

THE EFFECTIVENESS OF PROTECTED AREA FUNDING FOR
FOREST CONSERVATION AND HUMAN DEVELOPMENT
IN THE PERUVIAN AMAZON

BY

KATIA SOFIA NAKAMURA LAM

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Natural Resources and Environmental Sciences
in the Graduate College of the
University of Illinois Urbana-Champaign, 2022

Urbana, Illinois

Doctoral Committee:

Associate Professor Richard Brazee, Chair
Associate Professor Daniel C. Miller, University of Notre Dame, Director of Research
Doctor Anthony Waldron, University of Cambridge
Professor Kathy Baylis, University of California, Santa Barbara

ABSTRACT

Protected areas (PAs) are the most prominent conservation tool worldwide. Considerable evidence shows that PAs, from national parks to Indigenous and community conserved areas, effectively protect forests. However, many PAs do not perform at their highest potential due to inadequate access to financial resources. Studies have assessed the effects of protection, but there are no rigorous quantitative studies on the impacts of PA funding. This dissertation addresses this gap in the literature by estimating the impacts of PA funding on avoided deforestation and human development in the Peruvian Amazon. I developed a framework for estimating the impact of PA funding (Chapter 2), then applied it to quantify the effects of PA funding on avoided deforestation at the district level (Chapter 3) and the grid level (Chapter 5) and on the human development index (HDI) at the district level (Chapter 4). Data derive from a new method for identifying within-country conservation funding flows and a range of publicly available sources. I used quasi-experimental (Chapters 2–3) and machine learning (Chapter 5) approaches to reduce estimation bias. The results show generally positive impacts: PA funding avoided forest loss in the grid-level analysis and increased human development within districts while having mixed effects on forest cover at the district level. However, effect sizes were small, shaped by baseline forest characteristics and economic activities. Greater population density, Indigenous lands, non-state conservation areas, and mining areas had significant effects human development indicators. Funding avoided forest loss conditional on a number of biophysical and socio-economic factors, including temperature; baseline forest cover; poverty; and distance to towns, pastures, and mining. At the district level, altitude, forest cover outside PAs, and previous deforestation moderated the effect of funding, with higher effects in Andes-Amazon districts, as well as those with more unprotected forest cover and more deforestation before the treatment. Older PAs, PAs allowing sustainable use, and those that are comanaged showed larger impacts. PAs with greater funding and tourism were able to protect more forests. The most effective PAs were in the Amazon-Andes region, where their greater accessibility has made them more vulnerable to deforestation. On average, these PAs were also the most well-funded, receiving I\$1,500–I\$3,000/sq km. The least effective PAs were more remote, located on country borders, and received below-average funding. The findings of this dissertation suggest that investing more funds in PAs can lead to greater positive impacts for biodiversity and human development. However, the same amount of funding may have larger effects conditional on local threat levels. Investments addressing threats from illegal activities in highly accessible areas, promoting tourism, and securing forest-related livelihoods are found to be especially effective pathways to protect forests in the Peruvian Amazon.

ACKNOWLEDGMENTS

I want to express my gratitude to my adviser, Daniel Miller, for supporting and guiding me throughout these years of graduate education. Nobody gave me the space and opportunity to truly explore my professional and academic interests before, and I am deeply grateful for it. I want to thank Kathy Baylis for her patience and guidance on my great exploration of statistical methods. In parallel, Anthony Waldron shaped much of my academic work through his comments and discussions since I started studying conservation funding. Thanks to Richard Brazee for your openness and willingness to participate in my committee even when this topic was unfamiliar, making your comments and discussions even more valuable. You all have contributed to my intellectual growth in this field and taught me a world.

Through our small research lab, Miller Research Group, I met great people and minds. I am very grateful to have had the opportunity to get comments and meaningful discussions with Pushpendra Rana, Jennifer Zavaleta Cheek, Sarah Castle, Sonia Padonou, and Dikshya Devkota. Also, conversations with Johanna Eklund and J.T. Erbaugh helped clarify some ideas and technical difficulties along the road. Having the Scholarly Commons statistical consultation team at UIUC was of great support.

A great deal of my data collection and field research was possible thanks to the support and interest of Marco Arenas. He facilitated my visits to SERNANP, pointed me to key contacts, and access to the data. From his team, Elias Valenzuela was a great support. In addition, my trips to Peru would not have been as awesome and effective as they were without the help of my dad, my mom, Tía Momo, and Tiita, who sorted out many logistical issues for and with me. While they might not know what I do, they fully support my actions. For that and much more, I love them.

This dissertation would not have been possible without the financial support of a Fulbright grant, which allowed me to start my graduate studies at the University of Illinois. I am thankful to the MacArthur Foundation and the USDA Hatch program for providing me with a research assistant position that supported my graduate study. I enjoyed working on those research projects and learned so much. My fieldwork in Peru would not have been possible without the financial support of the ACES Graduate Student International Research Grant, the Tinker Foundation Field Summer Fellowship, and the Whitten Research Fellowship from the Center for Latin American and Caribbean Studies. Also, thanks to the NRES Educational Opportunity Travel Grant and the Jack and Anne Miller Scholarship to help me attend conferences in Colombia and Peru, where I shared my research and expanded my professional network.

Last and most importantly, I want to thank my husband Danil for joining me on this journey. Without his constant encouragement, emotional support, and intellectual nourishment, I wouldn't have made it. Now that "we" became three, we are stronger and happier than we ever imagined. Having Ryo in our lives turned all our life's priorities. I've devoted my daily energy to him over these past seven months, and in return, he has given me the strength I needed to finally push this dissertation out in the benefit of our collective interests. You both are my world, and I am blessed to have you in my life.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

The establishment of protected areas (PAs) expanded rapidly in the first decades of the twenty-first century, becoming the most common strategy used worldwide to protect nature (Watson et al. 2014; UNEP-WCMC 2022). Given their success, many countries signed the Convention on Biological Diversity (CBD), promising to protect at least 17% of their territory by the year 2020 (Convention on Biological Diversity 2011), with a new proposed target of protecting 30% by the year 2030 (Dinerstein et al. 2019; Waldron et al. 2020). Nonetheless, setting land and sea aside is not enough to protect nature because it also requires effective management to enforce the envisioned conservation targets. Global assessments have found that less than half of the world's PAs are effectively managed, and many do not achieve their basic objectives (Watson et al. 2014; Geldmann et al., 2018). A critical reason for this poor performance is not having enough resources to effectively manage the areas, especially in developing countries (Bruner et al. 2001; Gill et al., 2017; Waldron et al. 2017).

Conservation funding can be used to proxy for the capacity of resources available to manage a national park or other protected area as financial support – for staff to enable law enforcement and protection; build and maintain infrastructures such as roads, guard posts, and demarcation signs; purchase needed supplies such as uniforms, machetes, and binoculars, among many other needs – is required to establish and maintain them. In Australia, for example, PAs with adequate funding were found to have removed threats to almost all species, maximizing protection and resources (Kearney et al. 2020). Previous research has found funding to be a significant predictor of biodiversity outcomes worldwide (Waldron et al. 2017). Having resources for specifically for PA management and capacity development has been positively associated with changes in PA species populations (Geldmann et al. 2018). To achieve cost-effective allocation of funds there is a need for reliable information on conservation costs for specific interventions and their benefits (Cook et al. 2017; Iacona et al., 2018). However, conservation finance data are scarce mainly due to the lack of reliable financial datasets (Castro and Locker 2000; Naidoo et al. 2006; Nakamura 2017), impeding effective allocation of limited funds (McCarthy et al. 2012; Deutz et al. 2020).

To determine the effectiveness of PAs, researchers have used a range of quantitative impact evaluation (IE) methods (Baylis et al. 2015; Schleicher et al. 2019). The IE literature on PAs has focused on the impact of protection (e.g., Andam et al. 2008; Sims 2010; Miranda et al. 2015) or PA governance type (Nolte et al. 2013; Schleicher et al. 2017) but has not evaluated the impact of conservation investment

levels (Miller and Nakamura 2018). Funding has been recognized as a key factor for effective outcomes (Blackman et al. 2015; Pressey et al. 2015; Gill et al. 2017), but lack of access to reliable, spatially explicit funding data inhibits analysis as well as actual funding allocation decision-making (Pressey et al. 2015; Nakamura 2017). Management inputs, such as funding, can be measured as the means to implement conservation actions, leading to outputs and impacts. For example, evidence from the Peruvian Amazon suggests a weak correlation between management inputs and forest loss and degradation between 2006 and 2011 (Schleicher et al. 2019). Over the past decade, the standard approach has been to use matching methods and regression analysis in a quasi-experimental research design (Miller and Nakamura 2018; Börner et al. 2020). However, other recently developed methods in machine learning may uncover more accurate impact estimation for observational studies (Athey and Wager 2019; Rana and Miller 2019).

Historically, PAs were primarily created to protect wildlife and natural features in areas that seemed to have relatively little potential for economic use (Watson et al. 2014). However, the establishment of Yellowstone National Park in 1872 helped set a new example for protected areas for public use and tourism worldwide (Enkerlin-Hoeflich and Beissinger 2017). The popularization and growth of PAs increased their effects on local communities whose livelihoods depended on the protected resources, affecting in many cases their needs, leading to conflicts comparable to the effects induced by development projects (Agrawal and Redford 2009). By the 1930s, every country developed its own approach to PA management as there were no international guidelines for systematic management; hence there was no common language, consistency, or comparability between PAs (Dudley 2008). In 1978, the International Union for Conservation of Nature (IUCN) Commission on National Parks and Protected Areas developed a categories system for PAs, recognizing a “multiple-use management area” beyond strict PAs to accommodate the different management needs worldwide (Dudley 2008). This new category helped address the lack of integration of conservation and social needs such as poverty reduction and development. The current list includes six categories based on their management objectives, classified in two broad types: strictly protected areas and sustainable-use areas (Dudley 2008). In addition, there is further recognition that other conservation areas outside PAs such as community, indigenous, private, government, and shared governance arrangements are also effective for in situ biodiversity conservation (IUCN-WCPA Task Force on OECMs 2019).

Given the social and ecological nature of contemporary PAs, evaluation of their effectiveness needs to consider both of these aspects. Mainstreaming of biodiversity into development goals attracted and increased conservation investments following the policy discourse (Redford et al. 2015). After 1992, with the creation of the Global Environmental Facility, overall biodiversity conservation funding

increased, with almost three-quarters of the total amount assigned to investments that included conservation and development components (Miller 2014). This trend necessitated evaluators to address both outcomes in assessing PA effectiveness.

1.2 Literature review

There is strong evidence that terrestrial PAs conserve forests. The literature measuring the effectiveness of PAs on deforestation showed positive effects in Ecuador (Cuenca et al. 2016), Thailand (Liu et al. 2022), Costa Rica (Andam et al. 2008), Brazil (Nolte et al. 2013; Pfaff et al. 2015), Bolivia (Hanauer and Canavire-Bacarreza 2015), Madagascar (Eklund et al. 2016), Guatemala, Honduras, El Salvador (Muñoz Brenes et al. 2018), and Peru (Miranda et al. 2015; Schleicher et al. 2017) when using protection as treatment compared to unprotected land. Within this body of literature, authors explored the different aspects of PA governance, expecting different effects based on their rights and management. The definition of governance and the classification used in existing studies varies. When classifying PA governance by type of land-use regimes, PAs with strict protection have been more effective in avoiding forest loss under any level of pressure and indigenous lands were particularly effective in areas with high pressure (Nolte et al. 2013). A different study, based on PA management institution type, classified regimes in state-managed PAs, conservation concessions, and indigenous territories, showing they were all effective in avoiding deforestation and forest degradation. Still, on average, conservation concessions managed by private companies were the most effective of the three (Schleicher et al. 2017).

Additionally, other important factors explored were years of establishment in the Peruvian Amazon, where older PAs (funded before 1990) with sustainable use regimes showed to be effective in avoiding deforestation (Miranda et al. 2015). When looking closer at the measures of threat, deforestation shows heterogeneous effects based on the distance to a city (Hanauer and Canavire-Bacarreza 2015; Pfaff et al. 2015), the slope (Hanauer and Canavire-Bacarreza 2015), the distance to roads, the distance to the forest edge, and the subregion (Pfaff et al. 2015). The variation found on the interactions of factors with the treatment indicates there is more to be learned beyond the average treatment effects (Shah and Baylis 2015).

Regarding socioeconomic outcomes, consensus on the impacts of forests and other terrestrial protected areas remains elusive, with mixed impacts found (Pullin et al. 2013). Quantitative country case studies have shown that PAs reduced poverty in Thailand (Andam et al. 2010; Sims 2010), Costa Rica (Andam et al. 2010), Bolivia (Hanauer and Canavire-Bacarreza 2015), and Nepal (den Braber et al. 2018).

In contrast, no significant effect was found in Peru (Miranda et al. 2015). A systematic literature review found positive effects of being close to PAs for resource use, such as higher consumption of fish and meat, poverty reduction, economic benefits from tourism, mixed impacts in social capital, and adverse health outcomes in terms of higher exposure to disease, human-wildlife conflict and women's security (Pullin et al. 2013). The most common quantitative measures for socioeconomic outcomes in the literature to date are poverty (Andam et al. 2010; Sims 2010; Canavire-Bacarreza and Hanauer 2013; Miranda et al. 2015; Puri et al. 2016), income per capita (Miranda et al. 2015, Puri et al. 2016), and consumption per capita (Sims 2010; Miranda et al. 2015). Mechanisms have not yet been thoroughly described for poverty reduction observed, but available research suggests, for example, that nature-based tourism has played a role in reducing poverty. In Costa Rica, poverty reduction happen only when tourism is present, but not otherwise (Ferraro and Hanauer 2014), and living close to a national park entrance increases people's wages (Robalino and Villalobos 2015). A similar finding in Nepal showed tourism reduced poverty and extreme poverty without affecting inequality (den Braber et al. 2018). When observing PAs use, sustainable-use PAs were more likely to report positive socioeconomic outcomes than strict-use PAs. Generally, PAs with positive conservation impacts also showed positive livelihood outcomes (Oldekop et al. 2016). A review on the effects of PAs on well-being in the developing world found that populations living close to PAs with tourism had higher wealth levels and reduced likelihood of poverty, and children closer to multiple use PAs with tourism had better development measures than populations living further away (Naidoo et al. 2019). Beyond tourism, there is a general lack of understanding about the mechanisms and different impacts of conservation interventions in relation to social outcomes, but this literature is increasing along with study of the trade-offs between social and environmental impacts from PAs (Woodhouse et al. 2018).

1.3 Focus of this dissertation

This dissertation seeks to address current research gaps and advance knowledge of the social-ecological impacts of PAs by focusing on the key issue of funding for PAs and the potential pathways through which such funding might generate impacts. Focusing on the case of the Peruvian Amazon, I addresses the following research questions:

1. Have investments in protected areas in the Peruvian Amazon avoided forest loss?
2. Have investments in protected areas positively affected human development in the Peruvian Amazon?
3. What is the magnitude of these effects, if any?

4. What biophysical and socio-economic factors condition these impacts and how?

This dissertation examines the impacts of funding allocated to PAs in Peru from two perspectives. The first one looks to identify the ecological impacts of funding on forest loss, comparing protected funded areas to the unprotected landscape. Forest loss is one of the major undesirable impacts of human activities on tropical forests like the Peruvian Amazon. Learning about the relationship of deforestation to PA funding will help decision-makers better understand and effectively allocate the available funds to avoid forest loss. This analysis was done using different statistical methods and units of analysis in Chapters 3 and 5. The second perspective is the impacts on social outcomes, addressed in Chapter 4. I used the human development index (HDI), a multidimensional index composed of three components: monetary, health, and education. I analyzed the effects of PA funding on HDI and income to estimate the change in effect on human development and found that income was the component most likely to be affected. The ecological and social impacts of funding were moderated by environmental and socioeconomic factors that determine the magnitude of the impact. In Chapter 6, I summarized the overall results and concluded. The results will help inform the Peruvian PA system managers and decision-makers to make the most of PAs' financial assets based on scientific evidence. Learning from the impacts of previous investments, we can aim toward a more effective allocation of PA funds targeted by the sustainable financing initiative to make the most of every dollar invested.

This dissertation begins with a chapter (2) that provides a more extensive review of the literature to build and then demonstrate a theory of change for analyzing the impacts of PA funding. The three chapters that follow it analyze the impact of PA funding in the Peruvian Amazon. Chapter 3 evaluates the effect of PAs and their funding on forest loss and chapter 4 estimates the impact of PA funding on HDI, both at the district level. Chapter 5 estimates the effect of PAs and the change in effect when controlling for PA funding using a grid-level analysis. Chapter 6 concludes by summarizing the main findings across these chapters and drawing out their implications for future research and policy.

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CHAPTER 2: A FRAMEWORK FOR QUANTITATIVE ASSESSMENT OF THE SOCIAL-ECOLOGICAL IMPACTS OF PROTECTED AREA FUNDING

2.1 Introduction

Millions of dollars are invested in conservation annually to protect biodiversity. A significant portion of these funds is spent establishing and managing protected areas (PAs) and designing and developing related projects to achieve conservation goals (Waldron et al. 2020). Conservation investments have been found to reduce the rate of biodiversity loss at the country level, though this effect diminished as human development pressures, such as GDP growth and agricultural expansion, increased (Waldron et al. 2017). However, rigorous evidence on the impacts of PA and other conservation funding within countries remains scarce, and the current literature provides little theory to guide the needed in-country analysis. Such theory and a framework for analysis is sorely needed as countries seek to support the establishment and management of PAs to achieve post-2020 area-based conservation goals. A clear analytical framework is especially relevant for tropical low- and middle-income countries where most of the world's biodiversity is found, and poverty and human development are major social concerns (Fisher and Christopher 2007; Sachs et al. 2009).

Causal models and analytical frameworks are critical tools for generating credible quantitative evidence on conservation and other policy impacts (Ostrom 2011; Cheng et al. 2020). These tools provide a means to identify and conceptualize the relationships between inputs, outcomes, and impacts. They also enable an analysis of the conditions and factors that may affect a given policy intervention (treatment), the mechanisms through which it may generate impacts, and its outcomes. These conditions and factors include potential confounders, which should be specified a priori in modeling causal processes (Ferraro and Hanauer 2015). Statistical impact estimation requires accounting for the variables of selection into treatment and confounders that may affect the treatment's performance. Including these covariates in the analysis is necessary to eliminate rival explanations for a more accurate impact assessment (Ferraro and Pattanayak, 2006). A strong research design addressing rival explanations and hidden biases is crucial for obtaining reliable evidence (Ferraro and Hanauer 2014).

In the case of PAs, regular investments are needed to support implementation of management plans. Funding is the most relevant input for PA management, which determines and constrains the implementation of management and influences its impacts (Pressey et al. 2015; Geldmann et al. 2018). Expenditures on infrastructure, hiring and training staff, materials, community outreach, and other items turn plans into actions on the ground to actively manage and protect a PA. Together, funded conservation

efforts are expected to lead to direct, measurable outcomes such as fewer trees logged in an area or a larger population of birds. Some PAs may also have explicit human development objectives, such as increased income or improved health (Pullin et al. 2013; McKinnon et al. 2016). While each PA is likely to tailor desired outcomes according to its context and management interests, larger amounts of funds spent on conservation actions are, on average, expected to yield more effective outcomes (Coad et al. 2019; Waldron et al. 2017; Gill et al. 2017). And those PAs resulting in more positive socioeconomic outcomes are also expected to see more positive effects on biodiversity (Oldekop et al. 2016).

This chapter develops a framework to analyze PA investments using a causal model and demonstrates its utility through a case study of the Peruvian Amazon. The following sections describe the relevant pieces of the framework: the treatment, outcomes, mechanisms, moderators, and potential confounders. The relevance and implications of the different scales and units of analysis chosen are also discussed. The application of this framework allows testing the effects of PAs, quantifying the impacts of PA spending, and identifying the mechanisms and moderators shaping outcomes at different spatio-temporal scales in contexts across the globe. Studies using this framework are needed to help advance knowledge of the social-ecological impacts of protected areas generally and funding for them specifically as well as inform more efficient, effective, and equitable funding allocation in the future.

2.2 Protected area funding as a treatment

The first element to consider in a framework to analyze the impact of funding for protected areas is the specific policy intervention put in place—*treatment* in the program evaluation literature (Abadie and Cattaneo 2018). Importantly, the case of PA spending includes two treatments: (1) action to conserve species and ecosystems in a geographically bounded area—protected and conserved areas (section 2.2.1), and (2), the actual funds spent (section 2.2.2). The framework and theory of change (TOC) undergirding it must start with clearly defining these treatments, which can take multiple forms in practice.

2.2.1 Protected and conserved areas

The International Union for Conservation of Nature (IUCN) defines a protected area (PA) as “a clearly defined geographic space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values” (Dudley 2008). PAs are a legal instrument to achieve habitat and species conservation, protect ecological processes at risk that provide natural services to global communities, and preserve indigenous cultures. By 2020, 17% of terrestrial and inland water and 10% of coastal and marine areas were formally

protected (UNEP-WCMC and IUCN 2021), with a proposed international agreement aiming to protect 30% of the planet by 2030 (Dinerstein et al. 2019; Waldron et al. 2020). Effectively managing existing PAs and supporting the establishment of new PAs will require a major influx of funding.

PAs require legal protection, management actions, and inputs supporting their goals to achieve positive impacts. In addition to on-the-ground management, governance is a critical component affecting PA performance (Campese and Sulle 2019). Governance can determine a PA's management style, funding sources, and—critically—the diversity of inputs and interests incorporated in PA decision making (Borrini-Feyerabend 2014; Dawson et al. 2018; Miller and Nakamura 2018). IUCN PA management categories, however imperfect, provide a window into the governance of PAs (Dudley 2008; Miller and Nakamura 2018).

Management of PAs can fall within six management categories (Table 2.1). Each category has a specific primary management objective which should apply to 75% of the area (Dudley 2008). These categories can be grouped into two major groups based on the extent to which they allow direct resource use: strict (Categories I–IV) versus nonstrict or sustainable use PAs (Categories V–VI) (Nelson and Chomitz 2011).

Another way in which PAs are classified is based on the responsible governance authority. There are five such categories: the national state, subnational state actors, private actors, communities (indigenous peoples and local communities), and mixed governance, which includes more than one of these actors (Miller and Nakamura 2018). Historically, most PAs have been created under the first two categories, especially central governments (Miller and Nakamura 2018). Mixed governance is an increasingly popular form of governance, also known as comanagement or collaborative management between a government and nongovernment actors (Lemos and Agrawal 2006; Dudley 2008). Similarly, private PAs and community PAs also known as Indigenous and community conserved areas (ICCAs) have grown in recognition and number in recent decades (Berkes 2009; Palfrey et al. 2020; UNEP-WCMC and IUCN 2021). Every governance and management type has strengths and weaknesses, and the determination of which one is more appropriate will depend on the particular context of a given site.

A final relevant conservation category, other effective area-based conservation measures (OECMs), denotes conservation areas beyond PAs, which may or may not have conservation as their primary objective but can deliver in situ conservation (Table 2.1). OECMs exist to recognize the contribution to biodiversity from non-PAs in an international setting (Jonas 2020) through the World Database of Protected Areas (WDPA). They might overlap with other designations, such as ICCAs, which may also be classified as OECMs, if they are not PAs (Jonas 2020).

Table 2.1 IUCN-WCPA classification and definition of protected and conserved areas based on management.

PA	Use	IUCN category	Definition	Source
Protected Areas	Strict use	Category Ia: Strict nature reserve	Strictly protected for biodiversity and also possibly geological/geomorphological features, where human visitation, use, and impacts are controlled and limited to ensure protection of the conservation values.	Dudley (2008)
		Category Ib: Wilderness area	Usually large unmodified or slightly modified areas, retaining their natural character and influence, without permanent or significant human habitation, protected and managed to preserve their natural condition.	
		Category II: National park	Large natural or near-natural areas protecting large-scale ecological processes with characteristic species and ecosystems, which also have environmentally and culturally compatible spiritual, scientific, educational, recreational and visitor opportunities.	
		Category III: Natural monument	Areas set aside to protect a specific natural monument, which can be a landform, sea mount, marine cavern, geological feature such as a cave, or a living feature such as an ancient grove.	
		Category IV: Habitat/species management area	Areas to protect particular species or habitats, where management reflects this priority. Many will need regular, active interventions to meet the needs of particular species or habitats, but this is not a requirement of the category.	
	Sustainable use	Category V: Protected landscape	Where the interaction of people and nature over time has produced a distinct character with significant ecological, biological, cultural, and scenic value, and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values.	
		Category VI: Protected areas with sustainable use of natural resources	Areas which conserve ecosystems together with associated cultural values and traditional natural resource management systems. Generally large, mainly in a natural condition, with a proportion under sustainable natural resource management and where low-level nonindustrial natural resource use compatible with nature conservation is seen as one of the main aims.	
Non-PA		Other effective area-based conservation measures (OECMs)	A geographically defined area other than a Protected Area, which is governed and managed in ways that achieve positive and sustained long-term outcomes for the in situ conservation of biodiversity, with associated ecosystem functions and services and applicable cultural, spiritual, socioeconomic, and other locally relevant values.	IUCN-WCPA Task Force on OECMs (2019)

2.2.2 PA funding and spending

Protected areas have proven to be an effective conservation strategy for protecting forests and species populations and providing ecosystem services to local people (Geldmann et al. 2013; Oldekop et al. 2015; Naidoo et al. 2019). Delivering these outcomes requires financial investment. At a basic level, funding for PAs supports conservation actions and these actions cost money. PA costs within a given country usually fall within three categories: recurrent management costs for existing areas, systemwide expenses to support the PA network, and costs of bringing new areas into the system (Bruner et al. 2004). Key examples of the wide range of specific costs include: hiring, training and equipping PA personnel, such as guards; infrastructure, such as roads and guard stations; equipment, such as GPS, machetes, uniforms, binoculars; transportation, such as vehicles and gas. In addition, funded development-oriented projects may not contribute to management costs as they can have their own agenda and activities, particularly when funded by bilateral and multilateral aid agencies (Bruner et al. 2004).

Lack of financial resources is a major bottleneck for conservation actions (Gill et al. 2017; Coad et al. 2019; Börner et al. 2020). With many actions to achieve and not enough funding available, there is a need to prioritize the areas and actions that should receive more attention and financial resources (Flores et al. 2008). The amount of funding actually committed to a PA or PA system reflects the willingness of policy makers to protect biodiversity in a given area. However, to analyze the effect of such funding requires care in describing what the funding was actually used for on the ground and determining how much was spent on the outcome of interest. The lack of detail in most spending reports makes it difficult to isolate exact amounts. In addition, many of the conservation actions can affect (positively or negatively) a diversity of goals, making it hard to disentangle the direct and indirect effects of an amount invested for a specific goal. Conservation funding usually targets more than one goal at a time. Further, given the connectedness of species and the environment, protecting one umbrella species will likely benefit other species (Roberge and Angelstam 2004), and the resources they depend on. However, investments targeted toward a main goal are expected to have a proportionally larger effect on the aim intended.

Data on actual spending for PAs, with detail on the actions funded, would be the best indicator for policy efforts on conservation. However, such spending data are scarce and are not typically publicly unavailable. Available datasets include information primarily on committed funding for conservation, which is the amount a donor agreed to provide, rather than the actual expenditure (Nakamura 2017). These datasets often lack detailed information about the location and dates of the investments or the types of actions funded (Castro and Locker 2000; Castro and Riega-Campos 2014; Nakamura 2017).

Furthermore, spatial information on spending within and across PAs is largely unavailable even though evidence shows, for example, the importance of such information for efficient allocation of enforcement (Albers 2010).

These data constraints require certain compromises and assumptions to be made to enable analysis of conservation finance. These include the following, which are widely used in the literature on this topic (e.g. Waldron et al. 2017; Miller et al. 2013; Castro and Riega-Campos 2014). First, committed amount is used as a proxy for expenditure. Second, overall amounts of funding allocated to a PA are used to measure potential conservation actions, on the assumption that more funds allow for more substantial actions and better outcomes. Third, spending is assumed to be allocated unevenly throughout a given PA system or within individual PAs. For example, threats are more likely to be close to PA borders (Plumptre et al. 2014) but patrolling and enforcement of PA borders are not evenly distributed because not all borders are equally attractive for would-be infractors. People tend to extract resources strategically by targeting areas that are easier to access such as those close to roads, rivers, or previously deforested areas to reduce time, energy, and costs (MacDonald 1998; Plumptre et al. 2014). In the absence of spatially explicit PA expenditure data, assuming funds are distributed according to such threats and the PA objectives can allow the use of an adjusted spatially weighted measure of spending. Such a measure would, for example, assume the allocation of more spending to areas where deforesting activities are expected. These general assumptions would need to be adapted according to data availability and within-country contextual factors.

Based on the unit of analysis chosen, there are additional decisions to be made when making assumptions about the spatial allocation of funding. Different scales pertain to a whole PA system, an individual PA, subnational units such as a district or community, and pixel or grid levels. Each unit has different contextual factors and risks, requiring adjustments in assumptions for how spending might be allocated. Using a variety of different allocation methods can help to make causal inferences about the impact of funding more robust. If different methods yield varying results, then consideration of why the different approaches may have led to the variation found may give further guidance into the relationship between spending and outcomes.

2.2.3 Bias in treatment allocation

PAs and spending for them are not allocated at random, which means that allocation preferences can bias estimation of treatment effects. Analysis should account for the characteristics that determined a unit's selection into the treatment to reduce rival explanations (Ferraro and Hanauer 2014). In the case of PA siting, some PAs have been shown to be placed in remote areas, on land without much value, so as

to fulfill established international agreements while limiting costs to development (Joppa and Pfaff 2009). Studies have accounted for potential sources of bias such as elevation, slope, agricultural suitability, and distance to roads and cities as well as other context-dependent characteristics related to threats such as previous high levels of deforestation (Joppa and Pfaff 2009; Hanauer and Canavire-Bacarreza 2015).

In addition, PA spending is commonly driven by donor interests, which can include both socio-economic and conservation priorities (Bruner et al. 2004; Miller 2014). For example, areas with a higher risk of habitat degradation and land-use change may attract larger amounts of funds. The presence of endemic species with declining population trends or species with increased threat levels may also lead to greater funding. Similarly, PAs in contexts with higher shares of poverty and opportunities for development may also be more likely to attract more funding.

2.3 Social-ecological outcomes

PA establishment and management can have a range of different effects on nature and people. Identifying outcomes of interest, including based on the stated objective(s) of a given PA or PA system, is a critical step in constructing a theory of change linking PA funding to ultimate impacts. The outcome(s) of choice and the specific variables and measurements used will affect the way the analyst estimates and defines the size of the impacts. The choice of outcomes will reflect the interest of the analyst as well as data availability.

2.3.1 Ecological outcomes

PAs have historically been set up with a primary objective of nature conservation, an ecological outcome (Adams 2004; Watson et al. 2014). A wide range of potential ecological indicators exist at different levels (e.g., species, population, ecosystem) to measure the effectiveness of PAs and PA funding in both marine and terrestrial realms (Parrish et al. 2003; Mascia et al. 2017; Ghoddousi et al. 2022). In the literature on PA impacts, the most used outcome to evaluate ecological impacts is forest cover change (Börner et al. 2020), due to the pressing need and interest in protecting forests and the widespread availability of remotely sensed data covering the earth's surface (Hansen et al. 2013). Other variables used to indicate ecological change are species population trends (Geldmann et al. 2018), change in threatened species classification (Waldron et al. 2017), forest degradation (Rouget et al. 2006; Schleicher et al. 2017), change in forest fires (Nelson and Chomitz 2011; Nolte and Agrawal 2013), and amount of carbon emissions (Bebber and Butt 2017).

2.3.2 Social outcomes

PAs—and the funding that supports them—may generate a wide array of social outcomes. Generally, they relate to various dimensions of human well-being—particularly of those living in or near the PA or visiting it—and equity, given the differential effects PA interventions can have (Pullin et al. 2013; McKinnon et al. 2016; Ghoddousi et al. 2022). Despite the range of potential social outcomes that might be measured, income and assets are the dominant social outcomes analyzed in the literature (de Lange et al. 2016). This reflects, in part, a strong international policy interest in knowing the effects of PAs on changes in poverty, extreme poverty, and multidimensional poverty, particularly in the context of the Sustainable Development Goals (United Nations 2015).

Other less common but increasingly used social outcomes reflect nonmaterial social qualities such as well-being, inequality, human development, education, health, cultural resilience, attitudes, and justice (Pullin et al. 2013; Oldekop et al. 2016; Woodhouse et al. 2018). Nonmaterial indicators such as well-being are measured objectively or subjectively (Lee Kum Sheung Center for Health and Happiness 2017). The objective measures of well-being tend to be characterized by higher educational attainment, safe neighborhoods, and economic stability, reflecting social rather than individual perspectives. In contrast, subjective measures capture the individual’s cognitive and affective reactions.

2.4 Mechanisms

Understanding the mechanisms through which the treatment leads to impacts matters for future planning of effective investments. Identifying the actions that lead to positive or negative impacts within the framework will support or avoid these key actions to achieve the largest benefits and evaluate the potential trade-offs. A mechanism is an intermediate outcome in a causal pathway. That is, once it is affected by the treatment, it may cause the outcome of interest (Ferraro and Hanauer 2015). Potential mechanisms related to PA spending are improved ecosystem services leading to better health outcomes through increased monitoring and patrolling that avoided deforestation, secured clean water supply, and provided better health to local communities (Woodhouse et al. 2018). Investment in tourism infrastructure increased the quality of services offered and the number of visitors connected to local services, increasing income (Ferraro and Hanauer 2014; den Braber et al. 2018). PAs with increased wildlife populations can directly affect people’s livestock and physical health through “human-wildlife conflicts” (Pullin et al. 2013; Woodhouse et al. 2018). Some actions can have both positive and negative consequences for ecological and social contexts.

2.5 Moderators

Moderators create a conditionality of a treatment effect. In a causal model, there are characteristics independent of the treatment allocation and the outcome that may affect the performance of a treatment, affecting the direction and size of an effect (Ferraro and Hanauer 2014). For PA spending, characteristics such as governance type (Nolte et al. 2013; Oldekop et al. 2016; Schleicher et al. 2017), IUCN management category (Oldekop et al. 2016; den Braber et al. 2018), and age of a PA (Ferraro et al. 2011; Miranda et al. 2015) were shown to affect PA protection. These variables may also affect the performance of PA spending.

Management and governance characteristics affect the way money is spent. PAs' priorities differ between strict use and sustainable use PAs because they apply different strategies and actions to conserve the area. Their effects will also depend on other variables such as management quality. In locations with more population and economic activity, for example, we might expect sustainable use management to work better than strict management because collaboration with local communities and extractive enterprises may lead to more positive outcomes (Oldekop et al. 2016).

A PA with state governance may have more strict spending plans than a private PA or a comanaged area with a nongovernmental organization (NGO), where there is more flexibility using budgets. With more adaptive spending, actions can be guided toward on-the-ground evidence, needs, and learning processes rather than strictly planned management activities. Adaptive management is expected to encourage better outcomes over time (Stankey et al. 2005).

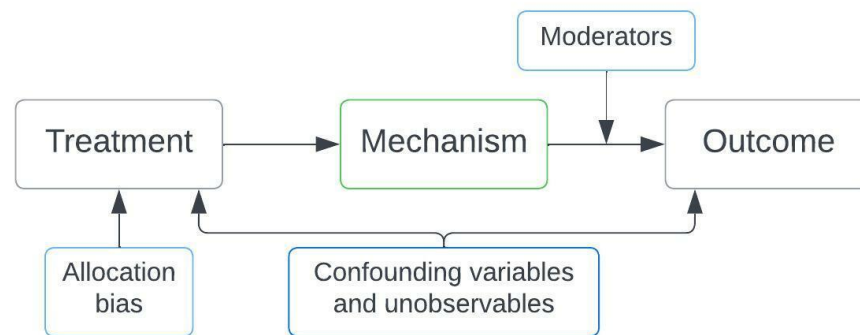
Older PAs may be more effective using their funds because they already have an established working culture and are familiar with the area and its threats. Younger PAs are expected to be less effective with spending. Also, the size of a PA influences the effectiveness of spending. Large and small PAs have different patterns of spending. Small PAs require more dollars per square kilometer for management than large ones (Bruner et al. 2004), affecting the size of the effect per dollar spent. Assuming a similar level of threat and characteristics, a dollar invested in a small PA will have a lower effect than a large one, making them less cost-effective. These are common moderators found in the literature, but researchers need to adapt moderators to the context of each study location.

2.6 Potential confounding factors

Confounding factors indicate a lack of independence between the treatment and the potential outcomes (Abadie and Cattaneo 2018). They are those variables “that jointly affect the treatment, mechanisms, and outcomes, and may mimic or mask the impacts of treatment” (Ferraro and Hanauer

2015, p. 3). Identifying the confounders will help reduce the possibility of estimating effects that should not be attributed to the treatment. There are two types of confounders: those that are potentially observed and those that are unobserved (Ferraro and Hanauer 2014) (Figure 2.1). This chain of events is guided by the goal for which the funds were originally spent.

Figure 2.1 A directed graph showing the causal link between the different elements in a causal model. The arrow indicates a causal effect. Own elaboration based on Figure 1 from Ferraro and Hanauer (2014).



2.6.1 Observed confounders

These observed variables affect the relationship between treatment and outcome but are not part of the evaluation. For PA spending, biophysical variables such as temperature, altitude, slope, rain, ecoregion, and agricultural suitability may confound the performance of funds in avoiding deforestation because biophysical variables determine the ecological conditions of a forest. Donors tend to fund different ecosystem types, and deforestation dynamics are not the same in high-altitude and low-altitude forests, or in dry and humid forests. Another type of confounder is socioeconomic characteristics. PAs closer to towns, roads, or areas with economic activities take on higher risks of habitat degradation, land conversion, and species populations than remote PAs. There is also higher spending on staff, infrastructure, and enforcement with higher risk. PAs vary in size, and larger areas may require more funds overall but smaller amounts per square kilometer (Bruner et al. 2004), potentially confounding the effects. Without considering these characteristics in the analysis of PA spending, the effect size may be biased, leading to unreliable findings.

2.6.2 Unobserved confounders

Potential unobservable confounders are variables that are hard to measure but may confound the effect (Gertler 2016). Having an a priori understanding of these potential variables will help

researchers to interpret the results. Examples of unobservables are motivation, ability, political instability and corruption, cost-benefit estimation of users, preferences, or personal values. Randomization helps with obtaining a balanced sample in terms of observable and unobservable characteristics, and difference-in-differences methods can help control time-invariant unobservables (Gertler 2016).

2.7 Scale dilemmas

Choosing the right scale to analyze PA funding impact has many implications. The choice of unit of analysis varies based on the research question and data availability. Ideally, an analysis of PAs should be done at the PA or PA system level. However, it is hard to apply in practice given the high variability in PA sizes within a network, making it unfeasible to find proper comparable control areas. In the literature on PA impacts, authors opted to use subnational units of analysis such as subdistricts (Sims 2010; den Braber et al. 2018), municipalities (Canavire-Bacarreza and Hanauer 2013), and census tracts (Andam et al. 2008). Working at the subnational unit is usually a choice based on the smallest political unit with available social data. Another option is to scale down the analysis at the grid level and aggregate up to a larger spatial scale like PAs (Miranda et al. 2015; Shah and Baylis 2015; Schleicher et al. 2017).

Each potential scale may provide different insights. Analysis at the subnational level provides a broader scale of impacts, considering leakage effects beyond PA borders and the possible effects of other interventions such as conservation actions in buffer zones and other actions that may confound the effect of PA spending. Comparatively, the grid level analysis offers a local perspective within PAs and is the closest to what it might look like on the ground. Having such a closer look at the data allows the identification of the spatial distribution of impacts and localized threats. However, finding available data at the grid level is often challenging, especially for socioeconomic variables.

An issue with using these two broad types of units of analysis in comparison to using a PA unit is the allocation of the treatment of interest. PA spending is reported at the PA level without further spatial detail on where, within the park, the funds were invested. Conservation actions are spatially bounded, particularly those related to threats such as in areas closer to PA borders and areas with easier access such as roads, paths, and rivers. For example, investment in tourism goes to building infrastructure, training guides, and obtaining logistical support for this activity. Tourism infrastructure is geographically focused, and the expected increase in visitors may have a different effect in that location than everywhere else in the park (Xavier da Silva et al. 2018). Still, it is also expected to have broad benefits at the PA level through indirect effects. Other funds, such as staff salaries, are hard to allocate spatially and

are expected to show overall PA impacts. Without spatially explicit allocated spending, there are a set of assumptions to be made to model the potential distribution of spending for its study (section 2.2.2).

2.8 Case study: The Peruvian Amazon

To illustrate the analytical framework presented in this chapter, I apply it to a case study from the Peruvian Amazon. Specifically, I describe the context of PAs in this study site and then construct a TOC framework to explicitly describe the rationale and expectations of how conservation investments may lead to ecological and social impacts. I illustrate various elements of the framework with data from the case study site.

2.8.1 Context and history of PAs in Peru

In the 1960s, conservation of nature was seen as an unwelcomed foreign concept by many government actors and others in Peru, including the Forestry Service, which focused on agricultural matters (Dourojeanni 2018). Nonetheless, even when there was no explicit reference in Peruvian law to PAs, Peru established its first PA in 1961: Cutervo National Park. The Forestry Service in the Ministry of Agriculture assumed responsibility for its management but lacked staff with relevant experience and budget (Dourojeanni 2018). In 1964, a project funded by the Food and Agriculture Organization (FAO) of the United Nations and the United Nations Development Programme (UNDP) brought foreign experts and professionals to develop professional forestry capacity building and help build the national forestry plan (Dourojeanni 2018). A specialist in PAs and wildlife management, Dr. Pierret, led the first draft of the PA system, considered a representative sample of the country's natural diversity (Dourojeanni 2018). The first definition of national parks in Peruvian legislation appeared in 1963 under the first forestry law (Law No. 14552), followed by an improved law (No. 21147) approved in 1977, with a dedicated chapter to forests and rules for conservation units (Solano 2009; Dourojeanni 2018). This law was the basis for the current law for national protected areas (Law No. 26834), approved in 1997 (Solano 2009; Dourojeanni 2018).

External NGOs took the responsibility to manage and finance many PAs, replacing the government's role due to a lack of interest (Dourojeanni 2018). In the 1980s and early 1990s, amidst terrorism and inflation during the first term of Alan García's presidency, the Peruvian Association for the Conservation of Nature (APECO) and Pronaturaleza channeled foreign resources to manage and maintain conservation toward the established PAs (Dourojeanni 2018). This crucial task slowly transferred to the newly created National Institute of Natural Resources (INRENA) in the 1990s and transferred to the

Peruvian National Park Service (SERNANP) under the Ministry of the Environment, both created in 2008 (Solano 2009).

By 2020, there were 75 PAs under national governance, covering 15.13% of the country's territory (19.5 million hectares) (SERNANP 2022). 21% of the Peruvian Amazon (16.8 million hectares) is dedicated to state PAs. SERNANP directly oversees 57 PAs under the national government's governance (48 established and 9 designated PAs-to-be or *zonas reservadas*), and 18 under comanaged governance (10 with indigenous communities and 8 with NGOs). With such a large area to protect, SERNANP lacks adequate conservation funding to support the system to manage all PAs (Villanueva 2005; Waldron et al. 2013; Casas et al. 2014). Since its inception, the PA system has relied heavily on external financial support for its design, capacity-building development, and management (Flores et al. 2008; Nakamura 2017; Dourojeanni 2018). Now, 60 years after establishing the first park, the PA system still relies on foreign financial support to meet its needs with an estimated 80% of funding deriving from international sources (Flores et al. 2008; Waldron et al. 2013; Nakamura 2017).

Beyond PAs, there are other forms of area-based conservation in Peru. Regional and private conservation areas are not legally established PAs under Peruvian laws but are recognized as "complementary" to the national system by the government (Solano 2009). Conservation concessions are areas that granted management rights to parties that fulfill certain legal, technical, and financial requirements to conserve land identified as a priority by the state (Solano 2009). Their aim is to develop projects related to conservation; prioritize scientific research, environmental education, and protection of the area; and maintain its ecosystem services (MINAGRI and DGFFS 2013). Lastly, indigenous lands are those that have been historically occupied by Indigenous peoples, with many legally recognized by the government through titles. Peru's Indigenous lands are separated into peasant communities (*comunidades campesinas*) and native or Amazonian communities (*comunidades nativas*). I refer to both of them as Indigenous lands throughout this dissertation. In Peru, some, but not all indigenous lands may be classified as ICCAs, and their contribution to biodiversity conservation should be examined on an individual basis. Nonetheless, on average, conservation concessions and Indigenous lands have been shown to be effective in conserving forests, even more than national PAs (Schleicher et al. 2017). In Peru, these areas include 25 regional conservation areas, 143 private conservation areas, 47 conservation concessions, and 5,684 Indigenous territories (MINAM 2017; SERNANP 2022).

From an international perspective, Peruvian private conservation areas are classified as PAs, as reported in the WDPA (UNEP-WCMC 2022) (Table 2.2). However, regional conservation areas, conservation concessions, and indigenous territories are not classified. These de facto effective

conservation areas outside PAs may be considered as OECMs (IUCN-WCPA Task Force on OECMs 2019), but to date they have not been designated in Peru (UNEP-WCMC 2022). Evidence on funding for these different area-based conservation measures is available from a number of sources (compiled and described in Nakamura, 2017), with a negligible amount of the reported funding flows going to other than state PAs. This allows for the assumption that nearly all funding was invested in state PAs.

Table 2.2 Classification and comparison of PAs and non-PAs by use and IUCN management categories, and governance at the international level and the Peruvian context.

Protected status		By use	IUCN category/designation	PA denomination in Peru	Governance type (#)
International	Peru				
Protected areas	Protected areas	Strict use	II National park	National park	State (13), shared (2)
			III Natural monument	National sanctuary, historical sanctuary	State (11)
			IV Habitat/species management area	Wildlife reserve	State (3)
		Sustainable use	V Protected landscape	Landscape reserve, historical sanctuary	State (4)
			VI Protected areas with sustainable use of natural resources	National reserve, community reserve, protected forest, hunting reserve	State (19), shared (14)
			Private PAs (PPAs)	Private conservation areas	Private (143)
Non-PA	Regional conservation areas		Regional conservation areas	Subnational state (25)	
	Conservation concessions	Conservation concessions	Private (47)		
	Indigenous lands	Indigenous lands	Community (5,684)		

2.8.2 Theory of change

The general framework and elements discussed previously enables the development of a more detailed TOC for the hypothesized pathways leading to PA funding impact. Here, I present such a TOC for in case of the Peruvian Amazon (Figure 2.2).

2.8.2.1 The goals of protected areas

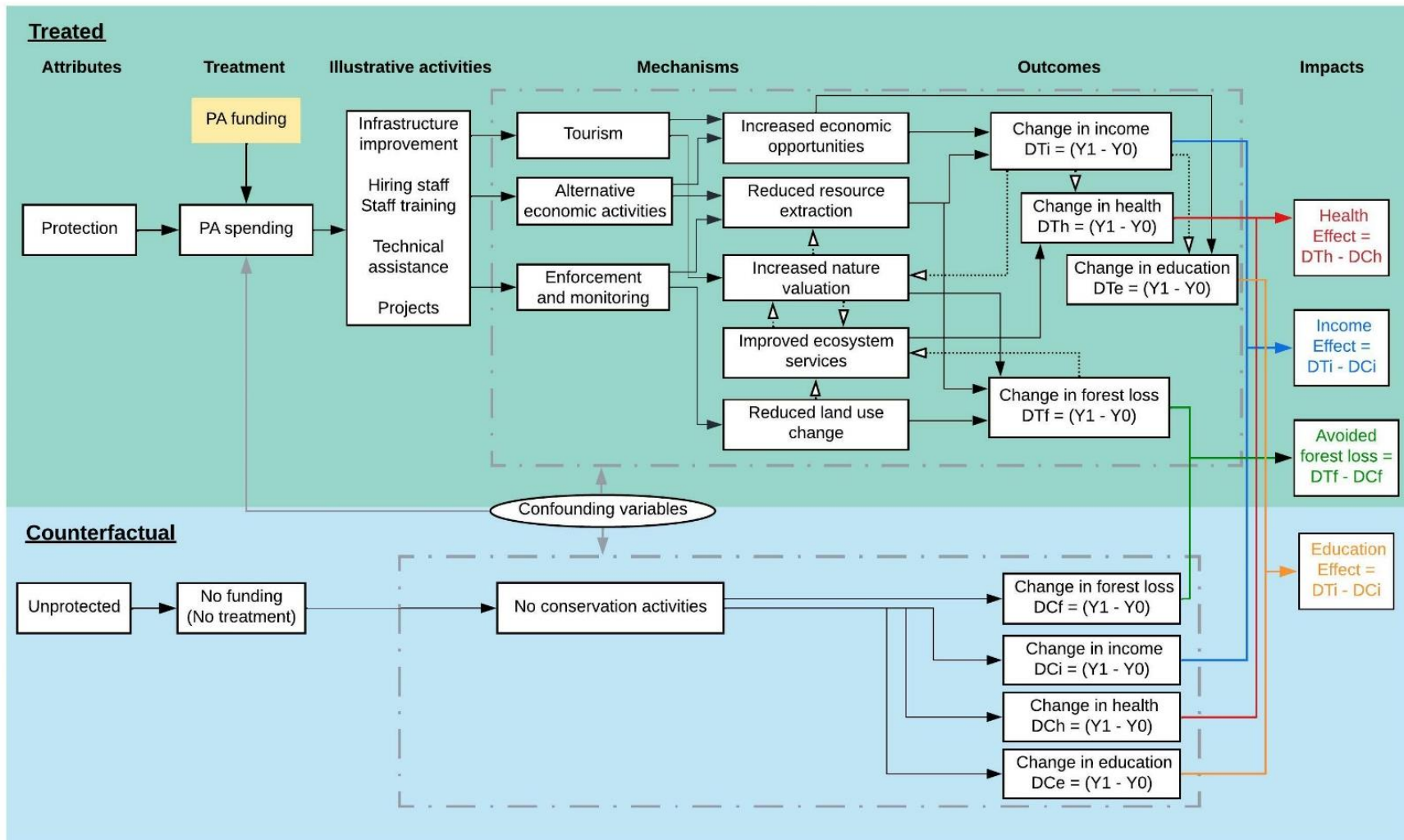
PAs in the Peruvian Amazon are under the management of SERNANP, the state agency in charge of National Parks. The agency's national strategic plan or *Plan Director* from 2009 states that PAs play a role toward sustainability, where conservation of wild habitats is at the center of the strategy, in addition to the protection of landscapes of cultural and natural beauty (SERNANP 2009). PAs are fundamental tools for human development, creating a balance between human well-being and their environment, and part of the solution to alleviate poverty (SERNANP 2009). This strategic plan was in place during the study period.

2.8.2.2 Treatment: Protected areas and spending

I included 29 forested Amazonian PAs under state ownership as treated units. PAs under the responsibility of the state receive the most funding for area-based conservation in the Peruvian Amazon and funding data are available for them (Nakamura 2017). This set of PAs was included in the sample because they had district-level social baseline data, which is relevant for the study of PA impacts. In addition to protection, I used each PA's cumulative funding as a base for allocating the treatment.

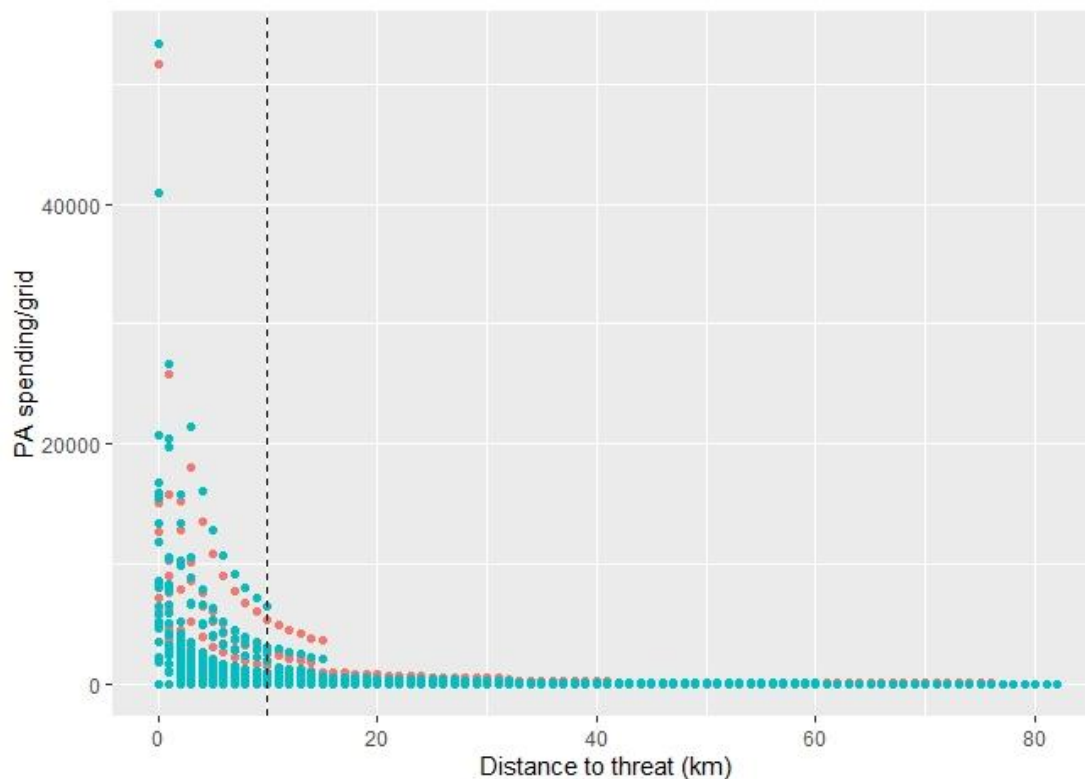
PA funding included data for management costs and projects, excluding network PA costs, from 2009 to 2015. I retrieved the data from SERNANP, the Peruvian International Cooperation Agency (APCI), and other sources detailed in Nakamura (2017). To compile a database with the amount of funding for each PA per year, I followed the methodology I previously developed for mapping biodiversity funding within a country (Nakamura 2017) with two additional steps. The first step was to assign multilocation projects to individual PAs based on the project description, allocating the proportion of funds committed weighted by the area (km²) of each PA and buffer zone when applicable. The second step was dividing the multiyear projects into equal parts per year, assigning them by weighted area to each PA. Then I aggregated all data per PA.

Figure 2.2 Theory of change illustrating how protected area spending may affect ecological and social outcomes in the Peruvian Amazon.



I obtained funding data at the PA level without details on the possible spatial distribution of funds within them. Spending is not equal across space because it faces different needs geographically, so I assumed spending went to areas with a higher risk of deforestation. Previous research in the Peruvian Amazon found that distance to agricultural plots and roads were the main drivers of forest loss, contributing to 77.6% of the information to predict deforestation (Rojas et al. 2021). I estimated risk in two ways. First, I estimated risk as the inverse minimum distance to roads or agricultural plots, giving double weight to areas within less than 1 km (Risk 1). Second, adding to the first strategy, I reduced by half the value of risk to areas above a 10-km threshold to prioritize and redistribute even more spending to riskier areas (Risk 2). I overlapped 1 sq km grids over the Peruvian Amazon and estimated spending by distributing the cumulative amount of funds allocated to each PA weighted by the risk of deforestation per grid. The difference between both strategies does not vary significantly (Figure 2.3). In this dissertation, I aggregated the values per district (Chapters 3 and 4). I also performed analysis at the grid level in Chapter 5, using dollar value allocated per grid as the treatment.

Figure 2.3 Comparison of the allocation of PA spending per grid under two deforestation risk strategies.



Note: Red points reference the first strategy (Risk 1), and green points reference the 10-km threshold strategy (Risk 2). The dashed line indicates the 10-km threshold used in the estimation of Risk 2.

At the country level, the impact of conservation spending has been shown to decrease with increases in human development pressures, which implies that funding would need to be adjusted (most likely increased) to counteract these risks (Waldron et al. 2017). In the case study context, PA spending in Peru was significantly correlated with more deforestation at baseline, higher population density, and a larger number of visitors to the PA, and negatively correlated with the presence of mining concessions within a 10-km radius (Nakamura 2017). These variables reflect a preference of funders toward the promotion of income-generating activities and protection against threats to forest cover. The most significant investments came from projects on reducing emissions from deforestation and forest degradation plus the sustainable management of forests and the conservation and enhancement of forest carbon stocks (REDD+) and tourism (Nakamura 2017).

2.8.2.3 Control: Unprotected areas

As a counterfactual scenario, I used the unprotected landscape (no presence of PAs) as control areas. In addition, I assumed no significant funding present for conserved areas (non-PAs for Peru from Table 2.2). I based this assumption on previous efforts to collect financial data from these locations, finding that direct reporting of the few interviewed accounted for only 0.1% by amount of all collected funding data in Peru (Nakamura, 2017). This small amount may not have a significant impact on conservation, but the legal boundaries of these areas might.

2.8.2.4 Outcomes

2.8.2.4.1 Ecological outcome: Biodiversity

Biodiversity is defined as “The variability among living organisms from all sources including terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are a part. This includes variation in genetic, phenotypic, phylogenetic, and functional attributes, as well as changes in abundance and distribution over time and space within and among species, biological communities and ecosystems” (IPBES n.d.). PAs protect the habitat within their limits through management actions. They limit users from free access and extraction of their resources, protecting the ecosystem and fauna from drastic changes that may affect habitats and populations. PA funds provide the financial support and ability to protect and manage these areas. Without protection, there would be no funding. Without funding, there would be no actions to avoid biodiversity loss. Particularly, funds provide resources to reduce threats such as promoting patrolling to reduce trespassing, illegal extraction, and habitat disturbance. Funds for research and monitoring of species allow having an understanding of the current status and population trends of the main species of interest within an ecosystem. There are many other ways conservation actions can affect biodiversity, and these are just a few illustrations.

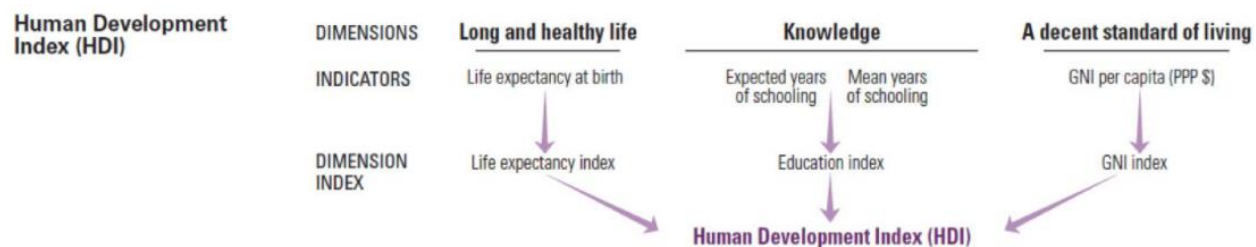
The aim of PAs to conserve nature is broad and can be measured in many ways. Measurable outcomes include a change in a population of birds and mammals, IUCN threatened status change, or habitat loss (Geldmann et al. 2013). I chose to focus on habitat conservation through the change in forest cover as a proxy for change in biodiversity. If forests are preserved, it provides suitable habitats for species populations to thrive. Current satellite forest cover change datasets are accessible and accurate, identifying deforested areas annually at grids with a resolution of 30×30 m (Hansen et al. 2013). A logged tree can be removed overnight and cannot be replaced in less than a year, which will show within the sampled year.

In this dissertation, I used primary forest cover change as the main ecological outcome, with data processed by the Peruvian Ministry of the Environment (MINAM) (GEOBOSQUES 2019). This dataset is based on the global Hansen et al. (2013) dataset with additional local expert correction (Vargas et al. 2014), making it suitable for the Peruvian context. They defined primary forests as “predominant arboreal ecosystem with a surface larger than 0.5 hectares, minimum width of 20 meters, and a minimum canopy cover of 10%. Its predominant vegetation is represented by woody trees with 2 meters tall, at minimum, in the coast and highlands, and 5 meters for the Amazonian rainforest,” and considered secondary forests, agricultural plots, mining areas, and grasslands as nonforest (Vargas et al. 2014). The forest cover change data have a 30×30 m resolution covering the Amazon biome.

2.8.2.4.2 Social outcomes: Human development index, income, education, and health

To capture social change in Peru, I used the human development index (HDI). The UNDP defined human development as “enlarging people’s choices,” aiming to “expand people’s freedoms— the worthwhile capabilities people value— and to empower people to engage actively in development processes on a shared planet. And it seeks to do so in ways that appropriately advance equity, efficiency, sustainability, and other key principles” (Alkire 2010). In 1990, the UNDP developed the HDI as a “measure of achievement in the basic dimensions of human development across countries” (UNDP n.d.). HDI is defined as “A composite index measuring average achievement in three basic dimensions of human development—a long and healthy life, knowledge, and a decent standard of living” (UNDP 2019). It includes three dimensions: income, education, and health (Figure 2.4) (UNDP 2019). The first component measures family income per capita to proxy for the capability to earn income for a basic standard of living. Second, education measures the number of years of instruction for adults aged 25+ years and the rate of high school graduates for ages 18+. Third, it refers to the capability to live a long and healthy life and is measured as the life expectancy at birth.

Figure 2.4 Dimensions and indicators used on the HDI. Source: UNDP (2021).



These data were modeled by the UNDP based on the national census data, household panel data, and other official databases (public services) following the HDI designed by Alkire and Foster (2010) and are representative at the district level (UNDP 2019). The HDI is the geometric mean of normalized indices for each of the three dimensions (Figure 2.4). No studies have used HDI to estimate the social impacts of PAs. In Peru, the regions with higher development are the most unequal, while less developed regions are similar. Higher HDI is associated with a larger share of nonagricultural jobs, while higher poverty is associated with larger shares of agricultural jobs, mostly due to subsistence farming (UNDP 2019).

2.8.2.5 Mechanisms

PAs legally restrict the access and free use of their resources. These restrictions per se may deter infractors, but they do not have real effect unless there is de facto enforcement. PA spending allows hiring permanent staff for patrolling and monitoring, improving infrastructure, developing research projects, and creating organized community involvement. Money spent on enforcement is expected to reduce forest loss and habitat disturbance, leading to an increase in ecosystem services and the protection of species populations. Improved ecosystem services can provide secure access to clean water and air, reduce health issues in local populations (Naidoo et al. 2019), and improve well-being (Woodhouse et al. 2018).

Nonetheless, this same action can have negative consequences on local people's livelihoods, cultural practices, and incomes through physical exclusion (Woodhouse et al. 2018). Improved enforcement can reduce income from restricted resource extraction of wood, nontimber forest products, or land used for agriculture or mining. Nonetheless, PAs with tourism potential attract investments. PAs with tourists may affect populations close to the park entrance and have regional economic effects (Vilela et al. 2018). Tourists visiting PAs tend to stay more than one day, and their expenditure feeds the local and regional economy (Vilela et al. 2018). Also, multilateral and aid agencies invest in alternative resource product initiatives through technical assistance and project development in PAs to change the

unsustainable extraction of resources and boost incomes. REDD+ investments support these alternative economic activities.

There are also positive feedback loops between outcomes and mechanisms in which an outcome feeds a mechanism and positively affects other outcomes. For example, increased income and health through the use of nature can increase the perceived value of nature and reduce habitat degradation and deforestation even without enforcement. In addition, better health and income can lead to more formal education by reducing the number of sick days and the economic burden on families. That way, children can attend more years at school. PAs with many international tourists can motivate children to learn a second language and graduate from high school to work in the tourism industry, potentially increasing education. However, this change may not be significant.

More spending on conservation actions is expected to lead to avoided forest cover loss and improved human development through effective enforcement, improved tourism services, and implementation of development-related projects. I addressed all three components of HDI separately, but overall, PA spending is expected to have a small but positive effect on human development.

2.8.2.6 Moderators

Biophysical and ecological characteristics define the ecosystem. Variables such as altitude, temperature, and rain are highly correlated and define forest types. Forest density depends on these characteristics and the level of human access to the resources through roads and rivers. PA spending, conditional on altitude, may show different effects on deforestation rates. Lower altitude forests (< 500 m) tend to have permanent and denser forest cover than higher altitude forests and are costlier to access due to having reduced road density. Slope may also play a role in which lower slope areas are more likely to be deforested because extraction and access to locations with slopes are riskier and cost more. However, if the land is deforested to grow crops such as coffee (Fleischer 2017) or coca, then higher altitude lands are more favorable than the lowlands.

Threats such as distance to roads and agricultural plots are indicators of land conversion and extraction risk in the Peruvian Amazon (Rojas et al. 2021). The expectation is that the closer a PA is to them, the more likely it will lose forests. Spending may have a larger impact in areas closer to them compared to areas with reduced risk. Another factor that may affect spending on avoided deforestation is having previously deforested areas close by, increasing the likelihood of deforesting happening again. Being closer to non-PA conserved areas may offer a buffer or extended protection to forest cover, when these areas effectively conserve forests. Given prior evidence that most of these conserved areas and

Indigenous lands were, on average, good at protecting forests, I expect their presence would positively affect PAs.

When observing PA characteristics, comparing governance and management type may condition the outcomes. PAs under state governance, compared to comanaged PAs, may affect the way conservation actions are performed. State bureaucracy tends to make plans and budgets more rigid than in an NGO/community setting, which can make management plans and actions adaptable to current needs and expecting an increased effect. Also, older and larger PAs may perform differently. Older PAs should have more experience and know-how to address threats than younger PAs. And larger PAs may need more funding overall but less funding per square kilometer to function than small ones.

2.8.2.7 Confounding variables

2.8.2.7.1 Observable confounders

There are potential confounders of the performance of PA spending on deforestation and human development from ecological, socioeconomic, and biophysical characteristics, as well as risk levels based on threats, the management and PA characteristics, and the presence of conserved areas that may affect the outcomes. Based on a review of the literature and my experience on-the-ground in the Peruvian Amazon, I identify 24 potential confounders for PA spending, describe their potential relationships with the treatment and outcomes, and list sources of data for each (Table 2.3). These variables need to be chosen and adjusted based on the unit of analysis, such as district versus grid level. In the case of districts, for example, distance to an attribute cannot be used in analysis, but density or district share can be. Another challenge for district-level analysis is categorical values, like agricultural suitability or ecoregion, which cannot easily be assigned to a district as many of their categories overlap in one unit, forcing to chose category with most coverage, if it makes sense.

I show the relationship between PA spending and the most relevant confounders found in the literature in Figure 2.5. I sampled the variables of PA spending, PA area, forest cover (% PA in 2009), forest loss (% PA 2008), and tourism (# tourists) at the PA level. Cumulative spending is also expected to be larger in older PAs. However, a set of PA characteristics such as the PA share of pretreatment forest loss and baseline forest cover, population density, PA area, number of tourists, and the presence of strict protection explained partially cumulative spending, and adding the number of years protected did not add a statistically significant improvement. Residual-residual plots of PA age and threat variables such as distance to agricultural plots (AgPlot), roads, rivers, mining concessions, and indigenous lands were sampled to estimate the minimum distance at the grid level (1 sq km) and aggregated at the mean per PA. As expected, larger PAs had more allocated funds ($r = 0.51$, p -value < 0.05 in Figure 2.5), and size was

positively correlated with increased distance to threats such as agricultural plots, roads, and indigenous lands because access to the core area in large PAs is harder, for which reason PA size needs to be included in statistical analysis. PAs spent more funds when they were farther away from Indigenous lands ($r = 0.47$, $p\text{-value} < 0.05$). PA spending as dependent variable regressed on this set of PA characteristics show the nonsignificant and slightly positive relationship ($r = 0.34$, $p\text{-value} = 0.08$) (Figure 2.6).

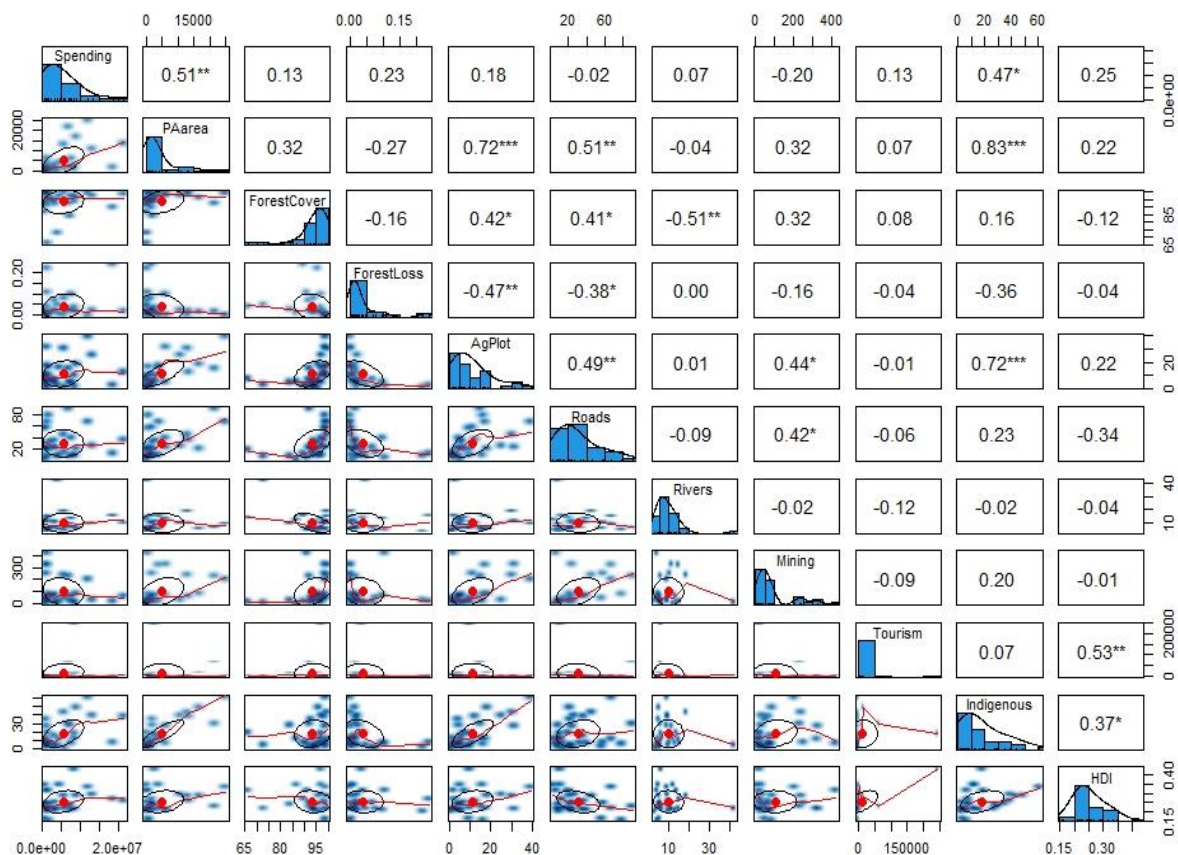
Table 2.3 Counterfactual variables and their relationships to PA spending, and the ecological and social outcomes in the Peruvian Amazon.

Variable	Unit	Relationship to treatment and outcomes	Years	Data source
Biophysical characteristics				
Altitude (mean)	Meters	Altitude affects the level of threat. Higher altitudes reduce the risk of deforestation because there is less forest cover. However, clearing land for agriculture may happen more often for certain altitude crops such as coca and coffee. Altitude represents ecosystem type and biodiversity levels, mixed with other environmental conditions.	2000	Farr et al. (2007)
Slope (mean)	Degree s	Higher slope on land reduces the amount of fertility in soil due to runoff and makes it less desirable for agriculture. Also, higher slopes increase the risk and costs of any activity. Higher slopes are associated with reduced threats and effectiveness against forest loss.	2000	Farr et al. (2007)
Annual precipitation	mm	Annual precipitation controls for the vegetation growth and ecosystem type.	2000	NASA (n.d.)
Temperature (mean)	Degree s Celsius	Annual temperature controls for ecosystem type and biodiversity mixed with other environmental conditions.	2000	NASA (n.d)
Agricultural suitability	Categorical	Land best suited for agriculture is expected to increase its risk of deforestation. However, most of the deforested areas in the Peruvian Amazon correspond to land suited for “protected forests” rather than agriculture (Dourojeanni 2022).	2000	Fischer et al. (2000)
Ecological Features				
Baseline forest cover	Percent	Having more forest cover before the treatment may affect the allocation of funds and spending priorities, as well as the outcome. Higher forest cover may attract loggers, conditional on access and patrolling. On the other hand, low forest cover shows increased need for conservation actions.	2009	GEOSBOSQUES (2019)
Pretreatment forest loss	Percent	More forest loss in the year prior to the treatment may attract funding (Nakamura 2017) due to a higher need to control its threats (Rojas et al. 2021).	2008	GEOSBOSQUES (2019)
Ecoregion	Categorical	SERNANP aims to preserve a representative sample of the ecoregions in Peru through PAs. Ecoregions represent specific climate and geographical conditions, which are relevant for ecosystem comparisons. It may affect the management needs (spending) and forest cover change rates. There are 12 ecoregions overlapping the Amazon and PAs.	2008	The Nature Conservancy (2016)
Access and threats				
Distance to roads	km	Distance to roads is a proxy for human access. Areas closer to roads have an increased threat of forest loss (Rojas et al. 2021; Dourojeanni 2022), and provide more access to markets, which help promote economic development (Andam et al. 2010). Areas closer roads may receive more funds due to higher risk and need of enforcement.	2011	MTC (2017)
Distance to rivers	km	Rivers provide access to forested areas, including remote locations within PAs where roads are not built, increasing the likelihood of deforestation (Bax et al. 2016).	2009	GEOSBOSQUES (2019)
Distance to the nearest town (> 20,000 habitants)	km	Areas closer to an established town are exposed to human interventions and closer to markets (Ferraro et al. 2011). Extractive economic activities such as logging or agriculture are more likely to happen than in areas farther away.	2007	INEI (2009)
Distance to the forest edge	km	Areas closer to a previously deforested location may have a higher risk of forest loss (Rojas et al. 2021). I considered the distance to an area without forests to have higher forest loss risk, and an increased probability of receiving funds.	2009	GEOSBOSQUES (2019)

Table 2.3 (cont.)

Variable	Unit	Relationship to treatment and outcomes	Years	Data source
Access and threats (continued)				
Distance to mining concessions	km	The closer an area is to a mining area, it is more likely to have negative ecological outcomes and detract conservation funding (Nakamura 2017).	2005–2011	GEOBOSQUES (2022)
Distance to agricultural plots	km	Agriculture is one of the main causes of forest clearing in the Peruvian Amazon (Dourojeanni 2022) and a predictor of deforestation risk (Rojas et al. 2021). The closer an area is to an existing agricultural plot, the higher the likelihood of having forests cleared. In addition, agricultural jobs are correlated with higher poverty (UNDP 2019).	2011	GEOBOSQUES (2022)
PA governance				
NGO comanagement	0/1	Shared governance between the state and NGOs through a comanagement contract. They increase the likelihood of attracting international funding (Nakamura 2017) and better outcomes.	2009–2015	SERNANP (2016)
Indigenous comanagement	0/1	Shared governance between the state and Indigenous communities, with community-based approaches. They increase the likelihood of obtaining better outcomes by including the community's interests and cultural values.	2009–2015	SERNANP (2016)
PA characteristics				
Years protected	Years	The longer an area has been established, it should have better outcomes because they have had more time to identify challenges and develop solutions (Ferraro et al. 2011). Older PAs have shown to be more effective at avoiding deforestation (Miranda et al. 2015).	2015	SERNANP (2022)
PA area	km ²	There is high variability in terms of PA size, which could potentially influence the performance of management and the outcomes. Larger PAs are harder to manage and control, they tend to receive more funds, and spending/area needed is lower than for smaller PAs (Bruner et al. 2004). Larger enforcement budgets are expected to have more impacts conditional on the level of risks faced by PAs	2009	SERNANP (2016)
Socioeconomic characteristics				
Human development (baseline)	Value	International donors support human development through international aid. Areas with lower human development increase the likelihood of attracting these investments. More funds toward sustainable development are expected to improve social and ecological outcomes through diverse mechanisms (Figure 2.1).	2007	UNDP (2019)
Employment in agriculture or forestry	District share	Higher dependence on agricultural or forestry resources as the main source of income increase the threat of forest loss. Small-scale agriculture for subsistence is associated with higher poverty rates (UNDP 2019).	2007	INEI (2009)
Tourism in PAs	Mean annual visitors	A higher number of visitors to a PA is beneficial for economic development (Vilela et al. 2018), but could also be detrimental for the environment. Tourism attracts donors (Nakamura 2017) and may promote valuation of nature by its users and beneficiaries.	2009–2017	SERNANP (2016)
Other conservation interventions				
Buffer zone	District share	There may be conservation actions happening in official buffer zones, potentially affecting the treatment allocation, use of funds, and the outcomes. In Peru, buffer zones were effectively avoiding forest loss in comparison with the unprotected landscape (Weisse and Naughton-Treves 2016).	2009–2017	SERNANP (2016)
Distance to conserved areas	km	Conservation areas that were not established as PAs may engage in conservation actions, potentially affecting positively the PAs' performance and outcomes.	2009	SERNANP (2016)
Distance to indigenous lands	km	Indigenous lands have shown to be effective at avoiding forest loss in the Peruvian Amazon (Schleicher et al. 2017). Areas closer to them may have a positive effect in forest cover.	2009	MINAM (2017)

Figure 2.5 Correlation plot between PA spending and the most theoretically relevant variables driving threat, and PA characteristics affecting the allocation of PA funding.



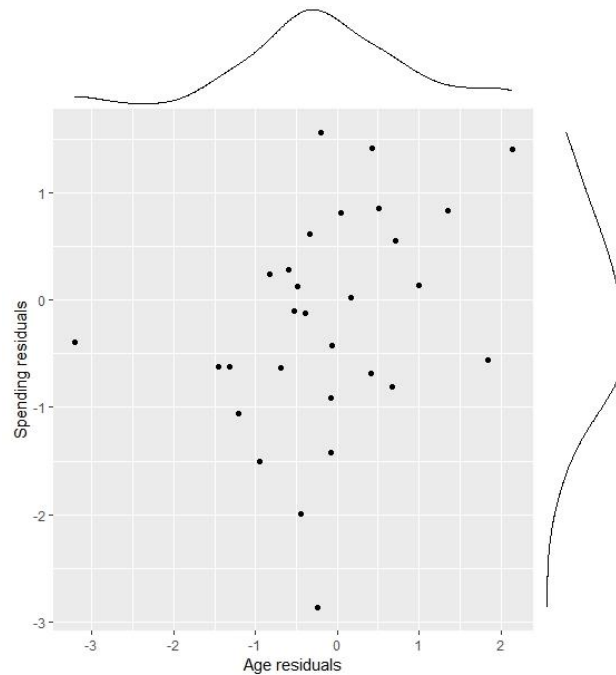
Note: Red line represent data trends and the red dot is the mean value, with the black circle highlighting clustered data. Significance levels are * $p < .05$, ** $p < .01$, *** $p < .001$

2.8.2.7.2 Unobservable characteristics

There are characteristics that may affect PA spending and their performance in avoiding forest loss and affecting human development that are hard to quantify and measure. Local cultural values and perceptions of the local communities are hard to estimate, given the multicultural setting in the Peruvian Amazon due to multiple traditional Indigenous cultures and Andean immigrants. Another relevant characteristic that may affect spending performance is the staff effectiveness, ability, and capability on their job. Salary amount or a scorecard evaluation based on their education level and years of experience might not reflect the actual job performance. Contextual political factors such as local governance and corruption may affect the development and ability to spend budgets. The need for bribes due to

ineffective bureaucracy can delay actions and lead to inaction in the field. This also affects the capacity of police support for intervening in illegal activities when needed, reducing enforcement and performance.

Figure 2.6 Residual-residual plot from PA age and PA spending.



2.9 Conclusion

In this chapter, I have developed a theoretical framework to estimate the socioecological impacts of PA spending with a case study from the Peruvian Amazon. The effects of protection and spending in a PA are hard to separate, but I have shown how both treatments may be analyzed in an integrated framework. Clearly defining the concepts in each part of the framework (or general model) and the expected effects of conservation funding form the basis for developing a strong research design capable of impact estimation that is as reliable as possible. The choice of scale for the study, treatment, and outcomes will frame and guide the implications of the results in a variety of ways. Hence, these main variables need to be chosen with care. In addition, the identification of rival explanations to causal effects found are important to consider so as to avoid hidden biases. Further, specifying the contextual characteristics that may condition the size and direction of the effects on each case study are important to consider. Together, accounting for these different issues can help advance our understanding of this critically important aspect of the conservation field.

Reliable, spatially explicit PA investment data remain largely unavailable. However, some governments and multilateral agencies promote financial transparency by sharing their datasets. For their

use in quantitative impact studies, nonetheless, we would ideally want details on spending objectives and spatial distribution. Without such information, we need to make clearly stated assumptions for impact assessment. The framework and illustrative case study elaborated a causal model and proposed a spatial allocation of PA spending based on risk of deforestation spatially. It is tested empirically in the following chapters.

This theoretical framework and case study can help inform and guide future research and generate evidence on the impacts of PA spending. The framework and results from research using it can, in turn, support prioritizing effective actions and targeting locations where funding provides the most benefits. Given the relevance and scarcity of financial resources for conservation, the outputs of this framework will serve as a tool for donors and decision-makers to improve cost-effective allocation of PA funds.

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CHAPTER 3: THE IMPACT OF PROTECTED AREA FUNDING ON FOREST LOSS IN THE PERUVIAN AMAZON

3.1 Introduction

Protected areas (PAs) are a crucial strategy for biodiversity conservation (Watson et al. 2014). Millions of dollars are spent annually on PAs worldwide, but evidence that this investment is spent effectively remains lacking (Coad et al. 2019). Given the insufficient funds available to protect nature globally (CBD 2020; Deutz et al. 2020), it is important to learn from our actions in the past to make better use of the existing financial resources in the future. Research has shown the role of conservation funding as a significant predictor of biodiversity outcomes worldwide (Waldron et al. 2017), and resources for management and capacity were positively associated with changes in PA species populations (Geldmann et al. 2018). However, achieving cost-effective funding allocation requires knowledge of costs for specific interventions and their benefits (Cook et al. 2017). Even though funding provides critical resources for conservation action, research on the effectiveness of conservation finance remains scarce. Studies that carefully account for potential confounding factors are especially rare. This dissertation chapter addresses this important research need by analyzing the impacts of PA funding on forest cover in the Peruvian Amazon. I hypothesize that PAs with fewer financial resources committed will be less able to effectively manage forest loss than other PAs with similar characteristics and facing similar threat levels.

Among the many objectives attached to establishing terrestrial PAs is the conservation of their habitat to maintain functioning natural ecosystems (Dudley 2008). Over the last decades, the increased demand for agricultural and forest products and infrastructure development (Leberger et al. 2020) have driven forest clearing. However, these anthropogenic actions and impacts vary across regions, showing higher rates of forest loss in tropical areas than other forest types (Leblois et al. 2017), and overextraction of resources was reported as the main threat to terrestrial PAs in developing countries (Schulze et al. 2018). Nonetheless, there is strong evidence that PAs have helped conserve forest habitats across diverse social-ecological contexts. The literature measuring the effectiveness of PAs on deforestation has shown positive effects in Ecuador (Cuenca et al. 2016), Thailand and Costa Rica (Andam et al. 2008), Brazil (Nolte et al. 2013; Pfaff et al. 2015), Bolivia (Hanauer and Canavire-Bacarreza 2015), Madagascar (Eklund et al. 2016), Guatemala, Honduras, El Salvador (Muñoz Brenes et al. 2018), and Peru (Miranda et al. 2015; Schleicher et al. 2017) when using protection as treatment compared to unprotected land. Within PAs worldwide, strict conservation areas showed patterns of less forest loss than those that allow human

activities and larger forest loss rates in areas with higher initial forest cover in developing countries (Leberger et al. 2020).

Over the last decade, the conservation field adopted impact evaluation methods to assess quantitative impacts of specific conservation interventions to reduce potential biases by controlling for external factors that may affect the outcomes (Baylis et al. 2015; Schleicher et al. 2019). The current impact evaluation literature on PAs focuses on the impacts of protection (e.g., Andam et al. 2008; Sims 2010; Miranda et al. 2015), ignoring funding despite its recognized importance in shaping PA outcomes (Blackman et al. 2015; Pressey et al. 2015; Gill et al. 2017). A previous study in Peru found that government funding for PAs in 2006 and funding from all sources in 2011 were correlated with the likelihood of avoided forest degradation between 2006 and 2011, not forest loss (Schleicher et al. 2019). Nonetheless, funding has not yet been included in impact evaluation assessments in PAs (Miller and Nakamura 2018), presumably due to the lack of access to reliable, spatially explicit funding data (Castro and Locker 2000; Naidoo et al. 2006; Pressey et al. 2015; Nakamura 2017).

This research applies impact evaluation tools to estimate the ecological effectiveness of PA funding. Ecological effectiveness is defined as the change in forest cover within PAs compared to unprotected areas (Eklund and Cabeza 2016), explained by the funding amount committed to PAs. The use of impact evaluation methods, such as the ones applied in this research, provides the opportunity to compare PAs with unprotected areas that are comparable to one another through the use of matching methods to identify a counterfactual scenario at baseline and control for external factors that may affect the outcomes (Angrist and Pischke 2015). The application of both matching and postmatching regression, known as *before-after-control-intervention* or difference-in-differences quasi-experimental designs, seeks to approximate an experimental design, estimating causal impacts and reducing bias (Jones and Lewis 2015).

Peru is a megadiverse developing country that depends on biodiversity to sustain its economy (Ministry of Economy and Finance 2013). With a neoliberal democratic government and the fastest-growing economy in Latin America between 2003 and 2014 (World Bank 2016), the country depends on mining, agriculture, fishing, and tourism as its main assets (MINAM 2010). More than half its territory is covered by the Amazon rainforest, which holds one of the remaining primary forests in the world. This forest is under threat by informal economic activities caused by inefficient smallholder agriculture (Rojas et al. 2021; Dourojeanni 2022). The lack of formal land titling and socioeconomic need lead to recurrent land invasion and land use change from forests to farmland, without proper treatment and care of the soil due to a lack of knowledge, interest, and resources (Dourojeanni 2022). Informal mining also affects

forests in particular areas (southwest and central regions) where gold mining attracts temporary workers (Dourojeanni 2022).

To protect the biological resources with the country, the Peruvian government established the Ministry of Environment (MINAM) and the Peruvian National Park Service (SERNANP) in 2008. There are 66 established PAs and 10 planned PAs identified under SERNANP's purview, but the agency lacks adequate conservation funding support (Villanueva 2005; Waldron et al. 2013; Casas et al. 2014). For this reason, the Peruvian government created the initiative Protection for Permanence (WWF 2018) to commit and secure funding over the next 20 years to effectively implement the management plans for all existing PAs. The aim is to control and monitor threats countrywide (SINANPE 2015) and consolidate sustainable financing for the Peruvian PA network. To maximize future PA investments, the program seeks to understand where and why the effects of past investments were larger and to allocate funding based on evidence to achieve the targets set by the sustainable financing initiative.

This research addresses this gap in knowledge by estimating the impacts of biodiversity conservation funding for PAs on forest loss through a case study in Peru. By assessing the ecological effects of the Peruvian Amazon PA network I seek to contribute to the body of scholarship by advancing theory and empirical knowledge on the causal impacts of PA funding. This study develops evidence for effective use of PA funding and support for better decision-making for conservation managers to make the most of every dollar invested in reducing forest loss.

3.2 Theoretical expectations

Researchers seeking to know the effect of PA investments on forest loss at the district level need to consider the spillover effects of protection on land-use change in the buffer zones and the unprotected landscape within each district (Ford et al. 2020). Buffer zones in the Peruvian Amazon have shown effectiveness against forest loss compared to the wider unprotected area outside them (Weisse and Naughton-Treves 2016). This evidence suggests that a protected district may reduce forest loss within PA boundaries due to protection and conservation actions (proxied by PA spending) and may also have a reduced effect on the buffer zone, which can create a leakage effect to unprotected zones. The expectation is that more investments done in a PA will avoid deforestation within the PA and its buffer zone to a smaller extent, but at the expense of increasing deforestation of unprotected areas. With more protected and conserved areas in a district, there is less opportunity for resource extraction. However, the effect will depend on the enforcement of the conserved areas to counteract the PA spillover effects. I expect a positive feedback effect between PAs and conserved areas to protect forests.

Other factors that may condition the effects of conservation funding are the social context of the district. In locations with more poverty and reduced access to social services, there is a higher need for income and resources for subsistence. This need can drive increased informal activities such as mining, logging, and agriculture, causing land-use change and forest loss. However, this effect will be dependent on access to forested areas through roads and rivers. Districts with a higher road density provide access to loggers and markets, increasing the effect of every dollar invested compared to areas without investment for conservation. The same expectation applies to districts with larger population density, mining areas, and more jobs in agriculture because they all pose higher threats to forest loss. With more forest cover available at baseline, there is a higher probability of deforestation, but it may depend on access and forest type. I expect, on average, that more funding in highly forested areas will reduce the likelihood of forest loss. This macro-level perspective considers the effects on forests beyond PAs, conditional on other factors such as the presence of conservation areas (non-PAs) and buffer zones, access to the forest, intensity of economic activities, and socioeconomic need.

At the PA level, PA funding in Peru was significantly correlated with more deforestation at baseline (year 2009), higher population density, and a larger number of visitors to the PA, and it was negatively correlated with the presence of mining concessions within a 10-km radius (Nakamura 2017). The correlations between tourists and forest loss were the strongest (at 1% significance), while mining and population density were weaker (at 10% significance). These funds aimed to improve tourism services and infrastructure, administrative costs, and implementation of REDD+ projects in PAs co-managed with NGOs. Not all funds may be the same in terms of potential conservation impacts. Operational costs are used within the year they were committed and may have tangible effects within that year. In contrast, funded projects may take some time to show effects on the ground because they need to overcome bureaucratic and operational processes before reaching their goal. Given the various sources and types of funding considered for this study, I used the cumulative amount of funds for management and projects per PA as the treatment. I expect the overall amount of funds to contribute, directly or indirectly, to preserve forest cover.

3.3 Data and methods

3.3.1 Study area

This study examines 29 PAs established in or before 2015 in the Peruvian Amazon managed by the government of Peru (Table 3.1). Most PAs were established before 2010, but two gained protected status more recently: Pucacuro National Reserve in 2010 and Sierra del Divisor National Park in 2015. I

Table 3.1 List of included PAs, with IUCN management category and number of years protected by 2015.

Protected Area Name	IUCN Category	# Years Protected
Pacaya Samiria National Reserve	2	44
Manu National Park	2	43
Rio Abiseo National Park	2	33
Pui Pui Protection Forest	6	31
Yanachaga Chemillen National Park	2	30
San Matias San Carlos Protection Forest	6	29
Alto Mayo Protection Forest	6	29
Tabaconas Namballe National Sanctuary	3	28
Yanesha Communal Reserve	6	28
Bahuaia Sonene National Park	2	20
Tambopata National Reserve	6	16
Cordillera Azul National Park	2	15
El Sira Communal Reserve	6	15
Amarakaeri Communal Reserve	6	14
Otishi National Park	2	13
Machiguenga Communal Reserve	6	13
Ashaninka Communal Reserve	6	13
Alto Purus National Park	2	12
Megantoni National Sanctuary	3	12
Allpahuayo-Mishana National Reserve	6	12
Purus Communal Reserve	6	12
Ichigkat Muja National Park	2	9
Tuntanain Communal Reserve	6	9
Pampa Hermosa National Sanctuary	3	7
Cordillera de Colán National Sanctuary	3	7
Matses National Reserve	6	7
Chayu Nain Communal Reserve	6	7
Pucacuro National Reserve	6	6
Sierra del Divisor National Park	2	1

excluded the four planned-PAs (*zonas reservadas* in Spanish) because they had no legal designation in the study's period. *Zonas reservadas* are “areas earmarked for the conservation of biological diversity and require further review to define the exact surface area and the appropriate category” which more likely lead to a PA designation, but there have been cases of decategorized areas (Solano 2009). Given their lack of formal protection and management, they formed part of the unprotected locations, defined as areas without legal protection for conservation. Initially, the sample included 34 PAs, but five were removed due to a lack of baseline social data (Güepi-Sekime National Park, Machu Picchu Historic Sanctuary, Huimeki Communal Reserve, and Airo Pai Communal Reserve) and not enough PA overlap with districts (Tingo Maria National Park). In addition, the visual examination of the overlap between district and PA boundaries revealed small areas caused by mapping mismatches. I removed these areas, which were mostly below 30 sq km.

In addition to PAs, the Peruvian Amazon has other conserved areas that are not PAs (see sections 2.2.1 and 2.8.1). I will refer to the private conservation areas, regional conservation areas, and conservation concessions (Table 2.2) as conserved areas from now on. They are recognized areas that contribute to the conservation landscape but are not formally recognized as PAs by the state. The presence of these areas needs to be included in the analysis via control variables.

3.3.2 Spatial data

To create a counterfactual scenario, I extracted information from the study area using district-level political boundaries as the unit of analysis from the National Institute of Statistics and Information (INEI 2009). Districts are the lowest administrative level unit of analysis for which relevant public data were available. The Peruvian Amazon overlaps with 450 districts in full or partially. However, 80 districts had less than 50% of their areas in the Amazon, and 30 lacked social baseline data, and 41 had less than 10% forest cover, which I excluded from the analysis, leaving 299 districts included in the sample. I extracted all spatial data using the intersect tool between polygons and calculated the overlapped area with the calculate geometry tool in ArcMap 10.7, and processed the raster data to get the mean and mode values using the *exact_extract* function (Baston 2020) using RStudio 2.3. I used a WGS84 UTM18S coordinate system and the South America Albers Equal Area projection to estimate areas.

3.3.3 Treatment and control

I examined two treatments related to PAs and funding. The first was a binary variable for the presence/absence of PAs. The second treatment was the amount of PA funding allocated to those districts with PAs, and the control districts had no PAs and funding. Following previous research, I used a 10% threshold of PA-district overlap to consider the district as treated (Andam et al. 2008; Sims 2010; den

Braber et al. 2018; Oldekop et al. 2018). This threshold has been repeatedly used for district level analysis of PAs based on work by Andam et al. (2008) who supported their decision using the PA share goal for countries proposed by the Convention for Biological Diversity (CBD) at the time. Nevertheless, I tested different shares of protection to see how this might affect the sample. With a 10% PA overlap, I had 58 treated districts. With 30% overlap, 34, and with 50% overlap, 12. I kept 10% threshold so as to enable a larger sample size and based on current best practice in the literature. I identified districts with no PA overlap as control districts and removed 33 districts with less than 10% PA share. This process left 58 treated districts and 208 controls in the sample. A list of the treated districts, their share of protected areas, funding amount committed, and the included PAs is presented in Table A.1.

3.3.4 Funding data

I estimated a deforestation risk-weighted dollar amount per square kilometer within study PAs as the main unit of analysis for this dissertation (Section 2.8.2.2 describes the rationale for this decision). Then, I summed the allocated funds per pixel belonging to each district. The district-aggregated PA amount was used as the treatment. Using this measure assumes that all funding allocated to a PA will have an impact on the outcome of interest (primary forest), even when budgets may have different objectives. The analysis will estimate the impact of all funding on forest loss even as some amounts allocated may have a direct effect and others indirect effects (see chapter 2 discussion).

Non-government conserved areas (see Chapter 2, Section 2.8.1) in the districts are assumed to have received no significant funding for conservation compared to state PAs. This assumption is based on an extensive effort to collect such data in 2016 (Nakamura, 2017). That effort yielded spending data for one regional conservation area, and six private conservation areas through owner interviews. The overall amount of funds was 0.1% of the overall funding collected. Conservation concessions were not specified in the previous research; however, an NGO (AMPA) reported some funding for one concession, but no further data were collected. There is no source to collect conservation funding for Indigenous lands because they are not formally PAs nor are they necessarily areas dedicated specifically for conservation; hence, it is difficult to know about their conservation funding sources, if any.

3.3.5 Outcome

The outcome variable is the area of primary forest loss (sq km) per district, estimated from the Amazon biome forest loss maps from MINAM (GEOBOSQUES 2019). Ideally, I would have used share of forest loss, but the values were very small where most rounded to zero. This dataset adapted the Hansen et al. (2013) global data with additional local expert correction (Vargas et al. 2014), making it suitable for the Peruvian context. MINAM defined a forest as a "predominant arboreal ecosystem with a surface

larger than 0.5 hectares, minimum width of 20 meters, and a minimum canopy cover of 10%. Its predominant vegetation is represented by woody trees with 2 meters tall, at minimum, in the coast and highlands, and 5 meters for the Amazonian rainforest" (Vargas et al. 2014). This dataset considered secondary forests, agricultural plots, mining areas, and grasslands as nonforest (Vargas et al. 2014). The forest cover change data has a 30 × 30 m resolution. I extracted the accumulated area in square kilometers for each district per year using the *exact_extract* function in R (Baston 2020). I measured forest loss for 2009–2018 and tested different time-lags in the response for one and three years. I included 1- and 3-year lags on the outcome from the treatment to test if there were differences in the effects.

3.3.6 Covariates

I selected 17 theoretically important variables to control for confounding effects on forest loss beyond PA funding and construct a counterfactual scenario (Table 3.2). The biophysical variables are time-invariant terrain characteristics that may attract or deter threats to deforestation. Higher altitudes and slopes are associated with less forest loss because their hard access makes them less likely to undergo land conversion and tend to be less suitable for agriculture, which may bias the impacts of PAs and need to be accounted for (Joppa and Pfaff 2009; Blackman 2015). Temperature and rainfall also fall within variables of relevance for land conversion (Schleicher et al. 2017), indices of ecosystem type, and vegetation growth.

Social needs lead to informal activities and land-use change. In Peru, agriculture is one of the main predictors of forest loss (Rojas et al. 2021) and is related to subsistence farming, informality, and poverty (UNDP 2019; Dourojeanni 2022). Controlling for the share of agricultural jobs and the share of agriculture plots in a district will allow for better comparisons and reduce bias in the effects. Hence, land suitability for agriculture may not be as relevant, given that land grabbing tends to be opportunistic rather than chosen by its characteristics (Bax et al. 2016). In addition to agriculture, the presence of pastures in the Amazon indicates human intervention and cattle. Distance to pasture was a significant predictor of deforestation (Rojas et al. 2021), which could increase forest loss risk. I used this variable as the share of pasture per district. Another informal economic activity affecting forest cover is gold mining, concentrated in the region of Madre de Dios (Rojas et al. 2021), which I included in the earliest year possible to the baseline, but its magnitude increased after 2011. This mining area had terrible ecological and social consequences (Wagner 2016), which should be accounted for in the analysis. In addition, I included a measure of baseline social development to control for the effect of social need affecting the

development of conservation actions and threats using the human development index (HDI). Having more social need, or lower HDI, could attract development aid funds targeting conservation efforts.

A relevant variable for socioeconomic development is access to markets through roads. An area closer to roads, rivers, and populated centers is vulnerable to deforestation and resource extraction

Table 3.2 Theoretically relevant confounding variables for protected areas in Peru used in matching, the mean values for the treatment and control groups (mean value before matching in parenthesis, and after matching without parenthesis), and the data source.

Type	Variable	Unit	Years	Value	Treated (mean)	Control (before) after	Source	Use
Biophysical	Altitude	Meter	1970–2000	Mean	924.20	(1381.24) 1275.25	Fick and Hijmans (2017)	M, R
	Slope	Degree	1970–2000	Mean	4.72	(6.70) 6.35	Altitude, ArcMap	M
	Rainfall	Millimeter	1970–2000	Mean	172.00	(159.60) 165.6	Fick and Hijmans (2017)	M
	Temperature	Degree Celsius	1970–2000	Mean	22.87	(20.91) 21.33	Fick and Hijmans (2017)	M
	District area in Amazon	Square kilometer	2007	Sum	5272.20	(1197.32) 2828.25	INEI (2009), MINAM (2017)	M,R
Access	Road density	Road/kilometer	2013	Sum	0.04	(0.20) 0.10	MTC (2017)	M,R
Ecological	Forest Loss (pretreatment)	Square kilometer	2008	Sum	5.60	(2.35) 4.71	GEOBOSQUES (2019)	M,R
	Baseline forest cover	Square kilometer	2009	Sum	4846.32	(990.87) 2523.27	GEOBOSQUES (2019)	M
	Baseline forest cover outside PAs	Square kilometer	2009	Sum	2502.30	(989.62) 2519.7	GEOBOSQUES (2019)	R
	Pastureland	Percent	2011	Sum	2.36	(11.58) 8.95	GEOBOSQUES (2022)	R
	Conserved areas	Percent	2009	Sum	11.40	(10.65) 15.74	MINAM (2017)	M,R
	Indigenous territories	Percent	2009	Sum	12.40	(20.94) 19.76	MINAM (2017)	M,R
	Buffer zones	Percent	2009	Sum	23.45	(9.11) 12.55	SERNANP (2016)	R
Socioeconomic	Population density	People/sq km	2005	Mean	19.31	(29.80) 20.56	CIESIN (2018)	M,R
	Human development	Value*100	2007	Mean	26.94	(24.29) 24.12	UNDP (2019)	M,R
	Jobs in agriculture	Percent	2007	Mean	35.36	(38.91) 40.53	INEI (2009)	M
	Agricultural plots	Percent	2011	Sum	3.29	(13.12) 7.17	GEOBOSQUES (2022)	M,R
	Mining concessions	Percent	2011	Sum	11.78	(18.89) 12.06	INGEMMET (2020)	R

Note: The use column shows its use in matching (M) and regression (R)

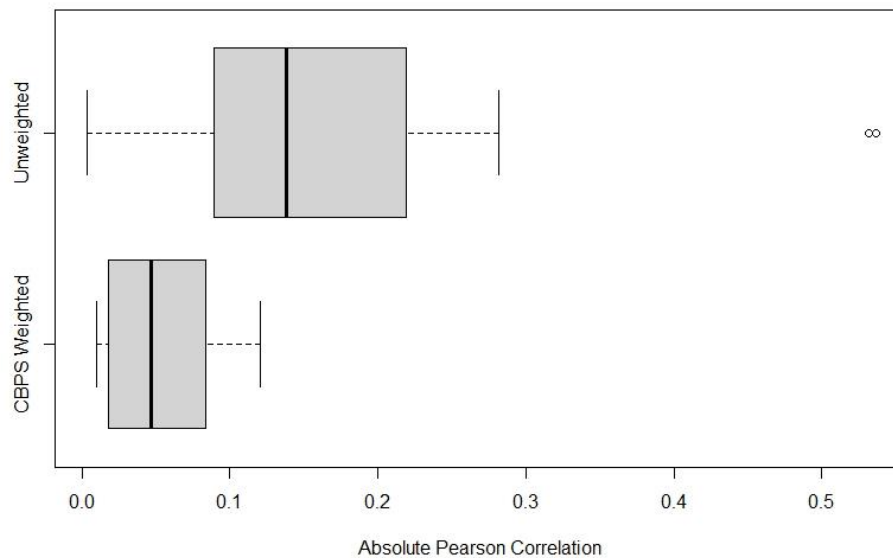
(Hanauer and Canavire-Bacarreza 2015; Pfaff et al. 2015). They are prone to forest loss and may be attractive to donors for such ecological need. Other ecological factors that may confound the effect of conservation actions on forest loss are the presence of conserved areas, which may help reduce overall deforestation by having a conservation area recognition, deterring intruders. Private conservation areas promoting ecological connectivity through habitat protection (Palfrey et al. 2022) and conservation concessions effectively avoided forest loss (Schleicher et al. 2017). In addition, Indigenous lands also play a significant role in avoiding forest loss and degradation (Nolte et al. 2013; Schleicher et al. 2017), as well as buffer zones (Weisse and Naughton-Treves 2016), which is why they are also included. To increase the district's comparability, I included the baseline forest cover area outside PAs in a district, forest loss before the treatment, and district area to help control for the likelihood of deforestation. These were expressed in square kilometers because using them as proportions of districts led to very small values. Some of these covariates were used in matching, and others were added to control for additional bias in the postmatching regression (see the "Use" column in Table 3.2).

3.3.7 Matching

To correctly estimate the effects of PA funding, I controlled for the influence of external factors that may bias the impact of PA funding on forest loss because conservation spending is nonrandom. At the PA level, it tends to go to places of higher ecosystem threat, biodiversity need, or the places of funders' interests (Miller et al., 2013; Nakamura 2017). An increase in deforestation can attract funding to stop forest loss, creating a potential problem of reverse causality (Waldron et al. 2017) in which avoided forest loss may be correlated with funding, creating an illusion of avoided forest loss driving funding, instead of funding driving avoided forest loss. To reduce the potential biases and endogeneity problems, I estimated the covariate balancing propensity score (CBPS) on 14 covariates (Table 3.2) on funding using the CBPS package to maximize covariate balance and prediction of the continuous treatment assignment (Fong et al. 2019) as in Waldron et al. (2017) (Figure 3.1). Matching needs to be done with variables not affected by the treatment, hence the set of selected variables. The excluded covariates are inherently affected by the presence of PAs in a district. For example, buffer zones are only present close to PA borders, reducing the probability to find a suitable match. The same happens with the baseline share of forest cover outside PAs, the share of pastureland, and mining areas. Their inclusion, although maybe relevant for protection and funding, reduced the quality of matching. These were included as covariates in the postmatching regression. I ran a nearest neighbor matching on the propensity score using protected and unprotected districts as a treatment, without replacement with the *matchit* package (Ho et

al. 2007). Matching reduced the normalized mean difference from -0.65 to -0.15 after matching. This is considered a balanced match, where values greater than 0.25 are unbalanced (Stuart 2010).

Figure 3.1 Covariate balance propensity score improvement before matching.

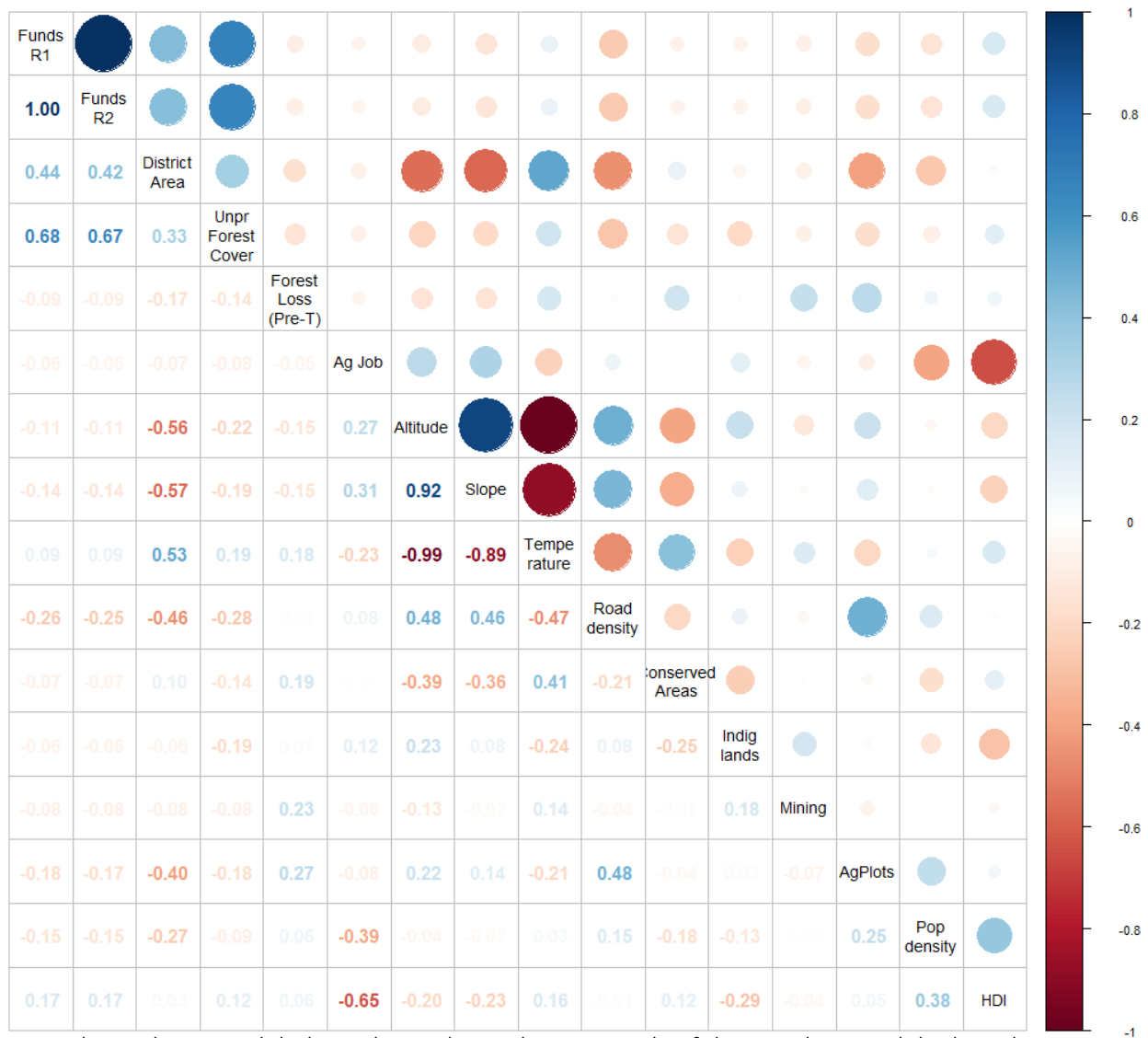


3.3.8 Postmatching regression

To estimate the effect of PA funding, I ran a postmatching regression with the matched variables and a set of additional covariates excluded in matching (Table 3.2) to control for biases (Jones and Lewis 2015). The data were in a cross-section form, including a one-year lag from the treatment to the outcome to leave time for the outcome to show the effects. Based on the distribution of the data, I applied a generalized linear regression model with a negative binomial distribution and log link, using the *glm.nb()* function in R. The model included the Department to which each district belonged as a factor to control for the effects of departmental laws, governance, and culture. Department is the highest sub-national politico-administrative level in Peru. I also tested interaction effects between funding and potential moderators such as threats through road density, population density, the share of mining concessions, and agricultural plots. In addition, potential moderators known to improve forested habitat are Indigenous lands and conserved areas, and the effects may vary based on ecological characteristics like altitude, district area, baseline forest cover, and forest loss before the treatment.

To avoid multicollinearity, I included covariates with correlations less than $|0.7|$ (Figure 3.2). I choose the model with the lowest Akaike information criterion (AIC) and highest loglikelihood (Zuur 2009). Given the presence of spatial autocorrelation in the error terms (Appendix A, Table A.2), I corrected the model using a spatial error model with a two-nearest neighbors spatial matrix, including the

Figure 3.2 Correlation table between potential covariates.



Note: The circle size and darker colors indicate the magnitude of the correlation, while the color type indicates the direction. Blue means positive correlation, and red is a negative correlation.

continuous variables (outcome and covariates) transformed with the inverse hyperbolic sine (IHS) given the presence of nonnormality and values containing zero (Bellemare and Wichman 2020). I tested six matrices for the spatial matrix selection: three using nearest neighbors ($n = 2, 3, 4$), and three using distance (min, mean, max). I ran Moran's I on the included districts using GeoDa 1.14 (Anselin et al. 2006) for the outcome, funding levels, and forest cover in 2009, and selected the highest overall sum value for the two-nearest neighbor matrix (Appendix A Table A.3).

The spatial error model (SEM) specification was as follows:

$$\begin{aligned} \text{IHS}(Y_i) &= \alpha + \text{IHS}(T_i)\beta_1 + \text{IHS}(X_i)\beta_2 + \gamma_i\beta_3 + \text{IHS}(T_i) * \text{IHS}(X_i)\beta_4 + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + u \end{aligned}$$

where Y_i is the amount in square kilometers of forest loss in district i with a one-year lag from treatment, T_i is the treatment variable in district i , X_i are the control variables used in matching (Table 3.2) that may affect the treatment in district i , and γ_i is the effect of the Department as a factor. The interaction term between treatment and covariates are for relevant variables that may significantly affect the impact of PA funding on the outcome, such as access, socioeconomic, and ecological variables. The last term of the equation, the error term, is composed of λ , the average spatial correlation among the errors conditional on W , $W\varepsilon$ as the spatially weighted matrix of neighbors among the residuals, and u as the error term with a normal distribution, which is independent and has constant variance.

I ran this model in two ways. First, I modeled protected districts using a binary treatment, which is the most common in the literature. Second, I used committed PA funds distributed by deforestation risk (Risk 1 in section 2.8.2.2) to estimate the additionality of PA funding over the impact of protection alone, which is the main research question of this chapter. As a robustness check, I used the same model using the mean outcome of the three years following the treatment to test the effects with additional time-lags in the outcome while keeping the baseline year. Additionally, I tested the alternative funding distribution (Risk 2) as funding treatment.

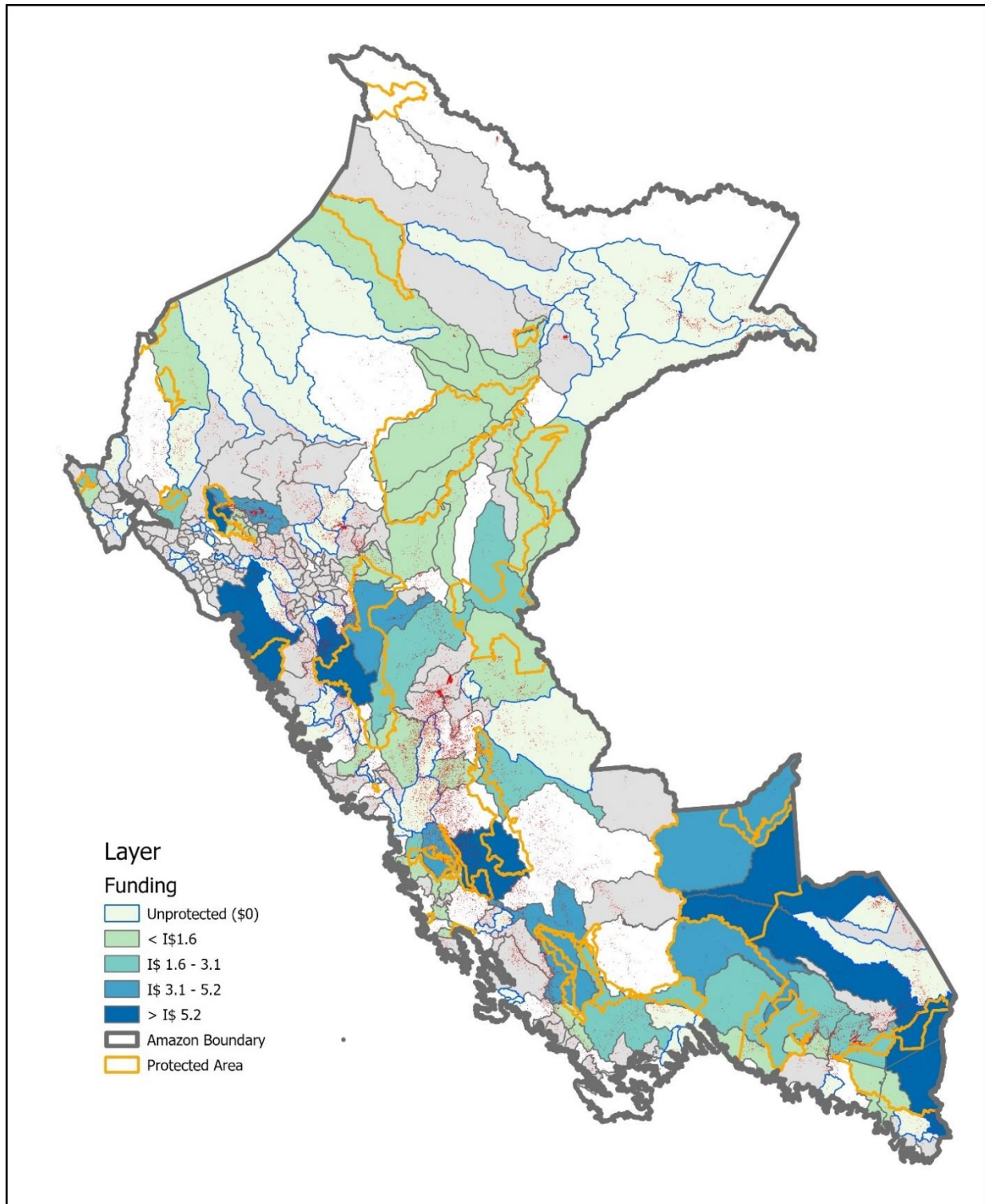
I estimated the average marginal treatment effect on the treated (AMTT) of funding, or the average treatment effect (ATT) of PA protection on forest loss in protected districts using the formula: $\text{AMTT} = (\beta_1 + \sum \beta_4 * X)$. The AMTT was estimated using the transformed X sample values for each treated district, and estimate the individual effects' sample average. The AMTT is the marginal effect on the percent change of forest loss when using funding as a treatment, or the effect of having a PA when using protection as a treatment. Due to the specification of the IHS-IHS model, I applied a $((1.x^{\text{AMTT}}) - 1) * 100$ to get the estimated impact of $x\%$ increase in funds on forest loss, where if I want to estimate the impact of 10% funds increase, 1.1 is used in the equation, or 1.32 for a 32% funds increase. For protection, I used $\exp(\text{ATT}) - 1 * 100$ to get the percent change in the outcome due to protection.

3.4 Results

3.4.1 Sample description of matched data

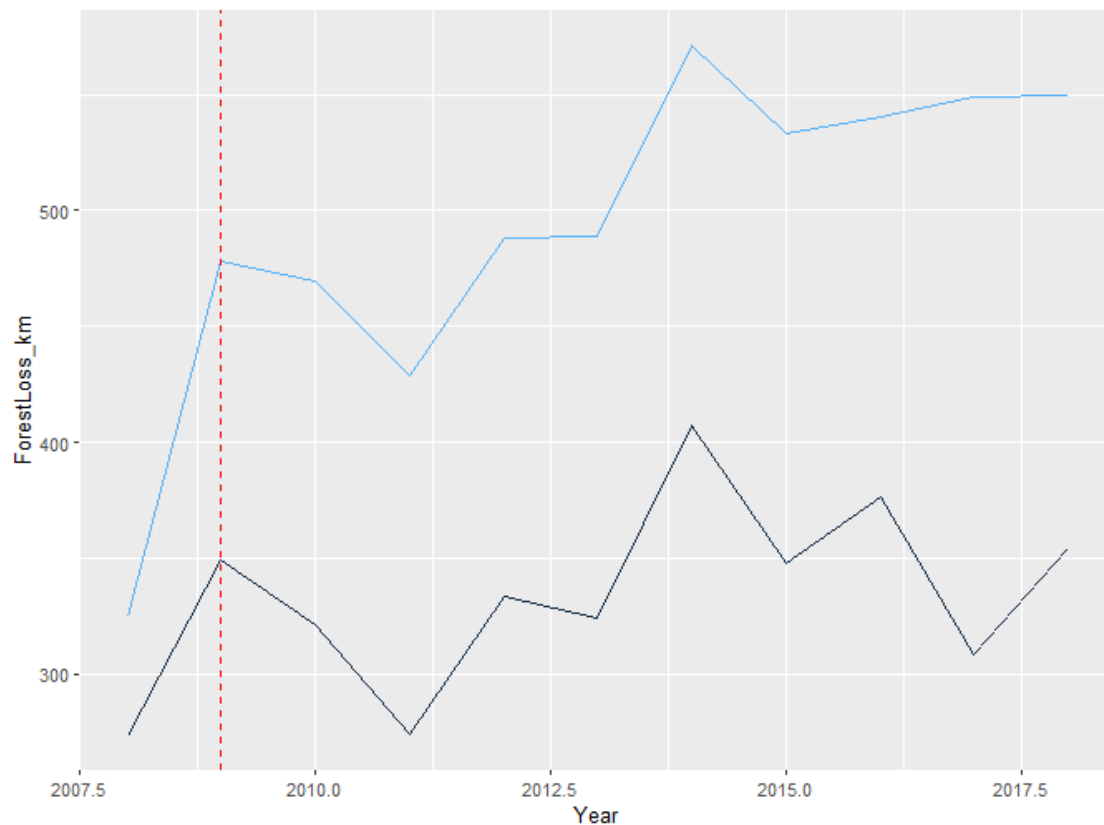
The dataset used for this analysis included 58 treated and 58 control districts (Figure 3.3). Treated districts had a 37.93% mean of area protected (min = 10.79, max = 89.27), and mean funding of \$2,154,402 (min = \$89,924, max = \$7,729,017) (detail per district in Appendix A, Table A.1). Forest loss before and throughout the treatment was higher in treated districts (Figure 3.4). In 2008, the baseline year, the amount of forest loss in treated districts was 325 sq km (mean = 5.60 sq km per district) compared to 273 sq km (mean = 4.71 sq km per district) in control districts. The overall amount of forest lost between 2010 and 2016 was 5,905 sq km, of which the majority (59.6%, 3,521 sq km) happened in treated districts, with a mean value of 60.70 sq km of forest loss per district. Both groups show roughly parallel forest loss trends after 2009 (Figure 3.4).

Figure 3.3.- Map of the Peruvian Amazon with treated and control (unprotected without funding) districts, showing PA funding levels and forest loss from 2010–2016 (red dots).



Note: Excluded Amazonian districts are colored white, and unmatched districts are in light grey. Protected areas' boundaries are in orange.

Figure 3.4. Annual aggregated forest loss in sampled districts.



Note: The blue line is for treated districts, and the black line for control districts. The red dotted line indicates the start of the treatment.

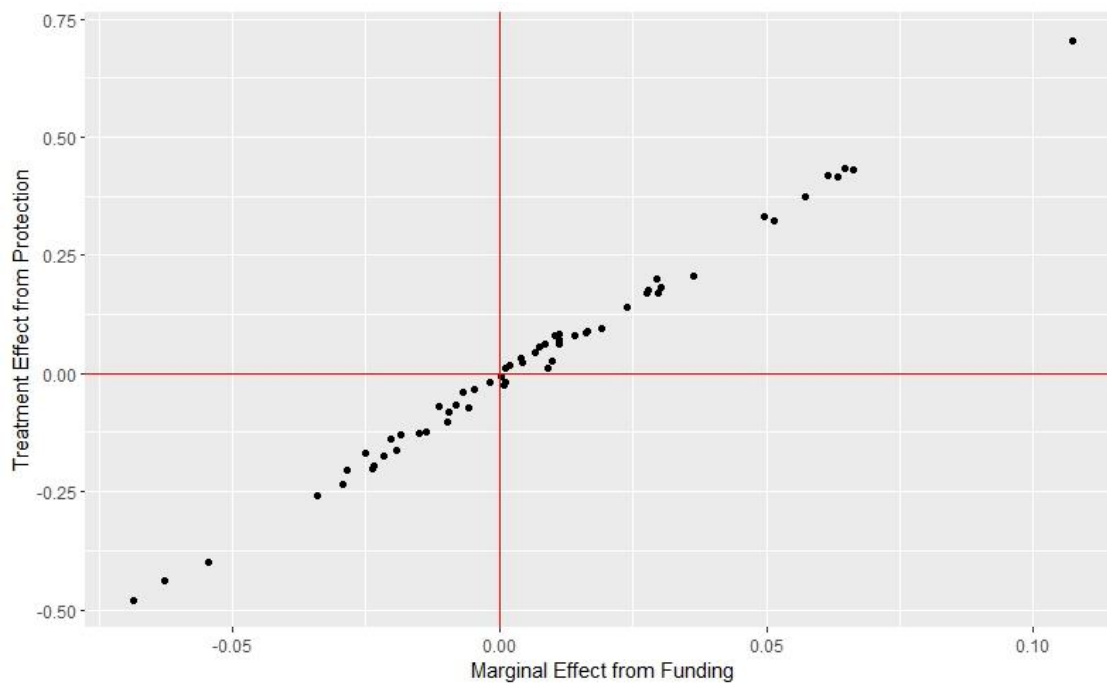
3.4.2 Marginal treatment effect on the treated

The best-fitting regression model to estimate the impact of protection and PA funding on forest loss is the SEM (Appendix A, Table A.2, and the residual plots in Appendix A, Figure A.1) with moderating effects from altitude (m), baseline forest cover in unprotected areas (sq km), and pretreatment forest loss (sq km) (Table 3.3). Contrary to the expectation, both treatments had positive effects on average. Districts with PAs had an ATT of 0.028, and a 0.0065 average marginal effect of PA funding for every IHS dollar (I\$, thousands), holding everything else constant and all interacting variables at their mean. I interpret this finding as 5.51% more forest loss in treated districts due to protection, and an increase in 20% of funding would have increased forest loss by 0.12%. However, examining the districts' individual marginal effects, conditional on the moderators, I found a wide range of both positive and negative effects (Figure 3.5), where funding in 60% of districts ($n = 35$) did not avoid forest loss. The mixed effects, in addition to the positive outlier, explain the unexpected positive average outcome.

Table 3.3 Postmatching regression results using a spatial error model and comparing two treatments: PA funding and protection.

Variables	PA funding				Protection (0/1)			
	Estimate	SE	Z-val	P-val	Estimate	SE	Z-val	P-val
(Intercept)	-1.7631	1.0016	-1.7602	0.0784	-1.6061	0.9918	-1.6194	0.1054
Treatment	0.4107	0.1248	3.2925	0.0010	2.7103	0.9274	2.9224	0.0035
District area	0.1057	0.1102	0.9586	0.3377	0.1128	0.1053	1.0711	0.2841
Altitude	0.0445	0.0974	0.4568	0.6478	0.0351	0.0973	0.3606	0.7184
Forest loss, Pre-T	0.7828	0.0669	11.7071	0.0000	0.7819	0.0657	11.9000	0.0000
Pasture	-0.0693	0.0481	-1.4391	0.1501	-0.0762	0.0483	-1.5774	0.1147
Conserved areas	0.0304	0.0262	1.1584	0.2467	0.0375	0.0261	1.4365	0.1509
Road density	-0.5375	0.4578	-1.1740	0.2404	-0.5323	0.4641	-1.1469	0.2514
Unprotected forest cover	0.3821	0.0850	4.4949	0.0000	0.3645	0.0811	4.4930	0.0000
Population density	0.1170	0.0385	3.0376	0.0024	0.1109	0.0388	2.8558	0.0043
Department (region)								
Cajamarca	-0.0405	0.2872	-0.1412	0.8877	-0.0091	0.2867	-0.0316	0.9748
Cusco	0.1591	0.2323	0.6850	0.4934	0.1662	0.2335	0.7120	0.4765
Huancavelica	-0.0363	0.3635	-0.0998	0.9205	-0.0252	0.3640	-0.0693	0.9448
Huanuco	0.1696	0.2292	0.7399	0.4593	0.1920	0.2311	0.8309	0.4060
Junin	0.1955	0.2714	0.7205	0.4712	0.1721	0.2736	0.6291	0.5293
Loreto	-0.5309	0.2610	-2.0344	0.0419	-0.5382	0.2633	-2.0439	0.0410
Madre de Dios	0.0798	0.2557	0.3122	0.7549	0.0688	0.2583	0.2664	0.7899
Pasco	0.7545	0.2743	2.7504	0.0060	0.7552	0.2749	2.7469	0.0060
Puno	-0.3930	0.2591	-1.5170	0.1293	-0.3808	0.2593	-1.4684	0.1420
San Martin	0.2808	0.2114	1.3288	0.1839	0.2644	0.2119	1.2476	0.2122
Ucayali	-0.0307	0.2627	-0.1167	0.9071	-0.0130	0.2652	-0.0491	0.9608
Funding:Altitude	-0.0316	0.0117	-2.6933	0.0071	-0.2070	0.0885	-2.3384	0.0194
Funding:Forest Loss (Pre-T)	-0.0020	0.0098	-0.2043	0.8381	-0.0281	0.0763	-0.3677	0.7131
Funding:Unprotected forest cover	-0.0226	0.0084	-2.6978	0.0070	-0.1490	0.0663	-2.2468	0.0247
Moran's I	-0.1161			0.5137	-0.0114			0.5129
Lambda	0.371			0.0079	0.3803			
BP test	27.942			0.218	28.338			0.2033
Jarque-Bera test	0.9401			0.625	1.4873			0.4754
AIC	133.8				131.59			
Loglik	-40.9021				-39.7955			

Figure 3.5 Relationship between the marginal effect of PA funding and the effect of protection on avoided forest loss.

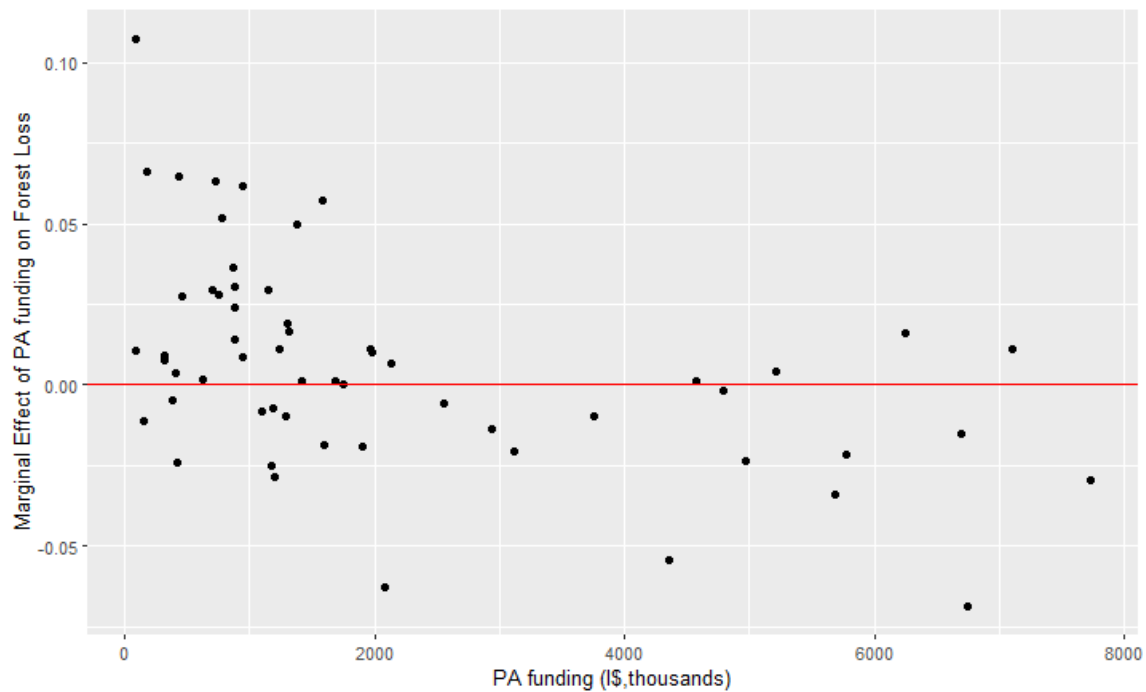


Note: Both axes have an IHS transformation, and each point represents a treated district. Negative effects mean the treatment avoided losing forests.

The individual district marginal effect of funding is significantly correlated with PA funding ($r = -0.48$, $p\text{-value} = 0.00$), so larger effects per are seen in districts with more investment (Figure 3.6), especially for cumulative amounts of over I\$2 million. Nonetheless, the largest effects are not exclusive to those well-funded districts, but also to poorly funded ones. Four well-funded districts showed no avoided forest loss from protection: Pardo Miguel (Alto Mayo Protection Forest, San Martin region), San Pedro de Putina Punco (Bahuaja Sonene National Park, Puno region), Fitzcarrald (Manu National Park, Madre de Dios region), and Palcazu (Yanachaga Chemillen National Park, Yanesha Communal Reserve, and San Matias San Carlos Protection Forest, Pasco region). Each spent over I\$4.5 million between 2009 and 2015.

The districts with the largest marginal effects from PA funding were Huicungo (Rio Abiseo National Park, San Martin region), Echarate (Megantoni National Sanctuary, Otishi National Park, Machiguenga Communal Reserve, Cusco region), and Rio Tambo (Ashaninka Communal Reserve, Otishi National Park, Junin region). And the districts with the highest negative effects are Iquitos (Allpahuayo Mishana National Reserve, Loreto region), Jenaro Herrera (Pacaya Samiria National Reserve, Loreto region), and Rioja (Alto Mayo Protection Forest, San Martin region).

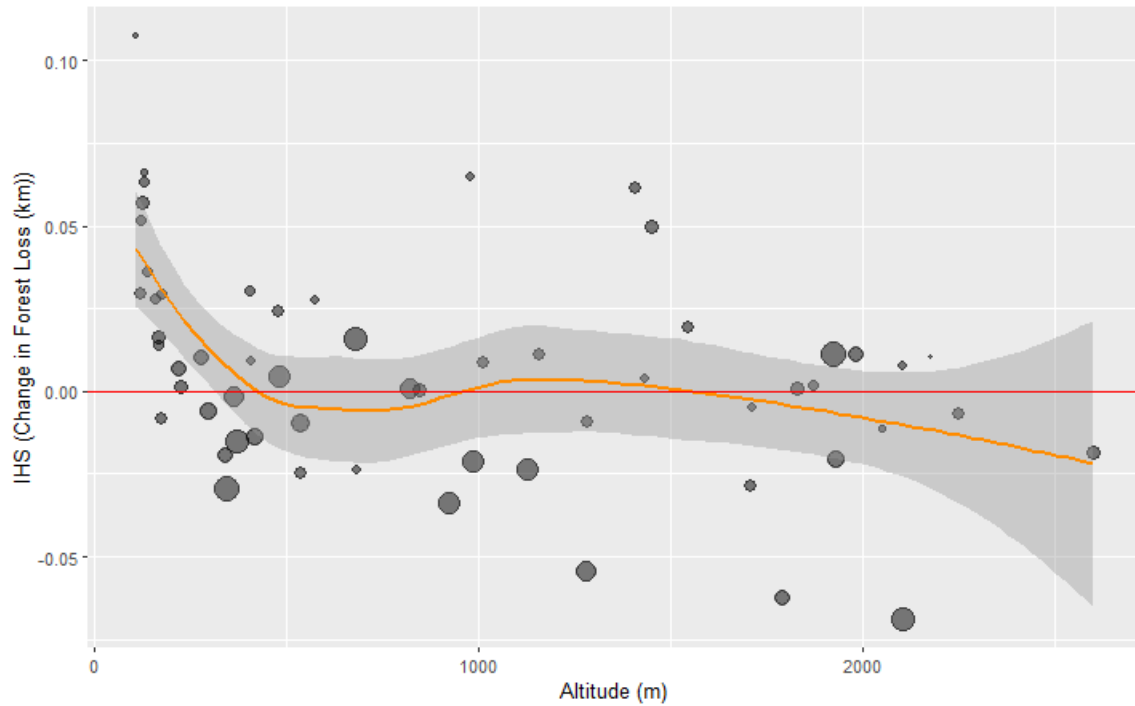
Figure 3.6 Relationship between the amount of committed PA funding and the marginal effect of funding on forest loss per district.



The moderating effects from altitude, pretreatment forest loss, and baseline forest cover in unprotected areas on funding showed a trend of increased effectiveness with higher values of the moderator. On average, funding was effective in avoiding forest loss at higher-altitude districts ($> 1,500$ m) (Figure 3.7), but also showed high variability, especially in the low-altitude group (min = -0.054 , mean = 0.012 , max = 0.107), of which some districts conserved forests due to PA funding. Funding in districts with more than 6 sq km of forest loss before the treatment (Figure 3.8A) and more than 3,700 sq km of unprotected forest cover at baseline (Figure 3.8B) were more effective at avoiding forest loss than below the threshold.

Population density showed a positive and significant correlation with forest loss (Table 3.3). Other variables with nonsignificant associations regarding reducing forest loss were road density and the share of pasturelands (Table 3.3). Contrary to the expectation, these indicators of economic activity would be associated with more forest loss. The presence of conserved areas showed an unexpected positive association with forest loss, although it was not statistically significant. Only two regions showed statistically significant associations: the Loreto region was associated with avoided forest loss ($\beta = -0.5303$) and the Pasco region with an increase in deforestation ($\beta = 0.7545$) compared to Amazonas (Table 3.3).

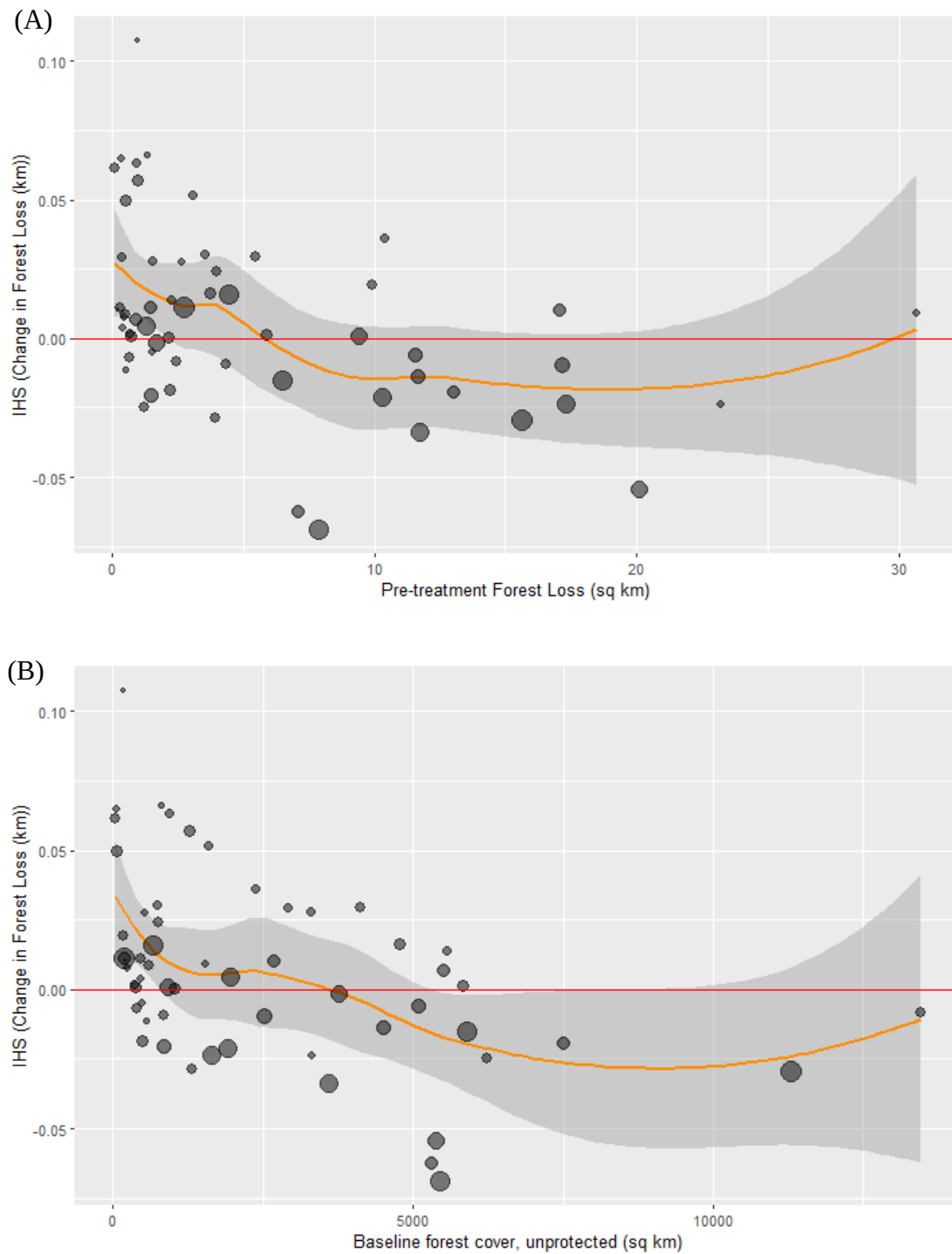
Figure 3.7 Effects of PA funding as a function of altitude.



Note: The size of the points indicates the amount of funding, where larger sizes show larger amounts.

As a robustness check, I used the same specified SEM model using forest loss with a three-year lag following the treatment, as well as replacing the funding allocation strategy to the allocation of funding using deforestation risk and a 10 km threshold (Risk 2 in section 2.8.2.2). In all cases, the results held, with the largest change being the change in sign for the interaction of funding and pretreatment forest loss when using a three-year lagged outcome, with an AMTT of 0.0061 (Appendix A, Table A.4).

Figure 3.8 Effects of PA funding as a function of (A) Pretreatment forest loss and (B) baseline forest cover.



Note: The size of the points indicates the amount of funding, where larger sizes show larger amounts.

3.5 Discussion

PA investments did not avoid forest loss at the district level, on average, but PA funding was effective in a handful of districts. It is reasonable to find that protection and funding did not avoid forest loss at the district level due to the presence of unprotected landscapes where other non-conservation-related activities may happen without much regulation, affecting forested habitats. These actions work together, pushing and pulling deforestation spatially. A district-level analysis offers a macro perspective of these diverse actions in place. Relevant actions affecting forest cover are agriculture, grazing, and mining, which I considered in this analysis as covariates. However, given the variation in PAs' share in treated districts, a more extensive unprotected landscape allows for an increased probability of deforestation, reducing the overall effects of PA funding at the district level, and even counteracting them through spillovers.

The results show a trend in which dollars invested in PAs had larger returns toward avoiding forest loss when the total investments were higher, especially above \$2 million, over the study period. This suggests that more funding had an exponential effect, where investments may have attracted even more investment, leading to increased conservation actions and impacts. Nonetheless, there were exceptions to this trend in four well-funded districts, where regardless of the presence of funding, they had more deforestation than their controls (Appendix A, Figure A.2). In Pardo Miguel district in the San Martin region, which overlaps with Alto Mayo Protection Forest, there was forest loss inside and outside the PA boundaries. This finding is supported by the fact that conservation actions in this PA faced complex social problems, high density of agricultural plots, and easy access through a main road. All these issues together may have led funds to become ineffective due to an inaccurate understanding of the local context and motivations of the participants on the intervention's design (Chambers et al. 2022). In Palcazu district in the Pasco region, most deforestation happened outside PA boundaries, exposed to a highly active agricultural landscape. In contrast, Fitzcarrald district in Madre de Dios and San Pedro de Putina Punco in Puno had relatively low forest loss with potentially low deforestation risk, overlapped largely with PAs, and were large districts. For San Pedro de Putina, most deforestation happened outside the PA.

Altitude moderated the marginal effect of funding, in which funds in districts at higher altitudes, associated with the Andean-Amazon slopes, avoided more deforestation. As expected, these areas are more connected to markets than lowland forests (Appendix A, Figure A.3). Hence, they are more at risk of deforestation. Even when higher altitude lands are less apt for agriculture and more costly to deforest on higher slopes, land-use change in the Peruvian Amazon is opportunistic rather than selective in its

characteristics (Bax, 2016), supporting this finding. Districts with more forest loss before the treatment indicate a larger risk of further forest loss, potentially attracting more funding to reduce its risk. However, given that PA funds are targeted to actions within PAs, districts with more forest loss outside PA limits may not reflect this trend. The results show more forest loss before the treatment avoided more deforestation in protected districts, suggesting that funding may have had a positive district-level effect.

This same logic applies to forest cover outside PAs, where unprotected forests tend to be affected by the spillover effects of protection. With restrictions imposed by PA boundaries, the actions that would have been performed within PAs tend to shift spatially toward the unprotected forests. Theoretically, more forests outside PAs reduce the probabilities of deforestation in PAs, confounding the effectiveness of PA funding. Nonetheless, PA funds perform better in districts with more unprotected forests after controlling for it. This finding may be explained using square kilometers as a measure instead of percent, where larger PA shares reduce unprotected forest cover. Treated districts with more unprotected forests showed less forest loss when compared to their controls, suggesting that the presence of PAs and their funding reduce the likelihood of deforestation in protected districts. Spatial analysis at a lower scale is needed to determine the level of spillover effects from PAs.

Buffer zones were not relevant in estimating the impacts of PA funds, contrary to the expectation. While they were effective in the Madre de Dios region (Weisse and Naughton-Treves 2016), they do not generally seem to have such an effect. More densely populated districts increase the probability of deforestation, which can be explained by the higher opportunity costs of not cutting the forest. Districts in the Pasco region contributed to deforestation, with an extensive area in the Andes-Amazon slopes in Oxapampa Province featuring active cattle ranching, coffee farming, and a highly connected roads network. In comparison, Loreto is the largest region in Peru, full of lowland seasonally flooded forests and extensive remote areas. Districts in this region had less forest loss, probably due to their lack of access and reduced deforestation risk. Nonetheless, Iquitos district holds the capital city of Iquitos, and tells a different story. Iquitos is the district with the highest positive marginal effect of PA funds (upper right outlier in Figure 3.5 and upper left outlier in Figure 3.6), which means that its funds were not effective in avoiding forest loss. The presence of the capital city and surrounding agricultural plots increasing deforestation can explain this case. It overlaps with Allpahuayo-Mishana National Reserve, half an hour drive away, which is why it is included in the sample.

Access is a relevant characteristic to consider when evaluating the threats to forest loss. Distance to roads is a persistent measure of threat to PAs and forest loss in Peru (Vuohelainen et al. 2012; Weiss and Naughton-Treves 2016; Schleicher et al. 2017) and elsewhere (Andam et al. 2008; Honey-Rosés et al.

2011; Shah and Baylis 2015; Cuenca et al. 2016). I measured access by road density per district, not distance, and it showed a not statistically significant relationship with forest loss. Huicungo district, the most effective avoiding forest loss, is a medium sized district and isolated area, with little access and populated centers. However, Echarate and Rio Tambo had large accessibility and populated centers outside PAs, but possibly less forest loss than was would have been expected given their characteristics. It is possible that including other ways to measure access could show their relevance at this level.

Extractive activities were present in both regulated and unregulated ways. Spatial data are more likely obtained for regulated activities than for illegal ones. In the case of mineral extraction, I included the share of legal mining and petroleum concessions per district, but it was dropped from the model. Illegal mining is concentrated primarily in the Madre de Dios region (Weisse and Naughton-Treves 2016; Rojas et al. 2021); it was not included in the model because it was relevant for only one region. Other potentially harmful extractive activities are illegal logging by selecting certain species of trees like mahogany, Spanish cedar, and tornillo (Garcia and Limachi 2008 in Vouhelainen et al. 2012). Such spatial data on legal and illegal extractive activities in the Amazon could hold highly valuable information for local enforcement personnel and decision-makers in the future. In addition, agriculture and pasture plots did not significantly affect funding performance. Both access and extractive activities were expected to play relevant roles affecting forest loss, and it is possible that using a lower scale unit of analysis and measure (distance instead of share) may influence the impacts when accounting for its geographical distribution, such as in analysis at the grid level.

PA funds have diverse objectives such as reducing habitat degradation, species protection, supporting community-based conservation, and improving management and infrastructure, among many others. In the Peruvian Amazon, avoiding forest loss is a common target in most funded projects and an overarching goal. However, using all committed funding and assuming homogeneity in its effects is the first step to identifying relationships and potential causal effects. Future research can disaggregate funds by goals and estimate their impact. The results presented do not uncover the precise mechanism through which funds affect avoided forest loss. Still, they describe the impacts of all funds and provide information on the contextual factors that help shape their effectiveness.

This study shows that PA funding was effective in avoiding forest loss under certain conditions, evidencing heterogeneity. In comparison, Schleicher et al. (2019) found PA management inputs in SERNANP were weakly correlated with the likelihood of forest loss between 2006 and 2011. This difference in findings may be explained by the fact that since the establishment of the SERNANP in 2008, more funding was channeled over time and better targeted across PAs (Nakamura 2017). The allocation

of funds based on needs could explain the increased effectiveness of funds found in some districts. However, targeted evaluations at the PA level may show larger effects of these funds. Funding for conserved areas and Indigenous lands was not considered due to lack of availability. Even when previous efforts for collecting this data was not successful and showed significantly low investments than in PAs, this oversight may affect the results as any other conservation efforts at the district level should be considered. Future studies may consider expanding the time period of this study to evaluate longer-term impacts and account for conservation efforts outside PAs.

Considering spatial components in a model helps make more accurate estimations. Nonetheless, many impact studies do not include the spatial relationships present in the models, potentially biasing their outcomes. In this research, the use of a spatial error model adjusted the covariates' significance level and, in some cases, the direction of the effect. This analysis contributes to the body of research supporting the use of spatial models for impact evaluation in conservation. A caveat from the district-level analysis is that districts with higher forest loss were not represented in the matched control districts, especially concentrated in the central part of the Amazon (Figure 3.3). However, this mismatch could be reduced by using smaller sampling units for a better comparison, such as at the community or grid level. Another caveat of the district-level analysis is that PA size could not be incorporated as part of the analysis. Larger PAs require less spending per sq km than smaller PAs to achieve the same effect, hence accounting for the size of PAs matter (section 2.6.1, Bruner et al. 2004). Oftentimes, districts overlap partially with PAs, and sometimes with multiple PAs, making it technically challenging. Using a different unit of analysis and comparator, such as making a comparison between PAs, will allow to include this variable.

Further research on PA funding mechanisms could shed more light on the sources of funds (domestic, international, private, or public), types of funding (flexible versus hard funding, short- versus long-term), and actual use, moving beyond committed amounts of funds. For this, detailed and updated data need to be tracked and reported correctly, especially on spending rather than committed amounts. Reporting is still a big limitation to obtaining funding data because recipients usually report on what donors expect to fund rather than what was done. Further analysis could also consider other outcomes such as the impacts on biodiversity, quality of resources such as water and soil, and social indicators to have a complete picture of the components of return on PA investments. Additionally, given the potential geographical heterogeneous distribution of the covariates within each district, further analysis using a smaller unit of analysis (e.g., grid level) may be needed to confirm the results hold at different geographical levels.

3.6 Conclusion

PA funding showed heterogeneity in avoiding forest loss at the district level. On average, funds did not avoid forest loss. However, the effects showed both positive and negative effects. Economic activities outside PA limits may have reduced or counteracted funding impacts in some districts. Nonetheless, ecological and geographical factors conditioned these impacts, which may need to be considered when planning future investments. Funds in districts with higher altitudes, having higher baseline forest cover in unprotected areas, and higher levels of previous forest loss increased the marginal effect of funds or were more effective per dollar invested. Also, districts with more funds, especially those above \$2 million, were more likely to have larger impacts in avoiding deforestation, suggesting an additive effect of the impact of funds. However, districts with PA funds below this threshold were effective.

In districts where PA investments did not avoid forest loss, the funded actions were insufficient to address the cause of deforestation. There are two potential scenarios for this: 1) Funding was invested in other objectives due to reduced deforestation pressure, and 2) there was more forest loss outside PA limits on which PA funds do not have a direct effect. Generally, PA funds were not expected to have an impact at the district level but within the PA, for which the effects of the funds considered here also considered leakage effects and other threats beyond PA borders. The amount of avoided forest loss reflects only one outcome out of the many others funding can impact. Further exploration of the effects of funding using finer spatial units targeted specifically on PAs can help disentangle more direct effects, the heterogeneity of the impacts, and the mechanisms at work. In addition, using a spatial model may show a smaller effect when comparing it to the magnitude of previous research estimates of PAs on forest loss because spatial models capture more accurate estimates by considering spatial relationships. Even at the district level, more forest loss would have occurred without those investments. These results add to the body of evidence that supports the need to increase biodiversity conservation funding to reduce forest loss.

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CHAPTER 4: THE IMPACT OF PROTECTED AREA FUNDING ON HUMAN DEVELOPMENT IN THE PERUVIAN AMAZON

4.1 Introduction

Over the last four decades, significant global investments were devoted to creating protected areas (PAs) as a primary conservation strategy (Miller and Nakamura 2018; UNEP-WCMC et al. 2018). Protecting nature to avoid and reduce ecological degradation in critical parts of the planet can maintain and restore the ecological systems (IUCN 2019). These natural systems and resources are extremely valuable to people, especially those living nearby, given the wide range of goods and services they provide (Holzman 2012; McKinnon et al. 2016). Yet human economic activities pose a threat to many of the world's PAs. Protections are often coupled with land use restrictions and rules, which potentially affect the livelihoods and well-being of populations living in and around PAs. Over time, conservationists and development practitioners have realized that land protection comes with additional responsibility to support local people for moral and instrumental reasons. For instance, a PA can potentially lead to good ecological outcomes. Still, if the imposed restrictions reduce a local population's ability to meet basic needs, the probability of conflict undermining the potential to conserve will increase. Overall, conservation interventions should, at a minimum, not harm local populations and enhance their well-being if possible (Beauchamp et al. 2018).

Previous research showed PAs worldwide avoided forest loss (Geldmann et al. 2013; Börner et al. 2020), although the evidence on its impacts on social outcomes is less consistent (Pullin et al. 2013). Populations living around PAs may be affected by the restrictions imposed with legal protection, removing their rights to access and benefit from its resources. An example of those effects are diminishing health through higher exposure to diseases, human-wildlife conflicts, and reducing women's security (Pullin et al. 2013). At the same time, tangible benefits may derive from this protection through increased resource availability, such as higher consumption of fish and meat, poverty reduction, and economic benefits from tourism (Pullin et al. 2013). When there are positive socioeconomic outcomes from PAs, it is more likely to find positive conservation outcomes (Oldekop et al. 2016).

The Sustainable Development Goals (SDGs) set the expectation to simultaneously achieve development and conservation goals (United Nations 2015). Conservation practitioners now recognize the importance of including social aspects in conservation planning as the best way to address and achieve conservation success under the social-ecological systems framework (Knight et al. 2010). Millions of dollars from international aid support conservation in developing countries every year; however, little

evidence has demonstrated such strategies' effectiveness (Agrawal and Redford 2006). Establishing evidence related to these programs' effects will help shape tools for planning, management, and effective investments.

The majority of the world's poor live in developing countries, co-occurring geographically with high-biodiversity locations (Adenle et al. 2015). PAs are established in chosen areas to protect a specific set of natural resources; hence they are not randomly located (Joppa and Pfaff 2009). However, given the potentially high economic value of particular locations for resource exploitation, PAs are more likely to be sited in places with lesser value. Siting of many PAs has been biased to areas in high elevations and slopes, a considerable distance from roads and cities (Joppa and Pfaff 2009), where there is limited access to markets, economic opportunities, education, health, and services. These limitations reduce the capacity of populations living in and around PAs to improve their standard of living. Given PAs' biased locations, researchers use experimental or quasi-experimental methods to provide evidence of its impacts (Baylis et al. 2015; Jones and Lewis 2015; Schleicher et al. 2019) beyond the naïve inside-outside comparisons.

Peru is a megadiverse high-middle income country that has based its economic growth on its natural resources (IMF 2020), especially the hydrocarbon and agricultural sectors, over the past decades (Cuba et al. 2014). As the fastest-growing economy in Latin America between 2003 and 2014 (World Bank 2016), its average income increased, which reduced monetary poverty, but had a limited effect on monetary inequality (Herrera 2017). Its geography and colonial history explain much of the social characteristics and dynamics between its territory and human development (UNDP 2019). There are three main regions in Peru: the coast, the highlands, and the rainforest. With the arrival of Spanish colonists by sea, most economic and political activities concentrated on the coast (Stratfor 2020), which led to the development of the largest urban centers, diversified production, and a higher human development index (HDI) (UNDP 2019). Comparatively, the Andes highlands are characterized by high altitudes, leading to harsh climate conditions, steeper slopes, increased soil drainage, and limited access to social services. Data shows that HDI decreased in higher altitudes (UNDP 2019). The rainforest in the Peruvian Amazon covers most of the country's territory and holds invaluable natural resources such as primary forests (Vargas et al. 2014) and high biodiversity (Fajardo et al. 2014). The Andes and the Amazon hold most of the country's natural resources, with a concentration of minerals in the south and petroleum in the north (Lauriani 2016). Andean communities are connected to the coast through roads, offering a path of access to markets and services. In contrast, connectivity is more costly for people in the Amazon because they must cross the Andes to get to the coast. This geographical barrier limited the

Amazonian region's ability to develop compared to the rest of the country and left its underground resources mostly unexploited until the first decade of the 2000s under Garcia's policies.

The second term of Alan Garcia's presidency (2006–2011) brought radical neoliberal policies based on extractive activities, welcoming foreign investment to take advantage of the “unused resources” in the Amazon (Arce 2014). This strategy led to civil unrest, which precipitated changes in the forestry law and created a “previous consultation” law looking to increase Indigenous peoples' inclusion. Although these events strengthened democracy in the country, mining concessions increased almost threefold during Garcia's term (Arce 2014). The expansion of legal concessions over the Amazon threatened Peru's Indigenous social and cultural patrimony and the natural environment. In 2008, the Peruvian Ministry of Environment (MINAM) was established to ensure environmental protection and regulation. The national park system was transferred from the Ministry of Agriculture to MINAM, establishing a specialized institution, the Peruvian National Park Service (SERNANP), to manage PAs. From 2008 on, SERNANP established a digital accounting and reporting system that tracks domestic expenses in detail.

Against this backdrop, this study examines the impacts of PA funding on human development through a case study in the Peruvian Amazon. It analyzes PA funding impacts from seven years of funding, from 2009 to 2015, using district-level data, and matching to find comparable units. The results help advance theory about the role of conservation funding on the development of populations coexisting with PAs. They can inform international aid and other funders to achieve more equitable social outcomes.

4.2 Literature review and theoretical expectations

The most common quantitative measures for social outcomes in the biodiversity conservation literature are monetary poverty (Andam et al. 2010; Canavire-Bacarreza and Hanauer 2013; Miranda et al. 2015; Puri et al. 2016; Sims 2010), income per capita (Miranda et al. 2015; Puri et al. 2016), and consumption per capita (Miranda et al. 2015; Sims 2010) rather than other human well-being outcomes (McKinnon et al. 2016). Economic outcomes such as income and expenditure are quantifiable, perceived as objective, and unidimensional. These monetary measures, based on demographic reports globally, do not reflect the effects of conservation interventions on people's lives (Milner-Gulland et al. 2014). These measures, commonly criticized for their simplistic approach to well-being and multidimensional poverty, provide a limited picture of social progress (Stiglitz et al. 2009). Measures like the Multidimensional Poverty Index (Alkire and Foster 2011) and the Human Development Index (HDI) (UNDP 2019) combine these monetary and nonmonetary (education, health, and social) dimensions into a statistical composite that would reflect a more holistic perspective on human deprivation and capabilities.

The impact evaluation literature shows PAs reduced monetary poverty in Thailand (Andam et al. 2010; Sims 2010), Costa Rica (Andam et al. 2010), Bolivia (Canavire-Bacarreza and Hanauer 2013), and Ethiopia (Estifanos et al. 2020). In contrast, no significant effect was found in Peru (Miranda et al. 2015). Using multidimensional indexes, PAs reduced multidimensional poverty and extreme poverty in Nepal, with no effect on inequality (den Braber et al. 2018). In Bolivia, PAs had no impact on the incidence of unmet basic necessities (Canavire-Bacarreza and Hanauer 2013). In a study across 34 developing countries, there was no evidence that living near PAs exacerbated monetary poverty, and in fact, it showed positive effects on human health and well-being (Naidoo et al. 2019). One correlational study found that human development is correlated with PA performance whereas low PA performance was more likely observed in areas with lower human development (Geldmann et al. 2019). The authors interpreted this finding as a reflection of systemic issues such as corruption, weak law enforcement, and low stakeholder involvement. All these studies showed the average effect of PAs on the outcomes, but these average values can hide potential variations in response to the treatment by subgroups within the population (Hanauer and Canavire-Bacarreza 2015).

The variables generating heterogeneity in the response, or moderators, are variables unaffected by the treatment, which moderate the effects' magnitude (Ferraro and Hanauer 2015). Some commonly tested moderators are geographic characteristics such as slope and altitude, park management categories, economic activities like tourism, and measures of access such as distance to roads. When comparing PAs' effects by management categories, sustainable-use PAs were more likely to report positive socioeconomic outcomes than strict-use PAs (Oldekop et al. 2016; den Braber et al. 2018). Generally, PAs with positive conservation impacts also showed positive livelihood outcomes (Oldekop et al. 2016). Areas with steeper slopes are more challenging and costly for agricultural work than less steep ones, putting flatter areas at higher deforestation risk. For example, in Bolivia, PAs with lower slopes and closer to cities were most effective at reducing poverty (Hanauer and Canavire-Bacarreza 2015). Understanding these various responses by identifying the subgroups can help to allocate and target more effective interventions.

Within the PA impact evaluation literature, the study of conservation management inputs is done by measuring and monitoring planned activities' compliance, the number of staff, and local NGOs' involvement without concluding evidence of impacts (Geldmann et al. 2013). Nonetheless, funding has not yet been included in impact evaluation assessments in protected areas regardless of its importance (Miller and Nakamura 2018). Studies have highlighted that funding is needed to increase conservation actions and effectiveness (Geldmann et al. 2018; Dixon et al. 2019). Insufficient funding may work as a

proxy for inadequate staff, equipment, and other management necessities, especially in developing countries (Bruner et al. 2004). However, given the importance of funding for PAs, no published research measures the role PA funding plays in social impacts. This gap in knowledge may be due to the lack of reliable financial data available (Castro and Locker 2000; Naidoo et al. 2006; Armsworth 2014; Iacona et al. 2018), and even less data that are geo-referenced at the subnational level (Nakamura 2017). Here, I theorize that the investment made in PAs may positively affect social outcomes through additional income from increased economic activities like tourism, affecting the livelihoods of local communities as well as through other nonmonetary indicators such as health improved by ecosystem services.

4.3 Data and methods

4.3.1 Peruvian Amazon PAs and matched districts

The Peruvian Amazon has an extension of 78,313,996 hectares, covering 60.9% of the country (Vargas et al. 2014). Of the 34 PAs established within the Amazon by 2015, I included 29 PAs (Table 3.1 in Chapter 3). I used the same matched sample as in Chapter 3, including 58 treated and 58 control matched districts (section 3.3.7).

4.3.2 Treatment: Funding data

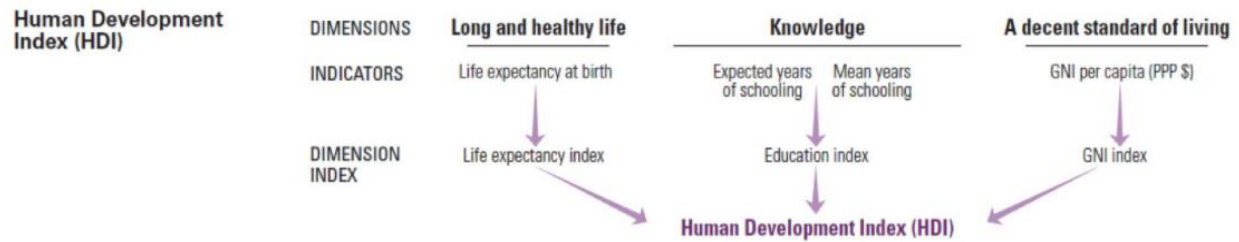
The treatment is the cumulative committed PA funding from 2009 to 2015, same as in Chapter 3 (section 3.3.4).

4.3.3 Outcome

To capture the change in development in Peru, I used the HDI and monetary income. HDI is a composite index including three dimensions: income, education, and health (UNDP 2019). The first component measures family income per capita to proxy for the capability of earning income for a basic standard of living. Second, education measures the number of years of instruction for adults 25+ years and the rate of high school graduates aged 18+. Third, it refers to the capability of living a long and healthy life and is measured as the life expectancy at birth. HDI is a measure that reflects the state and evolution between territories to help unveil social changes but not explain their cause. In this context, the regions with higher development are the most unequal. In contrast, less developed regions are similar, and higher HDI is associated with a larger share of nonagricultural jobs (UNDP 2019). The HDI is the geometric mean of normalized indices for each of the three dimensions (Figure 4.1). This data was modeled by the UNDP based on the national census data, household panel data, and other official databases (public services) following the IDH index designed by Alkire and Foster (2010) and is representative at the district level (UNDP 2019).

For this research, I used HDI and monetary income, its most time-sensitive component, as individual outcomes to test the potential effects PA funding has on a multidimensional index. The outcome variables are available for 2003, 2007, 2010, 2011, 2012, 2015, and 2017. To pair it with the treatment data, I used the year 2007 as pre-treatment and the year 2015 as the outcome.

Figure 4.1 Dimensions and indicators used on the HDI. Source: UNDP (2021).



4.3.4 Covariates

Covariates included variables related to PAs' selection and funds and the variables that may affect the outcomes, as in Chapter 3 (Table 3.2). Some of these variables were included in matching, and others were added to account for their influence in the postmatching regression. Their inclusion in each step is detailed in the "Use" column in Table 3.2 in Chapter 3. I included the relevant biophysical variables such as slope, elevation, rain, and temperature, which may affect the siting of PAs (Andam et al. 2008, Miranda et al. 2015, Weisse and Naughton-Treves 2016, Schleicher et al. 2017). Other forms of forest conservation, such as Indigenous lands have shown to be more effective at conserving forests than PAs in the Peruvian (Schleicher et al. 2017) and Brazilian Amazon (Börner et al. 2020). I included this variable as the share of Indigenous titled lands within districts. Separately, I included conserved areas such as regional and private conservation areas, and the various forms of concessions (forest, conservation, ecotourism, reforestation, fauna management, and permanent production forests), as the share within a district.

The measures of access and connectivity increase the probabilities of connecting people to markets and their opportunity costs (Hanauer and Canavire-Bacarreza 2015). I measured access through road density (sum of national and departmental roads/district area). Through deforestation and contamination, mining is a significant threat to the environment and its people in the Peruvian Amazon, but it could also improve income through increased employment. There was no relationship between mining and HDI at the country level as it is present in high and low HDI districts (UNDP 2019). However, its relationship may change in the Amazon Basin alone. I controlled for the share of mining and petroleum concessions (referred to as mining from now on) per district.

I included social variables at the baseline (2007) for population density, the share of agricultural jobs, and HDI to get comparable groups. The largest gaps in development at the national level are linked to structural characteristics of locations such as altitude, population density, and diversified production levels. At the district level, these gaps are related to educational attainment and income (UNDP 2019). Agricultural jobs are primarily for subsistence agriculture, correlated with a lower HDI, and are more prevalent in poorer districts (Naidoo et al. 2019). In addition, I included the share of agriculture and pasture plots per district, as their presence affect forest cover negatively but may add to local income.

4.3.5 Matching

The matching procedure was the same as used in Chapter 3 (section 3.3.7).

4.3.6 Postmatching regression

To estimate the effect of PA funding on HDI and income, I fit a postmatching regression to control for additional biases. I chose a suitable model using HDI, and then replicated the model specification for income. Given the distribution of the outcome, I fit an ordinary least squares regression, where the best-fitting model based on the lowest Akaike information criterion (AIC) value showed spatial autocorrelation and heteroskedasticity (Appendix B, Table B.1). The Lagrange multiplier test pointed to the use of a spatial error model (SEM). I fit a SEM using the *errorsarlm* function from the *spatialreg* package in R (Bivand and Piras 2015). For HDI, I adjusted the model for heteroskedasticity using the *GMerrorsar* function from the same package due to the presence of heteroskedasticity in the SEM (Appendix B, Table B.1).

I applied an inverse hyperbolic sine (IHS) transformation on the skewed variables, recommended over a logarithmic transformation for variables containing real zeroes (Burbidge et al. 1988; Bellemare and Wichman 2020). However, the outcomes had a normal distribution and were not transformed. I defined the equation as a cross-section regression with Department (region) as a factor to control for their unobserved political and cultural characteristics:

$$Y_i = \alpha + \text{IHS}(\text{Funding}_i)\beta_1 + \text{IHS}(X_i)\beta_2 + \gamma_i\beta_3 + \varepsilon$$

$$\varepsilon = \lambda W\varepsilon + u$$

where Y is the social outcome (HDI or income) in district i . HDI was multiplied by 100 given the values range between 0 and 1. Income was used as such, expressed in average monthly Peruvian soles. **Funding** is the treatment, as the cumulative amount of funding in district i . X is a vector of confounders that may affect the outcome in district i : share of agriculture plots, mining concessions, conserved areas,

Indigenous titled lands, population density, baseline HDI, and district area. γ_i is the effect of the Department to which the district belongs, and ε is the error term. ε is composed of λ , the average spatial correlation among the errors conditional on W , $W\varepsilon$ as the spatially weighted matrix of neighbors among the residuals, and u as the error term with a normal distribution, which is independent and has constant variance.

I tested interactions between potential moderating variables with funding, and they were statistically significant. In particular, more mining concessions, road density, and population density could pose higher threat levels to PAs, increasing funding. I expect that with more human threats, PA funds had more opportunities to improve HDI through alternative jobs and a safer environment. In terms of ecological characteristics, I theorize that more baseline forest cover in the presence of funds would increase HDI through better ecosystem services, and I have the same expectation because a larger presence of conserved areas could help boost protection and environmental characteristics, benefiting local people. More agricultural activity is correlated with lower HDI, which suggests that funds in areas with more agricultural activity could be detrimental to development. It might suppress and reduce access to land-use change, reducing agricultural labor and unemployment, unless funds offer alternative economic activities to improve HDI. In terms of geography, the districts located in the Andes-Amazon region have higher slopes, lower temperatures, and less rainfall compared to the lowlands. Harsher weather conditions are associated with a lower HDI (UNDP 2019). These environmental and cultural differences between highlands and lowlands may affect how PA funding moderates HDI.

To interpret the effects of PA funds on the outcomes, due to the $Y \sim \text{IHS}(X)$ model specification, I applied a $\beta_1 \times \log(1.x)$ to get the estimated impact of $x\%$ increase in funds on the outcomes, where if I want to estimate the impact of 10% funds increase, 1.1 is used in the equation, or 1.32 for a 32% funds increase. For HDI, I divided the coefficient by 100 to bring the HDI value back to its range.

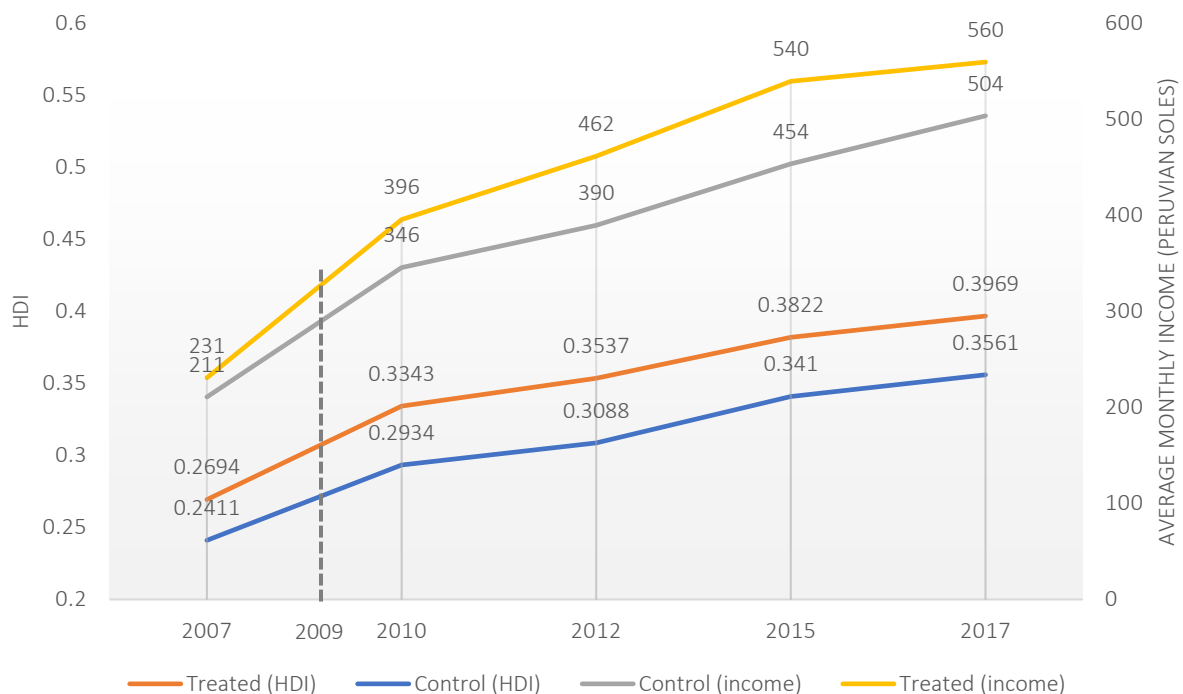
4.4 Results

4.4.1 Sample description of matched data

The dataset used for this analysis includes 58 treated districts and 58 controls (Figure 3.3 in Chapter 3). Treated districts had a mean percentage of area protected of 37.93% (min = 10.79%, max = 89.27%) and a mean funding committed of I\$2,154,402 (min = I\$89,924, max = I\$7,729,017) (detail per district in Appendix A, Table A.1). On average, HDI was higher before and throughout the treatment in treated districts compared to control districts with parallel trends (Figure 4.2). The naïve difference

between treated and control increased slightly over time from 0.0283 in 2007, to 0.0409 in 2010, and to 0.0449 in 2012, with slight drops to 0.0412 in 2015 and 0.0408 in 2017.

Figure 4.2 Change in HDI (main axis, left side) and income (secondary axis, right side) over time for treated and control districts.



Note: The dashed vertical line represents the first year of treatment.

4.4.2 Marginal average areatment effect

PA funding had a positive and statistically significant effect on HDI and income (Table 4.1). On average, a 10% increase in PA funds would have had an increase of 0.0003 on HDI ($\beta = 0.2919$, $p\text{-value} = 0.0245$), and 0.84 Peruvian soles of income per month ($\beta = 8.7912$, $p\text{-value} = 0.0366$). The magnitude of the effects are minimal compared to the naïve difference between treated and control districts. The effect on HDI is only 0.7% of the change in 2017, and 1.5% of the change in income. None of the theoretical modifiers had a significant interaction effect.

The covariates for population density, baseline HDI, share of conserved areas, and Indigenous lands had statistically significant associations with districts' HDI and income. The positive coefficients

Table 4.1 Effects of PA funding using a spatial error model on income and human development.

	SEM, income 2017				SEM_Robust, HDI2017			
	Estimate	SE	z-val	p-val	Estimate	SE	z-val	p-val
(Intercept)	-148.5941	156.1625	-0.9515	0.34133	6.3131	4.8443	1.3032	0.1925
Funding	8.7912	4.2055	2.0904	0.03658	0.2919	0.1298	2.2485	0.0245
Agricultural plots	19.8716	19.8543	1.0009	0.31689	0.9670	0.6437	1.5023	0.1330
District area	-27.7768	18.744	-1.4819	0.13837	-0.9463	0.5896	-1.6050	0.1085
Baseline HDI	22.8344	3.3256	6.8662	6.60E-12	0.9579	0.1079	8.8761	< 2.2e-16
Conserved areas	20.2224	9.3566	2.1613	0.03067	0.5809	0.2924	1.9868	0.0469
Population density	34.3191	19.9553	1.7198	0.08547	1.4202	0.6337	2.2409	0.0250
Indigenous lands	19.1811	9.8977	1.9379	0.05263	0.7252	0.3126	2.3201	0.0203
Mining	12.9248	9.4136	1.373	0.16976	0.4236	0.2878	1.4718	0.1411
Cajamarca	-63.5793	105.7963	-0.601	0.54787	0.6825	2.9296	0.2330	0.8158
Cusco	99.5852	90.4237	1.1013	0.27076	7.4119	2.5875	2.8645	0.0042
Huancavelica	113.6255	136.7233	0.8311	0.40594	5.7957	4.0246	1.4400	0.1499
Huanuco	104.106	88.5066	1.1763	0.23949	4.4007	2.6674	1.6498	0.0990
Junin	56.2696	107.8512	0.5217	0.60186	5.3546	3.1588	1.6951	0.0901
Loreto	149.1344	78.7197	1.8945	0.05816	6.4214	2.3551	2.7266	0.0064
Madre de Dios	299.8186	104.8427	2.8597	0.00424	12.9294	3.2181	4.0178	0.0001
Pasco	15.781	103.2335	0.1529	0.8785	2.9481	2.8887	1.0205	0.3075
Puno	145.3371	103.5513	1.4035	0.16046	10.8632	2.9355	3.7007	0.0002
San Martin	64.7148	71.4693	0.9055	0.36521	3.1411	2.1235	1.4792	0.1391
Ucayali	-27.7788	91.6994	-0.3029	0.76194	3.1609	2.7753	1.1390	0.2547
Moran's I	0.0351			0.3021				
Lambda	0.3165			0.0048	0.1619		0.93	
BP test	26.3060			0.1219				
Jarque-Bera test	16.2520			0.0003	7.1875			0.0275
AIC	1515.1000							
Loglik	-735.5535							

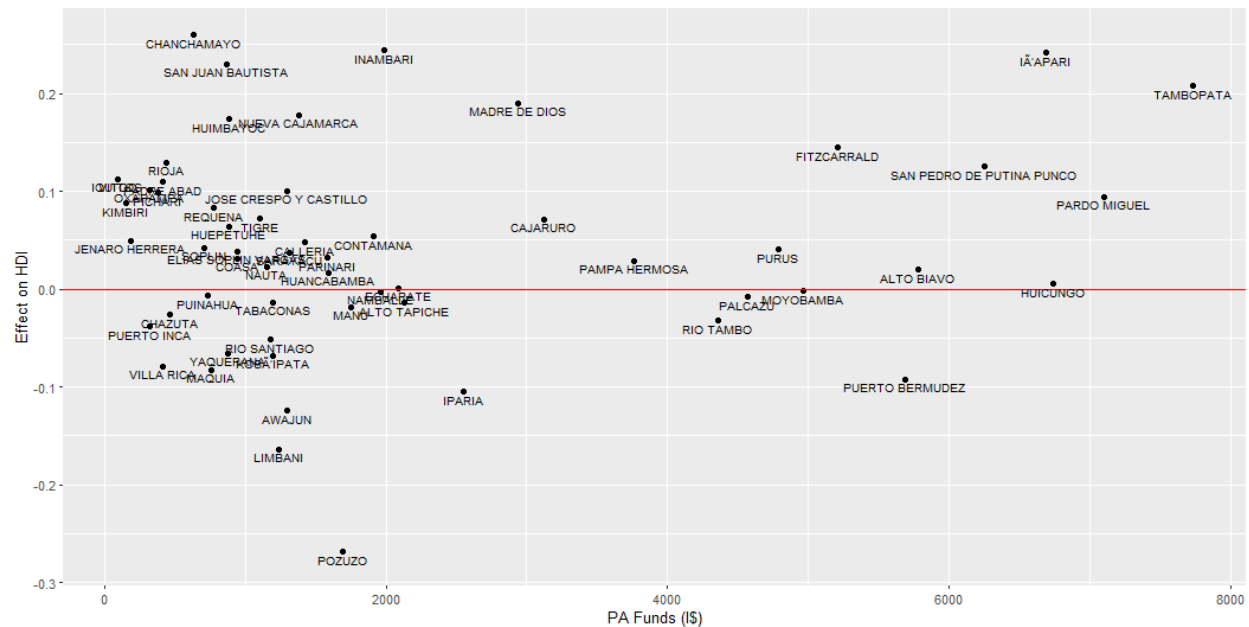
indicate a contribution toward their increase, with population density having the largest value. The regions of Cusco, Loreto, Madre de Dios, Puno, Huánuco, and Junin were associated with an increase in HDI compared to Amazonas (benchmark region), and Madre de Dios and Loreto for income.

4.4.3. Individual treatment effects

The individual district effects, estimated as the difference between treated and control districts on the predicted outcome, showed positive effects on social outcomes at both high and low funding levels, while negative effects were larger and more frequent in poorly funded PAs (Figure 4.3). Four well-funded districts (Puerto Bermudez, Rio Tambo, Moyobamba, and Palcazu) had negative effects on HDI and income. Twenty districts had negative effects on human development and 23 had reduced income

effects. Six districts (Echarate, Huancabamba, Coasa, Nauta, Parinari, and Sarayacu) had an increase in HDI but a reduction in income, and three districts (Tabaconas, Puerto Inca, and Puinahua) had reductions in HDI with an increase in income (Figure 4.4). All nine districts had below average PA funds.

Figure 4.3 Individual district effects of PA funding on income plotted against the effects of funding on HDI.



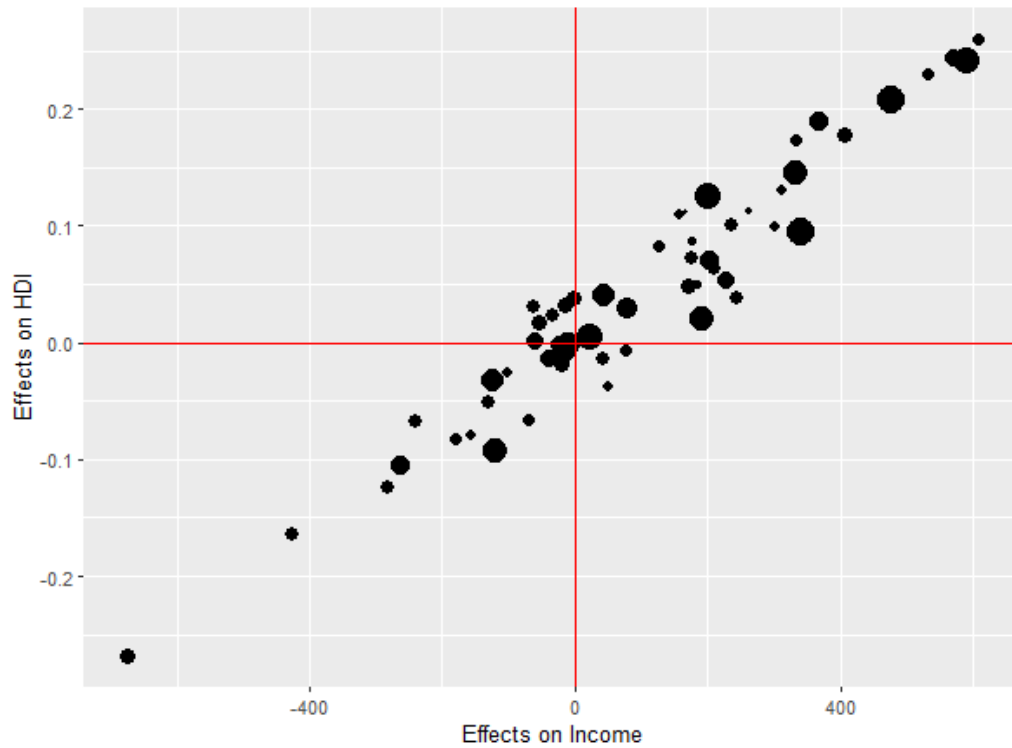
The effects of funding on HDI showed opposite trends when plotted against deforestation, where larger positive and negative social effects were observed in districts with less forest loss. Smaller effects were observed in districts with high and low deforestation (Figure 4.5). An exception to this trend is Inambari district in Madre de Dios region, with above mean deforestation and a high effect on HDI (Figure 4.5).

4.5 Discussion

This research gives evidence of the social effects of PA funding at the district level in the Peruvian Amazon. Human development and income increased in very small magnitudes with the presence of PA funding, on average. Given that many social outcomes related to forest PAs may take time to show results (Miller et al. 2017) and PAs in many districts represent a small fraction of district area, expecting PA funds to have district-level social impacts is asking a lot. Hence, the magnitude of this finding is not surprising. Most districts with positive effects on development also showed increased income, pointing to material benefits as one mechanism to achieve improved human development. None of the covariates moderated

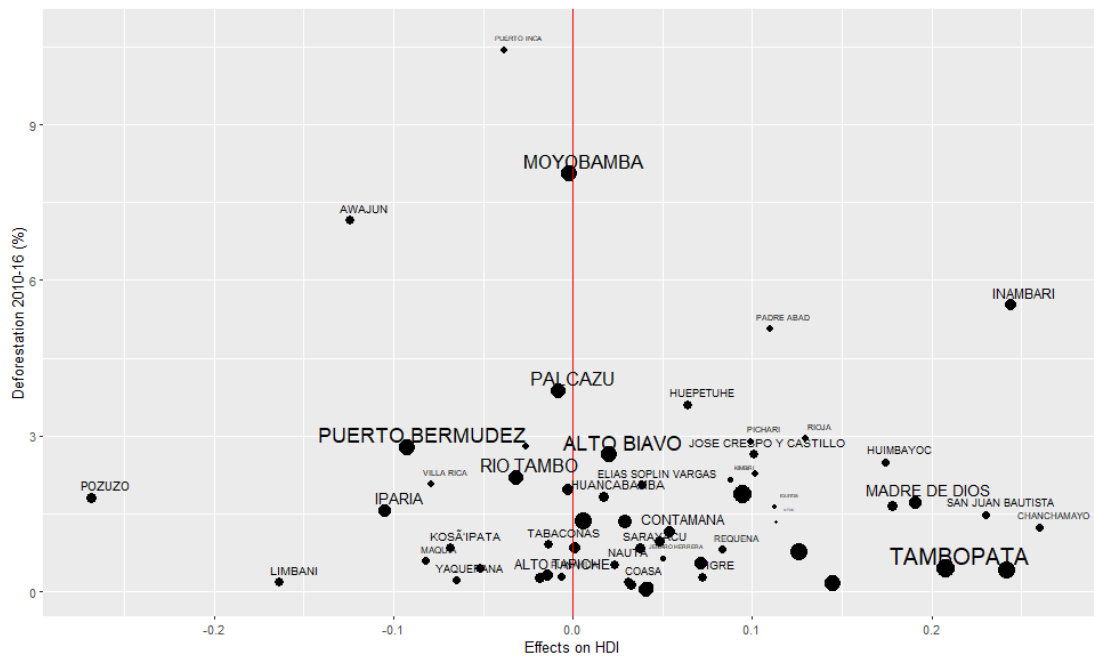
the effects of funding. However, some individual districts show slight trends with outliers that may not be statistically significant.

Figure 4.4 Individual district effects of PA funding on income plotted against the effects of funding on HDI.



Note: The dot size represents the amount of PA funding received, where larger size indicates more funding.

Figure 4.5 Individual district effects of PA funding on HDI plotted against the share of deforestation per district.



Note: The dot size represents the amount of PA funding received, where larger size indicates more funding. Labels show the districts' names.

Districts with more PA funds and lower shares of forest loss tend to have fewer negative effects on HDI. Having higher population density, conserved areas, and Indigenous lands are associated with increased development and income. These associations suggest that losing less forests in districts with more population density may provide larger benefits from ecosystem services such as a cleaner environment, access to natural resources, and better health. Contrary to the theoretical expectations, population density was inversely correlated with deforestation for all matched districts (Appendix B, Figure B.1). Districts with larger shares of conserved areas had lower deforestation (Appendix B, Figure B.2), increasing ecological connectivity and improving ecosystem services (Palfrey et al. 2022). Districts with more Indigenous lands had more deforestation (Appendix B, Figure B.2). Similarly, Indigenous lands may contribute to social outcomes through protecting forests (Schleicher et al. 2017). However, this effectiveness may not be strong at the district level because it considers deforestation within and outside Indigenous borders. Spatial deforestation patterns could provide a better understanding of the relationship and role of the different effects of land protection, deforestation, and social change.

Having a higher baseline HDI was associated with positive effects on HDI and income. More agricultural jobs are linked to lower HDI in Peru (Table 3.2 in Chapter 3), where most agricultural workers are subsistence farmers (UNDP 2019). Given their high correlation, HDI may work as a proxy for agricultural jobs. While having more agricultural jobs could lead to more clearing of forest plots, it seems the presence of any type of legal land protection may counteract it. The restrictions imposed by PAs and their enforcement reduce the probabilities of available land for agriculture. This restriction, combined with aid that promotes alternative economic activities (tourism, sustainable product harvest) and health, may help slowly increase income and HDI. However, there are no studies about the relationship between agriculture and PAs in Peru.

Accounting for agriculture plots was relevant to estimating the effects of PA funds, but the relationship was not statistically significant. Interestingly, the share of agricultural jobs was not correlated with more agriculture plots in a district (Table 3.2 in Chapter 3), which may potentially be explained by two things. First, the measure of agricultural jobs per district includes only those that legally reside in that district and declare agriculture-related activities as their main income. Many illegal agriculture plots are farmed by migrants from other regions not considered in that statistic. Second, districts with extensive agriculture parcels may belong to wealthy landowners or companies, which keep using the same land over time and are not a big cause of concern. Nonetheless, a close look at the most affected areas will provide more information on the reasons behind this lack of correlation and an understanding of the agricultural dynamics.

There were six districts in which development increased but not through income and three districts where more income did not increase development. All four districts containing Pacaya Samiria National Reserve were in this group with opposite effects. Nauta, Parinari, and Sarayacu showed less income and higher HDI, while Puinahua had more income and reduced HDI. This difference could be related to Puinahua having significantly less allocated funding (I\$ 0.7 M, compared to I\$ 1.16, 1.6, and 1.3 M) due to reduced risks, low shares of agriculture plots, and low population density, which have higher weight and thus affected HDI more than income. A common characteristic found among Huancabamba, Echarate, Coasa, and Tabaconas is they all are in the Andes-Amazon region, which implies more access to markets than in lowland areas and a higher risk of forest loss. However, Tabaconas is on the northern region of Cajamarca with a high share of Indigenous lands (32%) and mining (8.8% compared to 2.8%, 6.7%, and 3.2%, respectively), where mining could explain the increase in income through job security and better wages. Puerto Inca, on the other hand, is the district with the highest share of deforestation

(Figure 4.5) and it is one of the lowest funded (Figure 4.3), explaining increased income through the exploitation of forest resources and reduced HDI through decreasing environmental services.

The effects of PA funds compared to the impacts of PAs' presence were similar on average to case studies in other tropical developing countries such as Mexico (Sims and Alix-Garcia 2017), Bolivia (Canavire-Bacarreza and Hanauer 2013), Costa Rica (Andam et al. 2008; Ferraro and Hanauer 2014), Cambodia (Clements and Milner-Gulland 2015), Uganda (Tumusiime and Vedeld 2015), and Thailand (Sims 2010). With economic development concentrated in coastal districts, access to the Peruvian Amazon requires significant effort to cross the Andes, which has limited the spread of modern economic and social development. Bolivia is the most similar in terms of the geographical context of the studied countries, where the Andes meets the Amazon. However, the difference is that Bolivia's economic development is concentrated in the highlands, and access to the forest is through a downward slope, which comparatively takes less effort than crossing the highlands in Peru. Also, Bolivia integrated their rural and Indigenous peoples into society and the economy more than Peru because of its recognition as a plurinational state. These factors may explain why the social change in the Peruvian Amazon shows small significant impacts in relation to PAs compared to other similar contexts. This research, however, went one step further beyond legal protection to include PA funding, showing that investments had small statistically significant effects on human development and income. The low magnitude of the impacts of PA funds was expected. The magnitude of the effects of funding in Peru were significantly smaller than the overall effects of PAs, where funding accounts partially for the PAs' effects.

Changes at the district level hardly capture the expected effects PA funds may have on households in and around PAs, diluting the local effects into a larger sample unit. However, districts are the smallest political unit of analysis in Peru, used in most census data and publicly available social statistics. Regardless, previous research on poverty, income, and expenditure in the Peruvian Amazon at the household level showed no legal protection effects but exacerbated extreme poverty within 5 km of PAs between 2001 and 2006 (Miranda et al. 2015). I recommend doing future analysis with primary household-level data from the areas of interest to get more accurate estimates of PA funding impacts. Additionally, using Western indicators of social change may not reflect the actual changes in livelihoods for communities in the Amazon because some cultures do not prioritize engaging with the standard forms of education, income, and health, the indicators used to estimate HDI. This cultural conflict between Indigenous peoples and Western standards may also be a reason for the small effects, especially in rural areas where sampling errors are higher.

This study has limitations related to the availability of social datasets. The UNDP dataset used for this research is representative at the district level, the smallest political unit of analysis in Peru. However, a smaller unit of analysis, such as subdistricts or household-level data, would be preferable for analyzing PA social impacts in the Peruvian Amazon. I sought to carry out such analysis, including a household panel dataset called ENAHO (*Encuesta Nacional de Hogares* in Spanish) (INEI 2020). However, I could not use it for two reasons: a lack of continuity in the dataset for the years of interest in this research and the reduced number of households sampled within PAs and their buffer zones. Using household panel data would be ideal for capturing changes in local communities and observing their direct effects. A limitation derived from the lack of consistent panel data for the outcomes was using aggregated financial data as a treatment instead of using an annual panel due to the lack of synchrony in the outcome data. Collecting and designing primary household questionnaires with more culturally adapted indicators like food scarcity or illness incidence (Krishna 2011) could show better social change from PA investments.

Another limitation related to data availability was the lack of spatially explicit biodiversity measures with changes over time to include in the analysis. When working with PAs, biodiversity is an important variable to consider because it is a relevant driver of legal protection and its funds. The International Union for Conservation of Nature (IUCN) geospatial dataset (IUCN 2016) could be a great tool; however, the dataset only shares the latest updated species distribution and does not allow the reconstruction of species distribution known at particular points in time. This characteristic of the data limits its use in postintervention evaluations and quasi-experimental methods such as matching.

Peru is a highly heterogeneous country where social phenomena are deeply linked to its territory and history (UNDP 2019). The Peruvian Amazon has a vast lowland area with dense forests and remote areas, and the Andes-Amazon slopes feature lower-density forested areas and more roads. However, productive centers and mining create hotspots of higher income, like Madre de Dios, mainly due to illegal mining (UNDP 2019). Districts' political boundaries are larger in the lowlands than in the coast and highlands, and there are more state PAs in the lowlands than in higher-altitude forests. These political and natural characteristics reduced the accuracy of comparability at the district level even when the matched data, statistically speaking, shows acceptable differences. Covariate imbalance for economics-related variables such as road density, agriculture plots, and pastureland are inherent to the districts' treatment conditions, as well as conservation-related variables such as the share of buffer zones or baseline forest cover. These differences result from the historical inequalities in productive and economic centers within the country and need to be considered. It was surprising to find no heterogeneity in the marginal impacts of PA funds given the variability in contextual factors. Nonetheless, due to the small size

of the effects, the analysis may not be sensitive enough to have distinct patterns of response to the changes.

Lastly, most impact evaluation studies have overlooked the spatial relationships and effects between the analyzed units. Without the consideration of spatial autocorrelation, models give inaccurate or biased results. Here, using an SEM adjusted the size of the coefficients and their standard errors, providing reliable results.

4.6 Conclusion

The PA funds in state PAs had a small but significant effect, increasing HDI and income at the district level, on average. Most districts showed an increase in human development and income, suggesting that material economic benefits play a significant role on the pathway to achieving broader social impacts. I found no moderators for these effects. However, it is likely to find moderating effects of PA funding within PA borders. Social change at the PA level requires finer-scale data such as household or community level, which is not publicly available. This type of data would require strategic sampling design and data collection to get accurate estimates of the relationships and impacts of funding in PAs over time.

Districts with more funding committed showed fewer negative social effects and had less deforestation. Nine districts had the opposite effect between development and income. The difference in reduced HDI with higher income could be explained by grouping the districts with higher shares of mining concessions, potentially explaining the difference in the Andes-Amazon districts; high deforestation and low funding; and low risk of deforestation with low funding, economic activities, and forest loss.

A potential mechanism for the impacts of funding the increase of ecosystem services through avoided deforestation, where the imposed land-use restriction protected forest cover and promoted alternative economic activities other than agriculture within districts. Other social factors correlated with the increase of HDI were more conserved areas and Indigenous lands associated with more ecological connectivity. In addition, more population density provides human capital, increasing income opportunities. Future research frontiers may explore these impacts at a smaller scale, using case studies, to better understand the relationship of funding with social and ecological outcomes, their trade-offs, and their mechanisms.

This research contributes to the literature by creating quantitative evidence that PA funding contributed to human development, potentially through income and ecosystem services. The small magnitude of the effects may be due to the unit of analysis used here, whereas if it were at the community or household level in relation to the PA, the impacts may be larger, reflecting more accurate

estimation. The results evidence the importance of considering Peru's geographic and social diversity and its history to understand the dynamics of the effects of conservation investments on social change, even when the moderating effects were not statistically significant. The findings offer preliminary supportive information to decision-makers and may improve future funding allocations to achieve social as well as environmental goals relating to PAs.

4.7 References

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CHAPTER 5: CONDITIONAL IMPACTS OF PROTECTION AND PROTECTED AREA FUNDING IN THE PERUVIAN AMAZON ON FOREST LOSS

5.1 Introduction

Billions of dollars are invested in biodiversity conservation worldwide, but there is still not enough funding to manage the existing conservation actions (McCarthy et al. 2012; Deutz et al. 2020). Given this scarcity, it is especially important that conservation spending consider evidence of effective actions to efficiently allocate available resources and strengthen the case for additional funds. However, rigorous quantitative evidence of the impacts of conservation funding remains lacking. Evaluating and learning from past experiences can improve future allocation and investments of the available funds.

Impact evaluation studies in conservation estimate the effects of different strategies such as legal protection of territories through protected areas (PAs) (Andam et al. 2008; Miranda et al. 2015; Cuenca et al. 2016), monetary incentives through payments for ecosystem services (PES) (Wunder 2007; Börner et al. 2016), and Indigenous lands (Nolte et al. 2013; Schleicher et al. 2017; Börner et al. 2020). Most of these studies used quasi-experimental methods like matching and difference-in-difference, which consider a counterfactual scenario to estimate the difference in outcomes (Miller and Nakamura 2018; Börner et al. 2020). However, the application of machine learning to analyze impacts using decision-tree-based models, like causal forests, has proven viable and even more effective than quasi-experimental designs and maximizes the estimation of treatment heterogeneity (Athey and Wager 2019). Moreover, considering researchers' increasing interest in identifying heterogeneous treatment effects (Ferraro and Hanauer 2014; Shah and Baylis 2015; Athey and Imbens 2016), causal forests are an ideal tool. Evidence on such effects can help unveil the conditions under which the impacts were maximized, supporting better targeting of future treatments.

The Peruvian Amazon holds critical areas of primary forest threatened by extractive economic activities such as mining, logging, and agriculture (Holle 2019). Around 18% of Peru's terrestrial territory is protected (SERNANP 2022), but the lack of reliable financial support has undermined its conservation efforts (Flores et al. 2008). In 2016, the project Peru's Natural Legacy: Securing the Future of Peru's Protected Areas was launched to develop sustainable financing for its PAs (WWF 2017). Nonetheless, without quantitative evidence of previous funding impacts, decision-makers lack the empirical insights needed to maximize the effectiveness of future investments. This chapter responds to this knowledge gap by estimating the conditional average treatment effect of legal protection and funding on forest loss in the PAs of the Peruvian Amazon. I applied a machine learning method to estimate impacts on forest loss

of protection and funding as treatments to uncover the conditions under which PA funding was more effective.

5.2 Theoretical expectations

Peru is a country with high geographical diversity, social inequality, and uneven levels of infrastructure. With Peru's ecological and social diversity, I expect to find heterogeneity in the effects of protection conditional on environmental, socioeconomic, and access characteristics. An overall expectation is that legal protection significantly avoided forest loss and PA funding increased this effect.

The Amazonian humid forest or lowland rainforest (Britto 2017) dominates the landscape in the Peruvian Amazon. Below 500 meters of altitude, lowland rainforests are known for their nonseasonal forest cover and seasonal flooding. In comparison, highland forests (> 500 m) are globally known for their habitat uniqueness and high levels of endemism (Myers 1988) located between the Amazon and the Andes (Britto 2017). I expect to find a larger effect of PA funding in lowland forests due to their permanent forest cover and higher resource availability. However, many parts of the lowland forest have low access to markets and social services (UNDP 2019), showing the opposite effect. Other biophysical drivers of deforestation are slopes (Schleicher et al. 2017), where forest loss in steeper areas is less likely due to a seasonal forest cover, higher production costs of economic activities, and higher levels of poverty. For these reasons, I expect to find a larger effect in flatter areas (Hanauer and Canavire-Bacarreza 2015). Nonetheless, even when biophysical characteristics may play an important role in determining the effects, the most critical factor conditioning forest loss is the level of access to the resource.

Previous research showed accessibility as a predictor of deforestation in the Peruvian Amazon (Vuohelainen et al. 2012; Bax et al. 2016; Schleicher et al. 2017). Due to higher access, I expect protection and funding to be more effective in areas closer to roads, rivers, and towns. In addition, being closer to a deforested area increases the likelihood of losing more forest. In Peru, road infrastructure development generated economic growth, mainly associated with mining and agricultural industries (Vasquez and Bendezu 2008). Hence, I expect protection and conservation funding in locations closer to roads and closer to rivers in more rural areas to avoid more forest loss than in locations farther away.

The kind of activities happening in surrounding plots may affect forest cover. Being closer to other conservation areas should reduce the likelihood of deforestation (as discussed in Chapter 2). Indigenous lands showed to be more effective in protecting forests than state PAs (Nolte et al. 2013; Schleicher et al. 2017). I expect PAs closer to them would benefit from this protection, hence having

lower effectiveness of funding due to reduced risk. On the other hand, PAs closer to mining concessions are expected to show a larger effect because they are more susceptible to deforestation, increased infrastructure, and desertification from mercury contamination (Watsa 2014; Tripathy-Lang 2021).

In terms of socioeconomic characteristics, PAs in Costa Rica protected forests in areas with low and high baseline poverty levels (Ferraro et al. 2011). In the context of Peru, subsistence agriculture is mainly adopted by the poor, increasing the likelihood of forest loss (UNDP 2019). Given that agriculture is one of the sources of land conversion (Holle 2019), I expect more avoided deforestation in areas with more agricultural jobs, higher poverty, and land with lower constraints for agriculture.

At the PA level, older PAs should be more established in terms of conservation plans and infrastructure. With more experience working in the region, I expect to see more effective funds use than younger PAs (Miranda et al. 2015). The presence of tourism in a PA attracted funding within the study period (Nakamura 2017). Because not all PAs can offer tourism, tourists have an additional incentive to protect their habitat, making them more effective. Management characteristics also matter. There is not yet a consensus as to whether strict or sustainable use management is better for conservation outcomes (Nelson and Chomitz 2009; Blackman 2015; Miranda et al. 2015), which I would like to test. In addition, PAs with a management contract also tend to have more funding than those without one (Nakamura 2017), and given their commitment, they are more likely to achieve conservation outcomes.

5.3 Data

5.3.1 Study area

This study considered state PAs as the areas managed by the Peruvian government established before or in 2015 in the Peruvian Amazon ($n = 29$) (section 3.3.1). I included areas without formal protection and *zonas reservadas* as unprotected areas. To avoid potential spillover effects, I excluded all legal buffer zones established before 2015 ($n = 26$) and a 5-km unofficial buffer for the remaining PAs without established buffers. Other conserved areas such as regional and private conservation and various forms of concessions (conservation, ecotourism, reforestation, fauna management), permanent production forests, and Indigenous territories might bias the change in forest loss as these locations undergo some form of resource management. All these were excluded from the sample. I removed water bodies such as rivers and lagoons for both protected and unprotected areas.

Given that nature conservation exists within a social-ecological context, I included socioeconomic variables in the model collected at the district level in 2007 as pretreatment data from INEI (2009). Out of

the 1,874 existing districts in Peru, 44 districts showed no data on poverty. Hence, I removed those districts from the sample, affecting 33 districts.

5.3.2 Spatial data

I used 1 sq km grids as the main unit of analysis. However, some grids were smaller and uneven due to established political boundaries such as PAs, buffer zones, rivers, and lakes. Uneven grids represent the outer limits of PAs where most threats are felt, so I deemed it relevant to keep them in the analysis. Since some grids were deforested by 2009, I removed grids with forest cover below 40% (Graham et al. 2021). To reduce the processing burden and have similar size grids, I kept those with a surface area less than 0.8 sq km. Additionally, I removed isolated or "island" grids (without forested neighboring pixels) from the sample. The final database contains 284,847 grids. All spatial data were extracted using ArcMap 10.7 and RStudio 2.3. Minimum distances were measured using Euclidean geodesic distance from the grid's centroid using the Near tool in ArcMap. Other mean and mode values were extracted using the *exact_extract* function in R (Baston 2020).

5.3.3 Treatment and control

The definition of treated and control units to identify the effects of PA spending in the Peruvian Amazon is based on two variables: legal protection and the cumulative funding/grid (I\$ 2015 constant). I used a binary treatment for legal protection in the first model, and the amount of committed funding per grid, a proxy for spending, as a treatment for the second model. Two of the 29 PAs in the sample became protected over the time of the study: Pucacuro National Reserve in 2010, and Sierra del Divisor National Park in 2015. I included all grids that were protected by 2015 as treated. Under this classification, the sample contains 139,376 treated and 145,471 control grids.

5.3.3.1 Spending data

I used PA spending as the cumulative amount/grid of committed funding in 2009–2015 [2015 constant dollars (I\$)]. I allocated funding per grid based on the grid's deforestation risk (section 2.8.2.2). To test for sensitivity in the allocation of funding assumptions, I allocated funds in three ways. First, I assigned funding per square kilometer in equal parts (Type A). Second, I used deforestation risk weights based on the minimum distance to a road or agricultural plot (Risk 1 or Type B). Third, I added a risk threshold of 10 km, reducing the weight of risk in areas farther out (Risk 2 or Type C). The summary is presented in Table 5.1. One potential caveat of the funding distribution assumptions based on threats is that it may create circularity between the treatment and the effects, where more risk received more funds. In addition, assuming more funding into a place of higher risk will underestimate its impact if the real allocation was lower, and the opposite if it used more funding than assumed.

Table 5.1 Comparative summary statistics of allocated funding/PA grid using three methods.

	Min	Median	Mean	Max
	I\$			
Equal/sq km (Type A)	185.00	480.00	1,035.00	12,635.00
Risk 1 (Type B)	0.00	186.00	684.40	51,599.00
Risk 2 (Type C)	0.00	118.00	651.10	53,389.00

5.3.4 Outcome

The outcome variable is a cross-section of the percentage of forest loss within grids between the years 2010 and 2016 from the forest loss maps from MINAM (GEOBOSQUES 2019) as described in Chapter 2 (section 2.8.2.4.1). The outcome considers a one-year lag from the treatment and the response variable. I extracted the forest loss area in square kilometers for each grid using the *exact_extract* function in R (Baston 2020) and converted it into the share of forest loss per grid. The mean forest loss in unprotected areas was 2.00%, compared to 0.20% in PAs.

5.3.5 Covariates

To control for relevant variables that may bias the performance of the treatment on forest loss, I selected 19 theoretically confounding variables (Table 5.2). The biophysical variables are time-invariant terrain characteristics that may attract or deter threats to deforestation. Higher altitudes and slopes are associated with less forest loss. Their harder access makes them less likely to undergo land conversion and tend to be less suitable for agriculture, which may bias the impacts of PAs and need to be accounted for (Joppa and Pfaff 2009; Blackman 2015). Temperature and rainfall also fall within variables of relevance for land conversion (Schleicher et al. 2017) and indices of ecosystem type and vegetation growth. I extracted the mean values per grid for altitude, temperature, slope, and rainfall.

I used a categorical index of agricultural suitability based on agro-ecological zones (Fischer et al. 2000). The categories include no constraints (Class 1), slight constraints (1%–20% constrained, Class 2), moderate constraints (20%–40% constrained, Class 3), constraints (40%–60% constrained, Class 4), severe constraints (60%–80% constrained, Class 5), very severe constraints (80%–99% constrained, Class 6), and 100% constrained (Class 7). This sample shows the Amazon has, on average, soil with very severe constraints (80%–99% constrained). One of the goals of the Peruvian government is to protect a representative sample of ecoregions (SERNANP 2009). Each ecoregion has a unique set of environmental conditions and habitat structures representing its flora and fauna (WWF n.d.). I included all 12 ecoregions present in this sample as dummy variables.

Table 5.2 Theoretically relevant confounding variables for protected areas in Peru used in matching and the data sources.

Type	Variable	Unit	Years	Value	Mean (min, max)		Source
					Treated	Control	
Biophysical	Altitude	Meter	1970–2000	Mean	550.90 (88.82, 3675.00)	578.13 (64.82, 3770.14)	Fick and Hijmans (2017)
	Slope	Degree	1970–2000	Mean	2.60 (0.00, 49.35)	2.96 (0.00, 54.49)	Altitude, ArcMap
	Rainfall	Millimeter	1970–2000	Mean	187.16 (28.29, 450.14)	181.94 (39.48, 418.78)	Fick and Hijmans (2017)
	Temperature	Degree Celsius	1970–2000	Mean	24.25 (9.91, 27.08)	24.15 (8.06, 27.22)	Fick and Hijmans (2017)
	Agricultural suitability	Categorical (1–7)	2000	Mode	5.81 (3.00, 7.00)	5.99 (2.00, 7.00)	Fischer et al. (2000)
	Ecoregion	—	—	Dummy (12 ecoregions)	—	—	The Nature Conservancy (2016)
Access	Distance to rivers	Kilometer	2009	Minimum	9.28 (0.00, 50.43)	9.19 (0.00, 54.46)	GEOBOSQUES (2019)
	Distance to towns (> 20K people)	Kilometer	2007	Minimum	143.73 (4.70, 353.78)	144.80 (0.92, 388.88)	INEI (2009)
Forest Cover	Forest cover	Percent	2009	Share of grid area	98.20 (40.00, 100)	91.88 (40.00, 100.00)	GEOBOSQUES (2019)
	Distance to forest edge	km	2009	Minimum	1.24 (0.00, 12.97)	1.12 (0.00, 13.67)	GEOBOSQUES (2019)
	Neighbors' forest cover (queen matrix)	Percent	2009	Spatially weighted neighbors' forest cover	97.95 (9.00, 100)	37.18 (0.00, 100.00)	Forest cover in 2009, GeoDa
	Grid area	sq km	—	Total area	0.99 (0.80, 1.00)	0.99 (0.8, 1.00)	SERNANP (2016)
Socioeconomic	Poverty	Percent	2007	Mean	50.82 (10.40, 90.80)	66.36 (16, 99.70)	INEI (2009)
	Jobs in agriculture	Percent	2007	Mean	34.28 (3.00, 63.00)	39.79 (0.00, 72.00)	INEI (2009)
	Distance to mining	km	2009	Minimum	61.98 (0.00, 277.45)	34.74 (0.00, 369.53)	INGEMMET (2020)
	Distance to pasture	km	2011	Minimum	27.49 (0.00, 224.44)	38.97 (0.00, 220.78)	GEOBOSQUES (2022)
	Distance to Indigenous territories	km	2009	Minimum	35.31 (0.00, 117.34)	11.49 (0.00, 90.93)	MINAM (2017)
	Distance to conserved areas	km	2009	Minimum	48.95 (0.00, 183.82)	31.64 (0.00, 176.62)	SERNANP (2016)
	Department (region)	—	2007	Dummy (15 regions)	—	—	INEI (2019)
PA characteristics	Years protected	Years	2015	-	20.81 (1.00, 44.00)	—	SERNANP (2017)
	Management type (strict or sustainable use)	—	2009–2015	Dummy	—	—	SERNANP (2017)
	Tourism	Tourists/year	2009–2015	Mean	680.1 (0.00, 34,696)	—	SERNANP (2016)
	Co-management	—	2009–2015	Dummy	—	—	SERNANP (2017)

Different methods of access can affect deforestation differently. Areas closer to roads, rivers, and towns are vulnerable to deforestation through faster resource extraction and markets (Hanauer and Canavire-Bacarreza 2015; Pfaff et al. 2015). I measured the distance from the centroid of the grid to the closest rivers and towns with more than 20,000 people in 2009. Although the distances to roads and agricultural plots are highly relevant for deforestation, I did not include them in the analysis because I used them to allocate spending. Hence, if they were to be included, they would bias the results because these two variables were already considered in the treatment.

To increase the unit's comparability, I included the baseline forest cover (% , 2009), the grid size, the minimum distance to the closest deforested patch in 2009 or distance to forest edge, and the level of forest cover in neighboring grids as a weighted average of all surrounding grids using a queen matrix. The closest distance to pastureland is a predictor of forest loss in the Amazon (Rojas et al. 2021), so it was also included in the model. I also included relevant socioeconomic variables such as the share of poverty and jobs in agriculture per district. Poverty was defined as “the minimum amount of money a person must spend to acquire goods and services necessary to satisfy their basic needs” in relation to the region and zone (urban or rural) (INEI 2009). If the grid was divided between two districts, I assigned it to the district with the largest overlap. The department or administrative region was one predictor of forest loss in the Amazon (Schleicher et al. 2017). I included 12 regions as dummy variables to control for local policies, corruption, and culture.

There were four additional covariates observed only in PAs that could moderate the way funding was used, which were used in comparisons between PAs: number of years protected, mean number of tourists per year, type of IUCN management category (Dudley 2008), and presence of a co-management contract with an NGO. I calculated the number of years under protection since its establishment until 2015. PA visitors are reported annually per PA, but I used the mean tourists/year to obtain a more even value of tourists. The International Union for Conservation of Nature (IUCN) classifies PAs by management categories (Dudley 2008). In Peru, PAs fall within two larger categories: strict protection (IUCN Categories 2 and 3) or sustainable use management (Category 5 or Category 6) (Solano 2009). Some PAs had active co-management with NGOs, included as a dummy variable.

5.4 Methodology

To estimate the effects of PA funding on forest loss, I used two approaches:

1. Compare two models with the same specification, with the only difference being including spending in the covariates. Both models used legal protection as a binary treatment and

unprotected areas as control. Adding a covariate to the model creates interaction effects across all variables and modifies the model. When controlling for spending, it captures part of the effect of protection and gives a potential estimate of the impact of protection without considering funds. I estimated the conditional average treatment effect (CATE) for each model to compare their effects.

2. Estimate the effect of an additional unit spent between PAs, using spending as the treatment.

This model estimated the conditional average partial effect of every dollar invested on forest loss.

Causal forests are a recently developed method to uncover causal effects and are well-suited to analyze heterogeneity within treatments (Athey and Imbens 2016). The model is based on honest casual trees to estimate the CATE of treatment compared to its counterfactual, under the definition of the potential outcomes framework (Holland 1986). It is a non-parametric decision-tree-based model with a doubly robust estimation. This robustness comes from using the weighted outcome regression and the propensity of treatment, and the model is robust to misspecification of one, but not both, of these models (White 2018). The trained model builds on decision trees based on multiple iterations of random subsamples to avoid overfitting, making the trees honest (White 2018). On each iteration, the model uses the covariates (not the outcome) to decide where to make each split and produce the largest difference in treatment effects across leaves, making the trees causal (White 2018). The algorithm detects heterogeneity by minimizing the within-leaf treatment effect (Brand et al. 2021). The effects are estimated by averaging the difference between treated and control units within each leaf, using the out-of-bag (OOB) sample and the test dataset (Figure 5.1). The honesty condition of the trees allows for asymptotic normality on the estimates and gives reliable confidence intervals (Naushan 2021). The CATE in the causal tree is defined as:

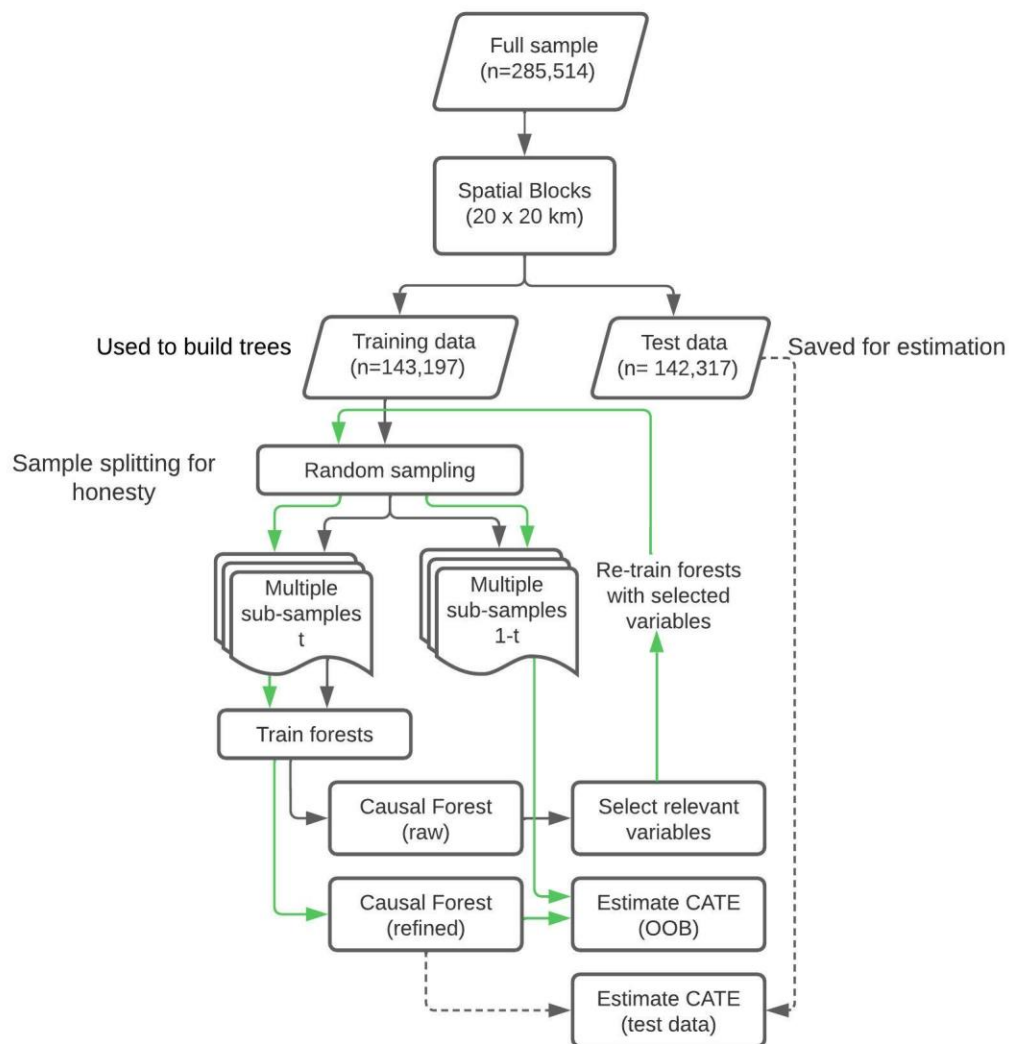
$$\tau(x; \pi) = E[Y_i^1 - Y_i^0 \mid X_i \in l(x; \pi)]$$

where τ is the CATE conditional on covariates x and decision tree π . Y_i^1 is the observed outcome on the treated unit i , Y_i^0 the observed outcome in control unit i . X_i are conditions corresponding to the leaf l under covariates x in decision tree π (Brand et al. 2021). Causal forests require two datasets to avoid model overfitting—one dataset trains the model, and the other tests it. When using predictors that may have spatial autocorrelation, like forest cover, it is recommended to use spatial blocks when splitting the train and test sets (Valavi et al. 2018). Here, I divided the full dataset into two equal parts using spatial blocks of 20 sq km with a checkerboard distribution (Appendix C, Figure C.2) with the *spatialBlock()*

function from the blockCV package (Valavi et al. 2018). For robustness, I tested the analysis using spatial blocks of 32 sq km.

The causal forest included a specific set of variables to estimate the propensity score for each treatment. I customized the variables for the propensity of legal protection using forest cover, dummies for ecoregion, and roads to measure human threat to PAs based on the principles SERNANP uses to protect the land (SERNANP 2009). For funding as a treatment, I used the share of deforestation per grid in 2008 (GEOBOSQUES 2019), distance to populated centers, distance to active mining concessions, and mean tourists per year (Nakamura 2017) with PAs as clusters.

Figure 5.1 Causal forest workflow.



When the propensity of treatment and the expected outcome over treatment give good estimates, it reduces confounding effects from the model, allowing the exclusion of some confounders from the equation but including modifiers (Athey and Wager 2019). Given this, I ran each model two times: the first included all covariates of interest, and the second only with the most relevant ones to increase the model's precision. The results section distinguished them as "raw model" and "refined model" and described the results using the latter. All causal forest models used the function *causal_forest()* from the *grf* package (Tibshirani et al. 2020) in R, following Athey and Wager (2019), with a minimum of 20 treated and control units per leaf, parameters tuned at "all," and the seed set at 123 for reproducibility.

To prioritize the covariates' relevance, I used the *variable_importance()* function based on relevance in the number of splits used to divide trees. I selected those covariates with a value higher than the mean as potential modifiers (Athey and Wager 2019). In the refined model, I used the potential modifiers as covariates and increased the number of trees to 10,000 to increase the accuracy of confidence intervals' estimation. I included clusters in the comparison between PAs and not when compared to the unprotected areas because there are no boundaries to cluster in the broad unprotected landscape. Finally, I estimated the doubly robust out-of-bag CATE using the *average_treatment_effect()* function on the causal forest in the sample overlap. I explored the individual mean CATE from the test data for each PA, estimated through the function *predict()*.

To test for robustness, I ran the same model specifications for the raw and refined models using the three different spending allocation methods and a 32 × 32 km spatial block to split the train and test datasets.

To estimate the presence of conditional effects, I ran a linear model between the OOB CATE and the covariates through the *test_calibration()* function. If the "differential forest prediction" variable was significant, I explored the effects conditional on the theoretical modifiers by plotting the variable against the estimated test CATE to examine the effect change. I identified thresholds for higher versus lower effects per variable from these plots. Then, I quantified the differences in the impact on the refined models' covariates by subsetting the sample by the identified thresholds and re-estimated the doubly robust CATE for the subgroups. To determine if the characteristics at the PA level (Table 5.2) were correlated with the effects, I aggregated both OOB and test individual CATEs because the test dataset did not sample all PAs. Then, I examined these variables against the CATE and the effects aggregated by PA.

5.5 Results

5.5.1 Average treatment effect of protection and funding

Legal protection and funding avoided losing 1.7 times more forest than what was already lost. The observed mean deforestation was 0.20% in PAs or 271.73 sq km. Without protection and funding, these areas would have lost 0.34% more forests, totaling 470.27 sq km (Model 3 in Table 5.3). After accounting for the effect of spending, the effect of protection was reduced by 0.23% (the difference between Model 4B and Model 3 in Table 5.3). There was no significant difference between the different allocations of spending (Models A, B, and C). Including PA funds as covariates in Models 2 and 4 decreased the impact of protection compared to the models without controlling for spending (Models 1 and 3 in Table 5.3), suggesting that spending accounts for about two-thirds of the effects of protection. This reduction was observed in both the raw and the refined models at different magnitudes. The robustness test showed similar results in pattern and direction of the effects for all three spending allocation methods (models 2A-C, and 4A-C), with the largest change in magnitude in Model 3 (Appendix C, Table C.1). PA funding was likely allocated because of its protected status, so they are better interpreted together.

In contrast, I found no effect from investing an additional dollar/grid in PAs when the comparison was made only between areas under protection (Models 5B-C in Table 5.3). The impact was positive and not statistically significant. Given the small magnitude and lack of statistical significance of the estimate, I interpret that having more spending did not improve the protection of forest cover.

5.5.2 Conditional treatment effects

The treatment effects showed signs of conditionality in both models, on the effect of protection and protection with funding. The causal forest model identified the following eight variables as potential modifiers: baseline forest cover, distance to towns, distance to the forest edge, distance to conserved areas, distance to mining, distance to pastures, temperature, and the share of the population living in poverty.

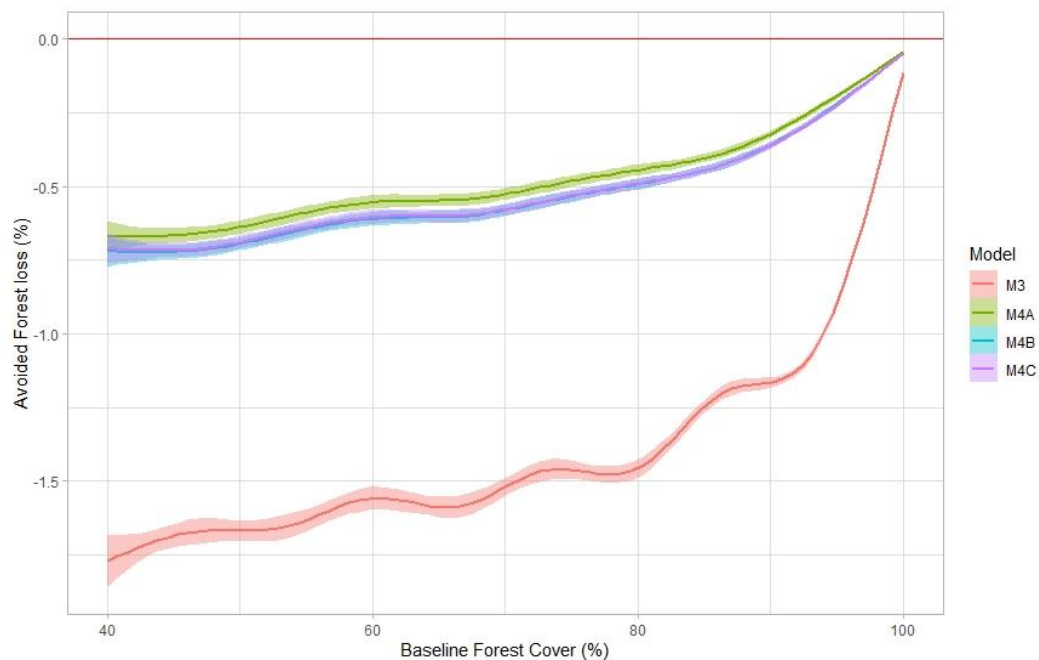
The level of baseline forest cover was the most relevant variable structuring the decision trees in Model 3. On average, protection and funding together protected forests more effectively in areas with less forest cover at baseline (Figure 5.2, Table 5.4). This treatment was the least effective in highly forested areas (> 90%). The largest effect was -1.17% of avoided forest cover below 90% forest cover, compared to the lowest effect (-0.24%) found in highly forested areas (Table 5.4). When accounting for funding, the effect of protection showed a similar pattern (Figure 5.2) with a lower effect size (Table 5.4).

Table 5.3 Impacts on avoided forest loss from protection and PA funding using causal forests.

	Model 1	Model 2A	Model 2B	Model 2C	Model 3	Model 4A	Model 4B	Model 4C	Model 5B	Model 5C
Description	Raw model				Refined model				Refined model	
Avoided forest loss (%)	-0.23	-0.12	-0.12	-0.12	-0.34	-0.10	-0.11	-0.11	6.06e-05	5.76e-05
Standard error	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00
Mean CATE (test data)	-0.24	-0.12	-0.13	-0.13	-0.41	-0.13	-0.15	-0.15	5.17e-05	4.71e-05
Mean CATE (OOB)	-0.24	-0.12	-0.13	-0.13	-0.37	-0.11	-0.12	-0.12	4.98e-05	4.56e-05
Calibration										
Predicted CATE	1.01 ***	1.40 ***	1.35 ***	1.36 ***	0.90 ***	1.17 ***	1.11 ***	1.11 ***	0.91 ***	0.84***
Diff. forest prediction	2.90 ***	3.76 ***	3.68 ***	3.68 ***	1.84 ***	2.43 ***	2.40 ***	2.39 ***	1.51***	1.53***
Variables										
Treatment	Protection				Protection				Spending (Risk 1)	Spending (Risk 2)
Spending in covariates	No	Yes (Equal)	Yes (Risk 1)	Yes (Risk 2)	No	Yes (Equal)	Yes (Risk 1)	Yes (Risk 2)	No	No
No. variables	20	21			8	9			8	
Variables included	All from Table 1, but PA characteristics	All from Model 1 plus spending			Forest cover, dist. to towns, forest edge, conserved areas, mining and pasture, poverty, and temperature	All from Model 3 plus spending			Distance to pasture and Indigenous lands, forest cover and neighbors' forest cover, slope, temperature, rain, and altitude.	
Three most relevant variables (% splits)	Forest cover (36%)	Dist. to pasture (25%)	Dist. to pasture (26%)	Dist. to pasture (25%)	Forest cover (52%)	Dist. to pasture (29%)	Dist. to pasture (29%)	Dist. pasture (30%)	Rain (59%)	Rain (55%)
	Dist. to pasture (16%)	Forest cover (21%)	Forest cover (22%)	Forest cover (22%)	Dist.to forest edge (13%)	Forest cover (16%)	Forest cover (18%)	Forest cover (18%)	Forest cover (16%)	Forest cover (18%)
	Dist. to town (14%)	Dist. to town (18%)	Dist. to town (19%)	Dist. to town (18%)	Dist. to pasture (10%)	Dist. to town (14%)	Dist. to town (13%)	Dist. to town (12%)	Neighbor's forest cover (10%)	Neighbor's forest cover (10%)
PA spending (% splits)	—	Funds (0.00%)	Funds (0.00%)	Funds (0.00%)	—	Funds (0.00%)	Funds (0.00%)	Funds (0.00%)	—	—

Note: Effects are expressed in %, and values with a negative sign mean the treatment was effective at avoiding forest loss. Significance level (***) $p < 0.00$. Forest cover refers to the share per grid of baseline forest cover. Dist. is short for distance.

Figure 5.2 Changes in avoided forest loss (%) plotted against baseline forest cover.



Note: The red line shows the effects of protection and funding (Model 3). The green line (Model 4A), the blue line (Model 4B), and the purple line (Model 4C) show the effects of protection.

Table 5.4 Conditional treatment effects for Models 3 and 4C.

		Threshold	Model 3 Effect of protection and funding		Model 4C Effect of protection	
			Estimated CATE	SE	Estimated CATE	SE
Biophysical	Temperature (degrees Celsius)	≥ 23.5	-0.37	0.03	-0.14	0.03
		< 23.5	-0.29	0.02	-0.02	0.01
Forest	Forest cover (%)	≥ 90	-0.24	0.02	-0.08	0.02
		< 90	-1.17	0.08	-0.34	0.07
	Distance to forest edge (km)	≥ 1	-0.03	0.02	0.00	0.01
		$> 0.5 \text{ \& } < 1$	-0.14	0.05	-0.10	0.05
		≤ 0.5	-0.57	0.3	-0.17	0.03
Access	Distance to towns (km)	≥ 100	-0.18	0.02	-0.06	0.02
		$> 35 \text{ \& } < 100$	-0.47	0.04	-0.11	0.03
		< 35	-0.98	0.15	-0.43	0.15
Socio economic	Distance to Conserved Areas (km)	≥ 25	-0.28	0.03	-0.09	0.03
		< 25	-0.41	0.03	-0.13	0.03
	Distance to pasture (km)	≥ 5	-0.19	0.02	-0.03	0.02
		< 5	-0.75	0.05	-0.30	0.05
	Distance to mining (km)	≥ 45	-0.15	0.02	-0.02	0.02
		< 45	-0.44	0.03	-0.15	0.03
	Poverty (%)	≥ 60	-0.21	0.02	-0.03	0.02
		< 60	-0.60	0.05	-0.26	0.05

As expected, the effectiveness increased in areas closer to a previously deforested area. Protection and funding had the largest impact in areas within 500 meters from deforested site. The magnitude of this effect was approximately 4 times higher than in areas between 500 m and 1 km away, and 19 times higher than in areas more than 1 km away (Table 5.4). When controlling for funding, this effect reduced significantly from -0.57% to -0.17% , suggesting that PA investments correlated with larger impacts. Both models' average treatment effects conditional on temperature showed higher effectiveness in warmer areas ($> 23.5^{\circ}\text{C}$), associated with lower altitudes and slopes (Appendix C, Figure C.3).

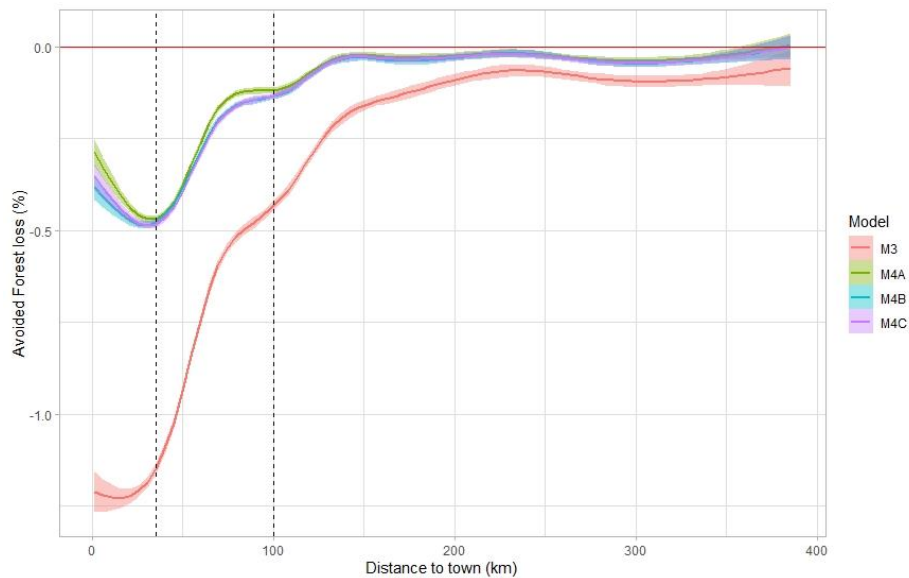
Accessibility is key in analyzing forest loss. Being within 35 km from the closest town showed the largest impacts from protection and funding on avoided forest loss (Table 5.4). The effect size reduced significantly (almost by half, from -0.98% to -0.47%) between 35 and 100 km, and the lowest impact (-0.18%) above 100 km. Accounting for funding reduced the effect of protection, especially within 100 km from towns with a stark difference within 35 km distance.

Economic extractive activities such as mining can have devastating consequences on forest cover. I found that areas closer to mining concessions avoided more forest loss than areas farther away. PAs within 45 km of mining areas were 2.3 times more effective than locations above that threshold (Table 5.4). After controlling for funding, the effect of protection reduced, especially in areas within 100 km (Appendix C, Figure C.4A). Other relevant economic activity for land conversion is agriculture. Protected grids closer to pastureland (< 5 km) had a largest effect conserving forests. Between 5 and 45 km, the effects reduce significantly and more than 45 km, the effect becomes minimal (Appendix C, Figure C.4B).

Other forms of legal boundaries that may affect forested regions conserved areas. I found the closer a PA grid was to them, the more forest loss was avoided by protection and funding (Appendix C, Figure C.5). Being 25 km from conserved areas showed the highest protection, while at 50 km the effect reached one of its lowest points. On average, grids closer to conserved areas avoided 0.41% forest loss, while areas farther away avoided 0.28% (Table 5.4).

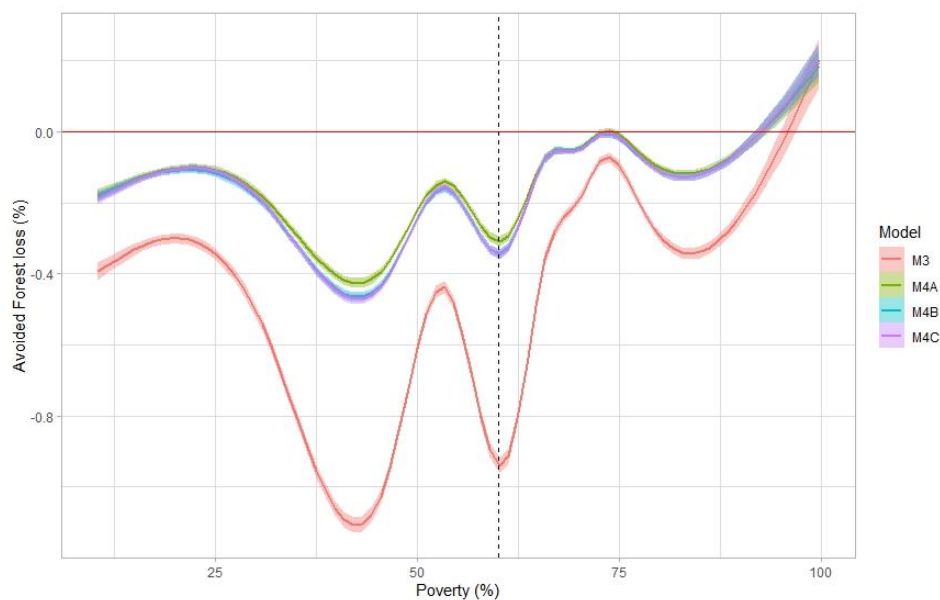
The relationship between protection and funding with baseline poverty varied. Protection and funding avoided losing the forests at around 40 and 60%, while the effects were the lowest at the extremes, in both the highest and lowest poverty areas (Figure 5.4). On average, the effect of protection and funding was 3 times larger in areas with less poverty ($< 60\%$) than in areas above that threshold (Table 5.4).

Figure 5.3 Changes in avoided forest loss (%) plotted against variables of accessibility: distance to the closest town.



Note: The red line shows the effects of protection and funding (model 3). The green line (model 4A), the blue line (model 4B), and the purple line (model 4C) show the effects of protection. Dashed lines show the identified thresholds for the change in conditional effects.

Figure 5.4 Changes in avoided forest loss (%) plotted against distance to the baseline poverty share.

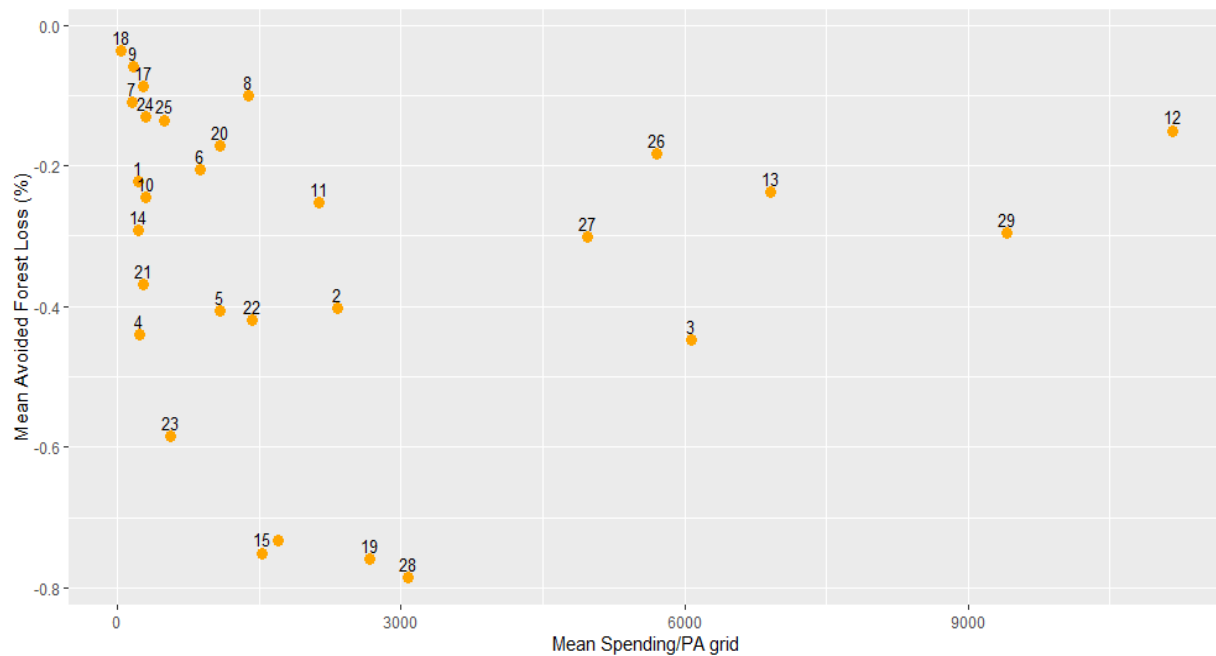


Note: The red line shows the effects of protection and funding (model 3). The green line (model 4A), the blue line (model 4B), and the purple line (model 4C) show the effects of protection. Dashed lines show the identified thresholds for the change in conditional effects.

5.5.3 PA level heterogeneity

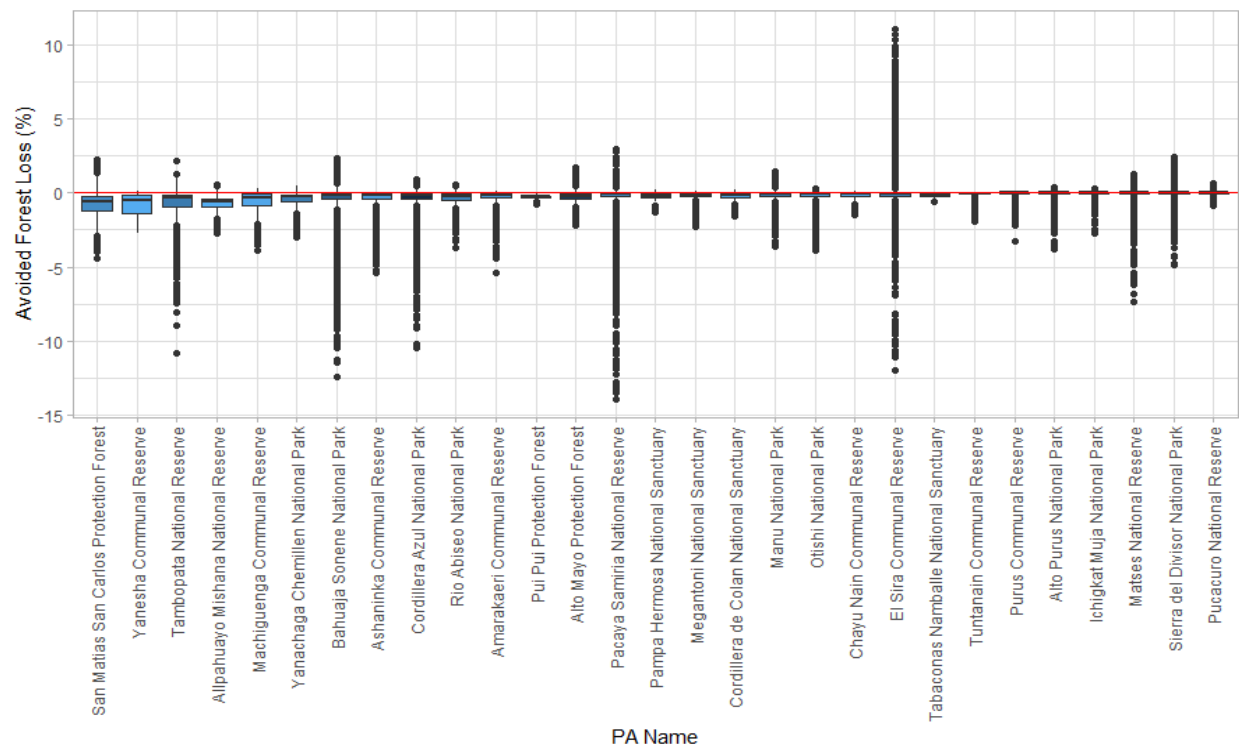
All parks avoided forest loss, on average (Figure 5.5). The estimated effects of protection and funding had the largest impacts in PAs with mean funding between I\$1500 – 3000 per grid, corresponding to San Matias San Carlos Protection Forest, Yanessa Communal Reserve, Tambopata National Park, and Allpahuayo-Mishana National Reserve (Figure 5.5; Appendix C, Table C.2). The two highest funded PAs, Tabaconas Namballe National Sanctuary and Alto Mayo Protected Forest had similar effects than parks with less investment, which suggests that more funding did not necessarily lead to larger impacts. El Sira Communal Reserve had mixed results, with more deforestation regardless of protection in specific sections, and avoided forest loss in others (Figure 5.6).

Figure 5.5 Mean avoided forest loss per mean PA spending per grid.



Note: Numbers represent PAs as follows: 1. Manu National Park, 2. Rio Abiseo National Park, 3. Yanachaga Chemillen National Park, 4. Bahuaja Sonene National Park, 5. Cordillera Azul National Park, 6. Otishi National Park, 7. Alto Purus National Park, 8. Ichigkat Muja National Park, 9. Sierra del Divisor National Park, 10. Megantoni National Sanctuary, 11. Pampa Hermosa National Sanctuary, 12. Tabaconas Namballe National Sanctuary, 13. Cordillera de Colán National Sanctuary, 14. Pacaya Samiria National Reserve, 15. Tambopata National Reserve, 16. Allpahuayo-Mishana National Reserve, 17. Matses National Reserve, 18. Pucacuro National Reserve, 19. Yanessa Communal Reserve, 20. El Sira Communal Reserve, 21. Amarakaeri Communal Reserve, 22. Ashaninka Communal Reserve, 23. Machiguenga Communal Reserve, 24. Purus Communal Reserve, 25. Tuntanain Communal Reserve, 26. Chayu Nain Communal Reserve, 27. Pui Pui Protection Forest, 28. San Matias San Carlos Protection Forest, 29. Alto Mayo Protection Forest.

Figure 5.6 Impacts of protection and funding on avoided forest loss (%) per PA.



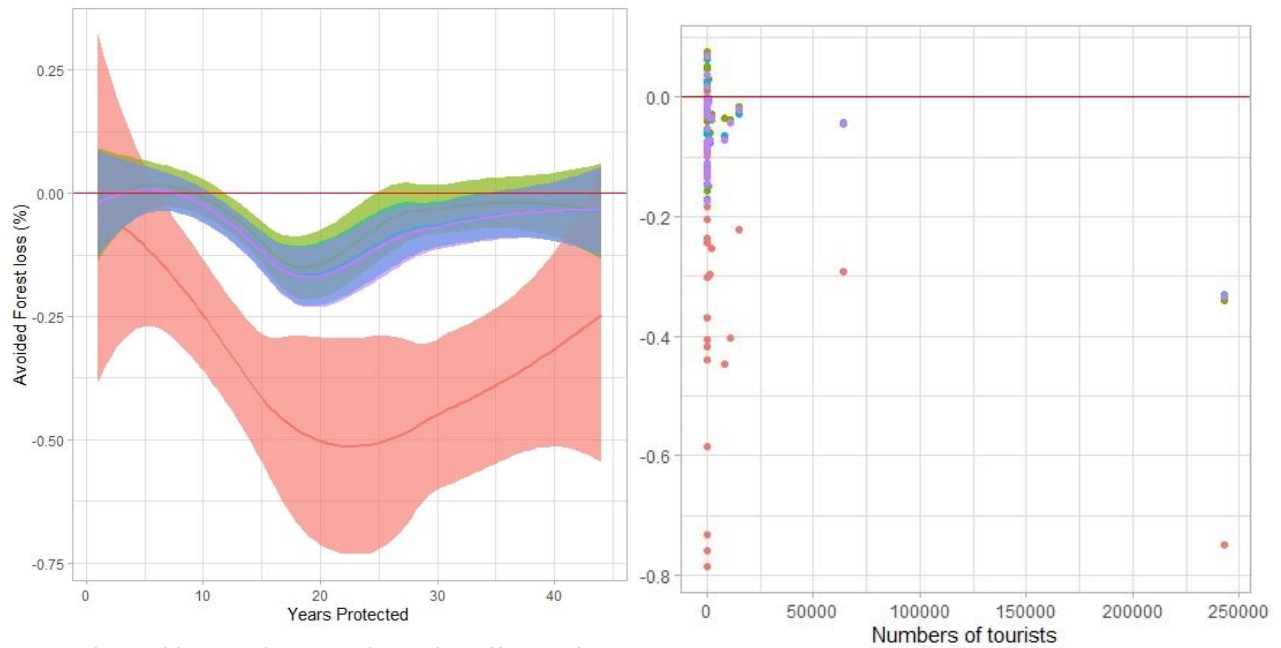
Note: Darker color fill show larger amounts of funding/sq km.

PA characteristics were not included in the model because they cannot be compared to control units without them. However, the grouped impacts may give insights into their relationship and forest loss. I found that older PAs were more effective protecting forests, with the largest impact seen after 23 years of protection (Figure 5.7A). Above that threshold, the effects reduced. PAs without visitors and the one with the most visitors, Pacaya Samiria National Reserve, were correlated with the highest effectiveness (Figure 5.7B). Twelve parks (41%) had no tourists.

On average, PAs with a management category aimed for sustainable use were correlated with more avoided forest loss (median -0.30) than strict use PAs (median -0.24) (Figure 5.8A). In terms of governance, co-managed PAs between the state and a NGO, showed higher avoided forest loss (median -0.44) than those managed only by the state (median $= -0.22$) (Figure 5.8B).

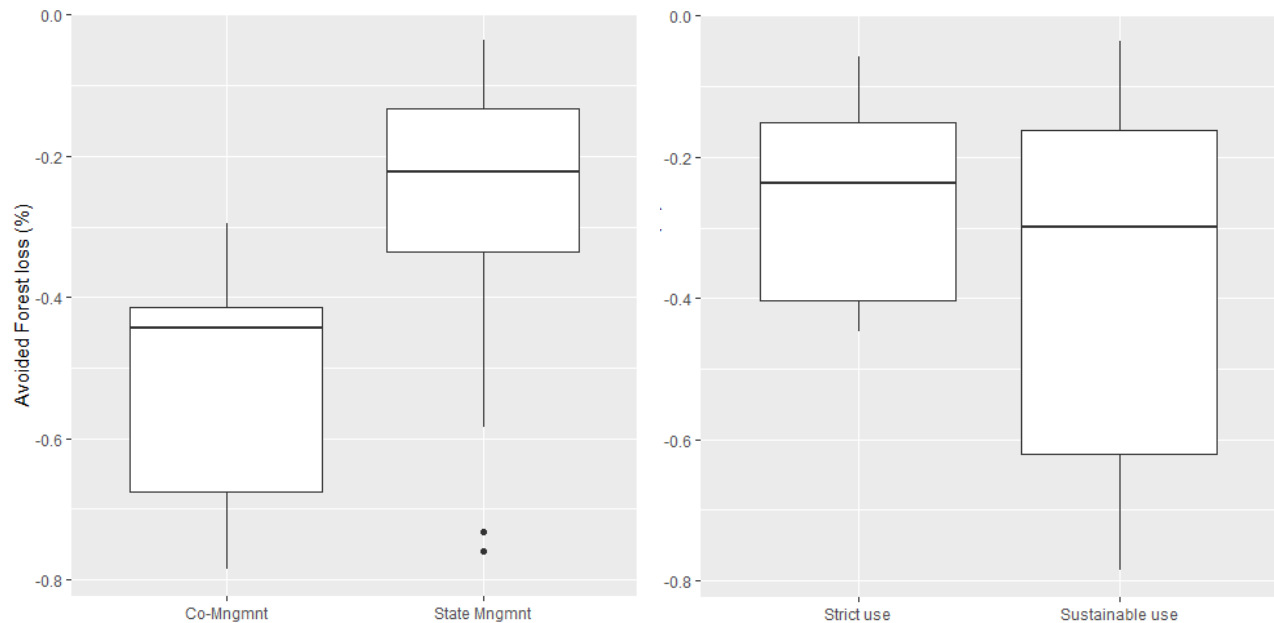
Figure 5.7 Estimated avoided forest loss from protection and funding plotted against PA characteristics:

(A) Number of Years protected, (B) Number of tourists.



Note: The red line and points show the effects of protection and funding (Model 3). The green line and points (Model 4A), the blue line and points (Model 4B), and the purple line and points (Model 4C) show the effects of protection.

Figure 5.8 Estimated avoided forest from protection and funding plotted against PA characteristics: (A) governance type, and (B) strict or sustainable use management category according to the IUCN.



5.6 Discussion

Protected areas and their committed funding effectively avoided forest loss in the Peruvian Amazon. I found a significant difference in the average treatment effects between models after controlling for funding, evidencing that protection with funding had a significantly larger effect than protection alone when compared to unprotected areas. This result supports the impact evaluation literature on the effect of protection worldwide (Andam et al. 2008; Honey-Rosés et al. 2011; Eklund et al. 2016).

Two previous studies in the Peruvian Amazon (Miranda et al. 2015; Schleicher et al. 2017) estimated a 4% avoided forest loss between 2000 and 2005 (Miranda et al. 2015) and 0.35% effect during 2006–2011 (Schleicher et al. 2017). Both papers used matching and postmatching regression as estimation methods, which differ from the method used here, potentially affecting the estimations. However, the largest difference found with Miranda et al. (2015) is the different delimitation of the Amazon, in which he excluded most of the Andean slopes. The similar finding in magnitude and direction with Schleicher et al. (2017) adds robustness to the findings here. All three analyses happened in different and continuous periods, in which deforestation increased proportionally in both PAs and the unprotected landscape (Appendix C, Figure C.6).

No studies have used PA spending as a treatment in impact evaluation. Here, I expected PA funds to be the means to improve management and effectiveness. Nonetheless, I found no evidence to support this argument comparing the effect of spending between PAs. This counterintuitive and unexpected finding may have three potential explanations. First, given the effectiveness of legal protection, there is a lowered risk of forest loss within PAs. With a low average of 0.21% forest loss in PAs, which is only 10% of what was observed in unprotected areas, the risk of deforestation was already reduced. With similar deforestation levels, any difference in funding would not show effects. Second, finding comparable units between PAs with enough variation in funding may be more challenging than finding an unprotected control unit. If there were a similar PA unit with differences in forest loss and no difference in funding, there would be no effect. Hence, more funding had no direct effect on avoiding forest loss. Third, the allocation of PA funds is not random, and even after controlling for the measurable and known drivers for financing, there are unobservable factors that may also mediate the way funds affect forest cover, which are not considered in this model. Management quality, corruption, and the efficiency of the working system, working environment, effective communication, and other variables not considered here may play essential roles in improving effectiveness. A suggestion for future analysis is to include grids with high deforestation risk only and estimate the marginal effect of spending within high-risk PA zones, and

methods that help reduce unobservable characteristics such as difference-in-differences. Considering unobservable characteristics may reduce the effects' estimates.

This finding does not mean funding has no effect, but it suggests that funding may not be a good proxy for avoided deforestation. PA funds are invested in many conservation actions with various time frames for impacts. For example, investment in tourism could indirectly help reduce forest loss by needing to protect the habitat to conserve biodiversity and attract visitors. However, it might not be the case. Operational costs are used within the committed year, potentially showing some short-term effects. In contrast, project funds can take time to show effects on the ground because they must overcome bureaucracy and operational processes before getting to the field. This indicates that the assumed pathways from management inputs into outcomes are more complex (Schleicher et al. 2019), with multiple factors affecting their performance. Not all funding works the same way. Some have restrictions and conditions in when and how they should be spent, while others are less restrained.

As expected, I found conditionality in the effects of protection and investments of PAs. The impacts were larger in areas exposed to economic activities such as those closer to towns, mining concessions, and pastureland. In areas with poverty levels below 60%, the impacts were higher, similar to the findings in Costa Rica (Ferraro et al. 2011). The land's agricultural suitability did not seem to influence the decision of whether to deforest or not (Bax et al. 2016), suggesting opportunistic as opposed to selective extraction of resources. In comparison to the analysis at the district level in Chapter 3, the moderating effects were related to the natural environment rather than economic activities.

At the grid level, having less forest cover at the beginning of the treatment increased the effects of protection and funding. Less forest loss implies that previous deforestation occurred, where previous paths of access may exist, or it has access through a river, increasing the possibility of more forest loss. Comparatively, the district-level analysis showed that protected districts with more unprotected forests avoided deforestation, suggesting a reduction of spillover effects in protected districts. The results are not comparable due to a difference in the measure of forest cover, leading to different interpretations.

Being closer to a previously deforested site increases the probability of future forest loss. Protection and funding were more effective in areas within 500 m of a previously deforested location, supporting previous findings (Schleicher et al. 2017). Given the multiple uses of the trees and land (logging, agriculture, mining), having the most suitable land for agriculture would have indicated clearing for agricultural plots as a leading cause, assuming prior knowledge. However, agricultural suitability was not relevant and distance to agricultural plots was excluded from the analysis because I included it to weight the allocation of funding, hence, to avoid multicollinearity. At the district level, more forest loss

before the treatment reduced deforestation in protected districts, in line with the potential positive district-level effects of the presence of protected areas and funding.

Sites with high average temperature, above 23.5°C, which corresponds with lowland forests, had larger effects from protection and funding. At the district level, I found the opposite effect, in which funds in higher-altitude districts located in the Andes-Amazon slopes reduced more forest loss. The opposite findings show that scale and purpose of deforestation matters. Lowland forests are denser but have reduced access compared to higher altitude forests, allowing for more extraction of wood per square kilometer. Higher-altitude forests offer more effective means of transportation. Both, highland and lowland forests, have relevant factors that may drive deforestation which protection and funding help to reduce.

Being close to conserved areas protected forests more than being farther away, reinforcing previous findings (IUCN-WCPA Task Force on OECMs 2019). This finding suggests a potential positive spillover effect of other forms of conservation into PAs, potentially through habitat preservation. Further research on the ways conserved areas contribute to environmental protection and realize their role in conservation will add to the body of evidence and solutions available for practitioners protecting forests.

At the PA level, older and sustainable use management PAs were more effective in avoiding forest loss, echoing previous findings (Miranda et al. 2015; Oldekop et al. 2016). Also, parks co-managed with NGOs were better at protecting forests than those managed by the state only, which may be explained by the additional input of funding, expertise, and human resources provided by this contract. PAs receiving tourists showed larger effects from protection and funding avoiding forest loss than PAs without tourism. These findings are in line with previous findings in Bolivia (Hanauer and Canavire-Bacarreza 2015). Many parks received significant funding to invest in infrastructure (Nakamura 2017). I suspect that tourism and economic activities within a PA create further regional and local incentives to protect those ecosystems (Kirby et al. 2011) because local populations may benefit (den Braber et al. 2018; Vilela et al. 2018; Naidoo et al. 2019). These variables suggest that future investments in protected areas directed toward areas with these characteristics may increase the return on investment.

At the PA level, the most funded PAs were not the most effective in avoiding forest loss, but they were highly effective in protecting forests. It was surprising to find that the different methods of allocating funding per grid did not affect the results greatly, as observed in the results between models A, B, and C. The equal funding/sq km model (type A) had a slightly higher effect of funding over protection, with the green line above the other models (e.g. Figure 5.2). The type B and C models accounted for deforestation risk, giving an adjusted and slightly reduced effect from funding compared to the type A

model. Through this finding, I confirm there is no endogeneity between the choice of spatial funding allocation and the effects. The results suggest that the marginal effect of funding between a high and low deforestation risk area may not make much difference and could be due to using committed funding without disaggregating funding by its goal. Future research could test the difference between the spatial use of targeted funding compared to the assumptions made here.

Yanesha Communal Reserve and San Matias San Carlos Protection Forest were the most effective in avoiding forest loss and were the top two PAs with the largest observed forest loss. Together with the sixth most effective PA, Yanachaga Chemillen National Park, they form a PA cluster in the Andes Amazon region of Pasco (Appendix C, Figure C.7). They are exposed to roads and rivers with an illegal logging problem (Andina 2016). With average funding of I\$3,069, I\$2,669, and I\$6,074/sq km, respectively, these PAs reduced their deforestation significantly (Appendix C, Table C.2). Tabaconas Namballe National Sanctuary, the PA with the highest funding per square kilometer, had relatively low effectiveness (placed 22 out of 29). It is one of the smallest PAs, with state governance and strict level of use with low risk of deforestation (Rojas et al. 2021). The third most effective PA at avoiding forest loss, Tambopata National Reserve, has been largely exposed to illegal gold mining (Wang 2016), especially in its buffer zone and borders (Rojas et al. 2021), and received the largest number of tourists. This higher risk of losing forests could explain its level of effectiveness when compared to the unprotected landscape. Previous research in the Peruvian Amazon identified four of the top six most effective PAs (San Matias San Carlos Protection Forest, Yanesha Communal Reserve, Allpahuayo Mishana National Reserve, and Yanachaga Chemillen National Park) as the few PAs with high deforestation risk (Rojas et al. 2021), supporting previous findings that PAs exposed to higher pressure show higher impacts (Börner et al. 2020).

Four out of the five least effective parks (Pucacuro National Reserve, Sierra del Divisor National Park, Ichigkat Muja National Park, and Alto Purus National Park) share boundaries with Ecuador and Brazil (Appendix C, Figure C.8). Due to their remoteness, illegal activities tend to be present. Alto Purus National Park borders with Brazil and has illegal logging, illegal coca plantations, and drug traffic problems (Fernandez Aguilar 2021). Sierra del Divisor is the newest park in the sample, just established in 2015, with a history of illegal coca, logging, and mining activities that deforested the high biodiversity area (MAAP, 2015). Ichigkat Muja National Park borders with Ecuador and is highly threatened by illegal mining since the 1980s, before its creation (Vera 2020a). Gold miners from Ecuador cross the border and, colluding with the police, extract minerals and process them inside the park as local police cannot process Ecuadorians due to a lack of minimal conditions after capture, and are sent to their territory where legislation is different, giving them a form of impunity (Vera, 2020b). Given these characteristics, it is

likely that control and enforcement are harder to achieve (Shah and Baylis 2015). I suggest taking a closer look and re-evaluating the PAs at political borders considering the factors such as economic activities and laws in neighboring territories that may affect its habitat.

There is evidence that management and adequate funding in PAs increase threat reduction for species protection (Schulze et al. 2018), reduction of threatened species (Waldron et al. 2017), and increased populations (Geldmann et al. 2013). However, PA management inputs, including funding, were weakly correlated with the likelihood of reducing deforestation and forest degradation when compared to unprotected areas in Peru between 2006 and 2011 (Schleicher et al. 2019). PA funding in Peru has increased annually since 2011 (Nakamura 2017). The median PA funds in 2011 were I\$98.56/sq km (Schleicher et al. 2019) and increased to I\$224.93/sq km in 2009–2015. This amount was calculated as the mean annual PA funds per square kilometer per PA, and then averaged. However, James et al. (1999) estimated that Peruvian PAs needed I\$287/sq km (\$190/sq km in 1996 US\$) to have adequate funding levels. After more than 20 years, only 13 out of 29 PAs sampled received that level of funding. Maybe the PAs with adequate funding improved their correlation with avoided forest loss, explaining the findings.

The findings suggest funding may increase the capability of enforcement and monitoring of trespassers as a mechanism to avoid further forest loss. Another possible mechanism would be that funding targeted to improve social inclusion in high poverty areas improved livelihoods and community engagement through economic alternatives like tourism, promoting the conservation of PAs' resources. Other potential alternative economic sources may come from sustainable agriculture projects, agroforestry, and REDD+ payments. Although this last source failed in Alto Mayo Protection Forest, it may have had successful outcomes in other PAs. A third possible pathway could be through the presence of other PAs (state PAs and conserved areas), where the close and clustered PAs have a larger and weakening effect on people's willingness to deforest as it is more likely to get into trouble, improving forest conservation.

A caveat of this study is that, in practice, funding is not spent equally per square kilometer nor by deforestation risk. Although it is more likely that funds went to the places with more need, without data on how much was spent and for which purpose, the only way to study it is by making assumptions. These results show the impacts were not sensitive to the spatial allocation funding, suggesting no circularity in the effects. Nonetheless, future case studies with geolocated funding within PAs over time will help minimize the generalizations and assumptions made with secondary data. Testing the differences found between these assumptions and the actual spatially explicit spending will help guide the development of tools for the evaluation of conservation funding.

5.7 Conclusion

This analysis shows the causal relationship of protection, not funding. Hence, I could not estimate the marginal effect of a dollar in avoided forest loss. Nonetheless, the results show that funding in addition to protection were more effective in protecting forests than protection alone, in comparison to unprotected areas. The magnitude of the effect of protection reduced significantly when controlling for its committed financing, exposing the relevant role of PA funding in avoiding forest loss. On average, I estimated 470 sq km of forests were not lost within PAs due to their protected status and the funding committed. However, the effect of PA funding became insignificant when the comparison was made between PAs. This may happen due to reduced deforestation risk within PAs, inappropriate control units, and potentially insufficient variation in funding and forest loss.

The effects of funding showed conditional effects based on socioeconomic, ecological, and biophysical characteristics that exposed forests. Being close to a mining concession or pastures increased the risk of deforestation, making funding more effective in comparison to places where deforestation was unlikely. Accessibility to the forest increased forest loss risk. PA sections close to towns and previously deforested areas were the most vulnerable to further loss, showing larger effects. There may be a positive feedback loop between state PAs and conserved areas when protecting forests.

PAs with sustainable use management and co-managed PAs were more effective in protecting forests. Older PAs and those receiving more tourists also avoided more forest loss. Three of the top six most effective PAs shared boundaries, forming a conservation cluster that may support each other's efforts to combat deforestation. Having above-average funding levels and being located in a mountainous area with access to roads and rivers, they were able to avoid deforestation significantly. The third most effective was the most visited park in the sample with above-average funds. The least effective PAs shared boundaries with other countries, were remotely located, hosted illegal activities, featured no tourism, and received below-average funding (except Ichigkat Muja National Park). Without protection and funding, all these areas would have been wildly deforested. PA funding played a relevant role in protecting PA forests in the Peruvian Amazon. Based on these results, I call for increasing investments, particularly in PAs located at the country's political boundaries, which are the most in need.

There are four contributions to the impact evaluation conservation literature: (1) testing the differences of magnitude in the impacts on avoided forest loss on PAs considering the potential effect of funding beyond legal protection, (2) the use of causal forests as a method of causal inference in conservation to estimate the effect on avoided forest loss, (3) the use of cumulative funding as a continuous treatment comparing between PAs, and (4) testing different assumptions for the allocation of

funding spatially. Future research can analyze funding targeted to reduce forest loss, including changes over time; study the effects of different funding sources; and update the funding period to estimate longer-term outcomes.

Many factors moderated the effect of protection and funding avoiding forest loss. Using average treatment effects can mask the wide variation in impacts, potentially misleading future applications. In this chapter, I begin to disentangle the correlation of the impact of protection and PA funding on forest loss and the conditionality in its effects. Here, I highlight the conditions under which legal protection and PA funding were the most and least effective in avoiding forest loss to guide the future allocation of funds in Peruvian state PAs to make the best use of the available funds.

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CHAPTER 6: CONCLUSION

6.1 Summary

Conservation investments in protected areas (PAs) in the Peruvian Amazon are needed to preserve the primary forests it houses and support the human populations that live in and around these forests. In this dissertation, I have quantitatively assessed the effectiveness of PA funding in achieving social and ecological outcomes in the Peruvian Amazon. The results show that PA funding had a small positive effect on improving social development, on average, and mixed effects on avoiding forest loss at the district level. When analyzed at the grid level, I found significant impacts from protection and funding on deforestation. The different results due to the scale of the analysis demonstrate the importance and potential implications of analytical choices made in assessing PA and PA funding impacts. Importantly, data availability, or lack of it, can sometimes force this choice.

In Chapter 2, I developed a theory of change to lay out the rationale behind the analysis of PA impacts. This chapter contributes to the body of literature in the field of conservation policy impact evaluation, where the most commonly evaluated intervention is legal protection from PAs. Given that the success of PAs depends on the funding available to support management actions within—and sometimes outside—their boundaries, proposing a clear and careful framework for estimating funding effects can help inform more effective financial resource allocation. I applied this framework and presented a case study in the Peruvian Amazon. Through this case study, I addressed the dilemma of the potential introduction of bias by the choices taken to distribute funds spatially within PAs. In Chapter 5, I compared three funding distribution choices and found that they did not significantly affect the average results.

In Chapters 3 and 5, I estimated the impacts of protection and PA funding on forest cover using different methods and units, addressing a similar question at different scales. The results show different results at the district level versus grid level analysis, where the larger-scale perspective considers the actions and interactions of non-conservation activities, spillover effects, and other conservation activities as inherent conditions within the outcome. The effects showed variation based on forest cover characteristics and biogeography at the district level. In contrast, distance to economic activities and socioeconomic variables were needed at the grid level. The effects of protection were larger than those of funding at the district level, while the grid level analysis suggests that funding may play a much more significant role in protection. Nonetheless, they are not independent of each other because protection would not happen without funding, and funding would not be allocated if the area was not protected.

Economic activities moderated the effects of funding on forest loss at the grid level. The marginal effects were higher in deforestation vulnerable areas closer to mining concessions, pastureland, and towns which are a proxy for markets supporting previous findings on threats (Watsa 2014, Tripathy-Lang 2012, Rojas et al. 2021, Schleicher et al. 2017). On average, grids with less poverty had larger effects, suggesting that fulfilling the need for subsistence may not be driving deforestation in the Peruvian Amazon. In addition, the effects were conditioned on the baseline condition of the forest, where having less forest cover and closeness to a previously deforested area increased the probability of deforestation and showed larger effects of protection and funding, which was supported by previous findings (Schleicher et al. 2017). At the district level, the more extensive forest cover outside PA boundaries and deforestation before the treatment determined a higher magnitude of the effects. This finding may potentially explain the positive effect of the presence of PAs and their funding reducing the likelihood of deforestation in protected districts. Further spatial analysis at a smaller scale is needed to determine the level of spillover effects from PAs.

The presence of other forms of conservation areas was relevant for PA funding at the grid level. Non-state conserved areas moderated the effect of PA funding, where their closeness increased the effects. The results suggest a positive feedback loop between all PA types and the effects of PA funding, potentially through increased forest cover, supported by their role increasing forest connectivity (Palfrey et al. 2022). In the literature, indigenous lands in the Amazon have shown to be effective in reducing deforestation (Nolte et al. 2013; Schleicher et al. 2017; Blackman et al. 2017). However, I did not find evidence to support this finding. One possibility for this (non)finding is that indigenous lands may not be as effective as PAs at deterring threats, such as from loggers, as state PAs (Rojas et al. 2021). At the district level, there may also be leakage effects from the restrictions imposed by the Indigenous titled lands on those who are not community members, explaining the larger amounts of forest loss associated with an increased presence of Indigenous lands within districts.

With grid level results aggregated per PA, all parks were effective in protecting forests, on average. The most funded PAs avoided forest loss, but more funding did not necessarily show larger effects. Parks with investments of I\$1,500–I\$3,000/sq km were the most effective, and PAs comanaged with NGOs, with sustainable-use management, and more tourists were associated with high effectiveness. The Andes-Amazon region held the majority of the most effective PAs, which had above-average funding and the most effective were exposed to the highest deforestation risk (Rojas et al. 2021). The least effective PAs shared boundaries with other countries in remote locations and had below-average funding levels. Policies between countries differ and enforcement in low funded and remote

areas is scarce, creating the conditions for illegal activities across country borders with somewhat legal immunity. Both the least and most effective PAs were exposed to illegal activities, but having more funding made a big difference in reducing threats for the most effective ones, and more funding may benefit the least effective. Previous evidence shows that conservation interventions in low pressure areas will have lower impacts compared to those under high pressure (Börner et al. 2020), supporting the findings. This pattern suggests that PA funding played a relevant role in protecting forests in the Peruvian Amazon. The findings at the district level were different. I showed that districts with funding larger than I\$2 million were the most effective. Nonetheless, the PAs contained in the most effective districts were not the same as those in the analysis at the grid level. The district level analysis considers forest loss outside PA boundaries, explaining the different conclusions found on the effects of funding.

In Chapter 4, on social outcomes, I found that the human development index (HDI) increased with PA funding with a very small magnitude. In parallel, my analysis showed positive effects on income, suggesting it as a pathway for development. Some districts showed HDI and income had opposite effects, a finding that can be explained by mining in the Andes Amazon and deforestation in the lowlands, both of which are extractive activities leading to income increases but not concomitant development ones. Districts with more funding showed fewer negative social effects and less deforestation, suggesting the improvement of ecosystem services through avoided deforestation as a potential mechanism that promoted alternative economic activities other than agriculture within districts. Other variables correlated with social impacts were population density, the share of conserved areas, and Indigenous land area. There were no statistically significant variables moderating these effects.

The findings from Chapters 3 through 5 contribute to the body of evidence of impacts from PAs in a highly biodiverse tropical developing country. This study represents the first time PA funding has been analyzed as a conservation treatment within a country, using a continuous treatment rather than the usual binary one. In addition, I tested the sensitivity of different assumptions on the spatial allocation of funding at the grid level, which did not make a significant difference in the results, suggesting their robustness. I used the most common impact evaluation tool in conservation: matching with postmatching regression (Schleicher et al. 2019) in Chapters 3 and 4. In addition, I used causal forests as an alternative and newer method to estimate impacts more accurately (Athey and Wager 2019) in Chapter 5. The marginal effects show the relationship between funding and the outcomes, with quantitative measures to identify where funding had larger impacts. PA funding with protection contributed to mixed outcomes in both ecological and social spheres. However, more funding did not necessarily lead to more impacts, and

point to areas where more funding might be needed. These results suggest locations where future funding could increase their return on investment through more effective allocation.

Peru is a country with high geographic variability and social inequalities. The conditional effects in the findings substantiate these contrasts, even in a primarily rural setting like the Amazon. The results show the importance of considering Peru's geographic and social diversity and its history to understand the dynamics of the effects of conservation investments on social and ecological outcomes.

6.2 Paths forward

This dissertation has estimated the effects of PA funding taking into account biophysical and socioeconomic characteristics to advance knowledge in the fields of conservation science and sustainable development. The results suggest a number of avenues for future research and hold importance for decision-makers and donors as well regarding the conditions that have affected the performance of past PA investments.

Overall, my research demonstrates that PA funding impacted deforestation and human development positively, but in relatively small magnitudes. The impacts on forest loss were conditional on baseline socioeconomic and forest characteristics. This result implies that funding allocation matters because the same unit invested in one PA in the Andes Amazon will not have the same effect when invested in a PA bordering with Ecuador. Location and context matter because they define the social and economic environment and its exposure to threats (Börner et al. 2020). These conditions will shape conservation and PA funding effectiveness.

These findings suggest that decisionmakers should prioritize PA funding flows to areas with a higher risk of deforestation, such as those closer to markets, and increase funding to PAs facing major threats. In the Peruvian Amazon, these include illegal logging, mining, and agriculture. In addition, results suggest guiding future investments toward PAs located near national political boundaries and increasing monitoring and enforcement. On existing PAs, the current administration in Peru has been working to promote more inclusive and participatory conservation governance forms. The evidence presented in this dissertation supports these efforts: co-managed PAs and sustainable use management were more effective in protecting forest cover, suggesting implementing these forms of governance and management will improve biodiversity conservation impacts.

A novel finding is the relevance of conserved areas (private and regional conservation areas and conservation concessions), which moderating funding toward avoiding deforestation, and were correlated with increasing human development. My research suggests the presence of spillover or

leakage effects from Indigenous territories on deforestation by those who are not community members and a positive spatial relationship between PAs and conserved areas' forest cover, where the closer these two forms of area-based conservation are, the better for biodiversity outcomes. More research is needed to investigate the mechanisms and spillover effects (positive and negative) of these forms of land protection for conservation, including Indigenous lands, into forest conservation—in the Peruvian Amazon and beyond. Quantifying these effects can provide further evidence to increase funder attention on conservation areas beyond state PAs and democratize conservation funding. Supporting the establishment and management of conserved areas may be a strategy with a higher return on investment than expected through an additionality effect that avoids deforestation in PAs while also contributing to local human development.

Another topic needing further exploration is the relationship between PAs and agriculture. Agriculture is a main predictor of deforestation in the Peruvian Amazon (Rojas et al. 2021) and is correlated with subsistence farming and low HDI (UNDP, 2019). Research using quantitative methods is very limited on the dynamics between agriculture and PAs and funding. Promoting alternative economic activities aside from agriculture can support a win-win scenario for both habitat conservation and local populations. However, further research on other social effects at the household level over time will inform which strategies work best for specific contexts. Investing in tourism is standard practice for PA revenue. Still, my results suggest the need for exploring and engaging in other economic activities, like including commodities from within and around PAs into the private sector value chain through agroforestry practices and value-added processing products. Looking for technical assistance and knowledge transfer solutions might be the most fundamental in incentivizing lasting social change. With positive social impacts, ecological impacts are more likely to manifest, as found in a global review of the literature on PA impacts (Oldekop et al. 2016).

Future relevant research topics to improve conservation funding impacts are the categorization of funding and the explicit spatial distribution to make more accurate estimations of the causal effects. Categorizing funding may include linking funding by source (domestic, international, private, or public), by type (flexible versus hard spending, short versus long-term), and by its actual use, moving beyond committed amounts of funds by the activities on which it was spent. In addition, evaluating case studies with explicit geospatial data of funding over time would help identify relevant areas of action and impacts in relation to actual spending. Also, testing the hypothesized mechanisms between funding and outcomes, such as the role of ecosystem services in improving income, will confirm the intermediate steps within the causal chain of actions for better planning.

The frontier for future research on forest cover is vast, especially with the constant amount of data collected through satellite images. However, social data remains lagging. The lack of consistent data at the household level in rural areas made the study of social impacts too widespread at the district level. Understanding the relevant pieces of how and when PA funding work in these social-ecological spaces will help maximize conservation investments to the best of our knowledge. Moreover, evaluating the effects on other outcomes such as species populations, climate change-related outcomes, carbon sequestration, and other social indicators like inequality can help give a complete picture of the components of the return on PA investments. With ecological and social outcomes, comparing the effects on both outcome types and their trade-offs can guide future double-impact planning.

Generally, studies at different scales are needed in other countries to build theory and evidence on the crucial topic of PA and PA funding effectiveness in meeting both environmental and social goals. In the Peruvian Amazon and elsewhere, on-the-ground case studies of particular PAs or local area-based conservation is needed to deepen understanding of the impacts of funding and triangulate results from PA system-wide studies, like as this dissertation. Such studies will provide a better idea of what strategies might be best-suited for different types of PAs. Regardless, remaining remote areas with intact primary forests should be actively protected no matter current threat level. Preventing their loss is crucial, even for relatively low-risk areas, for many reasons, not least that the Amazon rainforests is losing its resilience, taking longer to regenerate and imperiling its very future (Boulton et al. 2022).

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APPENDIX A: SUPPLEMENTARY MATERIAL FOR CHAPTER 3

Table A.1 List of treated districts, specifying the province and department (region) they belong to, the share of protected areas they overlap with, the name of the PAs, their IUCN category, and committed funding per district.

Department	Province	District	PA share (%)	PA Name	IUCN Category	Total Funds (I\$, Million)
Amazonas	Condorcanqui	Rio Santiago	10.79	Tuntanain Communal Reserve	6	1.18
			7.03	Ichigkat Muja-Cordillera del Condor National Park	2	
	Utcubamba	Cajaruro	6.06	Chayu Nain Communal Reserve	6	3.12
			21.73	Cordillera de Colan National Sanctuary	3	
Cajamarca	San Ignacio	Nanmballe	35.55	Tabaconas Namballe National Sanctuary	3	1.96
		Tabaconas	12.39	Tabaconas Namballe National Sanctuary	3	1.19
Cusco	La Convencion	Echarate	18.03	Megantoni National Sanctuary	3	2.08
			5.08	Otishi National Park	2	
			12.44	Machiguenga Communal Reserve	6	
		Kimbiri	11.58	Ashaninka Communal Reserve	6	0.16
		Pichari	20.91	Ashaninka Communal Reserve	6	0.38
	Paucartambo	Kosñipata	37.77	Manu National Park	2	1.20
Huanuco	Leoncio Prado	Jose Crespo y Castillo	24.50	Cordillera Azul National Park	2	1.29
	Puerto Inca	Puerto Inca	10.79	El Sira Communal Reserve	6	0.32
Junin	Chanchamayo	Chanchamayo	7.17	Pui Pui Protection Forest	6	0.63
			11.37	Pampa Hermosa National Sanctuary	3	
		Vitoc	10.69	Pui Pui Protection Forest	6	0.09
	Satipo	Rio Tambo	15.50	Ashaninka Communal Reserve	6	4.36
			24.70	Otishi National Park	2	
Loreto	Maynas	Iquitos	14.99	Allpahuayo Mishana National Reserve	6	0.09
		San Juan Bautista	14.75	Allpahuayo Mishana National Reserve	6	0.86
	Loreto	Nauta	31.91	Pacaya Samiria National Reserve	6	1.16
		Parinari	89.27	Pacaya Samiria National Reserve	6	1.58
		Tigre	30.94	Pucacuro National Reserve	6	1.10
	Requena	Requena	25.15	Matses National Reserve	6	0.77
			12.72	Pacaya Samiria National Reserve	6	
		Alto Tapiche	38.26	Sierra del Divisor National Park	2	2.13

Table A.1 (cont.)

Department	Province	District	PA share (%)	PA Name	IUCN Category	Total Funds (I\$, Million)
		Maquia	7.58	Pacaya Samiria National Reserve	6	0.76
			12.20	Sierra del Divisor National Park	2	
		Puinahua	81.96	Pacaya Samiria National Reserve	6	0.73
		Soplin	8.37	Matses National Reserve	6	0.71
			28.84	Sierra del Divisor National Park	2	
		Jenaro Herrera	19.48	Pacaya Samiria National Reserve	6	0.18
		Yaquerana	27.49	Matses National Reserve	6	0.88
			21.60	Sierra del Divisor National Park	2	
	Ucayali	Contamana	5.67	Sierra del Divisor National Park	2	1.91
			18.47	Cordillera Azul National Park	2	
		Pampa Hermosa	61.97	Cordillera Azul National Park	2	0.04
		Sarayacu	4.16	Cordillera Azul National Park	2	1.32
			9.91	Pacaya Samiria National Reserve	6	
Madre de Dios	Tambopata	Tambopata	9.47	Bahuaja Sonene National Park	2	7.73
			22.85	Alto Purus National Park	2	
		Inambari	20.31	Bahuaja Sonene National Park	2	1.98
			16.95	Tambopata National Reserve	6	
	Manu	Manu	1.62	Reserva Comunal Amarakaeri	6	1.75
			84.30	Manu National Park	2	
		Fitzcarrald	2.98	Amarakaeri Communal Reserve	6	5.21
			77.40	Manu National Park	2	
		Madre de Dios	38.14	Amarakaeri Communal Reserve	6	2.94
		Huepetuhe	36.24	Amarakaeri Communal Reserve	6	0.89
Pasco	Oxapampa	Iñapari	0.54	Purus Communal Reserve	6	6.69
			56.04	Alto Purus National Park	2	
		Oxapampa	12.69	Yanachaga Chemillen National Park	2	0.32
		Huancabamba	15.42	Yanachaga Chemillen National Park	2	1.59
		Palcazu	12.33	Yanesha Communal Reserve	6	4.57
			8.35	San Matias San Carlos Protection Forest	6	
			26.70	Yanachaga Chemillen National Park	2	
		Pozuzo	23.29	Yanachaga Chemillen National Park	2	1.69

Table A.1 (cont.)

Department	Province	District	PA share (%)	PA Name	IUCN Category	Total Funds (I\$, Million)
		Puerto Bermudez	32.35	El Sira Communal Reserve	6	5.68
			13.87	San Matias San Carlos Protection Forest	6	
		Villa Rica	20.17	San Matias San Carlos Protection Forest	6	0.41
Puno	Carabaya	Coasa	54.25	Bahuaja Sonene National Park	2	0.94
	Sandia	Limbani	60.49	Bahuaja Sonene National Park	2	1.24
		San Pedro de Putina Punco	85.68	Bahuaja Sonene National Park	2	6.25
San Martin	Moyobamba	Moyobamba	17.61	Alto Mayo Protection Forest	6	4.97
	Bellavista	Alto Biavo	62.95	Cordillera Azul National Park	2	5.78
	Mariscal Caceres	Huicungo	22.43	Rio Abiseo National Park	2	6.74
	Rioja	Rioja	11.96	Alto Mayo Protection Forest	6	0.44
		Awajun	34.78	Alto Mayo Protection Forest	6	1.30
		Elia Soplin Vargas	41.42	Alto Mayo Protection Forest	6	0.94
		Nueva Cajamarca	40.72	Alto Mayo Protection Forest	6	1.38
		Pardo Miguel	74.51	Alto Mayo Protection Forest	6	7.10
	San Martin	Chazuta	31.51	Cordillera Azul National Park	2	0.46
		Huimbayoc	45.80	Cordillera Azul National Park	2	0.88
Ucayali	Coronel Portillo	Calleria	42.56	Sierra del Divisor National Park	2	1.42
		Iparia	19.79	El Sira Communal Reserve	6	2.55
	Padre Abad	Padre Abad	15.67	Cordillera Azul National Park	2	0.42
	Purus	Purus	10.55	Purus Communal Reserve	6	4.79
			68.11	Alto Purus National Park	2	

Table A.2 Regression results for generalized negative binomial models, and the linear SEM. All models used cumulative forest loss after one year of treatment. For the spatial error model, the variables and the outcome were transformed using the inverse hyperbolic sine. Departments used Amazonas as the reference.

	GLM.NB, log link Full Model			GLM.NB, log link			Spatial Error Model		
	Spending			Spending			Spending		
	Estimate	SE	P-val	Estimate	SE	P-val	Estimate	SE	P-val
(Intercept)	2.7280	0.4781	0.0000	3.3690	0.2998	0.0000	-1.6061	0.9918	0.1054
Treatment	8.71E-05	0.0000	0.0405	-0.0001	0.0001	0.1642	2.7103	0.9274	0.0035
District area	-4.72E-05	0.0000	0.1091	-1.88E-06	3.19E-05	0.9531	0.1128	0.1053	0.2841
Altitude	-0.0006	0.0001	0.0000	-0.0006	0.0001	0.0000	0.0351	0.0973	0.7184
Forest loss, Pre-T	0.0815	0.0081	0.0000	0.0619	0.0084	0.0000	0.7819	0.0657	0.0000
Pasture	-0.0184	0.0097	0.0571	-0.0204	0.0091	0.0244	-0.0762	0.0483	0.1147
Conserved areas	0.0079	0.0030	0.0080	0.0114	0.0027	0.0000	0.0375	0.0261	0.1509
Road density	-3.5070	1.0330	0.0007	-4.1200	0.8815	0.0000	-0.5323	0.4641	0.2514
Unprotected Forest cover	0.0001	0.0000	0.0002	0.0001	0.0000	0.0171	0.3645	0.0811	0.0000
Population density	-0.0031	0.0015	0.0364	-0.0029	0.0013	0.0248	0.1109	0.0388	0.0043
Department (region)									
Cajamarca	0.5589	0.3421	0.1023	0.2711	0.3111	0.3836	-0.0091	0.2867	0.9748
Cusco	1.1740	0.3007	0.0001	1.0660	0.2543	0.0000	0.1662	0.2335	0.4765
Huancavelica	0.7353	0.7469	0.3248	0.5439	0.7025	0.4388	-0.0252	0.3640	0.9448
Huanuco	1.3440	0.3365	0.0001	1.1990	0.2743	0.0000	0.1920	0.2311	0.4060
Junin	0.7732	0.3605	0.0320	0.4340	0.3213	0.1768	0.1721	0.2736	0.5293
Loreto	-0.3788	0.3408	0.2664	-0.5692	0.2669	0.0330	-0.5382	0.2633	0.0410
Madre de Dios	0.0098	0.3881	0.9799	0.1728	0.2870	0.5472	0.0688	0.2583	0.7899
Pasco	1.3750	0.3301	0.0000	1.1010	0.2743	0.0001	0.7552	0.2749	0.0060
Puno	-0.0026	0.3684	0.9944	-0.0515	0.2957	0.8618	-0.3808	0.2593	0.1420
San Martin	0.9062	0.2938	0.0020	0.2620	0.2530	0.3005	0.2644	0.2119	0.2122
Ucayali	0.4553	0.3684	0.2165	0.6175	0.3052	0.0430	-0.0130	0.2652	0.9608
Spending*Altitude				1.30E-07	4.79E-08	0.0067	-0.2070	0.0885	0.0194
Spending*Forest Loss (Pre-T)				1.82E-05	5.18E-06	0.0004	-0.0281	0.0763	0.7131
Spending*Unprotected forest cover				-2.24E-08	8.49E-09	0.0083	-0.1490	0.0663	0.0247
Agriculture plots	-0.0233	0.0110	0.0340						
Baseline HDI	0.0171	0.0115	0.1367						
Buffer zone	-0.0006	0.0024	0.7850						
Indigenous lands	0.0068	0.0032	0.0348						
Mining	-0.0037	0.0032	0.2565						
Morans' I	0.16		0.02	0.1		0.09	-0.0114		0.5129
Lambda							0.3803		
BP test	43.46		0.01	46.119		0.0029	28.338		0.2033
Jarque Bera test	0.22		0.89	0.7569		0.6849	1.4873		0.4754
AIC	940.97			929.41			131.59		
Loglik	-815.45			-879.412			-39.7955		

Figure A.1 A) Predicted vs observed values for SEM B) Predicted vs residual values for SEM.

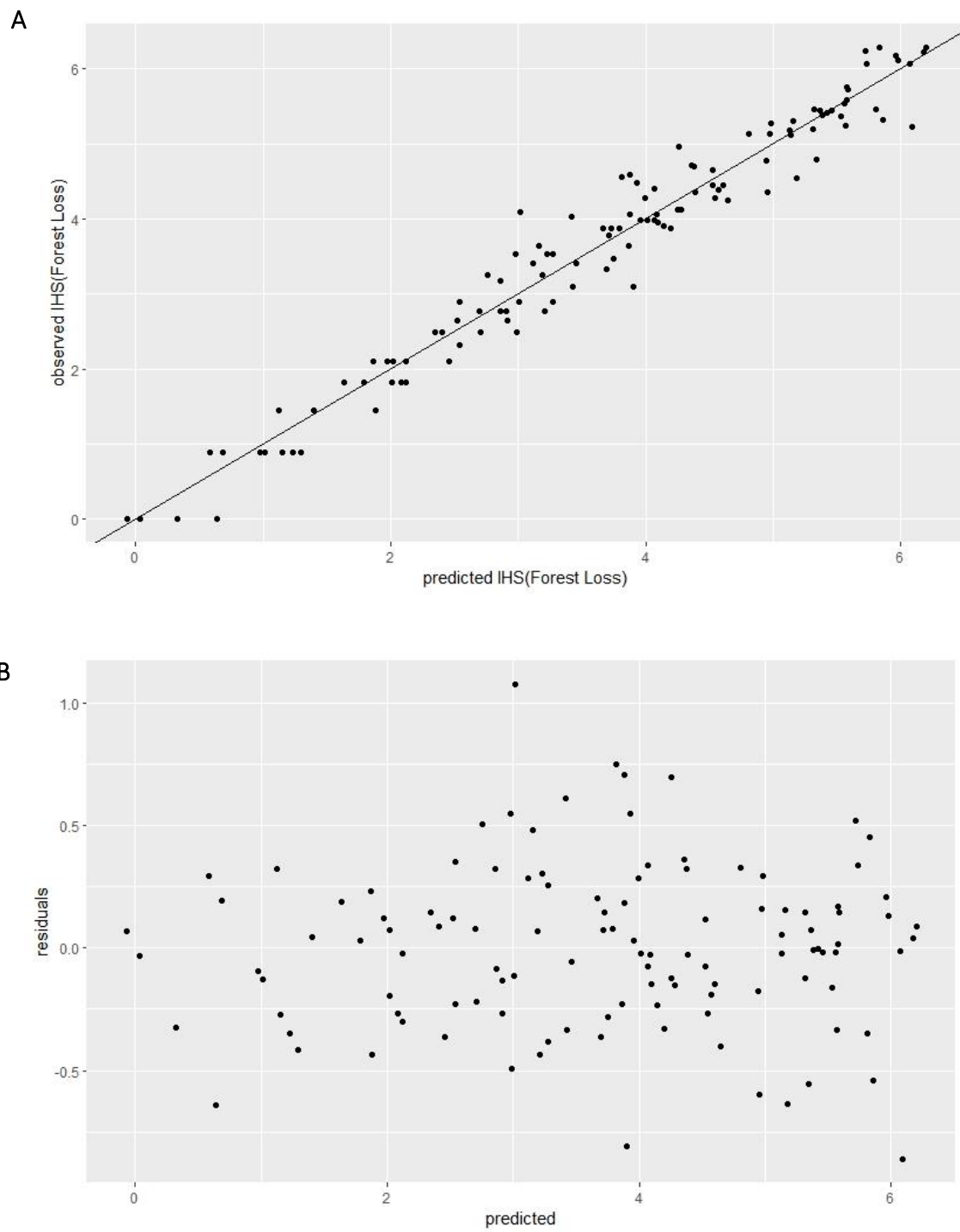


Table A.3 Moran's I test for various distance matrices. NN is for nearest neighbor (first 3 rows) tested on 2,3,and 4 km. Dis is for distance in kilometers (minimum, and 500 km).

	Forest Loss (t+1)		Spending (Risk1)		Baseline forest cover (sq km)		Σ Moran's I
	Morans	p-val	Morans	p-val	Morans	P-val	
NN 2K	0.442	0.001	0.192	0.022	0.436	0.001	1.070
NN 3K	0.416	0.001	0.148	0.020	0.395	0.001	0.959
NN 4K	0.384	0.001	0.121	0.024	0.354	0.001	0.859
Dis MinK	0.309	0.001	0.061	0.111	0.244	0.002	0.614
Dis 500K	-0.005	0.276	0.016	0.073	0.007	0.113	0.017

Table A.4 Robustness check for the effect of PA spending on forest loss. Regression results for main regression are at the left.

	SEM			SEM			SEM		
	Spending			Spending, Outcome 3-year lag			Spending R2, Outcome 1-year lag		
	Estimate	SE	P-val	Estimate	SE	P-val	Estimate	SE	P-val
(Intercept)	-1.7631	1.0016	0.0784	-2.4200	1.0367	0.0196	-1.7564	1.0006	0.0792
Treatment	0.4107	0.1248	0.0010	0.5003	0.1293	0.0001	0.4082	0.1248	0.0011
District area	0.1057	0.1102	0.3377	0.0590	0.1138	0.6039	0.1062	0.1100	0.3342
Altitude	0.0445	0.0974	0.6478	0.0931	0.1009	0.3563	0.0438	0.0973	0.6524
Forest loss, Pre-T	0.7828	0.0669	0.0000	0.7379	0.0688	0.0000	0.7833	0.0670	0.0000
Pasture	-0.0693	0.0481	0.1501	-0.0812	0.0497	0.1021	-0.0692	0.0482	0.1505
Conserved areas	0.0304	0.0262	0.2467	0.0312	0.0270	0.2481	0.0301	0.0263	0.2520
Road density	-0.5375	0.4578	0.2404	-0.4123	0.4710	0.3813	-0.5375	0.4581	0.2407
Unprotected Forest cover	0.3821	0.0850	0.0000	0.5180	0.0877	0.0000	0.3813	0.0849	0.0000
Population density	0.1170	0.0385	0.0024	0.1601	0.0397	0.0001	0.1167	0.0385	0.0025
Department (region)									
Cajamarca	-0.0405	0.2872	0.8877	-0.0159	0.3042	0.9583	-0.0394	0.2870	0.8908
Cusco	0.1591	0.2323	0.4934	0.2908	0.2457	0.2365	0.1603	0.2323	0.4901
Huancavelica	-0.0363	0.3635	0.9205	-0.2990	0.3810	0.4326	-0.0352	0.3634	0.9228
Huanuco	0.1696	0.2292	0.4593	0.0185	0.2394	0.9385	0.1713	0.2292	0.4549
Junin	0.1955	0.2714	0.4712	0.0819	0.2852	0.7740	0.1960	0.2713	0.4701
Loreto	-0.5309	0.2610	0.0419	-0.7194	0.2703	0.0078	-0.5304	0.2610	0.0421
Madre de Dios	0.0798	0.2557	0.7549	0.1811	0.2666	0.4970	0.0802	0.2557	0.7539
Pasco	0.7545	0.2743	0.0060	0.6798	0.2903	0.0192	0.7548	0.2743	0.0059
Puno	-0.3930	0.2591	0.1293	-0.0705	0.2737	0.7966	-0.3923	0.2590	0.1298
San Martin	0.2808	0.2114	0.1839	0.0949	0.2205	0.6670	0.2824	0.2115	0.1818
Ucayali	-0.0307	0.2627	0.9071	-0.1121	0.2731	0.6815	-0.0316	0.2628	0.9043
Spending:Altitude	-0.0316	0.0117	0.0071	-0.0369	0.0122	0.0025	-0.0314	0.0118	0.0076
Spending:Forest Loss (Pre-T)	-0.0020	0.0098	0.8381	0.0009	0.0101	0.9272	-0.0022	0.0098	0.8228
Spending:Unprotected forest cover	-0.0226	0.0084	0.0070	-0.0300	0.0086	0.0005	-0.0224	0.0084	0.0075
Morans' I	-0.1161		0.5137	-0.0072		0.4929	-0.0114		0.5126
Lambda	0.371		0.0079	0.4026			0.3796		0.0062
BP test	27.942		0.218	22.158		0.5107	28.43		0.2
Jarque Bera test	0.9401		0.625	1.7712		0.4125	1.4794		0.4773
AIC	133.8			139.33			131.68		
Loglik	-40.9021			-43.6658			-39.842		

Note: The model in the middle uses a 3-year lagged outcome, and the model in the right uses a different spending allocation model (Risk2). Departments used Amazonas as the reference.

Figure A.2 Four high-funded districts where funding did not avoid forest loss at the district level. Pardo Miguel district (top left), Palcazu (top right), Fitzcarrald (down left), and San Pedro de Putina Punco (down right). The district boundaries are in magenta, PA boundaries are in orange, brown lines are roads. Green dots are agriculture plots, and deforestation between 2010-16 are in red.

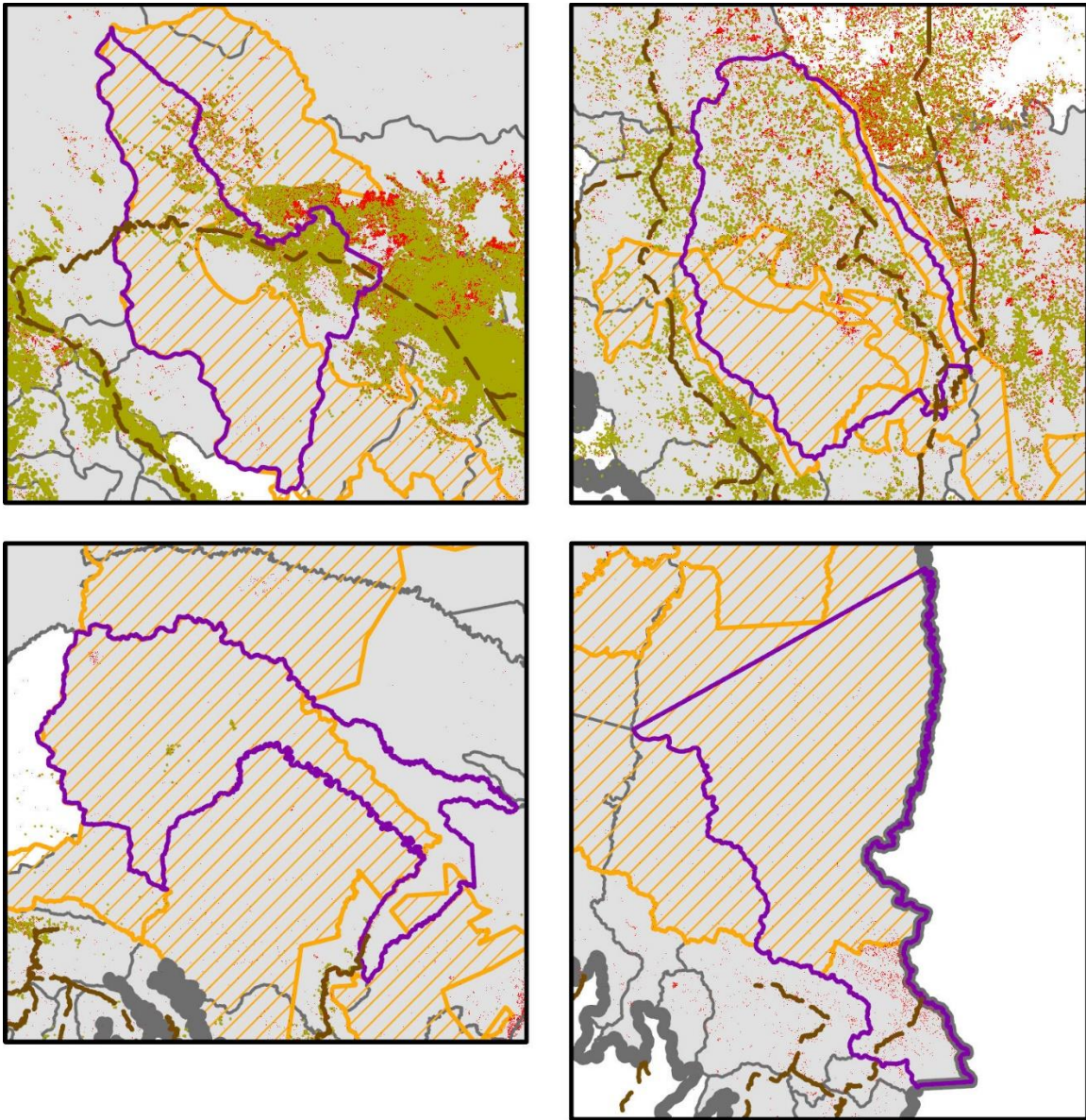
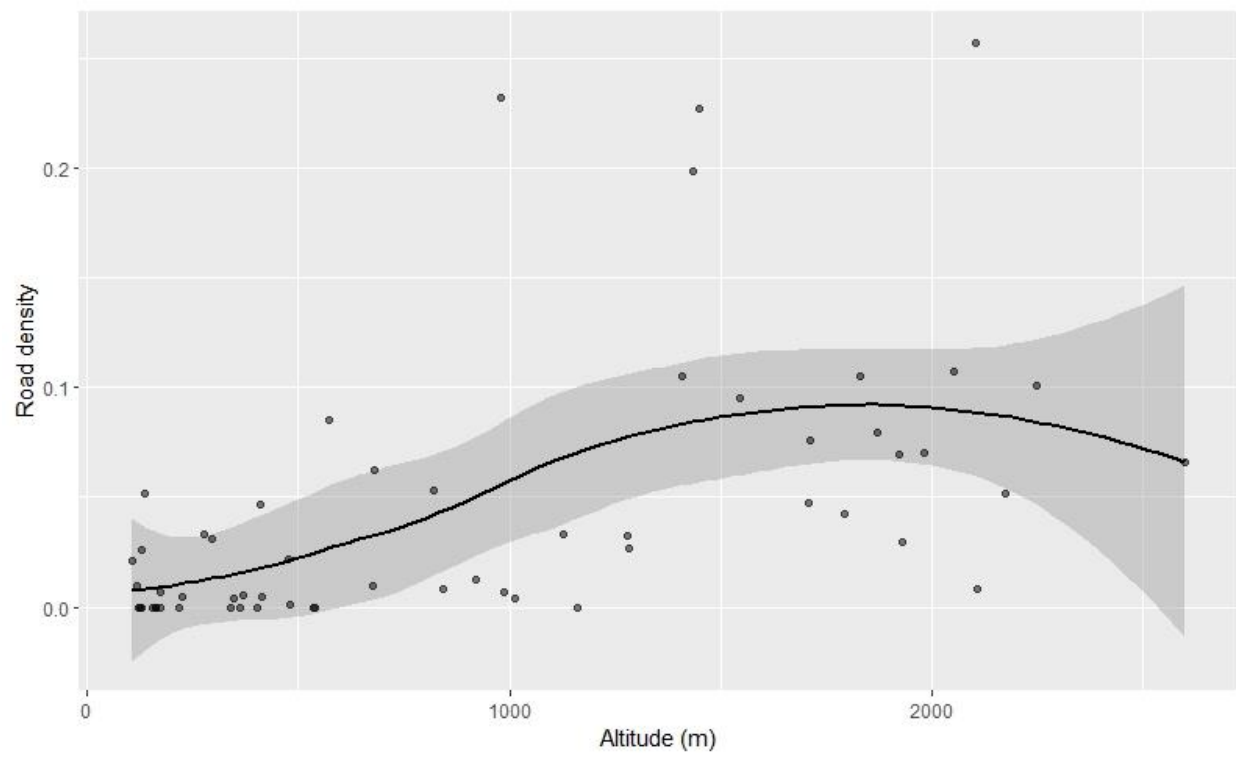


Figure A.3 Road density plotted against altitude for treated districts.



APPENDIX B: SUPPLEMENTARY MATERIAL FOR CHAPTER 4

Table B.1 Regression results for ordinary least squares (OLS) models, and the spatial error model (SEM).

	OLS. Full model			OLS, fitted, HDI2017			SEM, HDI2017		
	Estimate	SE	p-val	Estimate	SE	p-val	Estimate	SE	p-val
(Intercept)	-0.7139	12.8882	0.9560	6.1508	5.2280	0.2423	6.3451	4.8473	0.1905
Spending	0.0769	0.2195	0.7271	0.3052	0.1379	0.0292	0.2895	0.1301	0.0260
Agricultural plots	1.0751	0.8439	0.2060	1.1918	0.7228	0.1024	0.9381	0.6406	0.1431
District area	-0.8007	1.5877	0.6153	-0.8865	0.6401	0.1693	-0.9558	0.5892	0.1048
Baseline HDI	0.9506	0.1255	0.0000	0.9342	0.1211	0.0000	0.9610	0.1074	0.0000
Conserved areas	0.6302	0.3753	0.0966	0.5581	0.3154	0.0800	0.5835	0.2924	0.0460
Population density	1.5725	0.7420	0.0368	1.4185	0.6931	0.0434	1.4180	0.6326	0.0250
Indigenous lands	0.7877	0.3668	0.0344	0.7244	0.3414	0.0364	0.7261	0.3122	0.0200
Mining	0.5085	0.3110	0.1055	0.4396	0.3049	0.1527	0.4213	0.2886	0.1444
Department (region)									
Cajamarca	0.4544	3.1029	0.8839	0.2494	2.8943	0.9315	0.7483	2.9699	0.8011
Cusco	6.3193	2.7550	0.0241	7.0196	2.6366	0.0091	7.4810	2.6122	0.0042
Huancavelica	8.5584	4.6242	0.0675	6.4654	4.1535	0.1229	5.7117	4.0524	0.1587
Huanuco	5.1149	2.9584	0.0873	4.4839	2.8192	0.1150	4.3966	2.6775	0.1006
Junin	4.2541	3.5199	0.2300	5.5708	3.2602	0.0907	5.3410	3.1817	0.0932
Loreto	7.1091	3.5588	0.0488	6.2552	2.4811	0.0133	6.4606	2.3657	0.0063
Madre de Dios	14.0144	3.9966	0.0007	13.4217	3.4666	0.0002	12.8775	3.2225	0.0001
Pasco	3.2005	2.9742	0.2848	2.8779	2.8871	0.3214	2.9660	2.9243	0.3105
Puno	9.9217	3.2292	0.0028	10.7032	2.9473	0.0005	10.9013	2.9683	0.0002
San Martin	1.6403	2.5892	0.5280	2.9367	2.2321	0.1914	3.1684	2.1345	0.1377
Ucayali	5.7683	3.5081	0.1036	3.3809	2.9574	0.2558	3.1407	2.7837	0.2592
Forest loss (Pre-T)	-0.2334	0.7077	0.7423						
Pastureland	-0.7893	0.7307	0.2829						
Buffer zone	0.4479	0.3366	0.1867						
Altitude	1.1590	1.1874	0.3317						
Road density	-5.9294	6.7120	0.3794						
Unprotected forest cover	-0.2107	1.3133	0.8729						
Morans' I	0.1095		0.0815	0.1419		0.0374	0.0010		0.4544
Lambda							0.1822		0.0809
BP test	34.95		0.0891	29.6200		0.0568	30.1780		0.0496
Jarque Bera test	2.1753		0.337	7.7960		0.0203	3.9144		0.1413
AIC	721.2175			714.3093			713.2600		
Loglik							-334.6321		

Note: All models used HDI in 2017 as outcome, untransformed, eight years after the beginning of the treatment. The variables were transformed using the inverse hyperbolic sine (IHS). Departments used Amazonas as the reference.

Figure B.1 Deforestation share plotted against population density. The top graph includes treated districts only, and the bottom one includes matched control and treated districts.

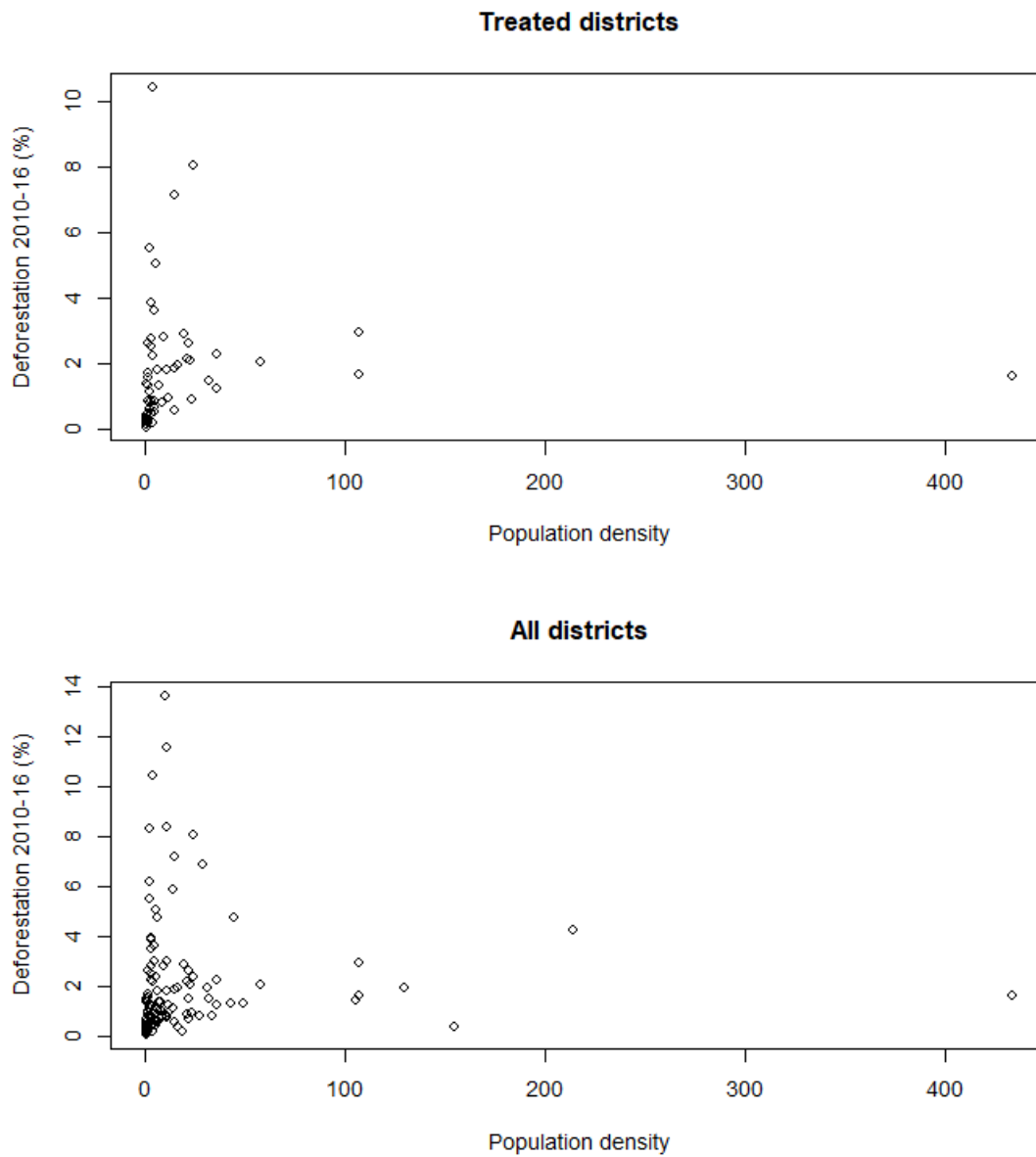
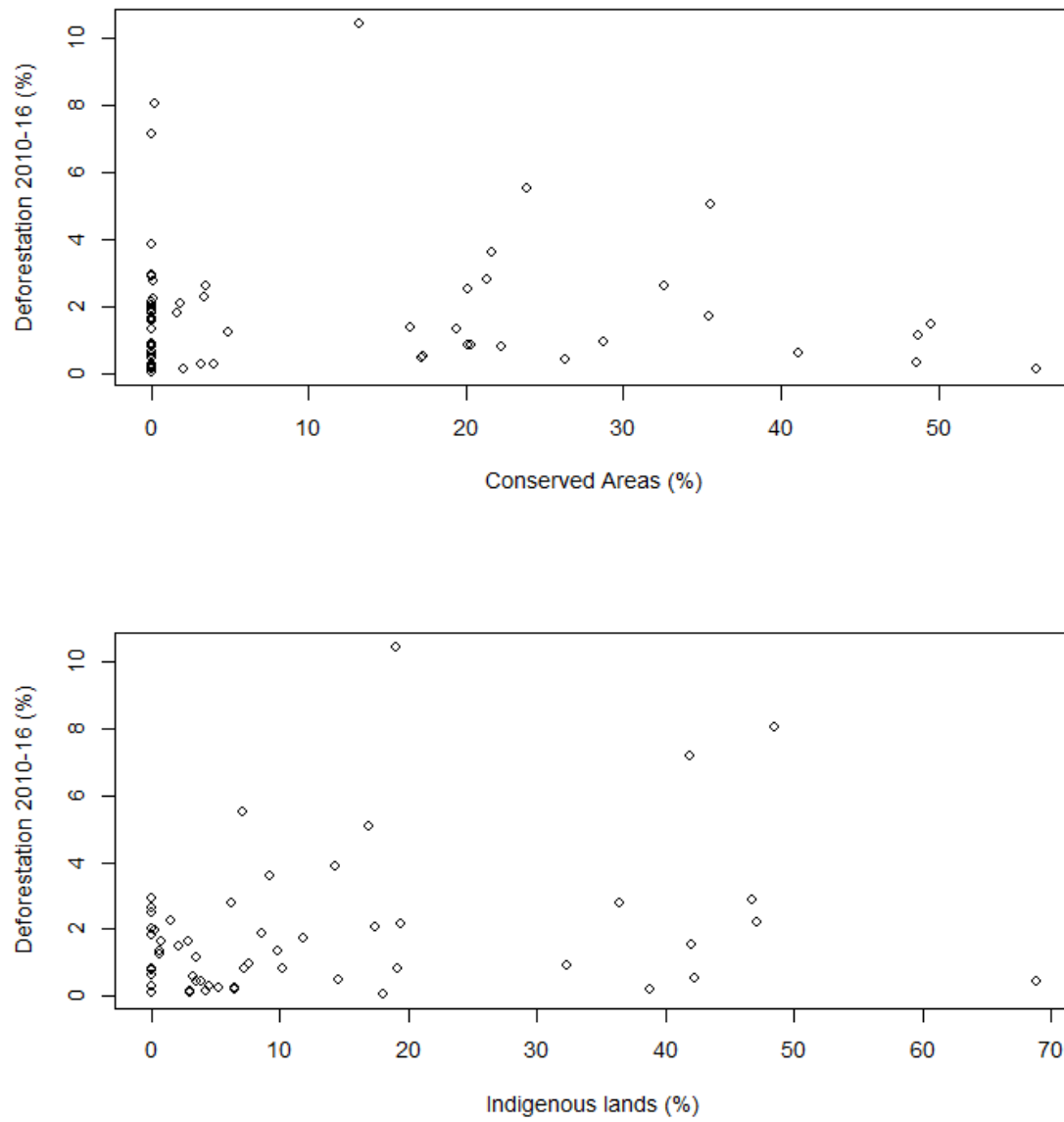


Figure B.2 Deforestation share plotted against the share of conserved areas (top) and indigenous lands (bottom) for treated districts



APPENDIX C: SUPPLEMENTARY MATERIAL FOR CHAPTER 5

Figure C.1. Propensity score of protection as treatment.

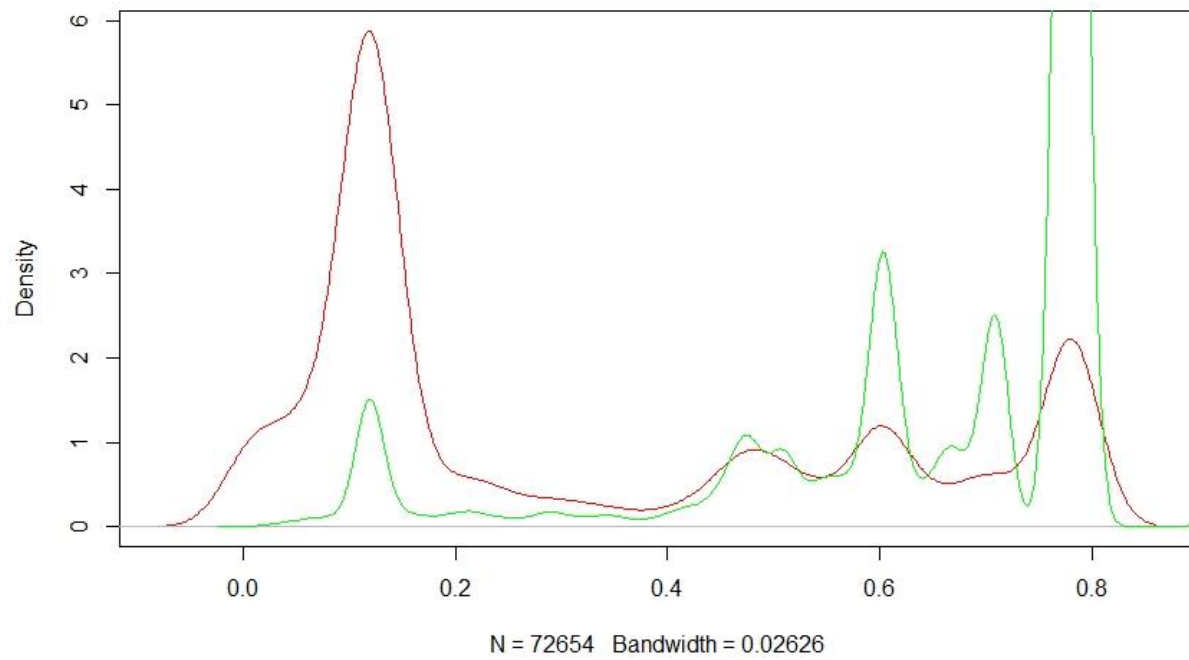


Figure C.2 Distribution of spatial blocks over the study area.

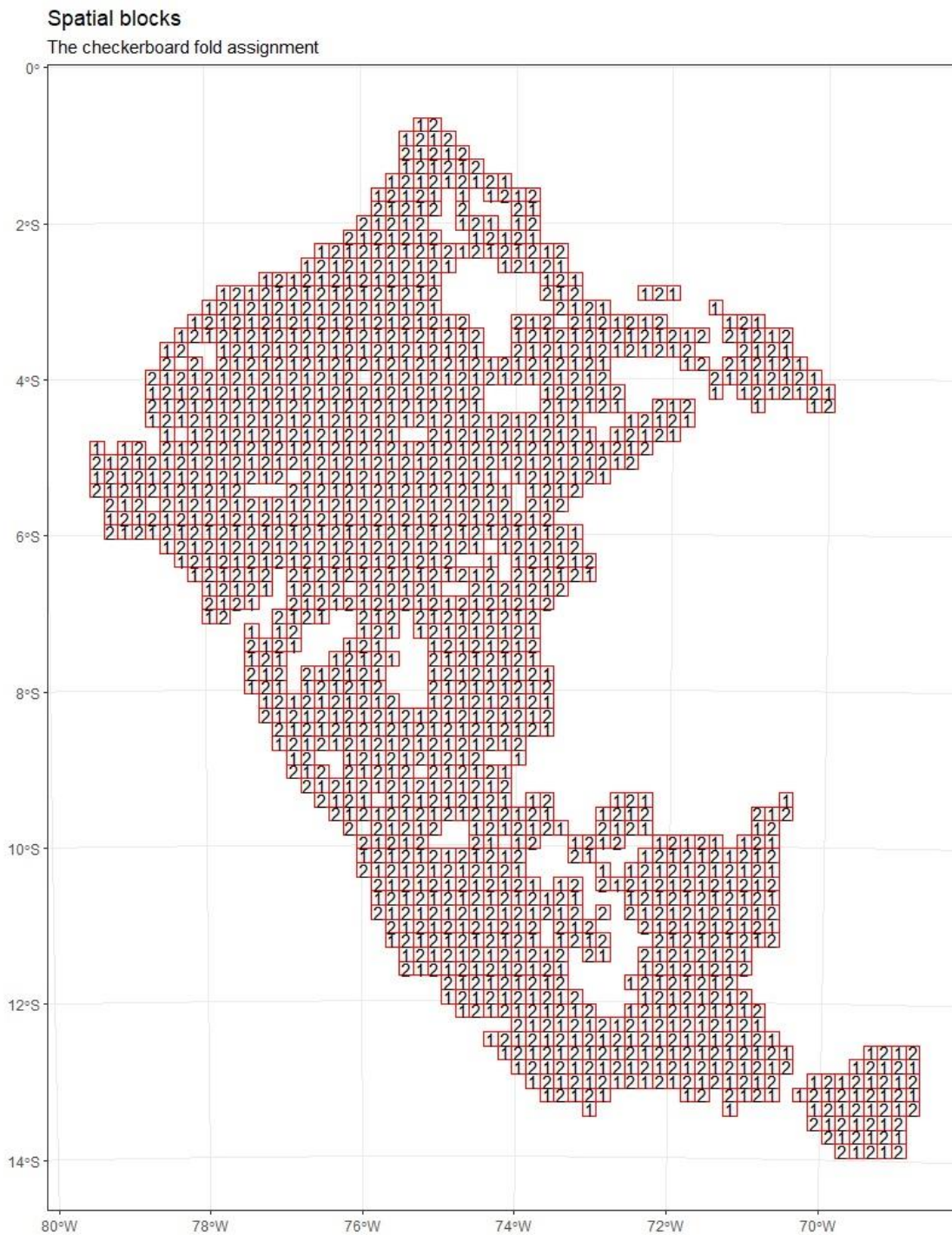


Table C.1 Robustness test for models 1-5 from Table 5.3. The models are run with the same specifications as in the text but using a different sample draw to train the model. The data sample was drawn using a spatial block size 32 sq km, with a checkerboard distribution. Significance level (***) $p < 0.00$

	Model 1	Model 2A	Model 2B	Model 2C	Model 3	Model 4A	Model 4B	Model 4C	Model 5B	Model 5C
Description	Raw model				Refined model				Refined model	
Avoided forest loss (%)	-0.26	-0.14	-0.14	-0.14	-0.41	-0.12	-0.13	-0.13	6.07e-05	5.76e-05
Standard Error	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.00	0.00
Mean CATE (test data)	-0.27	-0.14	-0.13	-0.15	-0.48	-0.16	-0.18	-0.18	5.17e-05	4.71e-05
Mean CATE (OOB)	-0.26	-0.14	-0.15	-0.14	-0.44	-0.14	-0.16	-0.15	4.98e-05	4.56e-05
Calibration										
Predicted ATE	0.93 ***	1.29 ***	1.26 ***	1.23 ***	0.98 ***	1.29 ***	1.27 ***	1.26 ***	0.91 ***	0.84***
Diff. forest prediction (Heterogeneity)	2.92 ***	3.56 ***	3.51 ***	3.52 ***	1.72 ***	2.13 ***	2.13 ***	2.12 ***	1.46***	1.53***
Variables										
Treatment	Protection				Protection				Spending (Risk 1)	Spending (Risk 2)
Spending in covariates	No	Yes (equal)	Yes (risk 1)	Yes (risk 2)	No	Yes (equal)	Yes (risk 1)	Yes (risk 2)	No	No
# Variables	20	21	21	21	8	9	9	9	8	8
Variables included	All from Table 1, but PA characteristics	All from Model 1 plus spending			Forest cover, dist. to towns, forest edge, conserved areas, and pasture, poverty, altitude, and temperature	All from Model 3 plus spending			Dist. to pasture and indigenous lands, forest cover and neighbors' forest cover, slope, temperature, rain, and altitude.	
Three most relevant variables (% splits)	Baseline forest cover (32%)	Dist. to town (31%)	Dist. to town (30%)	Dist. to town (30%)	Forest cover (51%)	Dist. to town (27%)	Dist. to pasture (26%)	Dist. to pasture (27%)	Rain (58%)	Rain (57%)
	Dist. to town (25%)	Dist. to pasture (22%)	Dist. to pasture (22%)	Dist. to pasture (22%)	Dist. forest edge (14%)	Dist. to pasture (26%)	Dist. to town (25%)	Dist. to town (25%)	Forest cover (16%)	Forest cover (17%)
	Dist. to pasture (13%)	Forest cover (14%)	Forest Cover (16%)	Forest Cover (16%)	Dist. to pasture (11%)	Temperature (13%)	Forest Cover (14%)	Forest Cover (13%)	Neighbor's forest cover (10%)	Neighbor's forest cover (10%)
PA spending (% splits)	-	Funds (0.007 %)	Funds (0.003 %)	Funds (0.007 %)	-	Funds (0.01%)	Funds (0.02%)	Funds (0.02%)	-	

Figure C.3 Correlation between covariates.

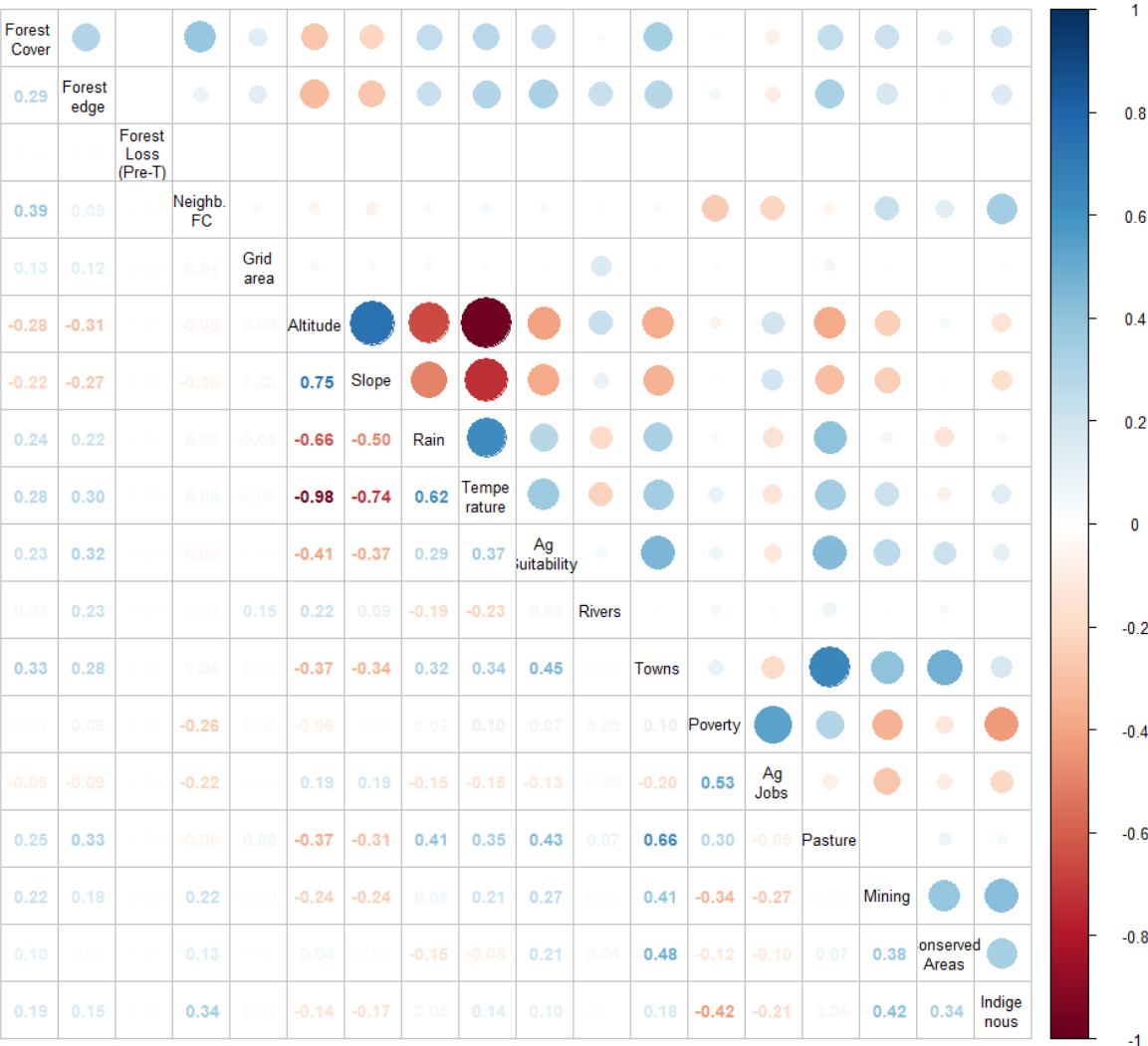


Figure C.4 Changes in avoided forest loss (%) plotted against (A) distance to the closest mining concession and (B) pastureland. The red line shows the effects of protection and funding (model 3). The green line (model 4A), the blue line (model 4B), and the purple line (model 4C) show the effects of protection. Dashed line show the identified threshold for heterogeneity.

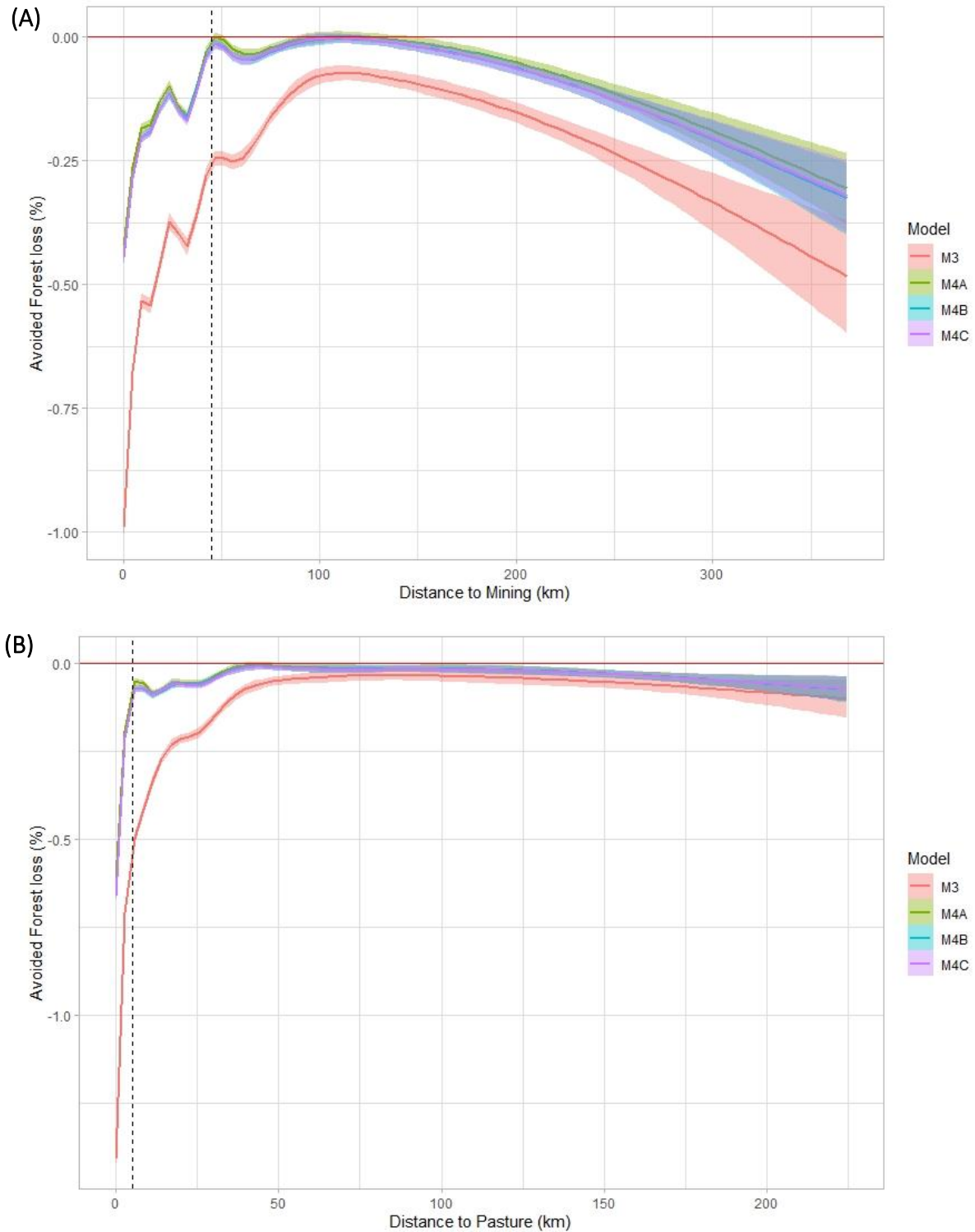


Table C.2 List of PAs with their corresponding mean CATE (avoided forest loss), funding/sq km, number of years protected, number of tourists, and mean forest loss (%).

Protected Area Name	Mean CATE	Funds/sq km (I\$)	# Tourists	# Years Protected	Total Forest Loss (%)
San Matias San Carlos Protection Forest	-0.79	565.57	0	29	1.58
Yanesha Communal Reserve	-0.76	537.06	0	28	1.94
Tambopata National Reserve	-0.75	432.31	242,873	16	0.22
Allpahuayo Mishana National Reserve	-0.73	323.21	344	12	0.33
Machiguenga Communal Reserve	-0.58	136.34	0	13	0.25
Yanachaga Chemillen National Park	-0.44	1059.63	8,067	30	0.59
Bahuaja Sonene National Park	-0.44	171.99	320	20	0.15
Ashaninka Communal Reserve	-0.42	255.04	0	13	0.34
Cordillera Azul National Park	-0.41	224.93	0	15	0.34
Rio Abiseo National Park	-0.40	380.65	10,782	33	0.61
Amarakaeri Communal Reserve	-0.37	160.78	0	14	0.12
Pui Pui Protection Forest	-0.30	331.38	0	31	0.10
Alto Mayo Protection Forest	-0.30	1458.11	1,132	29	1.51
Pacaya Samiria National Reserve	-0.29	45.21	63,977	44	0.18
Pampa Hermosa National Sanctuary	-0.25	850.66	1,994	7	0.36
Megantoni National Sanctuary	-0.24	63.26	363	12	0.17
Cordillera de Colan National Sanctuary	-0.24	1216.02	0	7	0.16
Manu National Park	-0.22	75.54	15,274	43	0.17
Otishi National Park	-0.21	148.23	0	13	0.15
Chayu Nain Communal Reserve	-0.18	1032.48	0	7	0.07
El Sira Communal Reserve	-0.17	177.72	0	15	0.70
Tabaconas Namballe National Sanctuary	-0.15	1804.95	810	28	0.38
Tuntanain Communal Reserve	-0.14	89.62	0	9	0.05
Purus Communal Reserve	-0.13	79.49	0	12	0.01
Alto Purus National Park	-0.11	68.52	10	12	0.04
Ichigkat Muja National Park	-0.10	270.67	0	9	0.07
Matses National Reserve	-0.09	45.15	0	7	0.04
Sierra del Divisor National Park	-0.06	0.00	0	1	0.16
Pucacuro National Reserve	-0.04	0.00	0	6	0.04

Figure C.5 Changes in avoided forest loss (%) plotted against distance to conserved areas. The red line shows the effects of protection and funding (model 3). The green line (model 4A), the blue line (model 4B), and the purple line (model 4C) show the effects of protection. Dashed line show the identified threshold for heterogeneity.

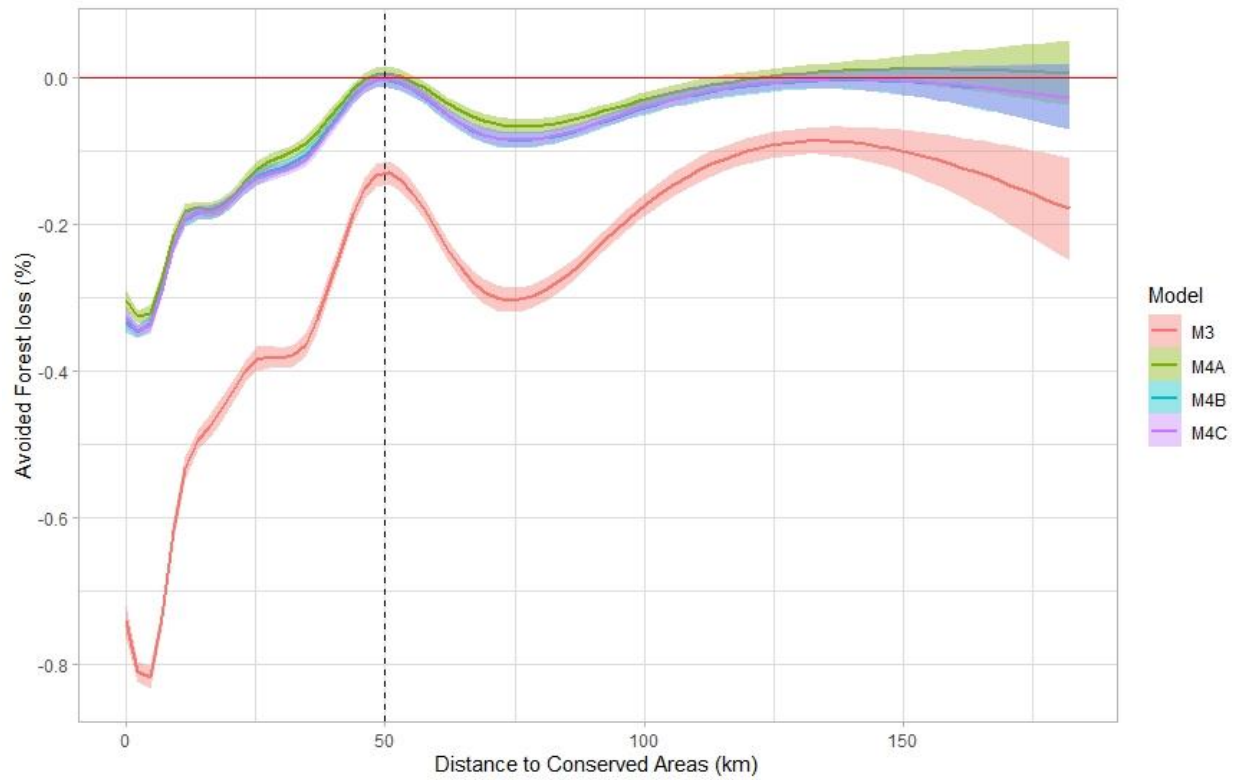


Figure C.6 Deforestation from 2001-2020 in state protected areas and the unprotected landscape in Peru.
Data source: GEOBOSQUES (2022).

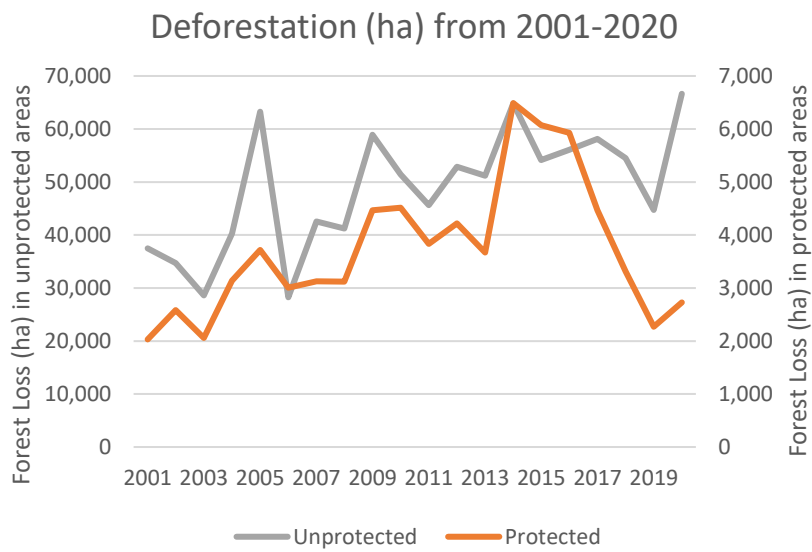
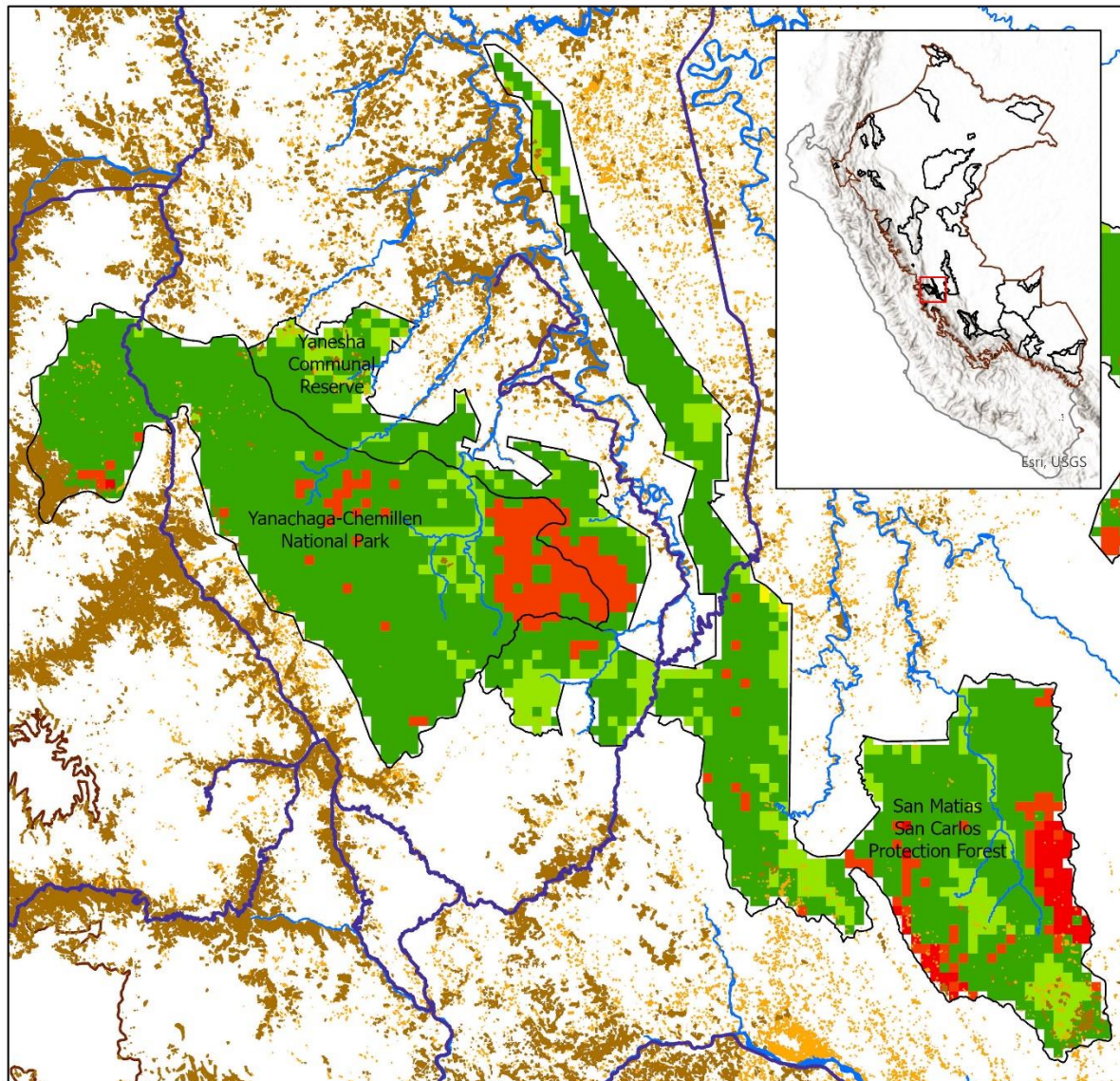


Figure C.7 Map of the cluster of three of the most effective PAs avoiding forest loss in the Peruvian Amazon showing the CATE (%) per pixel.



Effects from protection
and funding

CATE

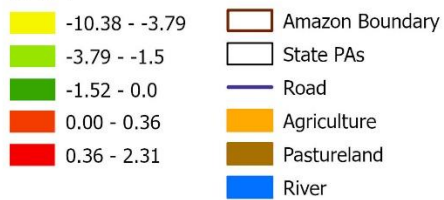


Figure C.8 Map of the CATE avoiding forest loss in PAs in the Peruvian Amazon, highlighting the five least effective PAs.

