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Environmental Indicators as Proxies for Corruption: An Econometric Approach to Economic Growth in Mexico

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Abstract

This study evaluates the relationship between corruption and environmental indicators, specifically tree density and the Normalized Difference Vegetation Index (NDVI), in Mexico's states. A Ridge Cross-Validation (RidgeCV) regression model was applied to mitigate multicollinearity and correct endogeneity. The dataset includes economic and environmental data from 32 states in Mexico. Results show that tree density is negatively correlated with economic activity, while NDVI has a marginally positive impact. These findings suggest that deforestation may be driven by economic and governance factors, highlighting the role of environmental degradation as a corruption proxy. This work contributes to institutional economics by providing empirical evidence for sustainable public policy design and enhancing corruption measurement through environmental indicators.

Keywords: Corruption, Economic growth, Forest density, Vegetation index, Sustainable development

1. Introduction

Corruption is a structural issue that weakens governance, distorts economic growth, and erodes public trust. Its negative impact on economic performance has been widely studied, yet challenges remain in establishing causality and generalizing findings across different institutional contexts. Mauro (1995) demonstrated that corruption discourages investment by increasing uncertainty and transaction costs, leading to slower capital formation and reduced economic expansion. Similarly, Tanzi and Davoodi (2000) highlighted how corruption inflates public spending on inefficient infrastructure projects, diverting resources from essential services like healthcare and education. These inefficiencies are particularly detrimental in developing economies, where institutional weaknesses exacerbate economic disparities (Gupta et al., 2000).

While corruption is generally viewed as an obstacle to economic development, some scholars propose an alternative perspective, commonly referred to as the "grease the wheels" hypothesis (Huntington, 1968; Leff, 1964). According to this argument, in highly regulated environments, corruption may facilitate economic transactions by bypassing bureaucratic inefficiencies. However, this view remains controversial, as more recent empirical studies suggest that any short-term efficiency gains are outweighed by the long-term institutional deterioration, reduced competitiveness, and deepening inequality caused by corruption (Dong & Torgler, 2020).

A growing body of research has begun to explore the relationship between corruption and environmental degradation, particularly deforestation. Weak institutional frameworks often allow illicit activities such as illegal logging, unauthorized land use, and regulatory circumvention to flourish, leading to environmental degradation as a direct consequence of corruption. Studies have linked governance failures to accelerated deforestation rates, with local officials' incentives driving land exploitation in contexts of weak law enforcement (Burgess et al., 2012). Dell (2010) found that regions with poor governance tend to experience more severe environmental damage, highlighting the role of corruption in shaping ecological outcomes.

Mexico presents a particularly relevant case for examining these relationships. The country ranks consistently low on international corruption indices, such as Transparency International's Corruption Perceptions Index and the World Bank's Governance Indicators. Additionally, Mexico faces severe deforestation, with illegal logging contributing significantly to forest loss (FAO, 2020). These environmental issues are often tied to governance failures, as local authorities exploit regulatory loopholes for personal gain. Political clientelism and bribery have been linked to increased deforestation rates, particularly in states with high biodiversity and weak institutional oversight (Brondízio et al., 2021). Given these dynamics, environmental indicators such as tree density and the Normalized Difference Vegetation Index (NDVI) offer a promising alternative to traditional corruption measures, providing a more objective, spatially detailed approach to assessing governance failures.

This study investigates the relationship between corruption and economic growth in Mexico, employing environmental proxies—specifically, NDVI and tree density—as instrumental variables to infer corruption levels. Unlike traditional studies that rely on perception-based indices, this approach utilizes satellite-derived data to capture the indirect effects of corruption on economic performance. By incorporating these proxies, the study addresses the measurement limitations commonly found in corruption research while offering new insights into the broader economic implications of governance failures.

A key methodological challenge in corruption-growth studies is **endogeneity**, as corruption and economic activity influence each other simultaneously. To overcome this issue, this study applies a **Ridge Cross-Validation (RidgeCV) regression model**, which mitigates multicollinearity among environmental indicators and corruption proxies while ensuring robust coefficient estimates. The model is calibrated using economic and environmental data from Mexico's 32 states, allowing for a comprehensive spatial analysis. This methodological approach enhances the reliability of the estimates and strengthens the validity of environmental indicators as proxies for corruption.

The results reveal a complex interaction between corruption, environmental degradation, and economic growth. The findings indicate that tree density is **negatively correlated** with economic activity, suggesting that deforestation—often linked to governance failures—may temporarily boost economic performance in some regions. This supports the idea that corruption-driven resource exploitation can produce short-term economic gains at the expense of long-term sustainability. In contrast, NDVI exhibits a **marginally positive effect** on economic growth, implying that better environmental conditions may contribute to economic resilience. These results reinforce the need to integrate environmental governance into economic policymaking, as corruption-related deforestation poses long-term risks to sustainable development.

By demonstrating the viability of environmental indicators as proxies for corruption, this study contributes to institutional economics and policy research. The use of satellite-based data offers an innovative alternative to subjective corruption indices, improving the empirical assessment of governance quality. Additionally, the findings provide valuable insights for policymakers aiming to design sustainable development strategies that balance economic growth with environmental conservation. Understanding the intricate linkages between corruption, governance, and environmental degradation can aid in formulating more effective anti-corruption strategies while promoting economic resilience.

2. Materials and methods

2.1 Methodological frameworks

In studying the relationship between corruption and economic growth, addressing endogeneity is crucial due to the simultaneous interaction between these variables, which biases ordinary least squares (OLS) estimators. To mitigate this, instrumental variables (IVs) are employed to isolate exogenous variations in corruption that are uncorrelated with the error term in the growth equation.

Vegetation indices are used as IVs under two conditions: **exogeneity** and **relevance**. Environmental degradation, such as deforestation, correlates with corruption in contexts where governance is weak. For instance, Dell (2010) links historical exploitation to environmental damage in poorly governed areas, while Burgess et al. (2012) show how corruption drives deforestation through illegal logging. This study uses vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and tree density, as IVs to estimate corruption in Mexican states, as supported by prior literature.

For validity, these indices must reflect external environmental factors without being directly influenced by economic growth. While economic activity may affect land cover, NDVI and tree density isolate the exogenous effects of governance quality and environmental law enforcement. Actions such as illegal logging, often linked to corruption, alter vegetation indices independently of broader economic processes. Studies by Olken (2007) and Dell (2010) confirm the exogeneity of these indices in econometric models by associating them with governance and policy enforcement rather than direct economic performance.

High-resolution satellite images, analyzed using Python's OpenCV library, allow for detailed local analyses, reducing subjectivity and bias associated with traditional corruption metrics.

2.2 Image Processing Methodology

This study utilized satellite imagery to analyze tree density and NDVI as proxies for corruption in Mexican states. High-resolution images were obtained from the **SAS.Planet** platform, utilizing Google Satellite and Bing Satellite services to evaluate forest cover. Image processing was carried out using the OpenCV library in Python.

- Data Collection: Up to 500 images per state were collected at a zoom resolution of 14, ensuring comprehensive territorial coverage.

- Timeframe: Images spanned two reference points—Bing Satellite images from 2021 and Google Satellite images from 2023—providing a robust basis for comparative analysis, despite a 5–15% margin of error introduced by cloud cover.

- Image Processing Steps: Images were converted to grayscale, smoothed, and processed using the Canny algorithm for edge detection, enhancing tree contour visibility.

2.3 Calculation of Tree Density

The calculation of tree density involved summing the detected tree contours in each image, providing the total number of trees in each study area. The study area in square meters was quantified using the cv2.contourArea() function. Tree density was determined by dividing the total number of detected trees by the total study area for each state using the formula:

$$\text{Tree Density per State} = \frac{\textit{Total Detected Trees}}{\textit{Total study area}}$$

A detailed comparative analysis of tree density by state between 2021 and 2023 was subsequently performed, showing that the national density per square meter decreased by 10% over these two years. The situation was not uniform across states; some, like Baja California, Durango, Chihuahua, and Quintana Roo, managed to increase their density, although only Baja California showed a significant increase exceeding 5%.

Table 1. Comparison of Tree Density in 2021 and 2023 by State

State	Density 2021	Density 2023	Var (%)
Aguascalientes	8.2457	6.8562	-16.9%
Baja California	5.0251	5.5610	10.7%
Baja California Sur	4.0620	3.0537	-24.8%
Campeche	3.3624	3.1001	-7.8%
Coahuila de Zaragoza	3.1977	2.4336	-23.9%
Colima	4.4537	2.8312	-36.4%
Chiapas	2.6991	2.6865	-0.5%
Chihuahua	6.3107	6.5838	4.3%
Mexico City	8.4206	7.8668	-6.6%
Durango	6.6240	6.9225	4.5%
Guanajuato	5.5866	4.8606	-13.0%
Guerrero	3.9341	3.9226	-0.3%
Hidalgo	6.5421	6.4376	-1.6%
Jalisco	5.5234	4.2844	-22.4%
Mexico State	6.3580	6.2963	-1.0%
Michoacán	4.5176	3.2451	-28.2%
Morelos	5.4137	3.9659	-26.7%
Nayarit	5.2565	5.2229	-0.6%
Nuevo León	5.5121	5.0102	-9.1%
Oaxaca	4.1033	4.0352	-1.7%
Puebla	6.7416	6.0398	-10.4%
Querétaro	5.7349	5.0604	-11.8%
Quintana Roo	1.9971	2.0503	2.7%
San Luis Potosí	4.2432	3.8308	-9.7%
Sinaloa	3.4461	3.2900	-4.5%
Sonora	4.7469	2.6100	-45.0%
Tabasco	2.0385	1.6723	-18.0%
Tamaulipas	2.7919	2.1844	-21.8%
Tlaxcala	7.0515	5.9594	-15.5%
Veracruz	2.4453	1.9268	-21.2%
Yucatán	2.0190	1.0424	-48.4%
Zacatecas	5.8656	5.8980	0.6%
Country	4.5896	4.1301	-10.0%

Source: Authors' own work with data from satellite images of Google and Bing.

The results in Table 1 show a general decrease in national tree density by 10% between 2021 and 2023. However, some states, such as Baja California, Durango, Chihuahua, and Quintana Roo, managed to increase their tree density, with Baja California standing out with an increase of 10.7%. On the other hand, Yucatán experienced a significant decrease of 48.4%, which could be related to specific economic or environmental activities in the region. These variations highlight the importance of considering regional and temporal factors when analyzing the relationship between tree density and economic growth.

These variations highlight the importance of considering regional and temporal factors when analyzing the relationship between tree density and economic growth.

2.4 Calculation of NDVI

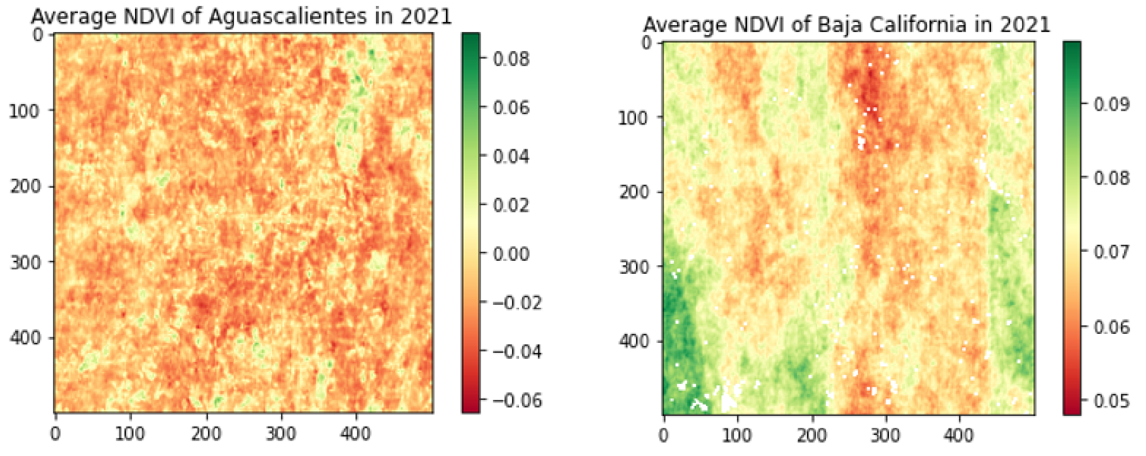
The same satellite images used for the tree density analysis were employed to calculate NDVI for 2021 and 2023, following these steps:

- Image Acquisition: Images were obtained from SAS.Planet, accessing Google and Bing Satellite services.
- Image Processing:
  - » Resized to 500x500 pixels for consistency.
  - » The red (RED) and near-infrared (NIR) bands were extracted from each image. The red band corresponds to channel 2 and the NIR band to channel 1 of the RGB images.
- NDVI Calculation: Using the standard formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Where NIR is the near-infrared band and Red is the red band of the image. **Figure 1** shows examples of NDVI calculations for Aguascalientes and Baja California.

Figure 1. Examples of Average NDVI for Aguascalientes and Baja California



Source: Authors' own work with data from satellite images from Google and Bing.

NDVI and TreeDensity meet the criteria of exogeneity and relevance as instrumental variables for corruption. TreeDensity reflects deforestation and forest degradation, often linked to illegal logging in regions with weak enforcement of environmental laws (Burgess et al., 2012). Similarly, NDVI signals vegetation health and land use changes tied to corrupt activities, such as illegal land permits or regulatory evasion (Dell, 2010; Olken, 2007). Olken (2007) demonstrated that satellite data in Indonesia revealed higher corruption in areas with severe environmental degradation. These indicators help isolate the exogenous component of corruption, ensuring robust analyses of its impact on economic growth.

In Mexico, the General Law of Sustainable Forest Development (LGDFS) regulates logging and deforestation under SEMARNAT and PROFEPA (SEMARNAT, 2020). Enforcement varies significantly across states, with weaker institutional capacity increasing vulnerability to illegal logging and corrupt practices (World Bank, 2022). Where oversight is limited, bribery-driven deforestation exacerbates environmental damage (Transparency International, 2023). This study assumes that weaker law enforcement fosters corruption-fueled deforestation, justifying the use of TreeDensity and NDVI to differentiate between legal and corrupt activities.

2.5 Econometric Model

This study applies to the RidgeCV econometric model to address multicollinearity and enhance estimation accuracy. This approach is particularly effective in cases where explanatory variables, such as Tree Density and NDVI, exhibit high correlations. To optimize the model, cross-validation was employed, enabling the determination of the optimal regularization parameter (alpha) by minimizing the mean squared error (MSE).

Model Variables

The variables used in the RidgeCV model are as follows:

- ITAEE: The Quarterly Indicator of State Economic Activity, calculated by INEGI, serves as the dependent variable. Expressed as an index based on 2018=100, ITAEE captures short-term economic performance at the state level, aggregating data from agriculture, industry, and services. This index enables comparison of economic activity across states and provides insights into regional economic dynamics in Mexico.

- TreeDensity: These variable measures forest cover and reflects environmental degradation often associated with corruption. Studies like Burgess et al. (2012) demonstrate that corruption accelerates deforestation, negatively impacting economic development. By capturing variations in forest density, this indicator links environmental corruption to regional economic disparities.

- log_UCORR: Derived from the National Survey of Quality and Government Impact (ENCIG) by INEGI, this variable represents the logarithmic transformation of the percentage of users reporting corruption. The log transformation normalizes the data, reducing skewness and capturing the non-linear relationship between corruption and economic growth. UCORR encompasses various corruption-related crimes, such as bribery and embezzlement, reflecting both public perception and direct experiences with corruption across Mexico's states. This broad coverage makes it a robust proxy for analyzing corruption's impact on economic performance.

- NDVI: The Normalized Difference Vegetation Index, obtained from satellite imagery, measures vegetation health and density. It captures the indirect effects of environmental quality on economic growth, linking vegetation conditions to agricultural productivity and broader economic outcomes. Pettorelli et al. (2005) validate NDVI as a reliable ecological indicator, making it essential for understanding how environmental factors influence economic systems.

The formulation of the Ridge regression model is as follows:

$$y = X\beta + \epsilon$$

Where:

- y is the vector of the dependent variable (ITAEE).

- X is the matrix of independent variables (Tree Density, log_UCORR, NDVI)

- β are the coefficients to be estimated.

- ϵ is the error term.

In addition to its ability to regulate the magnitude of coefficients, RidgeCV is based on a cost function that not only minimizes the mean squared error but also penalizes large coefficients to reduce variance and prevent overfitting, as shown in the following equation.

$$Cost = \sum_{i-1}^{n}(y_i - X_i\beta)^2 + \alpha\sum_{j-1}^{p}\beta_j^2$$

Where:

- α is the regularization parameter that controls the penalty applied to the coefficients.
- $\sum_{i-1}^{n}(y_i - X_i\beta)^2$ is the mean squared error term.
- $\alpha \sum_{j-1}^{p} \beta_j^2$ is the regularization term that penalizes large coefficients to reduce variance.

This approach ensures that the estimates obtained are robust and less sensitive to the correlation between variables, allowing for a better balance between model fit and predictive capacity. The parameter α was adjusted to 3.56 through cross-validation, optimizing the model to minimize the mean squared error (MSE).

Initially, socioeconomic indicators like Moderate Poverty, Extreme Poverty, and population density were considered as control variables due to their potential impact on ITAEE. However, their inclusion introduced multicollinearity with environmental variables (TreeDensity and log_UCORR) and did not significantly improve the model's fit. To maintain parsimony and robustness, these variables were excluded, focusing instead on environmental and corruption indicators, which proved more relevant for explaining variations in economic growth across Mexico's states.

The RidgeCV model effectively mitigated multicollinearity between TreeDensity and NDVI through regularization, ensuring robust estimates for both indicators without inflating their variance.

The validity of NDVI and TreeDensity as instrumental variables is supported by their correlation with governance quality and their independence from direct economic drivers (Olken, 2007; Burgess et al., 2012). These metrics capture dimensions of corruption tied to environmental malpractices, such as illegal deforestation and unregulated land use. By leveraging high-resolution satellite data, this approach ensures robust inference and minimizes biases associated with traditional corruption metrics.

2.6 Robustness and Diagnostic Tests

Several diagnostic tests were performed to ensure the robustness of the model:

1. **Multicollinearity**: The Variance Inflation Factor (VIF) confirmed that the variables did not exhibit excessive multicollinearity.
2. **Heteroscedasticity**: The Breusch-Pagan test indicated no significant evidence of heteroscedasticity (LM Statistic: 4.63, p-value: 0.20).
3. **Autocorrelation**: The Durbin-Watson statistic (1.54) suggested slight positive autocorrelation, within acceptable limits.
4. **Cross-Validation**: A 5-fold cross-validation showed consistent model performance across samples, with MSE values of 71.97 and 46.25 for the first and second periods, respectively.
5. **Sensitivity Analysis**: Testing different α values confirmed that 35.56 minimized MSE, aligning with the model's focus on balancing fit and regularization.

2.7 Alternative Models

To ensure the robustness of the results and validate the choice of the RidgeCV model, various alternative econometric models were evaluated, including LASSO and Elastic Net. The comparison of these models was carried out using fit criteria such as the mean squared error (MSE) and the coefficient of determination (R^2). The comparative results are detailed below:

RidgeCV: MSE of 149.28; R^2 = 0.0242; Alpha = 35.56

LASSO: MSE of 156.38; R^2 = -0.0223; Alpha = 100.0

Elastic Net: MSE of 156.38; R^2 = -0.0223; Alpha = 100.0

The results show that the RidgeCV model offered the best balance between fit and regularization, presenting the lowest mean squared error and a positive coefficient of determination (R^2). Both LASSO and Elastic Net resulted in higher MSEs and negative R^2 values, indicating that these models did not capture the relationship between the variables effectively. Additionally, LASSO and Elastic Net reduced the coefficients of key variables such as TreeDensity, log_UCORR, and NDVI to zero, further demonstrating their limitations in this context.

In contrast, RidgeCV maintained significant coefficients for TreeDensity (-0.4694), log_UCORR (0.8074), and NDVI (0.0165), showing its ability to handle multicollinearity without eliminating important variables. This comparative analysis reinforces the choice of the RidgeCV model for the study, highlighting its capacity to manage multicollinearity and provide more accurate and robust estimates in the context of economic growth and environmental factors across the states of Mexico.

3. Results and discussion

The RidgeCV model was used to predict the effects of corruption on state-level economic growth. The following results were obtained from the final model.

Table 2. RidgeCV Model Results

Metric	Value
Average RidgeCV MSE	149.28
Optimal Alpha	35.56
RidgeCV Model Coefficients	
Tree Density	-0.469418
log_UCORR	0.807358
NDVI	0.016450

Source: Authors' own work with model results in Jupyter Notebook

The average cross-validation MSE for the RidgeCV model was149.28, showing that the model behaves consistently across different samples. The Breusch-Pagan test showed no significant evidence of heteroscedasticity, and the Durbin-Watson test indicated slight positive autocorrelation, but within acceptable limits.

3.1. Interpretation of Results

The RidgeCV model demonstrated a significant improvement in prediction accuracy compared to alternative models, offering valuable insights into the relationship between corruption, environmental factors, and economic growth. Cross-validation identified an optimal alpha of 35.56, minimizing the mean squared error and effectively managing multicollinearity.

Tree Density: The negative coefficient for TreeDensity (-0.469418) highlights that higher forest cover correlates with decreased ITAEE, reflecting the economic disparity between rural and urban regions. Rural areas with dense forests often depend on agriculture and conservation activities, which generate lower economic output compared to industrialized regions. This result also suggests that deforestation driven by corrupt practices may temporarily boost economic activity in resource extraction sectors, ultimately undermining long-term sustainability.

log_UCORR: The positive coefficient for log_UCORR (0.807358) suggests that in certain contexts, corruption may "grease the wheels" of economic activity by circumventing inefficient regulations. While this challenges the conventional view of corruption as purely harmful, it highlights its dual role in regions with weak institutions. Corruption can facilitate short-term transactions but ultimately hinders equitable and sustainable growth in the long run.

NDVI: NDVI's small positive coefficient (0.016450) links vegetation health with increased ITAEE, indicating that environmental quality indirectly supports economic activity through improved agricultural productivity and ecological stability. Although modest, this finding underscores the importance of environmental health in fostering economic resilience.

The results validate the use of TreeDensity as a proxy for corruption, revealing its indirect impact on state-level economic growth. The negative correlation between tree density and ITAEE suggests that areas with higher forest cover, often rural, face governance challenges that limit economic opportunities. The relationship between NDVI and ITAEE further demonstrates the

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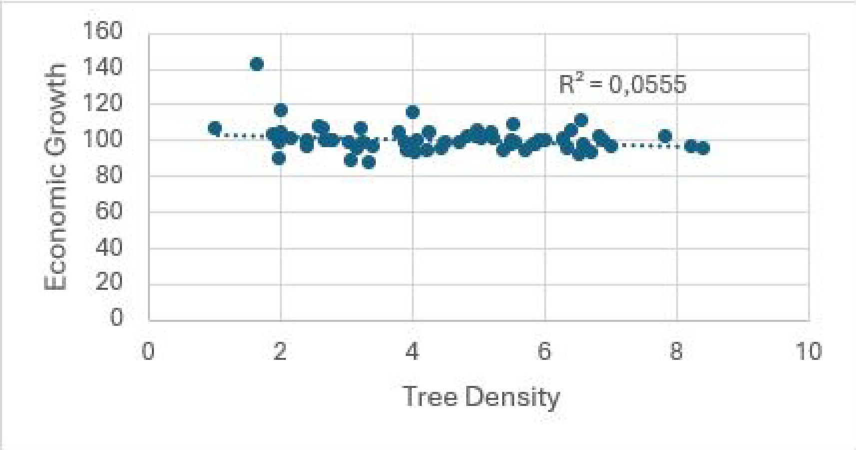
critical role of environmental health in sustainable economic outcomes, where corruption-driven deforestation undermines ecological resilience and long-term growth.

3.2 Implications of the Results

These results highlight the complexity of the relationships between environmental and economic factors in Mexico. The negative relationship between tree density and ITAEE suggests that regions with higher tree cover—often rural—have lower levels of economic activity as measured by ITAEE. However, the low correlation ($R^2 = 0.0555$) indicates that this relationship is weak and that other factors may be significantly influencing economic activity, as shown in Figure 2.

Figure 2. Comparison of Economic Growth and Tree Density

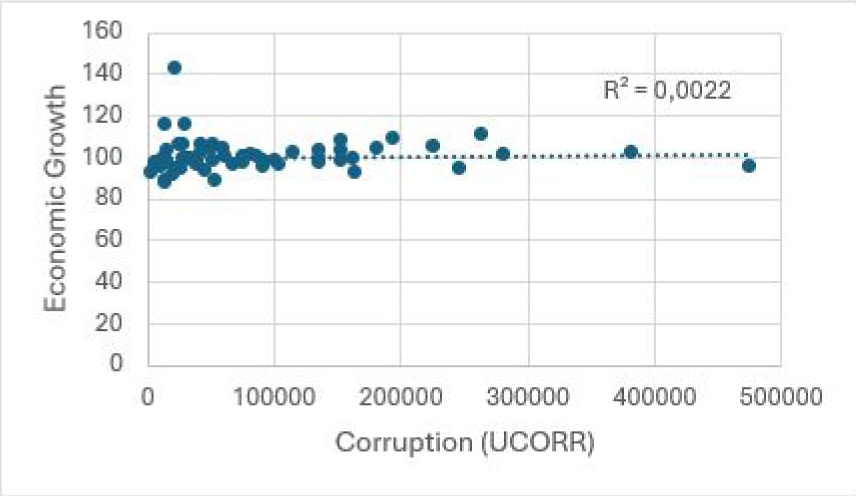


Source: Authors' own work with data from INEGI and satellite images from Google and Bing.

Similarly, the positive relationship of NDVI suggests that healthier and more abundant vegetation is associated with greater economic development in certain states. However, the correlation remains weak, emphasizing the need to consider other contextual and socioeconomic factors for a more accurate interpretation.

The small positive coefficient for UCORR with ITAEE raises interesting questions about the dynamics of corruption and economic growth. While corruption is generally perceived as detrimental to development, this result suggests that there may be compensatory mechanisms that mitigate the negative impact in some contexts. Alternatively, it could reflect the limitations of the corruption index in fully capturing the complexity of corruption's effects on economic activity, given an R^2 of 0.0022, as illustrated in Figure 3.

Figure 3. Comparison of Economic Growth and Corruption



Source: Authors' own work with data from INEGI

The results validate the use of Tree Density as a proxy for corruption, revealing its indirect impact on state-level economic growth. The negative correlation between tree density and ITAEE suggests that areas with higher forest cover face economic disadvantages linked to governance challenges. Additionally, the relationship between NDVI and ITAEE highlights the critical role of environmental health in fostering sustainable economic outcomes, demonstrating that corruption-driven deforestation undermines both ecological resilience and long-term economic stability.

These findings align with prior research by Burgess et al. (2012) on corruption and deforestation, and Dell (2010) on weak governance, illustrating how corruption mediates the interaction between environmental degradation and economic outcomes in Mexico. This work provides empirical evidence for policymakers to design strategies that balance economic growth with environmental sustainability, particularly in contexts where weak institutions exacerbate corruption and environmental harm.

3.3 Detailed Results by State

The following are the detailed results of the RidgeCV model for each state, highlighting how each variable affects ITAEE in each federal entity:

Table 3. RidgeCV Model Results by State

State	ITAEE 2021	ITAEE 2023	Model Prediction
Aguascalientes	8.24	6.86	7.34
Baja California	5.03	5.56	5.22
Baja California Sur	4.06	3.05	3.25
Campeche	3.36	3.10	3.08
Coahuila de Zaragoza	3.20	2.43	2.51
Colima	4.45	2.83	3.12
Chiapas	2.70	2.69	2.85
Chihuahua	6.31	6.58	6.34
Mexico City	8.42	7.87	8.02
Durango	6.62	6.92	6.77
Guanajuato	5.59	4.86	4.98
Guerrero	3.93	3.92	3.89
Hidalgo	6.54	6.44	6.50
Jalisco	5.52	4.28	4.52
Mexico	6.36	6.30	6.38
Michoacán de Ocampo	4.52	3.25	3.32
Morelos	5.41	3.97	4.05
Nayarit	5.26	5.22	5.15
Nuevo León	5.51	5.01	5.02
Oaxaca	4.10	4.04	4.06
Puebla	6.74	6.04	6.08
Querétaro	5.73	5.06	5.12

State	ITAEE 2021	ITAEE 2023	Model Prediction
Quintana Roo	2.00	2.05	2.12
San Luis Potosí	4.24	3.83	3.90
Sinaloa	3.45	3.29	3.34
Sonora	4.75	2.61	2.75
Tabasco	2.04	1.67	1.71
Tamaulipas	2.79	2.18	2.25
Tlaxcala	7.05	5.96	5.98
Veracruz de Ignacio	2.45	1.93	1.98
Yucatán	2.02	1.04	1.12
Zacatecas	5.87	5.90	5.85

Source: Authors' own work with data from the RidgeCV model

Table 3 presents the RidgeCV model predictions compared to the actual ITAEE values for the years 2021 and 2023 in each state. These results allow us to observe how the independent variables (tree density, UCORR, NDVI) affect ITAEE in different states. To illustrate these findings, representative states showing different trends in their results were chosen:

In Aguascalientes, the model's prediction shows a decrease in economic activity, although not as pronounced as observed. The decrease in ITAEE in Aguascalientes could be influenced by a reduction in tree density, highlighting how tree cover can affect the regional economy.

Baja California showed an increase in ITAEE that the model also predicts to a lesser extent. This increase could be associated with the observed increase in tree density in the state, suggesting that, in some cases, greater tree cover could be linked to improved economic activity.

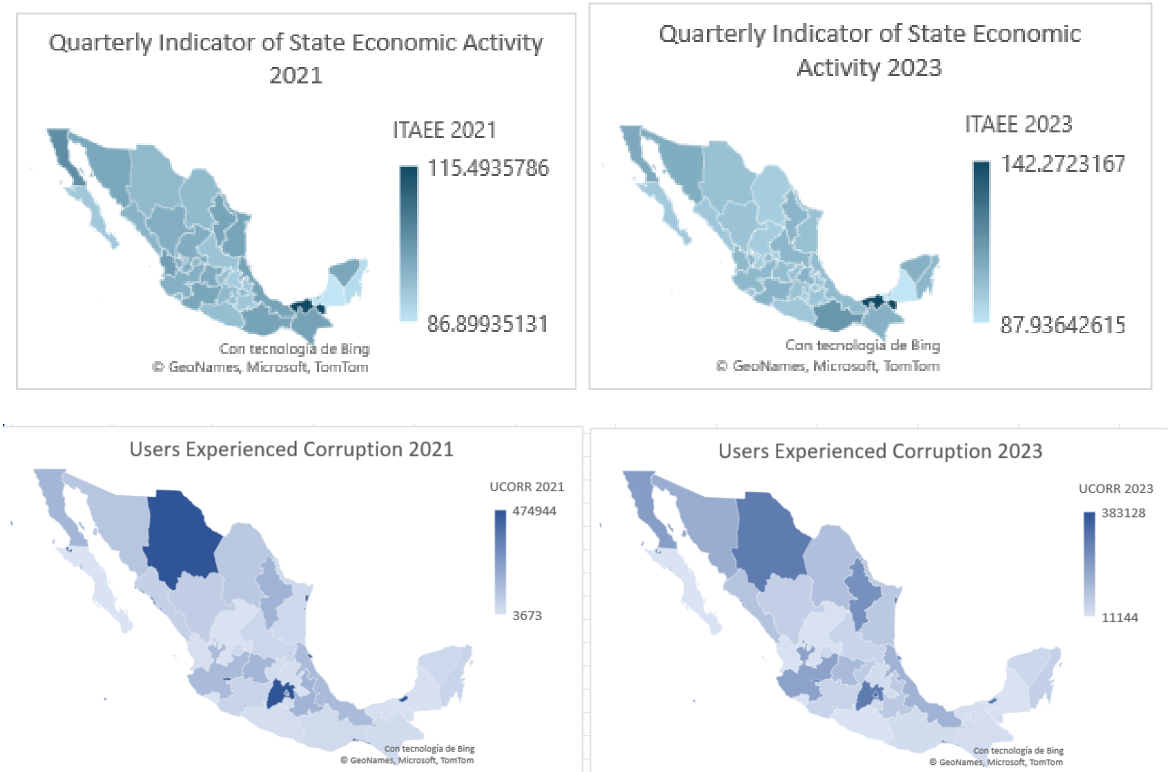
In Mexico City, the model's prediction aligns quite well with reality, suggesting that tree density and other environmental factors have a limited impact on this highly urbanized entity. This reinforces the idea that urban dynamics can significantly differ from rural ones in terms of how environmental factors influence the economy.

Yucatán experienced a significant decrease in ITAEE, which the model correctly predicts. The drastic reduction in tree density in Yucatán may be an important factor in this economic decline, underscoring the importance of tree cover for economic activity in certain states.These examples illustrate how the RidgeCV model can capture regional and temporal variations in the relationship between environmental factors and economic growth, providing a valuable tool for analysis and policy formulation.

3.4 Visual Analysis of Economic and Corruption Trends

The maps in Figure 4 illustrate the evolution of the Quarterly Indicator of State Economic Activity (ITAEE) between 2021 and 2023 and the number of users who experienced corruption during the same period. This visual representation provides valuable insights into the spatial distribution of economic activity and corruption across Mexican states.

Figure 4. Maps of ITAEE Evolution and Users Experiencing Corruption



Source: Authors' own work with data from INEGI (2023) and Bing technology

A clear regional pattern emerges in the ITAEE evolution maps. The states in the northern and central regions show relatively higher economic activity compared to those in the southern region, which aligns with national trends indicating industrial growth and stronger institutional capacity in the north. For instance, Baja California, Chihuahua, and Nuevo León experienced a notable increase in ITAEE from 2021 to 2023, reflecting ongoing industrial development and infrastructure investments. In contrast, states like Chiapas, Oaxaca, and Guerrero show minimal growth, underscoring persistent structural challenges in these regions.

The correlation between economic performance and corruption perception also reveals interesting dynamics. The Users Experienced Corruption maps suggest a reduction in reported corruption in some states, yet others, such as Mexico City and Veracruz, continue to report high levels. This aligns with prior research that highlights urban areas as more prone to corruption-related incidents due to the higher concentration of public services and administrative processes.

The spatial comparison underscores the complex interaction between governance quality, economic performance, and environmental factors. For instance:

- States with lower ITAEE growth and high corruption perception (e.g., Veracruz and Tabasco) reflect governance challenges that may impede economic development and increase vulnerability to corruption.
- States with moderate economic growth and lower corruption perception (e.g., Querétaro and Aguascalientes) highlight areas with potentially stronger institutional frameworks that foster sustainable growth.

- Highly urbanized entities like Mexico City exhibit unique patterns, where high corruption perception may coexist with resilient economic performance due to the diversified nature of the local economy.

These results reinforce the importance of tailored governance strategies. Policies should focus on strengthening institutional capacity in the southern states while promoting transparency and accountability in highly urbanized areas. Integrating environmental and economic monitoring into governance frameworks can provide early warnings of corruption and help mitigate its impact on long-term development.

4. Conclusion

This study analyzed the relationship between corruption, environmental factors, and economic growth in Mexico, emphasizing the role of environmental indicators as instrumental variables to address endogeneity. The results provide robust evidence that tree density and NDVI are valid proxies for governance quality, offering important insights for understanding how corruption influences regional economic performance.

The negative coefficient for tree density reflects the economic challenges often associated with rural areas characterized by higher forest cover. This pattern should be interpreted as a call for policies that promote sustainable economic diversification, rather than reducing forest cover to boost short-term growth. Strategies focused on reforestation, sustainable forestry, and ecotourism can create employment opportunities and contribute to regional development while preserving environmental resources. Payment for Environmental Services (PES) schemes, which offer financial incentives to landowners for maintaining forest cover, could further enhance these efforts.

NDVI's positive association with economic activity highlights the significance of sustainable agricultural practices. Promoting agroforestry and environmentally friendly farming techniques not only improves vegetation health but also strengthens local economies. Such initiatives can enhance resilience to climate change, increase agricultural productivity, and foster long-term economic stability in rural regions.

The findings on corruption reveal its complex role in economic dynamics. Although log_UCORR's positive coefficient suggests that corruption may occasionally bypass bureaucratic inefficiencies, it remains a significant obstacle to institutional development and equity. Anti-corruption policies should focus on increasing transparency and accountability, with digital solutions such as e-Government platforms playing a critical role in reducing opportunities for corrupt practices. Successful international experiences, such as Estonia's comprehensive digitization of public services, offer valuable lessons for Mexico in this regard.

Environmental education and public awareness campaigns are equally essential. Incorporating sustainability into educational programs and launching initiatives to promote environmental stewardship among communities can build long-term support for conservation efforts. Policies aimed at integrating environmental education at various levels could strengthen collective efforts to protect natural resources and promote responsible development.

The RidgeCV model proved effective in addressing multicollinearity and improving the accuracy of the estimates, allowing for a more precise understanding of the relationship between economic activity, governance, and environmental factors. These results contribute to the growing literature on corruption and economic growth by introducing a novel methodological approach that incorporates satellite data and geospatial analysis into econometric modeling.

While this research provides valuable insights, there are opportunities for further exploration. Future studies could incorporate additional indicators, such as water availability, pollution levels, or governance quality at the municipal level, to enrich the understanding of regional economic dynamics. The integration of political factors, such as election cycles or local political stability, could also offer a more comprehensive perspective on how corruption interacts with economic performance.

The evidence presented underscores the importance of designing policies that simultaneously promote transparency, strengthen institutional frameworks, and encourage environmental conservation. Balancing these priorities will be essential for fostering sustainable economic growth and improving governance in the states of Mexico.

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