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Technical Efficiency of the Nile Perch Fishing Fleet on Lake Victoria: A Comparative Perspective on the Three Riparian Countries Kenya, Tanzania and Uganda

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Abstract: Lake Victoria, which is shared by Kenya, Tanzania, and Uganda, faces escalating concerns over sustainable fisheries amidst expanding fishing efforts. This study aims to investigate how technical efficiency (TE) and labor productivity (LP) of the Nile perch fishing fleet vary across the three riparian countries. Using a nine-year dataset spanning from 2005 to 2021 and employing Stochastic Frontier Analysis, this study evaluates the TE of the fleet, where LP is determined as catch per crew hour fished in a day for three vessel types: motorized, paddled, and sailed. Motorized fleets had the highest mean technical efficiency (0.60–0.66), compared to paddled (0.29–0.49), and sailed vessel categories (0.24–0.46). Sailed vessels declined in all countries owing to their low TE. In Kenya, TE and LP increased for paddled vessels, especially in the period from 2015 to 2021, and a slight increase was also indicated for motorized vessels. Conversely, Uganda and Tanzania experienced gradual declines in TE and LP, particularly from 2015 to 2021, a period of rigorous law enforcement that led to declines in the number of paddled vessels by 50% and 7%, respectively, and a contrasting increase in motorized vessels. By 2021, the number of Ugandan motorized vessels had increased greatly but TE had declined compared to Kenya and Tanzania, a sign of overcapacity. The findings underscore the need for region-specific policies that address economic differences, policy implementation impacts, and resource health to promote sustainable transboundary fisheries management on Lake Victoria.

Keywords: fisheries management; fisheries technical efficiency; labor productivity; catch assessment; over capacity

Key Contribution: This study presents a novel cross-border comparison of technical efficiency and labor productivity in Lake Victoria's fishing fleet. Differences in vessel performance and labor output are shaped by factors such as economic growth, technology use, and regulations, with motorization emerging as a key driver of improved fleet efficiency.

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1. Introduction

Fisheries on Lake Victoria, Africa's largest freshwater lake, are an important socio-economic activity. The fisheries contribute significantly to regional food security and provide employment and livelihoods for the large lakeside populations [1]. The fisheries sector is of major economic importance and integral to the economies of the three riparian countries, contributing approximately 0.8%, 1.7%, and 3% of the Gross Domestic Product (GDP) in Kenya, Tanzania, and Uganda, respectively [2]. Lake Victoria's fisheries operate under limited restrictions on access. The three countries of Kenya (6%), Tanzania (51%), and Uganda (43%), which share the transboundary lake, have imposed regulations on fishing gear, registrations, and type of vessels to regulate fisheries efforts, but allow entry to the fishery after payment of a nominal access fee [3]. Fisheries management efforts suffer from access to reliable data and are plagued by data scarcity in both spatial and temporal dimensions, as well as irregular data collection practices. It is therefore important to seek ways in which the existing although limited data can be used [4].

The evolution of landed fish catches in Lake Victoria reflects notable shifts toward the focus on the Nile perch in the 1990s, which remains the most valued species and the primary fish export for the past three decades [5,6]. The significance of the Nile perch fishery is further underscored by the distribution of fishing effort, with up to 58% of the 210,620 fishers targeting the species, along with a comparable proportion of the 70,995 fishing crafts [7,8].

On the lake, fishery-related technological changes introduced by the early colonial governments replaced the inefficient and ancient traditional fishing methods. Modern fishing equipment, including synthetic gill nets and trawls, were used to increase catches per input, and outboard engines were introduced to expand access to fishing grounds [5,9]. The commercial importance of capture fisheries grew alongside increased markets and infrastructure development, leading to increased fishing efforts. This evolution has led to a shift in efficiency.

Technological advancements have led to reduced costs and transformed fishing fleets' performance in Lake Victoria. Three main types of vessel propulsion are used on the lake: motorized vessels with outboard engines, paddled vessels, and sail-powered vessels. The introduction of outboard engines in the 1950s led to sizeable changes in efficiency [9,10]. However, investment capacity is limited, and a small section of sailed vessels remains. The final vessel type, paddled vessels, is generally smaller than the other two, and its activities are limited to areas close to the shoreline [11].

While comparative studies on fleet performance have been conducted for some of the African lakes [12,13], no comparative study has been undertaken to assess the technical efficiency of the fishing fleets across the three riparian countries sharing Lake Victoria. Previous studies on technical efficiency have been conducted in individual countries, including research by [14] in Uganda and studies by [15,16] in Tanzania using cross-sectional data. In contrast, this study extends its analysis to nine years of panel data collected over 17 years (2005–2008; 2010–2011; 2014–2015; 2021). The utilization of panel data provides a unique opportunity to capture the dynamic and heterogeneous nature of fleet production units over time, considering factors such as country-specific technology adoption and economic and policy changes that may influence fleet technical efficiency. In addition to evaluating technical efficiency, the study also provides estimates of labor productivity (LP) for each vessel type across the three countries. LP, defined as the output (fish catches) per fisher over a specific period, is important in understanding the development of the fishery, given that Lake Victoria's fishery remains labor-intensive [17–19].

This study's objective is to assess the technical efficiency (TE) and labor productivity (LP) of the fishing fleet on Lake Victoria, comparing performance across Kenya, Tanzania, and Uganda, while identifying the key factors influencing these metrics.

The guiding research objectives are:

- To evaluate the status and historical development of the fishing fleet on Lake Victoria across the three riparian countries.
- To analyze the TE and LP scores of the fishing fleet across Kenya, Tanzania, and Uganda.
- Assess the impact of fleet development, regulatory frameworks, and fish stock health on TE and LP scores, and their influence on sustainability in Lake Victoria fisheries.

2. Materials and Methods

2.1. Measuring Technical Efficiency

Measurement of productive efficiency is commonly applied to fisheries to evaluate outcomes, policies, and development [20–24]. The Stochastic Frontier Approach (SFA) is used to estimate the technical efficiency of the Nile perch fleet. It models the relationship between outputs, such as fish catch, and inputs, such as fuel and labor, using a flexible functional form that represents underlying technology. The model is well-suited for single-species fisheries with multiple inputs and a single output, such as the Nile perch catches evaluated in this study [20,21], is flexible in dealing with complexity, and is versatile with respect to analyzing external factors of inefficiency [20,25,26]. The general approach is discussed in [27,28]. The model contains a composite error term, a random deviation, and an inefficiency term. The inefficiency term can contain a model of explanatory variables linking independent variables to the level of inefficiency [29]. Figure 1 shows a representation of the model terms.

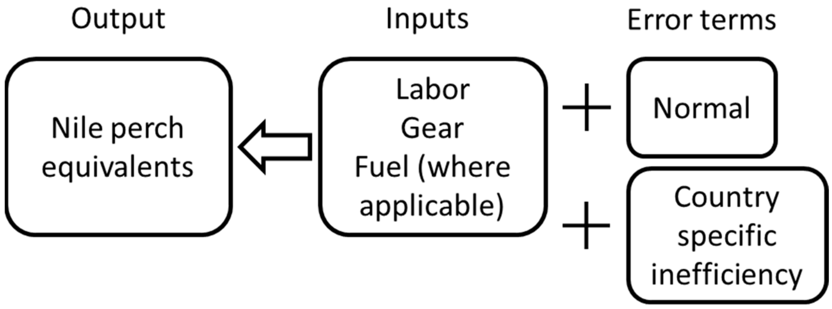

Figure 1. Representation of the empirical model used in the analysis, with output, inputs, and a composite error term.

2.2. Data Sources and Treatment

Two main datasets were used, a frame survey (FS) and catch assessment (CAS), with both obtained from the Lake Victoria Fisheries Organisation (LVFO) database. Frame survey data are generated from a complete census of all fishery variables, including the vessels, gears, and landing site facilities along the lake [7]. The data collected biennially on Lake Victoria was available for the period from 2000 to 2020 and was specifically used to answer this study's first objective, namely, to evaluate the status and historical development of the fishing fleet on Lake Victoria, including trends from 2000 to 2021 across the three riparian countries.

The second dataset and main dataset used to estimate TE and LP comprised the CAS data. It consists of nine-year vessel-level catch data (series of catch assessment surveys conducted with support from the Implementation of Fisheries Management Plan (IFMP) project during 2005–2008; and Lake Victoria Environmental Management Program (LVEMP1) 2011 and 2014 and 2015 by LVEMP2.) (2005–2008; 2010–2011; 2014–2015; 2021), collected over 17 years. The LVFO periodic survey data usually follows a two-stage sampling procedure where 10% of the landing sites in each country are identified as strata in the first stage and then vessels are randomly sampled at the landing sites in the second stage [30,31]. To address the missing variable of fuel use for motorized vessels, a supplemental survey was conducted: in Uganda between June and August 2017, and in Kenya and Tanzania from April to September 2020. Data were collected following the CAS data collection form, including vessel fuel use in liters as a variable. Fuel is a crucial input, especially for motorized vessels, as it is used to power engines and enable vessels to access their desired fishing grounds. The data obtained from the survey was used to predict fuel use for nine of the years in the period between 2005 and 2021. Details of the model are provided in Supplementary Materials.

The panel data, which consists of repeated observations of the same subjects over time [32], was organized as a series of independent cross-section surveys conducted between 2005 and 2021. Observations were grouped based on vessel propulsion as paddled, motorized, or sailed using gillnets and longlines and harvesting Nile perch. Initially, the CAS datasets were assessed independently to understand their structure, variables, coding, and measurements across different years. To ensure consistency throughout the nine years of sampling, data variables were renamed and re-coded wherever necessary, specifically to consolidate changes made in the standard operating procedures used for data collection in 2021 [30,31].

2.3. Variable Selection

Inputs included in the model were the number of units of gear, fuel (liters per fishing trip, where applicable), and labor (crew hours per trip), with the catch as the output variable. A single output measure (Nile perch quantity) was used for consistency [33,34]. In cases where bycatch such as Nile tilapia was present in the catch, the output was standardized to a Nile perch equivalent by dividing the catch value by the price of Nile perch.

2.4. Labor Productivity Computation

Labor productivity was calculated as the ratio of total fish catches (standardized to Nile perch equivalents) to the total labor input (measured as a product of the number of fishing crew in a vessel and hours fished in a day—24 h) for each vessel type [17]. The analysis was conducted separately for each country to identify differences in LP across the riparian states.

2.5. Data Summary Statistics

Table 1 provides a comprehensive overview of essential statistics for the output and input variables examined in this study. Sampled motorized vessels were highest in Uganda (50.8%), paddled vessels in Tanzania (52.1%), and sailed vessels dominated (45.9%) in Kenya.

Table 1. Summary statistics for the SFA model variables for the different vessel groups.

	Vessels			
	Motorized (N = 30,052)	**Paddled (N = 26,147)**	**Sailed (N = 19,192)**	**Total (N = 75,391)**
Country				
Kenya	2375 (7.9%)	1321 (5.1%)	8809 (45.9%)	12,505 (16.6%)
Tanzania	12,417 (41.3%)	13,631 (52.1%)	8252 (43.0%)	34,300 (45.5%)
Uganda	15,260 (50.8%)	11,195 (42.8%)	2131 (11.1%)	28,586 (37.9%)
Vessels by gear type				
GN	25,122 (83.6%)	14,026 (53.6%)	7659 (39.9%)	46,807 (62.1%)
LL	4930 (16.4%)	12,121 (46.4%)	11,533 (60.1%)	28,584 (37.9%)
Gear units				
Gillnets	61.373(20.058)	35.719 (24.877)	47.603(23.559)	51.433 (24.932)
Long lines	951.140 (740.370)	580.912 (559.374)	791.651 (452.081)	729.800(573.630)
Catch				
Mean (SD)	32.286 (37.101)	23.426 (25.704)	24.484 (29.592)	27.227 (31.904)
Range	0.000–705.000	0.000–470.000	0.000–1000.000	0.000–1000.000
Labor				
Mean (SD)	27.333 (14.231)	28.740 (15.609)	42.439 (20.462)	31.667 (17.658)
Range	2.000–299.000	1.000–282.000	2.000–168.000	1.000–299.000
Fuel				
Mean (SD)	20.429 (6.370)			20.429 (6.370)
Range	1.000–125.000			1.000–125.000

2.6. Technical Efficiency Empirical Model

The production frontier model for the three vessel groups was specified as the translog production. The SFA model and prediction of technical efficiencies for the fishing fleet were then performed using R version 4.2.2 with packages plm applied to organize a panel structure of the data and frontier to run the SFA model [35–38].

3. Results

3.1. The Status and Trend of Vessel Types on Lake Victoria

Motorized vessels exhibited a consistent increase in numbers, with the highest count of these recorded in 2020 in all three countries: around 17,000 in Uganda, 12,000 in Tanzania, and 5000 in Kenya (Figure 2). In contrast, paddle vessel usage in Uganda and Tanzania displayed parallel fluctuations from 2000 to 2016, followed by a decline of 53% and 7%, respectively, in 2020. Conversely, Kenya experienced a distinct trajectory, with a 19% decrease from its 2006 peak of 8324 vessels to 6749 in 2020. Sailed vessels steadily declined in use across all three countries during the same period.

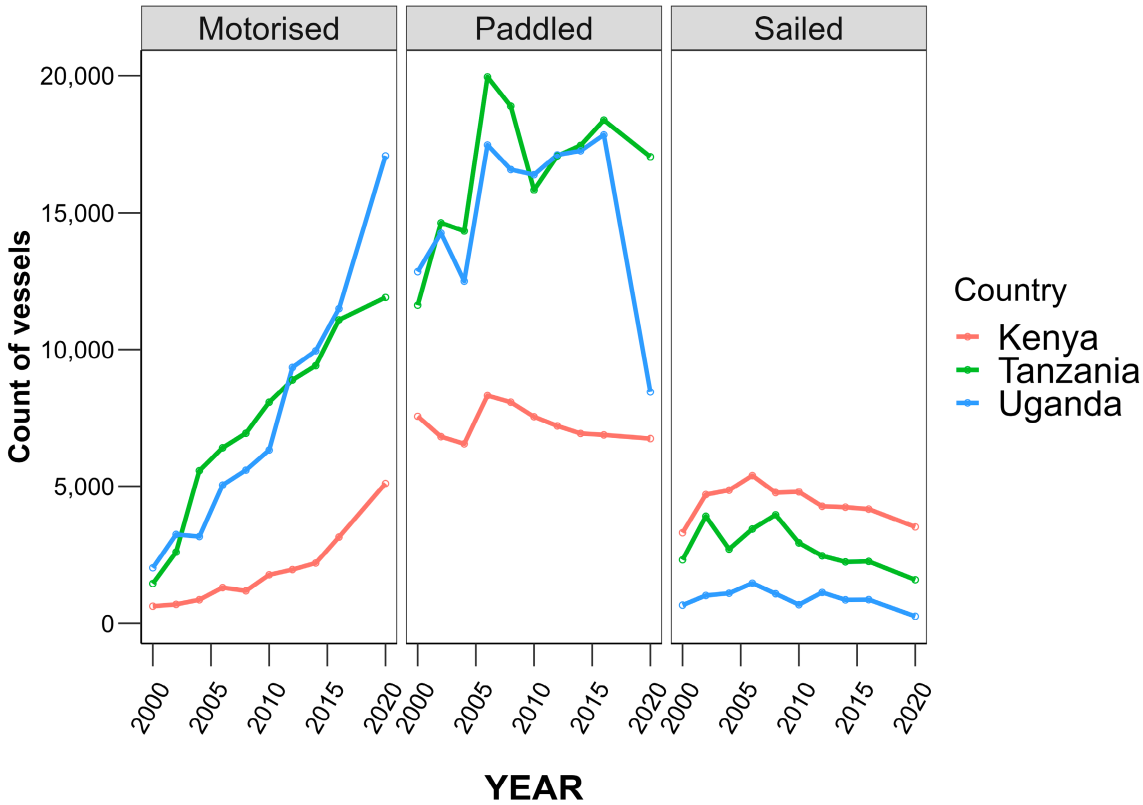

Figure 2. Status of vessel development by propulsion on Lake Victoria [7].

3.2. Technical Efficiency Estimation

Motorized fleets had the highest mean technical efficiency (0.60–0.66) compared to the paddled (0.29–0.49) and sailed vessel categories (0.24–0.46). Table 2 presents the estimates from the Translog stochastic production frontier analysis. The first-order parameters of vessel inputs (gear units, labor, and fuel for motorized vessels) and technical efficiency parameters (gamma and sigma squared) were all positive and significant across all vessel groups. These parameters represent output elasticities, with labor showing slightly higher elasticity than gear units and fuel. The gamma values were significant for all vessel groups (85% for motorized, 75% for paddled, and 70% for sailed vessels). The significant sigma squared σ^2 values further confirm the model's fit and the correctness of the composite error term's distributional assumption.

Table 2. Maximum likelihood estimates for the parameters of the stochastic frontier production function (SFPF).

SFA	Parameter	Motorized		Paddled		Sailed	
		Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	β_0	0.217	0.022 (***)	0.685	0.032 (***)	0.967	0.043 (***)
InUnits	β_1	0.158	0.005 (***)	0.169	0.0058 (***)	0.102	0.009 (***)
Ifuel	β_2	0.089	0.030 (**)				
ILabor	β_3	0.317	0.017 (***)	0.294	0.014 (***)	0.216	0.017 (***)
I(0.5 * InUnits^2)	β_{11}	0.071	0.007 (***)	0.042	0.004 (***)	0.007	0.008
I(0.5 * Ifuel^2)	β_{22}	−0.036	0.044				
I(0.5 * ILabor^2)	β_{33}	0.338	0.038 (***)	−0.089	0.026 (***)	−0.096	0.033 (**)
I(InUnits * Ifuel)	β_{13}	−0.034	0.020				
I(InUnits * ILabor)	β_{12}	0.086	0.012 (***)	0.038	0.007 (***)	−0.010	0.009
I(Ifuel * ILabor)	β_{23}	0.054	0.049				
Country-specific inefficiency effect							
Z_(Intercept)	z_0	−4.218	1.353 (**)	1.401	0.080 (***)	1.679	0.051 (***)
Z_CountryTanzania	z_1	−0.626	0.175 (**)	−1.292	0.082 (***)	−1.114	0.038 (***)
Z_CountryUganda	z_2	0.813	0.218 (***)	−0.966	0.067 (***)	−0.585	0.038 (***)
Variance variables							
sigmaSq	σ^2	3.391	0.656 (***)	1.561	0.072 (***)	1.128	0.026 (***)
gamma	γ	0.853	0.027 (***)	0.748	0.008 (***)	0.696	0.016 (***)

Significance denoted: 0 '***'; 0.001 '**'; 0.01 '*'.

The technical inefficiency model revealed significant z_0 values across all vessel groups, indicating country-specific inefficiencies. The signs of the z_1 and z_2 variables determined whether a vessel group was inefficient (positive sign) or efficient (negative sign). For instance, in Uganda, an increase in the number of motorized vessels was associated with increased inefficiency, while in Tanzania, more motorized vessels were likely to increase technical efficiency with respect to the Kenyan motorized vessels. For other vessel groups, negative z-variable signs indicated a reduction in inefficiency as vessel numbers increased.

3.3. Technical Efficiency Distribution and Change

Technical efficiency score indicates that vessels are fully efficient at score 1 and inefficient tending to 0. From the TE estimation, vessels across all groups were inefficient as the maximum efficiency values were less than 0.90 (Table 3). Across countries, the estimated mean TE values for all vessel groups were highest in Tanzania, while Uganda had the lowest estimated mean TE for motorized vessels. The lowest mean TE values for paddled and sailed vessels were recorded in Kenya.

Table 3. Mean TE values per country and vessel propulsion.

Country	Kenya				Tanzania				Uganda			
Statistic	Mean	Max	Min	N	Mean	Max	Min	N	Mean	Max	Min	N
Paddled	0.290	0.800	0.037	1463	0.490	0.880	0.036	13,719	0.440	0.870	0.045	11,877
Sails	0.240	0.830	0.030	9087	0.460	0.890	0.020	8283	0.350	0.830	0.040	2259
Motorized	0.640	0.89	0.06	2372	0.660	0.890	0.050	12,406	0.600	0.870	0.040	15,260

The TE distribution shows that at least 63% of motorized vessels operated with efficiency levels above 0.6. A similar proportion of paddled vessels operated from >0.41, while sailed vessels of the same proportion operated at <0.40, indicating that the latter were utilizing less than half of their capacity to maximize catches (Figure 3).

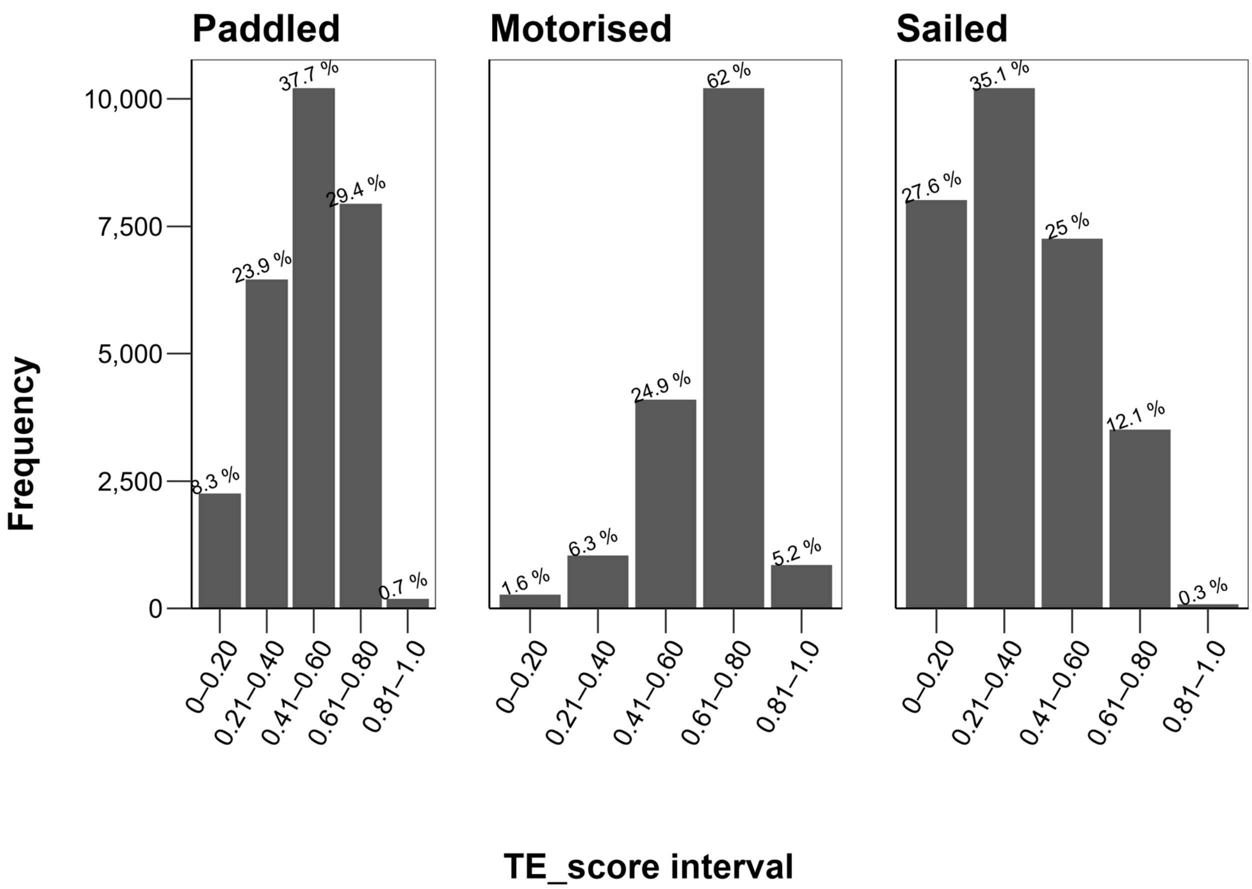

Figure 3. Distribution of TE scores for the three vessel groups, with scores categorized into groups.

Exploring the variations in technical efficiency (TE) throughout the study period (Figure 4) shows that both Uganda and Tanzania witnessed a noticeable reduction in technical efficiency (TE) across all vessel groups. The null hypothesis that there is no country-specific technical inefficiency was tested for each fleet segment. The hypothesis was always rejected, indicating that country-specific inefficiency differences exist for all vessel types. The most significant and consistent decline was observed in Ugandan motorized vessels, where the capacity to maximize catches for their given input and technology dropped by 22%, decreasing from 0.65 TE in 2005 to 0.50 in 2021. In Kenya, TE showed variations among different vessel types. Paddled vessels demonstrated an improvement in TE, increasing from 0.24 in 2011 to 0.38 in 2021, marking a substantial 50% enhancement in efficiency for this vessel category. Motorized vessels, on the other hand, exhibited a modest 2% increase in TE, while TE for sailed vessels declined by 12% between 2015 and 2021.

3.4. Labor Productivity

Labor productivity, defined as catch per hour fished, serves as a measure of fishers' productivity. From 2005 to 2015, all vessel groups experienced minor fluctuations in labor productivity. However, a significant increase in labor productivity was observed for motorized and paddled vessels in Kenya from 2015 to 2021 (Figure 5). In contrast, the same categories of vessels in Uganda and Tanzania showed minimal changes, with a slight downward trend from 2015 to 2020. Sailed vessels maintained a consistent level of labor productivity across all countries throughout the entire study period.

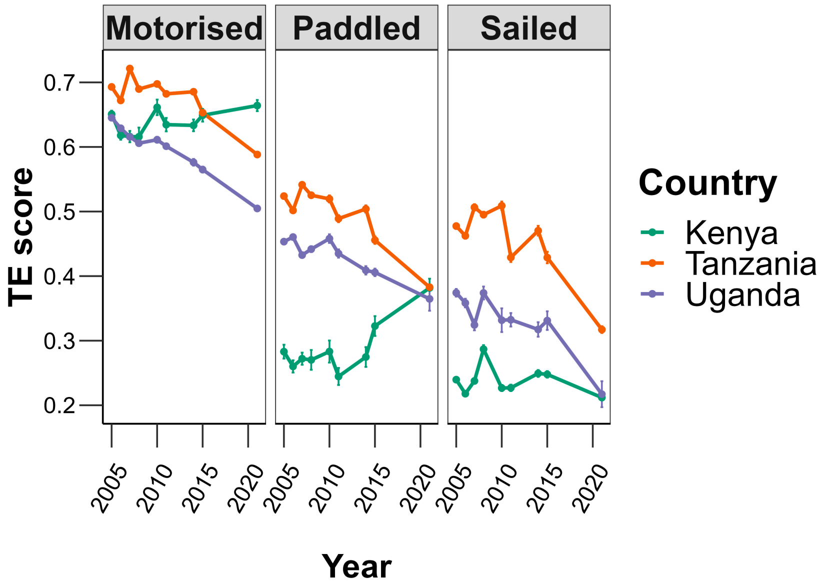

Figure 4. Technical efficiency (TE) estimates across vessel groups and countries over the study period.

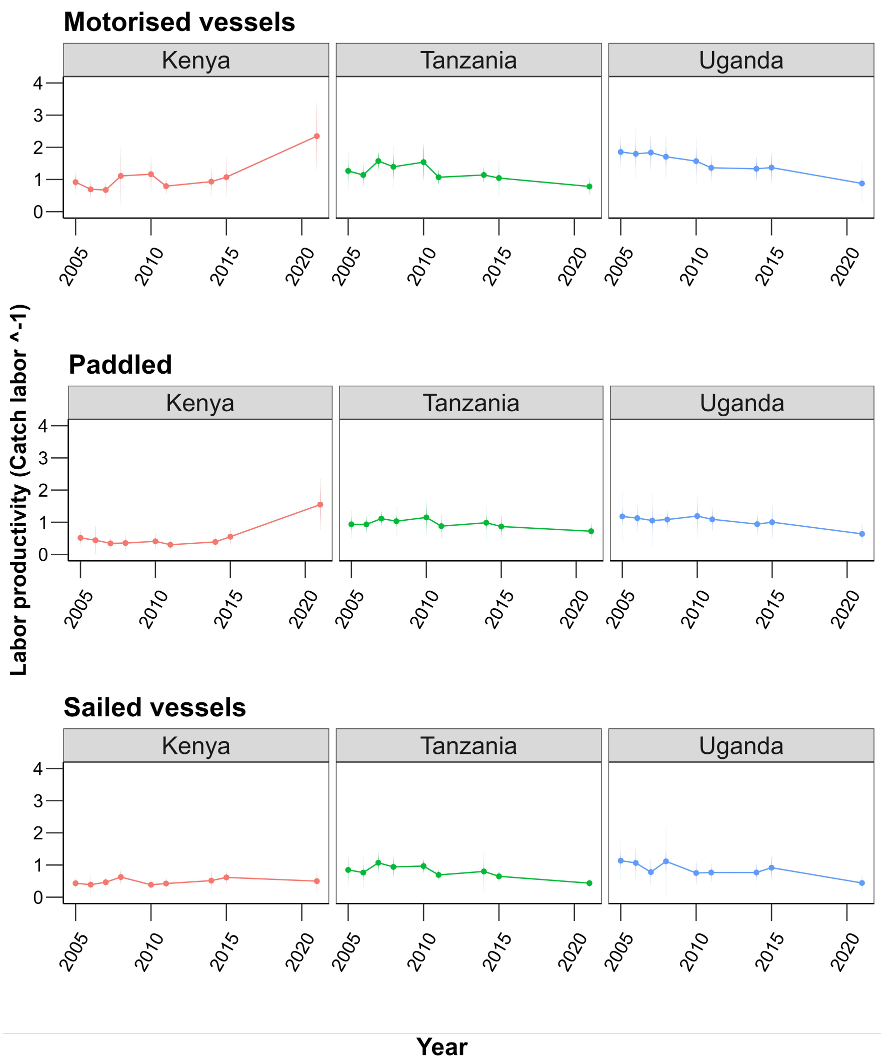

Figure 5. Comparison of labor productivity (LP) by vessel type and country (2005–2015).

4. Discussion

4.1. Vessel Group Fleet Changes and Technical Efficiency (TE)

The results show that efficiency and productivity vary between vessel groups, countries, and over time. This sheds light on the effects of technological development, policies, and natural and social conditions on economic outcomes in the fishing industry.

The finding that motorized fleets had the highest mean technical efficiency compared to the paddled and sailed vessel categories aligns with the research conducted by Kateregga and Sterner [14] in Lake Malawi [22], who highlighted the significance of vessel motorization in enhancing fish productivity. Similar effects have been observed by Branch et al. [39] regarding the motorized Fanti vessels in Liberia compared to their unmotorized counterparts [40]. The natural progression within the fishing industry is that fishers strive for more efficient operations, and this is evidenced by the general increase in the number of motorized vessels for all of Lake Victoria's riparian countries.

Motorized and paddled vessels form the two most important vessel types in the fishery. While the significant decline in paddled vessels in Uganda and Tanzania from 2016 to 2020 can be attributed to rigorous enforcement efforts to eradicate illegal fishing gear, the consistent decrease in these vessels in Kenya warrants further investigation to uncover the underlying factors.

On the other hand, sailed vessels have been declining in number. The low TE values in Kenya (<0.30) may explain the decline in sailed and paddle vessels. Motorized vessels across the three countries, with a TE of ≥ 0.60, could boost catches by 40% on average with current technology, while sailed vessels, the least efficient, have on average over 60% capacity for improvement. The motorized and paddled vessel groups were earlier described as commercial and artisanal, respectively, on Lake Victoria in Uganda [41,42]. Therefore, the shift to commercial fisheries indicates a within-sector improvement toward productivity growth [43–45], as fishers shift to motorized fishing vessels, the most technically efficient vessel type.

4.2. Comparative Analysis of Technical Efficiency and Labor Productivity across Countries and Vessel Groups

Country-specific comparisons show a difference in fleet development in Kenya versus Uganda and Tanzania. A shift towards more commercial vessel operations was observed across all countries, which is indicative of a boost in vessel productivity over time. In Tanzania and Uganda, the pattern for artisanal (paddled) vessels was similar, showing fluctuations for the first 15 years and a sharp decline between 2016 and 2020 due to fisheries enforcement. In contrast, Kenya has seen a consistent decrease in the use of paddled vessels since 2008, even though efficiency has been improving for this segment, a unique development for the fishery. This difference might be due to several factors, such as differences in fisheries management, economic development, and the different alternative values of labor in the three countries [39]. The three counties have had different fisheries policies in effect during the period. However, the most stringent policies have been found in Uganda and Tanzania, where technical efficiency and labor productivity have declined between 2015 and 2020. At the same time, improvements in technical efficiency and labor productivity were observed in Kenya. It is therefore difficult to attribute the development to fisheries management. Other forces could be at play. For example, countries where the population is large relative to capital and natural resources, the most productive sectors of the economy, are likely to have negligible to zero marginal productivity of labor and declining labor productivity, as is indicated in Uganda and Tanzania in this study [43,44]. Labor productivity results can highlight trends in labor markets such as increasing or decreasing employment and skills indicative of economic sustainability for the fishers; however, further analysis is needed on this issue.

The objective of the stringent fisheries enforcement in Uganda and Tanzania was to raise stock sizes of Nile perch by reducing illegal fishing activity, thereby improving fish exports [45]. The reported biomass estimates for the Nile perch before and after enforcement have followed a similar variable trend for all countries. Gear size and type had a small influence on fish stocks, as the Kenyan side maintained its biomass [8]. Successful policy implementation should lead to improved vessel efficiency, but the evidence for such effects regarding Uganda and Tanzania is weak [8,11,45–47]. This is in line with substantial literature that shows that policies that prioritize maximizing productivity may negatively impact the long-term sustainability of fish stocks, leading to depletion and even collapse of certain species [48–50]. The Ugandan and Tanzanian model of fisheries management illustrates the difficulty of regulating activities that people are compelled to undertake given their negative economic situation.

While the study demonstrates that the data used in this study can be effectively used to assess fishing fleet performance and inform fishery management in data-deficient contexts, it is important to recognize that the application of stochastic frontier production requires larger datasets to yield more robust results. As such, interpretations should be approached with caution, given the potential limitations in the data's scope of this study. Nevertheless, the findings still provide valuable insights into fleet efficiency and management strategies in resource-limited fisheries.

5. Conclusions

This study focuses on evaluating the technical efficiency of the Nile perch fishing fleet on Lake Victoria, categorizing vessels into three distinct groups based on their technology. Motorized vessels exhibited the highest efficiency (mean 0.60–0.66), showcasing their significant growth throughout the study. The declining trend observed in sailed vessels is reflected in their low technical efficiency across all countries, with specific variations observed for paddled vessels between Kenya and the other riparian countries.

The study acknowledges that vessel development mirrors the economic progress of the East African economies. The prevalence of paddled vessels in Uganda and Tanzania underscores their importance in artisanal fisheries, driven by a low opportunity cost of labor compared to Kenya. The improvement in technical efficiency and labor productivity in Kenyan vessels indirectly highlights gaps in fisheries management, questioning the effectiveness of enforcement, consideration of fish population status, and socio-economic conditions for alternative employment.

Overall, this study's primary contributions involve showing how sparse and deficient data can be utilized and interpreted in fisheries management, illustrating the application of technical efficiency in evaluating economic outcomes and fish stock health. It emphasizes the importance of incorporating CAS data into econometric models for resource assessment and policy evaluation, underlining the significance of monitoring fishery statistics. By analyzing transboundary fisheries data from Kenya, Uganda, and Tanzania, this study offers a unique perspective on factors impacting these fisheries, contributing to comparative studies on fishery performance in the African Great Lakes region.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/fishes9100414/s1, Table S1: Summary statistics of fuel model key variables; Table S2: Fuel model regression results for motorized vessels in Kenya. Remba and Kokach are landing sites; Table S3: Fuel model regression results for motorized vessels in Uganda; initial starting with L represents selected landing sites i.e., L_NK for landing site Nakatiba, V_SF is for Vessel type Ssese Flat and GG_Number is the number of gillnets; Table S4: Fuel model regression results for motorized vessels in Tanzania. G_GN for Gear_Gillnets, GG_number is Gillnets number.

Author Contributions: V.M.; conceptualization, methodology, investigation, visualization, writing—original draft: T.T.; supervision, funding acquisition, methodology, writing—original draft: D.M.K.; data curation, supervision, funding acquisition and writing—original draft: J.G.P.; conceptualization, methodology, data curation, supervision writing—original draft; C.S.N.; writing—review and editing A.T.-M.; writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

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