Impact Of Nile Perch (Lates Niloticus) Overfishing On Technical Efficiency Of Fishers In Lake Victoria Tanzania

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Impact Of Nile Perch (*Lates Niloticus*) Overfishing On Technical Efficiency Of Fishers In Lake Victoria Tanzania

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Abstract

Lake Victoria fishery activities are of crucial economic importance to the communities around East Africa as they support the majority of fishers specifically through Nile perch fishing. As a consequence, increasing fishing pressure had also led to overfishing. This study employed the Data Envelopment Analysis (DEA) and Propensity Score Matching (PSM) techniques to assess the impact of Nile perch overfishing on technical efficiency of fishers based on a survey of 268 fishers across 10 landing sites in Lake Victoria, Tanzania. Results from the DEA show that, overall Nile perch fishers have average technical efficiency of 30% which indicates a high level of inefficiency. Specifically, there is no statistically significant difference in the technical efficiencies for Nile perch fishers who are overfishing and those who are not overfishing due to fisher's mobility across the Lake. In addition, mode of propulsion and being a member of fishery organization were found to be statistically significant factors influencing inefficiency of Nile perch fishers. Furthermore, results from the probit estimates of the PSM show that being a member of fishery organization, quantity of Nile perch harvested per trip, age of a fishing vessel (boat), the gillnet mesh size and cost of fishing inputs have statistically significant effect in influencing the probability of Nile perch overfishing. However, further result indicates that Nile perch overfishing do not have statistically significant impact on fisher's technical efficiency. Therefore, this study recommends a need to monitor and formalize fisher's mobility as one of the alternative for co-management of the Lake. Also, overfishing can be controlled without necessarily affecting technical efficiency of Nile perch fishers through training and access to proper fishing gears.

Key words: Nile perch overfishing, DEA, PSM, technical efficiency

1. Background

Lake Victoria fishery activities are of crucial economic importance to the communities around East Africa as they support the majority of fishers (Mgaya and Mahongo, 2017). The Lake consists predominantly three fish species, such as the Nile Perch (*Lates niloticus*), Nile Tilapia (*Oreochromis niloticus*) and a native sardine called Dagaa (*Rastrineobola argentea*) (Njiru *et al.,* 2014). Among these species, Nile Perch (Linnaeus, 1758) is the most valuable and it supports an important commercial export industry mainly to Europe, with an estimated average net worth of US$ 350 million annually (Njiru *et al.,* 2014; Mkumbo and Marshall, 2015). Nile perch is a predatory fish and indigenous to the Ethiopian eco-region of Africa, it can grow to a length of 2 m, weigh up to 200 kg and live up to 16 years (Aloo *et al.,* 2017). It was introduced into the Lake in 1950s to utilize the majority species of endemic haplochromines (*Cichlidae*) which dominated the fish biomass in the lake and were not considered for commercial value andto promote fishery activities and livelihood of fishers around the Lake (Njiru *et al.,* 2014; Aloo *et al.,* 2017; Yongo *et al.,* 2017).

As a consequence, the introduction of the Nile perch into Lake Victoria has significantly changed the lake's ecology due to mass extinction and endangerment of the lake's smaller fish species because of predation (Aloo *et al.,* 2017; Kelly, 2018). Furthermore, increasing fishing pressure had also led to Nile perch overfishing, which is evidenced by the fluctuations of the catches and changes in population size-structure, combined with the recovery of haplochromine cichlids (Kishe-Machumu *et al.,* 2012; Yongo *et al.,* 2018).

According to Ding (2003),with the rising of human productivity, different countries have now begin to realize the impact of overexploitation of its natural resources. Particularly, overexploitation of fishery resources, which is also referred to overfishing, has become a major concern not only to users of the resource but society as a whole (Tetteh, 2010). While overfishing usually happens when more fish are caught than the population's ability to replace its stock naturally (WWF, 2018), technical efficiency (TE) in fishery sector, on the other hand, indicates the ability of a fisher to produce the maximum fishing output possible from a given set of inputs subject to the production technology, resource levels, weather conditions, and other technological constraints (Kirkley *et al.,* 1998). Nevertheless, Periss *et al.,* (2017) pointed that, fishery sector is usually a complex economic activity as its performance and productivity is not only affected by overfishing but other factors such as pollution, finance and the fishing technology available to fishers. Thus, in most cases it is difficult to conclude with certainty that overfishing is the major factor that lead to underperformance (which can be measured by technical efficiency) of fishery sector (Periss *et al.,* 2017). In addition, the key interest to policy makers is the sustainability of the fishery resources which implies a critical assessment of factors affecting efficiency for vital policy formulation aimed to ensure long term sustainability of the fishery resources (Otumawu-Apreku, 2013).

In Lake Victoria Tanzania, considerable studies have been conducted to assess the introduction and impact of the Nile perch. . . However, these studies had only focused on ecological and biological impact such as, loss of species, trophic dynamics, and altered habitats; and socio-economic impact such as, economic boom, edging out small scale fish operators, HIV/AIDS, border conflicts and food security (Muggidde *et al.,* 2005; Yongo *et al.,* 2005; Njiru *et al.,* 2008; Opio *et al.,* 2013; Aloo *et al.,* 2017). However, the impact of overfishing on the productivity and technical efficiency of fishery sector in Lake Victoria Tanzania has not been given serious attention in literature.. Understanding of the relationship between the technical efficiency and overfishing can help to design sound policy that will balance sustainability and fisher's livelihood. Therefore, this study aim to test whether Nile perch overfishing in Lake Victoria has direct impact on the technical efficiency of fishers by comparing the technical efficiency between fishers who overfish and those who do not.

2. Methodology

2.1 Study area

This study was conducted in Lake Victoria Tanzania. The Lake Victoria covers an area of 68 000 km^2 with a catchment area of 193 000 km^2 and Africa's largest freshwater fishery. The Lake is shared between Uganda (43%), Kenya (6%) and Tanzania (51%). It is relatively shallow with a mean depth of 40m, a maximum depth of 84 m, and it has a shoreline of 3,450 km. The lake is also the source of the River Nile and its resources contribute directly to supporting the livelihoods of over two million people through income, food and employment generation (Kolding *et al.,* 2014). Lake Victoria is the most important source of affordable animal protein, in the form of fish, in East Africa. The fishery is diverse, highly dispersed, and fragmented with about 1500 landing sites and more than 120 000 fishers (Cowx *et al.,* 2003).

2.2 Sampling and data collection procedure

The study was conducted in ten landing sites across four districts around Lake Victoria Tanzania in Mwanza region whereas Nile Perch capture fishery is the predominant occupation of the people in this area. Purposively sampling for choosing landing sites was applied because fishers who fish common species tend to stay in one site. Therefore those landing sites with the majority of fishers targeting Nile Perch fish were selected followed by random sampling approach in selection of fishers. For this case, six villages were randomly selected within four districts namely Magu, Ilemela, Nyamagana and Misungwi with 10 divisions, 8 wards. The villages whose landing sites were visited are Chole, Igombe, Kigangama, Kageye, Kayeme, Kayenze Zamani, Kayenze ndogo, Kigongo Ferry, Luchelele, Mihama, Mwanchimwa and Shadi. Therefore, a total of 268 Nile perch fishers were selected from a population. Data were collected from January to March 2018 by oral interview and administration of the structured questionnaire. The information collected include socio-economic characteristics such as operation gears and tools, catch production details, education status, age and fishing experiences.

2.4 Conceptual framework

The conceptual framework of this study is based on the theory of efficiency and extinction as explained by Bishop (1993). Previous studies on the causes of extinctions of living organisms found that, open access nature of some resources and externality of market-oriented activities are the main causes of extinction and biodiversity losses (Berk; 1979; Pearce and Turner, 1990; Pearce, 2007; Iritié, 2015). Bishop (1993) also pointed that, the extinction of living organisms such as fish is of economic concern because it may affect the sustainability of the resources and lead to economic losses imposed on future generations. With regards to the Nile perch overfishing in Lake Victoria, the link between the efficiency and extinction is illustrated in Figure 1.

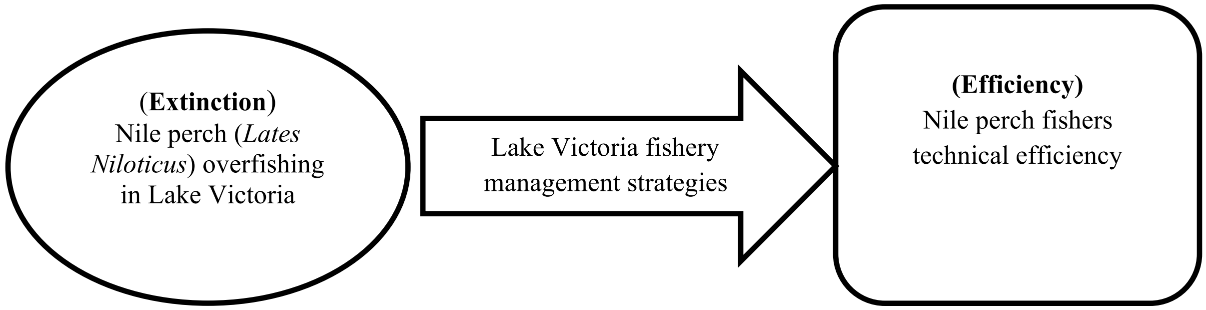


Figure 1: Conceptual framework of the linkage between sustainability and efficiency
Source: Own conceptualization

Based on the illustration in Figure 1,, due to the open access nature of Lake Victoria, if overfishing is not controlled it is predicted to cause massive extinction of Nile perch fish and other species that would otherwise improve the livelihood of fishers and national income in future (Odiwuor, 2017). Therefore, given the fishery management strategies imposed in the Lake to control for Nile perch overfishing such as slot size of 50 to 85cm TL, it is expected that technical efficiency of Nile perch fishers would be improve because fishing efforts and operations are now defined within the slot size. This implies that, the choice of fishing inputs and techniques will determine technical efficiency level subject to the slot size regulation. Thus, this study aimed at establishing the empirical linkage between Nile perch overfishing and technical efficiency of fishers in Lake Victoria.

2.5 Measuring technical efficiency

Technical efficiency measures the ability to obtain the maximum output from given inputs (Bezat, 2011). Technical efficiency can be measured using two major approaches i.e. Data envelopment analysis (DEA) and stochastic frontiers (SF). However, the nature of the two methods is very different and can lead to different estimates (Read, 1998). DEA is a non-parametric approach, which uses linear programming methods to estimate technical efficiency frontier on which only the most efficient Decision making unit (DMUs) are placed in the frontier. The DEA model can be either output or input oriented by which the latter aim at maximizing the outputs obtained by the DMUs subject to a given set of inputs whilst the input oriented models focus on minimizing the inputs used for processing the given amount of outputs (Fatulescu, 2013). In addition, technical efficiency can be estimated under the assumption of constant returns to scale (CRS) or variable returns to scale (VRS) models (Ogisi *et al.,* 2012).

DEA doesn't involve any functional form and it is less affected with misspecifications since it does not consider random error and therefore is not subject to the problems of assuming an underlying distribution of error term (Mendes *et al.,* 2012).

On the other hand, stochastic frontier approach is the parametric approach used to measure technical efficiency and it assumes a given functional form for the relationship between inputs and an output to estimate the parameters of both the stochastic frontier and the inefficiency functions (Bezat, 2011). The stochastic frontier approach treats deviations from production function as comprising both random error (white noise) and inefficiency (Mortimer and Peacock, 2002). In this study, output-oriented DEA model was used to analyze the technical efficiency of Nile perch fishers and followed by taking the efficiency scores as outcome variable into Propensity Score Matching (PSM) model for Nile perch overfishing impact analysis. DEA was selected because of its non-parametric nature which is the same with PSM approach. In fisheries, the DEA technique has been widely applied to measure technical efficiency of skippers, capacity utilization, policy-efficient management strategies in fisheries and efficiency of fisheries cooperatives (Tingley *et al.,* 2003; Pascoe, 2007; Griffin and Woodward, 2011; Vázquez-Rowe and Tyedmers, 2013; Jeyanthi *et al.,* 2018). Therefore, the output-oriented DEA model, developed by Charnes *et al.,* (1978) as adapted by this study is defined as:

$$Max_{\theta,\lambda}\theta,$$

Subject to
$$\begin{aligned} -\theta y_j + Y\lambda &\geq 0 \\ x_j - X\lambda &\geq 0 \\ N1'\lambda &= 1 \\ \lambda &\geq 0 \end{aligned} \tag{1}$$

where θ denotes the score for technical efficiency of fisher j compared to other fisher in the sample. y_j denotes the quantity of Nile perch catch of fisher j, x_j is the quantity of inputs used by fisher j, Y is the quantity of all fishers from the sample N, λ is the $N \times 1$ vector of constants, X is input data for all fishers from sample N while $Y\lambda$ and $X\lambda$ are the efficient estimations frontier. N1 denotes N x 1 vector ones. N1' λ = 1 is a constant that makes comparison only of fishers of similar characteristics, by forming a convex hull of intersecting planes, so the data is enveloped tightly.

From equation (1) above, a measure of technical efficiency is obtained from the "difference" between the observed and optimal output production for a certain inputs combination as follow:

$$TE = \frac{Y_i}{Y_i^*} = \frac{1}{\theta_i} \qquad 0 \le TE \le 1 \tag{2}$$

where Y_i i and Y_i^* are the observed and maximum possible (optimal) output, respectively.

In order to estimate the efficiency scores, Data Envelopment Analysis Program (DEAP) version 2.1 developed by Coelli, (1996) was used. The model follows two steps, a) estimation of the efficiency scores, b) assess factors which influence the technical efficiency using Tobit regression model since efficiency scores of DEA are bounded between 0 and 1 i.e. they are censored variables (Speelman *et al.,* 2007; Padilla-Fernandez *et al.,* 2009). Padilla-Fernandez *et al.,* (2009) pointed that, in the context of policy implications, it is more important to determine what influences inefficiency (or to which variables it is related) than simply to measure it. Therefore, following Greene (2012), the Tobit regression equation is given by;

$$y_i^* = X_i\beta + \varepsilon_i \tag{2}$$

$$y_i = 0 \ \text{ if } \ y_i \le 0,$$

$$y_i = y_i^* \ \text{ if } \ y_i > 0$$

where y^* is a latent variable; X_i represents a vector of explanatory variables; and β are the parameters to be estimated. It is assumed that the errors are normally distributed, with mean zero and ε, ε ~ N (0, σ).

However, Tobit model parameters do not directly correspond to changes in the dependent variable brought about by changes in independent variables. Thus, to obtain the correct regression effects for observations above the limit, the marginal effects was used and expressed as:

$$\frac{\partial E[y_i^* | x_i]}{\partial x_i} = \beta\Phi\frac{(\beta' x_i)}{\sigma} \tag{3}$$

2.6 Estimating the impact of Nile perch overfishing impact on technical efficiency

In this study, Nile perch overfishing was measured by using the slot size regulation of 50-85 cm TL. This slot size was introduced to protect immature fish and large adults in order to replace the stock while mature fish are being harvested (Msuku *et al.,* 2011). Fishers were asked about the average weight in kilogram (kg) of individual Nile perches harvested by them per trip. Thus, every fisher who fished an average weight of less than 2.1 kg per individual fish and thus a TL below 50 cm was considered to have overfished. This measurement was also supported by conventional measurement of weight and length following studies by Ogutu-Ohwayo (1999) and Yongo *et al.,* (2017), who found that a Nile perch with an average length of 55.38 cm TL weighs 2355 g (2.4 kg). In order to determine the impact of Nile perch overfishing on fishers technical efficiency, Average Treatment on Treated (ATT) technique was used to compare the Nile perch fishers who are overfishing and those who are not overfishing following the Propensity Score Matching (PSM) method as adopted from Rosenbaum and Rubin, 1983; Khandker *et al.,* 2010; Putra *et al.,* (2017). Also, PSM method was selected due to the assumptions of conditional independence and the presence of a reasonable overlap of propensity scores (common support) (Winters, 2010).

PSM analysis involved estimation of the propensity scores of Nile perch overfishing followed by matching the scores and estimation of the ATT. The first stage in this analysis, propensity scores were estimated using the probit model to estimate the probability of Nile perch overfishing. The second stage focused on calculating the area of common support in order to compare the two groups (i.e. Nile perch fishers who overfish and those who do not) with at least similar characteristics to eliminate biasness. Therefore, propensity scores which were outranged in scores distribution of the two groups were dropped. In addition, the second step employed balancing test to check whether the means of each covariate and propensity score were not significant different between the treated and un-treated groups.

The third stage involved matching the scores where Nile perch fishers who overfish were matched with Nile perch fisher who are not overfishing based on the closeness of their propensity scores that reflects the probability of Nile perch overfishing subject to different socio-economic, institutional and fishing efforts characteristics. Different matching algorithms, such as nearest neighbor matching (NNM), radius caliper matching and kernel matching are normally used in literature (Heckman *et al,* 1998; Smith and Todd, 2005).The fourth stage focused on estimating the mean difference (ATT) of the outcome (i.e. technical efficiency) between the two matched groups based on the probability of Nile perch overfishing.

2.6.1. Empirical modeling of PSM

Following Shehu and Sidique (2013), propensity score matching approach is used to examine the impact of Nile perch overfishing on fishers' technical efficiency. The method compares the technical efficiency of Nile Perch fishers who are overfishing with their counterfactual group that did not overfish. The propensity score is defined $P(X)$ as the conditional probability of receiving a treatment given pre-treatment characteristics as follow:

$$P(X) \equiv \Pr\{D_i = 1 | X\} = E\{D_i | X\}; P(X) = F(X) \tag{4}$$

where by D denotes the values of 1,0 and if $D_i = 1$ then it indicates Nile perch overfishing, referred to as 'treatment,' and the propensity score $P(X)$ is the probability of receiving the treatment given X while $F(X)$ is normal or logistic cumulative distribution.

In order to estimate the treatment effects based on the propensity scores, two assumptions were met. The first assumption was the conditional independence assumption CIA which states that for a given set of covariates participation is independent of potential outcomes (Becerril and Abdulai, 2010). Moreover, the second assumptions ensured that average treatment effect for the treated (ATT) was defined within the region of common support. For this case, it implies that Nile perch fisher with the same characteristics have a positive probability of being in a group of fishers who are overfishing and those who are not overfishing (Heckman *et al.,* 1998). Therefore, following Becerril and Abdulai (2010), once the propensity scores are computed, the ATT effect (treatment variable was overfishing while outcome variable was efficiency score from DEA calculated above) can be calculated as;

$$ATT = E(\Delta_i | D_i = 1)$$

$$ATT = E\left[E\{Y_{1i}|D_i = 1, p(X)\}\right] - E\left[E\{Y_{0i}|D_i = 0, p(X)\}D = 1\right] \qquad (5)$$

In addition, the study used nearest neighbour matching (NNM), Radius matching (R), stratification matching and kernel-based matching (KBM) to match the scores to obtain the ATT. The common support was imposed to estimate the matching estimates thus, treatment observations with weak common support were dropped, since inferences can be made about causality only in the area of common support (Heckman *et al.,* 1997) Also, the sensitivity of the estimated overfishing effects to hidden bias was tested using the Rosenbaum bounds sensitivity test (Rosenbaum, 2002). The test was done to indicate how strongly an unobservable variable must influence the selection process to undermine or reverse the findings based on matching on observables (Rosenbaum, 2005).

3. Results and discussion

Descriptive statistics of the socio-economic characteristics of Nile perch fishers and the inputs variable used in technical efficiency are presented in Table 1.

Table 1. Variables used in data envelopment analysis

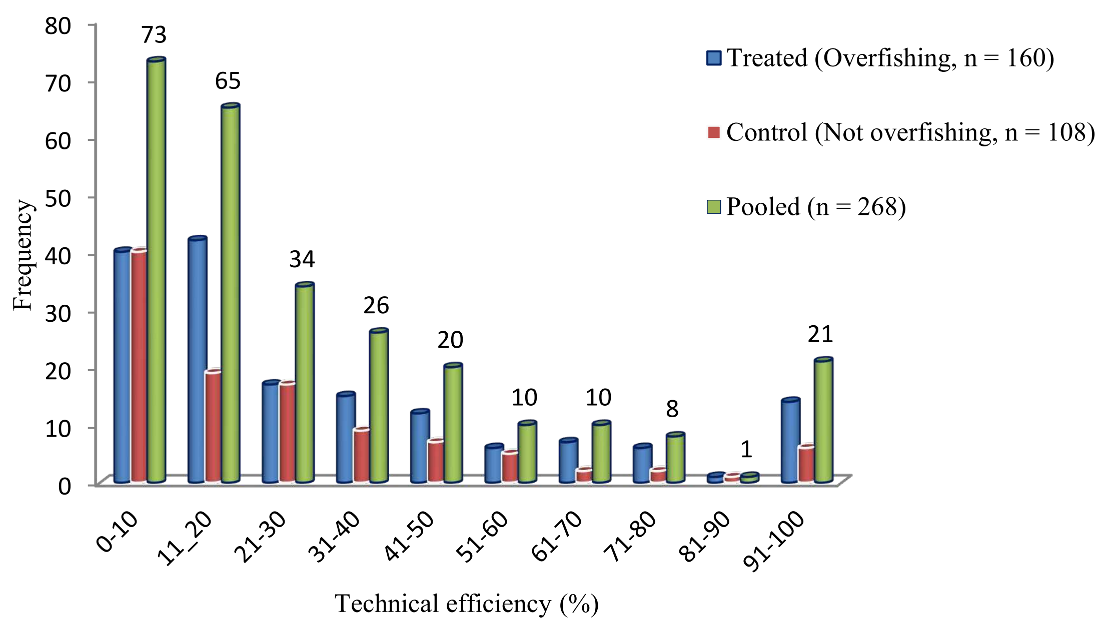
Variable	Description	Mean	Std. Dev.
Socio-economic variables:			
AGE	Age of fisher	36.679	10.928
EDU	Years spent in formal education system	7.481	1.472
EXP	Fishing experience	12.806	9.376
OFA	Other fishery activity (1 if engaged in other fishery activities, 0 otherwise)	1.231	1.049
Institutional factors:			
ACT	1 if access to credit; 0 otherwise	0.082	0.275
FAE	1 if accessed technical fishing advice; 0 otherwise	1.541	0.601
FRA	Fishery regulations awareness (1 if aware, 0= otherwise)	0.768	0.422
MOF	1 if a member of any fisher's organization, 0 otherwise	1.532	0.507
TIB	1 if received boat inspections; 0 otherwise	1.642	0.480
Inputs and fishing efforts variables:			
QTY	Quantity of Nile Perch catch (Kg)	27.560	25.910
CST	Crew size per fishing trip	3.317	0.581
PPT	Amount of Petrol per trip (Litres)	24.496	14.246

BTT	Number of Battery used per trip	3.082	1.050
NHT	Number of hooks used per trip	725.373	376.598
NGT	Number of mesh gillnets	2.002	0.825
VSL	Vessel size length (feet)	20.269	9.188
TVU	Time that the vessel has been used since purchased (months)	27.386	16.182
ECH	Engine capacity (horsepower)	13.030	2.580
HFG	Hours spent to reach fishing ground per trip	1.888	1.467
SGG	Size of mesh gillnet size (inches)	6.700	0.914
SGH	Size of long-line baited hooks	11.015	1.312
MOP	Mode of propulsion (1 of used non-motorized boat, 0 otherwise)	0.567	0.496
BQT	Quantity of bait (hooks baited with natural bait, e.g. small live fish, slices of meat, earthworms)	516.045	237.465
FTW	Number of fish trips per week	5.104	1.679
PFI[1]	Overall price of fishing inputs	508,558.2[2]	1,509,092

Source: Field Survey (2018)

3.1 Fishers' Technical Efficiency

The fishers' technical efficiency distribution from the Data Envelopment Analysis is presented in Figure 2.



[1] Fishing inputs include wages, food costs, fuel, gillnets, hooks, baits, etc.
[2] 1 USD = 2274 on June 2018 2274 Tanzania Shillings

Figure 2: Technical efficiency distribution results (n=268)
Source: Field Survey (2018).

Table 2: Summary statistics of technical efficiency of Nile perch fishers (n=268)

Technical efficiency	Overfishing (%)	Not overfishing (%)	Pooled (%)
Maximum	100	100	100
Mean	33.10	27.78	30.09
Minimum	3.7	3.8	3.7
Standard deviation	28.47	25.36	27.34

Source: Field Survey (2018).

The illustration in Figure 2 and Table 2 shows that high proportion of Nile perch fishers have technical efficiency ranging between 0 - 10% (73 fishers), followed by 11-20% (65 fishers), 21-30% (34 fishers) and 91-100% (21 fishers) respectively. The result also shows that there is no statistically significant difference in the technical efficiency of Nile perch fishers within the range of 0-10% and 21-30% efficiency who are overfishing and those who are not overfishing. Likewise, the technical efficiencies range of 31-40%, 41-50% and 91-100% indicate that fishers who are overfishing are more efficient than those who are not overfishing. In general, as majority of Nile perch fishers have between 0-10% technical efficiency range, it implies there is no significant difference between Nile perch fishers who are overfishing and those who are not overfishing The possible reasons could be the same Nile perch fisher can overfish or not overfish depending on the gears they are subjected to at the time of fishing. The majority of fishers in Lake Victoria do not own fishing boats and gears therefore they are hired by boat owners and they keep shifting from one landing site to another with changing of boat owners depending on the seasonality of fish harvest (Nunan, 2010). Murakwa *et al.,* (2004) pointed that Nile perch fish usually migrate seasonally across the Lake Victoria based on the pattern that seems to be related to rainfall distribution. Fishers also apply the same skills and efforts based on their experiences across different landing sites. In addition, other studies on Nile perch fishers mobility in Lake Victoria have shown that fisher's movement is influenced by other factors such as livelihood strategy, responding to fluctuating fish availability and prices (Murakwa *et al.,* 2004; Nunan, 2010; Nunan *et al.,* 2012). This implies that, it is difficult to separate fishers who are overfishing and those who are not and this might be a reason for similar technical efficiencies levels among them.

3.2 Determinants of technical inefficiency of Nile perch fishers

The result of the Tobit regression (using Stata 15 software to estimate the parameters and marginal effects) of the factors influencing technical inefficiency of Nile perch fishers in Lake Victoria Tanzania is presented in Table 5.

Table 5. Tobit regression for the factors influencing technical inefficiency of Nile perch fishers

Variables	**Coefficients**	**Marginal effects**	**Std. Err.**	**t**	**P>t**
AGE	0.002	0.002	0.002	1.23	0.221
EDU	-0.002	-0.002	0.011	-0.22	0.827
EXP	0.0019	0.001	0.002	0.86	0.391
MOP	-0.145	-0.128	0.033	-4.34	0.000***
SGG	0.0152	0.013	0.018	0.86	0.393
OFA	-0.012	-0.010	0.015	-0.78	0.434
ACT	-0.093	-0.082	0.058	-1.61	0.11
ECH	-0.008	-0.007	0.006	-1.34	0.182
SGH	0.015	0.013	0.012	1.24	0.215
MOF	0.065	0.058	0.032	2.02	0.045**
FTW	0.014	0.012	0.010	1.33	0.185
FRA	-0.018	-0.016	0.038	-0.48	0.629
Constant	0.174		0.266	0.65	0.514
Number of observations	268				
LR chi2(12)	38.49				
Prob > chi2	0.0001				
Pseudo R2	0.591				
Log likelihood	-13.345				

Notes: ** and *** denote 5% and 1% significance levels respectively

The results show that mode of propulsion had statistically significant negative effect in explaining technical inefficiency of Nile perch fishers. This implies that fishers who use non-motorized boats tend to be more efficient than those with motorized boats. This is because with the uses of non-motorized boat, fisher's operational costs becomes less and affordable which enable them to spend more time in the fishing ground and utilize the available fishing gears and catch more fish even if they don't sail for a long distance.

Being a member of fishery organization had statistically significant positive effect in explaining technical inefficiency of Nile perch fishers. This is because most of fishers in Lake Victoria are at least members of fishery organization particularly co-management organization known as beach management unit (BMU). Therefore, being a member of fishery organization, fishers tend to depend more on the information and training they receive from the organization and sometimes this can hinder their individual innovations in the context of fishing activities (Mkuna and Baiyegunhi, 2019a). Also, Tam *et al.,* (2018) noted that in absence of fishing organizations emphasis of individual and group innovations, fishers may not be motivated and this might affect their individual productivity.

3.3 Determinants of Nile perch overfishing: Probit model results

The results of probit model of the determinants of Nile Perch overfishing are presented in Table 3. These results provide the direction and causal relationship of the determinants of Nile Perch overfishing, but also they were used to calculate the propensity scores for the impact analysis. Moreover, the probability of chi-square, likelihood ratio (LR) chi-square statistics and pseudo R-square values presented in the Table 3 implies that the model specification fit well with the data as the explanatory variables were able to predict 70% of the sample observation from the study area.

Table 3: Probit model results of the determinants of Nile perch overfishing in Lake Victoria Tanzania

Variable	Coefficients	Std. Err.	z	Marginal effects	P>z
AGE	-0.006	0.010	-0.580	-0.002	0.564
TIB	-0.252	0.188	-1.34	-0.095	0.179
EDU	-0.013	0.064	-0.200	-0.004	0.84
FRA	-0.196	0.212	-0.930	-0.072	0.353
MOF	0.406	0.184	2.200	0.152	0.028**
EXP	0.012	0.012	0.990	0.004	0.324
OFA	0.035	0.079	0.440	0.013	0.659
FAE	0.028	0.147	0.190	0.010	0.851
ACT	0.074	0.343	0.210	0.028	0.83
QTY	0.006	0.004	1.660	0.002	0.096*
CST	-0.170	0.158	-1.070	-0.064	0.282
VSL	0.002	0.012	0.170	0.001	0.861
TVU	0.010	0.006	1.740	0.004	0.081*
ECH	0.002	0.034	0.060	0.001	0.95
HFG	-0.056	0.071	-0.780	-0.021	0.433
SGG	-0.216	0.106	-2.040	-0.081	0.041**

SGH	0.065	0.065	1.000	0.024	0.318
MOP	0.323	0.235	1.370	0.122	0.169
BQT	0.000	0.000	0.000	8.82e-08	1
NGT	-0.084	0.130	-0.640	-0.031	0.519
FTW	-0.006	0.058	-0.100	-0.002	0.923
PFI	-0.136	0.052	-2.630	-0.051	0.008**
_cons	2.625	1.736	1.510		0.131
Number of obs	248				
LR chi2(22)	35.450				
Prob > chi2	0.035				
Log likelihood	-146.843				
% correctly specified	66.9%				

Notes: *, ** denote 10% and 5% significance levels respectively

Results from this study are in line with the study by Mkuna and Baiyegunhi (2019b) which indicate that being a member of a fishery organization, quantity of Nile perch harvest per trip and the age of a fishing vessel (boat) were statistically and positive related to the probability of Nile perch fishers overfishing was statistically significant. In addition, the gillnet mesh size and the cost of fishing inputs were found to be statistically and negatively related to the probability of Nile perch overfishing.

3.4 Impact of overfishing on technical efficiency

The results of the average treatment effect on the Treated (ATT) using different matching methods are presented in Table 4.

Table 4: Average treatment effects: propensity score matching

Outcome variable	Matching algorithm	Overfishing	Not overfishing	ATT	t
Technical efficiency	Nearest neighboring	154	53	0.017 (0.044)	0.378
	Radius Matching	154	94	0.033 (0.040)	0.817
	Kernel Matching	154	94	0.011 (0.043)	0.248
	Stratification	154	94	0.005 (0.056)	0.092

Source: Field Survey (2018)

Results from all matching algorithms (Nearest Neighbour Matching (NNM), Kernel-based matching, Radius Matching (RM)) and Stratification indicated that Nile perch overfishing had no statistical significant effect on technical efficiency of Nile perch fishers in Lake Victoria

Tanzania. The possible reasons could be, fishers in Lake Victoria usually aim at harvesting more fish regardless of the size of fish catch and composition using different gears and inputs to earn more income. Thus, technical efficiency of fishers is not affected by the size of the fish catch because fishers will always adjust their gears to attain a certain quantity of fish catch rather than size as fish as the more quantity the more income. This result is supported by the study of Bishop (1993) which pointed that it is possible for individual efforts on natural resources to be efficient and sustainable, but efficiency does not necessarily guarantee sustainability. This implies that fishers can be efficient and at the same time overfishing. Njiru *et al.,* (2009) and Aloo *et al.,* (2017) pointed that, the increased demand of Nile perch, has influenced factories which were processed Nile perch with a minimum weight of 2 to 3 kg but due to increased competition for fish among factories and the reduced numbers of large ones, they now accept smaller fish even those which weigh 1 kg. This finding is also supported by the study of Cowx *et al.,* (2003) found that fishers are using more efficient illegal fishing gears and methods to get more fish irrespective of their sizes. Therefore, fishers are faced with livelihood challenges and decide to overfish to support their life however factories are also influencing overfishing to keep the factories operation and profitability.

3.5 Balancing Test for Conditional Independence Assumption (CIA) and sensitivity analysis

The balancing property test was used in estimating the propensity scores to ensures that a comparison group is constructed with observable characteristics distributed equivalently across quintiles in both the treatment (fishers who are overfishing) and untreated (fishers who are not overfishing) (Smith and Todd, 2005). In addition, sensitivity analysis was done to check the robustness of results between matching methods used.

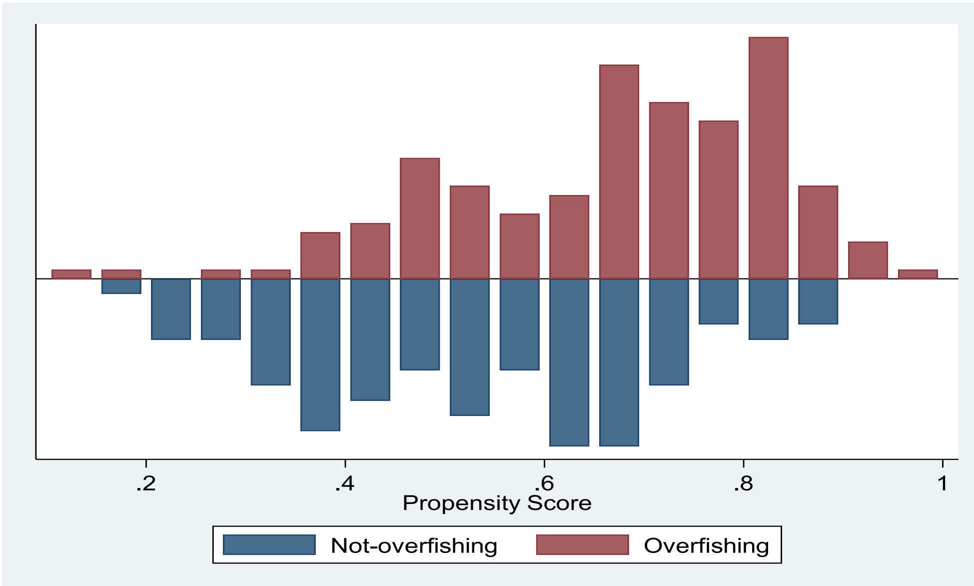


Figure 3: Propensity score distribution and common support for propensity scores estimation.

The histogram of the estimated propensity scores for Nile perch fishers who are overfishing and those who are not overfishing are presented in Figure 3. The upper half of the graph shows the propensity scores distribution for the fishers who are overfishing and the bottom half refers to propensity scores distribution of fishers who are not overfishing. This confirms that the common support condition is satisfied by assessing the density distributions of the estimated propensity scores for the two groups. Moreover, there is substantial overlap in the distribution of the propensity scores of both fishers who are overfishing and not overfishing.

3.6 Test of matching quality

In order to analyze the reliability of the PSM results presented above, the balancing test based on Kernel matching (bandwidth = 0.06) approach was used to evaluate the statistical significant differences between treated (fishers who overfish) and non-treated (fishers who do not overfish) and the results are presented in Table 5.

Table 5. Result of the test of matching quality

Variables	Mean		%bias	t-test	
	Treated	Control		t	p>t
AGE	36.531	39.241	-24.500	-1.900	0.058
TIB	1.628	1.683	-11.400	-0.990	0.325
EDU	7.441	7.241	13.600	1.360	0.176
FRA	0.745	0.600	33.700	2.650	0.008
MOB	1.586	1.648	-12.300	-1.090	0.278
EXP	12.945	16.393	-37.100	-2.590	0.010
OFA	1.303	1.221	7.600	0.610	0.543
FAE	1.545	1.697	-25.700	-2.230	0.026
ACT	1.924	1.959	-12.800	-1.250	0.213
QTY	27.303	27.49	-0.700	-0.060	0.953
CST	3.262	3.421	-27.500	-2.350	0.020
VSL	19.621	18.262	14.900	1.390	0.166
TVU	28.428	30.952	-15.500	-1.180	0.237
ECH	13.103	12.71	15.900	1.410	0.159
HFG	1.6345	1.972	-24.800	-2.520	0.012
SGG	6.7517	6.814	-7.00	-0.670	0.506
SGH	11.062	10.897	12.500	1.060	0.290
MOP	0.655	0.6275	5.600	0.490	0.626
BQT	523.1	508.62	6.100	0.530	0.598
NGH	1.9552	2.024	-8.700	-0.720	0.470
FTW	5.0483	5.290	-14.200	-1.240	0.216
PFI	10.64	10.701	-3	-0.320	0.751
Summary of the distribution (bias)					
Mean = 15.200					
Pseudo R2 = 0.096					
LR $\chi 2$ = 38.73 , P ($\chi 2$)= 0.015					

The results of balancing test based on Kernel matching (bandwith = 0.06) shows that the matching was valid and there is no statistical significant differences between treated and non-treated. An exception is on education, experience, fishing advice, access to credit, vessel length, engine capacity, size of fishing gears and number of gillnets. However, the standardized differences (percentage of bias) for the mean values of all covariates between treated and non-treated are 15.2 which are below 20 percent. Following Rosenbaum and Rubin (1985) this indicates that the balancing requirement is adequately satisfied. Moreover, Rosenbaum bounds test (kernel matching, bandwidth = 0.06) results for sensitivity analysis to assess the robustness of the estimates to unobservable covariates is presented in Table 6.

Table 6. Rosenbaum bounds test (kernel matching, bandwidth = 0.06)

(Γ)	Wilcoxon statistics	
	Upper bound significance level	Lower bound significance level
1	0.226	0.300
1.2	0.207	0.325
1.4	0.194	0.350
1.6	0.183	0.375
1.8	0.173	0.397
2	0.161	0.413
2.2	0.152	0.429
2.4	0.146	0.450
2.6	0.140	0.468
2.8	0.135	0.490
3	0.130	0.505

The results show that even when differential assignment to treatment is tripled (gamma =3) the results are still robust to hidden bias (unobservable). Therefore, the PSM results obtained are free from hidden bias and it implies that Nile perch overfishing do not have statistical significant impact on technical efficiency of fishers.

3.7 Heterogeneity technical efficiency impact among Nile perch fishers who are overfishing

The OLS regression model was used to estimate the extent of treatment effect on overfishing among Nile perch fishers who overfish and results are presented in Table 7.

Table 7. Heterogeneity technical efficiency impact among Nile perch fishers who are overfishing

Variables	Coefficients.	Std. Err.	t	P>t
AGE	-0.00093	0.000866	-1.08	0.283
TIB	-0.00869	0.014944	-0.58	0.562
EDU	0.002956	0.005438	0.54	0.588
FRA	-0.00626	0.017418	-0.36	0.72
MOB	-0.02203	0.014826	-1.49	0.14
EXP	0.001604	0.001034	1.55	0.123

OFA	-0.00112	0.006464	-0.17	0.863
FAE	0.000705	0.011036	0.06	0.949
ACT	0.007724	0.028504	0.27	0.787
QTY	0.009994	0.000291	34.3	0.000***
CST	-0.01903	0.01288	-1.48	0.142
VSL	-0.00067	0.000899	-0.75	0.454
TVU	0.00061	0.000456	1.34	0.183
ECH	-0.00348	0.002483	-1.4	0.163
HFG	0.002944	0.005625	0.52	0.602
SGG	-0.01597	0.00879	-1.82	0.072*
SGH	0.000954	0.004907	0.19	0.846
MOP	-0.01513	0.020103	-0.75	0.453
BQT	-6.5E-05	2.98E-05	-2.18	0.031**
NGH	-0.01711	0.009452	-1.81	0.073*
FTW	-0.0029	0.004698	-0.62	0.538
PFI	0.000932	0.004521	0.21	0.837
Constant	0.34446	0.139125	2.48	0.015
R-squared	0.93			
Adj R-squared	0.92			
Number of observation	160			
Root MSE	0.083			
Prob > F	0.000			

Notes: *, ** denote 10% and 5% significance levels respectively

The results indicate that the impact of technical efficiency differs significantly among Nile Perch fishers. For instance, quantity of Nile perch harvested increases the technical efficiency among the fishers who harvest more quantity than those with less quantity of fish. This is because the more quantity of catch increases the harvest given the fishing efforts and gears used although the probability of catching juvenile fish will increase. The negative and significant estimated coefficient of size of gillnet and size of long line hooks used suggests that fisher with small size of gillnet and longline hooks increases their technical efficiency as the chances to catch more fish increases than fishers with larger size of gillnets. This implies that, fishers who focus on fishing efficiently and catch more fish use small size of gillnet to maximize the catchability.

Also, the results show that coefficient of quantity of bait used has significant and negative relationship with the technical efficiency. This implies that, fishers with more quantity of baits have low technical efficiency as compares to fishers with less quantity of baits. This is because longline hook with large quantity of baits requires intensive control to catch more fish. However, Nile Perch fishers are not able to manage longline hooks if large quantity of baits are used due to the small size of their vessels and less number of crew size once the hooks catch more fish at once thus reduce the technical efficiency. On average one longline hook (*Timber*) has an ability to carry 400 hooks which requires the same quantity of baits since one hook carries one live bait.

4. Conclusion and recommendations

This study was undertaken to assess the impact of Nile perch overfishing on technical efficiency of fishers in Lake Victoria. The study found low technical efficiency for most Nile perch fishers due to increased pressure to harvest more fishes and earn additional income. This is an indication that fishers are not harvesting at the required level given the technology and fishing inputs they possess. Furthermore, the there is no statistically significant difference between technical efficiency of fishers who are overfishing and those who are not overfishing due to fisher's mobility across Lake Victoria. This can be well addressed by monitoring fisher's mobility as one of the alternative for co-management of the Lake and formalize their mobility by registering them and monitor their movement to ensure regulations adherence. Among the factors limiting Nile perch fishers efficiency is their membership of fisher's organization and the mode of propulsion. There is a need to create more awareness on better and sustainable fishing practices to enable fishers to improve their current efficiency. Specifically, fishers may be given credits to secure outboard engines which will enable them to sail for a long distance to the depth of the Lake and harvest required fish. Moreover, existing fishery organization need to be improve to ensure that individual innovations and efforts are acknowledged and monitored at each stage of fisher operations. Furthermore, the result that overfishing do not significantly affect technical efficiency of Nile perch fishers implies that overfishing can be control without necessarily affecting technical efficiency of Nile perch fishers. Since fishers aim at catching more fish regardless of fish size, they can be trained and equipped on how to harvest more fish of required size without affecting their current operations.

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Compliance with ethical approval

The authors declare that they have no conflict of interest. Ethical clearance for this study (Ref. HSS/1572/017D) was obtained from the University of KwaZulu-Natal Research office.

Authors' contributions

EM prepared and performed the data analysis of the manuscript and interpreted the data while LB provided suggestions/comments and proof-read the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due confidentiality of respondents, but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Figures

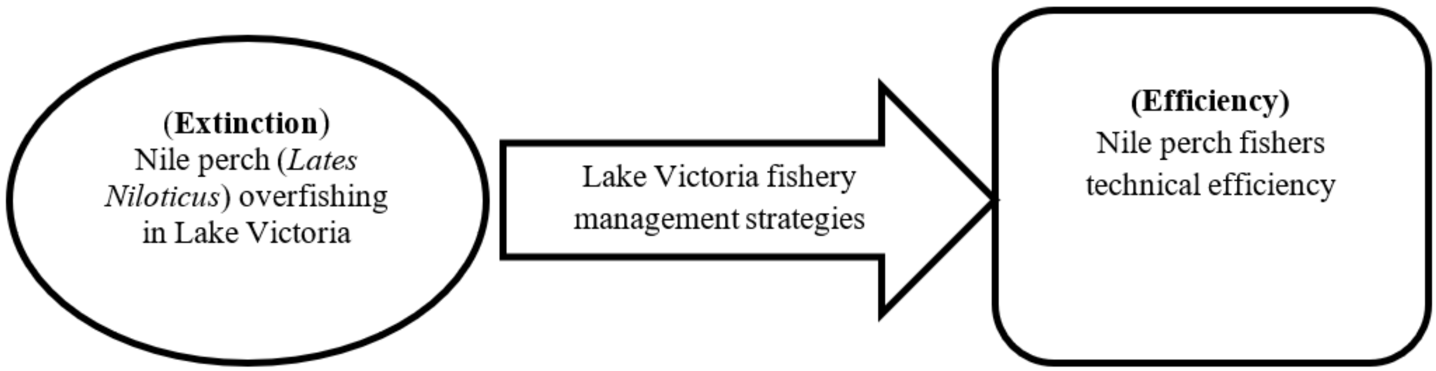

Figure 1

Conceptual framework of the linkage between sustainability and efficiency. Source: Own conceptualization

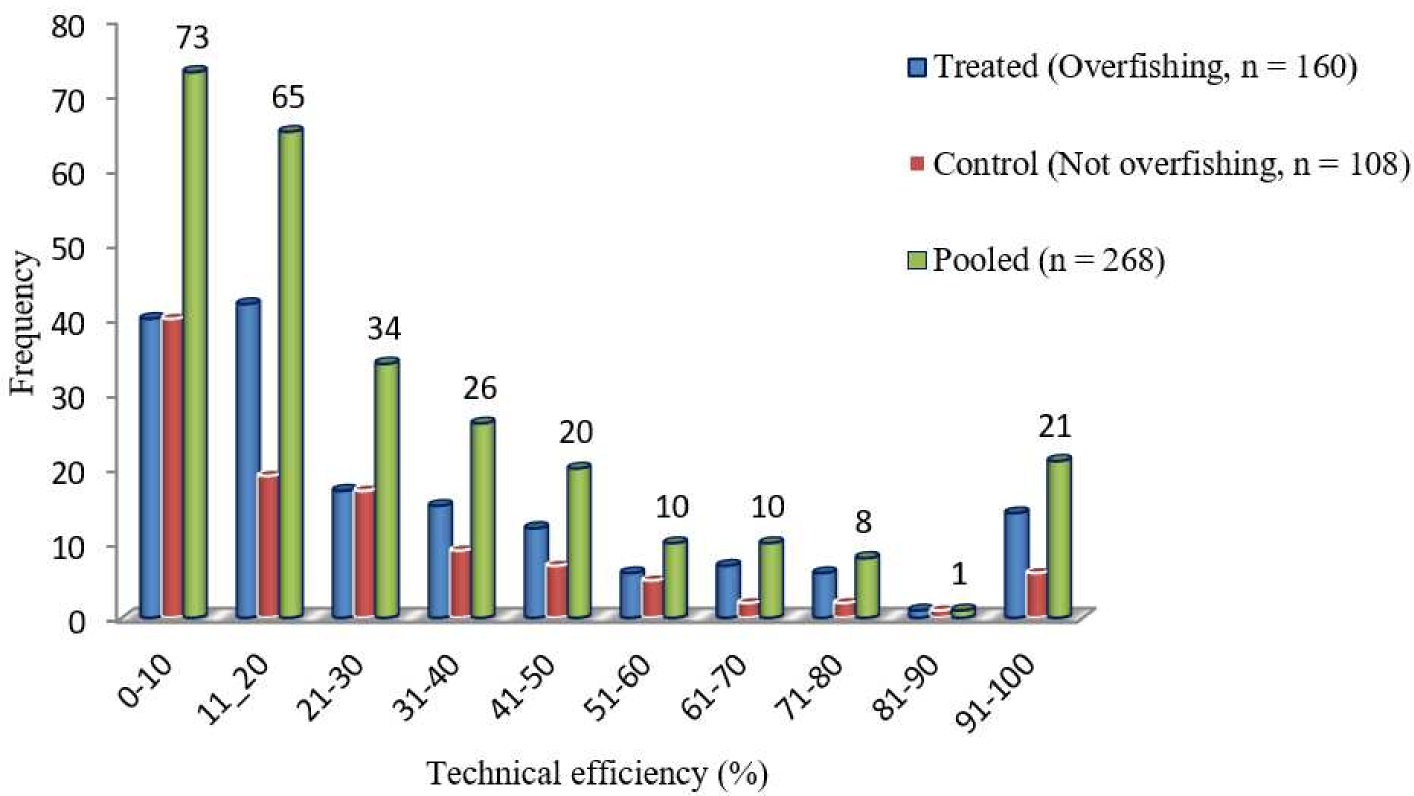

Figure 2

Technical efficiency distribution results (n=268) Source: Field Survey (2018).

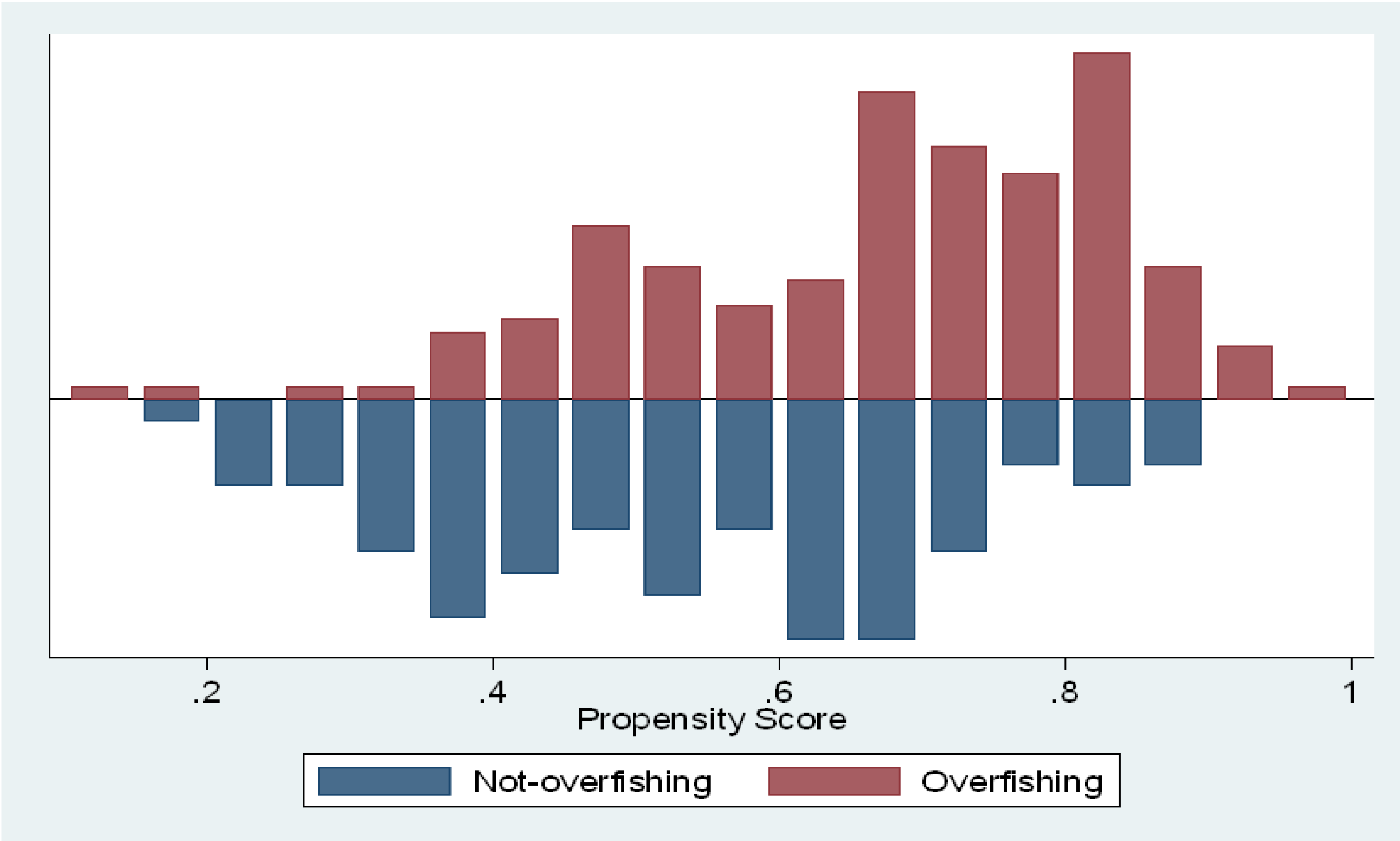

Figure 3

Propensity score distribution and common support for propensity scores estimation.