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Recreational value and optimal pricing of national parks: lessons from Maasai Mara in Kenya

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ABSTRACT

This paper estimates the recreational value and optimal pricing for recreation services in the Maasai Mara National Park in Kenya. To achieve this objective, data from 323 Park visitors were collected. Single-site individual travel cost method (ITCM) using count data models [zero truncated Poisson (ZTP), zero truncated negative binomial (ZTNB), negative binomial with endogenous stratification (NBSTRAT), and Poisson with endogenous stratification (PSTRAT)] was applied. Results show a consumer surplus of US$ 115 per visitor per day, which translates to a Park recreational value of is US$ 73.076 million per year. The optimal conservation fee that would maximize revenue for the Park was estimated at US$ 86.90 per day, a value which is less than the consumer surplus. To maximize revenue, the Park managers can therefore hike the price to capture some consumer surplus or invest in substitute facilities to increase expenditure at the site (onsite costs). It's also important to note that the value estimated in this study is for recreation only. There are other ecosystem services (provisioning, regulating, cultural and supporting) which are produced in the Park. These should also be captured and paid for, so as to avail more funds for conservation and production of more ecosystem services.

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1. Introduction

Increasingly, people are attaching more importance to leisure time and recreation, thus increasing the demand and value of public recreational resources. National parks and green spaces are examples of public recreational resources where people relax for they provide tourists and natives with many recreational opportunities, sightseeing and picnicking among others (Tang 2009). Globally, National Parks are protected areas for the conservation of extraordinary landscape and wildlife for posterity and also a symbol of national pride (Schägner et al. 2016). They are created, to protect the ecological integrity of one or more ecosystems for present and future generations; to exclude exploitation or occupation detrimental to the purposes of designation of the area; and provide a foundation for spiritual, scientific, educational, recreational, and visitor opportunities, all of which must be environmentally and culturally compatible. Parks therefore contribute to reduced loss of biodiversity, maintain beauty of landscapes and supply of ecosystem services (Muhumuza and Balkwill 2013). Despite these benefits, the financial resources and political support for nature conservation are limited, and halting ecosystem degradation remains a great challenge.

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The value of nature recreation and its economic opportunities can be used as a strong argument in favour of allocating financial resources towards nature conservation at different spatial scales (Balmford et al. 2015). For instance, nature recreation and tourism present a great economic value and an opportunity for rural economic development by generating income and employment through visitors' expenditures. The incomes generated from various recreation and tourism activities can boost Park conservation efforts and increase the production of ecosystem services. In Kenya, wildlife resources contribute a substantial proportion of total tourism earnings, since most visitors come first and foremost to view wildlife in the Parks. With 65 national parks and reserves spread across the country, Kenya hosts some of the most ancient, fragile, and diverse wildlife species on earth. These Parks and reserves produce a number of ecosystem services viz. provisioning, regulating, supporting and cultural services. However, most parks are not accorded the necessary attention in terms of financing and conservation and, being public utilities, their values may be partially appreciated. Recreational services form a proportion of the ecosystem services from the Parks, but due to the ease of collecting revenue from recreation, financing of Park conservation in Kenya is mainly from conservation or park fees charged to tourists at the gate. There are other sources which include government subvention, support from development partners, endowment fund, and other fund raising initiatives, all of which contribute limited funds for Park conservation. Therefore, recreational services contribute the largest proportion of funds for supporting conservation efforts, which in turn produce other ecosystems services. Due to limited funds from the other park ecosystem services, Park managers are forced to maximize revenues from the recreational services collections by segregating and charging Park conservation fees based on various experiences and recreation facilities offered in individual Parks.

Despite this significance as a source of revenue for conservation, the recreational value of most Parks in the country is poorly understood. The same could be said of the value of other ecosystems services provided by the parks. If these values were known, clear management decisions could be made on whether to conserve or convert the Parks to other uses. Such information could also assist in determining the contribution of all the ecosystem services in the total economic value of the Park and assist local governments and park officials to make efficient budget allocations. For instance, Park managers could make decisions on how much to invest on the recreation facilities and maintenance of the Park or how much to spend on amenity improvement (Sohngen 2000).

One such Park that would benefit from valuation of its ecosystem services is the Maasai Mara National Park (MMNP) in South Western Kenya. This Park covers an area of 1510 square kilometers (583 square miles). It's a major draw for visitors in Kenya because of its unparralled landscape and the Big five (Elephant, Buffalo, Rhino, Lion and Giraffe) attraction. Each year the Park plays host to the world's greatest natural spectacle, the Great Wildebeest Migration from the Serengeti in Tanzania – considered 'the 8th wonder of the 7 wonders of the world.' The national park is also Africa's greatest wildlife Park and the fourth preferred tourist destination of the world.

Despite its ecological and economic importance, the Park lacks an adopted management plan leading to outdated management infrastructure, equipment and systems. The Park has also been experiencing steep declines in wildlife numbers e.g. 50% decline in lions over the last 20 years, 75% decline in wildebeest since 1970s, and extinction of Roan Antelope and Greater Kudu. The Park is also experiencing external drivers and pressures which have reduced the ecosystem goods and services it provides. These include deterioration of the Mara River due to encroachment of agricultural producers on protected areas, and actual & planned infrastructural development. As a result, there has been deteriorating visitor experience on the services offered by the Park. It's against this background that we this study to estimate the recreational value of Maasai Mara National Park and determine an appropriate optimal entrance fee (price) for the conservation and development of the Park.

2. Recreational value using travel cost method

In absence of direct market valuation techniques, non-market valuation methods of estimating the monetary value of public goods and services including national parks, such as travel cost method, have widely been used. Non-market valuation techniques are broadly categorized into revealed preference (RP) methods and stated preference (SP) methods (Boardman et al. 2006). Revealed preference methods generally focus on how to value non-marketed goods and services based on observed behavior from individuals or consumers of such goods and services. Basing valuation on observed behavior is important because individuals reveal their preferences without having to be probed. This minimizes bias associated with studies of this nature. The common revealed preference methods used for non-market valuation include hedonic pricing, travel cost method (TCM) and market pricing methods (Pearce and Moran 1994).

Stated preference methods use surveys to elicit information from individuals pertaining to costs and benefits. Stated preference methods are mostly used to value some public goods which have very poor or no market proxies. For this reason, stated preference techniques make use of questionnaires to elicit information since respondents are not actually required to pay for their valuations of goods and services (Boardman et al. 2006). Over the past years, most economists have fronted the use of TCM as the best valuation tool of recreational sites and events since the technique relies on the revealed preferences of visitors (Bateman 1993; Day 2000; Anderson 2010). As a consequence, this technique has been widely used by environmental, leisure, recreation, tourism and cultural economists and researchers in the past decades to value varying recreational activities (Nde 2011). The method is commonly used to estimate the consumer surplus associated with travelling to the recreational sites such as parks, beaches and heritage sites (Hailu, Boxall, and Mcfarlane 2005). As an indirect method, it regards travel expenditure spent during the trip as a substitute price travelers pay for sites recreation or the service (Liston-Heyes and Heyes 1999). Practitioners in this area have either used the zonal travel cost method (ZTCM) – the oldest form of the travel cost method, or individual travel cost method (ITCM).

In ZTCM, visitors are grouped into different categories or zones based on certain similar characteristics such as geographical are of origin. It has been employed in numerous studies (e.g. Clawson and Knetsch 1966; Hanley 1989; Navrud and Mungatana 1994; Becker et al. 2005). Proponents of the ZTCM argue that the method warrants less intensive data gathering procedures, possesses the possibility to adjust frequency of visitations from zones with varying populations and that zones further from the site typically have fewer visitors, thereby ensuring the realization of the inverse price-quantity demand relationship (Bergstrom and Cordell 1991). However, the ZTCM has been criticized for its vagueness as a non-market valuation tool (Bell and Leeworthy 1990). For this reason, most researchers and economists have now turned to the ITCM. According to Vicente and de Frutos (2010), ITCM is deemed advantageous in that it follows conventional economic methods and also relies on people's actual behaviour. In addition, ITCM has become more popular in the last two decades following advances in information technology and the added advantage of being able to include socio-economic characteristics such as age, income, and education to help explain individual as opposed to zonal visitation (Blackwell 2007). For these reasons, it has been used in several studies (see Sarker and Surry 1998; Sohngen, Lichtkoppler, and Bielen 1999; Blackwell 2007; Anderson 2010).

There are two most widely used travel cost models in the ITCM; single-site model and random utility model (RUM). The RUM provides an individual with a full set of alternative sites to choose. It allows for different types of tastes in a great deal of ways (Murdock 2006). RUM is widely applied among many alternative sites with different quality characteristics i.e. multiple-sites (Parsons 2003). The method envisions that site qualities form an index to be associated with each good (a visit to a site). The method models how a representative consumer chooses from a set of discrete sites each of which embodies a vector of attributes or qualities (Pendleton and Mendelsohn 2000).

In the single-site model, the underlying assumption is that individuals make trips only to a single destination or site. The specifications of the models are even more diversified. Salanié (2006) states that travel cost models are generally of three types namely: discrete choice models which allow the modeling of recreational choices, count data models that estimate the demand functions of visits and systems of equations. For instance, Sarker and Surry (1998) and Bin et al. (2005) use count data models while Song, Lupi, and Kaplowitz (2010) use random utility maximization (RUM) models. The application of any of these models is contingent on the kind of data that is to be used for analysis Salanié (2006). In this study, we only consider one recreation site, thus single-site model would be an appropriate choice. Single-site model is often used in circumstances when one is interested in access value at only one site and the number of substitute sites is not large. This model is usually applied in estimating one targeted site or two comparable places. The access value is the total consumer surplus under the single-site demand function which is the difference between a person's total willingness to pay for trips and the actual trip cost incurred over a certain amount of time. The cost here indicates not only the admission fee, but also the expenditure for travelling to the site and time cost (Tang 2009).

3. Survey implementation and data collection

This study involved an onsite survey in the Maasai Mara National Park which was carried out between April 2013 and July 2014. The survey tool was a structured questionnaire which was administered with a target of 400 visitors to the Park using simple random sampling technique. Before the questionnaire was administered, pretesting was done and minor adjustments were made before administering full onsite survey. The questionnaire was divided into four sections: introduction; questions about costs and charges; considering other parks; and, general information. It took about 30 min to complete the questionnaire and most of the visitors opted that the questions be read to them, though some opted to read and answer the questions themselves. Reading the questions to the respondents was the most practical means of administering the questionnaires since succinct explanations regarding the questions could be made to the visitors. This approach also tends to reduce possible bias that might result from the wrong interpretation of the questions by the respondents. In total, 368 questionnaires were collected with seventeen of them being local (Kenyan) tourists. A total of 45 questionnaires had incomplete information or could not be used due to various reasons. In the end, 323 questionnaires were used for the analysis.

Table 1 gives statistics of visits and the pleasure from visits from the sampled questionnaires. The concern for wildlife ranged from 1 (lowest) to 7 (highest). The summary statistics indicate a mean of 6.23 showing that overall, tourists were concerned with wildlife. The number of visits to African parks ranged from 1 to 18, with a mean of 2.03 visits per person per year. Before travelling to Africa, 99% of the tourists indicated that they had been aware of the Maasai Mara National Park, whilst 55% had been aware of Serengeti National Park (neighboring Park in Tanzania). In addition, 73% indicated that the trip to Mara was part of a tour package. Further, 47% of the tourists indicated that they had visited or intended to visit other countries besides Kenya. The respondents visited Mara as individuals or in groups of up to 13 people. On average, the number of visitors per group was 2.68 persons. Figure 1 illustrates the number visitors against the number of days they stayed in the Mara.

From Figure 1, there was non-zero response on the number of days that visitors had stayed in the Mara. Most (168) of the visitors had stayed in the Mara for 2 days; 89 had stayed for three days, while 35 had stayed for 4 days. All the other days had reported seven or less visitors. From 2 days to 16 days, the number of visitors and number of days showed a decaying relationship function declining from 168 visitors who stayed for 2 days to 1 visitor who stayed for 16 days.

Table 1. Visits and utility from visits.

Statistic	Mean	Std. Dev	Min.	Max.
Wildlife concern	6.23	1.02	2	7
Visit Africa parks	2.03	2.54	1	18
Aware of Mara	0.99	0.11	0	1
Aware of Serengeti	0.55	0.50	0	1
Mara as a package	0.74	0.44	0	1
Visitors per group	2.68	1.87	1	13
Visit other countries	0.47	0.81	0	12

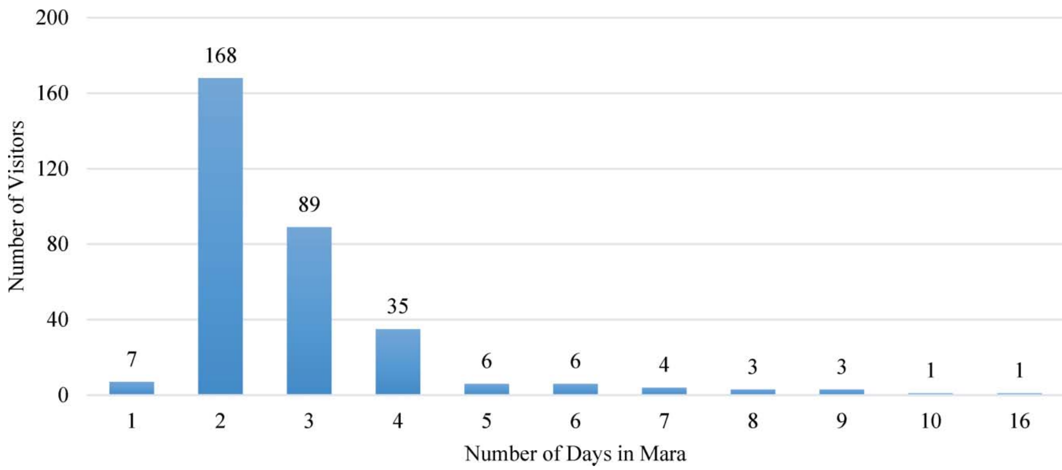

Figure 1. Number of visitors and days spent in Mara.

The survey instrument had questions on the total round-trip cost to Kenya from their origin, and the total cost of the trip including travel, lodging, meals and entrance free. There were also questions on the number of days spent in Mara, in Kenya and in other countries. This information together with the enjoyment (utility) experienced during the visit to these different localities were used in computation of total travel cost.

The number of days the tourists spent in Kenya ranged from 2 to 35 days with a mean of 8.15, while the number of days to be spent in the Park ranged from 1 to 16 with a mean of 2.85 days. The 47% of the visitors who had visited other countries had been there for an average of 5.28 days. The utility or satisfaction from different areas visited was estimated using visitors' subjective estimation of the enjoyment or utility one derived from the different localities. On average, the tourists had experienced a 52% utility in the Mara, 36% in other areas in Kenya, and 12% in other countries outside Kenya. Finally, the mean round trip cost to Kenya was US$ 1812, while the mean total travel cost including roundtrip cost, meals, lodging etc. was US$ 3683. Using these costs and other variables shown in Table 2, we computed the round-trip costs, onsite costs and opportunity cost for visiting Mara.

4. Computation of total travel cost

The total travel cost (TTC_T) for each visitor was computed by summing the roundtrip travel cost $(RTTC_T)$, onsite expenses (OSC_T), and the opportunity cost (OC_T). For most of the visitors, the travel itinerary comprised of multiple sites and their total travel cost (TTC_T) was a package for all different destinations, including Mara. The total travel cost (TTC_T) and total roundtrip travel cost $(RTTC_T)$ had been captured in the questionnaire. It was difficult to compute individual cost items

Table 2. Variables used in travel costs computation.

Statistic	Mean	Std. Dev
Total travel cost (US$)	3683.28	2167.91
Round-trip travel cost (US$)	1812.40	1152.28
Utility Mara (%)	0.52	0.20
Utility Kenya (%)	0.36	0.19
Utility outside Kenya (%)	0.12	0.16
Days in Kenya	8.15	4.69
Days in Mara	2.85	1.54
Days in other countries	5.28	8.23

e.g. accommodation and food costs for the individual visitors as the questionnaire was not framed to capture these costs separately. These costs items were therefore aggregated and captured under the component of onsite expenses (OSC_T). The Onsite expenses were calculated by deducting the roundtrip travel cost ($RTTC_T$) from total travel cost (TTC_T). It is Important to note that the total travel cost (TTC_T) and total roundtrip travel cost ($RTTC_T$) captured in the questionnaire include those of the respondent and any persons accompanying the respondent. From the information captured in the questionnaire, it was also possible to estimate the total opportunity cost of travel time (OC_T). Therefore, the decomposed total travel cost (TTC_T) was expressed as;

$$TTC_T = RTTC_T + OSC_T + OC_T \tag{1}$$

Using the same argument as in Equation (1), the total cost of travel to the Maasai Mara National Park also comprised of three parts: roundtrip total cost to Mara ($RTTC_M$); onsite expenses in the Mara (OSC_M) which consists of accommodation fee, access fee, and other expenses; and opportunity cost of travel time to Mara (OC_M). Note that opportunity cost of travel time could not be captured directly in the questionnaire, and had to be estimated. Onsite expenses for the Mara were calculated as the difference between the total travel cost to Mara (TTC_M) less the total roundtrip travel cost to Mara ($RTTC_M$). Therefore, the total travel cost to Mara (TTC_M) was expressed as;

$$TC_M = RTTC_M + OSC_M + OC_M. \tag{2}$$

The Park is not the only destination in the trip for most of visitors, i.e. these visitors have multiple purpose trips. The solution is therefore to get the travel cost allocation to the Park (TC_M) from the total travel cost (TTC_T) of the whole trip. Therefore, the roundtrip travel cost to Mara ($RTTC_M$), travel time opportunity cost to Mara (OC_M) and onsite costs in the Mara (OSC_M) were calculated based on the number of sites and days a visitor had visited and stayed or intended to visit and stay in each site, and then weighted based on the importance (utility) they attached to the Park as each directly revealed. The weights were the satisfactions (utilities) individual visitors enjoyed in different recreational areas; these being Mara, Kenya and outside Kenya. The total satisfaction for the three recreational areas was calibrated to sum up to 100%. These satisfaction proportions were used as the weights of enjoyment for the three sites.

Using this information, the roundtrip travel cost allocated to Mara ($RTTC_M$) was calculated by multiplying the roundtrip travel cost for the whole trip ($RTTC_T$) with the proportion of satisfaction (utility) a visitor allocated to Kenya (U_K) and the proportion of satisfaction (utility) a visitor allocated to Mara (U_M). Therefore, the roundtrip travel costs for all the days spent in Mara ($RTTC_M$) can be expressed as;

$$RTTC_M = RTTC_T * (U_K) * (U_M) \tag{3a}$$

One may also be interested in knowing the roundtrip travel cost for a single day in Mara ($RTTC_{MD}$), by dividing Equation (3a) and the number of days spent in the Mara as shown in Equation (3b).

$$RTTC_{MD} = \frac{RTTC_T * (U_K) * (U_M)}{D_M}, \tag{3b}$$

where U_K is the utility or satisfaction allocated to Kenya; U_M is the utility or satisfaction allocated to Mara; D_M are the total days spent in the Mara; while $RTTC_M$ and $RTTC_T$ are total roundtrip travel costs for Mara and roundtrip travel costs for the entire trip, respectively. The calculation of one day's onsite expenses in the Mara (OSC_{MD}) followed a similar argument as shown in Equation (3b) and can be expressed as

$$OSC_{MD} = \frac{(TTC_T - RTTC_T) * U_K * U_M}{D_M}. \tag{4}$$

Dividing the one day roundtrip costs $(RTTC_{MD})$ and one day onsite expenses (OSC_{MD}) by the number of visitors (n) in a group would give a day's roundtrip costs and a day's onsite expenses per person in the Mara.

Any recreation trip will consume time, part on traveling, and part on recreation. In the trip cost, time cost consists of the time spent in traveling to and from the site and time consumed on the site (Parsons 2003). If someone gives up his/her working time for traveling, the opportunity cost of time is the wage rate. Some studies include this opportunity cost of time as an additional travel cost (Martínez-Espiñeira and Amoako-Tuffour 2008), while others estimate time as a separate variable in the model (e.g. Loomis 2006). Still others (Ovaskainen, Mikkola, and Pouta 2001; Bhat 2003) do not include the opportunity cost of time either in the travel cost or as a separate variable in the model which could result in downward bias of consumer surplus. The underlying challenge in estimating the opportunity cost is to agree on the value allowed to time, and then to the lost opportunities.

According to Cesario (1976), the value of the time lost whilst traveling is set between a quarter and a half of an hourly wage rate as individuals may have flexible jobs and can substitute work time for leisure time at the margin. In literature, the rates range from zero (Bhat 2003); 0.2 (Nde 2011); 0.25 (Zawacki, Marsinko, and Bowker 2000); to 0.43 (Cesario 1976). In our study, we set a share equal to 1/3 (33%) of the hourly wage which is the most commonly used rate (Parsons 2003; Bujosa Bestard, and Riera Font 2009). In computing the opportunity cost of travel time to the Mara (OC_M), we assumed that all visitors to the Mara were gainfully employed.

To determine the average hourly wage rate of visitors, we assumed a 40 h work week which is typical of many world economies. This gives approximately 2080 work hours per year or 260 working days of 8 h each. Visitor incomes were recorded in 4 categories and for each visitor, we chose the midpoint of the stated range to represent his/her income. The visitor's annual income (m_A) was then divided by the 260 days to get the average daily wage rate (w_D) and then multiplied by 33% (0.33) which is the proportion of the wage allocated to travel time.

$$w_D = \frac{m_A}{260} \tag{5a}$$

The travel time comprises of two components i.e. the total time lost travelling (TT_L) and total time spend in recreation in the park. The total time spend in recreation is the number of days in Mara (D_M). The total time lost travelling (TT_L) is given by total travel time less the number of days in Mara $(T_D - D_M)$. The proportion of total time lost travelling allocated to Mara (TT_{LM}) is given by;

$$TT_{LM} = TT_L * U_K * U_M, \tag{5b}$$

where TT_{LM} is the proportion of total time lost travelling that is allocated to Mara. The other variables are as defined earlier. Therefore, the opportunity cost of one day spent in Mara is given by;

$$OC_{MD} = \frac{(TT_{LM} + D_M) * 0.33 * w_D}{D_M}. \tag{5c}$$

Dividing the a day's opportunity cost (OC_{MD}) by the number of visitors (n) in a group would give a day's opportunity cost per person in the Mara. Table 3 shows a summary of roundtrip travel

Table 3. Onsite, opportunity, round-trip and total travel costs per day in Mara.

Statistic	Mean	Std. Dev
Onsite cost	121.71	109.39
Opportunity cost	199.62	144.90
Round-trip travel cost	120.73	99.69
Total cost	442.07	256.67

costs, onsite costs, and opportunity costs to the Mara. These costs are estimated for a single day in Mara but are not expressed on per person basis. To express them on individual basis, the various costs need to be divided by the average number of visitors per group which is 2.68 people.

5. Estimating the recreational value of Mara park

5.1. Theoretical underpinnings of TCM

We use the consumer theory where an individual visitor i to a recreational site j who consumes two goods or services (i.e. non-marketed recreational goods and services (denoted as y_i) and all other private or marketed goods and services (denoted as x_i) but also faces a budgetary and time constraints (Sarker and Surry 1998). Also, assume that the prices of these two set of goods be p_y and p_x, respectively. The representative consumer can therefore spend his or her income (denoted as m_i) on the purchase of these two set of goods. Hence, the budget constraint of the individual visitor is given as:

$$m_i = wh_w = p_y y_i + p_x x_i \, , \tag{6}$$

m_i is the income level of the individual consumer i, w is the hourly wage rate and h_w is the total number of hours worked. The individual visitor also faces a time constraint as he or she must decide on how much time to spend on work and leisure (recreation). Similar to Equation (6) above, the time constraint can then be stated as;

$$T = h_w + h_l \tag{7}$$

where, T is the total time endowment of the consumer and h_l is time devoted to leisure (recreation). The quality of recreational sites is a key determinant of the visitor's choice of the site to visit. Therefore, if we denote the quality a recreational site as q_i, then the utility function of the representative recreation consumer can be written as;

$$U_{ij} = U(x_i, \; y_i, \; q_j). \tag{8}$$

Equation (8) is maximized subject to Equations (6) and (7), to obtain the ordinary or Marshallian demand functions for private goods and recreational goods as;

$$x_i = f(p_x, \; p_y, \; m_i, \; q_j) \tag{9a}$$
$$y_{ij} = g(p_x, \; p_y, \; m_i, \; q_j) \tag{9b}$$

Equations (9a) and (9b) represent the Marshallian demand functions of private goods and recreational goods, respectively. However, our focus is on Equation (9b) which is crucial in computing the consumer surplus (CS) per trip since it coefficients can be obtained econometrically. Note that it is difficult to measure the flow of the recreational services so as a consequence, the number of trips to, or number of days spent in the recreational site are used as surrogates (Sarker and Surry 1998).

5.2. Model specification

The demand for recreation in Maasai Mara National Park depends on a search process which results in individuals' utility maximization subject to budget constraints. Whether or not a visitor takes a trip to the Park depends upon the utility obtained from visiting the site. An individual evaluates whether the obtained utility from the recreational visit is worth the travel cost, which is a measure of travel cost for the trip and associated activities. In addition, the choice to visit Maasai Mara National Park depends on the perceived site quality, alternative sites, and complementing purposes available. Therefore, the demand of recreation in the Mara can be formulated as;

$$y_i = f(p_i, \boldsymbol{x_i}, \beta) + \varepsilon_i \quad \forall\ i = 1, \ldots,\ n, \tag{10}$$

where, y_i is the trip demanded by the individual to visit Maasai Mara National Park; p_i is the travel cost of the i^{th} individual associated with visiting the site. In travel cost model, the expenditure associated with recreational trips represents the price of recreation on that particular site; $\boldsymbol{x_i}$ is a vector of explanatory variables associated with the i^{th} individual; β is a vector of unknown parameters to be estimated, and ε_i is the error term. The non-negative integer nature of the data suggests using count data estimation techniques to obtain the recreational demand function, which have become the standard in estimating recreational demand models (Martínez-Espiñeira and Amoako-Tuffour 2008; Ovaskainen, Neuvonen, and Pouta 2012; Hynes and Greene 2013) following the theoretical underpinning discussed earlier. Count data models utilize data in which the observations are counted rather than ranked and the observations equally assume non-negative integer values (Parodi and Bottarelli 2006) as is the case with the days spent in Mara which is the dependent variable in this study.

The basic count data model is the Poisson, which according to Wackerly, Mendenhall, and Scheaffer (2008), Anderson (2010) and Parsons (2003), has the probability density distribution function is given by:

$$Prob(Y = y_i) = F_P = \frac{e^{(-\lambda_i)}\lambda^{y_i}}{y_i!}, \tag{11}$$

where, λ_i represents the conditional mean of y i.e. $[E(y_i|\boldsymbol{x})]$ which is y_i in Equation (10). Under a Poisson distribution, the underlying assumption is;

$$[E(y_i|\boldsymbol{x})] = \lambda_i = exp(\boldsymbol{x_i}, \beta), \tag{12a}$$

$$Var[(y|\boldsymbol{x})] = \lambda_i = exp(\boldsymbol{x_i}, \beta), \tag{12b}$$

that is, the mean and variance of the distribution are equal. This assumes equi-dispersion of the dependent variable in which case, the Poisson model would suffice for estimation. However, the dependent variable in the analysis is truncated at zero, since it consists the number of days that a visitor stayed in Maasai Mara National Park during the trip for which the data were collected. These data were collected for visitors already enjoying recreation in the Park which ranged from 1 to 16 days, so a zero response was not possible for the dependent variable. Failing to account for truncation yields biased and inconsistent estimates (Shaw 1988; Creel and Loomis 1990; Grogger and Carson 1991; Yen and Adamowicz 1993; Englin and Shonkwiler 1995). Therefore, equi-dispersion and truncation at zero requires a Poisson distribution which is truncated at zero for the count (y), which is given by;

$$\Pr[Y = y \mid Y > 0] = \frac{e^{-\lambda} - \lambda^{y}}{y!} \cdot \left[\frac{1}{1 - e^{-\lambda}}\right] \quad y = 1, \ldots, n \tag{13}$$

This assumption of equi-dispersion is rarely found in empirical studies (Carson 1991) especially in the presence of over-dispersion on a dependent variable. Chosing the negative binomial model allows for over-dispersion by introducing an unobserved heterogeneity for the i^{th} observation (Erdman, Jackson, and Sinko 2008). To correct for both truncation and over-dispersion the zero-truncated negative binomial distribution for the count (y) is appropriate, and its density is given by;

$$\Pr[Y = y \mid Y > 0] = \frac{\Gamma(y + \alpha^{-1})}{\Gamma(\alpha_i^{-1})\Gamma(y_i + 1)} (\alpha\lambda)^y (1 + \alpha\lambda)^{-(y_i + \alpha^{-1})} \left[\frac{1}{1 - (1 + \alpha\lambda)^{-\alpha^{-1}}}\right]. \tag{14}$$

Addressing the problem of over-dispersion and truncation with the zero-truncated negative binomial may not suffice for recreation demand data collected onsite as is the case in this study. This is because endogenous stratification must be accommodated within model estimation. In onsite surveys, it might be the case that the likelihood of sampling observations is dependent on a choice made by the subject of study which is in itself the dependent variable i.e. the likelihood of visitors being sampled is related positively to their number of trips to the site. Therefore, the bias under endogenous stratification is due to sampling according to a choice made by the respondents of how many times they visited the site rather than which site/s they visit (Shaw 1988; Hilbe and Martinez-Espineira 2005). Correcting for endogenous stratification is much more computationally demanding in the presence of over-dispersion.

If the assumption of equi-dispersion holds for onsite data sets, standard regression packages can be used. Shaw (1988) first considered a correction for endogenous stratification count data estimators by deriving a correction procedure for the Poisson model. A conventional Poisson regression model can be used to adjust for both truncation and endogenous stratification by using the transformed dependent variable $(y^* = y - 1)$ for equi-dispersed dependent variables (Haab and McConnell 2002; Loomis 2003). Adjusting the density of the Poisson distribution to correct for both zero truncation and endogenous stratification gives;

$$\Pr[Y = y \mid Y > 0] = \frac{e^{-\lambda} - \lambda^{y-1}}{(y-1)!} \qquad y = 1, \ldots, n \tag{15}$$

The rescaled log-likelihood function of this distribution is expressed as;

$$\begin{aligned} L(\boldsymbol{x\beta}; y_i) = {} & y_i \ln(\alpha) + (y_i - 1)\ln(\exp(\boldsymbol{x_i\beta})) - \left(y_i + {}^1/_\alpha\right)\ln(1 + \alpha(\exp(\boldsymbol{x_i\beta}))) - \ln\Gamma(y_i + 1) \\ & - \ln\Gamma\left({}^1/_\alpha\right) + ln\Gamma\left(y_i + {}^1/_\alpha\right) + \ln(y_i); \; y_i > 0 \end{aligned} \tag{16}$$

In cases where over-dispersion is significant, Englin and Shonkwiler (1995) extended the Shaw (1988) correction procedure to the negative binomial model. The density of their negative binomial distribution truncated at zero and adjusted for endogenous stratification is given by;

$$\Pr[Y = y \mid Y > 0] = y_i \; \frac{\Gamma\left(y_i + \alpha_i^{-1}\right)\alpha_i^{y_i}\lambda_i^{y_i - 1}[1 + \alpha_i\lambda_i]^{-(y_i + \alpha^{-1})}}{\Gamma(\alpha_i^{-1})\Gamma(y_i + 1)} \tag{17}$$

with

$$[E(y_i|x_i)] = \lambda_i + 1 + \alpha_i\lambda_i \tag{18a}$$

$$Var\left[(y|\boldsymbol{x})\right] = \lambda_i\left(1 + \alpha_i + \alpha_i\lambda_i + \alpha_i^2\lambda_i\right) \tag{18b}$$

where, Γ represents the gamma distribution and α_i denotes the over-dispersion parameter. Extending the model into a regression framework, we define by λ_i as a function of a vector $\boldsymbol{x}$ of regressor variables.

Given the basic functional form of count data models which is given as

$$\lambda_i = \exp(p, \boldsymbol{x}, \beta) \tag{20}$$

the conventional approach is to model expected latent demand, λi, as a semi-logarithmic function of price, i.e. travel cost, and other independent variables xj, such that;

$$\ln\lambda_i = \beta_0 + \beta_p TC_i + \sum_{j=1}^{J} \beta_j x_{ji} + \varepsilon_i \tag{21}$$

As observed by Cameron and Trivedi (1986), the estimation of the over-dispersion parameter, αi, has been challenge with most studies restricting it to a common value for all observations, such that $\alpha i = \alpha$. Englin and Shonkwiler (1995) used a less restrictive approach by specifying $\alpha i = \alpha_0/\lambda i$, whereas Martínez-Espiñeira and Amoako-Tuffour (2008) apply a more flexible approach by specifying αi as a function of visitor characteristics. For ease of estimation, the parameter $ln(\alpha i)$ rather than αi is estimated (Curtis and Stanley 2015) and defined as

$$\ln\,(\alpha i) = \gamma_0 + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \cdots \tag{22}$$

where z are variables measuring visitor characteristics. Hilbe and Martínez- Espiñeira (2005) developed a packaged routine (NBSTRAT) to facilitate the truncated negative binomial with endogenous stratification using STATA. The lnalpha is parameterized by the predictors entered within its parentheses. However, note that if the data are equi-dispersed but still truncated and endogenously stratified, this model is equivalent to running a Poisson with a transformed dependent variable $(y^* = y - 1)$. Hilbe (2005) also wrote a software application GNBSTRAT that parameterizes the negative binomial heterogeneity parameter as well as the standard parameter estimates of the negative binomial with endogenous stratification model. This allows researchers to understand the source of extra correlation, or over-dispersion, in the data (Loomis 2003). The empirical model used in this study took the form;

$$D_i = \beta_0 + \beta_p \ln TC_i + \beta_1 \ln OC_i + \beta_3 \ln Y_i + \beta_4 \ln A_i + \sum_{j=1}^{5} \beta_j \boldsymbol{x}_{\boldsymbol{ji}} + \varepsilon_i \tag{23}$$

where D is the number of days spent in Mara, TC is the rount-trip travel cost; OC are the onsite costs; while the vector $\boldsymbol{x_j}$ represents five other covariates, namely; income, age, gender, trips to Africa parks, utility derive in Mara, whether Mara trip was a package and, awareness of Serengeti National Park. The subscript i represents the individual, while j represents the covariate. Note that onsite costs i.e. cost of other goods or services accrued onsite (in the Park) but which confer different utilities from that of the Park itself were used as control for substitute goods. Lancaster (1966) and Becker (1965) developed the concept that the objects of choice are not the goods themselves, but the attributes possessed by those goods. Consumers use the attributes as input factors for a consumption technology that produces utility. For example, they combine time, travel, equipment, facilities, and the features of natural environments to produce outdoor experiences such as camping. Such is the case with onsite expenditures in the Park which may produce substitute utility to that of the Park. These costs need to be included separately in the model. Further, awareness of the Serengeti was used as a control for tastes and preferences of the visitors. The Mara and the Serengeti are in the same ecosystem and share the same animals. However, each of them offers experiences which may be preferable to different visitors. Therefore, a visitor who is aware of the Serengeti is more likely to make an informed choice when selecting to visit the Mara.

Estimation of the empirical model was done using four different models, viz., zero truncated Poisson model (ZTP), zero truncated negative binomial model (ZTNB), negative binomial with stratification (NBSRAT), and Poisson with stratification (PSTRAT). The choice of these models will be explained. All the models were maximized using the log likelihood function. After maximizing the models and getting the λ and y parameters, the consumer surplus or the access value of the Park can be estimated. The consumer surplus, which is the net benefit of a trip i.e. the difference between the value of a trip and the costs required to take that trip (Heberling and Tempelton 2009), is derived by integrating the trip demand function over the relevant price range according to Hellerstein and Mendelsohn (1993). It is expressed as

$$CS = \int_{p_0}^{p_c} \lambda_i dTC = \left| \frac{\lambda_i}{-\beta_p} \right|, \tag{24}$$

where βp is the coefficient on the travel cost variable; p_0 is the actual travel cost and p_c is the choke price. The visitor's CS per trip (or per visit) has more policy relevance and is expressed as $CS = -1/\beta_p$ implying that the mean trip denominator relates to all visitors, including those with zero trips demanded during the survey period (Curtis and Stanley 2015). The consumer surplus per person per visit is given by;

$$\frac{CS/person}{visit} = \frac{\left[\left(-1/\beta_p\right) * E(PD_i)\right]}{E(GS)} . \tag{25}$$

The numerator is the product of the reciprocal of travel cost coefficient and the predicted number of days a visitor is expected to stay during the visit (PD), which gives the estimate of the CS per group per visit. This is divided by the total group size (GS) to give the consumer surplus for primary destination visitors (Martinez-Espineira and Amoako-Tuffour 2008). The total consumer surplus for all visitors is given by;

$$TCS = \left| N.\left(\frac{\lambda_i}{-\beta_p}\right) \Big/ \lambda_i \right| = \left| \frac{N}{-\beta_p} \right| , \tag{26}$$

where TCS is the total consumer surplus, N is the total number of visitors to the park over the specified period, and $-\beta_p$ is the parameter estimate of the travel cost to the Park.

5.3. Recreational or access value of the Maasai Mara park

Table 4 presents the econometric estimation of trip demand function using four different models as stated earlier. These are zero truncated Poisson model (ZTP), zero truncated negative binomial model (ZTNB), negative binomial with stratification (NBSRAT), and Poisson with stratification (PSTRAT). In estimating the count data models, the basic model to start with is the Poisson. Since the data are truncated at zero, we first estimated the ZTP which takes care of the truncation. Due to the potential problem of over-dispersion, we also estimated ZTNB, to determine which of these models best fits the data. A cursory glance at the dependent variable (Days in Mara) shows are mean of 2.85 days and a standard deviation of 1.54 (variance of 2.37). This indicates that the mean and the variance are almost the same and over-dispersion may not hold. This is confirmed by the lnalpha statistic in ZTNB which is not significant. This being the case, we do not expect the coefficients of ZTP and ZTNB to vary as shown by the two model estimates. To choose the best fitting model we used other post-estimation statistics, in this case Akaike and Bayesian Information

Table 4. Model results.

	Number of days spent in the Mara			
Dependent variable	Model 1 ZTP	Model 2 ZTNB	Model 3 NBSTRAT	Model 4 PSTRAT
Log RTTC	−0.266**	−0.266**	−0.324***	−0.324***
	(−2.63)	(−2.63)	(−2.90)	(−2.90)
Log onsite cost	−0.103**	−0.103**	−0.126***	−0.126***
	(−2.70)	(−2.70)	(−2.99)	(−3.00)
Log Income	0.217**	0.217**	0.264***	0.264***
	(2.67)	(2.67)	(2.95)	(2.95)
Log Age	0.122	0.122	0.150	0.150
	(1.15)	(1.15)	(1.28)	(1.28)
Gender (male = 1)	0.0817	0.0817	0.0995	0.0995
	(1.09)	(1.09)	(1.20)	(1.20)
Visit Africa parks	0.0279**	0.0279**	0.0340**	0.0340**
	(2.32)	(2.32)	(2.56)	(2.57)
Utility Mara	0.294*	0.294*	0.359*	0.359*
	(1.63)	(1.63)	(1.80)	(1.81)
Mara trip package	−0.136*	−0.136*	−0.167*	−0.167*
	(−1.62)	(−1.62)	(−1.79)	(−1.79)
Aware of Serengeti	0.150*	0.150*	0.183**	0.183**
	(1.95)	(1.95)	(2.15)	(2.15)
Constant	0.944**	0.944**	0.580	0.580
	(2.11)	(2.11)	(1.17)	(1.17)
ln alpha Constant		−16.43	−7.066	
		(−0.05)	(−0.24)	
Chi-Square	71.35**	67.14**	87.97**	85.53**
Akaike IC	1033.04	1035.38	992.01	990.01
Bayesian IC	1070.82	1076.60	1033.57	1027.79
N	323	323	323	323

t-Statistics in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Criteria (AIC and BIC). The model with the lowest values of both these statistics is the best fit. In this case, the ZTP has values of 1033.04 and 1070.82 for AIC and BIC, respectively, hence the best fit model.

After determining absence of over-dispersion and taking care of truncation, the next step was controlling for endogenous stratification. Earlier, we indicated that if the data are equi-dispersed, both truncation and endogenous stratification can be adjusted using the transformed dependent variable ($y^* = y - 1$) in the conventional Poisson model, which in this case is the Poisson with Stratification (PSTRAT). Estimating both PSTRAT and NBSTRAT with equi-dispersion gives similar estimates. To pick the best of the two models, both were estimated as shown in Models 3 and 4. From NBSTRAT estimates, the lnalpha statistic is not significant, confirming equi-dispersion of the data. The estimates for the two models are the same so we used AIC and BIC to pick the best fitting model. The PSTRAT model has the lowest figures of 990.01 and 1027.79 for AIC and BIC, respectively. For this reason, it was chosen for the remaining calculations of consumer surplus and optimal pricing of the Park.

The PSTRAT model (and other models) estimates are linear-log in functional form for round-trip travel cost (RTTC) to Mara, onsite costs in the Mara, and income and age of the respondents, while the rest are of a linear level. From the coefficients, increase in RTTC and onsite costs are negatively related to the days spent in the Mara i.e. if they increase, the days decrease. By interpretation, doubling (100% increase) the round-trip travel cost would reduce the number of days spent by 0.324, while doubling expenditure on substitutes would reduce the number of spent in the Mara by 0.126. In addition, if the respondent incomes were to doubled, the number of days spent in the mar would increase by 0.264. Age and gender do not influence the number of days a visitor spends. However, visitors who had visited African Parks and those getting a lot of utility (pleasure) from the Mara are likely to spend more days. Visitors aware of Serengeti were likely to spend more days in

Table 5. Consumer surplus from different models.

	CS $(-1/\beta_p)$ US$	CS/person/day US$	CS/person/visit US$
ZTP	376.00	140.30	399.85
ZTNB	376.00	140.30	399.85
NBSTRAT	308.41	115.08	327.97
Poisson STRAT	308.41	115.08	327.97

the Mara as they most likely know the recreation and other services offered by the Serengeti. Finally, visitors who had booked the Mara trip as a package were likely to stay for fewer days. This is because the package already specifies the number of days to be spent in each destination. Those not booked in trip package have the discretion of extending or shortening their stay depending on the experience. This leeway provides for an opportunity for them to extend the stay if the Park and other onsite substitutes are exciting to the visitor.

In estimating the individual consumer surplus, we took absolute value the reciprocal of the coefficient of total travel cost from the different models and compared them. From the PSTRAT model, the reciprocal is given by $[CS = (1/0.324\ ) * 100]$. Note that the reciprocal is further multiplied by 100 due to the log-linear interpretation. This gives a value of US$ 308.41 per visit. If this value is divided by the average number of visitors per group $[E(GS)]$ which is 2.68 persons, it gives a consumer surplus of US$ 115 per person per day. It has also been shown that each visitor stays for an average of 2.85 days in the Mara i.e. $[E(PD_i) = 2.85]$. This then translates to a consumer surplus of US$ 328 per person per visit as shown in Table 5.

The Mara National Park records about 635,500 visitor days per year with 520,000 visitor days recorded in Maasai Mara National Park Narok, and 115,500 in the Mara Triangle. To get the access value of the Park, this figure is multiplied by the consumer surplus per visitor per day (US$ 115.08) as shown in Table 5. This gives a recreational or access value of US$ 73.076 million per year.

6. Estimating the optimal price of the Maasai Mara park

It has been argued that alongside recreational benefits, Parks also produce ecosystem goods and services through their conservation efforts. In an ideal situation, these ecosystems goods and services should have a price as they are produced at a cost. This price should be charged the same way as recreational facilities, but using different approaches such as payment for ecosystem services (PES). In the case of Maasai Mara and other Parks in Kenya, PES and other modes of charging for ecosystem goods and services is at its nascent stages. This leaves conservation fees collected at the Park gates as the key source of revenue for conservation and Park infrastructure improvements. Managers of the different Parks are therefore left with no option but behave like revenue maximizers given the limited revenue from other sources. For this reason, it would be important for them to know the optimal prices to charge in each Park. In this section, we estimate a conservation fee which will maximize the income (revenue) gained from each entrance ticket. Currently, foreign tourists are charged a conservation fee of US$ 80 per day in the Mara. The question to be answered is whether this is the revenue maximizing conservation fee for the Park.

We approach the optimal priding estimation from the elasticity of days spent in Mara due to change in the round-trip costs. The trip demand function is as an exponential relationship between number of days spent in the Mara (D_M), the round-trip total costs to the Mara (TTC_M), and other covariates. The assumption is that other covariates are known values which could be obtained by computing the average values of corresponding variables from the data. Using the corresponding coefficients of independent variables of PRSTRAT model in Table 4, we can get individual demand functions for visitors to the Mara.

$$D_M = \exp\left(\beta_0 + \beta_j \sum_{j=1}^{8} \boldsymbol{lnx_j} - \beta_1 lnTTC_M\right), \tag{27}$$

$$lnD_M = \beta_0 + \beta_j \sum_{j=1}^{8} \boldsymbol{lnx_j} - \beta_1 lnTTC_M \tag{28}$$

After substituting from the estimated model, the expression becomes;

$$lnD_M = 2.312 - \beta_1 lnTTC_M. \tag{29}$$

The elasticity of round-trip cost with respect to days a visitor stays in the Mara is expressed as;

$$E_{TTC_M,D_M} = \left|\frac{\Delta D_M/D_M}{\Delta TTC_M/TTC_M}\right| = \left|\frac{\partial D_M}{\partial TTC_M}\cdot\frac{TTC_M}{D_M}\right|, \tag{30}$$

where E_{TTC_M} is elasticity of round-trip travel cost. When the demand curve is linear like in this case – which is linear in logs, the elasticity would vary from 0 to infinite. In order to get a price that maximizes the revenue from entrance fee, there is an assumption that when conservation fees charged at the gate changes, the rest of trip costs remain the same. Introduction of conservation fees (P) assuming the other costs are constant gives;

$$lnD_M = 2.312 - \beta_1(lnTTC_M + lnP_M). \tag{31}$$

Since the other trip costs are already known from sample data, the demand function turns out to be the function between conservation fees and Days spent in the park. Therefore, Equation (30) is re-written as:

$$E_{P,D_M} = \left|\frac{\Delta D_M/D_M}{\Delta P_M/P_M}\right| = \left|\frac{\partial D_M}{\partial P_M}\cdot\frac{P_M}{D_M}\right|. \tag{32}$$

The entrance fee elasticity is between 0 and 1, which means the percentage change in days spent in Mara (D_M) is smaller than that of the conservation fees. Consequently, when Conservation fees increases, the total revenue gained from it will also be raised. The Conservation fees elasticity will keep on increasing as the fee goes up and the revenue reaches its maximum only when the elasticity rises up to 1. In order to get an optimal conservation fee maximizing the revenue, we set $\left(P_M^*\right)$ as the new price. Therefore, total revenue can be expressed as;

$$R_M = D_M * P_M^* * n, \tag{33}$$

where R_M is the revenue obtained from the tickets, and n is the number of visitors. Remember that revenue is maximized at the optimal price. Maximum revenue is obtained at the point where;

$$\frac{\partial R_M}{\partial P_M} = 0 \tag{34}$$

The calculation of the optimal price for the Mara is shown in Table 6. Note that we used Equations (31), (33) and (34) and the coefficients of travel cost were inserted accordingly.

Table 6. Calculation of optimal park prices.

PSTRAT model
$R_M = exp(2.312 - \beta_1(lnTTC_M + lnP_M^*))*P_M^**n$
$R_M = exp[2.312 - 0.324(5.5688) - 0.324(lnP_M^*)]*P_M^**n$
$R_M = exp[2.312 - 1.8043 - (0.324lnP_M^*)]*P_M^**n$
$R_M = exp[0.5077 - (1.475P_M^*)]*P_M^**n$
$R_M = [1.6614P_M^* - (1.3827P_M^*2)]*n$
$\frac{\partial R_M}{\partial P_M}\{[1.6614nP_M^* - 1.3827nP_M^*2]\} = 0$
$\frac{\partial R_M}{\partial P_M}\{[1.6614P_M^* - 1.3827P_M^*2]\} = 0$
$1.6614 - 1.9117P_M^* = 0$
$1.6614/1.9117 = P_M^*$
$P_M^* = 0.8691*\frac{1}{100} =$ US$ 86.91

Therefore, the optimal price which maximizes the recreational revenue is $P_M^* =$ US$ 86.90 Note that the value of P_M^* is multiplied by $(1/100)$ because the betas were from linear-log models where a change in round-trip travel cost variable x changes y by $(\beta/100)$ percent. The visitors are willing gaining US$ 115 per day even after paying the current conservation fees of US$ 80. If the optimal conservation fee of US$ 87 was charged, the consumer surplus would reduce to US$ 108. The optimal fees are therefore lower than the estimated consumer surpluses ($CS > P_M^*$). Since consumer surplus is the benefit the consumers get from the trip which is over and above the cost they pay for the trip, it means that the recreation and other ecosystems services offered by the Park offers much more than what the visitors are paying for i.e. Once visitors get to the Mara, they experience much more than they had actually paid for (either in unexpected or extra recreational experiences or other ecosystems services), and would be willing to pay much more for these extra services. However, presently, there is no way to capture this extra. Therefore, to skim some of the extra benefit, one of the natural reactions by Park managers is to increase the conservation fees, which is charged at the gate before entry. However, more innovative and less direct approaches of capturing the some or all of the extra benefit, including investing in alternative recreational activities to capture more onsite costs, can be explored.

7. Conclusion and recommendations

This study aimed at estimating the recreational value of Maasai Mara National Park in Kenya and also determine the optimal entrance fee to be charged if the Park revenue were to be optimized. The individual travel cost method was used and analysis were done using linear-log forms of ZTP, ZTNB, NBSTRAT and PSTRAT models. The data were truncated, equi-dispersed and endogenously stratified. These characteristics made PSTRAT the best model for the data. Onsite costs and awareness of Serengeti were used as controls for substitutes and tastes and preferences, respectively. Results indicate that, increase in round-trip travel costs, onsite costs decrease the number of days a visitor spends in the Mara. Improved incomes, awareness of Serengeti, and utility obtained in the Mara increase the days on stays in the Park.

From the estimates of the PSTRAT model, consumer surplus per visitor per day was estimated at US$ 115. Note that each visitor stays for an average of 2.85 days in the Mara. This then translates to US$ 328 per person per visit. To get the total Park recreation value, the consumer surplus per visitor per day was multiplied by the number of visitors per year. The Mara National Park records about 635,500 visitors per year with 520,000 visitors recorded in Maasai Mara National Park in Narok, and 115,500 in the Mara Triangle. Therefore, the access or recreational value of the Park is US$ 73.076 million per year.

We also estimated the optimal prices which maximize revenue for the park. From the PSTRAT model estimates, and using the elasticity of days spent in Mara and conservation fees, the optimal fee was estimated at US$ 86.90 per person per day. This price which optimizes revenue in Mara is unique to this Park since the data considered were unique to this Park. This fee is less than the consumer surplus. The Park managers have two options: A re-look at the pricing structure and determine whether to adjust the conservation fees upwards so as to capture some of the consumer surplus or investing in other recreational facilities in the Park i.e. development of substitute goods and capture more onsite costs.

Finally, there are other ecosystem goods and services generated in the course of conservation of Parks for recreational purposes. Determination of the economic value of these ecosystem services would help in calculating the total economic value of the Park. This will be important in pricing of other ecosystem goods and services, which would in turn increase the funds available for conservation, and also increase the production of all Park ecosystem services including recreational services.

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