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The Economic Valuation of Dryland Ecosystem Services in the South African Kgalagadi by the Local Communities

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Central America
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Tropical Agricultural Research and Higher Education Center (CATIE)
Email: efd@catie.ac.cr

China
Environmental Economics Program in China (EEPC)
Peking University
Email: EEPC@pku.edu.cn

Ethiopia
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: eepfe@ethionet.et

Kenya
Environment for Development Kenya
Kenya Institute for Public Policy Research and Analysis (KIPPRA)
University of Nairobi
Email: kenya@efdinitiative.org

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

Tanzania
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

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Abstract

This study seeks to value ecosystem services in the Kgalagadi area in South Africa by applying the choice experiment technique. The values placed on dryland ecosystem services by indigenous communities are estimated using a conditional logit model, a random parameter logit model and a random parameter logit model with interactions. The results show that local communities would prefer increased grazing, firewood collection, hunting opportunities, and harvesting of medicinal plants.

Key Words: choice experiment, conditional logit, ecosystem services, local communities, random parameter logit

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Introduction

This study seeks to value ecosystem services in the Kgalagadi area in South Africa by applying the Choice Experiment technique. Instead of finding the value of the whole ecosystem, this study seeks to value selected ecosystem services from the point of view of local communities. The results show that local communities would prefer getting increased grazing, firewood collection, hunting opportunities and harvesting of medicinal plants.

Our study area is located in the Siyanda District Municipality (comprising six local municipalities) of the Northern Cape province of South Africa, bordering Botswana and Namibia. The district is approximately 120,000 square kilometres and includes large areas in the Kgalagadi Desert. The Mier Local Municipality (one of the six local municipalities) is located next to the Kgalagadi Transfrontier Park.

Despite the harsh Kgalagadi dryland ecosystem environment, this area harbours a wide variety of animals and plants. Thus, like many other dryland areas, the Kgalagadi area produces ecosystem services which benefit the broader society.[1] In fact, the area provides a wide variety of ecosystem services, including medicinal plants, wild fruits, fuel wood, water, grazing (i.e., provisioning services); erosion control, climate regulation (i.e., regulating services); Carmel

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* Johane Dikgang, corresponding author, School of Economics, University of Cape Town and Department of Economics and Econometrics, University of Johannesburg, South Africa. Tel. +27 (0)11 559 2017. Email: jdikgang@uj.ac.za. Edwin Muchapondwa, School of Economics, University of Cape Town, Private Bag X3, Rondebosch 7701, South Africa. Email: edwin.muchapondwa@uct.ac.za. We are grateful to Louise Swemmer and Wendy Annecke of SANParks (South African National Parks) for assistance with data and materials. Funding from FORMAS and Sida (Swedish International Development Cooperation Agency) is gratefully acknowledged. Additional funding from ERSA (Economic Research Southern Africa) is also gratefully acknowledged.

[1] According to the MEA (2005), an ecosystem is a dynamic complex community of plants, animals, and smaller organisms' communities and the non-living environment, and an ecosystem service is a direct benefit that people obtain from ecosystems. Ecosystem services are classified into provisioning services (e.g., food and fodder); regulating services (e.g., climate regulation); supporting services (e.g., crop pollination); and cultural services (e.g., spiritual and recreational benefits).

thorn trees (i.e., supporting services); and eco-tourism, cultural and spiritual benefits (i.e., cultural services). While most visitors to the area mostly enjoy the recreational amenities, the Kgalagadi dryland ecosystem enables local communities, especially the Khomani San, to practice their culture and heritage.[2]

Valuation of ecosystem services is not only of economic interest, but also has social and political implications, particularly in cases of land restitution in South Africa, where policy makers ought to keep track of whether the intended outcomes have been achieved. This is particularly true in the case where public investment is needed to uplift rural communities and where additional sources of income for the local communities are urgently required. This suggests that the economic valuation of ecosystem services can demonstrate to decision-makers how maintaining public conservation investments can benefit those who have received land restitution rights.

This study assesses the economic value of ecosystem services in the Kgalagadi area in an attempt to establish the economic importance of conservation in the area. Computing the economic value of ecosystem services for local communities can complement the value of resource extraction, as calculated by other studies, such as Thondhlana et al. (2011), to derive a full environmental income measure.

This study seeks to value ecosystem services in the Kgalagadi area by applying the Choice Experiment (CE) technique. By assessing the dryland ecosystems in the study area, we acknowledge the importance of these systems; seek to understand the trade-off between consumptive use and conservation; and propose using market instruments in a manner that will incentivise the locals to utilize these assets sustainably. Given the levels of biodiversity degradation in the area, there is a need to promote greater roles for local communities in conservation in the Kgalagadi area. This paper contributes to the limited literature on estimation of values of dryland ecosystem services by indigenous communities using CE.

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[2] The Khomani San and Mier communities are located in the Mier Municipality. Livelihood strategies in this area traditionally combine pastoralism, hunting and gathering. The status of the dryland ecosystem affects the wellbeing of local communities.

Literature Review

Valuation of environmental and natural resources has come a long way since the first work carried out in the United States in the 1960s, which primarily applied the Contingent Valuation Method (CVM) and the Travel Cost Method (TCM). Since then, valuation of non-market goods and/or services has been conducted in many fields, ranging from environmental and health, to transport and public infrastructure disciplines.

There has long been a recognition of the need for valuation techniques that enable the estimation of values for specific attributes of ecosystems. The choice experiment (CE) method has emerged as the panacea, as it allows for multi-attribute valuation. As a valuation technique, the CE is seen as a more generalized version of the single attribute dichotomous choice CVM. Indeed, both CE and CVM are considered to be stated preference valuation methods (Adamowicz et al. 1998).

An increase in the application of CE can be attributed to various reasons, including the technique's capability to minimize some potential bias of the CVM; the fact that more information is elicited from each respondent relative to CVM; and the prospect of testing for internal consistency (Alpizar 2002). For example, several studies conducted in the past 15 years show that CE has many advantages over the CVM. A study by Boxall et al. (1996) about moose hunting found that CEs were more appropriate than CVMs when substitution effects were important.

However, one possible disadvantage compared to a CVM may be that, because CE surveys are detailed, they can be more challenging for respondents or they may make potential respondents less likely to participate (Raheem et al. 2009). Furthermore, a study by Adamowicz et al. (1998) showed that CE has the same problem of negative welfare measures as the CVM. The challenge of negative welfare measures was familiar from the CVM literature. The CE studies that followed have tried in different ways to address or minimize this problem. A study by Haffen, Massey and Adamowicz (2005) applied different hurdle models to differentiate serial nonparticipants from other respondents, while Carlsson and Kataria (2005) developed a spike model where demanders are distinguished from non-demanders. The use of these models can go some way in minimizing the problem posed by negative welfare measures.

Methodology

In generating the choice sets for use in the survey, there are a number of design decisions that researchers need to make. These include whether to use main effects or interactive effects;

generic or specific alternative titles; and the sample size. There are now several customized software packages designed to assist with CE design and analysis. The CE design in this study was modelled using SPSS. The sub-sections below go through each of the design options and motivate the decisions for those that were adopted.

Main Effects versus Interactive Effects

The Kgalagadi area produces ecosystem services which benefit local communities. Instead of finding the value of the whole ecosystem, this study seeks to value selected ecosystem services from the point of view of both local communities and visitors. In implementing the CE method, we specify seven attributes associated with the Kgalagadi ecosystem for local communities, namely Camel thorn trees (X_1) (a source of numerous ecosystem services, described in Table A1), seeing predators (X_2), bush food/recreational restrictions (X_3), medicinal plants (X_4), traditional hunting (X_5), grazing opportunities (X_6) and the bid vehicle (X_7). The simple choice model would evaluate design *i* in terms of:

$$Z_i = \text{f}\,(X_{1i}, X_{2i}, X_{3i}, X_{4i}, X_{5i}, X_{6i}, X_{7i}) \tag{1}$$

This is known as a main effects design because it ignores interactive effects. Ignoring interactive effects is synonymous with settling on a first-order approximation of the true model (Louviere 1988). Thus, by estimating the model with main effects only, we are making an implicit assumption that all the interaction effects are insignificant. The model with main-effects only has the benefit of significantly reducing the number of treatment combinations required. However, this benefit comes at a cost because each treatment combination represents a separate piece of information, and by using only a *fraction* of possible treatment combinations, we are in effect throwing away a significant amount of information (Hensher, Rose and Greene 2005). All the same, main effects designs tend to account for as much as 80% of the explained variance in choice models. Thus, it is generally believed that a simple main-effects design predicts choices fairly well, and is therefore adequate for the task at hand.

Determining the Sample Size

Given a desired list of attributes and attribute levels, we can apply the following rule of thumb to calculate the sample size needed for the CE survey:

$$N = 500\frac{NLEV}{NALT \times NREP} \tag{2}$$

where *N* is the sample size, *NLEV* is the largest number of levels in any attribute, *NALT* is the number of alternatives per choice set, and *NREP* is the number of choice sets/questions per respondent (Johnson et al. 2006). Therefore, applying the formula to our CE design yields a sample size of 208 for the local communities.

It should be noted that the experimental design for local communities requires seven attributes at 4 levels each. So the full factorial design is given as $L^A = 4^7 = 16384$. This is for just one of the alternatives. If, however, we estimate a fractional factorial main-effects design, we need a minimum of 22 degrees of freedom, which corresponds to 22 choice sets, i.e., $df = L - A = (4 \times 7) - 7 = 21$, and adding 1 degree of freedom for the error term gives 22 degrees of freedom. However, if we wish to maintain orthogonality, the search for an orthogonal array reveals that we need 32 treatment combinations. These are far more manageable than 1,638,487 treatment combinations for a full factorial design. This is termed a *saturated* design - the smallest design that can be made. More importantly, a saturated design does not need to be the recommended design, but provides some context for the recommended design size (Kuhfeld 2010). A search for an orthogonal design yields one with 32 choice sets. Each of the designs is orthogonal - every pair of levels occurs the same number of times across all of the pairs of factors in each design. For example, the design for each of the 22 pairs appears once across the seven pairs of factors.

In order to create the choice sets from the levels combinations, we use the technique of cyclical design (i.e., shifting). We first produce the 32 combinations for the experimental design using SPSS. These combinations define the first profile (alternative) in each of the 32 choice sets. From this, we create additional alternatives in each choice set by cyclically adding alternatives to the set. For example, the levels of these added attributes add one to the level of the previous alternative. When the highest level is attained, the level of the attribute is set to its lowest level. This works well for our case because we have a generic design.

Creating the choice sets this way ensures that there is no overlap in attributes (by construction). When attributes do not vary in a choice set, the researcher does not obtain any information about respondent trade-off preferences from that observation. Clearly, this is not a good feature for choice set design, and we will generally want to minimize its occurrence (Johnson et al. 2006; Chrzan and Orme 2000).

In making the decisions stated above, we had to consider issues around level balance and orthogonality. Level balance provides an equal number of observations for each attribute level. Our design is balanced in that each level occurs equally, often within each attribute, which means that the intercept is orthogonal to each effect. This essentially ensures that we obtain the most information possible about each individual parameter. Introducing imbalance is undesirable as it would increase the information we obtain about one particular parameter at the expense of another (Johnson et al. 2006). When every pair occurs equally often across all pairs of factors, the design is orthogonal. Balanced orthogonal designs are desirable as they are 100% efficient and optimal. We are mainly interested in estimating the linear main effects – the effect of each attribute on utility – and not the interaction between them. The final design used in the study was balanced and orthogonal.

Choice Modeling Framework for Kgalagadi Dryland Ecosystem Services

The attributes and attribute levels are developed based on reviews of the literature, personal observations from 2009 to 2011, and communications with stakeholders and other researchers working in the study area. The attribute descriptions and their levels[3] are shown in Table A1 in the appendix. However, Table 1 shows one of the typical choice sets presented to local respondents.

Our choice set entails asking respondents to choose between the status quo (SQ) and two possible alternatives to enhancing ecosystem services preservation. The SQ is the base line for valuation. Alternative options to the status quo would entail a cost to the households. However, the subtle message for the status quo is that, while no payment would be required, the ecosystem would naturally continue to be under severe pressure going forward.

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[3] As far as the data setup is concerned, it should be noted that there is no dummy coding of quantitative variables (i.e., camel thorn trees, predator, medicinal plants, bushmen cultural heritage and grazing opportunities).

Table 1. A typical choice set presented to local communities[4]

Attribute	Status Quo	Alternative 1	Alternative 2
Camel thorn trees	Three quarters of a bundle	1 bundle	1 and a half bundles
Predator	448	448	700
Bush food	Half Container / small bag	2 Containers / small bags	Half Container / small bag
Medicinal plants	Half Container / small bag	Container / small bag	1 and a half Containers / small bags
Bushmeat traditionally hunted	2 stingboks	4 stingboks	6 stingboks
Grazing opportunities	719 large stock units	1198 large stock units	1437 large stock units
Levy	R 0	R 50	R 75
Your Choice (Tick)			

The inclusion of the status quo option means that a respondent can select the status quo for all attributes; in that case, the individual is applying a simple decision rule and failing to make the necessary trade-offs. As a result, the information on trade-offs is lost if individuals prefer the status quo for all choices, but this is also more realistic in terms of generating policy-relevant results. Therefore, it is crucial that a test is performed to check for status quo bias; see Table 2 below.

Table 2. Choice frequencies for local communities

Choice	Frequency	Percent
Alternative 1	353	42
Alternative 2	408	49
Status Quo	71	9
Total	832	

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[4] A reviewer has pointed out that one of the major content validity issues in CE is that of scenario design (i.e., whether the attributes and their levels are described in an understandable and clear manner). This is correct, hence the authors undertook a pilot study prior to finalizing the questionnaire. For example, in the case of the tree attribute, the levels were defined both as the absolute kilograms of collected firewood and number of bundles. Our observation from the fieldwork is that there was no confusion with regard to attribute definitions.

Table 2 shows the number of times each alternative was chosen (out of 208 x 4 choice sets = 2,496 choice sets across all respondents), and shows that the status quo was chosen 9% of the time. Nine percent of local communities chose the status quo, and so preferred to leave the ecosystem as it is, which would naturally continue to be under severe pressure going forward. Although a bias toward the status quo appears, it is insignificant. Therefore, the local communities have demonstrated that they have not applied a simple decision rule and we can conclude that they have made the necessary trade-offs.

The Economic Model and Estimation Technique

The main aim of our analysis is to estimate welfare measures. To be more specific, we intend to obtain the marginal rates of substitution (MRS) or marginal willingness to pay (MWTP). In order to evaluate the welfare effects of changes in the attributes, information is needed regarding locals' preferences for attributes of the Kgalagadi dryland ecosystem services. According to Bennett (1999), the MRS between attributes can be estimated by modelling how respondents switch their preferred alternative in response to the changes in the attribute levels. Note that we assume a linear utility function:

$$V_{ik} = \beta a_i + \mu \chi_1 \qquad \text{Where} \quad \chi_1 = M_k - P_1 \tag{3}$$

Our goal is to express the monetary value that respondent k attaches to a change in attribute *i*. The MRS or MWTP between an attribute and money is:

$$MRS/\ MWTP = \frac{\partial V_{ik}}{\partial a_{ik}} \Big/ \frac{\partial V_{ik}}{\partial \chi_1} = \frac{-\beta_i}{\mu} \tag{4}$$

Thus, marginal values are estimated from the MRS between a coefficient β_i and the coefficient for the price parameter, μ, (i.e., the amount visitors would be willing to forgo to conserve dryland ecosystems). By using the monetary attribute (cost to the respondent), we are able to estimate the average individual's MWTP. Note that, because this is a ratio, the scale parameters cancel each other out. Therefore, we can compare across models. A vital point to note is that this welfare measure is not comparable to welfare estimates from CVM-generated estimates for the whole good, as this is the MWTP for one attribute only (Carlsson 2008).

To illustrate the basic model behind the CE presented here, consider a local resident's choice for a dryland ecosystem conservation initiative and assume that utility depends on choices made from a set *C*, i.e., a choice set, which includes all the possible conservation options. The representative resident is assumed to have a utility function of the form:

$$U_{ij} = V(Z_{ij}) + \varepsilon\,(Z_{ij}) \qquad \textbf{(5)}$$

where, for any respondent i, a given level of utility will be associated with any ecosystem conservation alternative j, V is a nonstochastic utility function, and ε is a random component. Utility (U_{ij}) derived from any of the conservation alternatives is assumed to depend on the attributes (Z), such as the probability of seeing predators and recreational restrictions. The attributes may be viewed differently by different individuals, whose socio-economic profiles will affect utility.

The Conditional Logit Model (CL) has been the work-horse model in CE. The main reason is simplicity in estimation. However, the last 10 years or so have seen a rapid development of other models as computer capacity, and algorithms have made this model somewhat less important. Given that the CL is restrictive (Alpizar, Carlsson and Martinsson 2001), we also consider a number of extensions. These extensions “solve” different shortfalls encountered in the CL models.

The Mixed Logit Models (ML) and Latent Class Model (LCM) are extensions which can approximate any random utility model (McFadden and Train 2000). The former obviates the limitations of the CL because the alternatives are not assumed to be independent, i.e., the model does not exhibit IIA, modelling the distribution explicitly accounts for *unobserved* heterogeneity in taste, and it is possible to extend to panel data. Thus, the stochastic component of the indirect utility function for alternative *i* and individual *k* is now decomposed into two parts: one deterministic and in principle observable, and one random and unobservable:

$$V_{ik} = ba_{ik} + \eta_k a_{ik} + \varepsilon_{ik} = \beta_k a_{ik} + \varepsilon_{ik} \qquad \textbf{(6)}$$

where β is the alternative specific constant (ASC) which captures the effects on utility of any attributes not included in the choice specific ecosystem conservation initiative attributes. The coefficient vector can be expressed as $\beta_k = b + \eta_k$, where the first term expresses population mean, and the second is the individual deviation that represents the locals’ taste relative to the average tastes in the respective population groups. Now we assume that the error term $\varepsilon_{ik}\ is$ IID type I extreme value, in which case the model is now referred to as an ML (or random parameter logit - RPL) (Alpizar, Carlsson and Martinsson 2001). The individual deviation term is a random term with mean zero.

In LCMs, heterogeneity is cast as a discrete distribution, a specification based on the idea of endogenous taste segments (Bhat 1997; Wedel and Kamakura 2000). The sample consists of a finite number of groups of individuals (i.e., segments), each assumed to consist of homogeneous tastes. However, tastes, and hence utility functions can vary between segments. The advantage of using this technique is its ability to explain the taste variation across individuals, conditional on the probability of membership in a latent segment. The fundamental idea behind the LCM analysis is simply that some of the parameters of a postulated statistical model differ across unobserved subgroups. These subgroups form the categories of a categorical latent variable (Vermunt and Magidson 2002).

Given the membership in class c, the CL is used to estimate the probability.

$$L_k(i|c) = \frac{\exp(\beta_c a_j/\tau)}{\sum_{j\epsilon Sm} exp(\beta_c a_j/\tau)} \qquad \textbf{(7)}$$

With C classes, the basic choice probability is:

$$L_k(i|c) = \sum_{j\epsilon Sm} P(c) \frac{\exp(\beta_c a_j/\tau)}{\sum_{j\epsilon Sm} exp(\beta_c a_j/\tau)} \qquad \textbf{(8)}$$

The class membership probabilities, P(c), and the class-specific betas are to be estimated in the model. P(c) is normally estimated using multinomial logit specification, with or without covariates.

The ratio of choice probabilities between two alternatives in a choice set is unaffected by the other alternatives that are available in the choice set and the levels of the attributes of the other alternatives. This requirement may or may not be satisfied; in many cases, it is not. Violations of IIA imply error heterogeneity resulting from omitted variable bias (see McFadden 1986). Applying the CL model assumes that it is the true model in the application of interest and that IIA is fulfilled (Carlsson 2008). If there is a violation of this assumption, then the Heteroskedastic Extreme Value (HEV) or Random Parameter Logit (RPL) models can also be estimated and reported. The Hausman-McFadden test for IIA violation should be performed (1984).

Data Collection and Descriptive Statistics

A face-to-face survey was undertaken in May 2012 in the broader Kgalagadi area in an attempt to determine how preferences for particular dryland areas are formed. A survey instrument was prepared in both English and Afrikaans. English and Afrikaans speaking survey enumerators were recruited from among university students and residents in the study area. These enumerators were trained and supervised. The survey[5] attempted to measure what people think about dryland ecosystem services conservation in the Kgalagadi area.

Randomly selected households were surveyed in the Khomani San and Mier communal land respectively. Sample size determination took into consideration the elicitation format, as well as the budget constraints. Two hundred and eight randomly selected households were interviewed. At the time of the survey, only 120 Khomani San out of 320 households were using the land returned to them; therefore, our sample size of 104 is representative of the San population. Thus, we restricted the San sample to those who could plausibly have taken up the offer to use land restored to the Khomani San. In terms of the Mier, we made settlement maps, and identified each household. Then, we used a random function in Stata. Thereafter, we gave lists of household numbers and maps to enumerators.

During the interviews, a map of the Kgalagadi dryland ecosystem location and colour photographs were shown to each respondent. Enumerators described the Kgalagadi dryland ecosystem and its location and ecological importance, then enumerated its ecosystem services.

The household heads were interviewed in each household. Where the respondents were household members other than the heads, their responses were interpreted as coming from the heads themselves. An introductory section explained to the respondents the context in which the choices were to be made and described each attribute and its levels, present status, and hypothetical future status, based on whether or not preservation action was taken. Moreover, respondents were told that there were no right or wrong answers, and that all answers were strictly confidential.

A total of 208 respondents were split equally between the Khomani San and Mier people. In addition to the CE questions, the survey gathered personal information about respondents to gain more insights about factors that affect the way people feel about dryland ecosystems. The

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[5] As indicated earlier, the payment vehicle was tested beforehand to ensure its credibility. As pointed out by the reviewer, contingent valuations conducted in poor communities in developing countries have used labour contributions (i.e., willingness to contribute labour) as opposed to financial contributions. In contrast, a study on valuation of biodiversity by the South African Khomani San (Dikgang and Muchapondwa, 2012) shows that those who want to contribute labour also have a WTP>0. On that basis, we believe that the monetary measures of WTP used in this study are not biased downward.

information is used as explanatory variables to investigate heterogeneity in preferences. The descriptive statistics of the sub-samples are presented in Table 3.

Table 3. Summary statistics of the respondents

KGALAGADI LOCAL RESPONDENTS[6]		
Variable	*Mean*	*Std.Dev.*
Harvest medicinal plants from communal land	0.581	0.493
Collect bush-food from communal land	0.533	0.499
Collect firewood from communal land	0.856	0.351
Make crafts	0.327	0.469
Involved in game farming	0.130	0.336
Involved in livestock farming	0.423	0.494
Involved in traditional hunting	0.188	0.390
Involved in tracking activities	0.163	0.369
Undertake other activities in communal land	0.048	0.214
Undertake activities in other areas	0.323	0.468
Gender of respondent	0.361	0.480
Age of respondent	44.230	15.195
Responsible for paying household bills	0 .683	0.476
Household size	5.683	3.246
Involved in conservation in communal land	0.221	0.415
Education years of respondent	6.697	3.879
Respondent employment status (1=fulltime employment; 2=part-time employment; 3=self-employment; 4=fulltime student; 5=part-time student; 6=retired; 7=other)	5.269	2.233
Household Income (Rands)	27 019.20	30 249.60

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[6] It is vital that we analyse the Khomani San's preferences pertaining to activities that take place inside the park given that they have resource rights inside the park. This information will shed light on the local people's attitudes towards conservation in the area as a whole.

Given that the livelihoods of the majority of the Kgalagadi dryland communities are based on the natural environment, it is not surprising that most are involved in firewood collection, collection of medicinal plants, and bush food collection on their communal land. The percentage reported for firewood collection is much higher than that reported in previous studies (see Dikgang and Muchapondwa 2012). One possible explanation is that they collect more than usual during winter periods. While the collection of data during winter may explain the larger percentage of respondents reporting firewood collection, it should be noted that the majority of the respondent are female (64%), whom by African traditions are the ones involved in firewood collection. Thus, it is vital to control for gender, or else the conclusion based on weather conditions might be misleading. Given that the Kgalagadi local people are traditionally involved in livestock farming, the significant number of livestock farmers reported in this study is consistent.

Of particular interest, 81 percent of the Khomani San people were not involved in traditional hunting, although they there are historically hunters and gatherers. Most seem to be so affected by modern development and lifestyles that they are pushing away from their traditional lifestyle. According to Crawhall (2001), the creation of the Kalahari Gemsbok National Park (now incorporated within the KTP) in 1931 was the main reason that the majority of the San people were forced to give up their hunting and gathering lifestyle to become farm workers. Only a few families remained in the park to work as labourers and trackers until they were also removed in the 1970s. The few San people who are still traditional hunters and gathers are unable to hunt as much as they would like due to budget constraints. The San community leaders set hunting quotas every year during the hunting time, which is normally in winter. They also set hunting fees, varying from R300 for a springbok to R600 for a gemsbok for non-community members, and R150 for a springbok to R300 for a gemsbok for community members. Although the fees are lower for community members, very few can afford the hunting fees due to their relatively low income levels.

Over half (64 percent) of the respondents are female. A sample of 64 percent women represents the underlying population in rural areas as men tend to either be working or engaging in income generating activities away from home, hence they are not available to answer survey questions directed to the household head. It should be noted that the fact that majority of the interviewed local communities are female (64%), this kind of survey results should be expected (i.e., that they don’t hunt, do collect firewood, and have lower incomes). In most cases in Africa, rural women do not have income. They also tend to be younger than males. Average number of household members is 5.7 persons. On average, most of the local respondents have not completed primary schooling (7 years). Most respondents indicated that there are not aware of any public conservation project within their communal land. The local respondents experienced a high unemployment level of 47 percent.

Results and Discussion

In most cases, we observe respondents making several choices. Stated preference literature often assumes that the preferences are stable over the experiment. As a result, the utility coefficients are allowed to vary among respondents but are constant among the choice sets for each individual. In a case where we have ASCs that are randomly distributed, then we would have a random effects model.

We estimate RPL[7] models, taking into consideration that respondents are making repeated choices – the panel nature of the data. Although the RPL model can account for unobserved heterogeneity, the model is unable to identify the sources of heterogeneity (Boxall and Adamowicz 2002). The inclusion of interactions of respondent socio-economic characteristics with choice specific attributes and/or with ASC in the utility function is one way to detect the sources of heterogeneity while accounting for unobserved heterogeneity (Birol, Karousakis and Koundouri 2006). Thus, we also estimate a RPL[8] model with interactions.

Thus, we estimate a CL and two RPL models. RPL model results are obtained using Halton sequences used for simulations, based on 500 draws. The RPL model was estimated with all attributes being randomly and normally distributed. The choice of distribution and the question of which parameters should be random are difficult choices. There is hardly any model specification which shows a clear dominance. Nonetheless, a specification test was undertaken.

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[7] Given that we want to use the RPL, we firstly just run the RPL model where all the attributes are random (except the cost attribute). Then we check which of the standard deviations of the random attributes are significant. Thereafter, we run the RPL model again and use only those attributes with random significant standard deviations. This is because, if the standard deviations are not significant, there is no unobserved heterogeneity in tastes of the respondents, and therefore no need to have those attributes random.

[8] A reviewer has pointed out that, because of the use of different distributions in the RPL models, it would be more prudent to estimate implicit prices in the 'willingness to pay space'. The authors agree with this point, and are indeed grateful. According to Hole and Kolstad (2010), "this approach has been found to produce more realistic WTP estimates. The WTP space approach is not yet widely used, probably partly because it has not been implemented in standard econometric software packages". With our econometric package (i.e., LIMDEP 9 for NLOGIT 4), we actually have this constraint. To the best of our knowledge, only LIMDEP 10 in NLOGIT 5 pioneers the new developments for estimation on "WTP space", hence our study's inability to report WTP in space.

The parameter estimates for the CL and RPL model for the local respondents[9] are reported in Table 410. The attribute levels details are shown in Table B1 in the Appendix.

Table 4. CL, RPL and RPL with interactions– local communities

CL Model[11]		**RPL Model**		**RPL Model with Interactions**	
Variable	***Coefficient (s.e)***	***Variable***	***Coefficient (s.e)***	***Variable***	***Coefficient (s.e)***
Alfa	1.490 *** (0.248)	***Random Parameters in Utility Functions***		***Random Parameters in Utility Functions***	
Cost	-0.008*** (0.002)	Predator	0.000 (0.000)	Tree	-0.003 (0.052)
Tree	0.009	Medicinal plants	0.701 (0.407)	***Nonrandom Parameters in Utility Functions***	

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[9] A reviewer has pointed out that the San people appear to be very poor and relatively uneducated. The choice experiment by its nature is a complex technique which places a cognitive burden on respondents. This is correct, particularly given that each San respondent was exposed to 4 choice sets with 3 alternatives each, and that each alternative comprised 7 attributes – a very complex experiment. Based on the evidence from the fieldwork, the San understood the choice scenarios and the trade-offs. The evidence of the choice frequencies shows that the San respondents did not choose the status quo option all the time and engaged in a decision-making process. Moreover, a study on valuation of biodiversity by the San (see Dikgang and Muchapondwa 2012) shows that despite their low education, the San understand complex environmental issues.

[10] The reviewer suggested that we undertake Klein's test, and the test of auxiliary regressions, to make sure that the initial design was correct. We are grateful to the reviewer for this contribution. To test for multicollinearity for the Kgalagadi ecosystem choice experiment, we first ran the full regression and then ran an auxiliary regression and compared the two R^2 values. Using Klein's Rule of Thumb, if the R^2 for the auxiliary regressions is higher than for the original regression, then we probably have multicollinearity. Our tests suggest that multicollinearity is not a problem. In addition, we examined the Variance Inflation (VIF) factors to see if there is multicollinearity in our sample, and it was not found to be a problem.

[11] Essentially, if IIA is satisfied, then the ratio of choice probabilities should not be affected by whether or not another alternative is in the choice set. One way of testing IIA is to remove one alternative and re-estimate the model and compare the choice probabilities. Although you can test for IIA, for generic experiments we often get problems with attributes with little variation when we drop an alternative (Carlsson 2008). With our data, we actually have this problem. Thus, we could not confirm its validity. Accordingly, we ran the RPL. According to Carlsson (2008), a mixed logit model is a CL model with random coefficients that are drawn from a cumulative distribution function. One of the advantages of mixed models is that the alternatives are not assumed to be independent, i.e., the model does not exhibit IIA.

	(0.011)				
Predator	0.000 (0.000)	Bushmeat traditionally hunted	0.131*** (0.045)	Alfa	1.520 *** (0.272)
Bush food	0.058 (0.101)	***Nonrandom Parameters in Utility Functions***		Cost	-0.008 *** (0.002)
Medicinal plants	0.122 (0.158)	Alfa	2.164*** (0.434)	Predator	0.000 (0.000)
Bushmeat traditionally hunted	0.074*** (0.026)	Cost	-0.009 *** (.003)	Bush food	0.117 (0.119)
Grazing Opportunities	0.001*** (0.000)	Tree	0.013 (0.019)	Medicinal plants	0.164 (0.177)
		Bush food	0.111 (0.162)	Bushmeat traditionally hunted	0.085*** (0.030)
		Grazing Opportunities	0.001*** (.000)	Grazing Opportunities	0.001*** (.000)
		Derived Standard Deviations of Parameter Distributions		***Heterogeneity in mean, Parameter: Variable***	
		Predator	0.003 (0.001)	Gender	0.028 (0.028)
		Medicinal plants	4.729*** (1.077)	Age	-0.001 *** (0.001)
		Bushmeat traditionally hunted	0.003*** (0.151)	Household Size	0.007 *** (0.005)
				Derived Standard Deviations of Parameter Distributions	
				Tree	0.148** (0.059)

In the standard CL model, because the coefficients are confounded by a scale parameter, we cannot interpret the magnitudes of the coefficients. But we can interpret the sign and significance of the coefficients. From a statistical point of view, a parameter is statistically significant if the probability of rejecting a true null hypothesis is very low. In our case, the null hypothesises for each of the above estimated parameters are that the true parameter values of the corresponding attributes is zero. This means that there is no relationship between the attributes and the outcome variable (the probability of choosing an alternative containing that particular attribute). The sign of the parameter indicates the direction of the relationship between the attribute and the likelihood of choosing the alternative, i.e., whether the probability of choosing an alternative increases or decreases when the level of the attribute increases or decreases.

As shown in the second column of Table 4 above, the intercept is positive and significant, implying that, with everything constant, the respondents would prefer one of the new alternatives to the status quo. The coefficient of cost is negative, as expected, and it is significant at the 1% level of significance. This means that, all else equal, an alternative with a high cost is less likely to be chosen. The coefficient of grazing opportunities is positive and significant at the 1% level of significance. This implies that an alternative with this attribute is more likely to be chosen. This is consistent with the priori positive expectation that people tend to like an improved grazing condition of the farmland area. Similarly, we can see from the column that the coefficient of bushmeat is positive and significant at the 1% level of significance, which also suggests that the respondents are more likely to choose an alternative with this attribute.

The output shown in Column 4 is obtained by restricting the coefficients of the Carmel thorn trees, predator and bushmeat attributes to be random and normally distributed. The randomness restriction suggests the presence of taste heterogeneity in the local sample for these three attributes. This limitation only holds if the estimated derived standard deviations are statistically significant. Our results show that there exists taste heterogeneity in the population for the medicinal plants and bushmeat attributes. Our results indicate that the local people do not value the predator attribute differently.

As for the rest of the results, Alpha is the ASC common for the new alternatives. Its significance indicates the effect on respondents' utility that is not captured by the attributes listed in the alternatives. In particular, when both positive and significant, it implies that it is more likely that respondents choose one of the new alternatives instead of the status quo, *ceteris paribus*. Thus, our results show that the Kgalagadi local respondents are supportive of the alternatives. As expected, the cost coefficient is negative, as well as significant. This implies that an alternative with high costs is unlikely to be chosen, *ceteris paribus*. The coefficient of grazing opportunities is positive and significant. This implies that alternatives with these attributes are more likely to be chosen. Given that livestock farming is one of the main livelihood sources, it is not surprising that an alternative that includes maximization of grazing opportunities is preferred.

In the sixth column, sex, age and household size are interacted with the Carmel thorn trees attribute. In other words, we assume that there is preference heterogeneity for this attribute across sex, age of respondents and household size. Indeed, our results show that the estimated mean interaction coefficients, Age and Household size, are statistically significant, but the coefficient of Gender is not significant. Our results imply that older people tend to have lower preferences for the Carmel thorn tree attribute than younger people, and that respondents with larger household sizes are more likely to choose an alternative to a Carmel thorn tree attribute, ceteris paribus. All other estimated parameters can be interpreted in the same way as in Column 4 (RPL model).

Both CL and RPL models were used to obtain local respondents' MWTP for continued provision of Kgalagadi dryland ecosystem services. The MWTP estimates are presented in Table 5, below.

Table 5. Marginal Willingness to Pay (MWTP) for dryland ecosystem attributes[12]

Attributes	CL Model (R)	95% Confidence Interval	Attributes	RPL Model (R)	Confidence Interval	Attributes	RPL Model with Interactions (R)	Confidence Interval
Tree	1.20	1.47-4.53	Predator	-0.01	0.23–0.71	Male	139.18 **	52.66–162.36
Predator	0.00	0.02–0.06	Medicinal plants	-598.80*	318.31-1023.13	Female	139.27 **	52.68–162.44
Bush food	7.52	12.42-38.30	Bushmeat traditionally hunted	-112.36**	43.25-133.35	Whole	139.24 **	52.68–162.42
Medicinal plants	15.84	20.53-63.31	Tree	-1849.41**	702.45–2165.89			
Bushmeat traditionally hunted	9.64**	3.81–11.75	Bush food	7.75***	2.86–8.82			
Grazing Opportunities	0.08**	0.03–0.09	Grazing Opportunities	-11.05	15.63-48.19			

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[12] US$ 1 = South African Rand (R) 8.48 at the time the paper was written.

In the table above, a positive sign suggests the MWTP for that particular attribute, holding everything else constant. In contrast, a negative sign implies WTA compensation for a change that brings about that particular attribute, holding everything else constant. The CL model shows that, all else equal, respondents are willing to pay R9.64 for an alternative with bushmeat (wild meat) and R0.08 for grazing opportunities.[13]

The RPL model indicates that only the MWTP for bush food is positive and significant. For instance, local respondents are willing to pay R112.36 to maintain the current bushmeat levels.

From Column 8, we can see that females are willing to pay slightly higher amounts than males. Females have a MWTP of R139.27 for a program that maintains the current firewood collection levels of their farmland. Males have a MWTP of R139.18 to remain on the same indifference curve. The MWTP for the whole local sample is R139.24.

Conclusion

This paper uses a choice experiments technique to analyse preferences of local people toward the preservation of the Kgalagadi dryland ecosystem, and to evaluate the economic values of dryland ecosystem attributes. We contrasted two different models, namely the CL and RPL (without and with interaction).

In particular, our results show that a preservation initiative that is aimed at increasing grazing and hunting opportunities would be supported by the dryland communities. Although the Khomani San indigenous people are traditionally hunters and gatherers, over time a significant number have switched to livestock farming. Given that livestock farming is one of the main livelihood sources in the Kgalagadi dryland area, the ecosystem service that supports such a livelihood source is an important determinant of mode choice. Furthermore, there is considerable taste heterogeneity within the local communities. The MWTP results for the local sample give considerably low MWTP compared to park visitors (see Dikgang and Muchapondwa 2013). Overall, both males and females anchor in the same way.

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[13] The San farmlands carrying capacity is around 958 large stock. Two-thirds of the range has become overgrazed and was not productive; stocking rates should be kept to a minimum until vegetation had recovered.

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