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

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Abstract

Studies about the forestry sector have been more directed to energy questions and environmental challenges, despite their importance for the competitiveness and long-term survival of other forest-based industries. There have been few studies focus on economic growth and welfare. In this context, Brazil has favorable conditions and great growth potential for forestry production. For this reason, this paper measured the efficiency and productivity evolution of 49 main Brazilian forestry-producing Micro-Regions in converting the expansion of the economic growth from the forestry sector into social welfare, from 2009 to 2015 (a period of sectorial growth in the country). For achieving this goal, a novel combination of the Slack-Based Measure (SBM) – Data Envelopment Analysis (DEA) model, Malmquist Productivity Index (MPI), and Windows Analysis, followed by a solution for infeasibility issues was used. The results indicated that the sectoral growth was not followed by human development in most Micro-Regions. Also, huge regional and state differences were observed, and the productive potential of the Northeastern Region has been neglected. Besides, Micro-Regions with the lowest human development index are close to sensitive environmental areas. In this way, the current results contribute to the design of public policies and governmental decision-making to increase the efficiency and productivity of the forestry sector as well as social indicators. Also, the proposed approach can be replicated for guiding sustainable policies in other contexts and countries.

Key words: Forestry Sector, Social Welfare, Rural Development, Data Envelopment Analysis (DEA), Malmquist Productivity Index (MPI)

Resumo

Os estudos sobre o setor florestal têm sido mais direcionados para questões energéticas e desafios ambientais, apesar de sua importância para a competitividade e sobrevivência de longo prazo de outras indústrias de base florestal. Existem poucos estudos focados no crescimento econômico e no bem-estar. Nesse contexto, o Brasil apresenta condições favoráveis e grande potencial de crescimento da produção florestal. Por isso, este trabalho mediu a evolução da eficiência e produtividade das 49 principais microrregiões florestais brasileiras em converter a expansão do crescimento econômico do setor florestal em bem-estar social, de 2009 a 2015 (período de crescimento setorial no país). Para atingir este objetivo, uma nova combinação 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 foi usada. Os resultados indicaram que o crescimento setorial não foi acompanhado pelo desenvolvimento humano na maioria das Microrregiões. Além disso, foram observadas grandes diferenças regionais e estaduais, e o potencial produtivo da Região Nordeste tem sido negligenciado. Além disso, as Microrregiões com menor índice de desenvolvimento humano estão próximas a áreas ambientais sensíveis. Desta forma, os resultados atuais contribuem para o desenho de políticas públicas e tomadas de decisões governamentais para aumentar a eficiência e produtividade do setor florestal, bem como indicadores sociais. Além disso, a abordagem proposta pode ser replicada para 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 explores how the transition to sustainable forest management in countries with significant forested frontiers has impacted selected Brazilian Regions in terms of local economic growth, quality of life, and employment of the local population. By investigating the effects of the forest industry expansion in this stage, we aim to understand how it has shaped the economic, social, and environmental conditions in these regions.

The forest industry in Brazil has experienced significant growth in recent years, largely due to favorable conditions for the activity as well as investments in technology to boost productivity. According to the National Planted Forests Development Plan (PNDF), the planted area is projected to grow at a rate of 1.2% per year, reaching 2 million hectares by 2030 (Brazil, 2018). With these positive changes, the Brazilian forestry sector is well-positioned to compete on the global market, driving sustainable development and operational excellence.

The forest productivity of Brazil is remarkably high, with an average of 38.9 m³ ha/year for eucalyptus plantations and 29.7 m³ ha/year for pine plantations, surpassing global averages. This highlights the role of knowledge and technology in driving a modern, sustainable agriculture (IBA, 2022). In addition, the sector maintains 6 million hectares of conservation areas, storing up to 4.5 billion tons of CO2 equivalent (IBA, 2022).

Higher productivity has enabled Brazil to offer more competitively priced products in the world market (IBA, 2017). This has resulted in a high demand for the sector's products both domestically and internationally. Brazil is one of the world's leading producers and exporters of paper derived from planted forests and has tremendous potential for growth (FAO, 2021). In 2020, Brazilian exports of paper and cellulose totaled nearly US$10.0 billion, ranking ninth among the nation's most exported products and representing about 6% of total exports (SNIF 2021). Additionally, according to the Observatory of Economic Complexity (OEC 2021), Brazilian wood products, paper, and pulp goods accounted for about 6% of total Brazilian exports in 2018.

From a social and economic standpoint, the Brazilian forest sector accounts for 1.3% of the country's Gross Domestic Product (GDP) and has had a significant impact on socio-economic development, creating over 513,000 jobs and directly or indirectly affecting the lives of 3.8 million people (IBA, 2019). This suggests that Brazil has the potential to become a leader in terms of sustainability, productivity and innovation, as well as a major exporter in the forest industry (IBA, 2019). Consequently, it is crucial to investigate whether the growth of this sector has contributed to the improvement of local populations' welfare and human development.

This research seeks to measure the efficiency and productivity of the 49 major Brazilian forestry-producing Micro-Regions in converting economic growth into welfare between 2009 and 2015. To do so, the Data Envelopment Analysis (DEA) – Slack-Based Measure (SBM) output-oriented model and the Malmquist Productivity Index (MPI) are applied. The goal is to identify the relative efficiency of these regions in terms of transforming sectoral economic growth into social gains, such as higher overall employment, higher human development index (HDI), and higher overall production outputs. The results will be used to support the management and implementation of government programs that use the forest industry to improve regional quality of life, while also stimulating a sector that plays a key role in the Brazilian economy. The study focuses on Micro-Regions with significant forested areas that have experienced notable social, economic, and environmental changes due to the establishment of paper and pulp-producing companies.

The hypothesis of this study is to analyze whether economic growth based on the pulp and paper industry has positively impacted the wellbeing of regional populations. Given that economic growth is widely seen as essential for raising the living standards of a nation (O'Sullivan and Sheffrin 2006), it is crucial to examine the quality of economic growth that determines the welfare of a population, and its capacity to reduce extreme poverty, decrease inequalities, and become self-sustaining (López and Miller 2008; Robalino-López et al. 2015).

We chose this topic due to the lack of studies on forestry production using DEA and MPI in the Brazilian context. In the literature, many papers 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, 2021; Sarmento et al., 2017).This research can contribute academically in an original way by utilizing Data Envelopment Analysis (DEA) to evaluate the efficiency and productivity of welfare in the primary forestry-producing Micro-Regions of Brazil. On a practical level, this research can provide information to inform and guide governmental decision-making and planning.

The paper is organized into five sections. Section 2 provides a contextualization of Brazilian Forests and social efficiency and productivity using DEA and MPI. The method description and econometric analysis are shown in Section 3. The results and discussions followed by efficiency analysis are presented in Section 4. Finally, Section 5 summarizes the considerations of the paper.

2. Contextualization

2.1 Brazilian Forests in a Global Framework

In Brazil, forestry is one of the most significant economic activities. The country's favorable soil and climate make it ideal for forestry endeavors. On a global scale, Brazil is renowned for its extensive native and planted tropical forests. 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 the world's total forest coverage (FAO, 2021). FAO (2021) has reported that Brazil is among the countries with the largest forested territory in the world, second only to Russia. There is about 493.5 million hectares of forested land, which constitutes 58% of the total land area of the country. Around 485 million hectares are primary or otherwise naturally regenerated forests, while the remaining 7.7 million hectares is planted forest, mainly consisting of introduced species such as Eucalyptus and Pine, and to a lesser extent Acacia, Teak and Rubber wood (Timber Trade Portal, 2023) The vast majority of the country's planted forests are located 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 great growth potential (FAO, 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 (WITS, 2020).

In 2018, the total area of planted trees in Brazil reached 7.83 million hectares. Moreover, the inventory of CO_2 equivalent reached 4.2 billion ton. According to Gandour et al. (2021), Brazil's Nationally Determined Contribution in 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 restore and reforest 12 million hectares of forests, enforce the implementation of the Forest Code, create public policies and measures to achieve zero illegal deforestation, encourage sustainable native forest management, adopt and accelerate 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 (IBA, 2019).

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 (INPE, 2021). This has generated major concerns both in the domestic and international organizations due to the potential climate change effects that have been associated with deforestation and forestry degradation.

The removal of native vegetation cover is one of the first actions on the environment caused by economic activities. The incorporation of new areas to agriculture, the expansion of urban areas and the connection of different regions by highways end up eliminating or reducing on a large scale the original vegetation (Campoli; Stivali (2023).

Lovejoy and 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 be a forest, as well as 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 exert a decrease in rainfall and will also 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, low CO_2 emission to avoid climate change have become very important concepts in these last decades. They have been employed by a progressive number of people and firms as major drivers of demand 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 a great 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 important, considering that forests not only play a fundamental role in maintaining the biological and climatic characteristics of the planet, but are also relevant for the generation of wealth through the use of forest resources according to Good habits. In Brazil, 35% of total wood production is destined to the pulp and paper sector, responsible for the largest share, both in exports and in world imports of forest products (Selvatti, 2015).

In Brazil, the pulp industries produce the main paper input which is cellulose, for this reason, in most countries, the pulp industries are integrated with the paper industries. In this commercial dynamic, most of the pulp produced is destined for the foreign market. Therefore, the installation of the pulp and paper industries are located 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 (Brazilian Technical Association of Paper and Cellulose, 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 9th position in the ranking of world manufacturers. The forest area preserved by companies operating in this industrial segment is 2.9 million hectares. For industrial purposes, the pulp and paper sector plants over 2.2 million hectares, most of which are certified forests. This sustainable action – which preserves the environment and simultaneously generates social compensation from its activities – ensures that biodiversity is protected, as well as water resources. In this way, the forests planted by the sector generate environmental contribution, by capturing CO_2, soil conservation and restoration of degraded lands (Brazilian Technical Association of Paper and Cellulose, 2023).

2.2 DEA and MPI evaluating in transforming Economic Growth into Welfare

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

In this section, the search filter combined the keywords "Welfare" and "Industry" and "DEA" or "Malmquist", since the year of 2018, using Scopus databases. We selected article about industry to improve social welfare.

Sun and 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 industrial layout were more rational in provincial capitals and large cities. Almost all cities have experienced an increase in single-factor productivity, and technological progress contributed most to the total factor productivity growth. The development environment in most cities has remained stable, and the social welfare has increased and distributed more equitably.

Zhang et al. (2022) measured the ecological wellbeing performance (EWP) of 284 cities in China, from 2007 to 2020, using the superefficient SBM-DEA model. The results showed that the EWP is fluctuating, but increasing over time. In terms of 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 important area of China's former industrial base, and its environmental pollution levels are severe, which makes the EWP lower. Regarding influencing factors, level of financial development, secondary industry structure, openness and urbanization significantly improved China's EWP.

About sustainable development, Camioto and 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) in the top positions of efficiency. The emerging countries have stood out in the sustainability question, showing that have policies that show sustainable awareness. On the other hand, the economic crisis of 2008 has impacted more the developed countries and is importante the G7 countries invest more in sustainable development. The results obtained can be useful 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 wellbeing 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 different, which corroborates with Zhang et al. (2022). The study presented limitation, 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.

In relation about the 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 evaluated economic, environmental, and social factors of China's provinces, from 2003 to 2016. The findings demonstrated that China's overall eco-efficiency presented a low level, with regional differences which corroborates 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 factors affecting overall were economic growth level, marketization level, and social input level.

About urban agglomerations, Kourtit et al. (2020) developed an advanced methodology for assessing economic and sustainability-oriented performance strategies for global cities, by developing and applying a super-efficient Data Envelopment Analysis (DEA) model. They compared 40 global cities – included in the Global Power City Index (GPCI) database – in order to trace the highest-performing urban regions from both 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 – similar Zhang et al., (2022); Hou et al., (2020); Ren et al., (2020). Moreover, the efficiency level in the production stage is declining, while the stage of environmental governance and social input is increasing.

Liu et al. (2019) provided a new method to provide some decision-making references for the improvement of the urban ecological efficiency in Henan province. They used DEA-SBM and Malmquist Productivity Index, during the period of 2005-2016. Based on this, the bootstrap regression model is applied in analyzing the influencing factors of the urban ecological efficiency. The results showed that the urban ecological efficiency is low in Henan province. The MPI demonstrate that overall growth trend, and the technological progress has played a major role in promoting the urban ecological efficiency. The influencing factors were governmental financial, level of opening to the outside world, urban population density and the 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 strong social inequality; (c) applying used 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. Method

3.1 Data Envelopment Analysis (DEA) and Slack-Based Measure (SBM)

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, as well as to 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 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 and Rebelatto (2014), there are several models of DEA that 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 such that 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 the incorporation of the Variable Returns to Scale (VRS) assumption allowing to determine efficiency's gains of scale (Dyckhoff and Souren 2020).

An SBM-VRS model was utilized to measure the relative efficiency of micro-regions concerning their surplus of inputs and deficiency of outputs for the Brazilian forestry industry in this study. Inputs must be considered as comparative variables between each DMU, such that "the less, the better" for efficiency measure purposes, while 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.

3.2 Malmquist Productivity Index (MPI)

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

The DEA-based MPI can be computed considering four distance measures based on a comparison of 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 (16):

$$MPI_{CRS}=\sqrt{\frac{D^{t}_{CRS}\,(x^{t+1},y^{t+1})\cdot D^{t+1}_{CRS}\,(x^{t+1},y^{t+1})}{D^{t}_{CRS}\,(x^{t},y^{t})\cdot D^{t+1}_{CRS}\,(x^{t},y^{t})}}=\sqrt{\frac{D^{t}_{CRS}\,(x^{t+1},y^{t+1})\cdot D^{t}_{CRS}\,(x^{t},y^{t})}{D^{t+1}_{CRS}\,(x^{t+1},y^{t+1})\cdot D^{t+1}_{CRS}\,(x^{t},y^{t})}}\cdot\frac{D^{t+1}_{CRS}\,(x^{t+1},y^{t+1})}{D^{t}_{CRS}\,(x^{t},y^{t})} \tag{16}$$

Where: $D^{t}_{CRS}\,(x^{t},y^{t})$: is the efficiency of the DMU under analysis in period t in comparison to the frontier in period t; $D^{t+1}_{CRS}\,(x^{t+1},y^{t+1})$: is the efficiency of the DMU under analysis in period $t+1$ in comparison to the frontier in period $t+1$; $D^{t}_{CRS}\left(x^{t+1},y^{t+1}\right)$: is the intertemporal score of the DMU in period $t+1$ in comparison to the frontier in period t; $D^{t+1}_{CRS}\,(x^{t},y^{t})$: is the intertemporal score of the DMU in period t in comparison to the frontier in period $t+1$.

The MPI (Equation 16) allows for the measure the productivity changes through time, decomposed into catch-up effect (Efficiency Changes - EC) and frontier shift effect (Technological Changes - TC). The EC is a comparison between efficiencies of the DMUs 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 and can result from technological innovations or efficiency changes (Ferreira and Gomes 2020). The decomposition of the model under CRS assumptions can be seen in Equations 17 to 19 (Fare et al. 1994):

$$TC_{CRS} = \sqrt{\frac{D^{t}_{CRS}\,(x^{t+1}, y^{t+1})\cdot D^{t}_{CRS}\,(x^{t}, y^{t})}{D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})\cdot D^{t+1}_{CRS}\,(x^{t}, y^{t})}} \tag{17}$$

$$EC_{CRS} = \frac{D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})}{D^{t}_{CRS}\,(x^{t}, y^{t})} \tag{18}$$

$$MPI_{CRS} = \sqrt{\frac{D^{t}_{CRS}\,(x^{t+1}, y^{t+1})\cdot D^{t}_{0}\,(x^{t}, y^{t})}{D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})\cdot D^{t+1}_{0}\,(x^{t}, y^{t})}}\cdot\frac{D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})}{D^{t}_{CRS}\,(x^{t}, y^{t})} = TC_{CRS}\cdot EC_{CRS} \tag{19}$$

The efficiencies ($D^{t}_{CRS}\,(x^{t}, y^{t})$ and $D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})$) values are between 0 and 1 and the intertemporal scores ($D^{t}_{CRS}\left(x^{t+1}, y^{t+1}\right)$ and $D^{t+1}_{CRS}\,(x^{t}, y^{t})$) 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 that of a DMU with $EC <= 1$; it indicates a better improvement. In other words, a DMU_1 with $D^{t}_{CRS}\,(x^{t}, y^{t}) = 0.1$ and $D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1}) = 0.2$ improved its efficiency while a DMU_2 with $D^{t}_{CRS}\,(x^{t}, y^{t}) = 1.0$ and $D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1}) = 0.5$ reduced its efficiency, and therefore expresses a higher efficiency than DMU_1, despite the better (higher?) EC of DMU_1.

The same comparisons can be made under the VRS assumption. The MPI_{CRS} and MPI_{VRS} are related as follows in Equation 20 (Tone 2011):

$$MPI_{CRS}=MPI_{VRS}\cdot SEC \tag{20}$$

Where SEC is the Scale-Efficiency Changes (a comparison between CRS and VRS) as seen in Equation 21 (Tone 2011):

$$\mathrm{SEC} = \sqrt{\frac{\dfrac{D^{t}_{CRS}\,(x^{t+1}, y^{t+1})}{D^{t}_{VRS}\,(x^{t+1}, y^{t+1})}\cdot\dfrac{D^{t+1}_{CRS}\,(x^{t+1}, y^{t+1})}{D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})}}{\dfrac{D^{t}_{CRS}\,(x^{t}, y^{t})}{D^{t}_{VRS}\,(x^{t}, y^{t})}\cdot\dfrac{D^{t+1}_{CRS}\,(x^{t}, y^{t})}{D^{t+1}_{VRS}\,(x^{t}, y^{t})}}} \tag{21}$$

The decomposition of the model under VRS assumptions is like the CRS one and it can be seen in Equations 22 to 24 (Tone 2011):

$$TC_{VRS} = \sqrt{\frac{D^{t}_{VRS}\,(x^{t+1}, y^{t+1})\cdot D^{t}_{VRS}\,(x^{t}, y^{t})}{D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})\cdot D^{t+1}_{VRS}\,(x^{t}, y^{t})}} \tag{22}$$

$$EC_{VRS} = \frac{D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})}{D^{t}_{VRS}\,(x^{t}, y^{t})} \tag{23}$$

$$MPI_{VRS} = \sqrt{\frac{D^{t}_{VRS}\,(x^{t+1}, y^{t+1})\cdot D^{t}_{0}\,(x^{t}, y^{t})}{D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})\cdot D^{t+1}_{0}\,(x^{t}, y^{t})}}\cdot\frac{D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})}{D^{t}_{VRS}\,(x^{t}, y^{t})} = TC_{VRS}\cdot EC_{VRS} \tag{24}$$

Similar to the model under CRS, despite the efficiencies ($D^{t}_{VRS}\,(x^{t}, y^{t})$ and $D^{t+1}_{VRS}\,(x^{t+1}, y^{t+1})$) being values between 0 and 1, the intertemporal scores ($D^{t}_{VRS}\left(x^{t+1}, y^{t+1}\right)$ and $D^{t+1}_{VRS}\,(x^{t}, y^{t})$) 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 the 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), about the infeasibility in MPI under VRS assumptions, one solution for avoiding this difficulty is to assign 1 to the score (when it is infeasible), since probably there is no means to evaluate the DMU within the evaluator group. Also, the common "big-M" approach could solve infeasibility problems in the super-efficiency model. And a "one-model" approach was proposed by Chen and Liang (2011).

In the MPI, intertemporal scores can take on values greater than 1 and are calculated in a manner similar to that of 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 then be explored (Zhu 2001).

According to Tone and 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, but even the oriented versions also can suffer from infeasibility. So, in this paper, as it is needed to use the output-oriented Super-SBM-VRS model to calculate the intertemporal scores, it is needed 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.

In this paper, a new approach inspired by the work of Chen et al. (2011) and Tone (2017) is adopted. When the values are lower than 1, the output-oriented SBM-VRS in Equations 11 to 15 is applied. If the value is equal to 1, then an output-oriented Super-SBM-VRS in Equations 31 to 35 is applied. If the value is greater than 1, or if the problem is infeasible, then a non-oriented Super-SBM-VRS in Equations 25 to 30 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 similar to the standard SBM and linear Equations ranging from 25 to 30 (Fang et al. 2013):

$$\min \tau^{super} = t + \frac{1}{m} \sum_{j=1}^{m} \frac{H_j}{x_{j0}} \tag{25}$$

Subject to:

$$t - \frac{1}{n} \sum_{i=1}^{n} \frac{H_i}{y_{i0}} = 1 \tag{26}$$

$$\sum_{k=1}^{z} x_{jk} \cdot \Lambda_k - H_j - t \cdot x_{j0} \leq 0 \qquad j = 1,2...., m \tag{27}$$

$$\sum_{k=1}^{z} y_{ik} \cdot \Lambda_k + H_i - t \cdot y_{i0} \geq 0 \qquad i = 1,2...., n \tag{28}$$

$$\sum_{k=1}^{z} \Lambda_k = t \tag{29}$$

$$\Lambda_k \geq 0,\ H_i \geq 0,\ H_j \geq 0,\ t > 0 \tag{30}$$

Where τ^{super*} is the optimal super-efficiency, τ^{super} is the super-efficiency score, H_i is the linearized input savings rate for the linear problem ($H_i = th_i$), H_j is the linearized output surplus rate for the linear problem ($H_j = th_j$), h_i is the input savings for the super-efficiency model, h_j is the output surplus for the super-efficiency model. The other parameters and variables are the same as in Equations 5 to 10.

Finally, the output-oriented Super-SBM-VRS model is as follows in Equations 31 to 35 (Tone 2001, 2017):

$$1/_{\tau^{super*}} = Max\ 1- \frac{1}{n} \sum_{i=1}^{n} \frac{H_i}{y_{i0}} \tag{31}$$

Subject to:

$$\sum_{k=1}^{z} x_{jk} \cdot \Lambda_k - H_j \leq x_{j0} \qquad j = 1,2...., m \tag{32}$$

$$\sum_{k=1}^{z} y_{ik} \cdot \Lambda_k + H_i \geq y_{i0} \qquad i = 1,2...., n \tag{33}$$

$$\sum_{k=1}^{z} \Lambda_k = 1 \tag{34}$$

$$\Lambda_k \geq 0,\ H_i \geq 0,\ H_j \geq 0 \tag{35}$$

Where: this model has the same variables and parameters from the model in Equations 25 to 30 (and $t = 1$).

3.3 DEA Window Analysis

The idea behind DEA Window Analysis 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). To determine the size and number of windows, Equations 36 and 37 from Cooper et al. (2007) are used, where k represents the number of periods and p denotes the window width. The data from each year is then divided into distinct sets, referred to as windows.

$$Window\ size\ (p) = (k + 1)/2 \tag{36}$$

$$Number\ of\ windows = k - p + 1 \tag{37}$$

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. This allows for the standard-deviation and average efficiency of the Decision-Making Units (DMUs) to be studied. After analyzing each window, the Data Envelopment Analysis (DEA) is used to determine the efficiency. The result of the efficiency of each DMU is the average of all the windows' efficiencies for the period under analysis.

3.4 Empirical methodological procedures

We structured the empirical methodological procedures of this article into four stages: a) selection of variables; b) econometric analysis; c) efficiency and Window Analysis from 2009 to 2015; and d) Malmquist Productivity Index.

3.3.1 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. Next, we identified variables that expressed the relative importance of the forestry sector on the economy of each Micro-Region, 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. The local Human Development Index (HDI) was used to measure the quality of life over the period of the analysis in the local economies. Figure 1 displays these selected Micro-Regions.

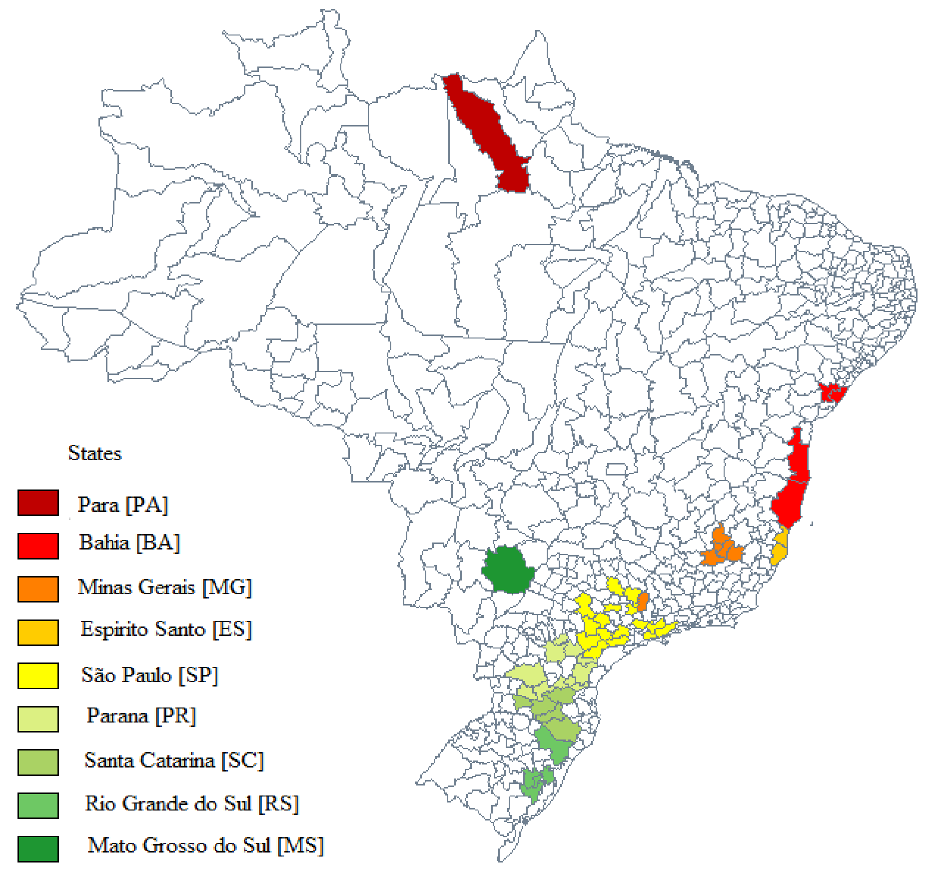

Figure 1. Selected micro-regions[1]
Source: Own elaboration

Table 1 displays the variables chosen and the definition of the dimension attributed to each, their data source, and their basic theoretical definition. The theoretical basis for the variable selection was derived from the literature review. The databases consulted were those from the Brazilian Institute of Geography and Statistics (IBGE 2021a; IBGE, 2021b; IBGE, 2021c), where we obtained in terms of the Micro-Regions the following variables: average wood cost (BRL/m³), 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). Table 1 presents the selected variables for the efficiency model as inputs and outputs.

[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.

Table 1. Variables selected for the analysis

Variable	Dimension	Source	Theoretical basis	Variable
Average wood cost (BRL/m³)	Economic	(IBGE 2021a)	Proposal of this research	Input
Employment in forestry and paper and pulp production	Social	(IBGE 2021a)	Proposal of this research	Input
Gross Domestic Product (GDP)	Economic	(IBGE 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	(IBGE 2021c)	Sun and 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: Own elaboration

The summary dataset is presented in Table 2.

Table 2. Descriptive data analysis

Variables	Obs.*	Mean	Std. Dev.	Min	Max
Average wood cost (BRL/m³)	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

Source: Own elaboration

The average wood cost is expressed in Brazilian currency (BRL) per cubic meter (m³) and GDP is expressed in Brazilian currency (BRL- Brazilian Real) (IBGE, 2021a; IBGE, 2021b IBGE, 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 the Brazilian municipalities and it ranges 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 of outputs and input, using regression analysis. This procedure is used to define the efficiency model when input-output combinations are confirmed by their statistical significance level.

3.5 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:

$$Y=K^{\alpha}A^{\gamma}L^{\beta} \quad (1)$$

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_{GDP}), total number of people employed (Y_{JOBS}) and an index of human development (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):

$$lnY_{GDP}= \alpha_0+\alpha_1 lnKA+\alpha_3 lnL+\varepsilon \tag{2}$$

$$lnY_{jobs}= \beta_0+\beta_1 lnKA+\alpha_3 lnL+\varepsilon \tag{3}$$

$$lnY_{HDI}= \delta_0+\delta_1 lnKA+\alpha_3 lnL+\varepsilon \tag{4}$$

Where: $\alpha_{n,}\ \beta_{n.}\ \delta_n$ ($n = 0,\ldots, 3$) are the estimated constant coefficients of the equations; lnY_{gdp} is the total GDP for each Micro-Region; lnY_{jobs} is the total number of employed people at each Micro-Region; lnY_{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 and Rebelatto, 2016). 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: Own elaboration

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 micro-regions where the wood cost and forest sector workforce are higher, so is the GDP (Y) variable.

The average wood cost and number of workers in forestry and paper and pulp production also presented positive coefficients and significant at 1 percent (p<0.01) when explaining the total number of people employed at each Micro-Region. This finding suggests that those Micro-Regions with higher wood cost and forest sector workforce also presented the 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 that have the highest HDI also have the higher wood cost and forest sector workforce. After the econometric validation, the efficiency model was characterized as described in Table 4.

Table 4 Efficiency Model

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

Source: Own elaboration

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.

4.Results and Discussion

First, we presented the efficiency scores by DEA and Window Analysis to include the period 2009 to 2015. In the sequence, we presented the productivity scores by MPI.

4.1 Efficiency Scores and Window Analysis

For the elaboration of the model to converting the expansion of the economic growth into welfare for the period that runs 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. Comparing 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 to Northeastern Region.

Rio Claro (SP), Sao Joao da Boa Vista (SP) and Sorocaba (SP) are DMUs from the Southeastern Region of Brazil, specifically from Sao 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 already highlighted that not only for pulp-producing Regions of the inner Regions of Sao Paulo state requires development policies, but also the palm-heart producing Micro-Regions (Varella et al. 2021). This way, demonstrating 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 similar to Rio Claro (SP), Sao Joao da Boa Vista (SP), and Sorocaba (SP), therefore, it requires immediate assistance for not losing efficiency. In this way, the results of the Window Analyses were consistent with the previous temporal analyses (*MPI*, *TC*, and *EC*), as highlighted in the Table 5.

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: Own elaboration

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. The efficient DMUs from Southern region were from Rio Grande do Sul (RS), while the inefficient DMUs are from Paraná (PR).

Similar to China (Zhang et al., 2022; Hou et al., 2020; Ren et al., 2020; Kourtit et al., 2020) this demonstrates the existence of inequality of efficiency among Regions and states in Brazil. Hence, the proposed method is useful to direct investments and policies towards 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 São Paulo and Minas Gerais as the most efficient alternatives, however, the authors did not consider human development aspects.

Also, in Table 5, it is observed that the cumulative growth rate of efficiency, in the period of 2009 – 2015, increased 16.42% over time, recording the most significant rise was 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 inputs and the drop trajectory indicates the opposite. Santa Catarina (SC) is also a Southern state. It demonstrates that, while the increase of production in Paraná results in positive human development, the increase of production 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 fundamental to encompass human development in the analysis.

Finally, Três Lagoas (MS) and Almeirim (PA) require a cautious interpretation. Firstly, because they are both in environmentally sensitive areas. Três Lagoas (MS) is in the Center-Western Region close to the Pantanal, a natural biome that encompasses the world's largest flooded grasslands and the world's largest tropical wetland area. Besides, the pulp production of Três Lagoas (MS) is the hugest in Brazil and one of the hugest in the world. However, the production is not converting into human development. Priority should be done to human development and environmental preservation.

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 very critical and requires intense vigilance against illegal deforestation. Besides recommending investing in human development for improving performance, in this particular case, it is recommended that policymakers consider eliminating the pulp production, and exchanging it for a less ecologically impacting activity, such as palm-heart production (Varella et al. 2021).

4.2 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 at the second period compared to its status in the first period, indicating how much the efficiency of each Micro-Regionv (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 it can be seen in Table 5, 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: Own elaboration

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) are efficient only in the second period, while 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 onto 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) keeps its productivity improvement, it indicates that it could be efficient in the next 12 years. While Mogi Mirim (SP) already 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 by means of 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 they can 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 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 taken as benchmarks for national-level planning. At the macro-regional level, priority should be given to improving human development in the states of Paraná and Santa Catarina, in order to bring them up to the same level as the southern state of Rio Grande do Sul. To do this, production-fostering policies should be implemented. At the state level, the micro-regions 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 micro-regions of São Paulo also need attention to maintain their efficient position.

The models proposed in this research serve as simplifications of the actual scenario of economic growth and quality of life in the paper and pulp sector. While other factors such as sustainable development and infrastructure can influence the efficiency and productivity of each Micro-Region, this study does not provide exhaustive conclusions. Nevertheless, it has developed important methods to evaluate economic growth and foster welfare, as discussed in the article. 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 policy makers take into account 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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