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Analysis of Economic Efficiency of Wildlife Law Enforcement in Serengeti Ecosystem Tanzania

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Abstract

Law enforcement remains to be the main strategy used to combat poaching and account for high budget share in protected area management. Studies on efficiency of wildlife law enforcement in the protected areas are limited. This study analyzed economic efficiency of wildlife law enforcement in terms of resource used and output generated using three different protected areas (PAs) of Serengeti ecosystem namely Serengeti National Park (SENAPA), Ikorongo/Grumeti Game Reserves (IGGR) and Ikona Wildlife Management Area (IWMA). Three years (2010-2012) monthly data on wildlife law enforcement inputs and outputs were collected from respective PAs authorities and supplemented with key informant interviews and secondary data. Questionnaire surveys were conducted to wildlife law enforcement staff. Shadow prices for non-marketed inputs were estimated, and market prices for marketed inputs. Data Envelopment Analysis (DEA) was used to estimate economic efficiency using Variable Return to Scale (VRS) and Constant Return to Scale (CCR) assumptions. Results revealed that wildlife law enforcement in all PAs was economically inefficient, with less inefficiency observed in IWMA. The less inefficiency in IWMA is likely attributed to existing sense of ownership and responsibility created through community-based conservation which resulted in to decrease in law enforcement costs. A slacks evaluation revealed a potential to reduce fuel consumption, number of patrol vehicles, ration and prosecution efforts at different magnitudes between studied protected areas. There is equal potential to recruit more rangers while maintaining the resting time. These finding forms the bases for monitoring and evaluation with respect to resource usage to enhance efficiency. It is further recommended to enhance community participation in conservation in SENAPA and IGGR to lower law enforcement costs. Collaboration between protected area, police and judiciary is fundamental to enhance enforcement efficiency. Despite old dataset, these findings are relevant since neither conservation policy nor institution framework has changed substantially in the last decade.

Keywords

Serengeti Ecosystem, Wildlife Law Enforcement, Data Envelopment Analysis

1. Introduction

Protected areas (PAs) remain to be the main strategy for conservation of wildlife and their habitat in developing countries [1]. Sustainability of these PA depends on effective and efficient wildlife law enforcement. Law enforcement is fundamental in wildlife conservation as it represents a primary deterrent of poaching through anti-poaching patrols [2] and dismantling of wildlife trade networks outside the protected area [3]. According to [2], it is imperative for conservation laws to be supported by effective enforcement, because voluntary compliance is nearly impossible [4], particularly in developing countries where poaching is attributed with local peoples' livelihood [5]. Despite its importance, law enforcement is often reported to be the leading expensive activity in parks budget share [6] [7] [8] and its financing often remains to be a critical challenge in most tropical protected areas [9]. As such, limited resources in terms of equipment, manpower, field gears and budget constraints to meet necessary training, salaries and sophisticated technology and tools have often limited the effectiveness of the enforcement operations [4] [10]. Moreover, ineffective law enforcement on management of wildlife resources has remained to be a challenge in most protected areas and contributes to increased decline in habitat quality and human-wildlife conflicts [11]. Since conservation has politically remained marginalized in the policy agenda in African governments, the future improvements in budget allocation for wildlife law enforcement are unlikely [9]. This calls for the need to devise optimal enforcement strategies that could maximize resource efficiency in wildlife law enforcement operations. This is by optimizing the enforcement efforts, and hence cost, while maintaining the conservation objective [4] or delivering greater conservation outcomes for the same limited budget [12]. Suboptimal allocation of limited resource in enforcement operation may result to inefficiency and poor conservation performance.

Previous scholars have studied performance of wildlife law enforcements using efficiencies in allocation of resources. For example [6] assessed the budgetary requirement for reducing illegal activities to the level that does not impact conservation outcome. The author used monitoring feedback to inform the management decision to improve cost-effectiveness and performance of law enforcement. [12] used structured decision-making to find the most cost-effective allocation of patrol effort with a limited budget to get the best return on investment.

[13] used decision support software "Marxan" to minimize the costs of conserving viable populations of key species and a representative sample of habitats, given the variable costs of law enforcement and expected poaching threats at different sites in Greater Virunga Landscape of Democratic Republic of Congo. In general, most of these efficiencies studies in wildlife law enforcement have largely concentrated on anti-poaching patrols with specific focus on deterrent and detection of illegal activities [14]. However, the scope of wildlife law enforcement does not end with anti-poaching patrol efforts, it also includes the chain of intelligence, investigations, prosecution and court proceedings [15] [16]. These attributes account for significant portion of enforcement budget of protected areas authority and in many cases they are reflected in planning and budgeting as a package [9]. Difference in wildlife management regimes and resource limitations may cause protected areas to have different levels of enforcement performance [17]. However, studies that evaluate and compare efficiency levels of law enforcement are limited. It is therefore difficult to judge the efficiency of various levels of the law enforcement and further challenging to set performance evaluation system based on resource use.

This study therefore aims to evaluate wildlife law enforcement efficiency levels in three protected areas (Serengeti National Park (SENAPA), Ikorongo/Grumeti Game Reserves (IGGR) and Ikona Wildlife Management Area (IWMA)) of Serengeti ecosystem in Tanzania. SENAPA is a strictly protected area where regulated photographic tourism is allowed. SENAPA is managed by government parastatal organization named Tanzania National Park Authority (TANAPA). The IGGR is under Tanzania Wildlife Management Authority (TAWA). Both regulated photographic tourism and trophy hunting are permitted in IGGR. IWMA is managed by local communities through a Community Based Organization and similar to IGGR, consumption through trophy hunting and photographic tourism is regulated. Therefore, this study specifically 1) identified wildlife law enforcement inputs and outputs, 2) estimated the costs of wildlife law enforcement, 3) estimated the economic efficiency of wildlife law enforcements and 4) assessed factors influencing efficiency levels of wildlife law enforcement. Findings from this study are important to set the baseline for current and future monitoring and evaluation of wildlife law enforcement performance in terms of resource use efficiency, with particular case of Serengeti ecosystem. Although this study uses relatively older dataset (2010 to 2012), it is certain that the findings are still valid to inform park managers and regulators on appropriate resource allocation, since neither relevant conservation policies nor institution framework have significantly changed between the time of the study and the time this paper is submitted for publication.

2. Methodology

2.1. Description of the Study Area

The study was conducted in three protected areas of Serengeti Ecosystem including Serengeti National Park (14,763 km^2), Ikorongo-Grumeti Game Reserves (3767 km^2) and Ikona Wildlife Management Area (242.3 km^2) (**Figure 1**). Serengeti ecosystem is located between 34˚45'E - 35˚50'E and 2˚S - 3˚20'S. It covers approximately 30,000 km^2 straddling the boarder of northern Tanzania and southern Kenya [11]. It is one of the Africa's strongholds for wildlife. It has unique ecosystems that are highly dominated by the (*Connochaetestaurinus*) wildebeest population [18]. It is also home to four globally threatened or endangered species; black rhinoceros, elephant, wild dog and cheetah [19]. These protected area forms the core part of the Serengeti ecosystem, yet it is arguable to experience significant challenge of poaching and spend huge resources in law enforcement operations due to land-use changes as result of increased anthropogenic pressures and changes in various national policies [11]. All protected areas operate in relatively homogenous region, perform the same type of functions and have identical goals and objectives; a avalid assumption for using a novel analytical tool for estimating efficiency "Data Envelopment Analysis" [20] [21].

2.2. Data Collection

2.2.1. Sampling and Sampling Size

A total of 153 Wildlife Law Enforcement Staff (WLES) were randomly selected

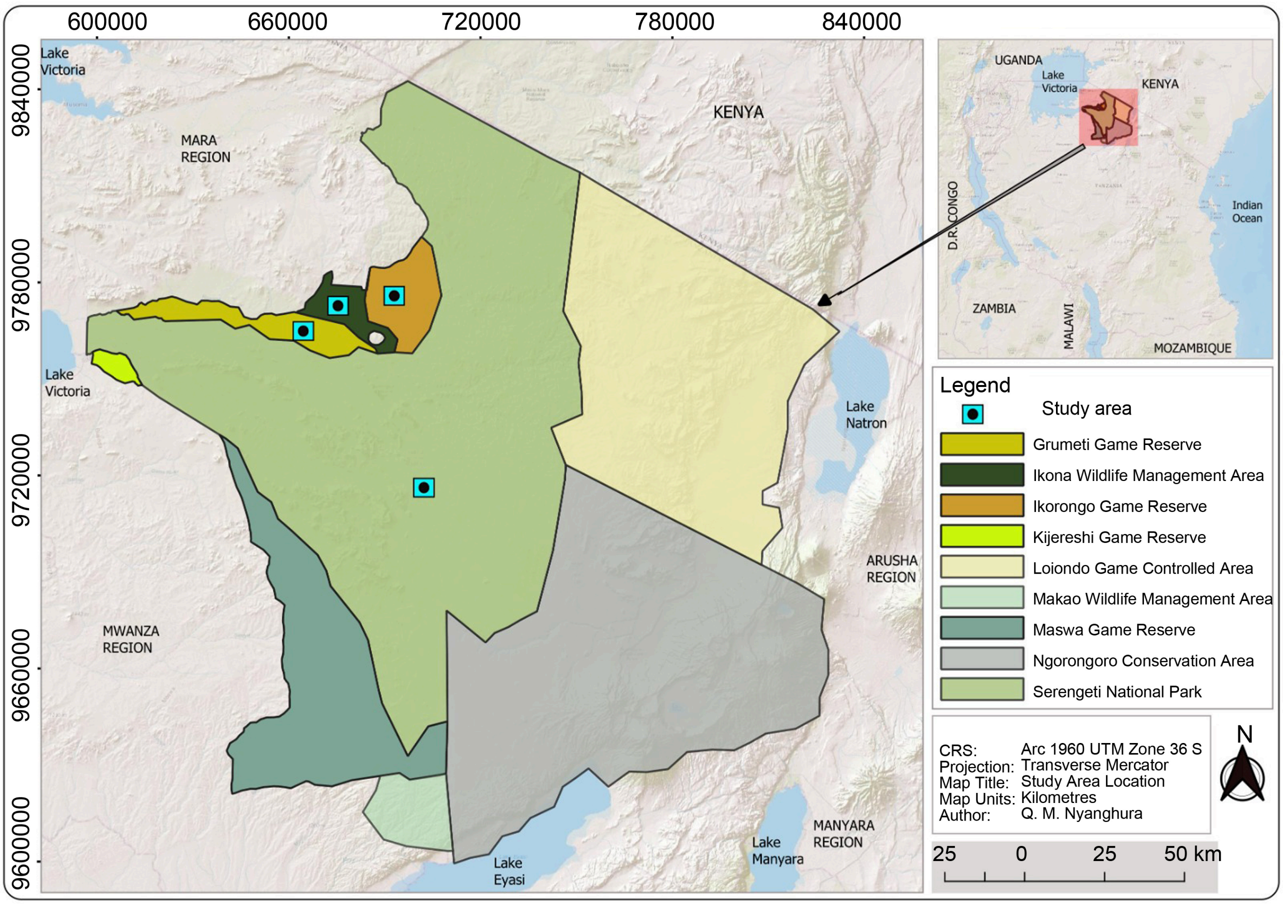

Figure 1. The map showing the study area.

from the staff registers as the sampling frame. The sample represents 31% of the total WLES in three PAs defined as Decision-Making Units (DMUs). The sample size for each DMU is presented in Table 1.

2.2.2. Identification and Quantification of Input and Output

We used Data Envelopment Analysis (DEA) to determine the relative efficiency of wildlife law enforcement. DEA is a non-parametric technique for evaluating the relative efficiency using multiple inputs and outputs. An important feature of DEA is that performance measures can be judged comparatively, so it is effective in comparing the efficiency of the Decision-Making Units (DMUs) that possess the same classes of inputs and outputs. Different from other efficiency methods, DEA can reveal the hidden and ignored relationships and can quantitatively analyze the causes of the inefficiency in DMUs [20]. DEA is relatively novel in the environmental conservation literatures [22], often applied in developed countries [23] [24] [25] and limitedly tested in developing world such as Tanzania.

Selection of wildlife law enforcement inputs and outputs were based on conceptualization, related literature review, possibility of data availability and personal experience. A consultative meeting with law enforcement leaders from each DMU was conducted before data collection to identify the possible inputs and outputs. Inputs collected were personnel (number of WLES), vehicles (number of patrol cars), fuel (litres)/month and meal/ration (kg)/month. Other relevant efforts exerted by the protected areas authorities in wildlife law enforcement were based on prosecution. This is through recruitment of prosecution officer and allocated to courts of law to facilitate effective prosecution and clearance of wildlife cases. In this regard, the frequency of prosecution of wildlife cases from DMU/month and frequency of WLES to attend the court of law for witnessing/month (both proxied by number of man-days) were considered. Though intelligence was considered as one of the integral components for law enforcement performance, it was difficult to obtain its data because of its sensitivity. Specific spatial and temporal anti-poaching patrol data were equally scarce and therefore we didn't account in this study.

Outputs collected were numbers of poachers arrested per month and number of wildlife cases cleared at the courts of the law per month. Both poachers arrested inside the borders of PAs and outside were considered. Inclusion of

Table 1. Distribution of sample size in three DMUs.

DMU	Number of WLES	Sample size
SENAPA	335	77 (22.9%)
IGGR	135	57 (42.2%)
IWMA	23	19 (82.6%)
Total	**492**	**153 (31.1%)**

wildlife cases cleared was considered as important output because of engagement of PAs in prosecutions through their recruited prosecution officer. Three years' monthly data from January 2010 to December 2012 were collected from the key informants (Chief Park Warden of SENAPA, Project Manager from IGGR, and secretary of IWMA). Monthly data on law enforcement provides adequate information for decision making than annual figures that are commonly used [3]. Other key informants were court magistrate of Serengeti, Bunda, Bariadi, Ngorongoro, Tarime, Magu, Meatu and Shinyanga districts where wildlife crime perpetrators from DMUs are sent. The information from the key informants was supplemented by monthly and annual reports, accounts records, cases files and court registers.

2.2.3. Pricing of Inputs

Estimation of economic efficiency under DEA requires inputs to be priced. Local market survey at Serengeti district was done using checklist of questions to determine the price of inputs (fuel and meal ration). Monthly indicative price of diesel at Serengeti district, provided by [26] was considered as monthly prices of fuel. Other inputs with no market price were estimated based on shadow pricing. Inputs and measure of shadow pricing in brackets includes wildlife law enforcement staff (basic monthly salary), Vehicles (monthly maintenance costs), Court witnessing (daily subsistence allowance paid to WLES to attend the court of law for witnessing and prosecution effort (daily subsistence allowance paid to prosecutors recruited by DMU). The costs were collected from the heads of DMUs.

It should be noted that the scope of wildlife law enforcement operations involved a chain of participating institutions including 1) police where the arrested poachers are sent and investigation are executed 2) prosecution office where prosecution is undertaken and 3) court of law where proceedings are done and judgements are offered. The costsborne by these institutions were not included in this study. This study considered only inputs and their costs incurred by respective protected area authorities in wildlife law enforcement operations along the chain of those institutions. To take care of inflation, collected nominal prices were deflected to January, 2010 constant price as the base month, using monthly Consumer Price Index. The reason for choosing January, 2010 was the fact that this study used data collated from the same month. Deflection price was calculated using Equation (1).

$$\text{Real price} = \text{Current nominal price} \times \frac{\text{Consumer price index of the base month}}{\text{Consumer price index of the current month}} \quad (1)$$

2.2.4. Questionnaire Surveys to WLES

Questionnaires survey was used to collect data from 153 WLES in three protected areas between January and March 2013 as shown in Table 1. Face-to-face interview was conducted to respondents who were ready to participate. Both open and closed questions were used to collect information on socio-economic variables, including number of rest-days offered/month (days) and incentives[1] offered (TZS)/month). These variables were used to determine factors influencing the estimated efficiency levels in the study area.

2.3. Data Analysis

Data were analysed in two stages. The first stage involved DEA approach and censored regression analysis in the second stage. In the first stage, DEA was used to estimate efficiency score of each DMU using inputs, outputs and corresponding cost of unit input with two assumptions of DEA: Constant Return to Scale (CRS) or CCR model assumption and Variable Return to Scale (VRS) or BCC model assumption. CCR model assumes a constant rate of substitution between inputs and outputs, while BCC model assumes existence of economy of scale, where the increase in one or more inputs may cause greater or less than proportional increase in outputs [28]. The models were then extended to account for cost or economic and allocative efficiencies. Data Envelopment Analysis Program (DEAP) software version 2.1 package developed by [29] was used for estimation of efficiency. Since inputs variable were more controllable by the DMUs comparatively to outputs, it was reasonable to consider input-oriented DEA model which aims at minimizing inputs with given set of outputs. As argued by [30], consistently with [31], efficiency estimation leads to a natural decomposition of cost efficiency into its technical and allocative components. Here technical efficiency reflects the ability of the DMU to minimize inputs from a given set of output (input-oriented). Allocative efficiency reflects the ability of a DMU to use the inputs in optimal proportions, given their relative prices and the underlying production technology. The economic (or cost) efficiency is then product of the two.

2.3.1. Technical Efficiency of DEA

As proposed by [20], input-oriented DEA model which assumed Constant Returns to Scale (CRS) was performed to compute the relative efficiency of each DMU by comparing it to all the other observations in the sample. Using duality in linear programming the following model was used to calculate the technical efficiency:

$$\begin{aligned} & \mathrm{Min}_{\theta,\lambda}\theta, \\ & \mathrm{St}\ -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned} \tag{2}$$

where; θ is a scalar and λ is $N \times 1$ vector of constants. x_i and y_i are respectively vectors of input and output in a particular DMU. X and Y are respectively input matrix and output matrix which represents data of all N DMU's. N is the num-

[1]Incentives are defined as inducement designed and implemented to influence or to motivate people to act in a particular way [27]. For the purpose of this study, incentives involved payment (in Tanzanian Shillings) to which the DMU awards to its law enforcement staff or every arrested poacher and/or wire snare destroyed.

ber of DMUs. The value of θ obtained will be the efficiency score for the i-th DMU. It will satisfy $\theta \leq 1$, with a value of 1 indicating point on the frontier and hence technically efficient DMU. The linear programming problem must be solved N times, once for each DMU in the sample. Estimating efficiency under CRS assumption implies that DMU operate at an optimal scale. However, constraints in the operating environment, for instance, imperfect competition, financial and human resource constraints, amongst other, may cause a DMU to operate at non-optimal scale [32]. Moreover, the use of the CRS specification when not all DMUs are operating at the optimal scale will result in a measure of technical efficiency which is confounded by scale efficiency. [33] suggested an extension of the CRS DEA model to provide for Variable Returns to Scale (VRS) situations. The use of the VRS DEA specification permits the calculation of scale inefficiency. Therefore, the CRS linear programming problem was modified to account for VRS by adding the convexity constraint: $N1'\lambda = 1$ to Equation (2) where $N1$ is an $N \times 1$ vector of one's [33]. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS canonical hull and thus provides technical efficiency scores which are equal to or greater than those obtainable by means of the CRS model.

$$\begin{aligned} &\text{Min}_{\theta,\lambda}\theta, \\ &\text{St } -y_i + Y\lambda \geq 0, \\ &\theta x_i - X\lambda \geq 0, \\ &N1'\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{3}$$

2.3.2. Scale Efficiency

Scale inefficiency is indicated as the difference between CRS and VRS technical efficiency. Thus, the input-oriented scale efficiency (SE) is defined in Equation (4).

$$\text{SE} = \text{TECRSi}/\text{TEVRSi} \tag{4}$$

2.3.3. Allocative and Economic Efficiency

With respect to the case of VRS cost minimization (which aims to estimate the cost-minimizing input quantities for a given input price vector), the input-oriented DEA model in Equation (3) was slightly modified to Equation (5) as follows;

$$\begin{aligned} &\text{Min}_{\lambda,x_i} w_i x_i^*, \\ &\text{St } -y_i + Y\lambda \geq 0, \\ &x_i^* - X\lambda \geq 0, \\ &NI\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{5}$$

where w_i is a vector of input prices for the i-th DMU and x_i^* is the cost minimizing vector of input quantities for the i-th DMU, given the input prices w_i and the output level y_i. The cost efficiency (CE) or economic efficiency of the i-th

DMU is then obtained through Equation (6)

$$\mathrm{CE} = \frac{W_i x_i^*}{W_i x_i} \tag{6}$$

Whereas allocative efficiency (AE) is obtained through Equation (7).

$$\mathrm{AE} = \mathrm{CE}/\mathrm{TE} \tag{7}$$

2.3.4. Censored Regression Model

In the second stage of analysis, the censored regression model Equation (8) was used to analyze factors influencing efficiency level of wildlife law enforcement of which STATA software version 10.1 was used to run analysis.

$$Y_i^* = x_i \beta + \varepsilon_i \tag{8}$$

where $Y_i = 0$ if $Y_i^* \le 0$ and $Y_i = Y_i^*$ if $Y_i^* > 0$ and $\varepsilon_i \sim N\left(0, \delta^2\right)$, X_i is the vector of exogenous variables and β a vector for unknown parameters. Y_i^* denotes the latent variable and Y_i as DEA relative efficiency scores. Applied to wildlife law enforcement the censored regression model for analysis was as highlighted in Equation (9)

$$Y_i^* = \beta_1 + \beta_2 \mathrm{INCTV} + \beta_3 \mathrm{RSTD} + \varepsilon_i \tag{9}$$

where INCTV denotes incentives offered to law enforcement staffs. Incentives was considered as amount of money (TZS) to which DMU provide to her law enforcement staff to motivate them, hence positive efficiency is expected. The RSTD represents number of days offered for the law enforcement staffs to rest per month. It is expected that, since law enforcement activities are energy intensive work then provision of less rest days would decrease efficiency.

3. Results and Discussion

3.1. Wildlife Law Enforcement Inputs and Outputs

The results show that the monthly average number of WLES for the three years was 291, 134 and 23 for SENAPA, IGGR and IWMA respectively (**Table 2**). The number ranged from 223 to 335 in SENAPA and127 to 146 in IGGR. By the time this study was conducted, the total number of WLES was 335, 135 and 23 for SENAPA, IGGR and IWMA. The number of vehicles used for law enforcement operations were 34 in SENAPA, nine in IGGR and two in IWMA. All vehicles were using diesel with mean monthly consumption of 422.6 liters per vehicle in SENAPA, 763.2 liters in IGGR and 592.2 liters in IWMA. 96.9% of consumed fuel at IGGR was supplied by Grumeti Tourist Company (GTC) which has invested in photographic tourism and trophy hunting in the reserves. These variation between DMU could probably be due to difference in budget allocation and resource management. For example, SENAPA limit fuel usage to 400 liters per vehicle per month while in IGGR there was no limitation in the use of fuel; refueling was done any time when needed.

All food varieties were estimated in kilogram (Kg) and aggregated as a unit. On average, IWMA had relative higher meal consumption per person per day of

Table 2. Wildlife law enforcement inputs and outputs; monthly mean estimates.

Variable inputs and outputs	DMUs		
Inputs	SENAPA	IGGR	IWMA
Personnel	291	134	23
Patrol vehicles	34	9	2
Fuel/diesel	14,368	6869	1184
Meal/Ration	3030	3641	298
Court witnessing	396	70	-
Prosecution effort	96	-	-
Outputs			
Poachers arrested	74	24	4
Wildlife cases cleared	17	5	-

1.24 kg/person/day compared to 1.19 kg/person/day in IGGR and 0.808 kg/person/day in SENAPA. This variation could be due to difference in budget availability. SENEPA management provided meal to only 125 law enforcement staff of Moru (64), Ndasiata (41) and Nyamarumbwe (20) posts which constituted about 43% of the total law enforcement staff. IGGR through GTC contributed 100% of ration to all law enforcement staffs, likewise game scouts from IWMA obtained ration from their office.

As an effort towards clearance of cases registered to the courts of law, each PA was responsible to send their staff to attend and provide evidence before the court of law after getting the court summons. Table 2 shows a monthly mean of 396 and 70 man-days used for WLES to attend the court of law from SENAPA and IGGR respectively. Higher frequencies from SENAPA were attributed by a higher number of cases submitted to eight resident magistrate courts than IGGR which submitted their cases to Serengeti and Bunda. Limited number in IWMA was associated by the fact that mechanisms for resolving cases particularly non-trophy offences were often based on by-laws settled by villagers of which were not accounted in this analysis. In the same efforts, SENAPA recruited three (3) public prosecutors, and allocated each to Serengeti, Bunda and Shinyanga magistrate district. These prosecutors were responsible to prosecute wildlife related cases particularly from SENAPA. On average, 96 man-days were reported to be used for prosecuting wildlife cases from SENAPA (Table 2). No prosecution efforts were executed by IGGR and IWMA.

With regard to output, the finding showed that on average 74 poachers per month in SENAPA, 24 in IGGR and 4 in IWMA were detected, arrested and reported to the police (Table 2). The mean number of cases cleared in the courts of law per month was17 in SENAPA and 5 in IGGR. The range is between 4 and 42 in SENAPA, with 58% monthly conviction rate while in IGGR the range is between 0 and 13 with 33% monthly conviction rate. Poor conviction rate in

IGGR is partly attributed by limited efforts invested in the prosecution and monitoring of their cases, which results to loopholes for corruptions and often distortion of the cases (Kiswaga, S., Serengeti district magistrate, pers. comm). These results are in line with the findings of [34] who pointed out that lower conviction rate of wildlife cases from northern zone of Tanzaniais attributed by limited prosecution efforts, weak evidence and lack of cooperation between the zonal game office and the prosecution office. Limited conviction rates are likely to lower the marginal costs to perpetrators and may jeopardize deterrent of poaching crimes in the ecosystem [35].

3.2. Wildlife Law Enforcement Costs

Monthly estimate of costs incurred for the wildlife law enforcement were TZS 223, 274,741, TZS 78,990,394 and TZS 5,541,928 in SENAPA, IGGR and IWMA respectively (**Table 3**). Of the total cost incurred, 67.2%, 65.7% and 33.2% accounted for personal emolument (salaries) in SENAPA, IGGR and IWMA respectively. Our results support the findings of [35] who found that the staff salaries account for larger share of the expenditure budget at SENAPA and IGGR.

Fuel costs accounted for 11.4% and 15.5% of the total wildlife law enforcement costs in SENAPA and IGGR and 8.8% and 12.2% for the maintenance of the patrol vehicles respectively. In IWMA, the fuel constituted the larger portion (42.7%) of the total wildlife law enforcement. Generally, higher costs of fuel correspond to vehicle fuel consumption in which together with maintenance costs are likely to be influenced by the nature of the patrol areas and seasons. For example, during rainy season fuel consumptions and maintenances were reported relatively higher than during dry season because of often breakdowns caused by destructed patrol roads, often attributed by rain. Accordingly, type and age of the vehicle may also have contributed to higher fuel consumption and frequent maintenances. For example, it was stated that Landcruiser Toyota-pick-ups which constituted about 75%, 88.9% and 100% of the anti-poaching patrol vehicles in SENAPA, IGGR and IWMA respectively were inefficient in patrolling during rain seasons and therefore consumed more fuel than during dry seasons. While the use of old model Land rover TDI 110 were appreciated as best all-weather patrolling vehicles with less fuel consumption and limited maintenance, the new model Land rover TDVI – PUMA in SENAPA were claimed to have frequent and complicated maintenances, *i.e.*, high maintenance costs (Msumi, S., Protection Manager, SENAPA, pers. comm).

3.3. Efficiency Estimates

Our empirical results show that all DMUs were technically efficient under BCC Model (**Table 4**). This suggested that all DMUs had a better use of their physical inputs to attain the desired output. Technical efficiency under CCR model was 74.5%, 68.9% and 32.5% in IGGR, SENAPA and IWMA respectively, implying inefficiency of 25.5%, 31.1% and 67.5% in that order. Differences in technical efficiency score between VRS and CCR model were the result of different scale

Table 3. Costs of wildlife law enforcement inputs; Monthly mean estimates.

DMU	Input costs	Mean Total costs (TZS)	Mean unit cost (TZS)	Min (TZS)	Max (TZS)
SENAPA	WLES salary	150,044,230 (67.2)	514,928	309,692	1,584,339
	Meal costs	4,021,615(1.8)	1327	1097	1531
	Maintenance cost	19,598,524 (8.8)	604,737	109,850	1,565,170
	Fuel costs	25,484,710 (11.4)	1779	1577	2090
	Allowance to witnesses	19,130,590 (8.6)	52,033	43,019	60,000
	Allowance to prosecutor	4,995,072 (2.2)	52,033	43,019	60,000
	Total	**223,274,741**	**1,226,837**	**508,256**	**3,273,129**
IGGR	WLES salary	51,883,726 (65.7)	387,192	179,247	5,692,106
	Meal costs	4,905,495 (6.2)	1354	1120	1562
	Maintenance cost	9,621,029 (12.2)	1,069,003	0	3,357,94
	Fuel costs	12,276,619 (15.5)	1779	1577	2090
	Allowance to witnesses	303,525 (0.4)	4336	3585	5000
	Allowance to prosecutor	-	-	-	-
	Total	**78,990,394**	**1,463,664**	**185,529**	**9,058,700**
IWMA	WLES salary	1,837,299 (33.2)	79,883	77,904	172,115
	Meal costs	239,772.5 (4.3)	953	788	1100
	Maintenance cost	1,098,788 (19.8)	937,038	0	5,412,227
	Fuel costs	2,366,068 (42.7)	1779	1577	2090
	Allowance to witnesses	-	-	-	-
	Allowance to prosecutor	-	-	-	-
	Total	**5,541,928**	**1,019,653**	**80,270**	**5,587,531**

Note: In brackets are percentages.

efficiencies obtained [36] [37]. Scale efficiency scores of 32.5%, 68.9% and 74.5% of IWMA, SENAPA and IGGR respectively implying that the effect of outputs (number of poachers arrested and cases cleared) from change in wildlife law enforcement inputs may relatively be smaller in IWMA than SENAPA and relatively higher to IGGR. That means SENAPA and IGGR could benefit by optimally input usages with the same output levels. To overcome scale inefficiency, adapting the new technologies in operation of wildlife law enforcement may serve the purpose. Our discussion with PA managers reveled limited application of sophisticated technologies and few which were used, for example GPS was not effectively utilized to generate reasonable and meaningful information that could guide decision making and efficient anti-poaching patrols including planning and resource utilization. As reported by [16] application of the sophisticated technologies like thermal imaging equipment, unmanned aerial vehicles or drones, radar surveillance and detection systems and GPS-based monitoring devices are likely to enhance efficiency in law enforcement operations. Innovative and user-friend analytical tools like CAPTURE (Comprehensive Anti-Poaching tool with Temporal and observation Uncertainty REasoning) proposed by [38] may also help to augment effectiveness and efficiency by conducting anti-poaching patrols that are well informed and therefore increase the precision of the operations. CAPTURE analyzes real-world data in wildlife protection domain to learn the ranger-poacher interaction, predict unobserved poaching activities, and anticipate poaching activities in the future.

Similar to technical efficiency, the allocative efficiency was relatively higher under BCC than CCR model. The mean allocative efficiency under BCC model for SENAPA, IGGR and IWMA was found to be 78.5%, 87.9% and 97.3% respectively, while under CCR model was 74.9%, 72.6% and 96.6% in the same order (**Table 4**). Our results in each model specification implies that all the DMUs have limited ability of selecting the correct mix of inputs and relatively less conscious about the input prices when they apply input quantities in enforcement operations. Allocative inefficiency could be explained by range of possible reasons includes institutional and structural impediments to modifying the input mix and limited management capacity to deal with market dynamics [39]. Proper allocation may reduce the law enforcement input costs by around 22 - 25 percent in SENAPA, 12 - 27 percent in IGGR and 3 per cent in IWMA without reducing output. In other words, SENAPA and IGGR have relatively greater potentials to reduce costs than IWMA. According to [12], efficient allocation of input resources can be possible by prioritizing enforcement based on cost-effectiveness. Prioritization may be informed by the application of efficient and effective decisions tools such as CAPTURE together with cost-conscious in planning by protected area planners and managers.

The mean economic efficiency score for each DMU were the same as allocative efficiency under VRS (*i.e.*, 78.5%, 87.9% and 97.3% for SENAPA, IGGR and IWMA respectively). This is because all the DMU were at the technical frontier. Economic efficiency estimated under CRS in SENAPA, IGGR and IWMA were 51.9%, 54.5% and 31.7% respectively, far lower than under VRS. However, in either model, our findings implies that wildlife law enforcement in all DMUs were economically inefficient. This suggests that, it is inevitable to reduce law enforcement operation costs in order to attain economic efficiency. Our results are consistent with those of [40] who argued that, law enforcement in police may not always achieve maximum efficiency, due to the fact that its outputs are not always measurable or visible for some of its tasks. This argument can be contextualized in our case where wildlife law enforcement staff and other inputs are often directed to perform invisible and indeterminate tasks, such as responding to problem animal control and supervising tourism activities. These tasks cannot be evaluated in terms of wildlife law enforcement efficiency because they do not produce relevant and measurable law enforcement outputs, at least based on our output definition.

Table 4. Efficiency scores of SENAPA, IGGR and IWMA.

DMU	Variable (model)	Mean	Min	Max
SENAPA	TE (CRS)	0.689 (0.229)	0.248	1
	TE (VRS)	1.000 (0.000)	1.000	1
	AE (CRS)	0.749 (0.152)	0.413	1
	AE (VRS)	0.785 (0.126)	0.627	1
	CE (CRS)	0.519 (0.222)	0.171	1
	CE (VRS)	0.785 (0.126)	0.627	1
	SE	**0.689 (0.229)**	**0.248**	**1**
IGGR	TE (CRS)	0.745 (0.261)	0.258	1
	TE (VRS)	1.000 (0.000)	1.000	1
	AE (CRS)	0.726 (0.19)	0.377	1
	AE (VRS)	0.879 (0.084)	0.718	1
	CE (CRS)	0.545 (0.263)	0.192	1
	CE (VRS)	0.879 (0.084)	0.718	1
	SE	**0.745 (0.261)**	**0.258**	**1**
IWMA	TE (CRS)	0.325 (0.261)	0.083	1
	TE (VRS)	1.000 (0.000)	1.000	1
	AE (CRS)	0.966 (0.03)	0.869	1
	AE (VRS)	0.973 (0.03)	0.858	1
	CE (CRS)	0.317 (0.259)	0.076	1
	CE (VRS)	0.973 (0.03)	0.858	1
	SE	**0.325 (0.261)**	**0.083**	**1**

Note; TE (VRS) = Technical Efficiency under Variable Return to Scale, TE (CRS) = Technical Efficiency under Constant Return to Scale, AE (VRS) = Allocative Efficiency under Variable Return to Scale, AE (CRS) = Allocative Efficiency under Constant Return to Scale, CE (VRS) = Cost Efficiency under Variable Return to Scale, CE (CRS) = Cost Efficiency under Constant Return to Scale, SE = Scale Efficiency. Numbers in parenthesis are Standard Deviations.

Economic efficiency scores under VRS implies that wildlife law enforcement was less inefficient in IWMA compared to IGGR and SENAPA. This could be due to the existence of sense of ownership and responsibility developed by surrounding communities in management of their natural resources through Community Based Conservation (CBC) approach. This is different from SENAPA and IGGR where integration of community in management of wildlife is relatively limited. Community participation motivates positive attitudes towards conservation, increasing compliance behaviors [41], and stimulates cooperation and agreement between different actors. In this way illegal extraction of natural resources can be reduced and overall law enforcement costs minimized [42]. As described by [16], local community participation is key and integral to the effectiveness and efficiency of law enforcement operations in order to address the current wave of wildlife crime in Africa. A further study done by [43] highlighted the importance of strengthening community-ranger relations as a strategy to enhance efficiency in law enforcement operations in wildlife protected areas of Uganda.

3.4. Efficiency Improvement

3.4.1. Slack Evaluation and Target Input

Wildlife law enforcement inputs were evaluated based on their average slack values. The target column (Table 5) shows the levels of inputs that an inefficient DMU should be using in order to be efficient, while the potential improvement column shows how much, in percentage terms, an inefficient DMU use of inputs needs to change to become efficient. To calculate the target values for inputs, the input value was multiplied with an optimal efficiency score and then slack amounts were subtracted from this amount similar to the study of [28].

Results revealed higher difference between the observed inputs and corresponding target inputs under CCR model assumptions relatively to BCC model assumption. This implies that DMUs needs to reduce more inputs under CCR

Table 5. Potential improvements of inputs to target level.

DMU	Input/ output	Mean input/ output	Mean Technical Efficiency		Mean slacks value		Target input/output		Potential improvement (%)	
			CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC
SENAPA	WLES	291	0.689	1.000	24	20	177	271	39.2	6.9
	RTN	3029	0.689	1.000	212	0	1875	3029	38.1	0
	VH	34	0.689	1.000	5	5	18	29	47.1	14.7
	FUEL	14,294	0.689	1.000	2186	2025	7663	12,269	46.4	14.2
	FW	396	0.689	1.000	20	55	253	341	36.1	13.9
	FP	96	0.689	1.000	8	6	58	90	39.4	6.1
IGGR	WLES	134	0.745	1.000	7	2	93	132	30.7	1.5
	RTN	3624	0.745	1.000	178	64	2522	3560	30.4	1.8
	VH	9	0.745	1.000	0	0	7	9	25.5	0
	FUEL	6869	0.745	1.000	979	559	4138	6310	39.8	8.1
	FW	70	0.745	1.000	7	14	45	56	35.5	20
IWMA	WLES	23	0.348	1.000	0	0	8	23	65.2	0
	RTN	298	0.348	1.000	2	18	102	280	65.8	6.0
	VH	2	0.348	1.000	0	0	1	2	50.0	0.0
	FUEL	1184	0.348	1.000	6	72	406	1112	65.7	6.1

Note; BCC = Benker, Charnes and Cooper Model, CCR = Charnes, Cooper and Rhodes Model, WLES = Wildlife Law Enforcement Staff, RTN = Ration/Meal, FW = Frequency of WLES (man-days) to attend the court as a witness, FP = Frequency (man-days) of wildlife cases prosecution, POA = Poachers arrested, and CC = wildlife cases cleared.

than BCC model assumption. Here, we interpreted our findings based on VRS assumption for the reasons described before and by argument raised by [44], who underscored the importance of feasibility and practicability of assumptions and estimates in slacks analysis. According to [28], adjustments are often permitted within certain ranges, and only selected options "considering other factors such as institutional settings and policy" could be considered for implementations. The findings show that the monthly target number of WLES in SENAPA and IGGR is 271 and 132, which suggests the decrease in WLES by 7% and 1.5% respectively (**Table 5**). This finding, however, may be feasible with assumption that all WLES are engaged entirely on activities that are directed towards two wildlife law enforcement outputs highlighted before. Nevertheless, in real situation not all staff were reported to work on wildlife law enforcement operations at a time [44]. For example, by the time this study was conducted, on average 127 (38%) of WLES in SENAPA, 33 (24.4%) in IGGR and 15 (65.2%) in IWMA were assigned other tasks on daily basis that are not directly related to wildlife law enforcement operations and therefore translated to limited outcome on wildlife law enforcement output. These tasks included to supervise tourism activities in the lodges, campsite, airstrip and entry gates. Again, others were absentees for various reasons including sickness, family matters, annual leaves and rest break. Excluding those who are engaged in those activities plus absentees, means creating more labor demand to perform law enforcement operations. In this case, protected areas would need to increase the number of staff by employing 64 staff in SENAPA and 30 in IGGR to reach the target. Nonetheless, employing park rangers than managers may be considered the first best option since they are on the forefront of the law enforcement operations and their wage bills per capital was relatively small to lower general enforcement costs. Our findings is supported by the study of [45] which recommended to increase the number of rangers in SENAPA where are relatively limited than IGGR.

The slacks analysis shows that SENAPA need to reduce fuel usage by 2025 liters (14.2%) per month while IGGR and IWMA need to reduce the same by 8.14% and 6.1% respectively. The number of patrol vehicles need to be reduced by around 15% in SENAPA. The reduction of fuel and vehicles suggests intensifying foot patrols and appropriate management of vehicle-routes for the remaining cars. The former implies increasing number of WLES and adopting technologies that may facilitate precise patrol activities. This further suggests reallocation of enforcement budget from fuel and vehicles maintenances to recruitments of more WLES and possibly investing in a precise, innovative and cost-effective patrol. Management of vehicle-routes could be done through application of vehicle-tracking-system; an experience that can be adopted from IGGR vehicles. The decision to reduce patrol-vehicles should take into account the cost of operating and maintaining them as a function of age and brand type as described before.

The efforts towards clearance of wildlife cases could equally be reduced to ensure pare to efficiency. **Table 5** shows that an average of 90 man-days per month is quite enough for prosecution of wildlife cases registered in different courts from SENAPA. On the other hand, the frequencies of WLES to attend the court per month can be reduced by 13.9% in SENAPA and 20% in IGGR. This can be possible through close monitoring of cases and collaboration between PAs, police and judiciary. This finding supports the argument of other researchers such as [15] who emphasized the importance of coordination and collaborations between PAs authorities and other legal system to undertake effective and efficient proceedings and ultimately judgement. Close collaboration may also reduce many potential transaction costs along the chains, corruptions and possibilities of case distortions. These challenges have often been reported by many protected areas managers and cited by different researchers such as [34] [35].

3.4.2. Factors for Inefficiencies in the Wildlife Law Enforcement

Estimated monthly technical, allocative and cost inefficiencies score for the year 2012 under both model specifications were regressed separately with the corresponding rest-days (days) and incentives (TZS). Only these variables were used because variation of other socio-economic data like age, experience and education level which were believed to influence efficiency [46] had to be treated annually and its corresponding possible dependent variable which might be annual estimated efficiency of wildlife law enforcement were few (only three from three DMUs for three years), therefore difficulty to justify any outcome. The reason for using monthly explanatory variables of year 2012, was the difficulties for the respondents to recall past years information. Rest-days and incentives from IWMA were constant throughout the year, resulting to multicollinearity, hence not included in the model. Similarly, 100% technical efficiency under BCC model assumptions in all DMUs resulted to unqualified censored dependent variables. The regression results of **Table 6**, indicates that explanatory variables explain about 1.9% to 45%, and 12.3% to 46%, of the variation in efficiencies scores under CRS and VRS assumption respectively. This suggests that, the model fits relatively well with VRS estimates than CRS. Possibly, higher model fitness could have been attained if other socio-economic factors were included in the model.

3.4.3. Rest-Days

The mean numbers of days offered per person per month for resting were 3, 8 and 15 days in SENAPA, IGGR and IWMA respectively. A day was estimated to correspond 8 to 12 working hours. **Table 6** shows that, with BCC model assumption, days given for the WLES to rest (rest-days) had significant negative influence on allocative efficiency and economic efficiency with similar coefficient of 0.041 in SENAPA at 5% level of significance. This implies that increase in rest time by one day will decrease economic efficiency by 4.1%. Apparently, increase number of resting days means reducing labor force in the operation which will encourage vehicle intensive patrols, leading to higher fuel and maintenance costs. Vehicle patrols may equally reduce anti-poaching effectiveness by

Table 6. Factors for inefficiency of wildlife law enforcement in each DMU.

DMU	Variable	Constant Return to Scale			Variable Return to Scale		
		TE	AE	CE	TE	AE	CE
SENAPA	Constant	−0.29 (0.76)	0.94** (0.32)	0.18 (0.45)	NA	0.83*** (0.16)	0.83*** (0.16)
	Rest-days	−0.001 (0.06)	−0.036 (0.03)	−0.026 (0.04)	NA	−0.041** (0.015)	−0.041** (0.015)
	Incentives	5.20e−07 (2.21e−06)	−2.2e−07 (9.66e−07)	2.37e−07 (1.37e−06)	NA	−3.38e−07 (4.91e−07)	−3.38e−07 (4.91e−07)
	LL-value	−0.907	8.15	4.84	NA	15.7	15.7
IGGR	Constant	2.95* (1.37)	1.77 (1.07)	2.77* (1.28)	NA	1.36 (0.30)	1.36 (0.30)
	Rest-days	−0.272 (0.16)	−0.133 (0.12)	−0.262* (0.15)	NA	−0.392 (0.03)	−0.392 (0.03)
	Incentives	2.75e−06 (1.9e−06)	5.35e−07 (8.71e−07)	1.29e−06 (1.04e−06)	NA	1.36e−07 (2.36e−07)	1.36e−07 (2.36e−07)
	LL-value	−3.87	−0.25	−1.79	NA	12.31	12.31

Note: *, ** and *** represents 10%, 5% and 1% significance level respectively, LL = Log likelihood, in brackets are standard error, NA = not applicable, TE = Technical Efficiency, AE = Allocative Efficiency, CE = Cost Efficiency.

minimizing probability of detection [35] [47]. Reducing rest days may not be a feasible option either, as it may results to staff exhaustion leading to ineffective performance. Given the importance of resting time in law enforcement particularly anti-poaching patrols, it is necessary to increase the number of labors by employing more staffs. It is only when enough WLES are recruited, rest time can be increased to enhance efficiency. Increased resting time is reported by 97% of respondents in SENAPA as the most critical for their welfare and work performance.

3.4.4. Incentives

Economic efficiency of the wildlife law enforcement in DMUs studied was not influenced by incentives because none of the coefficients of the incentive variable was significant as indicated in Table 6. The findings are consistent with that of [48] who argues that bonuses and rewards paid to wildlife law enforcement staff in MBOMIPA (*Matumizi bora yamalihai Idodina Pawaga*) WMA had insignificant influence on the effectiveness and efficiency of wildlife law enforcement. Therefore, DMU's decision to terminate the reward scheme may be optimum decision in this case, as the resources may be redirected to other needs, such as equipment and maintenances. Otherwise, rewards schemes should be reviewed so that it can significantly act as incentives and enhancing efficiency. The latter suggestion is in line with the responses of interviewer who claims less incentives and some of them they were not been reviewed for long time, for example, rewards obtained from apprehending poachers and destroying of snares in SENAPA was TZS 10,000 per poacher apprehended and TZS 1000 per wire snare confiscated respectively. These rewards were set fifteen years ago and not reviewed to the time of this study.

4. Conclusion and Recommendation

Wildlife law enforcement in studied DMUs was economically inefficient with relatively more inefficiency under CCR than BCC model assumption. The mean economic efficiency estimates justify that with VRS assumption, wildlife law enforcement in IWMA was less economically inefficient, than IGGR and SENAPA. This may be due to sense of ownership and responsibility developed through community-based wildlife management, which resulted in to decrease in usage of law enforcement inputs and therefore costs. The slacks evaluation suggests decreasing in number of inputs in all DMUs including fuel and man-days for WLES attending the court of law for witnessing. Others are number of patrol vehicles and man-days for prosecutions in SENAPA, and ration in IGGR and IWMA. However, because of multi-tasked responsibilities assigned to limited number of WLES, it was noted to be feasible for PAs to increase number of staffs by recruiting new rangers, more to SENAPA than IGGR and IWMA. This will equally offset the negative impact of increasing rest-days on economic efficiency observed in SENAPA.

It is recommended that the PAs to invest in activities directed to clearance of wildlife cases by recruiting public prosecutors with wildlife management and/or forensics knowledge and to enhance monitoring of wildlife cases sent to the police and courts. It is further important to strengthen the work-relationships between actors in the chain of wildlife law enforcement operations, particularly police and judiciary to enhance efficient management of cases. To ensure proper allocation of inputs, we recommend training to wildlife law enforcement managers on optimal resource management strategies including cost-conscious planning. Active participation of local communities in management of wildlife is strongly suggested to SENAPA and IGGR, since it attributes to lower the input usage and sharing of law enforcement costs.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Watson, J.E.M., Dudley, N., Segan, D.B. and Hockings, M. (2014) The Performance and Potential of Protected Areas. *Nature*, **515**, 67-73. https://doi.org/10.1038/nature13947

[2] Rowcliffe, J.M., de Merode, E. and Cowlishaw, G. (2004) Do Wildlife Laws Work? Species Protection and the Application of a Prey Choice Model to Poaching Decisions. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, **271**, 2631-2636. https://doi.org/10.1098/rspb.2004.2915

[3] Risdianto, D., *et al.* (2016) Examining the Shifting Patterns of Poaching from a Long-Term Law Enforcement Intervention in Sumatra. *Biological Conservation*, **204**, 306-312. https://doi.org/10.1016/j.biocon.2016.10.029

[4] Keane, A., Jones, J.P.G., Edwards-Jones, G. and Milner-Gulland, E.J. (2008) The Sleeping Policeman: Understanding Issues of Enforcement and Compliance in Conservation. *Animal Conservation*, **11**, 75-82. https://doi.org/10.1111/j.1469-1795.2008.00170.x

[5] Knapp, E.J. (2012) Why Poaching Pays: A Summary of Risks and Benefits Illegal Hunters Face in Western Serengeti, Tanzania. *Tropical Conservation Science*, **5**, 434-445. https://doi.org/10.1177/194008291200500403

[6] Jachmann, H. (2008) Monitoring Law-Enforcement Performance in Nine Protected Areas in Ghana. *Biological Conservation*, **141**, 89-99. https://doi.org/10.1016/j.biocon.2007.09.012

[7] Robinson, E.J.Z., Kumar, A.M. and Albers, H.J. (2010) Protecting Developing Countries' Forests: Enforcement in Theory and Practice. *Journal of Natural Resources Policy Research*, **2**, 25-38. https://doi.org/10.1080/19390450903350820

[8] Thiault, L., *et al.* (2020) Predicting Poaching Risk in Marine Protected Areas for Improved Patrol Efficiency. *Journal of Environmental Management*, **254**, Article ID: 109808. https://doi.org/10.1016/j.jenvman.2019.109808

[9] Kideghesho, J.R. (2016) Reversing the Trend of Wildlife Crime in Tanzania: Challenges and Opportunities. *Biodiversity and Conservation*, **25**, 427-449. https://doi.org/10.1007/s10531-016-1069-y

[10] Börner, J., Wunder, S., Wertz-Kanounnikoff, S., Hyman, G. and Nascimento, N. (2014) Forest Law Enforcement in the Brazilian Amazon: Costs and Income Effects. Glob. *Global Environmental Change*, **29**, 294-305. https://doi.org/10.1016/j.gloenvcha.2014.04.021

[11] Kija, H.K., *et al.* (2020) Spatio-Temporal Changes in Wildlife Habitat Quality in the Greater Serengeti Ecosystem. *Sustainability*, **12**, Article 2440. https://doi.org/10.3390/su12062440

[12] Dhanjal-Adams, K.L., Mustin, K., Possingham, H.P. and Fuller, R.A. (2016) Optimizing Disturbance Management for Wildlife Protection: The Enforcement Allocation Problem. *Journal of Applied Ecology*, **53**, 1215-1224. https://doi.org/10.1111/1365-2664.12606

[13] Plumptre, A.J., *et al.* (2014) Efficiently Targeting Resources to Deter Illegal Activities in Protected Areas. *Journal of Applied Ecology*, **51**, 714-725. https://doi.org/10.1111/1365-2664.12227

[14] Moreto, W.D. and Matusiak, M.C. (2016) "We Fight against Wrong Doers": Law Enforcement Rangers' Roles, Responsibilities, and Patrol Operations in Uganda. *Deviant Behavior*, **38**, 426-477. https://doi.org/10.1080/01639625.2016.1197015

[15] Arias, A., Pressey, R.L., Jones, R.E., Álvarez-Romero, J.G. and Cinner, J.E. (2016)

Optimizing Enforcement and Compliance in Offshore Marine Protected Areas: A Case Study from Cocos Island, Costa Rica. *Oryx*, **50**, 18-26. https://doi.org/10.1017/S0030605314000337

[16] D'udine, F.A.C., Henson, D.W. and Malpas, R.C. (2016) Wildlife Law Enforcement in Sub-Saharan African Protected Areas: A Review of Best Practices. International Union for Conservation of Nature. https://doi.org/10.2305/IUCN.CH.2016.SSC-OP.58.en

[17] Gok, M.S. and Sezen, B. (2011) Analyzing the Efficiencies of Hospitals: An Application of Data Envelopment Analysis. *Journal of Global Strategic Management*, **5**, 137-146. https://doi.org/10.20460/JGSM.2011515804

[18] Hunninck, L., May, R., Jackson, C.R., Palme, R., Røskaft, E. and Sheriff, M.J. (2020) Consequences of Climate-Induced Vegetation Changes Exceed Those of Human Disturbance for Wild Impala in the Serengeti Ecosystem. *Conservation Physiology*, **8**, coz117. https://doi.org/10.1093/conphys/coz117

[19] Bevanger, K. (2018) Global Biodiversity Threats and Development Trends. Apple Academic Press, Burlington. https://doi.org/10.1201/9780429487743-1

[20] Charnes, A., Cooper, W.W. and Rhodes, E. (1978) Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, **2**, 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

[21] Mohammadi, A., Rafiee, S., Mohtasebi, S.S., Mousavi Avval, S.H. and Rafiee, H. (2011) Energy Efficiency Improvement and Input Cost Saving in Kiwifruit Production Using Data Envelopment Analysis Approach. *Renewable Energy*, **36**, 2573-2579. https://doi.org/10.1016/j.renene.2010.10.036

[22] Zhou, H., Yang, Y., Chen, Y. and Zhu, J. (2018) Data Envelopment Analysis Application in Sustainability: The Origins, Development and Future Directions. *European Journal of Operational Research*, **264**, 1-16. https://doi.org/10.1016/j.ejor.2017.06.023

[23] Hernandez-Sancho, F., Picazo-Tadeo, A. and Reig-Martinez, E. (2000) Efficiency and Environmental Regulation. *Environmental and Resource Economics*, **5**, 365-378. https://doi.org/10.1023/A:1008359714729

[24] Dyckho, H. and Allen, K. (2001) Measuring Ecological Efficiency with Data Envelopment Analysis (DEA). *European Journal of Operational Research*, **132**, 312-325.

[25] Bosetti, V. and Locatelli, G. (2006) A Data Envelopment Analysis Approach to the Assessment of Natural Parks' Economic Efficiency and Sustainability. The Case of Italian National Parks. *Sustainable Development*, **14**, 277-286. https://doi.org/10.1002/sd.288

[26] EWURA (Energy and Water Utilities Regulatory Authority of Tanzania) (2013) Public Notice on Indicative and Cap Petroleum Products Prices in the Country. Ministry of Energy and Minerals of Tanzania, 2013. https://shorturl.at/qEX28

[27] Emerton, L. (2000) Economic Incentives for Community Nature Conservation. IUCN-The World Conservation Union Eastern Africa Regional Office and Economics Unit.

[28] Ozcan, Y.A. (2008) Health Care Benchmarking and Performance Evaluation: An Assessment Using Data Envelopment Analysis (DEA). Springer, New York.

[29] Coelli, T. (2002) A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program. Centre for Efficiency and Productivity Analysis, Department of Econometrics, University of New England, Australia.

[30] Alam, F. (2011) Measuring Technical, Allocative and Cost Efficiency of Pangas

(*Pangasius hypophthalmus*: Sauvage 1878) Fish Farmers of Bangladesh: Pangas Fish Production Efficiency in Bangladesh. *Aquaculture Research*, **42**, 1487-1500. https://doi.org/10.1111/j.1365-2109.2010.02741.x

[31] Farrell, M.J. (1957) The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A*, **120**, 253-290. https://doi.org/10.2307/2343100

[32] Coelli, T., Rahman, S. and Thirtle, C. (2002) Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A Non-Parametric Approach. *Journal of Agricultural Economics*, **53**, 607-626. https://doi.org/10.1111/j.1477-9552.2002.tb00040.x

[33] Banker, R.D., Charnes, A. and Cooper, W.W. (1984) Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, **30**, 1031-1142. https://doi.org/10.1287/mnsc.30.9.1078

[34] Salum, J., Eustace, A., Malata, P.F. and Mbangwa, O.F. (2018) Wildlife Crime Promoted by Weak Governance. *African Journal of Ecology*, **56**, 101-108. https://doi.org/10.1111/aje.12424

[35] Thirgood, S., *et al.* (2008) Who Pays for Conservation? Current and Future Financing Scenarios for the Serengeti Ecosystem. In: Sinclair, A.R.E., Packer, C. and Mduma, S.A.R., Eds., *Serengeti III: Human Impacts on Ecosystem Dynamics*, University of Chicago Press, Chicago, 443-470. https://doi.org/10.7208/chicago/9780226760353.003.0015

[36] Sauer, J. and Abdallah, J.M. (2007) Forest Diversity, Tobacco Production and Resource Management in Tanzania. *Forest Policy and Economics*, **9**, 421-439. https://doi.org/10.1016/j.forpol.2005.10.007

[37] Sezen, B. and Gok, M.S. (2011) Analyzing the Efficiencies of Hospitals: An Application of Data Envelopment Analysis. *Journal of Global Strategic Management*, **5**, 137-146. https://doi.org/10.20460/JGSM.2011515804

[38] Fang, F., *et al.* (2017) Predicting Poaching for Wildlife Protection. *IBM Journal of Research and Development*, **61**, 3:1-3:12. https://doi.org/10.1147/JRD.2017.2713584

[39] Yin, R.S. (2000) Alternative Measurements of Productive Efficiency in the Global Bleached Softwood Pulp Sector. *Forest Science*, **46**, 558-569.

[40] Sun, S. (2002) Measuring the Relative Efficiency of Police Precincts Using Data Envelopment Analysis. *Socio-Economic Planning Sciences*, **36**, 51-71. https://doi.org/10.1016/S0038-0121(01)00010-6

[41] Atuo, F.A., Fu, J., Connell, T.J.O., Agida, A. and Agaldo, J.A. (2020) Coupling Law Enforcement and Community-Based Regulations in Support of Compliance with Biodiversity Conservation Regulations. *Environmental Conservation*, **47**, 104-112. https://doi.org/10.1017/S0376892920000107

[42] Lund, S. (2002) Community Participation in Natural Resource Management Projects. *The Journal of Transdisciplinary Environmental Studies*, **1**, 1-17.

[43] Moreto, W.D., Brunson, R.K. and Braga, A.A. (2017) Anything We Do, We Have to Include the Communities': Law Enforcement Rangers' Attitudes towards and Experiences of Community-Ranger Relations in Wildlife Protected Areas in Uganda. *The British Journal of Criminology*, **57**, 924-944. https://doi.org/10.1093/bjc/azw032

[44] Kao, C. (1994) Efficiency Improvement in Data Envelopment Analysis. *European Journal of Operational Research*, **73**, 487-494. https://doi.org/10.1016/0377-2217(94)90243-7

[45] Rija, A. and Kideghesho, J. (2020) Poachers' Strategies to Surmount Anti-Poaching Efforts in Western Serengeti, Tanzania. In: Durrant, J.O., *et al.* Eds., *Protected Areas in Northern Tanzania*, Springer, Cham, 91-112.

https://doi.org/10.1007/978-3-030-43302-4_7

[46] Msuya, E. and Ashimogo, G. (2005) Estimation of Technical Efficiency in Tanzanian Sugarcane Production: A Case Study of Mtibwa Sugar Estate Outgrowers Scheme. https://mpra.ub.uni-muenchen.de/3747/

[47] Hilborn, R., *et al*. (2006) Effective Enforcement in a Conservation Area. *Science*, **314**, 1266. https://doi.org/10.1126/science.1132780

[48] Ford, A. (2005) An Evaluation of Wildlife Monitoring and Anti-Poaching Activities. Master's Thesis, University of London, London.