African Journal of
Agricultural and Resource Economics
Volume 20, Number 3 (2025), pp 239–253

Preferences for water and willingness to pay for water supply improvements among rural households in the Upper Ewaso Ng'iro North Catchment Area: A discrete choice experiment

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Received: March 2025
Published: September 2025

DOI: https://doi.org/10.53936/afjare.2025.20(3).14

Abstract

Rural areas across the developing countries in every region of the world lag behind their urban counterparts in many important sectors and, most importantly, in improved water supply services. Financing is a key hindrance to bridging this gap. An alternative financing mechanism is the demand-driven approach or the service delivery approach, which stresses the importance of incorporating user demand, mostly measured as willingness to pay (WTP) for improvements in water supply services. We employed the discrete choice experiment (DCE) methodology to investigate rural households' preferences for various water supply improvement options and their economic value, using a sample of 585 households from the Upper Ewaso Ng'iro North Catchment. Data was analysed using the multinomial logit, conditional logit, the random parameters mixed logit and the willingness to pay space (WTP-space) random parameters mixed logit models without interactions. The results show that households prefer good-quality water, a private tap, water with high pressure and a good quantity that is available daily without interruptions. Households in the study area are heterogeneous with respect to water preferences. We recommend that upcoming rural water improvements offer rural multi-use water systems, balancing the need for quality water delivered through a private tap, with high pressure and quantity, and that is available daily at the least cost. Policy interventions should thus focus on enhancing water quality, while offering flexible service packages that accommodate different household preferences.

Key words: discrete choice experiment, ecosystem service, water supply, mixed logit, conditional logit model, catchment management, Upper Ewaso Ng'iro North Catchment

1. Introduction

The global water situation post-Covid-19 continues to look bleak, with water demand projected to significantly outpace supply. It is projected that, by 2030, there will be a 40% gap between fresh water supply and demand (World Economic Forum 2023). The widening water gap is anticipated to have significant negative effect on global GDP and food security, with climate change exacerbating the situation even further. Prior to the Covid-19 pandemic, 2.2 billion people globally lacked safely managed drinking water, while 4.2 billion people lacked safely managed sanitation. The implications of Covid-19 are that three billion people worldwide lack basic hand-washing facilities at home, yet hand washing is the most effective method for the prevention of Covid-19 (United Nations [UN] 2020). Kenya has the third largest number of people in absolute numbers in Sub-Saharan Africa, and by percentage of population that rely on unprotected surface water (UNICEF 2018). With a population of 54 million, 15 million Kenyans lack access to safe water and 37 million lack access to a safe toilet (Water Org, 2025). More than 40% of Kenyans, particularly in rural areas, lack access to clean water (Marshall 2011). While Kenya is a water-poor country, with water resources of around 500 cubic metres per person, the water stress is likely to increase substantially with rapid population growth, urbanisation, industrialisation, climate change and the Covid-19 pandemic. Kenya, under Sustainable Development Goal 6, has committed itself to achieve universal and equitable access to safe and affordable water for all, access to adequate and equitable sanitation and hygiene for all, and put an end to open defecation, paying special attention to the needs of women and girls and those in vulnerable situations by 2030 (UNICEF 2020). Achieving universal access to safe water by 2030 requires an estimated $14 billion in investment in water supply over the next 15 years (World Bank 2018).

Rural areas across the developing countries in every region of the world lag behind their urban counterparts in many important sectors, and most importantly in improved water supply services (Marks *et al*. 2020). For instance, in Kenya in 2015, access to improved water sources stood at 82% for urban households, but only 57% for rural households (UNICEF 2018). Previous studies have shown that some of the causes of the rural lag in water supply services include financing (Abramson *et al*. 2011), the traditional idea that water is a human right and should be provided for free (Harvey 2007), and social exclusion and lack of tenure status (Sinharoy *et al*. 2019).

To overcome these barriers, policy makers have traditionally depended on government and external assistance in the form of grants and concessionary loans. Due to the recent demand for water investments and constrained financing from development partners, there has been a need to mobilise new sources of financing, including commercial financing for commercially viable investments. For instance, the Kenyan government's commercial borrowing for water improvements, as of 2018, stood at $25 million sourced from private capital through commercial loans from different international sources (World Bank 2018). While the commercial financing of water services can bridge the gap to ensure improvements in supply, it is prone to pitfalls, including a lack of credit guarantees, the diversion of funds, transparency, neglect and corruption. An alternative financing mechanism is the demand-driven approach or the service delivery approach, which stresses the importance of incorporating user demand, mostly measured as willingness to pay (WTP) for improvements in water supply services (Abramson *et al*. 2011; Moriarty *et al*. 2013). The demand-driven approach empowers the beneficiaries to become controllers of their development and refers to a development strategy through which the people themselves are expected to take the initiative and responsibility for improving their water supply situation, rather than being passive recipients of government services (Saxen-Rosendahl 1995; Whittington *et al*. 1998; Moriarty *et al*. 2013).

We employed the discrete choice experiment (DCE) methodology to investigate rural farmers' preferences for various water supply improvement options and their economic value. According to Weber (2019), DCE is a quantitative technique used for eliciting preferences in the absence of revealed preference data, using stated preferences. In recent years, DCEs have become popular in environmental valuation research (Weber 2019), and more specifically in water valuation research (Kanyoka *et al*. 2008; Abramson *et al*. 2011; Bell *et al*. 2014; Latinopoulos 2014; Wang *et al*. 2018; Anteneh *et al*. 2019). Modelling farmers' choices will allow us to evaluate how they would trade off different levels of water attributes, as described in Lancaster's theory of consumer choice (Lancaster 1966), which states that consumers derive utility from the attributes of a good, and not just from the good.

2. Empirical model

Discrete choice experiments represent an empirical application and extension of the theoretical work of Lancaster (1966), which states that preference orderings rank different goods indirectly according to the characteristics or attributes that they possess. When faced with choices over non-uniform alternatives, it is assumed that the rational consumer will choose the bundle of goods that maximises his/her utility, subject to a budget constraint. As a result, by observing consumers' choices (in the case of the study choices regarding water attributes), it is possible to make inferences regarding the marginal utility of one trait relative to others (Lancaster 1966).

Suppose that an individual i faces *J* alternatives contained in a choice set, *S*, during occasion *t.* We can define the underlying latent variable, V_{ijt}^{*}, which denotes the value function associated with individual i choosing option $j \epsilon S$ during occasion *t.* For a fixed budget constraint, random utility maximisation implies that individual i will choose alternative *j*, as long as $V_{ijt}^{*} > V_{iqt}^{*} \forall_{q} \neq j$. The researcher does not directly observe V_{ijt}^{*}, but directly observes the choice denoted V_{ijt}, where $V_{ijt} = 1$ if $V_{ijt}^{*} = \max(V_{i1t}^{*}, V_{i2t}^{*}, \dots\dots.., V_{ijt}^{*})$, and 0 otherwise (McFadden, 1973).

We can write the individual *i's* latent function as:

$$V_{ijt}^{*} = X_{ijt}^{\prime}\beta + \varepsilon_{ijt}\text{q}, \tag{1}$$

where $X_{ijt}^{\prime}$ is a vector of attributes for the j^{th} alternative, β is a vector of taste parameters (a vector of weights mapping attribute levels into utility), and ε_{ijt} is a stochastic component of utility that is independent and identically distributed across individuals and alternative choices. This stochastic component of utility captures unobserved variations in tastes, as well as errors in consumers' perceptions and optimisation.

The probability of observing $V_{ijt} = 1$ (i.e. the consumer chooses option *j* given all other alternatives in S) can be written as:

$$Prob\left(V_{ijt} = 1\right) = Prob\left(X_{ijt}^{\prime}\beta + \varepsilon_{ijt} > X_{iqt}^{\prime}\beta + \varepsilon_{iqt}\right) \forall j, q \in S, \forall q \neq j \tag{2}$$

We assume that the random component of utility, ε_{ijt}, follows a Gumbel (extreme value type I) distribution. Therefore, under the assumption that $\varepsilon_{i1t}, \varepsilon_{i2t}, \varepsilon_{i3t}, \dots\dots, \varepsilon_{ijt}$ are identically and independently distributed, we can write the expression for the probability of observing alternative *j chosen* over all other alternatives, conditional upon the observed levels of the attribute vector for all alternatives in the choice set, *S*, as follows:

$$Prob\left(V_{ijt}=1\middle|X'_{i1t},X'_{i2t},\ldots..X'_{ijt},\beta\right)=\frac{exp\left[X'_{ijt}\beta\right]}{\sum_{q=1}^{Q}exp[X'_{iqt}\beta]} \tag{3}$$

Equation (3) is the basic conditional logit (CL) model, and can be estimated using maximum likelihood.

However, considering that farmers are heterogeneous, their preferences regarding different water attributes might also be heterogeneous. There are several ways of dealing with this preference heterogeneity, but the most common method is through the estimation of the random parameters logit (RPL) model, which is also called the mixed logit model (MXL). According to McFadden and Train (2000), the MXL model is regarded as a highly flexible model that can approximate any random utility model and relax the limitations of the basic multinomial logit by allowing random taste variation within a sample according to a specified distribution.

Furthermore, the CL model is prone to the violation of the independence of irrelevant alternatives (IIA) assumption, with the possibility of existence of preference heterogeneity, thus resulting in biased estimators (Sándor & Wedel 2005). To overcome the violation of the IIA assumption, the study applied the random parameters mixed logit model (MXL) to address the limitations of the CL model regarding the IIA assumption. Mixed logit models are unique among choice data models since they allow random coefficients. Random coefficients provide a solution to the IIA assumption problem in multinomial logit models (STATA 2020). MXL therefore allows the study to relax the two strong assumptions used in the CL model, i.e. the IIA assumption and the assumption of fixed coefficients (Dahlberg & Eklöf 2003; Christiadi & Cushing 2007; Wang *et al*. 2019).

Following Train (2003), the probability that individual *i* therefore chooses alternative *j* from the choice set *S* in situation *t* is given by:

$$Prob\left(V_{ijt}=1\middle|X'_{i1t},X'_{i2t},\ldots..X'_{ijt},\Omega\right)=\frac{exp\left[X'_{ijt}\beta_i\right]}{\sum_{q=1}^{Q}exp[X'_{iqt}\beta_i]}\,f(\beta|\Omega)d\beta, \tag{4}$$

where Equation (4) is the MXL model, β_i is a vector of taste parameters specific to individual *i*, and the matrix Ω defines the parameters characterising the distribution of the random parameters, i.e. the family (e.g. normal, lognormal or triangular). For this study, we allowed all the parameters to vary normally.

Finally, the marginal rate of substitution of money for each of the corresponding attributes, that is the willingness to pay (WTP) for the different attributes, can be computed as:

$$WTP_j=-1\times\left(\frac{\beta_i}{\beta_{price}}\right). \tag{5}$$

3. Materials and methods

3.1 Study area

The study was conducted in the Upper Ewaso Ng'iro North Catchment Area (ENNCA), which is the catchment area for the Ewaso Ng'iro River basin. The Ewaso Ng'iro River basin is the largest basin in Kenya (Ewaso Ng'iro North River Basin Development Authority [ENNDA] 2019). According to Mungai *et al*. (2004), the Upper Ewaso Ng'iro North Basin is located to the north and west of Mount Kenya, extending to the Aberdare Ranges between longitudes 36°30´E and 37°45´E and latitudes

0°15´N and 1°00´N. The Upper Ewaso Ng'iro Catchment Area has 21 sub-catchments demarcated using the tributaries of the Ewaso Ng'iro River, spreading from the northern slopes of Mount Kenya to the slopes of the Aberdare Ranges (Centre for Training and Integrated Research in ASAL Development [CETRAD] 2014). The upper catchment area is highly utilised for agricultural production due to favourable weather conditions, fertile soils and the availability of irrigation water through river abstractions. The main economic activity in Upper Ewaso Ng'iro North Catchment is small-scale farming (rain-fed and irrigation), small-scale fishery and pastoralism. The area ranges from having a high potential at a high altitude to low-potential arid and semi-arid zones. Due to the arid nature of most parts of the basin, the atmospheric demand for water is very high (Mutiga *et al*. 2010; Ericksen *et al*. 2012).

Data was collected in the period between September 2019 and March 2020 from a sample of 585 households. A multistage sampling technique was employed in the study. In the first stage, eight sub-catchments were sampled randomly out of the 21 sub-catchments of the Upper ENNCA; as a result, the following sub-catchments were sampled: Ewaso Narok, Pesi, Rongai, Naromoru, Likii, Timau, Sirimon and Ngare Ndare. In the second stage, stratified sampling was done disproportionately to population size of these eight sub-catchments, since the number of households in each sub-catchment was unknown. Finally, simple random sampling was undertaken using a list from the water resource users associations (WRUAs).

We utilised both primary and secondary data sources. Primary data was collected from households, WRUAs and key informants. Secondary data was collected from sources such as books, journals and reports. Data collected for the study included household data, group data, farm produce data and income data. A semi-structured questionnaire was administered to the small-scale farmers through face-to-face interviews by trained enumerators, using the World Bank's Computer Aided Personal Interview (CAPI) Program. Data for the study was analysed using STATA version 15.0 statistical software.

3.2 Experimental design

In the construction of a discrete choice experiment (DCE) design, the most important component is the identification of attributes (Lutta *et al*. 2019). To design the DCE, we conducted a pilot study and key informant interviews to understand the current rural water supply situation and identify key improvements that farmers desire so as generate the relevant water-related attributes. Apart from the pilot study, focus group discussions and key informant interviews, we also used evidence of water attributes and previous studies to validate the attributes. The attributes considered to describe rural water supply improvements include mode of delivery, water availability, water quality, water pressure and quantity, and the water use charge. While a number of water attributes are observable and easily measurable, such as water delivery, water availability, and water quantity and pressure, water quality is highly subjective, but also equally important in water DCEs.

The study addressed the subjectivity of water quality by defining water quality using observable characteristics at the local level, following Bateman *et al*. (2023). These included water clarity (turbidity), colour, smell/odour, taste, the presence of visible suspended or floating materials or dirt and the need for further treatment before consumption. Therefore, the study defined good-quality water as clear water, transparent, without odour and without floating or suspended solids, fit for human and livestock consumption without the need for further treatment, boiling or filtration. As such, poor water quality is the converse of good water quality. In the status quo situation, farmers remain with water of which the quality is not guaranteed. In the choice experiment, the *water quality* attribute had two levels. Good quality referred to water that is treated and safe to drink straight from the tap, with a clear/colourless appearance and no noticeable smell or unpleasant taste—thus no household treatment (boiling or filtration) is required. Poor quality denoted water for which treatment is not reliable and that may at times be cloudy/coloured or have an unpleasant smell/taste, and therefore requires boiling or filtration before drinking. For estimation, we coded a dummy variable, good quality, which was 1 for 'good quality' and 0 for the base level ('poor quality'), hence positive coefficients indicate a preference for drinking-quality water relative to the base. The attributes and respective levels are presented in Table 1.

Table 1: Water attributes and levels used in the DCE

Attributes	Definitions	Levels	Coding
Mode of delivery	Mode of water delivery to the household	Communal tap outside the compound	0
		Private tap in the compound	1
Water availability	Frequency of water availability on a weekly basis	Water available two days per week	0
		Water available every day	1
Water quantity and pressure	The amount of water quantity and pressure from the tap	Low quantity and pressure	0
		High quantity and pressure	1
Water quality	Treated water and safe to drink straight from the tap without any boiling or filtration. Water is clear/colourless and has no noticeable smell or unpleasant taste	Maintain (status quo). Water not reliably treated; may at times be cloudy/coloured or have unpleasant smell or taste and therefore requires boiling or filtration before drinking	0
		Improve water quality to make water safe to drink as it is, without further treatment, boiling or filtration	1
Seasonal water fees	Water fees to be paid by households for water use per cropping season.	KES 250	Continuous
		KES 500	
		KES 1000	
		KES 1500	

Note: KES = Kenyan shilling
Source: Authors

3.3 DCE water attributes and levels

Water delivery was taken at the two levels dominant in the study area, i.e. the communal tap shared by several households at a communal water point and the private tap in the compound. We considered the categorical nature of this attribute to be adequate, since households would be able to relate with it from their real-life experiences regarding access to water in their respective circumstances. We considered water availability on a weekly basis, since the majority of the informants reported that water rationing cycles could even take three weeks, especially during the dry season, and one week in the rainy season on average. We also took the water quantity and pressure qualitatively, since most water systems in the study area are gravity-fed and households would not be able to estimate water pressure in conventional terms. However, the majority of the informants felt that the water pressure had declined over time due to the increased number of users, and users mostly doing irrigation cropping.

Similarly, we treated water quality qualitatively at two levels for two reasons: first, most households reported that they used the same water for domestic use, livestock and irrigation cropping, eliciting the multi-use nature of water. Second, this simple assessment of water quality was considered adequate due to the difficulty or limited capacity of the respondents to measure water quality conventionally or psychometrically (through taste, smell and taste) with a uniform standard. Finally, the monetary attribute was included in the design to enable the calculation of a welfare measure. Currently, households who are community water development project members pay an average of KES 200 (2 USD) per month (translating to KES 800 or 8 USD, assuming a cropping season of four months), not to mention development charges, which average KES 5 000 (50 USD) annually. The money is meant for maintenance and WRUA permit fees. The farmers agreed that given the improvements in water availability, access and quality, they would be willing to pay KES 0, 250, 750 and 1 250 more per cropping season due to the anticipated increases in farm productivity as a result of improvements in the water service. This therefore informed the price levels of KES 250, 500, 1 000 and 1 500. After the identification of the attributes and levels, the next step involved the combination of the attribute levels to raise alternative scenarios. To achieve this objective, we used a fractional factorial design to identify the combinations of attributes and options in a choice set using the *dcreate* STATA command to ensure orthogonality, while at the same time reducing the D-error and increasing model efficiency to attain a good level of D-optimality (Hole 2016). The *dcreate* STATA command uses the modified Fedorov algorithm (Cook & Nachtsheim 1980; Zwerina *et al*. 1996; Carlsson & Martinsson 2003; Hole 2016). The final design had 32 paired-choice profiles that we randomly blocked into eight sets of four choice tasks.

Each respondent was randomly assigned to one of the eight choice sets and asked to choose the most preferred option in each choice task. Each choice task had three alternatives, A, B and C – the baseline status quo depicting the conditions as they were without any interventions. We illustrate one of the choice sets in Table 2.

Table 2: Example of a choice set card used in the DCE

Attribute	Option A	Option B	Option C (status quo)
Water delivery	Community taps outside the household	Private tap in the household	No change
Water availability	Yes, available every day	No, available twice per week	No change
Water quantity and pressure	High quantity and pressure	Low quantity and pressure	No change
Water quality	Bad quality	Good quality	No change
Price KES/cropping season	250	1 000	No fees
Which alternative do you prefer?	☐	☐	☐

Source: Author

3.4 Results of discrete choice experiment

To measure willingness to pay for water, we used the discrete choice experiment (DCE) methodology to assess rural households' preferences for different water attributes, with multinomial logit (MNL), conditional logit (CL), mixed logit (MXL) and the WTP-space MXL models without interactions. The use of all the models is important, since it offers an opportunity for robustness checks. It is equally important to note that the failure of the IIA assumption in MNL and CL models can lead to misspecification. Hence, to check and ascertain that this misspecification was not present, the Hausman and McFadden (1984) test for the IIA property was conducted.

The likelihood ratio tests were conducted for all the four distinct subsets of all the choice alternatives (choice sets) to check whether IIA holds in the CL model. From the tests, it was found that IIA only holds for alternative 2 (212.51 and $p = 0.01$) and alternative 4 ($p = 0.01$), while it does not hold for alternative 1 (-14.90) and alternative 3 (-17.66). In both the latter cases, it was found to be negative, implying a violation of the IIA assumption. To overcome the violation of the IIA assumption, the study applied the random parameters mixed logit model (MXL) with 50 random draws to address the limitations of the MNL and CL models regarding the IAA assumption. Mixed logit models are unique among choice data models because they allow random coefficients. Random coefficients provide a solution to the IIA assumption problem in multinomial logit models (STATA 2020). MXL therefore allows the study to relax the two strong assumptions used in the CL model, i.e. the IIA assumption and the assumption of fixed coefficients (Dahlberg & Eklöf 2003; Christiadi & Cushing 2007; Wang *et al*. 2018). The other strength of using the MXL-type models lies in their ability to account for preference heterogeneity (Train 2009). Mixed logit is a highly flexible model that can approximate any random utility model (McFadden & Train 2000). It obviates the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train 2009). Despite the MXL model having strong advantages over MNL and CL, its main shortcoming is in the estimation of the WTP for changes in product attributes, obtained through the division of the estimated parameters of a 'preference space' utility model by the negative of the price parameter (Helveston 2023). This common approach has been documented to yield unreasonable distributions of WTP across the population in heterogenous random parameter MXL models (Train & Weeks 2005; Sonnier *et al*. 2007; Helveston *et al*. 2018; Helveston 2023).

According to Helveston (2023), an alternative approach is to re-parameterise the utility model into the 'WTP-space' prior to estimation. The estimation of a WTP-space model allows the modeller to directly specify assumptions of how WTP is distributed, which has been found to yield more reasonable estimates of WTP (Train & Weeks 2005; Helveston 2023). WTP-space is superior to the random parameters MXL model, since it has been found to be more consistent with the respondents' true underlying preferences (Beaumais *et al*. 2014), and since WTP estimates are independent of error-scaling, they can conveniently be compared across different models estimated on different data (Helveston 2023).

As a result, the MXL and the WTP-space MXL models were more appropriate in the data analysis of this study compared to the MNL and CL models. However, the results of all the models are reported in Table 3 for comparison purposes and robustness checks.

Table 3: Conditional logit and mixed logit estimation results

Variables	**MNL model**	**CL model**	**MXL model**	**WTP-space model**
	Basic model	**Basic model**	**Basic model**	**Basic model**
KES/season	0.03*** (0.00)	-0.000*** (0.000)	-0.000*** (0.000)	0.005*** (0.002)
Private tap	-0.713*** (0.11)	1.14*** (0.072)	1.871*** (0.225)	728.673*** (139.614)
Available daily	1.831*** (1.40)	0.989*** (0.073)	1.321*** (0.174)	405.271*** (88.03)
High pressure & quantity	-0.241* (0.105)	1.13*** (0.082)	1.738*** (0.225)	241.442*** (71.127)
Good quality	0.227*** (0.14)	2.441*** (0.083)	5.83*** (0.572)	2 536.06*** (338.92)
STD deviation effects	-	-		
Private tap	-	-	1.736*** (0.293)	828.72*** (183.35)
Available daily	-	-	1.285*** (0.308)	251.14 (203.41)
High pressure & quantity	-	-	1.679*** (0.340)	616.30*** (157.36)
Good quality	-	-	3.983*** (0.572)	1 984.42*** (283.49)
Log likelihood	-1 120.26	-1 117.49	-989.096	-977.21
LR chi^2	957.59***	2 873.56***	256.79***	160.03***
Pseudo R^2	0.30	0.56	-	-
Number of observations	2 325	6 975	6 975	4 650

Note: * and *** indicate significance at the 10% and 1% levels, respectively

The results show that all the models fitted well, as indicated by the likelihood ratio test that is highly significant ($p = 0.01$), and the high parametric fit parameter pseudo R^2 for both MNL (pseudo $R^2 = 0.30$) and CL models (pseudo $R^2 = 0.5625$). According to Louviere *et al*. (2000) and Koutsoyannis (1992), pseudo R^2 values between 0.2 and 0.4 are indicative of extremely good model fit, equivalent to the range of 0.7 to 0.9 in linear functions such as the ordinary least squares (OLS) regression. The MXL and WTP-space MXL models also fitted well, as shown by the highly significant likelihood ratio test, which was significant at 1%. In all the models, all attributes were found to be significant determinants of choice and preference ($p = 0.001$). From the results, all utility function parameters have consistent signs with the theory. The model results show that the sign of the payment vehicle (KES/cropping season) was either negative or negligible (tends to zero) and significant ($p = 0.01$), as was expected in all the models. This negative sign is consistent with economic theory, indicating a lower preference (utility) for a given choice when the price/cost of the choice increases.

Reporting the coefficients in order of preference shows that households held higher preference for good-quality water in the MXL and WTP-space MXL models, as shown by the highly positive and significant coefficient for good-quality water. This finding was expected, since households prefer quality water in terms of cleanliness, colour, taste and smell, and will most likely choose alternatives with better water quality due to the dual nature of water use in the study area, where rural households use the same water for domestic purposes, livestock production and irrigation. The finding also shows that households understand the dangers/pitfalls of bad/low quality water – from the health aspects to the economic aspects – such as water-borne diseases, water-borne disease vectors and water-borne parasites, which affect both humans and livestock. The economic losses that emanate from the consumption of low-quality water arise from the lost days from productive household work during sickness, both directly for the sick and indirectly for the caregivers. Further losses arise from the cost of seeking medication and the actual cost of medication. With respect to livestock production, low-quality water implies economic losses due to lost production, either through the loss of the affected livestock (death) or reduction in production. Furthermore, the cost of drugs and veterinary care for the livestock reduce household welfare by redirecting resources.

The positive and significant coefficient of a private tap shows that households prefer to have a private tap in the family compound as compared to a communal or shared tap in a public place outside the family compound. This implies that households are more likely to choose combinations with a private tap rather than a communal water point. The finding implies that households are better off with a private piped water connection rather than a communally shared water point. High water pressure and quantity was found to be positive and significant. In other words, households prefer water with high pressure and volume. This was expected, since it would increase the household utility of irrigation water, since most households use gravity-fed sprinkler irrigation systems. As a result, households can irrigate more land in less time compared to the status quo, considering that the mainstay economic activity in the study area is farming, with a particular emphasis on micro-irrigation.

Finally, households preferred water that was available daily as opposed to rationed water, as shown by the positive and significant coefficient of ‘available daily’. As a result, increased water availability would have a positive impact on household utility due to better planning of the farm irrigation cropping activities compared to the status quo. Thus, in a nutshell, households prefer water of good quality (suitable for the multi-purpose nature of their needs), supplied through a private tap/ connection (piped water), with high pressure that is available daily without interruptions or rationing. The MXL and the WTP-space models revealed significant standard deviations for the coefficients of the four attributes, which were found to be highly significant at 1% ($p = 0.01$). These significant standard deviations imply that the different households in the study area have heterogeneous preferences over all the attributes at the 1% level of significance. This means that different households value water improvements differently, and their WTP varies based on a variety of factors. Therefore, understanding this heterogeneity is crucial for designing water management policies.

3.5 Mean WTP for the different attributes

The average implicit prices of the different water attributes are shown in Table 4, where we report the scaled WTP obtained from the WTP-space MXL model. From the tabulated results, it is evident that households place a high value on good-quality water and would be willing to pay KES 2 536 (USD 24.87) per cropping season for improvements in water quality. This result was expected, because, as discussed in the preceding section, water quality influences the household’s health status and has a significant bearing on the household’s economic situation. Furthermore, the results suggest that households would be willing to pay KES 728.67 (USD 7.14) per cropping season to have a private tap or private water point in the family compound. The results suggest that households would be willing to pay KES 405.27 to have an increment in water pressure and quantity, implying that the households are not satisfied with the status quo water pressure situation, and therefore would be willing to make contributions to change this situation. Finally, the findings suggest that households would be willing to pay KES 241.44 (USD 2.34) per cropping season to have water daily with minimal or no interruptions. This finding is quite interesting, since it suggests that daily water availability is not a major concern compared to quality water, a private tap, and high pressure and quantity of water. This can be explained by the fact that irrigation does not happen daily, and therefore if households get water of good quality through a private tap and high pressure (or rather stabilised pressure) for a few days a week, they will have more utility than in the status quo, where rationing can last for a week or longer in the dry season.

Table 4: Mean WTP for different water attributes

	Private tap	Available daily	High pressure and quantity	Good quality
MNL model	242.60	-623.66	82.22	-77.28
CL model	3 049.76	2 648.82	3 029.63	6 548.51
MXL model	3 282.20	2 317.20	3 048.60	10 228.67
WTP-space model	728.67	405.27	241.44	2 536.06

4. Discussion

While it is difficult to compare these results in detail with those from similar studies in other countries due to differences in hydrological and climatic conditions, in terms of actual water supply services, as well as in the socio-economic, institutional and cultural environment, there are very few studies that have been conducted on this topic in Kenya. However, it would be interesting to compare these findings with those of other recently stated preference surveys. The findings show the following aspects.

First, rural households hold a greater preference for good-quality water, as shown by the highly positive and significant coefficient of good-quality water. This finding was expected, since households prefer quality water and will most likely choose alternatives with better water quality. Previous studies have also shown households’ preference for quality water, such as Anteneh *et al*. (2019), who found that households in Ethiopia prefer high-quality risk-free water. Wang *et al*. (2018) found that households in China had a higher preference for improvements in water quality. Latinopoulos (2013) found that households were willing to pay for improvements in water quality in Greece. Similarly, Kanyoka *et al*. (2010) found that households in South Africa also had a significant preference for good-quality water, and Abramson *et al*. (2011) found that households in Zambia prefer high-quality water. Furthermore, households prefer private taps and water points. This finding is contrary to the findings of Abramson *et al*. (2011), who found that the attribute of a private tap had a negative sign, attributed to the respondents' unfamiliarity with or confusion over piped water services such as a hand pump.

However, the positive sign is consistent with the prior expectations of the study. The preference for a private tap over a communal tap could be explained by four factors. First, the economic losses sustained by fetching water from a communal tap in terms of money, labour and time, depending on its distance from the household, could be quite substantial. These resources could be used for other productive work in the farm setting. Second, the disempowerment associated with time and distance covered to fetch water, since it is mostly women and children who are involved in these activities (Crow & McPike 2009; Otufale & Coster 2012; Bisung & Elliot 2018). Third, the associated risk of conflict over the use of a communal water point by different members of the community. And finally, the risk of collapse due to neglect and vandalism, since a communal water point is a public good.

High water pressure and quantity was found to be positive and significant. The implication of this is that households prefer water delivered with high pressure and volume. This finding is similar to those of Kanyoka *et al*. (2010), Abramson *et al*. (2011), Latinopoulos (2013), Wang *et al*. (2018) and Anteneh *et al*. (2019), who found that households had a higher preference for higher water pressure and quantity. The reason for this is the time saved instead of having to fetch water, and the role of water pressure in micro-irrigation schemes, which are largely dependent on sprinkler irrigation. In the case of the study area, most water projects were dependent on gravity-powered sprinkler irrigation, suggesting that, depending on the farm location and the number of water connections in the neighbourhood, the water pressure may not be sufficient in the status quo scenario.

Finally, households seemed to have a preference for water that is available every day as opposed to rationed water, as shown by the positive and significant coefficient of available daily. This finding is consistent with those of Kanyoka *et al*. (2010), Latinopoulos (2013), Wang *et al*. (2018) and Anteneh *et al*. (2019), who found that households preferred a water supply with minimal interruptions. In the case of the study area, this is very important, especially during the dry season when spontaneous water-based resource conflicts and wildlife conflicts erupt between irrigators, pastoralists and wildlife due to reduced downstream river flow. The latter is usually attributed to up-stream abstractions and pumping for irrigation (Kiteme & Gikonyo 2002; Kiteme & Weismann 2015).

5. Conclusions and policy recommendations

The study has demonstrated that households prefer good-quality water (suitable for the multi-purpose nature of their needs), a private tap/connection (piped water), and water with a high and stable pressure that is enough for it to be available daily with no interruptions or rationing. Furthermore, the results have demonstrated that households are heterogeneous with respect to preferences for the different water attributes in the study area. From the WTP estimations, the marginal WTP for improvements in water quality was the highest in the ranking of attributes, which shows that rural households are aware of the importance of water quality and would want to obtain the highest utility from improvements in water quality. The high WTP for quality improvements is an indicator that households depend on un-improved water sources for domestic, livestock and irrigation. Households were also willing to pay more to have a private tap in the compound and to have water delivered at high pressure and quantity. The households were willing to pay the least to have water daily. We recommend that multi-use water improvement projects for rural household be carried out through wide-level community consultations in the planning and design stages so as to incorporate the heterogeneous nature of user preferences with regard to water attributes. A one-size-fits-all approach may not yield the desired project impacts. We further recommend that upcoming rural water improvements aimed at offering rural multi-use water utility need to balance the need for quality and delivery through private taps, possess high pressure and quantity, and consider delivering water daily at the least cost. Policy interventions should thus focus on enhancing water quality, while offering flexible service packages that accommodate the different household preferences.

Acknowledgements

The authors acknowledge the support accorded to the development of this manuscript by the UKID/GCBC-Bangor University – HABITAT project. Survey data for the study was collected with financial support from the AfDB/MoHEST/Egerton University Project, the Centre for Training and Integrated Research in ASAL Development (CETRAD) and the African Economic Research Consortium (AERC).

This material has been funded by UK International Development Funds; however, the views expressed do not necessarily reflect the UK government's official policies or those of the other funders. The authors are solely responsible for any errors in this paper.

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