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Modeling preference heterogeneity in recreation random utility models when relevant information about users is limited

We suggest a novel approach to analyze revealed preference heterogeneity in recreation random utility maximization models when information about users is limited to their place of residence. We assume that recreationists living in the same place act as a "cohort" and that their preferences are hence homogeneous. We adopt a location-specific distribution criterion. We empirically test the suitability of this spatial approach by comparing its econometric performance and welfare estimates with that of the standard individual framework. We use data on hunting in Sicily to empirically test the cohort approach. Results from individual-specific and location-specific mixed logit models suggest that econometric performance improves when modeling heterogeneity with a location-specific conditional distribution. Further, marginal willingness-to-pay mean values and distributions for site characteristics differ significantly.

Keywords: *Recreation demand, Heterogeneity, Location-specific mixed logit model, Willingness-to-pay space, Hunting.*
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1. **Introduction**

In modeling Random Utility Maximization (RUM) for multiple recreation sites, the analysis of revealed preference heterogeneity is focal to avoid misleading welfare measurements and to obtain suitable aggregation across users (Hynes *et al.*, 2008). When the demographic information about recreationists is restricted to the place of their residence, one promising approach for analyzing heterogeneity is to use an in-group conformity criterion (Rungie *et al.*, 2014). This criterion hypothesizes that outdoor recreation arises as a "group" or "cohort" activity. A cohort consists of individuals who share defined characteristics in a selected period, or have experienced a common event (Deaton, 1985). Cohort analyses are frequently used in marketing, demography, and medical research to detect aspects of the cohorts' development over time (Yang and Land, 2016). In the recreation field, the cohort approach has been used to forecast the implications of demographic changes on participation in outdoor recreation activities and to estimate demand trends related to tourism travel (Burkett and Winkler, 2019; Dwyer, 1994; Serra *et al.*, 2016; Winkler and Warnke, 2013).

In this regard, the identification of cohorts is critical. Generally, cohorts are identified on a case-by-case basis by combining available information and a priori hypotheses about the source of user heterogeneity. When information available about recreationists is limited to their place of residence, this datum can be considered a sufficient and valid criterion to define cohorts for two main rea-

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sons. First, users living in the same municipality face similar costs when traveling to different sites and may consequently have the same spatial interdependencies of preferences (Czajkowski *et al.*, 2017; Sagebiel *et al.*, 2017; Swait *et al.*, 2018). Second, the place of residence can be a significant social factor in deciding on the recreational site to visit. Thus, it is reasonable to assume that specialized recreationists – like hunters who live in the same place – more easily interact with each other; share similar beliefs, behavioral norms, and attitudes; face similar exposure to cultural and social aspects that affect their preferences; and then experience similar recreation benefits. The literature has revealed the relationships between hunters' beliefs, attitude toward the behavior, subjective norm, perceived behavioral control, intentions, and real behavior in the exercise of hunting activities. Hrubes *et al.* (2001) used Ajzen's (1991) theory of planned behavior to demonstrate that individuals' hunting intentions are strongly influenced by attitudes toward hunting and subjective norms and that their perceptions of behavioral control and their hunting intentions are strongly correlated with self-reported behavior.

In this study, we apply a location-specific approach to assess hunting preference heterogeneity and estimate welfare measures in a multiple-site extensive margin framework based on the RUM. Our approach is similar to that used by Budziński *et al.* (2018) for investigating spatially clustered stated preferences regarding landscape characteristics. Budziński *et al.* (2018) compared a geographically weighted multinomial logit choice model with a location-specific mixed logit (MXL) model by assuming, as in our analysis, that all individuals living in a particular location have homogeneous preferences and that, consequently, each location has a separate and independent set of parameters. Their estimates evidence that the location-specific MXL model, not only accommodates spatial dependence indirectly by supporting the calculation of the conditional expected values of random parameters, but also deals with unobserved preference heterogeneity better fitting the data.

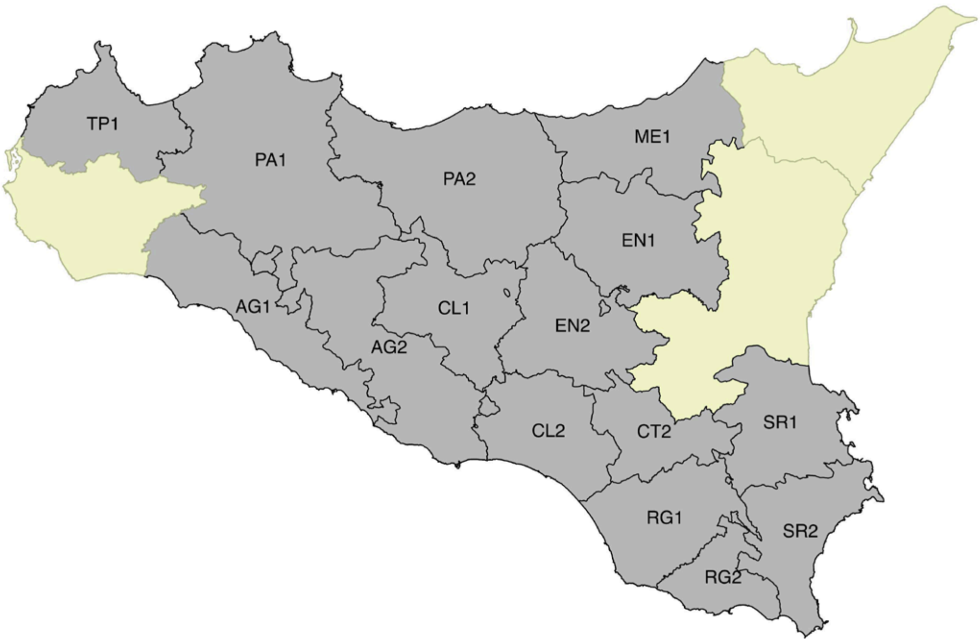
In this study, we empirically test the suitability of the cohort approach by comparing its econometric performance and welfare measures with that of the standard individual-specific framework. We use revealed data on hunting in Sicily. We specify and estimate two MXL models in the willingness-to-pay (WTP) space regime (Train and Weeks, 2005). We compare these models in terms of their econometric performance, posterior estimates of marginal willingness-to-pay (MWTP) distributions, and mean values to verify whether the municipality of residence could be a valid criterion to design cohorts. The accuracy of this hypothesis would support the use of a location-specific MXL model by directly providing location-specific estimates of MWTP. Our results suggest that econometric performance improves if heterogeneity is modeled among cohorts rather than among individuals and that the MWTP mean values for environmental attributes differ significantly.

2. Materials and method

2.1 Data

In Sicily, hunters are entitled to obtain permits to hunt sedentary fauna in three hunting districts in addition to the one in their area of residence. The number of permits available differs across hunting districts and hunting seasons. The "first-come, first-served" principle is applied in assigning additional permits to applicants. The maximum number of permits that will be issued in each hunting district is set every year by the regional hunting agency. In this study, we used data on a random sample of 918 successful applicants in the 2014-2015 hunting season.[1] In this season, applications were allowed only by the 15 hunting districts identified in the map shown in Figure 1. For hunters living in the yellow-colored districts (44% of the sample), the number of available sites was 15 for their choice of the first additional permit; the choice set decreased to 14 and 13, respectively, for the second and the third choices. However, for hunters residing in the gray-colored districts (56% of the sample), the number of available hunting sites for their first, second, and third choices were 14, 13, and 12, respectively. For each success-

Figure 1. Available districts for additional permits in the hunting season 2014/15.



[1] The sample was extracted from a population of 9,150 applicants.

ful applicant, we were able to gather information on the chosen additional sites, the order of the choice (from one to three additional sites), and the municipality.

In the sample, the number of available hunting sites (the choice set) was not fixed. Its dimension related to the applicants' municipality and order of choice for additional permits. The number of hunters living in the same municipality also varied widely, ranging between 1 and 162. We observed that 48% of the sample applied for only one additional district, 31% for two additional districts, and the remaining 21% for three more districts. We were aware that this choice context presents some complexities, which require more sophisticated models capable to handle the case that hunters choose the number of choice situations themselves, and capture dynamic effects among choices that are made by hunters to diversify their portfolio of available sites. As our specific goal, here, is to test the suitability of the cohort approach, we limited our analysis to only the first choice.[2]

We used Geographic Information System tools to map the land cover and use, and to assess the effective hunting surface area, the protected surface area, and the wetland surface area for each hunting district. The hunting surface area was equal to the total hunting district area net of the intensive agriculture areas, protected areas, urban centers, roads, and railways (including buffer zones of 100 m for the urban areas and 50 m for roads and railways). To calculate the protected area, we included the area covered by regional parks and reserves and by Natura 2000 sites. To assess the wetland surface area, we considered only wetlands outside parks and reserves.

In addition, we assigned to each district a hunting value expressed in terms of the richness of its sedentary fauna species. To measure this index, we estimated the number of such species in the habitat included in each district. The number of species potentially hosted in each Sicilian habitat ranged from zero to four. For each hunting district, we calculated the surface area covered by habitats hosting the same number of species. Then, we calculated the hunting value as the sum of such areas weighted for the number of species in the habitats, divided by the hunting district surface area. The hunting value index was calculated for both the hunting surface area and the protected areas included in each district. We also measured the landscape diversity through the Shannon habitat diversity index. This index was calculated on the basis of spatial habitat coverage using areas of 100 ha as reporting units. The index was 0 when the reporting units contained only one habitat (no diversity) and increased as the number of different habitat types increased and/or when the distribution of surface area among different types of habitat was more even. We used Corine Land Cover 2012 with a spatial resolution of 100 m, and the Analytical Tools Interface for Landscape Assessments of ArcGIS ESRI™.

Table 1 reports the main statistics for variables (or attributes) used for describing the hunting district quality and for measuring the access cost. The value for

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[2] We plan to analyse the complexity and dynamics effects of this choice context in a successive paper.

Table 1. Variables description and summary statistics.

Variable name	Description	Mean	Standard Deviation
Hunting surface	Site area where it is possible to hunt (km^2)	824.31	363.64
Protected surface	Site protected area (km^2)	160.70	238.31
Wetland surface	Site wetland surface (not included into the protected surface) (km^2)	3.53	3.63
Hunting value of the hunting area	Richness in sedentary fauna species in the hunting area	2.84	0.46
Hunting value of the protected area	Richness in sedentary fauna species in the protected area	2.29	0.67
Shannon index	Abundance and evenness of habitats into the hunting site	1.83	0.40
Travel Cost	Out-of-pocket expenses per hunter per visit including cost of time (€)	60.90	10.70

each environmental quality attribute of each hunting district was measured by calculating the difference between this attribute and the same environmental quality attribute for the hunting district in the area in which the applicants' residence was located. The value of the travel cost variable was measured in absolute terms; in the estimation, we considered the out-of-pocket expenses as well as the opportunity cost of travel time.[3] Centroid coordinates for the hunting district were used to calculate travel distances (in km).[4] We applied a coefficient equal to 0.18 €/km to convert the distance to out-of-pocket expenses.[5] For calculating the opportunity cost of travel time, in accordance with the current common practice (Parsons, 2017), we set its value to one-third the value of working time.[6] Travel time was calculated using the cost–distance functions available in Spatial Analyst of ArcGIS ESRI™, which allows computing the journey time (minutes) between two locations on a regular raster grid.

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[3] To obtain an additional permit, the applicants incurred a fee. This fee was fixed and proportionally higher for permits granted for two or three districts. We did not include this fee in our models, since we considered it a constant. Adding such a constant to the utility of alternatives does not affect the probability of choice (Haab and McConnell, 2002).

[4] Travel distances were calculated using the STATA module GEOROUTE (Weber and Péclat, 2017).

[5] This value corresponds to the estimate of the vehicle operating cost per km per person (Italian Automobile Association, ACI, 2019).

[6] The annual income of each hunter was set equal to the municipality average gross income; the total number of hours worked was equal to 1,744 hours/year.

2.2 Specification of econometric models

The RUM model assumes that hunters, when deciding on where to hunt because they can potentially obtain an additional permit, compare their likely conditional utility on hunting in a district included in the choice set with that for the others in this set, and then select the districts that provide the greatest level of utility (McFadden, 1974; McFadden, 2001). The conditional utility depends on measurable variables, such as the district characteristics and the hunter's travel cost, as well as on unobserved preference and site heterogeneity. As specified in section 2.1, the values for the environmental quality attributes of each hunting district were measured in terms of the difference in the level of the same environmental quality attribute describing the hunting district in the area in which the applicants resided.

In the RUM model, in which the time frame of a decision relates only to the extensive margin of choice (e.g., which additional district to choose for hunting), the conditional utility of the n-th hunter for the k-th additional site (U_{nk}) is divided into a systematic component (V_{nk}) and a random component (ε_{nk}):

$$U_{nk} = V_{nk} + \varepsilon_{nk} \tag{1}$$

The systematic (indirect) utility, V_{nk}, takes into account factors that affect the hunter's preferences for destination choices that are observable and measurable by the researcher. By contrast, the random component, ε_{nk}, captures variables that influence the choice but are not unobserved by the researcher.

Each hunter chooses the additional hunting district k among J districts if and only if $U_{nk} > U_{nj}$. In terms of probability:

$$\begin{aligned} P_{nk} &= Prob(U_{nk} > U_{nj}\ \forall\ k \neq j) = Prob(V_{nk} + \varepsilon_{nk} > V_{nj} + \varepsilon_{nj}\ \forall\ k \neq j) \\ &= Prob(\varepsilon_{nj} - \varepsilon_{nk} < V_{nk} - V_{nj}\ \forall\ k \neq j \end{aligned} \tag{2}$$

Following Train (2009), this probability is an integral of an indicator for the outcome of the behavioral process over all possible values of the unobserved factors:

$$P_{nkt} = \int_{\varepsilon} I(\varepsilon_{nj} - \varepsilon_{nk} < V_{nk} - V_{nj}\ \forall\ k \neq j) f(\varepsilon) d\varepsilon \tag{3}$$

where $I(.)$ is an indicator function that assumes the value of 1 if the expression in the parentheses is true, and 0 otherwise. Different models are drawn from different specifications of the density function of the stochastic part of utility $f(\varepsilon)$. We adopted an MXL model specification (McFadden and Train, 2000), assuming that ε_{nj} are independently and identically distributed Type 1 extreme value random variables.

The MXL model is generalized by allowing random distributions for the attributes' parameters among individuals, thus accounting for heterogeneity in their preferences (Train, 2009). In the MXL model specification, the coefficients are not fixed at the unit level but are specified at the individual level and are assumed to be distributed with density $f(\beta|\theta)$, where θ refers collectively to the parameters of the distribution. Any probability density function can be specified. However, normal, triangular, uniform, and lognormal are the most commonly used distributions. Assuming a linear and additive functional form in weights (α_n, $\beta'_{\boldsymbol{n}} = \beta_{1n}$, β_{2n}, … β_{6n}), trip cost (p_{nk}), the quality attributes of the hunting district ($\mathbf{x}_{nk} = x_{n1}, \ldots x_{n6}$) and the heterogeneity in tastes, equation (1) becomes:

$$U_{nk} = -\alpha_{nk} * p_{nk} + \boldsymbol{\beta}'_n * \mathbf{x}_{nk} + \varepsilon_{nj} \tag{4}$$

Using the MXL model specification, the probability that the n-th hunter chooses the k-th becomes:

$$P_{nk} = \int_{\varepsilon} L(y_n \mid \boldsymbol{\beta}_n) f(\beta_n \mid \boldsymbol{\theta}) d\boldsymbol{\beta}_n \tag{5}$$

where:

$$L(y_n|\boldsymbol{\beta}_n) = \frac{exp(-\alpha_{nk}*p_{nk}+\boldsymbol{\beta}_n*\mathbf{x}_{nk})}{\sum_{i=1}^{J} exp(-\alpha_{ni}*p_{ni}+\boldsymbol{\beta}_n*\mathbf{x}_{ni})} \tag{6}$$

Equation (6) represents the conditional (on $\boldsymbol{\beta}_n$) probability of observing a particular choice for each n-th respondent. In our dataset, J varies according to the scheme previously described.

Since equation (5) does not have a closed-form solution, we can only approximate the choice probability through simulation: for any given value of θ, a value of β_n is drawn from $f(\beta_n|\theta)$; the choice probability is calculated R times and finally averaged as in the following equation:

$$\check{P}_{nk} = \frac{1}{R} \sum_{r=1}^{R} L(\boldsymbol{\beta}_n^r) \tag{7}$$

The MXL was estimated using the WTP space regime proposed by Train and Weeks (2005). In the WTP space regime, equation (4) becomes:

$$U_{nk} = -\lambda_n \, p_{nk} + (\lambda_n \, \boldsymbol{w}_n)' \mathbf{x}_{nk} + \varepsilon_{nk} \tag{8}$$

where $\lambda_n = \alpha_n / \mu^2_n$, $\boldsymbol{w}_n = \boldsymbol{c}'_n / \lambda_n$, $\boldsymbol{c}_n = \boldsymbol{\beta}_n / \mu^2_n$, μ^2_n is the scale parameter for the n-*th* hunter.

Equations (8) is mathematically equivalent to its counterpart in preference space, and each parameter's distribution in equation (8) corresponds to a parameter's distribution in the traditional preference utility space formulation (Train and Weeks, 2005). In the WTP space estimation regime, the MWTP distribution parameters are directly derived. Further, the WTP space regime allows the possibility of easily assuming a random parameter also for the price (travel cost) coefficient and avoids situations where the MWTP distributions show excessively long tails due to the price parameter estimates being close to zero (Scarpa *et al.*, 2008).

To estimate the MXL model, we assumed a lognormal distributed coefficient for the negative of the travel cost variable, and random and normally distributed coefficients for the district variables. The parameters of the distributions were the mean and the standard deviation. The standard deviation associated with each β_n accommodates the presence of unobservable preference heterogeneity in the sample. Simulation was conducted through 1,000 random draws.

We estimated the specifications of two different MXL models, both based on 13,212 observations. In the first model, termed *individual-specific MXL model*, we grouped the hunters' preferences into 918 panels. This is the traditional approach. In the *location-specific MXL model*, we grouped the hunters' preferences into 163 panels (cohorts) by assuming that all individuals within a given location have homogeneous preferences.

The relative fit of each model was evaluated through Ben-Akiva and Swait's (1986) test. This test is suitable for comparing the econometric performance of models that have different functional forms or are based on sets of variables that differ by at least one element (no-nested specifications). It gives an upper bound for the probability that a model is the correct model for the data-generating process despite achieving a lower log-likelihood. This probability is asymptotically bounded by the function in the following equation:

$$Pr(|\rho_2^2 - \rho_1^2| \geq z) \leq \Phi\left(-\sqrt{-2NzLn(J) + (K_1 - K_2)}\right) \tag{9}$$

where:
- $\rho_j^2 = 1-[(L_j - K_j) / L(0)]$ where j can assume two values: it equals 1 for the model with the lower log-likelihood and 2 for the alternative non-nested model. L_j is the log-likelihood at convergence for the j-th model; $L(0)$ is the log-likelihood for the constants-only specification; and K_j are the independent variables used in the j-th model;
- z is the difference between the fitness measures for the two models;
- N is the number of observations;
- J is the choice set size;
- Φ is the standard normal cumulative distribution function.

3. Results and discussion

Table 2 reports the estimates of the coefficients for the individual-specific and location-specific models.[7] In both models, the coefficient estimates of the mean parameters were significant for all the independent variables and their signs were as expected. The probability of choosing a particular hunting district increased if the hunting surface area was more than the surface area in the own

[7] All coefficients were estimated using STATA 16.

Table 2. Coefficient estimates.

	Individual-specific MXL model			Location specific MXL model		
	Coefficient		S.E.	Coefficient		S.E.
Mean						
Hunting surface	0.0150	***	0.0014	0.0186	***	0.0019
Protected surface	-0.0224	***	0.0031	-0.0259	***	0.0030
Wetland surface	-0.9029	***	0.1587	-0.7830	***	0.1326
Hunting value of the hunting area	14.7817	***	2.2775	8.6284	***	2.3588
Hunting value of the protected area	-6.9058	***	0.8711	-7.4312	***	0.8305
Shannon index	21.2154	***	2.1713	18.0167	***	2.1221
Ln(-TC)	-1.7377	***	0.0487	-1.2329	***	0.0794
Standard Deviation						
Hunting surface	0.0000		0.0016	0.0086	***	0.0012
Protected surface	0.0267	***	0.0048	0.0337	***	0.0026
Wetland surface	0.4526		0.3113	0.7982	***	0.0995
Hunting value of the hunting area	0.0164		2.2582	11.3238	***	1.0455
Hunting value of the protected area	6.6315	***	0.9897	5.4757	***	0.4664
Shannon index	0.2284		7.0100	14.0800	***	1.4122
Ln(-TC)	0.0026		0.1181	0.6838	***	0.0949
Log Likelihood	-1589.47			-1318.99		
Akaike information criterion (AIC)	3206.94			2665.98		
Bayesian information criterion (BIC)	3311.78			2770.82		
χ^2	1516.81***			574.69***		

* p<0.05; ** p<0.01; *** p<0.001.

district. Further, the more the protected surface area in the other selected hunting districts compared with that in the own district, the lower the probability of the other districts being selected. Differences in the wetland surface area between the selected additional district and the individual's own district also significantly affected the hunting district choice. The latter independent variables showed a negative relationship with the dependent variable. Further, the probability of hunters visiting a district that had a higher hunting value was greater compared with the probability of their visiting a hunting district with a lower hunting value. Similarly, the probability of their visiting a hunting district with a larger hunting value of the protected area was lower than that of their visiting a district with a smaller hunting value. In addition, the hunter's utility increased as the Shannon index increased.

Table 3. Marginal Willingness to Pay (MWTP) estimates.

	Mean*	Quantile			Mean*	Quantile			t-test[a]		Kolmogorov-Smirnov test [b]	
		1st	2nd	3rd		1st	2nd	3rd				
Hunting surface (€/km²)	0.02 (0.00)	0.02	0.02	0.02	0.02 (0.00)	0.02	0.02	0.02	-22.63	***	0.81	***
Protected surface (€/km²)	-0.02 (0.01)	-0.03	-0.03	-0.01	-0.03 (0.02)	-0.04	-0.03	-0.02	7.62	***	0.36	***
Wetland surface (€/km²)	-0.90 (0.09)	-0.96	-0.92	-0.86	-0.81 (0.64)	-1.28	-0.83	-0.54	-4.27	***	0.37	***
Hunting value of the hunting area (€)	14.78 (0.00)	14.78	14.78	14.78	8.80 (6.12)	6.13	8.99	13.02	29.62	***	0.86	***
Hunting value of the protected area (€)	-6.90 (3.04)	-8.92	-7.48	-5.73	-7.18 (5.09)	-8.90	-7.30	-4.00	1.41		0.14	***
Shannon index (€)	21.22 (0.03)	21.12	21.21	21.22	18.92 (7.79)	14.38	17.09	22.28	8.94	***	0.68	***

*Standard error in parenthesis.
[a] The test was performed at individual level. The null hypothesis assumes that mean difference equal to zero.
[b] The null hypothesis assumes identical cumulative distributions.

Preference heterogeneity was significant for all random variables only in the location-specific model. In the individual-specific model, the standard deviation estimates of the protected surface area and its hunting value are the unique statistically significant coefficients, with $p < 0.001$.

In addition, Table 2 reports the values of statistics for model selection. All estimated statistics show that the location-specific model performed better than the individual-specific model. The Ben-Akiva and Swait test (1986) for non-nested models reveals that the difference in the final log-likelihood values between the two models was statistically significant at $p < 0.001$.

Table 3 reports the summary statistics (mean, standard deviation, 1st, 2nd and 3rd quantiles) of the MWTP for the random quality attributes of the hunting districts. The *t*-tests we conducted consistently indicated a statistical difference in the mean MWTP values for all the attributes obtained through the individual-specific and the location-specific models, with the exception of the attribute "hunting value for the protected area", for which means resulted statistically equivalent (*t*-statistic equals to 1.41). Statistics for two-sample Kolmogorov-Smirnov test show that cumulative distributions corresponding to the two model's specifications differ for all the attributes.

Given that the value of an attribute is measured as the difference between the level of the district characteristics and the level of the corresponding characteristics for the applicants' own district, the MWTP values have to be correctly interpreted. An increase in the difference of district-level characteristics between the candidate hunting site and the hunting site in the own district implies a different effect in terms of the MWTP for the considered site's attributes. For instance, in the location-specific model if the difference in terms of the Shannon index increases by 1, the hunter is willing to pay an amount equals to €16.50.

4. Conclusion

In this article, we proposed a location-specific discrete choice MXL model to estimate heterogeneity in preferences using the RUM travel cost method. Our model is based on the concept of the cohort, which assumes in-group conformity in preferences among individuals living in the same municipality. This model was compared with a traditional individual-specific discrete choice MXL.

The findings of this study prove that treating the heterogeneity among "cohorts" rather than among individuals can assure better statistical performance. The distributions of coefficient estimates differ between the models, and more heterogeneity in preferences is highlighted among cohorts than that indicated among individuals by the standard model. In addition, the findings always differ in terms of the MWTP mean values for attributes. The location-specific model produces MWTP estimates that systematically differ from their individual-specific counterparts. Fit statistics suggest the use of the location-specific model. In addition, the findings of this study are consistent with those presented in the literature, in particular, Budziński *et al.* (2018), who show the superiority of location-specific MXL models over other econometric models that explicitly treat spatial correlation.

Our application corroborates the suitability of adopting the "cohort" approach in modeling recreation demand, especially when information about the individual profile of recreationists is limited to their place of residence. In these circumstances, the "cohort" approach can legitimately support the hypothesis that individuals living in the same municipality act as a homogeneous group because they share similar recreation preferences.

This study highlights the importance of modeling hunter heterogeneity in a way that better matches the data availability, the source of heterogeneity among hunters, and the assumptions on the wildlife-based recreation generation process. The suggested spatial econometric model can be easily estimated using common statistical packages, and usefully employed to support land planning decisions for differentiating, improving, and monitoring the effectiveness of hunting planning interventions, and for achieving increased functional balance between conservation goals and wildlife resources management.

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