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Greenhouse Gas Emissions From Agricultural Production In The Brazilian States Of Alagoas And Sergipe Between 2006 And 2017.

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Abstract:
The research had the following specific objectives: a - to identify and quantify the municipalities in the states of Alagoas and Sergipe that showed a reduction or expansion in greenhouse gas (GHG) emissions between 2006 and 2017 and, as a result, meet one of the requirements for cultivating climate-smart agriculture; b - to aggregate the indicators that are supposed to have contributed to the reduction or expansion of GHG in the municipalities of these two states; c - to assess how GHG emissions respond to these synergies summarized in the indicators used. The research uses secondary data from the 2006 and 2017 Agricultural Censuses, from which information was extracted on the variables that are supposed to affect greenhouse gas emissions in the municipalities of the states of Alagoas and Sergipe over that 11-year period. The information on greenhouse gas (GHG) emissions was taken from the Greenhouse Gas Emissions Estimates System (SEEGOC, 2022). The relationship between GHG emissions in 2006 and 2017 was estimated to show where there was an increase or decrease in GHG emissions over that period of time. It was found that in 68 of the 176 municipalities studied (39%), there was a reduction in these emissions Several variables that could probably interfere with these emissions were tested. Of these variables, only six were relevant. The research objectives were achieved, but the results are still inconclusive, especially with regard to the variables that can influence GHG emissions from agricultural activities.

***Key Word**: Climate-smart agriculture; Climate-resilient agriculture; Semi-arid Brazil; Sustainability of productivity; Climate variations.*

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I. Introduction

In Brazil, agriculture plays a major role in the Gross Domestic Product (GDP). In order to meet the demand for grains and food, Brazilian agriculture has undergone several transformations in recent decades, especially since the 1970s, with the creation of the Brazilian Agricultural Research Corporation (EMBRAPA). These transformations were based on the creation and dissemination of new knowledge and applied research[1]. Agricultural activity has thus become more efficient, making Brazil one of the world's leading producers of food, fiber and bioenergy.

In this context, in order to continue contributing to the production of exportable food and raw materials and to meet the needs of the national agro-industry, the sector needs to be able to expand. In order not to cause major environmental impacts, this expansion must take place without the need to incorporate new areas into the production process, emphasizing technological progress that promotes advances in land productivity. In the last decade, an agricultural frontier called Sealba was created in the Northeast, made up of a group of municipalities in the states of Sergipe, Alagoas and Bahia, with high potential for agricultural production, substantially in grain production. But this agricultural frontier was not anchored in the use of new areas to grow these crops. It was because it was possible to detect that there were aptitudes there for the production of more capital-intensive crops, unlike those that are mostly cultivated throughout the Brazilian Northeast, including in these three states[2].

Agricultural activities, especially those practiced in more capital-intensive agriculture in the form of machinery and agrochemicals, are repeatedly accused of contributing to greenhouse gas emissions. So much so that in 2010 the United Nations created the concept of Climate Smart Agriculture (CSA). And this concept was practically based on the agricultural practices of the poorest economies, especially those that experience phenomena such as drought, as in the case of the Brazilian Northeast [3,4,5].

For agriculture to be considered climate smart, it has to meet three requirements: 1 - present sustainable income and productivity; 2 - be climate resilient agriculture (CRA); 3 - reduce or eliminate greenhouse gas emissions [3,4].

GHG emissions are due to the progressive increase in the consumption of fossil fuels, both through chemical fertilization and the burning of fuels in machinery used in agricultural activities, the intensification of the use of natural resources, unsustainable production and agricultural processes, poor waste management and changes in land use, such as deforestation. From this perspective, the agricultural sector emitted 492.2 million tons of CO_2, and of this total, Brazil contributed 25% of emissions [4,6].

To get around this situation, the use of practices is being sought so that agriculture progressively reduces carbon emissions and equivalent pollutants. This activity is justified by the need to reduce the sector's contribution to the country's total greenhouse gas emissions and due to the impacts that climate instability can have on the sector. Thus, low-carbon agriculture can be defined as agriculture that is capable of reducing greenhouse gas (GHG) emissions through agricultural practices and technologies that are capable of reducing their emission intensity [7,6,4].

This study is justified by the need to understand the impact of agricultural and livestock production on greenhouse gas (GHG) emissions in selected municipalities in the states of Alagoas and Sergipe, two of the states that are located in the Brazilian Northeast and which have a large part of their territory inserted in the semi-arid climate regime. The study seeks to assess how the agricultural activities practiced in the municipalities behaved in the period between the 2006 and 2017 Agricultural Censuses. To this end, this research aims to answer the following questions: 1 - How many municipalities in Alagoas and Sergipe behaved differently in terms of GHG emissions in the period between the 2006 and 2017 Agricultural Censuses? 2 - Which variables probably had an impact on the reduction or expansion of GHG emitted by the agricultural sector in the municipalities of the two states.

In order to answer these questions, the research has the following specific objectives: a - identify and quantify the municipalities in the states of Alagoas and Sergipe that showed a reduction and expansion in greenhouse gas (GHG) emissions between 2006 and 2017 and, as a result, meet one of the requirements for cultivating climate-smart agriculture; b - aggregate the indicators that are supposed to have contributed to the reduction or expansion of GHG in the municipalities of these two states; c - gauge how GHG emissions respond to these synergies synthesized in the indicators used.

The paper is structured as follows. In addition to this introductory section, there are three more sections. The second presents the methodology used in the research. The third section presents and discusses the results and the fourth section presents the conclusions.

II. Climate-Smart Agriculture

Agriculture faces three interlinked challenges: ensuring food security by increasing productivity and yields, adapting to climate variations and contributing to the mitigation of these variations [8,9,10,11]. Meeting these three challenges will require reducing the pressure on the use of natural resources, especially water, and will require drastic changes in our food systems, making them more efficient at all scales, from agricultural production to the global level. They need to be more efficient in their use of resources (using less land, water and chemical inputs to produce more food sustainably) and more resilient to changes and shocks, especially those caused in the semi-arid Northeast, where water instability is the norm [12,13].

It was to address these transformations that the FAO developed the concept of Climate Smart Agriculture (CSA), pointing to it as the way forward to guarantee food security in an ever-changing climate. CSA seeks to improve food security, help communities adapt to climate variations and contribute to mitigating these changes through the adoption of appropriate practices, the development of enabling policies and institutions, and the mobilization of the necessary financial resources [14].

Climate variations have already had an impact on agriculture [15] and are expected to continue to influence food production directly and indirectly. Among the climatic factors that have always affected agriculture are temperature fluctuations, intermittent rainfall, the occurrence of droughts, floods and frosts, and variations in the water balance that are the norm in areas located under climatic regimes such as the semi-arid region, for example, in which all nine Northeastern states are located and part of two Southeastern Brazilian states (Espírito Santo and Minas Gerais). A significant part of the populations of Brazilian municipalities (including those studied in this research) survive under this climate regime [16,17,11,18,19].

In short, climate-smart agriculture (CSA) is a fundamental strategy for guaranteeing food security in a context of climate instability, which is a challenge to overcome [20]. By suggesting sustainable agricultural practices that are resilient to climate instability and save greenhouse gas emissions, CSA seeks to optimize the use of natural resources. The implementation of CSA requires a joint effort by governments, farmers, researchers and civil society to build more efficient, equitable and resilient food systems [21,22,23]. However, it is crucial to recognize that the transition to CSA requires significant investments in research, technological development and farmer training, as well as public policies that encourage the adoption of sustainable practices [24,25,26].

It is worth noting that the literature is still quite scarce in terms of studies that have effectively sought to identify places on the planet where climate-smart agriculture can be said to exist. In this sense, the pioneering work by Bezerra[4] stands out as one of these attempts to gauge the existence of CSA in the Brazilian Northeast. The research carried out by this author shows that in three of the nine states of the Brazilian Northeast, for which the research was carried out, the three requirements for the existence of climate-smart agriculture are only partially met.

III. Material And Methods

The research uses secondary data from the 2006 and 2017 Agricultural Censuses, from which information was extracted on the variables that are thought to affect greenhouse gas emissions in the municipalities of the states of Alagoas and Sergipe over that 11-year period. The variables and data sources used are shown in Table 1. The state of Alagoas has 102 municipalities. Information on greenhouse gas emissions (GHG) is available for these municipalities from SEEG[27]. However, for only 58 of these municipalities was it possible to collect information from the 2006 and 2017 Agricultural Censuses on the variables that are assumed to interfere with these emissions.

The state of Sergipe has 75 municipalities, but information on GHG emissions is only available for 74 of them. On the other hand, only 52 of the state's municipalities have information on the variables that were used as probable influencers of these emissions.

Table 1 - Variables used to measure Greenhouse Gas (GHG) emissions, definitions of these variables, ways of measuring them, sources in the years 2006 and 2017 in the states of Alagoas and Sergipe

Variables	Definition	Units of measurement	Sources
GHG	Level of greenhouse gas emissions	Ton of CO2 and/or equivalent (ton CO2)	Greenhouse Gas Emissions Estimates System - SEEG (OC, 2022)
VEGCOV (Vegetation coverage)	(Areas with temporary crops + areas with permanent crops + areas with natural forests + areas with planted forests + areas with natural pastures and native pastures) / total area of the establishment)	Hectare	2006 and 2017 Brazilian Agricultural Census / IBGE
CATTLE (Cattle herd)	(Number of cattle / area of natural and cultivated pasture)	Cattle/ Hectare	2006 and 2017 Brazilian Agricultural Census / IBGE
MACHIN = (Tractors and machinery)/ ha	(Total tractors and machinery) / total area of the establishment)	Quantity of mechanical equipment and area in hectares	2006 and 2017 Brazilian Agricultural Census / IBGE
PESTIC = Agricultural pesticides	Number of liters of pesticides per establishment in the municipality	Liters of pesticides	2006 and 2017 Brazilian Agricultural Census / IBGE
RAINFA = Average annual rainfall	Average annual rainfall in the municipality	Annual millimeters	NOAA (2022)
CVRAIN = Rainfall coeficient of variation.	Standard deviation of observed rainfall / average rainfall	%	NOAA (2022)

Source: Prepared on the basis of data from SEEG, the Agricultural Census (2006 and 2017) and NOAA (2022)[28,29,30].

Methodologies used to meet each research objective.

The strategies for achieving the research objectives consist of first constructing the indicators to be used. Since the aim is to assess whether there have been changes in GHG emissions between 2006 and 2017 and how the variables listed in Table (1) affect these emissions, the indicators are constructed as follows: The relationships between the observed values of both GHG and the variables that are supposed to interfere with them in 2017 (the final year of observations) and 2006 (the initial year of observations) are estimated. In doing so, the construction of the variables already shows whether there was a reduction or increase in each of them between 2006 and 2017. Thus, in municipalities where the GHG2017/GHG2006 ratio is greater than one, it means that there was an increase in the emission of these gases over the time period studied. If the ratio is less than one (1), it implies a reduction in emissions between 2006 and 2017. The same procedure will be followed for the explanatory variables. Table 2 shows the construction of the indicators.

Table 2 - Construction of the dependent (GHG) and explanatory (indicators) variables used in the research	
Variable/indicators	How they were built
Y_i	$\mathbf{GHG}_{2017}$ / $\mathbf{GHG}_{2006;}$
X_{i1}	$\mathbf{VEGCOV}_{2017}$ / $\mathbf{VEGCOV}_{2006;}$
X_{i2}	$CATTLE_{2017}$/ $CATTLE_{2006}$
X_{i3}	$MACHIN_{2017}$ / $MACHIN_{2006}$
X_{i4}	$PESTIC_{2017}$/ $PESTIC_{2006}$
X_{i5}	$RAINFA_{2017}$/ $RAINFAL_{2006}$
X_{i6}	$CVRAIN_{1901a2017}$/ $CVRAIN_{1901a2006}$
Source: Variables to be tested in the research.	

Having transformed the variables into indicators, as shown in Tables 1 and 2, the methodological procedures for achieving each of the objectives are outlined, which are divided into three (3) stages. The first stage identifies and quantifies the municipalities that had a reduction in GHG emissions between 2006 and 2017 and the municipalities that had an increase in these emissions over that period of time. Then the discrete geometric growth rates of GHG emissions by municipalities are estimated, as well as each of the variables used in the research as drivers of these emissions. In the second stage, the partial interactions between the variables are assessed. To this end, the factor analysis method is used, using the principal component decomposition technique. At this stage, k < n variables are generated which bring together the characteristics of two or more of the variables defined at this stage of the research. Based on this synergy, a GHG emission index (IGHG) is constructed which will condense the information they share. In the third stage, the probable dependency relationship between GHG emissions and the unobserved variables (factor scores) generated in this stage is assessed using multiple regression analysis.

Methodology for achieving the first objective (objective a)

To achieve this objective a, the levels of GHG emitted between 2006 and 2017 are identified and aggregated by their respective averages. The groups in which the GHG ratios were less than 1 (municipalities that showed a reduction in emissions in the period under review) and the averages of the GHG and the indicators studied observed in the municipalities in which the ratio is greater than one are separated, including the municipalities in which there is no information for the variables that are supposed to affect these emissions. The same is done for the variables that are supposed to affect these emissions, obviously in municipalities where this information is available.

The research then assesses whether there was stagnation, evolution or involution of GHG and the variables that are supposed to affect these emissions in the municipalities of Alagoas and Sergipe between 2006 and 2017. To this end, the discrete geometric growth rates (DGGR) of GHG emissions between 2006 and 2017 are estimated, as well as the variables used to explain these emissions. The discrete DGGR are estimated using the equation:

$$DGGR = (V_n / V_0)^{(1/T)} - 1 \quad (1)$$

In equation (1) V_0 is the initial value (observed in 2006) of the variable for which the DCGT is to be estimated; V_n is its final value (observed in 2017). T is the elapsed time, 11 years in this case. The constant "r", measured as a percentage, will measure the average annual percentage by which V will vary between periods "0" and "n". In this study, V_0 can be either GHG emissions in 2006 or the indicators used to explain these emissions. V_n represent the values observed for these indicators in 2017. The time span T will be between 2006 and 2017, 11 years. By multiplying equation (1) by 100, the DGGR reading is the average percentage change of the variable on the left-hand side of the equation. If the value of DGGR > 0 means that the variable expanded between 2006 and 2017, the average annual expansion being defined by the magnitude of DGGR. On the other hand if DGGR < 0, it means that the value of the variable decreased between 2006 and 2017, with the annual magnitude of the DGGR.

Methodology for achieving the second objective (objective b)

In order to estimate the synergy between the indicators that are supposed to interfere with GHG emissions, the factor analysis (FA) procedure was adopted, using the principal component decomposition technique. A brief summary of the factor analysis method, as used in this study, is presented below.

In general, a factor analysis model can be represented as follows:

$$X = af + e \quad (2)$$

In equation (1) $X = (X_1 , X_2 , ... , X_n)^T$ is a transposed vector of "p" observable random variables; f = (f , f , ... , f $)^T$ is a transposed vector r < p of unobservable variables or latent variables called factors; a is a matrix (p x r) of fixed coefficients called factor loadings; e = (e1, e2, ..., ep$)^T$ is a transposed vector of random terms. Normally, E(e) = E(f) = 0.

In general, the initial structure of the factor loadings estimates is not definitive. In order to confirm or reject the initial structure, the factor analysis method offers the possibility of rotating this initial structure. In the specific case of this study, the varimax method of orthogonal factor rotation was used. This procedure has the additional advantage of making the factors orthogonal or independent. Readers interested in more details on this and other rotation methods (including oblique rotation procedures) can find them in the works by [31,32,33,34].

To construct the index, the scores associated with the factors obtained after orthogonal rotation of the initial factor structure are estimated. By definition, the factor score will place each observation in the space of common factors. Thus, for each factor fi the i-th factor score that can be extracted is defined by Fi , and can be expressed by the following equation (3):

$$F_i = b_1X_{i1} + b_2X_{i2} + ... + b_pX_{ip} \text{ ; } i = 1, 2, ... , n; j = 1, 2, ... , p \tag{3}$$

Where $b_1, b_2, ..., b_p$ are regression coefficients; $X_{i1}, X_{i2}, ..., X_{ip}$ are p observable variables.

The variable F_i is not observable, but it can be estimated using existing factor analysis techniques, using the matrix X of observable variables. Equation (3) can thus be rewritten in a compact form using matrix notation, as follows:

$$F_{(n\ x\ q)} = X_{(n\ x\ p)}.B_{(p\ x\ q)} \tag{4}$$

In equations (3) and (4), the factor scores will be affected by both the magnitude and the units in which the X variables are measured. To avoid this type of problem, the variable X is replaced by the normalized variable Z, where:

$$Z_{ij} = [(X_i - m_{xi})/s_{xi}] \tag{5}$$

where m_{xi} is the mean of x_i , and s_{xi} is its standard deviation. In this way, equation (5) can be modified to obtain the following result:

$$F_{(n\ x\ q)} = Z_{(n\ x\ p)}.b_{(p\ x\ q)} \tag{6}$$

In equation (6) the vector b replaces B, because the variables are normalized on both sides of the equation. Pre-multiplying both sides of equation (6) by the value $(1/n)Z^T$, where n is the number of observations, and Z^T is the transposed matrix of Z, gives the result shown in equation (7):

$$(1/n)Z^TF = (1/n)Z^TZb \tag{7}$$

The expression $(1/n)Z^TZ$ is actually the correlation matrix between the terms of X, which will be designated by R. The matrix $(1/n)Z^TF$ represents the correlation between the factor scores and the factors themselves, and will be identified by L. Equation (7) can now be redefined as follows:

$$L= R.b \tag{8}$$

If it can be assumed that R is a non-singular matrix, this is done using the Bartlet test. For the procedure to proceed, the hypothesis that the matrix of correlations between the variables is not an identity matrix must be rejected, with at least a 5% error level (Fávero, 2017).

If the hypothesis that R is non-singular matrix is accepted, we can pre-multiply both sides of equation (8) by the inverse matrix of R (R^{-1}). In this case, the following result is obtained:

$$b= R^{-1}.L \tag{9}$$

In order for the estimated model to be used, the Kaiser-Meyer-Olkin (KMO) test must be carried out, and the estimated statistic must be greater than 0.5. In addition, the total variance explained by the estimated orthogonal factors must be greater than 50% [34].

Methodology adopted to achieve objective "c".

Having estimated vector "b", as shown in equation (9), the third objective of this research can be achieved, which is to assess how GHG emissions respond to the synergies synthesized between the indicators used. To this end, the compositions of each estimated factor are identified through the magnitudes of the loadings. These "k" factors, to which the original "n" variables have been reduced (k<n), can be redefined and given new names based on the magnitudes of the factor loadings that the variables present in each component factor. The principal component reduction procedure allows for the generation of coefficient scores which allow for the formation of factor scores. These FE factor scores are normalized variables with a mean of zero and a standard deviation of one. Therefore, positive and negative values gravitate around the zero mean of these FE. They can be transformed into partial indices associated with the ith municipality (Ii), using equation (10). These partial indices can be supplemented, depending on the variables that were added to the composition of each factor score that generated it.

$$I_i = (FE_i - FE_{MN})/(FE_{MX} - FE_{MN}) \tag{10}$$

In equation (10) FE_i is the i-th normalized factor score; FE_{MN} is its minimum value and FE_{MX} is its maximum value. When constructed in this way, Ii will have values varying between zero and one and it is in this form that it is used in this study to find the predicted results for the third objective (objective c) based on the procedure shown in equation (11).

$$GHG_i = f(I_1; I_2, ..., I_p) \tag{11}$$

IV. Result And Discussion

The state of Alagoas has 102 municipalities, but only 58 of them had information on all the variables shown in Table 1. The state of Sergipe, in turn, has 75 municipalities, of which only 52 had the information used in this study.

The reasons for the reduction in the number of municipalities studied were due to the lack of information on the variables evaluated in at least one of the Agricultural Censuses from which this information was extracted. However, it is believed that the results achieved with data from approximately 57% of the municipalities in Alagoas and 69% of the municipalities in Sergipe can be useful in answering the questions posed by this research.

Of the total number of municipalities in the state of Alagoas, 39 (38.2%) saw a reduction in GHG emissions. However, the sample used in this study, due to the difficulties explained in the previous paragraph, only used 17 of these municipalities.

In the state of Sergipe, there was a reduction in GHG emissions in 39 (52%) between 2006 and 2017. However, in the sample of municipalities used in this study, due to the difficulties presented in the previous paragraph, only 26 of these municipalities were used.

Table 3 summarizes the results obtained in aggregate for the states of Alagoas and Sergipe, for municipalities where GHE2017/2006 < 1 and for those where the ratio was greater than 1.

Table 3 - Total municipalities, average values of GHG emissions, estimates of DGCR, as well as the variables assumed to affect GHG emissions in the states of Alagoas and Sergipe between 2006 and 2017

	Municipalities where there was a reduction in GHG between 2006 and 2017 (Ratio < 1.0)			Municipalities where there was an increase in GHG between 2006 and 2017 (Ratio > 1.0)		
Variables	**Obs**	**Mean**	**DGGR (% a.a.)**	**Obs**	**Mean**	**DGGR (%)**
GHG*	25	0,75	-1,36	42	1.38	1.54
GHG	43	0.82	1.01	67	1.38	1.02
VGCOVER	43	1.01	-0.53	67	1.00	-0.44
CATTLE	43	0.93	0.35	67	1.00	0.80
MACHINE	43	1.44	0.14	67	1.44	0.24
PESTICIDE	43	1.39	-1.00	67	1.42	-0.99
RAINFALL	43	1.13	-	67	1.13	-
CVRAINFALL	43	1.01	-	67	1.02	-

Sources: IBGE. 2006 and 2017 Agricultural Censuses. System for Estimating Greenhouse Gas Emissions and Removals - SEEG. National Oceanic and Atmospheric Administration - NOAA.

GHG* Municipalities that have information on GHG emissions, but do not have information on the variables that are supposed to explain these emissions.

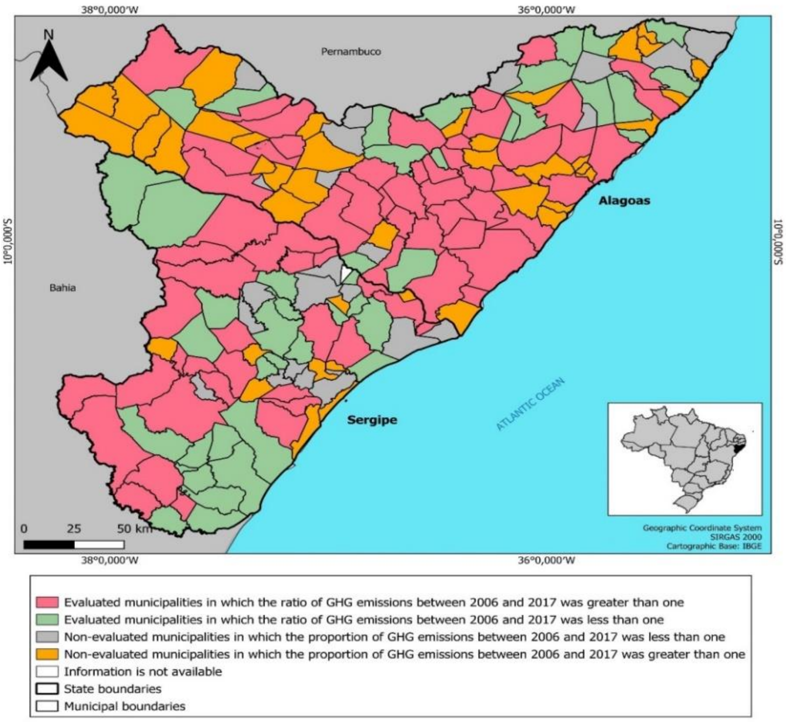
The results shown in Table 3 suggest that the average ratio of GHG emissions by the agricultural sector in the 68 municipalities in Alagoas and Sergipe where there was a reduction in emissions between 2006 and 2017 was 0.82. In the 109 municipalities in the two states that saw an increase in GHG emissions, the average ratio was 1.38.

The average ratio in the use of agricultural pesticides of 1.39 and the intensity ratio of cattle per hectare of around 0.93, among the municipalities that had a reduction in GHG emissions between 2006 and 2017, seem to have been those that contributed most to this result among the indicators studied. This is because the relationships between these indicators in the municipalities that had an increase in the GHG emission ratio, the ratios between these two indicators were 1.42 and 1.00 respectively (Table 3).

One of the worrying results is that presented by the discrete geometric growth rate (DGGR) of vegetation cover), showing that, in the municipalities where there was a reduction in GHG emissions from the agricultural sector, its magnitude was -0.53% per year. In the municipalities that saw an increase in GHG emissions, DGGR was -0.44% per year. If these DGGR drop rates continue in the future, many municipalities that had a reduction in GHG emissions may soon have this situation reversed. (Table 3).

Figure 1 shows the positions of municipalities in which $GHG_{2017}/_{2006} < 1$ and those in which the relationship was greater than 1, both for those that were studied and for those that were not included due to lack of data. Figure 1 shows that the state of Sergipe has a greater relative number of municipalities with reduced GHG emissions than the state of Alagoas over the period studied.

Figure 1 – $GHG_{2017/2006}$ relationship for the municipalities of Alagoas e Sergipe



Source: Greenhouse gas emissions and removalls estimation system– SEEG.

Results obtained in measuring the third objective (objective "c")

Table 4 shows the results found using the principal component decomposition procedure of the factor analysis (FA) used in the research. This analysis makes it possible to evaluate the actions of the variables not in isolation, but in synergistic ways.

The results shown in Table 4 show that it was possible to carry out the factor analysis, given that the correlation matrix between the variables used is not an identity, as can be seen from the statistics obtained through Bartlet's test of sphericity of the order of 80.725 with 15 degrees of freedom, with 15 degrees of freedom at a significance level of less than 1%. Three orthogonal factorial components were extracted from the six original variables, given that the varimax method was used to estimate these components. The Kaiser-Meyer-Olkin statistic, which measures sampling adequacy, was low, but higher than the minimum accepted critical level of 0.5. The total variance explained by the three factors is 68.06%, with the relative shares of each component being 29.25%, 19.55% and 19.26% respectively (Table 4).

It can be seen that with component 1 the variables with the highest factor loadings were the relationships between rainfall (loading = - 0.896) and the relationships between CVs (loading = 0.912). Based on this information, this factor can be called the "Rainfall Instability Index" = INS.

The second component generated has the highest factor loadings with the variable machinery ratio (loading = 0.749) and pesticide ratio (loading = 0.705). This component is called the "modernization index" (IMO).

The third component obtained in the analysis brings together the highest loadings in vegetation cover (loading = 0.770) and cattle density per pasture area (loading = - 0.644). This factorial component was designated in the research as the environmental index (IEN)

Table 4 - Result of factor analysis after orthogonal rotation using the varimax method

Variabels	Factor 1 (INS)	Factor 2 (IMO)	Factor 3 (IEN)	Communalities
X_{i1} = **VEGCOV**$_{2017}$ / **VEGCOV**$_{2006}$	0.191	0.199	**0.770**	0.668
X_{i2} = CATTLE$_{2017}$/ CATTLE$_{2006}$	0.256	0.271	**-0.644**	0.553
X_{i3} = MACHINE$_{2017}$ / MACHINE$_{2006}$	-0.100	**0.749**	0.265	0.641
X_{i4} = PESTICIDE 2017/ PESTICIDE$_{2006}$	0.092	**0.705**	-0.280	0.584
X_{i5} = RAINFALL $_{2017}$/ RAINFALL$_{2006}$	**-0.896**	0.027	0.020	0.803
X_{i6} = CVRAIN $_{1901a2017}$/ CVRAIN $_{1901a2006}$	**0.912**	0.031	-0.002	0.833
Explaneid Variance (%)	29.248	19.549	19.261	
Keiser-Meyer-Okult (KMO) Estatistics		0.514		
Bartlett's Chi-Square Test		80.725*		

Sources: IBGE. 2006 and 2017 Agricultural Censuses. System for Estimating Greenhouse Gas Emissions and Removals - SEEG. National Oceanic and Atmospheric Administration - NOAA.
Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Component scores.
*Statistically different from zero with less than 3% error

Based on this information, we tested the hypothesis that these three partial indices interfere totally or partially in the emission of GHE as shown in equation (11) in the Methodology section and now adapted to the research evidence.

$$GHE_i = \beta_0 + \beta_1 INS_i + \beta_2 IMO_i + \beta_3 IEN_i + \beta_4 D + \epsilon_i \quad (11)$$

In equation (11), which was adapted to the research results, the variable D is a dummy that takes on the following values: D = 0 when the GHE emission ratio between 2006 and 2017 is less than 1, i.e. in municipalities where there was a reduction in emissions over that period of time. The variable D = 1, in municipalities where the ratio of GHG emissions between 2017 and 2006 is greater than 1. The angular coefficients β1; β2 and β3, if they are statistically different from zero, measure, respectively, the sensitivity of the ratio of GHG emissions between 2006 and 2017 to each of the variables they are associated with. The angular coefficient, being statistically different from zero, means that emissions ratios less than one are statistically different from ratios greater than 1. Table 5 shows the results found when estimating the parameters of equation (11).

Table 5 - Results found for the adjustment of GHE emissions in response to the tested variables.

Explanatory variables	Coeficients	Student Statistics (t)	P value
Constant	0.921	7.212	0.000
INS	0.185	1.746	0.084
IMO	-0.007	-0.066	0.947
IEN	-0.363	-1.648	0.102
D	0.550	11.310	0.000
Adjusted R^2	0.557		

Sources: IBGE. 2006 and 2017 Agricultural Censuses. System for Estimating Greenhouse Gas Emissions and Removals - SEEG. National Oceanic and Atmospheric Administration – NOAA

The results found at this stage of the research and shown in Table 5 suggest that the rainfall instability index (INS) was statistically different from zero at the 8.4% error level and the environmental index (IEN) was statistically different from zero at the 10.2% error level. It can also be seen that the modernization index (IMO) was not statistically different from zero at acceptable levels. Therefore, the results suggest that only the variables INS and IEN, among those studied, can be attributed to interferences in the magnitudes of GHG emissions between 2006 and 2017 in the states of Alagoas and Sergipe. The statistical significance of the constant, at a zero percent error level, suggests that the levels of GHG emissions in the municipalities that had a reduction are statistically different (lower) than those observed in the municipalities that had an increase in GHG emissions, those whose ratio was greater than one (Table 5).

From the results shown in Table 5, we can write the two equations that apply to the 43 municipalities in Alagoas and Sergipe that had GHE emissions between 2006 and 2017 lower than one (reduction in emissions in the period, equation 11a) and for the 67 municipalities that had a GHE emissions ratio in that period higher than one (increase in emissions in the period, equation 11b).

$$GHE_{2006/2017}^{<1.00} = 0.921 + 0.185INS - 0.007IMO - 0.363IEN \quad (11a)$$

$$GHE_{2006/2017}^{>1.00} = 1.478 + 0.185INS - 0.007IMO - 0.363IEN \quad (11b)$$

The positive sign associated with the INS variable suggests, as expected, that greater rainfall instability should lead to higher GHG emissions. The negative sign associated with IEN, also as expected, suggests that greater vegetation cover associated with a lower intensity of cattle per hectare of pasture induces a reduction in GHG emissions. With regard to the variables that indicate modernization in the agriculture practiced in the municipalities studied in the two states, the result was inconclusive. This is also to be expected, given that agricultural activities in these two states still make little use of these types of inputs.

V. Conclusion

The research sought to show how GHG emissions evolved or involuted in the 102 municipalities studied in the state of Alagoas and the 75 municipalities studied in the state of Sergipe between 2006 and 2017, based on two samples comprising 58 municipalities in Alagoas and 52 municipalities in Sergipe, given that only these municipalities had information on the variables for which it was hypothesized that they influenced these emissions.

The results showed that in 28 municipalities in Alagoas there was a reduction in GHG emissions, while in the other 74 there was an increase in GHG emissions between 2006 and 2017. On the other hand, of the 75 municipalities that make up the state of Sergipe, 39 saw a reduction in GHG emissions in that period. In 35 of these municipalities there was an increase in these gases. In one municipality in the state of Sergipe, there was no information on GHG emissions in 2006 and 2017.

The results show that in 68 (39%) of the municipalities sampled in the two states, there was an average increase in emissions of these gases, with a geometric growth rate of 0.14% per year. In the 109 municipalities that showed an increase in GHG emissions between 2006 and 2017, the expansion occurred at an average annual rate of 1.22% per year.

Six variables were tested which were thought to have contributed to these emissions. The hypothesis was that these variables would act synergistically and could therefore interfere with GHG emissions in the agricultural sectors of the municipalities studied. The variables were grouped using the principal component decomposition technique of the factor analysis method. Three variables were generated as a result of combining them two by two using the procedure adopted. The conclusion is that rainfall instability, measured by a reduction in rainfall observed in 2017 compared to 2006, in synergy with greater instability in 2017 compared to 2006, measured by a higher CV in 2017, contributed positively to the increase in GHG emissions between those years. The other combination of variables that interfered with the variation in GHG emissions between the two periods was the synergy between vegetation cover and the density of cattle per grazing area.

The research was able to answer the two questions on which it was based, and the objectives that served as its anchor were all met. However, the results found in the study can be considered preliminary and not yet conclusive, in terms of the variables that can influence the increase or reduction of GHG emissions from agricultural activities in these two states. But they can serve as starting points for future studies in this promising and current line of research.

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