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

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Abstract

Forest ecosystem services are critical for human well-being as well as 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 are also generally unknown in developing countries. Using a case study of the Mau forest conservancy the study applied a choice experiment technique employing the efficient design criteria to value salient forest ecosystem services among forest adjacent communities. The values attached to various ecosystem services were estimated using the conditional logit, random parameter logit model and random parameter logit model with interactions. The results revealed high level of preference heterogeneity across households and that communities would prefer conservation programs that would guarantee them improved forest cover, reduced flood risk and high water quality and quantity for drinking but would experience a loss in welfare for choosing an alternative with medium wildlife population. One significant finding from the study is the altruistic nature of forest adjacent communities as revealed by the high willingness to pay for flood mitigation showing that they are not just concerned with the private benefits accruing to them but also the welfare of the society. Overall, we found that there is much appreciation for the role of forest ecosystem services and that forest adjacent communities are more pro conservation mainly motivated by the direct use and non-use values. In terms of policy, the information forms a basis for the design of market based incentives such as PES and the roll out, design and implementation of participatory

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forest management. Policy makers also need to focus on policy options with higher mean welfare impacts to deepen community involvement in forest conservation while taking into account the heterogeneity in preferences to ensure equity.
Key words: Choice experiment, Ecosystem services, Incentives, PES
JEL codes: Q23, Q28, Q51, Q57

1 Introduction

Forest ecosystem services[1] are critical for the functioning and growth of world economies (Ferraro et al., 2011). These services play a significant role in contributing to human well-being hence have been of significant value to rural households of developing countries that have often been faced with problem of little physical capital (d'Arge et al., 1997). According to the Assessment (2005), there are four classes namely: provisioning services; support services; regulating services; and cultural services. These services are often, although not exclusively, 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. Other ecosystem services like climate mitigation and recreation services are public good mostly because of poor enforcement of property rights, market and policy failure among others. The optimization of ecosystem service provision and protection between the beneficiaries of the ecosystem service and those who affects its provision have however been hampered with ill-defined property rights, information asymmetry and externalities (Ferraro and Kiss, 2002).

The existence of market and policy failures in provision and regulation of ecosystem services thus implies that environmental depletion is often more than the socially optimal level, while the provision of ecosystem services is below the socially optimum level (Ferraro and Kiss, 2002). In Kenya, just like the rest of the world, market and policy failures are some impediments to protection and conservation of important global forest ecosystem (Müller and Mburu, 2009). To secure standard levels of forest and environmental quality, there is need to increase revenue of benefit providers and improving management from society's perspective. For this to be achieved, policy tools such as Payment for Ecosystem Services (PES) are essential for identification of form of marketing. Therefore, valuation of these ecosystem services is an essential step towards the design of such policy tools (Assessment, 2005).

1.1 Value of Forest Ecosystem Services in Kenya

Kenya has five major water towers classified as montane forests namely; Mount Kenya, the Abardares 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

[1] Defined as the benefits people receive from their ecosystems (Assessment, 2005)

are surrounded by mostly densely populated areas since 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; promoting biodiversity; nutrient cycling and soil formation; reduced soil erosion and siltation; and timber and non-timber forest products thus providing insurance value to other key sectors of the economy and consequently having significant impact on economic resilience of the country (UNEP, 2012a). These forests therefore sustain many natural habitats in the lower areas of the catchments hence producing direct economic value to its citizens. Apart from supporting livelihoods of downstream communities, some of these forests like the Mau also hosts indigenous communities like the Ogiek whose main economic activity is hunting and gathering and have been the only communities with rights to live inside the forest.

However, the ability of these forests to supply the various ecosystem services has been hampered by increased degradation resulting from human activities, rent seeking behavior of government officials[3] as well as 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 250m^3/ha with estimated cash value of USD 13.62 million (equivalent to USD 2720/ha per year) in 2010 hence the incentive for rampant deforestation. Despite the revenue streams, the cost to the economy is quite high especially through losses of regulating services (UNEP, 2012a). It is estimated that the cost to the economy as a result of reduction in the provision of regulating services from the effects of degradation was USD 36.52 million per year more than 2.8 times the revenues from such deforestation activities. The effects were namely; reduced agricultural output by USD 22.62 million in 2010, reduced hydro power generation by USD 0.12 million (which has reasonable multiplier effect on the 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 incidences was estimated to have cost the government USD 3.95 million hence additional health cost to the government through loss of productivity (UNEP, 2012b). Finally, "due to the interdependence of various sectors, the decrease in regulating services due to deforestation caused a total impact of USD 0.058 billion in 2010 implying that the cost of limiting regulating ecosystem services as a production factor for the economy was all in all 4.2 times higher than the actual cash revenue of USD 0.013 billion" (UNEP, 2012a).

[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 effort 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.

Due to the significance and importance of forest ecosystem services (Assessment, 2005), as many other countries, Kenya has strengthened measures towards conservation of forests through various initiatives. Efforts have been made by the government to integrate forest conservation and rural development to incorporate social concerns. Some of these efforts includes enactment of the Forest Act (2005) and the National Forest Policy (2014) aimed at devolution of forest management to forest adjacent communities (MENR, 2005, 2014). The policy and Act introduced Participatory Forest Management (PFM) that seeks to engage local communities and promote private sector investment in gazetted 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 Scheme (PELIS); and adoption of ecosystem approach to management of forests among others. Communities have in turn been able to form community based organizations known as Community Forest Associations (CFAs) in collaboration with the Kenya Forest Service (KFS). This is a departure from prior practice where the government assumed full responsibility of gazetted forest reserves.

However, despite these efforts there are still increased cases of degradation within CFAs, the knowledge about the extent of the benefits of these forest ecosystem services is quite scant. The values attached to various ecosystem services by forest adjacent communities are also unknown. Moreover, even though the benefits to local communities is substantial including use and nonuse values, the prices of these services are non-existent. It is therefore evident that the forestry sector's contribution to the economy[4] is based on formal market transactions since the value of non-marketed forest products is unaccounted for[5]. According to the UNEP the challenge for developing countries facing natural resource degradation like Kenya is institutionalization of 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 mechanism forest adjacent communities will hardly include them in their management objectives unless constrained by command and control policies hence forest management will rarely achieve the social optimum.

We have all along valued the forest for products like timber and wood products that have tangible monetary worth but what about the values of forest ecosystem services that are priceless or hard to measure? The question of concern is thus how can we attach a value on flood mitigation, wildlife habitat, clean water, air and climate? What is the scenic value of a pristine grove of pine? These services are worth paying for especially since the costs and responsibilities

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

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

are not in the public domain. How can providers of the ecosystem service be compensated by the users? To obtain public support for conservation programs, an understanding of the values, attitudes and preferences towards various environmental services is necessary. The Ecosystem services trade-offs have also received limited attention in terms of 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. Humans are also less likely to take necessary steps to protect ecosystem services if they do not understand or appreciate the values these ecosystem services have on their quality of life. The goals of devolution of forest management may therefore never be realized. Valuation of these services is also expected to help raise awareness of their importance and stimulate support for appropriate conservation measures, furthering policy design and development of incentive schemes such as Payment for Ecosystem Services (PES) to incentivize local communities. This is also critical for engaging their participation in behavioural change and encouraging adoption of ecosystem oriented management practices hence informing devolution of forest management through PFM.

Moreover, literature on valuation of local indigenous communities' preference for ecosystem services within developing country context specifically Kenya are anecdotal and scant hence the need to contribute to the debate. The most common valuation approach in the available empirical studies has been CVM and PEV with very few using the choice experiment approach and mostly in other fields. The advantage of the CE is that it is able to elicit trade-offs between different policies and also avoids biases associated with CVM and PEV approaches. Much of the literature generally focus on a single attribute of community forest (Carlsson et al., 2003). Hence difficult to assess preference heterogeneity in the case of valuation of just a single attribute like in CVM. Most of the studies on valuation of ecosystem services have also been in developed countries (see GarcíaLlorente et al. 2012; Gatto et al. 2013; Shoyama et al. 2013; Smith and Sullivan 2014; Yao et al. 2014) with very few in developing countries (see Gelo and Koch 2012; Dikgang and Muchapondwa 2014, 2016). In addition, most studies that have used the choice experiment approach have often relied on the orthogonal design (see Dikgang and Muchapondwa 2012; Shoyama et al. 2013; Pienaar et al. 2014) rather than the efficient design (see Gatto et al. 2013; Czajkowski et al. 2014). The efficient design has the advantage of producing more reliable and efficient estimates at smaller sample sizes. The application of efficient design is also quite scant within developing countries. Due to the significant variation in terms of preferences and values attached to various ecosystem services as well as the context specific factors, a context specific analysis is therefore critical. This study therefore, seeks to, determine the economic value of a range of salient forest ecosystem services in Mau forest conservancy in Kenya and assess whether they are sufficient to incentivize local communities to engage in forest conservation through PES schemes and the implication on devolution of forest management to local communities through PFM.

In this study we contribute to the CE literature on valuation of forest ecosystem services by applying the Bayesian efficient experimental design from a developing country perspective using Kenya as a case study with a goal of aiding the design of appropriate PES scheme and informing devolution of forest management through PFM to support ecosystem service provision. There is also the potential to transfer the estimates from this valuation exercise to other policy contexts. The rest of the paper is structured as follow. Section 2 presents a review of some of the related literature, section 3 presents a description of the study area. Section 4 presents the methodology, survey design and data collection, empirical model, WTP estimation, and experimental design. Section 5 presents the model estimation results. The conclusions and policy recommendation are presented in section **6.**

2 Related Literature

The use of choice experiment (CE) in environmental economics dates back to the works of (Adamowicz, 1995; Boxall et al., 1996). The method is now considered more preferable and superior to other approaches like the contingent valuation method (CVM) and participatory environmental valuation (PEV). Unlike CVM and PEV, the CE allows inclusion of multiple attributes and allows estimation of the value of each attribute hence can elicit trade-offs between different policies. It also avoids biases associated with other methods like CVM.

There is growing literature on the use of CE to value ecosystem services in various contexts. The values for ecosystem services therefore varies across countries based on what the society values most. Studies have therefore yielded different results for example, Gatto et al. (2013) found that respondents had high preference for recreation and carbon sequestration but no other ecosystem services. Whereas Qin et al. (2008) in investigating farmers' preferences for property rights attributes found that the major concern of farmers is type of right a contract provides. Dikgang and Muchapondwa (2014) also assessed using CE the potential for ecosystem services to improve livelihood of Khomani-San through PES and found that visitors preferred more pristine recreational opportunities but disapproved granting more access inside the Kgalagadi. They also assessed the supply side and found that locals would prefer, collection of bush food and increased grazing opportunities (Dikgang and Muchapondwa, 2016).

García-Llorente et al. (2012) also examined preferences for a range of land use management options using Multinomial logit model and the random parameter logit (RPL) model to account for preference heterogeneity. They found that respondents would support management plans, focusing on river quality and traditional farming. However, Birol et al. (2009) had different findings with respondents deriving significant welfare improvement from flood risk reduction over welfare improvements from both river accessibility for recreation and conserving high biodiversity level. In New Zealand, Yao et al. (2014) estimated the non-market values for a program aimed at enhancement of biodiversity using a two-stage modelling process by first estimating individual specific WTP values and then exploring their spatial and socioeconomic determinants. Using RPL model in the first stage they found higher WTP for increased quantities of native birds than for nonbird species. In the second stage, they found WTP for biodiversity enhancement was mainly influenced by distance from large planted forests and other socioeconomic characteristics such as attitude towards the program. Similarly, Shoyama et al. (2013) found that the public strongly preferred biodiversity conservation over climate change mitigation in the form of carbon sequestration through increasing area of forest managed. Studies have also shown that farmers place high values on ecosystem services, although they consider them moderately manageable since they consider the economic costs of maintaining ecosystem service provision as a threat (Smith and Sullivan, 2014).

Communities have also shown that private and quasi development interventions can sufficiently incentivize them to engage in anti-poaching enforcement, re-vegetation of wildlife habitat and wildlife monitoring (Pienaar et al., 2014). However, most of these CE studies have been biased towards developed countries where preference for various forest ecosystem services are significantly different given the levels of economic development and variation in social and cultural contexts hence the mixed results. Literature on valuation of forest ecosystem services in the Eastern Africa and specifically Kenya are quite scant, past studies have used mainly CVM and PEV (see Carson and Mitchell 1989; Emerton 1996; Emerton and Mogaka 1996). Most recently Anderson Kipkoech et al. (2011) estimated total economic value of a section of the Mau forest at approximately KES 17 billion (USD 0.17 billion).

It is also important to note that most of these past choice experiment studies have relied on orthogonal designs (e.g. Dikgang and Muchapondwa 2012; Shoyama et al. 2013; Pienaar et al. 2014) mainly because it is easy to construct and understand. In orthogonal experimental designs, statistical independence of the attributes is achieved by forcing them to be orthogonal (Louviere et al., 2000). However, while orthogonality could be an important criterion for determining independent effects in linear model, the orthogonality property may run counter to some desirable properties of econometric models employed in analyzing stated choice data especially since discrete choice models are nonlinear (Petrin and Train, 2003). Over time studies have revealed that efficient experimental designs can produce more efficient data and that we can still get reliable parameter estimates even with a lower or equal sample size (Bliemer and Rose, 2010). However, the use of efficient designs has been mostly applied in transport economics and market research while quite scant in environmental or resource economics (see Gatto et al. 2013; Czajkowski et al. 2014). Domínguez-Torreiro (2014) compared two experimental designs i.e. Optimal Orthogonal in the differences design and the D-efficient design and found that OOD design based on no prior knowledge is not inferior in terms of estimation efficiency to the efficient designs. He however, noted that the contradiction might have been as a result of sufficiently large sample that outweighed the expected loss of efficiency based on zero prior estimates.

An overview of the CE literature also reveals significant differences in applied definition, contextual factors and methodological approaches hence making comparison difficult. Moreover, attempts to estimate different forest ecosystem services and their trade-offs are still rather scarce on regional scale and especially within the African context. The application of efficient designs in CE is also mainly in developing countries with hardly any in Africa. As a departure from most studies, this study takes a different approach by employing a state of the art CE valuation method using the Bayesian D-efficient design.

3 Description of the study area

The study was conducted in the Mau forest conservancy. The choice of Mau forest was based on a set of criteria namely: high susceptibility to degradation; long history of community forestry and high level of biodiversity. It is also the largest closed canopy forest among the five major Water Towers in Kenya that 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[6], 21 of which are gazetted and managed by Kenya Forest Service (KFS). The other is Mau Trust land Forest (46, 278 ha) managed by the Narok County Council (NEMA, 2013).

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 upper catchment of numerous rivers[7]that supply water to communities and urban centers in the region thus supporting livelihoods and economic development of the region. These rivers feed into various lakes e.g. Nakuru, Baringo, Natron, Naivasha, Turkana, and Victoria among others. 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 hydro power generation in the Mau forest catchment is approximately 535 MW accounting for 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 among others, the forest also supplies global public goods and services such as; carbon sequestration, wildlife habitat[8], and biodiversity conservation (Anderson Kipkoech et al., 2011). The upper catchment of the forest also hosts the last group of indigenous communities whose main economic activity is hunting and gathering the Ogiek (Force, 2009).

[6] South Molo, Transmara, Eastern Mau, Mt. Londiani, Ol Pusimoru, Maasai Mau, Mau Narok, Western Mau, South West Mau, Eburu and Molo. In the northern section are the forests of Tinderet, Timboroa, Northern Tinderet, Kilombe Hill, Nabkoi, Metkei, Lembus, Maji Mazuri, and Chemorogok.

[7] Including the Yala, Nzoia, Nyando, Mara, Sondu, Kerio, Ewaso Ngiro, Molo,Njoro, Nderit, Naishi and Makalia rivers.

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

4 Methodology

4.1 Survey design and data collection.

This exercise involved a series of design and testing. 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 the Focus Group Discussions (FGDs) and expert judgment. The structured questionnaire was divided into three parts, part one collecting information on general attitudes and perceptions towards forest ecosystem services, part two involved the choice modelling scenario and last part collecting information on socio-economic characteristics and institutional variables.

The choice experiment approach involved households being presented with three different alternatives. Option C is the status quo, this option described "as at today" i.e. no change in forest conservation and management. This option does not involve any policy intervention and no cost to the household meaning the respondents are comfortable with current condition (status quo/low) of the forest regardless of the future condition of the forest without any intervention. Option A and B involves a combination of new policy interventions that may affect future condition of the forest catchment. The impact of the new policy interventions in 5 years' time are predicted and described by the attributes considered to have direct influence on well-being of forest adjacent communities.

The choice of attributes was based on what the local communities could easily understand and what they interacted with most. 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 be considered to imply limited supply of these services. The cover also by extension could easily depict the aesthetic 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.

These forests also act as habitat for various wildlife animals such as elephant, monkeys, leopards bongo, buffaloes etc. About 99% of the respondents agreed to be 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 (KWS), about 90% claimed not to be involved in trapping the wild animals. Communities also complained of rampant human wildlife conflict. Hence wildlife population was included as an attribute to gauge their preference and perception towards wildlife conservation and whether they would consider conserving the forest for other benefits and cope with the increasing wildlife population. This would also show their attitude towards biodiversity conservation and preservation of wildlife for future generations i.e. bequest values.

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 forest 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 the continuous degradation would mean high social and economic costs of flooding episodes borne by locals, downstream settlers and nearby towns and urban centres. This attribute was therefore included to gauge the behavioural aspects of forest adjacent communities that is, whether they are altruist or or self-centred. 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. The levels of each attribute used in the pilot and final survey are shown in table 1. The levels for the various attributes were chosen following past studies (Pearce, 1994; Fitzgibbon et al., 1995; Adamowicz et al., 1998; Nielsen et al., 2007; Gatto et al., 2013). For each of the attributes except the cost, we considered low medium and high levels of each with low being the status quo i.e. choosing no management option. For the wildlife population low represented 753 elephants, medium 1103 elephants and high 1203 elephants. Whereas for the forest structure, low represented 56.25%, medium 82.5% and high 90% forest cover. The water purification and supply attributes was reflected in million cubic meters with low being 11850, medium 17380 and high being 18960. Being that quantifying risk of flooding required more technical expertise, this was just reflected by low medium and high risk flooding. We preferred the use of coding in terms of high, medium and low due to the fact that with the status quo we cannot quantify/predict the exact future condition of the forest hence respondents are left to imagine future condition of the forest if they continue with current practices without any intervention though we expect the levels to be low or worse. It was also chosen for ease of coding and choice designing in Ngene. The last was the monetary attribute that is additional annual cost per household in the form of annual levy.

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

Household were informed that the levy would be channeled into a special conservation fund set up to fund conservation and management of the forest catchment. They were further informed that the fund will be managed by officials selected by CFA members and that an independent auditor will ensure the money is 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 digital manipulation of a "control" picture depicting more or less of the attribute. This approach ensured changes in attribute levels are easily identifiable holding other factors of the forest ecosystem service constant.

However, the status quo alternative was just represented as "As today" instead of pictorially since the respondent had knowledge of the current low state of the forest ecosystem services provision and was left to imagine what the situation would be in the next five years if they continued with current practices with the forest as it is today[9]. They were however informed that it could be low as presented pictorially in other options or even worse. To ensure understanding and scenario acceptance by respondents, the accompanying text in the structured questionnaire and images were tested in FGDs and a pilot to test the validity and construct of the survey instrument. The sample choice card is shown in figure 1.

The pilot questionnaire was presented to 44 households in Londiani CFA of Kericho county in October 2015. In the pilot 15 choice tasks were generated and respondents were presented with 5 choice tasks. From the pilot exercise, we estimated Multinomial logit model betas which were used as priors in the final statistical design. Final survey was conducted betweeen November and December 2015 in which a random sample of 321 jouseholds were interviewed across 22 CFAs. For the final survey we generated a design with 30 choice tasks. To reduce the answering load, each respondent would answer five choice tasks picked randomly from the choice tasks generated in Ngene.

5 Theoretical Framework

5.1 Empirical Model

The choice experiment approach has its roots in two theories namely, the 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

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

Thus

$$U_{nsj} \; = V_{nsj} \; + \varepsilon_{nsj} \tag{2}$$

Where S is the set of all possible alternatives and 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 impact 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 β_s are unknown parameters to be estimated then we have,

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

$$V_{nsj} = \sum_{k=1}^{K} \beta_k x_{nsjk} \tag{3}$$

In our case, β_k appears in the utility function of multiple alternatives j. Hence generic over these alternatives. Assuming the unobserved components is $i.i.d$, the probability P_{nsj} that respondent n selects alternative j from a choice situation S is given by the Multinomial logit model (McFadden, 1974).

$$P_{nsj} = \frac{\exp V_{nsj}}{\sum\limits_{j\epsilon Jns} \exp V_{nsi}} \tag{4}$$

In the first step, equation 4 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. Implying 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 Random Parameter Logit (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; García-Llorente et al., 2012). Following Colombo et al. (2009) the RPL model is described in equation 5.

$$U_{nsj} \ = \beta X_{nsj} \ + \phi_n X_{nsj} \ + \varepsilon_{nsj} \tag{5}$$

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 the individual's taste. Individual tastes are assumed constant across choices made but not across the entire sample); and ε_{nsj} is a random term and is IID (GarcíaLlorente et al., 2012). 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). The probability of respondent n's observed sequence of choices is given by the integral in equation 6 assuming homogeneous tastes across all choice situation.

$$P_{n[y1 \cdot y2 \ldots ys]} = \int \cdots \int \prod_{s}^{S} \left[\frac{e^{Xnsj\beta n}}{\sum\limits_{i=1}^{J} e^{Xnsi\beta n}} \right] f(\beta) d\beta \tag{6}$$

Integral (6) is estimated by simulation since it has no analytical solution (Colombo et al., 2009).

The simulated probability $\hat{P}_n$ is given in equation 7.

$$\hat{P}_n = \frac{1}{R}\sum_{r=1}^{R}\left(\prod_{s}^{S}\left[\frac{e^{Xnsj\beta nr}}{\sum_{i=1}^{J} e^{Xns\beta nr}}\right] f(\beta)d\beta\right) \tag{7}$$

$\hat{P}_n$ is unbiased estimate of P_n whose efficiency increases as R increases (Train, 2003). The index nr on β implies that for each respondent, the probability is calculated using R different sets of β vectors (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 socioeconomic variables). In addition, although the RPL is better than the CL models in terms of welfare estimates and overall fit 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 miss-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).

$$-2(LLBase - LLEstimated) \tag{8}$$

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

5.2 Estimating Marginal WTP

The marginal WTP measures is given by the ratio of two parameters[10] as presented in equation 9 (Hensher et al., 2005).

$$WTP = -(\frac{\beta_{attribute}}{B_{price}}) \tag{9}$$

Beyond the MWTPs 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)

$$Welfare\ change = -\frac{1}{\beta \cos t}(V_0 - V_1) \tag{10}$$

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.

[10] Both parameters must be statistically significant

5.3 Experimental Design

To generate different choice tasks, an experimental design criterion is needed. In this study we employed the Bayesian D-efficient design. This was chosen due to the uncertainty on the nature of the parameter estimates for each of the attributes. Compared to orthogonal designs, efficient designs are capable of producing robust estimates at smaller sample sizes (Bliemer and Rose, 2009, 2010). The efficient designs are also less restricted and easy to find than the orthogonal and often allows much smaller number of choice sets (Greiner et al., 2014). Due to the advantage of the efficient design, we used the D-error criterion to optimize the efficiency of the experimental design. However, to generate an efficient design priors are needed. Since using zero priors would be same as using the orthogonal design we used a method proposed by Bliemer and Rose in Ngene forums when we have no knowledge of the priors but have an idea of the expected signs of the parameters.

We assumed a uniform distribution of the parameters as the priors to be used to generate a Bayesian D-efficient design using Ngene[11]. 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. The efficient statistical design for the pilot was thus built using Ngene 1.1.2[12]. We then conducted a pilot/pre-test so as to validate the design in principle. The purpose of the pilot was to: check the validity and construct of the questionnaire; review the survey instrument in its totality and identify any issues with comprehension or completeness; contribute preliminary choice data for analysis; and to check understanding of the choice task by respondents, complexity and cognitive burden for respondents. From the pilot respondents showed a clear understanding of the choice task. Other sections of the questionnaire that were not easily understood were then modified as suggested during the focus group discussions.

Data from the pre-test was then analyzed using MNL in Stata 13 and resulting parameter estimates used as priors for development of a refined and more efficient design for the final survey. Due to complexity of running an efficient design using RPL we opted for the MNL despite its weaknesses[13]. 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.

[11] Using uniform priors rather than normal priors reflects directions and weak priors. Since we know the signs we use the formula (sign (midpoint of prior(x)*midpoint of attribute level) = 0.5, if say the attribute levels are (1,2,3) then the midpoint is 2, we have X*2=0.5 hence X=0.25 but assume the expected sign is negative then the prior is bound between 0 and -0.25 we get the prior as (X+0)/2=-0.25 giving an x of -0.5 hence the prior is uniformly distributed between -0.5 and 0.

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

[13] First it does not easily accommodate the presence of preference heterogeneity within choice data; secondly it does not allow for the fact that with SC data, each decision maker typically responds to multiple choice tasks; and lastly the MNL imposes some constant error variance assumptions across all alternatives across the model (Bliemer and Rose, 2010).

The choice sets for the full survey were developed based on priors from the pilot. Priors β_k for parameter k were defined as Bayesian prior distributions normally distributed with mean value $\hat{\mu_k}$ and standard deviation $\hat{\sigma_k}$ so that $\beta_k \sim N(\hat{\mu_k}, \hat{\sigma}_k{}^2)$. The use of Bayesian priors, leads to more robust efficient design as it accounts for uncertainty about prior parameter values (Sandor and Wedel, 2001). Both pre-test and revised Bayesian design parameters are presented in table 6 in the appendix.

In both pilot and full survey, we checked for 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. The global efficiency level of the design is commonly expressed as the Bayesian D-error. More statistically efficient designs are achieved at smaller D-error. The D-error for the final design was 0.0616.

6 Results and Discussion

6.1 Descriptive statistics

A total of 321 households were interviewed. Other than the Choice experiment questions, socioeconomic and demographic profiles of respondents were also collected to gain more insight on factors affecting people's perception about the various forest ecosystem services. This information forms a basis for investigating heterogeneity in personal preferences. A summary statistics of the profiles of respondents interviewed is shown in table 7 in the annex. The results show that whereas all respondents considered the forest to be of significant value, approximately 73% of the respondents visited the forest to fetch water and 78% visited to collect firewood. The summary statistics also show that approximately 61% of the respondents own PELIS plots in the forest. About 88% of the respondents are also married and only 29% employed in off-farm jobs. The average households size is also approximately six members and the average distance from the nearest edge of the forest is about 1.4 kilometres.

6.2 Model estimation results

NLOGIT 4.0 and Stata 13 econometric software were used to estimate the models. Instead of coding the attributes using the dummy variables, attributes were effect coded as this provides estimates that are uncorrelated to the model intercept (Louviere et al., 2000; Hensher et al., 2005). Effect coding implies one level of attributes is dropped as the base category. However, for the water attribute we merged the low and medium level and classified it as low since it made more economic sense for a respondent to just pay for clean water hence the water attribute had just one level high and the reference category. The estimated coefficient for each of the remaining levels show the respondent's preference for change from the reference (omitted) level to 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 0-cost option, or protest behavior. 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 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. This information is however still more useful for policy purposes. Testing for status quo bias is therefore necessary. Table 2 show 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.

6.3 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 $\rho^2$is 0.47 which is a bit high by conventional standards[14]. The coefficients are however 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 peribus*, low and medium flood risk, higher levels of Water quality, and high and medium forest cover increases the likelihood of selecting a given management scenario. While medium wildlife population[15] decreases the probability of selecting a given management option. The negative and significant coefficient of the ASC shows that people want a change from the SQ i.e. they want a conservation program aimed at improving forest condition.

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. We also found considerable consistency with economic theory. Specifically, that the cost of a conservation program reduce demand for a given conservation program. Our results therefore suggest the existence of significant values and preferences for the stated forest ecosystem attributes. However, if the IIA assumption does not hold then 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 IIA assumption is thus evident from the results. Hence the

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

[15] During the survey we noted that most households were not concerned about the destructive nature of wildlife animals such as monkeys or elephants. They said in case of damage it was often shared since most farms in the forest are in one area. The main worry was if the population increases then human wildlife conflict would arise hence tension with Kenya Wildlife officials. However, the main concern was with leopards that often attacked their sheep at night yet no compensation from relevant authorities.

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

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

6.4 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, for prescription of policies that take into account equity concerns, accounting for preference heterogeneity is critical (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 that is: which coefficients are assumed random; type of distribution for the random parameters; and the economic interpretation for those coefficients.

To determine which variables are actually random, we used the Lagrange Multiplier test by McFadden and Train (2000) to test the presence of random components. The test works as follows; we first compute the artificial variable z_{tnj} given by

$$z_{tnj} = \frac{1}{2}(x_{tnj} - x_{tnC})^2, \text{with } x_{tnC} = \sum\nolimits_{k \epsilon C} x_{tnk} P_{nk} \tag{11}$$

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 non-random coefficient of attribute x is rejected if the coefficients of the artificial variables are significantly different from zero (McFadden and Train, 2000). Based on this test, Wild_H, Tree_M, Tree_H, Water_H and Flood_M were found to be random parameters. Some studies that have used this test are (Brey et al., 2007; Liljenstolpe, 2008; Hoyos et al., 2009). But according to Brownstone (2001), the test is not good for identification of random factors for inclusion in a general RPL specification. For robustness, we employed the t-test on the standard deviations assuming all parameters are random to test if they give same results. The test showed that Tree_M, Tree_H, Flood_M and Flood_L are random based on the significant t-values of the standard deviations[16]. 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 Wild_M and cost since both tests showed Wild_M to be non-random. The cost attribute was treated as fixed so that distribution of MWTP is just the distribution of the attribute coefficient. This also places a non positive restriction on the cost variable.

[16] M denotes medium level for Tree and wildlife. M and L denotes medium and low risk for flood. whereas H denotes high level for water attributes

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 reveals significant and large derived standard deviation for Wild_H, Tree_M, Tree_H, Flood_M and Flood_L an indication 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 ($-2\Delta l = -2(-671.1730{+}664.0608) = 14.224 > x^2_{6,0.05} = 12.592$) 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. Hence the need for an RPL model with interactions.

6.5 Random Parameter Logit Model with Interactions

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

We tested various interactions of the various forest ecosystem services attributes with respondents socioeconomic and demographic characteristics collected during the survey. We found, household size, employment status of household head, distance to nearest edge of the forest and whether a household owns a PELIS plot or not fits the data best. Column (3) of table 3 presents these results. The model is statistically significant (chi square 2277.19 with 26 degrees of freedom). The overall model fit shown by the pseudo R squared is ρ^2=0.6457 hence a better fit than the RPL model without interaction. The null hypothesis of equality between regression parameters for RPL model and RPL model with interactions is further rejected at 0.5% significance level using the LR test ($-2\Delta l = -2(-664.0608 + 624.6797) = 78.7622 > x^2_{19,0.005} = 38.582$). This implies that the inclusion of demographic and socio-economic characteristics as interaction 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 however 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 correct sign except for the interaction between household size and high wildlife population attribute. However, all the random parameters[17] except Water_H had high and significant standard deviations.

The RPL model with interactions therefore decomposes any observed heterogeneity within the random parameters hence providing an explanation for existence of any heterogeneity. For instance, the interaction between ownership of PELIS plot in the forest and attribute of high wildlife population is negative and significant showing that those who own PELIS plots are less likely to choose alternative with High population of wildlife. This is expected since high population of wildlife would mean higher chances 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 in part be explained by whether a household owns a PELIS plot or not in the forest. 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 higher the household size the less likely the household is to select an alternative with high/medium forest cover. This is expected since most populated households may consider forest as occupying alternative land that they could use for agriculture purposes. There are also chances of these households choosing 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 fact that the more the scarcity of the resource the higher the incentive for collective action and vice versa. However, the results suggest that the higher 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 and constant human wildlife conflict. A possible explanation for this choice could be just the love for wildlife or more wildlife would mean more food if they are hunters or just "warm glow" associated with being pro wildlife.

Finally, the results revealed that the employment status of household head could also partially explain differences in marginal utilities for 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 alternative with high/medium forest cover and high quantity and quality water for drinking. Moreover, the higher the distance a household is from the nearest edge of the forest, the less likely the household is to choose alternative with medium/high forest cover or high wildlife population. This is expected given that households further away from the forest may find it costly to enjoy forest resources directly hence may not view the forest cover to be of significance. This shows that opportunity cost with respect to distance matters.

[17] Wild_H, Tree_M, Tree_H, Water_H, Flood_M and Flood_L

6.6 Estimation of Willingness to Pay

There is ongoing debate regarding the appropriateness of calculating WTP estimates from RPL models of CE data. 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 modelled 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 coefficient of the cost attribute. 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.

The t-test of WTP estimates from the three model differ significantly at alpha=0.05 significance level or less. Positive (negative) marginal values 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 hence would choose an intervention that maximizes his/her utility. The results suggest that respondents have preference for improved forest cover followed by reduction in flood risk then water quality and quantity attributes. 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 positive preference for this attribute but in absolute terms they would be willing to accept the amount as compensation to accept the policy with medium wildlife population. People would not be willing to choose an intervention with this attribute due to the destructive nature of wildlife and 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 hence prone to attacks by wild animals. During the survey communities expressed a lot of concern especially with 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[18]. This explains why communities would develop negative attitude towards wildlife animals. The high wildlife population was however insignificant although we expected that the high wildlife population would lead to even a larger loss in welfare than medium wildlife population. This is result is however hard to explain but we can attribute it to the effect of education levels. However, the results suggest that

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

devolution of forest management through PFM to CFAs will be more successful where human-wildlife conflict is lesser.

Our results are in tandem with findings from various studies on valuation of forest ecosystem services. For example, García-Llorente et al. (2012) found that people had higher WTP for river quality which essentially implies water quality and quantity. Our results are also consistent with Hanley et al. (2006) who found positive and significant effect of river ecology attribute on 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. Czajkowski et al. (2014) also found preference for improved forest cover by respondents specifically extending areas under passive protection over areas of ecologically valuable forests in Poland hence lending support to our findings.

6.7 Welfare Estimates

The MWTP estimates show that in general the average respondent in the Mau forest conservancy is willing to pay for forest conservation. However, they do not provide welfare estimates for alternative policy scenarios. From policy perspective, welfare estimate derivation is the most useful aspect of the CE exercise especially for assessment of cost benefit analysis. We therefore need to compare utility between 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 impacts that different policy interventions have on respondent's welfare. The welfare measure for each household is then given by the overall WTP for a change from the status quo based on RPL model with interactions estimates. The new policy scenarios are projected as follows:

Scenario 1: Forest conservation: wildlife population-SQ; Forest Structure-high; Water Quality-High; Flood Risk-medium.

Scenario 2: Flood mitigation and forest conservation: Wildlife Population-SQ; Forest Structure-High; Water quality-SQ; Flood Risk-Low

Scenario 3: Water conservation and Flood mitigation: Wildlife Population-medium; Forest Structure-medium; Water Quality-high; Flood Risk-low.

Scenario 4: Water conservation and forest conservation: Wildlife Population-medium; Forest Structure-high; Water Quality-high; Flood Risk-medium.

Scenario 5: Water conservation and wildlife conservation: Wildlife Population-medium; Forest Structure-medium; Water Quality high; Flood Risk-medium.

The welfare estimates are presented in table 8 in the annexe. 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 for the Forest conservation policy of USD 104.19 is highest followed by Flood mitigation and forest conservation policy. This means that an average respondent would be willing to make an annual payment of USD 104.19 to avoid any environmental damage as described by the Forest conservation policy scenario1. 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 respondents. Moreover, if the sample is representative, these values could be aggregated across the sampled population in order to compute the total economic value for the policy scenarios. The total economic value can be compared to the costs of conservation of the Mau forest for policy purposes.

6.8 Implication for design of PES schemes and Participatory Forest Management

PES[19] involves a situation where local agreement is made for beneficiaries or users of an ecosystem service to compensate the ecosystem service providers. The compensation is often agreed in advance between the users and the provider and the money paid go to the provider not in general public purse. A clearly defined user and supplier of the service is therefore necessary for PES to exist. It is important to note however, that our MWTP values provides an overview of the supply and not the demand side of the market for ecosystem services. How can the beneficiaries of these services compensate the service providers to conserve the forest ecosystem? Are the buyers or beneficiaries of these ecosystem services willing to pay for their conservation and whether the suppliers of the service have adequate incentives to deliver the services. PFM and PELIS alone is not adequate to incentivize communities to conserve these forests.

If public and private partners can come together, policy instruments like PES can ensure socially optimal supply of ecosystem services through improving resource management, creating income and sustainable livelihoods for rural and urban populations. This is because the PES concept introduces the notion of scarcity of the ecosystem service hence encouraging users not to over use or undervalue the resource. PES is also more easy to understand by locals and can play a significant role in raising environmental awareness. For example, the commercial value of water is relatively easy to calculate compared to protection of key wildlife habitat or protection of soil type or flood mitigation which does not easily translate to cash value.

The Mau forest is the source of water for a large number of towns and cities in Kenya, Lake Naivasha, Lake Victoria and Baringo rely on over 60% of their water from this forest. The Rift Valley water services board which supplies water to major towns in the Rift Valley and water companies such as Keringet mineral water company in Molo as well as the Coca cola company which need pure drinking water could therefore work in partnership with KFS and CFAs to explore the possibility of using a water fund as a possible financing mechanism.

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

This could be funded by the public through increased water fees aimed at protection of the quality and quantity of water to surrounding towns and municipalities. Surrounding counties could also come up to establish voluntary conservation funds for biodiversity conservation and related ecosystem services making use of the estimated MWTP values. Finally, given that forest adjacent communities consider forest to be of significant value to them, there should be more effort towards devolution of forest management to forest adjacent communities especially in areas where communities have been reluctant in taking up PFM. Incentive schemes like PES can therefore incentivize communities to conserve forest resources through CFAs. However, an assessment of the contextual factors, historical and expected trends in demand and supply is vital especially if we are to target payments to those CFAs that can actually deliver the desired service.

7 Policy Implications and Conclusions

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 raising acceptance within communities. There is also considerable preference heterogeneity which to a large extent was determined by employment status of 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)[20], 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 more pro conservation mainly motivated by the direct and few 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 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 livelihoods of locals.

We also found considerable consistency with economic theory. Specifically, the cost of a conservation program reduce demand for a given conservation

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

program. Whereas increase in forest cover, water quality and reduction of flood risk increases 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 more concerned with reduction in flood risk as a result of forest destruction. This is an indication that respondents are more altruist and not only concerned with direct use values but also non-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 side is needed as well as consideration of issues as to what private partners may consider worth involving in PES schemes. Bundling different services together may also help in diminishing transaction costs. A cost benefit analysis and assessment of political climate in cases where communities have strong attachment to their forests either for cultural values may also be important in designing the PES schemes.

In addition, a demonstration of the significance of ecosystem services as input 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[21]. The government should therefore increase roll out and incentivize communities that have been hesitant at adopting PFM to adopt the programme taking into account the heterogeneous preferences to address equity concerns as well.

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 MWTP for the various forest ecosystem attributes may also help policy makers in understanding the values attached to these services by respondents. In effect the study provides policy makers with reliable input for maximizing social welfare which has always been shown to be determined by non-market forest externalities. In summary, the study provides an entry point for designing future forest management policies in Kenya and provides valuable

[21] 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 as managers of the forests for the communities fully own the scheme. Some felt a proportion of revenue from PELIS could be channeled to construction of social amenities within the society e.g. school and health facilities.

comparison for studies in other countries.

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Table 1: Attributes used in final and Pilot DCE design

Type of Attribute	Attribute Definition	Attribute Levels
Wildlife	Wildlife population (biodiversity)	Low, medium, High
Forest Structure	Tree population/forest cover	Low, Medium, High
Water purification	Water Purification and supply (Level of water Quality and quantity)	Low, Medium, High
Flood	Risk of flooding: regulating services	Low, Medium, high
Cost	One off payment (ksh) per year for three years	0,1744, 2683, 2951

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

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 = 1605		N =1605			N=1605		
Log-Likelihood= -671.1730		Log-Likelihood=-664.0608			Log-Likelihood=-624.6797		
Variable	Coeff .(s.e)	Variable	Coeff(s.e)	Coe .Std (s.e)	Variable	Coeff. (s.e)	Coeff .Std (s.e)
ASC	-1.5073***	**Random Parameters**			**Random Parameters**		
	(0.5746)	Wild_H	0.2398	1.1652**	Wild_H	0.1561	1.1071*
Wild_M	-0.3665**		(0.2112)	(0.6053)		(0.4318)	(0.5741)
	(0 .1616)	Tree_M	1.7923***	0.9655**	Tree_M	3.7825***	0.8919*
Wild_H	0.1067		(0.2171)	(0.4654)		(0.5757)	(0.4878)
	(0.1697)	Tree_H	4.0959***	0.9655**	Tree_H	6.3764***	0.8919*
Tree_M	1.5041***		(0.3811)	(0.4654)		(0.8157)	(0.4878)
	(0.1563)	Water_H	0.7877***	0.1636	Water_H	0.6486***	0.1612
Tree_H	3.5216***		(0.1530)	(0.7013)		(0.1709)	(0.6210)
	(0 .2708)	Flood_M	1.4927***	1.6582***	Flood_M	1.2260***	1.6612***
Water_H	0.6411***		(0.1797)	(0.3619)		(0.2324)	(0.3723)
	(0 .1170)	Flood_L	2.6174***	1.6582***	Flood_L	1.8427***	1.6612***
Flood_M	1.2429***		(0.2537)	(0.3619)		(0.2386)	(0.3723)
	(0.1101)	**Non-Random Parameters**			**Non-Random Parameters**		
Flood_L	2.1300***	ASC	-1.1761*		ASC	-1.6057**	
	(0.1503)		(0.7008)			(0.7246)	
Cost	-.00061***	Wild_M	-0.3783**		Wild_M	-0.4764**	
	(0.0002)		(0.1933)			(0.2002)	
		Cost	-0.0006***		Cost	-0.0008***	
			(0.0002)			(0.0002)	
					WildH*PELIS	-0.4933*	
						(0.2773)	
					WildH*Dist	-0.2313**	
						(0.1056)	
					WildH*HHsize	0.1057**	
						(0.0520)	
					TreeM*Dist	-0.2912**	
						(0.1236)	
					TreeM*HHsize	-0.2750***	
						(0.0626)	
					TreeM*Empl	1.0030**	
						(0.4331)	
					TreeH*Dist	-0.4311***	
						(0.1648)	
					TreeH*HHsize	-0.2931***	
						(0.0814)	
					TreeH*Empl	2.0138***	
						(0.6321)	
					WaterH*Empl	0.7974**	
						(0.3166)	
					FloodM*PELIS	0.6420**	
						(0.2673)	
					FloodH*PELIS	0.8020**	
						(0.3223)	
					FloodH*Dist	0.3535***	
						(0.1258)	
$\rho 2$	0.4733		0.6234			0.6457	

Standard errors in Parentheses *** p<0.01, ** p<0.05, * p<0.1

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

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.
Wild_M	-604.76	(-589.67 - -619.85)	-627.92	(-612.25 - -643.59)	-601.61	(-586.59 - -616.62)
Tree_M	2481.99	(2420.04 - 2543.93)	2974.55	(2900.32 - 3048.78)	4776.73	(4657.50 - 4895.96)
Tree_H	5811.19	(5666.13 - 5956.25)	6797.80	(6628.12 - 6967.48)	8052.41	(7851.42 - 8253.39)
Water_H	1057.94	(1031.53 - 1084.34)	1307.37	(1274.74 - 1340.01)	819.13	(798.68 - 839.57)
Flood_M	2051.04	(1999.84 - 2102.24)	2477.44	(2415.61 - 2539.27)	1548.24	(1509.59 - 1586.89)
Flood_L	3514.77	(3427.03 - 3602.51)	4343.99	(4235.58 - 4452.41)	2326.98	(2268.90 - 2385.07)

Figure 1: Sample choice card used in the final survey

SCENARIO 12

Attribute	OPTION A	OPTION B	OPTION C (SQ)
Wildlife			As today
Forest Cover			As today
Water purification and supply			As today
Flood Risk			As today
COST	1744	2951	0
Tick Your Choice			

Annex 1

Table 6: Attribute priors employed for Bayesian efficient design for pre-test/pilot and full survey

Attribute	Pilot: initial prior estimates defined by a and b	Full survey: Revised $\hat{\mu}$ and $\hat{\sigma}$ obtained by MNL modelling of pre-test and pilot DCE responses
Wildlife	u (-0.5,0)	High $\hat{\mu}$ =-0.32 and $\hat{\sigma}$ =0.31 Medium $\hat{\mu}$ =-0.033 and $\hat{\sigma}$ =0.28
Forest Structure	u (0,1)	High $\hat{\mu}$ =2.23***and $\hat{\sigma}$ 0.33 Medium $\hat{\mu}$ =0.67**and $\hat{\sigma}$=0.33
Water Purification	u (0,1)	High $\hat{\mu}$ =0.10and $\hat{\sigma}$ =0.27 Medium $\hat{\mu}$ =-0.23and $\hat{\sigma}$ =0.28
Flood	u (-0.5,0)	High $\hat{\mu}$=0.70*** and $\hat{\sigma}$ =0.27 Medium $\hat{\mu}$ =0.43and $\hat{\sigma}$ =0.29
Cost	u (-0.000426,0)	$\hat{\mu}$ =-0.000689***and $\hat{\sigma}$=0.0001229

*=significant at p<0.1, **=significant at p<0.05, ***=significant at p<0.01

Table 7: Summary statistics of the respondents

variable	N	mean	sd
Waterforest: dummy=1 if household collect water from the forest and 0otherwise	4815	0.732	0.443
Fetch Firewood: Dummy=1 if respondent fetch firewood from forest, 0 otherwise	4815	0.776	0.224
ForestValue: Dummy =1 if respondent consider forest as of value, 0 otherwise	4815	1	0
DistForest:: Distance from household to the nearest edge of the forest in km	4815	1.445	1.408
hhsize: Number of people in the household including household head	4815	5.994	2.541
MaritSta: Dummy=1 if married, 0 not married	4815	0.882	0.323
Education:Dummy=1 if household head has post primary education 0 otherwise	4815	0.361	0.480
Employment: Dummy=1 if employed in off farm, 0 if self-employed i.e. farming	4815	0.293	0.455
PELIS: Dummy=1 if household owns a PELIS plot and 0 otherwise	4815	0.607	0.488
HHWealth: Total value of household asserts	4815	1.160e+06	1.346e+06

Table 8: 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 structure	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(USD(65.42)