# National scale mapping of supply and demand for recreational ecosystem services

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# Title: National scale mapping of supply and demand for recreational ecosystem services

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**Keywords**

Accessibility; attractiveness; cultural services; paths; protected areas; travelling distance

**Abstract**

Cultural ecosystem services (CES) are often underrepresented in ecosystem service assessments, despite the importance of these benefits. Recreation is often used to represent CES, however identifying, quantifying, and mapping these services continues to be a challenge. In this study, we develop a national CES map predicting recreation demand (e.g. walking, hiking, cycling) for the United Kingdom (UK). Recreation demand is calculated as the number of projected visits for local recreation estimated using the universal law of human mobility which accounts for the attractiveness of an area. Recreation demand was found to be the greatest in areas surrounding high population centres, compared with protected sites which were deemed more attractive but were in more remote areas. This pattern was most pronounced when evaluating weekly visits, but was still evident where the visit frequency was reduced to annual. In this study, we also evaluate whether this demand is met for recreation by assessing the presence of paths. The mean for met demand (paths present) was 4.5 times greater than unmet demand (paths absent) for yearly visits across the UK. Generally, in the areas of highest demand close to populated centres, paths were present, making 84% of all yearly recreational demand met by path infrastructure. However, paths are lacking from 42% of the UK, with some of these areas coinciding with higher recreation demand, for example in the northeast and parts of Wales. Our study therefore highlights not only where the recreation demand is highest and access should be maintained, but also where demand for recreation exists but the infrastructure including paths are not present, and therefore has the potential to be improved. This information is useful for policy makers and land managers, as it allows areas to be prioritised for the maintenance and improvement of recreation provision under new land management policy.

## 1. Introduction

Ecosystem services are an important concept in conservation policy and land management. There is a need to quantify and understand the spatial distribution of these services if they are to be effectively incorporated into policy and planning. However, modelling and mapping of ecosystem services is often focussed on provisioning (e.g. food, water) and regulating services (e.g. pollination, air quality) with well-defined biophysical functions. Cultural ecosystem services (CES; defined as the *"non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation and aesthetic experience"* (Millennium Ecosystem Assessment, 2005)) are consequently underrepresented in ecosystem service assessments (Boerema et al., 2016; Crossman et al., 2013; Martnez-Harms and Balvanera, 2012; Wong et al., 2015). This is predominantly because, despite the importance of these intangible benefits (Willcock et al., 2016), they can be challenging to identify and map (Daniel et al., 2012) because the functions linking the characteristics of the landscape to the level of service delivery are often unique to the individual or the particular aspect of CES concerned.

Recreation is often used to represent CES (Crossman et al., 2013; Hermes et al., 2018), largely because it is relatively simple to quantify compared with other CES (Chan et al., 2016). Recreation is defined as "*recreational pleasure people derive from natural or cultivated ecosystems*" (Millennium Ecosystem Assessment, 2005; TEEB, 2010), which could include hiking up a mountain, strolling through the park or cycling alongside a river. The physical and physiological benefits gained from the diverse range of recreational activities is well established (Lackey et al., 2021; Pereira et al., 2021; Thomsen et al., 2018), thus the need to identify areas within the landscape which are important for these benefits is essential (Hermes et al., 2018). Recreation in natural or managed environments is often regarded as a public good, and access is sometimes enshrined in local rights. However, rarely do land managers/owners benefit directly from the provision of such services. For example, around 71% of the land in the UK is utilised for agriculture (including rough grazing on semi-natural grasslands and heathlands) (DEFRA, 2022), and there is high degree of public access including hundreds of thousands of miles of public paths, bridleways, and other rights of way, yet current agricultural payment schemes do not incentivise investment in improving these services, beyond the designated maintenance required by the access rights (Natural England, 2015). Future schemes, e.g. those adopting a payment for ecosystem services approach, could encourage the development of farmland to maximise recreation potential or at least assess the extent to which recreation shows trade-offs or synergies with other priorities such as pollution reduction, biodiversity conservation and agricultural production.

Any incentives driven, for example by payments for ecosystem services, require recreation to be identified and quantified which can occur using several approaches. For example, several studies have mapped visitor numbers or expenditure per unit of space (Schägner et al., 2016; Spalding et al., 2017). However, this approach has limitations, firstly because not every area visited for recreation has an entrance fee or any means of assessing visitor numbers, and secondly there are large variations between people's preferences or benefits gained from a particular activity. Because of this, many studies have aimed to quantify CES through stakeholder engagement, via interviews and, more recently, through participatory mapping (Garcia et al., 2018; Muñoz et al., 2020). Although these approaches provide more detailed information on the locations and benefits gained, they can be intensive in terms of resources and thus often limited geographically (Buendía et al., 2019; Rall et al., 2019), as well as sometimes suffering from low response rates (Brown and Fagerholm, 2015).

Despite the increasing number of CES studies, identifying, quantifying and mapping these services thus continues to be a challenge. Often specific regions or landscapes are assessed and even within these locations, protected areas (with high levels of supply) or urban areas (with high levels of demand) are usually the focus (Ament et al., 2016; Booth et al., 2010; Cheng et al., 2021; Crouzat et al., 2022; Ko and Son, 2018), even though important CES can be delivered within agricultural ecosystems for example (Assandri et al., 2018; Power, 2010). The wider landscape must therefore be considered when examining CES. Furthermore, if CES are to be incorporated within national policy or planning initiatives, recreation needs to be mapped at the country-scale as a minimum. The creation of these maps is important not only for identifying existing areas which offer high recreation value and experience high demand, but also for recognising locations which need to be enhanced for recreation (i.e. high demand and low supply). This allows policy makers and planners to prioritise and target the most appropriate areas for maintaining and improving locations for recreation.

A promising approach to addressing the limitations of current CES mapping involves predictive mapping of recreation demand through accessibility to natural and semi-natural habitat using population centres and transport networks (Ala-Hulkko et al., 2016; Paracchini et al., 2014). This would allow large spatial extents to be evaluated using a consistent approach, without direct need for the time and monetary resources involved in conducting questionnaires. In this study, we use this approach to develop a national CES map for the UK, predicting recreation demand representing activities such as walking, hiking, cycling, etc, i.e., 'outdoor non-vehicular recreation', which we refer to as recreation hereon. Recreation demand is calculated as the number of projected visits for local recreation estimated using the universal law of human mobility (Schläpfer et al., 2021), taking into account the attractiveness of an area. The resulting output is a UK map showing the predicted recreation demand at 250 m resolution, where areas of high demand can be identified, but also where demand is not met through the absence of paths. We validate this output and suggest potential further uses of such maps in the landscape scale planning of ecosystem service supply and demand.

## 2. Method

### *2.1. Study area*

The study area of the United Kingdom (UK), comprising the countries of England, Wales, Scotland and Northern Ireland (Figure 1), is 242,495 $km^2$, with an estimated population of more than 67 million people in 2020 (Office for National Statistics, 2021a). Land cover consists of improved grassland (27%) and arable (20%), semi-natural habitats (26%), with some woodland (15%) and a relatively low cover of urban areas (9%) (Marston et al., 2022). Nearly 28% of the land area is protected under national and international legislation (JNCC, 2021), and these include Areas of Special Scientific Interest (Northern Ireland); Sites of Special Scientific Interest (England, Scotland and Wales); National Nature Reserves; Ramsar Sites; Special Areas of Conservation, Special Protection Areas; Areas of Outstanding Natural Beauty; National Scenic Areas; and National Parks.

### *2.2. Recreational demand function*

Our prediction of recreation demand is expressed as the total number of projected visits for local recreation in target cells. Calculations were performed using Matlab v7.14.0.739; codes can be found at github.com/dhooftman72/RecreationalValue. We used a cell size of 250 m x 250 m, which is comparable with other recreation mapping studies (Byczek et al., 2018; Komossa et al., 2021; Long et al., 2021). At a finer resolution, recreation is driven by complex spatial factors such as the presence of specific habitat features, species or facilities, which are difficult to map at a national scale. We assume that people not having their residence in a grid cell drive to the location to walk or hike, for which the opportunity is provided by the presence of paths. To estimate the total number of projected visits in each 250 m target cell, we used a bespoke version of the universal law of human mobility (Schläpfer et al., 2021), as seen in the function below:

$$\text{Demand}_\text{i} = \text{Attractiveness}_\text{i} \times \sum_{\text{j}=1}^{\text{all}} \left( \frac{\text{Population}_\text{j}}{(\text{Frequency}_\text{ij} \times \text{Traveling distance}_\text{ij})^{\propto}} \right) \qquad \text{Eq. 1}$$

with *i* the target cell, *j* the source cell and the scaling factor $\alpha = 2.17$, following Schläpfer *et al.* (2021); frequency is expressed as number of visits per year; travelling distance in kilometres.

The distance decay gravity function considers the number of visits to single target cells (*i*) depending on the *Population* size in a source cell (*j*), corrected by the *Traveling distance* from that source cell to the target cell and the *Attractiveness* of the target cell – the assumed relative likelihood of visiting that target cell. As well, Eq. 1 includes the number of visits per year from the source cell to the target cell i.e. the *Frequency*, since people tend to visit more often where there is a shorter distance to travel. For a single given target cell, Eq. 1 is summed over all potential source cells. Since Eq. 1 is asymptotic to 0, summed visit densities below 1 per $km^2$ are rounded. Therefore, the value of 0 denotes effectively a lower density than 0.5 visit per $km^2$. Independently, it is then repeated for all target cells (i). Hence for a given distance more predicted visits will arise from more densely populated cells compared with less populated cells, whereas at shorter distances more visits are predicted than at longer distances for a given source population density. Urban areas were removed as target cells using the 2020 UKCEH Land Cover Map (Morton et al., 2021), which identified 250 m cells that were dominated by the urban land class. This is because we were interested in recreation demand in the wider landscape, and the large number of projected visits in urban areas would skew the distributions and resulting outputs. Urban areas were still used as source cells since a large portion of the demand originates from these areas. The following sections describe the inputs required for each element of the recreation demand function.

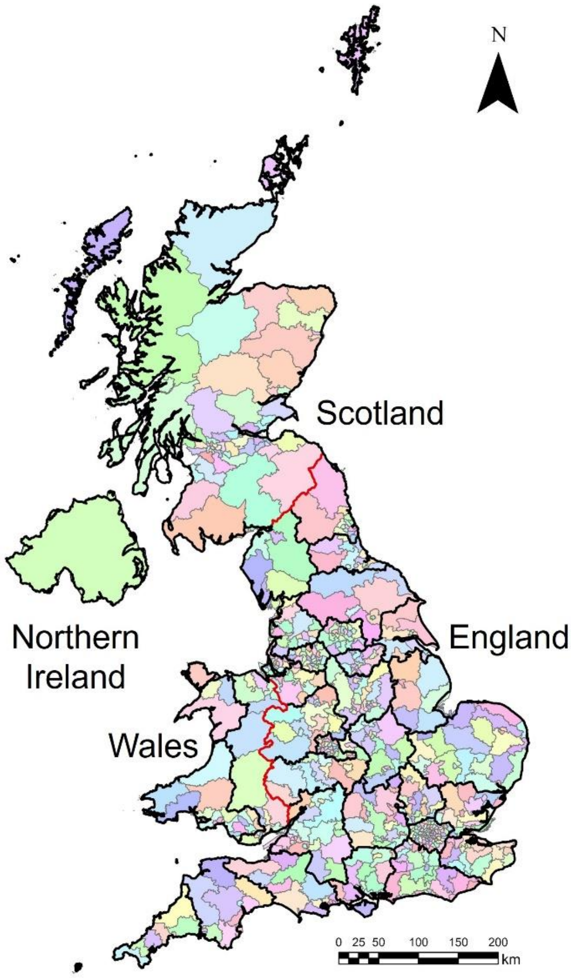


**Figure 1.** The United Kingdom comprising of the countries of England, Wales, Scotland and Northern Ireland (red borders). Shown are the validation units at two scales: the 631 electoral constituencies coloured, the colours are only to allow distinction among different units; and the 33 regions as bold lining.

2.2.1. *Population and frequency*

The population density for the year 2020 per source cell was based on WorldPop unconstrained density (Lloyd et al., 2019) in original 0.00083333° resolution with a WGS 1984 projection (≈ 75 meters in the UK). This raster was resampled into our standardised 250 m grid using bilinear recalculations and subsequent multiplication by $(250/75)^2$. Unlike Schläpfer et al. (2021), we had no information regarding visit frequency related to source and target cells in the UK. Therefore, we calculated for three different assumptions, and consequently produced three outputs; the demand for the number of visits for people that visit a target cell once per year, once per month and once per week. As Eq. 1 required visits per year, the respective values for frequencies were 1, 12 and 52. Frequency being part of the denominator in Eq. 1 made the demand of the more frequent visits skew closer to home, which is in line with the findings from Schläpfer et al. (2021).

*2.2.2. Travelling distance*

Cost weighted distance functions are more suitable for assessing travelling distance across the UK compared with the Euclidean distance, since the quickest route via the fastest road may not be the most direct route. To determine the travelling distance between a population source cell (j) and the target cell (i) (Eq. 1) we calculated a cell-to-cell distance in kilometres at a 250 m scale by summing two raster grids. The first of which was a long-range cost weighted distance raster at a 2.5 km scale along road networks in the UK (details in the next paragraph). The second was a small-range 250 m raster with the Euclidean distance to the nearest road. The use of the two gridded datasets was required as calculating the cost weighted distance for every target cell to every cell at the 250 m scale in the UK would need over 4 million unique maps to be generated, which is unfeasible.

Roads were according to freely available Open Street Map data (Geofabrik, 2018) and included motorways, trunk roads, primary, secondary and tertiary roads. We added slow oversea connections between mainland UK and Northern Ireland/other surrounding islands (e.g. Outer Hebrides). Travel from Ireland into Northern Ireland was not considered. We used the average travelling speed in Great Britain (GB) on each road type in 2014 (Statista, 2015), to derive cost weighted rasters to classify the minimal resistance of travelling through a cell (see Table 1); i.e., the resistance associated to the speed of the quickest road type present within a cell. The cost-weight per cell was calculated as a ratio relative to the average travelling speed on a motorway. For example, a cost-weight value of 1.45 means that it would cost 45% more time to cross a cell compared to having a motorway, which is expressed as 45% more distance (see Figure S1). Cells in remote areas where roads were absent were assigned a weight value of 25, to correspond with walking speed (Table 1). See Hooftman et al. (2021) for further details on such cost-weighted method. We generated a 2.5 x 2.5 km raster for the UK in ArcPro v2.9.0, with the lowest weight through that cell assigned as the value. This was used to calculate the travelling distance between the centre of the target cell to all other cells across the UK, resulting in 39,968 individual maps, one unique to each target cell.

Once the long-range cost weighted distance raster (2.5 km) had been produced, the short-range distance raster was added, which calculated the Euclidean distance to the nearest road at a 250 m scale. Therefore, this approximated the straight-line distance one needs to travel to get to the roads on our network within one larger cell. Although the cost distance weights were derived from the average travelling time in miles per hour, the value itself is an independent weight which didn’t require conversion.

**Table 1**. Conversion of Open Street Map road types to cost-weights using the average traveling speed (Statista, 2015) on roads types in the UK.

| OSM Road type | Statista road type | Car average speed* | Weight factor |
|---|---|---|---|
| Motorway | Motorways | 110 kph† | 1 |
| Motorway link | Motorways | 110 kph† | 1 |
| Trunk road | Single carriage ways | 75 kph† | 1.45 |
| Trunk link road | Single carriage ways | 75 kph† | 1.45 |
| Primary road | Single carriage ways | 75 kph† | 1.45 |
| Primary link road | Single carriage ways | 75 kph† | 1.45 |
| Secondary road | 40mph built-up roads | 28 kph‡ | 3.89 |
| Secondary link road | 40mph built-up roads | 28 kph‡ | 3.89 |
| Tertiary road | 30mph built-up roads | 24 kph‡ | 4.53 |
| Tertiary link road | 30mph built-up roads | 24 kph‡ | 4.53 |
| Overseas links | Slow travel | 11 kph§ | 10 |
| No through roads¶ | High resistance | 4 kph | 25 |

†Assumed more or less straight routes through grid cells; ‡ including a factor 2 curviness through grid cells (*i.e.*, it takes twice as much true distance to cross a cell); § assumption to create a large traveling time; ¶ Making sure that in all but the most remote areas these cells will not be crossed.
* translated from mph.

*2.2.3. Attractiveness*

We used the presence of protected areas as a proxy for attractiveness, with the assumption that a higher level of protection equates to a more attractive area. Although attractiveness is subjective and variable from person to person, several other studies have used a similar approach with protected areas or areas of natural/semi-natural habitat (Casado-Arzuaga et al., 2014; Chan et al., 2006; Mitchell et al., 2021). Our approach is therefore restricted to recreation that values “natural” landscape aesthetics, intact habitats and high biodiversity. However, the attractiveness factor is flexible and can be modified or replaced with other spatial data in future analyses. We extracted the UK terrestrial protected area network from the UNEP-WCMC (2022). The International Union for Conservation of Nature (IUCN) category assessment (II to V) was used to relate to the level of attractiveness, where II was maximum protection and so the most attractive, whilst V was the lowest, but still higher than no status. For listed areas that had not (yet) a reported IUCN category, assignments were made to resemble similar areas (see Table S1). We used a linear conversion to define attractiveness, with IUCN status V being twice as attractive as no status area, status IV three times, III four times and II five times as attractive (Figure S2a). Following the reasoning that people will preferentially visit more attractive areas (Dolan et al., 2021), attractiveness is incorporated in Eq. 1 as proportions in which the highest status area (II) gets its full potential of demand (i.e., has a weight value of 1), whereas no status areas receives a 1/5 of the potential demand. Accordingly, the other proportions are 2/5 (status V), 3/5 (status IV) and 4/5 (status III).

*2.3. Met vs unmet recreation demand*

To determine whether the demand for recreation had been met or not, we identified whether a path was present in the target cell (Figure S2b). Public rights of way aid outdoor recreation in the UK, however there is no centralised dataset of this available. Instead, we use a path network extracted from Open Street Map, which has been found to be a good representation of public rights of way (Hornigold et al., 2016). Paths were categorised as bridleways, footways and paths (Geofabrik, 2018).

We excluded residential roads, steps, pedestrian zones, paved roads and tracks, even though in some cases they may connect paths. We defined that where a path was present, recreation demand had been met since the opportunity for such recreation was provided. This assumes there are no rights to free-roam outside of the paths, which is true for most areas of England, Wales and Northern Ireland, whereas in Scotland rights-to-roam are more prevalent. However, most people tend to stick to paths and are encouraged to do so even in a free-roam situation due to the convenience, safety or to protect the surrounding environment (National Trust, 2020), thus the assumption remained valid. These paths, which were polylines, were rasterised to a 1 km grid to provide a raster of cells with or without present paths, with present defined as containing at least one path. A 1 km grid was used to reduce the influence of stochasticity, as well as to use a more visual based scaling; people could 'visit' a 250 m cell by experiencing its attractiveness from a path in the neighbouring cell.

### *2.4. Validation*

Validation of recreation across the UK is challenging due to the lack of standardised existing visitation data at this scale. Many recreational datasets are only available at the regional scale or for specific areas such as national parks (Statista, 2020). However, we identified three datasets that could be associated with recreation demand across the UK. These were compared with our predicted recreation demand, for cells where demand was met (i.e. a path was present, Table 2):

1) Tourist expenditure for 2013 in GB £ for NUTS2 administrative regions (≈ counties; Office for National Statistics, 2016). We chose to compare with tourist expenditure since the number of visitors is an important indicator of the contribution of recreation to the local economy (Schägner et al., 2016). We omitted data from inbound tourism since this did not relate the to the UK population density.

2) The Monitor of Engagement with the Natural Environment (MENE) survey for the years 2009-2019 (Natural England, 2019). The MENE survey (N = 468,370) is based solely in England with the aim of capturing time spent in the natural environment via in-person interviews. From the survey we used the frequency of weekly visits to the natural environment, which we interpreted as largely close to home visits. As part of this survey, the starting and visiting postcodes were collected, which we plotted using the centroid location for all such postcodes in the UK (Office for National Statistics, 2021b).

3) The People and Nature Survey for England (PANS) for the years 2020-2021 (Natural England, 2021). PANS (n = 12,674) supplements the earlier MENE study, by collecting data online about how people use, enjoy and understand the natural environment. Amongst this information, GPS locations that were visited by respondents were collected and plotted. For this survey, respondents were located in England but could select visit locations in Scotland or Wales.

We validated our predicted recreation demand with the three datasets outlined above, by comparing the sum of met-demand at two scales: within regions (n = 33; Figure 1) and electoral constituencies (n= 631; Figure 1). We compared with i) domestic tourist income, ii) the average visit frequency of the MENE survey, iii) the sum of the total frequency of respondents of the MENE survey and iv) the sum of the visit frequency of the PANS (one visit per respondent) (Figure S3 & S4). For (i) data was only available at the region scale for the whole of the UK, whilst ii and iii could only be assessed for England.

Comparisons were based on Spearman's rank correlation (Matlab corr-tool with Spearman link). For the constituencies, we used 250 bootstraps of 50 paired values each, to avoid significance through just having a high sample size, without enough explanatory effect size. Prior to correlation, we employed a double-sided Winsorising protocol for normalisation for all data sets (Hooftman et al., 2022; Verhagen et al., 2017). This to avoid the impacts of extreme values without eliminating such data-points and to scale all factors identically. This normalisation protocol uses the values associated to the 2.5% and 97.5% percentiles of number of datapoints to define the 0 and 1 values (values below or above these percentiles became 0 or 1 respectively; Hooftman et al., 2022). We are aware the effect of this Winsorising protocol on a ranking index is relatively small, being independent on the absolute range of the data. All recreational demand layers were $\log_{10}$-transformed, to meet the requirements of normality.

**Table 2.** Summary of validation datasets, their source and the metric used for comparing with met-demand in the available locations.

| Survey/Data | Source (shortened URL) | Metric | Location |
|---|---|---|---|
| Tourist expenditure for 2013 in GB £ | ons.gov.uk/.../2013/regionalreferencetables | Domestic tourist income per region in GB £. | UK |
| Monitor of Engagement with the Natural Environment | publications.naturalengland.org.uk/file/MENE | Mean weekly visits to the natural environment; number of respondents visiting the natural environment. | England |
| The People and Nature Survey for England | assets.publishing.service.gov.uk/.../Y2Q2_PANS_Data_v2 | Number of recorded visits to the natural environment using visit longitude and latitude location data. | England, Scotland and Wales |

## 3. Results

### *3.1. Recreation demand*

The demand for recreation for once per year visits, one per month visits and one per week visits across the UK (urban areas excluded) can be seen in Figure 2. For all visit frequencies, the greatest demand is skewed closer to the more densely populated areas. This is most apparent for the weekly demand, since remote areas of Scotland and Wales (see Figure 1 for the country borders) have a predicted demand density of 0 which is unsurprising given the large distance to a densely populated area. Rural landscapes at the edges of cities attracted a higher density of people with a higher frequency than areas of outstanding natural beauty in Scotland or Wales, even though the latter might be considered more 'attractive' for recreation. For the latter more remote areas, the demand for recreation is mainly on a once per year visit frequency.

### *3.2. Met vs unmet recreation demand*

The difference between met (paths present) and unmet (paths absent) demand for weekly, monthly and yearly visits across the UK can be seen in Figure 2. The range of visit densities was larger for areas where demand was met for weekly, monthly and yearly visits, whereas visit densities tended to be lower for unmet areas. Most yearly demand across the UK was met, with only 16% of areas without paths (unmet). This contrasts with 42% of the UK not containing paths. There was a 4.5-fold difference between mean demand for met (84.6 ± 14.7 STD visits per hectare) and unmet (18.9 ± 35.3 STD) demand for yearly visits across the UK. For monthly and weekly visits the proportional difference between those met and unmet demands was 4.7 and 3.5-fold respectively. Paths tend to be focused around the more inhabited areas that have a higher demand (Figure S2b). Therefore, the higher demand around more populated areas is mostly met through paths, whereas areas with lower demand paths are absent and demand remains unmet.

Following that paths were more prevalent close to major populated areas, the proportion of yearly demand in cells without paths –the unmet demand– was greater in Scotland (45%) and Wales (35%) compared England (11%; Figure 3). The proportion of unmet demand decreased with visiting frequency because of the reduced distances travelled (Figure 2; 23%, 22% and 6% respectively for yearly, monthly and weekly). There was a negative relationship between population density and unmet demand; the least dense areas, at constituency scale, had the largest proportion of unmet demand, especially in Wales and Scotland ($R^2$ = 0.53; Figure S5). These general patterns were similar across yearly, monthly and weekly visits (Figure 3). In England, there is a distinct ring around 50 to 100 km from the centre of London in which the path infrastructure could be improved to meet the predicted demand.

### *3.3. Validation*

The correlation between our predicted met-demand (paths present) and the three validation datasets was variable at the region and constituency scale (Table 3). When compared at the region scale, there was good correspondence between the met-demand and the three datasets, particularly with PANS and to a lesser extent the domestic tourism income. However, at the finer constituency scale, these correlations were much lower, particularly with the MENE survey, where very little association was found. This may be because MENE is a short-range index which reflects the location of the respondent rather than of the visit. Thus, at the region scale, respondent location and visit location may overlap, whereas at the constituency scale, a short-range visit to the natural environment could easily fall in a neighbouring constituency.

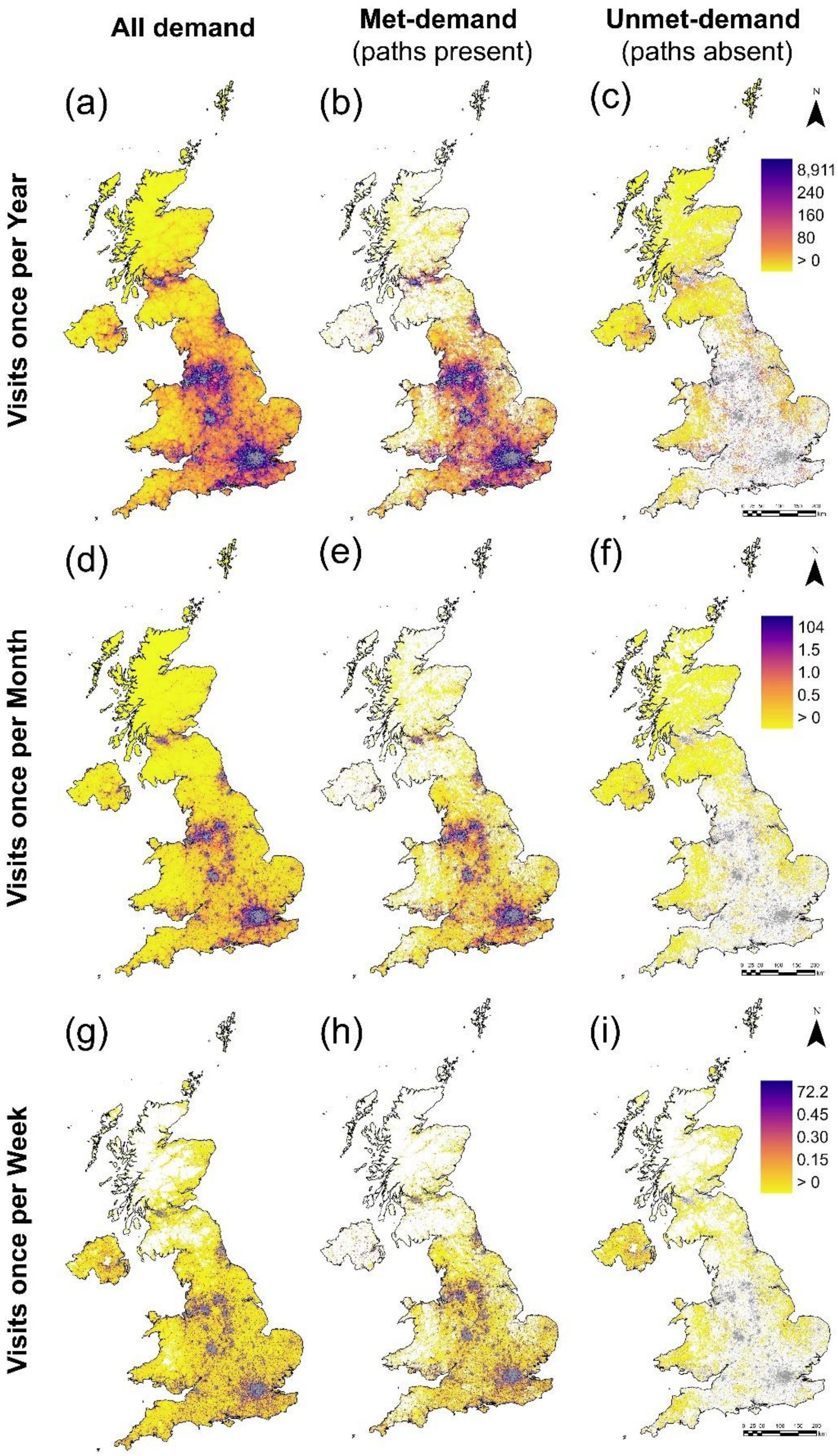


**Figure 2.** Demand for recreation determined using a population density gravity distance function combined with attractiveness for a once per year frequency of visits (a-c), once per month visits (d-f) and once per week visits (g-i). Urban areas in grey are not considered here, blank areas equal 0 (rounded). From columns on the left to right, (1) all demand in the UK for non-urban areas, (2) met-demand, where paths are present and (3) unmet-demand, where paths are absent. The mapped combination of the second and third column equals the first column on the left for each frequency type.

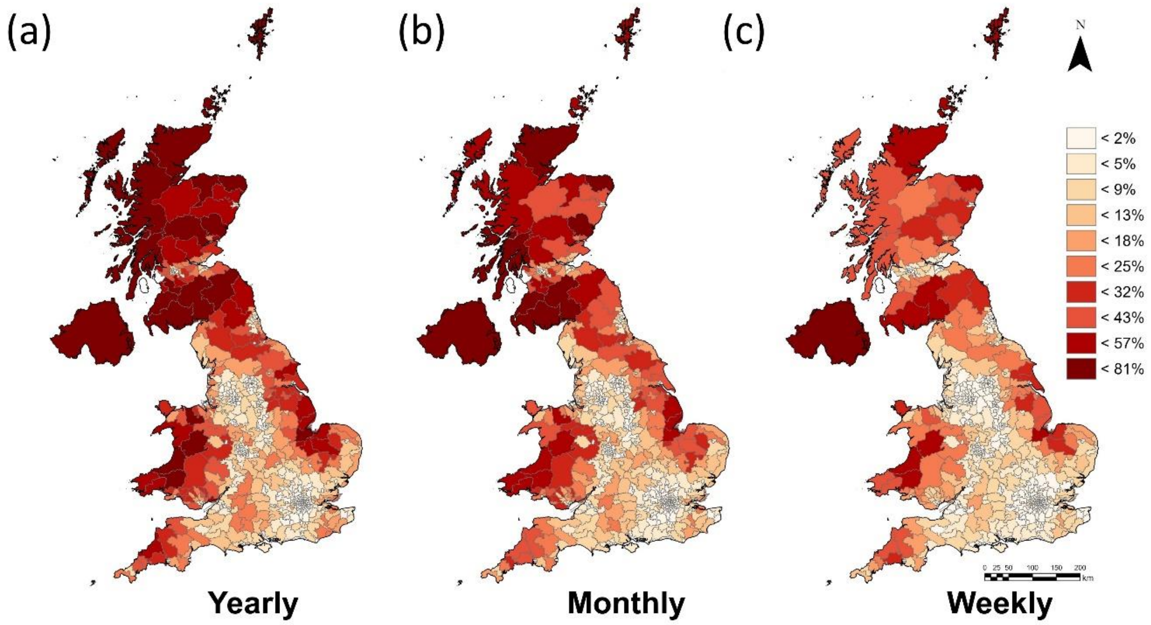


**Figure 3.** Proportion of unmet-demand as [unmet-demand/full demand] per UK constituency (a) for once per year visits; (b) for once per month visits (frequency is 12 times per year); (c) once per week visits (frequency is 52 times per year).

**Table 3.** Spearman rank correlation between the total number (†) or density (‡) of visits versus predicted met-demand in cells with paths infrastructure present for two spatial scales (region and constituency). For PANS and MENE, only England was assessed.

| | **People & Nature Survey # visits[†] (PANS)[¶]** | **MENE survey** | | **Domestic tourism income[†]** |
|---|---|---|---|---|
| | | **Mean weekly visits to NE per respondent[‡]** | **# respondents[†]** | |
| *Regions (n = 33)* | | | | |
| Yearly Visits | 0.72*** | 0.38* | 0.49** | 0.54** |
| Monthly visits | 0.69*** | 0.38* | 0.46** | 0.53** |
| Weekly visits | 0.54** | 0.34 | 0.41* | 0.61*** |
| *Constituencies (n = 631, bootstraps of 50 each)* | | | | |
| Yearly Visits | 0.47*** | 0.25 | 0.07 | -[§] |
| Monthly visits | 0.47*** | 0.22 | 0.07 | -[§] |
| Weekly visits | 0.44** | 0.16 | 0.05 | -[§] |

* P<0.05; ** P< 0.01; *** P <0.001; § data present at regional scale only; ¶ Last visit to the natural environment per respondent

## 4. Discussion

In this study we created a recreation demand map for the whole of the UK, by incorporating information on accessibility and attractiveness. The maps show that recreation demand was greatest in areas surrounding high population centres. This pattern was most pronounced when evaluating weekly visits, with the highest demand identified for the outskirts of the UK's most populous cities: London, Birmingham, Manchester and Leeds. These patterns are consistent with other studies which identify high recreation value close to highly populated areas or urban centres (Eigenbrod et al., 2009; Paracchini et al., 2014; Ridding et al., 2018). For example, Long et al. (2021) used geotagged images from Flickr in a Maxent model to assess the supply and demand for recreation across Europe. They found that natural areas near population centres delivered more recreational benefits than attractive sites in remote locations. This supports our findings whereby protected sites which are deemed more attractive in remote areas of Scotland and Wales demonstrated less demand compared with areas close to large cities, even when visit frequencies were reduced to annual. This has important implications for planners and policymakers regarding preserving and improving recreation opportunities in these areas.

As well as identifying areas of high recreation demand, we also evaluated whether this demand is met by assessing the presence of paths. Generally, in the areas of highest demand close to populated centres, paths were present, thus the demand is met. However, there were other parts of the country for example in the north-east, where demand for recreation exists but no path infrastructure is available to utilise. Our study therefore highlights not only where the recreation demand is the highest and should be maintained, but also where demand for recreation exists but the infrastructure is not present, and therefore has the potential to be improved. There are current campaigns running in GB which aim to connect all towns, cities and villages via paths and trails (SlowWays, 2022), thus identifying not only where paths are absent, but also where the demand is greatest, will allow planners to prioritise the most important areas for such campaigns to ensure they have the greatest impact on recreational access. Expansion of the path network could be enhanced by providing public access through agricultural land, which could be encouraged through payment to farmers/land managers. The UK is currently undergoing considerable policy change in terms of the management of semi-natural and agricultural habitats, following its departure from the EU Common Agricultural Policy. Although the exact form of the new policies has yet to emerge, the proposed Environmental Land Management scheme shifts the basis of farm payments from land ownership and productivity towards payment for provision of public goods. If recreational services were included under the Environmental Land Management schemes, land managers could use our demand outputs to identify if they could provide a new 'service' by enabling public access to their land. For example, the current English Woodland Creation Offer (ECWO) allows additional payments of up to £2,200 per hectare where creating woodland delivers recreational access (Forestry Commission, 2022). Payments under ECWO can be stacked where woodland delivers other benefits (e.g. nature recovery, flood risk mitigation), so this exemplifies another potential use of our maps, for land managers to identify potential synergies between recreational access and other ecosystem service goals, such as agricultural production and biodiversity conservation, via spatial planning tools (e.g. E-Planner, Redhead et al., 2022). Such uses depend on the availability of data derived via uniform methods over large spatial extents at relatively fine spatial resolutions, such as presented here, in order to allow consistent targeting over a range of spatial scales (national, regional, landscape, farm).

There was good concurrence between our recreation demand map and the validation datasets at the regional scale. The correlation values detected in our study were comparable to those in the literature; Casado-Arzuaga et al. (2014) found a correlation (r = 0.38) between frequency of visits and recreation potential in Bilbao, Spain, whilst Long et al. (2021) revealed a linear regression model with an $R^2 = 0.30$ for predicted visitor density and actual visitor density across Europe. The greatest concurrence was found with the PANS validation dataset. This is likely because this survey captures more localised casual visits such as a local evening walk, which is more relevant particularly for the weekly frequency demand maps. Furthermore, outdoor recreation such as a local walk are unlikely to result in any expenditure, which may explain why we see less concurrence with the tourism expenditure validation dataset. At a finer scale there was less agreement between predicted demand and the validation datasets in our study, however this is more likely to reflect the differences in the dataset types and the artificial use of relatively coarse scaled constituency boundaries to perform the analysis. We would expect the $r_s$ values to be low since the validation datasets are not directly comparable with our output and therefore generate different levels of noise. Because of this we also performed additional analyses to explore whether several factors were associated with our demand distribution, such as local property prices, the distance to London and the proportion of an area that is considered more attractive (see Supplementary Material S6).

As with other recreational studies in the literature, there are limitations with the methodology applied and the assumptions made (Casado-Arzuaga et al., 2014; Nahuelhual et al., 2013). The main limitation in this study is the classification used for attractiveness. Not all humans are attracted to areas for recreation in the landscape for the same reason – it may be because of landscape qualities (biodiversity, topography, aesthetics etc), landscape features (historic sites, amenities, attractions etc) or subjective reasons (personal history, sense of place) (e.g. Brown and Brabyn, 2012; Ciesielski and Stereńczak, 2021; Ridding et al., 2018). Furthermore, our assumption of a higher IUCN category does not necessarily mean the location is more attractive, even under the assumption that higher biodiversity increases attractiveness. For instance, in England only 38% of SSSIs are actually in favourable condition despite the designation (JNCC, 2021). However, since attractiveness is included as a separate factor in Eq. 1, this part can easily be removed or improved in the future to account for differences in attractiveness (see Figure S7). Further research is needed to better quantify landscape attractiveness in different contexts, and the ways in which it can be represented by available spatial data. The estimated recreation demand may also be influenced by additional factors not considered in this study. For example, we assume that accessibility is equal across the UK, however factors such as wealth and deprivation will influence the ability to travel, with unaffordable costs and limited access to the road network. However, our demand outputs could be used alongside existing published data, for example the Indices of Deprivation (Ministry of Housing Communities and Local Government, 2022). This could be used to identify and further prioritise areas for recreation improvement by targeting areas of high deprivation where the benefits of recreation are likely to be more significant.

Despite these limitations, the methodology used to generate the recreation demand output for the UK in this study is readily adaptable for use in other focal areas or even internationally, provided there are reliable estimates of population density and good road maps for travelling distance. The recreation demand output has several uses; firstly, to identify hotspots for recreation, which is important for ensuring these areas are acknowledged and maintained in the future. Secondly, they can be used to highlight where recreation exists, but demand is not met due to the lack of appropriate infrastructure. This is particularly important, as it allows certain areas to be prioritised over others, which is critical at a time where funding for such improvements is limited. Furthermore, a comparison of the relative demand between different visitation frequencies for a given area can help determine which type of infrastructure is required. Finally, the output can be used to represent CES in ecosystem service assessments where trade-offs with other services may be examined.

## 5. Conclusion

In this study, we use a flexible method based on readily available data to develop a CES map predicting recreation demand for the UK. We find that the areas with highest demand are located near to populated centres compared with those that are more remote, even if they are more attractive, although the balance between these factors shifts with visit frequency. Locating these areas of high demand is important for policymakers and planners to ensure these areas are maintained and enhanced for recreation in the future. This study also has important implications for the mapping of recreational CES in general because the findings highlight the importance of incorporating accessibility via population size and travelling distance into recreation assessments. We also identify where recreation demand is not met via the absence of paths, and thus find areas where the impact of improvements to the path infrastructure would have the greatest influence on meeting recreational demand. Policymakers and land managers in the changing landscape of UK agricultural policy are likely to need to identify and prioritise opportunities to improve recreation provision in the UK, and to explore trade-offs and synergies with other ecosystem services. The methods we present here for mapping both supply and demand, using a consistent method over large spatial extents at relatively fine spatial resolutions, form a potentially valuable tool for meeting these needs.

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## Data Availability Statement

This data is published and freely available via the Environmental Information Data Centre (EIDC) https://doi.org/10.5285/bd3bf607-a3b2-423b-b07b-9c41e84746ee

## References

Ala-Hulkko, T., Kotavaara, O., Alahuhta, J., Helle, P., Hjort, J., 2016. Introducing accessibility analysis in mapping cultural ecosystem services. Ecol. Indic. 66, 416–427. https://doi.org/10.1016/j.ecolind.2016.02.013

Ament, J.M., Moore, C.A., Herbst, M., Cumming, G.S., 2016. Cultural Ecosystem Services in Protected Areas : Understanding Bundles, Trade-Offs, and Synergies. Conserv. Lett. 0, 1–11. https://doi.org/10.1111/conl.12283

Assandri, G., Bogliani, G., Pedrini, P., Brambilla, M., 2018. Beautiful agricultural landscapes promote cultural ecosystem services and biodiversity conservation. Agric. Ecosyst. Environ. 256, 200–210. https://doi.org/10.1016/j.agee.2018.01.012

Boerema, A., Rebelo, A.J., Bodi, M.B., Esler, K.J., Meire, P., 2016. Are ecosystem services adequately quantified? J. Appl. Ecol. 1–13. https://doi.org/10.1111/1365-2664.12696

Booth, J.E., Gaston, K.J., Armsworth, P.R., 2010. Who benefits from recreational use of protected areas? Ecol. Soc. 15. https://doi.org/10.5751/ES-03450-150319

Brown, G., Brabyn, L., 2012. An analysis of the relationships between multiple values and physical landscapes at a regional scale using public participation GIS and landscape character classification. Landsc. Urban Plan. 107, 317–331.

https://doi.org/10.1016/j.landurbplan.2012.06.007

Brown, G., Fagerholm, N., 2015. Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. Ecosyst. Serv. 13, 119–133. https://doi.org/10.1016/j.ecoser.2014.10.007

Buendía, A.V.P., Albert, M.Y.P., Giné, D.S., 2019. PPGIS and public use in protected areas:Acase study in the Ebro Delta Natural Park, Spain. ISPRS Int. J. Geo-Information 8. https://doi.org/10.3390/ijgi8060244

Byczek, C., Longaretti, P.Y., Renaud, J., Lavorel, S., 2018. Benefits of crowd-sourced GPS information for modelling the recreation ecosystem service. PLoS One 13, 1–23. https://doi.org/10.1371/journal.pone.0202645

Casado-Arzuaga, I., Onaindia, M., Madariaga, I., Verburg, P.H., 2014. Mapping recreation and aesthetic value of ecosystems in the Bilbao Metropolitan Greenbelt (northern Spain) to support landscape planning. Landsc. Ecol. 29, 1393–1405. https://doi.org/10.1007/s10980-013-9945-2

Chan, K.M.A., Balvanera, P., Benessaiah, K., Chapman, M., Díaz, S., Gómez-Baggethun, E., Gould, R., Hannahs, N., Jax, K., Klain, S., Luck, G.W., Martín-López, B., Muraca, B., Norton, B., Ott, K., Pascual, U., Satterfield, T., Tadaki, M., Taggart, J., Turner, N., 2016. Why protect nature? Rethinking values and the environment. Proc. Natl. Acad. Sci. U. S. A. 113, 1462–1465. https://doi.org/10.1073/pnas.1525002113

Chan, K.M.A., Shaw, M.R., Cameron, D.R., Underwood, E.C., Daily, G.C., 2006. Conservation planning for ecosystem services. PLoS Biol. 4, 2138–2152. https://doi.org/10.1371/journal.pbio.0040379

Cheng, X., Van Damme, S., Uyttenhove, P., 2021. A review of empirical studies of cultural ecosystem services in urban green infrastructure. J. Environ. Manage. 293, 112895. https://doi.org/10.1016/j.jenvman.2021.112895

Ciesielski, M., Stereńczak, K., 2021. Using Flickr data and selected environmental characteristics to analyse the temporal and spatial distribution of activities in forest areas. For. Policy Econ. 129. https://doi.org/10.1016/j.forpol.2021.102509

Crossman, N.D., Burkhard, B., Nedkov, S., Willemen, L., Petz, K., Palomo, I., Drakou, E.G., Martín-Lopez, B., McPhearson, T., Boyanova, K., Alkemade, R., Egoh, B., Dunbar, M.B., Maes, J., 2013. A blueprint for mapping and modelling ecosystem services. Ecosyst. Serv. 4, 4–14. https://doi.org/10.1016/j.ecoser.2013.02.001

Crouzat, E., De Frutos, A., Grescho, V., Carver, S., Büermann, A., Carvalho-Santos, C., Kraemer, R., Mayor, S., Pöpperl, F., Rossi, C., Schröter, M., Stritih, A., Sofia Vaz, A., Watzema, J., Bonn, A., 2022. Potential supply and actual use of cultural ecosystem services in mountain protected areas and their surroundings. Ecosyst. Serv. 53. https://doi.org/10.1016/j.ecoser.2021.101395

Daniel, T.C., Muhar, A., Arnberger, A., Aznar, O., Boyd, J.W., Chan, K.M.A., Costanza, R., Elmqvist, T., Flint, C.G., Gobster, P.H., Gret-Regamey, A., Lave, R., Muhar, S., Penker, M., Ribe, R.G., Schauppenlehner, T., Sikor, T., Soloviy, I., Spierenburg, M., Taczanowska, K., Tam, J., von der Dunk, A., 2012. Contributions of cultural services to the ecosystem services agenda. Proc. Natl. Acad. Sci. 109, 8812–8819. https://doi.org/10.1073/pnas.1114773109

DEFRA, 2022. National statistics - Chapter 2: Structure of industry [WWW Document]. URL https://www.gov.uk/government/statistics/agriculture-in-the-united-kingdom-2021/chapter-2-structure-of-industry (accessed 9.30.22).

Dolan, R., Bullock, J.M., Jones, J.P.G., Athanasiadis, I.N., Martinez-Lopez, J., Willcock, S., 2021. The flows of nature to people, and of people to nature: Applying movement concepts to ecosystem services. Land 10, 1–18. https://doi.org/10.3390/land10060576

Eigenbrod, F., Anderson, B.J., Armsworth, P.R., Heinemeyer, A., Jackson, S.F., Parnell, M., Thomas, C.D., Gaston, K.J., 2009. Ecosystem service benefits of contrasting conservation strategies in a human-dominated region. Proc. R. Soc. B Biol. Sci. 276, 2903–2911. https://doi.org/10.1098/rspb.2009.0528

Forestry Commission, 2022. England Woodland Creation Offer [WWW Document]. URL https://www.gov.uk/guidance/england-woodland-creation-offer (accessed 11.2.22).

Garcia, X., Benages-Albert, M., Vall-Casas, P., 2018. Landscape conflict assessment based on a mixed methods analysis of qualitative PPGIS data. Ecosyst. Serv. 32, 112–124. https://doi.org/10.1016/j.ecoser.2018.07.003

Geofabrik, 2018. OpenStreetMap Data Extracts [WWW Document]. URL https://download.geofabrik.de/ (accessed 8.3.22).

Hermes, J., Van Berkel, D., Burkhard, B., Plieninger, T., Fagerholm, N., von Haaren, C., Albert, C., 2018. Assessment and valuation of recreational ecosystem services of landscapes. Ecosyst. Serv. 31, 289–295. https://doi.org/10.1016/j.ecoser.2018.04.011

Hooftman, D., Kimberley, A., Cousins, S.A.O., Escribano-Avila, G., Honnay, O., Krickl, P., Plue, J., Poschlod, P., Traveset, A., Bullock, J.M., 2021. Dispersal limitation, eutrophication and propagule pressure constrain the conservation value of Grassland Green Infrastructure. Biol. Conserv. 258, 109152. https://doi.org/10.1016/j.biocon.2021.109152

Hooftman, D.A., Bullock, J.M., Jones, L., Eigenbrod, F., Barredo, J.I., Forrest, M., Kindermann, G., Thomas, A., Willcock, S., 2022. Reducing uncertainty in ecosystem service modelling through weighted ensembles. Ecosyst. Serv. 53. https://doi.org/10.1016/j.ecoser.2021.101398

Hornigold, K., Lake, I., Dolman, P., 2016. Recreational use of the countryside: No evidence that high nature value enhances a key ecosystem service. PLoS One 11, 1–14. https://doi.org/10.1371/journal.pone.0165043

JNCC, 2021. UK Biodiversity Indicators 2021 [WWW Document]. URL https://jncc.gov.uk/our-work/uk-biodiversity-indicators-2021/ (accessed 8.1.22).

Ko, H., Son, Y., 2018. Perceptions of cultural ecosystem services in urban green spaces: A case study in Gwacheon, Republic of Korea. Ecol. Indic. 91, 299–306. https://doi.org/10.1016/j.ecolind.2018.04.006

Komossa, F., Wartmann, F.M., Verburg, P.H., 2021. Expanding the toolbox: Assessing methods for local outdoor recreation planning. Landsc. Urban Plan. 212, 104105. https://doi.org/10.1016/j.landurbplan.2021.104105

Lackey, N.Q., Tysor, D.A., McNay, G.D., Joyner, L., Baker, K.H., Hodge, C., 2021. Mental health benefits of nature-based recreation: a systematic review. Ann. Leis. Res. 24, 379–393.

Lloyd, C.T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F.R., Gaughan, A.E., Nieves, J.J., Hornby, G., MacManus, K., Sinha, P., Bondarenko, M., Sorichetta, A., Tatem, A.J., 2019. Global spatio-temporally harmonised datasets for producing high-resolution gridded population distribution datasets. Big Earth Data 3, 108–139. https://doi.org/10.1080/20964471.2019.1625151

Long, P.R., Nogué, S., Benz, D., Willis, K.J., 2021. Devising a method to remotely model and map the distribution of natural landscapes in Europe with the greatest recreational amenity value (cultural services). Front. Biogeogr. 13, 1–13. https://doi.org/10.21425/F5FBG47737

Marston, C., Rowland, C.S., O'Neil, A.W., Morton, R.D., 2022. Land Cover Map 2021 (10m classified pixels, GB). https://doi.org/10.5285/a22baa7c-5809-4a02-87e0-3cf87d4e223a

Martnez-Harms, M.J., Balvanera, P., 2012. Methods for mapping ecosystem service supply: A review. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 8, 17–25. https://doi.org/10.1080/21513732.2012.663792

Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. World Resources Institute, Washington DC.

Ministry of Housing Communities and Local Government, 2022. Indices of Multiple Deprivation (IMD) 2019 [WWW Document]. URL https://data-communities.opendata.arcgis.com/datasets/communities::indices-of-multiple-deprivation-imd-2019-1/explore (accessed 6.19.23).

Mitchell, M.G.E., Schuster, R., Jacob, A.L., Hanna, D.E.L., Dallaire, C.O., Raudsepp-Hearne, C., Bennett, E.M., Lehner, B., Chan, K.M.A., 2021. Identifying key ecosystem service providing areas to inform national-scale conservation planning. Environ. Res. Lett. 16. https://doi.org/10.1088/1748-9326/abc121

Morton, R.., Marston, C.., O'Neil, A.., Rowland, C.S., 2021. Land Cover Map 2020 (10m classified pixels, GB). https://doi.org/10.5285/35c7d0e5-1121-4381-9940-75f7673c98f7

Muñoz, L., Hausner, V.H., Runge, C., Brown, G., Daigle, R., 2020. Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway. People Nat. 2, 437–449. https://doi.org/10.1002/pan3.10083

Nahuelhual, L., Carmona, A., Lozada, P., Jaramillo, A., Aguayo, M., 2013. Mapping recreation and ecotourism as a cultural ecosystem service: An application at the local level in Southern Chile. Appl. Geogr. 40, 71–82. https://doi.org/10.1016/j.apgeog.2012.12.004

National Trust, 2020. Walkers urged to stick to paths to help reduce damage to landscapes and wildlife as social distancing increases erosion [WWW Document]. URL https://www.nationaltrust.org.uk/press-release/walkers-urged-to-stick-to-paths-to-help-reduce-damage-to-landscapes-and-wildlife-as-social-distancing-increases-erosion (accessed 9.30.22).

Natural England, 2019. Monitor of Engagement with the Natural Environment. Technical Report to the 2009-2019 surveys [WWW Document]. URL https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/875153/MENE_Technical_Report_Years_1_to_10v2.pdf

Natural England, 2015. Public rights of way: landowner responsibilities [WWW Document]. URL https://www.gov.uk/guidance/public-rights-of-way-landowner-responsibilities (accessed 11.2.22).

Office for National Statistics, 2021a. Population estimates [WWW Document]. URL https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/ (accessed 8.3.20).

Office for National Statistics, 2021b. Code-Point® Open. Office for National Statistics licensed under the Open Government Licence v.3.0. Contains Ordnance Survey data © Crown copyright and database right 2021. Contains Royal Mail data © Royal Mail copyright and database right 2021.

Office for National Statistics, 2016. Regional value of tourism estimates for NUTS 1 and NUTS 2 areas [WWW Document]. URL https://www.ons.gov.uk/peoplepopulationandcommunity/leisureandtourism/datasets/regionalvalueoftourismestimatesfornuts1andnuts2areas (accessed 8.5.22).

Paracchini, M.L., Zulian, G., Kopperoinen, L., Maes, J., Philipp, J., Termansen, M., Zandersen, M., Perez-soba, M., Scholefield, P.A., Bidoglio, G., 2014. Mapping cultural ecosystem services: A framework to assess the potential for outdoor recreation across the EU. Ecol. Indic. 45, 371–385. https://doi.org/10.1016/j.ecolind.2014.04.018

Pereira, H.V., Palmeira, A.L., Encantado, J., Marques, M.M., Santos, I., Carraça, E.V., Teixeira, P.J., 2021. Systematic Review of Psychological and Behavioral Correlates of Recreational Running. Front. Psychol. 12. https://doi.org/10.3389/fpsyg.2021.624783

Power, A.G., 2010. Ecosystem services and agriculture: Tradeoffs and synergies. Philos. Trans. R. Soc. B Biol. Sci. 365, 2959–2971. https://doi.org/10.1098/rstb.2010.0143

Rall, E., Hansen, R., Pauleit, S., 2019. The added value of public participation GIS (PPGIS)for urban green infrastructure planning. Urban For. Urban Green. 40, 264–274. https://doi.org/10.1016/j.ufug.2018.06.016

Redhead, J.W., Burkmar, R., Brown, M., Pywell, R.F., 2022. E-Planner: A web-based tool for planning environmental enhancement on British agricultural land. Environ. Model. Softw. 155, 105437. https://doi.org/10.1016/j.envsoft.2022.105437

Ridding, L.E., Redhead, J.W., Oliver, T.H., Schmucki, R., McGinlay, J., Graves, A.R., Morris, J., Bradbury, R.B., King, H., Bullock, J.M., 2018. The importance of landscape characteristics for the delivery of cultural ecosystem services. J. Environ. Manage. 206, 1145–1154. https://doi.org/10.1016/j.jenvman.2017.11.066

Schägner, J.P., Brander, L., Maes, J., Paracchini, M.L., Hartje, V., 2016. Mapping recreational visits and values of European National Parks by combining statistical modelling and unit value transfer. J. Nat. Conserv. 31, 71–84. https://doi.org/10.1016/j.jnc.2016.03.001

Schläpfer, M., Dong, L., O'Keeffe, K., Santi, P., Szell, M., Salat, H., Anklesaria, S., Vazifeh, M., Ratti, C., West, G.B., 2021. The universal visitation law of human mobility. Nature 593, 522–527. https://doi.org/10.1038/s41586-021-03480-9

SlowWays, 2022. About [WWW Document]. URL https://beta.slowways.org/Page/about (accessed 8.8.22).

Spalding, M., Burke, L., Wood, S.A., Ashpole, J., Hutchison, J., zu Ermgassen, P., 2017. Mapping the global value and distribution of coral reef tourism. Mar. Policy 82, 104–113. https://doi.org/10.1016/j.marpol.2017.05.014

Statista, 2020. Number of domestic tourism trips to national parks in Great Britain 2016 to 2019, by park [WWW Document]. URL https://www.statista.com/statistics/613118/great-britain-national-park-by-number-of-visits-uk/ (accessed 6.19.23).

Statista, 2015. Average speed on roads in Great Britain in 2014, by road and vehicle type [WWW Document]. URL https://www.statista.com/statistics/303443/average-speed-on-different-roads-in-great-britain-by-vehicle-type/ (accessed 8.3.22).

TEEB, 2010. The Economics of Ecosystems and Biodiversity: Mainstreaming the Economics of Nature: A synthesis of the approach, conclusions and recommendations of TEEB.

Thomsen, J.M., Powell, R.B., Monz, C., 2018. A systematic review of the physical and mental health benefits of wildland recreation. J. Park Recreat. Admi. 36.

UNEP-WCMC, 2022. Protected Area Profile for United Kingdom of Great Britain and Northern Ireland from the World Database on Protected Areas [WWW Document]. URL https://www.protectedplanet.net/country/GBR (accessed 8.3.22).

Verhagen, W., Kukkala, A.S., Moilanen, A., van Teeffelen, A.J.A., Verburg, P.H., 2017. Use of demand for and spatial flow of ecosystem services to identify priority areas. Conserv. Biol. 31, 860–871. https://doi.org/10.1111/cobi.12872

Willcock, S., Hooftman, D., Sitas, N., O'Farrell, P., Hudson, M.D., Reyers, B., Eigenbrod, F., Bullock, J.M., 2016. Do ecosystem service maps and models meet stakeholders' needs? A preliminary survey across sub-Saharan Africa. Ecosyst. Serv. 18, 110–117. https://doi.org/10.1016/j.ecoser.2016.02.038

Wong, C.P., Jiang, B., Kinzig, A.P., Lee, K.N., Ouyang, Z., 2015. Linking ecosystem characteristics to final ecosystem services for public policy. Ecol. Lett. 18, 108–118. https://doi.org/10.1111/ele.12389