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Social media and deep learning reveal specific cultural preferences for biodiversity

Ilan Havinga[1] | Diego Marcos[2] | Patrick Bogaart[3] | Dario Massimino[4] | Lars Hein[1] | Devis Tuia[5]

[1]Environmental Systems Analysis Group, Wageningen University, Wageningen, 6708 PB, The Netherlands

[2]Inria, University of Montpellier, Montpellier, 34090, France

[3]National Accounts Department, Statistics Netherlands, Henri Faasdreef 312, The Hague, 2492 JP, The Netherlands

[4]British Trust for Ornithology, The Nunnery, Thetford, Norfolk, IP24 2PU, UK

[5]Environmental Computational Science and Earth Observation Laboratory, Ecole Polytechnique Fédérale de Lausanne, Industrie 17, Sion, Switzerland

Correspondence
Devis Tuia
Email: devis.tuia@epfl.ch

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Abstract

1. Social media has created new opportunities to map cultural ecosystem services (CES) related to biodiversity at large scales. However, using these novel data to understand people's preferences in relation to these CES remains a challenge.
2. To address this, we trained a deep learning model to capture people's interactions with selected flora and fauna on Flickr as a cultural service related to biodiversity and compared this with citizen science data on iNaturalist, with photos of individual species considered as human–species interactions.
3. After mapping the distribution of people's interactions in Great Britain on Flickr and iNaturalist, we find significant spatial differences in people's preferences on the two platforms.
4. Using a second, pretrained deep learning model, we were also able to identify different preferences for species groups such as birds on social media versus citizen science.
5. To better understand people's preferences, we also compared peoples' interactions with species richness and abundance for a group of 36 bird species, sometimes finding large differences between people's interactions and these ecological measures.
6. Our findings demonstrate that social media can be used to include a wider range of preferences in CES assessments along-side citizen science data. However, these preferences reflect only a limited first-hand experience of biodiversity.

KEYWORDS
AI, biodiversity, citizen science, conservation, cultural ecosystem services, machine learning, social media

1 | INTRODUCTION

The importance of biodiversity for human well-being is widely recognised (Bowler et al., 2010; Cardinale et al., 2012). Alongside its intrinsic value, biodiversity generates a great amount of value for people through its contributions to a variety of instrumental and relational benefits (Chan et al., 2016). For example, contact with living species can improve an individual's mental health (Bratman et al., 2012; Hartig et al., 2003; Remme et al., 2021) while also contributing to better social relations (Kuo & Sullivan, 2001; Strevey, 2008; Weinstein et al., 2015) and a stronger sense of collective identity (Chan et al., 2018; Hausmann et al., 2016). These contributions represent cultural ecosystem services (CES) which can be broadly defined as ecosystems' contributions to the nonmaterial benefits arising from human–ecosystem relationships (Chan, Guerry, et al., 2012; United Nations et al., 2021).

The complex socioecological relationships that determine the provision of CES by ecosystems require a wide range of methods to measure these services (Chan, Satterfield, et al., 2012; Daniel et al., 2012), all of which help encourage the inclusion of cultural values in environmental assessments and policy-making (Satz et al., 2013). For example, participatory mapping and deliberative approaches employing qualitative methods from the social sciences have been used to examine CES in local settings (Kenter et al., 2016; Klain & Chan, 2012). These approaches are able to represent the context-specific and situated knowledges in which ecosystems generate cultural value (Gould, Adams, & Vivanco, 2020). However, to inform decision-making at large scales, a level of generalisation is still needed (Gould et al., 2019; Norton et al., 2012). The generalising perspective put forward by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) therefore suggests a universally applicable set of CES categories (Díaz et al., 2018), as does the System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA) framework which aims to better represent ecosystem value in national statistics (Edens et al., 2022; Hein et al., 2020).

Generally, such large-scale applications require quantitative, spatially explicit methods to measure CES (Gould et al., 2019; Havinga et al., 2020). The spatial representation of CES supports assessments at multiple scales (Hernández-Morcillo et al., 2013), addresses issues of double-counting (Bagstad et al., 2013) and enables the identification of CES 'hotspots' to focus management efforts (Allan et al., 2015). However, these methods are still faced with the challenge of capturing the large variety of preferences that underpin CES (Bieling & Plieninger, 2013) and in determining which ecosystem attributes are generating these services (Gould et al., 2019). In particular, the connection between CES and biodiversity remains an underexplored area of research (Echeverri et al., 2020; Hevia et al., 2017; McGinlay et al., 2017), especially on a spatially explicit basis (Gould et al., 2019; Plieninger et al., 2013). Consequently, more investigation of CES provision and biodiversity is needed to better understand the complex interplay between CES and land management policies (Gould, Bremer, et al., 2020), including those related to conservation (Echeverri et al., 2021; King et al., 2017).

In this context, spatial methods using social media data have gained an increasing amount of attention in CES applications (Ghermandi & Sinclair, 2019; Havinga et al., 2020). This is because social media data enable large-scale analyses of CES based on a wide range of self-reported, revealed preferences, with the level of detail necessary to identify specific ecosystem attributes as contributing factors (Havinga et al., 2021a; Richards & Friess, 2015; van Zanten et al., 2016). Still, research on people's spatial interactions with biodiversity on social media has so far been limited (August et al., 2020). More specific data for these purposes are available such as the data generated by eBird and iNaturalist, two citizen science platforms through which millions of amateur naturalists record their interactions with individual species (Havinga et al., 2020). Nevertheless, human–species interactions occur in numerous ways and citizen science initiatives do not capture the full range of people's interactions with biodiversity (Schröter et al., 2017). For example, a holiday trip can facilitate interactions with local biodiversity through wildlife photography (Hausmann et al., 2018). Closer to home, a walk in the park can lead to a number of casual interactions related to social and physical activities which are then shared via social media (Lopez et al., 2020). Different interactions may also occur on social media due to variations in the socio-demographic characteristics of users versus citizen science (Ghermandi & Sinclair, 2019).

Social media platforms therefore present themselves as promising sources of data in capturing a wider range of CES related to biodiversity. Flickr, an image-led platform, has already been broadly utilised in environmental research, offering a wide range of photography including images of individual species (Ghermandi & Sinclair, 2019). To process these data in large quantities, however, requires machine learning methods (Pan et al., 2022; Richards & Tunçer, 2018). Here, deep learning, which uses artificial neural networks to generate image predictions, has proven to be especially useful in examining CES and the biophysical elements generating these services (Egarter Vigl et al., 2021; Havinga et al., 2021a; Lee et al., 2022). In some recent examples using Flickr, deep learning models have accurately identified plant species (August et al., 2020), detected birdwatching activities (Koylu et al., 2019) and classified the preferences of national park visitors (Väisänen et al., 2021). Crowdsourcing constitutes an important part of these new techniques to capture a broad range of cultural preferences (Ghermandi & Sinclair, 2019). Meanwhile, deep learning is being directly integrated into citizen science platforms to support species classifications (McClure et al., 2020), enabling the release of pretrained models for species detection (Van Horn et al., 2018).

These technological developments now enable large-scale CES analyses using social media. By utilising such large social datasets alongside citizen science data, large-scale CES assessments related to biodiversity can potentially include a greater diversity of individual preferences both due to demographic variations and the core purpose of different platforms (Fox et al., 2021; Scowen et al., 2021). At the same time, the detail with which particular aspects of biodiversity can be identified using deep learning, including specific species of flora and fauna, means that better connections can be made between biodiversity and CES (Echeverri et al., 2020). For example, Cardoso et al. (2022) categorised CES related to biodiversity by identifying images of species on social media using deep learning and a training dataset labelled by the authors themselves. These techniques also allow predictions of very specific ecological characteristics, such as the class of species (Jarić et al., 2020). Such detailed information can ultimately shed new light on the types of preferences being expressed on different platforms, including social media, and how these relate to specific biophysical features, such as individual species and biodiversity measures, thus enabling a better understanding of the types of individual preferences available to CES assessments (Gould, Bremer, et al., 2020; Satz et al., 2013). Drawing on crowdsourced data will in turn incorporate a larger sample of preferences versus those labelled by a small group of people (Dubey et al., 2016), therefore allowing CES assessments to scale at regional and country levels.

The objective of our study is to assess the potential of deep learning and social media to measure people's appreciation of biodiversity as a cultural service. We focus on Great Britain as our case study area and use iNaturalist data to compare activity between social media and citizen science. In doing so, we seek to answer the following research questions: (1) How can deep learning and crowdsourced data capture a broad range of human–species interactions on Flickr? (2) What is the distribution of human–species interactions using Flickr data as a measure of CES related to biodiversity? (3) What species and species groups are users interacting with? (4) How do users' species interactions compare with biodiversity metrics as an indicator of wider cultural value? Answering these research questions will help create a better understanding of the types of preferences being expressed on social media in relation to biophysical features, an important aim of CES assessment. We hypothesised that Flickr users would have preferences for different species to users of citizen science data (Hausmann et al., 2018; Levin et al., 2017) and that these revealed preferences would not necessarily match ecological measures of biodiversity (Dallimer et al., 2012).

2 | METHODS

2.1 | Study design

Our study focused on examining people's interactions with species using deep learning and Flickr images (Figure 1). We defined a human–species interaction as an image depicting an individual species as its main subject and broadly conceptualised these interactions as a cultural service related to the cognitive enjoyment of biodiversity (Havinga et al., 2020). To capture people's interactions on social media, we first trained and applied a deep learning model using a novel training technique designed to identify images of taken by users with the intention of documenting individual species, which we classed as human–species interactions. To determine what species users were interacting with, we applied a second, pretrained deep learning model to generate individual species classifications. For each of these steps, we compared our results to iNaturalist user activity to better understand social media as an alternative source of data. Finally, we compared users' interactions with bird population density data to examine the connection to biodiversity metrics as indicators of wider cultural value.

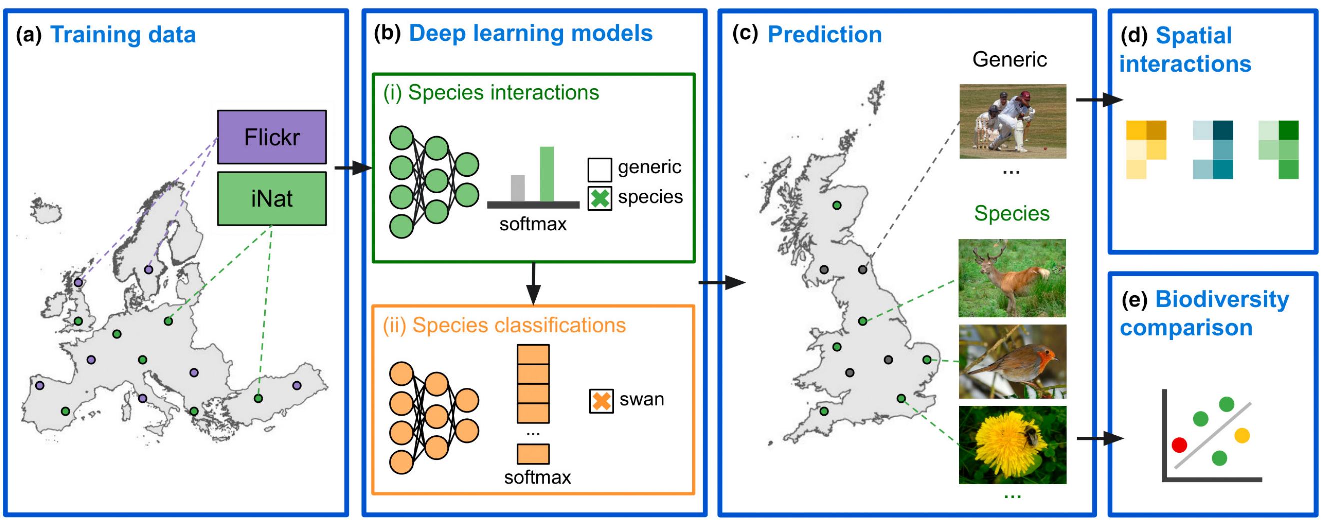

FIGURE 1 The overall study design. (a) Training data were collected using a random sample of Flickr and iNaturalist images within Europe. These were used to (b) (i) train a deep learning model to detect human–species interactions in Flickr images, defined as images depicting an individual species as their main subject. Then, (b) (ii) the species depicted in these images were classified by a second, pretrained deep learning model. Predictions were generated for (c) Great Britain. These were used to examine and compare (d) spatial interactions with species and (e) biodiversity indicators using modelled bird population data.

2.2 | Study area data

To apply our deep learning approach at national scale in Great Britain, we used a Flickr image dataset created in previous research which provided 9.8 million geo-located images depicting outdoor scenes (Havinga et al., 2021a). These images were downloaded using metadata records retrieved through the Flickr Application Programming Interface (API) and filtered to outdoor images using the Places365 deep learning model (Zhou et al., 2017). At the same time, for comparison, we compiled a new dataset of research-grade iNaturalist observation metadata, including image urls, by using the RINAT package in R to access the iNaturalist API. In total, we downloaded 1.1 million iNaturalist records for Great Britain. The image corresponding to each record was accessed using the image urls during model prediction. Additional taxonomic information was downloaded using the TAXIZE package in R. Ethical approval was not required for this study.

2.3 | Species interaction model

2.3.1 | Training and test data

To identify human–species interactions in images, we compiled a large dataset of images from iNaturalist and Flickr to train our deep learning-based species interaction model. For training, we used images uploaded to iNaturalist as a representation of people's interactions with individual species and Flickr images as a representation of all other, 'generic' types of interactions to train our model. To download the images, we used the 'flickrapi' library in Python to access the Flickr API and the RINAT package in R to access the iNaturalist API. We downloaded images using a randomly generated sample grid, representing a 10% random sample of a 25 km resolution grid over the whole of Europe (Supporting Information Figure S1). Within each grid cell, we downloaded an equal number of images from each source by randomly downsampling the greater image set in the case of imbalances. This produced a 50/50 training dataset of 1.3 million Flickr and iNaturalist images. Finally, the images were split into training (70%), validation (10%) and test (20%) sets using a block holdout approach so that spatial overlap between training, validation and testing samples was prevented by drawing from nonoverlapping grid cells.

2.3.2 | Model architecture

Our model consisted of a ResNet-18 with an additional five layers replacing the two final layers (He et al., 2016). The model was developed using the 'PyTorch' library in Python. Using PyTorch's built-in model library, we downloaded the original architecture with the model weights pretrained on the ImageNet database. We then adapted the model to produce a binary output, each converted to a 0–1 range using a softmax transformation. This output represented either a human-species interaction, such as those observed on iNaturalist, or a generic interaction, consisting of any other kind of interaction. Generic interactions were only observable in the Flickr data and included, for example, images of buildings, sporting events, transport and landscapes.

2.3.3 | Model training

The first step was to train the model to distinguish between images depicting human–species interactions and generic interactions. All iNaturalist images were labelled as human–species interactions and all Flickr images were labelled as generic interactions. We set our deep learning model to train on the image dataset for 10 epochs with an initial learning rate of 1e^{05} for the weights of the final two layers and 1e^{04} for the rest of the network. The learning rate was halved every epoch. If the model failed to converge, we also tried halving the initial learning rates. We used Adam as our optimisation algorithm and a cross-entropy learning loss (Kingma & Ba, 2014). Therefore the standard, cross-entropy loss for a single image during model training was calculated as:

$$\mathcal{L}(y,\hat{y}) = \sum_{i=1}^{C} y_i \cdot log(\hat{y}_i). \tag{1}$$

with $\mathcal{L}$ denoting the loss calculated over y, the training labels, and $\hat{y}$, the model predictions, for C number of classes (two), with a softmax applied to the model class predictions before calculating the loss.

During normal training, the model is penalised if it identifies a Flickr image as a human–species interaction because all Flickr images are labelled as generic interactions. However, the Flickr image may still be of an individual species, in which case it is beneficial to introduce a level of leniency into the training scheme by adding noise robustness to the image training label. This supports the inclusion of this type of Flickr image within the species image decision boundary of the final model (Figure 2). To do this, we applied a special minimum entropy dilution technique in the training scheme to adjust the influence of the model's predictions versus the training labels in the case of generic-labelled images (Marcos et al., 2022; Reed et al., 2015; Yves & Yoshua, 2006). Keeping the cross-entropy learning loss unchanged for species-labelled images, we integrated a β dilution coefficient in the learning loss for generic-labelled images as follows:

$$\mathcal{L}(y,\hat{y}) = \sum_{i=1}^{C} \left(\beta \cdot y_i + (1-\beta) \cdot \hat{y}_i\right) \cdot log(\hat{y}_i). \tag{2}$$

with $\mathcal{L}$ denoting the loss calculated over y, the training labels, and $\hat{y}$, the model predictions, with each training label y_i adjusted for the β coefficient. For example, if $\beta = 0.1$, this places a 10% emphasis on the original training labels, putting more trust in the predictions of the current model. On the other hand, if $\beta = 1$ this would represent the baseline model with only the training labels considered in the training. Model accuracy on the test set is reported in the results.

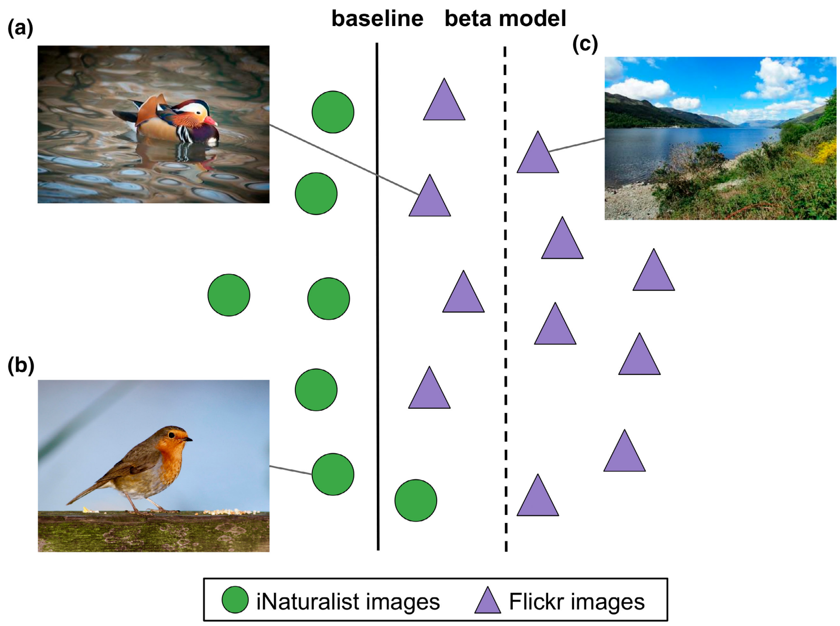

FIGURE 2 The effect of the β dilution coefficient on the species interaction model's decision boundary. By placing a less strict emphasis on the training labels, applying the β coefficient allows more images within the Flickr dataset to be identified as human–species interactions. For example, image (a) joins image (b) as a human–species interaction as a result of the decision boundary being moved versus the baseline model, while image (c) is still predicted as a generic interaction.

2.3.4 | Selecting the dilution coefficient

To help identify the most optimal β dilution coefficient, we calculated the entropy across the species classification scores predicted by the species classification model (introduced in Section 2.4) in Flickr and iNaturalist observation images in Great Britain. A much larger entropy across Flickr images predicted as human–species interactions as compared to generic image predictions and iNaturalist images would indicate a significant drop in model confidence and suggest the inclusion of irrelevant images as human–species interactions. We calculated entropy as:

$$H = \sum_{i=1}^{n=8142} P(\hat{y}_i) \bullet logP(\hat{y}_i). \quad (3)$$

with H denoting the entropy across the 8142 individual species classification scores $\hat{y}$. As an additional accuracy measure, we also conducted a visual check of the images predicted as human–species interactions in the test dataset at 0.1 softmax intervals for each model with a dilution coefficient. We report these results in Supporting Information Table S1. Based on the model test accuracy statistics, the entropy across the species classification model's predictions and visual inspection of the predictions, the most optimal species interaction model was selected. This model was then used to predict the distribution of human–species interactions on Flickr in Great Britain.

2.4 | Species classification model

To better understand the types of human–species interactions occurring on social media versus citizen science, we applied a second deep learning model to classify the individual species in Flickr images identified as human–species interactions and compared this with iNaturalist. Using the species classification model's predictions, we examined what the most frequently photographed species were at the genus level on Flickr versus iNaturalist. To make the fairest comparison and control for biases between datasets, we also ran the model on the images of the iNaturalist observations and used its predictions to compare the two datasets.

To classify species in images, we applied the pretrained 2018 iNaturalist competition winner model, which is capable of detecting 8142 species. The model consists of a fine-tuned Inception V3 deep learning model, pretrained on ImageNet.[1] Because the model is trained to identify species sampled from a global geographic range, we were not primarily interested in using the individual species classifications as many would not be present in Great Britain. Rather, we were interested in their corresponding genus, family and species class classifications, hypothesising that their accuracy would be sufficient to analyse the types of human–species interactions occurring.

Still, we felt it necessary to apply a second filtering step when conducting our analysis at the genus and family levels because model accuracy was found to be fairly low at these classification levels versus the taxonomic data associated with iNaturalist observations (Supporting Information Table S2 and S3). This second image filter excluded all species images with a classification score entropy higher than 2.42. This cut-off point was identified based on the entropy distribution across the iNaturalist image predictions, 2.42 reflecting the mean entropy of image classification scores in the dataset (Supporting Information Figure S2). At species class level this filter was not needed because accuracy at phylum level was already found to be high at 89%. However, at genus and family level, accuracy needed to be improved to support the reliability of the results.

2.5 | Comparison to biodiversity

2.5.1 | Bird species richness

Bird biodiversity in Great Britain is of high cultural value, with particular emphasis placed on it through nationwide conservation efforts (Burns et al., 2020). To gain a better understanding of the cultural preferences being expressed on social media, we compared human–species interactions on Flickr with ecological measures of biodiversity as an indicator of wider cultural value. This wider value includes the intrinsic and relational values of nature associated with stewardship and the living existence of species irrespective of any in situ interactions with people (Anderson et al., 2022). To do this, we compared perceived bird species richness based on the number of species in Flickr images with a measure generated using modelled species density data. To better understand the variation in species richness versus citizen science, we also compared the predictions of the species classification model for iNaturalist observations and, as an additional point of reference, human population density which was sourced from the Office for National Statistics (ONS) and the Scottish Statistical Office (ONS, 2019; Statistics Scotland, 2019).

The bird species abundance maps were generated in previous work using generalised additive models (GAMs; Massimino et al., 2015). These modelled species abundance per km^2 at 1 km resolution using explanatory variables including the percentage of different land cover types such as forest, grassland, coastal and urban land cover, as well as a three-dimensional thin plate penalised spline with longitude, latitude and elevation. The models also accounted for the detectability of bird species. We calculated the total number of birds at 10 km resolution and then, to compensate for the high variability in population density across species, we counted a species as present if the density per bird species was greater than its median density. As such, our indicator of species richness using modelled abundance data can be regarded as a high-likelihood measure of species presence on a grid cell basis.

We selected 36 bird species. This included a wide range of species from a number of different habitats including Kestrels, Swallows, Goldfinchs, Mallards, Curlews, Great Tits and Swifts. In some cases we grouped the modelled densities of individual bird species within the same genus to enable a better comparison with the species classification model's predictions at genus level. This was because the model's predictions were more reliable at this taxonomic classification level. As with the bird density maps, we counted the number of Flickr images of bird species per 10 km grid cell using the species classification model's predictions.

In most cases, we used the predictions of the model at the genus level for comparison with individual species. However, in some cases the visual variety within the genus was deemed to be too great to accurately capture the individual species in the bird density maps. In this case, we excluded some of the species model's predictions for individual species classifications within the genus. In other cases, it was more appropriate to group the model's predictions at the family taxonomic level. A full list of the bird species densities used, the corresponding species classification model classes and justifications can be viewed in Supplementary Table S4.

2.6 | Bird species abundance

To examine the relationships between people and bird species in more detail, we also compared the total number of human–species interactions on Flickr with the 36 selected bird species and their total population. In doing so, we sought to gain an insight into the most frequently photographed bird species versus their relative abundance. We did this by summing the modelled bird population densities per 10 km grid cell and comparing this to the total number of Flickr interactions per species. To better understand the individual relationships between species interactions and total population, we fitted a linear model to capture the overall relationship between the two variables. At the same time, we also considered their conservation status in Britain to understand whether this had an effect on the preferences of Flickr users, adding this as a categorical variable to the linear model to test for significance.

2.7 | Threatened migratory species

Finally, we also examined interactions over time on Flickr and iNaturalist with threatened migratory bird species. In doing so, we sought to understand people's preferences for a set of culturally significant and highly valued species from a conservation perspective. At the same time, this also allowed us to validate the interactions against known migratory periods as well as verified iNaturalist observation data. Four migratory bird species were examined: the Nightingale (*Luscinia megarhynchos*), Swifts (*Apodidae*), Turnstones (*Arenaria*) and Wheatears (*Oenanthe*). All species feature on Britain's Birds of Conservation Concern Red or Amber List (Stanbury et al., 2021). We filtered the species classification model predictions using these individual and taxonomic groups with a species model class entropy score < 2.42.

3 | RESULTS

3.1 | Species interaction model

The accuracy of the species interaction models trained using different β coefficients is shown in Table 1. The overall accuracy of the models on the test dataset decreased with the value of the β

Model	Test: overall	Test: generic interactions	Test: species interactions	Entropy: species interactions	Entropy: generic interactions
$\beta = 1$	97.8%	98.0%	97.6%	2.85	5.20
$\beta = 0.1$	97.6%	99.2%	96.0%	2.81	5.25
$\beta = 0.01$	95.6%	99.8%	91.4%	3.06	5.34
$\beta = 0.001$	90.0%	100%	79.0%	3.87	5.42

TABLE 1 Overall accuracy of the species interaction model on the test dataset using different β dilution coefficients and the species classification entropy associated with each models' predictions for the Flickr image dataset in Great Britain. In comparison, a mean entropy of 2.42 was reported against the iNaturalist observation dataset.

coefficient. The overall accuracy of the baseline ($\beta = 1$) model was high, at 97.8%. The $\beta = 0.1$ model achieved a similarly high 97.6% accuracy, followed by the $\beta = 0.01$ model with a 95.6% accuracy and the $\beta = 0.001$ model, with an accuracy of 90%. Increasing the value of the β coefficient by another factor of 10 to $\beta = 0.0001$ failed to produce a working model.

The drop in accuracy in detecting generic interactions in Flickr images can be directly related to the human–species interactions that are also found within the Flickr dataset. This was also reflected in the ability of the $\beta = 0.001$ model to predict images from iNaturalist as human–species interactions with almost perfect accuracy. This shows how the dilution coefficient enables the model to detect a wider range of human–species interactions. However, there was a much larger drop in accuracy in detecting generic interactions relative to this accuracy improvement and versus the accuracy of the baseline model. We therefore found the $\beta = 0.01$ model to be the most optimal in terms of its accuracy on the test dataset, maximising its ability to detect human–species interactions while maintaining a high level of overall accuracy.

For each β model's image predictions of human–species interactions, we also calculated the mean entropy across the species class scores predicted by the species classification model. We found entropy to increase from 2.85 for the baseline model to 3.87 for the $\beta = 0.001$ model. This amounted to a 36% increase. For the $\beta = 0.1$, a much smaller increase of 1% to 2.89 was observed, with a small increase of 7% for the $\beta = 0.01$ model. The entropy recorded against the models' generic image predictions stayed relatively similar, only increasing from 5.20 for the baseline to 5.42 for the $\beta = 0.001$ model. In comparison, the entropy recorded for the species model predictions on the iNaturalist dataset for Great Britain was 2.42.

A full set of randomly sampled images of each β models' predictions at different confidence levels can be found in Supporting information Table S1 online. Overall, we observed a good ability by the $\beta = 0.01$ model to identify species images, even at low confidence levels, with a very small amount of generic-type images present among the models' predictions and the most and least confident predictions staying consistent. Based on these results, the test accuracy and species model entropy, we selected the $\beta = 0.01$ model to predict human–species interactions using Flickr images in Great Britain.

3.2 | Human–species interactions

Table 2 shows the total number of species interactions and interactions per user on Flickr for the main taxonomic groups. In all cases, the median number of images per user was quite low at one to two images. Birds were the most popular species with 349,522 images taken by 24,912 users. These saw the highest average amount of 14 images per user with one user taking 21,086 images. Plants were the second most popular species, with 254,852 images taken by 24,352 users, similar to birds. The maximum number of images taken by one user was much lower at 3064 images.

Insects were captured in 135,596 images by 12,616 users, about half of the level of activity for plants, with a similar average number of images per user. Mammals were captured by more users than insects, with 16,146 users, but there were less images at 92,032 interactions. Reptiles and Fungi saw a further drop in the number of interactions and users. In total, the species interaction model identified 941,812 images, representing 44,523 users. These took on average 21.2 species images each with one highly active user taking 27,930 images.

Figure 3 shows the spatial distribution of species images on Flickr in Great Britain, and is compared to iNaturalist observations at a more local scale for different species groups in the Peak District and Greater London area. At national scale, human–species interactions were concentrated around urban areas with large cities such as London, Birmingham, Manchester, Edinburgh and Glasgow showing some of the largest concentrations of interactions. On the other hand, higher elevation areas such as Snowdonia National Park in Wales, the North Pennines in England and the Scottish Highlands showed very little amounts of interaction.

At a more local scale, differences in the types of human–species interactions occurring on Flickr versus iNaturalist could be observed. Flickr users appeared to have a stronger preference for mammals, as observed in the Peak District, with similar levels of interaction with bird species in both the Peak District and Greater London area, although in different areas. For plant species, Flickr users showed lower levels of interest as compared to iNaturalist, both in the Peak District and Greater London area. This difference was even more pronounced for insects, as observed in the Greater London area,

TABLE 2 The total number of human–species interactions per user and taxonomic class on Flickr.

Species	Number of images	Number of users	Images per user (median)	Images per user (mean)	Images per user (max)
Birds	349,522	24,912	2	14	21,086
Plants	254,852	24,352	2	10.5	3064
Insects	135,596	12,616	2	10.7	4546
Mammals	92,032	16,146	1	5.7	4431
Reptiles	31,402	9167	1	3.43	957
Fungi	19,866	5202	1	3.82	1133
Other	58,542	23,058	1	2.54	470
Total	**941,812**	**44,523**	**2**	**21.2**	**27,930**

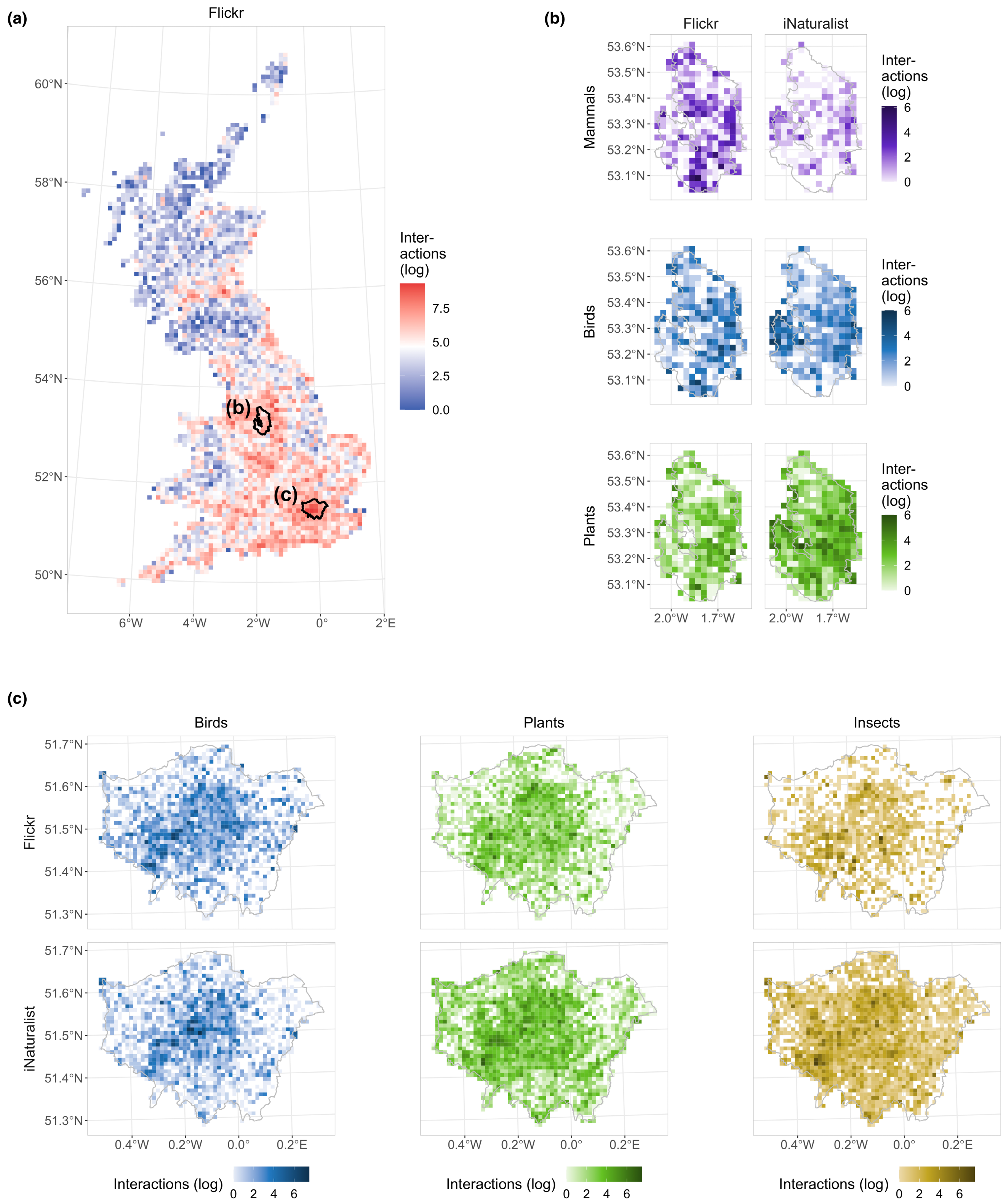

FIGURE 3 Distribution of (a) all human–species interactions on Flickr in Great Britain at 10 km resolution, (b) human–species interactions by taxonomic class on Flickr and iNaturalist in the Peak District at 2.5 km resolution, as well as (c) human–species interactions by class and source in the Greater London area at 1 km resolution. A full species count comparison between Flickr and iNaturalist at the national level can be found in Supporting Information Figure S3.

with a much larger number of interactions on iNaturalist versus Flickr.

The tendency of Flickr users to capture large, common species was also evident at the genus classification level (Figure 4). Flickr users took the most pictures of swans, ducks and robins. Herons were also popular, as were squirrels, black geese, deer, gulls, thrushes and white/grey geese. In comparison, iNaturalist users took the most pictures of butterflies with three genera appearing in the top 10 most popular classes. Geraniums, lady bugs, honey bees and clover where also popular, again reflecting a much larger interest in plants and insects versus Flickr users. However, similar to Flickr, ducks, swans and thrushes were also captured a large number of times. Notably, the number of images per species was also more evenly distributed on iNaturalist than on Flickr.

3.3 | Comparison to biodiversity

3.3.1 | Bird species richness

Figure 5 shows a comparison of species richness based on models of species abundance versus perceived species richness on Flickr and iNaturalist for a selected group of 36 bird species. Most of England and Wales saw a high level of species richness, with reductions in large urban areas such as London, Birmingham and Manchester. On the other hand, very low species richness was recorded in higher altitude areas such as Snowdonia National Park in Wales, the Yorkshire Dales and the Peak and Lake Districts. Similarly, the high altitude areas of Scotland including the Scottish Highlands also saw low bird species richness. However, richness increased further south in Scotland around key urban centres such as Edinburgh and Glasgow.

In contrast, the perceived species richness on Flickr was mainly concentrated in areas with large human populations such as London and other big cities in the north including Birmingham, Sheffield and Leeds. Coastal cities also saw a large variety of species captured by Flickr users, including Portsmouth and Exeter in the south. Two notable exceptions were the coastal and wetland areas on the northern coastline of Norfolk, England which saw a concentration of perceived richness away from a major urban centre. Also notable was the moderate amount of species richness perceived in some higher elevation areas such as in the Peak and Lake Districts, even in the northern part of the Cairngorms national park, in contrast to the species richness based on models of species abundance.

Higher perceived species richness in urban areas also occurred on iNaturalist and in similar cities such as in London and Edinburgh as well as the large cities in the north including Birmingham and Sheffield. However, notably, a much larger number of species were observed in and around the cities of Liverpool and Manchester. Higher elevation areas including the Lake and Peak Districts as well as similar parts of the Cairngorms, like Flickr, saw moderate amounts of perceived species richness. The higher level of perceived richness on the north coast of Norfolk was also observed for iNaturalist.

3.4 | Bird species abundance

Figure 6 shows the comparison between people's interactions on Flickr with 36 bird species and species population as well as their

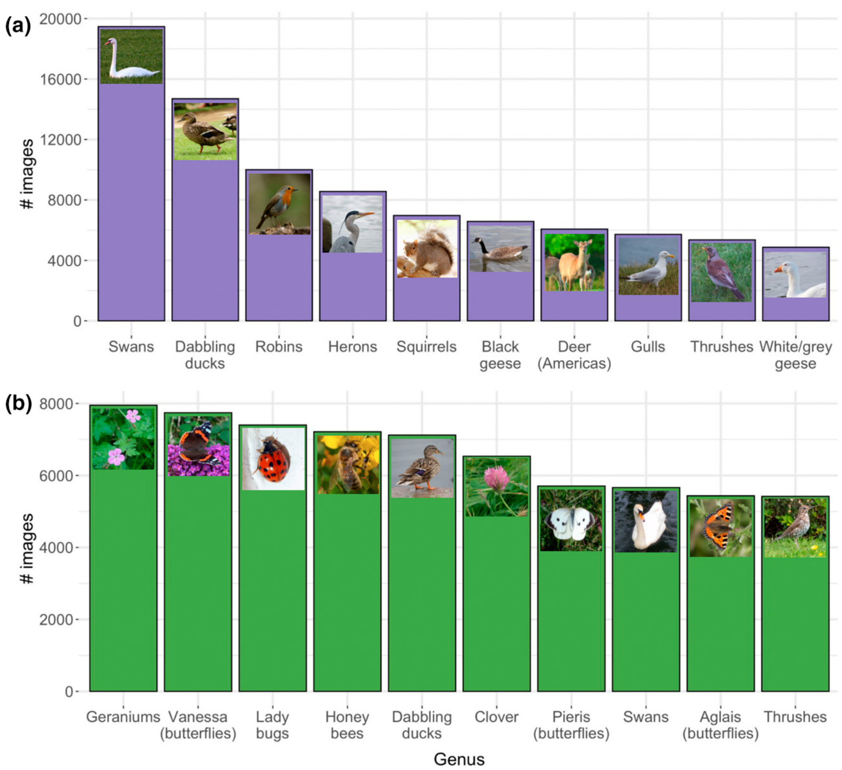

FIGURE 4 The most popular genera predicted by the species classification model in (a) Flickr species images and (b) iNaturalist observation images. Photos (top left to bottom right) © sagesolar, Peter Trimming, Peter Trimming, Gareth Williams, Steve G Jones, Steve Parker, Peter Hurford, Daniel, Ron Knight, Julian Burgess, Daniel Cahen, William Stephens, Barry Walter, William Stephens, Stephen McWilliam, Daniel Cahen, Barry Walter, Jon Mortin, Alec Mcclay, Don Loarie (cc-by-2.0 and cc-by-4.0, cropped from originals). Species model accuracy statistics against the iNaturalist observation dataset can be found in Supplementary Table S3.

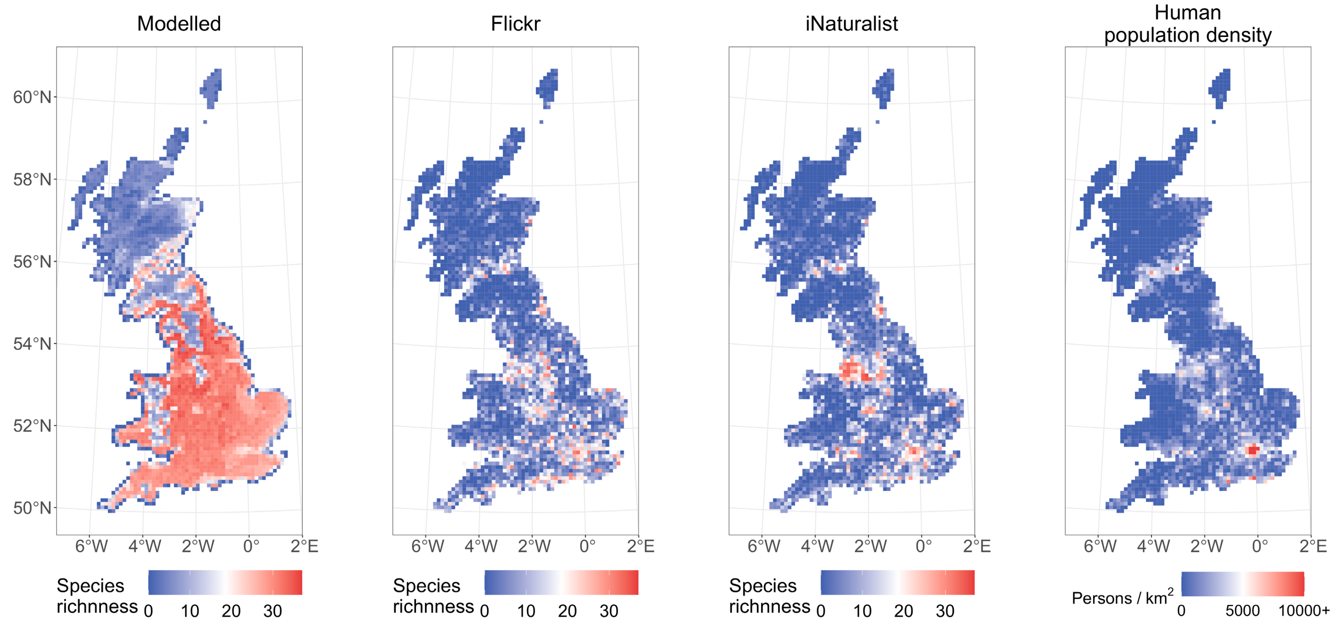

FIGURE 5 Species richness for a selection of 36 bird species calculated using models of species abundance, in comparison to the perceived species richness observed on Flickr ($R^2 = 0.14$) and iNaturalist ($R^2 = 0.12$) using the deep learning model predictions. Human population density is shown as an additional point of reference. The maps show different perceptions of species richness on Flickr and iNaturalist ($R^2 = 0.49$), with activity linked to high population areas.

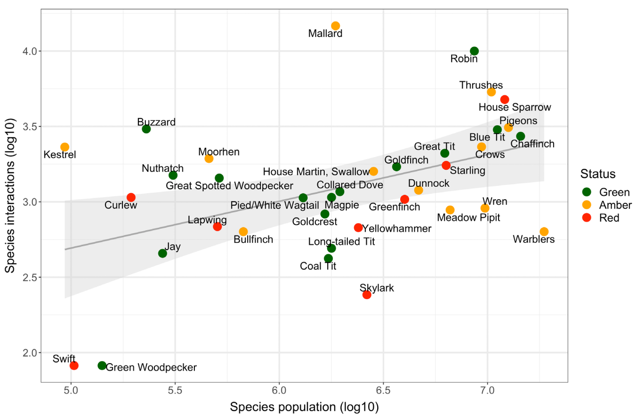

FIGURE 6 The total interactions on Flickr for a selection of 36 bird species compared to their total modelled population and conservation status in Britain. The grey line shows the line of best fit between interactions and total population with 95% confidence intervals ($R^2 = 0.17$). This shows a weak overall relationship and highlights a division between species more or less frequently photographed relative to their abundance. Conservation status was not found to be significant when it was added as an additional categorical variable to the linear model (Amber, p-value = 0.4 and Red, p-value = 0.7, $R^2 = 0.14$).

conservation status. A weak relationship was found between the two variables based on the linear model ($R^2 = 0.17$). A general divide can also be observed, as highlighted by the line of best fit, which shows two general groups of species. One group, below the line of best fit, see less interactions relative to their overall abundance while another group, above the line of best fit, see more interactions relative to their abundance. This pattern is most prominently featured towards the left side of the figure with large, charismatic and visible birds such as the Kestrel, Buzzard, Great Spotted Woodpecker and Nuthatch experiencing a large number of interactions relative to their population. Similarly, coastal and wetland birds such as the Curlew, Moorhen and Mallard also see a much larger amount of interactions versus their population.

Bird species that experienced similar levels of interactions versus their population included the Goldcrest, Magpie, Goldfinch, Great and Blue Tit as well as Thurshes, Crows, the House Sparrow and Pigeons. On the other hand, other small birds such as the Long-tailed Tit, Coal Tit, Meadow Pipit and Warblers saw less interactions relative to their abundance. Similarly, the Skylark saw a lower relative amount of interaction versus its total population. Swifts and the Green Woodpecker experienced very little amounts of interaction relative to their small population sizes. Overall, conservation status did not determine any kind of relationship between interactions and species abundance as an additional categorical variable to the linear model (Amber, p-value = 0.4 and Red, p-value = 0.7, $R^2 = 0.14$).

3.5 | Threatened migratory species

The total monthly interactions on Flickr and iNaturalist with four threatened migratory species are shown in Figure 7. The Nightingale saw no or less than one interaction per month from October to February. Interactions started increasing from March up till May at which point interactions began falling again to September.

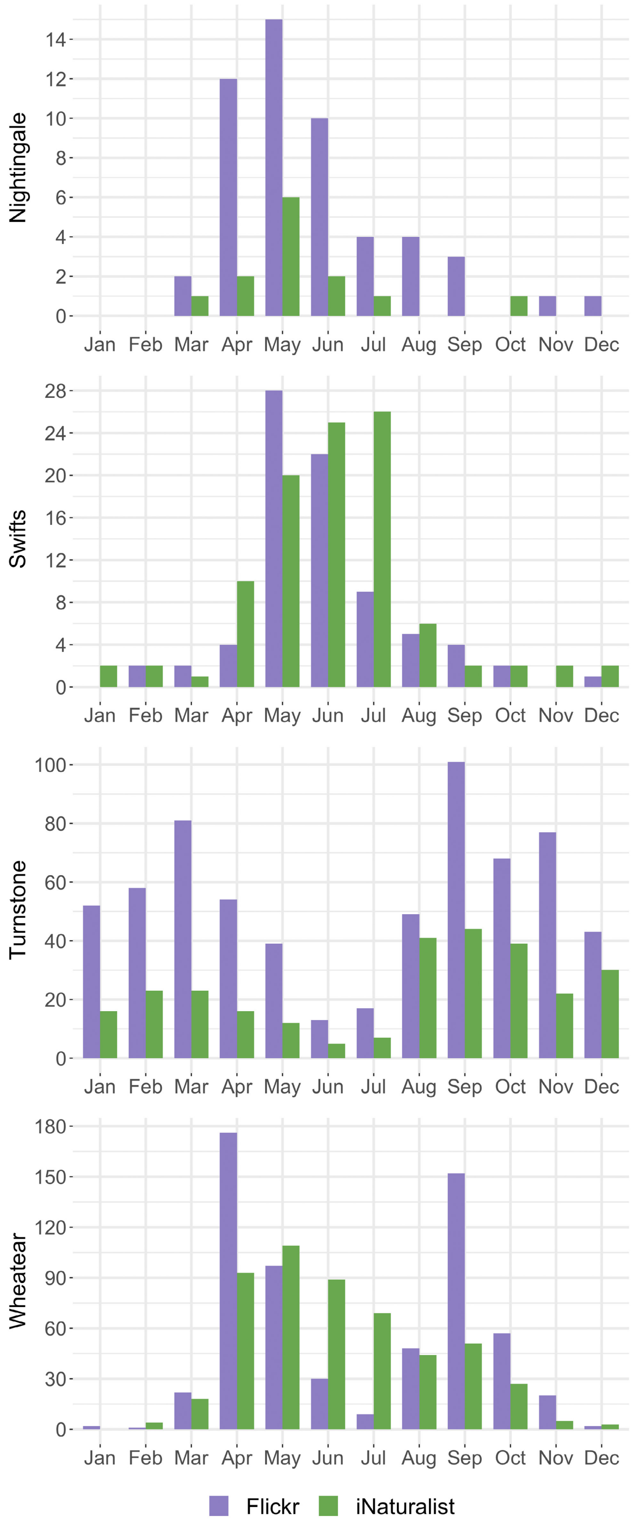

FIGURE 7 Total monthly interactions on Flickr and iNaturalist with migratory bird species of conservation concern.

There were a much larger number of interactions on Flickr versus iNaturalist.

Swifts saw a similar pattern of monthly interactions with interactions increasing from a very low baseline in April up into the summer months of June and July, before dropping off in August. In this case, there were similar amounts of interactions on Flickr versus iNaturalist with interactions on Flickr weighted towards the spring months and iNaturalist observations towards the summer months.

A different pattern in monthly interactions was observed for the Turnstone. In contrast, interactions peaked twice in the year. June and July saw the lowest amount of interactions, with interactions increasing up to the late summer and early winter months, before decreasing to a lower level, although higher than the lows in June and July. Interactions then peaked again around February and March. As with Nightingales, there were a much larger number of interactions on Flickr than on iNaturalist.

Lastly, for the Wheater, two peaks in the number of interactions were also observed which were again much more pronounced on Flickr than on iNaturalist. The first peak occurred in April/May and the second in August/September. This time, a slightly different pattern was observed in the interactions occurring on iNaturalist with much more interaction occurring on iNaturalist in June and July in comparison to Flickr.

4 | DISCUSSION

4.1 | Predicting cultural preferences for biodiversity using deep learning

Previous research has categorised images on social media related to human–species interactions using deep learning (Cardoso et al., 2022; Edwards et al., 2021; Lee et al., 2022). However, our study represents one of the first studies to do this at scale, using crowd-sourced data and with spatial metrics linked to specific species, a key research frontier in the field of CES research (Gould, Bremer, et al., 2020), especially in relation to biodiversity (Echeverri et al., 2020). Drawing on such a large dataset of images from iNaturalist meant the interactions of a wide range of people could be incorporated into the species interaction model. In turn, the inherent noise in the Flickr data could be better accounted for with the implementation of the β dilution coefficient. This meant the scope of cultural interactions with individual species could be expanded to include a broader representation of interest on Flickr without the need for manual labelling by the authors themselves.

The implementation of the β dilution coefficient drew on previous work in the machine learning literature surrounding noisy labels (Marcos et al., 2022; Reed et al., 2015). As a technical solution for deep learning applications, this limits overfitting and enables models to generalise better across new datasets (Song et al., 2020). We have used this technique to capture a broader set of interactions, and therefore preferences, between the two datasets, with accuracy improvements reflecting back on the percentage of species images captured by the model in the iNaturalist dataset. Further visual inspection confirmed the predictions as reliable. However, this also revealed that the β model approach did not solve the problem completely, as a small number of more generic images in the model's species image predictions remained such as images of stone carvings or people in natural settings. Nevertheless, the model's most confident predictions remained consistent. To further validate its predictions, the image tags and descriptions could be used which often contain information related to the purpose of the image (Havinga et al., 2021b). To address this issue, a more conservative β coefficient may also be utilised, as the $\beta = 0.1$ model revealed. Nevertheless, the level of entropy associated with the $\beta = 0.01$ model's species image predictions versus the baseline model did not show a substantial increase (7%) which suggests the $\beta = 0.01$ is still a valid choice in capturing the cultural preferences being expressed for individual species on social media.

The application of the species classification model connected cultural preferences to specific ecosystem features in the form of individual species classes. This is an important focus of CES research (Gould, Bremer, et al., 2020) and has also been highlighted in research linked to social media (Gould et al., 2019; Lee et al., 2022). However, some uncertainties associated with the species classification model's predictions should still be considered. Overall, across 8142 species classes, the accuracy of the species model at the genus level was fairly low without a filter and led to an overall accuracy of 32% (Supporting Information Table S2). This improved to 50% by applying the entropy filter. A more conservative entropy filter could further improve accuracy at the expense of reducing the size of the obtained dataset. However, the accuracy of the model varied with the genus (Supplementary Table S3). The majority of the most frequently captured genera were identified with 70% accuracy or more and the observed drop only concerned a limited amount of genera. This can be attributed to the great visual similarities between some species classes, such as in the case of the American deer *Odocoileus* genus, which was predicted as one of the most frequently captured species in Flickr images. This species is very similar in visual appearance to the European fallow deer *Dama dama*. In these cases, accurate model predictions at the family, order and phylum level can still provide useful information about how people are expressing preferences for specific species.

4.2 | Differences in user preferences between social media and citizen science

The results of our study reveal key differences between the interactions occurring on social media and citizen science. This was in line with our hypothesis that Flickr and iNaturalist users would express different preferences for individual species and supports calls to include a wider variety of big social datasets in CES assessment (Ghermandi & Sinclair, 2019; Scowen et al., 2021). Accurate information on the demographics of social media users is very difficult to obtain, especially at large scales (Lenormand et al., 2018). In the absence of such information, a greater number of datasets representing the cultural preferences of a wider range of people can produce a more representative picture of the CES being generated by nature, so-called 'data mashups' (Ghermandi & Sinclair, 2019). This would begin to account for the various motivations and preferences of people using different platforms such as Flickr and iNaturalist (Samani et al., 2018). For example, iNaturalist users have been found to upload a higher proportion of interactions than Flickr users in conservation spaces, suggesting a greater interest in ecology (Lopez et al., 2020).

In our study, Flickr users mostly shared their interactions with large, charismatic species, common to urban areas, with birds as the most popular type of species. This was in contrast to iNaturalist users, who were most interested in smaller species, including plants and insects. This trend was also visible at a spatial level, with users' activity concentrated in different areas. For example, in the case of people's interactions with bird and plant species in the Peak District (Figure 3). Our results are similar to those of other studies that show large-bodied mammals and birds are more frequently captured on Flickr versus iNaturalist, as well as other social media sites and surveyed preferences (Hausmann et al., 2018; Lopez et al., 2020). This may be because Flickr users can more easily capture these type of animals from a distance with high-specification cameras (Singla & Weber, 2011). Different user groups active on both platforms may be driving these differences, such as the active digiscoping community on Flickr (Lee & Tsou, 2018). As a result, Flickr can be a good additional source of data alongside citizen science data due to the number and variety of interactions occurring in the same locations (August et al., 2020; Mancini et al., 2018). While people of different ages and genders have been found to be active on Flickr (Cox et al., 2008; Kipp et al., 2017; Lenormand et al., 2018), citizen science volunteers are often middle aged, white and male (Aristeidou et al., 2021; Cooper et al., 2021).

Nevertheless, although we found differences in user preferences between platforms, these may only reflect the varying preferences of a small number of people (Mancini et al., 2019; Tenkanen et al., 2017). We discovered strong user biases within our results such as the 27,930 human–species interactions occurring through one user, about 3% of the total number of interactions (Table 2). For large-scale assessments, including national assessments, it is important that a representative sample is collected (Hein et al., 2020; Raymond et al., 2014). These biases therefore present a key challenge in capturing a complete range of preferences using these new methods (Ghermandi & Sinclair, 2019). Still, these biases highlight the importance of using a combination of data sources as these may prove to be complementary in gaining a more representative measure of CES (Tenkanen et al., 2017; Wilkins et al., 2022). Our study also highlighted how combining multiple data sources with a spatial approach can help in identifying a greater number of potential CES hotspots despite user biases (van Zanten et al., 2016).

4.3 | Comparison with bird biodiversity indicators

A large number of environmental policy and conservation efforts in Great Britain are focused on bird biodiversity (Burns et al., 2020). The importance placed on bird biodiversity through these efforts reflects the intrinsic and relational values of people (Anderson et al., 2022). This value, however, was not captured by people's activity on social media in our study with a mismatch between user–bird interactions and modelled abundance data. While some studies have found a connection between higher levels of biodiversity and first-hand cultural appreciation (King et al., 2017; Lindemann-Matthies et al., 2010), our comparisons at national level did not. For example, the perceived species richness of the 36 selected species on Flickr and iNaturalist was highest in urban areas. A misalignment between people's first-hand experiences and actual biodiversity has been reported in similar studies at smaller scales (Belaire et al., 2015; Dallimer et al., 2012; Graves et al., 2017). Preferences for bird species also showed no clear relationship with conservation status, nor were interactions necessarily related to species abundance. This further highlighted the effect of species visibility in terms of size, charisma and preferred habitat on the level of interaction, including factors such as the quality of photography equipment needed to capture some species (Singla & Weber, 2011). For example, the large number of interactions with Kestrels and Buzzards relative to their total population can be related to their iconic status, size and presence in the skies above open farmland. Mallards and Robins are also very visible and commonly found in urban areas. In contrast, other birds with less amounts of interaction such as the Meadow Pipit and the Skylark, besides its brief song flight, are mostly inconspicuous on the ground in agricultural areas, or Warblers, which are fast-moving and prefer woodland (Sharrock, 1976).

On the other hand, the monthly analysis of interactions with a set of threatened migratory species matched known migratory periods. Both Nightingales and Swifts begin arriving in Britain in April and May and start to leave in July and August (Holt et al., 2012; Hurrell, 1951). Turnstones and Wheatears see two key migratory periods in the spring and autumn months, as large populations make their way through Britain (Bairlein, 2008; Branson et al., 1978). This shows how the use of social media data can still enable an accurate analysis of how people express preferences for highly valued species from a conservation perspective (Di Minin et al., 2015). Notably, interactions were also much higher on Flickr versus iNaturalist. Generally, however, the weak connection between interactions and species conservation status shows how social media only reveals very specific interactions between people and biodiversity and therefore can only be directly related to a limited set of cultural preferences as they relate to biodiversity. Nevertheless, we only considered species richness in terms of the 36 bird species we selected. Considering a larger group of species across different taxonomic classes may reveal stronger relationships. For bird species richness, the use of a median threshold to count a bird species as present using the modelled data may also have affected our comparison as this value may not be appropriate for all species (Nenzén & Araújo, 2011).

4.4 | Application in large-scale CES assessments

The specificness with which cultural preferences for biodiversity can be measured using social media and deep learning presents both challenges and opportunities in conducting large-scale CES assessments. The key challenge facing decision-makers in ecosystem management is how to integrate culture in a way that both reveals its diversity and makes it amendable to systematic appraisal (Fish et al., 2016). The scale and level of detail provided by social media and deep learning enable the systematic appraisal of CES at large scales (Egarter Vigl et al., 2021). Such appraisals can support the quantification of CES beyond simple scoring methods (Boerema et al., 2017) and better link ecosystem condition and processes to CES (Gould, Bremer, et al., 2020). For example, we were able to identify specific species and locations generating CES in our study, and capture changes related to threatened bird species through the seasons. This is especially relevant to ecosystem service assessment frameworks such as the SEEA EA which aim to connect CES measurements to national statistics while monitoring ecosystem service supply and ecosystem condition over time (Hein et al., 2015, 2020). Making such information available, and in a format compatible with frameworks such as the SEEA EA, is one important way in which to make the ecosystem service concept more relevant to decision-making (Mandle et al., 2021).

However, in seeking to capture CES at large scales, deep learning and social media-based methods take on a reductionist approach to CES assessment which may ignore important context-specific meanings (Gould, Adams, & Vivanco, 2020). We approached our study of CES in very broad terms, relating human–species interactions to the cognitive enjoyment of biodiversity (Havinga et al., 2020). Still, there are many different individual, collective and sometimes overlapping contexts in which CES are generated and these may have varying degrees of value (Chan, Satterfield, et al., 2012; Fish et al., 2016). Much of this value may not be measurable through the quantification of single human–species interactions because not all are recorded on social media (Calcagni et al., 2019) or because they only emerge through deliberative approaches (Kenter et al., 2016). Nevertheless, the data that are available through social media do make it possible to untangle some of this cultural variation. For example, the text data associated with Flickr images can contain quite specific motivations for people's interactions (Havinga et al., 2021b). At the same time, social media also offers the opportunity to examine collective experiences through the presence of virtual communities (Langemeyer & Calcagni, 2022). It is therefore still important to use a variety of approaches to CES assessment with different epistemological underpinnings (Raymond et al., 2014; UK NEA, 2014).

5 | CONCLUSION

Our findings show that social media and deep learning capture unique cultural preferences for biodiversity, complementing data from citizen science. These data can therefore be used to broaden the range of preferences reflected in CES assessments. At the same time, using deep learning, these preferences can also be linked to specific ecological features, such as individual species classes, further enriching the information available to CES assessments. Nevertheless, social media, as well as the citizen science data available on iNaturalist, represent preferences for species that do not align with measures of bird species richness and abundance. Interactions with a set of threatened migratory species did, however, align with known migratory patterns over time. This shows how the data available through these platforms only captures part of the cultural value of biodiversity, highlighting the benefit of these novel techniques in capturing specific interactions linked to individual species classes but not overall biodiversity. Finally, the advantages of these techniques are especially useful to large-scale CES assessments related to biodiversity which require large amounts of spatial data on people's interactions with nature. Because of this, the application of social media and deep learning can support a wider and more detailed range of CES in ecosystem service assessments, potentially supporting much-needed future efforts in CES assessment at national scale.

AUTHOR CONTRIBUTIONS

Ilan Havinga, Diego Marcos, Patrick Bogaart, Lars Hein and Devis Tuia designed the research; Ilan Havinga and Diego Marcos performed the research; Ilan Havinga, Diego Marcos, Patrick Bogaart and Dario Massimino analysed the data; Ilan Havinga, Diego Marcos, Lars Hein and Devis Tuia wrote the paper; Lars Hein and Devis Tuia provided project administration and leadership. All authors reviewed the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicting interests.

DATA AVAILABILITY STATEMENT

The code and data associated with this study can be obtained at https://doi.org/10.5281/zenodo.7675393.

ORCID

Ilan Havinga https://orcid.org/0000-0001-5380-9784
Diego Marcos https://orcid.org/0000-0001-5607-4445
Patrick Bogaart https://orcid.org/0000-0002-8612-1289
Dario Massimino https://orcid.org/0000-0002-5855-4060
Lars Hein https://orcid.org/0000-0002-4651-2875
Devis Tuia https://orcid.org/0000-0003-0374-2459

ENDNOTE

[1] https://github.com/visipedia/inat_comp/tree/master/2018

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. European sample grid at 25 km resolution to download the Flickr and iNaturalist image training dataset showing the block-out approach used to test, train and validate the model.

Figure S2. Distribution of iNaturalist observation image entropy scores based on the species classification models' predictions.

Figure S3. The percentage of images per species "supercategory" in Flickr species images and the images of iNaturalist observations, as predicted by the species classification model.

Figure S4. Prediction confidence score distribution on the Flickr data in Great Britain using the beta = 0.01 model for human-species interactions (1.0 = most confident).

Table S1. Randomly sampled images (hyperlinks) of the species interaction model's predictions using different beta coefficients. Confidence bands reflect the confidence of the image being a species image (species image => 0.5, max = 1). Figure S4 shows the distribution of scores for the beta = 0.01 model.

Table S2. Overall accuracy of the species classification model at different taxonomic levels.

Table S3. Overall accuracy of the species classification model with a <2.42 entropy filter on the iNaturalist observation dataset for the most frequent genera predicted on Flickr and iNaturalist.

Table S4. Bird density and species model class groupings to conduct the biodiversity comparison.

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