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Protected areas can provide net benefits without reducing the loss of ecosystem area

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Protected areas can provide net benefits without reducing the loss of ecosystem area

Abstract

Evaluations of protected areas (PAs) commonly measure PA effectiveness by the avoided loss of ecosystem area, with many reporting a lack of effectiveness according to this measure. Here, we present evidence that avoided area loss can be a misleading measure of PA effectiveness, because it does not account for spatial variation in conservation benefits and costs. We evaluate PAs in India's coastal mangrove forests against both an avoided deforestation measure and alternative measures that account for spatially varying carbon stocks and agricultural land values. We find that the PA system did not significantly reduce overall deforestation during 1990–2015, yet it provided significant net climate benefits because carbon stocks were greater in areas where forest cover increased than in areas where it decreased. This favorable climate impact depends, however, on the carbon price used in the evaluation being sufficiently high to offset protection's opportunity cost. Our findings imply that PA evaluations should shift toward using more complete measures of effectiveness than avoided area loss.

Introduction

Protected areas (PAs) are the foundation of global efforts to conserve nature and the ecosystem services it provides to humankind[1]. Evaluating PA effectiveness is critical given the scarcity of conservation funding and the adverse local and global consequences of ecosystem service loss[1].

PA evaluations commonly measure effectiveness by the avoided loss of ecosystem area, with many reporting a lack of effectiveness according to this measure. For example, a review[2] of 54 peer-reviewed evaluations of PAs in tropical forests found that avoided deforestation and degradation accounted for nearly three-fifths (58%) of the outcomes considered by the evaluations and that PAs did not reduce deforestation and degradation in nearly a third (32%) of the cases. (See Fig. S3 in Ref. (2).) A recent global evaluation of more than 160,000 PAs spanning all biomes, not only tropical forests, concluded more sweepingly that "PAs have not been effective in curbing habitat loss within their boundaries"[3].

The implicit premise for using avoided area loss to measure PA effectiveness is that the area of an ecosystem is the primary predictor of the benefits and costs of protecting it. In practice, conservation benefits and costs are not simply proportional to area because they can vary greatly across sites due to differences in biophysical and socioeconomic conditions[4]. Spatial variation is well-documented for conservation benefits, for example for biodiversity protection[5] and carbon storage[6], and also for the opportunity cost of conserving ecosystems instead of converting them to agriculture or other human uses[7]. PA evaluations that account for this spatial variation can, in theory, yield qualitatively different results than those that do not[4]. Consider a hypothetical, costless PA system that reduces deforestation at some sites and raises it at others within the system, with no net impact on avoided deforestation. The PA system could

nevertheless have an overall positive conservation impact if the benefits of avoided deforestation at sites where the system reduces deforestation exceed the forgone benefits at sites where it raises deforestation.

Here, we investigate the empirical relevance of this theoretical difference in results between PA evaluations based on avoided area loss and evaluations based on outcome measures that account for spatial variation in conservation benefits and costs. As a test case, we evaluate the PA system (national parks and wildlife sanctuaries) established in India's coastal mangrove forests (Fig. 1) during 1975–1989. Mangroves provide a host of ecosystem service values that vary greatly across sites[8]. We incorporate spatially varying benefits and costs into a well-established, quasi-experimental impact evaluation method, nearest-neighbor covariate matching[9]. Matching methods have been used often to evaluate PAs[2,3,10,11]. Under certain assumptions[9], which we verify for our case, they can determine the causal effect of PAs on conservation outcomes, not simply the correlation between protection and outcomes.

Our investigation into the relevance of spatial variation for PA evaluation focuses on carbon storage. Few studies have rigorously evaluated the impacts of PAs on carbon storage[10,11]. Mangroves store more carbon per hectare than nearly any other forest type[12,13]. We compare the causal effect of India's mangrove PA system on avoided deforestation during 1990–2015 to the causal effect on physical and economic measures of carbon storage during the same period. To support this analysis, we developed new spatial datasets on mangrove presence/absence and PA locations in India (see Methods and Supplementary Information). We modeled spatial variation in PA benefits and costs using published information on carbon stocks in undisturbed[12,13] and converted[14–16] mangroves, carbon prices[17,18], and agricultural land values[7].

We emphasize that, in the context of the matching method we apply, the high average level of carbon storage in mangroves does not imply that evaluating India's mangrove PA system against a measure that accounts for carbon storage benefits and costs will necessarily yield different results than evaluating it against a simpler avoided deforestation measure. Results will differ only if benefits, costs, or both differ between sites where protection reduced deforestation and sites where it raised it. One might not be surprised if an evaluation determined that a PA system that significantly reduced deforestation also significantly increased carbon storage, as has been reported for PAs in African woodlands[11]. We are interested in the less obvious possibility that spatial variation in conservation benefits and costs could cause a PA system to provide net climate benefits despite not significantly reducing deforestation.

Results

Factors affecting PA establishment and deforestation

In India, state governments establish PAs under national legislation. Only two mangrove PAs existed in India before 1975. Twenty-two additional PAs were established during 1975–1989 and five more during 1991–2013. Among all sites where mangroves were present in 1990, the

fraction with mangroves still present in 2015 was much higher inside PAs (90%) than outside (68%). This difference suggests that PAs greatly reduced deforestation during 1990–2015.

A simple comparison of mangrove persistence inside and outside PAs could be misleading, however. It ignores biophysical and socioeconomic factors that might have affected state governments' selection of sites to protect and the persistence of mangroves even if the sites had not been protected[2]. Drawing on prior research[3,10,11,19] and an archive of government announcements of PA establishment in India[20], we prepared a directed acyclic graph (DAG)[21] to identify factors that plausibly affected protection decisions during 1975-1989 and subsequent deforestation during 1990-2015 (Fig. 2). Establishing the causal effect of PA establishment on mangrove deforestation (red arrow) is challenging due to the existence of environmental factors (green ellipses) and economic factors (orange ellipses) that affect both deforestation and the political incentives to establish, monitor, and enforce PAs (gray ellipses). For example, politicians are less likely to establish PAs in locations with high agricultural value due to the opportunity cost for local constituents, and PAs established in such areas are more likely to be encroached upon. Conversely, opportunity cost and encroachment risk are likely to be lower in locations where human-wildlife conflict is common. Cyclones can damage forest cover and also reduce the incentive to establish PAs in damaged areas due to the loss of wildlife habitat and thus the area's natural heritage and tourism value. Accessibility increases deforestation by enhancing agricultural value, decreases it by facilitating monitoring and enforcement, but also increases the incentive to establish PAs by facilitating tourism.

Nearest-neighbor covariate matching isolated the impact of PA establishment on mangrove deforestation by constructing a set of control sites outside PAs that were statistically equivalent to sites inside PAs with respect to observed covariates that directly or indirectly controlled for the confounding factors highlighted by the DAG[9]. We created an initial set of 16 covariates (Supplementary Information), which we reduced to six—tiger habitat, potential carbon stock (i.e., carbon stock in undisturbed, natural mangrove), cyclone frequency, 1970 population density at the tehsil level, 1975 road density at the district level, and 1975 share of protected areas in total district area—by applying a covariate-selection algorithm that removed redundant covariates[22,23]. (Districts are subdivisions of Indian states, and tehsils are subdivisions of districts.) Removing redundant covariates reduces bias and inefficiency in matching models[24,25]. Post-matching balance criteria[26] confirmed the statistical equivalence of the distributions of the six covariates for sites inside PAs and control sites outside them (Supplementary Table 1).

Impact of protection on avoided deforestation

The matching method estimated the "average treatment effect on the treated" (ATET): the mean difference between an observed outcome in PAs and the unobserved, counterfactual outcome that would have occurred in the absence of protection. With avoided deforestation as the outcome measure, the individual treatment effect for a particular protected site with mangroves

present in 1990 equaled 1 if mangroves were still present in 2015 but would have been absent without protection, −1 if mangroves were absent in 2015 but would have been present without protection, and 0 if protection had no effect on 2015 presence or absence.

Across protected sites, the ATET for avoided deforestation was positive but not significantly different from zero ($P = 0.101$) at the standard level in the PA evaluation literature ($\alpha = 0.05$) (Fig. 3, panel a, left). This result is consistent with previously reported findings that PAs have often not reduced the loss of ecosystem area[2,3].

Impact of protection on carbon benefits and costs

As an initial step toward accounting for spatial variation in program impact, we repeated estimation of the ATET with carbon storage as the outcome measure. This measure is a physical, noneconomic one that accounts for storage in three carbon pools: above-ground biomass (AGB), below-ground biomass (BGB), and soil carbon. Using this outcome measure, the ATET became not only positive but also significantly different from zero ($P = 0.011$): PAs generated additional carbon storage (Fig. 3, panel a, right). This result differed from the insignificant ATET for avoided deforestation because PAs were more likely to reduce deforestation at sites with higher carbon stocks (Fig. 4).

We re-estimated the ATET a third and final time using an economic outcome measure: the approximate net present value (NPV) of carbon storage. We used agricultural land value[7] to estimate the opportunity cost of protection and three carbon prices to value carbon stocks: a low price of US$6.78 $tCO2e^{-1}$, which is the 2023 average market price for REDD+ carbon credits[17]; and medium and high prices of $51 $tCO2e^{-1}$ and $190 $tCO2e^{-1}$, which are 2021 and 2023 estimates of the social cost of carbon (SCC), respectively[18]. The SCC is the carbon price that is necessary to achieve optimal climate mitigation.

The ATET was negative and not significantly different from zero ($P = 0.814$) at the low carbon price but positive and significantly different from zero at the medium ($P = 0.020$) and high ($P = 0.007$) prices (Fig. 3, panel b). The increased magnitude and significance of the ATET as price rose was influenced by a positive, significant spatial correlation between mangrove carbon stocks and agricultural land values ($r = 0.28$, $P < 0.0001$). This correlation suggests that sites that were more productive for mangrove tree growth were also more productive for agriculture.

Discussion

Our findings demonstrate that using avoided area loss to measure PA effectiveness can lead to the misleading conclusion that a PA system had no significant conservation impact. Using instead a measure that accounts for spatial variation in conservation benefits and costs can reveal significant impacts that an evaluation based on avoided area loss fails to detect. Our findings suggest that PAs might have been more effective than prior evaluations based on avoided area loss have reported. Although the specific case we investigated concerned PA impacts on carbon

storage in mangrove forests, the approach we used to account for spatial variation in conservation benefits and costs is a general one that could be applied to PAs in other types of ecosystems and to other ecosystem services.

We are not arguing that PA evaluations should ignore impacts on ecosystem area. Ecosystem area can indeed be positively correlated with the supply of ecosystem services, for example those associated with species richness[27]. Yet, avoided area loss is too crude an outcome measure to be the only one used in careful evaluations. Ecosystems of the same type and area can vary considerably in their delivery of services to humans. This variation can be caused by differences in factors such as local conditions or habitat quality. For instance, to take an example outside the forestry focus of our study, two grasslands of similar area could generate very different levels of forage productivity, carbon storage, and nitrogen uptake depending on the diversity of grasses and whether bison or other wild herbivores are present[28]. An outcome measure that accounted for this variation would be needed even if a PA system were primarily intended to deliver just one of these ecosystem services. It would be even more necessary if the system were intended to deliver multiple services, as PAs typically are.

Regarding the case we investigated, additional analysis would be required to determine why India's mangrove PAs reduced deforestation more in locations with larger carbon stocks, which underlies the difference in the estimated treatment effects across the outcome measures we considered. The six covariates we used to reduce the confounding of PA impacts on avoided deforestation offer a starting point for such analysis, but we caution that other factors might also have played a role. The selected covariates were sufficient for reducing confounding but could be controlling for other factors correlated with them[22].

Climate mitigation has not been a major driver of PA expansion either globally[10] or in India. Most mangrove PAs in India predate the 1992 United Nations Framework Convention on Climate Change. The government announcements that established the PAs mentioned only wildlife conservation as the reason for establishment[20]. Our finding that India's mangrove PAs provided significant additional carbon storage despite not being established for that reason adds to the mounting evidence that climate mitigation can be a significant, albeit unintended, co-benefit of PAs[10].

Our mangrove carbon stock estimates are cruder than those used in some recent PA evaluations[10], as they are modeled rather than directly measured. They do not account for partial degradation that falls short of outright deforestation. They are best interpreted as upper-bound estimates of potential stocks[12,29]. The 2018 launch of NASA's Global Ecosystem Dynamics Investigation (GEDI) has made direct measurement of AGB carbon stocks in global forests possible[10], but we could not use the GEDI data because they postdate the period we analyzed. In addition, modeling remains the most feasible approach for estimating carbon stocks in BGB and the soil, where most mangrove carbon storage occurs[13–16,29]. Our soil carbon model did not account, however, for recent findings on deposition of water-borne organic carbon in mangrove systems[30].

The benefits of additional carbon storage in India's mangrove PAs did not outweigh the costs when we valued carbon at the current market price for forest carbon credits. Policy action to move the market price toward the social cost of carbon would strengthen the financial incentive for India and other countries to protect mangroves. Mangroves supply many important ecosystem services in addition to carbon storage[1,8], including biodiversity conservation, which, as noted, motivated PA establishment in India. The estimated treatment effect for the NPV outcome measure might have been positive even at the low carbon price if it had included benefits beyond carbon storage.

Two limitations of our analysis point toward potentially useful future research directions. First, matching methods yield causal estimates of PA impacts under the assumption that all important factors that confound the estimation of PA impacts are observable and are controlled by the covariates used to match protected and unprotected sites[9]. Although our use of a DAG (Fig. 2) to guide the identification of potentially confounding factors and a covariate-selection algorithm to select a sufficient set of matching covariates reduced the risk of omitting important confounding factors, it does not rule out the possibility that unobserved confounders biased our estimated treatment effects. Impact evaluation methods other than matching can control for unobserved confounders (e.g., difference-in-differences models)[2] and have been applied to PAs[3], but our data structure did not allow their application. Other PA systems might provide opportunities to integrate spatial variation in conservation benefits and costs into evaluations that apply those methods.

Second, we investigated only one type of ecosystem change, i.e., area loss (deforestation in our case). Two other important changes can occur, area gain (forestation) and change in ecosystem quality (forest degradation or improvement). Studies on global mangrove change have reported substantial amounts of mangrove forestation[29] and degradation[31] in recent decades. The forestation area has been barely a quarter of the area deforested[29], but the area degraded has far exceeded the area deforested[31]. Replicating our analysis on datasets that account for not only deforestation but also forestation and, especially, degradation would be worthwhile.

A third research need concerns the World Database on Protected Areas (WDPA)[32], which has been a common source of PA information in prior evaluations[3,8,10,11,19]. Near the start of our research, we discovered severe problems—missing PAs, grossly inaccurate boundaries—in the WDPA's information on mangrove PAs in India (see Supplementary Information). These problems forced us to create our own PA map. A study on mangrove PAs in Thailand discovered similar problems with the WDPA[33]. These two instances suggest that future studies on PA effectiveness in mangroves, and perhaps other ecosystems too, should validate information in the WDPA against other data sources whenever possible.

Methods

We provide an overview of our data and methods here. The Supplementary Information provides additional detail.

Map of mangrove presence/absence, and sample for matching analysis

We used Landsat data and published methods[35] to develop a 30-m resolution spatial dataset on mangrove forest presence/absence in the coastal region of mainland India in 1975, 1990, and 2015. We did not include mangroves on islands far offshore (e.g., Andaman and Nicobar Islands, Lakshadweep).

We created the sample for the matching analysis by randomly drawing 22,659 pixels with mangroves present in at least one year in the dataset. Evaluating the impact of PAs on avoided deforestation required restricting the sample to pixels with mangroves present in 1990, which was the start of the treatment period in the matching analysis. This restriction along with other, more minor reasons reduced the sample to 11,198 pixels. These pixels were the units of analysis in the matching analysis.

Mangrove protected areas

We determined protection status by creating a digital mangrove PA map (Fig. 1), primarily based on Indian data sources[36,37]. The map included six national parks and 23 wildlife sanctuaries in the coastal region of mainland India. Of the 11,198 pixels in the analysis sample, 6,270 (56%) were located in protected areas and thus classified as treated.

Matching covariates, estimator, and balance

The identification of causal effects using matching methods relies on the assumption that the observed pretreatment characteristics used to match treated units to untreated control units are sufficient to control for factors that confound estimation of treatment effects. Confounders can include factors that affect treatment, outcomes, or both[22–25]. We created a set of 16 covariates that were plausibly associated with one or more of the confounders in our DAG (Fig. 2). All were either time-invariant or referred to years before 1975 or, in a few cases, the earlier part of the 1975–1989 period.

Including redundant covariates can increase the bias and reduce the efficiency of treatment effect estimates in matching models[22–25,38]. To obtain less biased and more precise ATET estimates, we used the data-driven CovSel Algorithm 2[23] to select a minimally sufficient covariate subset by running it on the set of 16 potential covariates, with 2015 mangrove presence/absence as the outcome variable and 1990–2015 protection status as the treatment variable. The algorithm selected six covariates: tiger habitat, potential carbon stock, cyclone frequency, 1970 population density at the tehsil level, 1975 road density at the district level, and 1975 share of protected areas in total district area. Tiger habitat and cyclone frequency were categorical, and the other four were continuous.

We matched with replacement given that our dataset included more pixels inside PAs than outside them. We implemented the matching procedure using the "teffects nnmatch" command in the statistical package Stata[39]. We used a bias-corrected, consistent estimator[34]

given that uncorrected nearest-neighbor matching estimators are not consistent when matching is on two or more continuous covariates[9]. We matched exactly on categorical covariates. We used robust standard errors to estimate the precision of the ATET. The matching procedure used a z statistic to test whether the estimated ATET, which is the mean difference between outcomes for the sample of treated pixels and the matched sample of control pixels, was significantly different from zero. The number of matched pairs for all the estimated ATETs reported in the text was 6,269.

We evaluated covariate balance using recommended guidelines[26]: (i) the absolute value of the standardized mean difference (SMD) between the treated and control groups should be below 0.1; and (ii) the ratio of the control-group variance to the treated-group variance should be within bounds given by the 2.5th and 97.5th percentiles of an F distribution with degrees of freedom equal to the number of treated pixels minus one. The SMDs and variance ratios satisfied these guidelines for all six covariates.

Spillover effects of protection

Establishing PAs can affect deforestation in unprotected forests through numerous channels[40]. For example, PAs might displace deforestation to unprotected forests. On the other hand, monitoring and enforcement activities along PA boundaries might have a "halo" effect that decreases deforestation in adjacent unprotected forests. Failing to account for such spillovers can bias ATET estimates in either a positive direction, as in the example of displaced deforestation, or a negative direction, as in the halo-effect example.

To investigate spillover effects, we examined how the ATET for avoided deforestation and covariate balance changed if we excluded untreated pixels that were within a specified distance (buffer) of any PA as of 1990. We varied the buffer from 0 to 8 km by 1 km increments. We used 8 km as the maximum buffer because the median distance to a PA in 1990 was 8.2 km. This value is also similar to the 10-km spillover distance used in a previous matching study on PA effectiveness[11]. The ATET estimates increased continuously and substantially up to 4 km (Supplementary Table 2). Our conservative interpretation of these results is that PAs reduced deforestation in untreated mangroves up to 4 km away, with no strong evidence that spillover effects changed substantially beyond that distance. We therefore estimated the matching models with a 4-km buffer imposed on untreated pixels.

Outcome measures

We estimated PA impacts on three alternative outcome measures: avoided deforestation, carbon storage, and the net present value (NPV) of carbon storage. (See Supplementary Table 3 for descriptive statistics.) For the analysis of avoided deforestation, we coded a pixel as 1 if mangrove forest cover was present in 2015 and 0 if it was absent.

We calculated the 2015 carbon stock (t ha^{-1}) in pixel i as

$$Carbon_i = [F_i \times C_i^P] + [(1 - F_i) \times C_i^A].$$

F_i is the 2015 binary forest cover indicator just mentioned (1 = present, 0 = absent). C_i^P and C_i^A are carbon stocks with mangroves present[12,13] and absent[14–16], respectively, and are described in more detail below.

We calculated the NPV (constant 2020 US$ ha^{-1}) of carbon storage similarly:

$$NPV_i = [F_i \times p \times C_i^P] + [(1 - F_i) \times (OC_i + p \times C_i^A)].$$

p is carbon price[17,18], and OC_i is agricultural land value[7]. Land value comes from only carbon storage when mangroves are present and the combination of agriculture and a smaller amount of carbon storage ($C_i^A < C_i^P$) when mangroves are absent. We label agricultural land value by OC_i because it is implicitly the opportunity cost of protection in this formulation of the NPV of carbon storage.

Carbon stocks

Our carbon stock estimates C_i^P and C_i^A represented aggregate carbon storage across three carbon pools: AGB, BGB, and soil down to a depth of 100 cm. The estimates with mangrove present, C_i^P, refer to potential carbon stocks in undisturbed, natural mangroves. For potential carbon stocks in the AGB pool, we first used a published model[12] to predict potential total AGB—carbon plus noncarbon—and then used a factor of 47.5%[41] to convert biomass to carbon. For potential carbon stocks in the BGB pool, we similarly used a published model to predict potential total BGB[12] and converted biomass to carbon using the same 47.5% factor[41]. For potential soil carbon stocks down to 100 cm, we began with a published 30-m resolution dataset[13], which provided data on approximately three-fifths of the pixels in our sample. We imputed missing values by following a prior study[15] that predicted potential soil stocks by applying a model that related stocks to latitude and bioclimatic variables. In a final step, we calculated carbon stocks with mangrove present by summing these three stocks (pixel subscript i suppressed for clarity):

$$C^P = C_{AGB} + C_{BGB} + C_{Soil}.$$

For carbon stocks with mangrove absent, C_i^A, we assumed that conversion to nonmangrove land uses would reduce the ABG stock by 91%[14], the BGB stock by 54%[15], and soil carbon by 43%[16]:

$$C^A = 0.09 \cdot C_{AGB} + 0.46 \cdot C_{BGB} + 0.57 \cdot C_{Soil}.$$

Carbon prices, value of land in nonmangrove uses, and NPV of carbon storage

In addition to carbon stock estimates, measuring the NPV of carbon storage required information on carbon price and the value of land in nonmangrove uses. We drew three carbon prices from published reports: the 2023 average price[17] of REDD+ carbon credits in the voluntary carbon market, US$6.78 tCO_2e^{-1}, and two estimates[18] of the SCC, a 2021 estimate of

US$51 tCO_2e^{-1} and an updated 2023 estimate of US$190 tCO_2e^{-1}. These prices are expressed in constant 2020 U.S. dollars, adjusted for inflation using the U.S. GDP deflator[42].

The large gap between the market price and the two SCC estimates results from current global policies to mitigate climate change being less stringent than the socially optimal levels implied by the SCC estimates. The two SCC estimates differ because the 2023 estimate is based on research that incorporated numerous methodological improvements[43], including use of a lower near-time social discount rate of 2% yr^{-1} instead of 3% yr^{-1}. Before multiplying the prices by the estimated carbon stocks, we converted them to US$ tC^{-1} using the ratio of the molecular weight of CO_2 to the atomic weight of carbon, 44/12.

We determined the value of land in nonmangrove uses using gridded (10-km resolution) estimates of agricultural land value[7]. The original estimates referred to 2019 and were already expressed in constant 2020 U.S. dollars. They represented the portion of annual net income from agriculture (i.e., farm profit) that was attributable to land as opposed to labor or capital, capitalized at a 5% yr^{-1} discount rate. For the NPV scenario that used the market price of carbon, we recapitalized them using a 4.36% yr^{-1} discount rate, which was the mean real interest rate in India during 2010–2020[44]. For the NPV scenarios that used the SCC estimates, we recapitalized them using the discount rates associated with the SCC estimates, i.e., 3% yr^{-1} for the 2021 estimate and 2% yr^{-1} for the 2023 estimate.

Data availability

Data associated with the analysis in this article are publicly available on Zenodo at [link to be inserted].

Code availability

Stata code used to generate results reported in this article is publicly available on Zenodo at [link to be inserted].

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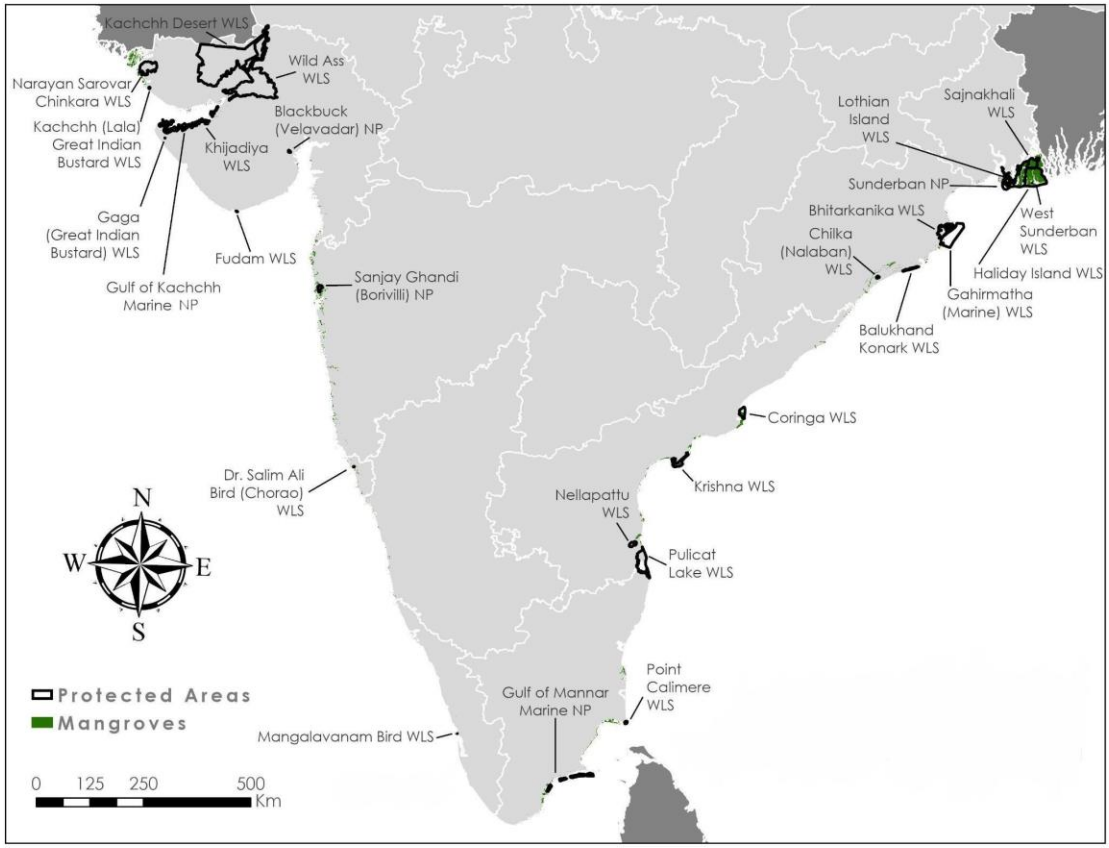


Fig. 1 | India's mangrove protected areas (2015) and mangrove forest cover (1990). NP = National Park, WLS = Wildlife Sanctuary. Pulicat Lake WLS is two adjacent protected areas established and administered separately by the state governments of Andhra Pradesh and Tamil Nadu. Not shown: Bhitarkanika NP, which is an enclave within Bhitarkanika WLS.

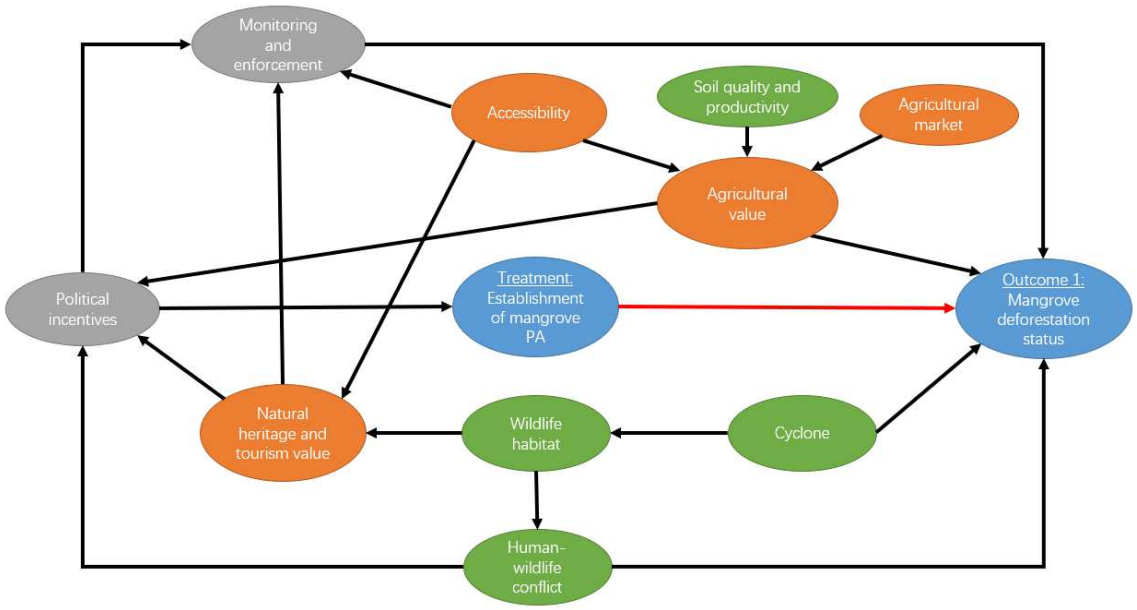


Fig. 2 | Directed acyclic graph for effects of a mangrove protected area (PA) in India on deforestation. The causal effect (red arrow) of establishing the PA (first blue ellipse) on deforestation (second blue ellipse) is confounded by biophysical factors (green ellipses) and socioeconomic factors (orange ellipses), with mediation by governmental processes (gray ellipses).

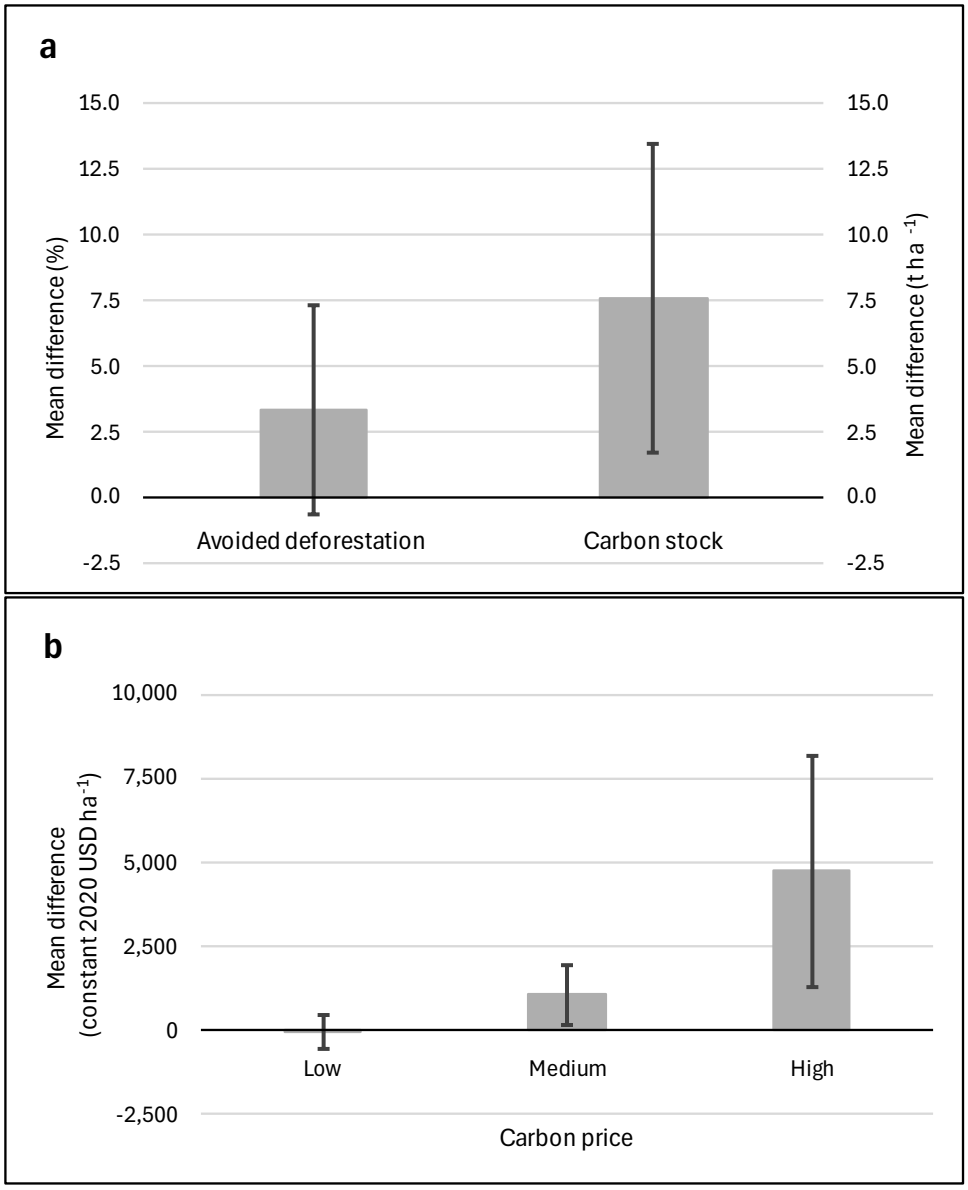


Fig. 3 | Average treatment effects on the treated (ATET), with 95% confidence intervals based on robust standard errors. Each bar shows the mean difference between observed 2015 outcomes in 6,269 randomly selected pixels in mangrove PAs and unobserved counterfactual outcomes that would have occurred in the absence of protection, based on nearest-neighbor covariate matching with replacement. ***Biophysical outcomes (panel a):*** PAs had an insignificant effect on avoided deforestation (left axis) but a significant effect on carbon storage (right axis). ***Economic outcomes (panel b):*** PAs' effects on the net present value (NPV) of carbon storage were larger and more significant at higher carbon prices. See text for price details.

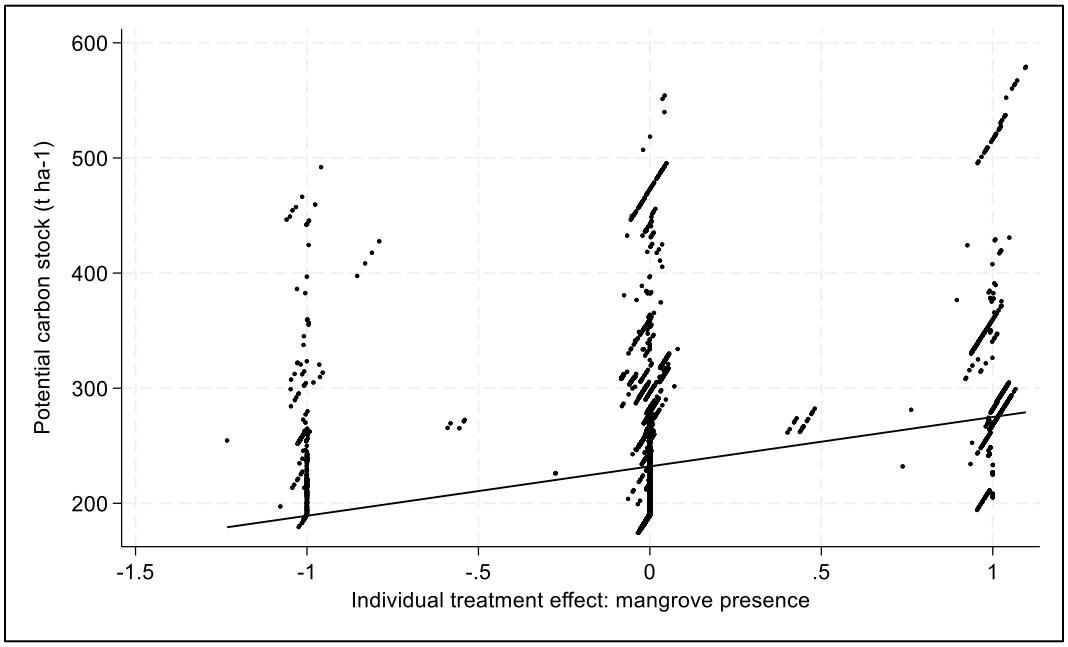


Fig. 4 | Potential carbon stocks in protected mangroves were higher in locations where protection reduced deforestation during 1990–2015 (treatment effect > 0) and lower in locations where protection raised deforestation (treatment effect < 0). Trend line: $y = 232 + 42.9x$ ($P < 0.001$ for both parameters); $F(1, 6267) = 527$ ($P < 0.0001$); $N = 6{,}269$ pixels in mangrove PAs. Fractional treatment effects are possible because matching is with replacement. Treatment effects can be < –1 or > 1 due to a bias adjustment in matching models that include more than one continuous covariate[32].

Supplementary Files

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