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A spatial-based model of multiple discrete continuous demand for assessing recreational use of nature sites: a case study of Italian National Parks

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This study proposes the use of a spatial-based travel cost model of multiple discrete/continuous demand to analyze recreational visits to five selected Italian National Parks. The proposed model has a spatial structure which allows us to capture potential patterns of environmental and economic dependency that may influence the destination choice and the number of trips taken to each destination. The model is estimated from revealed preference data collected through a general population survey of Italian National Park visitors. Results suggest that users are more inclined to visit destinations with improved visitor services and that those with similar economic characteristics show a similar sensitivity to changes in travel costs. Policy simulations based on the predicted number of visits across destinations are used to explore potential changes in travel patterns between sites. Simulation results suggest improving the site accessibility is likely to boost visitation rates for all national parks under study.

Keywords: environmental similarities; recreation demand; spatial dependency; travel cost model; travel preference behavior

1. Introduction

Recreation demand models are extensively applied to estimate benefits directly accruing to users of natural resources. A frequent goal is that of quantifying the effects of environmental quality changes at specific recreational sites on visitors' welfare. The method has a long history; the disciplinary folklore traces it back to the letter that Harold Hotelling sent in 1949 to the director of the US National Park Service and the first pioneering studies by Trice and Wood (1958) and by Clawson (1959). Since then, the method has enjoyed several substantive advancements, which we will summarize in what follows. These gradually delivered a much-improved understanding of individuals' preferences for visiting outdoor recreation sites, based on their socioeconomic profiles and the attributes of the visited locations. This evolution has culminated in the recent development of random-utility-based discrete-continuous models that jointly explain visitation decisions at the extensive and intensive margin.

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The aim of this article is to present a proof of concept for a stylized extension of this category of models. In our extension, based on a subset of Italian National Parks, we propose a spatial dependency structure that reflects environmental similarities (dissimilarities) across destinations. Our approach is desirable because it requires no normalization assumptions to be made by the analyst on the variance-covariance matrix. We illustrate the results with two policy simulations, one improving site accessibility, the other reducing travel cost.

Specifically, discrete-continuous models explain the economic and statistical features of discrete components (extensive margin: "what site to visit?") and continuous (intensive margin: "how many visits?") of recreation site decisions (Bockstael and McConnell 2007; Lupi, Phaneuf, and von Haefen 2020; Phaneuf 1999; Phaneuf and Herriges 1999; Signorello *et al.* 2009; von Haefen and Phaneuf 2003, 2005). A particularly successful class of recreation demand models has been that based on the theory of random-utility maximization (RUM) (Bockstael, Hanemann, and Kling 1987a; Creel and Loomis 1990; Milon 1988; Parsons, Jakus, and Tomasi 1999; Phaneuf and Smith 2005; Samples and Bishop 1985; von Haefen 2003; Yen and Adamowicz 1994). To provide context, it is worth briefly summarizing the critical stages of their historical development. Morey, Rowe, and Watson (1993) proposed a repeated discrete choice model with a no-trip alternative. Hausman, Leonard, and McFadden (1995), modifying the linked approach previously discussed by Bockstael, Hanemann, and Kling (1987b), developed a RUM-based framework that combined discrete choice and count models to quantify welfare losses due to natural resource damage.

The theoretical pillar that stood at the core of that framework was the assumption of a two-stage budgeting theory, with each stage being separately modeled. Whilst the second stage of the model accommodated the single decision made by travelers as to how many trips to take for recreational purposes, the first stage evaluated the probability of visiting each site in the choice set. The two stages were linked *via* an implicit price that corresponded to the price for a composite consumption commodity (attractiveness of destinations), computed from the first stage about recreation site decisions. A similar analytical framework was then implemented, among others, in Parsons and Kealy (1995) and Feather, Hellerstein, and Tomasi (1996).

RUMs based on the two-stage approach were particularly appealing thanks to their ease of interpretation of the parameter estimates (and their subsequent employment for welfare analysis). However, they suffered from two notable limitations. The first limitation related to the fact that decision-makers were assumed to make a single decision from a set of mutually exclusive destinations. So, recreation sites were implicitly assumed to be perfect substitutes for each other and the set of destination choices for visitors was assumed to be adequately defined for all. Doing so, however, disregards choice situations involving visitors selecting more than one destination (i.e. interior solutions) to be visited at the same time (Dube 1999; Hendel 1999). For example, in a sequence within the season, as well as the issue of inclusion and exclusion of a destination in the visitor's choice set. Further, the discrete choice model employed in the first stage (i.e. the Multinomial Logit model, McFadden 1968, 1974) failed to account for the diminishing nature of marginal utility arising with the repetition of trips to the same destination. The second limitation, in sequential (two-stage) estimation, results in estimates being asymptotically consistent but inefficient (Pellegrini and Scagnolari 2021).

A further step toward modeling both extensive and intensive choice margins in multiple site settings was made by Phaneuf (1999) who proposed a conceptual and operational framework allowing the simultaneous assessment of both corner and interior solutions. That approach greatly benefited from the development of a system of Karush-Kuhn-Tucker (KKT) conditions for optimality originally formalized by Wales and Woodland (1983). Computational constraints in place at the time were then overcome by Kim, Allenby, and Rossi (2002), who proposed a constant elasticity of substitution (CES) utility function and used a Geweke, Hajivassiliou, and Keane (GHK) simulator to evaluate a multivariate normal integral associated with the optimization of the resulting sample log-likelihood function. Bhat (2005, 2008) built further on this intuition and proposed a novel KKT approach. This is referred to here as the Multiple Discrete Continuous Extreme Value (MDCEV) model. It allows the estimation of optimal consumption quantities without resorting to any form of iterative simulation process. Specifically, the multiplicative log-extreme value error term embedded within a Box-Cox utility function results in a closed-form probability expression. This collapses to a single discrete choice model in the case of only one alternative being chosen (i.e. a single destination is visited). Abbott and Fenichel (2013) employed the MDCEV to investigate individual recreational fishing behavior, whereas Lloyd-Smith (2022) used Bhat's model to quantify the economic benefits of outdoor recreation in Canada. Abbott *et al*. (2018) and Lloyd-Smith *et al*. (2019, 2020) incorporated both time and monetary budgetary constraints into the MDCEV model structure to investigate intertemporal substitution behavior.

The objective of this article is to contribute to the existing literature on recreation demand methods by developing a spatial-based travel cost MDCEV model. The spatial structure we introduce allows us to capture potential proximity effects in environmental terms that underlie the decisions made by visitors with respect to what Park to visit, along with the number of trips to each of the selected Parks. The model proposed is then used to investigate outdoor recreation preferences for five selected Italian National Parks.

Two distance matrixes are included in the proposed methodological framework. The first distance matrix is employed to capture similarities (dissimilarities) in terms of environmental characteristics across nature reserve sites. For example, it is plausible that recreationists visit nature reserve sites which share the same natural features, such as the proportion of forest areas or the presence of water bodies. By incorporating a nature-based distance matrix, we are able to account for unobserved distance dependencies between destination sites that would be otherwise missed with traditional distance matrixes (Bhat, Astroza, and Bhat 2016).

The second distance matrix is designed to reflect proximity (distance), in economic terms, between travelers. The implementation of a socio-economic-based distance matrix allows us to unravel similar sensitivity patterns toward travel cost variations that may underlie the decision to visit a nature reserve site. We apply the inverse Euclidean measure to determine the elements of the environmental and socio-economic spatial matrices that are embedded within the discrete component (i.e. the choice of visiting a nature reserve) of the MDCEV model. In addition to exploring the determinants influencing the frequency of visits to protected areas, we conduct a simulation analysis to predict how trip demand to each site varies under different policy settings.

2. The case study

The spatial-based MDCEV model is used here to examine travel preferences held by a sample of Italian outdoor recreationists for five Italian national parks: the *Parco Nazionale delle Dolomiti Bellunesi* (PN-DB), the *Parco Nazionale dell'Appennino Tosco-Emiliano* (PN-ATE), the *Parco Nazionale delle Cinque Terre* (PN-CT), the *Parco Nazionale dell'Abruzzo, Lazio e Molise* (PN-ALM), and the *Parco Nazionale del Gargano* (PN-G). The locations of these parks are illustrated in Figure 1, within the context of the wider system of the 26 Italian National Parks. As shown in the figure, three nature sites located in mountainous terrain (PN-ALM, PN-ATE, PN-DB) while the other two include coastal areas, one on the Northwest (PN-CT) and one on the Southeast (PN-G), respectively.

Table 1 presents the characteristics of each national park in terms of land use/land cover (LULC), level of accessibility and tourist services and recreational facilities. The first block of the table describes the percentage of LULC with the aid of the following categories: urban, water bodies, wetlands, agricultural pressure outside the national park,[1] bare areas, cropland, grassland, and woodland. The reported LULC categories were extracted from the Climate Data Store platform Copernicus (https://cds.climate.copernicus.eu/#!/home). Of the national parks, PN-G and PN-CT have the highest values of urban land cover with 0.78 and 0.75 percentages, respectively, whereas PN-DB has zero percentage of urban land cover. The highest percentage of water bodies is found in the PN-G (8.04), followed by PN-CT and PN-DB. PN-G has the highest percentage of wetland coverage, while PN-ATE has the lowest. While PN-CT has no agricultural pressure outside its border, PN-G and PN-ALM are the two national parks that are subjected to the highest percentage of agricultural pressure, with values of 22.20% and 12.20%, respectively. Four national parks out of five report zero percentage of bare areas with only PN-DB having a percentage value greater than zero (0.14). PN-ALM has the second largest percentage of cropland, but it has the highest percentage of grassland amounting to 29.02%. PN-DB and PN-ATE are, on the contrary, ranked second and third with percentages of grassland of 22.01 and 13.32, respectively. Finally, PN-ATE has the highest forest land cover with 64.60% whilst PN-G is the national park with the lowest forest land cover (34.30%). The second block of the table outlines the different levels of accessibility for the five national parks listed in the study. As shown in the table, PN-DB is endowed with the longest network of roads and other infrastructures within a radius of 50 km, followed by PN-ATE and then by PN-G. PN-CT is the destination site located furthest from towns with more than 100,000 habitants, whereas PN-G is reported to be the closest one. In terms of bus services, PN-ALM has six bus routes providing access to the site, while PN-G has only one bus route. PN-ATE is the nearest destination site to a train station (13.3 kms). Data were collected using both Copernicus platform and Google Maps. The last block of the table shows that the maximum number of hiking trails is available at PN-ALM with 150 walking tracks, while PN-ATE has the lowest, with only 27 trails. The latter, however, has the second highest quantity of accommodation (273) while PN-G leads with 457. PN-ALM is ranked first for both the number of events organized and the availability of visitor centers, whereas it ranks second for number of flagship and iconic species (4) (www.parks.it).

Finally, Table 2 reports the temperature recorded in June, July, and August 2022 in each national park (https://climateknowledgeportal.worldbank.org/country/italy/climate-data-historical). Whilst PN-CT recorded the highest average temperature (21 degrees C, 70 Fahrenheit), and the highest temperature over the period in the month of August.

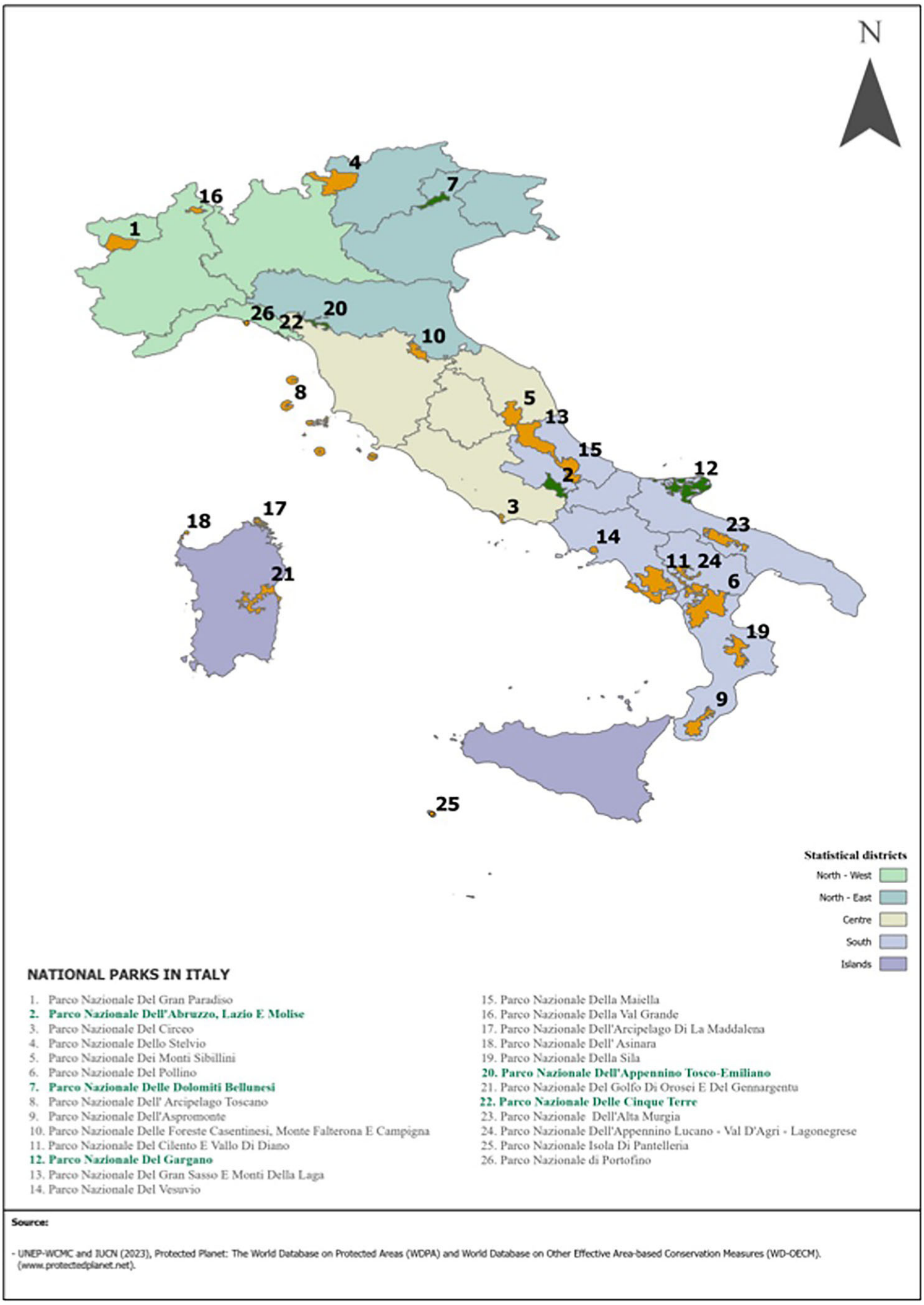

Figure 1. National Parks in Italy (in green color and in bold type the five National Parks examined in this study; colour online).

Instead, PN-ATE reported the lowest average temperature (11.167 degrees C or 52 Fahrenheit) and the lowest temperature, which was recorded in June (7 degrees C, 44.6 Fahrenheit).

Table 1. National Park characteristics.

	PN-ALM	PN-ATE	PN-CT	PN-DB	PN-G
Land cover variables					
Urban	0.15	0.07	0.75	0	0.78
Water bodies	0.24	0.05	0.45	0.28	8.04
Wetlands	0.04	0	0.54	0.07	1.26
Agricultural pressure outside the National Park	12.2	4.6	0	10.3	22.2
Bare areas	0	0	0	0.14	0
Cropland	2.01	1.03	0.05	0.24	9.58
Grassland	29.02	13.32	2.49	22.01	6.73
Forest	51.4	64.6	59.7	45.1	34.3
Accessibility variables					
Kilometers (kms) of roads, and other infrastructures within 50 km radius	4.59	9.2	4.29	12.88	5.43
Distance (in kms) from towns with more than 100,000 inhabitants	64.6	38.73	72.8	56.8	20.22
Number of bus services	6	4	2	2	1
Distance (in kms) to the nearest train station	43.2	13.3	14.4	17.8	18.1
Recreational facility and tourism variables					
Hiking trails	150	27	47	109	32
Accommodation	179	273	122	39	457
Events	14	3	4	0	0
Visitor centers	41	10	9	14	5
Flagship species	4	4	3	5	3

Table 2. Descriptive statistics for monthly temperature.

National Parks	June 2022 Average	July 2022 Average	August 2022 Average
PN-ALM	15	15.5	17
PN-ATE	10	11	12.5
PN-CT	20	21	22
PN-DB	13	14	15
PN-G	18.5	19.5	21

3. Econometric analysis

Assuming that a traveler i is a utility-maximizer who accrues utility from visiting one or more recreation sites (i.e. the five national parks under examination) subject to a linear non-negative budgetary constraint, as well as from a generic outside good. The additively separable utility for the decision-maker i can be written as follows (Bhat 2005, 2008):

$$U_i(\boldsymbol{x}) = x_{i1}\psi_{i1} + \sum_{k=2}^{K}\psi_{ik}\gamma_{ik}\ln\left(\frac{x_{ik}}{\gamma_{ik}} + 1\right)$$
$$\text{s.t.}\sum_{k=1}^{K}x_{ik}p_{ik} = E_i \tag{1}$$

In the above equation, the utility function $U_i(\boldsymbol{x})$ is assumed to be well-behaved (e.g. quasi-concave, increasing and continuously differentiable); $\boldsymbol{x}$ is a vector $(K \times 1)$ of consumption quantity (recreational trips) with elements $x_{ik} \geq 0$ ($k = 2, ..., K$ is an index for the K national parks); ψ_{i1} is the baseline marginal utility for the linear outside good x_{i1} (Saxena, Pinjari, and Bhat 2022; Saxena *et al.* 2024); and ψ_{ik} and γ_{ik} are parameters associated with the inside goods x_{ik} (which represent the trip frequency to national parks, i.e. inside goods). In the utility constraint, on the other hand, E_i represents the total number of trips undertaken by the traveler i and p_{ik} is the unit travel cost for visiting national park k, with $p_{ik} = 1$, for all k (Astroza, Guarda, and Carrasco 2022; Bhat, Astroza, and Bhat 2016; Pellegrini, Sarman, and Maggi 2021; Pellegrini and Rose 2025). Both ψ_{ik} and γ_{ik} can be further parametrized to accommodate heterogeneity in consumers' preferences such that:

$$\psi_{ik} = \exp\left(\beta_i' z_{ik} + \theta' q_{ik} + \epsilon_k\right) \tag{2.1}$$

$$\psi_{i1} = \exp(\epsilon_1) \tag{2.2}$$

$$\gamma_{ik} = \exp(r' d_{ik}) \tag{2.3}$$

In Equations (2), z_{ik} and q_{ik} describe the characteristics of the national park k and individual i, and β_i and θ are parameters to be estimated. Further, θ are treated as fixed parameters whilst β_i are random taste parameters that vary across visitors according to an unknown distribution. In the current article, the alternative-specific constants that are embedded within the vector of random parameter β_i are assumed to be a realization from a multivariate normal distribution, $\beta_{i,ASC} \sim f(\mu_{i,ASC}, \Omega_{i,ASC})$, with elements of the variance-covariance matrix $\Omega_{i,ASC}$ capturing the distance in environmental space across nature reserves. Spatial dependency across national parks is accommodated by using a spatial autoregressive (SAR) error structure of order one as follows:

$$\begin{aligned} \widetilde{\boldsymbol{\beta}_{ASC}} &= \rho \boldsymbol{W} \boldsymbol{\Lambda} + \xi_{ASC}, \\ \text{where } \boldsymbol{\Lambda} &= \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}_{5 \times 5} \end{aligned} \tag{3}$$

In the above equation, ρ represents the spatial autoregressive coefficient $(0 < \rho < 1)$, $\boldsymbol{\Lambda}$ corresponds to the covariance matrix (the off-diagonal elements are all zero and therefore no correlation patters are estimated), and $\boldsymbol{W}$ is a spatial-based matrix with diagonal elements being all equal to zero. Rather than implementing common distance matrices, such as the spatial distance in kms or the inverse of a continuous travel time specification (Pellegrini *et al.* 2025), we specify $\boldsymbol{W}$ such that each matrix element is the inverse Euclidean distance of the land cover characteristics of the destination site reported in the first block of Table 1. Doing so produces the resulting distance matrix $\boldsymbol{W}$, which reflects environmental similarities (dissimilarities) across these nature conservation sites. Equation (3) can be further re-written as:

$$\widetilde{\boldsymbol{\beta}_{ASC}} = \boldsymbol{G} \boldsymbol{\xi}_{ASC} \tag{4}$$

where $\boldsymbol{G} = [\boldsymbol{IDEN}_5 - \rho \boldsymbol{W}]^{-1}[5 \times 5]$, $\mathbf{IDEN}_5$ is the identity matrix of size 5 (that is, there are five national parks), and $\widetilde{\boldsymbol{\beta}_{ASC}} \sim f_5(0, \boldsymbol{G}\boldsymbol{\Lambda}\mathbf{G}')$. Finally, we can then write $\boldsymbol{\beta}_{ASC}$ as $\boldsymbol{\beta}_{ASC} = \boldsymbol{\mu}_{ASC} + \widetilde{\boldsymbol{\beta}_{ASC}}$, where $\widetilde{\boldsymbol{\beta}_{ASC}} \sim \boldsymbol{f}_5(0, \boldsymbol{G}\boldsymbol{\Lambda}\mathbf{G}')$.

Next, ϵ_k $(k = 1, ..., K)$ are error terms that recognize the existence of unobserved factors that influence the preferences held by individuals with respect to visiting national park sites. Under the assumption that the vector of error terms ϵ_k are all i.i.d. Gumbel with a scale parameter σ, the unconditional probability function of the individual i making recreational trips to M of the K national parks (i.e. decision-makers consume the first M of the K goods), needs to be integrated over the probability density function of the random parameters β. So, it can be written as:

$$P_i\left(x_{i1}^*, x_{i2}^*, ..., x_{iM}^*, 0, 0, ..., 0\right) = \int \frac{M!}{\sigma^M} \times \prod_{k=2}^{M+1} \frac{1}{x_{1k} + \gamma_{ik}} \times \frac{\prod_{k=2}^{M+1} \exp \frac{V_{ik}}{\sigma}}{\left(1 + \sum_{k=2}^{M+1} \frac{V_{ik}}{\sigma}\right)^{M+1}} f(\beta_i) d(\beta_i).$$

$$\text{where } V_{ik} = \beta_i' z_{ik} + \theta' q_{ik} - \ln\left(\frac{x_{ik}}{\gamma_{ik}} + 1\right) \tag{5}$$

The sample-likelihood function is the unconditional probability expression shown in the above equation written as a function of the parameters and it can be maximized via the application of the conventional simulation methods (Train 2009) applied to the equivalent log-likelihood.

3.1. Explanatory variables

In what follows, we begin by introducing the explanatory variables included in the discrete component of the model, after which we discuss those embedded within the continuous stage of the model.

The first explanatory variable that we include in the baseline preference is the accessibility index, which is calculated as a fraction between zero and one for each national park in the choice set. Values closer to one (zero) imply higher accessibility. The accessibility index is calculated from a generalization of a land-cover index first proposed in Bhat and Gossen (2004) and then re-adapted in Bhat, Astroza, and Bhat (2016):

$$\text{Accessibility index } A_k = \frac{\left[\sum_{k=1}^{K} \sum_{l=1}^{L} \left|\frac{Acc_{kl} - 1}{Acc_k}\right|\right]}{\left[\frac{2(L-1)}{L}\right]}, k = 1, ..., K;\ l = 1, ..., L. \tag{6}$$

where k corresponds to the kth national park site, l indicates the lth accessibility variable displayed in Table 1 ($L = 4$, that is, there are four accessibility variables) and Acc_{kl} represents the lth accessibility value for the kth national park site. Following the approach formalized in Bhat, Astroza, and Bhat (2016), we multiply the accessibility index by a function f of individual-specific characteristics to increase variation in the data (variation solely occurs at the national park level). In this sense, all visitors would perceive a given National Park (NP) destination as accessible as any other visitor. As such, the accessibility index effect would not be identified in estimation as it causes no utility difference across alternatives. The second explanatory variable, the attractiveness index, is constructed by applying Equation (6) to the tourism service variables reported in the third block of Table 2. The introduction of variation in the data is achieved by dividing the attractiveness index by the number of activities that each respondent performed in their latest visit to the kth national park, to obtain an individual measure of use.

The third explanatory variable is the travel cost. Four steps were followed to compute the monetary travel cost (in €). In the first step, the travel distance (in kilometers) between the municipality of residence and the *k*th national park was calculated using latitude and longitude coordinates. The next step involved the calculation of the travel time (in hours) required to reach the destination by road. To do this, we divided the travel road distance (in kilometers) resulting from the previous step by the average speed traveled by cars. The latter is determined by averaging the average speed traveled by cars on urban roads (29.5 km/h) and the average speed traveled by cars on highways (80 km/h). In the third step, we derived a proxy for the fuel cost per kilometer by generating a fuel cost distribution for each national park[2] and by taking the average of one thousand draws randomly drawn from each random distribution at the respondent level. We further assumed a vehicle efficiency factor of 7.04 liters for 100 km (14.2 km per liter). The final step focused on identifying how travelers value time versus travel cost, from origin to destination (i.e. the value of travel time). Typically, the monetary cost of travel time is assumed to be equal to a fraction of the hourly wage (see, English, Leggett, and McConnell 2015; Hanemann *et al*. 2004; Lupi, Phaneuf, and von Haefen 2020; Pellegrini, Pinjari, and Maggi 2021; von Haefen and Phaneuf 2003). However, it is unclear as to whether respondents trade off travel time and work time at the margin for recreational activities (Hausman, Leonard, and McFadden 1995). Hence, the value of travel time used here stems from the estimation of a multinomial logit that quantifies the probability of tourists visiting the *k*th national park. The attributes that we use to estimate the probability of traveling to the site consisted of the travel time and travel cost. Both attributes were re-constructed from the information provided by respondents with respect to their latest trip undertaken to each natural park, such as travel distance, toll-roads, and transportation related expenses. Table 3 illustrates the model parameter estimates of the multinomial logit model. By calculating the ratio between the travel time and travel cost parameters, the value of travel time is estimated to be 8.02 €per hour.

Then, the travel cost was computed as follows (see, for example, Bhat, Astroza, and Bhat 2016):

Cost (in €) = 2 × (one-way land travel distance in kms × fuel cost per km + one-way total travel time in hours × 8. 02 €) + round trip ferry/airplane cost (when applicable, such as for travelers from the islands).

The reader will note that the travel cost also accounts for potential expenses that may arise from trips requiring the use of either a ferry or an airplane to reach the Italian peninsula from the islands. This additional source of expense was set to be equal to 110 € (this latter value was computed from the examination of airline and ferry fares) and was only added to the expenditure of those respondents who traveled from either Sardinia or Sicily islands (see Web Appendix for the descriptive statistics for travel cost and travel time variables). The final explanatory variable embedded within the baseline preference specification is designed to capture spatial interactions between the travel cost variable and an economic spatial matrix. The latter serves a proxy for measuring the sensitivity of respondents toward travel expenditure. The underlying assumption is that recreationists with similar economic characteristics are likely to have a similar sensitivity toward travel costs (Richards, Gómez, and Pofahl 2012).

The indicator variables that we consider for the satiation specification of the spatial-based econometric model are the following: for respondent being a single

Table 3. Travel model results.

Parameters	Beta		(t-ratio)
ASC	1.170		2.277
Travel cost	−0.080		−2.497
Travel time	−0.641		−2.866
Initial log-likelihood		−2751.794	
Log-likelihood at convergence		−1986.035	
Rho^2		0.278	
Adj. Rho^2		0.277	
AIC		3978.071	
BIC		3996.930	

person household (one if single, 0 otherwise); for presence of minors in the household (one if with members under 18 years of age, 0 otherwise); for taking part in outdoor activities during the year (one if respondents takes part, 0 otherwise). A further variable enters the continuous component of the model. It is a climatic variable measuring the logarithm of the average minimum temperature recorded between June and August 2022. Given that temperature averages vary at the national park level but not at the respondent level, we divided this variable by the logarithm of travel time. In subjectivizing this variable to the respondent, we introduce adequate variation into the data thereby preventing instability estimation during the optimization of the simulated sample log-likelihood function.

In terms of model specification, the accessibility index, the activeness index, and the travel cost variables are assumed to be randomly distributed across respondents. A log-normal distribution is imposed to accommodate heterogeneity in the travel cost coefficient across respondents.[3] The remaining covariates are, on the other hand, treated as fixed parameters. The sample log-likelihood function is approximated with 700 pseudo-random draws of the MHLS type (Hess, Train, and Polak 2006).

3.2. Policy simulations

The proposed spatial-based econometric model is employed to calculate elasticities of travel demand under two hypothetical scenarios: (a) an increment of 25% in the level of accessibility of the destination, and (b) a reduction of 15% in the travel cost to reach the destination. The own and cross elasticities are calculated as the percentual change in the travel participation rate between the hypothetical and base scenarios (i.e. status quo). In this application context, the predicted number of trips (as well as repeat trips) are obtained from the application of the forecasting algorithm developed in Pellegrini, Rose, and Scarpa (2022), albeit without calibrating the ASCs due to the absence of recent data on leisure trips to Italian national parks. Specifically, we started off by drawing 1,000 MHLS realizations for all random terms of the utility function, after which we computed the predicted trips by each respondent for each random realization and then averaged the predicted trips across the draws to determinate the individual number of visits. Note that the set of MHLS draws taken was kept the same throughout the entire forecasting procedure, so as to assure consistency across policy settings.

3.3. Survey

The empirical analysis is based on recreational preference behavior data collected with a web-based survey administered online between 1 October 2022 and 3 November 2022 via the online platform Qualtrics (https://www.qualtrics.com). 1,100 adult respondents, drawn from all over Italy,[4] were invited to take part in the survey, 356 of these were excluded from the final dataset due to either unreasonable survey completion time (completion time was calibrated on a pilot involving 100 respondents) or for having provided systematically unreasonable answers to attitudinal questions, leaving an active sample of 794 eligible respondents. The geographical distribution of the centroids of the municipality of residence of sample respondents is shown in Figure 2. As can be seen from the figure, all administrative regions were represented in the sample.

After agreeing to partake in the survey, respondents were first asked to indicate whether they had visited at least one Italian national park during the previous two

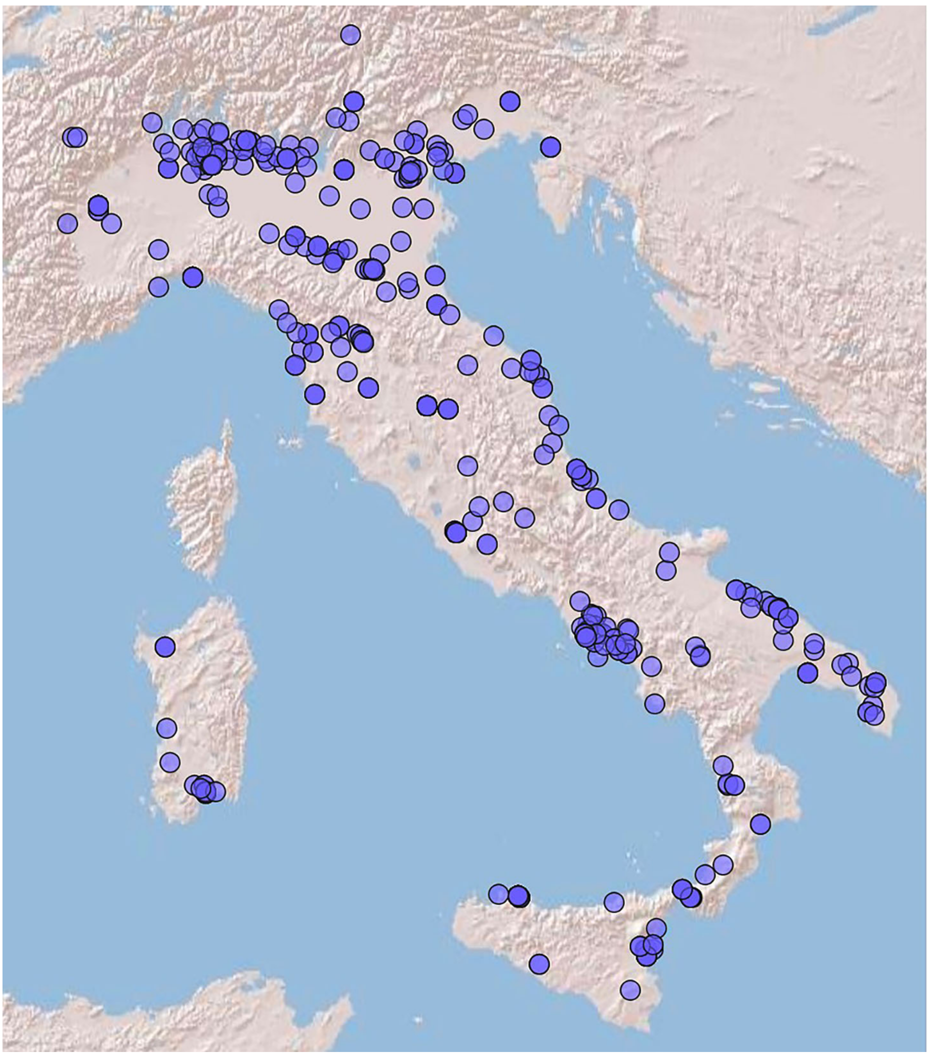

Figure 2. Geographical distribution of the sample of respondents.

Table 4. Travel participation rate.

National Parks	Travel participation (%)	Descriptive statistics for the number of trips among those who visited the National Parks		
		Mean	Median	Std. dev.
PN-ALM	264 (33.25%*)	4.08	1	8.52
PN-ALM	215 (27.08%)	3.77	1	5.61
PN-ALM	222 (27.96%)	3.37	1	8.21
PN-ALM	169 (21.29%)	3.83	1	6.76
PN-ALM	155 (19.52%)	3.67	1	8.47

*Relative frequencies are embedded within parenthesis.

years. Conditional on having visited one or more of these five national parks, respondents were then asked to answer a series of questions regarding their latest trip made to each of the sites they reported to have visited out of the five in the set. These included questions on travel mode choice used to reach the destination, type of accommodation used on site, duration of stay, number and types of recreational activities performed on site, travel party composition and size, trip related expenses (e.g. accommodation, events, transportation, food and beverages, etc.), among others. In the penultimate section of the survey, respondents answered a series of attitudinal questions about the impact that outdoor activities have on subjective well-being, as well as the roles that respondents expect protected areas to play in society. The survey ended with a range of socio-demographic and economic questions about household composition, level of education, household vehicle fleet composition, gender, age, type of employment, etc.

Table 4 presents the descriptive statistics on travel participation for each of the Italian national parks under scrutiny. As we can see from the table, in our sample PN-ALM was the destination site associated with the highest travel participation rate (33.25%) followed by PN-CT (27.96%) and PN-ATE (27.08). On the contrary, PN-G was the least visited, with approximately only 20% of the sample traveling to this protected area in the two years preceding the survey. Note that the travel participation rates do not add up to one as tourists can potentially visit more than one national park over two years. As for the number of trips (the second main panel of the table), on average respondents had visited PN-ALM and PN-ATE 4.08 and 3.77 times, respectively, with the former having the largest standard deviation (8.52 trips) of all five national parks. By contrast, PN-G reported the lowest number of trips with an average of 3.67 visits. The modal trip value is found to be equal to one for all five national parks in the destination set, suggesting that visitors tend to travel no more than once to the same national park, which is expected.

Table 5 reports the descriptive statistics for the final sample. The sample appears to be rather homogeneous in terms of place of residence and to have been drawn across all Italian administrative regions and with high sample density in the areas with the largest population density (see Figure 2). We report a slight oversample of respondents residing in the northeast (27.5%) area of the country. This is expected

Table 5. Descriptive statistics for the sample.

Sociodemographic and economic characteristics	Relative frequency				Istat 2023
Residential area					
Central	22.67%				19.80%
Northwest	23.80%				26.90%
Northeast	27.46%				19.70%
South plus Islands	26.07%				33.50%
Age					
18-29 years of age	11.46%				
30-49 years of age	41.81%				
50-69 years of age	37.66%				
over 69 years of age	9.07%				
Single person household					
Yes	5.67%				16.00%
No	94.33%				84.00%
Presence of children					
Yes	32.37%				39.50%
No	67.63%				60.50%
Outdoor activities					
Yes	59.95%				
No	40.05%				
	Min	Max	Average	Std. dev	
After-tax household income	14 839.68 €	63 523.40 €	30 250.67 €	13 139.54 €	

inasmuch as this region is one of the most populated and has the highest share of population regularly engaging in physical activities (Istat 2023). More than 70% of the sample falls into the age category *30–69 years of age*, with only 9% of tourists having declared being older than 69. Only six percent of families are made up of a single adult (age 18 or above), with most households sampled being childless. Six in ten individuals indicated they partake in outdoor activities during the year to improve their well-being and enjoy nature. Finally, the average yearly after-tax income stood at 30,250€ with a standard deviation of 13,139€.

4. Results

Table 6 shows the model parameter estimates associated with the best fitting model structure. The first panel of the table shows the parameter estimates for the baseline preference, whereas the second panel outlines those for the satiation parameters. The third panel illustrates the two parameter estimates related to the spatial dependencies for environmental factors and for the respondents, respectively, together with goodness of fit measures. The model specification that we report in Table 6 was also compared against a spatial MDCEV model in which the off-diagonal elements of the distance matrix are assumed to take the value of one if two national parks were located within 100 km, or 0 otherwise. The estimation of the latter model specification resulted in a log-likelihood at convergence of 3,511.501 against −3,505.227 recorded for the model developed herein. Given that the lowest Bayesian Information Criterion (BIC) was estimated for the proposed environmental spatial-based MDCEV model, we can conclude

Table 6. Model estimates.

Parameters	PN-ALM Par	PN-ALM (t-ratio)	PN-ATE Par	PN-ATE (t-ratio)	PN-CT Par	PN-CT (t-ratio)	PN-DB Par	PN-DB (t-ratio)	PN-G Par	PN-G (t-ratio)
Baseline constant parameter	0.499	1.106	−0.787*	−3.004	−0.705*	−1.849	−1.027*	−3.202	−0.860*	−1.930
Accessibility index										
Mean	0.684*	12.462	0.467*	14.448	0.483*	9.957	0.546*	11.089	0.367*	10.968
Std. dev	0.193*	7.217	0.007	0.127	0.221*	6.249	0.296*	7.542	0.216*	9.858
Attractiveness index										
Mean	0.628*	9.880	1.741*	14.167	0.784*	13.356	0.768*	11.178	3.212*	14.151
Std.Dev	0.111	0.994	0.003	0.020	0.007	0.111	0.081*	1.803	0.095	0.779
Travel cost (€/rescaled by 10)										
Mean	−2.419*	−23.242	−1.907*	−4.340	−3.332*	−11.951	−2.062*	−3.749	−4.690*	−7.790
Std.Dev	0.033	0.503	0.662*	2.698	0.607*	3.859	0.486*	5.135	0.423	1.415
Satiation constant parameter	0.605*	4.250	1.256*	4.026	0.869*	5.181	1.289*	3.758	1.610*	4.521
Single person household (No is base)	0.534	1.427	0.815*	2.558	0.234	0.813	−0.141	−0.339	0.517	1.179
Kids (No is base)	0.001	0.006	0.400*	1.983	−0.106	−0.595	−0.621*	−2.457	−0.018	−0.084
Outdoor activity (No is base)	0.399*	2.608	0.405*	1.863	0.243	1.390	0.457*	2.106	0.420*	2.000
Log of average minimum temperature	−0.108	−0.877	0.288*	2.255	0.127	0.948	0.257*	1.762	0.547*	4.079
Environment spatial matrix parameter					0.455* (15.637)					
Household spatial matrix parameter (rescaled by 10)					−0.056* (−1.956)					
Sigma					0.290* (14.052)					
Goodness of fit measures										
Initial log-likelihood					−10,464.265					
Log-likelihood at convergence					−3,505.227					
#of parameters estimated					60					
#of respondents					794					
Rho^2					0.659					
Adj. Rho^2					0.665					
AIC					7,130.454					
BIC					7,411.079					

*Parameters are statistically significant.

that capturing underlying environmental similarities between national parks helps assess trip preference patterns better.

Overall, the coefficient estimates provide interesting insights into the determinants that impact on the decision to visit national parks for recreational use. Focusing on the baseline specification, excluding for PN-ALM, the ASCs are found to be statistically significant and negative, with the sign being expected in view of the travel participation rates reported in Table 2. The mean structural parameters for the accessibility index are all positive and significant. We can, hence, conclude that visitors are more inclined to visit National Parks endowed with a comparatively high level of accessibility. The corresponding standard deviation parameters are all statistically significant (except that for PN-ATE), corroborating the assumption of heterogeneity in respondents' preference.

Similarly, the estimates for the means of the random coefficients for the attractiveness index are all positive and statistically significant, suggesting that visitors tend to select destinations with a wide range of tourism amenities. This result can be of particular interest for policymakers and stakeholders that operate in the tourism industry as potential investments aimed at extending the variety of attractions and services are likely to positively drive the recreation demand of the destination. The estimates for the standard deviation parameters are statistically significant only for PN-DB, revealing the existence of heterogeneity across decision-makers for this destination.

With respect to the impact of travel cost on the frequency of visit, the estimated mean coefficients are all negative and statistically significant. We can, hence, assert that, as expected, the propensity to visit a National Park diminishes as the travel cost increases (Franceschinis *et al*. 2022; Signorello *et al*. 2009; Sinclair *et al*. 2022). The statistical significance of some standard deviation parameters confirms the presence of heterogeneity in the way respondents perceive travel costs. Of interest, however, is the estimated parameter associated with the interaction between the economic spatial matrix and the travel cost variable. This is statistically significant and negative (−0.056), suggesting that recreationists with similar economic traits tend to have the same negative sensitivity toward travel related expenses. This is unsurprising, but this innovative interaction effect allows the model to capture a degree of economic proximity between individuals' travel behaviors that is likely to be ignored by traditional econometric models that omit spatial features of this type.

Now we turn our attention to the satiation parameters that represent the total number of trips demanded. In our results, satiation constants are all statistically significant and positive with that related to PN-DG having the highest satiation coefficient whilst that of PN-DLM being closest to zero. The interpretation of this finding is that tourists are more willing to make repeat visits to the former than to the latter before reaching satiation. Single person households seem to be more inclined to repeat trips to the PN-ATE compared to households with more than one adult. This finding perhaps captures the fact that large households are more likely to experience travel budgetary constraints than single adult households. So, they tend to limit the number of trips to distant national parks, preferring closer destinations. A further plausible explanation is that the choice of a holiday destination can be thought of as the outcome of a family decision-making process involving individuals who might have different preferences, and this process tends to favor different destinations, rather than repeat visits to the same recreation site.

Households with children appear to be less inclined to repeat trips to PN-DB, but positively inclined to repeat visits to PN-ATE. The negative coefficient for PN-DB might capture monetary constraint patterns across respondents. Although the Dolomites are world-renowned as quality destinations for family holidays, their tourism services tend to be comparatively more expensive, resulting in a lower number of repeat visits. Performing outdoor activities during the year is associated with repeating trips to destination sites, with the greatest satiation effect associated with PN-DB. Three out of five national parks have positive estimates of satiation parameters for the logarithm of the average minimum temperature recorded between June and August 2022. This implies that, as the minimum temperature increases, recreationists tend to repeat trips to these parks (Richardson and Loomis 2004; Scott, Jones, and Konopek 2007). The estimated autoregressive coefficient is positive and equals 0.46, suggesting the presence of strong environmental dependency across the five national parks under study. Finally, the scale parameter (i.e. sigma) is found to be statistically significant confirming that despite the absence of price variation it can be identified and estimated (Bhat 2018).

Tables 7 and 8 present the own and cross elasticities of travel demand under two policy scenarios, with these being (*a*) improving access, and (*b*) reducing travel cost. Table 7 displays that the travel participation rate to all National Parks decreases when their own destination accessibility improves (own elasticities are displayed in gray along the main diagonal of the table matrix). The highest own elasticity measure is observed for PN-ATE (+ around 31%), whereas the lowest value is associated with PN-ALM (17.22%). The cross elasticity measured between PN-ALM, and PN-G is −4.04%, suggesting that the expected travel participation rate to the latter will reduce compared to that of the base scenario when accessibility improves PN-ALM. The cross elasticity between PN-ATE and PN-CT also decreases by a similar magnitude of −3.15%, which reveals that the predicted probability of visiting PN-CT is estimated to diminish with respect to the base scenario. This finding is somewhat expected, as these two parks are likely to be competitors given their geographical proximity (the two national parks are at a reciprocal distance of approximately 65 km or 40 miles). PN-CT shows strong substitutability also with PN-G as well as with PN-ATE. Improving accessibility to PN-DB diminishes the travel participation rate to PN-ATE by 1.4%. Finally, accessibility improvements to PN-G are only likely to capture a very small proportion of the trips to PN-ATE as the cross elasticity is only −0.85%.

The results of the second simulated scenario are outlined in Table 8. Unsurprisingly, all own elasticities are found to be positive: the travel participation rate is expected to increase when own travel cost decreases by 15%. The highest increase in expected travel participation rate is associated with PN-ATE, with an own

Table 7. Increment of 25% in the level of accessibility.

Base scenario (status quo)	PN-ALM	PN-ATE	PN-CT	PN-DB	PN-G
PN-ALM	17.122%	−0.284%	−0.971%	−0.755%	−4.036%
PN-ATE	−0.993%	30.966%	−3.155%	−1.132%	−1.794%
PN-CT	−0.248%	−3.977%	18.689%	−3.396%	−4.036%
PN-DB	0.000%	−1.420%	−1.699%	18.868%	−1.794%
PN-G	−0.993%	−0.852%	−1.699%	−1.509%	19.731%

Table 8. Reduction of 15% in the travel cost.

Base scenario (status quo)	PN-ALM	PN-ATE	PN-CT	PN-DB	PN-G
PN-ALM	16.873%	−1.136%	−0.485%	−0.755%	−2.691%
PN-ATE	−0.496%	10.795%	−0.485%	−0.377%	−0.448%
PN-CT	−0.248%	−0.852%	9.223%	−1.887%	−1.794%
PN-DB	0.000%	0.000%	0.000%	6.792%	−0.897%
PN-G	−0.496%	0.000%	−0.243%	−0.377%	11.659%

elasticity of travel demand being equal to 18.87%. The travel demand for PN-ALM, PN-ATE, and PN-CT is inelastic to travel cost changes of PN-DB. On the other hand, the travel participation rate for PN-ALM is expected to decrease, relative to those observed in the base scenario when the travel costs to PN-G drops by 15%.

5. Discussion and concluding remarks

In this study, we develop a spatial-based MDCEV model to study preference for outdoor recreation at five national parks, with the proposed model being applied to data extracted from an online survey completed by 794 Italian outdoor recreationists. National parks are herein assumed to be imperfect substitutes, and the appeal of the MDCEV is that it allows the simultaneous assessment of the decisions regarding what national park to visit together with the trip frequency to each selected destination. Unlike previous spatial-based models published in the literature (Egan and Herriges 2006), we propose a spatial dependency structure that requires no normalization assumptions to be made by the analyst on the variance-covariance matrix to avoid convergence instability. In addition to this, the proposed specification allows for capturing unobserved correlation patterns across National Parks within the environmental space. This may be of interest to policymakers and stakeholders as it provides an improved understanding of whether travelers choose to visit certain nature sites that share some common features such as the proportion of water bodies or presence of wetlands.

Within the model specification, the national parks were described with the aid of the accessibility and attractiveness indexes, with both indexes being included in the discrete stage of the model. We find that the upgrade of the current accessibility level is likely to result in a higher travel participation rate to each recreation site. In a similar vein, improving the tourism offerings may attract a larger flow of visitors to these protected areas. We also estimate that, the likelihood of visiting these destinations is predicted to decrease, as one would expect. The parameter for the interaction between travel cost and the matrix of household distances reveals that travelers with similar economic characteristics are likely to show the same (negative) price sensitivity. This expected finding corroborates the ability of the employed individual's characteristics, which are based on a spatial matrix, to detect economic patterns that would otherwise remain unobserved in traditional travel cost models.

The model simulations of two policy scenarios are also informative. For example, in the first policy scenario we simulate an accessibility improvement of 25% and find that travel participation rate at each destination site also increases, which is a positive change to the extent of the recreation market. This finding can help destination marketers design targeted investments to improve access by strengthening the transport system around national parks. A possible policy action could be to improve public transport connectivity (e.g. better and more bus lines) operating between national parks and the nearest train station. The second scenario reveals that leisure visits are expected to decrease as the travel cost increases. Given that fuel costs make up a large proportion of the travel cost, destination managers may liaise with private transport operators so as to provide integrated mobility packages that pair, for example, private shuttle services (from airports, bus hubs, and rail stations to nature sites) with accommodation.

The model specification developed in this study could be further advanced to obtain a more comprehensive overview of travelers' preferences for nature reserves. For instance, it would be worthwhile incorporating interaction terms into the proposed utility structure to account for complementarity and substitutability across protect areas. Our utility function is additively separable and, hence, it fails to accommodate full substitution patterns in consumption (Bhat, Castro and Pinjari 2015; Pellegrini, Pinjari, and Maggi 2021; Pellegrini *et al*. 2019). A further advancement could be to employ a latent class spatial-based MDCEV model, with different spatial matrixes being employed in each latent segmentation class. This would help to unveil differences in individuals' travel preference behavior across segments of the sample.

Notes

1. The land cover index, Agricultural pressure outside the national park, corresponds to the intensity of expansion of agricultural activities in the proximity of the national park site.
2. The distributions for fuel prices are assumed to be uniform distributed with lower and upper intervals being the minimum and the maximum petrol prices reported in Italy between December 2020 and October 2022.
3. Given that the log-normal distribution spans solely the positive domain and the travel cost is expected to have a negative coefficient for all excursionists, the negative of the travel cost enters the model specification (see, Train 2009, chapter 6, 148).
4. The sampling strategy involved recruiting respondents from all 20 Italian regions, aiming for an adequate convergence in terms of nature and protected reserves. Also, the provider was instructed sample respondents to closely match the age and gender distributions of the Italian national population.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Supplemental data

Supplemental data for this article can be accessed here.

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