Title

Devising a method to remotely model and map the distribution of natural landscapes in Europe with the greatest recreational amenity value (cultural services)

Journal
Frontiers of Biogeography, 0(0)

Authors
Long, Peter R.
Nogué, Sandra
Benz, David
et al.

Publication Date
2020

DOI
10.21425/F5FBG47737

Devising a method to remotely model and map the distribution of natural landscapes in Europe with the greatest recreational amenity value (cultural services)

Peter R. Long[1]*, Sandra Nogué[2]*, David Benz[1], Katherine J. Willis[1]

*contributed equally

[1] Long-term Ecology Laboratory. Department of Zoology, University of Oxford, OX13PS, United Kingdom.

[2] School of Geography and Environmental Science, University of Southampton, Highfield, Southampton SO17 1BJ, United Kingdom.

Corresponding authors:
Peter Long: peter.long@zoo.ox.ac.uk
Sandra Nogué: s.nogue-bosch@soton.ac.uk

Abstract

With a growing emphasis on the societal benefits gained through recreation outdoors, a method is needed to identify which spaces are most valuable for providing those benefits. Social media platforms offer a wealth of useful information on where people prefer to enjoy the outdoors. We combined geotagged images from Flickr with several environmental metrics in a Maxent model to calculate the probability of a photograph being taken (the potential supply of recreational amenity). We then built a set of population density kernels to express the potential demand of recreational amenity. Linear regression was used to compare supply and demand layers to visitation records from 540 recreation sites across Europe. The result was a map estimating the number of visitors/km^2/year. Our analysis showed that natural areas near population centres deliver more recreational benefit than attractive sites in remote locations. The former should therefore be prioritised by planners and policymakers seeking to protect or improve recreational amenity.

Keywords: aesthetic value, cultural service, green health, natural capital, recreation, social media.

Highlights

- Our research furthers understanding of nature's contribution to human welfare by providing a model to remotely measure recreational amenity across European landscapes using freely available datasets including crowd-sourced GPS photographs.

- Our results show that recreation amenity is maximised in frequently visited natural areas near population centres. However, our model also shows that these areas may have low aesthetic value.

- Aesthetic appeal is maximised in places with high elevation, coastlines, and large viewshed areas. However, despite their potential, these areas do not deliver a high level of recreation amenity.

- We propose that for current and future conservation planning it is important to consider spatially explicit models of recreational amenity and aesthetic appeal as two separate entities.

Introduction

Policies to conserve and enhance biodiversity have seen a significant shift in their framing over the past decade. Increasingly there is a focus on the identification and conservation of aspects of nature (natural capital assets) that underpin important societal benefits (Diaz et al. 2018). Natural capital assets include the species, communities and landscapes that are important for carbon sequestration (e.g.

societal benefit: mitigating climate change), prevention of soil erosion (e.g. societal benefit: protecting water quality), water flow regulation (e.g. societal benefit: reducing flood risk), and cultural value (e.g. societal benefit: recreation). This last category is broadly defined as “non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation and aesthetic experience" (MA 2003). Despite the importance of cultural services, not enough is known about the types and spatial distribution of nature underpinning these services. In this study we therefore aimed to develop a methodology that could remotely distinguish the European landscapes with aesthetic appeal and importance for recreational amenity.

Determining the location of the biodiversity that provides cultural services has quickly gained political importance in many countries as a result of emerging scientific evidence indicating clear physiological and psychological benefits (Paracchini et al. 2014, Song et al. 2015, Hägerhäll et al. 2018, Twohig-Bennett and Jones 2018). Many of these studies have demonstrated improved physical and mental wellbeing outcomes from walking, exercising and relaxing in natural, biodiverse green landscapes (for a review see Hansen et al. 2017). Identification of the landscapes that are important for providing these recreational services is therefore a key priority.

Whilst there is widespread agreement on the need to determine where recreational service provision is high, doing so is not easy. There are a number of reasons for this. First, people often don’t pay to access the landscapes that provide these services. National parks and cultural heritage sites sometimes have gate receipts, but the vast majority of nature visited does not have a payment system for access. Second, there are large cultural variations between people’s preferences. What one community sees as aesthetically pleasing may well be viewed as less attractive by another. Third, when people are surveyed about their “willingness to pay” to access cultural landscapes, a strong socio-economic bias emerges whereby those with lower income are less willing to pay (e.g. Lo and Jim 2010). Fourth, aesthetic values are often associated with a particular view or landscape type and have no well-defined boundaries to enable mapping (Oteros-Rozas et al. 2018).

A number of studies in the past few years have therefore aimed to quantify the spatial distribution of cultural services using alternative techniques to traditional surveys, interviews and expert-based participatory mapping. In particular, there has been increased attention on the use of crowdsourced data including geo-tagged photographs uploaded to platforms such as Flickr and Panoramio (Wood et al. 2013, Antoniou et al. 2016, Hirons et al. 2017, Figueroa-Alfaro and Tang 2017) to determine people's preferences for wildlife, landscape types and aesthetics. These studies have shown some promising results. For example, to understand the effectiveness of using remotely captured data to survey the use of hiker trails in a national forest in Washington, Fisher et al. (2018) compared remotely captured visitor data, from internet-based trip reports and Flickr images, with those collected by more traditional survey methods. The latter included data captured from infrared sensors, time-lapse cameras and manual on-site counts. When the output from the internet-based data was compared with the traditionally collected data, the authors found a positive correlation with visitor numbers recorded. This study concluded that geo-tagged images and content on the internet could potentially provide an important new cost-effective and convenient way to assess visitation numbers to sites. Some interesting results also emerged from a study which looked at the use of internet-based photographs to determine preferences for different types of biodiversity in Kruger National Park, South Africa (Hausmann et al. 2018). Around 13,600 pictures shared on Instagram and Flickr by tourists visiting the park in a set time interval were compared to questionnaire-based output. There was strong similarity between the results captured using images and stated preferences for types of biodiversity that were captured using survey techniques.

Online crowdsourced data appear to hold great potential for recording visitor numbers and biodiversity type preference. However, in order to determine the most important landscapes for aesthetic recreational value (e.g. walking, contemplation, forest bathing, etc.), especially outside cities, research suggests that a number of other factors must also be taken into consideration. In a study where expert-based participatory mapping was used alongside crowd-sourced data (13,400 geolocated photographs from Flickr) to determine landscapes around Barcelona with the greatest aesthetic appreciation, distance and accessibility to the landscapes were found to be more important determinants than the 'pristineness' of nature (Langemeyer et al. 2018). Similarly, a study in the Hawaii Volcanoes National Park demonstrated that ease of access (i.e. infrastructure) and elevation were the most important components accounting for visitor distribution across the park (Walden-Schreiner et al. 2018).

Therefore, whilst there is an increasing demand to determine and conserve landscapes that are important for recreational amenities, there is still a knowledge gap around how to map these landscapes, especially outside urban regions. It is clear that information gleaned from social media platforms such as Flickr can provide some important data and that a number of variables need to be taken into consideration.

In our study we aimed to develop a new methododology combining these various approaches in order to model and remotely map the distribution of non-urban landscapes in Europe with the greatest recreational amenity value. We focused on non-material recreation and aesthetic values and excluded cultural heritage from our model. We used a combination of well-established models and evidence from freely available datasets, including Flickr photographs and recreational visitor numbers, plus distance to urban areas and environmental characteristics. The resulting output is a map covering Europe at 250 m resolution indicating an estimation of the number of people per km^2 per year who participate in outdoor recreation. We go on to discuss the accuracy of this approach and the use of such maps in current and future conservation planning for landscapes across Europe that are important for recreational amenity.

Methods

We define the ecosystem service of recreational amenity as the number of people per km^2 per year who participate in outdoor recreation in non-urban areas (Fig. 1).

Study area and environmental covariates

The study area chosen to model the provision of recreational amenity is Europe, including the European Economic Area (EEA) and countries geographically in Europe (excluding Turkey). As our baseline land cover we used the EU Corine Land Cover 2012 map (EEA 2012) at a resolution of 7.5" (each pixel approximately 230 x 230 m). We excluded urban classes from the final landcover map because our model is intended to measure cultural amenity in landscapes outside cities. A different resolution and set of considerations would need to be taken into account for urban green spaces (see for example Cortinovis et al. 2018).

We compiled a set of environmental covariates, including mean annual temperature (ºC) and total annual precipitation (mm) from Worldclim data (Hijmans et al. 2005) resampled from 30" to 7.5" resolution. In addition, we included elevation (m.a.s.l) (Danielson and Gesh 2011) and calculated viewshed area (km^2) using the formulae from Bishop (2003) and Husar et al. (2000) that take into account atmospheric effects and the earth's curvature, assuming a viewer height of 2m.

Visitation data

We obtained visitor data from the Schägner et al. (2017) database containing annual numbers of recreational visitors to 540 sites in 20 European countries (Fig. 2). These sites vary in size from urban parks to large national parks. However, all are accessible to the public free of charge. To calculate annual recreational visitor density (individuals/km^2/year), 410 of the sites were joined by name and country to Open Street Map (OSM) polygons[1] (Ramm et al. 2011). In sites where data for multiple

[1] https://planet.openstreetmap.org/, retrieved 22/11/2019.

years was available, we calculated a multi-annual visitor average. We also verified that the area of each OSM polygon matched that reported in the visitor dataset. This was followed by an analysis using zonal geometry to calculate the area of each polygon. This step was necessary because places with visitation data differed in size, and an area normalised measure was required for subsequent modelling. Finally, the annual visitor density was natural log transformed prior to analysis. Visitor density data was partitioned into training (n = 205) and validation (n = 205) sets in order to assess the accuracy of the final model (Fig. 1).

Volunteered Geographical information and density of non-urban Flickr records/km^2/year

We used Flickr records from Europe for December 2016 to November 2017 obtained from the Flickr public API. Flickr is a social media site which allows users to upload photographs with geolocation information. In this analysis we were not concerned with the content of the photographs, rather the event that a user has decided to take and share a photograph at a particular location. The coordinate precision of Flickr record locations is ~100m.

As the focus was on non-urban areas, we first filtered the Flickr records using the previously described landcover map to discard any record in a location with urban land cover class. A random sample of the remaining non-urban Flickr records was selected and the previously described environmental covariate values were extracted for each Flickr point. A random sample of locations not associated with Flickr images (i.e. background sites) in Europe was also selected and the same covariates were extracted to points. We also explored Flickr's seasonality, namely the abundance of records uploaded in each month (Fig. S1).

We calculated photo density using the non-urban Flickr records (density of non-urban Flickr records/km^2)(Fig. 3). To do this we calculated the kernel density of all non-urban Flickr records in Europe at various scales: 7.5", 15", and 30" resolution as an alternative set of covariates to explain visitor density. Flickr records are sparse, so at fine scales the measure tends to zero. However, this approach allows the capture of density at 'honeypot' sites, which receive very high numbers of visitors.

Human population

To calculate human population density in Europe, we obtained 1km data from the Gridded Population of the World 2015 dataset (CIESIN 2018).

Model for recreational visitor density

The model for recreational visitor density was constructed taking account of two classes of explanatory variables: 1) potential supply of recreational amenity, and 2) potential demand for recreational amenity as follows:

Potential supply layer

We assume that the potential of a landscape to supply opportunities for recreation will be some function of how attractive it is to people ('aesthetic appeal'). To understand the environmental features that might contribute to this aesthetic appeal we used the kernel density of non-urban Flickr records (described above) in combination with the environmental covariates (land cover class, elevation, viewshed area, temperature, and precipitation). These variables along with the visitor density data were used to build and validate distribution models using Maxent (Phillips et al. 2006). The Maxent output estimated the potential supply of recreation amenity according to its aesthetic appeal (Fig. 4).

Potential demand layer

We reasoned that the full ecosystem service of recreational amenity will depend not only on the potential of a landscape to supply recreation, but also on the ability to access the recreation areas. We therefore calculated a 'demand layer' making use of the human population density data (Fig. 5). We used distance kernels that varied across four different spatial extents. Total human population was measured in kernels ranging from 3x3 km up to 51x51 km. These grids represented the set of people potentially demanding opportunities to do outdoor recreation activities at nested scales from local (within 1km of home), to regional (within ~25km).

Model for recreational visitor density

To obtain the final model for recreational visitor density, we zonally summarised the potential supply layers and potential demand layers by the training set of polygons for which we have visitor density data. We then applied a linear regression model for annual recreation visitor density taking into account as explanatory variables both supply and demand layers. Our final set of models estimated visitor density in the training set of polygons as a function of explanatory variables as follows: probability of occurrence of Flickr records (pr(Flickr)), density of Flickr in kernels, and human population sum in kernels. A maximal model cotaining all covariates was stepwise refined using AIC to identify the most parsimonious minimum adequate model (Burnham and Anderson 2002). Finally, to make the final map of estimated number of recreational visitors/km^2/year, the minimum adequate model was evaluated using map algebra and the result was natural antilog transformed (because the response variable in the model was ln visitor density). This was then urban masked and land masked.

Validation

The validation set of polygons (with visitor density data not used to develop the model), was then used to zonally summarise the estimated visitor density in the final recreation amenity map. Regression was used to evaluate the performance of the model and uncertainty in the recreational amenity map.

Results

Flickr results

We obtained a total of 6,920,627 suitable Flickr records for Europe. When accounting for the month when Flickr records were submitted, we found a seasonal pattern: greater numbers of Flickr records are submitted from April to September (Fig. S1). Among European countries, Flickr records in 2017 were densest in the UK, where density values reached 3000 records/km^2/year. Other countries with high densities of Flickr records from non-urban environments were Belgium, Germany, the Netherlands, and Switzerland (Fig. 3).

Potential supply layer

Maxent results showed the landscape pattern of the probability of occurrence of Flickr record as a function of elevation (ma.s.l), mean annual temperature (ºC), total annual precipitation (mm), and viewshed area (km^2). Probability of occurrence of Flickr records varied greatly between mountain regions (e.g. the Alps, Pyrenees, Western Norwegian coast, and Scottish Highlands) and coastal regions (e.g. Croatia) (Fig. 4).

Potential demand layer

Human population within 5km represents the greatest demand for the service of recreation amenity (Fig. 5). Human population within several distance kernels were tested in the modelling process, however only human population density within 5km was retained in the final model (Table 1).

Model for recreational visitor density

According to our recreational amenity model, calculated as visitors/km^2/year, areas of nature that delivered the most recreational service were located near major European cities with values up to 1.2 million visitors/km^2/year (Fig. 3). In contrast, the environs of small and more isolated European cities did not display high levels of recreation amenity. The final recreational amenity model showed that there is little relationship between the landscapes with aesthetically appealing features such as mountains, lakes, and coastlines (e.g. Schirpke et al. 2016, Van Berkel et al. 2018), and the recreation service delivered (Fig. 6).

Validation

Comparison between the visitor density estimated by our model and actual visitor density (visitors/km^2/year) at 205 validation sites which had not been used to develop the model showed a decent performance (Linear regression: slope = 1.187 n = 205 sites, $p<0.001$, $R^2 = 0.30$) (Fig. 7). The R^2 value is relatively modest, but the model nonetheless explains a significant amount of variation in visitor density to validation sites. The slope, 1.187 is slightly greater than 1.

Discussion

The method we present here aims to meet a growing methodological need to remotely identify high-quality landscapes with the potential to deliver recreational opportunities, aesthetic appreciation, and human well-being (e.g. Twohig-Bennett and Jones 2018, Ghermandi and Sinclair 2019).

Previous assessments of land important for cultural services indicate that modelling social preference, aesthetic values, and recreation potential at landscape level is complex (e.g. Seresinhe et al. 2017). For example, Paracchini et al. (2014) found that when country-level frameworks for managing recreation were combined with population distribution and behavioural data from surveys, around 38% of EU territory was characterised as having high outdoor recreation potential with easy access. More recently, geo-tagged digital images from social media have been incorporated as a proxy for social preference and popularity (van Zanten et al. 2016a, Tenerelli et al. 2016, Heikinheimo et al. 2017), estimating provenance of social media users (Sinclair et al. 2020), and identifying types of visitors by their interests (Gosal et al. 2019). Compared to high-precision visitor datasets, social media (e.g. Instagram, Flickr, and Panoramio) can be considered an accessible and effective data source for determining cultural services (Tenkanen et al. 2017).

Away from urban areas, there is much evidence to suggest that areas with high 'natural' value and high recreational value do not tend to overlap. For example, a study of Flickr photographs by Mancini et al. (2019) concluded that the experience of wildlife viewing in Scotland tends to be carried out in areas where nature is easily accessible and facilities are provided. In addition, a case study from South Wales that used three social media websites (Flickr, Panoramio, and Geograph) idenfied hotpsots of key geographic features, suggesting that the interest of the population is not only limited to natural parks but is also related to accessibility (Gliozzo et al. 2016). Focusing specifically on European Natural Parks, a case study using Flickr datasets from Portugal identified that the highest recreation values were determined by distance to the ocean and distance to touristic and cultural infrastructure. The authors of the study concluded that the shore of the Natural Park is suffering high anthropic pressure but that the same region is most important economically and politically (Clemente et al. 2019).

In our study we found a similar trend. Our model represents an integrative approach that enables remote identification of high-quality European landscapes with the potential to deliver recreational opportunities and to enhance human well-being (per Hansen et al. 2017). We show that social media records, population density, environmental characteristics, and probability distributions can be integrated in spatially explicit models of aesthetic appeal (Fig. 4) and recreational amenity (Fig. 6). We first presented a pattern of aesthetic appeal across Europe, calculated as the probability of Flickr record occurrence. According to our results, mountain regions such as the Alps, Pyrenees, Western Norwegian coast, and Scottish Highlands possess the highest aesthetic value. However, the final output of our model shows that recreation amenity is maximised in places people visit frequently, within 5km of where they live. (Table 1). Figure 6 illustrates that although these highly visited places may be aesthetically unexceptional, with a low probability of Flickr record occurrence and without attractive landscape features like mountains or coasts, they are located near major European cities. These recreationally important locations could be broadly defined as highly popular.

We complemented our continent-scale map (Fig. 6a) with regional examples, highlighting four European metropolitan regions (Barcelona, Berlin, the Rhine-Ruhr area, and Paris) that typify the pattern of estimated recreational amenity across

Europe (Fig. 6b-e). The four examples illustrate how the highest recreation amenity values are on land immediately surrounding cities, or where patches of nature create gaps in the urban fabric. These areas should be prioritised in policies aiming to integrate natural sites and public health (Chen et al. 2019).

This study demonstrates that when balancing aesthetic appeal and distance to define landscapes for recreation and culture, distance is a more important factor. Places near (within 5km of) people's homes may be of lower aesthetic value generally, but they are visited much more frequently than remote, rural landscapes. A designation of land for outdoor recreation based on aesthetic appeal alone may therefore fail to include some of the most important areas.

Model considerations and validation

Our approach has several modelling uncertainties and limitations, including the multiple sources of uncertainty attached to the selected environmental covariates and, in our case in particular, to the social media datasets (Beale and Lennon 2012). In our approach we did not use *raw* Flickr data to measure the potential supply of recreation but instead we used it as an input (occurrence data) alongside other environmental covariates in a Maxent model. Our aims in doing so were to determine whether occurrence was based on specific environmental covariates and to map the patterns of aesthetic appeal across Europe. To minimise the risk of propagating uncertainties from the Maxent model to the final regression model we chose a small, well justified set of variables.

A second limitation is that our model slightly overestimates visitor density at sites where actual visitor density is low, and slightly underestimates visitor density where real density is high (Fig. 7). We did not find any reasonable explantion for why there are some datapoints that show higher modelled visitor densities. However, the misestimation was slight and so we do not think it has a substantial impact on our final output.

Third, there are certain limitations related to the representation of different demographic groups in social media and bias towards aesthetic values (van Zanten et al. 2016a, Clemente et al. 2019). Although social media has been shown to be an effective data source for monitoring visitor numbers, especially in popular natural areas (Tenerelli et al. 2016, Tenkanen et al. 2017), Flickr users are only one specific subset of social media users. As demonstrated in van Zanten et al. (2016b), social media platforms present varying results due to differences in their temporal cover, number of users, and demographic profile of their user base.

Fourth, social media users only represent the part of the general population with access to information technology (Girardin et al. 2008). Finally, the reliability of social media is limited by the quantity and quality of the images uploaded to each platform. Our Flickr datasets show that the frequency of records varies over time, with more photographs shared during summer months. But photographs are still uploaded to the platform throughout the year, yielding a good temporal resolution. This seasonality might reflect better weather conditions, when more people are expected to recreate outdoors (Fig. S1). We accommodate this limitation by working with probability distributions, through Maxent.

Conclusions

Our research contributes to the remote measurement of recreational amenity across European landscapes and shows that:

- The popularity of recreation sites can be predicted from a combination of social media, environmental, and population data. Our model was able to explain a significant amount of variation in a set of real visitation records.

- Natural sites near cities are the most important regions in terms of recreational use (Fig. 6). Most people travel 5 km or less to find recreation and leisure opportunities. Planners and policymakers aiming to increase the societal benefits derived from outdoor recreation should prioritise sites nearest to population centres over areas that are pristine or attractive but remote.

- European countries differ in their level of cultural service provision. Countries with low overall recreational amenity tend to be more sparsely populated, and so have lower demand. On the other hand, countries with an extensive network of accessible sites can provide a high level of recreational service to their populations. Natural sites between cities ensure high recreation amenity over a broad expanse.

The potential of modelling cultural services is broad, and may help planners at all levels to target areas that should be preserved or enhanced for public recreation. Consideration must be given to all aspects of the landscape, including its proximity to potential recreational users.

Acknowledgements

We thank the support of the European Commission, Directorate-General Environment grant LIFE12 ENV/UK/000473, the VISTA programme from the Norwegian Academy of Science and Letters (Project number 6158), and NERC NPIF Award NE/R011885/1. We also thank the Oxford Long-term Ecology Laboratory for stimulating discussion.

Author Contributions

PL, SN, and KJW conceptualised and designed the study. PL collected the datasets and perfomed the analysis. SN and KJW wrote the original draft with contributions from all co-authors. DB and PL created the figures.

Data Accessibility

Data and code for this study are available via the ORA-Data deposit at:
https://ora.ox.ac.uk/objects/uuid:2b4410a5-86e6-4b34-8243-643c9ca533f0

Supplementary Materials

The following materials are available as part of the online article at https://escholarship.org/uc/fb:
Figure S1: Seasonal distribution of non-urban Flickr records across Europe in 2017

References

Anderson, S. (2018) iNaturalist: understanding biodiversity through a digital medium. MA thesis, University of Waterloo.

Antoniou V., Fonte C.C., See L., Estima J., Arsanjani J.J., Lupia F., Minghini M., Foody G. & Fritz S. (2016) Investigating the feasibility of geo-tagged photographs as sources of land cover input data. ISPRS International Journal of Geo-Information, 5, 64.

Barve, V. (2014) Discovering and developing primary biodiversity data from social networking sites: a novel approach. Ecological Informatics, 24, 194-199.

Beale, C.M . & Lennon, J.J. (2012) Incorporating uncertainty in predictive species distribution modelling. Philosophical Transactions of the Royal Society B: Biological Sciences, 367, 247-258.

Bik, H.M. & Goldstein, M.C. (2013) An introduction to social media for scientists. PLoS Biology, 11, e1001535.

Bishop, I.D. (2003) Assessment of visual qualities, impacts, and behaviours, in the landscape, by using measures of visibility. Environment and Planning B, 30, 677-688.

Burnham, K.P. & Anderson, D.R. (2002) Model selection and multimodel inference: a practical information-theoretic approach. Springer, London.

Center for International Earth Science Information Network - CIESIN - Columbia University (2018) Gridded Population of the World, Version 4 (GPWv4):

Population Density, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).

Chandler, M., See, L., Copas, K., et al. (2017) Contribution of citizen science towards international biodiversity monitoring. Biological Conservation, 213, 280-294.

Chen, X., de Vries, S., Assmuth, T., et al. (2019) Research challenges for cultural ecosystem services and public health in (peri-)urban environments. Science of The Total Environment, 651, 2118-2129.

Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J.O. & Martins, M.J. (2019) Combining social media photographs and species distribution models to map cultural ecosystem services: the case of a Natural Park in Portugal. Ecological Indicators, 96, 5-68.

Cortinovis, C. & Davide, G. (2019) A framework to explore the effects of urban planning decisions on regulating ecosystem services in cities. Ecosystem Services, 38, 100946.

Danielson, J. & Gesh, D.B. (2011) Global multi-resolution terrain elevation data (GMTED2010). USGS Open-File Report 2011-1073, https://doi.org/10.3133/ofr20111073.

Daume, S. (2016) Mining Twitter to monitor invasive alien species - an analytical framework and sample information topologies. Ecological Informatics, 31, 70-82.

Diaz, S., Pascual, U., Stenseke, M., et al. (2018). Assessing nature's contributions to people. Science, 359, 270-272.

Di Minin, E., Tenkanen, H. & Toivonen, T. (2015) Prospects and challenges for social media data in conservation science. Frontiers in Environmental Science, 3, 63

Dowthwaite, L. & Sprinks, J. (2019) Citizen science and the professional-amateur divide: lessons from differing online practices. Journal of Science Communication, 18, A06.

European Environment Agency (2012) Corine Land Cover 2012. Available at: http://land.copernicus.eu/pan-european/corine-land-cover/clc-2012

Figueroa-Alfaro, R.W. & Tang, Z. (2017) Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. Journal of Environmental Planning and Management, 60, 266-281.

Fisher, D.M., Wood, S.A., White, E.M., Blahna, D.J., Lange, S., Weinberg, A., Tomco, M. & Lia, E. (2018) Recreational use in dispersed public lands measured using social media data and on-site counts. Journal of Environmental Management, 222, 465-474.

Ghermandi, A. & Sinclair, M. (2019) Passive crowdsourcing of social media in environmental research: a systematic map. Global Environmental Change, 55, 36-47.

Girardin, F., Dal Fiore, F., Ratti, C. & Blat, J. (2008) Leveraging explicitly disclosed location information to understand tourist dynamics: a case study. Journal of Location Based Services, 2, 41-56.

Gliozzo, G., Pettorelli, N. & Haklay, M. (2016) Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. Ecology and Society, 21, http://dx.doi.org/10.5751/ES-08436-210306.

Gosal, A.S., Geijzendorffer, I.R., Václavík, T., Poulin, B. & Ziv, G. (2019) Using social media, machine learning and natural language processing to map multiple recreational beneficiaries. Ecosystem Services, 38, 100958.

Gouraguine, A., Moranta, J., Ruiz-Frau, A., Hinz, H., Renones, O., Ferse, S.C.A., Jompa, J. & Smith, D.J. (2019) Citizen science in data and resource-limited areas: a tool to detect long-term ecosystem changes. PLoS One, 14, e0210007.

Hägerhäll, C.M., Ode Sang, Å., Englund, J.E., Ahlner, F., Rybka, K., Huber, J. & Burenhult, N. (2018) Do humans really prefer semi-open natural landscapes? A cross-cultural reappraisal. Frontiers in Psychology, 9, 822.

Hansen, M.M., Jones, R. & Tocchini, K. (2017) Shinrin-Yoku (forest bathing) and nature therapy: a state-of-the-art review. International Journal of Environmental Research and Public Health, 14, 851.

Hauff, C. & Houben, G.J. (2012) Geo-location estimation of Flickr images: social web based enrichment. In: Advances in information retrieval (ed. by R. Baeza-Yates, A.P. de Vries, H. Zaragoza, B. Barla Cambazoglu, V. Murdock, R. Lempel and F. Silvestri), pp. 85–96. Springer, Berlin, Heidelberg.

Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V. & Di Minin, E. (2018) Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas. Conservation Letters, 11, e12343.

Heikinheimo, V., Di Minin, E., Tenkanen, H., Hausmann, A., Erkkonen, J. & Toivonen, T. (2017) User-generated geographic information for visitor monitoring in a national park: a comparison of social media data and visitor survey. ISPRS International Journal of Geo-Information, 6, 85.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology, 25, 1965-1978.

Hirons, M., Comberti, C. & Dunford, R. (2016) Valuing cultural ecosystem services. Annual Review of Environment and Resources, 41, 545-574.

Husar, R.B., Husar, J.D. & Martin, L. (2000) Distribution of continental surface aerosol extinction based on visual range data. Atmospheric Environment*,* 34**,** 5067-5078.

Jeawak, S.S., Jones, C.B. & Schockaert, S. (2017) Using Flickr for characterizing the environment: an exploratory analysis. In: 13th International Conference on Spatial Information Theory (COSIT 2017) (ed. by E. Clementini, M. Donnelly, M. Yuan, C. Kray, P. Fogliaroni and A. Ballatore), pp. 21:1-21:13. Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl.

Langemeyer, J., Calcagni, F. & Baró, F. (2018) Mapping the intangible: using geolocated social media data to examine landscape aesthetics. Land Use Policy, 77, 542-552.

Lo, A.Y. & Jim, C.Y. (2010) Willingness of residents to pay and motives for conservation of urban green spaces in the compact city of Hong Kong. Urban Forestry & Urban Greening, 9, 113-120.

Mancini, F,. Coghill, G.M., & Lusseau, D. (2019) Quantifying wildlife watchers' preferences to investigate the overlap between recreational and conservation value of natural areas. Journal of Applied Ecology, 56, 387-397.

Millennium Ecosystem Assessment (MA) (2003) Ecosystems and human well-being: a framework for assessment. Island Press, Washington, DC. 245 pp.

Oteros-Rozas, E., Martin-Lopez, B., Fagerholm, N., Bieling, C. & Plieninger, T. (2018) Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. Ecological Indicators, 94, 74-86.

Paracchini, M.L., Zulian, G., Kopperoinen, L., Maes, J., Schagner, J.P., 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. Ecological Indicators, 45, 371-385.

Perrin, S. (2019) Mapping species distribution with citizen science. Ecology for the masses. https://ecologyforthemasses.com/2019/02/20/mapping-species-distribution-with-citizen-science/. Accessed 29 April 2019.

Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190, 231-259.

Pocock, M.J.O., Chapman, D., Sheppard, L.J. & Roy, H.E. (2014) A strategic framework to support the implementation of citizen science for environmental monitoring. Final report to SEPA, NERC/Centre for Ecology & Hydrology, Wallingford. 65 pp.

Ramm, F., Topf, J. & Chilton, S. (2011) Open street map: using and enhancing the free map of the world. UIT Cambridge Ltd., Cambridge.

Schägner, J.P., Maes, J., Brander, L., Paracchini, M.-L., Hartje, V. & Dubois, G. (2017) Monitoring recreation across European nature areas: a geo-database of visitor counts, a review of literature and a call for a visitor counting reporting standard. Journal of Outdoor Recreation and Tourism, 18, 44-55.

Schirpke, U., Timmermann, F., Tappeiner, U. & Tasser, E. (2016) Cultural ecosystem services of mountain regions: modelling the aesthetic value. Ecological Indicators, 69, 78-90.

Seresinhe, C.I., Preis, T. & Moat, H.S. (2017) Using deep learning to quantify the beauty of outdoor places. Royal Society Open Science, 4(7), 170170.

Sinclair, M., Mayer, M., Woltering, M. & Ghermandi, A. (2020) Using social media to estimate visitor provenance and patterns of recreation in Germany's national parks. Journal of Environmental Management, 263, 110418.

Song, W., Deng, X., Liu, B., Li, Z., Jin, G. & Wen, X. (2015) Impact Assessments of Land-Use Change on Valued Ecosystem Services. In: Impacts of land-use change on ecosystem services (ed. by Zhan, J.), pp. 79-108. Springer, Berlin, Heidelberg.

Tenerelli, P., Demsar, U. & Luque, S. (2016) Crowdsourcing indicators for cultural ecosystem services: a geographically weighted approach for mountain landscapes. Ecological Indicators, 64, 237-248.

Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L. & Toivonen, T. (2017) Instagram, Flickr, or Twitter: assessing the usability of social media data for visitor monitoring in protected areas. Scientific Reports, 7, 17615.

Twohig-Bennett, C. & Jones, A. (2018) The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. Environmental Research, 166, 628-637.

Van Berkel, D.B., Tabrizian, P., Dorning, M.A., Smart, L., Newcomb, D., Mehaffey, M., Neale, A. & Meentemeyer, R.K. (2018) Quantifying the visual-sensory landscape qualities that contribute to cultural ecosystem services using social media and LiDAR. Ecosystem Services, 31, 326-335.

van Zanten, B.T., Zasada, I., Koetse, M.J., Ungaro, F., Häfner, K. & Verburg, P.H. (2016a) A comparative approach to assess the contribution of landscape features to aesthetic and recreational values in agricultural landscapes. Ecosystem Services, 17, 87-98.

van Zanten, B.T., Van Berkel, D.B., Meentemeyer, R.K., Smith, J.W., Tieskens, K.F. & Verburg, P.H. (2016b) Continental-scale quantification of landscape values using social media data. Proceedings of the National Academy of Sciences USA, 113, 12974-12979.

Walden-Schreiner, C., Leung. Y.-F. & Tateosian, L. (2018) Digital footprints: incorporating crowdsourced geographic information for protected area management. Applied Geography, 90, 44-54.

Wood, S.A., Guerry, A.D., Silver, J.M. & Lacayo, M. (2013) Using social media to quantify nature-based tourism and recreation. Scientific Reports, 3, 2976.

Woolley, J.P., McGowan, M.L., Teare, H.J.A., Coathup, V., Fishman, J.R., Settersten, R.A., Sterckx, S., Kaye, J. & Juengst, E.T. (2016) Citizen science or scientific citizenship? Disentangling the uses of public engagement rhetoric in national research initiatives. BMC Medical Ethics, 17, 33.

Yoshimura, N. & Hiura, T. (2017) Demand and supply of cultural ecosystem services: use of geotagged photographs to map the aesthetic value of landscapes in Hokkaido. Ecosystem Services, 24, 68-78.

Submitted: 16 April 2020
First decision: 16 June 2020
Accepted: 9 Nov 2020
Edited by Janet Franklin

Figures:

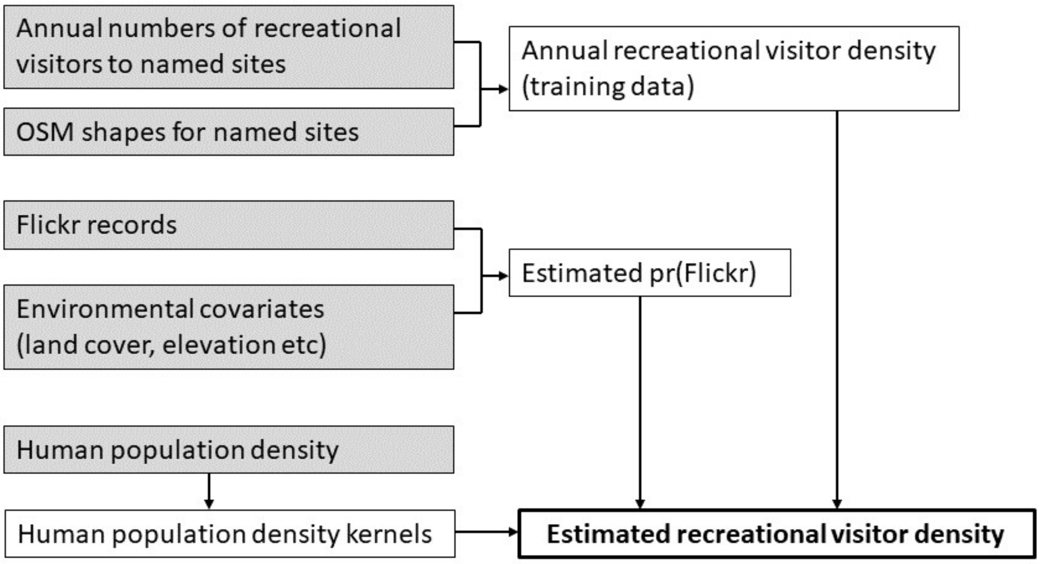

Figure 1: Outline of model for recreational amenity showing steps toward the final output. Raw data are in grey boxes while derived products are in white boxes. Pr(Flickr): probability of occurrence of Flickr records.

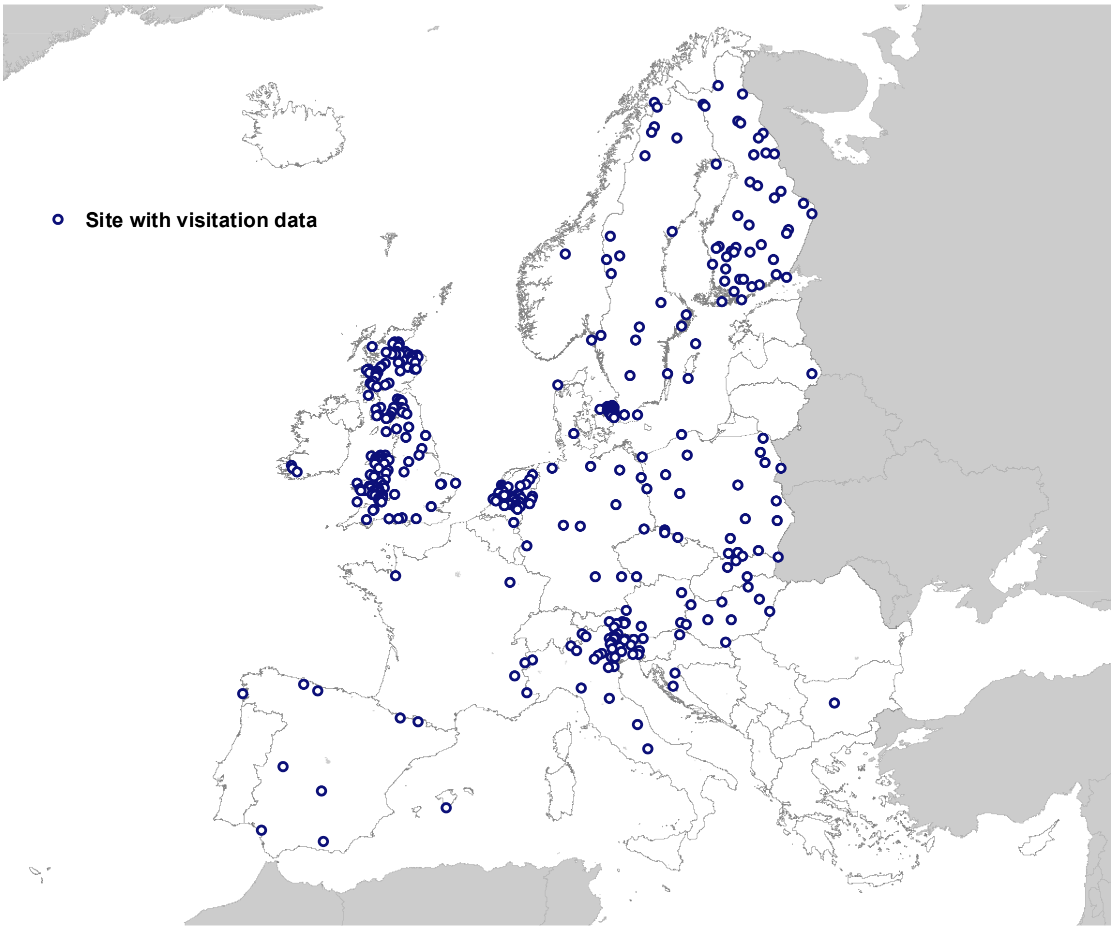

Figure 2: Location of sites with visitation data in Europe. Data from Schägner et al. (2017).

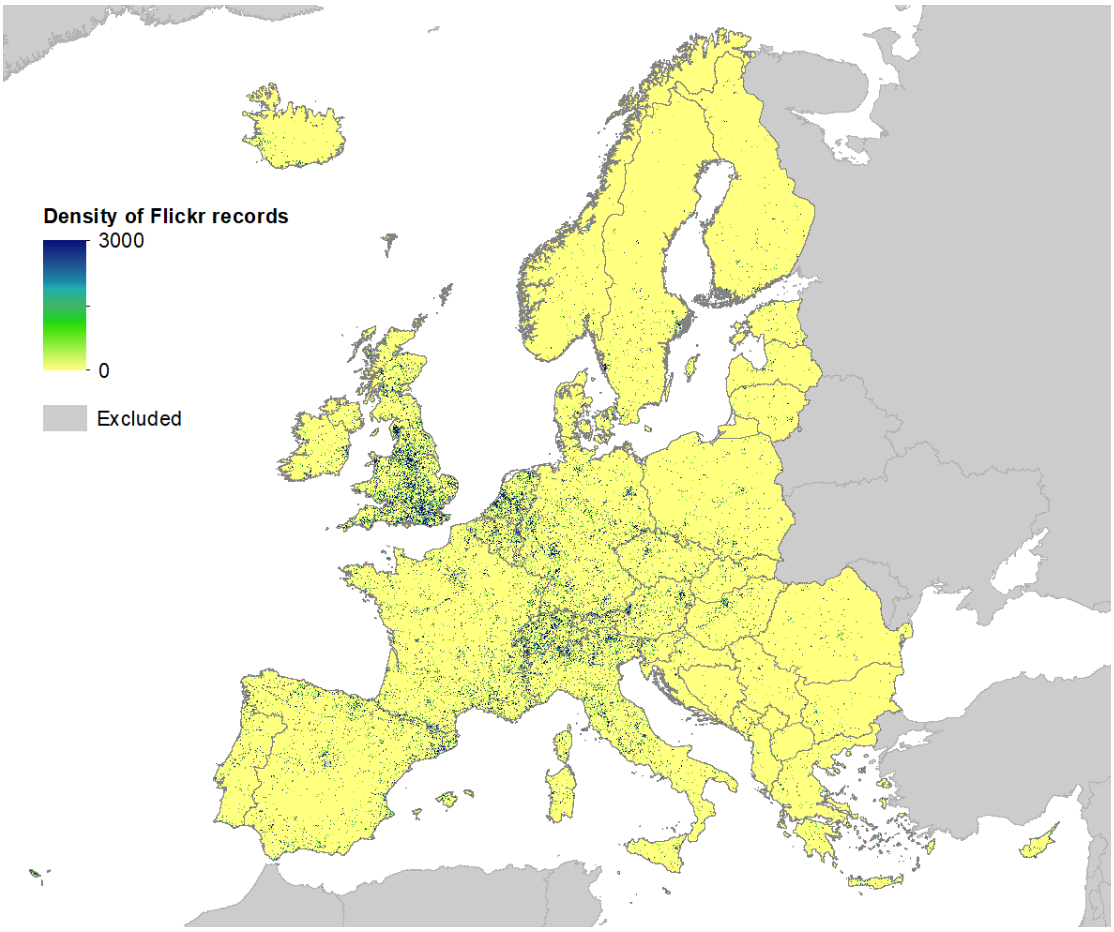

Figure 3: Density of non-urban Flickr records in Europe in 2017, measured as records/km^2. Values express the kernel-count of photographs taken at a particular location.

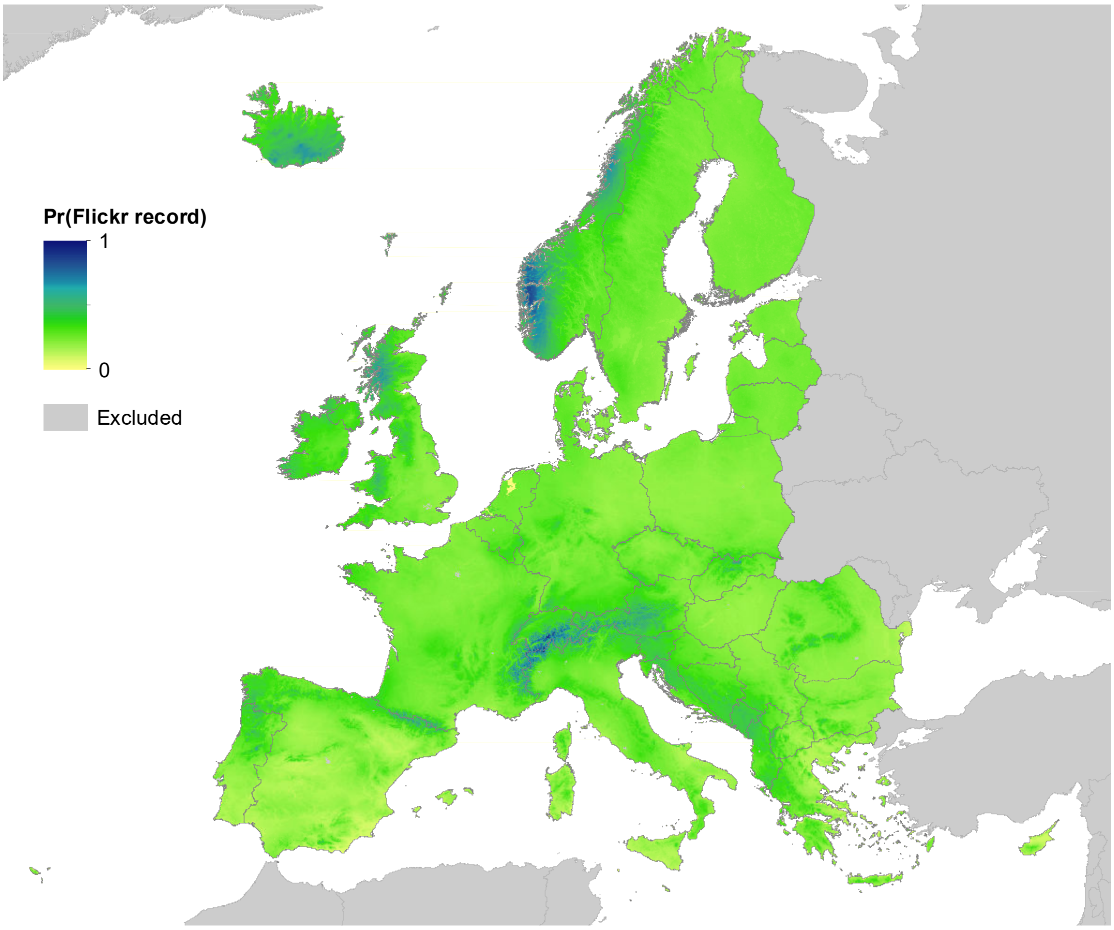

Figure 4: Potential supply map representing aesthetic appeal in Europe in 2017. The map shows the probability of occurrence of a Flickr record (Pr(Flickr)) as a function of environmental covariates. Areas in yellow or light green are predicted to have lower aesthetic value, while dark green to blue areas should have high aesthetic value.

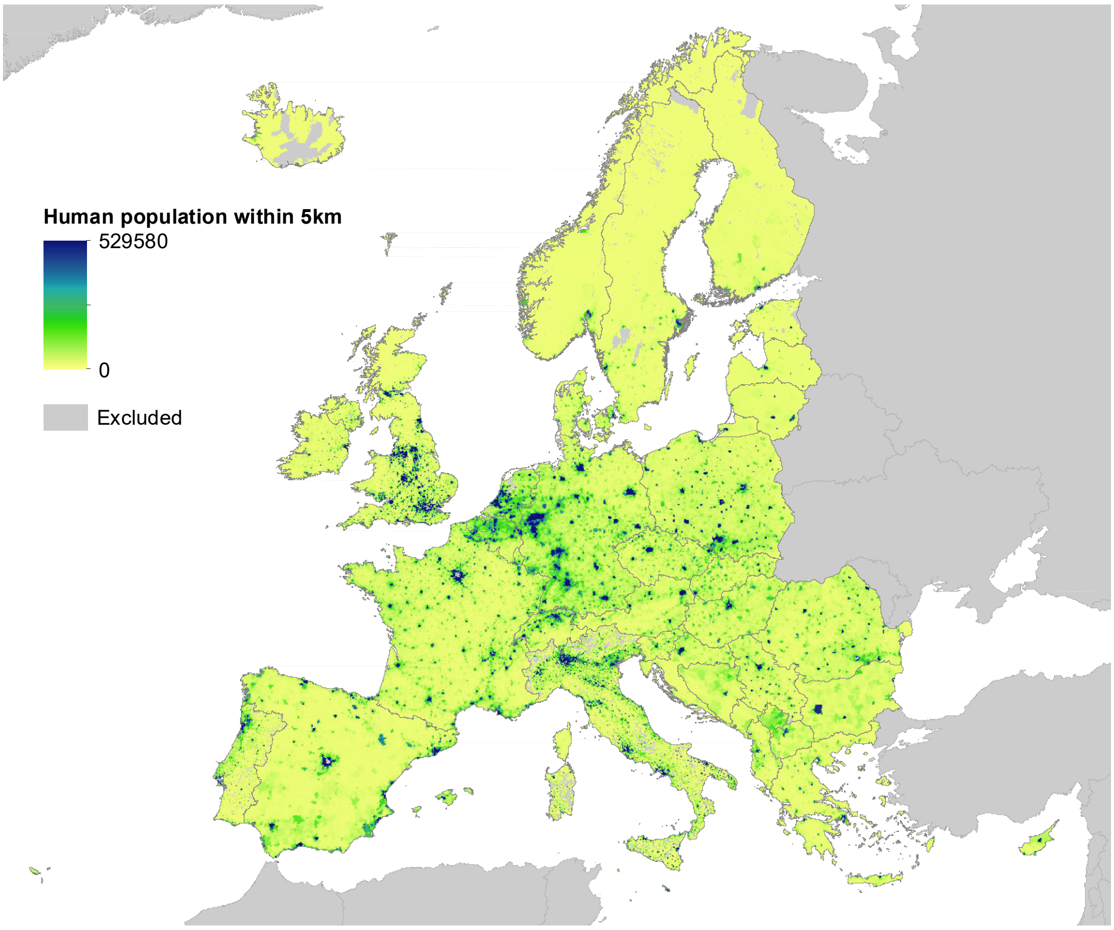

Figure 5: Map of total human population within 5km, representing the potential demand for recreational amenity. Areas in blue have high population, whereas areas in yellow are sparsely populated.

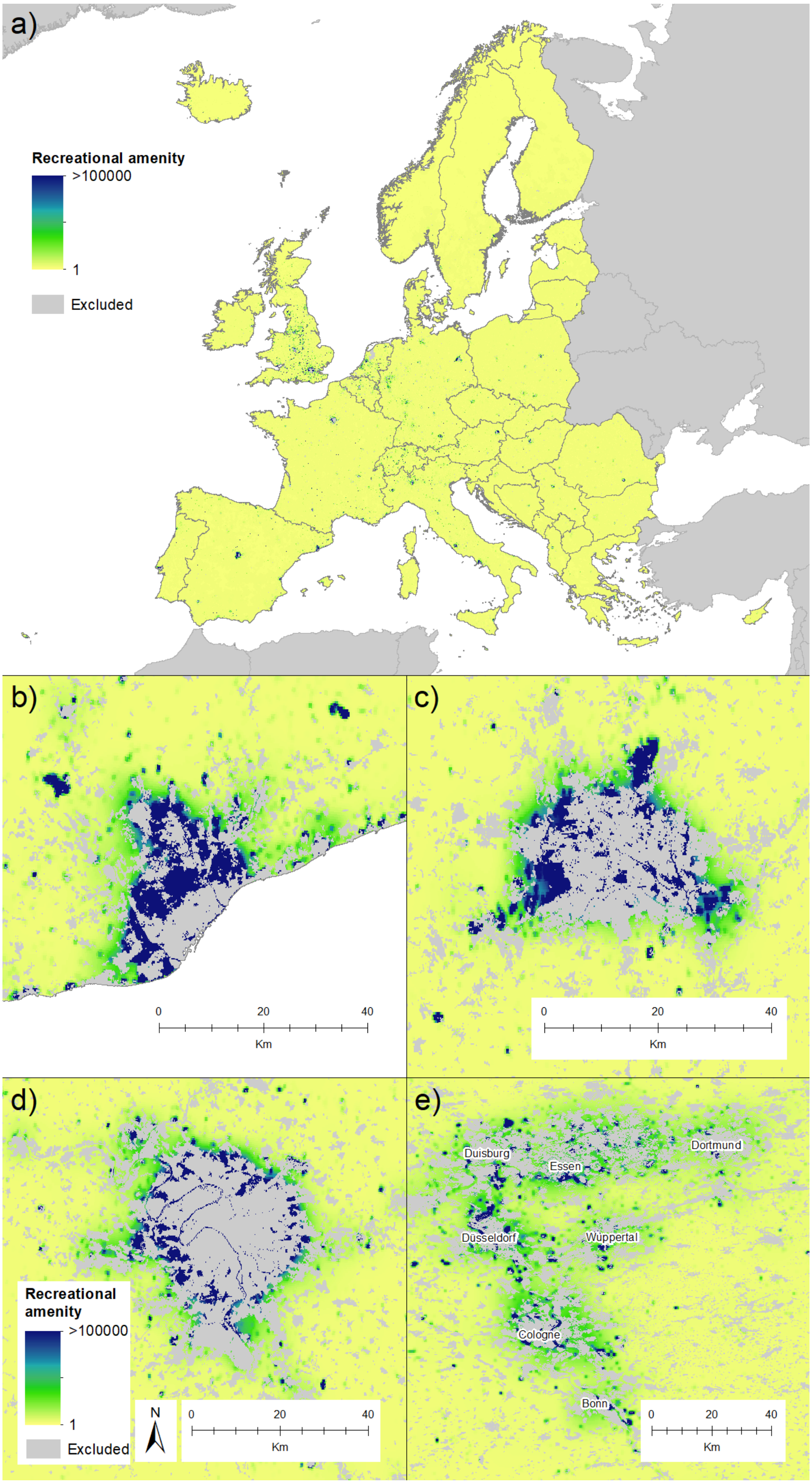
a)
Recreational amenity
>100000
1
Excluded
b)
0
20
40
Km
c)
0
20
40
Km
d)
Recreational amenity
>100000
1
Excluded
N
0
20
40
Km
e)
Duisburg
Dortmund
Essen
Dusseldorf
Wuppertal
Cologne
Bonn
0
20
40
Km

Figure 6: a) Final recreational amenity map, showing the pattern of estimated visitor density across Europe in 2017. Insets display recreational amenity at a finer scale for selected urban areas: b) Barcelona; c) Berlin; d) Paris; e) the Rhine and Ruhr Valleys. Blue represents high recreation service provision.

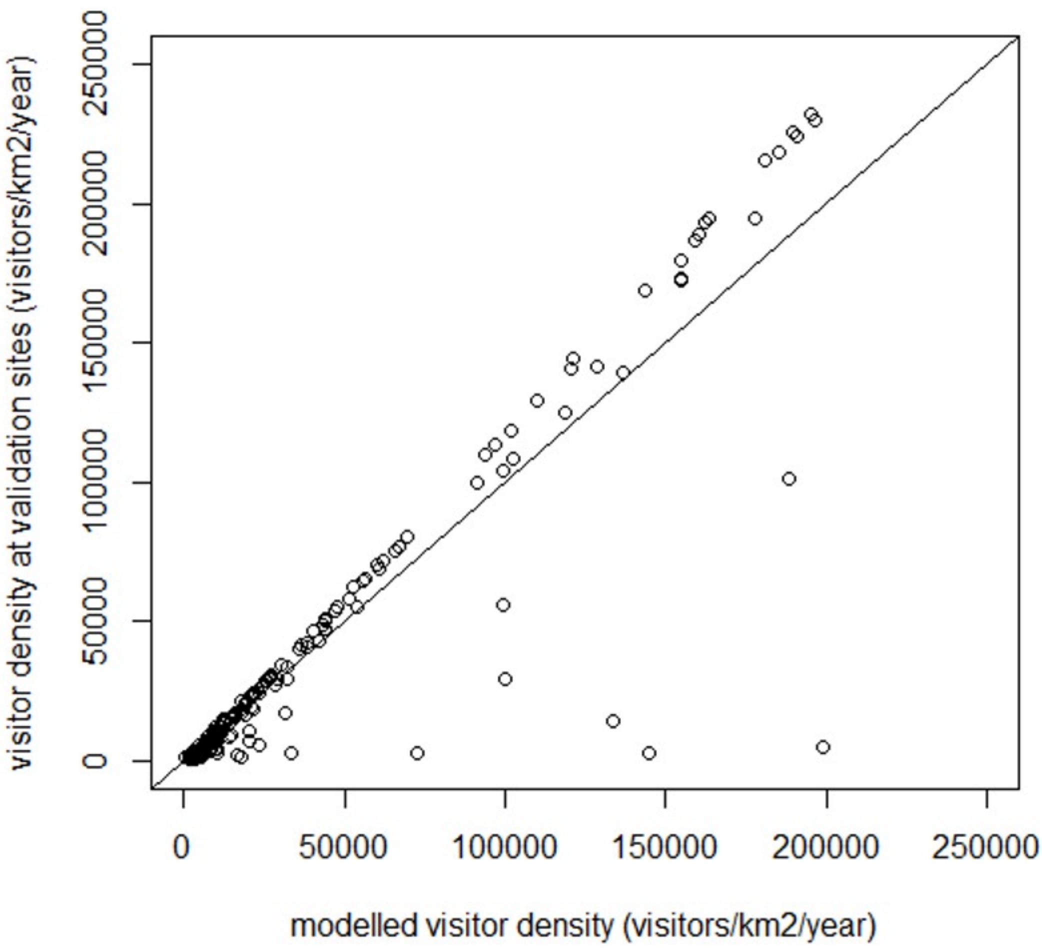

Figure 7: Validation of model output: estimated versus actual annual visitor density for recreation sites not used to train model. Solid line represents a 1-to-1 relationship.

Table 1. Minimum adequate model for visitor density in Europe as a function of Flickr record density and human population density within 5km. Multiple linear regression, n = 205 sites. The t-test statistics for partial slopes of the explanatory variables retained in the final model are reported. The coefficient of determination R^2 = 0.378

Response	Explanatory	Beta	t	p
ln(visitor density)	Intercept	7.248	61.22	<0.001
	Flickr density 1km	7.080	6.256	<0.001
	Human Population density within 5km	0.000047	12.831	<0.001
R^2 = 0.378, n = 205 sites, F = 110.9				