

The Impact of Forest Loss on Public Health: Evidence from Peru

Tracking changes in upstream forests and well-being in rural areas

By

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Executive Summary

This research is motivated by a desire to understand the relationship between nature and health. This relationship has been a key issue in global policy debates in the last decades. For example, the "One Health and Planetary Health" approach recognized the importance of human health by protecting the biological integrity of the Earth. Given this context, there has been growing evidence of the relationship between forest cover loss and the increased incidence of health issues for children under five, especially in rural areas. However, causal links between them need further exploration.

Given its extensive Demographic and Health Survey (DHS) database and environmental geospatial data, including forest cover change by Hansen et al. (2013) from 2004 to 2020, Peru is a great case study for this analysis. Considering the water channel as a causal mechanism, this study wants to test if forest cover loss in upstream areas impacts the increase of diarrhea and stunted growth cases for children in rural areas of Peru. Some studies have demonstrated the linkages between deforestation and diarrhea, but linkages between deforestation and stunted growth are still scarce. It is worth mentioning that diarrhea lasts a few days to a week causing short-term effects on individuals, while stunted has long-term effects, including poor cognitive skills and educational performance. In that way, this study would provide novel evidence of the impact of forest loss on human capital.

To perform this research study, we ran an Ordinary Least Square (OLS) estimation in the statistical software Stata 17 to identify the causal relationship between health problems and forest loss. Under a contemporaneous analysis, we used a dummy dependent variable for diarrhea (i.e., had diarrhea/did not have diarrhea) and an independent variable (i.e., the share of forest cover loss from the previous year). On the other side, under a cohort analysis, we used a dummy dependent variable for severely stunted growth (i.e., had suffered severely stunted growth/had not suffered severely stunted growth) and an independent variable (i.e., the share of forest cover loss in the year prior to the child's birth). We also included control variables from the DHS data used in similar studies, such as the sex of the child, the child's birth order, the mother's age at the child's birth, the height of the mother, and access to improved water sources, and fixed effects for survey-year and regions, provinces, and districts.

The results show that a 1% increase in upstream forest cover loss increased the incidence of childhood diarrhea by 0.16% and stunted growth by 0.28%. While the downstream forest cover loss did not show any significant effect on health issues. It is acknowledged that forests are providers of clean

drinking water to households, so the loss of this resource might contribute to the emergence of pathogens (bacteria, viruses, or parasites) that contaminate water and affect health. Therefore, the conservation of upstream forests is crucial for keeping a healthy environment and children's health. These results show new evidence of forest loss's impact on Peru's health, contributing to the growing body of evidence for other developing countries. In addition, this information provides insights into forest policies and interventions by public authorities.

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1. Introduction

Peru is ranked second in Latin America and among the top ten countries in the world with the greatest forest cover, representing 54% of the country's territory (FAO and SERFOR 2017). However, the country has experienced rapid deforestation of about 3.15 million ha between 2004 and 2020, equivalent to a 4% decrease in tree cover since 2000, and 2.03 Gt of CO₂e emissions (see Appendix A and B).¹ Five Amazon regions out of the twenty-five regions of Peru were responsible for 78% of all tree cover loss, including the Amazon regions of Loreto, Ucayali, San Martín, Madre de Dios, and Amazonas.² The use of wood as a fuel, the export of hardwoods, new lands for cultivation, livestock (Piu and Menton 2014), and the extraction of minerals were identified as the main direct causes of deforestation in the Peruvian Amazon (Swenson et al. 2011).

The loss of forests might have consequences for the environment but also for the welfare of people, particularly due to the lack of access to safe water and healthy watershed conditions (Herrera et al. 2017; Pienkowski et al. 2017; Rasolofoson et al. 2021). The main health consequences are the incidence of diarrheal disease (DD) episodes and intestinal parasitosis, which have clinical and epidemiological links to stunting (low height-for-age) in children (Howard et al. 2007; Checkley et al. 2008; Larsen et al. 2017). In the case of Peru, child health indicators have improved in the last two decades. In particular, the incidence of diarrhea and stunted growth decreased significantly more in children in rural areas than in urban areas, according to reports from Peru's National Institute of Statistics (INEI, by its Spanish acronym), which are based on the DHS program (See Appendix C and D). Despite the improvement in those health indicators for children due to various strategies from the Ministry of Health of Peru, diarrhea and stunted growth continue to be public health problems, mainly in rural areas.

Recent studies have found that within rural regions of developing countries, deforestation decreases access to improved water sources (Mapulanga and Naito 2019); and increases vector-borne diseases (Bauhoff and Busch 2020), airborne diseases (Bauch et al. 2015; Pienkowski et al. 2017), and waterborne diseases among children under 5 years of age in upstream forest areas (Herrera et al. 2017; Rasolofoson et al. 2021; Acharya et al. 2020). Long-term effects on labor productivity and income

¹ Global Forest Watch. "Tree cover loss in [Peru]". From www.globalforestwatch.org.

² Global Forest Watch. "Location of tree cover loss in Peru". From www.globalforestwatch.org.

from this health burden could affect the entire economy (Pattanayak and Pfaff; Pattanayak et al. 2009). Nevertheless, empirical evidence of the causal links between forests and human health is still scarce. Due to the COVID-19 pandemic and the increase in emerging zoonotic diseases in recent decades, there has been increasing international interest in the importance of promoting human health by protecting the biological integrity and the natural systems of the Earth under the emerging One Health and Planetary health holistic approach (de Castañeda et al. 2023). Therefore, a deeper comprehension of how deforestation affects human health can provide insights for the design of public policies that tackle collective challenges of public health and environmental protection.

What are the health impacts of forest loss in Peru? Does the upstream forest loss area influence rural health outcomes? How does the upstream forest loss area influence the spatial distribution of health and nutritional issues? This paper will examine the causal effect of upstream forest loss on health indicators of children under 5 years old, through the watershed conditions by identifying mechanisms that drive health impacts, using satellite images of changes in forest areas, watershed boundaries, and climate, and DHS georeferenced health and socioeconomic data from 2004 and 2020. To address the potential bias that may affect the analysis, downstream forest areas are used as a placebo test (i.e., a false treatment). The results suggest that upstream forest loss in the previous year of the survey had a significant effect on the increased incidence of diarrhea, and forest loss in the year prior to the child's birth on the incidence of stunted growth. Instead, downstream forest loss did not influence health outcomes.

The remainder of the paper proceeds as follows. Section 2 reports the review of the literature. Section 3 describes the health, forest, climate and socioeconomic data. Section 4 shows two estimations applied for the paper's analysis, namely, a contemporaneous and cohort analysis. Section 5 reports the findings of the study. The summary and conclusion are presented in Section 6, which is also the section that discusses further policy implications for the preservation of the forest environment and advancements in the public health of Peru.

2. Relevant Literature

The loss of natural forest cover (“deforestation”) is already impacting human health negatively in myriad ways. A growing body of scientific evidence shows that the felling of tropical forests creates optimal conditions for the spread of vector-borne scourges, including malaria and dengue (Walsh, Molyneux, and Birley 1993; Vittor et al. 2009; Berazneva and Byker 2017; Kalbus et al. 2021; Bauhoff and Busch 2020). On the other hand, additional research studies have discovered links between changing forest cover and the emergence of waterborne diseases (e.g., diarrhea) and airborne diseases (e.g., acute respiratory infections) (Pienkowski et al. 2017; Bauch et al. 2015; Herrera et al. 2017; Acharya et al. 2020; Rasolofoson et al. 2021). Also, there is evidence connecting deforestation to stunted growth via nutritional status associated with food supply from agricultural lands (Tata et al. 2019; Acharya et al. 2020), although it is necessary to investigate water sources (i.e., forest watersheds) as potential mechanisms.

The biggest global cause of infant mortality and morbidity is diarrhea disease (WHO 2017). DD is transmitted mainly by the fecal-oral route and is most often caused by ingesting pathogens, particularly those found in contaminated food, water, or unclean hands (Khalil et al. 2018; WHO 2019a). Among them, unsafe drinking water is the major cause of almost 42% of all diarrhea occurrences (WHO 2019b). A recent assessment of the impact of unsafe Water, Sanitation, and Hygiene (WASH) on childhood DD suggests that household connections to piped water of higher quality in communities reduced diarrhea risk by 75%, compared to a baseline of unimproved drinking water (Wolf et al. 2018). In fact, recurrent infections and symptomatic episodes brought by parasitic pathogens, as well as limited access to safe drinking water, can induce or exacerbate stunting (Zaveri et al. 2019). These health problems can also be caused by maternal-fetal issues, which are defined by “narrow birth intervals, high birth order, and younger maternal age at birth”, that hamper children's cognitive development which can persist through later life and successive generations (Gashu et al. 2016). Given this context, we believe that DD is a good indicator of short-term health effects and stunted growth as long-term health effects.

Forest ecosystems contribute to the supply of clean water and, therefore to the well-being of the population (Westling, Stromberg, and Swain 2020; Nath, Schuster-Wallace, and Dickson-Anderson 2022). Some studies have shown that investing in forest conservation can increase access to clean

drinking water (Mapulanga and Naito 2019), reducing considerable costs in water infrastructure (Postel and Thompson 2005; Edmonds, DeBonis, and Sunderland 2013), and the health burden on children (Herrera et al. 2017; Rasolofoson et al. 2021). In order to determine the causal relationship between deforestation and access to clean drinking water in Malawi, Mapulanga and Naito (2019) combined satellite data on weather and deforestation with DHS data. The results showed that for every one percentage point increase in deforestation, access to clean water is reduced by 0.93 percentage points. Using a multi-country database to investigate relationships between deforestation, watershed conditions, and childhood DD, Herrera et al. (2017) discovered that upstream tree cover is connected to a lower probability of DD downstream in rural regions. Another recent study examining water-borne channels in Haiti and Honduras found that upstream forest clearing can lower water quality and reduce the effectiveness of point-of-use chlorination while raising the risk of DD because contaminated water can shield pathogens from chlorine-based disinfectants (Rasolofoson et al., 2021).

3. Data and Methods

3.1. Data

The body of data employed to analyze the impact of upstream forest loss on downstream health outcomes can be divided into three subsets: (i) georeferenced data on health and socioeconomic indicators of children under 5 years of age, (ii) high-resolution spatial data of forest loss at sub-basin boundaries, upstream and downstream areas, (iii) spatial climate data to help identify the instances in which households have been exposed to anomalous episodes (extremely low or high temperature and precipitation levels).

3.1.1. Health and socioeconomic data

The first data set is obtained from Peru's Demographic and Health Survey, or *Encuesta Demografica y de Salud Familiar* (ENDES) conducted by INEI, which annually collects data on child health outcomes, household characteristics, and other socioeconomic variables. The cross-sectional design of this data follows DHS methodology based on a random sampling of clusters and urban-rural stratification. For this study, we constructed child health indicators on DD and stunted growth. The DHS surveys record whether each child has experienced DD in the last 24 hours or within the last 2 weeks. We used this information to construct a dummy variable that is equal to 1 if the child had DD within the last 2

weeks and 0 otherwise. The DHS surveys also provide data on height-for-age z-scores that can be used to construct stunting measures. We constructed a dummy variable on severe stunting (i.e., severe chronic malnutrition) that is equal to 1 if a child's height-for-age z-score is below 3 standard deviations below the mean of the World Health Organization (WHO) child growth standards (WHO 2009). We also compiled data on socioeconomic controls such as the child's gender, child's birth order, mother's age at the child's birth, mother's height, and whether the household has access to drinking water (as a proxy of wealth). Regarding the latter, we found that 13.59% of children living in rural areas, especially in the poor areas, do not have access to safe drinking water, while those living in urban areas less than 2% suffer from this problem (See Appendix E).

The final database contains continuous health and demographic data for 17 surveys, from 2004 to 2020, a significantly larger number compared to other countries in the DHS program. The data covers 24 regions, 196 provinces, and 1874 municipalities. It encompasses 187,648 non-migrant children, 120,848 of whom live in urban areas and 66,800 in rural areas and the number of clusters vary year by year (See Appendix F).

To link this dataset to external data sets on the environment and socioeconomic determinants of health outcomes, we georeferenced each cluster of the sample based on the DHS data from 2004 to 2020 for rural and urban areas (See Appendix G). However, this data does not report exact coordinates. Instead, the clusters included in the survey randomly displace the GPS coordinate within 2 km for urban clusters, and up to 5 km for rural clusters to protect the anonymity of the individuals in the survey. Given this fact, we used 5 km buffers for each cluster location (see Figure 1).

Figure 1 Cluster coordinates with 5 km buffer

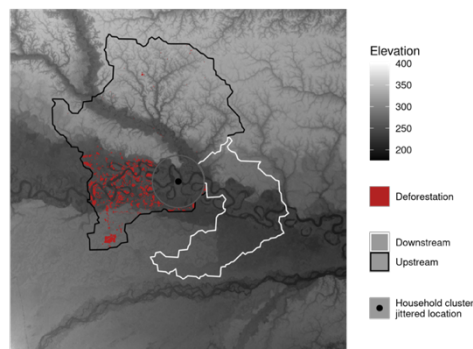


Note. 5km Buffer calculated according to Peru DHS cluster coordinates.

3.1.2. Forest cover loss and hydrological data

The second set of data is collected from two different sources using Google Earth Engine to identify forest cover loss at two sub-basin boundaries (i.e., upstream, and downstream). First, to identify the sub-basin level, we used the HydroBASINS geospatial product by Lehner and Grill (2013), extracted from the gridded HydroSHEDS core layers at 15 arc-second resolutions (approximately 500m at the equator), which was developed by the Conservation Science Program of the World Wildlife Fund, based primarily on elevation data obtained during NASA’s Shuttle Radar Topography Mission (SRTM) (Farr and Kobrick 2000). HydroBASINS is divided into 12 hierarchically nested levels using a modification of the Pfafstetter level system, where 1 corresponds to the continental scale, and level 12 has an average area of 130 km² (Verdin and Verdin 1999). At its highest level of sub-basin breakdown, HydroBASINS divides a basin into two sub-basins at every location where two river branches meet which each have an individual upstream area of at least 100 km². HydroSHEDS’ coding scheme also allows for the analysis of watershed topologies, by providing identifiers for the polygon immediately downstream of each sub-basin. Second, to estimate forest cover loss, we used the annual tree-cover area at a 30-meter spatial resolution from the Global Forest Change dataset by Hansen et al. (2013), standing forest in 2004, and track forest cover loss until 2020. For this study, each household cluster-buffer polygon is situated in either upstream or downstream sub-basins with the percentage of annual forest cover loss per pixel (see Figure 2). This division enables the analysis to be conducted for the upstream and downstream areas (as placebo tests).

Figure 2 Cluster-buffer, sub-basins, and upstream forest loss since 2000



Note. Hydrological boundaries and forest loss calculated according to HydroBASINS product by Lehner and Grill (2013) and Hansen et al. (2013), respectively.

3.1.3. *Climate data*

The third set of data is gathered from ERA 5 re-analysis, which provides hourly, monthly, and yearly estimates of a large number of atmospheric, land, and oceanic climate variables. This data covers the Earth on a 30 km grid and resolve the atmosphere using 137 levels (i.e., mode layers) from the surface up to a height of 80 km (Hersbach et al. 2018). Specifically, we used annual average temperature and precipitation data for each household cluster buffer from 2004 to 2020.

3.2. Empirical Strategy

A linear regression model in the statistical software Stata 17 has been used to investigate the causal relationship between a dummy dependent variable (e.g., had diarrhea/do not have diarrhea) and independent variables (e.g., forest cover loss from the previous year). Ordinary Least Square (OLS) is a common technique for estimating coefficients of linear regression equations which describe the relationship between one or more independent variables and a dependent variable (Wooldridge 2019). In addition, linear regression is generally the best strategy to estimate the causal effects of treatments on binary outcomes (Gomila 2021). Unlike nonlinear models such as logit and probit, linear regression allows for direct interpretation of the coefficients as probabilities and is safe when the model includes fixed effects or interaction terms (Freedman 2008; Beck 2018).

For the main specification, we estimated Equation 1 on the pooled sample of diarrhea cases (i.e., all the non-migrant rural children who reported whether they had an episode of diarrhea), where Y_{icgyt} is a dummy dependent variable for whether the child “i” experienced DD at the time of survey “t” and where the child “i” resides in cluster “c” of the region, province, and district “g”, and was born in year “y”. $Forest_{c,t-1}^{up}$ denotes the share of yearly forest cover loss the year preceding the survey year in the upstream catchment area. Given the fact the water flows downstream, upstream forest loss is orthogonal to downstream health. We also included climate controls X_{cgt} such as average temperature and precipitation because they are known to be significant predictors of DD (Bandyopadhyay, Kanji, and Wang 2012; Horn et al. 2018), and socioeconomic controls D_{icgt} such as child’s gender, child’s birth order, mother’s age at the child’s birth, mother’s height, and whether the household has access to drinking water. Lastly, we included fixed effects ρ_{gt} for the survey year, region, province, and district to control time-invariant unobservable differences. ϵ_{icgyt} is the error

term that explains the variation of DD that cannot be explained by the listed independent variables. α is the constant parameter or intercept coefficient, and β , λ , and θ are the regression coefficients.

Equation 1

$$Y_{icgyt} = \alpha + \beta \text{Forest}_{c,t-1}^{up} + \lambda X_{cgt} + \theta D_{icgt} + \rho_{gt} + \varepsilon_{icgyt}$$

To estimate the impacts of childhood stunting on forest cover loss via the water flow channel, from upstream to downstream areas, we used a similar method as Equation 1 but modified the timing of child exposure. Specifically, we exploited quasi-random variation in upstream forest loss experienced by different birth cohorts for children (i.e., by birth month and birth year) and compare the height outcomes between exposed and non-exposed cohorts. For the main specification, we estimated Equation 2 on the pooled sample of stunting cases (i.e., all non-migrant rural children who reported whether they suffered stunting) as the dummy dependent variable Y_{icgyt} . Thus, $\text{Forest}_{c,b-1}^{up}$ is the forest cover loss in the year prior to the child's birth (b-1) in the upstream catchment area. In this way, the analysis exploits variation within a geographic location in birth timing relative to forest loss exposure to identify β . The climate control variables X_{cgt} were also included because temperature and precipitation may influence the incidence of stunting (Baker and Anttila-Hughes 2020; Blom, Ortiz-Bobea, and Hoddinott 2022), as well as the socioeconomic variables D_{icgyt} . The child's birth month (γ_{icgmt}) and birth year (δ_{icgyt}) are included to account for age effects in health outcomes as well as unobserved seasonal shocks such as macroeconomic conditions or seasonal weather patterns, which might otherwise confound the relationship between forest exposure and height. Descriptive statistics of all the variables included in the models are reported in the Appendix H.

Equation 2

$$Y_{icgyt} = \alpha + \beta \text{Forest}_{c,b-1}^{up} + \lambda X_{cgt} + \theta D_{icgyt} + \gamma_{icgmt} + \delta_{icgyt} + \rho_{gt} + \varepsilon_{icgyt}$$

4. Results

Table 1 shows the effect of forest loss on the incidence of DD using a pooled OLS regression of DD from 2005 to 2020 (See Appendix). Columns 1, 2, and 3 report parameter estimates for three models that sequentially include controls related to climate, and individual and household characteristics, respectively. The coefficient on upstream forest loss in the previous year of the survey is robustly positive and significant at the 10% across all the specifications. These results suggest that the impact on DD is largely seen the year after forest loss occurred in the upstream catchment area, consistent with previous studies (Herrera et al. 2017; Rasolofoson et al. 2021). The complete model for upstream areas is shown in Column 3 which indicates that when a share of forest loss in the previous year of the survey increases from 0 to 1 (a 100-percentage point change), DD incidence increases by 0.0222 percentage points. In other words, a 1% decline in upstream forest cover significantly increases the likelihood of DD by 0.000222 percentage points, all else remaining constant.

The final row of Table 1 interprets the magnitude of the estimated impact of a 1% forest loss in terms of mean levels of DD incidence. Using the sample average of the probability of DD of 0.1340, 1% decline in upstream forest cover increases the probability of DD by 0.16%. This result is also robust in Columns 1 and 2 in which the models exclude demographic controls and access to drinking water. To validate the research design, we also perform a falsification test to examine the possibility that results are driven by spurious spatial or temporal patterns. Following Zaveri et al. (2020), we replace the upstream forest loss variable with the nearest off-river downstream forest cover data – a location that is disconnected from water flow dynamics and from where water cannot flow upstream to areas where health outcomes are measured. The result of Column 4 shows that there is no statistically significant effect of the falsified downstream forest loss variable on the incidence of DD. This is consistent with the upstream forest cover loss increasing the incidence of DD through a water mechanism.

Table 1: Impact of upstream forest loss on the incidence of Diarrheal Disease, 2005-2020

	Dependent variable: Incidence of Diarrheal Disease			
	1	2	3	4
Upstream forest loss t-1 to t	0.0222** (0.0110)	0.0200* (0.0109)	0.0222** (0.010)	
Downstream forest loss t-1 to t				0.0165 (0.0122)
Observations	41,524	41,524	41,524	39,958
Fixed Effects	Yes	Yes	Yes	Yes
Climate Controls	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes
Improved Water	No	No	Yes	Yes
R2	0.047	0.057	0.058	0.059
Mean DD incidence	13.40%	13.40%	13.40%	13.40%
Impact of a 1 percent loss in upstream forest	0.16%	0.15%	0.16%	

* p<0.10 ** p<0.05 *** p<0.01

Standard errors in parentheses

Notes: The table presents estimates of equation (1) where the dependent variable is the incidence of diarrhea for non-migrant children under the age of 5 between the years 2005-2020.

Each row represents loss in forest cover share upstream/downstream for respective periods.

Loss of forest cover and stunting due to water pollution may occur along a number of different plausible pathways. Previous studies have demonstrated that recurrent DD episodes and limited access to clean drinking water can increase the risk of nutritional deficits in children and, consequently, impaired child development, such as stunted growth (Larsen et al. 2017; Zaveri et al. 2019). Tables 2 shows the effect of forest loss on the incidence of stunting from 2006 to 2020 (See Appendix). In Columns 1, 2, and 3, three sequential models are displayed, each of which shows that the coefficient on upstream forest loss in the year before the child's birth is strongly positive and significant at the level of 10% considering all the parameters. Under the same interpretation of DD, the complete model of Column 3 indicates that a 1% decline in upstream forest cover increases the probability of stunting by 0.28%, holding other factors constant. The result of Column 4 shows that there is no statistically significant effect of the falsified downstream forest loss variable on the incidence of stunting.

Table 2: Impact of upstream forest loss on the incidence of Severe Stunting, 2006-2020

	Dependent variable: Incidence of Severe Stunting			
	1	2	3	4
Upstream forest loss t-1 to t	0.0176** (0.0090)	0.0196** (0.0088)	0.0197** (0.0088)	
Downstream forest loss t-1 to t				0.0348 (0.0103)
Observations	24,660	24,660	24,660	22,038
Fixed Effects	Yes	Yes	Yes	Yes
Climate Controls	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes
Improved Water	No	No	Yes	Yes
R2	0.034	0.068	0.068	0.069
Mean DD incidence	7.00%	7.00%	7.00%	7.10%
Impact of a 1 percent loss in upstream forest	0.25%	0.28%	0.28%	

* p<0.10 ** p<0.05 *** p<0.01

Standard errors in parentheses

Notes: The table presents estimates of equation (1) where the dependent variable is the incidence of severe stunting for non-migrant children under the age of 5 between the years 2006-2020.

Each row represents loss in forest cover share upstream/downstream for respective periods.

5. Conclusion

This study directly examines the causal relationship between deforestation and health outcomes through water channels using a large database of Peruvian non-rural children and high-frequency satellite imagery. By geolinking high-resolution forest loss data with individual-level health outcomes, our preliminary findings suggest that the protection of forested watersheds could play an important role in improving the health outcomes of children under 5 years old in upstream catchment areas. From a short-term perspective, the incidence of DD may be reduced by avoiding deforestation, as mentioned in the literature. Additionally, from a long-term perspective, we provide novel evidence that forest loss can have a significant impact on human capital through the increased incidence of childhood stunting.

Deforestation, childhood DD and stunting are significant problems for rural and distant communities in Peru. Policies are needed to simultaneously decrease the loss of tree cover areas, especially from illegal logging and mining activities, and thus ameliorate health outcomes for children. It is critical to adopt realistic approaches to balance the need for basic water services and environmental stewardship in the rural regions of Peru. For instance, the government must enforce forest laws to reduce illegal deforestation as well as strengthen reforestation partnerships across the country, especially in nearby watershed areas, because forested watersheds can improve water quality and enhance water storage, thereby facilitating access to improved drinking-water sources that have a positive impact on health outcomes.

Finally, identifying further effects from the reduction of forest area to health outcomes through forest policy interventions per region is an important avenue for future research. These interventions usually included the establishment of timber plantations, instruction in sustainable methods for managing non-timber forest products, and technical assistance for sustainable forest management (particularly, forest certification programs and reduced impact logging). Moreover, including other land use and land cover changes, such as agricultural and mining areas, as control variables might contribute to a deeper analysis.

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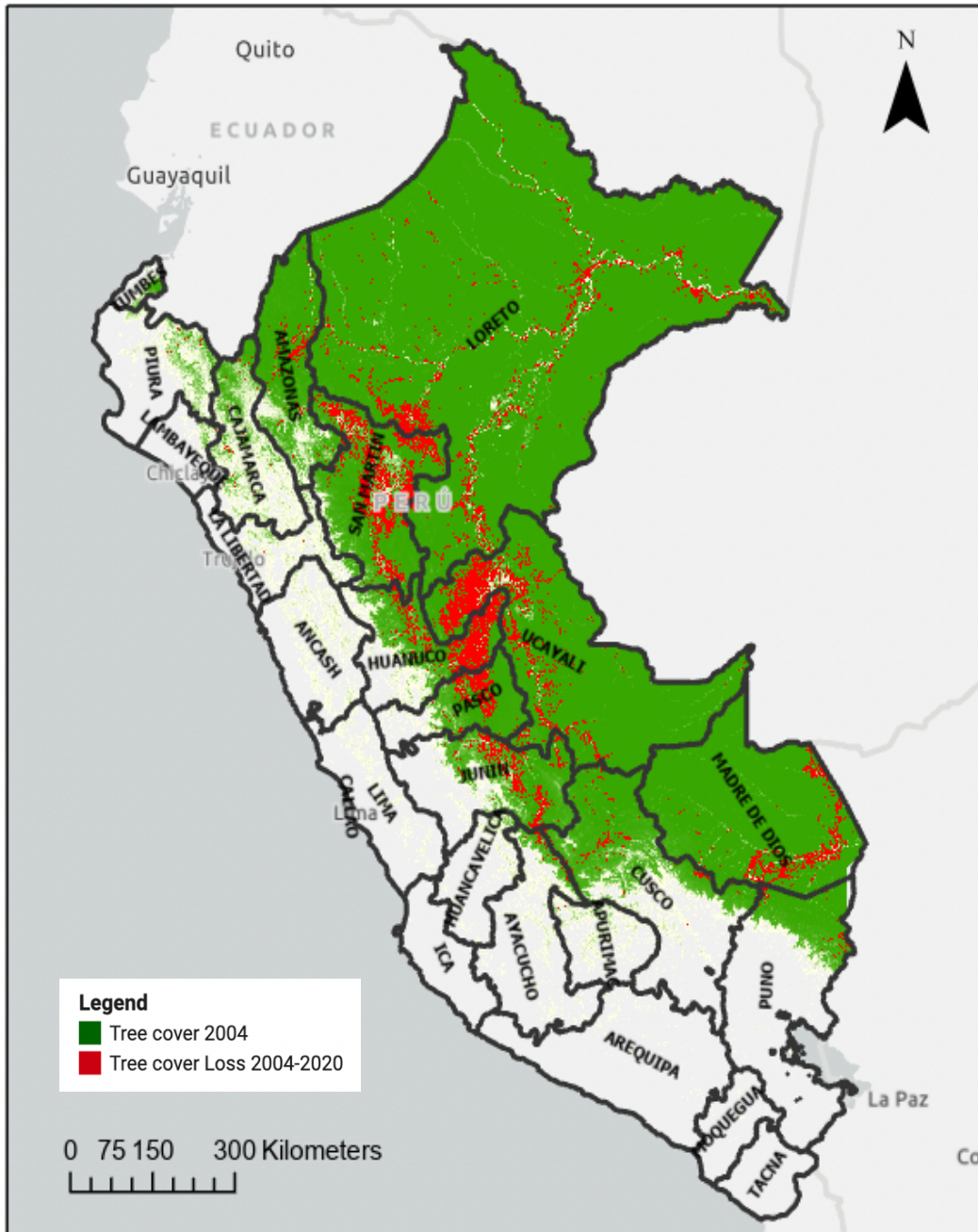
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7. Appendices

Appendix A: Tree Forest Cover and Loss in Peru (2004-2020)

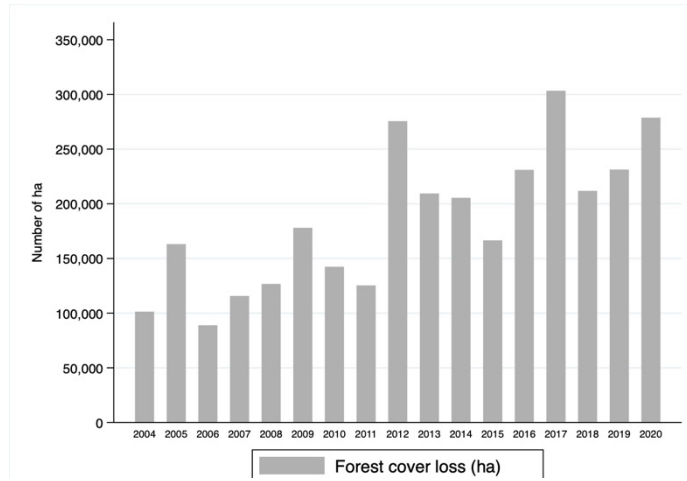


Spatial Reference
Name: GCS WGS 1984
GCS: GCS WGS 1984

Esri, HERE, Garmin, FAO, NOAA, USGS

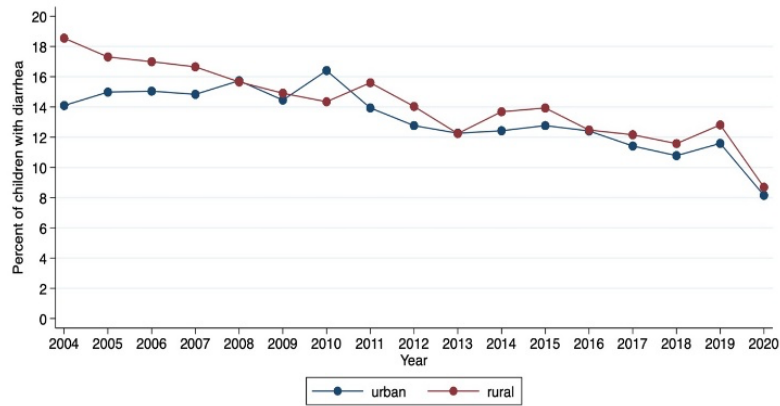
Note. Forest cover and loss area calculated according to geospatial data from Hansen et al. (2013).

Appendix B: Tree Cover Loss in Peru per year (2004-2020)



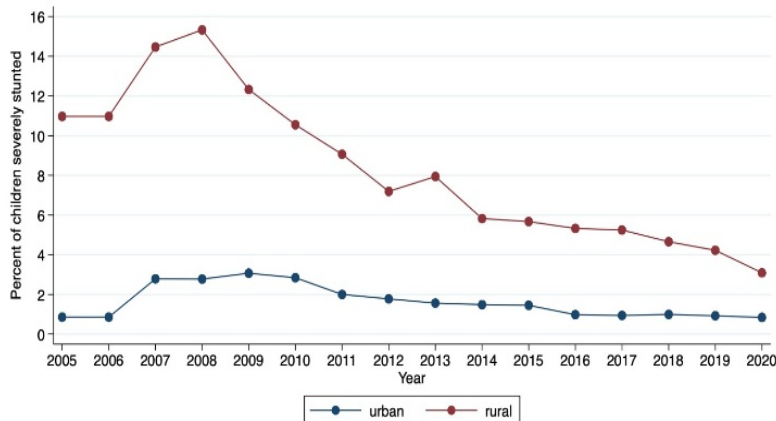
Note. Forest cover loss area calculated according to geospatial data from Hansen et al. (2013).

Appendix C: Percentage of Diarrheal among children aged 0-5 in Peru (2004-2020)



Note. Percentage of diarrhea among children under 5 calculated according to Peru DHS data.

Appendix D: Percentage of Severely Stunted Growth among children aged 0-5 in Peru (2005-2020)



Note. Percentage of severely stunted growth among children under 5 calculated according to Peru DHS.

Appendix E: Percent share of household's source of drinking water by urban/rural and wealth, 2004-2020

Water source	Urban	Rural	Urban Rich	Urban Poor	Rural Rich	Rural Poor
Clean drinking water	99.72	86.62	99.99	99.53	98.76	86.41
Unsafe drinking water	0.28	13.38	0.01	0.47	1.24	13.59
Total	100	100	100	100	100	100

Note. Data collected by author from “Peru Demographic and Health Survey” data.

Appendix F: DHS data per year, 2004-2020

Year	Clusters				Non-migrant Children		
	Rural ^a	Urban Region ^b	Urban Center ^c	Total	Rural	Urban	Total
2004	572	265	577	1,414	1,035	1,043	2,078
2005	572	265	577	1,414	2,236	2,089	4,325
2006	572	265	577	1,414	3,395	3,270	6,665
2007	572	265	577	1,414	4,630	4,328	8,958
2008	572	265	577	1,414	3,973	3,635	7,608
2009	440	386	306	1,132	3,824	4,788	8,612
2010	437	383	313	1,132	3,367	4,242	7,609
2011	437	383	313	1,132	3,314	4,220	7,534
2012	450	258	718	1,426	3,898	5,484	9,382
2013	450	258	718	1,426	3,121	4,469	7,590
2014	467	284	807	1,558	3,091	4,974	8,065
2015	828	929	1,413	3,170	6,016	14,226	20,242
2016	830	930	1,415	3,175	5,083	12,811	17,894
2017	830	930	1,415	3,175	4,720	13,296	18,016
2018	844	932	1,478	3,254	5,702	14,039	19,741
2019	843	932	1,478	3,253	4,745	13,038	17,783
2020	844	931	1,479	3,254	4,650	10,896	15,546
Total	10,560	8,861	14,738	34,157	66,800	120,848	187,648

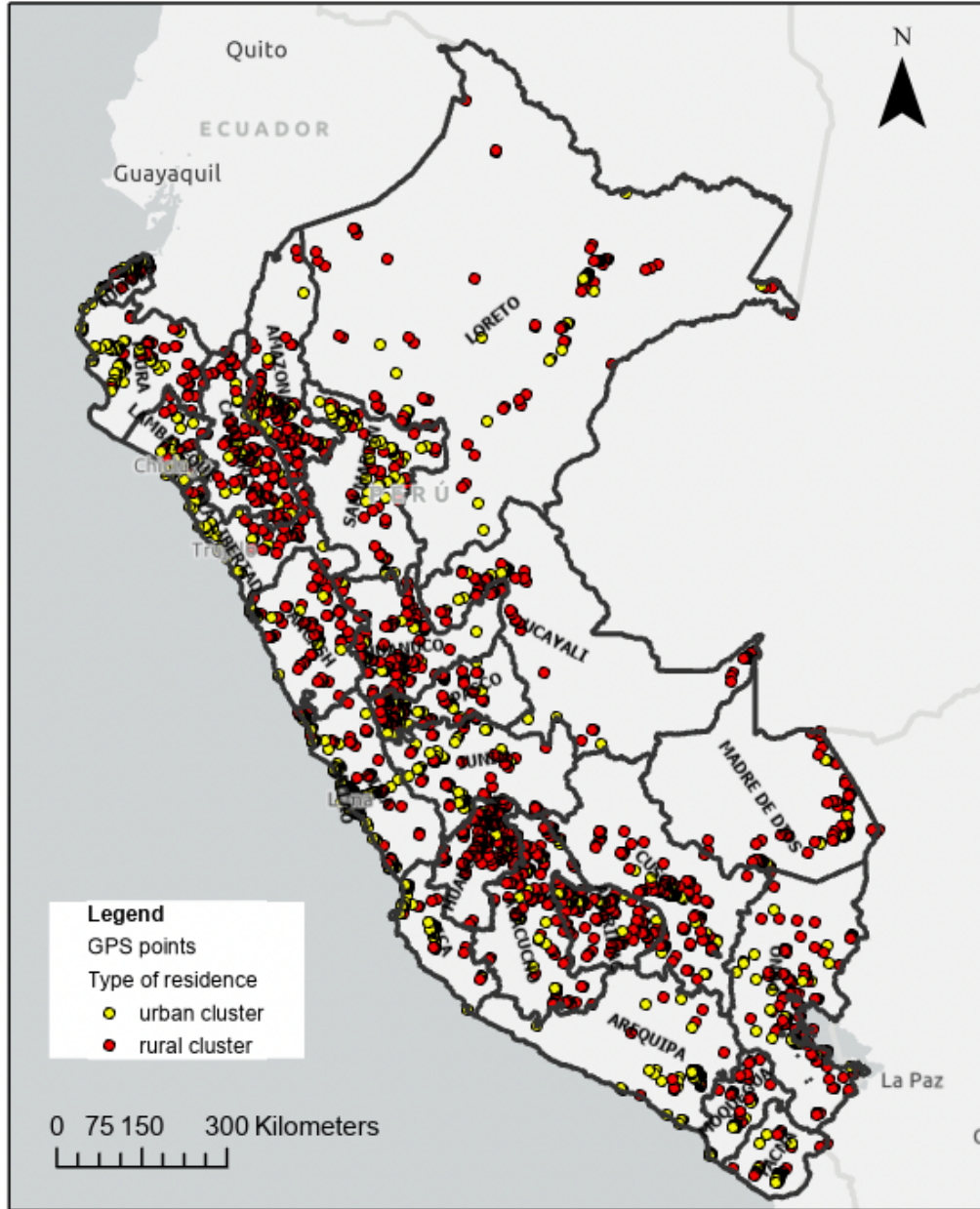
^a/localities with less than 2 thousand inhabitants

^b/localities from 2 thousand to 20 thousand inhabitants

^c/localities from 20 thousand or more inhabitants

Note. Data collected by author from “Peru Demographic and Health Survey” data.

Appendix G: GPS location points from DHS surveys in Peru (2020)



Spatial Reference
 Name: GCS WGS 1984
 GCS: GCS WGS 1984

Esri, HERE, Garmin, FAO, NOAA, USGS

Note. GPS location points calculated according to Peru DHS cluster coordinates.

**Appendix H: Descriptive Statistics of variables used in the study,
Means and SDs (in parentheses)**

Variable	DD model 2005-2020	Stunting model 2006-2020
Dependent		
Upstream forest cover loss t-1 to t (Percentage per pixel)	9.66 (23.25) (N=41,524)	8.10 (21.92) (N=24,660)
Downstream forest cover loss t-1 to t (Percentage per pixel)	8.71 (21.14) (N=39,958)	7.55 (20.19) (N=22,038)
Independent		
Diarrhea (0 = no; 1 = yes)	0.13 (0.35)	-
Stunting (0 = no; 1 = yes)	-	0.07 (0.26)
Improved water source (0 = no; 1 = yes)	0.87 (0.33)	0.88 (0.33)
Temperature t (Celsius)	14.59 (7.01)	15.46 (6.68)
Temperature t-1 (Celsius)	15.23 (6.95)	15.63 (6.74)
Precipitation t (meters)	0.005 (0.024)	0.004 (0.003)
Precipitation t-1 (meters)	0.004 (0.025)	0.004 (0.003)
Sex of the child (0 = male; 1 = female)	0.49 (0.49)	0.50 (0.50)
Child's birth order (1-4)	1.19 (0.42)	1.17 (0.41)
Mother's age at child's birth	28.09 (7.28)	28.17 (7.26)
Mother's height (cm)	150.31 (5.22)	150.35 (5.21)