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Paving the Way to Deforestation? Roads, Institutions, and Spatial Spillovers in the Peruvian Amazon

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Abstract

We study how the interaction between the protective effect of local institutions and the amplifying effect of road infrastructure jointly shape deforestation in the Peruvian Amazon. Using data from 289 districts, we construct a local institutional index via principal components analysis and estimate a Spatial Durbin Model to capture both direct and indirect (spillover) effects on cumulative deforestation between 2001 and 2023. Our results show that stronger local institutions are associated with a 5.51 p.p. reduction in cumulative deforestation, 1 p.p. stemming from a district's own institutions (direct effect) and 4.51 p.p. from those of neighboring districts (indirect effect). However, this protective role is entirely offset by proximity to paved roads, suggesting that road infrastructure significantly undermines institutional effectiveness. Our findings indicate that effective responses to deforestation cannot rely on isolated local actions. Because institutional spillovers extend across district borders, strengthening local governance requires coordination among municipalities. At the same time, road development—while important for connectivity and growth—can undermine institutional capacity to protect forests if not carefully managed. An integrated policy framework that combines institutional strengthening with strategic infrastructure planning is therefore essential to ensure that road investments reinforce, rather than weaken, collective efforts to curb forest loss.

Keywords: Deforestation, Institutions, Roads, Amazon, Spatial analysis.

JEL Codes: Q23, Q56, C21, R42.

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1 Introduction

Global deforestation has accelerated at an alarming pace in recent decades. Between 2010 and 2020, the world lost an estimated 4.7 million hectares of forest annually (FAO, 2024). In the Peruvian Amazon, more than 3 million hectares of forest were lost between 2001 and 2023 (SERFOR, 2024). This trend not only threatens biodiversity and local ecosystems but also carries significant global implications, particularly for climate change and the loss of natural heritage. Despite governmental efforts to curb deforestation—such as the creation of Protected Natural Areas—the problem remains persistent (Cotrina Sánchez et al., 2021; Almeyda Zambrano et al., 2010).

The literature underscores the important role of institutions and public policies in addressing deforestation. Studies such as Moreira-Dantas and Söder (2022) highlight the importance of law enforcement capacity, administrative efficiency, and low levels of corruption in reducing forest loss. However, other research points to the limitations in weak institutional settings, which are common in developing countries. This is particularly evident in Peru, where weak governance in managing environmental conflicts and the proliferation of illegal economies–such as coca cultivation–further exacerbates deforestation (Grima and Singh, 2019; Paredes and Manrique, 2021). Moreover, the expansion of road infrastructure in the Amazon has increased access to remote areas, enabling activities such as mining and small-scale agriculture, both of which are major drivers of forest loss (Barrantes et al., 2014; Imbernon, 1999).

While previous studies have assessed the individual effects of local institutions (Moreira-Dantas and Söder, 2022; Fischer et al., 2020; Gibson et al., 2000; Wehkamp et al., 2018) and road infrastructure (Arima, 2016; Da Silva et al., 2023; Barber et al., 2014; Nelson and Hellerstein, 1997) on deforestation, limited attention has been paid to how these factors interact. Specifically, it remains unclear whether the effectiveness of local institutions in protecting forests is influenced–or even undermined–by the presence of road infrastructure.

Our study addresses that gap by quantitatively analyzing how the interaction between local institutions and proximity to paved roads affects cumulative deforestation in the Peruvian Amazon. We use a dataset comprising 289 districts across 14 Peruvian regions affected by deforestation between 2001 and 2023. To measure local institutional strength, we construct a local institutional index using principal component analysis (PCA), incorporating indicators of administrative and operational capacity, fiscal and governance performance, service provision and enforcement, environmental and territorial governance, and socioeconomic context. We then apply spatial econometric methods to capture both the direct and indirect (spillover) effects of institutions, road infrastructure, and their interaction on deforestation.

Our findings indicate that stronger local institutions are significantly associated with lower deforestation rates, both within a given district and in neighboring areas. Specifically, a one-point increase in the institutional quality index is associated with a 5.51 percentage-point reduction in cumulative deforestation between 2001 and 2023—1.00 p.p. through direct effects within the district and 4.51 p.p. through spillover effects from neighboring districts. However, this protective influence is significantly moderated by proximity to paved roads. In districts located near road infrastructure, the effectiveness of local institutions is substantially weakened and ultimately offset, as road access amplifies economic activities—such as illegal logging and unregulated agricultural expansion—that frequently operate beyond institutional oversight. This dynamic reveals a critical tension: while stronger institutions can curb forest loss, their effectiveness is undermined by infrastructure-driven pressures that transcend local governance capacity.

This study makes three main contributions to the literature. First, it provides empirical evidence on the interaction between two critical drivers of deforestation—local institutions and road infrastructure—in the Peruvian Amazon. Second, it applies spatial econometric techniques to disentangle direct and spillover effects, thereby capturing spatial externalities that are often overlooked in deforestation research. Third, and most importantly, it offers policy insights: because institutional spillovers extend beyond district borders, isolated efforts are insufficient. Effective forest protection requires coordinated action among municipalities, ensuring that institutional strengthening is accompanied by the regulation of infrastructure-driven economic activity. Such coordination is essential to prevent road development from undermining governance capacity and to design policies that align infrastructure planning with collective efforts to curb forest loss.

The paper is structured as follows. Section 2 reviews the literature on deforestation, with particular attention to studies that employ spatial econometric approaches. Section 3 provides contextual background on deforestation in Peru, focusing on the roles of institutions and road infrastructure. Section 4 describes the dataset, while Section 5 outlines the methodological framework, including the construction of the institutional index and the empirical strategy. Section 6 presents the results, and Section 7 concludes with policy implications and final remarks.

2 Related Studies

Deforestation is a complex phenomenon shaped by a wide range of socioeconomic, political, and environmental factors. The literature has employed various approaches to investigate its causes and consequences (Hänggli et al., 2023; Bos et al., 2020; Armenteras et al., 2017; Bernhard et al., 2024). In recent years, spatial econometric methods have gained prominence for their ability to capture the spillover effects often associated with deforestation dynamics. In this section, we review studies that apply spatial analysis to study deforestation, categorizing them into two main groups: (i) those that examine specific drivers of deforestation, and (ii) those that assess its impacts on well-being or environmental indicators–particularly health and climate.

2.1 Explaining deforestation

The use of spatial econometric models has deepened our understanding of how land-use decisions in one region can influence outcomes in adjacent areas. A recurring topic in this literature is the effectiveness of protected areas (PAs) in curbing deforestation. For instance, Amin et al. (2019) apply a Dynamic Spatial Durbin Model to examine the protective effects of PAs in the Brazilian Amazon, finding that both fully protected areas and indigenous lands not only reduce local deforestation but also produce significant spillover effects in neighboring municipalities. In contrast, drawing on a Spatial Durbin Model for the Bolivian context, Boillat et al. (2022) find that Indigenous lands provide only direct protective effects, while protected areas deliver both direct and indirect effects. These findings suggest that land tenure and management regimes are key factors in determining whether conservation policies can yield benefits beyond their immediate boundaries.

Road infrastructure is another critical driver of deforestation, as it facilitates access to previously remote areas and enables economic activities that threaten forest stability. Arima (2016) use a Spatial Probit Model to simulate the impact of new roads in Loreto, Peru. While they find a moderate increase in deforestation and carbon emissions, their analysis may underestimate long-term effects and does not fully account for land-use changes resulting from improved market access.

Agricultural and livestock activities have also been widely linked to deforestation. Drawing on a Spatial Durbin Model, Kuschnig et al. (2021) find that in Mato Grosso, Brazil, agricultural crops create spatial spillovers that fuel deforestation, whereas the direct impact of cattle ranching has diminished. This contrasts with earlier studies that identified cattle as the primary driver of deforestation (Andrade de Sa et al., 2015; Santos et al., 2021; Ramírez et al., 2018). Coca cultivation represents another significant factor, particularly in Colombia, in areas where drug trafficking is widespread. Rivadeneyra et al. (2023) apply various spatial econometric methods and show that coca plantations have a strong positive effect on deforestation, including spillover effects in neighboring municipalities.

The literature further examines how macroeconomic and political dynamics shape deforestation outcomes. Employing Spatial Durbin and Spatial Lag models for the Brazilian Amazon, Faria and Almeida (2016) find that trade liberalization intensifies deforestation, largely through the expansion of soybean production and cattle ranching.

Similarly, Ferrer Velasco et al. (2020) employ Spatial Durbin and Spatial Error models to show that the relevance of deforestation drivers depends critically on geographic scale. Their cross-regional analysis—covering Africa, the Americas, and Asia—reveals that while population pressure and agricultural suitability consistently shape deforestation, their impacts differ markedly across spatial and regional settings.

2.2 Effects of Deforestation

A growing body of research has examined the consequences of deforestation for climatic and health-related outcomes. For instance, Silva et al. (2023) analyze the Brazilian Amazon and show that forest loss is associated with rising temperatures and declining precipitation, underscoring the climatic implications of deforestation.

The relationship between deforestation and public health has also emerged as a key area of inquiry, particularly in relation to vector-borne diseases. Several studies document a positive correlation between forest loss and malaria incidence. Aguirre et al. (2024), applying a Spatial Durbin Model to the Peruvian Amazon, estimate that the loss of 1,000 hectares of forest leads to approximately 69 additional malaria cases. Likewise, Santos et al. (2021) use a Spatial Durbin Error Model in the Brazilian Amazon and find that deforestation significantly increases malaria incidence both directly in affected municipalities and indirectly in neighboring ones.

The link between deforestation and other vector-borne diseases, such as dengue, has also been investigated. Da Silva et al. (2023), employing Geographically Weighted Regression (GWR), show that deforestation significantly raises dengue incidence rates across the Brazilian Amazon biome.

Taken together, this literature demonstrates substantial progress in applying spatial econometric models to assess the direct and spillover effects of deforestation. Yet important gaps remain. Most studies estimate the isolated impact of individual drivers without fully examining how these factors may interact or moderate one another's influence on forest loss. Our study seeks to address these limitations by analyzing not only the direct and indirect effects of local institutions and road infrastructure on deforestation, but also the extent to which their interaction shapes deforestation dynamics. In particular, we test whether the presence of road infrastructure mitigates—or amplifies—the protective effect of institutions against forest loss.

3 Background

Deforestation in Peru has increased drastically over the past decade, rising from an annual average of 105,221 hectares deforested between 2001 and 2010 to an annual 153,934 hectares between 2011 and 2023 (SERFOR, 2024). To put these figures into perspective and illustrate the severity of the issue, the 132,216 hectares lost in 2023 alone are equivalent to the 46.9% of the area of Metropolitan Lima, Peru's main city. Peru has 73.28 million hectares of forest, distributed across 15 of the country's 25 regions, covering 57.3% of the national territory (MINAM, 2016). The fifteen regions that recorded deforestation between 2001 and 2023 are: Amazonas, Ayacucho, Cajamarca, Cusco, Huancavelica, Huánuco, Junín, La Libertad, Loreto, Madre de Dios, Pasco, Piura, Puno, San Martín, and Ucayali. Since our study focuses only on the Peruvian Amazon, we do not include the Huancavelica region.

Institutions and public policies may play a fundamental role in controlling deforestation. According to Moreira-Dantas and Söder (2022), a government's ability to enforce laws, its administrative efficiency, and low levels of corruption can all contribute to reducing deforestation. In line with this, Peru has implemented several initiatives, such as the creation of Protected Natural Areas (Cotrina Sánchez et al., 2021) and the protection of Indigenous rights (Almeyda Zambrano et al., 2010). However, several authors highlight governmental inefficiency in addressing environmental conflicts (Grima and Singh, 2019) and in preventing the emergence of illegal economies—such as coca cultivation—that exacerbate deforestation (Paredes and Manrique, 2021). Political interests also play a critical role in deforestation. On this point, Rosa da Conceição et al. (2018) argue that the electoral and political agendas of bureaucrats often hinder the implementation of effective deforestation policies.

On the other hand, road infrastructure in the Peruvian Amazon has developed in response to the need to reduce transportation costs and facilitate both natural resource extraction and access to new markets (Barrantes et al., 2014). Between 1955 and 1965, road expansion in the Amazon surged by 440 percent, a rate more than six times higher than the 72 percent growth observed in other regions of Peru. This expansion continued at a moderate pace for three more decades, before accelerating again in the early 21st century at a rate comparable to that of the 1955–1965 period. However, this has also facilitated the development of deforestation-related activities, such as mining and small-scale agriculture. The literature emphasizes that the increase in deforestation has occurred mainly in areas near new roads in the Amazon (Imbernon, 1999). Specifically, some previous work has found that paved roads are the most commonly used type for such activities (Reyes et al., 2024), which is why our analysis will focus on this type of roads. We further examine the role of unpaved roads in subsection 6.2.

4 Data

We rely on deforestation and forest area data provided by Geobosques–MINAM for districts located within the 14 regions previously identified. Given data availability, our analysis is restricted to the year 2023. We construct the dependent variable—cumulative deforestation rate—by dividing cumulative deforestation up to 2023 by the forest area recorded in 2001 for each district. The final sample comprises 289 districts in the Peruvian Amazon, representing approximately 15 percent of all districts nationwide.

We also include a series of district-level explanatory variables that the literature identifies as influential in determining deforestation levels[1]. These include the Euclidean distance (in km) from the centroid of each district to the nearest nearest road (paved, dirt, gravel, and unpaved; as well as national, regional, and local roads). To construct these variables, we use data from the Ministry of Transport and Communications.

In addition, we use geospatial data from the National Service of Natural Protected Areas (SERNANP) to construct ratios indicating the proportion of each district's forest that falls within different protection regimes: Natural Protected Areas (NPAs), Regional Conservation Areas (RCAs), Forest Concessions (FCs), Private Conservation Areas (PRICAs), and Indigenous Communities (ICs)[2]. To control for climatic variation, we incorporate meteorological variables from NASA POWER, including the annual average of maximum temperature (°C) and precipitation (mm) for each district centroid. We also account for topography by including district-level elevation (in meters above sea level), obtained from the Geographic Institute of Peru.

On the demographic side, we draw on the 2017 National Census to obtain population density, and on the 2018 poverty map to capture district-level monetary poverty rates. For agriculture, we include the area planted with crops commonly associated with forest loss—such as coca (Cantillo and Garza, 2022), coffee, cacao, and particularly oil palm—using data from the 2012 National Agricultural Census (CENAGRO). Finally, we incorporate geo-referenced data on mining deposits provided by the Ministry of Energy and Mining (MINEM) to calculate the distance between each district centroid and the nearest mining site.

In some instances, relevant data were missing for variables such as harmful crop ratios and altitude. These missing values represent less than 10 percent of the sample, making interpolation a suitable approach. Given the spatial nature of our analysis, we employ Inverse Distance Weighting (IDW) spatial interpolation, following Cantillo and Garza (2022). This method estimates missing values using information from geographically proximate districts, assigning

[1]Descriptive statistics are shown in Table C.1.

[2]The share of protected forest is calculated by intersecting the forest area in 2001 with the spatial boundaries of each protection category, and then dividing this protected forest area by the total forest area in 2001 at the district level. Indigenous communities are included here as they may function as de facto protective mechanisms for forests.

greater weight to closer observations and less to those farther away. By doing so, the procedure ensures spatially coherent imputations while preserving the integrity of the dataset.

5 Methodology

To assess the role of local institutions in deforestation within the Peruvian Amazon, we divide our analysis into two parts. First, we build on Galarza Arellano et al. (2024) to construct a local institutional index using principal component analysis (PCA). Second, we estimate the effect of this index on the cumulative deforestation rate (2001 - 2023) employing spatial econometric methods.

5.1 Local Institutional Index

The concept of institutions has been widely discussed in the literature and assigned various definitions. According to North (1994), institutions form the foundation of a society's structure and can be classified as formal rules (e.g., laws, property rights) and informal norms (e.g., customs, traditions). For the purposes of this study, we adopt a definition that enables quantitative measurement. Considering that institutions are a cornerstone of governance systems, and consistent with the approach of Kaufmann et al. (2010), we define governance as the state's capacity to implement policy, citizens' respect for institutions, and the process by which governments are selected, monitored, and replaced.

Several authors have developed indexes to measure institutionality at national and regional levels using different methodologies and indicators. These indexes are typically categorized as either single-variable or composite. Single-variable indicators include measures of democracy (Lægreid and Povitkina, 2018; Wehkamp et al., 2018), urban development policies, property rights and land tenure (Geist and Lambin, 2002), environmental regulation, NGO participation, political rights, and regulatory compliance (Wehkamp et al., 2018). The most well-known composite measure is the Worldwide Governance Indicators (WGI), which include six dimensions: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.

At the regional level, many studies reuse variables initially developed for national indices. Frequently used variables include control of corruption (Rodríguez-Pose and Ketterer, 2020; Rodríguez-Pose, 2013; Barra and Ruggiero, 2022; Charron et al., 2014; Morrison, 2014); civic participation (Charron et al., 2014; Barra and Ruggiero, 2022; Arbolino and Boffardi, 2017); government approval (Morrison, 2014); government effectiveness (Rodríguez-Pose and Ketterer, 2020; Rodríguez-Pose, 2013; Barra and Ruggiero, 2022; Charron et al., 2014); regulatory quality (Charron et al., 2014; Rodríguez-Pose and Ketterer, 2020; Barra and Ruggiero, 2022); transparency levels (Rodríguez-Pose and Ketterer, 2020; Rodríguez-Pose, 2013); and property rights (Rodríguez-Pose and Ketterer, 2020; Rodríguez-Pose, 2013; Arbolino and Boffardi, 2017). In the Peruvian context, the Regional Competitiveness Index (INCORE) incorporates 40 indicators grouped into six dimensions: economic environment, infrastructure, health, education, labor, and institutions (Instituto Peruano de Economía (IPE), 2020).

Given that our analysis is conducted at the district level, the development of a local institutional index is of particular relevance. However, the literature on local institutional measurement remains limited, despite the fact that many institution functions operate at this level. To our knowledge, only two studies directly address this gap. First, Beer and Lester (2015) construct a local institutional "thickness" and effectiveness index in the Australian context, aggregating thirteen variables–such as local government expenditure capacity, tax revenue, and educational attainment–using a linear aggregation method. Second, Arbolino and Boffardi (2017) examine the effect of institutional quality and efficient investment on economic growth in Italy using a similarly structured local index. Their indicators include the quality of public infrastructure, percentage of waste collected, and number of public employees.

In our study, we construct a district-level local institutional index based on the availability of administrative data. The index incorporates five dimensions: Administrative and Operational Capacity, Fiscal and Governance Performance, Service Provision and Enforcement, Environmental and Territorial Governance, and Socioeconomic Context. The first dimension captures the operational and human resources of municipalities, including the log of heavy machinery and operational vehicles, the number of municipal employees per 1,000 inhabitants, and the presence of a formal budget execution unit. The second dimension reflects governance quality, measured through the budget execution rate and an accountability and communication index. The third dimension accounts for service provision and enforcement, including waste coverage and the existence of daily municipal patrols. The fourth dimension evaluates environmental and territorial governance, specifically the presence of high-capacity environmental management (PLANEFA and at least two other instruments). Finally, the fifth dimension provides socioeconomic context, measured by the economic activity ratio and the average years of schooling of the district population[3].

We use principal component analysis (PCA) to generate a composite index from these variables. This method addresses potential biases in simple additive indices that assign equal weight to all variables (Beer and Lester, 2015; Instituto Peruano de Economía (IPE), 2020; Kaufmann et al., 2010). PCA reduces the dimensionality of a large set of variables while minimizing information loss and capturing the maximum variance across the variable set (Jolliffe and

[3] Descriptive statistics for these variables are presented in Table A.2, covering 289 Peruvian Amazon districts in 2023, based on data availability.

Cadima, 2016). It transforms the original variables into a new set of orthogonal (uncorrelated) principal components, each representing a linear combination of the original variables. The first component explains the largest share of variance, followed by subsequent components (Abdi and Williams, 2010). The component loadings, or weights, reflect the relative importance of each variable (Nardo et al., 2005). In the case of our study, the loadings are shown in Figure A.2.

To determine the number of components to retain, we apply the Kaiser criterion, selecting those with eigenvalues greater than one (Jolliffe and Cadima, 2016; Kaiser, 1974). As shown in Figure A.1, three components meet this criterion. However, following standard practice to construct an unique index, we retain the first component, which explain almost 30% of the total variance (Figure A.3).

In addition, the suitability of applying PCA is empirically validated through the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity shown in Table A.4. The KMO statistic of 0.733 exceeds the conventional threshold of 0.70, indicating that the variables share sufficient common variance to justify factor analysis. Complementarily, Bartlett's test strongly rejects the null hypothesis that the correlation matrix is an identity matrix ($\chi^2(45) = 357.68$, $p < 0.0001$), confirming that the variables are significantly correlated. Together, these diagnostics provide robust evidence that the data structure is appropriate for principal component extraction, reinforcing the validity of our PCA-based institutional index.

To visualize the relation between our local institutional index and the deforestation in the Peruvian Amazon, we present the following Figure 1. It is divided into two maps: the left panel displays the Cumulative Deforestation Rate (2001–2023), while the right panel shows the Local Institutions Index for the 289 districts in the Peruvian Amazon.

5.2 Empirical Strategy

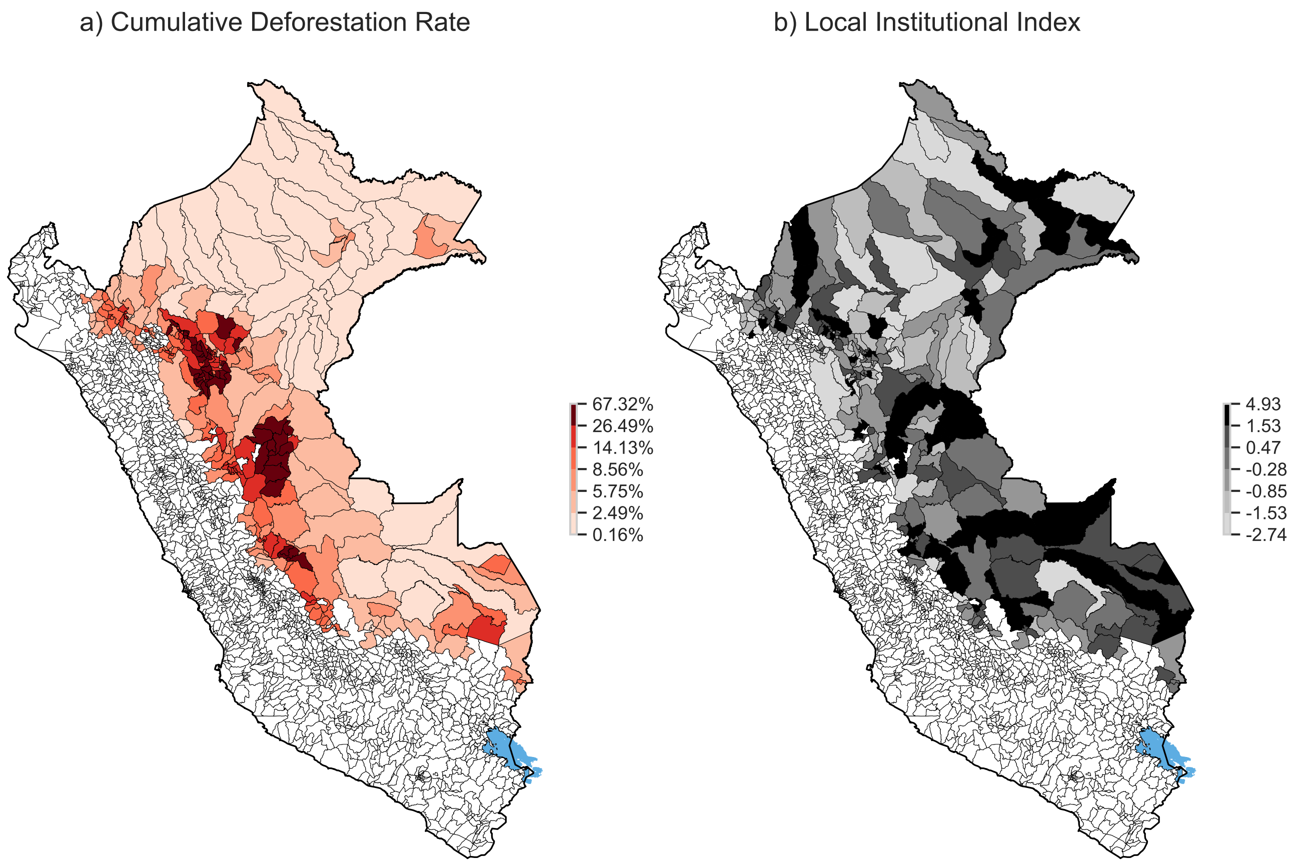
We aim to evaluate the relationship between a set of variables potentially correlated with deforestation, while accounting for spatial dependence and spatial autocorrelation—two key challenges in estimating effects influenced by spatial spillovers. In the absence of spatial autocorrelation, one could estimate the following linear model using Ordinary Least Squares (OLS):

$$Y_d = \beta_0 + \beta_1 \mathrm{I}_d + \beta_2 \log(\mathrm{D}_d) + \beta_3 \left(\mathrm{I}_d \times (\log(\mathrm{D}_d) \leq P_{10})\right) + \mathbf{X}_d \boldsymbol{\beta}_X + \epsilon_d, \tag{1}$$

where Y_d represents the cumulative deforestation rate in district d between 2001 and 2023. $\log(\mathrm{D}_d)$ is the logarithm of the distance (in kilometers) from the district centroid to the nearest paved road[4]. I_d denotes the local institutions index. The indicator $(\log(\mathrm{D}_d) \leq P_{10})$ equals 1

[4]Paved roads are particularly important in facilitating access to remote areas where deforestation-driving activities can expand (Reyes et al.,

Figure 1 – Map of Cumulative Deforestation Rate (2001–2023) and Local Institutions Index



Note: This figure presents the Cumulative Deforestation Rate (2001–2023) (panel a) and the Local Institutions Index (panel b) for all districts within the Peruvian Amazon (289). Data are grouped by sextiles. Districts outside the Amazon are omitted.

if the district is in the 10th percentile of shortest distances to a paved road. The interaction term $\mathrm{I}_d \times (\log(\mathrm{D}_d) \leq P_{10})$ captures how institutional quality moderates the effect of proximity to roads on deforestation. The control vector $\mathbf{X}_d$ includes: logarithm of distance to the nearest mining site (km); population density (per km$\hat{2}$); monetary poverty rate in 2018; the ratio of coca, coffee, cocoa, and oil palm cultivation to total agricultural land; proportion of forest under some protection status (Natural Protected Area (NPA), Private Conservation Area (ACP), Regional Conservation Area (ACR), Forest Concession (FC), or Native Community (CN)); average temperature (°C); elevation (m.a.s.l.); and precipitation (mm).

Ordinary Least Squares (OLS) estimation becomes problematic in the presence of spatial autocorrelation, as it leads to biased estimates and violates the assumption of independently distributed errors, thereby undermining statistical inference (LeSage and Pace, 2009; Seya et al., 2020). In the case of deforestation, the level of forest loss in one district may be influenced by

2023).

outcomes in neighboring districts. Furthermore, explanatory variables may themselves exhibit spatial dependence, reflecting shared institutional arrangements or historical legacies within provinces.

To address these issues, spatial econometric methods have been developed and are widely applied in deforestation studies (Aguirre et al., 2024; Ferrer Velasco et al., 2020; Kuschnig et al., 2021). Among them, the Spatial Durbin Model (SDM) is often preferred because it accounts for spatial autocorrelation in both the dependent variable and the covariates (Aguirre et al., 2024; Faria and Almeida, 2016; Kuschnig et al., 2021). Additionally, even when the true data-generating process corresponds to a more restrictive spatial model, the SDM tends to yield less biased and more consistent estimates of direct and indirect effects, thereby improving the accuracy of inference on spatial spillovers (Amin et al., 2019; Boillat et al., 2022).

The primary distinction between OLS and spatial models like the SDM lies in the inclusion of the spatial weights matrix W, which defines the spatial structure of inter-district interactions. Several specifications of this matrix are available, but the Queen contiguity matrix is among the most commonly employed in the literature (Mejía Tejada et al., 2024; Ramírez et al., 2018; Santos et al., 2021; Kuschnig et al., 2021), and we adopt this specification as our preferred choice. To evaluate the robustness of our results, we additionally consider alternative spatial structures, including Rook contiguity and k-nearest neighbors matrices, which allows us to assess the stability of the estimated effects across different weighting schemes.

The SDM is specified as follows:[5]

$$Y_d = \rho W Y_d + \beta_0 + \beta_1 \mathrm{I}_d + \beta_2 \log(\mathrm{D}_d) + \beta_3 \left(\mathrm{I}_d \times (\log(\mathrm{D}_d) \leq P_{10})\right) + \mathbf{X}_d \boldsymbol{\beta} + W \mathbb{X}_d \boldsymbol{\theta} + \epsilon_d \qquad (2)$$

This model includes two types of spatial lags: $\rho W Y_d$, the spatial lag of the dependent variable, and $W\mathbb{X}_d\boldsymbol{\theta}$, the spatial lag of the explanatory variables. The error term ϵ_d is assumed to be normally distributed. The SDM is the most comprehensive among spatial models. Other variants include the Spatial Durbin Error Model (SDEM), which includes spatial lags of covariates and spatially autocorrelated errors; the Spatial Autoregressive Model (SAR), which includes only spatial lags of the dependent variable; the Spatial Lag of X Model (SLX), which includes only spatially lagged covariates; and the Spatial Error Model (SEM), which accounts for spatial autocorrelation in the error terms.

Following model selection guidelines such as INSEE (2018), we first apply Lagrange Multiplier (LM) tests based on OLS residuals to detect spatial dependence. Results in Table B.1 provide strong evidence of spatial autocorrelation. Both LM Error and LM Lag tests are highly significant, indicating spatial dependence in the residuals (SEM) as well as in the dependent

[5] An alternative approach could directly interact I_d with $\log(\mathrm{D}_d)$, but this would not isolate the effect of very close proximity to roads.

variable (SAR). Among the robust versions, only the Robust LM Lag remains significant, pointing more clearly toward a SAR-type specification. Moran's I statistic (0.3543, $p < 0.01$) confirms the presence of strong positive spatial autocorrelation, while the SARMA test is also highly significant ($\chi^2 = 129.77$, $p < 0.01$), jointly rejecting the absence of both lag and error dependence. Together, these findings motivate the use of spatial models, with SAR, SDM, or SDEM appearing as plausible candidates.

To formally discriminate between competing specifications, we use likelihood ratio (LR) tests reported in Table B.2. The SAR vs. SDM comparison yields a χ^2 statistic of 35.39 ($p = 0.008$), and the SEM vs. SDEM comparison yields a χ^2 of 48.88 ($p = 0.0001$), both rejecting the null hypothesis that the simpler model suffices. These results favor the more general SDM and SDEM specifications over their nested SAR and SEM counterparts. By contrast, the SAR vs. SDEM comparison is not significant ($p = 0.10$), suggesting no statistical advantage of the SDEM over SAR in this case.

Model performance is further assessed using log-likelihood and information criteria. The SDM attains the highest log-likelihood (369.87), but the AIC slightly favors the SAR model (–662.34 vs. –661.73). Since AIC penalizes model complexity more strongly, this result is not unusual when comparing general and nested models. In such cases, the LR tests provide more reliable guidance, and our results clearly support the SDM as the preferred specification. Nonetheless, because SAR also performs strongly and is widely used in the deforestation literature, we report results for both models in the robustness section.

6 Results

6.1 Paved Roads

We estimate Equation 1, Equation 2, and additional spatial models, as presented in Table D.1. In the OLS specification, the institutional index has a negative and statistically significant coefficient at the 1% level, suggesting that stronger local institutional quality is associated with lower cumulative deforestation. Specifically, a one-unit increase in the index corresponds to a 1.22 percentage point reduction in deforestation. However, as previously discussed, the OLS model produces biased estimates by failing to account for spatial spillover effects from both dependent and explanatory variables. As we show in the spatial models, although the direction and significance of the institutional effect remain consistent, its magnitude is underestimated in the OLS framework.

Given the limitations of OLS, our analysis focuses on spatial econometric models, where coefficient interpretation explicitly accounts for the spatial structure defined by the weights

Table 1 – Direct, Indirect and Total Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by W, SDM

	Cumulative Deforestation Rate (2001-2023)					
	Direct effect $\left(\frac{\partial F_i}{\partial x_i}\right)$	s.e	**Indirect effect** $\left(\frac{\partial F_i}{\partial x_j}\right)$	s.e	**Total effect** $\left(\sum_j \frac{\partial F_j}{\partial x_i}\right)$	s.e
Queen Contiguity						
Local Institutional Index	-0.0100***	0.0036	-0.0451***	0.0160	-0.0551***	0.0182
log(Min. Distance to Paved Road)	-0.0260***	0.0068	-0.0538**	0.0236	-0.0799***	0.0250
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0276**	0.0126	0.1263**	0.0581	0.1539**	0.0679
Rook Contiguity						
Local Institutional Index	-0.0099***	0.0036	-0.0425***	0.0151	-0.0524***	0.0172
log(Min. Distance to Paved Road)	-0.0267***	0.0065	-0.0513**	0.0234	-0.0780***	0.0246
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0289**	0.0119	0.1294**	0.0550	0.1582**	0.0637
KNN (n=4)						
Local Institutional Index	-0.0102***	0.0037	-0.0364***	0.0130	-0.0466***	0.0148
log(Min. Distance to Paved Road)	-0.0360***	0.0068	-0.0488***	0.0173	-0.0848***	0.0189
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0208*	0.0123	0.0770*	0.0469	0.0979*	0.0555
KNN (n=5)						
Local Institutional Index	-0.0108***	0.0037	-0.0373***	0.0145	-0.0481***	0.0162
log(Min. Distance to Paved Road)	-0.0349***	0.0067	-0.0552***	0.0190	-0.0901***	0.0205
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0224*	0.0125	0.0922*	0.0550	0.1146*	0.0636

Note: This table reports the direct, indirect, and total marginal effects of the Local Institutional Index and its interaction with remoteness (measured as log(Min. Distance to Paved Road) $\leq P_{10}$) on the cumulative deforestation rate between 2001 and 2023. Estimates are obtained from Spatial Durbin Models (SDM) under alternative spatial weight matrices: queen contiguity, rook contiguity, and k-nearest neighbors (KNN). Controls include climatic variables (average temperature, precipitation, and elevation), forest protection measures (share of forest under private conservation areas, regional conservation areas, natural protected areas, forest concessions, and Andean communities), agricultural land uses (share of land planted with coffee, cocoa, oil palm, and coca), as well as socioeconomic and extractive factors (population density, poverty rate, and the logarithm of the minimum distance to the nearest mining site). Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are based on Monte Carlo simulations (reps=1000).

matrix. Based on the diagnostic tests reported in Table B.1 and Table B.2, we adopt the Spatial Durbin Model (SDM) as our preferred specification. Table 1 reports the estimated Direct Effect (DE), Indirect Effect (IE), and Total Effect (TE) of the Local Institutional Index on the cumulative deforestation rate (2001–2023), across alternative spatial weight matrices.

The DE measures the effect of institutional quality on deforestation within the same district. For districts not located in close proximity to paved roads, a one-point increase in the institutional index is associated with a 1 percentage point reduction in cumulative deforestation, significant at the 1% level. The IE captures spillover effects, showing that stronger institutions in one district reduce deforestation in neighboring districts by 4.51 percentage points, also significant at the 1% level. Combining these effects, the TE indicates that a one-unit increase in institutional quality lowers cumulative deforestation by 5.51 percentage points across the region. These protective effects are consistent with previous regional evidence (Mejía Tejada et al., 2024; Ramírez et al., 2018; Santos et al., 2021; Kuschnig et al., 2021). Importantly, however, these results reflect the baseline effect in districts without nearby road infrastructure. Where proximity to roads is high, the interaction term significantly alters the marginal impact of institutions, weakening—and in some cases offsetting—their protective role. We conclude that achieving substantial reductions in deforestation (5.51 pp) through institutional strengthening requires spatial coordination—neighboring districts must also exhibit robust institutional quality to form an effective regional barrier against forest degradation.

Regarding the minimum distance to the nearest paved road, we find that the direct effect (DE) is negative and statistically significant at the 1% level. A 10% increase in this distance—meaning that a district is located farther from paved road infrastructure—is associated with a 0.260 percentage point reduction in its cumulative deforestation rate. The indirect effect (IE) is likewise negative and significant at the 5% level, indicating that a 10% increase in distance reduces deforestation in neighboring districts by 0.538 percentage points. Combining these, the total effect (TE) suggests that a 10% increase in distance results in a 0.799 percentage point decline in deforestation across districts. These findings highlight that closer proximity to paved roads is systematically linked to higher deforestation, both locally and through spillovers to adjacent districts.

To assess how road proximity moderates the protective role of institutions, we interact the institutional index with a dummy equal to one for districts in the bottom 10th percentile of minimum road distance (i.e., relatively close to paved roads). While in districts farther from roads institutions exhibit a strong protective effect against deforestation, the interaction reveals a different dynamic near roads. The direct effect (DE) of the interaction is positive and statistically significant at the 5% level, amounting to 2.76 percentage points—more than twice the magnitude of the baseline direct effect of institutions (–1.00 p.p.). This erosion of institutional effectiveness also extends to neighboring districts: the interaction yields a total effect of 12.63 percentage points, significant at the 5% level. When combined with baseline effects, the overall total effect of the interaction reaches 15.82 percentage points, effectively offsetting their protective role.

Overall, our findings underscore the importance of explicitly accounting for spatial dependence when analyzing the role of institutions and infrastructure in shaping deforestation. Conventional approaches such as OLS provide only a rough approximation and systematically underestimate the magnitude of effects by neglecting spatial interdependence. In contrast, spatial econometric models allow the decomposition of impacts into direct and spillover components, offering a more nuanced understanding of the mechanisms at play. The results show that stronger institutions reduce deforestation in districts located farther from paved roads, but this protective effect is substantially weakened—and can even be offset—when districts are situated in close proximity to road infrastructure.

6.2 Other Road Types

When shifting the focus from paved to unpaved roads, the results show a somewhat different pattern. The institutional index continues to exert a protective effect, but its magnitude is weaker: a one-point increase reduces local deforestation by 0.75 percentage points, compared to 1 percentage point in the paved road specification. Spillovers are also present but more modest, with neighboring districts experiencing a 2.40 percentage point reduction. Importantly, the interaction term between institutions and proximity to unpaved roads is positive but small and statistically insignificant, suggesting that institutional capacity remains largely effective in these areas. This stands in contrast with paved road contexts, where institutional effectiveness is significantly eroded by proximity to infrastructure. The results therefore highlight that institutional protections are more robust when dealing with unpaved roads, where the economic incentives for forest clearing are likely lower than those created by paved road access.

Table 2 – Direct, Indirect and Total Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Road Type, SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)					
	Direct effect $\left(\frac{\partial F_i}{\partial x_i}\right)$	s.e	**Indirect effect** $\left(\frac{\partial F_i}{\partial x_j}\right)$	s.e	**Total effect** $\left(\sum_j \frac{\partial F_j}{\partial x_i}\right)$	s.e
Paved Roads						
Local Institutional Index	-0.0100***	0.0036	-0.0451***	0.0160	-0.0551***	0.0182
log(Min. Distance)	-0.0260***	0.0068	-0.0538**	0.0236	-0.0799***	0.0250
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0276**	0.0126	0.1263**	0.0581	0.1539**	0.0679
Unpaved Roads						
Local Institutional Index	-0.0075**	0.0036	-0.0240	0.0160	-0.0315*	0.0182
log(Min. Distance)	-0.0394***	0.0057	-0.0509**	0.0227	-0.0903***	0.0248
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0064	0.0090	0.0145	0.0441	0.0209	0.0507
All Roads						
Local Institutional Index	-0.0072**	0.0035	-0.0239	0.0158	-0.0311*	0.0178
log(Min. Distance)	-0.0402***	0.0057	-0.0525**	0.0223	-0.0928***	0.0245
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_{10})$	0.0049	0.0089	0.0100	0.0449	0.0150	0.0514

Note: This table reports the direct, indirect, and total marginal effects of the Local Institutional Index and its interaction with remoteness (measured as log(Min. Distance) $\leq P_{10}$) on the cumulative deforestation rate between 2001 and 2023. We use a queen contiguity spatial weight matrix. Estimates are obtained from different road types. Controls include climatic variables (average temperature, precipitation, and elevation), forest protection measures (share of forest under private conservation areas, regional conservation areas, natural protected areas, forest concessions, and Andean communities), agricultural land uses (share of land planted with coffee, cocoa, oil palm, and coca), as well as socioeconomic and extractive factors (population density, poverty rate, and the logarithm of the minimum distance to the nearest mining site). Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are based on Monte Carlo simulations (reps=1000).

The analysis of unpaved roads also underscores the distinct channels through which infrastructure shapes deforestation. Unlike paved roads, unpaved routes often face limitations in year-round accessibility, higher transportation costs, and lower integration into broader markets (Reyes et al., 2024). These constraints appear to dampen the extent to which road proximity undermines institutional capacity. In other words, while paved roads may trigger substantial land-use change and weaken institutional control, unpaved roads present a more manageable challenge for local governance. The results suggest that institutional strengthening in these areas can still yield measurable benefits in curbing deforestation, even in districts relatively close to unpaved networks.

Turning to the broader category which includes all the roads, the results reflect a combination of the dynamics observed for paved and unpaved infrastructure. Institutions continue to reduce deforestation both locally and through spillovers, with magnitudes that fall in between the two specific cases. The distance to roads also shows a strong protective association: a 10% increase in distance to any road is associated with nearly a 0.93 percentage point reduction in deforestation across districts. However, the interaction between institutions and proximity to roads loses much of its statistical strength in this specification, which is consistent with the idea that aggregating paved and unpaved roads masks the heterogeneous effects documented above. This aggregation thus highlights the importance of distinguishing between road types when assessing how institutions interact with infrastructure to influence forest outcomes.

In sum, the comparison across paved, unpaved, and all roads confirms that paved infrastructure poses the greatest challenge to institutional effectiveness in protecting forests. While institutions remain protective near unpaved roads, their role is substantially weakened in the presence of paved networks. This underscores the need for spatially differentiated policy responses, with stronger institutional safeguards in areas most exposed to the pressures of paved road expansion.

7 Robustness Checks

To ensure the reliability of our results, we conduct a series of robustness checks that examine whether the main findings are sensitive to alternative measurement strategies, model specifications, and threshold definitions. Specifically, we implement three complementary exercises. First, we test the consistency of results when constructing alternative versions of the Local Institutional Index through PCA, incorporating or excluding socioeconomic variables. Second, we assess the stability of our conclusions across different spatial econometric models, comparing the SDM to SLX, SAR, SEM, and SDEM alternatives. Finally, we evaluate whether our findings hold when varying the definition of remoteness, using alternative percentiles of the minimum distance to paved roads.

To assess the robustness of our main results, we re-estimate the Spatial Durbin Model (SDM) using alternative specifications of the Local Institutional Index constructed through PCA. As detailed in Table A.3, the baseline index partially incorporates the Socioeconomic Context category, excluding low birth weight share and business density. We then test two alternative versions. The Local Institutional Capacity Index excludes the entire Socioeconomic Context category, focusing exclusively on administrative, fiscal, enforcement, and environmental dimensions of governance. Conversely, the Extended Local Institutional Index expands the baseline by incorporating all socioeconomic variables, including low birth weight and business density.

Results reported in Table E.1 indicate that the protective role of institutions against deforestation is robust across these alternative measures. In all specifications, the institutional index is negatively and significantly associated with cumulative deforestation, while the interaction with road proximity weakens or offsets this protective effect. Although magnitudes differ slightly, the overall pattern remains consistent: institutional quality reduces deforestation in districts more remote from paved roads, but this effect diminishes near road infrastructure. This confirms that our findings are not driven by a particular construction of the institutional index, but rather reflect a systematic relationship between local governance capacity, road proximity, and deforestation dynamics.

To further assess the robustness of our findings, we re-estimate the main specification using alternative spatial econometric models beyond the Spatial Durbin Model (SDM). Specifically, we consider the Spatial Lag of X (SLX), the Spatial Durbin Error Model (SDEM), and the Spatial Autoregressive Model (SAR), all under a queen contiguity weights matrix. As shown in Table E.3, the results are highly consistent across specifications: stronger local institutions reduce deforestation both directly and through spillover effects, while road proximity weakens these protective effects. The magnitude of the institutional effect varies slightly across models but remains statistically significant and negative in all cases.

Finally, we vary the threshold used to define proximity to paved roads, considering deciles from the 10th to the 90th percentile of the distribution of minimum distances. The results, presented in Figure E.1, confirm the consistency of our baseline conclusions. The protective effect of institutional quality remains negative across most deciles, while road proximity is systematically associated with higher deforestation. Crucially, the interaction between institutional quality and road proximity is persistently positive across thresholds, indicating that institutional effectiveness is weakened in districts located closer to paved roads. Although the magnitude of the interaction effect varies, the overall pattern underscores the moderating role of infrastructure in shaping institutional impacts on deforestation. As expected, the interaction effect loses statistical significance at higher percentiles, since districts located farther from roads face limited direct deforestation pressures from infrastructure, thereby reducing the scope for institutions to counteract road-induced forest loss.

Taken together, the robustness checks strengthen the credibility of our main results. Alternative institutional index specifications, different spatial model formulations, and varying thresholds of road proximity all point to the same conclusion: institutional quality plays a central role in curbing deforestation, but its effectiveness is strongly conditioned by the presence of road infrastructure. These findings highlight the need for integrated policy approaches that combine institutional strengthening with careful regulation of road expansion in order to contain forest loss more effectively.

8 Concluding Remarks

We examine the drivers of deforestation in the Peruvian Amazon, emphasizing the critical roles of local institutions and road infrastructure. Using spatial econometric techniques, we decompose the direct and indirect effects of institutional quality and proximity to paved roads on cumulative deforestation between 2001 and 2023. Our results demonstrate that omitting spatial dependence, as in conventional OLS models, leads to substantial underestimation of key effects. We find that stronger local institutional quality is significantly associated with reduced deforestation, both within districts and in their neighbors.

However, this protective institutional effect is fully offset in areas near paved roads. Road infrastructure facilitates access to remote areas, promoting economic activities such as small-scale agriculture and mining that accelerate deforestation. This dynamic presents a policy dilemma: while institutional strengthening is vital for environmental protection, unregulated road expansion can undermine its impact. The moderating effect between institutional quality and road infrastructure reveals the need for integrated, spatially aware interventions to prevent the erosion of governance benefits.

Our work also allows us to increase the awareness that effective forest conservation in the Peruvian Amazon requires not only strengthening local institutions but also adopting a more deliberate approach to infrastructure planning. This includes enforcing stricter regulations on road development and promoting sustainable land use practices in already accessible regions. A coordinated strategy that jointly addresses institutional capacity and infrastructure expansion is essential to combat deforestation and preserve forest ecosystems in the region.

In terms of the future venues for research we identify, these include gathering better information to exploit the time variation in spatial dependence. The estimation of spatial differences-in-difference models could then be implemented. From a more practical perspective, qualitative analysis focused on selected geographical areas could help enhance our understanding of the mechanics behind institutional drivers fostering forest conservation. This endeavor aligns well with the identification of deforestation hotspots, which could be used as a tool to prioritize policy interventions.

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Appendices

A Principal Component Analysis

To construct the municipal institutional index, we compile a comprehensive set of standardized indicators grouped into five broad categories (see Table A.1): Administrative and Operational Capacity, Fiscal and Governance Performance, Service Provision and Enforcement, Environmental and Territorial Governance, and Socioeconomic Context. This classification reflects the multidimensional nature of local governments' institutional capacities.

Administrative and Operational Capacity is measured through three complementary indicators. The Operational Logistics Capacity is defined as the log of the total number of heavy machinery and operational vehicles, capturing municipalities' ability to deliver basic services and respond to local needs. The Municipal Staff per 1,000 People variable reflects the scale of local government administration, adjusted for population size and expressed in logarithms. Finally, the Execution Unit Presence is a binary indicator capturing whether municipalities have an internal execution or enforcement unit, signaling their institutionalization of formal budget implementation mechanisms.

Fiscal and Governance Performance emphasizes accountability and financial effectiveness. The Public Budget Execution Rate measures the proportion of the approved municipal budget effectively spent by year-end. In turn, the Accountability and Communication Index is a composite measure that combines (i) the transparency portal score (0–3), (ii) the availability of fixed and mobile communication lines, and (iii) the log of active lines. Together, these indicators capture both fiscal discipline and citizens' access to transparent information.

Service Provision and Enforcement focuses on local service delivery and security enforcement. The Waste Coverage Score assigns municipalities a score between 0.25 and 1, depending on the proportion of the population covered by formal solid waste collection systems. The Daily Municipal Patrols variable is a binary indicator equal to one if municipalities reported conducting daily security interventions in 2022, reflecting their enforcement capacity in public safety.

Environmental and Territorial Governance is captured by the High-Capacity Environmental Management indicator, which takes the value of one when municipalities implemented the official environmental plan (PLANEFA) and at least two additional environmental instruments. This variable signals the degree of formalization and institutional investment in territorial and environmental governance.

Finally, Socioeconomic Context provides a broader perspective on the local environment. The Economic Activity Ratio measures the share of economically active individuals relative to the working-age population, while Average Years of Schooling reflects local educational attainment levels. We also add two complementary indicators: the Low Birth Weight Share, defined as the percentage of newborns with low birth weight relative to total births, and Business Density (log), measuring the log of newly registered limited liability corporations per 1,000 inhabitants in 2023. These additions capture health vulnerabilities and entrepreneurial dynamics that interact with local institutional strength.

As seen in Table A.3, our preferred specification, denoted as the Local Institutional Index, includes all five categories but excludes Low Birth Weight Share and Business Density to focus on direct institutional capacity rather than outcomes or broader structural conditions. As robustness checks, we construct two alternative indices. The Local Institutional Capacity Index excludes the entire Socioeconomic Context category, allowing us to concentrate exclusively on core institutional mechanisms. In contrast, the Extended Local Institutional Index incorporates the full Socioeconomic Context, including both health and business density measures, thereby providing a comprehensive benchmark. This triangulation of indices allows us to assess the sensitivity of results to alternative definitions of local institutional capacity.

Table A.1 – Description of variables used in the PCA

Category	Variable	Description	Units	Source	Year
Administrative and Operational Capacity	Operational Logistics Capacity	Log of the total number of heavy machinery and operational vehicles	Count (log)	RENAMU	2023
	Municipal Staff per 1,000 People	Log of the number of municipal employees per 1,000 inhabitants	Workers per 1,000 (log)	RENAMU	2023
	Execution Unit Presence	Dummy indicating the presence of a formal budget enforcement or execution unit	Binary [0/1]	RENAMU	2023
Fiscal and Governance Performance	Public Budget Execution Rate	Percentage of municipal budget effectively spent by year-end	Ratio [0,1]	RENAMU	2023
	Accountability and Communication Index	Composite index including transparency portal score (0–3), availability of fixed and mobile lines, and log of the number of active communication lines	$[0, \infty)$	RENAMU	2023
Service Provision and Enforcement	Waste Coverage Score	Score based on the proportion of population with access to formal solid waste collection (0.25 if <25%, 0.5 if 25–50%, 0.75 if 50–75%, 1 if >75%)	Score [0.25–1]	RENAMU	2023
	Daily Municipal Patrols	Binary indicator equal to one if the municipality conducted daily security patrols in 2022.	Binary [0/1]	RENAMU	2022
Environmental and Territorial Governance	High-Capacity Environmental Management	Dummy equal to 1 if PLANEFA and at least two other environmental instruments are implemented	Binary [0/1]	RENAMU	2023
Socioeconomic Context	Economic Activity Ratio	Share of economically active population relative to working-age population	Ratio [0,1]	INEI	2017
	Average Years of Schooling	Average number of years of education of the municipal population	Years	INEI	2017
	Low Birth Weight Share	Percentage of newborns with low birth weight relative to total births	Ratio [0,1]	INEI	2017
	Business Density	Log of the number of registered firms per 1,000 inhabitants in 2023	Log	INEI	2023

Table A.2 – Descriptive Statistics of Variables Used in the Local Institutional Index (Principal Component Analysis)

Variable Description	Mean	Std Deviation	Min	Max	Observations
Operational Logistics Capacity (log)	1.2607	3.0095	0.0	21.8714	289
Municipal Staff per 1,000 People (log)	1.7117	0.7317	0.2548	6.1347	289
Execution Unit Presence	0.8102	0.1438	0.244	0.997	289
Public Budget Execution Rate (%)	7.8232	1.1707	4.9	11.8	289
Accountability and Communication Index	2.9255	1.8581	0.0	8.4012	289
Waste Coverage Score	0.7399	0.0695	0.516	0.887	289
Daily Municipal Patrols	0.6367	0.4818	0.0	1.0	289
High-Capacity Environmental Management	0.2353	0.4249	0.0	1.0	289
Economic Activity Ratio	0.8311	0.2005	0.25	1.0	289
Average Years of Schooling	0.2976	0.458	0.0	1.0	289
Low Birth Weight Share	0.0681	0.0361	0.0	0.2537	289
Business Density per 1,000 People (log)	3.6134	0.7841	1.0065	5.5113	289

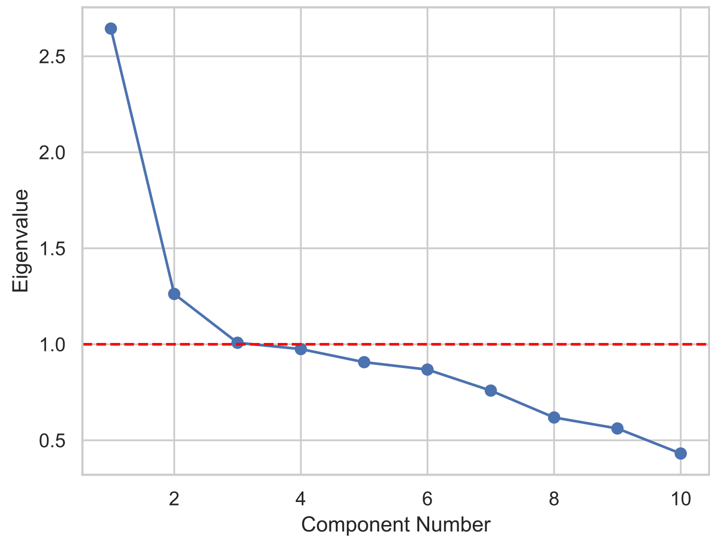
Note: This table reports descriptive statistics for the variables included in the municipal institutional index, which is constructed using a principal component analysis. Not available data was estimated using inverse exponential distance weights interpolation techniques as in Cantillo and Garza (2022)

Table A.3 – Variable inclusion across alternative PCA specifications for the Local Institutional Index

Category	**Local Institutional Index**	**Local Institutional Capacity Index**	**Extended Local Institutional Index**
Administrative and Operational Capacity	✓	✓	✓
Fiscal and Governance Performance	✓	✓	✓
Service Provision and Enforcement	✓	✓	✓
Environmental and Territorial Governance	✓	✓	✓
Socioeconomic Context	Partial (excl. Low Birth, Business Density)	Excluded	Full (incl. Low Birth, Business Density)

Note: The main specification (*Local Institutional Index*) excludes Low Birth Weight Share and Business Density from the Socioeconomic Context category. The robustness check (*Local Institutional Capacity Index*) excludes the entire Socioeconomic Context category. The extended version (*Extended Local Institutional Index*) includes all variables in the Socioeconomic Context category.

Figure A.1 – Eigenvalues by principal components - Local Institutional Index



Note: This scree plot displays the eigenvalues associated with each principal component. Components with eigenvalues above 1 are typically retained following the Kaiser criterion.

Figure A.2 – Factorial loadings for each variable - Local Institutional Index

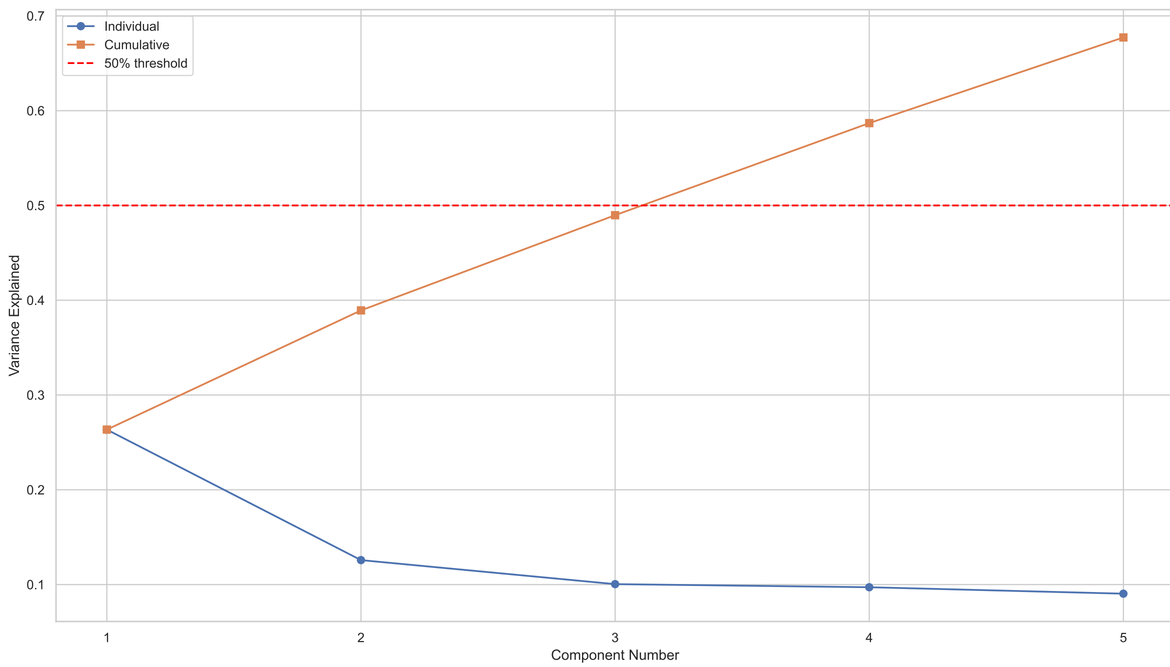
Note: The heatmap shows the standardized loadings of each variable across principal components. High absolute loadings indicate a strong contribution of the variable to the corresponding component.

Table A.4 – Sampling Adequacy and Bartlett's Test for PCA Validity - Local Institutional Index

Test	Result
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.733
Bartlett's Test of Sphericity	$\chi^2(45) = 357.68$, $p < 0.0001$

Note: The Kaiser-Meyer-Olkin (KMO) statistic evaluates whether the data are suitable for factor analysis. A KMO value of 0.733 is considered "middling to meritorious" (Kaiser, 1974), indicating sufficient common variance among variables to perform principal component analysis (PCA). Bartlett's Test of Sphericity examines the null hypothesis that the correlation matrix is an identity matrix. The test result is highly significant ($p < 0.0001$), suggesting that the variables are sufficiently correlated to justify the use of PCA.

Figure A.3 – Variance explained by each component - Local Institutional Index



Note: This plot shows the proportion of total variance explained by each principal component. The cumulative variance helps determine how many components should be retained for analysis.

B Spatial Models Tests

Table B.1 – Lagrange Multipliter Tests, SARMA and Moran

Test	χ^2	Degrees of Freedom (df)	p-value
OLS vs SEM (LM Error)	82.266	1	0.0000
OLS vs SAR (LM Lag)	128.25	1	0.0000
OLS vs SEM (Robust LM Error)	1.528	1	0.2164
OLS vs SAR (Robust LM Lag)	47.509	1	0.0000
SARMA	129.77	2	0.0000
Moran's I	0.3543	—	0.0000

Note: This table reports results from spatial dependence tests applied to the OLS specification. LM tests compare OLS with alternative spatial models: the Spatial Error Model (SEM) and the Spatial Autoregressive Model (SAR), including robust versions. The SARMA test jointly evaluates lag and error dependence. Moran's I assesses residual spatial autocorrelation. A significant test statistic indicates the presence of spatial dependence and motivates the use of spatial models. We use a queen contiguity spatial weight matrix.

Table B.2 – Likelihood Ratio Tests between Spatial Models

Model Comparison	χ^2 Statistic	Degrees of Freedom	p-value
SAR vs. SDM	35.39	18	0.0084
SEM vs. SDEM	48.88	18	0.0001
SAR vs. SDEM	25.95	18	0.1009

Note: Likelihood Ratio Tests (LRT) are presented. The test statistic follows a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between models. A statistically significant p-value (e.g., $p < 0.05$) indicates that the more general model provides a significantly better fit to the data, leading to rejection of the null hypothesis that the simpler (nested) model is sufficient. We use a queen contiguity spatial weights matrix.

C Descriptive Statistics

Table C.1 – Descriptive Statistics

Variable	Mean	Std Deviation	Min	Max	Observations
Cumulative Deforestation Rate	0.1341	0.1302	0.0016	0.6732	289
Local Institutional Index	-0.0	1.6261	-2.7399	4.9318	289
Local Institutional Capacity Index	0.0	1.4401	-2.5351	3.7275	289
Extended Local Institutional Index	0.0	1.7885	-3.5232	5.3235	289
log(Min. Distance to Paved Road)	2.8884	1.2904	0.025	5.8936	289
Temperature (°C)	22.914	4.7968	8.7	30.17	289
Precipitation (mm)	862.9983	687.1908	215.44	2917.52	289
Elevation (m.a.s.l.)	959.7356	839.8341	76.0	4356.0	289
Private Conservation Area (Forest %)	0.007	0.032	0.0	0.2643	289
Regional Conservation Area (Forest %)	0.016	0.0629	0.0	0.5261	289
Natural Protected Area (Forest %)	0.0316	0.0978	0.0	0.7701	289
Forest Concession (Forest %)	0.0633	0.1152	0.0	0.5828	289
Andean Communities (Forest %)	0.0993	0.1768	0.0	0.9482	289
Coffee (Agricultural Land %)	0.1607	0.1955	0.0	0.8725	289
Cocoa (Agricultural Land %)	0.0579	0.0886	0.0	0.425	289
Oil Palm (Agricultural Land %)	0.0060	0.0282	0.0	0.2743	289
Coca (Agricultural Land %)	0.0090	0.0319	0.0	0.2083	289
Population Density (per km^2)	30.6161	92.665	0.0708	1302.2221	289
Poverty Rate	0.3286	0.1471	0.019	0.768	289
log(Min. Distance to Mine)	4.1282	1.1135	0.4113	6.5854	289

Note: This table presents descriptive statistics for the main variables used in the empirical analysis. The local institutional index is constructed using the first three components from a principal component analysis (PCA) of local government capacity indicators. Distance variables are expressed in natural logarithms and originally measured in kilometers. Precipitation is measured in millimeters, temperature in degrees Celsius, and elevation in meters above sea level. Variables referring to protected areas indicate the percentage of forest land within the district under each protection category as of 2001. Crop-related variables represent the percentage of total agricultural land used for each crop. Population density is measured in people per square kilometer. All statistics are based on a sample of 289 districts from the Peruvian Amazon. Not available data was estimated using inverse exponential distance weights interpolation techniques as in Cantillo and Garza (2022)

D Results

D.1 Spatial Models Regressions

Table D.1 – Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Spatial Model - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)									
	SDM		SLX		SDEM		SAR		OLS	
	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e
Local Institutional Index	-0.0064**	0.0032	-0.0086**	0.0041	-0.0095***	0.0036	-0.0063**	0.0031	-0.0122***	0.0044
log(Min. Distance to Paved Road)	-0.0217***	0.0068	-0.0291***	0.0087	-0.0265***	0.0067	-0.0193***	0.0053	-0.0392***	0.0073
Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0175*	0.0096	0.0212*	0.0123	0.0214*	0.0118	0.0119	0.0096	0.0102	0.0136
Temperature (°C)	4e-04	0.0025	2e-04	0.0032	0.0015	0.0024	0.0026	0.0017	0.0059**	0.0024
Precipitation (mm)	-2.8e-06	2.7e-05	2.2e-07	3.5e-05	-8.2e-06	2.6e-05	-3.3e-06	8e-06	-3.5e-05***	1.1e-05
Elevation (m.a.s.l.)	-4e-05***	1e-05	-5.5e-05***	1.3e-05	-4.2e-05***	1.1e-05	-3.3e-05***	9.7e-06	-4.4e-05***	1.4e-05
Private Conservation Area (Forest %)	0.1790	0.1533	0.2683	0.1968	0.1410	0.1622	0.0454	0.1339	-0.0334	0.1885
Regional Conservation Area (Forest %)	-0.1173	0.0731	-0.2244**	0.0933	-0.1792**	0.0815	-0.1019	0.0659	-0.1443	0.0925
Natural Protected Area (Forest %)	-0.1073**	0.0475	-0.1123*	0.0610	-0.1185**	0.0483	-0.1188***	0.0437	-0.1965***	0.0613
Forest Concession (Forest %)	-0.0334	0.0482	-0.0118	0.0619	-0.0152	0.0511	-0.0307	0.0447	-0.0242	0.0630
Andean Communities (Forest %)	-0.0351	0.0364	-0.0324	0.0468	-0.0367	0.0368	-0.0311	0.0300	-0.0792*	0.0419
Coffee (Agricultural Land %)	0.0759**	0.0319	0.0975**	0.0409	0.0837***	0.0318	0.0794***	0.0262	0.1092***	0.0369
Cocoa (Agricultural Land %)	-0.2191**	0.0883	-0.2006*	0.1135	-0.1908**	0.0855	-0.0488	0.0593	0.0803	0.0836
Oil Palm (Agricultural Land %)	0.4048**	0.1635	0.4361**	0.2099	0.4751***	0.1728	0.3487**	0.1497	0.3691*	0.2110
Coca (Agricultural Land %)	0.2075	0.2077	0.2857	0.2665	0.3258	0.2152	0.2945*	0.1640	0.1834	0.2312
Population Density (per km^2)	3.4e-05	5.3e-05	4.9e-05	6.8e-05	3e-05	5.5e-05	-4.2e-05	4.8e-05	-1e-04	6.8e-05
Poverty Rate	-0.0349	0.0464	-0.0345	0.0596	-0.0431	0.0471	-0.0699*	0.0362	-0.1913***	0.0507
log(Min. Distance to Mine)	-0.0148	0.0112	-0.0107	0.0143	-0.0106	0.0103	-0.0023	0.0053	0.0097	0.0075
Constant	0.0499	0.0839	0.3001***	0.1059	0.1425	0.1369	0.1017**	0.0453	0.2039***	0.0635
W. Local Institutional Index	-0.0148**	0.0062	-0.0265***	0.0078	-0.0237***	0.0087	-	-	-	-
W. log(Min. Distance to Paved Road)	-0.0091	0.0111	-0.0332**	0.0139	-0.0389***	0.0144	-	-	-	-
W. Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0418**	0.0200	0.0624**	0.0257	0.0499*	0.0281	-	-	-	-
W. Temperature (°C)	0.0034	0.0038	0.0026	0.0048	0.0090**	0.0045	-	-	-	-
W. Precipitation (mm)	1.2e-05	3e-05	-1.3e-05	3.8e-05	7.9e-06	3.2e-05	-	-	-	-
W. Elevation (m.a.s.l.)	4.2e-06	1.8e-05	-4.8e-05**	2.3e-05	-1.3e-05	2.5e-05	-	-	-	-
W. Private Conservation Area (Forest %)	-0.0253	0.2310	0.1865	0.2966	-0.0209	0.2835	-	-	-	-
W. Regional Conservation Area (Forest %)	-0.5919***	0.1537	-0.9596***	0.1958	-0.6334***	0.1996	-	-	-	-
W. Natural Protected Area (Forest %)	-0.0371	0.0934	-0.2035*	0.1191	-0.1147	0.1307	-	-	-	-
W. Forest Concession (Forest %)	0.1012	0.0897	0.0848	0.1152	0.1166	0.1151	-	-	-	-
W. Andean Communities (Forest %)	0.0740	0.0573	0.0772	0.0736	0.0079	0.0704	-	-	-	-
W. Coffee (Agricultural Land %)	0.1204**	0.0558	0.2542***	0.0709	0.1477**	0.0714	-	-	-	-
W. Cocoa (Agricultural Land %)	0.2589**	0.1287	0.3467**	0.1653	0.1879	0.1691	-	-	-	-
W. Oil Palm (Agricultural Land %)	0.4458	0.2883	1.1095***	0.3647	0.8367**	0.4231	-	-	-	-
W. Coca (Agricultural Land %)	0.1020	0.2976	0.1804	0.3823	0.2648	0.4150	-	-	-	-
W. Population Density (per km^2)	5.8e-05	2e-04	-4.2e-05	2e-04	1e-04	2e-04	-	-	-	-
W. Poverty Rate	-0.0581	0.0672	-0.2118**	0.0855	-0.0774	0.0924	-	-	-	-
W. log(Min. Distance to Mine)	0.0204	0.0130	0.0302*	0.0168	0.0100	0.0154	-	-	-	-
Observations	289		289		289		289		289	
Log-Likelihood	369.87		331.42		365.15		352.17		282.75	
AIC	-661.73		-586.83		-652.29		-662.34		-525.51	
λ	-		-		0.655		-		-	

Note: The table reports estimated coefficients and standard errors from five regression models: Spatial Durbin Model (SDM), Spatial Lag of X (SLX), Spatial Durbin Error Model (SDEM), Spatial Autoregressive Model (SAR), and Ordinary Least Squares (OLS). We use a queen contiguity spatial weights matrix. The dependent variable is the cumulative deforestation rate. All models include controls for socioeconomic, geographic, and climatic characteristics. Spatial lags of covariates are indicated by "W.". Standard errors are reported next to each coefficient. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations, AIC, log-likelihood, and λ (where applicable) are reported at the bottom of the table.

Table D.2 – Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Road Type, SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)			
	Unpaved Road		All Roads	
	β	s.e	β	s.e
Local Institutional Index	-0.0055*	0.0031	-0.0053*	0.0030
log(Min. Distance)	-0.0353***	0.0055	-0.0360***	0.0055
Local Institutional Index $\times(\log(D) \leq P_{10})$	0.0053	0.0069	0.0041	0.0070
Temperature (°C)	6e-04	0.0023	8e-04	0.0023
Precipitation (mm)	3.1e-06	2.6e-05	3.8e-06	2.6e-05
Elevation (m.a.s.l.)	-2e-05**	1e-05	-2e-05**	1e-05
Private Conservation Area (Forest %)	0.2006	0.1472	0.2036	0.1470
Regional Conservation Area (Forest %)	-0.0800	0.0695	-0.0872	0.0693
Natural Protected Area (Forest %)	-0.0504	0.0465	-0.0495	0.0464
Forest Concession (Forest %)	-0.0218	0.0452	-0.0213	0.0451
Andean Communities (Forest %)	-0.0189	0.0346	-0.0168	0.0346
Coffee (Agricultural Land %)	0.0414	0.0311	0.0409	0.0311
Cocoa (Agricultural Land %)	-0.2052**	0.0840	-0.2020**	0.0837
Oil Palm (Agricultural Land %)	0.3711**	0.1558	0.3762**	0.1556
Coca (Agricultural Land %)	0.0976	0.1954	0.1016	0.1953
Population Density (per km^2)	9.8e-06	5e-05	1.2e-05	5e-05
Poverty Rate	-0.0384	0.0441	-0.0365	0.0441
log(Min. Distance to Mine)	-0.0216**	0.0097	-0.0190*	0.0097
Constant	-0.0720	0.0763	-0.0628	0.0759
W. Local Institutional Index	-0.0060	0.0058	-0.0062	0.0058
W. log(Min. Distance)	0.0023	0.0098	0.0019	0.0097
W. Local Institutional Index $\times(\log(D) \leq P_{10})$	0.0024	0.0157	0.0014	0.0158
W. Temperature (°C)	0.0052	0.0035	0.0044	0.0035
W. Precipitation (mm)	1.9e-05	2.9e-05	1.6e-05	2.9e-05
W. Elevation (m.a.s.l.)	1e-05	1.8e-05	6.4e-06	1.8e-05
W. Private Conservation Area (Forest %)	-0.1861	0.2224	-0.1729	0.2219
W. Regional Conservation Area (Forest %)	-0.5528***	0.1459	-0.5635***	0.1458
W. Natural Protected Area (Forest %)	-0.0519	0.0894	-0.0506	0.0893
W. Forest Concession (Forest %)	0.0744	0.0837	0.0902	0.0837
W. Andean Communities (Forest %)	0.0688	0.0535	0.0738	0.0533
W. Coffee (Agricultural Land %)	0.0919*	0.0555	0.0970*	0.0552
W. Cocoa (Agricultural Land %)	0.2838**	0.1185	0.2636**	0.1182
W. Oil Palm (Agricultural Land %)	0.4114	0.2722	0.4470	0.2722
W. Coca (Agricultural Land %)	0.0627	0.2819	0.1162	0.2825
W. Population Density (per km^2)	3.3e-06	1e-04	7e-06	1e-04
W. Poverty Rate	-0.0406	0.0621	-0.0351	0.0622
W. log(Min. Distance to Mine)	0.0305***	0.0116	0.0298**	0.0117
Observations	289		289	
Log-Likelihood	381.78		382.41	
AIC	-685.57		-686.82	
λ	-		-	

Note: The table reports estimated coefficients and standard errors from five SDM models by road type: Paved Road, Unpaved Road, and All Roads. The dependent variable is the cumulative deforestation rate. All models include controls for socioeconomic, geographic, and climatic characteristics. Spatial lags of covariates are indicated by "W.". We use a queen contiguity spatial weights matrix. Standard errors are reported next to each coefficient. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations, AIC, log-likelihood, and λ (where applicable) are reported at the bottom of the table.

D.2 Marginal Effects

Table D.3 – Direct, Indirect and Total Effect of Covariates on Cumulative Deforestation Rate (2001–2023), SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)					
	Direct effect $\left(\frac{\partial F_i}{\partial x_i}\right)$	s.e	**Indirect effect** $\left(\frac{\partial F_i}{\partial x_j}\right)$	s.e	**Total effect** $\left(\sum_j \frac{\partial F_j}{\partial x_i}\right)$	s.e
Temperature (°C)	0.0011	0.0023	0.0089	0.0076	0.0100	0.0079
Precipitation (mm)	-9.1e-07	2.6e-05	2.4e-05	3.9e-05	2.3e-05	2.9e-05
Elevation (m.a.s.l.)	-4.4e-05***	1.2e-05	-4.9e-05	4.5e-05	-9.3e-05*	5.2e-05
Private Conservation Area (Forest %)	0.1953	0.1631	0.2033	0.5256	0.3986	0.5916
Regional Conservation Area (Forest %)	-0.2453***	0.0850	-1.5939***	0.4433	-1.8392***	0.4977
Natural Protected Area (Forest %)	-0.1272***	0.0480	-0.2470	0.2168	-0.3742	0.2340
Forest Concession (Forest %)	-0.0178	0.0505	0.1938	0.2175	0.1760	0.2390
Andean Communities (Forest %)	-0.0250	0.0359	0.1263	0.1249	0.1013	0.1330
Coffee (Agricultural Land %)	0.1081***	0.0312	0.4010***	0.1315	0.5091***	0.1396
Cocoa (Agricultural Land %)	-0.1951**	0.0876	0.2990	0.2511	0.1039	0.2660
Oil Palm (Agricultural Land %)	0.5388***	0.1798	1.6667**	0.6722	2.2055***	0.7575
Coca (Agricultural Land %)	0.2517	0.2201	0.5494	0.6380	0.8011	0.7139
Population Density (per km^2)	5e-05	6.1e-05	2e-04	4e-04	2e-04	4e-04
Poverty Rate	-0.0503	0.0463	-0.1908	0.1419	-0.2411	0.1517
log(Min. Distance to Mine)	-0.0126	0.0103	0.0271	0.0190	0.0145	0.0172

Note: This table presents the estimated direct, indirect, and total marginal effects of geographic and socioeconomic covariates on the cumulative deforestation rate between 2001 and 2023. The estimates are derived from a Spatial Durbin Model (SDM) using a queen contiguity spatial weights matrix. Direct effects capture the marginal impact of a variable on its own location; indirect effects represent spatial spillovers from neighboring units; and total effects are the sum of both. Standard errors are calculated via Monte Carlo simulations (reps=1000). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Robustness Checks

E.1 Alternative Local Institutional Indices

Table E.1 – Direct, Indirect and Total Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Alternative Local Institutional Indexes, SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)					
	Direct effect $\left(\frac{\partial F_i}{\partial x_i}\right)$	s.e	**Indirect effect** $\left(\frac{\partial F_i}{\partial x_j}\right)$	s.e	**Total effect** $\left(\sum_j \frac{\partial F_j}{\partial x_i}\right)$	s.e
Local Institutional Index						
Local Institutional Index	-0.0100***	0.0036	-0.0451***	0.0160	-0.0551***	0.0182
log(Min. Distance to Paved Road)	-0.0260***	0.0068	-0.0538**	0.0236	-0.0799***	0.0250
Local Institutional Index $\times(\log(D) \leq P_{10})$	0.0276**	0.0126	0.1263**	0.0581	0.1539**	0.0679
Local Institutional Capacity Index						
Local Institutional Capacity Index	-0.0098**	0.0039	-0.0396**	0.0176	-0.0494**	0.0201
log(Min. Distance to Paved Road)	-0.0261***	0.0070	-0.0580**	0.0238	-0.0841***	0.0256
Local Institutional Capacity Index $\times(\log(D) \leq P_{10})$	0.0356***	0.0133	0.1420**	0.0659	0.1776**	0.0760
Extended Local Institutional Index						
Extended Local Institutional Index	-0.0095***	0.0036	-0.0458***	0.0160	-0.0553***	0.0183
log(Min. Distance to Paved Road)	-0.0260***	0.0066	-0.0539**	0.0238	-0.0800***	0.0252
Extended Local Institutional Index $\times(\log(D) \leq P_{10})$	0.0268**	0.0110	0.1203**	0.0521	0.1471**	0.0604

Note: This table reports the direct, indirect, and total marginal effects of the Local Institutional Index and its interaction with remoteness (measured as log(Min. Distance to Paved Road) $\leq P_{10}$) on the cumulative deforestation rate between 2001 and 2023. We use a queen contiguity spatial weight matrix. Estimates are obtained from different local institutional index specifications (see Table A.3 for more detail). Controls include climatic variables (average temperature, precipitation, and elevation), forest protection measures (share of forest under private conservation areas, regional conservation areas, natural protected areas, forest concessions, and Andean communities), agricultural land uses (share of land planted with coffee, cocoa, oil palm, and coca), as well as socioeconomic and extractive factors (population density, poverty rate, and the logarithm of the minimum distance to the nearest mining site). Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are based on Monte Carlo simulations (reps=1000).

Table E.2 – Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Alternative Local Institutional Indexes, SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)					
	Local Institutional Index		Local Institutional Capacity Index		Extended Local Institutional Index	
	β	s.e	β	s.e	β	s.e
PCA Institutional Index	-0.0064**	0.0032	-0.0066**	0.0033	-0.0058*	0.0030
log(Min. Distance to Paved Road)	-0.0217***	0.0068	-0.0214***	0.0068	-0.0217***	0.0069
PCA Institutional Index $\times(\log(D) \leq P_{10})$	0.0175*	0.0096	0.0242**	0.0103	0.0171*	0.0089
Temperature (°C)	4e-04	0.0025	6e-04	0.0025	6e-04	0.0025
Precipitation (mm)	-2.8e-06	2.7e-05	-2.2e-06	2.7e-05	-5.2e-06	2.7e-05
Elevation (m.a.s.l.)	-4e-05***	1e-05	-3.9e-05***	1e-05	-3.9e-05***	1e-05
Private Conservation Area (Forest %)	0.1790	0.1533	0.1684	0.1532	0.1883	0.1530
Regional Conservation Area (Forest %)	-0.1173	0.0731	-0.1103	0.0732	-0.1137	0.0730
Natural Protected Area (Forest %)	-0.1073**	0.0475	-0.1107**	0.0475	-0.1063**	0.0475
Forest Concession (Forest %)	-0.0334	0.0482	-0.0345	0.0481	-0.0319	0.0482
Andean Communities (Forest %)	-0.0351	0.0364	-0.0347	0.0363	-0.0378	0.0363
Coffee (Agricultural Land %)	0.0759**	0.0319	0.0749**	0.0319	0.0748**	0.0319
Cocoa (Agricultural Land %)	-0.2191**	0.0883	-0.2140**	0.0887	-0.2233**	0.0881
Oil Palm (Agricultural Land %)	0.4048**	0.1635	0.3963**	0.1648	0.4043**	0.1633
Coca (Agricultural Land %)	0.2075	0.2077	0.1953	0.2077	0.2286	0.2081
Population Density (per km^2)	3.4e-05	5.3e-05	1.5e-05	5.2e-05	3.5e-05	5.3e-05
Poverty Rate	-0.0349	0.0464	-0.0268	0.0448	-0.0390	0.0475
log(Min. Distance to Mine)	-0.0148	0.0112	-0.0146	0.0111	-0.0145	0.0112
Constant	0.0499	0.0839	0.0387	0.0831	0.0530	0.0837
W. PCA Institutional Index	-0.0148**	0.0062	-0.0119*	0.0064	-0.0156***	0.0060
W. log(Min. Distance to Paved Road)	-0.0091	0.0111	-0.0099	0.0111	-0.0092	0.0112
W. PCA Institutional Index $\times(\log(D) \leq P_{10})$	0.0418**	0.0200	0.0421*	0.0223	0.0397**	0.0181
W. Temperature (°C)	0.0034	0.0038	0.0033	0.0038	0.0037	0.0037
W. Precipitation (mm)	1.2e-05	3e-05	8.9e-06	3e-05	1.6e-05	3e-05
W. Elevation (m.a.s.l.)	4.2e-06	1.8e-05	4.8e-06	1.8e-05	6.8e-06	1.8e-05
W. Private Conservation Area (Forest %)	-0.0253	0.2310	-0.0451	0.2306	0.0124	0.2305
W. Regional Conservation Area (Forest %)	-0.5919***	0.1537	-0.5459***	0.1538	-0.5836***	0.1529
W. Natural Protected Area (Forest %)	-0.0371	0.0934	-0.0545	0.0933	-0.0296	0.0935
W. Forest Concession (Forest %)	0.1012	0.0897	0.0972	0.0905	0.1113	0.0902
W. Andean Communities (Forest %)	0.0740	0.0573	0.0677	0.0580	0.0728	0.0573
W. Coffee (Agricultural Land %)	0.1204**	0.0558	0.1182**	0.0559	0.1216**	0.0558
W. Cocoa (Agricultural Land %)	0.2589**	0.1287	0.2770**	0.1285	0.2607**	0.1291
W. Oil Palm (Agricultural Land %)	0.4458	0.2883	0.4331	0.2945	0.4273	0.2887
W. Coca (Agricultural Land %)	0.1020	0.2976	0.0989	0.2972	0.1274	0.3003
W. Population Density (per km^2)	5.8e-05	2e-04	-1e-05	2e-04	6.4e-05	2e-04
W. Poverty Rate	-0.0581	0.0672	-0.0388	0.0659	-0.0848	0.0687
W. log(Min. Distance to Mine)	0.0204	0.0130	0.0214*	0.0130	0.0181	0.0131
Observations	289		289		289	
Log-Likelihood	369.87		369.18		370.02	
AIC	-661.73		-660.37		-662.05	
λ	-		-		-	

Note: The table reports estimated coefficients and standard errors from three spatial durbin models which differs by institutional index construction: local institutional index, local institutional capacity index, and extended local institutional index (see Table A.3 for more detail). We use a queen contiguity spatial weights matrix. The dependent variable is the cumulative deforestation rate. All models include controls for socioeconomic, geographic, and climatic characteristics. Spatial lags of covariates are indicated by "W.". Standard errors are reported next to each coefficient. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations, AIC, log-likelihood, and λ (where applicable) are reported at the bottom of the table.

E.2 Different Spatial Models

Table E.3 – Direct, Indirect and Total Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Spatial Models, Queen Contiguity W

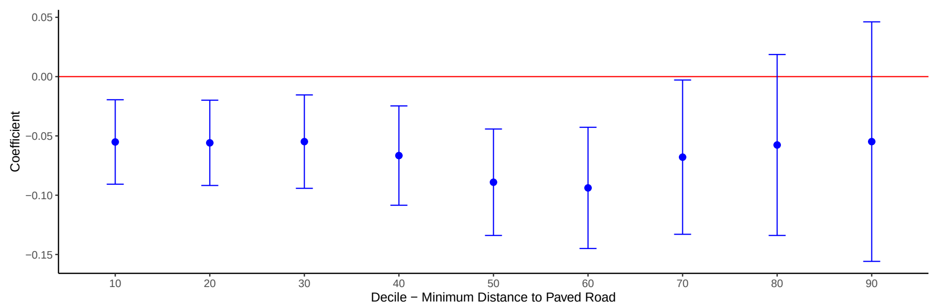
	Cumulative Deforestation Rate (2001-2023)					
	Direct effect $\left(\frac{\partial F_i}{\partial x_i}\right)$	s.e	**Indirect effect** $\left(\frac{\partial F_i}{\partial x_j}\right)$	s.e	**Total effect** $\left(\sum_j \frac{\partial F_j}{\partial x_i}\right)$	s.e
Spatial Durbin Model (SDM)						
Local Institutional Index	-0.0100***	0.0036	-0.0451***	0.0160	-0.0551***	0.0182
log(Min. Distance to Paved Road)	-0.0260***	0.0068	-0.0538**	0.0236	-0.0799***	0.0250
Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0276**	0.0126	0.1263**	0.0581	0.1539**	0.0679
Spatial Lag of X Model (SLX)						
Local Institutional Index	-0.0086**	0.0041	-0.0265***	0.0078	-0.0351***	0.0085
log(Min. Distance to Paved Road)	-0.0292***	0.0087	-0.0332**	0.0139	-0.0624***	0.0116
Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0212*	0.0122	0.0625**	0.0256	0.0837***	0.0308
Spatial Durbin Error Model (SDEM)						
Local Institutional Index	-0.0095***	0.0038	-0.0238***	0.0093	-0.0333***	0.0117
log(Min. Distance to Paved Road)	-0.0265***	0.0072	-0.0389***	0.0154	-0.0654***	0.0171
Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0214*	0.0126	0.0500*	0.0300	0.0714*	0.0399
Spatial Autoregressive Model (SAR)						
Local Institutional Index	-0.0074**	0.0037	-0.0139*	0.0077	-0.0213*	0.0112
log(Min. Distance to Paved Road)	-0.0228***	0.0064	-0.0430***	0.0141	-0.0658***	0.0197
Local Institutional Index $\times(\log(\text{D}) \leq P_{10})$	0.0139	0.0111	0.0262	0.0227	0.0402	0.0335

Note: This table reports the direct, indirect, and total marginal effects of the Local Institutional Index and its interaction with remoteness (measured as log(Min. Distance to Paved Road) $\leq P_{10}$) on the cumulative deforestation rate between 2001 and 2023. We use a queen contiguity spatial weight matrix. Estimates are obtained from different spatial models. Controls include climatic variables (average temperature, precipitation, and elevation), forest protection measures (share of forest under private conservation areas, regional conservation areas, natural protected areas, forest concessions, and Andean communities), agricultural land uses (share of land planted with coffee, cocoa, oil palm, and coca), as well as socioeconomic and extractive factors (population density, poverty rate, and the logarithm of the minimum distance to the nearest mining site). Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are based on Monte Carlo simulations (reps=1000).

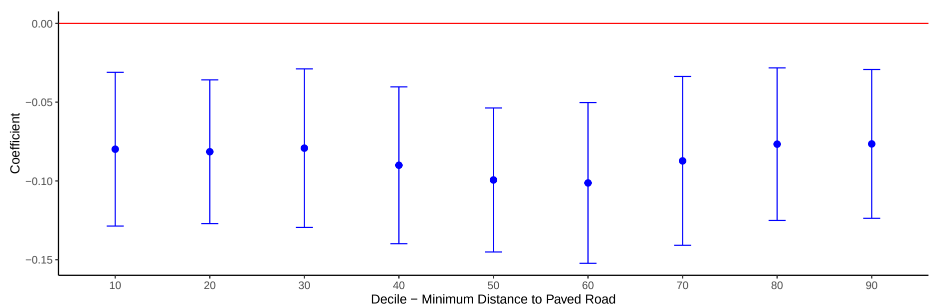
E.3 Different Deciles of the Minimum Distance to Paved Road

Figure E.1 – Total effects of institutional quality, road proximity, and their interaction on cumulative deforestation by treshold minimum distance to paved road (2001–2023), SDM - Queen Contiguity W

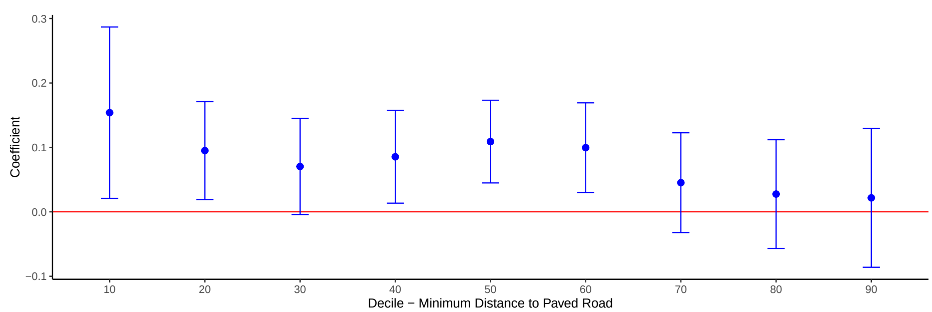
(a) Local Institutional Index (P10 - P90)



(b) $\log(\text{Min. Distance to Paved Road})$ (P10 - P90)



(c) Local Institutional Index $\times(\log(\text{D}) \leq P_X)$ (P10 - P90)



Note: These figures report the total effects of the Local Institutional Index and its interaction with remoteness, measured as $\log(\text{Min. Distance to Paved Road}) \leq P_X$, on the cumulative deforestation rate between 2001 and 2023. Estimates are obtained from Spatial Durbin Models (SDM) under the queen contiguity spatial weight matrix. The interaction varies according to the percentile threshold P_X, capturing differences between districts closer and farther from paved roads. Controls include climatic variables (average temperature, precipitation, and elevation), forest protection measures (share of forest under private conservation areas, regional conservation areas, natural protected areas, forest concessions, and Andean communities), agricultural land uses (share of land planted with coffee, cocoa, oil palm, and coca), as well as socioeconomic and extractive factors (population density, poverty rate, and the logarithm of the minimum distance to the nearest mining site). Confidence intervals are at 95%. Standard errors are based on Monte Carlo simulations (reps=1000).

Table E.4 – Effect of Local Institutional Index on Cumulative Deforestation Rate (2001–2023) by Different Deciles of the Minimun Distance to Paved Road, SDM - Queen Contiguity W

	Cumulative Deforestation Rate (2001-2023)																	
	P_{10}		P_{20}		P_{30}		P_{40}		P_{50}		P_{60}		P_{70}		P_{80}		P_{90}	
	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e	β	s.e
Local Institutional Index	-0.0064**	0.0032	-0.0057*	0.0033	-0.0064*	0.0036	-0.0067*	0.0039	-0.0107***	0.0041	-0.0088*	0.0046	-0.0097*	0.0051	-0.0069	0.0058	-0.0081	0.0095
log(Min. Distance to Paved Road)	-0.0217***	0.0068	-0.0200***	0.0067	-0.0197***	0.0068	-0.0212***	0.0068	-0.0224***	0.0068	-0.0230***	0.0069	-0.0199***	0.0069	-0.0200***	0.0069	-0.0201***	0.0068
Local Institutional Index $\times(\log(\mathrm{D}) \leq P_X)$	0.0175*	0.0095	0.0058	0.0061	0.0069	0.0057	0.0065	0.0055	0.0124**	0.0054	0.0080	0.0056	0.0077	0.0059	0.0033	0.0066	0.0041	0.0099
Temperature (°C)	4e-04	0.0025	3e-04	0.0025	5e-04	0.0025	8e-04	0.0025	8e-04	0.0024	3e-04	0.0024	1e-04	0.0024	-4.3e-05	0.0024	-1.3e-05	0.0025
Precipitation (mm)	-2.8e-06	2.7e-05	-2.4e-06	2.7e-05	-2.8e-06	2.7e-05	-3.8e-06	2.7e-05	-2.3e-06	2.7e-05	-4.7e-06	2.7e-05	-9.6e-07	2.7e-05	-2.7e-06	2.8e-05	-4.5e-06	2.8e-05
Elevation (m.a.s.l.)	-4e-05***	1e-05	-3.9e-05***	1e-05	-3.9e-05***	1e-05	-3.8e-05***	1e-05	-3.8e-05***	1e-05	-3.8e-05***	1e-05	-4e-05***	1e-05	-4.1e-05***	1e-05	-4.1e-05***	1e-05
Private Conservation Area (Forest %)	0.1789	0.1533	0.1786	0.1533	0.1963	0.1540	0.2119	0.1538	0.2029	0.1527	0.2142	0.1530	0.1901	0.1552	0.1882	0.1549	0.1840	0.1547
Regional Conservation Area (Forest %)	-0.1172	0.0731	-0.1368*	0.0737	-0.1204	0.0735	-0.1284*	0.0735	-0.1358*	0.0729	-0.1298*	0.0731	-0.1096	0.0734	-0.1063	0.0736	-0.1058	0.0738
Natural Protected Area (Forest %)	-0.1073**	0.0475	-0.1089**	0.0475	-0.1114**	0.0477	-0.1116**	0.0475	-0.1106**	0.0472	-0.1027**	0.0476	-0.1117**	0.0480	-0.1099**	0.0482	-0.1142**	0.0490
Forest Concession (Forest %)	-0.0334	0.0482	-0.0363	0.0485	-0.0385	0.0488	-0.0315	0.0488	-0.0263	0.0484	-0.0180	0.0487	-0.0292	0.0492	-0.0322	0.0490	-0.0350	0.0492
Andean Communities (Forest %)	-0.0351	0.0364	-0.0359	0.0364	-0.0360	0.0365	-0.0332	0.0364	-0.0282	0.0363	-0.0248	0.0367	-0.0380	0.0368	-0.0382	0.0368	-0.0389	0.0369
Coffee (Agricultural Land %)	0.0759**	0.0319	0.0778**	0.0318	0.0717**	0.0319	0.0733**	0.0318	0.0736**	0.0316	0.0790**	0.0318	0.0731**	0.0320	0.0738**	0.0321	0.0736**	0.0321
Cocoa (Agricultural Land %)	-0.2191**	0.0883	-0.2369***	0.0894	-0.2243**	0.0889	-0.2268**	0.0884	-0.2337***	0.0878	-0.2380***	0.0879	-0.2234**	0.0885	-0.2232**	0.0888	-0.2222**	0.0888
Oil Palm (Agricultural Land %)	0.4049**	0.1635	0.4358***	0.1635	0.4066**	0.1632	0.3888**	0.1633	0.3939**	0.1615	0.3980**	0.1621	0.4054**	0.1636	0.4093**	0.1645	0.4129**	0.1643
Coca (Agricultural Land %)	0.2075	0.2077	0.2099	0.2075	0.1836	0.2080	0.2068	0.2076	0.2181	0.2069	0.2166	0.2071	0.1981	0.2085	0.1872	0.2091	0.1865	0.2094
Population Density (per km^2)	3.4e-05	5.3e-05	4.6e-06	5.4e-05	2.2e-06	5.5e-05	1.6e-06	5.4e-05	-9e-06	5.4e-05	6.2e-06	5.4e-05	1.3e-05	5.4e-05	2.2e-05	5.4e-05	2.3e-05	5.3e-05
Poverty Rate	-0.0349	0.0464	-0.0325	0.0465	-0.0373	0.0466	-0.0352	0.0467	-0.0350	0.0461	-0.0227	0.0464	-0.0267	0.0468	-0.0306	0.0470	-0.0323	0.0469
log(Min. Distance to Mine)	-0.0148	0.0112	-0.0136	0.0111	-0.0152	0.0111	-0.0134	0.0111	-0.0111	0.0111	-0.0129	0.0111	-0.0154	0.0112	-0.0154	0.0112	-0.0155	0.0112
Constant	0.0501	0.0839	0.0329	0.0848	0.0307	0.0869	0.0016	0.0888	0.0050	0.0852	0.0247	0.0845	0.0575	0.0848	0.0739	0.0839	0.0791	0.0837
W. Local Institutional Index	-0.0149**	0.0062	-0.0159**	0.0063	-0.0144**	0.0067	-0.0190**	0.0075	-0.0250***	0.0081	-0.0277***	0.0090	-0.0156	0.0103	-0.0146	0.0117	-0.0126	0.0189
W. log(Min. Distance to Paved Road)	-0.0091	0.0111	-0.0115	0.0112	-0.0104	0.0112	-0.0135	0.0113	-0.0174	0.0113	-0.0165	0.0115	-0.0125	0.0115	-0.0086	0.0113	-0.0088	0.0112
W. Local Institutional Index $\times(\log(\mathrm{D}) \leq P_X)$	0.0419**	0.0200	0.0310**	0.0132	0.0199	0.0123	0.0264**	0.0120	0.0313***	0.0112	0.0309***	0.0116	0.0091	0.0122	0.0070	0.0131	0.0041	0.0200
W. Temperature (°C)	0.0034	0.0038	0.0040	0.0038	0.0037	0.0038	0.0044	0.0038	0.0047	0.0038	0.0044	0.0038	0.0030	0.0038	0.0026	0.0037	0.0024	0.0037
W. Precipitation (mm)	1.2e-05	3e-05	1.4e-05	3e-05	1.1e-05	3e-05	1.5e-05	3e-05	1.3e-05	3e-05	1.2e-05	3e-05	4.3e-06	3e-05	3.7e-06	3e-05	5.3e-06	3e-05
W. Elevation (m.a.s.l.)	4.2e-06	1.8e-05	6.7e-06	1.8e-05	9e-06	1.9e-05	1.3e-05	1.9e-05	1.2e-05	1.8e-05	1e-05	1.8e-05	8.6e-06	1.9e-05	5.8e-06	1.9e-05	4.9e-06	1.9e-05
W. Private Conservation Area (Forest %)	-0.0252	0.2310	-0.0217	0.2306	-0.0401	0.2315	0.0245	0.2329	0.0609	0.2310	0.0956	0.2354	-0.0267	0.2329	-0.0475	0.2332	-0.0577	0.2327
W. Regional Conservation Area (Forest %)	-0.5921***	0.1537	-0.6089***	0.1542	-0.5806***	0.1551	-0.5841***	0.1542	-0.6042***	0.1534	-0.5883***	0.1532	-0.5543***	0.1541	-0.5523***	0.1546	-0.5559***	0.1553
W. Natural Protected Area (Forest %)	-0.0370	0.0934	-0.0485	0.0933	-0.0484	0.0938	-0.0446	0.0934	-0.0489	0.0927	-0.0463	0.0933	-0.0394	0.0945	-0.0447	0.0955	-0.0479	0.0987
W. Forest Concession (Forest %)	0.1013	0.0897	0.0991	0.0897	0.1022	0.0901	0.1258	0.0904	0.1677*	0.0912	0.1816*	0.0936	0.1457	0.0960	0.1162	0.0933	0.1093	0.0927
W. Andean Communities (Forest %)	0.0742	0.0574	0.0670	0.0572	0.0694	0.0575	0.0803	0.0576	0.0881	0.0572	0.0826	0.0575	0.0774	0.0581	0.0664	0.0578	0.0643	0.0581
W. Coffee (Agricultural Land %)	0.1204**	0.0558	0.1175**	0.0557	0.1131**	0.0561	0.1140**	0.0555	0.1151**	0.0552	0.1007*	0.0551	0.1034*	0.0556	0.1039*	0.0558	0.1041*	0.0559
W. Cocoa (Agricultural Land %)	0.2592**	0.1287	0.2553**	0.1285	0.2506*	0.1289	0.2251*	0.1271	0.1894	0.1265	0.1838	0.1271	0.2049	0.1278	0.2189*	0.1279	0.2183*	0.1281
W. Oil Palm (Agricultural Land %)	0.4457	0.2883	0.4919*	0.2854	0.4716	0.2868	0.4518	0.2861	0.4321	0.2839	0.4027	0.2869	0.4779*	0.2875	0.5163*	0.2878	0.5079*	0.2895
W. Coca (Agricultural Land %)	0.1014	0.2976	0.1409	0.2971	0.1486	0.2988	0.2515	0.3026	0.2578	0.2975	0.2702	0.3003	0.1289	0.2997	0.1117	0.2997	0.1165	0.2999
W. Population Density (per km^2)	5.8e-05	2e-04	-4.8e-05	2e-04	-5.1e-05	2e-04	-7.6e-05	2e-04	-6.9e-05	2e-04	-5e-05	2e-04	-7.4e-06	2e-04	-6.2e-06	2e-04	-3.6e-06	2e-04
W. Poverty Rate	-0.0581	0.0672	-0.0486	0.0669	-0.0521	0.0674	-0.0530	0.0674	-0.0414	0.0666	-0.0370	0.0669	-0.0287	0.0677	-0.0405	0.0674	-0.0399	0.0675
W. log(Min. Distance to Mine)	0.0203	0.0130	0.0201	0.0130	0.0223*	0.0130	0.0228*	0.0129	0.0204	0.0129	0.0207	0.0129	0.0222*	0.0131	0.0222*	0.0131	0.0228*	0.0130
Observations	289		289		289		289		289		289		289		289		289	
Log-Likelihood	369.87		370.24		368.70		369.83		372.86		371.21		367.84		366.98		366.85	
AIC	-661.73		-662.47		-659.39		-661.65		-667.72		-664.42		-657.69		-655.95		-655.69	
λ	-		-		-		-		-		-		-		-		-	

Note: The table reports estimated coefficients and standard errors from nine spatial durbin models divided by different deciles of the minimum distance to paved road. We use a queen contiguity spatial weights matrix. The dependent variable is the cumulative deforestation rate. All models include controls for socioeconomic, geographic, and climatic characteristics. Spatial lags of covariates are indicated by "W.". Standard errors are reported next to each coefficient. Significance levels are denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations, AIC, log-likelihood, and λ (where applicable) are reported at the bottom of the table.