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Do drivers of nature visitation vary spatially? The importance of context for understanding visitation of nature areas in Europe and North America

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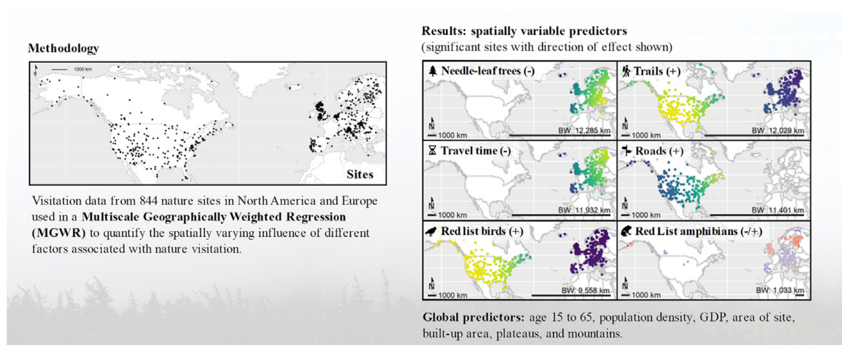
HIGHLIGHTS

- Geographically Weighted Regression can be used to understand nature visitation.
- MGWR allows a deeper understanding of processes in different geographic contexts.
- Both stationary and spatially variable predictors can be identified.
- Spatially variable predictors highlight the context-dependency of nature visitation.
- The approach shows the need for cultural sensitivity in recreation assessments.

GRAPHICAL ABSTRACT



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ABSTRACT

Nature visitation is important, both culturally and economically. Given the contribution of nature recreation to multiple societal goals, comprehending determinants of nature visitation is essential to understand the drivers associated with the popularity of nature areas, for example, to inform land-use planning or site management strategies to maximise benefits. Understanding the factors related to nature, tourism and recreation can support the management of nature areas and thereby, also conservation efforts and biodiversity protection. This study applied a Multiscale Geographically Weighted Regression (MGWR) to quantify the spatially varying influence of different factors associated with nature visitation in Europe and North America.

Results indicated that some explanatory variables were stationary for all sites (age 15 to 65, population density (within 25 km), GDP, area, built-up areas, plateaus, and mountains). In contrast, others exhibited significant spatial non-stationarity (locally variable): needle-leaf trees (conifers), trails, travel time, roads, and Red List birds and amphibians. Needle-leaf trees and travel time were found to be negatively significant in Europe. Roads were found to have a significant positive effect in North America. Trails and Red List bird species were found to have a positive effect in both North America and North Europe, with a greater effect in Europe. Red List amphibians was the only spatially variable predictor to have both a positive and negative impact, with selected sites in North America and northern Europe being positive, whereas Iceland and central and southern Europe were negative. The scale of the response-predictor relationship (bandwidth) of these locally variable predictors was smallest for Red List amphibians at 1033 km, with all other spatially variable predictors between 9558 and 12,285 km.

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The study demonstrates the contribution that MGWR, a spatially explicit model, can make to support a deeper understanding of processes associated with nature visitation in different geographic contexts.

1. Introduction

Nature areas provide significant Cultural Ecosystem Services (CES), including recreation (Chan et al., 2012). The contribution of recreation and tourism to the physical and mental well-being of visitors is of important economic value (in terms of consumer surplus) Additionally, visitor expenditure contributes substantially to local economies, for example by providing income and employment (Balmford et al., 2015; Teoh et al., 2018). Empirical and theoretical evidence shows a positive correlation between mental health and recreation within nature areas, such as parks and nature reserves (Maller et al., 2006). Green spaces and parks can contribute to public health and increase the quality of citizens' lives directly or indirectly and across their lifespan (Keniger et al., 2013; Sandifer et al., 2015; Townsend et al., 2015). Recreation and time spent in protected areas can be linked to the development of positive attitudes and behaviours towards nature and its protection (Teisl and O'Brien, 2003). Moreover, a positive correlation has also been found between recreation in nature and life satisfaction (Biedenweg et al., 2017). Making these contributions explicit can make a case for preserving natural areas and restoring degraded ecosystems; thereby support biodiversity protection and nature conservation more broadly.

Given the contribution of recreation to multiple societal goals, it is crucial to understand the drivers associated with the visitation of some nature areas, for example, to inform land-use planning or site management strategies. A number of studies have investigated the drivers of visitation to nature areas; however, most of these focus on relatively small case study areas. Natural characteristics (including tranquillity; water bodies; naturalness and landscape diversity), accessibility by trails and roads, structural differentiation, age of the park, park area, distance from the nearest metropolitan area, tourism services outside the park (e.g. restaurants) and the socio-economic characteristics e.g. (race and age) in surrounding municipalities have been found to be significant drivers of visitation (de Valck et al., 2017; Giles-Corti et al., 2005; Mills and Westover, 1987; Neuvonen et al., 2010; Schägner et al., 2016, 2018; Zanon et al., 2013). Landcover classes have also been found to be predictors of visitation, wetland and broadleaf land cover to have a negative effect on visitation, whereas water was found to be a positive predictor (Schägner et al., 2016). Landforms have also found to be a predictor of visitation, Sen et al. (2012) found mountains to have a significant positive effect on predicting visitation. National parks with higher biodiversity have been found to attract more visitors than parks with low biodiversity (Siikamäki et al., 2015). The regional climate has an impact on national park visitation by affecting outdoor recreational activities (Jones and Scott, 2006), and being partly responsible for the quality experience of the visit (Amelung et al., 2007). Climate change could increase visitor numbers to national parks in the future due to increased warm weather (Fisichelli et al., 2015; Jones and Scott, 2006). At the same time, climate change increases the need for protection of areas that provide manifold ecosystem services and functions and biodiversity (Lindley et al., 2019).

Cultural differences can exist for different societal groups for landscape or park preference (Buijs et al., 2009; Hamstead et al., 2018), though cultural differences in relation to nature area visitation are still under-investigated in the existing literature. The appeal with biological factors may vary, i.e. Norwegian and Polish people have been found to highlight different environmental values, i.e. scenery and biological diversity, or hunting and fishing, respectively (Brown et al., 2015). Local population size, national wealth and remoteness have been found to be significant predictors for Europe; natural attractiveness and remoteness for North America and Latin America; national wealth and remoteness for Africa; and national wealth and natural attractiveness for Asia/Australasia (Balmford et al., 2015).

Previous studies have included regional statistical models; however, they did not consider sub-continental variation in the drivers of visitation, with the exception of the UK (Balmford et al., 2015). Therefore, their results are more useful in indicating overall trends in nature recreation rather than providing context-specific insights and implications. Schägner et al. (2016) used regression methods that assumed spatial homogeneity, i.e. that drivers do not vary across geographical space. Therefore, could not provide insights into the spatial variability of the drivers of nature recreation across different parts of the study area. Studies investigating CES often only consider recreational value, since this tends to be easier to quantify than other values such as spiritual, educational and aesthetics (Boerema et al., 2017; Nahuelhual et al., 2013; Paracchini et al., 2014; van Riper et al., 2012). However, differences in the relative importance of landscape features can occur depending on the cultural values obtained (Brown and Brabyn, 2012). Whereas studies provide valuable insights into the drivers of nature recreation within these areas, but their conclusions cannot be reliably scaled to a broader geographical area or applied to other locations. Thus, it is also valuable to explore whether drivers vary across different parts of the world in order to develop contextually relevant solutions and make culturally sensitive recommendations.

To the authors' knowledge, this is the most extensive global visitation study to date. We test the effects of a wide range of biophysical, climate, infrastructure, socio-economic and site variables (calculated through GIS processing techniques) on visitation numbers, including analysis of whether and how these effects vary spatially. Here, we use the Multiscale Geographically Weighted Regression (MGWR) approach to identify spatial variability in recreational drivers. MGWR allows consideration of different cultural preferences for nature recreation in different locations. Existing studies in this area emphasise that recreation potential and delivery of CES is context-specific (Fish et al., 2016; Tenerelli et al., 2016). Hence, variation in preferences based on the geographical location of nature recreation areas is to be expected. Thus, this paper aims to answer what is the spatial variation in the drivers of visitation to nature areas in Europe and North America, including the possibility of variation in the spatial scale of these drivers.

This paper extends the existing literature by investigating how the drivers of visitation to nature areas varies *within the* continents as well as *between* them, focusing on Europe and North America. We investigate whether spatial differences in the drivers of nature recreation can be identified across and within Europe and North America, which contain over 80% of the world's terrestrial protected areas (Balmford et al., 2015). We augmented visitation data substantially from Schägner et al. (2016) with extensive data collection, resulting in 844 sites with mean annual visitor numbers. A spatially explicit modelling technique, Multiscale Geographically Weighted Regression, was then used to quantify the scales of associated process of several predictor variables.

2. Materials and methods

2.1. Study area

A total of 844 sites were included; 246 sites from North America (38 from Canada and 208 from the USA), and 598 sites from Europe (see Fig. 1). Site selection was based on data availability, though sites had

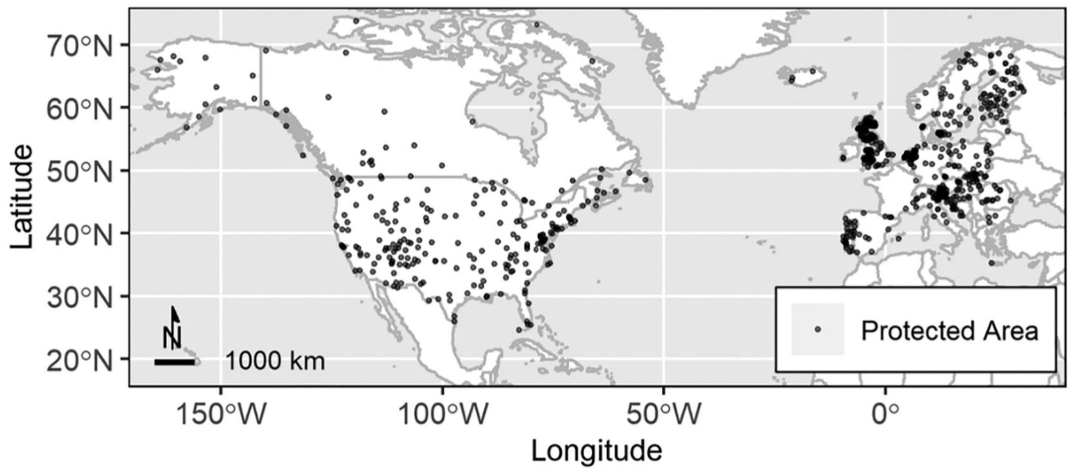

Fig. 1. Centroid locations of study sites ($n = 844$) in North America and Europe. Sites are semi-transparent to demonstrate localised clustering of sites.

to have a 'nature' aspect to them and be terrestrial. Larger nature areas such as protected areas were included (see Supplementary materials: Table S1). These included large nature areas such as Nature Parks and National Parks. North America data covered 49 states of the United States of America (excluding Hawaii) and all ten provinces and three territories of Canada. Overseas territories were excluded due to inappropriate geographic boundaries of either geographic areas. Our geographic definition of Europe covers the European Union countries, those in the Schengen Area and the UK. A total of twenty-seven countries from this 'Europe' region are included in this study.

2.2. Variables and data sources

A total of eleven groups of variables were operationalised from thirteen data sources, ranging from biophysical to socio-demographic, that used to measure their importance on PA visitation. The outcome variable was 'visitation per km^2', with the predictor variables of age (age 15 to 65, age over 65, age under 15), population (population density (25 km), population density (50 km), and travel time), economic (Gross Domestic Product), anthropogenic (Global Human Footprint), accessibility (roads, trails), physical (area, slope), weather (precipitation, summer temperature), landcover (broadleaf trees, needle-leaf trees, grass and shrubland, snow and ice, built-up area, water, wetland, landcover diversity), landforms (plains and lowlands, plateaus, mountains) and biological (Red List amphibians, Red List birds, Red List reptiles, Red List mammals, tree height). The following section briefly describes the sources and how the data was processed to operationalise the variables (see Supplementary materials: Table S2 for more information).

2.2.1. Boundaries

Shapefiles of the site areas were collected from the CDDA (Common Database on Designated Areas v.15) (European Environment Agency, 2017), Government of Canada (Parks Canada, 2015), National Park Service (National Parks Service, 2018), and from a personal communication (P. Schägner) where the latter were used in Schägner et al. (2017). Centroids for each recreational area were calculated. The extent of the site in km^2 was calculated from shapefiles of each area.

2.2.2. Visitation figures

Visitation data was collected as annual visitation, with values ranging from 1981 to 2017. As some of the sites only had values for limited years, the entire dataset was checked for trends using linear regression. Where no significant trend was found, the mean was used. Alternatively, where a significant trend was found, the value from the median year of 2010 was used to detrend the data. See Supplementary materials: Table S1 for a full list of sources and extended notes. Values were converted to mean visitation per km^2 using area calculations from shapefiles of each site.

2.2.3. Age and GDP

The Organisation for Economic Co-operation and Development's (OECD) dataset of Regional Demography (OECD, 2018a) provides the proportion of the population for different age categories. Those aged 15–64 are defined as the working-age population. This was operationalised as three separate predictors of the mean percentage (between 1990 and 2017) of the population for those aged under 15, between 15 and 64, and those 65 and over. The OECD's regional economy dataset (OECD, 2018b) provides GDP per capita at purchasing power parity (PPP) (in millions USD, constant prices, constant PPP with the base year as 2015). This was operationalised as a single predictor using the mean of the years between 1990 and 2016. Both age and GDP were extracted at the large regional scale, or Territorial Level 2 (OECD, 2011) under which the area of study was considered. In cases of overlap between regions, the weighted mean of the area was used.

2.2.4. Population density

The European Union Joint Research Centre's Global Human Settlement Layer (Freire and Pesaresi, 2015) provides a depiction of the density of population across the world. This was operationalised as two predictors: population density (within both a 25 km and 50 km radius, as used in previous studies by Sonter et al. (2016) and Schägner et al. (2016) respectively).

2.2.5. Travel time

The Accessibility to Cities dataset from the Malaria Atlas Project (Weiss et al., 2018) provides travel time in minutes to the nearest densely populated area (>1500 people/km^2). This was operationalised as a single predictor by calculating the mean distance in hours from each study site pixel (1 km resolution) to the nearest densely populated area.

2.2.6. Global Human Footprint v2 (GHF)

The Wildlife Conservation Society and Center for International Earth Science Information Network, Columbia University (WCS and CIESIN, 2005) provide this dataset. It is made from nine different layers reflective of anthropogenic pressure, including population, infrastructure, and land use (1 km resolution). This was operationalised as a single predictor of the mean GHF for each study site.

2.2.7. Roads

The Global Roads Open Access Data Set (v1, 1980–2010) was used to calculate the total km of roads within each study area (CIESIN and ITOS, 2013).

2.2.8. Trail density

OpenStreetMap (2018a) data were downloaded from Geofabrik (2018). Osmosis v.0.47 (OpenStreetMap, 2018b) a command-line Java application, was used to extract all vector elements with the key 'highway'. This was operationalised as a predictor by extracting all highway tags that inferred usage by non-motorised traffic; bridleway, footway, path, cycleway, track or steps and calculating the mean length (m) of trails per km^2 in each study site.

2.2.9. Slope

The USGS' Global Multi-resolution Terrain Elevation Data 2010 (Danielson and Gesch, 2011) provides a 7.5 arc-seconds resolution data layer. This was operationalised as a single predictor as the mean slope in degrees for each study area.

2.2.10. Temperature and precipitation

The Willmott and Matsuura Global (land) precipitation and temperature datasets based on Global Historical Climatology Network and the Global Surface Summary of Day station record archives (Matsuura and Willmott, 2018a, 2018b) provide data in 0.5-degree resolution. The data were operationalised as two predictors: mean annual precipitation between 2007 and 2017 and mean air temperature in summer (June–August, between 2007 and 17) for each study site.

2.2.11. Landcover

For Europe, data were sourced from Copernicus High Resolution imperviousness, forests, grassland, and water and wetness layers (Langanke et al., 2016a, 2016b, 2017a, 2017b) as 20 m resolution raster files. They were operationalised by using the imperviousness layer for built-up area, water and wetness layer for water, and the grassland layer, to calculate the mean percentage of landcover type. The forests layer was totalled to broadleaf and needle-leaf types. The Corine land cover 2012 100 m resolution raster (European Environment Agency, 2016) was used for snow and ice. For North America, data from the North American Land Change Monitoring System (NALCMS) initiative was used for all landcover classes in the analysis (Commission for Environmental Cooperation, 2017). All predictors were calculated as the percentage of the area present in the study location.

2.2.12. Landforms

Classifications for landforms based on Meybeck et al. (2001) and relief classes calculated by Iwahashi and Pike (2007) were used as three predictors. They were grouped as plains and lowlands (plains, mid-altitude plains, high altitude plains, lowlands and rugged lowlands), plateaus (very low plateaus, low plateaus, mid-altitude plateaus, high altitude plateaus, very high altitude plateaus and hills) and mountains (low altitude mountains, mid-altitude mountains, high altitude mountains and very high altitude mountains) as a mean percentage in each study site.

2.2.13. Red List species

Spatial data for IUCN Red List of Threatened Species for amphibians, reptiles and terrestrial mammals for known ranges as polygons were retrieved from the IUCN (2018). Species distribution data for threatened bird species were sourced from BirdLife International (2018). Data was operationalised as four predictors for each group by calculating total counts (all threatened category types) for each study site. Red List species data was treated as non-presence of species where the variable reported a zero value.

2.2.14. Tree canopy height

The mean forest canopy height (Simard et al., 2011) for each site was calculated in meters.

Geospatial processing of the data was conducted in Google Earth Engine (Gorelick et al., 2017), QGIS v3.4 (QGIS.org, 2018) or ArcMap v10.3. All variables were processed and transformed (see supplementary materials: Table S3) in R (R Core Team, 2020). Geographically weighted regression (GWR) models, as with Ordinary Least Squares (OLS) regressions assume the errors are independently normally distributed with zero mean and common variance (Comber et al., 2020). Upon examining the non-constant error variance, the data was found to be heteroscedastic, which was addressed through the transformation of the data (Supplementary materials: Fig. S1). All variables were z-transformed and checked for symmetry in distribution through calculating skewness. Where skewness was >1 or <−1, either logarithmic or square root transformations were applied (Supplementary materials: Table S3). The condition number of the matrix was calculated to detect collinearity.

2.3. Statistical analysis

The model selection followed the GWR route map described in Comber et al. (2020). First, visitation was modelled by individual predictors using OLS and by specified predictor groups (age, population, economic, accessibility, landcover, landforms and biological) using multi-predictor models (Table 1). Given the scale of the analysis, we chose to report significant variables with a $p < 0.1$ threshold while also reporting those that are still significant at $p \leq 0.5$ and $p < 0.01$.

GWR (Brunsdon et al., 1996) is a spatially varying coefficient model that investigates how relationships between the response and predictor variables, in a regression, may vary across space. It reflects Tobler's First Law of Geography (Tobler, 1970) describing an expectation of variable spatial autocorrelation and process spatial heterogeneity. It also puts forward the notion that global or whole map statistical models like Ordinary Least Squares (OLS) regression make unreasonable assumptions around variable independence and process stationarity (Openshaw, 1996). This approach provides a measure of process spatial heterogeneity in data relationships. In essence, it uses a moving window (kernel) and determines local regression models at discrete locations in the study area (using the observation locations or a grid of locations). Data under the kernel are weighted by their distance to the kernel centre.

Table 1
Variable selection using Akaike Information Criterion (AIC) of the Ordinary Least Squares regression models.

Model ID	Model	Number of predictors[a]	AICc	Delta AICc
Single predictors (with intercept)				
1.1–1.30	Single predictor variables[b]	2	1725.85–2399.82	544.56–1218.53
Multivariate models				
2	All predictor variables (IVs)	31	1203.75	22.46
3	Age IVs	4	2388.25	1206.96
4	Populations IVs	4	1932.34	751.05
5	Accessibility IVs	3	1949.44	768.15
6	Physical IVs	3	1717.65	536.36
7	Weather IVs	3	2366.35	1185.06
8	Landcover IVs	9	2031.71	850.42
10	Landform IVs	4	2219.23	1037.94
11	Biological IVs	6	2339.55	1158.26
12	Stepwise selected (backward) IVs	16	1181.29	0

[a] All models include an intercept.
[b] Economic and Anthropogenic predictors (IVs) are included in bivariate models in Supplementary materials: Table S3.

In its standard form, a single kernel size (bandwidth) is used to calibrate a GWR model. This may be unrealistic because it assumes a single degree of spatial variation for all the factors in each local regression. It ignores the possibility that some relationships may operate at different scales. To address this limitation, mixed (or semi-parametric) GWR was proposed (Brunsdon et al., 1999) in which some relationships are assumed to be stationary (i.e. global, similar to assumptions in OLS) and others non-stationary. This was further extended to multiscale GWR (MGWR) (Fotheringham et al., 2017; Yang, 2014), in which the bandwidth for each relationship is determined, allowing each response-predictor relationship to vary spatially.

The input parameters determined through model section were then used as input to different geographically weighted models. The *GWmodel* R package (Gollini et al., 2015; Lu et al., 2014) was used to run GWR and semiparametric GWR models using the selected predictors from the OLS model. The python model *mgwr*, from Python spatial analysis library (PySAL), was used to run MGWR models (Oshan et al., 2019), with several kernel types assessed to find the most parsimonious model. Strong linear relationships between predictors cause collinearity and associated problems of model reliability and precision (Comber et al., 2020). Local multicollinearity issues were investigated through the assessment of local Condition Numbers (CNs). Monte Carlo simulations (with 1000 iterations) were used to test for spatial variability of the predictors. This test holds the model specification constant and recalibrates the model on randomised data before computing variability of the predictor estimates (Oshan et al., 2019).

3. Results

An automatic OLS stepwise selection procedure was used to discern the best model fit. Variable collinearity was examined using Variance Inflation Factors (VIFs) for models with all predictors, with high VIF predictors removed, before backward stepwise selection (based on Akaike Information Criterion (AIC)) was used to find the most parsimonious model. The condition number (CN) of the matrix was 8.08, falling under the 'rule of thumb' value of 30 that indicates disturbing levels of collinearity (Belsley et al., 1980; Comber et al., 2020). At least one predictor from each of the predictor groups, apart from the weather and anthropogenic groups, was selected (see Table 2). These predictors were used in the GWR model selection (Table 3). The most parsimonious model was found to be the MGWR, utilising a Gaussian kernel (Table 4). The MGWR model found six predictors were found to be significantly spatially variable (Fig. 2), with ten predictors being significant at a 'global' bandwidth. These were age 15 to 65, population density (25 km), GDP, area, snow and ice, built-up area, plateaus and mountains (see Supplementary materials: Fig. S2). Age over 65 was not found to be significant for any site in the MGWR, though was significant in the OLS model.

Table 2
Ordinary least squares regression, showing estimate, confidence intervals (CIs), variance inflation factors (VIFs) for each predictor.

Predictors	Visitation		
	Estimates	CI	VIF
Intercept	0.00	−0.03–0.03	
Age 15 to 65	-0.09^{***}	−0.13 to −0.04	2.05
Age over 65	-0.08^{***}	−0.14 to −0.03	2.71
Population density (25 km)	0.14^{***}	0.08–0.20	3.61
Travel time	-0.15^{***}	−0.22 to −0.09	4.08
GDP	0.07^{***}	0.03–0.11	1.55
Roads	0.03^{*}	−0.00–0.07	1.23
Trails	0.26^{***}	0.21–0.31	2.27
Area	-0.61^{***}	−0.66 to −0.55	2.88
Needle-leaf trees	-0.09^{***}	−0.14 to −0.04	2.36
Snow and ice	0.04^{**}	0.00–0.08	1.48
Built-up area	0.08^{***}	0.04–0.11	1.42
Plateaus	-0.05^{***}	−0.09 to −0.02	1.42
Mountains	0.14^{***}	0.10–0.18	1.54
Red List amphibians	-0.10^{***}	−0.13 to −0.06	1.24
Red List birds	0.23^{***}	0.19–0.28	1.86

$R^2 = 0.772$; Adjusted $R^2 = 0.768$; $F(15,828) = 186.9$, $p < 0.001$.
AICc = 1181.288.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3
Geographically Weighted Regression model selection.

GWR model variant	Kernel[a]	RSS	Adjusted R^2	AICc	Delta AICc[b]
GWR	Gaussian	136.81	0.81	1090.98	38.96
Semiparametric GWR	Gaussian	198.08	0.72	1401.57	349.55
MGWR[c]	Gaussian	143.18	0.81	1052.02	0.00
	Boxcar	177.43	0.78	1123.64	71.62
	Bi-square	166.63	0.79	1107.10	55.08

[a] All kernels were calibrated as 'fixed', rather than 'adaptive' with a maximum of 1000 iterations for model calibration using a back-fitting procedure (Lu et al., 2017).
[b] Delta AICc calculated against most parsimonious GWR model variant.
[c] Recursive variable selection from varying coefficients to fixed coefficients.

Mapping of significant predictors per site showed a range of spatial patterns (Fig. 2). Needle-leaf trees were found to be negatively significant in Europe and showed an east-west gradient from lower to higher values (Fig. 2a). Similarly, travel time was found to have a significant negative effect in Europe, again showing an east to west, low to a high gradient (Fig. 2c). Roads were found to have a significant positive effect in North America, showing an east to west, high to low gradient (Fig. 2d). Trails and Red List bird species were found to have a positive effect in both North America and North Europe, with a greater effect in Europe (Fig. 2b, e). Red List amphibians were found to have the smallest bandwidth of 1033 km and was the only spatially variable predictor to have both a positive and negative impact (Fig. 2f). Selected sites in North America and northern Europe were positive, whereas Iceland and central and southern Europe were negative. All other spatially variable predictors had a bandwidth between 9558 and 12,285 km. All spatially variable predictors were significant at the $p < 0.05$ level, apart from trails which was significant at the $p < 0.1$ level.

The significant global (but non-significantly spatially variable) predictors displayed the same sign in both the OLS and MGWR, with age 15 to 65, area, and plateaus having a negative effect, and population density (25 km), GDP, snow and ice, built-up area and mountains having a positive effect. The global bandwidth and non-spatial variability of these predictors suggest no cultural difference between Europe and North America for these predictors (this does not mean there is no biophysical difference). These predictors were significant for all sites, apart from snow and ice, which was only significant for six sites in Alaska.

4. Discussion

4.1. Landcover and biodiversity related spatial variability

In alignment with other studies, we report a negative effect of needle-leaf trees in Europe. Schägner et al. (2016) suggested the abundance of vegetation in national parks can act as a deterrent to visitors. The negative effect seen in our study reinforces this suggestion. The pattern we describe with a lower negative effect in western Europe may relate to lower needle-leaf tree percentages in forests that can be seen in these areas (Kempeneers et al., 2011). Sen et al. (2012) and Schägner et al. (2016) also found that for predicting the location of recreation sites in Great Britain and Europe respectively, percentage of needle-leaf trees showed a non-significant, but negative trend. This may suggest that the lowered presence of needle-leaf trees leads people to dislike them. As MGWR is designed to consider spatial non-stationarity, this may have aided the significance in our study, as the beta varied across space. Our model did not have any significant sites in Northern America, whereas Sonter et al. (2016) did not differentiate

Table 4
Multiscale Geographically Weighted regression and Monte Carlo test for spatial variability results.

Predictors	Visitation				
	Estimates			Bandwidths	
	Mean	SD	Range	Bandwidth	Adjusted t-values (95%)
Intercept	0.161	0.000	0.161–0.162	Global	1.967
Age 15 to 65	−0.119	0.000	−0.120 to −0.118	Global	1.984
Age over 65	−0.051	0.000	−0.052 to −0.051	Global	1.977
Population density (25 km)	0.141	0.001	0.139–0.142	Global	1.975
Travel time* **	**−0.108**	**0.058**	**−0.156 to −0.008**	**11,932 km**	**2.212**
GDP	0.080	0.002	0.076–0.082	Global	1.977
Roads **	**0.041**	**0.031**	**0.020–0.124**	**11,401 km**	**2.232**
Trails *	**0.228**	**0.026**	**0.181–0.253**	**12,029 km**	**2.181**
Area	−0.602	0.000	−0.602 to −0.601	Global	1.980
Needle-leaf trees **	**−0.067**	**0.046**	**−0.104–0.020**	**12,285 km**	**2.190**
Snow and ice	0.035	0.002	0.033–0.039	Global	1.986
Built-up area	0.045	0.001	0.043–0.045	Global	1.979
Plateaus	−0.051	0.001	−0.051 to −0.049	Global	1.985
Mountains	0.090	0.001	0.089–0.092	Global	1.986
Red List amphibians* **	**0.055**	**0.363**	**−2.249–1.624**	**1033 km**	**3.302**
Red List birds* **	**0.272**	**0.086**	**0.124–0.334**	**9558 km**	**2.269**

$R^2 = 0.830$; Adjusted $R^2 = 0.815$.
AICc = 1052.015.
Monte Carlo test for spatial variability using 1000 simulations.
Rows in bold denote spatially significant predictors.
Global bandwidth is reflective of the total bandwidth available within the spatial model. Significances refer to whether the predictor is significantly spatially variable. Out of the non-spatially variable predictors, age over 65 was not significant for any site, and snow and ice were significant for only six sites. The remaining global predictors were significant for all sites.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

between the needle-leaf and broadleaf forests and found that less forest cover was significant in predicting higher visitation to conserved lands in Vermont, USA. It must also be noted that despite the negative effect of needle-leaf trees we see, studies have found that deforestation also negatively affects visitation (Sonter et al., 2016). In summary, needle-leaf trees appear to be a negative driver of visitation in Europe,

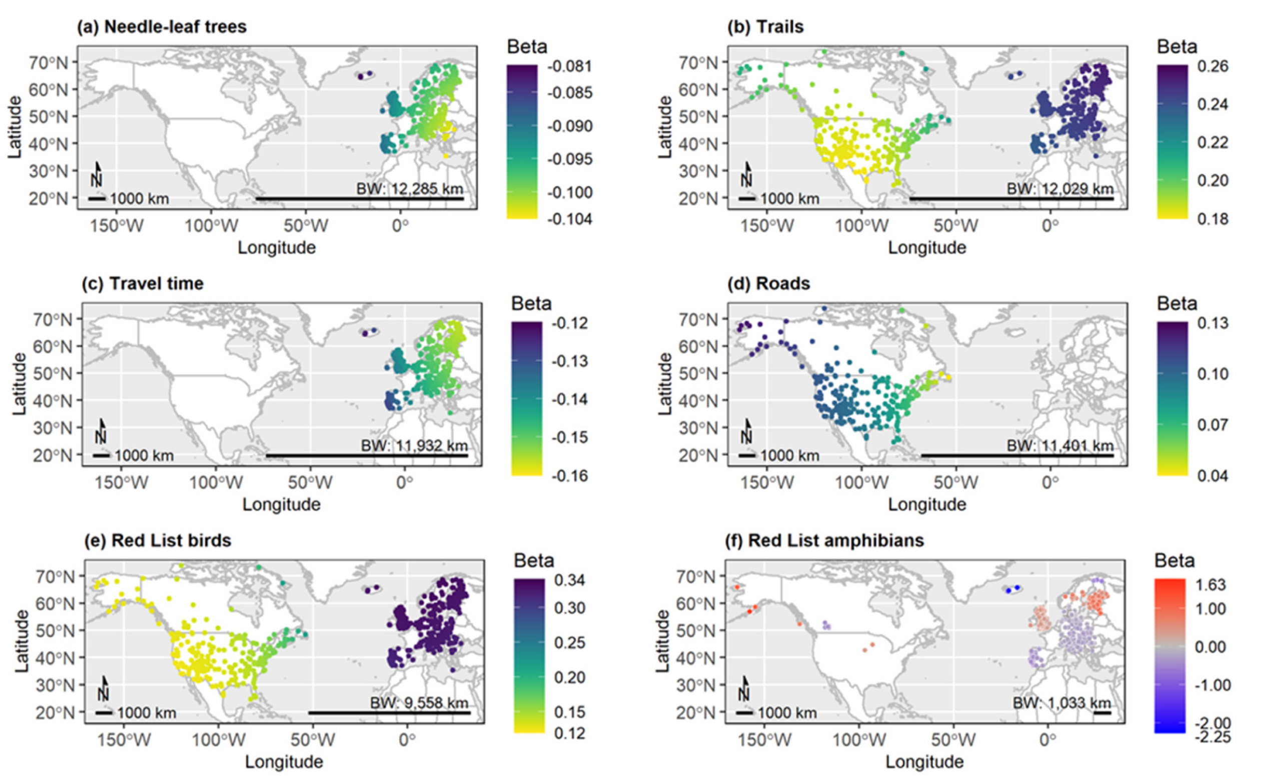

Fig. 2. Spatial variability of locally significant MGWR predictors variables filtered by t-value to show only sites with significant effect for the predictor. Variables are sorted from largest to smallest bandwidth. Panel (f) uses a divergent colour palette to reflect both negative and positive values in coefficients, which does not occur in the other predictors. Predictors with global bandwidths were found to be significant at all sites for the intercept, age 15 to 65, population density (25 km), GDP, Area, Built-up areas, plateaus and mountains (Table 4) for all 844 sites. Age over 65 was not significant for any site, and snow and ice was significant for only six sites (see Supplementary materials: Fig. S2).

suggesting they are not culturally popular in this context but do not act as a deterrent in North America, although neither do they act as a draw for visitors.

Red List birds and amphibians were the two, spatially significant fauna biodiversity predictors. In general, only a few studies investigated biodiversity as a determinant of nature-based tourism. Following the biophilia hypothesis, which assumes that humans have an innate affinity to nature (Wilson, 1984), Siikamäki et al. (2015) found that species diversity has a positive effect on nature-based tourism. However, the authors also found supporting evidence for Neuvonen et al. (2010) that for tourists, biodiversity is most important on the habitat-level. Loomis (2004) found a significant effect of elk and bison populations on visitation numbers in a national park in Wyoming. In contrast, Schägner et al. (2016) found no significant effect of red-list species numbers when accounting for spatial correlation. The pattern of the east coast of North America having higher coefficient values may relate to the increased value on trails in these areas, with visitors interested in birds, also those more appreciative of trail availability. Hence, the studies suggest ambiguous results and highlight the need to differentiate further between Red List species and to account for spatial patterns.

In Europe and North America, amphibians are the most threatened vertebrates due to habitat loss (Stuart et al., 2004). In these regions, protected areas largely cover the geographical range of critically endangered frogs, especially in North America where nature based-tourism plays an essential role in financing the protection of critically endangered frogs (Morrison et al., 2012). Nevertheless, current literature lacks empirical evidence of amphibians' impact on tourism. Though tourism can also be a threat to amphibians through disturbance and the potential to increase habitat loss. The findings of this study suggest that on one hand Red List amphibians are highly relevant for understanding visitation to nature areas as indicated by the large beta values, on the other hand, the ambiguity remains because the direction of the coefficient is both negative and positive depending on the geographical range. A level of caution must be advised when interpreting these findings, as the incidence of amphibians may be a proxy of other factors, such as habitat, or protection status of the area, or a statistical artefact of the method employed. This is discussed later. One possible explanation is that in Northern Europe amphibians are quite rare compared to central and southern Europe (Sillero et al., 2014) and in general, rare species are valued more than common ones (Angulo and Courchamp, 2009). Cultural aspects and lack of education programmes result in a relatively low awareness for amphibians in the general public (Gibbons, 2003). Hence, public knowledge is low, and often people fail to recognise amphibians in the wild (Wells, 2007). Correspondingly, Czech et al. (1998) argue that differences in valuation of species are caused by social construction. Inline, Ceríaco (2012) illustrated how attitudes towards animals are influenced by knowledge and cultural beliefs (including folklore) and how this affects people's relation to amphibians and conservation efforts. Their study investigated attitudes in Portugal, an area that also shows a strong negative correlation in our analysis as illustrated by Fig. 2f.

Unlike amphibians, we found that Red List bird species have an overall positive effect in Europe as well as in North America with varying spatial intensity. Disentangling birds from other taxa, such as amphibians that partly show a negative impact on visitation rates, seem to give more precise results than applying all Red List species taxa in the model as in Schägner et al. (2016). Unlike some other taxonomic groups, such as beetles and nettles, birds have been found to be considered as a charismatic species group positively influencing recreational and other benefits of landscapes (McGinlay et al., 2017). Studies show the positive effect of nature sounds such as tweeting of birds contribute towards stress recovery (Alvarsson et al., 2010) and restorative potential (Ratcliffe et al., 2020) as well as aesthetical evaluation of outdoor settings (Alvarsson et al., 2010), underlining the overall positive effect of birds on recreational potential. However, results indicate the spatial variation of Red List bird species is important for visitation, showing higher values in Europe than for the North American continent. This could be explained by spatial variation in the occurrence of threatened species. IUCN data show a low concentration of threatened bird species in Europe (IUCN, 2018), which could lead to high attraction level for NP visitors, because of their rarity (Angulo and Courchamp, 2009). Visitors to nature areas can have a negative impact on biodiversity through human-induced disturbance, as tourism and outdoor recreation can both generate direct and indirect effects that threaten wildlife (Cole and Landres, 1996), though Sutherland (2007) suggests reducing visitors to sensitive sites and managing visitors on site to help minimise the impact of disturbance on bird species.

4.2. Infrastructure related spatial variability

Travel time was found to be significant and has a negative effect in Europe, with a west-east gradient, though the betas exhibit a small variation. Increased travel time can have an impact on both the visitor (time, travel cost) and complexity of planning, which may explain the negative effect seen in Europe, though it may also be a result of less 'far away' travel destinations due to the smaller sizes of countries within Europe compared to North America. The increase negative effect seen in north-eastern Europe may be related to a 'harsher' climate in the north, as opposed to other parts of Europe. The act of travel itself can be a pleasant facet of recreation, and distant sites can be attractive as the number of visitors can be lower than more accessible sites (Mealey, 1988). For national parks in the USA, Hanink and White (1999), found aggregate travel to have a negative impact on demand for overnight stays in national parks. Although when paired with either park age or aggregate area, aggregate travel was found to be positive. Our results support the findings in various previous studies. Among these is Sen et al. (2012), who found increasing travel time to be a highly significant negative predictor of the number of visits from an outset area to potential recreational visit sites in England. Lower travel times have been found to significantly influence the proportion of visitors to woodland areas (Coles and Bussey, 2000; Roovers et al., 2002).

Similarly, albeit on much larger scales, our results confirm previous studies, which have found significant positive effects of trails (e.g. Schägner et al., 2017; Sonter et al., 2016). This is also in agreement with Neuvonen et al. (2010) who found that park facilities, such as trails were significant for predicting the popularity of a national park in Finland and Kienast et al. (2012) showed that hiking trails are a predictor for green spaces near Swiss towns. In parks and protected areas in Norway, visitor use is highly influenced by the number and level of management of trails (Kuba et al., 2018). The differences between Europe and North America could be explained by the customary use of informal trails in many parks across the USA (Leung et al., 2011), which would not be captured within the "trail density" variable. The variability in the coefficient is more considerable in North America than Europe, with the smallest effect seen in southern-central North America, which could infer the increased role of trails nearer the coast.

Our analysis finds that road density (measured by total km of roads within a given area) has a statistically significant effect in North America, though not in Europe. This may reflect the greater reliance on cars in North America for nature visitation, given that it is less densely built and has weaker public transport than many European countries (Bok and Kwon, 2016). Fig. 2d shows that the effect of roads follows an east-west gradient, with lower values in the east (i.e. less of an influence on nature visitation) and higher values in the west. This may be explained by the lower population density in the western USA and Canada than the east (Freire and Pesaresi, 2015), meaning there is likely to be greater reliance on driving cars to access nature areas. The strongest effect was found to be in Alaska and western Canada while the weakest effect was found on the north-eastern US coast and south-western Canadian coast. Our study shows a significant positive effect on roads as found by Schägner et al. (2016), though in direct contrast, we find the significant effect only for North America and not Europe. The distance to the nearest main road has been found to be a weakly significant negative predictor of site arrivals (Brainard et al., 2001). The differences that can be seen in North America and Europe could be attributed to the cultural and historical differences around nature area creation. An example can be seen in the establishment of English national parks, whereby several parliamentary reports dismissed the American style of large, publicly-owned spaces, arguing England was densely populated and developed, instead proposing measures to protect the countryside and manage rural development and farming (Fisher and Carver, 2018). Hence, there already exists a historical gulf in the cultural understanding of what a nature area should be. This helps to explain the difference in roads being a significantly positive parameter in North America (with larger spaces demanding good transport routes) and non-significant in Europe. Apart from the effect of roads on human visistation, roads can also be the cause of ecological disturbance including habitat fragmentation and interfering with species mobility (Wemple et al., 2018), hence caution should be exercised before considering changes in infrastructure in nature areas.

4.3. Non spatially variable predictors

Three significant global predictors had negatives coefficient ranges, namely, age 15 to 65, area size, and plateaus. Our results may indicate that a higher percentage of working-aged individuals in a local population reduces the visitation rates for local sites, in coherence with Zanon et al. (2013) who reported that younger people could suffer from 'lack of time' and competing interests to visit parks. However, in contrast, Neuvonen et al. (2010) found no age class significant as a predictor for visitation. The study area size is regularly used in studies to analyse recreational ecosystem service values (Schägner et al., 2018), with park size and travel distance together have been found to be better predictors of park visitation than distance alone (Giles-Corti et al., 2005). In line with Schägner et al. (2016), the effect of site size was found to be globally negative on the visitation per km^2. This may be due to larger sites being more difficult to navigate and attracting less visitors per unit area. As we considered visitation per km^2, and not per site, two differently sized sites may receive the same visits, though the visitation per km^2 will vary. Balmford et al. (2015) found that site size was positively correlated with visit rates in UK National Parks, though did not find a significant effect for the rest of Europe or North America. However, as we used a normalised value for site visitation, this may not be directly comparable. The last negative global predictor was plateaus. Plateaus are usually flat and elevated above surrounding land. The negative effect may be attributed to the flat character, as mountain areas were found to have a positive effect.

Five significant global predictors were found to have positive coefficient ranges. These were population density (25 km), GDP, snow and ice, built-up area and mountains. The population density was found to significant within 25 km radius, similar to Schägner et al. (2016) who found population density within 50 km to be the second largest significantly positive variable in predicting national park visitors. Sonter et al. (2016) also found that greater numbers in the surrounding population contribute to significantly higher visits to conserved lands. This reinforces the notion that the larger the pool of local visitors, the larger the number of site visits, hence remote parks are predicted to have less visitation. We found that GDP was significant positive predictor, similar to Balmford et al. (2015) who found wealth had a significant positive effect using a Generalised Linear Model (GLM) for Europe (with no significant effect in the North America GLM), and a significant positive effect using univariate regression for North America (but no significant effect for the univariate regression for Europe). Disposable income is correlated to a significant variable in estimating nature recreation (Loomis et al., 1999). This is in contrast with Schägner et al. (2016) who described a significant negative effect of GDP/capita in an intermediate model without spherical spatial correlation structure, though after spatial patterns were accounted for became insignificant. Our study accounted for built-up area as a positive predictor of visitation. Urban areas are recounted to be significantly positive predictors of recreation sites within an area, although the account as a negative predictor of numbers of visits to a site (Sen et al., 2012). Our results may be indicative of urban areas often being associated with more amenities, and when present within nature areas, such as in national parks in the UK, may attract more visitors. This is in coherence with Neuvonen et al. (2010) who found a number of 'tourism services', such as the number of beds in accommodation services, outside national parks in Finland significant predictor of visitation. Mountains (combined with moor and heathland) have been found to be a significant negative predictor of recreation sites within an area (Sen et al., 2012). Although as a predictor of visitor numbers to a site, both mountains (combined with moor and heathland), and mountain substitute availability were found to be positively significant. Sen et al. (2012) suggest that this is indicative of high-quality recreational experiences. Similarly, Puustinen et al. (2009) found that the highest number of national park visits in Finland was to mountainous parks. Snow and ice were found to be a significant positive predictor in our study, though unlike the other global predictors, which were significant for all 844 sites, this was only significant for six sites in Alaska. Winter recreation may have been captured by the fact that visitors go to mountainous areas by the mountain landform globally significant predictor in this study. Sonter et al. (2016) found that opportunities for snow sports was significant for 'in-state' visitors to conserved lands in Vermont, USA, and may explain the relevance for Alaska in our results.

Wilderness, by interpretation and appeal to visitors, can be seen to differ between North America and Europe. Nash (2014) suggests that wilderness is a term that may seem concrete at first, but is highly subjective and an individual's specific mood or feeling generated from wilderness, as a quality, may also be place specific. Areas of 'pristine' wilderness in Europe are seen to be lacking in comparison to North America (for example, using criteria in the U.S. Wilderness Act) (Diemer et al., 2003). The greater extent of wilderness, remote areas, and resulting differences in physical characteristics in North America compared to Europe will influence the outcomes of this study.

In this study, we have attempted to discuss the patterns from our investigation in relation to previous literature. It could be argued, that as with as all modelling approaches, some of the identified effects might not be related to causality, but to coincidentally correlated effects or simply to type I errors. Sellke et al. (2001) show, for example, that the probability of rejecting a true null hypothesis (that there is no effect) is at least 7% for standard p-values of 0.01. However, this probability is estimated based on perfectly simulated data. On the contrary, real-world data (as used in this study) encounter common statistical problems, which, to a certain degree, violate the basic assumptions of linear regression analysis and model extensions. These violations may inflate p-values and increase the risk of type I errors. Among the violations probably the most relevant are (1) biased sampling errors, (2) dependencies among observations (e.g. spatial auto-correlation) (3) missing covariates and (4) measurement errors in the covariates (biased covariates). In this study, we used an upper threshold of 0.1, hence the uncertainty related to the significance will be larger, i.e. for the roads predictor in the OLS and trails predictor in the MGWR. Finley (2011) highlights the importance of validating GWR models by understanding the underlying mechanism generating the data, as both GWR and Bayesian spatially-varying coefficients (SVC) methods were found to generate different regression coefficient surfaces on an analysis of ecological data upon comparison. Hoeting (2009) highlights the importance of accounting for spatial correlation, in ecological data. Importantly, Finley (2011) highlights that a simple regression slope coefficient may not always reflect the spatial variable and scale-dependent relationships between dependent variables and predictors. The ability for MGWR to consider predictors at varying spatial scales allows the limitation that all processes occur at the same spatial scale to be overcome (Fotheringham et al., 2017). In this study, both spatially varying global predictors demonstrate that MGWR indeed helps overcome this limitation. Global predictors in our study were found to have the same sign in both the OLS and MGWR. Wheeler and Tiefelsdorf (2005) suggest that despite variables being non-correlated, local regression coefficients can be collinear in GWR, which would require caution in interpreting the results. This study has attempted to mitigate this through the analysis of local condition numbers, which were 13 or under for all sites (see Supplementary materials: Fig. S3, panel b).

The comprehensive availability of visitation data from national park authorities or literature was a limitation in this study. This could either be due to lack of collection of visitation data by the relevant authority or the data not being publicly shared. Another limitation was in the geospatial predictor data, as this was sourced at different resolutions in this study (see Supplementary materials: Table S2), as for example, information integrity can change at varying resolutions, or upscaling, of spatial data (Gupta et al., 2000).

The authors encourage a cautious but motivated mindset to the results, as further research is needed to validate patterns that are seen in the predictor variability across spatial scales. This is especially important for those predictors whose spatial patterns are mechanistically difficult to explain. This includes Red List species, for example, the positive effect seen for birds on the east coast of North America and the patterns seen for amphibians. Nevertheless, to understand further and validate the results of this study, there is a need for real-life surveys. Is there an effect in reality, or are the detected effects just picking up artefacts in the model? This is a valid question for all modelling attempts but is highlighted primarily due to the novelty of using the method to predict nature visitation. This study has assumed that the visitors are national, and hence the differences are cultural. The contribution of international visitors has not been accounted for and needs further investigation. An individual's choice to visit a nature site could be motivated through individual preferences rather than general cultural differences, for example by hobbies such as availability of suitable paths/trails for running or bird watching shelters (hides) for bird watchers. Thereby individuals will be more likely to visit sites that cater to activities they wish to engage in. However, an individual's perception is also shaped by culture through socialisation associated with cultural norms and concepts. Thus, recreational values are not only evaluated in terms of satisfaction of individual recreation preferences but are also reproduced via culture (Trainor, 2006). In this study, we did not investigate the effect of coupling predictors, whereas other studies have used coupled factors as predictors (e.g. Giles-Corti et al., 2005). We did not explore multivariate analysis based on groupings in the MGWR analysis. These could have been essential predictors and warrants further research efforts. To make the results for both North America and Europe comparable, we used the same model. We have assumed that the scales of variation are equally applicable in both North America and Europe. Though to investigate further the context specificity, future research needs to model both regions separately. Research in nature areas beyond North America and Europe, for example, expanding in the northern hemisphere (i.e. Asia) and in the southern hemisphere (e.g. South America) needs further investigation. Though there are potential data limitations in terms of both visitation data, and predictor variable data, that are necessary for this type of analysis. This study does not explicitly investigate whether there is a non-cultural aspect of how physical characteristics of Europe and North America impact visitation to nature areas. Factors such as Europe being highly populated, and nature sites usually being populated compared to North America having more wilderness and remote areas will have influenced the outcome of this study. This merits further investigation.

5. Conclusions

The importance of the spatially variable predictor variables seems to vary dramatically in space. From these predictors, needle-leaf trees, trails, and most significant sites for Red List amphibians were found to be only significant in Europe, roads only in North America, and trails and Red List birds in both regions. As visitation to nature areas is important for physical and mental well-being, managing visitation within cultural context is critical. By taking into consideration local variability of predictors and using localised regressions, the perceptions of 'local' visitors can be discerned. Understanding the drivers of nature visitation and place-specific perception, which, as above-argued is also driven by culture, is essential for conservation management and planning. It is a tool to assess recreational value expressed by nature visitation, as well as qualities of protected areas (e.g. presence of needle-leaf trees, mountains, and wildlife) which matter for the quality of recreation. Therefore, it should be considered complementary to other means of value assessments, e.g. economic valuation studies. It contributes to the challenge faced by decision-making to account for the multiple values of protected areas.

Furthermore, understanding the varying spatial scales of the different factors associated with the use of nature recreation areas by the public is important in order to use increase the efficiency of the use of the (scarce) resources distributed to conservation efforts. Spatially explicit modelling techniques, such as Multiscale Geographically Weighted Regression, that quantify the scales of associated process and thereby context dependencies support the identification of factors relevant for conservation management. This kind of analytical approach allows the limited management and promotional resources available to nature areas to be utilised more effectively than the more usual using an a-spatial, 'one size fits all' modelling approach.

Declaration of competing interest

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

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Appendix A. Supplementary data

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