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National scale mapping of supply and demand for recreational ecosystem services

Danny A.P. Hooftman a,b,*, Lucy E. Ridding b,*,1, John W. Redhead b, Simon Willcock c,d

a Lactuca: Environmental Data Analyses and Modelling, The Netherlands
b UK Centre for Ecology & Hydrology, Wallingford OX10 8BB, UK
c Net Zero and Resilient Farming, Rothamsted Research, Harpenden, Hertfordshire AL5 2JQ, UK
d School of Natural Sciences, Bangor University, Bangor, Gwynedd LL57 2DG, UK

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...
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recreation demand representing activities such as walking, hiking, this approach to develop a national CES map for the UK, predicting resources involved in conducting questionnaires. In this study, we use consistent approach, without direct need for the time and monetary initiatives, recreation needs to be mapped at the country-scale as a areas for maintaining and improving locations for recreation. policy makers and planners to prioritise and target the most appropriate minimum. The creation of these maps is important not only for identi
tions, 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 eco
tress 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., ‘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 UK, comprising the countries of England, Wales, Scotland and Northern Ireland (Fig. 1), is 242,495 km², 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

Fig. 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.
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 https://github.com/dhooftman72/RecreationalValue. We used a cell size of 250 m × 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:

\[
\text{Demand} = \text{Attractiveness} \times \sum_{j=1}^{\text{all}} \left( \frac{\text{Population}_j \times \text{Traveling distance}_{ij}}{\text{Frequency}_{ij}} \right)\]

(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 km² are rounded. Therefore, the value of 0 denotes effectively a lower density than 0.5 visit per km². 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 UKEH 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.

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 0.000083333˚ resolution with a WGS 1984 projection (~75 m 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 unfavourable.

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 overseas 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 Fig. S1). Cells in remote areas where roads were absent were assigned a weight value of 25, to correspond with walking speed (Table 1). See Hooffman et al. (2021) for further details on such cost-weighted method. We generated a 2.5 × 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.

<table>
<thead>
<tr>
<th>OSM Road type</th>
<th>Statista road type</th>
<th>Car average speed</th>
<th>Weight factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorway</td>
<td>Motorways</td>
<td>110 kph†</td>
<td>1</td>
</tr>
<tr>
<td>Motorway link</td>
<td>Motorways</td>
<td>110 kph†</td>
<td>1</td>
</tr>
<tr>
<td>Trunk road</td>
<td>Single carriage ways</td>
<td>75 kph‡</td>
<td>1.45</td>
</tr>
<tr>
<td>Trunk road link</td>
<td>Single carriage ways</td>
<td>75 kph‡</td>
<td>1.45</td>
</tr>
<tr>
<td>Primary road</td>
<td>Single carriage ways</td>
<td>75 kph‡</td>
<td>1.45</td>
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<tr>
<td>Primary link road</td>
<td>Single carriage ways</td>
<td>75 kph‡</td>
<td>1.45</td>
</tr>
<tr>
<td>Secondary road</td>
<td>40mph built-up roads</td>
<td>28 kph³</td>
<td>3.89</td>
</tr>
<tr>
<td>Secondary link road</td>
<td>40mph built-up roads</td>
<td>28 kph³</td>
<td>3.89</td>
</tr>
<tr>
<td>Tertiary road</td>
<td>30mph built-up roads</td>
<td>24 kph§</td>
<td>4.53</td>
</tr>
<tr>
<td>Tertiary link road</td>
<td>30mph built-up roads</td>
<td>24 kph§</td>
<td>4.53</td>
</tr>
<tr>
<td>Overseas links</td>
<td>Slow travel</td>
<td>11 kph‡</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>High resistance</td>
<td>4 kph‡</td>
<td>25</td>
</tr>
</tbody>
</table>

*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 travelling time; § Making sure that in all but the most remote areas these cells will not be crossed. † translated from mph.
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.

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

![Fig. 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.](image)
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 Great Britain (GBP £) 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 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 = 468,371) 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 = 53; Fig. 1) and electoral constituencies (n = 631; Fig. 2). Following the reasoning that people will preferentially visit more attractive areas (Dolan et al., 2021), attractiveness is incorporated in Eq. (1) as proportional to 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 (Fig. S2b). Public rights of way aid outdoor recreation in the UK, however there is no centralised dataset of this available. Instead, we use a 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 (Fig. 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 gets its full demand of 631, 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).

Compared to the MENE and PANS datasets, the survey was collected, which we plotted using the centroid location for all such postcodes in the UK (Office for National Statistics, 2021b).

Comparison was 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 avoids the impact of extreme values without eliminating such data-points and scales 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 of the effect this Winsorising protocol on a ranking index is relatively small, being independent on the absolute range of the data. All recreational demand layers were log10-transformed, to meet the requirements of normality.
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 Fig. 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 Fig. 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 Fig. 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 (Fig. 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%; Fig. 3). The proportion of unmet demand decreased with visiting frequency because of the reduced distances travelled (Fig. 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 ($R^2 = 0.53$; Fig. S5). These general patterns were similar across yearly, monthly and weekly visits (Fig. 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.

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 \( r \) 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; Gieselski and Stereticzak, 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 Fig. 57). 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

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**Table 3** Spearman rank correlation between the total number (\( \bullet \)) or density (\( \ddagger \)) 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.

<table>
<thead>
<tr>
<th>Regions (n = 33)</th>
<th>People &amp; Nature Survey</th>
<th>MENE survey</th>
<th>Domestic tourism income$^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># visits$^3$ (PANS)$^6$</td>
<td>Mean weekly visits to NE per respondent$^7$</td>
<td># respondents$^7$</td>
</tr>
<tr>
<td>Yearly Visits</td>
<td>0.72***</td>
<td>0.98*</td>
<td>0.49**</td>
</tr>
<tr>
<td>Monthly visits</td>
<td>0.69***</td>
<td>0.38*</td>
<td>0.46**</td>
</tr>
<tr>
<td>Weekly visits</td>
<td>0.54**</td>
<td>0.34</td>
<td>0.41*</td>
</tr>
<tr>
<td>Constituencies (n = 631, bootstraps of 50 each)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yearly Visits</td>
<td>0.47***</td>
<td>0.25</td>
<td>0.07</td>
</tr>
<tr>
<td>Monthly visits</td>
<td>0.47***</td>
<td>0.22</td>
<td>0.07</td>
</tr>
<tr>
<td>Weekly visits</td>
<td>0.44**</td>
<td>0.16</td>
<td>0.05</td>
</tr>
</tbody>
</table>

$^6$ $P < 0.05; ^{**} P < 0.01; ^{***} P < 0.001; ^{†} $ data present at regional scale only; $^‡$ Last visit to the natural environment per respondent.
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, which may be examined. 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.

CRediT authorship contribution statement

Danny A.P. Hooftman: Conceptualization, Methodology, Formal analysis, Software, Validation, Data curation, Writing – review & editing. Lucy E. Ridding: Writing – original draft, Writing – review & editing, Data curation. John W. Redhead: Writing – review & editing. Simon Willcock: Conceptualization, Methodology, Funding acquisition, Project administration, Writing – review & editing.

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.

Data availability

This data is published and freely available via the Environmental Information Data Centre (EDC) https://doi.org/10.5285/bd3bf607-a382-423b-b07b-9c41e84746ee.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110779.

References
