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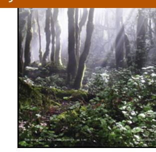

Mapping recreational visits and values of European National Parks by combining statistical modelling and unit value transfer

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ABSTRACT

Recreation is a major ecosystem service and an important co-benefit of nature conservation. The recreational value of National Parks (NPs) can be a strong argument in favour of allocating resources for preserving and creating NPs worldwide. Managing NPs to optimize recreational services can therefore indirectly contribute to nature conservation and biodiversity protection. Understanding the drivers of recreational use of national parks is crucial.

In this study we use a combination of primary data on annual visitor counts for 205 European NPs, GIS and statistical regression techniques to analyse how characteristics of NPs and their surroundings influence total annual recreational visitor numbers. The statistical model can be used for land-use planning by assessing the impact of alternative conservation scenarios on recreational use in NPs. The recreational use of new NPs can be estimated ex-ante, thereby aiding the optimisation of their location and design.

We apply the model to: (1) map recreational visits to potential new NPs across Europe in order to identify best NP location; (2) map recreational visits to a proposed new NP in the west of Germany in order estimate monetary values and to show how visits are distributed across the site; and (3) predict annual visits to all NPs of 26 European countries. Total annual visits amount to more than 2 billion annually. Assuming a mean value per visit derived from 244 primary value estimates indicates that these visits result in a consumer surplus of approximately € 14.5 billion annually.

1. Introduction

National Parks (NPs) are protected areas for the conservation of extraordinary landscape and wildlife for posterity and as a symbol of national pride. NPs contribute to stopping the loss of biodiversity, maintaining the naturalness and beauty of our landscape and the supply of ecosystem services. Thereby, NPs contribute to achieving the targets defined in EU biodiversity strategy 2020, such as “halting the loss of biodiversity and the degradation of ecosystem services” (EC, 2011), and the Aichi targets, such as “to improve the status of biodiversity by safeguarding ecosystems, species and genetic diversity” (CBD, 2013).

However, financial resources and political support for nature conservation are limited and halting ecosystem degradation remains a great challenge. In the past, major policy goals on biodiversity protection have typically not been met, such as those set by the Convention on Biological Diversity, ratified after the global summit in Rio de Janeiro (1992) (Barbault, 2011; Leadley et al., 2010). And still, the future outlook reveals that biodiversity remains under threat and substantial action needs to be undertaken (SCBD, 2014).

One major co-benefit of nature conservation is the supply of recreational opportunities. NPs provide opportunities for visiting, experiencing, enjoying and learning about nature and biodiversity, and thus contribute to human well-being and environmental awareness. Nature recreation and tourism present a great economic value and an opportunity for rural economic development by generating income and employment through visitors’ expenditures. The value of nature recreation and its economic opportunities can be used as a strong argument in favour of allocating financial resources towards nature conservation at different spatial scales (Balmford et al., 2015).

Nature conservation should not only focus on biodiversity and habitat protection, but should also take recreational co-benefits into account. Efficient land-use planning needs to consider all

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ecosystem services supplied. For allocating resources for nature conservation, it can be important to know how recreational co-benefits of nature conservation can be optimized. The most important indicator of the contribution of recreation to the local economy is the number of visitors (Jones, Bateman, & Wright, 2003; Bateman, Day, Georgiou, & Lake, 2006). Therefore, understanding the drivers that determine the number of visitors to protected areas is crucial for protected area management and for protected area designation.

The aim of this study is to analyse the effects of NP characteristics and their spatial context on total annual visits that are considered the main determinant of recreational economic value (Bateman et al., 2006). To this end, we develop regression models of visitor numbers using primary data for European NPs combined with additional spatial variables derived from GIS data. The estimated models give insights into the drivers of recreational use within European NPs and thus allow the prediction of visitor numbers for designated new NPs and alternative management scenarios. Similar to the study of Balmford et al. (2015), we combine our predicted visitor numbers with a mean value estimate per recreational visit, but derived from a much larger set of primary valuation studies. Thereby, the relative importance of recreational services is highlighted as compared to other ecosystem services and man-made goods.

Several studies have modelled visitor numbers of protected areas or nature areas based on spatial variables. One widely applied approach is to use choice models to predict recreational behaviour at the individual level. Typically, such studies use survey data containing information on the origin and destination of an individual recreational trip. However, such datasets are time-consuming to develop and are usually only available for relatively small areas (Pouta & Ovaskainen, 2006; Bateman et al., 2011; Hausman, Leonard, & McFadden, 1995; Jones, Wright, Bateman, & Schaafsma, 2010; Loomis, 1995; Feather et al., 1995; Parsons & Hauber, 1998; Sen et al., 2013; Shaw & Ozog, 1999; Termansen, Zandersen, & McClean, 2008). The purpose of the present study is to investigate the determinants of recreational use of NPs at a European scale and therefore we use data from visitor monitoring studies for NPs across Europe. Some existing studies have used similar approaches in order to investigate drivers of recreational park visits. For example, Neuvonen, Pouta, Puustinen, and Sievänen (2010) analyse effects of park characteristics on visitation rates for 35 Finnish NPs. Mills and Westover (1987) model the visitation rates for 121 Californian State Parks using four predictors representing park characteristics and the distance to the nearest population agglomeration. Hanink and White (1999) model recreational demand for 36 US National Parks using age and size as variables for describing the park, its distance and the population of the closest metropolitan area, as well as substitute availability as context characteristics. Hanink and Stutts (2002) model the demand for 19 recreational battlefields in the US. They use a substitute availability indicator weighted by individual substitute's characteristics. Loomis, Bonetti, and Echohawk (1999) find a significant effect of GDP per capita and of availability of wilderness on the number of recreational trips to wilderness areas per capita in the US. Ejstrud (2006) use a number of GIS indicators for modelling visitor frequency to 10 Danish open-air museums using six predictor variables, but do not report whether they show significant effects. The only study using international visitor data is from Balmford et al. (2015), which uses visitor data of protected areas worldwide. Their study uses only a limited number of relatively simple predictor variables and finds few significant effects. Their model may be appropriate to assess overall trends in protected area visitation rates, but may have few site specific implications. Loomis (2004) uses regression techniques to estimate the effect of elk and bison populations on visitation rates in Grand Teton National Park, US, using explanatory variables on how the park changes over time, but does not compare effects of alternative sites' characteristics.

All except one of the above mentioned studies use national data only for their statistical analysis. Thereby, the number of primary observations is in general relatively low. The purpose of the present study is to investigate drivers of recreational use for NPs Europe-wide and therefore, use visitor data from NPs in 21 European countries comprising 205 case study areas in total. Consequently, we can include more predictors in our initial model and try to estimate a more robust model. For example, national study areas are relatively small and therefore climatic conditions are often too similar to be considered as a predictor in a recreational demand model. Furthermore, we use more refined site and context characteristics as predictors in our model, which are computed and extracted from Europe-wide GIS data layers. As all our predictors are derived from large scale GIS data layers, the final model can easily be used to make predictions of visitors' frequency for any potential NP in Europe. Thus, recreational use can be mapped for any location in Europe without the need for an additional collection of information on the predictor values. Our spatial assessment can thereby be used for ecosystem service mapping as required by the EU Biodiversity Strategy 2020, improving resource allocation and calculating a green GDP (UN, 2014; Maes et al., 2012). Finally, we use a number of different statistical regression techniques to deal with spatial autocorrelation for a more in-depth identification of the spatial dimension of recreational use.

This paper is organized as follows: in section two we describe the data we use, first the primary data of visitor monitoring studies and second the predictors used in our models. In section three we explain the statistical regression techniques applied and present the estimated visitor models. The results are presented and discussed in section four and five, with conclusions provided in section six.

2. Data

2.1. Primary data

Our primary data are 205 total annual visitor estimates to European NPs and 245 estimates of monetary values per recreational visit for 147 separate nature areas in Europe. We collected the data through internet searches, review of relevant literature and by contacting researchers involved in this field, NP administrations and relevant governmental bodies in all EU countries. The data is described more in detail in (Schägner et al., submitted).

For the visitor data to be included, we required as a minimum quality criteria that the total annual visitor estimates are based on some form of on-site visitor monitoring, which is then scaled up to the entire area and the entire year. In order to check whether the quality criteria is met, we analysed the relevant publications on the visitor monitoring programs. In cases in which the information was not available or not accessible due to language barriers, we contacted the authors and relevant institutions. In total we could obtain annual visitor observations for 205 separate case study areas within Europe, which are either an entire NP or a subsection of a NP (see Fig. 1). All collected data were attached as attributes to a spatial layer in vector format, containing the boundaries of NPs or of their surveyed part. We obtained NP polygons from (World Data Base of Protected Areas) and the CDDA (Common Database on Designated Areas) (IUCN & UNEP, 2015; EEA, 2013) and from national agencies. If case study areas differed from the available polygons, we tried to obtain polygons from the authors of the studies, the park management or other stakeholders. In some cases we manually draw polygons with ArcGIS, based on information available in the case study publications or supplied by the authors. If multiple

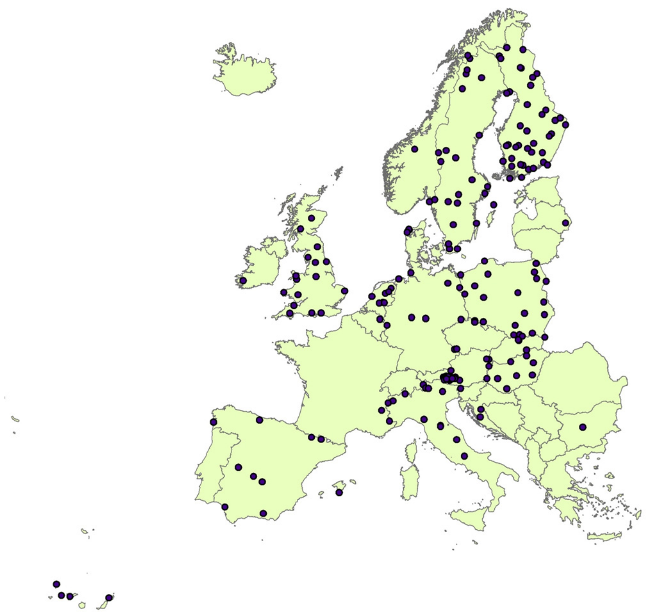

Fig. 1. Location of visitor counts across Europe.

observations of visitor numbers are available for the same study area, we used the average.

NP and case study area characteristics differ widely in terms of size, location, visitation rate and ecosystem characteristics. The smallest case study area is a nine hectare beach within the Wadden Sea NP in Germany, whereas the largest case study area is the Cairngorms NP in Scotland comprising 3816 km^2. Most of the case study areas in our database are located in Northern Europe. For Southern Europe we could obtain visitor numbers for all Spanish, most Italian and French NPs. For our statistical analysis we divided the total annual visitor numbers by the total terrestrial area of the single study areas[1] and thereby obtained total annual visitor densities per ha as our dependent variable in our models. Visitor numbers range from 0.03 visitors/ha/year in the large Sarek NP in northern Sweden up to 56,680 visitors/ha/year on a small beach within the Wadden Sea NP. The total median and mean is 13 and 368 with standard deviation of 3962 visitors/ha/year, indicating a skewed distribution with a tail of very high visitation rates. The *mean relative deviation* is about 167%. For more information on the primary data, it can be accessed via the ESP Visualisation Tool (Drakou et al., 2015).

For our statistical analysis we divided the total annual visitor numbers by the total terrestrial ha size of the single study areas and thereby obtained total annual visitor densities per ha as our dependent variable in our models, which is common within species distribution modelling.

The valuation studies use either Travel Cost Method (TCM) (57%) or Contingent Valuation Method (CVM) (43%). For the valuation studies, we transfer all value estimates to Euro 2013 price level using purchasing power parity and country specific inflation data. We exclude one outlier with an extreme deviation of 60 times the mean value. The remaining value estimates range from € 0.16 to 64.7 per visit with a mean of €7.17, a median of €2.8, a standard deviation of 11 and a *mean relative deviation* of 95%. Most study sites are located in Western Europe (51%). The UK has the highest number of observations (81), followed by Italy (32), Ireland (28), Finland (27) and Germany (22).

[1] We used the terrestrial area not including area covered with water because some NP – in particular marine NP – comprise mainly of water. Including the area of water would bias our analysis since this area is hardly visited.

2.2. Explanatory variables

Explanatory variables used to model visitation rates can be divided into three categories: (1) site characteristics, which describe the NP itself; (2) context characteristics, which describe the spatial context of the NP; and, (3) study characteristics, which describe the methodology of primary data collection. The selection of variables was based on a review of the literature on recreational demand modelling and environmental recreational value transfer studies. However, limitations in the availability of comprehensive and consistent Europe-wide data sets and in the information provided in visitor monitoring publications restricted our choice of predictors. A complete list of all predictors used in our analysis is presented in Table 1. Detailed description is presented in the following sections. Each variable is available in geospatial raster format, therefore site and context characteristics for each site could be easily calculated in a GIS environment. We extracted mean values of all predictor variables for each case study area using an automated model built in ArcGIS, including the use of the zonal statistics tool (ArcGIS 10.1). The raster layers of the predictors were either taken from available GIS data sets or we computed them by reprocessing or combining existing data sets using ArcGIS (ArcGIS 10.1). Then we conducted an exploration of our data following the recommendations of (Zuur, Ieno, & Elphick, 2010) in order to gain initial insights into distributions and dependencies. For some predictors we used logarithmic or square root transformations either because they showed a relatively skewed distribution or because we wanted to approximately linearize an expected non-linear relationship. We tested all our predictors for multicollinearity, but could not identify anything of concern.

2.2.1. Site characteristics

The following site characteristics are used to model visitation rates: (1) Share of land cover/use: We used the CORINE land cover/use data set (EEA, 2006) to determine the shares of different land cover/use classes and aggregates of single land cover/use classes for each NP. In particular we focused on natural vegetation cover. We do not, however, have strong prior expectations regarding the signs of these land cover predictors. In general, one may assume that natural vegetation supports nature recreation. However, NPs typically offer plentiful natural vegetation and therefore additional natural vegetation of any kind may not necessarily attract additional visitors. Our analysis of the different land covers has an exploratory character and does not aim to test specific hypotheses. The separate classes and aggregated areas are presented in Table 1. (2) Water bodies: We computed a 300 m resolution grid of the share of surface area covered with rivers, lakes or ocean using the Euro Regional Map as input data set (EG, 2010). Then we applied a kernel density function tool (ArcGIS 10.1) to compute the amount of surface covered with water within a 3 km radius of each pixel. The density function allows water area that is further away to be weighted less than water nearby and thereby incorporates a distance decay effect. The presence of water bodies in a NP are expected to have a positive impact on recreational use (Termansen et al., 2008).

We expect that more diverse landscapes are perceived as more beautiful (Dramstad & Tveit, 2006) and thereby attract more visitors. Based on the basic economic principle of decreasing marginal utility and rates of substitution, diversity tends to be rated higher than uniformity (Mankiw, 2001). In order to account for landscape diversity we computed three different indicators. (3) Three dimensionality: We computed the area visible from each pixel within a 30 km radius using the view shed tool (ArcGIS 10.1)

Table 1
List of predictors used in the models.

Type	Variables	Explanation[a]	Mean/Standard Deviation
Site Characteristics:	Sqrt (grassland)	Share of grasslands cover of the study area (100 m resolution raster)	0.2/0.24
	Sqrt (wetland)	Share of wetlands cover of the study area (100 m resolution raster)	0.14/0.23
	Sqrt (water)	Share of water bodies of the study area (300 m resolution raster)	0.23/0.26
	Log (broadleaf)	Share of broadleaf forest of the study area (100 m resolution raster)	0.73/0.86
	Conifer	Share of conifer forest of the study area (100 m resolution raster)	4.44/4.63
	Log (forest edge)	Transition area between forest and other land use/cover (25 m resolution raster)	0.83/0.4
	Sqrt (land cover diversity)	Simpson Diversity Index of Corine land use/cover within a 3 km radius (100 m resolution raster)	1.61/0.22
	Log (viewshed)	Area visible from each location within in a 30 km radius (1 km resolution raster)	5.43/0.69
	Log (red list species)	Total number of red list species found in study area	2.65/0.84
	Temperature	Total number of days with maximum temperature above 5° Celsius (10 km resolution raster)	256/57.5
	NP age	Years since NP foundation until 2015	40.6/26.94
	Log (trails)	Trail density using density function in order to account for distance decay effect	5.69/1.87
	Log (roads)	Density of minor roads using density function in order to account for distance decay effect (100 m resolution raster)	0.9/0.83
	Study area km^2	Size of the study area in km^2	352/621
Context Characteristics:	Log (NP substitutes)	Area of NP within 130 km radius of the study area using a Gaussian weight function in order to account for distance decay (1 km resolution raster)	11.35/1.5
	Log (Population 50 km^2)	Population living within 50 km radius of the study area using a Gaussian weight function in order to account for distance decay (100 m resolution raster)	12.88/1.75
	GDP/capita	GDP/capita in the NUTS 2 or 3 region in which the study area is located	21,856/7713
Study Characteristics:	Survey year	Year of visitor monitoring survey	2005.6/4.16
	Survey quality	Quality of the visitor monitoring survey methodology and study area definition	7.17/1.53

[a] For all predictors mean values per study area were computed.

and a 1000 m resolution digital elevation map from the European Environmental Agency (EEA, 2015a). We believe that visitors prefer three-dimensional landscapes offering great views. (4) Land use/cover diversity: Based on the CORINE land use/cover dataset we computed the Simpson Diversity Index (Magurran, 1988) of land use/cover within a 3 km radius for each pixel of the CORINE map. In their study (Neuvonen et al., 2010) use the number of biotopes as a diversity indicator and find a significant positive effect on visitation frequency in Finnish NPs. However, the number of biotopes may be positively correlated with the study area size. Therefore, this predictor may pick up part of the size effect. Furthermore, larger NPs may have more biotopes even if their landscape is not more diverse. (5) Forest edges: Using the Joint Research Centre forest cover map (EC, 2006), we computed the number of forest pixels (25 m resolution) that are not classified as forest core. We consider these forest pixels as the transition area between forest and other land use/cover and therefore, as a major visible change in the ecosystem type (EC, 2006). (6) Temperature: We applied a dataset from (Biavetti, Karetsos, Ceglar, Toreti, & Panagos, 2014) indicating the number of days with maximum temperature above five degrees Celsius. Due to the predominance of southbound tourism fluxes in Europe, we expect temperature to have a positive effect on visitation rates. (7) Regions: Sites were further classified according to their membership of bio-geographical and geographical regions. We do not have expectations regarding the signs of these factor variables, but might discover some cultural effects. (8) Trail density: We used trail density as proxy for overall recreational facilities, which may attract visitors. From the OSM (Open Street Map) dataset (OSM, 2012), we extracted all vector elements that can be classified as non-motorized traffic infrastructure. We used five OSM classes: trails; foot paths; bike paths; bridle paths and, steps. On a 100 m resolution we applied the line density tool (ArcGIS 10.1) to compute an indicator for trail availability. Again, trails that are further away from a pixel were weighted less than trails close by. Other studies found significant positive impacts of trails (Neuvonen et al., 2010) or recreational facilities in general (Mills & Westover, 1987), but they used individual park data and no comprehensive large scale GIS data sets. (9) Street density: Similar to trail density we computed an indicator for street availability for all minor roads (Tele Road Atlas road classes 4–6) based on the Tele Road Atlas dataset (TS, 2006). Roads are an important infrastructure for accessing remote locations and thereby are expected to increase visitor numbers. However, if roads are too abundant, they may negatively affect the quality perception of nature recreation in a NP and thus, deter visitors. (10) Study area size: We expect that area size has a negative impact on the mean number of visitors per ha because of two reasons: First, larger study areas act as a substitute in itself, because visitors can be distributed across a larger area. Second, visitor counting tends to result in lower mean visitor numbers for larger areas. If a visitor hikes through a large study area, he is counted once. If the same study area is split into separate study areas, the same visitor may eventually be counted several times. Most existing studies of NP visits use total visitor numbers as the dependent variable and therefore find a positive influence of study area size on visitor numbers (Hanink & Stutts, 2002; Hanink & White, 1999; Mills & Westover 1987). However, by working with linear models they potentially miss out that visitor numbers do not increase in direct unitary proportion to the size of the study area. (11) Age of NP: Finally, we characterized each NP by its age (number of years since foundation until 2015). Existing studies have found a positive correlation between park age and visitor numbers (Neuvonen et al., 2010; Mills & Westover, 1987; Hanink & Stutts, 2002; Hanink & White, 1999). This may be caused by the general tendency that the most attractive locations were designated as protected areas earlier or that older NPs have had more time to establish recreational facilities. The designation of a NP may create an advertisement effect and establish a good reputation increasing the parks popularity over time. (12) Biodiversity: In this case we used the total number of red list species encountered in a study area as an indicator for biodiversity (IUCN, 2013).

2.2.2. Context characteristics

As context characteristics we used the following variables: (1) Accessibility: We expect that the number of people that can access a certain location within a certain time is likely to have a positive effect on the visitation rate. We define this variable as the total population living within a 50 km radius around the site, using population data from (Batista e Silva, Gallego, & Lavalle, 2013). In order to account for distance decay, we applied a Gaussian weight function, which causes the population that is further away from the NP to be weighted less than the population nearby. The weight function was calculated so that 95% of its integral was located within the 50 km radius. Other studies find significant positive effects of accessibility on visitor numbers. They use for example distance to nearest towns (Mills & Westover, 1987) or consider the population of metropolitan areas (Hanink & Stutts, 2002; Hanink & White, 1999) and do not include distance decay effects (Neuvonen et al., 2010). (2) NP substitutes: We computed a raster in which each pixel is the sum of areas classified as NP within 130 km radius. The Europe-wide NP data set was a combination of sites from the WDPA and CDDA data bases. In order to account for distance decay, we used the same methodology as for population. As a result, large NPs and NPs with small distance from each other have a relatively high availability of substitutes. Other studies have found negative influences of substitute availability on visitor numbers. They use for example distances to competing recreational sites (Hanink & White, 1999; Hanink & Stutts, 2002) or the number of parks within a certain distance (Neuvonen et al., 2010). They do not, however, account for the size of substitute areas. (3) Finally, we introduce GDP per capita as a proxy of visitor income, which we extracted from the Eurostat database (EC, 2013). We took the mean values of the last ten years (as far as available) and the highest data resolution available, which is either NUTS2 or NUTS3 level. We expect that visitation rates are likely to be higher in locations with higher per capita GDP. Existing studies have observed that people engaging in nature recreation have above average incomes (Loomis et al., 1999).

2.2.3. Study characteristics

Initially, we considered collecting detailed information on study characteristics describing the methodology of the visitor monitoring procedure for each case study area. In that way, we hoped to identify the influence of different visitor monitoring techniques on the final total annual visitor estimate. Similar attempts have been successfully implemented in *meta*-analysis studies of environmental economic valuation studies (Zandersen & Tol, 2009; Brouwer, Langford, Bateman, & Turner, 1999). However, we encountered difficulties in coding such methodological study characteristics due to the language and incomplete reporting in the underlying case study publications. Therefore, we only introduce two study characteristics as predictors in our analysis: (1) the year of the visitor monitoring survey for which we used the mean values of the years in which visitor monitoring took place. (2) Furthermore, we classified all visitor monitoring studies according to different levels of primary data collection quality from one for the lowest and ten for the highest quality. The quality judgment represents a composite indicator of different quality dimensions: the type of publication (scientific vs. grey literature); the visitor monitoring study purpose (scientific vs. political); the institution conducting the study (academic, NP management, others); the methodological documentation of study (full, incomplete, none). If the documentation for the study was available, we assessed the quality of methodologies based on details such as the temporal and spatial counting resolution, manual or electronic counting devices and the temporal and spatial up-scaling methodology. Finally, a very important aspect for the visitor monitoring studies quality is the description of the study area. Some publications do not supply maps and only rough descriptions of the study area. If the area of the study area is uncertain, then the number of visitors per hectare is uncertain as well.

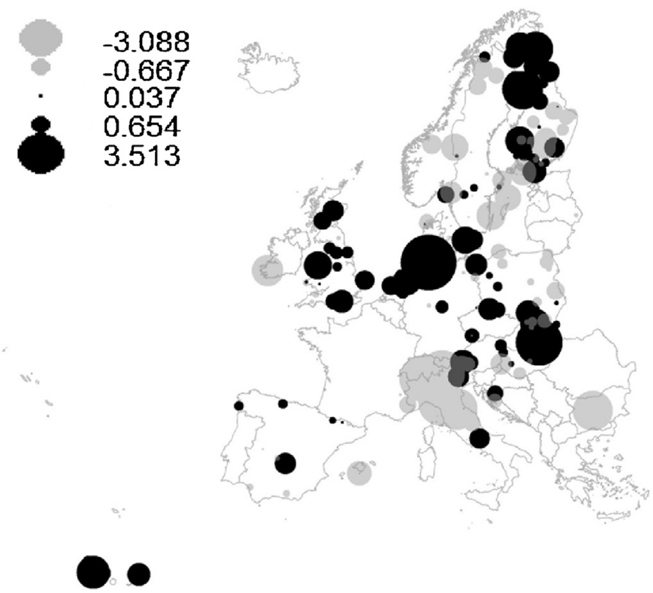

Fig. 2. Bubble plot of the spatial distribution of the full model's residual without spatial correlation structure.

3. Methodology

We applied a number or regression techniques in order to model the total annual visits per ha to European NPs using the above described predictors. All models were estimated using the open source statistical software R. We started our analysis with a simple linear regression, but it showed a strong spread of the residuals for larger fitted values and therefore a violation of the homogeneity assumption. We tried to control this effect by introducing a number of different variance structures, but were not successful in eliminating the heterogeneity to an acceptable degree.

As our dependent variable is a count, we continued our analysis with generalized linear models using a Poisson and a negative binomial distribution (using R-package glmmADMB, MASS, lme4, nlme and gamlss (Bolker et al., 2012; Ripley et al., 2015; Bates et al., 2015; Pinheiro et al., 2015; Stasinopoulos, Rigby, Voudouris, Akantziliotou, & Enea, 2015), which are typical distributions of count data (O'Hara & Kotze, 2010). However, model results show spatial residual patterns similar to the one displayed in Fig. 2. The negative (grey bubbles) and positive residuals (black bubbles) are clustered, which is a violation of the independence assumption of general linear regression analysis. In order to overcome this problem we added a spatial residual structure, either by a spatial random effect or a spatial autocorrelation, but we ran into numerical conversion problems of the optimization algorithm trying to solve the complex statistical model. We therefore abandoned this approach and do not present the interim results of these attempts.

Because our count data shows relatively large values (mean value 367), log transformation is an alternative approach, which should have a negligible effect on the parameter estimates but decreases the model processing complexity substantially (O'Hara & Kotze, 2010). We therefore continued our analysis with linear log transformed model of the following form:

$$\log(V_i) = \alpha + \beta * X_i + \mu_i \quad \text{where} \quad \mu_i \sim \mathrm{N}(0, \sigma^2)$$

V stands for the dependent variable (in our case the total annual visits per ha), α is a constant, β represents a vector of parameters, X is a vector of explanatory variables and μ is the residual, which is normally distributed with mean of zero and variance σ. Again, we had to deal with spatial residual patterns, which we tried to control for using a spatial random effect in a mixed model[2] and by a residual spatial autocorrelation structure. We tried a number of different random intercepts and random slopes in the mixed model and also a number of spatial autocorrelation structures.[3] We investigated all estimated models on how successful they are in controlling for the spatial residual patterns and on their AIC and BIC scores (as criteria for model selection). The best model contained a spatial spherical correlation structure, which models the residuals' correlation across space a spherical function of distance. The model formula remains the same as before, but this time we assume that the residuals μ_i of different locations are correlated based on the function f and their distance.

$$\mathrm{cor}(\mu_a, \mu_b) = \begin{cases} 1 & \textit{if } a = b \\ f(\mu_a, \mu_b, \rho) & \textit{else} \end{cases}$$

We used this model as a starting point and conducted stepwise model selection by dropping the least significant predictor until every predictor was significant. We determined starting values for the range (maximum distance of spatial correlation) and the nugget (one minus the correlation of two arbitrarily close observations) of spatial correlation structure based on interpretation of variogram and spatial residual plots in order to improve consistency across the different models. In the following section on results, we present detailed results on our initial log transformed model, the starting model including the spatial spherical correlation structure and on the final model after stepwise model selection. We validated our final model against the assumptions of linear regression analysis. Therefore, we plotted our residual against fitted values and against each predictor. We could not identify any linear or non-linear patterns of concern. To present a comparable measure of the goodness of fit of all models we compute the root mean square deviation (RMSE) and the coefficient of variation of the RMSD (CV RMSE).

We use our final model (1) to make predictions of the total annual visits to all European NPs within the countries covered by our explanatory variable layers, (2) to map the total annual visits to a fictive new 80 km^2 NP, located anywhere in the European countries covered by our explanatory variable layers and (3) to map the distribution of the predicted total annual visits to a proposed new NP (Teutoburger forest and Senne heathland) in the western part of Germany.

In order to predict the number of visits to NPs of most European countries, we extracted all shape files from the WDPA and the CDDA (IUCN & UNEP, 2015; EEA, 2013), which fall into the IUCN category II (National Park). Furthermore, we accessed national databases to obtain shapes of NPs, which were missing in those two databases. In total we included 449 separate NPs areas. It is to be noted that not all of these sites fall into IUCN category II. No uniform definition of the term NPs exists and it was used long before the IUCN categories system was created. Many existing NPs all over the world are differently managed than demanded by the requirements of category II ((International Union for Conservation of Nature) IUCN, 2008), but are still called NP based on the decision of governments and other local stakeholders. We used vector layer of all NPs boundaries and zonal statistics (ArcGIS 10.2) to drive mean values for the explanatory variables. Predictions were made using the rms R-package (Harrell, 2015). In order to improve our predictions and account for unobserved effects on visitation rates, we kriged the residuals of our model across the entire study area using the gstat, GeoR and raster R-packages (Pebesma & Graeler, 2015; Hijmans et al., 2015; Diggle, Ribeiro, & Peter, 2015). We then added the result to the prediction of each NP.

For predicting the number of visits of a marginal increase of NP area, we assume a fictively created medium size NP of 80 km^2. We then created explanatory variable raster layers accounting for the average substitute effect of the new NP and the size of the new NP. The quality of the visitor monitoring methodology, which is one explanatory variable in our model, was set to the highest quality available in our primary data base (9.5). The NP age was set to zero. We then used the model to map the annual number of visits for each 1 km^2 resolution grid cell across Europe, as though it is part of the newly created NP. The mapping was conducted using the raster, gstat and geoR R-packages. Again, we added the kriged residuals to our predictions.

In order to test our visitor mapping procedure in a realistic policy setting, we applied it to a proposed new NP in the western part of Germany (Teutoburger forest and Senne heathland). The area of this proposed NP is approximately 20,000 ha and comprises a forested mountain range and a heathland, which had been used as an army base in the past. It is already largely protected and has been proposed for NP designation (NABU, 2015). We made predictions on 1 ha resolution in order to estimate total visits to the area and show how visitors distribute across the area.

Finally, we combine the predicted number of visits with a monetary value estimate, derived by taking the overall mean value per visit (7.17€) from the 244 value estimates described above, which is almost the same value estimate applied in a similar study by Balmford et al. (2015) (7$), but based on much larger primary valuation data base. This approach, so-called *unit value transfer* or *average value transfer* and is a common approach used for value transfer and ecosystem service value mapping (Schägner, Brander, Maes, Hartje, 2013; Rosenberger & Loomis, 2001; Balmford et al., 2015) and a method considered for aggregating ecosystem service values to develop a System of Environmental-Economic Accounting (SEEA) (UN, 2014). It assumes a constant value per recreational visit across space, which is indeed a simplification. However, as the value per recreational visit varies by far less across space than the number of recreational visits (Bateman et al., 2006; Jones et al., 2003), its effect on the overall recreational value of an area is relatively small. Given the fact that we focus only on NPs and on an area of relatively similar socioeconomic and cultural characteristics, we consider unit value transfer as a good approximation for the case study presented (see discussion for further details).

4. Results

The results of the statistical NP visitor model using a log-transformed dependent variable are presented in Table 2. 14 of the 19 predictors show statically significant coefficients and the multiple R^2 of 0.68 indicates relatively high explained variance. Most coefficients have the expected sign. However, the residual plots of the model show some spatial patterns, which are to be controlled for. The residual bubble plot in Fig. 2 shows the spatial distribution of the full model's residual without spatial correlation structure shows clustering of positive and negative residuals across Europe.

[2] In other disciplines, mixed modelling is also referred as to multilevel analysis, nested data models, hierarchical linear models, and repeated measurements.

[3] For an introduction into mixed modelling we would like refer the reader to (Zuur, Ieno, Walker, Saveliev, & Smith, 2009) and for in introduction into spatial autocorrelation to (Bivand, Pebesma, & Gómez-Rubio, 2013).

Table 2
National park visitor model. Dependent variable is the log of annual number of visitors per hectare. Spatial patterns in the residuals are not controlled for.

Variable	Coefficient	p-value	
(Intercept)	15.64	0.79	
Sqrt (grassland)	−0.75	0.19	
Sqrt (wetland)	−1.05	3.49E-02	*
Sqrt (water)	1.32	4.50E-03	**
Log (broadleaf)	−0.51	3.70E-03	**
Conifer	−0.04	0.18	
Log (forest edge)	−0.48	0.13	
Sqrt (land cover diversity)	1.47	3.60E-03	**
Log (viewshed)	0.34	3.28E-02	*
Log (red list species)	−0.39	3.71E-02	*
Days > 5°	6.70E-03	9.40E-03	**
NP age	8.08E-03	3.44E-02	*
Log (trails)	0.47	0.00E + 00	***
Log (roads)	0.38	5.00E-03	**
Study area km^2	−4.91E-04	7.00E-03	**
Log (NP substitutes)	−0.25	1.13E-02	*
Log (Population 50 km)	0.48	0.00E + 00	***
GDP/capita	−3.50E-05	3.02E-02	*
Survey year	−1.12E-02	0.70	
Survey quality	−2.93E-02	0.68	
Multiple R^2: 0.68	RMSE: 1.21	AIC: 796.9	
Adjusted R^2: 0.65	CV(RMSD): 0.45	BIC: 864.5	

Significant codes: "***" ≤ 0.001, "**" ≤ 0.01, "* " ≤ 0.05, ". " ≤ 0.1.

We applied a number of different techniques to control for these patterns.

First we added different regional factor variables to the model, in order to explain the spatial patterns. We tried bio-geographical regions, geographical regions and countries[4] as factor variables. However, adding one of these variables reduced the degrees of freedom and increased the complexity of the model to such an extent that we ended up with models having a lot of non-significant variables. Also most of the different levels of the regional factor variables did not show any significant effect. In addition, AIC and BIC values did not show any favourable scores for the models.

Then, we tried to implement a mixed model by adding the regional variables as a random part in order to control for the spatial patterns in the residuals. We tried various combinations of random intercept and random slope models, which significantly improved the model in terms of AIC and BIC values, but a considerable spatial residual pattern still remained. Finally, we tried different spatial autocorrelation structures, which improved the model's AIC and BIC values substantially, beyond all the models we tried before. The best model in terms of AIC and BIC values as well as in controlling for the spatial residual patterns applied is a spherical spatial correlation structure. The result of the full model including the spatial autocorrelation structure is shown Table 3. In total, 13 predictors of the full model show a significant correlation with total annual numbers of visits per ha. After stepwise elimination of the least significant variable until only significant predictors remained (at least at the 0.1 level), we ended up with the same 13 significant predictors as before and substantially low AIC and BIC values (see Table 4).

Our final models show a spatial autocorrelation between single observations up to a range of 530 km for the full model and up to a range of 580 km for the final model. The nugget refers to differences between observations, which can neither be explained by the model nor by the spatial autocorrelation due to measurement errors or micro variability.

A strong positive and highly significant influence is shown for the presence of water bodies, both in the full and in the final model. The beta coefficients indicate that it is the fourth most important predictor for explaining recreational use in our models. Interestingly, even though we did not have strong prior expectations regarding the signs of predictors representing the type natural vegetation, all of them – broadleaf and coniferous forest, grassland and wetlands – show negative signs in the full model. Only broadleaf forest and wetlands show a significant effect in the full model as well as in the final model. Also the variable forest edges, contrary to our expectations, shows a negative and significant sign. However, forest edges are strongly correlated with total forest (the sum of broadleaf and coniferous forest). Therefore, forest edges may pick up some of the negative impacts of forest cover on recreational use in our model. Both, broadleaf and coniferous forests have negative signs, even if only broadleaf forest shows a significant effect. We initially thought that we could separate the effect of forests on the numbers of visits from the effect of forest edges by including single predictors for broadleaf and conifer forest. One explanation of the negative signs of the vegetation cover predictors could be that NPs do have natural vegetation to such an extent, that it becomes abundant and thereby, more of it deters visitors. The transformation of the predictors indicates that their negative effect on the number of visits decreases with their increasing share of land cover. Nevertheless, the beta coefficients of the single vegetation-cover predictors indicate that they only have a relative small effect on the total visitation rate. Also the predictor measuring land cover diversity shows a significant positive effect. On the contrary, the predictor view shed and red list species abundance do not prove to have a significant effect. Red list species abundance has a negative sign, which is contrary to our expectations. Nevertheless, both variables drop out of the model during the variable selection procedure. We also find a positive effect of the numbers of days with a maximum temperature above five degrees. Another predictor, which shows a significant positive but relatively small effect on the number of visits is the age of the national park. The most important and highly significant predictor is the availability of trails. In the final model, it explains almost 17% of the number of visits. However, the question of correlation and causality is in particular relevant for this predictor. To what extent trails attract visitors and to what extent trails are put in place due to high visitor numbers cannot

[4] For the country variable we combined some countries to one region in order to reduce the levels of the factor variable, such as Benelux countries, Alpine countries and Baltic countries.

Table 3
Full model including spherical spatial correlation structure.

Variable	Coefficient	p-value		Beta coefficient
(Intercept)	−9.30	0.88		2.02%
Sqrt (water)	1.61	3.00E-04	***	7.26%
Sqrt (grassland)	−0.61	0.27		2.53%
Sqrt (wetland)	−0.98	3.77E-02	*	3.98%
Log (broadleaf)	−0.39	2.72E-02	*	5.74%
Conifer	−0.03	0.37		2.31%
Log (forest edge)	−0.55	6.91E-02	.	3.84%
Sqrt (land cover diversity)	1.34	5.50E-03	**	5.02%
Log (viewshed)	0.13	0.40		1.54%
Log (red list species)	−0.24	0.28		3.46%
Days > 5°	7.43E-03	3.59E-02	*	7.40%
NP age	1.07E-02	5.10E-03	**	4.98%
Study area km^2	−5.69E-04	3.40E-03	**	6.12%
Log (trails)	0.44	0.00E + 00	***	14.24%
Log (roads)	0.50	1.70E-03	**	7.16%
Log (NP substitutes)	−0.30	1.57E-02	*	7.82%
Log (population with 50 km)	0.37	6.00E-04	***	11.19%
GDP/capita	−1.00E-06	0.96		0.13%
Survey year	2.40E-03	0.94		0.17%
Survey quality	−0.12	0.10	.	3.11%
Spherical spatial correlation structure	RMSE: 1.26	AIC: 768.7		
Range: 530 km, nugget: 0.40	CV(RMSD): 0.48	BIC: 842.7		

Significant codes: "***" ≤ 0.001, "**" ≤ 0.01, "* " ≤ 0.05, ". " ≤ 0.1.

Table 4
Final model after stepwise model selection including spherical spatial correlation structure.

Variable	Coefficient	p-value		Beta coefficient
(Intercept)	−3.35	0.11		2.26%
Sqrt (water)	1.8	0.00E + 00	***	9.29%
Sqrt (wetland)	−0.83	4.81E-02	*	3.84%
Log (broadleaf)	−0.31	3.41E-02	*	5.18%
Log (forest edge)	−0.57	3.32E-02	*	4.53%
Sqrt (land cover diversity)	1.32	4.70E-03	**	5.65%
Days > 5°	6.89E-03	3.72E-02	*	7.83%
NP age	1.07E-02	4.30E-03	**	5.72%
Study area km^2	−5.14E-04	5.20E-03	**	6.31%
Log (trails)	0.46	0.00E + 00	***	16.95%
Log (roads)	0.44	2.90E-03	**	7.26%
Log (np substitutes)	−0.36	2.50E-03	**	10.81%
Log (Population with 50 km)	0.32	1.20E-03	**	10.98%
Survey quality	−0.11	0.1	.	3.38%
Spherical spatial correlation structure	RMSE: 1.29	AIC: 727.5		
Range: 580 km, nugget: 0.38	CV(RMSD): 0.48	BIC: 782.8		

Significant codes: "***" ≤ 0.001, "**" ≤ 0.01, "* " ≤ 0.05, ". " ≤ 0.1.

be answered by this analysis. The same may apply to the availability of minor roads, which also show a significant positive effect but being less important for explaining the observed visitor numbers. A significant negative impact can be found for the size of the study area of the visitor monitoring study, but a low beta coefficient indicates a relatively low importance. A stronger and significant, but negative impact shows the availability of other national park areas within the region. It is the third most important variable in our models. The second most important variable in explaining the observed number of visits is the population living in the region of the study area, which shows a significant positive effect. A minor negative but not significant effect is found for the GDP/capita and the year of the visitor monitoring survey. This is contrary to our initial expectations. It could be that other cultural aspects interfere with this effect. It may also be that Southern European countries with lower GDP/capita (e.g. Italy and Spain) receive more visitors in NPs because of high tourist visits, whereas richer Northern European countries (e.g. Scandinavian countries) receive fewer visitors because of lower tourist numbers. At the edge of the 0.1 significance level, the predictor measuring the quality of the visitor monitoring study shows a relatively small and negative effect. Initially, this variable was considered for explaining residual patterns. We expected that visitor monitoring studies with a lower quality judgment would result in less precise visitor estimates and therefore in higher residuals. However, in our pre-analysis we could not find a significant effect of the visitor monitoring quality on the residuals. Moreover, we find that visitor monitoring studies of lower quality tend to overestimate visitor numbers. This could be caused by the incentive of NP managers to highlight the importance of their NP and thereby use assumptions made within the visitor monitoring study in favour of higher visitor numbers. Visitor monitoring studies of higher quality may allow for less of these assumptions to be made (by more complete counting and less up-scaling). Furthermore, complete reporting of the assumptions made may stimulate more realistic judgments.

We used our final model to make predictions for all NPs sites in our primary visitor database and also for all NPs in most of the EU[5] as well as in Norway and Switzerland. Comparing our predictions

[5] We could not make predictions for some EU countries for which we are missing raster layers of the explanatory variables in our model. These countries are Bulgaria, Croatia, Cypress, Island and Malta.

with our primary data, we estimate an average relative prediction error of about 185% (the full model 174%), which seems reasonably good. Interestingly, the four observations contributing most to our relative prediction error are all located in Italy.

Using our model to predict the number of visits to all 449 NPs across our study area, we estimate a total annual number of visits of more than 2 billion (2,016,028,000; lower and upper 95% confidence interval: 1,217,818,000; 3,404,254,000).[6] Combining this estimate with the average monetary value per visit (7.17 €, prices 2013), which we extracted from a meta-analysis of recreation valuation studies, the total recreational value of the 449 NPs amounts to € 14.5 billion annually. The result compares well to the estimates of Balmford et al. (2015), who estimate 3.8 billion visits annually and a value of $US 26.9 billion for all protected areas within Europe, not only NPs. Our aggregated estimates per country are shown in Table 5.

Most visits are received by British NPs, which results from the large total area of NPs, high population density and intensive recreational facilities in terms of trail densities. Also other densely populated countries such as Denmark, Belgium and the Netherlands show relatively high visitor numbers. On the contrary, countries such as Sweden, Finland and Norway show relatively low visitor numbers for their large and mainly forested NPs in the low populated north. Germany shows exceptionally high visitor numbers considering the relatively small NP area. However, these numbers are dominated by one large NP, for which our model may overpredict the total number of visits. The Wadden Sea NP – an UNESCO natural heritage – is by far the largest NP of Germany and stretches almost all along the North Sea shore of Germany. The area lies in the catchment of large cities such as Hamburg and Bremen. It is a touristic hot spot receiving by far the highest number of day and overnight visits of German NPs (Job, Woltering, Harrer, 2010). All variables used in our model, except size, show values in favour of high visitor numbers for the Wadden Sea NP. This combination of such variable values is exceptional in our data and may cause an unreasonable over prediction.

Our predictions of visits per ha for a marginal increase of NP supply in Europe are shown in Fig. 3. We assume a hypothetical newly created NP of about 80 km anywhere throughout Europe an estimate the number of visits it would receive. All urban areas are excluded from this prediction (EEA, 2015b), as it seems unrealistic that such areas would be converted into a NP and because urban areas are typically characterized by explanatory variable values that lie beyond the range of the explanatory variable values of our primary data. The map shows values from almost zero up to the maximum of about 147,000 annual visits per ha. Low numbers of visits are predicted for remote areas, which are characterized by low population and little access infrastructure. The maximum predicted visits of 147,000 per ha seems high, but 34 visitors for an average daylight hour may not be unreasonable for a popular visitor hot spot in a NP. However, it should be considered that the predicted visitor numbers are strongly skewed with a mean and median values of about 87 and 4.8. More than 90% of the pixels receive visitors of less than 100 visitors a year and anything above 2000 is to be expressed in per mile. A map presenting the spatially explicit economic values can be found in Appendix of Supplementary material (Fig. S1 and S2).

To exemplify our model for a realistic setting we chose the Teutoburger forest and the Senne heathland in the west of Germany, which is proposed for NP designation. Fig. 4 shows how the predicted annual visits per ha distributed across the area. On average, we expect about 283 annual visits per ha for the area. The highest visitation rate is predicted in the peripheral areas, close to the population centres of cities of Detmold and Paderborn receiving up to 24,000 visits per ha and year. In contrast, the center of the proposed NP, which is hardly accessible, is predicted to receive less than one visit/ha/year. In total we predict about 5.8 million annual visits

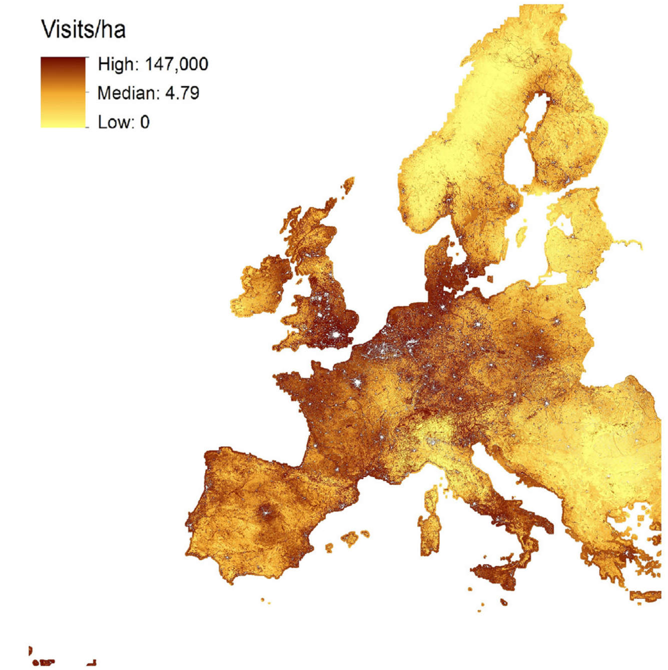

Fig. 3. Predicted visits per ha and year for a potential new National Park of about 80 km^2.
Note that the predicted total visitor number of the entire area is less than the sum of the predicted visitors for each ha because of two reasons: visitors may cross more than one ha during a visit and it is not possible to take the linear mean of a model containing non-linear variables.

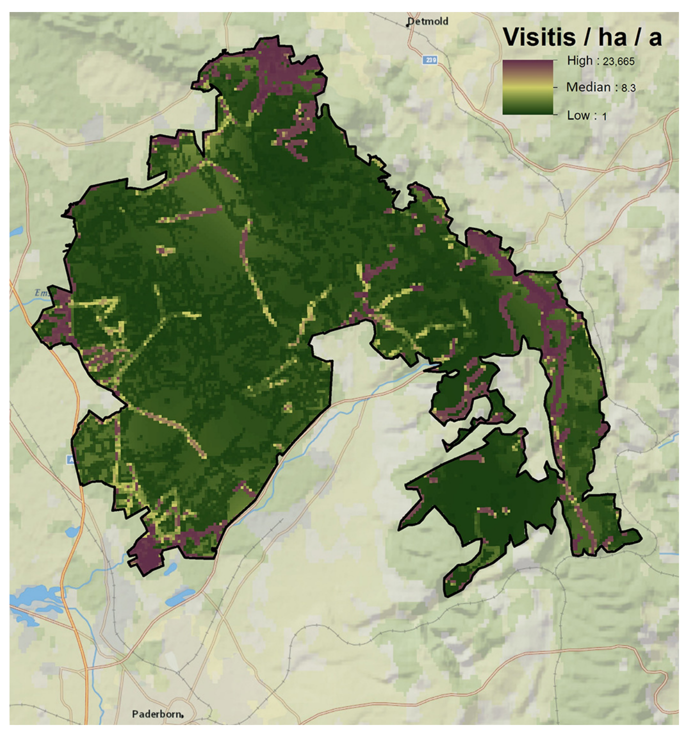

Fig. 4. Predicted visits per ha and year for a potential National Park in the Teutoburger forest and the Senne heathland (west of Germany).

[6] We used the rms R-package for estimating confidence intervals.

Table 5
Estimates of total annual visits to National Parks in European countries and their estimated monetary value.

Country	Km^2 of NP	Predicted Visits	95% Confidence Interval (lower/upper)	Monetary Value
Austria	3098	24,098,000	14,001,000/41,660,000	172,684,000 €
Belgium	3200	63,569,000	32,294,000/125,388,000	455,527,000 €
Switzerland	170	135,000	72,000/256,000	969,000 €
Czech Republic	3543	32,835,000	17,148,000/63,127,000	235,290,000 €
Germany	2363	534,188,000	309,773,000/921,987,000	3,827,911,000 €
Denmark	846	77,623,000	55,797,000/108,203,000	556,236,000 €
Spain	10,450	121,666,000	89,810,000/170,467,000	871,840,000 €
Estonia	1618	2,182,000	1,561,000/3,078,000	15,635,000 €
Finland	8196	6,427,000	4,564,000/9,456,000	46,054,000 €
France	13,565	71,408,000	36,506,000/140,680,000	511,700,000 €
United Kingdom	21,754	700,862,000	429,126,000/1,162,686,000	5,022,270,000 €
Greece	4677	14,713,000	10,287,000/21,934,000	105,432,000 €
Hungary	6234	18,543,000	11,457,000/30,336,000	132,878,000 €
Ireland	2221	3,510,000	2,447,000/5,070,000	25,152,000 €
Italy	17,419	145,719,000	93,198,000/231,777,000	1,044,203,000 €
Lithuania	1345	2,398,000	1,482,000/3,909,000	17,186,000 €
Luxembourg	465	2,912,000	1,560,000/5,441,000	20,866,000 €
Latvia	3201	3,711,000	2,508,000/5,538,000	26,592,000 €
Netherlands	1889	93,133,000	48,749,000/182,005,000	667,375,000 €
Norway	30,696	2,150,000	1,821,000/2,602,000	15,404,000 €
Poland	10,168	46,227,000	25,125,000/85,506,000	331,254,000 €
Portugal	930	15,245,000	10,006,000/23,227,000	109,244,000 €
Romania	5670	2,662,000	1,565,000/4,546,000	19,077,000 €
Slovakia	7679	18,218,000	9,079,000/37,180,000	130,544,000 €
Slovenia	1157	4,121,000	2,425,000/7,004,000	29,531,000 €
Sweden	8370	7,773,000	5,457,000/11,191,000	55,700,000 €

for the entire area (95% confidence interval lower bound 3.38 and upper 9.91 million),[7] which accounts for an annual monetary value of approximately € 41.5 million. A map presenting the spatially explicit economic values can be found in the Appendix of Supplementary material (Fig. S1 and S2).[8] Negative impacts on the number of visits include the relatively low presence of water bodies, high forest cover, low trail availability and the low age of the potential new NP. Positive impacts include the small size of the NP, the high population pressure, low substitute availability and the high land cover diversity. The number of visits is expected to increase with the age of the NP and if recreational facilities are established.

5. Discussion

5.1. Spatial effects and modelling

Our estimated model fits the data reasonably well and therefore offers valuable information on the main drivers of recreational use within European NPs. All predictors with statistically significant effects on the number of recreational visits have signs that are in line with our interpretations and theoretical expectations.

Nevertheless, there are some uncertainties in the model and prediction accuracy which may be improved by further research. The question remains, what may be the source of the spatial autocorrelation. In an optimal statistical textbook world, introducing spatial autocorrelation in a model would not influence parameter estimates, but only reduce the degrees of freedom of the model. However, looking at real world spatial data, this is hardly ever the case. If parameter estimates are affected as in our case, this may indicate some common spatial econometric problems, such as missing predictors, which are picked up by the spatial error term, a spatial weight matrix or a non-linear relationship (Diggle, Morris, & Wakefield, 2000; Smith & Lee, 2011; Fingleton & Le Gallo, 2010). A likely explanation could be that unobserved determinants of recreational visits exist, which are spatially related. Such determinants could be manifold and include everything from site, context and methodological study characteristics as well as their interactions. One important aspect could be related to the social-cultural context and path dependencies, which may result in specific recreational patterns in certain countries and regions. Also differing property rights could play an important role. Investigating human recreational behaviour across a study area as big as Europe is such a complex issue that all of these econometric problems may arise. There may hardly be any model that can incorporate all relevant drivers of recreational use, their interactions and non-linear effects.

Encountering such problems is common for modelling spatial data and therefore, we have to be cautious in interpreting p-values and parameter estimates. An option to gain further insights and confidence in model result interpretations is to try different spatial modelling approaches and compare their results. In particular, compare the confidence intervals of the parameter estimates. There is number of model setups, which would qualify for evaluating such spatial data sets. Since in this study we are analysing count data, one option would be to use a negative binomial or a quasi-Poisson distribution, even though it should not change the model results too much (O'Hara and Kotze, 2010). However, there are only a very limited number of statistical R-packages, which allow for combining these distributions with spatial autocorrelations and as we stated above we had problems in solving the maximization algorithms for these models. An option would be to try alternative models incorporating the spatial autocorrelation either within the fixed or the random part of the model, such as a spatial lag model, a Durbin model, spatial autoregressive models with autoregressive disturbances, geographically weighted regressions or even by using Bayesian approaches. However, there is no consensus on which model to use best for this specific purpose. Fitting all or at least some of these models and comparing their results may be subject to further research (Bivand, 2011; Elhorst, 2010; Gerkman, 2011; Brunsdon, Stewart Fotheringham, & Charlton, 1996).

Nevertheless, considering the complexity of the spatial processes driving human recreational behaviour, we can confidently

[7] Note that the map displaying the recreational ecosystem service values should be interpreted with caution, because we do not account for spatial variations within the value per recreational visit, which may alter the total value estimate for certain locations considerably.

[8] Note that for illustrative purpose the color scheme is set to display the same amount of pixels per color shade.

say that we model recreational use reasonably well. None of the predictors' signs differ across the different estimated models, neither for models without autocorrelation nor for the mixed models, which indicates the robustness of our analysis. Anyhow, other publications conducting spatial modelling of recreational use do not at all engage to such a depth in the spatial dimensions nor do they take into account such considerations on uncertainties, potential alternative regression techniques and model setups (Neuvonen et al., 2010; Mills & Westover, 1987; Hanink & Stutts 2002; Hanink & White 1999).

Future research on this issue may benefit from greater and more reliable primary data availability. Errors in primary data collection impose huge difficulties for identifying relevant predictors. In recent years visitor monitoring studies encountered a huge dynamic in terms of interest and technical advancement. Recent remote controlled electronic visitor counters allow far more accurate visitor estimates at lower costs as compared to conventional personal counting. More refined GIS data sets may allow for more accurate, detailed and comprehensive predictors for modelling recreational demand.

5.2. Valuation of recreational services

Another aspect of improvement may be to account for spatial variations in the value per recreational visit by applying a value function transfer (such as meta-analytic value transfer). Using a unit value transfer for mapping ecosystem service values across a larger area is associated with transfer errors, in particular with so-called generalisation errors. Nevertheless, the value of a recreational visit varies across space due to differences in ecosystem characteristics and the local population's preferences, differences that are not accounted for in a unit value transfer (Rosenberger & Loomis, 2001). Value function transfer allows adjusting transferred values to site specific circumstances and may therefore be more accurate for ecosystem service value mapping. However, even though, value function transfer is considered to produce lower transfer errors, there is no consensus on which value transfer method is best for specific circumstances. Evidence on transfer errors show mixed results and unit value transfer may be superior to other value transfer techniques for some applications (Navrud & Ready, 2007; Rosenberger & Phipps, 2007; Johnston & Rosenberger, 2010; Brouwer 2000; Rosenberger & Stanley, 2006; Lindhjem & Navrud, 2008). In ecosystem service value mapping, the unit value transfer method is most common (Schägner et al., 2013). It is also proposed for the aggregation of values to set up, for example, a System of Environmental-Economic Accounting (SEEA), even though aggregation over a large area is controversial and should be interpreted with caution (UN, 2014; Costanza et al., 1998).

In the case of recreational services, meta-analysis of recreational valuation studies show that most of the variations in the value per visit result from different valuation methodologies and not from site specific circumstances, indicating large measurement errors. Moreover, it remains difficult to identify robust relationships between spatial explanatory variables and the final value estimate. Meta-analysis on recreational valuation studies identify only few significant and typically weak effects of biophysical, socioeconomic and regional or national dummy variables (Shrestha, Rosenberger, & Loomis, 2007; Zandersen & Tol, 2009; Brander, Eppink, Schägner, van Beukering, & Wagtendonk, 2015; Sen et al., 2013; Sen et al., 2011; Rosenberger & Loomis, 2001; Londoño & Johnston, 2012). By using the mean value of a large number of primary valuation studies, we aim at averaging out measurement errors within our value transfer (Johnston, Elena, Ranson, 2006), which may result in lower transfer errors as compared to the usage of single studies or regional subsets, even though cultural differences across countries may affect value per recreational visit (Ready & Navrud, 2006; Shrestha & Loomis, 2001; Lindhjem & Navrud, 2008; Kaul, Boyle, Kuminoff, Parmeter, & Pope, 2013; Hynes, Norton, & Hanley, 2012).

Finally, the overall recreational value of a site is predominantly determined by spatial variations in the number of recreational visits. Spatial variations in value per recreational visit play only a minor role (Bateman et al., 2006; Jones et al., 2003). This insight is also supported by mean relative deviations of our primary data, which is considerably higher for the visitor numbers as compared the value per visit estimates. In consequence, accurate visitor estimates are by far more important for defining the overall recreational value of a certain location than accurate estimates of the recreational value per visit. As compared to meta-analysis of recreational valuation studies, the explanatory power of our spatial variables explaining visitor numbers is high. We are therefore confident that we capture the main spatial variations in the overall recreational value NP recreation and that the value estimates give a good indication of the relative importance of European NP recreation as compared to other ecosystem services and man-made goods.

5.3. Policy implications

The model can be used for a number of policy applications: (1) The model may contribute to the fulfilments of the EU biodiversity strategy 2020, which require of EU members states to "*map and assess the state of ecosystems and their services in their national territory by 2014, assess the economic value of such services, and promote the integration of these values into accounting and reporting systems at EU and national level by 2020*" (EC, 2011) and the achievement of the Aichi Targets, which aim at *"reflecting the values of biodiversity in spatial planning and resource management exercises including through the mapping of biodiversity and related ecosystem services"* (CBD, 2013). (2) The mapped recreational visitor numbers and the related economic value of recreational ESS can act as a spatial value data base that can be used for value transfers. Policy makers can quickly derive a value estimate of the recreational services of any NP across Europe by consulting the map. (3) The maps may contribute to an efficient resource allocation by allowing policy makers to prioritize areas for conservation due to their high recreational value. In addition, recreational infrastructure may be designed to match the needs of the expected visitor numbers within a given NP. Furthermore, it may be valuable to compare the model's predictions with real world observations on recreational use and values (if available) and, for example, investigate why some NPs might remain below their recreational potential and how the recreational use and its value could be increased. However, it should be noted that the model allows only for assessments of NP. Even if predictions can be made for a new hypothetical NP, no conclusion can be made on whether NP designation results in an increase or decrease of recreational use and its values. (4) The model allows to evaluate the effect of land use policies within European NP on recreational services and values. (5) Finally, the estimated recreational service values may contribute to the setting up of a green GDP or a System of Environmental-Economic Accounting (SEEA) as proposed by the UN (2014), which may act as a counterpart to traditional GDP accounts and represent an additional measure for the impacts of human action on human well-being.

6. Conclusion

We model recreational use of European NPs using a large number of spatially variable predictors. Our model fits the data reasonably well and we identify the main determinants of variation in recreational use in European NPs. Among analysed variables trails density, population density, presence of substitutes, presence of water bodies and number of days with temperature above 5° are those that show a higher explanatory value. The model allows the estimation and valuation of total recreational use of existing and planned NPs. For our study area covering most of Europe and in total 449 NPs, we estimate more than 2 billion recreational visits a year, with an economic value of approximately € 14.5 billion. The latter information is particularly relevant to support the task that EU countries should fulfil by 2020, according to EC (2011) of assessing the economic value of ecosystem services and integrate such values into accounting and reporting systems by 2020.

Since all our predictors are obtained from GIS raster layers, which cover entire Europe, the model can be applied for ex-ante evaluation of alternative policy scenarios of change for existing NPs and on the creation of new NPs at a European scale. This information may be useful in planning the supply of recreational facilities such as parking and accommodation. Furthermore, NP locations and design features optimizing recreational use can be identified. Thereby, the model has implications for NP policy of European countries. Based on our findings, we can conclude that to ensure high numbers of recreational visits, potential new NPs should be located in close proximity to populated areas but not close to other NPs. The total conservation area should be used for a larger number of small parks rather than for a smaller number of large ones. The availability of water bodies and the diversity of the land cover contribute to higher visitation rates, whereas extensive forest cover tends to deter visitors. However, it should be kept in mind that the main purposes of NPs are not to supply recreational services but preserve a beautiful and natural landscape as well as biodiversity for posterity. Recreational opportunities are a co-benefit of NPs, which can be used as an argument for allocating resources towards NP creation and conservation.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jnc.2016.03.001.

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