ZENTRUM FÜR ENTWICKLUNGSFORSCHUNG (ZEF)

The effectiveness and efficiency of forest conservation policies to reduce deforestation in the Peruvian Amazon

Dissertation

zur Erlangung des Grades

Doktor der Agrarwissenschaften (Dr. agr.)

der Landwirtschaftlichen Fakultät

der Rheinischen Friedrich-Wilhelms-Universität Bonn

von

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aus

Lima, Peru

Bonn 2023

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Tag der mündlichen Prüfung: 15. November 2022

Angefertigt mit Genehmigung der Landwirtschaftlichen Fakultät der Universität Bonn

TO

MICKELLY, CONSTANZA & DARIO

Acknowledgements

First of all, I would like to express my inmense gratitude to my wife, who with her enormous efforts and sacrifices throughout these years, allowed me to carry out and conclude my research work. Without her support, my thesis would not have been possible. Thanks, from the bottom of my heart!

I am extremely grateful to my supervisor, Prof. Dr. Jan Börner, for his consistent support, and objective and rigorous guidance during the course of my research work. Thanks for the time and kindness to help me finding the best way to answer my research questions. I would like to extend my sincere thanks to Prof. Dr. Joahim von Braun and Prof. Dr. Christian Borgemesiter for their comments and suggestions. I would like to acknowledge Dr. Valentina Robiglio and Paul-Gregor Fischenich for having encouraged me to persue my doctoral degree at an early stage.

Many more people and institutions enabled me to complete my research to whom I am deeply thankful. My colleagues and friends at the Center for Development Research (ZEF): Dr. Elias Cisneros, Dr. Javier Miranda, Dr. Johannes Schielein, Galia Figeroa, Dr. Nina Pkhikidze, Fernanda Martineli, James Henderson, Gabriel Frei, Dr. Hugo Rosas, Dr. Emmanuel Rukundo, Dr. Pablo Evia, and Dr. Chiara Kofol. Thank you all for your time and for having discussed research as well as personal issues with me; you are the best! My colleagues at the GIZ-CBC project in Peru for having provided research assistance and collaboration. Thanks to the *Programa Bosques*' directors and staff for their unconditional collaboration with my project. The members of the indigenous communities of Loma Linda – Laguna and San Pedro de Pichanaz, who took the time to answer my questions. In addition, I would like to thank Mikaela Weisse, Cesar Ipenza, Julio Guzman, Jose Luis Capella, Elena Borasino, and Dr. Sven Wunder whose insight and knowledge about the Peruvian Amazon highly contributed with my research.

I would like to offer my special thanks to the administration staff of the Bonn International Graduate School for Development Research (BIGS-DR), and to ZEF's press and public relations, and administration teams, for their assistance. My gratitude extends to the German Academic Exchange Service (DAAD) for the scholarship I received to undertake my studies and persue my doctoral degree. Similarly, I would like to thank the Robert Bosch Foundation, the Federal Ministry of Education and Research (Prodigy Project), the Bonn Graduate Center of the Bonn University, and the “Friends of ZEF” for their financial support. I am very grateful to my friends Dr. Maria Pia Chaparro and Dr. Rob Williams, and the Center Translation Service of the University of Bonn for providing proofreading support.

I would also like to express my gratitude to my mother and aunt for their understanding and encouragement to finish my research work. I also appreciate all the support I received from family members and friends.

Finally, thank you Constanza for all your love, and thank you Dario for the brief but eternal joy you brought to me, I will always love you!

Abstract

Between 2015 and 2020, 9.3 million hectares of tropical forests were annually deforested. Deforestation represents the second largest source of carbon emissions globally, reduces biodiversity and ecosystem services, and threatens livelihoods. Reducing deforestation is considered a cost-effective climate change mitigation strategy and key to achieve sustainable development goals in tropical regions. The last decade has seen significant investments in designing and implementing forest conservation policies. Yet their environmental and socioeconomic impacts, as well as trade-offs between these, are rarely evaluated. Such an understanding is crucial for designing better forest conservation interventions and avoiding unintended negative effects on local populations.

This thesis provides a three-step methodological approach to analyze the environmental effects of forest conservation interventions, their costs and benefits, and trade-offs between avoiding deforestation cost-effectively and welfare effects. I provide policy makers with evidence-based policy recommendations to design and implement conservation interventions in the Peruvian Amazon. Peru is a good study case because although the government is increasingly trying to stop forest clearing, the deforestation rate is still increasing and policies against deforestation have seldom been evaluated.

First, I identify the factors that affected the effectiveness of Peru's National Forest Conservation Program (*Programa Bosques*) during its pilot phase (2011-2015). *Programa Bosques* provides cash transfers to individual indigenous communities, conditional on avoided deforestation and the adoption of sustainable production systems for a period of five years. I use a spatially explicit quasi-experimental and counterfactual approach to assess the program's effectiveness. Between 2011 and 2015, *Programa Bosques* reduced deforestation by about 557 (± 490) hectares. This reduction was the result of spillover effects on land not enrolled for conservation. Avoided deforestation was negligible because enrolled areas presented low deforestation threats.

Second, I estimate the net economic benefit of *Programa Bosques'* avoided deforestation by means of a cost benefit analysis. I consider spatial heterogeneity in conservation opportunity costs as well as uncertainty across a wide range of parameters by applying the Monte Carlo method. I use the social cost of carbon to value benefits. Costs and benefits are considered from the perspectives of the local communities, the country, and the global society. Results indicated that deforestation was avoided at a net cost (USD 13.7 Million). This poor conservation performance was due to high implementation costs (~67% of total budget), and the short permanence of the avoided deforestation in time (≤ 5 years). The Peruvian economy bore most of these costs and only marginal benefits were provided to the local communities and the global society.

Third, I explore alternative policy design options that incorporate a mix of incentives and disincentives to mitigate the potential trade-offs between cost-effective deforestation reductions and landholders' income losses. I develop a spatially explicit model simulating landholders' decision to deforest and use it to estimate the costs, cost-effectiveness, and welfare effects of a policy-mix of payments for ecosystem services and fines for deforestation. Simulations showed that a policy approach solely based on fines is more cost effective than

one based on payments. Nevertheless, results indicated a trade-off between cost-effectiveness and welfare because rural incomes were considerably reduced when only fines were applied. Introducing payments mitigated this trade-off by compensating the income losses of landholders that reduced deforestation.

These findings highlight the importance of accounting for spatially heterogeneous contexts to increase forest conservation effectiveness. In turn, to increase forest conservation's net benefits, it is necessary to secure the permanence of the avoided deforestation as long as possible, and minimize implementation costs, whilst paying attention to distributional outcomes. Finally, regarding policy mixes to avoid deforestation, there is no silver bullet that will deliver both high cost-effectiveness and welfare gains. Nevertheless, adding payments to a command and control approach could compensate otherwise high-income losses among vulnerable populations, making such a policy mix more politically viable.

Zusammenfassung

Zwischen 2015 und 2020 wurden jährlich 9,3 Millionen Hektar tropischer Wälder abgeholzt. Entwaldung ist die zweitgrößte Quelle von Kohlenstoffemissionen weltweit. Außerdem verringert Entwaldung die biologische Vielfalt und die Ökosystemleistungen und bedroht Lebensgrundlagen. Die Verringerung von Entwaldung gilt als kosteneffiziente Strategie zur Eindämmung des Klimawandels und als Schlüssel zur Erreichung der Ziele für eine nachhaltige Entwicklung in tropischen Regionen. In den letzten zehn Jahren wurden erhebliche Investitionen in die Gestaltung und Umsetzung von Waldschutzmaßnahmen getätigt. Ihre ökologischen und sozioökonomischen Auswirkungen sowie die damit verbundenen Zielkonflikte werden jedoch nur selten bewertet. Ein solches Verständnis ist entscheidend für die Gestaltung besserer Waldschutzmaßnahmen und die Vermeidung unbeabsichtigter negativer Auswirkungen auf die lokale Bevölkerung.

In dieser Arbeit wird ein dreistufiger methodischer Ansatz zur Analyse der Umweltauswirkungen von Waldschutzmaßnahmen, ihrer Kosten und ihres Nutzens sowie der Kompromisse zwischen der kosteneffizienten Vermeidung von Entwaldung und den Wohlfahrtseffekten vorgestellt. Ich gebe politischen Entscheidungsträgern evidenzbasierte Empfehlungen für die Gestaltung und Umsetzung von Naturschutzmaßnahmen im peruanischen Amazonasgebiet. Peru ist ein geeigneter Studienfall, denn die Entwaldungsrate nimmt immer noch zu, obwohl die Regierung zunehmend versucht die Abholzung von Wäldern zu stoppen. Maßnahmen gegen die Entwaldung wurden bisher nur selten evaluiert.

Zunächst ermittle ich die Faktoren, die die Wirksamkeit des peruanischen Nationalen Waldschutzprogramms (Programa Bosques) während seiner Pilotphase (2011-2015) beeinflusst haben. Das Programa Bosques bietet einzelnen indigenen Gemeinschaften Geldtransfers über einen Zeitraum von fünf Jahren an, um Entwaldung zu vermeiden und nachhaltige Produktionssysteme einzuführen. Dies ist an Bedingung geknüpft. Ich verwende einen räumlich expliziten quasi-experimentellen und kontrafaktischen Ansatz, um die Wirksamkeit des Programms zu bewerten. Zwischen 2011 und 2015 reduzierte das Programa Bosques die Entwaldung um etwa 557 (± 490) Hektar. Diese Verringerung war das Ergebnis von Spillover-Effekten auf Flächen, die nicht für das Programm registriert waren. Die vermiedene Entwaldung war vernachlässigbar, da die erfassten Gebiete nur in geringem Maße von Entwaldung bedroht waren.

Zweitens schätze ich den wirtschaftlichen Nettonutzen der durch das Programa Bosques vermiedenen Entwaldung mit Hilfe einer Kosten-Nutzen-Analyse. Dabei berücksichtige ich die räumliche Heterogenität der Opportunitätskosten des Naturschutzes sowie die Ungewissheit über eine breite Palette von Parametern durch Anwendung der Monte-Carlo-Methode. Ich verwende die sozialen Kosten des Kohlenstoffs, um den Nutzen zu bewerten. Kosten und Nutzen werden aus der Sicht der lokalen Gemeinschaften, des Landes und der globalen Gesellschaft betrachtet. Die Ergebnisse zeigen, dass die Vermeidung von Entwaldung mit Nettokosten verbunden war (13,7 Millionen USD). Diese schlechte Erhaltungsleistung war auf die hohen Umsetzungskosten (~67 % des Gesamtbudgets) und die kurze Beständigkeit der vermiedenen Entwaldung (≤ 5 Jahre) zurückzuführen. Die peruanische Wirtschaft trug den größten Teil dieser Kosten, während die lokalen Gemeinschaften und die Gesellschaft weltweit nur einen geringen Nutzen daraus zogen.

Drittens untersuche ich alternative politische Gestaltungsoptionen, die eine Mischung aus Anreizen und Negativanreizen beinhalten, um die potenziellen Zielkonflikte zwischen einer kosteneffizienten Verringerung der Entwaldung und den Einkommensverlusten der Landbesitzer abzumildern. Ich entwickle ein räumlich explizites Modell, das die Entscheidung von Landbesitzern zur Entwaldung simuliert, und verwende es, um die Kosten, die Kosteneffizienz und die Wohlfahrtseffekte eines Politik-Mixes aus Zahlungen für Ökosystemleistungen und Geldstrafen für Entwaldung zu schätzen. Die Simulationen zeigten, dass ein politischer Ansatz, der ausschließlich auf Geldstrafen beruht, kosteneffizienter ist als ein auf Zahlungen basierender Ansatz. Dennoch deuteten die Ergebnisse auf einen Zielkonflikt zwischen Kosteneffizienz und Wohlfahrt hin, da die Einkommen der ländlichen Bevölkerung beträchtlich sanken, wenn nur Geldstrafen verhängt wurden. Die Einführung von Zahlungen milderte diesen Zielkonflikt ab, indem sie die Einkommensverluste von Landbesitzern, die die Entwaldung reduzierten, kompensierte.

Diese Ergebnisse zeigen, wie wichtig es ist, räumlich heterogene Kontexte zu berücksichtigen, um die Wirksamkeit des Waldschutzes zu erhöhen. Um wiederum den Nettonutzen des Waldschutzes zu erhöhen, ist es notwendig, die Beständigkeit der vermiedenen Entwaldung so lange wie möglich zu sichern und die Umsetzungskosten zu minimieren, wobei die Verteilungsergebnisse zu berücksichtigen sind. Was schließlich den Politik-Mix zur Vermeidung von Entwaldung betrifft, so gibt es kein Patentrezept, das sowohl eine hohe Kostenwirksamkeit als auch Wohlfahrtsgewinne bringt. Dennoch könnte die Ergänzung eines *command and control* Konzepts durch Zahlungen hohe Einkommensverluste bei gefährdeten Bevölkerungsgruppen ausgleichen, was einen solchen Politik-Mix politisch tragfähiger macht.

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ATT	Average treatment effect on the treated
C	Carbon
CBA	Cost-benefit analysis
CCT	Conditional cash transfer
CE	Cost-effectiveness
CFZ	Conservation forest zone
C&C	Command and control
CO_2	Carbon dioxide
FD	First differences
FEMA	*Fiscalía Especializada en Materia Ambiental*
GHG	Greenhouse gas
$GgCO_2$-eq	Giga grams of CO_2-eq
GIZ	*Deutsche Gesellschaft für Internationale Zusammenarbeit*
ha	Hectare
HFLD	High forest cover with low deforestation rates
IBC	*Instituto del Bien Común*
ICDP	Integrated conservation and development projects
INEI	Instituto Nacional de Estadística e Informática
LMIC	low-and-middle-income countries
LULUCF	Land use, land use change, and forestry
MC	Monte Carlo
MINAM	*Ministerio del Ambiente;* Ministry of Environment
MTC	*Minsiterio de Transportes y Telecomunicaciones*
NFCP	National Forest Conservation Program
NFV	Net future value
NPV	Net present value
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary least squares
OSINFOR	*Organismo de Supervisión de los Recursos Forestales y de Fauna Silvestre;* Agency for the Supervision of Forest Resources and Wildlife
OUZ	Other use zone
PES	Payments for ecosystem services
PNCB	Programa Nacional de Conservación de Bosques
PNCBMCC	Programa Nacional de Conservación de Bosques para la Mitigación del Cambio Climático
PSAH	Payments for Hydrological Services Program; *Pagos por servicios ambientales hidrológicos*
REDD+	Reducing emissions from deforestation and forest degradation
RQ	Research question
SCC	Social cost of carbon
SD	Standard deviation
SE	Standard error
SERFOR	National Forest and Wildlife Service;

	Servicio Nacional Forestal y de Fauna Silvestre
SERNANP	National State Protected Areas Service;
	Servicio Nacional de Áreas Naturales Protegidas por el Estado
TEV	Total economic value
UNFCCC	United Nations Framework Convention on Climate Change
UNODC	United Nations Office on Drugs and Crime
USD	United States Dollars

1 Introduction

1.1 Motivation

Between 1990 and 2020, it is estimated that 420 million ha of forests were lost, with more than 90% of this deforestation having occurred in the tropics (FAO, 2020). The rate of deforestation, however, has declined, both at the global and tropical scales, with an annual deforestation rate of 10.2 million ha and 9.3 million ha, respectively, between 2015 and 2020 (FAO, 2020). Such levels of deforestation are associated with 37% (Houghton and Nassikas, 2018) and 12% (Le Quéré et al., 2018) of total gross and net anthropogenic carbon emissions, respectively, making deforestation the second largest source of global carbon emissions (van der Werf et al., 2009), and thus still an important driving force of climate change (Seymour and Busch, 2016).

Although forest conversion to other productive land uses such as cattle pastures, soya crop fields, and oil palm plantations provide substantial economic benefits (Abram et al., 2016; Bowman et al., 2011; Nepstad et al., 2014, 2009), conversion does not come without costs. Deforestation implies the loss of ecosystem goods and services such as biodiversity, hydrological services and water supplies, cultural and recreational benefits, soil formation, food and fibre provisioning, and a cost-effective option to remove carbon dioxide (CO_2) from the atmosphere (Kaimowitz, 2018; Seymour and Busch, 2016). Deforestation is also part of a vicious cycle, which, together with climate change, could exacerbate poverty, putting lives and livelihoods at risk (Seymour and Busch, 2016).

Peru has the second largest forest area in South America, totaling 72 million ha as of 2020 (FAO, 2020), 68 million ha of which (94%) are located within the Amazon Basin (MINAM, 2016a). Recent official estimates indicate that deforestation between 2001 and 2019 totaled 2.4 million ha and that the annual forest loss area has increased from 83,000 ha in 2001 to 148,000 ha in 2019.[1] As part of its national environmental goals and international commitments, the Peruvian government has developed a national strategy for reducing deforestation as a contribution to climate change mitigation (MINAM, 2016b). Forest conservation goals rely on a list of strategic actions, some of which are already being implemented through incentive, disincentive, and enabling policy instruments (MINAM, 2016b). However, to date there are few empirical analyses of the effectiveness, cost-effectiveness (CE), and potential welfare effects of these policies. The purpose of this thesis is to address this lack of data and to provide information to policy makers to assist in evaluating the design and implementation of forest conservation policy instruments in the Peruvian Amazon.

1.2 Background: money for nothing?

The last decade has seen a significant amount of financial resources committed to support efforts to reduce deforestation and forest degradation in tropical regions of low-and-middle-income countries (LMIC) (Watson and Chalatek 2021). For example, since 2008, USD 5.2

[1] Deforestation data is taken from the Peruvian forests monitoring system: http://geobosques.minam.gob.pe/geobosque/view/perdida.php

billion have been pledged by Norway, the United Kingdom, Germany, the United States, and other high-income countries to multilateral climate funds (e.g. UN-REDD Program, Forest Carbon Partnership Facility, the Amazon Fund) to finance activities to reduce carbon emissions from deforestation and forest degradation (Watson and Chalatek 2021). Since 2008, USD 2.8 billion were already approved for disbursement (Watson and Chalatek 2021). Many LMIC themselves have been investing additional public funds in designing and implementing alternative public policy instruments to reduce deforestation and forest degradation, such as payments for ecosystem services (PES), to complement their already existing command and control (C&C) policy instruments (Börner et al., 2015b). In 2020, Costa Rica had a budget of USD 27 million only for transfers within its PES program (FONAFIFO, 2020). Similar examples exist from Ecuador (de Koning et al., 2011), Brazil (Cunha et al., 2016), Indonesia (Mafira et al., 2020), Peru (Giudice and Börner, 2021), among many other LMIC (Börner et al., 2016a; Ezzine-de-Blas et al., 2016; Samii et al., 2014; Snilsveit et al., 2019; Wunder et al., 2008). The private sector is also increasingly investing in reducing deforestation efforts by developing interventions to remove deforestation from their commodity supply chains (Heilmayr et al., 2020; Lambin et al., 2018).

There are good reasons why investing in forest conservation and reducing deforestation is important. First, deforestation contributes to approximately 12% of the total anthropogenic net carbon emissions causing climate change (Le Quéré et al., 2018). The figure jumps to 37% if instead gross emissions are considered (Houghton and Nassikas, 2018). This makes the forest sector an important climate change mitigation option and thus an opportunity to contribute to achieving the Paris Agreement goal (Griscom et al., 2020). Second, reducing tropical deforestation is considered a cost-effective means to mitigate climate change (Busch and Engelmann, 2017; Eliasch, 2008; Grieg-Gran, 2008; Griscom et al., 2020; Kaimowitz, 2018; Stern, 2007). Estimates indicate that a carbon price of USD 20 per ton of carbon dioxide (tCO_2) would avoid 41 Giga tCO_2 or around 24% of expected total emissions from tropical deforestation, if no additional forest conservation policies were implemented for the period between 2006 and 2050 (Busch and Engelmann, 2017). This is further supported by the relatively low social costs of carbon (SCC) recently estimated for tropical countries, which range between USD 0 and USD 20 per tCO_2 (Ricke et al., 2018). A third reason is that besides the ecosystem service of carbon storage, forests provide a myriad of other ecosystem goods and services which are key for the sustainable development of millions of people living in tropical regions. Tropical rural livelihoods depend on healthy forest ecosystems to secure food, water, medicines, and regular income sources associated with timber and non-timber forest products (Angelsen et al., 2014; Sunderlin et al., 2005), ecotourism, biodiversity and many other environmental benefits (Seymour and Busch, 2016). Forests are key to identifying poverty alleviation opportunities (Angelsen and Wunder, 2003), in providing safety net functions (Debela et al., 2012), and helping households to cope with environmental and socio-economic risks and shocks (Börner et al., 2015c; Pattanayak and Sills, 2001; Takasaki et al., 2004; Wunder et al., 2014). Fourth, in many tropical countries the land use, land use change and forestry (LULUCF) sector represents today the major source of CO_2 emissions (van der Werf et al., 2009), indicating the importance of reducing deforestation for achieving nationally determined contributions (Grassi et al., 2017; Griscom et al., 2020; Gurgel et al., 2019; Meehan et al., 2019).

Hence, the available financial resources are currently being invested in funding a variety of forest conservation initiatives (Pirard et al., 2019), which fall into three broadly defined policy instruments types: enabling conditions, incentives, and disincentives (Börner and Vosti 2013). Hundreds of projects and programs exist in tropical countries to prepare national and subnational governments and other stakeholders in implementing actions to reduce deforestation (e.g. by designing and establishing forest monitoring systems) and to provide payments or other incentives (e.g. in kind) for measured, reported, and verified carbon emissions reductions from avoided deforestation (Pirard et al., 2019; Snilsveit et al., 2019), the so called results-based payments (Angelsen et al., 2018). This incentive-based approach adds to and complements traditionally implemented C&C policies, such as protected areas and fines (Börner et al., 2015b; Cunha et al., 2016; Montoya-Zumaeta et al., 2019). And yet, the majority of these interventions lack rigorous assessments of their effectiveness and CE in achieving their environmental and socioeconomic goals (Börner et al., 2016a; Samii et al., 2014; Snilsveit et al., 2019; Vincent, 2016; West et al., 2020), as well as the trade-offs between these (Pirard et al., 2019), making the evidence base for forest conservation policies still limited (Wunder et al., 2020).

1.3 Problem statement and literature review: money for something?

In recent years, there have been several pledges from conservation scholars to conduct empirical evaluations of forest conservation programs and policies through rigorous impact evaluation designs (Baylis et al., 2016; Ferraro, 2009; Miteva et al., 2012). Such designs aim to compare the interventions' outcomes (e.g. area of standing forests) to outcomes from credible counterfactual scenarios to measure the causal or attributable effects of a specific intervention. Measuring and assessing causal effects by rigorous methodological approaches and theory of changes allow us to not only estimate the quantitative effects of an intervention, but also to understand the factors that drive the emergence of such effects (Baylis et al., 2016; Börner et al., 2017; Ferraro, 2009; Ferraro and Hanauer, 2014a; Wunder et al., 2020). Such an understanding is crucial for designing cost-effective interventions (Baylis et al., 2016; Ferraro and Simpson, 2002; Snilsveit et al., 2019) and building the evidence base required in environmental policy regarding what type of interventions work and under what conditions (Börner et al., 2020; Ferraro and Hanauer, 2014b). With such knowledge, policy makers, donors, scientists, and practitioners could push for the design of better forest conservation policy instruments to achieve environmental as well as social goals (Ferraro and Hanauer, 2014b; Snilsveit et al., 2019; Wunder et al., 2020). In addition, scarce resources for conservation could be put into more effective uses (Baylis et al., 2016). In fact, several institutions and funding governments are currently promoting experimental evidence and science based policy making in the land use sector (Reinecke et al., 2020; Snilsveit et al., 2019).

Although there is a growing body of empirical evaluation studies of forest conservation initiatives impacts (Pirard et al., 2019), the evidence is still limited (Börner et al., 2017; Wunder et al., 2020), as most studies come mainly from a few countries (Börner et al., 2017, 2016a) and many still use methods that do not avoid biased estimations (Snilsveit et al., 2019). For example, a recent meta-analysis of the effects of PES on environmental and socio-economic outcomes in LMIC found that, from the 44 studies assessed, 31 were conducted in only three countries: Mexico, Costa Rica and China (Snilsveit et al., 2019). The same study found that

only six studies (13%) accounted for selection bias by applying randomized control trials (2) and quasi-experimental approaches (4) (Snilsveit et al., 2019), which are the most rigorous methods for evaluating impacts (Ferraro and Hanauer, 2014a). Five years prior, another meta-analysis had reported similar results (Samii et al., 2014).

Selection bias arises when participants are selected and/or self-select themselves into a forest conservation intervention, based on characteristics that affects both the treatment assignment and the expected outcome (Ferraro, 2009; Persson and Alpízar, 2013). A similar bias affects treatment effect estimations when there are contemporaneous factors correlated with the treatment assignment and outcomes (Ferraro, 2009; Sills et al., 2017). Again, such bias could be controlled using experimental and quasi-experimental approaches (Ferraro and Hanauer, 2014a). Lack of proper accounting for such biases leads to over or underestimations of effects, thus making programs appear more successful than they really are, or failed programs to go undetected (Ferraro, 2009). Given that forest conservation interventions' assignment mechanisms (e.g. voluntary non-random) tend to promote biases (Börner et al., 2017), accounting for this issue in forest conservation evaluation is key to avoid biased estimations (Andam et al., 2008; Börner et al., 2016a; Cisneros et al., 2015; Ezzine-de-Blas et al., 2016; Ferraro, 2009; Honey-Rosés et al., 2011).

Another source of bias found in previous studies arises from the lack of group equivalence between treated units and controls (Pattanayak et al., 2010; Samii et al., 2014; Snilsveit et al., 2019). Controls are used to compare the outcome with that of the treated units, thus building a counterfactual scenario which represents the expected outcome of the treated units had the intervention not taken place (Blackman, 2013; Bos et al., 2017; Ferraro, 2009; Sills et al., 2017; Velly and Dutilly, 2016). Put in simple words, controls must be as similar as possible to the treated units, except for not being treated, in order to build valid counterfactuals and estimate unbiased treatment effects. Nevertheless, many projects and programs still lack the use of valid counterfactuals. For example, a recent study found that the lack of rigorously developed counterfactuals led to significant overestimations of emissions reductions from voluntary REDD+[2] projects in the Brazilian Amazon (West et al., 2020).

Biases also arise when spillover effects are not accounted for when estimating treatment effects (Alix-Garcia et al., 2012; Baylis et al., 2016; Blackman, 2013; Honey-Rosés et al., 2011; Robalino and Pfaff, 2012). Spillover effects occur when areas not enrolled in a forest conservation program, or any non-treated units in general, are affected by the program, thus violating an important assumption when conducting impact evaluations, i.e. the stable unit of treatment value assumption (Blackman, 2013; Velly and Dutilly, 2016). Forest conservation policy instruments could have positive or negative spillover effects, depending on whether the effect of the program on these non-treated units adds or subtracts from the outcome within treated units, respectively (Honey-Rosés et al., 2011). For example, if only a fraction of the landowners' property is enrolled into a forest conservation program, the non-enrolled portion could be subject to increased deforestation due to a production substitution effect (Alix-Garcia et al., 2008, 2012) and hence a negative spillover effect or leakage occurs. If, on the contrary, deforestation is also reduced in the non-enrolled areas by means of the program´s intervention, a positive spillover effect occurs (Alix-Garcia et al., 2012).

[2] Reducing emissions from deforestation and forest degradation

Still another potential source of bias is the scale and unit of analysis considered for estimating the effectiveness of forest conservation programs (Avelino et al., 2016; Velly and Dutilly, 2016). Units of analysis that are too small or too large relative to the scale at which land use decisions are made may produce biased treatment estimates (Avelino et al., 2016). Such choices also affect the precision in measuring the independent variable values, which in turn could bias estimated coefficients (Avelino et al., 2016). Using large units of analysis fails to capture spatial heterogeneity (Costedoat et al., 2015) and using small units could generate spatial autocorrelation, leading to biases (Avelino et al., 2016; Miteva et al., 2015; Qi and Wu, 1996). To date, however, only few impact evaluations have considered these spatial issues (see for example Avelino et al., 2016; Börner et al., 2015a; Buchanan et al., 2018; Cisneros, 2020; Giudice et al., 2019).

Based on the available evidence to date, we know that forest conservation policy instruments could in fact reduce deforestation but, irrespective of the type of instrument implemented, their effectiveness is on average low (Börner et al., 2020; Snilsveit et al., 2019). More importantly, the evidence suggests that the context in which policies are implemented is more critical for understanding their success or failure than the type of instrument used (Börner et al., 2020, 2017). To better understand these contexts, designing clear theories of change on how and why the interventions would achieve their expected outcomes is necessary and important (Baylis et al., 2016; Börner et al., 2020; Wunder et al., 2020). Recent studies have summarized the main findings of our understanding of which and how contextual, design, and implementation factors affect the environmental and socioeconomic outcomes of conservation policies (Börner et al., 2020, 2017; Miteva et al., 2012; Wunder et al., 2020). For example, PES success is considerably hindered by adverse self-selection, inadequate administrative targeting, ill-enforced conditionality, and the lack of political will to improve policy design and implementation, among others (Wunder et al., 2020, 2018). Börner et al. (2020) also argue that contextual economic factors, such as opportunity costs of forest conservation, affect the location of implemented policies, which in turn could limit their effectiveness. Contextual factors affecting the effectiveness of forest conservation policies are also related to other public policies, especially those associated with development goals, for example roads development (Börner et al., 2020). Although this evidence is still incipient, several design options for improving the effectiveness of forest conservation interventions have been provided, such as spatial targeting towards areas with high deforestation risk, payment differentiation (recognizing spatially heterogeneous opportunity costs among participants and environmental values from different areas), and enforced conditionality (Wunder et al., 2020, 2018). Unfortunately many forest conservation policy instruments and programs still lag behind this evidence-based design and implementation options (Wunder et al., 2018).

The research literature on forest conservation is also lagging behind the assessment of the CE of conservation interventions and programs, as only few studies have assessed the CE or cost-efficiency of forest conservation programs (Börner et al., 2016a; Jayachandran et al., 2017; Miteva et al., 2015, 2012; Pattanayak et al., 2010; Sims and Alix-Garcia, 2017; Snilsveit et al., 2019; Vincent, 2016). The importance of such indicator lays in the fact that a particular program could have an additional and significant effect on reducing deforestation, but if the costs (i.e. implementation and opportunity costs) are too high, they could make the initiative not worthwhile (Börner et al., 2016a; Vincent, 2016). Cost effectiveness is usually defined in terms of the amount of additional deforestation reduced, i.e. the impact or average treatment

effect on the treated (ATT), relative to the overall costs (Börner et al., 2015b, 2014). As most impact evaluations estimate the ATT only in biophysical terms (e.g. avoided deforestation measured in hectares) (Blackman, 2013), this approach is useful for comparing alternative forest conservation policy instruments such as direct incentives and C&C measures within the same regions (Börner et al., 2015b; Sims and Alix-Garcia, 2017). This is because this approach implicitly assumes that environmental benefits and costs are homogenously distributed in space, and thus only a hectare of avoided deforestation, and not its economic value, is accounted as the benefit for assessing the CE of an intervention (Vincent, 2016). However, environmental benefits of forest conservation, as well as their costs, do vary spatially (Bateman et al., 2013; Naidoo and Ricketts, 2006).

From an economic perspective, for policy makers and program implementers, it is perhaps more important to understand the difference between their economic benefits and costs of forest conservation, in order to maximize the efficiency in using scarce financial resources. For this, biophysical indicators of benefits are a poor proxy for the economic value or the return on forest conservation investments. For example, a small impact effect in reducing deforestation could still imply that a forest conservation program is delivering economic benefits above its overall costs and justify its further roll-out or scale-up (Vincent, 2016). Hence, conducting ex-post benefit-cost analysis of forest conservation impact evaluations by means of economic valuation of benefits and costs has been proposed as a methodological complementary approach to provide more relevant economic information for policy makers (Miteva et al., 2012; Vincent, 2016). However, to my knowledge, there is only one published article to date which assesses the CE of a forest conservation policy instrument, namely PES, by undertaking an ex-post cost-benefit analysis of its effect on reducing emissions from deforestation in Uganda (Jayachandran et al., 2017). One of the main reasons for the lack of benefit-cost analyses is the difficulty in valuing environmental benefits spatially explicitly (Vincent, 2016). Nevertheless, in terms of climate change mitigation, nowadays it is at least possible to estimate the economic value of reduced emissions from deforestation by taking into account the SCC (Nordhaus, 2017) and spatially explicit models of the biomass content in forests (Baccini et al., 2012; Saatchi et al., 2007).

Finally, and as already mentioned above, contextual factors affecting the effectiveness of forest conservation include other policies (environmental oriented or not). In fact, incentive-based conservation approaches are usually complemented by already existing conservation instruments, including C&C or disincentive-based policy instruments such as fines and protected areas (Börner and Vosti, 2013). We still do not know how mixing these policies affect the CE of such so-called policy mixes in forest conservation policy (Börner et al., 2015b). Similarly, the evidence base on how these policy mixes affect the income from rural landholders simultaneously subject to incentives and disincentives, is almost non-existent (Montoya-Zumaeta et al., 2019). The findings from the few studies that have looked into this question show that incentive-based approaches could complement rather than be the main policy approach for increasing the CE, but there appears to be a trade-off between cost effectiveness and welfare effects (Börner et al., 2015b).

1.4 Filling the research gap

Although considerable amounts of financial resources are being used in designing and implementing forest conservation policies, the lack of evidence hampers our understanding of why and when such interventions are effective and cost-effective in achieving their goals. Thus, many programs are poorly designed and implemented, and present relatively small effectiveness and CE levels (Wunder et al., 2018). In addition, the lack of ex-post cost-benefit analyses of the estimated treatment effects of forest conservation interventions hinders the provision of relevant economic information on the true value of such programs (Vincent, 2016). With such information, policy makers could better understand the importance of improving the design and implementation approaches of their forest conservation investments. Finally, we do not know how policies mixing incentive- and disincentive-based forest conservation affect the CE of forest conservation and the welfare of rural populations (Börner et al., 2015b). This is important as in many countries, C&C policies are still the main policy approach with incentive-based forest conservation complementing or reinforcing them (Börner and Vosti, 2013).

1.4.1 Impacts of forest conservation interventions in Peru

Peru is one of those countries where only a few forest conservation interventions have been subjected to rigorous assessments to evaluate their effectiveness and CE (Blackman et al., 2017; Giudice et al., 2019; Miranda et al., 2016; Montoya-Zumaeta et al., 2019; Solis et al., 2021). This is alarming, since Peru is among the countries receiving considerable financial resources for reducing emissions from deforestation and forest degradation (Figure 1.1).

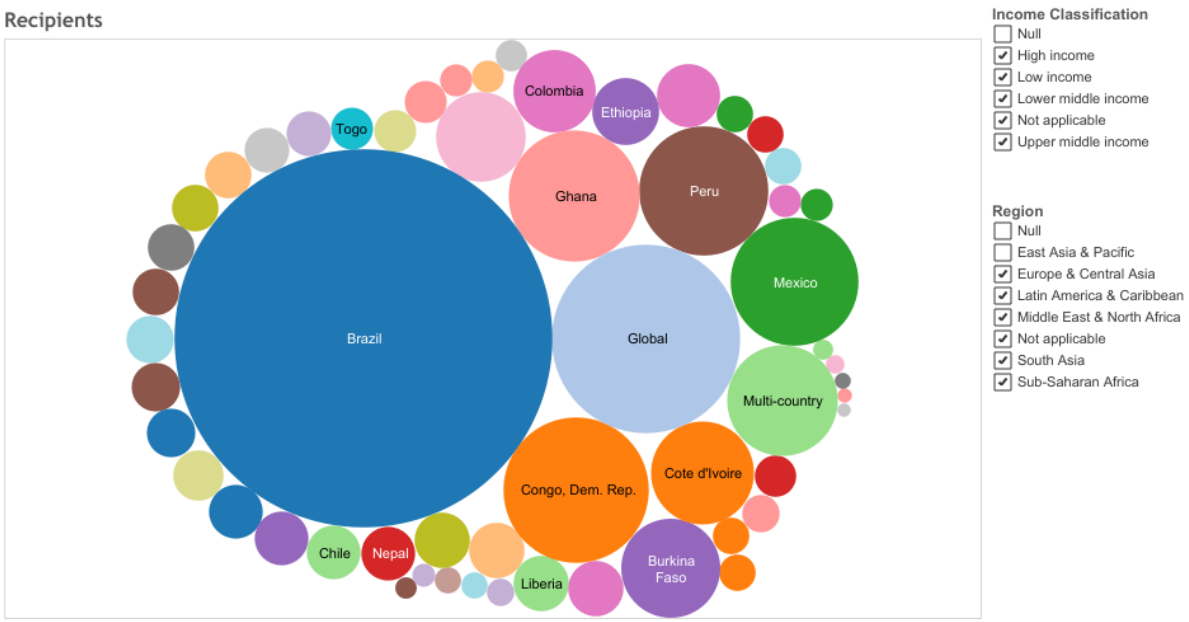

Figure 1.1 REDD+ Funds by recipient country

Note: Cumulative funds that have been officially approved and earmarked to specific projects and programs since 2003 and December 2020 by country recipients globally. Peru: 95.4 USD millions; Brazil: 817.4 USD million.

Source: Taken with permission from Climate Funds Update: https://climatefundsupdate.org/data-dashboard/themes/

As shown in Figure 1.1, as of 2020, a total of USD 95.4 million had been approved from climate funds to specific REDD+ projects and programs in Peru. Other forest conservation interventions, particularly disincentive-based approaches such as protected areas and fines for illegally deforesting, have been long in place (Miranda et al., 2016; Oliveira et al., 2007), especially in the Peruvian Amazon, where 94% of the country's total natural forests exist (MINAM, 2016a). Nevertheless, annual deforested areas in the whole Peruvian Amazon have been increasing since 2001 (Potapov et al., 2014; Vargas et al., 2014a, 2014b, 2014c) (Figure 1.2).

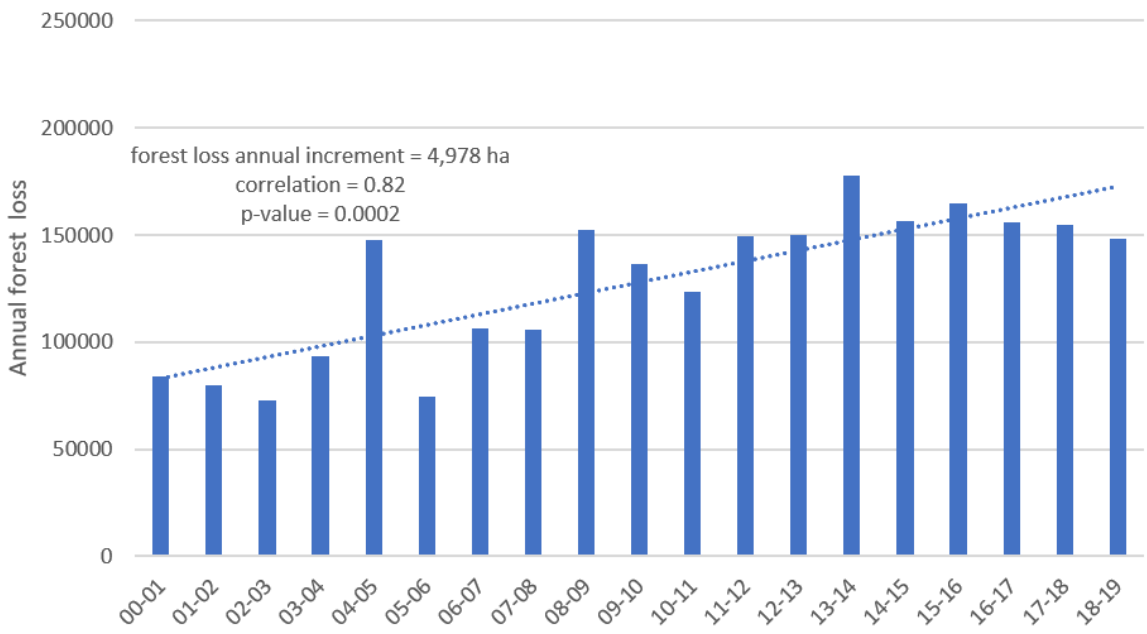

Figure 1.2 Annual forest loss in the Peruvian Amazon

Note: The annual forest loss (in ha) between 2000 and 2019 shows a statistically significant increasing trend.

Source: GeoBosques Monitoring System: http://geobosques.minam.gob.pe/geobosque/view/perdida.php

The most recent deforestation monitoring results indicate an annual average of 128,000 ha per year between 2001 and 2019 (MINAM, 2020), with an increasing rate of approximately 5,000 ha per year (Figure 1.2). Although in the last three years (2016-2017, 2017-2018 and 2018-2019) a small reduction trend has been observed, the annual average for that period is higher than that of previous years, at 156,000 ha per year. This deforestation trend represents a total deforested area of almost 2.5 million ha between 2001 and 2019. Nevertheless, the remaining forest area is still relatively large, 68.3 million ha as of the end of 2019, representing 78% of the total Peruvian Amazon (MINAM, 2015). These characteristics point into a transition from a "high forest cover with low deforestation rates" (HFLD) country[3] to one with increasing deforestation rates (HFMediumD) (Griscom et al., 2009).

[3] I calculated the forest cover as the proportion of remaining forest in 2019 (68.3 million ha) relative to that in 2000 (71 million ha), and the deforestation rate as the annual average deforested area between 2001 and 2019 (relative to the forested area in 2000 using the Peruvian deforestation

Deforestation accounts for most of the total gross and net national emissions in Peru. According to the most recent national inventory report, total net greenhouse gas (GHG) emissions in 2014 were 167,630 Giga grams of CO_2-eq ($GgCO_2$-eq) (MINAM, 2019). From these, 45% corresponded to the LULUCF sector, mainly due to deforestation in the Peruvian Amazon (MINAM, 2019). Total emissions without considering carbon intake by forests (regrowth) were in the same year 189,677 $GgCO_2$ corresponding to a 51% of gross emissions (MINAM, 2019).

Given this context, and as a means to achieve national and international commitments to reduce deforestation and corresponding carbon emissions to mitigate climate change, the government of Peru has elaborated the National Strategy for Forests and Climate Change (MINAM, 2016b). This strategy includes the national determined contribution to the Paris Agreement goal, offering to reduce up to 40% of total GHG emissions by 2030 relative to a business-as-usual scenario, leading to a maximum emission allowance of 208,8 Million tCO_2-eq in 2030 (Gobierno del Peru, 2020). The strategy proposes several forest conservation interventions, including incentives, disincentives and enabling conditions. One of the proposed incentive-based actions is the provision of conditional cash transfers to indigenous communities as a compensation for further conserving the natural forest within their titled lands (Blackman et al., 2017). This incentive-based policy was originally designed and implemented between 2011 and 2015 under the National Forest Conservation Program, seeking to provide financial and technical assistance for indigenous peoples as compensation for the opportunity costs of forest conservation (Giudice et al., 2019). The program represented one of the main proposed contributions of the Peruvian government to the global efforts to mitigate climate change, together with the goal of reducing net deforestation to zero by 2021 (Giudice et al., 2019; Rosa da Conceição et al., 2015). Nevertheless, the government has not conducted an official evaluation of the effect and CE of this first phase. Moreover, the goal of zero net deforestation has not been achieved.

A second action considered in the strategy entails the strengthening of the environmental enforcement authorities for allowing more field operations to combat illegal deforestation by means of sanctions, including fines and imprisonment (MINAM, 2016b). Nevertheless, no previous assessment on the potential costs and effectiveness of such an approach, and its potential welfare effects on local landholders, compared against the above explained incentive approach has been conducted.

This scenario constitutes a great research opportunity to provide policy-based recommendations to contribute with the improvement of design and implementation of public policies in the Peruvian Amazon. It is imperative for forest conservation interventions to be assessed at the local level so that policy makers can understand how contextual, design, and implementation factors of specific interventions could affect their environmental and socioeconomic goals (Börner et al., 2017).

monitoring results (see Griscom et al., 2009 for the original approach). (Griscom et al., 2009 used the global average deforestation rate of 0.22%, not clear for which period, maybe 1990-2005; see Fig.3, and the remaining forest in 1996 relative to the original based on Bryant et al., 1997 WRI).

1.4.2 Research purpose

The main purpose of this thesis is to provide policy makers with rigorous evidence-based policy recommendations that could contribute with the design and implementation of effective and cost-effective policies to reduce deforestation and promote sustainable development in Peru. From a research perspective, the thesis' purpose is to respond, in part, to the described methodological challenges of conducting rigorous impact evaluations of forest conservation which have been well summarized by the so-called Conservation Evaluation 2.0 program research (Miteva et al. 2012) and thus to contribute with filling the research gap in terms of: (1) measuring program impact variations by biophysical context and using a theory of change to help in results interpretation (Chapter 2), (2) identifying spatial spillover effects to unenrolled areas (Chapter 2), (3) assessing the CE of programs by means of cost-benefit analysis (Chapter 3), and (4) assessing trade-offs between CE and welfare effects on rural populations of policy mixes (Chapter 4).

In so doing, I propose a three-step methodological framework that could complement the existing assessment toolkit of forest conservation interventions (Figure 1.3) and be applied in the Peruvian Amazon. The framework allows me to present the thesis' research questions, as I explain below. Importantly, the three analytical steps of the framework assess three of the six recently revised criteria proposed by the Organization for Economic Cooperation and Development (OECD) for evaluating development co-operation and other public policy interventions (OECD, 2021), including forest conservation policies, programs and projects, namely: (1) effectiveness, (2) efficiency, and (3) coherence.

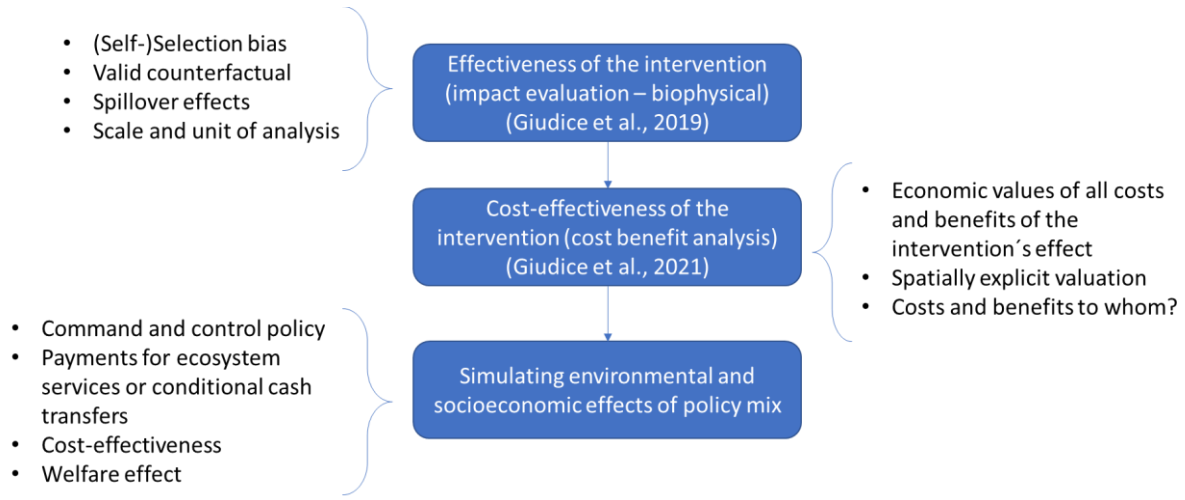

Figure 1.3 Analytical framework

Note: the framework shows the three steps to evaluate a forest conservation intervention.

The first step proposes to conduct a rigorous impact evaluation to estimate and understand the biophysical effect of a forest conservation intervention in reducing deforestation.[4] Such an

[4] Ideally, the design of the impact evaluation should occur in hand with that of the intervention and before its implementation (Gertler et al., 2016). Not doing so constitutes a miss opportunity for advancing knowledge in conservation impact evaluation (Miteva et al., 2012).

evaluation would need to use the most up-to-date methodological approaches to avoid biases produced by self-selection into the intervention, find a valid counterfactual, account for spillover effects, and consider the implications of using different scales and units of analysis. The second step proposes a follow up cost-benefit analysis to express the intervention's impact in economic terms and from different perspectives. The CE of the intervention is assessed by considering the spatially heterogeneous costs and environmental benefits derived from the implementation. Finally, the third step proposes a simulation approach to explore the effect of mixing disincentive- (C&C) and incentive-based (PES) forest conservation policies on CE and welfare effects of local populations. In that sense, I explore whether the policy mix is coherent regarding the socioeconomic context of the study area, in particular regarding poverty levels.

1.5 Research questions

The thesis seeks to answer the following overarching question: What are the environmental and socio-economic impacts of public policies to avoid deforestation in the Peruvian Amazon?

To answer this overarching question, further questions are considered in each of the three analytical chapters, responding to the three analytical steps described above.

Chapter 2 addresses the two following research questions (RQ):

RQ.2.1: What is the effect of *Programa Bosques* on reducing deforestation within participating communities during its early implementation phase, between 2011 and 2015?

RQ.2.2: What are the main factors affecting the effectiveness of *Programa Bosques* on reducing deforestation?

Chapter 3 seeks to answer the following questions:

RQ.3.1: How cost-effective was *Programa Bosques* in reducing deforestation during its initial phase (2011-2015) and what factors affected the CE?

RQ.3.2: How are costs and benefits distributed among the participating communities, the country, and the global society?

RQ.3.3: How can targeting be adjusted to increase *Programa Bosques*' cost-efficiency?

Chapter 4 answers the following questions:

RQ.4.1: Which forest conservation policy mixes of incentives and disincentives would deliver the most cost-effective deforestation reductions?

RQ.4.2: What is the effect of a forest conservation policy mix of incentives and disincentives on its CE and income change of landholders?

1.6 Organization of the thesis

The thesis is organized in five chapters. After presenting the background, problem statement, research objectives, and the research questions in this first introductory chapter (Chapter 1), the thesis addresses each of the research objectives and questions in three analytical chapters (Chapter 2, Chapter 3, and Chapter 4).

Chapter 2 assesses the effectiveness of the Peruvian National Forest Conservation Program in reducing deforestation by conducting a quasi-experimental impact evaluation of its initial phase between 2011 and 2015. The evaluation considers different aerial units of analysis and spillovers to explore their effect on the impact estimates. Based on the results and on a proposed theory of change, the evaluation identifies the key factors that affected the effectiveness of the National Forest Conservation Program and thus provides policy design recommendations that could improve its effect.

Chapter 3 estimates the CE of the National Forest Conservation Program and expressed it in economic terms. Based on the effectiveness estimated in Chapter 2 and on the corresponding economic values of benefits and costs of the avoided deforestation, an ex-post benefit cost-analysis was developed. As such, Chapter 3 contributes with the impact evaluation literature by expressing the effect of a forest conservation program in economic rather than in pure biophysical terms. This chapter also discusses the distribution of costs and benefits derived from the attained deforestation reduction among the participating communities, the country, and the global society. As such this chapter contributes with identifying the policy design options that could increase *Programa Bosques* CE and cost-efficiency.

Chapter 4 presents a spatial explicit simulation model of landholders' decision to deforest based on varying design options of a policy-mix of PES and fines, and enforcement probabilities for the whole Peruvian Amazon. The model allows for estimating the costs, CE, and welfare effects on landholders of alternative policy-mix designs. In so doing, this chapter identifies the policy-mix designs that could mitigate the potential trade-offs between cost-effective deforestation reductions and income changes among landholders.

The last chapter (Chapter 5) includes conclusions and provides a summary of policy recommendations.

2 Selection biases and spillovers from collective conservation incentives in the Peruvian Amazon[5]

Abstract

Payments for ecosystem services are becoming popular components in strategies to conserve ecosystems and biodiversity, but their effectiveness remains poorly documented. Here we present counterfactual-based evidence on the conservation outcomes of the pilot stage of Peru's National Forest Conservation Program (NFCP)[6]. The NFCP provides direct payments to indigenous communities in the Amazon, conditional on avoided deforestation and the adoption of sustainable production systems. Using a spatially explicit quasi-experimental evaluation design, we show that the payment scheme has achieved only small conservation impacts, in terms of avoided deforestation. Counter-intuitively, these materialized largely on land not enrolled for conservation, due to spillover effects. Conservation effects on contracted land were negligible because communities were not chosen according to high deforestation threats, and they self-enrolled low-pressure forest areas for conservation. Occasional non-sanctioned contract incompliance contributed to these outcomes. We highlight implications for the design and implementation of up-scaled national conservation programs. Methodologically, we demonstrate the important role of choosing the appropriate spatial scale in evaluating area-based conservation measures.

2.1 Introduction

PES are voluntary transactions between services users and providers, conditional on natural resources management rules that generate off-site services (Wunder, 2015). PES may potentially be more direct and cost-effective than traditional conservation tools, such as integrated conservation and development projects (ICDP), and have thus become a popular policy instrument (Ezzine-de-Blas et al., 2016; Ferraro and Kiss, 2002; Ferraro and Simpson, 2002). Existing PES schemes often target hydrological services, carbon sequestration, and landscape beauty (Grima et al., 2016). REDD+ could become an important climate change mitigation strategy (FAO, 2016). The Paris Agreement encourages LMIC to implement results-based payments such as REDD+ to preserve forests and secure non-carbon co-benefits.

And yet, how effective are PES in practice? Many scholars have scrutinized the environmental and social outcomes of PES (Börner et al., 2016a), but few counterfactual-based evaluations exist (Baylis et al., 2016; Ferraro and Pattanayak, 2006; Miteva et al., 2012). Early results suggested mixed evidence (Börner et al., 2017); more research is needed to understand why outcomes differ across programs and sites (Baylis et al., 2016; Ferraro and Hanauer, 2014b, 2014a; Grima et al., 2016). Understanding the role of intervention contexts versus scheme design in determining conservation outcomes is an important research gap (Börner et al.,

[5] This chapter is published as Giudice, R., Börner, J., Wunder, S., Cisneros, E., 2019. Selection biases and spillovers from collective conservation incentives in the Peruvian Amazon. Environ. Res. Lett. 14, 045004. https://doi.org/10.1088/1748-9326/aafc83

[6] Throughout the text, the terms NFCP, Programa Nacional de Conservación de Bosques para la Mitigación del Cambio Climático (PNCBMCC), Programa Nacional de Conservación de Bosques (PNCB) and *Programa Bosques* refer to the same forest conservation intervention.

2017). This study makes two contributions to address this gap. First, we focus on collective rather than individual PES contracts, designed to conserve community-owned forests – a common institutional arrangement in tropical forests. Second, we provide PES impact estimates at both community and sub-community scales to better account for intra-community spillover effects.

In addition, we contribute methodologically to the conservation impact evaluation literature by estimating effects at two different spatial scales, namely, at the scale of polygons of different sizes, defined by the boundaries of communities, and at grid cells of 225 ha each, located within the communities´ polygons. Avelino et al. (2016) demonstrated a scale effect on impact estimates, resulting from loss of heterogeneity and variation when moving to higher aggregation levels (i.e. spatial aggregation bias). Few forest conservation evaluations have taken this potential source of bias into account (Börner et al., 2015a; Costedoat et al., 2015), and thus deserves further scrutiny.

We estimate the environmental impact of a collective PES scheme in Peru, run by the NFCP in indigenous communities enrolled between 2011 and 2013, using remotely sensed deforestation data from 2001 to 2015 (Potapov et al., 2014; Vargas et al., 2014c, 2014a, 2014b). We use spatial matching techniques (Honey-Rosés et al., 2011) to control for self-selection bias and post-matching regression analyses to eliminate unobserved time-invariant heterogeneity (Imbens and Wooldridge, 2009). Our findings indicate positively significant, but marginally sized conservation effects. These accrue outside of self-enrolled community conservation areas, which we attribute to economic and behavioral mechanisms.

2.1.1 National Forest Conservation Program´s background

In 2012, 51% of total GHG emissions in Peru originated from deforestation in the Amazon (MINAM, 2016), primarily driven by shifting agriculture (Velarde et al., 2010), gold mining (Asner and Tupayachi, 2016), and cash-crop plantations such as oil palm (Gutiérrez-Vélez et al., 2011) and coca (*Erythroxylum spp*) (UNODC et al., 2016). Estimates of deforestation suggested an increasing trend (Potapov et al., 2014), with an average of 160,000 ha per year between 2011 and 2016 (Vargas et al., 2014b). As a contribution to climate change mitigation, the government communicated a zero-deforestation target to the United Nations Framework Convention on Climate Change (UNFCCC) by 2021 (Brown and Zarin, 2013). In 2010, the Peruvian Ministry of Environment (MINAM) created the NFCP "to contribute to the conservation of tropical forests and the generation of income for the most vulnerable, poor and marginalized peoples" (MINAM, 2010) [author´s translation]. The NFCP seeks to: (i) map forestlands, (ii) promote sustainable production systems, and (iii) strengthen forest conservation capacities (MINAM, 2010). Given the government´s lack of experience in paying cash to landholders for not deforesting, conditional 'projects' had to be implemented to provide local compensatory benefits, while also striving to 'green' local livelihoods. This collective PES-*cum*-ICDP intervention intended to align conservation with poverty alleviation goals, piloted in selected Amazon indigenous communities (Börner et al., 2016b) -- some of the poorest population groups in Peru (Blackman et al., 2017). From the approximately 1,300 titled native communities (Blackman et al., 2017) controlling roughly 12 million ha of forests (Figure 2.1), 50 communities were enrolled between 2011 and 2013 for the pilot phase (Table 2.1). These communities were selected non-randomly, using criteria ranging from forest conditions to accessibility indices (PNCBMCC, 2011a), and subsequently applied at two spatial-

administrative levels: first, at the province level (second highest sub-national political unit in Peru), and second, at the community level. The logic behind this approach was to first prioritize the provinces with the highest threats of deforestation and then to select communities within them. However, eventually those criteria were not implemented consistently and transparently (see chapter 2 Appendix section A.1.1), leaving room for discretional targeting decisions. Together with the fact that communities voluntarily decide to participate (see chapter 2 Appendix section A.1.2), institutional selection created de facto a source of adverse selection bias (Persson and Alpízar, 2013): as we show under Results, communities with historically higher deforestation were underrepresented in the NFCP.

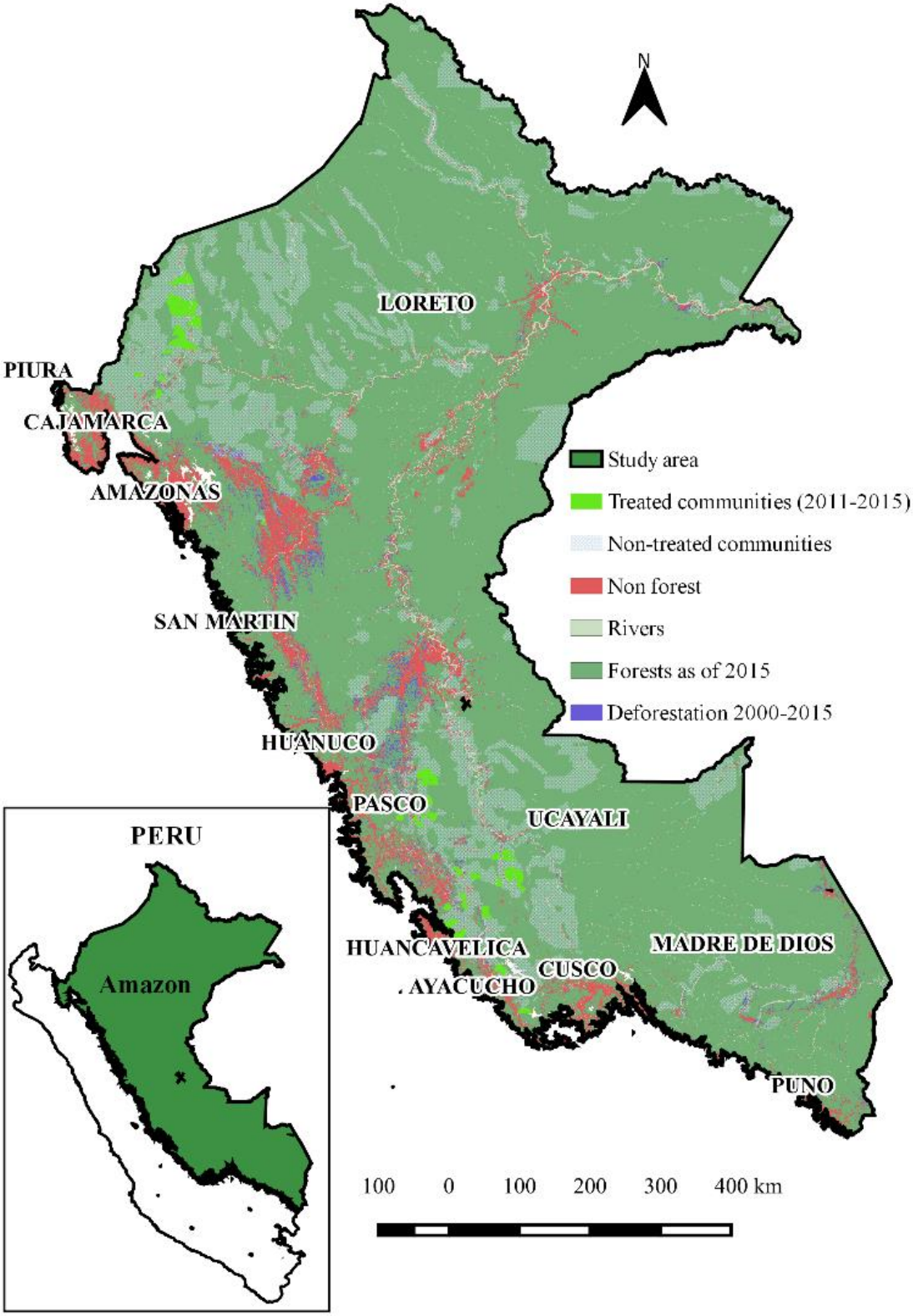

Figure 2.1 Study area

Note: Map showing non-forest (includes no forest classes such as savannah vegetation and deforested areas up to 2000), treated communities between 2011 and 2015, all other non-treated communities, rivers, primary forests as of 2015, and deforested areas between 2000 and 2015.

Table 2.1 Payments and enrolled communities

	2011	2012	2013	2014	2015
Number and area of beneficiaries considered					
Number of newly enrolled communities	17	15	18	0	0
Number of cumulatively enrolled communities	17	30	45	40	40
Number of communities evicted	0	2	3	5	0
Total area of enrolled communities (ha)	196,960	278,981	558,997	506,116	506,116
Total area of enrolled communities' CFZ (ha)	141,808	193,729	414,901	374,679	374,679
Participating families					
Total number of participant families	693	1,759	3,380	2,960	2,960
Payments					
Total (soles)	1,418,080	1,937,290	4,149,010	3,746,790	3,746,790
Per participating family (PEN)	2,046	1,101	1,228	1,266	1,266

Note: soles = Peruvian currency ~USD 0.29 in 2015; CFZ = Conservation forest zone; ha = hectares

The NFCP provides collective payments of 10.00 soles per year and ha of forest enrolled under five-year contracts, supplemented by technical assistance. The payment is publicly funded and is conditional upon (i) its spending on a collectively agreed investment plan to finance forest-friendly production (e.g. agroforestry, aquaculture, and small animal husbandry), community forest patrolling, and public services or infrastructure, and (ii) the maintenance of forest cover in "conservation forest zones" (CFZ) that communities define themselves. This community self-selection of land constitutes a second source of adverse selection bias (Persson and Alpízar, 2013). The remaining land, i.e. "other use zones (OUZ)", is not subject to land use restrictions and typically contains homesteads, agricultural fields, and secondary as well as primary forests remnants (Figure 2.2). Our empirical strategy seeks to measure the NFCP´s impact during its five initial years (2011-2015) on deforestation in the community lands, as a whole, and in both the CFZ (primary effect) and OUZ (spillovers). We use the term "spillover" to denote that the NFCP's intervention to avoid deforestation, targeted

at the enrolled CFZ, may also have indirect yet measurable impacts on the unenrolled subareas of the treated communities (OUZ).

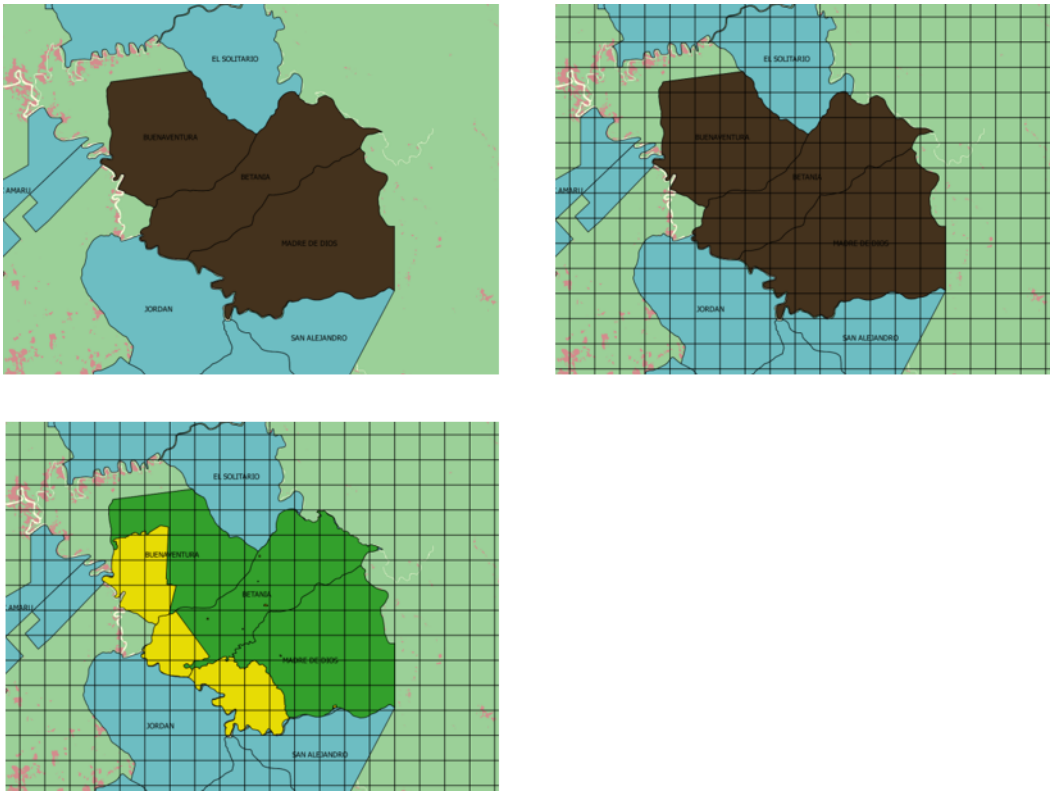

Figure 2.2 Units of analysis and zones

Note: Top-left panel presents polygons as the unit of analysis and whole communities as the zones; for three indigenous communities we show treated polygons (brown) and non-treated communities (light blue). Top-right panel presents cells (225ha) as units of analysis and whole communities as zones. Bottom-left panel presents cells (225ha) as units of analysis and CFZ (green) and OUZ (yellow) zones.

2.2 Expected impact channels

The main NFCP's strategy follows a PES-*cum*-ICDP logic (payments combined with productive change) (see chapter 2 Appendix Figure A.1), assuming implicitly that capital and technical constraints prevent the adoption of sustainable land use systems (Blom et al., 2010). Payments and assistance thus enable "integrated projects" to provide income streams and compensate for the opportunity costs of avoiding deforestation within CFZ. Economic theory, however, suggests that communities will define areas with low opportunity costs as CFZ (Alix-Garcia et al., 2015): being widely unsuitable for agricultural use, and thus unthreatened, their formal 'protection' provides little if any reductions in deforestation. Moreover, income generation from projects require access to markets and qualified technical assistance, the lack of which has often dampened the success of ICDP (Blom et al., 2010). In addition, community forest patrolling could reduce land tenure insecurity and deforestation (Robinson et al., 2014). However, we expect little forest impact here, due to under-funding of this component (annually only 3-4 paid-for patrolling rounds). Similarly, social investments (e.g. improving school

infrastructure) are in-kind payments with disputed linkages to deforestation (Wunder, 2007), which we expect to be marginally influential on land-use decisions.

We consider two rival explanations of conservation outcomes in CFZ and, by way of spillover effects, in OUZ. First, project implementation (e.g. tree-crop plantations, alternative livelihood investments) will directly increase labor demand in the short run, thus reducing labor available for traditional land-use activities, and thus mitigating deforestation pressures. Second, awareness in participating communities of NFCP's forest monitoring could produce short-run behavioral changes: in order to avoid upfront conflicts and please implementers, communities consciously curb deforestation, i.e. the so-called Hawthorne effect (McCambridge et al., 2014). Data limitations prevent us from explicitly testing for these alternative impacts, but insights below from a dynamic treatment effect analysis provide some supporting evidence.

2.3 Methods

2.3.1 Data

We created two datasets, one for community polygons and one for cells. The first is comprised of 992 communities (50 treated and 942 non-treated), for which we could gather geographical, biophysical, and socioeconomic attributes (see chapter 2 Appendix Table A.2 Covariates, units, sources, description, scale and years represented in the data.). The second only includes cells that partially or fully overlap with polygons representing community lands, including those in CFZ and OUZ (Figure 2.2), and that present a deforestation risk larger than 1%. We developed a deforestation risk model to cope with the fact that the distribution of the observed annual deforestation is skewed towards zero and thus to focus only on cells with a minimum risk of 1% of having been deforested between 2001 and 2010 (see chapter 2 Appendix section A.8). We fit a logistic regression model, where the outcome is measured as the fraction of a cell deforested between 2001 and 2010, and covariates include: population, number of houses, area of coca plantations, number of population centers, community area, slope, precipitation, distance to protected areas, forest loss density in 2010, distance to population centers within communities, internal distance to the community's boundaries, share area of forest in 2010, spatially lagged biomass, and distance to deforestation in 2010. Using the fitted values of the model, we discard all cells with a fitted value smaller than or equal to 0.01. This effectively reduced the number of total cells and treated cells with no deforestation in any year between 2001 and 2015 to only 11%. Only the trimmed cell-dataset is used for impact evaluation.

We define the outcome variable as the total area (ha) of annual gross deforestation within community lands for both units of analysis. We used a deforestation dataset, covering 15 years (2001-2015), within the Peruvian Amazon (Potapov et al., 2014; Vargas et al., 2014c, 2014a, 2014b), and define deforestation as the complete removal of forest cover from a Landsat pixel (Potapov et al., 2014).

2.3.2 Empirical approach

We use a quasi-experimental approach that combines matching and double difference regression models to estimate the ATT. As a pre-processing approach, matching reduces the selection bias due to the non-random selection of enrolled communities and CFZ, an approach that is increasingly used to measure conservation outcomes (Alix-Garcia et al., 2015, 2012;

Andam et al., 2008; Arriagada et al., 2012; Joppa and Pfaff, 2010; Miranda et al., 2016; Nelson and Chomitz, 2011), including in the context of the Peruvian Amazon (Blackman et al., 2017; Miranda et al., 2016; Schleicher et al., 2017). We measure effects at different spatial scales in both enrolled and non-enrolled community lands (see chapter 2 Appendix section A.2). We start by comparing outcomes at the scale of decision units using spatial polygons and cells (225 ha each) of treated and untreated-communities (see chapter 2 Appendix section A.3 and Table A.1). We chose an aggregated area of 225 ha because the minimum sizes of (i) treated community polygons and (ii) CFZ-polygons are 2,700 ha and 1,500 ha, respectively. Thus, there are at least approximately 12 and 6 units covering each of these polygons. We believe that aggregating the outcome variable from 0.09 ha to 225 ha improves the representation of the land use decision unit and reduces potential bias arising from spatial autocorrelation (Avelino et al., 2016; Qi and Wu, 1996).

This approach, however, aggregates over intra-community effects, given that payments restrict deforestation only in CFZ. Avoided CFZ deforestation could be partially outweighed by added OUZ deforestation (negative spillover, i.e. leakage). Alternatively, participants could shift resources to fulfil the NFCP´s rules and thereby reduce deforestation in OUZ (positive spillover). Thus, we also estimate the ATT in CFZ and OUZ cells, separately. For this, we model at the cell level which areas of non-participating communities would have most likely been selected as CFZ and OUZ from which to withdraw a control group (see chapter 2 Appendix section A.4).

We use one-to-one nearest neighbor matching with replacement to find a control group from the pool of untreated communities and cells (see chapter 2 Appendix section A.5), using the Genetic algorithm (Diamond and Sekhon, 2012) of the R Match function and the Mahalanobis distance for polygons and cells, respectively, and the exact distance for the Department identifier in both. We use a set of covariates from a pre-treatment data set of geo-biophysical, land-use and land-cover, infrastructure, and socioeconomic variables (see chapter 2 Appendix section A.6 and Table A.2 Covariates, units, sources, description, scale and years represented in the data.). These covariates include[7]: (i) **biophysical**: elevation† (m), slope† (°), above ground live woody biomass†† (Mg/ha), temperature† (°C), precipitation† (mm), distance to rivers† (m); (ii) **infrastructure**: distance to roads† (m), accessibility†† (index), distance to district´s capitals† (m), distance to population centers† (m); (iii) **land use/land cover**: forest cover area in 2010†† (%), deforestation density in 2010† (ha/km^2), community´s total area††† (ha), distance to deforestation outside communities††† (m), distance to protected areas†† (m), internal distance to community´s boundary† (m), deforestation risk†; (iv) **spatial lags**††† for: deforestation (ha), forest cover area in 2010 (%), slope (°), above ground live woody biomass (Mg/ha), elevation (m); (v) **socioeconomic**: density of coca plantations†† (ha/km^2), years passed since communal land titled††† (years), population†† (person), number of houses††† (house), access to drinking water††† (%), access to electricity† (%), population centers within a community†† (center), per capita income†† (soles), human development index† (index), total poverty†† (%), and extreme poverty††† (%). These covariates are likely to affect both the

[7] Superscripts †, ††, and ††† denote whether covariates are related to our hypothesis (e.g. they are proxies for the opportunity costs of conservation); are part of the NFCP targeting criteria; or have reportedly influenced treatment assignment and outcomes of conversation initiatives in Peru (Mäki et al., 2001; Miranda et al., 2016; Naughton-Treves, 2004; Velarde et al., 2010; Vuohelainen et al., 2012) and elsewhere (Soares-Filho et al., 2010), respectively.

selection of participating communities and deforestation, but are not affected by the treatment (Stuart, 2010). Treated and control units were drawn from a total number of 992 communities (polygons), 18,319 community-cells (cells), 30,782 CFZ-cells, and 15,984 OUZ-cells. The number of unique treated and control units for each level of analyses is: communities (polygons, 50 treated and 36 untreated); communities (cells, 986 treated and 495 untreated); CFZ (cells, 523 treated and 304 untreated); and OUZ (cells, 655 treated and 305 untreated). The treatment variable is continuous from 0 to 1 in both polygons and cells as units of analysis. In the first case it denotes the fraction of the year in which a community polygon has been treated. In the second case it denotes the share area of polygons representing treated communities/CFZ/OUZ within a cell and the fraction of the year in which the cell has been treated. The control units always have a treatment value of zero.

We use the matched dataset and apply a fixed-effect regression model to a panel dataset of 15 years (2001-2015). The original model at the community level is:

$$\boldsymbol{Y_{ctd} = \beta D_{ct} + tX'_c\delta + \gamma Out_{pres_{ct}} + \varphi_t + \alpha_c + t\omega_d + u_{cdt}} \qquad (\mathbf{Eq.}\ 2.1)$$

And at the cell level:

$$\boldsymbol{Y_{ictd} = \beta D_{ict} + tX'_i\delta + \gamma Out_{pres_{ict}} + tW'Z'_i\lambda + \varphi_t + \alpha_i + t\omega_d + u_{icdt}} \qquad (\mathbf{Eq.}\ 2.2)$$

Where Y_{ctd} is the annual deforestation in each community *c*, in year *t*, located in department *d* (highest sub-national political-administrative unit in Peru). D_{ct} is the treatment indicator at the community level, turning positive in year *t* when a community is enrolled (Eq. 2.1). Enrolled communities become a treatment indicator larger than 0 and up to 1 in the year of enrollment, depending on the number of treated months during that year. Thereafter, the indicator is 1 if the community is still treated. Similarly, Y_{ictd} is the annual deforestation in each cell *i*, located in community *c*, in year *t*, in Department *d*. D_{ict} indicates treatment at the cell level using the treated share of cell *i* in year *t* (Eq.2.2). Cells within communities have a share of one, and cells at the margin of community borders have a share between 0 and 1. *X´* is the vector of time-invariant pre-treatment characteristics, such as slope. These variables can influence the deforestation trend, and are therefore interacted with time indicator *t*. Out_pres_{it} is the average distance from community *i* in year *t*, to deforestation patches (>1ha) located outside communities, and represents external deforestation pressure. In Eq.2.2, WZ' represents a vector of spatially lagged covariates weighted by a standardized queen contiguity matrix (W) (Honey-Rosés et al., 2011). *δ*, *γ*, and *λ* are coefficients to be estimated. Year fixed effects, denoted by φ_t, control for yearly factors influencing all units of analysis equally, such as, policy changes to the Peruvian forestry rules (Blackman et al., 2017). Individual fixed effects ($\alpha_c$or α_i) represent the individual unobserved time-invariant heterogeneity (e.g. soil quality). ω_d is introduced to capture department-specific forest conservation efforts. Finally, u_{cdt} or u_{icdt} denote the idiosyncratic errors (Wooldridge, 2010).

Taking first differences (FD) of Eq.2.1 and Eq.2.2 eliminates all time-invariant unobserved heterogeneity (α_c and α_i), which could have biased our estimates (see chapter 2 Appendix section A.7). The coefficient β represents the ATT on annual deforestation changes for all years after treatment. For communities, we estimate the FD of Eq.2.1:

$$\Delta \boldsymbol{Y_{cdt}} = \boldsymbol{\beta} \Delta \boldsymbol{D_{ct}} + \boldsymbol{X'_c \delta} + \boldsymbol{\gamma} \Delta \boldsymbol{Out_{pres_{ct}}} + \Delta \boldsymbol{\varphi_t} + \boldsymbol{\omega_d} + \Delta \boldsymbol{u_{cdt}} \qquad (\mathbf{Eq.}\, 2.3)$$

For cells we estimate the FD of Eq.2.2:

$$\Delta \boldsymbol{Y_{ictd}} = \boldsymbol{\beta} \Delta \boldsymbol{D_{ict}} + \boldsymbol{X'_i \delta} + \boldsymbol{\gamma} \Delta \boldsymbol{Out_{pres_{ict}}} + \boldsymbol{W' X'_i \lambda} + \Delta \boldsymbol{\varphi_t} + \boldsymbol{\omega_d} + \Delta \boldsymbol{u_{icdt}} \qquad (\mathbf{Eq.}\, 2.4)$$

By comparing fixed and random effects models using the Hausman test (Hausman, 1978), we rejected the null hypothesis ($p<0.01$) in all cases, thus indicating that a fixed effects model was more appropriate. Given that treatment assignment occurs at a higher level than the cell, namely, at the community level, we cluster standard errors (SE) of β at the level of the community polygon to avoid inconsistent variance-covariance matrices due to heteroscedasticity and autocorrelation in the error terms (Abadie et al., 2017; Croissant and Millo, 2008) (see chapter 2 Appendix section A.7). In addition to the overall effect across 2011-2015, we also estimate the effect of the NFCP over the years after enrollment by replacing the treatment variable in Eq. 2.3 and 2.4 with five new treatment variables, each one representing year zero through year four after enrollment. The estimated coefficients for each of these variables are interpreted as the average effect of the NFCP after t years of enrollment (Cisneros et al., 2015). Used models are presented in chapter 2 Appendix section A.9 (Effects over time).

2.4 Results

2.4.1 Matching

After matching, balance between treated and non-treated groups improved in almost all covariates for all levels of analysis (see chapter 2 Appendix Table A.3 to Table A.6). We use the normalized difference, the mean difference in the standardized empirical-QQ plot (as proposed by Ho et al., 2007) and the mean difference between treated and control groups to assess covariate balance after matching. For a few time invariant covariates normalized differences remained above the rule of thumb of 35% even after matching (Fleiss et al., 2013). This potential source of bias is addressed by using the fixed effects model to estimate treatment effects (Ferraro and Miranda, 2017).

2.4.2 Main results

Annual averages of deforestation between 2001 and 2015 of all treated communities, non-treated communities, and the matched control group increase over time (Figure 2.3). The NFCP predominantly selected communities with relatively lower deforestation threats. Chapter 2 Appendix Figure A.2 confirms this by comparing three alternative measures of pre-treatment deforestation levels among the 50 treated communities and top-50 non-treated communities.

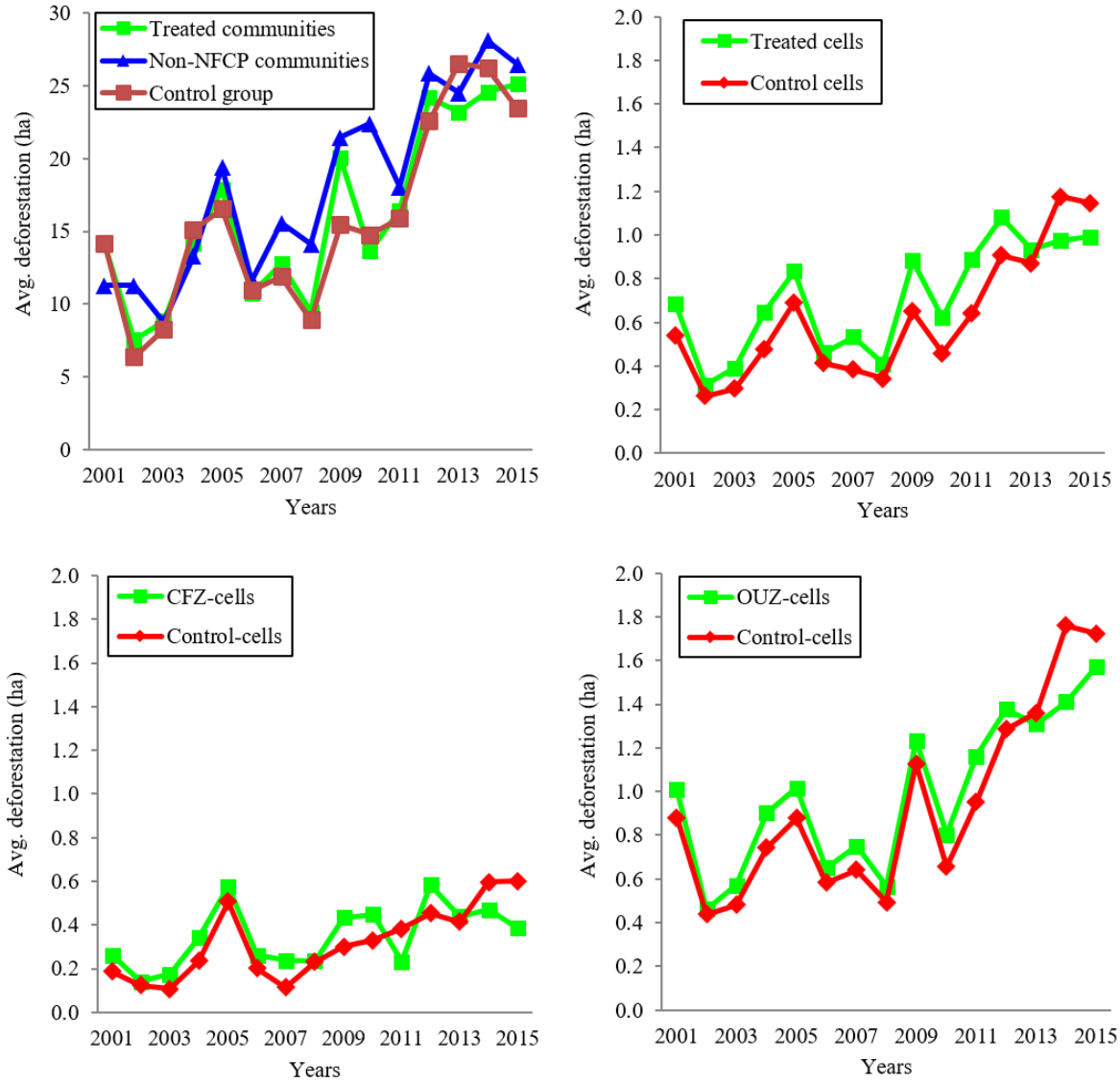

Figure 2.3 Annual averages of deforestation

Note: (top-left) treated communities (N=50), non-treated communities (N=492) and the matched control group (N=50); (top-right) treated community cells (N=986) and the matched control group (N=986); (bottom-right) CFZ cells (N=523) and the matched control group (N=523); and (bottom-left) OUZ cells (N=655) and the matched control group (N=655).

Trends were similar at the cell level, where treated cells, CFZ-cells and OUZ-cells, and their corresponding matched control groups, exhibited increased deforestation (Figure 2.3). Non-zero, but low levels of deforestation in the CFZ of treated communities (see chapter 2 Appendix Figure A.3) also suggest mild levels of non-compliance in most cases. In eight communities, however, the percentage of the deforested area relative to the area of the CFZ exceeds the threshold of 0.3% (PNCBMCC, 2017), above which a community is allegedly to be evicted from the NFCP. Nonetheless, from these eight communities, only two were expelled in 2014, the rest remained enrolled. Another eight communities were also evicted (Table 2.1), but due to causes not related to deforestation in their CFZ (e.g. non-compliance with their investment plan).

In addition, we observe that there are substantial differences between the CFZ and the OUZ of participating communities regarding characteristics that could affect both the selection of an area as a CFZ and deforestation outcomes. These include: slope, elevation, distance to rivers, distance to population centers within the community, deforestation previous to the start of the NFCP (2010) and deforestation risk (Table 2.2).

Table 2.2 Means and standard deviations (SD), and normalized differences between characteristics of the CFZ and the OUZ cells participating in the NFCP between 2011 and 2015.

Variable	Mean for CFZ cells	SD for CFZ cells	Mean for OUZ cells	SD for OUZ cells	Normalized difference (%)
Geographical and biophysical					
Slope (grade)	12.73	7.82	8.11	7.36	60.8
Elevation (m)	745.31	521.40	485.02	393.74	56.3
Precipitation (mm)	2025.67	524.01	2014.86	527.82	2.1
Biomass (MgC/ha)	280.15	33.34	246.76	65.40	64.3
Distance to rivers (m)	2822.58	1964.35	1139.64	1159.35	104.3
Infrastructure					
Distance to roads (m)	20055.44	19386.28	21130.86	21588.08	5.2
Accessibility index	84737.83	45639.46	83025.84	40980.86	3.9
Distance to district´s capitals (m)	24427.38	15900.91	27236.61	16401.90	17.4
Distance to population centers within community (m)	3697.51	1767.44	2344.95	1348.55	86.0
Land use/Land cover					
Outside deforestation 2010 (m)	3243.66	2115.08	3132.36	2580.57	4.7
Internal distance to community boundary (m)	927.25	862.73	711.13	669.31	28.0
Deforestation in 2010 (ha)	2.81	9.20	10.74	13.04	70.2
Distance to protected areas (m)	19635.37	17831.75	19398.12	16096.96	1.4
Deforestation risk	0.023	0.018	0.042	0.035	68.0
N	524		655		

The ATT of the NFCP at community scale is statistically significant and negative (Table 2.3, column 1) at polygon scale (Eq.2.3), but insignificant at cell scale (Table 2.3, column 2, and Eq.2.4). However, our results in columns 1 and 2 might have been affected by the independent effects occurred within CFZ and OUZ leading to a relatively less precise ATT (Avelino et al., 2016). Therefore, in column 3 and 4 we present the independent effects of the NFCP within CFZ and OUZ, respectively. Assessing intra-community effects (Eq.2.4), we only find statistically significant and negative effects in OUZ, not in CFZ (Table 2.3, column 5). This implies that the NFCP may have avoided deforestation within OUZ-cells by an average of 0.4±0.2 ha/yr (Mean±SE), in every subsequent year after treatment. This estimate represents

a total of 557 ha (considering SE: 59-1,056 ha) of avoided deforestation between 2011 and 2015, corresponding to a 5.8% reduction (0.61-11.1%).

Table 2.3 Impact of the NFCP on deforestation

	Δ Deforestation (ha)			
	Communities (polygons)	Communities (cells)	CFZ (cells)	OUZ (cells)
	(1)	(2)	(3)	(4)
Δ $\text{Enrollment}_{i/cdt}$	-6.902*	-0.245	0.039	-0.386*
SE	(3.624)	(0.153)	(0.09)	(0.21)
Spatial lagged covariates	No	Yes	Yes	Yes
Number of clusters (communities)	86	179	158	155
Cumulative number of observations (14 years)	1,400	27,608	14,644	18,340
Adjusted R^2	0.027	0.020	0.013	0.030

Note: table reports FD estimates with the dependent variable being the annual change of the yearly new deforested area (ha). SEs are clustered at the community level. Significance level: *p<0.1.

2.4.3 Conservation effects over time

In addition to the overall effect for each scale of analysis, we also explore how the effect evolves over time (Figure 2.4). When analyzing community effects, we find statistically significant and negative ATTs only in the first year after enrollment at the polygon (-8.5±3.5 ha) and cell scales (-0.27±0.13 ha). When analyzing intra-community effects at the cell scale, we only find significant and negative ATTs in the second (-0.21±0.1 ha) and first years after enrollment (-0.45±0.17 ha) for CFZ and OUZ cells, respectively.

These results do not change our previous conclusions regarding overall effects (Cisneros et al., 2015), but provide additional clues to understand the potential impact channels. The fact that significant effects throughout are only present in the initial years, dissipating thereafter, suggests that the NFCP might have induced a behavioral change, but probably only for a short period.

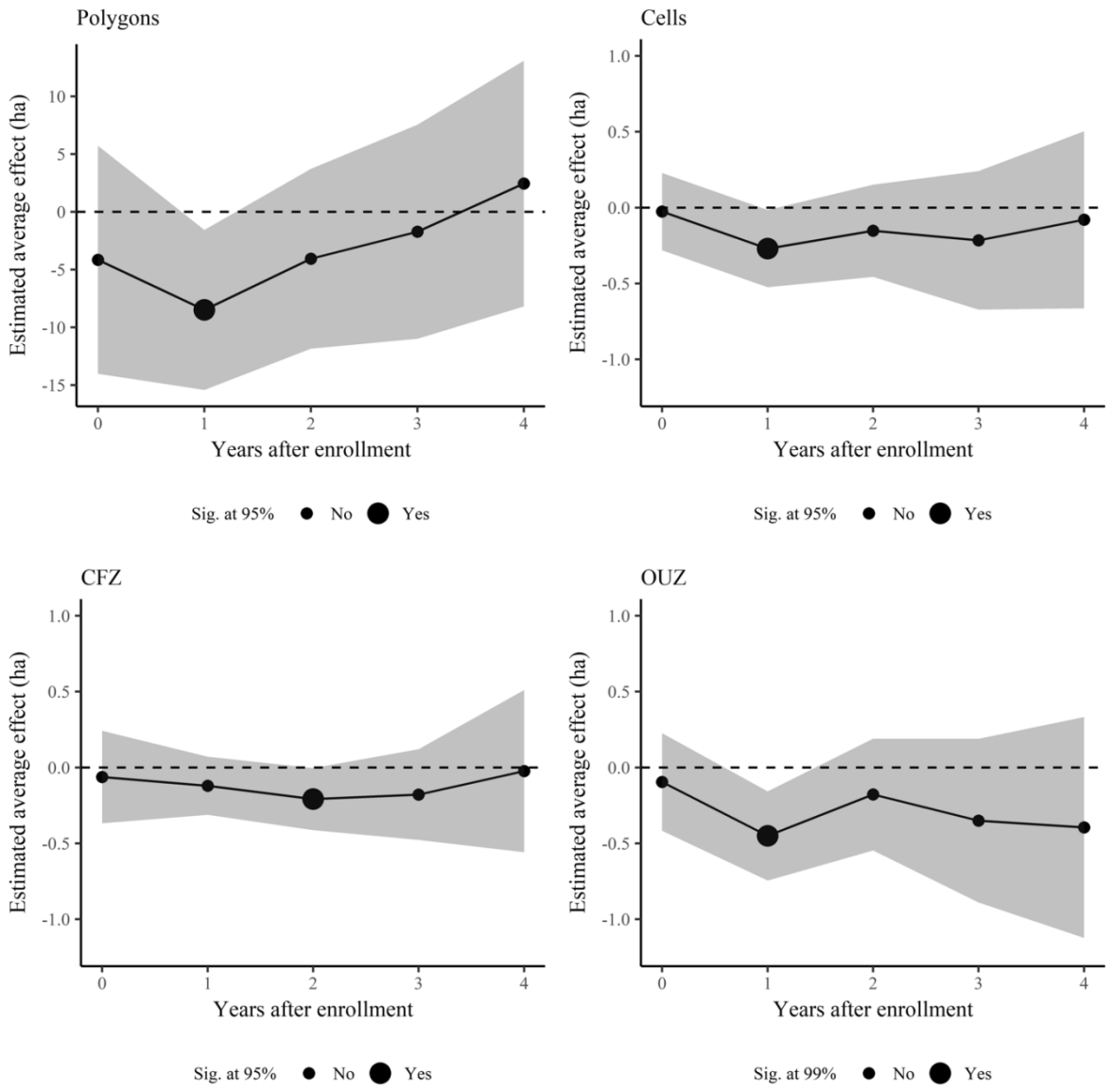

Figure 2.4 Estimated conservation ATT over time

Note: (top-left) polygons; (top-right) community cells; (bottom-left) CFZ cells; and (bottom-right) OUZ cells. Grey bounds represent 95% confidence intervals.

2.5 Discussion

We provide new evidence on the effectiveness of a collective PES-*cum*-ICDP scheme in indigenous communities in the Peruvian Amazon. We assess impacts at two different spatial scales, using a quasi-experimental approach with a 15-yr panel of deforestation. We show that the use of polygons or cells affects the significance of the ATT. This effect has only recently received attention in conservation policy evaluation and appears to stem from well-known challenges in geospatial statistics (Avelino et al., 2016). Avelino et al. (Avelino et al., 2016) found that conservation effects in Mexico increase and become less precise with aggregation and that large units of analysis could generate biased estimates when treatment is coarsely measured. Hence, we believe that measuring the effect of the NFCP using highly

aggregated units of analysis, such as polygons (mean = 12,000 ha), which are defined as treated mainly with a binary variable, could bias the ATT. Consequently, it is key that we also estimate the NFCP impact at the cell level for the entire community, so as to have a "second opinion" at a lower level of aggregation. In doing so, we found no statistically significant results at the cell level and thus conservatively conclude that there is no robust evidence for NFCP impact if the entire community is considered. Further analyses including a broader spectrum of spatial scales and larger numbers of treated communities may be needed to further explore which spatial scale is more suitable.

To explain our finding, we note that deforestation in participating communities (as well as within their separate CFZ and OUZ) has not been halted after the start of the NFCP. This indicates partial non-compliance and failures in the NFCP´s monitoring and enforcement capacity. This finding of deficient enforcement of conditionality is not uncommon to PES schemes around the world (Wunder et al., 2018).

Given that communities' conservation agreements with the NFCP only include a subset of community land, we also explored impacts in CFZ and OUZ separately. Counterintuitively, we only find a small but significant conservation effect in the non-contracted OUZ.

We attribute the program's lack of impact in CFZ to adverse selection at two levels: first, having targeted communities with already low deforestation rates (i.e. an adverse administrative selection) and second, self-selection bias allowing communities to enroll widely unthreatened forests. This is a problematic issue in many conservation programs (Alix-Garcia et al., 2012; Börner et al., 2017; Robalino and Pfaff, 2013) and can be avoided by adopting appropriate targeting criteria (Sims et al., 2014) and enrolling total community area (Alix-Garcia et al., 2008).

Even if the NFCP had adopted and appropriately implemented targeting criteria, we do not expect that this would have *per se* led to a much better outcome. Ultimately, adverse self-selection bias at the community-level is likely to be the main reason for the low effectiveness of the NFCP.

Why, then, would we find a negative (pro-conservation) ATT in non-contract areas? We point to two potential causal mechanisms that may complement each other (figure S1 in SI). First, participating community members know that the NFCP wants to see forest conservation within the whole community area. When a program is recently started, this might produce a so-called "honeymoon" or "Hawthorne" effect (McCambridge et al., 2014): communities adopt short-lived conservation measures to honor the goals of their contract partners, but this effect dissipates over time. Second and in the short-run, increased labor demand for project implementation may have mitigated recurrent deforestation pressures, e.g. the opening up of new agricultural fields. Most communities (N=36) invested the bulk of their received payments in adopting agroforestry on abandoned lands -- usually a labor-intensive task (Angelsen, 2010; Angelsen et al., 2001) implemented in their OUZ. If deforestation was constrained temporarily through this mechanism, it was a direct result of NFCP transfers and could thus be labelled a positive economic spillover effect.

To address the above-mentioned sources of bias in program design, the NFCP should adapt and test additional selection criteria, giving more weight to the targeted enrollment of threatened forests at the community level. Otherwise, adverse selection biases will continue

to jeopardize conservation outcomes (Sims et al., 2014). Specifically, we propose the following measures for an up-scaled program design:

1. Pre-target communities with higher deforestation threats,
2. offer voluntary PES contracts that cover the whole community area,
3. and ensure the conditionality of payments.

Earlier impact assessment work suggests that the trade-off between boosting additionality of enrolling the highest threatened communities and the opportunity costs of implementing the NFCP in such communities is manageable (Börner et al., 2016b). However, some high-threat communities may decline participation due to negative (real or perceived) welfare effects (Persson and Alpízar, 2013), so future research should also explore motivations of participation, adopt both monetary and non-monetary approaches to cost-benefit analyses (Jayachandran et al., 2017; Vincent, 2016), and consider program implementation costs (Wunder et al., 2018).

Notably, a PES scheme that effectively curbs forest loss in indigenous communities could affect traditional productive and cultural activities or jeopardize food security (Corbera, 2012). We thus stress that participation in the scheme must remain genuinely voluntary and emphasize that *redesigning the scheme as suggested above does not interfere with use and access rights. It merely ensures that communities are being flexibly compensated according to how much deforestation they are able and willing to avoid.*

In closing, we recognize that, in addition to the small conservation effects we found, the NFCP may have delivered other important benefits to recipient communities, e.g. in terms of social services and economic development that may justify the program's average annual budget of 3.9 million USD. Many public services remain precarious in Amazon indigenous communities (Instituto Nacional de Estadística e Informática (INEI), 2008). However, from a conservation point of view, we point to a large potential for boosting impacts through improved design and implementation.

3 Benefits and costs of incentive-based forest conservation in the Peruvian Amazon[8]

Abstract

A growing literature focuses on evaluating the effectiveness of forest conservation policies, but few studies explore where and under which conditions programs produce net positive benefits. Quantifying the costs and benefits of conservation policy instruments contributes to making impact evaluation more relevant for policy makers and can help to improve program design. Here we analyze the costs and benefits of deforestation avoided by the Peruvian *Programa Bosques* between 2011 and 2015. Our approach builds on an *ex post* counterfactual-based impact evaluation and considers spatial heterogeneity in conservation opportunity costs as well as uncertainty across a wide range of parameters. We rely on existing SCC estimates to value benefits and calculate implementation and administration costs from primary and secondary sources. Our estimates suggest that deforestation was avoided at a negative net future value (NFV) of USD 13.7 Million in 2015. Poor conservation performance is mainly due to high implementation and administration costs (~67% of total budget). Nevertheless, participating communities benefited from an estimated net transfer of USD 7.7 Million. Our result emphasizes the need to boost impact, secure the permanence of the avoided deforestation, and minimize program implementation costs, while paying carefully attention to distributional outcomes.

3.1 Introduction

Governments in tropical countries are experimenting with incentive-based forest conservation approaches, such as PES, to mitigate climate change, conserve biodiversity, and improve forest-dependent livelihoods. To evaluate such programs, scientists are increasingly relying on counterfactual-based impact evaluations and advanced methods to identify the mechanisms underlying overall program´s impacts (Ferraro and Hanauer, 2014a; Wunder et al., 2018). As new evidence provides explanations for failure or success, tax payers can hold donors and governments accountable and scarce resources for conservation can be put to more effective uses (Baylis et al., 2016; Börner et al., 2020). However, the usefulness of impact evaluations for decision making in conservation still hinges on the availability of economic measures of program´s performance (Vincent, 2016). Few studies have incorporated information on costs, thus allowing for CE analyses and comparisons between different forest conservation instruments and approaches (Sims and Alix-Garcia, 2017; Somanathan et al., 2009). Sims and Alix-Garcia (2017) compared Protected Areas and PES in Mexico, finding that the two instruments achieved environmental and social goals at similar levels of CE. Similarly, Somanathan et al. (2009) compared forest management in India across administrative levels and found that village forest councils managed forests ten times more cost-effectively. Their study thus made a strong argument for decentralization of forest management in similar country settings.

[8] This chapter is published as Giudice, R., Börner, J., 2021. Benefits and costs of incentive-based forest conservation in the Peruvian Amazon. For. Policy Econ. 131, 102559. https://doi.org/10.1016/j.forpol.2021.102559

Comprehensively valuing conservation impacts further involves estimates of the environmental benefits achieved by programs, which, net of costs, allow for the calculation of net-benefits as a result of an *ex post* cost-benefit analysis (CBA) (Vincent 2016). By using spatially explicit maps of forest ecosystem values, the usefulness of CBA as an input for program redesign can be substantially enhanced (Naidoo and Ricketts, 2006; Strand et al., 2018). For example, a program with a small average effect on deforestation may not be locally or globally inefficient (Costello and Polasky, 2004; Vincent, 2016), if small deforestation reductions were achieved on a highly valuable area, such as a biodiversity hotspot with high biomass density. Conversely, a large impact may have been associated with forbiddingly high implementation costs and thus render the whole intervention inefficient. Vincent (2016) therefore warned against misguiding decision makers by exclusively focusing evaluation research on biophysical outcome measures (e.g. avoided deforestation). Unfortunately, few conservation evaluation studies provide extended results from CBA (Börner et al., 2015a; Jayachandran et al., 2017). For example, Jayachandran et al. (2017) conducted an *ex post* CBA of the effect of a PES program in Uganda, and found that the avoided deforestation resulted in an environmental benefit 2.4 times larger than the overall costs (Jayachandran et al., 2017). Even fewer studies consider the heterogeneous spatial distribution of costs and environmental benefits, such as the distribution of aboveground biomass and opportunity costs.

The purpose of this study was to contribute to the development of conservation evaluation as a decision tool. Hence, we compared the environmental benefits and costs of *Programa Bosques* building on a previously estimated causal effect (Giudice et al. 2019) using an *ex post* CBA from three perspectives: the local participating communities, Peru as a Nation, and the global society. *Programa Bosques* is a voluntary cash transfer program that provides collective payments and technical assistance, conditional on avoiding deforestation, to largely self-selected indigenous communities in the Peruvian Amazon (Giudice et al. 2019). Communities sign a 5-year contract and must thereof invest payments in the implementation of production projects (MINAM, 2010). The intervention logic is that increasing production will lead to income increases and compensation of the conservation opportunity costs thus leading to the long-term reduction of deforestation induced emissions and promoting sustainable development (MINAM, 2010). MINAM launched *Programa Bosques* in 2010 as the main Peruvian contribution to the global climate change mitigation efforts. *Programa Bosques* started in 2011 and it is still ongoing (Giudice et al., 2019).

Specifically, the study addressed the following questions:

1. At what costs did *Programa Bosques* reduced deforestation during its initial phase (2011-2015)?
2. Did *Programa Bosques* generate any net future positive benefits from the standpoint of 2015?
3. How do net future benefits vary from the perspectives of participating local communities, the Peruvian economy, and the global society?
4. How can targeting be adjusted to increase *Programa Bosques'* benefit-cost ratio?

3.2 Conceptual framework

Any incentive-based forest conservation intervention, having achieved some level of avoided deforestation, implies a series of costs and benefits at different scales from the perspective of different actors (Andersen et al. 2002). This is also the case for *Programa Bosques*. In Figure 3.1, we present the main components and some examples necessary to implement a CBA of such an intervention from the perspective of the local participating communities, Peru as a Nation, and the rest of the global society.

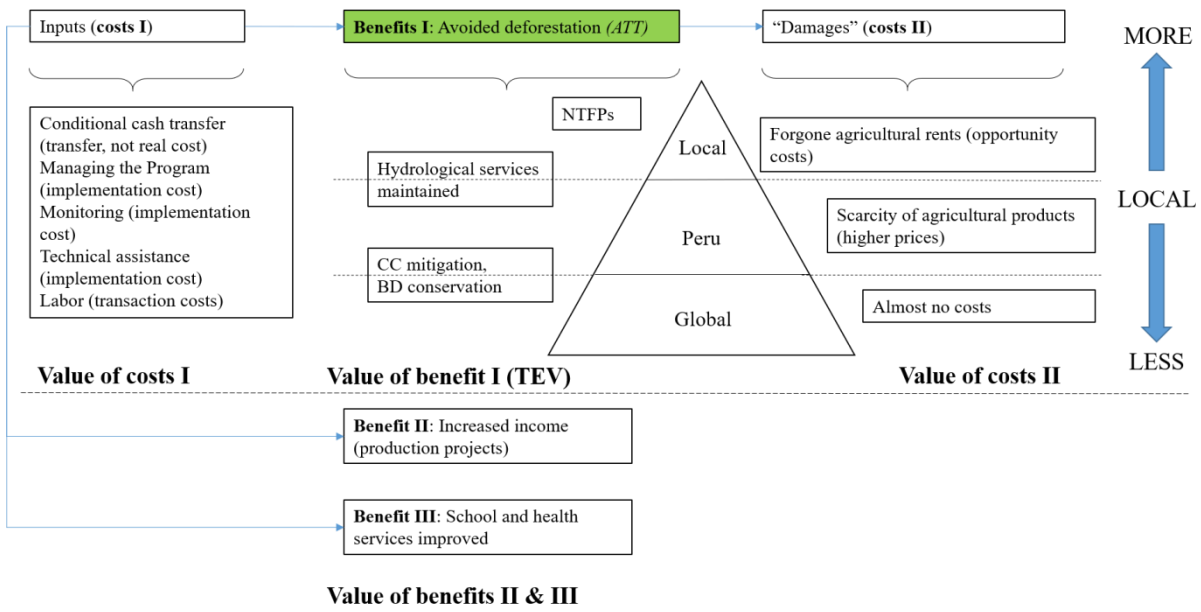

Figure 3.1 Conceptual framework

Note: The framework shows the costs and benefits arising from the implementation and effect on avoiding deforestation of a forest conservation program from three perspectives: the local participating communities, the Peruvian Economy, and the global society. CC: climate change; BD: biodiversity; ATT: average treatment effect on the treated; NTFP: non-timber forest products

First, a series of inputs are necessary to implement *Programa Bosques*, including a conditional cash transfer or payment, implementation and administration activities, technical assistance, and monitoring compliance. These activities impose costs on the Peruvian economy (Giudice et al., 2019). If transfers must be locally invested into sustainable production, transaction costs accrue to the recipient communities (Giudice et al., 2019). Once the intervention is finalized and effectively reduced deforestation, different benefits and costs accrue to actors at various scales.

From the perspective of local communities, avoided deforestation would imply, for example, improved availability of timber and non-timber forest products. On the other hand, the avoided deforestation imposes opportunity costs. From a national perspective, avoiding deforestation could reduce fire incidence (Brando et al., 2014; Soares-Filho et al., 2012), which in turn, imposes losses for regional timber and agricultural sectors (Andersen et al., 2002; de Mendonça et al., 2004; Oliveira et al., 2019). Depending of the magnitude of avoided deforestation, however, fewer areas for agricultural activities could increase the prices of

agricultural products (Angelsen, 2010). Finally, from the perspective of the global society, avoided deforestation provides significant climate change mitigation and biodiversity conservation benefits (Seymour and Busch, 2016), but relatively small opportunity costs to, for example, international consumers who experiment a reduction in protected species´ harvesting (Balmford and Whitten, 2003) or potentially increased agricultural prices (Angelsen, 2010).

Forest conservation could deliver other non-environmental benefits, such as increased revenues to participating households from sustainable production activities (Bauch et al., 2014; Montoya-Zumaeta et al., 2019; Weber et al., 2011). Similarly, social benefits could include improved health and education outcomes. Nevertheless, the evidence supporting these secondary effects is scarce and shows small impacts (Weber et al., 2011).

Our approach to quantifying the elements of the framework laid out in Figure 3.1 relied on the concept of total economic value (TEV), considering direct use, indirect use, option and existence values (Pearce, 1993) and the environmental benefits to be valued were chosen following recommended types of forests values (Sheil and Wunder, 2002).

3.3 Methods

We assessed whether *Programa Bosques* generated net future benefits during its initial phase by conducting *ex post* CBA from the three perspectives discussed above (see Figure 3.1). We used Monte Carlo (MC) simulations under two different scenarios that differ in terms of the time horizon (short versus long-term). Time horizons are defined by the assumed permanence of the estimated avoided deforestation and MC is used to generate probability distributions of the NFV of *Programa Bosques* from each perspective in each scenario. With this approach we account for parameter uncertainty (i.e. costs, benefits, discount rates).

Costs and benefits of avoiding deforestation vary in space (Naidoo and Ricketts 2006). Our approach accounted for this by relying on spatially explicit measures of costs and benefits whenever possible, for example, to allow for location-specific adjustments in program design. We also included the implementation and administration costs, and the transfers to communities. However, given data constraints, we only included spatially heterogenous benefits for climate change mitigation and opportunity costs, and complemented these with existing non-spatial marginal values for other environmental benefits.

3.3.1 Benefits

Climate change mitigation was one of the main motivations to design *Programa Bosques* (MINAM 2010). Although mitigation is not the only potential benefit, it is allegedly the most important one due to its large economic value vis-à-vis other locally abundant ecosystem services (Andersen, 2015; Andersen et al., 2002; Franklin and Pindyck, 2018; Strand et al., 2018). To value the program's contribution to mitigation, we first simulated the deforestation that would have occurred annually between 2011 and 2015 with and without *Programa Bosques* in the non-enrolled forest areas of participating communities (OUZ), where statistically significant deforestation reductions have been found (Giudice et al. 2019).

For this purpose, we relied on the FD panel data model estimated by Giudice et al. (2019):

$$\Delta\widehat{\boldsymbol{Y}}_{\boldsymbol{ictd}} = \widehat{\boldsymbol{\beta}}\Delta\boldsymbol{D}_{\boldsymbol{ict}} + \boldsymbol{X}'_{\boldsymbol{i}}\widehat{\boldsymbol{\delta}} + \widehat{\boldsymbol{\gamma}}\Delta\boldsymbol{Out}_{\boldsymbol{pres}_{\boldsymbol{ict}}} + \boldsymbol{W}'\boldsymbol{X}'_{\boldsymbol{i}}\widehat{\boldsymbol{\lambda}} + \Delta\boldsymbol{\varphi}_{\boldsymbol{t}} + \boldsymbol{\omega}_{\boldsymbol{d}} \qquad (\mathbf{Eq.}\,3.1)$$

Where $\Delta\hat{Y}_{ictd}$ is the annual deforestation change in cell i (225 ha) within community c, in year t, within *Departamento* d (2nd order political-administrative unit). The coefficient $\hat{\beta}$ represents the ATT on annual deforestation changes for all years after treatment. D_{ict} indicates treatment, defined as the share of cell i in year t. X' is the vector of time-invariant covariates. Out_pres_{ict} represents pressure from external deforestation on cell i within community c in year t. WZ' represents a vector of spatially lagged covariates weighted by a standardized queen contiguity matrix (W). $\hat{\delta}$, $\hat{\gamma}$, and $\hat{\lambda}$ are coefficients to be estimated. Year fixed effects, denoted by φ_t, control for yearly factors influencing all units of analysis equally. Individual fixed effects (α_i) represent the individual unobserved time-invariant heterogeneity. ω_d is introduced to capture department-specific forest conservation efforts.

We changed the coefficient $\hat{\beta}$ to zero to represent the scenario without *Programa Bosques* and applied the model to all OUZ-cells (N=946) (in Giudice et al. 2019 only a subset of these cells (N=665) with a minimum deforestation risk of 1% of having been deforested between 2001 and 2010 were used). We used the R package plmNeviim to predict values (Cisneros, 2017). To simulate deforestation in each year t within each cell i ($Def_{t,i}^{NP\ or\ P}$), for both scenarios (NP: without program; P: with program), we added the predicted value of deforestation annual change in cell i and year t ($\Delta\hat{Y}_{t,i}^{NP\ or\ P}$) to the deforestation in cell i in the previous year $t-1$ ($Def_{t-1,i}^{NP\ or\ P}$), as shown in equations 3.2 and 3.3:

$$Def_{t,i}^{NP} = Def_{t-1,i}^{NP} + \Delta\hat{Y}_{t,i}^{NP}\ where\ t = 2002, \dots, 2015 \qquad (\text{Eq. } 3.2)$$

$$Def_{t,i}^{P} = Def_{t-1,i}^{P} + \Delta\hat{Y}_{t,i}^{P}\ \ where\ t = 2002, \dots, 2015 \qquad (\text{Eq. } 3.3)$$

For the simulated deforestation in 2002, we added the predicted value in 2002 to the observed deforestation in 2001. For all subsequent years, we added the predicted value of the deforestation change in deforestation to the simulated deforestation of the previous year. The annual avoided deforestation in ha in each cell i is:

$$AD_{t,i} = Def_{t,i}^{NP} - Def_{t,i}^{P}\ where\ t = 2002, \dots, 2015 \qquad (\text{Eq. } 3.4)$$

To incorporate the model´s uncertainty (i.e. SE), we applied equations 1-3, using first the upper and then the lower values of the significant 90% confidence interval of the estimated coefficient (Boardman et al., 2018):

$$CI_{0.90}^{\hat{\beta}} = \left[\hat{\beta} - 1.645 * SE(\hat{\beta}), \hat{\beta} + 1.645 * SE(\hat{\beta})\right] \qquad (\text{Eq. } 3.5)$$

Where $SE(\hat{\beta})$ is the SE (0.21) of the estimated ATT $\hat{\beta}$ (-0.38, 90%) (Giudice et al. 2019). Following this approach, we generated five central, five lower and five upper annual avoided deforestation estimates, corresponding to each year. The latter two estimates were used as the lower and upper quantiles (5% and 95%, respectively) of a normal probability distribution used in the MC simulations (see chapter 3 Appendix section B.3 and Table B.1 Input table).

3.3.1.1 Avoided carbon emissions

Had *Programa Bosques* not avoided deforestation, more carbon would have been emitted, with the corresponding associated damages, affecting the Peruvian and global societies (OECD, 2018; Tol, 2009). To account for the avoided damage, we calculated potential emissions from each cell (see chapter 3 Appendix section B.1). As in the case of the annual avoided deforestation, we generated five central, five lower and five upper annual avoided emissions estimates, the latter two were again used as lower and upper quantiles (5% and 95%) of a normal probability distribution used in the MC simulations (see chapter 3 Appendix Table B.1 Input table).

3.3.1.2 Value of delayed carbon emissions

To value the delayed emissions, we assumed two scenarios of permanence of the avoided deforestation. The first scenario assumes reversion by the end of 2016, that is, one year after the end of the program's initial phase in 2015, and we named this the short-term scenario. The second (long-term) scenario assumes a reversion period of 500 years (2015-2516). This period is supported by the theory of change of *Programa Bosques*, which assumes that the implemented projects will provide alternative sources of income to compensate the forgone rents of agricultural expansion and hence deforestation, indefinitely (MINAM, 2010). In the short-term scenario, the delayed carbon emissions are valued as follows:

$$PV_{carbon_t} = TAE_t * Adjusted_{annual_{SCC_t}} * \left\{1 - \frac{1}{(1+i)^{2016-t}}\right\} (where\ t = 2011, \dots, 2015) \quad (\text{Eq. } 3.6)$$

The present value of the avoided carbon emissions (PV_carbon_t) in each year t is defined by the amount of the estimated annual avoided emissions (TAE_t) multiplied by a fraction of the adjusted annual SCC. The SCC is the net present value (NPV) of the damage caused by emitting an additional ton of carbon (OECD 2018). Several authors have estimated different SCC which could vary significantly depending on the models and assumptions considered (Greenstone et al., 2013; Nordhaus, 2014, 2017; Pindyck, 2019; Stern, 2007; Tol, 2009). For the Peruvian perspective, we considered the official SCC (USD 6.6 per tCO_2, (MEF, 2019)) and that estimated by Ricke et al., (2018) at USD 1 per tCO_2 as the lower and upper values, respectively, of a uniform distribution used in the MC simulations (see chapter 3 Appendix Table B.1). For the global perspective, we used the SCC in 2015 estimated by Nordhaus (2017) at USD 31 per tCO_2, as the lower bound of a uniform distribution. This SCC represents the NPV of emissions related damages from 2015 to 2515. The upper bound for the same uniform distribution, USD 100 per tCO_2, was defined by that reported in Pindyck (2019) as the upper bound of the most plausible estimation of the SCC based on experts´ opinion.

Calculations of the adjusted SCC are presented in chapter 3 Appendix (section B.2, Adjusted SCC). For Peru, we used the official discount rates for programs associated with climate change mitigation (MEF, 2019), corresponding to lower and upper bounds of 4% and 8%. Similarly, for the case of the global society, we applied a discount rate between 2% and 5%, similar to previous studies (Franklin and Pindyck, 2018; Nordhaus, 2017).

In the long-term scenario, the present value of the delayed emissions in year t is estimated by using the full value of the annual adjusted SCC:

$$PV\_carbon_t = TAE_t * Adjusted\_annual\_SCC_t \ (where\ t = 2011, \dots, 2015) \qquad (\text{Eq. } 3.7)$$

3.3.1.3 Other environmental values

As explained in our conceptual framework, the participating communities, the country, and the global society will benefit from the avoided deforestation in terms of various environmental benefits. Chapter 3 Appendix Table B.2 documents the minimum and maximum economic values for the environmental benefits considered for each. For the participating communities we considered three important use values: timber, non-timber forest products and ecotourism. The minimum and maximum economic values considered are based on previous research in the Peruvian Amazon (Giudice et al., 2012; Kirkby et al., 2010; Pinedo-Vasquez et al., 1992). As in many areas, these benefits will be zero due to the lack of resources or facilities (e.g. no commercial timber volume, no tourism infrastructure), the minimum benefit is zero or near zero. For both, the national and global levels, minimum and maximum economic values were taken from estimated marginal ecosystem values (Andersen, 2015; Andersen et al., 2002) and one spatially estimated value for protection against fires in the Brazilian Amazon (Strand et al., 2018). Again, due to the uncertainties associated to all these values we used the MC approach to generate values for the total sum of these environmental benefits for each perspective. Equations used to calculate the present value of the environmental benefits are presented in chapter 3 Appendix (section B.4, Other environmental values).

We used larger discount rates for the participating communities relative to those use for Peru and the global society, to reflect the common situation in rural areas of high private rates (Kremen et al., 2000) and previously used rates in our study area (Börner et al., 2016b). Thus, we set the lower and upper bounds of a uniform probability distribution at 10 and 20% for the communities' perspective. The discount rates used for Peru and the global society are the same as the ones reported in section 3.3.1.2.

3.3.1.4 Conditional cash transfers

From the perspective of the participating communities, the conditional cash transfers received represent a benefit. We acquired the total amount disbursed by *Programa Bosques* in each year between 2011 and 2015 (see chapter 3 Appendix Table B.3) and added to the corresponding present value of total benefits as shown in Eq.3.8 (below). Note that this benefit only accrues to the participating communities and cancels out at the national level, where the benefit to the communities is equivalent to the cost to MINAM.

Finally, both, the annual present value of delayed carbon emissions (PV_carbon_t) and that of the other environmental benefits (PV_envB_t) are added up to the annual total present value of benefits for each perspective in each scenario:

$$PV\_benefits_t = PV\_carbon_t + PV\_envB_t + Total\_transfers_t \qquad (\text{Eq. } 3.8)$$

3.3.2 Costs

The reduction of carbon emissions attained by *Programa Bosques* resulted in a set of costs. We considered: (1) the opportunity costs of forest conservation for the communities, and (2) the implementation and administration costs.

Opportunity costs of forest conservation in our study area have been previously estimated by Börner et al. (2016). These opportunity costs represent the NPV of agricultural rents following different land use trajectories during 10 years after forests were cleared, at a discount rate of 10% (Börner et al., 2016b). The benefits generated by unsustainable timber extraction were also accounted for (Armas et al., 2009). Rents were modified as a function of the distance to local markets to account for heterogeneous transportation costs (Börner et al., 2016b). The estimated opportunity costs in soles per ha (soles/ha) are depicted on a map of 4 x 4 km pixels (see chapter 3 Appendix Figure B.2). We assigned the opportunity cost to each overlapping OUZ-cell using their centroids (Figure B.2).

We converted the opportunity costs to annuities, assuming constant annual rents during 10 years:

$$A_i = \frac{NPV_i * r}{1 - (1 + r)^{-t}} \qquad (\text{Eq. } 3.9)$$

Where, NPV_i is the net present value of the opportunity cost in cell i, A_i is the annuity, r is the discount rate (10%) and t is the number of periods (10 years). We multiplied the annuity by the estimated avoided deforestation in cell i in year t ($AD_{t,i}$), which represents the annual opportunity cost:

$$AD_{t,i} * A_i = annual\ opportunity\ cost_{t,i}\ (where\ t = 2011, \ldots, 2015) \qquad (\text{Eq. } 3.10)$$

All cells´ annual opportunity costs in year t then sum up to the total annual opportunity cost:

$$Total\ annual\ opportunity\ cost_t = \sum_{i=1}^{n} annual\ opportunity\ cost_{t,i} \qquad (\text{Eq. } 3.11)$$

Again, we generated five central, five lower and five upper total annual opportunity cost estimates, as a function of the estimated avoided deforestation, and used them in the MC simulations. In both, the short- and long-term scenarios, we assumed that opportunity costs only accrue to the participating communities during the period between 2011 and 2015. For the short-term scenario, the opportunity costs of avoiding deforestation turn zero once the avoided deforestation is reverted after 2015. In the long-term scenario we assumed that the

production projects generated the necessary income to compensate the opportunity costs during the 500-yr period, a rather optimistic scenario but in correspondence to *Programa Bosques´* theory of change (Giudice et al., 2019). Thus, the present value of opportunity costs in each year for both scenarios is defined by the same equation:

$$PV\_opportuntiy\_cost_t = total\_annual\_opportuntiy\_cost_t \sum_{t=2011}^{2015} \frac{1}{(1+r)^{2015-t}} \quad (\text{Eq. 3.12})$$

Second, we also accounted for the implementation and administration costs (see Table B.3). We defined the CE of *Programa Bosques* by relating the total annual implementation and administration costs (IAC_t) to the estimated total annually avoided deforestation by:

$$\frac{IAC_t}{\sum_{i=1}^{n} AD_{t,i}} \quad (\text{Eq. 3.13})$$

The opportunity costs add to these implementation and administration costs during those five initial years to come to an annual present value of total costs (PV_costs_t):

$$PV\_costs_t = PV\_opportuntiy\_cost_t + implementation\_cost_t + adminsitration\_cost_t (\text{Eq. 3.14})$$

We transformed these and all subsequent values into 2010 US Dollars by using the Lima monthly average consumer price index for 2010 (101,53; base year 2009) and the OECD 2010 exchange rate of 2.825 soles/USD.

3.3.3 NFV in 2015

We compounded all annual present values of costs and benefits, from the *ex post* standpoint of the end of 2015, to arrive at the NFV of *Programa Bosques* for each scenario and perspective:

$$NFV_{2015} = \sum_{t=2011}^{2015} PV\_benefits_t * (1+r)^{2015-t} - \sum_{t=2011}^{2015} PV\_costs_t * (1+r)^{2015-t} \quad (\text{Eq. 3.15})$$

Where t is the running year between 2001 and 2015 and r is the interest rate. Our decision rule was based on whether the sum of the all NFV was positive, in which case, *Programa Bosques´* implementation would have been justified.

3.3.4 Comparing net benefits locally

Based on the previously assessed effectiveness of *Programa Bosques* and its budget (Börner et al. 2016, Giudice et al. 2019) we did not expect to find an overall positive NFV, specifically in the short-term scenario. We therefore complemented our study by additionally exploring whether there will be regions in which potential deforestation reductions could generate total net positive future values, from all perspectives as a whole. By so doing we attempted to

provide an additional targeting criterion which could help improve the overall cost-efficiency of *Programa Bosques* (see chapter 3 Appendix section B.6).

3.4 Results

3.4.1 Avoided deforestation and avoided emissions

Based on the model in Giudice et al. (2019) and its associated uncertainty, we estimated that *Programa Bosques* avoided a total of 826 ± 743 ha of deforestation between 2011 and 2015 (Table 3.1). This represented a 16 ± 14% reduction relative to the business as usual scenario, in which a total of 5,160 ha would have been deforested without *Programa Bosques*. This reduction was equivalent to 333,433 ± 300,260 tons of avoided CO_2 emissions.

Table 3.1 *Programa Bosques´* estimated avoided deforestation and corresponding avoided emissions

	Avoided deforestation (ha)			Avoided emissions (tCO_2)		
Year	Lower	Central	Upper	Lower	Central	Upper
2011	1.6	15.9	30.1	665	6,684	12,704
2012	10.0	100.3	190.7	4,043	40,640	77,236
2013	23.4	235.0	446.6	9,424	94,719	180,014
2014	23.6	237.2	450.8	9,521	95,695	181,869
2015	23.6	237.2	450.8	9,521	95,695	181,869
Total	82.1	825.6	1,569.0	33,173	333,433	633,692

Note: Estimated annual lower, central and upper avoided deforestation and corresponding avoided emissions as a function of the 90% confidence interval defined by the estimated average treatment effect on the treated (central) and its SE.

3.4.2 Annual opportunity costs of avoided deforestation

The estimated annually avoided deforestation implied foregone agricultural rents for participating communities. We estimated these opportunity costs to range between USD 4,385 ± 3,950 in 2011 to USD 48,293 ± 43,489 in 2015, where variation was a function of the amount of avoided deforestation and its location (Table 3.2). Note that this level of opportunity costs was applied in both the short- and the long-term scenarios, reflecting the assumption of a permanent shift to the new sustainable production activities in the long-term scenario.

Table 3.2 Total annual opportunity costs of avoided deforestation between 2011 and 2015

Year	Lower	Central	Upper
2011	436	4,385	8,334
2012	2,853	28,679	54,505
2013	5,596	56,251	106,906
2014	5,389	54,162	102,936
2015	4,805	48,293	91,782

Note: opportunity costs are expressed in USD 2010

3.4.3 Implementation and administration costs

Implementing *Programa Bosques* also implied budgetary expenditures by MINAM. Table 3.3 shows annual expenditures by category. Most of the expenditures corresponded to the implementation and administration costs, with annual means of 53% and 14% from the totals, respectively. In contrast, the payment presented an annual mean of only 33%. When comparing the relationship between the payment and both the implementation and administration costs on an annual basis, we observe that the latter represented an average of 2.26 times the payment expenditure (max=3.4, min=1.1).

Table 3.3 *Programa Bosques´* annual expenditures

	Budgetary expenditures (in 2010 US Dollars)				
Category	2011	2012	2013	2014	2015
Payment	485,608	1,425,665	1,199,242	1,689,489	1,569,172
Implementation	1,650,254	1,562,782	2,825,434	1,807,321	1,726,101
Administration	-	-	420,250	1,330,739	1,757,831
Annual Total	2,135,862	2,988,448	4,444,927	4,827,549	5,053,103

In addition, we calculated the annual CE of *Programa Bosques* in terms of the relationship between all MINAM´s costs and the avoided deforestation (Table 3.4) or emissions (Table 3.5). Since a transfer is not a cost for the national economy, we also excluded the payment for comparison. We present the medians as the annual central measures due to the large CE values for 2011. This is due to the relatively small amount of avoided deforestation and corresponding avoided carbon emissions estimated in that year. The lower, central and upper values correspond to the avoided deforestation and avoided emissions estimated by considering the confidence interval (see Eq.3.4). As such, the lower the estimated avoided deforestation, the larger the relationship between costs and avoided deforestation, and thus the lower the CE. As such, we can see that the CE varied significantly (Table 3.4), as a function

of the lower and upper bounds of the estimated avoided deforestation. Similar variations were found when the medians are expressed in USD per ton of avoided CO_2 emissions (Table 3.5).

Table 3.4 The CE of *Programa Bosques*

	Total budgetary expenditure (USD/ha)			Budget expenditure without CCT (USD/ha)		
Year	Lower	Central	Upper	Lower	Central	Upper
2011	1,353,692	134,678	70,864	1,045,917	104,058	54,752
2012	299,380	29,785	15,672	156,558	15,576	8,196
2013	190,133	18,916	9,953	138,835	13,813	7,268
2014	204,572	20,353	10,709	132,978	13,230	6,961
2015	214,130	21,304	11,209	147,635	14,688	7,729
Median	214,130	21,304	11,209	147,635	14,688	7,729

Note: The CE is expressed as the annual expenditures (in 2010 USD) relative to the estimated avoided deforestation (USD/ha) with and without accounting for conditional cash transfers (CCT). Opportunity costs were not considered.

Lower/central/upper are correspondingly associated with the lower/central/upper avoided deforestation in Table 3.1, as these values represent the quotient between estimated annual avoided deforestation and annual expenditures in Table 3.3.

Table 3.5 Annual expenditures (in 2010 USD) relative to the estimated avoided emissions (USD/tCO_2).

	Total budgetary expenditure (USD/tCO_2)			Budget expenditure without CCT (USD/tCO_2)		
Year	Lower	Central	Upper	Lower	Central	Upper
2011	3,212	320	168	2,481	247	130
2012	739	74	39	387	38	20
2013	472	47	25	344	34	18
2014	507	50	27	330	33	17
2015	531	53	28	366	36	19
Median	531	53	28	366	36	19

Note: Lower/central/upper are correspondingly associated with the lower/central/upper avoided emissions in Table 3.1, as these values represent the quotient between annual avoided emissions and annual expenditures in Table 3.3.

3.4.4 Programa Bosques NFV

By means of the MC simulations we obtained probability distributions for the NFV based on approximately 10,000 simulations from each perspective under the short- and long-term scenarios (see chapter 3 Appendix Figure B.3). In both the short- and long-term scenario, the distributions exhibited only positive NFV for communities and the global society, with higher NFV in the long-term scenario, particularly for the global society. The distribution mean was equivalent to USD 8.1 million for communities and USD 23.9 million for the global society in the long-term scenario, and USD 7.7 million and USD 0.81 million, respectively, in the short-scenario (Table 3.6 and Table 3.7). On the other hand, the distributions of the NFV for Peru in both the long- and short-term scenarios boasted only negative values and their means were similar (-USD 12-14 million). This similarity was due to the large magnitude of the future values of the implementation and administration costs, such that the NFV was only marginally affected by the difference in the future value of benefits between both scenarios (Table 3.6 and Table 3.7).

When we added the NFV distributions´ means from each perspective, in each scenario, without accounting for the payments to communities (see section 3.3.1.4), the overall NFV of *Programa Bosques* turned out to be positive (USD 11.8 million) with a benefit-cost ratio of 1.79, and negative (-USD 13.8 million) with a ratio of 0.08, in the long- and short-term scenarios, respectively. The difference is mainly attributable to the large NFV accruing to the global society in the long-term scenario (Table 3.6 and Table 3.7). The permanence of the avoided deforestation would have to be extended up to 2063 for *Programa Bosques* to break even (see chapter 3 Appendix section B.7 and Table B.5).

We also found that the means of payments in both scenarios were 14 times larger than those of the opportunity costs (Table 3.6 and Table 3.7), suggesting that transfers largely overcompensated the opportunity costs at community level. This finding confirms results from *ex ante* assessments of *Programa Bosques* (Börner et al., 2016b).

Not surprisingly, the permanence assumption is a critical determinant of the estimated climate change mitigation benefits. In the long-term scenario, the distribution mean of the mitigation benefit was 13 times larger than that of the other environmental values, as opposed to only a threefold difference in the short-term scenario. Note that in contrast to the environmental benefits, the SCC used in the analyses increased with time (see chapter 3 Appendix Eq. B.6). The reason is that marginal costs of CO_2 emissions are higher when climate change has further advanced (Jayachandran et al., 2017).

Table 3.6 Distributions´ means of the NFVs from each perspective and overall in the long-term scenario.

	Future values (average) in 2010 USD						
Perspective	Climate change mitigation	Other environmental benefits	Opportunity costs	Implementation costs	Administration costs	Payments	NFV
Participating communities	0	553,789	561,463	0	0	8,117,563	8,109,888
National	1,398,942	938,648	0	10,758,880	3,640,358	0	-12,061,649
Global society	23,472,143	435,123	0	0	0	0	23,907,266
Overall NFV	24,871,085	1,927,559	561,463	10,758,880	3,640,358	0	11,837,942

Note: the payments are not included in the overall NFV as they are a transfer and not a true cost.

Table 3.7 Distributions´ means of the NFVs from each perspective and overall in the short-term scenario.

	Future values (average) in 2010 USD						
Perspective	Climate change mitigation	Other environmental benefits	Opportunity costs	Implementation costs	Administration costs	Payments	NFV
Participating communities	0	157,370	561,510	0	0	8,107,408	7,703,268
National	103,947	118,623	0	10,761,128	3,640,597	-	-14,179,156
Global society	778,387	37,722	0	0	0	0	816,109
Overall NFV	882,333	313,715	561,510	10,761,128	3,640,597		-13,767,187

Note: the payments are not included in the overall NFV as they are a transfer and not a true cost.

3.5 Discussion

Few *ex post* evaluation studies assess the costs and benefits of forest conservation programs (examples are Jayachandran et al. 2017, Börner et al. 2015). Traditionally, CBA are conducted *ex ante* assuming that the interventions will successfully meet their goals (Kremen et al., 2000; Naidoo and Ricketts, 2006). As impact evaluation is being mainstreamed in the conservation sector, the increasing availability of spatial indicators for environmental costs and benefits represents an opportunity to move from impact evaluation to *ex post* assessments of CE (Vincent, 2016). Such information is relevant for program implementers and policy makers as funding for conservation becomes increasingly performance-based. This study provides the first spatially explicit *ex post* CBA of a national forest conservation program, the Peruvian *Programa Bosques*, from three relevant perspectives: local communities, the Peruvian economy, and the global society.

Our results illustrated that future benefits and costs strongly depend on the analytical perspective. Communities and the global society experienced net benefits, whereas the Peruvian economy bore net costs, irrespective of assumptions related to the permanence of avoided deforestation and delayed carbon emissions. Hence, *Programa Bosques* paid off only under the strong assumption that the avoided deforestation and averted emissions were permanent, least up to 2063. High implementation costs and low *de facto* effectiveness are the main reasons for the program to result in net costs at the national level. In comparison, the similar *Socio Bosque* achieved a much higher effectiveness in northern Ecuador, reducing deforestation by up to 70% between 2011 and 2013 (Jones et al., 2017).

Our main finding compares unfavorably to the recent study (Jayachandran et al. 2017), which estimated implementation and administration costs at USD 0.26 per averted tCO_2. In comparison, our central estimate is 138 times larger. Jayachandran et al. (2017) found a benefit-cost ratio below one (0.8) when assuming avoided deforestation is short-lived (i.e. one year), but their estimate is larger than ours by a factor of ten. Increasing the period of avoided deforestation in their study to four years boosts the benefit-cost ratio to 2.4 making the program cost-effective. Börner et al., (2015) found that the costs of field-based enforcement in the Brazilian Amazon relative to the estimated avoided emissions ranged between USD 1.2 and USD 3 per averted tCO_2. Our central estimate for the CE of *Programa Bosques* is 12 times larger. Looking at the implementation costs of the Mexican Payments for Hydrological Services Program (PSAH), Sims and Alix-Garcia (2017) found that governmental expenditure amounted to USD 1-2 per enrolled ha. For the Peruvian program, we find the equivalent indicator to lie at USD 9 per ha per year. Finally, an *ex-ante* assessment of the potential CE of a PES program in the whole Brazilian Amazon found a cost of USD 900 per ha of avoided deforestation. Our estimated median for the Peruvian program (USD 14,600) is considerably larger.

In sum, we showed that high implementation and administration costs, coupled with a low impact, led to inefficient conservation outcomes. This is important because public funds for forest conservation are scarce and should thus be used efficiently. By documenting which factors affect *Programa Bosques'* cost-efficiency, we identified entry points for adjustment in design and implementation strategies. For example, most of the total implementation costs were incurred in terms of personnel costs and services (e.g. consultancies, field trips) related to interactions with communities, technical assistance, and forest monitoring. Centralized

implementation from the Peruvian capital may thus make the program unnecessary costly, but shifting administrative responsibility to local authorities must be discussed vis-à-vis evidence on the effectiveness of decentralized forest management (Coleman and Fleischman, 2012; Miteva et al., 2012; Somanathan et al., 2009). In addition, targeting areas with potentially positive NFV for program implementation could increase the overall NFV, but only if the current ratio of costs to the estimated avoided deforestation, was considerably reduced (by 86%) (see chapter 3 Appendix section B.6).

In principle, our findings suggest that CE could be achieved by increasing impact and securing the long-term permanence of the avoided deforestation. Higher opportunity costs under increased impact would likely be compensated for by conservation benefits. It is thus important to discuss assumptions about what will happen to deforestation when payments stop (see also Jones et al., 2017). *Programa Bosques´* theory of change assumes that investments into sustainable production activities will bear fruits after five years and compensate the opportunity costs of forest conservation permanently (MINAM, 2010). This is a strong assumption given the short duration of the contracts. Previous research on integrated conservation and development programs (Blom et al., 2010) found that short-lived projects do rarely result in the structural change needed to secure their ambitious long-term goals (Chan et al., 2007), especially in the case of conservation outcomes (Baral et al., 2007). The short-term scenario may thus be the most plausible suggesting that *Programa Bosques* can so far hardly be justified purely as an environmental conservation program.

From a poverty alleviation perspective, on the other hand, the indigenous recipient communities likely experienced a net gain, because irrespective of the scenario (Table 3.6 and Table 3.7) payment volumes exceed their opportunity costs on average. This finding is non-trivial given high poverty rates within indigenous communities (INEI, 2008), which also motivated the program. The welfare gain is relatively small, however. Deducting the future value of the opportunity cost from the future value of the payment (Table 3.6) and dividing the result by the number of all participating families (11,752) (Giudice et al., 2019), the hypothetical net gain for the period 2011-2015 is USD 643 for an average family. Assuming two working persons per family this implies an average monthly transfer of USD 5.4 per capita, or 3.9% of the average per capita income in the Peruvian rural Amazon in 2015 (~USD138/per capita) (INEI, 2019). Similar welfare gains could have been achieved at much lower costs in a targeted poverty alleviation program, with probably lower distortive effects on distributional outcomes (Banerjee et al., 2015; Börner et al., 2016b).

Our *ex post* CBA thus remains limited in that we only considered the environmental benefits and not its economic nor its social benefits (e.g. education and health improvements or increased incomes from the sustainable production projects, see Figure 3.1). Notably, however, a preliminary assessment of the socio-economic effects of *Programa Bosques* (Euler, 2016) found no measurable income effects of the production projects in nine communities. Low agricultural productivity and lack of access to markets, a common scenario in the Peruvian Amazon (Gutiérrez-Vélez et al., 2011; L'Roe and Naughton-Treves, 2014; Zwane, 2007), were cited as causes (Euler, 2016). Thus, we do not expect that significant socio-economic benefits, here unaccounted for, could further compensate for the excessive costs. Moreover, we have not estimated the transaction costs of participation by indigenous communities (e.g. time spent in meetings), which could have further reduced the overall NFV.

All things considered, our results would thus appear as a relatively unbiased approximation of *Programa Bosques'* economic performance during its early years of implementation.

3.6 Conclusion

Under the most plausible scenario of avoided deforestation permanence, the implementation of *Programa Bosques* was inefficient in avoiding deforestation and thus cannot be justified purely from the perspective of environmental conservation. For a program at this scale, *Programa Bosques* had a very small but measurable impact on reducing deforestation (826 ± 743 ha). Hence, costs exceeded environmental benefits by a factor of 12. Our sensitivity analyses showed, however, that the unfavorable benefit-cost ratio is also driven by excessive implementation (e.g. personnel salaries, hired services), and centralized administration costs. Thus, although the focus should be on increasing effectiveness, measures to reduce implementation and administrative costs must be explored as well.

We identify the following entry points to increase *Programa Bosques*' environmental CE:

1. The excessive share of administrative and implementation costs in theprogram budget could be capped. The Costa Rican and Mexican national PES programs, for example, legally limit these costs relative to the total program budget to 10% and 4%, respectively (Wunder et al., 2008). This could be achieved by decentralizing: (1) the process of community enrollment, (2) the management of investment projects, and (3) the provision of technical assistance.
2. Enrolling communities should consider the spatial location of potential net future benefits, low opportunity costs, and deforestation pressure as complementary selection criteria, which could increase the program's potential to induce additional conservation benefits (see also, Giudice et al. 2019).
3. Payment modalities could be adapted to better reflect actual conservation opportunity costs, with potential to improve distributional outcomes (see also, Börner et al. 2016).

In closing, we reiterate that our CBA did not consider the effect of temporarily alleviating rural poverty among participating communities. We stress, however, that this desirable effect could have arguably been achieved at much lower cost than by means of implementing a primarily conservation-oriented policy instrument.

4 Cost-effectiveness and income effects of alternative forest conservation policy mixes for the Peruvian Amazon

Abstract

To reduce deforestation and mitigate climate change, the Peruvian government proposed and partially implemented incentive- and disincentive-based forest conservation policies, especially in the Amazon, where most of the country's deforestation occurs. However, to date, little is known about the policy mix that optimally balances policy cost-effectiveness and welfare effects among the affected land users. To explore this question, this paper develops a spatially explicit simulation model of landholders' deforestation decisions based on fines, payments for ecosystem services (PES), and the probability of enforcement that incorporates enforcement costs. Simulations show that a policy approach solely based on disincentives (i.e., fines) is more cost effective than an incentive-based approach in the form of PES. Nevertheless, our results indicate a trade-off between cost-effectiveness and welfare effects because rural incomes would be considerably reduced if only fines were applied. Thus, mixing fines with PES emerges as a policy mix that could balance this trade-off and reduces substantial income losses among rural populations.

4.1 Introduction

Between 2001 and 2018, deforestation in the Peruvian Amazon increased by on average 5,500 ha/year, putting Peru among the five top deforesters in the region (GFW, 2020). Although deforestation has stabilized at approximately 160,000 ha per year between 2015 and 2018, this significant deforestation is an obstacle to achieving the government's goal of reducing net deforestation to zero by 2021 (Brown and Zarin, 2013). Several measures were proposed to tackle deforestation and reduce carbon emissions. The Peruvian National Strategy on Forests and Climate Change (a.k.a. REDD+ strategy) proposes five strategic actions, including strengthening the monitoring, supervision, enforcement, control, and sanction systems against illegal deforestation and increasing the value of standing forests through, for example, implementing incentive-based forest conservation (MINAM, 2016b). The Ministry of Environment proposed that such interventions should be designed and implemented to maximize their CE and be integrated with enforcement and interdiction activities (MINAM, 2016b). Given this scenario, the Peruvian government needs to identify the conservation policy instruments to implement and how to integrate them to cost-effectively reduce deforestation.

Forest conservation policy instruments are grouped into enabling measures, disincentives, and incentives (Börner and Vosti, 2013). The latter two, which are the main focus of this study, provide incentives and disincentives to actors who contribute to achieving a given environmental objective by changing their behavior (Börner and Vosti, 2013). Examples of disincentives include taxes, fines, standards, bans, and protected areas (Cunha et al., 2016), and incentives include subsidies for sustainable production practices, payments for environmental services (PES) (Börner and Vosti, 2013), and conditional cash transfers (Alix-Garcia et al., 2019; Giudice et al., 2019), among others. Two important aspects emerge when designing and implementing these instruments, namely, their CE and welfare effects.

Governments could not invest scarce resources implementing expensive and ineffective policies and need to anticipate the policy's welfare effects on local populations because these could include vulnerable groups (Holling and Meffe, 1996). Then, one question that governments must answer is how to balance cost-effective forest conservation and potential negative welfare effects.

The literature on balancing the CE and welfare effects of both incentive and disincentive-based forest conservation policies in tropical regions is still scarce. Disincentives appear to be highly cost effective (Börner et al., 2015b, 2014) or at least as cost effective as incentive-based approaches, such as PES (Sims and Alix-Garcia, 2017). Nevertheless, such disincentives could imply significant income losses in the form of the opportunity costs of reducing agricultural expansion and from applied environmental fines, especially for large-scale producers but also for vulnerable smallholders (Börner et al., 2014; Duchelle et al., 2017). However, importantly, disincentives and their associated regulatory enforcement are a precondition for effective incentive-based approaches (Börner et al., 2015b) and tend to be the most suitable approach in areas with unclear tenure rights or in which deforestation was already restricted by law (Almeida et al., 2008; Börner et al., 2010; Robinson et al., 2010; Soares-Filho and Rajão, 2018). Studies in the Brazilian Amazon suggest the potential for mixing both approaches to compensate for otherwise substantial income losses of purely C&C policies, making such an approach more politically accepted by different groups (Börner et al., 2015b, 2014). In Peru, only a few studies assessed the effectiveness, CE, or welfare effects of either incentive- or disincentive-based forest conservation (Giudice et al., 2019; Giudice and Börner, 2021; Montoya-Zumaeta et al., 2019). No study explored how to mix both policy instruments to deliver cost-effective outcomes without jeopardizing the well-being of local populations.

This study aims to analyze how to design a policy mix that includes both incentive- and disincentive-based instruments to balance the CE and welfare effects of reducing deforestation in the Peruvian Amazon. To do so, we develop a spatially explicit simulation model of deforestation decisions based on fines, PES, and the probability of enforcement that considers the heterogeneous distribution of the opportunity costs of conservation and a logistical budget constraint to cover field enforcement operations. The main policy contribution of this study is to provide information that could help the Peruvian government in designing and implementing its planned forest-based climate change mitigation activities. Through this approach, we want to answer the following questions:

1. Which policy approaches would deliver the most cost-effective deforestation reductions?
2. What is the effect of a forest conservation policy mix of incentives and disincentives on the CE and the income change of landholders?

The paper is organized as follows. In the next section, we briefly describe the current disincentive- and incentive-based conservation policy scenario in the Peruvian Amazon. In section 4.3, we present the conceptual framework that defines deforestation decisions, the CE and welfare changes attributable to policy implementation, and the expected effects. In section 4.4, we present the data and methods used to implement our model. In section 4.5, we present the corresponding results. The results are discussed in section 4.6, and the conclusion is presented in section 4.7.

4.2 Current disincentive- and incentive-based conservation scenario

Disincentive-based forest conservation is currently based on imposing administrative and penal sanctions on those deforesting illegally according to Peruvian laws. Several national and subnational agencies conduct field-based enforcement and control operations in their competence areas. These include the Agency for the Supervision of Forest Resources and Wildlife (OSINFOR) on public forestland granted to private actors, the National State Protected Areas Service (SERNANP) in protected areas, the National Forest and Wildlife Service (SERFOR), or the regional forest management authorities in private and non-designated public lands. All of these authorities must confirm whether any forest cover removal or land use change—from forest to agricultural lands—is conducted under previously granted authorizations. Otherwise, sanctions—including fines—are imposed that could reach between 43,000 and 21.5 million total soles (sol = USD 0.28) per case (Law N° 29763, Article 109°). In addition, the Peruvian Penal Code considers unauthorized deforestation a crime. Offenders could be imprisoned for four to six years (Peruvian Penal Code, Article 310°) depending on the outcome of a trial and are subject to paying a civil reparation. This process starts when prosecutors from the Environmental Public Prosecutor Office (FEMA) identify illegal deforestation in the field (Shanee and Shanee, 2020; Weisse et al., 2019).

Multiple agencies' interventions generate duplication and unclear enforcement responsibilities (Weisse et al., 2019; Weisse and Naughton-Treves, 2016), limiting the effective application of forest monitoring tools and follow-up enforcement actions on the ground (Weisse et al., 2019). This also implies that no common enforcement strategy exists in terms of, for example, the areas to prioritize for interventions. In addition, inadequate funding for field operations and the lack of political will are limiting factors (Weisse et al., 2019). Some agencies (FEMA, OSINFOR) appear to prioritize cases with large deforested areas, which could be reached at the lowest logistic costs and for which a land owner or intruder is likely to be found (Weisse et al., 2019; C. Ipenza, pers. comm., 2020; R. Carrasco pers. comm., 2020). Nevertheless, there is no systematized data on the geographic location and applied sanctions to those who deforest illegally. Moreover, widely known is that fines and jail sentences are rare if at all applied, and several years could pass between the moment at which a prosecutor starts investigating and a judge imposes a sanction (National Environmental Attorney, pers. Comm., 2020).

In contrast, incentive-based forest conservation is being implemented at the national and subnational levels by both public and private institutions through PES or PES-like initiatives, primarily to safeguard watersheds and mitigate climate change through REDD+ (Montoya-Zumaeta et al., 2021). Many REDD+ projects exist at the local and jurisdictional levels, some of which have already received results-based payments from the voluntary carbon market (Montoya-Zumaeta et al., 2021). At the national level, the National Forest Conservation Program represents the only government-financed PES-like intervention, transferring cash and technical assistance to indigenous communities conditional on avoiding deforestation within their titled lands (Giudice et al., 2019; Giudice and Börner, 2021; Montoya-Zumaeta et al., 2021).

4.3 Conceptual framework

By considering the previously described scenario, we adapt the approach developed by Börner et al. (2015, 2014) to simulate the effect of a forest conservation policy mix on landholders' deforestation decisions. To do so, we develop a spatially explicit model that simulates the landholders' decision to deforest—within spatial units of 4 × 4 km—based on an assumed rational choice of weighing the resulting agricultural rents against the likelihood of being fined when deforesting and/or compensated, if deforestation is reduced.

The policy mix is conceived as a mixture of C&C and incentive-based forest conservation instruments, namely, fines and PES, respectively. Our approach relies on (1) economically motivated decisions, (2) spatially explicit information on costs and benefits, and (3) imperfect compliance (Sandmo, 2002). We simplify the complexities previously explained by, first, assuming that only one enforcement authority conducts field-based operations against illegal deforestation. Second, this authority is also responsible for implementing PES. Third, any effect of implementing this policy approach is additional to any previous effect of law enforcement and PES initiatives.

The landholder's decision to deforest is conditioned on the difference between agricultural rents and expected sanctions, subject to an enforcement probability. We introduce PES, which could further reduce the incentive to deforest but, as opposed to a fine, would increase the landholders' income as defined in:

$$d_{1,0} =: \begin{cases} 0, for\ r - p_{enf}(F + PES) \leq 0 \\ 1, for\ r - p_{enf}(F + PES) > 0 \end{cases} \qquad (\text{Eq. } 4.1)$$

where illegal deforestation[9] d is modeled as a binary choice and equals zero if r, the NPV of the 10-yr expected agricultural rents after deforesting (10% discount rate), is smaller than the expected fine (F) or an equivalent sanction cost, and a payment (PES) conceived as a per-ha disincentive and incentive, respectively. Alternatively, if r is greater, deforestation equals one, and an annual mean deforestation is assigned to a gridcell of 4 × 4 km. This deforestation represents a baseline scenario prior to the policy mix implementation.

Enforcement is imperfect because of a logistical budget constraint, a common situation in LMIC (Robinson et al., 2010). Thus, the enforcement probability (p_{enf}) in our model varies between zero and one. Depending on this probability, an illegal deforester expects to be detected, fined, and lose the payment. Hence, the enforcement authority cannot go everywhere to deter deforestation, which, we assume, is achieved by enforcing the law after the deforestation has occurred. Offenders and potential offenders are deterred from continuing the deforestation by demonstrating that deforestation is sanctioned. In that sense, we assume that the enforcement authority's strategy seeks to maximize deterrence by maximizing the deforested area inspected at the lowest cost possible. Hence, the authority prioritizes the locations with historically larger total deforested areas and fewer deforested patches to visit

[9] PES will not only be conditional on complying with the law but could also include other conditions, such as, for example, taking children to the health post to comply with immunization schedules. We assume that the opportunity costs of these other conditions for an entire year are constant across space and are negligible.

that could be reached at the lowest logistical costs. Thus, cells with such characteristics present greater enforcement probability.

The CE of the policy mix is measured in terms of reduced deforestation $\left(D_i - D_i^R\right)$, where D_i and D_i^R represent, respectively, the baseline deforestation and the deforestation after the policy mix implementation, as determined in Eq.4.1, and total implementation costs:

$$CE = \frac{\sum_{i=1}^{I}\left(D_i - D_i^R\right)}{B + \sum_{i=1}^{I} PES\left(D_i - D_i^R p_{enf,i}\right) + \sum_{j=1}^{J} P_j * c * p_{enf,i}} \qquad \text{(Eq. 4. 2)}$$

The denominator in Eq.4.2 is the sum of the enforcement authority's logistical budget to cover field enforcement operations (B), the sum of PES to compliers and to undetected non-compliers, and the sum of the administrative costs (c) incurred to determine the illegality and liability of deforestation cases. $P_j$represents the number of deforested patches (i.e., cases) within each grid cell for which deforestation equals one (Eq.4.1) after the policy mix is implemented and $p_{enf,i} > 0$. Thus, if deforestation is avoided ($D_i^R = 0$), the landholder receives the full amount of PES (i.e., $PES * D_i$). Our model allows some deforestation to be compensated for as a function of the enforcement probability. Thus, if deforestation is not avoided ($D_i^R = D_i$), compensation could be greater than zero such that the compensation is larger when $p_{enf,i}$tends to zero, and the compensation is smaller when it tends to one. The denominator in Eq.4.2 could additionally include the value of all of the fines that the enforcement authority could collect from detected offenders ($-D_i^R p_{enf,i} F$), which reduces the total implementation costs.

The welfare effect (W) is defined by the aggregated income changes in all cells as determined by:

$$W = \sum_{i=1}^{I} PES\left(D_i - D_i^R p_{enf,i}\right) - \left(D_i - D_i^R\right) r_i - D_i^R p_{enf,i} F \qquad \text{(Eq. 4. 3)}$$

The first term in Eq.4.3 represents the compliers' and undetected non-compliers' income from PES, the second term represents the opportunity costs for those who reduced deforestation, and the third represents the value of the fines paid by detected non-compliers.

Using our model, we can assess how changes in the logistical budget, the fine, and PES simultaneously affect the policy's CE and the landholders' aggregated income. Thus, based on the model structure previously described and on the spatial dynamics of deforestation in the Peruvian Amazon (Figure 4.1), the following predictions can be made. First, increasing the logistical budget leads to (1) increasing the reduction in deforestation but at a diminishing rate, given that most deforestation and the largest deforested patches are concentrated around major cities and main roads (Figure 4.1); (2) for the same reason, increasing total administrative costs and total imposed fines at a diminishing rate; (3) decreasing total PES payments, given that the number of non-compliers receiving PES will decrease as the logistical budget increases; (4) consequently, the CE will increase up to the point at which the marginal costs of enforcement become too large relative to the marginal effectiveness gains.

The CE will then decrease as compliance increases and marginal deforestation reductions become smaller; and (5) aggregated income losses will increase because of the fewer PES payments to non-compliers, higher total opportunity costs, and more fines being imposed.

Second, increasing the fine level, at constant enforcement probabilities and PES levels, will lead to (1) more deforestation being avoided, given that more landholders face higher fines and decide not to deforest; (2) decreasing administrative costs and fines because less deforestation exists to be sanctioned (i.e., fewer field operations are necessary); (3) thus, increasing the CE; and (4) increasing aggregated income loses because of increasing opportunity costs.[10]

Third, increasing the PES level at constant enforcement probabilities and fine levels leads to (1) more reduced deforestation because the incentive to avoid deforestation will increasingly compensate for the opportunity costs; (2) decreasing administrative costs (for the same reason as above), (3) increasing total PES payments; (3) hence, increasing CE up to the point at which too large payments (i.e., large overcompensation of opportunity costs) outweigh the gains in effectiveness—and then the CE decreases; and (4) increasing aggregated income.

Finally, at constant levels of avoided deforestation and based on the previous predictions, we expect a trade-off between CE and welfare, with gains in CE and losses in welfare as the fine level is increased and vice-versa when the PES level is increased. In other words, the CE of a policy mix that relies more on fines will be more cost effective than one based more on PES. However, in contrast, the former policy mix will generate larger aggregated income losses than the latter.

[10] We expect that the effect of higher total opportunity costs is stronger than that of higher imposed fines on the aggregated income change attributable to the prevailing low opportunity costs in the study area (Börner et al., 2016b). In other words, higher fine levels lead to lower total imposed fines but higher total opportunity costs.

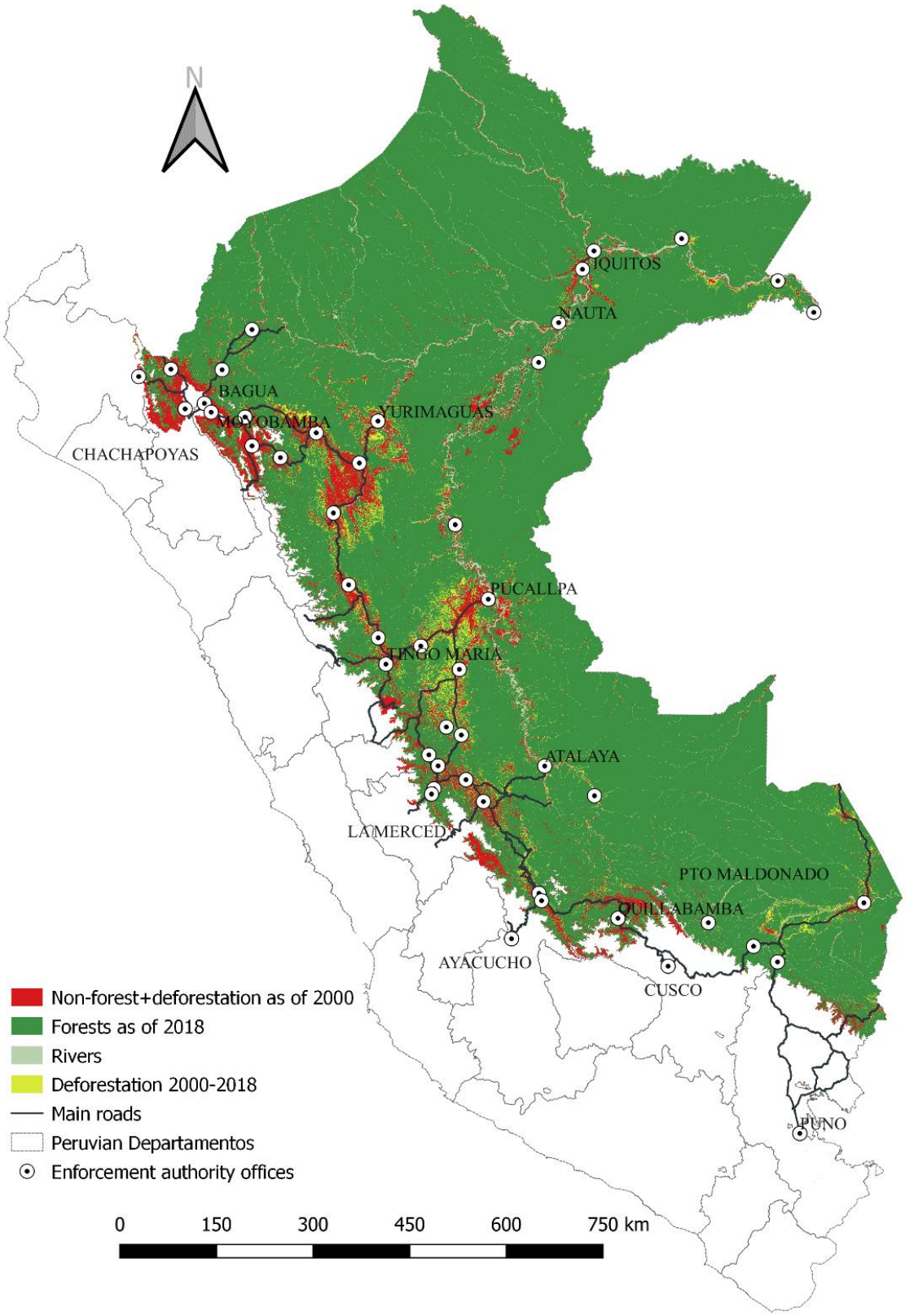

Figure 4.1 Locations from which enforcement field trips depart and historical deforestation in Peruvian Amazon.

4.4 Data and model implementation

We use different spatial sources and parameters to implement our model (Table 4.1 and Table 4.2).

Table 4.1 Spatial data sources

Layer	Source
Annual forest cover loss 2001-2018	GeoBosques at (accessed in 2020): http://geobosques.minam.gob.pe/geobosque/view/index.php (see chapter 4 Appendix section C.1 and Figure C.1)
Forest cover 2000	GeoBosques at (accessed in 2020): http://geobosques.minam.gob.pe/geobosque/view/index.php
Deforestation risk in 2010	Estimated (see chapter 4 Appendix section C.2)
Opportunity costs	(Börner et al., 2016b)
Travel time from authority's offices to grid cell centroids	Estimated (see chapter 4 Appendix section C.4)

Table 4.2 Parameters of policy mix design

Parameter	Value range/estimation	Comments
Baseline deforestation (ha/cell)	Calculated for each grid cell based on monitored deforestation between 2001 and 2018	This reference scenario is used to assess the effect of the policy mix (see chapter 4 Appendix sections C.1 and C.2)
PES (soles per-ha)	0–5,000	No defined value yet at the Amazonian jurisdictional level. Although not strictly a PES scheme, the PNCB provides an incentive of 10 soles/ha
Logistical budget (soles)	5–50 million	Assumed logistical budget based on budgetary data from enforcement agencies (see chapter 4 Appendix section C.5)
Deforested patches (#/cell)	Calculated as the annual average number of deforested patches in each grid cell between 2015 and 2018	From the forest cover loss map
Administrative cost of sanction (soles/case)	1,008: average administrative cost of sanctions	(OSINFOR, 2018) No other official agency documents this cost
Field enforcement operations costs (soles)	Estimated for each grid cell based on enforcement agencies' costs and travel time map	See chapter 4 Appendix section C.4 and Table C.3

We work at 4 × 4 km resolution with 50,773 grid cells covering the entire Peruvian Amazon biome (MINAM, 2016a). To assess the effect of the policy mixes, we first generate a baseline

deforestation scenario. To do so, we calculate and assign the annual average number of deforested pixels (30-m resolution) between 2001 and 2018 to cells with at least one deforested pixel, as depicted in the annual forest cover loss map (see chapter 4 Appendix Figure C.1). The deforested number of pixels in each cell is calculated using the Dinamica EGO 5.1.0 map algebra algorithms (https://dinamicaego.com/). Cells with no deforestation throughout this period are assigned the annual mean of similar deforested cells on the basis of a deforestation-risk similarity between deforested and non-deforested cells (see chapter 4 Appendix sections C.1 and C.2). The baseline scenario entails a deforestation of 114,371 ha/year, which is slightly lower than the 118,000 ha/year used in the Peruvian Forest Reference Emission Level in the Amazon that is based on the 2001–2014 period (Peru, 2016). Cells with a forest cover share of zero and up to 25% (400 ha) as of 2018 are excluded from the analysis (N = 3,478) because we assume that the enforcement authority will only go to areas in which enforcement could deter future deforestation. Obviously, this is not the case for areas with no or nearly no forests.

Second, we estimate the enforcement probabilities by developing an optimization procedure that simulates the authority's strategy based on the ratio between probabilistically defined deforested areas and the field enforcement costs. As such, cells with a higher probability of presenting the largest deforested areas and in which field enforcement costs are the lowest become higher enforcement probability (see chapter 4 Appendix section C.3). We estimate the spatial field operations costs as a function of the travel time to each cell and to the deforested patches within them. To do so, we first developed an accessibility model that calculates the shortest travel time from the 49 urban municipalities from which field enforcement operations depart to rural areas depicted by the centroids of 3,132,238 grid cells of 500-m resolution (see chapter 4 Appendix Figure C.3). We implement this model using Dinamica EGO 5.1.0 (see chapter 4 Appendix section C.4). We then multiply the resulting travel time of each cell by the field enforcement costs (see chapter 4 Appendix Table C.3) and add those of visiting additional patches to generate a field enforcement operations cost map (Figure 4.2). We assume that visiting an additional patch takes an extra hour, implying a travel time of 5 km/hour. The number of patches in each cell represents the annual mean number of patches observed between 2015 and 2018 and is calculated by overlaying the grid cells on the forest loss map, assigning a label to each patch within each cell, and counting the unique patches within. Cells without deforestation are assigned an annual mean patch number from similar cells according to their deforestation-risk similarity (see chapter 4 Appendix section C.2).

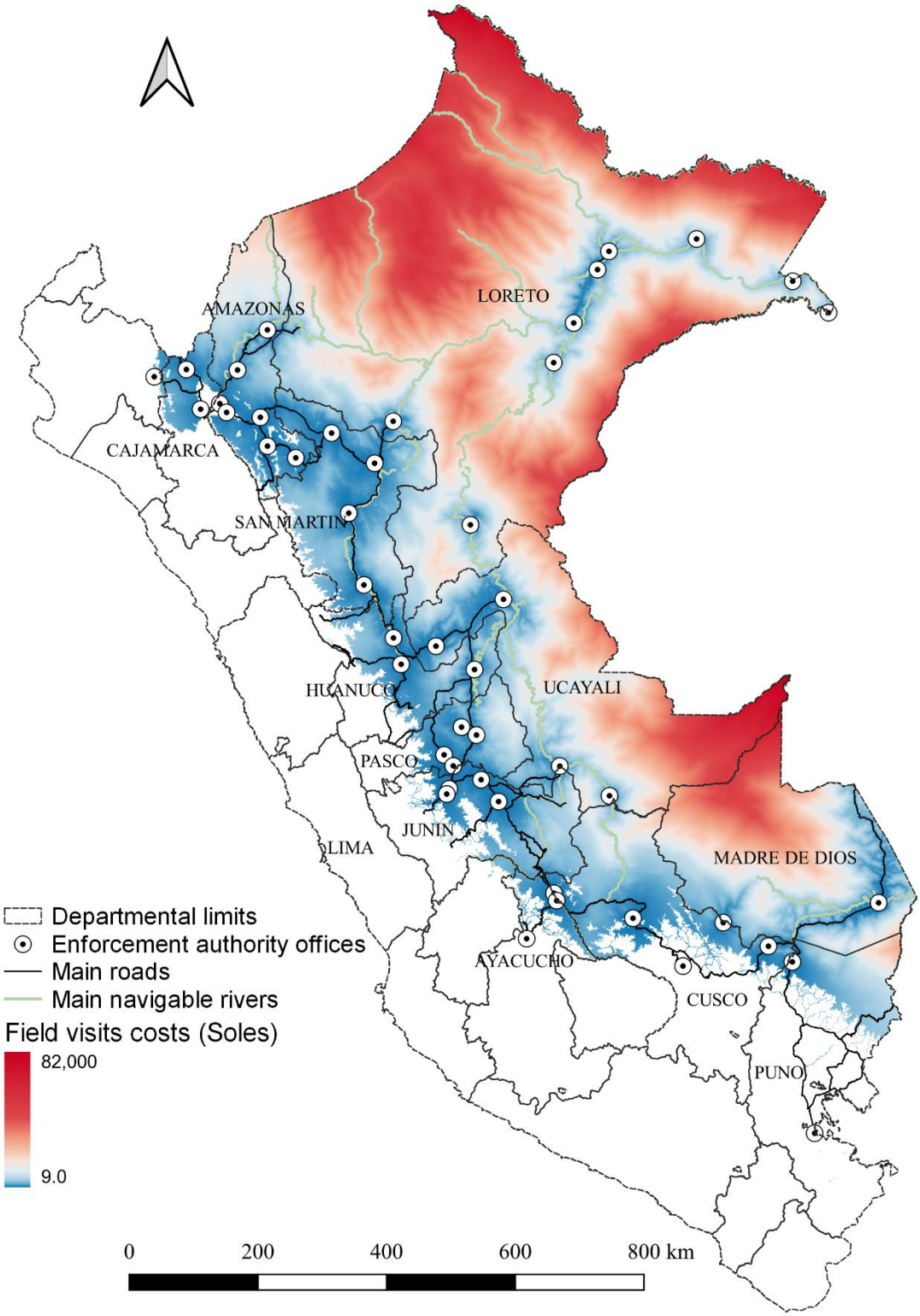

Figure 4.2 Field enforcement operations cost map in Peruvian Amazon.

4.5 Results

4.5.1 The cost of avoiding deforestation

A key parameter in our framework is the NPV of the land user's 10-year expected agricultural rent after deforesting. Any conservation strategy must consider the spatial variations of these rents because setting a fixed per-ha fine and/or PES too low would not generate significant deforestation reductions (Robinson et al., 2010). In contrast, setting PES too high implies inefficiently reducing deforestation because many land users would be overcompensated. Moreover, setting fines too high could imply unaffordable costs to those who deforest, especially for those with low incomes, making the policy politically inviable (Rodríguez–Ibeas, 2002).

By considering previously estimated agricultural rents (Börner et al., 2016b), at approximately 4,300 soles/ha, we find that half of the baseline deforestation (57,000 ha/year) could be reduced by providing PES to landholders (Figure 4.3). In theory, the same deforestation could be reduced by applying the same per-ha fine to offenders. Thus, we set the per-ha fine and PES levels around this value, as we present in the following sections. Note that this opportunity cost implies a competitive carbon cost of 6 soles/tCO_2 or 1.5 USD/tCO_2 vis-à-vis voluntary REDD+ offsets of 3.8 USD/tCO_2 (Donofrio et al., 2020) when considering the average carbon content in the aboveground biomass of 200 tC/ha of the Peruvian Amazon (Malaga et al., 2014).

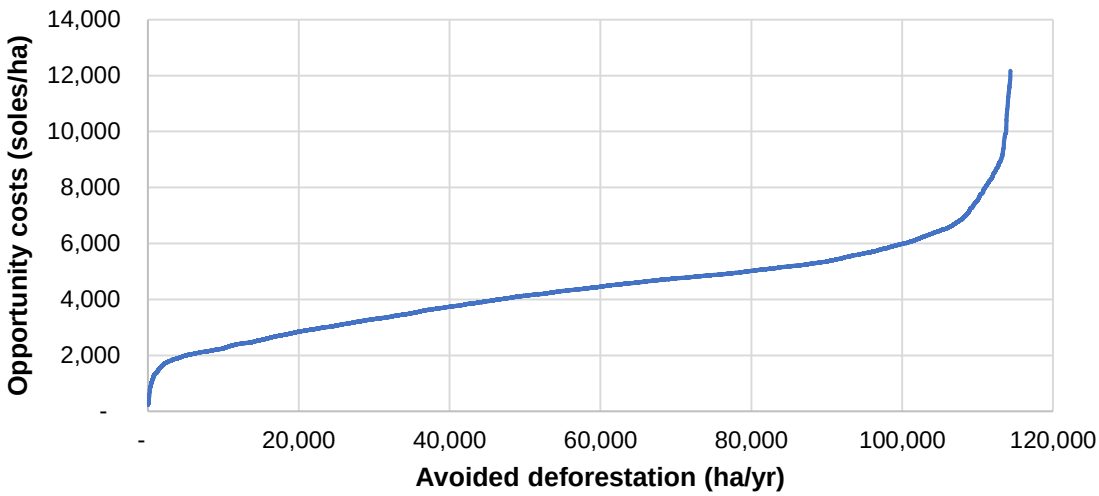

Figure 4.3 Accumulated opportunity cost curve of avoided deforestation relative to baseline deforestation scenario

4.5.2 Trade-offs between CE and income changes

In Figure 4.4, the logistical budget and avoided deforestation are held constant along the transition from a pure C&C policy to a pure PES policy (i.e., from top left to bottom right). We do not consider fine revenues to the enforcement authority because these are rarely collected. Hence, the value of the fine faced by the offender could be attributed to alternative coercive measures leading to no revenues (e.g., confiscation or destruction of assets). As expected,

we find that a greater CE results in a greater aggregated income loss. In the pure C&C scenario, the maximum CE is 4.7 ha of avoided deforestation per 10,000 soles invested, or 2,128 soles/ha (<1 USD/tCO_2), with an aggregated income loss of 425 million soles. Conversely, in the pure PES scenario, we find an aggregated income gain of 146 million soles. Nevertheless, this gain implies a 3.6-fold CE reduction at 1.3 ha of avoided deforestation per 10,000 soles (7,692 soles/ha or ~2.6 USD/tCO_2) and a higher total implementation cost of 550 million soles. By mixing "sticks" with "carrots" at a fine and PES levels of approximately 1,200 and 3,800 soles/ha, respectively, we observe that the policy mix produces a neutral effect on income and a CE of 1.6 ha of avoided deforestation per 10,000 soles invested or 6,250 soles/ha. In this case, the aggregated income loss could be fully compensated, but the policy mix remains more expensive than in the pure C&C scenario—at an annual total cost of 456 million soles and a reduction of 66% in the CE.

Hence, our results suggest that deforestation could be avoided more cost-effectively by imposing sticks alone. At the same levels of avoided deforestation, PES imply higher total implementation costs and lower CE. In contrast, PES generate an aggregated income gain for land users, whereas the pure C&C policy generates an aggregated income loss.

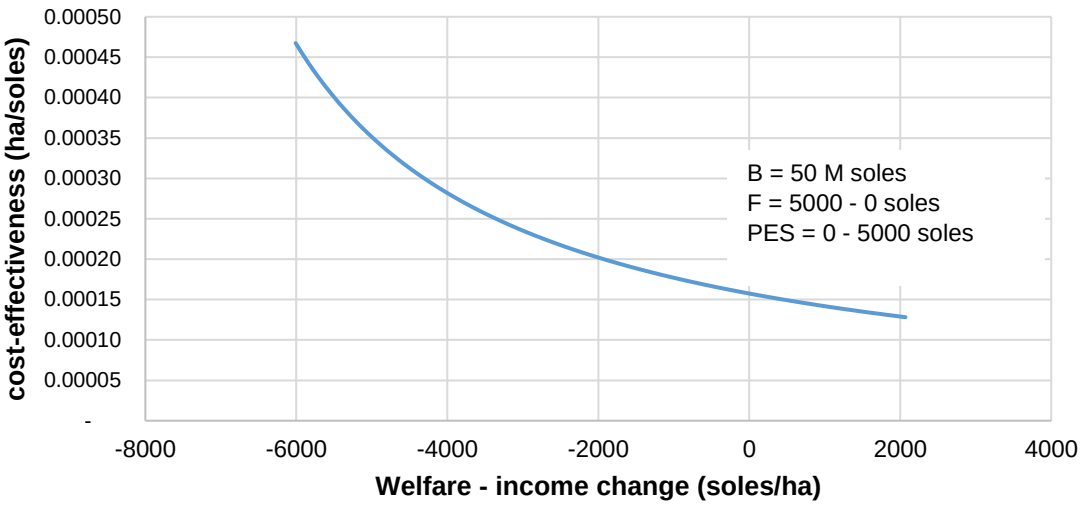

Figure 4.4 Relationship between CE and income change

Note: The figure shows the effect of alternative fine and PES levels from a pure C&C (top left) to a pure PES (right bottom) policy on the CE and aggregated income change of reducing approximately 71,000 ha of forest loss at a logistical budget of 50 million soles (the sum of the fine and PES is always 5,000).

Arguably, the CE (Eq. 4.2) is calculated only from the perspective of the enforcement agency and does not include the uncompensated opportunity costs accruing to landholders who avoided deforestation by considering the probability of being fined. However, from a broader societal perspective, both effective (i.e., compensated opportunity costs) and ineffective (paid to undetected non-compliers) PES do not count as true costs because they represent transfers from the enforcement authority to the landholders and, thus, cancel out (Sims and Alix-Garcia, 2017). Therefore, regardless of the size of the PES level, it does not count as a cost; therefore,

from a societal perspective, the CE increases as PES increase because the overall level of uncompensated opportunity decreases to the point at which all opportunity costs are fully compensated as the PES increases. However, assuming that such transfers imply no costs to the economy is unrealistic. For example, paying more to landholders requires increasing taxes, hence, increasing the costs to taxpayers. Such a general equilibrium effect on the economy is beyond the scope of this research. Therefore, the focus of this research remains on the perspective of the enforcement authority to understand how the authority could improve its CE when enforcing the law against deforestation.

4.5.3 CE and avoided deforestation

We show how the CE from the perspective of the enforcement agency is affected by increasing the logistical budget at varying amounts of fines and PES. By relaxing the logistical budget constraint, all else remaining equal, the authority's mobility increases, and more areas present higher enforcement probabilities (Figure 4.5). As a result, the reduction in deforestation is larger.

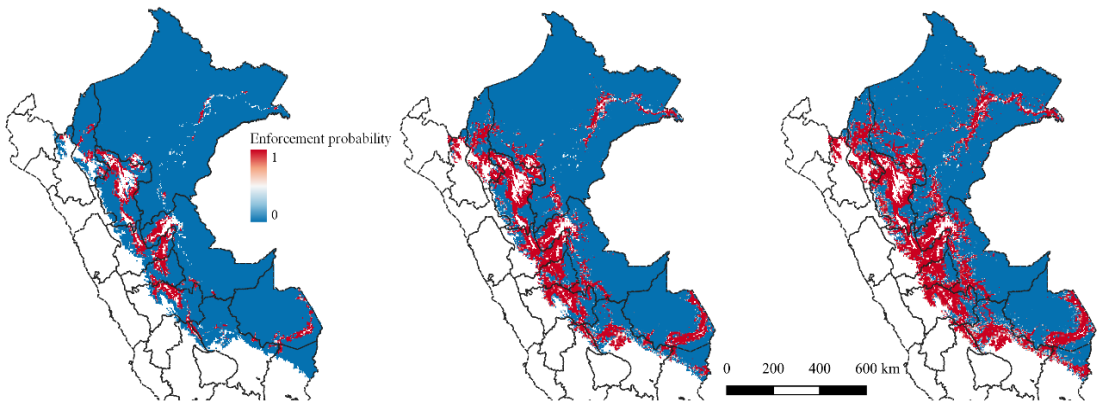

Figure 4.5 Spatial distribution of enforcement probabilities

Note: From left to right, the enforcement budget grows from 5 million, to 25 million, to 50 million soles.

Hence, Figure 4.6–Figure **4.8** illustrate the relationship between the reduced deforestation area and the CE from the perspective of the enforcement agency, given increasing logistical budgets from 5 to 50 million soles and varying policy mix designs: pure C&C, pure PES, and a mix of both. Initially, we do not consider fine revenues. First, regarding the pure C&C policy, reducing more deforestation maintains the CE constant at low avoided deforestation but reduces it as more deforestation is avoided, at constant fines (Figure 4.6). This reduction occurs because the marginal costs of policy implementation become larger than the marginal deforestation reductions, given that traveling to further locations results in smaller and more costly deforestation reductions—at distant places, both total deforestation and deforested patches decrease (Figure 4.1). Additionally, the total administrative sanctioning costs also increase as greater mobility implies more cases to be sanctioned. Nevertheless, higher fines at a constant budget could result in larger deforestation reductions—at a maximum of 71,000 ha—equivalent to a 62% deforestation reduction from the baseline scenario of 114,353 ha. At this level of avoided deforestation, a CE of 4.7 ha of avoided deforestation per 10,000 soles invested (or 2,128 soles/ha) is achieved. In contrast, if only 42,000 ha of deforestation were

avoided (37% from the baseline), the CE will be larger at the lowest budget—at 7 ha of avoided deforestation per 10,000 soles invested (or 1,429 soles/ha). These results indicate that the highest levels of potentially avoided deforestation do not imply the highest CE and, thus, suggest that, from the perspective of the enforcement agency, not all deforestation should be sanctioned and avoided.

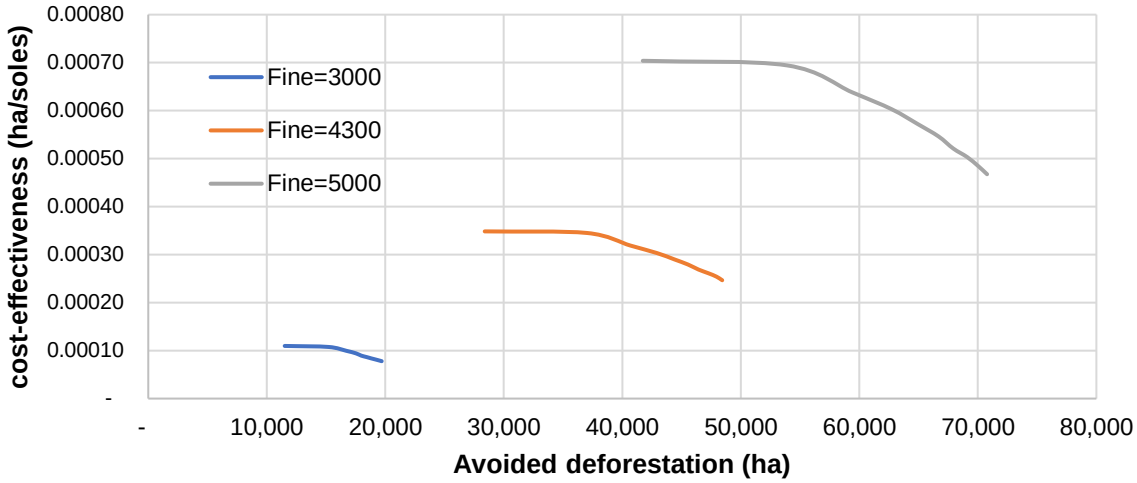

Figure 4.6 CE of reducing deforestation at different fine levels

Note: Effect on CE of pure C&C policy of increasing the budget (from 5 to 50 million soles) and the corresponding deforestation reduction at three fine levels: 3,000, 4,300, and 5,000 soles/ha.

Second, a pure PES policy tends to result in a higher CE from increasing reductions in deforestation at constant PES levels. However, this trend levels off at greater avoided deforestation (Figure 4.7). The CE increases from decreasing unconditional PES made to undetected non-compliers because the enforcement authority transfers decreasing levels of total PES to non-compliers (Eq.4.2) as the enforcement probability increases and PES recipients maintain low compliance levels. However, at high compliance and high enforcement probabilities, the authority experiences increasing and larger marginal operational costs than the marginal deforestation reductions; hence, the CE levels off. This leveling off implies that the enforcement agency might find it convenient to enforce PES contracts in accessible areas but—again—allow some degree of unsanctioned deforestation and unconditional compensation in remote areas with low deforestation and high logistics costs. Note also that the CE is always smaller than that achieved when only fines are applied.

Applying a PES of 5,000 soles/ha can reduce deforestation at the highest CE, showing that higher PES tends to increase the CE. Nevertheless, at smaller deforestation reductions (<50,000 ha), a smaller fine is more cost effective (Figure 4.7) because achieving such deforestation reductions with a smaller PES requires a much larger logistical budget that, in turn, implies less unconditional PES.

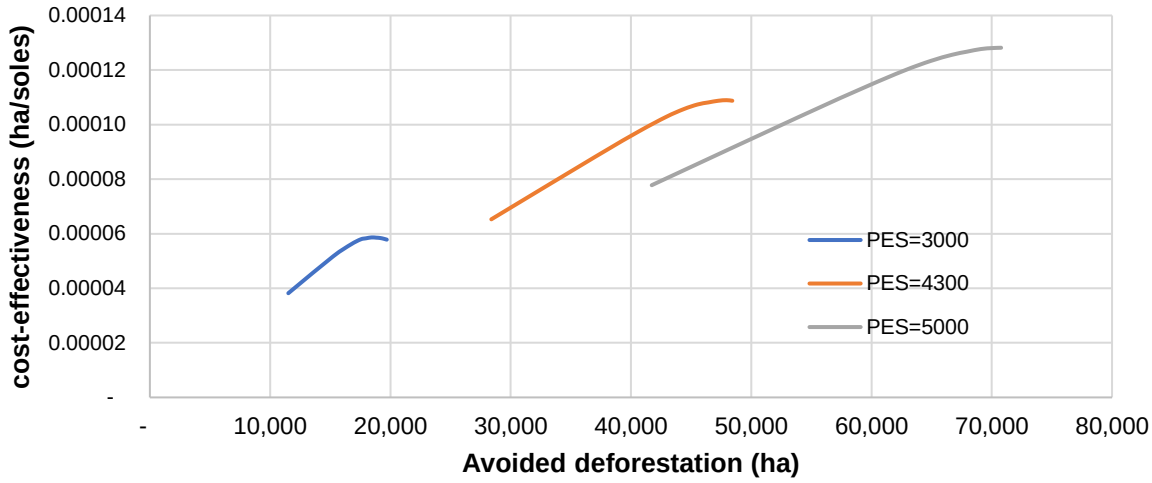

Figure 4.7 CE of reducing deforestation at different PES levels

Note: Effect of increasing the budget (from 5 to 50 million soles), and the corresponding levels of avoided deforestation, on the CE of the PES-only policy at three PES levels (3,000, 4,300, and 5,000 soles/ha).

4.5.4 Policy mix scenarios analysis

Finally, we design three policy mixes that all attain the same deforestation reductions (~30,000–51,000 ha) at increasing logistical budgets between 5 and 50 million soles. First, we define a "large-sticks-small-carrots" scenario with a fine of 4,300 soles/ha and a small PES of 100 soles/ha. Second, we invert the levels of the fine and PES for a "small-sticks-large-carrots" scenario. Third, we equalize the fine and PES for an "equal-sticks-carrots" scenario at 2,200 soles/ha each. We find that the "large-sticks-small-carrots" scenario is the most cost-effective approach, slightly increasing the CE at low levels of avoided deforestation and decreasing it at higher levels (Figure 4.8). The initial increase is the result of large marginal deforestation reductions and decreasing unconditional PES relative to increasing marginal operations and administrative costs. The trend is inverted when marginal costs become larger than the marginal effectiveness gains (Figure 4.8). In the "small-sticks-large-carrots" scenario, we find that the CE is much lower, given larger total PES. Nevertheless, the CE continuously increases with more deforestation reductions—up to approximately 50,000 ha—and then starts leveling off (Figure 4.8). The increasing trend is the result of decreasing unconditional PES as the enforcement probability increases (Eq. 4.2). Nevertheless, marginal deforestation reductions decrease as the authority's mobility increases. A similar trend, but at higher CE, is produced in the "equal-sticks-carrots" scenario. Here, smaller PES increase the CE but still at much lower levels than in the "large-sticks-small-carrots" scenario.

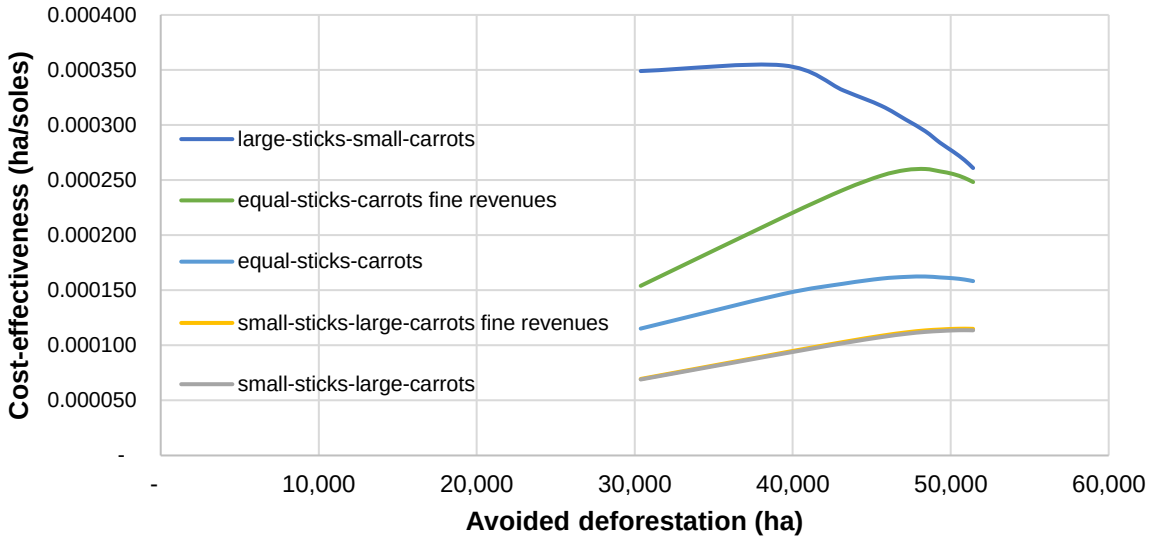

Figure 4.8 CE of reducing deforestation at varying policy mixes

Note: Effect of increasing the budget (from 5 to 50 million soles) and the corresponding levels of avoided deforestation (ha) on the CE of policy mixes, including both C&C and PES policies with and without fine revenues.

We additionally consider the collection of fine revenues. First, fine revenues we find that in the "large-sticks-small-carrots" scenario overcompensate for the total policy implementation costs at all levels of avoided deforestation, producing a negative CE (not shown in the graph). In the "small-sticks-large-carrots" scenario, fine revenues do not significantly increase the CE because of the low fine (its curve mostly overlaps with the same scenario without fine revenues) (Figure 4.8). A significant effect of fine revenues is observed in the "equal-sticks-carrots" scenario, in which the CE is increased, especially at high levels of avoided deforestation. Moreover, at the highest levels of avoided deforestation, this scenario approaches the CE of the "large-sticks-small-carrots" scenario.

These results suggest that increasing the sanctioning capacity of the enforcement authority to effectively charge fines should be an important objective of the Peruvian government. Doing so could pay for the entire policy implementation or at least increase its CE, even when higher PES and lower fines are applied.

4.5.5 Income changes and avoided deforestation

We now turn to the effects on income of changing the policy mix parameters. Aggregated income changes are defined by: (1) PES received by landholders, by those who reduce deforestation, and by those who deforest without being sanctioned, (2) the compensated and uncompensated opportunity costs of reducing deforestation, and (3) the fine (see Eq. 4.3). In Figure 4.9, we set a fixed fine and consider three PES amounts. We observe that the average income change per-ha of avoided deforestation is always reduced as more deforestation is avoided irrespective of the amount of the PES. This reduction is caused by increasing total opportunity costs and decreasing unconditional PES. Nevertheless, the income reduction is mitigated when the PES are increased. In addition, average income changes could become negative (net income losses), even for a relatively low budget when PES are low. Again, this possibility is avoided by increasing PES.

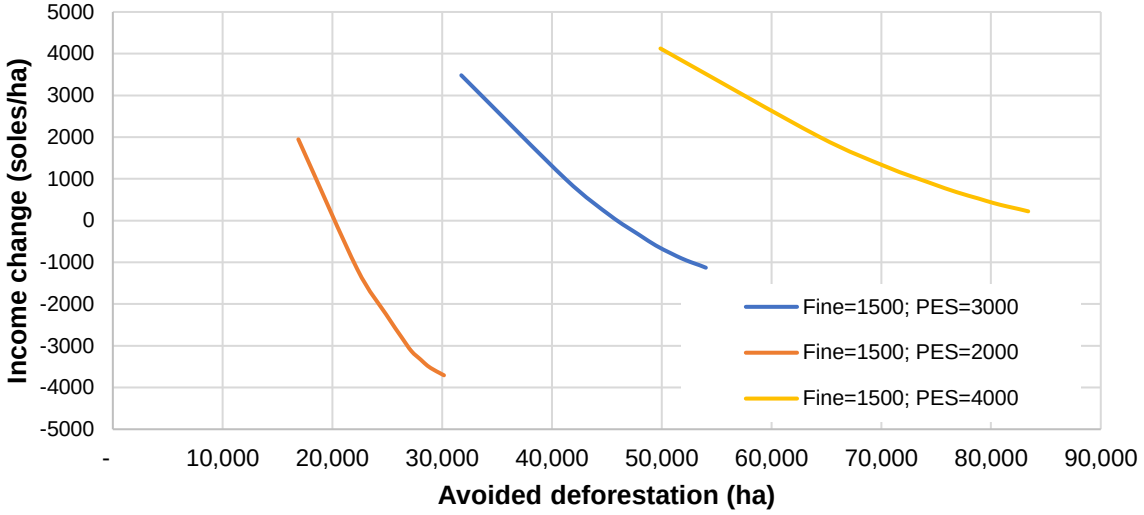

Figure 4.9 Effect of avoided deforestation on average income change at varying policy mixes

Note: Effect of varying PES levels and fixed fine on average income change per-ha of avoided deforestation with varying levels of avoided deforestation achieved by the policy mix.

Significant spatial heterogeneity occurs among landholders' income changes as a result of variations in enforcement probabilities, opportunity costs, and baseline deforestation. Our model determines that the first group of landholders located in areas with both the highest opportunity costs and the highest enforcement probabilities continue to deforest after the C&C-only policy implementation (see Eq. 4.1) and view the fine as a deforestation fee. Paying the fine represents an income loss for these landholders. In turn, the second group of landholders who face smaller opportunity costs avoid the fine and assume the opportunity costs by reducing deforestation even though they face smaller income losses than the first group. The third group of landholders in areas with both smaller enforcement probabilities and much smaller opportunity costs continue to deforest and experience no income losses because no sanctions are applied in these areas. When the PES component is introduced, the latter group receives windfall gains from unconditional PES. Nevertheless, these income gains are relatively low, given their low historical deforestation, which determines the amount of unconditional PES (see Eq. 4.1). Landholders in the second group receive larger PES and compensate for their opportunity costs as long as they avoid deforestation, thus experiencing smaller income losses. Again, for those with the highest opportunity costs, PES makes no difference in their decision to deforest, thus paying the fine and forgoing the payment.

Under this model setting, we find that when only fines are applied (5,000 soles/ha), total income losses will reach a maximum of 305,000 soles per cell. The highest income losses are located in areas with relatively good accessibility, for which enforcement probabilities are high (Figure 4.10). In such areas, deforesters with opportunity costs greater than 5,000 soles/ha pay the fine, whereas those with lower opportunity costs (<5,000 soles/ha) avoid deforestation and assume the opportunity costs. The relatively small opportunity costs in the study area (Börner et al., 2016b) imply that most income losses stem from the opportunity costs of avoiding deforestation rather than from fine payments. The income change will be zero in most remote areas, as deforestation was not sanctioned there (Figure 4.5).

When PES are introduced and increased from the “large-sticks-small-carrots” to the “small-sticks-large-carrot” scenario at the same logistic budget, income losses are reduced for all landholders because their opportunity costs are compensated with higher PES, and deforesters have to pay smaller fines. Landholders with medium opportunity costs in accessible areas face the greatest income gains because their opportunity costs will be overcompensated, reaching a grid cell maximum of 140,000 soles, primarily in the central Amazon (Figure 4.10). Landholders in remote areas start receiving unconditional PES that, however, are low and close to zero compared with the second group—the result of the very low historical deforestation in these locations.

If we assume that the poorest landholders are located in the most remote areas, we expect that no policy mix scenario considerably affects them, given the small historical deforestation observed in remote areas (low PES payments) and low enforcement probabilities (no fines). However, if this assumption is to be correct, we expect that higher opportunity costs—as a proxy for income levels—are positively correlated with accessibility. Nevertheless, our opportunity cost and accessibility maps are not perfectly correlated. That is, we find high/low opportunity costs (i.e., low/high poverty) in areas with low/high accessibility. Thus, by using poverty levels at the following district levels, we further explore the relationship between income changes and poverty.

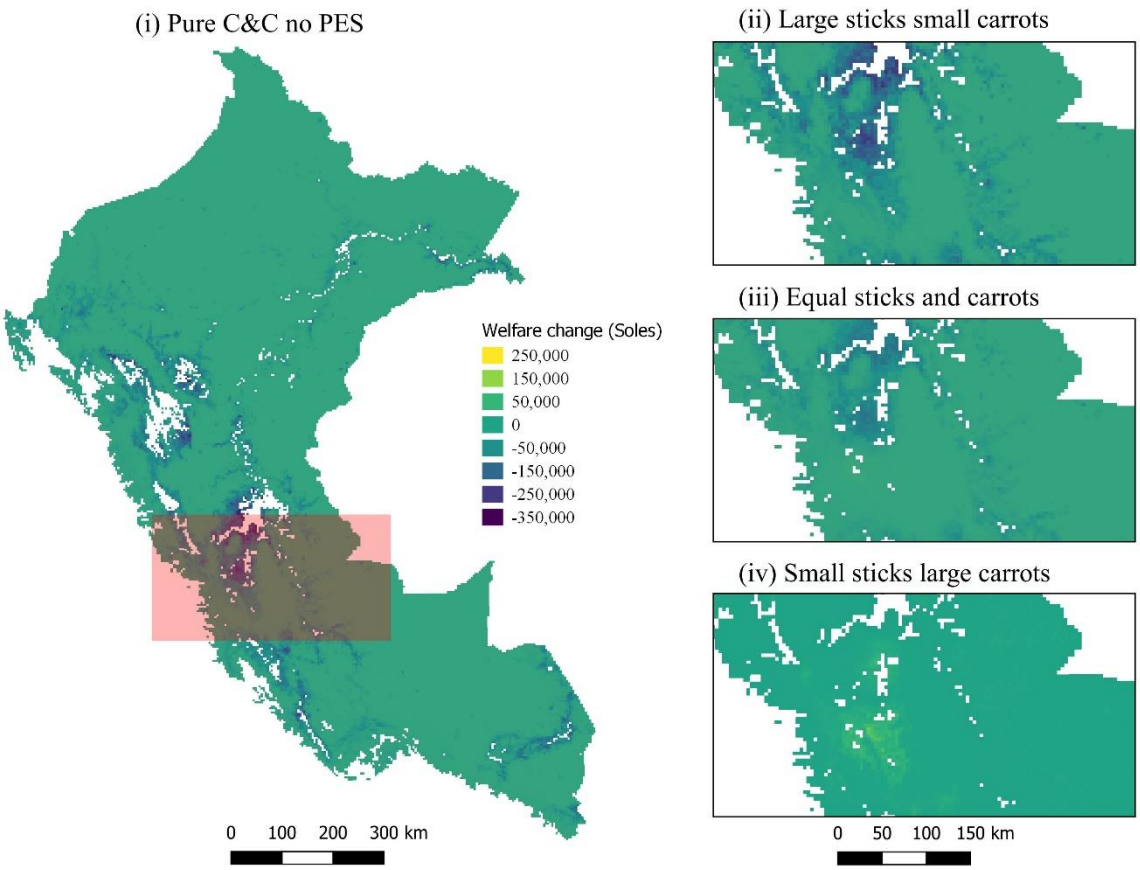

Figure 4.10 Aggregated income changes at varying policy mixes

Note: Aggregated net income changes (soles) per grid cell 4 × 4 km with varying policy mix designs. (i) F = 5,000 soles/ha PES = 0; (ii) F = 4,300 soles/ha PES = 100 soles/ha; (iii) F = 2,200 soles/ha PES = 2,200 soles/ha; and (iv) F = 100 soles/ha PES = 4,300 soles/ha

4.5.6 Income changes and poverty levels

In addition to considering the CE and overall net income change of the policy scenarios, we assess the effect of the policy mixes on the net income changes per capita relative to the districts' poverty levels. We still consider the reduction of 71,000 ha of deforestation achieved with an enforcement budget of 50 million soles. We aggregate the net income changes at the district level and normalize them by the district's rural population according to the 2017 population census.[11] The aim is to explore how each policy mix affects the well-being of the districts' rural populations given their poverty levels. We use the map of poverty for 2018 (INEI, 2019), which depicts the percentage of the district's population living below the total poverty line. In the rural Peruvian Amazon, this line is set at a monthly per capita food and non-food consumption of 242 soles, equivalent to 2,904 soles per year (INEI, 2019). For our study area (378 districts), the total poverty rate varies from 2% to 81%, with an average of 36% (see chapter 4 Appendix Table C.4, which presents the list of districts and their corresponding poverty levels, aggregated income changes, and income change per capita).

[11] See http://censo2017.inei.gob.pe/ for databases

The net income change per capita varies according to each scenario, presenting null or negative values in the pure C&C policy scenario and varying ranges of negative to positive values in each of the other policy mix scenarios. When only fines are applied (fine = 5,000 soles/ha), we found that most districts (373) present a net income loss between zero and 2,475 soles per capita. From these, the majority (234) are classified as medium poor (>28%–≤55%) (Figure 4.11a). Although this income loss range is the lowest (least negative), its maximum value represents 82% of the annual consumption level defining the poverty line, which implies that up to 55% of the total rural population in some medium-poor districts could see their well-being seriously affected by the pure C&C policy. In fact, the 10 districts with the highest income losses within this group present a range between 2,343 and 900 soles per capita (approximately 80%–31% of the poverty line). In contrast, the poorest districts (27) would only experience relatively low-income losses, with a maximum of 200 soles per capita—well below the poverty line and implying that this policy will not significantly affect their well-being in a negative way. From the least poor districts (117), four present a medium net income loss per capita of between 2,600 and 4,500 soles; and only one presents the highest income loss of 7,424 soles per capita. This finding implies that the negative effect will be greater in these districts. Although the proportion of poor people living in these districts is lower, the income losses per capita are significant because they are similar or even higher than the poverty line. Also note that that the average annual income level in the rural Peruvian Amazon is 5,064 soles per capita (INEI, 2019), less than the simulated maximum income loss of 7,424 soles per capita. In such districts, this policy should probably be avoided.

Turning into a mix of fines (= 4,300 soles/ha) and PES (= 100 soles/ha), Figure 4.11b shows that most districts (371) present a net income loss between zero and 3,515 soles per capita. From this, the majority (230) are again classified as medium poor. However, in this scenario, the 10 districts within this group with the highest income losses present lower income losses than in the previous scenario—ranging from 2,020 to 780 soles per capita (approximately 70%–27% of the poverty line). Thus, this policy mix already has a positive effect on this group by reducing the income losses per capita. Similar to the previous scenario, this policy mix does not imply a large, negative effect on the rural population of the poorest districts. In fact, the range of the income loss is lower in this scenario, with a maximum of 170 soles per capita and a minimum of 0.3 soles per capita. From the least poor districts, two present the highest income losses of 7,000 and 4,000 soles per capita, the rest face a medium income loss per capita. Nevertheless, from the latter, only four experience a relatively high income loss of more than 900 soles (31% of the poverty line). As suggested in the previous scenario, this policy mix should probably be avoided in these six districts, given the expected high-income losses relative to the poverty line. The important difference in this scenario is that, even with the introduction of a small PES level, four districts already experience small but net income gains ranging from 0.01 to 18 soles per capita. All four of these districts are classified as medium-poor.

Figure 4.11c shows that most districts (315) present a net income loss between zero and 982 soles per capita at equal levels of fines and PES; from these, the majority (192) are again classified as medium poor. However, in this scenario, the 10 districts with the highest income losses within this group present much lower income losses than in the two previous scenarios, ranging from 970 and 320 soles per capita (approximately 33%–11% of the poverty line). Again, this policy mix has a substantial effect on reducing the income losses per capita in this

group. Most of the poorest districts (24) face even lower income losses that range between 80 and 0.2 soles per capita. Instead, the remaining three districts now experience a net income gain per capita of up to 290 soles. From the least poor districts, six present the highest income losses covering a considerably smaller range between 1,960 and 1,000 soles per capita, and only one faces an income loss of approximately 900 soles per capita. Nevertheless, such results still call for caution if this policy is to be implemented in these districts. In contrast, 12 districts from this group would experience a net income gain of up to 1,150 soles per capita.

Finally, in the scenario in which PES are larger than fines, most districts (283) now face a net income gain between 0.01 and 9,335 soles per capita, from which only one is classified as the least poor (Figure 4.11d). Importantly, 18 of the poorest districts now face an income gain per capita ranging between 0.01 and 584 soles per capita. This result suggests that the medium-poor districts are those who benefit the most with this policy mix. From those districts that still face income losses, 9 and 51 are among the poorest and medium-poor classes. Nevertheless, the income losses per capita are very low, ranging from only 0.01–7 soles per capita.

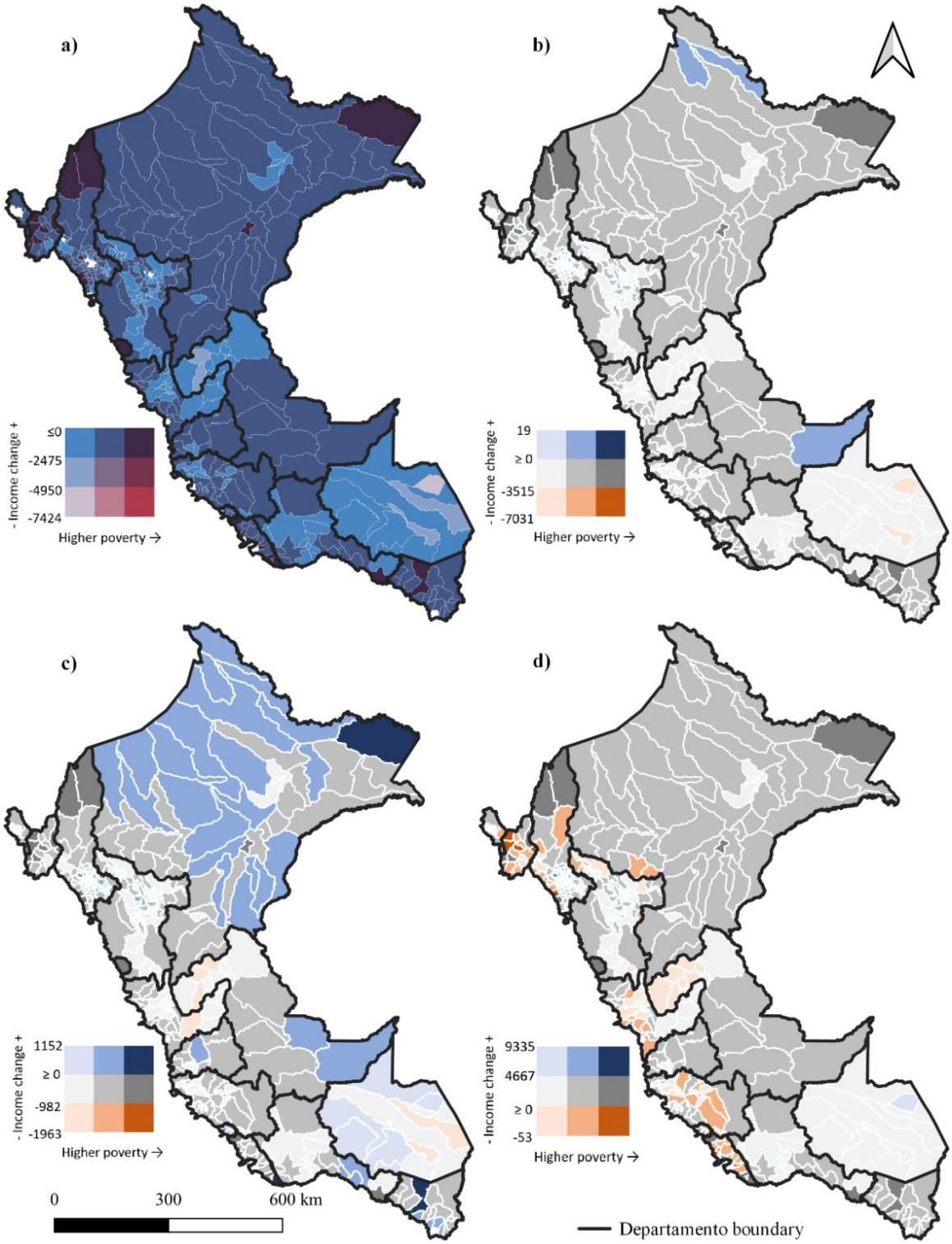

Figure 4.11 Income changes relative to districts' poverty levels under four policy mix scenarios

Note: Income changes in soles per capita (rural population) relative to districts' poverty levels under four policy mix scenarios of C&C and PES. **a)** Fine = 5,000 soles/ha, PES = 0; **b)** fine = 4,300 soles/ha, PES = 100 soles/ha; **c)** fine = PES = 2,200 soles/ha; and **d)** fine = 100 soles/ha, PES = 4,300 soles/ha. An equal interval classification was used to visualize both the income change per capita and the poverty variables at the district level. The poverty level is classified into 2%–28%, 28%–55%, and 55%–81%.

In summary, because fines are gradually reduced and PES are increased, more districts experience higher income gains per capita and smaller income losses. The poorest districts are seldom or relatively less affected than the least- and medium-poor in all scenarios that, from a poverty reduction perspective, is important to bear in mind when implementing a policy mix of C&C and PES. In contrast, the least poor districts could be negatively and significantly affected when fines are large and PES are small because the amounts of income losses are larger than the poverty line considered in the rural Peruvian Amazon. However, this negative effect is considerably reduced as PES increase, and many medium- to least-poor districts also start benefiting from the policy mix of large carrots and small sticks. As previously mentioned, this change could make the policy mix implementation more acceptable. In addition, the maps presented could provide a tool for analyzing different PES and fines levels at the district level and exploring equity issues.

4.6 Discussion

As part of its national REDD+ strategy, the Peruvian government proposed implementation incentive- and disincentive-based forest conservation actions. In this context, we explore the implications of implementing a policy mix with alternative levels of fines and PES regarding the CE of reducing deforestation and the effect on landholders' income. To do so, we develop a spatially explicit model that simulates landholders' decisions to deforest on the basis of an assumed rational choice of weighing the resulting agricultural rents against the likelihood of being fined when deforesting and/or compensated if deforestation is reduced.

Our study constitutes the first ex-ante assessment of combining "carrots" and "sticks" at the whole Peruvian Amazon level and, thus, contributes to filling the research gap of assessing forest conservation policy design and potential effects. In addition, our approach contributes to including economic values in environmental policy assessments, which is still rare in Peru (Börner et al., 2016b; Rosa da Conceição et al., 2015). Moreover, only few studies assessed the CE or welfare effects of incentive- and disincentive-based forest conservation in Peru (Giudice et al., 2019; Giudice and Börner, 2021; Montoya-Zumaeta et al., 2019), and no study explored how to mix both policy instruments to deliver cost-effective outcomes without jeopardizing local populations' well-being.

Our results indicate that reducing deforestation by providing PES to landholders could be a competitive conservation policy instrument, given estimated opportunity costs (Börner et al., 2016b) and average values of REDD+ carbon offsets (Donofrio et al., 2020). Nevertheless, reducing the same amount of deforestation by relying only on PES is much costlier from the enforcement authority's perspective relative to a C&C-policy approach, making the PES instrument less cost effective. Conservation scholars and donors are increasingly calling for boosting the CE of conservation policy interventions (Baylis et al., 2016; Börner et al., 2016a; Miteva et al., 2012; Wunder et al., 2020); therefore, our results suggest that PES alone might not be a good policy choice. In contrast, our findings suggest that the focus should be on fines and/or coercive measures. However, we find a trade-off: higher CE comes at the expense of welfare. Aggregated income losses are the highest when the CE is maximized. Mixing the two policy approaches emerges then as a sensible choice to balance CE and welfare effects, which is particularly important in the Peruvian Amazon because many areas present high poverty levels; thus, focusing on CE alone might lead to adverse effects on vulnerable groups.

We recognize that our model relies on several simplifications and assumptions. First, we abstract from the current governance scenario by assuming only one enforcement agency. By doing so, we assume that only one enforcement strategy exists that leads to a certain spatial pattern of enforcement probabilities and costs. However, different agencies might have variable strategies that could both over or underestimate the CE of the policy implementation. Unfortunately, the specific strategies of each particular agency are unknown to us. Nevertheless, when defining the costs of field enforcement operations, we consider the unit costs incurred by any of the agencies, and the total costs include the wage costs of an enforcement team composed of several governmental representatives (e.g., prosecutors, local authority, and police). In addition, the strategy we apply is likely to be the rational choice in a setting with limited budgets, as also described in the Brazilian Amazon (Börner et al., 2015b). Thus, our CE estimations are expected to be close approximations to those that would be estimated by considering the different existing enforcement agencies in the Peruvian Amazon.

Second, we assume that rents are only generated by small-scale traditional agriculture and disregard other activities, such as alluvial mining or extensive oil palm plantations, which might generate larger rents (Bennett et al., 2019; Swenson et al., 2011; Tollefson, 2020; Vijay et al., 2018). Having done so requires larger incentives and disincentives to be able to outcompete these other alternatives that, in turn, increase the implementation costs of the policy mix and reduce its CE, especially when introducing PES. However, the lack of district-level data on those rents precluded us from implementing a varying per-ha fine and PES accordingly. Thus, our estimations should be viewed cautiously, especially in areas in which such other activities dominate the forest frontier (Scullion et al., 2014).

Third, we assume that PES and fines could be simultaneously applied everywhere irrespective of land tenure security issues (Robinson et al., 2014; Wunder et al., 2020), which could preclude potential PES recipients to secure land use restrictions and deforestation reductions from third parties (Börner et al., 2010; Wunder et al., 2020) and irrespective of whether forest conversion is allowed by law. In principle, PES should be applied in areas with legal changes in forest cover; otherwise, any avoided deforestation would not be *de jure* additional (Börner et al., 2010). Such areas are restricted to agricultural plots within private and indigenous communities' lands and to undesignated public lands once a land use change authorization is obtained and considering that a minimum of 30% of the plot must be kept under natural forest cover (Law N° 29763, Article 38°). In turn, paying PES in areas with illegal deforestation (protected areas, forestry concessions, indigenous communities' forest lands, and undesignated public lands without authorization) implies accepting these payments as a compliance subsidy, especially for forest dwellers with some *de jure* use rights (e.g., native peoples within indigenous lands, forest concessionaires) but also, potentially, to small-scale landholders who illegally settled on public lands (Pokorny et al., 2021). Although not politically acceptable for many, this is part of the current scenario of REDD+ implementation in the Peruvian Amazon, and many projects have been implemented within protected areas and forestry concessions (Entenmann, 2012; Hajek et al., 2011; Kowler et al., 2014, Simonet et al., 2020). This approach is applied by the NFCP by providing transfers to indigenous communities conditional on conserving forests that are not *de jure* allowed to be deforested (Giudice et al., 2019). Thus, in principle, we believe that our assumption holds for most areas in the Peruvian Amazon. Had we excluded some areas from the possibility of receiving PES

or other types of incentives (Pokorny et al., 2021), we would not expect significant changes in our CE estimations because the areas in which deforestation is illegal are mainly located in remote areas with historically low deforestation. In addition, implementing PES requires complementary investments and further design characteristics to secure additionality and avoid leakage (Wunder et al., 2020), which we have not considered. For example, the NFCP also provides technical assistance to invest the cash transfers, incurring substantial additional costs (Giudice and Börner, 2021). Taking into account these additional costs does not change the CE and income change trends observed when using PES but might shift the observed curves downwards because they will imply more implementation costs.

4.7 Conclusion

Although recent forest conservation interventions in LMIC have increasingly relied on incentive-based instruments (Wunder et al., 2020), C&C should remain the central approach in any forest conservation policy. As we anticipated, we show that relying on such a policy approach, namely, imposing fines or equivalent coercive measures to deforesters, is the most cost-effective way to reduce deforestation relative to an incentive-based approach in the form of PES. Approximately 71,000 ha of deforestation in the Peruvian Amazon could be reduced at an investment cost of 2,128 soles/ha (<1 USD/tCO_2), whereas a much higher investment is needed if only PES are applied—6,667 soles/ha (~3 USD/tCO_2). Nevertheless, such an approach could imply an aggregated income loss to landholders of up to 425 million soles. In contrast, if only PES were applied, an aggregated income gain of 146 million soles could be reached—but at a threefold CE reduction.

We also confirmed that larger logistical budgets increase the aggregated income loss (see Figure 4.9) because of less PES to non-compliers and more opportunity costs; these budgets also decrease the CE (see Figure 4.6 and Figure **4.7**) as more deforestation is reduced. The CE is reduced because of the spatial dynamics of deforestation in the Peruvian Amazon, where more deforestation is located near the main roads and cities, making additional deforestation reductions in remote areas costlier relative to the effectiveness gains. Similarly, we confirmed that increasing the fine level increases the CE (see Figure 4.6) because additional deforestation reductions imply lower overall enforcement costs and increases in the aggregated income loss (see Figure 4.4). Moreover, if fine revenues are collected by the enforcement authority, the CE will be even larger (see section 4.5.4). Finally, we confirmed that increasing the PES level also results in increasing the CE (see Figure 4.7) for the same logistical budget. However, at larger logistical budgets, a lower PES level could be more cost-effective than a larger PES level at lower logistical budgets, given the lower total unconditional payments in the former case (see Figure 4.7). Increasing the PES level always creates smaller income losses and even income gains for low logistical budgets (see Figure 4.9).

We conclude that a forest conservation policy mix of sticks and carrots could mitigate the observed trade-off between CE and income loss by compensating for the opportunity costs of forest conservation to those who reduce deforestation, especially in areas presenting medium agricultural rents. This mitigation effect could make effective enforcement more politically acceptable. From a poverty alleviation perspective, mixing sticks with carrots also makes sense because the income losses derived from the pure C&C could otherwise be significant to rural populations living below or near the poverty line. From a CE perspective, allowing

small, unenforced, and unsanctioned deforestation in areas with smaller additional gains of enforcement than their marginal costs also supports this idea.

Finally, our study provides a policy design evaluation tool for the Peruvian government to identify the effects of varying policy parameters, namely, per-ha fines, PES, and enforcement logistical budgets, on the CE and the welfare effects of reducing deforestation. When designing a policy mix that includes both incentive- and disincentive-based instruments to balance the CE and welfare effects of reducing deforestation, we provide the following recommendations.

1. The government should invest more (a higher logistical budget) in enforcing the law against deforestation by strengthening the capacity of enforcement agencies to conduct field enforcement operations and effectively sanction offenders.
2. Collecting fine revenues should be a key goal of the enforcement system because such revenues could provide significant financial resources to cover the enforcement costs, even at relatively medium-level fines (2,200 soles per-ha).
3. To compensate for the potential income loss associated with an increased application of fines and the opportunity costs of reducing deforestation, the government should continue promoting forest conservation using incentive-based instruments, such as PES.
4. Implementing this policy mix approach might be worth testing first in areas in which the opportunity costs of conservation are not the highest.

5 Conclusion

This thesis aimed to identify the environmental and socio-economic impacts of forest conservation policies in the Peruvian Amazon. In particular, I focused on (1) the existing National Forest Conservation Program (*Programa Bosques*), an incentive-based forest conservation program, implemented within indigenous communities, and (2) a simulated scaled-up forest conservation intervention which would mix incentives and disincentives (i.e. fines and PES) within the whole Peruvian Amazon. Below, I describe the main findings and contributions, implications for future research, and policy implications.

5.1 Main findings and contributions

Based on two quantitative empirical analyses of *Programa Bosques*, I can conclude that pre-policy-intervention compliance rates (i.e. historical deforestation), spatial targeting, and sanctioning compliance are important contextual, design, and implementation factors to consider when designing and implementing incentive-based forest conservation policies. The results indicate that policy interventions, such as *Programa Bosques* – which disregarded such factors – are likely to achieve only small, if at all, environmental impacts. Moreover, if such an implementation setting and outcomes coincide with high administration and implementation costs, the intervention's overall economic benefits will be largely exceeded by their costs, especially when the intervention is short-lived (e.g. 5 years) and the permanence of the avoided deforestation is not secured. This will lead to highly cost ineffective forest conservation interventions, as was the case of *Programa Bosques*. Nevertheless, the costs and benefits of such an intervention will be distributed unevenly across the participating local communities, the country, and the global society. My results show that the Peruvian economy bore most of the costs and that only marginal benefits were provided to the local communities and the global society. In turn, based on a modelling analysis of landholders' deforestation decisions facing policy mixes of incentives and disincentives, I conclude that a C&C forest conservation policy approach, based on fines, would achieve the most cost-effective deforestation reductions. However, such reductions would imply significant income losses, which in turn could affect vulnerable local populations given the widespread poverty found in the Peruvian Amazon. Nevertheless, such losses could be compensated by a policy mix that introduces PES.

In conducting the empirical evaluation of the effect of *Programa Bosques* on deforestation (Chapter 2), I have accounted for the risk of biased estimates by applying a quasi-experimental approach (Ferraro and Hanauer, 2014a). This approach combined spatial matching techniques to find a valid counterfactual group, with a difference-in-difference fixed effects regression model. This methodology is currently considered among the best options to account for biases in evaluating the impacts of conservation interventions (Sills et al., 2017). I also considered the potential for spillover effects (Alix-Garcia et al., 2012; Baylis et al., 2016; Blackman, 2013; Honey-Rosés et al., 2011; Robalino and Pfaff, 2012) and the effect of the scale and unit of analysis used (Avelino et al., 2016; Velly and Dutilly, 2016) to account for such biases. These are all the most up-to-date methodological recommendations to avoid biased estimations, as summarized in the Conservation Evaluation 2.0 program research (Miteva et al., 2012).

Given the relatively small effects of *Programa Bosques* on reducing deforestation, in Chapter 3 I explored whether the overall economic benefits of those reductions had nevertheless exceeded the overall economic costs. It has been suggested that small estimated biophysical impacts (i.e. avoided deforestation in ha) might not be a good proxy for economic impact (Vincent, 2016), as benefits and costs could considerably vary in space (Naidoo and Rickets, 2006, Strand et al., 2018). Estimating and expressing impacts on economic terms is considered to be more relevant for policymakers needing to make decisions on implementing forest conservation policies (Vincent, 2016). Nevertheless, estimating such impacts involves considering important uncertainties about the heterogeneous spatial values of environmental goods and services. Although new spatially explicit maps of environmental values are being produced for some regions of the Amazon basin (e.g. Strand et al., 2018) and elsewhere (Bateman et al., 2013), uncertainties will remain, relative to, for example, lack of data for some regions or the spatial scale at which that data is generated (Strand et al., 2018). While such uncertainties will always affect the accuracy of the estimations, using a MC simulation approach allowed me to cope with the uncertainties by considering a range of values in the estimation of the NFV of *Programa Bosques*. The analysis of costs and benefits of *Programa Bosques* shows that the small deforestation reductions achieved by the program generated only small benefits relative to the overall costs. I can conclude, then, that depending on the magnitude of the effect and that of the environmental benefits, small effects could still imply very inefficient policy interventions.

My simulation approach in Chapter 4 proved to be effective in finding out which policy mix would deliver the most cost-effective deforestation reductions, and in identifying the expected trade-off between CE and welfare effects that had been previously found in the Brazilian Amazon (Börner et al. 2015, 2014). Although from the enforcement authority's perspective it would make more sense to rely on C&C approaches to achieve deforestation reductions cost-effectively, introducing PES into the policy mix could mitigate income losses, making the implementation of a scaled-up forest conservation program more politically viable. My research clearly illustrates that achieving significant deforestation reductions in the Peruvian Amazon is possible, but it also raises the question of how more lucrative land uses other than those arising from agricultural expansion could be compensated, especially when, for example, illegal gold mining is considered. Curbing such activities will probably require much more complex efforts in terms of enforcement budgets, fighting corruption, sustainable production alternatives, and strengthening the judiciary system.

Finally, my research contributes by filling a gap in conservation science given that the evidence on the impacts and CE of forest conservation interventions is still limited (Börner et al., 2017; Wunder et al., 2020). This is because most prior studies come from a few countries (Börner et al., 2017, 2016a) and many still present a critical risk of bias (Snilsveit et al., 2019). My results provide rigorous evidence-based policy recommendations, based on the impact evaluation of *Programa Bosques*. Moreover, the impact is expressed not just in biophysical, but also in economic terms, which has been identified as a way to improve the decision-making processes of designing and implementing forest conservation interventions. My research also provides new data on how the economic impact of *Programa Bosques* is distributed among the local communities, the country, and the global society, and how these could change by considering varying permanence scenarios for the estimated avoided deforestation. Finally, I

provide a simulation tool to test the potential effects of a policy mix on CE and welfare effects on the local population.

5.2 Implications for future research

My results show that the choice of the unit of analysis and aerial unit matter when estimating impacts of forest conservation interventions using a spatially explicit approach. Thus, spatially explicit impact evaluations should use different pixel sizes to avoid biased estimations, which had already been suggested in a few publications (see for example Avelino et al., 2016), but not received enough attention yet. My research suggests that smaller units of analysis, rather than whole polygons, are to be preferred when estimating spatially explicit impacts of forest conservation policy interventions. To complement my results, further analysis of *Programa Bosques* could consider a larger range of units of analysis' sizes.

In addition, the assessment of costs and benefits of the effect of forest conservation policy interventions could be better informed by new and more accurate data on environmental values. Thus, my approach could be updated by considering new ranges of such values. Given the important effect of the permanence assumption on the costs and benefits, an interesting follow-up research would be to estimate the effect of *Programa Bosques* once payments have stopped, and assess the permanence of the avoided deforestation achieved by this program.

Finally, further and more detailed policy-mix scenarios analyses at the local level would require considering other land uses apart from agriculture, and thus their associated social and environmental costs and benefits. For instance, forest conversion due to alluvial gold mining activities is an important aspect in several locations in the Peruvian Amazon. Hence, the model implemented in Chapter 4 could be applied to particular locations by changing some of its parameters (e.g. opportunity costs). Similarly, the enforcement costs associated with fighting such informal and illegal activities, which many times involved additional costs to fight criminal violence and corruption at all administrative and political levels, should be valued and also considered.

5.3 Policy implications

Based on these conclusions, the design and implementation of incentive-based forest conservation policies in the Peruvian Amazon, as well as elsewhere, should consider targeting forest areas with high deforestation threats to avoid low or no additionality. Similarly, participation should be conditional on enrolling whole forest lands of participating landholders, rather than just a subarea. Again, such a condition would avoid a negative self-selection bias, thus avoiding the enrollment of the least threatened subareas within participating landholders' lands. These two recommendations could likely increase the impact of forest conservation interventions such as *Programa Bosques*. In addition, my results suggest that *Programa Bosques* should reduce its implementation and administration costs, and target areas that could potentially provide the highest environmental values. By doing so, *Programa Bosques* might be able to achieve more cost-effective environmental outcomes.

Regarding the implementation of policy mixes, my research suggests that a mix of fines and PES in the Peruvian Amazon should be considered, rather than basing the efforts of reducing deforestation on just one instrument. Nevertheless, when setting the levels of the fines and PES, caution should be taken to avoid harming vulnerable populations with relatively high

fines. The process of balancing the trade-off between CE and welfare impacts could be informed by my results at the district level, regarding the poverty levels of local populations. Importantly, my results also show that increasing the sanctioning capacity of the enforcement authorities to effectively charge fines should be an important objective of the Peruvian government, as it could finance the policy mix implementation and increase its CE, even when higher PES and lower fines are applied.

A Chapter 2 Appendix

A.1 Targeting and functioning

In this section we describe the main three processes through which communities were enrolled in the NFCP.

A.1.1 Targeting

According to the initial NFCP´s rules (MINAM, 2010), targeting is designed as a means to identify and prioritize potential participating communities and is conducted at two subsequent steps: first, targeting Provinces (second highest sub-national political-administrative unit in Peru) and secondly, targeting potential participating communities within the previously targeted Provinces. Using different sets of criteria for each level (area of primary forests, biennial deforestation rate and poverty rate for Provinces; and area of primary forests, percentage of conserved forest relative to the total community area, and accessibility relative to intermediate towns and markets for communities) and a factorial analysis, Provinces and then communities had to be prioritized for intervention (MINAM, 2010). Nevertheless, the three Provinces (*Satipo* in *Junin* Department, *La Convención* in *Cusco* Department and *Oxapampa* in *Pasco* Department), from which the first group (2011) of participating communities was enrolled, were targeted without applying the NFCP´s rules, as no list of prioritized Provinces was produced (PNCBMCC, 2011b). Several former NFCP´s staff members explained to us that these Provinces were partly targeted based on a political interest of the government to increase its efforts on promoting sustainable alternative activities to coca leaf cultivation, as illegal coca plantations were present in this area (UNODC et al., 2011). Within these three Provinces, the corresponding criteria were indeed used to produce a ranking of 102 communities and the first 50 communities were prioritized for offering the Program (PNCBMCC, 2011b). Similarly, in 2012, three new Provinces were targeted (*Condorcanqui* and *Bagua* in *Amazonas* Department, and *El Dorado* in *San Martín* Department). Again it is not completely clear how these three Provinces were selected (Tejada, 2011) and a list of prioritized communities was only produced for *Condorcanqui* (Fischenich et al., 2013). There is no record on how and which communities were prioritized within the other two Provinces. In addition, the list of 26 targeted communities in *Condorcanqui* was generated using a set of criteria different from the original one (Armas et al., 2013) and included: deforestation rate, remnant forest, biomass, accessibility, proximity to national protected areas, ecological systems, poverty (at the district level) and population. Thus, it is difficult determine which variables were used where and when to prioritize potential participating communities. This could have led to administrative selection biases, by prioritizing communities that do not present the highest threats of deforestation. Moreover, several of the variables used to target communities also affect deforestation outcomes (e.g. accessibility, population), which, if not accounted for in the empirical analysis could lead to biased estimates.

A.1.2 Engagement

Once potential participating communities are identified, the NFCP organizes workshops in which these communities are invited and present its activities, benefits and conditions. Each community´s decision to participate is then collectively and voluntarily taken. Communities willing to participate must have a legal title to their land and a board of representatives (*Junta*

Directiva). In addition, communities previously or currently developing logging activities must have a record of no sanctions by the corresponding forestry authority, otherwise these will preclude them from being enrolled or will cause their eviction from the NFCP. Voluntary participation could generate further biases, as has been the case for other forest conservation programs (Persson and Alpízar, 2013). For example, communities more willing to conserve their forests and thus with *a priori* lower deforestation threats are more likely to decide to participate in the NFCP (i.e. adverse self-selection bias). In fact, from the top 20 communities with the largest deforestation in 2010 (out of the 992 from our database), none were enrolled in the NFCP. From the top 100 communities, only three (ranked 27, 66, 82) were enrolled.

A.1.3 Enrollment and payment

Once a community fulfills all requisites, it is considered eligible. The community first collectively and freely decides the total area and location of the CFZ. The NFCP does not impose any restrictions on location or extent and only provides cartography and navigation systems to set the CFZ´s boundaries. Again, this voluntary decision could generate an adverse selection bias (Persson and Alpízar, 2013) because communities will likely enroll areas with low or zero opportunity costs of conservation (Alix-Garcia et al., 2015) (see Table 2.2 in chapter 2).

Second, communities elect a management group (*Comité de Gestión*), which, assisted by the NFCP, develops an investment plan that is composed by four components: (i) productive systems, (ii) environmental, (iii) social and (iv) management. Communities decide how to allocate the total payment between these four components and which activities to implement. Communities must comply with this plan, otherwise they are suspended or evicted from the NFCP. Finally, the community and the NFCP officials sign a 5-year agreement, whose validity is annually evaluated based on the NFCP´s conditions as well as on the availability of funds. The community is then entitled to receive the annual payment. The cash must be mostly invested in implementing the production systems (i.e. buying inputs, paying wages, etc.) as described in the investment plan. The rest can be used to build communal infrastructure, such as health or education facilities, acquire medicines or cover the costs of patrolling the communal lands against encroachers.

Seventeen communities were enrolled in 2011, but from these, only ten communities had been ranked among the 50 prioritized communities; from the rest, two communities were ranked above 50, and five were not part of the prioritized list (PNCBMCC, 2011b). In 2012, 33 communities were enrolled, of which 13 are located within the new 3 provinces (11 in *Condorcanqui*, 1 in *Bagua* and 1 in *El Dorado*) and the rest are located in the previous prioritized Provinces. Ten communities out of the former group of 13 were in the prioritized list in *Condorcanqui*, and only nine of the latter group were in the list of 50 prioritized communities. The rest (i.e. 14 communities) were not originally prioritized or had higher ranks.

In sum, we can see that not all enrolled communities were selected following the NFCP´s rules and that there appears to have been room for discretional decisions on which communities to consider for potential participation. This was a consequence of the fact that some non-prioritized communities communicated their interest in participating in the NFCP, and given the lack of interest of some prioritized communities, these were accepted to fill the gap and be able to spend the available funds. Again, this adds to the lack of complete information on

how communities were selected and to the generation of potential biases. We therefore had to use additional covariates in our empirical strategy, as we describe in the main text.

Finally, in our analysis, we consider three enrollment groups rather than just two (see Table 2.1 in chapter 2). This is because, 18 communities which got enrolled in 2012 actually signed their 5-yr agreements at the very end of December 2012 and therefore we consider them to have been enrolled in early 2013.

A.2 Treated units

We identify treated units based on two aspects: (i) enrollment date and subsequent annual participation, and (ii) units of analysis and implementation (i.e. where the NFCP intervenes). First, we consider the month of the year in which a community signed its 5-yr agreement and it is subsequently considered treated if it received its annual payment in every following year. We consider expelled communities as non-treated (D_{it} = 0) in the corresponding year of eviction. Communities that were suspended in one year and re-enrolled in the following were still considered treated in both years. Based on interviews with NFCP´s staff, these latter cases never implied a complete cease of the NFCP´s activities, either because technical assistance was still being delivered or because funds did not completely run out. Second, we identify treated units differently according to the unit of analysis and the implementation unit. We used two types of units of analysis: **polygons** representing whole communities as the NFCP´s implementation unit, and **cells** representing: (i) parts of whole communities and (ii) sub-areas within communities (i.e. CFZ and OUZ) (see Figure 2.2 in chapter 2). Identifying treated units when using polygons in any given year is straightforward. A polygon treated in at least one year between 2011 and 2015 is assigned to the treatment group. Polygons that were never treated are potentially included in the control group. Polygons enrolled in 2014 and 2015 are not considered in either group. In regressions however, the treatment variable could take values between zero and one in the year of enrollment, depending on the month in which the polygon was enrolled. We divided the number of months after enrollment by 12. So, if a polygon was enrolled by the start of July, its treatment variable receives a value of 0.5.

The approach is different when we use cells. First, for the whole community as implementation unit (see Figure 2.2 in chapter 2), the cell´s share covered by treated and non-treated polygons defines their treatment status. Rules apply as follows: (i) if there are no polygons overlapping a cell, the cell is identified as a no-community cell; (ii) if the cell´s share covered by treated polygons is larger than that covered by non-treated polygons (>50%), it is identified as a treated cell (TC); and (iii) if the cell´s share covered by non-treated polygons is equal to or larger than that covered by treated polygons (≤50%), it is identified as a non-treated community cell (NTC), and thus becomes a potential control cell. If the cell´s share covered only by either a treated or non-treated polygon is larger than zero, the cell is identified as TC or NTC, correspondingly. The treatment variable D_{ict} in equations 2.1 and 2.2 (see section 2.3.2 in chapter 2) is defined as:

$$D_{ict} = \sum_{j}^{n} \frac{(Area\_TC_{jt})}{225} \qquad \text{(Eq. A. 1)}$$

where $(Area\_TC_{jt})$ represents the area of overlapping treated polygon *j* (*j* = 1,2,…,*n*) with cell *i* in year *t* (t=2001,…, 2010, 2013, 2014, 2015). The treatment variable must also consider the months of participation for the enrollment years (2011 or 2012) as shown below:

$$D_{ict} = \sum_{j}^{n} \frac{\left(Area\_TC_{jt} * \frac{months_{jt}}{12}\right)}{225} \qquad \text{(Eq. A. 2)}$$

where $\frac{months_{jt}}{12}$ represents the fraction of the year *t* (t=2011, 2012) during which the polygon *j* participated in the NFCP.

Second, for the community´s sub-areas (see Figure 2.2 in chapter 2), the definition of a treated cell relies on the cell´s share of CFZ´s polygons relative to those of the OUZ. If the area of a CFZ-polygon within a given cell is larger than that of an OUZ-polygon, it is considered a CFZ-cell. Alternatively, if the area of the OUZ is equal to or larger than the CFZ, the cell is considered an OUZ-cell. The treatment status in this level of analysis is only defined for cells overlapping CFZ- or OUZ-polygons. All other cells´ characteristics remain the same.

A.3 Cells

Using a set of GIS softwares (Dinamica EGO 3.0.17, QGIS 2.18.0) we generate a grid of cells of 225 ha each, which represent our second type of unit of analysis (Table A.1). We lay this grid over the maps of our covariates to extract the sums or means of their values and assign them to each cell (Costedoat et al., 2015). With this approach we want first to disaggregate the binary treatment variable from the irregular boundaries of polygons to a continuous treatment variable representing the share treated area of each cell. This is important, since it has been found that aggregation increases bias when using a binary or, more generally, a discrete variable, (2). Second, we want to build a spatial database of consistent resolution based on data sources of different formats and scales (Costedoat et al., 2015). For example, whereas most of the biophysical covariates were originally acquired in raster format of varying resolutions (e.g. 30m, 90m, etc.), community boundaries are represented in vector format (polygons). Other covariates present population centers´ attributes (e.g. population size) and come from tabular sources and georeferenced points. By spatially overlaying the grid over pixels, polygons or points, we build a spatial database of consistent resolution. Third, given that it has been showed that the choice of scale and areal unit could affect the estimated impact of a program (Avelino et al., 2016; Börner et al., 2015a), we also use cells instead of only polygons to provide new evidence of the effect of such a choice from our study. Finally, this approach allows us to generate a set of simulated CFZ and OUZ within non-treated communities from which to withdraw a valid control group as we explain below.

A.4 Modeling untreated CFZ and OUZ

Using a binary variable (Y) that indicates whether a cell has ever been a CFZ (Y=1) or an OUZ (Y=0) we estimate the probability of a cell *i* being a CFZ cell, $\pi(x_i) = Pr[Y=1|x_i]$, where x_i implies a set of covariates for cell *i*. To do so, we fit a logistic regression model using the log-likelihood method with R´s glm function to estimate the following equation:

$$ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right) = \beta_0 + X'_i\beta + Z'_i\gamma + \theta W'def_i + \lambda W'A'_i \qquad \text{(Eq. A. 3)}$$

Where X'_i is vector of time-invariant covariates, including: slope, precipitation, temperature, biomass, distance to protected areas, distance to rivers, distance to roads, distance to districts´ capitals, deforestation density, accessibility, distance to population centers within communities, internal distance to community´s boundary, deforestation risk, and the cell´s share covered by forest in 2010. Z'_i is a vector of time-varying covariates, including: annual deforestation between 2001 and 2010; distance to deforestation patches >1ha outside community boundaries ("Outside-deforestation") in years 2001, 2002, 2004 and 2010 (we exclude some years to avoid multicollinearity issues), $W'def_i$ is a spatially lagged time-varying covariate (annual deforestation between 2001 and 2010) weighted by a standardized queen matrix (W´) (Honey-Rosés et al., 2011). $W'A'_i$ is a vector of two spatial lagged covariates (biomass and the cell´s share covered by forest in 2010) weighted by a standardized queen matrix (W´). $\beta, \gamma, \theta, \lambda$ are the estimated regression coefficients. Using Eq.A.3 we obtain fitted values for CFZ- and OUZ-cells and conduct a Hosmer-Lemeshow goodness of fit test (Hosmer and Lemeshow, 2000) to compare the distributions between the fitted values and the observed ones (Figure A.4). We could not reject the null hypothesis that the distributions were similar (*p*=0.298). We subsequently use our estimated logit model to predict the probability of a non-enrolled community cell to become a CFZ-cell. Cells with a probability larger than 0.72, which represents the median of the fitted values of actual CFZ-cells, were defined as potential CFZ controls. Similarly, cells with a probability smaller than 0.22 were defined as potential OUZ controls. With this data we construct two separated datasets: one for treated and potential controls for both CFZ and OUZ. These datasets were used as inputs to find the matched sample data in each case.

A.5 Matching

When using polygons, we apply the GenMatch function of the R´s Matching package to our full set of communities (N=992) to find the best balance between the set of covariates of the treated and control groups. GenMatch is a generalization of the propensity score and Mahalanobis distance matching and avoids the need to manually and iteratively check for the best propensity score as it provides a search algorithm that iteratively improves the covariate balance (Diamond and Sekhon, 2012). We use it to conduct a 1-to-1 nearest-neighbor matching with replacement using covariates described in Table 2.2 (in chapter 2). We find one control community for each of the 50 treated communities, and built a database consisting of the pre and post-treatment characteristics of the matched sample. The sample includes 36 unique control communities.

When using cells, we apply the Match function of the same R´s package to construct a matched sample of cells using 1-to-1 matching with replacement, the Mahalanobis distance as the distance measure, and an exact distance for the Department variable. We also use covariates described in Table 2.2. The matched sample was drawn from a total of 18,319 community-cells (deforestation risk > 0.01), and included 986 treated-control pairs, with 495 unique cells. We applied the same function to build our CFZ and OUZ matched samples (see section A.4 above). The matched sample of CFZ was composed by 523 treated-control pairs, with 304 unique controls, and that of OUZ was composed by 655 treated-control pairs, with

305 unique controls. Covariates balances for all units and zones of analysis are presented in tables A3 to A6.

A.6 Covariates

Given the fact that it is not completely clear which variables were used for targeting the assessed communities (see section A.1.1 above), we consider a larger set of covariates than the one originally stated by the NFCP´s manual. Thus, we selected covariates based on the existing evidence of their relation with deforestation in Peru (Mäki et al., 2001; Miranda et al., 2016; Naughton-Treves, 2004; Velarde et al., 2010; Vuohelainen et al., 2012), and also in the Amazon region (Soares-Filho et al., 2010), as well as on their potential effect on treatment assignment (Miranda et al., 2016). Covariates included geo/biophysical, infrastructure, land use and land cover, socioeconomic, and other derived attributes. Depending on the unit of analysis, values for each covariate were calculated differently. For polygons, we calculate the sum, average or share area of all pixels´ or points´ values overlapping a polygon, as well as the Euclidian distance from the closest feature (e.g. river) to a polygon´s boundary (see Table 2.1 in chapter 2). For cells, we calculate the sum, average or share area of all pixels´ values within a cell. Distance variables represent the average of all pixels´ Euclidean distances, from the centroid to the nearest pixel representing a feature. In addition, for variables representing community level attributes, such as for example the total population of a community, we calculate an area weighted average for each cell *i* as follows:

$$Population_i = \sum_{j}^{n} \frac{\left(Area\_comm_j * Total\_pop_j\right)}{225} \qquad \text{(Eq. A. 4)}$$

Where $Area\_comm_j$ is the area of community *j* within cell *i* and $Total\_Pop_j$ is the total population of each community *j*.

A.7 Specification tests

We conduct specification tests for our estimated models (Eq.2.3 and Eq.2.4 in section 2.3.2) using R´s plm package version 1.6-5 (Croissant and Millo, 2008). First, to test whether a pooled ordinary least squares (OLS) model would produce unbiased ATT we use a Breusch and Pagan´s Lagrange multiplier test (Breusch and Pagan, 1980). The null hypothesis that individual effects were not significant was rejected ($p<0.01$) in all cases. Second, to choose between a random effects or a fixed effects model, we applied the Hausman test (Hausman, 1978) to compare both type of models. The null hypothesis was rejected ($p<0.01$) in all cases, thus indicating that a fixed effects model was appropriate. Third, general serial correlation and Wooldridge´s test for serial correlation in “short” fixed effects panels were both highly significant ($p<0.001$). Additionally, Wooldridge´s FD-based test (Wooldridge, 2010) for serial correlation of differenced errors was also highly significant. These tests indicate that serial correlation in the error terms of our models could not be corrected by either the within or the FD estimators. Nonetheless, we use the FD estimator as a means to potentially control for unobserved time-variant heterogeneity, for which we test the parallel trend assumption, as we explain below. Finally, we estimated the SE, using the clubTamal package version 1.0 in R (Cisneros, 2017), which provides consistent estimators of covariance, when

heteroscedasticity and autocorrelation are present, and also allows for clustering SE at a higher level than the individual observations. In our case, this implies that clusters are defined by each community polygon and not by each cell.

One of the main assumptions of the differences-in-differences estimation is that of the common trends, which assumes that in the absence of an intervention, the trends in the outcome of both treated and control units would have remained parallel (Angrist and Pischke, 2009). Of course, once the intervention is implemented it is impossible to observe and confirm this assumption. Nonetheless, if trends were similar before the start of the intervention, one could assume that, in the absence of the intervention, trends would have remained parallel afterwards (Angrist and Pischke, 2009). In our case, we expect that had there be no NFCP between 2011 and 2015, the changes in the average deforestation of treated and control communities would have been very similar. As we cannot check this, we rely on what happened between 2001 and 2010. A visual inspection of Figure 2.3 (in chapter 2) suggests that after matching there is a common trend in the annual average deforestation changes of treated and control groups before the start of the NFCP (2011). Similar to Cisneros et al., (2015), we test this assumption by applying the following model to our matched samples (polygons and cells) using notation in Eq.2.3 and Eq.2.4 in section 2.3.2:

For polygons we estimate:

$$\Delta Y_{cdt} = \beta D_c + \lambda_1 t + \lambda_2 t \cdot D_{cd} + \Delta X'_c \delta + \gamma \Delta Out_{pres_{cdt}} + \omega_d + \varepsilon_{cdt} \qquad (\text{Eq. A. 5})$$

For cells we estimate:

$$\Delta Y_{icdt} = \beta D_{ic} + \lambda_1 t + \lambda_2 t \cdot D_{icd} + \Delta X'_i \delta + \gamma \Delta Out_{pres_{icdt}} + W'X'_i \lambda + \omega_d + \varepsilon_{icdt} \qquad (\text{Eq. A. 6})$$

Where λ_1 represents the deforestation trend of control communities and the deforestation trend of the participating communities is the linear combination of $\lambda_1 + \lambda_2$. Hence, if trends of both groups were similar then $\lambda_1 + \lambda_2 = \lambda_1$ or $\lambda_2 = 0$, which we tested as null hypothesis using the Wald test for linear combinations. After applying the Wald test, we could not reject the null hypothesis of equal time trends between the treated and control communities (polygons) prior to the start of the NFCP (F-statistic=0.84, p-value=0.36). Similarly, we could not reject the null hypothesis of equal time trends between treated and control communities using cells (F-statistic=0.2, p-value=0.66). Neither did we find significant differences between CFZ trends and their controls' (F-statistic= 0.89, p-value=0.35), nor for OUZ trends and their controls' (F-statistic=0.42, p-value=0.52). With such results, we are confident that our estimations are not biased due to unobserved time-varying heterogeneity.

A.8 Deforestation risk model

The annual deforestation data presents skewed distributions towards zero, because there is a large percentage of cells within communities (53%) that experienced zero deforestation during the whole period of analysis (2001-2015). This also occurs for treated cells, where 38% of treated cells never got deforested, before and after being enrolled. This could generate potential biases in our estimations. First, previous studies have dealt with such a distribution using tobit (Alix-Garcia et al., 2012) or Poisson (Busch et al., 2012) models. In our case,

however, the observed skewness disappears once we applied the FD transformation (Eq.2.3 and Eq.2.4), generating a bell-shaped distribution with mean near zero. This type of distribution made us confident to estimate our models using OLS. Second, the large number of zeros in the differenced dependent variable could still bias our estimations. When measuring the relationship between changes in treatment and in deforestation, we will encounter a relatively small variance in the latter relative to the former. In other words, no matter how much a cell is treated, deforestation change will, relatively often, be zero, thus being unable to find an effect or underestimate it. To cope with this, we developed a deforestation risk model to keep cells with an estimated probability of being deforested between 2001-2010 larger than 1% (higher minimum threshold values reduced the number of treated cells to a level that would have made our analysis statistically irrelevant).

Using a variable (Y) that denotes the fraction of the cell deforested between 2001 and 2010, $0 \leq Y \leq 1$, we estimate the probability of a cell *i* having been deforested between 2001 and 2010, $\pi(x_i) = Pr[Y=1|x_i]$, where x_i implies a set of covariates for cell *i*. To do so, we fit a logistic regression model using the log-likelihood method with R´s glm function to estimate the following equation:

$$ln\left(\frac{\pi(x_i)}{1-\pi(x_i)}\right) = \beta_0 + X'_i\beta \qquad \text{(Eq. A. 7)}$$

Where X´ is a vector of biophysical independent variables including: population, number of houses, area of coca plantations, number of population centers, community's total area, slope, precipitation, distance to protected areas, forest loss density, distance to population centers within communities, internal distance to the community's boundaries, share area of forest in 2010, spatially lagged biomass, and distance to deforestation in 2010. β represents the estimated regression coefficients for each covariate. Using the fitted values of Eq. S9, we discard all cells with a fitted value smaller than or equal to 0.01. This effectively reduced the number of cells with no deforestation in any year between 2001 and 2015 to only 11% of both all cells and treated cells. This trimmed cell-dataset is the one we used in our estimations.

A.9 Effects over time

Given that not all communities were enrolled in the same year and that some communities were evicted from the NFCP (Table 2.1), we also explore how the effect of the NFCP might have varied over the years after enrollment. Varying effects could show for example, that the NFCP had an increasing, a declining or a short run effect during the period of analysis (Laporte and Windmeijer, 2005). Such dynamic effects could help us to better understand the potential channels that might have contributed or not with the overall ATT and to improve the NFCP´s design (Börner et al., 2016a; Cisneros et al., 2015).

To estimate the effects of the NFCP after *t* years of enrollment, we follow the approach presented in (Autor, 2003) and replace the treatment variable by five new treatment variables, each one representing year zero through year four after enrollment. The new treatment variable for year zero (i.e. year of enrollment) takes a value between zero and one, if treated, and zero for all subsequent years. The following four new treatment variables take a value of one, if treated in the corresponding year, and zero for all previous and subsequent years. The

coefficients for each of these indicators are interpreted as the average effect of the NFCP after *t* years of enrollment (Cisneros et al., 2015). Following the same notation as in Eq.2.3 and Eq.2.4, we estimate for polygons:

$$\Delta Y_{cdt} = \sum_{k=0}^{4} \Delta D'^{k}_{ct}\beta_k + X'_c\delta + \gamma\Delta Out_{pres_{ct}} + \Delta\varphi_t + \omega_d + \Delta u_{cdt} \qquad (\text{Eq. A. 8})$$

Where, k is the number of years passed after enrollment.

For cells, we estimated:

$$\Delta Y_{icdt} = \sum_{k=0}^{4} \Delta D'^{k}_{ict}\beta_k + X'_i\delta + \gamma\Delta Out_{pres_{ict}} + W'X'_i\lambda + \Delta\varphi_t + \omega_d + \Delta u_{icdt} \qquad (\text{Eq. A. 9})$$

A.10 Figures

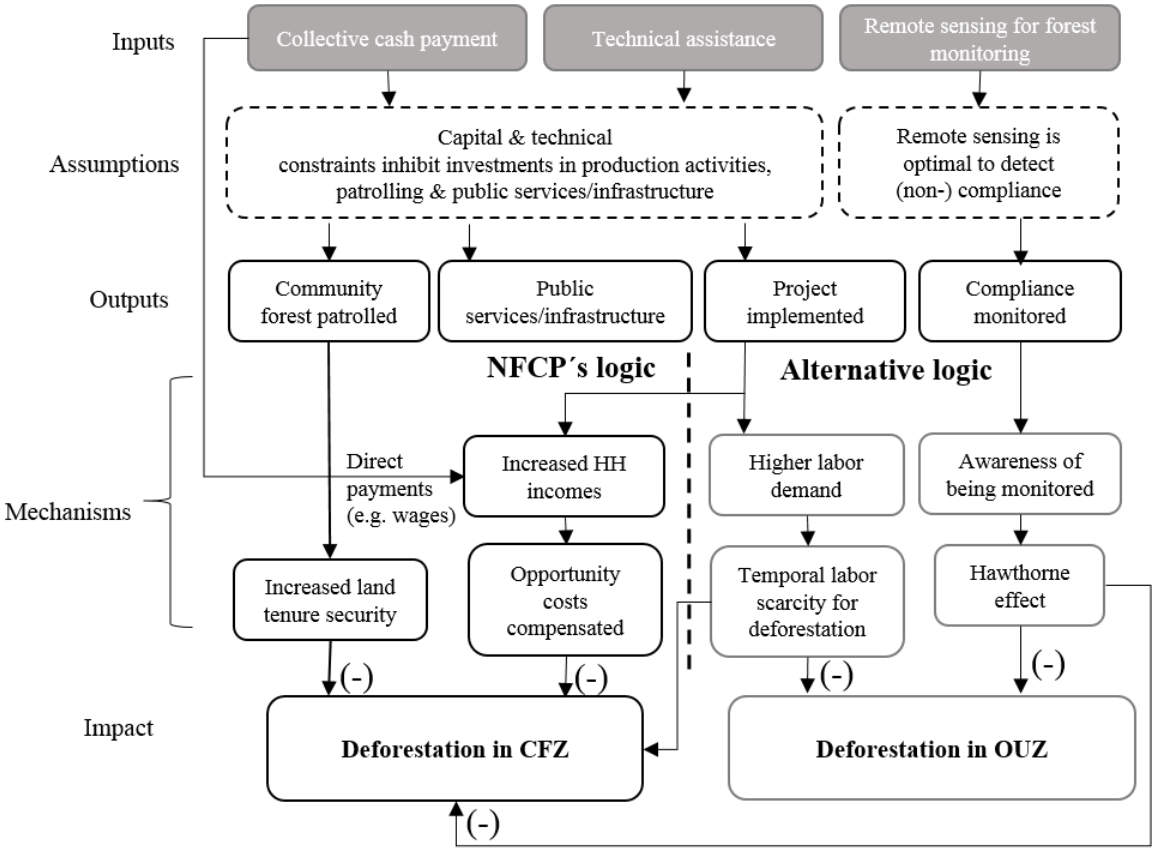

Figure A.1 Theory of change of the National Forest Conservation Program

Note: Theory of change presenting inputs, assumptions, outputs, expected mechanisms following the NFCPs logic and alternative hypotheses (alternative logic), and impacts in terms of avoided deforestation within the CFZ and the OUZ.

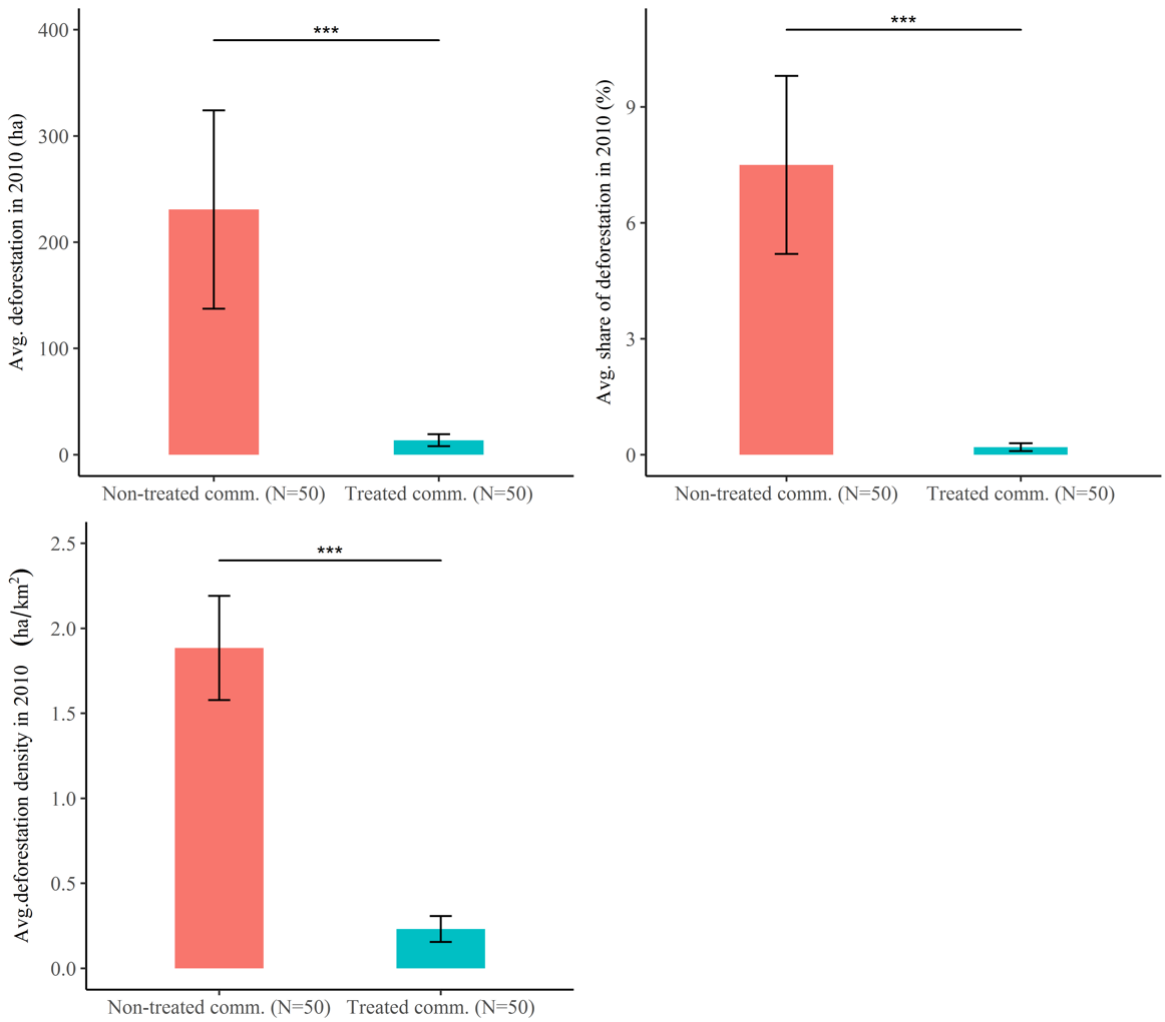

Figure A.2 Comparison of deforestation characteristics between treated and non-treated communities

Note: Comparison of: (i) average deforestation in 2010, (ii) average share of deforestation in 2010 and (iii) average deforestation density (deforestation in 2010/forest in 2010) between treated communities (N=50) and subsamples of non-treated communities (N=50) with the highest values for each variable. Error bars represent 95% confidence intervals. ***p<0.001.

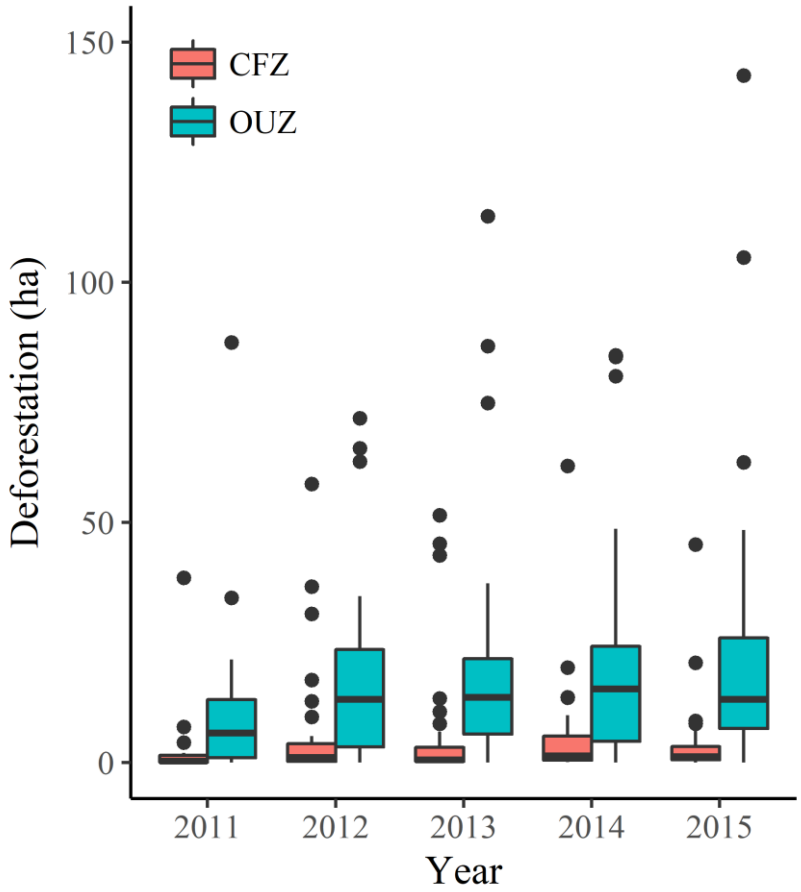

Figure A.3 Deforestation within CFZ and OUZ

Note: Boxplots of total deforestation (ha) within CFZ and OUZ between 2011 and 2015. Dots represent outliers. The number of observations in each year is the same for both CFZ and OUZ and varies as follows: N_{2011}= 17; N_{2012}= 30; N_{2013}= 45; N_{2014}= 40; N_{2015}= 40.

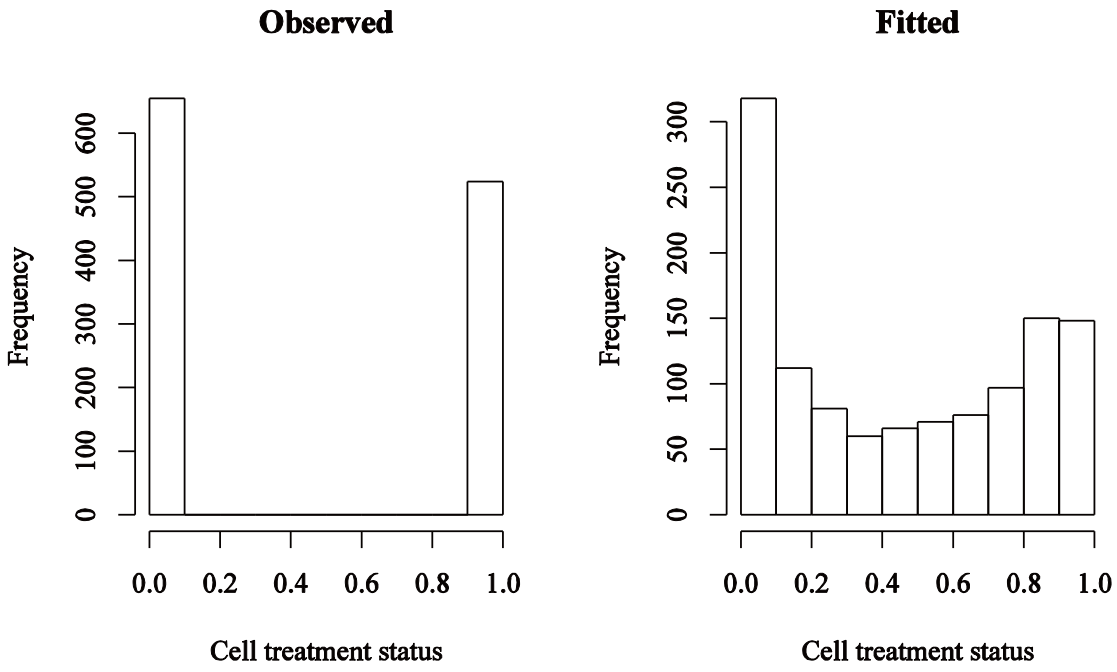

Figure A.4 Distributions of observed and fitted values of CFZ and OUZ cells

Note: For CFZ cells, cell treatment status = 1; and for OUZ cells, cell treatment status = 0. Fitted is the product of the logit model that produces similar distributions between the observed and fitted values according to the Hosmer-Lemeshow goodness of fit test (*p=0.298*).

A.11 Tables

Table A.1 Zones and units of analysis

Zone	Unit of analysis (UA)	Size (ha)
Whole community	Polygon	Variable
Whole community	Cell	225
CFZ	Cell	225
OUZ	Cell	225

Table A.2 Covariates, units, sources, description, scale and years represented in the data.

Variable	Units	Source/Description	Resolution	Years	Used in matching and/or regressions and level of analysis
Outcome					
Deforestation in year t	ha	GeoBosques[12]/Sum of annual deforestation within each unit of analysis (UA), only within the share of a cell covered by communities´ lands.	30 m	2001-2015	In matching, only in the period between 2001-2010; in regressions, the whole period 2001-2015
Community data					
All communities		IBC-GIZ/Polygons depicting boundaries of treated and non-treated communities.	1:1,000,000	NA	NA
CFZ and OUZ		NFCP/Polygons depicting boundaries of CFZ and OUZ	1:1,000,000	2011-2012	NA
Treatment					
NFCP	[0,1]	NFCP/Community participation in the NFCP in year t	1:1,000,000	2011-2015	NA
CFZ/OUZ	[0,1]	NFCP/Sub-area of the community enrolled, or not, in the NFCP in year t	1:1,000,000	2011-2015	NA
Covariates					
Geographical and biophysical					
Elevation	m	CGIAR-CSI[13]/Mean elevation of all pixels within the UA	90 m	2008	In both and in all levels of analysis (polygons and cells)
Slope	Degrees	Derived from DEM map/Mean slope of all pixels within the UA	90 m	2008	In both and in all levels of analysis
Biomass	Mg C/ha	WHRC[14] (Baccini et al., 2012)/Mean aboveground live woody biomass of all pixels within the UA	500 m	2007-2008	In both and in all levels of analysis
Temperature	°C	BioClim[15]/Mean annual average temperature of all pixels within the UA	1 km	1950-2000	In both and in all levels of analysis

Precipitation	mm	BioClim/Mean annual precipitation of all pixels within the UA	1 km	1950-2000	In both and in all levels of analysis
Distance[16] to rivers	m	Derived by the author[17]/Distance from closest river to community´s boundary or mean distance of all pixels within a cell	Shapefile: 1:100,000 Raster: 30 m	2010	In both and in all levels of analysis
Infrastructure					
Distance to roads in 2010	m	Ministry of Transport and Communications (MTC)[18]/Distance from closest road of the national road network to community boundary or mean distance of all pixels within a cell	Shapefile: 1:100,000 Raster: 30 m	2010	In both and in all levels of analysis
Accessibility	Index	Derived by the author/Mean of all pixels´ cost-distance values from community to nearest municipality (Friction map surface´s values: roads=1; rivers=3; and forests=5) within polygon.	30 m	2010	In matching in all levels of analyses; in regressions only in polygons
Distance to districts´ capitals	m	Derived from INEI´s database[19]/Distance from closest municipality´s capital to community boundary or mean distance of all pixels within a cell	Shapefile: 1:100,000 Raster 30 m	2009	In both and in all levels of analysis
Distance to population centers within communities	m	IBC-INEI-GIZ/Mean distance of all pixels within a UA to the nearest pixel representing a community center within a community	30 m	2009	In both, but in regressions, only in the cell level analysis
Land use/Land cover					

[12] http://geobosques.minam.gob.pe:81/geobosque/view/descargas.php#
[13] DEM by http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1
[14] http://whrc.org/publications-data/datasets/pantropical-national-level-carbon-stock/
[15] http://www.worldclim.org/bioclim
[16] All distance maps refer to the Euclidean distance
[17] Rivers raster file was generated from Landsat imagery by MINAM´s REDD+ Project
[18] http://www.mtc.gob.pe/estadisticas/descarga.html
[19] http://www.minem.gob.pe/descripcion.php?idSector=10&idTitular=6040

Percentage of forest cover area in 2010	%	Derived by author/Percentage of remaining forest area in 2010 within the UA	30 m	2010	In both and in all levels of analysis
Deforestation density	ha/km^2	GeoBosques[20]/Mean density of all pixels within the UA	270 m	2010	In both and in all levels of analysis
Community´s total area	ha	IBC/Total SIG area of each polygon representing a community. For cells, this variable represents the average of all communities' total areas overlapping a cell, weighted by the overlapping area of each community with that cell and divided by 225.	1:1,000,000	2007-2009	In both and in all levels of analysis
Outside deforestation pressure in year t[21]	m	Derived by the author/Mean annual distance of all pixels within the UA to the nearest deforestation patch outside communities larger than 1ha	30 m	2001-2015	In both and in all levels of analysis; in matching only 2001-2010 period; in regressions, the whole period 2001-2015
Distance to Protected Areas (PA)[22]	m	SERNANP[23], derived by the author/Mean distance of all pixels within the UA to nearest PA	30 m	2010	In both and in all levels of analysis
Internal distance to community´s boundary	m	Derived by the author/Mean distance of all pixels within a cell inside a community to the community´s boundary	30 m	NA	In both but only in the cell level analysis
Deforestation risk		Derived by the author/Probability of a cell being deforested as defined in *Deforestation risk model*	30 m	2010	In both but only in the cell level analysis

[20] http://www.bosques.gob.pe/archivo/81ea34_nota_tecnica_1_2016.pdf
[21] Forest edge is defined as forest adjacent to deforestation patches larger than 1 ha
[22] National protected areas include both strictly and non-strictly protected areas, managed by the central government
[23] http://geo.sernanp.gob.pe/geoserver/principal.php

Spatially lagged variables					
Lagged deforestation in year t	ha	Derived by the author/Annual weighted average of deforestation (inside communities only) of cell-neighbors of $cell_i$	30 m	2001-2015	Only in matching in the cell level analysis
Lagged forest cover 2010	%	Derived by the author/Weighted percentage of remaining forest area in 2010 of neighbors of $cell_i$	30 m	2010	In both but only in the cell level analysis
Lagged slope	Degrees	Derived by the author/Weighted average of the slopes of cell-neighbors of $cell_i$	30 m	2008	In both but only in the cell level analysis
Lagged biomass	Mg C/ha	Derived by the author/Weighted average of the biomasses of cell-neighbors of $cell_i$	30 m	2007-2008	In both but only in the cell level analysis
Lagged elevation	m	Derived by the author/Weighted average of the altitudes of cell-neighbors of $cell_i$	30 m	2008	In both but only in the cell level analysis
Socioeconomic					
Coca density in 2010	ha/km^2	UNODC[24]/Mean density (Kernel) of coca leaf plantations area within the UA	1:1,000,000	2010	In matching and regressions in all levels of analysis
Years passed since titling in 2011	Years	IBC[25]/number of years passed between the community received its titled and the NFCP started; area weighted average for cells	Community	2007-2009	In matching and regressions in all levels of analysis
Population	Person	INEI/Number of individuals in a community; area weighted average for cells	Community	2007	In matching and regressions in all levels of analysis
Number of houses	House	INEI/Number of houses in a community; area weighted average for cells	Community	2007	In matching and regressions in all levels of analysis

[24] http://www.unodc.org/documents/peruandecuador//Informes/MonitoreoCoca/Monitoreo_de_coca_Peru_2015_WEB.pdf (United Nations Office on Drugs and Crime)
[25] http://www.ibcperu.org/

Access to drinking water	% of houses	INEI/percentage of houses in a community with access to drinking water; area weighted average for cells	Community	2007	Only in matching in all levels of analysis
Access to electricity	% of houses	INEI/percentage of houses in a community with access to electric lights; area weighted average for cells	Community	2007	Only in matching in all levels of analysis
Population centers within a community	Center	INEI/Number of population centers within a community; area weighted average for cells	Community	2007	In matching and regressions in all levels of analysis
Per capita income in 2009	soles	INEI/District´s per capita income assigned to the corresponding UA	District	2009	Only in matching in the cell level analysis
Human development index (HDI) in 2010	Index	UNDP/District´s HDI assigned to the corresponding UA	District	2010[26]	Only in matching in all levels of analysis
Total poverty in 2009	%	INEI/percentage of HH below poverty line assigned to the corresponding UA	District	2009	Only in matching in the polygon level analysis
Extreme poverty in 2009	%	INEI/percentage of HH below extreme poverty line assigned to the corresponding UA	District	2009	Only in matching in all levels of analysis

Note: INEI = Instituto Nacional de Estadística e Informática; IBC = Instituto del Bien Común; GIZ = Deutsche Gessellschaft für Internationale Zusammenarbeit

[26] Published in 2013, http://www.pe.undp.org/content/peru/es/home/library/poverty/Informesobredesarrollohumano2010/IDHPeru2010.html

Table A.3 Balances of community-level (polygons) covariates before and after matching

Covariate	Status	Mean PNCB	Mean non-PNCB	Difference in means	Normalized difference (%)	Mean QQ difference	improvement mean difference
Community's total area (ha)	Unmatched	11,949.51	10,396.00	1,553.51	12.88	0.143	
	Matched	11,949.51	9,823.00	2,126.51	17.63	0.066	-0.37
Community's number of houses in 2007	Unmatched	80.86	64.73	16.13	14.61	0.049	
	Matched	80.86	74.70	6.16	5.58	0.041	0.62
Access to drinking water in 2007 (%)	Unmatched	1.9	1.18	0.72	9.97	0.02	
	Matched	1.9	0.46	1.44	19.95	0.036	-1.00
Access to electricity in 2007 (%)	Unmatched	1.48	8.0	-6.52	-103.36	0.071	
	Matched	1.48	0.28	1.20	19.03	0.025	1.18
Community's population in 2007	Unmatched	369.76	290.81	78.95	14.25	0.04	
	Matched	369.76	326.30	43.46	7.84	0.054	0.45
Elevation (m)	Unmatched	876.27	430.13	446.14	63.57	0.265	
	Matched	876.27	799.10	77.18	11.00	0.04	0.83
Temperature (°C)	Unmatched	23.28	25.03	-1.75	-60.52	0.234	
	Matched	23.28	23.63	-0.35	-12.00	0.034	0.80
Precipitation (mm)	Unmatched	1,998.25	2,223.92	-225.66	-39.78	0.125	
	Matched	1,998.25	2045.93	-47.68	-8.40	0.032	0.79
Biomass (Mg C/ha)	Unmatched	276.62	269.25	7.38	29.55	0.092	
	Matched	276.62	278.85	-2.22	-8.92	0.057	0.70
Slope (°)	Unmatched	13.17	6.62	6.56	86.53	0.266	
	Matched	13.17	13.17	0.01	0.11	0.038	1.00
Distance to protected areas (m)	Unmatched	19,114.95	38,207.91	-19,092.96	-102.92	0.195	
	Matched	19,114.95	14,795.33	4,319.62	23.28	0.086	0.77
Deforestation density (ha/km^2)	Unmatched	0.23	0.31	-0.07	-27.23	0.054	
	Matched	0.23	0.20	0.03	10.81	0.041	0.59
% of total community area covered by forest in 2010	Unmatched	92.44	81.34	11.11	149.30	0.17	
	Matched	92.44	92.44	0.01	0.13	0.039	1.00
Deforestation in 2001 (ha)	Unmatched	14.15	11.27	2.89	14.68	0.066	
	Matched	14.15	14.18	-0.03	-0.15	0.022	0.99
Deforestation in 2002 (ha)	Unmatched	7.54	11.28	-3.74	-33.31	0.049	
	Matched	7.54	6.35	1.18	10.54	0.032	0.68
Deforestation in 2003 (ha)	Unmatched	8.82	8.74	0.08	0.62	0.035	

	Matched	8.82	8.24	0.58	4.28	0.051	-5.92
Deforestation in 2004 (ha)	Unmatched	14.16	13.29	0.87	4.30	0.045	
	Matched	14.16	15.11	-0.95	-4.74	0.046	-0.10
Deforestation in 2005 (ha)	Unmatched	17.89	19.42	-1.53	-4.80	0.018	
	Matched	17.89	16.53	1.35	4.25	0.032	0.12
Deforestation in 2006 (ha)	Unmatched	10.72	11.60	-0.89	-6.20	0.051	
	Matched	10.72	10.94	-0.23	-1.57	0.052	0.75
Deforestation in 2007 (ha)	Unmatched	12.75	15.56	-2.81	-12.99	0.042	
	Matched	12.75	11.89	0.86	3.96	0.048	0.70
Deforestation in 2008 (ha)	Unmatched	9.46	14.12	-4.66	-28.59	0.057	
	Matched	9.46	8.90	0.57	3.47	0.049	0.88
Deforestation in 2009 (ha)	Unmatched	20.02	21.46	-1.44	-5.12	0.049	
	Matched	20.02	15.46	4.56	16.16	0.048	-2.16
Deforestation in 2010 (ha)	Unmatched	13.63	22.39	-8.76	-43.07	0.029	
	Matched	13.63	14.77	-1.15	-5.64	0.065	0.87
Outside-deforestation in 2001 (m)	Unmatched	13,314.75	13,540.74	-225.99	-2.49	0.092	
	Matched	13,314.75	13,650.67	-335.92	-3.70	0.035	-0.49
Outside-deforestation in 2002 (m)	Unmatched	10,689.31	10,459.15	230.16	3.31	0.107	
	Matched	10,689.31	10,118.47	570.84	8.20	0.045	-1.48
Outside-deforestation in 2003 (m)	Unmatched	9,860.14	9,438.52	421.62	6.35	0.107	
	Matched	9,860.14	9,638.53	221.61	3.34	0.055	0.47
Outside-deforestation in 2004 (m)	Unmatched	8,357.36	8,542.82	-185.47	-3.89	0.122	
	Matched	8,357.35	8,293.86	63.49	1.33	0.049	0.66
Outside-deforestation in 2005 (m)	Unmatched	8,088.04	7,613.96	474.08	9.78	0.126	
	Matched	8,088.04	7,470.24	617.80	12.75	0.049	-0.30
Outside-deforestation in 2006 (m)	Unmatched	7,066.26	6,923.79	142.46	3.81	0.132	
	Matched	7,066.25	7,008.01	58.24	1.56	0.041	0.59
Outside-deforestation in 2007 (m)	Unmatched	6,721.14	6,409.01	312.13	8.78	0.136	
	Matched	6,721.14	6,474.83	246.31	6.93	0.04	0.21
Outside-deforestation in 2008 (m)	Unmatched	6,460.09	6,012.24	447.86	13.49	0.146	
	Matched	6,460.09	6,188.74	271.35	8.17	0.033	0.39
Outside-deforestation in 2009 (m)	Unmatched	6,233.41	5,575.11	658.31	20.32	0.148	
	Matched	6,233.41	6,077.74	155.67	4.80	0.028	0.76
Outside-deforestation in 2010 (m)	Unmatched	6,161.63	5,341.85	819.78	25.22	0.154	
	Matched	6,161.62	5,968.98	192.65	5.93	0.027	0.77
Distance to roads (m)	Unmatched	16,701.50	119,996.50	-103,295.00	-572.18	0.196	
	Matched	16,701.50	14,069.56	2,631.94	14.58	0.043	0.97

Distance to district's capitals (m)	Unmatched	22,357.59	24,722.70	-2,365.11	-17.98	0.073	
	Matched	22,357.59	22,524.27	-166.68	-1.27	0.04	0.93
Dist. to population centers within communities (m)	Unmatched	1,139.23	964.39	174.84	46.17	0.162	
	Matched	1,139.23	1,082.15	57.08	15.07	0.074	0.67
Distance to rivers (m)	Unmatched	15.47	278.96	-263.48	-240.75	0.047	
	Matched	15.47	84.96	-69.49	-63.49	0.032	0.74
Accessibility (Index)	Unmatched	111,186.80	126,865.50	-15,678.70	-34.44	0.096	
	Matched	111,186.80	108,625.70	2,561.10	5.63	0.05	0.84
Extreme poverty rate in 2009 (District) (%)	Unmatched	32.10	30.31	1.80	8.85	0.055	
	Matched	32.10	31.64	0.47	2.29	0.025	0.74
Total poverty rate in 2009 (District (%)	Unmatched	63.97	60.53	3.44	14.71	0.082	
	Matched	63.97	64.77	-0.81	-3.45	0.022	1.23
Coca density in 2010 (ha/km^2)	Unmatched	0.01	0.01	-0.01	-28.43	0.015	
	Matched	0.01	0.00	0.00	16.08	0.035	0.33
HDI in 2010 (District)	Unmatched	0.24	0.26	-0.02	-38.31	0.096	
	Matched	0.24	0.24	0.00	-7.80	0.026	0.80
Community's number of population centers	Unmatched	1.68	1.99	-0.31	-18.37	0.02	
	Matched	1.68	2.02	-0.34	-20.05	0.036	-0.09
Years passed since titling in 2011	Unmatched	20.12	22.64	-2.53	-26.69	0.071	
	Matched	20.12	19.78	0.34	3.59	0.027	0.87

Table A.4 Covariate balance for whole community zone using cells as units of analysis

Covariate	Status	Mean PNCB	Mean non-PNCB	Difference in means	Normalized difference (%)	Mean QQ difference	% improvement mean difference
Community´s population in 2007	Unmatched	719.565	372.213	347.352	40.439	0.104	
	Matched	719.565	595.54	124.025	14.439	0.03	0.64
Community´s number of houses in 2007	Unmatched	151.658	83.772	67.886	39.131	0.111	
	Matched	151.658	132.127	19.531	11.258	0.036	0.71
Deforestation in 2001 (ha)	Unmatched	0.684	0.556	0.128	6.013	0.007	
	Matched	0.684	0.541	0.143	6.688	0.013	-0.12
Deforestation in 2002 (ha)	Unmatched	0.313	0.552	-0.239	-31.566	0.014	
	Matched	0.313	0.264	0.049	6.458	0.011	0.79
Deforestation in 2003 (ha)	Unmatched	0.392	0.434	-0.042	-4.384	0.004	
	Matched	0.392	0.296	0.096	9.974	0.016	-1.29
Deforestation in 2004 (ha)	Unmatched	0.648	0.666	-0.018	-1.406	0.007	
	Matched	0.648	0.479	0.169	12.995	0.023	-8.39
Deforestation in 2005 (ha)	Unmatched	0.835	0.997	-0.162	-8.098	0.005	
	Matched	0.835	0.692	0.143	7.152	0.014	0.12
Deforestation in 2006 (ha)	Unmatched	0.461	0.581	-0.12	-11.158	0.006	
	Matched	0.461	0.413	0.048	4.475	0.008	0.60
Deforestation in 2007 (ha)	Unmatched	0.533	0.789	-0.256	-22.608	0.008	
	Matched	0.533	0.383	0.15	13.251	0.025	0.41
Deforestation in 2008 (ha)	Unmatched	0.41	0.71	-0.3	-27.106	0.015	
	Matched	0.41	0.342	0.068	6.176	0.008	0.77
Deforestation in 2009 (ha)	Unmatched	0.883	1.093	-0.21	-12.898	0.009	
	Matched	0.883	0.651	0.232	14.233	0.027	-0.10
Deforestation in 2010 (ha)	Unmatched	0.621	1.137	-0.516	-36.343	0.014	
	Matched	0.621	0.458	0.163	11.501	0.021	0.68
Access to electricity (%)	Unmatched	4.446	4.557	-0.111	-1.154	0.037	
	Matched	4.446	1.96	2.486	26.013	0.066	-21.40
Access to drinking water (%)	Unmatched	2.93	0.927	2.003	24.021	0.067	
	Matched	2.93	0.831	2.099	25.17	0.049	-0.05
HDI in 2010 (District)	Unmatched	0.193	0.194	-0.001	-1.022	0.05	
	Matched	0.193	0.197	-0.004	-5.196	0.014	-3.00
Coca density in 2010 (ha/km^2)	Unmatched	0.005	0.007	-0.002	-12.599	0.011	
	Matched	0.005	0.004	0.001	6.269	0.017	0.50
Per capita income 2009 (District) (soles)	Unmatched	182.309	208.773	-26.464	-33.809	0.059	

	Matched	182.309	187.526	-5.217	-6.665	0.019	0.80
Community's number of population centers	Unmatched	2.767	2.469	0.298	11.871	0.08	
	Matched	2.767	2.572	0.195	7.771	0.016	0.35
Extreme poverty rate in 2009 (District) (%)	Unmatched	25.217	20.133	5.084	23.718	0.072	
	Matched	25.217	25.291	-0.074	-0.347	0.008	0.99
Total communal area (ha)	Unmatched	17,954.72	15,564.95	2389.77	10.593	0.099	
	Matched	17,954.72	11,963.39	5991.33	26.556	0.072	-1.51
Slope (°)	Unmatched	10.129	6.373	3.756	47.062	0.163	
	Matched	10.129	10.654	-0.525	-6.583	0.03	0.86
Elevation (m)	Unmatched	607.186	437.008	170.178	35.007	0.158	
	Matched	607.186	604.205	2.981	0.613	0.023	0.98
Precipitation (mm)	Unmatched	2,009.17	2,180.20	-171.031	-32.287	0.09	
	Matched	2,009.17	2,044.71	-35.534	-6.708	0.026	0.79
Temperature/10 (°C)	Unmatched	244.463	250.375	-5.912	-30.179	0.103	
	Matched	244.463	244.145	0.318	1.626	0.017	0.95
Biomass (Mg C/ha)	Unmatched	260.82	257.593	3.227	5.697	0.04	
	Matched	260.82	263.175	-2.355	-4.157	0.021	0.27
Distance to protected areas (m)	Unmatched	19,561.79	34,969.16	-15407.37	-88.132	0.175	
	Matched	19,561.79	19,893.05	-331.26	-1.895	0.029	0.98
Distance to rivers (m)	Unmatched	1,932.72	1,981.59	-48.872	-2.715	0.037	
	Matched	1,932.72	1,982.33	-49.61	-2.756	0.018	-0.02
Distance to roads (m)	Unmatched	21,489.61	79,966.68	-58477.07	-271.791	0.142	
	Matched	21,489.61	16,656.48	4833.13	22.464	0.055	0.92
Distance to district's capitals (m)	Unmatched	25,545.94	27,606.24	-2060.3	-12.551	0.031	
	Matched	25,545.94	25,116.25	429.69	2.617	0.015	0.79
Deforestation density (ha/km^2)	Unmatched	0.329	0.503	-0.174	-55.051	0.05	
	Matched	0.329	0.343	-0.014	-4.444	0.032	0.92
Accessibility in 2010 (Index)	Unmatched	83,110.62	106,547.50	-23436.88	-53.402	0.063	
	Matched	83,110.62	76,835.88	6274.74	14.297	0.042	0.73
Distance to population centers within community (m)	Unmatched	2,989.95	3,535.97	-546.022	-32.308	0.04	
	Matched	2,989.95	2,859.92	130.029	7.694	0.018	0.76
Years passed since titling in 2011	Unmatched	21.721	18.524	3.197	29.236	0.084	
	Matched	21.721	21.552	0.169	1.538	0.022	0.95
% of total cell area covered by forest in 2010 (%)	Unmatched	81.314	74.893	6.421	27.411	0.065	
	Matched	81.314	81.882	-0.568	-2.423	0.019	0.91
Lagged slope (°)	Unmatched	10.127	6.436	3.691	49.673	0.125	

	Matched	10.127	10.838	-0.711	-9.57	0.027	0.81
Lagged biomass (Mg C/ha)	Unmatched	260.975	260.661	0.314	0.859	0.054	
	Matched	260.975	262.537	-1.562	-4.269	0.022	-3.97
Lagged elevation (m)	Unmatched	613.986	442.686	171.3	35.924	0.159	
	Matched	613.986	618.299	-4.313	-0.905	0.023	0.97
Lagged % of cell area covered by forest 2010 (%)	Unmatched	81.862	76.711	5.151	32.546	0.068	
	Matched	81.862	81.603	0.259	1.638	0.011	0.95
Outside-deforestation in 2001 (m)	Unmatched	11,522.20	9,076.51	2445.693	23.614	0.079	
	Matched	11,522.20	10,567.24	954.96	9.22	0.033	0.61
Outside-deforestation in 2002 (m)	Unmatched	7,847.66	6,756.10	1091.557	14.627	0.065	
	Matched	7,847.66	6,823.02	1024.632	13.73	0.035	0.06
Outside-deforestation in 2003 (m)	Unmatched	7,004.61	5,782.88	1221.731	18.248	0.062	
	Matched	7,004.61	6,242.17	762.435	11.388	0.028	0.38
Outside-deforestation in 2004 (m)	Unmatched	4,951.35	5,012.98	-61.631	-1.45	0.041	
	Matched	4,951.35	4,589.36	361.99	8.516	0.022	-4.87
Outside-deforestation in 2005 (m)	Unmatched	4,735.66	4,486.20	249.458	5.802	0.047	
	Matched	4,735.66	4,366.83	368.837	8.579	0.023	-0.48
Outside-deforestation in 2006 (m)	Unmatched	3,863.53	3,995.40	-131.87	-4.505	0.041	
	Matched	3,863.53	3,933.31	-69.781	-2.384	0.016	0.47
Outside-deforestation in 2007 (m)	Unmatched	3,414.94	3,616.99	-202.045	-8.385	0.043	
	Matched	3,414.94	3,523.82	-108.877	-4.518	0.019	0.46
Outside-deforestation in 2008 (m)	Unmatched	3,309.51	3,322.05	-12.545	-0.525	0.047	
	Matched	3,309.51	3,428.68	-119.172	-4.99	0.022	-8.50
Outside-deforestation in 2009 (m)	Unmatched	3,130.85	3,047.04	83.805	3.63	0.049	
	Matched	3,130.85	3,200.70	-69.854	-3.025	0.015	0.17
Outside-deforestation in 2010 (m)	Unmatched	3,075.99	2,867.21	208.777	9.029	0.054	
	Matched	3,075.99	3,136.83	-60.838	-2.631	0.015	0.71
Lagged deforestation in 2001 (ha)	Unmatched	0.629	0.49	0.139	14.456	0.025	
	Matched	0.629	0.581	0.048	4.983	0.018	0.65
Lagged deforestation in 2002 (ha)	Unmatched	0.297	0.492	-0.195	-50.005	0.03	
	Matched	0.297	0.323	-0.026	-6.838	0.022	0.87
Lagged deforestation in 2003 (ha)	Unmatched	0.359	0.381	-0.022	-4.297	0.011	
	Matched	0.359	0.336	0.023	4.613	0.011	-0.05
Lagged deforestation in 2004 (ha)	Unmatched	0.611	0.596	0.015	2.156	0.021	
	Matched	0.611	0.555	0.056	7.88	0.022	-2.73
Lagged deforestation in 2005 (ha)	Unmatched	0.797	0.895	-0.098	-8.153	0.01	

	Matched	0.797	0.805	-0.008	-0.625	0.011	0.92
Lagged deforestation in 2006 (ha)	Unmatched	0.44	0.521	-0.081	-14.839	0.018	
	Matched	0.44	0.467	-0.027	-5.011	0.016	0.67
Lagged deforestation in 2007 (ha)	Unmatched	0.492	0.724	-0.232	-38.077	0.019	
	Matched	0.492	0.446	0.046	7.714	0.018	0.80
Lagged deforestation in 2008 (ha)	Unmatched	0.368	0.638	-0.27	-48.763	0.036	
	Matched	0.368	0.391	-0.023	-4.191	0.018	0.91
Lagged deforestation in 2009 (ha)	Unmatched	0.808	0.983	-0.175	-20.676	0.025	
	Matched	0.808	0.722	0.086	10.021	0.023	0.51
Lagged deforestation in 2010 (ha)	Unmatched	0.599	1.035	-0.436	-55.526	0.026	
	Matched	0.599	0.557	0.042	5.325	0.016	0.90
Internal distance to community´s boundary (m)	Unmatched	885.851	899.487	-13.636	-1.676	0.041	
	Matched	885.851	657.671	228.18	28.051	0.061	-15.73
Deforestation risk (probability)	Unmatched	0.034	0.044	-0.01	-33.052	0.044	
	Matched	0.034	0.032	0.002	6.237	0.021	0.80

Table A.5 Covariate balance for CFZ matching analysis

Covariate	Status	Mean treated	Mean non-treated	Difference in means	Normalized difference (%)	Mean QQ difference	% improvement mean difference
Community´s population in 2007	Unmatched	647.987	319.981	328.006	39.708	0.095	
	Matched	649.125	542.167	106.958	12.942	0.025	0.67
Community´s number of houses in 2007	Unmatched	141.921	71.107	70.814	41.066	0.109	
	Matched	142.168	124.491	17.677	10.247	0.024	0.75
Deforestation in 2001 (ha)	Unmatched	0.262	0.079	0.183	24.873	0.021	
	Matched	0.262	0.186	0.076	10.294	0.017	0.58
Deforestation in 2002 (ha)	Unmatched	0.142	0.084	0.058	12.658	0.008	
	Matched	0.142	0.124	0.018	3.94	0.012	0.69
Deforestation in 2003 (ha)	Unmatched	0.175	0.075	0.1	17.475	0.012	
	Matched	0.175	0.106	0.069	12.095	0.02	-
Deforestation in 2004 (ha)	Unmatched	0.341	0.106	0.235	22.748	0.02	
	Matched	0.341	0.235	0.106	10.324	0.021	0.55
Deforestation in 2005 (ha)	Unmatched	0.58	0.209	0.371	20.866	0.02	
	Matched	0.578	0.507	0.071	3.976	0.005	0.81
Deforestation in 2006 (ha)	Unmatched	0.263	0.128	0.135	16.614	0.012	
	Matched	0.262	0.203	0.059	7.324	0.012	0.56
Deforestation in 2007 (ha)	Unmatched	0.238	0.186	0.052	7.147	0.009	
	Matched	0.239	0.114	0.125	17.179	0.029	-1.40
Deforestation in 2008 (ha)	Unmatched	0.235	0.163	0.072	10.666	0.011	
	Matched	0.236	0.23	0.006	0.91	0.006	0.92
Deforestation in 2009 (ha)	Unmatched	0.434	0.22	0.214	20.608	0.017	
	Matched	0.435	0.302	0.133	12.819	0.025	0.38
Deforestation in 2010 (ha)	Unmatched	0.455	0.344	0.111	7.05	0.011	
	Matched	0.449	0.33	0.119	7.587	0.017	-0.07
Access to electricity (%)	Unmatched	4.983	4.009	0.974	8.247	0.047	
	Matched	4.992	1.854	3.138	26.551	0.102	-2.22
Access to drinking water (%)	Unmatched	1.105	1	0.105	3.125	0.062	
	Matched	1.107	0.48	0.627	18.744	0.044	-4.97
HDI in 2010 (District)	Unmatched	0.199	0.216	-0.017	-19.628	0.039	
	Matched	0.2	0.206	-0.006	-7.335	0.014	0.65
Coca density in 2010 (ha/km^2)	Unmatched	0.006	0.003	0.003	13.183	0.043	
	Matched	0.006	0.004	0.002	10.749	0.032	-
Per capita income 2009 (District) (soles)	Unmatched	189.395	232.546	-43.151	-53.756	0.062	

	Matched	189.708	196.402	-6.694	-8.363	0.016	0.84
Community's number of population centers	Unmatched	2.607	2.731	-0.124	-5.016	0.04	
	Matched	2.611	2.825	-0.214	-8.613	0.043	-0.73
Poverty rate in 2009 (District) (%)	Unmatched	51.65	48.322	3.328	11.375	0.049	
	Matched	51.739	52.154	-0.415	-1.423	0.017	0.88
Extreme poverty rate in 2009 (District) (%)	Unmatched	26.177	23.617	2.56	11.801	0.045	
	Matched	26.222	26.304	-0.082	-0.376	0.013	0.97
Total communal area (ha)	Unmatched	15,509.29	46,292.30	-30783.01	-139.213	0.17	
	Matched	15,537.99	12,105.08	3432.91	15.517	0.04	0.89
Slope (°)	Unmatched	12.729	7.34	5.389	68.95	0.213	
	Matched	12.736	13.131	-0.395	-5.047	0.024	0.93
Elevation (m)	Unmatched	745.314	535.611	209.703	40.219	0.17	
	Matched	745.262	778.001	-32.739	-6.273	0.032	0.84
Precipitation (mm)	Unmatched	2,025.67	2,222.51	-196.842	-37.564	0.09	
	Matched	2,027.64	2,059.88	-32.245	-6.17	0.035	0.84
Temperature/10 (°C)	Unmatched	238.556	246.508	-7.952	-37.544	0.131	
	Matched	238.558	237.276	1.282	6.046	0.026	0.84
Biomass (Mg C/ha)	Unmatched	280.152	289.849	-9.697	-29.089	0.055	
	Matched	280.371	285.875	-5.504	-16.683	0.043	0.43
Distance to protected areas (m)	Unmatched	19,635.37	35,151.35	-15515.98	-87.013	0.145	
	Matched	19,573.31	17,698.08	1875.23	10.54	0.035	0.88
Distance to rivers (m)	Unmatched	2,822.58	3,782.10	-959.525	-48.847	0.081	
	Matched	2,827.58	3,379.76	-552.185	-28.131	0.088	0.42
Distance to roads (m)	Unmatched	20,055.44	129,197.30	-109141.86	-562.985	0.312	
	Matched	20,059.20	17,126.37	2932.83	15.114	0.032	0.97
Distance to district's capitals (m)	Unmatched	24,427.38	38,290.49	-13863.11	-87.184	0.217	
	Matched	24,430.35	25,166.52	-736.17	-4.625	0.042	0.95
Deforestation density (ha/km^2)	Unmatched	0.369	0.23	0.139	43.408	0.288	
	Matched	0.37	0.38	-0.01	-3.332	0.026	0.93
Accessibility in 2010 (Index)	Unmatched	84,737.82	169,026.50	-84288.68	-184.684	0.293	
	Matched	84,679.38	88,261.13	-3581.75	-7.844	0.049	0.96
Distance to population centers within community (m)	Unmatched	3,697.51	8,739.29	-5041.778	-285.258	0.314	
	Matched	3,701.25	4,130.22	-428.967	-24.276	0.075	0.91
Years passed since titling in 2011	Unmatched	21.498	18.281	3.217	28.793	0.069	
	Matched	21.532	20.64	0.892	7.998	0.028	0.72
% of total cell area covered by forest in 2010 (%)	Unmatched	92.625	96.211	-3.586	-29.845	0.063	

	Matched	92.74	94.994	-2.254	-19.212	0.069	0.37
Lagged slope (°)	Unmatched	12.414	7.279	5.135	71.092	0.162	
	Matched	12.413	12.823	-0.41	-5.676	0.023	0.92
Lagged biomass (Mg C/ha)	Unmatched	275.418	288.342	-12.924	-46.195	0.12	
	Matched	275.603	281.26	-5.657	-20.435	0.06	0.56
Lagged elevation (m)	Unmatched	742.974	533.265	209.709	40.941	0.171	
	Matched	742.756	772.704	-29.948	-5.841	0.034	0.86
Lagged % of cell area covered by forest 2010 (%)	Unmatched	89.682	95.086	-5.404	-51.379	0.185	
	Matched	89.765	91.336	-1.571	-15.175	0.054	0.71
Outside-deforestation in 2001 (m)	Unmatched	9,775.45	21,564.20	-11788.748	-133.596	0.241	
	Matched	9,785.44	8,788.84	996.596	11.287	0.024	0.92
Outside-deforestation in 2002 (m)	Unmatched	6,860.00	17,522.05	-10662.048	-187.945	0.281	
	Matched	6,864.41	6,720.85	143.562	2.529	0.047	0.99
Outside-deforestation in 2003 (m)	Unmatched	6,153.23	15,838.28	-9685.05	-180.956	0.281	
	Matched	6,156.29	6,314.20	-157.917	-2.948	0.061	0.98
Outside-deforestation in 2004 (m)	Unmatched	5,084.70	14,544.52	-9459.824	-209.889	0.299	
	Matched	5,093.34	5,538.37	-445.031	-9.874	0.071	0.95
Outside-deforestation in 2005 (m)	Unmatched	4,872.94	13,583.56	-8710.618	-191.265	0.289	
	Matched	4,881.18	5,067.61	-186.427	-4.093	0.049	0.98
Outside-deforestation in 2006 (m)	Unmatched	3,823.67	12,416.78	-8593.106	-317.861	0.317	
	Matched	3,829.91	4,711.72	-881.816	-32.633	0.073	0.90
Outside-deforestation in 2007 (m)	Unmatched	3,465.69	11,871.84	-8406.147	-394.708	0.325	
	Matched	3,471.24	4,341.77	-870.531	-40.909	0.078	0.90
Outside-deforestation in 2008 (m)	Unmatched	3,429.07	11,455.58	-8026.51	-378.793	0.317	
	Matched	3,434.55	4,290.75	-856.205	-40.439	0.076	0.89
Outside-deforestation in 2009 (m)	Unmatched	3,309.87	10,858.56	-7548.69	-355.19	0.312	
	Matched	3,315.12	4,170.13	-855.013	-40.257	0.075	0.89
Outside-deforestation in 2010 (m)	Unmatched	3,243.66	10,506.68	-7263.025	-343.393	0.307	
	Matched	3,248.78	4,074.31	-825.536	-39.054	0.073	0.89
Lagged deforestation in 2001 (ha)	Unmatched	0.405	0.103	0.302	34.568	0.068	
	Matched	0.406	0.317	0.089	10.13	0.03	0.71
Lagged deforestation in 2002 (ha)	Unmatched	0.173	0.088	0.085	26.941	0.029	
	Matched	0.174	0.147	0.027	8.619	0.015	0.68
Lagged deforestation in 2003 (ha)	Unmatched	0.211	0.083	0.128	37.112	0.039	
	Matched	0.211	0.162	0.049	14.131	0.031	0.62
Lagged deforestation in 2004 (ha)	Unmatched	0.439	0.126	0.313	44.36	0.068	

	Matched	0.44	0.37	0.07	9.865	0.028	0.78
Lagged deforestation in 2005 (ha)	Unmatched	0.722	0.226	0.496	40.277	0.07	
	Matched	0.723	0.672	0.051	4.171	0.012	0.90
Lagged deforestation in 2006 (ha)	Unmatched	0.289	0.12	0.169	41.745	0.046	
	Matched	0.289	0.234	0.055	13.743	0.033	0.67
Lagged deforestation in 2007 (ha)	Unmatched	0.306	0.211	0.095	19.634	0.036	
	Matched	0.307	0.239	0.068	13.959	0.033	0.28
Lagged deforestation in 2008 (ha)	Unmatched	0.273	0.169	0.104	22.963	0.03	
	Matched	0.274	0.279	-0.005	-1.264	0.011	0.95
Lagged deforestation in 2009 (ha)	Unmatched	0.533	0.236	0.297	45.781	0.056	
	Matched	0.534	0.409	0.125	19.146	0.057	0.58
Lagged deforestation in 2010 (ha)	Unmatched	0.532	0.348	0.184	21.109	0.041	
	Matched	0.532	0.483	0.049	5.614	0.018	0.73
Internal distance to community´s boundary (m)	Unmatched	927.254	2,075.39	-1148.138	-133.082	0.119	
	Matched	928.846	938.955	-10.109	-1.172	0.045	0.99
Deforestation risk (probability)	Unmatched	0.023	0.011	0.012	69.447	0.391	
	Matched	0.023	0.019	0.004	21.016	0.134	0.67

Table A.6 Covariates balance for OUZ matching analysis

Covariate	Status	Mean treated	Mean non-treated	Difference in means	Normalized difference (%)	Mean QQ difference	% improvement mean difference
Community´s population in 2007	Unmatched	741.565	295.873	445.692	54.244	0.152	
	Matched	741.565	643.758	97.807	11.904	0.054	0.78
Community´s number of houses in 2007	Unmatched	153.828	61.862	91.966	56.701	0.182	
	Matched	153.828	139.643	14.185	8.746	0.051	0.85
Deforestation in 2001 (ha)	Unmatched	1.009	0.428	0.581	22.619	0.04	
	Matched	1.009	0.882	0.127	4.956	0.009	0.78
Deforestation in 2002 (ha)	Unmatched	0.462	0.434	0.028	3.094	0.012	
	Matched	0.462	0.437	0.025	2.782	0.014	0.11
Deforestation in 2003 (ha)	Unmatched	0.571	0.304	0.267	22.85	0.025	
	Matched	0.571	0.482	0.089	7.62	0.015	0.67
Deforestation in 2004 (ha)	Unmatched	0.904	0.467	0.437	30.906	0.034	
	Matched	0.904	0.743	0.161	11.388	0.024	0.63
Deforestation in 2005 (ha)	Unmatched	1.016	0.572	0.444	20.823	0.027	
	Matched	1.016	0.878	0.138	6.478	0.018	0.69
Deforestation in 2006 (ha)	Unmatched	0.651	0.338	0.313	25.525	0.028	
	Matched	0.651	0.583	0.068	5.553	0.012	0.78
Deforestation in 2007 (ha)	Unmatched	0.749	0.465	0.284	22.441	0.026	
	Matched	0.749	0.641	0.108	8.54	0.02	0.62
Deforestation in 2008 (ha)	Unmatched	0.566	0.406	0.16	12.347	0.015	
	Matched	0.566	0.492	0.074	5.702	0.013	0.54
Deforestation in 2009 (ha)	Unmatched	1.235	0.699	0.536	28.979	0.033	
	Matched	1.235	1.128	0.107	5.758	0.012	0.80
Deforestation in 2010 (ha)	Unmatched	0.803	0.534	0.269	18.805	0.021	
	Matched	0.803	0.656	0.147	10.244	0.019	0.45
Access to electricity (%)	Unmatched	3.576	5.99	-2.414	-30.503	0.035	
	Matched	3.576	0.862	2.714	34.283	0.135	-0.12
Access to drinking water (%)	Unmatched	3.816	0.614	3.202	32.821	0.115	
	Matched	3.816	1.267	2.549	26.126	0.057	0.20
HDI in 2010 (District)	Unmatched	0.193	0.181	0.012	15.885	0.053	
	Matched	0.193	0.196	-0.003	-4.928	0.022	0.75
Coca density in 2010 (ha/km^2)	Unmatched	0.003	0.002	0.001	5.011	0.023	

	Matched	0.003	0.001	0.002	14.041	0.022	-1.00
Per capita income 2009 (District) (soles)	Unmatched	180.923	200.571	-19.648	-26.619	0.066	
	Matched	180.923	185.161	-4.238	-5.742	0.03	0.78
Community's number of population centers	Unmatched	2.872	2.412	0.46	18.682	0.103	
	Matched	2.872	2.951	-0.079	-3.176	0.036	0.83
Poverty rate in 2009 (District) (%)	Unmatched	48.738	53.534	-4.796	-17.956	0.087	
	Matched	48.738	50.421	-1.683	-6.301	0.021	0.65
Extreme poverty rate in 2009 (District) (%)	Unmatched	24.30	29.41	-5.11	-24.369	0.099	
	Matched	24.302	25.019	-0.717	-3.417	0.015	0.86
Total communal area (ha)	Unmatched	18,233.04	23,372.69	-5139.65	-25.113	0.059	
	Matched	18,233.04	13,538.34	4694.7	22.939	0.052	0.09
Slope (°)	Unmatched	8.111	3.078	5.033	68.408	0.273	
	Matched	8.111	8.284	-0.173	-2.348	0.025	0.97
Elevation (m)	Unmatched	485.02	246.29	238.734	60.632	0.329	
	Matched	485.022	468.492	16.53	4.198	0.029	0.93
Precipitation (mm)	Unmatched	2,014.86	2,299.17	-284.309	-53.864	0.142	
	Matched	2,014.86	2,053.77	-38.909	-7.371	0.033	0.86
Temperature/10 (°C)	Unmatched	249.349	258.12	-8.771	-54.651	0.194	
	Matched	249.349	249.407	-0.058	-0.361	0.025	0.99
Biomass (Mg C/ha)	Unmatched	246.76	262.79	-16.033	-24.514	0.069	
	Matched	246.756	243.778	2.978	4.554	0.03	0.81
Distance to protected areas (m)	Unmatched	19,398.12	49,641.77	-30243.65	-187.884	0.286	
	Matched	19,398.12	19,869.75	-471.63	-2.93	0.038	0.98
Distance to rivers (m)	Unmatched	1,139.64	1,574.77	-435.13	-37.532	0.057	
	Matched	1,139.64	983.373	156.27	13.479	0.033	0.64
Distance to roads (m)	Unmatched	21,130.86	170,826.10	-149695.24	-693.416	0.336	
	Matched	21,130.86	15,123.58	6007.28	27.827	0.067	0.96
Distance to district's capitals (m)	Unmatched	27,236.61	42,252.14	-15015.53	-91.548	0.149	
	Matched	27,236.61	27,850.15	-613.54	-3.741	0.035	0.96
Deforestation density (ha/km^2)	Unmatched	0.29	0.17	0.116	40.447	0.215	
	Matched	0.285	0.272	0.013	4.774	0.033	0.89
Accessibility in 2010 (Index)	Unmatched	83,025.84	178,393.30	-95367.46	-232.712	0.22	
	Matched	83,025.84	81,470.70	1555.14	3.795	0.022	0.98
Distance to population centers within community (m)	Unmatched	2,344.95	4,264.83	-1919.873	-142.366	0.158	
	Matched	2,344.95	2,387.51	-42.56	-3.156	0.012	0.98
Years passed since titling in 2011	Unmatched	21.968	17.369	4.599	44.908	0.118	
	Matched	21.968	23.146	-1.178	-11.499	0.034	0.74

% of total cell area covered by forest in 2010 (%)	Unmatched	72.322	76.626	-4.304	-16.512	0.051	
	Matched	72.322	68.929	3.393	13.02	0.061	0.21
Lagged slope (°)	Unmatched	8.414	3.235	5.179	73.828	0.189	
	Matched	8.414	8.644	-0.23	-3.283	0.014	0.96
Lagged biomass (Mg C/ha)	Unmatched	251.708	267.638	-15.93	-41.771	0.129	
	Matched	251.708	247.836	3.872	10.153	0.04	0.76
Lagged elevation (m)	Unmatched	505.197	252.218	252.979	63.727	0.333	
	Matched	505.197	495.691	9.506	2.394	0.027	0.96
Lagged % of cell area covered by forest 2010 (%)	Unmatched	76.37	79.81	-3.436	-21.011	0.099	
	Matched	76.373	72.998	3.375	20.639	0.064	0.02
Outside-deforestation in 2001 (m)	Unmatched	13,220.83	18,454.20	-5233.37	-47.168	0.086	
	Matched	13,220.83	12,548.49	672.34	6.06	0.024	0.87
Outside-deforestation in 2002 (m)	Unmatched	8,828.47	13,027.05	-4198.582	-50.094	0.105	
	Matched	8,828.47	8,794.75	33.714	0.402	0.016	0.99
Outside-deforestation in 2003 (m)	Unmatched	7,907.20	11,638.25	-3731.049	-50.154	0.099	
	Matched	7,907.20	8,059.65	-152.452	-2.049	0.019	0.96
Outside-deforestation in 2004 (m)	Unmatched	4,872.52	10,493.64	-5621.122	-150.184	0.162	
	Matched	4,872.52	5,023.23	-150.713	-4.027	0.021	0.97
Outside-deforestation in 2005 (m)	Unmatched	4,662.68	9,355.65	-4692.974	-124.52	0.151	
	Matched	4,662.68	4,741.90	-79.222	-2.102	0.019	0.98
Outside-deforestation in 2006 (m)	Unmatched	4,065.89	8,827.60	-4761.704	-152.3	0.16	
	Matched	4,065.89	4,383.02	-317.123	-10.143	0.022	0.93
Outside-deforestation in 2007 (m)	Unmatched	3,601.12	8,261.03	-4659.904	-171.032	0.169	
	Matched	3,601.12	4,054.74	-453.614	-16.649	0.031	0.90
Outside-deforestation in 2008 (m)	Unmatched	3,416.42	7,391.27	-3974.846	-148.035	0.163	
	Matched	3,416.42	3,938.01	-521.59	-19.426	0.044	0.87
Outside-deforestation in 2009 (m)	Unmatched	3,184.85	6,440.76	-3255.911	-126.498	0.161	
	Matched	3,184.85	3,761.31	-576.46	-22.396	0.056	0.82
Outside-deforestation in 2010 (m)	Unmatched	3,132.36	5,983.52	-2851.162	-110.486	0.147	
	Matched	3,132.36	3,666.07	-533.716	-20.682	0.05	0.81
Lagged deforestation in 2001 (ha)	Unmatched	0.85	0.307	0.543	47.33	0.115	
	Matched	0.85	0.779	0.071	6.157	0.019	0.87
Lagged deforestation in 2002 (ha)	Unmatched	0.414	0.369	0.045	10.199	0.037	
	Matched	0.414	0.468	-0.054	-12.506	0.037	-0.20
Lagged deforestation in 2003 (ha)	Unmatched	0.481	0.245	0.236	40.429	0.064	
	Matched	0.481	0.444	0.037	6.379	0.021	0.84
Lagged deforestation in 2004 (ha)	Unmatched	0.758	0.367	0.391	56.053	0.09	

	Matched	0.758	0.713	0.045	6.466	0.02	0.88
Lagged deforestation in 2005 (ha)	Unmatched	0.847	0.455	0.392	33.643	0.067	
	Matched	0.847	0.789	0.058	5.011	0.02	0.85
Lagged deforestation in 2006 (ha)	Unmatched	0.584	0.305	0.279	45.394	0.069	
	Matched	0.584	0.649	-0.065	-10.589	0.032	0.77
Lagged deforestation in 2007 (ha)	Unmatched	0.634	0.359	0.275	41.516	0.067	
	Matched	0.634	0.639	-0.005	-0.727	0.013	0.98
Lagged deforestation in 2008 (ha)	Unmatched	0.465	0.34	0.125	20.097	0.035	
	Matched	0.465	0.437	0.028	4.514	0.024	0.78
Lagged deforestation in 2009 (ha)	Unmatched	1.042	0.565	0.477	51.221	0.087	
	Matched	1.042	1.018	0.024	2.542	0.031	0.95
Lagged deforestation in 2010 (ha)	Unmatched	0.647	0.443	0.204	30.002	0.05	
	Matched	0.647	0.648	-0.001	-0.134	0.011	1.00
Internal distance to community´s boundary (m)	Unmatched	711.133	1,085.12	-373.991	-55.877	0.065	
	Matched	711.133	699.83	11.303	1.689	0.017	0.97
Deforestation risk (probability)	Unmatched	0.042	0.026	0.016	45.971	0.228	
	Matched	0.042	0.041	0.001	2.383	0.023	0.94

B Chapter 3 Appendix

B.1 Potential carbon emissions

We used a map depicting the distribution of aboveground live woody biomass density in Mg/ha at a 25 ha pixel resolution (Baccini et al., 2012) (Figure B.1). Using QGIS 3.8 we overlaid a grid of cells, 225 ha each, on top of this map, and on top of the OUZ and the enrolled areas of participating communities (the conservation forests zones). The biomass density of each OUZ-cell i (AB_i) was then calculated as the mean density of all pixels overlapping the OUZ-cells (Fig. B1). This spatially explicit approach is more accurate than the standard approach (see Jayachandran et al. 2017) of applying the same average carbon content to all units of analysis as it allows us to account for the spatial heterogeneity in biomass carbon and related ecosystem services (Naidoo and Rickets 2006).

We then multiplied each cell´s average biomass density by: (1) the standard factor of 0.5 of carbon content in biomass (Chave et al., 2005; Houghton et al., 2001) to obtain tons of carbon per ha (tC/ha), (2) by 0.85, representing the fraction of CO_2 emissions immediately released into the atmosphere after deforestation (Soares-Filho et al., 2010) , and (3) by 3.65 to convert to tons of CO_2/ha potentially released to the atmosphere by deforestation:

$$PE_i = AB_i * 0.5 * 0.85 * 3.65 \qquad \text{(Eq. B. 1)}$$

We then multiplied the potentially emitted CO_2 from each cell (PE_i) by the simulated annual avoided deforestation ($AD_{t,i}$) to calculate the annual amount of avoided emissions from each cell ($AE_{t,i}$):

$$AE_{t,i} = PE_i * AD_{t,i} \ (where\ t = 2011, \ldots, 2015) \qquad \text{(Eq. B. 2)}$$

Finally, we summed up all cells´ avoided emissions for each year to calculate total annual avoided emissions in year t (TAE_t):

$$TAE_t = \sum_{i=1}^{n} AE_{t,i} \qquad \text{(Eq. B. 3)}$$

B.2 Adjusted SCC

The adjusted SCC was defined by:

$$Adjusted\_annual\_SCC_t = \left(\frac{SCC_{2015}}{(1 + SCC\_growth\_rate)^{2015-t}}\right) \qquad \text{(Eq. B. 4)}$$

As such, we reduced the value of the SCC for 2015 to apply it in each year between 2011 and 2014. Then, the fraction of this adjusted annual SCC is defined by the factor:

$$\left\{1 - \frac{1}{(1+i)^{2016-t}}\right\} \qquad \text{(Eq. B. 5)}$$

Where i stands for the effective discount rate (Jayachandran et al. 2017), which is a combination of the time discount rate r and the annual rate at which the SCC rises (SCC_growth_rate), and is defined by:

$$i = \frac{1+r}{1+SCC\_growth\_rate} - 1 \qquad \text{(Eq. B. 6)}$$

Both parameters (r and SCC_growth_rate) vary in MC simulations assuming uniform distributions and the discount rate also varies across scale perspectives (Table B.1). For the case of the global society, The growth rate of the SCC was set at a lower bound of 2% and an upper bound of 3% (Jayachandran et al., 2017; Nordhaus, 2017).

B.3 Monte Carlo simulations

The MC simulations were implemented using the R package decisionSupport (Luedeling et al., 2021), which requires as inputs: (1) Equation 3.15 (see section 3.3.3 in chapter 3) coded in R (R Core Team, 2020), and (2) a table with the name of the variables used by the function, probability distributions from which to randomly draw samples for each variable (e.g. normal, uniform), and the corresponding lower and upper quantiles (5% and 95%, correspondingly), representing thus confidence intervals with a 90% chance of containing the variables´ value of interest. The function was run 10,000 times for each permanence scenario and for each standpoint. Table B.1 below summarizes the input table.

To account for high correlations between the estimated annual avoided deforestation and corresponding avoided emissions and opportunity costs, we provided a correlation matrix as an additional model input. Correlations among these variables were calculated based on the simulated values of avoided deforestation, avoided emissions, and opportunity costs for each cell, as described in Equations 3.4, B.2 and 3.10, respectively, and using the spearman correlation test in R (R Core Team, 2019). As shown in Table B.1, the distribution used for these variables is a normal distribution, in which the lower and upper bounds correspond to the simulated values using the confidence interval for the average treatment effect on the treated. In this case, there is a small percentage (<5%) of simulated values which are negative. As our conceptual framework and the data generating process described in Giudice et al. (2019) do not consider forest regrowth and negative emissions, we run the function for 15,000 times and subsequently ignored the negative values. As a result, we generated probability distributions for *Programa Bosques´* NFV using approximately 10,000 random draws for each variable (see Figure B.3 below).

B.4 Other environmental values

In the short-term scenario, the present value of the sum of the environmental benefits is defined by the avoided deforestation in each year and the discounted value of these benefits between that year and 2015, for each perspective:

$$PV_{envB_t} = avoided\_def_t * sum\_other\_env\_values \sum_{t=2011}^{2015} \frac{1}{(1+r)^{2015-t}} \qquad \text{(Eq. B. 7)}$$

In the long-term scenario, the present values of the annual environmental benefits are calculated by considering the reversion period of 500-yr, between 2011 and 2515:

$$PV_{envB_t} = avoided\_def_t * sum\_other\_env\_values \sum_{t=2011}^{2015} \frac{1}{(1+r)^{2015-t}} \qquad \text{(Eq. B. 8)}$$

B.5 Costs

Based on the program budget (MEF, 2019), we categorized spending as follows: (1) implementation, (2) administration, and (3) payments. Implementation involved three activities: (1) the enrollment of communities, (2) technical assistance to the implementation of investment plans, and forest monitoring (Table B.3 below). For MINAM, the transfer is considered a cost within the first activity, but we accounted for this separately, because transfers only accrue as benefits to the participating communities. Program administration merged two budgetary elements: (1) "*Acciones comunes*" (common actions), which represented administrative and logistic costs of actions that could not be individually associated to one particular activity, but support all of them (i.e. program management); and (2) "*Acciones centrales*" (central actions), which represented costs associated with managing physical assets, and human and financial resources (i.e. administrative management), and monitoring and evaluation.

B.6 Comparing net benefits locally

We re-calculated Eq.3.15 in chapter 3, for the short-term scenario, without accounting for the annual estimated avoided deforestation in each cell ($AD_{t,i}$) but only for the potential emissions (PE_i) instead (see Eq.B.1 above). Furthermore, we included the CE as defined in Eq.3.13 (i.e. the median annual ratio of implementation costs and the estimated avoided deforestation). All parameters used were the distribution means produced by the MC simulations. The NFVs are spatially explicit expressed in terms of USD per ha of potentially avoided deforestation. Eventually, in future targeting procedures, areas with large values should be prioritized as, if deforestation is reduced there, benefits cold compensate overall costs.

Given the high implementation and administrative costs and relatively low conservation effectiveness, we found no areas with potential net future benefits after a five-year period of implementation. We thus explored at what level of CE the program would achieve its declared enrolment goal, i.e. 10 million ha with net positive benefits. This is the case at only 14% (USD

2,056 as opposed to 14,688 per ha of avoided deforestation) and the 10 million ha that could be conserved at net positive environmental benefits are mainly located in the vicinity of indigenous communities within the departments of Madre de Dios and Loreto, in the northern and southern Peruvian Amazon (see Figure B.4 below).

B.7 Increasing the effect of *Programa Bosques*

To illustrate how *Programa Bosques* could have produced overall net benefits we ran a complementary scenario analysis. First, we assumed that *Programa Bosques* reduces all deforestation within OUZ in the short-term scenario, but this was not enough to produce positive future net benefits. Alternatively, we explored for how long the avoided deforestation would have to be retained, for *Programa Bosques* to break even. We found the breakeven point to lie between the years 2063 and 2064. Assuming fully avoided deforestation under this extended permanence scenario, the overall NFV will increase to USD 67 million (Table B.5). Net future benefits for communities would remain relatively unaffected by these changes, as we have assumed that the opportunity costs of forest conservation are compensated for by shifting to sustainable production alternatives. Relaxing this assumption implies that communities would either revert to deforestation as soon as payments stop or bear the opportunity costs with associated welfare losses. Nevertheless, these losses could be compensated for via international transfers given that sizeable associated net benefits would accrue at global scale.

B.8 Figures

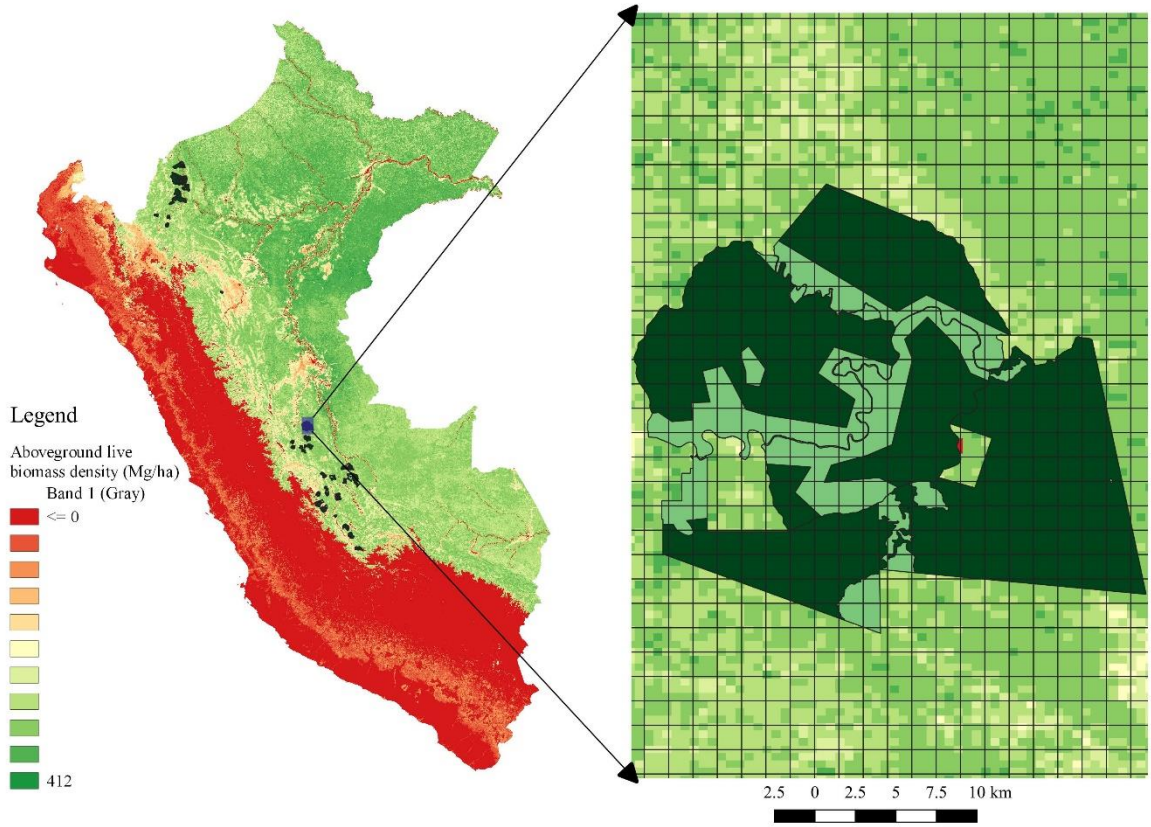

Figure B.1 Aboveground live woody biomass density in Peru

Note: Left: aboveground live woody biomass density in Peru (Baccini et al. 2012); right: a grid of cells of 225 ha each, overlaid on top of the previous map, and on top of the CFZ and OUZ of four participating communities: *Divisoria, Platanillo, Puerto Davis* and *Belen* in the *Puerto Bermudez* District, *Oxapampa* Province, *Pasco* Departament.

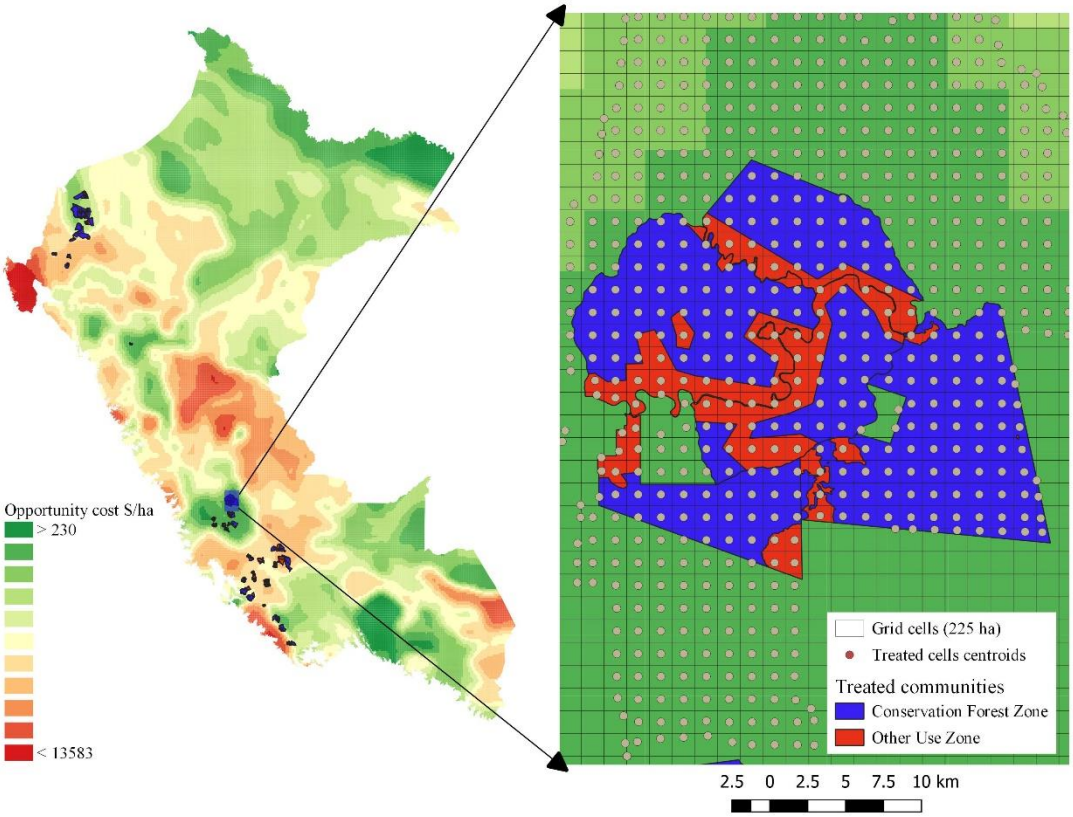

Figure B.2 Opportunity costs

Note: Left: opportunity cost map in the Peruvian Amazon at a pixel resolution of 4 x 4 km (Börner et al., 2016b); right: a grid of cells, 225 ha each, overlaid on top of the previous map and on the CFZ and OUZ of four participating communities: *Divisoria, Platanillo, Puerto Davis* and *Belen* in the *Puerto Bermudez* District, *Oxapampa* Province, *Pasco* Departamento. The centroids of the CFZ cells and OUZ cells were used to assign the opportunity cost values to the corresponding individual cells.

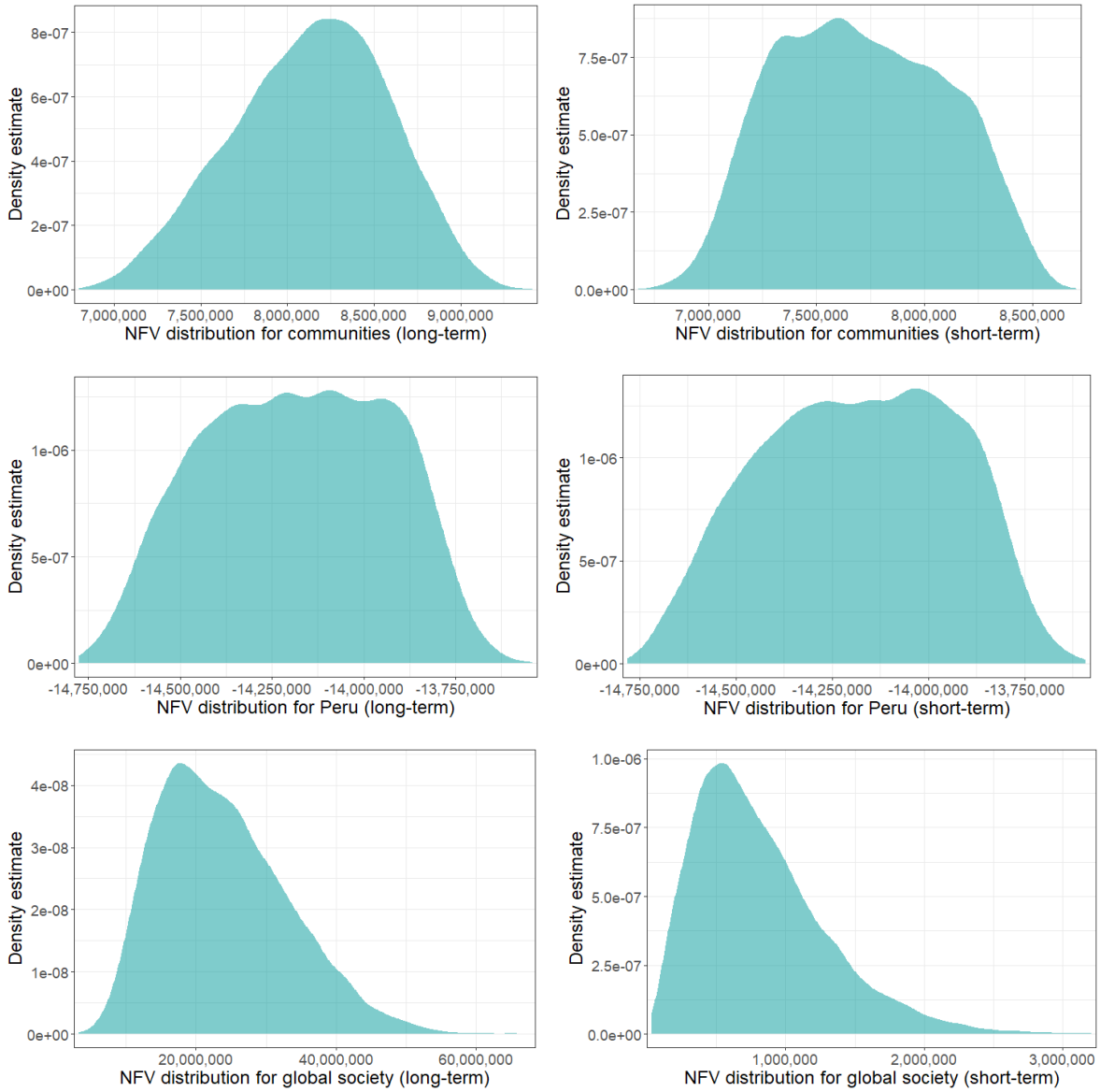

Figure B.3 Probability distributions of the NFVs

Note: Probability distributions of the NFV in the short- and long-term scenarios from the three assessed perspectives. The NFVs are expressed in 2010 USD at the end of 2015.

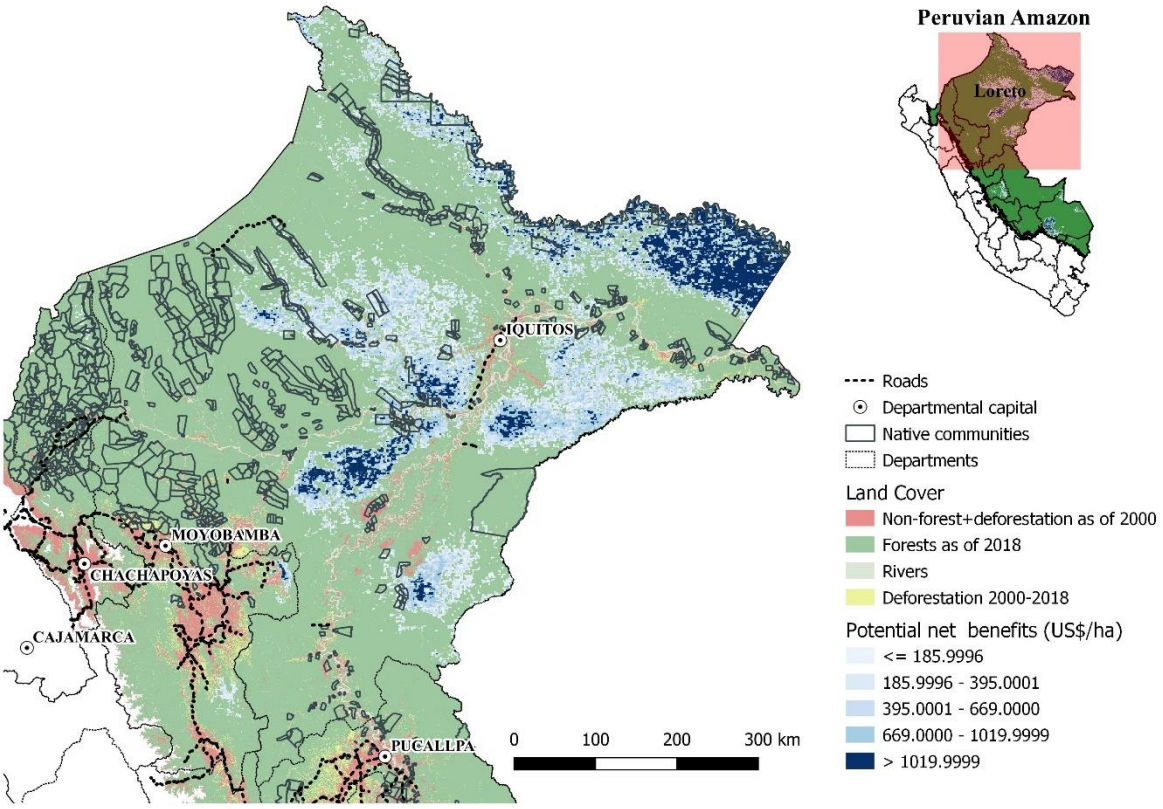

Figure B.4 Net positive returns

Note: Areas in the Peruvian Amazon showing the highest net positive returns if costs of implementation and administration, relative to avoided deforestation, were reduced to 14% of those observed between 2011 and 2015.

B.9 Tables

Table B.1 Input table

		Perspective					
		Local		Peru		Global	
Variable	Distribution	Lower	Upper	Lower	Upper	Lower	Upper
Sum of other environmental benefits (USD $ha^{-1}year^{-1}$)	Uniform	0.5	136.0	11.0	102.0	3.8	32.6
SCC (USD/tCO_2)	Uniform	-		1.0	6.6	31.2	100.0
Avoided deforestation in 2011 (ha)	Normal	1.6	30.1	1.6	30.1	1.6	30.1
Avoided deforestation in 2012 (ha)	Normal	10.0	190.7	10.0	190.7	10.0	190.7
Avoided deforestation in 2013 (ha)	Normal	23.4	446.6	23.4	446.6	23.4	446.6
Avoided deforestation in 2014 (ha)	Normal	23.6	450.8	23.6	450.8	23.6	450.8
Avoided deforestation in 2015 (ha)	Normal	23.6	450.8	23.6	450.8	23.6	450.8
Avoided emissions in 2011 (tCO_2)	Normal	665	12,704	665	12,704	665	12,704
Avoided emissions in 2012 (tCO_2)	Normal	4,043	77,236	4,043	77,236	4,043	77,236
Avoided emissions in 2013 (tCO_2)	Normal	9,424	180,014	9,424	180,014	9,424	180,014
Avoided emissions in 2014 (tCO_2)	Normal	9,521	181,869	9,521	181,869	9,521	181,869

Avoided emissions in 2015 (tCO_2)	Normal	9,521	181,869	9,521	181,869	9,521	181,869
Opportunity costs in 2011 (USD)	Normal	436.0	8,334	436.0	8,334	436.0	8,334
Opportunity costs in 2012 (USD)	Normal	2,853	54,505	2,853	54,505	2,853	54,505
Opportunity costs in 2013 (USD)	Normal	5,596	106,906	5,596	106,906	5,596	106,906
Opportunity costs in 2014 (USD)	Normal	5,389	102,936	5,389	102,936	5,389	102,936
Opportunity costs in 2015 (USD)	Normal	4,805	91,782	4,805	91,782	4,805	91,782
Implementation costs in 2011 (USD)	Constant	-		1,650,254		-	
Implementation costs in 2012 (USD)	Constant	-		1,562,782		-	
Implementation costs in 2013 (USD)	Constant	-		2,825,434		-	
Implementation costs in 2014 (USD)	Constant	-		1,807,321		-	
Implementation costs in 2015 (USD)	Constant	-		1,726,101		-	
Administration costs in 2011 (USD)	Constant	-		0		-	
Administration costs in 2012 (USD)	Constant	-		0		-	

Administration costs in 2013 (USD)	Constant	-		420,250		-	
Administration costs in 2014 (USD)	Constant	-		1,330,739		-	
Administration costs in 2015 (USD)	Constant	-		1,757,831		-	
Payment in 2011 (USD)	Constant	485,608		-		-	
Payment in 2012 (USD)	Constant	1,425,665		-		-	
Payment in 2013 (USD)	Constant	1,199,242		-		-	
Payment in 2014 (USD)	Constant	1,689,489		-		-	
Payment in 2015 (USD)	Constant	1,569,172		-		-	
Discount rate	Uniform	0.1	0.2	0.04	0.08	0.03	0.05
SCC real growth rate	Uniform	-	-	0.02	0.03	0.02	0.03

Note: The table shows the variables, probability distributions, and their lower (5%) and upper (95%) quantiles for each standpoint used in both scenarios.

Table B.2 Environmental benefits

Environmental benefit	Minimum (USD/ha/year)	Maximum (USD/ha/year)	Sources
Participating communities			
Timber	0	19.8	Giudice et al. 2012
NTFP	0.5	20	Pinedo-Vasquez et al. 1992; Andersen 2002
Ecotourism	0	96	Kirkby et al. 2010
Sub-Total	*0.5*	*136*	
Peru			
Water recycling	0	60	Andersen 2015, 2002
Protection against fires	11	39	Andersen 2002; Strand et al. 2018
Watershed protection	0	3	Andersen 2015, 2002
Sub-total	*11*	*102*	
Global society			
Biodiversity protection	2	30	Andersen 2015, 2002
Recreational value	0.8	1.6	Andersen 2015, 2002
Existence value	1	1	Andersen 2015, 2002
Sub-total	*3.8*	*32.6*	
Total	15.3	270.4	

Note: these are other environmental benefits in addition to those associated with climate change mitigation considered for each of the three standpoints used in the cost-benefit analyses

Table B.3 *Programa Bosques´* budget spent between 2011 and 2015.

	2011		2012		2013		2014		2015		Totals	
Implementation + CCT total cost (in US$ nominal) and %	**2,207,833**	**100.0**	**3,202,069**	**100.0**	**4,433,368**	**90.5**	**3,976,930**	**72.4**	**3,880,684**	**65.2**	**17,700,885**	**81.4**
1. Communities´ enrollment and participation	**2,207,833**	**100.0**	**2,182,984**	**68.2**	**3,094,364**	**63.2**	**2,841,598**	**51.8**	**2,779,960**	**46.7**	**13,106,740**	**60.3**
Goods and services	1,629,087	73.8	655,408	20.5	1,683,002	34.4	917,005	16.7	932,022	15.7	5,816,525	26.7
Conditional cash transfers (CCT)	*501,972*	*22.7*	*1,527,576*	*47.7*	*1,321,021*	*27.0*	*1,921,460*	*35.0*	*1,847,938*	*31.1*	*7,119,966*	*32.7*
Non-financial assests	76,774	3.5	-		90,341	1.8	3,133	0.1	-	-	170,248	0.8
2. Technical assistance	-		**649,207**	**20.3**	**1,087,571**	**22.2**	**651,275**	**11.9**	**640,390**	**10.8**	**3,028,445**	**13.9**
Goods and services	-		592,860	18.5	1,046,252	21.4	638,271	11.6	640,390	10.8	2,917,773	13.4
Others	-		227	0.0	189	0.0	-	-	-	-	416	0.0
Non-financial assets	-		56,121	1.8	41,130	0.8	13,005	0.2	-	-	110,255	0.5
3. Forest monitoring	**-**		**369,878**	**11.6**	**251,433**	**5.1**	**484,057**	**8.8**	**460,333**	**7.7**	**1,565,701**	**7.2**
Goods and services	-		256,822	8.0	247,506	5.1	479,011	8.7	460,333	7.7	1,443,672	6.6
Others	-		-		-		-		-			-
Non-financial assets	-		113,057	3.5	3,927	0.1	5,045	0.1	-	-	122,029	0.6
Adminsitration total costs (in US$ nominal) and %												
Program management (common actions)	**-**		**-**		**-**		**806,726**	**14.7**	**848,004**	**14.3**	**1,654,730**	**7.6**
Non-finacial assets	-		-		-		-	-	20,655	0.3	20,655	0.1
Goods and services	-		-		-		806,726	14.7	827,349	13.9	1,634,075	7.5
Others	-		-		-		-		-		-	-
Central actions	**-**		**-**		**462,925**	**9.5**	**706,726**	**12.9**	**1,222,109**	**20.5**	**2,391,760**	**11.0**
1. Administrative management	-		-		**462,925**	**9.5**	**706,726**	**12.9**	**841,793**	**14.1**	**2,011,444**	**9.2**
Goods and services	-		-		431,836	8.8	701,476	12.8	841,749	14.1	1,975,061	9.1
Others	-		-		128	0.0	103	0.0	43	0.0	274	0.0
Non-financial assets	-		-		30,961	0.6	5,147	0.1	-	-	36,108	0.2
2. Monitoring and evaluation	-		-		-		-		**380,316**	**6.4**	**380,316**	**1.7**
Non-financial assets	-		-		-		-		19,486	0.3	19,486	0.1
Goods and services	-		-		-		-		360,831	6.1	360,831	1.7
Total annual budget spent	**2,207,833**	**100%**	**3,202,069**	**100%**	**4,896,294**	**100%**	**5,490,383**	**100%**	**5,950,797**	**100%**	**21,747,376**	**100%**

Table B.4 Distributions´ means of the NFVs (short-term)

	Future values (average) in 2010 USD						
Standpoint	**Climate change mitigation**	**Other environmental benefits**	**Opportunity costs**	**Implementation costs**	**Administration costs**	**Payments**	**NFV**
Participating communities		944,400	3,341,125			8,107,408	5,710,683
National	603,299	710,037		10,761,128	3,640,597		-13,088,389
Global society	4,501,092	224,880					4,725,972
Overall NFV	5,104,391	1,879,317	3,341,125	10,761,128	3,640,597		-10,759,142

Note: These are the distributions´ means of the NFVs from each standpoint and overall in the short-term scenario, had *Programa Bosques* reduced 100% of deforestation, vis-à-vis the business as usual scenario.

The payments are not included in the overall NFV as they are a transfer and not a true cost.

Table B.5 Distributions´ means of the NFVs (short-term 2063)

	Future values (average) in 2010 USD						
Standpoint	**Climate change mitigation**	**Other environmental benefits**	**Opportunity costs**	**Implementation costs**	**Administration costs**	**Payments**	**NFV**
Participating communities		3,297,731	3,343,302			8,115,697	8,070,126
National	6,475,587	5,247,121		10,761,777	3,640,666		-2,679,735
Global society	68,069,012	2,176,116					70,245,128
Total NFV	74,544,599	10,720,968	3,343,302	10,761,777	3,640,666		67,519,822

Note: These are the distribution means of the NFVs from each standpoint and overall in the short-term scenario, had *Programa Bosques* reduced 100% of deforestation, vis-à-vis the business as usual scenario, for a permanence period up to 2063.

The payments are not included in the overall NFV as they are a transfer and not a true cost.

C Chapter 4 Appendix

C.1 Baseline deforestation scenario

In our study, the baseline deforestation scenario refers to the deforestation scenario we used to assess the effect of the policy mixes. To construct this scenario, we first used QGIS software (Version 3.14) to create a vector grid of polygons of 4 × 4 km each, whose extension covered that of our annual forest cover loss map (Figure C.1). The vector grid was then rasterized into a grid of cells of the same resolution and, using Dinamica EGO (Version 5.1.0), overlaid onto the annual forest cover loss map to calculate zonal statistics, specifically the number of deforested pixels in each year between 2001 and 2018 within each grid cell (N = 50,773). Dinamica EGO's map algebra algorithms were used to complete this task and to calculate the means. This deforestation is expressed as the average number of deforested pixels per year within each cell i:

$$Average\ number\ of\ deforested\ pixels_i = \frac{1}{18}\sum_{t=2001}^{2018} Deforested\ pixels_{t,i} \qquad (\mathrm{Eq.\ C.1})$$

Based on the annual forest cover map (Figure C.1), the observed deforestation averaged 126,942 ha/yr. Nevertheless, as depicted in Figure C.1, not all cells presented deforestation in this period. A total of 9,882 cells (15.8 million hectares) experienced no deforestation throughout this period.

Some amount of deforestation was required to be assigned to these cells to develop an enforcement probability for them. To do so, we assigned the observed annual mean number of deforested pixels of cells with a similar deforestation risk, as we describe as follows.

C.2 Deforestation risk and similarity

As previously mentioned, we generated and used a deforestation risk map that depicts the probability of a grid cell of 4 × 4 km being deforested to define the similarity between deforested and non-deforested cells and to assign the annual mean of the number of deforested pixels within a deforested cell to a non-deforested cell. We applied the same procedure for assigning the average number of deforested patches to cells without deforestation.

We first used the *weights of evidence* method (Soares-Filho et al., 2006, 2010) to generate the deforestation probability of each cell. This method is based on Bayesian probability estimation and calculates a probability (weights) using observed patterns of change (the evidence) and spatially observed factors occurring in the same spot (Figure C.2). We implemented this model using Dinamica EGO (Soares-Filho et al., 2006, 2010). As an initial step, we needed to generate two forest cover maps to be compared and identify the change from forest in 2010 to no forest in 2018. Given the lack of a forest cover map in 2010, we generated one by subtracting from the forest cover map of 2018 the monitored deforestation between 2011 and 2018. Second, we built a set of spatial factors related to this change, including: (1) distance to existing paved and unpaved roads, (2) distance to deforestation, (3) distance to navigable rivers by medium boats, (4) distance to rivers only navigable with small boats, (5) opportunity costs (i.e., agricultural rents), (6) elevation, (7) slope, (8) attraction to

urban centers, (9) national protected areas, (10) indigenous communities, (11) valid forest concessions, (12) private conservation areas, and (13) regional conservation areas.

Third, the deforestation probability map was determined as a function of the relation of each of these factors (A, B, …N) and the observed occurrence of a deforested cell i and is given by:

$$P(DeforestedPixel|A \cap B \cap C \cap \ldots \cap N)_i = \frac{e^{\sum_{k=1}^{N} W_{k(i)}}}{1 - e^{\sum_{k=1}^{N} W_{k(i)}}} \qquad \text{(Eq. C. 2)}$$

where $W_{k(i)}$ is the k-factor's weight of evidence in each cell i. The method's only assumption is that the factors are not spatially correlated (Soares-Filho et al., 2006, 2010). To test this assumption, we followed Soares-Filho et al. (2010) and analyzed the correlation between each pair of the aforementioned factors using the Crammer's coefficient pairwise test. We found no correlation between our factors. Finally, we validated the map of deforestation probability using the reciprocal fuzzy comparison method (see Soares-Filho et al., 2010) to assess the output of a simulation of deforestation between 2010 and 2018, which uses the deforestation probability map as an input. We attained a similarity of 86%–89% between the observed deforestation map in 2018 and the simulated map using a comparison window of 1,500 m. All sources and information for each layer are presented as follows and in Table C.1.

In turn, to define the similarity between deforested and non-deforested cells as a function of their deforestation risk maps, we ran a propensity score matching analysis in R Studio using the R package MatchIt (Ho et al., 2021) and applying the 1:1 nearest neighbor method and the logistic regression to estimate the distance measure. Treated cells were defined as those without any deforestation between 2001 and 2018, and control cells were those that experienced any level of deforestation for the same period. The annual mean number of deforested pixels of deforested cells was then assigned to the corresponding pairs of non-deforested pixels. As previously mentioned, the annual mean number of deforested patches of deforested cells was assigned to the corresponding pairs.

C.2.1 Data sources and details

The roads layer was acquired from the official MTC geodata. We only considered the existing road network up to 2018 and reclassified all roads into either paved or unpaved according to their registered surface. Planned roads were excluded from the analysis. The distance to this road network was calculated using QGIS (3.18).

The navigable rivers layer was acquired from Schielein et al. (2021). This dataset differentiates between small- and medium-size boat navigable rivers. After a visual inspection and based on our field experience of traveling by rivers in the Peruvian Amazon, we decided to include both classes. Typically, what Schielein et al. (2021) defined as small-size boat navigable rivers are rivers that could be used as transportation means—at least during the rainy season—using a paddling canoe or the traditional "*peque-peque"* 16-horse-power motor attached to a wooden canoe. In turn, medium-size boat navigable rivers are defined as those in which off-board motors (~60–120HP) can be used throughout the year, such as in the Amazonas, Madre de Dios, Ucayali, and Marañón rivers.

The distance on the previous deforestation map is based on the observed deforestation as of 2010 and was again calculated using QGIS (3.18). The opportunity cost map is taken from (Börner et al., 2016b). The digital elevation model map was taken from the CGIAR-CSI consortium platform and used to derive the slope map using QGIS (3.18). The urban attraction map was built using Dinamica EGO (5.1) algorithms to represent the influence of population centers on deforestation. The urban attraction factor is calculated using a unidirectional gravity-type model for each cell i,j by adding the populations from the population centers within the Amazon biome weighted by each center's distance to cell i,j (Soares-Filho et al., 2006). We used a distance decay exponent of 1. Only population centers with more than 2,000 inhabitants, according to the 2017 population census, were considered, producing a total of 167 population centers. The land cover map depicting cells with forest, non-forest, or deforestation was acquired from the GeoBosques Platform of MINAM. Forests refers to primary (i.e., old-growth) forests; non-forests refers to natural non-forest cover, such as savanna vegetation type, old, deforested areas (previous to 2000), and urban centers; and deforestation refers to deforested areas between 2001 and 2018. The protected areas were taken from the public available spatial datasets of SERNANP and SERFOR. We did not consider any land use categories established after 2018.

C.3 Estimating the probability of enforcement

We simulated the probability of enforcing the law against deforestation based on the assumed enforcement authority's strategy. First, we conceptualized this strategy as having the aim of deterring future deforestation by signaling to land users that illegally deforesting implies the possibility of being sanctioned. Second, our approach entailed the application of this strategy in only one period, in which the enforcement authority prioritizes field operations in areas with the largest historical deforestation, with significant remaining forest cover (≥25% of the 4 × 4 km cell) and fewer number of patches, which could be reached at the lowest costs given a budget constraint. Once the enforcement team reaches an area (i.e., a cell), the enforcement agents will visit all deforested patches within that cell. This strategy was conceptualized based on enforcement practices conducted by IBAMA (the Brazilian Environmental Protection Agency) in the Brazilian Amazon, as reported in Börner et al. (2014) and Assunção et al. (2013), and on reports (Solis, 2016; Weisse et al., 2019) and interviews with former and current representatives of Peruvian environmental agencies (e.g., OSINFOR, MINAM, SERFOR) and the Peruvian Environmental Prosecutor Office (FEMA).

In Brazil, IBAMA seeks to deter illegal deforestation by prioritizing large over small deforestation patches following a two-stage planning procedure (Börner et al., 2014). In the first stage, historical deforestation patterns are considered for planning field enforcement operations (Börner et al., 2014). In the second, near real-time (15 days) satellite imagery is used to guide enforcement agents to recently deforested patches (Assunção et al., 2013). In Peru, larger deforested areas appear to be also prioritized by the enforcement authorities, as commented by some of the authorities' representatives. However, no empirical data about the spatial patterns of enforcement activities were available from any of the authorities enforcing the law against illegal deforestation. Also recognized is that field enforcement operations are still based on voluntary complaints, mostly by landholders experiencing encroaching and deforestation within their lands (Shanee and Shanee, 2020). Nevertheless, since 2016, the availability of regular satellite imagery and forest monitoring at both annual and near-real-time

bases, have allowed several enforcement institutions to use such tools to prioritize the areas in which to enforce the law against deforestation (Weisse et al., 2019). The adoption and regular use of near-real-time deforestation alerts is increasing rapidly among several public authorities (e.g., FEMA, SERNANP, *Programa Bosques*) (see Weisse et al., 2019).

By considering these factors, we implemented our spatial enforcement model by first using the average number of deforested pixels in each cell to parameterize a Poisson distribution and generate 500 random values for each cell, according to the following probability function:

$$P(x) = \frac{\theta^x e^{-x}}{x!} \qquad \text{(Eq. C. 3)}$$

where x = 0,1,2,3…, and $\theta = average\ number\ of\ deforested\ pixels_i$

Thus, the 500 values represent a random variable that we assumed is Poisson distributed. We used RStudio software to generate the 500 values for each cell and group them into 500 deforestation scenarios. Thus, our cells contain a set of 500 scenarios of simulated deforestation patterns (means) that we used to calculate the probability of enforcement.

Third, we calculated a ratio for each cell i in scenario s, between the deforestation value of cell i in scenario s, and the costs of field enforcement operations to reach that cell, as depicted in Figure 4.2 (in chapter 4), plus the total cost of visiting all additional deforested patches present in that cell:

$$Ratio_{i,s} = \frac{Deforestation_{i,s}}{Logistic\ costs_i + AddPatchCost_i} \qquad \text{(Eq. C. 4)}$$

The total cost of visiting all additional patches was calculated as:

$$AddPatchCost_i = (total\ number\ of\ patches_i - 1) * \frac{758}{2} \qquad \text{(Eq. C. 5)}$$

The reason one is subtracted from the total number of deforested patches in cell i is because the field enforcement costs were already calculated as a function of one deforested patch within that cell (see section C.4). We assumed half an hour to reach each additional patch by foot; thus, 758 is divided by two (see Table C.3).

We then ranked the ratios of all cells in descending order and independently for each scenario. We calculated the cumulative sum of the logistical and visiting additional-patches costs of each cell according to their rank and compared the available budget to cover such costs to this accumulated sum (see section C.5 for a description of the used budget). Ranked cells whose cumulative sum did not exceed the total available budget were assigned a value of one, and those that exceeded it were assigned a value of zero. We repeated this procedure for the 500 deforestation scenarios. Finally, the enforcement probability of each cell i ($P_{enf,i}$) was calculated as the proportion of 1s for each cell:

$$P_{enf,i} = \frac{1}{500}\sum_{s=1}^{500} Value_{s,i} \qquad \text{(Eq. C. 6)}$$

where $Value_{s,i}$= : 1 or 0. The total available budget was changed, and these steps were repeated to generate different enforcement probability scenarios, as depicted in Figure 4.5 in chapter 4.

C.4 Map of field enforcement operations costs

To generate the map of field enforcement operation costs, we first developed an accessibility model that calculates the shortest travel time (in hours) from the urban centers where the enforcement agencies' offices are located to rural areas in the Peruvian Amazon. The agencies considered included OSINFOR, SERFOR, regional governments, SERNANP, and FEMA. We implemented this model using the Dinamica EGO platform for environmental modeling (Version 5.1.0). Dinamica EGO provides a "pushgrow" type algorithm that calculates a travel time map, that is, a map showing the accumulated time required to traverse the region from one specific location to a source. In our case, sources represent the locations of the enforcement agency's offices. The algorithm also uses a friction surface representing the time to traverse grid cells, in our case of a 500-m resolution, depending on their land cover/surface. We applied specific traverse speeds to each cell's land cover, which included as of 2018 paved and unpaved roads, navigable rivers, forests, non-forests, and deforested lands (Table C.2). We assumed that all roads are traveled using cars, rivers with either small- or medium-size boats, and all other surfaces or land cover types by foot. Given that enforcement field trips could involve walking time to reach distant areas within a cell, we adjusted the travel speed to travel on foot according to the cell's slope and elevation. We followed the approach used in Weiss et al. (2018) and applied the Tobler's Hiking function, capped the Tobler's walking speed at a maximum of 5 km/h, and divided it by 5 to calculate a fraction of the maximum travel speed (see Eq.C.7 and Eq. C.8).

$$Tobler's\ walking\ speed = 6e^{-3.5|\tan(0.01745*slope\ angle)+0.05|} \qquad (\text{Eq. C. 7})$$

$$Slope\ adjustment\ factor = \frac{Tobler's\ walking\ speed}{5} \qquad (\text{Eq. C. 8})$$

We also applied an elevation adjustment factor as in Weiss et al. (2018):

$$Elevation\ adjustment\ factor = 1.016e^{-0.0001072*elevation} \qquad (\text{Eq. C. 9})$$

Next, we multiplied the accumulated travel time of each cell by the costs of the field enforcement operations (Table C.3) to generate the map of field enforcement operations costs (Figure 4.2 in chapter 4). Because the efficiency of gasoline consumption (km/gallon) differs between cars and boats, we added the cost of gasoline consumption to the total transportation cost (soles/hour) as a function of whether transportation occurs on roads (+17 soles/hour) or on rivers (+14 soles/hour).

C.5 Available budget for enforcement authority

Unfortunately, the available budget for field enforcement operations against deforestation in the Peruvian Amazon is unknown. Therefore, we consulted several unpublished sources to define the used range of the available budget. A document elaborated on by the GIZ reported from different environmental authorities 185 million soles as the total budget in 2016 for the supervision and control of timber harvesting, supervision and control of illegal activities in the forestry sector, management of protected areas, and strengthening of forest sector authorities (GIZ, unpublish.). This amount is similar to the total public budget estimated by BID (2017) for 2013 for environmental licensing, surveillance, and control in Peru. OSINFOR reported a total 2018 budget for supervision of 7.1 million soles and 2.7 million soles for control activities. FEMA had a total 2018 budget of 41 million soles. Note that in no case were the reported budgets exclusively referred to the Amazon biome in Peru. Based on these sources, we defined the available budget for enforcement operations against deforestation in the Peruvian Amazon to range between 50 and 100 million soles.

C.6 Figures

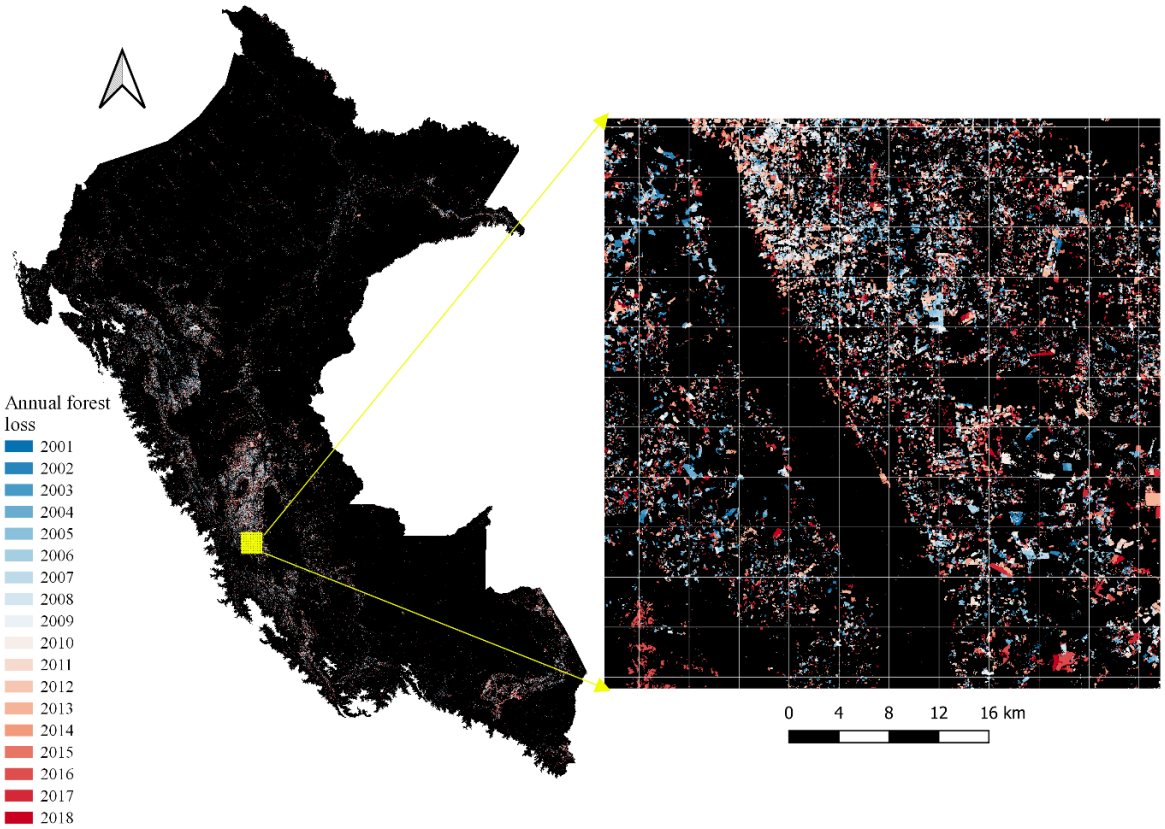

Figure C.1 Annual forest cover loss map (2001-2018)

Note: Each color represents the year when deforestation was detected on a 30-m pixel. Pixels in black represent areas where no deforestation occurred or where no forest is present (either previous deforestation to year 2000 or other land cover). A grid of cells (4 × 4 km each) was overlaid on top of this map to generate the baseline deforestation map.

Source: GeoBosques: http://geobosques.minam.gob.pe/geobosque/view/index.php

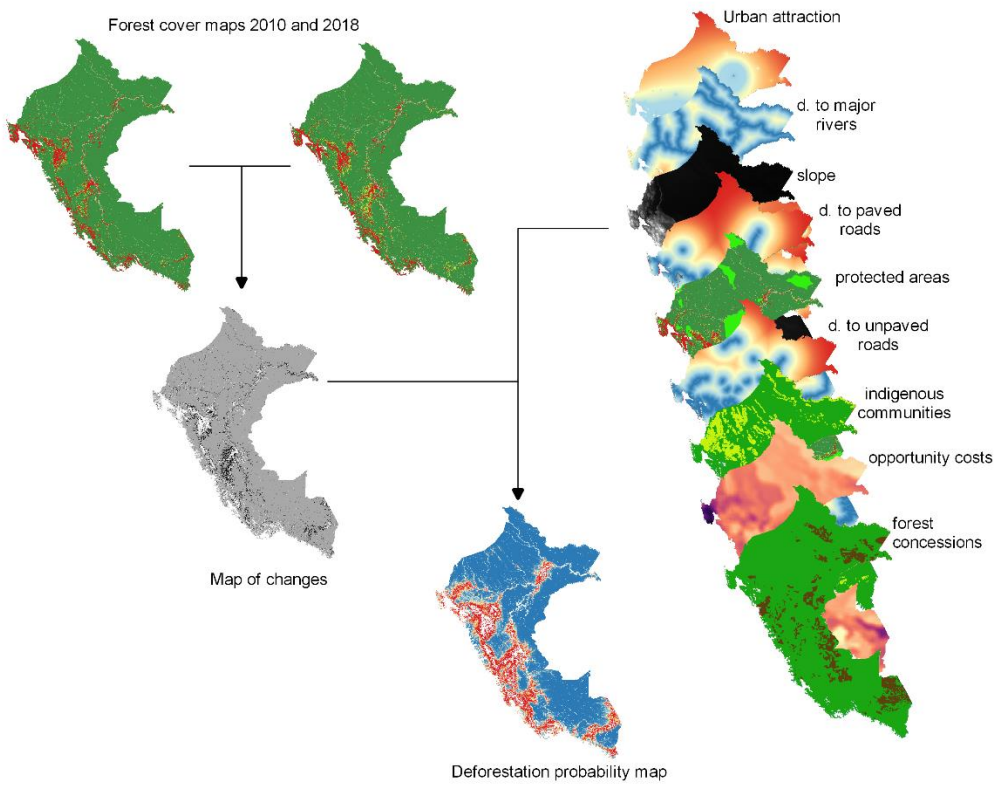

Figure C.2 Calculation and application of weights of evidence to produce the deforestation probability map (risk map)

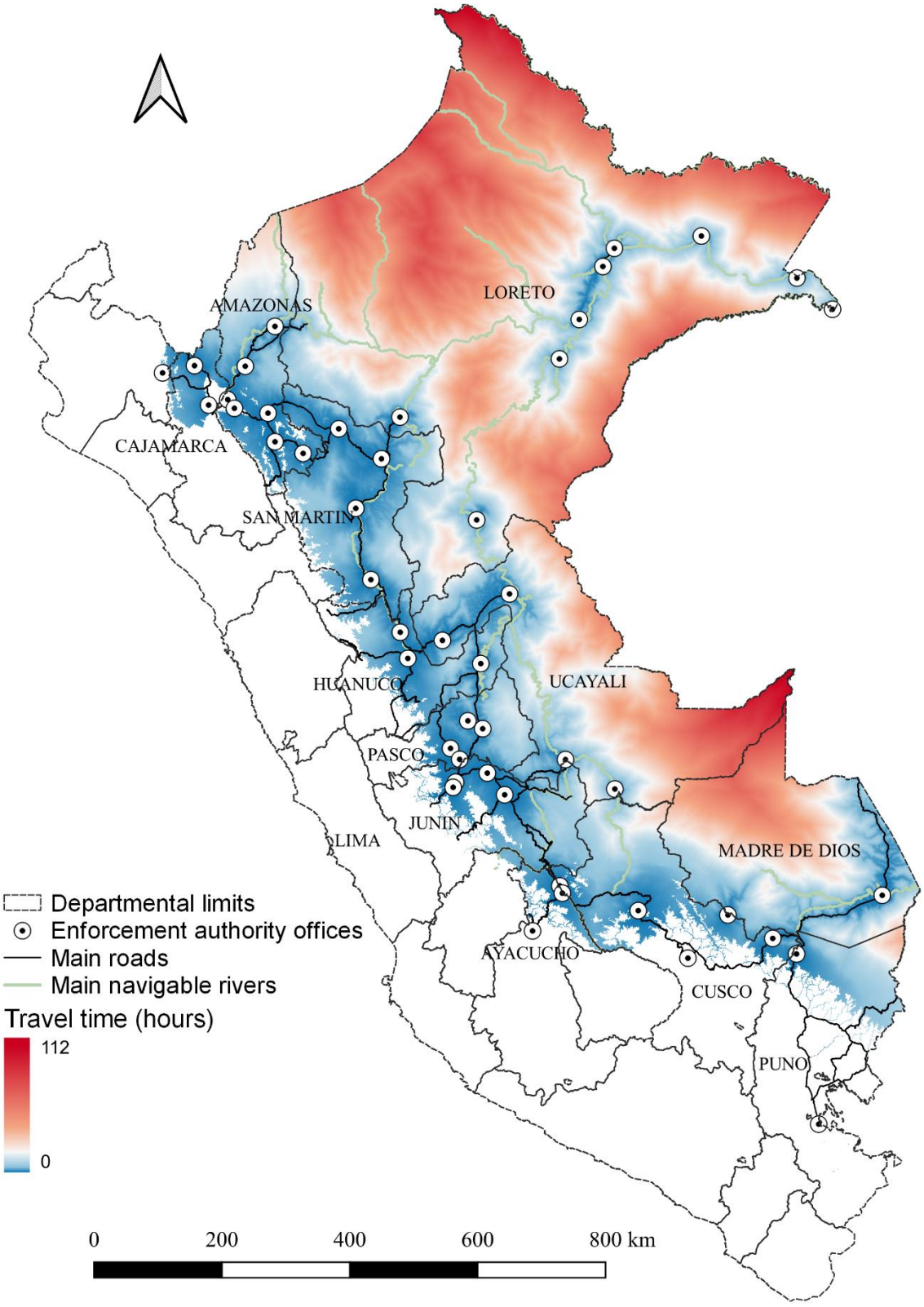

Figure C.3 Travel time map

Note: the map shows the accumulated fastest travel time (in hours) to reach each location (cells) in Peruvian Amazon from the enforcement authorities´ offices.

C.7 Tables

Table C.1 List of inputs and data sources for developing the deforestation risk map

Spatial factor	Source
Paved and unpaved roads	https://portal.mtc.gob.pe/estadisticas/descarga.html https://www.geoidep.gob.pe/servicios-idep/catalogo-nacional-de-servicios-web/servicios-de-publicacion-de-objetos-wfs
Navigable rivers	(Schielein et al., 2021)
Opportunity costs	(Börner et al., 2016b)
Elevation	https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/
Slope	Derived from the above map
Attraction to urban centers	Derived from urban centers´ populations and their distances to all cells
National protected areas	http://geo.sernanp.gob.pe/visorsernanp/#
Indigenous communities	(Giudice et al., 2019)
Timber concessions	https://geo.serfor.gob.pe/visor/
Private conservation areas	http://geo.sernanp.gob.pe/visorsernanp/
Regional conservation areas	http://geo.sernanp.gob.pe/visorsernanp/
Distance to deforestation in 2010	https://geobosques.minam.gob.pe/geobosque/view/index.php

Table C.2 Travel speeds

Land cover	Speed (km/h)	Source
Paved roads	60	(Börner et al., 2014)
Non-forest	3	Same as above
Forest	1.62	Same as evergreen broadleaf forest in (Weiss et al., 2018)
Navigable rivers (small boats)	5	(Schielein et al., 2021)
Deforestation	3	Educated guess based on Weiss et al. (2018) (based on barren or sparsely vegetated, cropland/natural vegetation)
Unpaved roads	25	Börner et al., 2014
Navigable rivers (medium boats)	10	Weiss et al., 2018, Börner et al., 2014

Note: These are travel speeds (in km/h) to traverse different land cover types used to calculate the fastest accumulated travel time to reach a specific area in Peruvian Amazon.

Table C.3 Field enforcement operations costs

	Quantity/unit	soles/unit per month	soles/h
Manpower			
Prosecutors	2	9,286	116
Authority	2	2,800	35
Police	4	3,000	75
Sub-Total	**8**		**226**
Gasoline	Efficiency (km/gallon)	Speed	
SUV	35	60	17
Boat (off-board motor)	7	10	14
Sub-total			**35**
Transport hire/use			
SUV	2	160,000	384
Boat (off-board motor)	2	350 per day	88
Sub-total			**472**
Others (food, housing, etc.)	8	60 per day	**60**
Total (soles/h)			**758**
Administrative costs		1,008 per process	

Source: Interviews with current and former representatives of OSINFOR. Angel Armas personal communication for SUV cost and gasoline consumption. OSINFOR (2018) for administrative costs.

Table C.4 List of districts

					Aggregated income change (soles)				Income changes per capita			
Departament	Province	District	Rural population	Poverty rate (%)	a	b	c	d	a	b	c	d
Amazonas	Bagua	Aramango	6983	0.39	-692768	-607473	-307772	-8070	-99.21	-86.99	-44.07	-1.16
Amazonas	Bagua	Copallin	2212	0.25	-4438	-4266	-1771	725	-2.01	-1.93	-0.8	0.33
Amazonas	Bagua	Imaza	20445	0.54	-3424946	-2942931	-1451469	39993	-167.52	-143.94	-70.99	1.96
Amazonas	Bagua	La Peca	2335	0.35	-10785	-10504	-4614	1277	-4.62	-4.5	-1.98	0.55
Amazonas	Bongara	Chisquilla	306	0.42	-64413	-62697	-28666	5364	-210.5	-204.89	-93.68	17.53
Amazonas	Bongara	Churuja	287	0.21	-13819	-13440	-5497	2446	-48.15	-46.83	-19.15	8.52
Amazonas	Bongara	Corosha	772	0.55	-71374	-65382	-33451	-1521	-92.45	-84.69	-43.33	-1.97
Amazonas	Bongara	Cuispes	669	0.46	-53623	-52287	-24242	3804	-80.15	-78.16	-36.24	5.69
Amazonas	Bongara	Florida	2260	0.34	-343118	-330338	-164700	937	-151.82	-146.17	-72.88	0.41
Amazonas	Bongara	Jazan	1174	0.23	-72102	-70302	-32513	5277	-61.42	-59.88	-27.69	4.49
Amazonas	Bongara	Jumbilla	1337	0.3	-41581	-40568	-19295	1978	-31.1	-30.34	-14.43	1.48
Amazonas	Bongara	Recta	208	0.39	-15256	-14857	-6477	1902	-73.35	-71.43	-31.14	9.15
Amazonas	Bongara	San Carlos	489	0.29	-42724	-41587	-17721	6146	-87.37	-85.05	-36.24	12.57
Amazonas	Bongara	Shipasbamba	1539	0.36	-130579	-127291	-58243	10805	-84.85	-82.71	-37.84	7.02
Amazonas	Bongara	Valera	874	0.21	-963	-934	-324	285	-1.1	-1.07	-0.37	0.33
Amazonas	Bongara	Yambrasbamba	3378	0.44	-1358357	-1303080	-627909	47262	-402.12	-385.75	-185.88	13.99
Amazonas	Chachapoyas	Asuncion	262	0.37	-4310	-4184	-1540	1104	-16.45	-15.97	-5.88	4.22
Amazonas	Chachapoyas	Balsas	1136	0.46	-1699	-1631	-666	298	-1.5	-1.44	-0.59	0.26
Amazonas	Chachapoyas	Cheto	642	0.39	-22788	-21716	807	23329	-35.5	-33.83	1.26	36.34
Amazonas	Chachapoyas	Chiliquin	585	0.53	-33806	-32600	-7263	18073	-57.79	-55.73	-12.42	30.89
Amazonas	Chachapoyas	Granada	480	0.44	-2498	-2376	176	2727	-5.2	-4.95	0.37	5.68
Amazonas	Chachapoyas	La Jalca	1588	0.48	-1102	-1054	-52	950	-0.69	-0.66	-0.03	0.6
Amazonas	Chachapoyas	Leimebamba	822	0.26	-33542	-32342	-12402	7537	-40.81	-39.35	-15.09	9.17
Amazonas	Chachapoyas	Levanto	794	0.41	-868	-833	-95	643	-1.09	-1.05	-0.12	0.81

Amazonas	Chachapoyas	Magdalena	852	0.31	-22479	-21662	-4505	12652	-26.38	-25.43	-5.29	14.85
Amazonas	Chachapoyas	Mariscal Castilla	1367	0.39	0	1	24	48	0	0	0.02	0.03
Amazonas	Chachapoyas	Molinopampa	2176	0.36	-121847	-115790	11271	138331	-56	-53.21	5.18	63.57
Amazonas	Chachapoyas	Montevideo	496	0.39	-4990	-4619	54	4726	-10.06	-9.31	0.11	9.53
Amazonas	Chachapoyas	Olleros	375	0.48	-8414	-8173	-3112	1949	-22.44	-21.79	-8.3	5.2
Amazonas	Chachapoyas	Quinjalca	769	0.47	-4705	-4499	-162	4174	-6.12	-5.85	-0.21	5.43
Amazonas	Chachapoyas	San Francisco De Daguas	295	0.3	-494	-470	33	537	-1.68	-1.59	0.11	1.82
Amazonas	Chachapoyas	San Isidro De Maino	580	0.43	-18189	-17509	-3345	10820	-31.36	-30.19	-5.77	18.65
Amazonas	Chachapoyas	Soloco	1224	0.41	-12127	-11579	-166	11248	-9.91	-9.46	-0.14	9.19
Amazonas	Condorcanqui	El Cenepa	9891	0.63	-1323164	-1135023	-451148	232728	-133.77	-114.75	-45.61	23.53
Amazonas	Condorcanqui	Nieva	14551	0.51	-5400205	-4665763	-2343719	-21676	-371.12	-320.65	-161.07	-1.49
Amazonas	Condorcanqui	Rio Santiago	13953	0.6	-938189	-885876	-25611	834654	-67.24	-63.49	-1.84	59.82
Amazonas	Luya	Camporredondo	2329	0.5	-84175	-72364	-36454	-544	-36.14	-31.07	-15.65	-0.23
Amazonas	Luya	Cocabamba	1881	0.56	-71522	-69842	-34562	718	-38.02	-37.13	-18.37	0.38
Amazonas	Luya	Colcamar	1853	0.42	-31285	-30106	-15353	-601	-16.88	-16.25	-8.29	-0.32
Amazonas	Luya	Conila	1840	0.5	-81432	-78323	-37247	3829	-44.26	-42.57	-20.24	2.08
Amazonas	Luya	Inguilpata	498	0.4	-14753	-14393	-7274	-155	-29.63	-28.9	-14.61	-0.31
Amazonas	Luya	Longuita	839	0.57	-7577	-7322	-3725	-128	-9.03	-8.73	-4.44	-0.15
Amazonas	Luya	Lonya Chico	842	0.47	-17690	-17268	-8406	456	-21.01	-20.51	-9.98	0.54
Amazonas	Luya	Luya	1601	0.3	-2735	-2670	-1310	49	-1.71	-1.67	-0.82	0.03
Amazonas	Luya	Luya Viejo	388	0.54	-20958	-20417	-9067	2284	-54.02	-52.62	-23.37	5.89
Amazonas	Luya	Maria	744	0.52	-42172	-40827	-19617	1593	-56.68	-54.87	-26.37	2.14
Amazonas	Luya	Ocalli	3556	0.45	-85151	-76485	-38853	-1221	-23.95	-21.51	-10.93	-0.34
Amazonas	Luya	Ocumal	3446	0.52	-160129	-143413	-73210	-3007	-46.47	-41.62	-21.24	-0.87
Amazonas	Luya	Pisuquia	4768	0.59	-161254	-152080	-77719	-3358	-33.82	-31.9	-16.3	-0.7
Amazonas	Luya	Providencia	1316	0.55	-19880	-17087	-8529	28	-15.11	-12.98	-6.48	0.02
Amazonas	Luya	San Francisco Del Yeso	695	0.49	-42426	-41230	-17878	5474	-61.04	-59.32	-25.72	7.88

Amazonas	Luya	San Jeronimo	633	0.47	-107697	-104840	-46113	12613	-170.14	-165.62	-72.85	19.93
Amazonas	Luya	San Juan De Lopecancha	419	0.56	-5559	-5421	-2521	379	-13.27	-12.94	-6.02	0.9
Amazonas	Luya	Santa Catalina	1888	0.6	-158090	-153820	-64150	25520	-83.73	-81.47	-33.98	13.52
Amazonas	Luya	Santo Tomas	3012	0.47	-2996	-2888	-946	997	-0.99	-0.96	-0.31	0.33
Amazonas	Luya	Tingo	1265	0.4	-7418	-7089	-3509	72	-5.86	-5.6	-2.77	0.06
Amazonas	Rodriguez De Mendoza	Chirimoto	2498	0.38	-180629	-175461	-70167	35127	-72.31	-70.24	-28.09	14.06
Amazonas	Rodriguez De Mendoza	Cochamal	595	0.33	-133192	-126928	4574	136076	-223.85	-213.32	7.69	228.7
Amazonas	Rodriguez De Mendoza	Huambo	2620	0.23	-16392	-15564	1833	19230	-6.26	-5.94	0.7	7.34
Amazonas	Rodriguez De Mendoza	Limabamba	2280	0.37	-514939	-495479	-89328	316822	-225.85	-217.32	-39.18	138.96
Amazonas	Rodriguez De Mendoza	Longar	1631	0.26	-35773	-34017	2870	39756	-21.93	-20.86	1.76	24.38
Amazonas	Rodriguez De Mendoza	Mariscal Benavides	1506	0.22	-121227	-115426	5912	127250	-80.5	-76.64	3.93	84.5
Amazonas	Rodriguez De Mendoza	Milpuc	453	0.32	-19831	-19218	-6345	6528	-43.78	-42.42	-14.01	14.41
Amazonas	Rodriguez De Mendoza	Omia	8793	0.4	-254134	-246204	-79674	86856	-28.9	-28	-9.06	9.88
Amazonas	Rodriguez De Mendoza	San Nicolas	1027	0.21	-50001	-48056	-7222	33613	-48.69	-46.79	-7.03	32.73
Amazonas	Rodriguez De Mendoza	Santa Rosa	512	0.25	-343	-333	-116	101	-0.67	-0.65	-0.23	0.2
Amazonas	Rodriguez De Mendoza	Totora	282	0.23	-3585	-3451	-634	2183	-12.71	-12.24	-2.25	7.74
Amazonas	Rodriguez De Mendoza	Vista Alegre	2812	0.51	-1154381	-1119534	-395160	329214	-410.52	-398.13	-140.53	117.07
Amazonas	Utcubamba	Bagua Grande	14895	0.25	-164625	-151047	-77211	-3375	-11.05	-10.14	-5.18	-0.23
Amazonas	Utcubamba	Cajaruro	14988	0.36	-689818	-669186	-283049	103089	-46.02	-44.65	-18.89	6.88
Amazonas	Utcubamba	Cumba	4811	0.37	-45894	-39483	-20100	-717	-9.54	-8.21	-4.18	-0.15
Amazonas	Utcubamba	El Milagro	2893	0.27	-4200	-3612	-1848	-84	-1.45	-1.25	-0.64	-0.03
Amazonas	Utcubamba	Jamalca	6620	0.36	-199610	-193606	-92743	8120	-30.15	-29.25	-14.01	1.23
Amazonas	Utcubamba	Lonya Grande	6254	0.32	-145955	-126768	-64556	-2343	-23.34	-20.27	-10.32	-0.37
Amazonas	Utcubamba	Yamon	2927	0.38	-42925	-36916	-18887	-859	-14.67	-12.61	-6.45	-0.29

Ayacucho	Huanta	Ayahuanco	1196	0.53	-44222	-38027	-19369	-710	-36.98	-31.8	-16.19	-0.59
Ayacucho	Huanta	Canayre	3520	0.44	-608353	-523183	-267666	-12148	-172.83	-148.63	-76.04	-3.45
Ayacucho	Huanta	Llochegua	5151	0.32	-702762	-604336	-308341	-12346	-136.43	-117.32	-59.86	-2.4
Ayacucho	Huanta	Pucacolpa	2523	0.78	-162275	-139412	-68211	2989	-64.32	-55.26	-27.04	1.18
Ayacucho	Huanta	Santillana	3852	0.6	-2014	-1732	-886	-40	-0.52	-0.45	-0.23	-0.01
Ayacucho	Huanta	Sivia	6680	0.46	-647122	-556450	-283082	-9715	-96.87	-83.3	-42.38	-1.45
Ayacucho	Huanta	Uchuraccay	3522	0.81	-2095	-1801	-907	-12	-0.59	-0.51	-0.26	0
Ayacucho	La Mar	Anchihuay	4039	0.65	-123218	-105950	-53817	-1685	-30.51	-26.23	-13.32	-0.42
Ayacucho	La Mar	Anco	5521	0.46	-474426	-407934	-207153	-6372	-85.93	-73.89	-37.52	-1.15
Ayacucho	La Mar	Ayna	2399	0.39	-131037	-112666	-57090	-1513	-54.62	-46.96	-23.8	-0.63
Ayacucho	La Mar	Chungui	4218	0.62	-36956	-31928	-15264	1399	-8.76	-7.57	-3.62	0.33
Ayacucho	La Mar	Oronccoy	1020	0.7	-392	-291	843	1977	-0.38	-0.28	0.83	1.94
Ayacucho	La Mar	Samugari	4012	0.42	-153208	-131721	-66590	-1458	-38.19	-32.83	-16.6	-0.36
Ayacucho	La Mar	Santa Rosa	3018	0.32	-289448	-248907	-126971	-5034	-95.91	-82.47	-42.07	-1.67
Cajamarca	Jaen	Bellavista	7642	0.53	-5976	-5139	-2629	-120	-0.78	-0.67	-0.34	-0.02
Cajamarca	Jaen	Chontali	9810	0.61	-131045	-112608	-55656	1296	-13.36	-11.48	-5.67	0.13
Cajamarca	Jaen	Colasay	10238	0.55	-126150	-108489	-55506	-2523	-12.32	-10.6	-5.42	-0.25
Cajamarca	Jaen	Huabal	7642	0.69	-16888	-14524	-7431	-338	-2.21	-1.9	-0.97	-0.04
Cajamarca	Jaen	Jaen	12566	0.22	-134625	-115778	-59235	-2693	-10.71	-9.21	-4.71	-0.21
Cajamarca	Jaen	Las Pirias	4275	0.42	-1709	-1470	-752	-34	-0.4	-0.34	-0.18	-0.01
Cajamarca	Jaen	Pomahuaca	8344	0.55	-132643	-114042	-57688	-1335	-15.9	-13.67	-6.91	-0.16
Cajamarca	Jaen	Pucara	2493	0.44	-4990	-4292	-2196	-100	-2	-1.72	-0.88	-0.04
Cajamarca	Jaen	Sallique	7033	0.77	-23021	-19767	-9445	876	-3.27	-2.81	-1.34	0.12
Cajamarca	Jaen	San Felipe	4693	0.67	-4737	-4058	-1733	593	-1.01	-0.86	-0.37	0.13
Cajamarca	Jaen	San Jose Del Alto	6960	0.49	-416503	-358169	-182735	-7301	-59.84	-51.46	-26.25	-1.05
Cajamarca	Jaen	Santa Rosa	7293	0.57	-10484	-9016	-4613	-210	-1.44	-1.24	-0.63	-0.03
Cajamarca	San Ignacio	Chirinos	11748	0.37	-24500	-21070	-10780	-490	-2.09	-1.79	-0.92	-0.04
Cajamarca	San Ignacio	Huarango	13308	0.57	-305854	-262810	-129628	3554	-22.98	-19.75	-9.74	0.27

Cajamarca	San Ignacio	La Coipa	17189	0.57	-140325	-120680	-61743	-2807	-8.16	-7.02	-3.59	-0.16
Cajamarca	San Ignacio	Namballe	9098	0.69	-748462	-643603	-327700	-11797	-82.27	-70.74	-36.02	-1.3
Cajamarca	San Ignacio	San Ignacio	21440	0.42	-289925	-249336	-127567	-5799	-13.52	-11.63	-5.95	-0.27
Cajamarca	San Ignacio	San Jose De Lourdes	14305	0.48	-686529	-589759	-277644	14474	-47.99	-41.23	-19.41	1.01
Cajamarca	San Ignacio	Tabaconas	17651	0.66	-546133	-469578	-238179	-6780	-30.94	-26.6	-13.49	-0.38
Cusco	Calca	Lares	5753	0.51	-2254	-2178	-569	1040	-0.39	-0.38	-0.1	0.18
Cusco	Calca	Yanatile	6157	0.35	-360197	-348269	-131297	85675	-58.5	-56.56	-21.32	13.92
Cusco	La Convencion	Echarate	19359	0.23	-4474967	-4313932	-1143573	2026787	-231.16	-222.84	-59.07	104.69
Cusco	La Convencion	Huayopata	2268	0.24	-208641	-202594	-98382	5831	-91.99	-89.33	-43.38	2.57
Cusco	La Convencion	Inkawasi	4285	0.46	-85696	-78684	-31928	14829	-20	-18.36	-7.45	3.46
Cusco	La Convencion	Kimbiri	6149	0.25	-1185532	-1058110	-526023	6065	-192.8	-172.08	-85.55	0.99
Cusco	La Convencion	Maranura	4134	0.15	-25002	-24285	-9228	5829	-6.05	-5.87	-2.23	1.41
Cusco	La Convencion	Megantoni	6969	0.34	-1844028	-1750009	-311131	1127747	-264.6	-251.11	-44.64	161.82
Cusco	La Convencion	Ocobamba	4327	0.36	-350428	-341110	-150755	39599	-80.99	-78.83	-34.84	9.15
Cusco	La Convencion	Pichari	5830	0.31	-965526	-904871	-412190	80491	-165.61	-155.21	-70.7	13.81
Cusco	La Convencion	Quellouno	13311	0.22	-1360521	-1320162	-499587	320988	-102.21	-99.18	-37.53	24.11
Cusco	La Convencion	Santa Ana	4014	0.08	-42944	-41571	-12906	15759	-10.7	-10.36	-3.22	3.93
Cusco	La Convencion	Santa Teresa	5972	0.22	-249402	-239845	-115703	8438	-41.76	-40.16	-19.37	1.41
Cusco	La Convencion	Vilcabamba	9557	0.38	-568152	-550321	-195327	159668	-59.45	-57.58	-20.44	16.71
Cusco	La Convencion	Villa Kintiarina	1974	0.41	-383087	-340318	-172538	-4759	-194.07	-172.4	-87.41	-2.41
Cusco	La Convencion	Villa Virgen	1980	0.43	-157652	-138284	-61991	14302	-79.62	-69.84	-31.31	7.22
Cusco	Paucartambo	Challabamba	8433	0.52	-2143	-1968	1319	4605	-0.25	-0.23	0.16	0.55
Cusco	Paucartambo	Kosñipata	4403	0.31	-372853	-337717	393094	1123904	-84.68	-76.7	89.28	255.26

Cusco	Paucartambo	Paucartambo	7881	0.46	-18680	-17479	5842	29162	-2.37	-2.22	0.74	3.7
Cusco	Quispicanchi	Camanti	2219	0.15	-892025	-860202	-292887	274428	-401.99	-387.65	-131.99	123.67
Cusco	Quispicanchi	Marcapata	4307	0.58	-66694	-64843	-29048	6746	-15.49	-15.06	-6.74	1.57
Cusco	Urubamba	Machupicchu	822	0.24	-34199	-32492	-16196	100	-41.61	-39.53	-19.7	0.12
Huancavelica	Tayacaja	Huachocolpa	3218	0.4	-11498	-10855	443	11741	-3.57	-3.37	0.14	3.65
Huancavelica	Tayacaja	Roble	1300	0.54	-125354	-108255	-54747	-1239	-96.43	-83.27	-42.11	-0.95
Huancavelica	Tayacaja	Surcubamba	4601	0.47	-376	-338	140	619	-0.08	-0.07	0.03	0.13
Huancavelica	Tayacaja	Tintay Puncu	3010	0.44	-62881	-60089	-26710	6670	-20.89	-19.96	-8.87	2.22
Huanuco	Dos De Mayo	Marias	5571	0.54	-143234	-133733	-68266	-2798	-25.71	-24.01	-12.25	-0.5
Huanuco	Huacaybamba	Cochabamba	1576	0.46	-374175	-336246	-163573	9099	-237.42	-213.35	-103.79	5.77
Huanuco	Huacaybamba	Huacaybamba	3232	0.47	-40400	-38745	-12379	13986	-12.5	-11.99	-3.83	4.33
Huanuco	Huamalies	Arancay	1356	0.45	-9137	-8913	-4209	495	-6.74	-6.57	-3.1	0.37
Huanuco	Huamalies	Jircan	1412	0.52	-112912	-103491	-52314	-1137	-79.97	-73.29	-37.05	-0.81
Huanuco	Huamalies	Monzon	5832	0.27	-1299298	-1174712	-593705	-12698	-222.79	-201.43	-101.8	-2.18
Huanuco	Huanuco	Chinchao	9639	0.41	-697440	-603217	-305941	-8665	-72.36	-62.58	-31.74	-0.9
Huanuco	Huanuco	Churubamba	12737	0.46	-15454	-13518	-6525	468	-1.21	-1.06	-0.51	0.04
Huanuco	Huanuco	San Pablo De Pillao	8350	0.31	-396741	-341153	-173583	-6014	-47.51	-40.86	-20.79	-0.72
Huanuco	Leoncio Prado	Castillo Grande	1130	0.14	-228747	-204013	-104379	-4744	-202.43	-180.54	-92.37	-4.2
Huanuco	Leoncio Prado	Daniel Alomia Robles	6142	0.29	-1269995	-1235453	-523658	188137	-206.77	-201.15	-85.26	30.63
Huanuco	Leoncio Prado	Hermilio Valdizan	3475	0.29	-286914	-279519	-141811	-4104	-82.57	-80.44	-40.81	-1.18
Huanuco	Leoncio Prado	Jose Crespo Y Castillo	5220	0.19	-2231437	-2041559	-1028477	-15395	-427.48	-391.1	-197.03	-2.95
Huanuco	Leoncio Prado	Luyando	3965	0.1	-68118	-66166	-31842	2483	-17.18	-16.69	-8.03	0.63
Huanuco	Leoncio Prado	Mariano Damaso Beraun	5685	0.25	-1557071	-1451040	-728650	-6261	-273.89	-255.24	-128.17	-1.1
Huanuco	Leoncio Prado	Pucayacu	3724	0.24	-560462	-543910	-214819	114272	-150.5	-146.06	-57.69	30.69
Huanuco	Leoncio Prado	Pueblo Nuevo	4143	0.19	-908228	-841144	-430353	-19561	-219.22	-203.03	-103.87	-4.72
Huanuco	Leoncio Prado	Rupa-Rupa	1837	0.14	-537895	-481063	-246125	-11187	-292.81	-261.87	-133.98	-6.09

Huanuco	Leoncio Prado	Santo Domingo De Anda	2527	0.24	-282392	-268763	-134657	-551	-111.75	-106.36	-53.29	-0.22
Huanuco	Marañón	Cholon	3139	0.37	-1869241	-1654861	-817276	20309	-595.49	-527.19	-260.36	6.47
Huanuco	Marañón	La Morada	2790	0.29	-1136238	-1021584	-512145	-2706	-407.25	-366.16	-183.56	-0.97
Huanuco	Marañón	Santa Rosa De Alto Yanajanca	2199	0.29	-703191	-619237	-295134	28970	-319.78	-281.6	-134.21	13.17
Huanuco	Pachitea	Chaglla	5763	0.3	-1833910	-1738105	-811984	114137	-318.22	-301.6	-140.9	19.81
Huanuco	Pachitea	Panao	12601	0.48	-521720	-466567	-237709	-8851	-41.4	-37.03	-18.86	-0.7
Huanuco	Pachitea	Umari	11055	0.54	-1988	-1688	-411	867	-0.18	-0.15	-0.04	0.08
Huanuco	Puerto Inca	Codo Del Pozuzo	4699	0.27	-11187958	-10874836	-4942766	989303	-2380.9	-2314.3	-1051.9	210.53
Huanuco	Puerto Inca	Honoria	4814	0.27	-4021360	-3588667	-1790710	7247	-835.35	-745.46	-371.98	1.51
Huanuco	Puerto Inca	Puerto Inca	4415	0.23	-8459044	-8219237	-3215682	1787872	-1916	-1861.7	-728.35	404.95
Huanuco	Puerto Inca	Tournavista	5447	0.27	-10495760	-9917417	-4905819	105778	-1926.9	-1820.7	-900.65	19.42
Huanuco	Puerto Inca	Yuyapichis	5769	0.15	-11970965	-11657083	-5228185	1200713	-2075.1	-2020.6	-906.25	208.13
Junin	Chanchamayo	Chanchamayo	3161	0.15	-521376	-449295	-229163	-9030	-164.94	-142.14	-72.5	-2.86
Junin	Chanchamayo	Perene	19682	0.31	-2196378	-1916293	-977142	-37990	-111.59	-97.36	-49.65	-1.93
Junin	Chanchamayo	Pichanaqui	16319	0.31	-2961551	-2653862	-1321864	10135	-181.48	-162.62	-81	0.62
Junin	Chanchamayo	San Luis De Shuaro	4157	0.22	-378931	-326133	-166859	-7585	-91.15	-78.45	-40.14	-1.82
Junin	Chanchamayo	San Ramon	5047	0.15	-455918	-392060	-199963	-7865	-90.33	-77.68	-39.62	-1.56
Junin	Chanchamayo	Vitoc	1814	0.14	-219784	-188951	-95322	-1694	-121.16	-104.16	-52.55	-0.93
Junin	Concepcion	Andamarca	3502	0.47	-9162	-8307	-3309	1689	-2.62	-2.37	-0.94	0.48
Junin	Concepcion	Cochas	1923	0.48	-2547	-2476	-996	484	-1.32	-1.29	-0.52	0.25
Junin	Concepcion	Comas	5377	0.31	-6680	-6230	-2282	1666	-1.24	-1.16	-0.42	0.31
Junin	Concepcion	Mariscal Castilla	1394	0.23	-3398	-3268	-1241	786	-2.44	-2.34	-0.89	0.56
Junin	Huancayo	Pariahuanca	5130	0.32	-9422	-8716	-1439	5837	-1.84	-1.7	-0.28	1.14
Junin	Huancayo	Santo Domingo De Acobamba	6222	0.39	-67828	-65144	-24362	16420	-10.9	-10.47	-3.92	2.64
Junin	Jauja	Apata	4284	0.33	-20063	-19415	-8841	1732	-4.68	-4.53	-2.06	0.4
Junin	Jauja	Molinos	1573	0.29	-38459	-37481	-16943	3595	-24.45	-23.83	-10.77	2.29
Junin	Jauja	Monobamba	1662	0.29	-473223	-424567	-212572	-577	-284.73	-255.46	-127.9	-0.35

Junin	Junin	Ulcumayo	4283	0.52	-261598	-253719	-119760	14199	-61.08	-59.24	-27.96	3.32
Junin	Satipo	Coviriali	5778	0.38	-255475	-219708	-112409	-5110	-44.22	-38.03	-19.45	-0.88
Junin	Satipo	Llaylla	6544	0.28	-208354	-179146	-90820	-2494	-31.84	-27.38	-13.88	-0.38
Junin	Satipo	Mazamari	20265	0.35	-5889275	-5125681	-2612328	-98974	-290.61	-252.93	-128.91	-4.88
Junin	Satipo	Pampa Hermosa	3690	0.49	-462814	-397964	-202401	-6839	-125.42	-107.85	-54.85	-1.85
Junin	Satipo	Pangoa	31988	0.38	-4409771	-3903285	-1952333	-1380	-137.86	-122.02	-61.03	-0.04
Junin	Satipo	Rio Negro	25389	0.34	-1489972	-1282346	-656084	-29822	-58.69	-50.51	-25.84	-1.17
Junin	Satipo	Rio Tambo	26036	0.52	-11610292	-10195894	-4983043	229808	-445.93	-391.61	-191.39	8.83
Junin	Satipo	Satipo	11138	0.22	-2620898	-2253956	-1152842	-51728	-235.31	-202.37	-103.51	-4.64
Junin	Satipo	Vizcatan Del Ene	4252	0.28	-1864069	-1604421	-819042	-33663	-438.4	-377.33	-192.63	-7.92
Junin	Tarma	Huasahuasi	5371	0.34	-32281	-28820	-13973	874	-6.01	-5.37	-2.6	0.16
Junin	Tarma	Palca	2438	0.24	-6521	-5605	-2820	-35	-2.67	-2.3	-1.16	-0.01
Junin	Tarma	San Pedro De Cajas	637	0.27	-2786	-2715	-1214	287	-4.37	-4.26	-1.91	0.45
La Libertad	Pataz	Ongon	1250	0.59	-253621	-217471	-97435	22601	-202.9	-173.98	-77.95	18.08
Loreto	Alto Amazonas	Balsapuerto	13707	0.53	-5418170	-4672058	-2330484	11089	-395.28	-340.85	-170.02	0.81
Loreto	Alto Amazonas	Jeberos	1580	0.36	-1513594	-1440550	-473027	494495	-957.97	-911.74	-299.38	312.97
Loreto	Alto Amazonas	Lagunas	3929	0.44	-814226	-724148	-87260	549628	-207.23	-184.31	-22.21	139.89
Loreto	Alto Amazonas	Santa Cruz	3967	0.44	-1378328	-1248819	-579098	90624	-347.45	-314.8	-145.98	22.84
Loreto	Alto Amazonas	Teniente Cesar Lopez Rojas	2365	0.33	-2958314	-2576764	-1293874	-10984	-1250.9	-1089.5	-547.09	-4.64
Loreto	Alto Amazonas	Yurimaguas	13593	0.32	-5712384	-5164406	-2629759	-95111	-420.24	-379.93	-193.46	-7
Loreto	Datem del Marañón	Andoas	11714	0.48	-185731	-128954	757886	1644727	-15.86	-11.01	64.7	140.41
Loreto	Datem del Marañón	Barranca	4196	0.38	-1566139	-1401076	-454753	491570	-373.25	-333.91	-108.38	117.15
Loreto	Datem del Marañón	Cahuapanas	6336	0.51	-2249398	-2114451	-946326	221799	-355.02	-333.72	-149.36	35.01
Loreto	Datem del Marañón	Manseriche	5653	0.5	-2154124	-1851686	-884069	83548	-381.06	-327.56	-156.39	14.78

Loreto	Datem del Marañón	Morona	4191	0.4	-873161	-760889	157945	1076779	-208.34	-181.55	37.69	256.93
Loreto	Datem del Marañón	Pastaza	5078	0.43	-641512	-571852	186542	944936	-126.33	-112.61	36.74	186.08
Loreto	Loreto	Nauta	9225	0.42	-794391	-753676	50456	854588	-86.11	-81.7	5.47	92.64
Loreto	Loreto	Parinari	6085	0.49	-210413	-187366	260154	707675	-34.58	-30.79	42.75	116.3
Loreto	Loreto	Tigre	6448	0.51	-464464	-404207	695973	1796152	-72.03	-62.69	107.94	278.56
Loreto	Loreto	Trompeteros	8396	0.37	-342005	-285235	717966	1721168	-40.73	-33.97	85.51	205
Loreto	Loreto	Urarinas	8913	0.5	-378200	-306587	736672	1779931	-42.43	-34.4	82.65	199.7
Loreto	Mariscal Ramon Castilla	Pebas	7291	0.5	-3188376	-3081295	-940251	1200794	-437.3	-422.62	-128.96	164.7
Loreto	Mariscal Ramon Castilla	Ramon Castilla	8472	0.37	-4323557	-3994192	-1861758	270677	-510.33	-471.46	-219.75	31.95
Loreto	Mariscal Ramon Castilla	San Pablo	7312	0.49	-3956198	-3837375	-1479737	877902	-541.06	-524.81	-202.37	120.06
Loreto	Mariscal Ramon Castilla	Yavari	8366	0.46	-2893007	-2777869	-919432	939005	-345.81	-332.04	-109.9	112.24
Loreto	Maynas	Alto Nanay	2855	0.49	-377624	-347058	180357	707772	-132.27	-121.56	63.17	247.91
Loreto	Maynas	Belen	8026	0.27	-301328	-291304	-83257	124790	-37.54	-36.3	-10.37	15.55
Loreto	Maynas	Fernando Lores	7694	0.49	-1496521	-1442897	-412206	618484	-194.5	-187.54	-53.58	80.39
Loreto	Maynas	Indiana	6313	0.5	-461383	-439733	-76328	287077	-73.08	-69.66	-12.09	45.47
Loreto	Maynas	Iquitos	1783	0.09	-170807	-163993	-23514	116966	-95.8	-91.98	-13.19	65.6
Loreto	Maynas	Las Amazonas	5389	0.51	-479521	-451490	62874	577237	-88.98	-83.78	11.67	107.11
Loreto	Maynas	Mazan	7591	0.51	-1552493	-1497601	-419703	658196	-204.52	-197.29	-55.29	86.71
Loreto	Maynas	Napo	11158	0.48	-902634	-825812	537498	1900808	-80.9	-74.01	48.17	170.35
Loreto	Maynas	Punchana	5809	0.2	-670387	-644584	-114407	415769	-115.4	-110.96	-19.69	71.57
Loreto	Maynas	San Juan Bautista	13388	0.21	-1865914	-1794054	-297248	1199559	-139.37	-134	-22.2	89.6
Loreto	Maynas	Torres Causana	4230	0.48	-18163	117	338227	676338	-4.29	0.03	79.96	159.89
Loreto	Putumayo	Putumayo	610	0.4	-35420	-17781	338788	695358	-58.07	-29.15	555.39	1139.93

Loreto	Putumayo	Rosa Panduro	520	0.37	0	9714	213697	417680	0	18.68	410.96	803.23
Loreto	Putumayo	Teniente Manuel Clavero	2317	0.42	-257046	-218243	559376	1336996	-110.94	-94.19	241.42	577.04
Loreto	Putumayo	Yaguas	1277	0.61	-19524	-1698	372648	746994	-15.29	-1.33	291.82	584.96
Loreto	Requena	Alto Tapiche	1515	0.54	-218415	-189228	361644	912516	-144.17	-124.9	238.71	602.32
Loreto	Requena	Capelo	2566	0.57	-123727	-113140	-20225	72689	-48.22	-44.09	-7.88	28.33
Loreto	Requena	Emilio San Martin	3374	0.54	-464301	-436463	-37579	361306	-137.61	-129.36	-11.14	107.09
Loreto	Requena	Jenaro Herrera	1012	0.51	-456473	-427889	-190736	46417	-451.06	-422.82	-188.47	45.87
Loreto	Requena	Maquia	4870	0.53	-509320	-461514	155802	773118	-104.58	-94.77	31.99	158.75
Loreto	Requena	Puinahua	2019	0.42	-327268	-302690	74732	452155	-162.09	-149.92	37.01	223.95
Loreto	Requena	Requena	2438	0.43	-1278826	-1125153	-516479	92196	-524.54	-461.51	-211.85	37.82
Loreto	Requena	Saquena	3365	0.53	-397385	-381337	-79871	221594	-118.09	-113.32	-23.74	65.85
Loreto	Requena	Soplin	569	0.48	-60766	-51513	85291	222096	-106.79	-90.53	149.9	390.33
Loreto	Requena	Tapiche	881	0.42	-166336	-157126	679	158483	-188.8	-178.35	0.77	179.89
Loreto	Requena	Yaquerana	1929	0.49	-708116	-645656	25714	697084	-367.09	-334.71	13.33	361.37
Loreto	Ucayali	Contamana	6454	0.33	-5877379	-5037145	-2167348	702449	-910.66	-780.47	-335.81	108.84
Loreto	Ucayali	Inahuaya	1738	0.24	-668200	-573546	-269687	34173	-384.46	-330	-155.17	19.66
Loreto	Ucayali	Padre Marquez	3697	0.53	-1752376	-1500950	-637000	226951	-474	-405.99	-172.3	61.39
Loreto	Ucayali	Pampa Hermosa	5388	0.52	-5452536	-4840623	-2279400	281823	-1012	-898.41	-423.05	52.31
Loreto	Ucayali	Sarayacu	8140	0.51	-1996940	-1736629	-359606	1017416	-245.32	-213.35	-44.18	124.99
Loreto	Ucayali	Vargas Guerra	1035	0.48	-2425429	-2093077	-1000300	92477	-2343.4	-2022.3	-966.47	89.35
Madre De Dios	Manu	Fitzcarrald	1402	0.17	-243357	-215787	153172	522132	-173.58	-153.91	109.25	372.42
Madre De Dios	Manu	Huepetuhe	1942	0.07	-594324	-553043	304954	1162951	-306.04	-284.78	157.03	598.84
Madre De Dios	Manu	Madre De Dios	3744	0.02	-2621446	-2488038	247842	2983722	-700.17	-664.54	66.2	796.93
Madre De Dios	Manu	Manu	2356	0.11	-265422	-227329	556570	1340468	-112.66	-96.49	236.23	568.96
Madre De Dios	Tahuamanu	Iberia	270	0.08	-2004557	-1898343	311077	2520498	-7424.3	-7030.9	1152.14	9335.18

Madre De Dios	Tahuamanu	Iñapari	2391	0.02	-1727100	-1641008	22654	1686316	-722.33	-686.33	9.47	705.28
Madre De Dios	Tahuamanu	Tahuamanu	2865	0.03	-2287505	-2105121	-366268	1372584	-798.43	-734.77	-127.84	479.09
Madre De Dios	Tambopata	Inambari	3784	0.06	-7031442	-6720466	-1173736	4372994	-1858.2	-1776	-310.18	1155.65
Madre De Dios	Tambopata	Laberinto	1014	0.1	-4531123	-4027761	-1990393	46974	-4468.6	-3972.2	-1962.9	46.33
Madre De Dios	Tambopata	Las Piedras	1630	0.05	-6586509	-5658135	-2760282	137571	-4040.8	-3471.3	-1693.4	84.4
Madre De Dios	Tambopata	Tambopata	2929	0.05	-4567563	-3954435	-1584089	766260	-1559.4	-1350.1	-540.83	261.61
Pasco	Oxapampa	Chontabamba	2579	0.21	-221243	-214398	-71094	72210	-85.79	-83.13	-27.57	28
Pasco	Oxapampa	Constitucion	6111	0.37	-3778630	-3619334	-279735	3059863	-618.33	-592.27	-45.78	500.71
Pasco	Oxapampa	Huancabamba	3675	0.33	-663294	-640167	-162879	314409	-180.49	-174.2	-44.32	85.55
Pasco	Oxapampa	Oxapampa	4790	0.21	-388310	-375145	-143578	87989	-81.07	-78.32	-29.97	18.37
Pasco	Oxapampa	Palcazu	7130	0.38	-2042543	-1925974	514216	2954405	-286.47	-270.12	72.12	414.36
Pasco	Oxapampa	Pozuzo	4511	0.37	-407700	-392273	-89495	213283	-90.38	-86.96	-19.84	47.28
Pasco	Oxapampa	Puerto Bermudez	11081	0.48	-5143291	-4917213	-226181	4464852	-464.15	-443.75	-20.41	402.93
Pasco	Oxapampa	Villa Rica	4359	0.3	-838283	-777971	-362633	52705	-192.31	-178.47	-83.19	12.09
Pasco	Pasco	Huachon	1480	0.48	-124570	-120313	-35578	49157	-84.17	-81.29	-24.04	33.21
Pasco	Pasco	Paucartambo	3078	0.47	-41213	-39959	-16712	6535	-13.39	-12.98	-5.43	2.12
Pasco	Pasco	Ticlacayan	3261	0.55	-7244	-6987	-3149	689	-2.22	-2.14	-0.97	0.21
Piura	Ayabaca	Ayabaca	24867	0.53	-667	-570	-214	142	-0.03	-0.02	-0.01	0.01
Piura	Huancabamba	El Carmen De La Frontera	11186	0.53	-458476	-394247	-200784	-7322	-40.99	-35.24	-17.95	-0.65
Piura	Huancabamba	Huancabamba	18481	0.44	-8087	-6942	-3270	402	-0.44	-0.38	-0.18	0.02
Piura	Huancabamba	Sondor	7140	0.53	-64359	-55346	-28256	-1166	-9.01	-7.75	-3.96	-0.16
Puno	Carabaya	Ayapata	6677	0.44	-1369117	-1316244	-223887	868470	-205.05	-197.13	-33.53	130.07
Puno	Carabaya	Coasa	3045	0.66	-94981	-87939	25902	139743	-31.19	-28.88	8.51	45.89
Puno	Carabaya	Ituata	7526	0.48	-39931	-37828	-679	36470	-5.31	-5.03	-0.09	4.85
Puno	Carabaya	Ollachea	3390	0.45	-19026	-18342	-4041	10260	-5.61	-5.41	-1.19	3.03
Puno	Carabaya	San Gaban	6832	0.37	-150733	-145765	-46613	52538	-22.06	-21.34	-6.82	7.69

Puno	Carabaya	Usicayos	5293	0.48	-301	-197	1220	2638	-0.06	-0.04	0.23	0.5
Puno	San Antonio De Putina	Sina	1649	0.52	-20701	-19994	-5346	9301	-12.55	-12.12	-3.24	5.64
Puno	Sandia	Alto Inambari	6604	0.37	-1383004	-1224159	-603430	17298	-209.42	-185.37	-91.37	2.62
Puno	Sandia	Limbani	2970	0.45	-142431	-134172	-97	133977	-47.96	-45.18	-0.03	45.11
Puno	Sandia	Patambuco	3863	0.52	-808	-583	2105	4793	-0.21	-0.15	0.54	1.24
Puno	Sandia	Phara	5091	0.32	-96210	-92413	-39619	13175	-18.9	-18.15	-7.78	2.59
Puno	Sandia	Quiaca	2131	0.45	-6827	-6146	616	7378	-3.2	-2.88	0.29	3.46
Puno	Sandia	San Juan Del Oro	3733	0.45	-169208	-164470	-74737	14996	-45.33	-44.06	-20.02	4.02
Puno	Sandia	San Pedro De Putina Punco	9124	0.36	-2868951	-2530423	-1115810	298802	-314.44	-277.34	-122.29	32.75
Puno	Sandia	Sandia	6263	0.34	-13803	-12650	1882	16414	-2.2	-2.02	0.3	2.62
Puno	Sandia	Yanahuaya	1936	0.32	-132134	-126314	-29011	68293	-68.25	-65.24	-14.98	35.28
San Martin	Bellavista	Alto Biavo	3878	0.4	-4779304	-4579216	-736720	3105776	-1232.4	-1180.8	-189.97	800.87
San Martin	Bellavista	Bajo Biavo	10774	0.2	-4961336	-4817002	-1790419	1236164	-460.49	-447.1	-166.18	114.74
San Martin	Bellavista	Bellavista	705	0.28	-73279	-70756	-17784	35189	-103.94	-100.36	-25.22	49.91
San Martin	Bellavista	Huallaga	2711	0.28	-1077850	-1040908	-265137	510635	-397.58	-383.96	-97.8	188.36
San Martin	Bellavista	San Pablo	2274	0.46	-190527	-183600	-38133	107334	-83.78	-80.74	-16.77	47.2
San Martin	Bellavista	San Rafael	774	0.38	-7924	-7658	-2057	3544	-10.24	-9.89	-2.66	4.58
San Martin	El Dorado	Agua Blanca	2330	0.25	-26754	-25251	6312	37875	-11.48	-10.84	2.71	16.26
San Martin	El Dorado	San Jose De Sisa	3895	0.37	-84570	-80211	11339	102888	-21.71	-20.59	2.91	26.42
San Martin	El Dorado	San Martin	7803	0.39	-1578345	-1525030	-405415	714200	-202.27	-195.44	-51.96	91.53
San Martin	El Dorado	Santa Rosa	4107	0.3	-46789	-44483	3943	52369	-11.39	-10.83	0.96	12.75
San Martin	El Dorado	Shatoja	3004	0.32	-30044	-28838	-3494	21850	-10	-9.6	-1.16	7.27
San Martin	Huallaga	Alto Saposoa	1800	0.24	-2219074	-2128776	-237170	1654437	-1232.8	-1182.7	-131.76	919.13
San Martin	Huallaga	El Eslabon	2106	0.19	-5109	-4894	-366	4161	-2.43	-2.32	-0.17	1.98
San Martin	Huallaga	Piscoyacu	2087	0.19	-391924	-377528	-75201	227125	-187.79	-180.89	-36.03	108.83
San Martin	Huallaga	Sacanche	2450	0.19	-331933	-321719	-107225	107269	-135.48	-131.31	-43.77	43.78
San Martin	Huallaga	Saposoa	5154	0.24	-1199912	-1153687	-182962	787763	-232.81	-223.84	-35.5	152.85

San Martin	Huallaga	Tingo De Saposoa	789	0.12	-17512	-16872	-3425	10022	-22.2	-21.38	-4.34	12.7
San Martin	Lamas	Alonso De Alvarado	7093	0.28	-428708	-416295	-155633	105030	-60.44	-58.69	-21.94	14.81
San Martin	Lamas	Barranquita	2676	0.15	-3751921	-3267439	-1662378	-57316	-1402.1	-1221	-621.22	-21.42
San Martin	Lamas	Caynarachi	3691	0.26	-2798052	-2623181	-1213377	196426	-758.07	-710.7	-328.74	53.22
San Martin	Lamas	Cuñumbuqui	1247	0.15	-20042	-19090	902	20894	-16.07	-15.31	0.72	16.76
San Martin	Lamas	Lamas	1525	0.22	-12401	-12024	-4099	3826	-8.13	-7.88	-2.69	2.51
San Martin	Lamas	Pinto Recodo	5870	0.36	-1083568	-1055038	-471280	112478	-184.59	-179.73	-80.29	19.16
San Martin	Lamas	San Roque De Cumbaza	1635	0.31	-388322	-376016	-126557	122902	-237.51	-229.98	-77.4	75.17
San Martin	Lamas	Tabalosos	4043	0.45	-870723	-842678	-253733	335212	-215.37	-208.43	-62.76	82.91
San Martin	Lamas	Zapatero	3059	0.28	-9228	-8772	805	10383	-3.02	-2.87	0.26	3.39
San Martin	Mariscal Caceres	Campanilla	9001	0.24	-2484008	-2414358	-982294	449769	-275.97	-268.23	-109.13	49.97
San Martin	Mariscal Caceres	Huicungo	3837	0.33	-6129910	-5659619	-2683531	292558	-1597.6	-1475	-699.38	76.25
San Martin	Mariscal Caceres	Juanjui	3178	0.2	-920378	-895012	-370033	154946	-289.61	-281.63	-116.44	48.76
San Martin	Mariscal Caceres	Pachiza	2282	0.33	-2948506	-2772748	-1273936	224876	-1292.1	-1215.1	-558.25	98.54
San Martin	Mariscal Caceres	Pajarillo	5345	0.29	-735543	-711819	-213626	284568	-137.61	-133.17	-39.97	53.24
San Martin	Moyobamba	Calzada	529	0.16	-150750	-129645	-66330	-3015	-284.97	-245.08	-125.39	-5.7
San Martin	Moyobamba	Habana	1675	0.16	-51103	-43948	-22485	-1022	-30.51	-26.24	-13.42	-0.61
San Martin	Moyobamba	Jepelacio	8860	0.35	-1275375	-1201897	-589705	22487	-143.95	-135.65	-66.56	2.54
San Martin	Moyobamba	Moyobamba	18601	0.16	-8890187	-7827822	-3984664	-141507	-477.94	-420.83	-214.22	-7.61
San Martin	Moyobamba	Soritor	5848	0.34	-1895243	-1814450	-819428	175594	-324.08	-310.27	-140.12	30.03
San Martin	Moyobamba	Yantalo	631	0.16	-98721	-84900	-43437	-1974	-156.45	-134.55	-68.84	-3.13
San Martin	Picota	Buenos Aires	2924	0.29	-50959	-49466	-18102	13261	-17.43	-16.92	-6.19	4.54
San Martin	Picota	Caspisapa	2126	0.18	-47881	-46465	-16740	12986	-22.52	-21.86	-7.87	6.11
San Martin	Picota	Picota	961	0.25	-414569	-403942	-187947	28049	-431.39	-420.34	-195.57	29.19
San Martin	Picota	Pilluana	865	0.24	-16256	-15860	-7544	772	-18.79	-18.33	-8.72	0.89
San Martin	Picota	Pucacaca	185	0.16	-62878	-61128	-24389	12351	-339.88	-330.42	-131.83	66.76

San Martin	Picota	San Cristobal	1192	0.18	-8815	-8579	-3894	791	-7.39	-7.2	-3.27	0.66
San Martin	Picota	San Hilarion	1098	0.25	-123596	-119416	-31636	56144	-112.56	-108.76	-28.81	51.13
San Martin	Picota	Shamboyacu	5857	0.5	-2949589	-2778861	-1409745	-40628	-503.6	-474.45	-240.69	-6.94
San Martin	Picota	Tingo De Ponasa	1343	0.42	-1223371	-1189701	-574674	40353	-910.92	-885.85	-427.9	30.05
San Martin	Picota	Tres Unidos	3889	0.38	-1823332	-1747939	-809596	128747	-468.84	-449.46	-208.18	33.11
San Martin	Rioja	Awajun	4600	0.31	-835422	-750805	-378349	-5893	-181.61	-163.22	-82.25	-1.28
San Martin	Rioja	Elias Soplin Vargas	2777	0.44	-201333	-194509	-82243	30023	-72.5	-70.04	-29.62	10.81
San Martin	Rioja	Nueva Cajamarca	6778	0.28	-300220	-285459	-139624	6210	-44.29	-42.12	-20.6	0.92
San Martin	Rioja	Pardo Miguel	6935	0.37	-1237380	-1113415	-563572	-13729	-178.43	-160.55	-81.26	-1.98
San Martin	Rioja	Posic	1919	0.31	-67200	-57792	-29568	-1344	-35.02	-30.12	-15.41	-0.7
San Martin	Rioja	Rioja	1935	0.17	-169516	-158754	-79773	-792	-87.61	-82.04	-41.23	-0.41
San Martin	Rioja	San Fernando	1240	0.16	-35635	-30646	-15680	-713	-28.74	-24.71	-12.64	-0.57
San Martin	Rioja	Yorongos	2446	0.31	-133916	-130521	-59226	12069	-54.75	-53.36	-24.21	4.93
San Martin	Rioja	Yuracyacu	404	0.28	-40558	-34880	-17845	-811	-100.39	-86.34	-44.17	-2.01
San Martin	San Martin	Alberto Leveau	841	0.2	-16178	-15657	-4705	6246	-19.24	-18.62	-5.59	7.43
San Martin	San Martin	Chazuta	3141	0.55	-872387	-843778	-254182	335414	-277.74	-268.63	-80.92	106.79
San Martin	San Martin	Chipurana	2249	0.37	-82467	-78693	-15200	48294	-36.67	-34.99	-6.76	21.47
San Martin	San Martin	El Porvenir	2399	0.37	-2626772	-2469406	-1133943	201521	-1094.9	-1029.4	-472.67	84
San Martin	San Martin	Huimbayoc	2619	0.47	-1307564	-1261656	-315711	630234	-499.26	-481.73	-120.55	240.64
San Martin	San Martin	Juan Guerra	162	0.22	-44843	-42912	-2361	38190	-276.81	-264.89	-14.57	235.74
San Martin	San Martin	La Banda De Shilcayo	3827	0.16	-108503	-104182	-15594	72995	-28.35	-27.22	-4.07	19.07
San Martin	San Martin	Papaplaya	2073	0.37	-583717	-562216	-147119	267977	-281.58	-271.21	-70.97	129.27
San Martin	San Martin	San Antonio	1674	0.2	-40598	-39054	-6641	25773	-24.25	-23.33	-3.97	15.4
San Martin	San Martin	Sauce	1515	0.36	-58584	-56663	-16311	24040	-38.67	-37.4	-10.77	15.87
San Martin	San Martin	Shapaja	1943	0.17	-248630	-238692	-29983	178725	-127.96	-122.85	-15.43	91.98
San Martin	San Martin	Tarapoto	592	0.07	-1556	-1488	-63	1362	-2.63	-2.51	-0.11	2.3
San Martin	Tocache	Nuevo Progreso	6834	0.26	-1627868	-1526091	-724552	76986	-238.2	-223.31	-106.02	11.27

San Martin	Tocache	Polvora	7263	0.26	-2256665	-2160390	-973281	213828	-310.71	-297.45	-134.01	29.44
San Martin	Tocache	Shunte	1315	0.33	-297086	-287403	-102309	82785	-225.92	-218.56	-77.8	62.95
San Martin	Tocache	Tocache	7956	0.16	-1026292	-926664	-459089	8487	-129	-116.47	-57.7	1.07
San Martin	Tocache	Uchiza	7783	0.2	-1299498	-1129805	-572518	-15230	-166.97	-145.16	-73.56	-1.96
Ucayali	Atalaya	Raymondi	17359	0.32	-12255019	-10820748	-5157195	506358	-705.97	-623.35	-297.09	29.17
Ucayali	Atalaya	Sepahua	3567	0.32	-3026045	-2620429	-1219655	181118	-848.34	-734.63	-341.93	50.78
Ucayali	Atalaya	Tahuania	6109	0.3	-4869086	-4371366	-1953486	444396	-797.03	-715.56	-319.77	72.74
Ucayali	Atalaya	Yurua	1975	0.53	-358946	-310240	13328	336896	-181.74	-157.08	6.75	170.58
Ucayali	Coronel Portillo	Calleria	5792	0.06	-5409413	-4636510	-2028384	579743	-933.95	-800.5	-350.2	100.09
Ucayali	Coronel Portillo	Campoverde	9624	0.12	-4027475	-3463628	-1772089	-80549	-418.48	-359.89	-184.13	-8.37
Ucayali	Coronel Portillo	Iparia	10328	0.34	-5246322	-4497200	-1976014	545173	-507.97	-435.44	-191.33	52.79
Ucayali	Coronel Portillo	Manantay	1985	0.1	-914860	-869852	-401027	67798	-460.89	-438.21	-202.03	34.16
Ucayali	Coronel Portillo	Masisea	7740	0.33	-4517570	-3856662	-1276738	1303186	-583.67	-498.28	-164.95	168.37
Ucayali	Coronel Portillo	Nueva Requena	2680	0.12	-6170204	-5304491	-2673432	-42374	-2302.3	-1979.3	-997.55	-15.81
Ucayali	Coronel Portillo	Yarinacocha	4857	0.08	-685255	-589288	-300822	-12355	-141.09	-121.33	-61.94	-2.54
Ucayali	Padre Abad	Alexander Von Humboldt	1283	0.13	-288080	-248906	-127347	-5789	-224.54	-194	-99.26	-4.51
Ucayali	Padre Abad	Curimana	4124	0.09	-10737032	-9237759	-4705109	-172458	-2603.6	-2240	-1140.9	-41.82
Ucayali	Padre Abad	Irazola	3761	0.13	-10931798	-9964327	-5081638	-198949	-2906.6	-2649.4	-1351.1	-52.9
Ucayali	Padre Abad	Neshuya	3873	0.12	-3643170	-3155168	-1614272	-73376	-940.66	-814.66	-416.8	-18.95
Ucayali	Padre Abad	Padre Abad	6398	0.09	-11122319	-9722154	-4912955	-103755	-1738.4	-1519.6	-767.89	-16.22
Ucayali	Purus	Purus	2860	0.32	0	15273	335995	656718	0	5.34	117.48	229.62

Note: columns a, b, c, and d correspond, respectively, to scenarios: a) Fine = 5,000 soles/ha, PES = 0; b) Fine = 4,300 soles/ha, PES = 100 soles/ha; c) Fine = PES = 2,200 soles/ha; and d) Fine = 100 soles/ha, PES = 4,300 soles/ha.

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