Applying the contingent behavior method at the regional level: Evidence from forest recreation

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Abstract

Contingent behavior (CB) studies typically analyze changes in recreation demand at single sites by presenting identical scenarios to all respondents. This prevents assessing demand responses under diverse future conditions and across broader spatial scales. The present study applies the CB method using a general population survey, integrating self-reported site characteristics with an experimental design to define CB scenarios. This allows recreation demand to be modeled as a function of multiple environmental attributes and analyzed regionally but requires adjusting the prediction procedure. Using data on forest recreation in Mecklenburg-Western Pomerania, Germany, we propose approaches for site- and region-level predictions.

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1. Introduction

Understanding how environmental conditions and changes thereof affect well-being is crucial for effective environmental management if the aim is to improve social welfare. One component of this is the recreational value that nature sites generate. The combined travel cost and contingent behavior (TC-CB) method has long been used to assess not only the recreational value of a particular site but also the effects of potential changes in site conditions on visit frequencies and recreational value. A wide range of locations, among them beaches (Börger, Mmonwa, and Campbell 2023; Egan et al. 2023), lakes (Lankia, Neuvonen, and Pouta 2019; Tienhaara et al. 2021), forests (Christie, Hanley, and Hynes 2007; Melichar 2022), and urban ecosystems (Mäntymaa et al. 2021) have been studied using the TC-CB method. Typically, these studies are based on data collected at one (or a small number of) recreational sites. As a result, there is little or no variation in current site characteristics.[1] Moreover, such on-site studies usually present predefined scenarios of changing site conditions which all relate to the current conditions at the investigated site as a baseline (e.g., Egan and Herriges 2006; Barry, Van Rensburg, and Hynes 2011; Kipperberg et al. 2019). Recently, however, the literature has seen TC-CB studies based on general population surveys which do not refer to one specific site but ask respondents about visits to a particular site *type* (e.g., Bertram et al., 2020; Börger et al., 2021).

Bertram et al. (2020) ask respondents to indicate their most frequently visited location at the German Baltic Sea coast in a mapping tool implemented in an online survey. These authors then ask respondents to assess several water quality attributes at these locations and present three scenarios of potential quality changes, for which they record the number of future CB trips. The study by Börger et al. (2021) draws on a general population survey conducted in 14 European countries. The survey asks respondents to identify the last blue-space location they have visited and then goes on to collect information on this visit. The latter includes information on perceived water quality at the site, which is then varied in two CB scenarios.

Basing the TC-CB method on data from general population surveys, rather than conducting on-site questionnaires at many different locations, and eliciting perceived site characteristics facilitates applying the methodology at a regional scale. In particular, it makes the approach independent from the availability of comprehensively defined site-level data. By contrast, revealed-preference discrete choice travel cost models require the characterization of both visited and unvisited sites to estimate a utility function and derive welfare measures. Some discrete choice studies have relied on high-resolution spatial information to characterize large numbers of recreation sites at a regional scale (e.g., Agimass et al. 2018; Becker, Börger, and Meyerhoff 2025). For several attributes central to the present analysis, however, comprehensive environmental data are not available, which is one motivation for the use of the TC-CB method in this study. Further motivations for using this approach include its ability to jointly inform the estimated behavioral parameters through revealed and stated preference information and its capacity to test for consistency between observed and contingent behavior. Finally, the panel structure of the combined revealed and stated trip counts offers a way to account for unobserved heterogeneity through fixed or random effects that absorb individual-specific influences (cf. Englin and Cameron 1996; Egan and Herriges 2006). As omitted variables that covary with travel costs are a main concern in travel cost models (Randall 1994), this aspect is particularly useful to avoid corresponding biases.

Besides regional scope, a key feature of the present TC-CB study is the use of an experimental design to construct CB scenarios that vary across respondents. Specifically, we define CB scenarios according to a full factorial design of environmental attributes and present each respondent with a randomized subset of all possible scenarios. This approach increases the variation in the changes presented to respondents and thereby enables the TC-CB method to capture recreation demand as a function of a broader range of site characteristics. In the deterministic setting where all respondents face the same predefined scenarios, the analyst is confined to evaluating a few specific shifts between fixed attribute levels. When scenarios are varied experimentally across respondents, by contrast, marginal effects for a much wider range of environmental changes can be assessed. An experimental variation of CB scenarios is thus particularly useful when several environmental conditions are relevant and trade-offs among them are of interest.

Applying the TC-CB method at a regional scale through a general population survey with an embedded experimental design, however, has two important implications. First, since respondents typically have access to more than one recreation site in a region—and different individuals visit different sites—current site conditions vary across respondents and are typically unknown to the researcher. Valuing environmental change, however, requires at least information on the status quo (SQ) at the visited sites. The few existing TC-CB studies considering multiple locations have therefore based the definition of the SQ on respondents' self-reported assessment of environmental conditions (Hanley, Bell, and Alvarez-Farizo 2003; Lankia, Neuvonen, and Pouta 2019; Bertram et al. 2020). In the absence of consistently available environmental information, using such perception data is typically the only approach that allows to recover an estimate of the current regional distribution of site qualities, which can then serve as a baseline to evaluate potential changes.[2]

Second, the fact that the resulting data contain information on multiple visited sites whose conditions are experimentally varied in the CB scenarios affects how predictions of future visit frequencies under changing environmental conditions must be made. Within this framework, contingent visits for an environmental change (e.g., an increase in the deadwood level) are only recorded for a subset of respondents—those who have visited a site where this attribute level was not already present and who were exposed to the corresponding change in at least one CB scenario. The resulting data structure thus limits the available information for certain environmental changes and requires additional assumptions—as well as a modified approach—to enable predictions of the associated shifts in demand.

Building on previous TC-CB studies that use general population surveys, perception-based SQ conditions, and refer to multiple recreation sites (Bertram et al. 2020; Börger et al. 2021), the present study extends this line of work by focusing on the corresponding predictions procedure. Specifically, we address how demand changes can be predicted in a framework that combines these elements with experimentally varied CB scenarios. We discuss the assumptions required for generating such predictions and introduce two procedures: (1) a *single-site effect approach,* suited to predicting changes in visitation at the individual site level, and (2) a *regional extrapolation approach* appropriate for assessing changes in visit frequency at a regional scale. We then compare demand effects across both approaches for four forest management scenarios.

In addition to Bertram et al. (2020), who were the first to randomly assign quality levels to CB scenarios, we further increase the variation in the experimentally defined environmental changes by conditioning them on respondents' perceived site characteristics and excluding the SQ combination from the set of possible scenarios. This design feature should help improve model efficiency and allow for a more precise analysis of marginal effects. Finally, we use a set of hand-drawn pictograms to illustrate forest attributes. While the use of images is not new in stated preference studies (e.g., Larsen and Nielsen, 2007; Sacher et al., 2022), we aim to contribute to best practices by integrating the same pictograms into the revealed preference part of the survey to elicit respondents' perceptions of forest attributes in the SQ, which are subsequently used in the CB scenarios to depict hypothetical changes. This consistent visual format is intended to improve communication and reduce potential misinterpretation of environmental characteristics.

The application of this study is forest recreation in the federal state of Mecklenburg-Western Pomerania (MWP) in northern Germany. Forests provide a wide range of ecosystem services (Grammatikopoulou and Vačkářová 2021), but face increasing pressures in Europe that include extreme weather events and pest infestations, among others (Forzieri et al. 2021; Vacek, Vacek, and Cukor 2023). In response, high level policies such as the New EU Forest Strategy for 2030 (Commission of the European Union 2021) call for management approaches that enhance climate resilience and halt biodiversity loss in European forests. Recreation, as the most important cultural ecosystem service (Hanley, Shaw, and Wright 2003), is likely to be affected by changes in forest conditions that result from departures from current management practices. Against this background, the present study examines how potential future shifts in forest conditions—driven by a transition towards management approaches focused on resilience and biodiversity—may affect recreation demand in the study region.

The remainder of this paper is structured as follows. In Section 2, we explain the selection of attributes and describe the CB design as well as the computation of travel costs. In Section 3, we present the econometric approach used to model recreation demand and explain how predictions should be conducted in the proposed modeling framework. Results are provided in Section 4 and interpreted in terms of the welfare implications of four environmental changes. Section 5 presents a discussion of the results and some conclusions.

2. Methods

Survey design and selection of structural forest attributes

The present study collected data in a web-based survey[3] in which respondents were first asked whether they live in MWP and have visited a forest in this federal state in the past six months. Those who did not meet both criteria were screened out. To account for seasonal variation, the survey was conducted in two waves: the first at the end of March 2023, collecting data on past forest visits during the colder half of the year (October to March) and planned visits for the upcoming warmer season (April to September); the second at the end of September 2023, capturing past trips during the warmer season and planned trips for the colder months. A total of 1,361 individuals participated in the survey, with 951 of them providing complete data, corresponding to a response rate of 69.9%.

Respondents included in the sample were asked to indicate the forest site they had most recently visited from their place of residence by placing a marker in an interactive mapping tool based on standard OpenStreetMap (OSM) tiles. They were then asked to characterize this site with respect to three structural forest attributes: (1) the tree species composition (deciduous, mixed, or coniferous), (2) the level of deadwood (low or high), and (3) the tree size variation (uniform or diverse). Thematically, these attributes were selected in light of growing demands for a shift away from even-aged, production-oriented forest management (plantation forestry) towards more nature-based stand structures in Europe (German Federal Ministry of Food and Agriculture 2020; Commission of the European Union 2021). Such a transition towards nature-based management practices (Gamborg and Larsen 2003; Larsen and Nielsen 2007) calls for a better understanding of how the resulting forest structures affect recreational value.

Nielsen et al. (2007) identify the three structural forest characteristics that are central when adopting such a management approach in the temperate nemoral zone to which the study region belongs: (1) The tree species composition which in nature-based forests corresponds to broadleaf or mixed broadleaf stands that are adapted to the nutrient potential of the soil, do not impair its fertility, and exhibit greater resilience to biotic and abiotic stressors than coniferous stands in that region. (2) The trees size variation (or canopy structure), which serves as a direct proxy for the silvicultural system applied.[4] Higher levels of size variation result from selective harvesting under nature-based management, whereas intensive even-aged management practices involving clear-cuts produce structurally poor stands with little or no variation. (3) The amount of deadwood, including standing and fallen dead trees as well as other coarse woody debris. These elements are an important feature of nature-based forests and known to promote biodiversity (e.g., Esseen et al., 1997; Jonsson et al., 2005), whereas intensively managed forests typically show low levels of such residues.

<<Fig 1 around here>>

To elicit the characteristics of the status quo, respondents were asked to describe the forest they had most recently visited with respect to these three attributes. For this purpose, the survey used twelve forest pictograms developed by Sacher et al. (2022) based on original drawings by Anders Busse Nielsen, each representing a unique combination of attribute levels (see Fig 1). The elicitation process was structured into three steps. First, respondents were asked to select the tree species composition—broadleaf, mixed, or coniferous—using three corresponding pictograms displayed on a dedicated survey page (see first column of Fig 1). On the next survey page, respondents were then shown two pictograms illustrating the binary tree size variation attribute. These pictograms reflected the tree species composition selected in the first step but corresponded to different size structures (uniform vs. diverse), and respondents were asked to select the pictogram that best matched their most recently visited forest. Third, the deadwood level was recorded by presenting two pictograms—one showing a high, the other a low level of deadwood—while the other forest attributes were again matched to the characteristics indicated previously. Finally, respondents were shown the forest pictogram corresponding to their combined selections and asked to either confirm the displayed attribute levels or return to the first step to revise their SQ forest description.

This stepwise procedure ensured that the pictograms were displayed at an adequate size—especially on mobile devices, which tend to play an increasingly important role in web-based environmental valuation surveys (Sandorf, Grimsrud, and Lindhjem 2022). It also simplified the task of describing the visited forest by introducing only one attribute at a time. After determining the SQ perceptions, respondents were asked how often they had visited this forest in the past six months and how often they intend to visit this forest in the next six months under unchanged conditions.

The next survey page introduced the purpose and structure of the ensuing CB questions by explaining that forest management has an impact on forests' tree composition, tree size variation, and deadwood volume, and that the survey investigates how these characteristics affect the attractiveness of forests for recreational purposes. Respondents were also informed that they would be presented with four scenarios of potential changes to the forest they had last visited and that, for each scenario, they would be asked how often they would visit this forest in the future. Lastly, it was mentioned that these scenarios would be illustrated by pictograms contrasting the forest in its current state with an altered version.

The scenarios presented to respondents were drawn randomly without replacement from the full factorial of forest attribute combinations shown in Fig 1, but excluding the individual-specific SQ forest. In each CB question, the pictograms of the most recently visited forest under current and hypothetical conditions were presented side by side to illustrate the corresponding environmental changes. On this basis, respondents were asked how often they would visit the forest in the subsequent six months under the altered conditions, while also being reminded of their previously stated intended visit frequency under unchanged conditions. Finally, respondents were asked to indicate the location of their place of residence with a second marker in the mapping tool and to report the transport mode they used to reach the forest.[5]

Travel costs

To construct travel costs, travel distances were computed as the shortest paths along the road network using the Open Source Routing Machine by Luxen and Vetter (2011) in combination with OSM data. Travel times were computed using the same tool, and the opportunity cost of travel time was conservatively estimated as one third of the product of hourly income and travel time (in hours).[6] Travel costs were then calculated as the sum of the opportunity cost of travel time and vehicle operating cost. The latter covers depreciation and maintenance (Czajkowski et al. 2019) and was assumed to be EUR 0.30 per kilometer for car travel (tax reimbursements for motorized travel to work in Germany) and EUR 0.06 for travel by bicycle, following Brühbach (2009). For respondents who walked to the forest site, only the opportunity cost of travel time was considered.

The present approach of locating trip origins and destinations via an interactive mapping tool allowed us to elicit visit information with a high spatial resolution. Compared to travel cost studies that often rely on postal codes (e.g., Czajkowski et al., 2015) or location names (e.g., Hanley et al., 2003a) to identify residences and/or site locations, this method likely enhances the precision of the spatial information—assuming the accuracy of the markers placed by respondents in the mapping tool exceeds, for example, the resolution of postal code areas. This is particularly relevant in the presence of a large share of short-distance trips, as even small location inaccuracies can lead to considerable relative errors in travel cost estimates.

3. Econometric approach

A joint econometric model of actual trips in the past and hypothetical future trips must address several issues. First, the dependent variable is a non-negative integer, which requires a count data modeling approach. Second, the dependent variable is a (quasi) panel variable, in which one observation per respondent refers to past visits and is pooled with additional observations that refer to future visits under current and hypothetical conditions by the same respondent. Hence, a suitable model needs to account for intra-respondent correlations of trip counts, reflecting that respondents who conducted more visits in the past are likely to also visit more frequently in the future. Third, the number of past trips is a zero-truncated variable, as only respondents who made at least one visit in the past six month are included in the visit demand model. Non-visitors cannot be included as the site they would potentially visit is unknown so that no travel cost variable can be constructed.

Econometric approaches handling zero truncation have typically addressed this issue jointly with the problem of endogenous stratification (Shaw 1988; Creel and Loomis 1990; Grogger and Carson 1991; Englin and Shonkwiler 1995), i.e., an overrepresentation of avid site users in on-site samples, on which most TC-CB studies are based. Datasets derived from general population surveys, however, do not suffer from endogenous stratification as the probability of being sampled is independent from past visitation frequency. The number of future CB trips, however, remains incidentally truncated (Egan and Herriges 2006), as the strict truncation of past trips increases the likelihood that CB trips are truncated as well. Yet zero visits may still occur in case respondents anticipate to not visit a site under changed conditions. Therefore, a suitable model must account for both the strict truncation of past visits and the incidental truncation of CB trips to recover recreation demand for the whole population. Finally, an appropriate count data model should allow for the possibility of overdispersions, that is, situations in which the conditional variance of trip counts exceeds their conditional mean (Wooldridge 2001).

The multivariate Poisson lognormal model

To analyze the recorded trip count data, we employ the multivariate Poisson lognormal (MPLN) model (Egan and Herriges 2006). This model is based on a system of count data equations that are linked via correlated error terms and that can accommodate the previously mentioned issues including incidental truncation. To derive the MPLN visit count probabilities, consider a respondent i who reports J trip counts $\boldsymbol{y}_i = [y_{i1}, y_{i2}, \dots, y_{iJ}]$ to a recreation site, where $j = 1$ represents past trips, $j = 2$ future trips under current conditions, and $j > 2$ CB trips under altered conditions. As the number of trips is a count variable, Poisson distributions are suitable to express the probability of respondent i to report y_{ij} visit counts in scenario j. To account for strict zero truncation of past trips, these must be modeled employing the zero-truncated version of the Poisson distribution, i.e.,

$$\Pr\left(Y = y_{i1}|\lambda_{ij}\right) = \frac{e^{-\lambda_{ij}}\lambda_{ij}^{y_{ij}}}{y_{i1}!}\left[\frac{1}{1-e^{-\lambda_{ij}}}\right], j = 1 \quad [1]$$

whereas future hypothetical trips are modeled using the untruncated Poisson distribution:

$$\Pr\left(Y = y_{ij}|\lambda_{ij}\right) = \frac{e^{-\lambda_{ij}}\lambda_{ij}^{y_{ij}}}{y_{ij}!}, j > 1. \quad [2]$$

The expected individual trip demand λ_{ij} can then be parameterized as $\lambda_{ij} = \exp\left(\phi_j + \boldsymbol{\beta}'_j\mathbf{x}_{ij}\right)$, where $\mathbf{x}_{ij}$ is a vector of respondent and site characteristics, $\boldsymbol{\beta}_j$ a parameter vector to be estimated, and ϕ_j a set of scenario specific constants. In the present study, we assume that $\boldsymbol{\beta}_j = \boldsymbol{\beta}$ for all j, i.e., the effects of socio-demographics and site characteristics on visit frequency are constant across the observed and CB visits. Intra-respondent correlations between trip counts are accounted for via a scenario-specific error term following a multivariate normal distribution with mean zero and covariance matrix $\boldsymbol{\Sigma}$, i.e., $\boldsymbol{\varepsilon}_i \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Sigma})$. With $\mathrm{J} = 6$ trip counts per respondent, the elements of $\boldsymbol{\Sigma}$ are given by

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} & \sigma_{16} \\ & \sigma_2^2 & \sigma_{23} & \sigma_{24} & \sigma_{25} & \sigma_{26} \\ & & \sigma_3^2 & \sigma_{34} & \sigma_{35} & \sigma_{36} \\ & & & \sigma_4^2 & \sigma_{45} & \sigma_{46} \\ & & & & \sigma_5^2 & \sigma_{56} \\ & & & & & \sigma_6^2 \end{bmatrix}. \quad [3]$$

The joint probability of a series of J trip counts $\mathbf{y}_i$ is the J-dimensional integral over the correlated trip count equations:

$$Pr(y_i|\lambda_i) = \prod_{j=1}^{J} Pr\left(Y = y_{ij}|\lambda_{ij}\right) = \int\int \dots \int \prod_{j=1}^{J} \frac{e^{-\lambda_{ij}}\lambda_{ij}^{y_{ij}}}{y_{ij}!} \frac{\exp(-0.5\boldsymbol{\varepsilon}_i'\Sigma^{-1}\boldsymbol{\varepsilon}_i)}{\sqrt{(2\pi)^J|\Sigma|}} d\boldsymbol{\varepsilon}_i \quad [4]$$

The advantage of linking the demand equations for hypothetical behavior ($j > 1$) with the zero-truncated distribution representing observed past trips ($j = 1$) via a correlated error structure is that this allows to account for incidental truncation in hypothetical future trips. The parameters

$\boldsymbol{\beta}$ and ϕ_j are estimated via simulated maximum likelihood employing Latin hypercube sampling with 1,000 random draws per individual using R (R Core Team 2023). Other studies employing the MPLN model include Awondo et al. (2011), (Börger et al. 2021; Börger, Mmonwa, and Campbell 2023), and Voltaire and Koutchade (2020).

Consumer surplus

As a result of the semilog specification of the expected number of trips λ_{ij}, the consumer surplus (CS) of an average trip is $-{\beta_{tc}}^{-1}$, where β_{tc} is the coefficient of travel cost. The effects of varying environmental quality on CS in a certain period can then be calculated as

$$\Delta \mathrm{CS}_i = \frac{-1}{\beta_{tc}}(\lambda_i(\mathbf{x}_{i1}) - \lambda_i(\mathbf{x}_{i0})), \qquad [5]$$

where $\mathbf{x}_{i0}$ contains the environmental qualities perceived by respondent i in the SQ, and $\mathbf{x}_{i1}$ the environmental qualities in a specific CB scenario. Note that the welfare effect of a change in site characteristics depends on the difference between the predicted number of trips under current and hypothetically changed site quality levels. Confidence intervals for the expected changes in CS can be computed by means of simulation (Krinsky and Robb 1986).

Predictions of changes in recreation demand

As the MPLN formulation employed in this study corrects for both strict and incidental zero-truncation and accounts for intra-respondent correlation in trip counts via a correlated error structure, predictions must be generated by inserting the estimated behavioral parameters together with all potential trip counts into equation (4). This is necessary to compute the visit expectation for a future reporting period. Using $\hat{\lambda}_{ij} = \exp\left(\hat{\phi}_j + \hat{\boldsymbol{\beta}}_j \mathbf{x}_{ij}\right)$ directly to compute respondent i's expected number of visits under site conditions $\mathbf{x}_{ij}$, and then averaging across the sample to estimate population-level effects would lead to biased results. With a reporting period of six months (or 183 days) in the present study, the predicted number of trips for respondent i under scenario j is

$$\hat{Y}_{ij} = \sum_{n=1}^{183} nPr(Y = n|\hat{\lambda}_{ij}) = \sum_{1}^{183} n \int \frac{e^{-\hat{\lambda}_{ij}}\hat{\lambda}_{ij}^{n}}{n!} \frac{\exp(-0.5\boldsymbol{\varepsilon}_i'\Sigma^{-1}\boldsymbol{\varepsilon}_{\mathbf{i}})}{\sqrt{(2\pi)^J|\Sigma|}} d\boldsymbol{\varepsilon}_{\boldsymbol{j}}\,, \qquad [6]$$

where $\hat{\lambda}_{ij}$ represents the expected number of trips as a function of the estimated parameters. $\int(\ldots)\ \delta\varepsilon_j$ is the partial integrand over the error component corresponding to scenario j.

An advantage of the present modeling framework with random variations in the CB scenarios is that the effects of any isolated or combined change of site characteristics in the model domain can be estimated. This is achieved by comparing the predicted number of future trips under a given change scenario with those predicted under baseline conditions. A key aspect in this context is the treatment of the baseline. In the present setup, unlike in single site CB studies, current conditions differ across respondents, as they reflect individual perceptions and typically refer to different sites. Correspondingly, environmental changes at the regional level will typically affect only a subset of sites. A deadwood enrichment policy that raises deadwood levels from low to high, for example, will only affect those sites where deadwood levels are currently low. As a result, the relevant population will also only be partially affected. When regional welfare or demand changes are of interest, the attribute levels under scenario $j = 2$ should therefore be retained as perceived by respondents during their visit. This procedure—hereafter referred to as the *regional extrapolation approach*—by using perceived status quo conditions to calculate baseline demand expectations, implicitly accounts for the current distribution of site characteristics and ensures that region-level predictions reflect who is actually affected by potential changes.

Alternatively, one might be interested in evaluating demand and welfare effects at the level of a single site that is subjected to a particular change. In this case, the targeted attributes should be set to a common base level for all respondents to derive a baseline demand expectation. In the deadwood enrichment example, this means artificially setting the deadwood level to low, even where respondents perceived it as high, and then predicting baseline demand for $j = 2$

under these conditions. An advantage of this procedure, which we refer to as the *single-site effect* approach, is that it allows using the full sample of respondents and the complete set of simulation draws to approximate the integral over the error term in Equation (6) when generating a site-level prediction. Since forest sites in the current setup represent a generic good—referring to different locations visited by different individuals—it is also conceptually reasonable to include all respondents in the prediction process. The resulting effects thus represent the expected change in recreation demand at a representative site undergoing the specified change in characteristics.

Two further considerations related to the post-change demand prediction are important in the present framework. The first concerns the treatment of the attributes being examined for their effects on recreation demand. Since CB scenarios are assigned randomly, only a subset of respondents will have been exposed to a specific change of interest, such as an increase in deadwood. To ensure that predictions can be calculated consistently across all respondents and scenarios, the attributes targeted by a given policy should therefore be set to their post-change levels for all scenarios $j > 2$. Keeping the targeted attributes at their originally assigned levels, by contrast, would restrict predictions to those scenarios in which respondents were actually presented with the post-change values of interest. This, in turn, would sharply reduce the number of usable observations, particularly for changes involving multiple attributes.

The second consideration concerns the treatment of attributes not affected by a given policy in the change scenarios ($j > 2$), such as tree species composition under a deadwood enrichment policy. Unlike traditional TC-CB studies that present predefined scenarios to respondents, the current setup allows all attributes to vary randomly. To isolate the effect of interest, non-targeted attributes should therefore be set to the same levels used to predict the demand baseline. Leaving them unchanged risks bias, as the attribute combinations shown to respondents—even when drawn uniformly from a full factorial design—still reflect the existing distribution of site characteristics in the region. For instance, if tree size variation is predominantly diverse, respondents will likely have encountered more scenarios with uniform tree size, since the status quo configuration is not repeated. This correlation between targeted and non-targeted attributes would introduce endogeneity and thereby bias predictions. A summary of the two prediction approaches suitable within the present TC-CB framework is provided in Table 1.

<<Table 1 around here>>

4. Results

Sample and perceived site characteristics

The survey was conducted in March and September 2023, yielding a total of 951 completed responses. Table 2 shows the perceived site characteristics. It also reports sample averages for travel distances and costs to the most recently visited forest site, as well as the number of actual and hypothetical trips during the colder and warmer halves of the year. Respondents in the first survey wave in March conducted an average of 13.45 forest visits in the colder half of the year (*visits.winter*) and anticipated 13.99 trips for the upcoming warmer season (*hyp.visits.summer*). Those in the second wave (September) took an average of 12.14 forest visits in the warmer half of the year (*visits.summer*) and anticipated 10.73 trips for the upcoming colder season (*hyp.visits.winter*).

The average travel cost of a forest trip in the region is EUR 4.69 per respondent, and the average travel distance in the road network is 13.31 km. Table 2 also provides information about the type of activity carried out during the last forest visit. According to this, 31% of the respondents walked their dog during that visit, 22% engaged in a sportive activity such as running or cycling, and 13% in a nature-based activity such as mushrooming or bird watching, while 35% reported doing something else.

<<Table 2 around here>>

The distribution of perceived environmental attributes at the most recently visited forest sites is presented in Table 3. It shows that 71% of respondents reported having most recently visited a forest with a mixed tree composition, while only 7% visited coniferous sites. This relationship does not solely reflect respondents' preferences for mixed forests over broadleaf or coniferous ones, but at least partially corresponds to the actual distribution of the tree species composition in MWP. Of the 558,000 hectares of forest in MWP—covering 24% of the area of the federal state—50% are covered by conifers and 50% by broadleaf trees, with mixed forests being most common (41%), followed by predominantly broadleaf (33%) and pure coniferous stands (26%) (Ministry for Climate Protection, Agriculture, Rural Areas and the Environment Mecklenburg-Western Pomerania 2012). Moreover, 68% of respondents stated that the forest they last visited featured multiple canopy layers, and 39% perceived the deadwood level there as high. With an actual share of multi-layered forests of 60% in the region (Ministry for Climate Protection, Agriculture, Rural Areas and the Environment Mecklenburg-Western Pomerania 2012), the self-rated description of tree size variation aligns well with the actual distribution of this forest characteristic in the region. Regarding deadwood volume, no environmental data are available that would allow a comparison to the actual regional distribution of this attribute.

<<Table 3 around here>>

MPLN results

The results of the MPLN model are presented in Table 4. Estimates of the trip count correlation parameters (cf. Eq. 3) are omitted for brevity. Besides environmental and sociodemographic variables, the estimated model includes two constants. Since the CB scenarios in this study were defined randomly and do not carry intrinsic scenario-specific meaning, we restrict the model to a single general constant (*const*) capturing the baseline level of trip demand, and an additional dummy variable (*const.CB*) indicating hypothetical behavior ($j > 1$). The latter accounts for systematic differences between the reporting of actual and hypothetical trips. As can be seen in

Table 4, the *const.CB* variable enters the model with a small but statistically significant positive coefficient, indicating slightly higher stated trip counts under hypothetical conditions. Moreover, its interaction with travel cost is positive and highly significant, showing that respondents are less sensitive to travel costs in the hypothetical setting. Together, these results are consistent with the presence of some level of hypothetical bias in the CB responses. However, because both the baseline and change scenarios pertain to future trips within the stated-preference domain, the estimated difference between revealed and stated behavior does not directly affect the predicted demand and welfare outcomes.

In addition, all coefficients in the trip frequency equation are statistically significant at the 5% level and, consistent with expectations, the effect of travel cost (*travel.cost*) on expected visit counts is negative. Based on this parameter, the average value of a recreational forest visit in MWP is EUR 38.46 [95% confidence interval: 34.28, 42.27]. This estimate lies in the upper range of values reported in the travel cost literature. A meta-analysis of 26 European forest valuation studies by Zandersen and Tol (2009) finds, for example, mean consumer surplus (CS) estimates between EUR 0.66 and 112 per trip (mean = EUR 17.30, median = EUR 4.52). More recent revealed preference studies report comparable or lower mean values, ranging from EUR 3.76 in a national study of Denmark (Termansen, McClean, and Jensen 2013) to EUR 21–97 across different regions in Switzerland (Borzykowski, Baranzini, and Maradan 2017). For example, Kaya (2022) estimates a mean CS of EUR 8.76 per trip for forest recreation in Ankara Province, Turkey, Bertram and Larondelle (2017) find EUR 14.95 per visit for an urban forest in Berlin, and Grilli, Paletto, and Meo (2014) report a mean recreational value of EUR 10.57 (median EUR 5.30) based on a meta-analysis of 32 European studies concerning mountain forest.

<<Table 4 around here>>

Note that due to the semilog specification of the MPLN model, the estimated parameters are semi-elasticities, indicating the percentage change in trip frequency resulting from a one-unit change in the corresponding explanatory variable, *ceteris paribus*. Regarding the effect of forest characteristics, two attribute levels have a positive impact on recreation demand, as indicated by their positive coefficients. First, broadleaf forests (*broadleaf.forest*) are, on average, more attractive than mixed forests (the baseline) and associated with 3.7% more expected forest visits. Second, forests with multiple canopy layers (*layer.mult*) also tend to be more appealing and generate, on average, 4.1% more visits than forests with a uniform tree size variation (baseline). In contrast, purely coniferous forest patches (*coniferous.forest*) are expected to receive 11.2% fewer visits than mixed forests. A high level of deadwood (*deadwood.high*) also has a negative effect on expected forest recreation demand, reducing it by 10.6% relative to forests with a low deadwood level (baseline).

With regard to sociodemographic factors, respondents with a university degree (*university.education*) and those who are not fully employed (*not.fully.employed*) make fewer forest visits, as indicated by the negative coefficients. The same is true for respondents who had company during their last forest visit (*company*) or were engaged in a nature based activity (*nature.activity*) such as mushrooming or birdwatching. Age (*age*) has a negative effect on visit frequency, whereas household income (*ln.hh.income*) is positively associated with trip counts. Respondents who have a garden at home (*garden*), and those who walk their dog (*walking.dog*) or engage in sport activities such as jogging or cycling (*sport.activity*) during forest visits, on the other hand, undertake more trips than those who were simply taking a walk (baseline). Finally, the expected number of forest visits also increases with the average duration of a forest stay (*duration*).

Prediction of demand and welfare effects for environmental changes

The following section presents the expected changes in forest visits and CS in response to all examined isolated environmental changes, comparing the two suggested prediction approaches. We begin with the relative predicted changes in recreation demand resulting from changes in tree species composition, level of deadwood, and tree size variation under both approaches (see Fig 2).

<<Fig 2 around here>>

The largest relative change in anticipated forest visits occurs for a shift in forests' tree species composition from mixed to coniferous, which results in an average expected reduction of trips by 9.8% under the single-site effect prediction approach and by 9.3% under the regional extrapolation approach. A change in tree species composition from mixed to broadleaf, on the other hand, increases the number of expected visits by 2.3% at the level of a specific forest site using the hypothetical baseline approach and by 1.6% at the regional level using the actual baseline approach. An increase in the level of deadwood is associated with a reduction of trips. The average expected decrease for a management intervention that increases the level of deadwood is 9.3% at the level of an affected site and 6.4% at the regional level. In contrast, changes in silvicultural practices that increase the tree size variation from uniform to diverse have a positive impact on recreation demand. At the site level, this leads to 2.4% more expected visits under the hypothetical baseline approach and at the regional level to 0.8% more visits using the actual baseline approach. Except for this last scenario representing a regional increase in tree size variation, all predicted changes are significantly different from zero at the 95% confidence level, as indicated by the corresponding confidence bands in Fig 2.

As expected, the magnitude of the predicted relative change is smaller when the regional extrapolation approach is used. This reflects the fact that not all respondents are affected by a potential policy targeting a specific environmental attribute, as their SQ site may already exhibit the intended post-change attribute level. Accordingly, the difference in predicted demand changes between the two approaches depends on the current distribution of site characteristics. When an environmental change is feasible at only a limited number of sites—because the desired post-change condition is already present in many locations (e.g., 68.4% of the visited forests already feature multiple canopy layers)—the discrepancy between the two approaches becomes more pronounced. This is because a substantial portion of the regional population remains unaffected by such a change. Empirically, the differences between the single site and regional prediction approaches are particularly large for policies aimed at increasing deadwood levels and tree size variation. This indicates that many of the visited forest sites in MWP already exhibit the corresponding target conditions.

<<Table 5 around here>>

Table 5 shows the expected absolute changes in the average number of annual forest visits and the corresponding changes in CS per visitor (cf. Eq. 5). These results are reported for each of the four isolated environmental changes and both prediction approaches. The largest change in forest recreation demand and CS is associated with a change in tree composition from mixed to coniferous, which would result in 2.75 fewer visits per year at the level of an average affected site and corresponds to an average annual CS loss of EUR 121.85. The second largest change is linked to a policy aimed at increasing deadwood, which would lead to 2.58 fewer trips per year and person at the site level and a corresponding reduction of EUR 114.67 in average annual CS.

By contrast, transitioning from a mixed to a broadleaf-based silvicultural regime and increasing tree size variation, both lead to gains in recreation demand and welfare. At the level of an affected site, converting the tree species composition from mixed to broadleaf increases annual CS by EUR 31.64, while increasing the tree size variation results in CS gains of EUR per respondent and year, on average. As before, all predicted changes—except for an increase in tree size variation at the regional level—are significantly different from zero at the 5% level, as indicated by the 95% confidence intervals reported in brackets in Table 5 (which exclude zero). The largest differences between the two prediction approaches occur for increases in deadwood and tree size variation, although only the difference for deadwood is statistically significant. As discussed previously for the relative demand effects, this reflects the fact that many forest sites in MWP already exhibit the respective target conditions. By preserving the current distribution of site characteristics, the regional extrapolation approach captures this and reveals the limited population-wide effect of such changes.

5. Discussion and conclusions

This study employed the TC-CB method to estimate demand for forest recreation in the German federal state of Mecklenburg-Western Pomerania (MWP) and investigated the effects of changing forest characteristics on visit frequencies. In contrast to previous TC-CB studies, which almost exclusively assessed the implications of deterministically predefined environmental changes at a specific site, we adopted an approach that combines a general population survey with an experimental design to construct CB scenarios and individual specific SQ conditions based on respondents' perceptions. As outlined in the introduction, drawing scenarios from the full factorial of site conditions increases the variation of attributes in the model domain and allows us to estimate the effects of a wide range of potential future forest conditions without having to present a large number of scenarios to each respondent. Employing deterministically predefined scenarios, by contrast, requires presenting one CB scenario for each environmental change of interest. This quickly becomes impractical (even with few environmental attributes), as the size of the full factorial of site conditions grows exponentially with the number of attribute levels considered. The approach used in the present study is therefore particularly useful for evaluating complex environmental goods characterized by multiple relevant attributes. It also facilitates the quantification of trade-offs among different environmental features, which is crucial if the goal is to balance different ecosystem services efficiently and maximize social welfare.

Empirically, this study quantifies the effects of changing forest conditions on recreational value and visit demand. A considerable body of work has investigated human preferences for forest characteristics, finding that the recreational value of forests is shaped by a variety of factors. These include non-structural forest attributes such as travel distance, recreational amenities, traffic infrastructure, and nature area features (e.g., Christie, Hanley, and Hynes 2007; Termansen, McClean, and Jensen 2013; Giergiczny et al. 2015), as well as structural forest characteristics (e.g., Edwards et al. 2012; Abildtrup et al. 2013; Agimass et al. 2018). Regarding the latter, differences in preferences revealed by different studies suggests that these are shaped at least partly by cultural, geographical, and subjective considerations (Nielsen, Olsen, and Lundhede 2007). Regional evidence is therefore essential to obtain a realistic representation of preferences.

In the present study, we describe the forest environment using three structural attributes that are central to nature-based forest management in the temperate, nemoral broadleaf zone to which the study region belongs: tree species composition, deadwood volume, and tree size variation. Our results indicate that all three environmental factors significantly influence the number of past and anticipated future recreation visits. Specifically, changing a forest’s tree composition from mixed to coniferous reduces expected demand by 9.8%, while transitioning from mixed to a broadleaf increases it 2.3%, *ceteris paribus*. These findings align with previous studies showing that mixed and broadleaf forests are generally preferred over coniferous stands in many European countries (Scarpa et al. 2000; Nielsen, Olsen, and Lundhede 2007; Termansen, McClean, and Jensen 2013; Abildtrup, Olsen, and Stenger 2015; Giergiczny et al. 2015; Agimass et al. 2018). A notable exception is Finland, which belongs to the boreal forest zone and where preferences tend to favor coniferous stands (Tyrväinen, Silvennoinen, and

Kolehmainen 2003). In the study region, where pines currently make up 50% of the tree population, a shift towards nature-based forest management would involve increasing the share of broadleaf species. Given our findings, following such an approach would not only promote biodiversity conservation and strengthen climate resilience, but also enhance recreational value—particularly when broadleaf species are introduced into predominantly coniferous stands.

With respect to tree size variation, we find that increasing the number of canopy layers in a given forest leads to a 2.4% increase in expected forests visits, *ceteris paribus*. As tree size variation serves as a direct proxy for silvicultural practice—with timber production-oriented plantation forestry typically resulting in uniform stands and nature-based forest management in high levels of size variation—this indicates a synergetic relationship between recreational value and nature-based forest management in this dimension as well. These findings are consistent with earlier results suggesting that uneven-aged stands are generally preferred over even-aged ones (Nielsen, Olsen, and Lundhede 2007; Giergiczny et al. 2015; Filyushkina et al. 2017). Regarding the relevance of that feature for recreation, a Delphi study among European forest experts found substantial regional differences; tree size variation was ranked the second most important forest attribute in the UK but only the eleventh most important in Central Europe (Edwards et al. 2012). In present study, tree size variation emerged as the least influential of the three examined forest characteristics.

Concerning deadwood, we find a negative relationship between higher levels of deadwood and recreation demand. Increasing the visible amount of deadwood in forests that currently exhibit low levels is associated with a 9.3% decline in expected and anticipated forest visits. The literature on the recreational impact of deadwood, of which Sacher et al. (2022) provide a recent overview, is somewhat ambivalent. For instance, Rathmann et al. (2020) found deadwood to be the second most photographed forest feature in a visitor employed photography study. While this underlines its importance in forest perception, the authors found an overall moderately positive but highly heterogeneous impact of deadwood on recreational attractiveness. Hauru et al. (2014) examined aesthetic preferences for logs and report that sites with fresh logs were preferred over sites with older or no logs. They recommend leaving downed logs in locations where they do not interfere with recreational use. Sacher et al. (2022), who employed the same forest pictograms that were used in the present study in a stated choice experiment (alongside photographic depictions of deadwood), found that deadwood levels had no noticeable effect on respondents' recreational choices. These authors argue that there are no severe conflicts between an increased occurrence of deadwood to promote biodiversity and the recreational value of forests. Pelyukh et al. (2019), on the other hand, find that low amounts of deadwood were preferred over higher levels that are typical for natural forest management. Similarly, Arnberger et al. (2018), Edwards et al., (2012), and Ribe (2009) report negative preferences for large quantities of deadwood.

The present study, overall, finds limited evidence for a conflict between nature-based forest management and recreational forest values in the study region. Two key structural changes when adopting such a silvicultural regime—an increased share of broadleaf trees and greater tree size variation within forest stands—were found to positively influence recreation demand. While higher levels of deadwood had a negative effect on recreational value, this potential conflict with biodiversity goals could be mitigated by concentrating deadwood retention in less-frequented forest areas and by minimizing its presence along commonly used forest paths.

Methodologically, the regional scope of the present study required using perceived site conditions to approximate the current distribution of forest characteristics that can then serve as a baseline to evaluate environmental changes. In combination with a modeling approach that corrects for both strict zero truncation of past trips and incidental truncation of CB trips (Egan and Herriges 2006), this regional baseline enabled us to make statements that are representative at the regional level instead of referring to a single or small number of sites. The combination of perceived SQ conditions—which naturally vary across respondents—and CB scenarios drawn randomly from the full factorial of attribute level combinations, however, posed several challenges for predicting likely future demands under altered site conditions. We introduced an approach to adequately conduct predictions at both the regional level and with respect to an average single recreation site and discussed the necessary assumptions. This renders the TC-CB framework based on experimentally varied CB scenarios, respondent-specific SQ conditions, and general population surveys more accessible, and facilitates its application in regional contexts and across a broad set of environmental changes.

Examining how the definition of CB scenarios can be further improved to increase statistical efficiency in comparison to a random assignment of attributes to CB scenarios is an interesting question for future research. Concepts from the efficient design literature on stated choice experiments such as balancing of characteristics and minimal overlap (between baseline and CB conditions) could provide a useful starting point for methodological improvements in the present TC-CB modeling context.

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References

Abildtrup, Jens, Serge Garcia, Søren Bøye Olsen, and Anne Stenger. 2013. "Spatial Preference Heterogeneity in Forest Recreation." *Ecological Economics* 92 (August): 67–77. https://doi.org/10.1016/j.ecolecon.2013.01.001.

Abildtrup, Jens, Søren Bøye Olsen, and Anne Stenger. 2015. "Combining RP and SP Data While Accounting for Large Choice Sets and Travel Mode – an Application to Forest Recreation." *Journal of Environmental Economics and Policy* 4 (2): 177–201. https://doi.org/10.1080/21606544.2014.986210.

Adamowicz, Wiktor, Joffre Swait, Peter Boxall, Jordan Louviere, and Michael Williams. 1997. "Perceptions versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Models of Environmental Valuation." *Journal of Environmental Economics and Management* 32 (1): 65–84. https://doi.org/10.1006/jeem.1996.0957.

Agimass, Fitalew, Thomas Lundhede, Toke Emil Panduro, and Jette Bredahl Jacobsen. 2018. "The Choice of Forest Site for Recreation: A Revealed Preference Analysis Using Spatial Data." *Ecosystem Services*, Assessment and Valuation of Recreational Ecosystem Services, vol. 31 (June): 445–54. https://doi.org/10.1016/j.ecoser.2017.11.016.

Ahtiainen, Heini, Eija Pouta, and Janne Artell. 2015. "Modelling Asymmetric Preferences for Water Quality in Choice Experiments with Individual-Specific Status Quo Alternatives." *Water Resources and Economics* 12 (October): 1–13. https://doi.org/10.1016/j.wre.2015.10.003.

Arnberger, Arne, Martin Ebenberger, Ingrid E. Schneider, et al. 2018. "Visitor Preferences for Visual Changes in Bark Beetle-Impacted Forest Recreation Settings in the United States and Germany." *Environmental Management* 61 (2): 209–23. https://doi.org/10.1007/s00267-017-0975-4.

Awondo, Sebastain N., Kevin J. Egan, and Daryl F. Dwyer. 2011. "Increasing Beach Recreation Benefits by Using Wetlands to Reduce Contamination." *Marine Resource Economics* 26 (1): 1–15. https://doi.org/10.5950/0738-1360-26.1.1.

Baranzini, Andrea, Caroline Schaerer, and Philippe Thalmann. 2010. "Using Measured Instead of Perceived Noise in Hedonic Models." *Transportation Research Part D: Transport and Environment* 15 (8): 473–82. https://doi.org/10.1016/j.trd.2010.06.002.

Barry, Luke, Tom M. Van Rensburg, and Stephen Hynes. 2011. "Improving the Recreational Value of Ireland's Coastal Resources: A Contingent Behavioural Application." *Marine Policy* 35 (6): 764–71. https://doi.org/10.1016/j.marpol.2011.01.009.

Becker, Oliver, Tobias Börger, and Jürgen Meyerhoff. 2025. "Sampling of Alternatives in Spatial Decision Contexts with Logit and Logit Mixture Models: Simulation and

Application to Freshwater Recreation in Germany." *Resource and Energy Economics*, no. 84 (August): 101535. https://doi.org/10.1016/j.reseneeco.2025.101535.

Bertram, Christine, Heini Ahtiainen, Jürgen Meyerhoff, Kristine Pakalniete, Eija Pouta, and Katrin Rehdanz. 2020. "Contingent Behavior and Asymmetric Preferences for Baltic Sea Coastal Recreation." *Environmental and Resource Economics* 75 (1): 49–78. https://doi.org/10.1007/s10640-019-00388-x.

Bertram, Christine, and Neele Larondelle. 2017. "Going to the Woods Is Going Home: Recreational Benefits of a Larger Urban Forest Site — A Travel Cost Analysis for Berlin, Germany." *Ecological Economics* 132 (February): 255–63. https://doi.org/10.1016/j.ecolecon.2016.10.017.

Birol, Ekin, Eric Rayn Villalba, and Melinda Smale. 2009. "Farmer Preferences for Milpa Diversity and Genetically Modified Maize in Mexico: A Latent Class Approach." *Environment and Development Economics* 14 (4): 521–40. https://doi.org/10.1017/S1355770X08004944.

Börger, Tobias, Danny Campbell, Mathew P. White, et al. 2021. "The Value of Blue-Space Recreation and Perceived Water Quality across Europe: A Contingent Behaviour Study." *The Science of the Total Environment* 771 (June): 145597. https://doi.org/10.1016/j.scitotenv.2021.145597.

Börger, Tobias, Kolobe Mmonwa, and Danny Campbell. 2023. "Hazardous Human–Wildlife Encounters, Risk Attitudes, and the Value of Shark Nets for Coastal Recreation." *American Journal of Agricultural Economics*, May 28, ajae.12413. https://doi.org/10.1111/ajae.12413.

Borzykowski, Nicolas, Andrea Baranzini, and David Maradan. 2017. "A Travel Cost Assessment of the Demand for Recreation in Swiss Forests." *Review of Agricultural, Food and Environmental Studies* 98 (3): 149–71. https://doi.org/10.1007/s41130-017-0047-4.

Brühbach, D. 2009. "Ökonomische Vorteile Des Fahrradfahrens Für Unternehmen." https://www.fahrrad-fit.de/default.asp?Menue=225.

Christie, Michael, Nick Hanley, and Stephen Hynes. 2007. "Valuing Enhancements to Forest Recreation Using Choice Experiment and Contingent Behaviour Methods." *Journal of Forest Economics* 13 (2–3): 75–102. https://doi.org/10.1016/j.jfe.2007.02.005.

Commission of the European Union. 2021. *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions — New EU Forest Strategy for 2030*. (Brüssel).

Creel, Michael D., and John B. Loomis. 1990. "Theoretical and Empirical Advantages of Truncated Count Data Estimators for Analysis of Deer Hunting in California." *American Journal of Agricultural Economics* 72 (2): 434–41. https://doi.org/10.2307/1242345.

Czajkowski, Mikołaj, Heini Ahtiainen, Janne Artell, et al. 2015. "Valuing the Commons: An International Study on the Recreational Benefits of the Baltic Sea." *Journal of Environmental Management* 156 (June): 209–17. https://doi.org/10.1016/j.jenvman.2015.03.038.

Czajkowski, Mikołaj, Marek Giergiczny, Jakub Kronenberg, and Jeffrey Englin. 2019. "The Individual Travel Cost Method with Consumer-Specific Values of Travel Time Savings." *Environmental and Resource Economics* 74 (3): 961–84. https://doi.org/10.1007/s10640-019-00355-6.

Domínguez-Torreiro, Marcos, and Mario Soliño. 2011. "Provided and Perceived Status Quo in Choice Experiments: Implications for Valuing the Outputs of Multifunctional Rural Areas." *Ecological Economics* 70 (12): 2523–31. https://doi.org/10.1016/j.ecolecon.2011.08.021.

Edwards, David, Marion Jay, Frank S. Jensen, et al. 2012. "Public Preferences for Structural Attributes of Forests: Towards a Pan-European Perspective." *Forest Policy and Economics* 19 (June): 12–19. https://doi.org/10.1016/j.forpol.2011.07.006.

Egan, Alexandra L., John Rolfe, Sue Cassells, and B. Louise Chilvers. 2023. "Recreational Impacts of an Oil Spill in a World Heritage Area: A Combined Travel Cost and Contingent Behaviour Method Approach." *Journal of Environmental Economics and Policy*, August 24, 1–17. https://doi.org/10.1080/21606544.2023.2248951.

Egan, Kevin, and Joseph Herriges. 2006. "Multivariate Count Data Regression Models with Individual Panel Data from an On-Site Sample." *Journal of Environmental Economics and Management* 52 (2): 567–81. https://doi.org/10.1016/j.jeem.2006.03.002.

Englin, Jeffrey, and Trudy Ann Cameron. 1996. "Augmenting Travel Cost Models with Contingent Behavior Data: Poisson Regression Analyses with Individual Panel Data." *Environmental & Resource Economics* 7 (2): 133–47. https://doi.org/10.1007/BF00699288.

Englin, Jeffrey, and J. S. Shonkwiler. 1995. "Estimating Social Welfare Using Count Data Models: An Application to Long-Run Recreation Demand Under Conditions of Endogenous Stratification and Truncation." *The Review of Economics and Statistics* 77 (1): 104–12. https://doi.org/10.2307/2109996.

Esseen, Per-Anders, Bengt Ehnström, Lars Ericson, and Kjell Sjöberg. 1997. "Boreal Forests." *Ecological Bulletins*, no. 46: 16–47.

Filyushkina, Anna, Fitalew Agimass, Thomas Lundhede, Niels Strange, and Jette Bredahl Jacobsen. 2017. "Preferences for Variation in Forest Characteristics: Does Diversity between Stands Matter?" *Ecological Economics* 140 (October): 22–29. https://doi.org/10.1016/j.ecolecon.2017.04.010.

Forzieri, Giovanni, Marco Girardello, Guido Ceccherini, et al. 2021. "Emergent Vulnerability to Climate-Driven Disturbances in European Forests." *Nature Communications* 12 (February): 1081. https://doi.org/10.1038/s41467-021-21399-7.

Gamborg, Christian, and Jørgen Bo Larsen. 2003. "'Back to Nature'—a Sustainable Future for Forestry?" *Forest Ecology and Management* 179 (1): 559–71. https://doi.org/10.1016/S0378-1127(02)00553-4.

German Federal Ministry of Food and Agriculture. 2020. *Richtlinie Zum Erhalt Und Zur Nachhaltigen Bewirtschaftung Der Wälder: Nachhaltigkeitsprämie Wald*. Berlin.

Giergiczny, Marek, Mikołaj Czajkowski, Tomasz Żylicz, and Per Angelstam. 2015. “Choice Experiment Assessment of Public Preferences for Forest Structural Attributes.” *Ecological Economics* 119 (November): 8–23. https://doi.org/10.1016/j.ecolecon.2015.07.032.

Glenk, Klaus. 2011. “Using Local Knowledge to Model Asymmetric Preference Formation in Willingness to Pay for Environmental Services.” *Journal of Environmental Management* 92 (3): 531–41. https://doi.org/10.1016/j.jenvman.2010.09.003.

Grammatikopoulou, Ioanna, and Davina Vačkářová. 2021. “The Value of Forest Ecosystem Services: A Meta-Analysis at the European Scale and Application to National Ecosystem Accounting.” *Ecosystem Services* 48 (April): 101262. https://doi.org/10.1016/j.ecoser.2021.101262.

Grilli, Gianluca, Alessandro Paletto, and Isabella De Meo. 2014. “Economic Valuation of Forest Recreation in an Alpine Valley.” *BALTIC FORESTRY* 20 (1).

Grogger, J. T., and R. T. Carson. 1991. “Models for Truncated Counts.” *Journal of Applied Econometrics* 6 (3): 225–38. https://doi.org/10.1002/jae.3950060302.

Haab, Timothy C., and Kenneth E. McConnell. 2002. *Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation*. New Horizons in Environmental Economics. E. Elgar Pub.

Hanley, Nick, David Bell, and Begona Alvarez-Farizo. 2003. “Valuing the Benefits of Coastal Water Quality Improvements Using Contingent and Real Behaviour.” *Environmental and Resource Economics* 24 (3): 273–85. https://doi.org/10.1023/A:1022904706306.

Hanley, Nick, Douglas W. Shaw, and Robert E. Wright. 2003. *The New Economics of Outdoor Recreation*. Edward Elgar Publishing Ltd.

Hauru, Kaisa, Saara Koskinen, D. Johan Kotze, and Susanna Lehvävirta. 2014. “The Effects of Decaying Logs on the Aesthetic Experience and Acceptability of Urban Forests – Implications for Forest Management.” *Landscape and Urban Planning* 123 (March): 114–23. https://doi.org/10.1016/j.landurbplan.2013.12.014.

Hess, Stephane, John M. Rose, and David A. Hensher. 2008. “Asymmetric Preference Formation in Willingness to Pay Estimates in Discrete Choice Models.” *Transportation Research Part E: Logistics and Transportation Review* 44 (5): 847–63. https://doi.org/10.1016/j.tre.2007.06.002.

Jonsson, Bengt Gunnar, Nicholas Kruys, and Thomas Ranius. 2005. “Ecology of Species Living on Dead Wood – Lessons for Dead Wood Management.” *Silva Fennica* 39 (2). https://www.silvafennica.fi/article/390.

Kaya, Güven. 2022. “Estimating Regional Aggregate Economic Value of Forest Recreation Services with Linked Travel Cost Model.” *Forests* 13 (10): 10. https://doi.org/10.3390/f13101561.

Kipperberg, Gorm, Yuko Onozaka, Linh Thi Bui, Marthe Lohaugen, Greta Refsdal, and Sandra Sæland. 2019. “The Impact of Wind Turbines on Local Recreation: Evidence from Two Travel Cost Method – Contingent Behavior Studies.” *Journal of Outdoor Recreation and Tourism* 25 (March): 66–75. https://doi.org/10.1016/j.jort.2018.11.004.

Krinsky, Itzhak, and A. Leslie Robb. 1986. “On Approximating the Statistical Properties of Elasticities.” *The Review of Economics and Statistics* 68 (4): 715. https://doi.org/10.2307/1924536.

Lankia, Tuija, Marjo Neuvonen, and Eija Pouta. 2019. “Effects of Water Quality Changes on the Recreation Benefits of Swimming in Finland: Combined Travel Cost and Contingent Behavior Model.” *Water Resources and Economics*, Inland and Marine Water Valuation, vol. 25 (January): 2–12. https://doi.org/10.1016/j.wre.2017.10.002.

Larsen, J.B., and A.B. Nielsen. 2007. “Nature-Based Forest Management—Where Are We Going?” *Forest Ecology and Management* 238 (1–3): 107–17. https://doi.org/10.1016/j.foreco.2006.09.087.

Luxen, Dennis, and Christian Vetter. 2011. “Real-Time Routing with OpenStreetMap Data.” *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* (New York, NY, USA), GIS ’11, 513–16. https://doi.org/10.1145/2093973.2094062.

Mäntymaa, Erkki, Mikko Jokinen, Artti Juutinen, Tuija Lankia, and Pauliina Louhi. 2021. “Providing Ecological, Cultural and Commercial Services in an Urban Park: A Travel Cost–Contingent Behavior Application in Finland.” *Landscape and Urban Planning* 209 (May): 104042. https://doi.org/10.1016/j.landurbplan.2021.104042.

Marsh, Dan, Lena Mkwara, and Riccardo Scarpa. 2011. “Do Respondents’ Perceptions of the Status Quo Matter in Non-Market Valuation with Choice Experiments? An Application to New Zealand Freshwater Streams.” *Sustainability* 3 (9): 1593–615. https://doi.org/10.3390/su3091593.

Masiero, Lorenzo, and David A. Hensher. 2010. “Analyzing Loss Aversion and Diminishing Sensitivity in a Freight Transport Stated Choice Experiment.” *Transportation Research Part A: Policy and Practice* 44 (5): 349–58. https://doi.org/10.1016/j.tra.2010.03.006.

Melichar, Jan. 2022. “The Economice Valuation of the Change in Forest Quality in the Jizerske Hory Montains: A Contingent Behavior Model.” *Public Recreation and Landscape Protection - with Environment Hand in Hand?* https://doi.org/10.11118/978-80-7509-831-3.

Ministry for Climate Protection, Agriculture, Rural Areas and the Environment Mecklenburg-Western Pomerania. 2012. “Dritte Bundeswaldinventur Für Mecklenburg-Vorpommern.”

Nielsen, Anders Busse, Søren Bøye Olsen, and Thomas Lundhede. 2007. “An Economic Valuation of the Recreational Benefits Associated with Nature-Based Forest Management Practices.” *Landscape and Urban Planning* 80 (1–2): 63–71. https://doi.org/10.1016/j.landurbplan.2006.06.003.

Pelyukh, Oksana, Alessandro Paletto, and Lyudmyla Zahvoyska. 2019. “People’s Attitudes towards Deadwood in Forest: Evidence from the Ukrainian Carpathians.” *Journal of Forest Science* 65 (5): 171–82. https://doi.org/10.17221/144/2018-JFS.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Manual. R Foundation for Statistical Computing. https://www.R-project.org/.

Randall, Alan. 1994. “A Difficulty with the Travel Cost Method.” *Land Economics* 70 (1): 88. https://doi.org/10.2307/3146443.

Rathmann, Joachim, Philipp Sacher, Norman Volkmann, and Marius Mayer. 2020. “Using the Visitor-Employed Photography Method to Analyse Deadwood Perceptions of Forest Visitors: A Case Study from Bavarian Forest National Park, Germany.” *European Journal of Forest Research* 139 (3): 431–42. https://doi.org/10.1007/s10342-020-01260-0.

Ribe, Robert G. 2009. “In-Stand Scenic Beauty of Variable Retention Harvests and Mature Forests in the U.S. Pacific Northwest: The Effects of Basal Area, Density, Retention Pattern and down Wood.” *Journal of Environmental Management* 91 (1): 245–60. https://doi.org/10.1016/j.jenvman.2009.08.014.

Sacher, Philipp, Jürgen Meyerhoff, and Marius Mayer. 2022. “Evidence of the Association between Deadwood and Forest Recreational Site Choices.” *Forest Policy and Economics* 135 (February): 102638. https://doi.org/10.1016/j.forpol.2021.102638.

Sandorf, Erlend Dancke, Kristine Grimsrud, and Henrik Lindhjem. 2022. “Ponderous, Proficient or Professional? Survey Experience and Smartphone Effects in Stated Preference Research.” *Environmental and Resource Economics* 81 (4): 807–32. https://doi.org/10.1007/s10640-022-00654-5.

Scarpa, Riccardo, W. George Hutchinson, Susan M. Chilton, and Joseph Buongiorno. 2000. “Importance of Forest Attributes in the Willingness to Pay for Recreation: A Contingent Valuation Study of Irish Forests.” *Forest Policy and Economics* 1 (3): 315–29. https://doi.org/10.1016/S1389-9341(00)00026-5.

Shaw, Daigee. 1988. “On-Site Samples’ Regression: Problems of Non-Negative Integers, Truncation, and Endogenous Stratification.” *Journal of Econometrics* 37 (2): 211–23. https://doi.org/10.1016/0304-4076(88)90003-6.

Termansen, Mette, Colin J. McClean, and Frank Søndergaard Jensen. 2013. “Modelling and Mapping Spatial Heterogeneity in Forest Recreation Services.” *Ecological Economics*, Land Use, vol. 92 (August): 48–57. https://doi.org/10.1016/j.ecolecon.2013.05.001.

Tienhaara, Annika, Tuija Lankia, Olli Lehtonen, and Eija Pouta. 2021. “Heterogeneous Preferences towards Quality Changes in Water Recreation: Latent Class Model for Contingent Behavior Data.” *Journal of Outdoor Recreation and Tourism* 35 (September): 100386. https://doi.org/10.1016/j.jort.2021.100386.

Tyrväinen, Liisa, Harri Silvennoinen, and Osmo Kolehmainen. 2003. “Ecological and Aesthetic Values in Urban Forest Management.” *Urban Forestry & Urban Greening* 1 (3): 135–49. https://doi.org/10.1078/1618-8667-00014.

Vacek, Zdeněk, Stanislav Vacek, and Jan Cukor. 2023. “European Forests under Global Climate Change: Review of Tree Growth Processes, Crises and Management Strategies.” *Journal of Environmental Management* 332 (April): 117353. https://doi.org/10.1016/j.jenvman.2023.117353.

Voltaire, Louinord, and Obafèmi Philippe Koutchade. 2020. “Public Acceptance of and Heterogeneity in Behavioral Beach Trip Responses to Offshore Wind Farm

Development in Catalonia (Spain).” *Resource and Energy Economics* 60 (May): 101152. https://doi.org/10.1016/j.reseneeco.2020.101152.

Wooldridge, Jeffrey M. 2001. *Econometric Analysis of Cross Section and Panel Data*. 1st ed. MIT Press.

Zandersen, Marianne, and Richard S.J. Tol. 2009. “A Meta-Analysis of Forest Recreation Values in Europe.” *Journal of Forest Economics* 15 (1–2): 109–30. https://doi.org/10.1016/j.jfe.2008.03.006.

Tables

Table 1: Possible prediction approaches.

Approach	Baseline scenario ($j = 2$)	Targeted attribute(s) ($j > 2$)	Non-targeted attributes ($j > 2$)
Regional extrapolation	All site attributes are maintained as they were perceived by respondents.	Set to post-change levels for all sites.	Held constant at perceived baseline levels.
Single site effect	All site attributes are set to a common ground state, including the targeted attributes under evaluation.	Set to post-change levels for all sites.	Held constant at the same common ground state.

Table 2: Sample characteristics.

Variables	Description	Mean	Std. dev.	Min.	Max.
visits.winter	Actual visits between October 2022 and March 2023.	13.45	22.62	1.00	183.00
visits.summer	Actual visits between April 2023 and September 2023.	12.14	24.33	1.00	183.00
hyp.visits.winter	Hypothetical visits between October 2023 and March 2024.	10.73	23.86	1.00	183.00
hyp.visits.summer	Hypothetical visits between April 2023 and September 2023.	13.99	23.40	1.00	183.00
travel.cost	Travel costs in EUR.	4.69	6.86	0.01	88.39
distance.km	One-way road network distance in kilometers.	13.21	23.03	0.01	255.89
second.wave	Survey wave (0 - Oct22-Mar23, 1 - Apr23-Sep23)	0.56	0.50	0.00	1.00
male	Respondent gender (1 - male, 0 - female)	0.42	0.49	0.00	1.00
age	Age in years	38.65	13.56	16.00	83.00
ln.hh.income	Log of household income in EUR	7.84	0.63	5.70	9.90
university.education	University education (1 - yes, 0 - no)	0.19	0.39	0.00	1.00
not.fully.employed	Employed less than 35h per week (1 - yes, 0 - no)	0.44	0.5	0.00	1.00
garden	Garden access (1 - yes, 0 - no)	0.64	0.48	0.00	1.00
walking.dog	Walking the dog was main activity (1 - yes, 0 - no)	0.31	0.46	0.00	1.00
sport.activity	Cycling, jogging, hiking, horseback riding, or picnicking was main activity (1 - yes, 0 - no)	0.22	0.42	0.00	1.00
nature.activity	Mushrooming, hunting, or watching birds/animals was main activity (1 - yes, 0 - no)	0.13	0.34	0.00	1.00
duration	Time spent in the forest in hours	2.61	2.64	0.50	24.00
company	Forest visit with company (1 - yes, 0 - no)	0.77	0.42	0.00	1.00

Table 3: Characteristics of visited forests.

Variables	Description	Mean	Std. dev.	Min.	Max.
broad-leafed.forest	Forest type (1 if visited forest is broad-leafed, 0 otherwise)	0.22	0.41	0	1
mixed.forest	Forest type (1 if mixed, 0 otherwise)	0.72	0.45	0	1
coniferous.forest	Forest type (1 if coniferous, 0 otherwise)	0.07	0.25	0	1
layer.mult	Tree size variation (1 if diverse, zero otherwise)	0.68	0.47	0	1
deadwood.high	Level of deadwood (1 if high, 0 otherwise)	0.39	0.49	0	1

Table 4: Multivariate Poisson lognormal model.

Variable	Coeff.	s.e.	p
constant	1.358***	0.141	<0.001
const.CB	0.061*	0.025	0.015
travel.cost	–0.026***	0.001	<0.001
*const.CB*travel.cost*	0.011***	0.001	<0.001
second.wave	0.117***	0.014	<0.001
coniferous.forest	–0.112***	0.014	<0.001
broadleaf.forest	0.037**	0.012	0.003
deadwood.high	–0.106***	0.010	<0.001
layer.mult	0.041***	0.010	<0.001
age	–0.002*	0.001	0.003
male	0.316***	0.022	<0.001
ln.hh.income	0.086***	0.018	<0.001
university.education	–0.328***	0.025	<0.001
not.fully.employed	–0.329***	0.016	<0.001
garden	0.293***	0.021	<0.001
walking.dog	1.018***	0.024	<0.001
sport.activity	0.601***	0.027	<0.001
nature.activity	–0.459***	0.033	<0.001
duration	0.124***	0.003	<0.001
company	–0.243***	0.016	<0.001
Log-likelihood	–16178		
Observations	951		

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. Likelihood simulated with 1000 random draws using modified Latin hypercube sampling.

Table 5: Changes in expected number of visits and individual consumer surplus (CS) per year for isolated environmental changes.

Variable description	Single site effect	Regional extrapolation
I: Tree composition (mixed → broadleaved)		
Absolute change in average no. of annual visits	0.71 (0.37, 1.01)	0.46 (0.14, 0.78)
Absolute change in average annual CS per visitor (EUR/year)	31.64 (15.53, 42.69)	21.14 (7.37, 29.66)
II: Tree composition (mixed → coniferous)		
Absolute change in average no. of annual visits	-2.75 (-3.53, -2.31)	-2.84 (-3.31, -2.14)
Absolute change in average annual CS per visitor (EUR/year)	-121.85 (-140.83, -97.57)	-113.92 (-137.28, -93.29)
III: Deadwood level (low → high)		
Absolute change in average no. of annual visits	-2.58 (-2.86, -2.13)	-1.72 (-1.95, -1.53)
Absolute change in average annual CS per visitor (EUR/year)	-114.67 (-126.44, -94.88)	-72.56 (-89.14, -67.24)
IV: Tree size variation (uniform → diverse)		
Absolute change in average no. of annual visits	0.69 (0.31, 1.07)	0.22 (-0.18, 0.53)
Absolute change in average annual CS per visitor (EUR/year)	30.62 (14.56, 48.30)	10.24 (-7.85, 21.62)

Note: 95% confidence intervals are based on 1000 Latin Hypercube Draws and 100 simulations (Krinsky and Robb, 1986).

Figures

Fig 1. Forest pictograms used in the survey to illustrate all 12 combinations of tree species composition, deadwood level, and tree size variation.

Notes: (c) of all forest drawings Anders Busse Nielsen.

Fig 2. Predictions for all (isolated) environmental changes using the two prediction procedures detailed in Table 1.

Notes: The single-site effect refers to the relative change in visits due to changes at a single representative site, while the regional extrapolation effect reflects the corresponding change across all sites within a geographical region (some of which remain unaffected). Note that the confidence intervals are based on simulations of the mean prediction—i.e., they reflect the distribution of the average rather than respondent-specific predictions—and derived from 100 simulations.

Endnotes

[1] In the presence of numerous sites and diverse environmental conditions documented through site-level data, discrete choice travel cost models have become the dominant tool to analyze recreation decisions (see, e.g., Haab and McConnell, 2002).

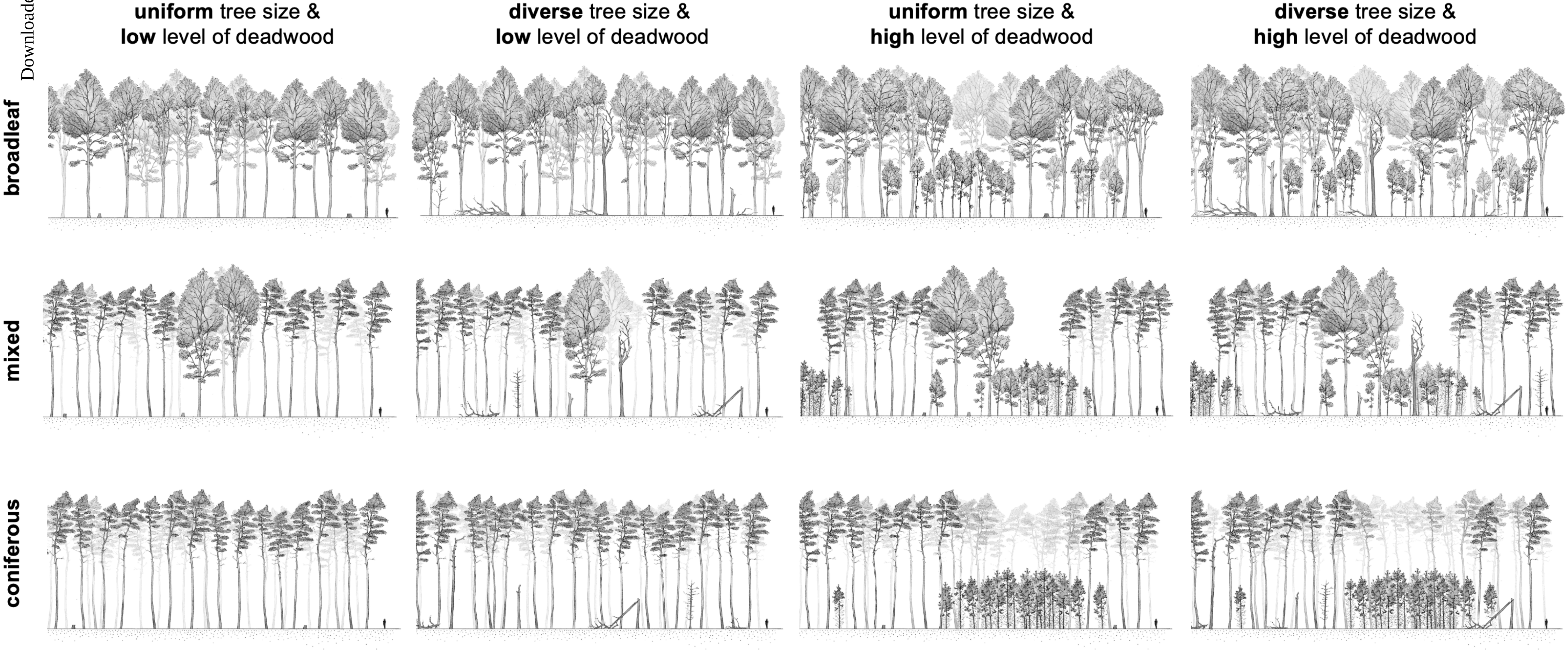
[2] While the majority of valuation studies provide respondents with a description of SQ conditions based on objective assessments, several stated preference applications rely on respondents' own perceptions of environmental conditions to define SQ conditions (e.g., Hess, Rose, and Hensher 2008; Birol, Villalba, and Smale 2009; Masiero and Hensher 2010; Glenk 2011; Ahtiainen, Pouta, and Artell 2015). A few studies have also explored how using perceived versus externally defined SQ conditions affects welfare estimates, both in stated preference settings (Marsh, Mkwara, and Scarpa 2011; Domínguez-Torreiro and Soliño 2011) and revealed preference contexts (Adamowicz et al. 1997; Baranzini, Schaerer, and Thalmann 2010). These comparisons suggest that perception-based SQ definitions can result in notable differences in estimated values, while both approaches can lead to biases.

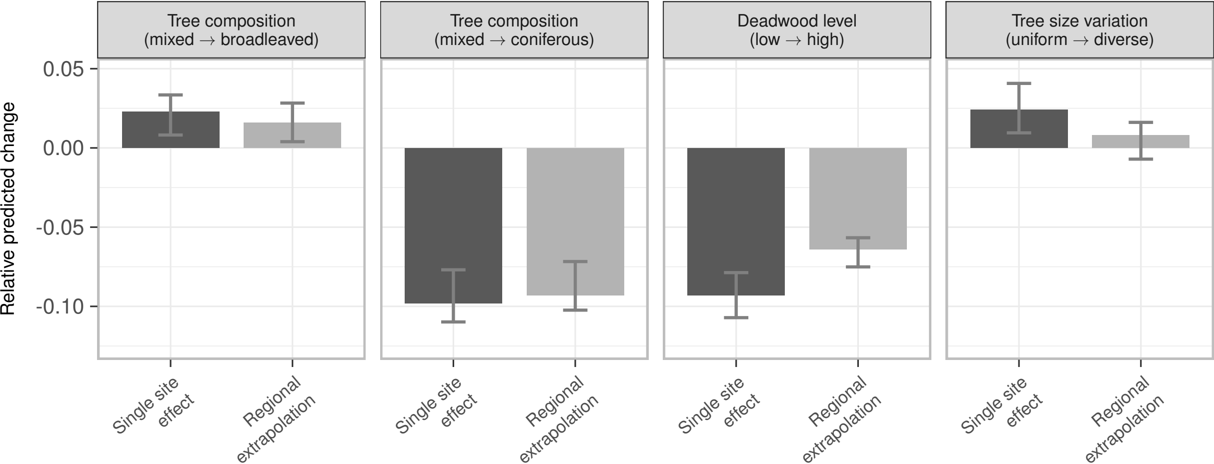
[3] The full survey instrument is available as supplementary material in Appendix A.

[4] The tree size variation attribute corresponds to the number of canopy layers in a forest patch. One canopy layer corresponds to a uniform tree size variation and multiple canopy layers to a diverse one.

[5] To protect respondents' privacy and account for potential concerns about sharing precise home locations, respondents were asked to indicate the nearest street intersection to their residence.

[6] Hourly income was assumed to equal the minimum wage in Germany which was equal to EUR 12.00 at the time of the survey.


uniform tree size &
low level of deadwood
diverse tree size &
low level of deadwood
uniform tree size &
high level of deadwood
diverse tree size &
high level of deadwood
broadleaf
mixed
coniferous


Tree composition (mixed → broadleaved)
Tree composition (mixed → coniferous)
Deadwood level (low → high)
Tree size variation (uniform → diverse)
Relative predicted change
0.05
0.00
-0.05
-0.10
Single site effect
Regional extrapolation
Single site effect
Regional extrapolation
Single site effect
Regional extrapolation
Single site effect
Regional extrapolation