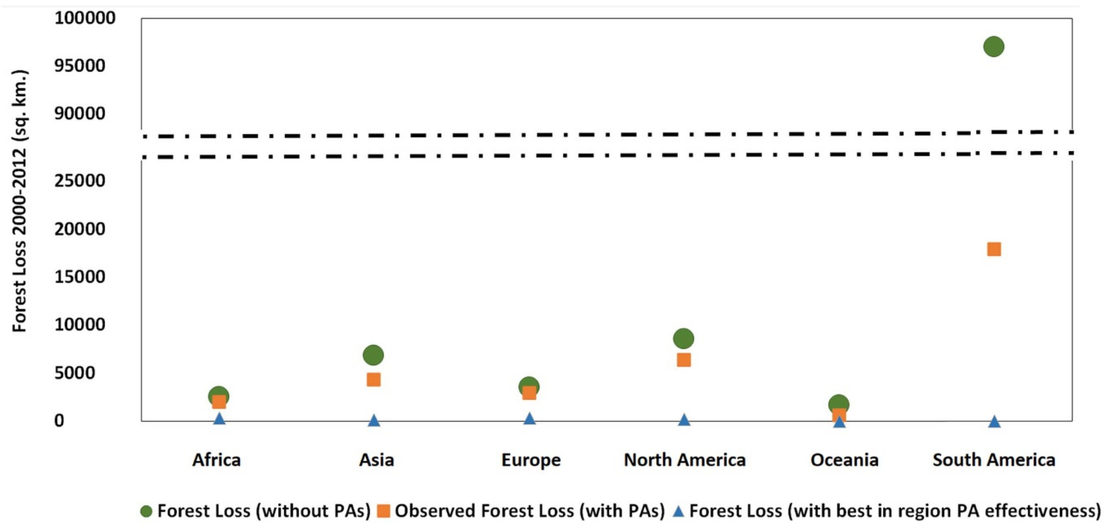

Figure 2. PA effectiveness estimates by region.
Notes: In figure 2 we show the estimated forest loss without PAs, the observed forest loss with PAs and the forest loss that would have occurred with best in region PA effectiveness. The results for Southeast Asia and Russia/China/South Asia have been combined into a single category: Asia. The exact details are shown in SI table 5 in supplementary information.

accounted for 39% of the reduced forest loss. In figure 2, we show the observed forest loss within new PAs and the estimated forest loss that would have occurred without the new PAs for each region (see SI figure 1 in supplementary information for the observed forest loss within new PAs and estimated forest loss without PAs for the different income groups within each region). PAs in upper-middle income countries in South America reduced forest loss by 85% compared to what would have occurred without protection. PAs in high income countries in Oceania reduced forest loss by 65% while PAs in lower-middle income countries in South America, PAs in lower-middle income countries in Asia and PAs in upper-middle income countries in Africa reduced forest loss by almost half. All other income and region groups had relatively smaller PA impacts of less than 40% reduction in forest loss compared to what would have occurred without protection.

In figure 3, we show the estimates of PA effectiveness (i.e. forest loss reduced by PAs per km^2 of PA with forest cover in 2000) by country, grouped by income and region. In Asia and globally, PAs in Cambodia were the most effective, with 13.2% forest loss avoided. In Oceania, PAs in New Zealand had the highest PA effectiveness of 10.9% forest loss avoided. In North America and South America, PAs in Guatemala and Brazil had relatively higher effectiveness of 7.5% and 7.2% forest loss avoided, respectively. In Africa, PAs in South Africa recorded the highest effectiveness of 8.3% and in Europe, PAs in Latvia had the highest effectiveness of 7.3% forest loss avoided. Of the 81 countries, new PAs in 37 countries were found to have a statistically significant decrease in forest loss while six countries were found to have statistically significant increase in forest loss within PAs, but for the most part, these increases were small.

Strict PAs reduced forest loss by 81% whereas less strict PAs reduced forest loss by 67% over the 12 year period, compared to what would have occurred without protection. Strict PAs in South America, Oceania, Africa, Europe, North America and Asia reduced forest loss by 94%, 76%, 54%, 54%, 35% and 30%, respectively while less strict PAs in South America and Asia reduced forest loss by 76% and 49%, respectively. Less strict PAs in all other regions reduced forest loss by less than 35%. In figure 4, we show the observed forest loss within new strict and less PAs and the estimated forest loss that would have occurred without the new strict and less strict PAs for each region. SI table 6 in supplementary information provides more details on the impact of strict and less strict PAs by region. Strict PAs were found to have higher PA effectiveness in 32 of the 49 countries compared to less strict PAs. Of these 32 countries, the differences in PA effectiveness estimates were significant for 18 countries. Less strict protection was more effective at reducing forest loss in 17 out of the 49 countries, though the difference in PA effectiveness estimates was significant in only 7 countries. In SI figure 2 in supplementary information, we show the PA effectiveness estimates for strict and less strict PAs by country. In SI table 3, we provide additional details on PA effectiveness estimates for strict and less strict PAs at the country level.

If strict PAs were less strictly protected, globally there would have been a 75% increase in forest loss compared to the forest loss that was avoided within the strict PAs. Figure 4 shows the estimated forest loss that would have been avoided by region if strict PAs were less strictly protected. Strict PAs were more effective at reducing forest loss compared to matched counterfactuals from less strict PAs in 33 of the 49 countries, with the effect being significant in

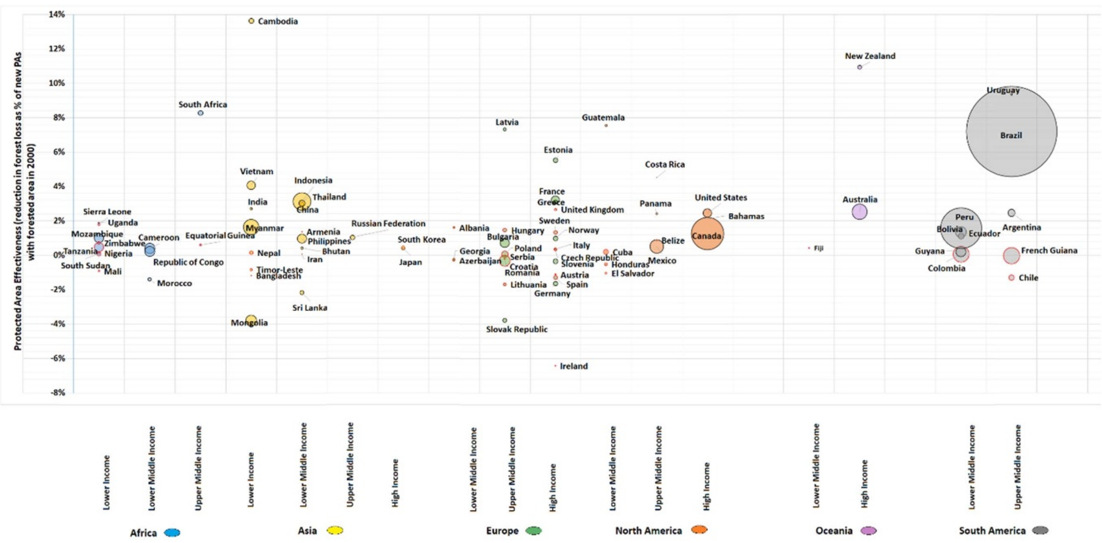

Figure 3. PA effectiveness by country.
Notes: In figure 3,we show the country-level PA effectiveness estimates grouped by income and region. The bubble area represents the area of newly protected forested PAs that were established between 2000 and 2012; black outlines indicate coefficient estimates from univariate regression were significant at least at the 5% level; red outlines indicate coefficient estimates were not significant at 5%.

21 countries. Alternately, in 16 countries, strict PAs were less effective in reducing forest loss compared to matched counterfactuals from less strict PAs with the effect being significant in 8 countries.

If less strict PAs were strictly protected, globally there would have been a 120% larger reduction in forest loss compared to what was avoided within less strict PAs between 2000 and 2012. Figure 4 shows the estimated forest loss that would have been avoided by region if less strict PAs were strictly protected. Less strict PAs were less effective at reducing forest loss compared to matched counterfactuals from strict PAs in 33 of the 49 countries, with the effect being significant in 25 countries. Alternately, in 16 countries, less strict PAs were more effective in reducing forest loss compared to matched counterfactuals from strict PAs with the effect being significant in 11 countries.

If every country's PAs were as effective as the country with the most effective PAs within the same region, they could have reduced deforestation by 99%, avoiding 119 082 km^2 of forest loss—an additional 33 020 km^2 (38%) compared to their estimated actual impact. In figure 2, we show the estimated forest loss that would have occurred with best-in-class effectiveness of new PAs alongside the estimated forest loss that would have occurred without new PAs and the observed forest loss with new PAs by region. The results for Southeast Asia and Russia/China/South Asia have been shown together under the category 'Asia'. However, SI table 5 (in supplementary information) provides the detailed estimates for the seven regions. Due to the large variation in PA effectiveness across countries even within the same region, we find that several regions' PA networks could have avoided substantially more forest loss had they achieved best-in-class effectiveness. PAs in Europe could have reduced forest loss by more than 4.4 times, while PAs in Africa and North America could have reduced forest loss by more than 2.5 times if all countries' PAs would have been as effective as the country with the highest effectiveness in that region. PAs in South America could have reduced forest loss by 22% with best in class effectiveness, though in absolute terms that would have amounted to an additional 17 890 km^2 of forest loss avoided. If every country's PAs were as effective as the country with the most effective PAs within the same income group in the same region, they could have reduced deforestation by an additional 26% compared to the actual impact, avoiding 108 562 km^2 of forest loss. We show these results in SI figure 1 and SI table 7 (in supplementary information).

In figure 5, we show the country-level and location-based deforestation threats facing PAs along with the relative differences in PA effectiveness estimates (as indicated by the differences in bubble size). In SI table 2 (in supplementary information), we provide details by country on the forest loss per km^2 within PAs, in matched counterfactual areas and for the entire country. We find both country-level deforestation and the location-based deforestation threat are associated with higher PA effectiveness (with significant correlation coefficients of 0.47 and 0.23 respectively). PAs toward the upper right—e.g. Brazil, Cambodia, Guatemala, Latvia and Estonia—faced the highest threats both at the location and at the country level between 2000 and 2012; these PAs also had the highest effectiveness within their region and income group. PAs toward the lower right were placed in locations with lower deforestation threat despite the fact

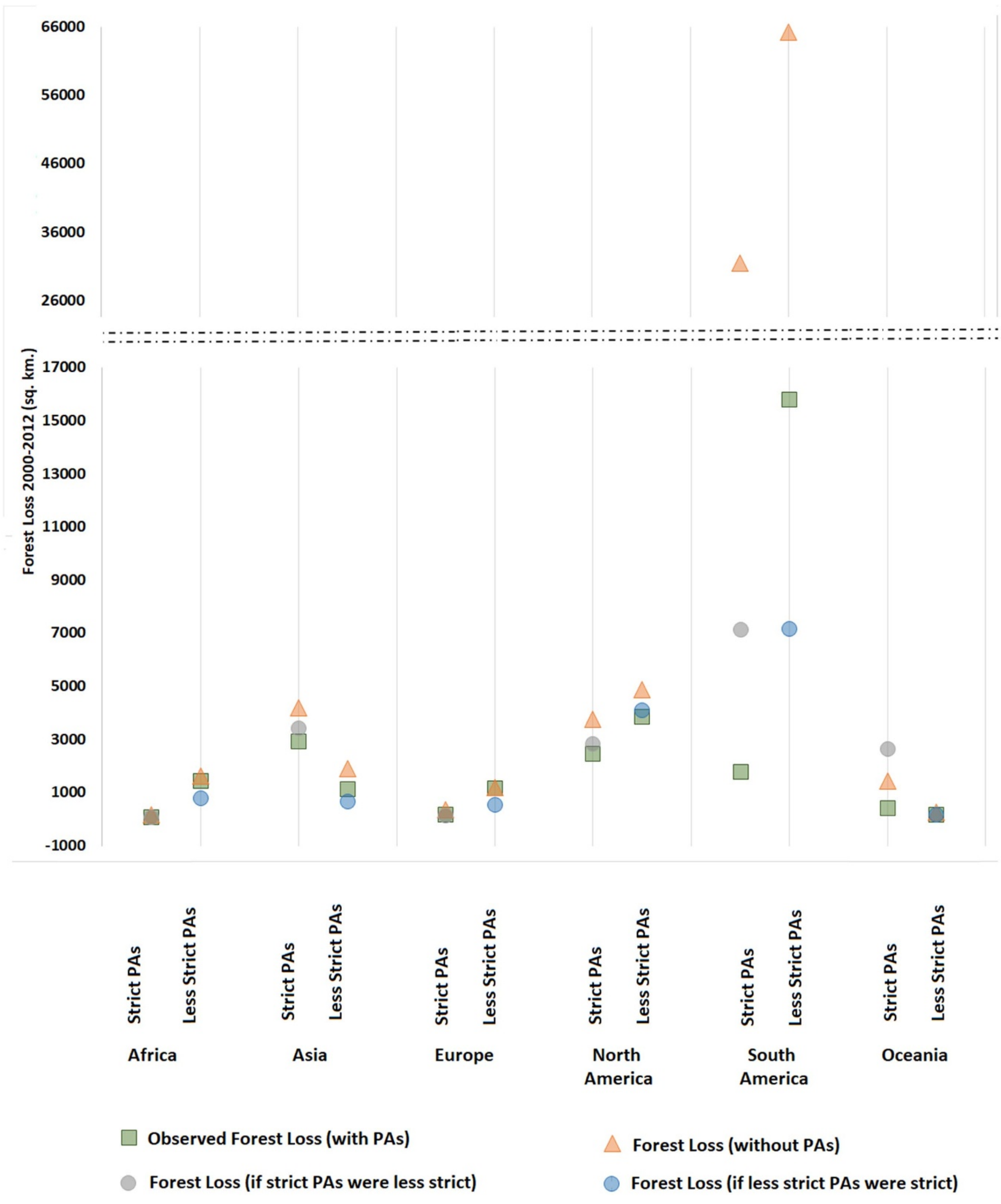

Figure 4. PA effectiveness estimates by strictness of protection.
Notes: In figure 4 we show the estimated forest loss without strict and less strict PAs, the observed forest loss with strict and less strict PAs, the forest loss that would have occurred with strict PAs had they been less strictly protected and the forest loss that would have occurred with less strict PAs had they been strictly protected. The exact details are shown in SI table 6 in supplementary information.

that they were in countries that faced high deforestation levels; these PAs also had relatively higher effectiveness compared to other PAs in the same region and income group. PAs toward the lower left of figure 5 faced lower deforestation threats both at the specific PA location and at the country level. All six countries with statistically significant negative PA effectiveness were located in this lower left section. However, there are also several outliers such as Mali and New Zealand. PAs in Mali had a small and insignificant negative PA effectiveness of −0.9% even though these PAs were placed in areas with high deforestation threat. PAs in New Zealand had a large and significant positive effectiveness even though their PAs were placed in areas with low deforestation threat in a country facing relatively lower deforestation levels.

We find that for 60 countries, there is a significant difference in the dynamics of PA effectiveness between PAs established between 2000 and 2005 and PAs established between 2006 and 2012; while for 3 countries, we do not find a significant difference in PA effectiveness. Of the 60 countries, in 31 countries the PA effectiveness of parks established earlier (i.e. between 2000 and 2005) is higher than

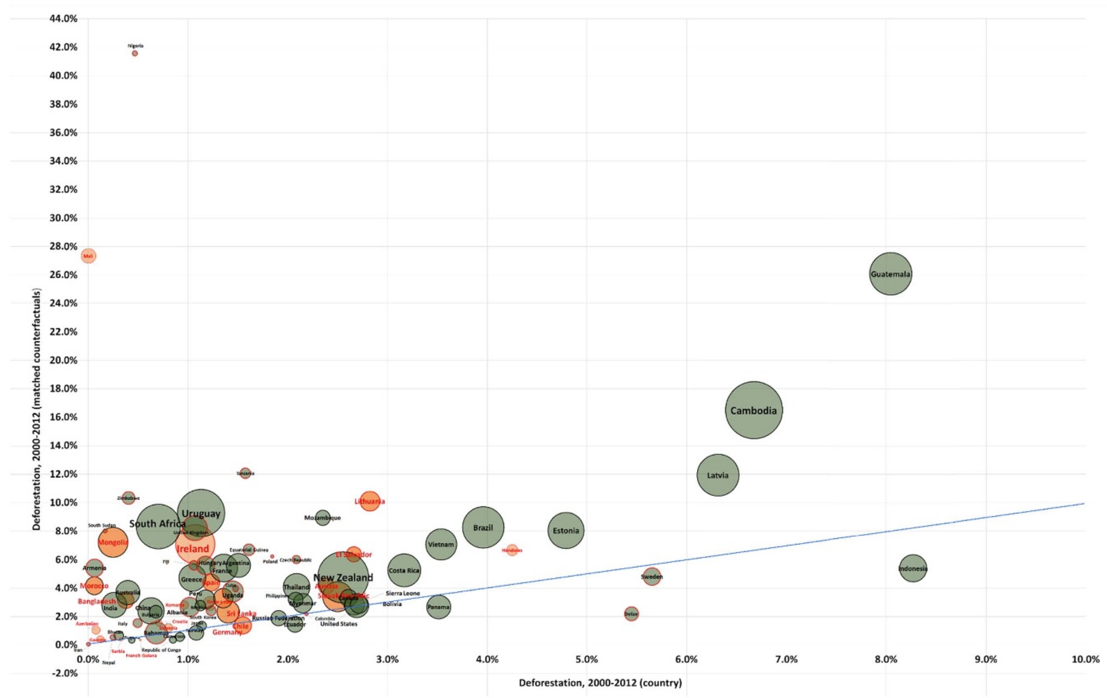

Figure 5. Deforestation pressure versus PA effectiveness.
Notes: In figure 5, we map each country's newly established PAs on a plot reflecting the location-specific deforestation threats to PAs (y-axis) and country-level deforestation threats (x-axis). The area of bubble is proportionate to PA effectiveness estimate. The blue-line indicates the 45° line. Orange bubbles indicate negative PA effectiveness and green bubbles indicate positive PA effectiveness. Black outlines indicate coefficient estimates from univariate regression were significant at least at the 5% level; red outlines indicate coefficient estimates were not significant at the 5% level.

the PA effectiveness of parks established later (i.e. between 2006 and 2012). These results are shown in SI table 2.

The indicators that had the strongest association with PA effectiveness were agricultural activity, economic growth, percentage of land set aside for protection before 2000, and governance quality. Panel A of figure 6 illustrates the results based on regression tree and panel B shows the results based on bagging tree. We also evaluated the partial dependence plots (PDP) and individual conditional expectation (ICE) plots for all the continuous variables to understand the marginal effect of each variable on PA effectiveness (see SI figure 3 in supplementary information).

Arable land, an indicator of agricultural activity, was an important predictor of PA effectiveness based on both regression tree and bagging tree results. Availability of arable land was the second split in the regression tree (as seen in panel A of figure 6), indicating that it was a powerful discriminator between countries with relatively high and low PA effectiveness. Countries with less arable land and relatively better governance quality (as shown in the right most node in the regression tree) tended to have higher PA effectiveness. Conversely, countries with more arable land and larger rural population growth rates tended to have lower PA effectiveness (as shown in left most nodes on the regression tree). PDP and ICE plots also confirm that increases in arable land led to lower PA effectiveness. Agricultural value added to GDP and net trade in agricultural products per capita were also important predictors of PA effectiveness. PDP and ICE plots indicate that larger net trade in agriculture per capita was associated with lower PA effectiveness.

The two economic growth indicators, GDP per capita growth rate and GDP growth rate, also emerged as important predictors of PA effectiveness based on regression tree and bagging trees. GDP per capita growth rates above 5.4% are associated with higher PA effectiveness as shown in the first split in the regression tree. Both indicators also emerged as important predictors based on bagging tree with PDP indicating that higher economic activity led to a small but positive jump in PA effectiveness.

The percentage of land in protection prior to 2000 was found to be an important predictor in determining PA effectiveness. The PDP plot indicates that new PAs in countries with more terrestrial area in PAs prior to 2000 experienced relatively larger effectiveness. Two other important indicators of PA effectiveness were governance quality and rural population growth rates. PDP plots and regression tree splits both indicated that better governance quality was associated with greater PA effectiveness. A higher growth rate in rural population resulted in lower PA effectiveness as indicated by both regression tree and bagging trees. Urbanization, urban population growth rates, percent of forested area and tropical climate were found to be less important in predicting PA

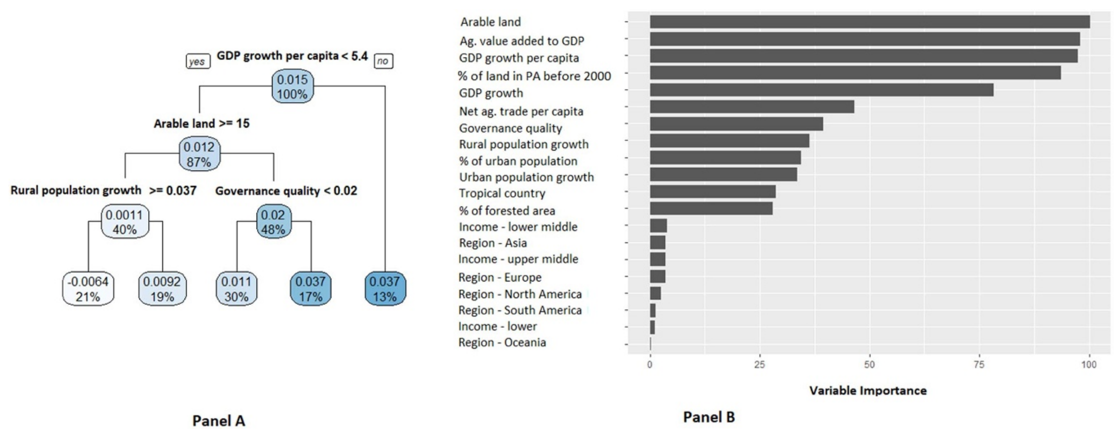

Figure 6. Regression tree and bagging tree results.
Notes: Each split in the regression tree in panel A lists the average PA impact and the % of observations explained. The variable importance plot shown in panel B is based on bagging trees. Each importance bar shows by how much a split on that variable cab reduce the prediction error.

effectiveness. Differences based on geographic location or income groups were found to be the least important in predicting PA effectiveness.

4. Discussion and conclusion

New PAs established between 2000 and 2012 accounted for 3.2 million km^2 of terrestrial area across 81 countries. These new PAs avoided 86 062 km^2 of forest loss between 2000 and 2012. However the expansion and effectiveness of PAs in reducing forest loss varied greatly across regions and income groups. Tropical countries, especially in South America, and in upper-middle income groups, had relatively higher PA effectiveness. PA effectiveness also varied based on the strictness of protection, though these effects were heterogenous across countries. On average strict PAs were more effective at reducing forest loss though less strict PAs in several countries performed better. While a variety of factors including strictness of protection and PA placement contributed to PA success, PAs in countries with lower agricultural activity, higher economic growth rates and better governance were generally associated with greater PA effectiveness.

Our finding that agricultural activity is associated with reduced PA effectiveness accords with studies that have shown a strong and positive relationship between agriculture and deforestation (DeFries *et al* 2010, Carter *et al* 2017). Land is a limited resource so allocating land for protection, especially land that is suitable for agriculture, creates larger pressures for potential illegal deforestation even within PAs. Thus, countries facing larger threats from agricultural activity should continue to protect existing and new terrestrial areas in order to avoid increasing deforestation. This is especially important as vast PAs in the Amazon and even some parts of North America are being downgraded, downsized or degazetted (Mascia and Pailler 2011, Mascia *et al* 2014, Naughton-Treves and Holland 2019).

We found that countries with a greater percentage of land that was in protection prior to 2000 experienced higher levels of PA effectiveness. Studies to date have not systematically evaluated the effect of existing PAs on new protection. It is important for future studies to estimate how increasing the size of a PA network and the location of new protection within the same country or in nearby areas can impact the effectiveness of the new PAs.

We found that higher economic growth rates were associated with higher PA effectiveness. Other studies have shown that economic growth often comes at the cost of higher deforestation (Busch and Ferretti-Gallon 2017), e.g. by increasing spending on road infrastructure and leading to more deforestation (López and Galinato 2005). However, our results indicate that countries with higher economic growth rates were associated with greater PA effectiveness.

The regression tree results further indicate that PA effectiveness estimates are higher for the group of countries with better governance quality. This is consistent with the findings of (Abman 2018). Culas (2007) shows that better governance and environmental policies can help countries achieve higher economic growth rates without the expected increase in deforestation. While our measure of governance quality focuses on only six broad indices of governance characteristics, it indicates the importance of governance quality and institutional factors on increasing PA effectiveness. However, these indices do not capture governance constraints in particular country contexts. Moreover, PAs are often established and or monitored and enforced by sub-national governing agencies or non-government organizations. In such cases, localized governance indicators maybe more appropriate in understanding and predicting PA effectiveness. Future studies can look at more country-specific as well as sub-national governance measures and their impact on PAs.

Though the results using global data provide a broad overview of the effectiveness of PA networks, this scale of analyses has several limitations. The data we use to estimate global forest cover loss (Hansen *et al* 2013) is less reliable in tropical areas, for non-homogeneous vegetation types and identifying small scale changes in forest cover (Alix-Garcia and Millimet 2020). In our PA effectiveness estimates, we do not distinguish between the key drivers of forest loss and whether the forest loss is due to permanent or temporary land use change. Curtis *et al* (2018) identify the spatial heterogeneity in dominant drivers of global forest loss. They show that while large deforestation and shifting agricultural practices are key drivers of forest loss in South America, Africa and Southeast Asia, rotation based forestry and wildfires are key drivers of forest loss in Europe, North America, Oceania, South Asia, Russia and China.

Due to the global scale of analyses, we limit our list of covariates to factors that can be easily observed for all countries. However, the PA effectiveness estimates are biased to the extent that we fail to include important covariates in the matching process. Thus any policy decision pertaining to PAs should take into account similar analyses with a greater focus on country-specific and even PA-specific details. Our study is limited to PAs established between 2000 and 2012. However, more than 75% of global PAs were established prior to 2000 and future studies should consider the effectiveness of these PAs for a more complete understanding of PA network's ability to reduce deforestation. While the bagging tree results indicate that existence of PAs can be an important predictor of the success of new PAs, our results are not conclusive and more evidence is needed to better understand the role of additional protection on PA effectiveness. Furthermore, we only consider the effectiveness of PAs in reducing forest loss within PAs and do not consider the leakage effects which can enhance or reduce the overall PA effectiveness. Several impact evaluation studies show that an increase in protection in one area displaces deforestation activities to other areas (Ferraro 2002, Oliveira *et al* 2007, Meyfroidt and Lambin 2009). Conversely, a few studies have found negative forest leakage, where protection increases the forest conservation on adjacent lands (Gaveau *et al* 2009, Honey-Rosés *et al* 2011, Pfaff *et al* 2014). Previous studies that model leakage account for how changes in prices as well as local demand and supply conditions can impact leakage (Wu 2000, Wear and Murray 2004, Baylis *et al* 2013). Thus, both empirical and theoretical studies provide evidence that the impact of leakage on overall PA effectiveness can be mixed. Future studies need to consider leakage to arrive at a more accurate estimate of PA effectiveness.

We also find limited evidence that dynamics of PA effectiveness can shift over time. This supports previous studies' underscoring the importance of using more frequent observations on forest cover change with increased monitoring of PAs in high pressure areas to ensure the success of long term conservation efforts (Andam *et al* 2008, Joppa *et al* 2008, Barber *et al* 2012). More work is needed using data on forest protection and forest cover change over an extended period of time to better understand the dynamics of PA effectiveness.

Our estimates of PA effectiveness rely largely on PA placement and baseline deforestation threat facing the country. PAs that are located in high-threat areas or are within a country that faces high deforestation levels have a greater potential to avoid deforestation. Our results corroborate previous findings that the effects of regulatory strictness can vary across countries (Ferraro *et al* 2013, Nolte *et al* 2013, Pfaff *et al* 2014). However, while stricter PAs are often associated with greater levels of avoided deforestation, these differences in PA effectiveness, based on strictness of IUCN category, are not always large and can be attributed to a variety of factors which need further investigation. Previous studies indicate that stricter PAs maybe assigned to areas which are less likely to be disturbed (Pressey and Bottrill 2008, Joppa *et al* 2009, Ferraro *et al* 2013). Alternately, less strict protection is more likely to be assigned to lands facing higher anthropogenic pressures and thus result in larger avoided deforestation (i.e. higher PA effectiveness) even while permitting more disturbances than strictly PAs. Thus, more evidence is needed to guide policymakers in the choice of PA management categories. Moreover, PAs are established for achieving a variety of objectives and their strictness level and locations can be driven by motivations other than preventing land clearing. For example, PAs targeting areas of biodiversity conservation may be situated in low-threat areas. Thus, future studies should take into account several different measures of effectiveness in order to understand the success of PAs.

Scientists have called for protecting 30% of the world's terrestrial area by 2030 (Dinerstein *et al* 2019). But allocating more land for PAs occurs at the expense of other productive uses of that land in the economy. Indeed one of the mainstays of systematic conservation planning is how to achieve maximum conservation benefits at the minimum possible cost (Naidoo *et al* 2006). We find that if every country's PA network were as effective as the most effective national PA network in the same region, 38% additional forest loss would have been avoided. Thus, in addition to setting targets for increasing the area under protection, conservation policy should include PA effectiveness goals and highlight the importance of making existing PAs more effective. Within every geographic and income group, we have found a wide range of PA effectiveness;

thus most countries have scope to improve PA effectiveness. PAs in countries with increased agricultural activity, lower economic growth rates and lower governance quality are likely to be more vulnerable to increased deforestation and thus should be provided with more support to achieve PA success.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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