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PRELIMINARY REPORT

Technical Performance and Productive Dynamics in Angolan Maritime Fisheries: An Intertemporal DEA-VRS Approach

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ABSTRACT
The study aims to evaluate the trend of relative technical efficiency within the context of the optimization of productive resources of the seven Decision Making Units. The study encompasses the seven provinces of the Angolan coast. The Data Envelopment Analysis (Variables Returns to Scale model), with an input-oriented approach, was used, adapted to the Angolan production context, which is marked by financial constraints and exchange rate instability. The results show an upward trajectory of mean efficiency across the five analysis windows used, with a moderate positive trend. The results also revealed that intertemporal factors explain, in a differentiated way, a relevant part of the variation in the technical efficiency of the provinces, highlighting Cabinda, Zaire, Bengo, and Kwanza Sul, which showed upward evolution, and, on the other hand, Luanda, Benguela, and Namibe, which showed low performance or decline. Between 2016 and 2023, no province showed full technical efficiency, highlighting gaps in the optimization of available resources. The total fish catch load was a more critical variable, registering high levels of pure technical inefficiency, requiring a sustainable increase in production at the sectoral level. The absence of previous studies on technical efficiency in the Angolan fishing sector reinforces the pioneering nature of this research, which can serve as a basis for future investigations and the formulation of public policies.

Keywords: *Angolan maritime fishing, Intertemporal technical efficiency, DEA-VRS*

JEL Classification: C61; H57; Q22

INTRODUCTION

With the exception of the coastal strip belonging to the province of Cabinda, the coastlines of Angola, Namibia, and South Africa are part of the vast marine ecosystem known as the Benguela Current (BCF), considered one of the richest areas in biodiversity and productivity on the planet (ANGOLA, 2023). This strategic condition gives Angola a competitive advantage for the development of various activities linked to the maritime economy, especially the fishing sector.

A preliminary SWOT analysis of the Angolan fisheries sector, conducted by the United Nations Conference on Trade and Development (UNCTAD) in 2017, resulted in the following diagnosis: strengths such as the existence of technical training centers, support for artisanal fishing, waters rich in biomass, and a well-irrigated interior; weaknesses referring to limited infrastructure for fish processing and transportation, high dependence on the export of primary products, and low levels of maritime security; opportunities involving the development of aquaculture (such as tilapia and catfish), expansion of the supply chain, adding value to fishery products, and creating

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cold chains with synergistic potential for other foods; and threats including the high cost of operation in the sector, inefficient management of fishery resources, and post-harvest losses. Given the above, the following research question is raised: how did the size of the fishing fleet relate to the levels of productive efficiency in the maritime fishing sector in Angola between 2016 and 2023?

Since Data Envelopment Analysis (DEA) is a technique within a non-parametric model of central tendency, it becomes difficult to formulate statistically validated hypotheses around certain mean values (Anderson T. , 2003). Thus, based on the literature on the analysis of fishing efficiency, we expect to observe that provinces with larger fishing fleets exhibit lower levels of productive efficiency, relating the excess of vessels to the inefficiency recorded.

Aiming to achieve results and partially aligned with the problem raised, this study aims to evaluate the trend of relative technical efficiency within the process of optimizing productive resources across the seven DMUs (Decision Making Units), corresponding to the seven provinces that make up the Angolan coast.

DEA is a methodology based on mathematical programming, used to measure the relative efficiency of a set of DMUs in productive resource optimization processes, considering multiple inputs and outputs. Its application has proven effective in evaluating the performance of units with diverse institutional profiles. In this study, the model assuming the variable returns to scale (DEA-VRS) was chosen to capture the heterogeneity between the DMUs, since not all operate on the same scale. An input-oriented approach was adopted, as it is more suitable for the Angolan economic context, characterized by state financial constraints, exchange rate instability, and uncertainties stemming from global financial markets, exacerbated by customs tariffs and the prospects of interest rate hikes by central banks. Thus, this study aims to fill an empirical gap related to the lack of published results on technical performance in the Angolan maritime fisheries sector.

THEORETICAL BACKGROUND

The evaluation of Angolan production units or sectors using DEA models is relatively recent, with the earliest records in the consulted bibliography dating from the 2000s. However, its production has increased in recent years, as evidenced by studies by Santos, Dieke, & Barros (2008), Kirigia, Emrouznejad, Cassoma, Asbu, & Barry (2008), Barros & Assaf (2009), Barros & Managi (2009), Barros, Assaf, & Ibiwoye (2010), Seabra (2011), Dumbo (2011), Barros & Antunes (2013), Barros & Assaf (2009), Barros & Managi (2009), Barros, Liang, & Peypoch (2014), Macanda (2015), Barros, Leão, Macanda, & Mendes (2016), Wanke, Barros, & Emrouznejad (2016), Barros, Wanke, Dumbo, & Manso (2017), (Hadi-Vencheh, Wanke, & Jamshidi (2020), Costa (2020), Silva (2021), (Chávez, Ortega, & Ibarra (2022), (Hadi-Vencheh, Khodadadipour, Tan, Arman, & Roubaud (2024), Pires, Santos, & Silva (2023), Sanches-António (2024), Sanches-António (2025), Sanches-António (2025). Nevertheless, there is no record of studies on evaluating the performance of the fish capture sector, which is the subject of this study.

Literature on the intertemporal evaluation of the relative technical efficiency of DMUs in the fisheries sector, in African countries and the rest of the world, has been widely used, with references to studies by (Mustapha, Aziz, & Hashim, 2013), (Schrobback, Schrobback, Pascoe, McWhinnie, & Hoshino, 2023), and (Ewedji & Dehlor, 2024). Within the scope of evaluating the activity researched using the DEA methodology, the specialized literature frequently presents studies that integrate multiple analytical approaches, particularly those of an economic-environmental nature. Such investigations, as conducted by Vázquez-Rowe, Iribarren, Moreira, & Feijoo (2010) and Martínez-Ibáñez, et al. (2024), serve as examples. This study proposes a broader understanding of productive efficiency, incorporating dimensions that transcend purely economic boundaries. In these studies, the impacts of fishing activity are placed at the heart of the analysis, considering not only the effects on marine ecosystems, but also the repercussions on sectoral productivity, social well-being, and environmental sustainability.

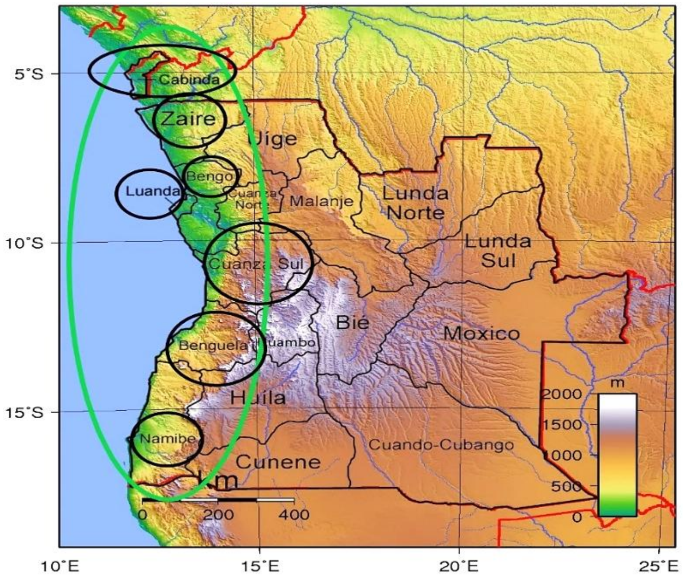

Figure 1. Geographical location of the maritime fishing area

Source: from Plural (2025)

From an economic standpoint, the emphasis is on the fishing sector's capacity to generate added value, optimize resource use, and contribute to the growth of local and national production chains. In the social dimension, the role of fishing as a source of food security is highlighted, especially in coastal communities, where access to high-nutritional-value protein is fundamental for public health and socioeconomic stability. On the other hand, the environmental aspect focuses on analyzing the pressure exerted by fishing activity on marine biomass stocks, addressing issues such as overfishing, habitat distribution, and cumulative effects on ocean biodiversity.

These integrated approaches allow DEA to be applied not only as a tool for measuring technical efficiency, but also as an instrument to support the formulation of public policies, strategic planning, and the sustainable management of fisheries resources. By simultaneously considering economic, social, and environmental variations, the selected studies promote a more holistic understanding of fishing activity and support analyses aligned with the principles of the blue economy, maritime conservation, and sustainable development.

EMPIRICAL APPROACH

Specifications: Model and Analysis Window

In practice, the assumption that the results verified in the context of the optimization of productive resources by DMUs are constant is more likely to be accompanied by their operational reality, considering factors of a difficult and varied nature, exogenous: such as the current economic policy, or the regulation of the markets in which they are inserted; or endogenous related to their heterogeneity. Thus, meeting the validated condition of variable returns to scale, according to Charnes, Cooper, & Rhodes (1978), the DEA-VRS model assumes non-proportionality between inputs and outputs; that is, variations in inputs cause variations in outputs with different magnitudes. In its input-oriented configuration, its formulation appears in (1).

$$Maximize\ h_k = \sum_{r=1}^{m} u_r y_{rk} - u_k$$

subject to:

$$\sum_{i=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} - u_k \leq 0$$

$$\sum_{i=1}^{n} v_i x_{ik} = 1 \qquad (1)$$

and

$$u_r, v_i \geq 0$$

where; y: inputs; x: outputs; u e v: weights; r:1,..., m; i:1,..., n; j:1,....., N.

In the DEA literature, there is a consensus that no standard methodology exists for setting analysis windows; however, Cooper, Seiford, & Tone (2007) postulate that the number of DMUs must be at least greater than the sum of the total inputs and the total outputs, a criterion that has been adopted as a standard for the calibration of DEA windows, as shown in (2).

$$n \geq max.\{[(m)(s)]3(m + s)\} \qquad (2)$$

where:
- n: number of DMUs;
- m: number of inputs;
- s: number of outputs.

When dealing with multiple time periods, the process of evaluating the efficiency of DMUs presents an increased challenge due to the intertemporal effects inherent in their operational dynamics. This contingency can be confirmed in studies of (Sengupta, 1996), (Řepková, 2014) and (Apan, Alp, & Öztel, 2019).

In this line of thought, studies such as those by Cooper, Seiford, & Tone (2007) and Cooper, Seiford, & Zhu (2011) provide theoretical support for empirical approaches in various research projects related to the efficiency dynamics of DMUs, as presented in the following mathematical formulations, whose practical application is shown in Tables 1 and 2.

$$\begin{aligned} w &= k - p + 1 \\ v &= n(p - 1)(k - 1) \\ z &= (n)(p) \\ h &= (n)(p)(w) \end{aligned} \qquad (3)$$

where:
- w: number of windows;
- v: variation in the number of DMUs;
- z: number of DMUs in each window;
- h: number of different DMUs;

- *p*: window width ($p \leq k$);
- *k* = Periods to which the data refer.

As shown in Table 1, considering the number of DMUs (7) and the number of periods to which the data refers (6 years), a window width of 4 years was selected, since the number of DMUs exceeds that obtained when window widths of 2 and 3 years are used. Thus, with the greater number of different DMUs in each window, the adopted window width allows for greater discriminatory power for obtaining efficiency improvements, thereby validating the efficient DMUs condition with greater reliability.

Table 1. DEA Window calibration

Components	**Formulas**	**p = 4 years**
Number of windows	k – p +1	(8 – 4 + 1) = 5
Number of DMUs in each window	(n) (p)	[(7) (4)] = 28
Number of different DMUs	(n) (p) (w)	[(7) (4) (5)] = 140
Variation in the number of DMUs	n (p – 1) (k – 1)	[(7) (3) (7)] = 147

Source: Author`s calculations in Microsoft Excel (2019)

Based on the procedures adopted for setting the range of the analysis windows, as presented in Table 1, Table 2 shows their configuration in the form of moving means, which, by successively removing the initial year and including the final year immediately afterwards in each period, allows the evaluation process to obtain more reliable results when comparing periods.

Table 2. Window configuration

Periods		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Windows	1	2016	2017	2018	2019				
	2		2017	2018	2019	2020			
	3			2018	2019	2020	2021		
	4				2019	2020	2021	2022	
	5					2020	2021	2022	2023

Source: Author`s calculations in Microsoft Excel (2019)

Methodology and Data

According to Basias and Pollalis (2018), based on measurable and observable data, the statistical method is used to facilitate the development of the assessment through quantitative indicators. Thus, with the objective of capturing changes and levels of efficiency recorded by scientific DMUs, this method employed procedures related to the description, measurement and evaluation of quantitative aspects of scientific reality. Similarly, as part of the adopted procedures, the comparative analysis method was used to examine the phenomenon under study, specifically by identifying trends, differences, and similarities in the performance of the DMUs, over the analyzed period, finding theoretical support in Prodanov and Freitas (2013).

The data supporting the study were obtained from secondary sources, namely official documents from the Angolan Ministry of Fisheries and Marine Resources (MINPERMAR), specifically its statistical yearbooks for (2017), (2022) and (2024), published by the Angolan National Institute of Statistics (INE). Thus, in order to more comprehensively capture the dynamics of the process of optimizing productive resources in the Angolan fishing sector, over the period from 2016 to 2023, data recorded for both industrial and semi-industrial fishing in the provinces of Cabinda, Zaire, Bengo, Luanda, Kwanza Sul, Benguela, and Namibe were considered. The mean values, by variable, for the period 2016-2023, appear in Table 3.

Table 3. Mean values per variable

DMUs	Number of vessels	Population fishing	Captur total
Cabinda	2	17	16984
Zaire	1	9	48193
Bengo	1	8	33801
Luanda	149	2975	162565
Kwanza Sul	8	180	34520
Benguela	53	1107	136914
Namibe	45	773	64738

Source: Author`s calculations in SPSS 26.0 (2019)

Similarly, in order to analyze the longest period permitted by the availability of published data, statistical imputation, specifically the technique of replacing missing data or extreme values with their respective means, was employed. This was achieved by incorporating data for the year 2017 (not published at the time of this study), in order to ensure continuity in the dynamics of the trends observed.

With regard to the statistics included in the model, the results adopted were based on their operational relevance, reflecting the resources used in the Angolan maritime fishing sector (inputs: the fishing fleet comprised of the number of vessels operating in the trained period, representing the sector's installed productive capacity; and the fishing population comprised of the number of workers employed by the sector) and the results (outputs: total catch and marketing revenue, representing the physical indicator of fisheries production).

The descriptive statistics of the sample used in the DEA assessment, presented in Table 4, reveal important structural characteristics of the Angolan maritime fishing sector. The variable number of shipments shows a significant range, with values varying between zero and 184, a mean of 37, and a standard deviation of 51, indicating strong heterogeneity among the DMUs (Detailed Management Units). This high dispersion suggests that some provinces operate with a substantial fishing fleet, while others have no registered vessels during the period. The fishing population variable also shows high variability, with values between 0 and 4,391. Its median of only 115 reveals an asymmetrical distribution, with activity concentrated in a few provinces and a predominance of limited fishing population contingents in most coastal regions. This configuration may reflect regional inequalities in the productive structure and community organization of fishing, directly influencing the levels of efficiency offered, especially in input-oriented models.

The total variable capture, used as the main proxy for productive output, presents a median of 54,423, suggesting a less asymmetrical distribution than the previous variables, although still marked by strong dispersion.

Table 4. Statistics descriptive

Variables	Minimum	Maximum	Median	Media	Std deviation
Number of vessels	0	184	8	37	51
Population fishing	0	4391	115	707	1103
Total capture	2673	225116	54423	68463	53665

Source: Author`s calculations in SPSS 26.0 (2019)

Considering the institutional heterogeneity and statistical limitations observed in the Angolan maritime fishing sector, the sample data did not present a normal distribution, which justified the application of the non-parametric Spearman rank correlation coefficient (ρ^{o}), suitable for productive contexts with asymmetrical and dispersed variables. Table 5 presents the results of the brightness matrix between the variables considered for inclusion in the DEA model, revealing high and statistically significant coefficients at the 0.01 level (two extremes). The demonstration of $\rho^{o} = 0.971$ between the number of vessels and the fishing population stands out, showing a strong structural association between these two inputs, which is consistent with the operational logic of the sector, where the volume of vessels tends to directly reflect the human contingent involved in fishing activity. Despite the demonstrated increase between these variables, it was decided to maintain both in the model due to the limitations of alternative data that could serve as complementary proxies, as well as the greater operational stability and statistical availability of the number of vessels variable. This methodological decision aims to preserve the representativeness of the inputs without compromising the robustness of the model, ensuring that, although correlated, the variables capture distinct dimensions of the productive capacity of the DMUs. As a production variable, the total catch variable was maintained to directly reflect the productive performance of the demonstrated units and to present evident manifestation coefficients with the inputs ($\rho^{o} = 0.723$ with vessels and $\rho^{o} = 0.694$ with fishing population), reinforcing its suitability as an outcome indicator in the DEA model.

Integrating inspection analysis with the selection of variations allows for greater methodological consistency and contributes to building a technical efficiency model more suited to the specificities of the sector, while respecting the criteria of statistical validity and operational relevance. This approach strengthens the interpretation of results and expands the potential for practical application of the findings, especially in the context of formulating public policies and strategies for optimizing resources in the fisheries sector.

Table 5. Non-parametric correlation matrix between variables

ρ^{o}	Number of vessels	Population fishing	Capture total
Number of vessels	1,000	0.971 **	0.723 **
Population fishing	0.971 **	1,000	0.694 **
Total capture	0.723 **	0.694 **	1,000
**. The correlation is significant at the 0.01 level (2 tails).			

Source: Author`s calculations in SPSS 26.0 (2019)

RESULTS AND DISCUSSION

Table 6 presents the overall results of efficiency levels for each DMU (province) and in each year. Thus, using the heat map applied to the results, it is possible to see that the DMU with the best mean efficiency record and over the largest number of years were the provinces of Zaire, Bengo and Cabinda respectively, also highlighting the efficiency scores recorded by the provinces of Luanda and Cabinda with a positive trend, despite the high variability (minimum values in 2016 and maximum values in 2023).

The provinces of Kwanza Sul and Namibe showed consistently low performance with little variation, suggesting the prevalence of persistent structural inefficiency in their operational processes. The year 2016 shows results indicating high levels of dispersion among efficiency forecasts for the sector as a whole, i.e., the coexistence of efficient and inefficient DMUs (Daily Management Units) in similar numbers. This contrasts with the period between 2020-2023, which shows a trend of overall improvement and reduced variability. This may indicate the effect of public policies stimulating fishing activity, investments, or operational adjustments in the sector.

The results of the efficiency scores obtained in isolation are consistent with those expected and mentioned in the introduction. They are corroborated in the literature related to the analysis of fishing efficiency. In this regard, studies by Anderson (2002) e Pascoe, Kirkley, Gréboval, & Morrison-Paul (2003), are notable, as they attest to the non-proportionality in the relationship between the size of the fishing fleet and efficiency; in other words, DMUs with larger fleets of vessels tend to be less efficient.

Table 6. Summary of efficiency scores

DMUs	2016	2017	2018	2019	2020	2021	2022	2023	Mean	Std. dev.
Cabinda	0	50	17	75	100	100	100	100	68	41
Zaire	100	50	17	75	100	100	100	100	80	31
Bengo	0	50	33	75	100	100	100	100	70	38
Luanda	15	100	47	53	65	100	61	100	68	31
Kwanza Sul	0	7	9	15	25	25	6	11	12	9
Benguela	100	72	63	24	27	97	91	100	72	32
Namibe	24	10	23	6	2	2	2	2	9	9
Mean	34	48	30	46	60	75	66	73	-	-
Std. dev.	46	33	19	31	42	42	44	46	-	-

Source: Author`s calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)

Figure 1 highlights significant disparities in pure efficiency among the seven provinces tested. The overall mean efficiency, at 54%, serves as a benchmark for evaluating the relative performance of each region. The provinces of Zaire (80%), Benguela (72%), Bengo (70%), Cabinda (68%), and Luanda (68%) stand out positively, all above the national mean. These results suggest greater rationality in the allocation of productive inputs, possibly associated with factors such as consolidated infrastructure, institutional capacity, effective public policies, or greater integration with local production chains. In contrast, Kwanza Sul (12%) and Namibe (9%) present critical levels of efficiency, including underutilization of available resources and possible operational bottlenecks. The poor performance of these regions may reflect structural limitations, lack of targeted investments, weak management, or discontinuity of sectoral policies. These results reinforce the need for specific instructions, such as technical training programs, equipment modernization, institutional strengthening, and encouragement of interprovincial cooperation.

These results are in line with studies by UNCTAD (2022), that explain why disparities in technical efficiency between provinces or fishing regions are not only a reflection of natural conditions, but above all of available infrastructure, institutional capacity, effective public policies and integration with local production chains.

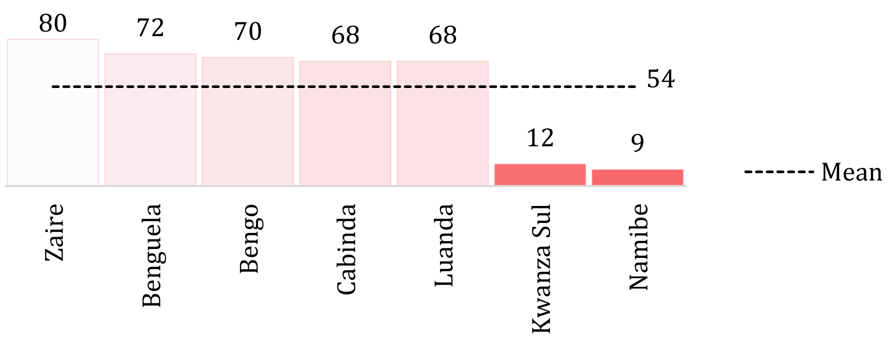

Figure 2. Pure technical efficiency (%)

Source: Author`s calculations in Microsoft Excel (2019)

Figure 3 presents the annual evolution of mean sectoral technical efficiency during the period (2016-2023), revealing a predominantly upward trajectory, albeit marked by occasional fluctuations. In 2016, performance began at 34%, reflecting a scenario of low institutional efficiency. In subsequent years, an alternation between advances and setbacks is observed: in 2017, there is a recovery to 48%, followed by a drop to 30% in 2018, which may indicate operational instability or the absence of structuring policies in the sector.

From 2019 onwards, the trend becomes more consistent, with progressive growth: 46% in 2019, 60% in 2020, and a peak of 75% in 2021. This period suggests the implementation of corrective measures, strategic reorganization, or institutional maturation. Despite a slight decrease to 66% in 2022, performance rises again in 2023, reaching 73%, which reinforces the hypotheses of reported improvements.

The linear trend line fitted to the data shows a coefficient of determination of 76%, indicating that 76% of the variation in mean efficiency can be explained by the annual time progression. This value is statistically robust and confirms the existence of a positive trend over the years. However, the observed fluctuations, especially in 2018 and 2022, suggest the presence of exogenous or non-linear factors, recommending the use of complementary methodological approaches.

Between 2016 and 2023, the mean technical efficiency of the Angolan fishing sector showed a fluctuating, but upward, trajectory, as mentioned. Thus, it was found that the results of the study are aligned with those of MINPERMAR, and consistent with its statistical yearbooks for the years 2017, 2022, and 2024.

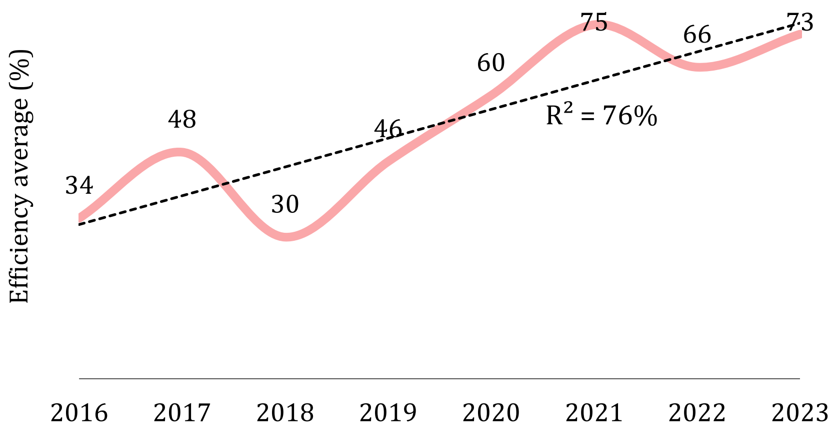

Figure 3. Annual dynamics in sectoral efficiency

Source: Author`s calculations in Microsoft Excel (2019)

Figure 4 shows the evolution of mean efficiency (%) across five analytical windows, revealing an upward trajectory with occasional fluctuations. In the first window, an extremely low efficiency level is observed (18%). From the second window onwards, a significant jump to 64% is seen, indicating the introduction of corrective measures, operational reorganization, or strategic investments.

In the third window, there is a drop to 56%, which may reflect internal configurations, seasonality, or temporary external impacts. However, in the following windows (4 and 5), efficiency returns to the 64% level and reaches 67%, establishing improvements and greater stability in sectoral performance.

The linear trend line has a coefficient of determination R^2 of 58%. This value indicates that 58% of the variation in mean efficiency can be explained by the linear progression between the windows, reinforcing the existence of a moderate positive trend. However, the remaining 42% of variability not captured by the model suggests the influence of non-linear or exogenous factors.

These results, with means smoothed over time, are consistent with the equally increasing trend of catches in African marine areas, including over a much longer period (1975-2023), according to data from (FAO, 2025).

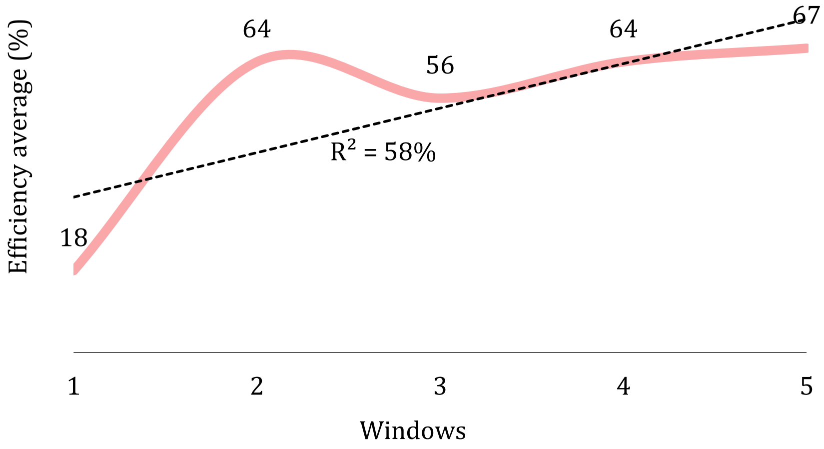

Figure 4. Inter-window dynamics in sectoral efficiency

Source: Author`s calculations in Microsoft Excel (2019)

The information that appears in Figure 5 validates the percentage variation in efficiency rates across the five windows, which is explained by the temporal (linear) trend. Thus, the values obtained for each are R^2 respectively: (Cabinda: the trend in efficiency improvements was 70% upward, i.e., a significant improvement in its levels of productive resource combination, a reduction that intertemporality is a good predictor of improvement, possibly due to investments or institutional reorganization); (Zaire: strong upward trend, having increased consistently, with intertemporality explaining 74% of the observed variation); (Bengo: showed a moderately positive upward trend in efficiency, therefore, intertemporality explains a significant part of the variation that occurred between the analyzed years, namely 63%; however, there are factors that conditioned its performance, and which are not fully explained by technological variations); (Luanda: 15% upward trend: very weak trend. The level of efficiency is low and little influenced by intertemporality. This may indicate stagnation or absence of ineffective management practices); (Kwanza Sul: 70% upward trend, despite low inter-window efficiency rates, these show a tendency to recover or increase efficiency, albeit at levels considered lower); (Benguela: 44% upward trend, weaker compared to those recorded by other provinces, with intertemporal factors explaining less than half of the recorded variation, showing the influence of one-off factors or operational instability) and (Namibe: 29% downward trend, a downward trend in efficiency over time. Intertemporal factors explain little of the recorded variation; however, a possible structural decline or loss of competitiveness in the face of excessive scientific expertise).

Despite the overall upward trend, as mentioned in the discussion of Figure 4, the results for the provinces of Benguela and Namibe, in Figure 5, also show alignment with those obtained in Schrobback, Schrobback, Pascoe, McWhinnie, & Hoshino (2023) and Ewedji & Dehlor (2024), highlighting that, in several fishing regions, mean efficiency remained low over time, revealing a high degree of technical inefficiency and the presence of persistent idle capacity.

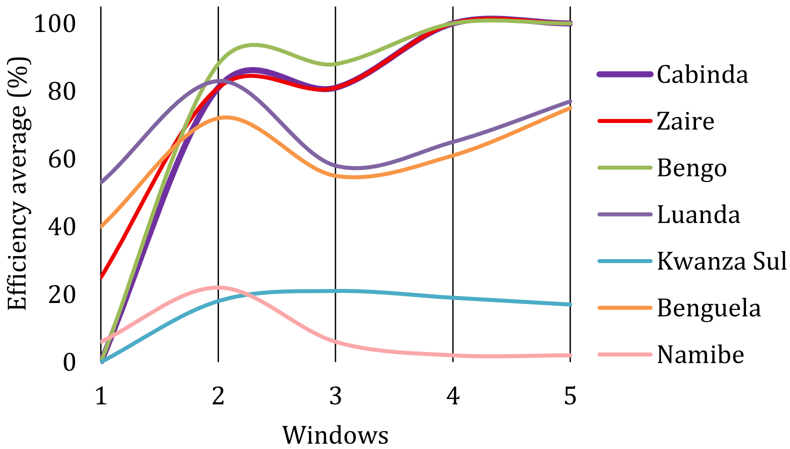

Figure 5. Inter-window dynamics in provincial efficiency

Source: Author`s calculations in Microsoft Excel (2019)

To provide a more comprehensive view of the factors influencing the performance of the provinces shown in their resource optimization process within the context of fishing activity, Table 6 presents the results relating to the mapping of efficiency losses and respective operational slack, by variable. From the results obtained, it is possible to observe that, both in the variable of the number of vessels and in the variable of total catch, the provinces consistently operate below the efficient frontier, without reducing the disproportionate combination of these inputs. These records indicate performance below the optimum, originating from the scale or intensity of their operations.

Although the sources of inefficiency are respected, the greatest attention falls on the total variable catch of the fishery, with a persistent record of maximum inefficiency, within the joint operational scope. From the student provinces. Thus, it can be observed that the corresponding slack periods also show records of high slack.

These results are consistent with studies covering longer time periods, which show that the performance of the African continent as a whole over the last 70 years has recorded inefficiencies equivalent to a loss of 2 million tons of fish production per year, as reported in Ye, Ndiaye, & Al-Husaini (2024). This reflects a trend of degradation in the level of optimization of fisheries resources and fisheries production in Angola and across the continent.

Table 5. Inter-window sectoral inefficiency

Windows	Number of vessels		Population fishing		Total capture	
	Inefficiency (%)	Slack	Inefficiency (%)	Slack	Inefficiency (%)	Slack
1	60	0	36	7	100	43568
2	80	0	20	7	100	5489
3	96	0	4	23	100	5164
4	93	0	7	119	100	5402
5	93	0	7	171	100	6843
Mean	84	0	15	65	100	13293

Source: Author`s calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)

CONCLUSION

The combination of empirical evidence from different contexts confirms patterns already identified in the international literature on fisheries efficiency, such as those of Anderson (2002) and Pascoe et al. (2003), which highlight the non-proportionality between fleet size and efficiency. The Angolan results reinforce this finding, showing that increasing installed capacity does not guarantee efficiency gains.

The growing and relatively stable trajectory of technical efficiency between 2016 and 2023 aligns with studies by UNCTAD (2022) and FAO (2025), which point to the importance of institutional and infrastructural factors in improving fisheries performance. Thus, this study contributes by demonstrating that, in Angola, institutional advances and public policies played a decisive role in the gradual recovery of efficiency, although still far from full optimization.

The critical variable of total fish catch load confirms findings by Schrobback et al. (2023) and Ewedji & Dehlor (2024), which highlight the persistence of idle capacity and technical inefficiency in several fishing regions. The unique contribution of this study lies in showing, with recent and specific data from Angola, how this limitation compromises the exploitation of the potential of the marine ecosystem and requires sustainable growth strategies.

From a political point of view, the results corroborate the literature on fisheries governance (Ye, Ndiaye & Al-Husaini, 2024), which emphasizes significant production losses due to technical inefficiency. The novelty here is the application of interprovincial benchmarking, which allows the identification of good local practices (as in Zaire) and specific bottlenecks (as in Luanda), offering a practical tool to guide structural and operational reforms.

Institutional and community capacity building, already advocated in regional studies by FAO and UNCTAD, gains an applied dimension in this work for the Angolan context, highlighting that the integration of coastal communities in resource management is a necessary condition to reduce waste and increase productivity.

In summary, this study not only confirms trends already documented in the international literature on fisheries efficiency, but also offers a unique contribution: a detailed analysis of Angola's trajectory between 2016–2023, with an interprovincial focus, which highlights both institutional advances and persistent operational challenges. This approach provides original input for national and regional public policies by integrating internal benchmarking with international comparisons, broadening the debate on efficiency and sustainability in the African fisheries sector.

The study, although relevant, has limitations that compromise its scope and robustness. This is the case with the high level of standard deviations recorded in provinces such as Cabinda and Kwanza Sul, which weakens the reliability of the efficiency scores obtained from DEA models, while the centrality of the catch load as the main variable reduces the analytical dimension by excluding institutional and environmental factors. Furthermore, the time frame from 2016 to 2023 does not contemplate long-term cycles, limiting the understanding of the dynamics of structural efficiency. Therefore, it is recommended to incorporate additional variables, expand the historical series, and use complementary methodologies, such as polynomial regressions and stochastic frontier analysis, capable of offering greater sensitivity and analytical consistency.

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APPENDIX

Inter-window sectoral efficiency

DMUs	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Mean**	**Std. dev.**
	0	0	0	0					0	0
		100	25	100	100				81	38
Cabinda			25	100	100	100			81	38
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	0	50	17	75	100	100	100	100	68	41
	100	0	0	0					25	50
		100	25	100	100				81	38
Zaire			25	100	100	100			81	38
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	100	50	17	75	100	100	100	100	80	31
	0	0	0	0					0	0
		100	50	100	100				88	25
Bengo			50	100	100	100			88	25
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	0	50	33	75	100	100	100	100	70	38
	15	100	46	51					53	35
		100	60	73	100				83	20
Luanda			35	44	54	100			58	29
				44	54	100	63		65	24
					50	100	59	100	77	27
Mean	15	100	47	53	65	100	61	100	68	31
	0	0	0	0					0	0
		13	13	20	25				18	6
Kwanza Sul			13	20	25	25			21	6
				20	25	25	6		19	9
					25	25	6	11	17	10
Mean	0	7	9	15	25	25	6	11	12	9
	100	44	16	0					40	44
		100	100	46	41				72	33
Benguela			72	25	23	100			55	38
				25	23	100	95		61	42
					21	91	87	100	75	36
Mean	100	72	63	24	27	97	91	100	72	32
	24	0	0	0					6	12
		20	51	16	2				22	21
Namibe			18	3	2	2			6	8
				3	2	2	2		2	0
					2	2	2	2	2	0
Mean	24	10	23	6	2	2	2	2	9	9
General mean	34	48	30	46	60	75	66	73	-	-
General Std. dev.	44	35	21	33	44	47	47	50	-	-

Source: Author calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)