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Decoding the drivers and effects of deforestation in Peru: a national and regional analysis

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Abstract
High deforestation rates in tropical forests of South America lead to biodiversity loss, climate change and alterations in nature's contributions to people. Deforestation drivers vary across scales due to the heterogeneity of environmental and socioeconomic conditions and forest types. Here, we test the effects of deforestation drivers on deforestation rate from 2000 to 2020 at national and regional scales using Peru as a study case. To do that, we selected nine deforestation drivers commonly used in tropical deforestation analyses. We used the forest cover loss dataset of Global Forest Change to calculate deforestation rates. We conducted five path analyses, one for the national scale and the others for the four regions, using the district as a spatial unit. The national path model explained 34% of the total observed variance and showed that temperature, agriculture, transport network, precipitation, rural population and fire had a positive effect on deforestation, while the slope had a negative effect. The regional path models (63% of the total observed variance in the Coast region, 32% in the Andean, 60% in the High Rainforest and 75% in the Low Rainforest) showed that many national drivers remained at the regional scale. However, we found that the strength, relation (positive/negative) and type (direct/indirect) may vary. Therefore, identifying regional differences in deforestation dynamics is crucial for forest conservation planning and for addressing effective policies in tropical countries. However, improving the quality and availability of national data is essential for further advancing our understanding of this complex process.

Keywords Tropical forests · Demographic variables · Socioeconomic variables · Accessibility variables · Land use variables · Biophysical environmental variables

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1 Introduction

Tropical countries have the highest proportion of forests worldwide (45%), and the largest continuous cover of the world's tropical forests is in Latin America (FAO, 2020a). These forests contain most of the world's biodiversity and provide fundamental nature's contributions to people with worldwide recognition, such as global climate stability and the functioning of biogeochemical and hydrological cycles. Even though there is an ongoing implementation of multiple initiatives for their conservation (Abbas et al., 2020; Foley et al., 2007; Myers et al., 2000), the rates of tropical deforestation have remained consistently at high levels and more than 90% of deforestation takes place in the tropics (FAO, 2020a). South America was the region with the highest deforestation rate for the 2000–2020 period (FAO, 2020a; Potapov et al., 2022). Deforestation of tropical forests is leading to staggering losses of biodiversity, carbon stores thus increasing global temperatures and imbalances in the world hydrological cycle (Foley et al., 2007; Nobre et al., 2016; Vargas Zeppetello et al., 2020; Xu et al., 2022). Moreover, negative synergies between deforestation and human-driven global warming would push South American forests toward savannah configurations, thus reducing continental rainfall and resulting in insufficient moisture to support rainforests (Lovejoy & Nobre, 2019). Because of the high variability of environmental conditions, forest types and human dimensions, there are large differences in deforestation rates and drivers among countries in Latin America (Armenteras et al., 2017; Hänggli et al., 2023). Moreover, drivers also vary at a subnational scale (among regions within a country), but there are few studies that analyze drivers at national and regional scales (Armenteras et al., 2013; Ferrer Velasco et al., 2020). However, it is crucial to understand and differentiate regional drivers to develop efficacious policies for reducing or halting deforestation rates.

In the last decades, substantial efforts have been undertaken to understand the drivers of tropical deforestation. Deforestation drivers change over time, act synergistically and vary across the landscape (Geist & Lambin, 2002; Rudel, 2007; Rudel et al., 2009). The drivers of deforestation are divided into the proximate causes or direct drivers and the underlying driving force or indirect drivers (Geist & Lambin, 2002). The direct drivers are anthropic activities and immediate actions that directly impact the forest cover. Direct drivers are still the most frequently reported in Latin America, with agricultural practices, cattle grazing and infrastructures as the most cited deforestation causes in the literature (Armenteras et al., 2017; Defries et al., 2010; Hosonuma et al., 2012; Leblois et al., 2017). The underlying drivers are demographic, economic, technological, cultural and political factors operating at multiple scales (Geist & Lambin, 2002). Demographic and socioeconomic variables are highlighted as deforestation drivers in tropical deforestation analyses (Armenteras et al., 2013; Fagua et al., 2019; Sanchez-Cuervo & Aide, 2013). Moreover, environmental factors are also linked to forest cover change (Fagua et al., 2019; Geist & Lambin, 2002). The environmental variables commonly included in the models relate to land accessibility (both natural -rivers- and anthropic -roads-; Aguirre et al., 2021; Barber et al., 2014; Laurance et al., 2001), topography (elevation and slope gradients, Armenteras et al., 2011; Bax et al., 2016) and climate variability (Bax & Francesconi, 2018). Furthermore, climate variables determine conditions for human establishment and development of activities that conduce deforestation (Armenteras et al., 2011; Bax & Francesconi, 2018). Thus, precipitation intensity and seasonality, temperature and drought severity can also affect the susceptibility of ecosystems to fire (Armenteras & Retana, 2012; Armenteras et al., 2020).

Peru's geographical location and unique features, such as the Andes mountain range and the cold Humboldt current, make it a megadiverse country (Reynel et al., 2013) with the fourth largest tropical forest area in the world and the second largest in Latin America (72 million ha in 2020, accounting for around 60% of the Peruvian surface (FAO, 2020b), Peru boasts a wide variety of forest types, including tropical and subtropical dry forest, tropical montane forest and tropical lowland forest (MINAM, 2015; Reynel et al., 2013). Furthermore, Peru has experienced rapid economic growth in recent decades, with its economic performance remaining above the regional average, thanks to the development of agriculture, mining, and other extractive activities (Che Piu & Menton, 2014; De La Torre Ugarte et al., 2021; MINAM, 2016). Despite having a lower national deforestation rate than other Latin American countries, Peru's national and regional deforestation rates have accelerated from 2000 to 2020, with different dynamics in different regions (Móstiga et al., unpublished data). Previous analyses of Peruvian deforestation drivers have been conducted as part of global analyses (Armenteras et al., 2017; Hänggli et al., 2023), in specific regions (e.g., tropical montane forest; Bax & Francesconi, 2018), or within protected areas (Aguirre et al., 2021). However, no analysis of the drivers of deforestation in Peruvian forests at the national and regional levels has been conducted yet. This makes Peru an ideal setting to explore the environmental, economic, and social characteristics that contribute to tropical deforestation. Furthermore, Peru has various forest types, including tropical mountain forests and tropical dry forests, that have received less attention, even though they are disappearing at a faster rate than the tropical lowland forests. (Armenteras et al., 2011, 2017; Rudel, 2017; Salazar et al., 2015; Schröder et al., 2021). Moreover, while studies on tropical deforestation have mostly focused on lowland tropical forests (Armenteras et al., 2011; Hänggli et al., 2023; Salazar et al., 2015; Schröder et al., 2021), there is surprisingly little precise information available on the actual drivers of deforestation in the Peruvian Amazon (Che Piu & Menton, 2014; Espejo et al., 2018; Finer & Novoa, 2017; Glinskis & Gutiérrez-Vélez, 2019; Hänggli et al., 2023; MINAM, 2016; Ravikumar et al., 2017).

The aim of this study is to investigate the effect of tropical deforestation drivers on the context of accelerated deforestation rates and economic development considering environmental, economic, and social variations that include the less studied South American forests. What sets this study apart from prior research is its integrated, comprehensive approach, and its focus on consolidating available datasets and knowledge about deforestation in Peru spanning two decades. Consequently, this study intends to examine the potential drivers of deforestation in Peru from 2000 to 2020, taking regional variations into consideration. Specifically, we address the following questions: (1) Which are the drivers of deforestation at the national level? (2) Do these drivers vary among regions? To do this, we have selected prevalent tropical drivers pertinent to Peru. We have then built a concise model to explain deforestation regarding all reasonable relationships between variables. In the final stage, with a path analysis for the whole area and for each region separately we have examined the direct and indirect effects of these drivers.

2 Materials and methods

2.1 Study area

Our study area is the entire country of Peru which covers more than 1.28 million km^2 in South America, the third largest country in the region. The Peruvian territory is

politically divided into 24 departments, 196 provinces and 1874 districts (IGN, 2021). We focused our study on districts that had more than 500 ha of forest cover in the year 2000, according to the end products of Global Forest Change-GFC (GFC, 2022), resulting in 790 districts to homogenizing all variables (Table 1). For the regional analysis, according to MINAM (2019) (Fig. 1a) we have defined four regions that differ in their ecology and human occupation (Supplementary Figs. 1 and 2): (1) Coast (10% of the country area) a very populated region, hot and dry, that extends from the sea level to approximately 1500–2000 m in a slightly uneven topography; (2) Andean (30%), highly transformed region that ranges from semi-warm arid to cold wet or cold dry, with a forest cover that extends from 1500 to 4500 m in a sloped to extremely steep relief; (3) High Rainforest (14%) sparsely populated region, humid or sub-humid with permanent fog and steep slopes and; (4) Low Rainforest (46%) sparsely populated region, humid and rainy forest with seasonal or permanent flooded forest in the Amazon plain. In each region we included all districts with more than 50 % of their territory in this region, resulting in: 37 districts for the Coast region, 421 for the Andean region, 209 for the High Rainforest region and 123 for the Low Rainforest (Fig. 1b).

2.2 Datasets

2.2.1 Forest cover

We used the end products of Global Forest Change (GFC hereafter) version 1.8 update to 2020, forest cover (baseline:2000) and forest cover loss (2001 to 2020) maps with a 30 m resolution (GFC, 2022). Hansen et al. (2013) estimated the GFC using a decision tree approach based on the multitemporal profile of spectral metrics derived from Landsat satellite images. Forest loss was defined as pixels with disturbance or complete removal of tree cover without regard to forest gain (i.e., the exclusion of pixels after a deforestation event annually) (GFC, 2022). Our study area spanned five GFC tiles that were clipped to match their boundaries. We calculated the district forest cover by converting the pixels (30 × 30 m) of forest cover maps into areas (unit: Hectares, ha) using ArcGIS 10.5 (ESRI, 2016).

2.2.2 Potential deforestation drivers

We selected explanatory variables that are usually used in tropical deforestation analysis (Armenteras et al., 2013; Barber et al., 2014; Bax & Francesconi, 2018; Geist & Lambin, 2002) and that were available for the whole country. We excluded from the analyses those variables that were distributed in a few districts or in districts of a specific region or whose data was insufficient such as: illegal coca crop, legal and no legal mining and hydrocarbons (Supplementary Fig. 4). Likewise, we did not include cattle because the last agricultural census was ten years old (INEI, 2014). Moreover, to avoid multicollinearity we excluded one of each pair of variables with correlation coefficients higher than 0.7. The nine selected variables are summarized in Table 1 and can be classified into six categories: demographic (1 variable), socioeconomic (2), biophysical environmental (3), accessibility (1) and land use (2).

Table 1 Summary of the different types of explanatory variables for deforestation considered in this study

Type	Variable	Units	Description	Variable range	Transform method	Source(s)	Original spatial resolution
Demographic	Rural population	Number of inhabitants	Population in rural areas in 2017	0–63 516	Square root	INEI(1) (2018)	District
Socio economic	Unsatisfied basic needs (UBN)	%	Percentage of the population with at least one unsatisfied basic need (UBN) according to data from 2017 national census. UBN is an indicator of poverty that considers the follow unsatisfied basic need: access to housing, access to health services, access to education and economic capacity	2.10–99.40	None	INEI(1) (2018)	District

Table 1 (continued)

Type	Variable	Units	Description	Variable range	Transform method	Source(s)	Original spatial resolution
	Human Development Index (HDI)	no units	Geometric mean of three dimensions: Quality of life (family income per capita) + Healthy life (life expectancy at birth) + Education and skills (average years of schooling + expected years of schooling) based on 2017 census	0.09–0.77	None	UNDP(2) (2019)	District
Biophysical environment	Slope	%	Average slope by district	1.61–75.90	None	Farr et al. (2007)	30 m
	Precipitation	mm/year	Average of the total annual precipitation by district of 1970–2000 period	6.96–5 054.17	Square root	Fick and Hijmans (2017)	1 km
	Temperature	°C	Average annual mean temperature by district of 1970–2000 period	1.97–27.01	Square root	Fick and Hijmans (2017)	1 km
Accessibility	Transport network	km/ha	Road and navigable rivers density by district	0–0.03	Square root	MTC(3) (2019) MARINA DE GUERRA DEL PERÚ. pers.comm	0.5 m; 1:100000

Table 1 (continued)

Type	Variable	Units	Description	Variable range	Transform method	Source(s)	Original spatial resolution
Land use	Agriculture	ha	Agricultural surface by district in 2018 that includes those with transitory and permanent crops and fallow	0–100 901	Square root	MIDAGRI(4) (2021)	10 m
	Fire	ha	Surface affected by forest fires by district, considering a minimum area of 0.5 ha, from 2017 to 2020	0–11 175.61	Log-transform	SERFOR[(5)]pers.comm	10 m

INEI[(1)] Instituto Nacional de Estadística e Informática del Perú; UNDP[(2)] United Nations Development Programme; MTC[(3)] Ministerio de Transporte y Comunicaciones del Perú; MINAGRI[(4)] Ministerio de Desarrollo Agrario y Riego; SERFOR[(5)] Servicio Nacional Forestal y de Fauna Silvestre

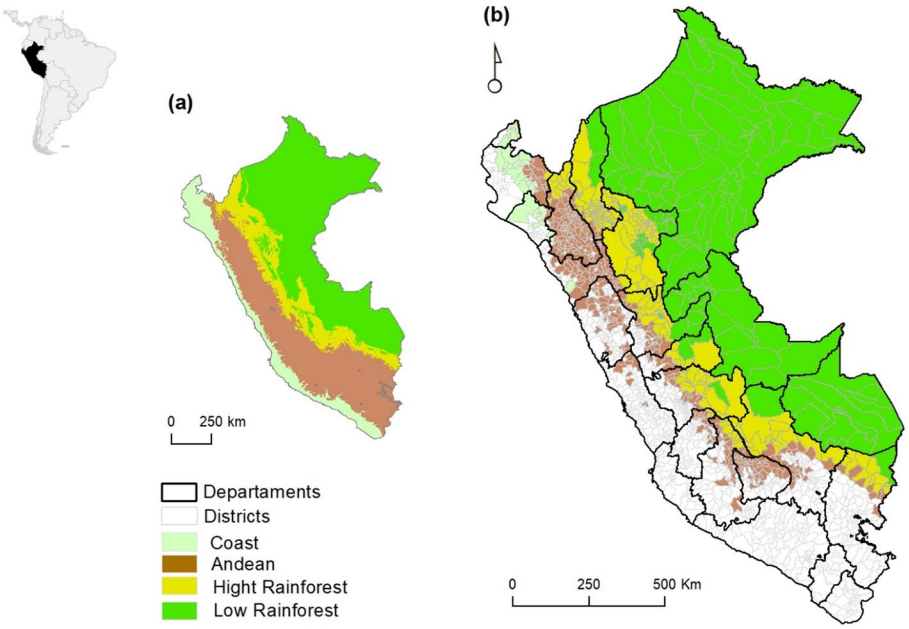


Fig. 1 Study area. **a** Regions. **b** Districts selected by regions for the analysis (forest surface $\geq$500 ha)

- The demographic variable was the rural population (number of inhabitants) obtained from the 2017 national census of the Instituto Nacional de Estadística e Informática del Perú- INEI- for each district (INEI, 2018).
- The socioeconomic variables were Unsatisfied Basic Needs -UBN- (%), extracted from the 2017 national census from INEI Perú for each district (INEI, 2018), and the Human Development Index-HDI-, obtained from United Nations Development Programme (UNDP, 2019).
- The biophysical environmental variables were slope, temperature and precipitation. Slope (in percentage) derived from a map of elevation (in m) based on the Shuttle Radar Topography Mission (SRTM, 30 m resolution) (Farr et al., 2007). Total annual precipitation (mm/year) and mean annual temperature (°C) were obtained from WORLDCLIM with 1 km resolution (Fick & Hijmans, 2017).
- The accessibility variable was the Transport Network that included the density (km/ha) of roads (including paved and unpaved roads) and navigable rivers. They were obtained from Ministerio de Transporte y Comunicaciones del Perú, with 0.5 m resolution, and Marina de Guerra del Perú respectively.
- The land use variables were Agriculture and Fire. The agricultural surface in 2018 was derived from the processing of orthorectified RapidEye satellite images, Sentinel-2 satellite images and high-resolution images available on Google Earth by Ministerio de Agricultura y Riego (MIDAGRI, 2021). Fire included the surface affected by forest fires from 2017 to 2020 with a 10 m resolution, considering a minimum area of 0.5 ha, which was calculated by the Unidad Funcional de Monitoreo Satelital (UFMS) of Servicio Nacional Forestal y de Fauna Silvestre (SERFOR, pers. comm.).

The nine selected variables were integrated into a GIS database to calculate their value at the district level (which was the analysis unit). Before the analysis, we normalized several variables with log-transform (fire) and square root (precipitation, temperature, agriculture, rural population and transport network) to reach normality.

2.3 Data analysis

We calculated the standardized deforestation rate (r, in $\%\cdot\ yr^{-1}$) proposed by Puyravaud (2003) for each district:

$$Deforestationrate\left(r;\% \cdot yr^{-1}\right) = \frac{1}{(t2 - t1)} \ln \frac{A2}{A1} 100$$

where A1 and A2 are the district forest cover (in ha) in the years t1 and t2, respectively (in this study, t1 = 2000 and t2 = 2020). Then, we summed district forest cover either for the region considered or for the whole of Peru to calculate the national and regional deforestation rate. Before the analysis, we also normalized this variable with log-transform.

We carried out five path analyses, one for Peru and the others for the four regions. Path analysis is a broad statistical analysis that combines factor analysis and multiple regression analysis from a hypothetical initial model to obtain direct and indirect effects between several variables allowing more than one dependent variable (Li, 1986). In this study, we computed the path analyses using the LAVAAN package in R (Rosseel, 2012; R CoreTeam, 2021). The initial path model (Fig. 2) was based on expert criteria. Final models for national and regional analysis were the path models resulting after excluding non-significant variables ($p > 0.05$) until reaching a good model fit. The final model in terms of goodness-of-fit was selected following these guidelines: (1) Root Means Square Error of Approximation (RMSEA) value ≤ 0.06, with confidence interval at 90% values should be between 0 and 1.00; (2) Standardized Root Mean Square Residual (SRMR) value ≤ 0.08; and (3) Confirmatory Factor Index (CFI) and Tucker Lewis Index (TLI) values ≥ 0.95 (Gana & Broc, 2019). The diagram path of each final model included the standardized coefficients (direct effects), the coefficients of determination (R^2) of dependent variables and the variance (U) of dependent variables related to unknown causes. The total effect coefficient (total effect) is the sum of the effects exerted along direct and indirect paths.

3 Results

Peru as a whole had a deforestation rate of $0.23\%\cdot\ yr^{-1}$ varying among regions, with values of 0.36 in the High Rainforest; 0.20 in the Low Rainforest; 0.21 in the Andean and 0.12 in the Coast region (Table S1). The rates per district were mainly between 0 and $0.5\%\cdot\ yr^{-1}$, the highest district rates were in the north and center of the Low and High Rainforest regions with a clustered pattern (Supplementary Fig. 5). Moreover, there were some dispersed high rates on the Coast, Andean and south of Low Rainforest regions (Supplementary Fig. 5).

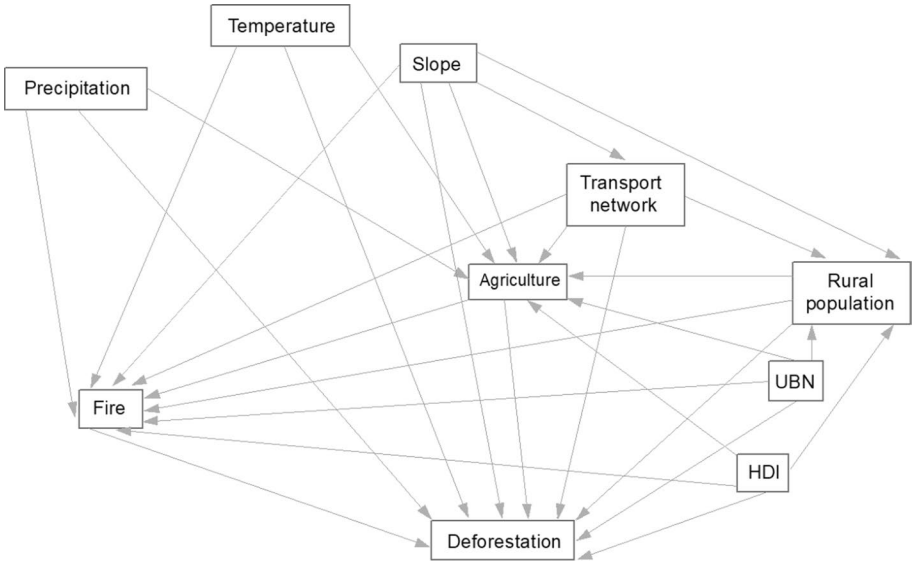


Fig. 2 Initial path model with demographic (rural population), socioeconomic (unsatisfied basic needs -UBN- and human development index -HDI-), biophysical environmental (slope, temperature and precipitation), accessibility (transport network) and land use (agriculture and fire) variables and interactions among them for the national and regional analyses

3.1 National deforestation drivers

The model goodness-of-fit indices of the final path model at the national level are summarized in Table 2. The final path model for Peru accounted for 34% of the total observed variance in deforestation. The variables explaining deforestation were temperature, agriculture, transport network, precipitation, rural population, fire, and slope (Fig. 3a and Table 3). All variables had a positive total effect on deforestation rate except slope which was negative (Table 3).

Table 2 Indices of model goodness-of-fit for the national and regional path analyses

Indices	Peru	Regions			
		Coast	Andean	High rainforest	Low rainforest
Comparative Fit Index (CFI)	0.999	1	0.984	1	1
Tucker-Lewis Index (TLI)	0.997	1.033	0.957	1.001	1.013
Root Mean Square Error of Approximation (RMSEA)	0.024	0.000	0.059	0.000	0.000
90% confidence interval—lower	0.000	0.000	0.008	0.000	0.000
90% confidence interval—upper	0.056	0.212	0.106	0.115	0.122
Standardized Root Mean Square Residual (SRMR)	0.010	0.023	0.026	0.010	0.007

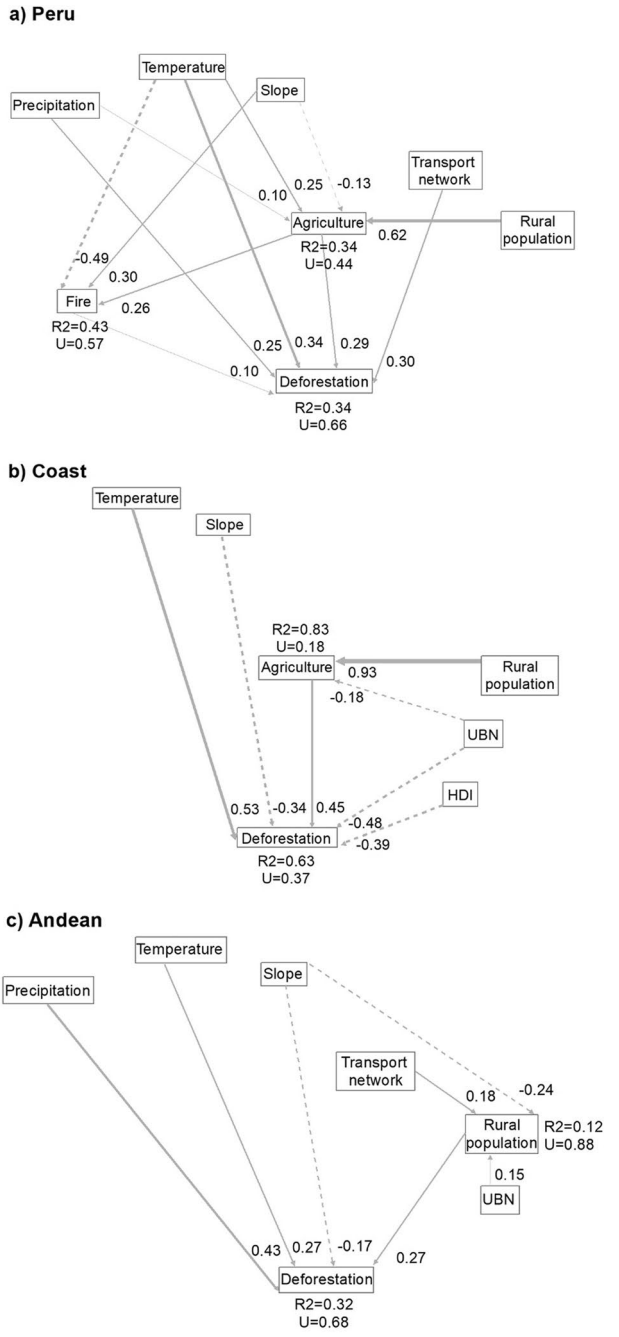
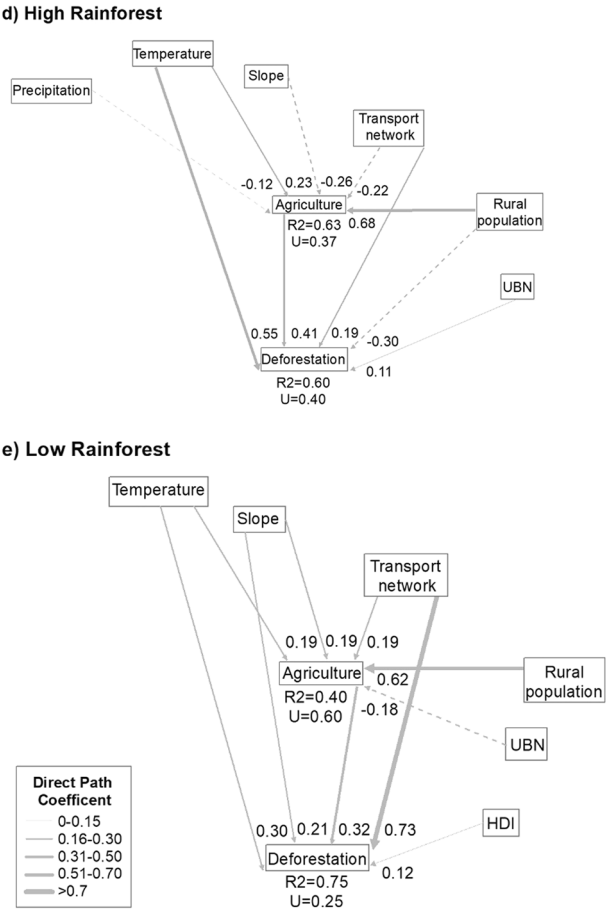


Fig. 3 Path diagrams for the different national and regional analyses. **a** Peru; **b** Coast; **c** Andean; **d** High Rainforest and **e** Low Rainforest. Line thickness indicates the magnitude of the absolute value of the direct path standardized coefficient. Solid and dashed lines indicate positive and negative direct effects, respectively. All path coefficients are significant ($p < 0.05$)

Fig. 3 (continued)



3.2 Regional deforestation drivers

The model goodness-of-fit indices explain the relative reliability of all regional models (Table 2). The path diagrams in Fig. 3b–e show the final path models for each of the four regions, while Table 3 summarizes the direct, indirect, and total effects of these path models. The observed variance of deforestation explained in the final path model of each region was: 63% in the Coast region; 32% in the Andean; 60% in the High Rainforest and 75% in the Low Rainforest.

The drivers of deforestation and their effects varied among regions (Table 3). Temperature, rural population, slope and UBN were deforestation drivers in all regions. Other variables only were significant drivers in some regions: agriculture in the Coast, High and Low Rainforest regions; transport network in the Andean; High and Low Rainforest; precipitation in the Andean and High Rainforest and IDH in the Coast and Low Rainforest, while fire was not significant in any region.

Temperature had a strong and positive effect on the deforestation rate in all regions. Rural population had a positive effect in all regions, except in the High Rainforest region which was negative. The slope has a negative effect on the deforestation rate in all regions,

Table 3 Direct, indirect and total path effects of the national (a) and regional (b to e) analyses

	a) Peru			Regions											
				b) Coast			c) Andean			d) High rainforest			e) Low rainforest		
To Deforestation	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Temperature	0.338	0.031	0.369	0.525	–	0.525	0.273	–	0.273	0.547	0.093	0.640	0.301	0.062	0.363
Rural population	–	0.194	0.194	–	0.423	0.423	0.273	–	0.273	−0.298	0.274	−0.024	–	0.201	0.201
Slope	–	−0.012	−0.012	−0.343	–	−0.343	−0.166	−0.066	−0.232	–	−0.106	−0.106	0.206	0.061	0.267
UBN	–	–	–	−0.483	−0.081	−0.564	–	0.041	0.041	0.106	–	0.106	–	−0.058	−0.058
Agriculture	0.290	0.025	0.315	0.454	–	0.454	–	–	–	0.406	–	0.406	0.322	–	0.322
Transport network	0.296	–	0.296	–	–	–	–	0.049	0.049	0.190	−0.089	0.101	0.725	0.060	0.785
Precipitation	0.248	0.030	0.278	–	–	–	0.429	–	0.429	–	−0.048	−0.048	–	–	–
HDI	–	–	–	−0.388	–	−0.388	–	–	–	–	–	–	0.120	–	0.120
Fire	0.097	–	0.097	–	–	–	–	–	–	–	–	–	–	–	–

except in the Low Rainforest regions which was positive. UBN, precipitation and HDI had positive and negative effects on the deforestation rate according to the region. Thus, UBN had a positive effect on the deforestation rate in the Andean and High Rainforest regions and had a negative effect on the Coast and Low Rainforest. Precipitation had a positive effect only in the Andean region but a negative effect in the High Rainforest, while HDI had a positive effect in the Low Rainforest but a negative effect on the Coast.

4 Discussion

4.1 Deforestation drivers and their effects at national scale

Our findings are consistent with several previous studies that have identified drivers of deforestation in tropical forests across Latin America. These drivers include biophysical factors such as temperature, precipitation, and slope, as well as land use practices like agriculture and fire. Accessibility via transport networks and demographic factors such as rural population density were also found to be drivers of deforestation (Table 3; Armenteras et al., 2017; Barber et al., 2014; Curtis et al., 2018; Hänggli et al., 2023; Jayathilake et al., 2021). Surprisingly, our analysis did not reveal any direct or indirect effects of socioeconomic variables, such as UBN and IDH, at the national scale (Fig. 3a). However, socioeconomic variables related to poverty and economic index had an effect in other countries of the region (Armenteras et al., 2013; Fagua et al., 2019; Sanchez-Cuervo & Aide, 2013).

We found that temperature had the strongest and most positive total effect on deforestation (Table 3). In tropical regions, climate conditions (specifically temperature and precipitation) create favorable conditions for activities that transform landscapes, as noted in previous studies (Armenteras et al., 2011; Bax & Francesconi, 2018). Agriculture significantly contributed to deforestation, although it was challenging to distinguish between small-scale individual farmers and larger agro-industrial operations. While the majority of national agricultural land was categorized as family agriculture and traditional livelihood systems (MIDAGRI, 2021), there is evidence that agro-industrial crops intensified in Peru in the last decades, and could be more associated with deforestation (Móstiga et al., unpublished data). Moreover, secondary forest cover produced after small-scale agriculture is stable through time and both the area and the rate of expansion into non-perturbed forests are modest when compared to forest conversion due to colonization and industrial plantations in Peru (Coomes et al., 2022).

Accessibility by roads and navigable rivers is another main driver of deforestation in Peru (Table 3), likely due to the increased national road network, allowing access to new forest areas (Móstiga et al., unpublished data). National road network increased by 34% in the last 20 years (Aguirre et al., 2021). Rural population had a positive effect on deforestation in Peru, but it was indirect through agriculture (Fig. 3a and Table 3), as rural population is not directly associated with forest loss in the tropics (Defries et al., 2010).

We also detected a low positive effect of fire on deforestation (Table 3). In tropical forests, fire is often used by agricultural practices to change land use (i.e., deforestation; Andela et al., 2017; Armenteras et al., 2021). While fire is an indicator of the early stages of natural resource exploitation in the Amazon and Andean countries, not all fires take place in forests, and some could be in previously deforested areas (Fig. 3a; Armenteras et al., 2013, 2017; Bax & Francesconi, 2018; Zubieta et al., 2021). Moreover, we only

analyzed partial data of fire, during four years of the total 20 years analyzed (Table 1 and 3).

On other hand, we found a total negative indirect effect of slope on deforestation through agriculture and fire, which showed opposite patterns (Table 3). Thus, the slope effect through agriculture was negative because areas with abrupt topography tend to be difficult to access to agriculture and, thus, to deforestation (Bax & Francesconi, 2018; Fagua et al., 2019; Fig. 3a). But the slope effect on fire was positive because strong slopes spread fire and, thus, favor deforestation (Fig. 3a; Singh & Zhu, 2021).

4.2 Regional effects of deforestation drivers

Although most national deforestation drivers were found to operate at the regional scale, their strength, relationship (positive or negative), and type (direct and/or indirect) varied across regions and between the national and regional scales (Table 3). Again, as was the case at the national scale, temperature emerged as the main positive driver of deforestation in all four regions. However, while precipitation had a positive effect at the national level, this effect was only significant in the Andean region, with non-significant or even slightly negative values observed in other regions (Table 3). This strong and direct effect of climatic variables (precipitation and temperature) in the Andean region may be attributed to the traditional livelihood systems that rely heavily on these factors (INEI 2014; Bax & Francesconi, 2018). However, precipitation regimes are different in the High Rainforest region, here the permanent and strong precipitation on steep slopes without forests produces high soil erosion (Móstiga et al., unpublished data) that is negative to the development of agricultural activities thus resulting in less deforestation. Another related variable, slope, showed a negative effect on deforestation rates at both the national and regional scales, as highly sloped land makes it difficult to use land and resources, thereby limiting deforestation. However, this effect changed to a positive value in the Low Rainforest region, which may be explained by the presence of low-sloped land with high precipitation (Supplementary Fig. 1), making it more suitable for some activities that drive deforestation.

The transportation network, which showed a positive but moderate value at the national level, was the main deforestation driver in the Low Rainforest region (Table 3). Therefore, both navigable rivers and roads allowing the colonization of new areas favor deforestation (Aguirre et al., 2021), as detected in other Amazon tropical low forests (Barber et al., 2014). Low Rainforest districts had a low density of population (Supplementary Fig. 2) and the population growth resulted from migration from the Andes or other Amazon areas that established new colonization frontiers (Dourojeanni, 2019; Menton & Cronkleton, 2019) as was detected in another countries with lowlands Amazon forests (Armenteras, et al., 2017). On the contrary, the transport network had a lower effect on deforestation rate in the Andean and High Rainforest regions (Table 3) because forests are remote in these regions (Sylvester et al., 2017). Moreover, the transport network did not have an effect in the Coast region (Table 3). Although at present dry forests exist as fragments of once large forests and extend in a very populated region with abundant roads within (Portillo-Quintero & Sánchez-Azofeifa, 2010; Supplementary Fig. 2). A large surface of them, around 40% in 2020, are inside protected areas with a low deforestation rate (Móstiga et al., unpublished data) nulling the effect of the transport network in the region.

Agriculture also was a deforestation driver with a strong effect at the national and regional scales although it did not have an effect in the Andean region (Table 3). In this

region, contrary to the others, there is evidence of a long history of human occupation of forests, with the only presence of current relict forests mainly located at high altitudes and steep slopes that are not suitable for agriculture (Sylvester et al., 2017). Moreover, agriculture reduces its effect in the Low Rainforest region where the transport network had the strongest effect (Table 3). Rural population had a strong indirect and positive effect on deforestation through agriculture at both national and regional levels, except in the Andean region, where the positive effect of rural population on deforestation is direct, not through agriculture (Fig. 3). In the Coast region, the strong positive indirect effect of rural population on deforestation is related to the characteristics of the region, where 61.1% of the population was permanently dedicated to agriculture (INEI, 2014). Moreover, the dry forest has historically supported high human population densities because of their suitable conditions for human life and the development of infrastructure (Portillo-Quintero & Sánchez-Azofeifa, 2010; Rudel, 2017; Schröder et al., 2021). In the High Rainforest region there was also, together with the indirect effect through agriculture, a negative direct effect of rural population to deforestation (Fig. 3d; Table 3). This could be explained because the deforestation process in the High Rainforest region was more recent than in the Andean or Coast regions and was related to the migration and colonization processes that resulted in a disorganized extension of the agricultural frontier related to agricultural livelihood systems (Dourojeanni, 2019; Menton & Cronkleton, 2019). The environmental conditions of the High Rainforest region provide natural conditions for the large-scale production of rice, coffee, palm oil and cacao in this region that has also developed in the last decades (Fig. 3d; Bax & Francesconi, 2018; MIDAGRI 2021). Therefore, deforestation rates in this region could be associated with both agroindustrial activities and agricultural livelihood systems, as indicated by Ravikumar et al. (2017). Furthermore, sustainable production systems of cocoa linked to conservation and development goals, as promoted by government bodies or international agencies, paradoxically intensify production and attract smallholders into forest frontier areas increasing deforestation rates (Lock & Alexander, 2023).

Despite fires being recognized as the biggest hazard for tropical dry forests (Schröder et al., 2021), in Peru their frequency and intensification in the last decades could be associated with dry forest dynamics of deforestation (Móstiga et al., unpublished data). Furthermore, there has also been an increase in the frequency and extension of fires in both the Amazon basin and northern South America in the last two decades (Armenteras et al., 2020). In this study, we have not identified fire as an important driver. However, it is important to note that there is evidence of the use of fire in illegal carbonization, burning by beekeepers, invasions and burning practices to start agricultural campaigns (Schröder et al., 2021), but all of them remain poorly documented (Armenteras et al., 2020; Rudel, 2017).

The analysis of two complementary socioeconomic variables, HDI and UBN, allowed differentiation between the effect of the whole human development (HDI) and the fraction poor of the district population (UBN) on deforestation. We associated further IDH with the development of extensive or industrial activities, mainly agriculture, in regions with significant effects of this variable (the Coast and Low Rainforest regions). Although cross-national studies on socioeconomic variables in emerging economies suggest that the increase of development, i.e. HDI and the access to clean fuels and technologies for cooking, conduce to reducing carbon emissions and deforestation (Bakehe & Hassan, 2022; Banday & Kocoglu, 2023). We only found regional effects of socioeconomic variables on deforestation, but varying their relationship among regions (Table 2). In the Coast, the socioeconomic variables revealed that the districts with less HDI but not the poorest (lowest UBN) had the highest deforestation, probably due to the development of

technical agriculture in the region (INEI, 2014). In the Low Rainforest region, the poorest population (districts with higher UBN) neither resulted in high deforestation but the districts with more HDI had more deforestation, suggesting that deforestation could be more associated with industrial activities than with agricultural livelihood systems. There is evidence that agro-industrial crops such as palm oil, coffee, cacao and other fruits and other legal and illegal activities related to hydrocarbons or minerals were extended in the last decades in the Low Rainforest region (Móstiga et al., unpublished data). On contrary, we detected that UBN (indicating poorer districts) was positively related to deforestation in the Andean region. It is the poorest region in the country, with 48.1% of the total poor population of Peru, and in this region the development of traditional livelihood systems could promote deforestation (INEI, 2014, 2015). Similarly, the districts with high UBN also had more deforestation in the High Rainforest region, which also supports the presence of agricultural livelihood systems in the region.

5 Conclusion

Our study underscores that variations in climate, associated forest types and their interaction with population have produced different regional effects by deforestation drivers in Peru. Our findings also provide crucial information for supporting the conservation efforts of tropical forest covers in Peru. Moreover, these findings provide a guide to decision-makers and politicians for improving conservation planning and appropriate policy actions that could be based on each regional context. However, there are some conflicting policies between forest conservation legislation and other economic sectors, for instance agriculture or transport, which could actively promote deforestation. Our analysis of drivers also urges policymakers to address legislative deficiencies and strengthen the forest cover change legislation based on the main national and regional drivers identified here. The main conclusion of this study emphasizes the relevance of considering different spatial scales based on ecological and socio-cultural characteristics when analyzing tropical deforestation dynamics. This is valuable in terms of conservation planning of tropical forests due to still existing areas with little research attention, but accelerated deforestation rates or emerging deforestation drivers as a consequence of economic development pressure and aggravated by climate change.

Despite the challenges of obtaining consistent and accessible data in Peru, our analysis contributes to a better understanding of the dynamics of tropical deforestation, including some of the most significant forest covers of Latin America. However, our path analyses have revealed the complexity of relationships between the variables that define tropical deforestation dynamics. For this reason, we highlight the need for improving the quality and availability of national data in future analyses to enhance our understanding of the effects of other variables such as fire, cattle, or different types of legal or illegal crops and products. Moreover, distinguishing between the effect of small-scale individual farmers, sustainable production systems, i.e. agroforestry programs, and larger agro-industrial operations on deforestation is needed. Lastly, given the emerging trends on the importance of legal, illegal and illicit activities, solid data on these topics is urgent.

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Data availability The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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