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RESEARCH ARTICLE

Effectiveness of China's protected areas in reducing deforestation

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Abstract
Protected areas (PAs) are considered a cornerstone of biodiversity conservation, and the number and extent of PAs are expanding rapidly worldwide. While designating more land as PAs is important, concerns about the degree to which existing PAs are effective in meeting conservation goals are growing. Unfortunately, conservation effectiveness of PAs and its underlying determinants are often unclear across large spatial scales. Using PAs in China as an example, we evaluated the effectiveness of 472 PAs established before 2000 in reducing deforestation between 2000 and 2015. Our results show that the majority (71%) of the PAs were effective in reducing deforestation. Without their establishment, deforestation within the PAs would have increased by about 50% (581 km^2), with about 1271 megaton of carbon per year not being sequestered. We also found some attributes of PAs, including surrounding deforestation level, roughness of terrain, and travel time to the nearest city, are significantly related to their effectiveness in reducing deforestation. Our findings highlight the need of systematically evaluating the effectiveness of PAs and incorporating this effectiveness into conservation planning and management to more fully realize the goals of PAs not only in China but also around the world.

Keywords Ecological performance · Nature reserves · Deforestation · Carbon · Conservation planning

Introduction

Protected areas (PAs) are one of the primary conservation tools used to combat global biodiversity loss (Liu and Raven 2010; Xu et al. 2017). The number and coverage of PAs have increased by more than 400% over the last half century (IUCN and UNEP-WCMC 2017; Watson et al. 2014). By the end of 2016, there were more than 200,000 PAs, covering about 15% of the Earth's land surface (UNEP-WCMC and IUCN 2016). To better conserve biodiversity worldwide, a more ambitious

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target of protecting more than 50% of global land was recommended during the last World Parks Congress held in Sydney, Australia (IUCN World Park Congress 2014).

While the international community has made important progress toward placing more land under protection, global biodiversity continues to decline and the effectiveness of PAs has been questioned (Butchart et al. 2010; Liu et al. 2001; Mascia and Pailler 2011). The definition of PAs by the International Union for Conservation of Nature (IUCN) establishes that PAs are geographic spaces where regulations are in place to conserve nature (UNEP-WCMC and IUCN 2016). Unfortunately, evidence from previous studies indicates that many PAs are only "paper parks" (Di Minin and Toivonen 2015) lacking effective management and have failed to deliver the expected conservation benefits (Babcock et al. 2010; Liu et al. 2001; Watson et al. 2014). Even ecosystems under the protection of some globally renowned PAs experienced serious degradation, largely due to ineffective management (Brodie and Waterhouse 2012; Liu et al. 2001). To address this crucial issue, there is a growing call for empirical evaluations of PAs' effectiveness in achieving their intended conservation goals, as well as to understand the reasons behind their success or failure (Andam et al. 2008; Coetzee 2017; Leverington et al. 2010; Watson et al. 2014).

Although several studies (e.g., Bruner et al. 2001; Oliveira et al. 2007) have evaluated the effectiveness of individual PAs, assessments covering networks of PAs at large spatial scales (e.g., entire countries) are lacking (Coetzee 2017). In addition, effectiveness of PAs in previous studies was often measured in terms of their spatial overlap with biodiversity hotspots (e.g., Rodrigues et al. 2004; Venter et al. 2014; Xu et al. 2014), areas providing particular ecosystem services (e.g., Craigie et al. 2010; Melillo et al. 2016; Viña and Liu 2017; Xu et al. 2017), and/or areas of suitable habitat for endemic or threatened species (Viña et al. 2010; Yang et al. 2017). Such analyses focus on the ability of PAs to capture ecologically important areas and assume that a PA will provide strong protection once established. Alternatively, effectiveness has been measured as a function of management efforts (e.g., availability of funding, number of staff, development of management plans) (Geldmann et al. 2015; Hockings 2006; Leverington et al. 2010), assuming that increased levels of management will translate into positive conservation outcomes such as reducing deforestation and increasing biodiversity. Although those studies provided important insights, the conservation effectiveness of PAs—effects of PAs on conservation outcomes—can be decoupled to the measurements used in those studies, and few empirical studies have quantified the conservation effectiveness of PAs (Coetzee 2017; UNEP-WCMC and IUCN 2016). Furthermore, understanding the relationships between biophysical and socioeconomic conditions of PAs and their conservation effectiveness is essential for planning and management (Di Franco et al. 2016). The few existing studies evaluating conservation effectiveness (e.g., Ament and Cumming 2016; Andam et al. 2008; Joppa and Pfaff 2011; Sala and Giakoumi 2017) have mainly focused on quantifying PAs' contribution to conservation objectives, while the relationships between biophysical and socioeconomic conditions and conservation effectiveness have not been empirically investigated.

Using the network of terrestrial PAs in China as an example, we quantified the conservation effectiveness of 472 PAs in reducing deforestation and evaluated the relationships between conservation effectiveness and selected socioeconomic and biophysical conditions, including travel time to the nearest city, surrounding deforestation rate, and terrain roughness. China is a highly biodiverse country, harboring more than 34,000 vascular plant species and over 4300 vertebrate species, about half of which are endemic to China (Chen 2015). China is also the world's most populous country with a fast-growing economy. The unique flora and fauna in China have been seriously threatened by the drastic increase and encroachment of human activities in recent decades (Liu and Raven 2010). For example, due to deforestation between the 1950s and the 1980s, forest cover in the Yangtze River Basin was reduced by half, causing serious soil erosion, which contributed to extreme floods in downstream areas during 1998 (Liu et al. 2008; Yin and Li 2001). To address such environmental crises, the Chinese government initiated a series of conservation programs since the beginning of this century. These include the Wildlife Conservation and Nature Reserves Development Program, which aims to protect China's wildlife resources by expanding the PA network (Viña et al. 2016; Wang et al. 2007). From 2000 to 2013, the total area under protection increased from about 0.9 million km^2 to about 1.5 million km^2 (Fig. 1), covering about 15% of China's land surface. Although some studies have evaluated how well China's PAs overlap with biodiversity hotspots (Wu et al. 2011) and with areas providing particular ecosystem services (Xu et al. 2017), the conservation effectiveness of China's PAs in reducing deforestation and its underlying determinants remain unclear.

This study provides a national-level evaluation of the effectiveness of PAs in reducing deforestation. Specifically, we (a) quantify the effectiveness of 472 PAs established before 2000 in reducing deforestation between 2000 and 2015; (b) estimate the area of avoided deforestation due to PA establishment and its contribution to carbon sequestration; and (c) evaluate the relationships between the surrounding deforestation level, terrain roughness, and travel time to the nearest city of the PAs and their effectiveness in reducing deforestation.

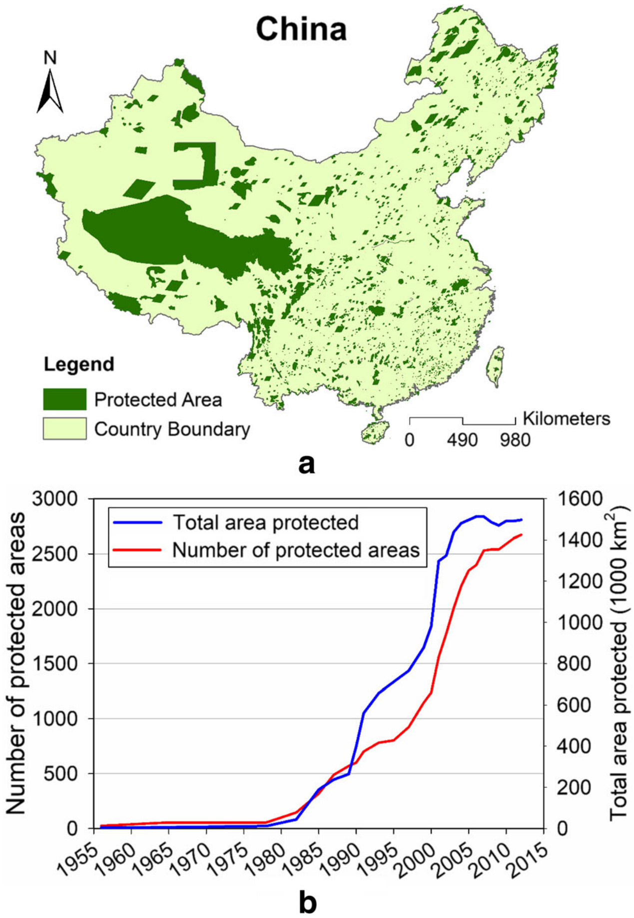


Fig. 1 Protected areas in China. **a** Spatial distribution of PAs in China in 2013. **b** Expansion of protected areas in China between 1956 and 2013. In this study, 472 terrestrial protected areas with forest in them were selected for effectiveness assessment (see "Selection of PAs" section)

Methods

Selection of PAs

The boundaries of terrestrial PAs in China were obtained from the World Database on Protected Areas, downloaded in June 2017 (IUCN and UNEP-WCMC 2017). A total of 2234 PAs included in the inventory are located in China. PAs that lacked boundary information ($n = 1393$) were excluded from further analysis. Since we were interested in evaluating the effectiveness of PAs in reducing deforestation from 2000 to 2015, we excluded PAs established after 2000 ($n = 121$). We further excluded 18 PAs that were established through one or more of the three international agreements (World Heritage Site, Ramsar Sites, UNESCO Man and Biosphere Reserves), because previous studies indicated they often lack management entities to enforce regulations (Rodrigues et al. 2004; Venter et al. 2014; Watson et al. 2014). PAs that did not have forest cover in 2000 ($n = 190$) were also excluded. In addition, we excluded 40 PAs for which the matching method, discussed below, failed to find suitable forest stands in their buffer zone. These exclusions left a final set of 472 PAs included in our analysis. The forest within our final set of PAs (104,726 km^2) counts for about 99% of the total forest within the PAs that have boundary information and were established before 2000 ($n = 512$).

Study design for estimating the effectiveness of individual PAs

We estimated the conservation effectiveness of each PA by quantifying its effect on deforestation using a matching approach (Rubin 1973). Forest distribution and deforestation information for the effectiveness assessment was obtained from a 30-m resolution global forest change dataset (Hansen et al. 2013). We derived a 300-m resolution binary forest map from the forest change dataset for the year 2000 (see "Spatial data on forest change" section). From this binary forest map, we selected a representative random sample of forest pixels within each PA as well as within its 50-km buffer zone for quantifying the PA's effect on deforestation (Fig. 2). The sampling process reduced the number of pixels, and thus the computation time, involved in the effectiveness evaluation while not compromising the reliability of the estimation.

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 determined the required sample sizes using the following equation (Krejcie and Morgan 1970):

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

where N is the total number of forest pixels in the PA or its 50-km buffer; X^2 is the chi-square for the specified confidence level (95% 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

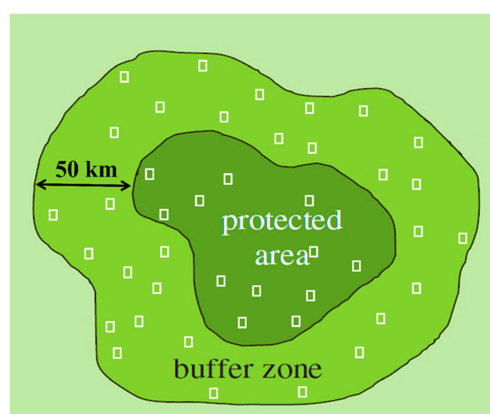


Fig. 2 Forest stand sampling. For each protected area, we drew a representative sample of forest pixels (size = 300 m × 300 m) inside the PA and within its 50-km buffer zone

proportion of forest pixels that may be deforested, which was set to 0.5 to provide the maximum sample size that may be required to achieve the desired level of accuracy as suggested by (Krejcie and Morgan 1970). Using this sampling approach, a large portion of forest pixels are included in the effectiveness estimation when the total forest area in a PA or a PA's buffer is small. For example, if the forest area within a PA is less than 360 ha, more than 90% of the forest pixels were included in effectiveness estimation.

After sampling each PA and its 50-km buffer zone, we used the matching approach to estimate the effect of each PA on deforestation rate. The goal of the matching method as used here is to control for the differences inside and outside of each PA that may influence both the designation of an area as a PA and the observed deforestation (i.e., confounding factors). For example, the distribution of PAs is often biased toward remote areas where the land value is low (Joppa and Pfaff 2009). Therefore, without controlling for remoteness, the observed difference in deforestation between protected and unprotected forest pixels may be biased and not reliably reflect the effectiveness of the PA. Once observable confounding factors were accounted for, the deforestation experienced by the unprotected forest in the buffer of the PA reasonably represents the counterfactual deforestation that would have occurred within the PA if the PA were not established. Therefore, the difference in deforestation between the protected forests in PAs and their counterparts in the buffer with similar confounding factors can provide a measure of the effect of the PA on deforestation.

For forest pixels sampled inside a PA, the matching method finds counterparts in the 50-km buffer zone that are similar in terms of 16 socioeconomic and biophysical attribute variables, including tree cover, distance to forest edge, elevation, slope, aspect, terrain roughness, topographic wetness index, human influence index, travel time to the nearest city, precipitation, temperature, soil carbon, soil depth, soil acidity, and amount of bulk and clay in the soil. Table 1 presents the descriptions and data sources for all of these variables. This 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 the16 biophysical and socioeconomic attribute variables. The propensity score summarized the attribute variables into a single scalar variable (Rosenbaum and Rubin 1983; Stuart 2010) and was used to determine the similarity between each protected forest pixel and those in the buffer zone. To calculate the propensity scores, we constructed, using the sample of pixels from each PA and its 50-km buffer zone, an empirical logistic model that links the pixels' 16 attributes to their protection status (i.e., being protected or not). To improve the matching quality, a caliper was used to constrain the difference in propensity score between protected and unprotected forest pixels to within the 0.5 standard

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	Unitless	Whether the pixel experienced deforestation 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 Map (GDEM) / 30 m
Slope	Radian	Slope calculated using GDEM elevation.	
Aspect	Radian	Aspect calculated using GDEM elevation.	
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	Unitless	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	minute	The travel time to the nearest city with more than 50,000 people in 2000.	(Nelson 2008) / 1 km
Precipitation	mm	Average annual mean precipitation from 1970 to 2000.	(Fick and Hijmans 2017) / 1 km
Temperature	°C	Average annual mean temperature from 1970 to 2000.	
Soil carbon	ton/ha	Soil organic carbon stock for a depth interval from 0 to 2 m.	(Hengl et al. 2017) / 250 m
Soil depth	m	Absolute depth to bedrock.	
Soil bulk	kg/m^3	Bulk density at a 1 m depth.	
Soil acid	Unitless	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.	

deviation of their propensity scores. The matching was done with replacement. An unprotected forest pixel in the buffer zone could be matched to multiple protected forested pixels if it was the most similar to them. Using the matched protected and unprotected forest pixels, the effect of a given PA on deforestation was estimated using a bias-adjustment estimator (Abadie and Imbens 2006). The estimator addresses the potential bias in the effect estimation due to the remaining differences in the 16 contextual biophysical and socioeconomic attribute variables between forest pixels within PA and their matched forest pixels in the PA's buffer zone.

We applied this propensity score matching approach to estimate the effect of each of the 472 selected PAs on deforestation. To facilitate interpretation, the additive inverse of the effect value was used to measure the effectiveness so that a positive (negative) value implies that the PA was effective (ineffective) in reducing deforestation. The effectiveness values range from − 100 to 100%, given that deforestation rates can extend from 0 to 100%. We performed the matching analyses in R (R Development Core Team 2013) using the "Matching" packages (Sekhon 2011).

Spatial data on forest change

We obtained information on forest cover using a 30-m resolution continuous fields tree cover product developed by (Hansen et al. 2013). This dataset was aggregated from 30 to 300 m using the mean algorithm in ArcGIS 10.5 (ESRI, Redlands, CA). We then converted this aggregated tree cover map into a binary forest/non-forest map using the threshold of 10% tree cover. We chose this threshold based on the definition by the Food and Agriculture Organization of the United Nations that "forest refers to land with a tree canopy cover of more than 10 percent" (The Forest Resources Assessment Programme 2015). This binary forest cover map was used to generate samples of forest pixel for estimating PA effectiveness. Using this binary forest map, we also generated a data layer characterizing the distance of each pixel to the edge of the nearest forest patch using ArcGIS 10.5 (ESRI, Redlands, CA).

The outcome variable in evaluating the effectiveness of each PA is the deforestation rate. We obtained this variable from a 30-m resolution binary forest loss map included in the forest change dataset provided by Hansen et al. (2013). This forest loss map records all forested areas that experienced deforestation between 2000 and 2015. We aggregated this binary forest loss map from its original resolution of 30 m to 300 m using the mean algorithm in ArcGIS 10.5 (ESRI, Redlands, CA). This aggregation generated a continuous measurement of deforestation. Each aggregated pixel has an average forest loss value ranging from 0 to 100%, representing the proportion of forest within the pixel that experienced deforestation between 2000 and 2015. It should be noted that this measurement focuses on the deforestation disturbances that PAs often aim to stem and does not consider forest gains during this period.

Estimating the avoided deforestation area and its impact on carbon sequestration

The calculated effectiveness of a PA on deforestation rate multiplied by the total forest area in the PA provides an estimate of the area that avoided deforestation due to that PA's protection. We calculated the total area of avoided deforestation between 2000 and 2015 due to the establishment of the 472 PAs in our sample using the equation:

$$\textit{Avoided deforestation area} = \sum_{i=1}^{n} (E_i \times F_i) \qquad (2)$$

where, n represents the number of all PAs in our sample (i.e., 472); E_i and F_i represent the effectiveness of the ith PA in our final PA sample and the forest area within it, respectively.

Using the information obtained from the Terra/MODIS MOD 17A3 product (1 km/pixel) in 2000 (https://lpdaac.usgs.gov/data_access), we then estimated the contribution of the avoided deforestation to carbon sequestration. We estimated this contribution for each PA using a two-step procedure. First, we calculated the difference in average NPP between forest and non-forest areas for each PA and used that to represent the effect of deforestation on NPP. In this step, we used NPP of non-forest area in PA to approximate the NPP after deforestation because the land cover of non-forest pixels in PA may better represent the land cover outcomes if deforestation happened. Second, we multiplied the avoided deforestation area in each PA by the NPP difference to obtain the impact of each PA on annual carbon sequestration. We can formally represent this estimation process using the following equation:

$$\textit{Carbon sequestration} = \sum_{i=1}^{n} \left[\left(NPP_{i,\text{forest}} - NPP_{i,\text{non-forest}} \right) \times E_i \times F_i \right] \qquad (3)$$

where, n is the number of PAs in our final sample; $NPP_{i,\text{ forest}}$ and $NPP_{i,\text{ non-forest}}$ are the average NPP of forest pixels and non-forest pixels for the ith PA; E_i and F_i represent effectiveness and forest area, respectively, of the ith PA in our final sample. The product $E_i \times F_i$ represents the amount of avoided deforestation in the ith PA while the difference $NPP_{i,\text{ forest}} - NPP_{i,\text{ non-forest}}$ represents the impact of deforestation per unit area of forest on NPP per year.

To perform this two-step procedure, we resampled the 300-m resolution binary forest cover map using the majority algorithm and co-registered it to the 1-km resolution NPP map using ArcGIS (ESRI, Redlands, USA). We then randomly drew a representative sample of pixels within each PA and its 50-km buffer. The sample size for each PA was determined by Eq. (1). We then estimated the mean difference in NPP between forest and non-forest pixels in the sample for each PA and evaluated the impact of PA establishment on carbon sequestration using Eq. (3).

Estimating the relationship between PA effectiveness and socioeconomic and biophysical conditions

Three factors that might relate to the effectiveness of PAs were considered: surrounding deforestation level, travel time to the nearest city, and terrain roughness. We chose these three variables because they have important management implications. Previous studies in China and other places (e.g., Joppa and Pfaff 2009; Cao et al. 2015; Baldi et al. 2017) have found that PAs are mostly located in remote areas where human pressure on ecosystems is low, which may limit the potential of PAs to contribute to conservation goals such as reducing deforestation. We chose the surrounding deforestation level to measure human pressure on the forests, and terrain roughness and travel time to the nearest city as measures of PA's remoteness.

We measured all the three attributes at the PA level using the data layers presented in Table 1. The surrounding deforestation level was measured as the average deforestation rate between 2000 and 2015 of the sample forest pixels in the 50-km buffer zone generated for assessing PA effectiveness (see "Study design for estimating the effectiveness of individual PAs" section). To generate the values of the other two factors for each PA, we drew new random samples of pixels within each PA, regardless of their forest cover status in 2000. The sample size of pixels was determined using Eq. (1). The two attribute values for each PA were measured by the mean values of the random pixels from corresponding data layers (Table 1) within that PA.

Based on the value of each of the three variables, we compared PAs with low values (below 25% percentile) against those with high values (above 75% percentile) using the propensity score matching approach (see "Study design for estimating the effectiveness of individual PAs" section). The goal of the matching procedure here is to control for the differences between PAs in the high and low categories of each of the three socio-biophysical variables. PA attributes used as control variables in the comparisons include forest area, tree cover, elevation, aspect, precipitation, temperature, soil carbon, soil depth, soil acidity, and amount of bulk and clay content in the soil. Except for the forest area that was obtained from the binary forest map, the other control variables were generated for each PA using the mean values of the random sample of pixels from the corresponding data layers presented in Table 1 within that PA.

Results

Deforestation was common within and surrounding the PAs evaluated. From 2000 to 2015, about 1157 km^2 (1.1%) of forest within the 472 PAs experienced deforestation. About half of the PAs in our analysis had a high deforestation rate (i.e., deforestation rate between 2000 and 2015 > 1%) (Fig. 3a). The deforestation rate in the areas surrounding PAs was higher than that inside the PAs. Deforestation rates > 1% were observed in the 50-km buffer zones of about 68%

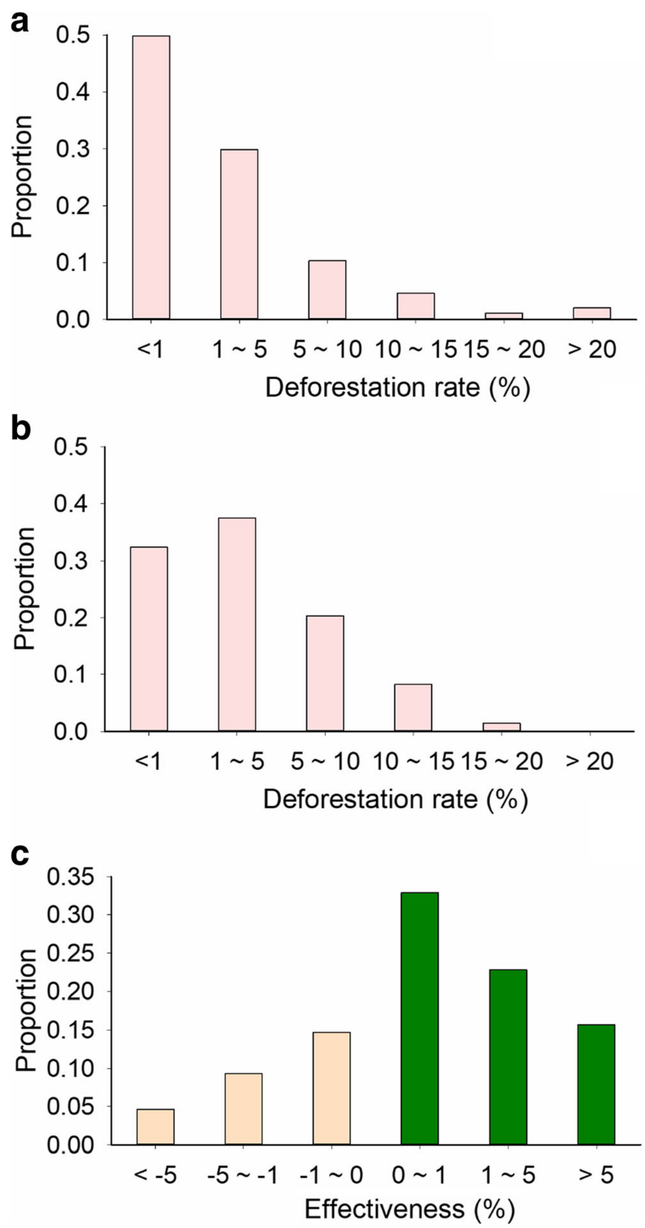


Fig. 3 Distribution of deforestation rates inside and outside the protected areas and effectiveness of protected areas in reducing deforestation. **a** Distribution of deforestation rate inside protected areas. **b** Distribution of deforestation rate within the 50-km buffers of protected areas. **c** Distribution of the effectiveness of protected areas in reducing deforestation rate

of the PAs (Fig. 3b), while the average deforestation rate in the 50-km buffers of the 472 PAs was 1.8%.

Although deforestation was common within the PAs, the majority (71%) reduced deforestation (Fig. 3c). Without their establishment, the deforested area from 2000 to 2015 within the PAs would have been 50% larger (or 581 km^2 more). The estimated amount of carbon sequestered by the forests that avoided deforestation within PAs was about 1271 megaton C/year.

While the majority of the PAs included in the analysis were found to be effective in terms of reducing deforestation, a considerable proportion (29%) were found to be ineffective (effectiveness value < 0) (Fig. 3c). In addition, the effectiveness for 46% of the PAs, although positive, was small (i.e., effectiveness value is between 0 and 1%), indicating that they contributed only modestly to reducing deforestation.

The average effectiveness of PAs in reducing deforestation varied among provinces (Fig. 4). Provinces with effective PAs (i.e., provinces with an average effectiveness value > 0) were mainly those exhibiting high overall deforestation rates (i.e., deforestation rate > 1%). Of the 19 provinces with effective PAs, 14 had a high deforestation rate.

This positive relationship between deforestation rate and PA effectiveness was also evident at the level of individual PAs. Of the three socioeconomic and biophysical factors evaluated, surrounding deforestation had the strongest relationship with a PA's effectiveness (Table 2). On average, the effectiveness of PAs with small surrounding deforestation rates (below 0.7%, the 25th percentile) was 2.41% lower ($p < 0.001$) than those with large surrounding deforestation rates (over 6%, the 75th percentile).

Travel time to the nearest city also had a strong relationship with the effectiveness of PAs (Table 2). PAs closer to a city had higher effectiveness. On average, the effectiveness of PAs with a travel time to the nearest city shorter than 178 minutes (the 25th percentile) was about 1.44% higher ($p < 0.001$) than similar PAs with travel time to the nearest city longer than 562 minutes (the 75th percentile).

Terrain roughness was another factor closely related with PA's effectiveness ($p < 0.001$) (Table 2). PAs in areas with average terrain roughness values less than 21.7 (the 25th percentile) had an effectiveness of 0.56% higher than their counterparts with terrain roughness values larger than 562.8 (the 75th percentile).

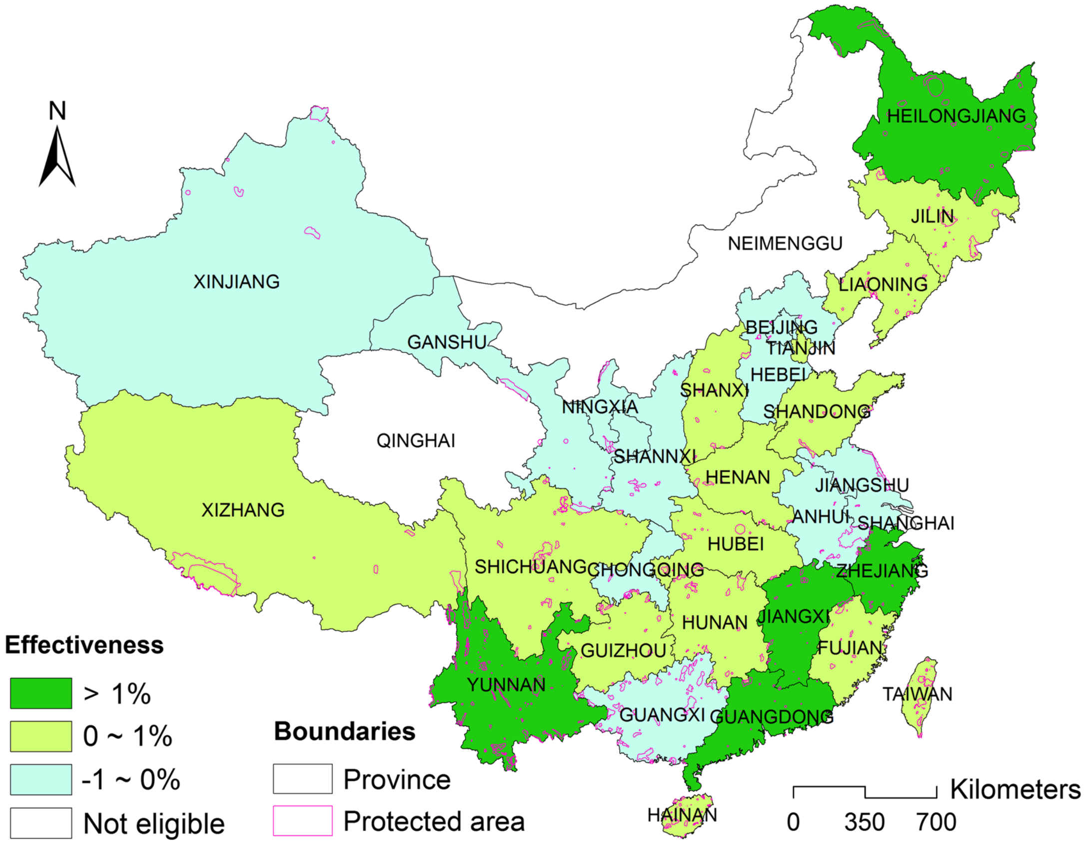
Discussion

Our findings suggest that China's PAs are overall effective in reducing deforestation. Our estimates of avoided deforestation and gains in carbon sequestration attributable to PAs may be conservative because a large number of PAs in the dataset did not have boundary information and hence were excluded from our analysis. However, the exclusion of those PAs is unlikely to have had a major impact on the conclusions of our study, because the total areas of the PAs without boundary information account for only 3% of the area of all PAs in China.

In addition to increasing carbon sequestration, the areas exhibiting avoided deforestation likely offer many other ecosystem services such as soil retention, sandstorm prevention, water purification, and flood mitigation. Although these ecosystem services were enhanced locally, the benefits may have extended regionally, nationally, and even globally (Ouyang et al. 2016). For instance, although carbon sequestration in forests occurs at local level, the associated benefits (e.g., climate change mitigation) are spread worldwide (Liu et al. 2015). Without the establishment of these PAs, many environmental problems such as biodiversity loss may have been worse than they currently are.

Nevertheless, our results indicate that PAs in China are far from reaching their full potential in the conservation of forests. Deforestation exists within many PAs, and a considerable proportion (29%) of PAs were ineffective in reducing deforestation during the study period. A reason for this ineffectiveness may be the lack of regulation enforcement. The Chinese government has issued many guidelines and regulations for PA management, but they are rarely strictly enforced, especially when there is a conflict between conservation goals and demands for socioeconomic development (Li et al. 2016; Liu and Raven 2010; Xu and Melick 2007). For example, like in many areas around the world, management authorities of PAs in China often divide the protected landscapes into three zones—experimental, buffer, and core zones—where different levels of human impacts are allowed. However, even in some flagship PAs, human activities (e.g., construction of tourism infrastructure, livestock husbandry) often encroach into the core zones where socioeconomic development activities are in theory strictly prohibited (Hull et al. 2011; Zhang et al. 2017; Yang et al. 2018).

Another issue that impedes the effectiveness of PAs in China is the shortage of conservation funding. Although the total investment in PAs in China has increased over the last few decades, the average investment per square kilometer under protection is only between 337 and 718 yuan (US$53.5 to US$114 as of April 2018), corresponding to less than one-tenth of that in developed countries (US$2074.3) and less than the average of developing countries (US$158.3) (Zhang 2012). In addition, the majority of PAs in China are partly or fully financed by provincial or county governments, yet most of China's PAs are located in economically poor provinces or counties (Xu and Melick 2007). Insufficient funding in some PAs has resulted in increased revenue-raising activities (e.g., tourism development, extraction of natural resources), causing degradation of ecosystems within these PAs and compromising their conservation effectiveness (Boori et al. 2014; Dai et al. 2012).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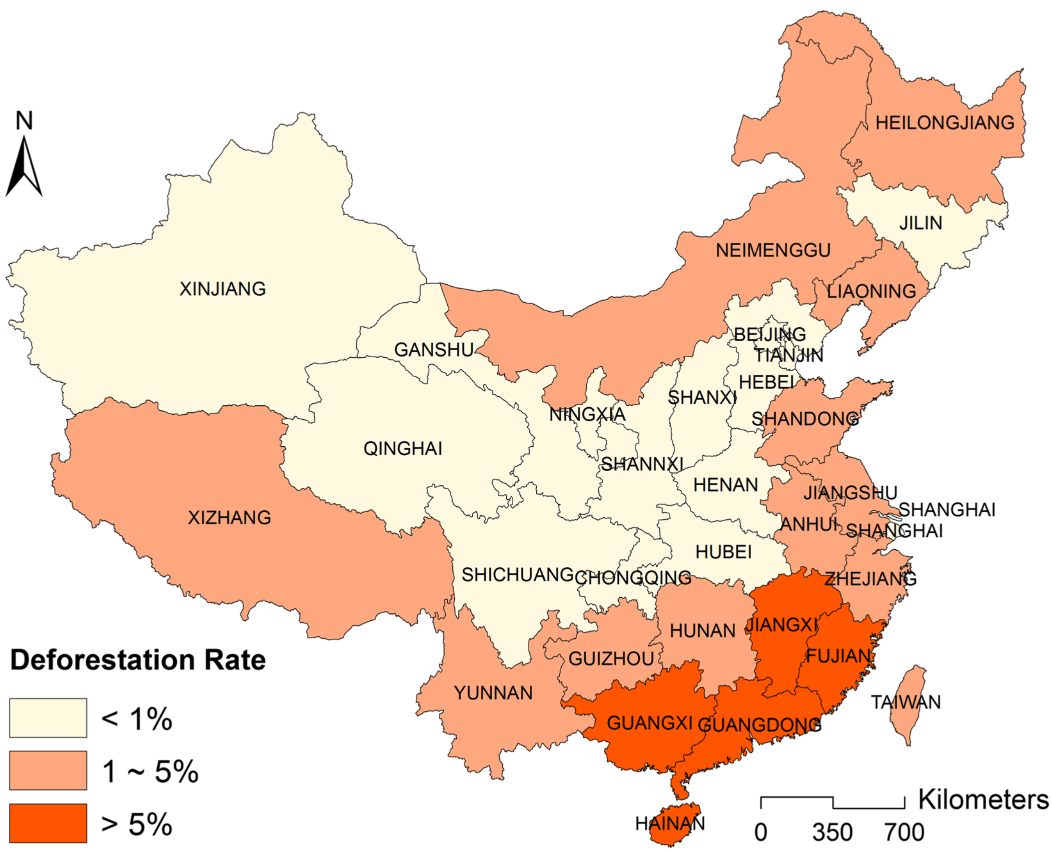
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GUANGDONG
HAINAN
Deforestation Rate
< 1%
1 ~ 5%
> 5%
Kilometers
0 350 700

b

Table 2 Effectiveness of protected areas with different socioeconomic and biophysical conditions in reducing deforestation

PA comparisons	Population in each category	Mean effectiveness (%)	Difference in effectiveness (%)
Low vs. high surrounding deforestation	(105, 105)	(0. 13, 0. 62)	− 2.41***
Long vs. short travel time to city	(106, 105)	(0.16, 0.29)	− 1.44***
Rough vs. flat terrain	(104, 107)	(0.15, 0.12)	− 0.56***

***$p \leq 0.001$; two-tailed tests

Our results also show that some socioeconomic and biophysical conditions of PAs were closely related to their effectiveness. PAs close to cities or having flat terrain tended to exhibit high effectiveness in reducing deforestation. Two reasons may explain these results. First, the relatively low cost of transportation to markets may provide an incentive for deforestation activities (e.g., timber harvesting) in the areas surrounding the PAs located close to cities. Second, unprotected forest areas located close to cities or with flat terrain often have a greater economic value and thus are more likely to be converted to other land uses (e.g., agriculture, urban) (Deng et al. 2009). Without protection, forests within PAs may have experienced deforestation as pronounced as the forests in their surrounding areas. In other words, PAs located close to cities or in areas of flat terrains tended to contribute more to the conservation goal of reducing deforestation. These results also indicate that the designation of PAs should not only consider the ecological importance of the land they protect (e.g., overlap with biodiversity hotspots) but also their location-related attributes that could influence PAs' conservation effectiveness.

Unfortunately, in China, as in many other parts of the world, the location of PAs is usually biased toward remote regions and areas with rugged terrain mainly because the economic value of the land in these areas is low (Joppa and Pfaff 2009; Xu et al. 2017). Our results suggest that PAs established in such regions may fail to generate a major impact on conservation outcomes. The conservation resources invested in those PAs could perhaps be better utilized to protect highly threatened ecosystems in other regions and thus to achieve greater conservation gains. Even worse, to maintain the operation of these ineffective PAs, natural resources under protection by those PAs may be overexploited for revenue generation activities (e.g., tourism infrastructure development), compromising ecosystem health and defeating conservation goals. Therefore, future PA expansion should pay more attention to ecosystems that are or will be highly threatened by human activities. The effectiveness assessment in this study provides a foundation for identifying potential areas for establishing new PAs. However, it is important to underline that further analyses are required to explicitly and comprehensively consider human and natural factors such as land tenure, PA management capacity, and distribution of biodiversity and ecosystem services before any management actions are taken.

More evidence-based evaluations of PA effectiveness should be performed in the future to support the management and planning of PAs in complex ecological, social, and economic contexts. Besides forest cover and carbon sequestration evaluated here, the effectiveness of PAs in generating other conservation benefits (e.g., water and soil retention) and its relation to socioeconomic and biophysical conditions should also be systematically evaluated using approaches similar to those used in this study. With improved understanding of the effectiveness of PAs and its underlying determinants, scientists, policy makers, and conservation practitioners will be able to develop more effective strategies to fully realize the potential of PAs for ecosystem conservation in China and beyond.

◀ **Fig. 4** Spatial distribution of the effectiveness of protected areas and deforestation rate across different provinces. **a** Effectiveness of protected areas in reducing deforestation aggregated to the provincial level. **b** Deforestation rate at the provincial level

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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