Developing Analytical Tools to Understand Sustainable Development Goals synergies and trade-offs

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Summary

The Sustainable Development Goals (SDGs) is the current framework for development. It is important to note that the technical synergies and trade-offs between SDGs, as well as how people value trade-offs between goals, will determine the possible and socially desirable level of development. In this thesis, I explore the interactions between SDG 1 [Poverty], SDG 2 [Food Security] and SDG 15 [Land Ecosystems]. Until now, most research on forest poverty dynamics has studied the effect of forest-related policies on monetary poverty, ecosystem services, agricultural productivity and food security. All of these policies affect people's lives and shape forest landscapes. Nevertheless, as far as we know, no study has yet analysed what people's preferences are regarding forest conservation versus poverty alleviation. In chapter 2, I carry out a systematic mapping of the literature to identify research gaps and possible research questions for the project. In chapter 3 and 4, I use secondary data, merging spatially referenced household data (Demographic and Health Survey) and high-resolution forest cover/land cover data from Peru. This data is used to construct a quasi-experiment, which combined with covariate balancing generalized propensity score (CBGPS) weights and multiple regression analysis allows the isolation of treatment effects from potentially confounding socioeconomic and biophysical factors. Chapter 3 studies the effect of forest pattern on multidimensional poverty (MPI), finding small but important results. All forest metrics used increase MPI; however when decomposing MPI on its dimensions, some trade-offs appear. Here becomes apparent that forest fragmentation plays a role in poverty alleviation, and that looking into only one poverty dimension or forest metrics will hide the contribution of forest on poverty alleviation. Chapter 4 analyses the effect of Peruvian social programme Juntos (conditional cash transfer) on forest patterns and land-use change, finding that it prevents deforestation and promotes reforestation in 2016, 2020 and 2021. Chapter 5 builds on previous findings to look at how Peruvians value trade-offs between forest conservation, food security and housing quality. The study uses a discrete choice experiment (DCE) to assess the relative preferences over attributes that characterise the outcomes of interest and elicit citizen preferences between them. For this study, a sample of 250 members of the Peruvian public completed an online DCE questionnaire. The data from the DCE is analysed using regression techniques to obtain information on the relative preferences between outcomes. I find that citizens value policies favouring forest conservation over nutrition-related policies, unless they live in an insecure household. Combined my findings highlight that forest and socio-economic outcomes interact with each other; and the forest-poverty dynamics need to be examined using a multidimensional approach.

To Dad, for always believing in me and helping me fulfil my dreams.

I will miss you forever.

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Doing a PhD was a roller coaster of stress, exhaustion, learning, frustration, and wondering why I was doing this to myself, followed by periods of real inspiration and fulfilment. I really enjoyed the ride.

Author’s declaration

I declare that this thesis is my original work, but owes substantially to the guidance and intellectual contributions of my supervisors Aki Tsuchiya and Johan A. Oldekop. No parts of this work has been submitted for a degree at this or any other institution.

Contents

1 General introduction

The adoption of the Sustainable Development Goals (SDGs) Agenda pairs poverty alleviation with sustainable development, aiming for a continuous socioeconomic growth, social development and environmental protection (Griggs et al., 2013). So far, forest-poverty related research has studied the effect of forest-related policies on multiple dimensions of poverty, ecosystem services, agricultural productivity or food security (Alix-Garcia, McIntosh & Sims, 2013; den Braber, Evans & Oldekop, 2018; Andam et al., 2010; Ferraro & Hanauer, 2014; Rasolofoson et al., 2018). But very few have focused on how rural landscapes' configuration is linked (or not) to socioeconomic outcomes (Ferraro & Simorangkir, 2020; Alix-Garcia, McIntosh & Sims, 2013; Cunha, Rodrigues Neto & Morsello, 2022; Dyngeland, Oldekop & Evans, 2020; Gilliland, Sanchirico & Taylor, 2019), and little is known on how poverty-related policies affect environmental outcomes (Alpízar & Ferraro, 2020). Moreover, understanding public preferences is vital for informed decision-making prioritisation and for an optimal allocation of resources. It requires the consideration of "what is technically possible" (with the available resources), but also "what is socially acceptable". This thesis uses an empirical approach to try to understand the positive (synergies) and negative (trade-offs) interrelationships between rural landscape's configuration (SDG15), socioeconomic outcomes (SDG1, SDG2, SDG3), and vice versa. Furthermore, it uses preference elicitation techniques to understand how people value those interrelationships.

1.1 The Sustainable Development Goals framework

The 2030 United Nations Agenda for Sustainable Development, an action plan for people, planet and prosperity, adopted the Sustainable Development Goals as the current framework to achieve multiple development aims by 2030. The SDGs pledge to "ensure no one will be left behind" by putting equity and poverty eradication as its core objectives and ensuring the protection of the environment (United Nations, 2015). To achieve these objectives under a sustainable development approach requires that deprivation and disadvantages due to discrimination, geography, socio-economic status, governance and climate-change vulnerability be addressed as a whole. Moreover, it will require that the public sector, private sector and international cooperation work together to build capacities and create new solutions and financial instruments for a positive change (UNDP, 2018).

Understanding the synergies and trade-offs within the SDGs framework has been a central concern since its inception (Griggs et al., 2014) to minimise the effects of the latter, maximise those of the former, and establish an optimal allocation of time and resources. Highlighting the interlinkages between SDG elements (goals, targets or indicators) could promote policy coherence and a better use of governmental resources by evidencing barriers and potentialities between sectors. Some studies therefore suggest that a nexus approach, looking for connections between two or more elements, could help to better understand interlinkages between different sectors, scales and geographic context, helping policymakers to think outside "policy silos", and promote integrated strategies towards sustainable development (Boas, Biermann & Kanie, 2016; Liu et al., 2018; Bleischwitz et al., 2018).

1.2 Sustainable Development Goals and nature

Human welfare is at the core of sustainable development. Natural resources contribute to human well-being through the provision of services, which play an important role in food security, climate regulation and human health (United Nations, 2015). However, public policies and human activities can affect nature, creating benefits and costs (Freeman, Herriges & Kling, 2014). The report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES; Diaz et al., 2019) highlighted the complex role of nature in the achievement of Sustainable Development Goals. Nature directly supports the achievement of goals for water and sanitation, climate action, life below water and life on land, poverty, hunger, health and sustainable cities, while being also relevant to goals for education, gender equality, inequalities reduction and peace promotion, justice and strong institutions (Diaz et al., 2019). Some of these relationships between nature and SDGs have been explored already, as evidenced in Chapter 2, but some others have been omitted due to the focus on SDG wording and experts' knowledge. This thesis therefore focuses on the relationship between nature, poverty, hunger and health since their importance for sustainable development.

Understanding the relationship between SDG 1, 2, 3 and 15 is critical. Nilsson, Griggs & Visbeck (2016), Zhang et al. (2016), McCollum et al. (2018), Weitz et al. (2018), Fader et al. (2018), Fuso Nerini et al. (2018), Mainali et al. (2018), and Singh et al. (2017) have researched the underlying mechanisms between SDG1 (No poverty), SDG2 (Zero hunger), SDG3 (Good health and wellbeing) and SDG15 (Life on Land). The authors presented conceptual linkages based on expert knowledge to judge the interrelationships between these goals, categorising them as either positive (synergy) or negative (trade-offs). Their results showed that the relationships between goals depend on the context, method used or the initial evaluation element (goal, target or indicator) (Nilsson, Griggs & Visbeck, 2016). As informative as these studies are, they relied on existing knowledge or the wording of the SDGs to characterise relationships. Pradhan et al. (2017) studied the association between indicators using a correlation analysis, which revealed patterns previously missed in other studies. The approaches of these studies highlight the importance of empirical approaches when studying the relationships between SDGs but also the necessity to better understand the causal links shaping them.

A better understanding of these causal links is critical for sustainable development policy and practice. Impact evaluation methods seek to understand causal relationships between outcomes; causal inference methods have rapidly been adopted and provide a more rigorous approach to studying sustainability outcomes however, evidence is still scarce (Alpízar & Ferraro, 2020).

1.3 People's preferences and resource allocation

Optimising the allocation of resources is another critical element for sustainable development. The production possibilities frontier (PPF), a concept used in economics, can be illustrated by a curve that represents the outer boundary of all possible combinations of goods that can be produced given the available resources in a system, and captures Pareto efficient use of resources (Figure 1.1; Mankiw, 2008). The gradient at any point of the PPF is the marginal rate of transformation in production (MRT) in production, defined as "the amount of a good Y that the producer will have to give up producing for an increase in production of good X" (Sloman, 2006), i.e. go from point A to B in Figure 1.1. In the context of the SDGs, the PPF represents the set of Pareto efficient sustainable development outcomes, given the synergies and trade-offs of the framework, while the MRT measures the trade-offs at different points along the PPF.

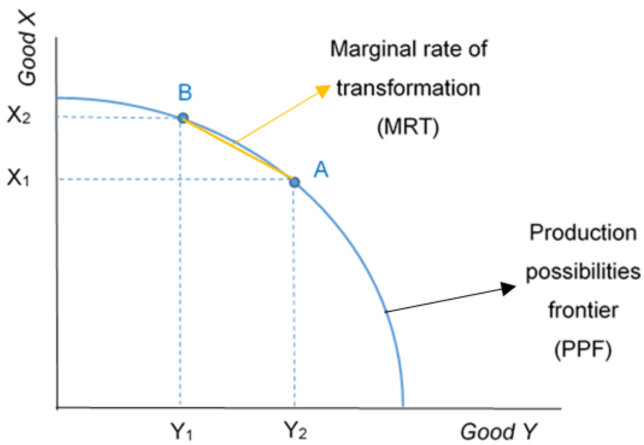

Figure 1.1. *Production possibilities frontier (PPF) and the marginal rate of transformation (MRT) in production.*

However, identifying factual synergies and trade-offs and being on the PPF is not enough to achieve a socially efficient resource allocation, and we need to include social preferences to ensure that decisions are also publicly optimal. To identify which point on the PPF is socially optimal, we need to know how society values multiple objectives. A social indifference curve shows combinations of X and Y goods that represent the same level of satisfaction or social welfare to the entire society (Gugl, 2014). The marginal rate of substitution (MRS) is the gradient at any point of the curve and shows how much of one good (Y) society is willing to give up to obtain an extra unit of another good (X) and stay on the same indifference curve, i.e. from C to D on Figure 1.2. A stated preference study, where respondents are asked to rate or rank hypothetical alternatives composed of combinations of different goods, can be conducted to elicit people's preferences and to calculate the relevant marginal rates of substitution (Freeman, Herriges & Kling, 2014). The optimal combination of goods is at the point where the production possibility curve is tangential to the indifference curve (Figure 1.3). In other words, the tangency point represents the combination of sustainable development that aligns what society desires with what it is capable of producing efficiently, maximising overall social welfare.

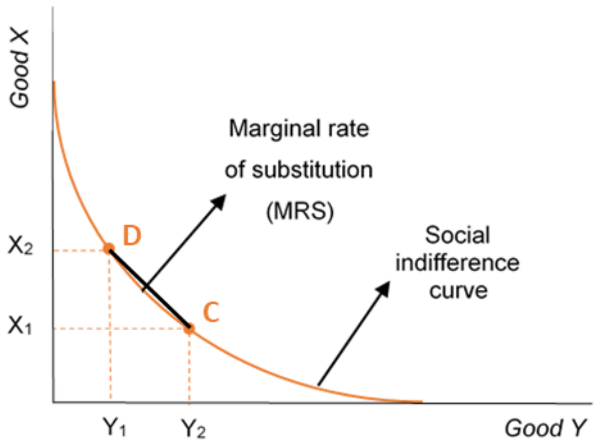

Figure 1.2. *Social indifference curve and marginal rate of substitution (MRS) in consumption.*

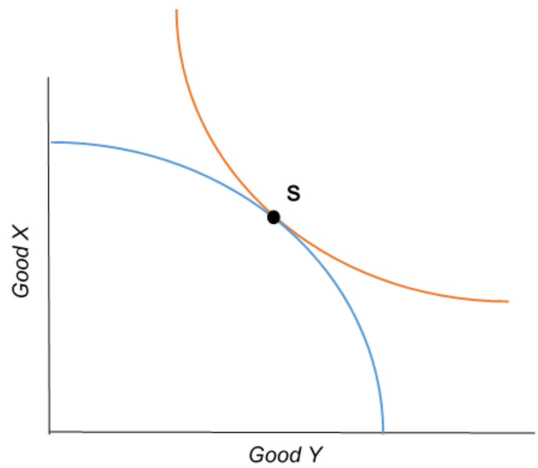

Figure 1.3. *Optimal combination of goods (S) point where the production possibility curve (blue) is tangential to the indifference curve (orange).*

The conceptual model discussed so far illustrates how factual information on what is technically possible is insufficient from a policy-maker's perspective, who also needs information about society's preferences to achieve the most desirable and attainable mix of sustainable development. Identifying a unique social preference is often tricky, since different people and groups will likely to have different values. Thus, there is no unique way to allocate resources. Nevertheless, simply analysing the factual technical information is inadequate for a socially optimal decision.

Beyond the theoretical model, its actual implementation within a PhD project encounters a set of practical considerations. Society preferences should ideally be studied using a face-to-face survey, on a large and representative sample and repeated over time; yet, none of these is typically practical within the restrictions of a PhD project. The model is based on a liberal and individualist framework of social decision-making, and analysing their impact on social decision-making is beyond the scope of the thesis. Moreover, the elicitation study based on an unassisted online survey will be building on an individualistic approach to people's values, while more collective and discursive methods are also possible (e.g. citizens' jury). Exploring the pros and cons of such preference elicitation approaches is beyond the scope of the thesis.

This thesis will study the factual synergies and trade-offs between SDGs 1, 2, 3 and 15, and analyse how people value the relative importance of these goals' outcomes to better understand their implications in resource allocation.

1.4 Thesis structure

The remainder of the thesis is divided into five chapters.

Chapter 2 presents two systematic literature reviews. The first review identifies the conceptual understanding of synergies and trade-offs between SDG1 [Poverty], SDG2 [Food Security], SDG3 [Health] and SDG15 [Terrestrial Environments] elements. The second review finds empirical studies researching the causal links between outcomes related to SDG 1, 2, 3, and 15.

Chapter 3 assesses the relationship between forest patterns on multidimensional poverty in Peru using secondary data. Specifically, I use causal inference approach to assess how forest metrics (forest cover percentage, number of forest patches per km^2, mean of patch area) are associated with a modified multidimensional poverty index (MPI) and its individual dimensions (health, education, standard of living) in the Peruvian Amazon.

Chapter 4 studies the effect of "Juntos", a cash transfer programme in Peru, on natural vegetation cover. It uses information from the Demographic and Health Survey, forest/ no forest data, and land-use change data, to analyse the impact of Juntos from 2014 to 2021 in the Peruvian Amazon.

Chapter 5 describes a small-scale Discrete Choice Experiment (DCE) to determine "what is socially acceptable" between forest conservation and multidimensional poverty. Specifically, it seeks to understand how Peruvian citizens value forest cover, nutrition and housing quality outcomes relative to each other.

Chapter 6 presents the main findings of the overall thesis, summarising the main contributions and limitations of the research, and recommendations for further research.

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2 Synergies and trade-offs in achieving the Sustainable Development Goals: a systematic map of the literature through two separate reviews

Abstract

Understanding the interrelationships between the Sustainable Development Goals framework and their components is vital to effectively achieve the goals by 2030. This chapter explores the intricate relationships among four Sustainable Development Goals (SDGs): SDG1 [Poverty], SDG2 [Food Security], SDG3 [Health] and SDG15 [Terrestrial Environments]. It combines two separate reviews with related aims: *i)* study the conceptual links among the whole SDG framework, and *ii)* study the empirical interactions between SDG 1, 2, 3 and 15, gathering evidence about the interrelationships and methods used. Overall, the first review synthesises findings from 9 studies, while the second review compiles 31 studies, highlighting the main interactions and research methods, providing a comprehensive understanding of the complex interactions among SDG goals. Results show that poverty, lack of education, and poor sanitation are linked to adverse health outcomes such as stunting, infectious diseases, and mortality. Similarly, environmental factors, including access to clean water and deforestation, also shape health outcomes. However, these reviews also identifies key research gaps, including: a) the need for more robust causal inference as well as more and better data; b) the use of methods that capture complex interactions over time and feedback loops; c) more integrated approaches and context-specific studies.

2.1 Introduction

In 2015, the United Nations member states agreed on a new global blueprint aiming to tackle the world's most pressing challenges: the Sustainable Development Goals (United Nations, 2015). This framework is a collection of 17 interconnected goals designed to achieve a more sustainable and equitable future for all by 2030. They address a broad spectrum of issues, from eradicating poverty and hunger to ensuring quality education, promoting gender equality, fostering sustainable economic growth, and combating climate change (UN News Centre, 2015). They represent a comprehensive to-do list for humanity, recognizing that these challenges are not isolated but deeply intertwined.

The Millennium Development Goals (MDGs), predecessors of SDGs, focused primarily on social development in developing countries with a set of eight goals (United Nations, 2015a). The SDGs take a much broader and ambitious approach, are universal and apply to all countries, emphasizing that sustainable development requires collective actions across the globe (SDG 17). Moreover, they explicitly advocate for the integration of “sustainability”, which is a key differentiator with MDGs.

The interrelated nature of SDGs necessitates interdisciplinary research to understand the complex interaction and potential trade-offs between different goals. Moreover, the ambitious 2030 timeline underscores the urgency for timely and effective implementation strategies. Consequently, the expanded scope of SDGs and their link to environmental sustainability creates a substantial research gap to understand how to effectively achieve these interconnected goals within the specific timeframe, considering the diverse contexts and challenges faced by different nations and regions. This urgency and complexity highlights the critical need for comprehensive reviews that synthesise existing knowledge, identify best practices and pinpoint areas requiring further investigation to ensure the successful realization of the SDGs by 2030.

This chapter consists of two separate literature reviews: 1) to capture the literature related to the underlying mechanisms between any of the SDG elements, and 2) to review literature that includes empirical analyses about causal links specifically between SDG1 [Poverty], SDG2 [Food Security], SDG3 [Health] and SDG15 [Terrestrial Environments]. The objective was to gather information about the methods used to analyse the underlying mechanisms within the SDG framework and identify the empirical methods used to analyse synergies and trade-offs between goals of interest.

Both reviews follow a systematic mapping methodology, developed to outline and categorise the existing literature and identify research gaps (Grant & Booth, 2009). Since the interest of the reviews is to recognise associations across goals, this chapter focused on studies that assessed components across two or more goals. Therefore, the review excluded studies that referred to a single SDG or target, addressed indicator performance, programme monitoring, legislation, or implementation of SDGs.

2.2 Review 1: interrelationships between any of the SDG framework

2.2.1 Methods of the first review

The first review focused on literature published since 2015 when the SDG agenda was launched, to gather evidence about the links between goals within the SDG framework. As to the date of the review, almost 5 years have passed since the introduction of the framework; this duration is enough to observe some initial trends and patterns and assess early impacts of various interventions aimed at achieving the goals. The primary data source for this review was the Web of Science and Scopus databases, and the search was carried out between November 2018 and January 2019. The review was limited to English peer-reviewed academic literature due to the number of researchers conducting the review (only one reviewer), language proficiency and time constraints. Using Web of Science and Scopus databases, allowed the establishment of a foundation of well-established academic knowledge about SDGs, and a more precise and manageable search strategy. However, it is important to acknowledge that research from non-English speaking regions might be underrepresented, and relevant articles may not be indexed in the chosen databases. Excluding grey literature could limit the understanding of practical implementation challenges, policy debates and real-world impact of SDG-related initiatives. Yet, these studies are out of the scope of the review.

The search was limited by time (published studies from 2015 to 2018) and by topic (title, abstract and keywords). Additional articles were identified by following up the reference lists of full text screened studies. The review uses an iterative process to define key search terms. First, we used the following string of English terms: "sustainable development goal" AND (framework OR interrelationships). Later, in order to improve the search, we added secondary terms: map, framework, network, link*, inter*. The inclusion of quotation marks (" ") limited the search to studies referring to SDGs only (see Table 2.1). Finally, we combined and screened the search results for duplicates using Mendeley (Mendeley Ltd, 2019) reference management software.

Table 2.1 *Keywords and syntax used for literature about SDGs framework*

#1: Main topic	("sustainable development goal") AND
#2: Secondary terms	(map OR framework OR network OR link* OR inter*)

Article screening and study eligibility criteria

For a publication identified in the search to be included in the review, it had to meet all of the inclusion criteria and none of the exclusion criteria:

A. Inclusion criteria:

I. The abstract reports analyses of relationships across any of the sustainable development goals, targets or indicators of the SDG framework.

II. The text develops a conceptual analysis of the relationships between goals, targets or indicators of the SDG framework.

B. Exclusion criteria:

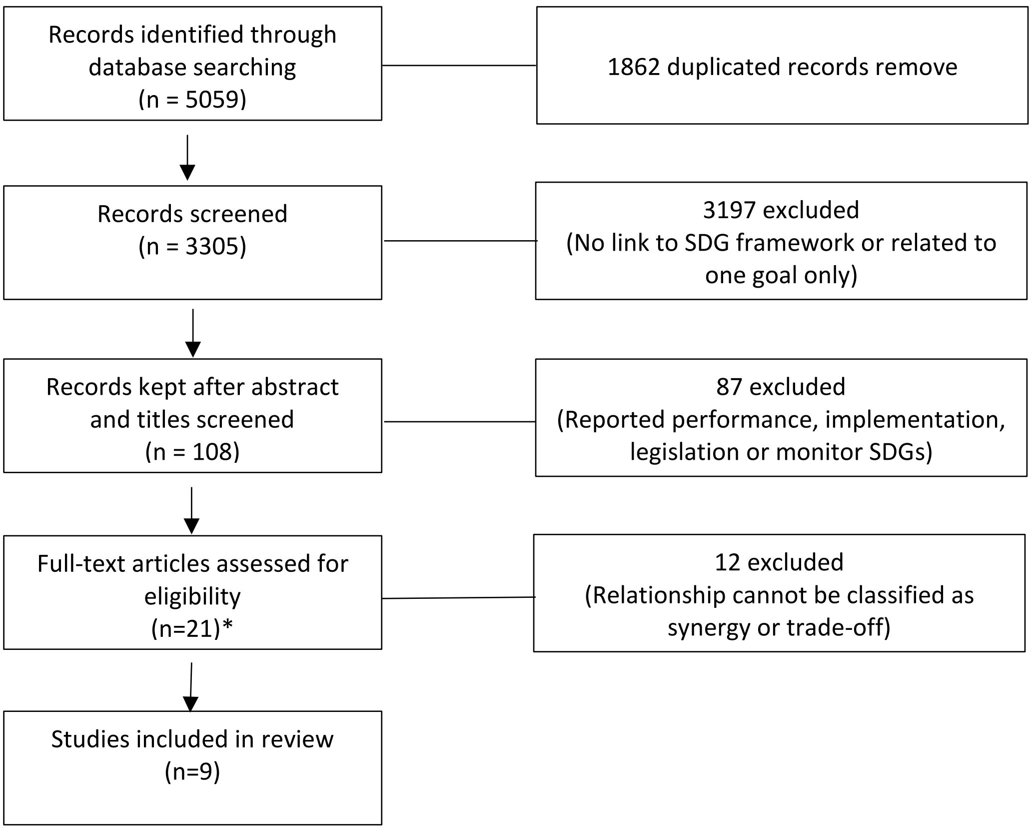
I. The study does not refer to outcomes of the SDG framework.

II. The study reports performance, implementation, legislation or monitoring of SDGs, by either quantifying or assessing them.

III. The study look at multiple targets/indicators within a single SDG.

IV. The study assesses associations between SDG elements but they are not reported or cannot be interpreted in terms of synergies or trade-offs.

After removing duplicates, the search strategy produced 3305 hits, of which 21 articles remained after the abstract filter stage (Figure 2.1). These 21 articles were examined at full-text for information about interrelationships between SDG elements. Following the full-text revision, nine were included in the review.



**Includes 3 papers identified using the reference lists of full text screened studies.*

Figure 2.1 *PRISMA flow diagram showing the selection process of studies included in the review.*

These nine studies published between 2016 and 2018 conceptualise synergies and trade-offs using different approaches and methods. The methods were classified as qualitative (if they used expert elicitation, scores or causal relationships supported by published literature or experts' knowledge) or quantitative (if they used mathematical models such as correlations or the concept of mathematical interaction). Seven of the nine studies used a qualitative approach; one used a quantitative approach; and one, a combination of both. The studies reported a selection of goals, targets and/or indicators to test. A summary of the nine studies included is in Table 2.2.

Table 2.2 ***Summary of studies included in the review, ordered by year of publication.***

Authors by date of publication	SDG[1] element	Method	Qualitative/ Quantitative	Indirect links?
Nilsson et al. (2016)	17 SDG goals, targets or indicators	7-point scoring scale	Qualitative	No
Zhang et al. (2016)	17 Goals	Causal loop diagram	Qualitative	Yes
Pradhan et al. (2017)	17 SDG Goals & indicators	Spearman's rank correlation	Quantitative	No
McCollum et al. (2018)	All Targets (but SDG 17)	7-point scoring scale	Qualitative	No
Weitz et al. (2018)	34 targets selected across SDGs	7-point scoring scale	Qualitative	Yes
Fader et al. (2018)	Targets SDG2, 6 & 7	8-point scoring scale	Qualitative	No
Fuso Nerini et al. (2018)	Targets SDG 7	Experts knowledge	Qualitative	No
Mainali et al. (2018)	SDG1, 2, 6, 7 & indicators	Network Analysis / Advance sustainability analysis	Qualitative & Quantitative	No
Singh et al. (2018)	17 SDG goals & SDG14 targets	Hierarchical framework based on experts knowledge	Qualitative	No

[1] SDGs= Sustainable Development Goals

2.2.2 Findings of the first review

Nilsson, Griggs & Visbeck (2016) presented a conceptual framework to analyse interrelationships between SDG elements. They proposed a seven-point scale (+3: indivisible, +2: reinforcing, +1: enabling, 0: consistent, -1: constraining, -2: counteracting, -3: cancelling) to classify the nature of the interrelationship based on expert's knowledge. This scale considered reversibility, direction, strength and certainty of the interaction between SDG elements on a one-to-one basis. A positive score denoted a synergy while a negative score, a trade-off. The advantage of this method is that it allows classifying and assessing the degree of interaction between SDG elements, and its simplicity makes it easy to understand for policymakers and implementers. However, the classification of interactions depends on previous knowledge and, as the authors stated, the direction of the interrelationships could change according to national circumstances and the level of development of the countries. The application of this framework requires knowledge of the interactions at the local level given that generalisations may not be accurate due to geographical, technological, and governance factors influencing the results of the scoring scale.

Zhang et al. (2016) used a causal loop diagram to build a conceptual system model using SDG 6 as an entry point and illustrated synergies and trade-offs between the 17 SDGs. They defined a causal loop as a tool in systems thinking that links factors based on their relationships, identifying archetypes and leverage points to describe the relationships between goals. They produced a conceptual model based on the causal links and identified archetypes in the model by comparing their conceptual model to existing system archetypes. They recognised three archetypes based on published literature: reinforcing growth, limits to growth, and growth & underinvestment. Using the causal loop diagram, they identified direct and indirect relationships with either a positive or a negative influence on other SDGs. This model also identified leverage points or enablers such as gender equality, sustainable management of water and sanitation, alternative perspectives to manage resources (i.e. resource recovery from waste), sustainable livelihood standards, and global partnerships. Goals within the Reinforcing Growth archetype were synergistic, but those on the Limits to Growth archetype opposed each other. Goals on the Growth and Under-investment loop had the capacity of influence in the performance of the whole system if they are enforced. They evaluated the SDG framework as an integrated system, however, relied on literature to identify causal links.

Pradhan et al. (2017) analysed synergies and trade-offs using data from the Inter-Agency and Expert Group on SDG Indicators from 227 countries and calculated the Spearman's correlation coefficient (ρ) between indicators, as proxies to describe the complex mechanisms between indicators. They used ρ to conceptualise synergies and trade-offs. A correlation coefficient value greater than +0.6 was interpreted as a synergy (positive association) while a value less than −0.6 as a trade-off (negative association). Correlation coefficient values between +0.6 and -0.6 were not classified. This analysis consists of a pairwise comparison between SDG indicators' data, except for SDG14 and SDG15, due to data availability. By calculating the proportion of synergies and trade-offs between SDG indicators for different regions and countries, the authors demonstrated that the interrelationships between SDG elements are complex and interdependent. However, this method did not assess causality between indicators, given that it cannot control for confounders, and requires a large amount of data for the analysis, but allows pairwise comparisons between SDG elements.

McCollum et al. (2018) explored the interactions between energy (SDG7) and all the other SDG targets. They performed a literature review and characterised the findings applying Nilsson et al. scoring tool, they implemented an "internal expert elicitation" to assess the robustness of the evidence, the degree of agreement based on the literature and the level of confidence in the interaction. They found that some interrelationships showed more robust evidence and highlighted the fact that synergies and trade-offs are often "context-dependent and case-specific". They accounted for the directionality of the interaction (unidirectional or bidirectional) since they found that a pair of targets could affect each other, not always in a symmetrical way. Their approach allowed them to gather information from the academic and grey literature, as well as identify inconsistencies between targets' links. However, this method still depended on experts' knowledge to identify the key literature.

Weitz et al. (2018) assessed the interrelationships between targets using Nilsson et al. (2016) scoring scale and represented them in a system network. They chose two targets per goal (34), building a cross-impact matrix and scoring the interactions according to the authors' knowledge. Then, they translated this matrix into a network diagram, where every target represented a node, and lines were colour coded (given score values) to visualise the complexity of the system. This system network could be divided into sub-networks according to the degree of interaction or elements of interest, and second-order interactions could be assessed to understand indirect interactions. Indirect interrelationships were assessed using a mathematical expression that calculates the net influence of the targets on a second-order network, interpreting scores as cardinal numbers. The total net influence of each target depended on their first and second-order interactions. The links between targets were unevenly distributed in the framework forming clusters or high concentration of links, denoting circles of influence, which can help decision-makers to develop strategies and partnerships or prioritisation. A system network is a very useful tool where it is easier to visualise the direction and degree of the interrelationships compare to a table, but it depends on experts' knowledge for scoring the interactions. Additionally, this tool supports policy-making and calls for an integration of different policy silos.

Fader et al. (2018) analysed the synergies and trade-offs between SDG2 (zero hunger), SDG6 (clean water and sanitation) and SDG7 (affordable and clean energy) targets using pairwise comparison and a scoring scale. First, they assessed the environmental cost of reaching each target in terms of resources (water, land & soil, electricity & fuel) and infrastructure (health care & hospitals; education, technology & research; grey infrastructure) or if they implied a risk or benefit for provisioning and regulating ecosystem services. Then they assigned a value of +1, 0 or -1 to each category, depending on the needs to reach the target (-1 if the target needed resources or if it risked a provisioning or regulating ecosystem services, +1 if infrastructure was needed or if it benefited a provisioning or regulating ecosystem services, 0 was assigned otherwise). Finally, they used a nine-point scale (based on the Nilsson et. al. scale, modified to include restricting and supporting interactions) to describe trade-offs or synergies between pairs of targets. Although they introduced environmental costs, other resources or infrastructure costs were not included in the analysis nor were cultural ecosystem services. The analysis did not account for resource constraints either, and still, it depended on experts' knowledge for the assessment of synergies and trade-offs. The advantages are that it can be adapted to any region and provide useful information for local policymakers, or, given a particular development pathway, it could be used to calculate cascading effects between two targets on a third.

Fuso Nerini et al. (2018) characterised interrelationships between targets (169) and energy systems (SDG7) based on published literature. The authors, who are experts in engineering, natural and social sciences, reviewed the literature and classified the interrelationships between targets. A single study was sufficient to determine a synergy or trade-off. Their analysis assessed the interrelationships in terms of human wellbeing, infrastructure and the environment, which evidenced the complexity of the interactions. The method used in this study demonstrated how SDGs interrelationships could change under different contexts and claimed an interdisciplinary approach to deal with the synergies and trade-offs.

Mainali et al. (2018) used quantitative and qualitative methods to analyse synergies and trade-offs between SDG7 (energy access), SDG6 (clean water and sanitation), SDG2 (food security and sustainable agriculture), and SDG 1 (poverty alleviation). They applied a network analysis, which is a qualitative method to assess the interactions based data and literature, and validated those interlinkages using Pearson correlation coefficients. Then, they characterised the interaction in an Advance Sustainability Analysis (ASA). The Advance Sustainability Analysis quantified the relationships given the change direction of the interaction. Here, a synergy is understood as a mathematical interaction between two independent variables given a linear relationship. Thus, a synergy happened if the combined change of two or more variables is greater than their individual value. Interactions ranged from -1 to 1, where a negative value corresponded to trade-offs. The advantage of the method is that it helps to quantify the previously identified relationships and observe how they differ according to the country and time. The main disadvantage is that ASA analysis is limited to pairwise comparisons across targets and that data availability affects the precision of the interrelationship quantification.

Singh et al. (2018) used a hierarchical framework to characterise interrelationships between SDG14 (Life below water) and targets within the goal that contribute to other SDG goals. They differentiated links into five categories: co-benefit-prerequisite-context-independent, co-benefit-optional-context-dependent, co-benefit-optional-context-independent, trade-off-optional-context-dependent, and neutral. They used a series of workshops and experts' knowledge to classify and validate the interrelationships. This method conceptualised synergies and trade-offs as compatibilities, and causal interrelationships as pre-requisites. Additionally, it recognised that these interrelationships could change depending on the context. The advantage of this method is that it can help policy-makers to determine which targets present the largest proportion of co-benefits or trade-offs at different scales and contexts. However, the method was designed to classify relationships into positive or negative and cannot determine how much a target contributes to another, which is important for policy prioritisation.

2.2.3 Discussion of the first review

The extensive search yielded qualitative and quantitative studies published between 2016 and 2018, which corresponds to the period since the SDG framework came into force to 2018. A quick search in 2024, using the same key words, for studies published between 2019 and 2023 produced 3616 research papers. The ratio of hits to in this study was 3055 to 9, if assuming that the same ratio holds, the missing studies could be 10. However, the aim of this chapter was to summarise the conceptual understanding of synergies and trade-offs across elements of the SDG framework, which is achieved in the review.

The nine studies found in this review focus on understanding the complex relationships between different Sustainable Development Goals (SDGs), emphasising the interconnected nature of global challenges. Several studies developed frameworks for analysing SDG interactions, using scoring scales or causal loop diagrams to map and classify relationships (Nilsson et al., Zhang et al., Weitz et al, Fader et al., Singh et al.). Some others synthesise existing literature to characterise those relationships (McCollum et al., Fuso Nerini et al.). Either way, they often employ expert knowledge to assess the robustness of evidence, which could be subjective to a certain extent. To account for a possible bias, they outlined the process of summoning groups of experts with the exception of Zhang et al. Pradhan et al. used a quantitative approach, applying a correlation analysis to quantify associations between SDG indicators, uncovering patterns that might be missed by the experts. Moreover, Mainali et al. use a mixed methods approach combining network analysis with quantitative measures like correlation coefficients to assess and validate SDG interlinkages.

A central theme is that SDGs are not isolated goals but interconnected in complex ways, with synergies and trade-offs influencing their achievement. The studies highlight the presence of both synergies (mutually reinforcing relationships) and trade-offs (conflicting relationships) between different SDGs. Likewise, several studies emphasise that the nature of SDG interrelationships can vary depending on the specific context, including national circumstances, level of development, and geographical factors. The review underscores the need for a systems thinking approach to understand the complex web of interactions and identify leverage points for effective policy interventions. Finally, while quantitative data can reveal associations, in the review studies expert knowledge is often crucial for interpreting these relationships and classifying them as synergies or trade-offs.

The review also highlighted a few limitations in terms of causality, data availability and expert elicitation. Most studies focus on identifying and classifying relationships, but few establish clear causal links between SDGs. The availability of data can limit the scope and precision of quantitative analyses. Moreover, the reliance on expert knowledge can introduce subjectivity in classifying SDG interrelationships.

This is the first systematic review to be conducted in relation to the conceptualisation of the synergies and trade-offs between SDG goals, and the methods used for that purpose. It has some strengths: it was carried out in a comprehensive way using two search engines to gather relevant studies and a citation search of full-text review articles and includes a wide range of articles. However, the review had potential limitations, including the restriction to sources in electronic databases available at the University of Sheffield, the narrow timeframe that limited research findings (2015-2019), the exclusion of grey literature, and the use of only one reviewer.

Finally, these studies provide valuable insights into the complex dynamics of SDG interactions. There is no unique pattern in the findings: different studies found different interactions between SDG elements, depending on the method, initial evaluation goal, target or indicator, and country or region in question. The analyses also showed an increased complexity when analysing interactions among indicators. Moreover, they highlight the need of a multidisciplinary or holistic approach to achieve

SDG goals, given the interlinked nature of the framework, and offer tools and frameworks for policymakers to consider when designing and implementing sustainable development strategies.

2.3 Review 2: empirical analyses about causal links specifically between outcome measures related to SDGs 1, 2, 3 or 15.

2.3.1 Methods of the second review

The second review answers to the lack of quantitative studies analysing SDGs interactions underscored in the previous section. Quantitative studies may reveal interactions that can be capture by qualitative research, this search aims to find quantitative studies analysing causal links specifically between SDG1 [Poverty], SDG2 [Food Security], SDG3 [Health] or SDG15 [Terrestrial Environments], which form the focus of the thesis.

The review was conducted between February and March 2019, on the Web of Science and Scopus databases. The resulting titles were combined and screened for duplicates using Mendeley. A first search was limited by time (studies published from 2015 to 2018) and by topic (title, abstract and keywords). Focusing on literature from 2015 onwards ensures that the review is relevant to the SDG agenda and better positioned to provide insights into the empirical evidence and causal pathways specifically related to achieving SDG 1, 2, 3, or 15. Additionally, consistent with the previous review, it only included peer-reviewed studies in English due to time constraints, language proficiency and number of reviewers (a single reviewer). A second search included the review of the Google Scholar profiles of key researchers working on poverty and environmental outcomes, followed by a snowball method on their citations. The objective of this review was to gather information about causal pathways, datasets, study designs and research methods used in their analyses.

We used a series of a string of English terms based on the wording of the goals, including the following: sustainable development goal, SDG, poverty, hunger, food, nutrition, agriculture, health, well-being, terrestrial ecosystems, forest, desertification, land, degradation, and biodiversity. We combined keywords this way to capture the literature related to outcomes reflecting indicators' interactions (Table 2.3).

Table 2.3 *Keywords and syntax used for literature about causal links between SDGs 1, 2, 3 and 15.*

Search	Key words
#1: SDG1 & SDG2	(sustainable development goal OR SDG) AND (poverty) AND (hunger OR food OR nutrition OR agriculture)
#2: SDG1 & SDG3	(sustainable development goal OR SDG) AND (poverty) AND (health OR well-being)
#3: SDG1 & SDG15	(sustainable development goal OR SDG) AND (poverty) AND (terrestrial ecosystems OR forest OR desertification OR land Or degradation OR biodiversity)
#4: SDG2 & SDG3	(sustainable development goal OR SDG) AND (hunger OR food OR nutrition OR agriculture) AND (health OR well-being)
#5: SDG2 & SDG15	(sustainable development goal OR SDG) AND (hunger OR food OR nutrition OR agriculture) AND (terrestrial ecosystems OR forest OR desertification OR land Or degradation OR biodiversity)
#6: SDG3 & SDG15	(sustainable development goal OR SDG) AND (health OR well-being) AND (terrestrial ecosystems OR forest OR desertification OR land Or degradation OR biodiversity)

After the first sift of papers, we realised that some recent literature was excluded from the review probably because they did not explicitly use the terms “sustainable development goal” or “SDG” in their text. Thus, we complemented the search by including key names of researchers focusing on poverty and environmental outcomes (i.e. Jennifer Alix-Garcia, Allen Blackman, Randall Bluffstone, Gustavo Canavire, Paul Ferraro, Merlin Hanauer, Pamela Jagger, Daniela Miteva, Cristoph Nolte, Johan A. Oldekop, Subhrendu Pattanayak, Alex Pfaff, Volker Radeloff, Taylor Ricketts, Erin Sills, and Katharine R. E. Sims). We used their Google Scholar profiles to search for articles related to the review aim. Those that satisfy the inclusion criteria below were included in the literature review.

Article screening and study eligibility criteria

The below protocol was used to screen hits that matched the search strategy. Publications included meet all of the inclusion criteria and none of the exclusion criteria:

A. Inclusion criteria:

I. The abstract mentions two or more SDG outcome measures that capture poverty (SDG1), hunger (SDG2), health (SDG3) and/or forest (SDG15).

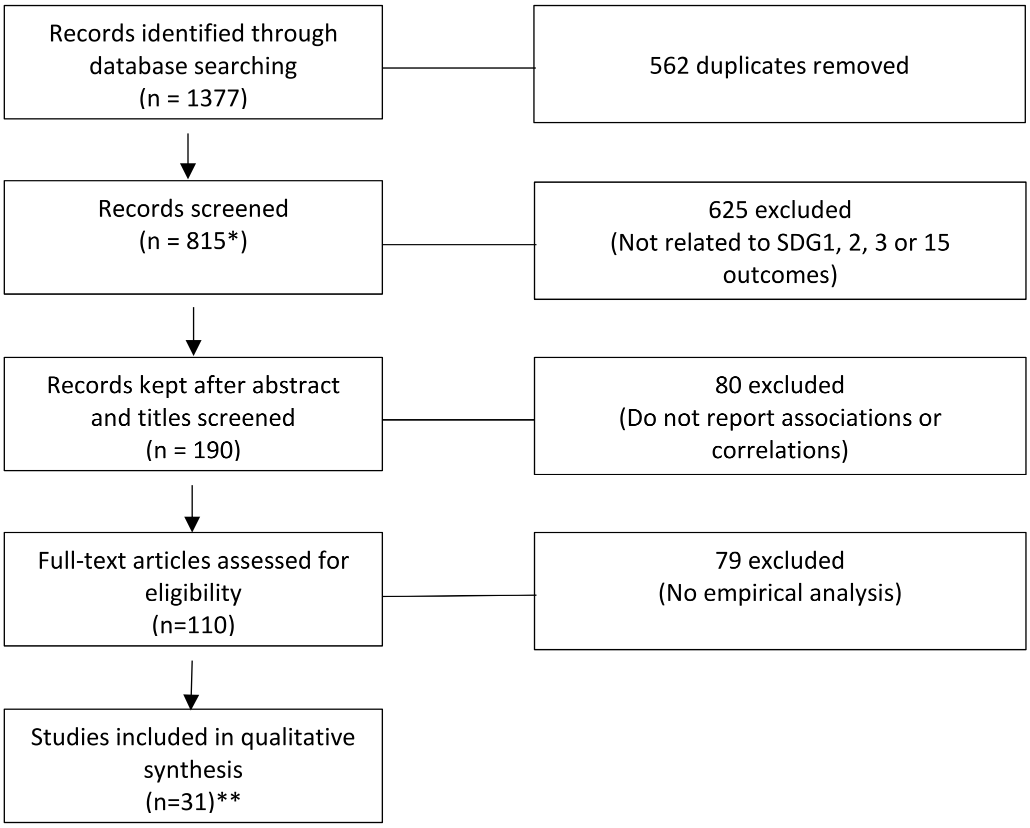
II. The text reports associations or correlations across two or more SDG outcome measures that capture poverty (SDG1), hunger (SDG2), health (SDG3) and/or forest (SDG15).

B. Exclusion criteria

I. The study does not refer to at least two SGD outcomes across at least two of SG1, SG3 or SG15.

II. The study conceptualises interactions without including empirical analyses.

The data extracted from the final set of identified publications were compiled in a database. The information used to categorise and describe the papers included: author(s), year of publication, title of study, publication type, aim of research, country of study, variables surveyed, methods, and key findings.After removing duplicates, the final search strategy produced 815 articles, 110 of which remained after the abstract filter stage (Figure 1.2). Following full-text examination of these 110 publications for empirical assessment of determinants or associations between goals’ indicators, 80 additional studies were excluded since they did not include an empirical approach. Thirty-three studies explored empirical evidence about the associations between indicators of interest and were thus included in the review.



*Includes 81 studies from Google Scholar profiles. **Includes 9 studies from cited references.

Figure 2.2 *PRISMA flow diagram showing the selection process of studies included in the review.*

Studies included in the review dated from 1997 to 2018, since we also included those cited by research papers and that met the inclusion criteria. Most of the included studies analysed interactions between two or more SDG1, SDG2, SDG3 and SDG15 indicators, while only four of them analysed interactions across three or more goals. The studies were classified depending on the empirical approach used for their analysis (study type) and whether they focus on statistical relationships or perform more advanced causal analyses (post-ante analysis). Table 2.5 presents a summary of included studies.

Table 2.5 *Overview of empirical studies analysing outcome measures for SDGs 1, 2, 3 and 15 ordered by first-author surname. See S1 in the Appendix for full list of SDG1, 2, 3 and 15 indicators.*

Authors	Study country	Study type	Regression model	Causal inference	SDG[1]				Indicators[2]
					1	2	3	15	
Akombi et al. (2017)	Nigeria	Observational (Cross-sectional)	Yes	No	X	X			[1.1.1], [1.2.1], [2.2.1]
Alix-Garcia, McIntosh & Sims (2013)	Mexico	Quasi-Experimental	Yes	Yes	X			X	[1.1.1], [1.2.1], [15.1.1]
Allen et al. (2017)	LLMICs[3]	Literature Review (Narrative)	No	No	X		X		[1.1.1], [1.2.1], [3.5.2], [3.a.1]
Andam et al. (2010)	Costa Rica & Thailand	Quasi-Experimental	Yes	Yes	X			X	[15.1.2], [1.1.1], [1.2.1], [1.2.2]
Andrewin, Rodriguez-Llanes & Guha-Sapir (2015)	CARICOM[4]	Observational (Ecological)	Yes	No	X	X			[2.4.1], [1.5.1]
Bauch et al. (2015)	Brazil	Observational (Panel Data)	Yes	No			X	X	[15.1.2], [15.4.1], [3.3.3], [3.4.1]
Beal et al. (2018)	Indonesia	Literature Review	No	No	X	X			[1.1.1], [1.2.1], [2.2.1]
Canavire-Bacarreza & Hanauer (2013)	Bolivia	Quasi-Experimental	Yes	Yes	X			X	[15.1.2], [15.4.1], [1.2.2]
Carter et al. (2018)	Global	Modelling	Yes	No	X		X		[1.1.1], [1.3.1], [3.3.2]
Cluver et al. (2016)	South Africa	Observational (Longitudinal)	Yes	No	X	X	X		[1.3.1], [2.1.2], [3.3.1], [3.3.2], [3.4.2], [3.5.2]
Cowman et al. (2017)	Kenya	Observational	Yes	No	X		X		[1.1.1], [1.2.1], [3.3.5]
Daoud, Halleröd & Guha-Sapir (2016)	67 LMICs	Observational	Yes	No	X				[1.5.1], [1.5.4], [1.1.1], [1.2.1]

Authors	Study country	Study type	Regression model	Causal inference	SDG[1]				Indicators[2]
					1	2	3	15	
den Braber, Evans & Oldekop (2018)	Nepal	Quasi-Experimental	Yes	Yes	X			X	[15.4.1], [1.1.1]
Ferraro, Hanauer & Sims (2011)	Costa Rica & Thailand	Quasi-Experimental	Yes	Yes	X			X	[1.1.1], [15.1.1]
Ferraro & Hanauer (2011)	Costa Rica	Quasi-Experimental	Yes	Yes	X			X	[15.1.2], [15.4.1], [1.2.1], [1.2.2]
Ferraro & Hanauer (2014)	Costa Rica	Quasi-Experimental	Yes	Yes	X			X	[1.1.1], [15.1.1]
Grocke & McKay (2018)	Nepal	Mixed-Methods	No	No		X			[2.1.2], [2.2.2]
Huda et al. (2018)	Bangladesh	Observational	No	No	X	X			[1.1.1], [1.2.1], [2.2.1]
Imai, Cheng & Gaiha (2017)	Developing countries	Observational (Panel Data)	Yes	No	X	X			[2.4.1], [1.1.1], [1.2.1], [1.2.2]
Keats et al. (2018)	Kenya	Observational	Yes	No	X	X	X		[3.7.1], [2.1.1], [2.2.2], [1.1.1], [1.2.1], [1.2.2], [1.4.1], [3.2.1]
Kerr et al. (2004)	Costa Rica	Observational	Yes	No	X			X	[1.1.1], [15.1.1], [15.4.2]
Mainali et al. (2018)	South Asia	Modelling	No	No	X	X			[1.2.1], [2.1.1], [2.3.1], [2.3.1], [2.1.1]
Maitra, (2017)	India	Observational (Survey)	No	No	X	X			[1.1.1], [1.2.1], [1.2.2], [1.4.2], [2.1.2]
Miteva, Loucks & Pattanayak (2015)	Indonesia	Quasi-Experimental	Yes	Yes	X	X	X	X	[2.4.1], [15.1.1], [15.4.2], [3.9.1], [1.2.1]
Nkonki, Tugendhaft & Hofman (2017)	HIC, LIC, MIC[5]	Literature Review (Systematic)	No	No		X	X		[3.8.1], [3.c.1], [3.3.3], [3.2.2], [3.2.1], [3.4.1], [2.2.2]

Authors	Study country	Study type	Regression model	Causal inference	SDG[1]				Indicators[2]
					1	2	3	15	
Pattanayak & Sills (2001)	Brazil	Observational	Yes	No	X			X	[15.2.1], [1.1.1]
Pattanayak et al. (2012)	Indonesia	Observational	Yes	No			X	X	[15.1.1], [3.3.3]
Shifa, Ahmed & Yalew (2018)	Ethiopia	Observational (Case-Control)	Yes	No			X		[3.7.1], [3.2.1]
Tripathy & Mishra (2017)	India	Observational (Survey)	Yes	No	X		X		[1.2.1], [3.1.1], [3.2.1], [3.2.2]
Ugwu & Zewotir (2018)	Nigeria	Observational	Yes	No	X		X		[1.1.1], [3.3.3]
Waldron et al. (2017)	Global	Commentary/Essay	No	No	X	X		X	[2.4.1], [2.3.1], [2.1.2], [1.1.1], [1.2.1], [15.1.1], [15.4.2]

[1] SDG= Sustainable Development Goals
[2] List of indicators can be found in S1
[3] LLMICs= Low- and lower-middle income countries
[4] CARICOM= Caribbean Community
[5] HIC= High-income countries, LIC= Low-income countries, MIC= Middle-income countries

2.3.2 Findings of the second review

In terms of SDG interrelationships, most research studies assessed links between poverty reduction (SDG1), food security (SDG2) and health (SDG3) (Table 2.5) generally within one country. Only few studies have researched interactions between multiple countries in one region (1), with similar income levels across regions (4), or at a global scale (1).

Poverty and socioeconomic factors (Primarily SDG 1)

Several papers studied the links between poverty, socioeconomic factors, and other outcomes relevant to SDGs 1, 2 and 3. Allen et al. (2017) highlighted the association between socioeconomic status and unhealthy behavioural risk factors for non-communicable diseases. Huda et al. (2018) found increasing inequities in child stunting in Bangladesh, with poverty being a major contributing factor. Maitra (2017) found a substantial prevalence of food insecurity in low-income slum households in Kolkata, India, suggesting income, education, and job opportunities as key intervention areas. Furthermore, Ugwu & Zewotir (2018) identified poverty as a significant socioeconomic factor increasing malaria transmission risk among young children in Nigeria.

Several studies explored the relationship between poverty and deforestation, with Kerr et al. (2004) noting a direct link in Costa Rica. Alix-Garcia et al. (2013) found that a poverty alleviation program inadvertently increased deforestation in Mexico. In contrast, a body of research (Andam et al., 2011; Canavire-Bacarreza & Hanauer, 2013; den Braber et al., 2018; Ferraro & Hanauer, 2014; Ferraro et al., 2011; Ferraro & Hanauer, 2011) indicated that protected areas could contribute to poverty reduction in various countries. Daoud et al. (2016) also found a positive correlation between natural disasters and increased child poverty in LMICs. Finally, Carter et al. (2018) and Cluver et al. (2016) demonstrated the potential of social protection interventions (a key aspect of SDG 1) to positively impact tuberculosis incidence and adolescent health outcomes, respectively.

Child health and nutrition (Primarily SDG 2 & 3)

Some authors studied child-stunting risk factors. Akombi et al. (2017) identified several risk factors for stunting and severe stunting in Nigerian children under five, including male sex, small birth size, poor household wealth, prolonged breastfeeding, regional residence, and recent diarrhoea. Beal et al. (2018) literature review in Indonesia corroborated factors like socioeconomic status, maternal health and education, child feeding practices, and community factors as key determinants of child stunting. Huda et al. (2018) also highlighted socioeconomic status, parental education, and maternal health-seeking behaviours as contributors to child undernutrition inequalities in Bangladesh.

Regarding child mortality, Keats et al. (2018) identified factors associated with a reduction in under-five mortality in Kenya, including increased maternal literacy, household wealth, and access to reproductive health services. Shifa et al. (2018) found that lack of Vitamin A supplementation and immunisation were strong predictors of under-five mortality in Southern Ethiopia, along other care-related factors. Tripathy & Mishra (2017) identified key causes and predictors of neonatal, post-neonatal, and maternal deaths in India, emphasizing the role of socioeconomic factors and healthcare access.

About the link between infectious diseases and the environment, Bauch et al. (2015) found a negative correlation between strict environmental protection in the Brazilian Amazon and the incidence of malaria, acute respiratory infections, and diarrhoea. Moreover, Pattanayak et al. (2010) also found a negative association between primary forest cover and child malaria in Indonesia. Cowman et al. (2017) identified environmental and demographic factors associated with cholera incidence in Kenya. Ugwu & Zewotir (2018) linked environmental factors like poor sanitation and inadequate housing to increased malaria risk in Nigeria.

Regarding malnutrition, Nkonki et al. (2017) systematic review highlighted the cost-effectiveness of community health worker interventions in improving various child health outcomes, including reducing mortality and malnutrition. Grocke & McKay (2018) found that while a new road in Nepal improved access to market foods, it did not necessarily improve micronutrient intake and contributed to a double burden of malnutrition.

Environment and Health/Livelihoods (Primarily SDG 15, some links to SDG 1 & 2)

Several studies explored the relationship between forest and human livelihoods. Bauch et al. (2015) indicated that protecting natural resources (reducing deforestation) in the Brazilian Amazon could lead to improved public health outcomes (reduced malaria, ARI, diarrhoea). Forest worked as a safety net, as evidenced by Pattanayak & Sills (2001), with increased collection of non-timber forest products during agricultural shortfalls. Moreover, Kramer et al. (1997) highlighted the economic benefits of forest protection by estimating the economic value of forests in Eastern Madagascar in mitigating flood damage.

Some studies focused on the role of protected areas in environmental protection. Miteva et al. (2015) found that FSC certification in Indonesia reduced deforestation and air pollution, among other environmental benefits. Ferraro et al. (2011) and Ferraro & Hanauer (2011) also found that protected areas contributed to lower deforestation rates in Costa Rica and Thailand. While other focused on the effect of agriculture on food security, poverty or natural disasters. Waldron et al. (2017) argued that agroforestry has the potential to enhance food security, improve soil fertility, and provide ecosystem services, aiding smallholder farmers. Imai et al. (2017) found that agricultural growth in developing countries is generally more effective in lowering poverty, although it can sometimes negatively impact inequality. Andrewin et al. (2015) found that increased agricultural land use was a predictor of flood- and storm-related fatalities in CARICOM countries.

Crosscutting Themes and SDG Interlinkages

Two studies analysed the relationship between social protection and SDG 1/ SDG 3. Carter et al. (2018) explicitly linked social protection (SDG 1) to reductions in tuberculosis incidence (SDG 3). Cluver et al. (2016) also examined the impact of social protection on adolescent health (SDG 3).

Only one study analysed the interconnections between multiple goals. Mainali et al. (2018) analysed the interconnections between SDGs 1, 2, 6, and 7 in developing countries, revealing strong synergies but also some variations across contexts.

Datasets and study design

Many studies used demographic and health surveys (DHS) or other large datasets to examine associations between variables. These are primarily observational studies, including cross-sectional (Akombi et al., 2017; Ugwu & Zewotir, 2018) and longitudinal designs (Cluver et al., 2016), ecological studies (Andrewin et al., 2015) examining population-level data, and case-control studies (Shifa, Ahmed & Yalew, 2018). Several studies utilised quasi-experimental designs to assess the impact of policies or interventions, particularly related to protected areas and poverty alleviation (Andam et al., 2011; Ferraro & Hanauer, 2014; Miteva, Loucks & Pattanayak, 2015; den Braber et al., 2018). These studies often employed matching techniques to create comparison groups. Three studies were reviews of existing literature, including systematic reviews (Nkonki, Tugendhaft & Hofman, 2017) and narrative reviews (Allen et al., 2017; Beal et al., 2018).

Research methods

In terms of research methods, several studies used regression models. They include multilevel regression (Akombi et al., 2017; Keats et al., 2018; Imai, Cheng & Gaiha, 2017), logistic regression (Akombi et al., 2017; Cluver et al., 2016; Shifa, Ahmed & Yalew, 2018), generalised linear mixed models (Ugwu & Zewotir, 2018), zero-inflated negative binomial regression (Cowman et al., 2017), and multivariate probit regression (Pattanayak et al., 2010). One study used a mixed methods approach combining qualitative and quantitative data collection methods (Grocke & McKay, 2018). The studies using a quasi-experimental approach applied different methods including regression discontinuity (Alix-Garcia, McIntosh & Sims, 2013), genetic matching (Canavire-Bacarreza & Hanauer, 2013; den Braber et al., 2018), Mahalonobis distance and nearest neighbour matching (Andam et al., 2011; Miteva, Loucks & Pattanayak, 2015), and Mahalanobis nearest-neighbour covariate matching (Ferraro & Hanauer, 2011, 2014; Ferraro, Hanauer & Sims, 2011).

2.3.3 Discussion of the second review

The second review was comprehensive, used two search engines to gather peer-reviewed studies only, and included a directed search of publications through Google Scholar profiles. However, it was limited to electronic databases available at the University of Sheffield, timeframe (2015 to 2018) and grey literature was not searched. The search mainly returned studies analysing associations across indicators but also captured some causal analyses, and included studies published between 1997 and 2018 due to citation search and studies from the key authors' list. It is important to notice that the initial search did not capture any causal studies; they were included thanks to the list of selected authors. Dr Johan Oldekop suggested the list, and the authors are researchers working on forest-poverty dynamics using a causal approach.

We expected that any relevant study, including elicitation of preferences or values across SDGs 1, 2, 3 or 15, would come up in the literature search. However, only one relevant paper was found. Barbier and Burgess (2017) estimated the willingness to pay for the reduction of poverty (SDG1) and calculated the expenditure necessary to compensate the trade-off with other SDG indicators. This analysis was preliminary, indicative and used this assessment to illustrate the welfare analysis of potential trade-offs; moreover, they did not involve the empirical elicitation of preferences. Therefore, the Barbier and Burgess (2017) study was not included in the review since it did not meet the inclusion criteria.

Overall, most studies found positive associations between the indicators across SDG1, 2, 3 and 15; with the exception of Alix-Garcia, McIntosh & Sims (2013) who demonstrated a negative association between poverty alleviation and forest cover. While many studies identified synergies and trade-offs between SDG elements, fewer stablished clear causal relationships. Some studies used a quasi-experimental design and matching techniques to approximate causal inference. These studies focused on the effect of environmental policies (i.e. protected areas, forest concessions) on poverty, and only one looked into the impact of poverty alleviation policies (cash transfer) on forest conservation.

Poverty, lack of education and poor sanitation are consistently associated with adverse health outcomes, including stunting, infectious diseases, and mortality. Social protection programmes can have a positive impact on various health related indicators. Environmental factors, such as access to clean water and sanitation, deforestation, and climate-related events, play a significant role in health outcomes. Protected areas can have both positive and potentially negative impacts on poverty depending on the context. The studies highlighted the complex interrelationships between various Sustainable Development Goals (SDGs), such as poverty reduction, health, and environmental sustainability. Moreover, significant geographic disparities in health and socioeconomic outcomes are evident, with rural and specific regions often facing greater challenges.

2.4 Overall conclusion from the two reviews

The interrelationships among Sustainable Development Goals (SDGs) 1 [Poverty], 2 [Food Security], 3 [Health] and 15 [Terrestrial Environments] are essential for reaching sustainable development. The body of literature reviewed, 40 studies, offered valuable insights into these complex linkages, though significant research gaps remain.

The first review provided an overlook of the interactions between different elements of the SDG framework, highlighting the need for a systems thinking approach to understand the complex web of interactions that varied by element, method, initial evaluation goal, and region. Most of the studies based their results in qualitative approach (expert's knowledge) and only two used a quantitative approach (Pradan et al., 2017; Mainali et al., 2018). However, conceptual framework studies (Nilsson et al., Zhang et al., Singh et al.) and network analysis (Weitz et al.) provided valuable tools to understand the complex, multi-directional interrelationships between the SDGs, even if they did not establish direct causality.

In the second review, a recurring theme was the strong association between poverty (SDG1) and health and nutritional outcomes (SDG 2 & 3). Studies like Akombi et al. (2017) and Huda et al. (2018) stressed the prevalence of stunting and undernutrition within low-income populations, illustrating the direct impact of economic status on child health. Likewise, Maitra (2017) reported the high occurrence of food insecurity in low-income households, confirming the association between poverty and hunger.

Furthermore, it highlights the role of environmental factors (SDG 15) on health and nutrition (SDGs 2 & 3). Studies such as Bauch et al. (2015) revealed a positive link between protected areas and reduced disease rates, suggesting that healthy ecosystems can contribute to human health. On the other hand, studies like Kerr et al. (2004) and Pattanayak et al. (2010) examined the effect of deforestation on malaria incidence, underlining the negative impact of environmental degradation on health. Kramer et al (1997) presented evidence of the economic impact of forests in flood prevention, which in turn protects agricultural productivity.

The studies examining the reciprocal relationship between poverty (SDG 1) and environmental degradation (SDG 15), found mixed evidence. Protected areas can contribute to poverty alleviation (Ferraro & Hanauer, 2011, 2014), work as safety nets (Pattanayak & Sills, 2001), and reduce child poverty cause by natural disasters (Kramer et al., 1997). However, agriculture and agroforestry can potentiate food security (Waldron et al., 2017), and reduce poverty (Imai et al., 2017). Moreover, Alix-Garcia, McIntosh & Sims (2013) found that poverty alleviation programmes increased deforestation.

In terms of datasets and study design, most of the studies used secondary data (National surveys) and are observational studies or use a quasi-experimental approach with matching. Among the matching methods used, the most common are genetic matching (Canavire-Bacarreza & Hanauer, 2013; den Braber et al., 2018), Mahalonobis distance and nearest neighbour (Andam et al., 2011; Miteva, Loucks & Pattanayak, 2015), and Mahalanobis nearest-neighbour covariate (Ferraro & Hanauer, 2011, 2014; Ferraro, Hanauer & Sims, 2011).

Despite these valuable insights, we identified several research gaps and limitations:

- **Context-Specific Variations**: The studies emphasised the context-dependent nature of SDG interrelationships, but further research is needed to understand the differences across various geographical regions and socioeconomic contexts.
- **Integrated Approaches**: While the conceptual framework studies emphasised the need for integrated approaches, more research is needed to develop and evaluate practical approaches for implementing integrated SDG interventions.
- **Feedback Loops and Dynamic Interactions**: The studies mainly focused on pairwise interactions, so further research is needed to explore the feedback loops and dynamic interactions between SDGs over time.
- **Quantitative Measurement of Interrelationships**: While correlation analysis provided quantitative insights, there is a need for more advanced methods to assess and model the intricate interactions among SDGs.
- **Limited Causal Inference**: Although numerous studies indicated associations, fewer were able to established clear causal links. Quasi-experimental designs were used in some studies to approximate causality, but additional research applying robust causal inference methods is needed.
- **Data availability**: Several studies mentioned the lack of data as a limitation.

In conclusion, the literature provides a foundation (as of September 2019) for understanding the interrelationships between SDGs 1, 2, 3, and 15. This chapter has shown that the evidence on synergies and trade-offs between SDGs is limited (but growing) and mixed. However, addressing the existing research gaps is crucial for developing effective strategies to achieve these goals and promote sustainable development.

This thesis will contribute to the evidence base by answering the following research questions: a) *what are the synergies and trade-offs between SDG 1, 2 and 15 in Peru, and b) how people value the relative importance of forest and poverty outcomes?*. Chapters 3 and 4 attempt to shed light on the overarching question of how these SDG goals are interrelated in the Peruvian Amazon; that is, the factual possibilities of achieving the SDGs. Chapter 5 focuses on understanding the relative value of forest and poverty outcomes for Peruvian citizens; assessing “what is socially acceptable” to accomplish within the SDG framework. Due to data availability, SDG3 was not included in the analyses.

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2.6 Supplementary Information

S1- *List of targets and indicators for SDG1, SDG2, SDG3, and SDG15 based on* UN (2024)

Goal 1. End poverty in all its forms everywhere	
Targets	**Indicators**
1.1 By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than \$1.90 a day	1.1.1 Proportion of population below the international poverty line, by sex, age, employment status and geographical location (urban/rural)
1.2 By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions	1.2.1 Proportion of population living below the national poverty line, by sex and age
	1.2.2 Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions
1.3 Implement nationally appropriate social protection systems and measures for all, including floors, and by 2030 achieve substantial coverage of the poor and the vulnerable	1.3.1 Proportion of population covered by social protection floors/systems, by sex, distinguishing children, unemployed persons, older persons, persons with disabilities, pregnant women, new-borns, work-injury victims and the poor and the vulnerable
1.4 By 2030, ensure that all men and women, in particular the poor and the vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property, inheritance, natural resources, appropriate new technology and financial services, including microfinance	1.4.1 Proportion of population living in households with access to basic services
	1.4.2 Proportion of total adult population with secure tenure rights to land, with legally recognized documentation and who perceive their rights to land as secure, by sex and by type of tenure
1.5 By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters	1.5.1 Number of deaths, missing persons and persons affected by disaster per 100,000 people
	1.5.2 Direct disaster economic loss in relation to global gross domestic product (GDP)a
	1.5.3 Number of countries with national and local disaster risk reduction strategies
	1.5.4 Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies

Goal 1. End poverty in all its forms everywhere	
Targets	**Indicators**
1.a Ensure significant mobilization of resources from a variety of sources, including through enhanced development cooperation, in order to provide adequate and predictable means for developing countries, in particular least developed countries, to implement programmes and policies to end poverty in all its dimensions	1.a.1 Proportion of resources allocated by the government directly to poverty reduction programmes
	1.a.2 Proportion of total government spending on essential services (education, health and social protection)
1.b Create sound policy frameworks at the national, regional and international levels, based on pro-poor and gender-sensitive development strategies, to support accelerated investment in poverty eradication actions	1.b.1 Proportion of government recurrent and capital spending to sectors that disproportionately benefit women, the poor and vulnerable groups

Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture	
Target	**Indicator**
2.1 By 2030, end hunger and ensure access by all people, in particular the poor and people in vulnerable situations, including infants, to safe, nutritious and sufficient food all year round	2.1.1 Prevalence of undernourishment
	2.1.2 Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale (FIES)
2.2 By 2030, end all forms of malnutrition, including achieving, by 2025, the internationally agreed targets on stunting and wasting in children under 5 years of age, and address the nutritional needs of adolescent girls, pregnant and lactating women and older persons	2.2.1 Prevalence of stunting (height for age <-2 standard deviation from the median of the World Health Organization (WHO) Child Growth Standards) among children under 5 years of age
	2.2.2 Prevalence of malnutrition (weight for height >+2 or <-2 standard deviation from the median of the WHO Child Growth Standards) among children under 5 years of age, by type (wasting and overweight)
2.3 By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and	2.3.1 Volume of production per labour unit by classes of farming/pastoral/forestry enterprise size
	2.3.2 Average income of small-scale food producers, by sex and indigenous status

Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture	
Target	**Indicator**
opportunities for value addition and non-farm employment	
2.4 By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality	2.4.1 Proportion of agricultural area under productive and sustainable agriculture
2.5 By 2020, maintain the genetic diversity of seeds, cultivated plants and farmed and domesticated animals and their related wild species, including through soundly managed and diversified seed and plant banks at the national, regional and international levels, and promote access to and fair and equitable sharing of benefits arising from the utilization of genetic resources and associated traditional knowledge, as internationally agreed	2.5.1 Number of plant and animal genetic resources for food and agriculture secured in either medium or long-term conservation facilities
	2.5.2 Proportion of local breeds classified as being at risk, not-at-risk or at unknown level of risk of extinction
2.a. Increase investment, including through enhanced international cooperation, in rural infrastructure, agricultural research and extension services, technology development and plant and livestock gene banks in order to enhance agricultural productive capacity in developing countries, in particular least developed countries	2.a.1 The agriculture orientation index for government expenditures
	2.a.2 Total official flows (official development assistance plus other official flows) to the agriculture sector
2.b Correct and prevent trade restrictions and distortions in world agricultural markets, including through the parallel elimination of all forms of agricultural export subsidies and all export measures with equivalent effect, in accordance with the mandate of the Doha Development Round	2.b.1 Producer Support Estimate
	2.b.2 Agricultural export subsidies

Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture	
Target	**Indicator**
2.c Adopt measures to ensure the proper functioning of food commodity markets and their derivatives and facilitate timely access to market information, including on food reserves, in order to help limit extreme food price volatility	2.c.1 Indicator of food price anomalies

Goal 3. Ensure healthy lives and promote well-being for all at all ages	
Target	**Indicator**
3.1 By 2030, reduce the global maternal mortality ratio to less than 70 per 100,000 live births	3.1.1 Maternal mortality ratio
	3.1.2 Proportion of births attended by skilled health personnel
3.2 By 2030, end preventable deaths of new-borns and children under 5 years of age, with all countries aiming to reduce neonatal mortality to at least as low as 12 per 1,000 live births and under-5 mortality to at least as low as 25 per 1,000 live births	3.2.1 Under-five mortality rate
	3.2.2 Neonatal mortality rate
3.3 By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases	3.3.1 Number of new HIV infections per 1,000 uninfected population, by sex, age and key populations
	3.3.2 Tuberculosis incidence per 100,000 population
	3.3.3 Malaria incidence per 1,000 population
	3.3.4 Hepatitis B incidence per 100,000 population
3.3 By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases	3.3.5 Number of people requiring interventions against neglected tropical diseases
3.4 By 2030, reduce by one third premature mortality from non-communicable diseases through prevention and treatment and promote mental health and well-being	3.4.1 Mortality rate attributed to cardiovascular disease, cancer, diabetes or chronic respiratory disease
	3.4.2 Suicide mortality rate

Goal 3. Ensure healthy lives and promote well-being for all at all ages	
Target	**Indicator**
3.5 Strengthen the prevention and treatment of substance abuse, including narcotic drug abuse and harmful use of alcohol	3.5.1 Coverage of treatment interventions (pharmacological, psychosocial and rehabilitation and aftercare services) for substance use disorders
	3.5.2 Harmful use of alcohol, defined according to the national context as alcohol per capita consumption (aged 15 years and older) within a calendar year in litres of pure alcohol
3.6 By 2020, halve the number of global deaths and injuries from road traffic accidents	3.6.1 Death rate due to road traffic injuries
3.7 By 2030, ensure universal access to sexual and reproductive health-care services, including for family planning, information and education, and the integration of reproductive health into national strategies and programmes	3.7.1 Proportion of women of reproductive age (aged 15-49 years) who have their need for family planning satisfied with modern methods
	3.7.2 Adolescent birth rate (aged 10-14 years; aged 15-19 years) per 1,000 women in that age group
3.8 Achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality and affordable essential medicines and vaccines for all	3.8.1 Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, new-born and child health, infectious diseases, non-communicable diseases and service capacity and access, among the general and the most disadvantaged population)
	3.8.2 Proportion of population with large household expenditures on health as a share of total household expenditure or income
3.9 By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination	3.9.1 Mortality rate attributed to household and ambient air pollution
	3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services)
	3.9.3 Mortality rate attributed to unintentional poisoning
3.a Strengthen the implementation of the World Health Organization Framework Convention on Tobacco Control in all countries, as appropriate	3.a.1 Age-standardized prevalence of current tobacco use among persons aged 15 years and older

Goal 3. Ensure healthy lives and promote well-being for all at all ages	
Target	**Indicator**
3.b Support the research and development of vaccines and medicines for the communicable and non-communicable diseases that primarily affect developing countries, provide access to affordable essential medicines and vaccines, in accordance with the Doha Declaration on the TRIPS Agreement and Public Health, which affirms the right of developing countries to use to the full the provisions in the Agreement on Trade-Related Aspects of Intellectual Property Rights regarding flexibilities to protect public health, and, in particular, provide access to medicines for all	3.b.1 Proportion of the population with access to affordable medicines and vaccines on a sustainable basis
	3.b.2 Total net official development assistance to medical research and basic health sectors
	3.b.3 Proportion of health facilities that have a core set of relevant essential medicines available and affordable on a sustainable basis
3.c Substantially increase health financing and the recruitment, development, training and retention of the health workforce in developing countries, especially in least developed countries and small island developing States	3.c.1 Health worker density and distribution
3.d Strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction and management of national and global health risks	3.d.1 International Health Regulations (IHR) capacity and health emergency preparedness

Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	
Target	**Indicator**
15.1 By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements	15.1.1 Forest area as a proportion of total land area
	15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type
15.2 By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally	15.2.1 Progress towards sustainable forest management

Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	
Target	**Indicator**
15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world	15.3.1 Proportion of land that is degraded over total land area
15.4 By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development	15.4.1 Coverage by protected areas of important sites for mountain biodiversity
	15.4.2 Mountain Green Cover Index
15.5 Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species	15.5.1 Red List Index
15.6 Promote fair and equitable sharing of the benefits arising from the utilization of genetic resources and promote appropriate access to such resources, as internationally agreed	15.6.1 Number of countries that have adopted legislative, administrative and policy frameworks to ensure fair and equitable sharing of benefits
15.7 Take urgent action to end poaching and trafficking of protected species of flora and fauna and address both demand and supply of illegal wildlife products	15.7.1 Proportion of traded wildlife that was poached or illicitly trafficked
15.8 By 2020, introduce measures to prevent the introduction and significantly reduce the impact of invasive alien species on land and water ecosystems and control or eradicate the priority species	15.8.1 Proportion of countries adopting relevant national legislation and adequately resourcing the prevention or control of invasive alien species
15.9 By 2020, integrate ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts	15.9.1 Progress towards national targets established in accordance with Aichi Biodiversity Target 2 of the Strategic Plan for Biodiversity 2011-2020
15.a Mobilize and significantly increase financial resources from all sources to conserve and sustainably use biodiversity and ecosystems	15.a.1 Official development assistance and public expenditure on conservation and sustainable use of biodiversity and ecosystems
15.b Mobilize significant resources from all sources and at all levels to finance sustainable forest management and provide adequate incentives to developing countries to advance such management, including for conservation and reforestation	15.b.1 Official development assistance and public expenditure on conservation and sustainable use of biodiversity and ecosystems

Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	
Target	**Indicator**
15.c Enhance global support for efforts to combat poaching and trafficking of protected species, including by increasing the capacity of local communities to pursue sustainable livelihood opportunities	15.c.1 Proportion of traded wildlife that was poached or illicitly trafficked

S2- Summary of papers included in the second literature review, by first-author surname.

Akombi et al. (2017) studied the factors associated with stunting and severe stunting among children under five in Nigeria, using data from the 2013 Nigeria Demographic and Health Survey. They used the number of standard deviations from height-for-age z-score (HFAz) to define stunting (HFAz<-2SD) and severe stunting (HFAz<-3SD). Their result showed a prevalence of stunting and severe stunting of 29% and 16.4%, respectively, for children between 0-23 months, and 36.7% and 21%, respectively, for children aged 0-59 months. The most consistent significant risk factors were male sex, small birth size, poor household wealth, breastfeeding period greater than 12 months, residence in the country's North East, North West, or North Central zone, and diarrhoea in the 2 weeks before the survey.

Alix-Garcia, McIntosh & Sims (2013) utilised the introduction of Mexico's Oportunidades program to assess the effects of poverty alleviation on deforestation. They capitalised on a community-level eligibility rule and random variation during the pilot phase to identify the causal relationship between increased income and deforestation. Findings suggested that the program led to an uptick in deforestation within treated areas, indicating that poverty alleviation initiatives could inadvertently harm the environment.

Allen et al. (2017) reviewed existing research on the relationship between socioeconomic status and non-communicable diseases in low-income and lower-middle-income countries. They found that individuals from lower socioeconomic backgrounds were more likely to use tobacco and alcohol, consume fewer fruits, vegetables, fish, and fibre, and eat more meat compared to their higher socioeconomic counterparts. On the contrary, those with higher socioeconomic status exhibited higher levels of physical inactivity and a greater intake of fats, salt, and processed foods. The authors concluded that the prevalence of behavioural risk factors is influenced by socioeconomic status in these countries, urging governments to address the link between poverty and health to reduce premature mortality from non-communicable diseases.

Andam et al. (2011) analysed the impact of protected areas on poverty in Costa Rica and Thailand. Using a quasi-experimental design, they compared poverty levels in communities adjacent to protected areas with those in similarly situated communities lacking such proximity. They discovered that communities near protected areas experienced lower poverty rates, highlighting protected areas' potential role in poverty reduction.

Andrewin et al. (2015) analysed risk factors for deaths related to floods and storms in the Caribbean Community (CARICOM) countries from 1980 to 2012. Using an ecological study design, they developed a regression model through multivariate analysis with a generalised logistic regression framework.

They identified that the strongest predictors for flood- and storm-related fatalities included an increase in the proportion of land used for agriculture, a rise in urban population rates, and the timeframe of 2000-2012.

Bauch et al. (2015) examined the effects of conservation policies on health outcomes in the Brazilian Amazon. They utilised a municipal-level panel dataset encompassing public health, conservation policies, and various land-use change factors to assess the impact of conservation initiatives on disease rates, applying random effects and quantile regression models. Their results indicated a significant negative correlation between malaria, acute respiratory infections (ARI), and diarrhoea incidence in areas under strict environmental protection. However, the relationships between other protected areas, roads, and mining types demonstrated more complexity and varied depending on the disease. The authors concluded that protecting natural resources could lead to additional benefits, including improved public health.

Beal et al. (2018) conducted a literature review on the causes of child stunting in Indonesia, employing the World Health Organization's conceptual framework on child stunting. They identified 29 relevant studies and found that the primary factors influencing child stunting included maternal aspects (like maternal height and education), household and family conditions (such as socioeconomic status and access to clean water and sanitation), as well as child feeding practices (including breastfeeding and complementary feeding). Additionally, community and societal elements, such as healthcare access and living in rural areas, were found to be related to child stunting.

Canavire-Bacarreza & Hanauer (2013) examined the effects of protected areas in Bolivia on poverty levels, finding a significant inverse relationship between protected areas and poverty, indicating that such areas could effectively reduce poverty in Bolivia. Their research utilised spatial data from 327 municipalities in Bolivia and included analyses of datasets from the 1992 and 2001 censuses, the World Database on Protected Areas, NASA, and Conservation International, focusing on municipal-level poverty measures through an asset-based index and basic needs index. They employed genetic matching to compare the treatment and control groups, followed by ordinary least squares (OLS) regression for association analysis and sensitivity tests using the Rosenbaum bounds method.

Carter et al. (2018) explored the connection between social protection, poverty, and the incidence of tuberculosis. They developed a conceptual framework that links key indicators of progress on Sustainable Development Goal (SDG) 1 to tuberculosis incidence through various risk factors. Using an exponential decay model, they estimated that achieving SDG 1 could reduce global tuberculosis cases by 33.4% by 2035, with expanding social protection coverage potentially leading to a 76.1% decrease in incidence by the same year. The authors concluded that fully achieving SDG 1 could significantly impact the global burden of tuberculosis.

Cluver et al. (2016) investigated the effects of social protection, either cash support or psychosocial assistance, on adolescent health outcomes in South Africa. They conducted a longitudinal survey involving 3,515 adolescents aged 10 to 18 between 2009 and 2012. Through a gender-disaggregated analysis that included multivariate logistic regression and assessed interactions between social protection and various socio-demographic factors, they found that social protection was associated with significant improvements in health-related outcomes for adolescents.

Cowman et al. (2017) explored the relationship between environmental and demographic factors and the incidence of cholera cases at the district level in Kenya from 2008 to 2013. They employed a zero-inflated negative binomial regression model to address the data's characteristics and revealed crucial associations between these factors and cholera outbreaks.

Daoud, Halleröd, and Guha-Sapir (2016) investigate the link between exposure to natural disasters and poor governance with absolute child poverty across sixty-seven middle- and low-income countries. Their findings suggest that an increase in disaster victims correlates with elevated child poverty rates. Moreover, they identify that improved governance is associated with reduced child poverty but does not alter the relationship between child poverty and natural disasters. The authors recommend that development agencies consider these findings and create more equitable global policies aimed at protecting vulnerable populations particularly children.

den Braber et al. (2018) investigated the impact of 32 protected areas in Nepal on poverty, extreme poverty, and inequality. They used a quasi-experimental framework combining national census-derived poverty estimates from 2001 and 2011 with statistical matching to create a control group and mitigate potential confounding variables due to non-random treatment allocation. Their findings indicated that areas surrounding protected areas showed lower rates of overall and extreme poverty, with inequality remaining stable. Moreover, tourism emerged as a significant factor in reducing poverty, although protected areas also contributed to alleviating extreme poverty in regions with minimal tourism.

Ferraro and Hanauer (2011) revisited the impact of protected areas in Costa Rica on poverty and deforestation reduction. Using census data from 1973 and 2000, they compared poverty rates in communities near protected areas with those in comparable communities not near any protected area. Using matched sampling techniques and analysing deforestation data, they found that protected areas reduced poverty in both countries and contributed to significant decreases in deforestation rates.

Ferraro, Hanauer, and Sims (2011) explored the effects of protected areas on poverty and deforestation in Costa Rica and Thailand. Through the analysis of census data from 1973 and 2000 in Costa Rica and 2000 in Thailand, their quasi-experimental design compared poverty rates in communities neighbouring protected areas to those in similar areas without such proximity. They utilised matched sampling techniques to analyse the impact on both poverty and deforestation rates, concluding that protected areas reduced poverty in both nations while also contributing to lower deforestation rates.

Ferraro & Hanauer (2014) investigated the effects of protected areas on poverty alleviation in Costa Rica, analysing the mechanisms through which they contributed to poverty reduction. They utilised census data from 1973 and 2000 along with various external sources to assess the impact at the census tract level through a quasi-experimental design. Their findings indicated that communities near protected areas experienced decreased poverty, predominantly driven by tourism-related opportunities.

Grocke and McKay (2018) explore the impact of the first road built in the mountainous Humla District of Nepal on food security and nutrition in two villages. They employed a mixed-methods approach, incorporating participant observation, interviews, the Household Food Insecurity Access Scale, and a food frequency questionnaire tailored to the region. Their research reveals that while the new road enhances access to market-sourced food, villagers still consume micronutrients below recommended levels since most available market foods are nutrient-poor. Additionally, they found that the community experiences a double burden of malnutrition, with instances of both underweight and overweight individuals.

Huda et al. (2018) analyse the social determinants contributing to inequalities in child undernutrition in Bangladesh. The authors created a concentration curve and concentration index using data from the 2004 and 2014 Bangladesh Demographic and Health Surveys. Their results highlight substantial inequities in stunting prevalence, with higher rates concentrated among impoverished populations. They also observed that inequalities in stunting increased from 2004 to 2014, with key contributors including household economic status, parental education, maternal health-seeking behaviours, sanitation, fertility, and maternal height.

Imai, Cheng, and Gaiha (2017) assessed the role of agriculture in mitigating inequality and poverty using cross-country panel data from developing nations. Their multilevel analysis compares agricultural growth with non-agricultural growth regarding poverty alleviation and inequality reduction. They discovered that agricultural growth is generally more effective in lowering poverty, although it sometimes has a negative impact on inequality. The authors argue that their findings support the need to revitalise the agricultural sector in discussions post-2015.

Keats et al. (2018) applied a multilevel logistic regression model to identify factors linked to the reduction of under-five mortality in Kenya from 1990 to 2015. Analysing data from the Kenya Demographic and Health Surveys, the Ministry of Health, and other resources, they found a 50% drop in under-five mortality from 1993 to 2014. This decline was associated with several determinants, including greater maternal literacy, increased household wealth, and improved access to sexual and reproductive health services. However, children residing in Nairobi faced a higher mortality risk compared to those in other areas of Kenya.

Kerr et al. (2004) investigated the connections between poverty and deforestation in Costa Rica, using various data sources such as satellite imagery, census data, and household surveys. Although the document did not describe a specific analytical method, the authors found a clear link between poverty and heightened deforestation rates, highlighting that this relationship is intricate and influenced by factors like the type and location of poverty and the level of economic development. They noted that marginalised individuals in poverty typically have limited access to productive land, which can exacerbate deforestation.

Kramer et al. (1997) assessed the economic value of forests in mitigating flood damage in Eastern Madagascar. Using a three-stage methodology, they linked economic values (specifically, avoided flood damage) to forests' ecological functions in flood prevention. Firstly, they analysed the relationships between deforestation and flooding through remotely sensed data to estimate historical deforestation rates. They modelled flood dynamics using data from two experimental watersheds. Secondly, interviews with local farmers addressed flooding’s impact on agricultural production. Lastly, a productivity analysis approach modelled the economic repercussions of flooding on agricultural output. The authors estimated that establishing Mantadia National Park resulted in a $126,700 decrease in flood damage, concluding that protecting tropical rainforests yields substantial economic benefits.

Mainali et al. (2018) were included in the previous literature review. They devised an analytical framework to analyse sectoral connections and assess potential synergies and trade-offs among energy access (SDG 7), clean water and sanitation access (SDG 6), food security and sustainable agriculture (SDG 2), and poverty alleviation (SDG 1) in developing countries. Their study, utilising examples from South Asia and Sub-Saharan Africa and employing network analysis and Advanced Sustainability Analysis (ASA), revealed strong synergies among various SDG targets, with some variations across countries and periods.

Maitra (2017) utilised survey data from 500 households in the slums of Kolkata, India, to assess the prevalence of food insecurity in low-income families. Food insecurity was evaluated using an experiential scale adapted from the United States Household Food Security Survey Module. The study concluded that 15.4% of the participants faced food insecurity and indicated that intervention programs focusing on income, education, and job opportunities are likely to address food insecurity effectively.

Miteva, Loucks, & Pattanayak (2015) evaluated the social and environmental outcomes of the Forest Stewardship Council (FSC) program in East Kalimantan, Indonesia. Using a quasi-experimental setup, they compared changes in deforestation rates, fire occurrence, air quality, and other relevant metrics in 67 certified villages against 33 similar villages without certification, as a control. The results indicated that FSC certification accounted for a five-percentage point reduction in deforestation, a 31% reduction in air pollution, a 33% decrease in firewood reliance, a 32% drop in respiratory infection cases, and a reduction of malnutrition by one individual per village. They also observed an increase in the area of perforated forest by approximately four km^2.

Nkonki, Tugendhaft, and Hofman (2017) performed a systematic review of existing literature to analyse the cost-effectiveness of community health worker (CHW) interventions aimed at improving child health outcomes. Their search through four public health and economic evaluation databases identified 19 qualifying studies across high-income, middle-income, and low-income nations, covering a diverse range of interventions. The authors categorised the studies based on their objectives. They found substantial evidence supporting the cost-effectiveness of CHW interventions in reducing malaria and asthma, decreasing neonatal and child mortality, enhancing maternal health, promoting exclusive breastfeeding, combating malnutrition, and positively influencing children's overall health and developmental progress.

Pattanayak & Sills (2001) explored tropical forests' role as a safety net for households in the Brazilian Amazon, hypothesising that households tend to gather non-timber forest products (NTFPs) during years of poor agricultural output. They employed an event-count model to estimate the relationship between NTFP collection and agricultural production while controlling for several factors. The results indicated a higher likelihood of NTFP collection in years of poor agricultural performance, especially among households lacking alternative coping mechanisms, concluding that forests play a crucial role in helping households manage consumption-related risks.

Pattanayak et al. (2010) investigated the correlation between forest conditions and child malaria in Flores, Indonesia. They applied a multivariate probit regression model to analyse the relationship between child malaria occurrences and the amount of primary and secondary forest cover while controlling for various individual, family, and community factors. Their findings indicated a negative association between primary forest extent and child malaria incidence, while a positive correlation was found with secondary forest cover. The authors concluded that conserving forests might effectively reduce child malaria cases.

Shifa, Ahmed, and Yalew (2018) investigated the factors related to under-five mortality in Southern Ethiopia using a case-control study design, matching 381 cases of under-five deaths with 762 controls (living under-five children). They employed conditional logistic regression to analyse the relationship between under-five mortality and various risk factors, including socioeconomic and environmental aspects, personal health management, child feeding, newborn care practices, and maternal and child characteristics. The absence of Vitamin A supplementation and immunisation emerged as the strongest predictors of under-five mortality. Additional factors that increased the likelihood of under-five mortality included insufficient post-natal care, not breastfeeding, bathing the newborn within 24 hours, short birth intervals, having a deceased sibling, multiple births, and having a live birth after the index child.

Tripathy and Mishra (2017) explored the causes and predictors of neonatal, post-neonatal, and maternal deaths in India. Utilising data from the District-Level Household Survey-4, conducted nationwide in 2012-2013, the authors revealed that the main causes of neonatal deaths include birth injuries, low birth weight, and prematurity, while acute respiratory infections and diarrhoea primarily cause post-neonatal deaths. For maternal deaths, the leading causes were excessive bleeding and pregnancy-induced hypertension. The study also noted several socioeconomic and household factors contributing to an elevated risk of mortality, such as poverty, lack of education, and rural residence. The authors emphasised the need for improved healthcare access, particularly for women and children in rural areas, along with calls for further research on maternal and child mortality predictors.

Ugwu & Zewotir (2018) analysed the socioeconomic, demographic, and geographic factors that influence malaria transmission in Nigeria using a generalised linear mixed model. Their study utilised data from the 2015 Nigeria Malaria Indicator Survey, targeting children aged 6 to 59 months. They observed increased malaria risk linked to age, anaemia, and living in rural areas. Additional significant risk factors included low maternal education, poverty, larger household sizes, poor sanitation, the age of the household head, lack of electricity, and inadequate roofing materials. Furthermore, children from the Northern and South-West regions showed higher malaria prevalence. The authors concluded that initiatives to reduce malaria should prioritise socioeconomic development and improving living standards, especially in Nigeria's Northern and South-West regions.

Waldron et al. (2017) examined the potential of agroforestry in enhancing food security, particularly in developing nations. Agroforestry involves the integrated cultivation of trees and crops. The authors claimed that this agricultural approach could boost crop yields, enhance soil fertility, and deliver various ecosystem services. Furthermore, they argued that agroforestry could assist smallholder farmers in adapting to climate change and other shocks. They concluded that agroforestry presents a viable strategy for achieving food security and fulfilling other sustainable development objectives in developing regions.

3 Forest and poverty: Hidden contributions of forest cover and forest configuration to multidimensional poverty

Abstract

For the past two decades, the role of forests in poverty alleviation has been central to global discussions on sustainable development, biodiversity conservation, and climate change mitigation. Although much research has explored the impact of forest-related policies on monetary poverty, ecosystem services, agricultural productivity, and food security, the specific effect of forests and forest configuration on poverty remains largely unknown. This study investigates the complex relationship between forest metrics (forest cover percentage, number of forest patches, and mean patch area) and multidimensional poverty in the Peruvian Amazon. Using a quasi-experimental design, we analyse spatially referenced cross-sectional data from 3564 households across five waves of Peru's Demographic and Health Survey (2014-2019), combined with high-resolution satellite-based forest cover data (2000-2019). We construct a modified multidimensional poverty index (MPI) encompassing health, education, and standard of living dimensions, and employ covariate balancing generalised propensity score weights and multiple regression to isolate the impact of forest metrics on poverty, controlling for a range of socioeconomic and biophysical confounders. Our findings reveal a nuanced picture of forest-poverty dynamics. Although higher forest cover initially appears associated with increased overall MPI, disaggregating the MPI reveals crucial trade-offs. Greater forest cover correlates with improved child nutrition but reduced educational attainment. Conversely, a higher number of forest patches, indicative of fragmentation, shows opposite effects. Furthermore, the interaction between forest cover and mean patch area suggests that the positive effects of forest cover on nutrition are amplified in less fragmented landscapes. Our results highlight the importance of considering forest configuration, not just cover, in understanding forest contributions to poverty alleviation and underscore the limitations of relying solely on aggregate poverty measures. These findings have implications for forest-based sustainability interventions and suggest that intermediate stages of deforestation may offer opportunities for integrated conservation and poverty reduction strategies.

3.1 Introduction

Forests are central to international sustainability agendas and fundamental to rural livelihoods. In low and middle-income countries, forests contribute to the well-being of rural households by providing income through the sale of forest products that can account for up to half of household revenue streams (Miller, Mansourian & Wildburger, 2020). Forests contribute to the provision of forest foods and other ecosystem services as well, which can have positive nutritional effects and act as safety nets in times of need (IPBES, 2019; Mooney et al., 2005). The relationship between forests and livelihoods is largely determined by the configuration of rural landscapes (a combination of forest fragments and agricultural lands) and how these change over time. This configuration can affect agricultural production systems and market dynamics (Oldekop et al., 2013) as well as access to forests and the availability of forest products, including foods and materials used for commercial and subsistence purposes.

Most research on forests and livelihoods has examined the contribution of forests to rural livelihoods using local case studies at single points in time. These studies have shed light on the types of livelihood contributions that forests can make (Angelsen et al., 2014). However, large N-longitudinal analyses of forest-poverty dynamics are rare, and our understanding of the role of forests in alleviating poverty continues to be limited (Jagger et al., 2022). Gaining a better understanding of forest-poverty dynamics has the potential to influence forest-based sustainability interventions and is essential given the increased political attention and financial support for forest conservation and restoration, as well as nature-based solutions to climate change.

We address this gap by assessing how forest metrics (forest cover percentage, number of forest patches per km^2, mean of patch area) are associated with a modified multidimensional poverty index (MPI) and its individual dimensions (health, education, standard of living) in the Peruvian Amazon. The underlying theory of change is that forests play a key role in supporting rural livelihoods by providing income, food, and other ecosystem services. These benefits are however, influenced by a range of household, socioeconomic, and environmental factors. To measure the effect of forest metrics accurately, our analysis controls for multiple confounding factors, including social programs (due to their direct influence on health, education and living standards), agricultural activities, remoteness, as well as geographical and climatic conditions. We do so by combining spatially referenced cross-sectional data for 3564 households from five waves of Peru's Demographic and Health Survey (Encuesta Demográfica y de Salud Familiar- ENDES, 2014-2019) and high-resolution satellite-based forest cover data (2000-2019). To address the challenges of isolating causal effects in observation studies, we employ a quasi-experimental design using propensity score weights to approximate causal effects within a cross-sectional framework. Specifically, we use Covariate Balancing Generalised Propensity Score (CBGPS) weights to minimise correlations between potentially confounding factors and forest metrics, allowing us to estimate the average treatment effect of forest metrics on multidimensional poverty at specific time points. While the non-randomized nature of our design precludes definitive causal attribution, the robustness of our causal inferences is supported by several design features and sensitivity analyses. Our identification strategy is based on the plausibly exogenous conditional variation of forest cover metrics that arises after controlling for factors that have influenced land use and development patterns in the region (see Methods). We test the robustness of our results by considering various historical deforestation patterns preceding the year of our assessment (1, 5, and 10 years) and by controlling for spatial independence of our sampling units. This study focuses on forest cover percentage, number of forest patches, and mean of patch area because they are metrics used to describe forest fragmentation in ecological studies (Gergel & Turner, 2001). We conduct our analysis at the level of individual ENDES survey sampling clusters that collate information for a group of households (see Methods). Each cluster's centroid is georeferenced, which allowed us to link socioeconomic data with forest cover and other geospatial data (e.g., remoteness, slope, elevation, rainfall, temperature) per year. Forest metrics are calculated for a 10km buffer surrounding each centroid, using the "Landscapemetrics" R package (Hesselbarth et al., 2019a) (Figure 3.1).

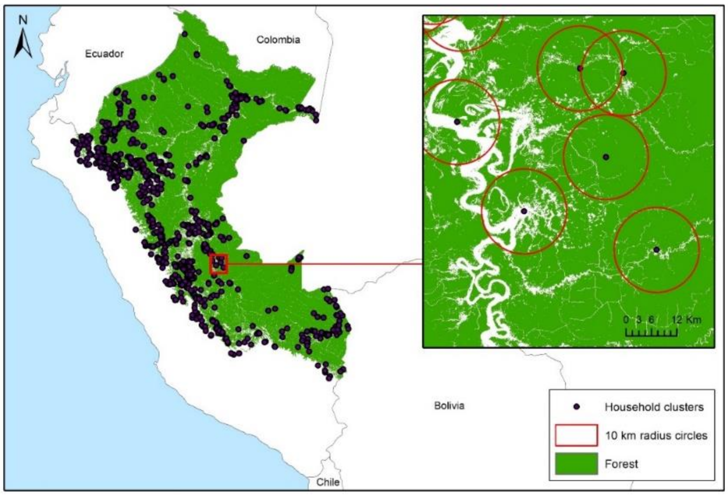

Figure 3.1. *Map showing forest cover in 2015 and cluster centroids for ENDES 2015. In zoomed section: centroid + buffer + forest within a buffer of 10 km.*

Our choice of Peru is justified in several ways. The country had 78.7 Mha of natural forest (61% of its territory) in 2010 but has seen a substantial deforestation rate (2.47 Mha loss between 2002 and 2022) in the last 20 years (Global Forest Watch, 2021). The country has also seen a strong economic development in the last few years (The World Bank Group, 2021) and approximately 6 million people (18% of the total population) live within 5 km of a forest (Newton et al., 2020). Peru, along with Brazil, Colombia, Venezuela, Ecuador, and Bolivia, is part of the Amazon basin. Therefore, the lessons from Peru may provide helpful insights for other forests rich countries. Critically, relevant government agencies have made the necessary data publicly available for integration across sources and spatial scales.

3.2 Methods

Our analysis uses Peru as a case study and compiles socioeconomic, biophysical, and bioclimatic data for the period between 2014 and 2019 from publicly available national and global datasets. Socioeconomic data are collected from the Demographic and Health Survey (Encuesta Demográfica y de Salud Familiar – ENDES), which is run annually to compile information on maternal and child health, fertility, and mortality from women between 12-49 years of age and children under 5 years of age. Geographic information such as forest cover, deforestation and elevation were extracted from the forest cover change monitoring platform of the Ministry of Environment, and road and river features from the Ministry of Transport and Telecommunications. Bioclimatic variables were extracted from historical monthly weather data from WorldClim from 1960-2018 (CRU-TS 4.03; Harris et al., 2014) downscaled with WorldClim 2.1 (Fick & Hijmans, 2017).

The analysis used a quasi-experimental design that includes key biophysical and socioeconomic variables to control for potential factors affecting our outcomes of interest and to generate propensity score weights. The selection of covariates was guided by the study's theory of change, which posits that poverty is influenced by a combination of factors including household characteristics, agricultural activities, remoteness, geographical conditions, climatic conditions and social programs. We also included a series of robustness tests to verify that our results are not biased due to spatial autocorrelation. All analyses were performed with ArcGIS 10.7.1 and R version 4.0.2.

A. Unit of analysis

This study compiled repeated cross-sectional data at the cluster level from 2014-2019. A cluster (“*conglomerado*”, in Spanish) is the main sampling unit for the DHS survey, and the number of clusters per region is proportional to the number of households in the area. In rural areas, the clusters correspond to a larger catchment area called rural registration area (“*area de empadronamiento rural”*). Each cluster groups around 10 and 15 households per region, in urban and rural areas, respectively. These households are representative of the underlying regional population in terms of the number of children under 5 years of age and women of childbearing age, according to census data. Nationally, there were more than 3000 clusters per wave (3,175 clusters in waves 2015-2017 and 3254 in 2018-2019). The Peruvian Demographic and Health Survey (DHS) georeferenced clusters only, displacing households to local population centres, keeping the locations of individual households hidden.

We confined our analysis to rural clusters in the Amazon basin, given that, in urban areas, the forest-poverty dynamics are likely very different from rural areas. The combined data set includes a total of 1066 rural clusters and 3786 households, across 2014 to 2019

B. Outcome: Multidimensional Poverty Measure (MPI)

Socioeconomic information from each household is used to construct a modified MPI, which is spatially linked with geographical, biophysical, and bioclimatic data. We used data from the DHS 2014 to 2019 to build a MPI for each cluster. The MPI measures the "the percentage of people [headcount ratio] who are multidimensional poor adjusted by the average share of deprivations among the poor [intensity]" (Alkire & Jahan, 2018a) using 10 indicators: nutrition, child mortality, years of schooling, housing and asset ownership; categorised in three dimensions: health, education, and living standards. We modified the MPI by excluding child mortality in the health dimension [due to data availability], and adding boat ownership as an asset in the living standards dimension [since it is the main mean of transport in the area]. Additionally, our nutrition indicator combined information on underweight and stunted children under 5 years of age, measuring food insecurity in rural clusters. All indicators are generated using the DHS guidelines (Croft et al., 2018) (see Table S1)

C. Spatial Data and Forest metrics calculation

We used 30 m resolution Landsat-derived forest loss data produced by Geobosques, the Peruvian Government's Forest Cover Change Monitoring Platform. This dataset uses a combination of Landsat and Rapid Eye images to validate its classification (Potapov et al., 2014) and is restricted to the humid tropical forest of Peru. Geobosques defines forest as an area with trees above 5m and a tree canopy of more than 30% within each pixel, including natural forest, secondary regrowth and tree plantations. Forest cover loss is defined as the complete or nearly complete removal of tree cover within pixels. The Geobosques dataset contains a baseline forest cover for the year 2000 and forest loss data from 2001 to 2019. We calculated forest cover per year by subtracting accumulated forest loss values from the 2000 forest cover map. Our measure focused on forest and natural vegetation cover loss for the humid tropical forest biome of Peru.

The DHS survey unit is a cluster or group of households, which is a georeferenced unit and randomly displaced by a maximum of 5 km in rural areas. We calculated forest metrics and forest loss per year in a 10-km circular radius surrounding the centroid coordinates of each cluster using Landscapemetrics

R package (Hesselbarth et al., 2019a). It is important to notice that these cluster areas rarely overlap across the years.

To delineate individual forest patches and calculate landscape metrics, we used the lsm_l_ta, lsm_l_np, and lsm_l_area_mn functions from the landscapemetrics R package. We extracted the following forest metrics at landscape level:

- Percentage of forest cover. This metric was calculated using the lsm_l_ta function, which calculates the total area (TA) of all forest patches within the 10km buffer surrounding each cluster centroid. It represents the percentage of the area within the 10km buffer classified as forest. The percentage of forest was calculated by: [FP = Forest cover/cluster area *100]. Unit: percentage.

- Number of forest patches per km^2. The lsm_l_np function calculates the number of patches (NP) at the landscape level. A forest patch was defined as one or more contiguous pixels meeting the Geobosques forest definition (trees >5m and canopy cover >30%). Given that the Geobosques dataset has a spatial resolution of 30m, each pixel represents a 30m x 30m area. Contiguity between pixels was defined using 8-way connectivity (queen's case), meaning that pixels were considered part of the same patch if they touched each other by an edge or a corner. Therefore, patch delineation was based on the connectivity of pixels, not on distance-based isolation. NP describes the fragmentation of a cluster, higher number= higher fragmentation[1]. Unit: patches/km^2.

- Mean of patch area. This metric was calculated using the lsm_l_area_mn function, which calculates the mean area of all forest patches within the 10km buffer surrounding each cluster. It represents the average area of individual forest patches within the buffer2. MN = zero if all patches are small. Unit: square-kilometres (km^2).

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[1] The number of patches reflects the fragmentation of a cluster by quantifying the number of discrete forest units. A higher number indicates that the forest is divided into more patches. While the number of patches describes the fragmentation of the landscape, it does not directly measure patch isolation. Landscapes with a high number of patches can exhibit both high and low degrees of fragmentation depending on the spatial configuration of the patches.

[2] Mean patch area describes the composition of a cluster landscape and, in conjunction with the number of patches, provides information on patch structure (e.g., many small patches vs. few large patches). Mean patch

D. Covariates

We included several household and geographical characteristics (or their proxy) that could influence poverty and forest data, to the extent possible, with available data. These variables were used to calculate the covariate balance generalised propensity scores and were also used as control variables in our regression models. All covariates were aggregated at the cluster level and included the following:

i. *Household characteristics.* The size of the household and the sex, age, and education of each head of the household can significantly influence the level of poverty, and livelihoods strategies, including interactions with forest, as they are some of the drivers of poverty (INEI, 2011; Urbina Padilla & Quispe, 2016). We used the mean, mode or proportion to aggregate values at the cluster level, i.e., mean household size, the mean age of head of household, the proportion of households with a male head of household, and the mode of the highest educational level of the head of household given that is a categorical variable.

ii. *Agricultural activities*. The ownership of titled land and land dedicated to agriculture and/or livestock, as these activities can affect both household income and forest cover (e.g. through deforestation for agricultural expansion). To control for these, we used the value of the proportion of households that own land for agriculture or livestock within each cluster, as well as the proportion of households that own more than 5ha of agricultural land, since larger areas are frequently related to cash crop cultivation (GRADE, 2015) and linked to greater amounts of deforestation.

iii. *Social programmes*. These programmes are specifically designed to improve outcomes in MPI dimensions. Juntos a conditional cash transfer, require children to attend school and receive health check-ups, directly affecting education and health dimensions. Vaso de Leche, Comedores populares and Wawa wasi are food assistance programmes directly addressing nutrition (a health dimension) and food security (which influences living standards). To control for these we included the proportion of households enrolled in those programmes for each cluster.

iv. *Remoteness*. We used distance from roads, rivers, and cities as proxy for remoteness and market access, which can influence both access to forest resources and economic

area approaches zero if all patches are small and increases without limit as patch areas increase. Forest cover and mean patch area are used in combination to characterise fragmentation.

opportunities. For each measure, the Euclidean distance from the centre of the cluster (centroid) to the closest feature is expressed in meters.

v. *Slope and elevation*. We calculated the average slope (in degrees) and average elevation (in meters) at the centroid of each cluster using the global digital elevation model, on the basis that both can affect agricultural productivity, natural vegetation cover, and accessibility.

vi. *Rainfall and temperature*. We controlled for mean annual temperature and precipitation, as they can influence agricultural yields, forest dynamics, and food security. For these, we calculated the average values of these variables per cluster surface area.

vii. *Year dummy*. We used year dummies for 2015, 2016, 2017, 2018, and 2019 to control for time-related effects, such as macroeconomic changes or policy interventions, that may affect poverty levels. Year 2014 was our baseline.

viii. *Latitude and longitude*. We used latitude and longitude in meters to control for spatial autocorrelation ensuring results are not biased by spatial patterns in data.

E. Analysis

The models tested the association between forest cover and forest configuration with the modified MPI, while controlling for household and geographical factors, we employed a quasi-experimental approach using the Covariate Balancing Generalised Propensity Score (CBGPS) method (Fong, Hazlett & Imai, 2018). This method is an extension of the Covariate Balancing Propensity Score (CBPS) method (Imai & Ratkovic, 2014a) that improves the misspecification of the model in observational studies and can be applied to a continuous treatment variable such as forest cover.

The CBGPS method (Fong, Hazlett & Imai, 2018) offers two approaches: a) a parametric calculation that models the treatment (i.e. the percentage of forest cover) based on the pre-treatment covariates, and b) a nonparametric calculation that uses an empirical likelihood approach to select weights that represent inverse generalised propensity scores. In both approaches, the resulting propensity scores are used to create inverse probability weights to reduce the correlation between the treatment and the covariates. We selected the CBGPS approach based on the in-sample F-statistic, which serves as diagnostics for assessing covariate balance. A lower F-statistic indicates better balance between the treatment variable and the covariates after applying the weights; we selected the approach with the lowest value. This selection process resulted in a single set of CBGPS-derived weights for each analysis and ensured that the chosen weights optimally mitigate bias in the estimation of treatment effects.

We estimated a separate regression model for each outcome variable (MPI and its dimensions), using the CBGPS-derived weights. This process minimizes the influence of confounding variables, allowing us to estimate the average treatment effect of forest metrics on multidimensional poverty, conditional on the covariates included in the model. While our analysis is cross-sectional, the use of CBGPS weights allows us to approximate causal inference by balancing pre-treatment covariates, as if forest cover had been randomly assigned. To select the best-fitting model for each outcome, we used the Akaike Information Criterion (AIC). The AIC provides a measure of model fit that balances goodness of fit with model complexity. We compared models with different combinations of terms (accumulated deforestation, year interaction and forest metric interactions) and chose the model with the lowest AIC value as the final model for that outcome. This model selection process ensured that we selected the model that best explained the variation in the outcome variable, given the propensity score weighting applied to control for confounding. Within this chosen model, we then used p-values to assess the statistical significance of individual predictor variables. This two-step approach allowed us to first identify the best overall model structure and then interpret the significance of individual effects within that model.

Robustness checks

We conducted several robustness tests to assess whether our results still hold when including or excluding accumulated deforestation values in the previous 1, 5, and 10 years. The series of models analyses the effect of one forest metric (treatment) at a time and interactions between forest metrics while including/excluding accumulated deforestation values in the previous 1, 5, and 10 years. We also checked that our results were not influenced by spatial autocorrelation by comparing residuals from models including/excluding latitude and longitude values, using spatial plots (Schleicher et al., 2020).

3.3 Results

Our study evaluated the associations between forests metrics (percentage of forest cover (FP), number of patches per km^2 (NP), and mean of patch area (MN)) and a modified MPI and its dimensions, considering different levels of accumulated deforestation (1, 5 and 10 years), socioeconomic and biophysical covariates as well as year dummies. Models used one forest metric as treatment variable and Covariate Balancing Generalised Propensity Score (CGBGPS) weights to balance covariates. We ran 72 models to evaluate the robustness of our analysis, and used the Akaike Information Criterion (AIC) to assess goodness of fit. Models including 5-year accumulated deforestation were the best fitting models.

We ran additional models to test the interaction between the treatment variable and year dummy (Figure 3.2). We found that the estimated treatment effect of these forest metrics is consistent over time for both outcomes: MPI and its three dimensions. We also evaluated the interaction effect of FP and NP or MN on MPI and its dimensions (health, education, and standard of living) (Figure 3.3 and Figure 3.4). The associations between forests metrics vary with the outcome, as explained bellow.

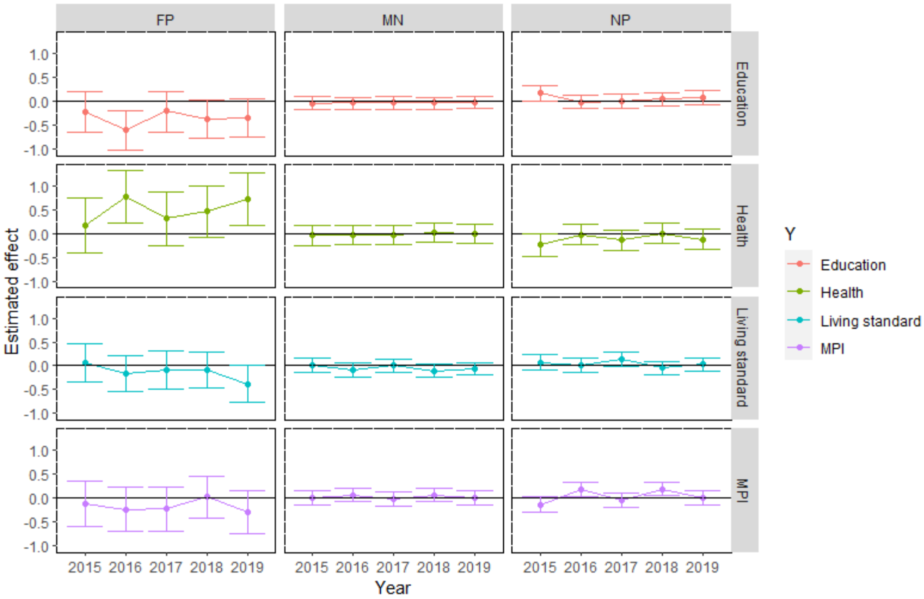

Figure 3.2. *Effect of the interaction between treatment and year from 2015 to 2019. Estimated coefficients and 95% confidence intervals, per treatment and MPI dimension.*

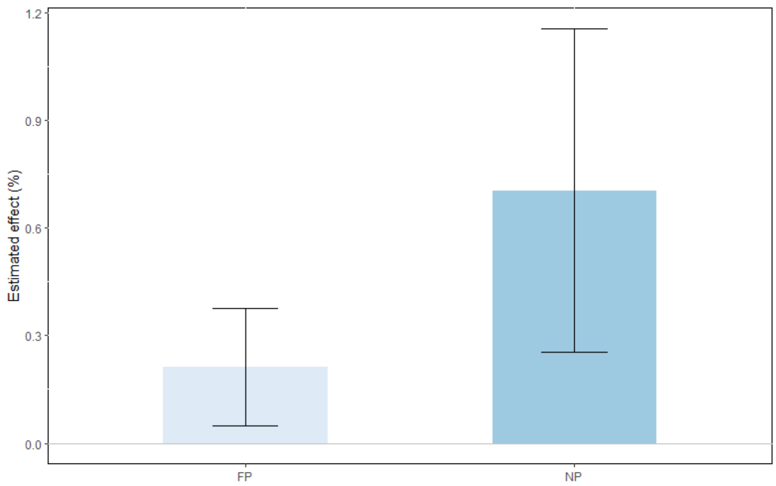

Figure 3.3. *Bar graph showing the effect of forest cover on overall MPI, estimated coefficients and 95% confidence intervals.*

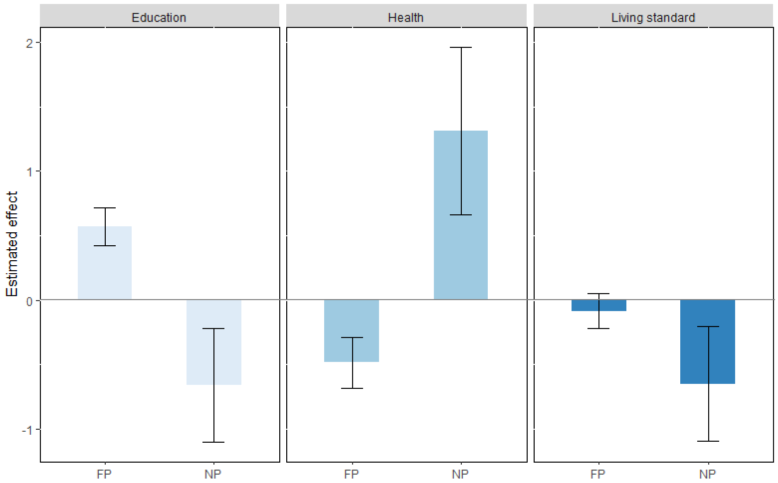

Figure 3.4. *Bar graph showing the effect of forest cover and number of patches in MPI dimensions, estimated coefficients and 95% confidence intervals.*

Effect of forest metrics on MPI

When analysing the individual associations between FP, NP and MN and MPI, adjusted for confounding variables using propensity score weighting, we found that greater values of these variables are generally associated with a higher levels of deprivation (for full model specifications, see Table S4.1).

At the cluster level, the average treatment effect suggest that for each additional percentage increase in forest cover within a radius of 10 km, the average MPI is associated with a 0.2% increase [SE = 0.001, P = 0.011]. Given that forest cover is a percentage of the area within the 10km buffer, this suggests that higher forest cover is associated with higher multidimensional poverty.

Similarly, the average MPI is associated with a 0.7% increase [SE = 0.002, P=0.002] for each additional forest patch per km^2 within the radius. Considering that this metric reflects the number of forest patches per unit area, this result indicates that greater number of patches is associated with higher multidimensional poverty.

The average MPI within clusters also increased by 0.53% [SE =0.000, P= 0.019] for each additional square-kilometre of mean patch area. Given that the mean patch area describes the average size of forest patches, this suggests that larger average patch sizes are associated with higher multidimensional poverty. For context, the mean patch area in our study area ranged from 0 to 38.395 square-kilometres.

For models evaluating the interaction between FP and NP (Table S4.2), we found that the interaction was non-significant [-0.002%, SE = 0.000, P=0.914] but the average MPI within clusters increased by 0.8% [SE = 0.002, P=0.000] for each additional percentage in forest cover. These suggest that the effect of forest cover on MPI does not depend on the number of patches. When analysing the interaction between FP and MN, the interaction was significant [0.65%, SE = 0.000, P=0.000] and the average MPI within cluster increased by 0.4% [SE = 0.001, P=0.000] for each additional percentage of forest cover. This indicates that the effect of forest cover on MPI is slightly boosted in clusters with fewer large patches of forest.

Effect of forest metrics on health dimension

We found that only FP and NP were statistically significantly associated with child malnutrition (health dimension) (Table S4.3). At the cluster level, the percentage of households with child malnutrition decreased by 0.48% [SE = 0.100, P=0.000] for each additional percentage increase in forest cover within the radius of 10 km, suggesting that higher forest cover is associated with lower child malnutrition. In contrast, child malnutrition increased 1.31% [SE = 0.331, P=0.000] for each additional forest patch per km^2, indicating that greater number of patches is associated with higher child malnutrition.

However, when evaluating the interaction between forest metrics, we found that the interaction between FP and MN was significant [-0.663%, SE = 0.138, P=0.000] and that the percentage of people deprived in the health dimension (child nutrition) decreased by 0.674% [SE = 0.112, P=0.000] for each additional percentage increase in forest cover. This suggest that the effect of forest cover percentage on child nutrition depends on the mean patch area. Specifically, forest cover effects are higher in less fragmented clusters (fewer numbers of patches), which together with the results in the previous paragraph suggest a trade-off between number of patches and mean patch area.

Effect of forest metrics on education dimension

We found that FP and NP were significantly associated with deprivation in educational attainment (education dimension) (Table S4.4), while MN was not significantly associated. At the cluster level, the percentage of households with educational deprivation increased by 0.57% [SE = 0.075, P=0.000] for each additional percentage increase in forest cover, indicating that higher forest cover is associated with higher educational deprivation. In contrast, educational deprivation decreased by 0.66% [SE = 0.223, P=0.003] for each additional forest patch per km^2, suggesting that greater number of forest patches and lower forest cover had higher school attainment.

When analysing the interaction between forest metrics, FP and MN association was significant [0.331%, SE = 0.108, P=0.002] and the effect of forest cover on educational deprivation was 0.657% [SE= 0.088, P=0.000]. This suggest that higher forest cover and fewer larger patches are associated with lower school attainment.

Effect of forest metrics on standard of living dimension

We found that the NP was statistically significantly associated with deprivation of living standards while FP and MN were not significantly associated (Table S4.5). At the cluster level, the average deprivation of living standards decreased by 0.65% [SE = 0.227, P=0.005] for each additional forest patch per km^2 within the radius of 10 km. This indicates that areas with higher number of forest patches tend to have better living conditions. In addition, while the interaction between FP and MN was significant [0.332%, SE = 0.089, P=0.000] the effect of the treatment [FP] on the standard of living dimension was non-significant.

3.4 Discussion

Our results highlight the complexity of forest-poverty dynamics in rural areas and that forest contributions to alleviating poverty can hide behind aggregate poverty measures. These findings add evidence to crucial debates in the literature. The magnitude and direction of the observed relationships align with the previous literature on the contribution of forest configuration to diet diversity (Rasmussen et al., 2020a; Hall et al., 2022; Rasmussen et al., 2023) and reveal nuanced associations between forest metrics and multidimensional poverty. It is important to acknowledge that our study estimates associations, adjusted for confounding variables using propensity score weighting, rather than demonstrating direct causal relationships. Our results are specific to the case of Peru, and similar studies would need to be conducted in other contexts. However, our findings indicate the potential importance of considering forest configuration in poverty alleviation strategies, while also acknowledging potential trade-offs.

First, when analysing the estimated effect of forest metrics on overall MPI, a measure of progress towards development and poverty alleviation, we found that the three of them (forest cover, number of patches per km^2, and mean of patch area) are associated with exacerbated poverty. The interaction between forest cover and mean of patch area also were associated with an increased MPI. However, when we decompose the MPI on its dimensions we can see some trade-offs between forest metrics and different aspects of deprivation. Child malnutrition was lower in higher forest cover landscapes and higher in landscapes with larger number of patches. However, when analysing the association between forest fragmentation (forest cover and mean patch area interaction) and child malnutrition, it was observed that malnutrition decreased in landscapes with higher forest cover and few large patches. Educational deprivation, that is children not going to school, was lower in landscapes with a larger number of patches, while larger in landscapes with higher forest cover and few large patches.

Overall, the results suggests that people living in areas with less forest cover will benefit school attendance and living standards compared to those living in areas with higher forest cover. This is consistent with the argument that households with access to infrastructure and located in areas with less forest cover have higher wealth scores. However, households in areas with higher forest density have a better nutritional level, a possible explanation is that these households have better access to wild food resources, and therefore forest access, reducing child stunting (Rasolofoson et al., 2018).

Forest loss also play a role in the forest-poverty dynamic. In our analysis, a larger number of patches represented a higher forest loss in a given area. The number of patches showed a positive association with overall MPI and the health deprivation, while presenting a negative association with poor living standards. This suggests that areas with higher forest loss will have better living standards, but lower nutritional levels and wealth scores. A possible explanation is that households in these areas used forest resources to increase their living standards in detriment of their food security. These results add to other studies (Hall et al., 2022; Johnson, Jacob & Brown, 2013) who found that forest cover loss reduced the consumption of fruits and vegetables.

However, when analysing the effect of forest fragmentation, that is the interaction between forest cover and mean of patch area, we observed that there is an opposite effect between fragmentation and forest loss. While forest loss decreases nutritional levels, they increase in landscapes with fewer large patches. This is supported by several studies, which suggest that access to wild foods from forest edges, access to markets or agriculture and cultivated species increasing diet diversity (Hickey et al., 2016; Powell et al., 2015; Rasmussen et al., 2020a). Yet forest cover could be more important than access to markets or increased income for diet diversity (Friant et al., 2019; Jendresen & Rasmussen, 2022; Rasmussen, Wood & Rhemtulla, 2020). These results suggest that on a mixed landscape comprising agricultural areas and forested areas, access to forest areas helps to reduce malnutrition and food insecurity in deprived rural households. Thus, forest configuration appears to be an important factor on poverty alleviation, and intermediate stages of deforestation may present an opportunity for forest conservation and poverty alleviation efforts.

It is important to recognize certain limitations in our analysis. Although we measured fragmentation using the number of forest patches, we understand that this metric does not fully capture forest fragmentation. The number of patches indicates how much forest cover is divided into smaller units, but it does not directly assess the isolation of those patches. Landscapes with a large number of patches can show different levels of fragmentation depending on how those patches are arranged spatially. For instance, a landscape with numerous patches that are close together might show lower fragmentation effects compared to a landscape with the same number of patches that are widely dispersed. To address this, we also considered the mean patch area, which offers further insights into the size and configuration of forest patches. Nevertheless, future studies could provide additional insights by integrating additional landscape metrics that specifically evaluate patch isolation and connectivity to achieve a more thorough understanding of how fragmentation influences poverty metrics.

Another limitation is that our models include variables that could be related: educational level of household head and education variables from the MPI dimension, as covariate and outcome respectively. However, it is important to highlight that they capture distinct aspects of education. The household head's education level is used as a control variable to account for the influence of the household's overall socioeconomic background on poverty outcomes. It represents the educational attainment of the primary decision-maker in the household. In contrast, the MPI education component measures educational deprivation at the household level, specifically focusing on 'no school attendance' (whether any household member has completed six years of schooling) and 'child education' (whether any school-age child is not attending school). Thus, while the household head's education level can influence these household-level measures, they are not identical. After running a Variance Inflation Factor (VIF) analysis, multicollinearity is not severely impacting the results. Future research could explore this relationship further. For instance, alternative regression techniques or more detailed sensitivity analyses could be employed to assess how different specifications of the education variables influence the findings. Additionally, gathering more granular data on education within the household could provide a more nuanced understanding of these relationships.

Previous studies focus on the contribution of forests to wealth scores or income generation, and while the MPI is a more comprehensive way of thinking about poverty when compared to monetary poverty, this study shows that it has its disadvantages. Our findings reveal synergies and trade-offs of the effect of forest configuration on MPI dimensions, thus limiting the analysis to the overall index actually miss the real contributions of forests to other important aspects of well-being. These findings raise intriguing questions about the nature and extent of forests in poverty alleviation and may encourage new avenues of thought to understand the dynamics of forest and poverty.

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3.6 Supplementary Information

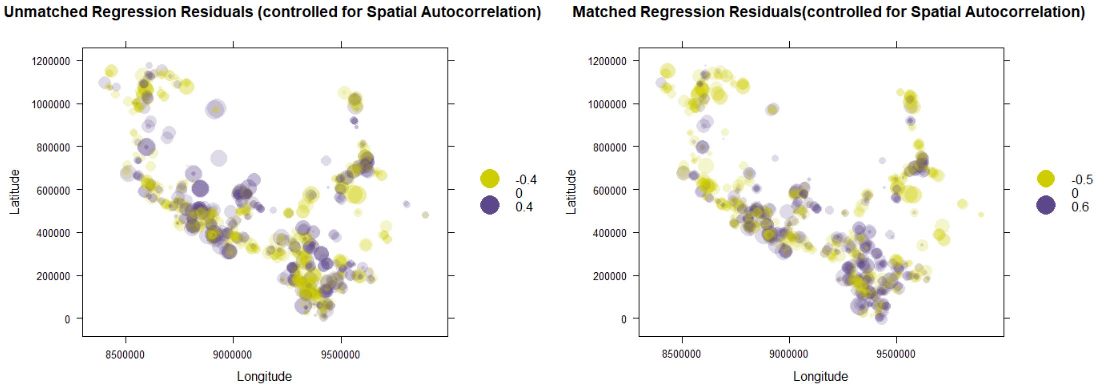

Figure S1 *Spatial autocorrelation of residuals before and after matching for ATE of forest percentage on MPI.*

Table S1 *Multidimensional Poverty Index. Dimensions. indicators, and weights of the modified measure.*

Dimension	Indicators		Weight
Health	**Child nutrition** *(At least one child in the household is undernourished)*		0.33
Education	**No school attendance** *(No household member has completed six years of schooling)*		0.166
	Child education *(At least one school-age child in the household not attending school)*		0.166
Living standards	**No electricity** *(Household without access to electricity)*		0.055
	Inadequate sanitation *(Household without public system or septic tank)*		0.055
	Unsafe water *(Household without piped water)*		0.055
	Inadequate building materials *(Household whose household floor, walls or roof is made of natural or rudimentary materials)*		0.055
	Cooking fuel *(Household that cooks with dung, wood, charcoal, or coal)*		0.055
	No assets *(Household who does not own)*	Car/truck/boat, radio, television, telephone, computer, animal cart, bicycle, motorbike, or refrigerator.	0.055

Table S2. *Descriptive statistics of numeric variables included in the final model. Minimum, maximum, mean and standard deviation at cluster level. Year dummies are not included in the table.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.050	0.822	0.322	0.175
Health related poverty (%)	0.000	100.000	47.278	21.793
Education related poverty (%)	0.000	54.240	8.958	13.685
Living standard related poverty (%)	0.000	100.000	43.764	16.274
Forest cover (%)	0.000	98.464	49.581	27.857
Number of patches per km^2	0.000	13.098	3.139	2.443
Mean patch size (km^2)	0.000	38.395	0.571	2.141
Forest loss in previous 5 years (ha)	0.000	5590.170	814.144	864.532
Forest cover 2000 (ha)	0.090	31172.400	17593.047	9136.426
Number of households	2.000	9.000	3.552	1.389
Prop. of households with a male head of household (HH)	0.000	1.000	0.904	0.178
Mean household size	2.500	10.000	5.413	1.275
Mean age of HH	20.500	61.000	37.719	7.146
HH education level (mode)	0.000	3.000	1.382	0.571
Prop. of households that owns agricultural land	0.000	1.000	0.673	0.329
Prop. of households that owns >5 ha of agricultural land	0.000	1.000	0.051	0.160
Prop. of households that owns livestock	0.000	1.000	0.810	0.253
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.352	0.342
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.616	0.334
Prop. of households enrolled in "Comedor popular" social programme	0.000	1.000	0.021	0.099
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.067	0.187
Average Elevation (m)	79.507	4126.430	981.007	1031.228
Average Slope (degree)	0.720	32.128	10.433	9.058
Mean annual temperature (ºC)	6.708	27.135	22.637	4.781
Mean annual precipitation (mm)2	527.944	5391.492	1859.783	816.396
Distance to river or road (km)	0.000	7.425	0.522	1.040
Distance to closest city (km)	0.000	128.749	15.080	16.779
Longitude (m)	-2987.235	1177560.696	471068.626	277421.811
Latitude (m)	8404223.563	9892534.293	9133387.874	342107.480

Table S3a. *Descriptive statistics of numeric variables in the final model - year **2014**, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.073	0.734	0.347	0.171
Health related poverty (%)	0.000	85.707	47.971	20.750
Education related poverty (%)	0.000	49.985	6.878	11.128
Living standard related poverty (%)	14.293	100.000	45.151	15.734
Forest cover 2000 (ha)	0.090	30733.020	16713.969	9167.263
Forest loss in previous 5 years (ha)	0.000	5229.900	867.741	984.336
Forest cover (%)	0.000	97.601	47.573	27.996
Number of patches per km^2	0.000	9.524	3.154	2.310
Mean patch size (km^2)	0.000	5.283	0.396	0.777
Number of households	2.000	9.000	3.964	1.663
Prop. of households with a male head of household (HH)	0.500	1.000	0.916	0.137
Mean household size	2.667	8.000	5.278	1.178
Mean age of HH	20.500	51.667	37.976	6.938
HH education level (mode)	1.000	3.000	1.434	0.567
Prop. of households that owns agricultural land	0.000	1.000	0.730	0.288
Prop. of households that owns >5 ha of agricultural land	0.000	1.000	0.082	0.217
Prop. of households that owns livestock	0.286	1.000	0.841	0.209
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.273	0.340
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.639	0.315
Prop. of households enrolled in "Comedor popular" social programme	0.000	0.500	0.027	0.097
Prop. of households enrolled in "Wawa-wasi" social programme	0.000	0.800	0.029	0.124
Average Elevation (m)	95.059	3657.016	975.305	969.457
Average Slope (degree)	0.964	31.090	10.652	9.437
Mean annual temperature (ºC)	9.969	26.861	22.527	4.617
Mean annual precipitation (mm)2	685.836	4671.336	1825.059	863.811
Distance to river or road (km)	0.006	4.594	0.557	0.786
Distance to closest city (km)	0.050	128.749	14.605	16.908
Longitude (m)	8456359.449	9710824.609	9106219.390	337742.104
Latitude (m)	12006.495	1153167.674	466928.477	281828.641
Total number of households		329		
Total number of clusters		83		

Table S3b. *Descriptive statistics of numeric variables in the final model - year **2015**, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.054	0.822	0.316	0.167
Health related poverty (%)	0.000	85.707	46.964	21.833
Education related poverty (%)	0.000	49.985	9.578	13.392
Living standard related poverty (%)	14.293	100.000	43.458	14.612
Forest cover 2000 (ha)	29.880	31172.400	17203.617	8892.088
Forest loss in previous 5 years (ha)	0.090	5590.170	934.456	1051.001
Forest cover (%)	0.091	98.424	48.322	26.277
Number of patches per km^2	0.025	10.421	3.080	2.221
Mean patch size (km^2)	0.000	38.395	0.932	4.285
Number of households	2.000	8.000	3.596	1.431
Prop. of households with a male head of household (HH)	0.000	1.000	0.924	0.173
Mean household size	3.000	9.800	5.382	1.180
Mean age of HH	22.500	61.000	36.677	7.318
HH education level (mode)	0.000	3.000	1.397	0.541
Prop. of households that owns agricultural land	0.000	1.000	0.706	0.328
Prop. of households that owns >5 ha of agricultural land	0.000	1.000	0.068	0.182
Prop. of households that owns livestock	0.000	1.000	0.856	0.230
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.365	0.324
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.624	0.342
Prop. of households enrolled in "Comedor popular" social programme	0.000	0.667	0.018	0.088
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.050	0.177
Average Elevation (m)	81.646	4126.430	1041.110	997.937
Average Slope (degree)	0.883	31.423	11.500	9.109
Mean annual temperature (ºC)	6.708	27.117	22.348	4.646
Mean annual precipitation (mm)2	527.944	5075.037	1817.121	862.270
Distance to river or road (km)	0.000	7.425	0.911	1.369
Distance to closest city (km)	0.000	92.424	14.184	13.633
Longitude (m)	8404223.563	9694918.362	9125974.897	338835.183
Latitude (m)	-2987.235	1145106.523	442117.945	289827.282
Total number of households		*561*		
Total number of clusters		*156*		

Table S3c. *Descriptive statistics of numeric variables in the final model - year **2016**, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.056	0.745	0.320	0.173
Health related poverty (%)	0.000	85.707	48.358	20.785
Education related poverty (%)	0.000	54.240	6.803	12.308
Living standard related poverty (%)	14.293	100.000	44.838	16.708
Forest cover 2000 (ha)	6.570	31065.840	17005.392	9625.800
Forest loss in previous 5 years (ha)	0.000	4115.610	693.616	752.074
Forest cover (%)	0.021	98.464	49.037	29.013
Number of patches per km^2	0.006	10.794	2.725	2.228
Mean patch size (km^2)	0.006	30.912	0.754	2.728
Number of households	2.000	8.000	3.357	1.218
Prop. of households with a male head of household (HH)	0.333	1.000	0.921	0.165
Mean household size	3.500	10.000	5.545	1.286
Mean age of HH	24.000	55.333	38.457	6.879
HH education level (mode)	0.000	3.000	1.317	0.537
Prop. of households that owns agricultural land	0.000	1.000	0.679	0.328
Prop. of households that owns >5 ha of agricultural land	0.000	0.667	0.047	0.134
Prop. of households that owns livestock	0.000	1.000	0.813	0.249
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.336	0.350
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.616	0.335
Prop. of households enrolled in "Comedor popular" social programme	0.000	0.750	0.011	0.068
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.061	0.184
Average Elevation (m)	80.828	4126.430	1007.378	1110.752
Average Slope (degree)	0.865	32.128	10.295	9.665
Mean annual temperature (ºC)	6.708	27.135	22.529	5.076
Mean annual precipitation (mm)2	527.944	5036.706	1889.473	857.345
Distance to river or road (km)	0.000	6.902	0.518	1.105
Distance to closest city (km)	0.000	104.343	16.588	17.406
Longitude (m)	8420681.024	9716692.996	9141066.770	338826.008
Latitude (m)	7143.520	1150872.073	476570.945	272847.354
Total number of households	*668*			
Total number of clusters	*199*			

Table S3d. *Descriptive statistics of numeric variables in the final model - year **2017**, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.056	0.745	0.327	0.174
Health related poverty (%)	0.000	85.707	47.642	20.449
Education related poverty (%)	0.000	54.240	6.833	12.281
Living standard related poverty (%)	14.293	100.000	45.525	16.647
Forest cover 2000 (ha)	24.030	30800.790	17719.682	8965.490
Forest loss in previous 5 years (ha)	0.360	5011.920	807.927	806.173
Forest cover (%)	0.070	96.166	50.164	27.132
Number of patches per km^2	0.006	11.672	3.139	2.390
Mean patch size (km^2)	0.008	5.450	0.432	0.808
Number of households	2.000	8.000	3.376	1.238
Prop. of households with a male head of household (HH)	0.333	1.000	0.921	0.165
Mean household size	3.500	10.000	5.578	1.301
Mean age of HH	24.000	55.333	38.408	6.877
HH education level (mode)	0.000	3.000	1.312	0.539
Prop. of households that owns agricultural land	0.000	1.000	0.675	0.330
Prop. of households that owns >5 ha of agricultural land	0.000	0.667	0.044	0.126
Prop. of households that owns livestock	0.000	1.000	0.813	0.247
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.346	0.352
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.627	0.337
Prop. of households enrolled in "Comedor popular" social programme	0.000	0.750	0.012	0.069
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.065	0.188
Average Elevation (m)	80.071	3825.051	925.997	962.863
Average Slope (degree)	0.865	31.718	9.903	8.803
Mean annual temperature (ºC)	8.342	27.115	22.953	4.454
Mean annual precipitation (mm)2	537.741	5067.126	1837.667	761.677
Distance to river or road (km)	0.000	6.064	0.473	1.016
Distance to closest city (km)	0.000	104.343	17.030	17.740
Longitude (m)	8420681.024	9716692.996	9135252.748	345820.769
Latitude (m)	7143.520	1150872.073	484331.770	277611.101
Total number of households			*638*	
Total number of clusters			*189*	

Table S3e. *Descriptive statistics of numeric variables in the final model - year* ***2018****, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.050	0.822	0.313	0.174
Health related poverty (%)	0.000	85.707	47.004	22.836
Education related poverty (%)	0.000	49.985	11.150	15.797
Living standard related poverty (%)	10.005	100.000	41.846	15.360
Forest cover 2000 (ha)	2.160	30479.940	17581.286	9113.917
Forest loss in previous 5 years (ha)	0.000	3637.710	808.189	783.066
Forest cover (%)	0.007	96.406	48.759	28.076
Number of patches per km^2	0.003	11.026	3.305	2.483
Mean patch size (km^2)	0.002	5.267	0.421	0.839
Number of households	2.000	9.000	3.496	1.337
Prop. of households with a male head of household (HH)	0.000	1.000	0.900	0.174
Mean household size	3.000	9.500	5.291	1.196
Mean age of HH	21.500	54.500	36.777	6.851
HH education level (mode)	0.000	3.000	1.429	0.624
Prop. of households that owns agricultural land	0.000	1.000	0.675	0.328
Prop. of households that owns >5 ha of agricultural land	0.000	1.000	0.036	0.140
Prop. of households that owns livestock	0.000	1.000	0.800	0.254
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.377	0.352
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.576	0.333
Prop. of households enrolled in "Comedor popular" social programme	0.000	0.667	0.026	0.107
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.130	0.238
Average Elevation (m)	79.507	4111.566	1030.219	1095.570
Average Slope (degree)	0.905	29.867	10.589	8.751
Mean annual temperature (ºC)	6.801	27.071	22.377	5.107
Mean annual precipitation (mm)2	621.667	5052.805	1819.975	776.090
Distance to river or road (km)	0.000	7.294	0.443	0.997
Distance to closest city (km)	0.064	91.978	12.572	13.723
Longitude (m)	8423166.987	9892534.293	9130546.157	342413.831
Latitude (m)	6319.625	1140286.707	465836.691	279692.743
Total number of households			*832*	
Total number of clusters			*238*	

Table S3f. *Descriptive statistics of numeric variables in the final model - year* ***2019****, including number of observations. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	Minimum	Maximum	Mean	Std. Dev.
Multidimensional Poverty Index (MPI) - modified	0.057	0.773	0.325	0.189
Health related poverty (%)	0.000	100.000	46.149	23.268
Education related poverty (%)	0.000	49.985	10.873	14.128
Living standard related poverty (%)	0.000	100.000	42.979	17.802
Forest cover 2000 (ha)	2.160	30942.900	18734.955	8996.705
Forest loss in previous 5 years (ha)	0.000	5262.480	830.859	895.464
Forest cover (%)	0.007	97.510	52.349	28.359
Number of patches per km^2	0.003	13.098	3.392	2.810
Mean patch size (km^2)	0.007	6.123	0.489	0.953
Number of households	2.000	9.000	3.771	1.526
Prop. of households with a male head of household (HH)	0.000	1.000	0.855	0.213
Mean household size	2.500	9.667	5.354	1.418
Mean age of HH	21.000	58.167	38.157	7.786
HH education level (mode)	0.000	3.000	1.423	0.588
Prop. of households that owns agricultural land	0.000	1.000	0.611	0.342
Prop. of households that owns >5 ha of agricultural land	0.000	1.000	0.053	0.184
Prop. of households that owns livestock	0.000	1.000	0.770	0.287
Prop. Of households enrolled in "Juntos" social programme	0.000	1.000	0.364	0.324
Prop. of households enrolled in "Vaso de Leche" social programme	0.000	1.000	0.639	0.332
Prop. of households enrolled in "Comedor popular" social programme	0.000	1.000	0.031	0.141
Prop. of households enrolled in "Wawa wasi" social programme	0.000	1.000	0.028	0.122
Average Elevation (m)	79.507	4111.566	904.059	987.511
Average Slope (degree)	0.720	29.097	9.965	8.862
Mean annual temperature (ºC)	6.801	27.041	23.023	4.558
Mean annual precipitation (mm)2	621.667	5391.492	1945.773	817.080
Distance to river or road (km)	0.000	5.301	0.349	0.739
Distance to closest city (km)	0.000	105.094	15.615	20.116
Longitude (m)	8533402.837	9892534.293	9144368.847	349181.371
Latitude (m)	6319.625	1177560.696	483523.568	268832.918
Total number of households			*758*	
Total number of clusters			*201*	

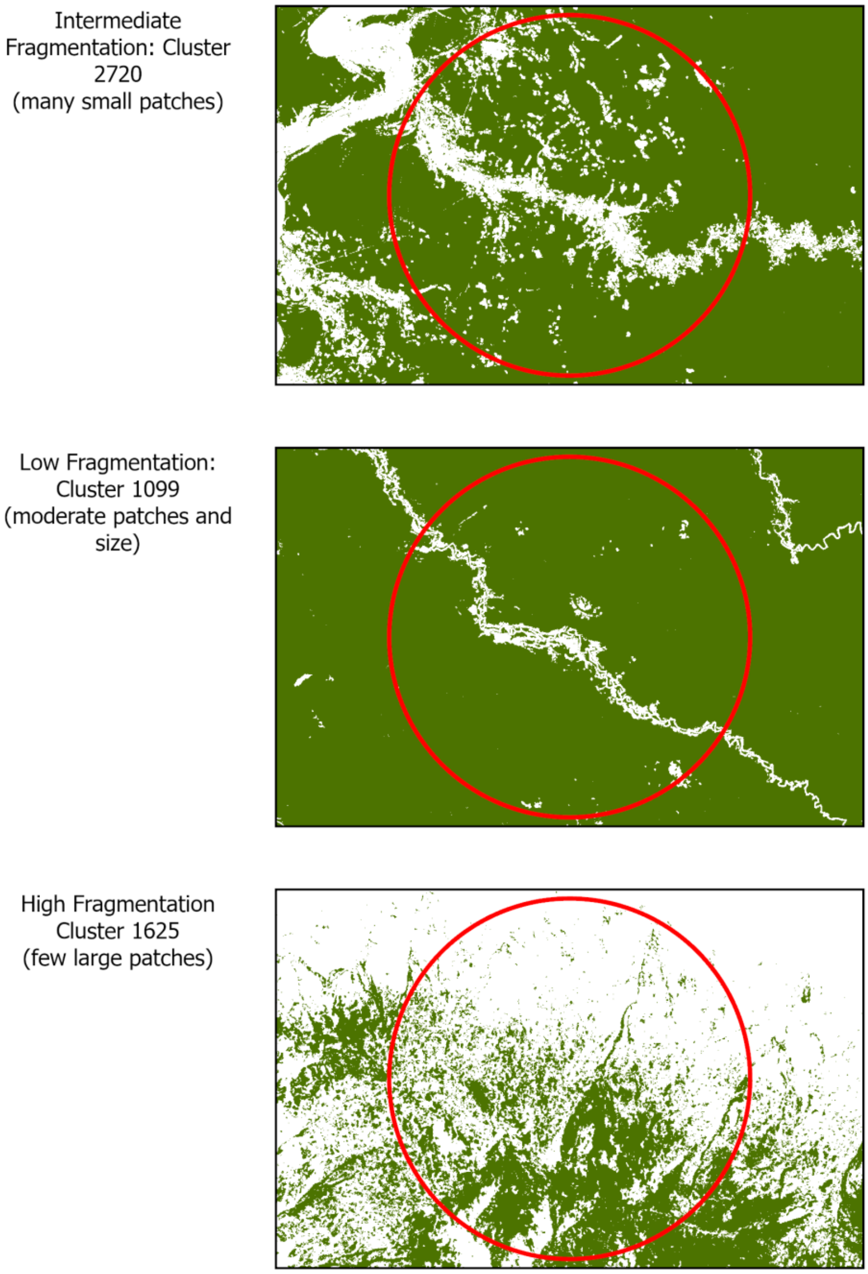

Figure S2. Examples of low, intermediate and high forest fragmentation pattern across clusters.

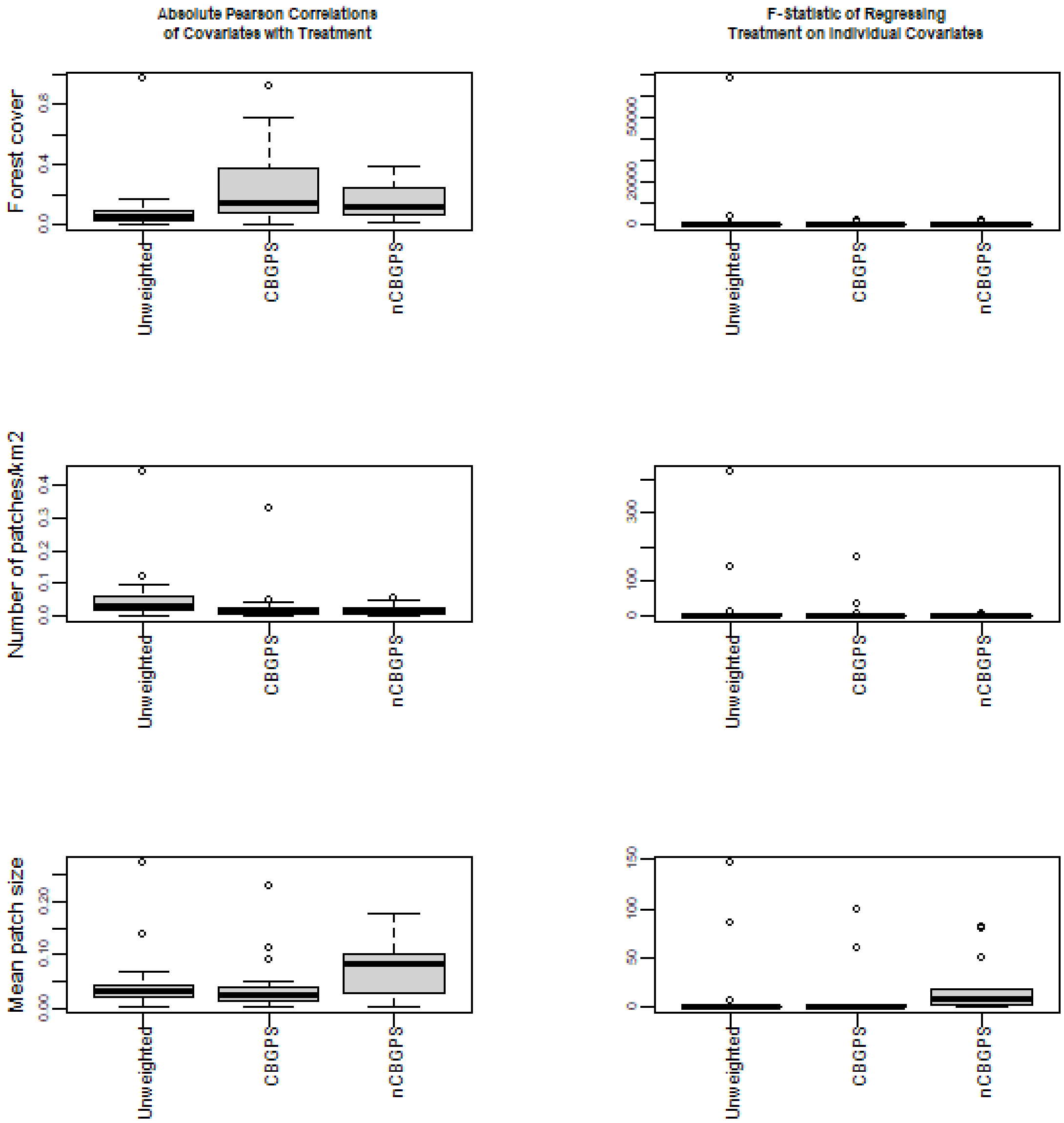

Figure S3. Balance of covariates before and after CBGPS. Absolute Pearson Correlations of covariates with treatment variables (forest cover, number of patches per km2 and mean patch area) and F-statistic of regressing treatment variable on individual covariates.

Table S4.1 *Final model specifications: average treatment effect (ATE) of forest cover metrics on multidimensional poverty (MPI). Treatment variables are shown in bold letters.*

Treatment	***Forest cover***			***Number of patches per km2***			***Mean of patch area***		
Variables	*Estimate*	*Std. error*	*P-value*	*Estimate*	*Std. error*	*P-value*	*Estimate*	*Std. error*	*P-value*
(Intercept)	0.317	0.179	0.077	0.088	0.171	0.607	-0.168	0.167	0.315
Forest cover (%)	**0.002**	**0.001**	**0.011**						
Number of patches per km^2				**0.007**	**0.002**	**0.002**			
Mean patch size (km^2)							**0.005**	**0.002**	**0.019**
Forest loss in previous 5 years (ha)	0.000	0.000	0.046	0.000	0.000	0.139	0.000	0.000	0.078
Forest cover 2000 (ha)	0.000	0.000	0.005	0.000	0.000	0.131	0.000	0.000	0.544
Number of households	-0.010	0.005	0.054	-0.011	0.005	0.027	-0.023	0.005	0.000
Prop. of households with a male head of household	-0.028	0.005	0.000	-0.021	0.005	0.000	-0.016	0.005	0.001
Mean household size	0.023	0.006	0.000	0.058	0.006	0.000	0.050	0.005	0.000
Mean age of head of household	-0.037	0.005	0.000	-0.039	0.005	0.000	-0.041	0.005	0.000
Head of household education level (mode)	-0.019	0.006	0.001	-0.018	0.005	0.000	-0.018	0.005	0.000
Prop. of households that owns agricultural land	0.097	0.006	0.000	0.031	0.005	0.000	0.031	0.006	0.000
Prop. of households that owns >5ha of agricultural land	-0.030	0.004	0.000	0.009	0.005	0.064	-0.003	0.005	0.478
Prop. of households that owns livestock	-0.063	0.006	0.000	-0.023	0.005	0.000	-0.013	0.005	0.011
Prop. of households enrolled in "Juntos"	0.008	0.005	0.127	0.016	0.005	0.001	0.006	0.005	0.248
Prop. of households enrolled in "Vaso de Leche"	-0.025	0.006	0.000	-0.003	0.005	0.518	0.004	0.005	0.475
Prop. of households enrolled in "Comedor popular"	-0.003	0.006	0.571	0.012	0.004	0.003	0.005	0.005	0.339
Prop. of households enrolled in "Wawa wasi"	0.046	0.004	0.000	0.002	0.005	0.652	0.002	0.005	0.675
Average Elevation (m)	-0.105	0.047	0.025	-0.082	0.039	0.036	-0.066	0.039	0.096
Average Slope (degree)	0.002	0.013	0.860	0.033	0.010	0.001	0.022	0.010	0.029
Mean annual temperature (ºC)	-0.085	0.041	0.035	-0.061	0.036	0.093	-0.047	0.037	0.207
Mean annual precipitation (mm)	-0.026	0.006	0.000	0.006	0.006	0.340	-0.002	0.006	0.708
Distance to river or road (km)	0.013	0.003	0.000	0.020	0.004	0.000	0.013	0.005	0.004
Distance to closest city (km)	0.076	0.005	0.000	0.038	0.005	0.000	0.040	0.005	0.000
Longitude (m)	0.000	0.000	0.000	0.000	0.000	0.982	0.000	0.000	0.070
Latitude (m)	0.000	0.000	0.923	0.000	0.000	0.170	0.000	0.000	0.002
Dummy variable year 2015	-0.060	0.021	0.005	-0.067	0.020	0.001	-0.054	0.020	0.007
Dummy variable year 2016	-0.044	0.022	0.050	-0.019	0.020	0.328	-0.049	0.019	0.011
Dummy variable year 2017	0.017	0.022	0.453	-0.035	0.020	0.075	-0.046	0.020	0.019
Dummy variable year 2018	-0.096	0.023	0.000	-0.004	0.019	0.850	-0.042	0.019	0.029
Dummy variable year 2019	0.027	0.024	0.249	-0.009	0.020	0.652	-0.026	0.019	0.182

Table S4.2. *Final model specifications: average treatment effect (ATE) of forest cover percentage on multidimensional poverty (MPI), including the interaction between forest metrics. Treatment variables are shown in bold letters.*

Treatment	***Forest cover***					
Variables	*Estimate*	*Std. error*	*P-value*	*Estimate*	*Std. error*	*P-value*
(Intercept)	-0.010	0.182	0.955	0.033	0.180	0.856
Forest cover (%)	**0.008**	**0.002**	**0.000**	**0.004**	**0.001**	**0.000**
Number of patches per km^2	0.026	0.011	0.015			
Mean patch size (km^2)				-0.628	0.106	0.000
Forest loss in previous 5 years (ha)	0.000	0.000	0.013	0.000	0.000	0.007
Forest cover 2000 (ha)	0.000	0.000	0.000	0.000	0.000	0.000
Number of households	-0.012	0.005	0.022	-0.017	0.005	0.002
Prop. of households with a male head of household	-0.029	0.005	0.000	-0.027	0.005	0.000
Mean household size	0.023	0.005	0.000	0.002	0.005	0.644
Mean age of head of household	-0.039	0.005	0.000	-0.035	0.005	0.000
Head of household education level (mode)	-0.013	0.006	0.021	-0.027	0.006	0.000
Prop. of households that owns agricultural land	0.094	0.005	0.000	0.097	0.006	0.000
Prop. of households that owns >5ha of agricultural land	-0.028	0.004	0.000	-0.030	0.004	0.000
Prop. of households that owns livestock	-0.068	0.005	0.000	-0.067	0.006	0.000
Prop. of households enrolled in "Juntos"	0.007	0.005	0.147	0.022	0.005	0.000
Prop. of households enrolled in "Vaso de Leche"	-0.019	0.006	0.002	-0.029	0.006	0.000
Prop. of households enrolled in "Comedor popular"	0.002	0.006	0.738	-0.001	0.006	0.838
Prop. of households enrolled in "Wawa wasi"	0.045	0.004	0.000	0.043	0.004	0.000
Average Elevation (m)	-0.105	0.046	0.022	-0.113	0.045	0.013
Average Slope (degree)	0.005	0.013	0.708	-0.021	0.013	0.105
Mean annual temperature (ºC)	-0.089	0.040	0.026	-0.115	0.039	0.003
Mean annual precipitation (mm)	-0.015	0.006	0.013	-0.025	0.006	0.000
Distance to river or road (km)	0.015	0.003	0.000	0.012	0.004	0.002
Distance to closest city (km)	0.066	0.005	0.000	0.069	0.005	0.000
Longitude (m)	0.000	0.000	0.000	0.000	0.000	0.000
Latitude (m)	0.000	0.000	0.236	0.000	0.000	0.066
Dummy variable year 2015	-0.072	0.021	0.001	-0.046	0.021	0.027
Dummy variable year 2016	-0.038	0.022	0.081	-0.034	0.023	0.138
Dummy variable year 2017	0.018	0.022	0.404	-0.020	0.023	0.382
Dummy variable year 2018	-0.094	0.022	0.000	-0.096	0.023	0.000
Dummy variable year 2019	0.023	0.023	0.310	0.016	0.024	0.504
Forest cover*Number of patches	0.000	0.000	0.914			
Forest cover*Mean patch size				0.006	0.001	0.000

Table S4.3. Final model specifications: average treatment effect (ATE) of forest cover metrics on health dimension. Treatment variables are shown in bold letters. Est.= estimate value, SD=standard deviation, p= p value. Models 4 and 5 include interaction between forest metrics.

Variables	**Models**														
	1			**2**			**3**			**4**			**5**		
	Est.	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*
(Intercept)	58.804	21.487	0.006	161.833	24.569	0.000	181.231	23.764	0.000	89.052	21.917	0.000	43.798	22.574	0.053
Forest cover (%)	**-0.484**	**0.100**	**0.000**							**-0.868**	**0.183**	**0.000**	**-0.674**	**0.112**	**0.000**
Number of patches per km^2				**1.307**	**0.331**	**0.000**				-0.943	1.271	0.458			
Mean patch size (km^2)							**-0.108**	**0.321**	**0.737**				65.041	13.234	0.000
Forest loss in previous 5 years (ha)	-0.005	0.001	0.000	-0.005	0.001	0.000	0.001	0.001	0.499	-0.005	0.001	0.001	-0.003	0.001	0.020
Forest cover 2000 (ha)	0.002	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.517	0.003	0.000	0.000	0.002	0.000	0.000
Number of households	0.480	0.624	0.442	0.296	0.687	0.667	0.072	0.669	0.914	0.670	0.614	0.275	0.398	0.672	0.554
Prop. of households with a male head of household	-1.798	0.572	0.002	-1.955	0.659	0.003	-0.864	0.678	0.203	-1.642	0.562	0.004	-3.515	0.567	0.000
Mean household size	-3.471	0.674	0.000	1.225	0.803	0.127	-0.124	0.781	0.874	-3.425	0.662	0.000	-5.161	0.651	0.000
Mean age of head of household	-0.352	0.617	0.568	1.027	0.717	0.152	1.190	0.727	0.102	-0.199	0.607	0.743	0.062	0.634	0.922
Head of household education level (mode)	1.375	0.704	0.051	1.675	0.706	0.018	3.620	0.676	0.000	0.752	0.699	0.282	0.966	0.725	0.183
Prop. of households that owns agricultural land	-3.086	0.664	0.000	0.073	0.778	0.925	0.207	0.799	0.796	-2.832	0.654	0.000	-1.596	0.690	0.021
Prop. of households that owns >5ha of agricultural land	1.971	0.484	0.000	-0.064	0.716	0.929	-0.597	0.681	0.381	1.773	0.477	0.000	1.810	0.519	0.001
Prop. of households that owns livestock	1.757	0.662	0.008	-1.394	0.731	0.057	-0.856	0.736	0.245	2.328	0.657	0.000	1.869	0.705	0.008
Prop. of households enrolled in "Juntos"	-0.940	0.628	0.135	-0.299	0.707	0.672	-0.816	0.700	0.244	-0.884	0.617	0.152	0.203	0.603	0.736
Prop. of households enrolled in "Vaso de Leche"	-1.108	0.725	0.126	-0.680	0.728	0.350	0.420	0.704	0.551	-1.735	0.719	0.016	-2.578	0.744	0.001
Prop. of households enrolled in "Comedor popular"	1.232	0.697	0.077	-1.272	0.576	0.027	-1.476	0.669	0.028	0.747	0.691	0.280	1.932	0.733	0.009
Prop. of households enrolled in "Wawa wasi"	-0.731	0.525	0.164	1.924	0.687	0.005	0.861	0.681	0.206	-0.620	0.516	0.230	-1.888	0.542	0.001
Average Elevation (m)	11.907	5.583	0.033	16.713	5.580	0.003	-5.953	5.608	0.289	12.433	5.498	0.024	17.696	5.675	0.002
Average Slope (degree)	-5.037	1.588	0.002	-4.919	1.486	0.001	-0.965	1.406	0.493	-5.446	1.564	0.001	-6.427	1.643	0.000
Mean annual temperature (ºC)	10.391	4.861	0.033	15.054	5.200	0.004	-5.353	5.241	0.307	11.236	4.788	0.019	17.583	4.870	0.000
Mean annual precipitation (mm)	-2.353	0.698	0.001	-3.162	0.910	0.001	-2.127	0.906	0.019	-3.549	0.711	0.000	-1.797	0.712	0.012
Distance to river or road (km)	0.702	0.408	0.086	-0.048	0.603	0.937	-0.216	0.659	0.743	0.506	0.410	0.218	0.732	0.465	0.116
Distance to closest city (km)	-4.675	0.584	0.000	-3.745	0.703	0.000	-1.783	0.721	0.014	-3.715	0.595	0.000	-4.501	0.637	0.000
Longitude (m)	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.078
Latitude (m)	0.000	0.000	0.803	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.215	0.000	0.000	0.880
Dummy year 2015	-4.660	2.539	0.067	-11.224	2.884	0.000	-0.785	2.817	0.781	-3.263	2.505	0.193	-8.104	2.624	0.002
Dummy year 2016	-2.100	2.689	0.435	-2.790	2.832	0.325	1.479	2.760	0.592	-2.533	2.645	0.338	-3.610	2.868	0.208
Dummy year 2017	-13.157	2.684	0.000	-8.278	2.822	0.003	0.498	2.787	0.858	-13.075	2.642	0.000	-18.242	2.844	0.000
Dummy year 2018	-1.277	2.753	0.643	-9.501	2.785	0.001	-1.449	2.712	0.593	-1.410	2.705	0.602	-1.311	2.932	0.655
Dummy year 2019	-15.628	2.817	0.000	-9.299	2.828	0.001	-1.484	2.757	0.590	-15.068	2.771	0.000	-19.472	2.964	0.000
Forest cover*Number of patches										-0.036	0.028	0.189			
Forest cover*Mean patch size													-0.663	0.138	0.000

Table S4.4. Final model specifications: average treatment effect (ATE) of forest cover metrics on education dimension. Treatment variables are shown in bold letters. Est.= estimate value, SD=standard deviation, p= p value. Models 4 and 5 include the interaction between forest metrics.

Variables	**Models**														
	1			**2**			**3**			**4**			**5**		
	Est.	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*
(Intercept)	127.727	16.081	0.000	15.736	16.538	0.342	-4.217	15.154	0.781	107.025	16.464	0.000	150.893	17.724	0.000
Forest cover (%)	**0.572**	**0.075**	**0.000**							**0.847**	**0.138**	**0.000**	**0.657**	**0.088**	**0.000**
Number of patches per km²				**-0.662**	**0.223**	**0.003**				0.788	0.955	0.410			
Mean patch size (km²)							**0.130**	**0.205**	**0.525**				-32.291	10.391	0.002
Forest loss in previous 5 years (ha)	0.006	0.001	0.000	0.004	0.001	0.000	0.000	0.001	0.899	0.006	0.001	0.000	0.005	0.001	0.000
Forest cover 2000 (ha)	-0.002	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.496	-0.003	0.000	0.000	-0.002	0.000	0.000
Number of households	1.468	0.467	0.002	0.222	0.463	0.632	0.514	0.427	0.229	1.343	0.461	0.004	1.692	0.527	0.001
Prop. of households with a male head of household	1.135	0.428	0.008	1.374	0.444	0.002	0.338	0.432	0.434	1.030	0.422	0.015	2.916	0.446	0.000
Mean household size	2.768	0.504	0.000	-1.318	0.540	0.015	-0.567	0.498	0.255	2.738	0.497	0.000	4.148	0.511	0.000
Mean age of head of household	-0.787	0.462	0.089	0.442	0.483	0.360	-0.121	0.464	0.794	-0.892	0.456	0.051	-0.931	0.498	0.062
Head of household education level (mode)	-2.439	0.527	0.000	-1.615	0.475	0.001	-3.041	0.431	0.000	-2.023	0.525	0.000	-2.569	0.569	0.000
Prop. of households that owns agricultural land	2.506	0.497	0.000	-0.964	0.524	0.066	-0.917	0.509	0.072	2.339	0.491	0.000	1.190	0.542	0.028
Prop. of households that owns >5ha of agricultural land	-1.930	0.362	0.000	-0.437	0.482	0.364	0.215	0.434	0.621	-1.795	0.358	0.000	-1.935	0.408	0.000
Prop. of households that owns livestock	-3.812	0.496	0.000	-0.265	0.492	0.591	-0.334	0.469	0.477	-4.194	0.493	0.000	-3.921	0.554	0.000
Prop. of households enrolled in "Juntos"	-1.470	0.470	0.002	-1.147	0.476	0.016	-0.405	0.446	0.364	-1.508	0.464	0.001	-2.419	0.474	0.000
Prop. of households enrolled in "Vaso de Leche"	1.449	0.542	0.008	1.005	0.490	0.041	-0.123	0.449	0.784	1.869	0.540	0.001	2.373	0.584	0.000
Prop. of households enrolled in "Comedor popular"	-1.078	0.522	0.039	1.236	0.388	0.001	1.260	0.427	0.003	-0.746	0.519	0.151	-1.768	0.576	0.002
Prop. of households enrolled in "Wawa wasi"	1.345	0.393	0.001	-0.671	0.462	0.147	-0.230	0.434	0.597	1.270	0.388	0.001	2.435	0.425	0.000
Average Elevation (m)	2.055	4.178	0.623	-13.972	3.756	0.000	5.342	3.576	0.136	1.750	4.130	0.672	-4.057	4.456	0.363
Average Slope (degree)	2.231	1.188	0.061	3.614	1.000	0.000	1.097	0.897	0.221	2.494	1.175	0.034	3.951	1.290	0.002
Mean annual temperature (ºC)	2.231	3.638	0.540	-13.419	3.500	0.000	4.921	3.342	0.141	1.706	3.597	0.635	-4.981	3.823	0.193
Mean annual precipitation (mm)	0.656	0.522	0.209	1.826	0.612	0.003	0.875	0.578	0.130	1.458	0.534	0.006	0.718	0.559	0.200
Distance to river or road (km)	0.013	0.305	0.965	-0.478	0.406	0.239	-0.445	0.420	0.289	0.155	0.308	0.615	-0.042	0.365	0.908
Distance to closest city (km)	1.095	0.437	0.012	1.754	0.473	0.000	0.138	0.460	0.764	0.447	0.447	0.317	1.150	0.500	0.022
Longitude (m)	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.540	0.000	0.000	0.000	0.000	0.000	0.000
Latitude (m)	0.000	0.000	0.000	0.000	0.000	0.434	0.000	0.000	0.452	0.000	0.000	0.000	0.000	0.000	0.000
Dummy year 2015	2.875	1.900	0.131	11.342	1.942	0.000	2.825	1.796	0.116	1.947	1.882	0.301	6.049	2.061	0.003
Dummy year 2016	2.638	2.012	0.190	2.337	1.907	0.221	-0.455	1.760	0.796	2.943	1.987	0.139	3.777	2.251	0.094
Dummy year 2017	2.338	2.009	0.245	3.295	1.899	0.083	-0.070	1.777	0.969	2.304	1.984	0.246	8.230	2.233	0.000
Dummy year 2018	2.739	2.060	0.184	9.163	1.875	0.000	4.399	1.730	0.011	2.837	2.032	0.163	2.023	2.302	0.380
Dummy year 2019	13.101	2.109	0.000	8.248	1.903	0.000	3.943	1.758	0.025	12.739	2.082	0.000	16.419	2.327	0.000
Forest cover*Number of patches										0.021	0.021	0.311			
Forest cover*Mean patch size													0.331	0.108	0.002

Table S4.5. Final model specifications: average treatment effect (ATE) of forest cover metrics on standard of living dimension. Treatment variables are shown in bold letters. Est.= estimate value, SD=standard deviation, p= p value.

	Models														
Variables	**1**			**2**			**3**			**4**			**5**		
	Est.	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*	*Est.*	*SD*	*p*
(Intercept)	-86.531	14.914	0.000	-77.570	16.841	0.000	-77.015	17.019	0.000	-96.078	15.436	0.000	-94.691	14.565	0.000
Forest cover (%)	**-0.088**	**0.070**	**0.205**							**0.021**	**0.129**	**0.870**	**0.018**	**0.072**	**0.805**
Number of patches per km²				**-0.645**	**0.227**	**0.005**				0.155	0.895	0.862			
Mean patch size (km²)							**-0.023**	**0.230**	**0.922**				-32.750	8.539	0.000
Forest loss in previous 5 years (ha)	-0.001	0.001	0.087	0.001	0.001	0.147	-0.001	0.001	0.290	-0.002	0.001	0.097	-0.002	0.001	0.052
Forest cover 2000 (ha)	0.000	0.000	0.083	0.000	0.000	0.349	0.000	0.000	0.766	0.000	0.000	0.733	0.000	0.000	0.488
Number of households	-1.949	0.433	0.000	-0.518	0.471	0.272	-0.586	0.479	0.222	-2.013	0.433	0.000	-2.090	0.433	0.000
Prop. of households with a male head of household	0.663	0.397	0.095	0.581	0.452	0.199	0.526	0.485	0.279	0.611	0.396	0.123	0.599	0.366	0.102
Mean household size	0.703	0.468	0.133	0.092	0.550	0.867	0.691	0.560	0.217	0.687	0.466	0.141	1.012	0.420	0.016
Mean age of head of household	1.140	0.428	0.008	-1.470	0.492	0.003	-1.069	0.521	0.040	1.091	0.428	0.011	0.869	0.409	0.034
Head of household education level (mode)	1.064	0.489	0.030	-0.060	0.484	0.902	-0.579	0.484	0.232	1.271	0.492	0.010	1.603	0.468	0.001
Prop. of households that owns agricultural land	0.580	0.461	0.208	0.891	0.534	0.095	0.711	0.572	0.215	0.493	0.461	0.284	0.406	0.445	0.362
Prop. of households that owns >5ha of agricultural land	-0.042	0.336	0.901	0.502	0.491	0.307	0.382	0.488	0.433	0.023	0.336	0.946	0.125	0.335	0.708
Prop. of households that owns livestock	2.055	0.460	0.000	1.658	0.501	0.001	1.190	0.527	0.024	1.866	0.463	0.000	2.051	0.455	0.000
Prop. of households enrolled in "Juntos"	2.409	0.436	0.000	1.446	0.484	0.003	1.221	0.501	0.015	2.392	0.435	0.000	2.215	0.389	0.000
Prop. of households enrolled in "Vaso de Leche"	-0.341	0.503	0.498	-0.324	0.499	0.516	-0.297	0.504	0.556	-0.133	0.506	0.792	0.205	0.480	0.670
Prop. of households enrolled in "Comedor popular"	-0.154	0.484	0.750	0.036	0.395	0.927	0.216	0.479	0.652	-0.001	0.487	0.999	-0.165	0.473	0.728
Prop. of households enrolled in "Wawa wasi"	-0.614	0.364	0.092	-1.253	0.471	0.008	-0.631	0.488	0.196	-0.649	0.363	0.074	-0.547	0.350	0.118
Average Elevation (m)	-13.962	3.875	0.000	-2.741	3.825	0.474	0.611	4.016	0.879	-14.183	3.872	0.000	-13.640	3.661	0.000
Average Slope (degree)	2.806	1.102	0.011	1.304	1.019	0.201	-0.132	1.007	0.896	2.952	1.102	0.007	2.476	1.060	0.020
Mean annual temperature (ºC)	-12.622	3.374	0.000	-1.635	3.564	0.647	0.432	3.754	0.908	-12.941	3.372	0.000	-12.602	3.142	0.000
Mean annual precipitation (mm)	1.697	0.484	0.000	1.336	0.624	0.032	1.252	0.649	0.054	2.091	0.501	0.000	1.079	0.459	0.019
Distance to river or road (km)	-0.715	0.283	0.012	0.526	0.414	0.203	0.662	0.472	0.161	-0.661	0.289	0.022	-0.690	0.300	0.022
Distance to closest city (km)	3.580	0.405	0.000	1.991	0.482	0.000	1.645	0.517	0.001	3.268	0.419	0.000	3.351	0.411	0.000
Longitude (m)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Latitude (m)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dummy year 2015	1.784	1.762	0.312	-0.119	1.977	0.952	-2.040	2.017	0.312	1.316	1.764	0.456	2.055	1.693	0.225
Dummy year 2016	-0.538	1.866	0.773	0.453	1.942	0.816	-1.024	1.977	0.605	-0.410	1.863	0.826	-0.167	1.850	0.928
Dummy year 2017	10.818	1.863	0.000	4.983	1.934	0.010	-0.428	1.996	0.830	10.771	1.861	0.000	10.012	1.835	0.000
Dummy year 2018	-1.462	1.911	0.444	0.338	1.909	0.859	-2.949	1.942	0.129	-1.427	1.905	0.454	-0.713	1.892	0.707
Dummy year 2019	2.526	1.955	0.197	1.051	1.938	0.588	-2.459	1.975	0.213	2.329	1.952	0.233	3.053	1.912	0.111
Forest cover*Number of patches										0.015	0.019	0.432			
Forest cover*Mean patch size													0.332	0.089	0.000

4 The impact of Juntos on natural vegetation cover and land-use change in the Peruvian Amazon

Abstract

Considerable efforts has been invested in evaluating the social impacts of environmental policies, yet the environmental effects of social policies targeting rural poverty alleviation remain poorly understood. Conditional cash transfer (CCT) programs, designed to alleviate poverty and improve well-being, have largely overlooked their potential environmental impact. Here we examined the effect of *Juntos*, a CCT initiative in Peru launched in 2005, on forest fragmentation and land-use change using a quasi-experimental approach based on the Covariate Balancing Generalised Propensity Score (CBGPS) method. We use a series of cross-sectional analysis combining socioeconomic data from the Peruvian Demographic and Health Survey (DHS) with spatial data on forest cover and land-use change between 2014 and 2021, for 8230 rural households in 1973 sampling clusters in Peru. Our analysis compared clusters with different forest configuration with similar socioeconomic and biophysical characteristics. We found that *Juntos* has contributed to the prevention of deforestation and/or promotion of reforestation in 2016, 2020, and 2021, years affected by the expansion of the project. Our results highlight the necessity for interdisciplinary approaches to forest conservation and pave the way for further research on the impact of CCT programs on environmental outcomes.

4.1 Introduction

Understanding how policy interventions affect forest landscapes has been a key research focus over the past decade and a half. While there have been considerable efforts to assess the social outcomes of environmental policies, little is known about the environmental impacts of social policies designed to address poverty in rural areas (Alpízar & Ferraro, 2020). Poverty alleviation policies, often under the banner of social protection programmes, take on many forms but often involve some sort of conditional cash transfer (CCT) mechanism in which vulnerable populations can receive cash or money transfers conditional on children's enrolment in education and/or regular health checks (e.g., programmes in Mexico, Brazil, Ecuador and Peru; Bastagli et al., 2016).

There are several mechanisms through which conditional cash transfers can affect deforestation (Ferraro & Simorangkir, 2020). For example, cash transfers can change forest consumption patterns and/or agricultural investment patterns or can promote forest cover if the cash transfers are linked to environmental conditionalities. However, evidence about the environmental outcomes of social protection programmes to date is inconclusive, with some studies showing positive or mixed environmental effects, while others show negative effects. For example, an assessment of Mexico's CCT programme (Oportunidades) showed that the programme increased deforestation by growing demand of more land-intensive products (Alix-Garcia, McIntosh & Sims, 2013). This effect was larger in remote areas with poor access to markets suggesting a mediator effect of them. In contrast, Ethiopia's Productive Safety Net Program (PSNP) increased tree cover, showing larger impacts in less populated areas with steep slopes and existing forests and croplands (Hirvonen et al., 2022). Moreover, research on Indonesia's CCT programme (Keluarga Harapan) found that it reduced deforestation and that this effect increased with the number of participants per hectare of forest and in villages with better access to markets (Ferraro & Simorangkir, 2020). Similarly, Cunha et al. (2022) also find that Indigenous communities receiving CCTs in Brazil converted less land for agriculture, probably by replacing local agricultural goods with purchased ones. Furthermore, analyses of Brazil's CCT programme (Bolsa Familia) showed both positive and negative effects on vegetation cover, depending on the biome (Dyngeland, Oldekop & Evans, 2020).

Here, we contribute to the study of environmental outcomes of social protection programmes by studying the effect of Peru's "Juntos" programme on natural vegetation cover in the Peruvian Amazon. Juntos ("Together" in Spanish) is a conditional cash transfer programme delivered by the Ministry of Development and Social Inclusion of Peru (MIDIS, by its initials in Spanish) across the country. Juntos was implemented in 2005 and rapidly expanded from 2 to 1325 municipalities in 2019 (MIDIS, 2024). The aim of the programme is to reduce poverty and interrupt the intergenerational transmission of poverty by targeting pregnant or nursing women and their children until 14 years of age. Juntos consists of a bi-monthly transfer of 200 Soles stipend (local currency, ~54 US dollars) to families in poverty and extreme poverty with the condition that children of beneficiary families attend school and go to regular health check-ups. Selected families either live within districts with poverty rates of at least 40% or belong to an Indigenous population in the Amazon. The programme's recipients are women, who are responsible for signing up to the programme and fulfilling its conditions. In exchange, they receive the stipend via bank transfers or in cash. Previous research has demonstrated that Juntos can change household consumption patterns and promote agricultural activities by relaxing cash constraints and increasing non-productive agricultural assets (Cirillo & Giovannetti, 2018; del Pozo Loayza & Guzmán Pacheco, 2011; Fernandez & Saldarriaga, 2014). These changes provide evidence for a potential mechanism through which Juntos could affect forest cover.

Two key structural changes to the Juntos programme allow us to assess its effects on forest cover. First, the programme significantly expanded in 2016, extending participation to Indigenous communities and increasing the coverage of Juntos in the Amazon region (Echarry Ccorahua, 2017). Second, Peru was heavily affected by the COVID-19 pandemic, setting back poverty and extreme poverty rates to 2012 and 2015 levels, respectively (World Bank, 2023). This setback was probably caused by social isolation and/or immobilization during the crisis to which the government responded by increasing their social assistance with six cash transfer bonuses between March 2020 and August 2021 (Gop.pe, 2021). They used Juntos' household prioritisation system to distribute the cash transfers. Moreover, due to the lack of employment in large cities, around 200 000 people returned to their regions of origin between 2020 to 2021, to work mainly in agriculture (34%) or ranching (5%), either on their lands or newly acquired lands (Fort et al., 2021). Given these changes to the programme over time, we can hypothesise to see accompanying changes in forest cover.

Peru's territory is largely covered by forest, around 60% of its territory is forested, occupying 82.5 million ha in 2020 of which 94.2% is Amazonian forest. However, between 2001 and 2021, Peru lost a total of 2.8 million hectares of Amazonian forests, with an annual average loss of 132 122 hectares (MINAM, 2023a). Moreover, in 2012 the estimated amount of forest-proximate people in Peru was 6.33 million people, which is 0.18% of world's population living within 5km of forest (Newton, 2020). Forest-proximate people may depend on forest for their subsistence, and their livelihood choices could shape rural landscapes.

We used a quasi-experimental approach and publicly available data from national and global sources to study the effect of Juntos on forest cover. We carried out a cross-sectional analysis combining land cover and land-use change spatial data with socioeconomic data from eight waves of the Peruvian Demographic and Health Survey (DHS) (8230 rural households in 1973 sampling clusters) for the years 2014 to 2021. Based on previous studies and Peru national context, one could expect Juntos to cause changes in natural vegetation cover by altering household expenditure and labour patterns, freeing people from agricultural work and integrating them into the market. These changes could prevent deforestation if people decide to invest their income in non-agricultural products or reduce the time spent at the farm. Conversely, Juntos could promote deforestation if beneficiaries decide to invest cash in agricultural production and livestock, for example. We expect to find a larger effect of Juntos after 2016, when the programme expanded.

4.2 Methods

Our analyses compile socioeconomic, biophysical, and bioclimatic data from 2014-2021 from global datasets and publicly available national information. We analysed these data using a quasi-experimental design based on the Covariate Balancing Generalised Propensity Score (CBGPS) method.

We used socioeconomic data from the Peruvian Demographic and Health Survey (DHS) and geographic information on forest cover extracted from the Geobosques, or land-used change, from Sentinel 2-10m land use/land cover maps. Using two vegetation datasets (Geobosques and Sentinel 2-10m) that differ in resolution, periodicity, and information (forest/no forest vs. land-cover types), allowed us to evaluate the average treatment effect of Juntos over longer time and assess the programme effect on different outcomes. The Geobosques dataset is available from 2001 to 2019 and contains information about forest cover at a 30m resolution, allowing us to test the effect of Juntos on forest pattern and capture the effect of programme expansion. Sentinel 2-10m contains information about land-use change and it is available from 2017 to 2022, allowing us to test the effect of Juntos on different land cover types and capture the programme effect during the COVID pandemic. Road and river features stem from the Ministry of Transport and Telecommunications. Weather variables such as temperature and precipitation were extracted from the WorldClim historical dataset (Hijmans et al., 2017). We used ArcGIS Pro 3.2 to process our geospatial data and R (R Core Team, 2023) for all statistical analyses.

A. Unit of analysis

We used DHS sampling clusters as our unit of analysis. The Peruvian Demographic and Health Survey (DHS) only georeferences clusters and these are randomly displaced by 5km to protect confidentiality. We therefore generate buffers of 10km to ensure that our analysis captures the environmental conditions of each cluster. The buffer size is further justified because it is a reasonable distance to walk or navigate within a day (Rasmussen et al., 2020). Our combined dataset includes 1066 rural clusters for the 2014-2019 period and 907 for the 2018-2021 period.

B. Outcomes

Forest cover change

The Geobosques forest loss data (MINAM, 2023b) is a 30m resolution Landsat-derived dataset produced by the Forest Cover Change Monitoring Platform for the Government of Peru. This dataset is restricted to the humid tropical forest, characterising the presence or absence of forest cover. Forest cover is defined by pixels with trees above 5m and >30% tree canopy, while forest loss is a pixel with completed or nearly complete lack of forest cover. Forest cover includes natural forest, secondary regrowth and tree plantations. The Geobosques dataset consists of a baseline forest cover layer for year 2000 and forest loss data from 2001 to 2019. We calculated forest cover and number of patches within a 10km buffer around clusters’ centroid using Geobosques data and Landscapemetrics R package (Hesselbarth et al., 2019b) for the period 2014-2019.

Land use change

The Sentinel 2-10m land use/land cover Time series dataset (Karra et al., 2021) is a 10m resolution global product derived from ESA Sentinel 2 imagery and available from 2017 to 2022. It uses a deep learning segmentation model trained on over 5 billion human-labelled pixels to classify each pixel into one of ten land categories.

We extracted data for the following pre-classified categories: trees, flooded vegetation, crops and rangeland to measure land used change for the period 2017-2022. They are defined as follows, according to Karra et al.:

- Trees category: comprehends any cluster of tall (15 feet or higher) vegetation with a closed or dense canopy, e.g. wooded vegetation, dense tall patches within savannahs, plantations, swamp or mangroves.
- Flooded vegetation: is defined as vegetation within intermixing of water throughout most of the year or seasonally flooded mix of grass/shrub/trees/bare ground, e.g. flooded mangroves, emergent vegetation, rice paddies, inundated agriculture.
- Crops: are defined as human planted/potted areas and crops not at three height, e.g. cereal, grass, corn, wheat, soy, fallow plots of structured land.
- Rangeland: is an open area covered by homogeneous grasses with little to no tall vegetation without obvious human plotting or a mix of plants and exposed soil or rock, e.g. natural meadows, open savannahs, golf courses, pastures, sparse cover of bushes, shrubs and tufts of grass, or savannahs with sparse grasses, trees or other plants.

With the aim to assess the effect of social programmes on tree cover loss, flooded vegetation loss, agricultural land expansion and rangeland expansion, we measure the area for each category one year before and after each DHS wave (2018-2021) and then calculate the difference.

Potential overlapping of land use categories, for example, between grass and crops, scrub/shrub, flooded vegetation and crops, and bare ground and scrub/shrub is addressed by the authors (Karra et al., 2021) through a rigorous accuracy assessment using a "gold standard" validation dataset, which allows them to quantify and analyse the confusion between classes. Yards, parks and groves are classified as built area. It is important to notice that this product classify land-use at a global scale.

C. Analysis

We divide our analysis into two periods: 2014-2019 and 2018-2021. Period 2014-2019 assessed the effect of Juntos on forest cover percentage and number of patches per km^2 using DHS data and Geobosques dataset. Period 2018-2021, evaluated the effect of Juntos on tree cover loss, flooded vegetation loss, agriculture land and rangeland expansion using DHS data and Sentinel 2-10m data. This division responds to the datasets used in the analysis.

For period 2014-2019, we assessed how Juntos affected forest cover using forest cover percentage and number of patches per km^2. We do so by combining spatially referenced cross-sectional data for 1066 rural clusters from six waves of DHS survey (2014-2019) and high-resolution satellite-based forest cover data. We used these variables to construct a quasi-experiment and isolate the statistical relationship between Juntos enrolment and forest cover data from potentially confounding socioeconomic and biophysical factors. Specifically, we combined deforestation in previous 5 years, baseline forest cover (year 2000), household characteristics, multidimensional poverty level, remoteness, slope, elevation, temperature, precipitation, latitude and longitude (see Table S1) with Covariate Balancing Generalised Propensity Score (CBGPS) weights in a multiple regression analyses. We conducted our analysis at cluster level, which collates information for a group of households, and forest cover metrics were calculated from a 10km area surrounding each cluster centroid. We estimated each regression model individually and run additional models that included an interaction term to test the year effect of Juntos (Juntos*year) in the outcomes as well.

For period 2018-2021, we tested the effect of Juntos on four land-use change categories: tree cover loss, flooded vegetation loss, agricultural land gain and rangeland gain. We combined spatially referenced cross-sectional data for 907 rural clusters from four waves of DHS survey (2018-2021) and high-resolution satellite based land-use change data. We constructed a quasi-experiment to isolate the statistical relationship between Juntos enrolment and the outcomes from potentially confounding factors. Precisely, we combined household characteristics, multidimensional poverty level, remoteness, slope, elevation, temperature, precipitation, latitude and longitude, land use values from previous year (trees area, agricultural land area, rangeland area, and cloud cover) with CBGPS weights in a multiple regression analyses (see Table S1). Our analysis was conducted at cluster level and land-use change areas were calculated from a 10km buffer surrounding each cluster centroid. We estimated each regression model individually and additional models to test the year effect (Juntos*year) as well.

The treatment variable, Juntos, is expressed as proportion and thus a continuous variable; hence, in both analyses we use the Covariate Balancing Generalised Propensity Score (CBGPS) method (Fong et al, 2018) and include CBGPS weights in the regression model to reduce correlation between treatment and covariates.

We calculated heteroscedasticity-robust standard errors using the *coeftest* function from the lmtest package in combination with the function vcovHC from the sandwich package to obtain White standard errors (Zeileis, 2004; Zeileis, Köll & Graham, 2020; Zeileis & Hothorn, 2002). We also checked for spatial autocorrelation by visual inspections of spatial distribution patterns of residuals from models with/without latitude and longitude values (Schleicher et al., 2020)(Figure S1).

Addressing Potential Multicollinearity

We recognise the potential for multicollinearity among the covariates included in our analysis. Specifically, variables such as agricultural land area, rangeland area, forest cover, etc. within the same spatial unit may exhibit high correlation. To address this, we implemented the following strategies:

i. Model Specification: our primary method for addressing potential confounding and associated multicollinearity we employed a careful model specification approach. We avoided including highly correlated covariates in the same regression model. For example, when modelling forest change outcomes (e.g., tree cover loss), we included lagged values of agricultural land area as a predictor. Conversely, when modelling agricultural land change, we used lagged values of forest cover. This is supported in the understanding that past land-use patterns influence future land-use change and helps to avoid the problems associated with including contemporaneously correlated variables.

ii. Covariate Balancing Generalised Propensity Score (CBGPS): as a complementary strategy, we use the Covariate Balancing Generalised Propensity Score (CBGPS) method, as detailed by Fong et al. (2018). CBGPS is designed to directly optimise covariate balance in the presence of a continuous treatment. By minimising the correlation between the treatment variable (proportion of households enrolled in Juntos) and the covariates, CBGPS reduces the likelihood of biased estimates due to confounding. This approach also inherently mitigates multicollinearity that arises from covariate imbalance.

iii. Robust Standard Errors: To ensure the robustness of our statistical inference, we used robust standard errors in all regression models. These standard errors are less sensitive to heteroscedasticity and can provide more reliable estimates even if some degree of multicollinearity remains.

iv. Variance Inflation Factors (VIFs): While CBGPS is our main method to deal with multicollinearity, we acknowledge that examining Variance Inflation Factors (VIFs) can provide an additional check. We will include VIF analysis in future versions of the manuscript to further assess the presence of multicollinearity among the remaining covariates in each model.

By combining the CBGPS method with a careful model specification strategy and the use of robust standard errors, we aimed to minimise the potential biases and inefficiencies caused by multicollinearity, while maintaining a theoretically sound model.

4.3 Results

Here we present the results for both analysis: period 2014-2019, the effect of Juntos on forest cover, and period 2018-2021, the effect of Juntos on land use change. Juntos programme coverage was very similar for both periods (see Table S2 and S3). We run two models for each period: *i*) a main effects models and *ii*) a year-specific effects model. Year-interaction models are saturated interaction models. We found that there is a significant year effect on Juntos for both periods and no spatial correlation.

Period 2014-2019: Effect of Juntos on forest cover

In the main effects model, Juntos showed no significant average effect on forest cover (β= -0.32 percentage points, SE = 0.31, p-value= 0.30) or number of patches (β= -64.42 patches/km^2, SE = 59.08, p-value= 0.28) across all years (Table 4.1). When analysing year effects, in 2016 (year when Juntos expanded to support Indigenous communities) the programme was significantly associated with a 1.62 percent-point increase in forest cover [SE=0.61, p-value= 0.01], equivalent to a 3.3% relative increase[3] over to the baseline mean (49.58%, see Table S2). For a typical cluster (314.16 km^2), 1.62% represents an estimated 5.09 km^2 gain in forest area. For the same year, number of patches declined by 421.75 patches/km^2 [SE= 238.17, p-value= 0.08].

Table 4.1. *Effect of Juntos on forest cover percentage and number of patches per km^2 in main effects model and year interaction models. Result of multivariate regression models with robust standard errors. Column names refer to outcome in the regression.*

	Δ Forest cover %			**Δ Number of patches per km2**		
	Est.	*SE*	*p*	*Est.*	*SE*	*p*
Main effects model						
Juntos	-0.32	0.31	0.30	-64.42	59.082	0.276
Year interaction model						
Juntos	-0.91	0.52	0.08	186.72	202.66	0.36
Juntos*2015	0.65	0.71	0.37	-325.25	258.35	0.21
Juntos*2016	1.62	0.61	0.01	-421.75	238.17	0.08
Juntos*2017	0.93	0.82	0.26	-414.96	236.30	0.08
Juntos*2018	0.37	0.89	0.68	-239.04	233.24	0.31
Juntos*2019	-0.51	1.38	0.71	61.57	265.61	0.82

[3] Relative % Increase= (Estimated Effect/Baseline Mean) ×100= (1.62/49.58) ×100≈3.3%

Period 2018-2021: Effect of Juntos on land-use change

In the main effects model, no significant average effects were detected for tree cover loss (β = -0.63 km², p-value= 0.27), flooded vegetation loss (β = -0.13 km², p-value= 0.24), or agricultural/rangeland expansion (both p-value > 0.05). However, we found that the significance changed according to the year and outcome (Table 4.2). In 2020, tree cover loss (deforestation) decreased in 3.75 km^2 [SE=1.61, p-value=0.02; a 24.7% decrease compared to previous year] for each additional increase in the proportion of households enrolled in Juntos. Flooded vegetation loss increased marginally (β = 0.40 km², p-value= 0.06). In 2021, flooded vegetation loss decreased by 0.58 km^2 [SE= 0.26, p-value= 0.03; a 37.4% decrease from 2020 loss levels[4]] and rangeland expansion reduced by 3.32 km^2 [SE=1.52, p-value= 0.03; 52.8% decline from previous year]. Therefore, a greater proportion of households affiliated to the programme reduced forest conversion or promoted reforestation in 2020 and 2021.

Table 4.2. *The year effect of Juntos on tree cover loss, flooded vegetation loss, agriculture land and rangeland expansion. Result of multivariate regression models with robust standard errors. Column names refer to outcome in the regression.*

	Tree cover loss			Flooded vegetation loss			Agriculture land expansion			Rangeland expansion		
	Est.	SE	*p*	Est.	SE	*p*	Est.	SE	*p*	Est.	SE	*p*
Main effects model												
Juntos	-0.63	0.57	0.27	-0.13	0.11	0.24	-0.22	0.33	0.52	-0.67	0.51	0.19
Year interaction model												
Juntos	0.89	1.10	0.42	-0.09	0.09	0.32	-0.67	0.47	0.16	-0.29	0.94	0.76
Juntos*2019	-0.18	1.36	0.89	0.02	0.12	0.89	0.73	0.54	0.17	0.99	1.22	0.42
Juntos*2020	-3.75	1.61	0.02	0.40	0.22	0.06	0.02	1.34	0.99	0.39	1.14	0.73
Juntos*2021	-2.90	1.80	0.11	-0.58	0.26	0.03	1.12	0.71	0.12	-3.32	1.52	0.03

4.4 Discussion

Our study reveals that Juntos' environmental impacts were concentrated in specific years, with modest effect sizes in absolute terms but meaningful when scaled. The 1.62 percentage increase in forest cover in 2016 (3.3% relative to baseline) or 5.09 km^2 per cluster, scaled to the national level, could represent about 1012.91 km^2 of additional forest cover. Similarly, the 24.7% reduction in tree cover loss during 2020 (3.75 km²/cluster) could be scaled up to 753.75 km² of prevented deforestation and the 52.8% decline in rangeland expansion in 2021 (3.32 km²/cluster), these suggests Juntos may have disrupted pasture-driven deforestation.

[4] Previous year means: Tree cover (2019 = 15.2 km²), Flooded veg. (2020 = 1.55 km²), Rangeland (2020 = 6.29 km²).

Changes in the programme structure could explain the effect of the Juntos programme's effectiveness in 2016. That year, the programme was restructured to include households in Indigenous Communities, classified as extremely poor, increasing Juntos coverage from 1178 to 1290 districts (Echarry Ccorahua, 2017). Indigenous Communities are identified as tribal groups in the Amazon region, composed of clusters of families linked by language or dialect, cultural and social characteristics, and a common and permanent possession of the same territory (MINCUL, 2024). This could explain why Juntos was associated with a higher forest cover in 2016 since the number of beneficiaries in the Amazon region also increased; however, in 2017, the effect disappears. This transient effect aligns with evidence of 'program rebounds' in social protection literature. For example, cash transfers may initially reduce deforestation by easing liquidity constraints, but effects can fade if payments fail to keep pace with inflation or if households adapt by returning to land-intensive livelihoods (Alix-Garcia et al., 2013; Ferraro & Simorangkir, 2020). In Juntos' case, the 2016 rebound could reflect Indigenous households' unmet needs after initial inclusion, or the program's inability to offset broader economic pressures (e.g., post-2016 commodity booms).

Furthermore, this theory seems to be supported by the effect of 2020 and 2021 on Juntos programme effectiveness, which could be explained by changes during the COVID-19 pandemic. First, the Peruvian government responded with, among other measures, six cash transfer bonuses (Gop.pe, 2021) targeting urban and rural populations in an effort to buffer the effects of social isolation and immobilisation during the crisis. COVID-19 also produced an excess of deaths across regions, especially the poorest, due to the lack of health infrastructure and resources (Cajachagua-Torres et al., 2022). But, the pandemic also caused migration from cities to rural areas, many looking for employment or to cultivate their family land (Fort et al., 2021).

In 2020, the effect of Juntos centred on tree cover loss, shifting to agricultural areas and rangelands in 2021. In the Peruvian Amazon, large rangeland extensions do not naturally exist except for Pampas del Health, a tropical savannah inside the Bahuaja Sonene National Park with an area of 7,253.77 ha (SERNANP, 2023). We assume that all other rangeland areas correspond to cattle ranching. Flooded vegetation areas in the Amazon could refer to floodplains, lowlands along rivers, which are used for agriculture, given their access to markets and transportation. Jong et al. (2001) explored the dynamics of floodplain agriculture, hypothesising that land use changes could happen due to three main factors: market access, river floods and population pressure as villages become older. Moreover, previous studies about Juntos have found that the programme relaxes cash constraints, increasing access to markets or changing labour patterns of household members from agricultural activities (Cirillo & Giovannetti, 2018; del Pozo Loayza & Guzmán Pacheco, 2011; Fernandez & Saldarriaga, 2014; Perova

& Vakis, 2012). Therefore, given the mechanisms in which conditional cash transfers affect deforestation (Ferraro & Simorangkir, 2020); the prevention of deforestation in floodplains and expansion of rangelands by Juntos could be interpreted as the effect of changes in consumptions patterns: cash is use as insurance to face environmental shocks or deforestation-sourced goods can now be purchased or substitute by others in markets. Thus, prevented deforestation and/or promoted reforestation during 2020 and 2021 could be due to two reasons: 1) market changes, where agricultural products could not be transported out of the regions and therefore less profitable, or 2) healthy reasons, as people needed to look after relatives or their health, which either changed household priorities or reduced workforce.

A potential limitation of our study is the issue of multiple hypothesis testing. We conducted several statistical tests to examine the impact of the Juntos program on various outcomes, including different land use categories (tree cover loss, flooded vegetation loss, agricultural land expansion, and rangeland expansion). Conducting multiple tests increases the risk of Type I errors, meaning that some statistically significant findings could be due to chance rather than a true effect of the program. While we employed the CBGPS method, which reduces bias, we acknowledge that it does not directly address the issue of multiple comparisons. In future work, we will apply corrections for multiple hypothesis testing, such as the Benjamini-Hochberg procedure for controlling the False Discovery Rate (FDR), to provide a more stringent assessment of the statistical significance of our results. This will allow us to determine more confidently which observed impacts of the Juntos program on land use are robust to the problem of multiple comparisons.

Moreover, the potential for overlap and confusion between land use categories in the Sentinel-2 dataset, as highlighted by Karra et al. (2021), introduces a degree of uncertainty into our analysis. Specifically, confusion between categories such as 'trees' and 'flooded vegetation' or 'grass' and 'crops' could affect the accuracy of our land cover change measurements. This misclassification could lead to underestimating or overestimating changes in specific land cover types, potentially biasing our estimates of the Juntos program's impact. However, our use of lagged land cover variables as covariates partially mitigates this issue, as any misclassification in a given year has a reduced direct influence on the outcome variable in that same year. Furthermore, the consistent methodology applied in the Sentinel-2 dataset across the study period reduces the likelihood of systematic biases in change detection. Nonetheless, we acknowledge that these limitations warrant careful interpretation of our results, and we plan to conduct sensitivity analyses in future work to assess the robustness of our findings to these classification uncertainties.

Overall, our study suggests that a boost in CCT delivery can help prevent deforestation and that joint efforts could benefit both the environment and human well-being. The increased Juntos effect during 2016, 2020 and 2021 are in line with Ferraro & Simorangkir (2020) findings about the influence of increasing participants' density in CCT effectiveness, given that payments during the COVID-19 pandemic simulated a natural experiment and targeted people outside Juntos programme as well. Cash bonuses increased the amount of money received by beneficiaries and produced a spill over effect by increasing the number of people receiving the cash transfers. However, the design and implementation of social protection programmes need to be considered in both national and local contexts. Our study does not control for market or workforce changes, which could have an effect on deforestation (Alix-Garcia, McIntosh & Sims, 2013; Cunha, Rodrigues Neto & Morsello, 2022); focuses on large-scale dynamics, but CCTs effect can vary with the context (Dyngeland, Oldekop & Evans, 2020); and fails to assess the effect after COVID payments cease. These findings highlight the importance of multidisciplinary approaches for forest conservation and may encourage new research to understand the mechanisms by which CCT affect forest conservation.

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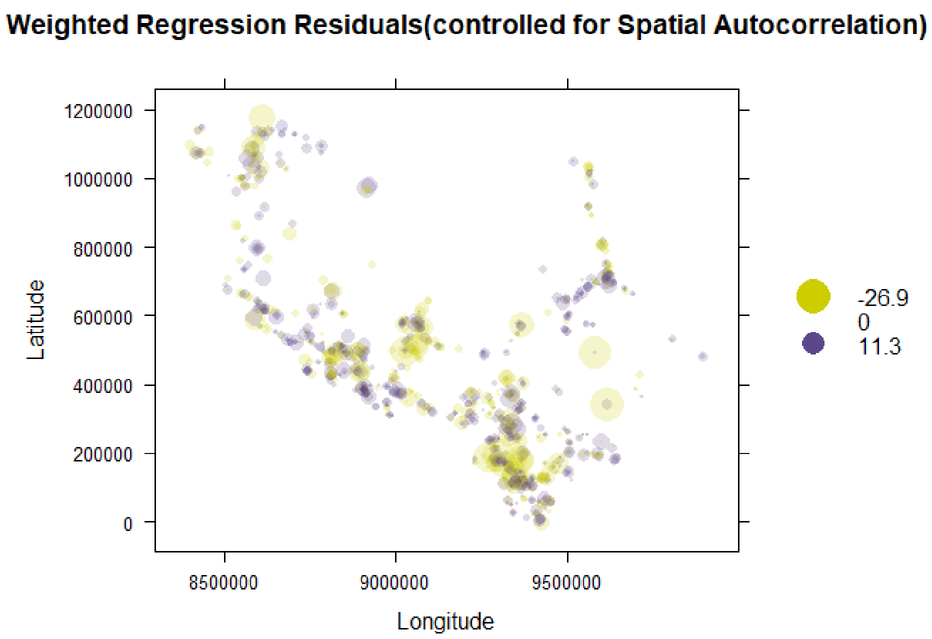
4.6 Supplementary information

Table S1. Variables description and data source.

	Variables	Description	Rationale for inclusion	Period 2014-2019	Period 2018-2021	Data source
Treatment variable	Prop. of households enrolled in Juntos	Proportion of households where at least one member benefits from the social programme within a cluster.	Treatment variable. Social programs like Juntos are designed to address poverty in rural areas. Conditional cash transfers can affect deforestation (Alpízar & Ferraro, 2020; Bastagli et al., 2016; Ferraro & Simorangkir, 2020).	x	x	Demographic and Health Survey (DHS)
Outcome variables	Percentage forest cover (%)	Percentage of remaining forest area within the cluster.	A direct measure of forest extent, crucial for assessing changes in forest area. Forest cover is a key indicator of environmental change and is often linked to the well-being of forest-dependent communities (Angelsen et al. 2014; FAO, 2014; Li et al., 2019).	x		Calculated from Geobosques (MINAM-Peru)
	Number of patches per km2	Sum of total number of patches per km2 within cluster.	Could indicate forest fragmentation. High fragmentation can negatively impact biodiversity and ecosystem services, affecting the livelihoods of people who depend on forests.	x		Calculated from Geobosques (MINAM-Peru)
	Tree cover loss (km2)	Area of tall (~15 feet or higher) dense vegetation with a closed canopy.	Measures deforestation, a critical aspect of forest change. Deforestation can have significant environmental and social consequences, including loss of habitat, reduced carbon sequestration, and impacts on local livelihoods (IPBES, 2019).		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Flooded vegetation loss (km2)	Area of seasonally flooded mix of grass/shrub/trees/bare ground.	Specific type of land cover change relevant in certain ecosystems (e.g., wetlands, mangroves). Changes in flooded vegetation can affect water regulation, fisheries, and local livelihoods.		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Agriculture land gain (km2)	Area of agricultural land not at tree height.	Indicates conversion of other land types (potentially forest) to agriculture. Agricultural expansion is a major driver of deforestation and can have implications for both environmental sustainability and poverty (through changes in land use and income) (Reed et al., 2017; Blaser et al., 2018; Amadu et al., 2020; Hughes et al., 2020).		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Rangeland gain (km2)	Open area covered by grass with little to no taller vegetation or mix of small vegetation clusters with exposed soil or rocks.	Similar to agriculture land gain, this measures the expansion of rangelands, which can also lead to deforestation or prevent reforestation.		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.

	Forest loss in previous 5 years (ha)	Sum of annual deforestation within each cluster.	Accounts for prior deforestation trends, which can influence future deforestation patterns. It helps to control for the history of forest change in the area.	x		Calculated from Geobosques (MINAM-Peru)
	Forest cover 2000 (ha)	Total area of forest in 2000 within the cluster.	Provides a baseline of forest cover, allowing for the assessment of changes over time. Initial forest cover can influence the likelihood of future changes.	x		Calculated from Geobosques (MINAM-Peru)
	Tree cover in previous year (km2)	Area covered by forest in the previous year.	Similar to forest cover 2000, but for a more recent baseline in the 2018-2021 analysis. Essential for controlling for immediate past conditions.		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Agricultural land in previous year (km2)	Area dedicated to agriculture in the previous year.	Controls for the existing extent of agricultural land, which is a key driver of deforestation (Lawrence & Vandecar, 2015).		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Rangeland in previous year (km2)	Rangeland area in the previous year.	Controls for the existing extent of rangeland, similar to agricultural land.		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
Covariates	Cloud in previous year (km2)	Area cover by clouds in previous year.	Cloud cover can affect the accuracy of satellite-based land cover measurements. Including this helps control for potential bias in the data.		x	Calculated from Esri Sentinel 2-10m land use/land cover global map.
	Cloud in next year (km2)		Similar to cloud cover in the previous year, this accounts for potential data inaccuracies due to cloud cover.		x	
	Multidimensional Poverty Index	Multi-dimensional poverty index for each cluster.	Poverty is often a driver of land-use change, and vice versa. Including this index helps to control for the socio-economic context and examine the interaction between poverty and forest change (Miller & Hajjar, 2020; World Bank, 2001). The IUFRO report emphasizes the complex relationship between poverty and forest resources (Angelsen et al. 2014; Sunderlin et al., 2005).	x	x	Calculated from Demographic and Health Survey (DHS) data
	Number of households	Number of households in a cluster.	Population size can influence land use and resource demand. A larger number of households may exert more pressure on forest resources.	x	x	Demographic and Health Survey (DHS)
	Proportion of male HH	Proportion of households which head is a male within a cluster.	Household structure and gender roles can influence resource management decisions and land-use practices (Agarwal, 2009).	x	x	Demographic and Health Survey (DHS)

Mean household size	Average number of member of each household within a cluster.	Larger households may have different resource needs and impacts on the environment compared to smaller households.	x	x	Demographic and Health Survey (DHS)
Mean age of HH	Average age of head of household within a cluster.	Age of household head can be related to farming practices, decision-making, and economic activities, all of which can influence land use.	x	x	Demographic and Health Survey (DHS)
HH education level (mode)	Most common education level of head of household within a cluster.	Education level can affect awareness of environmental issues, adoption of sustainable practices, and economic opportunities, indirectly influencing forest change.	x	x	Demographic and Health Survey (DHS)
Average Elevation (m)	Average elevation of all pixels within a cluster.	Elevation influences vegetation types, land use suitability, and accessibility, all of which can affect forest cover.	x	x	Aster Global Digital Elevation Model (ASTER GDEM), Ministry of Environment - Peru
Average Slope (degree)	Average slope of all pixels within a cluster.	Slope affects soil erosion, land suitability for agriculture, and the feasibility of logging, influencing forest management and change.	x	x	Derived from DEM map
Mean annual temperature (ºC)	Average annual average temperature of all pixels within the cluster.	Temperature is a key climatic factor that influences vegetation distribution and growth, and agricultural suitability, thus affecting forest cover (Lawrence & Vandecar, 2015). Climate change, as discussed in the IUFRO report, can significantly impact forests (IPBES, 2019).	x	x	WorldClim
Mean annual precipitation (mm)2	Average annual average precipitation of all pixels within the cluster.	Precipitation is another key climatic factor affecting vegetation, agriculture, and forest health.	x	x	WorldClim
Distance to river or road (km)	Euclidean distance from closest river or road to cluster's centroid.	Accessibility influences land use, deforestation (e.g., easier access for logging), and economic activities (Laurance et al., 2015).	x	x	Ministry of Transport and Communications (MTC)
Distance to closest city (km)	Euclidean distance from closest population to cluster's centroid.	Proximity to urban centers can affect market access, economic opportunities, and migration patterns, all of which can indirectly influence forest change.	x	x	Derived from INEI database
Longitude	Longitude coordinates WGS84	Geographic coordinates are essential for spatial analysis and mapping.	x	x	
Latitude	Latitude coordinates WGS84	Geographic coordinates are essential for spatial analysis and mapping.	x	x	



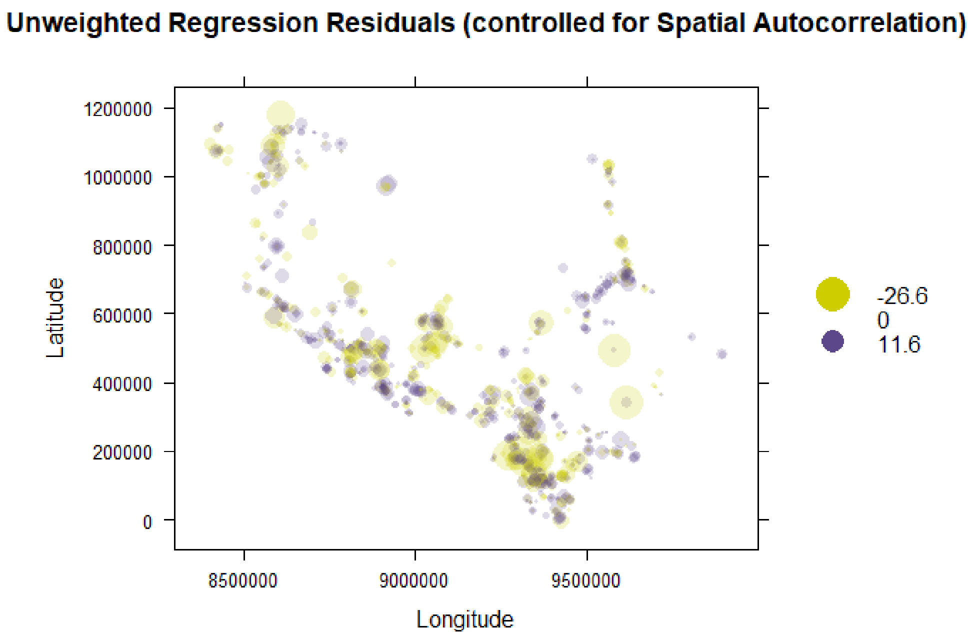
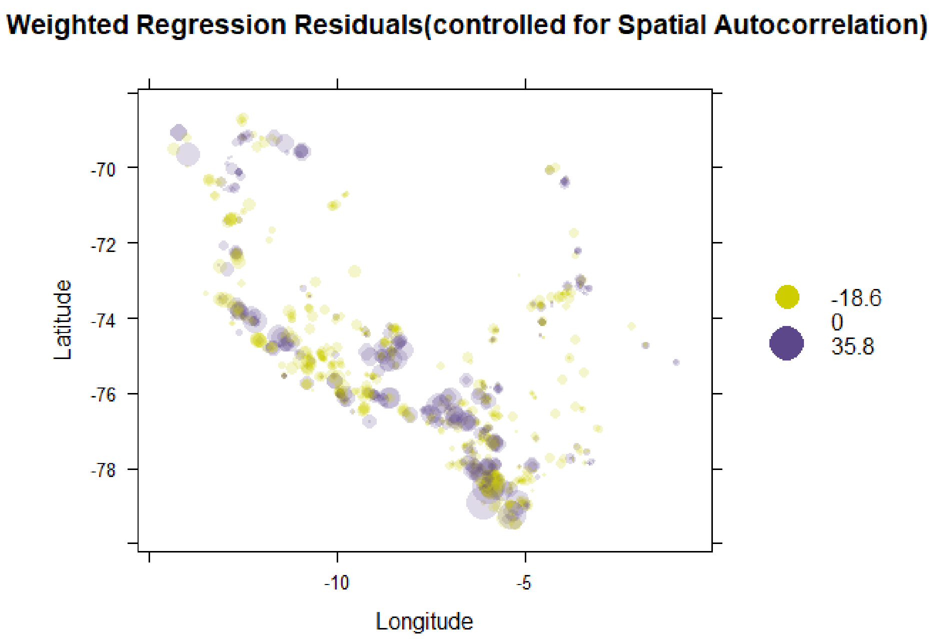


Figure S1. Spatial autocorrelation of residuals before and after matching for ATE of Juntos programme on forest cover for period 2014-2019.



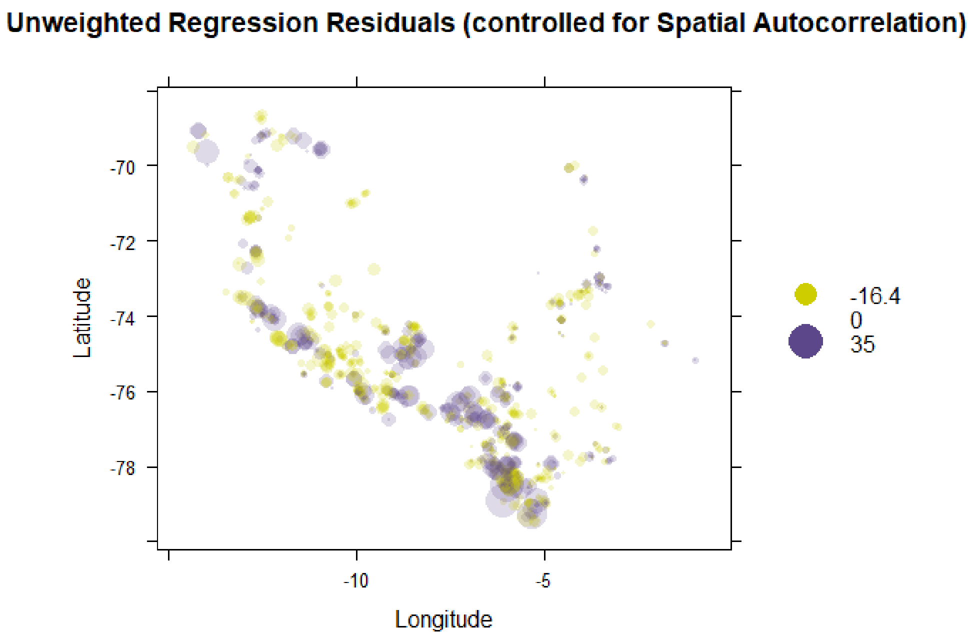


Figure S2. Spatial autocorrelation of residuals before and after matching for ATE of Juntos programme on tree cover loss for period 2018-2021.

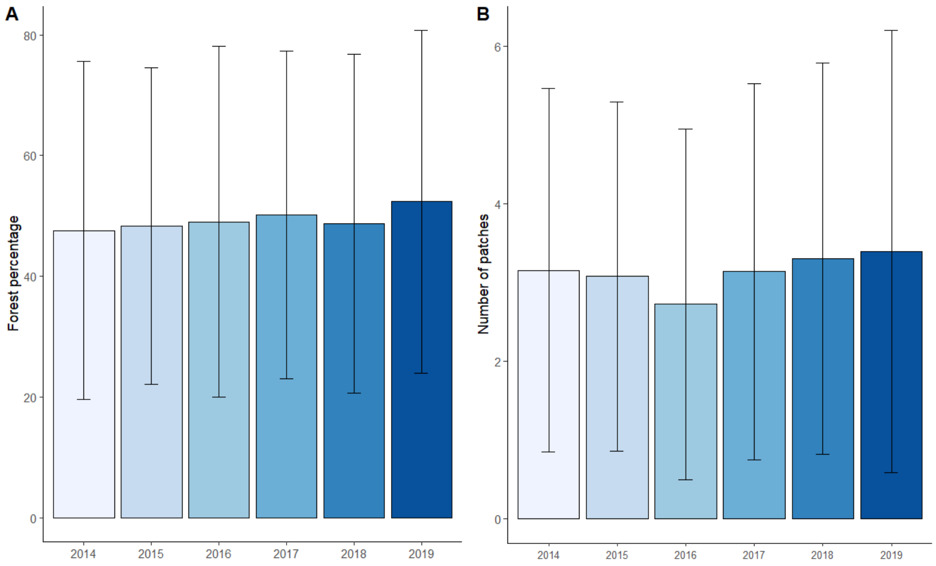


Figure S3. Changes in forest cover percentage and number of patches per km2 within clusters, from 2014 to 2019.

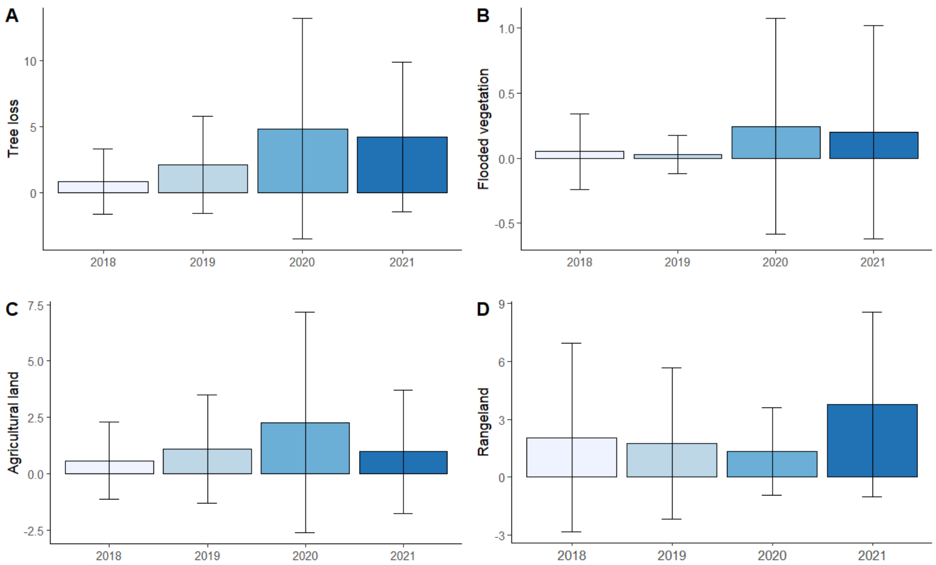


Figure S4. Changes in land-use within clusters from 2018 to 2021. A) Shows average tree loss in hectares per year, B) average flooded vegetation loss in hectares per year, C) average agricultural land gain in hectares per year, D) average rangeland gain in hectares per year.

Table S2. *Descriptive statistics of numeric variables,* ***period 2014-2019: effect of Juntos on forest fragmentation****. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	2014			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.27	0.34
Forest cover (%)	0.00	97.60	47.57	28.00
Number of patches per km2	0.00	9.52	3.15	2.31
Mean patch size (ha)	0.00	528.31	39.60	77.65
Multidimensional Poverty Index (MPI) - modified	0.07	0.73	0.35	0.17
Forest loss in previous 5 years (ha)	0.00	5229.90	867.74	984.34
Forest cover 2000 (ha)	0.09	30733.02	16713.97	9167.26
Number of households	2.00	9.00	3.96	1.66
Prop. households with a male head of household	0.50	1.00	0.92	0.14
Mean age of head of household	20.50	51.67	37.98	6.94
Mean household size	2.67	8.00	5.28	1.18
HH education level (mode)	1.00	3.00	1.43	0.57
Average Elevation (m)	95.06	3657.02	975.31	969.46
Average Slope (degree)	0.96	31.09	10.65	9.44
Mean annual temperature (ºC)	9.97	26.86	22.53	4.62
Mean annual precipitation (mm)2	685.84	4671.34	1825.06	863.81
Distance to river or road (km)	0.01	4.59	0.56	0.79
Distance to closest city (km)	0.05	128.75	14.61	16.91
Longitude (m)	8456359.45	9710824.61	9106219.39	337742.10
Latitude (m)	12006.50	1153167.67	466928.48	281828.64
Total number of households	329			
Total number of clusters	83			

Variable	2015			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.37	0.32
Forest cover (%)	0.09	98.42	48.32	26.28
Number of patches per km2	0.03	10.42	3.08	2.22
Mean patch size (ha)	0.62	3839.49	93.17	428.53
Multidimensional Poverty Index (MPI) - modified	0.05	0.82	0.32	0.17
Forest loss in previous 5 years (ha)	0.09	5590.17	934.46	1051.00
Forest cover 2000 (ha)	29.88	31172.40	17203.62	8892.09
Number of households	2.00	8.00	3.60	1.43
Prop. of households with a male head of household	0.00	1.00	0.92	0.17
Mean age of head of household	22.50	61.00	36.68	7.32
Mean household size	3.00	9.80	5.38	1.18
HH education level (mode)	0.00	3.00	1.40	0.54
Average Elevation (m)	81.65	4126.43	1041.11	997.94
Average Slope (degree)	0.88	31.42	11.50	9.11
Mean annual temperature (ºC)	6.71	27.12	22.35	4.65
Mean annual precipitation (mm)2	527.94	5075.04	1817.12	862.27

Distance to river or road (km)	0.00	7.43	0.91	1.37
Distance to closest city (km)	0.00	92.42	14.18	13.63
Longitude (m)	8404223.56	9694918.36	9125974.90	338835.18
Latitude (m)	-2987.24	1145106.52	442117.95	289827.28
Total number of households		*561*		
Total number of clusters		*156*		

Variable	2016			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.34	0.35
Forest cover (%)	0.02	98.46	49.04	29.01
Number of patches per km2	0.01	10.79	2.73	2.23
Mean patch size (ha)	0.63	3091.25	75.42	272.83
Multidimensional Poverty Index (MPI) - modified	0.06	0.75	0.32	0.17
Forest loss in previous 5 years (ha)	0.00	4115.61	693.62	752.07
Forest cover 2000 (ha)	6.57	31065.84	17005.39	9625.80
Number of households	2.00	8.00	3.36	1.22
Prop. of households with a male head of household	0.33	1.00	0.92	0.17
Mean age of head of household	24.00	55.33	38.46	6.88
Mean household size	3.50	10.00	5.55	1.29
HH education level (mode)	0.00	3.00	1.32	0.54
Average Elevation (m)	80.83	4126.43	1007.38	1110.75
Average Slope (degree)	0.87	32.13	10.30	9.67
Mean annual temperature (ºC)	6.71	27.14	22.53	5.08
Mean annual precipitation (mm)2	527.94	5036.71	1889.47	857.35
Distance to river or road (km)	0.00	6.90	0.52	1.11
Distance to closest city (km)	0.00	104.34	16.59	17.41
Longitude (m)	8420681.02	9716693.00	9141066.77	338826.01
Latitude (m)	7143.52	1150872.07	476570.95	272847.35
Total number of households		*668*		
Total number of clusters		*199*		

Variable	2017			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.35	0.35
Forest cover (%)	0.07	96.17	50.16	27.13
Number of patches per km2	0.01	11.67	3.14	2.39
Mean patch size (ha)	0.75	545.02	43.24	80.80
Multidimensional Poverty Index (MPI) - modified	0.06	0.75	0.33	0.17
Forest loss in previous 5 years (ha)	0.36	5011.92	807.93	806.17
Forest cover 2000 (ha)	24.03	30800.79	17719.68	8965.49
Number of households	2.00	8.00	3.38	1.24
Prop. of households with a male head of household	0.33	1.00	0.92	0.17
Mean age of head of household	24.00	55.33	38.41	6.88
Mean household size	3.50	10.00	5.58	1.30
HH education level (mode)	0.00	3.00	1.31	0.54

Average Elevation (m)	80.07	3825.05	926.00	962.86
Average Slope (degree)	0.87	31.72	9.90	8.80
Mean annual temperature (ºC)	8.34	27.12	22.95	4.45
Mean annual precipitation (mm)2	537.74	5067.13	1837.67	761.68
Distance to river or road (km)	0.00	6.06	0.47	1.02
Distance to closest city (km)	0.00	104.34	17.03	17.74
Longitude (m)	8420681.02	9716693.00	9135252.75	345820.77
Latitude (m)	7143.52	1150872.07	484331.77	277611.10
Total number of households		*638*		
Total number of clusters		*189*		

Variable	2018			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.38	0.35
Forest cover (%)	0.01	96.41	48.76	28.08
Number of patches per km2	0.00	11.03	3.31	2.48
Mean patch size (ha)	0.22	526.72	42.14	83.86
Multidimensional Poverty Index (MPI) - modified	0.05	0.82	0.31	0.17
Forest loss in previous 5 years (ha)	0.00	3637.71	808.19	783.07
Forest cover 2000 (ha)	2.16	30479.94	17581.29	9113.92
Number of households	2.00	9.00	3.50	1.34
Prop. of households with a male head of household	0.00	1.00	0.90	0.17
Mean age of head of household	21.50	54.50	36.78	6.85
Mean household size	3.00	9.50	5.29	1.20
HH education level (mode)	0.00	3.00	1.43	0.62
Average Elevation (m)	79.51	4111.57	1030.22	1095.57
Average Slope (degree)	0.91	29.87	10.59	8.75
Mean annual temperature (ºC)	6.80	27.07	22.38	5.11
Mean annual precipitation (mm)2	621.67	5052.81	1819.98	776.09
Distance to river or road (km)	0.00	7.29	0.44	1.00
Distance to closest city (km)	0.06	91.98	12.57	13.72
Longitude (m)	8423166.99	9892534.29	9130546.16	342413.83
Latitude (m)	6319.63	1140286.71	465836.69	279692.74
Total number of households		*832*		
Total number of clusters		*238*		

Variable	2019			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Prop. of households enrolled in Juntos	0.00	1.00	0.36	0.32
Forest cover (%)	0.01	97.51	52.35	28.36
Number of patches per km2	0.00	13.10	3.39	2.81
Mean patch size (ha)	0.68	612.27	48.95	95.30
Multidimensional Poverty Index (MPI) - modified	0.06	0.77	0.33	0.19
Forest loss in previous 5 years (ha)	0.00	5262.48	830.86	895.46
Forest cover 2000 (ha)	2.16	30942.90	18734.96	8996.71
Number of households	2.00	9.00	3.77	1.53

Prop. of households with a male head of household	0.00	1.00	0.86	0.21
Mean age of head of household	21.00	58.17	38.16	7.79
Mean household size	2.50	9.67	5.35	1.42
HH education level (mode)	0.00	3.00	1.42	0.59
Average Elevation (m)	79.51	4111.57	904.06	987.51
Average Slope (degree)	0.72	29.10	9.97	8.86
Mean annual temperature (ºC)	6.80	27.04	23.02	4.56
Mean annual precipitation (mm)2	621.67	5391.49	1945.77	817.08
Distance to river or road (km)	0.00	5.30	0.35	0.74
Distance to closest city (km)	0.00	105.09	15.62	20.12
Longitude (m)	8533402.84	9892534.29	9144368.85	349181.37
Latitude (m)	6319.63	1177560.70	483523.57	268832.92
Total number of households		*758*		
Total number of clusters		*201*		

Table S3. *Descriptive statistics of numeric variables,* ***period 2018-2021: effect of Juntos on land-use change****. Minimum, maximum, mean and standard deviation at cluster level.*

Variable	2018			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Proportion of households enrolled in Juntos	0.00	1.00	0.37	0.35
Tree cover loss (km2)	0.00	18.74	0.80	2.48
Agriculture land gain (km2)	0.00	12.96	0.57	1.71
Rangeland gain (km2)	0.00	26.75	2.05	4.88
Flooded vegetation loss (km2)	0.00	3.25	0.05	0.29
Tree cover in previous year (km2)	0.83	317.02	225.98	83.55
Agricultural land in previous year (km2	0.00	159.18	6.56	19.84
Rangeland in previous year (km2)	0.02	304.91	63.17	80.29
Cloud in previous year (km2)	0.00	83.16	6.08	13.62
Cloud in next year (km2)	0.00	72.59	3.11	9.44
Multidimensional Poverty Index (MPI) - modified	0.05	0.82	0.32	0.17
Number of households	2.00	9.00	3.60	1.42
Prop. of households with a male head of household	0.00	1.00	0.89	0.18
Mean household size	3.00	9.50	5.33	1.25
Mean age of head of household	21.50	54.50	36.95	6.97
HH education level (mode)	0.00	3.00	1.45	0.62
Average Elevation (m)	79.51	4111.57	986.39	1038.43
Average Slope (degree)	0.72	29.87	10.56	8.74
Mean annual temperature (ºC)	6.80	27.07	22.59	4.83
Mean annual precipitation (mm)2	621.67	5052.80	1853.44	795.50
Distance to river or road (km)	0.00	7.29	0.44	0.97
Distance to closest city (km)	0.06	91.98	13.23	14.09
Longitude (degrees)	-79.45	-69.08	-75.23	2.50
Latitude (degrees)	-14.19	-0.97	-7.90	3.01
Total number of households	930			
Total number of clusters	258			

Variable	2019			
	Minimum	**Maximum**	**Mean**	**Std. Dev.**
Proportion of households enrolled in Juntos	0.00	1.00	0.34	0.32
Tree cover loss (km2)	0.00	36.68	2.10	3.67
Agriculture land gain (km2)	0.00	12.47	1.10	2.40
Rangeland gain (km2)	0.00	37.37	1.75	3.94
Flooded vegetation loss (km2)	0.00	1.76	0.03	0.15
Tree cover in previous year (km2)	2.40	317.49	234.21	85.26
Agricultural land in previous year (km2	0.00	119.08	8.05	19.53
Rangeland in previous year (km2)	0.02	306.94	56.65	78.62
Cloud in previous year (km2)	0.00	135.80	4.81	15.75
Cloud in next year (km2)	0.00	140.51	3.98	15.56
Multidimensional Poverty Index (MPI) - modified	0.04	0.77	0.32	0.19
Number of households	2.00	9.00	3.77	1.50
Prop. of households with a male head of household (HH)	0.00	1.00	0.86	0.21
Mean household size	2.50	9.67	5.36	1.42
Mean age of head of household	21.00	58.17	37.86	7.70
HH education level (mode)	0.00	3.00	1.46	0.61
Average Elevation (m)	79.51	4111.57	955.67	990.40

Average Slope (degree)	0.72	29.10	10.32	8.90
Mean annual temperature (ºC)	7.06	27.08	22.80	4.54
Mean annual precipitation (mm)2	621.67	5391.49	1912.27	841.67
Distance to river or road (km)	0.00	5.30	0.35	0.72
Distance to closest city (km)	0.00	105.09	15.10	19.15
Longitude (degrees)	-79.45	-68.78	-75.20	2.35
Latitude (degrees)	-13.23	-0.97	-7.79	3.02
Total number of households		853		
Total number of clusters		226		

Variable	2020			
	Minimum	Maximum	Mean	Std. Dev.
Proportion of households enrolled in Juntos	0.00	1.00	0.30	0.32
Tree cover loss (km2)	0.00	69.82	4.80	8.35
Agriculture land gain (km2)	0.00	24.99	2.26	4.90
Rangeland gain (km2)	0.00	10.65	1.34	2.27
Flooded vegetation loss (km2)	0.00	6.97	0.24	0.83
Tree cover in previous year (km2)	37.13	314.19	242.07	67.23
Agricultural land in previous year (km2	0.00	118.91	7.82	19.78
Rangeland in previous year (km2)	0.04	265.16	48.27	63.74
Cloud in previous year (km2)	0.00	43.14	2.34	6.30
Cloud in next year (km2)	0.00	140.95	5.53	16.12
Multidimensional Poverty Index (MPI) - modified	0.02	0.89	0.31	0.19
Number of households	2.00	12.00	4.83	2.49
Prop. of households with a male head of household (HH)	0.00	1.00	0.87	0.20
Mean household size	2.50	9.00	5.11	1.25
Mean age of head of household	22.50	63.33	38.74	6.78
HH education level (mode)	0.00	3.00	1.52	0.59
Average Elevation (m)	79.71	3640.70	940.82	930.48
Average Slope (degree)	0.90	30.64	10.34	8.92
Mean annual temperature (ºC)	9.29	27.08	22.82	4.27
Mean annual precipitation (mm)2	700.63	5210.47	1907.64	879.86
Distance to river or road (km)	0.00	0.00	0.00	0.00
Distance to closest city (km)	0.00	0.00	0.00	0.00
Longitude (degrees)	-79.35	-68.66	-75.16	2.51
Latitude (degrees)	-13.99	-1.75	-8.10	3.02
Total number of households		971		
Total number of clusters		201		

Variable	2021			
	Minimum	Maximum	Mean	Std. Dev.
Proportion of households enrolled in Juntos	0.00	1.00	0.38	0.30
Tree cover loss (km2)	0.00	25.72	4.21	5.67
Agriculture land gain (km2)	0.00	20.47	0.97	2.75
Rangeland gain (km2)	0.00	25.72	3.77	4.77
Flooded vegetation loss (km2)	0.00	6.19	0.20	0.82
Tree cover in previous year (km2)	25.52	318.99	243.24	65.91
Agricultural land in previous year (km2	0.00	97.18	8.12	17.57
Rangeland in previous year (km2)	0.01	266.53	49.04	58.95
Cloud in previous year (km2)	0.00	134.22	5.26	13.98
Cloud in next year (km2)	0.00	68.90	2.76	7.75

Multidimensional Poverty Index (MPI) - modified	0.02	0.72	0.23	0.16
Number of households	3.00	12.00	7.61	1.96
Prop. of households with a male head of household (HH)	0.22	1.00	0.83	0.17
Mean household size	2.60	8.29	4.85	0.97
Mean age of head of household	27.00	54.00	37.62	4.40
HH education level (mode)	0.00	3.00	1.58	0.55
Average Elevation (m)	78.47	3585.33	1044.31	858.66
Average Slope (degree)	0.83	29.22	12.32	8.45
Mean annual temperature (ºC)	9.60	27.13	22.37	3.98
Mean annual precipitation (mm)2	674.05	5126.93	1831.64	855.45
Distance to river or road (km)	0.00	0.00	0.00	0.00
Distance to closest city (km)	0.00	0.00	0.00	0.00
Longitude (degrees)	-79.12	-69.18	-75.51	2.48
Latitude (degrees)	-14.34	-2.13	-8.03	2.91
Total number of households		1690		
Total number of clusters		222		

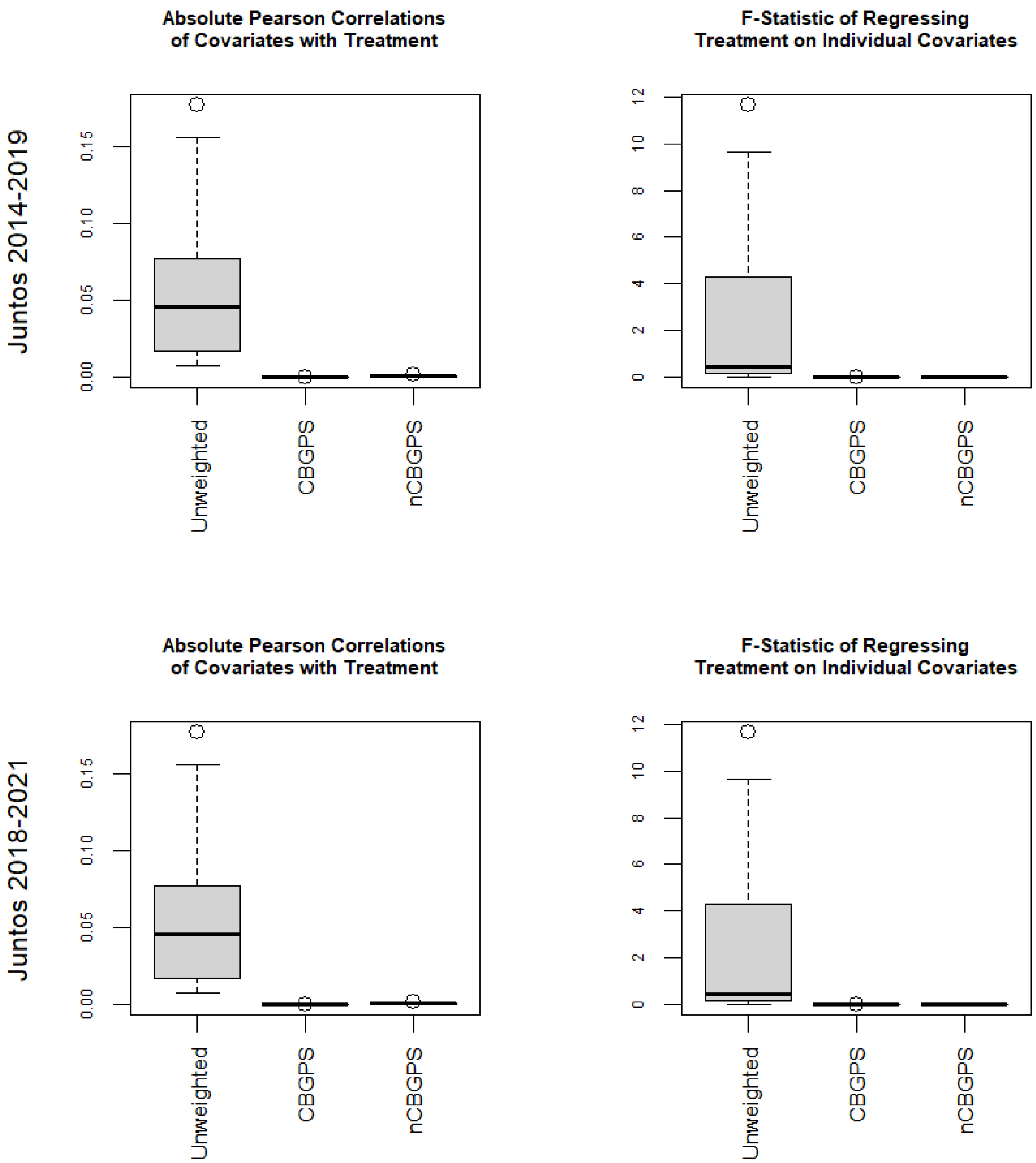


Figure S5. Balance of covariates before and after CBGPS. Absolute Pearson Correlations of covariates with treatment variables (Juntos) per period of analysis and F-statistic of regressing treatment variable on individual covariates.

Table S4. Final model specifications: *average treatment effect (ATE) of* Juntos *on forest fragmentation*, period 2014- 2019. Est.= estimate value, SE=standard error, p= p value.

	Outcome: Forest cover %					
Variables	Est.	SE	p	Est.	SE	p
(Intercept)	54.37	2.99	0.00	54.39	3.05	0.00
Prop. of households enrolled in Juntos	-0.32	0.31	0.30	-0.91	0.52	0.08
Forest loss in previous 5 years (ha)	-6.51	0.17	0.00	-6.53	0.17	0.00
Forest cover 2000 (ha)	29.49	0.07	0.00	29.51	0.07	0.00
Multidimensional Poverty Index (MPI) - modified	-0.02	0.11	0.88	0.00	0.11	0.98
Number of households	0.13	0.09	0.18	0.15	0.09	0.11
Prop. of households with a male head of household	0.15	0.12	0.23	0.15	0.12	0.23
Mean household size	0.10	0.13	0.41	0.12	0.13	0.34
Mean age of head of household	-0.12	0.11	0.29	-0.11	0.11	0.33
Head of household education level (mode)	-0.34	0.10	0.00	-0.32	0.10	0.00
Average Elevation (m)	1.88	0.72	0.01	1.75	0.73	0.02
Average Slope (degree)	0.06	0.21	0.76	0.08	0.21	0.70
Mean annual temperature (ºC)	1.49	0.68	0.03	1.35	0.70	0.05
Mean annual precipitation (mm)2	0.43	0.14	0.00	0.41	0.14	0.00
Distance to river or road (km)	-0.06	0.14	0.68	-0.06	0.14	0.67
Distance to closest city (km)	0.01	0.10	0.96	0.02	0.09	0.80
Longitude (m)	0.00	0.00	0.54	0.00	0.00	0.49
Latitude (m)	0.00	0.00	0.24	0.00	0.00	0.27
Year dummy 2015	-0.50	0.29	0.09	-0.71	0.45	0.12
Year dummy 2016	-0.89	0.27	0.00	-1.44	0.40	0.00
Year dummy 2017	-1.22	0.30	0.00	-1.52	0.45	0.00
Year dummy 2018	-1.99	0.36	0.00	-2.09	0.54	0.00
Year dummy 2019	-2.05	0.39	0.00	-1.85	0.65	0.00
Juntos*2015				0.65	0.71	0.36
Juntos*2016				1.62	0.61	0.01
Juntos*2017				0.93	0.82	0.26
Juntos*2018				0.36	0.89	0.68
Juntos*2019				-0.51	1.38	0.71

	Outcome: number of patches					
Variables	Est.	SE	p	Est.	SE	p
Intercept	480.81	645.08	0.46	440.44	635.84	0.49
Prop. of households enrolled in Juntos	-64.42	59.08	0.28	186.72	202.66	0.36
Forest loss in previous 5 years (ha)	452.60	27.60	0.00	456.35	27.65	0.00
Forest cover 2000 (ha)	-250.18	22.56	0.00	-253.96	22.56	0.00
Multidimensional Poverty Index (MPI) - modified	-7.69	24.33	0.75	-13.75	24.36	0.57
Number of households	29.06	20.66	0.16	23.27	20.67	0.26
Prop. of households with a male head of household	-3.26	19.78	0.87	-3.69	19.89	0.85
Mean household size	5.02	25.58	0.84	1.15	25.38	0.96
Mean age of head of household	18.37	22.88	0.42	15.92	22.84	0.49
Head of household education level (mode)	63.90	21.79	0.00	58.32	21.61	0.01
Average Elevation (m)	49.01	177.30	0.78	66.68	178.73	0.71
Average Slope (degree)	-3.59	43.68	0.93	-8.37	43.79	0.85

Mean annual temperature (ºC)	112.48	165.55	0.50	132.49	167.80	0.43
Mean annual precipitation (mm)2	-80.00	24.43	0.00	-74.57	24.07	0.00
Distance to river or road (km)	-7.05	20.31	0.73	-6.21	20.23	0.76
Distance to closest city (km)	11.80	22.08	0.59	6.16	21.29	0.77
Longitude (m)	0.00	0.00	0.02	0.00	0.00	0.01
Latitude (m)	0.00	0.00	0.39	0.00	0.00	0.42
Year dummy 2015	-17.90	92.66	0.85	91.05	133.52	0.50
Year dummy 2016	0.43	85.27	1.00	143.28	111.71	0.20
Year dummy 2017	60.47	86.03	0.48	201.35	116.80	0.09
Year dummy 2018	115.16	85.67	0.18	192.93	112.55	0.09
Year dummy 2019	155.46	90.64	0.09	130.25	123.03	0.29
Juntos*2015				-325.25	258.35	0.21
Juntos*2016				-421.75	238.17	0.08
Juntos*2017				-414.96	236.30	0.08
Juntos*2018				-239.04	233.24	0.31
Juntos*2019				61.57	265.61	0.82

	Outcome: Mean patch size					
Variables	Est.	SE	p	Est.	SE	p
Intercept	233.00	170.04	0.17	272.17	179.60	0.13
Prop. of households enrolled in Juntos	-3.64	14.12	0.80	-21.65	23.93	0.37
Forest loss in previous 5 years (ha)	-61.56	9.96	0.00	-62.17	9.99	0.00
Forest cover 2000 (ha)	80.55	11.20	0.00	81.60	11.51	0.00
Multidimensional Poverty Index (MPI) - modified	12.75	6.91	0.07	13.18	7.04	0.06
Number of households	-5.51	2.72	0.04	-4.28	2.84	0.13
Prop. of households with a male head of household	4.60	4.51	0.31	4.75	4.49	0.29
Mean household size	2.29	7.06	0.75	3.35	7.25	0.64
Mean age of head of household	2.84	4.90	0.56	3.31	4.83	0.49
Head of household education level (mode)	-0.75	5.11	0.88	0.14	5.11	0.98
Average Elevation (m)	-62.64	48.72	0.20	-56.88	49.94	0.25
Average Slope (degree)	5.27	13.91	0.70	6.55	14.16	0.64
Mean annual temperature (ºC)	-59.34	49.27	0.23	-52.08	50.75	0.31
Mean annual precipitation (mm)2	3.88	8.06	0.63	3.36	8.12	0.68
Distance to river or road (km)	1.88	7.17	0.79	1.53	7.18	0.83
Distance to closest city (km)	-3.23	6.25	0.60	-2.94	6.15	0.63
Longitude (m)	0.00	0.00	0.67	0.00	0.00	0.70
Latitude (m)	0.00	0.00	0.25	0.00	0.00	0.20
Year dummy 2015	48.68	29.85	0.10	69.70	51.35	0.17
Year dummy 2016	27.92	17.72	0.12	16.83	20.62	0.41
Year dummy 2017	-8.17	10.41	0.43	-24.40	14.43	0.09
Year dummy 2018	-6.43	10.00	0.52	-27.65	14.30	0.05
Year dummy 2019	-5.06	10.34	0.62	2.08	16.26	0.90
Juntos*2015				-57.62	82.15	0.48
Juntos*2016				33.89	44.25	0.44
Juntos*2017				47.95	29.51	0.10
Juntos*2018				62.62	29.03	0.03
Juntos*2019				-19.76	33.25	0.55

Table S5. Final model specifications: *average treatment effect (ATE) of* Juntos *on* l*and-use change,* period 2014- 2019. Est.= estimate value, SE=standard error, p= p value.

	Outcome: Tree cover loss					
Variables	Est.	SE	p	Est.	SE	p
(Intercept)	1.34	8.89	0.88	-0.27	8.94	0.98
Proportion of households enrolled in Juntos	-0.63	0.57	0.27	0.89	1.10	0.42
Tree cover in previous year (km2)	0.47	0.77	0.54	0.41	0.83	0.62
Agricultural land in previous year (km2	0.85	0.31	0.01	0.79	0.32	0.01
Rangeland in previous year (km2)	0.51	0.82	0.53	0.48	0.88	0.59
Cloud in previous year (km2)	-2.38	0.63	0.00	-2.41	0.63	0.00
Cloud in next year (km2)	3.89	1.01	0.00	3.89	1.00	0.00
Multidimensional Poverty Index (MPI) - modified	-0.27	0.20	0.18	-0.27	0.20	0.18
Number of households	0.01	0.28	0.96	0.02	0.28	0.95
Prop. of households with a male head of household	0.09	0.22	0.68	0.12	0.22	0.60
Mean household size	0.05	0.25	0.85	-0.01	0.24	0.98
Mean age of head of household	0.09	0.17	0.59	0.11	0.17	0.52
HH education level (mode)	-0.13	0.21	0.53	-0.13	0.20	0.51
Average Elevation (m)	0.54	1.93	0.78	0.65	1.90	0.73
Average Slope (degree)	0.42	0.47	0.38	0.44	0.46	0.34
Mean annual temperature (ºC)	1.14	1.62	0.48	1.35	1.60	0.40
Mean annual precipitation (mm)	-0.12	0.19	0.54	-0.12	0.19	0.53
Distance to river or road (km)	-0.01	0.14	0.96	-0.01	0.14	0.96
Distance to closest city (km)	-0.02	0.11	0.84	-0.02	0.11	0.84
Longitude (degrees)	0.02	0.11	0.88	0.00	0.11	0.98
Latitude (degrees)	-0.20	0.06	0.00	-0.21	0.06	0.00
Year dummy 2019	0.54	0.38	0.16	0.61	0.47	0.20
Year dummy 2020	2.19	0.51	0.00	3.47	0.68	0.00
Year dummy 2021	3.30	0.82	0.00	4.29	1.15	0.00
Juntos*2019				-0.18	1.36	0.89
Juntos*2020				-3.75	1.61	0.02
Juntos*2021				-2.90	1.80	0.11

	Outcome: agricultural land expansion					
Variables	Est.	SE	p	Est.	SE	p
(Intercept)	2.79	3.62	0.44	2.55	3.62	0.48
Proportion of households enrolled in Juntos	-0.21	0.33	0.52	-0.66	0.47	0.16
Tree cover in previous year (km2)	-0.64	0.39	0.10	-0.73	0.38	0.06
Agricultural land in previous year (km2	1.23	0.22	0.00	1.22	0.22	0.00
Rangeland in previous year (km2)	-0.10	0.39	0.80	-0.18	0.39	0.65
Cloud in previous year (km2)	0.14	0.10	0.19	0.11	0.10	0.28
Cloud in next year (km2)	-0.27	0.10	0.01	-0.27	0.10	0.01
Multidimensional Poverty Index (MPI) - modified	-0.18	0.10	0.06	-0.17	0.10	0.07
Number of households	0.10	0.14	0.47	0.10	0.14	0.47
Prop. of households with a male head of household	0.00	0.12	0.98	-0.02	0.11	0.84
Mean household size	-0.11	0.09	0.20	-0.11	0.09	0.20
Mean age of head of household	-0.03	0.10	0.78	-0.04	0.09	0.71
HH education level (mode)	-0.09	0.10	0.34	-0.09	0.09	0.36
Average Elevation (m)	3.97	1.21	0.00	3.98	1.17	0.00
Average Slope (degree)	-0.77	0.21	0.00	-0.75	0.21	0.00

Mean annual temperature (ºC)	3.52	1.07	0.00	3.52	1.04	0.00
Mean annual precipitation (mm)	-0.15	0.09	0.11	-0.14	0.09	0.12
Distance to river or road (km)	0.12	0.05	0.03	0.12	0.05	0.02
Distance to closest city (km)	0.12	0.08	0.11	0.11	0.08	0.14
Longitude (degrees)	0.03	0.05	0.50	0.03	0.05	0.58
Latitude (degrees)	-0.02	0.03	0.35	-0.02	0.03	0.46
Year dummy 2019	0.46	0.16	0.00	0.21	0.21	0.31
Year dummy 2020	1.92	0.40	0.00	1.90	0.48	0.00
Year dummy 2021	0.38	0.33	0.25	-0.02	0.38	0.97
Juntos*2019				0.73	0.54	0.17
Juntos*2020				0.02	1.34	0.99
Juntos*2021				1.12	0.71	0.11

	Outcome: Rangeland expansion					
Variables	Est.	SE	p	Est.	SE	p
(Intercept)	-22.49	9.26	0.02	-24.19	9.49	0.01
Proportion of households enrolled in Juntos	-0.67	0.50	0.18	-0.29	0.94	0.76
Tree cover in previous year (km2)	-0.98	1.13	0.39	-0.99	1.14	0.38
Agricultural land in previous year (km2	-0.52	0.34	0.13	-0.56	0.35	0.11
Rangeland in previous year (km2)	-0.16	1.13	0.89	-0.09	1.15	0.94
Cloud in previous year (km2)	1.01	0.41	0.01	1.05	0.41	0.01
Cloud in next year (km2)	-1.00	0.24	0.00	-1.02	0.24	0.00
Multidimensional Poverty Index (MPI) - modified	-0.18	0.16	0.27	-0.20	0.16	0.21
Number of households	-0.18	0.26	0.49	-0.18	0.23	0.45
Prop. of households with a male head of household	0.14	0.17	0.42	0.22	0.17	0.20
Mean household size	0.02	0.26	0.94	-0.05	0.23	0.83
Mean age of head of household	0.14	0.16	0.37	0.15	0.16	0.33
HH education level (mode)	-0.46	0.17	0.01	-0.49	0.17	0.00
Average Elevation (m)	-3.18	1.74	0.07	-3.34	1.71	0.05
Average Slope (degree)	0.23	0.39	0.55	0.21	0.39	0.58
Mean annual temperature (ºC)	-2.28	1.47	0.12	-2.35	1.43	0.10
Mean annual precipitation (mm)	-0.44	0.16	0.01	-0.42	0.16	0.01
Distance to river or road (km)	0.04	0.16	0.79	0.06	0.17	0.72
Distance to closest city (km)	-0.25	0.09	0.01	-0.25	0.09	0.01
Longitude (degrees)	-0.29	0.12	0.01	-0.31	0.12	0.01
Latitude (degrees)	-0.30	0.07	0.00	-0.32	0.07	0.00
Year dummy 2019	0.07	0.34	0.82	-0.24	0.45	0.58
Year dummy 2020	-0.09	0.43	0.84	-0.20	0.50	0.69
Year dummy 2021	2.46	0.80	0.00	3.63	1.09	0.00
Juntos*2019				0.99	1.22	0.42
Juntos*2020				0.39	1.14	0.73
Juntos*2021				-3.32	1.52	0.03

	Outcome: Flooded vegetation loss					
Variables	Est.	SE	p	Est.	SE	p
(Intercept)	6.58	2.80	0.02	6.49	2.67	0.02
Proportion of households enrolled in Juntos	-0.13	0.11	0.24	-0.09	0.09	0.32
Tree cover in previous year (km2)	-1.38	0.51	0.01	-1.36	0.49	0.01
Agricultural land in previous year (km2	-0.34	0.13	0.01	-0.34	0.13	0.01
Rangeland in previous year (km2)	-1.20	0.46	0.01	-1.17	0.44	0.01

Cloud in previous year (km2)	-0.19	0.08	0.02	-0.18	0.08	0.02
Cloud in next year (km2)	0.01	0.02	0.53	0.01	0.02	0.65
Multidimensional Poverty Index (MPI) - modified	0.03	0.05	0.59	0.02	0.05	0.66
Number of households	0.07	0.03	0.03	0.07	0.03	0.02
Prop. of households with a male head of household	-0.05	0.02	0.02	-0.04	0.02	0.06
Mean household size	0.07	0.03	0.05	0.06	0.03	0.07
Mean age of head of household	-0.05	0.04	0.14	-0.05	0.03	0.14
HH education level (mode)	0.03	0.02	0.20	0.02	0.02	0.31
Average Elevation (m)	0.12	0.21	0.57	0.08	0.21	0.70
Average Slope (degree)	0.15	0.09	0.09	0.14	0.09	0.10
Mean annual temperature (ºC)	0.17	0.23	0.45	0.14	0.23	0.54
Mean annual precipitation (mm)	0.08	0.05	0.10	0.08	0.05	0.09
Distance to river or road (km)	0.02	0.02	0.24	0.02	0.02	0.20
Distance to closest city (km)	-0.03	0.03	0.29	-0.03	0.02	0.29
Longitude (degrees)	0.08	0.03	0.02	0.08	0.03	0.02
Latitude (degrees)	0.08	0.03	0.01	0.07	0.03	0.01
Year dummy 2019	0.02	0.05	0.61	0.02	0.07	0.72
Year dummy 2020	0.22	0.07	0.00	0.08	0.07	0.22
Year dummy 2021	0.24	0.12	0.04	0.44	0.18	0.02
Juntos*2019				0.02	0.12	0.89
Juntos*2020				0.40	0.21	0.06
Juntos*2021				-0.58	0.26	0.02

5 Valuing forest and livelihoods

Abstract

The intricate relationship between forests and poverty requires a holistic approach to sustainable development considering ecological and social dimensions. Although research has explored the potential of forests to alleviate poverty, understanding public preferences for balancing forest conservation with poverty alleviation remains limited. This study aims to bridge this gap by eliciting citizen preferences regarding forest cover, nutrition, and housing quality using a Discrete Choice Experiment (DCE). A survey of 250 Peruvian citizens elicited their preferences between different policy scenarios. As expected, results indicate a strong preference for good to bad levels of forest cover, nutrition, and housing quality. However, food security was prioritised over housing quality, and forest conservation is valued equally to combined improvements in nutrition and housing. Individuals with better food security place greater importance on forest conservation and good nutrition. In additional exploratory analyses testing the interaction between respondents' characteristics and preferences, we found that food security was an important factor in our sample preferences. Thus, for those living in households with better food security, the difference between poor and bad forest levels and between good and bad nutrition was more important than for people living in food insecure households. This study provides valuable insights into public preferences, which can be used as prior for larger-scale studies that could inform policymaking about social values in conservation management and policy development. To our knowledge, this is the first study seeking to understand how people value public goods like forests along with private benefits like food security and housing, which is crucial for developing effective and forest conservation and development policies.

Keywords: forest conservation, poverty alleviation, public preferences, choice experiment, sustainable development

5.1 Introduction

There is growing evidence regarding the dynamic relationship between forest and poverty, especially about the role of forest in alleviating monetary poverty, sustaining ecosystem services, improving agricultural productivity, and safeguarding food security (Miller, Mansourian & Wildburger, 2020). Forest conservation and poverty alleviation policies, such as payment for ecosystem services, can modify and shape forest landscapes and affect rural livelihoods. Sustainable development hinges on the balance of improving people's lives while protecting the environment over time, subject to limited resources. However, maximising sustainable development thus requires an understanding of not only “what is technically possible” but also “what is socially acceptable”. What is possible is determined by causal relationships between multiple factors, ranging from technology to resources. This can be visualised as the Production Possibilities Frontier (PPF), an economic concept, illustrating the various combinations of environmental protection and poverty alleviation outcomes achievable with the available resources and technology. What is socially acceptable is determined by ideology, values and preferences that people hold as citizens (separately from preferences that people hold as private consumers). Therefore, to determine the most desirable outcome from the spectrum of technically feasible options, understanding societal preferences is crucial. This can be represented by social indifference curves, which exemplify combinations of environmental and social outcomes that provide the same level of societal well-being. When what is technically possible and what is socially acceptable agree, we find that the allocation of resources, in theory, would be socially optimal. Moreover, incorporating people’s desires into policymaking can make people perceive policymaking as fair, influencing people’s attitudes towards them and impacting their long-term sustainability (Sommerville et al., 2010), benefiting both social outcomes and biodiversity conservation.

Earlier chapters of this thesis explored “what is possible” in terms of forest and multidimensional poverty alleviation. Multidimensional poverty evaluates people’s deprivation in three dimensions: education, nutrition and living standards (Alkire & Jahan, 2018b). There is a close relationship between forests and poverty, as research on forest-poverty dynamics has shown: forests provide people with resources such as wild food, timber, fuel, ecosystem services and other goods that can help alleviate poverty directly or indirectly (Miller, Mansourian & Wildburger, 2020) by diversifying diets, improving people’s housing conditions or offering additional income opportunities to meet their needs. Thus, forest conservation is of vital importance to people’s livelihoods, especially if we aim to maximise nutrition and living standards in forested areas. However, the optimal outcome between forest conservation and multidimensional poverty cannot be identified without also considering what is socially acceptable. Preference elicitation methods, such as choice experiments, can provide some guidance into which outcomes people are more willing to support. For example, a set of Pareto efficient policies have been identified in the form of a PPF where it is not possible to improve on one policy outcome without worsening at least one other policy outcome. The policy maker now has to choose which point on the PPF to bring about; preference elicitation methods can guide the decision.

There is growing evidence about people’s preferences about money allocation for conservation and their willingness to pay for ecosystem services, forest management (Abdeta, 2022; Acharya, Maraseni & Cockfield, 2019; IPBES, 2022), either from the perspective of someone using the resources or paying for the services (Tsuchiya & Watson, 2017). To our knowledge, no previous study has examined the preferences of the public as a citizen (which societal outcome should policy bring about, or how much should the government budget allocate) in relation to forest conservation and resource optimisation. This study aims to elicit people's preferences as a citizen to determine "what is socially acceptable" between forest conservation and nutrition and housing quality, two key dimensions of poverty.

This chapter presents a small-scale DCE survey on a sample of 250 public Peruvian citizens aged 18 or more and with internet access. Our results could then be used as prior information for larger scale studies, and contribute to the literature by determining citizens' social preferences. This chapter will answer the following question: How do participants, as citizens, value forest cover, nutrition, and housing quality relative to each other?

5.2 Methods

5.2.1 Discrete choice experiment

The discrete choice experiment (DCE) is a research method used to elicit peoples' preferences by presenting them with a series of choice sets (ChoiceMetrics, 2018). Each choice set typically consists of two hypothetical alternatives, where each alternative is described by specifying a level for each attribute. Participants are required to choose one alternative over the other, which provides insight into their preferences for different attributes at different levels. In this particular study, participants were presented with alternatives that were described in terms of three attributes: forest cover, nutrition, and housing quality. The priority was to ensure that respondents could clearly grasp the concepts presented in the choice scenarios and make informed trade-offs between the attributes, considering that some participants may only have primary or secondary education.

The forest cover attribute was defined as the capacity of a forest to provide resources for the survival of animals, plants, and human beings. The higher the forest cover, the higher the amount of resources it can provide. Forest cover levels were described in terms of forest cover percentage, biodiversity, and landscape pattern. Level 1 (good) represents a landscape dominated by forest and minimal deforestation; level 2 (middle), a mixed landscape of forest and farms; and level 3 (bad), a landscape with extensive deforestation and few trees. The nutrition attribute referred to whether a person has enough food to consume a balanced diet and meet their nutritional needs for an active and healthy life. Nutrition levels were described in terms of the proportion of households without stunted children. Stunting in children is a sign that their nutrition is inadequate or that there is a lack of resources to feed them (WHO, 2023). Level 1 (good) is for areas where 90% of households present healthy children, without stunting; level 2 (middle), 70% of households have healthy children; and level 3 (bad), 50% of households have healthy children. The housing quality attribute is defined in terms of the conditions of an accommodation. A good quality home has: a) walls, floor or roof built with materials appropriate for the regional climate (brick, stone or wood); b) access to drinking water and sanitary services (toilet, latrine or composting toilet); and c) reasonable cooking facilities and the use gas or electricity to cook food. The housing quality level was expressed in terms of the proportion of good quality homes in an area: level 1 (good) represents an area where 90% of the houses are of good quality; level 2 (middle), 70% of houses are in good quality; and level 3 (bad), 50% of the houses are in good quality. Each attribute level is described accordingly in Table 5.1.

The attribute levels where chosen to represent a range of possible scenarios that are relevant to the Peruvian context. For example, remnant rainforest occupies 87.2% of Amazonian provinces in Peru, with an average deforestation rate of 4.1% in 2018 (MINAM, 2021); 11.5% of Peruvian children under 5 years of age suffered chronic malnutrition in 2021 (INEI, 2023), and 8.9% households in Peru live in houses in bad condition (INEI, 2023). These statistics representing the average situation in Peru are used as level 1 of each attribute and as the “good” baseline for comparison. This baseline indicates the reference category of the regression analysis. Therefore, while level 1 contextualises the experiment reflecting a typical situation, level 2 and 3 allow examining the public’s willingness to trade-off between these attributes.

The 'regular biodiversity' label used to describe the 50% forest cover level (level 2) is a simplification of the complex relationship between forest cover and biodiversity, which was motivated by the need to provide clear and accessible labels for a general public audience. It implies a mixed landscape of forest and agricultural land. The graphic representations of the forest cover levels were included to provide visual context for respondents, illustrating the spatial patterns of forest cover change, including fragmentation. The potential limitations of this simplification and its possible influence on the results is addressed in the Discussion section. Regarding the nutrition attribute, the definition focused on the proportion of households with healthy children (i.e., without stunting), is not a comprehensive measure of all aspects of nutrition, but it was intended to capture the core concept of household food security and nutritional well-being. We discuss this potential limitation further in the Discussion section, including the implications for interpreting our results.

Table 5.1 *Attributes and levels of the Discrete choice model (DCE).*

Attributes	**Level 1 = Good**	**Level 2 = Middle**	**Level 3 = Bad**

Forest cover	90% forest cover High biodiversity, forest in good conditions	50% forest cover Regular biodiversity, mix of forest and agricultural land	10% forest cover Low biodiversity, agricultural land & few scattered trees
Nutrition level	90% of households have healthy children, without stunting	70% of households have healthy children, without stunting	50 % of households have healthy children, without stunting
Housing quality	90% of houses are of good quality	70% of houses are of good quality	50% of houses are of good quality

In a DCE study the number of choice sets presented to the respondents is determine by the design type and number of attribute levels and alternatives. A systematic literature review of DCE studies in health economics found that DCE studies commonly have four to five attributes and use eight to 16 choice sets to estimate the parameters (De Bekker-Grob, Ryan & Gerard, 2012). In this study, given the number of attributes levels (three attributes with three levels) the total possible combinations of attribute levels is 27 [3x3x3=27]. They are presented as a set of two scenarios per choice set, then the total number of possible pairwise combinations of scenarios is 351 [=(27x26)/2)], but presenting a single individual with all these choice sets is not feasible. To solve this issue, DCE studies typically use a sample of choice sets, based on efficient experimental choice designs (Ryan et al., 2006). A DCE uses a regression model (see section 5.2.2. Analysis) to explain variation in the choice data using the attribute-level information of the alternative scenarios, hence, it is important to look at the correlations in the scenario attribute-levels, and minimise multi-collinearity in the explanatory variables of the DCE model.

An efficient design minimises the correlation within the attribute-levels (the explanatory variables of the DCE model), and thus minimising the standard error of the estimated parameters (ChoiceMetrics, 2018). In these designs, the minimum number of choice sets (S) is determine by the number of parameters (coefficients in model, K=6) and alternatives (J=2) presented to the respondents. In our study the minimum number of choice sets is 6 [K/(J-1)=S]. Common practice is to fix the number of choice sets to twice or three times the minimum to have sufficient degrees of freedom for the identification of parameter estimates (which is the difference between the minimum and the actual numbers of choice sets). Presenting respondents with an excessive number of choices can lead to respondent fatigue, reduced attention, and potentially lower-quality (ChoiceMetrics, 2018). The research team tested a questionnaire with 12 choice sets and observed that this quantity appeared taxing. Completing 12 choice sets demanded considerable concentration and time, raising concerns about the potential disengagement, especially as the similarity across choice tasks could lead to boredom or increased susceptibility to distractions after only a few. Recognising this, and acknowledging that the determination of the number of choice tasks often relies on the researcher’s judgement, we opted for nine choice sets. This number exceeds the minimum of six required for robust analysis while remaining sufficiently concise to mitigate fatigue and avoid the necessity of splitting the survey into blocks, which would necessitate a larger sample size.

An efficient design performs better if a prior parameter value is known, the final study use the attribute coefficients from the last pilot to construct the DCE design using the Ngene software (ChoiceMetrics, 2018a). Ten DCE efficient designs with nine choice sets were constructed, compared in terms of attribute level balance (attributes occur with equal frequency, which was always achieved), and estimated efficiency error (D-error, which did not vary much). D-error refers to how much information a given set of choices could generate, for example, by avoiding correlation and dominance across attributes. The selected best performing design (D-error= 0.99, lowest) appears on Table S1, where each row is a choice set and numbers represent the level of each attribute in the choice experiment.

The DCE was included in a self-completion online questionnaire hosted on the Qualtrics platform (Qualtrics, 2005). It first presented participants with an information sheet about the project and asked for consent. Then, an introductory text briefly explained the context, attributes and levels, followed by the DCE experiment itself. In the experiment, participants were asked to imagine they were a policy maker responsible for a hypothetical jurisdiction of 100 households, with access to a natural area within 5 km distance, and asked them to indicate which of the two policy outcomes they would prefer. The instructions stated that time, implementation cost and everything else not mentioned were the same for both scenarios. All respondents considered nine choice sets, in the same order, where each choice set presented the alternatives using tabulated verbal descriptions (Figure 5.1). Finally, they answered sociodemographic questions about their age group, gender, educational level, and household characteristics. The full questionnaire (in Spanish) is replicated in *S1*.

	Alternative 1	**Alternative 2**
Households have access to a natural area with…	50% forest cover Regular biodiversity A mix of forest and agricultural land	10% forest cover Low biodiversity Agricultural land and some scattered trees
The proportion of households with healthy children, without stunting, is…	90%	50%

The proportion of good quality housing is…	50%	90%
	Alternative 1	Alternative 2
Your choice	❑	❑

Figure 5.1 *Example of DCE choice set, respondents need to choose one of the two alternatives.*

5.2.2 Analysis

The theory of Discrete choice experiment(DCE) is based on the standard economic theory of consumer behaviour, where participants focus their choices (preferences) on maximizing benefit (utility) given a budget constraint, and the "random utility" concept developed by McFadden (1974), which states that individual choice behaviour is essentially probabilistic (Ryan et al., 2008). The choice made by the participants depends largely on the goods' attributes, but also has an unobservable component that can affect their choices.

Therefore, the utility function of an individual n for alternative i is defined by an explainable (systematic) component $V_{i,n}$ and a random (unexplainable) component $\varepsilon_{i,n}$ (Ryan et al., 2008):

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n}$$

A subject will chose alternative i over alternative j if $(V_{i,n} + \varepsilon_{i,n}) > (V_{j,n} + \varepsilon_{j,n})$ and therefore if $(V_{i,n} - V_{j,n}) > (\varepsilon_{j,n} - \varepsilon_{i,n})$, but given that the error terms are unknown, the probability of choosing i over j will be as follows:

$$P_{i,n} = \left[\left(\varepsilon_{jn} - \varepsilon_{in}\right) < \left(V_{in} - V_{jn}\right)\right]$$

Additionally, given e which follows a logit model distribution the probability of a person n choosing alternative i in a choice situation t is (Hess & Palma, 2019):

$$P_{i,n,t} = \frac{e^{V_{i,n,t}}}{\sum_{j=1}^{J} e^{V_{j,n,t}}}$$

This study used the Apollo package (Hess & Palma, 2019a) in RStudio (RStudio Team, 2020) to produce a multinomial logit model which objective function to be maximised is represented by:

$$U_{i,n} = \beta_1 Forest\_mid_{i,n} + \beta_2 Forest\_bad_{i,n} + \beta_3 Food\_mid_{i,n} + \beta_4 Food\_bad_{i,n} + \beta_5 Housing\_mid_{i,n} + \beta_6 Housing\_bad_{i,n} + \varepsilon_{i,n}$$

Where β_x are coefficients for the alternative-specific variables, and $\varepsilon_{i,n}$ are unobserved random variables.

In the present study, the choice model alternatives are described in terms of forest cover, nutrition and housing quality (categorical variables), using level 1 or “good” as a baseline level for all. A significant coefficient ($P<0.05$) implies that the attribute level has a statistically significant influence on the likelihood of a respondent choosing an alternative over the other. Given that the estimated model is a logit regression, the resulting coefficients are on a latent scale, thus not directly interpretable but their sign indicates whether the attribute level influence was positive or negative on the participant’s choice decision. Later, I will use the greatest coefficient to standardise the others, allowing the comparison of coefficients across attributes relative to the standard in size.

5.2.3 Piloting presentation of outcomes

The study went through two piloting stages between March and August 2023.

Pilot 1: University students

A preliminary version of the questionnaire (in Spanish) was answered by a convenience sample of non-academic staff and undergraduate students at the Universidad Peruana Cayetano Heredia (UPCH) in Peru between March and July 2023. The pilot had two aims: a) to improve the questionnaire’s structure and language, and b) to gather further qualitative information about participants’ thought processes. Thirty individuals participated in the pilot: six were asked to complete the online survey within a video interview conducted by CC, and 24 were asked to complete the online questionnaire only (on their own). Respondents were recruited via either email invitation sent to administrative, facilities, technical staff and undergraduate students at UPCH, or a recruitment post on social media solely for UPCH students.

At this point, the attribute’s wording was negatively framed. Forest cover was described in terms of deforestation percentage; nutrition, as proportion of stunted children per 100 households; and housing quality as proportion of houses in bad quality every 100 households (see Figure 5.2). During the online interviews, participants completed the questionnaire (see Supplementary Information -*S2*) and discussed them one choice set at the time. Respondents answered additional open-ended questions on their opinions about structure and language of the questionnaire as well as their though process in the selection of the alternatives. They were emphasised that ‘there are no right or wrong answers’. Nearly all 30 participants found the wording and instructions of the questionnaire were easy to follow, while many of them also mentioned that it was difficult to choose between alternatives because of the trade-offs between attributes. Some participants took into account factors such as chronic malnutrition may be harder to recover from and could have larger social costs than other factors. Some participants suggested that visual representations of attribute levels would improve understanding of the alternatives.

Pilot 2: Members of the public

Based on the findings of Pilot 1, two new versions of the questionnaire were generated to be tested out in a second pilot, across two arms. The sample was broken up randomly into two arms, each addressing a separate aim: the first arm, to check and enhance comprehension by incorporating graphic illustrations of the scenarios; and the second arm, to check the effect of a positive framing of the attribute levels.

The study invited a sample of 160 men and women over 18 years of age with internet access, across a range of socioeconomic status from Offerwise (an international research agency that manages an internet panel in Peru, https://www.offerwise.com). The URL to the pilot questionnaire hosted in Qualtrics was distributed among members of the Offerwise panel, and those participating were rewarded with points in the research agency system. This pilot did not used quota sampling, and the sampling population is the same used for the final study. The questionnaire link stopped working after meeting the quota number.

(1) The first arm

The first arm, consisting of 60 participants, used a version of the questionnaire designed to compare the effect of including graphics in the presentation of the alternatives. This incorporated a graphic illustration of the attribute levels alongside verbal descriptions in the introductory section followed by a series of nine choice sets. Choice set wording was not changed from the first pilot. This arm was further broken up randomly into two groups. Group A was given verbal descriptions and illustrations of attribute levels in the introduction only (so the actual choice tasks had verbal descriptions only, as in Pilot 1). Group B was given graphic illustrations alongside verbal descriptions in both the introduction and the actual choice tasks. Participants were asked for their opinions on the presentation, accordingly. See Figure 5.2 for examples of the choice tasks.

a) Example choice task with verbal descriptions of the attributes only (Group A)

	Alternative 1	**Alternative 2**

Households have access to a natural area with…	50% deforestation Regular biodiversity A mix of forest and agricultural land	10% deforestation Low biodiversity Agricultural land and some scattered trees
The proportion of households with healthy children, without stunting, is…	10%	50%
The proportion of good quality housing is…	50%	10%
Your choice	Alternative 1 ❑	Alternative 2 ❑

b) ***Example choice task with verbal description and graphic illustration of the attributes (Group B)***

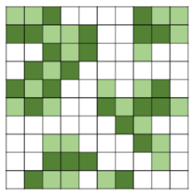
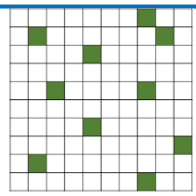
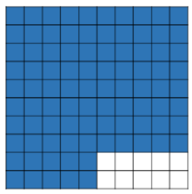
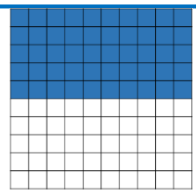
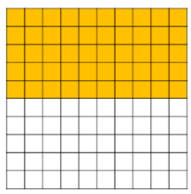
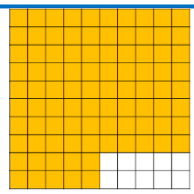
	Alternative 1	**Alternative 2**
Households have access to a natural area with…	 50% deforestation Regular biodiversity A mix of forest and agricultural land	 10% deforestation Low biodiversity Agricultural land and some scattered trees
The proportion of households with stunted children is…	 10%	 50%
The proportion of bad quality housing is…	 50%	 10%
Your choice	Alternative 1 ❑	Alternative 2 ❑

Figure 5.2 *Examples of choice tasks presented to Pilot 2 – first arm respondents.*

Most respondents across the two groups indicated that they understood the questionnaire, and found the inclusion of graphic illustrations in the introduction to be either helpful or highly beneficial. Subjects in Group A expressed that it would be advantageous to include the graphics in the actual choice tasks as well (Figure S1-c). Those in Group B mostly expressed that including graphics in the choice tasks was either helpful or very helpful (Figure S1).

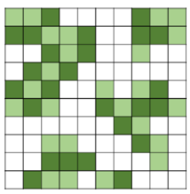
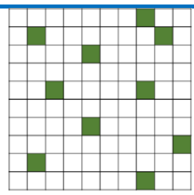
(2) The second arm

The second arm of Pilot 2 consisting of the remaining 100 participants tested the effect of a positive framing of the attribute levels, thus presenting attribute descriptions as forest cover percentage instead of deforestation, number of healthy children instead of stunted, and percentage of good quality houses instead of bad quality houses. The introduction section presented the attributes of the alternatives using the reworded verbal descriptions alongside the graphic illustrations. The sample was again divided into two groups, randomly: Group C was presented with graphics in the introduction only, while Group D was presented with graphics in both the introduction and the choice tasks. Figure 5.3 presents the same example choice task as that used in Figure 5.2, but with the positive framing.

a) Example choice task presents a verbal description of the attributes only (Group C)

	Alternative 1	**Alternative 2**
Households have access to a natural area with…	50% forest cover Regular biodiversity A mix of forest and agricultural land	10% forest cover Low biodiversity Agricultural land and some scattered trees
The proportion of households with healthy children, without stunting, is…	90%	50%
The proportion of good quality housing is…	50%	90%
Your choice	Alternative 1 ❑	Alternative 2 ❑

b) Example choice task presents verbal and graphic description of the attributes (Group D)

	Alternative 1	**Alternative 2**
Households have access to a natural area with…	 50% forest cover Regular biodiversity A mix of forest and agricultural land	 10% forest cover Low biodiversity Agricultural land and some scattered trees

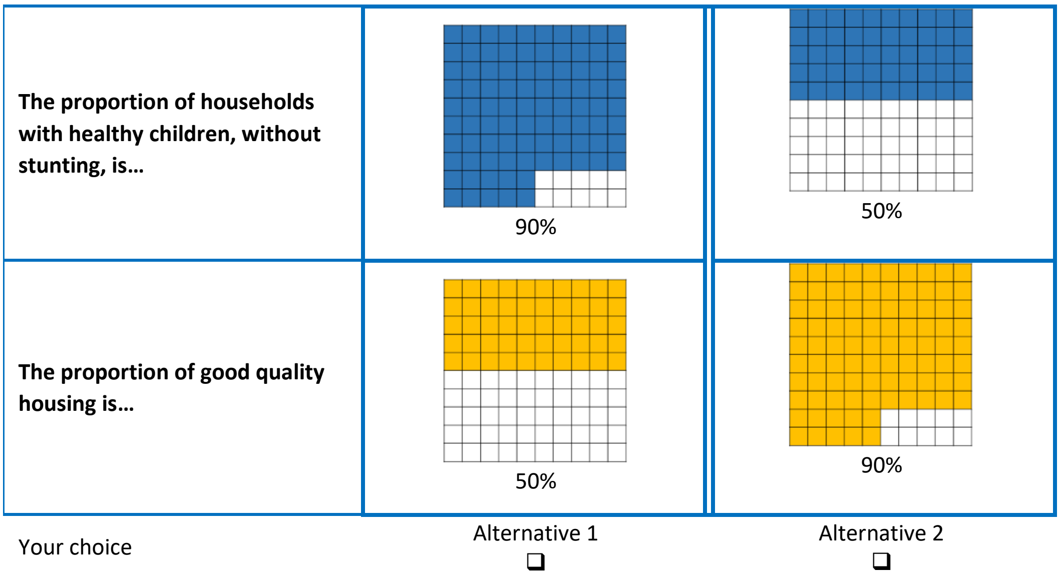


Figure 5.3 *Example of choice sets presented to Pilot 2 – second arm respondents, attribute descriptions presented in a positive language.*

Participants' opinions were similar to the first arm in terms of clarity and helpfulness of visual aids (Figure S2). However, upon comparing the DCE model results across all four groups, it was determined that the layout presented to Group C was the most suitable for the final DCE design. This is because the model for Group C presented the lowest AIC value, with four out of five coefficients being statistically significant (p-value <0.05) and having a negative sign as theoretically expected.

5.2.4 Study Sample

The sample size of the main survey was determined following the minimum required sample size calculation outlined in De Bekker-Grob et al. (2015), based on a MNL model with a significance level α= 0.05, standard statistical power level β= 0.20, the coefficients from Pilot 2, Group C as priors, and the DCE design matrix. Table 5.2 shows the required sample size for the main survey which ranges form 4-40 for the bad-level (level 3) variables and 78-2518 for the mid-level (level 2) variables, with the good-level (level 1) as the reference. We decided to use a sample of 250 participants. This sample size was chosen to allow for the identification of the level 3 coefficients of the regression model relative to level 1 (β_2, β_4 and β_6) (Table 3) and enable the conduct of subgroup analyses (e.g. forest user, good nutrition, good housing) which would require a sample size of 5-340 for bad-level variables for each subgroup. While a larger sample size would have provided greater statistical power for all analyses, this study was designed as a small-scale survey to provide preliminary estimates for use as prior information in future, larger-scale studies. Given the resources available, a sample size of 250 represented a reasonable balance between statistical considerations and the exploratory nature of this research.

Table 5.2 *Minimum sample size required to obtain power level 1-β =0.80 and confidence level 1-α=0.95, based on pilot priors.*

Analysis level	*Coefficients*						*Num. of obs.**
	β_1	β_2	β_3	β_4	β_5	β_6	
Main	1107. 8	6.0	78.4	4.0	2518.5	40.4	459
Subgroups							
Forest user	112.1	10. 9	44.0	5.4	106.5	22.0	207
Non forest user	2340.3	4.75	123.9	8.4	1167.1	340.5	252
Good nutrition	3276.2	4.8	74.8	5.6	388.1	146.0	297
Poor nutrition	340.5	12.7	148.5	7.8	57.2	31.6	162
Good housing	1029.2	6.1	107.5	6.8	5134.0	56.3	441
Poor housing	2.4×10^{31}	1.4×10^{9}	6.6×10^{8}	1.0×10^{8}	7.1×10^{11}	1.8×10^{9}	18

**Number of observations in Pilot 2, group C.*

Participants recruited from the Offerwise panel completed an online survey. This method was selected due to its practicalities in terms of time and cost, even though the panel members are mainly concentrated in urban areas and from the Peruvian capital, Lima. A random sample of adult participants (18 years or older) across a range of socioeconomic status, and with internet access was invited by Offerwise via email. The invitation included a URL link to the questionnaire hosted in Qualtrics and participants were rewarded with points in the Offerwise system.

5.2.5 Ethical approval

The study was reviewed and approved by: 1) the Research Ethics Committee at the School of Health and Related Research via the University of Sheffield Ethics Review Procedure (application reference number: 045051), and 2) the Comité Institucional de Ética en Investigación at the Universidad Peruana Cayetano Heredia (registration code: 210060). See *S3* for reference.

5.3 Results

Data collection took place in August 2023, from the 254 individuals who accessed the questionnaire, 250 (98.4%) were selected for analysis, as indicated in Table S2. The remaining four individuals were excluded due to them not completing the survey. On average, respondents spent 664.6 seconds with a median of 488.5 seconds to complete the whole survey (including the informed consent form). Respondents were mostly 30-39 years old, ~51% were women, ~79% were highly educated, and ~64% had childcare responsibilities (Table S2). Moreover, ~43% visit a natural area frequently, ~64% had no problem feeding their family during the past month, ~43% had enough quantity & quality of food to feed their family, and ~67% has good housing conditions (Table S3). The socio-economic characteristics of the sample, including education level, household size, and childcare responsibilities, were collected to assess the sample's representativeness of the national population and ensure that the results can be generalized to the broader Peruvian context.

Table 5.3 *Observed vs predicted probabilities of Alternative 1 being chose per choice set.*

Choice set	***Num. of obs. choosing Alternative 1***	**Probabilities***	
		Observed	*Predicted*
1	102	0.408	0.394
2	68	0.272	0.258
3	154	0.616	0.601
4	118	0.472	0.460
5	186	0.744	0.266
6	57	0.228	0.224
7	172	0.688	0.324
8	170	0.680	0.677
9	127	0.508	0.503

* Observed probability: actual frequency in the data. Predicted probability: value predicted from the regression model.

Table 5.3 shows the distribution of responses choosing Alternative 1 across the nine choice sets, which ranges from 23% to 74%. In correspondence, Alternative 2 ranges from 77% to 26%. Table 5.4 presents the results of the multinomial logit model; p-values are with respect to the good levels of the attribute. All six coefficients had a negative sign, consistently with our a priori hypothesis that respondents will favour the best level of attributes over worst levels and thus theoretical validity. When compared to the good level, out of the six coefficients, four (forest_bad, food_mid, food_bad and housing_bad) were found to have significant effect on respondents' decisions. Moreover, since the mid-level of attributes presented smaller decrements compared to the bad-levels, respondents preferred a "mid" level to a "bad" level of attributes, but with the exception of nutrition (food_mid), they are not significantly different from the good-level. It is important to notice that the study sample is below the minimum size required for the estimation of forest and housing quality mid coefficients (Table 5.2); however, the probabilities of choosing Alternative 1 predicted from the regression results (Table 5.3) are well aligned with the observed proportion of those actually choosing Alternative 1 in seven out of nine choice sets.

Table 5.4 *Results from the Multinomial logit model.*

	Coefficient	***SE***	***p-value***
Forest_mid (β_1)	-0.015	0.072	0.419
Forest_bad (β_2)	-0.857	0.068	0.000

Food_mid (β_3)	-0.127	0.074	0.044
Food_bad (β_4)	-0.503	0.066	0.000
Housing_mid (β_5)	-0.071	0.072	0.164
Housing_bad (β_6)	-0.344	0.066	0.000
Number of individuals		*250*	
Number of observations		*2250*	

As Forest_bad presented the largest effect, this coefficient was used to standardise the other coefficients and analyse their relative value (Table 5.5). If the difference between good and bad forest is set at the value of 1, then the difference between good and bad food security is 0.59 and between good and bad housing is 0.40. The numbers show that, within an attribute, going from good to mid-level has a much smaller impact than going from mid-level to bad-level, although the descriptive differences between the levels (good-mid; mid-bad) are the same (e.g. 40 percentage point differences between forest levels and 20 percentage point differences for food security and housing quality). The relative impact of going from good-level to mid-level, and from good-level to bad-level are larger for nutrition than housing, given that they are both 20 percentage points apart, from 90% to 70% (good to mid level) and 70% to 50% (mid to bad level).

Table 5.5 *Value of different attribute levels relative to bad forest cover (β_x/ β_2).*

	Standardised Coeff.	***SE***	***p-value***
Forest_mid (β_1 / β_2)	0.017	0.075	0.409
Forest_bad (β_2 / β_2)- reference	**1.000**	**0.000**	
Food_mid (β_3 / β_2)	0.148	0.085	0.041
Food_bad (β_4 / β_2)	0.587	0.093	0.000
Housing_mid (β_5 / β_2)	0.082	0.069	0.115
Housing_bad (β_6 / β_2)	0.401	0.070	0.000

To test the impact of selected household characteristics (respondents' own forest use, food security and housing quality) this study ran three separate models. Each model interacted the main effects with one of three dummy variables: forest_user (for visiting a forest/nature area often), good_nutrition (for living in a household with a good food security), or good_housing (for living in a good quality house), to examine if these variables can have an effect on respondents' preferences. As with the main analysis, the coefficients were standardised using forest_bad as reference level, and found different preferences between the models (Table 5.6). A significant standardised interaction term means that the variable has an additional effect on the preferences of the relevant subgroup: in our case, forest use and housing quality have no effect on respondents' preferences but nutrition does. Interestingly, at a significance level of 5%, the effect of having good nutrition is not on food security but on forest attributes. That is, on a scale where the gap between good and bad forest as valued by those with bad nutrition is set at 1.00, those with good nutrition value the gap between good and bad forest at 1.00 + 0.766 = 1.766. At a significance level of 10%, good nutrition has also an effect on food security. In other words, on a scale where the gap between good and bad forest as valued by those with bad nutrition is set at 1.00: (a) those with bad nutrition value the gap between good and bad nutrition at 0.615, and (b) those with good nutrition value the gap between good and bad nutrition at 0.615 + 0.413 = 1.029. Moreover, it is important to notice that in the study sample, there are only 14 individuals (or 6% of the sample) with poor housing, for which chances of being able to estimate significant main effects parameters with this model is extremely small.

Additionally, an exploratory subgroup analysis was run to the study to test the effect of bad relative to good/mid-level of attributes. The good and mid-levels of the DCE were merged in the regression analysis. Table 5.7 shows that the results are qualitatively no different from those reported in Table 5.6 so that relative to the difference between good/mid forest and bad forest, set to 1.00 by those with bad nutrition, those with good nutrition value the difference between the good/mid and bad levels of forest and food at 1.617 and 1.413 respectively. The other interaction terms across the subgroups were non-significant.

Table 5.6 *Subgroup effect on the value of attribute levels relative to bad forest cover (β_x / β_2).*

	Forest User			***Good nutrition***			***Good housing***		
	Coeff.	*SE*	*p-value*	*Coeff.*	*SE*	*p-value*	*Coeff.*	*SE*	*p-value*
Forest_mid (β_1 / β_2)	-0.035	0.117	0.386	-0.024	0.179	0.448	0.192	0.346	0.291
Forest_bad (β_2 / β_2)- ***reference***	**1.000**	**0.000**	-	**1.000**	**0.000**	-	**1.000**	**0.000**	-
Food_mid (β_3 / β_2)	0.168	0.129	0.097	0.278	0.211	0.093	-0.061	0.302	0.421
Food_bad (β_4 / β_2)	0.704	0.152	0.000	0.615	0.206	0.001	0.3606	0.312	0.123
Housing_mid (β_5 / β_2)	0.114	0.104	0.136	0.140	0.152	0.176	0.283	0.283	0.159
Housing_bad (β_6 / β_2)	0.483	0.103	0.000	0.539	0.154	0.000	0.520	0.294	0.038
Forest_mid*X (β_7 / β_2)	0.124	0.175	0.239	0.085	0.230	0.356	-0.186	0.353	0.298
Forest_bad*X (β_8 / β_2)	0.282	0.286	0.161	0.766	0.451	0.045	-0.094	0.307	0.378
Food_mid*X (β_9 / β_2)	-0.005	0.179	0.488	-0.103	0.241	0.334	0.207	0.333	0.268
Food_bad*X (β_{10} / β_2)	-0.105	0.184	0.284	0.413	0.276	0.068	0.185	0.370	0.309
Housing_mid*X(β_{11} / β_2)	-0.050	0.156	0.375	-0.044	0.199	0.413	-0.221	0.290	0.224
Housing_bad*X (β_{12} / β_2)	-0.076	0.162	0.319	0.059	0.207	0.390	0.309	0.309	0.298
Num. of ind. in X group		*108*			*149*			*236*	
Num. of total individuals		*250*			*250*			*250*	
Num. of observations		*2250*			*2250*			*2250*	

X=forest user, good nutrition or good housing as indicated in the heading.

Table 5.7 *Value of bad relative to good/mid-level of attributes, according to the subgroups (β_x / β_1).*

	Forest User			***Good nutrition***			***Good housing***		
	Coeff.	*SE*	*p-value*	*Coeff.*	*SE*	*p-value*	*Coeff.*	*SE*	*p-value*
Forest_bad (β_1 / β_1)- ***reference***	**1.000**	**0.000**		**1.000**	**0.000**		**1.000**	**0.000**	
Food_bad (β_2 / β_1)	0.611	0.108	0.000	0.479	0.147	0.001	0.512	0.347	0.069
Housing_bad (β_3 / β_1)	0.390	0.073	0.000	0.417	0.105	0.000	0.415	0.240	0.042
Forest_bad*X (β_4 / β_1)	0.203	0.227	0.187	0.617	0.333	0.032	0.043	0.395	0.456
Food_bad*X (β_5 / β_1)	-0.089	0.162	0.291	0.413	0.242	0.045	0.038	0.356	0.456
Housing_bad*X (β_6 / β_1)	-0.045	0.129	0.363	0.073	0.163	0.326	0.268	0.268	0.405
Num. of ind. in X group		*108*			*149*			*236*	
Num. of individuals		*250*			*250*			*250*	
Num. of observations		*2250*			*2250*			*2250*	

X=forest user, good nutrition or good housing, as indicated in the heading.

5.4 Discussion

The aim of this study was to conduct a small sample DCE, to elicit social preferences that individuals as citizens hold related to policies for forest conservation and two aspects of multidimensional poverty: food security and housing quality. A sample consisting of 250 members of the Peruvian public, largely representative in terms of age and gender, completed an online DCE survey. The DCE presented two alternatives at a time describing scenarios in terms of hypothetical policy outcomes, and asked respondents to indicate which they thought policy makers should bring about.

DCE results indicate that good levels of forest cover, nutrition and housing quality are preferred over bad levels, which agrees with our hypothesis that people will prefer better levels of the attributes to worst and it was expected. When comparing the relative value of the attributes, the impact of a bad level of food security is higher than a bad level of housing on respondent's choices. That is, if respondents are to choose between two alternatives where only nutrition and housing attributes differ, they will avoid choosing the alternative presenting a bad nutrition level even if that means choosing an alternative that shows a bad level of housing quality (i.e. 50% of houses are of good quality). Moreover, the benefit of going from bad to good forest cover is comparable to the benefit of going from bad to good nutrition, alongside bad to good housing quality, and the difference between the first is of 80 percentage points while the difference between the latter is of 40 percentage points. That is if a policy maker have to make a choice between improving forest or improving food security and housing quality together, it would be right to choose forest over the other two. Likewise, among the mid-levels, nutrition is the most important and only mid-level coefficient that is significantly different from the corresponding good-level baseline.

Additionally, the sample was divided in three different ways, according to three main characteristics (forest use, food security and housing quality) to run exploratory analyses on whether or not these characteristics can have an effect on respondents' preferences. Interestingly we found that at a significant level of 5%, only the interaction between nutrition and bad forest level showed an effect on respondent's choices. Respondents living in households with better food security regarded the difference between good and bad forest (at 5%) and between good and bad nutrition (at 10%) to be wider than those living in households with poor food security. There were no significant interaction terms in the other subgroupings. The subgroup analysis was repeated by merging the good-to-mid levels, which made no qualitative difference to the results.

This study have several limitations. First, it is worth acknowledging that the results reflect the preferences of a small sample of the Peruvian population with internet access, a competent level of

Spanish literacy and enrolled in the agency panel. Second, in terms of the subgroup analysis, our sample had very few respondents living in poor housing conditions, so the results of the subgroup analysis should not be taken to mean that housing status does not affect preferences. Third, the research team assigned the attribute levels; these selected levels may differ from the public understanding of deprivation, especially for food security and housing quality attributes, i.e. a respondent may live in communities where stunting proportion is higher and they may perceive it as normal, or 50% of poor housing quality may be acceptable for a respondent. Furthermore, we acknowledge that the 'regular biodiversity' label used for the 50% forest cover level represents a simplification of the complex relationship between forest cover and biodiversity, which may have understated the potential for biodiversity loss associated with reduced forest cover. Similarly, our simplified definitions of food security, nutrition, and stunting, may not fully capture the nuances of these concepts, potentially influencing how respondents weighed these attributes in their choices. Fourth, neither the choice design or the data analysis consider interactions between attributes but respondents may have considered them in their preferences (i.e. people may value forest conservation as important but if neighbouring people are in poor nutrition then forest may be even more important, unless they live in poor conditions). To capture these interactions between DCE attributes a much larger sample is needed. Given that, the sample size was determined by budget and time constraints, and to do what was feasible in those conditions, a main effects model and interactions with respondent characteristics was estimated.

To our knowledge is the first study that uses a DCE to elicit people's social preferences towards forest conservation and poverty alleviation. The respondents felt comfortable answering the questionnaire, understood the concept and were interested in the findings. In addition, in a preliminary manner, these results could be use as prior information for larger scale studies about social values in conservation management and development of policies. Moreover, this DCE analyses the effect of individual household benefits (food security and housing quality) and a public good (forest). The influence of forest on people's livelihoods is well supported since they provide them with food resources and housing materials, however, there was no evidence on how forest, food security and housing can influence people's preferences. Understanding how people as citizens value private benefits alongside public goods, especially in outcomes that influence each other, could benefit local communities and provide resilient solutions by incorporating local preferences and choices (LaRiviere et al., 2014), as well as maximising the effectiveness of resource allocation, transparency and accountability (Melamed, Devlin & Appleby, 2012).

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5.6 Supplementary Information

S1 Full study questionnaire

Encuesta al público en general sobre bosque y medios de vida

Usted ha sido invitado a participar en un proyecto de investigación. Antes de decidir si participa o no, es importante que entienda por qué se realiza la investigación y en qué consistirá. Tómese su tiempo para leer detenidamente la siguiente información y coméntela con otras personas si lo desea. Pregúntenos si hay algo que no esté claro o si desea más información. Tómese su tiempo para decidir si desea participar o no. Gracias por leer esto.

Hoja de información del participante

¿Cuál es el propósito del proyecto?

El propósito del estudio es averiguar cómo la gente valora la conservación de los bosques en relación con algunos aspectos de pobreza. Una mejor comprensión de las preferencias de las personas ayudará, a los gobiernos locales y a las organizaciones donantes, a tomar decisiones en políticas públicas más adecuadas. Esto es parte de un proyecto de investigación doctoral más amplio.

¿Por qué he sido elegido?

Recibió una invitación para participar en el proyecto porque ha aceptado participar en encuestas en línea, es mayor de 18 años y habla español.

¿Tengo que participar?

Es su decisión; si decide participar, pasará a desarrollar un cuestionario. Usted podrá retirarse en cualquier momento sin ninguna consecuencia negativa. No tiene que dar una razón para retirarse. Cualquier información que haya proporcionado hasta ese momento será eliminada.

¿Qué ocurrirá si participo? ¿Qué tengo que hacer?

Se le pedirá completar un cuestionario en línea donde elegirá entre pares de escenarios posibles. La duración del cuestionario es de aproximadamente 15 minutos, y no se registrará ningún dato personal. No hay respuestas correctas o incorrectas: simplemente buscamos su opinión. Sólo se le pedirá que participe una vez.

¿Cuáles son los beneficios de participar?

Aunque no hay beneficios inmediatos para las personas que participan en el proyecto, se espera que este trabajo contribuya a la investigación y ayude a los tomadores de decisiones a comprender mejor las preferencias de los ciudadanos.

¿Mi participación en este proyecto se mantendrá en privado?

Toda la información que recopilamos sobre usted durante la investigación se mantendrá estrictamente confidencial y anónima. No se le identificará en ningún informe o publicación.

¿Cuál es la base legal para procesar mis datos personales?

El tratamiento de sus datos personales sigue los lineamientos del Reglamento de protección de datos de la Unión Europea (GPDR-eu) y la legislación sobre protección de datos de Reino Unido y Perú. De acuerdo con esta legislación, debemos informarle que la justificación legal para el procesamiento de sus datos personales es que "el tratamiento (de datos) es necesario para realizar una tarea de interés público" (Artículo 6 (1) (e)). Puede encontrar mayor información en el Aviso de privacidad de la Universidad de Sheffield: https://www.sheffield.ac.uk/govern/data-protection/privacy/general

¿Qué pasará con los datos recogidos y los resultados del proyecto de investigación?

La base de datos se almacenará en servidores virtuales centralizados en la Universidad de Sheffield durante los diez años siguientes a la finalización del proyecto. Estos datos anonimizados podrán utilizarse para investigaciones y análisis adicionales o posteriores. Le pedimos consentimiento explícito para compartir sus datos de este modo.

¿Quién organiza y financia la investigación?

El estudio es financiado por el Centro Grantham para Futuros Sostenibles de la Universidad de Sheffield (Reino Unido) como parte de un proyecto de doctorado de Caterina Cosmópolis.

¿Quién es el Controlador de datos?

La Universidad de Sheffield actuará como controlador de datos para este estudio; esto significa que, la Universidad es responsable de cuidar su información y hacer un uso adecuado de la misma.

¿La ética del proyecto ha sido revisada?

Este proyecto ha sido aprobado por el Procedimiento de revisión ética de la Universidad de Sheffield, administrado por la Escuela de Salud e Investigaciones Relacionadas (ScHARR, por sus siglas en inglés) y el Comité Institucional de Ética en Investigación (CIEI) de la Universidad Peruana Cayetano Heredia.

¿Qué sucede si algo sale mal y deseo presentar una queja sobre la investigación?

Si desea presentar una queja sobre cualquier aspecto del estudio debe comunicarse con el supervisor del proyecto de doctorado, Profesor Aki Tsuchiya (a.tsuchiya@sheffield.ac.uk). Si cree que su queja no se ha manejado a su satisfacción, puede comunicarse con Profesor Mark Strong, Decano de ScHARR (m.strong@sheffield.ac.uk). Si su queja se relaciona con la forma en que se han manejado los datos personales de los participantes, puede comunicarse con el Oficial de Protección de Datos de la Universidad de Sheffield dataprotection@sheffield.ac.uk.

Puede encontrar información adicional sobre cómo presentar una queja en el Aviso de Privacidad de la Universidad:https://www.sheffield.ac.uk/govern/data-protection/privacy/general. Si cree que su queja no se ha manejado satisfactoriamente, puede comunicarse con la Oficina del Comisionado de Información.

Contacto para información adicional

Para cualquier otro problema, comuníquese con Armando Valdés-Velásquez (armando.valdes@upch.pe, teléfonos: +51 319 0000, +51 913 714099).

Si tiene alguna pregunta sobre sus derechos como participante en el Perú, por favor contactarse con el Presidente del Comité Institucional de Ética en Investigación (CIEI) de la Universidad Peruana Cayetano Heredia al teléfono -51 319 0005, anexo 2271.

<u>Consentimiento</u>

Si desea participar en el proyecto, haga clic en todas las opciones con las que esté de acuerdo:

- ❑ He leído y comprendido el texto anterior, o se me ha explicado detalladamente el proyecto, y se me ha dado la oportunidad de hacer preguntas sobre el mismo.

- ❑ Entiendo que mi participación es voluntaria y que puedo retirarme del estudio en cualquier momento. No tengo que ninguna razón por la que ya no deseo participar y no habrá consecuencias negativas si decido retirarme.

- ❑ Entiendo que, al elegir participar en el proyecto como voluntario en esta investigación, no se crea un acuerdo legalmente vinculante ni se pretende crear una relación laboral con la Universidad de Sheffield o la Universidad Peruana Cayetano Heredia.

Acerca de cómo se utilizará su información durante y después del proyecto, haga clic en todas las opciones con las que esté de acuerdo:

- ❑ Entiendo que mis datos personales, como el nombre y la dirección de correo electrónico, no se revelarán a personas ajenas al proyecto.

- ❑ Acepto ceder los derechos de autor que poseo sobre cualquier material generado como parte de este proyecto de la Universidad de Sheffield.

Al completar este formulario, confirmo que tengo más de 18 años y que hablo español. *Nota: Si la respuesta es "No", no podrá continuar con el cuestionario.*

- ❑ Si

- ❑ No

<u>Presentación del caso</u>

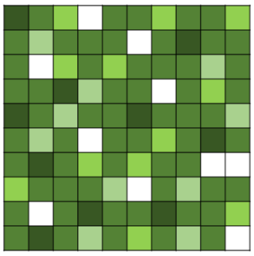
Los bosques albergan parte de la biodiversidad más importante de nuestro planeta y nos brindan muchos beneficios incluidos: alimentos, combustible, madera y fibra, aire limpio, agua dulce, polinización, control de inundaciones y la erosión, entre otros. Son importantes para la recreación, el turismo, la educación y tienen un valor cultural para las muchas personas que viven dentro y/o cerca de sus límites. Los bosques también nos ayudan a combatir la crisis del cambio climático y mejorar nuestra salud mental y física.

El cambio climático afecta la salud humana debido al empeoramiento de la calidad del aire y el agua, el aumento de la propagación de ciertas enfermedades y la alteración de la frecuencia o intensidad de los fenómenos meteorológicos extremos. También afecta la seguridad alimentaria, al aumentar la frecuencia y la gravedad de los desastres naturales llevando a más personas al hambre y la pobreza. Las personas que viven en pobreza pueden experimentar múltiples desventajas al mismo tiempo, por ejemplo: mala salud o desnutrición, falta de agua potable o electricidad, mala calidad de la vivienda o bajo nivel educativo. Los formuladores de políticas intentan encontrar soluciones para mejorar la vida de las personas y proteger los recursos para el futuro, pero esto requiere una planificación y gestión a largo plazo.

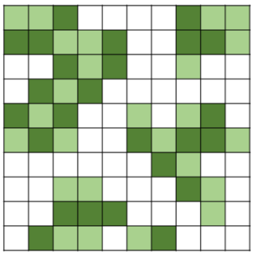
En la presente encuesta, le pedimos que se imagine que es un formulador de políticas que busca destinar cierta cantidad de dinero para mejorar los medios de vida locales. Sin embargo, dependiendo de las actividades implementadas, se pueden obtener diferentes resultados. Por ejemplo, una política (plan, proyecto y/o actividad) podría ayudar a las personas a obtener mejores condiciones de vivienda, pero empeorar la calidad del bosque en su entorno.

Nos gustaría que pensara cómo deberían decidir los formuladores de políticas en materia de cobertura forestal, seguridad alimentaria y calidad de vivienda. Cada uno de estos se explica con más detalle a continuación:

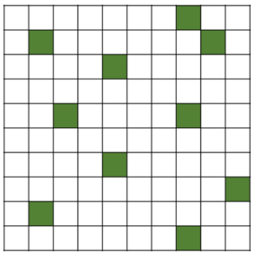
- ❑ **Cobertura forestal**: se trata de la capacidad del bosque para proporcionar recursos para la supervivencia de animales, plantas y seres humanos. Cuanto más grande sea la cobertura boscosa, más recursos podrá proporcionar. La cobertura forestal se expresará en términos de cobertura boscosa, biodiversidad (número de animales y plantas) y paisaje, en tres niveles:



90% cobertura boscosa
Alta biodiversidad
Bosques bien conservados

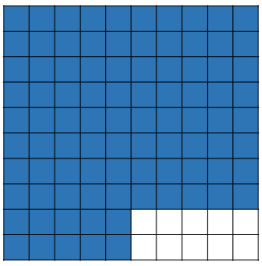


50% cobertura boscosa
Biodiversidad regular
Mezcla de bosques y tierras agrícolas

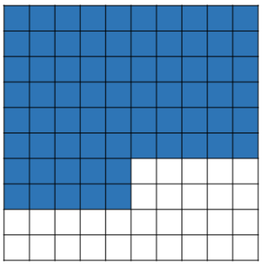


10% cobertura boscosa
Baja biodiversidad
Tierras agrícolas con algunos árboles dispersos

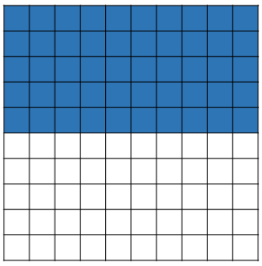
- **Seguridad alimentaria**: se refiere a si una persona tiene suficientes alimentos para consumir una dieta balanceada y cubrir sus necesidades nutricionales para una vida activa y saludable. Un signo de un niño que no recibe una nutrición adecuada o acceso a suficientes alimentos es el retraso en el crecimiento. La seguridad alimentaria se expresará en términos del porcentaje de hogares con niños sanos, sin retraso en el crecimiento, en tres niveles:



90% de los hogares tiene niños sanos, sin retraso en el crecimiento

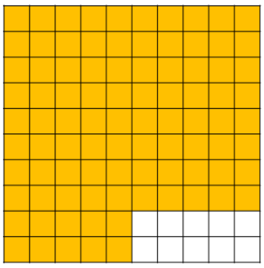


70% de los hogares tiene niños sanos, sin retraso en el crecimiento

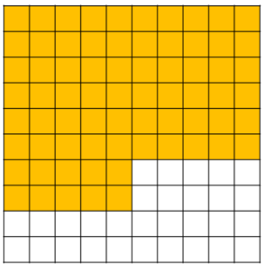


50% de los hogares tiene niños sanos, sin retraso en el crecimiento

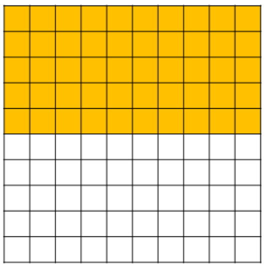
- **Calidad de vivienda**: depende de si una casa tiene las siguientes características, a) las paredes, piso o techo están construidos con materiales apropiados al clima de la región (ladrillo, piedra o madera), b) tiene acceso a agua potable y servicios sanitarios (inodoro, letrina o inodoro de compostaje), y c) tiene instalaciones razonables para cocinar y usa gas o electricidad para cocinar los alimentos. A una vivienda de buena calidad presenta todas esas características. La calidad de vivienda se expresará en términos del porcentaje de viviendas de buena calidad en una zona, en tres niveles:



90% de las viviendas es de buena calidad



70% de las viviendas es de buena calidad



50% de las viviendas es de buena calidad

A continuación, se presentan 9 situaciones, donde tendrá que elegir entre dos alternativas imaginarias. Cada alternativa describe el resultado de una política.

Lea atentamente la descripción de la situación y cada alternativa. Recuerde, no hay respuestas correctas o incorrectas, simplemente buscamos su punto de vista.

Situación 1

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	90% cobertura boscosa Alta biodiversidad Bosques bien conservados	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	50%	70%
La proporción de viviendas de buena calidad es...	70%	90%
Tu selección:	❑	❑

Situación 2

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	10% cobertura boscosa Baja biodiversidad	90% cobertura boscosa Alta biodiversidad Bosques bien conservados

	Tierras agrícolas con algunos árboles dispersos	
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	70%	90%
La proporción de viviendas de buena calidad es...	70%	90%
Tu selección:	❑	❑

Situación 3

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas	10% cobertura boscosa Baja biodiversidad Tierras agrícolas con algunos árboles dispersos
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	50%	90%
La proporción de viviendas de buena calidad es...	90%	70%
Tu selección:	❑	❑

Situación 4

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas	90% cobertura boscosa Alta biodiversidad Bosques bien conservados
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	90%	70%
La proporción de viviendas de buena calidad es...	50%	70%
Tu selección:	❑	❑

Situación 5

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	90% cobertura boscosa Alta biodiversidad Bosques bien conservados	10% cobertura boscosa Baja biodiversidad Tierras agrícolas con algunos árboles dispersos

La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	90%	50%
La proporción de viviendas de buena calidad es...	50%	90%
Tu selección:	❑	❑

Situación 6

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	10% cobertura boscosa Baja biodiversidad Tierras agrícolas con algunos árboles dispersos	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	70%	90%
La proporción de viviendas de buena calidad es...	50%	70%
Tu selección:	❑	❑

Situación 7

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	90% cobertura boscosa Alta biodiversidad Bosques bien conservados	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	70%	50%
La proporción de viviendas de buena calidad es...	90%	50%
Tu selección:	❑	❑

Situación 8

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	50% cobertura boscosa Biodiversidad regular Mezcla de bosques y tierras agrícolas	10% cobertura boscosa Baja biodiversidad Tierras agrícolas con algunos árboles dispersos
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	50%	70%

La proporción de viviendas de buena calidad es...	70%	50%
Tu selección:	❑	❑

Situación 9

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	10% cobertura boscosa Baja biodiversidad Tierras agrícolas con algunos árboles dispersos	90% cobertura boscosa Alta biodiversidad Bosques bien conservados
La proporción de hogares con niños sanos, sin retraso en el crecimiento es...	90%	50%
La proporción de viviendas de buena calidad es...	90%	50%
Tu selección:	❑	❑

<u>En la siguiente sección se le harán algunas preguntas adicionales</u>:

Acerca de su hogar...

¿Con qué frecuencia visita un área natural, ya sea con fines recreativos y/o para buscar recursos forestales?

- ❑ Nunca

- ❑ Rara vez
- ❑ A veces
- ❑ Muy seguido
- ❑ Siempre

En las últimas cuatro semanas, ¿se ha quedado sin dinero y le ha costado que toda la familia se alimente 3 veces al día?

- ❑ Si
- ❑ No

¿Cuál de estas frases describe mejor la alimentación en su hogar?

- ❑ Suficiente cantidad y variedad de alimentos para toda la familia, y de buena calidad y valor nutritivo que quiero/queremos comer.
- ❑ A menudo no hay suficiente para que toda la familia pueda comer.
- ❑ A veces no hay suficiente para que toda la familia pueda comer.
- ❑ Suficiente cantidad para toda la familia, pero no siempre el tipo de alimentos nutritivos y de buena calidad que quiero/queremos comer.

Su hogar tiene___________ de calidad ____________.

	Buena	Regular	Mala
Piso, paredes y techo de materiales adecuados al clima (ladrillo, piedra, madera)	❑	❑	❑
Acceso a agua potable	❑	❑	❑
Acceso a saneamiento mejorado (inodoro, letrina o inodoro de compostaje)	❑	❑	❑
Un espacio para cocinar y usa gas o electricidad para cocinar	❑	❑	❑

Acerca del cambio climático...

¿Qué tan informado considera que está de los efectos del cambio climático en su comunidad/país?

- ❑ Muy desinformado
- ❑ Desinformado
- ❑ Ni desinformado ni informado
- ❑ Informado
- ❑ Muy informado

¿Qué tan informado está de las políticas de su país para responder al cambio climático?

- ❑ Muy desinformado
- ❑ Desinformado
- ❑ Ni desinformado ni informado
- ❑ Informado
- ❑ Muy informado

¿Qué tan preocupado está por los efectos del cambio climático en su comunidad/país?

- ❑ Muy despreocupado
- ❑ Despreocupado
- ❑ Ni preocupado ni despreocupado
- ❑ Preocupado
- ❑ Muy preocupado

¿Qué tan de acuerdo está con la siguiente declaración?

"Mis respuestas a los escenarios de cobertura forestal, seguridad alimentaria y vivienda serían diferentes si me afectara el cambio climático."

- ❑ Totalmente de acuerdo
- ❑ En desacuerdo
- ❑ Neutral
- ❑ De acuerdo
- ❑ Totalmente de acuerdo

Preguntas adicionales sobre usted:

¿En qué región vive? _______________

Seleccione el nivel de educación más alto que haya alcanzado:

- ❑ Sin educación formal
- ❑ Educación primaria
- ❑ Educación secundaria
- ❑ Educación técnica o universitaria

¿Cuántas personas hay en su hogar, incluido usted mismo? ______________

¿Tiene hijos de 0 a 17 años a su cargo? Si/No

¿Cuál es su género?

- ❑ Masculino
- ❑ Femenino
- ❑ Otro, especifique si lo desea por favor ___________
- ❑ Prefiero no contestar

Indique su edad:

- ❑ 18-29
- ❑ 30-39

- ❑ 40-49
- ❑ 50-59
- ❑ 60-69
- ❑ 70+

Encuesta al público en general sobre bosque y medios de vida

Usted ha sido invitado a participar en un proyecto de investigación. Antes de decidir si participará o no, es importante que comprenda por qué se realiza la investigación y en qué consiste. Por favor, tómese un tiempo para leer detenidamente la siguiente información, puede consultar al entrevistador si hay algo que no le quede claro o si desea más información. Tómese un tiempo para decidir si desea participar o no. Gracias por leer.

<u>Hoja de información del participante</u>

¿Cuál es el propósito del proyecto?

El propósito del estudio es averiguar cómo la gente valora la conservación de los bosques en relación con algunos aspectos de pobreza. Una mejor comprensión de las preferencias de las personas ayudará, a los gobiernos locales y a las organizaciones donantes, a tomar decisiones en políticas públicas más adecuadas. Este es parte de un proyecto de investigación doctoral más amplio.

¿Por qué he sido elegido?

Recibió una invitación para participar en el proyecto porque ha aceptado participar en encuestas en línea, es mayor de 18 años y el español es su idioma materno. En este estudio piloto, se invitará a un máximo de 20 participantes.

¿Tengo que participar?

Depende de usted decidir si desea participar o no; si decide participar, pasará a desarrollar un cuestionario y/o una entrevista. Usted podrá retirarse en cualquier momento sin ninguna consecuencia negativa. No tiene que dar una razón para retirarse. Cualquier información que haya proporcionado hasta ese momento será eliminada.

¿En qué consiste mi participación? ¿Qué tengo que hacer?

Su participación consiste en completar un cuestionario en línea donde elegirá entre pares de escenarios posibles y/o una entrevista. Luego, se le harán algunas preguntas abiertas sobre el diseño y la redacción del cuestionario. No hay respuestas correctas o incorrectas, simplemente buscamos su punto de vista. Solo se le pedirá que participe una vez.

¿Seré grabado y cómo se usarán los medios grabados?

Solo las entrevistas se grabarán ya sea en audio (en persona) o en video (en línea, Google Meet). Las grabaciones se mantendrán en un lugar seguro y no se hará ningún otro uso adicional de ellos, sin pedir su permiso por escrito. Las respuestas al cuestionario son totalmente anónimas.

¿Cuáles son las posibles desventajas y riesgos de participar?

Algunos participantes pueden sentirse incómodos cuando se les pregunta sobre sus preferencias. Sin embargo, investigaciones previas en esta área han demostrado que los participantes generalmente están interesados y comprometidos cuando participan en este tipo de ejercicios. Recuerde que es libre de retirarse de participar en cualquier momento sin necesidad de justificación.

¿Cuáles son los beneficios de participar?

Aunque no hay beneficios inmediatos para las personas que participan en el proyecto, se espera que este trabajo contribuya a la investigación y ayude a los tomadores de decisiones a comprender mejor las preferencias de los miembros del público.

¿Mi participación en este proyecto se mantendrá en privado?

Toda la información que recopilamos sobre usted durante la investigación se mantendrá estrictamente confidencial y solo será accesible para los miembros del equipo de investigación. No se le identificará en ningún informe o publicación.

¿Cuál es la base legal para procesar mis datos personales?

De acuerdo con la legislación de protección de datos, estamos obligados a informarle que la base legal aplicada para procesar sus datos personales es la de que "el procesamiento es necesario para realizar una tarea de interés público" (Artículo 6 (1) (e)). Puede encontrar más información en el Aviso de privacidad de la Universidad de Sheffield https://www.sheffield.ac.uk/govern/data-protection/privacy/general.

¿Qué pasará con los datos recopilados y los resultados del proyecto de investigación?

En el caso de las entrevistas, los datos de contacto (nombre y dirección de correo electrónico) y la grabación se almacenarán en una carpeta de acceso restringido en el servidor de la Universidad de Sheffield. La información de contacto y las grabaciones se destruirán al finalizar el estudio piloto. Otros datos (como las notas tomadas durante la entrevista) se eliminarán 4 meses después de terminar el piloto. Las respuestas al cuestionario son totalmente anónimas. Los resultados de esta encuesta piloto se utilizarán para hacer que el cuestionario sea más legible y comprensible para la próxima etapa del proyecto.

¿Quién organiza y financia la investigación?

El estudio es financiado por el Centro Grantham para Futuros Sostenibles de la Universidad de Sheffield (Inglaterra) como parte de un proyecto de doctorado de Caterina Cosmopolis.

¿Quién es el Controlador de datos?

La Universidad de Sheffield actuará como controlador de datos para este estudio; esto significa que, la Universidad es responsable de cuidar su información y hacer un uso adecuado de la misma.

¿La ética del proyecto ha sido revisada?

Este proyecto ha sido aprobado por el Procedimiento de revisión ética de la Universidad de Sheffield, administrado por la Escuela de Salud e Investigaciones Relacionadas (ScHARR, por sus siglas en inglés) y el Comité Institucional de Ética en Investigación (CIEI) de la Universidad Peruana Cayetano Heredia.

¿Qué sucede si algo sale mal y deseo presentar una queja sobre la investigación?

Si desea presentar una queja sobre cualquier aspecto del estudio debe comunicarse con el supervisor del proyecto de doctorado, Profesor Aki Tsuchiya (a.tsuchiya@sheffield.ac.uk). Si cree que su queja no se ha manejado a su satisfacción, puede comunicarse con Profesor Mark Strong, Decano de ScHARR (m.strong@sheffield.ac.uk). Si su queja se relaciona con la forma en que se han manejado los datos personales de los participantes, puede comunicarse con el Oficial de Protección de Datos de la Universidad de Sheffield dataprotection@sheffield.ac.uk. Puede encontrar información adicional sobre cómo presentar una queja en el Aviso de Privacidad de la Universidad: https://www.sheffield.ac.uk/govern/data-protection/privacy/general. Si cree que su queja no se ha manejado satisfactoriamente, puede comunicarse con la Oficina del Comisionado de Información.

Contacto para información adicional

Para obtener información sobre el reclutamiento de participantes y la coordinación de entrevistas, comuníquese con Caterina Cosmopolis (caterina.cosmopolis@sheffield.ac.uk). Para cualquier otro problema, comuníquese con Armando Valdés-Velásquez (armando.valdes@upch.pe, teléfonos: +51 319 0000, +51 913 714099).

Si tiene alguna pregunta sobre sus derechos como participante, por favor contactarse con el Presidente del Comité Institucional de Ética en Investigación (CIEI) de la Universidad Peruana Cayetano Heredia al teléfono -51 319 0005, anexo 2271.

Consentimiento

Sobre formar parte del proyecto (seleccione todas las opciones que apliquen):

- ❑ He leído y entendido la información presentada, o se me ha explicado detalladamente el proyecto. Además, se me ha dado la oportunidad de hacer preguntas sobre el proyecto.
- ❑ Entiendo que mi participación en esta investigación es voluntaria, que puedo retirar mi participación en cualquier momento sin dar mayores explicaciones y que esto no tendrá consecuencias negativas para mi persona.
- ❑ Entiendo que, si deseo participar en el proyecto, esto no crea un acuerdo legalmente vinculante ni tiene la intención de crear una relación laboral con la Universidad de Sheffield o la Universidad Peruana Cayetano Heredia.

Acerca de cómo se utilizará su información durante y después del proyecto (seleccione todas las opciones que apliquen):

- ❑ Entiendo que mis datos personales, como el nombre y la dirección de correo electrónico, no se revelarán a personas ajenas al proyecto.
- ❑ Estoy de acuerdo en ceder mis derechos sobre cualquier material generado como parte de este proyecto a la Universidad de Sheffield.

Al completar este formulario, confirmo que tengo más de 18 años y mi lengua materna es el español. *Nota: Si la respuesta es "No", no podrá continuar con el cuestionario*.

- ❑ Si
- ❑ No

<u>Presentación del caso</u>

Los bosques albergan parte de la biodiversidad más importante de nuestro planeta y nos brindan muchos beneficios incluidos: alimentos, combustible, madera y fibra, aire limpio, agua dulce, polinización, control de inundaciones y la erosión, entre otros. Son importantes para la recreación, el turismo, la educación y tienen un valor cultural para las muchas personas que viven dentro y/o cerca de sus límites. Los bosques también nos ayudan a combatir la crisis del cambio climático y mejorar nuestra salud mental y física.

El cambio climático afecta la salud humana debido al empeoramiento de la calidad del aire y el agua, el aumento de la propagación de ciertas enfermedades y la alteración de la frecuencia o intensidad de los fenómenos meteorológicos extremos. También afecta la seguridad alimentaria, al aumentar la frecuencia y la gravedad de los desastres naturales llevando a más personas al hambre y la pobreza. Las personas que viven en pobreza pueden experimentar múltiples desventajas al mismo tiempo, por ejemplo: mala salud o desnutrición, falta de agua potable o electricidad, mala calidad de la vivienda o poca educación. Los formuladores de políticas intentan encontrar soluciones para mejorar la vida de las personas y proteger los recursos para el futuro, pero esto requiere una planificación y gestión a largo plazo.

En la presente encuesta, le pedimos que se imagine que es un formulador de políticas que busca destinar cierta cantidad de dinero para mejorar los medios de vida locales. Sin embargo, dependiendo de las actividades implementadas, se pueden obtener diferentes resultados. Por ejemplo, una política podría ayudar a las personas a obtener mejores condiciones de vivienda, pero empeorar la calidad del bosque en su entorno.

Nos gustaría que pensara cómo deberían decidir los formuladores de políticas en materia de cobertura forestal, seguridad alimentaria y calidad de vivienda. Cada uno de estos se explica con más detalle a continuación:

Cobertura forestal: se trata de la capacidad del bosque para proporcionar recursos para la supervivencia de animales, plantas y seres humanos. Cuanto más pequeña sea la cubierta forestal, menos recursos podrá proporcionar. La cobertura forestal se expresará en términos de biodiversidad y paisaje, en tres niveles:

- La proporción del bosque impactado es del 10%: alta biodiversidad y alta cobertura forestal,

- La proporción de bosque impactado es del 50%: biodiversidad regular y mezcla de bosques y tierras agrícolas,
- La proporción del bosque impactado es >90%: baja biodiversidad y tierras agrícolas con algunos árboles dispersos.

Seguridad alimentaria: se refiere a si una persona tiene suficientes alimentos para consumir una dieta balanceada y cubrir sus necesidades nutricionales para una vida activa y saludable. Un niño que no recibe una nutrición adecuada o acceso a suficientes alimentos durante la primera infancia es probable que sufra retraso en el crecimiento. La seguridad alimentaria se expresará en términos de la proporción de hogares con niños con retraso en el crecimiento, en tres niveles:

- Menos de 10 de cada 100 hogares tiene niños con retraso en el crecimiento;
- 30 de cada 100 hogares tiene niños con retraso en el crecimiento;
- Más de 50 de cada 100 hogares tiene niños con retraso en el crecimiento.

Calidad de vivienda: depende de si una casa tiene las siguientes características, a) las paredes, piso o techo están construidos con materiales apropiados al clima de la región (ladrillo, piedra, madera), b) tiene acceso a agua potable y servicios sanitarios (inodoro, letrina o inodoro de compostaje), y c) tiene instalaciones razonables para cocinar y usa gas o electricidad para cocinar los alimentos. A una vivienda de mala calidad le falta todo. La calidad de vivienda se expresará en términos de la proporción de viviendas de mala calidad en una zona, en tres niveles:

- Menos de 10 de cada 100 hogares presenta viviendas de mala calidad;
- 30 de cada 100 hogares presenta viviendas de mala calidad;
- Más de 50 de cada 100 hogares presenta viviendas de mala calidad.

A continuación, se presentan 9 situaciones, donde tendrá que elegir entre dos alternativas imaginarias. Cada alternativa describe el resultado de una política.

Lea atentamente la descripción de cada situación y alternativa. Recuerde, no hay respuestas correctas o incorrectas, simplemente buscamos su punto de vista.

Situación 1

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Biodiversidad regular Mezcla de bosques y tierras agrícolas	Alta biodiversidad Alta cobertura forestal
La proporción de hogares con niños con retraso en el crecimiento es...	30 de 100	Menos de 10 de 100
La proporción de viviendas de mala calidad es...	Menos de 10 de 100	Más de 50 de 100
Tu selección:	❑	❑

Situación 2

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Alta biodiversidad Alta cobertura forestal	Baja biodiversidad Tierras agrícolas con algunos árboles dispersos

La proporción de hogares con niños con retraso en el crecimiento es...	Más de 50 de 100	30 de 100
La proporción de viviendas de mala calidad es...	30 de 100	Menos de 10 de 100
Tu selección:	❑	❑

Situación 3

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Biodiversidad regular Mezcla de bosques y tierras agrícolas	Alta biodiversidad Alta cobertura forestal
La proporción de hogares con niños con retraso en el crecimiento es...	Más de 50 de 100	30 de 100
La proporción de viviendas de mala calidad es...	Más de 50 de 100	30 de 100
Tu selección:	❑	❑

Situación 4

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	Alternativa 2
El área natural al que tienen acceso los hogares presenta...	Alta biodiversidad Alta cobertura forestal	Baja biodiversidad Tierras agrícolas con algunos árboles dispersos
La proporción de hogares con niños con retraso en el crecimiento es...	Menos de 10 de 100	Más de 50 de 100
La proporción de viviendas de mala calidad es...	Menos de 10 de 100	Más de 50 de 100
Tu selección:	❑	❑

Situación 5

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	Alternativa 2
El área natural al que tienen acceso los hogares presenta...	Baja biodiversidad Tierras agrícolas con algunos árboles dispersos	Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños con retraso en el crecimiento es...	Menos de 10 de 100	30 de 100
La proporción de viviendas de mala calidad es...	Menos de 10 de 100	30 de 100

Tu selección:	❑	❑

Situación 6

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Alta biodiversidad Alta cobertura forestal	Baja biodiversidad Tierras agrícolas y algunos árboles dispersos
La proporción de hogares con niños con retraso en el crecimiento es...	30 de 100	Menos de 10 de 100
La proporción de viviendas de mala calidad es...	Más de 50 de 100	30 de 100
Tu selección:	❑	❑

Situación 7

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**

El área natural al que tienen acceso los hogares presenta...	Baja biodiversidad Tierras agrícolas y algunos árboles dispersos	Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños con retraso en el crecimiento es...	30 de 100	Más de 50 de 100
La proporción de viviendas de mala calidad es...	Más de 50 de 100	Menos de 10 de 100
Tu selección:	❑	❑

Situación 8

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Biodiversidad regular Mezcla de bosques y tierras agrícolas	Alta biodiversidad Alta cobertura forestal
La proporción de hogares con niños con retraso en el crecimiento es...	Menos de 10 de 100	Más de 50 de 100
La proporción de viviendas de mala calidad es...	30 de 100	Menos de 10 de 100
Tu selección:	❑	❑

Situación 9

Imagine que usted es un creador de políticas y tiene que decidir cuál política implementar. Su jurisdicción cubre una región con 100 hogares los cuáles tienen acceso a un área natural que se encuentra de 1 a 5 kilómetros de distancia (15 minutos a 1 hora caminando).

En la siguiente tabla tiene los resultados de dos políticas después de 5 años de implementación. ¿Cuál de estas 2 opciones prefiere? El tiempo, los costos de implementación y todo lo demás que no se menciona es igual para ambas alternativas.

	Alternativa 1	**Alternativa 2**
El área natural al que tienen acceso los hogares presenta...	Baja biodiversidad Tierras agrícolas y algunos árboles dispersos	Biodiversidad regular Mezcla de bosques y tierras agrícolas
La proporción de hogares con niños con retraso en el crecimiento es...	Más de 50 de 100	Menos de 10 de 100
La proporción de viviendas de mala calidad es...	30 de 100	Más de 50 de 100
Tu selección:	❑	❑

<u>En la siguiente sección se le harán algunas preguntas adicionales</u>:

Acerca de su hogar...

¿Con qué frecuencia visita un área natural, ya sea con fines recreativos y/o para buscar recursos forestales?

- ❑ Nunca
- ❑ Rara vez
- ❑ A veces
- ❑ Muy seguido
- ❑ Siempre

En las últimas cuatro semanas, ¿se ha quedado sin dinero y le ha costado que toda la familia se alimente 3 veces al día?

- ❑ Si
- ❑ No

¿Cuál de estas frases describe mejor la alimentación en su hogar?

- ❑ Suficiente cantidad y variedad de alimentos para toda la familia, y de buena calidad y valor nutritivo que quiero/queremos comer.
- ❑ A menudo no hay suficiente para que toda la familia pueda comer.
- ❑ A veces no hay suficiente para que toda la familia pueda comer.
- ❑ Suficiente cantidad para toda la familia, pero no siempre el tipo de alimentos nutritivos y de buena calidad que quiero/queremos comer.

Su hogar tiene____________ de calidad _____________.

	Buena	Regular	Mala
Piso, paredes y techo de materiales adecuados al clima (ladrillo, piedra, madera)	❑	❑	❑
Acceso a agua potable	❑	❑	❑
Acceso a saneamiento mejorado (inodoro, letrina o inodoro de compostaje)	❑	❑	❑
Un espacio para cocinar y usa gas o electricidad para cocinar	❑	❑	❑

Acerca del cambio climático...

¿Qué tan informado considera que está de los efectos del cambio climático en su comunidad/país?

- ❑ Muy desinformado
- ❑ Desinformado

- ❑ Ni desinformado ni informado
- ❑ Informado
- ❑ Muy informado

¿Qué tan informado está de las políticas de su país para responder al cambio climático?

- ❑ Muy desinformado
- ❑ Desinformado
- ❑ Ni desinformado ni informado
- ❑ Informado
- ❑ Muy informado

¿Qué tan preocupado está por los efectos del cambio climático en su comunidad/país?

- ❑ Muy despreocupado
- ❑ Despreocupado
- ❑ Ni preocupado ni despreocupado
- ❑ Preocupado
- ❑ Muy preocupado

¿Qué tan de acuerdo está con la siguiente declaración?

"Mis respuestas a los escenarios de cobertura forestal, seguridad alimentaria y vivienda serían diferentes si me afectara el cambio climático."

- ❑ Totalmente de acuerdo
- ❑ En desacuerdo
- ❑ Neutral
- ❑ De acuerdo

- [ ] Totalmente de acuerdo

Acerca de la encuesta:

¿Qué le pareció la encuesta? (ej. longitud, tiempo, diseño, tamaño del texto, etc.) _____________

¿Siente que entendió las preguntas que le hicieron? ¿Fueron claras y precisas? Si/No

¿Las instrucciones lo prepararon adecuadamente para las preguntas? Si/No

¿Qué tan difícil le resultó decidir sus respuestas?

- [ ] Muy fácil
- [ ] Fácil
- [ ] Neutral
- [ ] Difícil
- [ ] Muy difícil

Al decidir cuál escenario elegir, ¿qué tipo de cosas tuvo en cuenta? _____________

Al decidir cuál escenario elegir, ¿consideró el hecho de que algunos de los resultados no son igualmente recuperables una vez reducidos? (ej. bosque, nutrición, salud)

- [ ] No
- [ ] Si. Por favor, explique _____________

Al decidir cuál escenario elegir, ¿pensó en los efectos que causaría en los demás o en la sociedad?

- [ ] No
- [ ] Si. Por favor, explique _____________

¿Tiene alguna otra sugerencia para mejorar la encuesta? ____________

Preguntas adicionales sobre usted:

¿En qué región vive? _______________

Seleccione el nivel de educación más alto que haya alcanzado:

- ❑ Sin educación formal
- ❑ Educación primaria
- ❑ Educación secundaria
- ❑ Educación técnica o universitaria

¿Cuántas personas hay en su hogar, incluido usted mismo? ______________

¿Tiene hijos de 0 a 17 años a su cargo? Si/No

¿Cuál es su género?

- ❑ Masculino
- ❑ Femenino
- ❑ Otro, especifique si lo desea por favor ___________
- ❑ Prefiero no contestar

Indique su edad:

- ❑ 18-29
- ❑ 30-39
- ❑ 40-49
- ❑ 50-59
- ❑ 60-69
- ❑ 70+

S3 Ethical Approval

Downloaded: 17/10/2022
Approved: 17/10/2022

Caterina Helena Cosmopolis del Carpio
Registration number: 180226269
School of Health and Related Research
Programme: PhD Public Health, Economics and Decision Science

Dear Caterina Helena

PROJECT TITLE: Developing Analytical tools to Understand Sustainable Development Goals synergies and trade-offs
APPLICATION: Reference Number 045051

On behalf of the University ethics reviewers who reviewed your project, I am pleased to inform you that on 17/10/2022 the above-named project was **approved** on ethics grounds, on the basis that you will adhere to the following documentation that you submitted for ethics review:

- University research ethics application form 045051 (form submission date: 17/10/2022); (expected project end date: 30/09/2023).
- Participant information sheet 1112600 version 2 (17/10/2022).
- Participant information sheet 1101745 version 2 (18/02/2022).
- Participant information sheet 1101746 version 2 (18/02/2022).
- Participant consent form 1101748 version 1 (07/02/2022).
- Participant consent form 1101747 version 2 (18/02/2022).

If during the course of the project you need to deviate significantly from the above-approved documentation please inform me since written approval will be required.

Your responsibilities in delivering this research project are set out at the end of this letter.

Yours sincerely

Devianee Keetharuth
Ethics Administrator
School of Health and Related Research

Please note the following responsibilities of the researcher in delivering the research project:

- The project must abide by the University's Research Ethics Policy:https://www.sheffield.ac.uk/research-services/ethics-integrity/policy
- The project must abide by the University's Good Research & Innovation Practices Policy: https://www.sheffield.ac.uk/polopoly_fs/1.671066!/file/GRIPPolicy.pdf
- The researcher must inform their supervisor (in the case of a student) or Ethics Administrator (in the case of a member of staff) of any significant changes to the project or the approved documentation.
- The researcher must comply with the requirements of the law and relevant guidelines relating to security and confidentiality of personal data.
- The researcher is responsible for effectively managing the data collected both during and after the end of the project in line with best practice, and any relevant legislative, regulatory or contractual requirements.

UNIVERSIDAD PERUANA
CAYETANO HEREDIA

CONSTANCIA 308-29-23

El Presidente del Comité Institucional de Ética en Investigación (CIEI) de la Universidad Peruana Cayetano Heredia hace constar que el proyecto de investigación señalado a continuación fue **APROBADO** por el Comité Institucional de Ética en Investigación, bajo la categoría de revisión **EXPEDITA.**

Título del Proyecto	: **"Developing Analytical tools to Understand Sustainable Development Goals synergies and trade-offs"**
Código de inscripción	: **210060**
Investigador(a) principal(es)	: **Valdes Velasquez, Armando**

La aprobación incluyó los documentos finales descritos a continuación:

1. **Protocolo de investigación,** versión 4.0 de fecha 14 de junio del 2023.
2. **Consentimiento informado,** versión 4.0 de fecha 14 de junio del 2023.

La **APROBACIÓN** considera el cumplimiento de los estándares de la Universidad, los lineamientos Científicos y éticos, el balance riesgo/beneficio, la calificación del equipo investigador y la confidencialidad de los datos, entre otros.

Cualquier enmienda, desviaciones, eventualidad deberá ser reportada de acuerdo a los plazos y normas establecidas. El investigador reportará cada seis meses el progreso del estudio y alcanzará un informe al término de éste. La aprobación tiene vigencia desde la emisión del presente documento hasta el **16 de julio del 2024**.

El presente proyecto de investigación sólo podrá iniciarse después de haber obtenido la(s) autorización(es) de la(s) institución(es) donde se ejecutará.

Si aplica, los trámites para su renovación deberán iniciarse por lo menos 30 días previos a su vencimiento.

Lima, 17 de julio de 2023.

COMITÉ INSTITUCIONAL DE ÉTICA EN INVESTIGACIÓN
Universidad Peruana Cayetano Heredia
DUARI
- CIEI -

Dr. Luis Arturo Pedro Saona Ugarte
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Comité Institucional de
Ética en Investigación

Table S1. *DCE design for the survey. The number in the columns represent the level of each attribute per choice set and alternative.*

Choice task	**Alternative 1**			**Alternative 2**		
	Forest cover	*Nutrition level*	*Housing quality*	*Forest cover*	*Nutrition level*	*Housing quality*
1	1	3	2	2	2	1
2	3	2	2	1	1	1
3	2	3	1	3	1	2
4	2	1	3	1	2	2
5	1	1	3	3	3	1
6	3	2	3	2	1	2
7	1	2	1	2	3	3
8	2	3	2	3	2	3
9	3	1	1	1	3	3

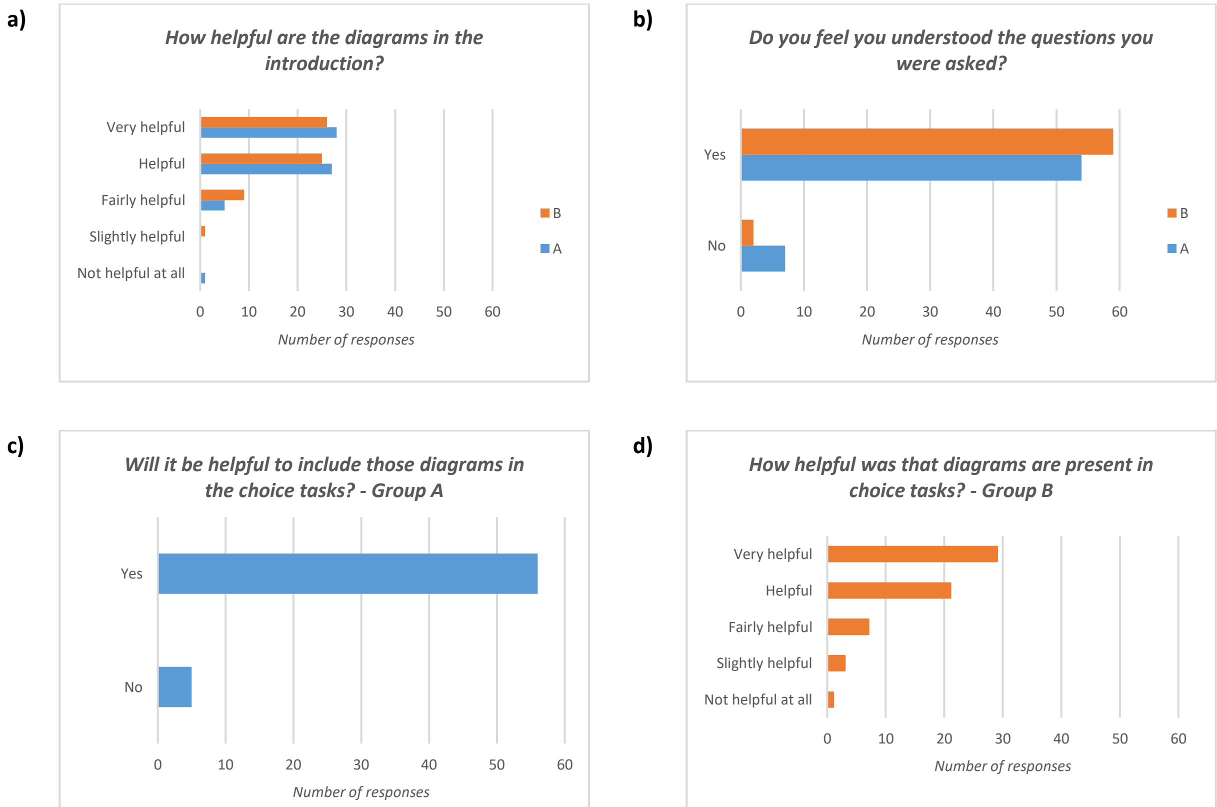

Figure S1. *Participant responses about introducing visual aids in the questionnaire, for clarity purposes, first arm pilot.*

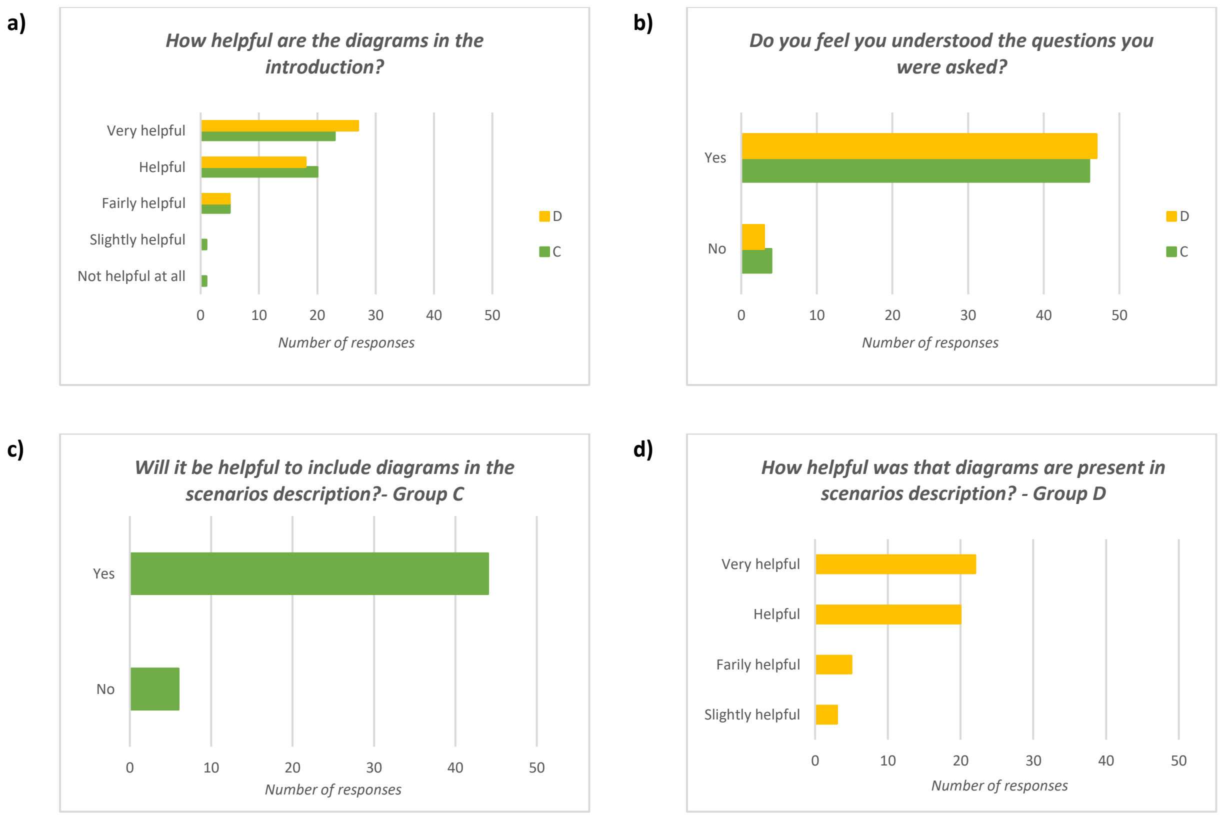

Figure S2. *Participant responses about introducing visual aids in the questionnaire, for clarity purposes, second arm pilot.*

Table S2. *Socioeconomic characteristics of sample participants in final survey.*

Characteristics	**N= 250**	**%**	**Peruvian population (%)***
Gender			
Female	125	50.0	
Male	115	46.0	50.8
Other	2	0.8	49.2
Prefer not to answer	8	3.2	
Age			
18-29	70	28.0	23.4**
30-39	91	36.4	22.7
40-49	58	23.2	19.3
50-59	22	8.8	15.1
60-69	9	3.6	10.4
70+	0	0.0	9.1
Educational level			
Non formal education	1	0.4	
Primary School	2	0.8	23.2
Secondary School	50	20.0	47.5
University or Technical qualification	197	78.8	29.3
Childcare responsibilities			
Yes	161	64.4	
No	89	35.6	

*Source: *National Institute of Statistic and Informatics – Peru (INEI). Total percentage of population over 20 years of age, as of June 30, 2022.*

*** Population between 20-29 years of age.*

Table S3. *Background information related to access to natural area, nutritional level and housing conditions of sample participants in the final survey.*

Survey question[1]	**N= 250**	**Frequency (%)**
How often do you visit a natural area, either for recreational purposes and/or for search for forest resources?		
Always	18	7.2
Often	90	36.0
Sometimes	107	42.8
Rarely	31	12.4
Never	4	1.6
In the last four weeks, have you run out of money and found it difficult to feed the whole family 3 times a day?		
Yes	90	36.0
No	160	64.0
Which of these phrases best describes the diet in your home?		
• *Sufficient quantity and variety of food for the whole family, and of good quality and nutritional value that I/we want to eat.*	108	43.2
• *There is often not enough for the whole family to eat.*	36	14.4
• *Sometimes there is not enough for the whole family to eat.*	26	10.4
• *Enough for the whole family, but not always the kind of good quality, nutritious food I/we want to eat.*	80	32.0
Your home has _____________ of ____________quality.		
Floor		
Good	168	67.2
Regular	78	31.2
Bad	4	1.6
Drinkable water		
Good	202	80.8
Regular	42	16.8
Bad	6	2.4
Sanitary services		
Good	202	80.8
Regular	42	16.8
Bad	6	2.4
Kitchen		
Good	182	72.8
Regular	63	25.2
Bad	5	2.0

[1] *Questions translated from Spanish.*

6 General discussion

The achievement of the SDG agenda will shape our future, however, that depends on the interrelationships between SDG elements to define what is technically possible. On the other hand, policy effectiveness and long-term policy sustainability also depends on people's attitude towards them, so is important to understand what is socially acceptable. This PhD thesis explored interrelationships between forest (SDG15) and multidimensional poverty (SDG1 & 2) using Peru as a case study. It applied counterfactual methods to understand "what is technically possible" through causal relationships, and studied "what is socially acceptable" using preferences elicitation methods.

In chapter 2, I assessed the current literature on synergies and trade-offs within the SDG framework and causal studies addressing outcomes related to SDG1, 2, 3 and 15 interactions. I found that the understanding of SDG interrelationships was mainly based on qualitative studies using experts' knowledge of those interactions; a handful of studies used a quantitative approach revealing hidden links. Additionally, causal approaches to forest-poverty links were scarce and produced mixed evidence, for example, Alix-Garcia, McIntosh & Sims (2013) demonstrated a negative association between poverty alleviation and forest cover, while Pattanayak & Sills (2001) showed a positive association. Most studies focused on the effect of environmental policies (i.e. protected areas, forest concessions) on poverty, and only one look into the impact of poverty alleviation policies (cash transfer) on forest conservation. The chapter results highlighted the need to understand SDG indicators synergies and trade-offs, especially about the causal links between SDG1, 2, 3 and 15 indicators, and to explore mediators or indirect relationships between them.

This thesis makes a novel contribution to the literature by moving beyond traditional analyses of forest-poverty dynamics. It employs a multidimensional approach to poverty, integrates the role of spatial forest patterns, examines the impact of a poverty alleviation policy on forest cover, and incorporates an analysis of public preferences. By combining these elements, it provides a more holistic understanding of the complex interrelationships between SDG 1, 2, and 15.

6.1 Main findings and contribution to the literature

Across the studies presented in this thesis, a more nuanced understanding of the relationship between forest and poverty in Peru emerges. Chapters 3, 4, and 5 each contribute a unique perspective to the understanding of forest-poverty-preference dynamics, and when synthesized, provide a more complete picture than any chapter in isolation.

Chapter 3 explored the links between forest pattern and multidimensional poverty index (MPI) in Peru and I found small but important effects. Higher forest cover, larger number of patches, and mean of patch area increased MPI; however if MPI is decomposed on its dimensions some trade-offs are evident. Forest cover increased nutrition while decreased education and living standards, and number of patches increased nutrition while decreased living standards. Likewise, forest fragmentation increased nutritional levels possibly mediated by the access to forest products and markets. This chapter made the insight that spatial forest arrangements influence poverty alleviation dimensions differently and using one poverty measure, such as monetary poverty, or one forest metric only can hide the real contributions of forest to wellbeing. Results are complex and synergies and trade-offs should be taken into account for an adequate sustainable development. Many different studies have done significant work on the forest-poverty dynamics (Miller, Mansourian & Wildburger, 2020), but this is possibly the first to study how forest pattern impact multidimensional poverty. Previous literature on the contribution of forest spatial arrangement to food security suggest that a mixed landscape could provide better access to wild foods from forest edges, access to markets or provide opportunity for agriculture and cultivated species increasing diet diversity (Hickey et al., 2016; Powell et al., 2015; Rasmussen et al., 2020). Yet forest cover could be more important than access to markets or increased income for diet diversity (Friant et al., 2019; Jendresen & Rasmussen, 2022; Rasmussen, Wood & Rhemtulla, 2020). Chapter results support these claims and bring new evidence about the hidden contributions of forest to poverty alleviation, indicating the potential of mixed landscapes for forest conservation and anti-poverty strategies when considering potential trade-offs.

Building on this analysis, in chapter 4 explored the influence of the Peruvian social programme Juntos (a conditional cash transfer) on biophysical changes in a forested landscape, showing that those programmes can prevent forest loss and/or promote reforestation under certain conditions. Juntos decreased deforestation in flooded vegetation and the expansion of rangeland and agricultural land. These effects were small and only observed when Juntos coverage increased as well, due to inclusion of new beneficiaries (in 2016) or the increase on payments during COVID-19, suggesting that CCT transfers could have an effect preventing deforestation but are currently insufficient. This findings are particularly relevant given that previous studies are scarce and inconclusive, showing mixed effects depending on the region and biome (Cunha, Rodrigues Neto & Morsello, 2022; Alix-Garcia, McIntosh & Sims, 2013; Ferraro & Simorangkir, 2020; Dyngeland, Oldekop & Evans, 2020; Hirvonen et al., 2022). COVID-19 simulated a natural experiment for CCT in Peru and this chapter is possible the first to study CCT under such conditions. The results add to the literature by illustrating how increasing the programme coverage could prevent deforestation; however, mechanisms behind these processes such as market and labour changes are also important.

Chapter 3 and 4 used several cross-sectional analysis at national scale covering 5 and 10 years of data, respectively, examining forest-poverty dynamics over an extended period. I focused on the effect of the spatial arrangement of forest and other land uses, instead of restricting the analysis to a single policy (i.e. protected areas, community manage forest, indigenous lands) as previous studies did. Moreover, the main characteristic of these studies is that they used DHS aggregated data at cluster level (group of households) and forest/land-use data calculated around a 10km radius area, to overcome the displacement on DHS data, and used a quasi-experimental approach. Previous studies (Rasmussen et al., 2020; Jendresen & Rasmussen, 2022; Rasmussen et al., 2023) have used 10km radius cluster as unit of analysis as well, to study the effect of forest on diet diversity and only the latest study incorporates a quasi-experimental approach. Chapter 3 and 4 also used Covariate Balancing Generalised Propensity Score method (CBGPS) (Fong, Hazlett & Imai, 2018) to reduce correlation between continuous treatment and covariates, controlling for heterogeneity and account for spatial autocorrelation comparing spatial plots of residuals (Schleicher et al., 2020).

Chapter 5 added a crucial dimension to the understanding of the preferences of Peruvian citizens regarding policy outcomes for forest conservation, nutrition and housing quality. The main finding revealed that forest conservation appears as an important value in the context of policy trade-offs, suggesting a societal willingness to support policies aligned with SDG15. However, this preference is not absolute; when confronted with food insecurity, citizens prioritise nutritional improvements. This highlights a potential trade-off between SDG 15 and SDG 2, underscoring the importance of considering social preferences in policy decisions. It is crucial to recognise that individuals rarely adhere to strict lexicographic ranking of priorities, dedicating all resources to one objective before considering others. Instead, as analogy of seeking food before perfecting a diet while lacking shelter illustrates, people tend to balance across various attributes. Improvements in one area might temporarily reduce its priority, leading to increase focus on other, previously less pressing concern. This dynamic interplay of needs and values, rather than absolute prioritization, shapes public preferences and should inform policy development.

Previous research has examined people’s preferences as a private consumer or willingness to pay regarding ecosystem services, forest management or money allocation for conservation (Abdeta, 2022; Acharya, Maraseni & Cockfield, 2019). This is possibly the first study referring to citizen preferences on forest and multidimensional poverty policies, and highlights that preference elicitation methods are also useful to study synergies and trade-offs between forest and socio-economic outcomes. Chapter 5 provides preliminary results for further studies in the subject.

Synthesizing across these chapters, it becomes clear that the relationship between forest and poverty is multifaceted, involving both synergies and trade-offs. Spatial forest patterns influence different dimensions of poverty in distinct ways, poverty alleviation policies can have positive impacts on forest conservation, and citizens' preferences reveal the social values placed on these interacting outcomes. This integrated understanding is crucial for designing effective policies that promote both poverty alleviation and sustainable forest management.

6.2 Limitations and recommendations

While this thesis offers valuable insights, it is important to acknowledge its limitations, which also point towards avenues for future research.

First, impact evaluations base their results on past situations and depend on context (i.e. time, location, political or climatic context), this thesis results are specific to the case of Peru and similar studies would need to be conducted in other contexts to assess similar impacts. However, the findings indicate the potential of forest conservation in poverty alleviation strategies when considering potential trade-offs.

Second, Chapter 3 and 4 used socioeconomic data from DHS surveys aggregated at cluster level, panel data was insufficient for a quasi-experimental design, which that is data driven and need large datasets to perform an accurate analysis. Additionally, clusters are georeferenced but displaced to hide household location. This thesis tried to overcome those issues by using cross-sectional regression models accounting for year effect, using clusters as unit of analysis and land cover data calculated for a 10km buffer around cluster centroid. While this approach allowed for the examination of spatial relationships, it cannot fully capture the dynamic interplay between forest change and poverty over time. Mortality data was available for up to several years before the survey but it was missing in some households, thus a modified MPI omitting mortality data was used in the analysis. The omission was justified since drivers of child mortality are closely related to health services' access instead of forest (WHO, 2024); it was assumed that any influence of forest on child mortality would be capture by the nutrition dimension. Future research could benefit from richer DHS data or from longitudinal studies to better understand the long-term effects of forest dynamics on-poverty and explore the direct and indirect pathways through which forest influences child mortality. Additionally, more sophisticated spatial analysis techniques could be employed to capture the complexity of landscape patterns.

Chapter 4 demonstrated that social protection programmes have different impacts on different land-use categories. Such studies did not investigate the mechanisms that can affect those outcomes, although they proposed some theoretical mechanisms based on the literature. Further research could investigate the role of market and labour changes and other factors that could mediate the relationship between social programmes and land-use change. The influence of external shocks, such as the effect of COVID-19, also warrants further attention. Similarly, given the link between forest and agriculture, future research could focus the analysis on agricultural policies that promote forest conservation and poverty alleviation.

Chapter 5 reflected the preferences of a small sample of individuals with certain characteristics: internet access, a competent level of Spanish literacy and enrolled in the agency panel, which is not fully representative of the broader Peruvian population. It showed that forest conservation played a major role citizen's preferences, followed by nutritional level. These results should be taken as preliminary, as the chapter was a first approximation to citizen's values about forest conservation and poverty alleviation policies. Attributes, their levels and wording were selected by the research team and due to time and budget constrains the design and analysis did not consider interactions between attributes. This study could be improved or applied in several ways. For example, a larger sample could test relationships that were not included in the study or preferences of people living in poor housing conditions. A larger sample could also allow the valuation of preferences regarding bad levels of attributes. DCE parameters could be used as priors to design larger scale studies about social values in conservation management and development of policies, or addressed a specific group of stakeholders. Future research could also test interactions between attributes, account for subgroup preferences based on sample characteristics, or compare preferences for citizens in rural areas vs urban areas. Additionally, further research could explore how to design policies that effectively incorporate and balance the diverse preferences of different stakeholder groups.

More broadly, this research focused on Peru. Future studies could examine these relationships in other geographical contexts, particularly in regions with different forest types or socio-economic conditions. Comparative studies could offer valuable insights into the generalizability of these findings. Given the interconnectedness of forest and agricultural land use, future research could also focus on the design of integrated agricultural policies that promote forest conservation and poverty alleviation.

6.3 Concluding remarks

Nature is vital to achieve SDG goals, and therefore sustainable development. This thesis demonstrates the complex interplay between forest and poverty in Peru, highlighting the importance of considering both synergies and trade-offs for achieving the Sustainable Development Goals.

Impact evaluations can help to understand causal inferences assessing environmental and socioeconomic outcomes between goals. Analysing the effect of spatial configuration of forest on poverty alleviation, and how social protection programmes (CCT) affect land-use change could inform policy implementation and management to achieve sustainable development, but also inform research studies about forest-poverty dynamics. The findings emphasize that analysing forest-poverty dynamics requires a multidimensional approach, as spatial forest patterns influence various dimensions of poverty in distinct ways. Moreover, the research indicates that social protection programmes can contribute to forest conservation, but their effectiveness depends on program design and context.

Furthermore, by incorporating citizen preferences, this work also underscores the need for policies to align with social values, balancing forest conservation with other development priorities. Understanding how people, as citizens, value private benefits alongside public goods, particularly when outcomes are interdependent, could have a positive impact on local communities' wellbeing and policy effectiveness by incorporating their preferences and choices.

While acknowledging the limitations of cross-sectional data, the focus on the Peruvian Amazon, and the sample representativeness in the preference elicitation, this research offers several avenues for future inquiry. These include longitudinal studies, expanded geographical contexts, investigations into mediating mechanisms, and policy design that integrates diverse stakeholder values.

Ultimately, this thesis contributes a nuanced understanding of forest-poverty-preference dynamics, providing valuable insights to the literature and opens new avenues of research.

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