Action needed to make carbon offsets from tropical forest conservation work for climate change mitigation

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Summary

Carbon offsets from voluntarily avoided deforestation projects are generated based on performance vis-à-vis *ex-ante* deforestation baselines. We examined the impacts of 27 forest conservation projects in six countries on three continents using synthetic control methods for causal inference. We compare the project baselines with *ex-post* counterfactuals based on observed deforestation in control sites. Our findings show that most projects have not reduced deforestation. For projects that did, reductions were substantially lower than claimed. Methodologies for constructing deforestation baselines for carbon-offset interventions thus need urgent revisions in order to correctly attribute reduced deforestation to the conservation interventions, thus maintaining both incentives for forest conservation and the integrity of global carbon accounting.

Keywords: REDD+; Payments for environmental services; Deforestation; Synthetic control; Impact evaluation.

Introduction

For nearly two decades, the performance-based payment mechanism for reduced carbon emissions from deforestation and forest degradation known as REDD+ has been under intense debate (Angelsen, 2017). While regulations and capacity for national REDD+ programs are still under development (Börner et al., 2018; FAO, 2019), many stand-alone, voluntary REDD+ projects are operational worldwide (Atmadja et al., 2022). These projects intend to conserve forests through multiple activities, like improved monitoring and control, promotion of sustainable

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practices, and local stakeholder engagement, often funded by the commercialization of carbon offsets (each corresponding to 1 Mg CO₂ either removed from or not emitted to the atmosphere). In 2021 alone, two-thirds of the 227.7 million offsets from the land-use sector (excluding agriculture) traded in environmental markets, with a total value of USD 1.3 billion, originated from REDD+ projects (Donofrio et al., 2022).

Numerous policy discussions and initiatives currently focus on how to scale and integrate the carbon emission reductions claimed by voluntary carbon-offset projects, particularly from REDD+ activities, into climate policies and Nationally Determined Contributions (NDCs) reported to the UNFCCC (FAO, 2019; Lee et al., 2018; Taskforce on Scaling Voluntary Carbon Markets, 2021; Verra, 2021a; Voluntary Carbon Markets Integrity Initiative, 2021). However, there is little rigorous evidence on the contributions of this type of initiative (Duchelle et al., 2018; Sills et al., 2017), with some studies suggesting that many are associated with little or no actual emission reductions (Badgley et al., 2021; Calel et al., 2021; Cames et al., 2016; Haya et al., 2020; Kollmuss et al., 2015; West et al., 2020).

Carbon offsets from REDD+ projects are issued based on the comparison between the observed forest cover in the project sites and deforestation baseline scenarios expected to have been realized in the absence of REDD+, which remain *de facto* unobservable (FAO, 2019). Many project baselines are informed by extrapolation of historical deforestation averages or trends (West et al. 2020). These crediting baselines may become unrealistic counterfactuals with changes in economic or political conditions influencing deforestation (Busch and Ferretti-Gallon, 2017; West and Fearnside, 2021). But baselines could also be opportunistically inflated by profiteers seeking to financially benefit from selling as many offsets as possible, even when these lack environmental additionality, i.e., are unlikely to reflect actual emission reductions (Rifai et al., 2015; Seyller et al., 2016; Wunder, 2007).

This study provides a pan-tropical comparison between *ex-post* deforestation counterfactuals, informed by observable control areas, and the *ex-ante* baselines adopted by 27 voluntary REDD+ projects in six tropical countries: Peru, Colombia, Democratic Republic of Congo (DRC), Tanzania, Zambia, and Cambodia (Tables S1 & S2; Fig. 1 & S1) certified under the Verified Carbon Standard (Verra, 2019). Because some projects are composed of multiple disconnected sites, we evaluate those areas individually, increasing our sample to 31 sites. We present both project-specific and cross-project analyses based, respectively, on the standard and generalized versions of the synthetic control (SC) method for causal inference, to estimate reductions in deforestation in project sites attributable to the REDD+ interventions (Abadie et al., 2021; Xu, 2017). The SCs were constructed based on selected control areas ("donors") exposed to similar levels of deforestation pressure (as measured by the average annual deforestation in the projects' 10-km buffer zones prior to the project implementation) and with similar characteristics as the REDD+ sites, from project-specific donor pools, which combined, could replicate the historical deforestation pattern in the project areas (see SI for details). Before interpreting results, we conducted project-specific "validation" tests to check whether the standard SC method was

able to construct SCs with similar deforestation rates as project areas during the immediate preproject period (West et al., 2020). Conservatively, we focus the discussion of our results on the projects with SCs that performed well in the validation test, i.e., with gaps between the project and its SC deforestation at the end of the validation period lower than 0.5% of the size of the project area (Tables S3 & Fig. S2). To address the concern that the selected control areas may not have the same chance to be selected as REDD+ project sites, we also estimated REDD+ impacts on deforestation based on the comparison of operational project sites with "yet-to-become" project areas throughout the study period using the matching-based methods for time-series cross-sectional data developed by Imai et al. (2018). Because the evaluated projects span multiple countries and contexts, our analyses can shed light on the robustness of the assumptions adopted for the construction of REDD+ baselines under a wide range of deforestation conditions (Fig. S3).

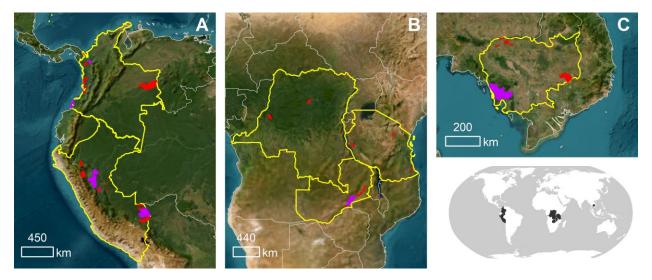


Figure 1. Voluntary REDD+ project sites included in the study (red areas) from Peru and Colombia (A), Democratic Republic of Congo, Tanzania, and Zambia (B), and Cambodia (C). Purple areas are the sites excluded from the analysis.

Individual REDD+ project impacts

The individual SC analyses show mixed impacts of the voluntary REDD+ projects on deforestation. Results from the validation tests suggest that the SC method could replicate relatively well pre-REDD+ deforestation trends in 29 of the 31 "to-be" project sites (Tables S1 & Fig. S2). After constructing the SCs for the 31 sites, we discarded one project (#1775-1) from the analyses due to the poor fit between the deforestation in the SC and the REDD+ site prior to project implementation. Four other projects (#985, #1360-1, #1389, and #1748) were also discarded because of substantial disagreements between the REDD+ sites' and the SCs' buffer deforestation during the pre-project period. Our final sample was thus reduced to 26 project sites.

Six of the evaluated 26 project sites showed some evidence of additional reductions in deforestation compared to their individual SCs, although generally not to the extent claimed by the projects based on their crediting baselines (Fig. 2, S4, & S5). Additionality was most likely in Peru, where half of the REDD+ sites had significantly less deforestation than the *ex-post* counterfactuals, with statistical significance confirmed by placebo tests. Only one of the seven Colombian project sites, and one of two Cambodian sites, achieved significant deforestation reductions according to the SCs and placebo tests. No evidence of avoided deforestation was found for the REDD+ sites in the DRC, Tanzania, and Zambia vis-á-vis their counterfactuals.

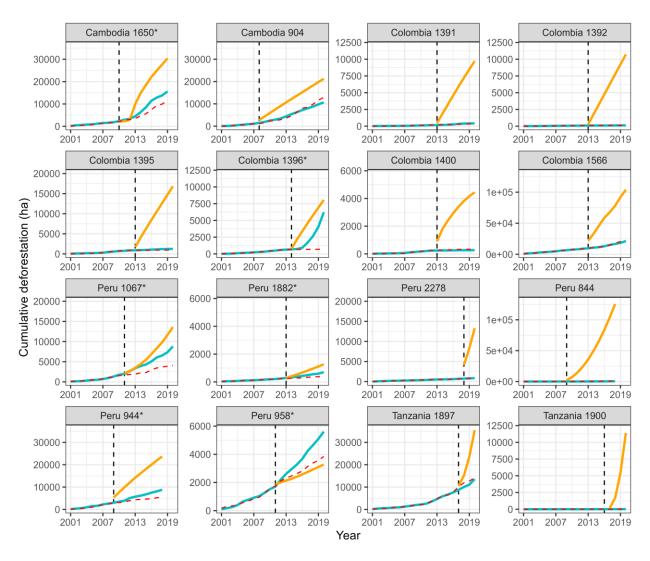


Figure 2. Cumulative post-2000 deforestation in the REDD+ project sites (dashed red line) and synthetic control (SC) areas (solid blue line) versus the baseline scenarios adopted by the REDD+ projects (solid orange line). Dashed black lines indicate the project implementation year. Asterisks indicate a significant reduction in deforestation in the REDD+ site compared to the SC (note: scales differ).

Average REDD+ project impacts

Average project impacts on deforestation (i.e., average treatment effects on the treated; ATT) in Peru, Colombia, and Africa (DRC, Tanzania, and Zambia) were estimated with the generalized SC (GSC) method (Fig. 3, upper panels). Cambodian projects were excluded from this analysis, due to the limited sample size. Unlike the individual project evaluations, the GSC analyses were based exclusively on annual deforestation rates and time-variant covariates. Such a distinction between the two methods increases the robustness of our results. The GSC analyses were based on two independent sets of selected control areas for each region: in the first set, only the donors selected for the construction of the individual SCs were considered, whereas in the second set, controls were selected based on a genetic matching technique (Diamond and Sekhin, 2013), independent of the SC analyses.

For the former set of selected controls, the average impact of the Peruvian projects on forest loss was -0.22% or 686 ha year⁻¹ (p-value = 0.10; Table S4). A similar ATT size was found for the African projects (-0.20% or 412 ha year⁻¹; Table S5), whereas a smaller effect was associated with the Colombian projects (-0.02% or 49 ha year⁻¹; Table S6). However, the estimates for both the Colombian and African projects were not significant (p-values of 0.61 and 0.26, respectively). Even assuming the estimated average reductions in deforestation to be significant in all three countries (a plausible assumption given our small sample sizes; Tables S4–S6), they would still be substantially lower than the average baseline deforestation rates adopted by the projects from Peru (3661 ha year⁻¹), Colombia (2550 ha year⁻¹), and Africa (2700 ha year⁻¹) through 2020. The Peruvian projects on average reduced deforestation in the REDD+ sites within the first four years following REDD+ implementation in comparison to the GSC (Fig. 3, lower panels). The GCSs indicate no significant reductions from projects in Colombia and the combined African countries.

These results are robust to using control areas selected with the genetic matching technique. Based on those controls, we estimate ATTs of the Peruvian, Colombian, and African REDD+ sites as -0.42% (1269 ha) year⁻¹, -0.05% (137 ha) year⁻¹, and -0.13% (258 ha) year⁻¹, respectively (Tables S7–S9 & Fig. S6, upper panel); again, only the Peruvian estimate was significant (p-values of 0.01, 0.34, and 0.33, respectively). Also similarly, the GSCs suggests that some average reduction in deforestation was achieved in Peru, but again restricted to the first four years of the project (Fig. S6, lower panels), with no significant reductions observed in Colombia or in the African countries.

Finally, results from the comparison between already operational and "not-yet-operational" project sites corroborate the findings from the GSC analyses. The average REDD+ impacts on deforestation ranged from -0.06% year⁻¹ to 0.10% year-1 (or -92 ha year⁻¹ to 103 ha year⁻¹), across all model settings, but none of the estimates were statistically significant (Fig. S7).

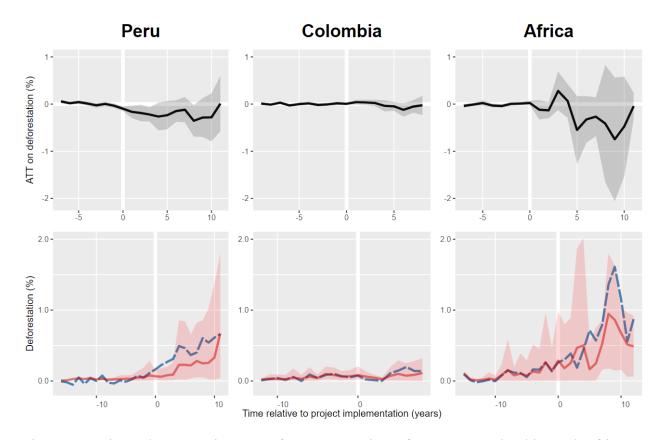


Figure 3. Estimated average impacts of REDD+ projects from Peru, Colombia, and Africa on annual deforestation, using the generalized synthetic control (GSC) method and selected controls from the individual synthetic control analyses. Upper panels display the average treatment effect on the treated (ATT) project sites. Lower panels display projects' (solid red line) and counterfactuals' (dashed blue line) deforestation averages. Shaded red areas represent bootstrapped 95% confidence intervals around the projects' deforestation average.

Carbon offset implications

We investigated the implications of our findings for the environmental integrity of the credits issued by the REDD+ projects. These implications are based on the 18 out of 27 sampled projects with sufficient publicly available information about baseline deforestation rates (Table S10; Fig. 2 & S8). According to the projects' *ex-ante* estimates, up to 89 million carbon offsets could potentially have been generated by the REDD+ projects from our sample until 2020. Yet, 63.2 million of these offsets (71%) would have originated from projects that have not significantly reduced deforestation (and emissions) compared to their SCs. The remaining 25.8 million offsets (29%) would have originated from projects likely associated with some avoided deforestation, but not to the extent expected by the project developers. If we replace the *ex-ante* baselines adopted by the projects with the deforestation observed from the SCs, our estimates suggest that only 5.5

million (6.2%) of the 89 million *ex-ante* offsets from the REDD+ projects would likely be associated with additional carbon emission reductions.

As of November 2021, those 18 REDD+ projects have issued 62 million carbon-offset credits (Table S2). Out of those, at least 14.6 million (24%) have already been used by individuals or organizations around the world to offset their greenhouse gas emissions. Thus, according to our SC-based estimates, these projects have already been used to offset almost three times more carbon emissions than their actual contributions to climate change mitigation—with another 47.4 million carbon offsets being readily available in the market.

Discussion

Overall, the weight of evidence suggests that voluntary REDD+ projects in our sample across six tropical countries achieved much less avoided deforestation than anticipated by project developers. Only a few projects achieved significant reductions in comparison to the *ex-post* counterfactuals. Our findings corroborate prior studies questioning the additionality, and thus environmental integrity, of this type of carbon-offset intervention (Badgley et al., 2021; Calel et al., 2021; Cames et al., 2016; Haya et al., 2020; Kollmuss et al., 2015; Seyller et al., 2016). Exaggerated baseline scenarios are the biggest part of the underlying problem; unexpressive conservation performance by the REDD+ projects supplements the picture.

In an evaluation of REDD+ projects in the Brazilian Amazon, West et al. (2020) pointed to the potential confounding effect created by Brazil's post-2004 policy interventions to control deforestation, triggering a substantial reduction in forest loss between 2004 and 2012 (West and Fearnside, 2021). As a result, the high regional deforestation rates observed prior to 2004, used to inform the Brazilian project baselines, likely led to an overestimation of the projects' performance. Yet, unlike Brazil, the six countries in this study did not experience a similar level of reduction in deforestation nationwide after the REDD+ projects were implemented (Fig. S3). Hence, the seemingly unrealistic ex-ante baselines adopted by many projects likely resulted from the use of methodologies that systematically fail to produce credible counterfactuals for the REDD+ interventions, compromising the evaluation of the projects' performance at mitigating deforestation and thus climate change. This may be due to potentially three complementary reasons: poor foresight, oversight of temporal changes in deforestation drivers, and "gaming." First, projects may have unintentionally overestimated future deforestation pressures based on alarming historical trends that poorly represent current conditions. Second, baselines of voluntary REDD+ projects tend to be fixed for a period of 10 years, discouraging potential adjustments to reflect changes in deforestation drivers over time. Finally, baselines may have been strategically inflated to maximize revenues from offset sales.

In contrast, both standard and generalized SC methods use pre-REDD+ information to identify control areas, but use contemporaneous information on deforestation in the project and control areas to estimate additionality. Following well-accepted guidelines for rigorous impact evaluation (Ferraro and Hanauer, 2014), if properly selected, such *ex-post* counterfactuals can

capture the effects of contemporaneous changes in deforestation drivers, thus being less biased by confounding external factors (Sills et al., 2017; West et al., 2020). If REDD+ projects were to adopt a similar dynamic approach, it would likely reduce the additionality problems with project baselines and offsets identified in this study. Promisingly, new methodological guidelines for future voluntary REDD+ projects may include the use of such "dynamic baselines" (Verra, 2021b).

Still, despite the clear advantages of using dynamic methods like the SC to construct *ex-post* deforestation baselines for REDD+ interventions, some implementation and monitoring challenges would likely arise from their adoption. First, given biophysical heterogeneity across tropical regions, ideal control areas for the project sites may not always be identified (Tables A1–A29), or they could be manipulated (e.g., intentionally degraded) to misleadingly improve project performance. Second, such dynamic baselines may still fail to account for all relevant determinants of deforestation due to data constraints. Finally, long-lasting voluntary REDD+ projects may eventually outlive suitable control sites needed to feed the dynamic baselines.

One alternative would be to require projects to adopt *ex-ante* jurisdictional baselines instead, pre-established by government agencies. While these baselines might still fall short of capturing contemporaneous changes in deforestation drivers, they could be updated more frequently than the individual project baselines so as to update recent deforestation pressures and spatial patterns. Most importantly, jurisdictional baselines may also better capture government efforts to control forest loss, thus mitigating the risk of wrongly attributing reductions in deforestation achieved through public policies to private REDD+ interventions (Sills et al., 2017). Transferring the responsibility of baseline construction from project developers to jurisdictions could also reduce the room for "baseline gaming." Hence, nesting voluntary projects into subnational jurisdictions appears to be a promising future pathway for REDD+, a practice being increasingly promoted worldwide (Lee et al., 2018).

But, turning to conservation performance, why have some projects seemingly failed to reduce deforestation at all? Some may have struggled with on-the-ground implementation and execution of envisioned conservation activities; others may have promoted ineffective actions—perhaps due to funding uncertainties, slow commercialization of carbon credits, or lack of experience (Laing et al., 2016; Seyller et al., 2016; Verra, 2018; Wunder et al., 2020). Notably, many projects claimed to have started much earlier than the year they were certified. While this allows projects to issue retroactive offsets right after certification (Linacre et al., 2015), it also implies that they may not have had access to funding during their initial years, potentially compromising the execution of planned conservation actions.

A recent evaluation on the effectiveness of the same type of REDD+ interventions reported significant reductions in deforestation rates, on average (Guizar-Coutiño et al., 2022). The study, based on gridded data, estimated an average deforestation rate of 0.2% year⁻¹ in the REDD+ sites versus 0.4% year⁻¹ for their matched control areas. The size of these estimates is in line with our results for the Peruvian and African projects, but in our case, they were statistically insignificant, potentially due to our lower sample sizes compared to the pixel-based samples from Guizar-

Coutiño et al. (2022). More importantly, from the offset perspective, the estimated average reductions—significant or not—remain substantially lower than reductions in deforestation claimed by the projects.

Our study provides further evidence on the effectiveness of voluntary REDD+ projects and questions their *de facto* additionality (Angelsen, 2008). Only a minority of the projects significantly reduced deforestation compared to the *ex-post* counterfactuals, and even those did not reduce deforestation to the extent claimed. Given that REDD+ payments are largely performance-based, and supported by those interested in offsetting their own emissions, only the offsets associated with additional reductions in deforestation should be eligible for trading in voluntary carbon markets (Angelsen, 2017; Seyller et al., 2016; Taskforce on Scaling Voluntary Carbon Markets, 2021). Certification schemes are allegedly in place to safeguard the additionality of offsets, but our results indicate that this is not enough. It is critical to develop new and rigorous methods for the construction of credible deforestation baselines for voluntary REDD+ interventions, and to properly and regularly assess their contribution to climate change mitigation.

Finally, the evidence from this and other studies indicate that some voluntary projects have effectively reduced deforestation (Guizar-Coutiño et al., 2022), particularly in Peru. For REDD+ to be scaled and achieve its ambitious goals worldwide, it is paramount that we better understand the factors responsible for their successes and failures, including their impacts on local communities. Researchers and practitioners will need to form effective partnerships to jointly meet these challenges, putting also a more realistic bar for forest carbon offsets that would help REDD+ initiatives fulfill their original promise.

Materials and Methods

Project sample

There are 27 voluntary avoided (unplanned) deforestation REDD+ projects in Peru, Colombia, DRC, Tanzania, Zambia, and Cambodia that were certified under Verra's *Verified Carbon Standard* (VCS; Verra, 2019) by July 2021 (Table 1; Fig. 2 & S1). We chose these six countries because they have a large number of projects and provide coverage of all tropical continents. We adopted VCS' unique IDs to identify the projects in our study. Because Project 1360 from Peru is composed of three disconnected areas, each of these areas was evaluated independently (identified with IDs 1360-1, 1360-2, and 1360-3). We adopted the same approach for Project 1775 from Tanzania. Project sites were defined by the geospatial polygons (i.e., KML files) provided by the project developers and available from the VCS project database (https://registry.verra.org/). While we intended to examine all VCS-certified projects in our focal countries, we removed projects that did not provide the correct geospatial data on their boundaries and those with corrupted KML files (i.e., Projects #868 from Peru and #1399 and #1695 from Colombia). Overall, officially reported project areas matched the areas of the KML files reasonably well, except for Project #1566 from Colombia and #1325 from Tanzania (Table S1).

Deforestation baselines adopted by these projects followed VCS-approved carbon-accounting methodologies (Table S1). While there are differences among these methodologies, they generally require baselines to be established *ex-ante* based on historical regional deforestation averages over 10-year intervals prior to project implementation.

Individual synthetic control analyses

Impact evaluations that define causality based on potential outcomes rely on the establishment of credible counterfactuals quantifying what would have happened in the absence of an intervention. These counterfactuals are inherently unobservable. The most common strategy for establishing robust counterfactuals is to observe outcomes in control areas, which are not exposed to the treatment under evaluation but which are otherwise very similar to those areas (Ferraro and Hanauer, 2014). Following West et al. (2020), we employed the SC method to construct project-specific weighted combinations of control areas, or "SCs," as our counterfactuals (Sills et al., 2020; Xu, 2017). We adopted this method due to the small sample size and likely heterogeneous effects of voluntary REDD+ projects (Abadie et al., 2021). SCs were constructed as a weighted average of control areas through a nested optimization procedure that minimizes the differences in pre-REDD+ characteristics of the project sites and their respective SCs (see Abadie et al., 2011, for details); the characteristics of the control areas (i.e., model covariates; Table S10) were weighted such that the resulting weighted average outcome of the selected areas most closely matched the cumulative pre-REDD+ deforestation rates in the project sites since 2001.

One of the key challenges with counterfactual-based impact evaluation is defining and characterizing potential controls, in this case, areas that could have been but are not REDD+ projects. West et al. (2020) defined potential controls as landholding polygons obtained from Brazil's national Rural Environmental Registry (CAR; Portuguese acronym), a spatially explicit database created to determine forest restoration requirements. However, similar databases are not available for the countries considered in this study. We addressed this limitation by creating a pool of 1000 circular spatial polygons, or "pseudo" control areas, for each project, randomly distributed across the focal countries, each the same size as the project site (Fig. S12). Prior to the construction of the SCs, we restricted our pool of control areas to a subset of potential SC "donors" that shared similar characteristics to the project sites. The inclusion of donors in the control sets was based on deforestation pressure (i.e., the average annual deforestation in the projects' 10-km buffer zones prior to the project start date). We first attempted to include donors with $\pm 10\%$ buffer deforestation as the project sites. We increased this range by an additional $\pm 10\%$ each time the resulting SC failed to replicate the historical deforestation pattern in the project site. This approach was of critical importance because, unlike in West et al. (2020), many of the projects' KML files from our sample were restricted to the forested areas within the project site at the start of project. Hence, without explicitly controlling for deforestation pressure surrounding the KML boundaries, the SCs would likely be based on control areas exposed to much lower risk of forest loss, rendering them poor counterfactuals for REDD+ sites (Guizar-Coutiño et al., 2022). Overall, most SCs

experienced similar levels of buffer deforestation as the REDD+ sites (see Annex A for the covariate balance between projects and SCs).

To construct the synthetic controls, we used covariates (listed in Table S8) that have been found related to deforestation (Busch and Ferretti-Gallon, 2017). We also included pre-REDD+ (13) annual and (14) cumulative deforestation rates for the construction of the SCs. Annual deforestation data for the focal countries, from 2001 to 2020, were processed in Google Earth Engine based on the Global Forest Change (GFC) product (Hansen et al., 2013). Many remote sensing studies highlight the differences in deforestation rates between GFC and the numbers officially recognized by governments (Griffiths et al., 2018; Milodowski et al., 2017; Qin et al., 2019). Such differences emerge from different mapping methodologies and definitions of deforestation and forest degradation.

The individual SC analyses were conducted with the *Synth* package (v.1.1-5; Abadie et al., 2011) available for R software (v.4.1.0). Results from the nested optimizations were refined based on the augmented method proposed by Becker and Klößner (2018).

Project-specific synthetic control validation

We validated the SC method following West et al. (2020), by constructing a SC for each project site based on data only from the first half of the pre-REDD+ period (i.e., training interval) and validated against the second half of the period (i.e., testing interval). In theory, the validity of the method would be empirically proven if the future REDD+ sites and their respective SCs shared a similar deforestation trend in the testing interval. This validation approach focuses on each REDD+ site individually. We considered the SC method validated for the sites in which the gaps between the project and SC deforestation at the end of the validation interval were lower than 0.5% of the project area (Tables S3 & Fig. S2). This "proof of concept" differs from standard model validation practices, because the donor areas selected to be part of the SCs based on the first half of the pre-REDD+ periods are not necessarily the same areas selected when the full pre-REDD+ period was used for the optimization. Still, such an exercise arguably increases the credibility of SC analyses that pass this validity test.

Placebo tests

We assessed the statistical significance of our individual findings with a series of placebo tests, in which we create SCs for all areas in the project-specific donor pool subsets and compute the difference in cumulative deforestation between each placebo and its SC in the years after that REDD+ project was implemented. Because placebo areas are not exposed to REDD+, any differences in forest loss between placebos and their SCs are considered statistical "noise." Following the previous literature (Abadie et al., 2011; West et al., 2020), we discarded placebo tests with mean squared prediction error (MSPE) five times higher than the MSPE of its respective REDD+ project. We then used the gaps in deforestation between the remaining placebos and their respective SCs to create 95% confidence intervals around the mean placebo effect (generally close to zero).

Generalized synthetic controls

Standard applications of the SC method target individual interventions (Abadie et al., 2021; Sills et al., 2015), which limits the generalization of results. The method developed by Xu (2017) proposes a generalization of the SC method, unified with a special case of the difference-in-differences estimator for causal inference in time-series cross-sectional data that relaxes the parallel trends assumption. This method is known as the *generalized synthetic control* (GSC). First, an interactive fixed-effects model is estimated based solely on the control group data, and a fixed number of *latent factors* (i.e., time-varying intercepts) is selected. Then, *factor loadings* (i.e., unit-specific intercepts) are estimated for each REDD+ project based on the linear projection of pre-REDD+ deforestation rates. This formulation allows for the estimation of the average treatment effect on the treated unit (ATT), which in our case, corresponds to the average relative REDD+ impact on deforestation (% year-1) across the project sites within a country or region. Last, the estimated latent factors and loadings are used to create GSCs, which in our case are the projects' average deforestation counterfactuals.

We adopted the GSC method as a way to generalize and estimate the average REDD+ project effect on deforestation in Peru, Colombia, and Africa (by analyzing the projects from DRC, Tanzania, and Zambia together because of their limited number of projects). In addition, because the GSCs are independent of the individual SCs—and based on annual, rather than cumulative, deforestation rates—they can also serve as robustness checks of the individual SC results. Following Xu (2017), we adopted Equation 1 as the underlying interactive two-way fixed-effects model of our GSC analyses:

$$D_{it} = \alpha_i + \xi_t + \delta_{it}T_{it} + X_{it}\beta + \lambda_i f_t + \varepsilon_{it}$$
 (1)

where, D_{it} is the annual deforestation in project site i in year t; α_i represents project site individual effects; ξ_t captures time effects; T_{it} is a dummy variable indicating project implementation; δ_{it} captures the heterogeneous REDD+ effect on unit i at year t; X_{it} is a matrix of observed timevariant covariates, i.e., precipitation and deforestation in 1-km and 10-km buffer zones (results from augmented Dickey-Fuller tests suggest stationarity of the deforestation time series at the unit level); β is a vector of unknown parameters; λ_i is a vector of unknown factor loadings; f_t is a vector of unobserved common latent factors; and ε_{it} represents unobserved idiosyncratic shocks with zero mean. Formulation 1 implies that time-invariant covariates are dropped from the model by demeaning. To improve the robustness of the GSC analyses, by indirectly considering the relevance of time-invariant covariates, the GSCs were constructed exclusively based on the same donor areas used to create the individual SCs.

The GSC analyses were implemented with the *gsynth* package (v.1.2.1) available for R software. The package allows for several different specifications. Estimates were produced with the Expectation Maximization algorithm (Gobillon and Magnac, 2016), which benefits from the project area information in the pre-REDD+ period. Due to the relatively low number of

observations in our data, we adopted the *gsynth*'s matrix completion method as the GSC estimator (Athey et al., 2017). A cross-validation procedure was implemented to select the optimal number of factors (or "hyper-parameters") in the matrix completion algorithm, ranging from zero to five. Last, uncertainty estimates were produced based on 1000-bootstrap runs (see Xu, 2017, for details).

The GSC analyses were based on two independent sets of selected controls, one exclusively based on the donors selected for the construction of the individual SCs and the other based on control areas selected with the genetic matching technique (Alexis and Sekhin, 2013), independent of the SC analyses. Each project site was matched to 10 control areas. The genetic matching was performed with the *Matching* package (v.4.10-8) available for available for R software (Sekhon, 2011), based on pre-project covariate information described in Table S11 (Fig. S13–S15).

Additional robustness test

An additional robustness test was performed where operational REDD+ sites were matched with "to-be" REDD+ sites based on the matching-based methods for cross-sectional panel data analysis developed by Imai et al. (2018) and implemented with the *PanelMatch* package (v.1.0.0) available for R software (Kim et al., 2020). Specifically, each operational REDD+ site was matched to up to 10 not-yet-operational REDD+ sites (or a weighted combination of those) sharing similar covariate history over a 5-year interval prior to project implementation and that remained not-operational over the given evaluation period (Fig. S16 & S17). Matching was performed based on three methods: propensity score matching, Mahalanobis distance, and propensity score weighting (Fig. S18). Once the matching sets were constructed from each matching approach, ATTs were annually estimated for evaluation periods ranging 1–5 years following project implementation.

Additionality of the carbon credits

We estimated the volume of (additional) carbon offsets from the voluntary REDD+ projects as compared to a counterfactual based on the observed deforestation from the individual SCs. Credits from these projects are generally issued after third-party audits. These credits are based on the estimated carbon emission reductions from the avoided deforestation brought about by the project activities, calculated as the net difference between the carbon emissions under the baseline and the REDD+ scenario (West et al., 2020). Under this crediting system, the *ex-post* volume of carbon offsets generated by the REDD+ projects is determined by deforestation in the REDD+ project as compared to the *ex-ante* baseline. We adopted a simplified approach to estimate such volumes by assuming a linear, per-hectare relationship between the baseline deforestation adopted by projects and their reported *ex-ante* volume of credits to be generated through 2020. Thus, projects with insufficient public information about *ex-ante* annual baseline deforestation rates and carbon stock were excluded from this assessment rates (Table S10; Fig. 2 & S8).

First, we identified the projects with significantly lower deforestation rates than their SCs according to the placebo tests. Projects that failed to achieve significant reductions in deforestation were assumed not to have reduced net carbon emissions. Then, we estimated the volume of credits

generated by each project that significantly reduced deforestation based on the difference in observed deforestation (ha) between the SC and the project sites. Finally, we compared our carbon offset estimates based on the SCs to the *ex-ante* volume of credits expected by the projects from the year of project implementation through 2020 (Table S10; Fig. 2 & S8).

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References

- Abadie, A. 2021. Using synthetic controls: Feasibility, data requirements, and methodological aspects. J. Econ. Lit., 59 391–425
- Abadie, A., Diamond, A., Hainmueller, J., 2011. Synth: An R package for synthetic control methods in comparative case studies. J. Stat. Softw. 42, 1–17. https://doi.org/10.18637/jss.v042.i13
- Atmadja, S. S., Duchelle, A. E., De Sy, V., Selviana, V., Komalasari, M., Sills, E. O., Angelsen, A., 2022. How do REDD+ projects contribute to the goals of the Paris Agreement? Environmental Research Letters 17, 044038.
- Diamond, A., Sekhon, J.S., 2013. Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies. Review of Economics and Statistics 95, 932945. https://doi.org/10.1162/REST a 00318
- Angelsen, A., 2017. REDD+ as result-based aid: General lessons and bilateral agreements of Norway. Rev. Dev. Econ. 21, 237–264. https://doi.org/10.1111/rode.12271
- Angelsen, A., 2008. Moving ahead with REDD: Issues, Options and Implications. Center for International Forestry Research (CIFOR), Bogor.
- Athey, S., Bayati, M., Doudchenko, N., Imbens, G., Khosravi, K., 2017. Matrix completion methods for causal panel data models. arXiv.
- Badgley, G., Freeman, J., Hamman, J.J., Haya, B., Trugman, A.T., Anderegg, W.R.L., Cullenward, D., 2021. Systematic over-crediting in California's forest carbon offsets program. Glob. Chang. Biol. 1–13. https://doi.org/10.1111/gcb.15943
- Becker, M., Klößner, S., 2018. Fast and reliable computation of generalized synthetic controls. Econom. Stat. 5, 1–19. https://doi.org/10.1016/j.ecosta.2017.08.002
- Börner, J., West, T.A.P., Blackman, A., Miteva, D.A., Sims, K.R., Wunder, S., 2018. National and subnational forest conservation policies—What works, what doesn't, in: Angelsen, A., Martius, C., de Sy, V., Duchelle, A., Larson, A., Pham, T. (Eds.), Transforming REDD+: Lessons and New Directions. Center for International Forestry Research (CIFOR), Bogor, pp. 105–116. https://doi.org/10.17528/cifor/007045
- Busch, J., Ferretti-Gallon, K., 2017. What drives deforestation and what stops it? A meta-analysis. Rev. Environ. Econ. Policy 11, 3–23. https://doi.org/10.1093/reep/rew013
- Calel, R., Colmer, J., Dechezleprêtre, A., Glachant, M., 2021. Do carbon offsets offset carbon? SSRN Electron. J. 5709. https://doi.org/10.2139/ssrn.3950103
- Cames, M., Ralph, O.H., Füssler, J., Lazarus, M., Lee, C.M., Erickson, P., Spalding Fecher, R., 2016. How additional is the Clean Development Mechanism? Öko-Institut e.V., Berlin.

- Guizar-Coutiño, A., Jones, J.P.G., Balmford, A., Carmenta, R. & Coomes, D.A. (2022). A global evaluation of the effectiveness of voluntary REDD+ projects at reducing deforestation and degradation in the moist tropics. *Conserv. Biol.*
- Donofrio, S., Maguire, P., Daley, C., Calderon, C., Lin, K., 2022. The Art of Integrity: State of the voluntary carbon markets 2022 Q3, 2022. Forest Trends' Ecosystem Marketplace, Washington, D.C.
- Duchelle, A.E., Simonet, G., Sunderlin, W.D., Wunder, S., 2018. What is REDD+ achieving on the ground? Curr. Opin. Environ. Sustain. 32, 134–140. https://doi.org/10.1016/j.cosust.2018.07.001
- FAO, 2019. From reference levels to results reporting: REDD+ under the United Nations Framework Convention on Climate Change. 2019 update. Food and Agriculture Organization, Rome.
- Ferraro, P.J., Hanauer, M.M., 2014. Advances in measuring the environmental and social impacts of environmental programs. Annu. Rev. Environ. Resour. 39, 495–517. https://doi.org/10.1146/annurev-environ-101813-013230
- Gobillon, L., Magnac, T., 2016. Regional Policy Evaluation: Interactive Fixed Effects and Synthetic Controls. Rev. Econ. Stat. 98, 535–551. https://doi.org/10.1162/REST a 00537
- Griffiths, P., Jakimow, B., Hostert, P., 2018. Reconstructing long term annual deforestation dynamics in Pará and Mato Grosso using the Landsat archive. Remote Sens. Environ. 216, 497–513. https://doi.org/10.1016/j.rse.2018.07.010
- Hansen, M.C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S. V.,
 Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013.
 High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342, 850–853.
 https://doi.org/10.1126/science.1244693
- Haya, B., Cullenward, D., Strong, A.L., Grubert, E., Heilmayr, R., Sivas, D.A., Wara, M., 2020. Managing uncertainty in carbon offsets: insights from California's standardized approach. Clim. Policy 20, 1112–1126. https://doi.org/10.1080/14693062.2020.1781035
- Imai, K., Kim, I.S., Wang, E., 2018. Matching Methods for Causal Inference With Time-Series Cross-sectional Data. Harvard University, Massachusetts Institute of Technology, Cambridge.
- Kollmuss, A., Schneider, L., Zhezherin, V., 2015. Has Joint Implementation reduced GHG emissions? Lessons learned for the design of carbon market mechanisms. Stockholm Environment Institute, Stockholm.
- Laing, T., Taschini, L., Palmer, C., 2016. Understanding the demand for REDD+ credits. Environ. Conserv. 43, 389–396. https://doi.org/10.1017/S0376892916000187
- Lee, D., Llopis, P., Waterworth, R., Roberts, G., Pearson, T., 2018. Approaches to REDD+ nesting: Lessons learned from country experiences. World Bank, Washington, D.C.
- Linacre, N., R., O., Ross, D., Durschinger, L., 2015. REDD+ Supply and Demand 2015-2025. Washington, D.C.
- Milodowski, D.T., Mitchard, E.T.A., Williams, M., 2017. Forest loss maps from regional satellite monitoring systematically underestimate deforestation in two rapidly changing parts of the Amazon. Environ. Res. Lett. 12, 094003. https://doi.org/10.1088/1748-9326/aa7e1e
- Qin, Y., Xiao, X., Dong, J., Zhang, Y., Wu, X., Shimabukuro, Y., Arai, E., Biradar, C., Wang, J., Zou, Z., Liu, F., Shi, Z., Doughty, R., Moore, B., 2019. Improved estimates of forest cover and loss in the Brazilian Amazon in 2000–2017. Nat. Sustain. 2, 764–772. https://doi.org/10.1038/s41893-019-0336-9
- Rifai, S.W., West, T.A.P., Putz, F.E., 2015. "Carbon Cowboys" could inflate REDD+ payments through positive measurement bias. Carbon Manag. 6, 151–158. https://doi.org/10.1080/17583004.2015.1097008.
- Seyller, C., Desbureaux, S., Ongolo, S., Karsenty, A., Simonet, G., Faure, J., Brimont, L., 2016. The "virtual economy" of REDD+ projects: does private certification of REDD+ projects ensure their environmental integrity? Int. For. Rev. 18, 231–246. https://doi.org/10.1505/146554816818966336

- Sills, E., Pfaff, A., Andrade, L., Kirkpatrick, J., Dickson, R., 2020. Investing in local capacity to respond to a federal environmental mandate: Forest & economic impacts of the Green Municipality Program in the Brazilian Amazon. World Dev. 129, 104891. https://doi.org/10.1016/j.worlddev.2020.104891
- Sills, E.O., de Sassi, C., Jagger, P., Lawlor, K., Miteva, D.A., Pattanayak, S.K., Sunderlin, W.D., 2017. Building the evidence base for REDD+: Study design and methods for evaluating the impacts of conservation interventions on local well-being. Glob. Environ. Chang. 43, 148–160. https://doi.org/10.1016/j.gloenvcha.2017.02.002
- Sills, E.O., Herrera, D., Kirkpatrick, A.J., Brandão, A., Dickson, R., Hall, S., Pattanayak, S., Shoch, D., Vedoveto, M., Young, L., Pfaff, A., 2015. Estimating the impacts of local policy innovation: The synthetic control method applied to tropical deforestation. PLoS One 10, 1–15. https://doi.org/10.1371/journal.pone.0132590
- Taskforce on Scaling Voluntary Carbon Markets, 2021. Phase 1- Final Report. Institute of International Finance, Washington, D.C.
- Verra, 2021a. Jurisdictional and Nested REDD+ (JNR) Program Guide. Verra, Washington, D.C. Verra, 2021b. Proposed updates to the VCS program. Verra, Washington, D.C.
- Verra, 2019. VCS Standard v4.0. Washington, D.C.
- Verra, 2018. Media Statement: Suruí Forest Carbon Project [WWW Document]. URL https://verra.org/media-statement-surui-forest-carbon-project/ (accessed 9.28.21).
- Voluntary Carbon Markets Integrity Initiative, 2021. Roadmap: Ensuring high-integrity voluntary carbon markets. Voluntary Carbon Markets Integrity Initiative (VCMI), London.
- Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T.C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Battle, K.E., Bhatt, S., Gething, P.W., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553, 333–336. https://doi.org/10.1038/nature25181
- West, T.A.P., Börner, J., Sills, E.O., Kontoleon, A., 2020. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. Proc. Natl. Acad. Sci. 117, 24188–24194. https://doi.org/10.1073/pnas.2004334117
- West, T.A.P., Fearnside, P.M., 2021. Brazil's conservation reform and the reduction of deforestation in Amazonia. Land use policy 100, 105072. https://doi.org/10.1016/j.landusepol.2020.105072
- Wunder, S., 2007. The efficiency of payments for environmental services in tropical conservation: Essays. Conserv. Biol. 21, 48–58. https://doi.org/10.1111/j.1523-1739.2006.00559.x
- Wunder, S., Duchelle, A.E., Sassi, C. de, Sills, E.O., Simonet, G., Sunderlin, W.D., 2020. REDD+ in theory and practice: How lessons from local projects can inform jurisdictional approaches. Front. For. Glob. Chang. 3, 1–17. https://doi.org/10.3389/ffgc.2020.00011
- Xu, Y., 2017. Generalized synthetic control method: Causal inference with interactive fixed effects models. Polit. Anal. 25, 57–76. https://doi.org/10.1017/pan.2016.2

Supplementary Information

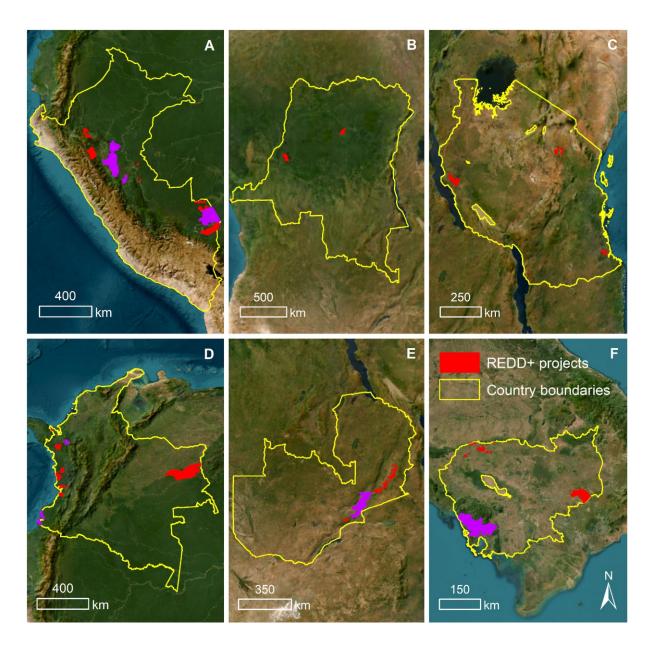


Figure S1. VCS-certified REDD+ project sites based on avoided unplanned deforestation implemented during 2009–2020 in Peru (A), Democratic Republic of Congo (B), Tanzania (C), Colombia (D), Zambia (E), and Cambodia (F). Purple areas are the sites excluded from the analysis.

Table S1. VCS-certified REDD+ projects based on avoided unplanned deforestation and degradation.

Country	Project ID	Project name	Start year	Adopted VCS methodology	Included in the analysis	Reported project area (ha)	Project polygon area (ha)	Area overlap	Project polygon average tree cover in 2000*
	1882	REDD+ Project in the Alto Huayabamba Conservation Concession (CCAH)		VM0015	Yes	53,410	53,357	100%	85%
	1360	Forest Management to reduce deforestation and degradation in Shipibo Conibo and Cacataibo indigenous communities of Ucayali region	2010	VM0015	Partially‡	127,004	127,098	100%	99%
	2278	The Jaguar Amazon REDD Project	2018	VM0006	Yes	183,015	183,120	100%	99%
Peru	1067	Reduction of deforestation and degradation in Tambopata National Reserve and Bahuaja-Sonene National Park within the area of Madre de Dios region–Peru	2011	VM0007	Yes	541,620	557,250	97%	98%
	985	Cordillera Azul National Park REDD Project	2009	VM0007	No†	1,351,964	1,352,298	100%	97%
	958	Biocorredor Martin Sagrado	2011	VM0015	Yes	295,654	295,412	100%	93%
	944	Alto Mayo Conservation Initiative	2009	VM0015	Yes	182,000	177,533	103%	89%
	844	Madre De Dios Amazon Redd Project	2009	VM0007	Yes	98,932	97,998	101%	99%
	1400	Concosta REDD+ Project	2013	VM0006	Yes	54,623	63,961	85%	97%
	1566	REDD+ Project Resguardo Indígena Unificado de la Selva de Matavén (RIU-SM)	2013	VM0007	Yes	1,150,212	1,753,035	66%	85%
	856	The Chocó-Darién Conservation Corridor REDD Project	2011	VM0009	Yes	13,465	12,710	106%	95%
	1396	Rio Pepe y ACABA REDD+ Project	2014	VM0006	Yes	48,177	57,051	84%	98%
Colombia	1395	Bajo Calima y Bahía Málaga (BCBM) REDD+ Project	2013	VM0006	Yes	83,452	91,831	91%	98%
	1392	Cajambre REDD+ Project	2013	VM0006	Yes	661,69	60,316	110%	98%
	1391	Sivirú, Usaragá, Pizarro y Pilizá (SUPP) REDD+ Project	2013	VM0006	Yes	47,667	55,104	87%	98%
	1390	Carmen del Darién (CDD) REDD+ Project	2014	VM0006	Yes	118,318	131,828	90%	94%
	1389	ACAPA – Bajo Mira y Frontera (ACAPA-BMF) REDD+ Project	2013	VM0006	No†	58,212	68,602	85%	95%

Table S1 (continued). VCS-certified REDD+ projects based on avoided unplanned deforestation and degradation.

Country	Project ID	Project name	Start year	Adopted VCS methodology	Included in the analysis	Reported project area (ha)	Project polygon area (ha)	Area overlap	Project polygon average tree cover in 2000*
	1748	Southern Cardamom REDD+ Project	2015	VM0009	No†	445,339	458,408	97%	93%
Cambodia	904	Reduced Emissions from Deforestation and Degradation in Community Forests – Oddar Meanchey, Cambodia	2008	VM0006	Yes	56,050	66,205	85%	42%
	1650	Reduced Emissions from Deforestation and Degradation in Keo Seima Wildlife Sanctuary	2010	VM0015	Yes	166,983	193,503	86%	73%
DD.C	934	The Mai Ndombe REDD+ Project	2011	VM0009	Yes	299,640	301,263	99%	89%
DRC	1359	Isangi REDD+ Project	2009	VM0006	Yes	187,571	188,489	100%	100%
	1325	Mjumita Community Forest Project (LINDI)	2011	VM0015	Yes	41,924	65,279	64%	51%
Tanzania	1900	Makame Savannah REDD	2016	VM0007	Yes	104,065	107,152	97%	10%
	1897	Ntakata Mountains REDD	2017	VM0007	Yes	216,994	204,203	106%	50%
7 1:	1775	Luangwa Community Forests Project	2015	VM0009	Partially‡	943,676	943,674	100%	23%
Zambia	1202	Lower Zambezi REDD+ Project	2009	VM0009	Yes	40,126	40,103	100%	24%

^{*} Processed in Google Earth Engine based on the 2000 Percent Tree Cover map from the Global Forest Change dataset (Hansen et al., 2013).

Source: Verified Carbon Standard (VCS) project database (https://registry.verra.org/).

[†] Discarded due to the poor quality of the synthetic control counterfactual.

[‡] Project composed of multiple sites, some of which were discarded due to the poor quality of the synthetic control counterfactual.

Table S2. VCS-certified REDD+ projects: carbon offsets issued and retired as of November 2021.

Country	Project ID	Project name	Start year	Adopted VCS methodology	Carbon offsets issued	Carbon offsets retired	Retired proportion (%)
	1882	REDD+ Project in the Alto Huayabamba Conservation Concession (CCAH)	2013	VM0015	171,673	14,443	8.4
	1360	Forest Management to reduce deforestation and degradation in Shipibo Conibo and Cacataibo indigenous communities of Ucayali region	2010	VM0015	4,852,836	763,786	15.7
	2278	The Jaguar Amazon REDD Project		VM0006	0	0	_
Peru	1067	Reduction of deforestation and degradation in Tambopata National Reserve and Bahuaja- Sonene National Park within the area of Madre de Dios region–Peru	2011	VM0007	3,678,270	704,766	19.2
	985	Cordillera Azul National Park REDD Project	2009	VM0007	25,240,371	6,323,967	25.1
	958	Biocorredor Martin Sagrado		VM0015	566,843	335,957	59.3
	944	Alto Mayo Conservation Initiative		VM0015	5,282,313	3,625,820	68.6
	844	Madre De Dios Amazon Redd Project	2009	VM0007	9,658,069	975,539	10.1
	1400	Concosta REDD+ Project	2013	VM0006	544,278	303,004	55.7
	1566	REDD+ Project Resguardo Indígena Unificado de la Selva de Matavén (RIU-SM)	2013	VM0007	22,274,745	6,068,608	27.2
	856	The Chocó-Darién Conservation Corridor REDD Project	2011	VM0009	435,188	158,822	36.5
	1396	Rio Pepe y ACABA REDD+ Project	2014	VM0006	567,286	419,209	73.9
Colombia	1395	Bajo Calima y Bahía Málaga (BCBM) REDD+ Project	2013	VM0006	1,620,202	747,709	46.1
	1392	Cajambre REDD+ Project	2013	VM0006	477,432	290,483	60.8
	1391	Sivirú, Usaragá, Pizarro y Pilizá (SUPP) REDD+ Project	2013	VM0006	1,021,146	625,751	61.3
	1390	Carmen del Darién (CDD) REDD+ Project	2014	VM0006	681,565	398,348	58.4
	1389	ACAPA – Bajo Mira y Frontera (ACAPA-BMF) REDD+ Project	2013	VM0006	783,133	323,456	41.3

Table S2 (continued). VCS-certified REDD+ projects: carbon offsets issued and retired as of November 2021.

Country	Project ID	Project name	Start year	Adopted VCS methodology	Carbon offsets issued	Carbon offsets retired	Retired proportion (%)
	1748	Southern Cardamom REDD+ Project	2015	VM0009	23,785,965	2,365,202	9.9
Cambodia	904	Reduced Emissions from Deforestation and Degradation in Community Forests – Oddar Meanchey, Cambodia	2008	VM0006	48,000	44,297	92.3
	1650	Reduced Emissions from Deforestation and Degradation in Keo Seima Wildlife Sanctuary	2010	VM0015	14,568,314	154,747	1.1
DDC	934	The Mai Ndombe REDD+ Project	2011	VM0009	13,322,276	2,572,569	19.3
DRC	1359	Isangi REDD+ Project	2009	VM0006	1,620,202	747,709	46.1
	1325	Mjumita Community Forest Project (LINDI)	2011	VM0015	10,000	2246	22.5
Tanzania	1900	Makame Savannah REDD	2016	VM0007	150,425	80,000	53.2
	1897	Ntakata Mountains REDD	2017	VM0007	726,000	84,115	11.6
7	1775	Luangwa Community Forests Project	2015	VM0009	6,147,649	1,911,839	31.1
Zambia	1202	Lower Zambezi REDD+ Project	2009	VM0009	1,570,196	689,134	43.9
TOTAL	-	-	-	-	139,804,377	38,154,319	22.3

Source: Verified Carbon Standard (VCS) project database (https://registry.verra.org/).

Standard synthetic control validation. Before assessing the impacts of the REDD+ projects, we explored whether the synthetic controls could accurately replicate deforestation trends in the project sites prior to project implementation. Synthetic controls were able to replicate pre-REDD+ deforestation trends reasonably well in most project sites (Table S3 & Fig. S2).

Table S3. Synthetic control validation: difference between project and synthetic control deforestation based on prior to project implementation.

Gt	Duniont ID	Final year of the	Project	Synthetic control	Difference between synthetic control	veen project and ol deforestation
Country	Project ID	validation period	deforestation (ha)	deforestation (ha)	(ha)	(% of project area)
Cambodia	1650	2010	2389.8	2142.0	247.8	0.1
Cambodia	1748	2015	3089.9	2700.8	389.0	0.1
Cambodia	904	2007	1122.3	1032.2	90.0	0.1
Colombia	1389	2013	929.9	927.2	2.7	0.0
Colombia	1390	2014	365.1	565.6	-200.5	-0.2
Colombia	1391	2013	55.2	190.9	-135.8	-0.2
Colombia	1392	2013	132.0	89.0	43.0	0.1
Colombia	1395	2013	554.8	890.7	-335.8	-0.4
Colombia	1396	2014	643.3	659.2	-16.0	0.0
Colombia	1400	2013	89.7	268.5	-178.7	-0.3
Colombia	1566	2013	10,761.7	9563.2	1198.5	0.1
Colombia	856	2011	88.6	147.9	-59.4	-0.5
DRC	1359	2008	1509.9	1572.4	-62.4	0.0
DRC	934	2010	8234.9	7975.1	259.8	0.1
Peru	1067	2011	1953.1	1687.8	265.4	0.0
Peru	1182	2013	243.6	252.3	-8.8	0.0
Peru	1360-1	2010	381.2	364.8	16.3	0.0
Peru	1360-2	2010	34.7	31.6	3.0	0.0
Peru	1360-3	2010	73.2	73.8	-0.5	0.0
Peru	2278	2018	995.8	718.3	277.4	0.2
Peru	844	2009	50.8	60.5	-9.7	0.0
Peru	944	2009	2626.6	2843.2	-216.6	-0.1
Peru	958	2011	1504.6	1749.0	-244.4	-0.1
Peru	985	2009	2914.3	2224.3	690.0	0.1
Tanzania	1325	2011	2913.9	3456.2	-542.3	-0.8*
Tanzania	1897	2017	4279.0	7701.1	-3422.2	-1.7*
Tanzania	1900	2016	16.3	7.1	9.2	0.0
Zambia	1202	2009	193.5	37.7	155.8	0.4
Zambia	1775-1	2015	1526.2	779.7	746.6	0.1
Zambia	1775-2	2015	136.5	406.9	-270.4	-0.2
Zambia	1775-3	2015	197.2	157.8	39.4	0.0

^{*}Projects with difference between project and synthetic control deforestation >0.5% of the project area are assumed to have failed validation.

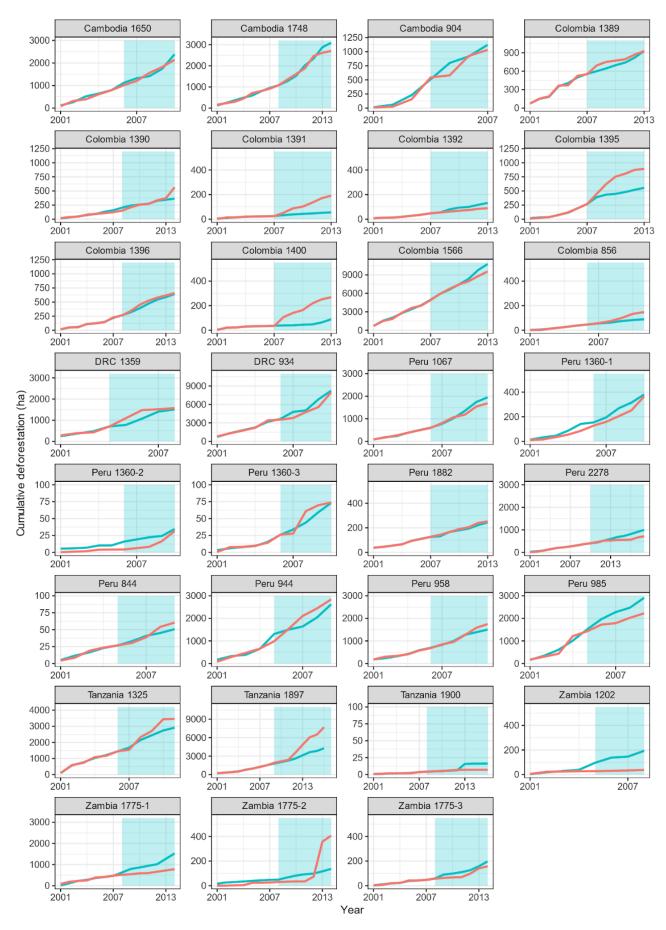


Figure S2. Validation of the synthetic control method. Pre-REDD+ deforestation in "to-be" REDD+ project areas (red) versus synthetic controls (blue). Shaded blue areas represent the validation periods (note: scales differ).

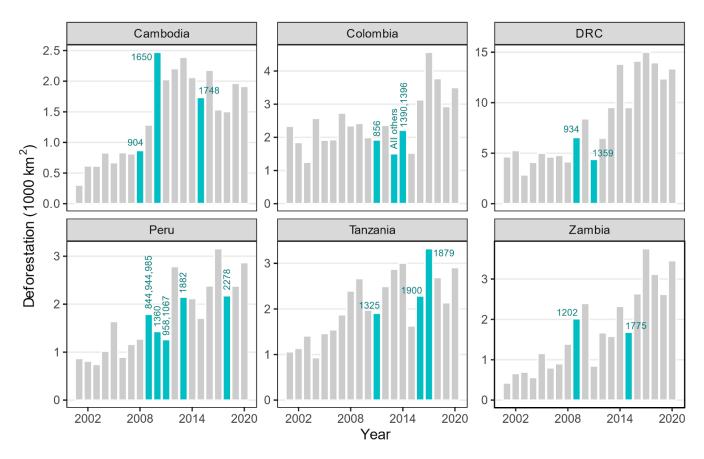


Figure S3. Annual deforestation rates $(1000 \, \text{km}^2)$ in the study countries based on the Global Forest Change dataset (bars). Blue bars indicate the implementation year of the VCS-certified REDD+ projects. Project IDs displayed in blue.

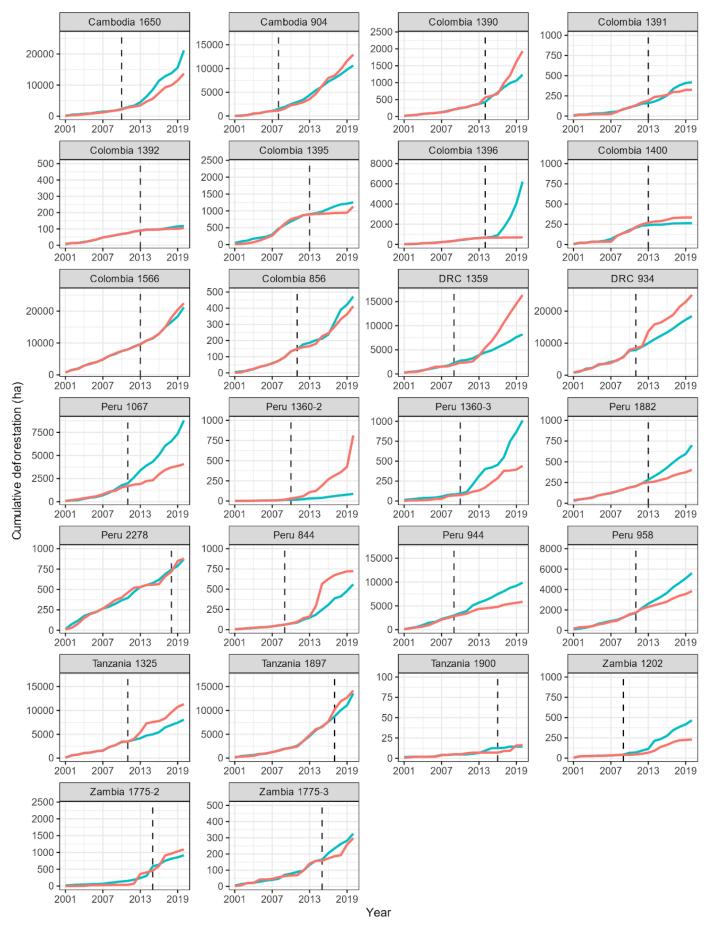


Figure S4. Cumulative post-2000 deforestation in REDD+ project areas (red) versus synthetic controls (blue). Dashed black lines indicate the project implementation year (note: scales differ).

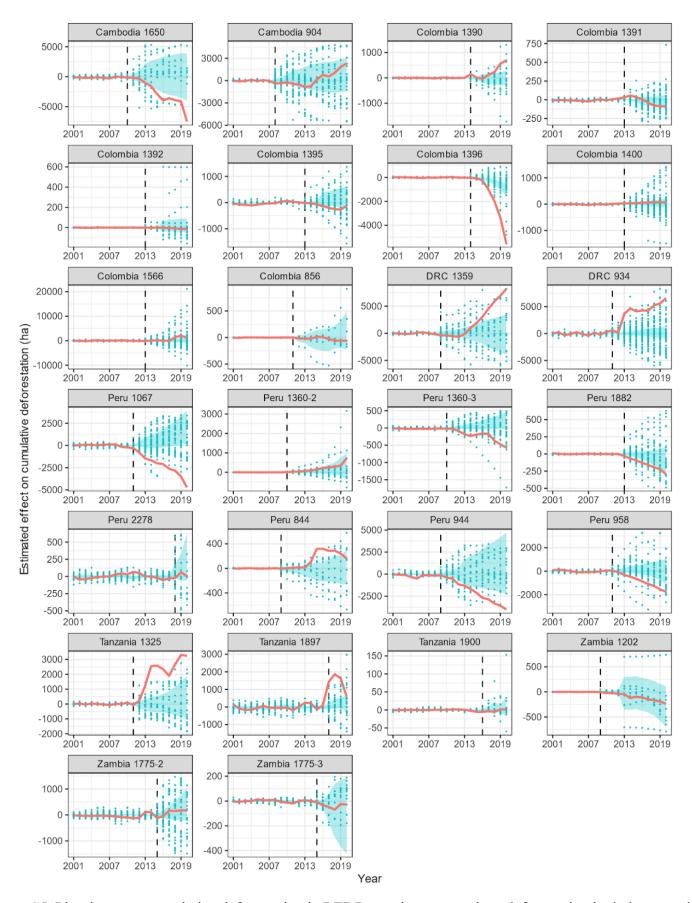


Figure S5. Placebo tests: cumulative deforestation in REDD+ project areas minus deforestation in their respective synthetic controls (red) and placebos minus their respective synthetic controls (blue dots). Dashed black lines indicate the project implementation year (assumed the same for placebos). Shaded blue areas represent 95% confidence intervals around the placebos' mean (note: scales differ).

Table S4. Estimated average REDD+ effect of the *Peruvian projects* on deforestation based on the selected control areas from the <u>individual synthetic controls</u>.

Years relative to	Average REDD+ effect on forest loss	Standard error	Confiden	ce interval	1	Sample size
project implementation	(ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-7	0.0568	0.0183	0.0209	0.0927	0.0019	0
-6	0.0178	0.0138	-0.0093	0.0449	0.1969	0
-5	0.0407	0.0193	0.0029	0.0785	0.0348	0
-4	0.0104	0.0219	-0.0324	0.0533	0.6335	0
-3	-0.0258	0.0263	-0.0774	0.0258	0.3267	0
-2	0.0026	0.0223	-0.0411	0.0462	0.9077	0
-1	-0.0339	0.0251	-0.0831	0.0153	0.1769	0
0	-0.0974	0.0259	-0.1482	-0.0466	2.00E-04	0
1	-0.1647	0.0659	-0.2939	-0.0355	0.0125	10
2	-0.1884	0.0887	-0.3623	-0.0145	0.0337	10
3	-0.2209	0.0756	-0.3691	-0.0727	0.0035	10
4	-0.2643	0.1499	-0.5582	0.0296	0.078	9
5	-0.236	0.152	-0.5339	0.062	0.1206	9
6	-0.1472	0.1163	-0.3751	0.0807	0.2055	9
7	-0.1193	0.1369	-0.3876	0.1491	0.3837	9
8	-0.3545	0.17	-0.6877	-0.0212	0.0371	9
9	-0.2853	0.2092	-0.6953	0.1247	0.1726	8
10	-0.2817	0.2581	-0.7875	0.2241	0.2751	8
11	0.01	0.2993	-0.5765	0.5965	0.9734	6
12	-0.7423	0.4433	-1.6111	0.1265	0.094	3
Mean ATT*	-0.2253	0.1362	-0.4923	0.0416	0.0981	_

^{*}Average treatment effect on the treated.

Table S5. Estimated average REDD+ effect of the *Colombian projects* on deforestation based on the selected control areas from the <u>individual synthetic controls</u>.

Years relative to	Average REDD+ effect on forest loss	Standard error	Confiden	ce interval	1	Sample size
project implementation	(ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-9	0.0108	0.0106	-0.0099	0.0315	0.3074	0
-8	-0.0111	0.0127	-0.0361	0.0138	0.3819	0
-7	0.0304	0.013	0.0048	0.056	0.0198	0
-6	-0.0284	0.0148	-0.0574	5.00E-04	0.0545	0
-5	-4.00E-04	0.015	-0.0297	0.029	0.9813	0
-4	0.0144	0.0166	-0.0182	0.047	0.3862	0
-3	-0.0175	0.0163	-0.0496	0.0145	0.2832	0
-2	-0.0064	0.0147	-0.0351	0.0224	0.6647	0
-1	0.0153	0.0183	-0.0206	0.0511	0.4046	0
0	0.0062	0.0121	-0.0176	0.0299	0.6106	0
1	0.0399	0.0263	-0.0116	0.0914	0.1287	9
2	0.0348	0.0297	-0.0235	0.0931	0.2416	9
3	0.0224	0.0335	-0.0432	0.088	0.5037	9
4	-0.0366	0.0605	-0.1552	0.082	0.5454	9
5	-0.0474	0.0476	-0.1407	0.0459	0.3196	9
6	-0.1223	0.0741	-0.2676	0.0229	0.0989	9
7	-0.0537	0.0672	-0.1854	0.0779	0.4237	9
8	-0.0256	0.1028	-0.227	0.1758	0.803	7
9	0.0503	0.099	-0.1437	0.2442	0.6113	1
10	0.1924	0.1496	-0.1007	0.4856	0.1982	1
Mean ATT*	-0.0195	0.0384	-0.0948	0.0558	0.6118	_

^{*}Average treatment effect on the treated.

Table S6. Estimated average REDD+ effect of the *African projects* on deforestation based on the selected control areas from the <u>individual synthetic controls</u>.

Years relative to	Average REDD+ effect on forest loss	Standard error	Confiden	ce interval	,	Sample size
project implementation	(ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-7	-0.0375	0.0213	-0.0793	0.0043	0.0784	0
-6	-0.0105	0.017	-0.0437	0.0228	0.5371	0
-5	0.021	0.027	-0.0318	0.0739	0.4359	0
-4	-0.0294	0.02	-0.0685	0.0098	0.1415	0
-3	-0.0409	0.0182	-0.0765	-0.0053	0.0244	0
-2	0.0042	0.0208	-0.0365	0.0449	0.8387	0
-1	0.0098	0.0155	-0.0205	0.0401	0.526	0
0	0.0234	0.0242	-0.024	0.0709	0.333	0
1	-0.1205	0.1065	-0.3292	0.0882	0.2579	9
2	-0.1319	0.0833	-0.2952	0.0314	0.1134	9
3	0.2803	0.2113	-0.1339	0.6945	0.1848	9
4	0.0664	0.1864	-0.2991	0.4318	0.7219	9
5	-0.5484	0.3778	-1.2889	0.1921	0.1467	8
6	-0.3244	0.2608	-0.8356	0.1868	0.2136	7
7	-0.2671	0.2169	-0.6921	0.158	0.2182	4
8	-0.4143	0.6538	-1.6958	0.8672	0.5263	4
9	-0.7475	0.6862	-2.0924	0.5974	0.276	4
10	-0.4781	0.5572	-1.5702	0.6141	0.3909	4
11	-0.0446	0.1506	-0.3398	0.2507	0.7673	2
12	-0.3831	0.2677	-0.9078	0.1416	0.1525	2
Mean ATT*	-0.2013	0.1777	-0.5496	0.147	0.2573	_

^{*}Average treatment effect on the treated.

Table S7. Estimated average REDD+ effect of the *Peruvian projects* on deforestation based on the selected control areas from the <u>genetic matching</u>.

Years relative to	Average REDD+ effect on forest loss	G. 1.1	Confiden	ce interval	,	Sample size
project implementation	(ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-7	0.0346	0.0180	-0.0006	0.0698	0.0544	0
-6	-0.0093	0.0142	-0.0371	0.0185	0.5118	0
-5	0.0300	0.0144	0.0018	0.0583	0.0372	0
-4	0.0173	0.0189	-0.0197	0.0544	0.3595	0
-3	-0.0186	0.0215	-0.0607	0.0236	0.3879	0
-2	-0.0009	0.0172	-0.0346	0.0328	0.9595	0
-1	-0.0150	0.0204	-0.0551	0.0250	0.4627	0
0	-0.0616	0.0204	-0.1015	-0.0217	0.0025	0
1	-0.2586	0.0997	-0.4540	-0.0631	0.0095	10
2	-0.2161	0.1461	-0.5024	0.0702	0.1390	10
3	-0.3496	0.1097	-0.5646	-0.1347	0.0014	10
4	-0.4890	0.1767	-0.8352	-0.1428	0.0056	9
5	-0.4058	0.1954	-0.7887	-0.0228	0.0378	9
6	-0.3026	0.1272	-0.5519	-0.0534	0.0173	9
7	-0.3171	0.1480	-0.6071	-0.0271	0.0321	9
8	-0.5807	0.1807	-0.9348	-0.2267	0.0013	9
9	-0.5316	0.2265	-0.9755	-0.0877	0.0189	8
10	-0.6137	0.2324	-1.0691	-0.1583	0.0083	8
11	-0.3770	0.2641	-0.8945	0.1406	0.1534	6
12	-1.0598	0.5736	-2.1840	0.0644	0.0646	3
Mean ATT*	-0.4170	0.1467	-0.7046	-0.1294	0.0045	_

^{*}Average treatment effect on the treated.

Table S8. Estimated average REDD+ effect of the *Colombian projects* on deforestation based on the selected control areas from the <u>genetic matching</u>.

Years relative to	Average REDD+ effect	Standard error	Confiden	ce interval	1	Sample size
project implementation	on forest loss (ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-9	0.0093	0.0142	-0.0185	0.0371	0.5121	0
-8	-0.0148	0.0151	-0.0444	0.0149	0.3286	0
-7	0.0211	0.0156	-0.0095	0.0516	0.1761	0
-6	-0.0211	0.0139	-0.0484	0.0061	0.1289	0
-5	0.0114	0.0168	-0.0215	0.0442	0.4968	0
-4	-0.0008	0.0158	-0.0317	0.0302	0.9612	0
-3	-0.0244	0.0248	-0.0729	0.0241	0.3247	0
-2	-0.0077	0.0129	-0.0331	0.0177	0.5518	0
-1	0.0155	0.0210	-0.0258	0.0567	0.4624	0
0	0.0014	0.0138	-0.0256	0.0284	0.9169	0
1	0.0301	0.0325	-0.0336	0.0938	0.3542	9
2	-0.0020	0.0323	-0.0653	0.0614	0.9519	9
3	-0.0377	0.0519	-0.1395	0.0641	0.4679	9
4	-0.1353	0.0960	-0.3234	0.0528	0.1587	9
5	-0.0619	0.0573	-0.1742	0.0504	0.2802	9
6	-0.1273	0.0949	-0.3133	0.0588	0.1800	9
7	-0.0937	0.0725	-0.2358	0.0484	0.1963	9
8	-0.0507	0.1097	-0.2656	0.1642	0.6439	7
9	0.0800	0.1131	-0.1417	0.3018	0.4795	1
10	0.2448	0.1719	-0.0921	0.5816	0.1544	1
Mean ATT*	-0.0539	0.0568	-0.1653	0.0575	0.3432	_

^{*}Average treatment effect on the treated.

Table S9. Estimated average REDD+ effect of the *African projects* on deforestation based on the selected control areas from the <u>genetic matching</u>.

Years relative to	Average REDD+ effect on forest loss	Standard error	Confiden	ce interval	,	Sample size
project implementation	(ATT*; %)	Standard error	Lower	Upper	p-value	(projects)
-7	-0.0294	0.0139	-0.0565	-0.0022	0.0340	0
-6	0.0054	0.0177	-0.0293	0.0400	0.7610	0
-5	-0.0078	0.0288	-0.0642	0.0486	0.7866	0
-4	-0.0115	0.0159	-0.0427	0.0197	0.4711	0
-3	-0.0492	0.0254	-0.0991	0.0006	0.0529	0
-2	0.0002	0.0123	-0.0238	0.0242	0.9858	0
-1	0.0242	0.0234	-0.0217	0.0701	0.3007	0
0	0.0234	0.0246	-0.0247	0.0715	0.3399	0
1	-0.0645	0.0604	-0.1830	0.0539	0.2856	9
2	-0.0570	0.0425	-0.1402	0.0262	0.1795	9
3	0.1536	0.1469	-0.1343	0.4415	0.2958	9
4	0.0524	0.1797	-0.2998	0.4046	0.7706	9
5	-0.3026	0.2012	-0.6969	0.0917	0.1326	8
6	-0.2556	0.1935	-0.6348	0.1237	0.1866	7
7	-0.2515	0.1548	-0.5550	0.0519	0.1043	4
8	-0.2118	0.3748	-0.9463	0.5227	0.5720	4
9	-0.3399	0.3851	-1.0948	0.4149	0.3775	4
10	-0.2594	0.3383	-0.9224	0.4037	0.4433	4
11	-0.2117	0.2055	-0.6144	0.1911	0.3030	2
12	-0.3983	0.2571	-0.9022	0.1057	0.1214	2
Mean ATT*	-0.1256	0.1285	-0.3774	0.1262	0.3281	_

^{*}Average treatment effect on the treated.

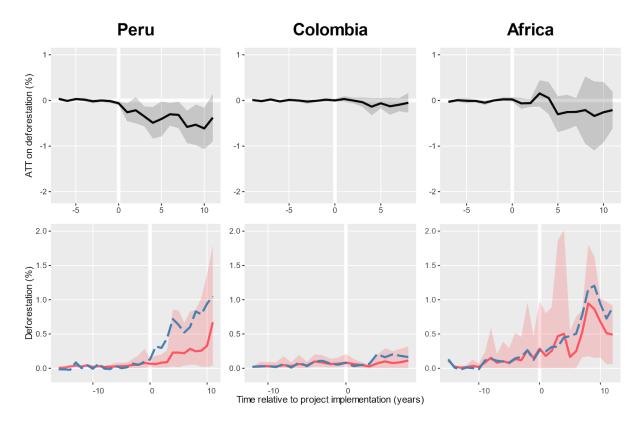


Figure S6. Estimated average impacts of REDD+ projects from Peru, Colombia, and Africa on annual deforestation, using the generalized synthetic control (GSC) method and selected controls from the *genetic matching*. Upper panels display the average treatment effect on the treated (ATT) project areas. Lower panels display projects' (solid red line) and counterfactuals' (dashed blue line) deforestation averages. Shaded red areas represent bootstrapped 95% confidence intervals around the projects' deforestation average.

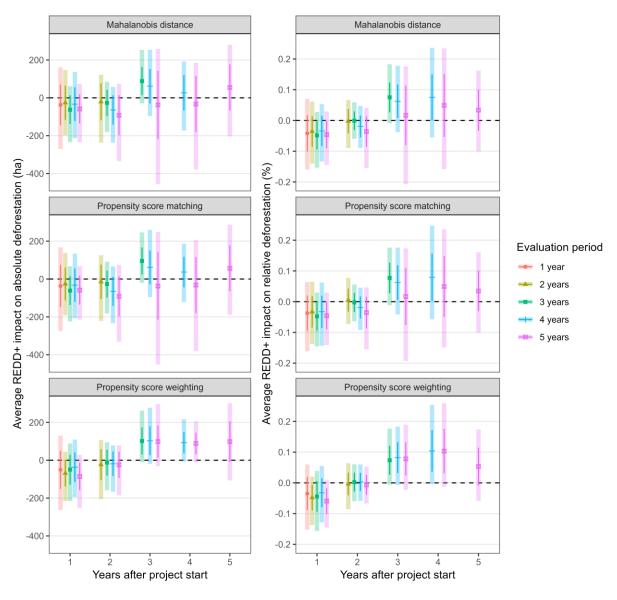


Figure S7. Estimated impacts of the REDD+ projects on the annual absolute and relative deforestation per evaluation period based on Mahalanobis distance, propensity score matching, and propensity score weighting (see Imai et al. 1 for details). Dark colored lines represent standard error bars. Light colored bars represent bootstrapped 95% confidence intervals. Impact estimates for the same year after project start vary across the evaluation periods due to changes in sample sizes (cf., West et al. 2).

¹ Imai, K., Kim, I.S., Wang, E., 2018. Matching Methods for Causal Inference With Time-Series Cross-sectional Data. Harvard University, Massachusetts Institute of Technology, Cambridge.

² West, T.A.P., Caviglia-Harris, J.L., Martins, F.R.V., Silva, D.E., Börner, J., 2022. Potential conservation gains from improved protected area management in the Brazilian Amazon. Biological Conservation 269, 109526.

Table S10. Differences in the expected volume of carbon offsets generated by the voluntary REDD+ projects: observed cumulative deforestation in the project areas versus project baselines (ex-ante) versus synthetic control deforestation (ex-post) through 2020.

Country	Project ID	Observed deforestation in the project area (ha)	Project baseline deforestation* (ex-ante; ha)	Observed deforestation in the synthetic control area (ex-post; ha)	Expected carbon offsets based on projects' ex-ante baseline† (Mg CO ₂)	Proportional carbon offsets based on the synthetic control deforestation (Mg CO ₂)	Evidence of significant reductions in deforestation;	Avoided deforestation based on the synthetic control (ha)	Carbon offsets based on the synthetic control (Mg CO ₂)
	1882	403	1268	702	356,960	197,623	Yes	299	84,057
	2278	878	13299	873	5,891,253	386,726	No	0	0
Peru	1067	4070	13581	8797	4,817,471	3,120,484	Yes	4727	1,676,658
Peru	958	3391	2924	4653	630,937	1,004,018	Yes	1262	272,313
	944	5454	23685	8783	5,151,165	1,910,183	Yes	3329	724,012
	844	699	125541	410	12,475,134	40,742	No	0	0
	1400	334	4450	264	1,657,098	98,299	No	0	0
	1566	22,473	103,908	21,228	31,325,923	6,399,752	No	0	0
Colombia	1396	693	8076	6219	1,489,786	1,147,190	Yes	5526	1,019,305
	1395	1129	16,835	1253	2,791,723	207,787	No	124	20,616
	1392	105	10,722	118	1,455,141	16,014	No	0	0

Table S10 (continued). Differences in the expected volume of carbon offsets generated by the voluntary REDD+ projects: observed cumulative deforestation in the project areas versus project baselines (ex-ante) versus synthetic control deforestation (ex-post) through 2020.

Country	Project ID	Observed deforestation in the project area (ha)	Project baseline deforestation* (ex-ante; ha)	Observed deforestation in the synthetic control area (ex-post; ha)	Expected carbon offsets based on projects' ex-ante baseline† (Mg CO ₂)	Proportional carbon offsets based on the synthetic control deforestation (Mg CO ₂)	Evidence of significant reductions in deforestation;	Avoided deforestation based on the synthetic control (ha)	Carbon offsets based on the synthetic control (Mg CO ₂)
Cambodia	904	12,950	21,252	10,632	1,626,420	813,669	No	0	0
Cambodia	1650	11,499	30,446	15,609	12,432,277	6,373,757	Yes	4110	1,678,272
DRC	1359	16,385	11,949	8,204	4,735,361	3,251,226	No	0	0
	1325	11,318	10,578	8,077	359,834	274,757	No	0	0
Tanzania	1900	16	11,407	14	348,019	427	No	0	0
	1897	14161	35,472	13,577	1,406,892	538,492	No	0	0
TOTAL					88,951,394	25,781,146			5,475,233

^{*} Reported by official project documents.

Note: Projects 856 and 1390 from Colombia, 934 from DRC, 1748 from Cambodia, and the Zambian projects and were excluded due to insufficient public information about ex-ante baseline deforestation rates. Projects with baselines ending before 2020 (e.g., 2018) were compared to their respective observed and synthetic control cumulative deforestations for the last available baseline year.

[†] Reported by official project documents exclusively for the projects' avoided deforestation and forest degradation.

[‡] Based on the results from the synthetic control analyses and placebo tests.

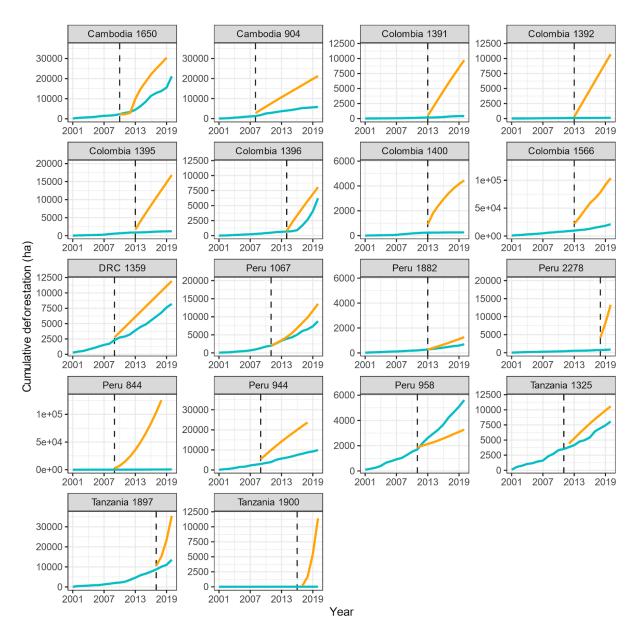


Figure S8. Cumulative deforestation from the baseline scenarios adopted by the REDD+ projects (orange) versus observed cumulative deforestation in the synthetic controls (blue). Dashed black lines indicate the project implementation year (note: scales differ).

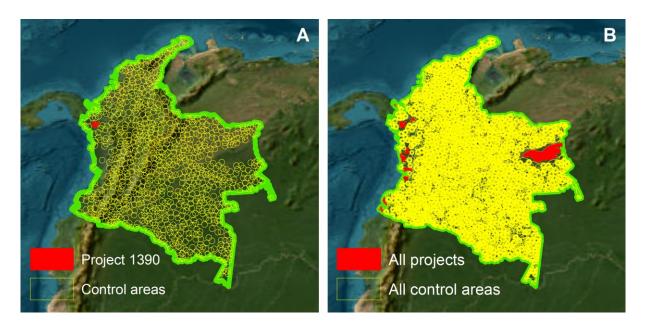


Figure S9. Example of the 1000 circular spatial polygons created randomly as potential control areas for Project #1390 in Colombia (A) and all combined polygons for the Colombian projects (B). Circular spatial polygons are later intersected with all covariate maps described in Table S8.

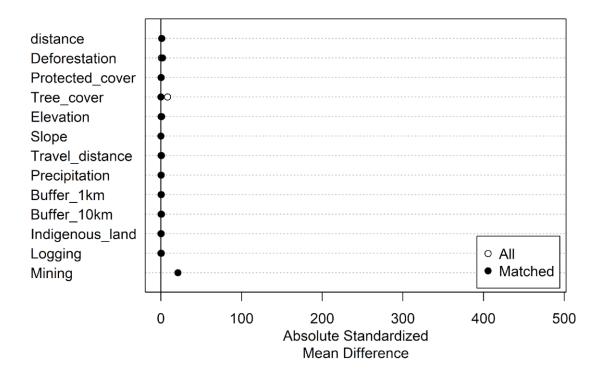


Figure S10. Covariate balance for the *Peruvian projects* before and after genetic matching. Absolute standardized mean differences within the vertical-line interval generally indicate well-balanced sets.

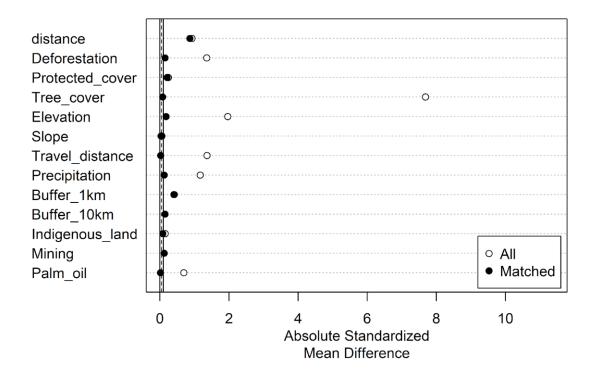


Figure S11. Covariate balance for the *Colombian projects* before and after genetic matching. Absolute standardized mean differences within the vertical-line interval generally indicate well-balanced sets.

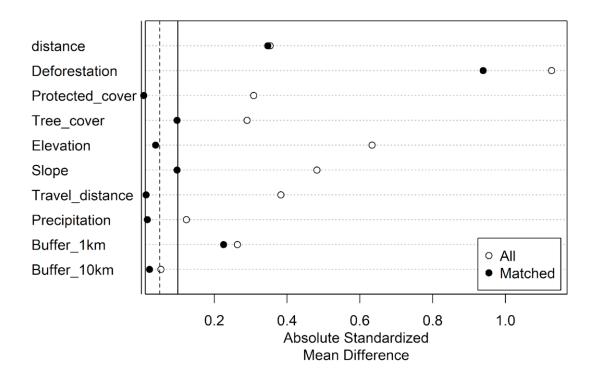


Figure S12. Covariate balance for the *African projects* before and after genetic matching. Absolute standardized mean differences within the vertical-line interval generally indicate well-balanced sets.

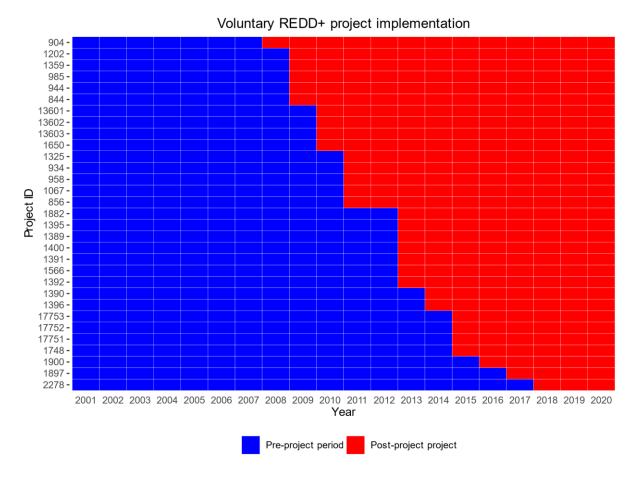


Figure S13. Treatment history: VCS-certified REDD+ project implementation.

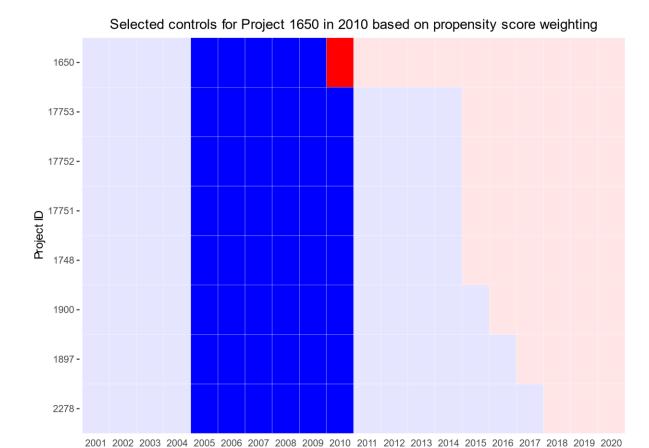


Figure S14. Example of selected controls ("to-be" REDD+ sites; blue) for the evaluation of operational Project 1650 in 2010 (red). Highlighted 2005–2009 period (blue) is the interval used for the identification of the control areas via matching.

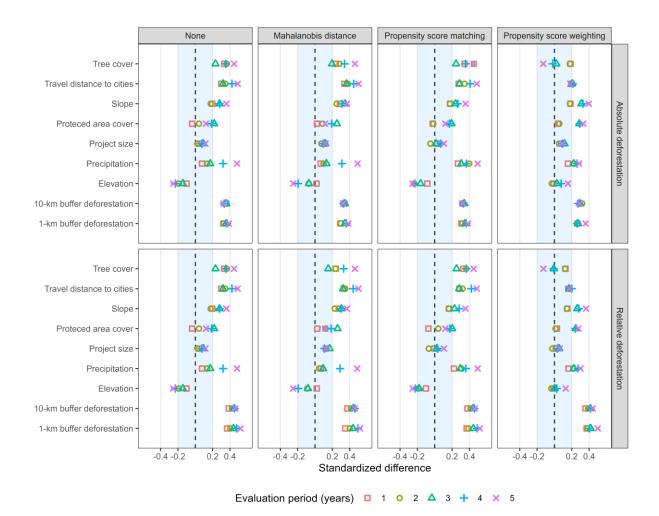


Figure S15. Covariate balance from propensity score matching, Mahalanobis distance, and propensity score weighting based on absolute (ha year⁻¹) and relative deforestation (% year⁻¹) for different evaluation periods (years). Time-varying covariates are represented by averages over the 5-year interval prior to project implementation used for the matching analyses (Fig. S17). "None" represents the original unmatched sample. Standardized differences within the shaded intervals generally indicate well-balanced sets.

Table S11. Data description.

Variable	Description	Geographical coverage	Source
Deforestation and average tree cover in 2000	2000–2020 forest cover and change, time-variant	Global	Global Forest Change dataset (Hansen et al., 2013), available in Google Earth Engine
Travel time to urban centers	Friction surface of land- based travel time (days); time-invariant	Global	Global Friction Surface 2019 (Weiss et al., 2018), available in Google Earth Engine
Elevation and slope	Average elevation and slope in project and control areas (m); time-invariant	Global	Global Multi-resolution Terrain Elevation Data (GMTED2010), available in Google Earth Engine
		Peru	National Service of Natural Areas Protected by the State (SERNANP; Spanish acronym)
Protected area	Location of protected areas;	Colombia	Colombian Environmental Information System (SIAC; Spanish acronym)
cover	time-invariant	Cambodia	Open Development Cambodia (https://opendevelopmentcambodia.net/)
		DRC, Tanzania, Zambia	Protected Planet (https://www.protectedplanet.net/)
Indigenous	Location of Indigenous	Peru	Body for the Formalization of Informal Property (COFOPRI; Spanish acronym)
land cover	lands; time-invariant	Colombia	National Land Agency (ANT; Spanish acronym)
		DRC	Map for Environment (https://mapforenvironment.org/)
Mining		Peru, Colombia, DRC	Global Forest Watch (https://www.globalforestwatch.org/)
concession cover	Location of mining concessions; time-invariant	Cambodia	Open Development Cambodia (https://opendevelopmentcambodia.net/)
		Tanzania	Map for Environment (https://mapforenvironment.org/)
Logging	Location of logging	Peru	Map for Environment (https://mapforenvironment.org/)
concession cover	concessions; time-invariant	DRC	Global Forest Watch (https://www.globalforestwatch.org/)
Palm oil	Location of palm oil	Colombia	Map for Environment (https://mapforenvironment.org/)
concession cover	concessions; time-invariant	Indonesia	Global Forest Watch (https://www.globalforestwatch.org/)
General concession cover	Location of multiple land concessions; time-invariant	Cambodia	Map for Environment (https://mapforenvironment.org/)
Precipitation	Annual cumulative precipitation (mm); timevariant	Global	Monthly Global Precipitation Measurement (GPM) v.6, available in Google Earth Engine
REDD+ jurisdictional programs and other conservation interventions	Central Africa Regional Program for the Environment (CARPE) in RDC, DRC's jurisdictional Maï Ndombe Emission Reduction Program, and DRC's Forest Investment Program; time-invariant	DRC	Map for Environment (https://mapforenvironment.org/)
Other REDD+ interventions	Other REDD+ intervention areas used for exclusion of control areas; time-variant	DRC	Map for Environment (https://mapforenvironment.org/)
Soil fertility	3-class ordinal map of soil fertility; time-invariant	Cambodia	Map for Environment (https://mapforenvironment.org/)

Appendix A. Optimized v-weights from the synthetic control (SC) analyses and covariate balance between the voluntary REDD+ project sites and SCs from 2001 to project implementation year (note: missing covariates indicate no covariate variation between the project and control areas; see Table S10).

Table A1. Covariate balance for Project 844 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	5.00E-09	0.99	0.98	0.813
Indigenous land cover (%)	5.00E-09	0	0.009	0.168
Protected area cover (%)	5.00E-09	0	0.43	0.184
Mining concession cover (%)	0.499943	0	0	0.027
Slope (degree)	0.499943	2.271	2.271	11.609
Elevation (m)	5.00E-09	331.537	232.917	1142.592
Timber concession cover (%)	5.00E-09	1	0.518	0.126
Travel distance to urban centers (days)	8.07E-06	0.038	0.038	0.05
Average annual deforestation (ha)	5.00E-09	6.785	6.38	87.424
Average cumulative deforestation (ha)	0.000106	25.668	25.987	369.073
Annual precipitation (mm)	1.17E-07	1874	2305.455	1932.274
Average annual buffer deforestation (ha)	5.00E-09	139.75	129.97	138.387
Average cumulative buffer deforestation (ha)	7.65E-08	445.125	502.823	584.46

^{*}Based on four control areas.

Table A2. Covariate balance for Project 944 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.00E-08	0.89	0.96	0.903
Indigenous land cover (%)	1.00E-08	0.011	0.341	0.14
Protected area cover (%)	1.00E-08	0.98	0.004	0.075
Mining concession cover (%)	1.00E-08	0	0.266	0.073
Slope (degree)	1.00E-08	17.249	10.755	8.95
Elevation (m)	1.00E-08	1751.28	1031.965	652.62
Timber concession cover (%)	1.00E-08	0	0.019	0.096
Travel distance to urban centers (days)	1.00E-08	0.076	0.056	0.049
Average annual deforestation (ha)	1	304.811	326.58	1133.672
Average cumulative deforestation (ha)	1.00E-08	1069.94	1252.255	4711.364
Annual precipitation (mm)	1.00E-08	1208.125	1665.75	1705.13
Average annual buffer deforestation (ha)	1.00E-08	1444.625	1157.125	1382.606
Average cumulative buffer deforestation (ha)	1.00E-08	5440.25	4319	5662.537

^{*}Based on one control area.

Table A3. Covariate balance for Project 958 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	9.30E-09	0.93	0.734	0.837
Indigenous land cover (%)	0.003971	0	0.088	0.196
Protected area cover (%)	9.30E-09	0	0.034	0.138
Slope (degree)	9.30E-09	23.243	20.099	10.722
Elevation (m)	9.30E-09	1831.213	2256.768	1061
Mining concession cover (%)	0.060823	0	0.021	0.063
Timber concession cover (%)	0.000219	1	0.202	0.088
Travel distance to urban centers (days)	0.003126	0.087	0.075	0.051
Average annual deforestation (ha)	9.30E-09	158.09	152.822	550.58
Average cumulative deforestation (ha)	0.929849	712.794	711.536	2803.392
Annual precipitation (mm)	9.30E-09	1139.8	1397.511	1830.01
Average annual buffer deforestation (ha)	9.30E-09	482.1	479.555	462.755
Average cumulative buffer deforestation (ha)	0.002012	2305	2425.142	2324.838

^{*}Based on four control areas.

Table A4. Covariate balance for Project 1067 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	8.21E-09	0.98	0.985	0.844
Indigenous land cover (%)	8.21E-09	0.002	0.019	0.19
Protected area cover (%)	8.21E-09	0.939	0.014	0.141
Slope (degree)	8.21E-09	0.929	1.604	11.508
Elevation (m)	8.21E-09	234.969	186.731	1120.772
Mining concession cover (%)	8.21E-09	0.001	0	0.054
Timber concession cover (%)	8.21E-09	0.124	0.731	0.108
Travel distance to urban centers (days)	7.71E-06	0.038	0.039	0.052
Average annual deforestation (ha)	0.178866	154.182	176.482	1374.262
Average cumulative deforestation (ha)	0.821126	658.882	642.699	6784.841
Annual precipitation (mm)	8.21E-09	2825.3	3309.608	1841.981
Average annual buffer deforestation (ha)	8.21E-09	1172.9	705.164	972.285
Average cumulative buffer deforestation (ha)	8.21E-09	5819.4	3352.26	4756.742

^{*}Based on two control areas.

Table A5. Covariate balance for Project 1882 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.63E-06	0.85	0.868	0.795
Indigenous land cover (%)	5.85E-09	0	0.003	0.179
Protected area cover (%)	0.413688	0	0	0.144
Slope (degree)	5.85E-09	26.758	5.291	10.457
Elevation (m)	1.97E-08	2855.566	507.714	1073.627
Mining concession cover (%)	9.29E-06	0	0.004	0.057
Timber concession cover (%)	5.85E-09	1	0.301	0.115
Travel distance to urban centers (days)	2.70E-08	0.091	0.037	0.046
Average annual deforestation (ha)	0.585399	20.024	20.024	46.98
Average cumulative deforestation (ha)	0.000901	123.477	123.016	252.864
Annual precipitation (mm)	1.29E-08	1319.333	2858.851	2034.109
Average annual buffer deforestation (ha)	5.85E-09	115.333	117.029	113.614
Average cumulative buffer deforestation (ha)	5.85E-09	677	713.303	625.602

^{*}Based on six control areas.

Table A6. Covariate balance for Project 2278 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.00E-08	0.99	0.985	0.862
Indigenous land cover (%)	1.00E-08	0	0.138	0.218
Protected area cover (%)	1.00E-08	0	0.001	0.133
Slope (degree)	1.00E-08	2.153	1.766	10.155
Elevation (m)	1.00E-08	361.254	277.825	949.285
Mining concession cover (%)	0.999878	0	0.029	0.06
Timber concession cover (%)	1.00E-08	1	0.792	0.122
Travel distance to urban centers (days)	1.00E-08	0.039	0.038	0.051
Average annual deforestation (ha)	1.00E-08	38.871	40.513	538.241
Average cumulative deforestation (ha)	0.000122	346.858	346.853	3803.924
Annual precipitation (mm)	1.00E-08	1980.765	3116.82	1891.379
Average annual buffer deforestation (ha)	1.00E-08	749.941	248.545	580.549
Average cumulative buffer deforestation (ha)	1.00E-08	5171.529	1376.397	4031.998

^{*}Based on three control areas.

Table A7. Covariate balance for Project 1360-1 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.59E-07	0.99	0.96	0.899
Indigenous land cover (%)	1.00E-08	0.998	0.917	0.156
Protected area cover (%)	1	0	0	0.067
Mining concession cover (%)	1.00E-08	0	0.205	0.038
Slope (degree)	1.00E-08	2.47	12.623	6.281
Elevation (m)	1.00E-08	277.081	1131.4	488.26
Timber concession cover (%)	1.00E-08	0	0	0.082
Travel distance to urban centers (days)	1.00E-08	0.038	0.06	0.043
Average annual deforestation (ha)	1.00E-08	28.031	85.193	806.992
Average cumulative deforestation (ha)	1.00E-08	104.729	310.309	3484.132
Annual precipitation (mm)	1.00E-08	3398	1508.889	1957.044
Average annual buffer deforestation (ha)	1.00E-08	2764.444	1071.444	1320.204
Average cumulative buffer deforestation (ha)	1.00E-08	12250.56	3886	5731.282

^{*}Based on one control areas.

Table A8. Covariate balance for Project 1360-2 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	9.99E-09	0.99	1	0.916
Indigenous land cover (%)	9.99E-09	0.998	0.349	0.226
Protected area cover (%)	4.07E-06	0	0.001	0.114
Mining concession cover (%)	0.998817	0	0	0.031
Slope (degree)	9.99E-09	0.634	1.723	8.815
Elevation (m)	2.42E-07	169	197.704	738.592
Timber concession cover (%)	9.99E-09	0.001	0	0.133
Travel distance to urban centers (days)	9.99E-09	0.037	0.038	0.051
Average annual deforestation (ha)	7.01E-05	1.859	1.58	66.026
Average cumulative deforestation (ha)	0.001108	5.266	5.405	300.644
Annual precipitation (mm)	9.99E-09	1625.778	2156.448	1947.459
Average annual buffer deforestation (ha)	9.99E-09	292	213.611	282.821
Average cumulative buffer deforestation (ha)	9.99E-09	1307.667	932.363	1270.729

^{*}Based on two control areas.

Table A9. Covariate balance for Project 1360-3 from Peru.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.00E-08	0.99	0.977	0.906
Indigenous land cover (%)	1.00E-08	0.989	0.203	0.171
Protected area cover (%)	0.99986	0	0	0.024
Mining concession cover (%)	1.00E-08	0	0.821	0.117
Slope (degree)	1.00E-08	0.726	4.336	7.854
Elevation (m)	1.00E-08	183.504	412.574	578.512
Timber concession cover (%)	1.00E-08	0	0.431	0.134
Travel distance to urban centers (days)	5.65E-08	0.037	0.042	0.046
Average annual deforestation (ha)	0.00014	7.757	9.204	89.47
Average cumulative deforestation (ha)	1.00E-08	25.114	44.374	410.975
Annual precipitation (mm)	1.00E-08	1641.556	4526.388	2305.322
Average annual buffer deforestation (ha)	1.00E-08	491.333	458.916	477.606
Average cumulative buffer deforestation (ha)	1.00E-08	1545.556	2017.51	2184.875

^{*}Based on two control areas.

Table A10. Covariate balance for Project 856 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	6.33E-07	0.95	0.919	0.611
Indigenous land cover (%)	8.58E-09	0.003	0	0.048
Protected area cover (%)	4.30E-08	0.961	0.744	0.1
Slope (degree)	8.58E-09	14.87	9.171	5.132
Elevation (m)	8.58E-09	443.552	655.756	440.963
Travel distance to urban centers (days)	8.58E-09	0.061	0.055	0.024
Average annual deforestation (ha)	0.857906	13.448	13.448	50.482
Average cumulative deforestation (ha)	0.000324	58.197	58.602	294.724
Annual precipitation (mm)	0.141769	2837.455	2837.454	2669.489
Average annual buffer deforestation (ha)	8.58E-09	332	301.513	318.576
Average cumulative buffer deforestation (ha)	1.05E-07	1819.091	1641.475	1881.325

^{*}Based on six control areas.

Table A11. Covariate balance for Project 1389 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	5.00E-09	0.95	0.99	0.71
Indigenous land cover (%)	0.5	0	0	0.015
Protected area cover (%)	5.00E-09	0.104	0	0.127
Slope (degree)	5.00E-09	1.567	1.736	2.661
Elevation (m)	5.00E-09	19.109	250.352	253.684
Palm oil concession cover (%)	5.00E-09	0.114	0	0.042
Mining concession cover (%)	0.5	0	0	0.004
Travel distance to urban centers (days)	5.00E-09	0.037	0.038	0.023
Average annual deforestation (ha)	5.00E-09	72.391	157.89	630.371
Average cumulative deforestation (ha)	3.75E-07	509.116	835.664	4138.333
Annual precipitation (mm)	5.00E-09	3096.25	2862.75	2983.195
Average annual buffer deforestation (ha)	5.00E-09	1254.25	986.917	1231.789
Average cumulative buffer deforestation (ha)	5.00E-09	8147.583	4981.667	7995.052

^{*}Based on one control area.

Table A12. Covariate balance for Project 1390 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	4.94E-09	0.94	0.967	0.576
Indigenous land cover (%)	4.94E-09	0.002	0.001	0.106
Protected area cover (%)	4.94E-09	0	0.626	0.133
Slope (degree)	2.34E-06	0.936	1.834	8.9
Elevation (m)	1.14E-07	23.101	255.41	1009.857
Mining concession cover (%)	0.494015	0	0	0.002
Travel distance to urban centers (days)	0.494015	0.038	0.037	0.032
Average annual deforestation (ha)	0.000999	28.59	28.374	178.222
Average cumulative deforestation (ha)	0.010968	161.489	161.673	1284.22
Annual precipitation (mm)	4.94E-09	4587	2662.707	2352.755
Average annual buffer deforestation (ha)	4.94E-09	235.231	196.72	233.208
Average cumulative buffer deforestation (ha)	4.94E-09	1595.692	1247.988	1688.764

^{*}Based on four control areas.

Table A13. Covariate balance for Project 1391 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.73E-05	0.98	0.977	0.623
Indigenous land cover (%)	1.00E-08	0.007	0.619	0.293
Protected area cover (%)	1.00E-08	0.513	0	0.16
Slope (degree)	1.00E-08	4.314	1.661	6.757
Elevation (m)	1.79E-06	56.516	120.435	1020.077
Palm oil concession cover (%)	1.00E-08	0.166	0	0.005
Mining concession cover (%)	0.999972	0	0	0.013
Travel distance to urban centers (days)	1.00E-08	0.039	0.038	0.036
Average annual deforestation (ha)	2.09E-06	14.192	12.819	21.904
Average cumulative deforestation (ha)	6.72E-06	55.714	60.846	141.402
Annual precipitation (mm)	1.00E-08	6758.25	4982.011	2918.984
Average annual buffer deforestation (ha)	1.00E-08	52.5	47.307	52.257
Average cumulative buffer deforestation (ha)	1.00E-08	237.833	288.669	341.149

^{*}Based on two control areas.

Table A14. Covariate balance for Project 1392 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.91E-07	0.98	0.588	0.687
Indigenous land cover (%)	1.30E-06	0	0.095	0.47
Protected area cover (%)	1.77E-07	0.014	0.363	0.185
Slope (degree)	0.998654	6.369	6.369	2.42
Elevation (m)	1.77E-07	65.338	816.682	256.4
Travel distance to urban centers (days)	2.12E-07	0.039	0.033	0.03
Average annual deforestation (ha)	0.000472	6.984	7.045	6.786
Average cumulative deforestation (ha)	0.000872	42.199	42.085	38.622
Annual precipitation (mm)	1.77E-07	5160.333	3701.342	3215.53
Average annual buffer deforestation (ha)	1.77E-07	13.75	13.663	13.712
Average cumulative buffer deforestation (ha)	1.77E-07	66.833	75.962	82.085

^{*}Based on five control areas.

Table A15. Covariate balance for Project 1395 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.93E-06	0.98	0.965	0.893
Indigenous land cover (%)	1.00E-08	0	0.22	0.367
Protected area cover (%)	1.00E-08	0.279	0	0.113
Slope (degree)	1.00E-08	2.891	3.175	7.928
Elevation (m)	1.00E-08	53.587	100.28	888.254
Palm oil concession cover (%)	1.00E-08	0.377	0.076	0.02
Mining concession cover (%)	0.999938	0	0	0.013
Travel distance to urban centers (days)	1.00E-08	0.038	0.039	0.047
Average annual deforestation (ha)	5.72E-05	72.962	72.719	63.174
Average cumulative deforestation (ha)	2.67E-06	352.45	380.712	394.998
Annual precipitation (mm)	1.00E-08	6213.583	6167.6	3092.443
Average annual buffer deforestation (ha)	1.00E-08	123.667	138.386	125.305
Average cumulative buffer deforestation (ha)	3.48E-08	552.833	704.622	803.245

^{*}Based on two control areas.

Table A16. Covariate balance for Project 1396 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.18E-08	0.98	0.761	0.487
Indigenous land cover (%)	6.69E-06	0.001	0	0.046
Protected area cover (%)	0.440264	0	0	0.097
Slope (degree)	5.24E-08	3.318	2.001	7.828
Elevation (m)	4.40E-09	48.842	270.013	676.986
Mining concession cover (%)	0.440264	0	0	0.003
Palm oil concession cover (%)	4.40E-09	0.018	0.192	0.184
Travel distance to urban centers (days)	4.40E-09	0.039	0.03	0.023
Average annual deforestation (ha)	4.40E-09	47.55	48.627	132.717
Average cumulative deforestation (ha)	0.119465	269.257	269.257	939.447
Annual precipitation (mm)	8.17E-09	7466.846	3114.119	2359.675
Average annual buffer deforestation (ha)	4.40E-09	297	297.722	296.405
Average cumulative buffer deforestation (ha)	4.40E-09	1755.308	2090.06	2126.976

^{*}Based on three control areas.

Table A17. Covariate balance for Project 1400 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	7.80E-09	0.97	0.936	0.571
Indigenous land cover (%)	7.80E-09	0.041	0.026	0.145
Protected area cover (%)	7.80E-09	0.5	0.423	0.137
Slope (degree)	7.80E-09	2.812	8.312	8.417
Elevation (m)	7.80E-09	50.619	1241.078	967.214
Mining concession cover (%)	7.80E-09	0	0.056	0.006
Palm oil concession cover (%)	7.80E-09	0.18	0.043	0.044
Travel distance to urban centers (days)	7.80E-09	0.038	0.056	0.032
Average annual deforestation (ha)	0.219686	20.939	19.509	63.069
Average cumulative deforestation (ha)	0.780314	88.433	92.332	407.686
Annual precipitation (mm)	7.80E-09	7152.667	4465.09	2584.668
Average annual buffer deforestation (ha)	7.80E-09	131.5	133.086	131.12
Average cumulative buffer deforestation (ha)	7.80E-09	646.417	693.196	836.637

^{*}Based on two control areas.

Table A18. Covariate balance for Project 1566 from Colombia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	3.04E-09	0.85	0.807	0.512
Indigenous land cover (%)	3.04E-09	0.901	0.498	0.126
Protected area cover (%)	5.60E-06	0	0.009	0.113
Slope (degree)	0.304029	1.076	1.076	6.187
Elevation (m)	4.81E-05	128.519	169.262	813.145
Mining concession cover (%)	0.091708	0.002	0.002	0.001
Travel distance to urban centers (days)	3.04E-09	0.037	0.032	0.021
Average annual deforestation (ha)	5.20E-05	732.768	743.14	2296.36
Average cumulative deforestation (ha)	0.303551	4694.777	4694.767	14677.86
Annual precipitation (mm)	0.300605	2828	2828	2431.834
Average annual buffer deforestation (ha)	7.18E-09	653.75	585.906	662.36
Average cumulative buffer deforestation (ha)	3.04E-09	4758.5	3731.181	4264.713

^{*}Based on six control areas.

Table A19. Covariate balance for Project 934 from the Democratic Republic of Congo.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	2.22E-08	0.89	0.589	0.639
Indigenous land cover (%)	0.835655	0	0	0.091
Protected area cover (%)	8.36E-09	0.787	2.623	2.361
Slope (degree)	8.36E-09	319.012	903.379	713.075
Elevation (m)	3.62E-08	0	0.642	0.441
Mining concession cover (%)	8.36E-09	0.697	0.016	0.25
Logging concession cover (%)	1.28E-08	1	0	0.051
REDD+ jurisdiction or other conservation program(s) cover (%)	3.21E-08	1	0.094	0.184
Travel distance to urban centers (days)	8.36E-09	0.038	0.022	0.024
Average annual deforestation (ha)	4.88E-06	797.509	764.554	360.083
Average cumulative deforestation (ha)	0.16434	3506.279	3506.282	1766.389
Annual precipitation (mm)	7.75E-08	1691.8	1380.623	1501.567
Average annual buffer deforestation (ha)	8.36E-09	294.2	329.185	291.748
Average cumulative buffer deforestation (ha)	8.36E-09	1345.8	1479.023	1429.909

^{*}Based on four control areas.

Table A20. Covariate balance for Project 1359 from the Democratic Republic of Congo.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.00E-08	1	0.981	0.83
Indigenous land cover (%)	7.82E-05	0	0.255	0.013
Protected area cover (%)	1.00E-08	1.522	4.072	2.732
Slope (degree)	0.000153	432.489	631.843	556.565
Elevation (m)	1.00E-08	0.006	0.396	0.575
Mining concession cover (%)	1.00E-08	0	0.133	0.206
Logging concession cover (%)	1.00E-08	1	0	0.095
REDD+ jurisdiction or other conservation program(s) cover (%)	6.64E-05	0.052	0.791	0.297
Travel distance to urban centers (days)	1.00E-08	0.039	0.042	0.034
Average annual deforestation (ha)	1.00E-08	196.545	213.683	1378.81
Average cumulative deforestation (ha)	0.999703	932.066	942.98	5828.416
Annual precipitation (mm)	1.00E-08	1728.75	1727.138	1516.734
Average annual buffer deforestation (ha)	1.00E-08	2367.125	1309.851	1538.826
Average cumulative buffer deforestation (ha)	1.00E-08	11344.88	6596.921	6608.888

^{*}Based on five control areas.

Table A21. Covariate balance for Project 1325 from Tanzania.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	6.20E-09	0.51	0.288	0.256
Protected area cover (%)	0.619576	0.176	0.176	0.317
Slope (degree)	6.20E-09	3.681	1.563	1.675
Elevation (m)	3.10E-07	313.465	556.702	804.17
Mining concession cover (%)	3.32E-07	0.086	0.052	0.03
Travel distance to urban centers (days)	6.20E-09	0.014	0.01	0.011
Average annual deforestation (ha)	1.45E-06	314.2	319.638	431.961
Average cumulative deforestation (ha)	7.88E-05	1689.107	1692.053	2159.901
Annual precipitation (mm)	0.380334	948	948	914.264
Average annual buffer deforestation (ha)	6.20E-06	807	803.937	766.278
Average cumulative buffer deforestation (ha)	2.26E-06	4272.727	4186.993	3868.108

^{*}Based on six control areas.

Table A22. Covariate balance for Project 1897 from Tanzania.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	0.000103	0.5	0.325	0.258
Slope (degree)	0.589418	5.122	5.117	2.198
Elevation (m)	4.72E-05	1389.528	1319.223	934.263
Mining concession cover (%)	5.89E-09	0.044	0.001	0.016
Travel distance to urban centers (days)	5.89E-09	0.016	0.015	0.012
Average annual deforestation (ha)	5.89E-09	481.319	475.931	706.79
Average cumulative deforestation (ha)	0.377348	2574.946	2588.453	5184.995
Annual precipitation (mm)	0.011534	1101.062	1113.8	903.495
Average annual buffer deforestation (ha)	5.89E-09	751.375	814.131	740.75
Average cumulative buffer deforestation (ha)	0.02155	3662.5	3713.207	5446.848

^{*}Based on four control areas.

Table A23. Covariate balance for Project 1900 from Tanzania.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	0.333299	0.1	0.1	0.156
Protected area cover (%)	0.333299	1	1	0.581
Slope (degree)	3.74E-05	0.804	0.804	2.526
Elevation (m)	3.33E-09	1172.476	1109.468	1068.004
Mining concession cover (%)	3.33E-09	0	0.041	0.028
Travel distance to urban centers (days)	0.333299	0.014	0.014	0.014
Average annual deforestation (ha)	3.33E-09	0.441	0.778	26.448
Average cumulative deforestation (ha)	6.65E-05	4.327	5.061	241.384
Annual precipitation (mm)	3.33E-09	551.562	581.125	779.517
Average annual buffer deforestation (ha)	3.33E-09	23.188	22.812	22.856
Average cumulative buffer deforestation (ha)	3.33E-09	147.75	107.062	196.002

^{*}Based on one control area.

Table A24. Covariate balance for Project 1202 from Zambia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	0.002879	0.24	0.24	0.254
Protected area cover (%)	7.83E-09	0.128	0.87	0.286
Slope (degree)	3.39E-05	4.378	2.122	1.276
Elevation (m)	7.83E-09	1093.45	925.286	1179.245
Travel distance to urban centers (days)	7.83E-09	0.015	0.015	0.013
Average annual deforestation (ha)	0.050949	4.716	4.716	40.79
Average cumulative deforestation (ha)	0.162489	26.411	26.351	152.984
Annual precipitation (mm)	0.783331	859.875	859.875	1070.829
Average annual buffer deforestation (ha)	0.000318	109.875	98.997	109.381
Average cumulative buffer deforestation (ha)	7.83E-09	530.375	328.277	398.26

^{*}Based on six control areas.

Table A25. Covariate balance for Project 1775-1 from Zambia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	1.00E-08	0.24	0.13	0.223
Protected area cover (%)	1.00E-08	0.963	1	0.451
Slope (degree)	1.00E-08	4.627	0.644	1.222
Elevation (m)	1.00E-08	659.448	1060.101	1086.366
Travel distance to urban centers (days)	1.00E-08	0.015	0.014	0.014
Average annual deforestation (ha)	1.00E-08	55.69	82.145	544.52
Average cumulative deforestation (ha)	1	459.236	587.923	3337.871
Annual precipitation (mm)	1.00E-08	904.143	832.214	991.243
Average annual buffer deforestation (ha)	1.00E-08	282.929	300.143	283.951
Average cumulative buffer deforestation (ha)	1.00E-08	2214.5	2347.929	1753.376

^{*}Based on one control area.

Table A26. Covariate balance for Project 1775-2 from Zambia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	9.75E-09	0.26	0.592	0.247
Protected area cover (%)	0.017502	0.995	0.975	0.199
Slope (degree)	9.75E-09	2.384	1.153	1.215
Elevation (m)	9.75E-09	697.335	1175.69	1202.202
Travel distance to urban centers (days)	0.974804	0.014	0.014	0.012
Average annual deforestation (ha)	9.75E-09	29.063	21.558	305.833
Average cumulative deforestation (ha)	0.007695	75.096	109.56	1808.967
Annual precipitation (mm)	9.75E-09	948.643	1214.721	1109.714
Average annual buffer deforestation (ha)	9.75E-09	331.786	299.896	333.088
Average cumulative buffer deforestation (ha)	9.75E-09	2034.071	2073.964	1936.154

^{*}Based on two control areas.

Table A27. Covariate balance for Project 1775-3 from Zambia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	9.99E-09	0.2	0.423	0.198
Slope (degree)	5.76E-07	1.186	1.043	1.095
Elevation (m)	9.99E-09	657.042	1182.804	1001.683
Travel distance to urban centers (days)	9.99E-09	0.013	0.014	0.014
Average annual deforestation (ha)	0.99903	11.275	11.275	106.349
Average cumulative deforestation (ha)	0.000968	59.63	60.052	685.327
Annual precipitation (mm)	9.99E-09	911	1224.422	976.04
Average annual buffer deforestation (ha)	2.04E-08	110.714	117.908	111.107
Average cumulative buffer deforestation (ha)	1.32E-06	678.714	672.593	706.651

^{*}Based on four control areas.

Table A28. Covariate balance for Project 904 from Cambodia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	0.000498	0.42	0.477	0.399
Protected area cover (%)	0.157606	0.443	0.442	0.169
Slope (degree)	8.35E-09	0.869	2.147	1.477
Elevation (m)	8.35E-09	69.484	106.046	96.806
Mining concession cover (%)	0.00411	0.153	0.116	0.125
Soil fertility level	8.35E-09	1.75	1.888	2.157
Other economic concessions cover (%)	0.002572	0.025	0.127	0.119
Travel distance to urban centers (days)	0.000616	0.012	0.017	0.005
Average annual deforestation (ha)	8.35E-09	147.463	152.14	1163.323
Average cumulative deforestation (ha)	0.834598	467.113	482.857	4554.692
Annual precipitation (mm)	8.35E-09	1407.286	1844.49	1824.241
Average annual buffer deforestation (ha)	8.35E-09	2541	1755.709	2107.064
Average cumulative buffer deforestation (ha)	8.35E-09	8162.571	6316.207	8230.669

^{*}Based on five control areas.

Table A29. Covariate balance for Project 1650 from Cambodia.

Covariate	V-weights	Project area	Synthetic control*	Control set average
Average tree cover (%)	0.000498	0.73	0.76	0.679
Protected area cover (%)	0.157606	0.97	0.732	0.677
Slope (degree)	8.35E-09	2.566	1.155	2.268
Elevation (m)	8.35E-09	197.462	86	144.59
Mining concession cover (%)	0.00411	0.736	0.208	0.248
Soil fertility level	8.35E-09	1.714	2	2.069
Other economic concessions cover (%)	0.002572	0.005	0.159	0.197
Travel distance to urban centers (days)	0.000616	0.014	0.037	0.024
Average annual deforestation (ha)	8.35E-09	214.199	232.645	1338.094
Average cumulative deforestation (ha)	0.834598	993.492	1135.273	5807.584
Annual precipitation (mm)	8.35E-09	2124.5	1800.2	1850.923
Average annual buffer deforestation (ha)	8.35E-09	3167.3	1343	1687.065
Average cumulative buffer deforestation (ha)	8.35E-09	12213.2	5575.8	7342.892

^{*}Based on one control area.