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Tobit Regression Analysis for the Environmental Impact Assessment (EIA) of Energy Conversion on the Island of Sumatra

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Abstract

This study focuses on an in-depth examination of Environmental Impact Assessments (EIA) for energy transition projects on the island of Sumatra, employing Tobit regression analysis a statistical method that enables the analysis of relationships between environmental variables and energy policies at a regional scale. Energy transition in Sumatra is a critical issue, as the shift from fossil fuels to renewable energy can significantly affect ecosystems and environmental balance. By utilizing the Tobit regression approach, this study aims to identify patterns of environmental change resulting from energy transition projects and to evaluate the effectiveness of EIA policies in supporting energy sustainability. Key challenges in this research include limited spatial data, the complexity of environmental variables, and uncertainties in energy policy, all of which may influence the accuracy of environmental impact predictions. The Tobit regression model is used to map the relationships among environmental regulations, renewable energy investments, and other factors related to the ecological impacts of energy transition projects. The findings are expected to provide data-driven recommendations for the government and stakeholders to design more sustainable energy transition strategies while minimizing negative impacts on ecosystems. Through this data-driven approach, the study contributes to enhancing environmental analysis capacity and supporting EIA policies that are more adaptive to ecological changes.

Keywords Impact of EIA Elaboration; Tobit Regression Analysis; Energy Conversion; Ecological Change; Environmental Regulation

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INTRODUCTION

The island of Sumatra faces significant challenges in transitioning from fossil fuels to renewable energy. Dependence on coal and petroleum has contributed to environmental degradation, including air pollution, ecosystem damage, and increased carbon emissions. In response to the growing urgency of climate change mitigation, the energy transition has become a key priority in sustainable development planning. Environmental Impact Assessment (EIA), known in

Indonesia as Analisis Mengenai Dampak Lingkungan (AMDAL), plays a crucial role in ensuring that energy development projects incorporate sustainability principles and minimize adverse environmental impacts. EIA provides an essential framework for evaluating the environmental feasibility of renewable energy projects and identifying potential risks that require appropriate mitigation measures. Environmental assessment and reclamation studies further emphasize the importance of regulatory compliance, environmental monitoring, and post-project recovery in promoting sustainable resource management (Jannah et al., 2025; Kamarullah et al., 2025; Oktorina, 2017; Rahmi et al., 2020; Ramadhan & Rahmawati, 2025).

Although EIA has been integrated into environmental and energy planning, accurately predicting how changes in assessment procedures and environmental regulations influence the energy transition remains challenging. These challenges include limitations in spatial data availability, the complexity of environmental variables, and uncertainties associated with energy policies and investment decisions. Previous studies have examined renewable energy potential using predictive planning tools and highlighted the importance of systematic approaches to energy resource assessment (Ulina et al., 2022). Furthermore, the application of statistical modeling provides opportunities to analyze complex relationships among environmental conditions, socioeconomic factors, and policy interventions. Time series forecasting, probabilistic modeling, and volatility analysis offer methodological foundations for examining temporal patterns and uncertainty in quantitative data (Maulana, 2018; Ross, 2010; Rohmaningsih et al., 2016). Spatial regression methods also provide a framework for investigating regional variations and spatial dependencies in environmental and socioeconomic phenomena (Yasin et al., 2020).

One potential analytical approach is spatial Tobit regression, which is suitable for analyzing spatially dependent observations when the dependent variable is censored at a particular threshold. The Tobit model provides a statistical framework for examining relationships involving limited dependent variables (Long, 1997), while spatial Tobit regression extends this approach to account for spatial relationships among observational units (Mustari & Zain, 2017). Its application may therefore support the investigation of regional variations in environmental indicators associated with energy transition policies. Nevertheless, the effectiveness of this approach depends on the availability and quality of spatial data, the appropriate specification of environmental variables, and the consideration of policy-related

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uncertainties. In addition, developments in artificial intelligence and predictive environmental analysis offer opportunities to improve the identification of environmental risks and support evidence-based decision-making.

Against this background, this study aims to develop a predictive model based on spatial Tobit regression to evaluate the relationship between changes in EIA processes and the energy transition in Sumatra. The proposed model will examine spatial patterns in environmental indicators and investigate the relationships among environmental regulations, renewable energy investments, and the ecological impacts of energy transition projects. By integrating spatial statistical analysis with environmental assessment data, the study is expected to improve the understanding of regional environmental variations and provide a quantitative basis for evaluating the effectiveness of environmental policies. The resulting model is also intended to support more systematic predictions of potential environmental impacts and strengthen the use of statistical evidence in sustainable energy planning.

The findings are expected to provide data-driven recommendations for improving environmental and energy policies in Sumatra. More reliable predictive modeling could help governments and relevant stakeholders formulate energy transition strategies that balance energy security, economic development, and ecosystem protection. Furthermore, this research is expected to strengthen regional spatial data analysis capabilities and support the development of more adaptive environmental assessment procedures. Through the application of spatial Tobit regression, the study seeks to contribute to the advancement of quantitative approaches to environmental impact prediction and sustainable energy management.

METHODS

This study adopts a quantitative approach using the Tobit regression method to predict the effects of changes in Environmental Impact Assessment (EIA), known in Indonesia as Analisis Mengenai Dampak Lingkungan (AMDAL), on energy conversion projects on the island of Sumatra. The study population comprises energy conversion projects in Sumatra for which EIA documents are available as the basis for environmental impact assessment. The sample is selected using purposive sampling, focusing on projects with sufficiently comprehensive environmental data, including carbon emissions, land-cover changes, and socioeconomic indicators. The selection process considers the geographical distribution of projects across the

provinces of Sumatra to facilitate spatial analysis and provide a more comprehensive understanding of regional variations and patterns in environmental impacts.

Data collection involves several methods. First, secondary data collection involves obtaining information from EIA documents, environmental reports, energy policies, and official publications issued by relevant government institutions, including the Ministry of Environment and Forestry and the National Development Planning Agency, as well as relevant academic publications. Second, spatial Tobit regression model simulation uses historical data from energy conversion projects to develop a predictive model. This approach is intended to examine relationships between environmental changes and spatial factors and estimate variations in EIA-related impacts across different regions of Sumatra. Third, environmental indicator identification focuses on carbon dioxide (CO_2) emissions, land-cover changes, including deforestation and urbanization, and socioeconomic impacts, particularly changes in community well-being associated with energy conversion projects. These variables are compiled from available sources and incorporated into the statistical model to investigate relationships and spatial patterns across regions. Fourth, model validation evaluates predictive performance by comparing model estimates with observed data from ongoing or completed projects. Cross-validation and the Akaike Information Criterion (AIC) are used, where appropriate, to assess model performance and determine the suitability of the model specification.

Data analysis is conducted through several stages. First, data exploration examines the distributions and characteristics of environmental variables and identifies potential spatial relationships among regions. Second, data processing involves data cleaning, normalization, and transformation, where necessary, to ensure consistency and suitability for statistical analysis. Third, spatial Tobit model estimation examines relationships between the dependent variable and explanatory variables while accounting for spatial dependence among regions through an appropriate spatial weighting matrix. The application of statistical modeling to environmental and regional data provides a methodological basis for investigating variations in environmental outcomes and supporting evidence-based environmental management (Yasin et al., 2020; Long, 1997; Mustari & Zain, 2017).

This research is expected to contribute to the evaluation of EIA policies, particularly in the context of energy conversion projects. By applying spatial Tobit regression, the study seeks to provide analytical insights that can assist government institutions and other stakeholders in formulating more targeted environmental policies, mitigating the adverse impacts of energy development, and promoting

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sustainability in Sumatra. The findings may also provide a foundation for developing predictive approaches to environmental management and strengthening data-driven decision-making in EIA implementation. In addition, research on post-mining land reclamation, green finance, and environmental management highlights the importance of integrating regulatory frameworks, environmental recovery, and sustainability considerations into resource development policies (Kamarullah et al., 2025; Mara et al., 2025; Masbut et al., 2025; Oktorina, 2017; Rahmi et al., 2020).

Data from various sources, including Statistics Indonesia (BPS), environmental management institutions, and other relevant agencies, do not provide complete information for all provinces on every variable initially identified in this study. Consequently, the research variables have been restricted to those with sufficiently consistent and overlapping data, as presented in Table 1. The analysis uses panel data covering 10 provinces on the island of Sumatra over a five-year period, yielding a total of 50 observations (\(n = 50\)). Only variables with compatible time coverage are included in the model to maintain consistency across observations and support reliable statistical estimation.

Table 1. Research Variables

Variable	Definition	Unit	Role
Y	Total of Deforestation	thousands ha	Response, left censored at 0
X1	CO2 Emission	million ton	Predictor
X2	Population Density	person/km²	Predictor

A negative net deforestation value (reforestation) occurred in only 2 out of 50 observations or 4%. Consequently, the Tobit results are similar to those of OLS.

FINDINGS AND DISCUSSION

Descriptive statistical analysis shows that the distributions of Y and X1 are highly right-skewed as shown in Table 2 below. The Pearson correlations are as follows: Total of Deforestation with CO2 Emission = 0.72, Total of Deforestation with Population Density = −0.25, and CO2 Emission with Population Density = −0.18.

Table 2. Descriptive Statistics

Statistics	Y	X1	X2
Mean	9,161	7,278	137,48
Std. Dev.	22,048	24,847	71,06

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Statistics	Y	X1	X2
Minimum	-2,312	0,001	71
Median	3,349	0,734	98,5
Maximum	142,011	158,330	273
Skewness	4,99	5,19	0,89

Calculation of Spatial Autocorrelation (Moran's I):

Table 3. Spatial Autocorrelation

Variable	I	Z	p-value	Decission
Y	0,0058	0,208	0,836	Non - Significance
X1	0,0099	0,240	0,810	Non - Significance
X2	−0,2935	−2,162	0,031	Significance
Residual of OLS	0,1301	1,192	0,233	Non - Significance

OLS Regression as Starting Point with *Formulation:* $\hat{\beta} = (X'X)^{-1} X'y$

Table 4. Ordinary Least Square (OLS) Regression

Parameter	Coeeficients	SE	t	p-value
β0	10,146	5,010	2,03	0,049
β1 (CO2)	0,615	0,090	6,81	<0,001
β2 (kepadatan)	−0,040	0,032	−1,26	0,215

R^2 = 0,528; R^2 adj = 0,508; F = 26,32 (p < 0,001); SSE = 11.236,05.

Tobit Estimation (Maximum Likelihood):

Table 5. Tobit Estimation

Parameter	Estimation	SE	z	p-value
β0	10,348	5,008	2,07	0,039
β1 (CO2)	0,616	0,090	6,87	<0,001
β2 (kepadatan)	−0,044	0,032	−1,39	0,165
σ	15,338	1,569	9,77	<0,001

From the OLS starting point (−ln L = 200.782), the iteration converged to −ln L = 200.753. Likelihood ratio test against the null model: LR = 2(−200.753 + 218.998) = 36.49, df = 2, p < 0.001. SAR-Tobit Estimation (EM + Concentrated Maximum Likelihood):

Table 6. SAR-Tobit Estimation

Parameter	Estimation	SE	z	p-value
β0	10,324	4,931	2,09	0,036
β1 (CO2)	0,6145	0,089	6,90	<0,001
β2 (population	−0,0467	0,032	−1,46	0,145

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Parameter	Estimation	SE	z	p-value
density)				
ϱ	0,030	0,087	0,35	0,730
σ^2	231,62	46,35	5,00	<0,001

Since the SAR-Tobit likelihood involves high-dimensional integrals, estimation is performed using the EM algorithm. The algorithm converges in 7 iterations. LR test for ϱ = 0: LR = 0.109, p = 0.742. No spatial effects are evident.

Table 7. Direct, Indirect and Total Effects

Variable	Direct	Indirect	Total
CO2 Emission	0,6147	0,0188	0,6335
Population Density	−0,0467	−0,0014	−0,0481

Each additional 1 million tons of CO2 emissions is associated with approximately 0.61 thousand hectares (±615 hectares) of additional deforestation. This is an association, not a causal relationship; both emissions and land clearing are likely driven by land fires. Population density has no significant effect on deforestation (p = 0.165). The influence between neighboring provinces is near zero (ϱ = 0.03; indirect effect = 0.019). The spatial model performs no better than a standard Tobit model. A significant Moran's I value is found only for population density (where densely populated provinces are adjacent to sparsely populated ones), but not for deforestation.

CONCLUSION

Deforestation in Sumatra is influenced by CO2 emissions within the province itself, rather than by spillover from neighboring provinces. For future research, it is suggested to: (1) Incorporate energy-related variables (electricity consumption, renewable energy mix, and the number of environmental impact assessment/management documents AMDAL/UKL-UPL) along with data at the regency/city level (±150 units) to make the spatial weight matrix (W) more informative; (2) Employ more robust estimators, such as Tobit-t, CLAD, or Bayesian SAR-Tobit (using MCMC or LeSage's approach) along with robust standard errors; also, consider applying a log(Y + c) transformation; (3) Conduct a sensitivity analysis by excluding outlier; (4) Include provincial and temporal fixed effects, and test alternative spatial weighting schemes (e.g., inverse distance or k-nearest neighbors); (5) Use the Environmental Quality Index (IKLH) after addressing zero values or the Water Quality Index (IKA) as an alternative response variable, covering a longer time

period; (6) Perform predictive validation (using training/test sets and RMSE) to ensure the objective of prediction is effectively met.

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