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MODELING HETEROGENEOUS PREFERENCES OF LAKE URMIA BASIN RESIDENTS CONCERNED WITH ITS RESTORATION: AN APPLICATION OF SCALE-ADJUSTED MULTILEVEL LATENT CLASS MODEL

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Abstract

One of the major challenges in the field of environmental valuation, is discovering the diversity of preferences and sensitivities that exist in the communities. During last years, environmental situation of Lake Urmia with all its geological, economic, social, water resources, climate and other aspects, has changed and followed a downward trend. Lake Urmia, as a public good, needs public contribution to prevent further deterioration. The success of restoration strategies is largely dependent on its acceptance by the beneficiaries and level of their participation. The purpose of this paper is to conduct a choice experiment for investigating public heterogeneous preferences on the non-market economic benefits of Lake Urmia restoration. A scale-adjusted multilevel latent class model is applied and a model with three latent classes at individual level, two classes at group level and two scale classes was selected as the preferred model. According to our results, most people who live geographically closer to Lake Urmia, belong to the same grand class. There were signs of homogeneity for all members of this grand class, while for other respondents, considerable heterogeneity could be observed. We have evidence from our results that individuals' characteristics, location and response certainty may provide explanations for heterogeneity.

***Keywords**: Choice experiment; Heterogeneity; Scale-adjusted multilevel latent class model; Lake Urmia*

Introduction

For many years, ecologists have introduced increasing economic activities as an important factor of depletion and destruction of natural resources and indicated that along this trend, sustainability and flexibility of ecosystems is exposed to serious threats. Economic valuation provides a background for measuring and comparing various benefits of natural resources and ecosystems and can be a powerful tool for improving their management [1]. One of the major challenges in the field of valuation is discovering the diversity of preferences and sensitivities that exist in the communities. Differing sensitivities are the basis for targeted communication programs and promotions. As consumer preferences and sensitivities become more diverse, it becomes less and less efficient to consider the community in the aggregate [2]. Hensher and Greene [3] believe that analyzing heterogeneity helps to reduce bias in the parameter estimates.

The lakes provide a wide array of benefits to society. The actual economic benefits of these services and amenities are often underestimated as many non-market goods and services

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are not easily measured and hence, metrics for environmental and economic decisions are often skewed. Investment in the ecological health of the lakes basin is pivotal to their long-term economic success [4]. Lake Urmia is the 20th largest lake in the world by area and the second most hypersaline lake [5], which has important socio-economical and ecological role in the Northwestern part of the Iran [6]. Some 1500 species of vascular plants, including unique *Artemia* sp., are distributed among 85 families and represent 15% of total number of flora species found in country. Because of its unique natural and ecological features, the lake has been designated as a National Park, Ramsar Site and a UNESCO Biosphere Reserve [7]. The watershed of the lake is an important agricultural region with a population of around 6.4 million people; an estimated 76 million people live within a radius of 500 km [8].

In the past decade, the lake's average water level has decreased significantly, endangering this unique ecosystem [9] (fig. 1). Considering no significant trend in the drought pattern, Lake Urmia's observed physiographic changes may be attributable to the construction of dams, irrigation projects and overuse of surface water and groundwater [9]. Scientists have warned that continued decline would lead to increased salinity, collapse of the lake's food chain and ecosystem, loss of wetland habitat, windblown "salt storms," alteration of local climate and serious negative impacts on local agriculture and livelihoods as well as regional health [8].

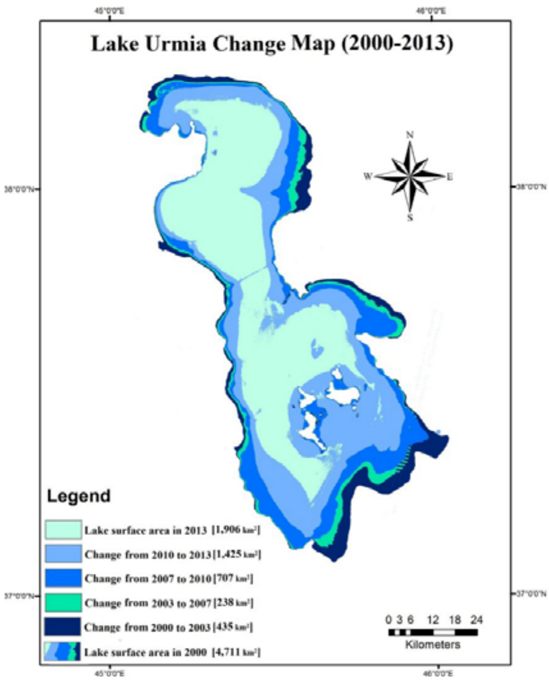

Fig. 1. Lake Urmia change map [10]

The nature of public goods implies that some functions would not survive without some form of collective action. Furthermore, the difficulty of determining optimal provision, alongside with a lack of reliable data on community demand, may lead to under-provision of services by the public sector. Thus, if there is no public intervention regarding public goods, there is a potential risk of their negligence [11]. Lake Urmia, as a public good, needs public contribution to prevent further deterioration that could have serious impacts on social welfare. Since continued decline would lead to the lake's ecosystem collapse and serious negative impacts on local livelihoods, some plans and special committees have been formed and developed for restoration of the lake. Also, the lake and its satellite wetlands have been selected as a demonstration site for the United Nations Development Program/Global Environment Facility conservation of Iranian Wetlands Project. Without a doubt, strategies for restoring the lake will affect regional stakeholders. The success of any strategy is largely dependent on its acceptance by the beneficiaries and level of their participation. As mentioned above, the purpose of this paper is to conduct a valuation exercise for investigating public preferences on the non-market economic benefits of Lake Urmia restoration.

There are many studies in the field of environmental valuation based on stated preferences techniques and specifically choice experiment, which tend to improve the quality and/or management of natural resources and environment. For these studies, choice experiment has recently been applied in wetland [12-16], water supply [17, 18], rivers [19-23] and coastal habitats [11, 24-29].

Some of these studies have managed the heterogeneity of preferences among individuals through the use of approaches such as random parameter and latent class models [11, 14-16, 18, 24, 27]. In addition to the heterogeneity based on personal preferences, another important source of heterogeneity named spatial heterogeneity has been introduced recently [30, 31] and presented in some studies [22, 23, 32]. This is often estimated as a distance decay effect which has had various and even unexpected results yet. Also, it is unable to exhibit undetected clustering [23]. *B.A. Farizo et al.* [33] and *B.A. Farizo et al.* [34], using a multilevel latent class model, focused on people's geo-physical locations and found that individuals' surroundings help to capture heterogeneity and reduce variability inside groups. In this paper, in addition to considering the heterogeneity in both individual and group levels, we introduce a novel aspect to detect heterogeneity by a scale-adjusted model, which adjusts for differences in scale (response error).

Materials and Methods

Choice experiment as a multi-attribute approach is based on the notion that attributes of an environmental good can be used to understand the general tradeoffs which an individual is willing to make. In most literature [18, 3536] departed from the model proposed by *M. Fishbein and I. Ajzen* [37], choice practice is also explained through some attitudinal and personal characteristics. Moreover, recently few studies like *C. Seong-Hoon et al.* [38], *F. Brereton et al.* [39] and *M. Soliño et al.* [40] showed the relevance of the local endowments (home-site factors) and discussed how preferences of individuals are partly inspired by the social and regional environment where they live. Thus, we hypothesize that individual characteristics and regional environment interact together to form preferences.

Aggregate logit was the first model ever implemented to analyze choice data. Aggregate estimation assumes that the respondent utility is equal to the average utility, which is a quite restrictive assumption and does not allow for idiosyncratic, individual effects in the sample, meaning that heterogeneity in the sample is simply not considered. Cluster analysis is the evolution of aggregate estimation. Latent class estimation detects subgroups of respondents with similar preferences and estimates utilities for each segment, allowing for heterogeneities across segments of respondents [41].

Methodology

We start from the conditional logit model for the response probabilities which are an instance of aggregate estimation. The notation is in table 1.

$$P(y_{it} = m | z_{it}^{att}, z_{it}^{pre}) = \frac{exp(\eta_m | z_{it})}{\sum_{m'=1}^{M} exp(\eta_{m'} | z_{it})} \quad (1)$$

where: η_m/z_{it} is the systematic component in the utility of alternative m for case i at replication t. In a latent class or finite mixture variant of this model, individuals belong to different latent classes that differ with respect to some of the β parameters. To indicate that the choice probabilities depend on class membership x, the model is now:

$$P(y_{it} = m|x, z_{it}^{att}, z_{it}^{pre}) = \frac{exp(\Pi_m|x, z_{it})}{\sum_{m'=1}^{M} exp(\Pi_{m'}|x, z_{it})} \quad (2)$$

The probability density associated with the responses of case i has the form:

$$P(y_i|z_i) = \sum_{x=1}^{K} P(x) \prod_{t=1}^{T} P(y_{it}|x, z_{it}^{att}, z_{it}^{pre}) \quad (3)$$

Here, $P(x)$ is the unconditional probability of belonging to class x or, the size of latent class x [42].

The fundamental assumption of standard LC models is that observations are independent. However, this assumption is often violated. In most cases, the under study populations are hierarchically structured. To take into account the hierarchical structure of the data, we consider a multilevel LC model [43] with individuals nested in regions, respectively representing the first (lower) and second (higher) level units. The hierarchical approach enables to identify different regional patterns and to achieve substantial results. Moreover, in presence of an explicit hierarchical structure, ignoring the nesting structure and treating within-region observations as independent may produce invalid standard errors [44]. Therefore, we hypothesize that the residence place of choice of deems to be a long-run decision resulting from previous information and experiences that affects subsequent short-run decisions and preferences.

The multilevel LC model consists of two parts. The first part connects the observations belonging to the same group [45]:

$$f(y_i) = \sum_{m=1}^{M} \pi(u_j = m)\, f(y_j | u_j = m), \quad f(y_j | u_j = m) = \prod_{i=1}^{n_j} f(y_{ij} | u_j = m) \quad (4)$$

where groups are assumed to belong to one of M latent classes with prior probabilities equal to $\pi(u_j = m)$ and observations within a group are assumed to be mutually independent given class membership of the group. For the second part of the model, we define a density conditional on the class membership of the higher-level unit:

$$f(y_{ij}|u_j = m) = \sum_{t=1}^{T} \pi(x_{ij} = t|u_j = m)\, f(y_{ij} | x_{ij} = t) \quad (5)$$

$$f(y_{ij} | x_{ij} = t) = \prod_{k=1}^{K} \pi(y_{ijk}|x_{ij} = t) \quad (6)$$

Compared with standard LC model, multilevel type has two advantages: i) we not only obtain information on class membership of individuals, but also on class membership of groups of district and ii) groups are assumed to differ with respect to the prior distribution of their members across lower-level classes.

According to *J.K. Vermunt* and *J. Magidson* [42], the probability structure for a multilevel LC choice model is:

$$P(y_j|z_j, z_j^g) = \sum_{x^g=1}^{K^g} \int f(F_j^g)\, P(x^g|z_j^g)\, P(y_j|z_j, x^g, F_j^g)dF_j^g \quad (7)$$

Our model contains random parameters over several attributes for each case i in group j. Thus, $P(y_j|z_j, x^g, F_j^g)$ has the following structure:

$$P(y_j|z_j, x^g, F_j^g) = \prod_{i=1}^{I_j} P(y_{ji}|z_{ji}, x^g, F_j^g) \quad (8)$$

where:

$$P(y_{ji}|z_{ji}, x^g, F_j^g)=\sum_{x=1}^{K} \int f(F_{ji})\, P(x|z_{ji}, x^g, F_j^g)\, P(y_{ji}|x, z_{ji}, F_{ji}, x^g, F_j^g)\, dF_{ji} \quad (9)$$

and

$$P(y_{ji}|x, z_{ji}, F_{ji}, x^g, F_j^g)=\prod_{t=1}^{T_i} P(y_{jit}|x, z_{jit}^{att}, z_{jit}^{pre}, F_{ji}, x^g, F_j^g) \quad (10)$$

To summarize:

- $P(y_j/z_j, z_{jg})$ is the marginal density of all responses in group j given group information.
- For grand classes or classes for groups (x^g) and grand random parameters for groups (F^g_j), the marginal density is approximated using Gauss-Hermite quadrature.
- Grand covariates or covariates for groups (z^g_j) affecting (x^g).
- We assume that the I_j observations belong to group j and are independent of one another given grand classes and grand random parameters.

Table 1. Notation

Latent class model	
z	Covariates
att, pre	Superscript for attributes and predictors respectively
M	Total number of alternatives
K	Total number of latent classes
T_i	Total number of replications for case i
y_{it}	Response to replication t by case i
Multilevel latent class	
J	Number of higher-level units
y_j	Full vector of responses of group j
y_{ijk}	Response of lower-level unit i within a higher-level unit j based on indicator k
y_{ij}	Full vector of responses of case i in group j
n_j	Number of lower-level units within higher-level units
x_{ij}	Latent class variable at the lower-level
u_j	Latent class variable at the higher-level
t	Particular class at lower-level
T	Number of latent classes at lower level
m	A particular latent class at higher-level
M	Number of latent classes at higher-level
K	Number of items
g	Superscript referred to the higher-level
F_{1i}	Random effect 1 referred to case i
x^s	A particular scale class

With this model, we are going to investigate how the choices for Lake Urmia restoration alternatives can be explained and determine the classes to which both individuals and groups of districts belong. In this way, a scale-adjusting practice is also considered. A scale factor is a term by which all logit parameters are multiplied, and which thus allows modeling proportionality of parameter values across conditions or groups. The inverse of the scale factor is proportional to the standard deviation of the error distribution of the choice utilities. Therefore, this option makes it possible to model heterogeneity in response (un)certainty [46].
When the scale model is used, the linear term $\eta_m/x, z_{it}$ in the regression model for the choice variable is replaced by $\eta_m/x, z_{it}\ \varphi_x^s\ zit$, where: $\varphi_x^s\ zit$ represents the multiplicative scale factor which may depend on predictors and/or scale classes. Now, the equation for the probability of selecting alternative m becomes [46]:

$$P(y_{it} = m \mid x, x^s, z_{it}) = \exp(\eta_m \mid_{x,\, zit}\ \varphi_x{}^s{}_{zit}) / \sum^{M}_{m'=1} \exp(\eta_{m'} \mid_{x,\, zit}\ \varphi_x{}^s{}_{zit}) \quad (11)$$

Survey design

The first step in CE design is to define the good to be valued in terms of its attributes and their levels. The good to be valued in this study is the lake restoration scenario. According to previous studies and concerns about the drying of Lake Urmia, significant attributes pertaining to the lake and their levels were identified as shown in table 2. Also, information from focus groups and experts' consultations were used in this step.

To construct the CE survey, a D-optimal fractional factorial design [47] with 72 alternatives was developed and divided into 24 choices sets (84.17% D-efficiency) with three alternatives per set plus the status quo. Moreover, the choice sets were blocked to 6 different versions, each with four choice sets.

Table 2. Description of attributes and levels

Attribute	Description	Levels
Animal habitat	The number of different species of animals, their population levels, the number of different habitats and their size	Current status Slight restoration Full restoration
Climate regulation and prevention from salt storms	The surface area of the lake contributes to regulating microclimate and stores inflowing salts.	Critical status Current status Full restoration
Aesthetic and ecotourism	The scenery and landscape of the lake is an important factor in attracting tourists in the region.	Current status Slight restoration Full restoration
Education and research	The educational, research and cultural information that may be derived from the existence of the lake.	Weak Desired
Payment (IRR)	Annual contribution to the Lake Urmia management fund	100000-200000-300000-400000

The survey was administered during July, August and September 2015 in 13 districts of Lake Urmia basin and exogenous stratified random sampling applied as sampling strategy. To determine stratums, concentric circles were drawn around the lake and 5, 4 and 4 districts with a population of high (more than 200000), medium (20000-200000) and low (less than 20000) were selected, respectively. These locations were chosen so as to represent a continuum of distances from the lake, as well as rural and urban population. Then, a random sample was drawn within each district's center. Total samples of 450 respondents were interviewed, proportionately to the population levels of the locations. This resulted in 382 completed questionnaires. It should be noted that in addition to the choice sets, data on the respondents social and economic characteristics, and 42 attitudinal and related questions measured with Likert scales were collected.

Results and Discussion

During this study, some models with different specifications estimated to investigate the effects on capturing variation. Based on fitting measures of these models and Bayesian Information Criterion (BIC) in particular, model with three latent classes at individual level, two classes at group level, a random effect and two scale classes was selected as the preferred model. One important thing to mention is that estimation performed in absence of covariates (socioeconomic characteristics), since they were not significant in previous estimations. This also is in accordance with *Farizo et al.* [33] and *Farizo et al.* [34]; they stated that covariates should be used to explain the composition of the classes rather than to explain choice itself.

Table 3 presents the results of the preferred model. First, we analyze the classes at lower level. All attributes under study, except animal habitat for class 3, are highly significant. But variation of signs causes their classification. In the class 1 which by covering 0.56 of the total respondents, is the biggest class, all attributes coefficients have the expected signs; that is, levels with negative and positive environmental effects have respectively negative and positive signs. This class is the most sensitive class to animal habitat and aesthetic and ecotourism attributes. Class 2 with 0.29 of the whole sample, has similar coefficients signs to class 1 (except slight restoration of aesthetic and ecotourism). For this class, climate regulation and prevention from salt storms, followed by education and research are most important attributes. Class 3 including 0.149 of the respondents is smallest class, most often choosing alternatives with negative environmental effects causes opposite signs. This class is the most sensitive class to payment. Payment is negative and therefore also in accord with standard economic theory. Studying respondents' socio-economic variables indicates that class 2 has the largest high-educated younger people who are more inclined to take part in conservation groups.

Table 3. Preferred model's results

Model for choices	**Levels**	**Class 1**	**Z statistic**	**Class 2**	**Z statistic**	**Class 3**	**Z statistic**
			Attributes				
Animal habitat	Current status	-12.533	-4.083	-9.813	-3.677	0.161	0.259
	Slight restoration	3.428	3.89	3.306	2.115	0.293	0.58
	Full restoration	9.105	3.937	6.506	3.566	-0.454	-0.713
Climate regulation and prevention salt storms	Critical status	-4.652	-3.463	-18.517	-3.277	-2.276	-2.637
	Current status	-4.268	-3.648	-4.72	-1.922	-4.461	-3.226
	Full restoration	8.921	3.867	23.238	3.938	6.738	3.786
Aesthetic and ecotourism	Current status	-8.233	-3.921	-2.778	-2.56	2.149	2.207
	Slight restoration	5.671	3.86	4.066	2.444	2.752	3.029
	Full restoration	2.561	3.223	-1.287	-0.833	-4.901	-3.104
Education and research	Weak	-1.351	-2.645	-6.489	-3.65	-0.821	-1.38
	Desired	1.351	2.645	6.489	3.65	0.821	1.38
Price		-0.0005	-4.046	-0.0004	-3.384	-0.0006	-3.733
			Random parameters				
Animal habitat	Current status	2.53	4	-	-	0.65	1.8
	Slight restor.	-1.4	-3.26	-	-	0.62	1.59
	Full restoration	-1.13	-1.98	-	-	-1.28	-2.72
Climate regulation and prevention from salt storms	Critical status	-1.4	-2.27	-	-	-	-
	Current status	1.78	3.17	-	-	-	-
	Full restoration	-0.37	-1.03	-	-	-	-
Aesthetic and ecotourism	Current status	-2.93	-4.18	-	-	-0.06	-0.2
	Slight restor.	1.68	2.79	-	-	-0.65	-1.75
	Full restoration	1.25	2.02	-	-	0.71	1.78
Education and research	Weak	-0.96	-2.7	0.65	2.3	-	-
	Desired	0.96	2.7	-0.65	-2.3	-	-
Grand classes: climate regulation	Levels		parameter			Z statistic	
Grand class 1	Critical status		0.989			3.689	
	Current status		0.023			0.143	
	Full restoration		-1.013			-3.453	
Grand class 2	Critical status		-0.989			-3.689	
	Current status		-0.023			-0.143	
	Full restoration		1.013			-3.453	
Scale model	Parameter					Z statistic	
Scale class 1	0					-	
Scale class 2	-2.75					-10.49	
Model for classes		Class 1	Z statistic	Class 2	Z statistic	Class 3	Z statistic
Grand class 1		2.16	2.84	-2.62	-1.75	0.45	0.59
Grand class 2		0.09	0.58	0.47	3.31	-0.56	-3.47
Model for grand classes	Grand class 1		Z statistic			Grand class 2	Z statistic
Intercept	-1.95		-1.35			1.95	1.35
Covariates							
Use and non use incentives		-1.87	-1.29		1.87	1.29	
Beneficiary decision-makers		-0.6	-0.81		0.6	0.81	
Environmental crisis		-3.91	-1.38		3.91	1.38	
Preservationists		-2.17	-1.73		2.17	1.73	
Environmentalists		-1.74	-1.13		1.74	1.13	
Model for scale classes	Scale class 1		Z statistic			Scale class 2	Z statistic
Grand class 1	0		-			0.19	0.9
Grand class 2	0		-			0.49	2.01

This class has visited the lake more than everyone and had the highest relation between their occupation and environment. Class 2 had the lowest household size and highest percentage of women contributions. On the contrary, in class 3 individuals older than 40 years old were in majority and had lower academic degrees. Households in this class had the largest size and lowest members with less than 16 years of age. Having highest income level and members with under 16 years of age can be referred as one of the prominent features of class 1. This group had fewer visits to the lake and was less likely to take part in conservation groups. Also, they had a weak relationship between their occupation and environment. In the case of other variables, average amounts observed. Considering all, class 1 can be named as an average class. Class 2 seems to have more environmental concerns than others. Whereas, class 3 states opposite ideas. The later also is seen in *Farizo et al.* [33].

Estimation of random parameters allows separate random effects for all classes. Class 1 consists of more than half of the respondents with special motivations and beliefs that makes it the most heterogeneous class. In fact, if we were to estimate a model for the total population (for example a random parameters logit model), it is more likely that the result would be analogous to this class. On the contrary, class 2 acts as a relatively homogenous group and there is not a large variability in their choices. It seems since the ideas and ideals of this group are involved in their motivations, more homogeneity and stable choices arise within this class. Members of class 3 reveal a wide variability in their choices toward animal habitat and aesthetic and ecotourism, the attributes for which restoration creates disutility in general.

During the estimation process, we recognized that higher-level classes affect the lower-level classes through a random component. This major random component is due to the climate regulation and prevention from salt storms. The effects of critical and current status levels of this attribute is positive and the effect of full restoration is negative for grand class 1, which is an indicative of the occurrence of conflicting preferences.

As referenced in the previous section (methodology), a scale-adjusted model prevents from forming spurious segments that mainly differ in terms of scale (response error), resulting in more meaningful segments that differ only in real preferences [48]. Our preferred model consists of two scale classes. Hence, two scale factor parameters are reported in table 3. Since the scale factor parameters are log-linear, we should exponentiate them to get estimates for scale factors. The estimated scale factors for class 1 and 2 are 1 and 0.063, respectively. This means that scale class 1 is particularly for low error respondents and their utilities are exactly the same as the part-worth in table 3. Whereas, scale class 2 is for the less certain or high error individuals and their utilities are obtained by multiplying the part-worth in table 3 by 0.063. According to our results, 53.1 and 46.8 percent of individuals belong to scale classes 1 and 2, respectively. Table 4 shows the proportions between scale classes and lower-level classes.

The basic idea of the multilevel latent class models is that coefficients not only differ across groups of individuals, but also across groups of places of residence. In this paper, 13 under study districts were assigned to two grand classes (table 4). In this regard, factor scores from a factor analysis of respondents' attitudes toward environmental issues were included. Grand class 2 is greater than grand class 1 and entire members of class 2 belong to it. Also, the majority of grand class 1 are composed of lower-level class 1.

Table 4. Proportions among grand classes, scale classes and classes

Propertions	Grand class 1	Grand class 2	Scale class 1	Scale class 2
Class size	0.433	0.564	0.531	0.468
Class 1	0.376	0.183	0.285	0.274
Class 2	0	0.29	0.165	0.125
Class 3	0.057	0.091	0.08	0.067

Five factors extracted from a factor analysis about respondents' attitudes, explained 66% of variance. The first factor includes items that measure use and non-use incentives of respondents in relation to the Lake Urmia. The second factor is in the issue of who has the right to make decisions about natural resources management and environmental problems or it is better to take a passive approach in this regard. The third factor examines the consequences of human intervention in nature and the possibility of environmental crisis. The fourth factor is in contact with people who are actively working to preserve the environment on a daily basis by doing things like using eco-friendly products and services, public transportation, etc. The fifth factor is associated with the willingness of citizens to high quality of environment. Names for factors are use and non-use incentives, beneficiary decision-makers, environmental crisis, preservationists and environmentalists.

These factors were entered into estimates as explanatory covariates of the grand classes. Their significance shows their importance in explaining the differences between geographical areas. All the factor scores are positive for grand class two. As mentioned above, all members of the class two that have more environmental concerns, are involved in grand class 2. Therefore, it can be concluded that the characteristics of the individuals and the factors are highly associated with assignment to the grand classes. Table 5 shows assignment of individuals from 13 districts into grand classes and scale classes. The results indicate the fact that people in districts close to the Lake Urmia are more likely to be members of grand class 2 which reveals the influence of location on the individuals' choices.

Table 5. Classification of districts into grand classes and scale classes

District	Grand class 1	Grand class 2	Scale class 1	Scale class 2	Total
1	5	45	27	23	50
2	0	23	16	7	23
3	4	22	12	14	26
4	8	52	29	31	60
5	6	21	9	18	27
6	2	28	19	11	30
7	16	9	13	12	25
8	16	0	7	9	16
9	24	0	14	10	24
10	22	0	17	5	22
11	17	2	12	7	19
12	25	7	12	20	32
13	21	7	17	11	28

In order to understand the impact of individuals' home-site factors on their willingness to pay for Lake Urmia restoration, marginal willingness to pay has been estimated through the preferred model (Table 6). Obviously, people are not willing to pay the same amounts to achieve environmental improvements. The greatest benefit derived from lake restoration is to obtain a full restored level of climate regulation and prevention from salt storms that is placed by class 2. The next most important benefit is to obtain a full restored level of animal habitat, wanted by class 1. In contrast, class 3 have the least WTPs than others and most often experience disutility towards attributes, led to welfare losses. The other attributes and levels are pursued by classes at different prices. Estimating various benefits for different groups in society can provide policy-makers with more accurate figures on the benefits of restoring Lake Urmia and comparing with estimated costs for achieving such improvements to ensure the success.

Table 6. Marginal willingness to pay (IRR)

Attributes	Levels	Class 1	Class 2	Class 3
Animal habitat	Current status	-250000	-245000	2666
	Slight restoration	68000	82500	4883
	Full restoration	182000	162500	-7500
Climate regulation and prevention from salt storms	Critical status	-93000	-462500	-37833
	Current status	-85200	-118000	-74333
	Full restoration	178400	580750	112166
Aesthetic and ecotourism	Current status	-164600	-69250	35666
	Slight restoration	51200	-32000	-81666
	Full restoration	113400	101500	45833
Education and research	Weak	-27000	-162000	-13666
	Desired	27000	162000	13666

Conclusions

Initially, discrete choice data were estimated through aggregate models, without considering sample's heterogeneity. Thereafter, cluster analysis developed to allow for heterogeneities across segments. Most of this heterogeneity was primarily incorporated through socio-economic variables; i.e. individuals' characteristics affect their behaviors and choices. The impact of individuals' surroundings on their attitudes and beliefs was introduced later. Thus, we expect that the impact of location will make similarities within communities and differences between communities. In this study, we assumed that conditions in local area shape Lake Urmia basin residents' preferences concerning its restoration. When the data has multiple structure, the multilevel class model is recommended. Here, we estimated a multilevel latent class model which classifies individuals and explains their assignment into classes based on attitudinal and location measures. Moreover, we brought a novel aspect to the previous literature by managing the heterogeneity through scale-adjusting.

Our empirical results identified three lower-level classes, reflects the fact that even without considering the location and geographical position, respondents do not have the same attitudes and subsequently the same choices. According to our results, most people who live geographically closer to Lake Urmia, belong to the same grand class. For all members of this class, signs of homogeneity and for other respondents, significant heterogeneity is observed. This class is willing to pay high amounts in order to restore the lake and climate regulation and prevention from salt storms is the most worrying environmental problem for them caused by the drying lake. Another important thing to note is that our scale-adjusted model classifies people based on response error, where each class has its own utility. Overall, we have evidence from our results that individuals' characteristics, location and response certainty may provide explanations for heterogeneity. Considering these three factors in future works may lead to better reducing heterogeneity.

In summary, if obtained results and size of classes accurately show the reality of the society, estimating an aggregate model will lose large volumes of information. So, gains and losses of implementing the management plans will not be calculated correctly and metrics for environmental and economic decisions will be biased. As previous studies have suggested and was confirmed in this study, multilevel class models by better capturing the heterogeneity, give us more robust and efficient estimates, influencing the design of appropriate management measures. Undoubtedly, capturing a great deal of preferences heterogeneity in the deterministic component of utility, can facilitate managing a geographical area through greater involvement of citizens and public acceptance.

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