Zonal Travel cost approaches to assess recreational wild mushroom picking value: trade-offs between online and onsite data collection strategies

Abstract

Mushroom picking is a growing recreational activity in Europe. Since the institutional environment moves towards regulating mycological resources, estimating the value of this ecosystem service becomes a key tool for policy-makers and rural entrepreneurs.

This paper applies the Travel Cost (TC) method to estimate the value of mushroom picking in three forest areas in the region of Catalonia, Spain. In particular, the main objective is to contrast different sampling strategies (online vs. onsite data collection) when used to build Zonal Travel Cost models. This intends to guide practitioners towards choosing the best sampling strategy according to existing time, monetary and accuracy constraints.

Eight TC models were derived using as regressors the zonal travel cost and selected picking and socio-economic variables. The resulting demand curves produce an estimate of the average site value per trip that ranges from 9.3 to 22.3€/visit considering the onsite data, and from 21.3 to 47.1 €/visit for Zonal TC implemented on the online data. These results reveal estimate differences across the approaches, and especially evident for one picking ground (Els Ports).

Our results point out that onsite surveys would be better suited when exploring the sample for an initial set up of permit fees, to set the permit boundaries and initial applications. On the other hand, the online data collection presents the problem of self-selection and self-reporting bias. We recommend practitioners to always perform a proper assessment of the effects of the context, chosen sampling strategy and validity of assumptions, when adopting valuation estimates for establishing a recreational price of ecosystem services.

Keywords

Ecosystem services; environmental valuation; non-wood forest products; policy; Spain

1. Introduction

Travel Cost (TC) is a method for economic valuation used to estimate the net benefit people obtain from the consumption of non-marketed goods which require a transportation mean and have direct use (*i.e.* beneficiaries can be easily identified). Firstly proposed by Hotelling (1949), TC estimates the Marshallian consumer surplus of travelling to perform an activity, often recreational. The main premise is that the efforts employed to conduct the activity (e.g. actual time and expenses) behave as surrogates of its hidden price, representing the value assigned by travellers (McConnell, 1985).

TC is the most widespread method to assess the recreational value of natural sites (Tobias & Mendelsohn, 1991; Fleming & Cook, 2008), of the urban-nature interface (Bishop, 1992), and of those recreational experiences which entail a specific provisioning aspect (e.g. fishing or harvesting of wild forest products) (Starbuck et al., 2004; Hau, 2016). More broadly, TC is also used to evaluate different cultural ecosystem services provided by forest and wetland habitats (Pascual et al., 2010). In the specific sector of non-wood forest products, TC generally has a good predictive power, as the purpose of the trip (i.e. harvesting and collecting) is often clearly identifiable (Poor & Smith, 2004).

The Zonal and the Individual TC (ZTC, ITC) are the two main approaches used of this method. While they both aim at estimating the associated consumer surplus, they differ in the underlying hypotheses and could generate different estimations that may potentially lead to misinterpretations (Zandersen & Tol, 2009). Both techniques have been compared in meta-analyses and benefit-transfer studies using secondary data sources (e.g. Zandersen & Tol, 2009). Additionally, they have been tested employing the same set of data in a series of studies (e.g. Herath, 1999), and in some of them recommending either ITC (Kowuor, 2003) or ZTC approaches (Brown et al., 1983). Across the years, the ZTC has been rejected in favour of individual-based models, given its intrinsic statistical inefficiency (Georgiou et al., 1997) and restrictive assumptions (Das, 2013). Nonetheless, Hellerstein (1995) shows that zonal models can outperform individual-based approaches when the average per capita demand is relatively small; while Brown et al. (1983) also theorize that individual models can lead to incorrect estimates if not adjusted on a per capita basis. Furthermore, ZTC approaches also require simpler data collection and sampling regimes (Bergstrom & Cordell, 1991; Poor & Smith, 2004; Bowker et al., 2009;), which explains why the ZTC is still widely used for evaluating recreational resources (e.g. in Fleming & Cook, 2008).

TC models are generally built with either online or onsite data collection protocols, depending on the specificities of the case under investigation. Establishing a sound protocol for data collection is thus key for the efficacy of the fitted TC model, as different sampling techniques might capture diverse sectors of the population, biasing the obtained results (Hynes et al., 2015). Additionally valuation approach are extremely sensitive to the quality and type of the data used (Champ, 2003). This is an important unexplored field of research, as it is crucial for both researchers and practitioners to know which is the best protocol for collecting data when applying the TC method.

Thereby, the objective of this study is to compare two different protocols of data collection to verify the effect of data collection on ZTC estimates: onsite (the collection of recreational users´ activity via surveys administered on the field) and online (through online interfaces and mailing lists that gather information on recreational users´ activity).This analysis is implemented in the frame of a study undertaken to estimate the non-market value of recreational mushroom picking in three forests in Catalonia, a north-eastern region of Spain.

The lessons learned from these comparisons may be useful for policy-makers and practitioners aiming to conduct similar studies for wild product-picking, as to assess which technique suits them best for data collection considering available time, and monetary and accuracy constrains.

2. Recreational mushroom picking in Catalonia

Wild mushroom picking is the activity of harvesting mushrooms generally (but not only) in forest areas, typically for eating purposes, entailing both recreational and commercial benefits for its pickers. From an ecosystem services perspective, it encompasses cultural services (i.e. the recreational benefit for pickers, and traditional value of mushrooms for local communities) and provisioning services (i.e. the collected food) (MEA, 2005).

Mushroom harvesting is a growing activity in European forests (Schulp et al., 2014). Within Spain, Catalonia has a long-lasting tradition in this activity (de Román & Boa, 2004), with 23% of the adult population practising mushroom picking at least once a year (CEO, 2014). The most typically collected species is *Lactarius deliciosus* (Martínez de Aragón et al., 2011), which grows in symbiosis with pine forests. In term of forest ownership, 80% of woodlands in Catalonia belong to private landowners. Landowners are *de jure* owners of mushrooms; yet, they do not usually capture mushroom-related value from external pickers. Some of them face annoyances derived from pickers roaming in their property, whereas others see mushroom picking as a business opportunity (Górriz-Mifsud et al., 2015).

Estimating the economic value that this activity has for pickers can help in the formulation of policy interventions dealing with the right to harvest this resource. More specifically, knowing its value provides crucial information for the setup of picking fees to potentially compensate landowners (Prokofieva et al., 2016). The TC method is well suited to assess the value that recreational mushroom picking has for society, since the direct beneficiaries can be clearly identified (i.e. the pickers), and they incur quantifiable travel efforts to conduct the activity, which vary according to pickers' origin (McConnell, 1985). Previous studies have applied the TC approach to estimate the mushroom picking value in Spain, finding a consumer surplus of 10.49 €/picker/visit in Eastern Castilla y León (de Frutos et al., 2009) (ZTC model) and 38.22 €/picker/visit for Central Catalonia (ITC model) (Martínez de Aragón et al., 2011). More recently, de Frutos et al., (2018) estimate a consumer surplus (€/picker/season) ranging from 6.22 to 79.6 in several regulated areas of Spain.

The application of the ZTC method was conducted in three forest areas where the Government of Catalonia launched a pilot study in 2014 for establishing mushroom reserves[1] (Fig.1):

[1] In the following, we refer to these forest areas as "picking grounds" in order to distinguish them from the "zones" of the ZTC.

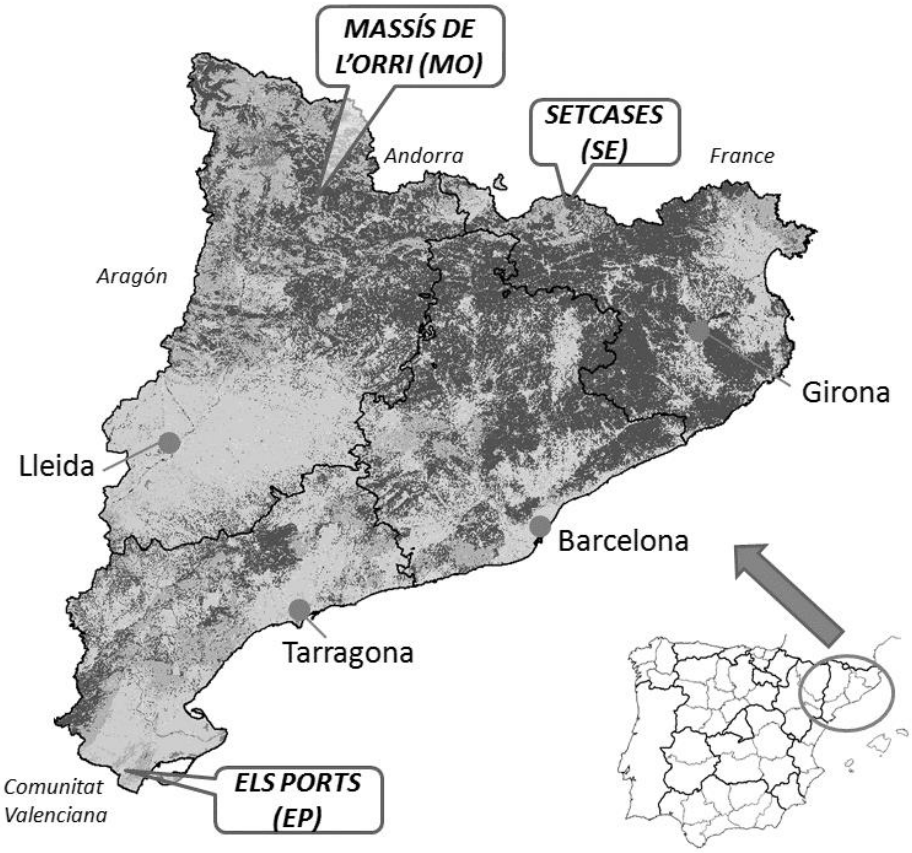
- Els Ports (EP), conformed by three forest estates covering 5,883 hectares in the southernmost part of Catalonia, owned entirely by the regional government. Its forests are mainly composed of *Quercus ilex*, *Pinus sylvestris* and *Pinus nigra*. The edible mushroom productivity has been estimated in 204 kg/ha [2].
- Massís de l'Orri (MO), conformed by 5 forest estates covering 7,689 hectares of Pre-Pyrenean woodlands mainly owned by the Government of Catalonia but also with some municipal forests. *P. nigra* and *P. sylvestris* are the most abundant species, with sparse *Q. ilex*. The edible mushroom productivity was estimated in 250 kg/ha.
- Muntanya de Sant Miquel, at Setcases (SE), a forest estate of 3,873 hectares located in the Oriental Pyrenees and owned entirely by the regional government. Its main vegetation is *Pinus uncinata* with some *Abies alba*. In autumn 2014 the estimated edible mushroom productivity was 350 kg/ha.

During that year, individuals had to apply for a picking license in the corresponding reserves that was cost free and issued through a website with the two-fold objective of: (i) collecting data on the pickers' profile, and (ii) raising awareness on the permit requirement for the following season. Besides their personal data, pickers could voluntarily provide their email so as to participate in a follow-up survey. 1,260 permits were issued to 1,100 different pickers of which 599 provided their email.

2014 has been recognised as the best-recorded year in Catalonia in terms of mycological productivity since records exists, mainly related to the exceptionally rainy summer (Martínez de Aragón, pers. comm). Such positive yield implies higher chances for pickers in the search of mushrooms; we therefore presume that good years might incentivise both regular and sporadic pickers. Consequently, we consider it reasonable to assume that both the onsite and online samples were drawn from the full potential population of pickers.

Figure 1 – Map of the forest surface in the four provinces of Catalonia, with the location of the three picking grounds studied (names in capital letters) and the province capitals. Source: based on Gracia et al., (2004).

[2] Edible mushroom productivity estimated by Martínez de Aragón (pers. comm.) based on main forest species and productivity data for 2014.



3. Materials and methods

3.1 Data collection: online and onsite questionnaires

Onsite data was collected by forest guards from August to October 2014 as part of their routine permit control (survey in Appendix A). Random groups of pickers nearby the forest roads were interviewed both on working and weekend days, generally once their daily picking activity had finished. Guards asked pickers about their town of residence and whether they used any accommodation or restaurant services. Guards also reported the type and amount of mushrooms picked, whether the picker possessed the picking permit, and whether they knew about the specific ownership status of the picking ground. The on-site survey was delivered to 168 groups covering 464 adult pickers, 36% in EP, 36% in MO, and 28% in SE.

Online data was gathered through an online survey sent immediately after the end of the mushroom season to the available email contacts. This questionnaire (see Appendix B) was more extensive and it was focused on the overall number of trips made during the whole season by each individual picker. It included questions on picking motivations, satisfaction, and socio-demographic profile. 198 pickers responded to the survey (*i.e.* 33% of the contacted), 28% in EP, 44% in MO and 28% in SE.

For both surveys, all entries were checked for accuracy and repetitions, deleting incomplete and erroneous replies. In addition, 13 observations from the online survey reporting a frequency of zero trips in the studied area were deleted as we focused the analysis only on active pickers in the studied areas (frequency of trips ≥1). The final total number of individual observations was 198 for the online database and 180 for the onsite database.

Travel cost in our analysis is the composite indicator of transport, meal and accommodation costs incurred when going mushroom picking, which is assumed to be the main objective of the trip. Transport costs were derived from GoogleMaps using the fastest way to a central point of the mushroom ground. An average petrol car was assumed, using 1.36 €/L as unleaded petrol 95 price for Spain in October 2014 (MINETUR, 2014). These costs were divided by the number of adults in the group, taking a reference car with four-person capacity, including children.[3] Restaurant costs were estimated on an average 12 €/menu (Papel, 2016), while overnight costs per person were set as 25 €/person averaging the price of hotels and rural houses in 2014 for the area (Toprural, 2015). Other vehicle costs (e.g. car running costs) were not included in the computation so as to minimize the overall effect on the estimated surplus (de Frutos et al., 2009). Moreover, we did not take into account free time value in the analysis. The amount of mushrooms picked in kg was extracted from the respondents' responses and/or according to the estimate made on site by the forest guards, assuming a standard weight of 3 kg of mushrooms per basket at full capacity.

Secondary sources were used for building some of the explanatory variables implemented in the demand models. Official census data for Catalonia, Aragón, Valencia and Andorra[4] were retrieved in order to estimate ZTC socio-economic variables (i.e. age, number of children). The ratio of potential pickers (p_{prov}) over the total population was estimated from the omnibus survey (CEO, 2014) for the four Catalan provinces and consulting mushroom picking experts regarding the neighbouring regions (Table 1). Observation in the onsite questionnaires were unbalanced between week and weekend days. This was probably due to the fact that forest guards tented to interview pickers in weekend and festive days, as more likely to find them on the site. A correction factor was applied to adjust onsite ZTC variables (Appendix C).

Table 1- Proportion of potential pickers per total population**.**

Province	**Region**	p_{prov}	**Source**
Barcelona	Catalonia	0.198	(CEO 2014)
Girona	Catalonia	0.377	(CEO 2014)
Lleida	Catalonia	0.300	(CEO 2014)
Tarragona	Catalonia	0.286	(CEO 2014)
Castellón	Valencian Community	0.213	Expert average[a]
Valencia	Valencian Community	0.138	Expert average[a]
Teruel	Aragón	0.250	Expert average[a]

[3] For example, four adults with two children were assumed to travel in two cars but the aggregated travel expenses were divided between four adults.
[4] Sources: IDESCAT, 2011; IAEST, 2011; peGV, 2011; Andorra Statistics, 2015.

Andorra	Andorra	0.195	Expert average[a]

[a] Four mushroom experts of the corresponding regions were contacted as to enquire about the ratio of adult pickers in provinces outside of Catalonia region. Average of responses are here reported.

3.2 ZTC model

A standard ZTC demand model considers the trips to the site taken by the population of a particular zone as the dependent variable. The demand model is represented by the following equation:

$$V_{zj} = f(TC_{zj}, S_z) \quad (1)$$

where V_{zj} is the total number of trips taken from a zone z to a specific picking ground j, TC_{zj} is the zonal travel cost to the picking area, and S_z represents other zonal socio-economic variables.

In our case, two different models of ZTC were estimated, each corresponding to a data collection protocol, onsite and online respectively, to evaluate their impact on model outcomes. More specifically, the onsite data collection consisted of a short questionnaire launched in the field (i.e. one-visit measure) while the dataset from the online survey covered the entire season (i.e. multi-visit).

Each town the pickers come from represents an observed zone, as further aggregation would have reduced the number of available observations. To allow the comparison between the two model outputs, we selected the zonal variables described in Table 2 that could match the explanatory variables sampled in the online survey. As the information at the town level regarding the educational level and the degree of participation in mycological associations is either too coarse or non-available, those variables were excluded from the ZTC model estimated with onsite data. The variable AGE was aggregated into percentages by four age classes. Lastly, in the ZTC model based on online data, only one trip per person per season was considered when aggregating at zone level.

In order to take into account the fact that mushroom picking is an activity performed only by a subset of the population on few occasions during the year, we used a weighted individual visitation rate VV_{zj} from town z to a picking ground, which was computed as follows:

$$VV_{zj} = \frac{V_{zj} \cdot w_{zj}}{AGE_z \cdot p_{prov}}; \quad (2)$$

Where:

- V_{zj} corresponds to the total pickers' trips from town z to the picking ground j;
- w_{zj} is a correction factor (Appendix C) to standardize observations evenly among week and weekend days (not used for the ZTC built from the online survey);
- AGE_z is the number of inhabitants of zone z aged 15 and older;

- p_{prov} is the corresponding provincial ratio of potential pickers for the given town z (Table 1).

In order to achieve the normality of the residual on the ZTC demand models, a Cox Box transformation was applied to the response variable, allowing identifying the natural logarithm as the best-fitted transformation:

$$\ln(VV_{zj}) = \alpha + \beta_1 TC_{zj} + \beta_2 S_z \tag{4}$$

Which then solved to:

$$VV_{zj} = e^{\alpha+\beta_1 TC_{zj}+\beta_2 S_z} \tag{5}$$

Such model was then run for both the online and onsite database and for each of the three picking grounds. Presence of multicollinearity across the explanatory variables was investigated and variables showing a Generalized Variance Inflation Factor (GVIF) higher than 2 were removed (Fox and Monette, 1992). Subsequently, a backward stepwise selection based on model Akaike Information Criterion (AIC) was also run to individuate the most significant variables and the best-fitted model. A k-fold cross-validation (k=10) was run on the three models to assess the model accuracy. All the statistical analyses were performed with the R software (R Core Team, 2014) .

The demand curve was estimated following equation 5, with the zonal consumer surplus (CS_{ij}) being the area below the curve contained between the average travel cost ($\overline{TC_\iota}$) and the Maximum Travel Cost (MTC). MTC corresponds with the choke price, i.e. the travel cost at which no trips are demanded. In order to estimate the consumer surplus, the demand function was integrated by the travel cost, obtaining (see Appendix E for additional information):

$$CS_{zj} = \int_{\overline{TC}_{zj}}^{MTC_j} VV_{zj} \quad dTC = -\frac{e^{\alpha+\beta_1\overline{TC}_{zj}+\beta_2 S_z}}{\beta_1} = -\frac{\widehat{VV_{zj}}}{\beta_1} \tag{6}$$

Where $\widehat{VV_{zj}}$ is the expected average visitation rate for each zone z, and β_1 is the coefficient of the zonal travel cost. Given the visitation rate formula (Eq.2), Equation 6, solves then to:

$$CS_{zj} = \frac{\widehat{VV_{zj}}\cdot AGE_z\cdot p_{prov}}{\beta_1} = -\frac{\widehat{V_{zj}}\cdot w_j}{\beta_1} \tag{7}$$

The zone CS was then used to compute the average per trip value TV_j in picking ground j for both data collection protocols:

$$TV_j = \frac{CS_{zj}}{\widehat{VV_{zj}}} = -\frac{1}{\beta_1} \tag{8}$$

Table 2- List of variables used to parameterize onsite and online ZTC demand models across the three picking grounds.

	ZTC from onsite data		ZTC from online data	
Variable	**Variable explanation**	**Type**	**Variable explanation**	**Type**
TRIP	Weighted[a] town pickers' visitation rate to the picking ground	Continuous	Weighted[a] town pickers' visitation rate to the picking ground	Continuous
TC	Average weighted picker's travel cost per town	Continuous	Average picker's travel cost per town	Continuous
CHILD	Total weighted children per pickers' group divided by town children population	%	Presence/absence of children in picker's visit averaged by town	Binary (Y-N)
EXPERT	Average weighted number of mushroom species picked per picker per town	Continuous	Average number of mushroom species picked per picker per town	Continuous
KMUSH	Average weighted kilos of mushroom picked per town	Continuous	Average kilos of mushroom picked per town	Continuous
ASS	-	-	Membership of mycological association averaged per town	Binary (Y-N)
STUDIES	-	-	Picker study level categories[c] averaged by town	Binary (Y-N)[d]
AGE	Percentage of inhabitants' age categories [e]	%	Picker's age categories averaged by town [f]	Binary (Y-N)[d]

[a] Weighted visitation rates were computed following Equation 2.
[b] Weighted correction factor used to standardize observations evenly among week and weekend days (Appendix C).
[c] "No education", " primary degree", "secondary degree", "Vocational Training", "University".
[d] The categorical variable was split into dummy binary variables (presence/absence) of each component.
[e] AGE A: <25, AGE B: between 26 and 39, AGE C: between 40 and 64, AGE D: >64.
[f] AGE A: <25, AGE B: between 26 and 40, AGE C: between 41 and 65, AGE D: >65.

4. Results

4.1 Online and onsite surveys descriptive statistics

Respondents in both surveys cover a large area of the Catalan territory, with 88% and 83% counties represented in the online and in the onsite survey, respectively (Table 3). It is worth noting that only one observation from the online survey came from outside Catalonia compared to 12 pickers in the onsite questionnaire (specifically 2 from Andorra, 2 from Aragon and 8 from the Valencian Community). Most pickers tend to go picking alone but some (10% in the onsite and 24% in the online survey) bring along their children. In the online survey, respondents were predominantly middle-aged (70%) and held a university degree (37%).

Regarding picking features, the largest picking efficiency is found in EP (around 3.7 kg/person/visit in the onsite) and MO (4 kg/person/visit only in the online survey). On average, two different mushroom species are picked across the areas for the onsite data, while online respondents reported eight species on average.

A test of differences conducted for the distance travelled by pickers showed significant differences between both surveys (Kruskal-Wallis, x^2= 49.5; *d.f.* = 1; p<0.001), and across zones (Kruskal-Wallis, x^2= 79.2; *d.f.* = 2; p<0.001). The onsite questionnaire reports shorter travelled distances compared to the online one. With respect to the picking ground, overall, EP pickers travel significantly shorter distances compared to MO and SE. In addition, EP pickers come from a reduced number of counties compared to MO pickers. The overall travel cost is found to be significantly smaller in the onsite questionnaire (Kruskal-Wallis, x^2= 26.4; *d.f.* = 1; p<0.001), and for EP pickers compared to the other two picking grounds (Kruskal-Wallis, x^2= 23.5; *d.f.* = 2; p<0.001).

Table 3-Sample characteristics for the onsite and online surveys. ± standard error. n.a.: not available data.EP = Els Ports; MO= Massís de l'Orri; SE= Setcases.

	Variables	Online survey [a]			Onsite survey [a]		
		EP	MO	SE	EP	MO	SE
Demography	Number of total questionnaires	55	87	56	66	66	48
	Total number of towns (counties) represented in the sample	21 (12)	48 (26)	40 (18)	23 (7)	32 (18)	36 (15)
	Number of surveyed adult pickers	55	87	56	167	168	129
	Median respondent educational level (%)	University (47.3)	University (36.8)	Vocational training (44.6)	n.a.	n.a	n.a.
	Median respondent age class (%)	Between 41 and 65 yrs old (61.8)	Between 41 and 65 yrs old (79.3)	Between 41 and 65 yrs old (62.5)	n.a.	n.a	n.a.
	% of pickers with children	33	17	21	17[b]	8.4 [b]	4.92 [b]

Picking Characteristics	Mean harvesting efficiency (kg/person/visit)	3.5 ±0.3	4.1 ±0.4	2.5 ±0.3	3.77±0.79 [b]	2.65 ±0.48 [b]	0.57±0.14 [b]
	Mean number of mushroom species picked [c]	5.2 ±0.3	7.1 ±0.3	7.7 ±0.4	1.50±0.14 [b]	1.62 ±0.21 [b]	1.17±0.33 [b]
	Most popular mushroom picked	*L. deliciosus*	*L. deliciosus*	*L. deliciosus*	*L. deliciosus*	*B. edulis*	*B. edulis*
	% of membership of a mycological association	1.8	3.4	14.3	n.a.	n.a.	n.a.
Trip characteristics	Mean one-way distance travelled (km)	55.2±8.9	124±8.0	121±6.5	28.8±3.8 [b]	85.0±11.8 [b]	64.9±17.0 [b]
	Mean total travel cost (€)	13.3±2.2	20.0±2.1	19.4±2.0	5.9±0.9 [b]	14.3±2.3 [b]	10.4±3.5 [b]
	Mean number of trips taken to the picking ground [d]	4.2±0.6	6.3±0.9	3.4±0.4	7.8±2.0n.a. [b]	4.9±1.5 [b]	2.7±0.8 [b]
	% of pickers reporting restaurant expenses	23.6	32.2	35.7	22.5 [b]	31.1 [b]	29.9 [b]
	% of pickers reporting accommodation expenses	9.0	5.7	5.3	0.96 [b]	6.06 [b]	1.82 [b]

[a] In the onsite survey questionnaire sheets were delivered to groups of pickers. In the online survey respondents correspond to single individuals.
[b] Values weighted with correction factor (Appendix C).
[c] Onsite survey computed on the visit; online survey computed on the overall season.
[d] Onsite survey average trips by town; online survey average trips by individuals.

4.2 ZTC estimates

In the ZTC model estimated with onsite data, the TC regression coefficient is significant across all picking grounds (Table 4 and graphical representations in Appendix F). Considering the additionally explanatory variables, we see that the higher the percentage of people in the 40-to 64-year-old range, the higher the visitation rates (MO and SE). On the other hand, being in the less than 25-year-old range (EP) and in the 25-to 39-year-old range (MO and SE) has a negative effect on the response variable. Consequently, the consumer surplus estimates per trip are 9.3 €/trip, 19.5€/trip, and 21.7€/trip for EP, MO, and SE, entailing respectively 0%, 59.1% and 92.2% of the recreational component (Table 5).

For the ZTC model estimated with the online dataset, Table 4 shows that the TC regression coefficient has a lower significance level compared to the online model, with one picking ground (EP) being not statistically significant at the p=0.05 level (p=0.242). In the models for the other two sites (MO and SE), the higher the educational level, the lower are the visitation rates of mushroom pickers. In addition, younger people are significantly related to higher visitation rates in MO, while being a member of mycological associations has a positive effect on the visitation rates in SE. The consumer surplus estimates of the ZTC model computed on the online dataset are 47.06 €/trip, 28.21

€/trip, and 21.31€/trip for EP, MO, and SE, entailing respectively 78.0%, 56.7% and 64.3% of the recreational component (Table 5)[5].

[5] As a robustness check, we calculated an Individual TC model with the same set of data of the ZTC built with online data. This analysis shows no significant differences in consumer surplus estimations (Appendix D for more details).

Table 4-ZTC demand models estimated with onsite and online data for the three picking grounds. . Explanatory variables estimates (p values) are presented. In bold significant variables ($p<0.05$). EP = Els Ports; MO= Massís de l'Orri; SE= Setcases.

		ZTC onsite data				ZTC online data			
		EP	**MO**	**SE**	**All zones**	**EP**	**MO**	**SE**	**All zones**
	Intercept	5.797 (0.162)	**-22.493 (0.003)**	**-10.501 (0.001)**	2.838 (0.166)	**-7.879 (<0.001)**	**-4.339 (<0.001)**	**-6.874 (<0.001)**	**-5.437 (<0.001)**
	TC	**-0.107 (0.022)**	**-0.051 (0.003)**	**-0.046 (0.001)**	**-0.045 (<0.001)**	-0.021(0.242)	**-0.035 (0.003)**	**-0.047 (0.007)**	**-0.029 (0.001)**
	CHILD	1.683 (0.154)	-	3.093 (0.023)	**1.353 (0.007)**	-	-0.626 (0.303)	-	-
	EXPERT	-	-	-	-	-	-	-	-0.133 (0.055)
	KMUSH	-	-	-	-	-	-0.154 (0.183)	0.168 (0.183)	-
Model estimates	STUDIES	-	-	-	-	C: 2.832 (0.105)	B: -0.793 (0.220) **E: -1.982 (0.001)**	C: -0.815 (0.180) **D:-0.996 (0.041)**	E: -0.625 (0.091)
	AGE	**A: -0.194 (0.037)** C: -0.187 (0.095)	**B: -0.362 (0.028)** **C: 0.705 (0.001)**	**B: -0.420 (<0.001)** **C: 0.335 (<0.001)**	**A: -0.221(<0.001)** B: -0.169 (0.044)	B: 1.951 (0.054)	**A: 3.521(0.041)** B: 0.973 (0.084)	B: -0.597 (0.202)	-
	ASS	-	-	-	-	-	-	**1.205 (0.041)**	-
	R^{2} [a]	0.53	0.53	0.74	0.42	0.28	0.47	0.47	0.15
	AIC (initial; final)	82.1; 79.6	131.4; 128.3	104.5; 99.28	349.8; 346.5	108.0; 100.0	181.7 176.7	132.4; 140.9	448.8; 434.3
	MSE[b]	1.73±0.01	3.88 ±0.02	1.75±0.01	3.72±0.01	-	2.88±0.01	1.88±0.01	3.47±0.01

[a] Multiple R-squared.
[b] Mean Squared Error estimated from a 10-fold cross-validation. (ZTC onsite data k=12, 11, 11, and 10 respectively; ZTC online data: 11, 12, 10, 10).

Table 5- Consumer surpluses estimations for the three picking areas and the two approaches (ZTC from online data and ZTC from onsite data). Value± standard error. EP = Els Ports; MO= Massís de l'Orri; SE= Setcases

		EP	MO	SE	All zones
ZTC online data	TV_j (€/trip)	47.1±38.9	28.2±8.9	21.3±7.4	34.0±10.2
	Recreational TV_j (€/trip)	36.7	16.0	13.7	23.6
	Provisioning TV_j (€/trip)	10.4	12.2	7.6	10.4
ZTC onsite data	TV_j (€/trip)	9.3±3.7	19.5±5.9	21.7±6.1	22.3±5.6
	Recreational TV_j (€/trip)	0	11.5	20.0	14.7
	Provisioning TV_j (€/trip)	9.3	8.0	1.7	7.6

5. Discussion and Conclusions

In this study we assess the performance of the Zonal Travel Cost model when employing two different survey techniques: on-site data collection via local officers and online data collection via electronic surveys. Constraints and biases of these two sampling alternatives are inspected with the aim of guiding practitioners and forest technicians in selecting the approach that best fits the resource under evaluation.

5.1 Impact of data collection processes on ZTC estimates

In-situ data collection for travel cost surveys is usually performed via local officers (*e.g.* tourism informants, forest guards) since their cost can be internalized as part of their daily tasks; however, it should be considered that proper training is required to ensure appropriate data collection. On the other hand, ex-situ surveys (*e.g.* household-based post, phone-based omnibus or online surveys) depend on availability of databases (*e.g.* census data, entry registers, tourism mailing lists). Among them, online surveys are progressively becoming more widespread, being a handful technique for obtaining TC parameters.

Some lessons can be extracted from our study when applying online surveys to estimate mushroom picking. Online surveys face an important sample bias derived from the requirement of internet literacy and access (Brenner, 2002), which may constitute a limitation for aged applicants or inhabitants in rural areas with poor internet connection. Our online sample shows an average university educational level, which is not representative of the overall population of mushroom pickers (dominated by lower education degrees as shown in the Omnibus survey - CEO, 2014). If we assume a positive correlation between high education and high income (and this is the case for Spain; INE, 2015), the online dataset may over represent wealthier pickers.

Moreover, we consistently find more skilful pickers (higher kg of mushrooms picked and higher richness of species) in the online than in the on-field survey. This could be attributed again to a self-selection bias in the incentives to reply to the online survey by expert or commercial pickers, in contrast with the random survey conducted on-field. Experts may travel more frequently and for longer distances, with its consequent effect on the picking value estimates. The time-lag between the picking event and the survey reply (at the end of the season) can lead to reporting on the above -average trips, which are easier to remember. The higher richness of species reported in the onsite survey is probably due to the fact that the online questionnaire was delivered to pickers only at the end of the season, allowing them to report a higher number of collected species. This highlights another important difference between the two sampling approaches.

In addition, online data including only pickers who actively asked for a permit may have left out unaware pickers or protesters. Expert and commercial pickers are likely to form part of the online sample as they more exposed to mushroom-related news. Differently, most pickers surveyed in the field were indeed unaware of the permit requirement, and hence they were not part of the online database. This is more conspicuous when pickers from outside Catalonia are included.

Regarding the onsite data collection, we encountered a non-homogenous probabilistic distribution among week and weekend surveying days, especially in the SE picking ground, which strongly affects the representativeness of the studied sample. To prevent this, a detailed sampling protocol for surveyors is needed. In our case, weighting factors were used to normalize the biased observations (see section 3.1). However, correction techniques might represent a new source of errors, unnecessarily inflating the variance of the model parameter estimates (Bollen et al., 2016). On the other hand, an online interface is less prone to weekday bias because it accounts for the trips during the entire mushroom season. However, the usage of weighting factors has shown a good data performance with differences in the results affecting only one picking ground.

Authors that have compared in-situ versus ex-situ survey methods found contrasting results with no clear pattern disentangled. Meisner et al. (2006) found non-significant differences across results when applying TC method to water-based recreation activities. Differently, Hynes et al. (2015) compared recreational fishing travel cost on two angler surveys and obtained significantly different welfare estimates. The authors argued that the survey samples might represent different segments of the population. In our study, we seem to have faced a similar scenario to that of Hynes et al. (2015) in the EP picking ground, where the online-based model retrieves values four times higher than the ZTC obtained from the onsite data collection. We hypothesize that this disparity may be due to the online survey in EP recording far more individuals travelling larger distances compared to the onsite questionnaire. This significantly increases the average travel cost (Table 3), affecting the inverse demand slope, i.e. the TV_j. This nuance should be taken into account when developing valuation strategies based on TC approaches; as Bowker et al. (2009) remark, including occasional visitors from remote locations (i.e. non-Catalans in our case) could entail a bias in the final model outcomes, given their large travel cost. In such situations, and as long as there are sufficient observations, we would recommend practitioners to develop models that are able to differentiate between individuals from remote locations and local residents in order to separately evaluate the two groups' behavioural responses. An example of this technique is presented in Bell & Leeworthy (1989).

The onsite and online data collection protocols followed different sampling strategies, which may support the hypothesis that diverse population subgroups were addressed (Hynes et al., 2015). The online interface was built for those pickers who applied for the pilot permit, restricting the sample only to those pickers aware of the pilot mycological regulation in the area. On the other hand, forest guards undertaking the onsite data collection were instructed to interview any person returning to their car after the picking activity, thus randomizing the selection of respondents. Respondents' self-selection in the online survey entails a risk of sample bias, which may hamper the generalisation of the results to the overall mushroom pickers' population. Hence, besides feasibility criteria (i.e. implementation and running costs, availability of personnel and facilities, time availability), deciding upon a survey typology should also take into account technical criteria (i.e. outcome expected) (Trochim, 2006).

To summarize, our results show that onsite data collection, if counting on forest guards, may have reduced costs and achieve randomized samples that will provide robust estimates. However, special care should be devoted to smooth the probabilistic distribution among week and week-end days. Our results seem to point out that onsite surveys would be better suited when exploring the sample for an initial set up of permit fees, to set the permit boundaries and initial applications. On the other hand, the online data collection presents the problem of self-selection and self-reporting bias. In a permit fee scenario, we would recommend the online data collection method to assess fees after their implementation, to test adoption and to profile of permit holders.

Lastly, it should be recognized that mushroom picking, although a large recreational activity practiced in Catalonia, is sparse in the territory, which makes it very difficult to obtain a high number of observations with both sampling techniques. This is especially true when the focus of the evaluation is single sites (as done in our study for three picking grounds). This is an important statistical limitation that should be acknowledged by technicians when estimating the monetary value of occasional recreational activities.

5.2 Comparison of model outcomes

Disentangling CS value per trip to appreciate specific costs and benefits for different subsets of the picker population is important, especially when assessing the implementation of a permit fee (de Frutos et al., 2018). In our case we record a substantial variation of CS across the picking grounds, which is mainly due to different sampling regimes, although some site-specific variables and the origin of the pickers have also played an important role.

The proximity of SE to two large urban areas (Barcelona and Girona) allows mushroom picking to be a day activity, whereas the remoteness of MO requires incurring additional accommodation expenses. In contrast, EP is not particularly known for mushroom production, but rather for other mountain recreational activities –as shown in its production estimates (Section 2). This variability across picking grounds may also be related to an unequal distribution of pickers' frequencies in terms of their geographical origin. SE has proportionally less pickers from local towns when compared to EP, where the highest frequency belongs to its county. MO, on the other hand, records the farthest average distance travelled (Table 3).

Additionally, it is important to acknowledge that mushroom picking is an extremely seasonal activity (de Frutos et al., 2009), which also influences model outcomes. Since 2014 had one of the best seasons in recent years in terms of mycological productivity, we would recommend to carry out a robustness check of this analysis, replicating the survey across different years.

Lastly, it is worth mentioning that the recreational component in all grounds except for one (EP for the onsite ZTC model; Table 5) accounts at least for 50% of the overall picking benefits. Previous studies (Martínez de Aragón et al., 2011) highlight the relevance of the recreational services of mushroom picking activities, independently from the amount of mushrooms picked (de Frutos, et al., 2016). Our results support these findings, since the quantity of mushrooms picked always results in non-significant values in the regression models estimated (Table 4).

5.3 Conclusions

This study presents relevant insights into data collection approaches and their impact on zonal travel cost estimates when assessing mushroom picking as a forest recreational activity. Results and insights are relevant for researchers and practitioners alike since regulatory frameworks are gradually being developed for this activity and future permit fees may well be based on travel costs estimates.

Our results show how consumer surplus estimates differ between online and onsite data collection procedures; this disparity is particularly acute in the instances where the survey samples seem to represent different shares of the population of pickers. Therefore, understanding the specificities of the picking area may be crucial for deciding on the sampling strategy beyond specific limitations of online and onsite protocols. Other key issues identified in this study relate to self-selection bias and self-reporting bias or non-homogenous probabilistic distribution, which should also be taken into account when evaluating recreational resources. This is especially true for wild mushroom picking, where availability of data is limited and overrepresentation/underrepresentation of specific sectors of the picker population is likely to occur.

Budgetary requirements or time constrains are the standard criteria traditionally considered when opting for different data collection protocols. This study concludes that the model accuracy due to different sampling methods is another crucial dimension that should be taken into account when evaluating recreational resources.

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Appendices

A. Onsite survey

Zone under surveillance: □ Ports; □ Massís de l'Orri; □ Setcases

A. **Have the people in the car collected mushrooms**? YES/NO
B. **Nr. people in the car**: □ adults: _____ ; □ children (>18 y.o.): _____
C. **Did they have the pass receipt?** YES/NO

D. **Type of pass corresponding to them:**

<table>
<tr><td rowspan="7">< 5 kg/day</td><td colspan="2">□ Municipality resident / □ 2nd house owner</td><td>0 €</td></tr>
<tr><td colspan="2">(only at Massís de l'Orri) □ Farmland owner</td><td>0 €</td></tr>
<tr><td colspan="2">□ <14 years / □ Pensioner (1 day a week)</td><td>0 €</td></tr>
<tr><td rowspan="2">□ County resident</td><td>1 day</td><td>2 €</td></tr>
<tr><td>annual</td><td>10 €</td></tr>
<tr><td rowspan="2">□ Non-county resident</td><td>1 day</td><td>5 €</td></tr>
<tr><td>2 days</td><td>8 €</td></tr>
<tr><td rowspan="5">>5 kg/day (Professionals)</td><td colspan="2">□ From 6 to 10 Kg - daily ticket</td><td>9 €</td></tr>
<tr><td colspan="2">□ From 10 to 15 Kg - daily ticket</td><td>13 €</td></tr>
<tr><td colspan="2">□ From 15 to 20 Kg - daily ticket</td><td>17 €</td></tr>
<tr><td colspan="2">□ From 20 to 25 Kg - daily ticket</td><td>21 €</td></tr>
<tr><td colspan="2">□ Over 25 kg - daily ticket</td><td>30 €</td></tr>
</table>

E. **Nº baskets: ______** / □ not using basket. **Kg estimation, approx.: ______**

F. **Species detected: __________ / ___________ / __________ / __________**

****

INTRODUCTION: During this year we are conducting a study regarding people who go mushroom picking in this zone. I will make some brief questions:

1. **Municipality of residence?** *(town)* ____________
2. **Did or will you overnight in the area**? NO/YES *(town)*: ____________
3. **Did or will you stay for lunch in a bar/restaurant?** NO/YES *(town)*: ________________
4. **Mushrooms belong to the landowner. Did you know this?** YES/NO

In this zone forests belong to the Government of Catalonia and to the municipalities, therefore mushroom regulation is expected to be regulated. For the next 2015 mushroom season the Catalan Government plans to charge the picking pass. The funds raised would be reinvested in the management of these local forests. Moreover, good picking practices will be promoted among pickers.

The cost for you would be: ___ € per person per day/year *[category question D]*

5. **Would you play this amount to pick mushrooms here?** YES/NO
6. **Other comments: ____**

Thank you for your collaboration!

B. Online survey

The whole online survey comprised 36 questions. Here we present only those question which are relevant for the analysis conducted. (*) stands for mandatory questions.

INTRODUCTION

This questionnaire aims to improve the permits program for mushroom picking in zones regulated by the Catalan Government, started in autumn 2014. The xx department of XX has launched a survey with those who acquired a pass during last autumn and left their email. We kindly appreciate your reply, both if you consider yourself a sporadic or an expert mushroom picker. This because we are interested in compiling the largest possible range of profiles. Your replies will be kept anonymous and the data will be later used for research purposes. This study is conducted under the framework of the European project StarTree. For any related doubt, please contact us: name, email, phone.

Regarding your mushroom picker experience in a regulated zone

(*) 1. For which zone did you acquire the (costless) pass during the 2014 season? □ Massís de l'Orri (Pallars) / □ Els Ports (Montsià/Baix Ebre) / □ Setcases (Ripollès)

(*) 2. How many times did you come to this forest for mushroom picking during the 2014 season? _____ *[number]*

(*) 3. And how many times did you go to other forests during the last mushroom season? ____ *[number]*

If you went more than once to the regulated forest, please reply to the next questions regarding forest visits in general terms.

(*) 4. Do you remember how many mushrooms did you collect when you went to this forest? *(if you don't know the weight, please indicate the number of standard baskets of a diameter of 40 cm)*
___ kg/day or __ nr. baskets [*number]*

(*) 5. Which mushrooms would you collect if you'd find them in the forest?
□ rovellons / □ camagrocs / □ ceps / □ black trumpets / □ llenegues/mucoses /□ rossinyol / □ fredolics / □ llengua de bou / □ ou de reig / □ don't know how to distinguish mushrooms / □ others (specify): ______ *[text]*

(*) 10. With how many people did you go, including yourself?
Number of adults: ___ *[number]*
Number of children (<18 years old): ___ *[number]*

(*) 11. Generally when do you go mushroom picking?
□ working days / □ weekend and/or holidays / □ any weekday

(*) 12. Thinking of the expenses you incur in when you went to this forest... *(multiple options possible)*
□ I brought my lunch with me (picnic-type to eat in the forest)
□ I had breakfast and/or lunch in a bar/restaurant in the area
□ I'd overnight in a touristic accommodation (not at my place)
□ other: ___________

(*) 14. Are you a member of any mycological association? □ Yes / □ No

About the mushroom regulation system:

(*) 20. The permit varies according to the quantity of mushrooms picked. Which category do you think best represents you? *[select an option]*

□ I pick less than 5 kg a day (this regulation considers you as a self-consumption mushroom picker)
□ I pick daily over 5 kg (this regulation considers you a professional)

(*) *[only if Q20= self-consumption]* **21. These are the permit categories for pickers for own consumption. In which category do you recognise yourself?**

□ Local or resident in the municipality where the regulated forest is located
□ 2nd home owner at the municipality where the regulated forest is located
□ Client of a restaurant or hotel in the municipality where the regulated forest is located
□ Children under 14 years
□ Pensioner
□ County resident– 1 day
□ County resident - season
□ Non County resident– 1 day
□ Non County resident– 2 days

<u>A bit about you</u>

33. Gender: □ Man / □ Woman

(*) **34. Age:** □ < 25 years / □ Between 26 and 40 / □ Between 41 and 65 / □ over 65 years

(*) **35. Post code of your habitual residence**: **__________**

(*) **36. Which is your latest study level?**

□ No studies / □ Primary / □ Secondary / □ Vocational training / □ University studies

Thank you for your interest and time!

C. Weighing adjustment for ZTC observations

In order to take into account the sampling bias in the ZTC database (over representation of interviews taken in weekend and holidays as oppose to work days), a weighting factor was introduced on the number of visits taken.

Such factor was calculated as:

$$w_{zj} = \frac{\%\, of\ calendar\ week(weekend)\ days_j}{\%\, of\ sampled\ week(weekend)\ days_j} \quad ,$$

where:

- the dividend represents population distribution i.e. the percentage of all calendar working days (or weekend/holidays) within the sampling period in each of the picking ground j;
- the divisor represents the observed distribution of actual sampled working (or weekend/holidays) days.

The following table represents a summary of the weighing factors for each of the picking ground's.

Table 3- Summary of observations sampled during the week and during the weekends and their weighting factors for each of the three picking grounds.

Zone	Calendar working day (%)	Calendar weekend/holidays (%)	Sampled working days(%)	Sampled weekend/holidays (%)	Weighting factor working days	Weighting factor weekend/holidays
Els Ports	20 (71.4%)	8 (28,6%)	11 (55%)	9 (45%)	1.30	0.64
Massís de l'Orri	10 (62.5%)	6 (37.5%)	2 (25%)	6 (75%)	2.50	0.50
Setcases	28 (63.6%)	16 (36.4%)	1 (9%)	10 (91%)	7.07	0.40

D. Individual Travel Cost (ITC) model with online data

In this appendix we have included a calculation of the ITC demand model using the online database of mushroom picking data (Section 3.1). We think this calculation could be useful for readers that wish to compare both methodologies on the same set of data.

The ITC demand model relates the total number of visits (V_{ij}) each individual picker i makes to a specific picking ground j during the mushroom season, with the individual travel cost to that picking ground (TC_{ij}), and other additional socio-economic characteristics of the individual (S_i) that might affect the final demand curve:

$$V_{ij} = f(TC_{ij}, S_i). \tag{1}$$

As the dependent variable (V) is made of non-negative integer count data, it was assumed to be best represented by a Poisson distribution (Hellerstein, 1991). The distribution of the probability of observing a mushroom picker taking V trips in a season is estimated through a zero-truncated Poisson model following Parsons (2003):

$$P(V|V > 0) = \frac{e^{-\lambda}.\lambda^{V-1}}{(V-1)!}; \tag{2}$$

where the λ parameter is the expected number of trips under the specifications of the demand model (eq. 1) taken with a log-linear form, and $V - 1$ the number of trips truncated at zero (Parsons, 2003).

Six explanatory variables apart from the travel cost were included in the model. Three were proxies for satisfaction and effectiveness of the picking activity: picker expertise on mushroom harvesting; kilograms of mushroom picked; and membership of a mycological association. Three standard socioeconomic variables were also considered: educational level, as proxy for income, age class, and presence/absence of children along with the adult pickers.

The mushroom picking demand function for the individual i at the picking ground j takes the logarithmic form to ensure non-negative probabilities, as follows:

$$\ln(\lambda_{ij}) = \alpha + \beta_1 TC_{ij} + \beta_2 CHILD_i + \beta_3 EXPERT_i + \beta_4 KMUSH_i + \beta_5 STUDIES_i + \beta_6 AGE_i + \beta_7 ASS_i \tag{3}$$

Presence of multicollinearity across the explanatory variables was investigated and variables showing a Generalized Variance Inflation Factor (GVIF) higher than 2 were removed (Fox and Monette, 1992). Subsequently, a backward stepwise selection based on model Akaike Information Criterion (AIC) was also run to individuate the most significant variables and the best-fitted model. A k-fold cross-validation (k=10) was run on the three models to assess the model accuracy. All the statistical analyses were performed with the R software (R Core Team, 2014).

In order to estimate the consumer surplus, the demand function was integrated by the travel cost, obtaining:

$$CS_{ij} = \int_{\overline{TC}_{ij}}^{MTC_j} \lambda_{ij}\, dTC = -\frac{e^{\alpha+\beta_1\overline{TC}_{ij}+\beta_2 S_i}}{\beta_1} =-\frac{\widehat{\lambda_{ij}}}{\beta_1} \tag{4}$$

Where S is the sum of all significant socio-economic explanatory variables and their respective regression coefficients, $\widehat{\lambda_{ij}}$ is the expected average number of trips for the mushroom picker i in the picking ground j, and β_1 is the travel cost coefficient.

Eq. 4 was then used to compute the average value per visit (TV_j) that is the value of making an additional picking mushroom trip in the picking ground j:

$$TV_j = \frac{CS_{ij}}{\widehat{\lambda_{ij}}} = -\frac{1}{\beta_1}$$

<u>Model results</u>

The following table shows all estimated ITC models. As expected, there is a significant and negative relationship between the explanatory variable travel cost and the number of trips undertaken.

In the EP ground, pickers between 26 and 40 years old, with a secondary degree, that travel with children, and have a mycological expertise, with a large amount of mushrooms picked in each visit are more likely to make more harvesting trips. In MO, similar features apply; however having a secondary degree negatively influences the number of visits to the picking ground, while being member of a local mycological association has a positive effect on the number of picking visits. SE shows more different patterns compared to the previous zones. Holding a primary degree is the variable that significantly influences the frequency of picking trips, while being aged between 26- and 40-years-old influences negatively the number of picking trips.

The average travel cost is 13, 20 and 19 €/person respectively for the three picking grounds with models yielding the highest estimate for MO site (6.21 visits per person) and much lower for EP (3.95 visits per person) and SE (3.07 visits per person).The consumer surplus associated with the probability of making another mushroom trip (the average value per visit; TV_j) is lowest in SE (21.4 €/trip), followed by MO (24.1 €/trip) and EP (40.7 €/trip) (Table 7). The average mushroom price paid to pickers (3 €/kg, Martínez de Aragón et al. 2011), along with mean harvesting efficiency (Table 4) were used to decouple the surplus value in its components, namely provisioning and recreational benefits. The recreational TV_j was estimated to hold 74.4% of the total TV_j in EP, 64.5% in SE and 49.5% in MO.

Table D.1-ITC demand models for the three picking areas. Explanatory variables estimates (p values) are presented. In bold significant variables (p<0.05). EP = Els Ports; MO= Massís de l'Orri; SE= Setcases.

		ITC			
		EP	**MO**	**SE**	**All zones**
Model estimates	Intercept	-0.525 (0.123)	**1.432 (<0.001)**	**1.915(<0.001)**	**1.115 (<0.001)**
	TC	**-0.025 (0.001)**	**-0.041 (<0.001)**	**-0.047(<0.001)**	**-0.033(<0.001)**
	CHILD	**0.382 (0.026)**	**0.292 (0.006)**	-	**0.265 (0.000)**
	EXPERT	**0.095 (0.001)**	**0.129 (<0.001)**	-	**0.087 (<0.001)**
	KMUSH	**0.240 (<0.001)**	-	-	**0.041 (<0.001)**
	STUDIES	B: -0.903 (0.102) **C: 1.094 (<0.001)** D: 0.374 (0.053)	**C: -0.574 (<0.001)**	**B: 0.541(0.012)**	**B: 0.250 (0.020)** **D: 0.161 (0.030)**
	AGE	**B:0.761(<0.001)**	**B: 0.316 (0.005)**	**B: -0.582 (0.006)**	A: -0.452 (0.091)
	ASS	-	**0.661 (0.010)**	-	-
	R^2 [a]	0.34	0.22	0.15	0.20
	AIC (initial; final)	285.6; 283.4	649.5; 645.4	282.1; 272.9	1399.1; 1395.8
	MSE[b]	21.65 ±0.86	65.59 ±4.54	18.31 ±0.96	43.17 ±2.29

[a] Nagelkerke pseudo R^2
[b] Mean Squared Error estimated from a 10-fold cross-validation.

Table D.2- ITC consumer surpluses estimations for the three picking areas. Value± standard error. EP = Els Ports; MO= Massís de l'Orri; SE= Setcases

		EP	**MO**	**SE**	**All zones**
ITC	TV_j (€/trip)	40.7±11.7	24.1±2.4	21.4±3.8	30.8±2.9
	Recreational TV_j (€/trip)	30.3	12.0	13.8	20.4
	Provisioning TV_j (€/trip)	10.4	12.2	7.6	10.4

E. Mathematical solution of the integration process

Given the following demand curve:

$$\ln(\lambda_{ij}) = \alpha + \beta_1 TC_{ij} + \beta_2 CHILD_i + \beta_3 EXPERT_i + \beta_4 KMUSH_i + \beta_5 STUDIES_i + \beta_6 AGE_i + \beta_7 ASS_i$$

We can rewrite it in its exponential form as:

$$\lambda_{ij} = e^{\alpha+\beta_1 TC_{ij}+\beta_2 CHILD_i+\beta_3 EXPERT_i+\beta_4 KMUSH_i+\beta_5 STUDIES_i+\beta_6 AGE_i+\beta_7 ASS_i}$$

assuming for reading simplification:

$$\beta_2 S_i = \beta_2 CHILD_i + \beta_3 EXPERT_i + \beta_4 KMUSH_i + \beta_5 STUDIES_i + \beta_6 AGE_i + \beta_7 ASS_i$$

We can obtain the definite integral of the function $\lambda_{ij}(TC)$ from the average Travel Cost ($\overline{TC}$) to the Maximum Travel Cost (MTC) (*i.e*. the choke price at which the number of trip goes to zero) as:

$$CS_{ij} = \int_{\overline{TC}_{ij}}^{MTC_j} e^{\alpha+\beta_1 TC_{ij}+\beta_2 S_i}\, dTC$$

Which solves to:

$$= \frac{e^{\alpha+\beta_2 S_i}}{\beta_1}\left[e^{\beta_1 TC_{ij}}\right]_{\overline{TC}_{ij}}^{MTC_j} = \frac{e^{\alpha+\beta_2 S_i}}{\beta_1}\left[e^{\beta_1 MTC_j} - e^{\beta_1 \overline{TC}_{ij}}\right]$$

Assumed the non-linear form of the demand model, we take the choke price as $+\infty$ as in Haab and McConnell 2002).

Given the negative form of the travel cost coefficient β_1:

$$e^{\beta_1 MTC_j} \rightarrow 0$$

Hence:

$$CS_{ij} = -\frac{e^{\alpha+\beta_1 \overline{TC}_{ij}+\beta_2 S_i}}{\beta_1} = -\frac{\widehat{\lambda_{ij}}}{\beta_1}$$

F. ZTC Demand model average/median values and graphical representations

Here are represented all mean and medium values used for representing the ZTC demand curves across the different picking grounds.

Model	Picking ground	Intercept	CHILD[b]	EXPERT	KMUSH	STUDIES[ab]	AGE[ac]	ASS[b]
ZTC onsite	EP	5.797	0.098	-	-	-	A: 23.23 C: 32.85	-
	MO	-22.493	-	-	-	-	B: 20.95 C: 35.23	-
	SE	-10.501	0.043	-	-	-	B: 21.20 C: 35.80	-
	All zones	2.838	0.085	-	-	-	A: 24.45 B: 21.20	-
ZTC online	EP	-7.879	-	-	-	C: 0	B: 0	-
	MO	-4.339	0	-	3.76	B,E: 0	A,B: 0	-
	SE	-6.874	-	-	2.51	C: 0 D: 1	B: 0	0
	All zones	-5.437	-	6.94	-	E:0	-	-

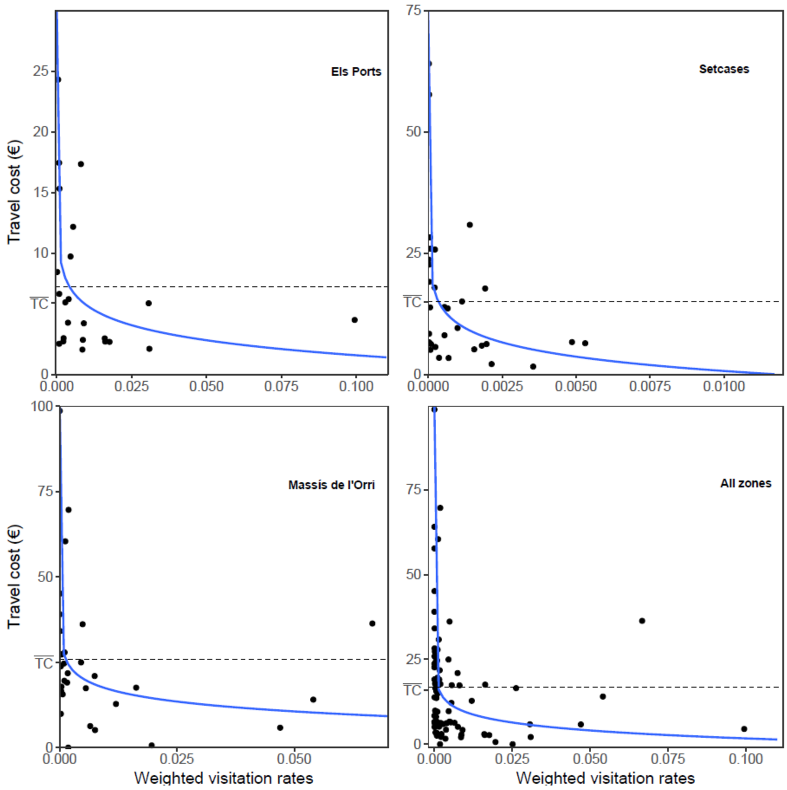
[a] STUDIES and AGE are multi-levels variables. STUDIES :(A:“no study”, B:“ primary degree”, C:“secondary degree”, D:”Vocational Training”, E:“ University”); AGE(A:“<25”,B: “between 26 and 40”,C: “between 41 and 65”, D: “>65”).

[b] Binary explanatory variables. For them the median value was considered except in the ZTC onsite models (mean of children per pickers’ group divided by town children population).

[c] In the onsite ZTC model AGE was computed as average of percentages of inhabitants’ age categories.

The following figures show the estimated Travel Cost (Zonal from onsite data, and Zonal from online data) inverse demand models for the three picking grounds and a cumulative version for all observations. $\overline{\mathbf{TC}}$ indicates the mean zonal travel cost across the observations. For graphic purposes the demand model was set as: $\boldsymbol{Y(TRIPS) = e^{\beta TC+\alpha}}$, where α is the sum of the model intercept and all additional explanatory variables kept constant to their overall mean (median in the case of binary variables) value. Each point correspond to an observed town.

Zonal Travel Cost – onsite data - demand curves



Zonal Travel Cost – online data - demand curves