Decentralized forest management simultaneously reduced deforestation and poverty in Nepal

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Summary Paragraph:

Halting global forest loss while reducing poverty is central to sustainable development agendas[1,2]. Since the 1980's, decentralized forest management has been promoted as a way to enhance sustainable forest use and reduce rural poverty[3], and rural communities manage increasing amounts of the world's forests[4]. Yet rigorous evidence using large-N data on whether community-based forest management (CFM) can jointly reduce both deforestation and poverty remains scarce. Studies to date have largely relied on cross-sectional analyses of single outcomes, or used qualitative poverty assessments that are difficult to compare across space or time[5]. We estimate impacts of CFM using a large longitudinal dataset that integrates national-census-based poverty measures with high-resolution forest cover change data, and near-complete information on Nepal's > 18,000 community forests. We compare changes in forest cover and poverty from 2000-2012 for sub-districts with presence or absence of CFM arrangements, but that are otherwise similar in terms of socioeconomic and biophysical baseline measures. Our results indicate that community-based forest management has, on average, contributed to significant net reductions in both poverty and deforestation across Nepal, and that CFM increases the likelihood of win-win outcomes. We also find that the estimated reduced deforestation impacts of community forests are lower where baseline poverty levels are high, and greater where community forests are larger and have existed longer. These results indicate that greater benefits may result from longer-term investments and larger areas committed to community forest management, but that community forests established in poorer areas may require additional support to minimize trade-offs between socioeconomic and environmental outcomes.

Main text:

Forests are critical to sustainable development. They regulate climate, sequester carbon, harbour biodiversity, and contribute to national incomes and local livelihoods[6]. Over the past four decades, governments and international organizations have promoted decentralized community-based forest management (CFM) to achieve sustainable forest use and reduce rural poverty[3]. In decentralized decision-making arrangements, the primary responsibility for day-to-day management rests with forest-user communities. Ideally, this allows communities to make better use of their time and place-specific knowledge to promote more efficient, equitable, and sustainable multi-functional landscapes[7].

Local communities now legally manage approximately 13% of the world's forests[4]. Debates about whether CFM truly reduces forest loss and alleviates poverty, nonetheless, continue[5,8]. Case studies from Latin America, Africa, and South Asia show that some CFM initiatives have improved forest and livelihood outcomes[9,10], but that others have not achieved intended objectives[3,11]. The vast majority of existing studies have focused on limited sets of cases, and have used qualitative assessments of poverty and livelihood outcomes that are difficult to compare across space and over time[5]. These studies have helped identify how land tenure, local autonomy, and collective action may contribute to effective and equitable CFM, but have not tested whether CFM programs lead to net environmental and socio-economic improvements at national scales[5]. Some studies use more rigorous evaluations of CFM but they generally focus on single outcomes, studying the relationship between CFM on either forests[12-14] or poverty[15,16], often at single points in time[17,18].

We analyse forest cover change and poverty alleviation outcomes of CFM for the case of Nepal using a high-spatial resolution, national-level, longitudinal dataset (see Methods). Our study makes three key advances. First, we analyse the average effects of CFM at a national scale using a near-complete census of Nepal's 18,321 registered community forests. Second, we combine these data with sub-district level, national census-based multi-dimensional poverty measures (2001-2011) and high-resolution forest cover change data (2000-2012). Finally, given the multiple drivers of deforestation[19] and poverty alleviation[20], our approach aims to separate CFM impacts from other potential socioeconomic and biophysical factors affecting the establishment of CFM that could also impact forest and poverty outcomes (see Methods). Specifically, we combine statistical matching and multiple regression analyses to control for potential geographic, economic and political drivers of outcomes at the sub-district level. These include: slope, elevation, precipitation, population density, agricultural effort, international migration, travel time to market and population centres, distance to district headquarters, presence of protected areas, and baseline measures of poverty and forest cover, as well as administrative-level fixed effects that control for factors common to each district such as government investments in education or health. These methods seek to ensure that treated and control groups are similar to each other[21], and follow established quasi-experimental approaches to evaluation of conservation interventions[22-24]. Our identification of impacts relies on plausibly exogenous conditional variation in CFMs arising from the history of multiple NGOs, government agencies, and international donors, operating in non-systematic ways across time and space (see Methods). We test the robustness of our results with respect to potential unmeasured confounding variables such as other government programs that may be correlated with CFM (see Sensitivity Analyses in Methods and Supplementary Information). Our analysis advances the literature by (*i*) assessing rigorously the effect of community forests on reductions in both deforestation and poverty alleviation, (*ii*) evaluating poorly understood trade-offs between the two outcomes, and (*iii*) investigating how poverty moderates the success of CFM - a critical link that has received only limited attention.

Several factors justify our Nepal focus. The country has a long-standing CFM programme first initiated in the 1970's and subsequently supported by key legislative reforms and substantial international aid from the late 1980's to the present[25,26]. Estimates suggest that a quarter of the country's forests are directly managed by more than a third of the country's predominantly rural population[26]. Nepal's forests are distributed across different eco-regions (subalpine high mountains = 32%, temperate and subtropical middle hills = 38%, tropical lowlands = 30%)[27]. The country's CFM program is large but not exceptionally so. Several countries (e.g., Mexico, Madagascar, and Tanzania) have similar CFM programs[12,15,28], and others are developing them (e.g., Indonesia). Although context may be somewhat different, lessons from Nepal may provide useful insights for other countries with similar types of forest decentralisation policies. Importantly, relevant government agencies made the necessary data available for integration across sources and spatial scales.

Various complex direct and indirect mechanisms may contribute to net reductions in deforestation and poverty as a result of CFM in Nepal and other countries.

Under CFM, community forest user groups can establish and enforce rules to promote more sustainable use and flows of forest resources over time. These CFM land use restrictions can limit agricultural production, logging, and forest product extraction, leading to less deforestation, reduced forest degradation, and faster reforestation rates. Substantial household benefits can come from the ongoing, but more sustainable, use of timber, construction materials, firewood, food and medicinal plants, and also fodder for livestock and composting materials for agriculture[29,30]. Households may also gain income directly from sales of forest products through forest-based enterprises. Such revenue streams can account for as much as half of households' income[29,31]. In some instances, communities also use internal levies from forest products to fund community-level infrastructure improvements, promoting long-term development and community benefits. However, both levies and use restrictions may disproportionally burden those unable to afford them[32]. In extreme cases, CFM benefits could be captured by only a few households, failing to reduce average poverty levels.

We first assessed the impact of CFM on deforestation and poverty using longitudinal data for 3832 of Nepal's 3973 Village Development Committees (VDCs, our unit of analysis - Fig. 1a), which are sub-district administrative units equivalent to municipalities in other countries. We compare VDCs with any CFM (mean area under CFM = 13%) with VDCs that are similar in biophysical and socioeconomic characteristics but without CFM (see Methods and Supplementary Information for robustness tests using treatment allocation thresholds). More than 80% of community forests were established between 1993 and 2002[25]. We thus focus on CFM arrangements established before 2000 for our main analysis (but see SI for additional analyses of CFM established after 2000, and for robustness checks that support our main findings using additional forest cover change data and comparisons of poverty metrics). Our approach uses variation in establishment of CFMs, after controlling for confounders, driven by multiple international donors and NGO's working with the government during this period (see Methods; see Supplementary Fig. 8).

After controlling for confounding variables, we find statistically significant net positive relationships between CFM and forest cover change ($P = 0.004$, Fig. 1b, Supplementary Table 1) and CFM and poverty alleviation ($P < 0.001$, Fig. 1c, Supplementary Table 1). At the level of individual VDCs, our results equate to an average of 1.6 hectares deforestation that is avoided (S.E. = 0.83), and 20 households lifted out of poverty (S.E. = 0.62) between 2000 and 2012. This compares to mean deforestation levels of 5 hectares (S.E. = 1.0) and poverty levels of 316 households (S.E. = 6.3) in matched control VDCs, meaning that our results translate to a 32.6% relative reduction in deforestation and a 6.4% relative reduction in poverty that is attributable to CFM. Our results are robust to the use of different remote sensing data, or separate analyses of forest gain and loss (Supplementary Information).

We also assessed whether the area under CFM and the duration of CFM arrangements affected deforestation and poverty, by focusing only on VDCs with CFM arrangements (n = 2138). We find that larger CFM areas (> 8.3% of VDC area) were significantly linked to reductions in poverty among CFM VDCs (P < 0.001, Fig. 1c, Supplementary Table 2). This effect is equivalent to larger CFM areas lifting 18 more households out of poverty per VDC than smaller CFM areas (S.E. = 0.65). This compares to 270 poor households in matched control VDCs (S.E. = 8.0), representing a relative poverty alleviation of 6.8% in VDCs with larger CFM area. Similarly, a longer duration of CFM arrangements (mean establishment duration > 3.4 years) led to significant reductions in deforestation (P = 0.012) and poverty (P < 0.001). These effects are equivalent to 1.2 hectares of avoided deforestation (S.E. = 0.34), and 14 households lifted out of poverty (S.E. = 0.68). This compares to mean deforestation levels of 5.1 hectares (S.E. = 0.78) and poverty of 288 households (S.E. = 7.5) in matched control VDCs, representing a 24% relative reduction in deforestation and a 4.8% relative reduction in poverty in VDCs with longer duration CFM arrangements. These results suggest that greater benefits result from longer-term investments and larger areas committed to decentralized CFM.

Reductions in poverty can be driven by environmentally degrading natural resource extraction (e.g., unsustainable logging). We, therefore, analysed whether CFM leads to “win-win” outcomes to understand whether impacts on deforestation and poverty alleviation trade off. To do so, we constructed a three-level ordinal outcome variable, defining VDCs with lower than the median deforestation and higher than the median poverty alleviation rates as “win-win” outcomes[9,10] (Fig. 2a, see Methods). We find that among matched VDCs, those with CFM had 58% higher probability of being linked to “win-win” outcomes relative to control VDCs (baseline win-win probability 29%, P < 0.001, Fig. 2b, Supplementary Table 1), and a 38% lower probability of being linked to “lose-lose” outcomes relative to control VDCs (baseline lose-lose probability 37%). Similarly, we find that among matched VDCs, those with CFM arrangements that had been in place for longer had a 5.6% higher probability of being linked to “win-

win” outcomes relative to control VDCs (baseline win-win probability 25%, P = 0.016), and 10% lower probability of being linked to “lose-lose” outcomes relative to control VDCs (baseline lose-lose probability 26%, Supplementary Fig. 1, Supplementary Table 2). The above median deforestation and poverty alleviation values are conservative classifications of “win-win” outcomes. To validate the effect of CFM on “win-win” outcomes, we also analysed different “win-win” thresholds (upper quartiles), a continuous joint outcome index, and datasets generated using decile deviations from median forest cover change and poverty alleviation values to establish whether outliers influenced our results (Supplementary Information) – all robustness checks led to similar results. These results build on recent efforts that evaluate either forest or poverty outcomes of CFM[12,13,15,16], and suggest that CFM has jointly improved social and environmental conditions in Nepal in the most recent decade.

Finally, we investigated how baseline poverty moderates the effects of CFM on forest and poverty outcomes. This analysis is important because the majority of community forests in Nepal have been established in less poor VDCs (Fig. 3b and Supplementary Fig. 2). Among matched VDCs, we find that community forests in VDCs with higher levels of baseline poverty (2001) have a lower reduced deforestation effect compared to community forests in VDCs with lower levels of baseline poverty ($P < 0.001$, Fig. 3a, Supplementary Table 1). These results suggest that new CFM established in poorer areas likely requires additional support to minimize socioeconomic and environmental trade-offs

Our analysis contributes to crucial debates in the literature by finding that CFM has contributed to lower deforestation levels and poverty alleviation through one of the world’s largest and longest standing decentralised forest management programmes[5]. The magnitude of socioeconomic and environmental benefits that we observe are similar to those attributable to other forest-based conservation and development interventions in other countries, such as payment for ecosystem services in Mexico[33], and have the potential to be self-funding in the long term. Although our results are specific to Nepal’s case and similar studies would need to be undertaken in other contexts, our findings indicate the potential for CFM as a conservation and poverty alleviation strategy by estimating the specific impacts of CFM on forest cover change and poverty alleviation.

Communities manage an increasing amount of the world’s forests globally, yet assessments of CFM outcomes are geographically skewed towards South Asian studies[5]. Social and environmental data are increasingly available at higher temporal and spatial resolutions, and future work should thus continue to estimate the large-scale joint social and environmental outcomes of CFM programmes in other countries. Yet large-scale analyses focusing on average treatment effects, such as the one we present here, also potentially mask variations in outcomes: CFM has not led to uniform reductions in deforestation and poverty (Figure 2a). We find that baseline poverty levels significantly affected CFM's ability to curb deforestation. Future efforts should continue seeking a better understanding of other factors driving variation in CFM impacts both across and within community forest user groups.

Unlike programmes in Mexico[28] or Madagascar[12], community forestry in Nepal has mainly not been managed for commercial markets[34], but there is still great heterogeneity in CFM arrangements in Nepal and some communities have raised substantial revenue. Future analyses should thus also use more detailed household data to understand how market forces and commercial forestry influence livelihood decisions and CFM outcomes. Given the complexity of deforestation and reforestation drivers and patterns, future analyses would benefit from investment in detailed CFM boundary data and improved land cover monitoring (including forest degradation).

Finally, decentralised forestry programmes between[35] and within countries[36] (including in Nepal) vary substantially in remit and governance structures that can substantially affect social and environmental outcomes. Future work should pay closer attention to understanding how different variants of decentralized forest management (and which aspects of difference) influence outcomes. A critically important analytical horizon concerns how (in terms of effect sizes) decentralised regimes compare to more centralized forms of forest management, such as national or even supranational protected areas[37], other policy interventions such as sustainability certification or payments for ecosystem services[33], as well as broader socio-economic and demographic shifts (e.g., international migration) which have also been linked to substantial changes in livelihoods and land cover[38].

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Contributions. J.A.O., K.R.E.S., M.J.W. and A.A. conceived and designed the study and statistical analysis. J.A.O compiled the dataset and performed the statistical analysis. J.A.O., K.R.E.S., B.K.K., M.J.W., and A.A. wrote the paper. K.R.E.S., M.J.W. and A.A. are joint senior authors.

Methods

Our analysis relies on the construction of a longitudinal dataset using publicly available global- and national-level datasets, and a series of statistical analyses using variation in CFM conditional on multiple controls to estimate impacts. Additional robustness checks are available in the Supplementary Information.

Dataset

Unit of analysis. Previous similar studies of impact estimations have predominantly used spatially explicit datasets on the interventions being assessed (e.g., protected areas[23] or land titles[24]). Such a spatially explicit dataset does not exist for Nepal's >18,000 community forests. Furthermore, data for many other variables - including poverty estimates and other data derived from the national census - can only be compiled at the level of individual VDCs. We therefore use VDCs as our unit of analysis. We compiled data on 3832 of Nepal's 3973 VDCs identified by an official VDC-level shapefile from Nepal's Department of Home Affairs. While our analyses cannot account for intra-VDC variation, our sample is sufficiently large to identify statistical relationships. Note that we excluded 141 VDCs from our analysis, including 129 VDCs not sampled in the 2001 census due to the armed conflict (Maoist insurgency), and 12 VDCs where the area under reported CFM was greater than the total area of the VDC. Including the 12 additional VDCs as a robustness check made no substantive differences to the results from our statistical analyses or to the conclusions drawn from them.

Outcomes

Forest cover change. We used the high-resolution forest cover change dataset v1.0[39] to assess changes in the amount of forested area (forest cover change) between 2000 and 2012. This dataset measures stand replacement (i.e., forest presence or absence, and does not include measures of degradation (i.e., forest quality). Measures of tree cover loss and tree cover gain are available as separate data files: to generate a measure of net change we first calculated the number of hectares lost and gained in each VDC and then expressed the difference between the two as percentages relative to baseline forest cover. Our measures of forest cover change clustered around zero with high kurtosis, and we used a Lambert W transformation to correct the variable's distribution and reduce the influence of outliers[40]. Average marginal effects were calculated using back-transformed values. We conduct a series of robustness tests using the individual forest gain and loss datasets, and with an additional forest cover change data produced by the International Centre for Integrated Mountain Development (ICIMOD) in Nepal (Supplementary Information). Results from these tests all support the findings from our main analysis.

Poverty. The Nepal 2001 and 2011 national census is the only representative national household survey, that we are aware of, that can be used to generate country-scale longitudinal measures of socioeconomic variables at the level of individual VDCs (our unit of analysis). We use data from both censuses to generate poverty measures for our analysis. The census does not contain household income or consumption estimates, which are often used to measure poverty. However, poverty is increasingly considered a complex and multidimensional concept encompassing more dimensions than the traditionally used measures of household income and consumption[41,42]. We use the Alkire and Foster method[43] to generate a multi-dimensional poverty index (MPI) that is similar to the global MPI generated by the Oxford Poverty and Human Development Initiative (OPHI). Like OPHI's index, our MPI includes health, education and living standards dimensions, although individual indicators differ slightly due to data availability. We gave equal weighting to the three dimensions (33.3%), and equal weighting to indicators within each dimension (8.3% or 16.6%, depending on the number of indicators in each dimension). We treated missing data in the same way as Alkire and Santos[44].

The health dimension included i) child mortality, measured as the proportion of households experiencing the death of one or more children (aged ≤ 5 years), and ii) premature mortality, measured as the proportion of households experiencing a household death below the period life expectancy.

The education dimension included i) school attendance, measured as the proportion of households with at least one school-aged child (aged 6 - 16 years) not attending school, and ii) years of schooling, measured as the proportion of households with at least one person, aged 11 years or older, with less than 5 years of schooling.

The living standards dimension included the proportion of households using i) dung or wood as cooking fuel, and the proportion of households lacking access to ii) electricity, iii), clean water (according to Millenium Development Goals (MDGs) guidelines[45] and used by the OPHI's global MPI), and iv) improved sanitation (according to Millenium Development Goals (MDGs) guidelines[45] and used by OPHI's global MPI)

We calculate the incidence, or head count ratio (*H*), of poverty in each VDC and use this measure in our principal analysis. We follow the method proposed by Alkire and Foster[43]: we aggregate indicators at the household level and define a household as being poor if the sum of weighted indicators within or across dimensions (*k*) is equal to or larger than 33.3%. We then calculate the incidence of poverty in each VDC relative to the total number of households sampled in each census. We use the incidence of poverty because international donors commonly use the number of people benefiting from an intervention as a key performance indicator[46]. However, we also compute a combined measure of incidence and intensity (M_0)[43] as a robustness test (results are equivalent, see Supplementary Table 9). To calculate M_0, we first generated a household-level intensity measure by summing up the number of indicators that a household was deprived in and then dividing this number by the total number of indicators (N = 8; Health dimension = 2, Education dimension = 2, Livelihood standard dimension = 4). We then calculated the average intensity of poverty in each VDC (*A*), and calculated M_0 as $H*A$.

We measured levels of poverty at baseline (2001), which we used as a covariate in our analysis (see below), and changes in poverty between 2001 - 2011, which we used as one of our principal outcome variables. We assess whether our measure is reflective of household consumption as a validity check by comparing District-level measures of our 2011 MPI (*H*) to a district-level consumption-derived poverty index[47] generated by the World Bank and Nepal's Central Bureau of Statistics using data from the 2011 Nepal Livelihoods Standards Survey (NLSS). The indices were highly correlated ($r = 0.68$, $N = 75$, Supplementary Fig. 17) suggesting that our MPI is reflective of household consumption.

Win-Win outcomes. We use the approach used by Persha et al.[9] and Chhatre and Agrawal[10] to construct a three-level, joint outcome ordinal variable. We use median deforestation and poverty estimates as cut-offs between levels. We define VDCs with lower than the median deforestation and higher than the median poverty alleviation rates as "win-win" outcomes (Fig. 2a). We define VDCs with higher than the median deforestation and lower than the median poverty alleviation as "lose-lose" outcomes, and the remaining two deforestation and poverty alleviation combinations as "tradeoffs". Please refer to the Supplementary Information for robustness checks related to this definition of joint outcomes.

Treatment

Community forest management. CFM can lead to reductions in deforestation and poverty through several complex direct and indirect mechanisms. For example, rights to land and resources, and the autonomy to make resource management decisions promote collective action and the design, establishment and enforcement of local resource management rules[48]. Forest dependent households can gain substantial commercial and subsistence benefits from forests in the form of timber, construction materials, firewood, food, and medicinal plants[49], and also fodder for livestock and composting materials for agriculture[29,30]. The implementation and enforcement of local management rules can lead to more equitable and sustainable management decisions. In some instances, communities also generate community-level income streams to fund community-level infrastructure improvements (e.g., schools and health posts) by establishing internal levies for forest products (note that although levies can contribute to broader benefits they can disproportionally burden those unable to afford them[32]). More sustainable forest management can enhance soil fertility, agricultural productivity, livestock production, and commercialisation of forest products through forest-based enterprises that can account for as much as half of a household's income[29,31]. CFM livelihood benefits could be reflected by better health and educational outcomes (e.g., through better food and nutritional security, and financial solvency to access healthcare and education), and investments in living standards improvements (e.g., improved access to electricity, sanitation, and water), which are often the focus on international donor funded projects in Nepal[25]. At the same time, CFM management rules can lead to land and resource use restrictions, and subsequent reductions in agricultural expansion, logging, and forest product extraction[50]. Similarly, livelihood improvements can reduce forest dependence. More sustainable forest resource use and livelihood improvements, either in combination or isolation, can thus lead to less deforestation, forest degradation and faster reforestation rates.

For each VDC, we used the information held in Nepal's Department of Forest's database on community forest user groups (CFUGs) to calculate i) the area under CFM (relative to VDC size), and ii) the mean numbers of years since CFM arrangements were set in place. We excluded CFUGs with missing data on VDC location, amount of area under community forest management, or establishment dates. Our final sample included information for 96% of all CFUGs held in the database (17,735 of 18,321 CFUGs). Some CFUGs held in the database might no longer be active. It is thus possible that we might be considering some areas as treated which effectively are not. However, this should bias our results towards finding no effect of CFUGs, rather than biasing the results towards the conclusions that we make.

We used the information from the database to conduct several analyses. First, we compare forest and poverty outcomes in VDCs with and without CFM. We use data from community forests established prior to 2000 for our main analyses (Supplementary Table 1) because i) as many as 80% of all CFUGs were established in the run-up to 2000[25] - our baseline year. Our estimates thus represent impacts due to CFM between 2000/1-2011/2; ii) because CFUGs were established in only 512 VDCs after 2000, and iii) because a significant number of community forests in our final sample (3341, equivalent to 38% of all CFUGs established after 2000) were established after 2006, and perhaps too close to the end of our study period (within 5 years from the 2011 national census and 6 years from the high-resolution forest cover change dataset) to observe significant gains in forest cover and poverty alleviation. We conduct two separate but parallel robustness tests. Our first test uses data on community forests established after 2000. This analysis does not suffer from potential feedback from treatment to control variables and corroborate our results (Supplementary Table 10). In our second test, we iteratively increase the area under CFM to assign treatment VDCs (10, 15, 20 and 25% of VDC area under CFM). Doing so provides sharper distinctions between areas with CFM and those without (results from this robustness test support our main findings).

Second, we analyze the effect of the area under CFM and the duration of CFM arrangements using the subset of VDCs that established community forests prior to 2000. We create two sets of binary treatment variables - one for CFM area and one for CFM duration - that we use for our matching pre-processing. We use median values (8% of VDC area under CFM, 3.4 years since the establishment of CFM arrangements) to generate equally sized treatment and control groups.

Matching Covariates

There are a range of biophysical and socio-economic covariates that can potentially influence CFM (selection into the treatment) and our two outcome variables[21,51], and we control for these in our analysis in both our matching and subsequent regression analysis. Our selection is based on known drivers of forest cover change[19,52], factors known to affect poverty outcomes of conservation policies[22], and variables thought to influence locations of CFM identified as part of a global systematic review of CFM[5] as well as Nepal-related reports[25,26].

Area. Area size has been previously associated with poverty outcomes of protected areas[22].

Baseline forest cover. We expressed baseline forest cover in each VDC as the proportion of forested area in 2000.

Baseline poverty. We use our 2001 census-generated MPI to control for baseline levels of poverty. We also examine the moderating effect of baseline poverty on community forest management using a baseline poverty and treatment interaction term.

Slope and elevation. We used the ASTER DEM v2[53] to calculate mean elevation and slope in each VDC because both can affect agricultural suitability, forest dynamics, and livelihood decision[54]

Precipitation. Agricultural production and forest dynamics are affected by precipitation. We used the WorldClim current precipitation (v1.4, 1950 - 2000) dataset[55] to assess mean precipitation levels in individual VDCs.

Population density. Resource overexploitation has been linked to population pressure and can drive rural migration patterns as people seek less degraded areas[19]. To control for this and urbanization, we include a measure of baseline population density (2001) in each VDC using data from Nepal's national census.

Agricultural effort. Agriculture is a principal driver of deforestation and land-cover change, globally[19]. We use the 2001 national census of Nepal to generate a baseline measure of agricultural activity, which we expressed as the total number of months dedicated to agriculture by above school age household members (> 16 years), divided by the number of sampled households in each VDC.

International migration. Nepal has high rates of international migration and remittances that have had substantial effects on livelihoods and forest cover[37, 56]. To control for the effects of international migration we use a proxy for remittance income: data from the 2001 national census of Nepal to measure the proportion of households within each year with at least one or more household members above school age (> 16 years) living abroad.

Travel time to population and administrative centers. Access to services (e.g., technical assistance), markets and nodes of transport can influence livelihood decisions and land-use patterns[19]. We measure travel time to district headquarters and population centers with ≥ 10,000 and ≥ 50,000 inhabitants by adapting the European Commission's Joint Research Centre's (JRC) travel time to major cities algorithm[57], and combining that with Nepal's Survey Departments road data and the JRC's global land cover dataset[58]. We used the ASTER DEM v2[51] to compute elevation and slope correction factors and used VDC centroids as points of departure for all our calculations.

Administrative areas. Districts are the administrative level above VDCs and have significant decision-making autonomy. Most donor-funded interventions and government programmes are implemented at this administrative level, and some Districts were particularly affected by the Maoist insurgency during the 1990's and early 2000's[59]. We included District as a dummy matching covariate and fixed effect in our post-matching regression to control for these and other potentially unobserved factors that are likely to be common to specific Districts.

Protected areas. VDCs inside protected areas and buffer zones are likely to be affected by different natural resource management legislation, state funding and tourism. We use the World Database on Protected Areas[60] to identify VDCs inside protected areas and buffer zones and included a dummy variable to control for these effects.

Analysis

Matching preprocessing and regression analysis

We used a statistical matching and regression approach to estimate the relationship between community forest management, and changes in forest cover and poverty[21,49]. Our approach estimates impacts using conditional variation in CFM between VDCs within the same district after controlling for confounders (see below). We use a form of propensity score matching (optimal full matching) that is particularly well suited for balanced datasets (such as ours)[49,61]. Post-matching regression results of our three treatments (presence, size and duration) are shown in Supplementary Tables 1 and 2.

We used *R*[62] for all our statistical analyses and the “MatchIt” package[63] for our statistical matching. We assessed covariate balance before and after matching, considering a post-matching standardized mean difference of < 0.25 as an acceptable propensity score and covariate balance between treatment and controls groups[49]. Matching significantly improved the balance between all treatment and control groups in the various datasets used in our analysis (Supplementary Figures 3-7 Supplementary Tables 3-7). However, because matching approaches cannot provide perfectly balanced datasets, we also included all matching covariates in our subsequent linear and ordinal regressions (i.e. a full model) to control for any remaining differences between our treatment and control groups.

We estimate predicted levels of net deforestation (in number of hectares per VDC) and poverty alleviation (in number of households lifted out of poverty per VDC) in the presence and absence of CFM, among the VDCs where CFM exists. The mean difference between these predicted values is equivalent to the Average Marginal Effect. We report the standard error of these estimates as a measure of the uncertainty in those estimates. We also report how these effects compare to the mean deforestation and poverty alleviation values in control VDCs, expressing these effects in percentage change terms. We calculate heteroskedasticity robust (Huber-White) standard errors using the “robcov” function in the “rms” package[64].

To assess the moderating effect of baseline poverty on CFM, we include a treatment (CFM prior to 2000 for our main analyses, CFM after 2000 for our robustness test) and baseline poverty interaction term (Supplementary Tables 1 and 10). To control for non-linearity of the effect of baseline poverty we also include a squared baseline poverty interaction term.

Identification strategy

A key assumption to establish causal inference based on our methods is that, once confounding factors have been controlled for, treatment allocation is "as if" random. We believe this is a plausible assumption in our case because of the history of CFM establishment within Nepal[25,26]. Over the past thirty years, international donors have contributed more than US$ 237 million to support community forest management in Nepal, with an additional US$ 8 million in funding provided by the government of Nepal. A rapid increase in CFM occurred after the passage of the 1993 Forest Act[25,26], which established formal mechanisms for devolution of power to CFUGs. Donor-supported programmes targeted different (but sometimes overlapping) areas of the country throughout this period[25]. Efforts spread mainly in the middle hills, which had historically experienced large amounts of deforestation. From our discussions with international donor agencies, areas for interventions were often selected on the basis of programme priorities (e.g. more development focused or more environment focused), and the process of approaching villages depended on somewhat random factors, such as whether staff of implementing agencies had contacts in particular villages. The government of Nepal also experienced considerable political instability and changes in priorities throughout this entire period. This externally driven, decentralized, and uncoordinated process of CFM support creates a plausible source of variation that is uncorrelated with CFM conditional on included controls.

We attempt to control and test for the ways in which these interventions could have been systematic or systematically correlated with other important drivers of outcomes. Given that CFM has often been led by motivations to address historically high deforestation rates - particularly in the middle hills, we include matching covariates related to deforestation rates, such as slope, elevation, and distance to market centres. We have similarly included covariates that might influence the targeting of community forests, including access to district headquarters, and baseline estimates of poverty and forest cover, which have been an emphasis of donor-funded programmes. We include District-level fixed effects to control for unobservable time-invariant factors common to each district, such as high levels of migration, urbanization or impacts of the Maoist insurgency (although note that some prior research suggests that community forest user groups were resilient to the insurgency[65]). We also conduct a series of additional robustness checks that support our core findings (see Supplementary Information).

We test that the conditional treatment (presence, duration of, and area under CFM arrangements) does appear to be random, and that our post-matching regression models do not suffer from spatial-autocorrelation. We do so by conducting Moran's I spatial auto-correlation tests, and performing visual inspections of spatial distribution patterns of regression residuals, and variograms. We use the "spdep" package[66] for our Moran's I tests, and the "gstat" package[67] to generate variograms.

To test for spatial auto-correlation of our treatment variables, we model our treatment variable as either a null model ($y_n = 1$), or as a function of our matching covariates. These latter models are equivalent to those used to calculate propensity scores. As expected, we observe a distinct spatial pattern before controlling for covariates, highlighting a higher likelihood of CFM in the middle hills. Moran's I tests and visual inspections of model residual distributions and variograms show that the spatial auto-correlation of our treatment variables decreased significantly after controlling for our matching covariates, and that the spatial distribution of the three treatment variables (presence, area, and duration of CFM) used in our post-matching regressions is close to random (Supplementary Table 8, Supplementary Figures 8, 9). Spatial auto-correlation tests of our post-matching regression models also show no spatial auto-correlation (Supplementary Table 8, Supplementary Figures 10-15). We interpret the results of these tests as consistent with the assumption that remaining sources of variation in treatment are plausibly exogenous.

Sensitivity Analyses

Since our identification strategy relies on assumptions about the process of CFM establishment that are untestable, it is still possible that important confounders (e.g., other interventions or government programmes) remain. We thus perform a series of hidden bias sensitivity analyses on our principal models to determine the potential importance of unobserved confounders for our results. We use the "causalsens" package[68], which has the additional benefit over other sensitivity approaches (e.g., Rosenbaum bounds[69]) of being able to determine how hidden bias alters both the magnitude and direction of causal estimates. Results from these sensitivity analyses (Supplementary Figures 10-15) suggest that to reduce the average treatment effect to zero, non-measured confounders would have to explain at least as much variation, or substantially more, than the median variation explained by most measured covariates.

Together with our spatial auto-correlation tests (see above), we interpret these results as suggesting that our models are moderately to strongly robust against hidden bias.

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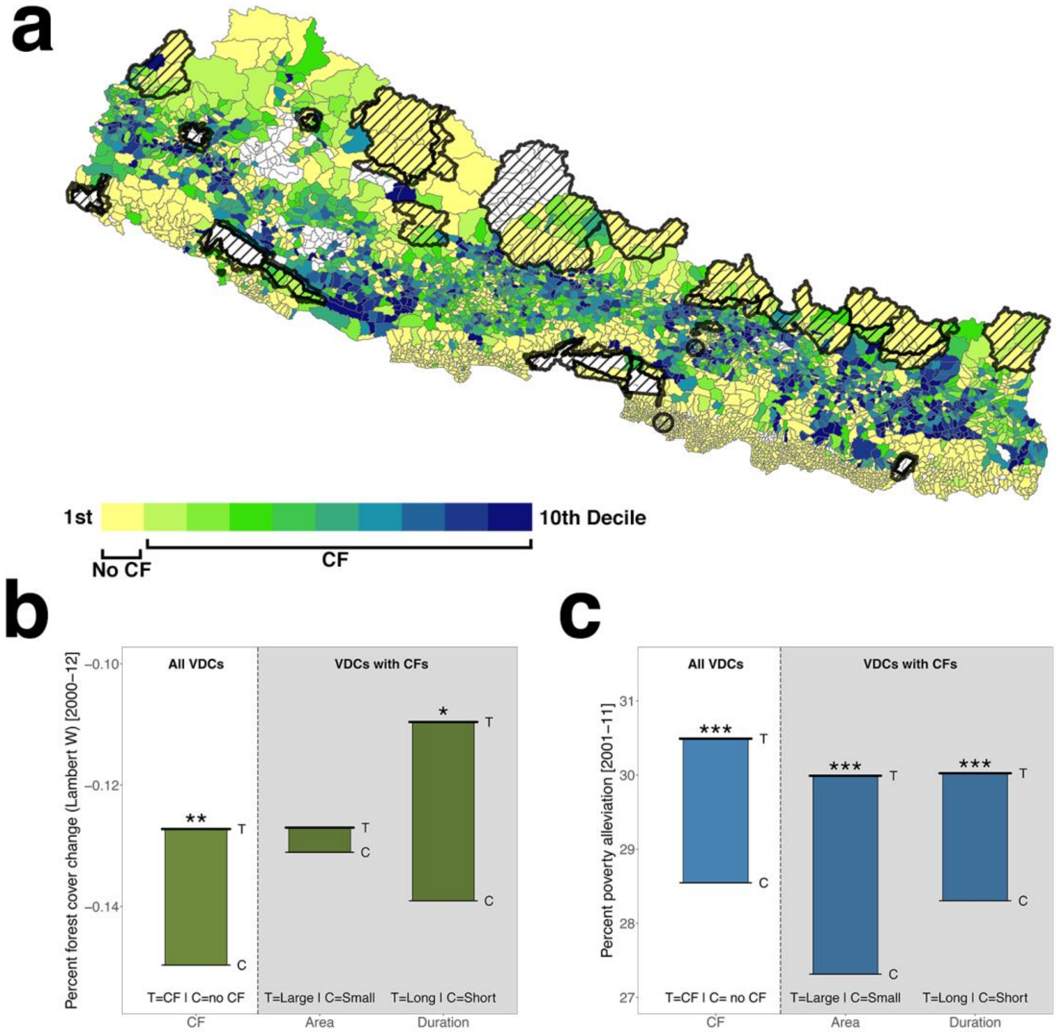


Figure 1 | Distribution of community forests in Nepal and mean post-matching differences in forest cover change and poverty alleviation due to community forest management arrangements. a-c, Area under community forest management in the 3823 Village Development Committees (VDCs – our unit of analysis) included in our sample. The data are presented as deciles. White areas represent excluded VDCs and hashed areas represent protected areas and buffer zones (see methods) (**a**). Post-matching differences in forest cover change (**b**) and poverty alleviation (**c**) comparing VDCs with (T = Treatment) and without (C = Controls) community forests (CF), and VDCs with large (T) and small (C) amounts of area under community forest management, as well as VDCs in which community forest management arrangements have been in place for long (T) and short (C) durations. Estimates were generated using predicted values used to estimate marginal effects and stars indicate post-matching linear regression results that are significantly different from zero (Supplementary Table 1). ***P < 0.001, **P < 0.01, *P < 0.05.

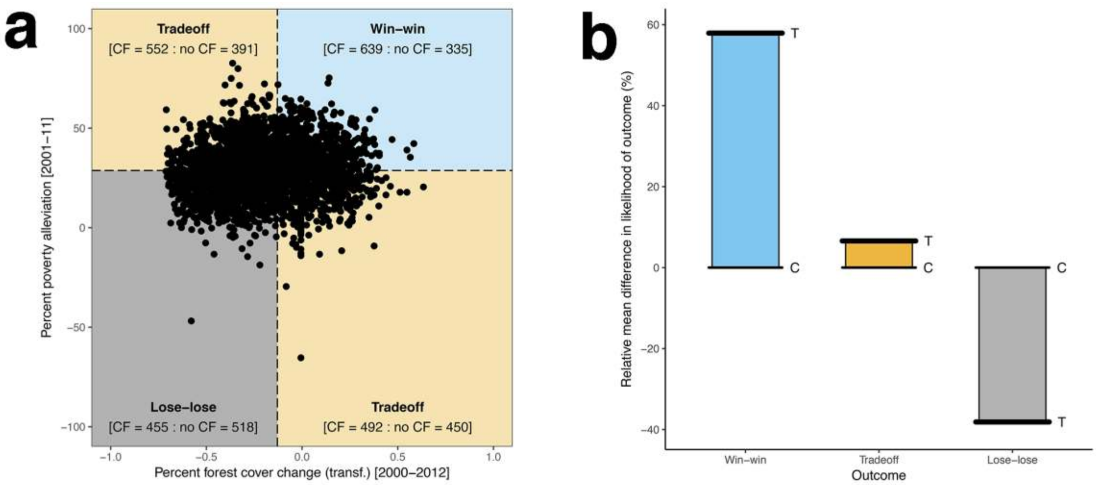


Figure 2 | Categorization and percentage mean difference in the likelihood of outcome for all different joint outcomes as function of presence or absence of community forest management. a-b, Median unmatched forest cover change and poverty alleviation values were used to generate an ordinal variable categorizing joint win-win (blue), tradeoff (yellow) and lose-lose (grey) outcomes (**a**). Areas with community forest (T) were 57.9% more likely to lead to win-win outcomes and 38.1% less likely to lead to lose-lose outcomes than areas without community forests (C). (Joint outcome logit coef. = 0.344, S.E. = 0.0714, P < 0.0001) (**b**).

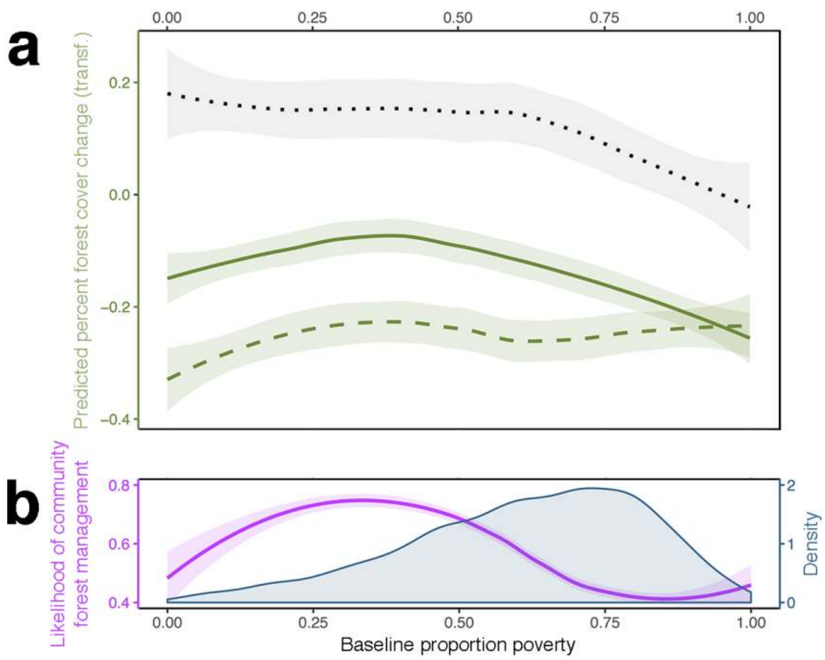


Figure 3 | Changes in predicted deforestation values and likelihood of VDCs having community forestry arrangements along increases in baseline poverty (2001) a-b, Predicted percent forest cover change in areas with (solid green line) and without community forests (green dashed line). The difference between both lines (dotted black line) shows the decreasing effect of community forest management on reductions in deforestation with increases in baseline poverty (**a**). Likelihood VDCs having community forestry arrangements (purple line) and frequency density plot of baseline poverty (blue line and area), showing that community forests are more likely to occur in less poor areas (**b**). Likelihood of community forest management arrangements corresponds to matching propensity scores. Both the predicted probabilities and frequency densities were calculated using the unmatched dataset. Lines and 95% confidence intervals (shaded areas) were generated using a LOESS smoothing function.

Supplementary Information

Robustness tests

We conducted several robustness tests to confirm the validity of our principal results that community forest management has driven joint reductions in both poverty and deforestation.

We first separately analyze the forest loss (deforestation) and gain (reforestation) layers of the high-resolution forest cover change dataset v1.0[34]. Both datasets were negatively skewed and were log transformed for analysis (0.1 was added to all values to account for 0). While there were no post-matching differences in deforestation between Village Development Committees with and without Community Forest Management (CFM) (Coef. = 0.07, SE = 0.04), we find that CFM VDCs had significantly higher levels of tree cover gain than VDCs with no CFM (Coef. = 0.22, SE = 0.04, $P < 0.0001$). These results corroborate findings from our net forest cover change analysis.

Further, validating global remote sensing products like v1.0 is challenging[37,70]. We, therefore, use an additional Landsat-derived forest cover change dataset[71] generated by the International Centre for Integrated Mountain Development (ICIMOD) in Nepal to confirm that community forest management has led to positive forest outcomes. Classification accuracy for the ICIMOD dataset ranges from 70-83%, depending on forest type. Baseline (2000) forest cover estimates of the v1.0 and ICIMOD datasets are highly correlated (r = 0.90).

Supplementary Figure 16a maps the difference between the v1.0 and ICIMOD datasets to show the spatial pattern at the VDC level. To the extent that there is a spatial pattern in the data, it suggests that the ICIMOD dataset underestimates deforestation in parts of the middle hills and overestimate deforestation in the tropical lowlands relative to the global forest cover change dataset v1.0. These spatial patterns could be attributable, at least in part, to inherent large ecological differences between forests in the two regions[27], and the way in which both remote sensing efforts categorise forests.

To understand how this may affect our results, we examined the spatial pattern of the differences. Differences in cover change estimates, calculated as the proportion cover change estimated using high-resolution forest cover change dataset v1.0 - the proportion cover change using the ICIMOD dataset, are not spatially auto-correlated when calculated across the entire dataset (Moran's I = 0.011, Standard deviate = 0.82, P = 0.21, n = 3832). Critically, these differences are uncorrelated with the regression residuals of the model used to estimate the propensity score of our main treatment variable (r = 0.002), and a post-matching regression shows no significant relationship between the presence of community forest management and differences between datasets (Coef. = -0.0005, S.E. = 0.0007, P = 0.52). This suggests that these differences are unlikely to bias our results.

However, the differences between datasets cluster around zero (Supplementary Figure 16b) and approximately 73% of VDCs fall within ± 0.05 from the median difference (-0.02) between datasets (Supplementary Figure 16c). We thus also conduct a spatial auto-correlation test for a subset of the data falling within ± 0.05 from the median difference between datasets. Results using this subset suggest that differences between forest cover change estimates are spatially auto-correlated in a substantial proportion of our dataset (Moran's I = 0.18, Standard deviate = 8.9, P < 0.001, n = 2816). These differences remain uncorrelated with the regression residuals of the model used to estimate the propensity score of our main treatment variable (r = -0.025), and a post-matching regression also shows no significant relationship between the presence of community forest management and differences between datasets (Coef. = -0.09, S.E. = 0.09, P = 0.33).

Ultimately, these differences highlight the need to corroborate our principal findings: that community forest management is associated with significant reductions in deforestation - using the dataset generated by ICIMOD. Results from a post-matching regression using ICIMOD forest cover change estimates instead of the v1.0 data, confirm that community forest led to significant positive forest outcomes (Coef = 0.110, S.E. = 0.048, P = 0.022, Supplementary Figure 7, Supplementary Tables 7 & 9). Post-matching regression residuals do not exhibit spatial auto-correlation (Moran's I = -0.002, Standard deviate = 0.32, P = 0.75, Supplementary Figure 11a, b), and our results are moderately to strongly robust to hidden bias (Supplementary Figure 11c, d). These results confirm that our main findings are not dependent on which dataset is used. This is likely due to the fact that our analytical approach uses biophysical conditions, including elevation, slope, and precipitation that are inherently different between the Terai and Middle Hills, to select matching treatment and control units that capture these key differences. Note that neither of the products we use here use the Nepal Forest Resource Assessment definition of forests, which is similar to the FAO's forest definition[71], and classifies forests as areas that are i) ≥ 0.5 ha in size, ii) > 20 m wide,

iii) have > 10% canopy cover, iv) tree heights of 5m at maturity. The use of a remote sensing product that uses FAO forest definitions would provide results that are more easily comparable to those generated by the Nepal Forest Resource Assessment[27].

For our second set of robustness tests, we first focus on VDCs in which community forests were only established after 2000 to evaluate the effect of CFM on deforestation and poverty (i.e., we know that for these sites treatment, CFM, occurred in between our measures of forest/poverty and so these analyses do not suffer from potential effects of our treatment variable influencing baseline values). Among matched VDCs, we find that those with CFM had less deforestation and significantly more households moving out of poverty (Supplementary Table 10). While the effect on deforestation is not statistically significant (although note the strong impact of CFM duration, which suggests this analysis is less likely to pick up significant results), we find a similar moderating effect of baseline poverty on deforestation, with CFM in poorer areas avoiding significantly less deforestation than CFM in less poor areas. Furthermore, we find a similar bias in where community forests were established, with poorer VDCs being less likely to have CFM arrangements (Supplementary Figure 2). Given that a significant number of VDCs were established within six years of the end of our study period for deforestation and that the sample size of VDCs that established CFM after 2000 is substantially smaller than VDCs established prior to 2000, we interpret these results as confirming those of our principal analysis.

We also iteratively increase the areas under CFM to assign our treatment. We use 10, 15, 20 and 25% of VDC area under CFM as thresholds, which provides a sharper distinction between areas with and without CFM. Since we do not find effects of CFM area on our measure of forest cover change (Figure 1, Supplementary Table 2), we focus this robustness test on our measure of poverty. We find that increasing the treatment threshold increases the effects size of CFM on our poverty outcome (Supplementary Figure 17, Supplementary Table 11)

For our third set of robustness tests we use several different approaches to confirm that community forests management led to joint positive outcomes. In all instances these robustness tests confirm that CFM leads to joint reductions in deforestation and poverty. First, we tighten our definition of “win-win” outcomes and use the upper quartiles of forest cover change and poverty alleviation in our unmatched dataset to generate our ordinal “win-win”, “tradeoff” and “lose-lose” variable. As in our main analysis focusing on medians to generate thresholds, we find that among matched VDCs, CFM was positively and significantly associated with joint positive outcomes (Logit coef. = 0.33, S.E. = 0.079, $P < 0.001$, Supplementary Table 12).

Second, we generated a joint forest cover change and poverty alleviation index using a Principal Component Analysis (PCA) and used the first principal component as our index. The first principal component explained 52 and 53% of the variation among the two outcome variables (forest and poverty) in both our unmatched and matched datasets respectively, and was highly correlated with both variables ($r = 0.72$ for our unmatched dataset, and $r = 0.72$ for our matched dataset). Again, among matched VDCs, those with CFM were more likely to lead to positive joint outcomes (Coef. = 0.16, S.E. = 0.026, $P < 0.001$, Supplementary Table 13).

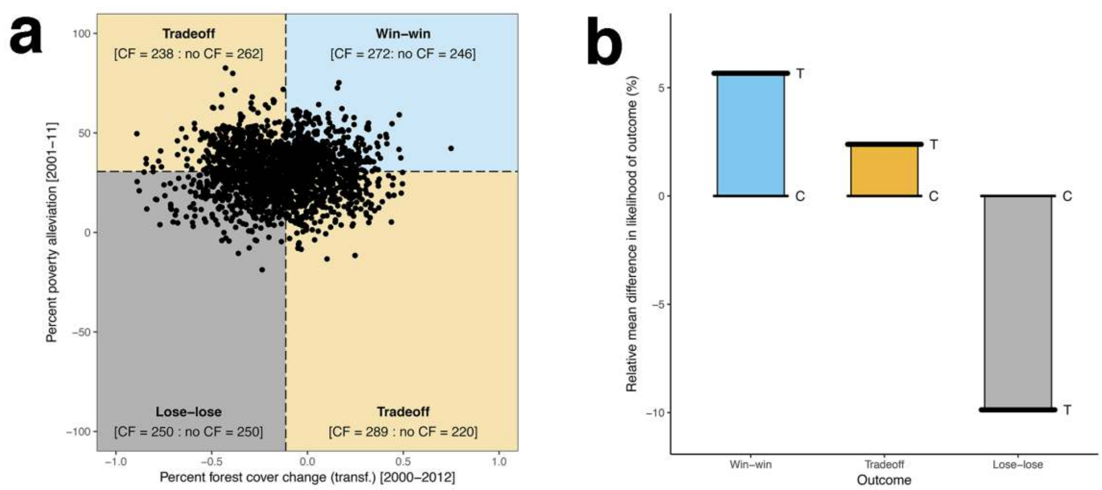
Third, we performed a sensitivity analysis to assess whether the effect of CFM on our median values generated ordinal joint outcome measure was due to the effect of outliers. To do so, we ran a series of iterative matched regressions on consecutively shrinking datasets generated using decile deviations from median forest cover change and poverty alleviation values (Supplementary Figure 19). We find that, among matched VDCs, our results that CFM leads to positive joint outcomes hold if more than 70% of our dataset is retained (Supplementary Table 14).

Nepal can be divided into distinct ecological zones that run North to South (High mountains, Middle hills, and Terai) and was until the 2015 constitutional change subdivided into five distinct development regions which ran from West to East. In our main analysis we control for climatic and biophysical changes by including altitude, slope and precipitation measures for individual VDCs and control for possible effects of differences between District, which have been responsible for coordinating the work of international donors, field agencies and government ministries. In our final robustness test we also include ecological zones and development regions as covariates. Results from our post-matching regression yield almost identical results to those of our main analysis (forest cover change coef. = 0.016, S.E. = 0.006, $P = 0.004$; poverty alleviation coef. = 2.0, S.E. = 0.35, $P < 0.0001$). We also run a model in which we replace ecological zone (longitude) and development region (latitude) with VDC centroid latitude and longitude coordinates. Results from these analyses are also similar to those from our main analysis (forest cover change coef. = 0.023, S.E. = 0.006, $P = 0.0002$; poverty alleviation coef. = 1.3, S.E. = 0.36, $P = 0.0004$).

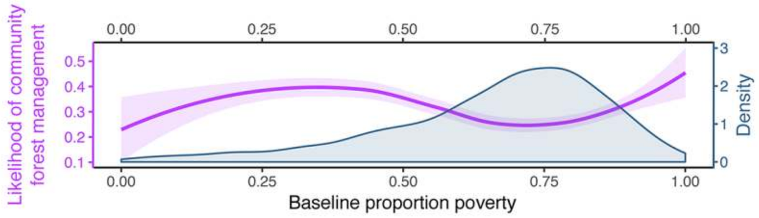
Supplementary Table 1 | Average effects of forest cover change and poverty reduction across all Village Development Communities (VDCs) as a function of community forest management arrangements established prior to 2001.

		No Interaction	Interaction	Squared interaction
	Before Matching **(T=2138, C=1694)**		After Matching **(T=1960, C=1468)**	
Forest cover change [2000-12]§				
Treatment: CF [Yes]	0.011 (0.008) [0.008]	0.016 (0.006)** [0.005]	0.078 (0.017)*** [0.015]	0.052 (0.011)*** [0.009]
Poverty [2001]	0.004 (0.020) [0.002]	-0.021 (0.021) [0.020]	0.037 (0.026) [0.027]	0.015 (0.022) [0.023]
CF [Yes] * Poverty [2001]			-0.10 (0.028)*** [0.025]	-0.093 (0.025)*** [0.021]
Forest loss (ha, controls)		-5.0 (1.0)		
Average marginal effect (ha)		1.6 (0.83)		
Relative difference (%)		-33		
[Adjusted R^2]	0.29	0.32	0.32	0.32
Poverty alleviation [2001-2011]				
Treatment: CF [Yes]	2.5 (0.46)*** [0.049]	2.0 (0.35)*** [0.36]	1.4 (1.1) [0.98]	2.0 (0.71)** [0.68]
Poverty [2001]	47 (1.1)*** [1.4]	53 (1.3)*** [1.5]	53 (1.6)*** [2.0]	40 (1.4)*** [1.8]
CF [Yes] * Poverty [2001]			1.0 (1.7) [1.8]	0.73 (1.6) [1.7]
Poverty alleviation (HH, controls)		316 (6.3)		
Average marginal effect (HH)		20 (0.62)		
Relative difference (%)		6.4		
[Adjusted R^2]	0.44	0.48	0.48	0.43
Joint outcome (ordinal)				
Treatment: CF [Yes]	0.25 (0.095)**	0.34 (0.071)***		
Win-win prob. (%): treat. (controls)		31 (19)		
Relative difference (%)		58		
Tradeoff prob. (%): treat. (controls)		46 (44)		
Relative difference (%)		6.6		
Lose-lose prob. (%): treat. (controls)		23 (37)		
Relative difference (%)		-38		
Residual deviance	6816	6095		

Values outside parentheses represent regression coefficients (average treatment effects); values in parentheses represent naïve standard errors; values in square brackets represent Huber-White corrected standard errors
§Percentages of forest cover change were transformed using a Lambert W function.
***P < 0.001, **P < 0.01, *P < 0.05



Supplementary Figure 1 | Categorization and percentage mean difference in the likelihood of outcome for all different joint outcomes as function of duration of community forest management. a-b, Median unmatched forest cover change and poverty alleviation values were used to generate an ordinal variable categorizing joint win-win (blue), tradeoff (yellow) and lose-lose (grey) outcomes (**a**). Areas with community forest (T) were 5.67% more likely to lead to win-win outcomes and 9.87% less likely to lead to lose-lose outcomes than areas without community forests (C). (Joint outcome logit coef. = 0.225, S.E. = 0.093, P = 0.0156) (**b**).

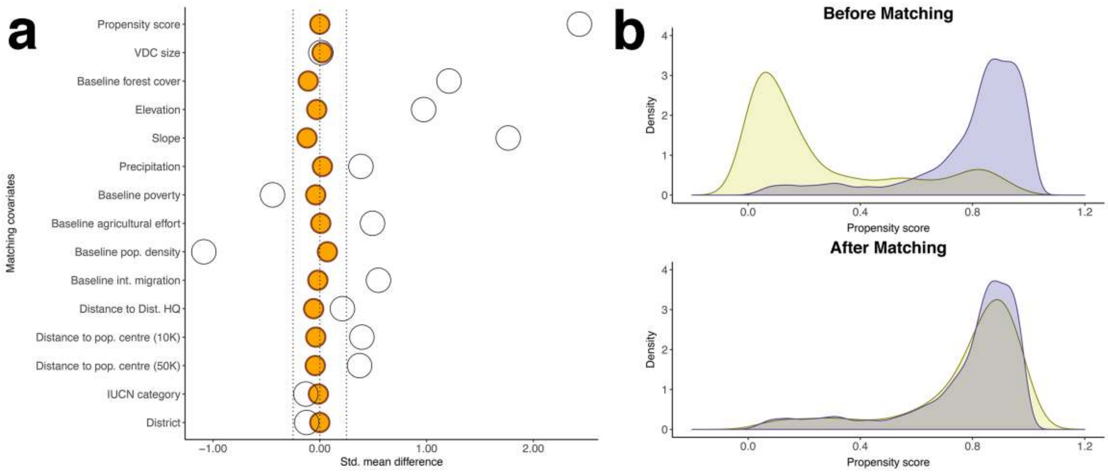


Supplementary Figure 2 | Likelihood of VDCs having community forestry arrangements established after 2000 and frequency density plot of baseline poverty. Likelihood VDCs having community forestry arrangements (purple line) and frequency density plot of baseline poverty (blue line and area), showing that community forests are more likely to occur in less poor areas (**b**). Both the predicted probabilities and frequency densities were calculated using the unmatched dataset. Lines and 95% confidence intervals (shaded areas) were generated using a LOESS smoothing function.

Supplementary Table 2 | Average effects of forest cover change and poverty alleviation across all Village Development Communities (VDCs) as a function of community forest area and duration for community forests established prior to 2000.

	Continuous	Before Matching	After Matching
Forest cover change[§]	**n = 2138**		
CF area[§§]	-0.009 (0.005) [0.005]		
CF duration[§§]	0.010 (0.005) [0.005]		
Adjusted R^2	0.37		
Poverty alleviation			
CF area	0.68 (0.23)** [0.24]		
CF duration	0.76 (0.25)** [0.25]		
Adjusted R^2	0.50		
Joint outcome (ordinal)			
CF area	-0.033 (0.051)		
CF duration	0.11 (0.051)*		
Residual deviance	3723		
Forest cover change[§]		**T=1069, C=1069**	**T=1053, C=1014**
CF area [Large]		-0.007 (0.009) [0.009]	0.007 (0.008) [0.008]
Forest loss (ha, controls)			-6.5 (1.9)
Average marginal effect (ha)			0.33 (0.065)
Relative difference (%)			-5.2
Adjusted R^2		0.37	0.32
Poverty alleviation			
CF area [Large]		1.1 (0.45)* [0.46]	1.8 (0.41)*** [0.40]
Poverty alleviation (HH, controls)			270 (8.0)
Average marginal effect (HH)			18 (0.65)
Relative difference (%)			6.8
Adjusted R^2		0.50	0.55
Joint outcome (ordinal)			
CF area [Large]		-0.050 (0.098)	0.11 (0.090)
Residual deviance		3723	3531
Forest cover change[§]		**T=1068, C=1070**	**T=1049, C=978**
CF duration [Long]		0.024 (0.009)** [0.009]	0.020 (0.008)* [0.008]
Net forest loss (ha, controls)			-5.1 (0.78)
Average marginal effect (ha)			1.2 (0.34)
Relative difference (%)			-24
Adjusted R^2		0.37	0.40
Poverty alleviation			
CF duration [Long]		1.4 (0.45)** [0.44]	1.3 (0.39)*** [0.37]
Net poverty alleviation (HH, controls)			288 (7.5)
Average marginal effect (HH)			14 (0.68)
Relative difference (%)			4.8
Adjusted R^2		0.50	0.58
Joint outcome (ordinal)			
CF duration [Long]		0.17 (0.098)	0.22 (0.093)*
Win-win prob. (%): treat. (controls)			26 (25)
Relative difference (%)			5.6
Tradeoff prob. (%): treat. (controls)			50 (49)
Relative difference (%)			2.4
Lose-lose prob. (%): treat.t (controls)			24 (26)
Relative difference (%)			-10
Residual deviance		3724	3372

Values outside parentheses represent regression coefficients (average treatment effects); values in parentheses represent naïve standard errors; values in square brackets represent Huber-White corrected standard errors
[§]Percentages of forest cover change were transformed using a Lambert W function.
[§§]Variables are scaled
***P < 0.001, **P < 0.01, *P < 0.05

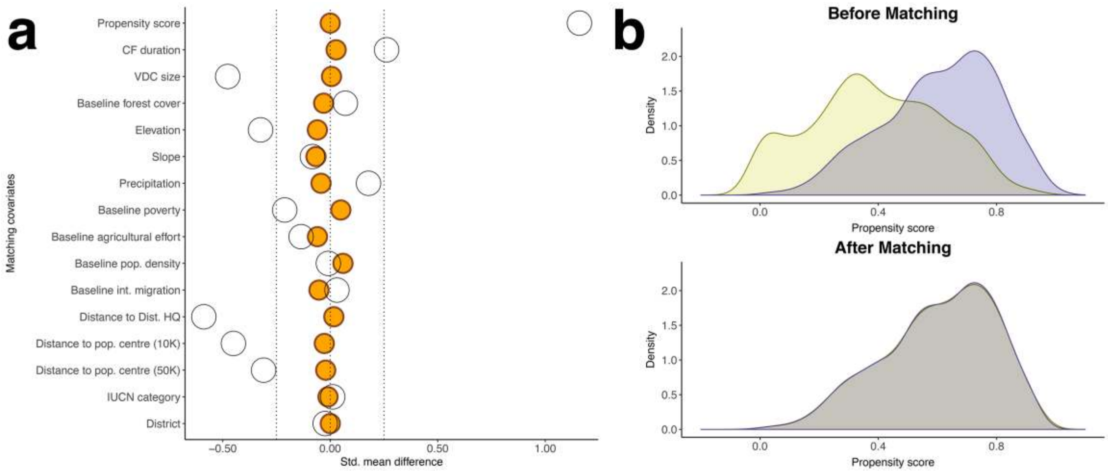


Supplementary Figure 3 | Covariate balance before and after full optimal matching using presence community forest management prior to 2000 as treatment. a-b, Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles) (**a**). Balance results for District and IUCN category are presented as means across all Districts and IUCN categories. Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey) (**b**). Matching resulted in a much-improved overlap between propensity scores.

Supplementary Table 3 | Covariate balance before and after optimal full matching using VDCs with community forest management before 2000 as treatment.

	Before matching			After matching		
	Means Treated *(n = 2138)*	Means Control *(n = 1684)*	Stand. Mean Diff.	Means Treated *(n = 1959)*	Means Control *(n = 1460)*	Stand. Mean Diff.
Propensity score	0.79	0.26	2.4	0.77	0.77	$1.5e^{-4}$
VDC size	3588	3526	0.010	3641	3506	0.021
Baseline forest cover	0.48	0.22	1.2	0.47	0.49	-0.11
Elevation	1385	649	0.97	1414	1436	-0.029
Slope	24	11	1.8	24	25	-0.12
Precipitation	144	129	0.39	142	141	0.024
Baseline poverty	0.57	0.66	-0.44	0.58	0.59	-0.038
Baseline agricultural effort	13	11	0.49	14	14	0.009
Baseline population density	2.5	5.5	-1.1	2.5	2.3	0.071
Baseline int. migration	0.16	0.082	0.55	0.15	0.16	-0.018
Distance to Dist. HQ	3.8	3.1	0.21	3.9	4.0	-0.057
Distance to pop. centre 10K	5.3	3.1	0.39	5.5	5.7	-0.038
Distance to pop. centre 50K	12	8.0	0.37	12	13	-0.043
IUCN category§	0.17	0.17	-0.13	0.17	0.17	-0.011
District§	0.014	0.014	-0.12	0.014	0.014	$1.8e^{-4}$

§ Data are presented as the mean across all IUCN categories and Districts

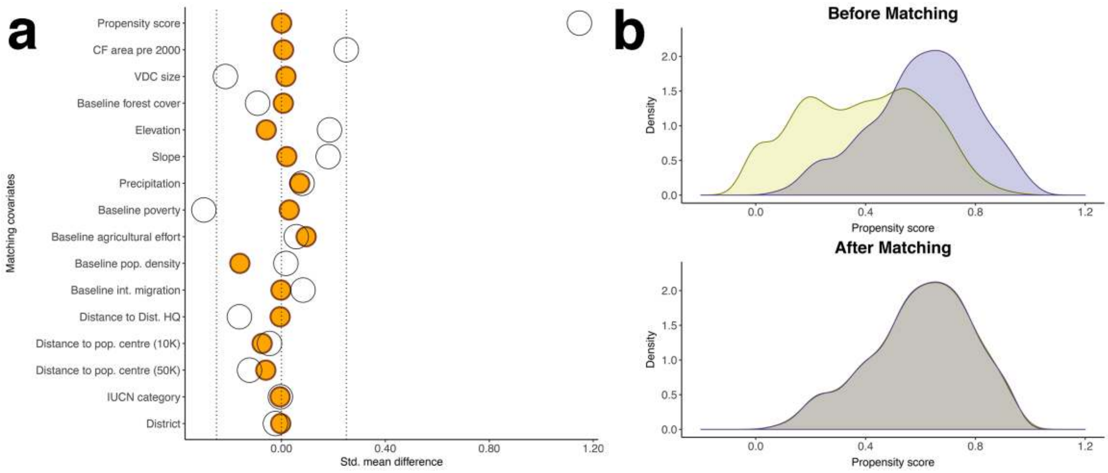


Supplementary Figure 4 | Covariate balance before and after full optimal matching using total area under community forest management prior to 2000 as treatment. a-b, Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles) (**a**). Balance results for District and IUCN category are presented as means across all Districts and IUCN categories. Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey) (**b**). Matching resulted in a near-perfect overlap between propensity scores.

Supplementary Table 4 | Covariate balance before and after optimal full matching using community forest management area before 2000 as treatment.

	Before matching			After matching		
	Means Treated *(n = 1069)*	Means Control *(n = 1069)*	Stand. Mean Diff.	Means Treated *(n = 1053)*	Means Control *(n = 1014)*	Stand. Mean Diff.
Propensity score	0.61	0.39	1.2	0.60	0.60	$8.4e^{-4}$
CF duration	3.7	3.3	0.26	3.6	3.6	0.027
VDC size	2824	4352	-0.48	2834	2815	0.006
Baseline forest cover	0.49	0.47	0.071	0.49	0.50	-0.031
Elevation	1289	1480	-0.32	1293	1328	-0.060
Slope	23	24	-0.083	23	24	-0.066
Precipitation	147	141	0.18	147	149	-0.043
Baseline poverty	0.55	0.59	-0.21	0.55	0.54	0.049
Baseline agricultural effort	13	14	-0.14	13	13	-0.059
Baseline population density	2.4	2.5	-0.009	2.4	2.3	0.059
Baseline int. migration	0.16	0.16	0.031	0.16	0.17	-0.052
Distance to Dist. HQ	3.1	4.5	-0.59	3.2	3.1	0.017
Distance to pop. centre 10K	4.4	6.2	-0.45	4.4	4.5	-0.027
Distance to pop. centre 50K	10	13	-0.31	10	11	-0.021
IUCN category[§]	0.20	0.20	0.011	0.20	0.20	-0.010
District[§]	0.014	0.014	-0.023	0.014	0.014	$3.1e^{-4}$

[§] Data are presented as the mean across all IUCN categories and Districts

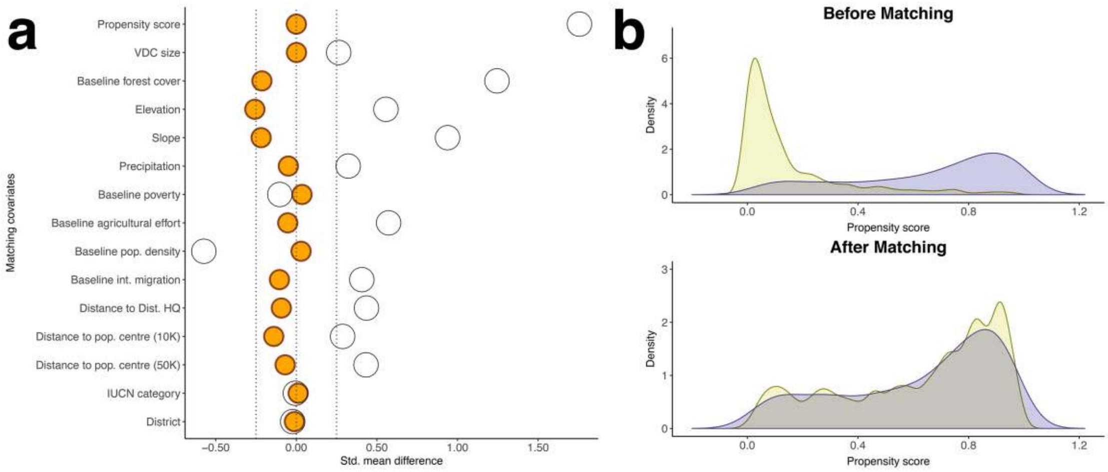


Supplementary Figure 5 | Covariate balance before and after full optimal matching using duration of community forest management arrangements prior to 2000 as treatment. a-b, Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles) (**a**). Balance results for District and IUCN category are presented as means across all Districts and IUCN categories. Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey) (**b**). Matching resulted in a near-perfect overlap between propensity scores.

Supplementary Table 5 | Covariate balance before and after optimal full matching using community forest management duration before 2000 as treatment.

	Before matching			After matching		
	Means Treated *(n = 1068)*	Means Control *(n = 1070)*	Stand. Mean Diff.	Means Treated *(n = 1049)*	Means Control *(n = 978)*	Stand. Mean Diff.
Propensity score	0.61	0.39	1.1	0.60	0.60	$5.6e^{-4}$
CF area pre 2000	0.14	0.11	0.25	0.14	0.14	0.008
VDC size	3136	4039	-0.22	2981	2909	0.017
Baseline forest cover	0.47	0.49	-0.092	0.48	0.48	0.007
Elevation	1449	1320	0.18	1418	1459	-0.059
Slope	24	23	0.18	24	24	0.021
Precipitation	145	142	0.080	147	144	0.070
Baseline poverty	0.54	0.60	-0.30	0.55	0.54	0.030
Baseline agricultural effort	14	13	0.057	14	13	0.095
Baseline population density	2.5	2.4	0.017	2.5	3.0	-0.16
Baseline int. migration	0.16	0.15	0.083	0.16	0.16	-0.002
Distance to Dist. HQ	3.5	4.1	-0.16	3.4	3.4	-0.005
Distance to pop. centre 10K	5.2	5.4	-0.046	5.0	5.3	-0.074
Distance to pop. centre 50K	11	12	-0.12	11	12	-0.060
IUCN category§	0.20	0.20	-0.004	0.20	0.20	-0.005
District§	0.014	0.014	-0.025	0.014	0.014	-0.003

§ Data are presented as the mean across all IUCN categories and Districts

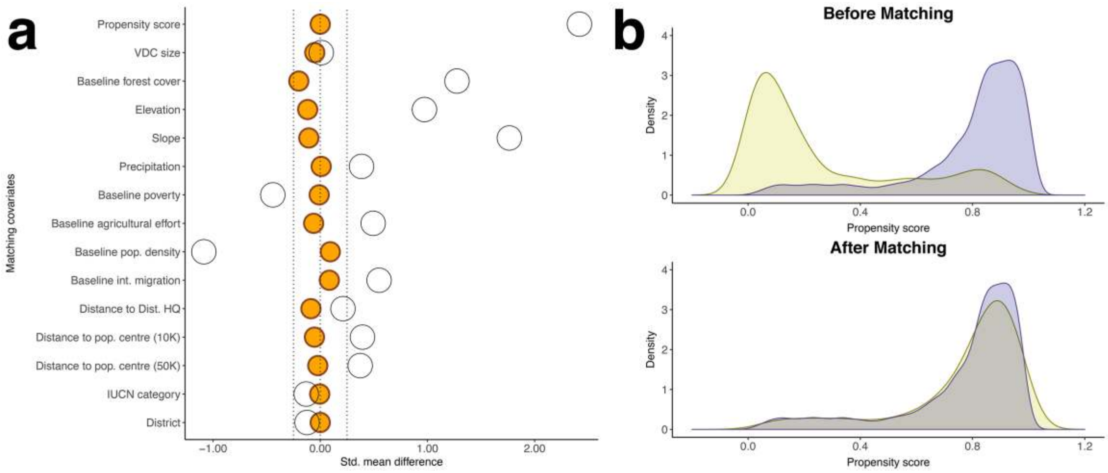


Supplementary Figure 6 | Covariate balance before and after full optimal matching using presence of community forest management after 2000 as treatment. a-b, Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles) (**a**). Balance results for District and IUCN category are presented as means across all Districts and IUCN categories. Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey) (**b**). Matching resulted in a much-improved overlap between propensity scores.

Supplementary Table 6 | Covariate balance before and after optimal full matching using community forest management after 2000 as treatment.

	Before matching			After matching		
	Means Treated *(n = 512)*	Means Control *(n = 1190)*	Stand. Mean Diff.	Means Treated *(n = 476)*	Means Control *(n = 1166)*	Stand. Mean Diff.
Propensity score	0.66	0.15	1.8	0.62	0.62	$3.2e^{-4}$
VDC size	5048	2871	0.26	5037	5026	0.001
Baseline forest cover	0.46	0.12	1.2	0.43	0.49	-0.21
Elevation	1024	488	0.56	1013	1261	-0.26
Slope	18	8.3	0.94	18	20	-0.22
Precipitation	136	126	0.32	135	136	-0.049
Baseline poverty	0.65	0.67	-0.10	0.65	0.64	0.036
Baseline agricultural effort	13	10	0.57	13	13	-0.053
Baseline population density	2.9	6.6	-0.57	3.0	2.8	0.030
Baseline int. migration	0.11	0.067	0.41	0.11	0.12	-0.10
Distance to Dist. HQ	4.3	2.6	0.44	4.2	4.6	-0.093
Distance to pop. centre 10K	4.5	2.6	0.29	4.4	5.4	-0.14
Distance to pop. centre 50K	11	6.6	0.43	11	12	-0.069
IUCN category§	0.20	0.20	-0.006	0.20	0.19	0.012
District§	0.014	0.014	-0.022	0.014	0.014	-0.012

§ Data are presented as the mean across all IUCN categories and Districts



Supplementary Figure 7 | Covariate balance before and after full optimal matching using ICIMOD's forest cover change dataset. a-b, Standardized mean difference for the propensity score and all matching covariates before (open circles) and after matching (orange circles) (**a**). Balance results for District and IUCN category are presented as means across all Districts and IUCN categories. Propensity score density distribution before and after matching for treatment (purple) and control (yellow) groups (overlaps between propensity score distributions are represented in grey) (**b**). Matching resulted in a much-improved overlap between propensity scores.

Supplementary Table 7 | Covariate balance before and after optimal full matching using ICIMOD's forest cover change dataset.

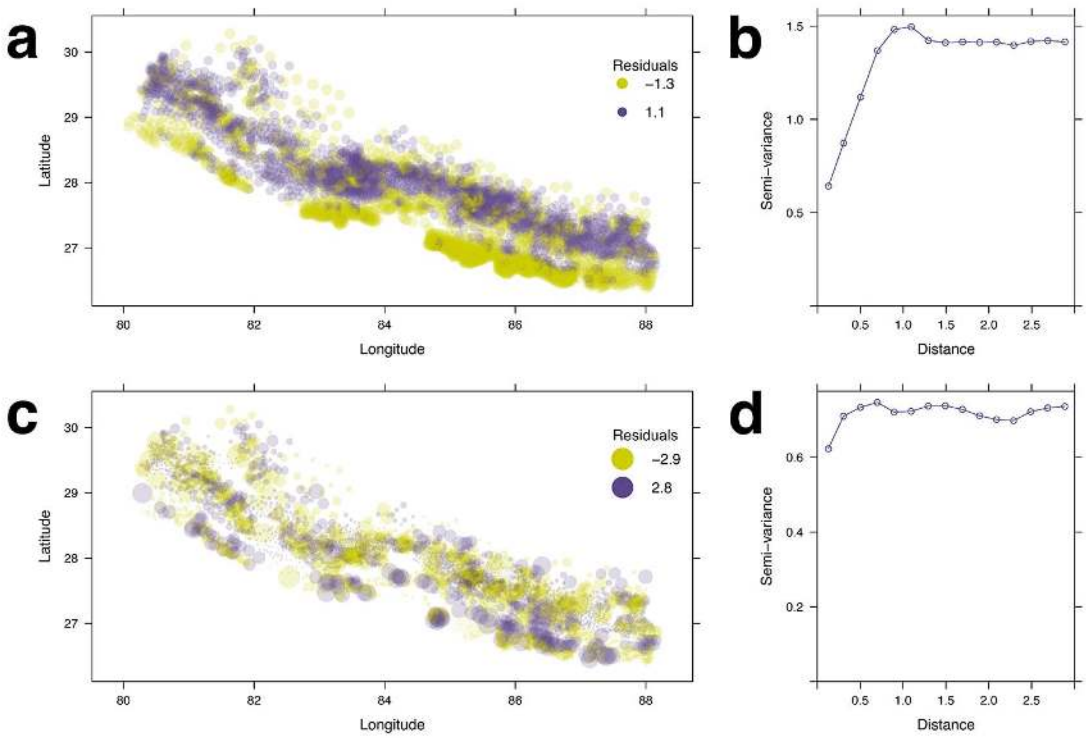
	Before matching			After matching		
	Means Treated *(n = 2138)*	Means Control *(n = 1694)*	Stand. Mean Diff.	Means Treated *(n = 1950)*	Means Control *(n = 1496)*	Stand. Mean Diff.
Propensity score	0.79	0.26	2.4	0.77	0.77	$-8.1e^{-4}$
VDC size	3588	3526	0.010	3642	3962	-0.051
Baseline forest cover	0.48	0.22	1.3	0.48	0.52	-0.20
Elevation	1385	649	0.97	1415	1504	-0.12
Slope	24	11	1.8	24	25	-0.11
Precipitation	144	129	0.39	142	142	0.009
Baseline poverty	0.57	0.66	-0.44	0.58	0.58	-0.010
Baseline agricultural effort	13	11	0.49	14	14	-0.062
Baseline population density	2.5	5.5	-1.1	2.5	2.2	0.094
Baseline int. migration	0.16	0.082	0.55	0.15	0.14	0.085
Distance to Dist. HQ	3.8	3.1	0.21	3.9	4.2	-0.087
Distance to pop. centre 10K	5.3	3.1	0.39	5.5	5.8	-0.054
Distance to pop. centre 50K	12	8.0	0.37	12	12	-0.023
IUCN category[§]	0.20	0.20	-0.13	0.20	0.20	-0.005
District[§]	0.014	0.014	-0.12	0.014	0.014	$-5.3e^{-6}$

[§] Data are presented as the mean across all IUCN categories and Districts

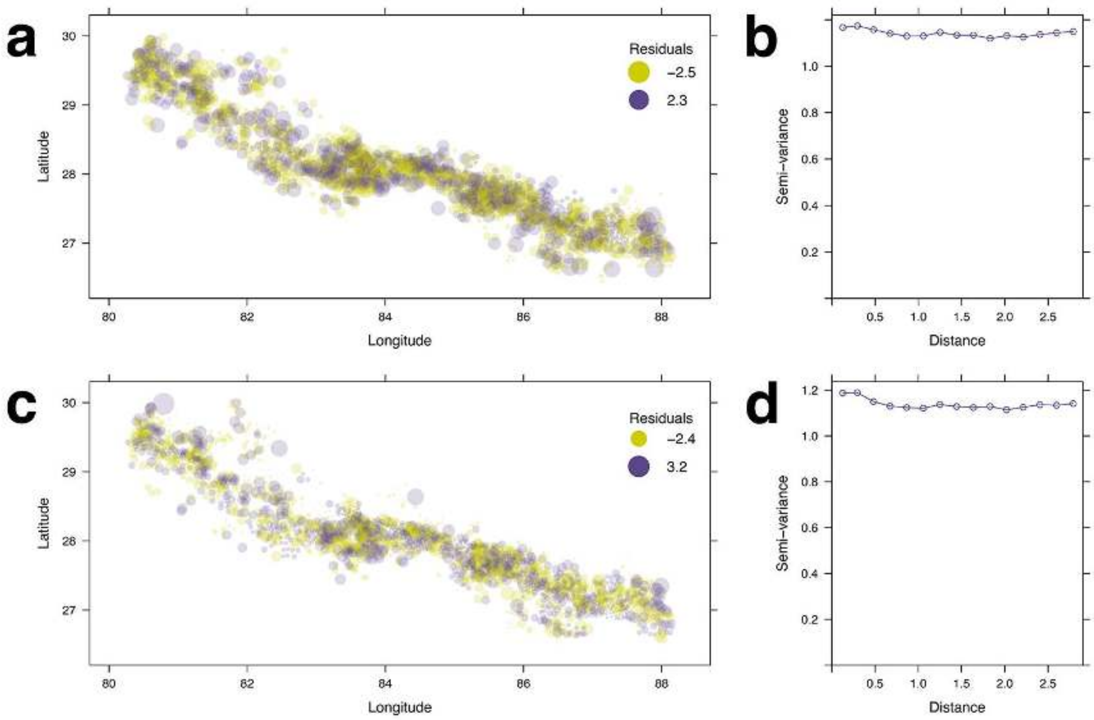
Supplementary Table 8: Spatial auto correlation results for treatment variables and post-matching regressions.

		Moran's I	
Treatment		Null model	Propensity score model
Presence of CF		0.23 (14)***	0.014 (0.99)
Area under CF		0.048 (2.0)*	-0.004 (1.2)
Duration of CF		0.039 (1.6)	-0.020 (1.1)
Post-matching model	Outcome		Moran's I
Presence of CF	Forest cover change [Hansen v1.0 - 2000-12]		-0.015 (-0.35)
Presence of CF	Forest cover change [ICIMOD - 2000-10]		-0.002 (0.32)
Presence of CF	Poverty alleviation [2001-2011]		0.007 (0.80)
Area under CF	Poverty alleviation [2001-2011]		0.026 (1.5)
Duration of CF	Forest cover change [Hansen v1.0 - 2000-12]		0.002 (0.56)
Duration of CF	Poverty alleviation [2001-2011]		-0.005 (0.32)

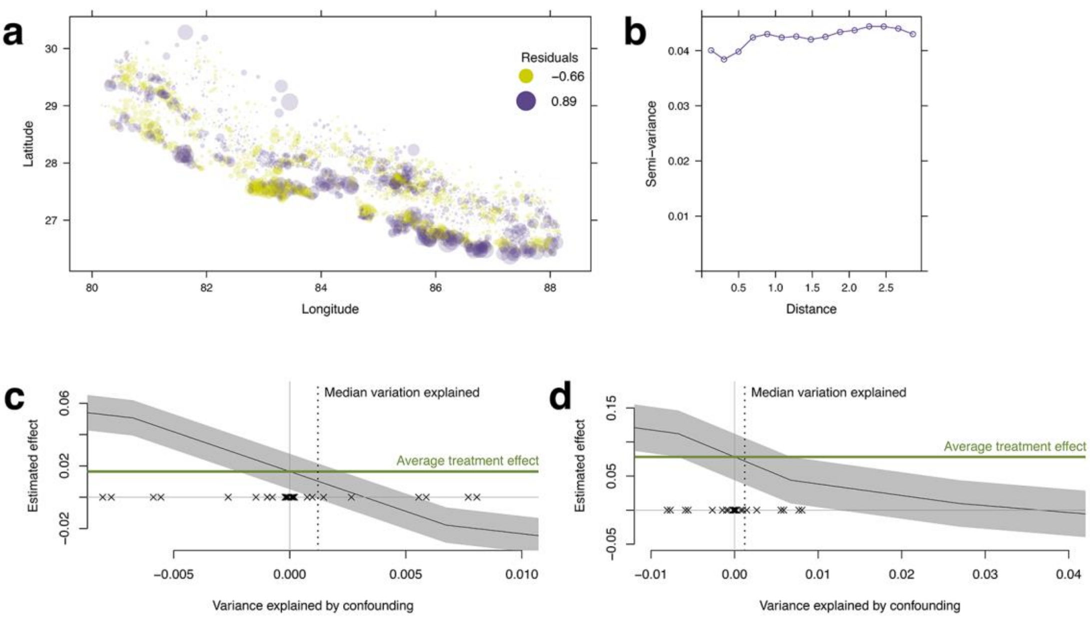
Values in parentheses represent standard deviate values.
[§]Correspond to models used to calculate propensity scores used in matching.
***$P < 0.001$, *$P < 0.05$



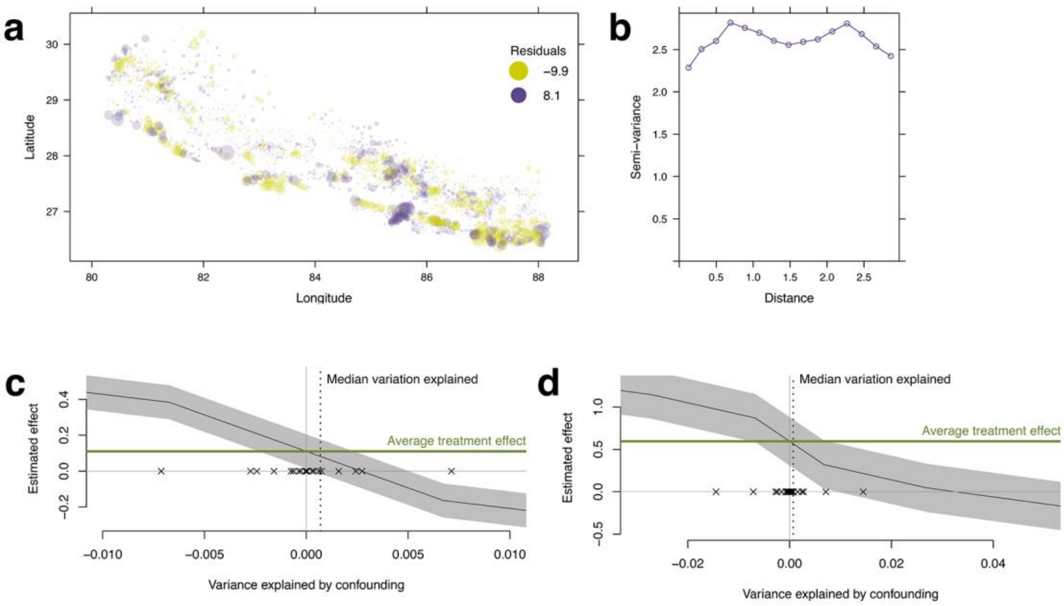
Supplementary Figure 8 | Model residual spatial distributions and variograms of regressions modelling presence of community forest. a-d, Model residual spatial distribution (**a**) and variogram (**b**) of community forest management (CFM) presence as a function of 1 (null model). Model residual spatial distribution (**c**) and variogram (**d**) of CFM presence as a function of matching covariates. Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis). Bubble size and colour (yellow, purple) correspond to the magnitude and direction (negative, positive) of model residuals. Visual inspection of model residual spatial patterns and substantial reductions in semi-variance demonstrate that controlling for matching covariates significantly reduced spatial auto-correlation of our treatment. This is statistically confirmed by Moran's I tests (Supplementary Table 9), suggesting that the spatial distribution of treatment assignment is close to random after controlling for covariates.



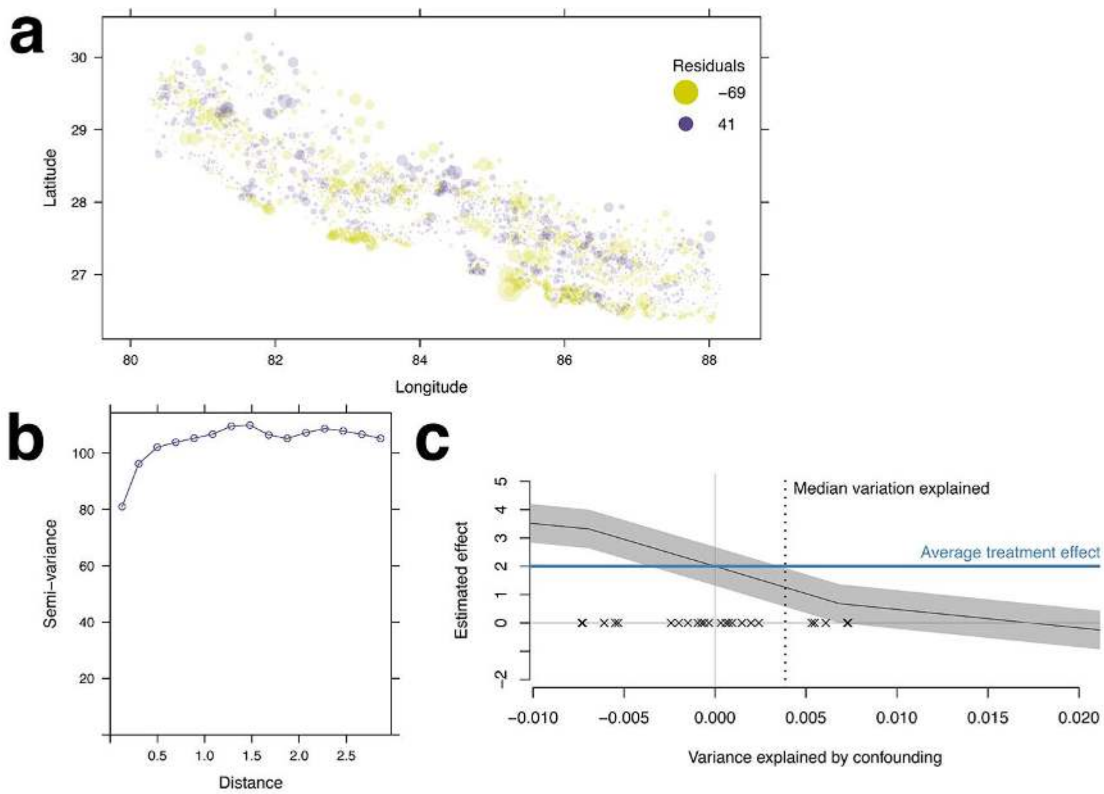
Supplementary Figure 9 | Model residual spatial distributions and variograms of regressions modelling area and duration of community forest management. a-d, Model residual spatial distribution (**a**) and variogram (**b**) of community forest area as a function of matching covariates. Model residual spatial distribution (**c**) and variogram (**d**) of community forest duration as a function of matching covariates. Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis). Bubble size and colour (yellow, purple) correspond to the magnitude and direction (negative, positive) of model residuals. Visual inspection of model residual spatial patterns and semi-variance suggest that, after controlling for matching covariates, treatment assignment is close to random. This is statistically confirmed by Moran's I tests (Supplementary Table 9.



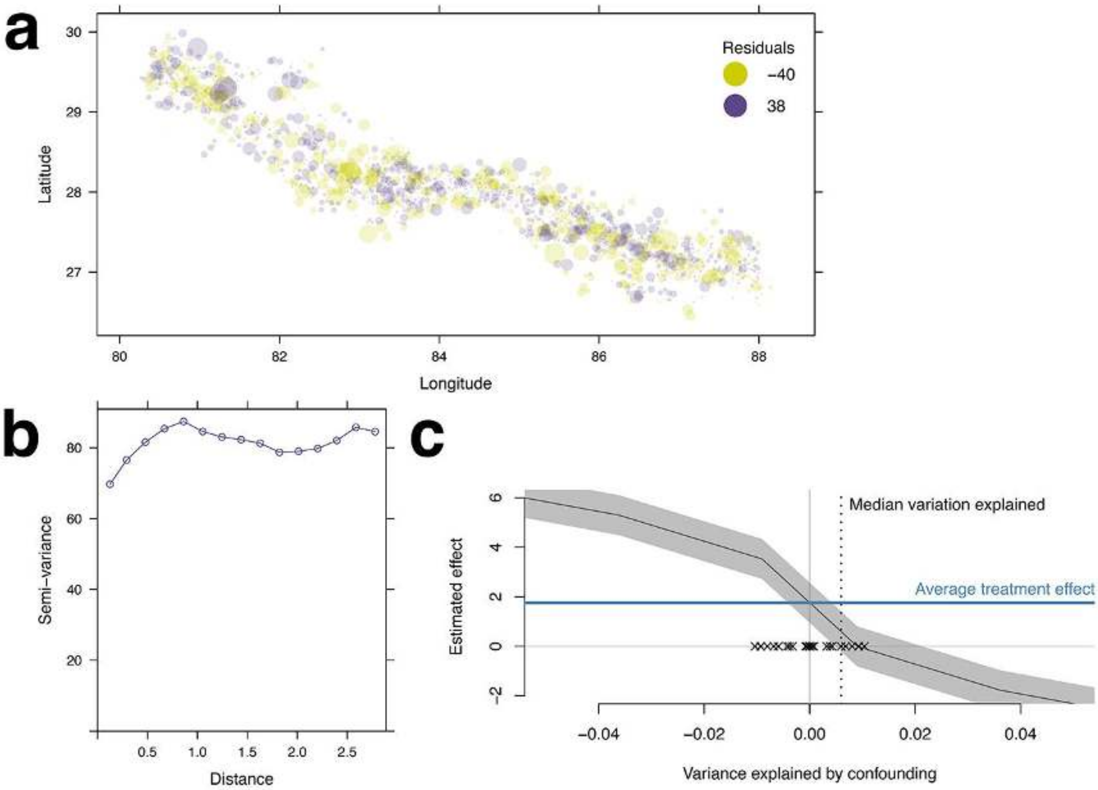
Supplementary Figure 10 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling forest cover change estimates using the global forest cover change v1.0 dataset. a-d, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial auto-correlation. This is confirmed by our Moran's I test (Moran's I = -0.015, Standard deviate = -0.35, P = 0.72). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (yellow, purple) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**), and one including a treatment (community forest management) and baseline poverty interaction term (**d**). Green horizontal lines correspond to treatment effects, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical lines represent the median covariate variation explained. Visual inspections of sensitivity analyses results suggest that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain substantially more than the median variation explained by measured covariates.



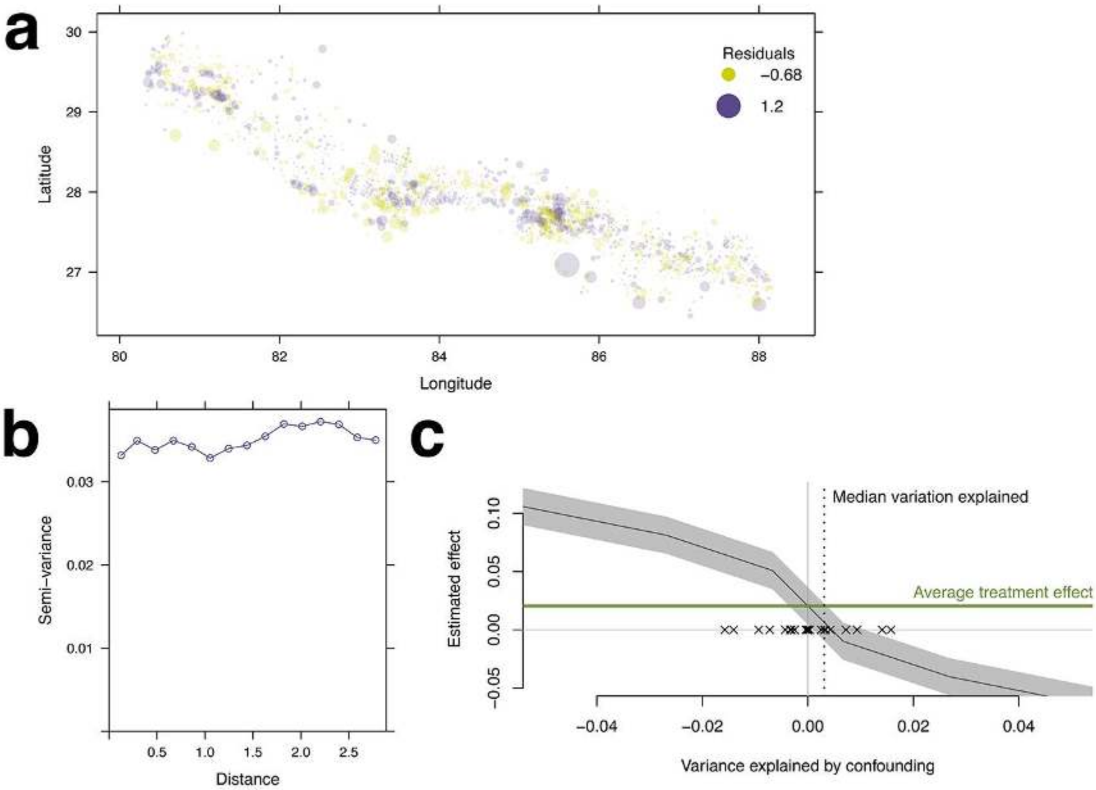
Supplementary Figure 11 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling forest cover change estimates using the International Centre for Integrated Mountain Development (ICIMOD) dataset. a-d, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial autocorrelation. This is confirmed by our Moran's I test (Moran's I = -0.002, Standard deviate = 0.32, P = 0.75). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (green, blue) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**), and one including a treatment (community forest management) and baseline poverty interaction term (**d**). Green horizontal lines correspond to treatment effects, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical lines represent the median covariate variation explained. Visual inspections of sensitivity analyses results suggest that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain substantially more than the median variation explained by measured covariates.



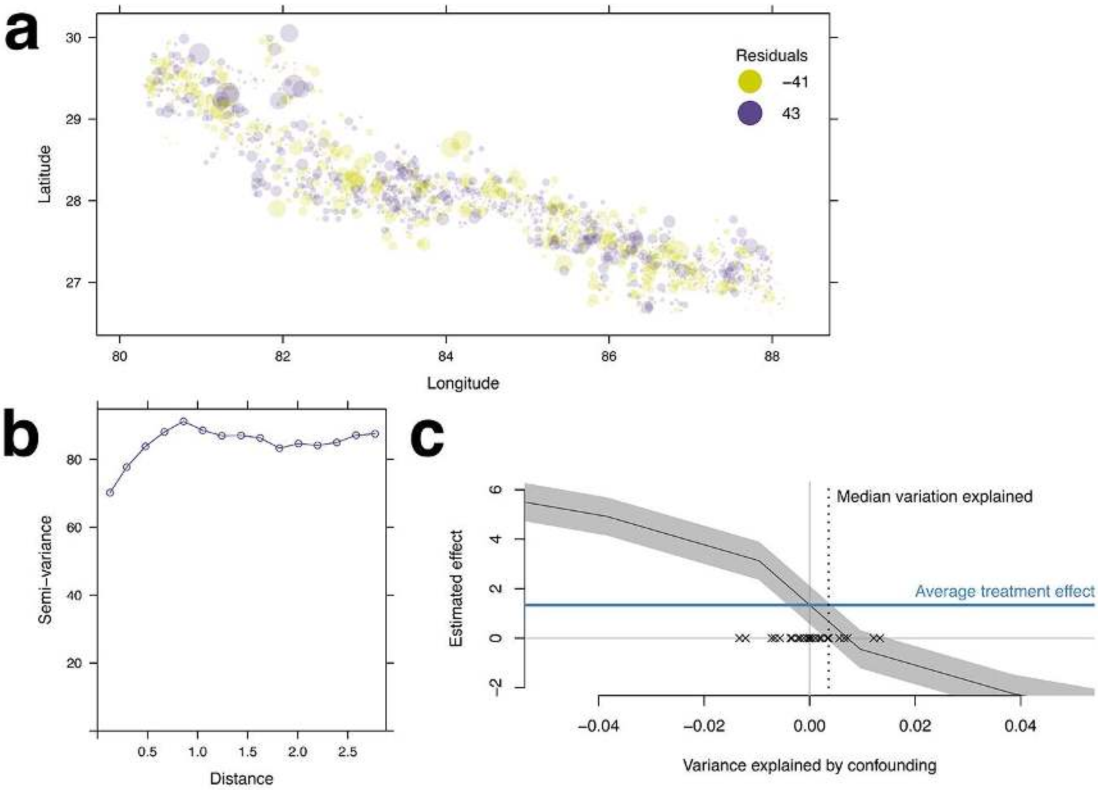
Supplementary Figure 12 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling poverty alleviation as a function of presence of community forest management. a-c, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial auto-correlation. This is confirmed by our Moran's I test (Moran's I = 0.007, Standard deviate = 0.80, P = 0.42). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (yellow, purple) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**) Blue horizontal line corresponds to the average treatment effects, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical line represents the median covariate variation explained. Visual inspection of sensitivity analysis results suggests that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain substantially more than the median variation explained by measured covariates.



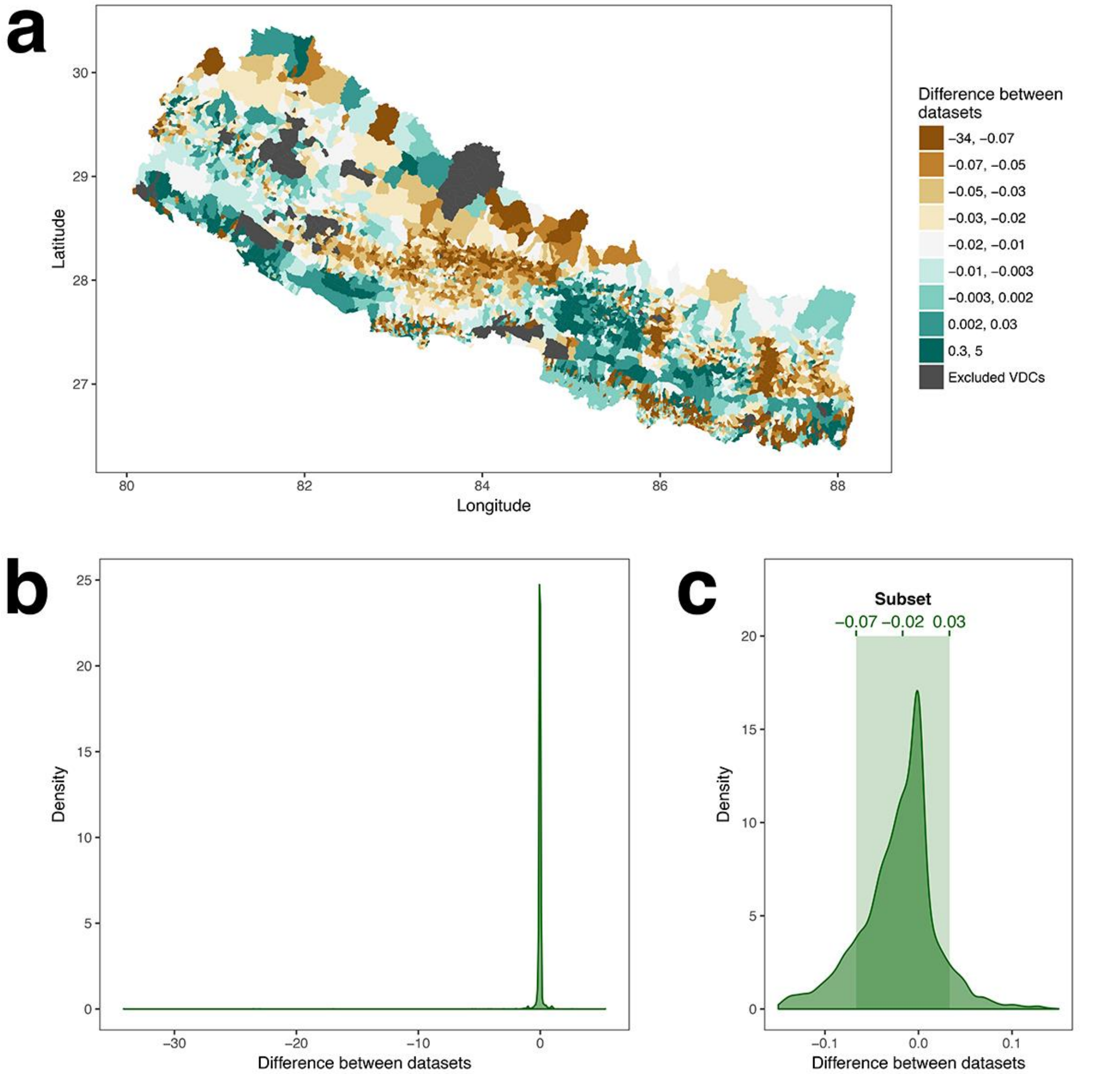
Supplementary Figure 13 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling poverty alleviation as a function of community forest management area. a-c, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial auto-correlation. This is confirmed by our Moran's I test (Moran's I = 0.026, Standard deviate = 1.5, P = 0.13). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (yellow, purple) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**) Blue horizontal line corresponds to average treatment effect, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical line represents the median covariate variation explained. Visual inspection of sensitivity analysis results suggests that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain more than the median variation explained by measured covariates.



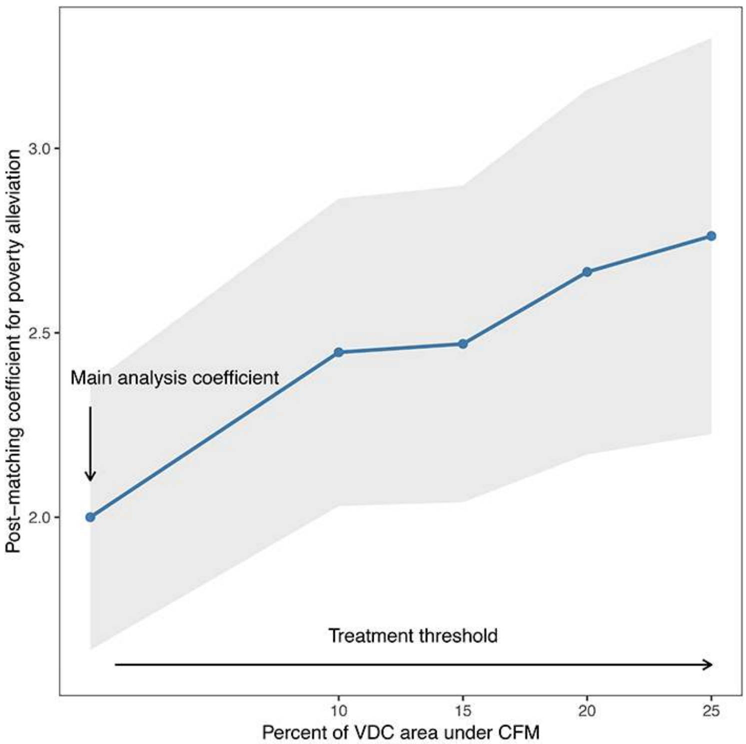
Supplementary Figure 14 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling forest cover change as a function of community forest management duration. a-c, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial auto-correlation. This is confirmed by our Moran's I test (Moran's I = 0.002, Standard deviate = 0.56, P = 0.58). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (yellow, purple) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**) Green horizontal line correspond to average treatment effect, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical line represents the median covariate variation explained. Visual inspection of sensitivity analysis results suggests that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain more than the median variation explained by measured covariates.



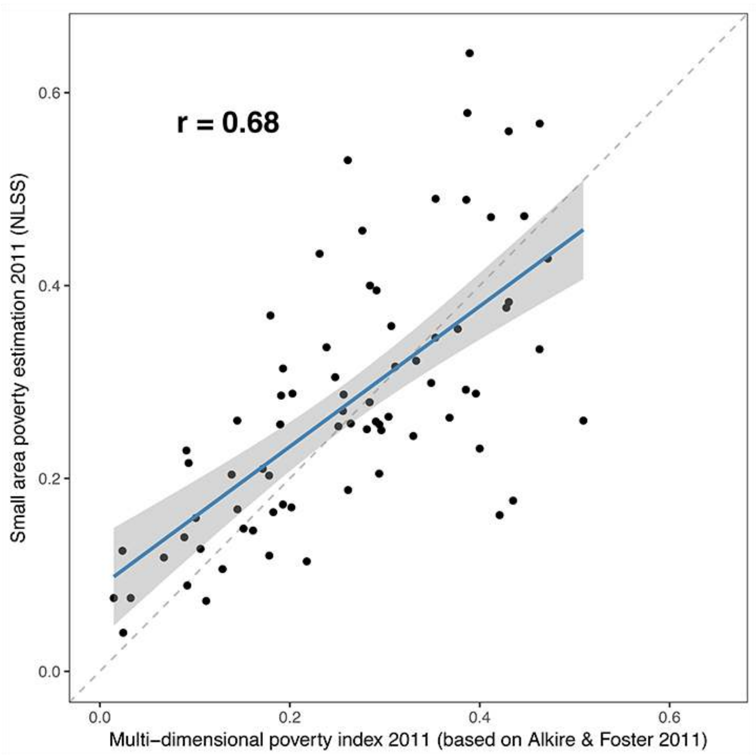
Supplementary Figure 15 | Spatial autocorrelation and sensitivity analyses for post-matching regressions modelling poverty alleviation as a function of community forest management duration. a-c, Visual inspection of the spatial distribution of post-matching regression residuals (**a**) and variogram (**b**) suggest negligible spatial auto-correlation. This is confirmed by our Moran's I test (Moran's I = -0.005, Standard deviate = 0.32, P = 0.75). Each bubble corresponds to a Village Development Committee (VDC - our unit of analysis) in our analysis. Bubble size and colour (yellow, purple) represent magnitude and direction (negative, positive) of residuals. The legend presents bubble size relative to the largest and smallest residual. Sensitivity analysis[66] of our principal model (**c**) Blue horizontal line correspond to average treatment effect, and x symbols correspond to individual covariates and the amount of variation that they explain in our models (partial R^2). Dashed vertical line represents the median covariate variation explained. Visual inspection of sensitivity analysis results suggests that to change the estimated effect of our treatment variable to zero, non-measured confounders would have to explain more than the median variation explained by measured covariates.



Supplementary Figure 16 | Spatial distribution of differences in forest cover change estimates. a-c, Spatial distribution of differences between cover change estimates between the high-resolution forest cover change dataset v1.0[37] and the International Centre for Integrated Mountain Development (ICIMOD) dataset[69] (**a**). Histogram of the difference between datasets for all VDCs (n = 3832) included in our analysis (**b**). Histogram of the difference between datasets for VDCs (n = 2816) where the difference falls within 0.05 points from the median difference (-0.2) between datasets (**c**). This subset represents 73% of VDCs within our dataset.



Supplementary Figure 17 | Post-matching coefficients of poverty alleviation analyses along an increased threshold of treatment assignment. Increasing the area of Village Development Committees (VDCs) under community forest management (CFM) to assign treatment provides a sharper differentiation between treatment and control units, and increases the treatment effects size on the outcome variable



Supplementary Figure 18 | Comparison of District-level small-area poverty estimates for 2011 and census-derived multi-dimensional poverty index for 2011. The national census-derived multi-dimensional poverty estimate in our analysis, which includes health, education and livelihood standards dimensions, is highly correlated with a household consumption-derived poverty index generated using the Nepal Living Standards Survey (NLSS)[45].

Supplementary Table 9 | Regression results for forest cover change using data from ICIMOD and combined incidence and intensity poverty alleviation measure (M_0) as a function of community forest management arrangements established prior to 2000.

		No interaction	Interaction
	Before Matching	After Matching	
Forest cover change [2000-10][§]	**T=2138, C=1694**	**T=1950, C=1496**	
Treatment: CF [Yes]	0.25 (0.068)*** [0.073]	0.11 (0.048)* [0.042]	0.60 (0.14)*** [0.12]
Poverty [2001]	-0.71 (0.17)*** [0.17]	-0.83 (0.17)*** [0.17]	-037 (0.22) [0.22]
CF [Yes] * Poverty [2001			-0.83 (0.23)*** [0.20]
Adjusted R^2	0.44	0.53	0.53
	Before Matching	After Matching	
Poverty alleviation [M_0]	**T=2138, C=1694**	**T=1948, C=1462**	
Treatment: CF [Yes]	0.011 (0.002)*** [0.002]	0.007 (0.002)*** [0.002]	
Poverty [M_0 2001]	0.59 (0.009) [0.050]	0.63 (0.01)*** [0.01]	
Adjusted R^2	0.67	0.71	

Values in parentheses represent naïve standard errors; values in square brackets represent Huber-White corrected standard errors.
[§]Percentages of forest cover change were transformed using a Lambert W function.
***P < 0.001, **P < 0.01, *P < 0.05

Supplementary Table 10 | Regression results for forest cover change and poverty reduction as a function of community forest management arrangements established after 2000.

		No Interaction effect	Interaction effect	Squared interaction
	Before Matching	After Matching		
Forest cover change [2000-2012][§]	**T=510, C=1184**	**T=466, C=1109**		
CF [Yes]	$-1e^{-5}$ ($3e^{-4}$) [$3e^{-4}$]	$1e^{-4}$ ($2e^{-4}$) [$1e^{-4}$]	0.002 (0.007)** [0.006]	0.001 (0.005)** [0.005]
Poverty [2001]	0.002 (0.001) [0.001]	$1e^{-4}$ ($8e^{-4}$) [$9e^{-4}$]	0.001 (0.001) [0.001]	0.001 (0.001) [0.001]
CF [Yes] * Poverty [2001]			-0.003 (0.001)** [0.001]	-0.002 (0.009)** [0.007]
Adjusted R^2	0.26	0.36	0.36	0.36
Poverty alleviation [2001-2011]				
CF [Yes]	0.024 (0.007)** [0.008]	0.014 (0.006)* [0.005]		
Poverty [2001]	0.43 (0.019)*** [0.024]	0.45 (0.023)*** [0.031]		
CF [Yes] * Poverty [2001]				
Adjusted R^2	0.40	0.54		

Values in parentheses represent naïve standard errors; values in square brackets represent Huber-White corrected standard errors.
[§]Proportions of forest cover change were transformed using a Lambert W function.
***P < 0.001, **P < 0.01

Supplementary Table 11 | Post-matching regression results for presence of CFM treatment thresholds on poverty.

Area under CFM	Before matching	After matching
	T = 949, C = 1649	**T = 848, C = 1159**
10%	2.1 (061)***[0.63]	2.4 (0.45)*** [0.42]
	T = 674, C = 1649	**T = 615, C = 996**
15%	0.24 (0.68)*** [0.68]	2.5 (0.48)*** [0.43]
	T = 467, C = 1649	**T = 443, C = 996**
20%	2.7 (0.76)*** [0.76]	2.7 (0.49)*** [0.49]
	T = 285, C = 1649	**T = 275, C = 973**
25%	3.1 (0.86)*** [0.88]	2.8 (0.66)*** [0.54]

Supplementary Table 12 | Ordinal logistic regression results for joint poverty and forest cover change outcomes as a function of the presence of community forest management arrangements using third quartile values.

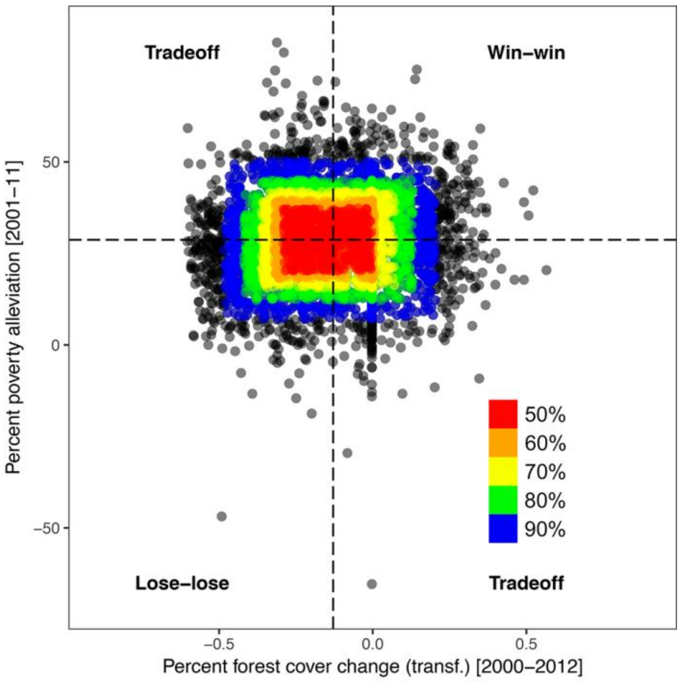
Outcome	Treatment	Before Matching **(T=2138, C=1694)**	After Matching **(T=1960, C=1468)**
Win-win	CF [Yes]	0.15 (0.10)	0.33 (0.079)***
Residual deviance		5964	4836

Values in brackets represent standard errors.
***P < 0.001, **P < 0.01

Supplementary Table 13 | Regression results for a PCA-calculated joint outcome variable as a function of community forest management arrangements established prior to 2000.

Outcome	Treatment	Before Matching **(T=2138, C=1694)**	After Matching **(T=1960, C=1468)**
Win-Win [PCA1]	CF [Yes]	0.17 (0.038)*** [0.40]	0.16 (0.026)*** [0.025]
Adjusted R^2		0.39	0.41

Values in parentheses represent naïve standard errors; values in square brackets represent Huber-White corrected standard errors.
***P < 0.001



Supplementary Figure 19 | Scatterplot and data inclusion thresholds. Data points included in the sensitivity analysis are based on values within 90% to 50% of the median poverty alleviation and deforestation values.

Supplementary Table 14 | Ordinal logistic regression results for joint poverty and forest cover change outcomes as a function of the presence of community forest management arrangements for 80% and 70% reduced dataset.

Outcome	Treatment	Before Matching **(T=1465, C=976)**	After Matching **(T=1343, C=734)**
Win-win (80% of dataset)	CF [Yes]	0.26 (0.12)*	0.31 (0.095)**
[Residual deviance]		[4504]	[3826]
		Before Matching **(T=1115, C=736)**	After Matching **(T=1054, C=532)**
Win-win (70% of dataset)	CF [Yes]	0.35 (0.14)*	0.20 (0.11)§
[Residual deviance]		[3413]	[2842]

Values in brackets represent standard errors.
**P < 0.01, *P < 0.05, §P = 0.075