



Spatial configuration of amazon deforestation: An analysis of market and land occupation spillovers in the San Martín region

Configuración espacial de la deforestación amazónica: Un análisis de desbordamiento ocupacional y de mercado en la región San Martín

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ABSTRACT

The boom in the cacao market is significantly altering the way land is utilized in our Amazon. Far from being the subject of rigorous analysis, current literature has overlooked this in many quantitative studies. Therefore, this study sought to analyze the influence of commercial variables associated with the cacao market on deforestation, focusing on the San Martín region, and to identify the existence of spillover effects. This was achieved by estimating a Spatial Durbin Model (SDM) using a Queen contiguity matrix, calculating the Global Moran's I, and contrasting its estimators with the traditional Ordinary Least Squares (OLS) method. It was concluded that there is a positive and significant spatial autocorrelation for forest loss, driven by externalities that expanded the agricultural frontier. Furthermore, it was determined that the most highly capitalized districts were the primary drivers of this expansion, and that it has now become a geographically interconnected phenomenon driven by economic incentives, demonstrating that local conservation policies proved ineffective by omitting spatial contagion.

Keywords: autocorrelation; cacao; land-use change; agricultural frontier; Durbin model

RESUMEN

El auge del mercado de cacao está modificando significativamente el modo en cómo aprovechamos los suelos de nuestra Amazonía. Lejos de ser objeto de análisis riguroso, la literatura actual lo ha pasado por alto en muchas investigaciones de índole cuantitativa. Por eso, este trabajo buscó analizar la influencia de variables comerciales asociadas al mercado del cacao sobre la deforestación, centrándose en la región San Martín, e identificar la existencia de efectos de desbordamiento o spillovers, lo que se logró estimando un modelo espacial de Durbin (SDM) con una matriz de contigüidad Reina, encontrando el índice de Moran global y contrastando sus estimadores con el método clásico de Mínimos Cuadrados Ordinarios (MCO). Se concluyó que existe una autocorrelación espacial positiva y significativa para la pérdida forestal, impulsada por externalidades que ampliaron la frontera agrícola. También se determinó que fueron los distritos más capitalizados quienes la impulsaron en mayor medida, y que ahora esta se ha convertido en un fenómeno geográficamente interconectado por incentivos económicos, lo que demostró que las políticas de conservación locales resultaron ineficaces al omitir el contagio espacial.

Palabras clave: autocorrelación; cacao; cambio de uso de suelo; frontera agrícola; modelo de Durbin



1. INTRODUCTION

Cocoa (*Theobroma cacao* L.) is one of the most important and indispensable raw materials for the global food industry (Borda et al., 2021; Huanca-Ccompe et al., 2026), mainly because of the high value of its fat-rich beans, which are used to produce cocoa butter and powder and are processed as part of the large-scale confectionery production chain (Kongor, 2024; Shilpa et al., 2026). However, this high demand is also posing a severe threat to the forest resources of the areas where cocoa is cultivated.

The Peruvian Amazon is undergoing a serious transformation in land-use patterns, showing that tree clearing is no longer an isolated phenomenon but rather part of an interconnected geographical dynamic (Urgilez-Clavijo et al., 2025). The San Martín region is among the areas most affected by this nationwide agricultural expansion, driven by growing domestic and international demand for cocoa. Although this demand has generated higher incomes for local family farming, it is also placing unprecedented pressure on major ecosystemss (González-González et al., 2021). La Rosa (2022) and Sims et al. (2025) agree that the agricultural sector is the main driver of deforestation at the national level.

From a traditional economic perspective, Ordinary Least Squares (OLS) is commonly used to determine which variables have the greatest influence on a given indicator. However, in the study of socio-environmental phenomena, this approach is insufficient because it assumes independence among all observed territorial units and ignores the spatial autocorrelation component of land-use change. This can lead to biased estimators and prevents an adequate understanding of how disturbances in one district can reshape the equilibrium of neighboring territories (Octaviani et al., 2023). For this reason, Hängli et al. (2023) argue that studies are needed to examine the relationships between subregional units and indirect effects on land use.

These patterns operate through market externalities. For example, if a district experiences a favorable price shock, the resulting economic incentive may cross its boundaries, generating a spillover effect or spatial spillover that expands the agricultural frontier at the provincial and regional levels (Baumann et al., 2022; Li et al., 2021).

This study aimed to test for the presence of spatial spillover effects and autocorrelation among the 77 districts of the San Martín region, demonstrate that deforestation is also driven by external market and production factors, and identify the actions that competent authorities should undertake to reduce forest cover loss in the Peruvian Amazon.

2. 2. MATERIALS AND METHODS

Study area

The study was conducted in the San Martín region and covered its entire territory, as this area records the highest cocoa production volumes in the country (Higuchi et al., 2022).

Research approach and design

The study adopted a quantitative approach, with an explanatory scope and a non-experimental longitudinal-spatial design, covering the period from 2016 to 2024.

Population and sample

The population consisted of the 77 districts that make up the San Martín region. A census-based sampling approach was used, including all district-level units in the analysis to avoid artificial selection bias and facilitate the accurate calculation of continuous geographic boundaries.

Operationalization of variables

The response variable was annual forest cover loss, measured in hectares. The independent variables included farm-gate cocoa prices and cocoa (*Theobroma cacao* L.) production volume. The Unmet Basic Needs Index (NBI) at the district level was also incorporated as a control variable and as a proxy for the socioeconomic conditions of the territories. All variables are detailed in Table 1.

Table 1. Performance of regenerative tourism indicators

Variable	Type	Operational description	Unit of measurement	Source	Expected sign
Deforestation (DEF)	Dependent	Annual forest cover loss	Hectares (ha)	Minam	N/A
Cocoa price (PRC)	Independent	Average annual farm-gate price	Soles per kilogram (S./kg)	Midagri	(+)
Cocoa production (PROD)	Independent	Annual physical production volume	Metric tons (t)	Midagri	(+)
Unmet Basic Needs (NBI)	Control	Proportion of the population with at least one basic structural deprivation	Percentage (%)	INEI	(-)
Population density (DEN)	Control	Level of demographic concentration	Inhabitants per square kilometer (inhabitants /km ²)	INEI	(+)

Data collection techniques and instruments

The data were obtained through documentary sources from statistical databases. Forest loss indicators were obtained from the Geobosques portal of the Ministry of the Environment (MINAM); economic information was obtained from the SIEA platform of the Ministry of Agrarian Development and Irrigation (MIDAGRI); and socioeconomic and geographic information was obtained from the National Institute of Statistics and Informatics (INEI). All of these are publicly accessible government sources; therefore, no primary data collection instruments were used.

Data analysis techniques

Econometric techniques designed to isolate and measure geographic spillover effects were employed. In the first stage, the presence of spatial autocorrelation was evaluated using the Global Moran's I. Territorial interactions were modeled through a row-standardized Queen contiguity spatial weights matrix (W), which identified as neighbors those districts sharing at least one vertex or edge along their administrative boundaries (Isnan et al., 2025). To isolate externalities, estimation was performed using the Spatial Durbin Model (SDM). To justify this decision, Moran's I was calculated and a scatterplot was generated for district-level deforestation, as shown in Figure 1.

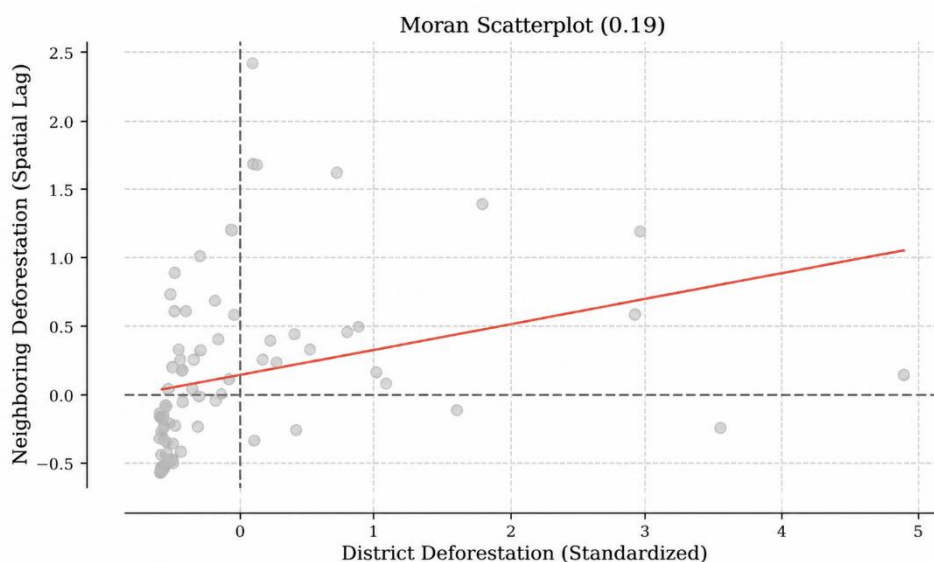


Figure 1. Moran scatterplot for district-level deforestation in San Martín

The scatterplot reveals a positive Global Moran's I of 0.19, a fitted line with a positive slope, and a high concentration of observations in quadrants I and III, confirming the presence of positive spatial autocorrelation. This demonstrates the need to employ a different method that incorporates these interactions and provides a more realistic representation of the phenomenon. To corroborate this mathematically, spatial dependence diagnostic tests were performed on the residuals of the conventional OLS model. The results are presented in Tables 2 and 3.

Table 2. Spatial diagnostic tests using Lagrange multipliers

Sarerr Test	df	Value	Prob
Lagrange multiplier (lag)	1	0.152	0.6965
Robust LM (lag)	1	3.974	0.0462
Lagrange multiplier (error)	1	0.054	0.8159
Robust LM (error)	1	3.877	0.0490
Lagrange multiplier (SARMA)	2	4.029	0.1334

Table 3. Tests for inclusion of WX spatial lags

Spatial Durbin Test	df	Value	Prob
LM test for WX	4	12.492	0.0140
Robust LM WX test	4	12.394	0.0147
Lagrange multiplier (lag)	1	0.152	0.6965
Robust LM lag - SDM	1	0.054	0.8159
Join test for SDM	5	12.546	0.0280

The robust versions of the Lagrange Multiplier tests confirmed the presence of spatial autocorrelation at a 5% significance level. Likewise, the tests focused on the SDM showed that the included spatial lags were highly significant in both the standard test ($p = 0.0140$) and its robust version ($p = 0.0147$). These results reject the null hypothesis of spatial independence and demonstrate that spillover effects on forest loss in San Martín arise from dynamic markets and the socioeconomic characteristics of neighboring areas.

All data processing, mapping, and estimations were carried out entirely in the Python-based Anaconda 3 environment using specialized libraries such as GeoPandas and PySAL.

3. RESULTS AND DISCUSSION

The following section presents the results obtained from the study, incorporating both descriptive and inferential statistical analyses, which are subsequently contrasted with previous findings.

3.1 Exploratory spatial data analysis

After compiling the statistical and geospatial data, the degree of impact of tree loss was compared across districts from 2016 to 2024. The evolution of this indicator was represented through an infrared heat map, as shown in Figure 2.

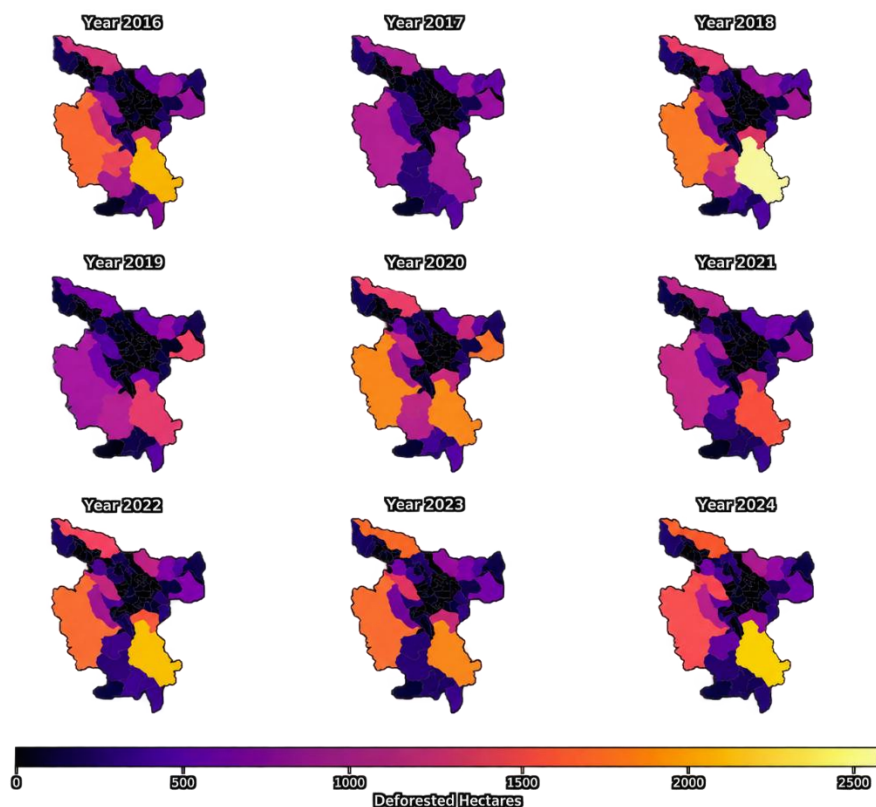


Figure 2. Heat-map evolution of district-level deforestation in San Martín (2016–2024). Prepared by the author based on data from the MINAM Geobosques platform

As observed, forest loss experienced a decline in intensity around 2018 and was concentrated in the southeastern cluster. In subsequent years, the impact of the spillover effect proposed by the Durbin model became evident, expanding forest loss toward neighboring jurisdictions.

These results are consistent with Tafur et al. (2022), who reported a notable decline in the deforestation rate in San Martín between 2018 and 2019, in contrast to other regions such as Pasco and Junín, which experienced increases ranging from 3.62% to 9.41%. Móstiga et al. (2025) identify agriculture, the transportation network, the rural population, and fire as the main drivers, with variations across regions.

It is also necessary to examine the most recent cross-sectional scenario in order to assess the current severity of the situation. Figure 3 presents the intensity levels of forest loss in 2024 and illustrates the static spatial distribution of the phenomenon.

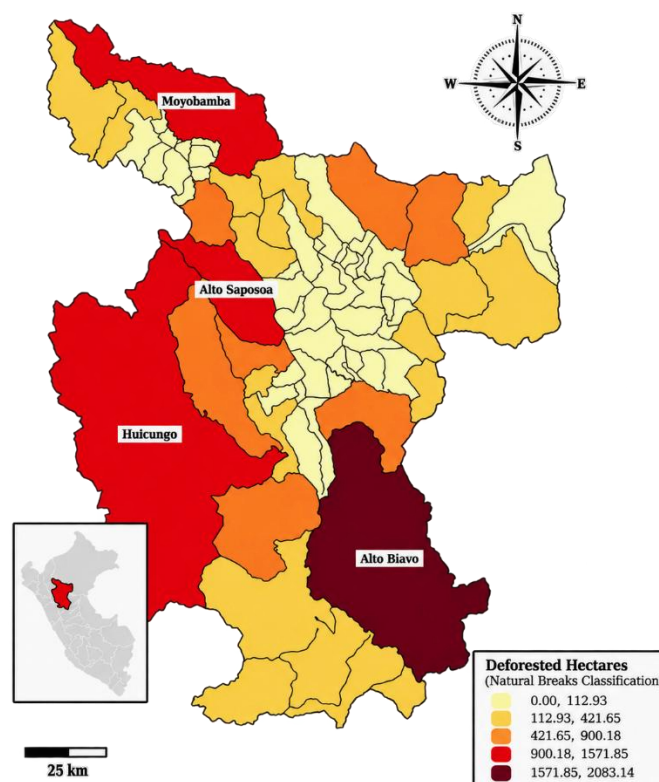


Figure 3. Impact of the cocoa boom on Amazonian deforestation at the district level in San Martín (2024). Prepared by the author based on data from the MINAM Geobosques platform

As shown in Figure 3, forest loss has not occurred randomly across the region. Rather, the most heavily affected districts have largely been surrounded by jurisdictions exhibiting similar behavior, confirming strong evidence of positive spatial autocorrelation and invalidating the independence assumption underlying the conventional OLS estimator.

These interconnections were identified through the spatial weights matrix. Table 4 describes the topology of San Martín based on the information provided by this matrix.

Table 4. Descriptive statistics of the spatial weights matrix (W)

Item	Value
Total number of districts (n)	77
Percentage of nonzero	6.95%
Average number of neighbors	5.35
Minimum number of neighbors	2
Maximum number of neighbors	9

It is important to note that the minimum degree of connectivity is two neighbors and the maximum is nine, ruling out the existence of districts operating as isolated spatial “islands.” In addition, the network density is 6.95%, making the matrix sufficiently robust to capture spillover effects and confirming that disturbances in the cocoa market in one district can feasibly be transmitted sequentially to surrounding areas.

The robustness of these results is consistent with Griffith and Paelinck (2018), who state that Queen contiguity makes it possible to represent observations connected through spatial neighborhood relationships, which is particularly appropriate when analyzing collective units composed of dynamic rational agents.

Figure 4 graphically presents the matrix, with the centroids of each district connected through edges representing channels of economic pressure and agricultural spillover.

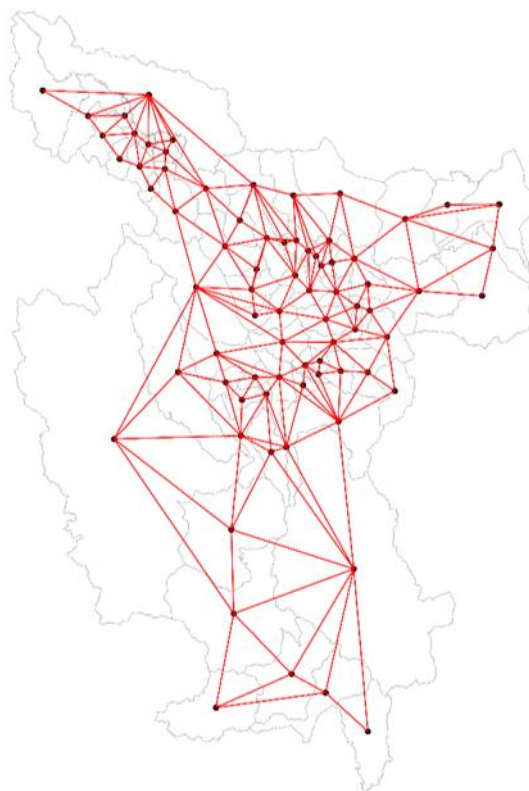


Figure 4. Spatial connectivity network (W matrix) of San Martín

The network configuration demonstrates that neighboring districts do not operate in isolation. This network therefore provides the matrix basis for estimating the Spatial Durbin Model developed in the following section.

The usefulness of this matrix is also supported by Suryowati et al. (2018), who argue that it allows the statistical neighborhood structure to be represented and reflects the spatial influence exerted among observations. Akolo (2022) further notes that this matrix-based method captures connections more effectively by considering observations that share either an edge or a vertex as neighbors, unlike rook contiguity, which relies only on shared edges.

3.2 Estimation of the Spatial Durbin Model

The statistical tests yielded metrics that further support the existence of strong correlations among the variables after introducing the W matrix into the district-level forest loss model.

Table 5. Preliminary results of the Spatial Durbin Model

Independent variable	Coefficient	Standard error	Z.Statistic
Local cocoa price (PRC)	-64.492**	28.848	-2.235
Local production (PROD)	-0.007	0.034	-0.211
Local population density	0.198	0.266	0.746
Local Unmet Basic Needs (NBI)	-5.585**	2.854	-1.956
Neighboring cocoa price (W-PRC)	108.769***	37.991	2.863

Neighboring production (W-PROD)	0.089*	0.045	1.952
Neighboring population density (W-DEN)	1.096	0.856	1.280
Neighboring Unmet Basic Needs (W-NBI)	-13.298**	6.408	-2.075
ρ (deforestation spatial lag)	0.035	0.173	0.203
Constant	-119.963	572.174	-0.209
Observations	77		
Pseudo R^2	0.317		

Note. The response variable is the local deforestation rate in hectares. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The cocoa price in neighboring districts (W-PRC) showed the largest impact, with an estimated coefficient of 108.769 and a high level of statistical significance. In contrast, the economic pressure associated with local farm-gate prices (PRC) exerted an inverse effect and was less significant. Although this result may appear paradoxical, it suggests that an increase in cocoa prices within the district under analysis does not necessarily generate sufficient incentives for farmers to further expand the agricultural frontier through additional tree clearing within that same territory.

The poverty level in neighboring districts (W-NBI) and local Unmet Basic Needs (NBI) also exerted inverse effects, although to a lesser extent. This can be explained by assuming the rational behavior of economic agents participating in this market. If socioeconomic conditions in neighboring districts are less precarious, there are stronger incentives within the surrounding area to remain competitive and rely more heavily on export-oriented agriculture, leading to additional tree clearing to expand productive capacity (Shao et al., 2024).

These results are consistent with Cruz et al. (2023) and Chen et al. (2025), who conclude that factors such as GDP, urbanization, agriculture, the timber industry, mining, infrastructure, climate change, poverty, and migration constitute some of the strongest drivers and tend to operate in a coordinated manner. Ravikumar and Lock (2025) further argue that Peruvian policies have not contributed as effectively as expected to reducing national deforestation rates because they do not directly address these underlying drivers. Likewise, Aguirre et al. (2021) note that forest protection policies become less effective when undermined by road infrastructure and that expanding protected areas, rather than improving existing measures, may worsen the situation.

3.3 Decomposition of spatial effects

Interpreting the preceding estimators in isolation is insufficient because endogenous feedback effects exist among districts. Therefore, following the methodology of LeSage and Pace, the effects must be decomposed into indirect and total effects. The final results are presented in Table 6.

Table 6. Decomposition of spatial impacts

Variable	Direct	Indirect (Spillover)	Total
Local cocoa price (PRC)	-63.7753	109.6775	45.9022
Local production (PROD)	-0.0068	0.0921	0.0854
Local population density (DEN)	0.2062	1.1370	1.3431
Local Unmet Basic Needs (NBI)	-5.6760	-13.9009	-19.5768

After introducing the LeSage and Pace multipliers, the results show a direct effect of -63.77 for cocoa market dynamics (PRC), suggesting that higher local prices in a given district are associated with lower agricultural expansion within its own boundaries, possibly because of land saturation or labor shortages. In contrast, the indirect effect dominates, with a coefficient of 109.67, demonstrating that positive market shocks, rather than remaining locally contained, export substantial environmental pressure and expand the agricultural frontier into neighboring territories, a consequence previously reported by Paredes and Pastor (2023).

This is consistent with the indirect effect of -13.90 for Unmet Basic Needs (NBI), which indicates that when poverty declines or greater capital accumulation occurs in neighboring districts, forest loss in the local district tends to increase. This suggests that wealthier jurisdictions that are more integrated into international markets are those driving tree clearing in more vulnerable neighboring territories.

The findings are consistent with Ledesma (2025), who concludes that forest loss is negatively associated with monetary poverty because poorer and more remote households have less capital available to expand agricultural production. Boillat et al. (2022) also support the existence of an inverse relationship between poverty and deforestation indicators in their study conducted in Bolivia. Ngouhouo-Poufoun et al. (2024) further report that many households in the Congo adopted the resource-extraction practices of neighboring communities while also being influenced by the dynamism of the cocoa market and open-access systems.

CONCLUSIONS

The study concluded that the rate of forest loss in the Peruvian Amazon does not operate in isolation, but rather as an interconnected geographic system. Validation of the Global Moran's I and the Lagrange Multiplier tests demonstrated the existence of strong positive spatial autocorrelation, which is ignored by the conventional OLS approach and therefore leads to biased estimators. The Spatial Durbin Model showed that the main driver of deforestation in the San Martín region is the spillover effect of the cocoa market, whereby districts experiencing favorable price shocks do not necessarily clear all available land within their own boundaries, but instead exert pressure on neighboring districts to do so. In addition, districts with low levels of Unmet Basic Needs (NBI) were found to act as drivers of agricultural expansion, directing it toward more vulnerable surrounding areas. These externalities reflect the ineffectiveness of pro-environmental policies implemented by successive governments, as such policies are focused on individual sectors and lead agricultural capital to be reallocated toward bordering territories. This makes it imperative to urgently redirect these measures toward a macroregional approach capable of internalizing the spatial contagion generated by the export-oriented economy.

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CONFLICT OF INTEREST

The author declares that there are no conflicts of interest related to the subject matter of this study.

AUTHOR CONTRIBUTIONS

1. Conceptualization: Renzo Aarón Rojas Chipana.

2. Data curation: Renzo Aarón Rojas Chipana.
3. Formal analysis: Renzo Aarón Rojas Chipana.
4. Funding acquisition: Renzo Aarón Rojas Chipana.
5. Investigation: Renzo Aarón Rojas Chipana.
6. Methodology: Renzo Aarón Rojas Chipana.
7. Project administration: Renzo Aarón Rojas Chipana.
8. Resources: Renzo Aarón Rojas Chipana.
9. Software: Renzo Aarón Rojas Chipana.
10. Supervision: Renzo Aarón Rojas Chipana.
11. Validation: Renzo Aarón Rojas Chipana.
12. Visualization: Renzo Aarón Rojas Chipana.
13. Writing – original draft: Renzo Aarón Rojas Chipana.
14. Writing – review and editing: Renzo Aarón Rojas Chipana.

DATA AVAILABILITY

The study was conducted using data from publicly accessible government repositories. Information on forest loss is available through the Geobosques portal of the Ministry of the Environment (MINAM); agricultural statistics can be downloaded from the SIEA platform of the Ministry of Agrarian Development and Irrigation (MIDAGRI); and socioeconomic information is available in the census database catalog of the National Institute of Statistics and Informatics (INEI). The processed and consolidated data are available from the corresponding author upon reasonable request.

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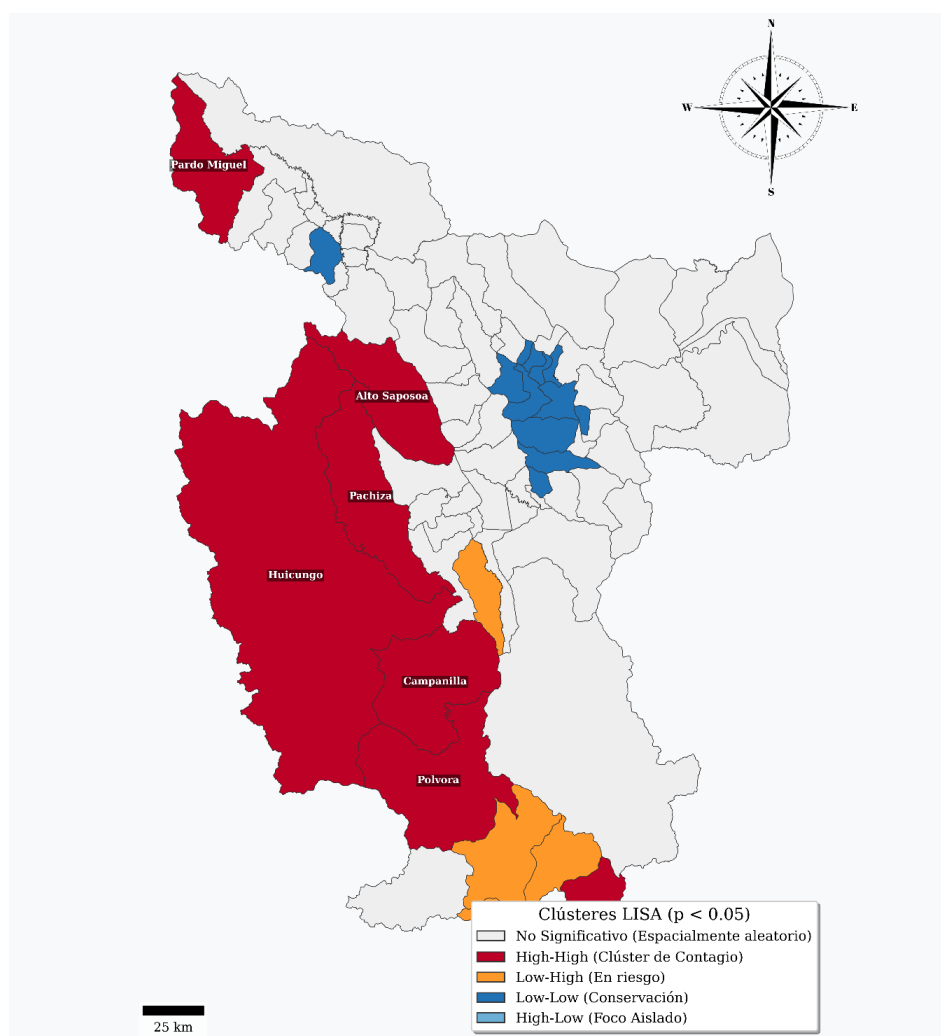
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Appendices

Appendix 1. Cluster map (LISA) of district-level deforestation in San Martín



Appendix 2. Spatial distribution of the residuals from the Spatial Durbin Model