Assessing Opportunity Costs of Conservation: Ingredients for Protected Area Management in the Kakamega Forest, Western Kenya

Jan Börner[a], John Mburu[b], Paul Guthiga[c], Stephen Wambua[b]

[a] International Center for Tropical Agriculture. Address:
Amazon Initiative Consortium
Embrapa Amazônia Oriental
Trav. Enas Pinheiro S/N
CEP-66095-780
Belém-PA, BRAZIL
(corresponding author: j.borner@cgiar.org, +55 91 3204 1108)

[b] University of Nairobi, Kenya, and International Livestock Research Institute (ILRI)
P. O. Box 30197 - 00100 ,
Nairobi, KENYA

[c] Kenya Institute for Public Policy Research and Analysis (KIPPRA)
P.O. Box 56445-00200
Nairobi, KENYA

Abstract

The Kakamega forest is the only remaining tropical rainforest fragment in Western Kenya and hosts large numbers of endemic animal and plant species. Protected areas were established decades ago in order to preserve the forest's unique biodiversity from being converted into agricultural land by the regions large number of small-scale farmers. Nonetheless, recent research shows that degradation continues at alarming rates. In this paper we address an important challenge faced by protected area management, namely, the design of a cost-effective incentive scheme that balances local demand for subsistence non-timber forest products against conservation interests. Using primary data collected from 369 randomly selected farm-households we combine a farm-household classification with mathematical programming in order to estimate the opportunity costs of conserving the Kakamega forest and restricting access to non timber forest product resources. We validate our model and analyze the impact of changes in major economic frame conditions on our results before we derive recommendations for an improved protected area management in the study region. Our findings suggest that a more flexible approach to determining the price of recently established forest product extraction permits would greatly enhance management efficiency without significantly compromising local wellbeing.

Keywords: Biodiversity conservation, smallholders, permit schemes, protected area

1 Introduction

Conversion of forests to agriculture is one of the prime causes of ecosystem services loss especially in the developing world (Barbier & Burgess 2001; MEA 2005). Nevertheless, tropical rainforests provide considerable benefits to both local communities and the global society (Turner et al. 2007). In many developing countries, forests represent a cheap and often important source of basic consumption goods for rural low-income households (Shackleton & Shackleton 2004). This has contributed to the belief that promoting non timber forest product (NTFP) extraction and improving related value chains represents an effective means to conserve forest resources and native biodiversity. Arnold and Pérez (2001), however, challenged this view and showed that NTFP harvesting often involves overuse and severe degradation of forest resources. Forest degradation usually comes with the loss of both locally and globally valued biodiversity services, such as endemic plant and animal species and other environmental services, such as carbon retention in forest biomass.

In many parts of the world, protected areas have proven to be an effective policy instrument to conserve valuable forest ecosystem services. Protected areas can be designed such that rural dwellers are not deprived of access to specific forest resources. Yet, too often, either local communities or the forest loose out due to inefficiently designed mechanisms to regulate natural resource access in and around protected areas (Naughton-Treves et al. 2005). A typical way of setting up protected areas in populated areas is to allow local dwellers limited access to defined resources. Resource access can be restricted through a variety of mechanisms, such as bans and fines, quotas on extraction quantities, closed seasons or user fee charges. Apart from monitoring and enforcement, which can be important bottlenecks for protected area management, the design of mechanisms to restrict and govern resource access poses major challenges. The main economic challenge is to design a cost-effective mix of conservation incentives with minimum adverse impacts on the poor forest dependent population. Outright bans on forest use are therefore often criticized for being biased against the rural poor. This has led park managers to increasingly experiment with more flexible conservation schemes involving user or extraction fee charges (Locke & Dearden 2005). Whether or not user fees are a cost-effective conservation mechanism depends among others on the appropriate size of the fee. For example, user fees have to be high enough to represent real incentives to avoid resource overexploitation. If fees are too high, on the other hand, poor forest users may not be able to afford them, which either aggravates poverty or encourages illegal forest product extraction whenever few or no substitutes exist for forest products.

In order to discourage resource overexploitation, fees have to adequately reflect the local value of forest goods and services. A crucial input to designing fair and cost-effective user fee schemes is thus the quantification of the local value of land and forest goods and services, i.e. the opportunity cost of strictly protecting the forest. This paper presents a household level analysis of the opportunity costs of maintaining forest cover and restricting access to forest products and services in Kakamega Forest, Western Kenya. The Kakamega Forest is one of the few remaining tropical rainforest fragments in Eastern Africa. The opportunity costs of conserving forest cover and the associated ecosystem services in the Kakamega district accrue mainly in the form of forgone profits from agricultural activities, which represent the only locally profitable alternative to keeping the forest until today and in the near future. The establishment of protected areas in the Kakamega Forest means that logging and conversion of forest to agriculture is no longer a legally accepted option. But, even if farmers do not legally face the choice of giving up NTFP extraction in favor of forest conversion for agriculture, setting the right incentives requires knowing what is at stake.

The paper combines household classification and economic modeling to assess the opportunity costs of restricting forest access under different scenarios. We test for the validity of our approach and apply it to answer the following empirical questions using representative field data:

1. What is the opportunity cost of maintaining forest cover in Kakamega for different types of representative farm-households?
2. What is the opportunity cost of restricting forest use for different types of representative farm-households?

Our answers to these research questions are intended to inform policy makers, development practitioners, and follow-up research in developing and targeting strategies towards increased cost-effectiveness of protected area management in the Kakamega district.

The paper is structured as follows: Section 2 briefly describes the study area, data and the methods used in the subsequent analysis. Section 3 presents the results of the farm-households classification and farm-household modeling. Finally, the findings are discussed in Section 4 and implications for management outlined in Section 5.

2 Data and methods

2.1 Description of the study area

The Kakamega Forest is the only remaining fragment of eastern African tropical rainforest in western Kenya (Figure 1). It covers an area of approximately 240 km^2 and is surrounded by a densely populated agricultural landscape with over 400 inhabitants per km^2 (Greiner 1991). The forest is one of species richest among Kenyan forests and hosts a large variety of endemic bird and butterfly species (Mungatana 1999, Lung and Schaab 2004).

To halt deforestation and reduce human disturbance, the remaining forest fragments have for several decades been managed by local and national entities, such as the Quakers Church (QC) and the Forest Department (FD). But it is only since about 25 years that a rigid management regime has been imposed by the Kenya Wildlife Service (KWS) on the northern part of the main forest block and one fragment, Kisere (Figure 1). The KWS does not allow extractive activities to take place and charges a fee for visits to the forest. The FD management system now operates in the southern forest block and in Malava fragment, while that of QC is functional in Kaimosi fragment (Figure 1). Both of the latter two management regimes provide free access for both local people and visitors, but require permits to be purchased for any kind of extractive forest use, e.g. grazing of animals on natural pastures, firewood extraction, harvesting of thatching grass, and collection of medicinal plants.

<Figure 1 about here>

After the installation of the permit system, the local population, primarily small-scale farmers, continued to make use of forest resources, both legally and illegally. This shows that considerable incentives exist for the local population to actively use the forest apart from the recreational and other non-use forest values.

The three existing forest management regimes in the Kakamega district can be characterized as *ad hoc* measures that are based on a perceived need for action rather that on scientific knowledge about ecologically sustainable extraction levels and techniques. For example, parts of the forest fragments managed by FD show severe signs of continuous degradation (KIFCON 1992, Lung and Schaab 2006), which indicates that the permit system does not provide sufficient incentives for keeping extraction at sustainable levels. On the other hand, monetary returns, e.g. captured by park entrance fees, to the more rigid KWS management are not used to compensate the local population for the foregone benefits of forest use and are hardly sufficient to justify the zero extraction policy on economic grounds (Mitchell 2004, Mugambi 2006). It is therefore desirable to improve the current forest management systems with respect to their conservation effectiveness (Bleher et al. 2006).

2.2 Analytical approach and data collection

Conservation opportunity costs can be measured in different ways ranging from static cost-benefit analyses to dynamic modeling and econometric analyses (see Grieg-Gran 2006 for a discussion of different approaches). Land prices, which under perfect market conditions could serve as an indicator for conservation opportunity costs, are of limited use in the study area, where an established land market does not exist. At household level, the opportunity cost of land and forest use is typically a result of various interacting factors, such as household composition, consumption and land use patterns as well as technology. Yet, in Kenya, like in many developing countries, data availability puts a limit on the application of data intensive econometric models to quantify the determinants of opportunity costs of land and forest use. As an alternative to econometric techniques, Hazell and Norton (1986) propose mathematical farm-household modeling. Mathematical programming models can be used to determine optimal production decisions subject to resource and production constraints by combining data from different sources, including expert knowledge. In this paper we apply a linear mathematical programming approach to analyze the opportunity costs of restricting representative farm-households' access to forest land and products. The representativeness of farm-household models can be increased by disaggregating field data into representative farm-household types. We identify representative household types from field data using statistical classification techniques (see Figure 2 and Section 2.3). For each farm-household type, in-depth interviews with five selected representative farm-households from each identified class were conducted to characterize cropping systems and obtain related technical coefficients (e.g., yields, labor, and capital requirements). Both field survey and technical coefficient data are used to specify the farm-household model (see Figure 2 and Section 2.4).

<Figure 2 about here >

A large-scale farm household survey conducted in Kakamega, Vihiga and Kapsabet districts, in a 12 km radius around the Kakamega forest serves as the empirical data base for all analyses (Figure 2). We interviewed 385 randomly selected rural households using a semi-structured questionnaire that covered basic demographic information as well as agricultural and forest extraction activities. After finishing the survey in December 2005, data cleaning resulted in a sample of 369 households. The households were classified into four representative sub-groups, which were revisited in July 2006 for detailed interviews on agricultural production techniques. The following two sections describe the classification procedure and the choice of modeling framework for the subsequent analyses.

2.3 Farm-household classification

Classifying farm-households is crucial to reducing the aggregation bias of farm-household models and provides clues about relevant factors that differ between farm types. A combination of hierarchical and k-means cluster analyses was used here to allow for the grouping to be determined by the data themselves instead of imposing a subjective stratification scheme (see Hair 1998, Wiedenbeck and Züll 2001). We determined the number of clusters through hierarchical cluster analysis (using squared Euclidean distances and the Ward algorithm) and then fed the result into a k-means cluster analysis to increase homogeneity within clusters. The variables selected for the classification are described in Table 1.

<Table 1 about here>

To evaluate the cluster solutions F-values for the homogeneity of the clustering process were calculated as follows:

$$F_g = \frac{V(j,g)}{V(j)}, \text{ for the homogeneity of a group g.} \qquad (1)$$

V(j,g) = variance of variable j in group g

V(j) = variance of j in the sample

Values above 1 indicate higher variance of a variable within a given group than in the whole sample and suggest relative heterogeneity.

For each of the clustered sample households the squared Euclidean distance to the cluster mean was calculated as a measure of representativeness of the household. Subsequently, the five households closest to the cluster mean of each of the four identified clusters were selected for interviews on production (technical) coefficients in July 2006.

The technical coefficient data, however, do not suggest clearly separable technologies across the four identified farm types. For example, maize and bean intercropping activities differ mainly in fertilizer application rates and method of land preparation. How much fertilizer is applied and whether land is prepared using ox-plows or manual labor seems to be rather a matter of cash availability (which depends on various but not always observable factors) and individual preferences. It was therefore decided to define production activities based on the full sub-sample of the households selected for technical coefficient interviews. Subsequently, households where divided up into tea farms (located on more fertile Acrisols that are appropriate for tea plantations in the tea agro-ecological zone) and sugar cane farms (located on less fertile Afisols in the so called “sugar cane zone”). The difference between tea and sugar cane farms is merely the option to plant either tea or sugar cane as cash crops and slightly higher natural soil fertility due to higher soil organic matter content (KIFCON 1992 and personal communication KARI[1] 2005). As a result we come up with eight different farm types that can be extrapolated to the sample universe using cluster affiliation.

2.4 Farm-household modeling

As data availability does not allow for the consistent econometric estimation of a fully specified farm-household model it was decided to represent farm-households as individual linear programming models (LP) with a joint objective function. This specification comes close to what is commonly referred to as agricultural sector model, albeit ignoring interaction among households and processing industry (see Hazell and Norton 1986). Several recent applications of farm-household optimization models exist that have enabled researchers to successfully address a broad range of development issues in both normative and positive forms of analysis (Shiferaw 1998, Barbier 1999, Kruseman 2000, Berger 2001, Vosti et al. 2002, Mudhara et al. 2004).

For each household type, individual LP are specified as stationary equilibrium (Hazell and Norton 1986) or equilibrium unknown life (McCarl and Spreen 1997) models according to the following basic structure:

$$
\begin{array}{llllll}
\max & \sum_j \sum_j & c_{je} x_{je} & & & \\
\text{s.t} & \sum_j \sum_j & a_{ije} x_{je} & \leq & b_i & \textbf{for all i} \\
 & & -x_{j,e-1} + x_{je} & \leq & 0 & \textbf{for all j and e > 0} \\
 & & x_{je} & \geq & 0 & \textbf{for all j and e}
\end{array}
\qquad (2)
$$

[1] Kenya Agricultural Research Institute (KARI)

where x_{je} is the level of the production activity *j* of age *e* (e.g., tea plantations at different ages); *c* is the annual per unit gross margin of *j* at age *e* and *a* are resource use (e.g., land and labor) coefficients. *b* are *i* constraints (e.g., on resource endowment and minimum consumption requirements). Activity levels are non-negative and take on the same value across all *e*.

The model was implemented in GAMS[2] and calculates annual per unit gross margins for production and forest use activities based on average yields (from survey data, technical coefficient, and local expert interviews) and prices (from official data), which vary seasonally according to information from local extension agents and market surveys. Resource use of each production activity is calculated based on technical coefficient data. The model features both fixed and flexible constraints on production and forest use that are derived from survey and technical coefficient data. For example, farm size is fixed for each farm type as far as agricultural production is concerned. However, the scale of cattle operations can be increased through the purchase of permits for grazing inside the Kakamega Forests natural pastures or through acquisition of fodder grass. Minimum consumption requirements (e.g. of calories, proteins, fat, vitamin A, and firewood) for adult males and females as well as children of different age classes are defined following James and Schofield (1990) and include minimum cash outlays for clothing and health.

For each farm-household type, labor availability is constrained by the number of adult female and male family members and non-adults in working age. Additional labor can be bought in at wage rates that increase stepwise as workers have to be hired from more distant communities. A limited amount of family labor days (informed by field data) can be sold off.

[2] General Algebraic Modeling System (www.gams.com)

3 Results and Analysis

3.1 Farm-household types

Figure 3 shows the cluster dendrogram as a result of the hierarchical cluster analysis, which led to the selection of four clusters and the respective cluster centers as an input to the k-means cluster analysis.

<Figure 3 about here>

The k-means cluster analysis produced a slight rearrangement of cases between clusters and the final groups are described in Figure 4. Group I, with 153 households, is the largest group and represents the archetypical *poor subsistence producer* in the study area with below average farm size, high dependency ratio and few wealth assets. Group II contains 92 households that are better endowed with wealth assets, characterized by a below average number of dependent family members and, like the first group, primarily subsistence producers located close to forests and markets (*better off subsistence producers*). In Group III (65 farms), households dispose of above average sized farms, but also a larger number of dependent family members. Group III farms are remote from both the forest and markets and own few wealth assets despite investments into cash crop production (*poor cash crop producers)*. Group IV households, also cash crop producers, are relatively well endowed with land and labor, have a better wealth status than Group III farms and generate a considerable amount of income off-farm (*better off cash crop producers*).

<Figure 4 about here>

Apart from farm size, distance to markets, family labor availability and overall asset wealth are significantly different between at least three of the four of the farm-household types. All farm-households have put almost all their land under cultivation, which is why the share of land under crops per farm is not significantly different between the farm types. All other characteristics were different at least between two of the household types, with a tendency to grow cash crops being found on farms that are more distanced from the forest, and surprisingly also from the output markets. To some extent this could be explained by the fact that the two main cash crops in the area, tea and sugar cane, are sold at farm gate and transport is taken care of by processing companies.

The cultivation of cash crops, however, does not seem to be positively related to asset wealth. Instead, Groups II and IV, which are the only ones with above average asset wealth, differ significantly in household labor endowment, dependency ratios, and education levels, which are more favorable than in Groups I and III.

3.1.1 Integration in labor and land markets

During technical coefficient interviews, representatives of Groups I and II both reported remarkable difficulties in hiring labor during February/March and July/August. Some more in depth interviews, however, revealed that these difficulties are not necessarily related to a lack of labor supply on rural labor markets, but to a lack of cash in-between harvest seasons. Daily wages range between EUR 0.53 -1.1 depending on the type of activity (cash crop labor is supposed to be more expensive) and agricultural season.

With regard to household labor supply, we attempted do elicit a reservation wage rate from each household head (HH) in the n=385 sample using a simple willingness to accept interview approach. Table 2 reports the elicited reservation wages for the four household groups.

Farmers generally reported not to be active in land markets and that changes in land tenure are mainly due to inheritance. Nevertheless, they were able to provide estimates of the total value of their property (land and buildings), which are reported in Table 2 below.

<Table 2 about here>

Reservation wage rates in Table 2 are reasonably consistent with actual daily wages and the estimated value of land appears meaningful given that owning land has an intrinsic value and that annual gross margins per ha of land for the typical crops vary between EUR 100 - 500. Note that the estimated value of land per ha is inversely related to farm size (compare with Figure 3), whereas reservation wage rates tend to be higher on larger farms.

3.2 Land use decisions and model validation

Table 3 reports the optimal distribution of land use categories available in the model as a share of the total farm size for each of the four groups in the tea and sugar cane zone.

<Table 3 about here>

According to the model, most farms invest in the type of cash crop production that is feasible in their particular region, i.e., either tea or sugar cane. But significant amounts of land are also dedicated to annual crops, especially intercropped maize and beans as well as sweet potatoes. It was expected *a priori* that more land will be allocated to cash crops than to annuals. All model farms keep cattle (not presented), but do not divert land to pastures or fodder production. Instead, they make use of public grazing land, e.g. inside Kakamega forest, or they buy additional fodder on local markets, which corresponds to observed behavior.

Table 4 shows that observed land allocation is quite different from our model results. On average, the lion's share of cropland is dedicated to annual food crop production and only a small share is diverted to sugar cane or tea production.

<Table 4 about here>

A few remarks seem appropriate. For a variety of reasons farm-household mathematical optimization models tend to overestimate investment into apparently profitable production activities, because some of the hidden costs involved in or barriers to adopting these technologies cannot be properly taken into account. One of the reasons why poor smallholders would rather not overspecialize in cash crop production is risk (Hardaker *et al.*, 2004). However, yields of sugar cane and tea are not subject to extraordinarily high variability (District Reports of Agricultural Ministry, Kakamega, 2001-5). To some extent risk is also reduced by the type of contracts, e.g. cash and in kind advances for inputs, price guaranties, typically exerted by the regional tea and sugar cane processing companies. All this would favor specialization into cash crops.

Nevertheless, entering the cash crop business involves transaction costs and commitments, as well as minimum standards with regard to soil quality, plot size and slope (sugar cane), which were not possible to enumerate in this study. In the case of tea, poor farmers eventually apply rather high individual discount rates, which would make investments into tea plantations with no short term returns unprofitable. Moreover, poor smallholders may be reluctant to divert scarce farm land into cash crops on the grounds of food security concerns. Aversion to food scarcity risks can thus not be ruled out as an explanatory factor for the deviation of empirical and simulated land use mix. Optimal model solutions, however, show that, at current prices, basic food requirements on all model farms are met primarily through on-farm production rather than food purchases even with considerable shares of farms under cash crops.

It is important to note that Table 4, which presents mere averages of land use categories over the whole sample, is somehow misleading in terms of the degree of specialization into cash crops, because our farm-household sample happens to be truncated, with regard to the degree of adoption of these crops. Only 7% of the smallholders in the sample actually produce tea, while about 27% of them produce sugar cane.

Tables 5, hence, reports the ratio of long season annual crop and tea/sugar cane coverage for tea and sugar cane producers separately and compares them with the model outcomes.

<Table 5 about here>

Although not perfectly so, the model seems to be able to explain land use on tea and sugar producing farms much better than the average sample land use patterns.

In summary, only land use observed on farms that have adopted sugar cane and tea production is reasonably reproduced by the farm-household model. While this would represent a severe limitation for studies that aim at predicting land use or aggregating results at the regional scale, the model remains useful for our purposes, i.e. the analysis of farm-level opportunity costs of forest conservation. Given the high returns of tea and sugar cane production per unit of land, however, the shadow values of land predicted by the model are likely to be at the upper limit of conservation opportunity costs in the region.

3.3 Value of extraction and opportunity costs of forest conservation

3.3.1 Value of forest use and extraction activities

The value of forest extraction was estimated by imposing a ban on forest extraction activities in the model. The marginal values of the respective constraints represent the shadow value of extracted products. Results are presented in Table 6.

<Table 6 about here>

It becomes obvious that forest use and extraction activities are relatively high valued on the model farms. In fact, a ban on forest use and extraction would reduce the value of non-essential consumption on smaller Group I farms by 62-76%. The larger Group IV farms would be less affected (13-15%), as their major share of non-essential consumption value is produced on-farm. Fire wood and thatching grass per unit extraction values do hardly differ between the different groups as they do not compete for land with farm production activities. Nevertheless, small differences in per unit values are motivated by transport costs depending on the distance of farms to the forest. These differences can become quite large if actual instead of average values for distance to markets and forest margins were used in the simulations. Finally, the shadow value of forest grazing per animal differs quite remarkably between households and the opportunity costs of a ban on external grazing in the forest are high especially for wealthier farms with many family members. This is because animal production potentially competes with other on-farm land uses leading to farm types responding differently a ban on forest use.

3.3.2 Individual opportunity costs of maintaining forest cover in Kakamega

As a result of the optimization process, the model provides the shadow values of land for each farm type. These shadow values represent the nominal opportunity costs of forest conservation, as they exclude the benefits derived per hectare of forest. Since most forest use activities are difficult to evaluate on a per hectare basis, a cost-benefit analysis of investments into forest conservation only makes sense at the regional level. The findings presented here, are understood as a first step towards a regional level analysis. Figure 5 depicts land opportunity costs and indicates their sensitivity to key parameters for the four model farms in the tea and sugar zone.

<Figure 5 about here>

As expected, the model suggests that land shadow values decrease when farm size increases (from Group I to IV) in both sugar and tea zones. Although land seems to be valued lower in the tea zone than on sugar producing farms, its valuation on tea producing farms is much more sensitive to changing input and output prices.

To understand why, it is necessary to detect the parameters that most affect changes in the shadow value of land. For that purpose we employ the concept of quasi-elasticities[3] following Krusemann (2000):

$$\nu_i = \alpha + \beta x_i + \varepsilon \qquad (3)$$

$$\theta = \beta \frac{x_0}{\nu_{i0}} \qquad (4)$$

where v is the model output in question (i.e. land shadow value) at step i of the sensitivity analysis, α and β are functional parameters, x is the model input that is varied in the sensitivity analysis (e.g. product price), and ε a constant of the regression equation. v_{i0} is the model output's value and x_{i0} the respective model input in the baseline.

By regressing the set of input variables values on the respective model outputs (equation 3) we obtain slope coefficient β, which can be used to obtain the quasi-elasticity θ (equation 4).

Table 7 presents the quasi-elasticities of the land shadow value with respect to selected parameters.

<Table 7 about here>

The table shows that tea farmers' shadow value of land is more sensitive to changes in the wage rate than that of sugar cane farms, which is due to the relatively high labor requirements for weeding and harvesting tea. Increasing wages, hence, reduces the profitability of tea and with it the valuation of land, which explains the relatively high negative oscillation in Figure 5. Tea farms also keep more cattle, which demands little labor, and thus respond more heavily to changes in beef prices. Finally, the land shadow value of tea producers is also more

[3] The quasi-elasticity represents the percentage impact on the indicator variable given a unitary change in the parameter.

sensitive to changes in the tea price than it is to changes in the sugar cane price in sugar cane zone.

Not all model farms are self-sufficient in all annual crop products. Especially in the case of sweet potatoes, some quasi-elasticities are negative suggesting that increasing sweet potato prices would result in more land being diverted to annual crops for home consumption.

4 Discussion

Limited data availability and non-existent or imperfect markets for land in our study area meant that both data intensive econometric modeling as well as land market analysis was not a feasible option to estimate the opportunity costs of different forest conservation scenarios. As a result, we opted for farm-level mathematical programming, because it allows for consistently analyzing the behavior of conservation opportunity costs under different economic conditions (Börner et al. 2007). Due to the inexistence of reliable data to calibrate supply and demand functions for major crop and input markets, our approach ignores farm-household interactions. While this would certainly compromise the analysis of agricultural output and land use at the regional level, the model is a valid tool to address our research questions, which are primarily concerned with the optimal design of conservation incentives and their impact at the farm-household level.

The model predicts shadow prices of land that are largely consistent with our expectations, previous annual gross margin estimates, and farmers' estimates of the value of their farm (land and buildings). This makes us confident that model results are valid and can be used for the subsequent analyses of the sensitivity of shadow values to key model parameters.

The model does not adequately represent average observed behavior in all of the identified groups of farms. It, however, satisfyingly explains land use on farms that engage in the production of the region's dominant cash crops, i.e. tea and sugar cane. Theoretically, both endogenous and exogenous social and economic factors could explain that. While we expect endogenous factors, such as risk aversion and household specific constraints, to be less relevant in explaining the deviation from observed land use, we cannot rule out that food security concerns contribute to low cash crop investments on some farms.

Nonetheless, tea and sugar cane are obviously profitable operations and investment barriers, such as liquidity, are minimized through the assistance programs of processing firms. This leads us to believe that the low engagement in cash crop production, especially in tea areas, is primarily due to exogenous reasons, i.e. regulation in a monopsonistic market, which cannot be explained by a farm-level modeling approach.

Despite its bias towards cash crop producing farms, the model provides an upper limit of conservation opportunity costs that are considered the basis for willingness to accept and pay considerations among farmers that do not actually cultivate cash crops. The model also gives us an idea of the direction, in which conservation opportunity costs may shift given changes in key economic indicators.

5 Conclusions

Knowing the local opportunity costs of restricting access to forest land and resources for conservation purposes is an important input to the design of cost-effective conservation schemes that minimize adverse effects on poor forest users. In this paper we develop a farm-household mathematical programming model with the objective to estimate the opportunity costs of alternative scenarios of access to Kakamega forest fragments. The analysis is built on the major assumption that currently forested land is no less suitable for agriculture than already deforested land. Our approach involves estimating shadow values of land and forest use (i.e., fire wood and thatching grass extraction as well as animal grazing) for a set of representative farm-households.

We find that valuation of land differs across farm types and between tea and sugar cane producing areas in a range of 160 - 250 Euros per hectare at current input output prices. Changes of 25% in wages and main product categories may however easily shift this valuation within a range of 40 - 800 Euros. Due to high labor demand, the model suggests that tea farmers' valuation of land is particularly dependent on changes in wage rates.

With respect to forest dependence, we find that all model farms prefer forest use to buying the respective products on local markets or establish non-forest dependent forms production, e.g. in the case of livestock keeping. However, depending on a variety of factors, including farm size and distance to forests, the value of some forms of forest use (especially grazing) vary considerably across farm types. Our findings thus indicate that the cost-effectiveness of forest management could be increased by differentiating the price of grazing permits according to individual opportunity costs. If permits for grazing are offered at the basis of willingness to pay instead of a fixed price approach, model farms with low opportunity costs tend to switch to other technologies, thus taking some pressure from forest lands. According to the model, the willingness to pay for grazing is roughly three to five times higher (depending on farm type) than the price actually charged. Techniques, such as permit auctions, where forest users self-reveal their willingness to pay for resource access thus appear as a potential alternative to current *ad hoc* price determination. If the forest's ecological carrying capacity with respect to the major extraction activities could be reasonably well established, auctions may result in permit prices that more realistically reflect demand and, at the same time, provide incentives based on resource availability.

Price differentiation, however, appears less rewarding in the case of firewood and thatching grass, for which few or only high cost alternatives exist on local markets. Shadow values of these NFTP vary little between farm types and seem to be depending primarily on the distance of farms to forest edges. However, to the extent that firewood and thatching grass extraction contributes to forest degradation, park managers are well advised to adjust prices to the forest's carrying capacity.

How much does forest conservation cost local farmers? It appears sensible to note, that the region's main socio-economic problems, e.g. malnutrition, poor health and educational standards, are certainly not primarily related to the management of the Kakamega forest. High population density and the very low amount of remaining forest land mean that clearing the forest to open up additional land for agriculture would bring about few economic gains even if the losses in the form of direct forest benefits were ignored. To illustrate this, suppose that all forest land was cleared and valued at 250 Euro per ha (upper limit shadow value at current prices). This corresponds to an additional approximately 6 million Euros of agricultural rents, which at a population density of 400 inhabitants per km^2 corresponds to 63 Euro per year and capita. The real economic gain is likely much lower, given that only few farms do actually cultivate cash crops, which represent the main reason for the high land shadow value.

The price for such a scenario would be the loss of one of the last Eastern African rainforest remnants, which not only in the face of emerging markets for carbon, biodiversity and tourism, might turn out to be a regret to future generations both locally and globally.

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Tables

Table 1: Variables used in cluster analysis

Variable	Description	Unit	Mean	St.Dev	Min	Max
fsize	Farm size	[ha]	1	0.93	0.04	6.46
shcrop	Share of land under crops of farm size	[%]	76.3	18.2	0	100
shcashcr	Share of cash crops (tea, sugar cane) of cropland	[%]	17.6	26.8	0	100
disforh	Distance to forest (hours)	[hours]*	0.9	0.9	0	5
dismah	Distance to output markets (hours) while walking	[hours]	0.8	0.7	0.01	4
deprat	Dependency ratio (HH members)	[%]	109.4	110.4	0	800
adeq	Adult labor equivalents	[No.]	3.2	1.7	0	9
avedu	Average education of HH members > 16 years	[years]	7.4	3.4	0	16
offinc	Per capita off-farm income	[Euro]	58.9	144.3	0	1558
subs	Share of commercialized value of crop production (beans, maize, sweet potatoes)	[%]	18	27.5	0	100
wid	Wealth index (subjective ranking)	[0-61]	13.2	12.7	0	61

Table 2: Reported reservation wage and estimated values of property

	Reservation wage [EUR/day]	Estimated value of property [EUR/ha]
Group 1	1.1	1967
Group 2	1.2	1698
Group 3	1.3	1639
Group 4	1.8[1]	1569[3]
Mean	1.3	1777

[1] Significantly different at $p < 0.05$ to group I (Tukey HSD)

[3] Significantly different at $p < 0.05$ to group III (Tukey HSD)

Table 3: Land use as a percentage share of total farm size in the optimal model solution (LS = long season, SS = short season, P = Perennial crops)

		Tea zone				Sugar cane zone			
		Group I	Group II	Group III	Group IV	Group I	Group II	Group III	Group IV
LS	Maize/Beans	59.0	31.6	19.7	24.2	36.2	23.0	21.8	22.6
SS	Maize/Beans	26.7	13.7	10.2	16.9	20.9	15.4	17.5	17.4
	Sweet Potatoes	32.4	17.9	9.5	7.9	24.8	17.1	13.1	11.1
P	Tea	40.0	68.3	80.1	75.8	-	-	-	-
	Sugar Cane	-	-	-	-	55.2	67.4	69.2	69.5
	Farm size	0.5	1.2	1.4	1.9	0.5	1.2	1.4	1.9

Table 4: Observed land use as a percentage of total farm size as a result of the farm-household classification

	unit	Group 1	Group 2	Group 3	Group 4	Mean
Size of all land holdings	[ha]	0.53	1.18	1.38	1.91	1.06
Area under crops	%	74	76	70	75	74
Area maize and beans LS	%	70	67	29	29	48
Area maize and beans SS	%	43	45	8	10	26
Area under sweet potatoes	%	7	8	10	10	9
Area under tea	%	2	5	5	7	5
Area under Sugar Cane	%	4	3	36	37	21

Table 5: Comparison of annual crop to cash crop cover ratios between field observations on farms that produce sugar can or tea and model solutions

	Group 1	Group 2	Group 3	Group 4
Observed sugar cane	0.90	0.65	0.47	0.39
Model sugar cane	0.66	0.34	0.32	0.33
Observed tea	1.25	1.06	0.09	0.30
Model tea	1.48	0.46	0.25	0.32

Table 6: Shadow values of a constraint (ban) of forest extraction activities imposed on the model farms (NEC = non-essential consumption)

		Forest grazing [EUR/ animal]	Thatching grass [EUR/kg]	Fire wood [EUR/kg]	Annual NEC with extraction [EUR]	Annual NEC without extraction [EUR]	Annual value of extraction [EUR]	Share of extraction in NEC [%]
Tea zone	Group I	10.47	0.11	0.03	106.51	40.52	65.99	61.95
	Group II	16.07	0.10	0.03	506.10	394.95	111.15	21.96
	Group III	14.32	0.11	0.03	277.89	218.00	59.89	21.55
	Group IV	13.79	0.11	0.03	555.87	486.05	69.82	12.56
Sugar cane Zone	Group I	12.85	0.11	0.03	106.62	25.32	81.30	76.25
	Group II	14.65	0.10	0.03	533.42	384.87	148.55	27.85
	Group III	11.67	0.11	0.03	314.55	241.93	72.63	23.09
	Group IV	16.48	0.11	0.03	605.84	516.75	89.09	14.70

Table 7: Quasi-elasticities (percentage changes) in the shadow value of land as a result of unitary changes in daily wages and output prices

		Wage	Farm gate prices					
			Maize	Beans	Sweet Potatoes	Tea	Sugar cane	Beef
Tea Zone	Group I	-172	89	54	-26	267	-	395
	Group II	-123	29	56	-13	429	-	441
	Group III	-126	21	6	-02	450	-	320
	Group IV	-121	45	38	08	460	-	345
Sugar zone	Group I	-64	-5	17	-7	-	233	169
	Group II	-47	2	18	22	-	245	163
	Group III	-66	47	24	4	-	243	119
	Group IV	-60	46	25	-9	-	251	123

Figure captions

Figure 1: Location of the Kakamega district and Kakamega forest fragments in Kenya

Figure 2: Research approach and timeline

Figure 3: Cluster dendrogram as a result of the hierarchical cluster analysis. Size of triangular shapes indicates group size. Colors indicate clusters that were completed at different stages in the clustering process.

Figure 4: Means of classification variables (z_scores) in final clusters. Colors and fill patterns indicate significantly different cluster variables in each cluster at $p < 0.05$ (ANOVA, Tukey HSD).

Figure 5: Shadow values of agricultural land in the tea zone and in the sugar zone. Vertical lines represent the range of potential changes in shadow values if model parameters, such as output prices, farm gate-market price band, and wage rate are varied by +/- 25%.