Conditions associated with protected area success in conservation and poverty reduction

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Protected areas are the dominant approach to protecting biodiversity and the supply of ecosystem services. Because these protected areas are often placed in regions with widespread poverty and because they can limit agricultural development and exploitation of natural resources, concerns have been raised about their potential to create or reinforce poverty traps. Previous studies suggest that the protected area systems in Costa Rica and Thailand, on average, reduced deforestation and alleviated poverty. We examine these results in more detail by characterizing the heterogeneity of responses to protection conditional on observable characteristics. We find no evidence that protected areas trap historically poorer areas in poverty. In fact, we find that poorer areas at baseline seem to have the greatest levels of poverty reduction as a result of protection. However, we do find that the spatial characteristics associated with the most poverty alleviation are not necessarily the characteristics associated with the most avoided deforestation. We show how an understanding of these spatially heterogeneous responses to protection can be used to generate suitability maps that identify locations in which both environmental and poverty alleviation goals are most likely to be achieved.

evaluation | parks | tropical forest | nonparametric | matching

Protected areas are the dominant approach to protecting biodiversity and the supply of ecosystem services (1). A fundamental concern surrounding the establishment of protected areas, particularly in developing countries, is that ecosystem conservation goals may conflict with poverty alleviation goals by reducing incomes or perpetuating poverty traps (2–6). A poverty trap, as described in the introduction to this special feature in PNAS (7), is a self-reinforcing mechanism that causes an area to remain poor. By restricting access to natural resources, protected areas might create new poverty traps or reinforce old ones.* Protected areas tend to be established away from major cities and on agriculturally undesirable land (9), characteristics that are also associated with high levels of poverty. We might, therefore, be concerned that protected areas would reinforce poverty traps. More optimistically, they might push local economies out of poverty traps by providing tourism business opportunities, improved infrastructure, or enhanced supplies of ecosystem services. For example, evidence from Costa Rica and Thailand suggests that protected areas in these two countries have, on average, reduced local poverty (10, 11).

To fully understand protected area impacts, one should consider environmental and socioeconomic outcomes jointly and quantify the heterogeneity in the impact. Unfortunately, there is little scientific evidence on the nature of this heterogeneity or the potential tradeoffs between environmental and socioeconomic outcomes (3, 12). Retrospective causal analysis of the socioeconomic impacts of developing country protected areas is limited (6, 10, 11, 13, 14). Only the work in Thailand and Costa Rica (10, 11, 13) also included information on environmental outcomes. However, those previous studies do not include sufficiently detailed analysis of heterogeneity in impacts to assess potential tradeoffs between ecosystem protection and poverty alleviation (15, 16).

Using data from Costa Rica and Thailand, we examine the heterogeneity of protected area impacts as a function of baseline poverty and covariates that are likely to moderate how protection affects outcomes (17). We select these two nations, because they have significant biodiversity, large protected area systems, and reliable spatially explicit data. Unlike previous studies that explore heterogeneous impacts of protected areas (11, 13, 18), we examine impacts on both avoided deforestation and poverty reduction and use a nonparametric method of locally weighted scatter plot smoothing (LOESS) (19, 20) and a semiparametric partial linear differencing model (PLM) (21–23). These models estimate more informative continuous relationships between observable characteristics and outcomes. We are, thus, able to identify covariate ranges that are associated with high conservation and poverty reduction outcomes (win–win), low conservation and poverty exacerbation outcomes (lose–lose), or incongruence, where one outcome is win and the other is lose (win–lose).

The rapidly growing conservation planning literature focuses on how to target conservation investments conditional on observable environmental and economic characteristics (24, 25). Planners interested in achieving both avoided deforestation and poverty reduction need to understand how these outcomes covary with observable characteristics. Such understanding allows for the development of conditional empirical success rules (p. 75 in ref. 15) that can be used to target interventions based on expected impacts as predicted by observable characteristics. We show how such rules can be visualized through suitability maps that identify locations associated with win–win, lose–lose, or win–lose scenarios.

Data

Previous studies estimated that protected areas resulted in significant avoided deforestation and poverty reduction in Costa Rica and Thailand (additional details in refs. 10 and 26 and *SI Appendix*) (10, 11, 26). About 11% of the area protected in Costa Rica would have been deforested had it not been protected (26). Using similar methods, we estimate that about 15% of protected forest in Thailand would have been deforested in the absence of protection (*SI Appendix*). Protected areas in Costa Rica accounted for about 10% of the poverty decline around the

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*For example, Robalino (8) predicts that protected areas would place a greater burden on nonlandowning workers, who are often the poor.

areas. In Thailand, protected areas reduced poverty by about 30% (10). We use data from these studies to explore the heterogeneity of protected areas' impacts.

Poverty. Poverty measures are based on national census data of household characteristics and assets (details in *SI Appendix*). Costa Rica analyses use 1973 and 2000 census tract poverty indices (10) from a principal components analysis (27) (*SI Appendix*). Thailand analyses use the subdistrict poverty headcount ratio, which is the share of the population in 2000 with monthly household consumption below the poverty line; this information comes from a poverty mapping analysis (28, 29). The sample comprises subdistricts in north and northeast Thailand, which is where the majority of protected forest areas are located. Larger values of both poverty measures imply greater poverty.

As in Andam et al. (10), we define a census tract or subdistrict as protected if at least 10% of its area is protected before 1980 (Costa Rica) or 1985 (Thailand; 249 census tracts and 192 subdistricts).[†] With protection assigned 15 or more y before poverty outcomes are measured, longer-term impacts can be measured. Unprotected units, from which matched controls are selected, comprise units with less than 1% protected before 1980 or 1985 (4,164 census tracts and 3,479 subdistricts).[‡] Protected areas comprise IUCN Categories I, II, IV, and VI in Costa Rica and International Union for Conservation of Nature (IUCN) Categories I and II in Thailand.

Avoided Deforestation. As a proxy for conservation success, we estimate avoided deforestation from protected areas (we acknowledge this is not the only possible measure of success). The unit of analysis for the deforestation data is a 3-ha land parcel (20,000 randomly selected) drawn from forested areas at baseline (Costa Rica in 1960 and Thailand in 1973). Each parcel is classified as deforested or forested by the end year (Costa Rica in 1997 and Thailand in 2000). A parcel is defined as protected if it lies within a protected area that was established before 1980 (Costa Rica) or by 1985 (Thailand). Control parcels were never protected.

Covariates. For each country, multiple spatial layers are used to create covariates for each census tract, subdistrict, or parcel (*SI Appendix*, Tables S1 and S2).

Study Design

To estimate the impact of protection on the protected units, one must establish what would have happened in the absence of protection. Like the studies from which we obtain our data (10, 26), we used matching to select unprotected control units that are similar at baseline to protected units. Preprocessing the data (30) through matching ensures that the distributions of key covariates believed to affect both outcome and selection into protection are balanced across protected and unprotected units (*SI Appendix*). The goal of matching, like standard regression techniques, is to control for differences in baseline characteristics that affect the designation of protected areas and poverty or deforestation (30–32). For example, protected areas are often placed on land less suited for agriculture (1, 9, 18). The matching strategy assumes that, after matching, the expected outcomes of protected and matched control units in the absence of protection are the same. Thus, the control group's outcome represents the protected group's counterfactual outcome. Although there is no direct way to test this assumption, the previous studies in Costa Rica and Thailand found that the estimates were robust to unobserved heterogeneity using our matching specifications (10, 26). The Thailand results were also confirmed using an instrumental variable approach (11). For the Costa Rica poverty sample and both deforestation samples, we used nearest neighbor Mahalanobis matching with replacement. For the Thailand poverty sample, we used propensity score matching with exact matching on district to control for baseline fixed effects. *SI Appendix* has details on the matching methods used and the covariates on which units are matched.

Postmatching, we use nonparametric LOESS (19, 20, 33) to estimate impacts as a function of baseline poverty. LOESS allows us to assess whether or not protected areas contributed to poverty traps. We use LOESS because we are interested in how poor areas, including all of the factors that make them poor, respond to protection (*SI Appendix* includes additional discussion of the choice of methods). To isolate the moderating effects on avoided deforestation and poverty from observable baseline characteristics net of other influences, we use semiparametric PLM (20–22) on the matched data. This two-stage estimator allows us to linearly control for other influencing covariates in the first stage and then estimate the outcome as a nonparametric function of the covariate of interest using LOESS in the second stage (*SI Appendix*). The benefit of this approach is that it allows us to conduct inference along a continuum of covariate values (e.g., distances from cities) while holding constant the potentially complimentary or countervailing covariates (e.g., slope). The results from the PLMs are then used in the suitability mapping exercise (more details in *SI Appendix*).[§]

Results: Heterogeneous Impacts

Fig. 1 presents the results. In each panel, the solid and dashed lines represent the estimated difference between protected and counterfactual units [i.e., the conditional average treatment effect on the treated (ATT) for avoided deforestation and poverty reduction, respectively]. The green or red shaded area around the solid or dashed line represents the 95% point-wise confidence band for the avoided deforestation (poverty reduction) ATT estimate (*SI Appendix*, Figs. S3, S4, and S5 have more detailed illustrations of all the impact heterogeneity results). The solid green or red horizontal line represents the zero line for the avoided deforestation (poverty reduction) estimate, at which there are no impacts from the establishment of protected areas.

Poverty Traps. We first test whether protected areas reinforced or exacerbated poverty traps in Costa Rica. If this were the case, we would expect to find that areas that were very poor at baseline would be negatively affected by protected areas. Based on theory, we would also expect that negative effects occur only when land-use restrictions are binding. Thus, any exacerbation of poverty should be accompanied by avoided deforestation.

The results in Fig. 1*A* confirm that avoided deforestation (solid line) in Costa Rica is positive across observed baseline poverty values. In other words, protected areas did impose binding land-use restrictions. Avoided deforestation is relatively constant along a majority of the baseline poverty range, although there is a dip between baseline poverty index values of 15 and 18. Poverty reduction (dashed line), however, appears to be U-shaped

[†]Andam et al. (10) select a 10% threshold, because it reflects the call by the fourth World Congress on National Parks and Protected Areas to protect 10% of each of the world's major biomes by 2000 and the call by the Conference of Parties to the Convention on Biological Diversity to conserve 10% of each of the world's ecoregions. Andam et al. (10) show that the estimated impacts are robust to changes in this threshold.

[‡]Units with 1–10% of their area protected are dropped from the analysis to avoid matching protected units to marginally protected units.

[§]As is done in the studies from which we draw information (10, 26), we implement bias adjustment techniques within all LOESS iterations (31, 34).

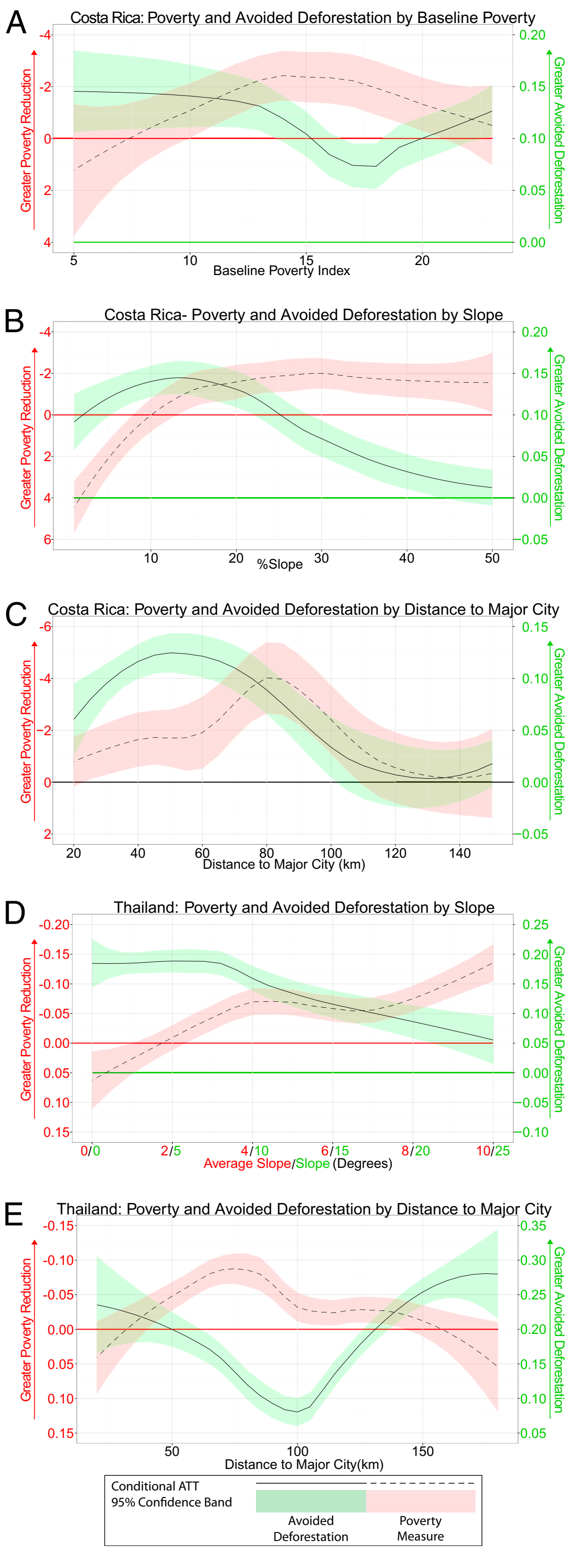

Fig. 1. Heterogeneous responses to protection.

(inverted) as a function of baseline poverty. The estimates suggest that protected areas achieved significant poverty reduction for most of the range above the median baseline poverty level (poverty index = 12). At very high levels of poverty, these effects are not significantly different from zero. The LOESS results, therefore, do not suggest that protected areas exacerbated poverty in the poorest populations. In fact, a majority of the poorest areas experienced poverty reduction compared with their estimated counterfactual poverty levels.[¶]

Moderating Covariates. To better understand the nature of protected areas' impacts on poverty, we next consider two covariates that are highly related to poverty and based on theory, are expected to moderate the impacts of protection: slope and distance to major cities. The primary driver of deforestation in Costa Rica and Thailand was agriculture (35–37).[‖] Slope is highly correlated with agricultural potential: the steeper the slopes, then the less suitable the land is for agriculture. Steeper slopes are, therefore, associated with lower deforestation pressure and therefore, lower opportunity costs of protection.[**] Slope and baseline poverty are also highly correlated: in Costa Rica, the mean slope for land among the poorest quartile is 16.4%, whereas for the richest quartile, it is only 3.8%.

Like slope, distance to city is also positively correlated with baseline poverty: in Costa Rica, the mean distance of the poorest quartile is 70 km, and the mean distance of the richest quartile is 9 km. However, the distance to a major market city has a more complicated theoretical relationship with deforestation and protection. On one hand, being far from cities lowers agricultural returns and thus, the returns to deforestation (because of, for example, higher transportation costs and poorer price information). On the other hand, being far from cities also means one is likely to be far from the nodes of enforcement of land-use regulations inside and outside protected areas, thus increasing returns to agriculture. Finally, if one believes that tourism and associated infrastructure development is a key mechanism through which protection reduces poverty, then greater distance from cities implies less potential for poverty reduction. Thus, the opportunity costs from protection can change nonlinearly as distance to cities increases.

Fig. 1 *B* and *C* presents the results of the analysis of the two moderating covariates in Costa Rica. Protection on low-sloped land is associated with significant tradeoffs in joint outcomes. We observe statistically significant poverty exacerbation up to an average slope of 10%, whereas the associated impact on avoided deforestation is relatively high along this range. Between ~15% and 40% slope, we observe win–win outcomes of avoided deforestation and poverty reduction statistically different from zero. The results help to explain why we do not observe an association between protected areas and poverty traps, despite evidence that land-use restrictions were binding. Fig. 1*B* also indicates that the protection of low-sloped land is associated with significantly more avoided deforestation than the protection of steeply sloped land (this relationship arises largely because the amount of deforestation in the absence of protection decreases with slope) (*SI Appendix*, Fig. S4). As noted by Andam et al. (27), protected lands are rarely located on lands highly suitable for agriculture, and thus, we can see why Andam et al. (10, 26) find a win–win outcome, on average. These results suggest that protected areas are not serving as poverty traps, partly because they tend to be sited in areas with low agricultural potential and thus, low opportunity costs.

¶As a robustness check, we run a parametric quantile regression. These results are consistent with the LOESS results (*SI Appendix*).

‖Logging was also an important source of deforestation during this time period, and large-scale logging often cleared the way for conversion of previously forested land to agricultural use. Forest cover in logged areas tends to regenerate in these nations unless used for agriculture.

**Slope captures other deforestation pressures as well, such as ease of logging (18), but agriculture is the key deforestation force in our study. In Costa Rica, slope has been shown to be a good proxy for agricultural suitability (13). Furthermore, the response functions conditional on slope and baseline labor force in agriculture exhibit similar trends (*SI Appendix*, Fig. S4).

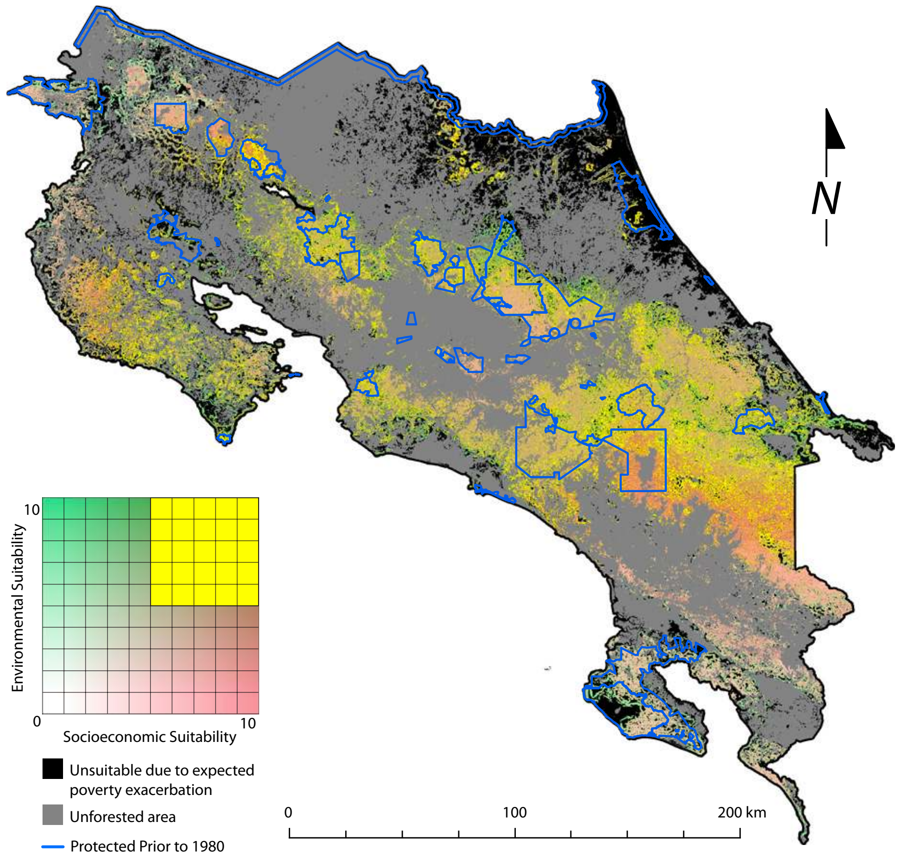

Fig. 2. Costa Rica protected area suitability map.

Fig. 1*C* confirms the conjecture that distance to major cities captures countervailing forces and thus, may generate nonlinear relationships between protection and outcomes. The interval at which poverty reduction is greatest is farther from cities than the interval at which avoided deforestation is greatest. Nevertheless, there is a substantial overlap of poverty reduction and avoided deforestation (win–win) at intermediate distances (∼40–100 km). These results provide indirect evidence that protected areas are not creating poverty traps, partly because they tend to be sited in localities that can respond to opportunities afforded by tourism and associated infrastructure development. They also suggest that poor localities far from cities may not respond as well to protection as poor localities closer to cities.

In Thailand, we lack baseline poverty data,[††] but we can examine the impact of protection on deforestation and poverty as a function of slope and distance to major cities. The shapes of the PLM graphs in Fig. 1*D* look remarkably similar to the shapes of the corresponding graphs for Costa Rica: slope is negatively related to avoided deforestation and positively related to poverty reduction. Although there is a range over which win–win outcomes are observed, the general trend of tradeoffs (more poverty reduction correlating with less avoided deforestation) is even more pronounced in Thailand. As in Fig. 1*C*, we observe, in Fig. 1*E*, a nonlinear relationship between avoided deforestation and poverty impacts as a function of distance from major cities. The relationship with avoided deforestation in Thailand looks different from the relationship observed in Costa Rica (lower avoided deforestation at intermediate distances), but the relationship between poverty impact and distance from cities looks strikingly similar in both nations: the largest reductions in poverty are observed at intermediate distances from major cities.

Results: Suitability Mapping

Fig. 1 suggests that the way in which areas respond to protected areas established in their midst will differ conditionally with observable baseline characteristics. An understanding of these heterogeneous effects offers insights into how protected areas can be established in the future to manage tradeoffs between environmental and poverty reduction goals.

Suitability mapping allows one to visualize the joint outcomes spatially. We use the results from the previous section to create illustrative protected areas suitability maps for Costa Rica and Thailand. We break the regions into 3-ha units and based on results from PLM models, assign each unit a suitability score according to the predicted impact on deforestation or poverty if the unit was protected (*SI Appendix*). For example, based on historical impacts of protected areas in Costa Rica, a land parcel located on a slope of ∼12% is highly suitable for protection in terms of avoided deforestation but only moderately suitable in terms of poverty reduction (recall that we are controlling for other parcel characteristics in the PLM estimation). By mapping underlying covariate relationships jointly with deforestation and poverty outcomes, we are able to identify areas of win–win, lose–lose, and win–lose. These maps, therefore, are a type of graphical illustration of conditional empirical success rules.

We classify a land parcel's suitability for protection based on its slope and its distance from major cities, which are two time-invariant characteristics that are typically available to decision makers [slope data are often used in global protected area

[††]Like Andam et al. (10), we address this lack of baseline poverty data by matching on a large number of baseline and time-invariant variables likely correlated with baseline poverty and including district fixed effects.

analyses (9, 33); details in *SI Appendix*]. Because protection is assigned mainly to forested areas in the two nations, we limit our classification to parcels that were forested in the final period of our analyses: 1997 for Costa Rica and 2000 for Thailand.

Figs. 2 and 3 display the illustrative suitability maps. The bivariate color grid represents increasing suitability for protected areas in terms of avoided deforestation (horizontal axis) and poverty reduction (vertical axis) based on historical impacts. Boundaries of the protected areas used to estimate the historical impacts of protection are in blue. In yellow, we highlight areas in the upper five deciles for both potential avoided deforestation and poverty reduction. These locations might be considered potential win–win locations (*SI Appendix*). In Costa Rica, 324,156 ha of forest in 1997 are classified as win–win locations (14% of the total), with an average environmental (socioeconomic) suitability score of 7.25 (6.77). In Thailand, 662,013 ha of forest in 2000 are classified as win–win (5% of the total), with an average environmental (socioeconomic) suitability score of 6.17 (6.38). In black, we highlight areas that, based on historical responses, would likely experience poverty exacerbation and thus, might be considered undesirable for establishing a protected area, regardless of environmental suitability. Because poverty exacerbation tends to occur where deforestation is reduced by protection, these black areas tend to be win–lose locations. In Costa Rica, 659,730 ha are classified as likely exacerbation locations (28% of the total forest area), with an average environmental suitability score of 5.2. In Thailand, 1,180,041 ha are classified as likely exacerbation locations (10% of the total forest area), with an average environmental suitability score of 6.6 (*SI Appendix*).

These maps are meant to be illustrative and used in conjunction with other sources of data and expertise. Other baseline conditions are likely to be important in determining tradeoffs. In future applications, suitability maps would incorporate knowledge of other indicators of biological value (e.g., endemic species) and other forms of expert knowledge about local conditions into a more sophisticated optimization algorithm (examples of algorithms given in ref. 25). Moreover, the maps are based on the assumption that past associations will hold for future outcomes, which may not be true in rapidly changing societies. Suitability maps present a static picture of expected relationships and do not capture potential general equilibrium effects: the protection of an area may fundamentally change the suitability of the remaining unprotected areas. Finally, future analyses should also incorporate an understanding of the differential impacts of protected area types (e.g., wildlife refuges vs. national parks) and other characteristics determining economic opportunities.

Discussion

Debates over the effectiveness of protected areas in achieving conservation results and affecting poverty are often based on little empirical evidence. Critics of protected areas highlight the role that protected areas can play in limiting agricultural development and exploiting natural resources. They would, thus, predict that observable characteristics associated with high levels of avoided deforestation from protection would also be associated with poverty exacerbation. Proponents highlight the role that protected areas can play in supplying ecosystem services, promoting tourism, and improving infrastructure. They would, thus, predict that characteristics associated with high levels of avoided deforestation from protection would be associated with high levels of poverty reduction. Our results indicate that the realities in Costa Rica and Thailand are more complicated than either of these two stereotypes.

Our results are not consistent with protected areas creating poverty traps. In fact, the results suggest that protection in areas associated with high poverty has, on average, reduced poverty while also reducing deforestation. Such win–win outcomes were

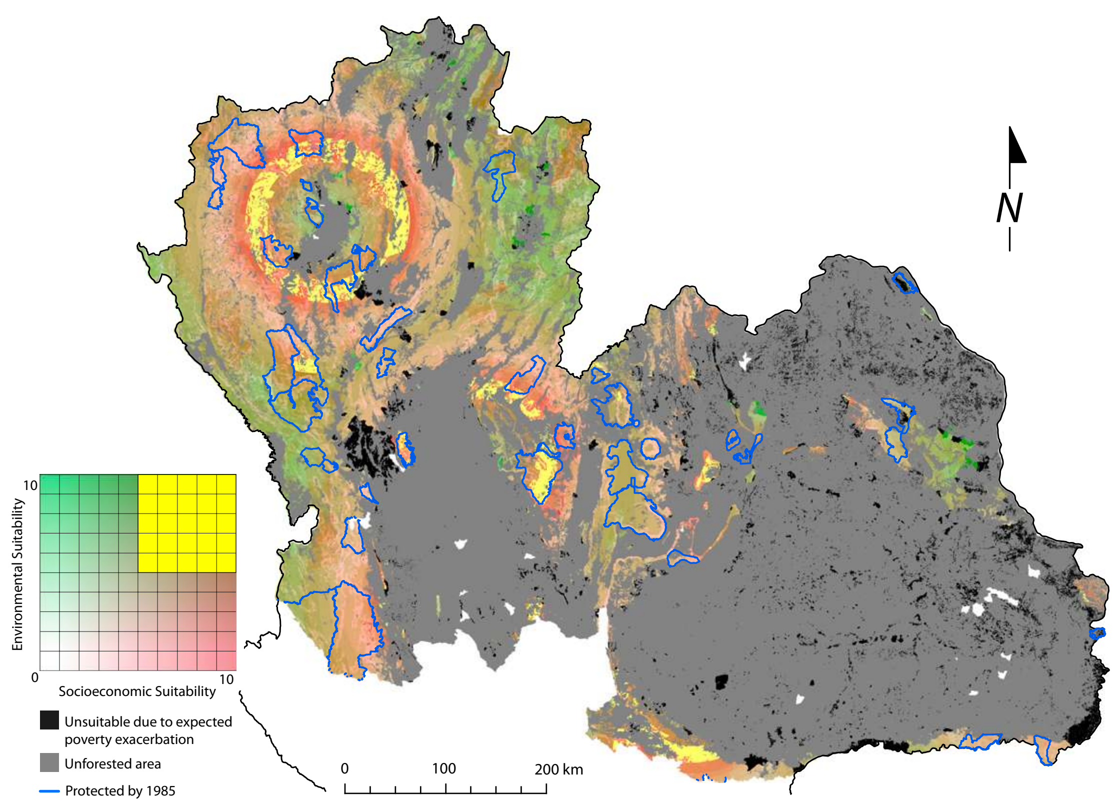

Fig. 3. Thailand protected area suitability map.

most commonly associated with locations at intermediate distances from major cities (40–80 km) and on land of moderate to poor agricultural potential. These patterns are consistent with a hypothesis that protected areas have reduced poverty by being placed on lands with little agricultural value that, by their proximity to major markets, can benefit from tourism and associated infrastructure development (thus, offsetting any losses from foregone agriculture and forest resource exploitation). To support this hypothesis, more explicit analyses of mechanisms will be necessary (38). Although we find no evidence that protection, on average, created poverty traps, our results do not imply that protection reduced poverty in all poor communities. Poverty may have been exacerbated in some poor communities.

Despite the lack of evidence for poverty traps from protected areas, the results do suggest potential tradeoffs: the most avoided deforestation is found on low-sloped land with high agricultural value, but these lands are often where poverty exacerbation is observed. Thus, although protected areas did lead, on average, to moderate levels of avoided deforestation and poverty reduction in Costa Rica and Thailand, our analysis points to tradeoffs if decision makers desire higher levels of either outcome. The potential for tradeoffs underscores the importance of conditional empirical success rules, especially as practitioners attempt to better target protected area investments to increase conservation effectiveness and policymakers look to protected areas as a means to obtain international financial transfers from reducing emissions from deforestation and forest degradation (REDD) programs.

Costa Rica and Thailand are middle-income countries, have made substantial investments in their protected area systems, and have relatively successful eco-tourism sectors. Whether our results would hold for other nations is an open question. Our approach can, and should be, replicated in other nations through cooperation between groups collecting spatially explicit data on poverty, protected areas, and land-use change. A greater understanding of heterogeneous impacts can improve conservation planning and offer insights into the potential tradeoffs between environmental and development goals in future efforts to reduce emissions from deforestation and degradation.

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