ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 13 (2023) No.3, pp. 517-532
DOI:10.33168/JSMS.2023.0335

An Applied Study of Data Envelopment Analysis on Brazilian Agriculture Data

Carlos Rosano Pena [1], Andre Luiz Marques Serrano [2], Lucas Oliveira Gomes Ferreira [3], Patrícia Guarnieri [1], Maria Gabriela Mendonça Peixoto [2], Clovis Neumann [2], João Carlos Félix Souza [2], Sé gio Ronaldo Granemann [2], Renata Castro [4] and Gilmar Santos [4]

[1] Department of Management, University of Brasília - UnB, Brasília, Brazil
[2] Department of Production Engineering, University of Brasília - UnB, Brasília, Brazil
[3] Department of Accounting, University of Brasília - UnB, Brasília, Brazil
[4] Federal District Government, Brasília, Brazil

lucasoliveira@unb.br (Corresponding author)

Abstract. This paper aimed to estimate and spatially analyze an agricultural eco-efficiency index for the Central-West Brazilian municipalities. To achieve this objective, we used methods of Data Envelopment Analysis (DEA) combined with directional distance functions and Moran Indexes. The results allow for two inferences: i) the ecoefficiency index verifies the possibilities of maximizing economic and environmental objectives by imitating the region's best practices, and ii) the evidence of a spatial correlation between the eco-efficiency index and the presence of three large territorial clusters. Based on this information, one can define priorities for local and regional environmental intervention to optimize the sustainability of farming and ranching in the region, confirming the shortage function and previous empirical studies. These results show that local and regional environmental intervention priorities can optimize agriculture sustainability in specified regions. Future studies can use data mining techniques to include other variables correlated to environmental issues.

Keywords: Eco-efficiency, Spatial Analysis, Agriculture, Central-West, Brazil.

1. Introduction

Humans have intensively used fossil fuels to expand production activities worldwide, negatively impacting the planet's natural resources. The logic of the economic system does not prioritize the preservation of these resources, as the search for economic growth is the leading market goal. In the meantime, scholars have mentioned the importance of environmental issues since the mid-1960s. However, only in the last thirty years has this issue achieved greater attention in the political and economic debates in many countries, showing the urgency of a balance between the unchecked production of products and services, excessive and unnecessary consumption, and accelerated use of limited natural resources.

The runaway economic production has made it evident that natural resources have been used accelerated, often higher than their natural growth, culminating with scarcities and fueling the debate on the importance of building protective policies for the natural environment worldwide. In this context, according to Lustosa and Young (2002), environmental policies shall be defined as a set of rules and instruments aiming to reduce the negative impacts of human activity on the environment.

Specifically in Brazil, the environmental policy is very recent, so there still needs to be effective measures adopted with broad and satisfactory results as seen in other countries. The Brazilian ecological management model consisted of enacting the National Environmental Policy. According to Lustosa and Young (2002), the Brazilian environmental policy was developed after the Stockholm Conference and focused on pollution control and conservation unit creation. According to the authors, although not enough, it should be recognized as an essential step towards a more general concern with natural environment protection in the Brazilian context of expressive growth of agriculture and cattle ranching drawn by decades of continued global demand growth.

The growth of Brazilian agriculture and cattle ranching has transformed the country into one of the world's largest food producers and exporters. According to Gasques et al. (2016), the country's agricultural and livestock production grew 3.83% per year, on average, between 1975 and 2018. This performance was higher than the world average, which, for instance, increased by 2.8% per year from 1961 to 2012 (Gasques et al., 2016). There are at least two explanations for this: the increase in total factor productivity (TFP) and the expansion of the agricultural frontier in Brazil, notably in the Central-West region. According to the Brazilian Institute of Geography and Statistics" agricultural census, the states that form the Central-West region of the country averaged a TFP growth of 3.27% per year between 1970 and 2015, well above the national average. As for the expansion of the agricultural frontier, it incorporated cattle and crop production in the Central-West region, representing roughly 20% of the country's area.

In turn, specific characteristics of that region explain this situation: the extensive availability of cheap land, its geographic location, and the soil and climate conditions, along with a significant increase in the technological toolset developed with the Brazilian Green Revolution (Peixoto et al., 2015). On the other side, the agricultural frontier expansion towards the Central-West region in Brazil brought, among others, the Central-West indiscriminate use of machinery, irrigation, chemical fertilizers, and biocides that seriously compromised environmental quality.

However, environmental problems are no longer local. The global concern with these impacts motivated the development of the environmental and economic efficiency concept, better known as ecoefficiency. In specialized literature, a measure of the performance of production units concerning best practices is laid out, considering the relationship between economic and environmental objectives. Moreover, most studies on agricultural efficiency in Brazil focus on the financial aspect; only a few seek to estimate the possibilities of maximizing economic performance subject to a constraint that internalizes either the environmental impacts or the use of natural resources in a sustainable fashion (Padrão et al., 2012; Campos et al., 2014; Rosano-Peña and Daher, 2015; Rosano-Peña et al., 2018).

In general, explanations of Brazil's spatial dependence and heterogeneity of ecoefficiency are yet to be developed. Consequently, more is needed regarding the spatial distribution of environmental sustainability, although studies use spatial data analysis techniques in agriculture and cattle ranching (Gomes, 2008). This paper contributes to estimating an eco-efficiency indicator that satisfies the Pareto optimal and simultaneously considers economic and environmental objectives. The best practices observed in the Central-West region's municipalities are the reference. Regarding the method, a Data Envelopment Analysis (DEA) method with directional distance functions, or shortage function (Luenberger, 1992), is used to analyze classic variables related to agricultural and livestock activity, as well as three variables that measure externalities (one positive and two negatives). Furthermore, the autocorrelation and spatial heterogeneity of the calculated efficiency index are examined to verify its validity.

There is an important gap in the literature concerning spatial dependence on environmental and economic efficiency because studies need to consider georeferenced variables to verify the supporting evidence. Hence, there are no previous local studies about ecoefficiency in Brazil or different countries.

The proposed methodology contributes to allocating symbiotic agricultural arrangements that accommodate the same geographical area. The paper has five sections. In addition to this introduction, the second section presents a theoretical framework, which reviews ecoefficiency and spatial analysis concepts and methodologies. The third section briefly characterizes the Brazilian Central-West region and the variables selected for the empirical analysis. In the fourth section, results are presented and analyzed. Finally, in the fifth section, conclusions are drawn.

2. Literature Review

Economic activities employ production factors to offer goods and services to grow economically and meet the population's needs, with little concern for natural resources and their sustainability. It has grown urgent to balance production, consumption, and environmental protection by devising preservation policies that seek joint solutions and encourage actions that do not do more than necessary harm to the environment. Cleaner technologies, renewable energy, and the effective management of natural resources and waste can be the solution (Hasan, 2017).

Over the years, it was believed that implementing technology would solve the imbalance between production, consumption, and environmental protection. Among specialists, innovation is a crucial factor in ensuring more output from fewer inputs, and its progress would be enough to generate the dissociation between economic growth and environmental impact. Thus, the study of economic and environmental efficiency (ecoefficiency) came to fill this gap, a new tool in the search for better solutions to continue increasing production while reducing environmental impacts (Mu et al., 2018).

In this context, the advancement in eco-efficiency studies has been considered one of the most widely used assets in academic research not only to analyze sustainability in different sectors of the economy (Huang et al., 2018; Huppes and Ishikawa, 2005) but also to establish a relative measure of sustainability (Figge and Hahn, 2004). The concept of ecoefficiency began to be addressed in the 1970s in the research of Freeman, Haveman, and Kneese (1973) to verify the environmental efficiency of businesses (Mu et al., 2018) due to the scarcity of natural resources and the environmental degradation that pushed for the efficient use of resources (Figge and Hahn, 2013).

Consequently, to face the possible consequences of environmental degradation on the planet, several international agreements and actions sponsored by the United Nations (UN) seek new initiatives that mitigate and reverse the growing impact of human production and consumption patterns on the environment. New concepts and models are being sought to measure performance in line with those initiatives.

Therefore, before the United Nations Conference on Environment and Development (UNCED), also known as the 'Earth Summit,' held in Rio de Janeiro, Brazil, in 1992, several corporations responded with a book entitled Change of Course: A Global Business Prospects on Development and the

Environment written by entrepreneur and philanthropist Stephan Schmidheiny for an organization now known as World Business Council for Sustainable Development - WBCSD (Lehni, 2000). The text highlighted that economic gains could not be achieved by unlimited exploitation of the Earth's natural resources, as if they did not have implicit costs. Thus, it emphasized the need to develop concepts that combine environmental and economic objectives, emphasizing the challenges related to environmental sustainability to productive units. This was the concept of ecoefficiency.

The WBCSD states that “eco-efficiency is achieved by the delivery of competitively priced goods and services that satisfy human needs and bring a quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the 'Earth's estimated carrying capacity” In line with this definition, the WBCSD highlights seven dimensions applied to the production process relevant to ecoefficiency: (a) reduce the intensity of material use; (b) reduce the intensity of water and energy use; (c) reduce the dispersion of toxic compounds; (d) promote recycling; (e) maximize the use of renewable resources; (f) extends the durability of products; and (g) increase the intensity of use of products and services.

Although the ecoefficiency concept includes several economic (competitive prices, satisfaction of human needs, quality of life) and environmental aspects (reduction of environmental impacts, reduction of natural resources use), it does not explicitly involve the concept of social progress, leaving out the idea of a socially equitable development that aims to reduce the gap in living standards between the most and least favored groups.

From this angle, ecoefficiency is a necessary but insufficient condition for achieving full sustainability. It is essential because it integrates two of the main dimensions of Schaltegger and Wagner (2011). It seeks to simultaneously meet economic and environmental objectives by satisfying growing human needs with competitive products and mitigating environmental change.

Following the definition of eco-efficiency, Tyteca (1996), Bilwell and Verfaillie (2000), and Kuosmanen and Kortelainen (2005) offer a measure of eco-efficiency as the ratio of the economic value generated to the environmental impact caused. In this context, eco-efficiency indicates the ability of a firm or economy to produce a given amount of output with the least amount of inputs and environmental impact, or equivalently, as one capacity to maximize production with a given amount of inputs and by-products. This ecoefficiency associated with a given combination of inputs (x) is reached at the frontier of the production possibility set (PPS), at a Pareto optimum allocation, when no other production process or combination of existing processes can produce the same level of output (y) while generating less environmental damage (b). Thus, the eco-inefficiency of a production plan can be measured by its distance from the PPC frontier. In other words, a company's eco-inefficiency can be measured by comparing its best production plan with its overall best strategy available in the economy (Rosano-Peña and Daher, 2015; Song et al., 2023).

However, as Callens and Tyteca (1999) point out, this indicator disregards the unknown capacity of the planet to absorb and support the "minimal" environmental damage estimated by the model, which can harm the balance of the ecosystem and the satisfaction of the needs of future generations. Finally, it should be noted that ecoefficiency has emerged as an essential environmental management tool, and, according to Lehni (2000), it is used as an indicator of a country's progress toward sustainable development. Braungart, McDonough, and Bollinger (2006) conceive it as a strategy of social action aimed at reducing the use of raw materials in an economy, minimizing undesirable environmental impacts, and producing relatively higher levels of economic wealth, which should be distributed more fairly.

3. Methodology

As stated in the introduction, the object of study of this research is the farming and livestock activities in municipalities of the Central-West region of Brazil, given its importance in the economic context of higher growth rates than other regions of the country. One of the five regions of Brazil, the Central-West region comprises the State of Goiás (GO), State of Mato Grosso (MT) and State of Mato Grosso do Sul (MS), and the Federal District (DF), the country's capital. With an area of 1,606,403.5 km2 and a population of 15.3 million, the Central West is the second-largest region in Brazil in terms of territory and the smallest in terms of inhabitants (IBGE, 2010).

Being occupied predominantly by a tropical savanna biome, referred to as Cerrado, the rural space of the region is dedicated to extensive livestock and crop production, which has been gaining prominence in recent decades, producing soybeans, cotton, corn, sugar cane, rice, and beans intensively. The participation of the Central-West region in the Agricultural Gross Domestic Product (GDP) increased from 7.4% in 1970 to 19.5% in 2009.

Several problems, however, are pointed out as potential drawbacks related to the competitiveness of agriculture and cattle ranching in the region. Among them, four aggravating environmental factors could be mentioned. The first is deforestation, which causes biological diversity loss, animal and plant species extinction, desertification, and erosion. The second aggravating factor is monoculture and the excessive use of pesticides in extensive plantations, which reduces biological diversity and contaminates soil, water table, and rivers. The third is soil compaction from extensive cattle raising and agricultural mechanization since soil densification reduces porosity, hinders water infiltration, and increases surface runoff, generating erosion. Last but not least is the increase in greenhouse gas emissions, resulting mainly from changes in land use, the burning of fossil fuels used in agricultural machinery, and animal flatulence and belching.

In this context, a stochastic frontier model was specified based on Robaina-Alves, Moutinho, and Macedo (2015) that evaluated ecoefficiency for European countries, drawing a similar approach to assess Brazilian municipalities from the country's Central-West region with expressive results in the participation of the country's Gross Domestic Product.

3.1. Model inputs and outputs

Considering the objective of ing agricultural productivity and, at the same time, preserving nature, it is developed an analytical model that considers the amounts of inputs used and the products generated, as well as the environmental impacts resulting from the production process.

Explicitly, the model incorporates a well-known set of classical inputs and outputs of the Economic Analysis of agricultural and ranching production (Gomes, 2008) and three environmental, one positive and two negative, externalities. The variables are:

- Inputs:

x1 - Labor force on the farms (number of people);

x2 - Capital depreciation (10% of the value of fixed assets);

x3 - Area used in agriculture and pasture (hectare, ha);

x4 – Other current expenses (in $).

- Outputs:

y1 - Revenues from sales of farm products (in $);

y2 - Revenues from sales of livestock, meat, and meat products (in $);

y3 - Other revenues (in $).

Externalities:

y4 - Desirable environmental output - Areas of preserved woods and natural forests on farms (hectare, ha). This variable is the proxy for the flow of benefits from environmental services farmers provide when they preserve part of the land on their farms.

b1 - Environmental undesirable product - Areas of degraded land on farms (hectare, ha), abandoned areas not included. This variable is the proxy for the flow of environmental damage to the land.

b2 - Biodiversity impact - the Shannon-Weaver (1949) diversity index, which considers the number of crops and the regularity of their distribution. Formally, according to Beltrán-Esteve et al. (2012), the production unit i index is given by

$$b_{2i} = e^{\sum_{k=1}^{t}(x_{ki}*\ln(x_{ki}))} \qquad (1)$$

Where ski is the proportion of the total area of I devoted to the production of crop k=1,...,t. Thus, the biodiversity index takes the value 1 when establishments are dedicated to monoculture, and its value decreases when the number of crops is more significant and more regular. This indicator is the proxy designed to capture the flow of environmental impacts generated by the degree of agricultural specialization based on evidence that monoculture reduces the diversity of wildlife. The data was taken from the 2006 agricultural census (IBGE, 2010) for the 466 municipalities from the Brazilian Central-West region.

3.2. Methodology Analysis

One of the most appropriate methods for estimating the production possibilities frontier (PPF) and eco-efficiency is the directional distance function combined with the Data Envelopment Analysis - DEA method (Lu and Wang, 2012; Goh, 2020). Chung, Färe developed this approach and Grosskopf (1997), Färe and Grosskopf (2000), and Färe et al. (2006) deal simultaneously with desirable and undesirable outputs in an asymmetric way. The innovative feature of this method is that it allows one to define distinct projection directions of eco-inefficient units on the efficient frontier employing a directional vector (- gx, gy, -gb). Thus, it offers a set of strategies to achieve eco-efficiency, which can even improve a group of variables without affecting the behavior of others. The directional distance function can be expressed as follows:

$$\vec{D}[\text{x,y,b};(-g_x, g_y, -g_b)]=\text{Max}\{\beta:(\text{x}-\beta g_x, \text{y}+\beta g_y, \text{b}-\beta g_b) \in \text{PPF}\} \qquad (2)$$

In which β ≥ 0 (the optimal value to be estimated) indicates the distance to the frontier, that is, the percentage in which the productive unit evaluated could increase all desirable products (y) and reduce, at the same time, inputs use (x) and environmental damage (b) along a given direction vector (-gx = x, gy = y, - gb = b), where β = 0 for the efficient production unit. Arandia and Aldanondo-Ochoa (2011), following Färe et al. (2006), show that Data Envelopment Analysis can estimate the directional distance functions and the β for each production unit - DEA, that is, by solving the following linear programming problem:

$$\begin{aligned}
&\vec{D}\text{i}=(\text{x,y,b}; -g_x,\ g_y, -g_b)=\text{Max } \beta \\
&\text{s.t.} \\
&\left(1+\beta g_y\right) * \mathbf{y}^{\text{i}} + \boldsymbol{s_y^i} = \mathbf{Y}\text{z} \\
&(1-\beta g_b) * \mathbf{b}^{\text{i}} - \boldsymbol{s_b^i} = \mathbf{B}\text{z} \qquad (3) \\
&(1-\beta g_x) * \mathbf{x}^{\text{i}} - \boldsymbol{s_x^i} = \mathbf{X}\text{z} \\
&z \geq 0
\end{aligned}$$

Where xi, yi, and bi denote, respectively, the vector of inputs, desired production, and undesired production of the i-th production unit; si is the slacks of the respective variables about the efficient levels; X is the matrix of inputs, Y denotes the matrix of desired products, and B is the matrix of undesired effects of all units evaluated; z is the vector of the intensity of each production unit in the efficient frontier.

The meaning of β can be illustrated graphically. Suppose that i = A, B, ..., K production units are being evaluated, all of them using the same amount of inputs to produce one desirable and undesirable output. In Figure 1, the area OABCDEJK represents the set of production possibilities whose efficient frontier is formed by the segment $\overline{\text{OABCD}}$. Thus, F (like E, G, H, I, J, and K) is eco-inefficient. Its inefficiency and projection to the frontier depend on the priorly defined direction vector. For example, the amount of the desired output of F that can be added with the same level of inputs and environmental impact in order to achieve the efficiency $g = (-gx = 0, gy = 1, -gb = 0)$ is estimated by PPL at point F'' = $[b\ F\ , y\ F\ (1 + \beta gy)]$. Alternatively, wanting to efficiently reduce the environmental impact while keeping the desired output and inputs constant, the PPL will project F at point F' = $[b\ F\ (1 - \beta gb), y\ F]$. Finally, with the intention of increasing y and reducing b simultaneously with the same inputs, the PPL will project F at point F''' = $[b\ F\ (1 - \beta gb), y\ F\ (1 + \beta gy)]$. Therefore, it is observed that by satisfying the Pareto optimal concept, it is possible to increase ecoefficiency in different ways.

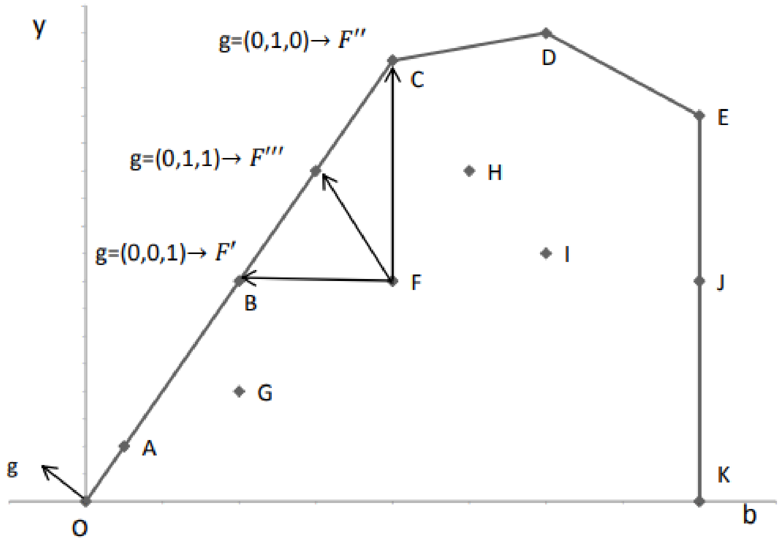


Fig. 1: Set of production possibilities with an efficient frontier.

It is worth noting that, in the dual linear programming problem, the corresponding value of z indicates the relative importance attributed to each variable (x, y, b) in determining the eco-efficiency index, often assigned in an arbitrary way (equal weight for all, for example) or with the help of expert opinions. With DEA models, the relative importance of the variables is estimated objectively for each evaluated unit, considering different possibilities of combining and weighting inputs and outputs according to the unit's characteristics of the units being evaluated. The assessed unit can be compared to the efficient units with the same profile.

3.3. Spatial Data Analysis Techniques

Anselin, Syabri, and Smirnov (2002) define Exploratory Spatial Data Analysis - AEDE as the set of statistics and graphics that describes the spatial distributions of a group of variables, identifying atypical local points, arrangements, and forms of association (spatial autocorrelation), as well as structures in geographic space (spatial heterogeneity). The spatial correlation is studied with Moran's Index and used to identify geographical distribution patterns and dependence of indicators employed to develop local, regional, and national monitoring, planning, and intervention programs.

The value of Morgan's spatial correlation index range from -1 to +1, similar to Pearson's coefficient. Values close to +1 suggest almost perfect positive autocorrelation; that is, the value of a variable in an area tends to be identical to the values of its neighbors. Values close to -1 indicate almost perfect negative autocorrelation. That is, they express vital dissimilarities among neighboring areas. Values close to zero indicate no significant spatial autocorrelation between what happens at a given point in space and what happens elsewhere; that is, the value of a variable of interest in a specific region i is independent of the value of that variable in neighboring regions j.

Spatial correlation stems from several phenomena, for example: 1) the ecological homogeneity of the agricultural space (e.g., water availability, and soil type and fertility); 2) cultural parity and corporate governance; 3) the consolidation of a common market that encourages the unrestricted mobility of goods and services; 4) the impacts of communications, transportation, infrastructure on territorial integration; 5) the consequences of the diffusion process, when the innovation made in a municipality is imitated and internalized by others; and 6) the spillover effects, which refers to the moment when the development of a region, seeking scale efficiency, spills over, externalizing the development of the neighboring region and regional convergence (Costa et al., 2013).

The first step to analyzing spatial correlation is to define the neighborhood matrix (W) that determines the spatial connectivity or proximity among municipalities. Each municipality in that matrix is connected to neighboring observations following an exogenously defined spatial pattern (Baumont et al., 2004). For example, municipalities that share a common border can be considered neighbors. In this way, W becomes a 0-1 binary matrix, where one is associated with areas with a common border and 0 otherwise. For convenience, the row-normalized normalized Queen matrix was used in this study, where the sum of the elements of each matrix row is equal to one. From this matrix, it is possible to extract global and local spatial association measures.

The global Moran index, one of the most widely used global indicators of spatial autocorrelation, provides a general measure of the spatial association in a data set. The index is calculated in the following way (Anselin, Syabri, and Smirnov, 2002):

$$I_i = \frac{n \sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_i \sum_j w_{ij}\right) \sum_i (x_i - \bar{x})} \qquad (4)$$

where n is the number of geographic units on the map, wij is the element of the neighborhood matrix W for pair i and j, xi and xj denote the observed values of the variable studied for municipalities i and j, respectively, and ($\bar{x}$) is the average of the observed values.

Once the Moran index has been calculated, testing the hypothesis that the result differs from zero is necessary. There are two basic methods for testing the hypothesis. The most direct way to test the Moran index hypothesis exhibited by a sample of n cases is that it was obtained from a population with a normal distribution with zero autocorrelation. Therefore, it can be significant if the result moves away from zero. Alternatively, for asymmetric data such as the eco-efficiency index, the Monte Carlo permutation test is applied. In this way, the data of the spatial units are exchanged (they permute) at random, obtaining different autocorrelation values whose distribution is compared with the obtained value.

To perform this type of test, the null hypothesis that responds to the statement Ho is initially defined: the spatial configuration occurs randomly, and the alternative Ha: the spatial arrangement does not happen randomly. Then the significance level is specified, indicating the probability of rejecting the null hypothesis being this true. It is usually chosen according to the importance of the problem and is generally 5% (0.05). The result of the test is the p-value. If the significance level exceeds the p-value, the null hypothesis is rejected, and the alternative is accepted. On the contrary, if the null hypothesis is verified, it can be said that the spatial configuration occurs randomly.

One way to interpret Moran's statistics is through the scatter diagram. As shown in Figure 2, it presents, in the Cartesian plane, the normalized value of the studied variable z (say the eco-efficiency index) for each of the geographical units on the abscissa and, on the ordinate axis, the mean of the standardized value of the same variable for the neighbors of this unit Wz. The diagram is complemented by the representation of a regression line, whose slope, according to Anselin (1992), indicates Moran's Index normalized value, which, for the example in Figure 2, is 0.87. Thus, the greater the inclination of the line concerning the horizontal axis, the greater the value of spatial autocorrelation.

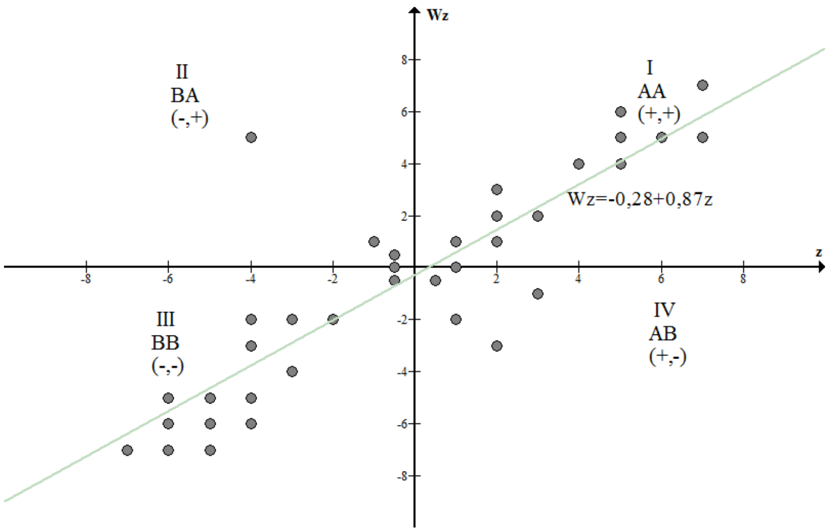


Fig. 2: Moran Index' 's two-region dispersion diagram. frontier.

According to Almeida et al. (2004), the Moran diagram can be divided into four quadrants, corresponding to four spatial association patterns between regions and their neighbors, as shown in Figure 2. The quadrant I (located in the upper right) shows high values for the variable under analysis, surrounded by regions that also present deals above the variable's mean. This quadrant is rated High-High (AA). The quadrant II (located in the upper left) shows regions with low values, surrounded by neighbors with high values. This quadrant is generally classified as High-Low (AB). The quadrant III (located in the lower left corner) consists of regions with low values for the variables under analysis, surrounded by regions with low weights. This quadrant is classified as Low-Low (BB). Finally, quadrant IV (located in the lower right corner) is formed by regions with high values for the variables under analysis, surrounded by regions with low values. This quadrant is classified as Low-High (BA).

The scattering of the points in the four quadrants should corroborate the result of the global Moran index. As shown in Figure 2, most of the points are in quadrants I and III, which indicates a positive spatial association. The other part of the points (minority), located in quadrants II and IV, can be seen as municipalities that do not follow the same pattern of spatial dependence as the other observations.

However, for a large number of municipalities, different regimes of spatial association likely occur, and more than one value as an indicator for the entire study area is needed. Examining these different association regimes in more detail should be of interest. Given this and to highlight the places where spatial dependence is even more pronounced and significant, Anselin (1995) suggests using the Local Indicators of Spatial Association (LISA). The LISA decomposes the global Moran's autocorrelation indicator into the local contribution of each observation considering the four quadrants of Moran's scatterplot. A local Moran Index's statistic becomes:

$$I_i = \frac{(x_i - \bar{x}) \sum_j w_{ij} \left(x_j - \bar{x}\right)}{\left(\sum_i (x_i - \bar{x})^2\right)/n} \qquad (5)$$

A positive and statistically significant value of the local Moran Index's Ii reveals the existence of a cluster of similar municipalities. On the other hand, a negative value suggests the presence of outliers, which are surrounded by municipalities with different values.

The limitations of the study are the spatial analysis conducted by municipalities, which prevents the identification of intra-municipal heterogeneity at the level of productive property, the results conditioned to the units evaluated, the variables used in the research, and the principle that all other factors involved are identical. Adding or deleting units and variables can derive different results. Moreover, comparing all the Brazilian region's data (North, Northeast, Central-West, South, and Southeast) can enhance analysis, but they were only partially available.

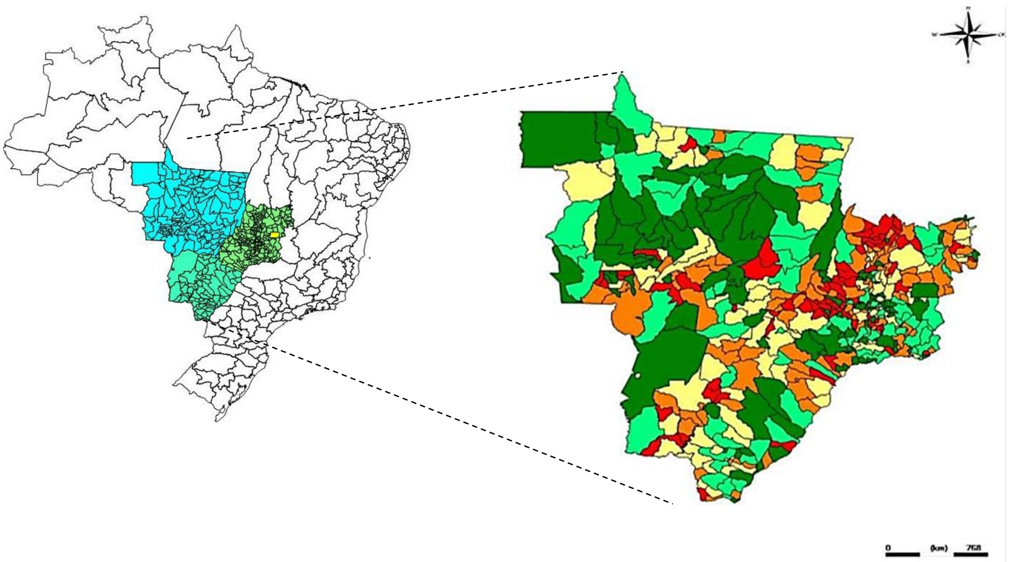
4. Results

This section evaluates the results of applying the tools described above to selected data. Initially, the eco-efficiency index varies between 0 and 1. The closer to 0, the more eco-efficient a decision unit, for example, a state or municipality.

The ecoefficiency of the Brazilian municipalities from the Central-West region was calculated to determine the increase in the desired output (y) and the decrease in the undesired output (b), possibly given the available inputs. This is done through the direction vector $g = (-gx = 0, gy = 1, -gb = 1)$. The results are presented in Figure 3, showing no signs of a regular geographical distribution pattern.

In Figure 3, the georeferenced β ecoefficiency indexes of the municipalities with better practices (β close to 0) are colored with shades of green, and the less ecoefficient ones (β far from 0) are colored with shades of red.

Disregarding the Federal District, analyzed as a whole, that obtained a β=0, one observes the largest concentration of ecoefficiency municipalities in the State of Mato Grosso. A possible explanation for this is that many of these municipalities, having the highest agricultural GDP in Brazil, are in regions belonging to the Mato Grosso Amazon Biome, where the Law requires that at least 80% of each rural property area shall be preserved. On the other hand, the highest ecoefficiency rates are concentrated in the State of Goiás, where only 20% of the scope of the property must be preserved.



Legend	Colors	Ecoefficient Units β =0	
Distrito Federal		1º Quartile with moderate ecoinefficiency 0< β ≤0.14	
Goiás		2º Quartile with medium ecoinefficiency 0.14< β ≤0.24	
Mato Grosso		3º Quartile with high ecoinefficiency 0.24< β ≤0.32	
Mato Grosso do Sul		4º Quartile with extreme ecoinefficiency 0.32< β	

Fig 3. Georeferenced β ecoefficiency indexes of the municipalities from the Central-West region of Brazil.

Table 1 shows the descriptive statistics of the betas of the municipalities. It is observed that the average index is 0.168 and the median 0.157. The latter indicates that 50% of the Central-West municipalities can increase the value of production of the desired products, preserved areas included, up to 15.7%, reducing the degraded areas and the impact on biodiversity in the same proportion. Imitating best practices can improve the scenario, i.e., by taking the 128 ecoefficient municipalities in these regions (with β=0) as a reference. The third quartile suggests that 75% of the municipalities have ecoefficiency indexes below 0.292. The large amplitude of the results, confirmed by the standard deviation and the extremes, indicates a wide heterogeneity in the region. Furthermore, the kurtosis and the asymmetry coefficients suggest that the distribution of β is less concentrated and symmetric than the normal distribution.

Table 1. Descriptive statistics of the β ecoefficiency indexes

Mean	0.168	First quartile	0.000
Median	0.157	Third quartile	0.291
Standard Deviation	0.146	Kurtosis	-1.227
Maximum (1 observation)	0.495	Assimetry	0.270
Minimum (129 observations)	0.000	Shapiro-Wilk	W=0.9, p-value=2.2e-16

The Shapiro-Wilk test gives confirmation that the β are not normally distributed, which an estimated p-value close to zero. One can better visualize this finding by analyzing the shape of the histogram function of the β, presented in Figure 4.

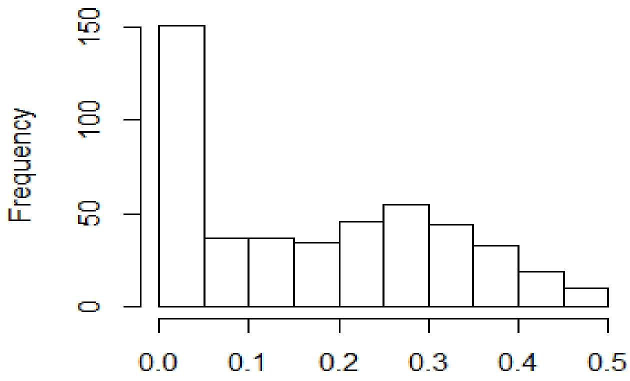


Fig. 4: Histogram of betas indexes of the Midwest region.

Figure 5 shows the boxplot for the Distrito Federal, the State of Goiás, the State of Mato Grosso do Sul and the State of Mato Grosso. Disregarding the Federal District, it is clear that the State of Mato Grosso is the best-performing state, followed by the State of Goiás and the State of Mato Grosso do Sul. The median β for Mato Grosso' 's municipalities is 0.077, while the State of Goiás and the State of Mato Grosso do Sul got 0.193 and 0.198, respectively. Moreover, Goiás, although grouping the most significant number of eco-efficient municipalities, is the most heterogeneous state.

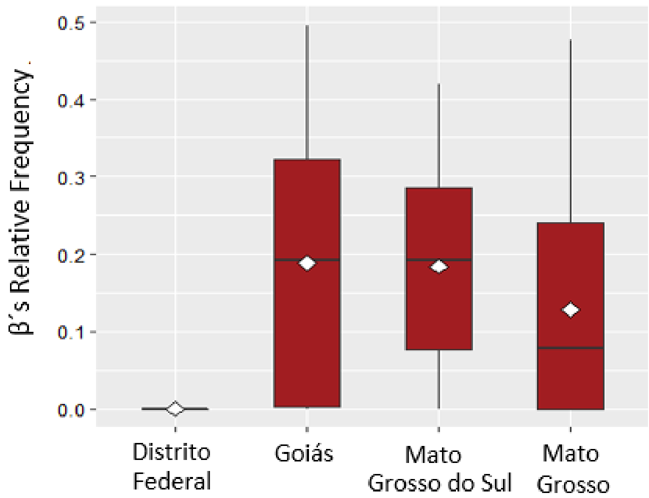


Fig. 5: Boxplot of the β of the municipalities by state and the Federal District.

The potential growth in the total value of the agricultural and ranching production is R$ 3.8 billion, plus the savings in economic and environmental resources. Table 2 shows the absolute values of the improvements needed for eco-efficiency in the region's municipalities. These results were obtained considering both the ecoefficiency indexes (β) and the slacks (slacks) estimated by the PPL (3).

Table 2. Possible Improvements to the ecoefficiency of the region's municipalities, by state, to achieve efficiency

Variable	Description
x_1	Workforce (un.)
x_2	Capital (R$ 1,000)
x_3	Area (ha)
x_4	Cost (R$ 1,000)
y	Vegetal production (R$ 1,000)
y_2	Animal production (R$ 1,000)
y_3	Production others (R$ 1,000)
y_4	Preserved areas (ha)
b_1	Degraded areas (ha)
b_2	Biodiversity impact

Variable	State				Total
	Goiás GO	Mato Grosso do Sul - MS	Mato Grosso MT	Distrito Federal – DF	Central-West RegionCO
x_1	-136,548.8	-46,600.06	-82,697.61	0	-265,846.39
x_2	-749,109.0	-631,467.0	-569,724.9	0	-1,950,301.0
x_3	-7,576,765.3	-6,527,349.3	-7,749,598.1	0	-21,853,712.6
x_4	-1,384,174.3	-1,450,754.4	-2,502,891.1	0	-5,337,819.7
y	768,449.78	691,303.55	613,354.89	0	2,073,108.22
y_2	710,754.08	579,780.93	371,181.97	0	1,661,716.97
y_3	16,315.34	15,377.88	7,117.38	0	38,810.60
y_4	1,992,982.5	1,188,548.5	1,767,459.1	0	4,948,990.1
b_1	-25,584.1	-16,001.7	-26,898.5	0	-68,484.4
b_2	-25%	-21%	-19%	0	-22%

Given these results, it is also possible to make a simple estimate of the potential increase in carbon sequestration. According to the National Forest Inventory – NFI, research conducted in the Brazilian savanna, it was found that the carbon stock is, on average, 1.61 ± 0.43 t/ha. Therefore, if the degraded areas of the Central-West region were to be recovered, the carbon sequestered would increase by 110,259.9 t, equivalent to 8% of the 1.368 million tons of CO2 equivalent emitted by Brazil in 2017.

Applying the Global and Local Moran Indexes to verify the spatial correlation of the ecoefficiency index among municipalities based on a normalized Queen neighborhood matrix returned a value of 0.23, statistically significant according to the Monte Carlo permutation test. These results indicate spatial dependence, i.e., the municipalities and their neighbors have similar overall eco-efficiency values.

Figure 6 presents the Moran Global Index map of the estimated β by intervals. The regions colored in shades of red and green present positive spatial dependence, while the regions colored in shades of brown and army green current negative spatial dependence. Accordingly, the Low-Low and High-High type regions gather the majority of municipalities, 62 %, while the Low-High, High-Low municipalities form the minority, 38 %. This information could be used for prioritizing environmental intervention. The primary target audience of environmental campaigns for improvements is the farmers in the dark red regions, followed by the light red ones, to emulate the dark-green experiences and practices.

The results found for the Local Moran Index, indicating a 95% significance level at the Monte Carlo permutation test, are presented in Figure 7. The analysis allowed the identification of three major clusters of municipalities with significant spatial dependence. The largest is of the high-efficiency type, formed by municipalities of the Amazon Biome located in the north of the State of Mato Grosso, and which is part of the list of the 100 municipalities with the highest agricultural GDP in Brazil. Highly inefficient municipalities form the second and third clusters in the hydrographic basin of the Tocantins and Araguaia rivers in the State of Goiás, a region characterized by very fertile soils. Municipalities comprise those groups with the lowest agricultural and cattle ranching GDPs in Goiás.

Legend
High Inefficient (28.47%)
Medium-to-Highly Inefficient (20.18%)
Medium-to-Highly Efficient (17.71%)
Highly Efficient (33.63%)

Fig 6: Moran Global Index map.

Fig 7: Moran Local Index map at 95% confidence level.

5. Conclusions

Many empirical studies seeking to elucidate and bring new contributions to the theme of ecoefficiency have been emerging in the academic literature. The growing interest in the subject is aligned with the need to increase production and the concerns about the natural environment.

This study fills an important gap in the literature for studying spatial dependence on environmental and economic efficiency. In this context, the present study applied a methodology to estimate a georeferenced ecoefficiency index for the Brazil Central-West region municipalities based on classic agricultural and livestock variables activity and the internalization of three environmental externalities, one positive and two negatives. To achieve this objective, a Data Envelopment Analysis (DEA) is combined with directional distance functions and Moran Indexes.

Among the main conclusions derived from this study, three stand out. First, the possibilities of simultaneously maximizing economic and environmental objectives were noted, merely imitating the region's best practices. Therefore, discussing ecological and economic issues does not necessarily result in a zero-sum game. Second, a spatial correlation of the eco-efficiency index was evident. Consequently, the region's ecological homogeneity and socioeconomic integration determine environmental economic competitiveness. Third, three large clusters were present, where spatial dependence is pronounced: one of the Low-Low type and two of the High-High type. Based on this information, local and regional environmental intervention priorities can optimize regional agriculture sustainability.

The method used, like any other, has limitations. On the one hand, the spatial analysis was conducted by municipalities, which prevents the identification of intra-municipal heterogeneity at the level of productive property. On the other hand, data envelopment analysis, a deterministic technique and estimating relative indexes concerning best practices, is very susceptible to the data used. These limitations mean that the results are conditioned to the units evaluated, the variables used in the research, and the principle that all other factors involved are identical. Adding or deleting units and variables can derive different results. Finally, future studies can include other variables correlated to environmental issues and use data mining techniques combined with big data and artificial intelligence (Chun and Cho, 2022; Kim, 2019).

References

Almeida, E. S., Haddad, E. A. (2004). MEECA: An econometric-spatial model for consistent projections of crops. Rural Economy Magazine. 42(3), 487-507. https://doi.org/10.1590/S0103-20032004000300006

Anselin, L. (1995). Local Indicators of Spatial Association – LISA. Geographical Analysis. 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L. (1992). SpaceStat tutorial: a workbook for using SpaceStat in spatial data analysis. Mimeo, University of Illinois.

Anselin, L., Syabri, I., Smirnov, O. (2002). Visualising Multivariate Spatial Correlation with Dynamically Linked Windows. Urbana, Regional Economics Application Laboratory (real), University of Illinois.

Arandia, A., Aldanondo-Ochoa, A. (2011). Pollution shadow prices in conventional and organic farming: An application in a Mediterranean context. Spanish Journal of Agricultural Research. 9, 363-376. https://doi.org/10.5424/sjar/20110902-541-10

Baumont, C., Cem, E., Julie, L. G. (2004). Spatial Analysis of Employment and Population Density: The Case of the Agglomeration of Dijon 1999. Geographical Analysis, 36(2), 146-176. https://doi.org/10.1111/j.1538-4632.2004.tb01130.x

Beltrán-Esteve, M., Picazo-Tadeo, A., Reig-Martínez, E. (2012). What makes a citrus farmer go organic? Empirical evidence from Spanish citrus farming. Span. J. Agric. Res. 10(4), 901–910. https://doi.org/10.5424/sjar/2012104-2957

Bidwell, R., Verfaillie, H. A. (2000). Measuring eco-efficiency: A guide to reporting company performance. World Business Council on Sustainable Development, Geneva, Switzerland, 2–37.

Braungart, M., McDonough, W., Bollinger, A. (2007). Cradle-to-cradle design: creating healthy emissions – a strategy for eco-effective product and system design. Journal of Cleaner Production. 15(13-14), 1337–1348. https://doi.org/10.1016/j.jclepro.2006.08.003

Callens, I., Tyteca, D. (1999). Towards indicators of sustainable development for firms: A productive efficiency perspective. Ecological Economics. 28(1), 41–53. https://doi.org/10.1016/S0921-8009(98)00035-4

Campos, S. A. B., Coelho, A. B., Gomes, A. P., Mattos, L. B. (2014). Efficiency and costs associated with environmental suitability for dairy production in Minas Gerais. Rural & Agroindustrial Organizations. 16(3), 324-342.

Chun, Y. & Cho, M. (2022). An Empirical Study of Intelligent Security Analysis Methods Utilizing Big Data. *Journal of Logistics, Informatics and Service Science*, 9(1), 26-35.

Chung, Y. H., Färe, R., Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. Journal of Environmental Management. 51 (3), 229–240. https://doi.org/10.1006/jema.1997.0146

Costa, C. C. de M., Almeida, A. L. T., Ferreira, M. A. M. (2013). Determinants of the development of the agricultural sector in the municipalities. RAUSP Management Review. 48(2), 295-309. https://doi.org/10.5700/rausp1089

Färe, R., Grosskopf, S. (1997). Intertemporal Production Frontiers: With Dynamic DEA, Journal of the Operational Research Society. 48(6), 656. https://doi.org/10.1057/palgrave.jors.2600779

Färe, R., Grosskopf, S. (2000). Theory and Application of Directional Distance Functions. Journal of Productivity Analysis. 13, 93–103. https://doi.org/10.1023/A:1007844628920

Färe, R., Grosskopf, S., Weber, W. L. (2006). Shadow prices and pollution costs in US agriculture. Ecol Econ. 56, 89-103. https://doi.org/10.1016/j.ecolecon.2004.12.022

Figge, F., Hahn, T. (2013). Value drivers of corporate eco-efficiency: Management accounting information for the efficient use of environmental resources. Management Accounting Research, 24(14), 387-400.

Figge, F., Hahn, T. (2004). Sustainable value Added—measuring corporate contributions to sustainability beyond eco-efficiency. Ecological Economics, 48 (2), 173-187. https://doi.org/10.1016/j.ecolecon.2003.08.005

Freeman, III, A. M., Haveman, R. H., Kneese, A. V. (1973). Economics of environmental policy. United States.

Gasques, J. G., Bacchi, M. P. R., Rodrigues, L., Bastos, E. T., Valdez, C. (2016). Productivity of Brazilian agriculture: The deceleration hypothesis. In: Vieira Filho, J. E. R., Gasques, J. G. (Orgs.) Agriculture, productive transformation and sustainability. Brasília: Ipea, 143-163.

Goh, H. (2020). Analysis of Static and Dynamic Efficiency for Sustainable Growth of Edu-Tech Companies. *Journal of Logistics, Informatics and Service Science*, 7(1), 87-101.

Gomes, E. G. (2008). Use of DEA models in agriculture: literature review. Engevista. 10(1), 27-51. https://doi.org/10.22409/engevista.v10i1.210

Hasan, M. R., Islam, M. S., & Akter, J. (2017). Energy Performance Analysis of an Office Building Using BIM: A Case Study. *Journal of System and Management Sciences*, 7(3), 34-53.

Huang, J., Xia, J., Yu, Y., Zhang, N. (2018). Composite eco-efficiency indicators for China based on data envelopment analysis. Ecological indicators. 85, 674–697. https://doi.org/10.1016/j.ecolind.2017.10.040

IBGE. (2010). Agricultural Census. Rio de Janeiro: Brazilian Institute of Geography and Statistics.

Huppes, G., Ishikawa, M. (2005). Eco-efficiency and Its xs Terminology. Journal of Industrial Ecology. 9, 43–46. https://doi.org/10.1162/108819805775247891

Kim, J. B. (2019). Implementation of the artificial intelligence system and traditional system: a comparative study. *Journal of System and Management Sciences*, 9(3), 135–146.

Kuosmanen, T., Kortelainen, M. (2005). Measuring eco-efficiency of production with data envelopment analysis. Journal of Industrial Ecology. 9(4), 59-72. https://doi.org/10.1162/108819805775247846

Lehni, M. (2000). Eco-Efficiency: creating more value with less impact, World Business Council for Sustainable Development, Geneva.

Lu, B. & Wang, X. (2012). Application of DEA on the measurement of operating efficiencies for east-Asia major container terminals. *Journal of System and Management Sciences*, 2(1), 1-18.

Luenberger, D. G. (1992). New Optimality Principles for Economic Efficiency and Equilibrium. *Journal of Optimization Theory and Applications*, 75, 221-264.

Lustosa, M. C., Young, C. E. F. (2002). Environmental Policy. In: Hasenclever, Lia; Kupfer, David. (Ed.). Industrial Economics: theoretical foundations and practices in Brazil.1 ed. Rio de Janeiro: Campus.

Mu, W., Kanellopoulos, A., Van Middelaar, C. E., Stilmant, D., Bloemhof, J. M. (2018). Assessing the impact of uncertainty on benchmarking the eco-efficiency of dairy farming using fuzzy data envelopment analysis. Journal of Cleaner Production. 189, 709-717. https://doi.org/10.1016/j.jclepro.2018.04.091.

Padrão, G. A., Campos, S. A. C., Lirio, V. S., Silva, M. L. (2012). Environmental efficiency and opportunity cost of the Forest Code for the Amazon. In: RIO+20 - International Society for Ecological Economics Conference. Rio de Janeiro. International Society for Ecological Economics Conference.

Peixoto, M., Castro, A. C., Nascimento, P. P. (2015). 'Roger's theory of diffusion of innovations and institutional changes in Brazilian rural advisory services. In: World Interdisciplinary Network for Institutional Research, Rio de Janeiro. 1, 1-21.

Robaina-Alves, M., Moutinho, V., Macedo, P. (2015). A new frontier approach to model the eco-efficiency in European countries. Journal of Cleaner Production. 103, 562–573. https://doi.org/10.1016/j.jclepro.2015.01.038

Rosano-Peña, C., Daher, C. E. (2015). The Impact of Environmental Regulation and Some Strategies for Improving the Eco-Efficiency of Brazilian Agriculture. In Decision Models in Engineering and Management. 295-322. Springer, Cham.

Rosano-Peña, C., Serrano, A. L. M., Britto, P. A. P., Franco, V. R., Guarnieri, P., Thomé, K. M. (2018). Environmental preservation costs and eco-efficiency in Amazonian agriculture: Application of hyperbolic distance functions. Journal of Cleaner Production. 197(1), 699-707. https://doi.org/10.1016/j.jclepro.2018.06.227.

Schaltegger, S, Wagner, M. (2011). Sustainable Entrepreneurship and Sustainability Innovation: Categories and Interactions. Business Strategy and the Environment. 20, 222–237. https://doi.org/10.1002/bse.682

Shannon, C. E. Weaver, W. (1949). The mathematical theory of communication. The University of Illinois. Urbana, Chicago, London. 3–24.

Song, W., Ahmad, A., & Sun, Z. (2023). Government Subsidy, Green Credit, Carbon. Information Disclosure and the moderation effect of Ownership Property: Evidence from Chinese Listed Agriculture-Related Firms. *Journal of System and Management Sciences*, 13(2), 462-487.

Tyteca, D. (1996). On the measurement of the environmental performance of firms: a literature review and productive efficiency perspective. Journal of Environmental Management. 46, 281–308. https://doi.org/10.1006/jema.1996.0022