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ARTICLE

Efficiency and productivity to social welfare: the case of the main forestry-producing micro-regions in Brazil

Eficiência e produtividade do bem-estar social: o caso das principais microrregiões florestais do Brasil

Jessica Suarez Campoli[1]*, Paulo Nocera Alves Junior[2], Tatiana Kimura Kodama[3], Marcelo Seido Nagano[3]*, Heloisa Lee Burnquist[1]

[1]Programa de Pós-graduação em Economia Aplicada, Escola Superior de Agricultura "Luiz de Queiroz", Universidade de São Paulo (USP), Piracicaba (SP), Brasil. E-mails: jessica.campoli@usp.br; hlburnqu@usp.br

[2]Escuela de Ingeniería, Universidad Católica del Norte (UCN), Coquimbo, Chile. E-mail: paulo.alves@ucn.cl

[3]Programa de Pós-graduação em Engenharia de Produção, Escola de Engenharia de São Carlos, Universidade de São Paulo (USP), São Carlos (SP), Brasil. E-mails: tatiana.kimura@usp.br; drnagano@usp.br

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Abstract: The studies on the forest sector focus on energy issues and environmental challenges, but they are limited to a small number of studies focused on economic growth and social welfare. In the forest sector, Brazil is among the five countries with large forest cover in the world, with favorable conditions and great potential for production growth. Therefore, this work aimed to measure the evolution of efficiency and productivity of the 49 Brazilian forestry microregions in converting the expansion of economic growth into social welfare from 2009 to 2015 (a period of sectoral growth in the country). The approach of the Slack-Based Measure (SBM) – Data Envelopment Analysis (DEA), Malmquist Productivity Index (MPI), and Windows Analysis model was combined, followed by a solution for infeasibility problems. The results show that the growth of the forestry sector was not accompanied by the Human Development Index (HDI) in most of the microregions, showing regional and state differences, with the microregions close to the sensitive environmental areas with the lowest HDI. Thus, the work contributes to the design of public policies and government decision-making to increase the sector's efficiency and productivity and to social indicators that can guide sustainable policies in other contexts and countries.

Keywords: forestry sector, social welfare, rural development, Data Envelopment Analysis (DEA), Malmquist Productivity Index (MPI).

Resumo: Os estudos sobre o setor florestal concentram-se em questões energéticas e desafios ambientais o que reflete em um número limitado de estudos focados no crescimento econômico e no bem-estar social. No setor florestal, o Brasil está entre os cinco países com a maior cobertura florestal do mundo com condições favoráveis e grande potencial de crescimento da produção. Portanto, o objetivo deste trabalho foi mensurar a evolução da eficiência e produtividade das 49 microrregiões florestais brasileiras em converter a expansão do crescimento econômico em bem-estar social, de 2009 a 2015 (período de crescimento setorial no país). Combinou-se a abordagem do modelo *Slack-Based Measure (SBM) – Data Envelopment Analysis* (DEA), *Malmquist Productivity Index* (MPI) e *Windows Analysis*, seguido de uma solução para problemas de inviabilidade. Os resultados obtidos apontam que o crescimento do setor florestal não foi acompanhado pelo Índice de Desenvolvimento Humano (IDH) na maioria das microrregiões apresentando grandes diferenças regionais e estaduais sendo as microrregiões próximas as áreas ambientais sensíveis com o menor IDH. Assim, o trabalho contribui para o desenho de políticas públicas e tomadas de decisões governamentais para aumentar a eficiência e produtividade do setor e para indicadores sociais podendo orientar políticas sustentáveis em outros contextos e países.

Palavras-chave: setor florestal, bem-estar social, desenvolvimento rural, *Data Envelopment Analysis* (DEA), *Malmquist Productivity Index* (MPI).

1. Introduction

This study examines how the transition to sustainable forest management has impacted selected Brazilian regions in terms of local economic growth, quality of life, and employment. By analyzing the expansion of the forest industry during this period, we aim to understand how it has shaped these regions' economic, social, and environmental conditions.

The forestry industry in Brazil has experienced significant growth in recent years, driven mainly by favorable conditions such as investments in technology aimed at increasing productivity. This growth has positioned the Brazilian forest sector to compete globally and fostered sustainable development and operational excellence, painting a promising picture for the future of the Brazilian economy.

Technological innovation has played a crucial role in this growth. As highlighted by Montebello & Bacha (2009), advances in research and technology in the forestry and industrial sectors have been essential in increasing productivity and reducing costs in the pulp industry. This has expanded the sector and contributed significantly to the socioeconomic development of the regions involved through job creation and substantial economic activities.

Forestry productivity in Brazil is remarkably high, with an average of 38.9 m^3/ha/year for eucalyptus plantations and 29.7 m^3/ha/year for pine plantations, surpassing global standards. This productivity underscores the role of knowledge and technology in advancing modern, sustainable agriculture (Indústria Brasileira de Árvores, 2022). Moreover, the sector maintains 6 million hectares of conservation areas, storing up to 4.5 billion tons of CO_2 equivalent (Indústria Brasileira de Árvores, 2022).

This high productivity has enabled Brazil to offer competitively priced products globally (Indústria Brasileira de Árvores, 2017), leading to substantial demand in both domestic and international markets. Brazil is a leading global producer and exporter of paper derived from planted forests, with significant growth potential (Food and Agriculture Organization, 2021). In 2020, Brazilian pulp and paper exports totaled nearly US$10 billion, ranking ninth among the country's most exported products and representing about 6% of total exports (Brasil, 2021). Furthermore, according to the Observatory of Economic Complexity (2021), Brazilian wood, paper, and cellulose products accounted for approximately 6% of total Brazilian exports in 2018.

From a socioeconomic perspective, the Brazilian forest sector accounts for 1.3% of the country's Gross Domestic Product (GDP). It significantly impacts socioeconomic development, generating over 513,000 jobs and directly or indirectly affecting the lives of 3.8 million people (Indústria Brasileira de Árvores, 2019). This suggests that Brazil has the potential to not only lead but also set new standards in sustainability, productivity, and innovation within the forestry sector (Indústria Brasileira de Árvores, 2019). Therefore, it is essential to investigate whether this sector's growth has improved local populations' welfare and human development. However, expanding forestry activities also presents challenges, particularly regarding sustainability, as Lara et al. (2021) discussed.

This research seeks to measure the efficiency and productivity of the 49 main microregions that produce Brazilian forests in converting economic growth into welfare between 2009 and 2015. These microregions were selected based on their significant forest areas and the notable social, economic, and environmental changes they have undergone due to the installation of pulp and paper-producing companies. The objective is to assess the relative efficiency of these regions in transforming sectoral economic growth into social gains, such as higher employment rates, a higher Human Development Index (HDI), and increased general production. The findings will inform the management and implementation of government programs that leverage the forestry industry to improve regional quality of life while stimulating a sector that plays a fundamental role in the Brazilian economy.

This study aims to evaluate whether economic growth driven by the pulp and paper industry has positively impacted the welfare of regional populations. Economic growth is essential for raising living standards (O'Sullivan & Sheffrin, 2006). However, it is crucial to examine the quality of economic growth and its capacity to reduce extreme poverty, decrease inequalities, and become self-sustaining (López & Miller, 2008; Robalino-López et al., 2015).

This topic was chosen due to the urgent need for studies on forestry production using DEA and MPI in the Brazilian context. While many studies have applied these methods to measure the welfare efficiency and productivity of countries, regions, and cities (Thore & Tarverdyan, 2009; Chen et al., 2009; Ülengin et al., 2011; Lábaj et al., 2014; Moreno‐Enguix & Lorente Bayona, 2017; Ahn et al., 2018; Wong, 2020; Song & Mei, 2022; Sarmento et al., 2017), this research contributes academically in an original way by utilizing Data Envelopment Analysis (DEA) to evaluate the efficiency and productivity of welfare in Brazil's primary forestry-producing microregions. On a practical level, this research can guide governmental decision-making and planning.

The paper is organized into five sections. Section 2 contextualizes Brazilian forests, social efficiency, and productivity using DEA and MPI through the theoretical foundation. Section 3 presents the methodology description and econometric analysis. Section 4 discusses the results, followed by an efficiency analysis. Finally, Section 5 summarizes the conclusions of the paper.

2. Theoretical foundation

2.1 Brazilian forests in a global framework

In Brazil, forestry is not just a significant economic activity, it is a cornerstone of the nation's economy. The country's favorable soil and climate make it an ideal hub for forestry endeavors. On a global scale, Brazil's extensive native and planted tropical forests are renowned. According to data from the United Nations Food and Agriculture Organization (FAO), in 2016, Brazil had 493.5 million hectares of forests, native and planted, which covered 57.96% of its territory. This represented 12.33% of worldwide forest coverage (Food and Agriculture Organization, 2021). Food and Agriculture Organization (2021) has reported that Brazil is among the countries with the largest forested territory in the world, second only to Russia. About 493.5 million hectares of forested land constitute 58% of the country's total land area. Around 485 million hectares are primary or otherwise naturally regenerated forests. The remaining 7.7 million hectares are planted forests, mainly consisting of introduced species such as Eucalyptus and Pine, and to a lesser extent, Acacia, Teak, and Rubberwood (Timber Trade Portal, 2023). Most of the country's planted forests are in the south of Brazil, while the native forests that provide timber are almost exclusively part of the Amazon.

This fact is reflected in the international scenario, where in 2018, Brazil was considered the second largest producer and exporter of pulp—behind only the United States—and one of the most important producers and exporters of paper with significant growth potential (Food and Agriculture Organization, 2021). In this context, according to the World Integrated Trade Solutions (WITS), Brazilian exports of forest products represented 21.57% of the world total in 2017 (World Integrated Trade Solutions, 2020).

In 2018, Brazil's total area of planted trees reached 7.83 million hectares. Moreover, the inventory of CO_2 equivalent reached 4.2 billion tons (Brasil, 2018). According to Gandour et al. (2021), Brazil's Nationally Determined Contribution to the Paris Agreement is to mitigate at least 43% of Greenhouse Gas (GHG) emissions by 2030. Because deforestation causes GHG, the Brazilian forestry sector can help to reach the goal of mitigating GHG emissions. In this context, Brazil is committed to restoring and reforesting 12 million hectares of forests, enforcing the implementation of the Forest Code, creating public policies and measures to achieve zero illegal deforestation, encouraging sustainable native forest management, adopting and accelerating the diffusion of integrated crop-livestock-forest systems, reach the share of 45% of renewable energy in the Brazilian mix, and increase the share of bioenergy to 18% by 2030 (Indústria Brasileira de Árvores, 2019). These measures, if implemented effectively, can pave the way for a sustainable future for the Brazilian forestry industry.

Despite these numbers, forest land cover in Brazil has declined over the last decades, with an average rate of deforestation in the Amazon of around 6,000 square km a year since 2010 (Instituto Nacional de Pesquisas Espaciais, 2021). This has generated significant concerns in domestic and international organizations due to the potential climate change effects associated with deforestation and forestry degradation.

Removing native vegetation cover is one of the first environmental actions caused by economic activities. The incorporation of new areas for agriculture, the expansion of urban areas, and the connection of different regions by highways eliminate or reduce the original vegetation on a large scale (Campoli & Stivali, 2023).

Lovejoy & Nobre (2018) argue that if Brazil does not stop deforestation in the Amazon and its destroyed vegetation cover exceeds 20% of the original vegetation, the largest tropical forest in the world will cease to exist, causing an imbalance in the regulation of rainfall and environmental damage at a global level. Leite Filho et al. (2021) corroborate this scenario since the accentuated forest loss will decrease rainfall and significantly impact agricultural losses.

According to Sun & Wang (2022), high-quality industrial development (HID) is a requirement of the modern economy and regional development. Therefore, sustainability and low CO2 emissions to avoid climate change have become fundamental concepts these last decades. They have been employed by a progressive number of people and firms as significant demand drivers for maintaining their share in domestic and international markets, such that economic and financial gains can be sustained.

Therefore, according to O'Neill et al. (2017), the forest sector is an excellent ally for society to be able to mitigate and adapt to possible climate changes, which would be linked to factors that include demography, human development, economy and lifestyle, policies and institutions, environmental technology environment, and natural resources.

According to Selvatti (2015), the study of the evolution of forestry is essential, considering that forests not only play a fundamental role in maintaining the planet's biological and climatic characteristics but are also relevant for the generation of wealth using forest resources according to good habits. In Brazil, 35% of total wood production is destined for the pulp and paper sector, which is responsible for the largest share of exports and world imports of forest products (Selvatti, 2015).

In Brazil, the pulp industry produces the primary paper input, cellulose. For this reason, in most countries, the pulp industries are integrated with the paper industries. In this commercial dynamic, most pulp produced is destined for the foreign market. Therefore, the pulp and paper industries are installed close to the forests. Regionally, production is distributed among the states of Espírito Santo, Minas Gerais, São Paulo, Bahia, Amapá, Rio Grande do Sul, and Mato Grosso do Sul (Coelho & Coelho, 2013).

The pulp and paper sector comprises 220 companies operating in 540 municipalities located in 18 states in Brazil, generating 128 thousand direct jobs and 640 thousand indirect jobs (Associação Brasileira Técnica de Celulose e Papel, 2023).

The pulp and paper sector, comprising 220 companies operating in 540 municipalities located in 18 states in Brazil, is not just a significant contributor to the nation's economy, but also a responsible steward of the environment. It generates 128 thousand direct jobs and 640 thousand indirect jobs (Associação Brasileira Técnica de Celulose e Papel, 2023). Brazil's pulp industry is the 4th largest in the world in terms of production volume, while the country's paper industry occupies the ninth position in the ranking of world manufacturers. The forest area preserved by companies operating in this industrial segment is 2.9 million hectares. The pulp and paper sector plants over 2.2 million hectares for industrial purposes, most of which are certified forests. This sustainable action – which preserves the environment and simultaneously generates social compensation from its activities – ensures that biodiversity and water resources are protected. In this way, the forests planted by the sector generate environmental contributions by capturing CO_2, soil conservation, and restoration of degraded lands (Associação Brasileira Técnica de Celulose e Papel, 2023).

2.2 DEA and MPI evaluating transforming Economic Growth into Welfare

This section presents a set of selected studies in the literature that used a methodological procedure similar to the one used in the present analysis. These studies are significant as they evaluate the performance reached by sets that compare different countries' and regions' efficiency by converting economic growth into welfare. They provide a comprehensive understanding of the theoretical and practical application of DEA and MPI methodologies.

In this section, the search filter was meticulously designed, combining the keywords "Welfare" and "Industry" and "DEA" or "Malmquist" since the year 2018, using Scopus databases. The selected article about the industry was chosen to enhance social welfare, ensuring a comprehensive and thorough research process.

Sun & Wang (2022) designed a four-dimensional High-quality industrial development (HID) evaluation of 17 cities in the Area of the Yellow River in China from 2005 to 2019. They used the entropy-weighted Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method and Malmquist Productivity Index based on relevant economic indicators. The results showed that the industrial structure and layout were more rational in provincial capitals and large cities. Almost all cities have experienced increased single-factor productivity, and technological progress contributed most to the total factor productivity growth. The development environment in most cities has remained stable, and social welfare has increased and distributed more equitably.

Zhang et al. (2022) measured the ecological welfare performance (EWP) of 284 cities in China from 2007 to 2020 using the superefficient SBM-DEA model. The results showed that the EWP fluctuates but increases over time. Regarding spatial distribution, the EWP of the West Region is greater than that of the East, Central, and Northeast Regions because it presents a better ecological environment. The Northeast Region is an essential area of China's former industrial base, and its environmental pollution levels are severe, which makes the EWP lower. Regarding influencing factors, the level of financial development, secondary industry structure, openness, and urbanization significantly improved China's EWP.

Regarding sustainable development, Camioto & Pulita (2022) compared emerging countries (BRICS) with the most developed countries (G7). They used DEA-SBM from 2005 to 2014. The findings showed that India, China, and Brazil (emerging countries) are in the top efficiency positions. The emerging countries have stood out in the sustainability question, showing their sustainable awareness policies. On the other hand, the economic crisis 2008 impacted the developed countries, and the G7 countries need to invest more in sustainable development. The results obtained can be helpful for public policies related to sustainable development.

As industrialization and urbanization in China have significantly increased ecological, Hou et al. (2020) established an evaluation index system that considers ecological, economic efficiency, and economic welfare efficiency: the ecological welfare performance (EWP). They used a two-stage super-efficiency slacks-based model (Super-SBM) and data envelopment analysis (DEA) from 2006 to 2017. The results showed that the average EWP value in the Chinese provinces was relatively low at 0.698 with significative regional differences, corroborating with Zhang et al. (2022). The study presented limitations, so factors in China's development should be studied to determine the EWP driving mechanisms and influence determinants, such as the relationships between industrial agglomeration, green technology development, and EWP.

Concerning eco-efficiency, Ren et al. (2020) constructed a theoretical framework for a composite economic-environmental-social system that reflects human welfare and sustainability. They used DEA to evaluate China's provinces' economic, environmental, and social factors from 2003 to 2016. The findings demonstrated that China's overall eco-efficiency presented a low level, with regional differences, corroborating with Zhang et al. (2022) and Hou et al. (2020). Moreover, the efficiency scores continued to rise during the environmental governance stage from 2003 to 2010 and rose overall, but with some fluctuations from 2011 to 2016. The overall factors were economic growth, marketization, and social input.

Regarding urban agglomerations, Kourtit et al. (2020) developed an advanced methodology for assessing global cities' economic and sustainability-oriented performance strategies by developing and applying a superefficient Data Envelopment Analysis (DEA) model. They compared 40 global cities in the Global Power City Index (GPCI) database to trace the highest-performing urban regions from an economic and environmental-climatological efficiency perspective. China's overall ecological efficiency is showed a low level, with regional differences high in the East and low in the West – like Zhang et al. (2022), Hou et al. (2020), and Ren et al. (2020). Moreover, the efficiency level in the production stage is declining while the environmental governance and social input stage is increasing.

Liu et al. (2019) provided a new method to provide some decision-making references for improving the urban ecological efficiency in Henan province. They used the DEA-SBM and Malmquist Productivity Index from 2005 to 2016. Based on this, the bootstrap regression model is applied to analyze the factors influencing urban ecological efficiency. The results showed that the urban ecological efficiency is low in Henan province. The MPI demonstrates that overall growth trends and technological progress have significantly promoted urban ecological efficiency. The influencing factors were the governmental finances, level of opening to the outside world, urban population density, and urban greening.

The contributions of this paper to welfare efficiency and productivity are: (a) analyzing the relationship between the forest industry and social welfare; (b) studying Brazil, a country that has a solid social inequality; (c) applying econometric modeling; the output-oriented Data Envelopment Analysis (DEA) – Slack Based Measure (SBM) to determine efficiency and Malmquist Productivity Index (MPI) to measure productivity; (d) measures of efficiency and productivity to analyze social welfare.

3. Methodology

We structured this article's empirical and methodological procedures into four stages: a) selection of variables; b) econometric validation; c) Data Envelopment Analysis (DEA) and Window Analysis from 2009 to 2015; and d) Malmquist Productivity Index.

3.1 Selected variables

We initially selected Brazilian Micro-Regions based on their forest industry production capacity of over 100,000 m³ of wood for pulp and paper production. Figure 1 displays these selected Micro-Regions.

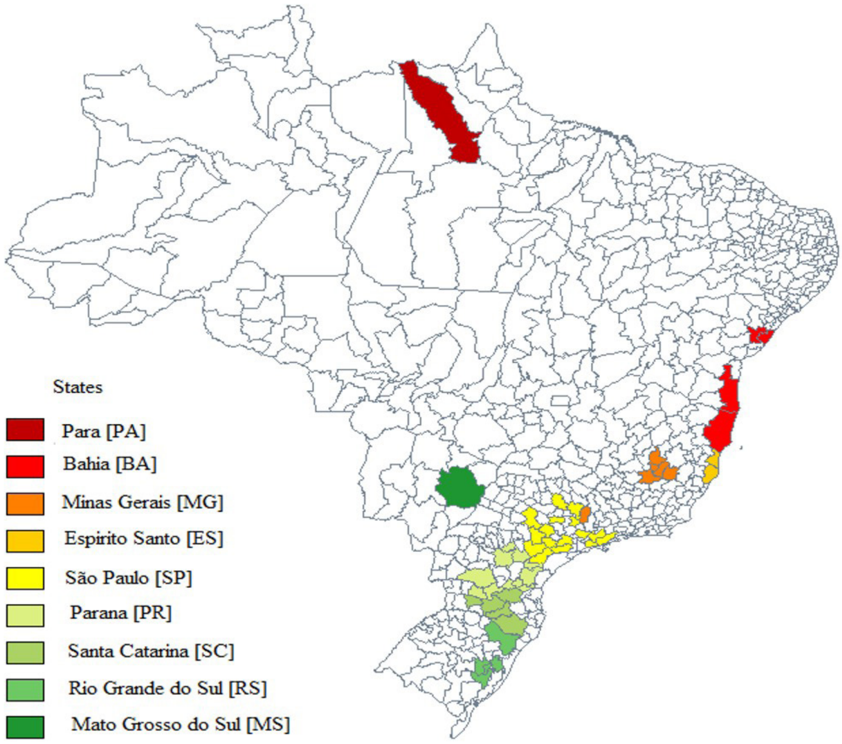

Figure 1. Selected micro-regions[1].
Source: Authors

Next, we identified variables that express the relative importance of the forestry sector on the economy of each Micro-Region. These variables, such as the average cost of wood, the number of workers in forestry and paper and pulp production, the overall economic growth (GDP), and the total number of people employed by the forestry sector, are crucial in understanding the economic impact of the forestry sector. The local Human Development Index (HDI), a key measure of the quality of life, was used throughout the Analysis of the local economies, further enriching our understanding.

Table 1 displays the variables chosen, the dimension attributed to each, their data source, and their basic theoretical definition. The empirical basis for selecting variables such as GDP, number of employed people, and HDI was derived from a comprehensive literature review.

[1] Nine states were analyzed and 49 micro-regions. In the Northern, Para (PA) state with the micro-region Almeirim. In the Northeastern, Bahia (BA) state with the micro-regions: Alagoinhas, Entre Rios, Ilheus – Itabuna, and Porto Seguro. In the Southeastern, Minas Gerais (MG) state with the micro-regions: Itabira, Guanhaes, Ipatinga, Caratinga and Pocos de Caldas, Espírito Santo (ES) state with the micro-regions Sao Mateus and Linhares, São Paulo (SP) state with the micro-regions: Ribeirao Preto, Bauru, Avare, Botucatu, Rio Claro, Sao Joao da Boa Vista, Mogi Mirim, Itapeva, Itapetininga, Capao Bonito, Piedade, Sorocaba, Braganca Paulista, Sao Jose dos Campos, Paraibuna/Paraitinga and Mogi das Cruzes. In the Southern, Paraná (PR) state with the micro-regions: Ibaiti, Telemaco Borba, Jaguariaiva, Guarapuava, Palmas, Uniao da Vitoria, Sao Mateus do Sul, Cerro Azul, Lapa, Curitiba and Rio Negro, Santa Catarina (SC) state with the micro-regions: Xanxere, Joacaba, Canoinhas, Curitibanos and Campos de Lages, and Rio Grande do Sul (RS) state with the micro-regions: Vacaria, São Jeronimo, Porto Alegre and Camaqua. In the Midweastern, Mato Grosso do Sul (MS) state with the micro-region of Tres Lagoas.

This thorough review ensures the reliability and validity of our research. Table 1 presents the selected variables for the efficiency model as inputs and outputs.

Table 1. Variables selected for the analysis

Variable	Dimension	Source	Theoretical basis	Variable
Average wood cost (BRL/m^3)	Economic	Instituto Brasileiro de Geografia e Estatística (2021a)	Proposal of this research	Input
Employment in forestry and paper and pulp production	Social	Instituto Brasileiro de Geografia e Estatística (2021a)	Proposal of this research	Input
Gross Domestic Product (GDP)	Economic	Instituto Brasileiro de Geografia e Estatística (2021b)	Sun & Wang (2022); Camioto & Pulita (2022); Zhang et al. (2022); Ren et al. (2020); Kourtit et al. (2020); Liu et al. (2019)	Output
Total number of employed people	Social	Instituto Brasileiro de Geografia e Estatística (2021c)	Sun & Wang (2022); Ren et al. (2020); Kourtit et al. (2020); Liu et al. (2019)	Output
Human Development Index (HDI)	Social	Firjan (2021)	Ren et al. (2020)	Output

Source: Authors

The databases consulted were those from the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística, 2021a, 2021b, 2021c), where we obtained in terms of the Micro-Regions the following variables: average wood cost (BRL/m^3), employment in forestry and paper employment in forestry and paper and pulp production, Gross Domestic Product (GDP), and total number of employed people. In the Firjan Index database (Firjan, 2021), we obtained the Human Development Index (HDI). The summary dataset is presented in Table 2.

Table 2. Descriptive data analysis

Variables	Obs.*	Mean	Std. Dev.	Min	Max
Average wood cost (BRL/m^3)	343	57.60	20.00	20.85	123.18
Number of workers in forestry and paper and pulp production	343	2,440.14	2,239.40	40.00	8,877.00
Gross Domestic Product (BRL)	343	141,397.65	287,640.26	2,784.00	1,573,928.00
Total number of employed people	343	13,034,463.62	24,539,969.50	227,424.00	143,794,029.00
Human Development Index (HDI)	343	0.6972	0.0817	0.4133	0.8168

*343 observations from 49 microregions and 7 years.
Source: Authors

The average wood cost is expressed in Brazilian currency (BRL) per cubic meter (m^3), and GDP is expressed in Brazilian currency (BRL- Brazilian Real) (Instituto Brasileiro de Geografia e Estatística, 2021a, 2021b, 2021c). The number of employed people and workers in forestry and paper and pulp production corresponds to the number of employers. The amount of wood produced in forestry is given in cubic meters. Furthermore, the Firjan Human Development Index (HDI) is calculated for all Brazilian municipalities, ranging from 0 to 1 (Firjan, 2021). In this study, the HDI is given by the average of the cities that make up each Micro-Region.

In the third step, econometric modeling was developed to validate the relation between outputs and input using regression analysis. This procedure defines the efficiency model when input-output combinations are confirmed by their statistical significance level.

3.2 Econometric validation

An econometric analysis was conducted to validate the input-output relations identified in the DEA through the estimation of linear regressions for each output variable as a function of the input variables selected for the DEA. The regressions were specified as a modified Cobb-Douglas production function and the statistical level of significance of the estimated coefficients was evaluated (Equation 1):

$$Y = K^{\alpha} A^{\gamma} L^{\beta} \tag{1}$$

In this function, the inputs are represented as capital (K), land (A) and labor (L), which represent numbers from the Micro-Regions defined as a first step, as explained before. In this study, the variable Average wood cost (BRL/m³) represents $K^{\alpha} A^{\gamma}$,since in this type of production the land is used intensively. The number of workers in forestry and paper and pulp production represents the L^{β}.

Since the analysis defined three outputs, which are total gross domestic product (Y_{GDY}), total number of people employed (Y_{EMP}) and an index of human development (Y_{HDI}), a regression equation was estimated with panel data for each of these outputs, where the inputs are specified as explanatory variables, in order to evaluate the capacity of each input in explaining the output variables. The regression equations were estimated in logarithm form, as shown by Equations 2, 3 and 4:

$$\ln Y_{GDP} = \alpha_0 + \alpha_1 \ln KA + \alpha_2 \ln L + \varepsilon \tag{2}$$

$$\ln Y_{EMP} = \beta_0 + \beta_1 \ln KA + \beta_2 \ln L + \varepsilon \tag{3}$$

$$\ln Y_{\ddot{u}} = \delta_{\ddot{u}} + \delta \ln KA + \delta \ \ln L + \varepsilon \tag{4}$$

Where: $\alpha_n \beta_n \delta_n \left(n = 0, \ldots, 3\right)$ are the estimated constant coefficients of the equations; $\ln Y_{GDP}$ is the total GDP for each Micro-Region; $\ln Y_{EMP}$ is the total number of employed people at each Micro-Region; $\ln Y_{HDI}$ is Human Development Index (HDI) for each Micro-Region; *K* is the average wood cost, given by the value of production in forestry (*K*) divided by the amount of wood produced in forestry representing the land (*A*).The number of workers in forestry and paper and pulp production are represented by labor (*L*). A Feasible Generalized Least Squares (FGLS) model was estimated to deal with the heteroscedasticity and autocorrelation (Moralles & Rebelatto, 2016; Campoli et al., 2024a, 2024b).

3.3 Data Envelopment Analysis (DEA) and Window Analysis

The Data Envelopment Analysis (DEA) is a method used to measure the relative efficiency of Decision-Making Units (DMUs). This method has been used to inform planning strategies and decision-making and compare the performance of different production systems. Efficiency scores are measured from 0 to 1, with DMUs being considered efficient when they reach a score of 1. The ranking of DMUs is generated by calculating the minimum proportion to which inputs can be reduced without reducing the quantity of produced outputs (Coelli et al., 2005).

Based on previous studies by Farrell (1957), DEA was first presented by Charnes et al. (1978) with the Constant Returns to Scale model. In 1984, Banker et al. (1984) presented the Variable

Returns to Scale model, making it possible to observe whether the return to scale is variable, increasing, or decreasing (Charnes et al., 1994).

According to Mariano & Rebelatto (2014), several models of DEA are distinguished by the type of return to scale (increasing, constant, or decreasing), its orientation (input or output), and the combination of variables (inputs and outputs).

Tone (2001) proposed the Slack-Based Measure (SBM) model, based on slacks, to construct a measure of efficiency. The efficiency value represents an average reduction of inputs and an average increase of outputs to reach the efficient frontier. In addition, the SBM model enables incorporating the Variable Returns to Scale (VRS) assumption to determine efficiency's gains of scale (Dyckhoff & Souren, 2020). The fractional programming of the SBM-VRS model is as follows in Equations 5 to 9 (Tone, 2001).

$$\text{Minimize } \tau = \frac{1-\left(\frac{1}{m}\right)\sum_{j=1}^{m} s_j^- / x_{j0}}{1+\left(\frac{1}{n}\right)\sum_{i=1}^{n} s_i^+ / y_{i0}} \tag{5}$$

Subject to

$$\sum_{k=1}^{z} \lambda_k x_{jk} + s_j^- = x_{i0} \qquad i=1,2,\ldots,m \tag{6}$$

$$\sum_{k=1}^{z} \lambda_k y_{rk} - s_i^+ = y_{i0} \qquad i=1,2,\ldots,n \tag{7}$$

$$\sum_{k=1}^{z} \lambda_k = 1 \tag{8}$$

$$\lambda_k \geq 0,\ s_j^- \geq 0, \text{ and } s_i^+ \geq 0 \tag{9}$$

Where τ is the efficiency, s_j^- is the slack of the input j, s_i^+ is the slack of the output i, λ_k is the participation of DMU k in the goal of the DMU under analysis, x_{j0} is the quantity of input j of the DMU under analysis, y_{i0} is the output i of the DMU under analysis, x_{jk} is the quantity of input j of the DMU k, y_{ik} is the quantity of output i of the DMU k, z is the number of DMUs, m is the number of inputs, and n is the number of outputs. And Equation 8 represents the VRS assumption.

For the output-oriented (O-O) SBM, we need to change the Objective Function in Equation 5 by Equation 10.

$$\text{Maximize } \tau^{O-O} = 1+\left(\frac{1}{n}\right)\sum_{i=1}^{n} s_i^+ / y_{i0} \tag{10}$$

This study utilized an SBM-VRS model to measure the relative efficiency of micro-regions in terms of their surplus of inputs and deficiency of outputs for the Brazilian forestry industry. Inputs must be considered comparative variables between each DMU, such that "the less, the better" for efficiency measures. At the same time, outputs can act as variables "the more, the better" for efficiency identification (Cook et al., 2014). For this research, the output-oriented

SBM-VRS model was chosen to assess the efficiency of the DMUs from the forestry industry, as it was desired to increase (maximize) the socio-economic outputs (welfare) without reducing the inputs and number of jobs in forestry and paper and pulp production.

To include the time factor, we used the Window Analysis; the idea is that one year of data is replaced with the following to maintain the homogeneity of the Decision-Making Units (DMUs) (Camioto et al., 2017). Expressions 5 and 6 are used to obtain the size of each window (Equation 11) and the number of windows (Equation 12) to be grouped, where k corresponds to the number of periods and p to the width of the window (Cooper et al., 2007).

$$Window\ size\ \left(p\right) = \left(k + 1\right)/2 \tag{11}$$

$$Number\ of\ windows = k - p + 1 \tag{12}$$

This paper covers the period from 2009 to 2015 and applies a window analysis with a window size of 4, resulting in a total of 4 windows.

3.4 Malmquist Productivity Index (MPI)

The analysis has also calculated DEA-based Malmquist Productivity Indexes (MPI), as developed by Fare & Grosskopf (1992) and Fare et al. (1994). MPI is a generalized index that measures the evolution of the productivity and economic drivers that result in frontier changes (sometimes referenced as technological progress) and a relative efficiency evolution concerning the DMUs.

Shah et al. (2024) proposed an SBM-DEA model to analyze forestry resource efficiency and MPI to estimate productivity and efficiency changes in China.

Long et al. (2020) developed a Super-SBM and global Malmquist to analyze spatial-temporal and logistics ecological efficiency and correlate it to regional economic development.

According to Yang & Soltani (2021), MPI has negative aspects because it is not circular and can lead to infeasibility under VRS assumption in some circumstances. To overcome these drawbacks, they developed an expanded global SBM-MPI.

The DEA-based MPI can be computed by considering four distance measures based on comparing the efficiencies of two periods. Under a Constant Returns to Scale (CRS) DEA model, the MPI proposed by Fare et al. (1994) is formulated as in Equation 13:

$$MPI_{CRS} = \sqrt{\frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{CRS}^{t}\left(x^{t}, y^{t}\right) D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)}} = \sqrt{\frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)}{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)}}\ \frac{D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{CRS}^{t}\left(x^{t}, y^{t}\right)} \tag{13}$$

Where: $D_{CRS}^{t}(x^{t} y^{t})$: is the efficiency of the DMU under analysis in period *t* in comparison to the frontier in period *t*; $D_{CRS}^{t+1}(x^{t+1} y^{t+1})$: is the efficiency of the DMU under analysis in period *t+1* in comparison to the frontier in period *t+1*; $D_{CRS}^{t}(x^{t+1} y^{t+1})$: is the intertemporal score of the DMU in period *t+1* in comparison to the frontier in period *t*; $D_{CRS}^{t+1}(x^{t} y^{t})$: is the intertemporal score of the DMU in period *t* in comparison to the frontier in period *t+1*.

The MPI (Equation 13) allows for measuring the productivity changes through time, decomposed into catch-up effect (Efficiency Changes - EC) and frontier shift effect (Technological Changes - TC). The EC compares the DMUs' efficiencies under analysis in periods *t+1* relative to *t*, while TC is a geometric average of the comparison between the benchmarks of the DMU under analysis in both periods (so it is a measure of the frontier shift, indicating technological innovations).

The MPI is a geometric average of the comparison between the DMU under analysis and both frontiers - so it is a measure of the productivity evolution. It can result from technological innovations or efficiency changes (Ferreira & Gomes 2020). The decomposition of the model under CRS assumptions can be seen in Equations 14 to 16 (Fare et al., 1994):

$$TC_{CRS} = \sqrt{\frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t}\left(x^{t}, y^{t}\right)}{D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)}} \tag{14}$$

$$EC_{CRS} = \frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right)}{D_{CRS}^{t}\left(x^{t}, y^{t}\right)} \tag{15}$$

$$MPI_{CRS} = \sqrt{\frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{0}^{t}\left(x^{t}, y^{t}\right)}{D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) D_{0}^{t+1}\left(x^{t}, y^{t}\right)}} \frac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right)}{D_{CRS}^{t}\left(x^{t}, y^{t}\right)} = TC_{CRS} EC_{CRS} \tag{16}$$

The efficiencies $\ddot{u}\,{}^{\ddot{u}}_{\ddot{u}}\left(\quad , \quad \right)$and $D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)$values are between 0 and 1, and the intertemporal scores ($D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) \mathit{and}\ D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)$) can be greater than 1, as well as the TCs, ECs, and MPIs. A value less than 1 indicates a decrease, while a value greater than 1 indicates an increase and a value of 1 indicates no change.

It is important to note that, for example, a DMU with *EC > 1* does not indicate that it is more efficient than a DMU with *EC <= 1*; it indicates a better improvement. In other words, a DMU_1 with $D_{CRS}^{t}\left(x^{t}, y^{t}\right) = 0.1$ and $D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) = 0.2$ improved its efficiency while a DMU_2 with $D_{CRS}^{t}\left(x^{t}, y^{t}\right) = 1.0$ and $D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) = 0.5$ reduced its efficiency, and therefore expresses a higher efficiency than DMU_1, despite the higher EC of DMU_1.

The exact comparisons can be made under the VRS assumption. The MPI_{CRS} and MPI_{VRS} are related as follows in Equation 17 (Tone, 2011):

$$MPI_{CRS} = MPI_{VRS} SEC \tag{17}$$

Where *SEC* is the Scale-Efficiency Changes (a comparison between CRS and VRS) as seen in Equation 18 (Tone, 2011):

$$SEC = \sqrt{\frac{\dfrac{D_{CRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{CRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_{VRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{VRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)}}{\dfrac{D_{CRS}^{t}\left(x^{t}, y^{t}\right) D_{CRS}^{t+1}\left(x^{t}, y^{t}\right)}{D_{VRS}^{t}\left(x^{t}, y^{t}\right) D_{VRS}^{t+1}\left(x^{t}, y^{t}\right)}}} \tag{18}$$

The decomposition of the model under VRS assumptions is like the CRS one, and it can be seen in Equations 19 to 21 (Tone, 2011):

$$TC_{VRS} = \sqrt{\frac{D_{VRS}^{t}\left(x^{t+1}, y^{t+1}\right) D_{VRS}^{t}\left(x^{t}, y^{t}\right)}{D_{VRS}^{t+1}\left(x^{t+1}, y^{t+1}\right) D_{VRS}^{t+1}\left(x^{t}, y^{t}\right)}} \tag{19}$$

$$EC_{VRS} = \frac{D_{VRS}^{t}\left(x^{t+1}, y^{t+1}\right)}{D_{VRS}^{t}\left(x^{t}, y^{t}\right)} \tag{20}$$

$$MPI_{VRS} = \sqrt{\frac{D_{VRS}^{t}(x^{t+1}, y^{t+1}) D_{VRS}^{t}(x^{t}, y^{t})}{D_{VRS}^{t+1}(x^{t+1}, y^{t+1}) D_{VRS}^{t+1}(x^{t}, y^{t})}} \frac{D_{VRS}^{t}(x^{t+1}, y^{t+1})}{(D_{VRS}^{t}(x^{t}, y^{t})} = TC_{VRS} EC_{VRS} \tag{21}$$

Similar to the model under CRS, despite the efficiencies ($D_{VRS}^{t}\left(x^{t}, y^{t}\right)$ and $D_{VRS}^{t+1}\left(x^{t+1}, y^{t+1}\right)$) being values between 0 and 1, the intertemporal scores $\left(D_{VRS}^{t}\left(x^{t+1}, y^{t+1}\right) and\ D_{VRS}^{t+1}\left(x^{t}, y^{t}\right)\right)$ can be greater than 1, as well as the TCs, ECs, and MPIs, and these values that can be greater than 1 is calculated similarly to a super-efficiency, so the model under VRS assumption in oriented models may suffer from infeasibility problems.

The non-oriented SBM-VRS does not have this problem, but the oriented versions can suffer from infeasibility, as in the BCC model (the first oriented model under VRS). Since the output-oriented SBM-VRS model was used in this study (Tone, 2017).

According to Tone (2011), regarding the infeasibility of MPI under VRS assumptions, one solution for avoiding this difficulty is to assign 1 to the score (when it is infeasible) since there is probably no means to evaluate the DMU within the evaluator group. Also, the standard "big-M" approach could solve infeasibility problems in the super-efficiency model. Furthermore, a "one-model" approach was proposed by Chen & Liang (2011).

In the MPI, intertemporal scores can take on values greater than 1 and are calculated like DEA Super-Efficiency. In other words, DEA Super-Efficiency is a technique in which a tested DMU (or a set of tested DMUs) is excluded from the reference set. For example, an efficient DMU can be excluded, and the ensuing efficiency frontier can be explored (Zhu, 2001).

According to Tone & Tsutsui (2017), the non-oriented super-SBM, even under VRS assumptions, does not incur an infeasibility problem. According to Tone (2017), if the corresponding SBM-MPI is found to be infeasible, another method is applying the non-oriented Super-SBM-VRS model because it does not have this problem. However, even the oriented versions also can need more infeasibility. So, in this paper, as it is necessary to use the output-oriented Super-SBM-VRS model to calculate the intertemporal scores, it is necessary to solve the infeasibility problem when the result is a value greater than 1.

Chen et al. (2011) proposed a mixed method for solving the infeasibility of an oriented model using a super-efficiency measure based on simultaneous input-output projection. In other words, it is using a non-oriented super-efficiency model when the oriented one is infeasible.

This paper adopts a new approach inspired by the work of Chen et al. (2011) and Tone (2017). When the values are lower than 1, the output-oriented SBM-VRS version of the model in Equations 6 to 10 is applied. If the value equals 1, then an output-oriented Super-SBM-VRS in Equations 28 to 32 is applied. If the value is greater than 1, or if the problem is infeasible when applying the output-oriented Super-SBM-VRS, then a non-oriented Super-SBM-VRS in Equations 22 to 27 is applied.

Tone (2002) proposed a Super-SBM with a form different from the standard SBM. Fang et al. (2013) provided an equivalent Super-SBM model with a form like the standard SBM and linear Equations ranging from 22 to 27 (Fang et al., 2013):

$$\tau^{super} = t + \frac{1}{m} \sum_{j=1}^{m} \frac{H_j}{x_{j0}} \tag{22}$$

Subject to:

$$t-\frac{1}{n}\sum_{i=1}^{n}\frac{H_i}{y_{i0}}=1 \tag{23}$$

$$\sum_{k=1}^{z}y_{jk}\Lambda_k - H_j - x_{j0}t\leq 0 \qquad j=1,2,\ldots,m \tag{24}$$

$$\sum_{k=1}^{z}y_{ik}\Lambda_k - H_i - x_{i0}t\geq 0 \qquad i=1,2,\ldots,n \tag{25}$$

$$\sum_{k=1}^{z}\Lambda_k = t \tag{26}$$

$$\Lambda_k\geq 0, H_i\geq 0, H_j\geq 0, t>0 \tag{27}$$

Where τ^{super*} is the optimal super-efficiency, τ^{super} is the super-efficiency score, t is the linearization variable, H_i is the linearized input savings rate for the linear problem $(H_{ii}=th)$, h is the input savings for the super-efficiency model, h_j is the output surplus for the super-efficiency model. Λ_k is the linear version of the λ_k for the linear problem ($\Lambda_k = t\lambda_k$). The other parameters and variables are the same as presented in the Equations 5 to 10.

Finally, the output-oriented Super-SBM-VRS model is as follows in Equations 28 to 32 (Tone, 2017):

$$\frac{1}{\tau^{O-O\_super*}}=Max\,1-\frac{1}{n}\sum_{j=1}^{n}\frac{H_i}{y_{i0}} \tag{28}$$

Subject to:

$$\sum_{k=1}^{z}x_{jk}\Lambda_k - H_j\leq x_{j0} \qquad j=1,2,\ldots,m \tag{29}$$

$$\sum_{k=1}^{z}y_{ik}\Lambda_k - H_i\geq y_{i0} \qquad i=1,2,\ldots,n \tag{30}$$

$$\sum_{k=1}^{z}\Lambda_k = 1 \tag{31}$$

$$\Lambda_k\geq 0, H_i\geq 0, H_j\geq 0 \tag{32}$$

Where: this model has the same variables and parameters as the model in Equations 22 to 27 (and $t = 1$), but for analyzing the output-oriented super-efficiency.

4. Results and Discussion

4.1 Econometric results

As explained in section 3.2 an econometric analysis was conducted to validate the input-output relationships identified in the DEA through the estimation of linear regressions for each output variable, using the input variables selected for the DEA. The regressions were specified as a modified Cobb-Douglas production function, and the statistical significance of the estimated coefficients was evaluated. The econometric estimates are shown in Table 3.

Table 3. Econometric estimates of equations relating outputs to inputs, as for the Efficiency Model

Inputs (Independent variables)		Outputs (Dependent variables)		
		Gross Domestic Product (GDP)	Total number of employed people	Human Development Index (HDI)
Average wood cost	*Coef.*	0.171***	0.0740***	0.0197***
	p-value	0.0000	0.0030	0.0000
	Std. Errors	0.0477	0.0253	0.0052
Number of workers in forestry and paper and pulp production	*Coef.*	0.261***	0.178***	0.00928***
	p-value	0.0000	0.0000	0.0010
	Std. Errors	0.0362	0.0242	0.0027
Constant	*Coef.*	12.80***	9.259***	0.556***
	p-value	0.0000	0.0000	0.0000
	Std. Errors	0.32600	0.21	0.03
Observations		343	343	343
Number of DMUs		49	49	49

*** p<0.01 ** p<0.05 * p<0.10.
Source: Authors

The average wood cost and number of works in forestry and paper and pulp production were statistically efficient at 1 percent (p<0.01) for explaining the Y (GDP) variable. This result indicates that in the micro-regions where the cost of wood and labor in the forestry sector is higher, the variable GDP (Y) is also higher.

The average wood cost and number of workers in forestry and paper and pulp production also presented positive coefficients. They were significant at 1 percent (p<0.01) when explaining the total number of people employed in each Micro-Region. This finding suggests that those Micro-Regions with higher wood cost and forest sector workforce also presented higher total employment levels by Micro-Regions.

Completing the econometric validation, wood cost, and number of workers in forestry and paper and pulp production. In that case, it is possible to identify which regions with the highest HDI also have the higher wood cost and forest sector workforce. After the econometric validation, to verify the efficiency of the main forestry-producing Micro-Regions in converting the expansion of economic growth into social welfare, the average wood cost, and the number of works in forestry and paper and pulp production were used as inputs. Furthermore, the GDP, the total number of employed people, and HDI were used as outputs. In this study, we choose the output-oriented SBM-VRS model to improve (maximize) the outputs (welfare) without reducing the inputs. After the econometric validation, the efficiency model was characterized as described in Table 4.

To verify the efficiency of the main forestry-producing Micro-Regions in converting the expansion of the economic growth into social welfare, the average wood cost and the number of works in forestry and paper and pulp production were used as inputs. And the GDP, the total number of employed people, and HDI were used as outputs. In this study, we choose the output-oriented SBM-VRS model to improve (maximize) the outputs (welfare) without reducing the inputs.

Table 4. Efficiency Model

Efficiency Model	
Inputs	**Outputs**
a) Average wood cost	1) Gross Domestic Product (GDP)
b) Number of workers in forestry and paper and pulp production	2) Number of people employed
	3) Human Development Index (HDI)

Source: Own elaboration

4.2 Efficiency Scores and Window Analysis

To elaborate on the model to convert the expansion of economic growth into welfare from 2009 to 2015, we employed variables to relate de-production (paper pulp industry) to welfare.

The efficient DMUs over time were: Ilhéus-Itabuna (BA), Rio Claro (SP), São Joao da Boa Vista (SP), Sorocaba (SP), Curitiba (PR), Vacaria (RS), and Porto Alegre (RS). Ilhéus-Itabuna (BA) is the only DMU from the Northeastern Region of Brazil. Compared to results in the next section (4.2), Ilhéus-Itabuna (BA) presented *EC=1*, *TC>1*, and *MPI>1,* and it was efficient in both periods (for the three analyses). In this way, Ilhéus-Itabuna (BA) could be a benchmark for policy-making and efficient investments in Northeastern Region.

Rio Claro (SP), Sao Joao da Boa Vista (SP), and Sorocaba (SP) are DMUs from the Southeastern Region of Brazil, specifically from São Paulo (SP) state, one of the most economically developed and pointed out by Rentizelas et al. (2019) as efficient, productive alternatives. About MPI, although Rio Claro (SP) and Sorocaba (SP) presented *EC=1*, Rio Claro (SP), São Joao da Boa Vista (SP), and Sorocaba (SP), they presented *TC<1* and *MPI<1*, which mean they are risking losing their position among the efficient DMUs. Consequently, these DMUs should be the focus of regional development policies. Besides, previous efforts have highlighted that not only pulp-producing regions of the inner Regions of Sao Paulo state require development policies, but also palm-heart producing Micro-Regions (Varella et al., 2022). This demonstrates that the state has great potential for the forestry sector.

Vacaria (RS) and Porto Alegre (RS) are DMUs from Southern Region of Brazil. Vacaria (RS) has a performance like Ilhéus-Itabuna (BA). Therefore, it can be assumed as a national benchmark, while Porto Alegre (RS) has a performance like Rio Claro (SP), São Joao da Boa Vista (SP), and Sorocaba (SP). Therefore, it requires immediate assistance to maintain efficiency. In this way, the results of the Window Analyses were consistent with the previous temporal analyses (*MPI*, *TC*, and *EC*), as highlighted in Table 5.

On the other hand, the Micro-Regions with efficiency below 10% were União da Vitória (PR), Guanhães (MG), Três Lagoas (MS), São Mateus do Sul (PR), Telêmaco Borba (PR), Cerro Azul (PR) and Almeirim (PA). União da Vitória (PR), São Mateus do Sul (PR), Telêmaco Borba (PR) and Cerro Azul (PR) are DMUs from Southern Region of Brazil. União da Vitória (PR), São Mateus do Sul (PR), Telêmaco Borba (PR) and Cerro Azul (PR) are DMUs from Southern Region of Brazil. The efficient DMUs from the Southern region were from Rio Grande do Sul (RS), while the inefficient DMUs were from Paraná (PR). These less efficient regions hold great potential for improvement, offering hope for a more balanced and efficient future.

The results demonstrate the existence of inequality of efficiency among regions and states in Brazil, a pattern also observed in China (Zhang et al., 2022; Hou et al., 2020; Ren et al., 2020; Kourtit et al., 2020). Hence, the proposed method helps direct investments and policies toward those areas that require the most. Parallelly, Guanhães (MG) is from the Southeastern state of Minas Gerais, while the efficient DMUs are from São Paulo. This may indicate that Minas Gerais should have priority on regional investments and policies. Rentizelas et al. (2019) pointed out that the most efficient alternatives are São Paulo and Minas Gerais. However, the authors did not consider human development aspects.

Table 5. Window Analyses and Efficiency scores

City	Efficiency Scores						
	Window 1	Window 2	Window 3	Window 4	Mean Efficiency (%)	Ranking	Growth rate (%)
Ilhéus-Itabuna (BA)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Rio Claro (SP)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
São João da Boa Vista (SP)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Sorocaba (SP)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Curitiba (PR)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Vacaria (RS)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Porto Alegre (RS)	1.0000	1.0000	1.0000	1.0000	100.00	1	0.00
Botucatu (SP)	0.8980	1.0000	0.9053	0.9053	92.72	2	0.82
Ribeirão Preto (SP)	0.8839	0.9178	0.9469	0.9331	92.04	3	5.57
Poços de Caldas (MG)	0.8303	0.8481	0.8931	0.9144	87.15	4	10.13
Entre Rios (BA)	0.8002	0.8002	1.0000	0.7806	84.53	5	-2.45
São José dos Campos (SP)	0.7398	0.8012	0.8458	0.9141	82.52	6	23.56
Paraibuna/Paraitinga (SP)	0.7874	0.7874	0.8314	0.8314	80.94	7	5.59
Mogi Mirim (SP)	0.5905	0.7297	0.8908	1.0000	80.27	8	69.36
Ibaiti (PR)	0.5665	0.7806	0.7806	0.7777	72.64	9	37.28
Bragança Paulista (SP)	0.5362	0.5998	0.7285	0.7819	66.16	10	45.82
Avaré (SP)	0.5929	0.6211	0.5367	0.5091	56.49	11	-14.15
Lapa (PR)	0.1771	0.3900	0.6008	0.8128	49.52	12	358.96
Camaquã (RS)	0.4843	0.5115	0.3555	0.3187	41.75	13	-34.19
Bauru (SP)	0.3678	0.3785	0.3725	0.3823	37.53	14	3.94
São Jerônimo (RS)	0.3003	0.3141	0.3826	0.4289	35.65	15	42.82
Piedade (SP)	0.2818	0.3395	0.3662	0.4026	34.75	16	42.86
Itabira (MG)	0.3300	0.3427	0.3341	0.3389	33.64	17	2.68
Mogi das Cruzes (SP)	0.3467	0.3318	0.3236	0.3141	32.91	18	-9.41
Ipatinga (MG)	0.3071	0.3239	0.3274	0.3263	32.12	19	6.25
Linhares (ES)	0.3412	0.3230	0.3035	0.3057	31.84	20	-10.39
Caratinga (MG)	0.1489	0.1989	0.2523	0.3000	22.50	21	101.52
Xanxerê (SC)	0.2088	0.2140	0.2097	0.2059	20.96	22	-1.39
Palmas (PR)	0.1791	0.1883	0.1937	0.2074	19.21	23	15.82
Itapetininga (SP)	0.2017	0.1836	0.1622	0.1431	17.26	24	-29.04
Campos de Lages (SC)	0.2735	0.1374	0.1389	0.1394	17.23	25	-49.03
Guarapuava (PR)	0.1557	0.1645	0.1694	0.1786	16.70	26	14.73
Capão Bonito (SP)	0.1572	0.1540	0.1463	0.1586	15.40	27	0.85
Joaçaba (SC)	0.1482	0.1481	0.1488	0.1591	15.10	28	7.37
Rio Negro (PR)	0.1333	0.1465	0.1528	0.1635	14.90	29	22.64
Porto Seguro (BA)	0.1216	0.1177	0.1237	0.1277	12.27	30	4.97
Canoinhas (SC)	0.1230	0.1225	0.1180	0.1164	12.00	31	-5.29
São Mateus (ES)	0.1246	0.1178	0.1131	0.1165	11.80	32	-6.46
Itapeva (SP)	0.1097	0.1067	0.1093	0.1194	11.13	33	8.80
Curitibanos (SC)	0.1095	0.1099	0.1059	0.1122	10.94	34	2.46
Alagoinhas (BA)	0.0933	0.0938	0.1057	0.1202	10.33	35	28.80
União da Vitória (PR)	0.0864	0.0946	0.1016	0.1105	9.83	36	27.99
Guanhães (MG)	0.0785	0.0870	0.0963	0.1036	9.13	37	32.02
Três Lagoas (MS)	0.0895	0.0835	0.0791	0.0746	8.17	38	-16.65
São Mateus do Sul (PR)	0.0707	0.0690	0.0693	0.0743	7.08	39	4.97
Telêmaco Borba (PR)	0.0647	0.0631	0.0615	0.0619	6.28	40	-4.24
Jaguariaíva (PR)	0.0585	0.0583	0.0568	0.0565	5.75	41	-3.41
Cerro Azul (PR)	0.0240	0.0246	0.0266	0.0298	2.63	42	24.18
Almeirim (PA)	0.0209	0.0216	0.0246	0.0288	2.40	43	38.09
Micro-regions mean	0.4070	0.4254	0.4386	0.4467	42.94	-	16.42

Source: Authors

Also, in Table 5, it is observed that the cumulative growth rate of efficiency in the period of 2009 – 2015 increased by 16.42% over time, recording the most significant rise in Lapa (PR) with 358.96% and demonstrating the highest drop in Campos de Lages (SC) with -49.03%. The growth trajectory indicates that the outputs raise more than the inputs, and the drop trajectory indicates the opposite. Santa Catarina (SC) is also a Southern state. It demonstrates that while the increase in production in Paraná results in positive human development, it does not promote human development at the same pace in Santa Catarina. Consequently, regional development policies and investments in the Southern Region should prioritize Paraná and Santa Catarina and focus more on converting production into human development in Santa Catarina. When analyzing the wood transportation infrastructure, Santa Catarina and Paraná were pointed out as efficient states by Rentizelas et al. (2019). However, it is crucial to emphasize the need for human development in the analysis, as it is a key aspect of regional policies.

Finally, Três Lagoas (MS) and Almeirim (PA) require a cautious interpretation because they are both in environmentally sensitive areas. Três Lagoas (MS) is in the Center-Western Region close to the Pantanal. This natural biome encompasses the world's most extensive flooded grasslands and the world's largest tropical wetland area. Besides, the pulp production of Três Lagoas (MS) is the largest in Brazil and one of the largest in the world. However, production is not converting into human development. Urgent action is needed to prioritize human development and environmental preservation in these areas.

Similarly, Almeirim (in Pará state—PA) is in the Northern Region (Amazon) of Brazil, in the Lower Amazon, on the border of the Jari Ecological Station. The localization is critical and requires intense vigilance against illegal deforestation. Besides recommending investing in human development to improve performance, in this case, it is recommended that policymakers consider eliminating pulp production and exchanging it for a less ecologically impacting activity, such as palm-heart production (Varella et al., 2022).

4.3 Malmquist Productivity Index (MPI), Technological Change (TC), and Efficiency Change (EC)

The *MPI*, *TC*, and *EC* were used to evaluate the productivity evolution of the main pulp-producing Micro-Regions through the 2009 – 2015 period, revealing which of the Micro-Regions (representing the DMUs) improved through the period of analysis.

The *EC* indicates if a DMU is closer or farther from the efficient frontier in the second period compared to its status in the first period, indicating how much the efficiency of each Micro-Region (DMU) has changed. There are 9 DMUs with $EC>1$: Mogi Mirim (SP), São José dos Campos (SP), São Mateus do Sul (PR), Vacaria (RS), São Mateus (ES), Ilhéus-Itabuna (BA), Curitiba (PR), Bragança Paulista (SP) and Mogi das Cruzes (SP), indicating efficiency increasing from 2009 to 2015.

Usually, DMUs with $EC=1$ indicate efficiency in both periods. As can be seen in Table 6, the DMUs efficient in both periods were also concentrated in the Southeast: Vacaria (RS), Curitiba (PR), Sorocaba (SP), Porto Alegre (RS), São João da Boa Vista (SP), Rio Claro (SP), and Paraíbuna/Paraitinga (SP), except for Ilheus-Itabuna (BA) in a Northeast state. Table 6 shows the results of these variables (*MPI*, *TC*, and *EC)* under the assumption of variable returns to scale (VRS) for the set of analyzed Micro-Regions (DMUs).

Table 6. Calculated Malmquist Productivity Index (MPI), Efficiency Changes (EC), and Technology Changes (TC) for forest producing Micro-Regions in Brazil.

Micro-Regions	MPI	Ranking	TC	Ranking	EC	Ranking
Caratinga (MG)	2.3686	1	0.9111	26	2.5998	2
Mogi Mirim (SP)	2.3273	2	1.0315	6	2.2562	3
União da Vitória (PR)	1.6607	3	0.9883	11	1.6804	6
São José dos Campos (SP)	1.4685	4	1.1077	2	1.3257	11
Piedade (SP)	1.3762	5	0.806	38	1.7076	4
Rio Negro (PR)	1.3356	6	0.894	30	1.494	8
Cerro Azul (PR)	1.3138	7	0.9445	16	1.3911	10
Almeirim (PA)	1.3115	8	0.858	33	1.5287	7
Guarapuava (PR)	1.2359	9	0.9366	18	1.3196	12
São Mateus do Sul (PR)	1.1972	10	1.0183	7	1.1756	20
Palmas (PR)	1.1966	11	0.9072	27	1.319	13
Vacaria (RS)	1.1599	12	1.1599	1	1.0000	28
Joaçaba (SC)	1.1513	13	0.9191	24	1.2526	15
Curitibanos (SC)	1.15	14	0.9223	23	1.2468	16
Bauru (SP)	1.1292	15	0.9185	25	1.2294	18
Alagoinhas (BA)	1.0655	16	0.8177	36	1.3031	14
São Mateus (ES)	1.0538	17	1.0076	9	1.0459	25
Ilhéus-Itabuna (BA)	1.0456	18	1.0456	5	1.0000	28
São Jerônimo (RS)	1.0233	19	0.6997	44	1.4626	9
Curitiba (PR)	1.0079	20	1.0079	8	1.0000	28
Sorocaba (SP)	0.9949	21	0.9949	10	1.0000	28
Itabira (MG)	0.9879	22	0.8838	32	1.1178	22
Lapa (PR)	0.9779	23	0.1449	49	6.7468	1
Bragança Paulista (SP)	0.9739	24	1.0624	4	0.9166	41
Ribeirão Preto (SP)	0.967	25	0.9582	14	1.0092	27
Itapeva (SP)	0.9666	26	0.7841	42	1.2328	17
Capão Bonito (SP)	0.9664	27	0.7926	39	1.2192	19
Campos de Lages (SC)	0.964	28	0.9028	29	1.0678	23
Xanxerê (SC)	0.953	29	0.9582	14	0.9946	36
Ipatinga (MG)	0.9443	30	0.8919	31	1.0588	24
Porto Alegre (RS)	0.9387	31	0.9387	17	1.0000	28
Mogi das Cruzes (SP)	0.9342	32	1.0982	3	0.8507	44
Guanhães (MG)	0.9173	33	0.8147	37	1.1259	21
Linhares (ES)	0.8922	34	0.9628	13	0.9267	40
Porto Seguro (BA)	0.8895	35	0.9276	20	0.959	37
Jaguariaíva (PR)	0.8807	36	0.9266	21	0.9504	38
Telêmaco Borba (PR)	0.847	37	0.9033	28	0.9377	39
São João da Boa Vista (SP)	0.8313	38	0.8313	35	1.0000	28
Poços de Caldas (MG)	0.8269	39	0.7914	40	1.0449	26
Canoinhas (SC)	0.8156	40	0.9243	22	0.8825	43
Botucatu (SP)	0.7742	41	0.4583	45	1.6894	5
Avaré (SP)	0.768	42	0.855	34	0.8983	42
Rio Claro (SP)	0.7094	43	0.7094	43	1.0000	28
Itapetininga (SP)	0.6372	44	0.9364	19	0.6804	47
Três Lagoas (MS)	0.6269	45	0.9776	12	0.6413	48
Paraibuna/Paraitinga (SP)	0.3453	46	0.3453	47	1.0000	28
Camaquã (RS)	0.3196	47	0.4016	46	0.7958	45
Ibaiti (PR)	0.2478	48	0.3213	48	0.7712	46
Entre Rios (BA)	0.0966	49	0.7898	41	0.1223	49

Source: Authors

The TC represents the shift in the efficient frontier, reflecting the benchmark performance from 2009 to 2015. Micro-Regions with a TC greater than 1 indicate that the benchmark was able to acquire more technology during this period. The Micro-Regions with *TC>1* were: Vacaria (RS), São José dos Campos (SP), Mogi das Cruzes (SP), Bragança Paulista (SP), Ilhéus-Itabuna (BA), Mogi Mirim (SP), São Mateus do Sul (PR), Curitiba (PR) and São Mateus (ES). Among these DMUs, São José dos Campos (SP) and Mogi Mirim (SP) were efficient only in the second period. At the same time Vacaria (RS), Ilhéus-Itabuna (BA), and Curitiba (PR) were efficient in both periods. It indicates that these DMUs with TC>1 were the main drivers of shifts in the frontier due to their continuous improvement of technology between 2009 and 2015. They benefited from welfare changes that affected all DMUs, while the other DMUs did not move on to the frontier, though their productivity did benefit from the benchmarks. The *MPI* measures the changes in productivity over time. The *MPI>1* means that a DMU improved its productivity based on the catch-up effect of the efficiency changes and the frontier shift. The Micro-Regions with *MPI>2* were: Caratinga (MG) and Mogi Mirim (SP). They were also among the three DMUs with EC>1. If Caratinga (MG) improves its productivity, it could be efficient in the next 12 years. Mogi Mirim (SP) achieved the efficient frontier in the second period.

DMUs between *1<MPI<2* were: União da Vitória (PR), São José dos Campos (SP), Piedade (SP), Rio Negro (PR), Cerro Azul (PR), Almeirim (PA), Guarapuava (PR), São Mateus do Sul (PR), Palmas (PR), Vacaria (RS), Joaçaba (SC), Curitibanos (SC), Bauru (SP), Alagoinhas (BA), São Mateus (ES), Ilhéus-Itabuna (BA), São Jerônimo (RS), and Curitiba (PR). Among these DMUs with *MPI>1*, Vacaria (RS), Ilhéus-Itabuna (BA), and Curitiba (PR) were efficient in both periods, indicating that despite being efficient, they kept their evolution and improving their productivity using the technological point of view.

Despite the other efficient DMUs maintaining their positions in the frontier with MPI <1 and TC < 1, Sorocaba (SP), Porto Alegre (RS), São João da Boa Vista (SP), Rio Claro (SP), and Paraíbuna/Paraitinga (SP) must pay attention to their productivity to ensure they remain among the efficient scores. Lapa (PR) and Botucatu (SP) were atypical cases, as they were not efficient in the first period, obtained TC<1 and MPI<1, but improved their efficiencies in the second period until reaching the efficiency frontier so that they could be studied in more depth.

5. Conclusions

This study evaluated the efficiency of 49 significant Brazilian forestry producing Microregions in converting economic growth into welfare from 2009 to 2015. During the analysis period, the forestry sector experienced a significant expansion of the paper and pulp industry. It is essential to identify the contribution of this expansion to human development at a regional level. To that end, the study applied both the Data Envelopment Analysis-Stochastic Boundary Model (DEA-SBM) and the Malmquist Productivity Index.

It has been shown that the impact of forestry activities on the quality of life of people in Brazil can vary between different regions and states. For instance, Ilhéus-Itabuna in the Northeastern region and Vacaria in the Southern region can be benchmarks for national-level planning. At the macro-regional level, priority should be given to improving human development in Paraná and Santa Catarina to bring them up to the same level as the southern state of Rio Grande do Sul. To this end, production-fostering policies should be implemented. At the state level, the microregions close to the capital of Rio Grande do Sul (Porto Alegre) require attention to ensure they do not lose efficiency. For the macro-regional level in the Southeastern region, Minas Gerais should take priority over Sao Paulo; however, the microregions of São Paulo also need attention to maintain their efficient position.

The models proposed in this research simplify the economic growth scenario and quality of life in the paper and pulp sectors. While other factors, such as sustainable development and infrastructure, can influence the efficiency and productivity of each Microregion, this study does not provide exhaustive conclusions. Nevertheless, as discussed in the article, it has developed essential methods to evaluate economic growth and foster welfare. One of the main challenges encountered in this work was finding a standardized database with a longer time horizon; in future works, a more up-to-date database may be used.

This method can also be applied to other economic sectors. Therefore, it is advised that policymakers consider regional and local inequalities and strive to ensure that human development keeps pace with economic growth. At the national level, more research needs to be done on the productive potential of the Northeastern region, and priority should be given to macro-regions that are far away from environmentally sensitive areas, such as the Pantanal and Amazon. In these areas, it is also recommended that further studies be conducted to investigate the viability of replacing pulp production with less damaging activities in the forestry sector, such as palm-heart production.

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References

Ahn, H., Afsharian, M., Emrouznejad, A., & Banker, R. (2018). Recent developments on the use of DEA in the public sector. *Socio-Economic Planning Sciences*, *61*, 1-3.

Associação Brasileira Técnica de Celulose e Papel – ABTCP. (2023). *O setor.* Retrieved in 2023, July 17, from https://www.abtcp.org.br/o-setor

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078-1092.

Brasil. Ministério da Agricultura e Pecuária. (2018). *Plano nacional de desenvolvimento de florestas plantadas.* Retrieved in 2023, July 17, from https://www.gov.br/agricultura/pt-br/assuntos/politica-agricola/outras-publicacoes/plano-nacional-de-desenvolvimento-de-florestas-plantadas.pdf/view

Brasil. Sistema Nacional de Informações Florestais – SNIF. (2021). *Série histórica das exportações (PFM): tabelas e gráficos.* Retrieved in 2023, July 17, from https://snif.florestal.gov.br/pt-br/emprego/146-producao-economia-e-mercado-florestal/dados-complementares-exportacao-produtos-florestais-madeireiros/332-serie-historica-das-exportacoes-pfm-tabelas-e-graficos

Camioto, F. D. C., & Pulita, A. C. (2022). Efficiency evaluation of sustainable development in BRICS and G7 countries: a Data Envelopment Analysis approach. *Gestão & Produção*, *29*, e022.

Camioto, F. D. C., Mariano, E. B., & Rebelatto, D. A. (2017). Sustainability improvement opportunities in Brazilian sectors: analysis of DEA slacks. *Brazilian Journal of Operations & Production Management*, *14*(3), 363-370.

Campoli, J. S., & Stivali, M. (2023). *Custo social do desmatamento nos biomas brasileiros.* Brasília: IPEA.

Campoli, J. S., Alves Junior, P. N., Kodama, T. K., Nagano, M. S., & Burnquist, H. L. (2024a). G20 countries' progress on the 7th SDG under circular economy DEA model. *Environmental Science & Policy*, *160*, 103839.

Campoli, J. S., Kodama, T. K., Nagano, M. S., & Burnquist, H. L. (2024b). Advancing circular economy: G20 nations' path towards 12th sustainable development goal. *Circular Economy and Sustainability*, 1-24. In press.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444.

Charnes, A., Cooper, W. W., Lewin, A. Y. and Seiford, L. M. (1994). *Data envelopment analysis: theory, methodology and applications*. Springer.

Chen, J.-X., Deng, M., & Gingras, S. (2011). A modified super-efficiency measure based on simultaneous input–output projection in data envelopment analysis. *Computers & Operations Research*, *38*(2), 496-504.

Chen, Y., & Liang, L. (2011). Super-efficiency DEA in the presence of infeasibility: one model approach. *European Journal of Operational Research*, *213*(1), 359-360.

Chen, Y., Su, X., & Hipel, K. W. (2009). An index aggregation approach to comparing the overall performance of emerging and developed countries. *Socio-Economic Planning Sciences*, *43*(1), 25-39.

Coelho, M. R. F., & Coelho, M. H. (2013). Panorama da indústria de celulose e papel no Brasil: 2001 a 2011. *Floresta*, *43*(3), 463-474.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis.* New York: Springer Science & Business Media.

Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: prior to choosing a model. *Omega*, *44*, 1-4.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software.* New York: Springer.

Dyckhoff, H., & Souren, R. (2020). Data envelopment methodology of performance evaluation. In H. Dyckhoff & R. Souren (Eds.), *Performance evaluation: foundations and challenges* (pp. 47-82). Cham: Springer International Publishing.

Fang, H.-H., Lee, H.-S., Hwang, S.-N., & Chung, C.-C. (2013). A slacks-based measure of super-efficiency in data envelopment analysis: an alternative approach. *Omega*, *41*(4), 731-734.

Fare, R., & Grosskopf, S. (1992). Malmquist productivity indexes and fisher ideal indexes. *Economic Journal*, *102*(410), 158-160.

Fare, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, *84*, 66-83.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253-290.

Ferreira, C. M. C., & Gomes, A. P. (2020). *Introdução à análise envoltória de dados: teoria, modelos e aplicação* (2ª ed.). Viçosa: Editora da UFV.

Firjan. (2021). *IFDM: Índice FIRJAN de Desenvolvimento Municipal: consulta.* Retrieved in 2023, July 17, from https://www.firjan.com.br/ifdm/

Food and Agriculture Organization – FAO. (2021). *FAOSTAT: forest production and trade.* Rome. Retrieved in 2023, July 17, from http://www.fao.org/faostat/en/#data/FO

Gandour, C., Diego, M., João Pedro, V., & Assunção, J. J. (2021). *Degradação Florestal na Amazônia: fenômeno relacionado ao desmatamento precisa ser alvo de política pública*. Rio de Janeiro: Climate Policy Initiative.

Hou, J., Ruan, X., Lv, J., & Guo, H. (2020). Two-stage super-efficiency slacks-based model to assess China's ecological wellbeing. *International Journal of Environmental Research and Public Health*, *17*(19), 7045.

Indústria Brasileira de Árvores – IBÁ. (2017). *Report 2017.* Brasília.

Indústria Brasileira de Árvores – IBÁ. (2019). *Report 2019.* Brasília.

Indústria Brasileira de Árvores – IBÁ. (2022). *Report 2022.* Brasília.

Instituto Brasileiro de Geografia e Estatística – IBGE. (2021a). *Average wood cost (BRL/m3) and employment in forestry and paper and pulp production.* Retrieved in 2023, July 17, from https://www.ibge.gov.br/estatisticas/economicas/precos-e-custos/9270-sistema-nacional-de-pesquisa-de-custos-e-indices-da-construcao-civil.html?=&t=o-que-e

Instituto Brasileiro de Geografia e Estatística – IBGE. (2021b). *GDP.* Retrieved in 2023, July 17, from https://www.ibge.gov.br/explica/pib.php

Instituto Brasileiro de Geografia e Estatística – IBGE. (2021c). *Total number of employed people.* Retrieved in 2023, July 17, from https://www.ibge.gov.br/estatisticas/sociais/trabalho.html

Instituto Nacional de Pesquisas Espaciais – INPE. (2021). *Terrabrasilis: geographic data platform.* Retrieved in 2023, July 17, from http://terrabrasilis.dpi.inpe.br/

Kourtit, K., Nijkamp, P., & Suzuki, S. (2020). Are global cities sustainability champions? A double delinking analysis of environmental performance of urban agglomerations. *The Science of the Total Environment*, *709*, 134963.

Lábaj, M., Luptáčik, M., & Nežinský, E. (2014). Data envelopment analysis for measuring economic growth in terms of welfare beyond GDP. *Empirica*, *41*(3), 407-424.

Lara, C. S., Costa, C. R., & Sampaio, P. T. B. (2021). O mercado de sementes e mudas de pau-rosa (*Aniba* spp.) no Estado do Amazonas. *Revista de Economia e Sociologia Rural*, *59*(3), e221035.

Leite-Filho, A. T., Soares-Filho, B. S., Davis, J. L., Abrahão, G. M., & Börner, J. (2021). Deforestation reduces rainfall and agricultural revenues in the Brazilian Amazon. *Nature Communications*, *12*(1), 2591.

Liu, T., Li, J., Chen, J., & Yang, S. (2019). Urban ecological efficiency and its influencing factors: a case study in Henan province, China. *Sustainability*, *11*(18), 5048.

Long, R., Ouyang, H., & Guo, H. (2020). Super-slack-based measuring data envelopment analysis on the spatial–temporal patterns of logistics ecological efficiency using global Malmquist Index model. *Environmental Technology & Innovation*, *18*, 100770.

López, R., & Miller, S. J. (2008). Chile: the unbearable burden of inequality. *World Development*, *36*(12), 2679-2695.

Lovejoy, T. E., & Nobre, C. (2018). Amazon tipping point. *Science Advances*, *4*(2), eaat2340.

Mariano, E. B., & Rebelatto, D. A. (2014). Transformation of wealth produced into quality of life: Analysis of the social efficiency of nation-states with the DEA's triple index approach. *The Journal of the Operational Research Society*, *65*(11), 1664-1681.

Montebello, A. E. S., & Bacha, C. J. C. (2009). Avaliação das pesquisas e inovações tecnológicas ocorridas na silvicultura e na produção industrial de celulose no Brasil. *Revista de Economia e Sociologia Rural*, *47*(2), 485-517.

Moralles, H. F., & Rebelatto, D. A. (2016). The effects and time lags of R&D spillovers in Brazil. *Technology in Society*, *47*, 148-155.

Moreno‐Enguix, M. D. R., & Lorente Bayona, L. V. (2017). Factors affecting public expenditure efficiency in developed countries. *Politics & Policy*, *45*(1), 105-143.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W. (2017). The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, *42*, 169-180.

O'Sullivan, A., & Sheffrin, S. M. (2006). *Economics: principles in action.* Upper Saddle River: Pearson Prentice Hall.

Observatory of Economic Complexity – OEC. (2021). *Brazil (BRA) exports, imports, and trade partners.* Retrieved in 2023, July 17, from https://oec.world/en/profile/country/bra

Ren, W., Zhang, Z., Wang, Y., Xue, B., & Chen, X. (2020). Measuring regional eco-efficiency in China (2003-2016): a "Full World" perspective and network data envelopment analysis. *International Journal of Environmental Research and Public Health*, *17*(10), 3456.

Rentizelas, A., Melo, I. C., Alves Junior, P. N., Campoli, J. S., & Aparecida do Nascimento Rebelatto, D. (2019). Multi-criteria efficiency assessment of international biomass supply chain pathways using Data Envelopment Analysis. *Journal of Cleaner Production*, *237*, 117690.

Robalino-López, A., Mena-Nieto, A., García-Ramos, J.-E., & Golpe, A. A. (2015). Studying the relationship between economic growth, CO2 emissions, and the environmental Kuznets curve in Venezuela (1980-2025). *Renewable & Sustainable Energy Reviews*, *41*, 602-614.

Sarmento, J., Renneboog, L., & Verga Matos, P. (2017). Measuring highway efficiency by a DEA approach and the Malmquist index. *European Journal of Transport and Infrastructure Research*, *17*(4), 530-551.

Selvatti, T. S. (2015). *Concentração da produção e da exportação mundial de celulose e de Medium Density Fiberboard (MDF)* (Dissertação de mestrado). Universidade Federal de Lavras, Lavras.

Shah, W. U. H., Hao, G., Yan, H., Shen, J., & Yasmeen, R. (2024). Forestry resource efficiency, total factor productivity change, and regional technological heterogeneity in China. *Forests*, *15*(1), 152.

Song, Y., & Mei, D. (2022). Sustainable development of China's regions from the perspective of ecological welfare performance: analysis based on GM (1, 1) and the Malmquist index. *Environment, Development and Sustainability*, *24*(1), 1086-1115.

Sun, Y., & Wang, N. (2022). Evolution and obstacle factors of high-quality industrial development in the π-shaped Curve Area of the Yellow River basin in China. *Journal of Geographical Sciences*, *32*(12), 2430-2452.

Thore, S., & Tarverdyan, R. (2009). Using data envelopment analysis to quantify ILO objectives and identify policies conducive to decent work in a globalizing world. *Socio-Economic Planning Sciences*, *43*(3), 151-164.

Timber Trade Portal. (2023). *Forest resources and context of Brazil.* Retrieved in 2023, July 17, from https://www.timbertradeportal.com/en/brazil/10/country-context

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498-509.

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, *143*(1), 32-41.

Tone, K. (2011). Slacks-based measure of efficiency. In W. W. Cooper, L. M. Seiford & J. Zhu (Eds.), *Handbook on data envelopment analysis* (pp. 195-209). Boston: Springer.

Tone, K. (2017). *Advances in DEA theory and applications: with extensions to forecasting models*. Hoboken: John Wiley & Sons.

Tone, K., & Tsutsui, M. (2017). Malmquist productivity index models. In K. Tone (Ed.), *Advances in DEA theory and applications.* Chichester: John Wiley & Sons.

Ülengin, F., Kabak, Ö., Önsel, S., Aktas, E., & Parker, B. R. (2011). The competitiveness of nations and implications for human development. *Socio-Economic Planning Sciences*, *45*(1), 16-27.

Varella, T. S., Oliveira Neto, G. C., & Sousa, T. B. (2022). Adoption of cleaner production in a pupunha palm heart factory: a systematic literature review and a case study. *Food Science and Technology*, *42*, e65720. http://doi.org/10.1590/fst.65720

Wong, S. Y. (2020). Assessment of public expenditure efficiency: a review. *Journal of Economics and Sustainability*, *2*(2), 12.

World Integrated Trade Solutions – WITS. (2020). *Data availability.* Retrieved in 2023, July 17, from https://wits.worldbank.org/tariff/non-tariff-measures/en/ntm-dataavailability

Yang, Z., & Soltani, N. (2021). A new SBM-based global Malmquist productivity index and target setting. *Computers & Industrial Engineering*, *158*, 107411.

Zhang, C., Li, J., Liu, T., Xu, M., Wang, H., & Li, X. (2022). The spatiotemporal evolution and influencing factors of the Chinese cities' ecological welfare performance. *International Journal of Environmental Research and Public Health*, *19*(19), 12955.

Zhu, J. (2001). Super-efficiency and DEA sensitivity analysis. *European Journal of Operational Research*, *129*(2), 443-455.

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