Science of the Total Environment 771 (2021) 145597

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

The value of blue-space recreation and perceived water quality across Europe: A contingent behaviour study

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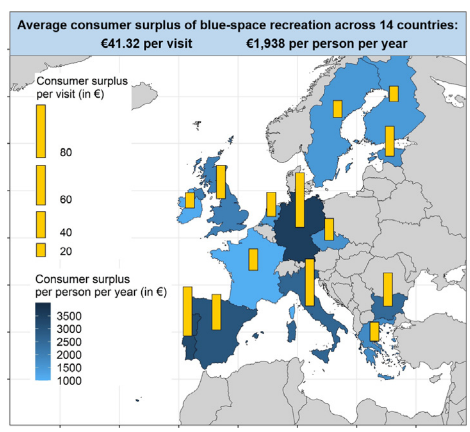
HIGHLIGHTS

- Valuation of recreational visits to blue-space sites across 14 EU Member States
- Visit consumer surplus (CS) estimated at €41.32 totalling €631bn pa for population
- A one-level improvement in water quality leads to 3.13 more visits (+6.67%).
- A one-level deterioration leads to 9.77 fewer annual visits (−20.83%).

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 11 December 2020
Received in revised form 29 January 2021
Accepted 29 January 2021
Available online 1 March 2021

Editor: Fernando A.L. Pacheco

Keywords:
Travel cost method
Contingent behaviour method

ABSTRACT

This study estimates the value of recreational visits to blue-space sites across 14 EU Member States, representing 78% of the Union's population. Across all countries surveyed, respondents made an average of 47 blue-space visits per person per year. Employing travel cost and contingent behaviour methods, the value of a visit is estimated at €41.32 which adds up to a recreational value of €631bn per year for the total adult population surveyed. Using the Bathing Water Directive's water quality designation, the analysis shows that a one-level improvement in water quality leads to 3.13 more visits (+6.67%), whereas a one-level deterioration leads to 9.77 fewer annual visits (−20.83%). This study provides valuations of benefits of recreation and changes of recreational values due to changes in surface water quality, which can be compared to the implementation and

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https://doi.org/10.1016/j.scitotenv.2021.145597

Water quality
Blue-space recreation
Incidental truncation
Count data models

monitoring costs of efforts under the EU's Bathing Water, Water Framework and Marine Strategy Framework Directives.

1. Introduction

Blue spaces, defined as "*outdoor environments—either natural or manmade—that prominently feature water and are accessible to humans*" (Grellier et al., 2017, p. 3), offer a multitude of benefits to visitors and users of such locations (White et al., 2020). These include opportunities for physical activity (Papathanasopoulou et al., 2016; Pasanen et al., 2019), enjoyment of nature (Wyles et al., 2019), marine wildlife watching (White et al., 2017), restoration of depleted emotional and cognitive resources (White et al., 2013; Garrett et al., 2019) and additional health benefits (McDougall et al., 2020a), but also reduction of urban heat island effects and air pollution (Depledge et al., 2019; Völker et al., 2013).

Economists and environmental planners have long been trying to value these benefits to aid decision-making, development and planning (Buckley et al., 2019; Torres and Hanley, 2016). The challenge is that access to blue-space sites, particularly small ones (e.g. ponds, streams and fountains) is free and no price or other value information such as entrance ticketing is available. Similarly, the benefits public blue-space sites provide are free to enjoy and consume for visitors meaning there is no market or price data on which economic valuation could be based. Instead, economists have employed non-market valuation techniques to capture the many benefits of blue (and green) spaces. Methods include hedonic pricing (e.g. Gibbons et al., 2014; Irwin et al., 2014), the travel cost and contingent behaviour method (e.g. Bertram et al., 2020; Czajkowski et al., 2015), as well as stated preference methods such as contingent valuation (e.g. Birol et al., 2006; Dahal et al., 2018; McDougall et al., 2020b) and choice experiments (e.g. Arnberger and Eder, 2011; Bertram et al., 2017; Grilli et al., 2020; Tu et al., 2016). Most valuation studies are site- or region-specific with a very small number of exceptions taking a national or international perspective (Bertram et al., 2020; Czajkowski et al., 2015; Lankia et al., 2019; Vesterinen et al., 2010).

One factor that may influence the recreational experience at blue-space sites is water quality which can be defined and monitored in a number of ways. It is therefore of major concern to environmental planners. In the European Union (EU), water quality is monitored at designated bathing sites under the Bathing Water Directive (BWD) (EC, 1976, 2006) focusing on concentrations of faecal bacteria. Water quality is further governed under the Water Framework Directive (WFD) (EC, 2000) which focuses on the good ecological and chemical status of inland water bodies. The Marine Strategy Framework Directive (MSFD) (EC, 2008) also looks at eutrophication (Ferreira et al., 2011), contaminant concentration and litter (Galgani et al., 2013) and covers coastal and offshore waters. Consequently, public funds are employed at the Member State and EU-level to maintain and improve the Directive-specific indicators of water quality in respective water bodies. Valuation of recreational benefits of blue spaces and particularly of the water quality at such sites provides crucial information to enable comparisons of the costs of water resource management to its wider benefits. However, the scaling up of site- or region-specific valuation studies for use in national- or EU-level cost-benefit analyses of water resource management can be challenging.

Against this background, this study presents an international valuation study, which is independent of specific sites and covers a wide range blue-space site types. While there are a small number of transnational valuation studies of this kind (Bertram et al., 2020; Czajkowski et al., 2015) which will be reviewed in Section 2, the present study goes beyond the existing literature in several ways. First, it covers valuation of blue-space recreation in 14 EU countries (Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom – Fig. 4), representing 50% of Member States and 78% of the population of the bloc at the time of the study. The use of a unified survey instrument across 14 countries allows for the comparison of blue-space recreation values across this large set of nations.

Second, the valuation study covers multiple blue-space site types and locations. Instead of focusing on one location of a specific type, such as a lake, a riverside or a stretch of coast, the study covers 17 different site types distributed across the 14 Member States.

Third, the study assesses the reactions of blue-space users to changes in (perceived) water quality. Specifically, respondents were asked to provide details of their most recent visit to a blue space in the past four weeks including location of the site and their home, site type, visit duration, activities undertaken, the number of times they had visited that location in the last four weeks and the perceived water quality aligned with existing bathing water quality standards based on the BWD ("Poor", "Sufficient", "Good", or "Excellent"). They were then asked how often they anticipated visiting this site in the next four weeks if bathing water quality were to change, specifically if it were to improve or deteriorate by one level compared to their assessment of its current state (Fig. 1).

Finally, the analysis employed a novel regression model to account for the fact that reported past visit frequencies are truncated at zero (because only observations with at least one past visit were used for analysis) and statements of future intended visits included zero visits (as some respondents planned to reduce their future visits to zero). The existing approach to model such visit count data, the multivariate Poisson lognormal (MPLN) model by Egan and Herriges (2006), also accounts for the fact that ardent visitors are oversampled in site-based travel cost and contingent behaviour studies. This model was adapted to a situation where such endogenous stratification is not present in the data since frequent visitors are not oversampled in the present study.

Specifically the study presents results on the following four Research Objectives: A) visitation frequencies to blue spaces and their distribution across site types and across 14 EU Member States; B) an exploration of demographic and site-specific determinants of visitation rates to blue-space sites; C) predictions of changes of visitation rates in reaction to one-level deterioration and improvement of perceived water quality; and, D) economic valuations of recreational visits to blue-space sites and changes of these values due to changes in perceived water quality levels on the individual and aggregated level. The subsequent section will present the methods used in this study, which is followed by Section 3 presenting the results. Section 4 provides some discussion and Section 5 concludes.

2. Methods

2.1. Travel cost and contingent behaviour methods

In a travel cost survey, data are collected on the number of recreational visits of an individual to a specific location in a recent period of time as well as on the characteristics of the trip (e.g. roundtrip distance between site and that individual's home, travel mode and the size of the travel party). The latter information is used to construct a travel cost

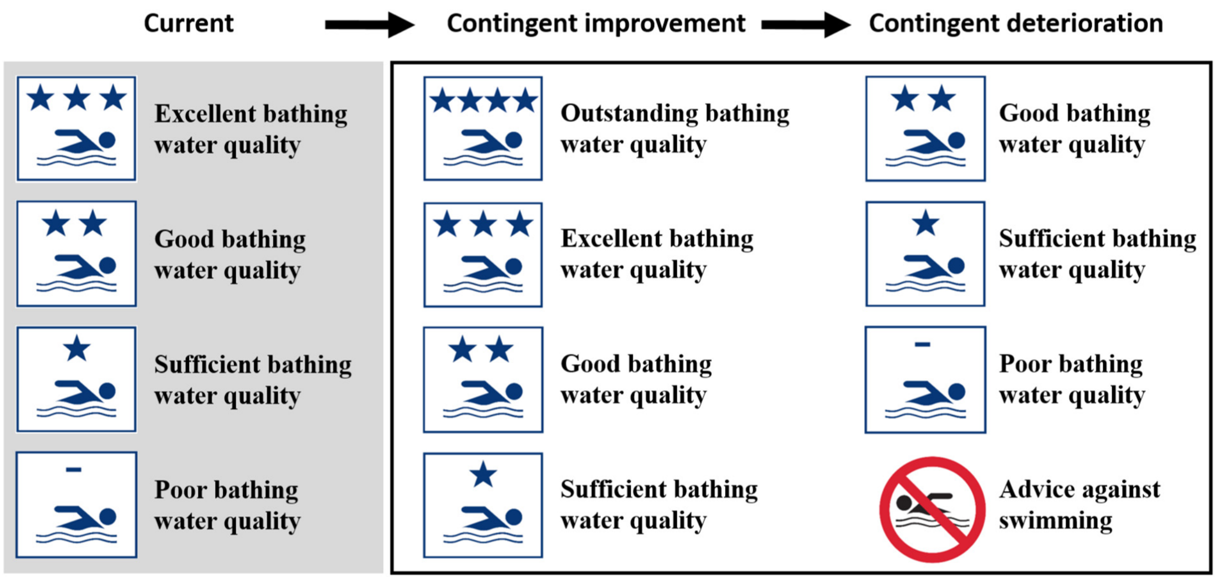

Fig. 1. Experimental design of variation in water quality signage. Current indicates the site's water quality as perceived by the respondent. The contingent improvement and deterioration are experimental variations presented to the respondents, using the respondent's stated current water quality level as basis. Note that the order of presentation of the contingent scenarios in the questionnaire was randomised across respondents.

variable. Count data regression of visit frequency on travel cost (including controls) yields the average sensitivity of visitation to travel cost. This, in turn, is used to estimate the average *consumer surplus of a visit*, which is a monetary indicator of the recreational value of the site for the user.

This method has traditionally been used to value recreational use of terrestrial sites, such as forests and woodlands (e.g. Bertram and Larondelle, 2017; Englin and Mendelsohn, 1991; Willis and Garrod, 1991), urban parks (Menedez-Carbo et al., 2020), national parks and protected areas (e.g. Martinez-Espineira and Amoako-Tuffour, 2008; Navrud and Mungatana, 1994), or related activities such as rock climbing (e.g. Hanley et al., 2001; Grijalva et al., 2002). However, there have also been a number of studies focusing on blue spaces including beaches and coastlines (Czajkowski et al., 2015; Pascoe, 2019), lakes (Egan and Herriges, 2006), reservoirs (Lienhoop and Ansmann, 2011), coral reefs (Ahmed et al., 2007) marine parks (Mwebaze and MacLeod, 2013), and associated activities such as sport fishing (Alberini et al., 2007; Hwang et al., 2021).

The travel cost method is frequently augmented with the contingent behaviour method, allowing valuation of changes in site conditions and accessibility (Englin and Cameron, 1996). Upon stating the number of past visits to the site, respondents are asked to indicate the number of planned visits in the future under changing conditions. These conditions are described in detail in the survey. Using these additional observations of anticipated visit frequencies, changes in visitation due to changing site characteristics and – in combination with the consumer surplus of a visit – their value are estimated. Focusing on blue-space sites, changes in environmental conditions that have been valued using the combination of travel cost and contingent behaviour method (henceforth referred to as TC-CB analysis) include water quality (Hanley et al., 2003; Lankia et al., 2019; Bertram et al., 2020), beach width (Parsons et al., 2013), coastal site accessibility (Barry et al., 2011; Rolfe and Dyack, 2011), coral reef condition (Kragt et al., 2009; Bhat, 2003), conservation of sharks (Zemah Shamir et al., 2019), angling conditions (Deely et al., 2019) and water levels (Lienhoop and Ansmann, 2011).

While most applications of TC-CB analyses are site- or at most region-specific, there is a small number of national-level and international valuation studies in the literature. Lankia et al. (2019), for instance, use the TC-CB approach to assess the value of recreational use of lakes, rivers and coastal waters in Finland using samples from the whole Finnish population. A similar approach is used by Vesterinen et al. (2010), who use a national recreation database to link participation in blue-space recreation (swimming, fishing and boating) to water quality levels. Results suggest no effects of water quality improvement on predicted boating trips but increased participation in fishing and swimming.

To apply the TC-CB in an international context, the recreational site has to be defined sufficiently broadly to be transboundary. Both Czajkowski et al. (2015) and Bertram et al. (2020) focus on recreation at the Baltic Sea coast. Czajkowski et al. (2015) present valuations of recreational visits to the Baltic Sea in all nine littoral countries based only on the travel cost method (i.e. not evaluating contingent scenarios). Bertram et al. (2020) conduct a TC-CB analysis to value recreational visits to the Baltic Sea coast in Finland, Germany and Latvia. Their contingent behaviour scenarios include a variation of changes in water clarity, presence of algae, fish and plant diversity and recreational facilities.

2.2. Survey and data collection

The data in the present study were collected as part of the H2020 BlueHealth project (Grellier et al., 2017). An international online survey was administered to adults in four, approximately four-week, seasonal waves (June 2017, September–October 2017, December 2017–January 2018 and March–April 2018). Seasonal waves were identical across countries. While collected in 18 countries/territories internationally, the study used data from 14 EU Member States at the time of data collection (Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the UK) who were asked contingent behaviour items. The survey questionnaire encompassed a number of question inventories pertaining to the use of green and blue environments, recreational activities therein, physical and mental health indicators, as well as socio-demographic information. The survey was conducted in the respective primary language in each country. Full methodological details are available online (Elliott and White, 2020).

As part of the questionnaire, and relevant for the TC-CB analysis reported here, respondents were asked about visits to greenspace and blue-space sites (see Supplementary materials A.1) in the four weeks prior to the survey. If respondents indicated they had made at least one such visit in that period to a blue space, they were asked further questions regarding the most recent visit, including the number of visits to that site, its location on a map (using a bespoke mapping tool), journey details, such as transport mode, number of people travelling together and the perceived water quality. The latter was to be indicated using the four-level bathing water quality scale: "Poor", "Sufficient", "Good" and "Excellent". Respondents were also asked whether the original blue-space visit was the main purpose of the trip (e.g. a day at the seaside) or a secondary activity accompanying another activity (e.g. visiting a relative); thus, the subsequent analysis was able to control for these different visit motivations, which in turn may affect the value of on-site recreation.

Subsequently, respondents were asked to indicate whether they would make more, fewer or the same number of visits and how many more or fewer visits, to the site in the coming four weeks if they had subsequently been informed that the official water quality assessment using the EU standards was: (i) one grade higher than their own assessment (i.e. an improvement); and (ii) one grade lower than their own assessment (i.e. a deterioration). Corresponding EU bathing water signage was displayed in this question which matched the quality rating originally selected and one-level improvements or deteriorations (Fig. 1). To accommodate change for respondents already at the upper or lower levels of water quality, two new categories were added. One quality level had to be invented for this exercise: improvements from excellent water quality were portrayed as "outstanding". Deteriorations from already poor water quality were labelled with the pre-existing "Advice against swimming" pictogram developed as part of the standards (Fig. 1). No complications from the use of these invented levels (and labels) were expected because at the time of the survey signage using the four official levels ("Poor" to "Excellent") had not been implemented across the EU. The order in which the contingent scenarios were presented (i.e. improvement first or deterioration first) were randomised across respondents to account for potential order effects.

Using the reported visit frequency to the most recently visited blue space site in the past four weeks and, under changing conditions of water quality, for the subsequent four weeks, a pseudo-panel of recreation demand was compiled. This pseudo-panel contains three visit count observations per respondent: 1) past visits under current conditions, 2) planned visits following a one-level improvement and 3) planned visits following a one-level deterioration.

As one of the main components of any TC-CB model is the monetary cost of travelling to the specific site a travel cost variable had to be constructed based on information collected in the survey. Roundtrip distance between respondents' home and the visited site was multiplied with a per-km value of travel cost which was specific to stated travel mode, group size and country (For further details on the construction of this variable see Supplementary materials B). Note that the opportunity cost of time is not included in the travel cost variable. The present study therefore follows suggestions in the literature that for studies in which the majority of visits constitute short-distance casual trips, as borne out by the present data, the travel to and from the site is likely part of the recreational experience (Tardieu and Tuffery, 2019). As a consequence, the time spent travelling to the site is not regarded as an expense for the enjoyment of recreation site.

2.3. A count data model to account for incidental truncation

Most TC-CB studies sample respondents at a particular recreation site. This brings about issues around zero-truncation since non-users of the site are systematically excluded and endogenous stratification as avid site users are more likely to be sampled. Econometric approaches to deal with both characteristics of the resulting survey data have been developed (Shaw, 1988; Creel and Loomis, 1990; Grogger and Carson, 1991; Englin and Shonkwiler, 1995). Another type of study employs general population surveys (e.g. Bertram et al., 2020; Czajkowski et al., 2015; Lankia et al., 2019; Vesterinen et al., 2010). The resulting datasets of this sampling procedure are characterised by a large share of respondents with zero visits, i.e. a spike at zero of the resulting visit frequency distribution. Similarly, econometric approaches have been proposed to accommodate this specific feature of such data.

The present study employs a hybrid approach to collecting visit frequency data. While a general population survey is used, the travel cost and contingent behaviour information are elicited with respect to the blue-space site a respondent has visited most recently. The focus on the latest visit is adopted from the Wales Outdoor Recreation Survey (NRW, 2015). As a consequence, the collected data are characterised by zero-truncation but *not* by endogenous stratification. Furthermore, truncation only applies to observed visits, but not to future visits under different conditions. The latter may well be zero if respondents decide not to visit a site anymore. Therefore the analysis employs the multivariate Poisson lognormal (MPLN) approach (Egan and Herriges, 2006), which accounts for incidental truncation of visit counts, but modifies it such that it does not correct for endogenous stratification.

Travel cost models use regression techniques to explain visit frequency over a certain period of time as a function of respondent and site characteristics and, most importantly, round-trip travel cost to the site (Englin et al., 2003; Parsons, 2017; Ward and Beal, 2000). For combined TC-CB data, such count data models pool past number of visits (observed behaviour – OB) and stated future visits under hypothetical conditions (conditional behaviour – CB) into a pseudo-panel with multiple observations per respondent and estimate a joint visit demand model (Englin and Cameron, 1996; Hanley et al., 2003; Parsons et al., 2013). Hence the number of visits y_{it} of individual i to a blue space in period t (where period may refer to past visits or future visits under equal or changed conditions),

$$y_{it} = g(c_i, X_i), \tag{1}$$

can be modelled as a function, $g(\cdot)$, of travel cost c_{it} and a vector X_{it} of characteristics of the site and the individual undertaking the visit. Since the number of visits is a non-negative integer, an appropriate statistical estimator such as the Poisson distribution has to be employed. In this case, the probability that a particular respondent i takes n visits in period t is

$$P(y_{it} = n) = \frac{e^{-\lambda}\lambda^n}{n!}, \tag{2}$$

where n is the actual number of visits taken. λ, the intensity of rate parameter, is the expected number of visits, i.e. $E(y_{it}) = Var(y_{it}) = \lambda$. This equidispersion property of the Poisson distribution is usually violated in cross section data.[1] In multivariate models of pseudo-panel data, however, equidispersion does not apply (Egan and Herriges, 2006; Whitehead et al., 2013). Therefore, the present TC-CB analysis worked with the Poisson distribution of visit counts.

λ is specified as a function of respondent and site characteristics as well as travel cost. Consequently, trip demand can be expressed as

$$\lambda = \exp\left(\beta_0 + \beta_c c_t + \beta_X{}' X_t + \varepsilon_t\right) \tag{3}$$

where β_0, β_c and β_{Xi} are (vectors of) coefficients of the constant, travel cost c_i and a vector of respondent and site characteristics x_i. ε_t is to be specified below.

Taking the basic Poisson model as their point of departure, past research has refined these models to correct zero-truncation (Shaw, 1988; Creel and Loomis, 1990; Grogger and Carson, 1991) and endogenous stratification (Englin and Shonkwiler, 1995) resulting from the way travel cost datasets are typically collected. Although the data in the present study are collected by means of a general population survey

[1] For cross sectional data violating the equidisperson assumption (i.e. $E(y_{it}) \neq Var(y_{it})$) the negative binomial regression model, which is based on the Gamma distribution, can be used (Englin et al., 2003, Martinez-Espineira and Amoako-Tuffour, 2008).

and therefore also include non-visitors, the count data models only employ a subsample of respondents who did make at least one visit to a blue-space site. For respondents who made zero visits in the previous four weeks the site they would have visited is unknown and so no travel cost variable can be constructed, effectively truncating the visit data at zero.[2] The data are, however, not endogenously stratified because the probability of being sampled does not vary with the number of visits a respondent report to have made over the previous four weeks. Consequently, any count data model in this analysis will need to correct for zero truncation but not for endogenous stratification.

To correct for zero truncation and to recover recreation demand of the whole population (visitors and non-visitors) a zero-truncated Poisson model could be used (Shaw, 1988; Creel and Loomis, 1990; Englin and Shonkwiler, 1995; Grogger and Carson, 1991). However, in the pseudo-panel of trip frequencies it is possible that respondents stated they would make zero visits under hypothetical conditions. So while the OB (i.e. past) visits are truncated at zero, the distribution of the CB (i.e. anticipated future) observations may well include zero as (some) respondents anticipate reducing their visits to zero as a reaction to the change in site conditions. Yet since the non-truncated CB data are only elicited from respondents with a strictly positive number of past visits, the CB data are incidentally truncated (Egan and Herriges, 2006): The fact that OB visit frequencies are strictly truncated at zero makes is more likely that CB frequencies are truncated, however as explained above, zero visits can still come up.

Existing models, such as early attempts to account for the pseudo-panel nature of the pooled OB and CB data using fixed effects (Englin and Cameron, 1996) or random effects Poisson or negative binomial models (Hanley et al., 2003; Whitehead et al., 2013), or random parameter (Hynes and Greene, 2016) and latent class models of visit counts (Hynes and Greene, 2013) are not able to deal with incidental truncation. The first model explicitly proposed to deal with incidental truncation is the multivariate Poisson lognormal (MPLN) model by Egan and Herriges (2006).[3] The model is multivariate in that it consists of a system of Poisson distributed count data equations with correlated error terms. This induces correlation between the number of visits made by the same individual in the past and under different future conditions, $y_{it}\ \forall\ t$.

While the MPLN model as proposed by Egan and Herriges (2006) also accounts for endogenous stratification, the model as employed in the present analysis does not do this as a consequence of the specific characteristics of the dataset. A multivariate system of Poisson equations can be set up as:

$$\begin{aligned} P(y_{i,OB}=n) &= \frac{e^{-\lambda}\lambda^n}{n!}\left[\frac{1}{1-e^{-\lambda}}\right], \\ P\left(y_{i,CB.imp}=n\right) &= \frac{e^{-\lambda}\lambda^n}{n!}, \\ P\left(y_{i,CB.det}=n\right) &= \frac{e^{-\lambda}\lambda^n}{n!}. \end{aligned} \tag{4}$$

Here, truncation is accounted for in observed visit counts ($y_{i,\ OB}$) whereas contingent behaviour visit counts for improved ($y_{i,\ CB.\ imp}$) and deteriorated water quality ($y_{i,\ CB.\ det}$) are non-truncated. Correlation between these visit counts is accounted for by modelling the scenario-specific error terms ε_t as following a multivariate normal distribution with mean zero, i.e. $\varepsilon_t \sim (0,\Sigma)$. For the three-equation model and following Egan and Herriges (2006), the elements of the variance-covariance matrix Σ are specified as

$$\Sigma = \begin{bmatrix} \sigma^2_{OB} & \sigma_{OB,CB.imp} & \sigma_{OB,CB.det} \\ & \sigma^2_{CB.imp} & \sigma_{CB.imp,CB.det} \\ & & \sigma^2_{CB.det} \end{bmatrix}. \tag{5}$$

It is further assumed that, except for water quality, the same set of independent variables X_t influences mean visits in each equation in Eq. (4). Water quality does differ between equations according to the experimental variation of increasing (decreasing) by one level in the improvement (deterioration) scenario according to Fig. 1. Coefficients are estimated by means of simulated maximum likelihood using 1000 Sobol random draws.

2.4. Welfare estimates and extrapolation

Even though the recreational experience at the site is non-priced, the cost of travel to the site is interpreted as a price for its enjoyment. So the visit frequency function (1) can be interpreted as a demand function which yields a downward-sloping demand curve for blue-space visits. The integral of this function with respect to price (i.e. travel cost) between the actual price for the visit, c_i^0 and the choke price c_i^{max} (the price at which demand becomes zero) is the consumer surplus (CS) measure:

$$CS_i = \int_{c_i^0}^{c_i^{max}} g(c_i, X_i)dc_i. \tag{6}$$

The estimated travel cost coefficient β_c can further be used to compute the average value of a recreational visit to the site as

$$CS = -\frac{1}{\beta_c}. \tag{7}$$

This is the sample average consumer surplus. Confidence intervals can be obtained by means of bootstrapping the likelihood function (Krinsky and Robb, 1986). Alternatively, the travel cost variable can be interacted with different group variables to estimate a vector of group-specific β_c and hence stratified consumer surplus. The present analysis estimated the consumer surplus of visits to blue space sites for the whole sample and stratified by country.

3. Results

3.1. Survey sample characteristics

The survey yielded a usable sample of $N = 11{,}443$ (see Supplementary materials A.1 for information on data cleaning) with between 699 (for Estonia) and 978 respondents (for the United Kingdom) per country. This sample was used to estimate total annual visitation figures to all blue-space types. The count data models employed the reduced travel cost sample of $N = 5937$, which was obtained after removing 2777 respondents who did not make any visit in the four weeks preceding the survey and a further 2729 respondents who made a visit but for whom no travel distance could be extracted (Supplementary materials A.3). There appeared to be no systematic exclusion of respondents with certain observable characteristics in this reduced sample as indicated by the comparison of columns 1 and 2 in Table 1.

Sampling weights for both samples were computed based on country, gender and age group. Characteristics of both samples are displayed in Table 1. These characteristics match the respective population shares in the underlying population. In terms of education, the vast majority of respondents (90% in the full sample/92% in the travel cost sample) had

[2] Generally in the literature, the reason for zero-truncation of the collected trip frequency data is that travel cost surveys are often conducted at the site the recreational value of which they are to assess. This results in the systematic exclusion of non-visitors from the survey sample.

[3] Despite the usefulness of the MPLN model the authors are only aware of one other application (Voltaire and Koutchade, 2020).

Table 1
Sample characteristics (all respondent-specific variables used in visit count modelling).

Variable	1 Full sample		2 Travel cost sample		3 Population[b]	
	N = 11,443		N = 5937		325.51m	
	N	%	N	%	N	%
Male	5533	0.48	2866	0.48	157.67m	0.48
Age group						
Age18–29	1955	0.17	1004	0.17	54.94m	0.17
Age30–39	1875	0.16	972	0.16	51.38m	0.16
Age40–49	2008	0.18	1048	0.18	56.31m	0.17
Age50–59	1940	0.17	1007	0.17	57.55m	0.18
Age60+	3665	0.32	1906	0.32	105.34m	0.32
Education						
Not complete primary education	59	0.01	29	0.00		
Completed primary education	1045	0.09	459	0.08		
Completed secondary/further education	4845	0.42	2467	0.42		
Completed higher education	5494	0.48	2983	0.50		
Marital status						
Married	6918	0.60	3722	0.63		
Single	4021	0.35	1956	0.33		
Neither	388	0.03	200	0.03		
Prefer not to answer	116	0.01	59	0.01		
Own dog	3490	0.31	1915	0.32	–	0.23[c]
Self-rated competent swimmer	5446	0.48	2927	0.49	–	–
Survey wave[d]						
Jun-17	2813	0.25	1621	0.27	–	–
Sep-17	2658	0.23	1544	0.26	–	–
Dec-17	2935	0.26	1356	0.23	–	–
Mar-18	3037	0.27	1416	0.24	–	–

Variable	1 Full sample		2 Travel cost sample		3 Population[b]	
	N = 11,443		N = 5,937		325.51m	
	Mean	SD	Mean	SD	Mean	SD
Household income (€1000)[a]	26.05	17.34	25.82	17.31		

Notes: Country-specific sampling weights applied.
[a] 14.6%/14.9% in either sample of observations had missing values for household income, which were imputed using country-specific mean of observed cases.
[b] Source: Eurostat "Population on 1 January by age group, sex and NUTS 2 region".
[c] Source: FEDIAF (2018).
[d] Respondents were sampled at the same time across all 14 countries.

completed secondary/further education (with half of those also completing higher education). Reported household income ranged between €1227 and €82,579 per year with an average of €25,852. There is substantial variation in the country-specific mean household income, ranging from €6640 in Bulgaria to €40,168 in Sweden, reflecting expected income differences across the 14 countries surveyed. 32% of the travel cost sample (31% of the full sample) owned a dog, and 49% in the travel cost sample (48% in the full sample) regarded themselves a competent swimmer. (Supplementary materials Tables A.2 to A.15 report country-specific sample characteristics.)

3.2. Descriptive statistics of blue space visits

Table 2 reports all visit-related variables for respondents included in the travel cost sample ($N = 5937$). Due to the truncation of visit frequencies at zero, all respondents in the travel cost sample made at least one visit to a blue-space site. In the previous four weeks, respondents made on average 4.37 visits to the selected blue space and reported on average just under 1 extra planned visit in the subsequent four weeks following hypothetical water quality improvements (5.11). They only stated a fraction fewer anticipated visits in response to deteriorations (4.08).

Calculated travel distances indicated that blue-space visits were casual, short-distance trips (average roundtrip distance 24.8 km; median = 9 km). The average cost of a visit is low (€4.35), but with substantial variation (Max = €216) demonstrating that travel cost reflects the variation in distance travelled and mode of transport used (Supplementary materials B).

Table 2
Summary of four-week visit frequency variables of travel cost sample.

Variable	Mean	SD	Min	Max
Visits (OB)	4.37	6.02	1	56
Visits (CB_improvement)	5.11	6.52	0	56
Visits (CB_deterioration)	4.08	6.10	0	56
Roundtrip distance travelled (in km)	24.80	48.58	0	702
Roundtrip travel cost (in €)	4.34	10.43	0	216

Variable	N	%
Type of visit		
Intentional (travel entirely to visit the site)	3685	0.62
Incidental (travel partly to visit the site)	2252	0.38
Perceived water quality		
Poor	388	0.07
Sufficient	1330	0.22
Good	2834	0.48
Excellent	1385	0.23

Notes: N = 5937 (This excludes respondents who made no blue space visits in the last four weeks or whose travel distances could not be extractEd.) OB = observed behaviour; CB = contingent behaviour. Country-specific sampling weights applied.

Regarding the purpose of the visit, 62% of respondents stated their visit was intentional, with the remaining 38% indicating an incidental visit. Most respondents who made at least one visit perceived the water quality at the site as "Good" (48%). Only 388 (7%) respondents perceived it as poor, with about a quarter of respondents stating water quality was either sufficient or excellent. Given that only 1.4% of bathing sites were categorised as poor, and 85% as excellent, in the EU assessment for the 2017 bathing season (EEA, 2018), this suggests that many respondents were visiting non-bathing water sites with genuinely poorer water quality (e.g. urban rivers). Their assessments of quality may be based on visual heuristics such as colour, clarity and presence of litter and therefore not perfectly correlated with the microbiological assessments of faecal loads. Responding to Research Objective A), the most frequently visited type of blue space was seaside promenade with 1075 (18%) respondents (Fig. 2). The least frequently visited site type was a salt marsh, estuary or lagoon with only 26 (0.43%) respondents having visited this site type in the last four weeks.

Total annual visits per individual to blue spaces can be extrapolated from the stated numbers of visits to a selected blue space over the preceding four weeks. Using the full sample ($N = 11,443$), the average respondents makes 46.91 blue-space visits per year (95%-confidence interval: [45.44–48.46], median: 19.96). Fig. 3 reports these figures broken down by country. Average annual visits ranged from 33.04 in France to 63.24 in Finland. No obvious geographical pattern is discernible across countries, with Mediterranean, Nordic and Western European countries found both among the low and high visit frequency countries, respectively.

3.3. Exploration of visit frequency

Referring to Research Objective B), multivariate Poisson lognormal models were used to explore visit behaviour (Table 3). In Model 1, which excluded country-specific travel cost dummies and used a pooled travel cost variable, there was a significant and negative association between travel cost and visit frequency as observed in the aggregate travel cost coefficient of −0.024. Respondents faced with higher travel costs to the site, due to distance or other components of the constructed travel cost variable, made fewer visits to those sites on average. There was a robust positive association between perceived water quality and visit frequency (indicated for instance by the coefficient 'Good' of 0.160).

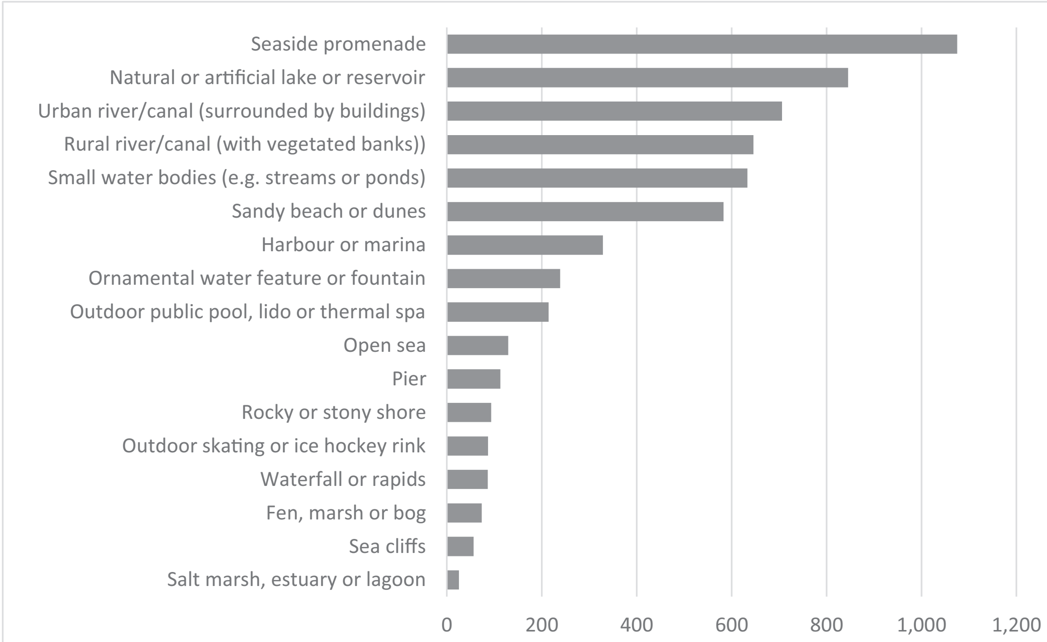

Fig. 2. Blue space site types visited (using the travel cost sample $N = 5937$. Country-specific sampling weights applied).

This pattern appeared to be linear. These results were consistent across both Models 1 and 2.

Visit frequency was also negatively associated with the duration of the selected past visit, reflecting the fact that long visits to blue spaces also tend to be far from home (Elliott et al., 2015). Dog owners and competent swimmers made more visits to blue-space sites, on average, than non-dog-owners/non-swimmers, respectively. Visit frequency was unrelated to gender, marital status, educational attainment or (log) income, but older adults tended to make more visits than younger adults.

In Model 2, the travel cost variable was interacted with 14 country indicators, yielding country-specific travel cost coefficients. These coefficients were cost sensitivity parameters for each of the 14 EU Member States. Results showed that the travel cost coefficients were negative and significant for all countries. Irish and Finnish respondents displayed the highest sensitivity to travel cost, whereas cost sensitivity was lowest for respondents in Portugal.

The estimated coefficients of Model 1 and 2 were used to predict blue space visit frequencies conditional on different water quality changes. Predicted changes in annual visit counts using only intra-respondent (i.e. experimentally-induced) variation, are reported in Table 4. On average across all baseline levels of perceived water quality, improving water quality by one level on the BWD designation led to 3.13 more predicted visits per respondent per year. This is equivalent to a 6.67% increase on the baseline of 46.91 annual visits. The reaction to a one-level deterioration of water quality was disproportionally stronger, with 9.77 fewer annual visits per respondent predicted as a reaction to such a change (equivalent to a 20.83% reduction). These figures further showed that the number of additional visits following

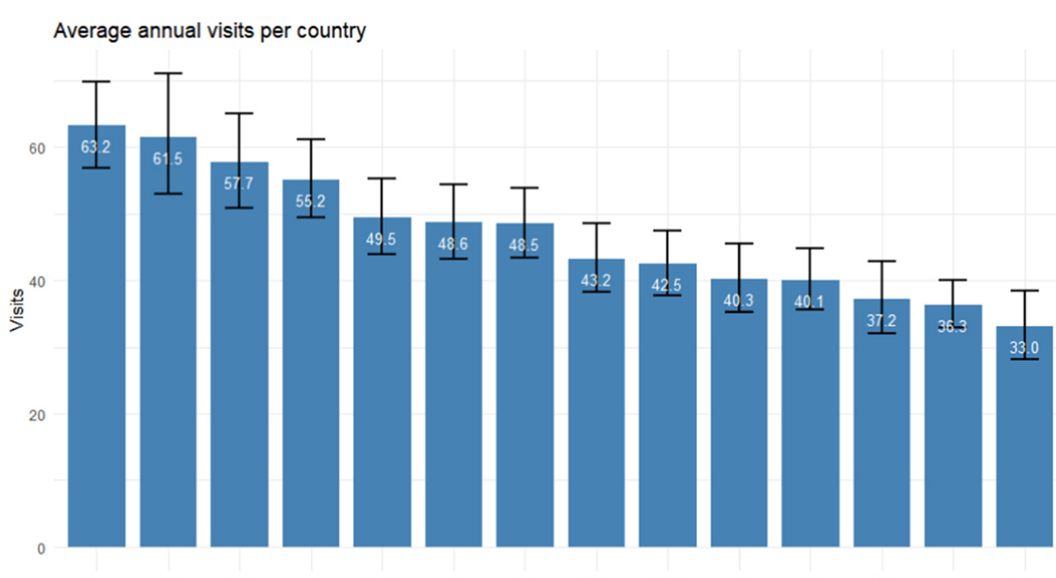

Fig. 3. Average annual visits to any type of blue space site (using full sample $N = 11{,}443$ and country-specific sampling weights).

Table 3
Multivariate Poisson lognormal (MPLN) regression models of OB and CB visit frequencies.

	Model 1		Model 2	
	Coef.	Std. error	Coef.	Std. error
Constant	0.563*	(0.310)	0.806**	(0.326)
Travel cost – Aggregate	−0.024***	(0.002)		
Travel cost – Bulgaria			−0.021***	(0.004)
Travel cost – Czech Republic			−0.033***	(0.007)
Travel cost – Estonia			−0.023***	(0.005)
Travel cost – Finland			−0.045***	(0.008)
Travel cost – France			−0.032***	(0.009)
Travel cost – Germany			−0.018**	(0.009)
Travel cost – Greece			−0.036***	(0.008)
Travel cost – Ireland			−0.045***	(0.009)
Travel cost – Italy			−0.016***	(0.005)
Travel cost – Netherlands			−0.029***	(0.004)
Travel cost – Portugal			−0.013*	(0.008)
Travel cost – Spain			−0.020***	(0.007)
Travel cost – Sweden			−0.041***	(0.015)
Travel cost – United Kingdom			−0.021***	(0.005)
Water quality (ref: Sufficient)				
Advice against swimming	−0.354***	(0.037)	−0.353***	(0.040)
Poor	−0.206***	(0.017)	−0.205***	(0.017)
Good	0.160***	(0.011)	0.159***	(0.011)
Excellent	0.324***	(0.015)	0.321***	(0.015)
Outstanding	0.491***	(0.019)	0.486***	(0.020)
Visit duration	−0.009***	(0.003)	−0.008***	(0.003)
Intentional visit	−0.063**	(0.028)	−0.063**	(0.027)
Male	0.034	(0.032)	0.038	(0.031)
Age group (ref: 18 to 29)				
age_30.to.39	0.032	(0.057)	0.024	(0.080)
age_40.to.49	0.124***	(0.047)	0.158**	(0.077)
age_50.to.59	0.136***	(0.046)	0.162*	(0.090)
age_60.and.over	0.209***	(0.042)	0.238***	(0.088)
Marital status (ref: Prefer not to answer)				
Married	−0.004	(0.057)	−0.137	(0.138)
Single	−0.030	(0.054)	−0.129	(0.130)
Neither	0.032	(0.110)	−0.051	(0.155)
Education (ref: Primary not completed)				
Primary completed	0.001	(0.130)	−0.087	(0.105)
Secondary completed	−0.002	(0.125)	−0.062	(0.096)
Higher completed	−0.008	(0.123)	−0.064	(0.098)
Log(household income)	0.024	(0.034)	0.010	(0.030)
Own dog	0.289***	(0.032)	0.304***	(0.032)
Competent swimmer	0.157***	(0.034)	0.163***	(0.035)
Site type (ref: harbour or marina)				
Fen	0.023	(0.187)	0.052	(0.129)
Lake	0.174***	(0.065)	0.131*	(0.071)
Open sea	0.310***	(0.080)	0.318	(0.251)
Fountain	0.152	(0.129)	0.003	(0.116)
Pool	−0.009	(0.094)	−0.084	(0.107)
Ice rink	−0.383***	(0.099)	−0.488***	(0.132)
Pier	0.418***	(0.158)	0.230**	(0.107)
Shore	0.123	(0.126)	0.209**	(0.089)
Rural river	0.501***	(0.071)	0.384***	(0.083)
Marsh	0.550**	(0.225)	0.386	(0.338)
Beach	0.251***	(0.065)	0.261***	(0.089)
Cliffs	−0.095	(0.132)	−0.116	(0.154)
Promenade	0.204***	(0.060)	0.113*	(0.065)
Streams	0.329***	(0.063)	0.317***	(0.072)
Urban river	0.302***	(0.073)	0.274***	(0.071)
Waterfall	0.030	(0.125)	−0.114	(0.433)
Survey wave (ref: Jun_2017)				
Sep_2017	−0.059	(0.045)	−0.020	(0.036)
Dec_2017	−0.185***	(0.048)	−0.112***	(0.038)
Mar_2018	−0.119**	(0.050)	−0.103**	(0.040)
Country (ref: Bulgaria)				
Czech Republic	−0.216***	(0.073)	−0.143*	(0.077)
Estonia	−0.401***	(0.075)	−0.327***	(0.081)
Finland	0.063	(0.070)	0.153*	(0.081)
France	−0.245***	(0.085)	−0.133	(0.110)
Germany	−0.354***	(0.088)	−0.321***	(0.093)
Greece	0.035	(0.069)	0.121	(0.097)
Ireland	−0.258***	(0.079)	−0.200**	(0.088)
Italy	−0.233***	(0.083)	−0.229***	(0.087)
Netherlands	−0.438***	(0.079)	−0.323***	(0.093)
Portugal	−0.198***	(0.066)	−0.228***	(0.084)
Spain	−0.134	(0.088)	−0.099	(0.119)
Sweden	−0.129*	(0.070)	0.024	(0.094)
United Kingdom	−0.418***	(0.090)	−0.361***	(0.089)
Log-likelihood	−35,955		−35,930	
Parameters	61		74	

Notes: $N = 5937$ respondents (with $n = 17{,}811$ observations). ***, ** and * indicate significance at the 1%-, 5%- and 10%-level of confidence.
1000 Sobol draws to simulate the likelihood.

water quality improvements did not depend on the baseline level of perceived water quality. Raising water quality starting at any one of the four possible levels increased the number of predicted visits by similar numbers. This picture was similar with respect to deteriorations where one-level decreases in water quality led to predicted reductions in visits clustered closely around the mean across all baseline levels.

3.4. The value of blue space recreation and changes in water quality

The travel cost coefficients estimated in Models 1 and 2 (Table 3) were used to calculate the consumer surplus (i.e. the recreational value) of a blue-space visit according to Eq. (4) in Section 4. Across the entire travel cost sample ($N = 5937$) the recreational value of visiting a blue-space site was €41.32 per adult visit (Table 5 – EU14). This value is an average over all site types, seasons and countries surveyed.

There was substantial variation between the 14 countries surveyed, with the recreation value of a single blue-space adult visit ranging from lows of €23.02 and €23.05 in Finland and Ireland, respectively, to a high of €82.95 in Germany. Note, however, that the estimates for Germany and Portugal (€74.41) come with comparably large uncertainties as expressed in the wide confidence intervals (and further reflected in the comparatively large robust standard errors of these travel cost coefficients in the MPLN model in Table 3).

The estimated recreational values of blue-space sites were combined with the predicted number of annual visits and figures of the total adult population of the EU14 and the individual countries (Table 5 Column 4). Predicted annual visits were calculated as the (sample weighted) average of stated visit numbers of the whole sample ($N = 11{,}443$), which included respondents with zero visits and those for whom travel distance could not be extracted. The result was the total annual recreational value of visiting blue-space sites across half of all EU Member States

Table 4
Predicted changes in annual recreational blue-space visits following improvement or deterioration of perceived water quality at the respective site.

Baseline level	Change after improvement		Change after deterioration	
	Mean	95% conf. int.	Mean	95% conf. int.
All levels	3.13	[2.42–3.80]	−9.77	[−10.39 to −9.13]
Poor	2.69	[1.31–4.06]	−8.39	[−10.66 to −5.97]
Sufficient	1.96	[0.76–3.12]	−11.05	[−12.51 to −9.64]
Good	3.02	[1.84–4.16]	−9.31	[−10.38 to −8.29]
Excellent	4.62	[2.67–6.48]	−9.89	[−11.14 to −8.71]

Notes: Based on estimates from Model 1 in Table 3. Draws of visit counts annualised as $visit \cdot {}^{365}/_{28}$. For computation details of confidence intervals see Supplementary materials C.

Table 5
Consumer surplus (CS) measures of visiting blue-space sites.

	1	2	3	4		5	
	Surplus (€/visit)	95% CI	Population (in 1000)	Total CS (in €1bn)	95% CI	CS/pax (€/year)	95% CI
EU14	41.32	[36.79–46.97]	325,514	630.93	[559.79–722.02]	1938	[1718–2212]
Bulgaria	50.45	[35.65–76.26]	5857	14.62	[10.09–22.36]	2495	[1722–3817]
Czech Republic	33.16	[20.49–60.51]	8661	13.96	[8.46–25.74]	1612	[977–2972]
Estonia	45.24	[31.60–69.34]	1067	1.79	[1.21–2.80]	1681	[1131–2623]
Finland	23.02	[16.30–34.76]	4446	6.47	[4.49–9.88]	1456	[1010–2221]
France	32.43	[22.01–51.70]	52,228	55.96	[36.52–90.53]	1071	[699–1733]
Germany	82.95	[33.10–183.77]	69,240	244.20	[96.01–543.29]	3527	[1387–7846]
Greece	28.87	[21.09–41.65]	8861	15.74	[11.03–23.24]	1777	[1245–2623]
Ireland	23.05	[17.02–32.74]	3634	4.06	[2.93–5.85]	1117	[805–1609]
Italy	71.18	[37.02–171.60]	50,662	130.97	[67.32–316.84]	2585	[1329–6254]
Netherlands	36.53	[24.42–59.61]	13,793	20.28	[13.18–33.49]	1470	[955–2428]
Portugal	74.41	[43.92–281.56]	8531	27.41	[15.93–103.34]	3213	[1867–12,113]
Spain	53.74	[34.00–95.01]	38,295	113.55	[70.59–202.23]	2965	[1843–5281]
Sweden	25.77	[16.60–44.06]	7997	11.90	[7.49–20.59]	1488	[937–2575]
United Kingdom	50.55	[86.47–2.29]	52,243	102.98	[66.71–182.16]	2027	[1277–3495]

Notes: CI - confidence interval (for computation details see Supplementary materials C). Estimates of "EU14" based on Model 1 in Table 3; all country estimates based on Model 2.

(and 78% of its adult population) in 2017/2018. This figure was €630.93bn. Note the wide variation across countries ranging from €1.44bn in Estonia to €192.32bn in Germany. This variation was mainly a reflection of differences in population size but partly also of different consumer surplus estimates and annual visit count predictions. Therefore, Column 5 in Table 5 (and yellow circles in Fig. 4) presents per-capita consumer surplus figures of blue space recreation across the EU14. While in Germany and Portugal citizens received the largest annual benefit from visiting blue-space sites (€3527 and €3213 per person, respectively), the annual benefits were lowest in France and Ireland (€1071 and €1117 per person, respectively).

The EU14-wide consumer surplus estimate of €41.32 per visit was further combined with the predicted changes in visit counts from Table 4 to arrive at valuations of water quality changes. Improving

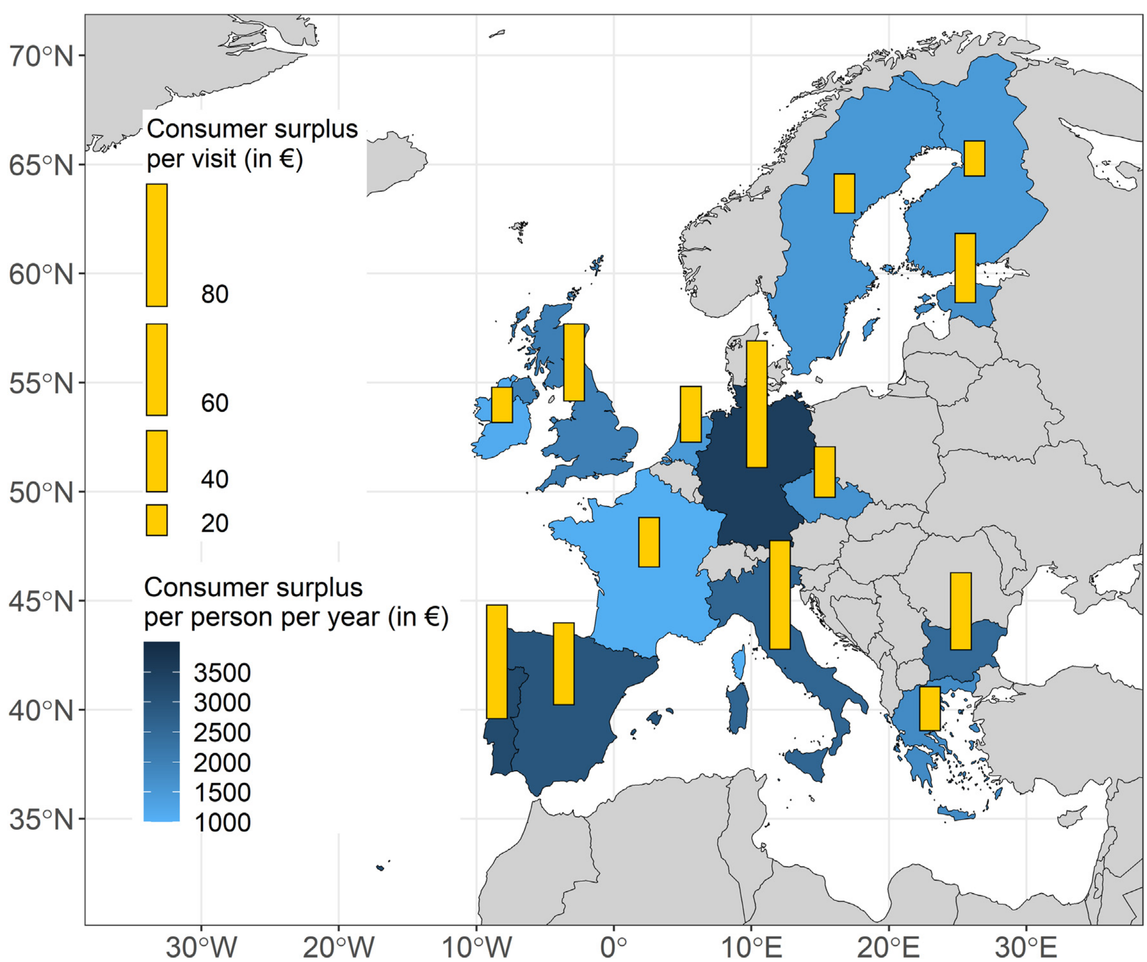

Fig. 4. EU Member States surveyed. Yellow bars indicate the value (consumer surplus) in € per blue-space visit; blue shading indicates average annual consumer surplus per person.

water quality led to 3.13 more visits annually, which was equivalent to an increased recreational value worth €129.25 (95% confidence interval: [96.09–161.27]) per adult per year. Deteriorating water quality made respondents undertake 9.77 fewer visits on average, which would result in a total value of €403.57 [352.92–470.00] lost per adult per year. Applying this to the estimated total value of blue space recreation, the total annual value of improving water quality in EU14 blue space sites by one BWD quality level was €41.89bn [31.14bn - 52.26bn] per year; compared to an annual loss of €130.79bn [114.37bn – 152.32bn] from reduced water quality by the equivalent one-level BWD quality standard.

4. Discussion

This paper reported results from a TC-CB study valuing recreational visits to blue-space sites as well are changes to those values due to changes in perceived water quality at these sites across 14 EU Member States. Referring to Research Objective A) the study found that seaside promenades as well as natural or artificial lakes or reservoirs were the most frequently visited types of blue spaces. It further finds that adults in 14 EU Member States visited blue spaces 47 times per year on average, with in part significant national differences. However, a regional pattern of blue-space visitation rates did not emerge from the data.

In response to Research Objective B) the analysis showed that higher perceived water quality was associated with greater numbers of visits. It is worth noting that these perceptions differed substantially from the actual levels of bathing water quality as reported by the European Environmental Agency (EEA, 2018). For the 2017 bathing season, 85% of sites were classified as having excellent water quality and only 1.4% of sites were rated "Poor" by the EEA. Note, however, that the EEA figures refer exclusively to bathing sites, whereas the type of sites covered in the present survey also included many non-designated bathing sites such as urban rivers, marinas and harbours and ornamental fountains. Moreover, respondents' assessments of quality were mostly likely based on visual heuristics such as colour, clarity and litter that may not be perfectly correlated with the microbiological assessments of faecal loads.

The analysis also found a positive association between visitation rates and respondent age, dog ownership and self-rated swimming ability, respectively. The duration of the visit was negatively associated with visitation reflecting the fact that shorter visits were more frequent. This idea, that the number of routine visits was higher than trips with blue-space recreation as their primary purpose was supported by the negative association between the visit being intentional and visit frequency. A seasonal pattern also emerged from the data whereby visit frequency elicited in the survey waves in December and March was significantly lower than in June.

For Research Objective C), predictions were presented of how changes in water quality influenced the use of blue space for recreation. While a one-level improvement of water quality was predicted to lead to a 6.67% increase in blue-space visits across 14 EU Member States, an equivalent deterioration of perceived water quality levels would cause 20.83% fewer visits. This stronger reaction to negative than positive changes in water quality was consistent with psychological research into strong emotional reactions (e.g. 'disgust') to contamination of food and water (Rozin and Royzman, 2001) and the principle of loss aversion in Prospect Theory which argues that losses tend to 'loom larger' than equivalent gains (Tversky and Kahneman, 1991).

The estimation of recreational and water quality values responded to Research Objective D). The average value of a recreational visit to blue-space sites was estimated at €41.32. Extrapolating that to the total adult populations of the 14 countries surveyed the study estimated that all recreational blue-space visits were valued at €631bn annually. This was equivalent to an annual benefit of €1938 per adult. To the best of the authors' knowledge, this is the first TC-CB valuation study conducted by means of a representative survey across a population as large as 78% of the EU. Results showed per-capita benefits of such recreation ranging between €1071 in France and €3527 in Germany. Blue-space recreational values with hypothetical one-standard increases in water quality were estimated to be worth an additional €42bn and decreases worth €131bn less in total across the countries surveyed.

The analysis extrapolated total visitation counts from the survey dataset for illustrative purposes. Therefore, these figures should be interpreted with caution. Nevertheless, care was taken to present conservative estimates of predicted visits and estimated values at every stage. For the MPLN count data model to estimate the value of a visit, respondents with overly large travel distances as well as improbably high visit counts (i.e. more than two daily visits) were discarded (see Supplementary materials A.3). Removing observations with both long distances (and hence travel costs) and high visit counts increased the estimate of cost sensitivity in the remaining sample and thereby yielded a smaller value estimate.

Furthermore, the MPLN model rightly accounted for incidental truncation of visit counts. Comparing the main valuation estimate above (€41.32) to those from the widely available random effects Poisson and random effects negative binomial models without truncation (€49.58 [95% confidence interval: 46.41–53.21] and €44.43 [41.93–47.25], respectively, Supplementary materials D) demonstrated that the MPLN estimates were conservative.

In addition, one needs to examine how the extrapolated total visit counts compare to other assessments of green and blue space use across Europe. Using the Monitoring Engagement with the Natural Environment (MENE) dataset for England, White et al. (2016) arrived at 1.23bn visits to natural environments (including both blue and green spaces). Breaking down the predicted 40.1 average annual visits for the UK in the current study (Fig. 3) for the 2018 adult population of England (43.9m) gives a total of 1.76bn visits, a figure similar to the numbers arrived at using the MENE dataset. White et al. (2016) looked at visits to all types of natural environment whereas the present study was concerned with blue spaces only. Nevertheless, blue-space sites as defined in the present study are often identical or closely connected to green spaces, which makes difficult a strict differentiation into the type of natural environment that respondents visited.

Regarding total visit counts per country, only self-reported visits to the most recently visited site type were taken into account. It is conceivable, even likely, that respondents will have made additional visits to sites of other types in the reporting period (past four weeks). Such visits are not recorded in the data and therefore systematically ignored.

Predictions of changes in visit frequencies resulting from changes in water quality at blue-space sites were entirely based on respondents who made at least one visit in the past four weeks. These predictions did not take into account that respondents who did not make any visits under current conditions may decide to start visiting blue-space sites if water quality changed. Building on the MPLN model suggested by Egan and Herriges (2006) the present analysis did account for respondents who reduced their planned visits to zero in reaction to a water quality change. Nevertheless, respondents with zero visits under current conditions were systematically ignored. The analysis attempted to counter this by producing a conservative estimate of total visits using a much larger sample ($N = 11{,}443$) including both visitors and non-visitors of blue-space sites.

These limitations notwithstanding, the results of the present study have a number of implications. Estimated values for changes in water quality can be compared to costs of implementation of BWD and WFD as well as monitoring efforts under the auspices of these Directives. However, such cost estimates are hard to come by. Georgiou and Bateman (2005) present BWD implementation costs (i.e. one-off capital investment and yearly maintenance) of up to €7.7bn for the UK and €16m for the Netherlands, which, even after accounting for inflation, remain far below the annual values of €103bn and €20bn, respectively, as estimated in the present study, suggesting that these are worthwhile investments.

Increased visitation at blue-space sites due to water quality improvements could support other economic opportunities at these sites e.g. services such as recreational equipment hires and cafes (Bergstrom et al., 1996). This has further implications for public health. Encouraging more people to exercise in and around blue spaces is both good for long-term mental and physical health, with potential substantial savings to health services (Papathanasopoulou et al., 2016). In contrast, the reductions in blue space visits predicted as a result of deteriorated water quality may mean that these wider economic benefits and health cost savings are lost. This risk is substantial because lost blue-space visits were predicted to be more than three-times the potential gains from an equivalent water quality improvement. The larger potential loss in recreational value resulting from water quality deteriorations calls for a risk-based approach for blue space water quality monitoring. Such a risk-based approach would go along with the MSFD moving towards risk-based assessments for the different descriptors, i.e. monitor only where there is a risk of failing to meet good environmental standards (Rages, 2019). As such, this refocusing on risk-based assessment would lead to better integration of MSFD and WFD.

Notwithstanding the preventative health and well-being benefits of blue-space recreation (White et al., 2020), encouraging visits to such sites does mean that other things need to be taken into consideration e.g. the potential health risks associated with increased visits (e.g. drowning, injury, stomach upsets); access and facilities may need to be improved; environmental implications of making these sites more attractive/accessible and the impact of increased recreational numbers on the natural environment, such as trampling or wildlife disturbance.

These results have implications for improved water quality testing and monitoring. Currently bathing sites are only monitored during the bathing season with only four samples per season required and a sampling interval of no longer than a month. Further, agencies are sometimes allowed to 'discount' samples if the public has been warned in advance that water quality is likely to be poor (e.g. during periods of heavy rainfall) so the 'official' bathing water quality standards might not match what people see in their everyday experiences. This in turn may influence their reactions to a specific site conditions (e.g. intentions to visit or not again in the future). Improving the understanding of people's perceptions of quality throughout the whole year and following contamination events (whether predicted or not) seems to be a priority for future research given the potentially strong implications for future behaviours and visits.

5. Conclusions

In conclusion, this study found substantial benefits of recreation at blue space sites across 14 EU Member States. The total annual value of recreational visits to blue spaces was estimated at €631bn based on an average per-visit value of €41.32. Perceived water quality at blue-space sites according to the Bathing Water Directive classification was an important driver of visitation. Although improvements in quality were likely to be rewarded with greater visit frequency, lapses in quality were likely to result in disproportionately large visit reductions and thus effort to maintain and improve bathing water quality standards are crucial for both human health and local blue-space-related economies.

CRediT authorship contribution statement

Tobias Börger: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Danny Campbell:** Methodology, Formal analysis, Writing – review & editing. **Mathew P. White:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Lewis R. Elliott:** Conceptualization, Data curation, Methodology, Writing – review & editing, Project administration, Funding acquisition. **Lora E. Fleming:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Joanne K. Garrett:** Investigation, Visualization, Writing – review & editing. **Caroline Hattam:** Conceptualization, Methodology, Writing – review & editing. **Stephen Hynes:** Methodology, Writing – review & editing. **Tuija Lankia:** Writing – review & editing, Funding acquisition. **Tim Taylor:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This project has received funding from the European Union's Horizon 2020 - Research And Innovation Framework Programme under grant agreement No 666773 (BlueHealth). Data collection in Finland was supported by the Natural Resources Institute Finland (Luke). Data collection in Portugal was supported by ISCTE – University Institute of Lisbon. Data collection in Ireland was supported by the Environmental Protection Agency, Ireland. The funders had no role in the conceptualisation, design, analysis, decision to publish or preparation of the manuscript.

We thank Ben Butler, Gavin Ellison, and Tom Powell at YouGov for managing the data collection pertaining to this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145597.

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