Forest and Society
Vol. 9(2): 665-683, December 2025
10.24259/fs.v9i2.44699

REGULAR RESEARCH ARTICLE

REDD+ Projects and Their Impact on Household Incomes in Indonesian Borneo

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RECEIVED 2025-06-10
ACCEPTED 2025-08-04

ABSTRACT

In Indonesia, early Reducing Emissions from Deforestation and Forest Degradation (REDD+) projects, established in the early 2010s, were required to self-fund through carbon credit sales or donor aid while supporting local livelihoods. This paper examines the impact of REDD+ projects on both agricultural and overall household incomes (i.e., from all economic activities, including agriculture). We hypothesize that the agricultural incomes of REDD+ participating households (or treated households) would decrease as REDD+ forbids forest clearance, but this loss would be offset by a subsequent rise in overall household income as REDD+ encourages income diversification. Additionally, we assess whether REDD+ implementation has an intra-community 'spillover' effect by comparing the incomes of households living in REDD+ villages but abstaining from participation, with those in non-REDD+ (control) villages. We evaluate two such projects in Indonesian Borneo (Kalimantan) using panel survey data from over 400 households, collected in 2010, 2014, and 2018. Our analysis employs panel difference-in-differences in matched samples. Overall, our results reveal a small, heterogeneous impact of REDD+ on household incomes. While we found no significant impact in East Kalimantan's BFCP site, participation in Central Kalimantan's KMP site led to a reduced agricultural income over the short term (2010-2014). However, we detected no improvement in overall household income, nor did we find this impact to be long-lasting. We also found no conclusive evidence of intra-community spillover effects. The short-term income shock observed at the KMP site, despite its small overall magnitude, indicates the need for strategies to support and safeguard household incomes against temporary disruptions associated with REDD+ implementation. Our research contributes to the broader discourse on REDD+ performance, echoing previous findings of its mixed and modest impact on local communities' incomes globally.

KEYWORDS
REDD+; Forest policy; Impact evaluation; Difference-in-differences; Matching; Household income.

1. INTRODUCTION

Tropical forests are important globally for the climate and locally for the wellbeing of their dwellers. By halting all tropical deforestation and sustaining the regrowth of degraded forests, the world could reduce total net greenhouse gas emissions globally by up to 30 percent (Seymour & Busch, 2016). On average, tropical forests also provide almost one-third of the total income of households living in and around these forested areas (Angelsen et al., 2014). Given these facts, it is universally agreed that the Reducing Emissions from Deforestation and Forest Degradation initiatives (REDD+) – an international programme adopted in mid-2000s to discourage human disturbance to tropical forests – must provide livelihood benefits, or at least do no harm, in addition to being effective in mitigating climate change (Duchelle et al., 2018). Early REDD+ projects were required to self-fund through carbon credit sales or donor aid support while striving to combat deforestation and forest degradation, while supporting the livelihoods of local people. To draw a convincing conclusion about REDD+ projects' performance, it is important to prioritize rigorous impact evaluations, enabling the attribution of observed results to interventions by establishing credible counterfactual scenarios depicting what would have occurred without REDD+ initiatives (Sills et al., 2017; Carrilho et al., 2022). Despite the call for such evaluations since the early 2010s (Caplow et al., 2011), rigorous counterfactual evidence to capture REDD+ performance has been relatively scarce (Duchelle et al., 2018), especially in Indonesia.

In this study, we aim to contribute to REDD+ counterfactual assessment literature by assessing the impact of two REDD+ projects in Indonesia on the incomes of participating households. Also, similar to Carrilho et al. (2022), we examine whether REDD+ resulted in an intra-community 'spillover' – whereby REDD+ projects affected the incomes of those living in REDD+ villages (but abstained from actively participating in the initiative) compared with those living in non-REDD+ villages. We look at two types of household incomes. First, we examine the income derived from agricultural activities, encompassing farming (including tree crops), livestock husbandry, and their derivative products. Second, we analyze the overall household income, which encompasses revenue generated from agricultural activities, forest product collection (timber and non-timber), and off-farm endeavours, such as businesses, government aid, and/or pension accounts.[1] In alignment with the REDD+ initiative's core objective of curbing new forest clearances and degradation for agricultural purposes, we hypothesize that participating households may experience a reduction in their agricultural income. But we also anticipate a simultaneous increase in overall household income since REDD+ also aims to provide societal co-benefits and promote alternative livelihoods. Should this scenario materialize, it may indicate that REDD+ can generate supplementary income streams, helping to offset reduced agricultural incomes.

We analyze data from two REDD+ projects located in Central and East Kalimantan provinces. Since REDD+ implementation generally does not allow for randomized assignments to treatment groups, we use a quasi-experimental method to attribute the observed outcomes to the presence of the respective REDD+ project. This approach allows us to establish a causal relationship between an intervention and its expected results. The two REDD+ projects in question were included in the Center for International Forestry Research's Global Comparative Study on REDD+ (GCS REDD+), which conducted a baseline survey in 2010 in both control and treated (or REDD+) villages. This survey was repeated twice – in 2014 and 2018 – using the same core survey instruments and with the same sample households (Sills et al., 2017).

REDD+ impact evaluation of non-carbon and livelihood outcomes is commonly investigated because of the early focus on preventing harm to local communities (Duchelle et al., 2018; Larson et al., 2018). Thus far, most studies have found modest and mixed impacts, whether positive or negative. For example, an earlier study from CIFOR's GCS REDD+ found the positive wellbeing impact was dependent on whether the projects were accompanied by incentive measures, such as payment for environmental services (Duchelle et al., 2017). In the Brazilian Amazon region, the REDD+ project was found to be effective in curbing deforestation and improving local communities' wellbeing, but these positive impacts ceased after the project ended (Carrilho et al., 2022). In other cases, the REDD+ impacts on income and subjective wellbeing were positive but insignificant, partly due to the limited scale and funding of

[1] Income data were collected in Indonesian rupiah and converted to US dollar (2021) purchasing power parity. The conversion factor is available at https://data.worldbank.org/indicator/PA.NUS.PRVT.PP?locations=PE%29-ID-PE-BR&name_desc=false.

the project (Sunderlin et al., 2017). REDD+ effects on local communities' incomes were also found to be insignificant in Uganda (Jayachandran et al., 2017) and in the Peruvian Amazon (Solis et al., 2021). Conversely, REDD+ implementation has posed risks to local wellbeing due to elite capture (Pasgaard, 2015); limited attention to gender in initiatives (Larson et al., 2018); unmet promises and expectations of incentives (Montoya-Zumaeta et al., 2022); and when projects were accompanied by disincentive measures, such as stricter law enforcement (Duchelle et al., 2017) and bans on certain local practices, including swidden agriculture (Ingalls & Dwyer, 2016). In Indonesia, findings from early REDD projects in Kalimantan from 2008 to 2011 show mixed results on some fronts. REDD-associated villages demonstrated significant intensification of the agricultural system, while showing worse welfare outcomes (i.e., more poverty cards issued, less access to free healthcare) compared with non-REDD villages (Jagger & Rana, 2017). However, it was unclear whether these welfare outcomes were predetermined characteristics as forest-rich villages often have high poverty rates. As a result, it is highly relevant to provide an update and new insights on REDD+ impacts in Indonesia as REDD+ projects are starting to mature.

While REDD+ in Indonesia has contributed to measurable reductions in carbon emissions, its socioeconomic outcomes remain unevenly distributed (Gatto & Sadik-Zada, 2024). A well-established body of literature has critically examined REDD+ as a complex environmental governance tool that is shaped by broader political economy dynamics, fragmented institutional arrangements, and unequal power relations and resource distribution. In Indonesia (and beyond), REDD+ implementation has often been challenged by overlapping land tenure claims, unclear and conflicting regulatory frameworks, limited enforcement capacity, and persistent issues of corruption (Sunderlin et al., 2014; Korhonen-Kurki et al., 2016; Brockhaus et al., 2017; Enrici & Hubacek, 2019). Smallholders and indigenous communities — those most affected by REDD+ interventions — have often had limited voice in project design and decision-making processes (Chomba et al., 2016). While efforts have been made to increase non-state actors' capacity and involvement in various REDD-related spaces (Astuti & McGregor, 2015; Tacconi & Muttaqin, 2019), a mixture of the dominance of external donor priorities, high level of bureaucracy, (re)centralization of forest and REDD+ governance, and the focus on technical aspects of REDD+ implementation often act as barriers to grassroot participation or even exclusionary practices (Astuti & McGregor, 2017; Fatem et al., 2018; Moeliono et al., 2020). Further adding to these challenges is the lack of clarity around benefit-sharing mechanisms and slow or unmet delivery of promised incentives (Sunderlin et al., 2014; Massarella et al., 2018). These constraints have contributed to growing skepticism and stakeholder fatigue, particularly among local communities who have not seen tangible improvements in their livelihoods despite years of involvement in REDD+ processes (Enrici & Hubacek, 2018).The remainder of this paper is structured as follows: Section 2 outlines the quasi-experimental approach we use to build reliable counterfactuals to evaluate the impact of REDD+ on household incomes. Section 3 describes the study sites, including the various types of activities implemented in the two REDD+ projects. We then present the estimation results in the fourth section. The final two sections discuss potential explanations for our results and provide conclusions.

2. METHODOLOGY

To assess the causal impact of REDD+ projects on household incomes, it is necessary to estimate how participation in REDD+ activities affects household income relative to what would have occurred had these same households not participated. This counterfactual scenario is fundamentally unobservable, as it is impossible to observe the same household both participating and not participating at the same time. To address this limitation, we adopt a research design that combines difference-in-differences (DID) with matching methods (Chervier & Costedoat, 2017; Simonet et al., 2019; Solis et al., 2021; Carrilho et al., 2022).

The DID approach estimates program impact by comparing changes in outcomes over time between treated and control groups (Abadie, 2005). It measures the difference in outcomes before and after the intervention for both groups and then subtracts these differences to isolate the program's effect. This method accounts for pre-existing differences between treated and control groups, provided these differences remain constant over time. Crucially, DID relies on the parallel trend's assumption: in the absence of treatment, outcomes for treated and control groups would have followed similar trajectories over time (Abadie, 2005; Bertrand et al., 2004). If treated and control households differ significantly in pre-treatment characteristics that influence outcomes, this assumption may not hold. In such cases, outcome trajectories could diverge even without the intervention, biasing the estimated treatment effect.

We implement DID on a matched sample, ensuring balance in pre-treatment characteristics between treated and control units. Matching involves identifying one or more control "twins" (i.e., non-participating households with similar characteristics known to affect both the outcome and the likelihood of treatment) for each treated household (Ho et al., 2007). By constructing a control group that mirrors the treated group in these observable variables, matching increases the plausibility that, in the absence of treatment, both groups would have experienced similar outcome trends. As stated earlier, we use the GCS-REDD+ database created by CIFOR as our main data source. For each project, households were randomly sampled within four control villages and four treated villages selected through a matching process described in Sills et al. (2017). For this specific study, our **control group** comprises randomly selected households who live in control villages and never participated in REDD+ activities and were surveyed during the three phases (n = 118/year in KMP, and n = 102/year in BFCP). To estimate the impact of REDD+, we compare the control households with our main **treatment group,** meaning households who live in an intervention village, were surveyed during the three phases, and participated in REDD+ activities in 2014 and 2018 (hereafter referred to as Model 1) (n = 19/year in KMP and n = 66/year in BFCP). To assess the intra-community spillover effect, we compare households who live in intervention villages but have never participated in REDD+ (n = 66/year in KMP and n = 8/year in BFCP) with our control group (hereafter referred to as Model 2). However, since we found only eight households that never participated in a BFCP REDD+ project during the entire data collection period, we decided to estimate the intra-community spillover effect only for the KMP site.

We perform matching at the household level using the MatchIt package in R Studio. Matching is conducted separately for each REDD+ project, utilizing control households from project-matched control villages. This procedure is applied for both Model 1 (the main impact estimate) and Model 2 (the spillover analysis). The covariates used are the baseline characteristics (obtained from the baseline survey conducted in 2010) that are likely to influence both participation in REDD+ activities and household incomes. The covariates presented in Table 2 were selected based on existing impact evaluation literature on forest people and their income (e.g., Mcelwee, 2008; Asfaw et al., 2013; Larson et al., 2018; Biland et al., 2021). To assess the performance of the matching procedure, we estimate the standardized mean difference (SMD) between the treated group and the control group for each covariate before and after matching. We consider the matching trustworthy if the absolute value of the SMD is below 0.25 (Stuart, 2010). The best balance for the KMP site was achieved using nearest-neighbor matching (with k = 1) with no replacement, whereas for the BFCP site, it was achieved using nearest-neighbor matching (k = 1) with a caliper width of 0.1.

We then estimate the average treatment effects on the treated (ATT) of our two target REDD+ projects using the following regression:

$$\mathrm{HHinc}_{it} = \beta_0 + \beta_1 \mathrm{HHchars}_{it} + \beta_3 \mathrm{Z}_{it} + \beta_4 \mathrm{year}_t + \beta_5 \mathrm{TREAT} \cdot \mathrm{year}_t + \varepsilon \qquad (1)$$

Where HHinc_{it} represents the income of household i at year t. HHchars refers to household characteristics listed in Table 2 that may influence income changes, while Z refers to time-varying covariates, namely the size of area used for agriculture where household i lives, and the household size. The ATT is represented by the coefficient of interaction terms between the treatment dummy and year, β_5. The standard errors are clustered at village level to account for potential heteroskedasticity within villages.

To provide a more nuanced understanding of both short- and long-term impacts, we conducted separate panel regressions for the periods 2010–2014 and 2010–2018 for each REDD+ project.

To assess the robustness of our results, we run alternative matching specifications and estimate our DID regression using the new groups of matched households. Specifically, we carry out optimal pair matching for the KMP site, and nearest-neighbor matching (k = 1) with a caliper width of 0.3 for the BFCP site. To avoid confusion, these robustness check models are hereafter referred to as Model 3 (robustness check for the main impact estimate) and Model 4 (robustness check for the spillover analysis), respectively.

Table 2. List of covariates used in this study

Variable	Description
Gender	Gender of household head, 0=male, 1=female
Age	Age of household head
Ethnicity	1=HH head belongs to the largest ethnic group in the village, 0=otherwise
TREAT	*Model 1:* 1=HH lives in REDD+ village and participated in REDD+ in 2014 and 2018, 0 = HH lives in control villages *Model 2:* 1= HH lives in REDD+ village but did not participate in REDD+, 0 = HH lives in control villages
Household size	Number of household member(s), including the head
Productivity index	Number of assets (0-4) owned to support work (car, truck, motorcycle, and boat)
Ha of agricultural land	Ha of land used for agriculture purposes
Agricultural income	Annual income (net) from agriculture (incl. livestock and livestock products)
Total household income	Annual income (net) from all sources

Lastly, we calculated the normalized effect size (represented by Cohen's *d*) as an indicator of the magnitude of impact on household incomes arising from participation in the REDD+ activities. While our panel regression analysis provides statistically rigorous causal estimates of REDD+ impact, controlling for confounding factors and unobserved heterogeneity, Cohen's *d* offers a standardized measure of practical significance and comparability. Cohen’s d refers to the standardized difference in means for the outcome variables observed between the treated and control groups (Coe, 2002), mathematically expressed as:

$$Cohen's\ d = \frac{M_1 - M_0}{Pooled\ SD} \qquad (2)$$

where M_1 and M_0 are the respective mean household incomes of treated and control groups, and the pooled SD is the combined standard deviation obtained by averaging the standard deviations of household incomes from both categories. This standardization is crucial for understanding the real-world importance of the effect and for comparing our findings to those of other studies that might use different income metrics or contexts. According to Sawilowsky (2009), Cohen's d coefficients range from 0.01 (very small), 0.2 (small), 0.5 (medium), 0.8 (large), to beyond 2.0 (huge).

3. CASE STUDIES

There are two REDD+ projects located in Indonesian Borneo to be evaluated in this study. The first is the Katingan-Mentaya project (KMP) in Central Kalimantan. KMP is among the largest and most commercially successful REDD+ projects in the world, managed by a private company named PT Rimba Makmur Utama. The Bogor and Sampit-based company aim to restore peat swamp forest, avoid deforestation, and promote entrepreneurialism and rural development. KMP is situated on the western side of Sebangau National Park, situated between the Mentaya and Katingan Rivers. PT Rimba Makmur Utama operates under an ecosystem restoration concession (ERC) granted in 2013 and 2016, which was updated in 2021 with a multi-business forest ecosystem restoration license covering 108,225 ha of forest and peat swamp forest.[2] It has been registered with Verra's Climate, Community & Biodiversity (CCB) Standards and Verified Carbon Standard (VCS) since 2016. Since 2017, the project has raised revenue mainly from carbon offset trading in voluntary markets. However, it does not provide direct, conditional payment as a form of benefit sharing to communities in its concession area. Instead, the revenue raised was shared with the community through various activities and programmes, some of which include peatland rewetting and water management; reforestation and enrichment planting; forest fire prevention and control; and local livelihood development (e.g., sustainable aquaculture and fisheries, non-timber forest products [NTFPs], agroforestry, and providing access to microfinance). Most villages and households in the surveyed area are located close to the project's boundaries, where most people make ends meet through agriculture as well as the collection of timber and NTFPs (Indriatmoko et al., 2014). According to the village focus group data results, the primary NTFP collected in the KMP area is rattan, while the main agricultural crops are coconut and rice.

The presence of KMP in the region has faced competition from interests in other land uses, such as neighboring oil palm plantations, and was marked by initial challenges in gaining trust and securing agreements from adjacent villages. This struggle stemmed from concerns that the project would restrict access to forest resources, akin to the experience with national parks. To address this, KMP has since established formal agreements that allow villagers to access forest resources. Nevertheless, encouraging a shift toward a more sustainable livelihoods beyond logging and gold mining has proven difficult, given the limited available alternatives (see Sanders et al., 2019; Afiff, 2015).

The second REDD+ project evaluated in this study is the Berau Forest Carbon Program (BFCP), located in the Berau District of East Kalimantan (Figure 2). The BFCP was kickstarted by the Nature Conservancy (TNC, now Yayasan Konservasi Alam Nusantara/YKAN) with the Government of Berau District. This project was considered

[2] See Environment and Forestry Ministerial Decree - PBPH-RE No. SK. 1182/MENLHK/SETJEN/HPL.0/11/2021.

the first jurisdictional REDD+ initiative in Indonesia, but they operated without a promise of result-based payments. Instead, as a REDD+ pilot district, BFCP was supported by aid funding from donor countries, organizations, and/or individuals. The overarching goal of the BFCP is to support the sustainable management of forests in Berau District, to prevent deforestation, and to enhance the economic conditions of communities living in and around the forests. Some of BFCP's focus areas include capacity building at institutional level; facilitating the transition to sustainable practices, such as reduced-impact logging; and the development of conservation-centric village development planning (Anandi et al., 2014). Just like KMP, the BFCP implementer does not provide conditional payments as a form of benefit sharing to individuals or households. Instead, it sets up additional funding of at least USD 20,000 per village with several conditions, such as limiting swidden agriculture (in areas that have been fallowed) to a maximum of 1 ha per household per year (ibid). The implementation of this conditional funding started in 2013 at two intervention villages (ibid), while the full implementation of BFCP started in 2016 (Yuniarti et al., 2019). According to village focus group data, most local people earn a living from agriculture, or as labourers in mining and timber concessions. BFCP focused on major agricultural crops, such as rice and vegetables; livestock (pigs and chickens); and NTFPs (honey and rubber).

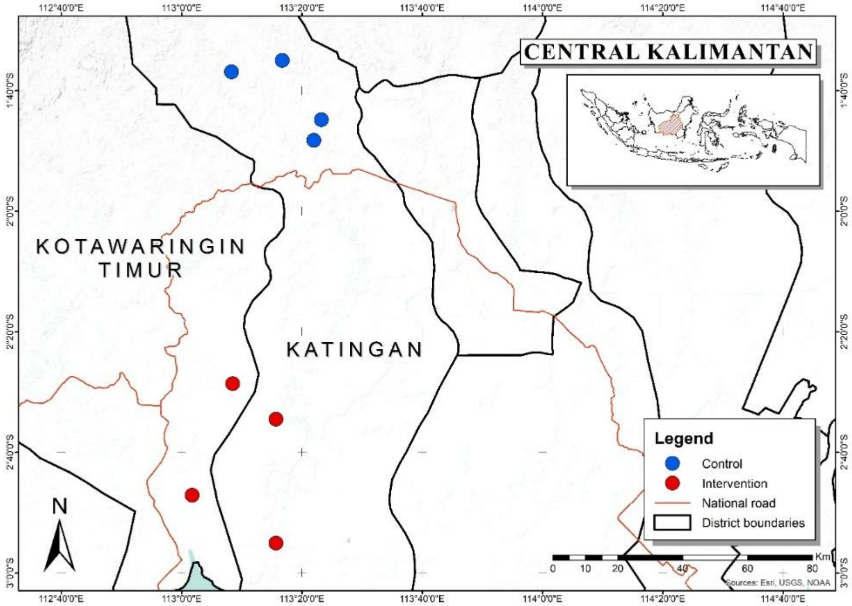

Figure 1. Map of KMP site, Central Kalimantan

Achieving avoided deforestation and livelihood benefits can be more challenging in jurisdictional-level programs like the BFCP than in site-specific projects such as the KMP. This difficulty arises from the greater heterogeneity within districts, where land tenure arrangements and local governance capacities may vary significantly. This has been documented, for instance, in Merabu Village Forest (a social forestry initiative) that demonstrated greater potential for carbon sequestration and leakage control than the Berau Barat Forest Management Unit (FMU) (Rochmayanto et al., 2019). These advantages are attributed to key structural features of social forestry: smaller management units (8,245 ha vs. the FMU's 786,021 ha), which are easier to oversee and monitor; the transfer of managerial authority to the smallest unit of administrative governance (the village); and increased community participation driven by empowered local user groups (ibid). Moreover, differing land use priorities across locations have also contributed to undermining BFCP objectives. For example, at the early time of BFCP, the district head (bupati) had already issued licenses for oil palm development in the northernmost part of Berau (an area with high forest cover). Additionally, the prospect of mining has motivated communities both within and around REDD+ villages to engage in land clearing (Anandi et al., 2014).

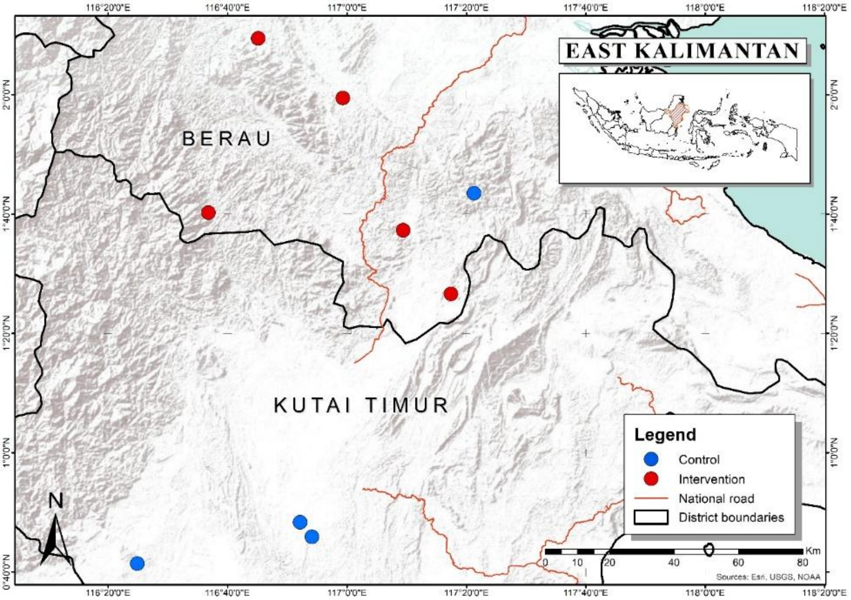

Figure 2. Map of BFCP site, East Kalimantan

Despite providing no direct cash payments to local communities for emission reductions, both KMP and BFCP – like other REDD+ projects across the tropics – are expected to yield a positive impact on local incomes through various indirect pathways (Sunderlin et al., 2024). These include activities aimed at enhancing access to markets and improving livelihood opportunities (Groom & Palmer, 2012; Resosudarmo et al., 2012; Ken et al., 2020). However, avoided deforestation and restoration activities associated with REDD+ projects remain unfavorable to local communities as they do not provide direct and relatively immediate benefits comparable to those from timber or oil palm plantations (Lamb et al., 2005). These REDD+ activities must compete with the tangible economic advantages offered by these commercial land uses.

Findings from village-level focus group data (Table 1) revealed that such activities fall under the "non-conditional livelihood enhancement", "environmental education", and "forest enhancement" categories. Examples of more activities under these categories were various training programmes; NTFP business development assistance; fire management; forest patrol; and the establishment of community-led plantations and seedling nurseries. In contrast, the activities categorized as "restrictions on forest access and/or conversion" and "tenure clarification" (such as social forestry and ERC boundary clarification) may have an adverse impact on incomes in local communities. This is primarily because these activities curtail swidden agriculture and prevent new forest clearing through burning, thereby limiting income sources that were once widely available to the local communities.

Table 2. Typology of activities conducted in both REDD+ and control villages, 2010–2018

Site	Type of activity	Intervention (REDD+ village)		Control village
		# of activities	Part of REDD+ strategy	# of activities
KMP	Environmental education	8	yes	-
	Forest cover enhancement	10	yes (4 no)	2
	Non-conditional livelihood enhancement	26	yes (9 no)	13
	Restrictions on forest access and/or conversion	12	yes	4
	Tenure clarification	4	yes	2
	Total	60		21
BFCP	Environmental education	17	yes (2 no)	2
	Forest cover enhancement	18	yes (2 no)	6
	Non-conditional livelihood enhancement	41	yes (5 no)	5
	Restrictions on forest access and/or conversion	26	yes (7 no)	5
	Tenure clarification	4	yes	5
	Total	106		23

[Source: GCS REDD+ village focus group data]

4. RESULTS

4.1 Post-matching sample balance

For *Model 1* (treated versus control groups), we obtained 38 matched households in the KMP site (19 in each treated and control group) and 92 matched households in the BFCP site (46 in each treated and control group). For *Model 2* (non-participant versus control groups), the matching resulted in a total of 188 matched households in the KMP site (94 in each treated and control group) and 76 matched households in the BFCP site (38 in each treated and control group). Table 3 shows that households in the comparison groups for *Models 1* and *2* initially differed statistically in terms of household heads' age; ethnicity; household size; size of agricultural area; productivity index (number of work-related assets, like cars, trucks, motorcycles, and boats); and agricultural income. However, the matching process successfully balanced these characteristics, resulting in SMDs below the conventional 25 percent threshold (Stuart, 2010).

Table 3. Summary statistics before and after matching (2010 data) – main matching specifications

Variable	Pre-matching mean comparison			Post-matching mean comparison		
Model 1 (treated vs. control groups)	Treated *n* KMP = 19 *n* BFCP = 66	Control *n* KMP = 118 *n* BFCP = 102	SMD	Treated *n* KMP = 19 *n* BFCP = 46	Control *n* KMP = 19 *n* BFCP = 46	SMD
Gender (household age)	0.00* 0.09†	0.04* 0.03†	-0.23* 0.21†	0.00* 0.02†	0.00* 0.07†	0.00* -0.15†
Age (household head)	41.05* 42.59†	43.78* 48.20†	-0.20* -0.53†	41.05* 43.80†	39.32* 43.48†	0.13* 0.03†
Ethnicity	0.79* 0.74†	0.92* 0.71†	-0.33* 0.08†	0.79* 0.76†	0.79* 0.74†	0.00* 0.05†
Household size	4.89* 4.39†	4.75* 4.91†	0.11* -0.38†	4.89* 4.57†	4.68* 4.52†	0.16* 0.03†
Productivity index	0.95*	1.12*	-0.33*	0.95*	0.95*	0.00*

Variable	Pre-matching mean comparison			Post-matching mean comparison		
	1.29†	1.34†	0.09†	1.24†	1.22†	0.04†
Ha of agricultural land	2.65* 2.41†	2.73* 5.37†	-0.02* -1.32†	2.65* 2.91†	1.99* 3.06†	0.15* -0.07†
Agricultural income	2,255.63* 1,040.10†	1,110.04* 1,777.65†	0.25* -0.36†	2,255.63* 1,335.17†	1,336.11* 1,423.65†	0.14* -0.03†
Total household income	4,709.20* 7,651.50†	5,152.64* 9,233.67†	-0.06* -0.24†	4,709.20* 7,037.50†	3,343.29* 7,584.53†	0.20* -0.08†
Model 2 (non-participant vs. control groups)	Non-participant *n* KMP = 94 *n* BFCP = 43	Control *n* KMP = 118 *n* BFCP = 102	SMD	Non-participant *n* KMP = 94 *n* BFCP = 38	Control *n* KMP = 94 *n* BFCP = 38	SMD
Gender	0.05* 0.07†	0.04* 0.03†	0.05* 0.16†	0.05* 0.03†	0.04* 0.08†	0.05* -0.21†
Age	44.09* 46.93†	43.78* 48.20†	0.02* -0.08†	44.09* 46.50†	43.17* 45.92†	0.07* 0.04†
Ethnicity	0.84* 0.70†	0.92* 0.71†	-0.23* -0.02†	0.84* 0.71†	0.91* 0.61†	-0.20* 0.23†
Household size	4.59* 4.60†	4.75* 4.91†	-0.10* -0.15†	4.59* 4.84†	4.68* 4.76†	-0.05* 0.04†
Productivity index	0.95* 1.09†	1.12* 1.34†	-0.25* -0.33†	0.95* 1.13†	1.04* 1.13†	-0.14* 0.00†
Ha of agricultural land	1.65* 2.70†	2.72* 5.37†	-0.46* -1.10†	1.65* 2.95†	1.74* 2.90†	-0.04* 0.02†
Agricultural income	633.98* 1,782.63†	1,110.04* 1,777.64†	-0.24* 0.00†	633.98* 1,569.93†	713.48* 1,516.86†	-0.04* 0.02†
Total household income	4,425.24* 7,627.22†	5,152.64* 9,233.66†	0.10* -0.17†	4,425.24* 7,774.45†	4,467.23* 8,148.51†	0.01* -0.04†

Notes: *KMP, †BFCP; SMD = Standardized Mean Difference; the numbers in red indicate SMDs above the 0.25 threshold.

The results from the robustness check using different matching specifications (*Models 3* and *4*) also suggest that we have constructed comparable counterfactuals (see Appendix A). For *Model 3*, we obtained 38 matched households in the KMP site (19 in each treated and control group) and 106 matched households in the BFCP site (53 in each treated and control group). For *Model 4* (only for the KMP site), the matching resulted in 132 matched households in the KMP site (66 in each treated and control group). In the case of the KMP site, it is important to note that even though the sample sizes (*n*) between *Models 1* and *3* (and subsequently between *Models 2* and *4*) are the same, the means and SMDs obtained for each variable were different. This indicates that the matching procedures resulted in different households being included in the comparison groups.

4.2 Model 1: How did the REDD+ projects affect the income of participating households?

Our analysis of *Model 1*, which examines the direct impact of REDD+ participation on household income, reveals heterogeneous outcomes across the project sites.

For the KMP site in Central Kalimantan, our panel difference-in-differences (DID) regression (Table 4) indicates a statistically significant short-term reduction in agricultural income for participating households between 2010 and 2014. Specifically, households participating in REDD+ in KMP experienced an average annual income that was USD PPP 2021 4,152.45 lower than what it would have been had they followed the same trend as the control group. This finding is robust across model specifications. However, while statistically significant, the Cohen's *d* value for this short-term agricultural income reduction is -0.18 (Table 5). According to Sawilowsky's (2009) guidelines, this suggests a 'small' practical effect size, meaning that while the average monetary reduction is notable, its impact relative to the typical variability in agricultural income within the population is modest. Crucially, we observe no sustained long-term impact on agricultural income through 2018. Furthermore, the effect of REDD+ participation on total household income at KMP is statistically insignificant in both the short-term and long-term. The corresponding Cohen's *d* values of -0.07 (short-term) and 0.23 (long-term) for total household income further underscore the lack of a substantial practical effect, with the long-term even showing a small positive, but statistically insignificant, effect in monetary terms.

In contrast, for the BFCP site in East Kalimantan, we found no statistically significant effect of REDD+ participation on either agricultural or total household income across both short-term (2010-2014) and long-term (2010-2018) timeframes (Table 4). For agricultural income, the observed changes were small, and for total household income, the changes were also statistically non-significant. This absence of statistical significance is further corroborated by the consistently 'very small' Cohen's *d* values for BFCP (Table 5), ranging from -0.01 to 0.02 for agricultural income, and from -0.21 to 0.02 for total household income. These minuscule Cohen's *d* values reinforce that, irrespective of statistical significance, the practical magnitude of any observed difference in income between treated and control groups at BFCP is negligible in monetary terms. These results collectively suggest a heterogeneity in project outcomes across the two REDD+ sites, with the KMP project showing a localized, small, and temporary negative impact on annual agricultural income in USD PPP 2021, while BFCP demonstrates no discernable direct income effects.

Table 4. Panel "difference in differences" (DID) result for Model 1: Treated versus control group

Site Province	**Matching specification**	**Agricultural income** Short-term (2010–14) *TREAT*· 2014	Long-term (2010–18) *TREAT*· 2018	**Total HH income** Short-term (2010–14) *TREAT*· 2014	Long-term (2010–18) *TREAT*· 2018
KMP Central Kalimantan	Main (Model 1)	-4,152.45** (1,947.11)	-1,710.62 (1,804.72)	-2,821.04 (2,268.16)	1,805.71 (3,584.42)
	Robustness check (Model 3)	-4,171.44** (2,002.76)	-1,923.70 (1,850.33)	-2,742.74 (2,256.25)	-4,052.24 (6,493.41)
BFCP East Kalimantan	Main (Model 1)	-380.68 (765.00)	1,078.08 (1,400.22)	-2,573.64 (2,298.58)	3,044.5 (2,321.24)
	Robustness check (Model 3)	-623.68 (730.35)	650.27 (1258.70)	-2,195.85 (2,586.81)	1,291.69 (2,221.16)

Notes: Standard errors are clustered at village level (in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Normalized effect sizes (Cohen's d) of the outcome variables (Model 1: Treated versus control group)

Site	Variable	Period	Cohens' d	Mean treated	Mean control
KMP	Agricultural income	Short-term (2010–14)	-0.18	1,373.34 (4,654.15)	2,243.30 (4,835.27)
		Long-term (2010–18)	-0.02	1,292.50 (4,683.30)	1,385.91 (3,624.39)
	Total HH income	Short-term (2010–14)	-0.07	4,522.77 (5,073.34)	4,927.38 (5,225.32)

Site	Variable	Period	Cohens' d	Mean treated	Mean control
		Long-term (2010–18)	0.23	7,141.70 (8,037.14)	5,333.89 (7,608.57)
BFCP	Agricultural income	Short-term (2010–14)	-0.01	1,545.71 (2,487.67)	1,565.50 (3,232.95)
		Long-term (2010–18)	0.02	2,281.40 (4,822.17)	2,174.74 (4,193.39)
	Total HH income	Short-term (2010–14)	-0.21	8,388.61 (7,284.61)	10,122.64 (8,966.26)
		Long-term (2010–18)	0.02	9,835.09 (8,057.37)	9,644.36 (8,381.18)

Notes: Standard errors are in parentheses.

4.3 Model 2: What about the intra-community spillover effect at KMP site?

We found no conclusive evidence of an intra-community spillover effect of REDD+ on either agricultural or total household income for non-participating households (Table 6). The DID coefficients for both agricultural and total household income were statistically insignificant across both the short-term (2010-2014) and long-term (2010-2018) periods. These findings indicate that the REDD+ project did not lead to a measurable income effect, either positive or negative, for those living within the project communities but not directly participating. Our finding aligns with previous research by Carrilho et al. (2022) and Simonet et al. (2019), who similarly found no evidence of intra-community spillover resulting from the Transamazon REDD project implementation, suggesting that these monetary benefits (or disbenefits) may not extend beyond direct participants.

Table 6. Panel DID result for model 2: non-participant vs. control group

Site Province	Matching specification	Agricultural income		Total HH income	
		Short-term (2010-14)	Long-term (2010-18)	Short-term (2010-14)	Long-term (2010-18)
		TREAT· 2014	*TREAT*· 2018	*TREAT*· 2014	*TREAT*· 2018
KMP Central Kalimantan	Main (model 2)	-306.10 (657.33)	328.26 (635.61)	-169.01 (1,547.21)	-1,402.23 (2,590.51)
	Robustness check (model 4)	-269.11 (662.88)	309.42 (646.69)	234.57 (1,491.87)	-880.95 (2,621.66)

Notes: Standard errors are clustered at village level (in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. DISCUSSION

Our results only partly corroborate our original hypothesis that REDD+ participation would induce a decrease in agricultural income while increasing total income due to diversified opportunities. Specifically, we found that participation in one of the REDD+ projects (KMP) resulted in a statistically significant short-term reduction in agricultural incomes, with these effects diminishing in the longer run. When considering impact magnitude, we found that participation in REDD+ activities in Indonesia had, at best, only a small practical impact on household incomes. Our study adds to the growing body of evidence regarding the performance of REDD+ projects, aligning with previous findings that suggest REDD+ initiatives have had a mixed and modest impact on the income of local communities (e.g., Duchelle et al., 2017; Sunderlin et al., 2017; Solis et al., 2021; Montoya-Zumaeta et al., 2022).

Our results demonstrated heterogeneity between the two REDD+ projects. Indeed, we did not find any significant impact estimates for the BFCP site. A possible explanation for these contrasting short-term findings may stem from differences in project management, scale, and location. KMP operates as a privately owned REDD+ enterprise on a relatively smaller site scale. BFCP, on the other hand, requires greater multistakeholder collaboration and multipolicy alignment due to its jurisdictional scale. To illustrate this complexity, in its earlier years, BFCP had to compete with the district's new policy on oil palm concessions in areas with good forest cover (Anandi et al., 2014). In contrast, several targeted villages in the KMP site received various kinds of support from NGOs and government due to their proximity to Sebangau National Park (Indriatmoko et al., 2014). While BFCP conducted more REDD+ interventions compared with KMP (Table 1), the differing underlying contexts and locations may have contributed to the diverging outcomes within their respective short-term implementation periods.

While the reduction in agricultural income due to REDD+ participation in KMP was temporary rather than permanent, we are careful not to interpret this as a sign of positive development without observing a significant positive impact on overall household income. Rather, this observation prompts further inquiry into the underlying factors shaping the economic outcomes of such projects. One plausible explanation for this phenomenon could be the absence of results-based payments (RBPs) or conditional payments to participating households, akin to the Payment for Environmental Services (PES) schemes implemented in projects like the Brazilian Transamazon REDD+ initiative (Simonet et al., 2019; Carrilho et al., 2022). Perhaps the primary orientation of KMP and BFCP towards a multitude of interventions (Table 1), instead of a conditional reward directly linked to the sale of forest carbon credits (Sunderlin et al., 2024), was insufficient to induce positive and significant changes to overall household incomes in the long run.

Conditional payments have been conceptualized as a core component of REDD+ since its inception, aimed at incentivizing forest conservation practices. Yet, we are aware of the challenges associated with establishing conditional payments. Projects often struggle to secure long-term funding due to the uncertain global REDD+ funding mechanism (Rakatama et al., 2018). In theory, projects must offer a conditional payment that is at least equal to the opportunity costs households face when forgoing activities that lead to deforestation and land degradation (Liu et al., 2020). However, achieving this is difficult with uncertain long-term funding. Moreover, conditional payments like PES schemes work optimally with clearly defined individual property rights, which are often lacking in rural Indonesian settings. Concerns also arise among local communities in other REDD+ project areas in Indonesia regarding the potential usurpation of their land rights by more powerful interests if REDD+ becomes financially profitable (Miles, 2021). Our findings underscore the necessity for strategies that support and safeguard overall household incomes against short-term shocks while ensuring long-term income improvement through REDD+ implementation. It is essential to develop mechanisms that can mitigate adverse economic impacts on participating households, ensuring that they do not suffer significant financial losses while transitioning to sustainable practices. In the absence of conditional payments or RBPs, we risk putting participating households in the same risky situations all over again.

Furthermore, since we did not find evidence of an intra-community spillover effect from REDD+ implementation in KMP, we cannot fully conclude that the short-term impact on agricultural income indicated a behavioral change across the entire KMP site.

As the incomes of only those directly participating were affected, the significant reduction in agricultural income may simply result from participants forgoing agricultural activity to directly engage with REDD+ initiatives. Future research must evaluate the deforestation reduction outcome of KMP to complement our findings and determine whether the local agriculture-related restrictions enacted at an early stage of the project (including the prohibition of fire-based land clearing or swidden agriculture) genuinely resulted in reduced deforestation.

Our study's validity warrants two cautionary remarks. First, given the varied interventions within the REDD+ initiative – spanning from environmental education and forest cover improvement to non-conditional livelihood enhancement, land use restrictions, and tenure clarification (Table 1) — any extension of findings to other REDD+ locations must account for the specific types and combinations of interventions employed, alongside local contextual factors (Carrilho et al., 2022). Second, we did not address the possible 'contamination' of our control households arising from the variety of similar interventions implemented in control villages (outside of the formal REDD+ scope). One challenge associated with isolating this issue is the lack of data to determine which household participated in which intervention. However, we believe this would not bias our estimation since both control and treated households received similar types of interventions across the study period.

6. CONCLUDING REMARKS

Our study sheds light on the nuanced impact of REDD+ initiatives on household incomes in Indonesia. While our results only partially confirm the hypothesis of an agricultural income reduction through REDD+ participation, they highlight the limited overall impact on household incomes. The heterogeneity in findings between sites strongly suggests that project scale and ownership structures significantly influence outcomes. Our study emphasizes the transient nature of short-term impacts on agricultural income due to project interventions, underscoring the critical need for strategies to support and safeguard overall household incomes from shocks associated with REDD+ implementation.

The absence of results-based or conditional payments, coupled with various implementation challenges — such as securing long-term funding and addressing concerns over land rights — underscores the multifaceted nature of implementing REDD+ initiatives effectively. Our findings contribute to the broader discourse on REDD+ performance, echoing previous research on its mixed and modest impact on local communities' incomes elsewhere in the world.

Author Contributions: SN and CC conceptualized and designed the study. ZA and AMM cleaned and curated the data. SN and ZA performed the data analysis. All authors contributed to writing, revision, and approval of the final manuscript.

Competing Interests: The authors declare no conflict of interests.

Acknowledgments: We thank Bimo Dwisatrio for his input on the earlier version of this paper. This research is part of CIFOR's Global Comparative Study on REDD+ (www.cifor-icraf.org/gcs). The funding partners that have supported this research include the Norwegian Agency for Development Cooperation (NORAD, Grant No. QZA-21/0124), the International Climate Initiative (IKI) of the German Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection (BMU, Grant No. 20_III_108), the United States Agency for International Development (USAID, Grant No. MTO 069033), and the CGIAR Research Program on Forests, Trees and Agroforestry (CRP-FTA) with financial support from the CGIAR Fund Donors. Furthermore, S.N. receives UK Research and Innovation (UKRI) grant number EP/X023222/1.

APPENDIX

Summary statistics before and after matching (2010 data) – for robustness check (Models 3 and 4)

Variable	Pre-matching mean comparison			Post-matching mean comparison		
Model 3 (treated versus control groups)	Treated *n* KMP = 19 *n* BFCP = 66	Control *n* KMP = 118 *n* BFCP = 102	SMD	Treated *n* KMP = 19 *n* BFCP = 53	Control *n* KMP = 19 *n* BFCP = 53	SMD
Gender (household age)	0.00* 0.09†	0.04* 0.02†	-0.22* 0.21†	0.00* 0.05†	0.00* 0.05†	0.00* 0.00†
Age (household head)	41.05* 42.59†	43.77* 48.19†	-0.19* -0.52†	41.05* 43.03†	39.31* 44.07†	0.12* -0.09†
Ethnicity	0.78* 0.74†	0.92* 0.70†	-0.32* 0.08†	0.78* 0.75†	0.78* 0.73†	0.00* 0.04†
Household size	4.89* 4.39†	4.75* 4.91†	0.10* -0.37†	4.89* 4.45†	4.84* 4.52†	0.03* -0.05†
Productivity index	0.94* 1.28†	1.11* 1.34†	-0.32* -0.09†	0.94* 1.26†	0.89* 1.20†	0.10* 0.09†
Ha of agricultural land	2.64* 2.41†	2.72* 5.36†	-0.01* -1.32†	2.64* 2.77†	2.41* 3.06†	0.05* -0.12†
Agricultural income	2,255.63* 1,040.10†	1,110.04* 1,777.65†	0.17* -0.36†	2,255.63* 1,229.78†	1,470.09* 1,494.50†	0.12* -0.12†
Total household income	4,709.20* 7,651.50†	5,152.64* 9,233.67†	-0.06* -0.23†	4,709.20* 7,748.75†	3,699.07* 7,774.93†	0.14* -0.00†
Model 4 (non-participant versus control groups)	Non-participant *n* KMP = 66	Control *n* KMP = 118	SMD	Non-participant *n* KMP = 66	Control *n* KMP = 66	SMD
Gender	0.07*	0.04*	0.12*	0.07*	0.06*	0.05*
Age	44.34*	43.77*	0.04*	44.34*	44.28*	0.00*
Ethnicity	0.83*	0.92*	-0.24*	0.83*	0.89*	-0.16*
Household size	4.51*	4.75*	-0.13*	4.51*	4.69*	-0.10*
Productivity index	0.90*	1.11*	-0.27*	0.90*	0.90*	0.00*
Ha of agricultural land	1.34*	2.72*	-0.65*	1.34*	1.31*	0.01*
Agricultural income	692.16*	1,110.03*	-0.18*	692.16*	1,093.25*	-0.17*
Total household income	4,908.98*	5,152.64*	-0.02*	4,908.98*	5,093.81*	-0.02*

Notes: *KMP, †BFCP; SMD = Standardized Mean Difference; the numbers in red indicate SMD above the 0.25 threshold. Model 4 is performed only for the KMP site.

REFERENCE

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The review of economic studies*, *72*(1), 1-19. http://dx.doi.org/10.1111/0034-6527.00321

Afiff, S. (2015). Learning from green enclosure practice in Indonesia: Katingan REDD+ case study project in Central Kalimantan. International Conference Paper Series No. 67, Chiang May University. Retrieved from https://www.iss.nl/sites/corporate/files/CMCP_67-Afiff.pdf

Anandi, C. A. M., Resosudarmo, I. A. P., Komalasari, M., Ekaputri, A. D., & Itarini, D. Y. (2014). TNC's initiative within the Berau forest carbon Program, east kalimantan, Indonesia. In Sills, E. O., S. Atmadja, C. De Sassi, A. E. Duchelle, D. L. Kweka, & I. A. P. Resosuda (Eds.), *REDD+ on the ground: A case book of subnational initiatives across the globe* (pp. 363-378). Center for International Forestry Research

(CIFOR).

Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., ... & Wunder, S. (2014). Environmental income and rural livelihoods: a global-comparative analysis. *World development*, *64*, S12-S28. https://doi.org/10.1016/j.worlddev.2014.03.006

Asfaw, A., Lemenih, M., Kassa, H., & Ewnetu, Z. (2013). Importance, determinants and gender dimensions of forest income in eastern highlands of Ethiopia: The case of communities around Jelo Afromontane forest. *Forest Policy and Economics*, *28*, 1-7. https://doi.org/10.1016/j.forpol.2013.01.005

Astuti, R., & McGregor, A. (2015). Responding to the green economy: how REDD+ and the One Map Initiative are transforming forest governance in Indonesia. *Third World Quarterly*, *36*(12), 2273-2293. https://doi.org/10.1080/01436597.2015.1082422

Astuti, R., & McGregor, A. (2017). Indigenous land claims or green grabs? Inclusions and exclusions within forest carbon politics in Indonesia. *The Journal of Peasant Studies*, *44*(2), 445-466. https://doi.org/10.1080/03066150.2016.1197908

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?. *The Quarterly journal of economics*, *119*(1), 249-275. https://doi.org/10.1162/003355304772839588

Biland, M., Zeb, A., Ullah, A., & Kaechele, H. (2021). Why do households depend on the forest for income? Analysis of factors influencing households' decision-making behaviors. *Sustainability*, *13*(16), 9419. https://doi.org/10.3390/su13169419

Brockhaus, M., Korhonen-Kurki, K., Sehring, J., Di Gregorio, M., Assembe-Mvondo, S., Babon, A., ... & Zida, M. (2017). REDD+, transformational change and the promise of performance-based payments: a qualitative comparative analysis. *Climate Policy*, *17*(6), 708-730. https://doi.org/10.1080/14693062.2016.1169392

Caplow, S., Jagger, P., Lawlor, K., & Sills, E. (2011). Evaluating land use and livelihood impacts of early forest carbon projects: Lessons for learning about REDD+. *Environmental Science & Policy*, *14*(2), 152-167. https://doi.org/10.1016/j.envsci.2010.10.003

Carrilho, C. D., Demarchi, G., Duchelle, A. E., Wunder, S., & Morsello, C. (2022). Permanence of avoided deforestation in a Transamazon REDD+ project (Pará, Brazil). *Ecological Economics*, *201*, 107568. https://doi.org/10.1016/j.ecolecon.2022.107568

Chervier, C., & Costedoat, S. (2017). Heterogeneous impact of a collective payment for environmental services scheme on reducing deforestation in Cambodia. *World Development*, *98*, 148-159. https://doi.org/10.1016/j.worlddev.2017.04.014

Chomba, S., Kariuki, J., Lund, J. F., & Sinclair, F. (2016). Roots of inequity: How the implementation of REDD+ reinforces past injustices. *Land use policy*, *50*, 202-213. https://doi.org/10.1016/j.landusepol.2015.09.021

Coe, R. (2002). *It's the effect size, stupid: What effect size is and why it is important.* British Educational Research Association Annual Conference, Exeter, United Kingdom. Retrieved from https://cebma.org/wp-content/uploads/Coe-2002.pdf

Duchelle, A. E., de Sassi, C., Jagger, P., Cromberg, M., Larson, A. M., Sunderlin, W. D., ... & Pratama, C. D. (2017). Balancing carrots and sticks in REDD+ implications for social safeguards. *Ecology and Society*, *22*(3). https://doi.org/10.5751/ES-09334-220302

Duchelle, A. E., de Sassi, C., Sills, E. O., & Wunder, S. (2018). People and communities: Well-being impacts of REDD+ on the ground. In Angelsen, A. E., Martius, C., de Sy, V., Duchelle, A. E., Larson, A. M., & Pham, T. T. (Eds)., *Transforming REDD+: Lessons and new directions* (pp. 131–141). CIFOR-ICRAF.

Enrici, A., & Hubacek, K. (2019). A crisis of confidence: stakeholder experiences of REDD+ in Indonesia. *Human ecology*, *47*(1), 39-50. https://doi.org/10.1007/s10745-019-0045-z

Enrici, A. M., & Hubacek, K. (2018). Challenges for REDD+ in Indonesia. *Ecology and Society*, *23*(2). https://doi.org/10.5751/ES-09805-230207

Fatem, S. M., Awang, S. A., Pudyatmoko, S., Sahide, M. A., Pratama, A. A., & Maryudi, A. (2018). Camouflaging economic development agendas with forest conservation narratives: A strategy of lower governments for gaining authority in the re-centralising Indonesia. *Land use policy*, *78*, 699-710. https://doi.org/10.1016/j.landusepol.2018.07.018

Gatto, A., & Sadik-Zada, E. R. (2024). REDD+ in Indonesia: An assessment of the international environmental program. *Environment, Development and Sustainability*, 1-16. https://doi.org/10.1007/s10668-024-05368-w

Groom, B., & Palmer, C. (2012). REDD+ and rural livelihoods. *Biological conservation*, *154*, 42-52. https://doi.org/10.1016/j.biocon.2012.03.002

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis*, *15*(3), 199-236. https://doi.org/10.1093/pan/mp1013

Indriatmoko, Y., Atmadja, S., Utomo, N. A., Ekaputri, A. D., & Komalasari, M. (2014). Katingan Peatland Restoration and Conservation Project, Central Kalimantan, Indonesia. In Sills, E. O., Atmadja, S. S., de Sassi, C., Duchelle, A. E., Kweka, D. L., Resosudarmo, I. A. P., & Sunderlin, W. D. (Eds)., *REDD+ on the ground: A case book of subnational initiatives across the globe*. CIFOR.

Ingalls, M. L., & Dwyer, M. B. (2016). Missing the forest for the trees? Navigating the trade-offs between mitigation and adaptation under REDD. *Climatic Change*, *136*(2), 353-366. https://doi.org/10.1007/s10584-016-1612-6

Jagger, P., & Rana, P. (2017). Using publicly available social and spatial data to evaluate progress on REDD+ social safeguards in Indonesia. *Environmental Science & Policy*, *76*, 59-69. https://doi.org/10.1016/j.envsci.2017.06.006

Jayachandran, S., De Laat, J., Lambin, E. F., Stanton, C. Y., Audy, R., & Thomas, N. E. (2017). Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation. *Science*, *357*(6348), 267-273. https://doi.org/10.1126/science.aan0568

Ken, S., Entani, T., Tsusaka, T. W., & Sasaki, N. (2020). Effect of REDD+ projects on local livelihood assets in Keo Seima and Oddar Meanchey, Cambodia. *Heliyon*, *6*(4), e03802. https://doi.org/10.1016/j.heliyon.2020.e03802

Korhonen-Kurki, K., Brockhaus, M., Bushley, B., Babon, A., Gebara, M. F., Kengoum, F., ... & Maharani, C. (2016). Coordination and cross-sectoral integration in REDD+: experiences from seven countries. *Climate and development*, *8*(5), 458-471. http://dx.doi.org/10.1080/17565529.2015.1050979

Lamb, D., Erskine, P. D., & Parrotta, J. A. (2005). Restoration of degraded tropical forest landscapes. *Science*, *310*(5754), 1628-1632. https://doi.org/10.1126/science.1111773

Larson, A. M., Solis, D., Duchelle, A. E., Atmadja, S., Resosudarmo, I. A. P., Dokken, T., & Komalasari, M. (2018). Gender lessons for climate initiatives: A comparative study of REDD+ impacts on subjective wellbeing. *World Development*, *108*, 86-102. https://doi.org/10.1016/j.worlddev.2018.02.027

Liu, G., Liu, Q., Song, M., Chen, J., Zhang, C., Meng, X., ... & Lu, H. (2020). Costs and carbon sequestration assessment for REDD+ in Indonesia. *Forests*, *11*(7), 770. https://doi.org/10.3390/f11070770

Massarella, K., Sallu, S. M., Ensor, J. E., & Marchant, R. (2018). REDD+, hype, hope and disappointment: The dynamics of expectations in conservation and development pilot projects. *World Development*, *109*, 375-385. https://doi.org/10.1016/j.worlddev.2018.05.006

Mcelwee, P. D. (2008). Forest environmental income in Vietnam: household socioeconomic factors influencing forest use. *Environmental conservation*, *35*(2), 147-159. https://doi.org/10.1017/S0376892908004736

Miles, W. B. (2021). The invisible commodity: Local experiences with forest carbon offsetting in Indonesia. *Environment and Planning E: Nature and Space*, *4*(2), 499-524. https://doi.org/10.1177/2514848620905235

Moeliono, M., Brockhaus, M., Gallemore, C., Dwisatrio, B., Maharani, C. D., Muharrom, E., & Pham, T. T. (2020). REDD+ in Indonesia: A new mode of governance or just another project? *Forest Policy and Economics*, *121*, 102316. https://doi.org/10.1016/j.forpol.2020.102316

Montoya-Zumaeta, J. G., Wunder, S., Rojas, E., & Duchelle, A. E. (2022). Does REDD+ complement law enforcement? Evaluating impacts of an incipient initiative in Madre de Dios, Peru. *Frontiers in Forests and Global Change*, *5*, 870450. https://doi.org/10.3389/ffgc.2022.870450

Pasgaard, M. (2015). Lost in translation? How project actors shape REDD+ policy and outcomes in C ambodia. *Asia Pacific Viewpoint*, *56*(1), 111-127. https://doi.org/10.1111/apv.12082

Rakatama, A., Pandit, R., Iftekhar, S., & Ma, C. (2018). Heterogeneous public preference for REDD+ projects under different forest management regimes. *Land Use Policy*, *78*, 266-277. https://doi.org/10.1016/j.landusepol.2018.07.004

Resosudarmo, I. A. P., Duchelle, A. E., Ekaputri, A. D., & Sunderlin, W. D. (2012). Local hopes and worries about REDD+ projects. In Angelsen, A., Brockhaus, M., Sunderlin, W. D., & Verchot, L. V. (Eds). *Analysing REDD+: Challenges and choices* (pp. 193–208). CIFOR.

Rochmayanto, Y., Nurrochmat, D. R., Nugroho, B., Darusman, D., & Satria, A. (2019). Implementation of REDD+ in the existing forest property rights: lessons from Berau, East Kalimantan Province, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *285*(1), 012007). https://doi.org/10.1088/1755-1315/285/1/012007

Sanders, A. J., Ford, R. M., Mulyani, L., Larson, A. M., Jagau, Y., & Keenan, R. J. (2019). Unrelenting games: Multiple negotiations and landscape transformations in the tropical peatlands of Central Kalimantan, Indonesia. *World Development*, *117*, 196-210. https://doi.org/10.1016/j.worlddev.2019.01.008

Sawilowsky, S. S. (2009). New effect size rules of thumb. *Journal of modern applied statistical methods*, *8*(2), 597–599. https://doi.org/10.22237/jmasm/1257035100

Seymour, F., & Busch, J. (2016). *Why forests? Why now?: The science, economics, and politics of tropical forests and climate change*. Brookings Institution Press.

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. *Global environmental change*, *43*, 148-160. https://doi.org/10.1016/j.gloenvcha.2017.02.002

Simonet, G., Subervie, J., Ezzine-de-Blas, D., Cromberg, M., & Duchelle, A. E. (2019). Effectiveness of a REDD+ project in reducing deforestation in the Brazilian Amazon. *American Journal of Agricultural Economics*, *101*(1), 211-229. https://doi.org/10.1093/ajae/aay028

Solis, D., Cronkleton, P., Sills, E. O., Rodriguez-Ward, D., & Duchelle, A. E. (2021). Evaluating the impact of REDD+ interventions on household forest revenue in Peru. *Frontiers in Forests and Global Change*, *4*, 624724. https://doi.org/10.3389/ffgc.2021.624724

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics*, *25*(1), 1-21- https://doi.org/10.1214/09-STS313

Sunderlin, W. D., Ekaputri, A. D., Sills, E. O., Duchelle, A. E., Kweka, D., Diprose, R., ... & Toniolo, A. (2014). *The challenge of establishing REDD+ on the ground: Insights from 23 subnational initiatives in six countries* (Vol. 104). CIFOR.

Sunderlin, W. D., De Sassi, C., Ekaputri, A. D., Light, M., & Pratama, C. D. (2017). REDD+ contribution to well-being and income is marginal: the perspective of local stakeholders. *Forests*, *8*(4), 125. https://doi.org/10.3390/f8040125

Sunderlin, W. D., Atmadja, S. S., Chervier, C., Komalasari, M., Resosudarmo, I. A. P., & Sills, E. O. (2024). Can REDD+ succeed? Occurrence and influence of various combinations of interventions in subnational initiatives. *Global Environmental Change*, *84*, 102777. https://doi.org/10.1016/j.gloenvcha.2023.102777

Tacconi, L., & Muttaqin, M. Z. (2019). Policy forum: Institutional architecture and activities to reduce emissions from forests in Indonesia. *Forest Policy and Economics*, *108*, 101980. https://doi.org/10.1016/j.forpol.2019.101980

Yuniarti, Y., Tendy, T., Budiman, B., & Prakoso, C. T. (2019). Political Economy of Berau Forest Carbon Program Implementation. *ICONEG 2019: Proceedings of the 1st International Conference on Environmental Governance* (pp. 58-65). http://dx.doi.org/10.4108/eai.25-10-2019.2300489