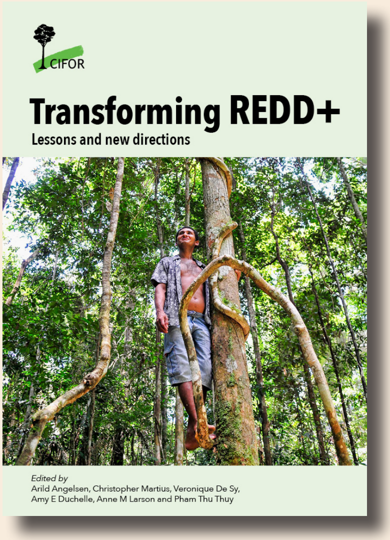
Chapter 10

Forests and carbon

The impacts of local REDD+ initiatives

Gabriela Simonet, Astrid B Bos, Amy E Duchelle, Ida Aju Pradnja Resosudarmo, Julie Subervie and Sven Wunder



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The impacts of local REDD+ initiatives

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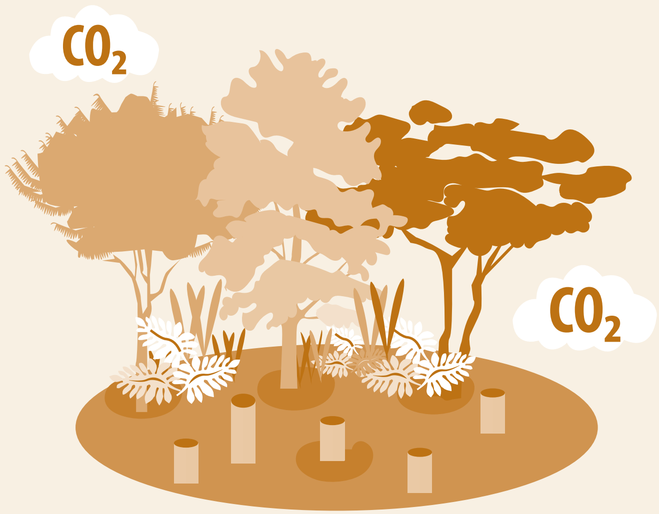
Key messages

- Only a few studies assess the impacts of local REDD+ initiatives on forests, due to the financial, methodological, data and political challenges of implementing rigorous impact evaluations.
- Local REDD+ projects and programmes frequently include a mix of interventions, i.e., incentives, disincentives and enabling measures. Disincentives are used to reduce deforestation, and incentives – either conditional on results or not – are used to help minimise the trade-offs between carbon and well-being outcomes.
- The scarce evidence that is available on local REDD+ outcomes shows modestly encouraging results for forest conservation and carbon stock enhancement. Three projects using conditional incentives showed positive results for forests, through reducing the negative impacts of smallholder agriculture and firewood collection.

REDD+ impact on forests and carbon in a nutshell



Hundreds of local REDD+ initiatives have emerged across the tropics, but few studies have assessed their impact on forests.

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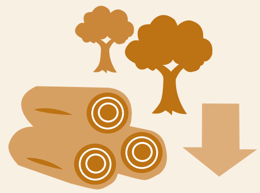
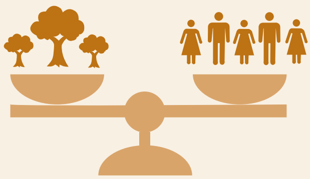


Disincentives are particularly important for reducing deforestation; whereas incentives are used to help minimise the trade-offs between carbon and well-being outcomes.



Conditional and non-conditional livelihood enhancements can help minimise trade-offs between carbon and well-being outcomes.

Existing studies show modestly encouraging results for forest conservation and carbon stocks.

Positive results come from locally adapted solutions that make smallholder agriculture more sustainable and reduce firewood collection. REDD+ projects and programmes with conditional incentives succeeded in reducing deforestation at several sites.

10.1 Introduction

Tropical deforestation and forest degradation play a major role in anthropogenic emissions of CO_2. REDD+ was created to counteract this, and the potential of REDD+ to help mitigate climate change was recognised in the Paris Climate Agreement. REDD+ stands apart from previous conservation instruments because of its results-based approach; financial incentives are tied to demonstrated reductions in deforestation and forest degradation – and, thus, emissions (Chapter 4). Although the UNFCCC initially agreed upon national-level REDD+ implementation, hundreds of local REDD+ projects have emerged across the tropics, of which about a third have already sold carbon credits on the voluntary market (Box 10.1). This is at least a tentative sign that these local initiatives have made some progress. However, although forest monitoring methods have evolved (De Sy *et al.* 2016), there are still surprisingly few rigorous studies on the carbon/land-use performance of REDD+ (Duchelle *et al.* 2018b).

Beyond its slow implementation, this probably reflects a mix of financial, technical and political challenges. First, it is expensive to undertake robust impact evaluations; acquiring the necessary data is costly. Second, results are often highly sensitive to the methods adopted to calculate a counterfactual baseline. Third, although robust evaluations can take time, funders are impatient: independent evaluations can be risky, as disappointing short-term evaluated impacts in a learning phase could jeopardise the future financing of REDD+ projects and programmes.

Box 10.1 REDD+ and its global potential to mitigate climate change

As of May 2018, around 350 REDD+ projects were underway in 53 countries, covering an area over 43 million ha – nearly the size of Morocco (Simonet *et al.* 2018a). Ten key countries currently host more than 10 REDD+ projects each: Brazil (48), Colombia (33), Peru (25), Indonesia (21), Kenya (21), Uganda (18), the Democratic Republic of Congo (17), China (13), India (12) and Mexico (12). However, when we look at the 'density' of REDD+ initiatives, i.e., the amount of forest area under REDD+ in relation to countries' total forest area (Figure 10.1), the leading countries change completely, with Kenya, Guatemala, Cambodia, Madagascar and Peru in the top five.

While their interventions and strategies differ vastly, REDD+ projects share a common objective: to mitigate climate change through reductions in deforestation, forest degradation and/or the enhancement of forest carbon stocks. Together, based on their project design documents, they are expected to avoid the emission of 84 million tCO_2 per year (with a mean lifespan of 33 years) (Simonet *et al.* 2018a) corresponding to around 1% of annual emissions from deforestation, forest degradation, harvesting and peat fires in the tropics (7.4 ± 4 $GtCO_2$ per year, Grace *et al.* 2014).

How much of this potential has been realised so far? Probably less than forecast, as less than 5% of total expected emissions reductions have actually been sold as carbon credits on the voluntary market (Simonet *et al.* 2018a). Slack demand on carbon markets is impeding the sale of sizeable quantities of already-verified emissions, with only a third of REDD+ project implementers having already sold some credits; another third have so far chosen not to generate carbon credits, instead relying on other financing sources.

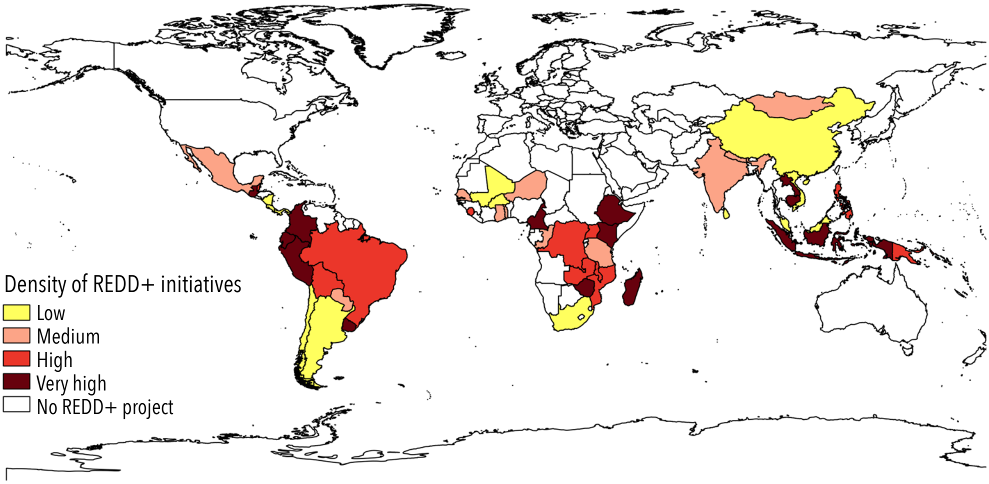


Figure 10.1 Density of REDD+ projects, defined as the area covered by REDD+ projects divided by country's (2015) forest area.

Note: Low density means that between 0.002% and 0.30% of country's forest area is covered by REDD+ projects; Medium ranges between 0.30% and 0.97%; High between 0.97% and 3.31%; and Very high between 3.31% and 66.36%.

Source: Based on Simonet *et al.* (2018a) and FAO data.

This chapter sets out to address two main questions: What methods and data are available to quantify the carbon/land-use outcomes of local REDD+ initiatives and other forest carbon-focused pilot experiments? What do the few early impact evaluation studies conclude?

10.2 Measuring impact on forests

10.2.1 Methods

Since the emergence of REDD+, monitoring of forest-cover change and land-use compliance has seen remarkable advances, even at project level (De Sy *et al.* 2016). However, genuine impact assessment is more complex, as this aims to attribute forest changes to specific interventions. This raises the hypothetical question, how would forests have fared without the intervention? This requires the construction of an explicit counterfactual scenario.

The challenge of constructing appropriate counterfactual scenarios could, in principle, be solved by randomly selecting a treatment group (that will be offered the REDD+ intervention) versus a control group (that will not) before the intervention begins. Although considered the gold standard for impact evaluation, randomised controlled trials (RCTs) like these are challenging to implement for logistical, financial, political and ethical reasons[1] (Athey and Imbens 2017). Randomisation is therefore rarely used for REDD+ and other conservation initiatives, apart from a few recent exceptions (e.g., Jayachandran *et al.* 2017; Jack and Jayachandran 2018; Pynegar *et al.* 2018).

Instead, REDD+ programme evaluation largely relies on observational studies; that is, studies where interventions have not been randomly assigned (Athey and Imbens 2017). These frequently use a before-after/control-intervention (BACI) design, where the sample includes both participating and non-participating individuals, with both groups surveyed at least twice (before and after the programme). 'Matching' control groups with comparable characteristics are chosen, so that any post-treatment difference in performance can be observed. In such cases, causal inference about the impact of a programme is often challenging, because those who are offered the programme may differ from those who are not, even before the programme starts. It is therefore hard to determine whether any difference between the two groups observed at the end of the programme results from the programme itself, or from this initial difference. This selection issue can be resolved using quasi-experimental methods, which include the matching approach and the difference-in-difference (DID) approach, as well as combinations of both (Box 10.2). Researchers have only recently begun to apply such quasi-experimental methods to the REDD+ context (e.g., Börner *et al.* 2013; Bos *et al.* 2017; Duchelle *et al.* 2017; Simonet *et al.* 2018b).

In the absence of comparison group data, some studies look at changes in the outcomes of participants over time, something referred to as the 'before-after' (BA) method or a 'naïve comparison', assuming nothing else changes (Poffenberger 2015; Pandey *et al.* 2016). These methods suffer from some biases when important events or strong trends prevail – i.e., when a 'time trend bias' (e.g., output prices, infrastructure development) drives results more than the intervention in question. Causal assessment is therefore difficult under BA. Combining BA and BACI to assess tree cover change at 23 REDD+ sites, Bos *et al.* (2017) found that the BACI approach indicated marginally better REDD+ performance than BA, especially at the most localised level (village rather than site). As such, BACI and BA tend to lead to different results.

10.2.2 Data

Getting the right data at the right scale is another impediment to assessing REDD+ impacts on forests and carbon stocks. Primary data sources are remote sensing images and carbon stock inventories carried out in the field, which can complement self-reported interview data.

1 Ethical problems arise when creating a group of individuals who will be denied a programme that is clearly beneficial, and who otherwise would have benefitted. This issue has been particularly discussed in medical research. An objection is that, in a situation of limited funding, randomisation can be seen as a fair solution. A potential solution to relieve ethical concern is to apply 'conditional randomisation': first select eligible participants who need the treatment, then randomly assign it within budget (Ravallion 2018).

Box 10.2 Commonly used quasi-experimental estimators

Various econometric methods using observational data have been developed to tackle the issue of selection (i.e., initial differences between treatment and control groups, due to non-random assignment of treatment). See Todd (2007) for an exhaustive and rigorous presentation of observational methods, and Athey and Imbens (2017) for recent developments of this literature. Three of these commonly used econometric methods are presented below:

- **The matching approach**: If we believe that factors creating selection bias are all observable, meaning that we can measure all of these factors using available data, we can use matching estimators to estimate the additional effect of a programme. Matching consists of comparing 'treated' farmers (those who were offered the programme) to observationally similar ones from the control group, i.e., comparing farmers who are as similar as possible.
- **The difference-in-difference (DID) approach**: If we believe that factors creating selection bias are constant over time, we can use the DID approach, which compares the changes in outcomes over time between the treated and the control group. The causal impact is measured by subtracting the pre-programme difference (A - B) from the post-programme difference (C - D) between these two groups (Figure 10.2).
- **The DID-matching approach**: This approach first uses matching to construct a control group that is observationally similar to the treatment group, and then uses DID to estimate a treatment effect. DID-matching combines the advantages of the matching approach and of the DID approach, as it controls for both observable and time-invariant, linear, unobservable, confounding factors. Matching and DID can be combined in at least two ways: (i) matching to pre-process the sample and then performing DID (see Ferraro and Miranda 2017) or (ii) integrating DID into the matching procedure (see Todd 2007).

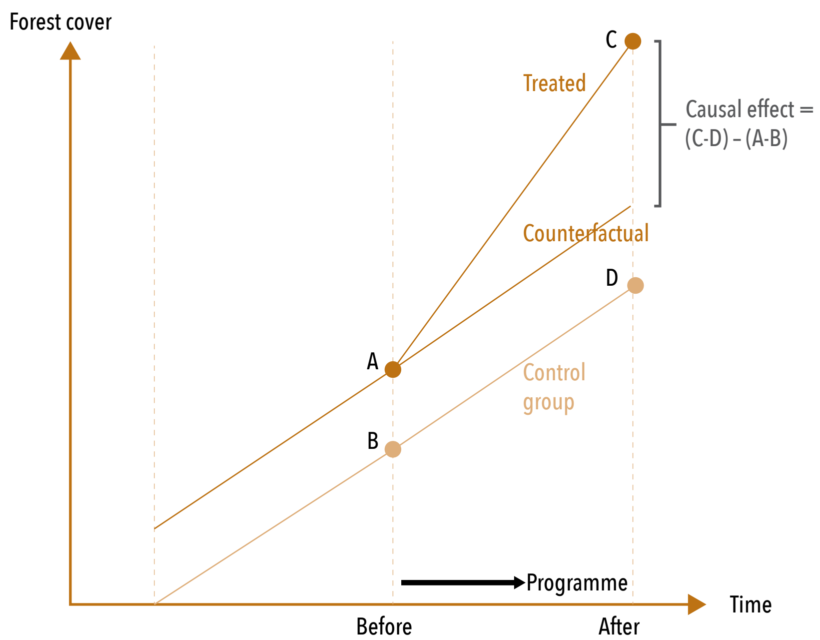


Figure 10.2 Illustration of the difference-in-difference (DID) approach

The plethora of tools and datasets available for forest monitoring through remote sensing can cause confusion among end users about which is correct or best for what purpose (Petersen *et al.* 2018). Beyond quantifying forest area changes, challenges persist in fully assessing the carbon stock contained in different carbon pools within a forest, including soil. When specific information is missing, IPCC emission factors are frequently used. However, these may not be representative of the forest type where interventions take place and come with significant uncertainties, resulting in even larger uncertainties in final carbon emission estimates (Romijn *et al.* 2015).

Self-reported interview data can help to 'ground-truth' remotely observed trends, and overcome some of the technical limitations of remote sensing, notably getting household-level information on land use, completing missing information in cloud-covered areas, tracking reforestation and forest degradation, or distinguishing between tree species. This data can also help to construct adequate theories of change about the causes behind observed land-use changes (Chapter 2). However, the costs associated with fieldwork data collection can be prohibitive, and the accuracy and bias (i.e., if local people fear losing benefits due to honest reporting of forest-clearing activities) of self-reported data can be hard to estimate.

10.3 The impact of local REDD+ initiatives on forests

Just like national REDD+ policies (Chapter 9), local REDD+ projects and programmes often include a mix of enabling measures, disincentives, and both conditional and non-conditional incentives (Table 10.1; Chapter 11).

Enabling measures aim to create the appropriate conditions for local REDD+ initiatives to operate. Such measures include local environmental education, capacity building, and activities aimed at clarifying ownership and access rights over forests, trees and carbon.

Disincentives restrict access to and/or conversion of forests. These can include enforcement of forest protection laws and regulation (e.g., Brazil's Forest Code), forest monitoring (e.g., by communities), or the imposition of fines.

Incentives (cash or non-cash) can be conditional or non-conditional, with the aim of inducing changes in landholders' behaviour, so as to reach REDD+ objectives, compensate them for any loss expected from these changes, direct them to more sustainable production, and/or improve their living conditions. They notably include technical assistance, the distribution of agricultural inputs (e.g., seeds and fertilisers), or the introduction of improved cooking stoves. When incentives are conditional on the protection of forests or the adoption of specific practices (e.g., reforestation or agroforestry), they can be classified as payments for environmental services (PES).

Impact evaluation studies developed so far eclectically combine the methods and data choices presented in Figure 10.3 and Table 10.1.

Table 10.1 Impact of REDD+ projects and programmes on forests

Study	Type of intervention (D=disincentives, I=incentives, E=enabling measures)	Location	Experimental design	Statistical method	Type of data (RS = remote sensing, CSM = carbon stock measurement, RLU = reported land use)	Findings
Börner *et al.* (2013)	D (improved protected area enforcement) and I (individual conditional payments)	Brazil	BACI	DID and DID-matching	RS	Decline of mean annual deforestation is 12% less in treated reserves (2000–2007 vs. 2008–2011).
Bos *et al.* (2017)	Variable mix of D, I and E among 23 initiatives studied	Peru, Brazil, Cameroon, Tanzania, Indonesia, Vietnam	BA and BACI	BA mean comparison and DID	RS	"Overall minimal impact of REDD+ in reducing deforestation on the ground thus far."
Duchelle *et al.* (2017)	Variable mix of D, I and E among 17 initiatives studied	Peru, Brazil, Cameroon, Tanzania, Indonesia, Vietnam	BACI	Mixed effects model	RLU	Higher forest impact for disincentives than for other intervention types.
Jayachandran *et al.* (2017)	D (patrol to reduce outsiders' access to forests) and I (individual conditional payments)	Uganda	RCT	Regression	RS and RLU	5.1% reduction in deforestation after two years of payments (2011–2013).
Pandey *et al.* (2016)	D (harvesting control), I (cooking stove distribution, income generating activity implementation) and E (awareness meetings)	Nepal	BA	BA mean comparison	CSM	Carbon stocks increased by 5.1 tC/ha per year (1.9–8.0) over a three-year period.

Study	Type of intervention (D=disincentives, I=incentives, E=enabling measures)	Location	Experimental design	Statistical method	Type of data (RS = remote sensing, CSM = carbon stock measurement, RLU = reported land use)	Findings
Poffenberger (2015)	D (forest fire control), I (subsidising fuel efficient stoves; promoting pig farming) and E (awareness meetings)	India	BA	BA mean comparison	CSM	Average forest fire area fell from 82.8 ha (2010–12) to 62.3 ha (2013–15); increase in biomass levels.
Resosudarmo *et al.* (unpublished data)	Variable mix of D, I and E among 17 initiatives studied	Peru, Brazil, Cameroon, Tanzania, Indonesia, Vietnam	BACI	Descriptive statistics	RLU	65% of treated households report land-use change; forest enhancement interventions generate the highest changes, followed by disincentives.
Simonet *et al.* (2018b)	D (enforcement of Brazilian Forest Code), I (individual conditional payments) and E (awareness meetings, environmental regularisation, administrative support)	Brazil	BACI	DID and DID-matching	RLU	~50% decrease in the average rate of deforestation in treated farms compared to the counterfactual deforestation rate (2010–2014).

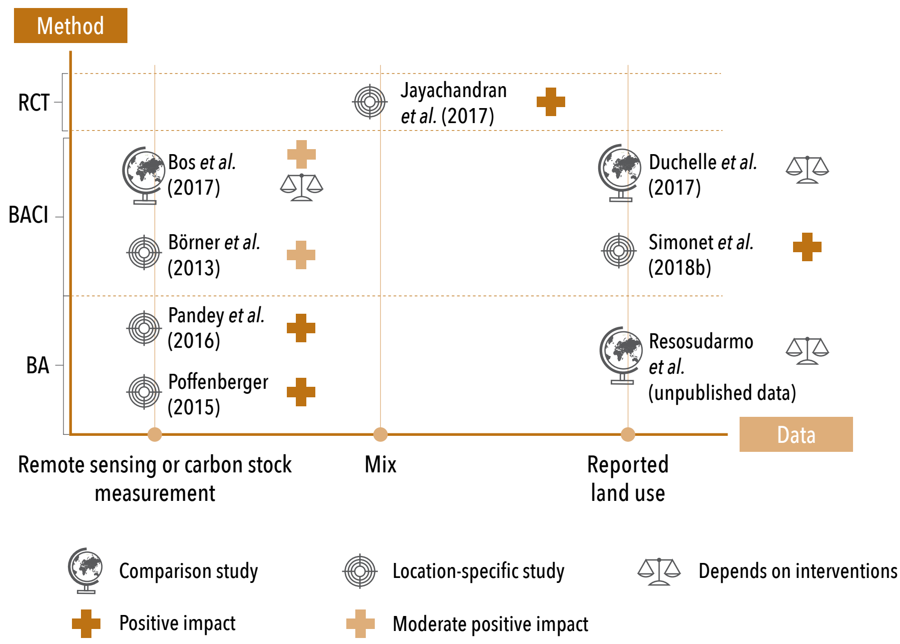


Figure 10.3 Methods and data used in the REDD+ and forest carbon impact literature

References to studies within this chapter mainly derive from Duchelle *et al.* (2018b), a systematic review of English-language peer-reviewed articles from 2015 to 2017 that include an *ex-post* assessment of REDD+ interventions, i.e., assessed after the programme has begun. More recent articles (2018) and those prior to 2015 were included based on the authors' knowledge of REDD+ impact evaluation literature. Here, we present the results of studies comparing interventions, e.g., weighing up the role of disincentives versus incentives in forest clearing. We then discuss the results found in location-specific studies, distinguishing non-conditional incentives from conditional ones. Given the hybrid nature of REDD+ projects and programmes, it is challenging to attribute outcomes to specific interventions.

10.3.1 Comparative studies: Deforestation reductions likely driven by disincentives

In 2010, CIFOR launched its Global Comparative Study on REDD+ (GCS REDD+) that collected BACI data from a pan-tropical sample of households in 23 REDD+ sites across Brazil, Cameroon, Indonesia, Peru, Tanzania and Vietnam. Using Global Forest Change (GFC) data (Hansen *et al.* 2013a) on these 23 sites, Bos *et al.* (2017) used both BA and BACI approaches to assess tree cover change at site and village scale, finding some reduction in tree cover loss at early stages of REDD+ interventions.

Duchelle *et al.* (2017) analysed the effect of different types of interventions on forest clearing, as reported by 4,000 households living over 17 sites. Authors found that households targeted by disincentives significantly reduced their forest clearing compared with those primarily receiving incentives or no intervention at all. Importantly, when applied on their own, disincentives negatively affected local perceptions of tenure security and well-being, however when applied with incentives, negative well-being effects were cushioned.

Drawing on the same global dataset as Duchelle *et al.* (2017), Resosudarmo *et al.* (unpublished data) analysed the perceived effects of different intervention types on land-use behaviour. They found that three-fourths of households at REDD+ sites were subject to at least one intervention designed to protect or restore forests. Among these households, 65% reported changes in agricultural and forestry practices, including reduction or cessation of forest clearing and burning for agriculture, and more sustainable management of timber and non-timber forest products. Disincentives, i.e., interventions restricting forest access and conversion, reportedly spurred these land-use changes in slightly more than half of the sample.

The few global REDD+ studies undertaken so far conclude that overall, moderate positive forest impact has been made, with disincentives seeming to play a major role in this. Bos *et al.* (2017) attribute this relatively low impact to the slow implementation of REDD+ initiatives, and the correspondingly low density of interventions. Likewise, the focus of REDD+ implementers on smallholders fails to address the larger-scale drivers of deforestation. Although disincentives may have better results, it seems crucial to compensate for any negative impacts they may have on smallholders' well-being by combining them with incentives. Studies presented hereafter provide insights into the performance of local REDD+ initiatives that use a diverse range of incentives (always in combination with disincentives and/or enabling measures).

10.3.2 Location-specific studies: Non-conditional incentives may slightly increase carbon stocks

Very little can be said about the capacity of non-conditional incentives to reduce deforestation, due to the absence of robust impact analysis dealing directly with this type of intervention. Using BA carbon pool inventories in a case study report on a REDD+ site in Nepal, Pandey *et al.* (2016) found an average increase of 5.1 tC/ha per year (1.9–8.0) in carbon stocks over a three-year period. The authors mainly attributed this result to the use of improved cooking stoves, which reduced pressure on forests for fuelwood. Using a similar approach, Poffenberger (2015) found that community conservation and reforestation activities in a REDD+ project in India led to an increased biomass, notably due to better fire control, enrichment planting and distribution of cooking stoves.

The two studies analysed projects that adopted a strategy focused on non-conditional incentives, combined with disincentives and enabling measures (Table 10.1). They showed that this type of intervention mix had a positive effect on carbon stocks. This result must be analysed in view of the limitations of the BA approach applied in both studies. In both cases, solutions aimed at reducing firewood consumption are highlighted as an element of success, but one which cannot be isolated from other elements, such as awareness meetings and forest controls, which were implemented simultaneously.

10.3.3 Location-specific studies: Conditional incentives demonstrate varying degrees of success

Some of the more robust studies examined the impact of incentives conditional on forest protection and/or enhancement. Using high-resolution satellite images and self-reported data, Jayachandran *et al.* (2017) estimated the effectiveness of a carbon-focused initiative offering individual payments to Ugandan smallholders in return for forest conservation and tree planting. After two years of implementation, satellite data demonstrated that tree cover had declined by 4.2% in the intervention villages, versus 9.1% in the control villages. Self-reported data were in line with this main result, with lower self-reported tree cutting in the intervention group. These encouraging results link not only to a reduction in participants' own deforestation, but also to increased patrolling so as to reduce others' open access to forests. Spillover effects seemingly played no role. However, if the programme was scaled up, the lower levels of timber extraction in treatment villages could increase prices, thus incentivising more tree cutting in neighbouring villages.

An early impact assessment of the Bolsa Floresta programme – among the first initiatives in Brazil to rely on individual conditional incentives to protect forests – used remote sensing data to uncover preliminary impacts on forests (Börner *et al.* 2013). The assessment found that while forest impacts remained small in terms of number of hectares, mean annual deforestation in Bolsa Floresta reserves was 12 percentage points lower than in other multiple-use protected areas. However, as Bolsa Floresta operates in a remote part of the Amazon where demand for converted land remains low and beneficiaries are relatively homogenous, this corresponds to a low absolute forest loss.

Using DID and DID-matching methods in a third assessment, Simonet *et al.* (2018b) found promising results regarding the possibility of stemming deforestation among smallholders in the Brazilian Amazon by offering PES-type incentives alongside enabling measures (e.g., awareness raising), in a context of strict governmental control (see Box 10.3).

These three studies focused on initiatives that included conditional incentives. All indicated significant reductions in deforestation, but to varying degrees of magnitude. In all cases, the REDD+ projects included a mix of interventions, so the

Box 10.3 Measuring impact: The 'Sustainable Settlements in the Amazon' initiative

Since the mid-2000s, deforestation has been significantly reduced in Brazil, yet less so among smallholders, who still rely much on land-extensive swidden agriculture (shifting cultivation) and cattle ranching for subsistence. Noncompliance with the Brazilian Forest Code, which requires conserving between 50% and 80% of their land as forest, has so far remained widespread. In this context, 350 smallholders living along the Transamazon Highway (Pará State) were offered an innovative REDD+ package including payments conditional on forest conservation, environmental education, and technical-administrative assistance (with forest restoration and adoption of fire-free agriculture systems added as later components).

Using DID and DID-matching, Simonet *et al.* (2018b) found that participants (whose initial mean forest cover spanned ~71 ha) saved an average of 4 more hectares of forest over the study period (2010–2014), compared to the counterfactual scenario with no REDD+ initiative. Although participants continued to clear forest, their deforestation rate was halved (Figure 10.4). The remote sensing-based plot-level data neatly mirrored the auto-declared deforestation data, providing a convincing reality check. Slowdown in the creation of new pastures is key. Just like Jayachandran *et al.* (2017), the authors found no evidence of spillover of deforestation from participating plots to neighbouring ones. Authors believe that the long-term presence of the project initiator, locally adapted solutions, and strong deforestation monitoring by the Brazilian government, may have all contributed to these encouraging results at a pilot stage of REDD+ implementation.

Using the most recent GFC data (version 1.5) (Hansen *et al.* 2013b) and applying the BACI method at village level (Bos *et al.* 2017), analysis showed that deforestation in the Transamazon intervention villages increased over time, but did so less than in control villages. These results do not necessarily contradict results obtained at household level, as less than 10% of households living in the villages marked as intervention villages actually participated in the project. This illustrates the complexity of combining different types of data and different scales of analysis.

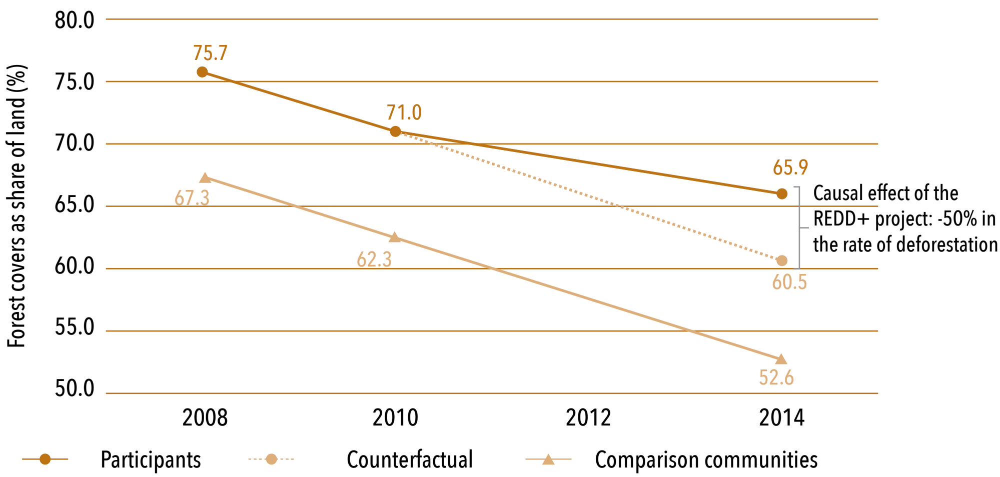


Figure 10.4 Impact of REDD+ on deforestation in Transamazon project

Source: Data from Simonet *et al.* (2018b) impact – if any – cannot be clearly attributed to any particular one. Across the three studies, the simultaneous presence of incentives and disincentives appears to be conducive to project success. The ability of landholders to exclude outsiders is also necessary, indicating that initiatives in areas with unclear and insecure tenure rights have less potential for success.

10.4 Lessons and ways forward

Local REDD+ projects and programmes are hybrids of enabling measures, disincentives and incentives. Due to the complexity of measuring heterogeneous treatments, over short timeframes, it is too early to establish a clear link between the type of REDD+ intervention and its success in reducing deforestation. However, we can see from local-level studies that restrictions on forest access and clearing have led to reductions in deforestation, and that conditional incentives showed positive results across several sites. Likewise, conditional and non-conditional incentives are clearly important in minimising the trade-offs between carbon and non-carbon benefits. The few studies that have investigated local spillovers found no such evidence (Jayachandran *et al*. 2017; Simonet *et al*. 2018b) but more systematic exploration is needed if programmes are to be scaled up.

Despite REDD+ debuting globally over a decade ago, robust studies on its carbon performance are still notably lacking. There is an urgent need to understand the effectiveness of early REDD+ projects and programmes when it comes to conserving forests and enhancing carbon stocks, to guide the design of future interventions. A good sign of progress towards this objective is independent evaluation of the effectiveness of several REDD+ projects – financed by a major funder, the Amazon Fund – which mainly takes a qualitative approach. More work is needed to evaluate the effects of different types of interventions, especially at the jurisdictional (rather than project) scale, which is the focus of the REDD+ mechanism. Increasing the number of robust impact evaluations on REDD+ and its underlying instruments is challenging, but not impossible. REDD+ funds or carbon markets could, for example, introduce more stringent requirements for proponents to demonstrate the carbon and non-carbon performance of their projects (see Chapter 10), while facilitating collaborations with independent researchers. More assistance to countries and subnational jurisdictions would also be beneficial, so that they can build up robust evaluation units to assess REDD+ interventions once underway.

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