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RESEARCH ARTICLE

Large-scale mammal monitoring: The potential of a citizen science camera-trapping project in the United Kingdom

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Abstract

1. In light of global biodiversity loss, there is an increasing need for large-scale wildlife monitoring. This is difficult for mammals, since they can be elusive and nocturnal. In the United Kingdom, there is a lack of systematic, widespread mammal monitoring, and a recognized deficiency of data. Innovative new approaches are required.
2. We developed MammalWeb, a portal to enable UK-wide camera trapping by a network of citizen scientists and partner organizations. MammalWeb citizen scientists contribute to both the collection and classification of camera trap data. Following trials in 2013–2017, MammalWeb has grown organically to increase its geographic reach (e.g. ~2000 sites in Britain). It has so far provided the equivalent of over 340 camera trap-years of wild mammal monitoring, and produced nearly 440,000 classified image sequences and videos, of which, over 180,000 are mammal detections.
3. We describe MammalWeb, its background, its development and the novel approaches we have for participation. We consider the data collected by MammalWeb participants, especially in light of their relevance to the main goals of wildlife monitoring: to provide spatial data, abundance data and temporal behavioural data.
4. MammalWeb can complement existing approaches to mammal monitoring. Explicit accounting for spatial and temporal patterns in animal activity enables accounting

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of bias relative to ad hoc observational data. Estimating abundance presents challenges, as for many camera-trapping studies, but we discuss the potential of the data as they stand, and opportunities to advance their value for abundance estimation.

5. Challenges remain to MammalWeb's central missions of enhancing engagement with and connection to nature, and delivering policy-relevant data on Britain's wild mammals. We discuss these challenges and the opportunities they provide for advances in respect of engagement, science and financial security.
6. Our approach reduces administrative burden and increases spatial coverage and, as such, MammalWeb provides a useful addition to existing case studies of citizen science camera-trapping program design. We believe MammalWeb is an important step towards fulfilling calls for UK-wide mammal monitoring and our description of challenges identifies an agenda for fulfilling that purpose.

KEYWORDS
biodiversity, camera traps, citizen science, conservation biology, engagement, mammal monitoring, population ecology

1 INTRODUCTION

Global ecosystems are undergoing rapid biodiversity loss strongly linked to human activities (Butchart et al., 2010). This loss degrades the ecosystem services provided by wildlife, affecting human livelihoods (Díaz et al., 2006; Perrings et al., 2011). To understand these dynamics, ecological monitoring across large spatial and temporal scales is required (Fischer et al., 2010; Steenweg et al., 2017; Stephens et al., 2015).

Citizen science is a powerful approach to close biodiversity data gaps and inform large-scale conservation efforts (Amano et al., 2016; Devictor et al., 2010; Fraisl et al., 2022). Citizen science biodiversity monitoring contributes to the United Nations Sustainable Development Goals (Fraisl et al., 2020) and its global economic value has been estimated to be over USD 2.5 billion annually (Theobald et al., 2015). Prominent and long-running examples have focused on monitoring birds, as demonstrated by schemes across the United States and Europe (Stephens et al., 2016) and the now-global eBird project (Sullivan et al., 2009), and on lepidoptera, also widespread in Europe (van Swaay et al., 2008). In contrast to birds and butterflies, mammal monitoring on large scales can be difficult, since mammals are often nocturnal, locally scarce and hard to detect (Battersby & Greenwood, 2004; McShea et al., 2015). In the United Kingdom, for example, bird monitoring has been widespread and systematic since the 1960s but there has, over the same period, been a lack of sustained mammal monitoring (Battersby & Greenwood, 2004; Croft et al., 2017; Mathews et al., 2018). Indeed, a recent study utilizing occurrence data from the UK National Biodiversity Network, together with published density estimates for UK mammals, estimated the UK-wild rabbit population to be between 2 million and 255 million individuals (Croft et al., 2017). This degree of uncertainty is problematic, because mammals are often important ecologically, economically and culturally.

MammalWeb is a citizen science camera trapping network to improve data collection for mammal monitoring. Crowdsourcing—a contributory form of citizen science (Shirk et al., 2012)—has been used successfully by many projects to classify professionally captured camera trap images (Locke et al., 2019). A prominent example is the Snapshot Serengeti project hosted on The Zooniverse platform (https://www.zooniverse.org/) which crowdsourced the classification of a 1.5 years backlog of camera trap images of wild African mammals (~1.2 million images) in less than 1 week (Swanson et al., 2016). Partially due to this success, the effort in the Serengeti has been expanded into the Snapshot Safari network, encompassing camera-trapping surveys across southern and eastern Africa (Pardo et al., 2021). Citizen scientists have also deployed camera trap surveys, such as under the American initiatives eMammal (https://www.eMammal.org/) (McShea et al., 2015), Candid Critters (Lasky et al., 2021) or Snapshot Wisconsin (Townsend et al., 2021).

Since 2015, we have collaborated with citizen scientists in the deployment of camera traps and the classification of images. Initially involving local communities in north-eastern England, MammalWeb has expanded nationwide with partnerships with other conservation organizations, schools and museums. Here, we describe the MammalWeb project, platform and model for engagement, consider whether this platform could play a role in improved mammal monitoring for the UK, as envisaged by Battersby and Greenwood (2004), and identify the challenges that must be overcome for that goal to be realized. We aim to identify the potential of, and challenges to, our approach so that our experiences and insights will be of value to other regions.

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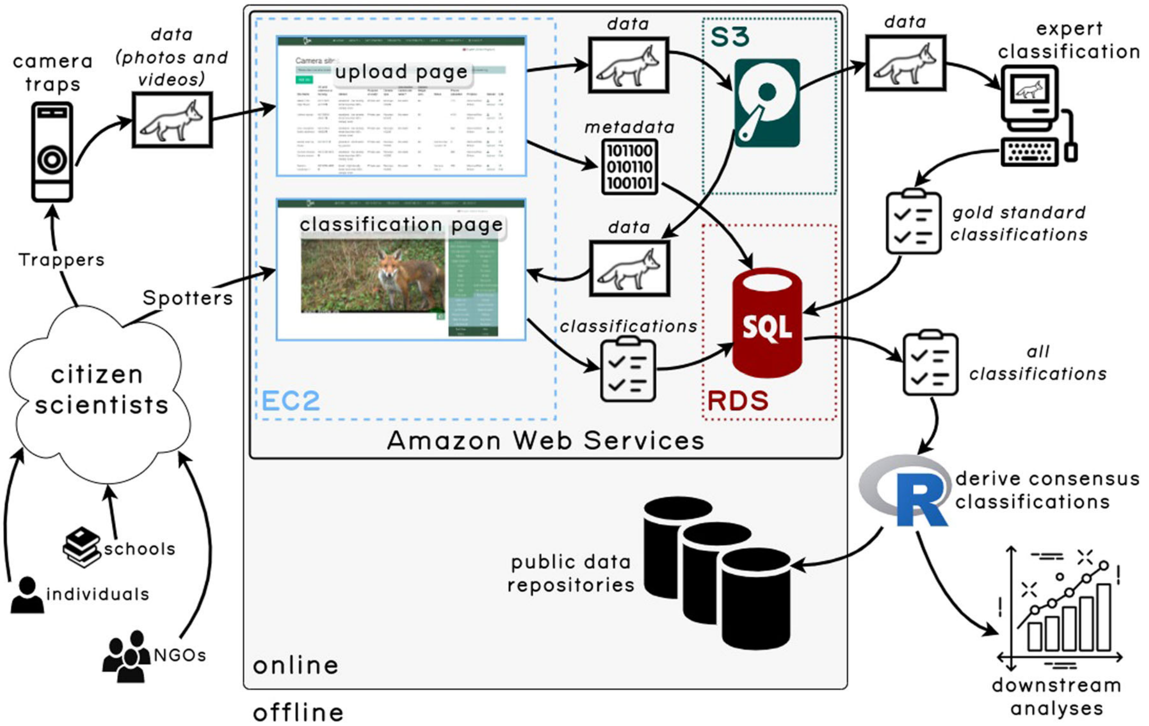

FIGURE 1 MammalWeb project organization. Project participants contribute camera trap photos (with metadata) and classify them on a web platform (https://www.MammalWeb.org/) hosted on Amazon Web Services (AWS). Multiple classifications can be obtained per photo record to achieve consensus, which forms the basis of downstream ecological analyses and submission to data repositories. NGOs, non-governmental organizations; EC2, Amazon Elastic Compute Cloud 2; S3, Amazon Simple Storage Service; RDS, Amazon Relational Database Service

2 | THE MAMMALWEB CITIZEN SCIENCE PLATFORM

2.1 | Background

In 2013/2014, we trialled a web platform at Durham University, UK, as the precursor to MammalWeb. County Durham is located in the north-east of England, an area identified as a 'data desert', due to a lack of high-resolution data on mammal occurrences (Croft et al., 2017).

In 2015, initially as a collaboration between Durham University and the Durham Wildlife Trust (DWT; a non-governmental conservation organization based in County Durham), and with subsequent contributions by a local software company (Rhombus Technology), we re-developed our platform and launched MammalWeb. We partnered with citizen scientists from the local community, including members of the DWT, in deploying camera traps—either their own or on loan from MammalWeb—across the region with ad hoc site selection, and uploading the captured wildlife photos to our web platform via a dedicated page (Figure 1). In addition to timestamps embedded in photos by the camera trap, MammalWeb data collectors were required to report details of their camera trap deployment, such as the camera trap model, location, height above ground, surrounding habitat type and the start and end times of the period of deployment to which each set of uploaded images related. This way, we sought to go beyond the value of ad hoc observational data, to measure effort and other covariates that might help to explain the frequency of detection of different species.

2.2 | Platform architecture

MammalWeb is hosted on the Amazon Web Services (AWS) Elastic Compute Cloud (EC2) with web interfaces for image data upload and classification, as well as data visualization. The user-facing front-end (the web platform) is managed using the Joomla! content management system, with custom code to link content and user actions to the back-end (the database and stored files). Images are stored on AWS Simple Storage Service (S3), while classifications and metadata are stored in a MySQL database (MySQL AB et al., 2015) running on the AWS Relational Database Service (RDS) (Figure 1). We have submitted a subset of our camera trap dataset to a repository on the Open Science Framework (OSF), and are working towards a streamlined, automated process for submission to the UK National Biodiversity Network (NBN) (see Data Availability Statement).

Registered MammalWeb citizen scientists can adopt two primary roles on the site. 'Trappers' deploy camera traps and contribute data. 'Spotters' classify the species pictured in image sequences. Trappers are asked to follow a data collection protocol but are free to choose the location for their camera's deployment, and whether to record photo sequences (three shots per trigger is recommended) or videos. Anyone can register on MammalWeb to classify animals within the contributed camera trap photos. They are presented with a sequence of photos taken in quick succession, or with a video, and the user tags it with species selected from a list (Figure 2) which includes plausible species of mammals and birds that might be encountered,

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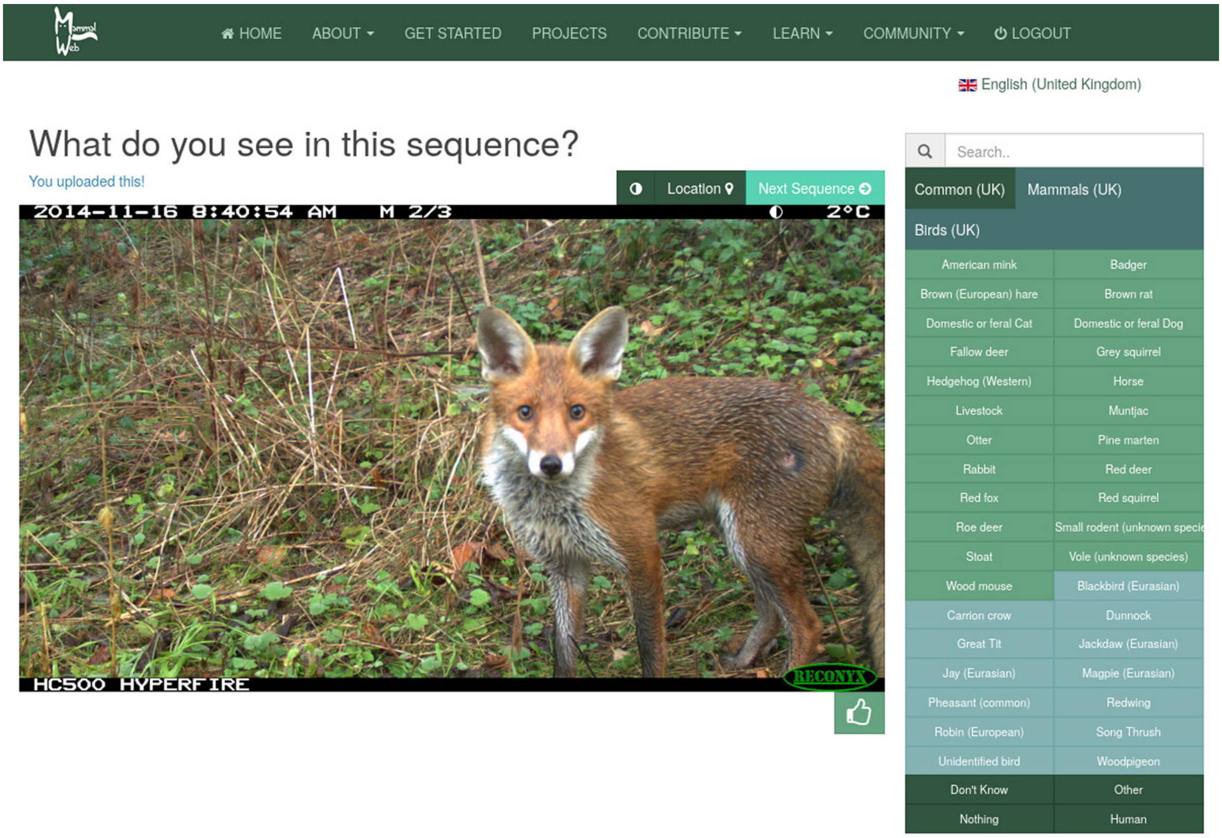

FIGURE 2 MammalWeb camera trap 'Spotter' classification page, where animals in camera trap photo or video sequences captured by citizen scientists can be identified and tagged

based on the specific project (described below). Having selected a species that they believe to be present in the images, the participant can add information on the number of individuals, and age (adult, juvenile or unknown) or sex (male, female or unknown) categories. 'Unknown' is the default for age and sex. To safeguard the privacy of any humans who might be inadvertently recorded by camera traps, any image tagged as 'Human' will not be shown again to other users. Since protected or threatened species might be recorded by MammalWeb-hosted projects, we limit the spatial resolution of publicly viewable camera trap data to 0.1×0.1 degrees of latitude and longitude (approximately 70 km^2). This is reflected, for example, on MammalWeb's maps for visualization of wildlife occurrences (https://www.mammalweb.org/en/discover-view). Additionally, we classified a subset of images as a gold standard to which user-contributed classifications could be compared (Hsing et al., 2018a).

2.3 | Participation, growth and engagement

Since its inception, MammalWeb citizen scientists have collected 617,000 image sequences and videos (totalling nearly 1.7 million image and video files) over 340 camera trap years of observation time, and across over 2300 sites (Figure 3). Of the collected camera trap image sequences, over 70% have received at least one classification so far from a citizen scientist. Median length of camera trap deployment is 32.7 days, with 90% of total deployments between 1.3 and 270.2 days.

As the project developed, recruitment of participants was initially by word of mouth, and the numbers of participants, volume of data and geographic spread of the project tended not to show sharply accelerating growth (Figure 3). Recruitment of new participants is now achieved through a variety of outreach and engagement activities including public talks to wildlife groups (both in-person and online), media articles and social media. MammalWeb has active accounts on Facebook, Twitter and Instagram (@MammalWeb) which provide potential to reach large and diverse audiences and which generate a significant proportion of new sign-ups. Engaging people via remote methods such as via social media and online talks has been of particular importance over the last 2 years as in-person events have been restricted due to the COVID-19 pandemic. Camera traps have been recognized as a valuable tool for wildlife monitoring during pandemic restrictions (Blount et al., 2021). MammalWeb saw a steep rise in participation in early 2020 (Figure 3a) that was likely due, at least in part, to UK pandemic lockdown and the search for activities that could be done from home. Other more sudden increases in metrics of engagement can be attributed to occasional competitions launched to stimulate wider interest. In one case, we organized a prize draw for a camera trap for Spotters who located one of the Christmas-themed images seeded among camera trap photos. During the 19 days of this competition, 245 newly registered Spotters

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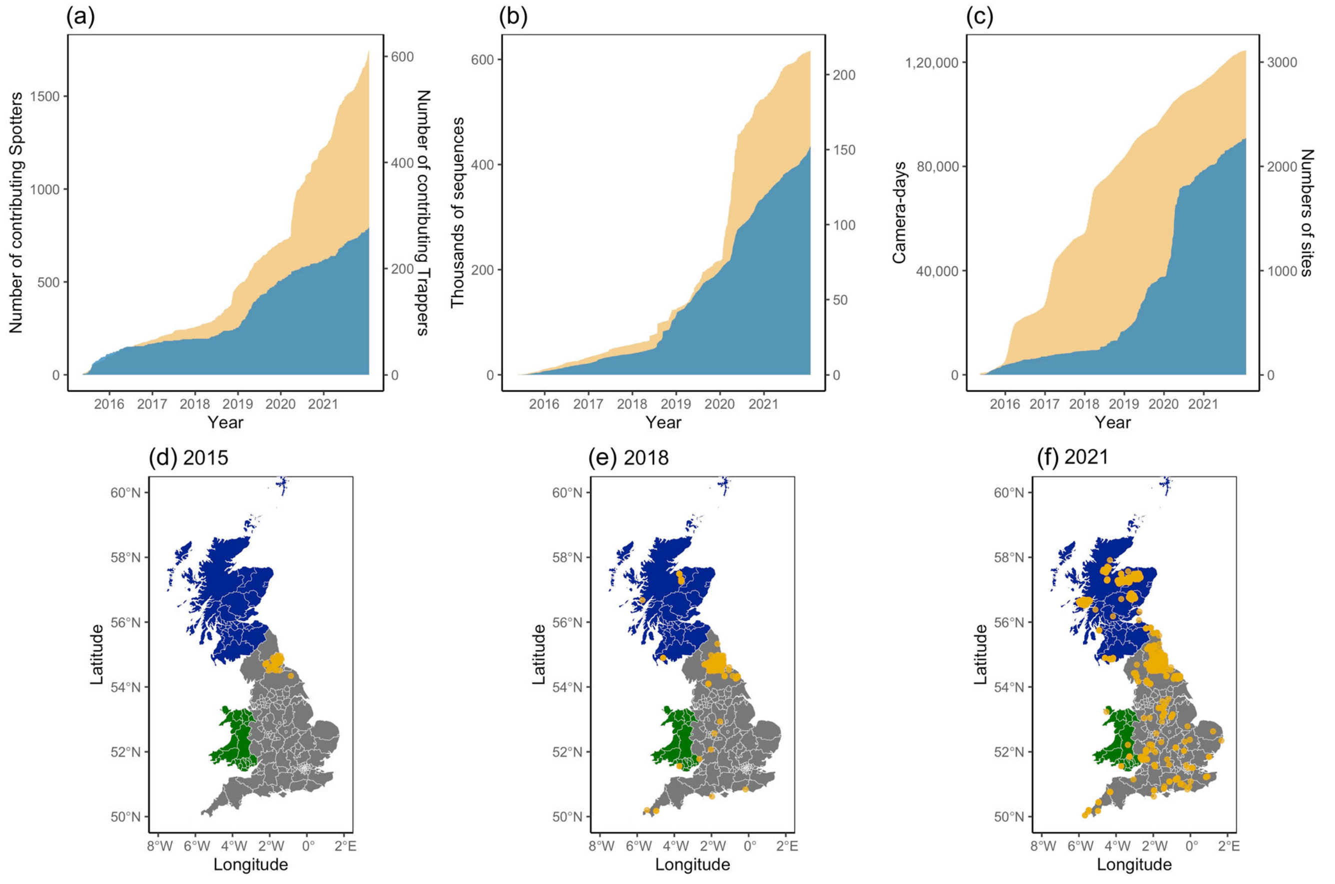

FIGURE 3 Indicators of cumulative growth of the project in Britain: (a) numbers of contributing spotters (orange) and trappers (blue); (b) numbers of sequences submitted (orange) and classified at least once (blue); (c) numbers of camera days (orange) and numbers of sites (blue); spread of cumulative sites (orange circles) by the end of 2015 (d) (94 sites), end of 2018 (e) (409 sites) and end of 2021 (f) (1994 sites)

classified photos (in contrast to 12 and 22 newly registered Spotters in equivalent periods before and after, respectively), and an 87% increase in the number of classifications submitted.

Maintaining correspondence with participants and keeping them informed has been shown to be very important for engagement and motivation (Geoghegan et al., 2016; Rotman et al., 2014). Participants may choose to sign up to a mailing list and receive a monthly email containing project updates, quizzes and a Spotters top 10 league table to motive classifications. They can also contact project organizers directly via email or social media to receive assistance or have queries answered. Receiving feedback can be very important for motivation (Baruch et al., 2016; Geoghegan et al., 2016); while we cannot yet give classifiers direct feedback on the accuracy of their classifications, they can choose to test their knowledge on a 'test yourself' feature of the website. They can also explore summaries and detailed reports of their trapping and spotting efforts, giving them feedback on the data they have generated.

Many individuals deploy camera traps for their own interest, but we have also engaged with other organizations, including schools, museums, community groups and larger non-governmental organizations (NGOs). Our work with schools has shown the potential benefits, particularly for children and young people, of deepening engagement with the natural world, beyond the data collected on mammals. Pupils we collaborated with from a local secondary school developed and delivered public engagement activities, presenting MammalWeb and ecological outreach at local events such as community fairs and the annual Celebrate Science Festival in Durham, which attracted over 2000 attendees (Hsing et al., 2020). These pupils documented their experiences and illustrated the workings of MammalWeb in a short, professionally produced documentary film (https://vimeo.com/237565215; Degnan, 2017) and, notably, co-authored a peer-reviewed publication reflecting on the MammalWeb and school collaboration (Hsing et al., 2020). Work with another group of students who, due to poor mental health, are educated outside of mainstream schools showed that MammalWeb participation had a positive impact on students' well-being, especially during the COVID-19 lockdown (Chapman, 2020). More recently, we have worked with large networks of primary schools; we have partnered with museums, the British Ecological Society and others to deliver engagement programs, lending camera traps out to schools and providing them with additional teacher training, pupil workshops and other resources. Preliminary results from these projects suggest that pupils benefit from involvement with MammalWeb in multiple ways, including increased knowledge and awareness of native wildlife, which is consistent with the eMammal

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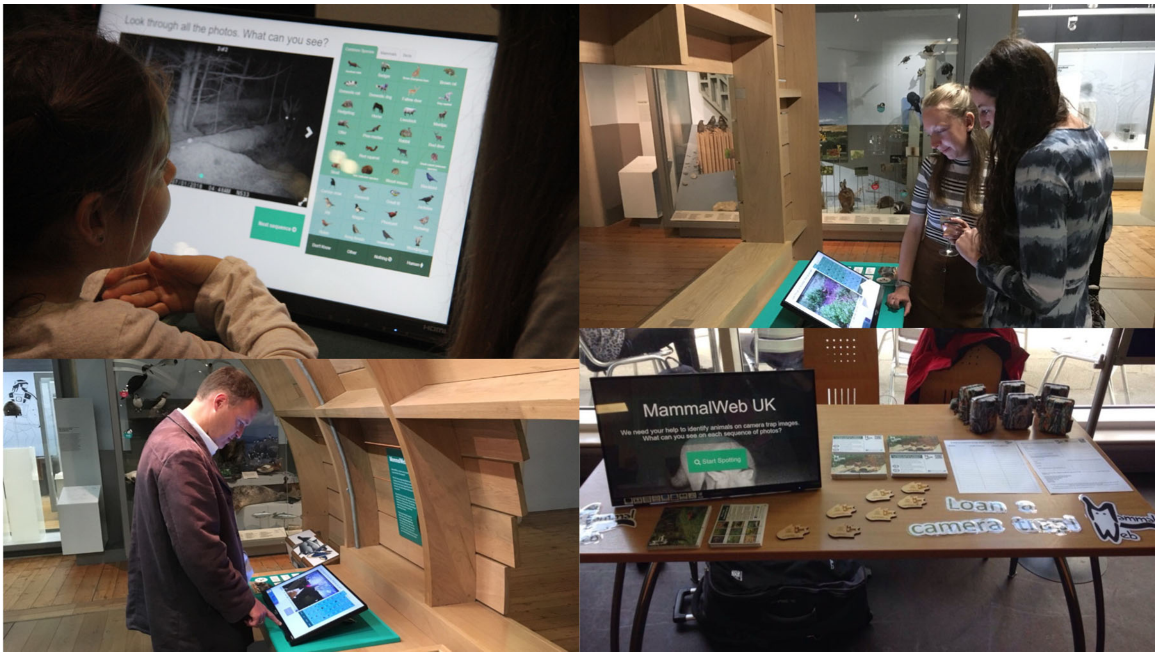

FIGURE 4 MammalWeb engagement at the Great North Museum: Hancock (left two photos); at primary schools (top right); and Mobile MammalWeb at public events (bottom right). Relevant consent was obtained for these photos.

citizen science camera-trapping project in the United States (Forrester et al., 2017)

Two additional innovations have helped us to broaden the groups involved, explaining part of the increase in the number of contributors since 2018. The first of these is hosting 'projects' by partner organizations. This allows user-facing options (such as lists of commonly observed species) to be tailored to the needs of different groups, and allows project administrators to access the data classifications for their project. A range of organizations have utilized this facility, from small-scale community groups to large NGOs or consortia operating at a regional scale. Notably, some MammalWeb citizen scientists initiated their own, independent wildlife surveys and their projects are now also listed. These partnerships help spread awareness of MammalWeb, further increasing participation. Regardless of project affiliation, all registered users can choose to classify images from specific projects or the global pool hosted on MammalWeb.

A second innovation has been the creation of 'Mobile MammalWeb' units, based around touch screens (Figure 4), which are taken to engagement events or placed in public spaces. A single login is associated with the unit and anyone can experience classifying data. These units have been used to interact with thousands of individuals at public events (such as New Scientist Live at London's O2 arena), and have been installed in buildings managed by partner organizations. Currently, for example, Mobile MammalWeb units are installed in the Great North Museum: Hancock (in Newcastle, UK), in the headquarters of the Durham Wildlife Trust and in the visitor centre of Deerbolt Young Offender Institution in County Durham.

As with many other citizen science projects, small numbers of contributors are responsible for collecting and classifying most data (Sauermann & Franzoni, 2015). For example, 34 Trappers (approximately 13%) have submitted 90% of the image data on the site, and 222 Spotters (approximately 15%) have submitted 90% of the existing classifications. Classification accuracy can vary greatly across species (e.g. 95.5% for badgers and 79.8% for hedgehogs; Hsing et al., 2018a); below, we discuss methods for making the process more efficient while accounting for species-specific effects.

3 | THE POTENTIAL FOR ECOLOGICAL INSIGHTS

To identify whether MammalWeb could play a role in the long-term monitoring of Britain's wildlife, we assess its capabilities in relation to the types of data required in wildlife monitoring: distribution, abundance and other temporal/behavioural data.

3.1 | Distribution data

Distribution data (presence-only or presence–absence) can be used to assess where a species occurs, and how that changes over time. Much data on wildlife occurrences consist of ad hoc observations, which can be subject to significant biases, owing to their detectability, activity schedules, habitat affinities and level of public interest (Stoudt et al., 2022). Camera trap data overcome significant biases associated with activity schedules, as well as those associated with the level of interest, but may retain habitat biases. In Britain, for example, rabbits (*Oryctolagus cuniculus*) are thought to be much more common than grey squirrels (*Sciurus virginianus*) (Mathews et al., 2018), but grey squirrel

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sightings are submitted to the National Biodiversity Network much more frequently than rabbit sightings (rabbit ~ 43,000; grey squirrel ~ 123,000, from 1 January 2017 to 25 August 2021; National Biodiversity Network, 2021). This is partly attributable to the diurnal activity and well-recognized non-native status of squirrels, which make them more likely to be observed and reported than the crepuscular and long-naturalized rabbit. In MammalWeb, the bias towards grey squirrels is less pronounced and is likely to be due to the rabbit's preference for improved grasslands and arable areas, which are substantially under-represented in the MammalWeb dataset, relative to the numbers of sites in forest, woodland and urban gardens. These biases can be controlled for, by breaking down analyses by habitat category. It is also possible to integrate camera trap wildlife observations with satellite remote sensing data, such as habitat types or plant productivity that might help to explain the observations (Townsend et al., 2021).

A major challenge in citizen science data is reliability of observations including image classifications (Baker et al., 2021). With large numbers of classifications per image sequence, consensus approaches can yield high confidence regarding the species pictured (Swanson et al., 2016). Even so, on average, we can have 95% confidence that a species is present in a camera trap image sequence with just one user-contributed classification indicating its presence, and seven classifications per sequence would provide 97.5% confidence in the presence of a species (Hsing et al., 2018a).

A further benefit of camera trapping is the potential to capture evidence of the presence of potentially non-native species. Camera trap photos can provide unequivocal evidence, and MammalWeb citizen scientists have reported both non-native raccoon (*Procyon lotor*) and ring-tailed coati (*Nasua nasua*), which have subsequently been removed by the relevant authority. Camera trap evidence of the raccoon in an urban area in northeast England enabled the UK Animal and Plant Health Agency (APHA) to deploy a follow-up camera trap survey and baited trapping to capture the individual. After health checks, the raccoon was sent to The Jungle Zoo in Cleethorpes, England. The coatis were escaped pets that were similarly captured by APHA, and eventually returned to their owner. These examples illustrate additional benefits from a nationwide network of citizen scientist camera trappers in reducing non-native population establishment risk.

3.2 | Abundance data

Although camera trapping has been used to estimate absolute abundance, this has mostly relied on using mark–recapture approaches for animals with individually recognizable coat patterns (Burton et al., 2015). This is not feasible for the majority of British mammals, as few are individually recognizable from their markings, although wildcats (*Felis silvestris*) (Kilshaw et al., 2015) and pine martens (*Martes martes*) (Rosellini et al., 2008) are exceptions that have been the focus of targeted projects on MammalWeb.

Methods are emerging to estimate abundance from camera traps for animals that do not have individual markings (Campos-Candela et al., 2018; Chandler & Royle, 2013; Howe et al., 2017; Luo et al., 2020; Moeller et al., 2018; Nakashima et al., 2018; Rowcliffe et al., 2008). These methods have important assumptions and, at present, the need to measure distance and angle to animals to estimate effective area sampled might place a substantial burden on most participants, both in deploying and calibrating camera traps, and classifying images. Advances in camera trap technology or platforms to measure distance and angle automatically would be beneficial, and initial developments show promise (Johanns et al., 2022; Leorna et al., 2022).

The additional need for a more systematic or predetermined random approach to camera placement is possible with a site 'adoption' approach (discussed below), especially when estimating absolute abundance is the goal. A stratified sampling approach is possible for specific MammalWeb projects, although it would need to be sensitive to issues of camera security and land access. It may be that the metadata available for each site, combined with the potential for subsampling, offers the potential to conduct habitat-specific analysis, but this has yet to be determined.

In the absence of estimates of absolute abundance, could the data from MammalWeb be useful for management purposes? It is possible that using photographic trapping rates to provide coarse categorizations of abundance or trends over time would be sufficient for some. Caughley (1977) argued that estimates of absolute abundance are an unnecessary luxury for many ecological problems. There is evidence for both carnivores and herbivores that, within species, and for specific regional or temporal comparisons, photographic trapping rates derived from camera traps might correlate well to independent estimates of abundance (Nimmo et al., 2015; Rovero & Marshall, 2009). Periodic, more detailed assessments of abundance in selected areas might provide confidence that this is the case for the data generated by MammalWeb.

3.3 | Temporal activity and behavioural data

Camera trapping can provide valuable insights into animal behaviour such as movement patterns (Rowcliffe et al., 2016) and human–wildlife interactions (Parsons et al., 2016). Temporal patterns in behaviour often respond to human activities (Gaynor et al., 2018), and can be readily measured by camera trapping. With measures of effort provided by MammalWeb participants, it is straightforward to assess patterns of activity (as inferred from the probability with which species appear in camera footage) from daily to seasonal scales (Figure 5). These analyses could be refined to subsample from different sites, balancing representation from different areas and accounting for differences between patterns of activity in different habitats. Continuing this monitoring over the long term could give insights into phenological shifts related to climate change (Hassall et al., 2019). In addition, urbanization has strong influences on phenology (Alberti et al., 2017) such as increasing the nocturnality of certain species (Gaynor et al., 2018). Extensive camera trapping could detect these changes along fine spatial scales, and—given the heterogeneous nature of Britain's developed landscape—along urban–rural gradients.

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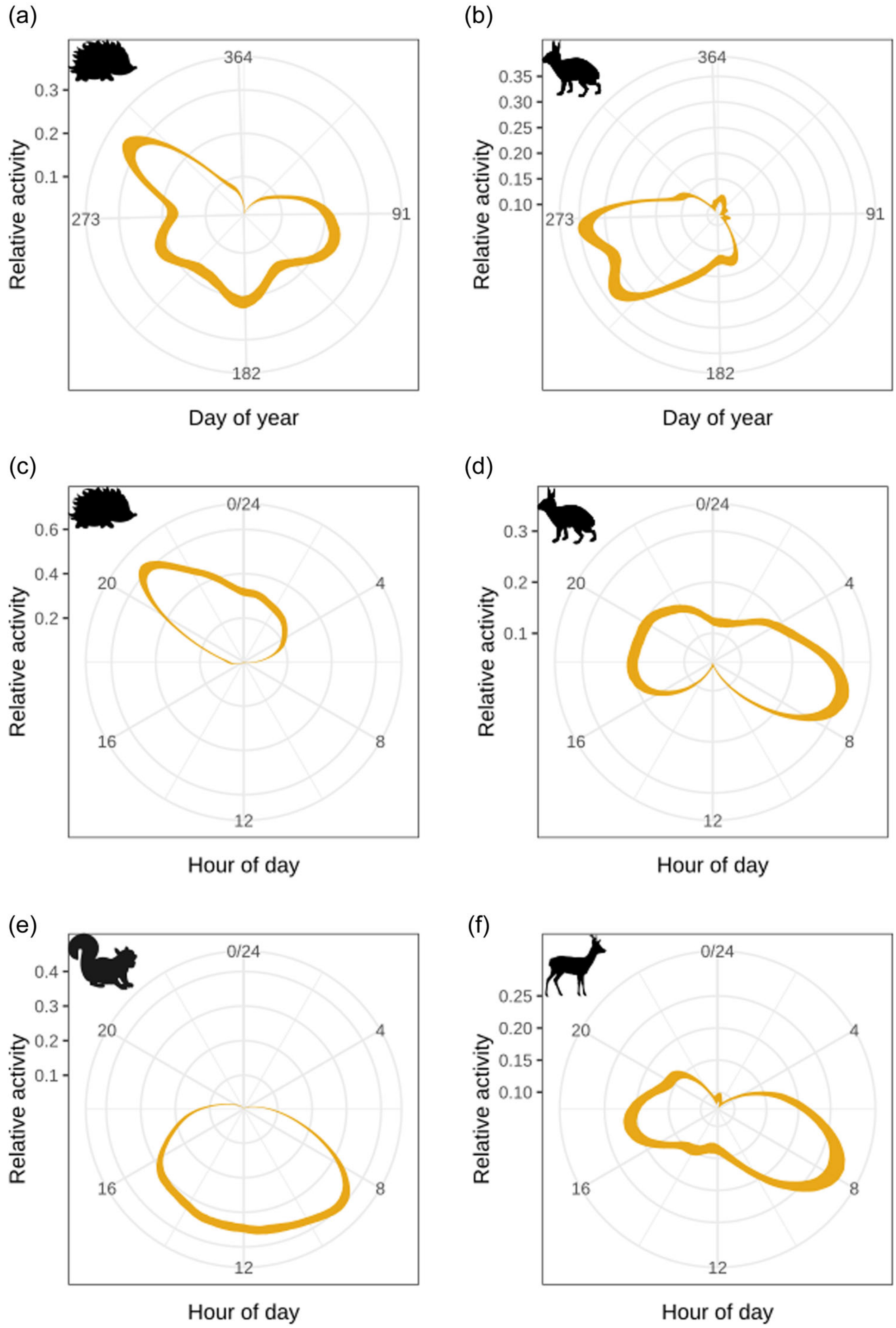

FIGURE 5 Examples of temporal activity patterns as determined from MammalWeb data. Annual relative activity showing the expected pattern of hibernation for the hedgehog (*Erinaceus europaeus*) (a), and evidence of heightened activity in late Northern Hemisphere summer/autumn in the European rabbit (b). Patterns of daily activity are shown for the hedgehog (c), rabbit (d), grey squirrel (e) and roe deer (*Capreolus capreolus*) (f), showing a variety of activity patterns, including diurnal, nocturnal and crepuscular. Kernel densities were fitted using the *fitact()* function in the R package '*activity*' (Rowcliffe, 2021). Polygons show confidence intervals estimated by 500 bootstrap resamples of the model.

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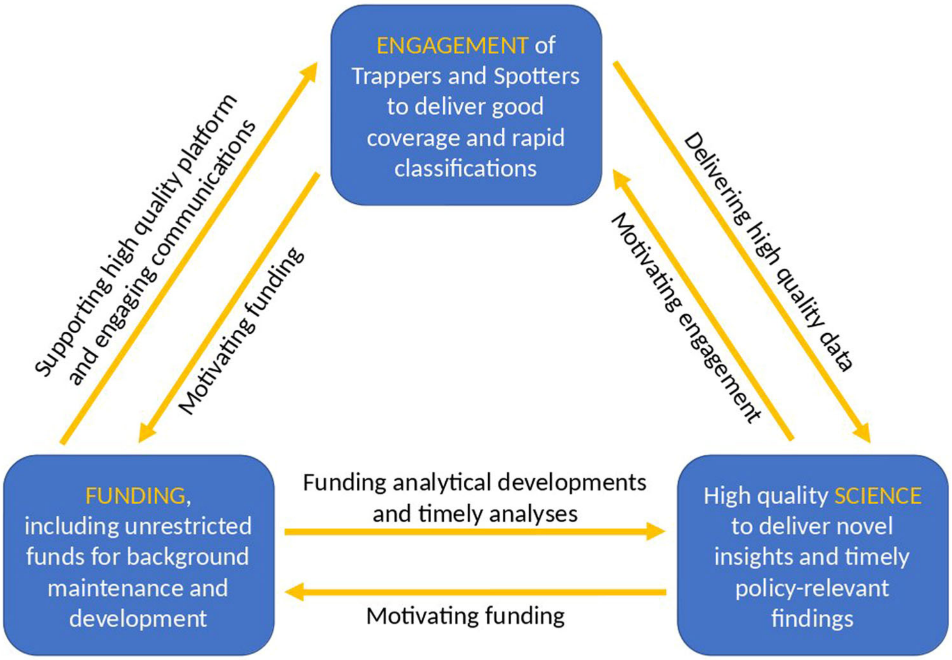

FIGURE 6 The tight linkages between engagement, science and funding in a citizen science camera trapping project lead to circularities that make it difficult to advance in respect of one area without first advancing in other areas that depend on it

4 | CHALLENGES, WIDER LESSONS AND FUTURE WORK

We have argued that citizen science camera trapping, as implemented in MammalWeb, can provide data appropriate to behavioural, temporal and spatial aspects of wildlife monitoring. Abundance is more complex but the dataset still makes a significant contribution to the available data on abundance, and that—treated cautiously—may be suitable for many management purposes. MammalWeb could, thus, play an important future role in monitoring Britain's mammals. Despite that, there are clearly challenges and, here, we outline those, along with major opportunities for development. Inevitably, engagement, science and funding are tightly interwoven, introducing complex trade-offs (Figure 6). Here, we focus on key aspects of each: the engagement of data collectors (Trappers) and classifiers (Spotters); the scientific challenges of abundance estimation and more rapid classification; and the non-trivial costs of running an online citizen science platform.

4.1 | Engagement

As we noted above, and consistent with levels of participation in similar citizen science projects (Sauermann & Franzoni, 2015), a minority of participants are responsible for most data in MammalWeb. Additional challenges are associated with the small number of participants, the local focus of the inception of our project and the lack of charismatic megafauna which may stimulate engagement (e.g. large African mammals; Veríssimo et al., 2011). MammalWeb also faces the challenge of recruiting citizen scientists both to collect and to classify camera trap photos. It is therefore necessary to consider approaches that may enhance participation and retention, or more efficiently utilize existing user effort. A particular challenge is engaging sufficient numbers of individuals to deploy camera traps in the field, and ensuring that rates of online image classification keep pace with contributed image data, providing sufficient classifications to deliver reliable classifications.

One possibility for increasing Trapper recruitment is a library loan scheme, since this overcomes the costs of camera ownership. Recently, the Candid Critters project successfully implemented this model with camera traps on loan from libraries (Lasky et al., 2021). Over 3 years, this project collaborated with over 500 citizen scientists to deploy more than 4000 camera traps across the entire state of North Carolina in the United States and the 2.2 million images obtained quintupled the state's wildlife records. These levels of data are unachievable by traditional field teams of professional ecologists, and the project also attracted more engaged citizen scientists. If there are still locations under-represented through citizen science camera trap deployments, they could be targeted through surveys run by the project organizers (Kays et al., 2021).

Another method for increasing the recruitment of Trappers relies on targeting already engaged communities within the UK—potentially by continuing to form partnerships with larger NGOs, whose members are inherently interested in (and often already monitoring) wildlife. Finding individuals and groups who are already making use of camera traps needs to be augmented with clear communications to identify the benefits of mass action and the added value that comes from contributing data from individual camera trapping to a growing national database. A key benefit of establishing these partnerships is monitoring wildlife on a national scale, which is difficult to achieve by a single

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organization. To our knowledge, while there is recent precedent for this model with camera-trapping surveys by professional scientists across southern Africa (Snapshot Safari; Pardo et al., 2021) and North America (over a span of 2 months in Snapshot USA; Cove et al., 2021; Kays et al., 2022), it has not previously been attempted in Europe (including the United Kingdom) with a network of NGOs and individual citizen scientists. While camera traps are widely used by individuals, community groups, scientists and NGOs, footage of non-target species is often deleted due to lack of capacity to store and classify those data (Swinnen et al., 2014), leading to the loss of valuable data. That, along with image archiving, ought to provide a powerful incentive to Trappers to participate, in addition to any assistance with classification. One of the biggest concerns among camera trappers is the potential for misuse of the data, emphasizing the need for communicating a clear data usage policy.

Recruiting individuals already engaged in wildlife monitoring promises to increase data volume but delivers less of an increase in public connection to nature. Four out of five children in the United Kingdom are growing up disconnected from, and with limited opportunity to interact with, nature (Richardson et al., 2015). Engaging children and young people in environmental citizen science has the potential to enhance connection to nature and bring many other benefits, as evidenced by our own work and that of others (Schuttler et al., 2018). There are over 20,000 primary schools in the United Kingdom. Working with less than even 1% of these to deploy cameras in school grounds or local green spaces would substantially increase spatial coverage (Harvey et al., 2020), bringing additional advantages through wider community engagement.

There is little to be gained from increasing the numbers of Trappers if rates of image classification cannot keep up. Other projects (e.g. Snapshot Safari: https://SnapshotSafari.org) have seen high success through releasing data in bursts ('seasons'). This makes the classification task much more obviously bounded, potentially increasing satisfaction as Spotters work towards a clear goal to classify the latest batch of data. Even then, however, the relative lack of variety in the pictured fauna for the United Kingdom and the high incidence of images lacking mammals can deter many potential contributors. These points provide strong incentives to develop and refine automated approaches to image classification and verification (Baker et al., 2021; Green et al., 2020; see further, below).

Increasing Spotter engagement could be achieved by incorporating real-time feedback into the user experience. One possibility is to 'seed' the MammalWeb image pool with expert-classified gold standard images, as in other crowdsourced data classification projects (Westphal et al., 2010). Feedback on classification accuracy can then be automatically generated (van der Wal et al., 2016), potentially encouraging Spotters to improve their accuracy (Kosmala et al., 2016).

4.2 | Scientific challenges

Two important scientific challenges are those associated with abundance estimation and automated data classification. Relevant designs for abundance estimation are likely to require camera trap deployment sites that are not currently reached by MammalWeb or its partners' cohort of citizen scientists, as well as technological or methodological innovations to estimate distance in camera trap photos. Alternatively, it might be achievable based on post hoc subsampling of sites. We have taken initial steps towards better abundance estimation by deploying a systematic, distance-calibrated camera trap grid in the Durham region, which largely overlaps with the initial core spatial coverage of MammalWeb citizen scientist-deployed camera traps (Mason et al., 2022). Assessing the relationships between the two data sets (systematic and ad hoc) will provide insights into the biases of ad hoc placement and the potential to calibrate photographic trapping rates for selected species. Results from Candid Critters, a similar citizen science project in the United States, suggest that opportunistic sampling via the ad hoc placement of camera traps can yield usable data for occupancy analysis at large sample sizes (Kays et al., 2021). Similarly, advances in occupancy modelling shows potential for deriving population trends based on biological records collected in an unstructured way (Coomber et al., 2021).

For systematic MammalWeb sampling, we could predefine deployment sites and put them up for 'adoption' by library patrons, similar to the Candid Critters project (Kays et al., 2021; Lasky et al., 2021). Evidence suggests that the broader spatial coverage achieved this way (i.e. sampling at more sites) may provide more statistical power for population analyses than high sampling intensity at fewer sites (Weiser et al., 2019). As additional motivation, prizes could be awarded to encourage long-term adoption of camera-trapping sites (Jennett et al., 2016).

A second major challenge is classifying image data more efficiently. This would increase the speed at which classifications could be regarded as robust and used for downstream analyses, and enhance engagement by reducing reclassifications. Our method for computing consensus classifications (Hsing et al., 2018a) could be used to make the current process more efficient. For example, a project administrator could set two confidence thresholds for retiring data: a high threshold (e.g. 99%) above which no more classifications are needed, and a low threshold (e.g. 60%) below which images are referred to expert adjudication. This way, crowdsourced classification effort could be focused on data with confidence levels falling within that range or species requiring more classifications to reach confident consensus. For example, for camera-trapping projects we organized, Spotter accuracy for badgers is 95.5% but as low as 79.8% for hedgehogs ('Nothing' was 97.5% with 43% of classified images in this category) (Hsing et al., 2018a). Photos of badgers could be retired quickly, redirecting Spotters to those requiring more classifications. Our work also highlighted a need to study species-specific effects when classifications for the same photo sequence are in conflict (Hsing et al., 2018a). For instance, when multiple classifications indicating the presence of a red fox (*Vulpes vulpes*) are contravened by one for a domestic dog, the reduction in confidence of the consensus is less than if the dissenting classification was for a badger (clearly more distinct from a red fox than a dog). In the future, accounting for the nature of conflicting classifications may improve the algorithm. Further analytical advances might therefore be possible by building on Bayesian methods for assessing species- and observer-specific impacts on classification accuracy (Santos-Fernandez & Mengersen, 2021).

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Automated approaches to object detection and image classification represent a field of intensive current research concurrent with efforts to derive consensus from human-originated classifications. Classified datasets—such as citizen-scientist-classified camera trap images—can be used to train machine learning algorithms to automate classification without human input (Krizhevsky et al., 2017; LeCun et al., 2015). Initial results from applying such techniques to detecting and identifying animals in camera trap photos have been fruitful (Thom, 2017), and a deep neural network was able, under certain conditions, to classify Snapshot Serengeti images at close-to-human accuracy (Norouzzadeh et al., 2018). This method has also been applied to identify badgers from still images and videos obtained in the United Kingdom (Chen et al., 2019). The generality and transferability of these approaches among faunas and environments is key to their widespread applicability. As automated classification of wildlife continues to mature, we expect it could supplant crowdsourcing human classifications for less charismatic species. We also stress the privacy benefits of automatically identifying and preventing images depicting humans from being shown to users such as those on MammalWeb.

Wild mammals in the British Isles are currently under-represented for purposes of automated image recognition. The existing MammalWeb dataset of almost 440,000 sequences of classified camera trap photos can broaden the diversity of training data for machine learning and help to fill this gap. For example, the Wildlife Insights platform trains machine learning algorithms on over 15 million camera trap images sourced from various studies to automate the classification of 993 animal species (https://www.wildlifeinsights.org/; Ahumada et al., 2020). This dataset could benefit from the introduction of species observed through MammalWeb. Moreover, the future of classifying large datasets may lie in the synergistic potential of crowdsourcing and artificial intelligence (Green et al., 2020; Palmer et al., 2021; Willi et al., 2019). Artificial intelligence could remove sequences without animals, helping to retain interest, and there is potential for mutual reinforcement where automated systems provide real time feedback for human classifiers (van der Wal et al., 2016), increasing their accuracy, which then produces a larger corpus of classified data on which to train more accurate machine learning algorithms (Pardo et al., 2021). Publication of camera-trapping datasets with full freedoms for reuse will aid not only the development of automated image recognition, but also wider spatial and temporal coverage of wild mammal monitoring, in general. In addition, camera-trapping management platforms such as MammalWeb, Wildlife Insights or the Zooniverse would benefit from implementing open-source application programming interfaces to expose individual functions and allow interoperability. For example, this would ease access to the machine learning algorithms developed by Wildlife Insights for projects seeking that specific capability.

4.3 | Funding

The annual operational budget of a citizen science project can be, in one example, over USD 110,000 (Fauver, 2016). MammalWeb has deliberately remained small to ensure affordability but, even so, the fixed annual costs for servers, data storage and platform maintenance are in the order of USD 6000. The cost of platform improvements is higher still, and we do not currently account for the time volunteered to the project by scientists and policymakers. We have been fortunate in attracting sufficient numbers of small, directed project grants to be able to meet our annual costs, hitherto. However, the funding landscape is inherently unstable, and long-term security will only be achieved through a sustainable financial model.

It is possible to conjecture several models for sustainable financing of citizen science projects, which are worth exploring. A common approach among NGOs is a membership model, in which participants contribute an annual sum to support the work of an organization. Among environmental NGOs, this is most common for those that take direct action or manage landscapes for wildlife protection. The British Trust for Ornithology presents an example of a membership-funded organization whose main focus is 'understanding birds and, in particular, how and why bird populations are changing' (BTO, 2010) and they run several monitoring schemes in which members pay for participation, suggesting that this is not necessarily a deterrent to engagement. However, this might be problematic for the wider participation that our platform is designed to foster. Alternatively, the eMammal platform charges camera trapping projects—instead of citizen scientists—for hosting their data (https://emammal.si.edu/about/costs/); doing so for larger collaborating organizations could be a viable way to fund the platform without deterring wider participation.

A second possibility to defray the fixed costs of the project would be to partner with an organization that already hosts online platforms and specializes in engagement. To such organizations, the cost of hosting MammalWeb would likely make less difference to their running costs than might be expected based on our current running costs. To date, our exploration of this possibility with two organizations have revealed technological limitations or compatibility issues that require upfront investment. Nonetheless, both avenues merit further investigation.

A third possibility is associated with sponsorship. MammalWeb is an online facility with the potential to reach large numbers of individuals with quite defined interests. This could be of interest to a commercial sponsor or advertising by relevant retailers.

Finally, the United Kingdom is obliged by the Bern Convention and associated UK statutes to ensure the conservation of wild plant and animal species, and by the Convention of Biological Diversity to provide biodiversity indicators as agreed from time to time. These can only be demonstrated with some degree of wildlife monitoring. Efficient tools to support that requirement are likely to be important but it remains to be seen whether core funding will be allocated for that purpose.

5 | SUMMARY

Projects relying on citizen scientists for both the long-term and large-scale deployment of camera traps and the classification of resultant images are rare, but this citizen science approach can deliver insights valuable for wildlife management (e.g. spatial and temporal patterns, and the identification of non-native species), ecological analyses in

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other contexts and for training machine learning algorithms for automated image recognition. In addition, the potential for involving varied partners in UK mammal monitoring—such as through our school and museum partnerships—can help to engage new audiences with biodiversity and environmental issues, redressing the 'extinction of experience'. With future developments, such as systematic camera trap surveys for abundance estimation (potentially facilitated by a library loan and site adoption scheme), liberal data-sharing, strategies for sustaining engagement despite relatively uncharismatic fauna and a sustainable financial model, we believe MammalWeb can serve not only as the long-term mammal monitoring first envisaged by Battersby and Greenwood (2004) but also as a useful case study for other citizen science wildlife monitoring projects in the United Kingdom and beyond.

AUTHOR CONTRIBUTIONS

All authors conceived the ideas and designed methodology. MammalWeb citizen scientists collected the data. Pen-Yuan Hsing and Philip A. Stephens analysed the data. Pen-Yuan Hsing and Philip A. Stephens led the writing of the manuscript with contributions from all authors. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

In addition to our work towards a data pipeline into the UK National Biodiversity Network (NBN), a subset of MammalWeb camera trap data and classifications is shared under the Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) license in an OSF repository: https://doi.org/10.17605/OSF.IO/ZNM6K (Hsing et al., 2018b). Code for MammalWeb infrastructure is shared under the GNU GPLv3 license from Git repositories hosted on GitHub and archived in Zenodo: https://doi.org/10.5281/zenodo.7023398 (Chappell & Bradley, 2022a), https://doi.org/10.5281/zenodo.7023390 (Chappell & Bradley, 2022b) and https://doi.org/10.5281/zenodo.7023394 (Chappell & Bradley, 2022c). Example R code computing consensus classifications is shared under the GNU GPLv3 license or any later version in a Git repository hosted on GitLab and archived in OSF: https://doi.org/10.17605/OSF.IO/VXYT8 (Hsing, 2022).

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