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Mapping the Recreational Value of Non-Urban Ecosystems across Europe: Combining Meta-Analysis and GIS

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Mapping the Recreational Value of Non-Urban Ecosystems across Europe: Combining Meta-Analysis and GIS

Abstract

We map recreational visits and the economic value per visit spatially explicit across Europe's non-urban ecosystems using GIS, meta-analysis and geostatistical modelling techniques.

Therefore, we developed a meta-analytic visitor arrival function and a meta-analytic value transfer function by regression analysis. Primary data on the dependent variables are collected from visitor monitoring and valuation studies. We analyse more than 225 studies including visitor counts and value estimates to more than 550 separate case study areas.

Focusing on continuous spatial biophysical and socio-economic predictor variables, we identify underlying spatial drivers of recreational ecosystem service values. By combining our models with spatial explanatory variable layers we predict annual recreational visits and the value per visit on a one km² resolution across Europe. The resulting maps illustrate spatial variations of recreational visitor numbers and the value per visit. In total we predict about 11 billion annual visits to Europe's non-urban ecosystems amounting an economic value of 57 billion €. Comparing our estimates with mean/unit value transfers reveals that the spatial variations of visitor numbers are substantially more important for determining the recreational value per ha than variations in the value per visit.

1. Introduction

Recreation is an ecosystem service supplied by non-urban ecosystems that is of substantial economic value and offers considerable economic opportunities for local communities in terms of income and employment (MA 2005; Maes et al. 2011; Nahuelhual et al. 2013; Peña, Casado-Arzuaga, and Onaindia 2015; Paracchini et al. 2014). To acknowledge this ecosystem service and to integrate it into land-use planning and resource allocation policies, spatially explicit information on the flow of visitors as well of the recreational economic value is fundamental (Maes et al. 2012; Schägner et al. 2013; TEEB 2011). In this study we map the value of recreational ecosystem services spatially explicit across all of terrestrial non-urban Europe by estimating a meta-analytic visitor arrival and meta-analytic value transfer function.

The number of studies assessing ecosystem service values spatially explicit has grown exponentially over recent years. Nevertheless, most studies use a relatively simple approach by applying mean value estimates to land cover classes. This is also the case for studies mapping of recreational services. Only a few studies assess the spatial variations of visitor flows and the economic value associated with these flows more in detail by applying some sort of spatially explicit modelling (Schägner et al. 2013) . Some studies map recreational ecosystem service values by spatially explicit models that are parameterized and validated based on primary data. However, only a few of them assess spatial variations in both, the number of visits and the value per visit separately and focus on a large continuous area covering various ecosystems. (Ghermandi and Nunes 2013) for example map global costal recreation by applying spatially explicit meta-analytic value transfer. In their model, however, the dependent variable is the recreational value per ha and thus no separate information on the visitor numbers and values per visit is available. (Bateman, Brainard, and Lovett 1995; Bateman, Lovett, and Brainard 1999) model visitor numbers to several forest sites in Wales using linear regression analysis. The predicted visits are combined with a constant mean value estimate per visit (unit value transfer) to derive value estimates for the considered forest sites and thus, spatial variations in the value per visit are not accounted for. In contrast, using an approach similar to the one we apply, (Brander et al. 2015) map both, recreational visits and values per visit throughout coral reef in Southeast Asia spatially explicit to assess the overall recreational value of different locations. They focus, however, only on one land cover type and use a limited set of spatial predictor variables. Within the UK National Ecosystem Assessment, recreational services are mapped at a national scale by using a count data model, which is based on data from a national recreation survey and by a meta-analytic value transfer function to predict the value per recreational visit (Sen et al. 2013; Bateman et al. 2011). Several other studies use survey data based models to predict visitors to certain locations by choice models or random utility models. A similar approach is applied by (Brainard 1999) to map the value of alternative forest sites, but values per recreational visit are estimated based on estimations of the travel cost between origin zone and the destination of each recreational trip (travel cost method, TCM). (Moons et al. 2008) instead combine (TCM) for estimating the value per recreational visit with a choice model that is based on survey data and predicts the probability of an individual visiting a certain site. The method is applied to evaluate the value of alternative hypothetical new forest sites in Flanders, Belgium. Also (Termansen, Zandersen, and McClean 2008) use a choice model to predict visitor numbers to forest sites in the area of Copenhagen and a random utility model to estimate the value per recreational visit. (Termansen, McClean, and Jensen 2013) model visitor numbers to Danish forest sites by modelling, first, the total demand for forest recreation and second the choice among alternative forest sites and the value per trip in a random utility model. The models are parametrized based on regression analysis of survey data and respondents to such survey may not be representative for the society as a whole. Furthermore, survey data do not capture visitors living beyond the scope of the surveyed area. Typically, such surveys data is available only at a regional and national level and thus, studies relying on such data do map recreation only at regional to national scale.

In this study, we map both: recreational visits and the value per recreational visit spatially explicit throughout all non-urban ecosystems across Europe by means of meta-analytic regression models. Primary data was collected from visitor monitoring studies and primary valuation studies. In total our databases are comprised of 1,267 visitor estimates of 518 separate sites and 245 value estimates from 147 case study areas. Multiplying the predictions of our two models allows us to predict the recreational value per ha at any location throughout non-urban Europe at a one 1km² resolution. These models can be used to support several policies: (1) the ex-ante evaluation of land-use policies, (2) efficient resource allocation by conservation prioritization of areas of high recreational value, (3) the design of recreational facilities in accordance with expected recreational visitor numbers or (4) the development of a green GDP or a System of Environmental Accounts (SEA) at different spatial scales. To our knowledge, we present the first study mapping recreational visitor numbers and recreational values across all land-cover classes at a continental scale. To estimate our models, we used large sets of innovative continuous biophysical and socio-economic predictor variables that we developed as spatial GIS raster layers.

The paper is organized as the following. In section 2, we present the primary data on our dependent variables as well the spatial predictor variables we use. Section 3 describes the statistical regression techniques we us to estimate or models. Results are presented and discussed in consecutive sections. Finally, we conclude.

2. Data

1.1. Primary Data

Our primary data that presents the dependent variables of our models consists of two separate data sets. The first data set represents of recreational visitor estimates and the second data set consists of estimates of the value per visit. Both data sets are developed by a broad literature review of the literature on recreational visitor monitoring and primary valuation studies. Studies are identified through internet searches, a review of relevant literature and by contacting researchers involved in this field.

Our primary data on the recreational use consists of 1,267 observations of the total annual visitor estimates at 529 separate case study areas throughout Europe. We derived the data from a review of 150 visitor monitoring studies and data bases as well as governmental reports. We divided the total number of visits by the hectare size of each case study area to obtain the visitor density (visitors per ha). The visitor density ranges from almost zero (0.03) up to 158,740 visits per ha and year. The distribution is however, highly skewed with a mean of 2,362 and a median of 35.8 (see Table 1).

Table 1: Descriptive statistics of visitor density (visits / ha/a).

N	mean	sd	median	min	max
529	2,362	12,061	35.8	0.03	158,740

Our primary data on recreational value consists of 245 estimates of monetary values per recreational visit for 147 separate nature areas in Europe. We obtain the data from 75 valuation studies using either Travel Cost Method (TCM) or Contingent Valuation Method (CVM). We transfer all value estimates to € values and to the 2013 price level using purchasing power parity and country specific inflation data. From the total data set we exclude one outlier, showing an extreme deviation of 60 times the mean value. The remaining 244 value estimates range from € 0.16 to 64.7 per visit with a mean of 7.17€ and a median of 2.8€ (see Table 2).

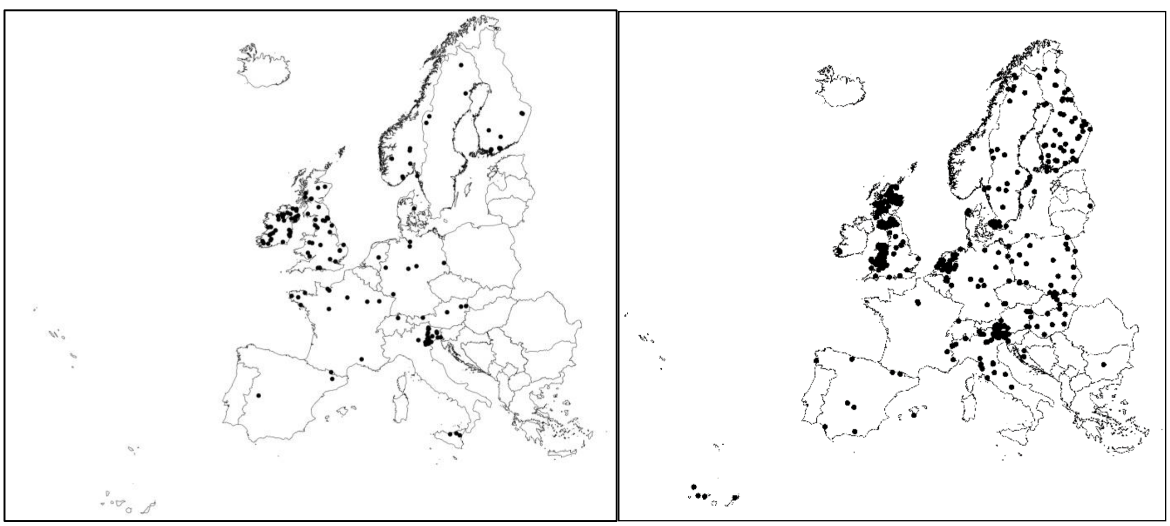
Table 2: Descriptive statistics of value per visit estimates in €, 2013.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	St. dev.

0.16	1.542	2.8	7.166	7.755	64.7	10.98

For each case study site we obtain or create a spatial layer in vector format, containing the boundaries of the surveyed nature area. Polygons for some nature areas are obtained from official sources (IUCN and UNEP 2015; EEA 2013) or from the case study authors. Most polygons are drawn manually in ArcGIS, based on information supplied by the case study publications, the study authors or based on information from internet inquiries. In several cases, we are not able to get any approximation of the location and shape of the case study area and thus could not include those studies in our data base. The case study areas differ widely in terms of size, location, the estimated value per visit and ecosystem characteristics. The size of case study area ranges from 1.9 ha, for a small Nature Park, east of Padova, Italy, up to 18,048 km² for the Jämtland mountain range in North Sweden. The distribution of the case study areas are presented in Figure 1.

Figure 1: Location of case study areas: right: represented in the primary valuation studies, left: represented in the visitor monitoring studies



1.2.Predictors

For the statistical regression analysis, we develop a number of predictor variables, divided into three categories: (1) study characteristics, describing the methodology of primary value estimation, (2) site characteristics, describing the study area itself and (3) context characteristics, describing the spatial context of the study area. We select the variables based on a review of past meta-analyses on recreational valuation studies and regression analysis of recreational visitor flows. A complete list of all predictors used in our analysis is presented in Table 3.

For the valuation we chose three methodological characteristics, which we assumed to have a strong influence on the valuation results (see also Table 3). First, we distinguish studies by their valuation method, which is relatively equally distributed with 140 studies using CVM and 104 using TCM. Second, we distinguish whether studies consider use-values only (226) or if they consider use and option values. Finally, we consider whether studies estimate values per visit, which is the case of the majority of studies (197), or if studies estimate the value per day visit, value per party visit or the value per month or year of access. For visitor data, we encountered difficulties to define methodological characteristics, because reporting on study methodologies was poor in most studies. Therefore, we classified all visitor monitoring studies according to primary **data collection quality** using one as the lowest and ten as the highest quality. The quality judgment represents a composite indicator of different quality dimensions: the type of publication (scientific vs. grey literature), the purpose of the visitor monitoring study (scientific vs. political), the institution conducting the study (academic, NP management, others) and the methodological documentation of study (full, incomplete, none). If the documentation of 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 visitor density is uncertain as well. In addition, we coded all observations in respect to the **year of primary data collection**.

The main focus of our analysis, however, is to identify the effects of spatial determinants of recreational values in order to produce spatially distributed predictions. Therefore, we prepare several EU wide geospatial layers of site and context characteristics in raster format. It is worth noting that limitations in the availability, accuracy, comprehensiveness and consistency of Europe-wide data sets restrict our choice of predictors and is one limitation to our statistical analysis. We use available GIS data sets and, if necessary the layers are processed in order to derive our predictor variable raster layers. The GIS processing is done with ArcGIS 10.2.

We use the following **site characteristics** in our regression analysis:

(1) Land cover: We can only use a limited number of land cover combinations in our analysis because several CORINE land cover classes occur only rarely, which would result in many zero values in our spread sheet, and thus, the detection of significant effects would become more difficult and vulnerable to outliers. In addition, aggregates of land cover classes are often correlated with each other and thereby can cause problems of collinearity. Based on the analysis of past meta-analyses of recreational valuation studies, we choose the following land cover/use classes as predictor variables for our analysis. To account for forest, we use the Joint Research Centre forest cover map (EC 2006) and compute the mean number of forest pixels (25m resolution) per hectare that are classified as either coniferous or broadleaved forest within each study site. For other land cover types we used the CORINE dataset (EEA 2006) to determine the percentage of several land cover classes in the study sites. In particular we determine the share of all natural vegetation, agricultural area and grassland.

(2) Land cover diversity: From the CORINE land cover data set we compute the Simpson Diversity Index (Magurran 1988) of land cover types within a 3km radius for each pixel of 100m resolution raster map covering all Europe. We assume that more diverse landscapes are perceived as more beautiful and may therefore positively affect the value per visit.

(3) Water bodies: We compute two 300m resolution grids of the share of surface area covered with rivers and lakes or ocean using the Euro Regional Map as input dataset (EG 2010). Then we apply a kernel density function tool to compute the amount of surface covered with water within a 3km radius of each pixel. The density function allows a water area that is more remote to be weighted less than water nearby, thereby incorporating a distance decay effect. We believe that water bodies attract visitors and cause the value per visit to be higher.

(5) Biodiversity: We use the total number of red list species encountered in a study area as an indicator for biodiversity (IUCN 2013). We assume that biodiversity may attract visitors from distant locations and result in higher values per visit. In addition, we use a dummy variable to indicate whether at least 50% of the study site is designated as a national park.

(4) Climate: We use three climatic variables in our model, under the assumption that better climate in terms of higher temperature, less rain and more sunshine attracts visitors from distant locations for longer recreational trips. As a temperature indicator, we apply a dataset from (Biavetti et al. 2014) indicating the mean number of days per year with maximum temperature above five degrees Celsius. We use a similar data set (Burek unpublished) indicating the mean number of days per year with at least some precipitation and the mean hours of sunshine per day.

(6) Topography: We use the slope of the digital elevation map from the European Environmental Agency (EEA 2015a) for two indicators describing the topography of the landscape. First, we use the slope value of the 100m digital elevation map. Second, we compute the area visible from each pixel within a 30km radius using the viewshed tool. In order to accelerate the viewshed processing we aggregated the digital elevation map to a 1000m resolution raster grid. We expect that mountain regions and regions offering large viewsheds imply special attraction for recreation and generate higher values per visit.

(7) Trail density: We use trail density as a proxy for overall recreational facilities, which may enhance the recreational experience. From the Open Street Map (OSM) dataset (OSM 2012), we extract all vector elements that can be classified as non-motorized traffic infrastructure. We use five OSM classes: trails, foot paths, bike paths, bridle paths and steps. On a 100m resolution we apply the line density tool to compute an indicator for trail availability. Again, the trails are weighted less with increasing distance from the pixel under analysis.

(8) Street density: Similar to trail density we compute an indicator for street density 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 are thereby expected to increase visitor numbers. However, the relationship between road density and the enjoyment of nature recreation is unclear. We do not have a specific hypothesis on the effect of streets on recreational values and our analysis has an exploratory character.

(9) Accessibility: The number of people that can access a specific location within a certain time is likely to have an effect on the visitation rate (Schägner, Maes, et al. submitted), which may in turn negatively affect the quality of nature recreation due to crowding effects (Kalisch 2012).

We use the weighted sum of the total population living within a 130km radius around each pixel, using population data from (Batista e Silva, Gallego, and Lavalle 2013). In order to account for distance decay, we applied a Gaussian weight function, so that the population is weighted less with increasing distance from the pixel under analysis. The weight function was calculated so that 95% of its integral is located within the 130km radius.

(10) Socio-economic effects: We use GDP per capita, the unemployment rate and the share of population with upper secondary or tertiary education as proxies for visitors' income and their recreational preferences. For these variables, we extract mean values for the last ten years (as far as available) and the highest data resolution available, which is either NUTS2[1] or NUTS3 level from the Eurostat database (EC 2013).

(11) Share of national area: We computed the share of each case study area that is designated as a national park. Information on national parks were derived from the World Database of Protected Areas (WDPA). National parks are considered to receive higher visitor flows (Fredman, Friberg, and Emmelin 2007).

Table 3: Predictor variables used in the regression analysis.

Type	Variables	Explanation*	Mean / Standard Deviation (visitor data)	Mean / Standard Deviation (valuation data)
Study Characteristics:	TCM	1 if TCM; 0 if CVM		0.43 / 0.5
	Use & option	1 if use value; 0 if use & option value		0.93 / 0.26
	V/visit	1 if V/visit; 0 otherwise		0.81 / 0.4
Site Characteristics:	Ln (ha)	Natural log of the study site area in ha		7.83 / 2.84
	Ln (sri)	Simpson Diversity Index of Corine land use/cover within a 3km radius (100 m resolution raster)		1.1 / 0.31
	Ln (forest)	Natural log of the share of forest cover of the study area (100 m resolution raster)		1.76 / 0.81
	Ln (natural LC)	Natural log of natural land cover of the study area (100 m resolution raster)		1.98 / 1.62
	Ln (agriculture)	Natural log of agricultural land cover of the study area (100 m resolution raster)		2.1 / 1.55
	Ln (grassland)	Natural log of grassland land cover of the study area (100 m resolution raster)		1.44 / 1.35
	Ln (inland water)	Natural log of inland water body area within 3km distance weighted by a kernel function (300 m resolution raster)		0.96 / 1.16
	Ln (ocean)	Natural log of ocean area within 3km distance weighted by a kernel function (300 m resolution raster)		0.5 / 1.11
	Red list species	Total number of red list species found in study area (1 km resolution raster)		8,991 / 3,144
	National Park	1 if site is a national park; otherwise 0		0.19 / 0.39
	Rain days	Mean number of days with rain per year (1 km resolution raster)		144 / 34
	H sun/day	Mean hours of sunshine per day (1 km resolution raster)		4.19 / 1.12

[1] NUTS is referred to as Nomenclature of Units for Territorial Statistics, which is a hierarchical system defined by Eurostat for dividing up the EU territory in order to produce regional statistics at resolution of different administrative levels.

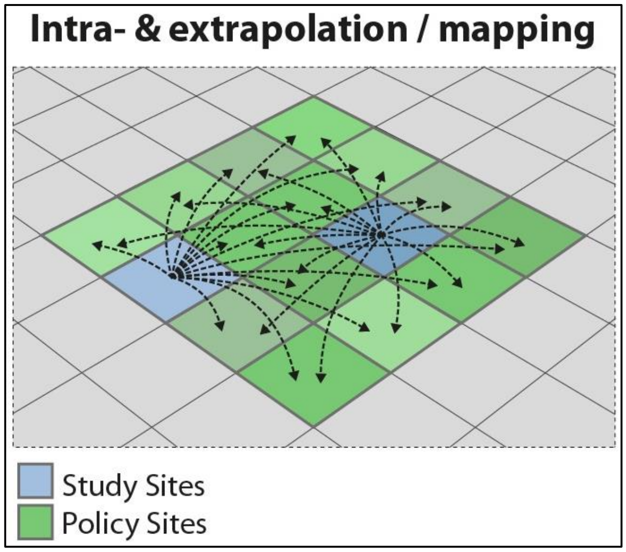
	Days 5^{0}C	Mean numbers of days with an average temperature of above 5 degrees (1 km resolution raster)	304 / 53
	Viewshed	Area visible from each location within in a 30km radius (1 km resolution raster)	276 / 214
	Slope	Slope (100 m resolution raster)	2.04 / 0.97
	Ln (trail)	Natural log of trail density using density function in order to account for distance decay effect (100 m resolution raster)	1.37 / 0.97
	Ln (small roads)	Natural log of small roads density using density function in order to account for distance decay effect (100 m resolution raster)	2.09 / 1.11
Context Characteristics:	Ln (population)	Population living within 130 km radius of the study area using a Gaussian weight function in order to account for distance decay (100 m resolution raster)	16.2 / 1.08
	GDP/capita	GDP/ capita in the NUTS 2 or 3 region in which the study area is located	25,768 / 6,593
	High education	Share of population with higher education in the NUTS 2 or 3 region in which the study area is located	70.4 / 11.5
	Unemployment	Unemployment rate in the NUTS 2 or 3 region in which the study area is located	6.24 / 3.29

* For all spatial predictors mean values per study site area are computed.

3. Methodology

To map recreational values per ha spatially explicit we transfer values from study sites (sites for which real world observations exist) to policy sites (sites for which we make predictions) by two models: one on the number of recreational visits and one on the economic value per recreational visit. Both models are developed by regression analysis of real world observations of the depend variables and by using comprehensive and continuous raster layers as predictor variables. By employing the estimated models to make predictions, we intra- and extrapolate visitor numbers and the value per visit across space (see Figure 2). By multiplying the predicted recreational visits per ha with their predicted value at each location of the map, we drive the overall recreational value per ha.

Figure 2: The concept of value transfer and ESS value mapping.



Before conducting the regression analyses to model the visitor density of the different case study areas and to model the value per recreational visit by using the predictor variables described above, we conduct an exploration of our data following the recommendations of (Zuur, Ieno, and Elphick 2010) in order to gain initial insights into distributions and dependencies. For some predictors we use logarithmic transformations either because they show a skewed distribution or with the aim to approximately linearize an expected non-linear relationship. We test all our predictors for multicollinearity, but do not identify anything of concern.

We apply a number of regression techniques to identify a model that fits the assumptions of linear regression best. All models are estimated using the open source statistical software R. We start our analysis with a general linear regression (GLM), but it shows a wider spread of the residuals for large fitted values for both our analysis and it is therefore a violation of the homogeneity assumption. We control for this effect by using a linear log-transformed models of the following form:

$$\mathrm{Ln}(Y_i) = \alpha + \beta * X_i + \mu_i \qquad \text{where} \qquad \mu_i \sim N(0, \sigma^2) \qquad (1)$$

Y stands for the dependent variables (either the number of visits per ha or the monetary value per recreational visit), 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 the mean of zero and a variance σ. The results are shown on the left (columns 2-4) in Table 4.

We validate our final model against the assumptions of linear regression analysis. Therefore, we plot our residual against fitted values and also against each predictor used in the model as well as predictors not used in the model. One concern is the potential for spatially related residuals.

Among our data base of the valuation studies, several studies use different valuation methodologies to value recreation at the same site. Therefore, it cannot be assumed that these observations are independent. Therefore, we use a general linear mixed model[2] (GLMM) introducing the study site as a random intercept. However, as the introduction of the study site as a random intercept has almost no effect on the model's results, we abandon this approach. Another concern is in regard to author effects. Several authors conduct multiple valuations of our data base and their specific approach may have an effect on the studies result. We therefore introduce the most common authors as random intercepts in a mixed model of the following form:

$$\mathrm{Ln}\left(Y_{ij}\right) = \alpha + \beta * X_{ij} + \gamma_j + \mu_{ij} \quad \text{where} \quad \mu_{ij} \sim N(0,\ \sigma_\mu^2) \quad \text{and} \quad \gamma_j \sim N(0,\ \sigma_\gamma^2) \qquad (2)$$

The random effect is specified by γ_j, representing the correlation of observations from the same sites and which is normally distributed with mean of zero and variance σ_γ. In terms of Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) the mixed effect improves the model considerably. The results of the mixed effects model are shown to the right of Table 4.

We do a similar analysis for the model on the visitor numbers and found that a linear model containing a spatial autocorrelation (SAC) structure performed best in controlling for spatial patterns in the residuals and in regards to AIC and BIC scores. The model's formula remains the same as the formula (1) presented above, but this time we assume that the residuals μ_i of different locations are correlated based on the function f and their distance.

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

For all models we conduct stepwise variable selection using maximum likelihood and restricted maximum likelihood estimators to compare AIC and BIC and the likelihood ratio test until all remaining variables are significant at the 0.1 level (see Table 5). We validate our final model against the assumptions of linear regression analysis. Therefore, we plot the residuals against fitted values and against each predictor. We do not identify any linear or non-linear patterns of concern. Models and validation plots are estimated using statistical software R and lme (Bates et al. 2015), lattice (Sarkar 2015, 2) sp (Pebesma et al. 2015) and gstat package (Pebesma and Graeler 2015).

In order to test the predictive use of the estimated model, we use the model characterized by the lowest AIC and BIC values to map the number of recreational visits per ha and the value per visit across rural Europe on a one km² resolution. We use a data set of urban morphological zones (EEA 2015b) to cut out all urban areas, because our primary data covers only non-urban ecosystems. The maps indicate how the number of visits and the value per visit differ across space. By multiplying the two raster maps (number of visits per ha and value per visit) we obtain the total recreational value per ha of any location throughout Europe. To analyze a realistic policy scenario in more detail we zoom in to a proposed new 200 km² national park in the western part of Germany (Teutoburger forest) (NABU 2015).

In a second step, we investigate the contribution of the spatial variation of the number of visits and the value per visit to the spatial variations of the overall recreational value per ha. Therefore, we conduct two analyses: (1) we compute the mean relative deviation of the predicted pixel scores for two raster data sets, the predicted visits and the predicted value per visit. Within a product of two variables, the mean relative

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

deviation at each pixel determines the relative influence of the two variables on the mean relative deviation of the output variable; the value per ha. (2) We compare our final results of the predicted recreational value per ha with two alternative estimations of the value per ha, for which we substituted either the predicted number of visits or the predicted value per visit by the arithmetic mean of our primary data on either the number of visits of the value per visit. Such a methodology is also referred as to a mean - or unit value transfer. In consequence, the alternative methods to estimate the overall recreational value per ha are characterized by spatial variations which depend either only on the spatial variations in the number of visits or only on spatial variations in the value per visit, because the other input variable is kept constant across space by taking its mean value. By estimating the correlation between our initial predictions with the two alternative methods, we identify to what extent the number of visits and the value per visits drive the total recreational value per ha.

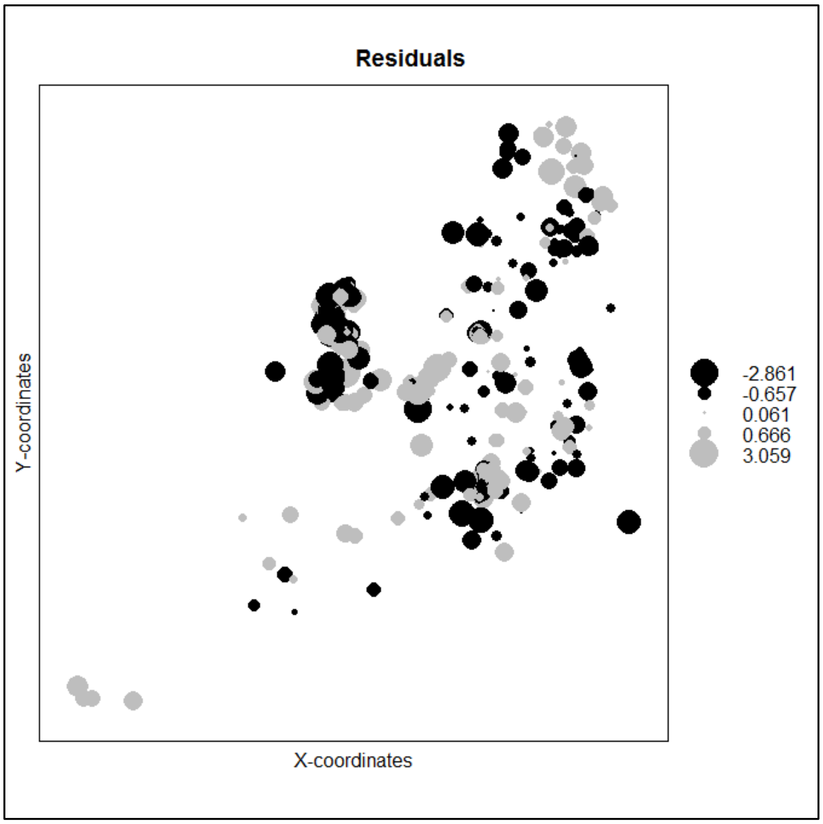
4. Results

The results of our regression analysis after variable selection are displayed in Table 4 for our visitor arrival model and in Table 5 for our meta-analytic value transfer function.

1.3. Visitor Arrival Model

The general linear model (GLM) of our visitor arrival model using a log-transformed dependent variable shows 14 predictor variables significant at the 0.1 level after variable selection (see left of Table 4). Most coefficients have the expected sign. However, the residual plots of the model show some spatial patterns. The residual bubble plot in Figure 3 shows the spatial distribution of the full model's residual without a spatial correlation structure. It shows clustering of positive and negative residuals across Europe. We applied a different spatial autocorrelation to control for these patterns in our second model, which improved the models AIC and BIC values considerably. The best model in terms of AIC and BIC values as well as in controlling for the spatial residual patterns, applies an exponential spatial correlation structure of the residuals. The model shows 12 predictor variables significant at the 0.1 level after variable selection (see right of Table 4) and spatially correlated residuals up to a distance of 364km. 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.

Figure 3: Bubble plot of the spatial distribution of the full model's residual without spatial autocorrelation structure (SAC).



A highly significant negative impact on the number of visits per ha can be found for the size of the study area of the visitor monitoring study, which supports theoretical considerations that larger recreational areas act as a substitute in itself. Visitors can spread across larger areas, which results in lower visitors numbers per ha. Interestingly, even though we did not have strong prior expectations regarding the signs of predictors representing forests, both the share of broadleaf and coniferous forests have negative significant signs in the GLM. However, only coniferous forests show a significant effect after introducing the SAC. The proximity to the coast shows a positive significant effect in both models, but only at the 0.1 level in the GLM. The GLM shows also a positive significant effects for land cover diversity and the view shed, but both variables are not significant in the model including the SAC. On the contrary, whether the study site is a national park shows a positive significant effect in the model containing the SAC, but not in the GLM after variable selection. The mean slope value indicating mountainous areas shows significant negative effect in the GLM, but also this variable is not significant in models containing SAC. We find a significant negative effect in both models for the average numbers of days with rain. All our predictor variables representing traffic access infrastructure show positive effects. The availability of large streets is however, only significant in the model containing SAC. Small streets and in particular the availability of trails are highly significant in both models. A highly significant effect is also shown in both models by the population living in the proximity of the study sites areas. The share of the population having upper secondary or tertiary education shows a positive significant effect in the GLM at the 0.1 level, but not after introducing the SAC. To our surprise the unemployment rate shows a significant positive effect in both our models. Our quality judgment of the visitor monitoring study shows a significant negative effect in both our models, whereas the year of the data collection in the visitor monitoring study shows a significant positive effect, but only after introducing the SAC. The negative effect of our quality judgment may indicate that visitor monitoring studies of higher quality result in more accurate estimates, whereas poor quality studies that rely on more assumptions tend to overestimate visitor numbers.[3]

Table 4: Linear fixed mode and model containing a spatial residual structure after stepwise variable selection (Ln (visits per ha) as dependent variable).

	Linear fixed effect model		Linear fixed effect model containing spatial residual structure	
Variable	**Coefficient**	**Sig. level**	**Coefficient**	**Sig. level**
Intercept	-2.79	*	-75.94	*
Ln(ha)	-0.53	***	-0.53	***
Ln(conifer forest)	-0.17	.	-0.21	*
Ln(broadleaved forest)	-0.34	***	—	—
Ln(ocean)	0.10	.	0.21	***
Land cover diversity	0.48	*	—	—
National park	—	—	3.84E-03	.
Viewshed	6.41E-04	*	—	—
Slope	-1.16E-02	*	—	—
Rain days	-7.03E-03	**	-7.75E-03	***
LN(trails)	0.29	***	0.20	***
Ln(Streets large)	—	—	0.21	**
Ln(Streets small)	0.16	**	0.29	***
Ln(pop)	0.57	***	0.49	***
Pop high education	1.41E-02	.	—	—
Ln(unemployment)	0.31	*	0.46	.
Study quality	-0.15	***	-0.15	**
Survey Year	—	—	3.75E-02	*
	AIC: 1997		AIC: 1916	
	R^2: 0.74		Range: 364km	Nugget: 0.48

[3] No significant effects are found in both models for variables describing the share of grassland, the share of arable land, proximity to inland water bodies, the number of IUCN red list species, the mean number of days per year above 5 degrees Celsius, the mean hours of sunshine per day and the GDP per capita.

1.1. Meta-Analytic Value Transfer Function

For statistical analysis of value per visit, the most important predictor is whether the valuation method is TCM or CVM, which shows significantly higher value estimates for TCM in both models. Whether the study assesses "*use values*" or "*use and option values*" does not show a significant effect in our analysis. It is noteworthy, that only a small share of all studies in our data base consider option value in the valuation approach, and it may therefore be difficult to identify a significant effect. Whether the study estimates the value of single visit or another valuation object (value per party visit, month of access etc.) does show significant negative effects in the mixed effect model, an outcome confirming expectations. It is however, not significant in the fixed effect model.

With respect to spatial predictor variables, six predictors show a significant effect in the GLM and seven in GLMM, which is considerably less than in our visitor arrival model. The explained variations of the GLM on the value per visit is considerably lower than the GLM of the visitor numbers with and R^2 of only about 0.39 as compared to 0.74.

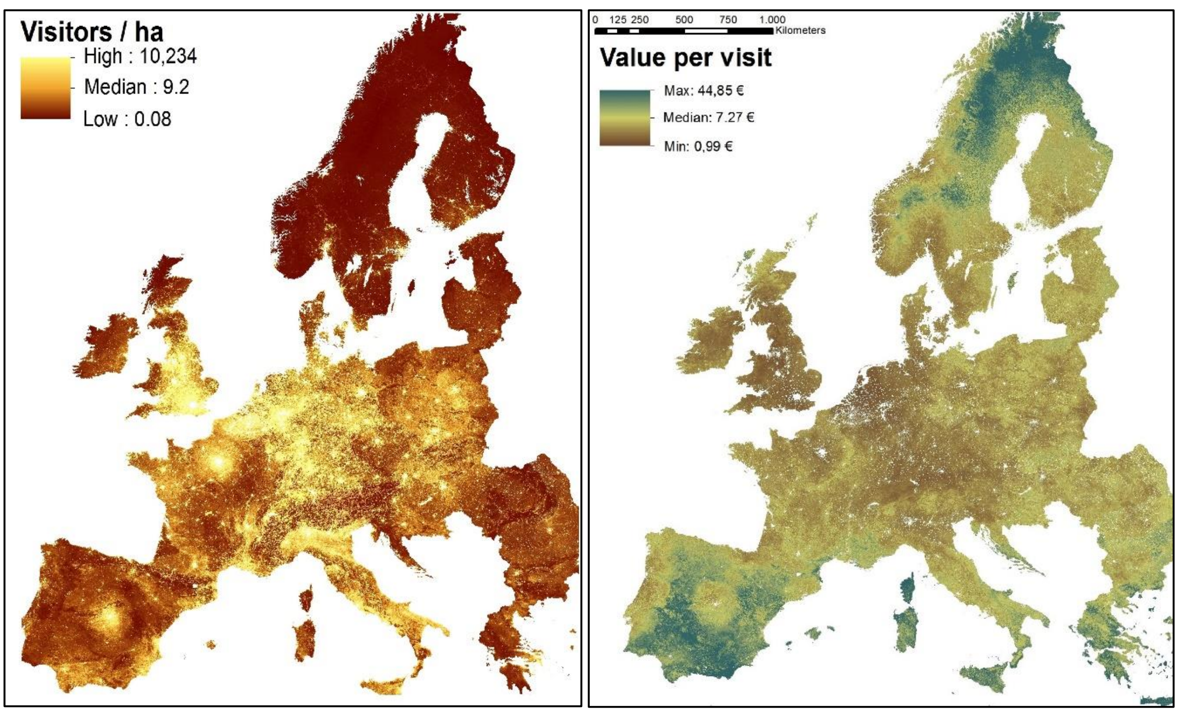
Contrary to the visitor arrival model, the study site size shows a positive significant effect for both models of the meta-analysis. This confirms our hypothesis that larger areas tend to have a higher recreational value per visit. Similar to the visitor arrival model, the share of forest cover shows significant negative effects in both models. Grassland also shows a negative significant effect in both our analysis, which is not the case for the visitor arrival models. The availability of water cover, either inland or ocean, shows no significant effect in the meta-analysis. On the contrary, in the visitor arrival model, the proximity to the ocean shows a positive effect. The number of days with precipitation has a significant negative effect on the value per visit in all our models, as it is also the case for the number of visits. The mean slope value of the study sites — an indicator for mountainous areas — shows a significant positive effect in GLM, but not in GLMM. This indicates that people derive greater pleasure from visiting mountains relative to other types of landscape. However, the GLM of the visitor arrival model indicates that viewer people tend to visit mountainous regions. Population pressure shows a strong and significant negative effect in all our models. This could indicate that people prefer nature recreation in areas with lower population density and value such trips higher. Nevertheless, population pressure shows strong positive effects on the number of visits. Unemployment shows a significant positive effect in both models on the value per visit, which again contradicts our expectations. However, a possible explanation could be that people travel far and have high values for visits to rural areas, which tend to have higher unemployment rates (Copus et al. 2006). Nevertheless, it has to be considered that data on unemployment is only available on the NUTS2 or 3 level, and are not spatially explicit. The average unemployment rate for all years available in EUROTSAT shows high values in our database for sites located in Finland, France, Germany Spain and Sweden and low for Italy. The variable could also pick up some regional or other unobserved effects, but could not identify any systematic pattern allowing for an explanation.

Table 5: Linear fixed and mixed effect models after stepwise variable selection (value per visit as dependent variable).

	Linear fixed effect model		Linear mixed effect model	
Variable	**Coefficient**	**Sig. level**	**Coefficient**	**Sig. level**
Intercept	6.103	***	5.128	***

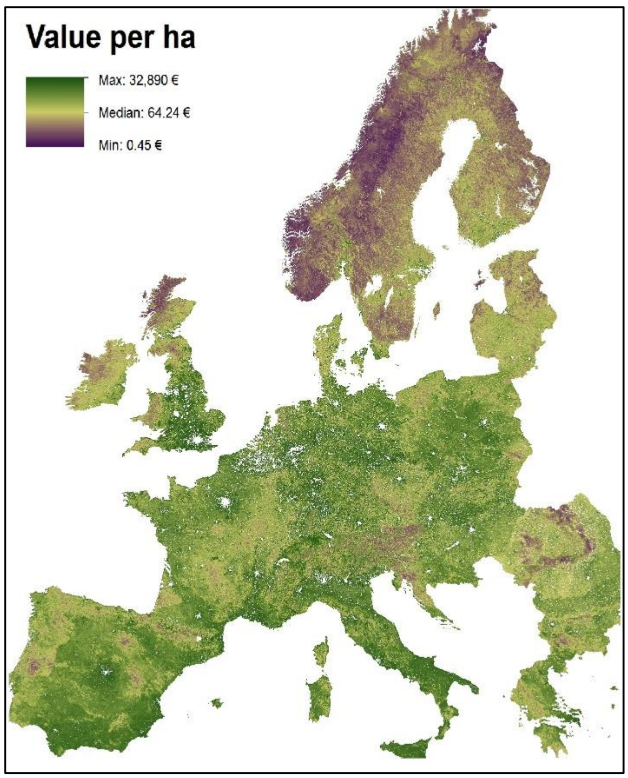
TCM	0.772	***	0.678	***
V/visit	—	—	-0.353	.
Ln(ha)	8.92E-02	***	7.25E-02	**
Ln(forest)	-0.174	*	-0.178	*
Ln(grassland)	-0.194	***	-0.105	.
Rain days	-6.27E-03	**	-5.89E-03	**
Slope	—	—	0.146	*
Ln(pop)	-0.316	***	-0.230	***
Unemployment	0.424	**	0.273	.
	AIC: 697.9		AIC: 661.1	$\hat{\sigma}_{\gamma}^{2}$ = 0.57
	BIC: 729		BIC: 702.5	$\hat{\sigma}_{\mu}^{2}$ = 0.79

Figure 4: Left: predicted visitors per ha and year, right: predicted value per visit.



Using our best models characterized by the lowest AIC values — the visitor arrival function containing a spatial autocorrelation and the meta-analytic value transfer function containing a random author effect — to make predictions result in two maps, one displaying the predicted visitors per ha and year and one displaying the predicted value per visit (see Figure 4). Both predictions are skewed with an average number of visits per ha 27 and median of about 9. The value per visits is shows a median of 8.34€ and a median 7.27€.[4] Due to the fact that the response variables are log-transformed we do have such skewed distribution and higher predilection errors for large values. It is obvious that the tow predictions, the number of visits and the value per visit are negatively correlated. High visitation rates are found mainly in the population centers of the Southeast of the UK, the Netherlands, Belgium, in the west of Germany and around Paris but also in parts of Italy. High values per visit are in contrast found in northern Scandinavia, southern Italy and Spain. By multiplying the two maps (number of visits with the value per visit), we obtain the overall value per ha (see Figure 5). The mapped values are again highly skewed with a mean value per ha of 151€ and a median value per ha of 64€. Making a prediction to aggregate recreational values across the entire part of Europe covered by our maps by assuming the median size of study sites in our primary data as a resolution results in 11 billion recreational visits to non-urban nature areas, which account for an annual value of about 57 billion € annually.[5]

Figure 5: Predicted recreational value per ha.



Comparing the three maps reveals that the value per ha is positively correlated with the predicted number of visits, but negatively correlated with the value per visit. Locations for example in the north of Scandinavia or Scotland receive low numbers of visits and also show a low recreational value per ha. Areas such as the southeast of the UK, the Netherlands, Belgium, and the west of Germany are characterized by high visitor numbers and do show also high values per ha. The correlation between the

[4] Note that for illustrative purpose the color shades of all maps are set to cover the same amount of pixels per color shade.

[5] It should be noted that in a log transformed model, it is not possible to take the linear mean to aggregate values across a larger area. For the aggregated prediction, we assume the median study site size as a resolution for the prediction of both the visits per ha and the value per visits.

visits per ha and the value per ha is 0.8, whereas the correlation between the value per visit and the value per ha is -0.1. If we substitute the predictions of one of our models by the mean estimate of our primary data — either the mean value per visit or the mean number of visits per ha — to compute the overall recreational value per ha, the resulting maps would be strictly proportional to either the predicted number of visits or the predicted value per visit. Thus, the correlations between the map of the value per ha and either the map of the predicted visitor number or the value per visit are the same. The mean relative deviation of the predicted visitor number is 112% whereas mean relative deviation of the predicted value per visit is only 39%.

5. Discussion

Our estimated models fit the data reasonably well and therefore offers valuable information on the main drivers of recreational use and its value across European non-urban ecosystems. The modelling approach can be used to support several policy applications. All predictors with statistically significant effects on the number of recreational visits have signs that are in line with our interpretations or theoretical expectations. Nevertheless, there are also uncertainties related to the model results and prediction accuracy which may be improved by further research.

5.1. Spatial Modelling

One major uncertainty in modeling our primary data is related to the independency of single observations, in particular spatial independency, which is one assumption of linear regression analysis.

For the visitor data we identified spatial autocorrelation of the residuals, which we accounted for by introducing a spatial residual structure. The question remains, what the source of the spatial autocorrelation is. 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 et al. 2000; Smith and Lee 2011; Fingleton and 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 (Bivand 2011; Elhorst 2010;

Gerkman 2011; Brunsdon, Fotheringham, and Charlton 1996; O'Hara and Kotze 2010). However, there are only a very limited number of statistical R-packages that are fully developed to allow for advanced geostatistical approaches as described in literature.

For the meta-analytic value transfer function the question of independence is of even greater concern. As several valuation studies use different valuation methodologies to value recreation at the same site, it cannot be assumed that these observations are independent. Even though, spatial autocorrelations of the residuals are obvious, controlling for these correlations is rejected, because the distance between several observations from virtually the same site is virtually zero. Statistical packages however, require a positive distance. This problem has so far been ignored in meta-analyses of recreational values (Ghermandi and Nunes 2013; Brander et al. 2015; Brander, Van Beukering, and Cesar 2007; Shrestha, Rosenberger, and Loomis 2007; Sen et al. 2013; Londoño and Johnston 2012). We aimed at controlling for spatial dependencies by introducing a random intercept for each study site, but it did not improve the model (as identified by the AIC and BIC values). Correlations across sites may be difficult to identify, because multiple observations per study site are only available for some of the observed sites. In addition, if multiple observations per site exist, the number of observations per site is typically small. Besides, we (and also the past meta-analyses cited above) find that the valuation method has a very strong impact on the value estimate, which also complicates the identification of correlations across observations from the same site. The fact that methodological variables are found to be the most important predictors explaining differences across the value per visit makes it also difficult to identify robust effects of spatial socio-economic and biophysical variables. We identify seven spatial variables with statistically significant effects on recreational values per visit. However, reviewing past meta-analyses on studies estimating the value per visit (Schägner, Brander, et al. submitted) find that the identified significance levels and also the predictors' signs differ strongly across studies for spatial variables. Results of meta-analysis are therefore to be interpreted with caution.

5.2. Primary Data Representativeness

Another aspect of uncertainties within our predictions may be related to the representativeness of the sites of primary data collection. All primary data used for our models is collected from literature and publication bias may be an issue. Visitor monitoring and recreational valuation literature may not be representative for non-urban ecosystems across Europe (Thornton and Lee 2000). Ideally, study sites of our primary data would be randomly selected as done in ecology for estimating species distributions (Keirle 2002). However, to the knowledge of the author, primary data has hardly been collected for randomly selected sites. According to our experiences from collecting studies, it seems rather likely, that our primary data is biased towards sites of relatively high recreational supply, such as protected areas and sites that are particularly managed for recreational purpose. One exception represents a visitor monitoring study of the UK Forestry Commission, in which several sampled forest blocks were randomly selected. Nevertheless, the study focuses on forest only (TNS and FCS 2006; TNS and FCS 2008; TNS and FCW 2005). However, there is little data available for any ordinary rural landscape, which is not drawn to receive a lot of recreational visits. This may result in an overestimation of total visitors and values per visit, because we are not certain about the extent to which our predictors capture all dimensions of recreational ecosystem services and to what extent relationships between dependent and explanatory variables are constant.

Similar to (Brander, Van Beukering, and Cesar 2007; Brander et al. 2015; Eagles 2014) we conclude that there are still insufficient high quality primary data available. Quality aspects of primary studies are often related to insufficient reporting, which hampers their use in secondary research. Often it is difficult to identify methodologies used for primary data collection. Quality and reporting standards for primary data collection have been repeatedly proposed in order to allow easier statistical assessments (Eigenbrod et al. 2010; Rosenberger and Phipps 2007; Johnston and Rosenberger 2010; Schägner, Jan Philipp et al. submitted). We find that in addition to past proposed reporting standards, spatial information on study sites gain increasing importance. With the advancement of GIS technology, the spatial dimension of ecosystem services has received increasing attention (Schägner et al. 2013; Maes et al. 2012; Maes et al. 2013). Therefore, exact reporting on the investigated case study area is fundamental, including coordinates, size and map illustration of the precise borders of the study area. If the only available information on the study site is, for example, a name of a forest in certain country, it may not be possible to identify the location without additional information from the study authors. However, if the site can be identified, researchers can assess site information ex-post, display sites in GIS maps and relate them to other spatial data. Several primary valuation studies in our data base could not be included in our analysis due to insufficient spatial information on the study sites. Several other sites are only approximated, which may add substantial random noise to our statistical analysis.

5.3.Drivers of the overall Recreational Values

Our predictions of the overall recreational value correlate strongly positive with the predictions of the number of recreational visits. On the contrary, the correlations between the predicted value per visit and the value per ha is low and negative. This indicates that spatial variations of the overall recreational value per ha are predominantly determined by the visitor numbers and not by variations in the value per visit. This is also supported by the mean relative deviation of the predicted visitor numbers and values per visit, which determines the influence of the two variables' deviations on the deviation of their product, the value per ha. Also the primary data that is used to estimate the models show similar mean relative deviation for these two variables. Consequently, we conclude that accurate estimates of recreational visitor numbers are by far more important than accurate estimates of the value per visit for deriving accurate estimates of the overall recreational value per ha. This finding has implications for allocating future research priorities. Our results represent empirical support for similar conclusions by (Bateman et al. 2006).

5.4. Policy Implications

The two models estimated in this studies can be used for a number of policy applications: (1) They may contribute to the fulfilments of the EU biodiversity strategy 2020, which require 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 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. 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 nature areas 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 in- or decrease of recreational use and its values. (4) The model allows us to evaluate the effect of land use policies throughout Europe on recreational services and values. (5) Finally, the estimated recreational service values may contribute to set up 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

Within this study we model recreational visitor numbers and the value per visit across non-urban ecosystems throughout Europe using a large number of spatially explanatory variables. Our models fit the data reasonably well and we identify spatial drivers or recreational services and its value. Nevertheless, we also highlight uncertainties related to such statistical modeling approaches.

Since all our predictors are obtained from GIS raster layers, which cover the entirety 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 for several policy applications such as in planning the supply of recreational facilities such as parking and accommodation as well as for resource allocation within conservation prioritization by identifying locations of high recreational value and for setting up green accounting.

Investigating the effect of spatial variations in the number of visits and the value per visit for determining the overall recreational value per ha, we find that variations in the visitor number are of substantially higher importance. Consequently, we conclude that accurate estimates of recreational visitor numbers are by far more important than accurate estimates of the value per visit. This finding may have important implications for allocating future research priorities in recreational ecosystem service valuations.

7. References

Bateman, Ian J., David Abson, Nicola Beaumont, Amii Darnell, Carlo Fezzi, Nick Hanley, Andreas Kontoleon, et al. 2011. "Chapter 22: Economic Values from Ecosystems." In *UK National Ecosystem Assessment: Understanding Nature's Value to Society, Technical Report*, 1466. Cambridge: UNEP-WCMC,.

Bateman, Ian J., Julii S. Brainard, and Andrew A. Lovett. 1995. "Modelling Woodland Recreation Demand Using Geographical Information Systems: A Benefit Transfer Study," CSERGE Working Paper, GEC 95-06. http://www.uea.ac.uk/env/cserge/pub/wp/gec/gec_1995_06.htm.

Bateman, Ian J., Brett H. Day, Stavros Georgiou, and Iain Lake. 2006. "The Aggregation of Environmental Benefit Values: Welfare Measures, Distance Decay and Total WTP." *Ecological Economics*, Environmental Benefits Transfer: Methods, Applications and New DirectionsBenefits Transfer S.I., 60 (2): 450–60. doi:10.1016/j.ecolecon.2006.04.003.

Bateman, Ian J., Andrew A. Lovett, and Julii S. Brainard. 1999. "Developing a Methodology for Benefit Transfer Using Geographical Information Systems: Modelling Demand for Woodland Recreation." *Regional Studies* 33 (3): 191–205.

Bates, Douglas, Martin Maechler, Ben Bolker, Steven Walker, Rune Haubo Bojesen Christensen, Henrik Singmann, Bin Dai, and Gabor Grothendieck. 2015. *lme4: Linear Mixed-Effects Models Using "Eigen" and S4* (version 1.1-8). https://cran.r-project.org/web/packages/lme4/index.html.

Batista e Silva, Filipe, Javier Gallego, and Carlo Lavalle. 2013. "A High-Resolution Population Grid Map for Europe." *Journal of Maps* 9 (1): 16–28.

Biavetti, Irene, Sotirios Karetsos, Andrej Ceglar, Andrea Toreti, and Panagiotis Panagos. 2014. "European Meteorological Data: Contribution to Research, Development and Policy Support." *Proceedings of Spie - the International Society for Optical Engineering* 9229: 922907. doi:10.1117/12.2066286.

Bivand, Roger S. 2011. "After 'Raising the Bar': Applied Maximum Likelihood Estimation of Families of Models in Spatial Econometrics." SSRN Scholarly Paper ID 1972278. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1972278.

Brainard, Julii S. 1999. "Integrating Geographical Information Systems Into Travel Cost Analysis and Benefit Transfer." *International Journal of Geographical Information Science* 13 (3): 227–46. doi:10.1080/136588199241337.

Brander, Luke M., Florian V. Eppink, Jan Philipp Schägner, Pieter J. H. van Beukering, and Alfred Wagtendonk. 2015. "GIS-Based Mapping of Ecosystem Services: The Case of Coral Reefs." In *Benefit Transfer of Environmental and Resource Values*, edited by Robert J. Johnston, John Rolfe, Randall S. Rosenberger, and Roy Brouwer, 465–85. The Economics of Non-Market Goods and Resources 14. Springer Netherlands. http://link.springer.com/chapter/10.1007/978-94-017-9930-0_20.

Brander, Luke M., Pieter Van Beukering, and Herman S.J. Cesar. 2007. "The Recreational Value of Coral Reefs: A Meta-Analysis." *Ecological Economics* 63 (1): 209–18. doi:10.1016/j.ecolecon.2006.11.002.

Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. 1996. "Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity." *Geographical Analysis* 28 (4): 281–98. doi:10.1111/j.1538-4632.1996.tb00936.x.

Burek, Peter Andreas. unpublished. "European Climate Data (based on JRC MARS, EU Aynop and Other Data), JRC (Joint Research Centre)."

CBD, (Convention on Biological Diversity). 2013. "Aichi Biodiversity Targets." *Aichi Biodiversity Targets*. https://www.cbd.int/sp/targets/.

Copus, Andrew, Clare Hall, Andrew Barnes, Graham Dalton, and Peter Cook. 2006. "Study on Employment in Rural Areas."

Diggle, Peter J., Sara E. Morris, and Jon C. Wakefield. 2000. "Point-Source Modelling Using Matched Case-Control Data." *Biostatistics* 1 (1): 89–105. doi:10.1093/biostatistics/1.1.89.

Eagles, Paul F. J. 2014. "Research Priorities in Park Tourism." *Journal of Sustainable Tourism* 22 (4): 528–49. doi:10.1080/09669582.2013.785554.

EC, (European Commission). 2011. *The Eu Biodiversity Strategy to 2020*. Luxembourg.

EC, (European Commission) eurostat. 2013. “Eurostat: Your Key to European Statistics.” http://ec.europa.eu/eurostat/home.

EEA, (European Environment Agency). 2006. “CORINE Land Cover.” *CORINE Land Cover*. http://www.eea.europa.eu/publications/COR0-landcover.

———. 2013. “CDDA (Common Database on Designated Areas).” *CDDA (Common Database on Designated Areas)*. http://www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-4.

———. 2015a. “Digital Elevation Model over Europe (EU-DEM).” *Digital Elevation Model over Europe (EU-DEM)*. http://www.eea.europa.eu/data-and-maps/data/eu-dem#tab-european-data.

———. 2015b. “Urban Morphological Zones 2000.” Data. http://www.eea.europa.eu/data-and-maps/data/urban-morphological-zones-2000-2.

EG, (eurogeographics). 2010. “EuroRegionalMap.” *EuroRegionalMap*. http://www.eurogeographics.org/products-and-services/euroregionalmap.

Eigenbrod, Felix, Paul R. Armsworth, Barbara J. Anderson, Andreas Heinemeyer, Simon Gillings, David B. Roy, Chris D. Thomas, and Kevin J. Gaston. 2010. “The Impact of Proxy-Based Methods on Mapping the Distribution of Ecosystem Services.” *Journal of Applied Ecology* 47 (2): 377–85. doi:10.1111/j.1365-2664.2010.01777.x.

Elhorst, J. Paul. 2010. “Applied Spatial Econometrics: Raising the Bar.” *Spatial Economic Analysis* 5 (1): 9–28. doi:10.1080/17421770903541772.

Fingleton, Bernard, and Julie Le Gallo. 2010. “Endogeneity in a Spatial Context: Properties of Estimators.” In *Progress in Spatial Analysis*, edited by Antonio Páez, Julie Gallo, Ron N. Buliung, and Sandy Dall’erba, 59–73. Advances in Spatial Science. Springer Berlin Heidelberg. http://link.springer.com/chapter/10.1007/978-3-642-03326-1_4.

Fredman, Peter, Lisa Hörnsten Friberg, and Lars Emmelin. 2007. “Increased Visitation from National Park Designation.” *Current Issues in Tourism* 10 (1): 87–95. doi:10.2167/cit293.0.

Gerkman, Linda. 2011. “Empirical Spatial Econometric Modelling of Small Scale Neighbourhood.” *Journal of Geographical Systems* 14 (3): 283–98. doi:10.1007/s10109-011-0147-7.

Ghermandi, Andrea, and Paulo A. L. D. Nunes. 2013. “A Global Map of Coastal Recreation Values: Results from a Spatially Explicit Meta-Analysis.” *Ecological Economics*, Sustainable Urbanisation: A resilient future, 86 (February): 1–15. doi:10.1016/j.ecolecon.2012.11.006.

IUCN, (International Union for Conservation of Nature). 2013. “IUCN Red List Species.” http://www.iucnredlist.org/.

IUCN, (International Union for Conservation of Nature), and (United Nations Environment Programme) UNEP. 2015. “WDPA - World Database on Protected Areas.” http://www.protectedplanet.net/.

Johnston, Robert J., and Randall S. Rosenberger. 2010. “Methods, Trends and Controversies in Contemporary Benefit Transfer.” *Journal of Economic Surveys* 24 (3): 479–510.

Kalisch, Dennis. 2012. “Relevance of Crowding Effects in a Coastal National Park in Germany: Results from a Case Study on Hamburger Hallig.” *Journal of Coastal Conservation* 16 (4): 531–41. doi:10.1007/s11852-012-0195-2.

Keirle, Ian. 2002. “Observation as a Technique for Establishing the Use Made of the Wider Countryside: A Welsh Case Study.” In *Monitoring and Management of Visitor Flows in Recreational and Protected Areas*, 40–45. Vienna, Austria: A. Arnberger, C. Brandenburg, A. Muhar.

Londoño, Luz M., and Robert J. Johnston. 2012. “Enhancing the Reliability of Benefit Transfer over Heterogeneous Sites: A Meta-Analysis of International Coral Reef Values.” *Ecological Economics* 78 (June): 80–89. doi:10.1016/j.ecolecon.2012.03.016.

Maes, Joachim, Leon Braat, Kurt Jax, Mike Hutchins, Eeva Furmanl, Mette Termansen, Sandra Luque, et al. 2011. “A Spatial Assessment of Ecosystem Services in Europe: Methods, Case Studies and Policy Analysis - Phase 1.” 3. PEER Report. Ispra, Italy: Partnership for European Environmental Research.

Maes, Joachim, Benis Egoh, Louise Willemen, Camino Liquete, Petteri Vihervaara, Jan Philipp Schägner, Bruna Grizzetti, et al. 2012. “Mapping Ecosystem Services for Policy Support and Decision Making in the European Union.” *Ecosystem Services* 1 (1): 31–39. doi:10.1016/j.ecoser.2012.06.004.

Maes, Joachim, Anne Teller, Markus Erhard, Camino Liquete, Leon Braat, Pam Berry, Benis Egoh, et al. 2013. “Mapping and Assessment of Ecosystems and Their Services:An Analytical Framework for Ecosystem Assessments under Action 5 of the EU Biodiversity Strategy to 2020.” doi:10.2779/75203.

Magurran, Anne E. 1988. *Ecological Diversity and Its Measurement*. Taylor & Francis.

MA, (Millennium Ecosystem Assessment). 2005. *Ecosystems and Human Well-Being: Synthesis*. Washington D.C.: Island Press.

Moons, Ellen, Bert Saveyn, Stef Proost, and Martin Hermy. 2008. “Optimal Location of New Forests in a Suburban Region.” *Journal of Forest Economics* 14 (1): 5–27. doi:16/j.jfe.2006.12.002.

NABU, (Naturschutzbund Deutschland e.V.). 2015. “Nationalpark Senne-Egge/Teutoburger Wald.” *Nationalpark Senne-Egge/Teutoburger Wald*. http://www.nachhaltigkeit.info/artikel/schmidt_bleek_mips_konzept_971.htm.

Nahuelhual, Laura, Alejandra Carmona, Paola Lozada, Amerindia Jaramillo, and Mauricio Aguayo. 2013. “Mapping Recreation and Ecotourism as a Cultural Ecosystem Service: An Application at the Local Level in Southern Chile.” *Applied Geography* 40 (June): 71–82. doi:10.1016/j.apgeog.2012.12.004.

O’Hara, Robert B., and D. Johan Kotze. 2010. “Do Not Log-Transform Count Data.” *Methods in Ecology and Evolution* 1 (2): 118–22. doi:10.1111/j.2041-210X.2010.00021.x.

OSM, (Open Street Map). 2012. “OpenStreetMap Contributors.” http://www.openstreetmap.org/about.

Paracchini, Maria Luisa, Grazia Zulian, Leena Kopperoinen, Joachim Maes, Jan Philipp Schägner, Mette Termansen, Marianne Zandersen, Marta Perez-Soba, Paul A. Scholefield, and Giovanni Bidoglio. 2014. “Mapping Cultural Ecosystem Services: A Framework to Assess the Potential for Outdoor Recreation across the EU.” *Ecological Indicators* 45 (October): 371–85. doi:10.1016/j.ecolind.2014.04.018.

Pebesma, Edzer, Roger S. Bivand, Barry Rowlingson, Virgilio Gomez-Rubio, Robert Hijmans, Michael Sumner, Don MacQueen, Jim Lemon, and Josh O’Brien. 2015. *Sp: Classes and Methods for Spatial Data* (version 1.2-0). https://cran.r-project.org/web/packages/sp/index.html.

Pebesma, Edzer, and Benedikt Graeler. 2015. *Gstat: Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation* (version 1.0-25). https://cran.r-project.org/web/packages/gstat/index.html.

Peña, Lorena, Izaskun Casado-Arzuaga, and Miren Onaindia. 2015. “Mapping Recreation Supply and Demand Using an Ecological and a Social Evaluation Approach.” *Ecosystem Services*, Best Practices for Mapping Ecosystem Services, 13 (June): 108–18. doi:10.1016/j.ecoser.2014.12.008.

Rosenberger, Randall S., and T. Phipps. 2007. “Correspondence and Convergence in Benefit Transfer Accuracy: Meta-Analytic Review of the Literature.” In *Environmental Value Transfer: Issues and Methods*, edited by Ståle Navrud and Richard Ready, 9:23–43. Dordrecht: Springer Netherlands. http://www.springerlink.com/content/l3516t17552pj1t2/.

Sarkar, Deepayan. 2015. *Lattice: Trellis Graphics for R* (version 0.20-33). https://cran.r-project.org/web/packages/lattice/index.html.

Schägner, Jan Philipp, Luke Brander, Joachim Maes, and Volkmar Hartje. 2013. “Mapping Ecosystem Services’ Values: Current Practice and Future Prospects.” *Ecosystem Services*, Special Issue on Mapping and Modelling Ecosystem Services, 4 (June): 33–46. doi:10.1016/j.ecoser.2013.02.003.

Schägner, Jan Philipp, Luke Brander, Maria Luisa Paracchini, Joachim Maes, Volkmar Hartje, and Florian Gollnow. submitted. “Exploring the Spatial Dimension of Recreational Values: A Combination of Meta-Analytic Value Transfer and GIS,” Ecological Economics, Schägner, Jan Philipp, Maes, Joachim, Brander, Luke, and Paracchini, Maria Luisa. submitted. "A Data Base on Total Anual Recreational Visitor Monitoring of European Natura Areas," Journal of Outdoor Recreation and Tourism,

Schägner, Jan Philipp, Joachim Maes, Luke Brander, Maria Luisa Paracchini, and Volkmar Hartje. submitted. "Determents of Recreational Use in European National Parks: An Empirical Analysis," Data in Brief,

Sen, Antara, Amii R. Harwood, Ian J. Bateman, Paul Munday, Andrew Crowe, Luke Brander, Jibonayan Raychaudhuri, Andrew A. Lovett, Jo Foden, and Allan Provins. 2013. "Economic Assessment of the Recreational Value of Ecosystems: Methodological Development and National and Local Application." *Environmental and Resource Economics* 57 (2): 233–49. doi:10.1007/s10640-013-9666-7.

Shrestha, Ram K., Randall S. Rosenberger, and John B. Loomis. 2007. "Benefit Transfer Using Meta-Analysis In Recreation Economic Valuation." In *Environmental Value Transfer: Issues and Methods*. Vol. 9. The Economics Of Non-Market Goods And Resources.

Smith, Tony E., and Ka Lok Lee. 2011. "The Effects of Spatial Autoregressive Dependencies on Inference in Ordinary Least Squares: A Geometric Approach." *Journal of Geographical Systems* 14 (1): 91–124. doi:10.1007/s10109-011-0152-x.

TEEB, (The Economics of Ecosystems & Biodiversity). 2011. *The Economics of Ecosystems and Biodiversity in National and International Policy Making*. London, Washington D.C.: Earthscan.

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

Termansen, Mette, Marianne Zandersen, and Colin J. McClean. 2008. "Spatial Substitution Patterns in Forest Recreation." *Regional Science and Urban Economics* 38 (1): 81–97. doi:16/j.regsciurbeco.2008.01.006.

Thornton, A., and P. Lee. 2000. "Publication Bias in Meta-Analysis: Its Causes and Consequences." *Journal of Clinical Epidemiology* 53 (2): 207–16.

TNS, (Travel & Tourism), and (Forestry Commission Scotland FCS. 2006. "All Forests Visitor Monitoring Survey of Visitors to FCS Forests Year 1: June 2004 to May 2005." Edinburgh, UK.

———. 2008. "All Forests Visitor Monitoring Survey of Visitors to FCS Forests Year 3: July 2006 to June 2007." Edinburgh, UK.

TNS, (Travel & Tourism), and (Forestry Commission Wales) FCW. 2005. "All Forests Visitor Monitoring, Survey of Visitors to Welsh Assembly Government Woodlands 2004." Edinburgh, UK.

TS, (Tele Atlas). 2006. "Tele Atlas NV Road Data, (Version: 2006)." http://navigation.teleatlas.com/portal/home-en.html.

UN, (United Nations). 2014. *System of Nvironmental-Economic Accounting 2012*. New York.

Zuur, Alain F., Elena N. Ieno, and Chris S. Elphick. 2010. "A Protocol for Data Exploration to Avoid Common Statistical Problems." *Methods in Ecology and Evolution* 1 (1): 3–14. doi:10.1111/j.2041-210X.2009.00001.x.