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Economic valuation of illegal fishing: An empirical study of beach seine ban enforcement in Lake Victoria, Kenya

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Abstract

Beach seining was banned in Kenya in 2001 largely due to growth overfishing. To-date compliance to this regulation remains a challenge to managers and policy makers. This paper analyses enforcement records in Lake Victoria between 2001 and 2012 and applies the model of rational criminality to estimate the economic incentives to violate the ban. The results show a positive expected net benefit of fishing in violation of this ban equal to Ksh[1] 1,079 for seine owners and 746.75 for fishing crew. . This result is mostly due to a low probability of detection ($p_d = 0.1390$) and arrest of perpetrators ($p_{a\_c} = 0.1136$, for crew and $p_{a\_o} = 0.2300$ for seine owner). Court penalty was on average Ksh 6.769.10 with most common fine of Ksh 10,000. Sensitivity analysis shows that although increasing fines can reduce violation very high fines would be needed to make violations unprofitable. On the other hand the analysis shows that violations can be made economically unprofitable for seine owners by relatively small increases in the probability of detection (26%), because of the cost to the owner associated with confiscation of detected seines. The results therefore indicate that an effective strategy to ensure compliance would be to increase detection rate by increasing surveillance effort.

Key words: Beach seine ban, Illegal fishing, Lake Victoria, Rational criminality

Introduction

Beach seine nets have been used in fisheries for several thousand years and on every continent (Von Brandt, 1984; Gabriel, Lange, Dahm, & Wendt, 2005). A typical beach seine is a net operated from the shore. The gear is composed of a bunt and long wings often lengthened with long ropes for towing the seine to the beach. The head-rope with floats is on the surface, the footrope is in permanent contact with the bottom and the seine is therefore a barrier which prevents the fish from escaping from the area enclosed by the net (FAO, 2011).The longer the hauling lines and the wings are the larger the fishing area that could be covered by the seine. There is no specific gear handling equipment required for fishing operations but a large number of people (depending on size of net) is needed for towing the seine to the shore. Mesh sizes for wings and bunt as well as the height of the head-rope vary considerably and has been demonstrated to influence to a great extent selectivity of this gear (Broadhurst & Wooden, 2007; Motlagh, Gorgin, Fazli & Abdolmaleki, 2011; Wooden, Cranston, Robins, 2010). In Lake Victoria, beach seines are usually set from wooden canoes, in many cases, without engine, and then

[1] 1 Ksh = 0.012USD

pulled from the lines simultaneously to the beach herding in-front of the bag. The net wings vary in mesh sizes from over 250 mm but reduces towards the bunt or code-end. The code-ends are made from manila twines with mesh size less than 25 mm. Worse situations are where fishers line the code-end with smaller mesh size nets (often between 5 – 10 mm) preventing all possible escape of juvenile fish (Kariuki, 2012).

Fishing with beach seines has become controversial over the years and in many fisheries because of adverse impacts to the habitats and growth overfishing (FAO, 2011; Malleret-King, *et al*., 2003; EAF-Nansen Project, 2010; McClanahan, 2007; King, 2000; Rubens, 1996). During a study on the impact of artisanal fishing gears on coral reef ecosystem in the Southern Kenya, Mangi and Robert (2006) observed that over 68% of fish catch from beach seine were juvenile. They further reported significantly lower coral density in areas where beach seining were used deducing possible impacts of this gear. This concurs with observations by Samoilys, Maina, Ater, and Osuka (2011) five years later. Case studies in a number of countries by FAO (2011), further confirmed this high level of juvenile fish in catches by beach seines. Motlagh (2011) and, Wooden, Cranston and Robins (2010) demonstrated that reduction of beach seine height and increasing mesh size could significantly reduce amount of by-catch in the catches. Mangi and Robert (2006) and Samoilys, Maina, Ater, and Osuka (2011) singled beach seines as the most destructive gear in Kenya's near-shore coastal waters emphasizing the need to enforce restrictions. Earlier work by Odada, Olago, Kulindwa, Ntiba and Wandiga (2004) pointed a finger on the policy of free and unrestricted access to the L. Victoria fisheries as a major loophole exploited by the rent-seekers.

The use of beach seine in L. Victoria is prohibited as a collective conservation effort among the L. Victoria riparian states through Lake Victoria Fisheries Organization - LVFO (Odada, Olago, Kulindwa, Ntiba, & Wandiga 2004) and a number of collective efforts have been instituted to ensure compliance. Monitoring Control and Surveillance (MCS) at regional and national level have paralleled co-management efforts with funding from both governments and external donor agencies. Kenya Gazette notice number 7565 of 2001 outlaws beach seine fishing as well as possession of beach seines in fishing Kenyan waters. Enforcement of this ban, over a 12 year period, has seen over 385 violators prosecuted and 841 beach seines confiscated. This has not been achieved without challenges including rent seeking, detection and arrest avoidance strategies, and further complicated by the fact that fishers make these gears in their own backyards and non-conventional places (Nyeko, Kirema-Mukasa, Odende, & Mahatane, 2009). Fisheries Frame Survey 2012 National Report indicated that 1063 beach seines operated in Kenya as at August 2012, a figure higher than 991 and 762 observed during 2010 and 2008 Frame Surveys respectively, with over 73% targeting Nile perch (Ministry of Fisheries Development, 2012). Continued operation of beach seines provides evidence for a typical case of imperfectly enforced regulations, as discussed by Anthony, Mazany, & Cross (1999). The continued use of beach seines casts substantial doubt in the sufficiency of the enforcement system as compared to the rewards of violations.

Rational criminality is one of the foundations of the study of crime and punishment (see Garoupa, 1997; Polinsky & Shavell, 2000; Polinsky & Shavell, 2006). This model looks at criminals as rational individuals that, like anyone else, seek to maximize their own well-being, but through illegal instead of legal means. Crime is seen as providing both monetary gains as well as costs. The costs involve both the cost of committing the crime, including opportunity cost, and the cost associated with penalty in the case of an arrest. Opportunity cost may take various forms, from loss of money that could have been earned through lawful means to loss of status resulting from criminal behavior. The penalties can vary from simple probation, fines to imprisonment. Becker (1968) pointed out the need to recognize that there are both benefits and costs associated with crime which together with probabilities of detection and punishment, create the incentives for criminal behavior. According to the theory, violations will occur if expected net benefits to the criminal are positive. From this perspective, crime is seen to respond to economic conditions and incentives, and that a criminal simply chooses crime because it is the best alternative available. The incentives for criminal behavior can be manipulated by negatively affecting expected net benefits. The smaller the expected net benefits the lower the level of crime. The number of offences will, therefore, decrease with increased levels of punishment as well as increased probabilities of detection, prosecution and conviction.

This approach to crime and punishment has been criticized particularly on the notion of rational utility maximizing agents and the lack of focus on other factors like social and moral norms. In response to this, economists have also introduced normative factors into the models of law enforcement as extensions to this basic model. Stigler's (1970) introduced the concept of marginal deterrence and explained that a marginal deterrence occurs when a more severe offence is deterred because its punishment exceeds that of a less severe offence. This is highly relevant under circumstances in which people can choose between committing several harmful acts, e.g. using poisonous or noxious substance to kill fish and fishing using undersize gill net. In this context, sanctions not only influence whether individuals commit offences, but also which harmful acts are chosen. All else being equal, it is socially preferable that enforcement policies create marginal deterrence so that the offences that are committed are less harmful ones. Many others have elaborated on the issue of marginal deterrence since the work of Stigler (1970) (see Shavell, 1992; Mookherjee & Png, 1994; Wilde, 1992).

Beckers model has been applied to fisheries several times. Coelho, Filipe, Ferriera, & Pedro (2008) and Sutinen & Andersen (1985) published studies on economic analysis of illegal fishing and fisheries law enforcement respectively, where they applied Becker's (1968) model to analyze regulatory compliance in fisheries giving emphasis on detection of violation and conviction of violators. As a basis for his empirical study of deterrence in fisheries, Furlong (1991) expanded the probability of detection and conviction into the probability of detection, and several conditional probabilities; prosecution given detection, conviction given prosecution, and punishment given conviction, and used this to estimate the supply of violations based on data on fishermen.

Therefore, this paper examines the private incentives of beach seine owners and crew to violate the ban on beach seining in Lake Victoria. It applies to classical model of rational criminality, put forth by Gary Becker (Becker, 1968). This model analyses crime as an economic activity and focuses on the expected gains of participating in criminal activity. This analysis helps understand the incentives involved in the continued violations of the beach seining ban and to identify the best strategies of changing these incentives to make the ban more effective.

Methodology

This study focused on all the 273 fish landing sites in Siaya, Kisumu and Homa bay counties (Figure 1) which accounts for 84.3% of the fishery of Lake Victoria Kenya. Fisheries law enforcement in these counties largely rely on law courts of Bondo (Siaya county), Winam (Kisumu) and Homa bay for prosecution of those suspected of violating fisheries regulations.

The Kenya Gazette notice number 7565 of 2001 was used to derive violations with regard to beach seining as follows;

- Fishing using a beach seine in Kenya fishery waters
- Possession of beach seine in fishing area

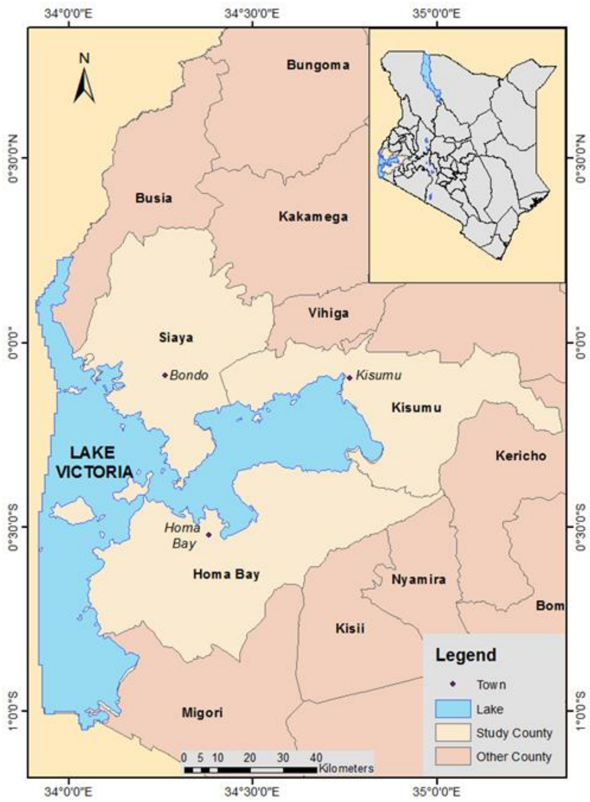

Figure 1: Map of Lake Victoria, Kenya showing counties of Siaya, Kisumu and Homa bay

Computation of model variables

Expected benefits from violation - π_{bs}

Expected benefits from beach seining were equated to catch revenue resulting from one day's successful operation of a beach seine. Denoting the violation – beach seining as *bs*, this can be expressed as;

$$\boldsymbol{\pi_{bs} = \varphi_{bs} * (1 - p_a)}$$

Where;

Total revenue $(\varphi_{bs}) = \sum (q_1 p_1 + q_2 p_2 + \cdots + q_n p_n)$

q_1, q_2, q_n - Quantities of fish in kg species *1, 2, ...n* landed

p_1, p_2, p_n - Price of fish (in Kenya shillings) per kg of species landed

p_a – The probability of violator being arrested

We assume that on average a group of eight people operate each beach seine and that their daily revenue is 30% of the overall revenue, which they share out equally amongst themselves. We assume that the owner of the beach seine receives on average 70% of the total revenue. Fish price was computed from Annual statistical bulletins (Ministry of Fisheries Development- Bulletin 2008, 2011). Mean fish price of Ksh 150.48 and Ksh 129.45 for Nile perch and Tilapia respectively. Average catches of a beach seine is assumed to be 140 kg of Nile perch and 20 kg of tilapia per seine per day over the period of study.

The expected benefits to each violator per incident was computed as follows

$$\boldsymbol{\pi_{bs\_c} = \frac{(30\% * \varphi_{bs})}{C} * (1 - p_{a\_c})}$$ for crew

$$\boldsymbol{\pi_{bs\_o} = (70\% * \varphi_{bs}) * (1 - p_{a\_o})}$$ for owner of beach seine

Where;

C - number of crews operating a beach seine

p_{a_c} and p_{a_o} are probabilities of beach seine crew and beach seine owner being arrested respectively having been detected.

$(1 - p_{a\_c})$ and $(1 - p_{a\_o})$ are probabilities that no arrest is made for crew and seine owner respectively

Expected cost of violation $(\in_{bs})$

The expected cost of violation, $\boldsymbol{\in_{bs}}$, can be simply expressed as the product of the probabilities of detection, arrest, prosecution and conviction and average fines , as described by (Eggert & Lokino, 2008 and Furlong (1991). This is given in general as

ϵ_{bs}=

p_d(detection)*p_a(arrested|detected)*p_g(guilty|arrested)*p_p(penalty|guilty)*penalty

Where;

p_d(detection) – probability of being detected doing a violation.

p_a(arrested|detected) – probability of being arrested having been detected

p_g(guilty|arrested) – probability of being proved guilty having been arrested

p_p(penalty|guilty): probability of being penalized having been proved guilty

Penalty - conviction (fines, jail term or community service order)

We will later generalize this to also include the appropriation cost to beach seine owners, which lose their equipment if arrested.

Probabilities of detection and conviction

Probability of detecting beach seining ban violation (p_d)

Records of beach seines seized during enforcement of the ban between 2004 and 2010 (Appendix 1) and those observed during Frame Surveys over the same period were used to compute probability of detecting violators of the ban. The Frame Survey figures (5803 in 2000, 1157 in 2002, 869 in 2004, 553 in 2006, 762 in 2008, 991 in 2010 and 1063 in 2012) were raised by 0.3 to arrive at better estimate of total number of seines within the fishing areas, regardless of whether or not the gear was in operation on the survey date. It is noteworthy that enforcement targets the gears in operation as well as those withdrawn from operation but is in the fishing areas (violation ii) while the Frame Surveys only captured seines in that were operated on the referenced date. The p_d was computed as;

$$\boldsymbol{Mean\ pd} = \frac{\mathbf{1}}{\boldsymbol{n}} * \sum \frac{\boldsymbol{B_s}}{\boldsymbol{B_e} * (\mathbf{1} + \boldsymbol{r})}$$

Where;

B_s − number of beach seines seized

B_e − number of beach seines found in Frame Survey

r − proportion of number of bs in fishing area but not operating during frame survey

n − number of years

Table 1: Summary of results of enforcement of ban on beach seining in Lake Victoria Kenya (source: MCS national working group report - Kenya)

Financial Year (FY)	Quarter	No. of suspects arrested	No of BS seized	Enforcement effort [1]
2004/2005	Q1	74	154	15
	Q2	42	126	18
	Q3	36	73	12
	Q4	16	102	15
2005/2006	Q1	23	56	14
	Q2	27	41	13
	Q3	8	19	9
	Q4	13	29	11
2006/2007	Q1	11	13	7
	Q2	17	28	12
	Q3	11	18	12
	Q4	16	17	8
2007/2008	Q1	6	29	10
	Q2	10	17	12
	Q3	6	13	9
	Q4	11	17	9
2008/2009	Q1	10	8	8
	Q2	8	17	8
	Q3	6	11	8
	Q4	17	14	6
2009/2010	Q1	6	16	11
	Q2	0	8	10
	Q3	8	6	10
	Q4	3	9	6
Totals		385	841	253

[1]Enforcement effort in terms of number of days enforcement unit is out for operation.

Probability of a violator being arrested (p_a)

Probability of arresting suspect/ seizing gear was treated conditional to detection (p_d). Data on enforcement operations (Appendix 1) was used to compute the probability of arrest. This is based on the number of suspects per violator category and number of beach seines seized during each quarter in a financial year computed as;

$$P_{a\_c} = \frac{\delta}{\beta * C} \quad \text{for crew}$$

$$\boldsymbol{P_{a\_o}} = \frac{\boldsymbol{\varpi}}{\boldsymbol{\beta}} \quad \text{for owner of seine}$$

$\delta -$ Total number of beach seine crews arrested over a period

$\beta -$ Total number of beach seines seized over the same period

$\varpi -$ Total number of beach seine owners arrested over a period

The overall mean for this period was used p_{a_c} and p_{a_o}values for years where data was missing.

Probability of suspect being proved guilty (p_g) and being penalized (p_p)

Probability of being proved guilty was used to assess the strength of prosecution of cases of beach seine ban violation in Court of Law. On production of arrested suspect before Court, the suspect may be proved guilty or not. If proved guilty, a convict may be penalized severity of which is dependent on presiding court. A total of 272 records of cases of beach seine violations for a period between 2001 and 2012 were used to compute these probabilities as follows;

$$\boldsymbol{p_g} = \frac{\boldsymbol{g}}{\boldsymbol{a}}$$

and

$$\boldsymbol{p_p} = \frac{\boldsymbol{p}}{\boldsymbol{g}}$$

Where;

g – Total number of suspects proved guilty of a violation over a period

a – Total number of suspects arraigned in court over same violation and period

p – Total number of convicts of a violation penalized over a period

Court penalty for violation

Fisheries Act cap 378 Laws of Kenya against which prosecutions of these violations are made provides for penalty of *fine not exceeding Ksh 20,000 or two years imprisonment or both* but subject to presiding court. Using the data on 272 cases of violation of this ban, the mean overall penalty was calculated and compared between the counties and violation categories. Each day of community service order per convict was valued at Ksh 250.00, where this was applicable, basing on rates for unskilled labor under Government *Kazi Kwa Vijana* initiative.

Expected cost of violating ban on beach seining($\in_{bs}$)

Detected beach seines are as a rule confiscated by the authorities and consequently destroyed. This constitutes a substantial loss to the beach seine owners and must be taken into account when measuring the cost of violations, $\boldsymbol{\in_{bs}}$. This cost will depend both the probabilities of detection, arrest and sentencing as well as the fine, $\boldsymbol{f}$, for the crew but in addition on the value of confiscated seines for seine owners. The cost for each group is therefore expressed as;

$$\boldsymbol{\in_{bs\_c}} = \boldsymbol{p_d} * (\boldsymbol{p_{a\_c}} * \boldsymbol{p_g} * \boldsymbol{p_p}) * f \text{ for crew}$$

$$\boldsymbol{\in_{bs\_o}} = \boldsymbol{p_d} * \left(\boldsymbol{Value_{bs}} + \left(\boldsymbol{p_{a\_o}} * \boldsymbol{p_g} * \boldsymbol{p_p}\right)\right) * \boldsymbol{f} \text{ for owner of beach seine}$$

The average time a beach seine is in operation depends on the probability of being detected, p_d, since the seine is confiscated if detected. The higher the probability the shorter the time the owner can expect to operate the seine before being detected. Value of beach seine at time of detection is a function its potential to generate income in the future, had it not been detected. We assume for simplicity that this value is relative to the cost of a new seine, $V_{(0)}$, and falls with increasing age of the seine. We therefore assume the seines value depreciates at a fixed relative rate, r. We further assume that the probability of detection is independent of the age of the seine and constant over time. Given these assumptions the life expectancy of a random seine follows a negative binomial distribution, measuring the probability of surviving a series of random trials with success. The expected net benefit of a random beach seine is therefore the expected net benefits of a function of a

$$E(C_{bs}) = \sum_{t=0}^{\infty}\left[\frac{C_{bs}}{(1+r)^t} p_d(1-p_d)^t\right]$$

$$E(C_{bs}) = C_{bs}P_d \sum_{t=0}^{\infty}\left[\left(\frac{1-p_d}{1+r}\right)^t\right]$$

But since the denominator in the sum is bigger than one and the nominator is smaller than one, the sum is convergent and the rule of infinite sums of geometric series applies resulting in;

$$Value_{bs} = V_{(0)} * \frac{p_d}{\left[1-\frac{(1-p_d)}{(1+r)}\right]}$$

negative binomial variable with one allowed failure. This is given by;

$V_{(0)}$ and r were taken to be Ksh 150,000 and 15% respectively.

Expected net benefit of violating ban on beach seining (ν_{bs})

The expected net benefits of violation of beach seine ban is expressed as;

$$\boldsymbol{\nu_{bs} = \pi_{bs} - \epsilon_{bs}}$$

Further analysis was done to identify enforcement variables which the expected net benefit is most sensitive.

Table 1: Summary of penalty, Expected benefit, Expected cost and Expected net benefits of violating beach seining ban in L. Victoria Kenya between 2001 and 2012.

Variable		Siaya		Kisumu		Homa bay		Overall	
		Owners	Crews	Owners	Crews	Owners	Crews	Owners	Crews
Penalty	Mean	3,583.33	4,049.48	6,520.34	11,428.57	8,750.08	9,047.30	7079.00	6620.92
	Std error	2,113.12	422.97	626.35	626.47	861.66	531.86	508.49	370.62
	Mode	N/A	3000	5000	10,000	10,000	10,000	10000.00	3000.00
Expected Benefits	Mean	12,223.57	776.13	12,135.62	700.51	14,413.08	815.83	12,811.50	786.34
	Std error	270.47	6.68	317.05	34.41	3.64E-13	1.33e-13	239.49	4.87
	Mode	12,419.51	788.54	14,413.08	558.55	14,413.08	815.83	14,413.08	815.83
Expected Cost	Mean	11,654.16	45.60	11,757.18	229.55	11,684.13	75.75	11,732.08	71.72
	Std error	70.15	4.60	25.54	37.83	15.52	4.45	18.19	5.38
	Mode	N/A	34.74	11,706.64	385.98	11,706.64	83.73	11,706.64	83.73
Expected Net Benefit	Mean	569.41	734.99	378.45	486.23	2,728.94	811.35	1,079.42	746.77
	Std error	266.38	9.35	328.26	76.06	15.52	4.45	247.73	9.79
	Mode	N/A	753.80	2,706.43	172.57	2,706.43	803.37	2,706.43	803.38
Sample size		**3**	**96**	**59**	**14**	**26**	**74**	**88**	**184**

Results

Summary of penalty, Expected benefit, Expected cost and Expected net benefits of violating beach seining ban in Lake Victoria Kenya between 2001 and 2012 is presented in Table 1.

Expected revenue from violation ($\boldsymbol{\pi_{bs}}$)

The results indicate an revenue π_{bs} to beach seine operators (both owners and crews) from a single day's operation if not arrested was Ksh 4,676.84 ± 350.36 with Ksh 815.83 being most common. Significant differences were however observed in the expected revenue to the violators between the counties (*p<0.001*) and violator category ($p<0.001$).The mean difference between the $\pi_{bs_c}$and π_{bs_o} across the counties was Ksh 12,025.16. Consideration by counties across violator category showed a mean highest π_{bs} of Ksh 4,351.12 ± 599.43 (n=100) in Homa bay county. This was Ksh 1,123.02 ± 198.44 (n=99) and Ksh 9,942.59 ± 589.06 (n=73) in Siaya and Kisumu counties respectively.

Expected revenue to each crew member(π_{bs_c})

In overall, the mean expected revenue to crews was Ksh 786.34 ± 4.87 (n=184) with most crews getting Ksh 815.83 if not arrested. There was significantly different ($p<0.001$) between the counties. Crews that operated in Homa bay county realized the highest mean $\pi_{bs\_\boldsymbol{c}}$ of Ksh 815.83 ± 1.33E-13 (n=74). Mean $\pi_{bs_\boldsymbol{c}}$in Siaya and Kisumu counties were Ksh 776.13 ± 6.68 (n=96) and Ksh 700.51 ± 34.41 (n=14) respectively. The most frequent $\pi_{bs\_\boldsymbol{c}}$ was Ksh 815.83 in Homa bay but Ksh 788.54 and Ksh 558.55 in Siaya and Kisumu counties respectively.

Expected benefits to beach seine owner (π_{bs_o})

The mean $\pi_{bs\_\boldsymbol{o}}$ across counties was Ksh 12,811.51 ± 239.49 (n=88) with most beach seine owners expecting Ksh 14,413.08. Significant differences between the counties was observed ($p<0.001$) with those in Homa bay county expecting the highest $\pi_{bs\_\boldsymbol{o}}$ of 14,413.08 ± 3.638E-13 (n=26) if not arrested. This was Ksh 12,223.57 ± 270.47 (n=3) and Ksh 12,135.62 ± 317.05 (n=59) in Siaya and Kisumu counties respectively. Most beach seine owners in Kisumu and Homa bay expected Ksh 14,413.08 from every day‘s beach seining operation if not arrested.

Although this model used mean prices, quantities and species of fish landed, it is necessary to acknowledge that real-time values varied over the years and could influenced by a wide range of factors.

Expected cost of violating ban on beach seining ($\in_{\boldsymbol{bs}}$)

The overall $\in_{bs}$across the three counties was Ksh 3,844.19 ± 331.44 (n=272) with Ksh 11,706.65 being the most common cost to the violator.

Comparative analysis by counties showed significant differences ($p<0.001$) between the counties. It was cheaper violating the beach seine ban in Siaya county where the expected cost of violation was Ksh 397.37 ± 201.07, n=99). Expected cost of same violation was Ksh 3,093.93 ± 511.77 (n=100) in Homa bay and Ksh 9,546.44 ± 535.30 (n=73) in Kisumu county. Further significant differences in $\in_{bs}$ was observed between violator categories with mean difference of Ksh 11,660.36.

Expected cost of violating the ban by crews ($\in_{bs\_c}$)

The mean $\in_{bs\_c}$ for crews was Ksh 71.72 ± 5.38 (n=184) with 83.73 being most common. This was significantly different between the counties ($p<0.001$). The $\in_{bs\_c}$ of fishing using beach seine was Ksh 45.60±4.60 (n=96) in Siaya County over this period but Ksh 75.75 ± 4.45 (n=74) and Ksh 229.55 ± 37.83 (n=14) in Homa Bay and Kisumu respectively over the same period.

Expected cost of violating the ban by beach seine owners ($\in_{bs\_o}$)

Basing on 88 cases, the mean $\in_{bs\_o}$ was Ksh 11,732.08 ± 18.19 with Ksh 11,706.64 being the most common. This was Ksh 11,654.16 ± 70.15, n=3 in Siaya county, but Ksh 11,757.18 ± 25.54 (n=59) and 11,684.13 ± 15.52 (n=26) in Kisumu and Homa bay counties respectively. The most common value of $\in_{bs_o}$to those convicted of possession of beach seine was 11,706.64 in Kisumu and Homa Bay counties. The observed difference between the counties was however not statistically significant ($p>0.05$).

Probabilities of detection, arrest, conviction and penalty

Mean probability of detecting the violation was 0.1390. This was highest in 2005 and 2006 ($p_d=0.2900$) but lowest in 2008 and 2009 ($p_d=0.0314$). Table 2 presents summary of probabilities violator being arrested, proved guilty and penalized. The highest mean p_{a_c} was attained during 2005/06 financial year ($p_{a\_c}=0.1886$) and lowest mean probability of 0.0718 during the year 2007/08. On the other hand, the highest mean p_{a_o} was 0.3021 attained in 2009/2010 financial year.

Table 2: Summary table of probabilities of arrest, proving guilty and being penalized

	p_{a_c}	p_{a_o}	p_g	p_p
Mean	0.1136	0.2263	0.9897	0.9891
Standard Error	0.0055	0.0145	0.0103	0.0333
Mode	0.0803	0.1296	1.0000	1.0000
Minimum	0.0131	0.0690	0.7000	0.0000
Maximum	0.3704	0.5294	1.0000	1.0000
Count	184	88	272	272
Confidence Level (95.0%)	0.0108	0.0287	0.0212	0.0682

Court penalty for violation

The mean overall penalty for those convicted was fine of Ksh 6,769.13 ± 299.62 (n=272) with the most common being Ksh 10,000. However, a significant difference ($p<0.001$) was observed in the penalties between the three counties. Violating ban on beach seining earned a mean penalty of Ksh 4,035.35 ± 413.52, (n=99), in Siaya county where this violation was cheapest for the period covered by this study. The mean penalty were Ksh 7,461.64 ± 413.52 (n=73), and 8,970.02 ± 413.52 (n=100), in Kisumu and Homa Bay respectively. The most common penalties were Ksh 3,000 (n=99) in Siaya, Ksh 10,000 (n=73) in Kisumu county and Ksh 10,000 (n=100) in Homa bay county.

Analysis by violator category showed a mean penalty to crew fishing using beach seine as Ksh 6,620.92 ± 370.62, (n=184) with the most common being Ksh 3,000.00. This was higher for the case of the owner of seine - Ksh 7,079.00 ± 508.49 (n=88) with most common fine being Ksh 10,000.00. This difference in penalties between seine owner and fishing crew was however not significant.

Although the fisheries laws stipulates that upon being proved guilty of a fisheries violation one could be penalized by way of fine or imprisonment or both, there were no cases, over this period, where both fine and imprisonment was applied.

Expected net benefits of violating ban ($\boldsymbol{v_{bs}}$

The mean v_{bs}across the counties and violator categories was Ksh 854.39 ± 80.67 (n=272). Although a significant differences in v_{bs}between counties ($p<0.001$) was observed, the expected net benefits was positive in all the counties. The overall $V_{(bs)}$ was Ksh 729.97 ± 11.59, n=99 in Siaya. This was Ksh 399.12 ±265.29 (n=73) and 1,309.93 ± 84.69 (n=100) in Kisumu and Homa bay counties respectively. There was a significant difference between the mean $V_{(bs)}$of those convicted of fishing using beach seine and those convicted of being in possession of beach seine.

Expected net benefits to fishing crews

The mean $v_{bs}$to crew was Ksh 746.77 ± 9.79 (n=184) with Ksh 792.79 being most common. A significant difference ($p<0.001$) in $v_{bs}$to the crews was observed between the three counties. This was highest in Siaya (v_{bs}=734.99 ± 9.35; n=96, mode Ksh 753.80) followed by Kisumu counties (v_{bs}= 486.23 ± 76.06; n=14, mode Ksh 172.57) and Homa Bay county (v_{bs}=811.35 ± 4.45; n=74).

Expected net benefits to seine owners

Overall mean v_{bs} to owner of seine was Ksh 1,079.42 ± 274.73 (n=88) with most common v_{bs} being Ksh 2,706.43. Comparison by counties showed significant difference ($p<0.001$) with highest v_{bs}in Homa bay county (v_{bs}= 2,728.94 ± 15.52; n=3) with net benefits to most violators being Ksh 2,706.43. This was Ksh 569.41 ± 266.38 (n=3) and Ksh 374.45 ± 328.26

(n=59, mode 371.88) in Siaya and Kisumu counties respectively.

Details of penalties, expected benefits, expected cost and net benefits for violators of beach seine ban in L. Victoria Kenya is shown in Appendix 3.

Sensitivity of Expected Net Benefits to changes in detection, arrest and prosecution

Violators of beach seine ban showed different sensitivity to changes in detection and conviction probabilities, revenue from fishing and cost of fishing gear as illustrated in Figure 2.

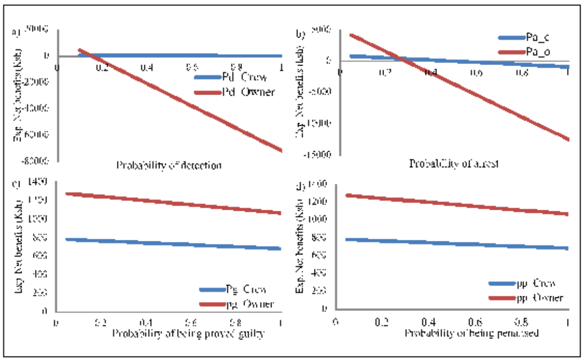

Figure 2: Sensitivity of Expected Net Benefits to changes in enforcement variables –a) detection, b) arrest, c) proven guilty, d) penalty to beach seine ban violators

The owners of seines were very sensitive to probability of being detected and would seize to expect positive net benefits at p_d*=0.175*, p_{a_o}*=0.30* and p_g*=0.55* *as* illustrated in Figure 2(*a*, *b*). Increasing probability of being proved guilty and or penalysed affected the expected net benefits (Figure 2d) but this remained positive even when pg and pp values are 1 (Figure 2c, d).

Increasing probability of detecting a crew fishing in violation of this regulation reduced the expected net benefits but does not deter a crew from attempting this violation given that the v_{bs}will be Ksh 50.15 even if p_d*=1* (Figure 2a). The crew are less sensitive to arrest realising zero expected net benefits when p_{a_c} is increased to 0.4960. Being proved guilty and being penalized did not affect the expected net benefits to crews significantly(Figure 2c, d).

Sensitivity of Expected Net Benefits to changes in revenue, cost of inputs and fine

Changes in quantity of fish caught, total revenue and cost of inputs affected the net expected benefits to the violators differently with owner of seine being more sensitive to it (Figure 3). The total revenue from a day's operation responded more to changes in quantity of Nile perch as opposed to that of tilapia in catch. Owner of seine made no profits when the value of catch from violation falls below Ksh 21,685. On the other hand the violation had positive net benefits to the crews as long as the total revenue did not go below Ksh 3,100 (Figure 3a). As illustrated in Figure 3b, this model predicts that this violation would not be profiting to the owner of seine if quantity of Nile Perch falls below 126 kg.On the other hand, the crew will have positive expected net benefits as long as the quantity of Nile perch in catch does not fall below 3.23 kg.

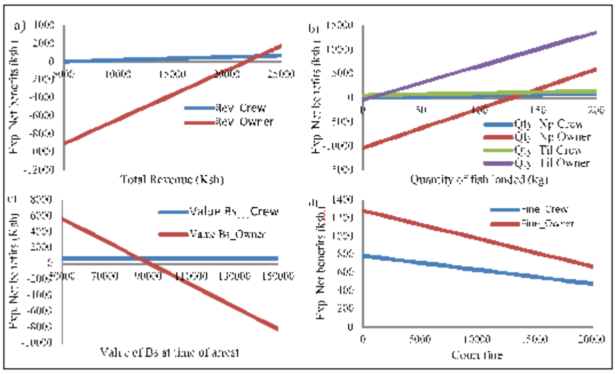

Figure 3: Sensitivity of expected net benefits to changes in revenue, cost of inputs and fine to beach seine ban violators

Beach seine owners will seize to get positive expected net benefits if value of seine at time of seizure exceedes Ksh 90,650 or 60% of its value when new as shown in Figure 3c. Although increase in fine decreases net benefits, the current maximum fine of Ksh 20,000 would not stop violation of the beach seining ban (Figure 3d).

This model illustrates that p_{d_o} and p_{a_o} are the most responsive of all the enforcement variables (Figure 4a). On the same note, small reduction of total revenue - which is closely linked with quantity of Nile perch in catch (Figure 4b), resulted in great reduction in expected net benefits to perpetuators of this violation.

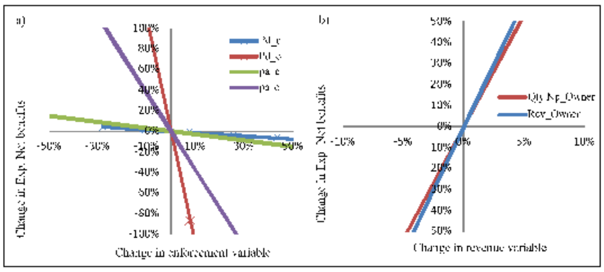

Figure 4: Most responsive variables in enforcing beach seine ban; a) enforcement variables, b) revenue variables

Discussion

This study showed that there are substantial benefits associated with violating ban on beach seining and the benefits exceed the cost of being detected. The benefits from violations vary with a different arrangement between crew and owner of seine, with fishing ground, season and fish prices alongside any form of investments that could lower probability of arrest and conviction. Since beach seining is an illegal activity, there are uncertainties surrounding the data on catch rates and value of fish caught with Mbuga, Getabu, Asila, Medard and Abila (1998) hinting the possibility of catch from such violations going for considerably lower prices. However, recent data suggests persistent violations of the beach seine ban, indicating that the observed positive expected net benefit is the driving force for continued violations of the ban.

The probabilities of a violation being detected and arrested are fundamental in enforcement of a regulation. It is therefore worrying to observe such low values (p_d=0.139, $p_{a\_}c$=0.114 and $p_{a\_}o$=0.226). There was a general increase in detection and arrest of violators from 2007 attaining highest figures (0.3021) during 2009/10 FY. This increase could be attributed to Implementation of Fisheries Management Plan (IFMP) project during which monitoring control and surveillance (MCS) was strengthened and Beach Management Units (BMUs) reformed and legally empowered as co-managers of the fisheries resources. In overall however, there exist high probability of not being arrested even after being detected with the probability of not arresting crews during violation being higher (88.64%) than that of the owners of beach seine (77.37%). This difference could be attributed to the fact that most crew abandon the gear once enforcement officers are spotted while on the contrast, some seine owners get tempted to follow their seized gears in an effort to be pardoned thereby raising probability of arresting them. Most enforcement activities are done from small canoes and small pick-up vehicles. This could cause a difficulty in arresting a violator or seizing gear, after detection, once carrying capacity is reached.

The high probability of proving a violation in court (99.0%) and penalizing the violator (98.9%) indicates an effective prosecution and judicial system with regard to this violation. Although penalties to beach seine crews and seine owners were not significantly different, the expected cost was, particularly in the cases where the seine owner loose the gear. Due to the relatively high revenues from violations and low detection and arrest probabilities the fines for violations do not constitute a marginal deterrent (Stigler, 1970; Shavell 1992; Mookherjee & Png 1994) and are therefor ineffective. Many scholars have recognized the role of probability and severity of penalties in making a crime less attractive. Strigler (1970) points at minimizing chances of violations not being detected, maximizing probability of sanction after detection, speeding up the process from detection to sanction, and making sanctions large as basic means of improving compliance. This study however indicated that although increasing severity of penalties reduces expected net benefits, the fines prescribed in the Fisheries Act Cap 378 Laws of Kenya could not stop this violation even if the upper limit (Ksh 20,000) was applied. This observation concurs with views of a number of experts who argue that severer penalty is not in the first-line of measures in the control illegal fishing (see Polinsky & Shavell, 1984; Coelho, Filipe, Ferriera, & Pedro, 2008; Eggert & Lokino, 2008).

There could be possibilities of violators investing in informers who relay information of pending enforcement operation while others used bribery and other forms of corruption behaviors along enforcement and judicial processes as earlier described by Mbuga, Getabu, Asila, Medard and Abila (1998). This study assumed these avoidance strategies though Malik (1990) and Polinsky and Shavell (2001) points out, could impact negatively in control of crime of this nature.

Although this study identifies probability of detecting a violation as most important, the observed value (mean p_d=0.139) imply that there is 86.11% chances that one would violate this regulation without being detected and thus a violator is 86% sure of scooping the benefits (Ksh 786.34 and Ksh 12,811.51 for crew and seine owner respectively). The observed low probability of being arrested further imply that even among the 14% of violators detected, a violator still has 89% for crew or 77% for owners chances of getting away with the benefits. This scenario appears not only be too attractive but also less competitive to the risk-takers, who are generally few in a society. Thus the few risk-takers may only view this ban as a ring-fence around their illegal activity from the rest of the community members who may be risk averse or just law abiding. It is obvious that enactment of regulations does not automatically remove the benefits from violation and the need for an effective enforcement and judicial mechanisms cannot be overemphasized. Sensitivity analysis clearly indicates that the most important variable to change is the probability of detection, p_d. The reason for this is clear. Beach seines are expensive. The higher the probability of detection the more likely a beach seine owner is to lose his seine to confiscation on any given fishing day. This cost creates by far the strongest deterrent. Small increases of the probability of detection, to $p_d=0.175$, would make expected net benefits to the owners negative. Assuming a linear relationship between surveillance and the probability of detection this indicates that an increase in surveillance by 25.94% would render beach seining unprofitable. Although this change looks small it would result in a probability of detection within the first year of about 60%.

It is clear from this study that the expected net benefits of violating beach seining ban in L. Victoria is positive. This is further supported by data on the introduction of new seines and possible replacement of those seized exhibited by the Frame Survey data. In situations of high un-employment and poverty typical of the communities living around L. Victoria**,** a positive expected net benefit makes the violation very attractive to both the crews and investors in beach seining. Although empirical evidence supports the role of incentives in criminal behavior, the high positive values indicated by this study do not seem to explain why the majority of fishers act in a way consistent with the law thereby suggesting that other factors could as well be contributing to compliance. Robinson and Darley (1997) indicated that other than the expected pay-offs, people follow the rules to avoid disapproval by one's social group and viewing violations as immoral. Enactment of this regulation was reached in consultation with the fisher-community, thus the majority view it as fair and for their own good. This perception seems to have enhanced acceptance of this regulation, a fact in aggrement with justice research (see Tyler, 1990; Huo, Smith, Tyler & Lind, 1996). Although the moral and legitimate concerns were not quantified in this study, this observations hinted some form of normative influence concurring with Kuperan and Sutinen (1998) and Sutinen and Kuperan (1999).

Eggert and Lokino (2008) working with artisanal fisheries of L. Victoria in Tanzania indicated the existence of small groups of persistent violators who found constant violation beneficial strategy, irrespective of deterrence variables or legitimacy and social variables. As observed by Eggert and Lokino (2008) and Scullion in FAO (2005), the beach seine ban violators in Kenya seem to perfect the art through unmeasured investments on evasion, bribery and rent seeking.

Conclusions and recommendations

Regulations are important in securing long-term benefits of a fishery. Effective enforcement of regulations is critical in realizing the objectives of fisheries regulations. Making violations un-profitable is fundamental to the effectiveness of regulation. This study demonstrates that the expected net benefit of violations of the beach seine ban in Lake Victoria are positive, both for beach seine owners and crew clearly undermining its objective. Sensitivity analysis showed that seine owners are more sensitive to changes in enforcement and the most influential variable is the probability of detection. The results indicate that the most effective strategy would be to target seine owners and focusing on detecting and confiscating seines rather then arrest and prosecution. This is both effective in addressing the violation rate and also a socially more acceptable strategy than large scale arrests of crew. Even though the probability of prosecution and conviction, given arrest, was high the marginal deterrence is insufficient to be effective. Strengthening fisheries law enforcement and judicial mechanisms is recommended. This goes along with building the capacity both in-terms of skill and equipment alongside logistics that go with effectiveness.

This study further recognizes the positive role of legitimacy of regulations and other social concerns in compliance to regulations alongside the basic model predictions. Continued violations by small group of violation perpetuators risk compromising the social and legitimate concerns of those complying, a situation which must be checked. Further, seeking legitimacy and social variables of violating the proposed regulation as well as mechanisms that would decrease the motivation to pursue it should be treated fundamental. Investigations on social variables of this violation as well as evasion investments could further be investigated.

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