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Article

Municipal Economic Development and Greenhouse Gas Emissions in Brazil

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RESUMO

As mudanças climáticas estão estritamente relacionadas com as perspectivas de dinâmicas econômicas e sociais de países e unidades subnacionais. No geral os estudos que analisam essa relação utilizam os Estados Nacionais como unidades de observação. Este trabalho buscou contribuir com a literatura no sentido de examinar unidade mais descentralizada, os municípios brasileiros. O Brasil é um país com dimensões continentais e heterogeneidade dos padrões de desenvolvimento entre os estados. O objetivo do artigo é analisar de que forma o desenvolvimento econômico dos municípios brasileiros impactam na emissão de gases do efeito estufa, considerando a disparidade de dinamismo das economias subnacionais existente no país. A metodologia empregada foi de modelo multinível com dois níveis. Como a estrutura dos dados estava configurada pelas emissões municipais de CO_2e por cada estado, a exceção do Distrito Federal, verificou-se um arcabouço de dados aninhados, por isso a escolha pela modelagem multinível. Os resultados indicam que complexidade econômica (negativamente associada às emissões de CO_2e), Produto Interno Bruto, nível de precariedade social, desmatamento e Índice Sebrae de Desenvolvimento Local dos estados foram variáveis significativas para explicar as emissões de CO_2e nos municípios brasileiros. Somado a isso, taxa de crescimento das emissões municipais nos estados que já possuíam altas emissões médias foi menor do que nos estados com médias baixas. Conclui-se que o estado em que o município está inserido importa quando observada a relação entre a estrutura de complexidade econômica e as emissões de CO_2e, respondendo por 63,5% da variância nas emissões municipais de CO_2e.

Palavras-chave: mudanças climáticas, desenvolvimento local, modelos multiníveis.

ABSTRACT

Climate change is closely linked to the economic and social dynamics of countries and subnational units. In general, studies analyzing this relationship tend to use nation-states as their unit of observation. This study aims to contribute to the literature by focusing on a more decentralized unit, Brazilian municipalities. Brazil is a country of continental dimensions and heterogeneity in development patterns across its states. The objective of this article is to analyze how the economic development of Brazilian municipalities affects greenhouse gas emissions, considering the disparity in subnational economic dynamism across the country. The methodology employed was a two-level multilevel model. Since the data were organized by municipal CO_2e emissions nested within each state, except for the Federal District, this justified the choice of a multilevel modeling approach. The results indicate that economic complexity (negatively associated with CO_2e emissions), Gross Domestic Product, level of social vulnerability, deforestation, and the Sebrae Index of Local Development at the state level were significant variables in explaining CO_2e emissions in Brazilian municipalities. Additionally, the growth rate of municipal emissions was lower in states that already had high average emissions compared to those with low average emissions. It is concluded that the state in which a municipality is located matters when analyzing the relationship between economic complexity and CO_2e emissions, accounting for 63.5% of the variance in municipal CO_2e emissions.

Keywords: climate change, local development, multilevel models.

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Introduction

On one hand, economic development is intrinsically linked to climate change. Several studies indicate that climate change and its impacts have negative effects on the economy and on people's quality of life, especially those in situations of social vulnerability who suffer from extreme weather events. On the other hand, economic development itself can be a driving force behind climate change, through historical strategies involving land-use transformation, industrialization, the reliance on polluting energy sources, and the construction of infrastructure projects (Metz & Kok 2011).

According to Beg et al. (2002), the most adverse effects of climate change are disproportionately concentrated in developing countries. Populations in these regions often lack the resources to adapt to environmental shifts, which exacerbates existing social inequalities. Moreover, the economic development models historically employed by developed nations, based on high carbon emissions and intensive resource exploitation, are neither environmentally sustainable nor replicable for developing countries in the current climate crisis (Romero & Gramkow 2021).

Based on data provided by Climate Watch (2025), Brazil ranks as the fifth-largest emitter of carbon dioxide equivalent (CO_2e) globally. The CO_2e metric is a measure used to compare the greenhouse gas emissions of different countries, taking into account the specific global warming potential of each gas.

Brazil's emissions displayed the following distribution according to Observatório do Clima (2025a) last data available[1]: 46.25% resulted from land-use change, 27.49% were attributed to the agricultural sector, 18.30% originated from the energy sector, while 3.99% came from waste and 3.97% from industrial processes. Among the five most carbon-intensive Brazilian states, regional diversity is observed: the state of Pará, the largest emitter, is located in the Northern region of the country; Mato Grosso, ranked second, is situated in the Midwest; Maranhão, in third place, is in Northeast; Minas Gerais, in fourth place, and São Paulo, in fifth, are in the Southeast region. Moreover, the main sources of greenhouse gas emissions vary among these states: Land Use and Land Cover is the leading source of emissions in Pará, Mato Grosso, and Maranhão; in Minas Gerais, agriculture plays this role, while in São Paulo it is the energy sector.

Although the North and Midwest regions have increased their contribution to the national Gross Domestic Product over the first two decades of the 21st century, they rank among the least developed regions in Brazil. In contrast, the Southeast remains the most economically dynamic region, even from a historical perspective (Furtado 1977; Neto 2014; Macedo & Porto 2020). The administrative division of a territory does not ensure internal homogeneity in development patterns. Even within the same state, areas with differing development levels can coexist (Chein et al. 2007).

The objective of this article is to analyze how the economic development of Brazilian municipalities affects greenhouse gas emissions, considering the disparity in subnational economic dynamism across the country. The research question is: How does the varying economic development among Brazilian municipalities influence greenhouse gas emissions? Development is defined as the process involving the generation of wealth, constrained by the availability of natural resources, energy, and labor within a society. It also implies the mitigation of social and environmental inequalities associated with the geographic location in which development takes place (Dawkins 2003; Theis 2022).

The literature addressing the relationship between environmental sustainability and economy focuses on seven macrostructural aspects of development: a) economic growth, b) energy consumption, c) land use, d)

[1] The Observatório do Clima last data available for greenhouse gas emission by state in Brazil refers to 2023 emissions.

industry, e) technological progress, f) urbanization, and g) structural economic changes (Carvalho 2013; Grossman & Krueger 1995; Li et al. 2021; Mealy & Teytelboym 2022; Romero & Gramkow 2021). This literature has generally focused on countries.

Studies addressing municipal greenhouse gas (GHG) emissions in Brazil have examined environmental efficiency of Brazilian municipalities (Soares & Cunha 2019), sub-national framework for the allocation of mitigation burdens from GHG (Ambrósio et al. 2021), specific geographic areas of the country (Ferreira-Paiva et al. 2022; Schmidt Dubeux & Rovere 2007) or focused on the level of atmospheric pollution associated with certain economic sectors (Alkimim & Clarke 2018; Garofalo et al. 2022; Bordonal et al. 2015; Silveira et al. 2000). Therefore, the contribution of the present article lies in its analysis of the constituent elements of local development and their relationship with GHG emissions across Brazilian municipalities.

The article is structured into four sections. The section following this introduction outlines the methodology employed in the study, including a description of the data and the statistical modeling. The third section presents the results concerning the contribution of municipal economic development to the variation in CO_2e emissions. The final section presents the conclusion.

Materials and Methods

Data Collection

Data on GHG emissions were collected from the Greenhouse Gas Emissions and Removals Estimation System (SEEG, in Portuguese), developed by the *Observatório do Clima*, for the year 2021[2]. This system includes all greenhouse gases listed in the national inventory, such as CO_2, CH_4, N_2O, HFCs, as well as CO_2e (Observatório do Clima 2025a). Thus, CO_2e is the dependent variable in this study, measured in tons.

To investigate the impact of municipal level economic development on GHG emissions in Brazil, the independent variables are categorized into five dimensions: environmental, public administration, social, economic, and geographic. The data were collected from different sources for the year 2021 and are described below.

Regarding environmental issues, since the primary source of GHG emissions in Brazil is Land Use and Land Cover (Observatório do Clima 2025a), data on the increase of deforestation (km^2) per municipality were obtained from the *TerraBrasilis* platform of the National Institute for Space Research (Instituto Nacional de Pesquisas Espaciais 2025). Land use also affects the urban area of municipalities (Li et al. 2021). Therefore, under the dimension of public administration, data were collected on the number of legal urban planning instruments in each municipality, available on the Sebrae Intelligence platform – Sebrae Index of Local Economic Development (Serviço Brasileiro de Apoio às Micro e Pequenas Empresas 2025).

In the social dimension, the variable selected to capture social inequality in each municipality was the precarity ratio, defined as the proportion of formal workers earning up to one minimum wage. This variable is available on the Sebrae Intelligence platform.

In the economic dimension, the analysis includes the Sebrae Index of Local Economic Development (ISDEL) for Brazilian states, also available on the Sebrae Intelligence platform. Additionally, municipal Gross Domestic Product (GDP) data were obtained from the Brazilian Institute of Geography and Statistics (IBGE 2024), and the Economic Complexity Index (ICE-R – Employment) was collected from DataViva (2025), a

[2] Greenhouse gas emission data were collected for the year 2021, as it was the most recent period with available information for all independent variables included in the study.

platform developed by the Center for Regional Development and Planning (CEDEPLAR) at the Federal University of Minas Gerais (UFMG) (CEDEPLAR 2025).

The Economic Complexity was constructed using formal employment data from Brazilian microregions, disaggregated by two-digit sectors according to the National Classification of Economic Activities (CNAE 2.0), as recorded in the Annual Social Information Report (RAIS), maintained by the Ministry of Labor and Employment (MTE). This index is used to analyze the complexity of local employment structures (Rezende et al. 2023).

Finally, state affiliation of each municipality was recorded. The collected data were organized into a dataset for statistical analysis. Observations for the Federal District were excluded from the dataset, as it contained only one municipality. In addition, municipalities that reported negative values for CO_2e emissions were also removed. This exclusion was necessary because the dependent variable underwent a Box-Cox transformation, performed using the powerTransformation function from the MASS package in R, which requires all values to be strictly positive. The following municipalities were excluded: Caieiras (SP), Ribeirão (PE), Chaval (CE), Minas do Leão (RS), Lauro de Freitas (BA), Guatapará (SP), Sabará (MG), Itaquaquecetuba (SP), Cruzeta (RN), Iperó (SP), Joaquim Nabuco (PE), Jambeiro (SP), Onda Verde (SP), Santa Isabel (SP), and Biguaçu (SC). After these adjustments, the final dataset included observations from 5,555 municipalities across the 26 Brazilian states, with data for all variables corresponding to the year 2021. Table 1 presents the descriptive statistics for all variables included in the analysis.

Table 1: Descriptive Statistics of the Variables

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
CO_2e GWP-AR5 (t)	3,955	50,562	106,460	431,402	261,274	77,387,645
Economic Complexity	−2.885	−0.701	−0.1045	−0.003763	0.604	3.329
Social Precarity	0.000	5.717	10.026	12.804	17.738	81.818
GDP (R$ million)	18,051	112,382	253,117	1,564,984	677,711	828,980,608
Deforestation (km²)	0.000	0.020	0.190	4.262	1.410	765.530
Urban Planning	0	3	11.5	9.684	15	16
State ISDEL	0.3010	0.3860	0.4490	0.4413	0.5110	0.5610

Source: Research's original results.

Given that each municipality is nested within one of the 26 Brazilian states, the data structure can be characterized as hierarchical. This nesting implies two levels of analysis: Level one corresponds to the municipalities, for which the deforestation, legal urban planning instruments, precarity ratio, GDP, and the Economic Complexity Index variables were measured, while Level two refers to the states, the Sebrae Index of Local Economic Development (ISDEL), which may influence municipal level outcomes through broader economic contexts. According to Hair Jr and Fávero (2019), the multilevel structure of the dataset justifies the use of hierarchical modeling techniques, as it allows for the estimation of within and between state effects on CO_2e emissions. This study uses secondary data from public institutional sources and is therefore exempt from ethics committee review, in accordance with Brazilian National Health Council Resolution n^0. 510/2016.

Analysis of the data collected

Multilevel modeling enables the analysis of data structured across different levels, with each level represented by a distinct set of parameters. This approach allows researchers to examine relationships among variables within each level and to explore cross level interactions. As a result, it offers a more precise and layered understanding of the phenomenon under investigation (Fávero & Confortini 2010).

In this framework, group level characteristics captured at Level two, those that do not vary across observations within the same group, may influence the results. An example is the ISDEL at the state level. Such characteristics can help explain differences in the intercepts and slopes (growth rates) of the models representing each group (Fávero & Belfiore 2017).

The general specification of the two level multilevel model (Equation 1) is as follows:

$$Y_{ij} = \gamma_{00} + \gamma_{p0}X_{pij} + \gamma_{0q}W_{qj} + \gamma_{pq}W_{qj}X_{pij} + \nu_{pj}X_{pij} + \nu_{0j} + \varepsilon_{ij} \tag{1}$$

Where:

Fixed effects components:

γ_{00} overall intercept;

- γ_{p0} average slope coefficient for Level 1 variables;
- γ_{0q} average slope coefficient for Level 2 variables;
- γ_{pq} average slope coefficient for the interactions between Level 1 and Level 2 variables.

Random effects components:

- ν_{pj} random slope component, representing variation in slopes across groups;
- ν_{0j} random intercept component, capturing intercept variability across groups;
- ε_{ij} idiosyncratic error term.

The multilevel model allows for the estimation of how much of the variance in the response variable (CO_2e emissions) is explained by differences between groups at Level two, in this case the states. It also enables the evaluation of slope variation across groups, reflecting how the effect of Level one predictors may change depending on the state. These components are quantified using the intraclass correlation coefficient (ICC) (Equation 2).

$$\rho = \frac{\tau_{oo} + \tau_{11}}{\tau_{00} + \tau_{11} + \sigma^2} \tag{2}$$

Where:

- τ_{oo} group variance (intercept);
- τ_{oo} slope variance;
- σ^2 errors variance

The final multilevel model proposed in this article follows the step-up strategy as outlined by Hair Jr. and Fávero (2019), Tabachnick and Fidell (2018), and Snijders and Bosker (2011). In the first stage, the focus was on the structure of the random components, starting with a null model to assess the variance decomposition.

This was followed by a model with random intercepts, and finally by a specification including both random intercepts and random slopes. In the second stage, fixed effects variables were introduced to the model.

Different transformations of the response variable were tested to ensure appropriate model fitting. The original (untransformed) variable did not result in parameter convergence. The log-transformed version improved model performance, but the best fit was obtained using the Box-Cox transformation. In the model specification, the response variable CO_2e appears with an asterisk, indicating that it has been transformed.

Results

The modeling began with the estimation of the null model, which makes it possible to determine whether there is variability in CO_2e emissions both among municipalities within the same state and across municipalities from different states. This model does not include independent variables. It evaluates the presence of an intercept and the error terms ν_{oj} and ε_{ij}. The model specification is presented in Equation 3.

$$CO_2e_{ij}{}^* = \beta_{oj} + \varepsilon_{ij}$$
$$\beta_{oj} = \gamma_{00} + \nu_{oj}$$
$$CO_2e_{ij}{}^* = \gamma_{00} + \nu_{oj} + \varepsilon_{ij} \tag{3}$$

Where:

- γ_{00} overall intercept;
- ν_{0j} random intercept component, capturing intercept variability across groups;
- ε_{ij} idiosyncratic error term.

Table 1 shows that the variance ν_{0j} is statistically significant, confirming the presence of a state level random effect in the model. This suggests that municipalities grouped within different states exhibit distinct average levels of CO_2e emissions. These results support the use of a multilevel model, which provides a better fit to the data compared to the ordinary least squares (OLS) approach.

Table 1: Determination of standard errors of variances in the random effects component null model

Random Effects Components	Variance Estimative	Standard Error	z	p-value
Var(v0j)	0.01760010	0.0050375057	3.493813	0***
Var(ε_{ij})	0.01179281	0.0002243129	52.573030	0***

Source: Research's original results. Data collected from Observatório do Clima (2025a). Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

The next step consisted of introducing fixed effects into the model with random intercepts. At this stage, independent variables at Level one (municipal level) were added to explain the variability in the response variable. These variables were treated as fixed effects, while the random intercepts continued to account for differences between states. The likelihood ratio test was used to evaluate whether the inclusion of each variable improved the model fit (Hair Jr. & Fávero 2019).

Table 2: Multilevel Model with random intercepts and fixed effects (level one)

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Economic Complexity	0.053593*** (0.001505015)	0.053421*** (0.001526795)	-0.040319*** (0.002023016)	-0.038559*** (0.001985209)	-0.038516*** (0.001997651)
Precarity ratio		-0.000127 (0.000189927)	0.000892*** (0.000151160)	0.000927*** (0.000148099)	0.000927*** (0.000148186)
Ln GDP			0.079109*** (0.001370186)	0.077006*** (0.001349344)	0.077067*** (0.001384892)
Deforestation				0.000694*** (0.000045220)	0.000694*** (0.000045224)
Urban Planning					-0.000043 (0.000219584)
Random Intercept (States)					
Var(ν_{0j})	0.018414350*** (0.005258911)	0.018360363*** (0.0052433595)	0.011931341*** (0.0034093679)	0.010594311*** (0.0030306928)	0.010597571** (0.0030308256)
Var(ε_{ij})	0.009592336*** (0.000182474)	0.009593418*** (0.0001825107)	0.005993602*** (0.0001140365)	0.005752524*** (0.0001094599)	0.005753518*** (0.0001094886)
Likelihood ratio test					
Pr(>Chisq)	2.2e-16***	0.0001164***	2.2e-16***	2.2e-16***	0.0001091***

Source: Research's original results. Data collected from Observatório do Clima (2025a). Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

As shown in Table 2, five models were tested. Model 4 included all statistically significant variables and demonstrated an improvement in the likelihood ratio. Therefore, it was selected for the continued development of the final model.

Once the Level one variable were selected, the next step was to test the inclusion of random slopes. At this stage, all fixed effect variables from Model 4 were considered for random slope specification, including urban planning. Although urban planning did not show significance in the fixed effect regression, it was tested here to examine whether it contributed meaningfully to the variance components at the group level.

Table 3: Specification of Random Slopes

Components	Variables				
	Economic Complexity	Precarity ratio	Ln GDP	Deforestation	Urban Planning
Var(ν_{0j})	0.0086047647*** (0.0024669811)	8.818638e-03** (2.586841e-03)	0.1532148218** (0.0460560576)	1.165034e-02*** (3.330708e-03)	1.499933e-02** (4.348224e-03)
Var(ν_{1j})	0.0006240704** (0.0002012868)	1.052124e-06 (5.941636e-07)	0.0005431943** (0.0001687994)	6.734579e-05* (3.162444e-05)	4.928053e-06** (1.853469e-06)
Var(ε_{ij})	0.0055155997*** (0.0001051939)	5.713868e-03*** (1.088627e-04)	0.0053741731*** (0.0001024626)	5.301430e-03*** (1.013365e-04)	5.668638e-03*** (1.082152e-04)

Source: Research's original results. Data collected from Observatório do Clima (2025a). Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

As shown in Table 3, all tested variables exhibited meaningful variance in their random slope components, except for the precarity ratio. Among the significant variables, economic complexity was selected as the random slope term to be included in the final model. This decision was based on the main objective of the study, which is to investigate how municipal economic development influences greenhouse gas emissions. Since economic development is intrinsically linked to structural change, understood as the transformation of the productive structure through the learning and adoption of new economic activities, economic complexity provides a meaningful proxy for capturing this process (Romero et al. 2022).

To complete the construction of the final model, two tests were conducted. The first included a Level 2 variable measuring the development of each state, using the ISDEL index for the federative units. The second test measured the existence of interactions between this Level 2 variable and the Level 1 variables. The first test was statistically significant, whereas the second was not. Table 4 presents the results of the final model.

Table 4: Final model

Independent Variable	**Coefficient**	**Std. Error**	**DF**	**t-value**	**p-value**
Intercept	3.966670	0.05062737	5524	78.35031	0.0000***
Economic Complexity	-0.043935	0.00527774	5524	-8.32457	0.0000***
Precarity Ratio	0.000998	0.00014717	5524	6.78270	0.0000***
Ln GDP	0.078194	0.00134179	5524	58.27579	0.0000***
Deforestation	0.000739	0.00004436	5524	16.64954	0.0000***
ISDEL States	-0.365712	0.10612906	24	-3.44591	0.0021**
Random Effects					
	Variance	Covariance	Std. Error	z	p-value
Intercept (ν_{0j})	0.0089861456	-0.928	0.0025942661	3.463849	0.001**
Economic Complexity (ν_{1j})	0.0006075917	-0.928	0.0001941959	3.128756	0.002**
Error (ε_{ij})	0.0055152694		0.0001051639	52.444514	0.000***

Source: Research's original results. Data collected from Observatório do Clima (2025a). Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

The final model (Equation 4) is specified as follows:

$$\begin{aligned} CO_2e_{ij}^{*} = {} & \gamma_{00} + \gamma_{10} Economic\ Complexity_{ij} + \gamma_{20}\ Precarity\ Ratio_{ij} \\ & + \gamma_{30} Ln\ GDP_{ij} + \gamma_{40} Deforestation_{ij} + \gamma_{01} ISDEL\ State_j + \nu_{oj} \\ & + \nu_{1j} Economic\ Complexity_{ij} + \varepsilon_{ij} \end{aligned} \tag{4}$$

Where:

- γ_{00} intercept;
- γ_{10} fixed effect coefficient for the variable economic complexity (Level 1);
- γ_{20} fixed effect coefficient for the variable precarity ratio (Level 1);
- γ_{30} fixed effect coefficient for the variable Ln GDP (Level 1);
- γ_{40} fixed effect coefficient for the variable deforestation (Level 1);
- γ_{01} fixed effect coefficient for the variable ISDEL – States (Level 2);
- ν_{oj} random intercept effect;
- ν_{1j} random slope effect;
- ε_{ij} idiosyncratic error term.

The multilevel model estimates the proportion of variance in the dependent variable, CO_2e emissions, that is attributable to differences between Level 2 groups, in this case, the Brazilian states. This proportion is calculated using the intraclass correlation coefficient, as shown in equation 2:

$$\rho = \frac{0.0089861456 + 0.0006075917}{0.0089861456 + 0.0006075917 + 0.0055152694} = 0.6349681$$

In the final model, the states accounted for approximately 63.50% of the variation in municipal CO_2e emissions, indicating the presence of group level effects. This result indicates that the state factor contributes to explaining variations in emissions in Brazil.

Discussion

In 2021, the average CO_2e emissions per municipality in Brazil was 431.402 tons. To examine how these emissions were spatially distributed across the country, a heat map (Figure 1) was constructed using the Getis-Ord Gi statistic. This index compares the average emissions of each municipality and its neighboring areas with the expected value under the assumption of a random and homogeneous distribution (Getis & Ord 1992).

The heat map classifies CO_2e emissions into seven categories: extremely high, high, slightly high, average, slightly low, low, and extremely low. According to the methodology proposed by Getis and Ord (1992), this classification is based on the Gi* statistic and the corresponding p-value. Emissions are considered extremely high when $Gi^* > 0$ and $p < 0.01$; high when $Gi^* > 0$ and $p < 0.05$; and slightly high when $Gi^* > 0$ and $p < 0.10$. When the p-value is not statistically significant, the classification is defined as average. For $Gi^* < 0$, the same thresholds are applied to determine slightly low, low, and extremely low emissions, respectively.

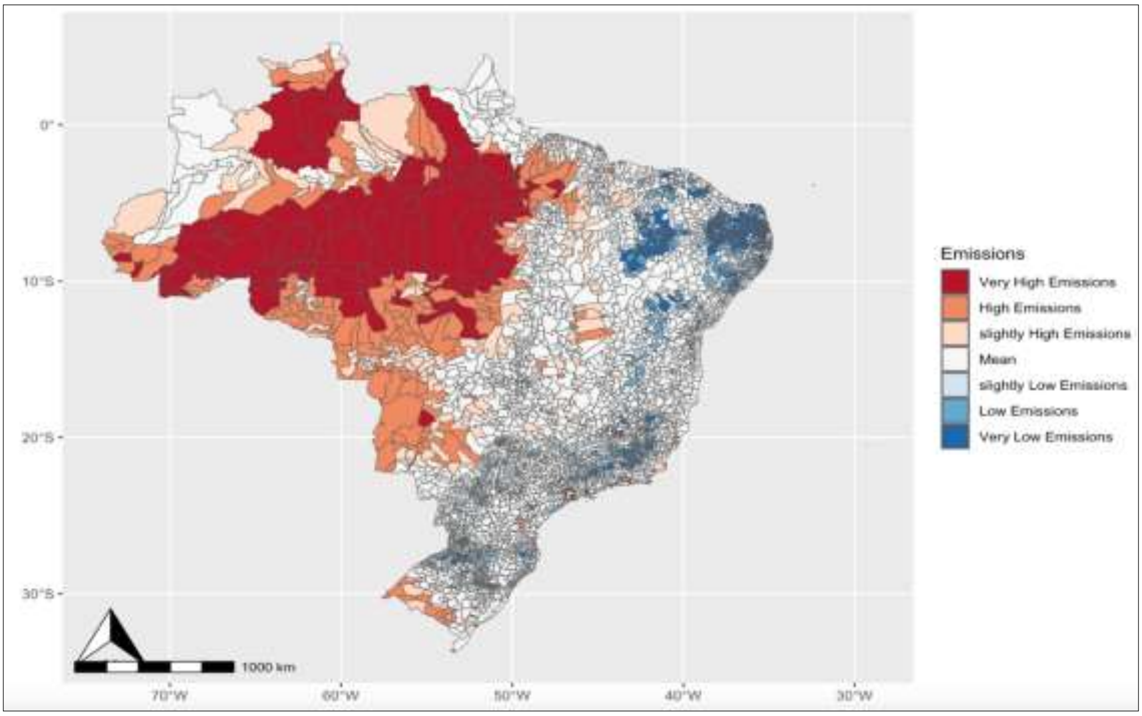

Figure 1: Heat Map of Brazilian CO_2e emissions in 2021. Source: Research's original results. Data collected from Observatório do Clima (2025a).

As shown in Figure 1, in 2021, extremely high CO_2e emissions were concentrated in the Legal Amazon region, which comprises the states of Acre, Amapá, Amazonas, Maranhão, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins (IBGE 2022). According to Observatório do Clima (2025a), deforestation and agricultural activity are the main sectors of emissions in these critical areas. In many of these municipalities, however, socioeconomic indicators were not among the lowest in their respective states (Pietrafesa et al. 2023), suggesting that the dominant development model, based on the expansion of agriculture and livestock, Brazil's second largest source of greenhouse gas emissions, has come at a high environmental cost. This expansion is associated with deforestation in the Amazon, Pantanal and Cerrado biomes, where the country's highest CO_2e levels are concentrated (Talanoa 2024).

Other regional factors contribute to the increase in greenhouse gas emissions. Contributing factors in the Amazon biome include wildfires, forest burning, illegal mining, large scale infrastructure projects without due consideration for socio-environmental impacts, land conflicts, and wildlife trafficking. In the Cerrado and Pantanal, soil erosion and contamination from pesticides and chemical fertilizers. The construction and planning of hydroelectric dams, together with the expansion of waterways to transport agricultural goods from the Midwest region, have also increased pressure on regional river systems. Furthermore, conflicts and disputes over the territories of traditional populations exacerbate both environmental and social challenges (Observatório do Clima 2025b).

In contrast, the states of the Northeast region, as well as Minas Gerais, São Paulo, Santa Catarina, and Rio Grande do Sul, recorded the highest number of municipalities with low or extremely low emissions.

While these territorial and environmental dynamics help explain the spatial distribution of CO_2e emissions in Brazil, they do not fully account for the structural conditions that shape local emission patterns. To address this, the multilevel model proposed in this study incorporates the variable economic complexity into both fixed and random components. According to Hidalgo (2021), this variable allows exploring the implications of economic structures on environmental issues. Empirical evidence, such as presented by Romero and Gramkow (2021), suggests a negative correlation between economic complexity and the intensity of greenhouse gas emissions, indicating that more diverse and sophisticated local economies tend to emit less per unit of economic output.

As presented in Table 4, the final multilevel model reveals statistically significant effects for: economic complexity, precarity ratio, Ln GDP, deforestation, and ISDEL – States. Notably, economic complexity is negatively associated with CO_2e emissions. The coefficient was equal to -0.043935, indicating that municipalities with more diversified and sophisticated productive structures tend to generate lower emissions. The results are consistent with findings in the existing literature (Neagu & Teodoru 2019; Romero & Gramkow 2021; Hidalgo 2021; Boleti et al. 2021; Can & Gozgor 2017). These studies suggest that economies with higher productive complexity and higher overall performance tend to achieve better environmental outcomes, including reductions in greenhouse gas emissions.

The coefficient associated with Ln GDP was equal to 0.078194, establishing a positive relationship between gross domestic product and CO_2e emissions at the municipal level. This result is consistent with the relationship between economic growth and environmental degradation described by Grossman and Krueger (1995), in which increases in income at lower development levels are associated with increases in pollution. Within the model, the coefficients of economic complexity and GDP point in opposite directions, which reflects the distinction between the scale of economic activity and the composition of the productive structure. Grossman and Krueger (1991) identified these as analytically separate channels through which economic development affects environmental quality, a distinction further elaborated by Liang and Wang (2023) in the context of total factor productivity and emissions. The positive association between GDP and emissions reinforces the relevance of structural economic variables in explaining the variation in CO_2e across Brazilian municipalities, as the level of economic output alone does not determine the direction of the effect on emissions.

Economic complexity is linked to increased interdependence among productive sectors, the sophistication of the production structure through technological advancement, and the diversification of knowledge and the capacity to produce a wide range of goods and services. In this context, industry and services tend to play a more significant role in the composition of GDP (Hausmann & Hidalgo 2013). Figure 2 presents the performance of municipal economic complexity by state in 2021.

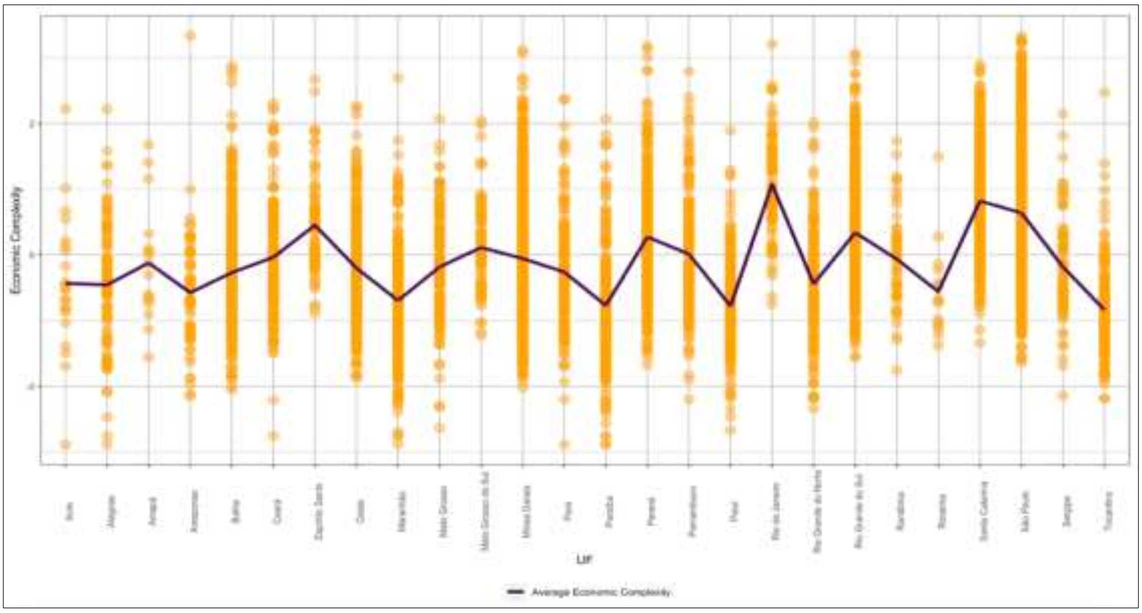

Figure 2: Average Performance of Municipal Economic Complexity by State (2021). Source: Research's original results. Data collected from CEDEPLAR – UFMG (2023).

As shown in Figure 2, the Southern and Southeastern states, except for Minas Gerais, record the highest municipal averages of economic complexity. However, the state of Amazonas, located in the Northern region, stands out by recording the highest economic complexity index for a municipality in the country. According to Romero and Silveira (2019), this result is attributed to the Manaus Free Trade Zone, which hosts a cluster of maquilas that contribute to the diversification of the local productive structure[3].

By 2021, Brazil's economic diversification remained concentrated in the Southern and Southeastern regions, which had a greater number of industries with comparative advantages and higher productive performance compared to the other regions. However, states such as Alagoas, Amazonas, Bahia, Ceará, Goiás, Paraíba, Pernambuco, Rio Grande do Norte, and Roraima reached diversification levels comparable to those of the Southeast, supported by advances in goods production efficiency.

Figures 3 and 5 explore the random components of the multilevel model. Figure 3 presents the estimated random intercepts, capturing baseline CO_2e emissions by state, while Figure 5 shows the random slopes associated with the growth of emissions in response to changes in municipal economic complexity.

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[3] One observation regarding the case of Manaus is that the export of more complex goods is not accompanied by significant productive diversification, since the core activity of the maquila industry is product assembly.

Figure 3: Random Intercept by State. Source: Research's original results

Figure 3 shows that municipalities in the states of Rondônia, Roraima, Acre, Mato Grosso, Mato Grosso do Sul, Amazonas, Pará, Goiás, Tocantins, Rio de Janeiro, Santa Catarina, Maranhão, and São Paulo started from higher average levels of CO_2e emissions compared to other states. This pattern is further illustrated in the violin plots presented in Figure 4, which show that in states like Acre, Rondônia, and Roraima, the lower quartile of municipal emissions exceeds the upper quartile in many other states, indicating high emission levels across most municipalities in these areas.

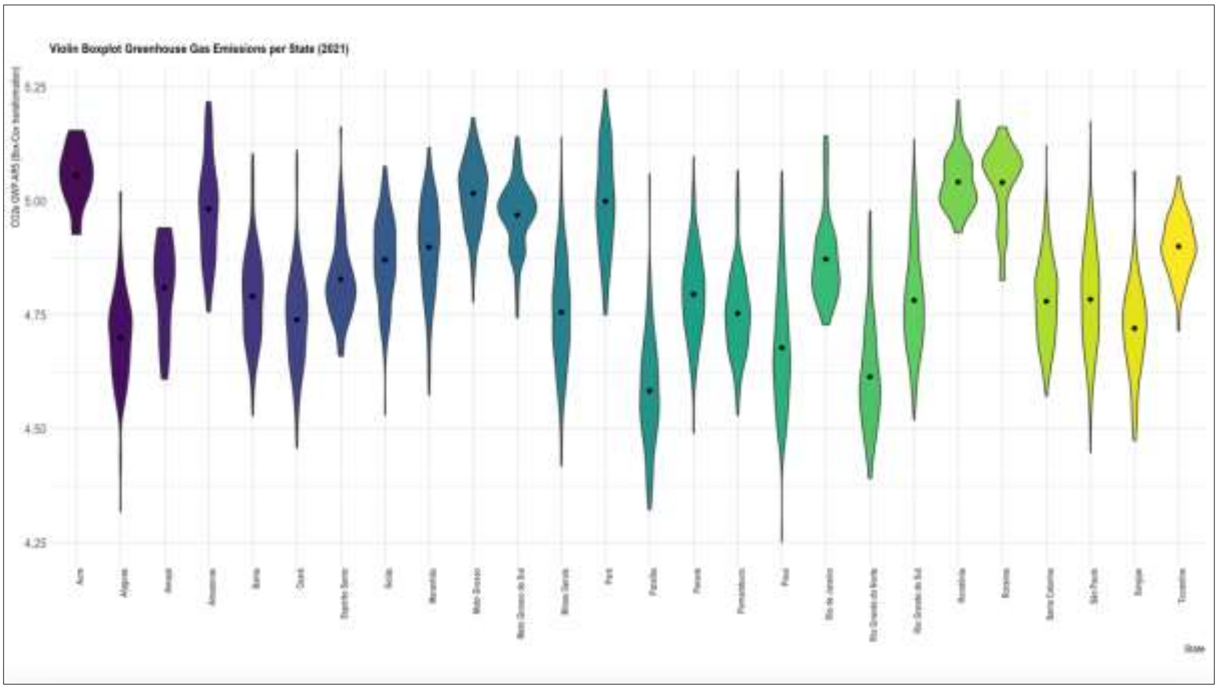

Figure 4: Violin plot Greenhouse Gas Emissions per State (2021). Source: Research's original results. Data collected from Observatório do Clima (2025a).

Figure 5 shows that in states where most municipalities have low or extremely low CO_2e emissions, increases in economic complexity are more closely associated with emission growth. In other words, the lower the initial emission levels, the steeper the slope linking complexity to emissions.

Figure 5: Random Slope by State. Source: Research's original results

Alagoas, Amapá, Ceará, Paraíba, Piauí, Rio Grande do Norte, and Sergipe exhibit greater disparities between municipalities with low economic dynamism and more developed ones. Furthermore, in these regions, Land Use and Land Cover, and agricultural activities that could increase greenhouse gas emissions are less prevalent (Observatório do Clima 2025a).

In industrialized states such as São Paulo, where the average level of municipal complexity index is high, the relationship between complexity and emission growth is present but moderate. This suggests that rising complexity does not translate into environmental gains and may, in certain contexts, accompany increased emissions due to industrial expansion or energy use patterns (Observatório do Clima 2025b).

Taken together, these findings indicate that the relationship between economic complexity and greenhouse gas emissions varies considerably across Brazil. While national level studies, such as Romero & Gramkow (2021), have identified a negative association between complexity and emissions, the subnational patterns observed in this research indicate variation at the subnational scale. As Soares and Cunha (2019) argue, local socioeconomic structures influence the environmental efficiency of municipalities, which helps explain the observed variation in slopes.

Conclusion

Brazil ranks as the fifth-largest emitter of greenhouse gases in the world. This is a cause for concern because it highlights the way the country has been dealing with the environment. Given its large size, there is local variability in the emissions pattern. The data made available by the Observatório do Clima and spatialized through the heat map (Figure 1) show the spatial distribution of high emissions in municipalities in the Legal Amazon, the Midwest and scattered across municipalities in the South and Southeast states.

Considering the spatial distribution of emissions and the economic dynamics of the municipalities, the central question of the study was how municipal economic development in Brazil influences greenhouse gas emissions. To organize a response based on data with hierarchically structured observations, a multilevel model was employed. Thus, the results of the final model indicate that the state to which a municipality belongs has an effect on CO_2e emissions. This is reflected in the variance of the random intercept, which shows differences in average emission levels across states. For example, municipalities located in Acre and Rondônia recorded higher averages, regardless of their local economic conditions. In addition, the ISDEL variable, which captures economic development at the state scale, was statistically significant in the model and suggests that the broader economic context influences municipal emissions. These findings demonstrate that, beyond local factors, state productive structures contribute to shaping emission patterns across Brazilian municipalities.

Another part of the answer to the research question concerns the growth rate of CO_2e emissions associated with a one unit increase in economic complexity. This variable reflects the local economic structure, capturing the degree of interdependence between sectors and the diversification of productive activities. The model results indicated that, in states with higher average emission levels, the increase in municipal emissions associated with economic complexity was smaller compared to states with lower averages. This was identified through the inclusion of economic complexity as a random slope variable in the multilevel model.

This second aspect of the analysis highlights a limitation of the study, related to the absence of a longitudinal approach to capture changes in emissions over time. The analysis is based on a cross-sectional dataset and does not account for long-term structural shifts at the municipal level. Despite this limitation, the findings contribute to the broader discussion on the relationship between local economic structure and greenhouse gas emissions, using subnational empirical evidence.

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