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Economic Valuation of Forest Ecosystem Services in Kenya

Implications for Design of PES Schemes and Participatory Forest Management

Bosco Okumu and Edwin Muchapondwa

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Research Program in Economics and Environment for Development in Central America Tropical Agricultural Research and Higher Education Center (CATIE)

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Ho Chi Minh City, Vietnam

Economic Valuation of Forest Ecosystem Services in Kenya: Implications for Design of PES Schemes and Participatory Forest Management

Bosco Okumu and Edwin Muchapondwa*

Abstract

Forest ecosystem services are critical for human well-being as well as the functioning and growth of economies. However, despite the growing demand for these services, they are hardly given due consideration in public policy formulation. The values attached to these services by local communities in developing countries are also generally unknown. Using a case study of the Mau forest conservancy in Kenya, this study applied choice experiment techniques to estimate the value attached to salient forest ecosystem services by forest-adjacent communities. The choices were generated from an efficient design, and three models (conditional logit, random parameter logit model and random parameter logit model with interactions) were applied to the resultant data. The results revealed high levels of preference heterogeneity across households, including preferences for programs that guarantee improved forest cover, reduced flood risk, and high drinking water quality and quantity. There was a demonstrated welfare loss from choosing alternatives with medium rather than low wildlife population. Further, the results demonstrated the altruistic nature of forest-adjacent communities, as revealed by the high willingness to pay for flood mitigation, showing that these communities are not only concerned with private benefits, but also the welfare of society. Policy recommendations are also highlighted.

Keywords: choice experiment, ecosystem services, incentives, PES

JEL Codes: Q23, Q28, Q51, Q57

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*Bosco Okumu (corresponding author: kodhis2000@gmail.com) and Edwin Muchapondwa, School of Economics, University of Cape Town, Private Bag Rondebosch 7701, Cape Town, South Africa. The authors gratefully acknowledge funding for the research project “An economic analysis of participatory forest management in Kenya” (15029 FSD Sida) from the Swedish International Cooperation Development Agency (Sida) through the Environment for Development initiative at the University of Gothenburg.

1 Introduction

Forest ecosystem services are critical for the functioning and growth of economies (Ferraro et al., 2011). They contribute to human well-being, and are of significant livelihood value to rural households in developing countries (Costanza et al., 1997). According to the MEA (2005), there are four classes of forest ecosystem services: provisioning; support; regulating; and cultural services. These services are often public goods that are enjoyed by populations free of charge since they are not traded in the market, and their benefits may materialize at different levels from local to global. Globally, the optimization of ecosystem service provision and protection between the beneficiaries of the ecosystem service and those who affect its provision has been hampered by ill-defined property rights, information asymmetry and externalities (see Ferraro and Kiss, 2002) as well as policy failure. The existence of market and policy failures in provision and regulation of ecosystem services implies that environmental depletion is often more than the socially optimal level, while the provision of ecosystem services is below the socially optimal level (Ferraro and Kiss, 2002). In Kenya, as in the rest of the world, market and policy failures are impediments to protection of globally important forest ecosystems (Müller and Mburu, 2009). To secure higher levels of forest and environmental quality in Kenya, an understanding of the value attached by local communities to forest ecosystem services is an essential step towards design of effective policy tools (MEA, 2005).

Forest products like timber and wood products have tangible worth reflected in prices, but what about the values of flood mitigation, wildlife habitat, clean water and air, climate, or the scenic value of a pristine grove? How can providers of the ecosystem service[1] be compensated by the users? To obtain public support for conservation programs through Participatory Forest Management (PFM), an understanding of the values, attitudes and preferences towards environmental services is necessary. In addition, ecosystem services trade-offs have received limited attention in the management of ecosystems. For policy makers to incorporate public values and preferences into forest management and conservation policies, an understanding of the social benefits and trade-offs is critical.

The goals of devolution of forest management through PFM may never be realized unless policy makers understand the values forest-adjacent communities attach to salient forest ecosystem services, as well as the indirect costs such as trade-offs among ecosystem services under different land use practices. Valuation of these services is also expected to raise awareness of their importance and stimulate support for appropriate conservation measures, furthering the development of incentive schemes such as PES to incentivize local communities. This is also critical for engaging communities in behavioral change and encouraging adoption of ecosystem-oriented management practices.

The literature on valuation of local indigenous communities' preferences for ecosystem services within a developing country context, specifically Kenya, is anecdotal and scant. Similarly, most of the existing valuation studies have been biased towards developed countries (see García-Llorente et al. 2012; Tao et al. 2012; Gatto et al. 2013; Shoyama et al. 2013; Smith and Sullivan 2014; Yao et al. 2014; Bösch et al. 2018) with very few in developing countries (see Gelo and Koch 2012; Leh et al. 2013; Dikgang and

[1] The Mau forest is a reserve forest under the management of the Kenya Forest Service (KFS) in collaboration with forest-adjacent communities through Community Forestry Associations (CFAs). Communities are thereby charged with the responsibility of conserving the forest and also derive benefits from it.

Muchapondwa 2014, 2016; Diafas et al. 2017; Pettinotti et al. 2018; Jahanifar et al. 2018). According to Acharya et al. (2019), as of 2017, low-income countries accounted for only 14% of the publications on valuation of forest ecosystem services, with about 80% of the 14% concentrated on regulating services. Some recent studies in Asia have assessed the opportunity cost of water allocated to afforestation projects, to consider the true costs of restoration planning (see Zhang et al. 2016). Yu et al. (2018) provided a framework for assessing the net value of the benefits provided by ecosystem services, while JY Lin et al. (2020) estimated the environmental benefits derived from investment in watershed improvement and found that the environmental benefits would exceed the operational and maintenance costs by the 26th year after investment, regardless of the investment cost.

Most past studies on valuation of ecosystem services in Kenya have used the Contingent Valuation Method (CVM) and participatory environmental valuation (PEV) (see Carson and Mitchell 1989; Emerton 1996; Emerton and Mogaka 1996), with very few using the choice experiment (CE) approach (see Diafas et al., 2017), and most have studied resources other than forestry. The advantage of the CE approach is that it is able to elicit trade-offs between different policies and also avoids biases associated with CVM and PEV. It is also difficult to assess preference heterogeneity in the case of valuation of just a single attribute as in CVM. In addition, most studies that have used the CE approach have relied on an orthogonal design (see Dikgang and Muchapondwa 2012; Shoyama et al. 2013; Pienaar et al. 2014) rather than an efficient design (see Gatto et al. 2013; Czajkowski et al. 2014; Müller et al. 2020). The efficient design has the advantage of producing more reliable and efficient parameter estimates at smaller sample sizes. The application of an efficient design is also quite scant within developing countries.

Preferences for forest ecosystem services are significantly different given the levels of economic development and variation in social and cultural contexts; this explains the mixed results from various studies. Due to the variation in preferences and values attached to various ecosystem services, differences in methodological approaches, and context-specific factors that make comparison difficult, a context-specific analysis is critical. Moreover, attempts to estimate different forest ecosystem services, especially the non-use values and their trade-offs, are still rather scarce on a regional scale and especially within the African context.

This study, therefore, seeks to fill these gaps and contribute to the debate on valuation of ecosystem services by addressing the following questions: (i) What is the economic value of a range of salient forest ecosystem services in Mau forest conservancy in Kenya? (ii) are the economic values sufficient to incentivize local communities to engage in forest conservation through payment for environmental services (PES) schemes? (iii) and what are the implications of the economic values of the forest ecosystem services for devolution of forest management to local communities through PFM? The study seeks to enlighten development practitioners on how we can place a value on forest ecosystem services to achieve development objectives such as improvements to health and safety and enhancement of energy and food security, among others.

Further, the study contributes to the valuation of ecosystem services literature by applying a choice experiment technique to estimate the value attached to salient forest ecosystem services by forest-adjacent communities. In summary the study reveals high levels of preference heterogeneity across households, including preferences for programs that guarantee improved forest cover, reduced flood risk, and high drinking water quality and quantity. There is also demonstrated welfare loss from choosing alternatives with medium rather than low wildlife population.

The rest of the paper is structured as follows. The next section discusses the value of ecosystem services in Kenya. Section 2 presents a description of the study area. Section 3 presents the methodology, survey design and data collection, empirical model, willingness to pay (WTP) estimation, and experimental design. Section 4 presents the model estimation results. The conclusions and policy recommendation are presented in section 5.

1.1 Value of Forest Ecosystem Services in Kenya

Kenya has five major water towers classified as montane forests: Mount Kenya, the Abardare ranges, the Mau forest complex, Cherengani Hills and Mount Elgon. These forests form the upper catchment of all major rivers in Kenya except the Tsavo, which originates from Mount Kilimanjaro. These forests are mostly surrounded by densely populated areas because they provide sufficient water for intensive agriculture and urban settlement (Akotsi et al., 2006). They also provide ecological goods and services including river flow regulation; water storage; water purification[2]; flood mitigation; recharge of groundwater; micro-climate regulation; biodiversity promotion; nutrient cycling and soil formation; reduced soil erosion and siltation; and timber and non-timber forest products. These provide insurance value to other key sectors of the economy and consequently have significant impact on the economic resilience of the country (UNEP, 2012a). These forests sustain many natural habitats in the lower areas of the catchments, thereby producing direct economic value.

The ability of these forests to supply ecosystem services has been hampered by increased degradation resulting from human activities. These include but are not limited to rent-seeking behavior of government officials[3] and intrusion by other communities and local politicians in an effort to grab forest land for agriculture purposes. According to UNEP (2012a), deforestation in Kenya's water towers between 2000 and 2010 amounted to 50,000 hectares (equivalent to 5000 hectares per year) yielding timber and fuel-wood volume of 250m3/ha with estimated cash value of USD 13.62 million (equivalent to USD 2720/ha per year). This value implies that there is a monetary incentive for rampant deforestation in Kenya. However, alongside such revenue streams, the cost to the economy is quite high, especially through loss of regulating services (UNEP, 2012a). It is estimated that the cost to the economy as a result of reduction in regulating services due to forest degradation was USD 36.52 million per year, which is 2.5 times greater than the revenues from such deforestation activities[4]. "Due to the interdependence of various

[2] Water yield in the Mau is approximately 15,800 million cubic meters per year, accounting for more than 75% of renewable surface water resources of Kenya (UNEP, 2012b)

[3] During the survey, we were informed by some community members that their conservation efforts would be in vain given the fact that some foresters colluded with loggers to harvest more than the licensed number of trees, and even indigenous trees that are meant to be protected.

[4] The effects were reduced agricultural output by USD 22.62 million in 2010, reduced hydropower generation by USD 0.12 million (which has a multiplier effect on other sectors of the economy), decline in inland fishing catches by USD 0.86 million due to siltation of rivers and lakes, and, lastly, increased cost of water treatment by USD 1.92 million (UNEP, 2012b). In addition, the forgone above-ground carbon storage value from deforestation in 2010 was estimated at USD 3.41 million, and malaria incidence was estimated to have cost the government USD 3.95 million in the form of additional health cost and loss of productivity (UNEP, 2012b).

sectors, the decrease in regulating services due to deforestation caused a total impact of USD 0.058 billion in 2010. This further implies that the cost of limiting ecosystem regulatory services as a production factor for the economy was effectively 4.2 times higher than the actual cash revenue from wood of USD 0.013 billion" (UNEP, 2012a).

Due to the importance of forest ecosystem services (MEA, 2005), Kenya, like many of her counterparts, has strengthened conservation of forests through various initiatives. Efforts have been made by the government to integrate forest conservation and rural development, thereby incorporating social concerns that affect forests. These efforts include enactment of the Forest Act (2005) and the Forest Act (2016) aimed at devolution of forest management to forest-adjacent communities (MENR, 2005, 2016). The two acts introduced PFM, which seeks to engage local communities in forest management while promoting private sector investment in gazetted (government published) forests. Some features of the Act and policy are devolution of forest conservation and management through PFM to local communities; introduction of benefit sharing arrangements such as Plantation Establishment and Livelihood Improvement Schemes (PELIS)[5]; and adoption of an ecosystem approach to management of forests. Communities subsequently formed community-based organizations known as Community Forest Associations (CFAs) in collaboration with the Kenya Forest Service (KFS), to enable them to participate in these initiatives.

The forests provide firewood, grazing land, drinking water, food crops, grass for thatching, herbs and medicines. To enjoy any of the resources, members pay user fees, a percentage of which goes to KFS and a percentage to CFA and the associated forest user group (FUG). This is a departure from prior practice where the government assumed full responsibility of gazetted forest reserves.

However, despite these efforts, there are increasing cases of degradation within CFAs. The values attached to various ecosystem services by forest-adjacent communities as well as the extent of the benefits of these forest ecosystem services remain unknown. Moreover, even though the benefits to local communities could be substantial, the value of most non-marketed forest products is unaccounted for, and the forestry sector's contribution to Kenya's economy[6] is measured solely by formal market transactions[7].

According to the UNEP, the challenge for developing countries like Kenya that are facing natural resource degradation is to institutionalize incentives to internalize the positive externalities from sustainable forest management. To protect natural resources like Kenya's water towers, "appropriate and well-funded policies, policy instruments and response strategies" are crucial (UNEP, 2012a). This is based on the premise that, when provision of ecosystem services is not rewarded through suitable mechanisms, forest-adjacent communities are not likely to include ecosystem services in their management objectives unless constrained by command and control policies. This implies forest management will rarely achieve the social optimum. This paper seeks to change this by investigating the components of such incentives.

[5] PELIS is an incentive scheme in which landless forest-adjacent communities are allowed to grow both plantation trees and food crops on small plots (half an acre), tending the trees and harvesting crops for 3-4 years until tree canopy closes. It is aimed at improving forest cover and improving livelihoods of local communities.

[6] The contribution of primary forests is estimated to be about 1.2% of the GDP (0.7% in the monetary sector and 0.5% in the non-monetary sector) (GOK, 2015)

[7] This implies that the forestry sector contribution to the Gross Domestic Product is undervalued.

2 Description of the study area

The study was conducted in the Mau forest conservancy. The choice of Mau forest was based on three criteria: high susceptibility to degradation, long history of community forestry, and high level of biodiversity. The Mau forest is also the largest closed canopy forest among the five major water towers in Kenya, which has lost over a quarter of its forest resources in the last decade (Force, 2009). It is situated at 0°30' South, 35°20' East within the Rift Valley Province. It originally covered 452,007 ha but, after the 2001 forest excisions, the current estimated size is about 416, 542 ha. The Mau comprises 22 forest blocks, 21 of which are gazetted and managed by KFS. The other is Mau Trust Land Forest (46, 278 ha), managed by the Narok County Council (NEMA, 2013).

The Mau Forest Complex supplies water to over 4 million people residing in 578 locations in Kenya and some parts of Northern Tanzania. The Mau ecosystem is also the upper catchment of numerous rivers that supply water to communities and urban centers in the region, thus supporting livelihoods and economic development. The rivers also provide water for pastoral communities and agricultural activity and ecological services in the form of micro-climate regulation, water purification, water storage and flood mitigation. In addition, the estimated potential hydropower generation in the Mau forest catchment is approximately 535 MW, equal to 47 percent of the total installed electricity generation capacity in Kenya (UNEP, 2008). Apart from provision of local public goods such as food, wood-fuel, herbs, building materials and fodder, the forest also supplies global public goods and services such as carbon sequestration, wildlife habitat[8], and biodiversity conservation (Kipkoech et al., 2011). The upper catchment of the forest also hosts the last group of indigenous communities in Kenya: the Ogiek[9] (Force, 2009).

3 Methodology

3.1 Survey design and data collection.

This exercise involved a series of design and testing steps, beginning with a qualitative review of literature on forest ecosystem services and expert opinions to identify and define the policy relevant attributes. The levels of the selected attribute were further refined using the additional information collected, observations from Focus Group Discussions (FGDs), and expert judgment. The structured questionnaire was divided into three parts: part one collected information on general attitudes and

[8] The Mau forest hosts over 450 recorded bird species and six key mammals of international concern: yellow-backed duiker, giant forest hog, bongo, golden cat, African elephant and leopard (Force, 2009). It also hosts numerous monkey and baboon species.

[9] The Ogiek are hunter-gatherers who have lived for centuries deep inside the Mau forest. The majority also grow vegetables and keep livestock. They used to hunt wild animals such as antelopes and wild pigs, but this is now illegal. Due to the influx of illegal settlers, which led to serious degradation of the Mau forest, the Kenyan government tried to evict everyone including the Ogiek from the forest. However, the Ogiek recently won their land case against the government.

perceptions towards forest ecosystem services; part two involved the choice modeling scenario; and the last part collected information on socio-economic characteristics and institutional variables.

The choice experiment approach presented households with three different alternatives (Options A, B and C). Option C was the status quo, described as "as of today", i.e., no change in forest conservation and management. This option does not involve any policy intervention and has zero additional cost to the household. Choosing this option meant that respondents were comfortable with the current condition (status quo) of the forest regardless of the future condition of the forest without any intervention. Options A and B involved a combination of new policy interventions that may affect the future condition of the forest catchment. The impacts of the new policy interventions in five years' time were predicted and described by the attributes considered to have direct influence on the well-being of forest-adjacent communities.

The choice of attributes was based on what the local communities could easily understand and what they had mostly interacted with. Forest structure was deemed significant by respondents since over 78% of the forest-adjacent communities relied on fuel wood as a source of energy; they also relied on the forest for grazing, hence a degraded forest would imply limited supply of these services. The extent of forest cover also could easily represent aesthetic (scenic) and cultural values, since some communities preserved certain sections of the forest for cultural activities, e.g., Mt Blacket, which Kalenjins have preserved for cultural practices[10].

These forests also act as habitat for various wildlife such as elephant, monkeys, leopards, bongo, buffaloes, etc. About 99% of the respondents were aware of the various types of wild animals in the forest and could name several. However, due to stringent rules by the Kenya Wildlife Service, about 90% claimed not to be involved in trapping the wild animals. Communities also complained of rampant human-wildlife conflict. Wildlife population was therefore included as an attribute to gauge their preference and perception towards wildlife conservation and whether they would consider conserving the forest for other benefits while coping with increasing wildlife population. This would also reveal their attitude towards biodiversity conservation and preservation of wildlife for future generations, i.e., bequest values. Elephants were chosen as representatives of wildlife, since they interacted frequently with the farmers.

Most forest-adjacent communities rely on water from the forest (73% of the respondents said they relied on water from the forest). Therefore, degradation of these forests would mean a reduction in quality and quantity of water for drinking and irrigation, as well as siltation of dams responsible for provision of various services to downstream users. In addition, forests play a significant role in flood mitigation and erosion reduction. This attribute was thus selected based on the fact that continuous degradation would mean high social and economic costs of flooding episodes borne by locals, downstream settlers and nearby towns and urban centers. This attribute was therefore included to gauge the behavioral aspects of forest-adjacent communities – that is, whether they are altruistic or self-centered. Based on these considerations, we settled on the following attributes of forest-based ecosystem services: forest structure/cover, wildlife population, water purification and supply, flood risk and cost to the household.

[10] It is important to note that we did not consider the diversity in tree species.

Following past studies (Pearce, 1994; Fitzgibbon et al., 1995; Adamowicz et al., 1998; Gatto et al., 2013), the levels of each attribute used in the pilot and final survey are shown in Table 1.

Table 1: Attributes used in pilot and final DCE design

Type of Attribute	Attribute Definition	Attribute Levels
Wildlife	Wildlife population (biodiversity)	753, 1103, 1203
Forest Structure	Tree population/forest cover	56.25%, 82.5%, 95%
Water purification	Water purification and supply (level of water quality and quantity)	11850, 17380, 19960
Flood	Risk of flooding: regulating services	Low, Medium, high
Cost	One-off payment (ksh) per year for three years	0,1744, 2683, 2951

Respondents were informed that any policy intervention aimed at forest management would have higher cost implications[11]. The cost would be shared by all people living around the forest as a three-year levy on government rates during the year, paid annually for three years. The size of the levy also depends on the management option chosen (either A or B).

Households were informed that the levy would be channeled into a special conservation fund set up to finance conservation and management of the forest catchment. They were further informed that the fund would be managed by officials selected by CFA members and that an independent auditor would ensure the money was spent wisely. Due to the subjective nature of valuation of forest ecosystem services, a verbal description can be interpreted differently based on variations in education levels or individual experiences. Each attribute level was therefore visualized by showing a "control" picture depicting more or less of the attribute. This approach ensured that changes in attribute levels were easily identifiable, holding other factors of the forest ecosystem service constant. However, the status quo alternative was just represented as "as of today" instead of pictorially. Although it was expected that provision of forest ecosystem services would be lower without any policy intervention, we could not quantify/predict the exact future condition of the forest.

Before the government's intervention through provision of incentives and devolution of forest management, the Mau forest was almost completely degraded through human interference, and the adverse effects were felt across the Rift Valley, western regions and other parts of the country[12]. Communities were therefore well aware of the outcome of no policy intervention. Based on past history, respondents were informed that without any policy intervention the forest risked further degradation. As a result of this, the supply of ecosystem services would be low, as pictorially presented in other policy presentations, or even lower than in the year 2000, when the forest was almost completely run down. Respondents were therefore told to imagine the condition of the forest in the next five years if they continue with current practices without any intervention, which would have zero cost implications for

[11] We used the estimated cost of rehabilitation of the Mau forest complex as per a project implemented by the Kenyan government and UNEP through European Union funding. We then divided the cost by the total population around the Mau forest conservancy. Due to the poverty of forest-adjacent communities, the amount was distributed into a three-year levy.

[12] Some of the adverse effects were drying of rivers, dams, and lakes; power outages; crop failure due to inadequate rainfall; and decline in wildlife population.

them in the current period[13]. To ensure understanding and scenario acceptance by respondents, the accompanying text in the structured questionnaire and images were tested in FGDs, and a pilot run was later conducted to ascertain the validity and construction of the survey instrument.

The pilot questionnaire was presented to a random sample of 44 households in Londiani CFA of Kericho County in October 2015 and in two FGDs. In the pilot, 15 choice tasks were generated, and respondents were presented with 5 choice tasks. All members of the community, even the ones that were less literate, demonstrated that they clearly understood the choice attributes from the images. From the pilot exercise, we estimated multinomial logit model betas which were used as priors in the final statistical design. The survey was conducted in the months of November and December 2015. In the final survey, we used a two-stage sampling procedure in data collection. In the first stage, a sample of 22 out of 35 CFAs were purposively identified to reflect the entire Mau forest. This was conducted with the help of the head of the Mau forest conservancy[14]. The CFAs covered the five counties of Bomet, Narok, Kericho, Nakuru and Uasin Gishu and thus were fully representative of the entire Mau forest. The CFA level data were collected through focus group discussions with CFA officials and other members at their offices in the forest station. In the second stage, a sample of 321 households from the 22 CFAs were identified through simple random sampling, in which every third household was interviewed, and snowballing was used in instances where the third household was not a CFA member[15]. This was conducted using individual household-level survey-administered questionnaires to household heads.

3.1.1 Experimental Design

To generate different choice tasks, we employed the Bayesian D-efficient design. This was chosen due to uncertainty on the nature of the parameter estimates for each of the attributes. The efficient designs are also less restricted and easier to find than the orthogonal and often allow a much smaller number of choice sets (Greiner et al., 2014). We used the D-error criterion to optimize the efficiency of the experimental design.

However, to generate an efficient design, priors are needed, but were not available for this study. Using zero priors would be same as using the orthogonal design, which led us to adopt an approach proposed by Bliemer and Rose in Ngene forums[16]. This involves assuming distributions of the parameters and specifying the expected signs for the parameters. We assumed a uniform distribution of the parameters

[13] This is one of the limitations of the study. Respondents may not have a clear picture of what the provision of ecosystem services may be in five years' time even if the current state is low; this limitation may influence their judgment and also bias the result to some extent. However, we believe that we can still get good estimates of the respondents' preferences.

[14] Although it is possible that the head of the conservancy may have referred us to CFAs that were doing well, we can confirm that this was not the case because we also got to visit some CFAs that were a total mess. The choice of CFAs was based on representativeness of the entire forest and ease of accessibility, since some areas are very difficult to access due to terrain and lack of motorable roads.

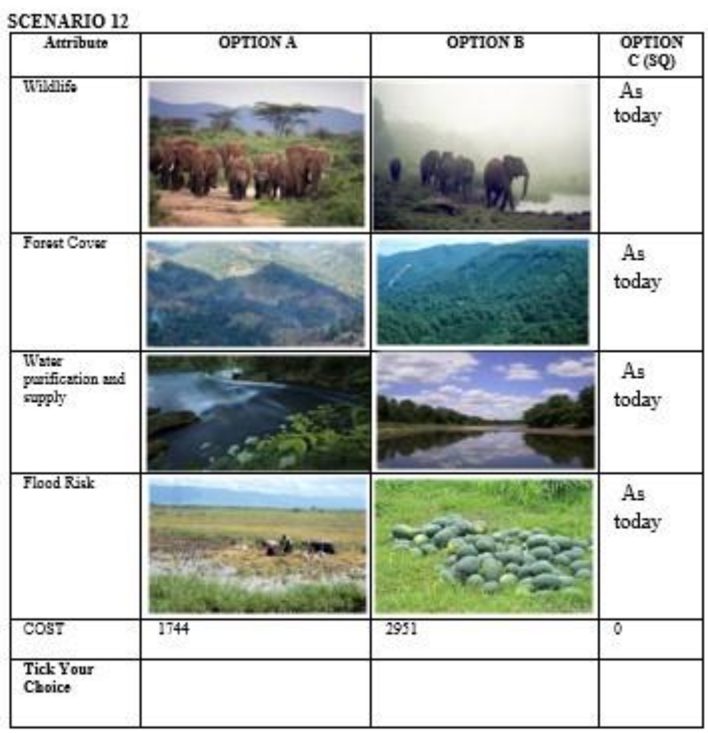
[15] In some instances, we interviewed CFA members at the farms in the forest or when there were collective activities such as tree planting or transportation of tree seedlings

[16] http://choice-metrics.com/forum/viewtopic.php?f=2&t=471

as the priors to be used to generate a Bayesian D-efficient design using Ngene[17]. The efficient statistical design for the pilot was thus built using Ngene 1.1.2[18]. We then conducted a pilot/pre-test to validate the design in principle. Data from the pre-test was then analyzed using multinomial logit (MNL) and resulting parameter estimates were used as priors for development of a refined and more efficient design for the final survey. Due to the complexity of running an efficient design using a Random Parameter Logit (RPL) model, we opted for the MNL despite its weaknesses. Although these weaknesses may significantly influence the statistical properties of the design, especially with inclusion of socio-demographic factors in the estimation model, the design still performs much better than the orthogonal or other designs.

The choice sets for the full survey were developed based on priors from the pilot. In both the pilot and full survey, we checked for the presence of dominant alternatives, finding limited dominance in the estimated design, and a similar distribution in the choice frequencies. The design was generated without accounting for covariates. For the final survey, we generated a design with thirty choice tasks. To reduce the answering load, each respondent would answer five choice tasks picked randomly from the thirty choice tasks generated in Ngene. A sample of the choice card used in the final survey is shown in Figure 1[19].

Figure 1: Sample choice card used in the final survey



[17] The uniform distribution was employed because it gives equal weight to all possible prior parameter values and because we may not be certain about the exact distribution.

[18] Choice Metrics, "Ngene 1.1. 2 User Manual & Reference Guide", Sydney, Australia: Choice Metrics (2014).

[19] The pictorial presentation was further described to the respondents to avoid any mix-up, especially to respondents who had trouble identifying the differences. This was, however, done only in the first choice since, after one illustration, the respondent easily picked up on the other choice tasks.

3.2 Theoretical Framework

3.2.1 Empirical Model

The choice experiment approach has its roots in two theories, namely, Lancaster's economic theory of value (Lancaster, 1966) and the random utility theory (McFadden, 1974). The random utility theory posits that an individual (household head) n chooses an alternative j from the choice set, s=1,2.....S, if the indirect utility of j is greater than that of any other choice i. That is

$$U_{nsj} > U_{nsi} \Longrightarrow V_{nsj} + \varepsilon_{nsj} > V_{nsi} + \varepsilon_{nsi} \forall j \neq i; i, j \epsilon s \tag{1}$$

where S is the set of all possible alternatives. A systematic component, $V_{nsj,}$ is the deterministic component; it is a vector of observable individual and alternative specific attributes. ε_{nsj} is the unobserved component; it includes all unobservable impacts and factors affecting the choice (Louviere et al., 2000). Assuming the observed component is a linear function of the observed attributes levels of each alternative X and their weights (parameters) β , where $\beta^0{}_s$ are unknown parameters to be estimated, then we have

$$V_{nsj} = \sum_{k=1}^{K} \beta_k x_{nsjk} \tag{2}$$

In our case, β_k appears in the utility function of multiple alternatives j. It is therefore generic over these alternatives. Assuming the unobserved components are independent and identically distributed (IID), the probability P_{nsj} that respondent n selects alternative j from a choice situation S is given by the MNL model (McFadden, 1974).

$$P_{nsj} = \frac{\exp V_{nsj}}{\sum\limits_{j \epsilon J_{ns}} \exp V_{nsi}} \tag{3}$$

In the first step, equation 3 was estimated by means of conditional logit (CL) regression following Hensher and Greene (2003), which assumes that choices are consistent with the Independence of Irrelevant Alternatives (IIA) property. This implies that the relative probabilities of the two alternatives being selected are not affected by removal or introduction of other alternatives (Luce, 2005). The model therefore assumes that respondents' preferences are homogeneous. Given this limitation, we applied other flexible approaches. The study used the RPL model, which is more flexible, allows for random preference variations between respondents, incorporates correlation in the utility between choices, and accounts for heterogeneity among individuals (McFadden and Train, 2000).

Following Colombo et al. (2009), the RPL model is described in equation 4.

$$Unsj = \beta Xnsj + \varphi nXnsj + \varepsilon nsj \tag{4}$$

The utility function U_{nsj} is split into three parts: X_{nsj} is a vector of observable attributes for the good in question; β is the vector of coefficients of the observed attributes; φ_n is a vector of deviation parameters (they represent individual tastes, which are assumed to be constant across choices made but not across the entire sample); and ε_{nsj} is a random term and is independent and identically distributed (IID). With the RPL model, we do not have to assume that the IIA property holds. In this model, preference heterogeneity is incorporated into the random parameters directly since each respondent has his own vector of deviation parameters (Ju and Yoo, 2014).

However, the RPL does not show the sources of heterogeneity. To account for sources of heterogeneity, the RPL was estimated with interaction (i.e., interacting the attributes with socio-economic variables). In addition, although the RPL is better than the CL models in terms of welfare estimates and overall fit (see Dikgang and Muchapondwa, 2014), the RPL model has some restrictive assumptions based on assumed distribution of the coefficient vector: mostly uniform, triangular, log-normal and normal distribution. If the distribution is mis-specified, the estimated results could be biased (Carlsson et al., 2003). Since most of our attributes were dummy coded, the uniform distribution was best suited (Hensher and Greene, 2002).

To determine the best model in terms of overall fit, the study employed the LR test following Hensher et al. (2005):

$$-2(LLBase - LLEstimated) \tag{5}$$

which is $\sim X^2$ (difference in the number of estimated parameters between the two models).

Estimating Marginal WTP

The marginal WTP measures are given by the ratio of two parameters[20] as presented in equation 8 (Hensher et al., 2005).

$$WTP = -\left(\frac{\beta_{attribute}}{\beta_{price}}\right) \tag{6}$$

Beyond the marginal WTPs for each attribute, we also estimated welfare change or compensating surplus in five hypothetical scenarios created using information compiled from the questionnaire. We estimated the cost of a given conservation policy option through comparison of the utility of any policy intervention to the status quo. Following Bennett and Blamey (2001) and Bergmann et al. (2008):

$$Welfare\ change = -\frac{1}{\beta_{cost}}(V_0 - V_1) \tag{7}$$

where V_0 is the utility of the status quo option, V_1 is the utility of the alternative option and β_{cost} is the estimated coefficient of the cost.

[20] Both parameters must be statistically significant

4 Results and Discussion

4.1 Descriptive statistics

A total of 321 households were interviewed. Socio-economic and demographic profiles of the respondents and their households were collected to gain more insight into people's circumstances and their perceptions of various forest ecosystem services. This information formed the basis for investigating heterogeneity in personal preferences. Summary statistics of the profiles of respondents interviewed are shown in Table A1 in the appendix. The results show that, whereas all respondents considered the forest to be of significant value, only 73% of the respondents had visited the forest to fetch water and 78% had visited to collect firewood. The summary statistics also show that approximately 61% of the respondents owned PELIS plots in the forest. About 88% of the respondents were married and only 29% employed in off-farm jobs. The average household size was six members and the average reported distance from the nearest edge of the forest was about 1.4 kilometres. The average household monthly income was about Ksh.13,492.

4.1.1 Model estimation results

NLOGIT 4.0 and Stata 13 econometric software were used to estimate the three models. All the attributes except cost were coded as low, medium and high levels for ease of analysis and interpretation[21]. The category 'low' represents the status quo, i.e., choosing no intervention option. For the wildlife population, 'low' represented 753 elephants, 'medium' 1103 elephants and 'high' 1203 elephants[22]. For the variable 'forest cover', 'low' represented 56.25%, 'medium' 82.5% and 'high' 95% forest cover. The water purification and supply attributes were reflected in million cubic meters with 'low' being 11850, medium 17380 and high 19960[23]. Because quantifying the risk of flooding required more technical expertise, this was just reflected by 'low', 'medium' and 'high' risk of flooding[24]. The last attribute was the monetary attribute, which was presented as the additional annual cost per household in the form of an annual levy.

The attributes were then effect coded because this provides estimates that are uncorrelated to the model intercept (Louviere et al., 2000; Hensher et al., 2005). Effect coding implies that one level of the attribute is dropped as the base category. However, for the water attribute, we merged the low and medium levels and classified them as low; it makes more economic and logical sense for a respondent to simply pay for clean water, since both medium and low quality and quantity would have the same health implications unless the water was treated[25]. The water attribute therefore had just one level (high) apart from the

[21] This was also for ease of coding and choice design in Ngene.

[22] Although elephants may be associated with a lot of damages to crops and therefore some negative attitudes towards them, we chose elephants because they are the wildlife animals that most community members interact with frequently. In some communities, they are also a tourist attraction.

[23] Because the differences in levels of the attribute may not be large enough, we made it easier for respondents to understand the variation through a pictorial presentation of these levels. To avoid confusing the respondents in terms of quality of the water, the pictorial presentation showed water that was clean and relatively plentiful to reflect the high level of this attribute.

[24] The risk of flooding was expressed in terms of water levels. High risk implies high above-ground water level and low risk implies low above-ground water levels as a result of flooding.

[25] Choosing medium or low quality and quantity of water may also imply that they do not attach any value to water.

reference category. The estimated coefficients for each of the remaining levels show the respondent's preference for change from the reference (omitted) level to a greater utility level (Bergmann et al., 2006). We also included a dummy equal to one for the status quo (SQ) and zero for the other options. This controls for the very important difference between SQ and non-SQ alternatives. It also measures some propensity to choose the zero-cost option, or protest behavior[26]. This information is also useful for policy purposes; testing for status quo bias is therefore necessary. Table 2 shows the frequency with which each alternative was chosen (out of 321*3*5 choice sets=4815 across all respondents). The status quo bias is significantly small (2.55%), implying that forest-adjacent communities within CFAs prefer conservation of forests for efficient provision of forest ecosystem services.

Table 2: Choice Frequency for Mau forest conservancy households

Choice	Frequency	Percent
Option A	762	47.48
Option B	803	49.97
Option C (Status Quo)	41	2.55
Total	1605	100

Source: Authors' calculation from survey

Conditional Logit (CL) model

Column (1) of Table 3 presents the results of the CL model. The overall fit of the model as measured by McFadden's ρ^2 is 0.47, which is a bit high by conventional standards[27]. The coefficients are highly significant at 5% and below, except for the high level of wildlife biodiversity and population. All the attributes have the expected sign. The significance of the attribute and the sign shows that, *ceteris paribus*, low and medium flood risk (i.e., low and medium water levels as a result of flooding), higher levels of water quality, and high and medium forest cover increase the likelihood of selecting a given management scenario, while medium wildlife population[28] decreases the probability of selecting a given management option. The negative and significant coefficient of the alternative specific constant (ASC) shows that people want a change from the SQ – i.e., they want a conservation program aimed at improving forest condition.

[26] Its inclusion is also important since it reflects some hidden characteristics that the respondent do not see in the choice task. The status quo inclusion means respondents are free to select the status quo for all attributes, hence failing to make any trade-offs. Therefore, information on trade-off is lost for every choice of the status quo.

[27] A value of ρ^2 that is within the range of 0.2 to 0.4 is considered good fit (Hensher and Johnson, 1981)

[28] During the survey, we noted that most households were not concerned about the destructive nature of wildlife such as monkeys or elephants. They said that damage was often shared since most farms in the forest are in one area. The main worry was that, if the population increases, then human-wildlife conflict would arise, resulting in tension with Kenya Wildlife Service officials. However, the main concern was with leopards that often attacked their sheep at night without compensation from relevant authorities.

Table 3: Conditional logit, Random Parameter logit model and Random Parameter logit model with interactions

(1)		(2)			(3)		
CL Model		**RPL model**			**RPL Model with interaction**		
N = 4815		N =4815			N=4815		
Log-Likelihood=-671.1730		Log-Likelihood=-664.0608			Log-Likelihood=-624.6797		
Variable	Coeff.(s.e)	Variable	Coeff (s.e)	Coeff.Std (s.e)	Variable	Coeff (s.e)	Coeff.Std (s.e)
ASC	-1.5073***	***Random Parameters***			***Random Parameters***		
	(0.5746)	Wildlife_High	0.2398	1.1652**	Wildlife_High	0.1561	1.1071*
Wildlife_Medium	-0.3665**		(0.2112)	(0.6053)		(0.4318)	(0.5741)
	(0 .1616)	Forest_Medium	1.7923***	0.9655**	Forest_Medium	3.7825***	0.8919*
Wildlife_High	0.1067		(0.2171)	(0.4654)		(0.5757)	(0.4878)
	(0.1697)	Forest_High	4.0959***	0.9655**	Forest_High	6.3764***	0.8919*
Forest_Medium	1.5041***		(0.3811)	(0.4654)		(0.8157)	(0.4878)
	(0.1563)	Water_High	0.7877***	0.1636	Water_High	0.6486***	0.1612
Forest_High	3.5216***		(0.1530)	(0.7013)		(0.1709)	(0.6210)
	(0 .2708)	Flood_Medium	1.4927***	1.6582***	Flood_Medium	1.2260***	1.6612***
Water_High	0.6411***		(0.1797)	(0.3619)		(0.2324)	(0.3723)
	(0 .1170)	Flood_Low	2.6174***	1.6582***	Flood_Low	1.8427***	1.6612***
Flood_Medium	1.2429***		(0.2537)	(0.3619)		(0.2386)	(0.3723)
	(0.1101)	***Non-Random Parameters***			***Non-Random Parameters***		
Flood_Low	2.1300***	ASC	-1.1761*		ASC	-1.6057**	
	(0.1503)		(0.7008)			(0.7246)	
Cost	-0.00061***	Wildlife_Medium	-0.3783**		Wildlife_Medium	-0.4764**	
	(0.0002)		(0.1933)			(0.2002)	
		Cost	-0.0006***		Cost	-0.0008***	
			(0.0002)			(0.0002)	
					WildlifeH*PELIS	-0.4933*	
						(0.2773)	
					WildlifeH*Distance to forest	-0.2313**	
						(0.1056)	
					WildlifeH*HHsize	0.1057**	
						(0.0520)	
					ForestM*Distance to forest	-0.2912**	
						(0.1236)	
					ForestM*HHsize	-0.2750***	
						(0.0626)	
					ForestM*Employment	1.0030**	
						(0.4331)	
					ForestH*Distance to forest	-0.4311***	
						(0.1648)	
					ForestH*HHsize	-0.2931***	
						(0.0814)	
					ForestH*Employment	2.0138***	
						(0.6321)	
					WaterH*Employment	0.7974**	
						(0.3166)	
					FloodM*PELIS	0.6420**	
						(0.2673)	
					FloodL*PELIS	0.8020**	
						(0.3223)	
					FloodL*Distance to forest	0.3535***	
						(0.1258)	
ρ^2	0.4733		0.6234			0.6457	

Standard errors in Parentheses *** p<0.01, ** p<0.05, * p<0.1, where M denotes 'medium', H 'high' and L 'low'

Source: Authors' calculation from survey

The results therefore indicate that forest-adjacent communities would prefer forest management options which would guarantee low levels of wildlife population and diversity, clean and abundant water, low or medium flood risk and higher or medium forest cover, as indicated by the significant coefficients. Our results therefore suggest the existence of significant values and preferences for the stated forest ecosystem attributes. We also found considerable consistency with economic theory. Specifically, the cost of a given conservation program reduces demand for that program. However, if the IIA assumption does not hold, then the CL model would yield biased estimates. We employed the Hausman and McFadden test under the null hypothesis of no violation to test the IIA assumption (Hausman and McFadden, 1984). The results are shown in Table 4. Violation of the IIA assumption is evident from the results. This implies that the

CL model may not be the appropriate model. This test has, however, been contested for giving inconsistent results (see Vijverberg, 2011).

Table 4: IIA/IID Hausman Test

Alternative dropped	Chi Square	Degrees of freedom	Comment
A	14.35	8	Violation at 10%
B	5.66	8	No violation
C (Status Quo)	-0.758	8	No violation

Source: Authors calculation from survey

Due to violation of the IIA property, we considered alternative models, namely the RPL model and RPL model with interactions, to identify the sources of heterogeneity.

Random Parameter Logit Model

Despite the violation of the IIA assumption, the CL model further assumes homogeneity across individual preferences. Since preferences are heterogeneous, we need to account for this heterogeneity in order to obtain unbiased estimates of individual preferences. In addition, accounting for preference heterogeneity is critical for policies to take into account equity concerns (Birol et al., 2006). We therefore used the RPL model by Train (1998). According to Hoyos (2010), three considerations need to be made in implementing an RPL model: which coefficients are assumed random; type of distribution for the random parameters; and the economic interpretation of those coefficients.

To determine which variables are actually random, we used the Lagrange Multiplier test by McFadden and Train (2000) to test for the presence of random components[29]. Based on this test, wildlife_high, forest_medium, forest_high, water_high and flood_medium were found to be random parameters. Some studies that have used this test are (Brey et al., 2007; Liljenstolpe, 2008; Hoyos et al., 2009). However, according to Brownstone (2001), the test is not good for identification of random factors for inclusion in a general RPL specification. For robustness checks, we employed the t-test on the standard deviations assuming all parameters are random to test whether they give same results.

The test showed that forest_medium, forest_high, flood_medium and flood_low are random based on the significant t-values of the standard deviations. This test has been applied by (Carlsson et al., 2003; Colombo et al., 2005; Wang et al., 2007). Based on these two tests, we decided to treat all attributes as random except wildlife_medium and cost, because both tests showed wildlife_medium to be non-random.

[29] The test works as follows; we first compute the artificial variable z_{tnj} given by $z_{tnj} = \frac{1}{}(x_{tnj} - x_{tnC})^2$,with $x_{tnC} = \sum_{k\epsilon C} x_{tnk} P_{nk}$ where t denotes the component of x_{nj} suspected to be random, C is the set of alternatives being offered and P_{nk} is the CL choice probability. The CL model is then re-estimated including these artificial variables z_{tnj}, and the null hypothesis of a non-random coefficient of attribute x is rejected if the coefficients of the artificial variables are significantly different from zero (McFadden and Train, 2000).

The cost attribute was treated as fixed so that distribution of marginal WTP is just the distribution of the attribute coefficient. This also places a non-positive restriction on the cost variable.

In terms of the distributional functions, since the random parameters were all dummies, we settled for the uniform distribution as suggested by Hensher and Greene (2002). The results for the random parameter logit model based on 500 Halton draws are presented in Column (2) of Table 3. The model is statistically significant (chi square value of 2198.424 with 7 degrees of freedom). The overall model fit as shown by the pseudo R squared is 0.62339, which is statistically acceptable for this class of models. The RPL estimates in Column 2 reveal large and significant derived standard deviations for wildlife_high, forest_medium, forest_high, flood_medium and flood_low, which indicate that our data supports choice-specific unobserved heterogeneity for these attributes.
The null hypothesis of equality of the regression parameters is rejected at 5% based on the LR test $(-2\Delta l = -2(-671.1730 + 664.0608) = 14.224 > \chi^2_{6,0.05} = 12.592)$ where *l* refers to the estimated log likelihood function. There is also a structural advantage in RPL over the CL, as shown by the significant standard deviations of the random parameters. However, according to Boxall and Adamowicz (2002), the RPL model does not show the sources of heterogeneity. To identify the sources of heterogeneity, we used an RPL model with interactions.

Random Parameter Logit Model with Interactions

To estimate the RPL model with interactions, we included interactions of individual-specific socio-demographic and attitudinal characteristics with attributes in the utility function. The interaction terms obtained by interacting random parameters with other socio-demographic characteristics decompose any heterogeneity observed with the random parameters, thereby showing sources of heterogeneity (Hensher et al., 2005).

We tested various interactions of the various forest ecosystem services attributes with respondents' socio-economic and demographic characteristics collected during the survey. We found the best fit based on household size, employment status of household head, distance to nearest edge of the forest and whether or not a household owns a PELIS plot . Column (3) of Table 3 presents these results. The model is statistically significant (Chi square value of 2277.19 with 26 degrees of freedom). The overall model fit shown by the pseudo R squared is ρ^2=0.6457, implying a better fit than the RPL model without interaction. The null hypothesis of equality between regression parameters for the RPL model and the RPL model with interactions is further rejected at the 0.5% significance level using the LR test ($-2\Delta l = -2(-664.0608 + 624.6797) = 78.7622 > \chi^2_{19,0.005} = 38.582)$. This implies that the inclusion of demographic and socio-economic characteristics as interactions improves the model fit. We then fixed out interaction terms that had insignificant heterogeneity around the mean parameter estimates, following Hensher et al. (2005). This does not affect the results in any way but just reduces the number of variables by eliminating the insignificant interactions (treating them as fixed). The significant interaction terms are of the expected sign, except for the interaction between household size and the high wildlife population attribute. However, all the random parameters except water_high had large and significant standard deviations.

The RPL model with interactions thus decomposes any observed heterogeneity within the random parameters, thereby providing an explanation for existence of any heterogeneity. For instance, the interaction between ownership of a PELIS plot in the forest and the attribute of high wildlife population is negative and significant, showing that those who own PELIS plots are less likely to choose an alternative with high wildlife population. This is expected since a high population of wildlife would mean higher likelihood of destruction of crops in the PELIS plots. Similarly, those who own PELIS plots are also more likely to select alternatives that have low or medium risk of flooding. This shows that differences in marginal utilities for low/medium flood risk and high wildlife population may be explained in part by whether or not a household owns a PELIS plot. Household size was also found to partly explain differences in marginal utilities for high wildlife population and high/medium forest cover. The results suggest that the greater the household size, the less likely the household is to select an alternative with high/medium forest cover. This is expected, since larger households may consider the forest as occupying land that they could use for agriculture purposes. There is also a chance that these households prefer low forest cover, with the hope that they will get plots through PELIS in an effort to reclaim the forest. This is also supported by the argument that the more scarce the resource, the higher the incentive for collective action and vice versa. However, the results suggest that the larger the household size, the more likely a household is to choose an alternative with high wildlife population. This is unexpected given that high wildlife population could mean destruction of food crops that the household depends on, as well as constant human-wildlife conflict. A possible explanation for this choice could be just the love for wildlife, or that more wildlife would mean more food if they are hunters, or the "warm glow" associated with being pro-wildlife.

Finally, the results revealed that the employment status of the household head could also partially explain differences in marginal utilities for the high quality and quantity water attribute and high/medium forest cover. The results indicate that household heads who are employed in off-farm jobs are more likely to select an alternative with high/medium forest cover and high quantity and quality water for drinking. Moreover, the greater a household's distance from the nearest edge of the forest, the less likely the household is to choose an alternative with medium/high forest cover or high wildlife population. This is expected given that households farther away from the forest may find it costly to enjoy forest resources directly and may not view the forest cover as being of significance. This shows that opportunity cost with respect to distance matters.

Estimation of Willingness to Pay

There is ongoing debate regarding the appropriateness of calculating WTP estimates from RPL models of CE data. A key concern is the RPL assumption regarding distribution of cost variable. By specifying the cost variable as fixed, as in our case, the assumption is that all respondents have same preference for cost, which is quite unreasonable. It may also be equally unreasonable to assume that the distribution of preferences for cost is normally distributed. However, no "gold standard" has been established. Since the cost is not modeled as random, we do not require non-parametric bootstrapping.

The marginal WTP was estimated by computation of the marginal rate of substitution between change in forest ecosystem service attribute and the marginal utility of income represented by the coefficient of the cost attribute. The WTP estimates are computed per household and are to be paid as an annual levy for three years. The WTP estimates for CL, RPL and RPL with interactions estimated using the Wald (Delta method) procedure in NLOGIT 4.0 are presented in table 5.

Table 5: Marginal WTP for Forest Ecosystem Services Attributes (Ksh/respondent (1 US$=Ksh.100)) and 95% C.I

Attributes	CL Model		RPL Model		RPL Model Interactions	
	WTP	C.I.	WTP	C.I.	WTP	C.I.
Wildlife_Medium	-604.76	(-589.67 - -619.85)	-627.92	(-612.25 - -643.59)	-601.61	(-586.59 - -616.62)
Forest_Medium	2481.99	(2420.04 - 2543.93)	2974.55	(2900.32 - 3048.78)	4776.73	(4657.50 - 4895.96)
Forest_High	5811.19	(5666.13 - 5956.25)	6797.80	(6628.12 - 6967.48)	8052.41	(7851.42 - 8253.39)
Water_High	1057.94	(1031.53 - 1084.34)	1307.37	(1274.74 - 1340.01)	819.13	(798.68 - 839.57)
Flood_Medium	2051.04	(1999.84 - 2102.24)	2477.44	(2415.61 - 2539.27)	1548.24	(1509.59 - 1586.89)
Flood_Low	3514.77	(3427.03 - 3602.51)	4343.99	(4235.58 - 4452.41)	2326.98	(2268.90 - 2385.07)

Source: Authors calculation from survey

The t-test of WTP estimates from the three models differ significantly at alpha=0.05 significance level or better. A positive (negative) marginal value for an attribute is an indication that the average respondent would experience an improvement in welfare with an increase (decrease) in the level of the attribute and would therefore choose an intervention that maximizes his/her utility. The positive WTP values for both high and medium forest cover and high water quality and quantity may depict use values, whereas the positive WTP estimates for medium and low flood risk may depict both use and non-use values. However, the negative WTP values for wildlife indicate that individuals would experience a loss in welfare for choosing an intervention with medium population of wildlife (approximately ksh 605 (USD 6.05) loss in welfare). The negative WTP suggests that people do not have a positive preference for this attribute but in absolute terms they would be willing to accept the amount as compensation to accept a policy that would guarantee medium wildlife population[30].

During the survey, communities expressed a lot of concern about destruction of crops and killing of their sheep by wild animals. Elephants, baboons, warthogs, wild pigs and leopards were the most notorious as reported by most CFAs[31]. Even if the damages are shared, since most PELIS farms are normally in same location, in case of any destruction they would still lose. This explains why communities would develop a negative attitude towards wildlife. The high wildlife population attribute was, however, insignificant, although we expected that a high wildlife population would lead to even a larger loss in welfare than a medium wildlife population. These results suggest that devolution of forest management through PFM to CFAs will be more successful where there is less human-wildlife conflict.

People would not be willing to choose an intervention with this attribute due to the destructive nature of wildlife. This is further supported by the fact that most forest-adjacent communities are farmers; some even own plots right inside the forest under the PELIS scheme, and hence are prone to attacks by wild animals.

[31] During the pilot in Londiani, we found the community having a meeting with Kenya Wildlife Service, Kenya Forest Service and other government departments over an attack on over 50 herds of sheep by rogue leopards the previous night.

Our results are in tandem with findings from various studies on valuation of ecosystem services, including those conducted in the developed world. For example, García-Llorente et al. (2012) found that people had higher WTP for river quality, which essentially implies both water quality and quantity. Our results are also consistent with Hanley et al. (2006), who found a positive and significant effect of a river ecology attribute on WTP for a river improvement project. Gatto et al. (2013) also found that respondents had no significant WTP for biodiversity conservation, similar to our findings that increased wildlife population leads to loss in welfare. However, our results differ from findings by Carlsson et al. (2003), Shoyama et al. (2013) and Yao et al. (2014), who found high preference for biodiversity conservation. The results are also consistent with Birol et al. (2009), who found significant preference for flood reduction relative to use and non-use values from recreation or biodiversity.

Welfare Estimates

The marginal WTP estimates show that, in general, the average respondent in the Mau forest conservancy is willing to pay for forest conservation. However, these estimates do not provide welfare estimates for alternative policy scenarios. From a policy perspective, welfare estimate derivation is the most useful aspect of the CE exercise, especially for cost-benefit analysis. We therefore need to compare utility between the status quo and a series of alternatives or policy interventions, each described by attribute levels employed in the experiment. The utility is then transformed into the impacts of different policy interventions on respondents' welfare. The welfare measure for each household is then given by the overall WTP for a change from the status quo based on the estimates from the RPL model with interactions. The new policy scenarios and the corresponding welfare estimates are presented in Table A2 in the appendix. The compensating surplus for a change from the status quo to the alternative policy scenarios increases with improved social, ecological and economic conditions, as expected. The mean WTP of USD 104.19 for the forest conservation policy is highest, followed by flood mitigation and forest conservation policy. This means that an average household would be willing to make an annual payment of USD 104.19 for the next three years to avoid any environmental damage as described by the first forest conservation policy scenario. This also implies that forest conservation policy and a combination of forest conservation policy and flood mitigation policy are perceived to provide higher welfare gains to the households. Moreover, since our sample represented the entire Mau forest, these values could be aggregated across the sampled population in order to compute the total economic value for the policy scenarios. For policy purpose, the total economic value can be compared to the costs of conservation of the Mau forest.

Implications for design of PES schemes and Participatory Forest Management

It is important to note that forest-adjacent communities are mainly poor, with no alternative land, and heavily reliant on these forests for their livelihoods. While these poor communities are charged with conserving these forests, companies downstream are major beneficiaries of forest ecosystem services; these include tea factories, energy and water companies, and tourism industries[32]. This implies that local communities are both demanders and suppliers of these services. As demanders, they pay user fees through the CFAs to enjoy the various forest resources through the Forest User Groups. Although willingness to accept (WTA) would be a good measure for the supply side, given the socio-economic

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status of forest-adjacent communities, we may not get reliable estimates on their values and preferences, since their preferences may be driven only by the compensation from a given policy scenario. Moreover, since the forest is a reserve forest where they have only limited user rights through CFAs (members only), estimating WTA becomes a challenge. We therefore preferred to assess their WTP for the various ecosystem services to determine how the forest-adjacent communities can be incentivized to sustainably manage these forest resources through CFAs. Our estimates therefore provide a good entry point for informing the design of incentive schemes such as PES[33].

5 Conclusion and Policy Implications

The main aim of the study was to determine the economic value of forest ecosystem services to forest-adjacent communities and its implication for design of PES schemes and PFM. The study found that there are positive and significant benefits associated with the various forest ecosystem services within the Mau forest conservancy that need to be considered when designing PFM programs and PES schemes, with the aim of maximizing social welfare and increasing acceptance within communities. There is also considerable preference heterogeneity, which to a large extent was determined by the employment status of the household head, ownership of PELIS plot, household size, and distance to the nearest edge of the forest.

Specifically, we found high WTP values for improvement in forest structure (between USD47.76 and USD80.52)[34], flood risk reduction (between USD15.48 and USD23.26) and high water quality and quantity (at USD 8.19) respectively. The results thus show that there is much appreciation by the average respondent for the role of forest ecosystem services and that forest-adjacent communities are pro-conservation, mainly motivated by the direct and indirect benefits they derive from these forest ecosystems. It is therefore clear that, within the African context, forest-adjacent communities are more concerned with use values, but also with some non-use values, contrary to findings from previous studies in developed countries (see Carlsson et al. 2003; Gatto et al. 2013; Shoyama et al. 2013; Yao et al. 2014). In terms of welfare, respondents revealed that forest conservation policy and a combination of flood mitigation and forest conservation policy would have high welfare impacts on local livelihoods.

We also found considerable consistency with economic theory. Specifically, the price of a given conservation program reduces demand for that program. Increase in forest cover, water quality and reduction of flood risk increase demand for a given conservation program. Contrary to findings from developed countries, we found that respondents would experience a loss in welfare for choosing an alternative with medium wildlife population as opposed to one with low wildlife population. A significant finding from the study was the high WTP values for reduction in flood risk, showing that forest-adjacent communities were very concerned with reduction in flood risk as a result of forest destruction. This indicates that respondents are more altruistic and not only concerned with direct use values but also non-

[33] PES is a voluntary transaction where a well-defined ecosystem service is bought from the ecosystem services provider by a buyer; it assures service provision for those who are willing to pay for the service (Wunder, 2005).

[34] This was supported by a finding from the interactions with the locals. Most said they would pay more for forest conservation; they compared the highest cost shown, USD30, with what they pay monthly per cow or sheep to graze in the forest and the number of cows and sheep they had. They considered the values that we proposed as a very small amount.

use values for the welfare of other members of the society. This aspect of the society thus motivates the design of an incentive schemes such as PES and roll-out of PFM programmes.

A number of policy recommendations can be highlighted from the study. First, the estimated economic values can inform the design of market-based instrument such as PES, which can significantly incentivize communities and enhance the roll-out, design and implementation of PFM. However, more research on the demand and supply side is needed, as well as consideration of which private partners may consider getting involved in PES schemes.

In addition, a demonstration of the significance of ecosystem services as inputs in the production process can play a role in increasing environmental awareness and motivating forest-adjacent communities to conserve forest resources through PFM. This can also encourage shifts from socially unacceptable land management activities towards ecosystem-oriented approaches. Incentive schemes like PELIS may also play a significant role in promoting PFM, as revealed by the fact that PELIS plot owners have more willingness to pay for improvement in forest cover[35]. The government should therefore increase roll-out of PELIS to incentivize communities that have been hesitant to adopt PFM, considering the heterogeneity in preferences to address equity concerns as well. . Incentive schemes like PES can therefore incentivize communities to conserve forest resources through CFAs. However, an assessment of the contextual factors and historical and expected trends in demand and supply is vital if we are to target payments to those CFAs that can actually deliver the desired service.

Lastly, policy makers need to focus on policy options with higher mean welfare impacts to increase community involvement in forest conservation. A comparison of the different marginal WTP for the various forest ecosystem attributes may also help policy makers in understanding the values attached to these services by respondents. In summary, the study provides an entry point for designing future forest management policies in Kenya and provides valuable comparison for studies in other countries.

[35] It is important to note that communities felt that, despite benefiting significantly from PELIS, the government benefited a lot from the revenue from timber sales; hence there was need to dedicate a proportion of this revenues to CFAs because managers of the forests for the communities fully own the scheme. Some felt that a proportion of revenue from PELIS could be channeled to construction of social amenities within the society, e.g., school and health facilities.

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Appendix

Table A1: Summary statistics of the respondents

Variable	N	mean	sd
Waterforest: dummy=1 if household collects water from the forest, 0 otherwise	321	0.732	0.443
MedIncome: Household monthly income	321	13492	10660
Fetch Firewood: Dummy=1 if respondent fetches firewood from forest, 0 otherwise	321	0.776	0.224
ForestValue: Dummy =1 if respondent consider forest of value, 0 otherwise	321	1	0
DistForest:: Distance from household to the nearest edge of the forest in km	321	1.445	1.408
hhsize: Number of people in the household including household head	321	5.994	2.541
MaritSta: Dummy=1 if married, 0 not married	321	0.882	0.323
Education:Dummy=1 if household head has post-primary education, 0 otherwise	321	0.361	0.480
Employment: Dummy=1 if employed off-farm, 0 if self-employed, i.e., farming	321	0.293	0.455
PELIS: Dummy=1 if household owns a PELIS plot and 0 otherwise	321	0.607	0.488
HHWealth: Total value of household asserts	321	1.160e+06	1.346e+06

Source: Authors' calculation from the survey

Table A2: Welfare change from hypothetical future scenarios

Attributes	Hypothetical future scenarios				
	Forest conservation policy	**Flood mitigation and Forest conservation policy**	**Water conservation and Flood mitigation policy**	**Water conservation and Forest conservation policy**	**Water conservation and Wildlife conservation policy**
Wildlife	SQ	SQ	Medium	Medium	Medium
Forest cover	High	High	Medium	High	Medium
Water	High	SQ	High	High	High
Flood risk	Medium	Low	Low	Medium	Medium
Welfare change	Ksh. 10419 (USD104.19)	Ksh.10379 (USD 103.79)	Ksh. 7321(USD73.21)	ksh.9818 (USD98.18)	ksh. 6542(USD65.42)

Source: Authors' calculation from the survey