Monitoring the UK's terrestrial mammals using camera traps: from the field to the classroom

Brown hare (*Lepus europaeus*) | Park House Farm, Barnard Castle, County Durham

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Declaration

The material contained within this thesis has not previously been submitted for a degree at Durham University or any other university. The research reported within this thesis has been conducted by the author unless indicated otherwise.

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Abstract

Across the world, biodiversity is being lost at an unprecedented rate, heavily driven by anthropogenic activities. In order to understand ecosystem changes, and to conserve or manage species effectively, ecological monitoring on large spatial and temporal scales is needed. For some taxa, this is relatively straightforward. However, due to the nocturnal and elusive nature of many species, monitoring of terrestrial mammals can be challenging. In this thesis, I explore how camera traps and citizen science can be used to improve terrestrial mammal monitoring efforts in the UK. Firstly, I use the camera trap distance sampling method to calculate densities of a range of mammal species in North-East England, UK. The density estimates produced were similar to previously published estimates, and estimates for some species are amongst the most precise produced to date. Secondly, I evaluate spatial bias in MammalWeb, a camera trap citizen science dataset, by comparing subsets of data from MammalWeb to data from my systematic camera trapping survey. Habitat bias in the MammalWeb dataset impacted the species captured and measures of occupancy and habitat at a regional-level. I show that by sub-setting analysis to habitat level, the impact of spatial bias can be reduced; however, expanding spatial coverage of the MammalWeb project would be valuable in the future. In the second part of the thesis, I focus on a study engaging primary schools in camera trapping to monitor wildlife in their school grounds. I show that school pupils benefitted from participating in this project by gaining knowledge of UK mammal species and increasing their connection to nature. Schools also contributed valuable data to the MammalWeb project by uploading footage from a range of habitats, including some currently under-represented in the MammalWeb database. Teachers were very positive about the project, although some noted challenges to engaging long-term; there were also differences in longevity of engagement, depending on whether schools took part in a pupil workshop or teacher training. The findings presented throughout this thesis will help drive forward how MammalWeb and other projects with similar objectives can use camera trapping and citizen science approaches to maximise benefits in the areas of both ecological monitoring and engagement. More generally, my results highlight the potential of citizen science and camera trapping for improving large-scale mammal monitoring and ultimately, for tackling the challenges we face in managing widespread biodiversity loss.

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Chapter 1: General introduction

Roe deer (*Capreolus capreolus*) | Raby Castle, County Durham

1.1 Motivation

Across the world, biodiversity is being lost at an unprecedented rate, heavily driven by human influences, including climate change, changes in land-use, and introductions of invasive species (Butchart et al., 2010; Foley et al., 2005). To understand these dynamics, ecological monitoring across large spatial and temporal scales is necessary (Fischer et al., 2010; Yoccoz et al., 2001). However, monitoring on such scales is challenging and current monitoring programs are often insufficiently robust to provide the data needed to make conclusions on the state of biodiversity (Buckland and Johnston, 2017). Citizen science has historically provided a solution to the challenge of collecting biodiversity data at large-scales (Miller-Rushing et al., 2012; Pocock et al., 2015; Silvertown, 2009). Advancements in digital technology have further enabled large biodiversity datasets to be collected (Ball-Damerow et al., 2019; Chandler et al., 2017); however, issues over data quality and bias mean that gaps in our knowledge still exist, particularly for some taxa that are difficult to monitor (Amano et al., 2016). Combining citizen science approaches with the use of large-scale camera trap networks could be particularly beneficial for surveying terrestrial mammals, a taxon currently under-recorded in the UK and many other countries (Burton et al., 2015; Steenweg et al., 2017).

Parallel to declines in biodiversity is a widening disconnect between people and nature (RSPB, 2013). The lack of connection to nature in children has been particularly well documented and is attributed to increasingly urbanised populations and a growth of digital technology, amongst other factors (Neuvonen et al., 2007; Pergams and Zaradic, 2006; Turner et al., 2004; Zhang et al., 2014). This disconnect is concerning on two levels: 1) because children are missing out on the many benefits of being connected to nature, including improved physical and mental health (Harvey et al., 2020; Whitten et al., 2018); and 2) as childhood nature experiences can positively affect adult environmental attitudes and behaviours (Bixler et al., 2002; Ewert et al., 2005; Kidd and Kidd, 1996), without these experiences there may be a lack of willingness to conserve biodiversity in the future, further fuelling the biodiversity crisis we are facing (Schuttler et al., 2018b). Therefore, there has been a growing call to re-connect people, particularly children, with nature for the benefit of both themselves and of nature, in general (Miller, 2005; RSPB, 2013; Soga and Gaston, 2016).

In this thesis, I explore how camera trap networks and citizen science could be used to improve large-scale terrestrial mammal monitoring. I also examine how involving schools in mammal monitoring efforts could help children re-connect with nature and learn about local species. In this introductory chapter, I outline the importance of ecological monitoring, including monitoring mammal species and the current state of mammal monitoring efforts in the UK. I then give a general background to camera traps and citizen science before considering engaging schools in scientific research, and the potential benefits for them engaging with ecological citizen science projects, specifically. I conclude the chapter with a brief overview of the MammalWeb project and an outline of the structure and aims of the thesis.

1.2 Ecological monitoring

1.2.1 The need for ecological monitoring

Ecological monitoring is commonly defined as the repeated collection of ecological data over time to detect long-term trends (Moussy et al., 2022; Spellerberg, 2005). It is essential for gathering data on species abundance and distribution, to further our understanding of the global biodiversity crisis and to inform decisions on conservation strategies (Butchart et al., 2010). Advances in technology, including the ability to collect, store and categorise data more efficiently, have resulted in a vast increase in the quantity of publicly available species occurrence data in recent years (Edwards et al., 2000; Oliver et al., 2021). In particular, the number of monitoring schemes initiated in low-middle income countries and countries with high biodiversity has grown substantially (Moussy et al., 2022). However, despite the increase in global monitoring efforts, there is still more to be done to tackle the extent of the challenge we are facing with the current biodiversity crisis (Buchanan et al., 2020).

Global ecosystems are undergoing rapid change with biodiversity loss comparable in rate and magnitude to historical mass extinction events (Barnosky et al., 2011; Dirzo et al., 2014). Unlike previous mass extinctions, the factors driving current biodiversity loss are driven by anthropogenic activity and include climate change, habitat loss, invasive species, overexploitation and pollution (Butchart et al., 2010; Dirzo et al., 2014; Foley et al., 2005). Large-scale biodiversity loss will have significant impacts on the ecosystem services from which humans benefit, including: provisioning services such as food, water and timber; regulating services that affect climate, floods, disease, and water quality; and cultural services that provide recreational, aesthetic and spiritual benefits (IPBES, 2019; Millennium Ecosystem Assessment, 2005). To reverse the trend in rates of biodiversity loss and to maintain ecosystem services, significant changes in policies and practices are needed (Buchanan et al., 2020; Millennium Ecosystem Assessment, 2005).

In 2002, world leaders committed, through the Convention on Biological Diversity, to achieve significant reductions in current rates of biodiversity loss (CBD, 2002). An updated version of the plan set out 20 Aichi Biodiversity Targets, and was agreed to in 2010 (CBD, 2010). However, two decades after committing to the initial targets, none of the 20 targets have been fully met (CBD, 2020; Buchanan et al., 2020; Butchart et al., 2019). Furthermore, as highlighted by Buchanan et al. (2020), progress towards many of the targets was difficult to track, owing to a lack of available data. As pressure to mitigate against the consequences of our current biodiversity crisis mounts, new post-2020 targets have been set under the Kunming-Montreal Global biodiversity framework (CBD, 2022). Included in this is a specific target for improving biodiversity monitoring to facilitate a more effective assessment of progress (CBD, 2022).

Ecological monitoring is crucial for understanding the state of biodiversity, the threats it faces, and the effectiveness of conservation or species management efforts. Furthermore, countries have obligations to monitor and report on the state of biodiversity under intergovernmental treaties (e.g., the Convention on Biological Diversity) and national legislation (e.g., the UK Environment Act 2021). Ideally, given the extent of biodiversity loss we are facing, monitoring schemes would be established over large spatial and temporal scales. However, monitoring programmes are often either targeted towards small spatial areas, or they have low power to detect change (Buckland and Johnston, 2017; Legg and Nagy, 2006). Whilst citizen science has, in some cases, provided a solution to collecting and categorizing biodiversity data on large scales (Bonney et al., 2014; Chandler et al., 2017), these datasets can be spatially or temporally biased (Ball-Damerow et al., 2015; Johnston et al., 2022; Millar et al., 2019;

Petersen et al., 2021). Development of robust, cost-efficient monitoring methods that can be deployed over large scales would help countries to meet targets for reversing biodiversity loss.

1.2.2 Mammal monitoring

There are many different methods to monitor mammal species including: line transects (Buckland and Turnock, 1992); track or dung counts (Hill et al., 2005); aerial surveys (Havens and Sharp, 1998); mark-recapture methods (Lettink and Armstrong, 2003); and DNA-based methods (Darling and Blum, 2007). However, to deploy these methods over large scales is inherently costly. Therefore, in comparison to some groups, such as birds and butterflies which have long-standing monitoring programs (Greenwood, 2003; Harris et al., 2020a; Sauer et al., 2013; Shirey et al., 2022), there is a lack of data on mammal distributions and densities in many countries (Brashares and Sam, 2005; Croft et al., 2017; Singh and Milner-Gulland, 2011; van Strien et al., 2016). As a result, academics have highlighted the need for improved large-scale monitoring schemes for this taxon, specifically (Battersby and Greenwood, 2004; Hsing et al., 2022).

The lack of knowledge on mammal populations is problematic due to their ecological and economical importance. Many mammals are important indicator species: changes in their populations can reflect the state of general ecosystem health (Jones et al., 2009; Mathur et al., 2011; Tognelli, 2005). Due to their charismatic nature, mammals are also often used as flagship species which can stimulate conservation awareness and action (Albert et al., 2018; Smith et al., 2012). Furthermore, invasive mammal species and species considered to be pests need careful management to limit negative impacts on ecosystems. Arguably, though, one of the most urgent reasons to address shortcomings in mammal monitoring is that many species of mammal are at risk of extinction (Bowyer et al., 2019; Davidson et al., 2017; Mathews and Harrower, 2020).

For various reasons, monitoring mammals can be challenging, particularly in comparison to birds. Firstly, many species of mammal are nocturnal and easily disturbed by observers, so are seldom seen. Therefore, traditional survey approaches that rely on observations of live animals, such as line transects, are not an effective survey technique for many mammal species (Moore et al., 2020; Plumptre, 2000). Catching and ringing birds has, for the past 100 years, been a common way of gathering information on breeding success, phenology, migration and population changes (Greenwood, 2009). However, with the exception of bat species and some small mammals (Hoffman et al., 2010), mammal species are typically harder to catch and mark / tag, making it difficult to monitor their survival rates. Furthermore, although specific projects offering training in mammal survey techniques have helped boost the number of skilled observers, in comparison to birds, mammals still attract fewer enthusiasts to take part in monitoring programs (Battersby and Greenwood, 2004). Due to some of the difficulties of surveying mammals, proxy measures of abundance, such as track or scat counts, are often used in efforts to monitor populations (Hill et al., 2005). Whilst these values can be useful for conservation management in some instances, how they relate to actual abundance and their value for informing policy has been questioned (Kuehl et al., 2007; Stephens et al., 2015; Yoxon and Yoxon, 2014). Clearly, more effective mammal monitoring methods are needed and, given the extent of the challenges biodiversity faces, these monitoring schemes need to be at large, preferably national, scales.

The difficulties of monitoring mammals are evident from the lack of current data available on many mammal species, with academics calling for more data to be collected in many different countries (Brashares and Sam, 2005; Croft et al., 2017; Singh and Milner-Gulland, 2011; van Strien et al., 2016). The urgency for more robust species monitoring in the UK became apparent in a recent report showing the UK to be one of the most nature-deprived countries in the world (RSPB, 2021; Sanchez-Ortiz et al., 2019). Without sufficient data on UK mammal species, it will be difficult to implement effective, evidence-based conservation projects to reverse current trends. Therefore, there is a need to assess the current state of mammal monitoring efforts in the UK, whether they need to be improved and, if so, how.

1.2.3 Mammal monitoring in the UK

Like many countries, the landscape of the UK has changed substantially in the last century, driven by human influences such as agricultural intensification, urbanisation, changes in land drainage, and increases in pollution (Donald et al., 2001; Smedema et al., 2004; Yang and

Rose, 2005). These changes have led to devastating effects on wildlife and, if left unchecked, will continue to do so in the future (Battersby and Greenwood, 2004; Hayhow et al., 2019). In Britain, one in four mammals are considered to be at risk of extinction (Mathews and Harrower, 2020). Some of these species' declines have been rapid; for example, the hedgehog population in the UK is estimated to have decreased by at least 46% over 13 years (Mathews and Harrower, 2020). Moreover, many mammal species in the UK are the subjects of national debates around their management, owing to them being considered pests (e.g., rats, rabbits, and deer), carriers of disease (e.g., badgers, *Meles meles*, carrying bovine tuberculosis), or invasive species (e.g., grey squirrels, *Sciurus carolinensis,* and greater white-toothed shrews, *Crocidura russula*). To implement effective evidence-based conservation or species monitoring programs for these species, data on the state of their populations and the threats they face are required.

Several schemes exist to monitor individual mammal species in the UK, such as national otter surveys where alternate 50km squares throughout England are surveyed by experienced ecologists, usually every 5 years (Crawford, 2010). Citizen science platforms are also available for people to submit opportunistic sightings or signs of any mammal species; in the UK, one of the largest of these is iNaturalist (https://www.inaturalist.org/). Furthermore, over the past two decades, mammals have been recorded by many of the volunteers who conduct the British Trust for Ornithology's (BTO) Breeding Bird Survey (BBS) (Harris et al. 2020a). However, despite these various monitoring schemes, many mammal species remain under-recorded (Croft et al., 2017; Mathews et al., 2018). The lack of data does not affect only rare species; often, common species are under-represented in databases. For example, in a study of mammal abundance in the UK, only 6 published estimates of density were found for the rabbit, one of the most common mammal species in the UK (Croft et al., 2017). This resulted in large uncertainty when scaling density estimates to national levels (Croft et al., 2017). Furthermore, data availability and survey effort across the UK is uneven, with some areas (e.g., North-East England) having very limited data available (Crawley et al., 2020; Croft et al., 2017).

Battersby and Greenwood, (2004) highlighted the need for a UK-wide program that collected data on all mammal species in a standardized way. Since then, the UK Mammal Society launched an app where participants can record mammal sightings or signs whilst also tracking their walk (https://www.mammal.org.uk/volunteering/mammal-mapper/). Collecting data in a standardized way where effort is quantifiable makes it amenable to formal analysis. However, given that many mammals are nocturnal or otherwise elusive, it is likely that many species will be missed. To improve monitoring of all terrestrial mammal species, techniques are needed to ensure monitoring 24 h a day, regardless of the weather. In this regard, camera traps, which have recently become much more affordable, are likely to be a valuable tool.

1.3 Camera traps

The first camera trap was made by George Shiras in the 1890s, who, with a tripwire-based camera, captured images of rarely seen animals, captivating audiences across the world and winning awards for wildlife photography (Kucera and Barrett, 2011; Sanderson and Trolle, 2005). Advances in technology, such as portable power sources and larger films meant that by the mid-twentieth century, camera traps were used widely in ecological studies (Kucera and Barrett, 2011). Today, the most common types of camera trap used in ecology use motion and passive infrared (PIR) sensors to detect wildlife (Rovero et al., 2013; Welbourne et al., 2016).

The advantages of using camera traps for ecological monitoring include: that they are non-invasive in comparison to other survey techniques (e.g., those involving physical handling and tagging); that they can operate in a range of habitats and climates; that they can be left in the field for long periods without human intervention; and that they provide an auditable dataset in the form of photos and videos which can be reviewed by other researchers (Swann et al., 2011). Cost has previously been cited as one of the main barriers to using camera traps in ecological research (Glover-Kapfer et al., 2019; Meek and Pittet, 2012; Newey et al., 2015); however, costs of commercial camera traps have declined in recent years and are likely to continue to, increasing their utility as a cost-effective survey method (Glover-Kapfer et al., 2019).

1.3.1 Ecological inferences from camera traps

The use of camera traps for conservation and scientific purposes has grown substantially over the past 20 years (Rovero and Zimmerman, 2016). Camera traps have been used in a wide variety of ecological research, with papers on population parameters, activity schedules, feeding behaviour, and species interactions (Cutler and Swann, 1999; Trolliet et al., 2014). Camera traps have also helped discover new species (Rovero and Rathbun, 2006; Surridge et al., 1999), or species deemed to be previously extinct (Wright et al., 2008). Furthermore, they have been used to identify and track expansion of non-native species (Caravaggi et al., 2016; Hsing et al., 2022). Most commonly today, though, published studies using camera traps focus on calculating ecological measures such as density, occupancy, and activity schedules (Trolliet et al., 2014).

Measuring animal density is important for monitoring trends in wildlife populations but can be challenging for many taxa (Fryxell et al., 2014; Morellet et al., 2007). Parallel to the increased use of camera traps as a tool for monitoring mammals has been the development of methods for calculating animal density, using data from camera traps. Karanth and Nicholls (1998) were the first to apply the existing 'capture-recapture' method, using images obtained from camera traps to assess the abundance of tigers in different parts of India. Since then, this method has been used in many studies for species which can be individually identified, including leopard (Chase Grey et al., 2013; Faure et al., 2022), hyaena (Faure et al., 2022), jaguar (Silver et al., 2004), ocelot (Trolle and Kéry, 2003), and Eurasian lynx (Kubala et al., 2019).

The first method to calculate density for species in which individuals could not be individually identified was the Random Encounter Model (REM) (Rowcliffe et al., 2008). This method, based on ideal gas theory (Hutchinson and Waser, 2007), has been used in several studies, producing density estimates similar to those obtained using other methods (Anile et al., 2014; Soofi et al., 2017; Zero et al., 2013). However, uptake of the method has remained low, in part due to the difficulty of obtaining information required by the model, such as speed of movement (Wearn et al., 2022). Several other models have been proposed to calculate density for unmarked species, including: the spatial count model (Chandler and Royle, 2013);

the random encounter and staying time (REST) model (Nakashima et al., 2017); camera trap distance sampling (CTDS) (Howe et al., 2017); the time to event, space to event, and instantaneous sampling models (Moeller et al., 2018); and models that consider home-range behaviour (Campos-Candela et al., 2018) and space-use (Luo et al., 2020). Studies attempting to compare these methods have concluded that no one method is optimal for camera trap data under all circumstances (Gilbert et al., 2021; Palencia et al., 2021). However, it has been suggested that CTDS is more suitable for low density species because it uses all species records, rather than only those records that clearly represent initial contacts with an individual (which other methods use as their sample) (Palencia et al., 2021). The ability to accumulate larger datasets more rapidly could also make CTDS beneficial for monitoring at large scales, using shorter, repeated surveys to track changes in populations.

CTDS is developed from traditional point transect distance sampling (Buckland et al., 2001), with the model assuming that detection is certain at distance zero but accounting for imperfect detection of animals further away from the camera. Pre-defined snapshot moments are used to discretize the number of times an animal could be detected. Horizontal radial distance and angle to the midpoint of the animal from the camera are recorded and the probability of an animal being observed by a camera within its angle of view and within a pre-set distance (defined by truncating data), defines the probability of detection for the animal (Howe et al., 2017). Promisingly, CTDS has been used to estimate densities that are consistent with either true, known densities (Cappelle et al., 2019; Harris et al., 2020b) or previously published estimates (Corlatti et al., 2020; Howe et al., 2017). However, as the methodology is still relatively new, further testing of the methodology under different field scenarios would be beneficial.

Studies using CTDS have often been small-scale, focussed on only one species (Cappelle et al., 2019; Corlatti et al., 2020; Harris et al., 2020b) and have all taken place over homogeneous landscapes with little human influence (Bessone et al., 2020; Cappelle et al., 2021, 2019a; Corlatti et al., 2020; Harris et al., 2020b). For CTDS to be used in large-scale multi-species monitoring schemes, in diverse landscapes such as the UK, then further testing is needed to assess its suitability. Furthermore, whilst the underlying point transect distance sampling methodology is well-defined, CTDS requires additional decisions to be made such as how to calculate the snapshot moment interval and where to truncate distance data. Clear guidelines on how to choose these measures are not always obvious, in part due to decisions being dependent on several factors which may differ between studies. For example, the snapshot moment has been calculated differently depending on whether video or photo was used (Howe et al., 2017; Corlatti et al., 2020; McKaughan et al., 2023) and the distance at which data is left-truncated may depend on the study's sample size and the body size of the targeted species (Bessone et al., 2020). Without clear guidelines for calculating / defining these measures, there is a risk that arbitrary decisions without thorough justification will be made. As the method continues to be tested with different species under different field scenarios, more clear guidelines on defining measures such as the snapshot moment and truncation decisions would be useful.

Whilst development, improvement and testing of models to estimate density from camera trap data is ongoing, occupancy modelling has become a prominent focus of published camera trapping studies (Delisle et al., 2021). Occupancy is defined as the probability of the target species being present at a site (MacKenzie et al., 2002). Unlike density, which requires measures of multiple covariates, occupancy only requires simple detection / non-detection data (MacKenzie et al., 2002). Camera traps have been used with occupancy models to evaluate distribution (Johnson et al., 2020; Long et al., 2011) and habitat use (Dechner et al., 2018; Dertien et al., 2017; Kalle et al., 2014) for a wide range of species. Some of these studies have been carried out over large scales that would be challenging without the use of camera traps (Steenweg et al., 2016). Furthermore, the development of community occupancy models has enabled simultaneous estimates of occupancy for multiple species as well as covariate effects, making it a useful tool for widespread community monitoring (Kéry and Royle, 2016).

Whilst conservation strategies may typically focus on monitoring population parameters, academics have highlighted the importance of also monitoring animal behaviour, particularly for documenting behavioural responses to anthropogenic impacts (Berger-Tal et al., 2011; Caravaggi et al., 2017; Tobias and Pigot, 2019). As camera traps are relatively non-invasive, and survey over a 24-hour period, they are also useful for looking at activity schedules of species. Many studies have used camera traps to show temporal responses of species to anthropogenic pressures such as hunting (van Doormaal et al., 2015), agricultural activity (Ramesh and Downs, 2013; Shamoon et al., 2018), and human recreational activity (Nix et al., 2018; Oberosler et al., 2017; Reilly et al., 2017). Camera trap studies have also investigated correlations between activity and body mass (Vallejo-Vargas et al., 2022), temporal separation between species (Romero-Muñoz et al., 2010), and shifts to nocturnality in species (Tan et al., 2013). Given the increasing anthropogenic pressures facing global ecosystems, monitoring changes in behaviour using camera traps will likely be an important tool for conservation practice, although this kind of monitoring over large scales remains a challenge (Caravaggi et al., 2017).

The many benefits of using camera traps for ecological research have meant that large-scale networks of camera traps have been suggested as a way of monitoring mammals (Steenweg et al., 2017). Deploying camera traps over large geographical areas and analysing vast volumes of footage would require a substantial amount of time and effort. Whilst this might be a challenge for individual research teams to achieve alone, citizen science can offer a solution to overcome that challenge.

1.4 Citizen science

Citizen science is the process of involving non-professionals in scientific enquiry (Silvertown, 2009). Although the term citizen science was only coined in the 1990s, projects enlisting the help of non-professionals to collect scientific data can be dated back to 1900 with the 'Christmas Bird Count' where volunteers were encouraged to count birds at various locations across North America (Silvertown, 2009). Today, thousands of citizen science projects span subject areas including ecology, astronomy, and machine learning (Dickinson et al., 2010). As well as the subject, citizen science projects vary by level of involvement, from contributory projects where participants primarily contribute data, to co-creation projects where participants are involved in the whole process of the project, from design to evaluation (Bonney et al., 2009).

1.4.1 Citizen science and ecological monitoring

There is a long history of volunteer involvement in biological recording in many countries (Miller-Rushing et al., 2012; Pocock et al., 2015). The continued growth and expansion of digital technology, including smartphone apps for efficient data entry, has further enabled data to be gathered at large spatial and temporal scales (Chandler et al., 2017). By gathering datasets at such scales, citizen science projects have been able to track changes in populations over time, including declines of rare species (MacPhail et al., 2019; Zapponi et al., 2017) and the spread of invasive ones (Delaney et al., 2008; Gallo and Waitt, 2011; Maistrello et al., 2016). Citizen science projects may also collect other environmental data (e.g., measures of water quality) which can help with further explorations of trends and factors driving species' population changes, including disease (Brown et al., 2020; Lawson et al., 2015) and pollution (Brooks et al., 2019; Nelms et al., 2022; Zipf et al., 2020).

The participatory nature of citizen science also means it is well suited to increasing public understanding of, and support for, the environment (Dickinson et al., 2012). Nature-based citizen science projects can have positive impacts on participants, including increased wildlife knowledge (Brossard et al., 2005; Forrester et al., 2017; Jordan et al., 2011) and positive changes in behaviours and attitudes towards the environment (Haywood et al., 2016; Lewandowski and Oberhauser, 2017). Many studies have attempted to define the motivations of citizen science participants, in order to refine projects to maximise both data collection and participant satisfaction (Kaplan Mintz et al., 2022; Rotman et al., 2012; West et al., 2021; Wright et al., 2015). These studies find that motivations to participate in environmental citizen science are diverse and include wanting to help wildlife and contribute to science, to learn new skills, or to spend time outdoors (West et al., 2021). Ultimately, for citizen science projects to recruit and retain participants successfully, offering multiple avenues for engagement is likely to be most beneficial (Kaplan Mintz et al., 2022).

One of the major challenges for ecological citizen science projects is dealing with bias (Dickinson et al., 2012). A large body of evidence shows that citizen science datasets can be biased due to variations in sampling over space and time (Ball-Damerow et al., 2015; Johnston et al., 2022; Millar et al., 2019; Petersen et al., 2021), taxa bias (Callaghan et al., 2021; Ward,

2014) and differences in participant skills and experience (Dickinson et al., 2010; Johnston et al., 2018). Whilst some bias can be controlled for with statistical methods or additional protocols (Mair and Ruete, 2016; Rapacciuolo et al., 2017), dealing with bias, particularly for large-scale datasets of opportunistic records, remains challenging (Johnston et al., 2022).

1.4.2 Citizen science and camera traps

Citizen science and camera trapping have been combined in various projects, with promising results (Hsing et al., 2022; McShea et al., 2016a). Citizen scientists have helped with deploying and collecting camera traps, allowing for surveys over larger spatial scales than could have been surveyed by single researchers or research teams (Lasky et al., 2021; McShea et al., 2016; Townsend et al., 2021). Some projects have lent camera traps to citizen scientists to deploy, in order to answer specific research questions or study a particular species (McShea et al., 2016). However, with the decreasing cost of camera traps, more people are also buying them for personal use; for example, to see what wildlife visits their garden. Some projects have used this as an opportunity to collect these data by asking for footage from camera traps deployed for personal use (Hsing et al., 2022). By doing this, projects can expand spatial coverage as researchers are not limited by the number of camera traps they have. However, the ad-hoc nature of participants deploying their own cameras at sites of their choosing could lead to issues with spatial bias which would need to be addressed to have confidence in ecological inferences from the data (Hsing et al., 2022).

Citizen scientists have also helped with classifying images. For example, many projects currently listed on the platform Zooniverse (https://www.zooniverse.org/) enlist the help of citizen scientists to classify images from camera traps to answer a variety of scientific questions. Most projects focus on identifying species within images (Swanson et al., 2015) but some also ask participants to enter information on behaviour (Arandjelovic et al., 2016) or to annotate images by marking individuals (Jones et al., 2018). By crowdsourcing classifications from citizen scientists, banks of camera trap images can be classified much more quickly than would be possible for individual researchers (Hsing et al., 2018; Swanson et al., 2015).

Whilst the primary aim of projects involving both camera traps and citizen science may be data collection, most projects have also included some level of public engagement that goes beyond normal participation. Engaging with schools, specifically, could be of particular benefit, with the projects eMammal and MammalWeb reporting positive impacts from projects engaging schools in camera trapping and citizen science (Hsing et al., 2020; Schuttler et al., 2019). Whilst this seems promising, these projects have been small-scale and lacking robust evaluation. A greater understanding of the impacts of such projects on school pupils, as well as approaches that work best, could help guide projects involving larger networks of schools.

1.5 Engaging schools in science research

1.5.1 Science research projects in schools

Across the world, science forms an important part of formal education. Science education includes building knowledge and understanding of scientific concepts and processes, and teaching skills such as observing, classifying, explaining and predicting (National Academies, 2016). Effective science teaching is essential for equipping the next generation of scientists with the skills and knowledge necessary to tackle 21st century problems (Turiman et al., 2012). However, there have been calls for science education in schools to include scope for more practical activities that have value beyond the classroom (Holman et al., 2016; Nistor et al., 2019; Parker et al., 2018). Specifically, engaging school pupils in citizen science projects could complement the formal science curriculum by providing real-life opportunities to learn and implement the scientific method to help solve local and global problems (Shah and Martinez, 2016; Bonney et al., 2014). The Monarch Larva Monitoring Project (Kountoupes and Oberhauser, 2008), School of Ants (Lucky et al., 2014) and LandSense (Olteanu-Raimond et al., 2018) are considered to be good examples of how citizen science projects can engage with schools, by providing equipment for them to collect and contribute scientific data to the project at large (Roche et al., 2020).

In the UK, specifically, several projects aim to engage schools in 'real' science research, such as the ones listed by the Institute for Research in Schools (https://researchinschools.org/projects/). In these projects, schools work with scientists to help answer specific questions on a range of topics. Whilst these projects have been designed with the primary aim of benefitting students, some have led to real-world impact beyond the classroom. For example, in a project where school students study levels of radiation on the International Space Station, a student identified an error in the data set they were working on, which had to be reported to NASA (BBC, 2017).

Involving schools in authentic science research, including engaging them in existing citizen science projects, could have huge benefits both in terms of collecting large amounts of data, and for improving science literacy amongst pupils (Kountoupes and Oberhauser, 2008; Roche et al., 2020; Schuttler et al., 2019). However, detailed reports on how to implement citizen science in formal education settings, and the benefits of doing so remain rare (Roche et al., 2020). Furthermore, most projects involving schools in citizen science, both globally and in the UK, have worked with only a small number of schools (< 10) for a short period of time (Blumstein and Saylan, 2007; Marchant et al., 2019; Prendergast et al., 2022; Saunders et al., 2018). For ecological monitoring, as discussed previously, citizen science plays a crucial role in gathering species data. If schools could engage with ecological citizen science projects this could help to expand the spatial and temporal extent of species monitoring but could also have benefits for the children and teachers who participate.

1.5.2 Increasing children's connection to nature through ecological citizen science

The term 'connection to nature' encompasses the range of feelings and attitudes that people have towards nature including: enjoyment of nature; having empathy for creatures; having a sense of oneness with nature; and having a sense of responsibility for the environment (RSPB, 2013; Cheng and Monroe, 2012). The benefits of connection to nature in children are well studied and include improved mental wellbeing (Barrera-Hernández et al., 2020; Whitten et al., 2018) and more positive behaviours and attitudes toward the environment (Otto and Pensini, 2017; Zhang et al., 2014). Studies investigating the mechanisms that lead to nature connection have found that 'meaningful' moments in nature that include elements of contact, emotion, compassion, and beauty are the main pathways for improving nature connectedness (Lumber et al., 2017; Richardson et al., 2022). For example, it has been suggested that activities to 'notice nature' (e.g., by watching, listening, or photographing) rather than just spending time in it, can lead to a deeper connection to nature (Richardson et al., 2022).

Alongside calls to increase connection to nature, many academics have highlighted the loss of environmental knowledge, including the ability to identify even common species, amongst children today (Pilgrim et al., 2008; Ballouard et al., 2011; Lindemann-Matthies, 2005). Although the link between knowledge, connection to nature and attitudes is not always clear (Lumber et al., 2017), environmental knowledge can facilitate attitude formation (Kollmuss and Agyeman, 2002) and positive pro-environmental attitudes can lead to pro-environmental behaviours (Duerden and Witt, 2010). Therefore, if the next generation are to help with conserving biodiversity in the future, it is important to increase both connection to nature and environmental knowledge amongst children. Participating in ecological citizen science projects could provide a mechanism for doing this, as it requires not just spending time in nature but noticing it through scientific recording. Participating in these projects could thus help foster stronger connections with nature and help participants to learn about local species, whilst also contributing to ongoing species monitoring (Pearce-Higgins, 2021; Schuttler et al., 2019).

A number of projects have engaged schools in ecological citizen science, with promising accounts of how pupils and teachers have benefitted from their involvement (Saunders et al., 2018; Schuttler et al., 2019). Furthermore, schools have generated ecological data valuable to monitoring schemes (Pearce-Higgins, 2021; Roche et al., 2020). For example, in a project set up to monitor variation in soil-invertebrate abundance on school playing fields, sufficient data were collected to model variation in abundance of 12 different invertebrate groups (Martay and Pearce-Higgins, 2018). Despite these successes, however, to date, most projects engaging schools in ecological citizen science have been small scale and required a lot of input from researchers (Blumstein and Saylan, 2007; Marchant et al., 2019; Prendergast et al., 2022; Saunders et al., 2018). Many of these projects have not included formal evaluations from either pupils or teachers, which is a missed opportunity, as evaluation data could help guide how future projects should be implemented for greatest effect (Soanes et al., 2020). Furthermore, when children are involved in collecting biodiversity data, there are often concerns over data quality (Miczajka et al., 2015; Saunders et al., 2018; White et al., 2018) which could limit how useful data from participating schools could be for species monitoring. Nevertheless, with more robust evaluation of benefits for participants, best practice approaches for data collection, and challenges teachers face for implementing such projects in schools, ecological citizen science projects in schools could have great potential for helping tackle both the challenge of large-scale ecological monitoring and re-connecting children with nature.

1.6 The MammalWeb project

Much of this thesis (Chapters 3-5) will focus on the MammalWeb project (www.MammalWeb.org) as a case study. MammalWeb was first set up in 2015 as a collaboration between Durham University and the Durham Wildlife Trust (a nature conservation charity) (Hsing et al., 2022). Whilst most citizen science camera trapping projects invite participants either to contribute or to classify data (e.g., McShea et al., 2016; Swanson et al., 2015), the MammalWeb project was the first to involve participants in both aspects of the process, with participants being able to upload and classify footage on one central platform (Hsing et al., 2022).

Most commonly, MammalWeb participants who upload footage use their own personal camera traps, which can be a range of makes and models. In some cases, camera traps are loaned out to individuals or groups from MammalWeb's supply. Participants who upload footage are free to choose a location for their camera, as well as whether they record videos or images. When they upload footage onto the platform, they input information on: site of deployment; camera model; habitat of deployment site; height of camera above ground; and deployment and collection date and time. Participants classifying footage on the platform are presented with the uploaded footage– either a sequence of photos taken in quick succession, or a video. Classifiers can then tag the sequence or video with a species selected from a presented list. Having selected a species, classifiers also have the option of adding information on the number of individuals, the age (adult, juvenile or unknown) or sex (male, female or unknown) of the species shown. To safeguard the privacy of any humans who might be accidently captured by a camera trap, any image / video tagged as 'Human' will not be shown again to other users.

To date, MammalWeb participants have contributed over 600,000 image sequences and videos from over 2,300 sites across the UK (Hsing et al., 2022). It has been suggested that MammalWeb could play a role in the long-term monitoring of UK wildlife; however, challenges over abundance estimation and quantifying bias in the dataset remain (Hsing et al., 2022). MammalWeb has also been used in schools, including a project where students co-authored a peer-reviewed paper about their experiences with MammalWeb (Hsing et al., 2020). Engaging a larger network of schools with the MammalWeb project and measuring impacts on pupils could demonstrate how MammalWeb and other ecological citizen science projects benefit pupils, identifying factors to consider when developing future projects. These considerations inspired the objective for my thesis.

1.7 Thesis structure and aims

This thesis aims to explore how camera trap networks combined with citizen science could be used to improve national mammal monitoring efforts. Chapters 2 and 3 of the thesis focus on two key elements of citizen science and camera trapping in relation to ecological monitoring while Chapters 4 and 5 explore two components of engaging schools in ecological monitoring with camera traps. My thesis concludes with a final general discussion chapter summarising findings and proposing future work. Below is a summary of the aims of each chapter.

1.7.1 Chapter 2 - Camera trap distance sampling for terrestrial mammal population monitoring: lessons learnt from a UK case study

Camera trap distance sampling could offer an effective solution to the challenges of monitoring mammal species over large spatial scales. However, previous studies using the method have all focused on homogeneous landscapes with little human influence (Bessone et al., 2020; Cappelle et al., 2019; Corlatti et al., 2020; Harris et al., 2020b). In this chapter, I present the first study to use the camera trap distance sampling methodology to calculate densities of a range of mammal species over a heterogeneous landscape (North-East England, UK). I calculate both survey-wide estimates and habitat-specific estimates; the latter could be particularly useful for filling current data gaps and for scaling up to national estimates. By comparing my estimates to previously published estimates, and discussing the practical and methodological challenges of the method, I evaluate whether the method would be suitable for national-level monitoring in the UK.

1.7.2 Chapter 3 - Spatial bias in a citizen science camera trap dataset and its impact on ecological inferences

One of the largest challenges for citizen science projects that collect data in an opportunistic way is dealing with bias (Ball-Damerow et al., 2019; Dickinson et al., 2012; Kosmala et al., 2016). Projects using camera traps overcome some bias, as cameras record all animals that pass in front of them; however, spatial bias may be retained. If the MammalWeb project is to play a role in UK-wide mammal monitoring, it is important to explore (and subsequently address) bias present in the dataset (Hsing et al., 2022). In Chapter 3, I compare subsets of the MammalWeb dataset to data from a systematic survey to evaluate bias and how it influences species assemblages captured, as well as measures of occupancy and activity. Results from this chapter will help to determine whether data from citizen science projects such as MammalWeb are spatially biased, suggesting steps needed to reduce bias and produce accurate ecological inferences.

1.7.3 Chapter 4 - Increasing connection to nature and knowledge of UK mammals through an ecological citizen science project in schools

Citizen science has been suggested as a way of reversing the growing disconnect between people and nature (Schuttler et al., 2018b) and could be particularly beneficial for children by offering opportunities to learn about and connect with local biodiversity (Saunders et al., 2018; Schuttler et al., 2019). However, robust evaluations assessing the impacts of involving children in ecological citizen science are currently lacking. In Chapter 4, I focus on benefits for participating primary school pupils who took part in an ecological intervention involving:

deploying camera traps to monitor wildlife in school grounds; taking part in a pupil workshop or teacher training session; and contributing to the citizen science project, MammalWeb. Using questionnaires completed before and after the intervention, I aim to determine impacts from our intervention and whether these differences were sustained three-months post-intervention.

1.7.4 Chapter 5 - Teacher engagement with citizen science: Experiences from an ecological camera trapping project and recommendations for future projects

Teacher perspectives on ecological citizen science are important because, without engaged teachers, there is little scope for ecological citizen science projects to be run independently, long-term, in schools. Whilst previous studies have reported positive feedback from small numbers of teachers who have participated in ecology-based projects (Schuttler et al., 2019; Soanes et al., 2020; White et al., 2018), a deeper exploration of how teachers engage with projects, and the feedback they give, could help to guide how future projects should be implemented. In Chapter 5, I look at how teachers engaged with the project MammalWeb, including if there were differences in the proportion of schools who engaged with MammalWeb depending on whether they received a pupil workshop or teacher training session. As schools could help to gather large-scale ecological monitoring data, I also look at the data that schools captured on camera traps and how these compare to data captured by general MammalWeb users in the same time frame. Finally, I summarise teacher feedback and, using this and our own experiences from the project, synthesise five recommendations for school-based ecological citizen science projects.

1.7.5 Chapter 6 – General discussion

In this general discussion chapter, I summarise findings and suggest areas of future work. My focus is principally on how MammalWeb can move forward; however, I also consider broader issues of relevance to any researchers using camera trap networks or citizen science for mammal monitoring or schools engagement. The chapter concludes with a reflection on the linkages between the two distinct areas of research considered in this thesis – ecological monitoring in Chapters 2 and 3 and schools engagement in Chapters 4 and 5. I propose that, owing to the broader contexts of the extinction crisis and the growing disconnects between people and nature, large-scale mammal monitoring projects should move forward with consideration of both, in order to maximise benefits.

1.8 General methods

The chapters in this thesis have used a broad range of methodologies. Within each chapter, I detail the specific methodologies used for both data collection and analysis. Here, I briefly outline some of the overarching rationale behind the methods used, including: choice of camera traps, choice of data analysed; the mixed methods approach; and ethical considerations taken.

Camera traps are used in each of the studies, with the same make and model (Browning Strike Force BTC-5HDP) used throughout. These cameras have a passive infrared (PIR) sensor, which detects movement and changes in temperature within a detection zone in front of the camera. PIR camera traps are the most common type of camera trap used today (Meek et al., 2014), and so the studies presented in this thesis should be relevant to the majority of people who use camera traps. Furthermore, the Browning model used is a mid-range priced camera trap (~£150), meaning it is more robust than other cheaper models, but still affordable for the quantity of cameras needed for my studies. According to the manufacturer's guide, the trigger speed on the camera is 0.3 s and a minimum delay of 1 s between captures can be set (Browning, 2017). For the camera trap survey presented in Chapters 2 and 3, cameras were set to record 8 images (the maximum) in quick succession. This setting was chosen as it allowed for the maximum amount of data to be collected (8 photos), but did not use up as much storage as video, which was an important consideration when cameras were deployed in remote areas and could not be checked regularly.

In Chapters 2 and 3, data from a large camera trapping survey is presented. Chapter 2 focussed on a specific methodology – camera trap distance sampling – details of which can be found in the chapter. For this chapter I focussed on estimating densities of 8 mammal species (details on how species were selected can be found in the chapter) so only data on these species were analysed. In Chapter 3, however, the whole dataset from the survey was used to look at overall species captured and trapping rates for different species groups. I decided to include domestic / livestock species and humans in this as, although these are not always the focus of camera traps studies, the impact of domestic / livestock species and humans on wild species is a topic of increasing interest (Schieltz and Rubenstein, 2016; Nyhus, 2016). Camera traps and / or citizen science could be a useful method to look at these impacts; however, it would first be useful to know about trapping rates and how these might compare between systematic and citizen science datasets, which is why these species were included in this chapter. Chapter 3 then focusses on key mammal species for looking at differences in occupancy and activity schedules. Specific details on how species were chosen and the methodologies used are outlined in the chapter.

Both Chapters 4 and 5 focus on a study involving primary schools in camera trapping and citizen science. Chapter 4 uses quantitative data collected from pupils using questionnaires at set points throughout the study. Details on the questionnaires and how data were analysed can be found in the chapter. Chapter 5 takes more of a mixed methods approach, using both quantitative and qualitative data. Mixed methods approaches can provide a greater depth and breadth of information than utilising single approaches in isolation (Almalki, 2016). Therefore, as I wanted to gain a deeper understanding of how teachers engaged with the project, including the benefits gained and challenges faced, a mixed method approach was beneficial for my study. Further details on the specifics of how data were collected and analysed using this approach can be found in Chapter 5.

For each of the studies presented in this thesis, ethical considerations were made, and ethical approval was granted by Durham University, where appropriate. For camera trap studies in general, one aspect to consider is what to do if humans are inadvertently captured. For the camera trapping survey I conducted (Chapters 2 and 3) images of humans were only seen by myself when tagging photos and were removed prior to uploading footage to MammalWeb. For the school study, the teachers at the school were responsible for uploading images and were asked to view all images and remove any photos of humans prior to uploading. If any photos of humans were accidently uploaded, the normal procedure that MammalWeb follows would apply that once it is tagged as human it would not be visible again (Hsing et al., 2022). As I was visiting schools to run pupil workshops and teacher training (for Chapters 4 and 5), I had an enhanced DBS check and there was always at least one teacher from the school present with me during the workshops. Further details on the ethical considerations made regarding data collection (e.g., anonymising questionnaires) for the schools study can be found in Chapters 4 and 5.

1.9 Author contribution statement

Other than the lead author (SM), the following authors have been involved with the studies presented in this thesis: Philip Stephens (PS), Russell Hill (RH), Mark Whittingham (MW), Jim Cokill (JC), Graham Smith (GS), and Lorraine Coghill (LC).

Authors contributed in the following aspects of each data chapter:

Chapter 2 (Camera trap distance sampling for terrestrial mammal population monitoring: lessons learnt from a UK case study): SM, PS and RH conceived the ideas and designed methodology; SM collected the data; SM, PS, RH and MW analysed the data; SM led the writing. PS, RH, MW, JC, and GC provided feedback on drafts.

Chapter 3 (Spatial bias in a citizen science camera trap dataset and its impact on ecological inferences): SM, PS and RH conceived the ideas and designed methodology; SM collected the data; SM analysed the data; SM led the writing. PS and RH provided feedback on drafts.

Chapter 4 (Increasing connection to nature and knowledge of UK mammals through an ecological citizen science project in schools): SM, PS, RH, MW and LC conceived the ideas and designed methodology; SM collected the data; SM analysed the data; SM led the writing. PS and RH provided feedback on drafts.

Chapter 5 (Teacher engagement with citizen science: Experiences from an ecological camera trapping project and recommendations for future projects): SM, PS, RH, MW and LC conceived the ideas and designed methodology; SM collected the data; SM analysed the data; SM led the writing. PS and RH provided feedback on drafts.

Chapter 2: Camera trap distance sampling for terrestrial mammal population monitoring: lessons learnt from a UK case study

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2.1 Abstract

Accurate and precise density estimates are crucial for effective species management and conservation. However, efficient monitoring of mammal densities over large spatial and temporal scales is challenging. In the UK, published density estimates for many mammals, including species considered to be common, are imprecise. Camera trap distance sampling (CTDS) can estimate densities of multiple species at a time and has been used successfully in a small number of studies. However, CTDS has typically been used over relatively homogeneous landscapes, often over large time-scales, making monitoring changes (by repeating surveys) difficult. In this study, we deployed camera traps at 109 sites across an area of 2,725 km^2 of varied habitat in North-East England, UK. The 4-month survey generated 51,447 photos of wild mammal species. Data were sufficient for us to use CTDS to estimate densities of eight mammal species across the whole survey area and within four specific habitats. Both survey-wide and habitat-specific density estimates largely fell within previously published density ranges and our estimates were amongst the most precise produced for these species to date. Lower precision for some species was typically due to animals being missed by the camera at certain distances, highlighting the need for careful consideration of practical and methodological decisions, such as how high to set cameras and where to left-truncate data. Although CTDS is a promising methodology for determining densities of multiple species from one survey, species-specific decisions are still required and these cannot always be generalised across species types and locations. Taking the UK as a case study, our study highlights the potential for CTDS to be used on a national scale, although the scale of the task suggests that it would need to be integrated with a citizen science approach.

2.2 Introduction

Measuring animal density and abundance is important for monitoring trends in wildlife populations and for developing effective conservation and management strategies (Fryxell et al., 2014). Yet, developing robust methods and tools to estimate population densities accurately and precisely over large spatial and temporal scales is challenging for many taxa (Morellet et al., 2007; Plumptre and Cox, 2006). Calculating density estimates for mammals can be particularly difficult given that many species are nocturnal and easily disturbed by observers, and many occur at low densities. Consequently, monitoring efforts often rely on indirect observations of presence, such as dung or footprints. These indirect observations can be converted into measures of animal density if conversion factors such as rates of production and decay are known; however, the accuracy and precision of this approach is often questioned (Kuehl et al., 2007; Yoxon and Yoxon, 2014).

The extent of the challenge of estimating the abundance of mammal species is evident in published estimates for mammal species in the UK. For example, a recent estimate of abundance for one of the UK's most common species, the rabbit (*Oryctolagus cuniculus)*, spanned two orders of magnitude, from 2 to 255 million (Croft et al., 2017). This imprecision largely results from a lack of species records overall, and a lack of habitat-specific density estimates, which makes it difficult to scale up to a national level. The lack of data on many mammal species is not unique to the UK and academics have highlighted the need for better monitoring of terrestrial mammals worldwide, including in Europe (ENETWILD-consortium et al., 2019; van Strien et al., 2016), Africa (Brashares and Sam, 2005) and Asia (Singh and Milner-Gulland, 2011). It is clear that new monitoring approaches are needed that can be deployed over large areas to generate a substantial number of records and produce reliable density estimates.

As technologies have developed, camera traps have been increasingly used as a means of passively monitoring species (Rovero and Zimmermann, 2016). Camera traps are particularly useful for monitoring elusive species and can gather large quantities of data more quickly than many more traditional survey methods (Burton et al., 2015). Methods for abundance estimation with camera traps have been developed for species in which individuals can be identified (Head et al., 2013; Silver et al., 2004; Williams et al., 2017) and for species in which individuals cannot be identified (Chandler and Royle, 2013; Gilbert et al., 2021; Howe et al., 2017; Luo et al., 2020; Moeller et al., 2018; Nakashima et al., 2017; Rowcliffe et al., 2008). Palencia et al., (2021) showed that three of these methods (REM, REST, and CTDS) could be used to estimate densities consistent with independent estimates from line transects and drive counts. Although there were no significant differences between estimates produced by the methods, Palencia et al., (2021) suggested that CTDS would be more suitable for low-density species because the number of records increases more rapidly than with other methods (which use only initial contacts as their samples). The potential to accumulate larger datasets more rapidly would be beneficial for monitoring over large spatial scales, using shorter repeated surveys to track changes in populations. As with traditional point transect distance sampling (Buckland et al., 2001), CTDS typically assumes that detection is certain at distance zero but accounts for imperfect detection of animals further away from the camera. CTDS has been used to estimate densities that are consistent with either true known densities (Cappelle et al., 2019) or previously published estimates (Corlatti et al., 2020; Harris et al., 2020b; Howe et al., 2017). CTDS has also been used to estimate densities of multiple species simultaneously (Bessone et al., 2020; Cappelle et al., 2021; Palencia et al., 2021).

In many countries, the level of monitoring is inconsistent among species, resulting in limited data on some species, even when they are considered common (e.g., rabbits in the UK (Croft et al., 2017) or wild boar across parts of Europe (ENETWILD-consortium et al., 2019)). By gathering data and estimating density for multiple species at a time, CTDS may help to address this imbalance, as well as saving time and resources by removing the need for multiple surveys of different species. To date, studies that have used the CTDS method have been carried out in landscapes with little variation in habitat and with little human influence (Bessone et al., 2020; Cappelle et al., 2019, 2021; Corlatti et al., 2020; Harris et al., 2020b; Howe et al., 2017). In many regions and countries, however, the landscape is much more varied and includes habitats heavily altered by humans. The method would need to be reliable and practical to employ over landscapes such as these if it was to be used for large-scale monitoring.

In this study, we aim to generate density estimates, including habitat-specific estimates, for a range of medium-large terrestrial UK mammal species. We assess our estimates against previously published density estimates for those species. Finally, taking the UK as a case study, we discuss the opportunities, limitations, and challenges of using CTDS for large-scale and long-term species monitoring.

2.3 Methods

2.3.1 Survey area

Data were collected in North-East England. The 2,725 km^2 study area covered County Durham, plus areas of Gateshead, Sunderland, and Darlington. The region's landscape is varied, with mountain, heath, and bog habitat in the west, improved grassland (high productivity grassland) in the centre of the region, and a variety of habitats in the east, including arable and urban (Figure 1; habitat classes from the Land Cover Map 2015, LCM; Rowland et al., 2017). The area's human population is around 1.1 million, with population densities ranging from 0.1 ha^{-1} in the most rural areas of County Durham to 20.2 ha^{-1} in urban areas such as Sunderland (ONS, 2021b). The Human Influence Index (HII) ranks human influence from 0 (no influence) to 64 (maximum influence) according to nine measures of human presence (WCS and CIESIN, 2005); average HII was 37 (range 14-64; WCS and CIESIN, 2005) across our study sites.

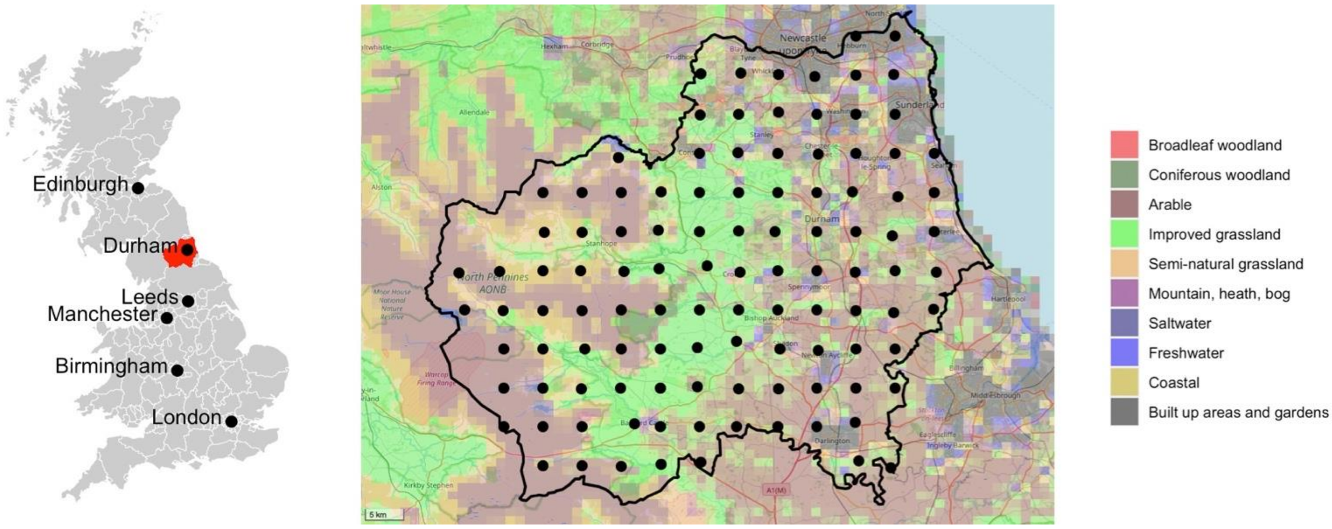


Figure 1. Left: Location of survey area in the UK shown in red. Right: Map of 109 sites where camera traps were placed in County Durham. Habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015). Background map: © OpenStreetMap contributors, © CARTO licensed under CC BY-SA 2.0.

2.3.2 Camera trap survey

Within the study area, a grid was defined with 5 km^2 spacing and random geographical origin, with camera traps placed at the coordinates of the centre point of each cell in the grid. For CTDS, the spacing of the grid where cameras are deployed does not influence density estimates as probability of detection is determined from the effective detection area in front of the cameras (Howe et al., 2017). A grid of 5 km^2 spacing was chosen as this was a large enough spacing to cover the whole survey area whilst still being feasible for one person to carry out the survey within the time set and with the number of cameras available for the study. The survey took place over 109 sites (Figure 1). Fifty Browning Strike Force BTC-5HDP cameras were rotated in a random order around these sites between June and October 2018. Orientation was randomly assigned for each camera. If cameras could not be placed in the exact pre-determined location or orientation due to land access, vegetation blocking the field of view, or other reasons, then we placed them at the nearest suitable point, within the same habitat and without targeting placement to increase or decrease detection probability. We aimed to have each camera deployed for a minimum of 14 days which allowed us to rotate cameras around all sites within the survey period.

Researchers usually recommend setting cameras at the shoulder height of the target species (Meek et al., 2016) but this is obviously problematic when surveying multiple species of varying sizes. We also had issues with cameras being triggered or the field of view being partially or entirely blocked by vegetation when set at lower heights. Therefore, cameras were placed at a height of between 0.7 and 1.0 metres from the ground and angled slightly downward. Cameras were set to 'rapid fire' mode, with 8 photos taken in quick succession each time the camera was triggered. The delay between triggers was set to the minimum of one second and the trigger speed of the camera was 0.3 s according to manufacturers (Browning, 2017).

2.3.3 Availability for detection and angle measurements

Camera trap distance sampling requires an estimate of the availability for detection (Howe et al., 2017). We estimated the proportion of time for which each species was available for detection by fitting a circular kernel model to radian time data, using the R package 'activity' (Rowcliffe et al. 2014) (Appendix S1). This method assumes that, at the daily peak, 100% of the population was available for detection. This assumption can be violated by any species but semi-arboreal species, in particular, will spend a proportion of their active period out of the view of camera traps. In our study, therefore, the assumption could have been violated for grey squirrels which spend a proportion of time in trees. However, our estimate for availability for grey squirrels (0.33) was very similar to published data on the proportion of time grey squirrels spent on the ground in Italy (0.35, calculated using radio collars and observations, and taking a weighted average of the two figures published for Spring/Summer and Autumn/Winter) (Wauters et al. 2002). Consequently, we used our calculated figures for availability in our density estimations but we acknowledge that this might over-estimate availability and underestimate density for grey squirrels.

Detection is likely to decrease towards the edges of the field of view (FOV) (Rowcliffe et al., 2011). However, if cameras are set to take long bursts or videos, then moving animals will still be detected at large angles; for this reason, Howe et al. (2017) used the full FOV of the camera in their CTDS density calculations. Despite this, it has been recommended that angles are measured as well as distances to check whether sensitivity of the sensor across angles is uniform (Howe et al., 2017). These checks could be particularly important where cameras are set to take single images (Corlatti et al., 2020) or where there are unavoidable delays between triggers, such as in our study. We measured angles to image subjects and used these data to calculate the effective detection angle (Hofmeester et al., 2017) (Appendix S1). As the effective detection angle differed from the FOV angle in almost all cases, we used this as our angle measurement for estimating density.

2.3.4 Distance sampling methodology

Howe et al. (2017) recommend defining snapshot moments to discretise the number of times an animal could be detected, and suggested values between 0.25 and 3 s are likely to be useful. Corlatti et al. (2020) suggested using the minimum interval between captures as the value for the interval between snapshot moments when cameras are set to take single photos. Although we set our cameras to record in bursts of 8 photos, there was an unavoidable delay of at least 0.3s between photos within a burst, and 1s between triggers (figures according to manufacturers; Browning, 2017). Therefore, we wished to set the snapshot interval to the average minimum interval between captures. However, as the figures reported in manufacturer's handbooks are not always accurate (Corlatti et al., 2020), we calculated the average of intervals between photos for periods of time when the camera was being constantly triggered during set up. We used this (0.8 s) as our snapshot moment interval.

During camera set up, reference photos were taken with distance markers placed at 2-metre intervals up to 10 metres along the centre and down the sides of the field of view. Distance intervals were further decreased to 1-metre intervals following data collection by using the overlaid grid tool in Adobe Photoshop (for details, see Caravaggi et al., 2016). As precise distances were more difficult to determine further away from the camera, animals at distances over 8 metres were assigned to either an 8-10 m or 10+ m category. We measured distances of animals in all images. Images were screened and tagged in DigiKam (www.digikam.org).

As data in the 10+ m category accounted for less than 5% of overall data for each species, we right-truncated at 10 m for all species (Buckland et al., 2001). Distance sampling methodology assumes that detection is certain at zero distance; however, in CTDS, this assumption could be violated by animals passing underneath the camera or through the field of view before the camera is triggered (Howe et al., 2017). For each species, we worked on the assumption that detectability was highest in the distance category with the most captures per unit area and we left-truncated at the left boundary of that category. Exceptions to this rule were made in cases where: a) data distribution was determined to be due to the presence of trails rather than animals being missed by the camera; b) left truncation resulted in data being present in fewer than 5 distance categories, causing poor model fit and inaccurate estimates of effective detection distance (required to calculate density estimates; Hofmeester et al., 2017); or c) species showed attraction to the cameras. In all cases where we made exceptions to the left-truncation rule, sensitivity to left-truncation was checked by calculating densities at different left-truncation scenarios. In addition, for roe deer that showed attraction to cameras mostly at night, we calculated density estimates using daytime-only captures (defined as between sunrise and sunset). For this, we adjusted the total sampling time and calculated a measure of availability for detection using the same method as above, but setting the bounds of the model to be the sunrise/sunset times of the middle day of the survey period. We did not left-truncate these data.

We calculated survey-wide density estimates for species where >80 photos (and >10 photo sequences) were obtained. This threshold was chosen as Buckland et al. (1993) originally recommended between 60-80 sightings for calculating density with distance sampling and other studies using CTDS have used similar thresholds (Bessone et al., 2020). We used the Land Cover Map 2015 (1 km dominant aggregate habitat class; Rowland et al., 2017) to assign a habitat to each site where a camera trap was positioned. Habitat-specific density estimates were calculated if (after truncation): a) the species had >80 photos in the habitat; b) there were >10 sites in that habitat; and c) data were present in five or more distance categories. To calculate density, we followed the methods of Howe et al. (2017) and used the model selection process proposed by Howe et al. (2019) (Appendix S2). We also explored the effect on density estimates and confidence intervals of variance in the effective detection angle and snapshot moment. All analyses used R version 4.1.2 (R Core Team, 2021), with final models and density estimates calculated using the 'Distance' package (Miller et al., 2019). We compare our density estimates to those published by the national mammal society in the UK (Mathews et al., 2018), and in a paper by Croft et al., (2017) who gathered data on mammal occurrence and abundances from across the UK and used a systematic modelling approach to produce national and habitat-specific density estimates.

2.4 Results

We were able to place cameras at the exact random point at 48 / 109 sites. Of the cameras which were displaced, the average displacement from the point was 0.30 km (range 0.02 – 1.76). Small displacements (< 0.1 km) were most commonly due to moving a camera to place it on a post or structure (e.g., at the edge of a field). Large displacements (> 0.5 km) were mostly due to a lack of access permissions. A small number of displacements (5) were due to points falling on buildings or roads. Displacements occurred across a range of habitats but, most commonly, were in improved grassland. More information on camera displacements is in Table S1.

Despite efforts to set cameras away from livestock and to reduce triggers from vegetation, these problems occurred at 41 sites; cameras were stolen from a further two sites. Wherever we were able, cameras were redeployed at these sites either immediately or as soon as possible after the previous deployment. We included data from all deployments in our analyses. Cameras at 18 sites were deployed for fewer than 14 days (range 4 – 13), owing to interference by livestock and / or saturated memory cards, with no possibilities for further deployments (or the same issue occurring on multiple deployments). Cameras with shorter deployments were in the LCM habitat classes: mountain, heath and bog (5); semi-natural grassland (4); improved grassland (4); arable (3); and built up areas and gardens (2).

Overall effort totalled 1,785 camera days. In total, the survey generated 435,024 images and 51,447 photos contained a wild mammal. We focussed our analyses on eight mammal species for which data were adequate to calculate density estimates at a survey-wide level (Table 1). The number of sites at which these species were detected ranged from 14 (badger) to 66 (rabbit). At 15 sites, none of the eight species were captured. Sites where species were detected varied between species, but the majority of captures were in the east of the survey area in grassland/arable/urban habitats, with fewer captures in the mountain/heath/bog habitats in the west (Figure 2; Figure S3-S8). Activity schedules (Figure 2; Figure S3-S8) and associated availability for detection (Table 1) were in line with expectations for the species studied, with strictly nocturnal species such as hedgehogs having lower availability for detection (0.13) than diurnal or crepuscular species such as brown hare (0.53; Table 1). Effective detection angles for all species were within the range of 0.51 – 0.60 radians with the exception of roe deer, the largest of the focal species, which was 0.77 (the same as the FOV angle determined by manual testing; Table 1). All effective detection angles were smaller than the FOV angle in the manufacturer's guide (0.96; Browning, 2017).

We left-truncated at the distance category with the largest number of captures per unit area for red fox, brown hare, rabbit, grey squirrel and stoat (Table 1). For three species (badger, hedgehog, and roe deer), following this rule was not appropriate and we made exceptions (Appendix S3). For these species, the point of left-truncation made only a small difference to the badger density estimate, but large differences for the roe deer and hedgehog density estimates (Table S2). Roe deer density estimates for the whole study area and habitat-specific estimates using daytime only captures were slightly lower than estimates calculated with all data but confidence intervals still overlapped (Table 1-2; Table S3).

Table 1. Species-specific information, including density estimates per km^2 [95% CI] calculated across the whole study area, ordered by species body size. For each species, we give: number of sites species was captured at; total number of photos (i.e., observations); proportion of time available for detection; effective detection angle; density per km^2 with 95% CI estimated from bootstrap; estimated coefficient of variation (C.V.) from bootstrap; density estimates (per km^2) with 95% CI where provided as published in Mathews et al. (2018; calculated by taking abundance published and dividing by area of Great Britain); density estimate (per km^2) range published in Croft et al. (2017) . Animal silhouettes by Anthony Caravaggi and Claus Rebler, licensed under CC BY-NC-SA 3.0.

Species	Sites captured	Number of photos	Availability for detection	Effective detection angle	Truncation left, right (m)	Density per km^2 [95% CI]	C.V.	Mathews et al. 2018 Density per km^2 [95% CI]	Croft et al. 2017 Density per km^2 estimate range
Roe deer (*Capreolus capreolus*) 	31	2742	0.39	0.77	1, 10	5.67 [2.67 – 10.52]	0.38	1.09 [0.89 – 1.22]	3.22 – 25.70
Badger (*Meles meles*) 	14	459	0.30	0.56	2, 10	1.32 [0.84 – 4.22]	0.40	2.31 [1.61 – 4.18]	0.42 – 5.08
Red fox (*Vulpes vulpes*) 	45	1397	0.43	0.59	2, 10	5.97 [1.37 – 21.15]	0.39	1.47 [0.43 – 2.66]	0.38 – 2.10
Brown hare (*Lepus europaeus*) 	28	3635	0.53	0.56	1, 10	5.97 [2.86 – 12.89]	0.43	2.39 [1.76 – 8.21]	0.58 – 16.48
Rabbit (*Oryctolagus cuniculus*) 	66	30725	0.48	0.55	2, 10	101.83 [51.63 – 186.65]	0.39	148.46	9.70 – 1192.00
Hedgehog (*Erinaceus europaeus*) 	26	2034	0.13	0.60	1, 10	23.31 [7.39 – 45.33]	0.46	2.15	3.42 – 56.06

Grey squirrel (*Sciurus carolinensis*) 	25	4181	0.33	0.59	1, 10	7.64 [3.73 – 13.03]	0.30	11.13 [5.52 – 15.63]	8.27 – 77.60
Stoat (*Mustela erminea*) 	17	163	0.55	0.51	0, 10	0.22 [0.07 – 0.44]	0.55	2.09	--

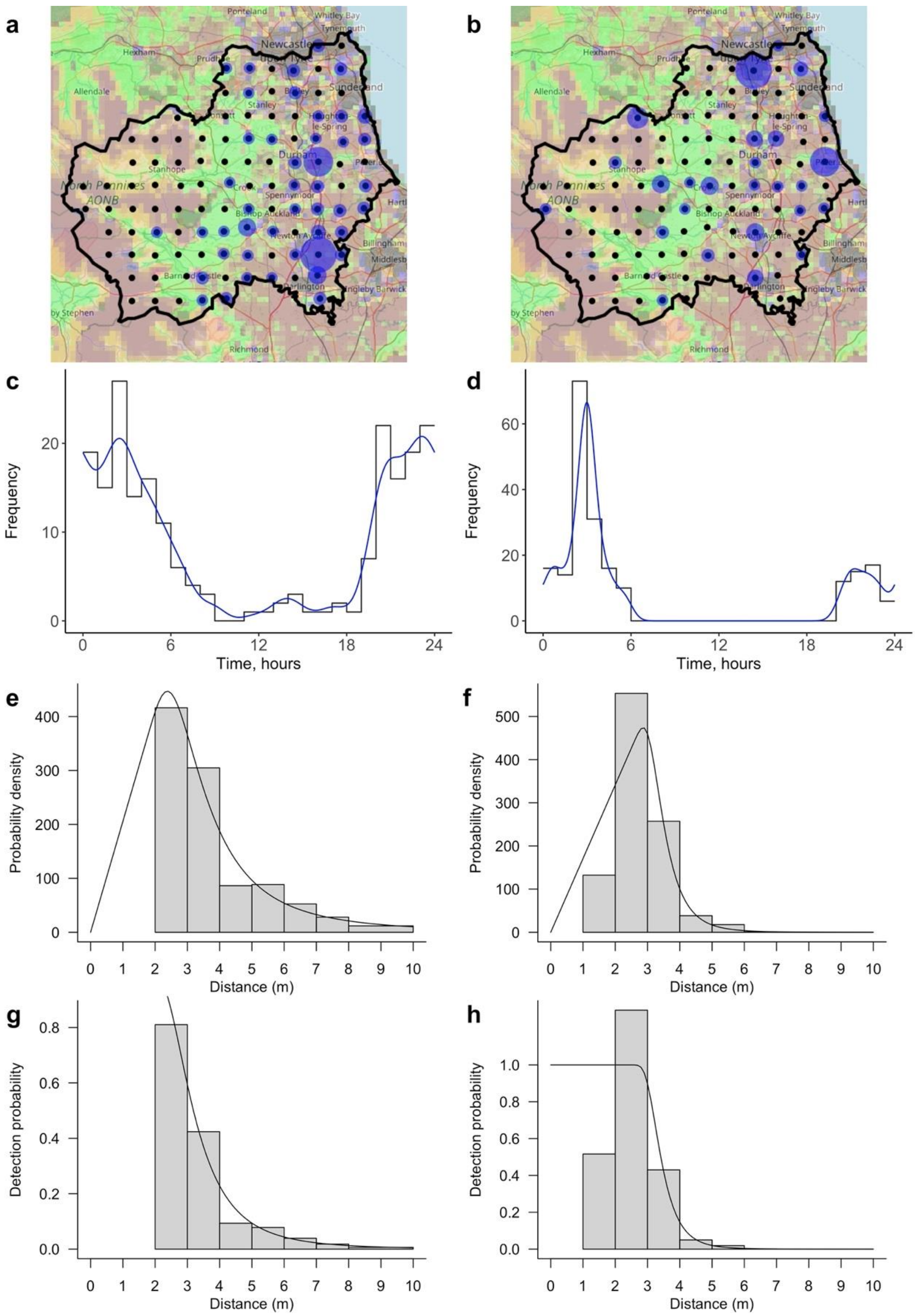


Figure 2. Example species distribution maps (a; b), activity schedules (c; d), probability density (e; f), and detection probability curves (g; h) for red fox (*Vulpes vulpes*; left) and hedgehog (*Erinaceus europaeus;* right). Species maps show locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedules show circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graphs show probability density of observed distances and detection probability graphs show detection probability as a function of distance from unadjusted hazard-rate point transect models.

The unadjusted hazard rate model was selected as the model of best fit for all species (following model selection criteria in Howe et al. 2019). Density estimates ranged from 0.22 per km^2 for stoat to 101.83 per km^2 for rabbit (Table 1). Coefficients of variation were all between 0.30 and 0.46, except for stoat, which had CV = 0.55 (Table 1). Density estimates were similar to estimates previously published by Mathews et al., (2018) and Croft et al., (2017), with almost all of our density estimates (except hedgehog, roe deer and stoat) falling within their published ranges and / or vice versa (Table 1). We also explored variation in the effective detection angle and snapshot moment and found that, because variance in these measures was very small (relative to the variance arising from spatial heterogeneity in captures), the effect of these sources of variance on density estimates and confidence intervals was also very small (Table S4).

Across the whole survey, cameras were placed within seven different habitat classes. Of these, four were represented at 10 or more sites and habitat-specific densities could be estimated. Data were adequate to produce at least one habitat-specific density estimate for each species, but not all species had sufficient data to support a density estimate for every habitat (Table 2). We used the same truncation distances for each species as in the survey-wide estimates (Table 1), but calculated habitat-specific availability for detection and effective detection angle measures (Table S5). The unadjusted hazard rate model was selected for all estimates, except for roe deer in arable habitat, for which the unadjusted half-normal model was selected.

The habitat-specific density estimates produced in our study largely fall within the ranges predicted for those habitats by Croft et al., (2017) (Table S5). Habitat-specific density estimates were often similar to survey-wide density estimates (i.e., falling within or close to the confidence interval range of survey-wide estimates), but with some notable differences (Table 2). Density estimates calculated for arable habitat were higher than survey-wide estimates for all species except hedgehog, for which the arable density estimate was ten times lower. For improved grassland, the density estimate was also much lower than survey-wide estimates for hedgehog and fox. Badger, brown hare, grey squirrel and stoat all had higher density estimates in improved grassland than the survey-wide estimates. For mountain, heath and bog habitat, there were sufficient data to estimate density for rabbit only. This density estimate was around a quarter of the survey-wide estimate.

Table 2. Density estimates per km^2 [95% CI] calculated across the whole study area and for four different habitats. Number of sites a camera was positioned at for each habitat shown in brackets in header. Cells marked with an Asterix indicate the species was captured in this habitat, however data were not sufficient to calculate density estimates; either due to not enough photos captured (*) or data being present in less than five distance categories (**). Blank cells indicate this species was not captured in this habitat during this survey. Animal silhouettes by Anthony Caravaggi and Claus Rebler, licensed under CC BY-NC-SA 3.0.

Species	Whole study area (109)	Arable (29)	Built up areas and gardens (16)	Improved grassland (38)	Mountain, heath, bog (13)
Roe deer (*Capreolus capreolus*) 	5.67 [2.67 – 10.52]	12.42 [3.89 – 32.28]	**	4.34 [3.33 – 49.99]	*
Badger (*Meles meles*) 	1.32 [0.84 – 4.22]	2.01 [0.78 – 5.82]		1.81 [0.17 – 2.87]	
Red fox (*Vulpes vulpes*) 	5.97 [1.37 – 21.15]	19.26 [3.60 – 28.97]	2.55 [0.40 – 13.19]	0.49 [0.35 – 1.83]	
Brown hare (*Lepus europaeus*) 	5.97 [2.86 – 12.89]	10.94 [2.88 – 34.83]		7.40 [2.60 – 14.06]	
Rabbit (*Oryctolagus cuniculus*) 	101.83 [51.63 – 186.65]		112.19 [7.74 – 334.96]	99.39 [45.60 – 164.71]	26.37 [8.92 – 51.75]
Hedgehog (*Erinaceus europaeus*) 	23.31 [7.39 – 45.33]	2.86 [0.76 – 7.67]	**	6.59 [1.40 – 13.03]	*
Grey squirrel (*Sciurus carolinensis*) 	7.64 [3.73 – 13.03]	8.76 [0.72 – 19.79]	3.88 [0.79 – 8.76]	10.83 [3.51 – 26.37]	
Stoat (*Mustela erminea*) 	0.22 [0.07 – 0.44]	*		0.55 [0.15 – 2.74]	*

2.5 Discussion

We used camera trap distance sampling to estimate survey-wide and habitat-specific densities for a range of UK mammal species across a varied landscape. The study was rapid, relative to previous studies of multiple species over large spatial scales, and the lessons learnt should have much wider implications for using CTDS on a large scale for country-wide mammal monitoring. Here, we discuss our findings with respect to three issues: 1) the calculated density estimates and how they compare to previous published estimates; 2) practical and methodological issues that need careful consideration in future; and 3) implications of the study for country-wide mammal monitoring.

2.5.1 Accuracy and precision of density estimates

Five of our eight species had density estimates which fell within the confidence intervals of the estimates in Mathews et al. (2018), and / or vice versa, and all but two of our density estimates fell within the ranges predicted by Croft et al. (2017). Our estimates are for North-East England only and, therefore, some differences to national estimates are expected. Estimates for three species (hedgehog, roe deer, and stoat) differed considerably from national estimates. For hedgehog, this could be due to the distribution of data (with few captures at both small and large distances) causing poor model fit and inaccurate density estimates. We estimated high densities of roe deer relative to national estimates; this result is expected because, although roe deer are widely distributed throughout the UK, North-East England (where our study was based) has a higher abundance than other areas, such as central and south east England (Crawley et al., 2020). For stoats, our density estimate was lower than that in Mathews et al., (2018), but they noted that their estimate was unreliable due to a lack of data (and hence no CI could be produced). Croft et al. (2017) were similarly unable to produce an estimate for stoat density, because of this lack of data.

Our study is the first CTDS survey to produce density estimates for both the whole-survey area and specific habitats within that area. The ability to produce these habitat-specific density estimates will be beneficial for conservation management, and will help to address data gaps. It is also useful for scaling up density estimates, as shown by Croft et al., (2017) who used habitat-specific density estimates to generate UK-wide density estimates. The confidence intervals surrounding our habitat-specific estimates are large in some cases (Table 2). However, considering the lack of data, and the published ranges of the current best density estimates for UK mammal species, our estimates are still amongst the most precise produced for these species to date.

2.5.2 Practical and methodological issues

The ability to use CTDS to generate density estimates across multiple species and habitats from one survey is encouraging, suggesting the method could be deployed on large scales for species monitoring. However, for countries such as the UK where the landscape is heterogeneous and includes human-altered habitats, there are practical limitations to consider. CTDS requires camera traps to be set at pre-determined (usually systematically random) points. In most surveys, the potential to deploy all cameras at pre-selected points is constrained. However, in our study, 56% of our cameras were displaced, some over quite large (>1 km) distances. Whilst Howe et al. (2017) states that small displacements should not bias estimates, if cameras are displaced to be put on trees or other features that species (e.g., semi-arboreal grey squirrels) may be attracted to, then those species could be captured more frequently at smaller distances which has implications for density estimation. Furthermore, it is unclear what the effect of larger displacements (usually caused by land access issues) would be on density estimates. Whilst we made sure that displaced cameras were still within the same habitat, previous studies have shown that even within the same habitat, small-scale factors – such as the presence of log / trail features - can result in large differences in capture rates (Kolowski et al., 2021; Kolowski and Forrester, 2017). This could be problematic for any large-scale camera trap survey (particularly in heterogeneous landscapes) that use CTDS or any other method that requires cameras to be set at pre-determined random locations. Alternative designs might be required to mitigate against displacements, such as deploying multiple cameras at each site (Kolowski et al., 2021). Ultimately, however, covariation between land access and animal abundance is always likely to constrain the accuracy of wildlife surveys.

Camera traps surveys are often vulnerable to camera theft, vegetation triggering cameras and livestock damaging cameras (Jumeau et al., 2017; Meek et al., 2019; Nichols et al., 2017; Swanson et al., 2015). The heterogeneous landscape of our study appeared to exacerbate this issue, with almost half of our cameras being affected and ~85% of photos resulting from vegetation / livestock triggers. This necessitated multiple and, in some cases, shorter deployments. Whilst multiple deployments were an inconvenience, we do not believe they biased density estimates; however, shorter deployments could influence survey-wide density estimates if shorter deployments occur more frequently in certain habitats. Relative to their frequency in the overall survey, improved grassland and semi-natural grassland had more short deployments. As some of the density estimates for improved grassland were different to the survey-wide estimates, shorter deployments in that habitat could have biased survey-wide estimates. Future surveys in heterogeneous landscapes must factor in ample extra time for redeployments due to practical challenges.

As well as these practical issues, CTDS also presents methodological challenges. These include the species-specific decisions that must be made and which need careful consideration, owing to their strong influence on density estimates. Perhaps the most challenging factor to consider is left-truncation. Left-truncation can be problematic if used inappropriately, because the loss of data results in extrapolation of the slope of the probability detection function at distance zero, which is then used to estimate density. Nevertheless, left-truncation is commonly used in CTDS when animals are likely moving underneath the camera, causing fewer than expected detections at small distances (Bessone et al., 2020; Cappelle et al., 2019, 2021; Howe et al., 2017; Palencia et al., 2021). In a large multi-species study, it would be beneficial to have one method for deciding when and by how much to left-truncate; hence, we trialled a rule across all species, left-truncating at the start of the distance category with the most captures per unit area surveyed. Whilst this rule worked for most species, it was inappropriate for three species: badgers, for which the lack of detections at short distances was more likely due to trails at a larger distance; hedgehogs, for which a lack of spread in the data caused problems when truncating; and roe deer, which showed attraction to cameras. These cases all demanded species-specific decisions about left-truncation distances (Appendix S3).

Other aspects of CTDS that must be considered on a species-by-species basis include identifying which species may be reacting to cameras, as this may lead to more detections than expected at distance zero. Multiple ways of dealing with this have been proposed, including left-truncation (Cappelle et al., 2019) and removing images where animals show a reaction to the camera (Bessone et al., 2020). In our study, we used left-truncation for roe deer as this species appeared to be attracted to cameras. However, because roe deer were mainly reacting to cameras at night (Figure S2), presumably due to the infrared flash (Henrich et al., 2020) we also produced estimates using daytime-only captures (Table S3) as an alternative to left-truncation. We found similar density estimates and estimates of variance produced by the two methods (restricting data to daytime captures only, or left truncating at 1 m), suggesting that either could be appropriate for dealing with reactivity to cameras. Future studies using CTDS should consider sample size and causes of reactivity to determine which method is most appropriate.

Semi-arboreal species pose particular problems for density estimation. For these, calculating availability for detection using the method outlined by Rowcliffe et al. (2014) may be inappropriate. This is because the assumption of 100% detection at times of peak activity may be especially problematic for species that spend time active out of the view of cameras. In our study, the proportion of time available for detection for grey squirrels (a semi-arboreal species) was highly similar to the figure calculated by Wauters et al. (2002) for proportion of time grey squirrels spent on the ground in Italy. Whilst this provides some reassurance, it would be preferable to have observational data on time on the ground for the period and location being studied.

To survey species of varying size, and to reduce vegetation-induced camera triggers, we set cameras higher than would be advised for many species in our study (Meek et al., 2016). Smaller-bodied animals may have been captured at a larger range of distances and angles if cameras were deployed at lower heights height (e.g., Rowcliffe et al., 2011). In turn, this might have obviated the need for some of the decisions around left-truncation, whilst rendering valid the full FOV. There is, of course, a trade-off between ideal placements for animals of different sizes and this identifies one of the limitations of community-wide (or multispecies) monitoring by this method. For effective multispecies monitoring using CTDS, deployments at different heights might be necessary to survey different components of the community.

2.5.3 Camera trap distance sampling for country-wide mammal monitoring

To carry out effective conservation and management for species, and to meet national and international obligations for species monitoring (e.g., CBD, 2010), large-scale monitoring in many countries needs to be improved. However, monitoring on a national level is inherently costly and approaches need to be cost-effective and practical to employ. CTDS offers a way to monitor multiple species concurrently, over large spatial scales, and uses a methodology (distance sampling) benefitting from existing resources and software. As highlighted by Schaus et al. (2020), the start-up cost of any camera trapping survey is high; however, cameras can be rotated around sites to reduce costs and can be used in repeated surveys for many years. CTDS is also less demanding of time than many other methods (e.g., line transects); our study was conducted over a large area, and calculated density estimates for multiple species, but was conducted by a single researcher. CTDS thus offers a promising solution to improve terrestrial mammal monitoring efforts in the UK and other countries.

There are multiple ways CTDS could be deployed on a national scale. If it would be beneficial to obtain regional densities (perhaps for local species management purposes) then setting up a grid of cameras across the country at the same resolution as in our study (5 km^2) might be most appropriate. Alternatively, it might be beneficial to have a stratified sampling approach to obtain habitat-specific density estimates, including for rare but important habitats. Either way, in order to achieve such large-scale monitoring, it is likely that support from citizen scientists would be required. Citizen scientists play a large and important role in ecological data collection in many countries, including the UK (Pocock et al., 2015). Citizen science projects already enlist volunteers to deploy camera traps (Hsing et al., 2018; Lasky et al., 2021; Locke et al., 2019; McShea et al., 2016). Such projects could collect data appropriate for CTDS by allocating sites to participants and training them to follow the methodology to calibrate cameras. Although the expertise of citizen scientists is sometimes questioned (Kosmala et al., 2016), many projects exist that require citizen scientists to follow strict protocols; for example, the UK's Breeding Bird Survey run by the British Trust for Ornithology (Harris et al., 2020b). Importantly, we note that accurate hedgehog densities using the Random Encounter Model were estimated with data collected by citizen scientists who deployed camera traps following a calibration methodology similar to that in CTDS (Schaus et al., 2020).

2.5.4 Conclusion

Despite the methodological and practical limitations we discuss, CTDS provides a promising method to achieve large-scale monitoring for many species. Further investigation of certain aspects of the methodology (such as left-truncation) is needed, and a 'one size fits all' approach for multiple species at a time may not be possible, especially for smaller species. However, we show that with careful consideration of these factors, realistic density estimates can be calculated for multiple species, including species for which density measures have previously proven difficult to obtain. The UK is one case study of where the lack of data on wild mammal species highlights the need for improved species monitoring on a national scale. Employing CTDS on a national scale for species monitoring would be inherently costly, but costs could be reduced by enlisting existing citizen science networks and projects. The benefits of employing such a scheme would be significant, given the increasing anthropogenic pressures facing species worldwide and the current gaps in our data and knowledge, which limit our ability to predict how species will respond.

2.6 Acknowledgements

We thank the land-owners for permission to deploy camera traps across our survey area. We also thank R. Ascroft and A. Kelly for their help with setting up cameras and students from Newcastle University who assisted with classifying images. Finally, we thank M. Rowcliffe for advice regarding R code for analysis.

2.7 Supplementary material

Appendix S1

Availability for detection

We estimated the proportion of time each species was available for detection by cameras by fitting a circular kernel model to radian time data, using the R package 'activity' (Rowcliffe et al., 2014). As recommended by Rowcliffe et al. (2014) we set the bandwidth multiplier to 1.5. To help ensure independence of observations of times of detection, Rowcliffe et al. (2014) suggest using only the time of the initial trigger, discarding all other photos taken of the animal for the time it remains in the field of view. We followed this approach, but in addition, discarded data if the animal returned to the field of view <2 minutes after the last photo was taken.

Effective detection angle

As detection probability is likely to decrease towards the edges of the field of view, we assigned animal locations within images to categories, with 0% being the vertical midline of the photo and 100% being the outer edge of the photo; the categories were 0-20%, 20-60% or 60-100%. We then converted categories into angles using the field of view (FOV) angle, which we calculated by measuring distances between objects at the outer edges of the FOV and using trigonometry to work out the angle. Effective detection angle was then calculated by fitting half-normal detection functions to angle data using package 'Distance' in R (for more information, see Hofmeester et al., 2017).

Snapshot moment

Howe et al. (2017) recommend defining snapshot moments to discretise the number of times an animal could be detected, and suggest values between 0.25 and 3 s are likely to be useful. Corlatti et al. (2020) suggested using the minimum interval between captures as the value for the interval between snapshot moments when cameras are set to take photos. We calculated the average of intervals between photos for periods of time when the camera was being constantly triggered during set up and used this (0.8 s) as our snapshot moment interval.

Appendix S2

Densities for all species were estimated using the R package 'Distance' with the equation set out in Howe et al., (2017):

$$\widehat{D} = \frac{n_k}{\pi w^2\ e_k\ \widehat{P}} * \frac{1}{A}$$

where $\widehat{D}$ is density, n_k is the number of observations at point k, w is the truncation distance beyond which records were discarded, $\widehat{P}$ is the estimated probability of detection of an animal at a snapshot moment as estimated by the modelled detection function. $e_k = \frac{\vartheta T_k}{2\pi t}$ is the sampling effort at point k. T_k is the total sampling time at point k in seconds, t is the time interval between snapshot moments (0.8 s), and θ is the effective detection angle, so $\frac{\theta}{2\pi}$ represents the effective proportion of a circle covered by the camera. Finally, A is the proportion of time available for detection.

Model selection

We considered models of the detection function with half-normal key function with 0, 1 or 2 Hermite polynomial adjustment terms, the hazard rate key function with 0, 1, or 2 cosine adjustments, and the uniform key function with 1 or 2 cosine adjustments. As many observations were not independent, Akaike's information criterion (AIC) is likely to select overly complex models (Buckland et al., 2001). Therefore, we used the two-step model selection process proposed by Howe et al., (2019), which calculates an overdispersion factor (ĉ) and associated adjusted model selection criteria (QAIC) to select among models of the same general form using QAIC, and then select among QAIC-selected models using ĉ. Further to this, we estimated variances from 999 nonparametric bootstrap resamples with replacement across camera locations.

Appendix S3

Left-truncation decisions

We left-truncated at the distance category with the largest number of captures per unit area for red fox, brown hare, rabbit, grey squirrel and stoat (Table 1). For three species, we made exceptions:

Badger: The majority of badger captures were at 3-4 m however this was largely driven by 44% of all badger photos being captured at only two sites, and just under half of the captures at these sites were recorded as 3-4 m. Therefore, we determined this pattern in detections to be due to the presence of trails (at these two sites) and not because badgers were being missed by cameras. Therefore, we left-truncated data at 2 m for badger, the same distance as for the red fox, a similarly-sized carnivore.

Hedgehog: The majority of hedgehog captures were at 2-3 m, but as there were no captures of hedgehogs at >6 m truncating at 2 m resulted in data being present in only four distance categories. Hofmeester et al., (2017) found that, in order to calculate reliable effective detection distances, a minimum of five distance categories was needed. This accords with our results as, when we left-truncated at 2 m for hedgehog, it resulted in poor model fit (see Figure S1) and density estimates that were inaccurate and imprecise (Table S2). We therefore truncated at 1 m for hedgehog.

Roe deer: Roe deer were attracted to the camera traps which resulted in more captures than expected at 0-1 m. We therefore left-truncated roe deer at 1 m.

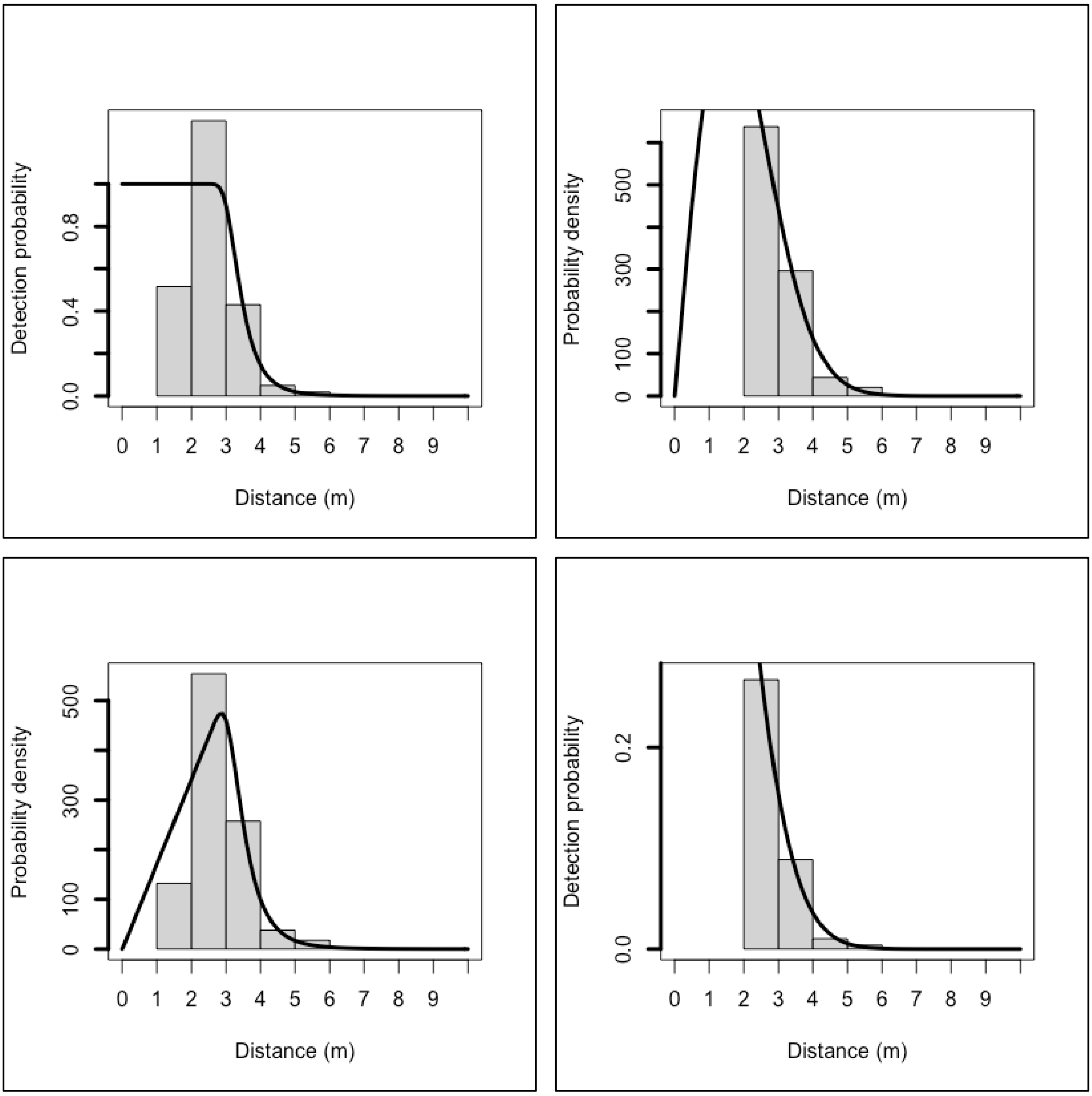


Figure S1. Detection probability as a function of distance (top) and probability density of observed distances (bottom) for hedgehog (*Erinaceus europaeus)* under two different left-truncation scenarios. Left: left-truncation at 1 m. Right: left-truncation at 2 m. Model selected for 1 m left-truncation scenario (left) was unadjusted hazard rate. Model selected for 2 m left-truncation scenario (right) was unadjusted half-normal.

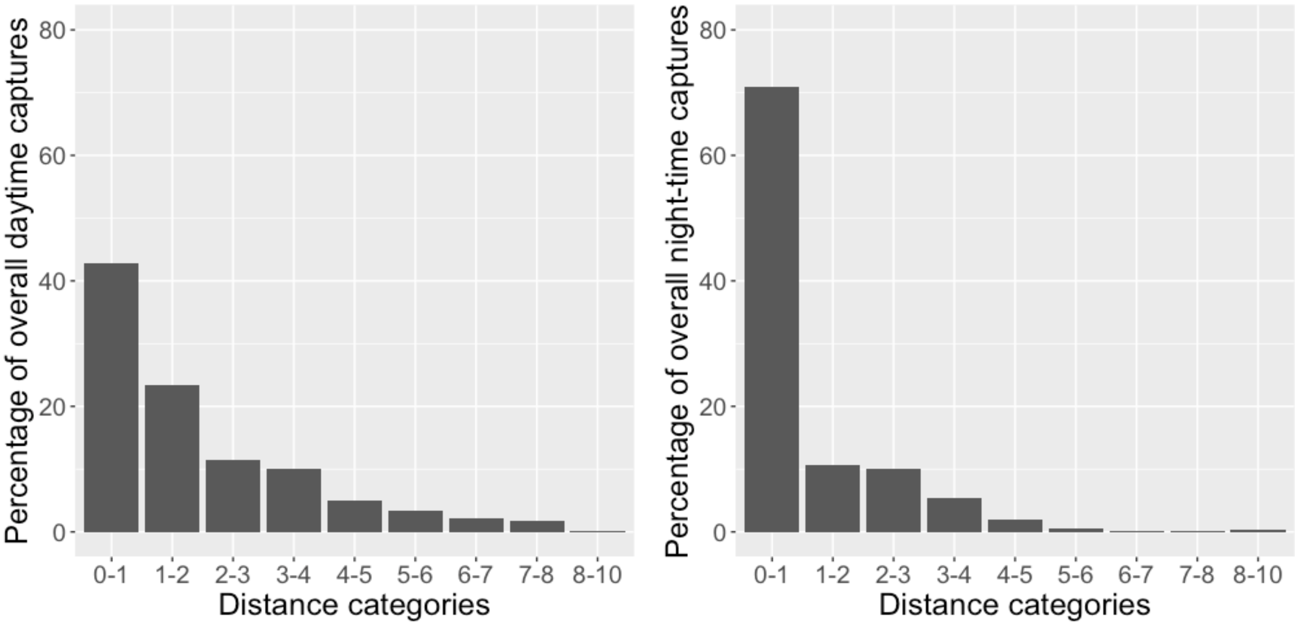


Figure S2. Percentage of captures in each distance category for roe deer (*Capreolus capreolus*) in the daytime (left) and the night-time (right). Daytime defined as the hours between sunrise and sunset.

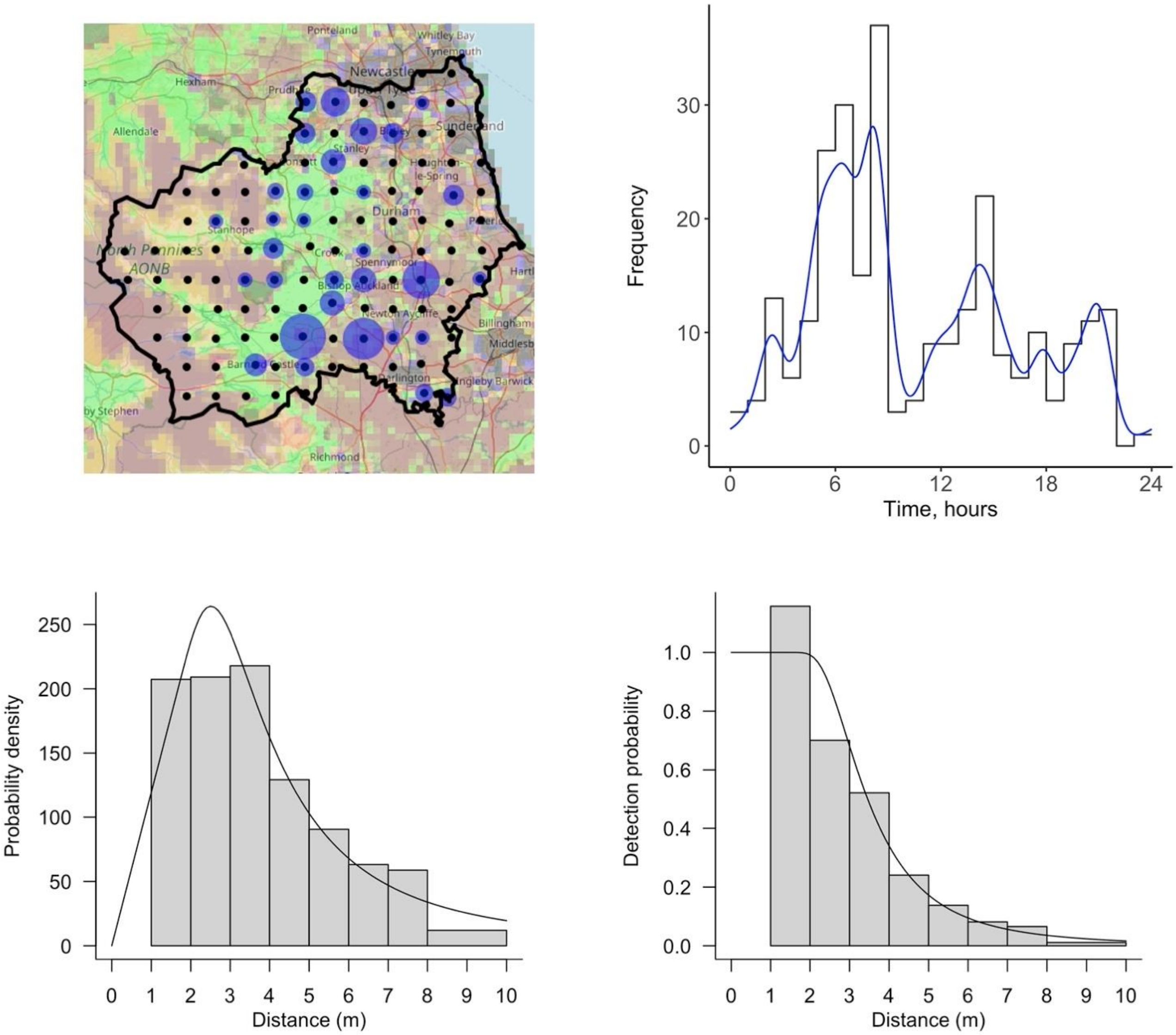


Figure S3. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for roe deer (*Capreolus capreolus*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

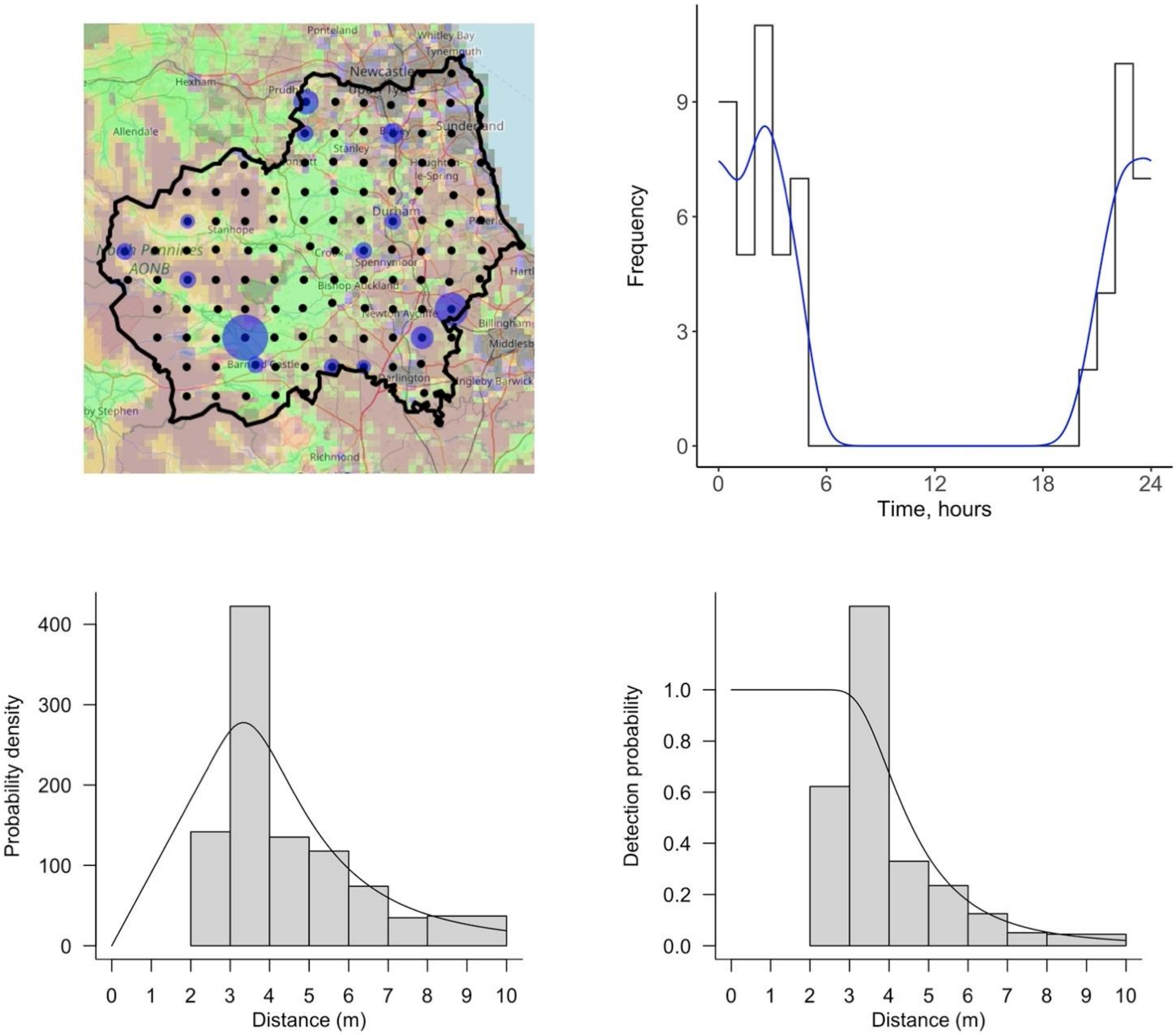


Figure S4. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for badger (*Meles meles*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

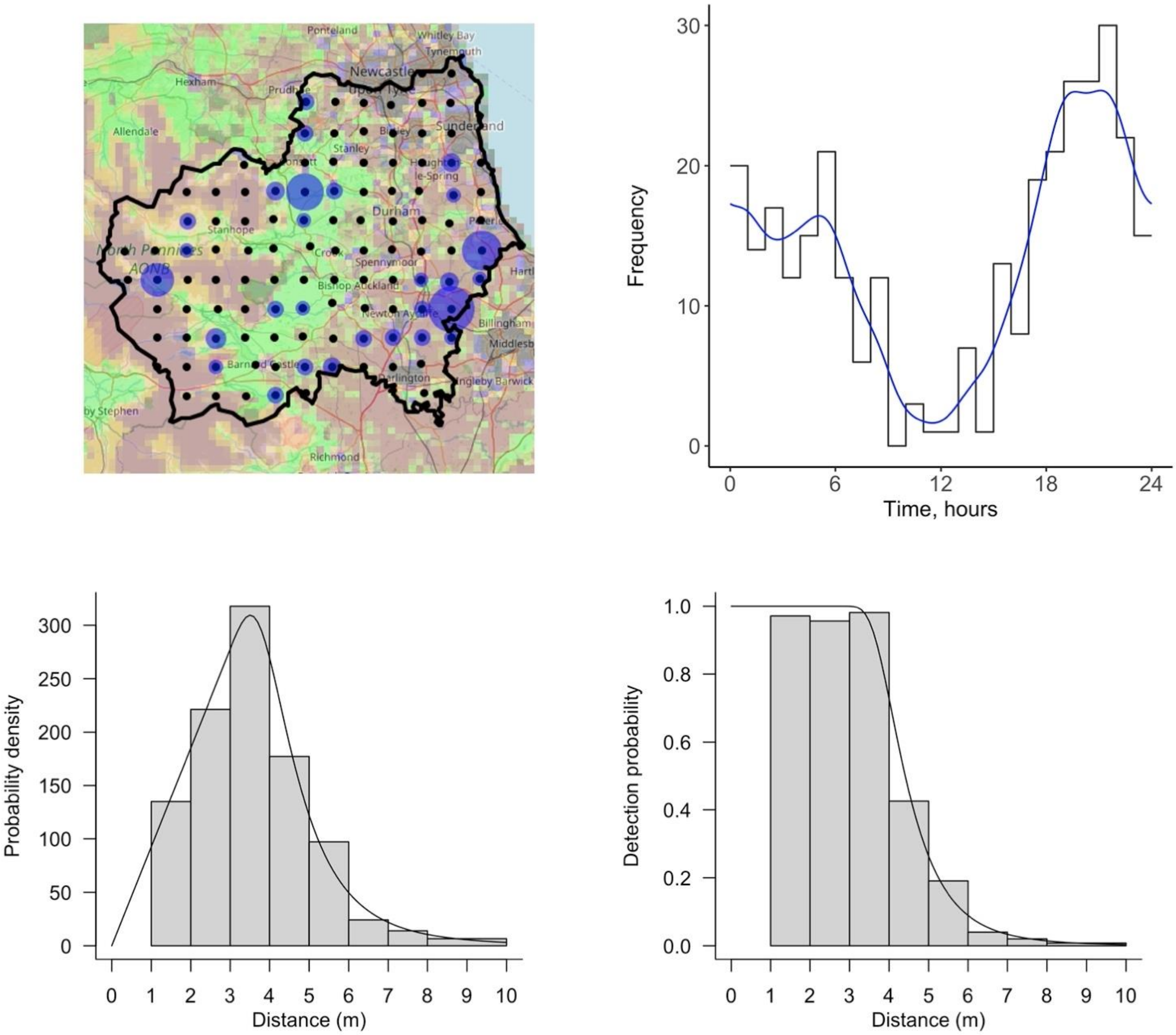


Figure S5. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for brown hare (*Lepus europaeus*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

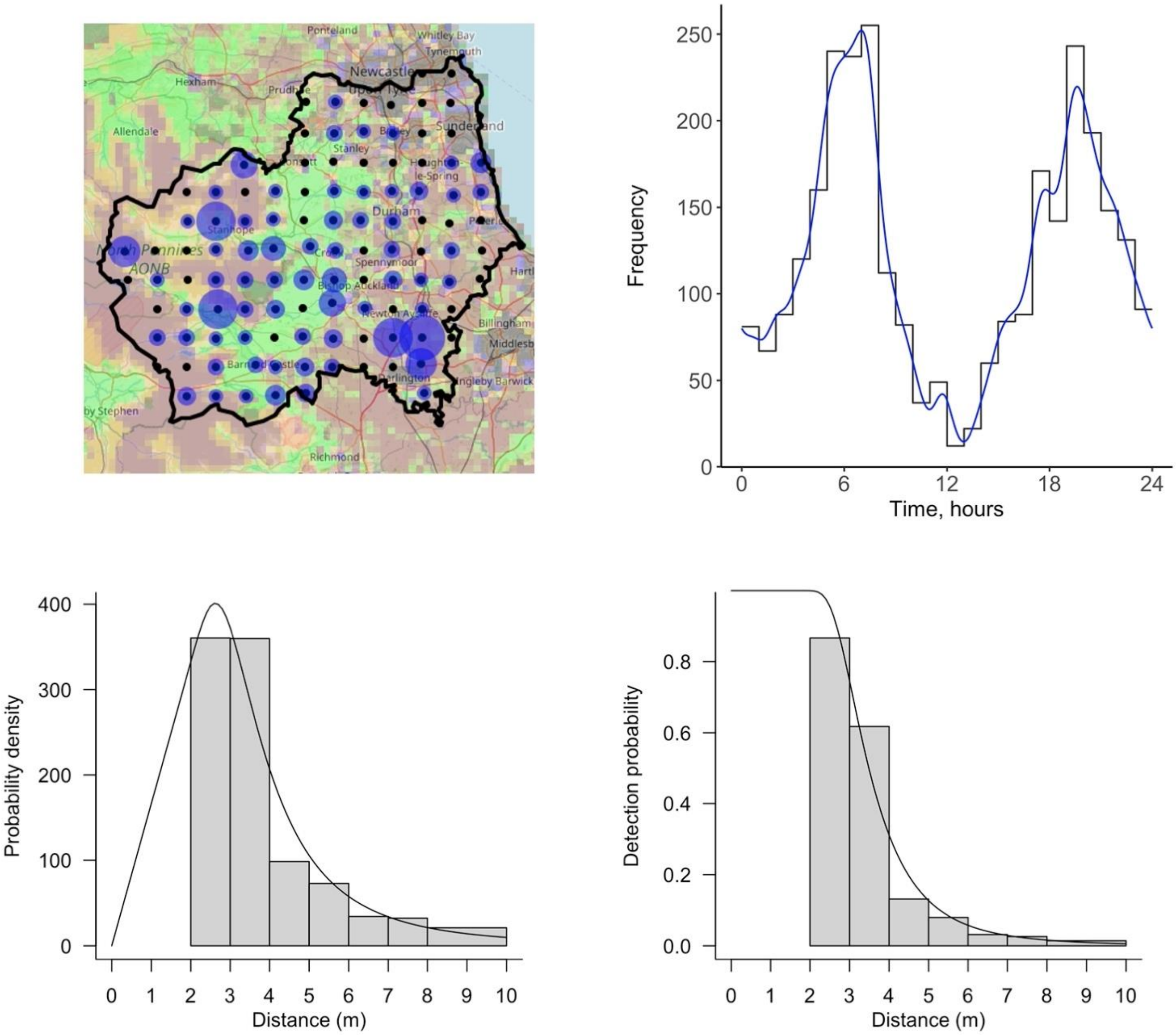


Figure S6. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for rabbit (*Oryctolagus cuniculus*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

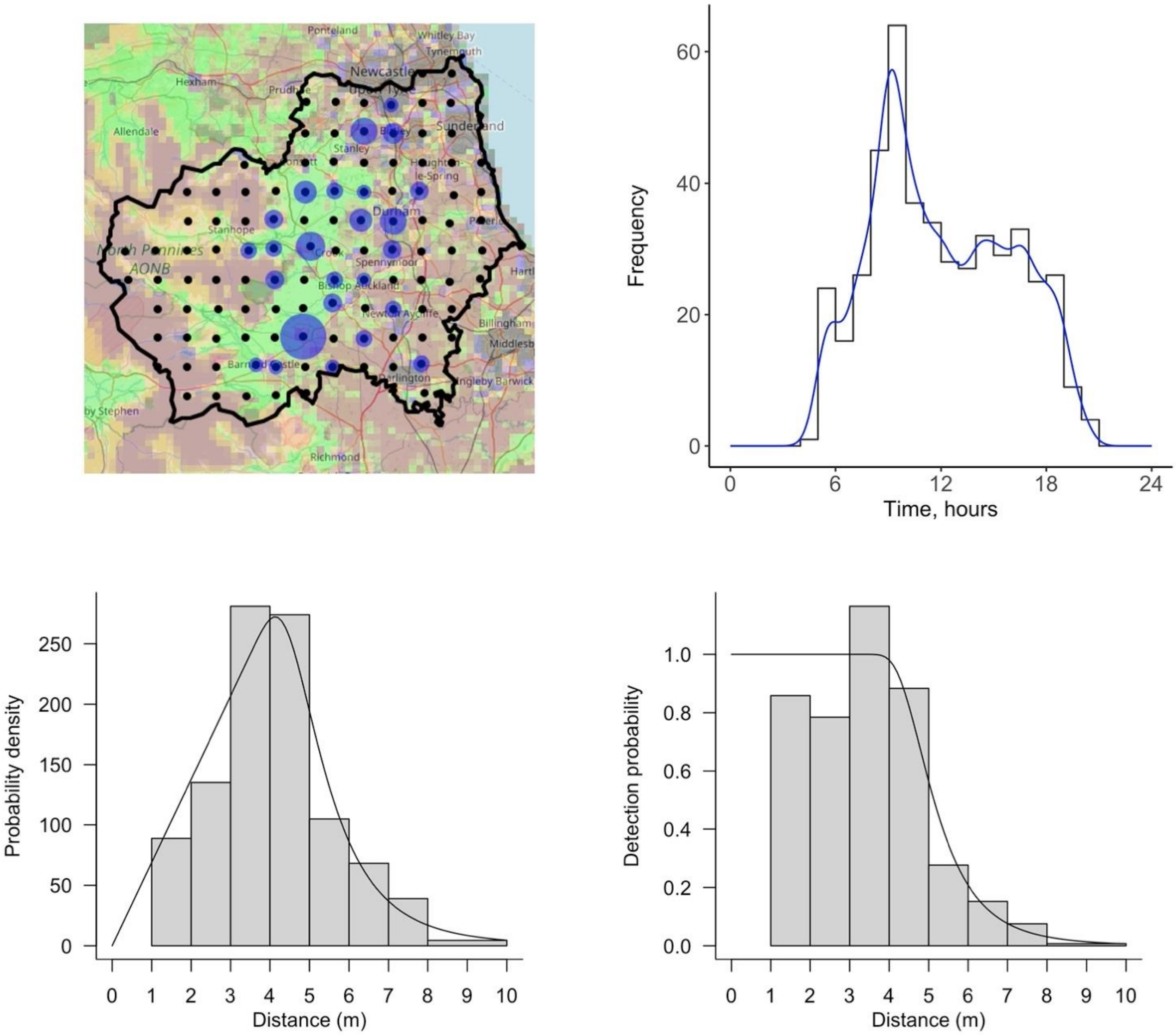


Figure S7. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for grey squirrel (*Sciurus carolinensis*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

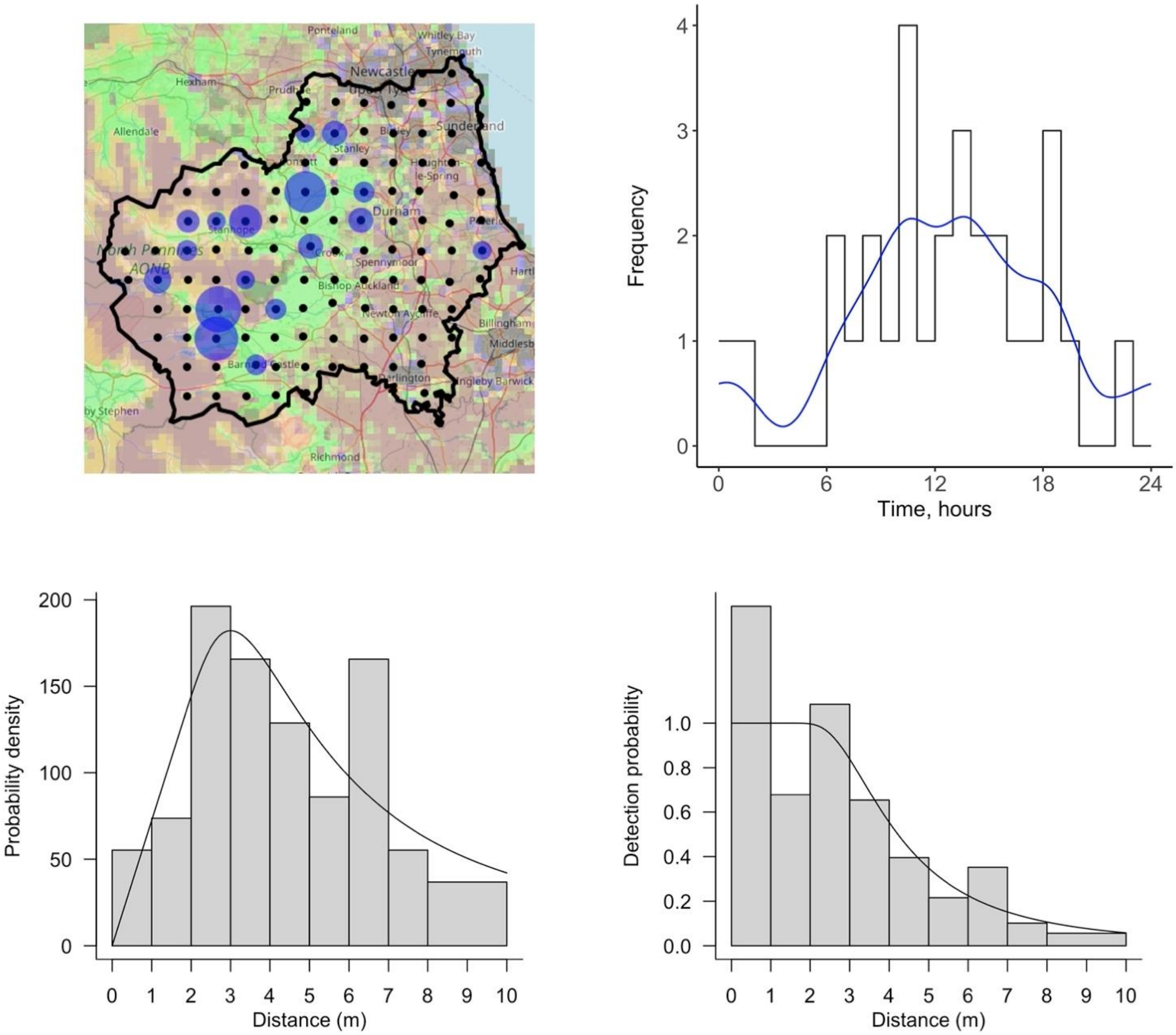


Figure S8. Species distribution map (top-left), activity schedule (top-right), probability density (bottom-left) and detection probability (bottom-right) graphs for stoat (*Mustela erminea*). Species map shows locations of all cameras (black circles) with locations of captures for the species (blue circles) scaled to the number of captures. Colours on map represent habitat data from Land Cover Map 2015 (1 km dominant aggregate class; Rowland et al., 2015) key for colours can be found in Figure 1. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0. Activity schedule shows circular kernel models fitted to radian time data of relative frequency of independent captures over the 24h period. Probability density graph shows probability density of observed distances and detection probability graph shows detection probability as a function of distance from unadjusted hazard-rate point transect model.

Table S1. Details of camera trap placements including information on which camera traps were displaced from the pre-determined random point and the reason for the displacement.

Location name	Habitat	Distance from original point (km)	Reason for displacement from original point
1	Semi-natural grassland	0	
2	Mountain, heath, bog	0	
3	Improved grassland	0.062	No post to place camera
4	Improved grassland	0.208	Livestock
5	Arable	0.514	Land access
6	Improved grassland	0.715	Land access
7	Arable	0.641	Land access
8	Mountain, heath, bog	0	
9	Mountain, heath, bog	0	
10	Semi-natural grassland	0	
11	Improved grassland	1.764	Land access
12	Improved grassland	0.062	No post to place camera
13	Improved grassland	0	
14	Arable	0.294	Vegetation
15	Arable	0	
16	Built up areas and gardens	0	
17	Built up areas and gardens	0.593	Livestock
18	Mountain, heath, bog	0	
19	Improved grassland	0	
20	Improved grassland	0.096	No post to place camera
21	Improved grassland	0.053	No post to place camera
22	Improved grassland	0	
23	Arable	0.279	Livestock
24	Improved grassland	0.102	Land access
25	Arable	0.115	Vegetation
26	Arable	0	
27	Arable	0	
28	Arable	0	
29	Mountain, heath, bog	0	
30	Semi-natural grassland	0	
31	Improved grassland	0.355	Vegetation
32	Mountain, heath, bog	0	
33	Improved grassland	0.020	No post to place camera
34	Improved grassland	0.343	No post to place camera
35	Improved grassland	1.024	Land access
36	Built up areas and gardens	0.212	Land access

37	Built up areas and gardens	0.208	Land access
38	Improved grassland	0	
39	Arable	0	
40	Mountain, heath, bog	0	
41	Improved grassland	0.085	Vegetation
42	Semi-natural grassland	0.095	No post to place camera
43	Mountain, heath, bog	0.033	No post to place camera
44	Mountain, heath, bog	0	
45	Coniferous woodland	0	
46	Improved grassland	0.049	Camera safety
47	Improved grassland	0	
48	Broadleaf Woodland	0	
49	Arable	0	
50	Arable	0.062	Land access
51	Arable	0.443	Vegetation
52	Arable	0.191	Vegetation
53	Semi-natural grassland	0.689	Vegetation
54	Semi-natural grassland	0.502	Land access
55	Semi-natural grassland	0	
56	Semi-natural grassland	0.154	No post to place camera
57	Improved grassland	0.409	Livestock
58	Improved grassland	0.316	Vegetation
59	Improved grassland	1.173	Land access
60	Improved grassland	0.218	Vegetation
61	Arable	0	
62	Built up areas and gardens	0.058	Building
63	Arable	0.219	Camera safety
64	Improved grassland	0	
65	Arable	0.242	Land access
66	Semi-natural grassland	0.165	No post to place camera
67	Semi-natural grassland	0.069	Vegetation
68	Mountain, heath, bog	0	
69	Improved grassland	0.378	Land access
70	Improved grassland	0.074	No post to place camera
71	Improved grassland	0.124	Vegetation
72	Improved grassland	0.373	Vegetation
73	Improved grassland	0	
74	Arable	0.069	No post to place camera
75	Arable	0.610	Land access
76	Built up areas and gardens	0.060	Road
77	Mountain, heath, bog	0	
78	Mountain, heath, bog	0	

79	Mountain, heath, bog	0	
80	Improved grassland	0.131	No post to place camera
81	Improved grassland	0	
82	Improved grassland	0.063	No post to place camera
83	Improved grassland	0	
84	Built up areas and gardens	0.065	Camera safety
85	Arable	0.463	Building
86	Arable	0.630	Camera safety
87	Arable	0	
88	Improved grassland	0.585	Land access
89	Built up areas and gardens	0	
90	Built up areas and gardens	0.179	Land access
91	Arable	0	
92	Built up areas and gardens	0.127	Road
93	Built up areas and gardens	0	
94	Arable	0	
95	Arable	0	
96	Improved grassland	0.087	No post to place camera
97	Arable	0	
98	Broadleaf Woodland	0.245	Camera safety
99	Arable	0	
100	Built up areas and gardens	0	
101	Built up areas and gardens	0	
102	Improved grassland	0.282	Camera safety
103	Improved grassland	0.324	Land access
104	Improved grassland	0.074	No post to place camera
105	Built up areas and gardens	0.380	Building
106	Arable	0	
107	Arable	0.217	Land access
108	Built up areas and gardens	0	
109	Built up areas and gardens	0	

Table S2. Densities [95% CI] calculated across whole study area under different left-truncation scenarios for species where truncation decisions were questioned due to: data not being consistent with understanding of species (badger); poor model fit (hedgehog); or animals being attracted to cameras (roe deer). Densities calculated are for truncation distances at the start of the distance category with the most captures, and for one metre below (badger and hedgehog) or above (roe deer) to mitigate against problems mentioned. Animal silhouettes by Anthony Caravaggi and Claus Rebler, licensed under CC BY-NC-SA 3.0.

Species	Density per km^2 [95% CI]		
	Left truncation = 0 m	**Left truncation = 1 m**	**Left truncation = 2 m**
Badger (*Meles meles*) 		1.14 [0.50 – 2.00]	1.32 [0.84 – 4.22]
Hedgehog (*Erinaceus europaeus*) 		23.31 [7.39 – 45.33]	113.08 [25.99 – 364.37]
Roe deer (*Capreolus capreolus*) 	16.71 [5.54 – 34.00]	5.67 [2.67 – 10.52]	

Table S3. Density estimates [95% CI] and other species/habitat specific information for roe deer using daytime capture data only. For each habitat: number of sites at which the species was captured; total number of photos (i.e., observations); proportion of time available for detection (calculated using method in Rowcliffe et al. 2014, adjusting for daytime only by setting bounds to be the sunrise/sunset times of the middle day of the survey period); effective detection angle (calculated using method in Hofmeester et al. 2017); left and right truncation; model selected (according to selection criteria in Howe et al., 2019), HN = unadjusted half-normal; density per km^2 with 95% CI estimated from bootstrap; estimated coefficient of variation from bootstrap; density estimate range published in Croft et al. (2017).

Species	Habitat (total sites)	Sites captured	Number of photos	Availability for detection	Effective detection angle	Truncation left, right (m)	Model selected	Density per km^2 [95% CI]	C.V.	Density per km^2 estimate range predicted by Croft et al., 2017
Roe deer (*Capreolus capreolus*)	Whole study area (109)	24	2323	0.68	0.81	0, 10	HN	4.45 [2.29 – 7.00]	0.57	3.22 – 25.70
	Arable (29)	5	1196	0.59	0.73	0, 10	HN	5.25 [0.76 – 12.98]	0.61	3.25 – 25.80
	Improved grassland (38)	13	707	0.63	0.81	0, 10	HN	2.83 [1.21 – 5.03]	0.36	3.12 – 24.80

Table S4. Densities [95% CI] calculated across whole study area including estimates presented in paper (standard) and lower and upper estimates which incorporate variation from effective detection angle and snapshot moment calculations. For the lower and upper estimates, we used the effective detection angle + standard error and the snapshot moment – standard error; for the upper estimate, we used the effective detection angle - standard error and the snapshot moment + standard error. These adjusted measures of effort were then used in the models to calculate density following the same procedure outlined in the paper. Animal silhouettes by Anthony Caravaggi and Claus Rebler, licensed under CC BY-NC-SA 3.0.

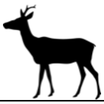
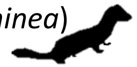
Species	**Density per km² [95% CI]**		
	Standard	**Lower**	**Upper**
Roe deer (*Capreolus capreolus*) 	5.67 [2.67 – 10.52]	5.47 [2.00 – 7.95]	5.89 [2.01 – 8.97]
Badger (*Meles meles*) 	1.32 [0.84 – 4.22]	1.25 [0.76 – 3.75]	1.39 [0.84 – 4.40]
Red fox (*Vulpes vulpes*) 	5.97 [1.37 – 21.15]	5.75 [1.36 – 26.38]	6.45 [1.56 – 31.16]
Brown hare (*Lepus europaeus*) 	5.97 [2.86 – 12.89]	5.81 [2.81 – 12.55]	6.12 [2.99 – 13.83]
Rabbit (*Oryctolagus cuniculus*) 	101.83 [51.63 – 186.65]	100.28 [50.12 – 155.53]	103.41 [58.43 – 216.55]
Hedgehog (*Erinaceus europaeus*) 	23.31 [7.39 – 45.33]	22.54 [7.11 – 44.61]	24.11 [7.56 – 48.34]
Grey squirrel (*Sciurus carolinensis*) 	7.64 [3.73 – 13.03]	7.44 [4.06 – 12.88]	7.85 [4.21 – 13.91]
Stoat (*Mustela erminea*) 	0.22 [0.07 – 0.44]	0.20 [0.07 – 0.42]	0.24 [0.08 – 0.51]

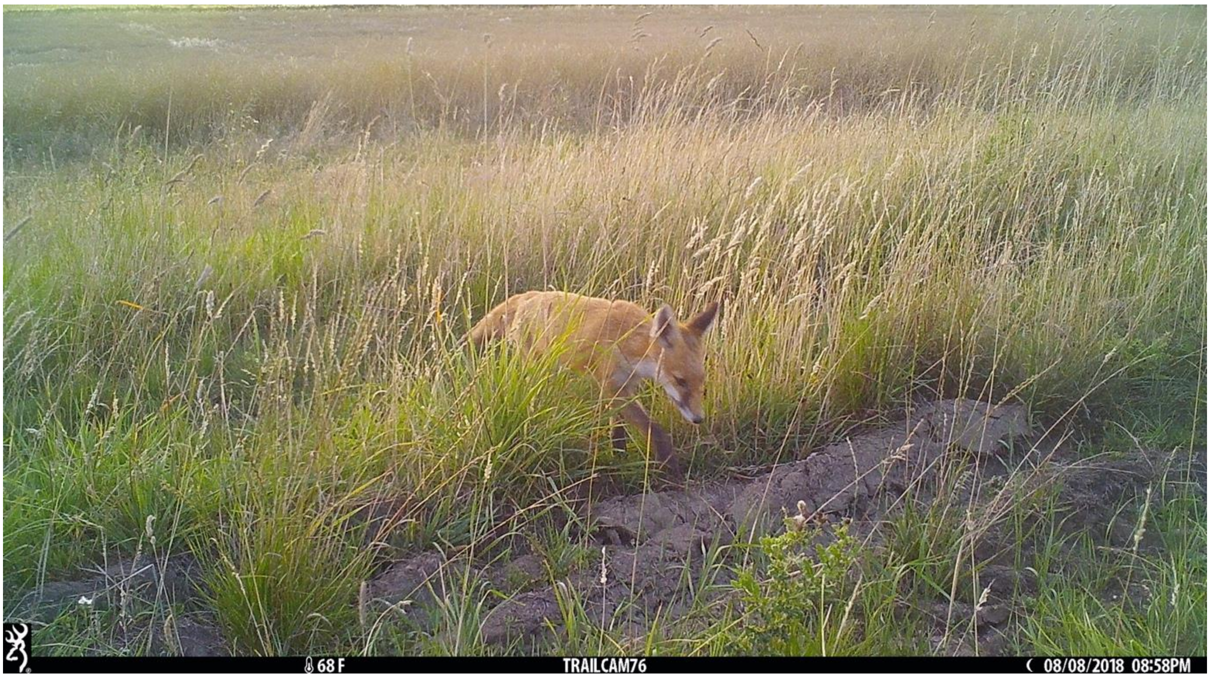
Table S5. Habitat-specific density estimates [95% CI] and other species/habitat specific information. For each species in each habitat: number of sites at which the species was captured; total number of photos (i.e., observations); proportion of time available for detection; effective detection angle; left and right truncation; model selected, HR = unadjusted hazard-rate; density per km^2 with 95% CI estimated from bootstrap; estimated coefficient of variation from bootstrap; density estimate range published in Croft et al. (2017). *All models failed to fit in calculation of effective detection angle, so effective detection angle from whole survey used. Animal silhouettes by Anthony Caravaggi and Claus Rebler, licensed under CC BY-NC-SA 3.0.

Species	Habitat (total sites)	Sites captured	Number of photos	Availability for detection	Effective detection angle	Truncation left, right (m)	Model selected	Density per km^2 [95% CI]	C.V.	Density per km^2 estimate range predicted by Croft et al., 2017
Roe deer (*Capreolus capreolus*)	Arable (29)	11	1371	0.31	0.80	1, 10	HN	12.42 [3.89 – 32.28]	0.53	3.25 – 25.80
	Improved grassland (38)	14	879	0.37	0.73	1, 10	HR	4.34 [3.33 – 49.99]	1.32	3.12 – 24.80
Badger (*Meles meles*)	Arable (29)	6	184	0.30	0.53	2, 10	HR	2.01 [0.78 – 5.82]	71031.86	0.43 – 5.13
	Improved grassland (38)	5	253	0.29	0.61	2, 10	HR	1.81 [0.17 – 2.87]	1.20	0.42 – 4.99
Red fox	Arable (29)	23	1045	0.36	0.56	2, 10	HR	19.26 [3.60 – 28.97]	0.50	0.35 – 1.89

(*Vulpes vulpes*) 	Built up areas and gardens (16)	6	83	0.33	0.74	2, 10	HR	2.55 [0.40 – 13.19]	0.89	0.30 – 2.22
	Improved grassland (38)	16	269	0.47	0.65	2, 10	HR	0.49 [0.35 – 1.83]	0.55	0.39 – 2.18
Brown hare (*Lepus europaeus*) 	Arable (29)	12	1947	0.52	0.49	2, 10	HR	10.94 [2.88 – 34.83]	0.67	0.67 – 16.47
	Improved grassland (38)	13	1618	0.49	0.67	1, 10	HR	7.40 [2.60 – 14.06]	0.41	0.62 – 16.14
Rabbit (*Oryctolagus cuniculus*) 	Arable (29)	15	9290	0.33	0.48	2, 10	HR	212.67 [43.56 – 455.01]	0.56	9.70 – 1203.00
	Built up areas and gardens (16)	4	1439	0.23	0.61	2, 10	HR	112.19 [7.74 – 334.96]	0.85	8.80 – 1260.00
	Improved grassland (38)	31	13768	0.49	0.59	2, 10	HR	99.39 [45.60 – 164.71]	0.32	9.50 – 1174.00

	Mountain, heath, bog (13)	7	1020	0.35	0.47	2, 10	HR	26.37 [8.92 – 51.75]	0.39	8.70 – 1318.00
Hedgehog (*Erinaceus europaeus*) 	Arable (29)	7	222	0.29	0.39	1, 10	HR	2.86 [0.76 – 7.67]	0.56	4.25 – 51.66
	Improved grassland (38)	10	598	0.35	0.60*	1, 10	HR	6.59 [1.40 – 13.03]	0.50	3.35 – 54.73
Grey squirrel (*Sciurus carolinensis*) 	Arable (29)	5	1400	0.37	0.53	1, 10	HR	8.76 [0.72 – 19.79]	0.64	8.22 – 77.57
	Built up areas and gardens (16)	4	214	0.41	0.59*	1, 10	HR	3.88 [0.79 – 8.76]	0.56	7.31 – 67.81
	Improved grassland (38)	13	1990	0.31	0.68	1, 10	HR	10.83 [3.51 – 26.37]	0.55	8.27 – 77.97
Stoat (*Mustela erminea*) 	Improved grassland (38)	10	115	0.49	0.55	0, 10	HR	0.55 [0.15 – 2.74]	21.70	--

Chapter 3: Spatial bias in a citizen science camera trap dataset and its impact on ecological inferences



Red fox (*Vulpes vulpes*) | Seaham Hall Farm, County Durham

3.1 Abstract

Citizen science projects can help with ecological monitoring at the broad spatial and temporal scales needed to understand ecosystem dynamics. In particular, opportunistic schemes which invite participants to submit species records without any standardised protocols can rapidly generate large species occurrence databases. However, choice over where, when and how participants submit data can lead to issues with data quality and bias. In this study, we explore bias in a dataset from a camera trap citizen science project, MammalWeb. By comparing subsets of the MammalWeb dataset to data generated from a systematic survey (described in Chapter 2), we look at differences in habitats surveyed and species assemblages captured as well as region-wide and habitat-specific measures of occupancy and activity. We found differences in habitats surveyed, with woodland over-represented in the MammalWeb dataset, and farmland and heath habitats either under-represented or missing completely. This habitat bias influenced species assemblages captured. Overall, the systematic dataset captured more species, owing to the presence of gamebird species; however, the MammalWeb datasets captured more mammal species by sampling spatially rare riverine habitats and capturing riparian specialists, including otter (*Lutra lutra*) and American mink (*Neovision vison*). Habitat bias distorted estimates of occupancy and activity at a regional level. Differences in occupancy between the systematic and MammalWeb datasets was most apparent for woodland-specialist species such as grey squirrel and roe deer. At a habitat level, occupancy was similar between the systematic and MammalWeb datasets for all species in improved grassland; however, occupancy differed for some species in broadleaf woodland. There were differences in activity between the datasets for all species. Moving forward, we conclude it would be valuable for the MammalWeb project to expand spatial coverage, by actively encouraging citizen scientists to survey habitats currently under-represented. This could be achieved by implementing a site adoption scheme and working with local groups of farmers or gamekeepers. By doing this, MammalWeb can have more confidence in the ecological inferences derived from the project's dataset.

3.2 Introduction

With global ecosystems undergoing rapid biodiversity loss, large-scale wildlife monitoring to help understand population trends is vitally important (Butchart et al., 2010; Fischer et al., 2010; Steenweg et al., 2017). Citizen science has become a powerful way of collecting vast quantities of biodiversity data at spatial and temporal scales that would otherwise be challenging (Dickinson et al., 2012). The applications of data collected by citizen scientists are varied, but they include monitoring population trends (Horns et al., 2018), creating species distribution maps (Sumner et al., 2019; Tiago et al., 2017) and detecting invasive species (Crall et al., 2015; Gallo and Waitt, 2011; Preuss et al., 2014).

Ecological citizen science schemes can range from standardised approaches to opportunistic submission of records. Standardised schemes typically concentrate on maximising data quality and may include volunteer training, following standardised data collection protocols, or predetermining sampling locations. Examples of such schemes include the UK Breeding Bird Survey organised by the British Trust for Ornithology (https://www.bto.org/our-science/projects/breeding-bird-survey) and the U.K. Butterfly Monitoring Scheme (https://ukbms.org/), which both involve volunteers repeatedly surveying a site using a standardised protocol. In contrast, opportunistic schemes give participants more freedom, with either no or limited prerequisites for when, where, and how they collect data. Opportunistic schemes include iNaturalist (www.inaturalist.org), eBird (www.ebird.org), and BeeWatch (https://beewatch.abdn.ac.uk/) where species records are submitted through digital platforms, allowing large datasets to be assembled quickly (Ball-Damerow et al., 2019).

Whilst opportunistic citizen science projects have the potential to generate large species occurrence databases, many academics have highlighted the difficulty of maintaining data quality and dealing with biases (Ball-Damerow et al., 2019; Feeley, 2015; Kosmala et al., 2016; Maldonado et al., 2015). Opportunistic citizen science datasets can be spatially and taxonomically biased by factors such as site accessibility (Geldmann et al., 2016; Millar et al., 2019; Petersen et al., 2021) and exclusion of common species over rare or charismatic ones (Ball-Damerow et al., 2015; Callaghan et al., 2021). Although statistical approaches to dealing with biases have been suggested (Mair and Ruete, 2016; Rapacciuolo et al., 2017), many studies using opportunistic datasets do not adequately address the issues of data quality and bias (Ball-Damerow et al., 2019).

Some of the issues arising from opportunistic citizen science can be mitigated when recording equipment such as camera traps are used. As camera traps record all animals that pass through the detection zone during the period for which the camera is active, bias in which species are recorded is reduced. However, biases in which habitats are surveyed may be retained, which could lead to differences in species assemblages captured and have impacts on key ecological outputs such as occupancy and activity. Although national networks of camera traps could help with monitoring many mammal species, a taxon typically under-recorded in many countries (Mason et al., 2022; Steenweg et al., 2017), identifying biases will be fundamental in order to have confidence in interpreting the data produced.

In this chapter, we explore biases within the MammalWeb citizen science dataset. MammalWeb is a citizen science project first established in 2015 as a collaboration between Durham University and the Durham Wildlife Trust (www.MammalWeb.org; Hsing et al., 2022). The project invites citizen scientists to deploy either their own, or borrowed, camera traps at a site of their choosing and to upload footage captured to an online digital platform. MammalWeb could help with long-term monitoring of Britain's wildlife, particularly by providing ecological insights on measures such as occupancy and activity schedules of key species (Hsing et al., 2022). However, as highlighted previously, before any citizen science project can start to draw inferences from data collected it is important to investigate biases present in those data (Kosmala et al., 2016; Petersen et al., 2021; Tiago et al., 2017).

To investigate possible biases in the MammalWeb dataset and their impact on ecological outputs we compare subsets of MammalWeb data to data derived from a systematic camera trapping survey carried out in North-East England, UK (as described in Chapter 2) (Mason et al., 2022). We begin by comparing habitats surveyed, species captured, and trapping rates for commonly captured species. We then use the datasets to calculate occupancy and activity schedules for a set of focal mammal species, examining differences in measures across datasets. Finally, we determine whether habitat biases can be controlled for by breaking down analysis into habitat categories, estimating occupancy and activity for a sub-set of species in two common habitats: improved grassland and woodland.

3.3 Methods

3.3.1 Study area

Data used in this study were from camera traps deployed within a 2,725 km^2 study area of North-East England, covering County Durham, plus areas of Gateshead, Sunderland, and Darlington. This study area is the catchment area of the local wildlife trust (Durham Wildlife Trust; https://www.durhamwt.com/), an organisation established to preserve wildlife and promote conservation throughout the region. The region's landscape is varied, with large areas of moorland in the west, and a variety of habitats in the east, including farmland, woodland, forest, urban and suburban habitats.

3.3.2 Data from MammalWeb

We use data submitted to MammalWeb by citizen scientists who have deployed camera traps. When uploading footage to MammalWeb, contributors also supply information on location, camera trap model, height above ground, surrounding habitat type (from options listed in Table S1), and start and end times of deployment. At the point of upload, camera trap images are sequenced by grouping images taken <10 seconds apart. Uploaded footage can be classified on the platform by contributors looking through the image sequences and selecting the species present from a list. Although MammalWeb hosts a variety of projects, to which contributors can upload data or supply classifications (https://www.mammalweb.org/en/project-list), we focus on data from just the main MammalWeb Great Britain project, which has been available since the project's inception. For further information about the MammalWeb project and how it operates see Hsing et al., (2022).

3.3.3 Data processing

To compare camera trap data generated from a systematic grid to opportunistic data collected via MammalWeb, we compared three datasets:

Systematic dataset – The first dataset was from camera traps deployed in a randomly-generated systematic grid (Figure 1). Fifty Browning Strike Force BTC-5HDP cameras were rotated in a random order around 109 sites between June and October 2018, with the majority of cameras deployed for a minimum of 14 days. Further details of how the grid was set up and how cameras were placed at sites can be found in Chapter 2 / Mason et al. (2022).

MammalWeb in-year dataset – The second dataset was a subset of data from the MammalWeb Great Britain project. First, we filtered data on MammalWeb to those photo sequences taken between the start and end times of the systematic survey (26th June 2018 – 10th October 2018). Then, photo sequences were filtered to those taken within the geographical study area, including removing any sites where contributors had not supplied location information. Once we had the photo sequences (n = 4921), we generated consensus classifications from MammalWeb to find out, for each sequence, what the majority of MammalWeb participants thought was captured. We then checked each photo sequence against these classifications and amended 368 classifications (7%) which were incorrect. We also classified a small number of sequences (29) which had not yet been classified on MammalWeb. MammalWeb datasets were therefore a mixture of citizen science and professional classifications. As we were interested in spatial bias of sites where citizen scientists deployed cameras, rather than classification accuracy, this should not impact the interpretation of the results.

MammalWeb multi-year dataset – For the third dataset we followed the same filtering process as for the MammalWeb in-year dataset; however, we also included data from between survey dates (26th June – 10th October) for the years 2016, 2017, 2019, 2020, and 2021. This created a dataset of comparable size to the systematic dataset (Table S2). As with the MammalWeb in-year dataset, we generated consensus classifications for these photo sequences (n = 25,552); however, due to the large dataset we only checked classifications of medium-large wild mammals. We amended 551 incorrect mammal classifications (9%) and classified 600 sequences that had no classifications on MammalWeb.

As parts of our analysis required measures of lengths of deployment, for the MammalWeb datasets we also checked camera trap deployment and collection times submitted on MammalWeb for obvious errors. There were 22 deployments at 17 sites (out of a total of 1,048 deployments at 120 sites) where either collection dates were before deployment dates, collection dates were set to the future, or photos uploaded were outside of deployment dates submitted. For these uploads we altered the deployment / collection times to be one minute before / after the first / last photo in that upload.

3.3.4 Data analysis

Analyses were conducted using R 4.1.2 (R Core Team, 2021). We compared the extent of monitoring within different habitats in the three datasets. We looked firstly at habitat classifications that participants can choose from on MammalWeb. There are 17 habitat classes to choose from on MammalWeb, each with a description to help participants choose the appropriate habitat type (Table S1). Participants are told on MammalWeb to choose the habitat immediately surrounding (within 10 m) where the camera trap is placed. For each dataset, we also used the Land Cover Map 2021 (LCM; 25 m aggregate habitat class; Marston et al., 2022) to assign a LCM habitat class to each site where a camera trap was positioned. We looked at the proportion of sites that were within each habitat type (both MammalWeb habitat classes and LCM habitat classes) to compare the three datasets. As the majority of sites (80%) in the MammalWeb datasets were within a 10km radius of Durham City Centre, we also compared the proportion of sites in each habitat type within this radius.

We generated rarefaction curves and diversity and richness estimates for the systematic dataset and the MammalWeb in-year dataset using 'iNEXT' (Hsieh et al., 2020). We did not do these calculations for the MammalWeb multi-year dataset as not all classifications were verified and, consequently, we do not know the total number of species present in that dataset. Trapping rates were calculated for each site as the number of half-hour periods in which a species was detected divided by number of operational camera days. A half hour period was chosen as a common interval for discerning independent detections (Burton et al., 2015; Green et al., 2022; Rovero and Zimmermann, 2016). We compared trapping rates between the three datasets for all mammal, bird and domestic species that yielded sufficient detections (>n = 50 sequences) in the systematic dataset. We also looked at trapping rates for a generic 'livestock' category that included all livestock species such as cattle, sheep, pigs, goats and horse.

Further analysis was carried out on a set of medium-large focal mammal species which had sufficient detections (> n = 50 sequences) in all three datasets. These species were: badger (*Meles meles*); brown hare (*Lepus europaeus)*; grey squirrel (*Sciurus carolinensis*); hedgehog (*Erinaceus europaeus*), rabbit (*Oryctolagus cuniculus*); red fox (*Vulpes vulpes*); and roe deer (*Capreolus capreolus*). For these species we calculated occupancy, detection probability, and activity schedules for all three datasets. For the four species captured the most across datasets (grey squirrel, rabbit, red fox, and roe deer) we also calculated these measures for the most common LCM habitat class in the systematic dataset, improved grassland, and the most common habitat class in the MammalWeb in-year / multi-year datasets, broadleaf woodland. We also calculated habitat-specific occupancy and activity for the most common habitat class on MammalWeb: woodland. For these habitat-specific measures we only compared data from the systematic and MammalWeb multi-year datasets due to the small sample size of the MammalWeb in-year dataset.

To calculate occupancy and detection probability, daily detection histories were generated using 'camtrapR' (Niedballa et al., 2016) for each focal species from each dataset. Detection histories were then used to fit occupancy models using the package 'unmarked' (Fiske and Chandler, 2011). Outputs were back-transformed to give estimates of the proportion of sites occupied by a species and the probability of its detection. Even though the MammalWeb multi-year dataset contained data from multiple years, we used single-season occupancy models for all datasets as we were interested in differences between datasets rather than differences between years. Similarly, because our aim was the comparison between different datasets, rather than to identify the factors driving occupancy of each species, we did not include covariates in our occupancy models. For each focal species, activity patterns from each dataset were compared by fitting a circular kernel model to radian time data, using the R package 'activity' (Rowcliffe, 2021). For this, in line with recent recommendations for this methodology, we used radian time data from all sequences rather than filtering to only independent detections (Peral et al., 2022). A Wald test was used to assess differences between the activity schedules produced by the different datasets for each species.

3.4 Results

The three datasets ranged in size from 32 sites (MammalWeb in-year dataset) to 120 sites (MammalWeb multi-year dataset; Table S2). The systematic dataset had the most photo sequences; however, a large proportion of these did not contain animals, resulting in a similar number of sequences (16044 vs 17115) containing animals for systematic and MammalWeb multi-year datasets (Table S2). The 109 sites from the systematic dataset were spread out in a grid of 5 km^2 spacing across the study area (Figure 1). Three sites on the western edge of the study area could not be surveyed due either to being in a Ministry of Defence area (1 site), or where landowners did not give permission to access land (2 sites). For the MammalWeb datasets, sites were generally clustered around Durham city centre, where the project was first initiated in 2015 and where a lot of contributors are based. The MammalWeb multi-year dataset, was slightly more spread out geographically, but still clustered around Durham. There was a lack of sites in the western and southern regions of the study area in both of the MammalWeb datasets (Figure 1).

More species were captured in the systematic dataset than in the MammalWeb in-year dataset, with the additional species in the systematic dataset mainly game birds and farmland birds, including black grouse, curlew, and red-legged partridge (Table 1; Table S3). There were, however, more medium-large mammal species captured in the MammalWeb datasets, due to American mink and otter being captured in these datasets, but not in the systematic dataset (Table S3). Shannon and Simpson diversity indices (both observed and estimated) were higher for the systematic dataset than the MammalWeb in-year dataset (Table 1). Rarefaction curves show that species diversity saturated more rapidly in the MammalWeb in-year dataset than in the systematic dataset, with the curve flattening for the MammalWeb in-year dataset before the maximum number of camera trap days, suggesting that all species had been captured at these cameras (Figure 2). For the systematic dataset, as the curve had not flattened by the maximum number of camera traps days, it is likely that not all species were captured and, therefore, estimated species diversity indices are higher than observed indices (Figure 2; Table 1).

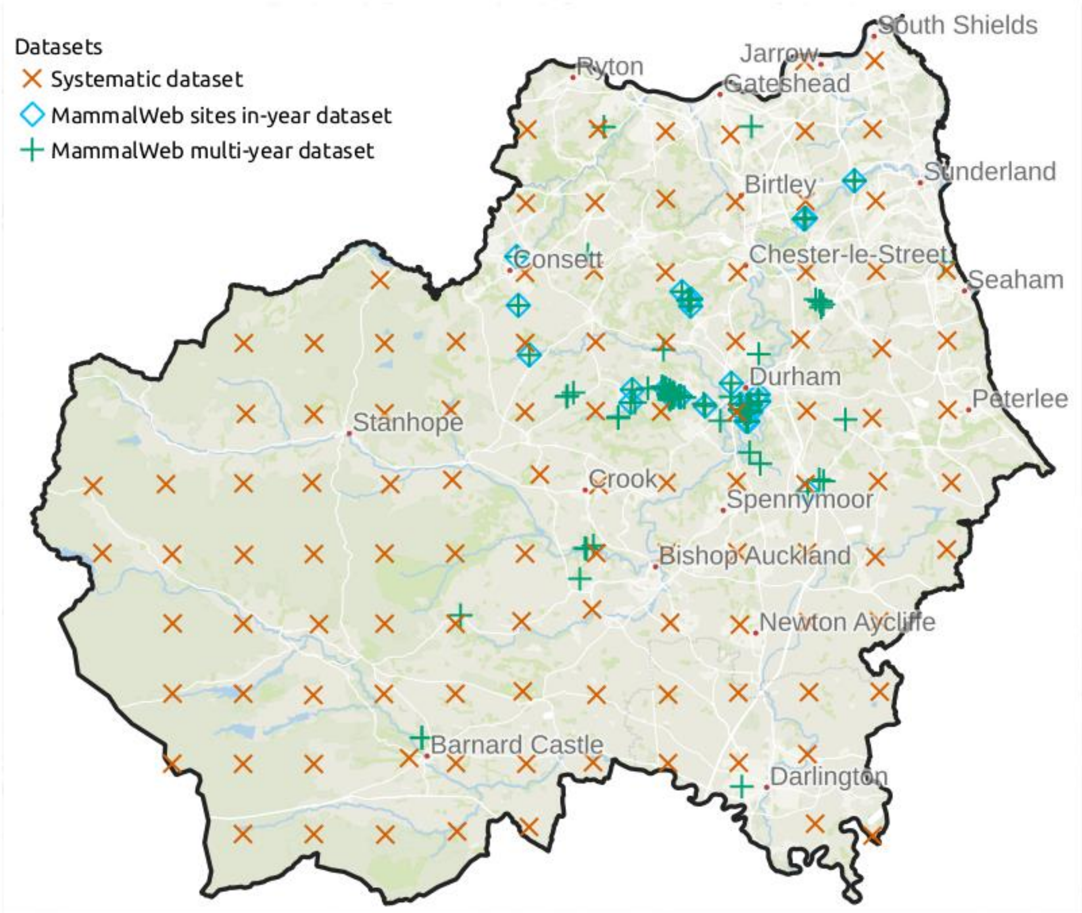


Figure 1. Distribution of sites within our geographic study area of County Durham, Gateshead and Darlington. Sites of camera trap locations from three datasets are shown: a systematic camera trap survey that took place June – October 2018 (the systematic dataset), camera trap sites on MammalWeb for the same survey period in 2018 (the MammalWeb in-year dataset), and camera trap sites on MammalWeb for the same summer survey dates but over multiple years (the MammalWeb multi-year dataset). Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0.

Table 1. Observed and estimated bird and mammal species diversity indices for two camera trap datasets. Indices shown include the Shannon diversity index which puts more weighting on species richness, and the Simpson reciprocal index which puts more weighting on relative abundances.

	Systematic dataset	MammalWeb in-year dataset
Species richness observed	51	44
Species richness estimator (SE)	63.09 (15.02)	44.00 (1.45)
Shannon diversity observed	19.70	15.90
Shannon diversity estimator (SE)	19.92 (0.33)	15.96 (0.22)
Simpson diversity observed	13.96	9.89
Simpson diversity estimator (SE)	14.02 (0.32)	9.90 (0.13)

For the MammalWeb datasets, habitat information was supplied for all sites in the MammalWeb in-year dataset and for 118 of 120 sites in the MammalWeb multi-year dataset. The most common habitat type for the MammalWeb datasets was woodland which made up ~50% of sites for the MammalWeb datasets but only 17% of sites in the systematic dataset (Figure 3A). Forest, scrubland, and riverbank were also over-represented in the MammalWeb datasets compared to the systematic dataset, whereas farmland and heath were under-represented (Figure 3A). In the systematic dataset, the proportion of sites in each LCM habitat class was the same as the overall habitat coverage across the whole study area for all habitats except broadleaf woodland where the proportion was slightly higher than expected (Figure 3B). This is likely due to small displacements from original random points for the systematic dataset, which were necessary to place cameras on trees or away from livestock; these displacements are likely to have favoured small patches of broadleaf woodland. As with the relative proportions of MammalWeb habitat classes, the MammalWeb datasets show an over-representation of broadleaf woodland and under-representation of arable and mountain, heath, and bog habitats (Figure 3). There is also an under-representation of improved grassland (high productivity grassland) in the MammalWeb datasets compared to the systematic dataset (Figure 3B).

When comparing sites within a 10km radius of Durham City Centre, the proportion of sites in each LCM habitat class was the same as overall habitat coverage in this area. This suggests that even though there were only 13 sites within this radius for the systematic dataset, it was a good representation of the landscape of the area as a whole. Similar to the full dataset, forest, scrubland, and riverbank were over-represented, and farmland under-represented, in the MammalWeb datasets compared to the systematic dataset (Figure S1). When looking at the MammalWeb habitat classes there was no difference in the proportion of sites in woodland between the databases. However, when looking at the LCM broadleaf woodland class, there were more sites in this habitat class for the MammalWeb datasets than in the systematic dataset (Figure S1). There was also a larger proportion of sites in built up areas and gardens in the systematic dataset than in the MammalWeb datasets (Figure S1).

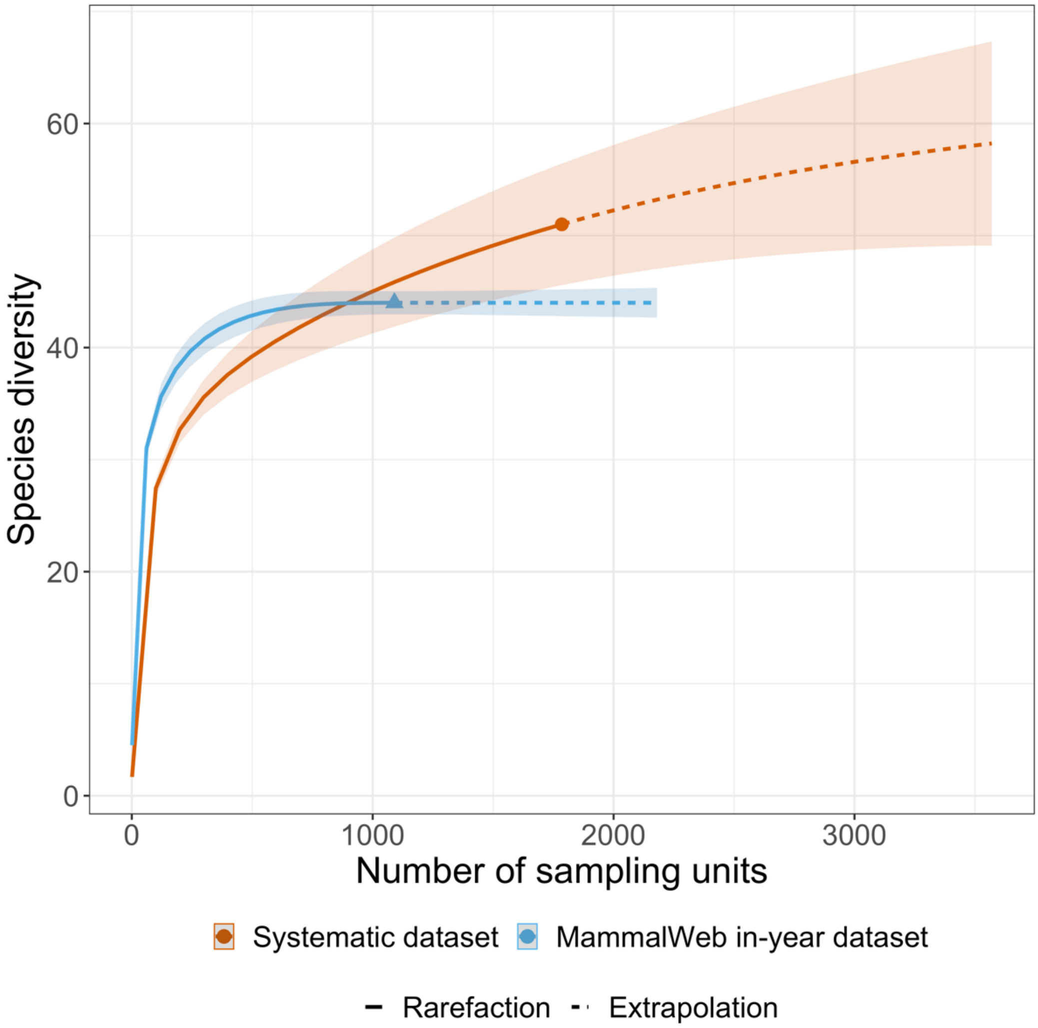


Figure 2. Rarefaction curve of bird and mammal species diversity for two camera trap datasets. Sampling units represent camera trap days (number of days a camera trap was active). Shaded areas of each curve represent the 95% confidence interval.

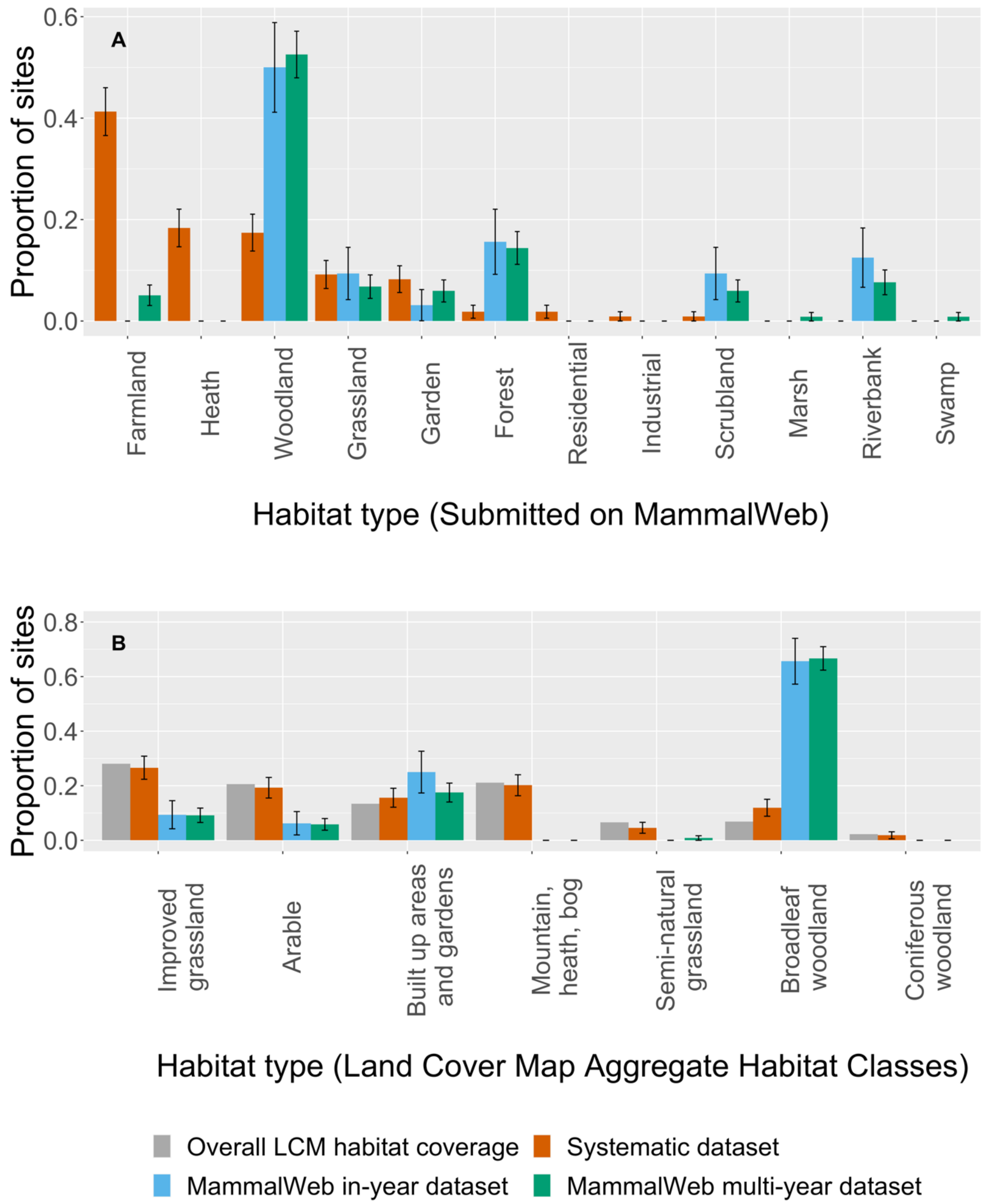


Figure 3. Proportion of sites in each camera trap dataset for each of the MammalWeb habitat classes (A) and the Land Cover Map 2021 (LCM) habitat classes (B; Marston et al., 2022). B also shows overall coverage within the study area for each LCM habitat class. Error bars show ± standard error.

There were some differences between datasets in trapping rates for mammals, most notably for brown hare; however, for most species these differences were not significant (Figure 4A). This is likely due to the large variation in trapping rates between sites within datasets, leading to large over-lapping confidence intervals (Figure 4A). As for mammals, there was large variation in bird trapping rates within datasets but, nonetheless, trapping rates were generally higher for all birds in the systematic dataset than in the MammalWeb datasets; this difference was statistically significant for house sparrow and jackdaw (Figure 4B). Two species, black grouse and red grouse, were amongst the most commonly captured birds in the systematic dataset but were not captured in either of the MammalWeb datasets. The trapping rate for livestock species was higher in the systematic dataset than the MammalWeb datasets, particularly the MammalWeb multi-year dataset (Figure 4C), but there was little difference in trapping rates for domestic cat or dog (Figure 4D).

Although detection probabilities differed between datasets for all species, occupancy was similar for three species (brown hare, hedgehog and rabbit) across the datasets (Figure 5). The most notable differences in occupancy were for woodland specialist species - grey squirrel and roe deer, as well as red fox, where occupancy was lower for the systematic dataset than for the MammalWeb datasets (Figure 5A). There were no significant differences in occupancy scores for any species between the MammalWeb in-year dataset and the MammalWeb multi-year dataset (see overlapping standard errors of estimates from in-year and multi-year monitoring in Fig. 5A, for each species), suggesting that occupancy in 2018 was broadly representative of occupancy over 2016-2021.

There were no differences between the systematic dataset and the MammalWeb multi-year dataset in occupancy in improved grassland (LCM habitat class) for the four species studied (Figure 6A). There were, however, differences in broadleaf woodland (LCM habitat class), with the largest differences being for grey squirrel and rabbit (Figure 6B), where occupancy was greater in the systematic dataset. When looking at occupancy for sites in the woodland habitat class on MammalWeb, these differences were smaller, with only rabbit appearing to be significantly different (Figure 6C).

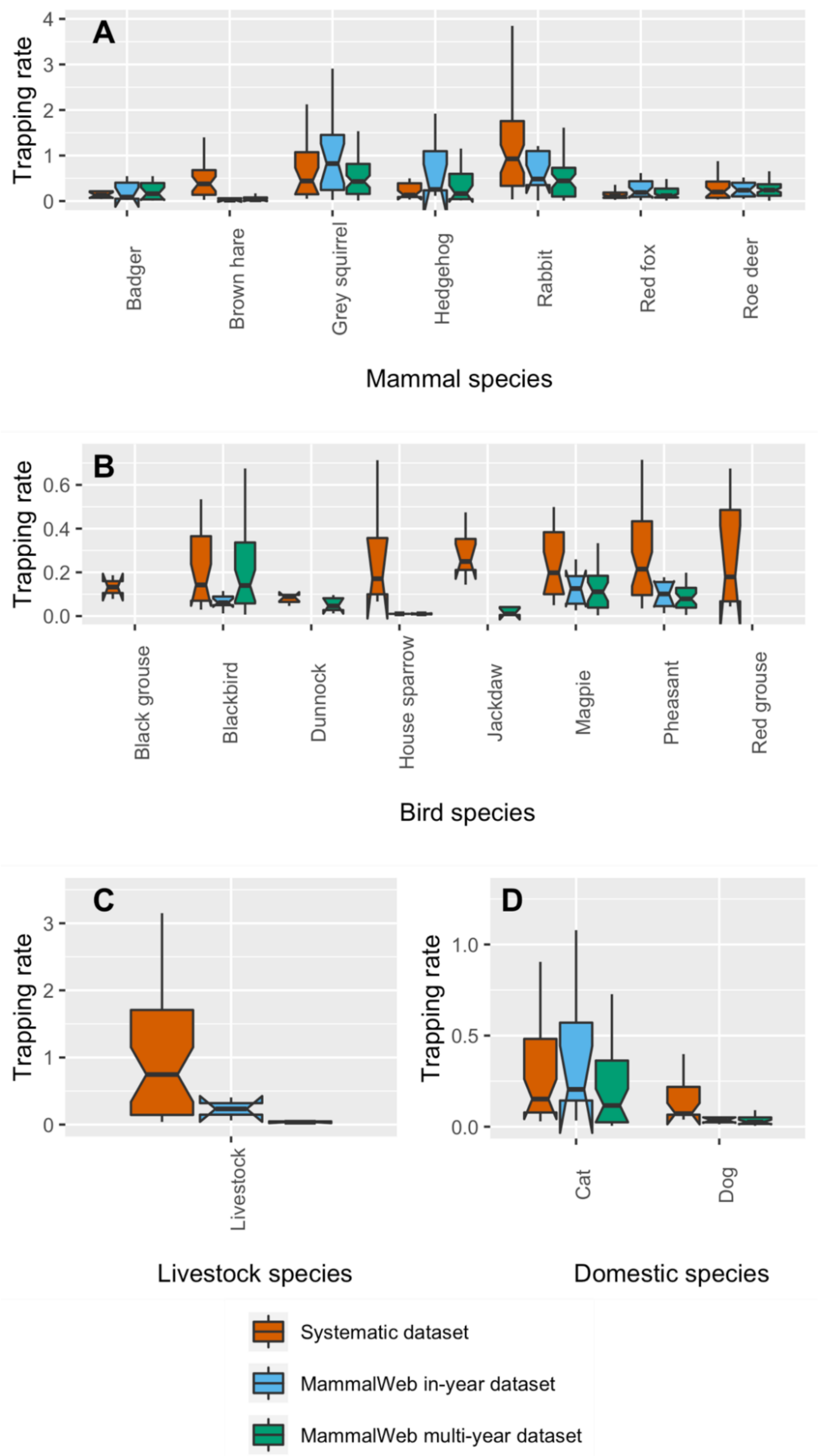


Figure 4. Trapping rates per mammal (A), bird (B), livestock (C) and domestic species (D) for each camera trap where the species was detected. Trapping rate was calculated for each site as number of half-hour periods in which a species was detected divided by number of operational camera days. Plots show median and inter-quartile range.

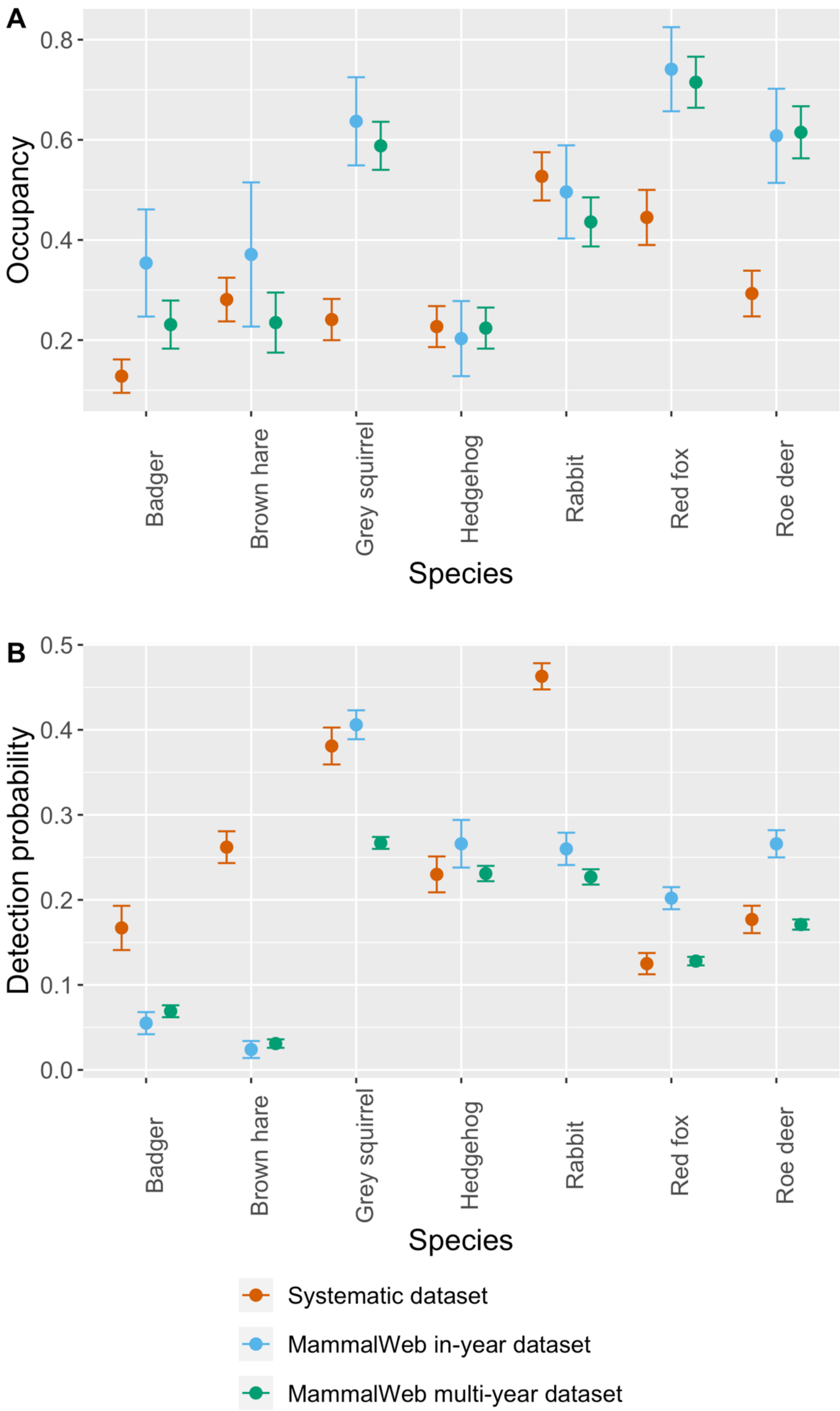


Figure 5. Occupancy (A) and detection probability (B) for each focal species in each dataset. Error bars show ± standard error.

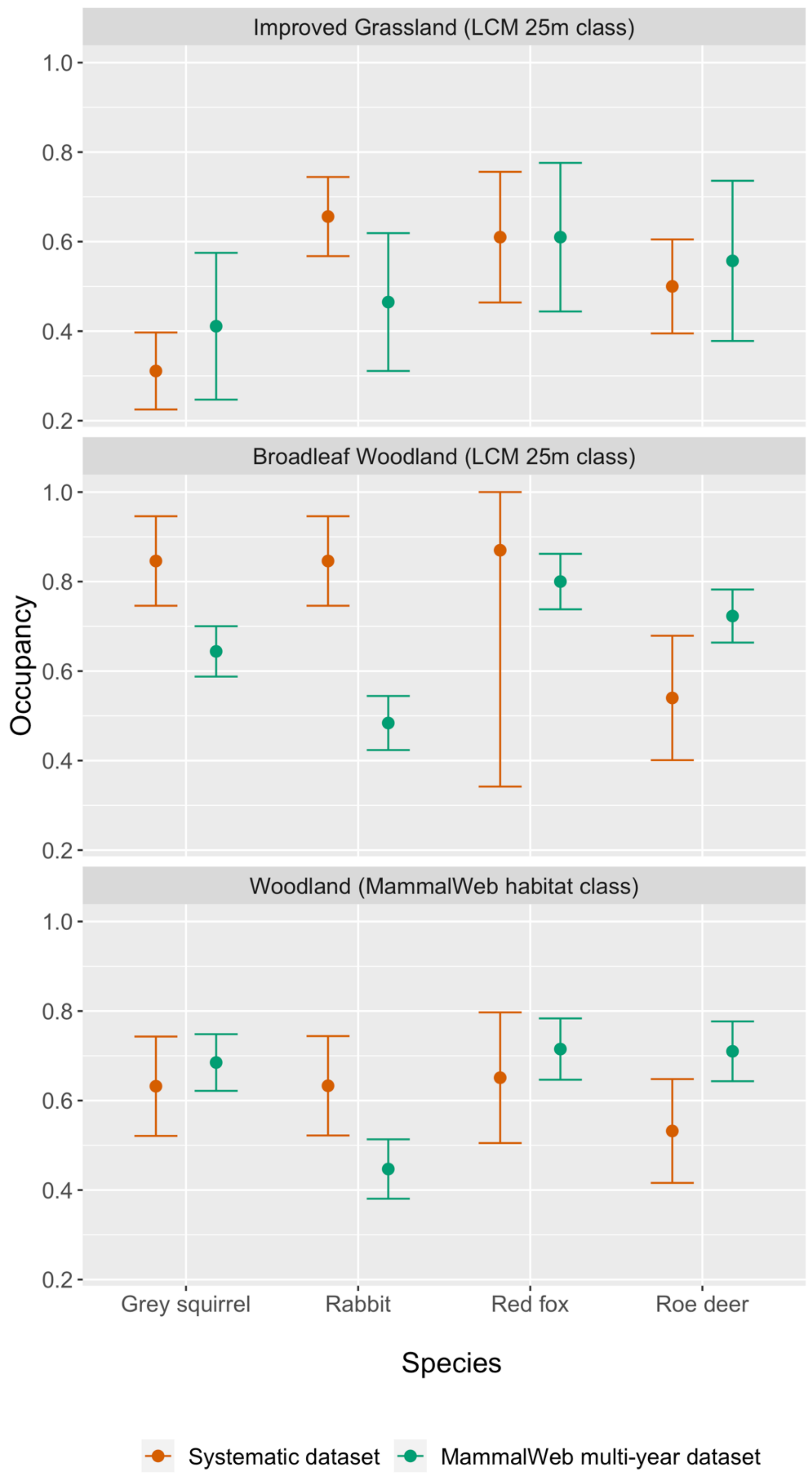


Figure 6. Occupancy in three habitat classes for four mammal species. Improved grassland and broadleaf woodland are habitat classes for the Land Cover Map 2021 (Marston et al., 2022) and woodland is a habitat class on MammalWeb representing the 10 m surrounding the camera trap (according to person deploying the camera). Error bars show ± standard error.

All species showed differences in activity schedules between the systematic dataset and at least one of the MammalWeb datasets (Figure 7; Table S4). There were also differences between the MammalWeb in-year dataset and the MammalWeb multi-year dataset for some species such as badger and red fox (Table S4). When looking at activity schedules for the three different habitat classes, there were differences across the datasets for at least one species in each of the habitat classes (Table S5).

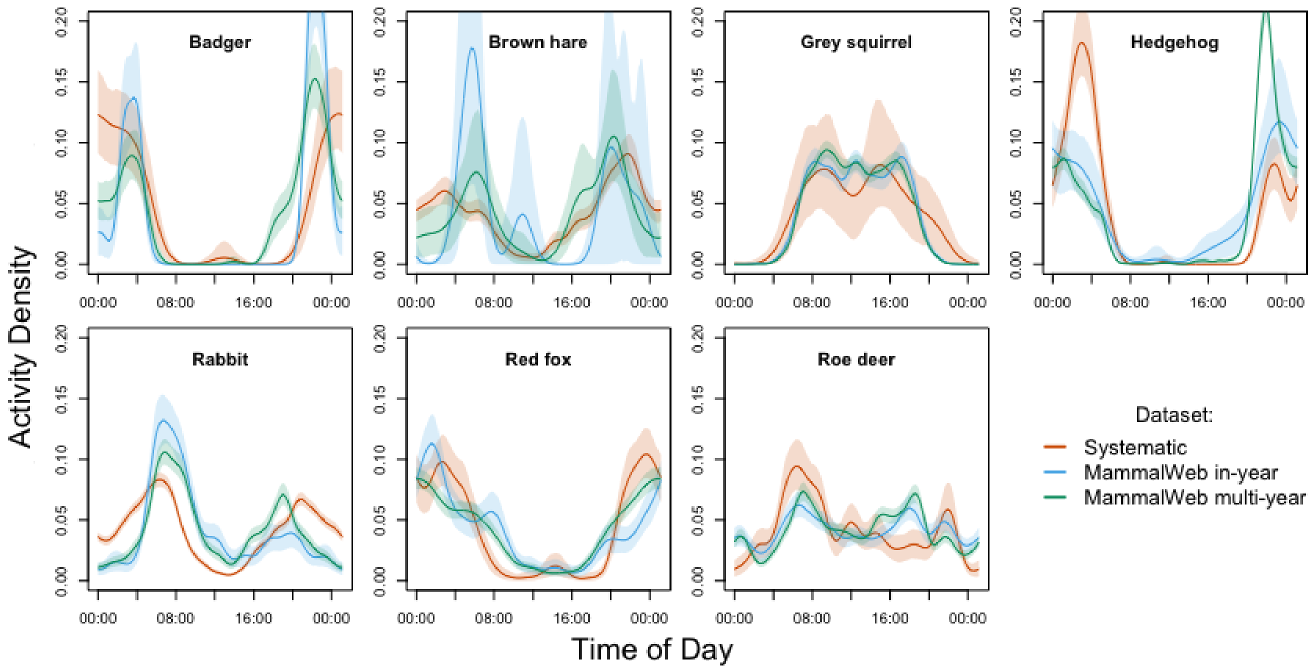


Figure 7. Activity schedules with 95% confidence limits for each of the 7 focal species based on radian time data from each dataset.

3.5 Discussion

We looked at differences between data from camera traps set up in a systematic grid and data from camera traps deployed opportunistically by citizen scientists participating in the project MammalWeb. We assessed the habitats surveyed and trapping rates, occupancy and activity schedules of species captured. We found large differences in habitats surveyed, which have implications for ecological outputs at a regional scale. There were also differences in occupancy and activity schedules for some species at a habitat level. By studying these differences, citizen science projects such as MammalWeb can have more confidence in data utilisation, going forward, and can also identify how biases might be addressed in the future. Here, we discuss our findings in relation to: a) the extent of spatial biases in the MammalWeb dataset; b) implications of bias for ecological measures at a regional and habitat level; and c) potential approaches to bias mitigation in the future.

3.5.1 Spatial bias and species captured

The issue of spatial biases in citizen science datasets has been highlighted by many academics (Boakes et al., 2016; Callaghan et al., 2019; Johnston et al., 2022; Millar et al., 2019; Petersen et al., 2021). At broad spatial resolutions, these biases tend to be driven by two main factors: accessibility (e.g., surveying areas easily accessible by road or close to where the participant lives) and natural interest (e.g., surveying protected areas or areas with high species diversity) (Boakes et al., 2016; Geldmann et al., 2016; Millar et al., 2019; Tiago et al., 2017). In our study, these factors likely contributed to the lack of sites surveyed by MammalWeb participants in the more remote farmland and moorland regions to the west of the survey area (Figure 1). Specific to camera trapping citizen science projects, participants must also consider security of camera traps and finding somewhere suitable to attach cameras (e.g., a tree trunk). This is also likely to have contributed to why woodland was largely over-represented (relative to its presence in the landscape) as a surveyed habitat in the MammalWeb datasets (Figure 2).

In our study, 80% of MammalWeb sites were clustered within a 10km radius of Durham City Centre. Whilst the factors that likely drove this broadscale-level of bias are considered above, we also considered whether bias was present within this smaller radius where the majority of MammalWeb cameras were placed. When we focussed habitat comparisons for sites within a 10km radius of Durham, the patterns of habitat bias were broadly the same as for the whole survey area, with forest, scrubland, and riverbank over-represented and farmland under-represented. Comparisons of sites in woodland habitat were more complex, with no difference in the proportion of sites in the MammalWeb woodland class, but a large difference for the LCM broadleaf woodland class. As mentioned previously, despite our best efforts to place cameras at pre-assigned co-ordinates, small displacements did occur to place cameras on trees or in a more secure position. This problem was exacerbated around the city centre, where suitable places to place a camera were limited, such that cameras were often placed in very small patches of woodland. Some of these patches of woodland in the city were likely so small that they would be classified as woodland on a 10m scale (for MammalWeb habitat classes) but not at a 25m scale (for LCM habitat classes); this helps to explain the difference when comparing proportions of sites in MammalWeb vs LCM woodland habitat classes. Despite Durham being a city with a large river running through it, there were still no sites in the systematic dataset that fell on riverbank (and LCM freshwater habitat only accounted for 0.39% of landscape coverage within the 10km radius), whereas ~10% of MammalWeb sites in this area were classified as riverbank habitat. Therefore, it seems that across both the whole survey area, and the area where the majority of participants place cameras, both woodland and river habitats are well-represented within the MammalWeb database and that effort should be made to improve coverage of other habitats such as farmland and moorland.

Inevitably, biases in habitats surveyed influence the species assemblages captured. Livestock was captured more than any wild animal in the systematic dataset, resulting in trapping rates for livestock being higher than in MammalWeb datasets (Figure 4). Whilst livestock may not be a target species for wildlife monitoring, given the increases in agricultural land cover to meet demands of global population increase (Wirsenius et al., 2010), and the potential effects of livestock species on wildlife (Gortazar et al., 2015), monitoring livestock species could be valuable. However, given the under-representation of livestock in the MammalWeb database, it would be inappropriate to assume that citizen-led camera trapping, with opportunistic placement of sites, would be an appropriate mechanism for monitoring livestock occurrence or relative abundance.

Cameras placed in a random systematic grid captured more species than cameras deployed by citizen scientists. This was due to these cameras capturing more game birds and farmland birds which, given the over-representation of woodland habitat surveyed, is unsurprising. Monitoring birds is seldom a strong focus of camera trapping, so this might not be especially problematic. In fact, given that the focus of most camera trapping is mammals, it is notable that the MammalWeb datasets captured more mammal species, owing to cameras deployed next to rivers which captured American mink and Eurasian otter. In the systematic survey, no camera sites fell on rivers, whereas in the MammalWeb datasets ~10% of sites were in riverbank habitats, consistent with previous studies that found presence of water to be a driving factor for where citizen scientists choose to survey and collect records (Boakes et al., 2016; Tiago et al., 2017). Just as systematic temporal surveys often miss rare events (Rose, 2000), systematic spatial sampling might well overlook rarer habitats altogether. In our study area, a systematic grid such as we used would not be suitable for surveying riverine species, but more targeted data from camera traps deployed by citizen scientists could help with monitoring efforts for these species.

3.5.2 Implications for ecological inferences

At a regional level, occupancy and activity schedules differed between datasets for many species. For occupancy, these differences were particularly evident for woodland specialist species such as grey squirrel and roe deer, for which occupancy was higher in the MammalWeb datasets (Figure 5). For activity schedules, there were differences between the systematic dataset and at least one of the MammalWeb datasets for all species. Given that we know that occupancy and activity are likely to differ for any given species, depending on habitat (Łopucki and Kiersztyn, 2020; Tobler et al., 2015), it is reasonable to assume that the habitat biases in the MammalWeb database are likely, at least in part, to be influencing the differences seen in ecological measures at a regional level. To test this, we also looked at occupancy and activity measures within three different habitat classes (two LCM 25 m habitat classes, and one MammalWeb habitat class).

At a habitat level, occupancy for all species was similar between the systematic dataset and the MammalWeb multi-year dataset for improved grassland; however, occupancy differed for some species in broadleaf woodland (Figure 6). When sites were grouped by MammalWeb habitat classes (which represented the habitat immediately surrounding the camera), differences in occupancy for woodland habitat were reduced or eliminated (Figure 6). For the first two habitat classes, we grouped sites according to aggregate habitat classes in the Land Cover Map 2022 at a 25 m scale (Marston et al., 2022). However, fine-scale (<25 m) habitat heterogeneity can also influence occupancy (Stirnemann et al., 2015). Our study took place in a highly heterogeneous landscape, particularly around more residential areas like the City of Durham, where the majority of MammalWeb sites were based (Figure 1). Therefore, it could be that fine-scale variations in habitat influence occupancy measures in our study, hence the differences seen in occupancy in broadleaf woodland. Whilst these differences seem to be reduced by looking at habitat on the finest scale (using the MammalWeb habitat class which is the immediate 10 m around the camera), some differences, such as for rabbit, still remain. As the presence of habitat features such as logs and trails can result in large differences in capture rates (Kolowski et al., 2021; Kolowski and Forrester, 2017) and citizen scientists are probably more likely to place cameras on trails in order to increase capture rates, this could also explain some of the habitat-specific differences in occupancy in our study.

Differences in habitat-specific activity schedules were seen for many species (Table S5). In comparison with other studies that used the same method (Lashley et al., 2018; Rowcliffe et al., 2014), our sample sizes at a habitat-level were small for estimating activity patterns. Therefore, overall activity measures are likely to be heavily influenced by individual sites where cameras were deployed. For example, 80% of hedgehog sequences in the MammalWeb multi-year dataset came from just two sites, meaning that hedgehog activity schedules will be highly influenced by the activity patterns of individual hedgehogs at those sites. Data from more sites should help overcome this problem, and once sample sizes are large enough, future research could subset the dataset to determine adequate sample sizes for calculating activity with citizen science data.

In our study, we have shown that spatial bias in the MammalWeb dataset influences occupancy and activity scores, particularly at a regional level. This is in contrast to the findings of Kays et al. (2021) who determined that in the North Carolina's Candid Critters project – a camera trapping citizen science project based in the USA – all habitats were surveyed sufficiently, with robust values of regional occupancy produced. However, although the majority of data from the Candid Critters project was opportunistic and came from citizen scientists, they did supplement data, with staff placing cameras in under-represented habitats, a necessary step for achieving adequate spatial coverage to calculate occupancy (Kays et al., 2021). Ultimately therefore, for the MammalWeb dataset, it is likely that camera traps need to be deployed at more sites across different habitats before accurate occupancy and activity measures can be determined.

3.5.3 Expanding spatial coverage

Moving forward, it would be beneficial for the MammalWeb project to pro-actively encourage participants to deploy cameras in habitats currently under-represented in the database. This could be done by engaging with farmers and gamekeepers, specifically, to encourage them to deploy camera traps on their land. Like several other projects (e.g., Lasky et al., 2021), MammalWeb operates a small-scale camera trap loan scheme where individuals and organisations can borrow a camera trap, free of charge, to deploy and upload captured footage to MammalWeb (Hsing et al., 2022). Priority to this scheme could be given to farmers / gamekeepers who could be recruited via social media campaigns, including specifically reaching out to regional groups such as the National Farmers Union North East (https://www.nfuonline.com/regions/north-east/).

Another method to reduce habitat bias would be to offer citizen scientists the opportunity to take part in the project in a more structured (rather than opportunistic) way by assigning survey sites to participants. This is done in many citizen science projects (e.g., the British Trust for Ornithology Breeding Bird Survey: https://www.bto.org/our-science/projects/breeding-bird-survey), including camera trapping projects (Kays et al., 2021), where sites are pre-determined and put up for 'adoption'. Assigning sites in this way has been shown to successfully increase spatial coverage (Kays et al., 2021; Lasky et al., 2021). Citizen scientists who take part in this way could be given additional training or protocols to follow, such as calibrating cameras for distance sampling, which would open up possibilities of collecting data for density estimation, as discussed in Chapter 2 (Mason et al., 2022). By following stricter protocols, such as not targeting placement of cameras on trails, this could also help to mitigate against the differences in trapping rates caused by fine-scale habitat variation, as discussed previously.

A dual approach of offering participants the opportunity to contribute in either an opportunistic way (as exists now, by them choosing sites) or in a more standardised form by assigning sites and following additional protocols would likely be beneficial for engaging with the different groups of citizen science participants. In common with findings from other citizen science projects (Boakes et al., 2016; Sauermann and Franzoni, 2015), MammalWeb participants typically fall into two groups: a small group of dedicated users who contribute large amounts of data regularly, and a larger group of users who contribute few records (Hsing et al., 2022). Whilst the latter group is more suited to contributing in the more opportunistic way, the former group could benefit from the deeper level of engagement that comes with the more standardised approach. Engaging with both of these groups of citizen scientists will be beneficial for expanding spatial coverage and for ensuring participants remain engaged with the project.

Whilst the purpose of our study was to compare data from our systematic camera trap survey to citizen science data on MammalWeb, the data generated from the systematic survey could be used to complement MammalWeb data in the future. The benefits of combining professional and citizen science data have been highlighted by previous studies and would likely help produce more accurate occupancy and activity measures by reducing overall habitat bias (Galván et al., 2021; Lasky et al., 2021; Soroye et al., 2018).

In conclusion, the data currently on MammalWeb are unsuitable for estimating occupancy and activity on a regional scale, due to the biases in habitats surveyed. It would be more appropriate to look at these measures at a habitat-level. However, more data in each habitat class in the MammalWeb dataset will increase confidence in parameter estimates. As described by Kays et al., (2021), implementing a "Plan, Encourage, Supplement" approach would be beneficial for expanding spatial coverage. This study has helped with the first planning stage of this approach, identifying key habitats that are currently under-represented in the data. Moving forward, expanding coverage could be achieved by: a) encouraging participants to deploy camera traps in under-represented habitats through assigning sites and working with farmers and gamekeepers; and b) supplementing citizen science data with professional data such as those collected in our systematic survey. By taking these steps to expand spatial coverage, citizen science datasets such as MammalWeb could be a valuable resource for long-term ecological monitoring.

3.6 Supplementary material

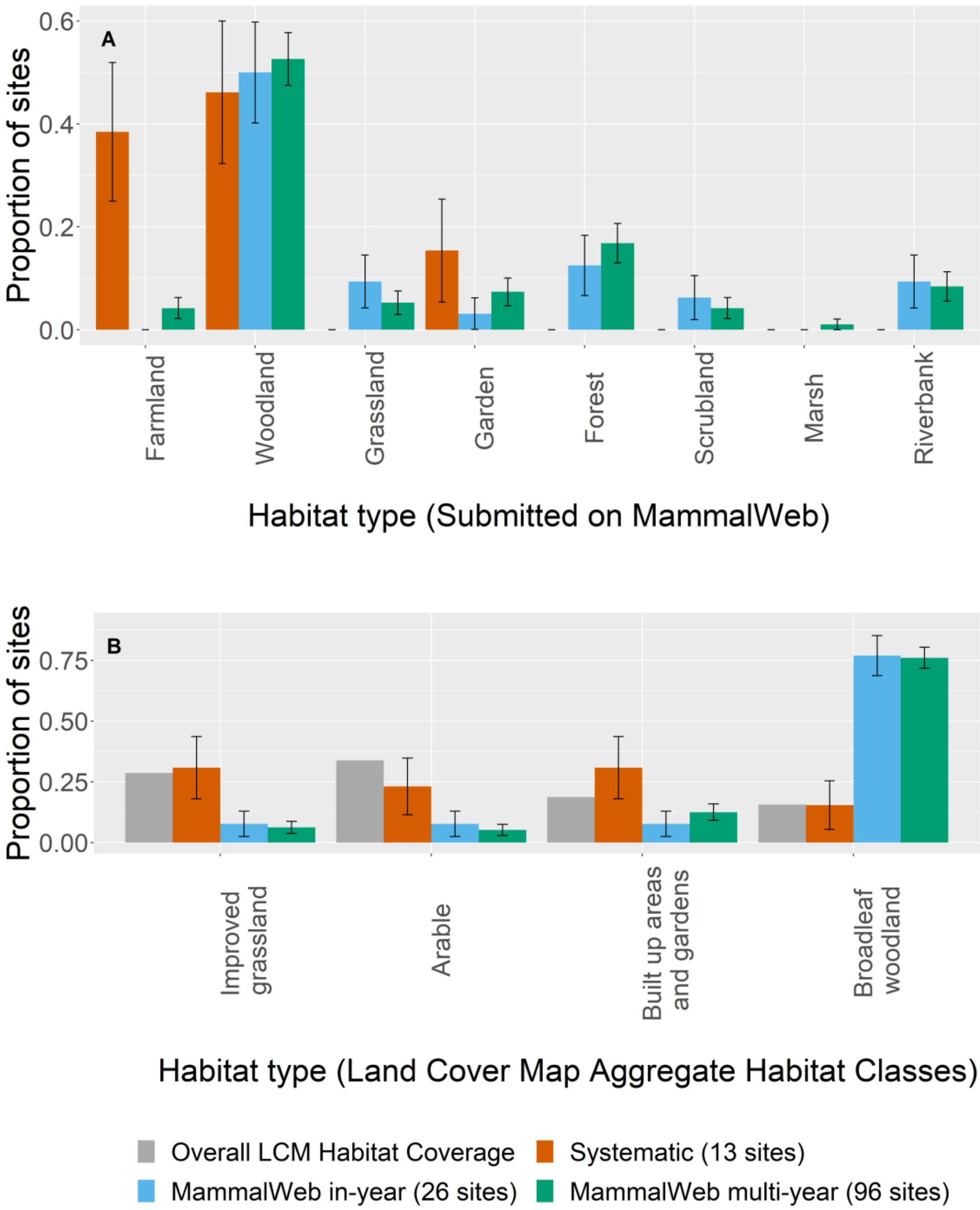


Figure S1. Proportion of sites within 10km radius of Durham City Centre for each of the MammalWeb habitat classes (A) and the Land Cover Map 2021 (LCM) habitat classes (B; Marston et al., 2022). B also shows overall coverage within the study area for each LCM habitat class. Error bars show ± standard error.

Table S1. Habitat descriptions on MammalWeb. When uploading footage to MammalWeb, participants are invited to select from this list the habitat immediately surrounding their camera trap.

Habitat descriptions on MammalWeb
forest – high density forest more than 60% canopy cover
woodland – low density forest less than 60% canopy cover
scrubland – dominated by shrubs, i.e. small to medium woody plants less than 8 m high
heath – a kind of scrubland characterised by open, low-growing woody plants less than 2 m high
grassland – dominated by grasses
marsh – a wetland dominated by herbaceous, i.e. non-woody plants
bog – a wetland with few/no trees, some shrubs, with lots of peat accumulation
swamp – a forested wetland
rocky – lots of bare rocks with little vegetation
coastal – right on the coast, beach
riverbank – right on the riverbank
farmland – pasture, etc.
garden – like a backyard garden, probably right next to a residence
park – recreational place
residential – houses, apartments, etc.
commercial – stores and offices
industrial – factories and warehouses

Table S2. Summary statistics for each dataset.

	Systematic dataset	MammalWeb in-year dataset	MammalWeb multi-year dataset
Total sites	109	32	120
Total sequences	48644	4921	25552
Sequences with animal captured	16044	3836	17115
Total camera trap days	1785	1090	4741

Table S3. Number of sequences of each species in each dataset.

Species	Number of sequences		
	Systematic dataset	MammalWeb in-year dataset	MammalWeb multi-year dataset
American mink	0	13	24
Badger	62	121	283
Bank vole	0	0	111
Black Grouse	92	0	0
Black-headed Gull	0	0	1
Blackbird (Eurasian)	591	62	1187
Blue Tit (Eurasian)	6	0	4
Brown (European) hare	584	10	51
Brown rat	2	21	32
Bullfinch (Eurasian)	2	4	17
Buzzard (Common)	0	1	1
Carrion crow	32	56	104
Chaffinch	0	1	31
Coal Tit	0	1	3
Collared Dove (Eurasian)	39	3	6
Common gull	2	0	0
Common shrew	0	0	62
Common vole	0	0	3
Coot (Common)	0	1	2
Curlew Sandpiper	5	0	0
Dipper (White-throated)	0	0	5
Domestic or feral Cat	1041	150	960
Domestic or feral Dog	425	25	173
Dunnock	68	0	42
Edible dormouse	0	0	1
Eurasian jay	12	0	2
Field vole	0	0	4
Goldfinch (European)	0	0	1
Great Crested Grebe	0	0	1
Great Spotted Woodpecker	0	6	11
Great Tit	22	3	21
Greenfinch (European)	0	0	4
Grey Heron	0	17	69
Grey Partridge	22	0	0
Grey squirrel	520	1030	3046
Grey Wagtail	0	0	12
Harvest mouse	0	0	2
Hedgehog (Western)	231	76	1970
Hooded crow	0	0	1
House mouse	0	0	3
House sparrow	61	1	3

Human	756	62	264
Jackdaw (Eurasian)	170	0	48
Jay (Eurasian)	0	19	55
Kestrel (Common)	1	0	0
Kingfisher (Common)	0	0	1
Lesser Spotted Woodpecker	0	2	2
Livestock	4602	26	35
Magpie (Eurasian)	229	18	174
Mallard	1	3	20
Mandarin Duck	0	0	11
Meadow Pipit	4	0	0
Merlin	0	0	1
Mistle Thrush	2	0	6
Moorhen (Common)	4	20	27
Nothing	32540	1085	8437
Nuthatch (European)	1	0	0
Otter	0	14	22
Peregrine Falcon	0	0	1
Pheasant (common)	791	123	529
Pied Wagtail	2	0	2
Pygmy shrew	0	0	28
Rabbit	3437	349	1359
Red fox	213	293	902
Red grouse (Willow Ptarmigan)	85	0	0
Red-legged partridge	34	0	0
Redwing	1	0	1
Robin (European)	27	42	135
Rock Dove/Feral Pigeon	0	0	5
Roe deer	268	707	1991
Rook	1	3	4
Shrew sp.	0	0	75
Small rodent	24	17	207
Song Thrush	26	39	128
Sparrowhawk (Eurasian)	0	0	4
Starling (Common)	14	0	0
Stoat	28	6	21
Stock Dove	0	1	1
Tawny Owl	1	2	6
Tree Sparrow	1	0	0
Vole (unknown species)	0	0	100
Water shrew	0	0	1
Weasel	1	0	3
Wood Duck	0	0	1
Wood mouse	43	68	250
Woodcock	0	3	9
Woodpigeon	1338	316	1395

Wren (Eurasian)	2	10	38
Yellow Wagtail (Western)	0	0	1
Yellowhammer	2	0	0

Table S4. Results of Wald test comparing activity patterns derived from three datasets for 7 focal mammal species. Differences between activity estimates for each dataset are shown along with standard error (SE), Wald statistic (W) and p value (P). *p < 0.05, **p < 0.01, ***p < 0.001.

Species	Datasets	Difference	SE	W	P
Badger 	*Systematic vs MammalWeb in-year*	0.167	0.036	21.616	<0.001***
	Systematic vs MammalWeb multi-year	0.063	0.038	2.766	0.096
	MammalWeb in-year vs MammalWeb multi-year	-0.104	0.028	13.275	<0.001***
Brown hare 	*Systematic vs MammalWeb in-year*	0.224	0.082	7.447	0.006**
	Systematic vs MammalWeb multi-year	0.063	0.083	0.570	0.450
	MammalWeb in-year vs MammalWeb multi-year	-0.161	0.104	2.384	0.123
Grey squirrel 	*Systematic vs MammalWeb in-year*	-0.103	0.036	8.121	0.004**
	Systematic vs MammalWeb multi-year	-0.073	0.035	4.367	0.037*
	MammalWeb in-year vs MammalWeb multi-year	0.030	0.024	1.525	0.217
Hedgehog 	*Systematic vs MammalWeb in-year*	-0.127	0.050	6.376	0.012*
	Systematic vs MammalWeb multi-year	0.033	0.019	2.90	0.088
	MammalWeb in-year vs MammalWeb multi-year	0.160	0.048	11.340	<0.001***
Rabbit 	*Systematic vs MammalWeb in-year*	0.186	0.030	38.137	<0.001***

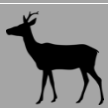
	Systematic vs MammalWeb multi-year	0.012	0.027	16.400	<0.001***
	MammalWeb in-year vs MammalWeb multi-year	-0.078	0.030	6.696	0.010*
Red fox 	*Systematic vs MammalWeb in-year*	0.031	0.048	0.426	0.514
	Systematic vs MammalWeb multi-year	-0.095	0.039	6.077	0.014*
	MammalWeb in-year vs MammalWeb multi-year	-0.126	0.047	7.173	0.007**
Roe deer 	*Systematic vs MammalWeb in-year*	-0.227	0.066	11.833	<0.001***
	Systematic vs MammalWeb multi-year	-0.125	0.053	5.672	0.017*
	MammalWeb in-year vs MammalWeb multi-year	0.102	0.053	3.726	0.054

Table S5. Results of Wald test comparing activity patterns derived from a systematic dataset and MammalWeb multi-year dataset for 4 mammal species in 3 different habitats. Differences between activity estimates for each dataset are shown along with standard error (SE), Wald statistic (W) and p value (P). *p < 0.05, **p < 0.01, ***p < 0.001.

Habitat	Species	Difference	SE	W	P
Improved grassland (LCM 25 m habitat class)	Grey squirrel	-0.019	0.069	0.073	0.787
	Rabbit	0.288	0.052	30.198	<0.001***
	Red fox	0.213	0.077	7.669	0.006**
	Roe deer	0.058	0.107	0.295	0.587
Broadleaf woodland (LCM 25 m habitat class)	Grey squirrel	-0.082	0.041	3.966	0.046*
	Rabbit	-0.015	0.038	0.161	0.688
	Red fox	-0.209	0.069	9.269	0.002**
	Roe deer	-0.221	0.052	17.817	<0.001***
Woodland (MammalWeb habitat class)	Grey squirrel	-0.090	0.037	5.980	0.014*
	Rabbit	0.022	0.047	0.226	0.634
	Red fox	-0.203	0.075	7.378	0.007**
	Roe deer	-0.163	0.061	7.182	0.007**

Chapter 4: Increasing connection to nature and knowledge of UK mammals through an ecological citizen science project in schools

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4.1 Abstract

Being connected to nature can have many benefits for children including improved mental and physical well-being and more positive attitudes towards the environment. However, a lack of opportunities to access nature, due to urbanisation and other factors, has led to many children growing up disconnected from nature and with little knowledge of local wildlife. Ecological recording, as part of a citizen science project, may offer new opportunities for children to learn about, and connect with, nature. In this study, we engaged 24 primary schools across North-East England in an ecological intervention where they: deployed camera traps to monitor wildlife in school grounds; took part in a workshop on mammals and camera trapping; and contributed to the citizen science project, MammalWeb. Using questionnaires from before and after participation, we assessed the impact on school pupils of being involved in the project, in terms of their perception of nature, knowledge of UK mammals, and connection to nature. We found that pupils could draw / name more UK mammals after our intervention, particularly species that were captured on the school's camera traps. Pupils could also name more mammals to species-level and identify native species. Although connection to nature scores did not significantly increase across all pupils, we found that there was an increase in scores for those pupils who had a low initial score. For younger children (aged 4 – 7), differences in their knowledge of UK mammals were not sustained three months post-intervention; however, differences were sustained for older pupils (aged 7 – 11). Furthermore, the connection to nature scores of children with a low baseline score continued to increase after our intervention. Our study demonstrates the positive impacts that using camera traps and participating in a citizen science project can have on school pupils by giving them the chance to learn about and connect with species to which they might otherwise have little exposure.

4.2 Introduction

Connection to nature can be defined as the mix of feelings and attitudes that people have towards nature (RSPB, 2013). For children, connection to nature is commonly centred around four components: enjoyment of nature; having empathy for creatures; having a sense of oneness with nature; and having a sense of responsibility for the environment (Cheng and Monroe, 2012). Being connected to nature brings many benefits to human well-being (Richardson et al., 2016; Richardson and Sheffield, 2017) and promotes pro-environmental behaviours (Barrera-Hernández et al., 2020; Richardson et al., 2016; Zhang et al., 2014). These benefits are particularly evident in the younger generation (Barrera-Hernández et al., 2020; Otto and Pensini, 2017; Whitten et al., 2018; Zhang et al., 2014). However, despite Robert Pyle having coined the phrase "extinction of experience" over four decades ago (Pyle, 1978), children today continue to have fewer opportunities to access local nature (Soga and Gaston, 2016). This increasing lack of contact with nature has been attributed to urbanisation (Neuvonen et al., 2007; Turner et al., 2004; Zhang et al., 2014) and the growing popularity of electronic entertainment media (e.g., watching television) as a recreational choice, as opposed to spending time outdoors and in nature (Pergams and Zaradic, 2006). As a result, in the UK, four out of five children are disconnected from nature (RSPB, 2013).

Alongside declining connection to nature there is also a loss in environmental knowledge, defined here as an understanding of the natural environment and the species within it. For example, children today often lack the ability to identify even common species (Pilgrim et al., 2008). Across Europe, studies have shown that children are more familiar with pets (Lindemann-Matthies, 2005), charismatic exotic species (Ballouard et al., 2011; Lindemann-Matthies, 2005), and even Pokémon characters (Balmford et al., 2002), than they are with local wildlife. Studies that have asked children to 'draw what they think nature is' show that their perception of nature is often of an environment lacking diversity, or is an environment based on imagination rather than real life (Aaron and Witt, 2011; Montgomery et al., 2022). Children are more willing to conserve biodiversity that they have more experience with, whether that be direct experiences or vicarious experiences (e.g., reading books or watching television; Soga et al., 2016). However, because opportunities for children to experience local nature are declining (Soga and Gaston, 2016), children are more willing to protect the charismatic exotic species with which they are more familiar, due to their representation on the internet and in popular culture (Ballouard et al., 2011; Clucas et al., 2008; Huxham et al., 2006).

This continuing decline in environmental knowledge and connection to nature is worrying, not only because children are missing out on the many benefits for themselves, but also from a biodiversity conservation perspective. Worldwide biodiversity is declining at alarming rates and the UK (where our study took place) is no exception to this (Hayhow et al., 2019). The loss of people's affinity towards to nature, due to decreasing natural spaces and lack of opportunities to connect with nature, can create a negative feedback loop whereby biodiversity is lost without people noticing or caring (Schuttler et al., 2018b). Given that childhood nature experiences can positively affect adult environmental attitudes and behaviours (Bixler et al., 2002; Ewert et al., 2005; Kidd and Kidd, 1996), creating more opportunities for children to experience, learn about, and connect with nature is crucial for conserving biodiversity in the long-term.

Participating in nature-based citizen science projects can increase participants' knowledge and awareness of local biodiversity (Forrester et al., 2017) and promote connections to local nature (Cosquer et al., 2012; Schuttler et al., 2018b; Toomey and Domrose, 2013). Particularly in the case of the latter, research has shown that connection to nature occurs more by noticing nature than by merely being in it (McEwan et al., 2019; Richardson et al., 2021; Richardson and Sheffield, 2017). Therefore, nature-based citizen science offers opportunities to connect with nature on a deeper level by not only increasing time spent in nature, but also noticing it through scientific recording. Further to this, citizen science projects that use camera traps offer unique opportunities for participants to see and learn about local species that are seldom seen, owing to nocturnal or otherwise elusive behaviours (Schuttler et al., 2018b). Although these experiences might be through photos or videos, rather than spending time in nature, these digital experiences of biodiversity are still important for informing children's attitudes towards, and willingness to conserve, species (Soga et al., 2016).

Although positive outcomes of participating in citizen science projects have been studied extensively for adults, very few studies have looked at positive effects on child participants (see review by Schuttler et al., 2018). In a school setting, there have been an increasing number of environmental education interventions including some involving citizen science; however, most are small-scale and few have offered robust evaluations of such initiatives (Blumstein and Saylan, 2007). Where evaluations of impacts on pupils have been undertaken, they have often only assessed immediate, short-term changes (Harvey et al., 2020; White et al., 2018). Here, we report one of the largest and most robust studies to date of impacts of participation in an ecological citizen science project on participating school pupils.

We engaged with 24 primary schools in a project where they: (a) borrowed a camera trap to use for one-month to monitor wildlife in their school grounds; (b) received a workshop about UK mammals and camera trapping; and (c) were invited to upload and classify data on an existing citizen science platform. Through questionnaires given to pupils pre- and post-intervention we aim to answer: (1) what is the baseline level of knowledge and awareness of UK mammals and connection to nature of school pupils; (2) whether our intervention changed this; and (3) whether this change was sustained, three months post-intervention.

4.3 Methods

4.3.1 Participating schools

The 24 participating primary schools were located across County Durham, Newcastle, and Middlesbrough in North-East England. The landscape of this area includes urban, suburban and rural areas, and schools in this study were located across all these environments. A recent report by Natural England showed that children living in North-East England spend less time outdoors than children in any other region, and this is likely due to the low socio-economic profile of the region (Natural England, 2019).

Schools were recruited through online advertisements and presentations given at teacher training days organised by the local council and other organisations. Once schools had signed up to the project, information was sent home to parents who were asked to provide opt-in consent to have their child included in the study (requiring the child to answer questionnaires). Verbal consent was also obtained by teachers from each child on the day they answered each questionnaire.

Schools were put into either an intervention group or a control group. Of the 24 participating schools, 21 were in the intervention group and 3 schools were wait-list control schools. Within the intervention group, schools were assigned to receive either a pupil workshop or teacher workshop. For this chapter, we analysed pupil workshop and teacher workshop schools together as one intervention group as there was insufficient data to analyse these groups separately (differences in engagement between schools taking part in pupil workshops vs teacher workshops are considered in Chapter 5). Although we made efforts to assign each school randomly to one of the intervention groups, this was constrained by geography and logistics, resulting in some schools (10) choosing which intervention group they wished to be a part of. Schools could decide how many classes from their school would take part. There were no pre-requisites for taking part in the project.

4.3.2 Intervention

Schools were lent a Browning Strike Force camera trap to use for one month. Within this month, schools received either a workshop for pupils or for teachers. The workshop lasted one hour and included going outside to learn about how and where to set up the camera trap and then classifying images from their own and other camera traps via the MammalWeb (www.MammalWeb.org) (Hsing et al., 2022) platform in the classroom. Further details of the content of both the pupil and teacher workshops can be found in Appendix S1 and Appendix S2. Each participating school had its own project set up on the MammalWeb platform and teachers were encouraged to upload and classify footage from their camera traps to this project page during or after the intervention. Most teachers used MammalWeb (uploading and classifying) with their class; however, outside of the workshops this was not monitored, and some teachers may have done the activities on MammalWeb on their own. Teachers also had access to a “Schools” page on MammalWeb which had additional resources including activity ideas and worksheets to be used alongside / after the intervention. Control group schools answered all questionnaires using the same timings as the intervention group before taking part in the intervention.

4.3.3 Questionnaires

We developed questionnaires that were filled in by school pupils at three time points: Q1: pre-intervention (in the two weeks prior to the start of the intervention); Q2: immediately post-intervention (at the end of the one-month intervention); and Q3: three months post-intervention. There were two different questionnaires tailored to the pupils' age. The first was filled in by pupils aged 4 – 7 in classes Reception to Year 2 in school (Early Years Foundation Stage and Key Stage 1 in the English education system). The second was filled in by pupils aged 7 – 11 in classes Year 3 to Year 6 (Key Stage 2). The overlap in age is because 7 year old pupils who turn 8 after September 2019 are in Year 2 (therefore in the younger group) and those who turned 8 before September 2019 are in Year 3 (and therefore in the older group). Pupils completed their questionnaires in class. Teachers were instructed not to give any contextual information to pupils about the project and to tell pupils that it was not a test.

For younger pupils, aged 4 – 7, the questionnaire consisted of just one activity where they were given a piece of paper and were asked to draw what they think nature is. They were given 10 minutes to complete the task and were encouraged to label their drawings if they were able. Teachers were instructed to help with labels where necessary. A drawing task was chosen over a writing task for this age group as they would likely have been too young to understand the written questionnaire (indeed, the connection to nature scale has only been validated for children 7+). Drawing exercises have been shown to help young children organise their own thoughts and narratives (Fargas-Malet et al., 2010) and have been used in a number of studies looking at interpretations of nature (e.g., Aaron and Witt, 2011; Drissner et al., 2013; Montgomery et al., 2022). Furthermore, younger pupils were asked about their perception of nature more generally, rather than specifically about mammals (which older pupils were asked about), as most pupils this age would not have been taught the characteristics of mammals and therefore might not be able to distinguish mammals from other taxa groups (Department for Education, 2015).

Older pupils aged 7 – 11 completed a two-page questionnaire (Appendix S3) and results in this chapter focus on two sections from that questionnaire: knowledge of UK mammals and connection to nature. To assess awareness and knowledge of UK mammals, the questionnaire asked "Please name all the mammals you know that live in the UK". We did not do any checks to test understanding of what a mammal is, because all pupils who participated in this questionnaire should have been taught this as part of the National Curriculum by this age (Department for Education, 2015). Furthermore, we wished to explore how many non-mammals were named, and whether this changed following our intervention. The limit for time spent on this (which was stated on the questionnaire) was five minutes and teachers timed pupils completing this section and asked them to move on to the next section after five minutes. Below this question the participants were then asked to underline the animals they had named that they think have come from another country.

To assess connection to nature, we used the Connection to Nature Index proposed by Cheng and Monroe (2012). This survey comprises 16 statements and participants indicate how they feel about those statements on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). An average is taken and reverse coded to produce an overall score where a higher score indicates a stronger connection to nature. The survey has been validated and recommended as the best measure of connection to nature for this age group, scoring highest (in comparison to other scales) for children's understanding of how to complete it (Bragg et al., 2013). Teachers followed the recommended protocol for using the scale with children, explaining that they were to read each statement carefully and tick the appropriate box (Bragg et al., 2013). Children were told they could ask for help if they did not understand a statement, in which case the teacher would try to explain the statement to the child. If they still did not understand the statement after the teacher's explanation, they could leave it blank.

4.3.4 Data processing

Nature drawings were translated into lists of everything that had been drawn. Although drawings were labelled in most cases, if a drawing was not labelled and it was not obvious what had been drawn, we either wrote down broadly what it was (e.g., "plant" or "animal"), and, if we were not able to determine that, we left it blank. For both the nature drawings and the question on naming UK mammals, spelling was not penalised and we recorded all answers in their singular form (e.g., “badger” rather than “badgers”). If the naming mammals question was left blank, we assumed that to be because the participant had chosen not to answer the question (rather than them not knowing any mammals that live in the UK) and therefore did not record data. For both the nature drawings and naming mammals question we assigned things drawn / written down to categories of either type of animal (e.g., wild terrestrial UK mammal) or other elements drawn / written (e.g., water or weather) (the full table of categories can be seen in Table S1). To assess knowledge and awareness of nature (for younger pupils) and UK mammals (for older pupils) and whether that increased post-intervention, we first looked overall at things that had been drawn / named and at what frequency. We then looked in more detail at the number of things drawn / written down in specific categories and whether that changed at each questionnaire time-point.

For the naming mammals question, we also scored each pupil on how many animals (from those named) that they correctly identified as being from / not from the UK. We restricted this to wild terrestrial UK mammals and exotic mammals but excluded animals that could be native / non-native (e.g., squirrel) or wild / domestic (e.g., rabbit)..). Answers were marked as correct if they had underlined non-native UK mammals or exotic mammals or not-underlined native UK mammals. The total score for each pupil was the number of correct answers. In addition, we also scored pupils on the number of wild terrestrial UK mammals that had been given to species level (e.g., grey squirrel instead of squirrel). Answers were marked as named to species level in all cases except where the animal they named has more than one species present in the wild in the UK. For example, “deer” would be marked as not to species level as there is more than one deer species in the UK. On the other hand, there is only one species of badger (*Meles meles*) in the UK (although there are more worldwide) and, since the question asked about mammals in the UK, we considered that ‘badger’ was adequate to be marked to species level. This may have resulted in more animals named to species level overall than if we had used an alternative marking system; however, because we are mainly interested in how this changes over time and between groups, and because we used this marking approach consistently throughout, our results are comparable.

4.3.5 Data analysis

Analyses were conducted using R 4.1.2 (R Core Team, 2021). To test differences in scores between intervention groups we used general linear mixed models (GLMMs) generated using ‘lme4’ (Bates et al., 2015). For both the drawing nature and naming mammals data, we modelled counts of drawings / animals in each of the categories using GLMMs with a Poisson error structure. We also used this approach to model the number of animals correctly identified as being from / not from the UK, and the number of UK mammals named to species level. For the connection to nature scores, we used a linear mixed model with Gaussian error structure. In all models, Questionnaire interacting with Intervention Group was used as a fixed factor and class and pupil identifiers as random factors. We considered including other factors within our models, such as level of urbanisation around the school or biodiversity found on school grounds; however, a lot of the pupils who participated in the study were from schools with similar characteristics (e.g., ~90% of pupils were from schools in urban environments) and, when we tried to include these factors in models, they failed to converge. We therefore kept our models simple but do consider further possibilities in the discussion. Model comparison tables were generated using ‘MuMIn’ (Barton, 2020) to select best-fitted models. For models where the best-fitted model included both questionnaire and intervention, we used Tukey’s HSD post-hoc analysis to compare values within each intervention group for different questionnaires. R^2 values for these models were calculated using the method described by Nakagawa and Schielzeth (2013).

We analysed both all data, and data restricted to those pupils who had answered all three questionnaires. For the connection to nature scores, as scores are typically left-skewed and therefore prone to ceiling effects (Harvey et al., 2020; Hughes et al., 2018), we also looked at changes in the scores from pupils who had a low initial score. To do this, we used the thresholds proposed by Hughes et al. (2018) which were calculated by linking scores to self-reported pro- environmental behaviours. Children in the lowest connection to nature score threshold (< 4.06) are likely to show little to no pro-environmental behaviours. We ran the same analysis as described previously but with a subset of data from pupils who had a low initial connection to nature score (< 4.06) and who had answered all three questionnaires.

We also looked at the proportion of pupils who drew (for younger pupils) or named (for older pupils) species that were captured on either their own school's camera trap or other schools' cameras. To aid understanding of pupils' naming of non-mammals on questionnaires, we also report on the proportion of bird species named that were captured on school camera traps.

4.3.6 Ethics statement

Approval for this study was granted by Durham University's Department of Anthropology Ethics and Data Protection Committee. Consent was obtained in writing from pupils' parents and verbally from pupils themselves. All questionnaires were anonymised by teachers assigning each participant a number. This number was then combined with a unique identifier for each school and each class, and this identifier was used to track questionnaires for individuals pre- and post- intervention. Therefore, we kept no personal information on pupils involved with the study.

4.4 Results

4.4.1 Questionnaire response rates

Overall, 1020 pupils from 94 classes in 24 schools completed questionnaires. These included 343 younger pupils (from 40 classes in 17 schools) who completed the nature drawing questionnaire and 677 older pupils (from 54 classes in 19 schools) who completed the naming mammals and connection to nature questionnaire. There were 185 pupils in the control group. For younger / older pupils, our sample sizes were 240 / 497 for pre-intervention questionnaires (Q1), 220 / 467 for immediately post-intervention questionnaires (Q2), and 94 / 292 for three-month post-intervention questionnaires (Q3). However, due to difficulties with absences, timing, questionnaires not being returned and identifier mismatches, only 54 younger pupils and 176 older pupils answered all three questionnaires; others answered only one or two questionnaires. For older pupils, we omitted connection to nature scores for four pupils who had not answered all statements, potentially biasing their scores.

4.4.2 Pre-intervention perception of nature and knowledge of UK mammals

Pre-intervention, the most common things drawn by pupils when asked “Please draw what you think nature is” were trees, sun, grass, birds and flowers (Figure 1; Figure S1). 68% of pupils’ drawings included one or more animals (excluding humans); the three most commonly drawn animals were birds, bees and butterflies (Figure 1). 21% of pupils drew a UK mammal (excluding humans and generic ‘animal’ and ‘mammal’) with the most commonly drawn being rabbit, deer and hedgehog (Figure 1). For older pupils who were asked to “Name all the mammals you know that live in the UK”, the five most commonly named animals pre-intervention were dog, cat, rabbit, human and horse (Figure 1; Figure S2). Excluding rabbit (which could be classified as a wild mammal or a pet), fox was the most commonly named wild mammal (Figure 1; Figure S2). One in four pupils named lion and one in five pupils named tiger in response to the question (Figure 1; Figure S2).

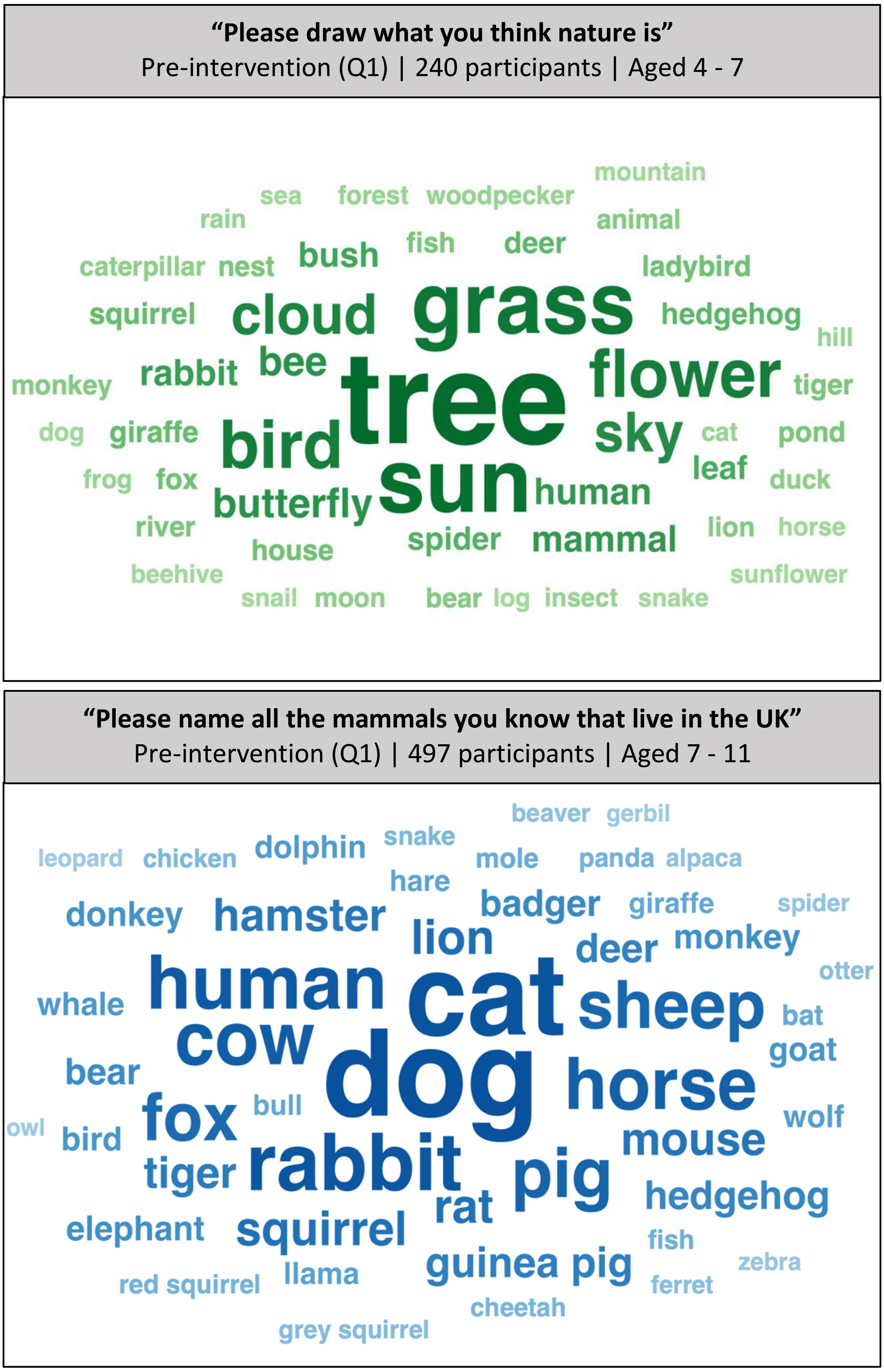


Figure 1. Word clouds of answers / drawings from two pre-intervention activities with participating pupils. Top (green) shows top 50 things participating pupils aged 4-7 drew when asked to draw what they think nature is. Bottom (blue) shows the top 50 animals named when participating pupils 7-11 were asked name all the mammals they know that live in the UK. Word size and colour is scaled to the number of individuals who drew / wrote it with the largest / darkest words being the most frequently written / drawn.

4.4.3 Post-intervention perception of nature and knowledge of UK mammals

Although, overall, the specific things drawn / written remained largely similar post-intervention (Figure S1-S3), there were some differences, particularly for wild terrestrial UK mammal species. For younger pupils, there was an increase in the percentage who drew deer, hedgehog, fox and mouse between Q1 and Q2. For older pupils immediately post-intervention, fox becomes the third most commonly named mammal (after dog and cat; Figure S2) and other wild UK mammals including deer, hedgehog, squirrel, badger, and otter now appear in the top twenty most commonly named animals. For younger pupils, these increases do not appear to be sustained at Q3 (Figure S1); however, for older pupils it is more mixed, with the increase being sustained for some species (e.g., deer, badger, grey squirrel, red squirrel) but not for others (e.g., hedgehog and otter; Figure S2). The two most common exotic animals named by older pupils (lion and tiger) were named by fewer pupils at Q2 with this decrease being sustained at Q3 (Figure S2).

Both questionnaire and intervention grouping had a strong effect on the number of wild terrestrial UK mammals drawn (Table S2). Predicted values from the best-fitted model showed no change in the number of wild terrestrial UK mammals drawn in the control group (Figure 2). For the intervention group there was a significant increase in the number drawn between Q1 and Q2 but then a decrease between Q2 and Q3 so there was no significant difference from baseline at Q3. Questionnaire and intervention grouping had no strong effect on the number of non-mammals or the number of exotic mammals drawn (Table S2). The best-fitted model was the same when we ran the analysis with all data, and with data restricted to only pupils who answered all three questionnaires (Table S2).

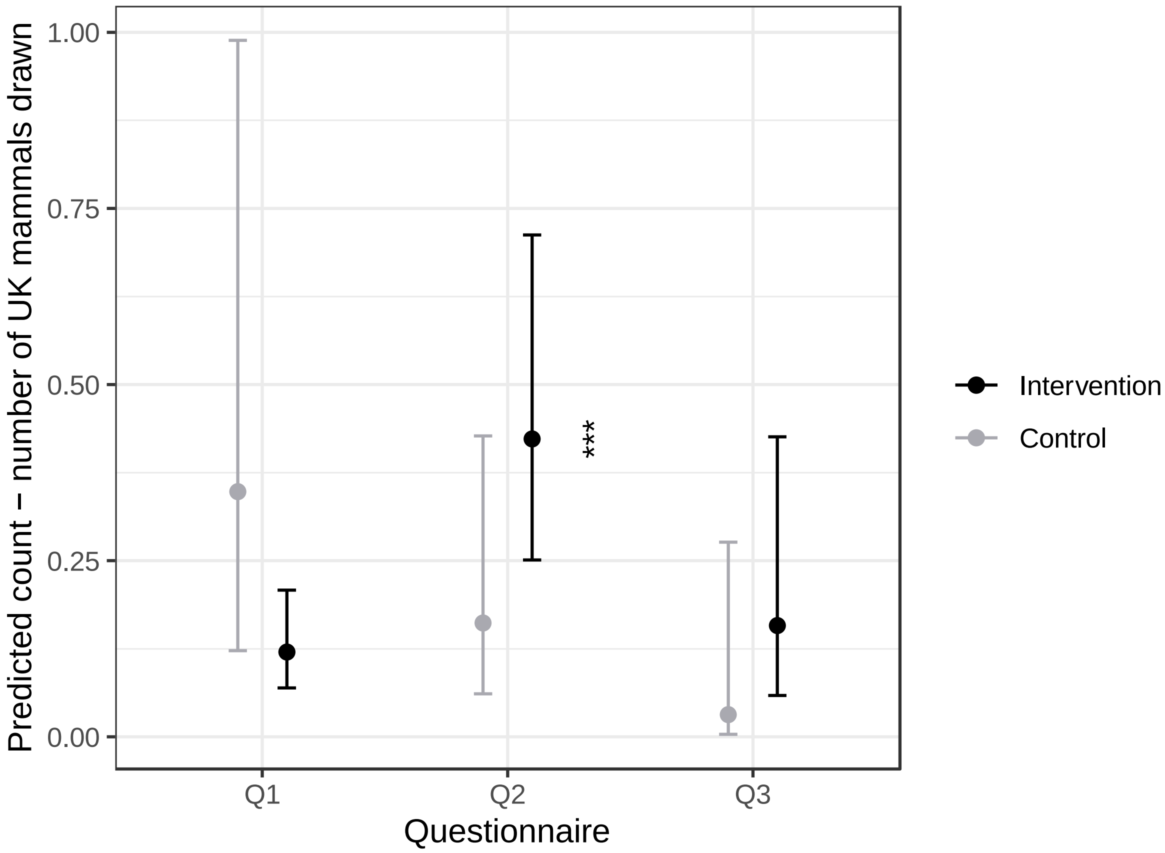


Figure 2. Predicted values from top candidate GLMM for counts of number of UK mammals pupils drew when asked to draw what they think nature is. Questionnaire (pre-intervention Q1, immediately post-intervention Q2, and three-months post-intervention Q3) and intervention group (Intervention or Control) were included as predictors in models and class and pupil ID as random effects. Error bars represent 95% confidence intervals. Significance levels shown at Q2 and Q3 are compared to baseline pre-intervention (Q1) for each group (Intervention / Control) and are based on Tukey HSD analysis (*p < 0.05, **p < 0.01, ***p < 0.001).

For analysis of answers from older pupils who answered the naming mammals question, we omitted the Extinct / Doesn't exist category and the generic Mammal category as sample sizes for these were extremely small (6 and 5 respectively). We also omitted Human because this was not a focus for our study. We analysed all other categories. The best-fitted model was the same in all but two cases (marine mammals and non-mammals) when we ran the analysis with all data, and with data restricted to only pupils who answered all three questionnaires (Table S2). Best-fitted models included both questionnaire and intervention group as fixed effects for all categories we analysed, except for domestic / farm animals (Table S2); our intervention did not impact the number of domestic / farm animals pupils named. Although questionnaire and intervention group were included in best-fitted models for marine mammals, post-hoc pairwise comparisons revealed no significant differences across values for this group and the best-fitted model did not include questionnaire when we restricted the data to pupils who had answered all three questionnaires. We therefore focus on the categories in Figure 3 for the rest of our analysis.

For the control group, the only significant change was a decrease in the number of non-mammals named over time (Figure 3C). There was no change in the number of non-mammals named by pupils in the intervention group (Figure 3C). In the intervention group there was an increase between Q1 and Q2 in: the number of wild terrestrial UK mammals named; the total number of animals named; the number of animals correctly identified as being from / not from the UK; and the number of animals named to species level (Figure 3). There was a decrease in the number of exotic mammals named between Q1 and Q2 (Figure 3B). Whether this change was sustained (i.e., value was significantly different from baseline at Q1) at Q3 varied, but it remained for the number of wild terrestrial UK mammals named, the number of exotic mammals named and the number of animals named to species level (Figure 3).

For both the drawing activity and the naming mammals activity, post intervention (in Q2) pupils drew / named species captured on either their own or other school's camera traps (Figure 4). This increase was not seen in the control group schools (Figure S4). There were decreases in the proportion of pupils who drew / named species captured between Q2 and Q3, particularly for younger pupils who took part in the drawing activity (Figure 4). For older pupils in the naming mammals activity, 42% of the bird species named in Q2 were species captured on cameras, compared to 12% in Q1.

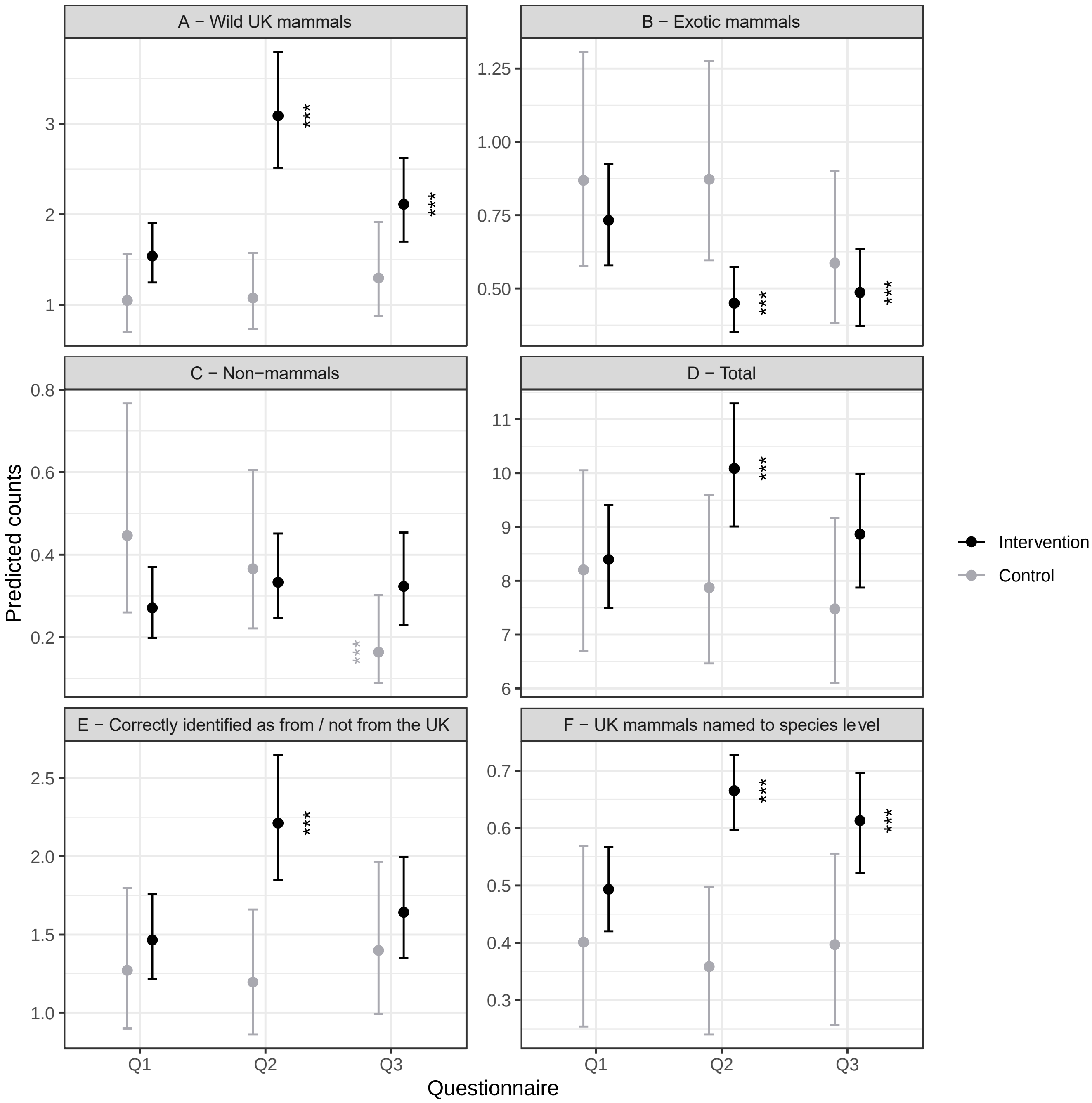


Figure 3. A - D show predicted values from top candidate GLMMs for counts of types of animals named when participating pupils were asked to name all the mammals they know that live in the UK. E - F graphs show predicted values from GLMMs for counts of number of animals correctly identified as being from / not from the UK (left) and number of animals named to species level (right). Questionnaire (pre-intervention Q1, immediately post-intervention Q2, and three-months post-intervention Q3) and intervention group (Intervention or Control) were included as predictors in models and class and pupil ID as random effects. Error bars represent 95% confidence intervals. Significance levels shown at Q2 and Q3 are compared to baseline pre-intervention (Q1) for each group (Intervention / Control) and are based on Tukey HSD analysis (*p < 0.05, **p < 0.01, ***p < 0.001).

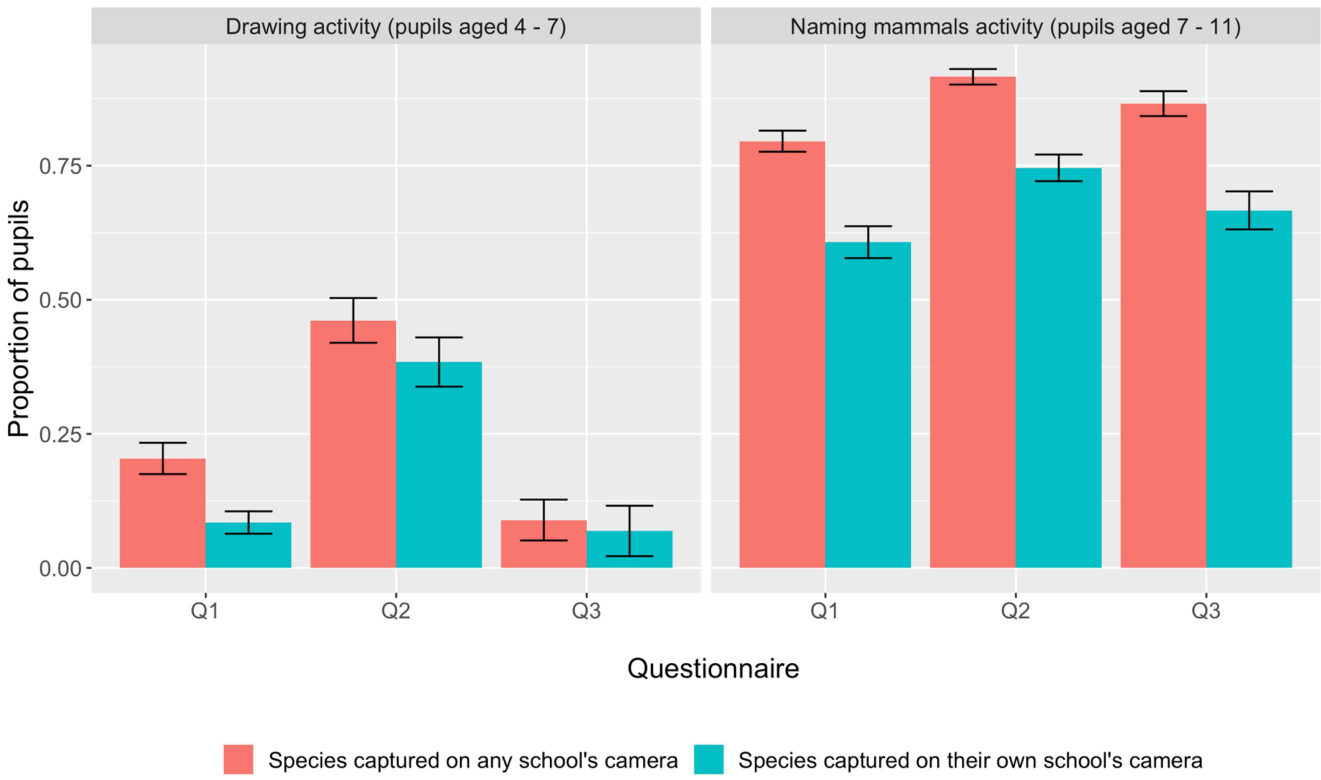


Figure 4. Proportion of pupils who drew / named species captured on either any participating school's camera trap or on their own camera trap. Left graph is for pupils aged 4 – 7 who were asked to draw what they think nature is. Right graph is for pupils aged 7 – 11 who were asked to name all the mammals they know that live in the UK. Error bars show ± standard error.

4.4.4 Connection to nature

Intervention grouping did not have a strong effect on model fits (for both all data and data restricted to pupils who answered all three questionnaires) (Table S2), suggesting there was no difference in connection to nature scores across the three questionnaires for the control or intervention group. When we ran the same analysis but restricting data to pupils with a low initial connection to nature score who had answered all three questionnaires (n = 44), the effect of intervention group was stronger, with the best-fitted model including both questionnaire and intervention group, although other models without these effects were also within 6 AIC units (Table S2). Predicted values from the top candidate model for pupils with low initial connection to nature showed that scores were higher than baseline Q1 (3.73) at both Q2 (4.00) and Q3 (4.16) for the intervention group, but there were no significant changes across questionnaires in the control group (Figure 5).

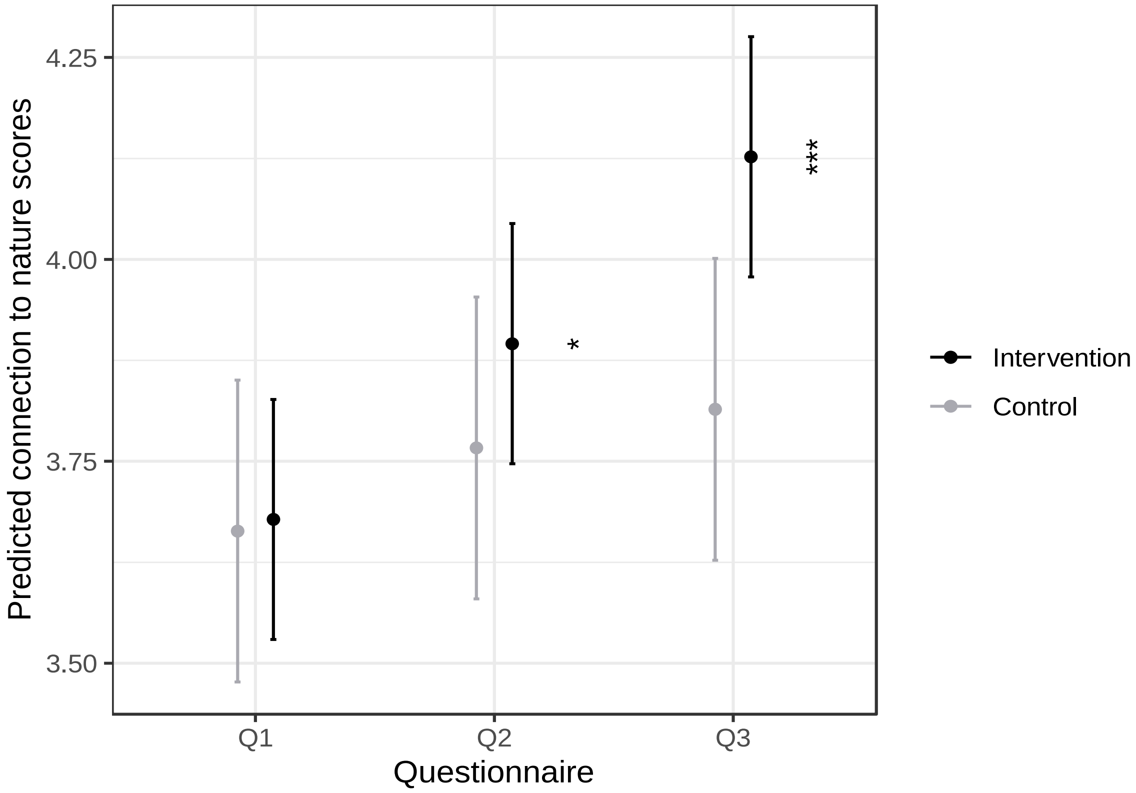


Figure 5. Predicted values from top candidate GLMM for connection to nature scores of pupils with a low initial score (< 4.06; threshold calculated by Hughes et al., 2018). Questionnaire (pre-intervention Q1, immediately post-intervention Q2, and three-months post-intervention Q3) and intervention group (Intervention or Control) were included as predictors in models and class and pupil ID as random effects. Error bars represent 95% confidence intervals. Significance levels shown at Q2 and Q3 are compared to baseline pre-intervention (Q1) for each group (Intervention / Control) and are based on Tukey HSD analysis (*p < 0.05, **p < 0.01, ***p < 0.001).

4.5 Discussion

Our study engaged over 1000 primary school pupils in an ecological citizen science program, offering them new opportunities to both learn about and connect with their local wildlife. We show that our intervention had positive impacts on pupils aged 4 to 11, including an increased knowledge and awareness of wild UK mammals. Although there was no increase in connection to nature across all pupils, our intervention had a positive effect on connection to nature for those with a low initial connection to nature, prior to the study. We also show that whilst some benefits are only short-term (e.g., awareness of wild UK mammals in younger pupils), some are maintained, or even increased, three-months after our intervention. Here, we discuss our results in relation to: the baseline (pre-intervention) level of knowledge of UK mammals and connection to nature; how this changed following our intervention; and the extent to which this change was sustained.

4.5.1 Measures pre-intervention

Previous studies have found that perceptions of nature in children are varied and wide-ranging (Aaron and Witt, 2011; Burgess and Mayer-Smith, 2011; Keliher, 1997). In contrast, our study showed that when children were asked to draw what they think nature is, the majority of pupils drew very similar things (e.g., trees, grass, flowers, sky). Of the animals that they drew, birds were the most common, followed by bees and butterflies. The national curriculum in England currently states that children aged 4-7 (Key Stage 1) should be able to "identify and name a variety of common animals including fish, amphibians, reptiles, birds and mammals" and that "Pupils should use the local environment throughout the year to explore and answer questions about animals in their habitat" (Department for Education, 2015). In the UK, mammals are seldom seen due to their tendency to be elusive (often nocturnal or shy) and to occur at lower densities than other taxa. Therefore, children may have fewer opportunities to experience and learn about mammals around them than they have for taxa such as birds and insects, which can be found and seen more easily. This could have contributed to why, despite previous studies showing that children have more knowledge, awareness, and preference for mammals (Gerl et al., 2021; Huxham et al., 2006; Lindemann-Matthies, 2005; Snaddon et al., 2008), they were less commonly drawn than other taxa in our study.

If, as suggested in our study, children do not associate mammals with nature, this could have implications for mammalian management and conservation. However, it is also possible that mammals were not drawn as often because, compared to animals such as bees and butterflies, they are more complex to draw. Furthermore, although drawing studies are considered a quick and effective method for assessing perceptions of nature (Montgomery et al., 2022), it is important to note that not being able to draw species is not indicative of poor perception / knowledge. Therefore, in the future it may be beneficial to do a drawing exercise alongside an interview to gain a deeper understanding of children's perception of nature.

For older pupils, who were asked to "Name all the mammals you know that live in the UK", pupils seemed most familiar with domestic pets and farm animals, naming them more than any other type of animal. On average, children named around eight animals in response to the question but only around one of these animals was a wild, terrestrial UK mammal. The number of exotic animals named, pre-intervention, was similar to the number of wild UK mammals (0.71 exotic vs 1.55 wild UK in intervention schools, 0.93 exotic vs 1.02 wild UK in control schools), with lion, tiger, bear, elephant, monkey, and wolf all appearing in the top thirty animals named by pupils, pre-intervention. The pupils are not wrong, as these animals can be found in UK zoos; nevertheless, our findings do cast light on which animals they are most familiar with, and which come to mind when answering this question. Our results accord with other indications that pupils are familiar with more exotic species, whereas their knowledge of local wildlife is poorer (Ballouard et al., 2011; Lindemann-Matthies, 2005). This is likely due to more representation of charismatic flagship species like lions and tigers in the media, in books, and at the zoo (Clucas et al., 2008; Huxham et al., 2006). We also noted that teachers often use exotic animals as examples in their teaching of the national curriculum. For example, in England, the Key Stage 2 curriculum requires teaching on adaptations of animals (Department for Education, 2015) – it is often easier to think of exotic charismatic animals such as stripes on tigers for camouflage and, as a result, teachers may use this as an example rather than species local to them.

Although the connection to nature scale goes from 1 to 5, consistent with other studies (Harvey et al., 2020; Hughes et al., 2018) we found that pre-intervention scores were left-skewed with the majority of scores (67%) being 4 or above. Hughes et al. (2018) proposed low, mild, and high connection to nature thresholds which reflect how a child's score relates to pro- environmental behaviours. Using these thresholds, pre-intervention scores in our study were split relatively evenly between the three groups: 24% high; 39% mild; and 37% low. This variability in scores pre-intervention could arise from a number of factors, including schools varying from urban to rural locations, a factor shown to influence connection to nature strongly (Bashan et al., 2021; Duron-Ramos et al., 2020). Other studies have found that children score more highly than might be expected using the Cheng and Monroe (2012) connection to nature scale, possibly due to social desirability bias (answering in a way that they believe you want them to) (Harvey et al., 2020).

4.5.2 Immediate impacts from our intervention

To date, the majority of school, nature-based interventions have focussed on pupils aged 7+ (e.g., Blackawton et al., 2011; Schuttler et al., 2019; White et al., 2018). Our study showed that our intervention had immediate benefits for children as young as 4. Our project offered a unique opportunity to help increase children's exposure to local mammals through camera trapping and citizen science. This was reflected in children's drawings of nature post-intervention, with wild UK mammals being drawn more frequently after participation in the project. Drawing studies with older children (8-11 years) have also found that nature-based interventions result in nature drawings depicting a greater diversity of species (Drissner et al., 2014; Montgomery et al., 2022). Furthermore, Montgomery et al. (2022) showed that through a nature-based intervention (that including camera trapping), school pupils drew more accurate representations of the biodiversity present on their school grounds. Given that, particularly in urban environments, children often have limited knowledge of local nature (Aaron and Witt, 2011), interventions that offer opportunities to experience species that are otherwise seldom seen (e.g., nocturnal mammals) could be important for building a stronger connection to and knowledge of nature.

Older pupils named a significantly increased number of wild UK mammals immediately post-intervention (Q2). As might be expected, mammals (such as fox, squirrel and deer) that were all caught on school camera traps were named by a greater percentage of pupils, post-intervention. More surprisingly however, there were also increases in the percentages of pupils who named rarer animals not caught on any of the school's cameras such as otter (3% at Q1 vs 25% at Q2), red squirrel (4% at Q1 vs 18% at Q2) and pine marten (<1% at Q1 vs 15% at Q2). Although none of these animals were caught on school camera traps, we often spoke about many species of wild mammals, including these, during the pupil workshops / teacher training sessions, and they do appear in the broader MammalWeb project from which pupils were encouraged to classify images. Nature interventions that offer multiple ways for participants to learn about and connect with nature appear to be most successful in eliciting change in participants (Harvey et al., 2020; Schuttler et al., 2019; Soga et al., 2016). This also appears to be the case for our project, with students learning not only from the camera traps but also from the workshops and overall citizen science project.

The number of non-mammals that pupils named decreased for pupils in control group schools but not for pupils in intervention group schools. Different groupings of animals and the characteristics of each are taught in Key Stage 1 (ages 4 - 7) in the national curriculum in England (Department for Education, 2015). Therefore all of the pupils who participated in this part of the study (Key Stage 2, ages 7 – 11) would have been taught this part of the curriculum already and should be familiar with what a mammal is. We did not monitor what topics were taught between questionnaires (partly because this varies between schools); however, it is likely that, although not part of the formal curriculum at this age, pupils will have done activities that reinforce learning of what is / is not a mammal. Hence, this is probably why we see a decrease in the number of non-mammals named in control group schools. For intervention group schools, 42% of birds named at Q2 (compared to 12% at Q1) were species such as pigeons, blackbirds and pheasants that were captured on school camera traps. It is possible that the lack of a reduction in non-mammals named by the intervention pupils arises because pupils are naming birds that were caught on cameras traps, perhaps because of the association of the questionnaire with the project.

We also showed that both the number of mammals correctly identified as from / not from the UK and the number of mammals named to species level increased post-intervention. Particularly in the case of the former, this shows a deeper level of understanding, as pupils are not only able to recall mammals but they also know something about their characteristics. Invasive species have driven extinction of native species for centuries and, with climate change causing shifts in species distribution, they will continue to pose a threat to biodiversity worldwide (Bellard et al., 2013; Dueñas et al., 2021; Tilman et al., 2017). It is important therefore that invasive species are managed carefully, to mitigate against their impact on native species (Tilman et al., 2017). Public perception of invasive species is varied, with some species being accepted (and management measures opposed) if the species has high aesthetic value (Kapitza et al., 2019; Verbrugge et al., 2013). If interventions such as ours could encourage an early understanding of the concept of invasive species and the threat they pose to biodiversity, this will likely be helpful with future conservation and management efforts.

In our study, we saw no effect of our intervention on connection to nature scores overall. We believe this lack of change is likely to stem from two sources. Firstly, as discussed above, a lot of children (63%) in our study already had a mild or strong connection to nature at the outset, resulting in a ceiling effect where there was little room for these children to improve. Secondly, as durations of nature-based interventions influence the positive outcomes on participants (Braun and Dierkes, 2017), it may be that our intervention was not long or intense enough to elicit a change in connection to nature amongst all children. Specifically, for citizen science projects, short-term involvement in citizen science has been shown to increase knowledge or project specific skills, but not attitudes (Forrester et al., 2017; Jordan et al., 2011; Overdevest et al., 2004). Our study was relatively light-touch, with a minimum of one hour of workshops for teachers / pupils during the month and any extra engagement largely being left to the teacher's discretion. Therefore, more sustained interventions where children are guaranteed to spend more time outdoors and doing more nature activities may yield better results. Nevertheless, we did show that connection to nature increased for those pupils who had a low initial score. Children with a low connection to nature are less likely to show conservation behaviours (Hughes et al., 2018) and are missing out on the many benefits of being connected to nature (see review by Chawla, 2020). Therefore, it is arguably most important that nature-based interventions such as ours provoke changes amongst these children.

4.5.3 Longer-term impacts

Our project is one of the first nature-based intervention projects that measured impacts on pupil participants not only immediately after the intervention, but also three months later. For younger pupils, although we saw an immediate increase, post-intervention, in the number of wild UK mammals drawn by pupils, this increase was not sustained three-months post-intervention. Reinforcing this knowledge in pupils at this age might require more prolonged engagement. For older pupils, the number of wild UK mammals named decreased slightly between Q2 and Q3 but still remained higher than baseline levels (at Q1). The greater endurance of the change in older pupils is likely because older children have a more developed working memory (Barrouillet et al., 2009). It could, however, be that teachers from Key Stage 2 (older children in this study) continued with project-related activities after our one-month intervention more so than teachers from Key Stage 1 (younger children in this study). This seems probable because there are more topics in the Key Stage 2 curriculum that can be related to this project than there are in the Key Stage 1 curriculum.

Unlike knowledge of UK mammals, connection to nature in our intervention groups continued to increase across all time points. Meanwhile, the control group did not show any significant increases in connection to nature scores. Although there were no prescribed activities for schools after the one-month intervention period, we know that 11 of the schools continued to engage with MammalWeb, and / or purchased their own camera trap to continue camera trapping, following the intervention (this is explored further in Chapter 5). These class activities likely helped to further increase connection to nature among pupils. This highlights the importance of sustained and repeated engagement with the project, post-intervention. Funding and capacity for researchers / individuals to continue interventions long-term is often limited and in a school setting, therefore, the best way to achieve this longer-term engagement is by influencing and inspiring teachers. Equipping teachers with knowledge and activities to continue the project post-intervention enables opportunities for benefits for pupil participants to be sustained or even to increase. In this context, more research into the barriers faced by teachers incorporating projects such as this into their day-to-day teaching, and how these barriers could be overcome, would be highly beneficial.

4.5.4 Limitations and future work

One limitation of our study was that there could have been a self-selection bias due to schools choosing to be part of the study, and parents having to agree to their child taking part. Schools / parents who opted for their child to take part likely had an interest in the study and so participating pupils could have a higher ecological knowledge / connection to nature than average. However, even if our sample is biased towards pupils with a high initial ecological knowledge / connection to nature, and if (as our connection to nature results suggest), our study has the greatest impact on those with initially low scores, our intervention would likely have greater benefits for the wider population than we have reported here. Another limitation was that we were unable to match the sample size of the control group to the intervention group. Whilst a balanced sample would have been preferable, unbalanced sample sizes are a common occurrence in school-based studies where it can be hard to recruit control schools (e.g., Harvey et al., 2020). We do not believe the unbalanced sample sizes in our study impacted our results as we still had enough statistical power to run our analysis and identify significant results. However, future studies may wish to increase efforts to recruit control schools, perhaps by starting the recruitment process earlier.

Further work could investigate some of the other factors that might influence knowledge of UK mammals and / or connection to nature, such as whether the school is in a rural or urban area. Other studies have found that children living in rural areas have more direct experiences in nature and, as a result, can have a higher connection to nature (Duron-Ramos et al., 2020; Mustapa et al., 2018; Wells and Evans, 2003). In our study, only ~10% of participating pupils were in rural schools. We therefore did not do any formal analysis looking at the influence of rurality on scores as we did not have a large enough sample of pupils in rural areas. However, we do know that, in contrast to what might be expected, 23% of pupils with a low initial connection to nature score were from rural schools. Caution should be taken over drawing any conclusions from this, however, as the sample size of this group was very small (44) and other factors could have influenced why these pupils had a low connection to nature. Linked to rurality, another factor that could influence how much pupils benefitted from the intervention is the biodiversity present on their school grounds. In Chapter 5, we discuss how the diversity of species caught varied greatly between schools. We know that pupils commonly named / drew species captured on cameras and, therefore, for schools with low biodiversity, pupils had more limited opportunities to learn about different species, although they did still learn about a range of species from the workshop and by classifying other projects on MammalWeb. Another line of investigation could be to look at whether certain activities (e.g., uploading footage or classifying) or intensity of engagement (both of which are looked at in Chapter 5) correlates with larger impacts on pupils.

Although, in this study, we considered connection to nature and knowledge of UK mammals separately, further analysis could explore any correlations that exist between pupils with low connection to nature and low knowledge of UK mammals. Previous studies have shown that increasing environmental knowledge is not necessarily a pathway for improving nature connection (Lumbar et al., 2017). However, environmental knowledge can facilitate attitude formation, in turn influencing pro-environmental behaviours (Kollmuss and Agyeman, 2002; Duerden and Witt, 2010). Further investigation could look at whether pupils with a low initial connection to nature also had limited knowledge of UK mammals, and whether those with low initial knowledge also benefitted more from the intervention. Further research looking at the links between connection to nature and knowledge, and assessing whether the intervention has a larger effect on certain groups of schools / pupils, could allow projects to be more specifically targeted to those that would benefit the most.

To conclude, our study showed that even with our relatively short intervention, children's knowledge of UK mammals and connection to nature can be improved, especially if it starts from a low baseline. Using camera traps and participating in a citizen science project offers school pupils the chance to learn about and connect with species they might have little exposure to otherwise. Ultimately, creating these opportunities will allow children to experience the benefits that come from increased connection to nature as well as increasing awareness of local species, which will help with biodiversity conservation in the long-term.

4.6 Supplementary material

Appendix 1

Pupil workshop

Objective: To engage pupils in using camera traps in their school ground to monitor wildlife, to introduce them to different UK mammal species, and make them aware of why monitoring is important.

Resources:

- Camera traps (with memory cards, batteries, a strap, and a lock)
- Mammal cards (laminated photos of UK mammals)
- Access to computer with internet
- Access to outdoor space

Length of session: One hour

5 mins – Introductions

- Introduce yourself, the project, and what you'll be doing today

5 mins – Looking at the camera trap

- Show pupils the camera trap
- Explain how the camera trap works
    - Triggered by motion and heat so when an animal walks past it takes a photo
    - Images stored on an SD card which can then be looked at on a computer

20 mins – Setting up the camera trap

- Before going outside ask pupils to keep an eye out (on their way outside) for any signs of animals. Ask pupils for suggestions of what they might look for (guide to answers such as footprints)
- Once outside, ask pupils what signs of animals they saw
- Go to where their school's camera trap is currently set up (or, if not set up yet to a place you think would be suitable to set it up)
- Ask pupils to give a thumbs up or thumbs down if they think this is a good or bad place to put a camera to get photos of animals
- Ask for a few suggestions of why they think it's a good / bad place
- Prompt pupils to think about setting the camera up near the footprints / other signs they might have seen

10 mins – UK mammals

- Give each pupil one mammal card
- Ask if anyone isn't sure what species of mammal their card is (answer by asking others for ideas)

- Ask pupils who think their animal is nocturnal to stand up (repeat for diurnal, explaining each term). Go through correct answers
- Ask pupils to stand up if they think the mammal on their card is not from the UK. Go through answers, picking out case studies (e.g., racoon that was caught on a camera trap in Sunderland)
- Explain how monitoring mammal populations is very important. For example, in tracking population growth and movement of non-native species.

10 mins – MammalWeb platform

- Introduce the MammalWeb website
- Go to the spotter page and classify a selection of images from a range of projects (including their schools page if they have uploaded)

5 mins – Mammal articulate

- Using everything they've learnt about different mammal species today, ask for volunteers to play mammal articulate
- Use the mammal cards and ask pupils to describe the mammal on their card (give examples of things they can use to describe e.g., nocturnal / diurnal, native / non-native)

5 mins – Summary and wrap up

- Summarise everything we've done and learnt about today

Appendix 2

Teacher training workshop

Objective: To increase teacher confidence and skills in using camera traps, teaching about UK mammals, and using the MammalWeb platform.

Resources:

- Camera traps (with memory cards, batteries, a strap, and a lock)
- Mammal cards (laminated photos of UK mammals)
- Access to computer with internet
- Access to outdoor space

Length of session: One hour

5 mins – Introductions

- Introduce yourself, the project, and what you'll be doing today

5 mins – Looking at the camera trap

- Pass the camera trap around
- Explain how the camera trap works
    - Triggered by motion and heat
    - Images stored on an SD card
    - Look at setting on the camera – set to take three images at a time and minimum interval between images.

20 mins – Setting camera traps up outside

- Pair up teachers, give each a camera trap
- Ask them to have a wander around and set up their camera trap in what they think is a good position
- Have a look at each of the camera trap set ups and for each one ask teachers to name one good thing and one bad thing about the placement (for tips on placement see MammalWeb's guide here: Camera-trap-placement-guide.pdf (mammalweb.org))
- Talk also about looking for signs and tracks of animals when placing the camera
- Take down camera traps and return inside

10 mins – UK mammals

- Give each teacher one mammal card
- Ask if anyone isn't sure what species of mammal their card is (answer by asking others for ideas)
- Ask teachers who think their animal is nocturnal to stand up (repeat for diurnal and crepuscular, explaining each term)
- Go through correct answers. Talk about how this exercise could be repeated with their class. Ask how the MammalWeb platform could be used to support this – e.g., looking at times of day / night when animals were captured

- Ask teachers to stand up if they think the mammal on their card is not from the UK. Go through answers picking out case studies (e.g., racoon that was caught on a camera trap in Sunderland)
- Explain how monitoring mammal populations is very important. For example, in tracking population growth and movement of non-native species.

10 mins – MammalWeb platform

- Introduce the MammalWeb website
- Show each teacher their school's project page
- Go to the trapper page and run through how they upload images from their camera trap
- Go to the spotter page and classify a selection of images from a range of projects

5 mins – Mammal articulate / charades

- Using everything they've learnt about different mammal species today, ask for volunteers to play mammal articulate
- Use the mammal cards and ask teachers to describe the mammal on their card (give examples of things they can use to describe e.g., nocturnal / diurnal, native / non-native)
- After a few rounds of articulate, do a round of charades where teachers act out the mammal species instead

5 mins – Summary and wrap up

- Summarise everything we've done today and how it can be used going forward (i.e., using the camera trap / activities / MammalWeb platform in the classroom)

Appendix 3

Durham University

MammalWeb

MammalWeb impact questionnaire
(Pupil)

We would be really grateful if you could complete this short questionnaire, which will take you around 10 minutes. If you cannot answer a question then either leave it blank, or ask a teacher. When you have completed the questionnaire, hand it back to your teacher.

Thank you!

Please tell us how old you are: ……………………………….

Please tell us if you are a boy or a girl: ……………………………..

Please name all the mammals you know that live in the UK.

Out of the mammals you have listed above, please underline all the ones you think are introduced (have come from another country).

Please tick all the things that come in to your mind when you hear the word 'science'.

- ☐ Rockets
- ☐ School
- ☐ Discovery
- ☐ Doctors
- ☐ Experiment
- ☐ Nature
- ☐ Tests
- ☐ Space
- ☐ Animals
- ☐ Explosions

Do you know any scientists? If so, please tell us who they are by ticking the box or boxes below.

- ☐ Mum or Dad
- ☐ Brother or Sister
- ☐ Aunt or Uncle
- ☐ Another family member
- ☐ A friend
- ☐ Someone else

When you are NOT in school, how much do you talk about science with other people?

- ☐ Never
- ☐ A little bit
- ☐ A lot

Please tick all the things you like to do when not in school.

- ☐ Read books
- ☐ Watch TV
- ☐ Play in the garden
- ☐ Go to museums
- ☐ Play video games
- ☐ Go on a nature walk
- ☐ Visit a zoo
- ☐ Crafts
- ☐ Do experiments or use science kits

Please tell us how much you agree or disagree with each of the following statements, by putting a tick in the relevant box.

Statements	**Strongly Agree**	**Agree**	**Neither agree or disagree**	**Disagree**	**Strongly Disagree**
I like to hear different sounds in nature					
I like to see wild flowers in nature					
When I feel sad, I like to go outside and enjoy nature					
Being in the natural environment makes me feel peaceful					
I like to garden					
Collecting rocks and shells is fun					
I feel sad when wild animals are hurt					
I like to see wild animals living in a clean environment					
I enjoy touching animals and plants					
Taking care of animals is important to me					
Humans are part of the natural world					
People cannot live without plants and animals					
Being outdoors makes me happy					
My actions will make the natural world different					
Picking up litter on the ground can help the environment					
People do not have the right to change the natural environment					

(Cheng and Monroe, 2010)

That is the end of the questionnaire.

Thank you!

Table S1. Categories used for analysing nature drawings and naming mammals activity on questionnaires.

Wild terrestrial UK Mammals [1]			
Native [a] (Younger and older years)	Non-native / non-native naturalised / vagrant / without established populations [b] (Older years)	Mix native / non-native [c] (Younger and older years)	Mix wild / pet [2] (Younger and older years)
badger bat beaver boar field mouse fox greater horseshoe bat hedgehog lesser horseshoe bat long eared bat mole mountain hare otter pine marten pipistrelle bat polecat red deer red squirrel	american mink black rat brown hare brown rat chinese water deer fallow deer grey squirrel house mouse mink raccoon reindeer wallaby	deer dormouse hare leveret mouse squirrel stag	bunny rabbit rat rodent

roe deer Scottish wildcat shrew stoat vole water vole weasel wild boar wildcat wood mouse			

Domestic / farm mammals [3] (Younger and older years)	Non-mammals [4] (Younger and older years)	Marine mammals [5] (Older years)	Exotic mammals (not found in the wild in the UK) [6] (Younger and older years)	Extinct / doesn't exist [7] (Older years)	Human [8] (Younger and older years)	Mammal [9] (Younger and older years)
alpaca	alligator	bottlenose dolphin	anteater	dinosaur	explorer	mammal
baby goat	ant	dolphin	antelope	haggis	family	
bull	barracuda	elephant seal	ape	mammoth	human	
cat	bee	humpback whale	arctic fox	unicorn	man	
chinchilla	beehive	killer whale	baboon		surfer	
cow	beetle	narwhal	bear		teacher	
degu	bird	porpoise	big cat			
dog	bird egg	sea otter	black bear			
domestic cat	birds about 50	seal	black panther			
domestic dog	blackbird	sperm whale	bobcat			
donkey	butterfly	walrus	brown bear			
farm animal	caterpillar	whale	buffalo			
ferret	centipede		camel			
foal	chick		cheetah			
gerbil	chicken		chimp			
ginger tabby	crab		chimpanzee			
goat	crocodile		chipmunk			
guinea pig	crow		duck billed platypus			
guinea pig	duck		elephant			
hamster	duckling		elk			
highland cow	egg					

hog	falcon		giraffe			
horse	fish		gopher			
kitten	flamingo		gorilla			
lamb	fly		grizzly-bear			
llama	frog		hippo			
mule	frog spawn		hyena			
pig	goldfish		jaguar			
pony	grasshopper		kangaroo			
puppy	hawk		koala			
sheep	honeybee		lemur			
sheepdog	hummingbird		leopard			
shetland pony	insect		liger			
skinny pig	kingfisher		lion			
stray cat	ladybird		lioness			
stray dog	lizard		lynx			
	lobster		meerkat			
	magpie		monkey			
	moth		moose			
	mushroom		mountain goat			
	octopus		ocelot			
	osprey		opossum			
	owl		orangutan			
	parakeet		ox			
	parrot		panda			
	pelican		panther			
	penguin		platypus			
	pigeon		polar bear			
	poison dart frog		porcupine			

	reptile robin rooster scorpion seagull shark slug snail snake spider starfish stingray swan tarantula tortoise turtle wasp woodlouse woodpecker worm pheasant blue tit peacock tadpole bug goose geese seahorse		puma red panda rhino skunk sloth snow leopard spiny ant eaters squirrel monkey sun bear tiger water hog wilddog wolf zebra zoo animal			

	jellyfish mealworm grass snake komodo dragon eagle eel woodpigeon ostrich raven red robin jackdaw hen ladybug budgie heron viper flower toad squid sword fish cockerel gecko turkey grouse black widow spider					

Animal [10] (Younger and older years)	Habitat / place [11] (Younger years)	Manmade [12] (Younger years)	Plant / part of plant [13] (Younger years)	Water [14] (Younger years)	Weather / atmosphere [15] (Younger years)	Other [16] (Younger years)
animal	beach	aeroplane	acorn	lake	air	fire
	bedrock	balloon	apple tree	ocean	cloud	heart
	cave	bench	ash tree	pond	lightning	hunting
	cliff	bird feeder	beanstalk	puddle	rain	moon
	field	bird house	berry	river	rainbow	poo
	forest	boat	blossom	sea	sky	star
	hill	bridge	blueberries	water	summer	
	island	car	branch		sun	
	jungle	chair	bush		sunshine	
	meadow	football	cactus		weather	
	molehill	hospital	coconut tree		wind	
	mountain	house	crops			
	mud	statue	daffodil			
	nest	table	daisy			
	rainforest	tree house	dandelion			
	rock	van	evergreen tree			
	sandpit	wall	flower			
	soil	watering can	grass			
	spiderweb		leaf			
	stone		log			
	volcano		mango			
	waterfall		oak tree			
	world		petals			

			plant root rose seed stick sunflower tree twig wood			

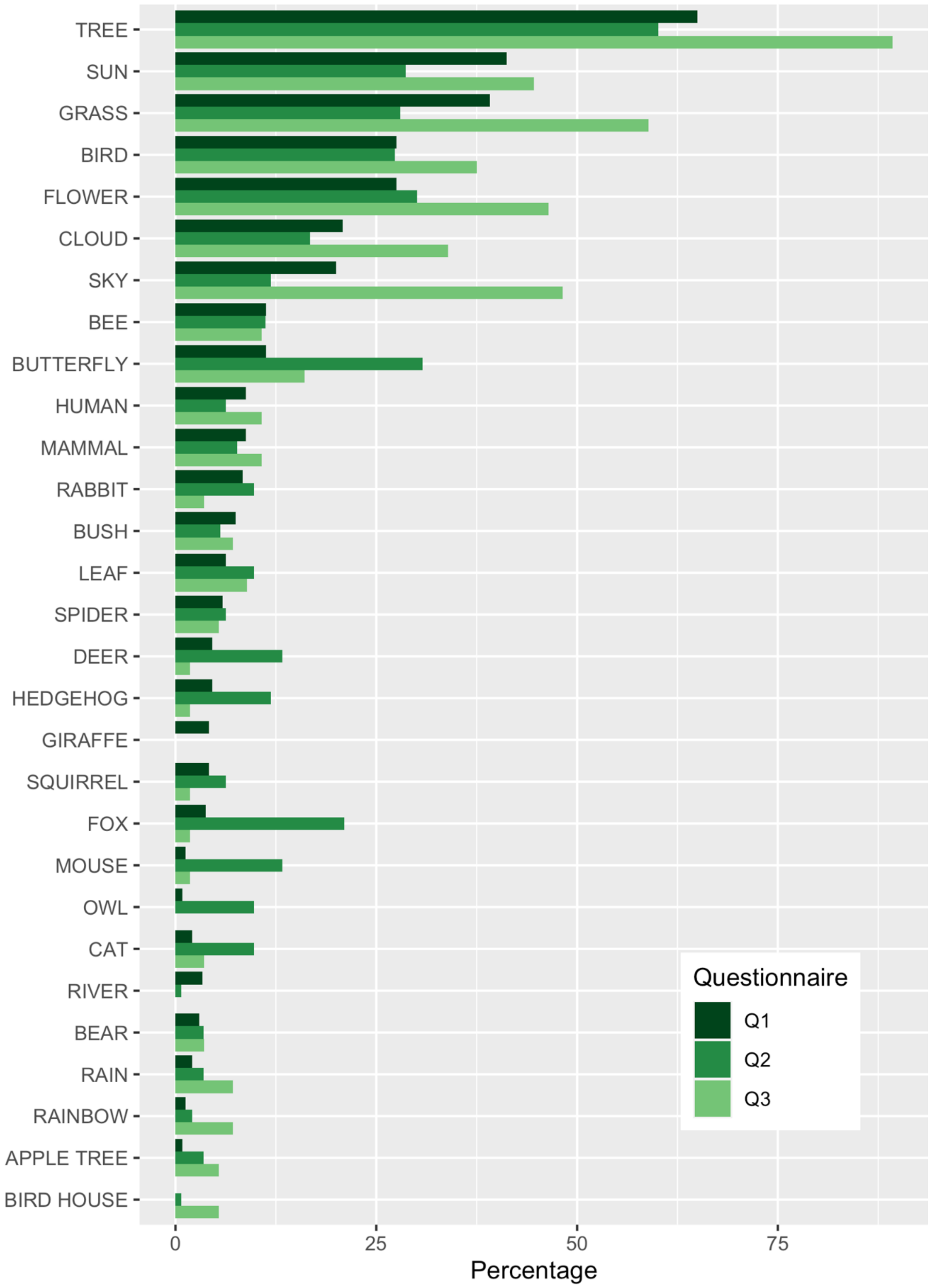


Figure S1. Drawings from when pupils were asked to draw what they think nature is and the percentage of pupils who drew them. Showing drawings that appeared in the top 20 things drawn in any of the questionnaires.

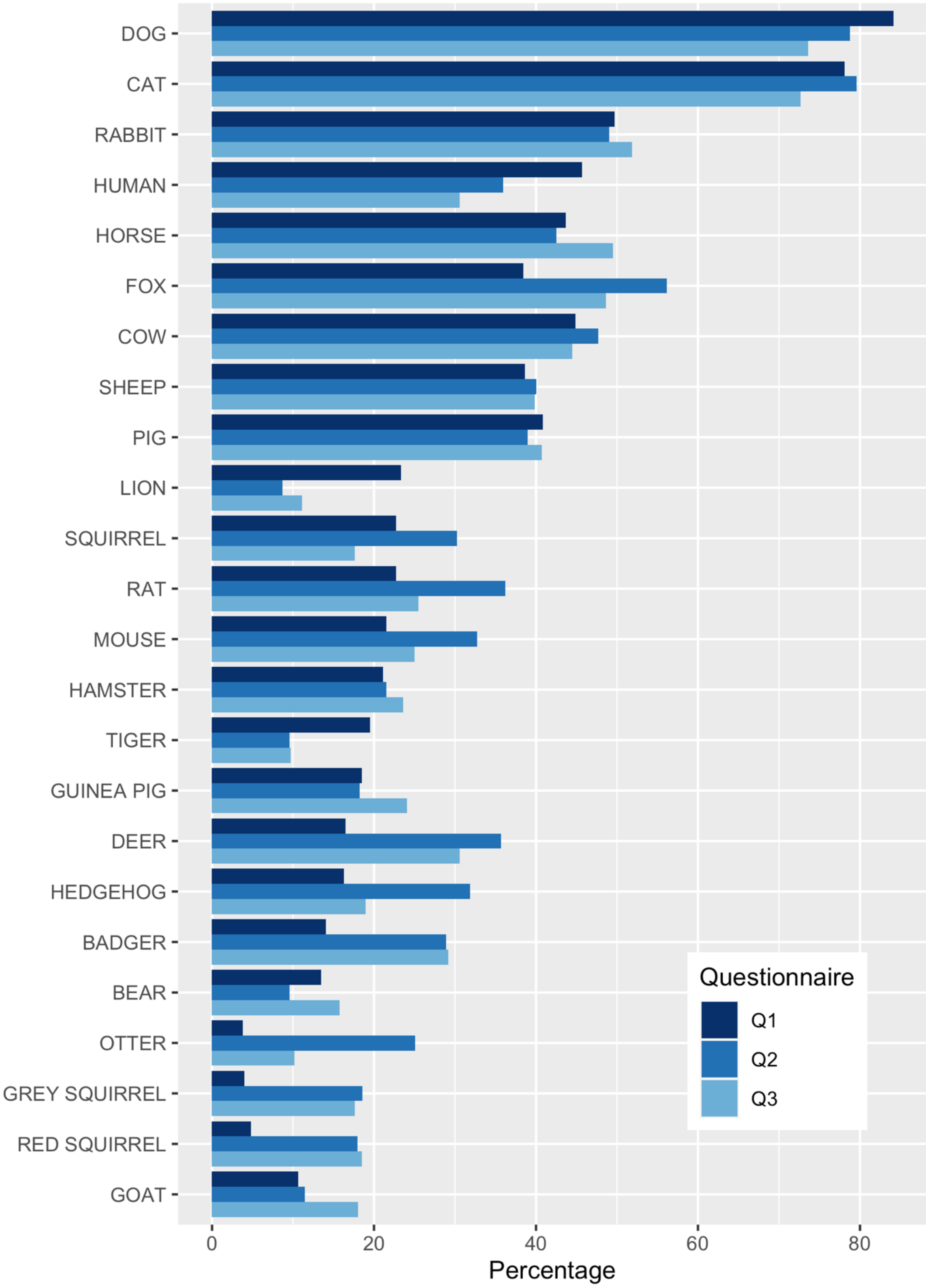
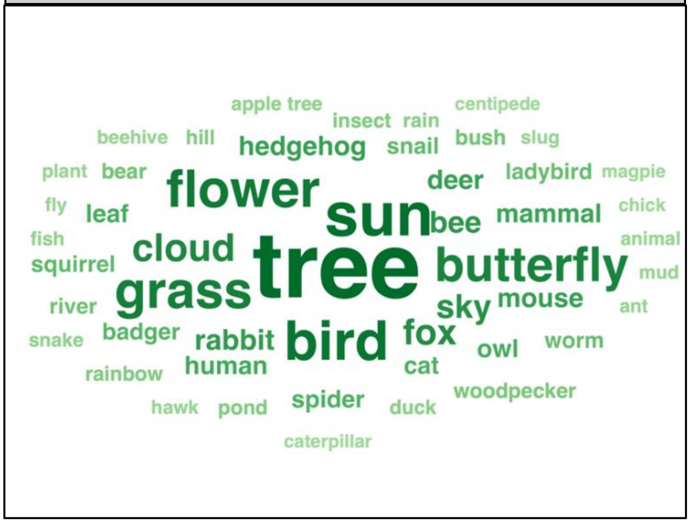


Figure S2. Species named when pupils were asked to name all the mammals they know that live in the UK and the percentage of pupils who named them. Showing species that appeared in the top 20 things drawn in any of the questionnaires.

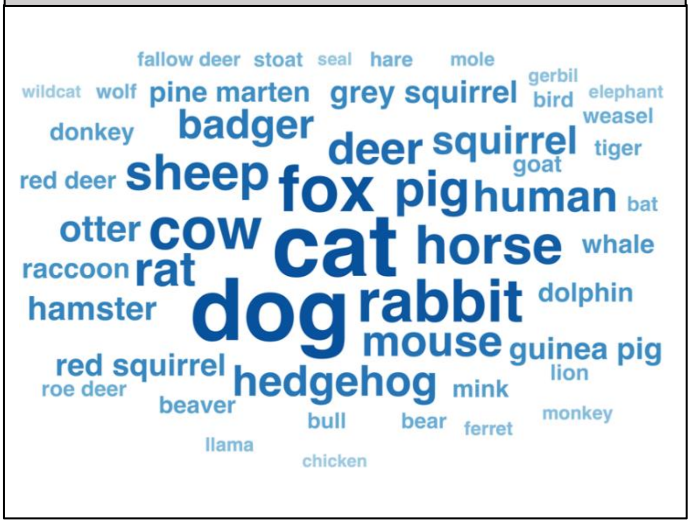
"Please draw what you think nature is"

Immediately post-intervention (Q2)
143 participants | Aged 4 - 7



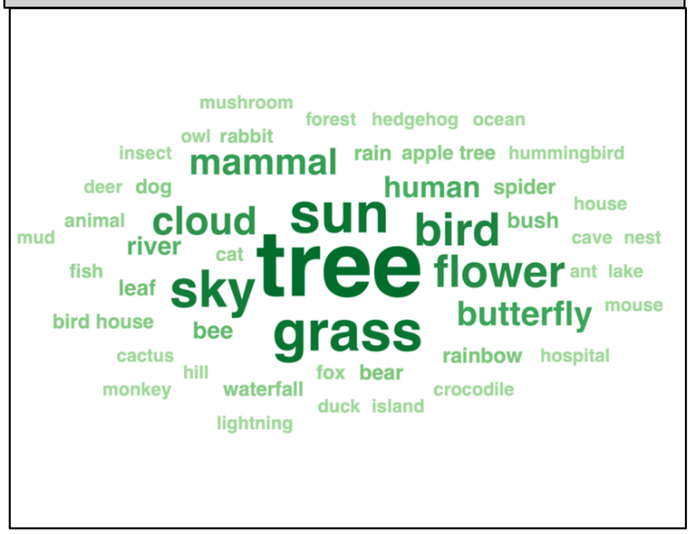
"Please name all the mammals you know that live in the UK"

Immediately post-intervention (Q2)
367 participants | Aged 7 - 11



"Please draw what you think nature is"

Three months post-intervention (Q3)
44 participants | Aged 4 - 7



"Please name all the mammals you know that live in the UK"

Three months post-intervention (Q3)
216 participants | Aged 7 - 11

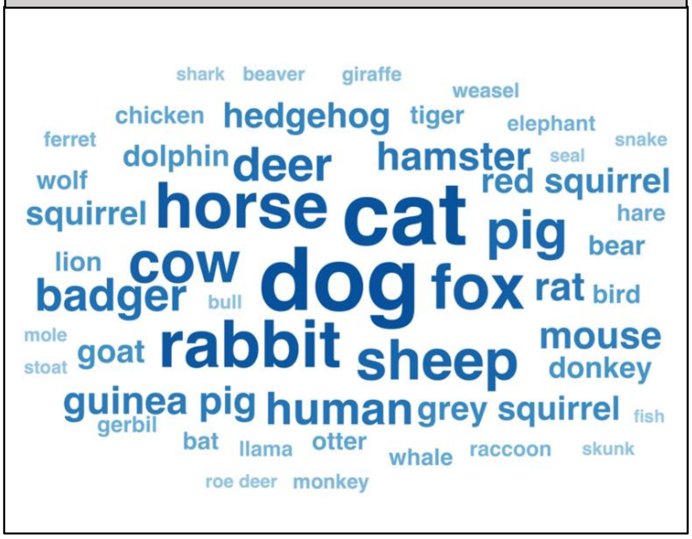


Figure S3. Word clouds of answers / drawings from two activities done with participating pupils immediately post-intervention (top) and three months post intervention (bottom). Left (green) shows top 50 things participating pupils aged 4-7 drew when asked to draw what they think nature is. Bottom (blue) shows the top 50 animals named when participating pupils 7-11 were asked to name all the mammals they know that live in the UK. Word size and colour is scaled to the number of individuals who drew / wrote it with the largest / darkest words being the most frequently written / drawn.

Table S2. Model outputs from GLMMs to test for influence of questionnaire and intervention on number of mammals drawn, number of animals (in various groupings) named, and connection to nature scores. Top candidate models and all models within 6 AIC are shown.

		(Intercept)	Questionnaire	Intervention Group	Questionnaire : Intervention Group	df	AICc	delta	Marginal R2	Conditional R2
Wild UK mammals drawn	All data (n = 343)	-1.056	+	+	+	8	791.3	0	0.112	0.410
Wild UK mammals drawn	Restricted (n = 54)	-1.888	+	+	+	7	133.2	0	0.762	0.793
		-2.206	+			4	136.3	3.13		
		-2.516				2	136.6	3.47		
		-2.206	+	+		5	138.4	5.25		
		-2.517		+		3	138.7	5.55		
Non-mammals drawn	All data (n = 343)	-0.345	+			5	1472.3	0		
		-0.245	+	+		6	1474.1	1.89		
		-0.143	+	+	+	8	1477.7	5.44		
Non-mammals drawn	Restricted (n = 54)	-0.320				3	370.9	0		

		-0.534	+			5	371.4	0.53		
		-0.291		+		4	372.9	1.99		
		-0.506	+	+		6	373.4	2.58		
		-0.469	+	+	+	8	376.8	5.96		
Exotic drawn	All data (n = 343)	-2.825	+			5	391.6	0		
		-2.852	+	+		6	393.6	2.04		
		-3.398	+	+	+	8	394.8	3.23		
Exotic drawn	Restricted (n = 54)	-3.561				3	93.4	0		
		-3.793		+		4	95.3	1.88		
		-3.081	+			5	95.4	1.93		
		-3.314	+	+		6	97.3	3.87		
		-3.506	+	+	+	8	99.0	5.60		
Wild UK mammals named	All data (n = 674)	0.04867	+	+	+	8	4954.8	0	0.127	0.674
Wild UK mammals named	Restricted (n = 176)	0.3217	+	+	+	8	2154.7	0	0.072	0.713
Domestic mammals named	All data (n = 674)	1.296	NA	NA	NA	3	5684.7	0		
		1.256	+	NA	NA	5	5685.0	0.34		
		1.319	NA	+	NA	4	5686.6	1.96		
		1.273	+	+	NA	6	5687.0	2.33		
		1.345	+	+	+	8	5687.9	3.29		

Domestic mammals named	Restricted (n = 176)	1.361	NA	NA	NA	3	2399.7	0		
		1.431	NA	+	NA	4	2401.4	1.76		
		1.484	+	+	+	8	2401.5	1.88		
		1.331	+	NA	NA	5	2402.5	2.85		
		1.401	+	+	NA	6	2404.3	4.62		
Non-mammals named	All data (n = 674)	-0.8065	+	+	+	8	2517.7	0	0.014	0.442
Non-mammals named	Restricted (n = 176)	-1.430	NA	NA	NA	3	877.4	0		
		-1.496	NA	+	NA	4	879.3	1.90		
		-1.434	+	NA	NA	5	881.1	3.72		
		-1.204	+	+	+	8	881.7	4.26		
		-1.500	+	+	NA	6	883.0	5.64		
Marine mammals named	All data (n = 674)	-2.610	+	+	+	8	1525.0	0	0.014	0.289
		-2.081	+	NA	NA	5	1525.8	0.78		
		-2.263	+	+	NA	6	1527.3	2.33		
		-2.120	NA	NA	NA	3	1528.4	3.43		
		-2.314	NA	+	NA	4	1529.9	4.89		
Marine mammals named	Restricted (n = 176)	-2.373	NA	+	NA	4	688.3	0		
		-1.953	NA	NA	NA	3	688.9	0.55		

		-2.542	+	+	+	8	690.2	1.85		
		-2.257	+	+	NA	6	690.8	2.44		
		-1.837	+	NA	NA	5	691.3	2.97		
Exotic mammals named	All data (n = 674)	-0.14080	+	+	+	8	3475.6	0	0.032	0.518
Exotic mammals named	Restricted (n = 176)	-0.21570	+	+	+	8	1495.6	0	0.027	0.468
		-0.10660	+	NA	NA	5	1497.4	1.80		
		-0.05347	+	+	NA	6	1499.3	3.71		
Total animals named	All data (n = 674)	2.104	+	+	+	8	7252.7	0	0.030	0.670
Total animals named	Restricted (n = 176)	2.190	+	+	+	8	3054.5	0	0.018	0.743
Correctly identified as from / not from the UK	All data (n = 674)	0.2402	+	+	+	8	4747.1	0	0.043	0.546
Correctly identified as from / not from the UK	Restricted (n = 176)	0.3519	+	+	+	8	2037.1	0	0.043	0.544

UK mammals named to species level	All data (n = 674)	-0.53390	+	+	+	8	4045.3	0	0.145	0.603
UK mammals named to species level	Restricted (n = 176)	-0.30090	+	+	+	8	1785.9	0	0.097	0.643
Connection to Nature Scores	All data (n = 674)	4.172	+	NA	NA	6	1397.1	0		
		4.224	+	+	+	9	1397.2	0.09		
		4.208	+	+	NA	7	1410.8	1.56		
Connection to Nature Scores	Restricted (n = 182)	4.278	+	NA	NA	6	451.6	0		
		4.245	+	+	NA	7	453.1	1.50		
		4.253	+	+	+	9	453.5	1.94		
		4.300	NA	NA	NA	4	456.8	5.26		
Low initial connection to nature scores	Restricted to pupils who answered all three questionnaires and had a low initial score (n = 44)	3.664	+	+	+	9	111.7	0	0.163	0.547
		3.682	+	NA	NA	6	112.7	1.02		
		3.579	+	+	NA	7	113.0	1.33		

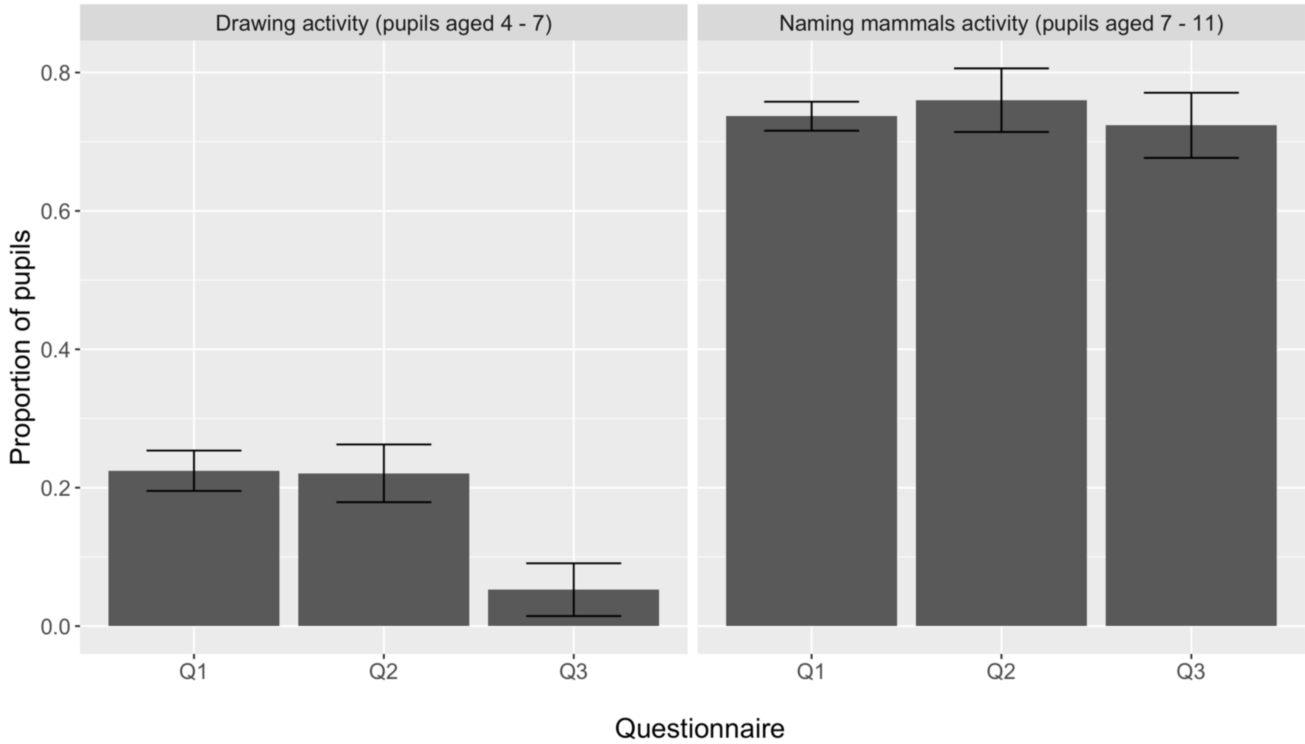


Figure S4. Proportion of pupils from control schools only who drew / named species captured on either any participating school's camera trap or on their own camera trap. Left graph is for pupils aged 4 – 7 who were asked to draw what they think nature is. Right graph is for pupils aged 7 – 11 who were asked to name all the mammals they know that live in the UK. Error bars show ± standard error.

Chapter 5: Teacher engagement with citizen science: Experiences from an ecological camera trapping project and recommendations for future projects

Hedgehog (*Erinaceus europaeus*) | Willington Primary School, County Durham

5.1 Abstract

Engaging schools in ecological citizen science projects can have positive impacts on pupils and could help expand spatial coverage for species monitoring. For projects to have the greatest impact, it would be beneficial to ensure teachers feel more confident and willing to continue engaging with the project long-term. However, robust evaluation of teacher perspectives on ecological citizen science projects is currently rare. Furthermore, it would be beneficial to know what types of intervention are most impactful, for example engaging with pupils directly or training teachers to carry out activities independently with their class. In this study, we evaluate how teachers engaged with a camera trapping citizen science project, MammalWeb. We focussed on: whether there were differences in engagement between schools who participated in a workshop for pupils or for teachers; the data that schools contributed to MammalWeb and how this compared to general MammalWeb users; and the quantitative and qualitative feedback received from teachers. We found no significant differences in the type (uploading data or classifying images) or level of engagement between the two intervention groups (pupil workshop and teacher workshop); however, schools that took part in teacher workshop engaged more with MammalWeb, independently, following the intervention period. Schools also designed their own classroom activities around the topic, including writing poems and making presentations on species captured. Schools collected data on a wide range of mammal and bird species and surveyed habitats such as grassland and park which are infrequently surveyed by general MammalWeb users. Feedback from teachers was, in general, very positive about the project, although several noted challenges to engaging with the project long-term, including: timing within the school year; a lack of species captured on their camera; and difficulty using the camera trap or platform. Reflecting on teacher feedback, as well as our own experiences of running the project, we make five specific suggestions for future projects with similar objectives.

5.2 Introduction

Nature-based citizen science projects can have positive impacts on participants including increased wildlife knowledge (Brossard et al., 2005; Forrester et al., 2017; Jordan et al., 2011) and positive changes in behaviours and attitudes towards the environment (Haywood et al., 2016; Lewandowski and Oberhauser, 2017). For children, specifically, participation in citizen science projects can offer the chance to become more connected to nature and gain ecological knowledge (see Chapter 4) which could help to reverse the "extinction of experience" and "nature deficit disorder" suggested to be negatively impacting children today (Louv, 2005; Pyle, 1978).

In addition to the potential benefits for the participants themselves, schools could make a substantial contribution to species monitoring efforts through participation in ecological citizen science projects. There are over 30,000 schools and over 600,000 teachers employed in the UK alone (ONS, 2021a); establishing biodiversity monitoring projects in even a fraction of these could vastly improve monitoring of many species. However, when children have been involved in ecological surveys, issues with data quality have been raised (Miczajka et al., 2015; Saunders et al., 2018; White et al., 2018). Any ecological citizen science projects in schools would need to ensure data quality is maintained, perhaps by a verification system. In the project presented here, biodiversity of school grounds is monitored using camera traps. Collecting footage of species surveyed, which can then be classified not only by the schools themselves but also verified by others, may help alleviate some of the potential problems around data quality.

To date, studies where children in schools have participated in citizen science projects have often been small scale (< 10 schools), short interventions, requiring a lot of time and input from scientists (Blumstein and Saylan, 2007; Marchant et al., 2019; Prendergast et al., 2022; Saunders et al., 2018). Schuttler et al. (2018) presented a study where 28 schools from across the world deployed camera traps in and around their schools to monitor wildlife, submitting their footage to the citizen science project eMammal. Promisingly, Schuttler et al. (2018) concluded that the schools contributed valid scientific data, important for conservation and research. However, the main limitation cited from the eMammal school project was that it was limited by the time scientists had available to support schools with deploying camera traps and analysing footage. With limited time available, it would be useful to know which approaches are most impactful. For example, engaging with pupils directly through workshops delivered by professionals can have many positive impacts including increasing knowledge of, or interest in a topic (Drissner et al., 2013; Laurson et al., 2007). Equally, training teachers to carry out activities themselves may help to achieve more large-scale and long-term engagement by increasing teacher confidence and enthusiasm to participate. By analysing different approaches, citizen science projects can design school-based interventions that will maximise engagement with the project, leading to benefits for all participants involved and increasing the quantity of data collected.

In any citizen science project, retaining participants long term is challenging (Sauermann and Franzoni, 2015; Seymour and Haklay, 2017). Retaining teacher participation is likely to come with its own challenges. Ecological citizen science projects often require participants to spend time outdoors, either surveying or setting up equipment. In previous studies, teachers have reported a number of barriers to spending time teaching outdoors, including a lack of confidence (Nundy et al., 2009; van Dijk-Wesselius et al., 2020; Waite, 2020), inflexible teaching schedules (van Dijk-Wesselius et al., 2020), and fear for children's safety (Skamp and Bergmann, 2001). Furthermore, there may be additional challenges to participating in citizen science projects, such as ensuring projects meet national curriculum aims or difficulty using specialist equipment. To date, most studies that have gathered feedback from teachers participating in citizen science projects have been small-scale, with feedback, in turn, gained from relatively few (< 10) teachers (Schuttler et al., 2018a; Soanes et al., 2020; White et al., 2018). Feedback from teachers is essential for understanding the barriers teachers face in participating in ecological citizen science in schools and for evaluating the approaches that work best for them. More detailed feedback from teachers will help future projects to work with schools more effectively.

In this study we aim to: (a) assess how teachers engaged with an ecological citizen science project in schools and whether there was a difference if they participated in pupil workshops or teacher workshops; (b) compare data submitted by teachers with data submitted by general citizen science participants; and (c) summarise quantitative and qualitative feedback from teachers on engaging with citizen science in schools. Using all of this we will provide recommendations for future projects wishing to use similar approaches in schools.

5.3 Methods

5.3.1 Participating schools and intervention

Participating primary schools in North-East England were recruited and assigned to an intervention group (pupil workshop or teacher workshop) as described in Chapter 4. In this Chapter, we present data from more schools than in Chapter 4 as there were schools that took part in the project overall but did not answer the pupil questionnaires. All interventions in schools took place between January and May 2019. Schools were lent a camera trap to use for one-month and during that month received either a workshop for pupils or for teachers. The content of the workshops was similar (see Appendix 1 and 2 in Chapter 4); however, teacher sessions were carried out only with teachers, usually after school during a staff meeting, and pupil workshops were carried out during the school day. Although teachers were usually present in the pupil workshops, they were not actively involved in activities and often did their own work (e.g., marking) in the classroom whilst the workshop was taking place. Wherever possible, schools were randomly assigned to one of the intervention groups. However, there were some cases (10 schools) where due to geography and logistics, schools chose which intervention group they wished to be a part of. This resulted in uneven sample sizes between the two intervention groups (teacher and pupil workshops). Whilst balanced, random samples would have been preferable, we still had a good number and variety of schools in each group, particularly in comparison to other school-based intervention studies (e.g., Marchant et al., 2019; Prendergast et al., 2022; Saunders et al., 2018). Therefore, we do not believe this limitation influenced our results.

Teachers were encouraged to upload and classify images from the project to MammalWeb (www.MammalWeb.org). They were encouraged to do this with their class, but some teachers may have done these activities on their own. Children could also set up their own accounts with their parents at home but we did not monitor these sign ups. Similarly, other teachers within the school could sign up to the project, but we only monitored the accounts of the lead teacher who had taken part in all aspects of the intervention (i.e., they or their class had done the workshop). Further details on the intervention, including outlines of the pupil and teacher workshops can be found in Chapter 4.

5.3.2 Data collection and analysis

We asked each school to confirm when they had registered on MammalWeb via email. Once they had confirmed they had registered on MammalWeb, we confirmed their user account was active and then used an anonymous ID number to track their engagement with the project. We used MammalWeb databases to look at how many users (and therefore schools) had uploaded footage and how many had classified footage. We provide summary statistics for how many image sequences were uploaded and classified and, on average, how many sessions (uploading or classifying) schools conducted on MammalWeb. We defined a session as starting at the point where a user either uploaded footage or classified one sequence and ending if there was an interlude of at least 30 minutes before further uploading or classifying. If a user uploaded footage and then immediately (within 30 minutes) classified footage, we counted this as two sessions as they are two different types of activity that require navigating to a different part of the website (indicating more engagement with the platform).

We looked at differences in engagement between the two intervention groups: pupil and teacher workshop. Firstly, we looked at the proportion of schools in each intervention group who had engaged with MammalWeb by either registering, uploading footage or classifying footage. We then looked at the proportion of schools in each group that had engaged with MammalWeb during the one-month intervention and up to two years (July 2021) after the intervention. As data were not normally distributed, we carried out Mann-Whitney U tests between the two groups for the number of upload / classification sessions overall and the number of sessions before and after the intervention.

All footage and metadata submitted by schools followed the standard image processing method for footage uploaded to MammalWeb (Hsing et al., 2022). This included schools being prompted to select, from a list of options, the habitat within which the camera trap was deployed. All schools had their own project set up on MammalWeb to which they uploaded footage. All schools uploaded images (rather than videos) from their camera traps and images were sequenced through MammalWeb in the standard way, by grouping images taken < 10 seconds apart (Hsing et al., 2022). All images submitted by schools for this project were classified on MammalWeb by both general and school users. We generated consensus classifications for each image sequence, and we then checked these classifications and amended any which were incorrect.

We looked at the differences in sites surveyed and species captured between school users and general MammalWeb users over the same timeframe. To do this, we took the earliest and latest dates from the images submitted by schools: 22nd January and 4th July 2019, respectively. We filtered image sequences on MammalWeb to within these two dates, and then further filtered to only sites which fell within the same geographical region in North-East England (within the boundaries of County Durham, Gateshead, Newcastle, Hartlepool, Sunderland and Middlesborough). We classified 27 image sequences from this period and area that had not already been classified on MammalWeb. All other image sequences (6,178) had one or more classifications from MammalWeb users. We generated consensus classifications and checked all sequences which had classifications of “Don’t know”, “Other” and “Unidentified bird” and amended any which were incorrect. We then used the consensus classifications, as well as our own classifications to produce the final species list for this dataset.

5.3.3 Teacher feedback

Qualitative and quantitative feedback was collected via paper questionnaires given out to all participating teachers, three months after the end of the intervention period. Questionnaires included Likert-scale questions about the MammalWeb platform and a space to give general qualitative feedback about the project (Appendix 1). Qualitative feedback from many teachers focused on multiple issues, so each teacher's feedback was split so that each individual piece of feedback focussed on only one issue. A thematic analysis was then carried out, with all individual pieces of feedback categorised to help summarise and evaluate the key themes. We had no preconceptions about the themes and therefore took an inductive approach to analysis, creating themes from the data available. An iterative approach was used by returning to the beginning of the sample every time a new theme was identified to ensure the feedback was not miscategorised. This type of thematic analysis has been shown to be beneficial for analysing qualitative feedback and has been used in a number of similar studies (Maguire and Delahunt, 2017; Fägerstam, 2012; Benavides-Lahnstein and Ryder, 2019).

5.3.4 Ethics statement

Approval for this study was granted by Durham University's Department of Anthropology Ethics and Data Protection Committee. Consent was obtained in writing from teachers. Personal data on MammalWeb is stored in a separate table and was only used during this study for confirmation of the accounts being created and to link each teacher to the appropriate project on MammalWeb. Analysis on the use of MammalWeb was carried out using anonymous user IDs. Teacher questionnaires were anonymised by assigning a number to each teacher.

5.4 Results

5.4.1 School engagement with MammalWeb

Overall, 34 schools took part in the project. Of these, 21 took part in the pupil workshops and 13 in the teacher workshops. Prior to the project, two schools (in the pupil workshop intervention group) were already registered and participating on MammalWeb, as they had been involved in a separate outreach project. We therefore removed these schools from the first part of our analysis looking at engagement with MammalWeb (leaving 32 schools) but included them in the species captured and teacher feedback analysis section.

Following the project, almost all schools (28/32) had confirmed that they had registered on MammalWeb. Around two thirds of all schools (20/32) uploaded footage to MammalWeb and a smaller proportion (14/32) classified footage. Of the schools that uploaded footage, the average number of sequences uploaded was 180, but this ranged widely from just 4 to 1088 sequences (Table 1). The number of sequences classified by schools also ranged widely from 2 to 347 and, although fewer schools participated in classifying, the average number of classification sessions was higher than upload sessions (3 vs. 2 respectively) (Table 1).

Table 1. Mean number of sequences uploaded and classified by schools and average number of sessions uploading or classifying for schools who participated in respective activities on MammalWeb. Numbers in square brackets show range.

Schools that participated in uploading footage (20)	**Schools that participated in classifying footage (14)**
Average number of sequences uploaded: 180 [4 – 1088]	*Average number of sequences classified:* 71 [2 – 347]
Average number of upload sessions: 2 [1 – 7]	*Average number of classification sessions:* 3 [1 – 11]

Overall, the level of engagement between the two intervention groups was very similar when looking at both the proportion of schools who had registered, uploaded, or classified footage (Figure 1) and the number of sessions on MammalWeb they had completed (Table S1). However, the timings of when schools had engaged with MammalWeb did differ between the two groups. More schools engaged with MammalWeb during the one-month intervention in the pupil workshop group (Figure 1), although the number of sessions they conducted on

MammalWeb was not significantly different between the two groups (Table S1). There was a large difference in the proportion of schools who had engaged with MammalWeb after the intervention period with only 3 / 19 pupil workshop schools engaging with MammalWeb during this time, compared to 9 / 13 of teacher workshop schools (Figure 1). Teacher workshop schools also did significantly more sessions on MammalWeb after the intervention (Table S1). Although we looked at engagement up to two years after the intervention, the longest period of engagement was only three months and no schools continued to engage with the project in the next academic year. We do know, however, that 14 schools from our project signed up to a new project involving MammalWeb in 2021, with 10 schools receiving a place on the new project. Through this project, these schools have participated on MammalWeb in 2021 and 2022.

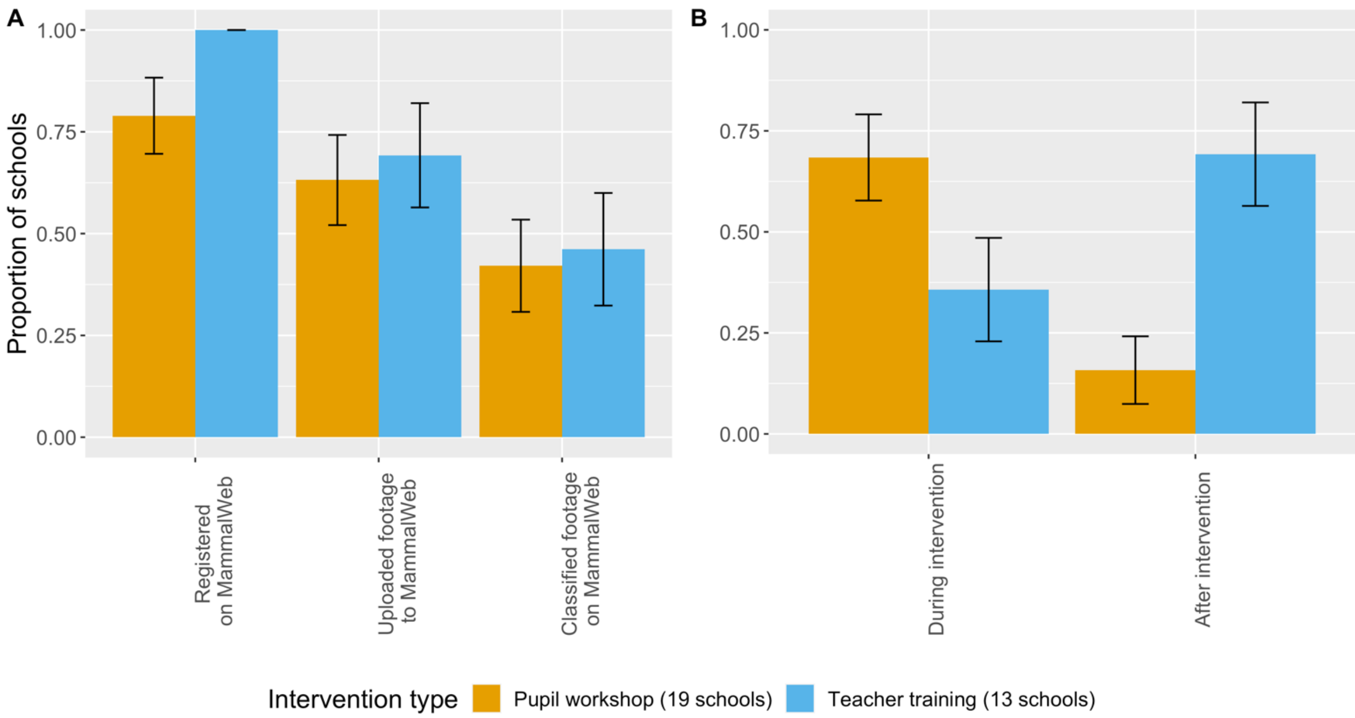


Figure 1. The proportion of schools that engaged in the MammalWeb project. Left (A) shows the proportion of schools for each intervention group (teacher training and pupil workshop) that engaged in MammalWeb by registering, uploading footage, and classifying footage. Right (B) shows the proportion of schools that engaged in MammalWeb (by registering, uploading, or classifying) during the one-month intervention and up to one year after the intervention. Error bars show ± standard error.

Through email conversations and post-project questionnaires we know that teachers also designed their own activities involving MammalWeb. These were usually activities that used the project to cover areas of the curriculum other than science. For example, one school created an English lesson around writing poems about the species they had classified on MammalWeb and displayed the poems in their classroom alongside their camera trap images (Figure 2). Another school instructed pupils to make PowerPoints about species they had learnt about on MammalWeb during a computer class. Teachers also reported using some of the worksheets provided on the MammalWeb school page: https://www.mammalweb.org/en/community/schools.

Figure 2. A display of poems written by pupils on which animals they had captured on their camera traps when participating in the MammalWeb project.

5.4.2 Species captured on camera traps

In total, 3672 camera trap image sequences were uploaded to MammalWeb by schools participating in this project. Of these, 2067 sequences did not contain any animals (Table S2). 70% of these blank images came from two schools (both pupil workshop schools) where poor camera trap placement meant cameras were being triggered by vegetation or the rising / setting sun. The 1605 image sequences that captured animals included 28 different species. Among those were wild mammal species (the focus of monitoring efforts on MammalWeb) such as badgers, hedgehogs, rabbits and roe deer (Figure 3; Table S2).

Figure 3. Photographs captured on camera traps by participating schools. Species captured during the project included badger (*Meles meles*) (A), hedgehog (*Erinaceus europaeus*) (B), rabbit (*Oryctolagus cuniculus*) (C), and roe deer (*Capreolus capreolus*) (D).

For the same time period (January – July 2019) and the same geographical area, 6205 sequences in the MammalWeb database had been uploaded by 12 general MammalWeb users. These sequences were obtained from 24 sites, of which 22 had habitat information attached to them. The most common habitat surveyed by general MammalWeb users during this period was woodland, followed by forest and garden (Figure 4A). In comparison, schools deployed cameras at 21 sites, with habitat information given for 16. These sites were in six different habitats, the most common being grassland and park (Figure 4A). Of the sequences uploaded, the proportion of sequences that contained no animals was 32% for general MammalWeb users and 56% for school users. Although the relative occurrence of many species was similar between school users and MammalWeb users (e.g., blackbird, red fox, pheasant), woodland specialist species such as woodpigeon, roe deer, and grey squirrel were less common in the school dataset, whilst corvids (carrion crow, jackdaw and magpie) were all better represented in the school dataset (Figure 4B).

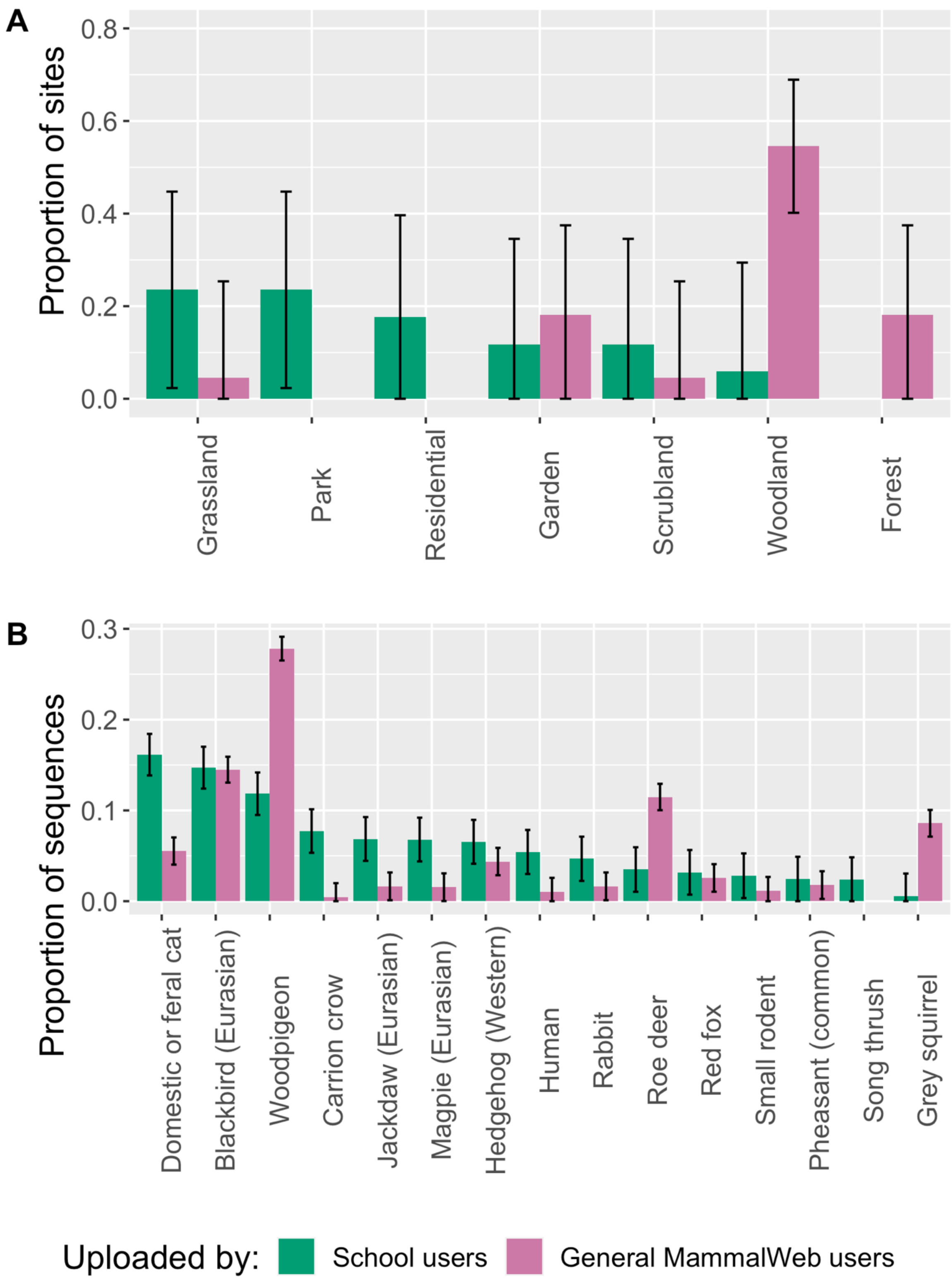


Figure 4. Habitats where camera traps were deployed (A) and most captured species (B) by school users and general MammalWeb users during the same survey period (January – July 2019) and in the same areas. All sites were within the regions of County Durham, Gateshead, Newcastle, Hartlepool, Sunderland and Middlesborough. Graphs show proportion of all sites surveyed in each habitat type (A) and proportion of sequences containing an animal for each of the ten most captured species by schools (B). Error bars show ± standard error.

5.4.3 Teacher feedback

Overall, 39 teachers from 22 schools submitted their post-intervention questionnaires. Responses to questions about MammalWeb were generally positive, with the majority of respondents either strongly agreeing or agreeing with statements about MammalWeb (Figure 5). The percentage of teachers who answered either neutrally or negatively was larger (in comparison to other questions) for statements about learning new things through MammalWeb and about MammalWeb being easy to use (Figure 5).

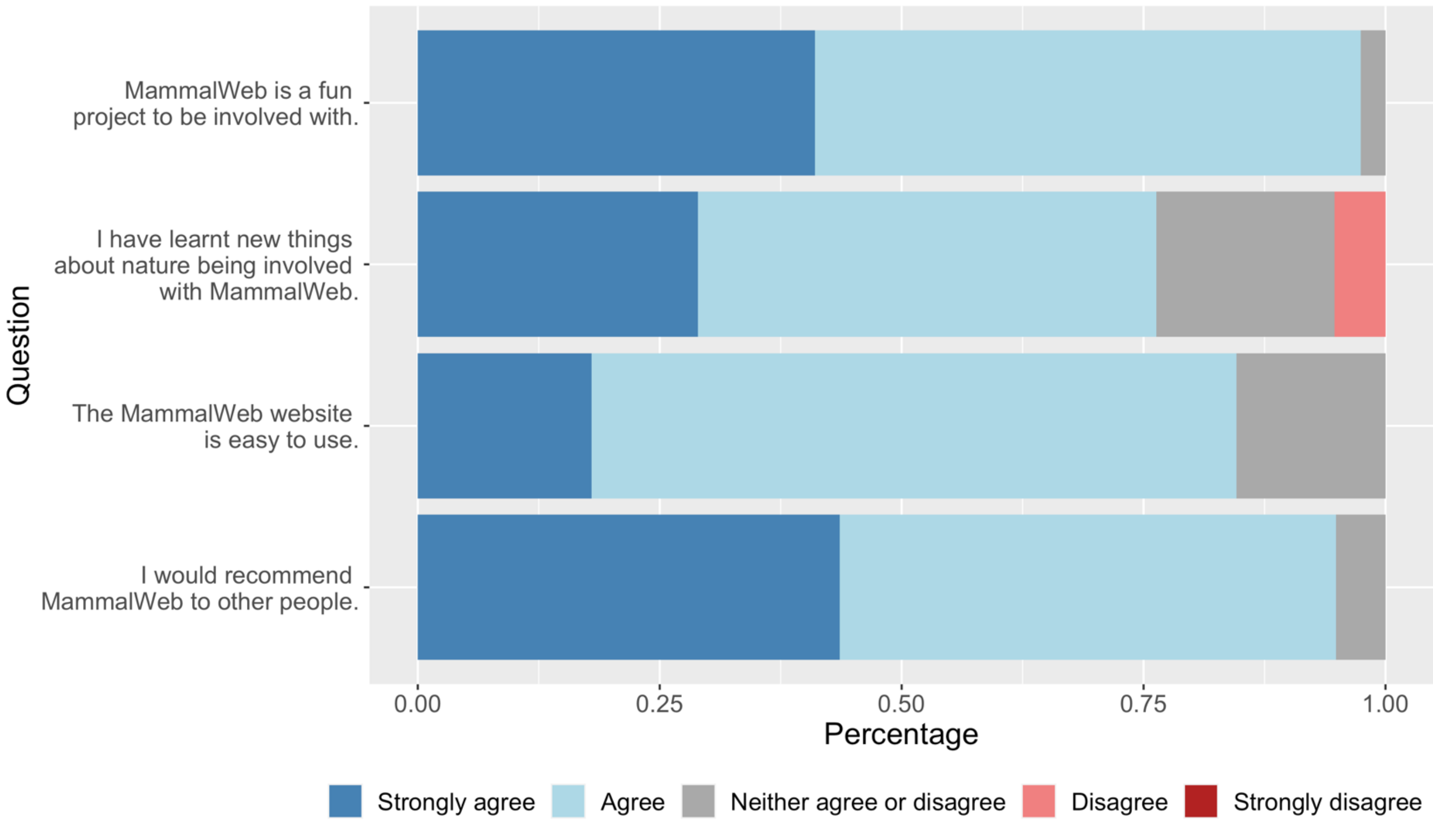


Figure 5. Teacher responses to questions about the MammalWeb project submitted via paper questionnaire after the intervention. Bars show percentage of teachers (out of 39 total) who responded with each answer from strongly agree to strongly disagree.

Qualitative feedback in the open text box of the submitted questionnaires was received from 25 teachers from 17 schools. After splitting the qualitative feedback into themes, 62% (23 of 37 points) was positive. There were six comments that did not focus on any one aspect of the project but were instead a general positive statement about their own or the children's experience (Table 2; Table S3). All other comments submitted were around general themes linking to things such as equipment (camera traps), the MammalWeb platform, timing, the workshops. The most common positive pieces of feedback were about the equipment, with eight teachers commenting that they enjoyed using the camera traps. The most common negative feedback was about the timing of the project – either that, in general, the teacher did not have enough time, or that the timing in the year was not good for their school as it interfered with tests or did not align with topics being taught (Table 2; Table S3). Although the comments were mostly positive about the MammalWeb platform, two teachers made negative comments about the platform. Two teachers commented that not much had been captured on their camera trap, and one teacher stated that they would have liked more resources following the project to carry it on.

Table 2. Qualitative feedback gathered from teachers via questionnaires submitted after the intervention. Grouped into categories of similar themes and presented here with number of teachers (out of 25 total) who provided feedback in each category. Shades (lighter to darker, respectively) indicate positive or negative feedback and rows ordered by number of feedback responses in each category.

Feedback category	Positive or negative	Number of teachers	Example quote
Equipment (positive)	Positive	8	"The children all really enjoyed using the camera trap and looking at the pictures captured by the mammal camera in our school."
General positive	Positive	6	"The children have been very excited and engaged."
Timing	Negative	6	"It would have been better timed earlier in the school year as I feel it got lost amid the changing of classes and I did not have the time to dedicate to it that I would have liked."
MammalWeb platform	Positive	5	"The children can find out more about the local environment as part of a wider scale project, making comparisons to other schools."
Pupil / Teacher Workshops	Positive	4	"The workshop gave the children the opportunity to tap into the knowledge of an expert."
MammalWeb platform	Negative	2	"MammalWeb could be more child friendly."
Species caught on camera	Negative	2	"It would have been better if we'd caught something on our camera!"
More resources	Negative	2	"Follow up material about the different animals/mammals living in the UK would have been useful."

Equipment	Negative	1	“The MammalWeb camera is a bit delicate inside (the battery cover has snapped off as a result of inquisitive parents and children). It's also hard to know if you have the batteries in the right way round.”
Teacher Workshops	Negative	1	“Shame we couldn’t do the staff training as well.”

5.5 Discussion

Our project was one of the largest studies to date to look at how schools engaged with an ecological citizen science project. Schools in North-East England participated in the citizen science project, MammalWeb, by deploying camera traps in their school grounds, uploading footage to the MammalWeb platform, and classifying footage uploaded by themselves and others. We found that almost all teachers engaged with our citizen science project, with some differences in the timing of engagement depending on whether schools received a workshop for pupils or for teachers. Schools captured a range of different species on their camera traps, making valuable contributions to species monitoring datasets on the MammalWeb platform. Teachers were generally very positive although many noted challenges to engaging with the project, particularly long-term. Here, we discuss our findings in respect to: how schools engaged with the MammalWeb platform and differences between our two interventions (pupil and teacher workshops); and the data generated by schools and how this compared to general MammalWeb users. Using teacher feedback, as well as our own findings and experiences from the project, we then make five recommendations for running ecological citizen science projects in schools.

5.5.1 Use of MammalWeb in schools

Although previous projects have engaged either individual or small groups of schools in science research (Blumstein and Saylan, 2007; Hsing et al., 2020; Saunders et al., 2018; Schuttler et al., 2018a), engaging schools in citizen science projects on larger scales remains challenging. For an ecological citizen science project to be run successfully in schools, there is a need to engage and enthuse teachers about the project. It is promising therefore, that our project has shown that teachers did engage with the citizen science project MammalWeb, including uploading and classifying footage and using the project to teach different areas of the curriculum.

Schools in our project took part in one of two different interventions: workshops for pupils or for teachers. Determining which formats of engagement work best might help future citizen science projects in schools to plan their approach more effectively. Short workshops delivered to pupils in schools, either by researchers or professional science communicators are a common format for schools outreach (e.g., https://hands-on-science.co.uk/). Whilst there is evidence that short, one-off experiences such as these can support content learning and increase interest in a topic (Bell et al., 2009; Laursen et al., 2007), it has been suggested that longer, more in-depth approaches are needed for lasting impact (Archer et al., 2021). Equipping teachers with the skills and confidence necessary for them to deliver lessons around the topic (in our case, contributing to an ecological citizen science project) might be expected to be more sustainable, because the teachers can then take what they have learnt and apply it to their future teaching. Indeed, short teacher training workshops that focus on practical and interactive science teaching ideas have been shown to have long-term impact (Lydon and King, 2009).

In our project, we saw very little difference in the number of schools who engaged with the project, and how much they engaged (i.e., how much they uploaded / classified footage) between the two intervention groups. This is perhaps unsurprising, given that the content of the two workshops was very similar. Our results did show, however, that more schools that participated in teacher workshops engaged with MammalWeb independently after the intervention period. This could be because, although teachers were present in the room during pupil workshops, they were not actively engaged with it and often were doing their own work in the background. Therefore, unlike the pupil workshops, the teacher workshops likely equipped teachers with the skills and confidence necessary for participating in MammalWeb independently after the intervention.

Whilst schools returned camera traps to us after the one-month intervention, we know that some schools (at least 3) did purchase their own camera trap after the project which would have enabled them to continue contributing data to MammalWeb. Furthermore, all schools had the opportunity to continue to use the MammalWeb platform by classifying images. However, even schools that did engage with MammalWeb after our one-month intervention did not continue to engage long-term (i.e., into the next academic year). In agreement with other studies (van Dijk-Wesselius et al., 2020; Waite, 2020), timing – including both a lack of time overall and timing of when the project took place – was a frequent comment from teachers about why they had been unable to engage either during or after the intervention. Working with teachers to refine the timing of projects to suitable points in the academic year may help alleviate some of the problem, but an overall lack of time - due to demands placed on teachers - is a much larger, systemic problem.

In feedback from teachers, comments were made on ease-of-use of the platform and the camera trap. Two schools (both in the pupil workshop intervention group) set camera traps in poor locations resulting in large numbers of false triggers. This could suggest, as might be expected, that teachers who attended the teacher workshop were better equipped to use the camera traps and set them in suitable locations. Some teachers also entered incorrect information on the deployment or collection dates of cameras; however, this occurred in schools in both the pupil and teacher workshop intervention groups. This suggests that further support and training for teachers wishing to use the MammalWeb platform would be beneficial.

Future research might also consider the impact of the different intervention types on the pupils themselves. Due to difficulties retrieving pupil questionnaires from teacher workshop schools, we were unable to test this within this project. However, research suggests that scientists' visits to schools have many positive effects on both science learning and pupils' attitudes towards science (Finson, 2002; Fitzakerley et al., 2013). Ultimately, therefore, if projects are able, then a combined approach of offering schools both teacher training to equip them with the skills necessary to participate, as well as researchers running workshops with the pupils themselves, is likely to be the best approach for maximising benefits.

5.5.2 Data submitted by participating schools

Schools collected valuable ecological data during this project that was uploaded to an existing citizen science platform and will contribute towards on-going species monitoring. In the UK, there have been calls for more records of many mammal species, to help with monitoring population trends (Battersby and Greenwood, 2004; Croft et al., 2017; Mason et al., 2022). Networks of camera traps have been suggested as a way to do this (Mason et al., 2022; Steenweg et al., 2017).

As well as having impacts on school pupils' knowledge of and connection to nature (see Chapter 4), a network of camera traps deployed in schools across the UK could make a huge difference to national mammal monitoring. As discussed in Chapter 3, citizen science databases are prone to spatial bias leading to over / under representation of certain habitats. The factors that drive this bias, such as accessibility of the site (Geldmann et al., 2016; Millar et al., 2019; Petersen et al., 2021) and (for camera trapping projects) placing cameras in secure locations, will not be present for schools deploying cameras in their grounds which are already accessible and, typically, reasonably secure (in comparison to public areas). In our study, we found that schools surveyed a range of different habitats and captured a range of different species, including many mammal species. In comparison to general MammalWeb users, schools surveyed more parks, grassland and residential habitats and less woodland and forest habitats. Schools may therefore fill in gaps in habitats surveyed and help to mitigate against the over-representation of woodland and forest habitats in the MammalWeb database.

5.5.3 Recommendations for ecological citizen science monitoring in schools

Our trial in 34 schools in North-East England can be viewed as a pilot, from which it is possible to distil lessons for future programmes with similar objectives. Here, we consider five specific recommendations that emerge from the teacher feedback, as well as our own experiences with running the programme.

Co-creation of projects with teachers – Across outreach and public engagement sectors there have been calls for more projects to be co-created with stakeholders to maximise benefits and reach under-represented audiences (Keith and Griffiths, 2021; Lubicz-Nawrocka, 2019; Villar, 2021). In citizen science, co-creating projects with scientists and stakeholders involved in the process from the outset can increase the likelihood that both the scientific and educational goals of the project are met (Roche et al., 2020). Therefore, for citizen science projects to run successfully in schools, inviting teachers to be involved in all stages of the project planning would likely be highly beneficial. Teachers would then be able to input on key elements of the project such as timing within the school year as well as helping to create curriculum-linked lesson plans and resources to help ensure the project is continued long-term. As highlighted by other academics (Kaminskiene et al., 2020; Lubicz-Nawrocka, 2019), being involved in the creation of the project will also likely give the teachers a sense of ownership and therefore increased confidence in running projects independently in their schools.

Adapting existing citizen science platforms for schools – Whilst the feedback on the MammalWeb platform was generally positive in our study, numerous teachers noted that the platform could have been easier to use and should be made more child-friendly. If a citizen science project is going to be used long-term in schools then it needs to be as engaging as possible for both the teachers and the pupils. Gamification of citizen science projects has been suggested as a way of maintaining engagement (Bowser et al., 2013) and could work particularly well for children (Bowser et al., 2013; Crawford et al., 2017). The MammalWeb platform already has some gamified elements, such as leader boards for number of classifications submitted and species identification quizzes. Expanding these elements and ensuring their suitability for children could help teachers to make better use of the project in the classroom.

Specific methods to engage with species-poor schools – In the UK, school grounds differ greatly in their size and extent of habitats available for wildlife which, as we found in our study, leads to differences in species assemblages captured; as a result, some schools capturing only one or two common species (e.g., woodpigeons and domestic cats). Some teachers commented that it was difficult to engage with the project when their camera traps did not capture many species. For all schools, but particularly those with low biodiversity, offering a range of different ways to participate in the project would be necessary. Digital experiences of nature (through photos and videos) are important for informing children's attitudes towards, and willingness to conserve, species (Soga et al., 2016). On MammalWeb, schools could classify images from either their own project or other projects (including other schools). Whilst we know that some schools classified images from other projects, it might be beneficial to make this a formal part of the project, for example by pairing schools in differing habitats and creating activities for them to compare the wildlife captured between schools. Ultimately, though, the species captured on the school's camera are likely to be the main focus of interest for both pupils and teachers. Therefore, schools could be encouraged to make changes to their school grounds to make them more wildlife friendly. A number of schemes already exist in the UK that encourage schools to make changes to their school grounds for nature (e.g., Learning through Landscapes projects: https://ltl.org.uk/projects/). Furthermore, part of the Department for Education's sustainability and climate change strategy includes the development of a new 'National Education Nature Park' which will encourage all schools in England and Wales to work on improving the biodiversity of their grounds (Department for Education, 2022). Citizen science projects could complement these schemes by offering support and advice to schools in how to improve their school grounds for a specific taxa. For example, MammalWeb could encourage schools to put gaps in their fence to allow species such as red fox and hedgehog to pass through. Schools could then carry out scientific investigations to monitor any changes in species captured before and after their school ground improvements.

Training and support for teachers – As discussed earlier, teacher training would be necessary to equip teachers with the skills and confidence needed to participate in ecological citizen science effectively and independently. Whilst our project involved just one short teacher training workshop, it would likely be beneficial for projects to have more on-going training as well as more resources to support teachers using citizen science in the classroom. Offering training opportunities on leading lessons outdoors to student teachers may be particularly beneficial (Barrable and Lakin, 2020). Citizen science projects could work with universities to run sessions for cohorts of student teachers, so they are equipped to participate in citizen science projects from the point at which they begin to teach in a school.

Structures for long-term engagement – Despite the positive feedback from teachers, none of the schools in our project continued to engage with MammalWeb independently in the following academic year. This suggests that one-month interventions such as ours are insufficient to achieve long-term independent engagement with the project. We do know, however, that in 2021 several schools applied for a new project which involves participating in MammalWeb and have engaged with the project in this capacity. This suggests that, for the schools that signed up at least, there was still an enthusiasm to take part in the MammalWeb project; however, more support and structured involvement clearly has greater appeal than using MammalWeb independently. Furthermore, the new project also gives schools a camera trap to keep, which, given the positive feedback about using camera traps in our study, was likely an appealing aspect of the project. Previous studies have shown that repeated engagements in schools are more successful and impactful than one-off interventions (Archer et al., 2021). Whilst our study did have positive impacts on pupils, with some of these impacts being sustained three-months post intervention (see Chapter 4), for teachers to continue projects independently there is a need for more prolonged engagement. By doing this, teachers can involve future cohorts of pupils, enabling them to gain the same benefits and allowing teachers the opportunity to continue to increase their own skills and confidence to participate in citizen science.

5.6 Supplementary material

Appendix 1

MammalWeb impact questionnaire

(Teacher)

If you could please fill in this questionnaire at the same time as the pupils are filling in their questionnaire. Once you've finished, place this questionnaire, along with all the pupils completed questionnaires, in the envelope provided. We will be in touch to collect the envelope soon.

Thank you!

These questions relate to how you found the MammalWeb project.

Statements	**1 Strongly agree**	**2 Agree**	**3 Neither agree or disagree**	**4 Disagree**	**5 Strongly disagree**
MammalWeb is a fun project to be involved with.					
I've learnt new things about nature being involved with MammalWeb.					
The MammalWeb website is easy to use.					
I would recommend MammalWeb to other people.					

Please use this space to give us any other feedback you have on any aspect of this study.

………

………

………

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………

Thank you!

Table S1. Mann-Whitney U test results from analysing differences between schools that took part in pupil workshops and schools that took part in teacher training sessions. Tests were run on: sequences uploaded and classified; upload and classification sessions; and MammalWeb sessions during and after intervention. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

	W-statistic	p-value
Sequences uploaded	122	0.953
Sequences classified	122	0.966
Upload sessions	132	0.745
Classification sessions	131	0.766
Sessions during intervention	80	0.078
Sessions after intervention	194	0.002**

Table S2. Species captured by schools and number of sequences each species appears in. Ordered by number of sequences species was captured in.

Species captured	Sequences containing species
Nothing	2067
Domestic or feral cat	259
Blackbird (Eurasian)	233
Woodpigeon	190
Carrion crow	124
Jackdaw (Eurasian)	110
Magpie (Eurasian)	109
Hedgehog (Western)	105
Human	87
Rabbit	75
Roe deer	56
Red fox	51
Small rodent	45
Pheasant (common)	39
Song thrush	38
Unidentified bird	19
Grey squirrel	10
Wood mouse	10
Badger	9
Robin (European)	8
Collared dove (Eurasian)	4
Domestic or feral dog	4
Great tit	4
House sparrow	4
Chaffinch	2
Peacock	2
Starling (Common)	2
Blue tit (Eurasian)	1
Brown (European) hare	1
Bullfinch (Eurasian)	1
Greenfinch (European)	1
Gull (unknown species)	1
Other	1

Table S3. All qualitative feedback gathered from teachers via questionnaires submitted after the intervention. Grouped into categories of similar themes. Shades (lighter to darker respectively) indicate positive or negative feedback and rows ordered by number of feedback responses in each category.

Feedback category	Positive or negative	Quote
Equipment (positive)	Positive	"The children all really enjoyed using the camera trap and looking at the pictures captured by the mammal camera in our school."
		"Gives them the opportunity to use specialist equipment."
		"Gave us the opportunity to see the benefits of having a camera trap."
		"Enjoyed seeing nature around our school."
		"You have inspired me (as science co-ordinator) to invest in some camera traps for the school."
		"It was very interesting to see which mammals pass or live on the school grounds."
		"Thank you - the children have loved checking our camera and being involved."
		"All children enjoyed learning about mammals in the UK and the images. Informative and enjoyable."
General positive	Positive	"The children have been very excited and engaged."
		"I hope our school can contribute to work with MammalWeb next year! Thank you."
		"Thank you very much myself and my class really enjoyed it."
		"The children were very excited about the activities with Sammy. They talked about it for days after she left. Great project."
		"Thank you! The kids loved it."
		"We really enjoyed this project, thank you."

Timing	Negative	“It would have been better timed earlier in the school year as I feel it got lost amid the changing of classes and I did not have the time to dedicate to it that I would have liked.”
		“It was hard to get the project off the ground - I wished we'd done the workshops sooner as these have really helped.”
		“If we could plan the mammal web into our existing curriculum, we would find time to use it.”
		“It might be useful to allow time within the session for staff to plan how and when they are going to use MammalWeb within their teaching of science.”
		“Due to time constraints we haven't accessed the MammalWeb website in the way we could have used it.”
		“Other than the workshop delivered in class, the MammalWeb project has not been an ongoing project due to time constraints.”
MammalWeb platform	Positive	“The children can find out more about the local environment as part of a wider scale project, making comparisons to other schools.”
		“MammalWeb was a fantastic opportunity for children to get an insight into the wildlife around them.”
		“Enjoyed comparing what we'd captured to other schools.”
		“Love the way lots of schools are linked to mammalweb.”
		“I enjoyed the activity and also the web pages and the info it gave me about the animals around me. Thank you.”
Teacher Training / Workshops	Positive	“The workshop gave the children the opportunity to tap into the knowledge of an expert.”
		“Great that Sammy in her talk shared her route through academia and good that the children have got to spend some time with a real life scientist.”
		“The workshops have also been great for sharing the camera project with the whole school.”

		“The CPD session was interesting and engaging.”
MammalWeb platform	Negative	“MammalWeb could be more child friendly.”
		“Difficult to upload photos to website.”
Species caught on camera	Negative	“It would have been better if we'd caught something on our camera!”
		“Depending on location of school the project has a different impact. Quite a lot of time for a limited result - one rat.”
More resources	Negative	“Follow up material about the different animals/mammals living in the UK would have been useful.”
		“Follow up information/activities would be helpful to staff to reinforce new learning in the workshop.”
Equipment	Negative	“The MammalWeb camera is a bit delicate inside (the battery cover has snapped off as a result of inquisitive parents and children). It's also hard to know if you have the batteries in the right way round.”
Teacher Training / Workshops	Negative	“Shame we couldn’t do the staff training as well.”

Chapter 6: General discussion

Badgers (*Meles meles*) | Gosforth Nature Reserve, Newcastle

In this thesis, I evaluated some of the benefits of camera trap networks for improving mammal monitoring efforts in the UK, including analysing some of the challenges of bias in camera trap citizen science projects. I also highlighted the potential of camera trap citizen science projects for engaging schools in biodiversity monitoring and the benefits for school pupils as participants. Much of this thesis (Chapters 3-5) has used the MammalWeb project as a case study. The results will help drive forward future priorities for MammalWeb project, but will also be of interest to general citizen science projects or researchers wishing to establish or use camera trapping networks for ecological research, engagement, or education.

My results have focussed around two main themes: ecological inferences from data generated by camera trap networks (Chapter 2 and 3) and school engagement with camera traps and citizen science (Chapter 4 and 5). In this discussion Chapter I will discuss these two themes, summarising my findings and suggesting how future work may proceed. I will then discuss how these two themes (ecological inferences and school engagement) are intrinsically linked and the benefits to be gained from moving forward with consideration of both.

6.1 Ecological inferences from camera trap networks

Across Chapters 2 and 3 of this thesis, I looked at how camera trap networks could be used to calculate ecological measures such as density (Chapter 2), and occupancy and activity (Chapter 3). In Chapter 2, I used camera trap distance sampling to calculate densities of a range of species. Unlike previous studies using this method (Bessone et al., 2020; Cappelle et al., 2019, 2021; Corlatti et al., 2020; Harris et al., 2020b; Howe et al., 2017), the survey was carried out over a heterogeneous landscape which included urban and sub-urban habitats. My density estimates were similar to previously published density estimates, giving confidence that this method could be used in landscapes such as the UK to improve national monitoring efforts. However, as highlighted in Chapter 2, it is likely that support from citizen scientists would be necessary to establish large-scale camera trap networks for distance sampling.

In Chapter 3, I explored a key issue for citizen science datasets: spatial bias. Using the MammalWeb dataset as a case study, I compare subsets of this citizen science dataset to data derived from the systematic camera trapping survey in Chapter 2. Comparing the datasets revealed that, as might be expected, the MammalWeb dataset is biased, with woodland and forest habitats over-represented and farmland, grassland, and heath habitats either under-represented, or missing completely. This had implications for species assemblages captured and ecological inferences of occupancy and activity. Whilst sub-setting analysis by habitat type helped to reduce or eliminate the impact of spatial bias in some instances, it is clear that, moving forward, it would be beneficial for MammalWeb to expand its spatial coverage, including actively surveying under-represented habitats. For the remainder of this section, I will discuss how citizen scientists could help with camera trap distance sampling, how Artificial Intelligence (AI) approaches might aid classifications for distance sampling, and how MammalWeb could expand spatial coverage through a site adoption scheme.

6.1.1 Camera trap distance sampling with citizen scientists

Citizen scientists can collect biodiversity data on scales unattainable by most research teams (Bonney et al., 2014; Dickinson et al., 2012). Therefore, to establish camera trap distance sampling at a national scale for mammal monitoring, a citizen science approach would likely be necessary. Citizen scientists participating on MammalWeb currently deploy camera traps at sites of their choosing and upload footage to the platform along with metadata such as deployment and collection dates. If citizen scientists were to deploy cameras for distance sampling, they would further be required to: a) place cameras at pre-determined random sites; and b) calibrate cameras by placing distance markers at set intervals. The former could be solved by pre-assigning sites or placing sites up for adoption which I will return to. Calibrating cameras involves the relatively easy task of placing markers in the ground. However, it is more time consuming than the normal camera trap deployment with which citizen scientists on MammalWeb and similar projects will be familiar. As with other citizen science projects (Boakes et al., 2016; Sauermann and Franzoni, 2015), MammalWeb participants typically fall into two categories: a small group of dedicated users who contribute large amounts of data regularly, and a larger group of users who contribute few records (Hsing et al., 2022). Research suggests that motivations for participation in citizen science projects may differ between these groups (Cox et al., 2018; Fischer et al., 2021; Tiago et al., 2017). Particularly for the most active contributors, offering clear opportunities for learning and gaining new skills can help to engage and retain this group (Cox et al., 2018). Therefore, this group of dedicated MammalWeb users, specifically, could be offered training in how to calibrate cameras for distance sampling, enabling them to learn new skills and helping to retain their engagement with the project.

Even if citizen scientists can deploy camera traps for distance sampling, challenges over classifying images will remain. Gathering consensus classifications (i.e., multiple users classifying each image) is an approach used by several citizen science projects and can help to classify large numbers of images in a short time (Hsing et al., 2022; Swanson et al., 2015). However, for distance sampling, not only do we need species classifications but also distance and angle. If this was to be done on a platform such as MammalWeb, all images would first have to be marked with lines representing the distance and angle intervals. Then options for citizen scientists to classify both species and distance and angle made available when classifying. However, as discussed in Chapter 2, and as a result of cameras being placed in random locations, I found a large proportion of the image set for distance sampling (~76%) were images without species captured or images of livestock (Mason et al., 2022). These images are likely less engaging for citizen scientists to classify, and therefore citizen science approaches may not be most appropriate for the task.

6.1.2 Artificial Intelligence approaches to aid distance sampling

The use of AI techniques to automate the classification of camera trap images has burgeoned over recent years (Green et al., 2020; Wäldchen and Mäder, 2018; Weinstein, 2018). The Wildlife Insights project (https://www.wildlifeinsights.org/) already offers a platform where individuals or organisations can upload image data and gain AI classifications for that data (Ahumada et al., 2020). Software packages have also been developed to help ecological projects utilise AI approaches for their own camera trap image classifications (Falzon et al., 2019; Tabak et al., 2019). As highlighted in this thesis, participating in citizen science schemes has many benefits for participants. Therefore, for projects such as MammalWeb, AI approaches should be seen not as a means of replacing citizen science efforts, but rather to complement and enhance participants' experiences. Green et al. (2020) outlined different ways in which citizen science and AI could be integrated, including using a combination of AI and citizen science classifications to reach a consensus, or using AI to filter out blank footage. Although some blank images can stimulate engagement (Bowyer et al., 2015), if citizen scientists were to help with classifying images for distance sampling, filtering out at least some of the blank / livestock images first could make the remaining image set more engaging for citizen scientists to classify.

Even more promisingly, AI approaches could soon help not only with species classifications but also with estimating distance from images. Haucke et al., (2022) presented a study using monocular depth estimation and depth image calibration methods to estimate animal to camera distances. This reduced the manual effort required to classify distances by a factor greater than 21 (Haucke et al., 2022). More recently, a proof-of-concept study expanded this approach by also removing the need for reference image material (i.e., calibrating cameras by holding distance markers) (Johanns et al., 2022). In Chapter 2, I also classified angles within images to calculate effective detection angles. To classify angle I marked images with four equally spaced vertical lines and then classified which section of the image the animal is present in. As AI approaches typically first determine where in the image an animal is present, outputting information on angle would likely be relatively simple. If AI approaches could be integrated into the MammalWeb system, so that citizen scientists upload images and automatically gain AI assisted classifications of species, distances, and angles, this could truly open up opportunities for camera trap distance sampling over large scales.

6.1.3 Expanding MammalWeb's spatial coverage through site adoption

If citizen scientists are to help with camera trap distance sampling for density estimation, they will need to deploy cameras at random, pre-determined sites. Furthermore, as discussed in Chapter 3, expanding MammalWeb's spatial coverage to help mitigate against spatial bias will help to produce reliable ecological measures such as occupancy and activity. Both of these factors mean that implementing a site adoption approach could be beneficial. This approach of predefining survey sites and putting them up for 'adoption' has been used in other camera trapping projects, such as the Candid Critters project (Lasky et al., 2021) as well as long-standing citizen science schemes such as the UK's breeding bird survey (Harris et al., 2021a). On MammalWeb, a 'discover' page already exists where participants can view a map with a grid cells sized 0.1 x 0.1 of latitude and longitude. Participants can see which grid cells have been surveyed and which species captured. This page could be adapted so that participants can not only view surveyed sites but can also sign up to 'adopt' grid cells not yet surveyed. For distance sampling, it would also be necessary to pre-determine the exact co-ordinates of the site within the grid cell and to instruct participants that, if they do need to place cameras away from the pre-determined site, they should not target placement to influence detection probability. As discussed in Chapter 3, farmland and moorland sites are particularly under-represented on MammalWeb, so actively reaching out to farmers and gamekeepers within grid cells not yet adopted should help not only to expand spatial coverage but also to reduce habitat bias, overall.

6.2 School engagement with camera traps and citizen science

In Chapters 4 and 5 of this thesis, I present results from a project working with primary schools across North-East England. This research adds to a growing body of evidence that outdoor learning and environmental education has benefits for pupils (Fägerstam and Blom, 2013; Gustafsson et al., 2012; Harvey et al., 2020; Marchant et al., 2019; White et al., 2018). The study was one of the largest schools-based citizen science projects to date, but it supports the findings of other smaller-scale studies by suggesting that citizen science specifically can offer unique opportunities for learning about local nature (Prendergast et al., 2022; Saunders et al., 2018; Schuttler et al., 2019).

In Chapter 4, I outline two of the main benefits to pupils who took part in the project: an increased knowledge of UK mammals and increased connection to nature for those with low initial scores. These results are promising, given the growing concern over children's disconnect from nature (RSPB, 2013; Soga and Gaston, 2016) and lack of knowledge of local species (Ballouard et al., 2011; Balmford et al., 2002; Lindemann-Matthies, 2005; Pilgrim et al., 2008). The study was one of the first nature-based intervention projects that measured impacts on pupil participants not only immediately after the intervention, but also three months later. I found that although increased awareness of UK mammals was not sustained for younger pupils aged 4 – 7, this change was sustained for older pupils in Key Stage 2 aged 7 – 11. Furthermore, for older pupils with a low initial connection to nature, their connection to nature scores continued to increase across all time points. This was likely due to class activities following the intervention, which further increased connection to nature among pupils. This highlights the importance of sustained and repeated engagement with the project, post-intervention, and prompted me to explore, in Chapter 5, how teachers engaged with the project and what challenges they faced to continue engagement.

The positive feedback received from teachers, and presented in Chapter 5 was encouraging; however, teachers also commented on challenges to continuing the project independently. Most of these challenges were around a lack of time to dedicate to the project, but a small number of comments also referred to the camera trap and the MammalWeb platform being difficult to use. Furthermore, whilst schools did contribute valuable data to MammalWeb, including surveying habitats currently under-represented in the ad hoc citizen science dataset, two schools noted that it was difficult to engage with the project when they did not capture many species on their cameras. With consideration to this teacher feedback, as well as my own findings and experiences from this project, I outlined, in Chapter 5, five recommendations for future projects. These recommendations have already assisted the development of follow-up work in schools of which MammalWeb has been a part. Specifically, our experience with working on MammalWeb with school teachers and pupils was a large part of the impetus for the "Connecting schools to nature" project, run by the British Ecological Society and funded by the Green Recovery Challenge Fund (https://www.britishecologicalsociety.org/british-ecological-society-awarded-green-recovery-grant-to-connect-school-children-with-nature/). For the rest of this section, I will briefly outline the connecting schools to nature project, with reference to how findings from this thesis informed its development. I will then discuss other areas of work that are worth exploring, including working with students with special educational needs and disabilities (SEND), how to maintain data quality when expanding school networks, and engaging with policy-makers on new education strategies.

6.2.1 Connecting schools with nature project and the Encounters platform

Encouraged by the promising outcomes of Chapter 4 and with consideration of the recommendations outlined in Chapter 5, MammalWeb has, over the past year, been involved in a project led by the British Ecological Society. The “Connecting schools to nature” project engages with 50 primary schools across North-East England. In line with one of the recommendations presented in Chapter 5, the project is co-created, with teachers offering their ideas and feedback through workshops and surveys at all stages of the project since its inception.

A central aspect of the project is the development of the “Encounters” platform. The Encounters platform is a website that can be accessed independently from MammalWeb, but with links to the main MammalWeb website for users to complete tasks such as uploading, classifying and taking part in species identification quizzes. Pupils, teachers, and volunteers supporting schools all have their own dashboards on the site where they complete nature-based activities grouped around key themes. As highlighted in Chapter 5, gamification of citizen science projects has been suggested as a way of maintaining engagement and could work particularly well to sustain children’s engagement (Bowser et al., 2013; Crawford et al., 2017). Taking this approach, users on the Encounters platform are awarded badges and points to encourage them to continue to engage with the project. MammalWeb forms a central part of the activities available to complete on the platform, but schools can also receive badges for participating in other citizen science schemes such as local bee and ladybird counts (e.g., https://www.nhsn.org.uk/north-east-bee-hunt/) or the RSPB garden birdwatch (https://www.rspb.org.uk/get-involved/activities/birdwatch/).

Further to species monitoring, the project also encourages schools to make improvements to their school grounds for wildlife. Exposure to green spaces at school has positive benefits for children and teenagers including enhanced cognitive development (Dadvand et al., 2015), improved mental wellbeing (Bates et al., 2018; Chiumento et al., 2018; van Dijk-Wesselius et al., 2018), and improved attention and behaviour (Taylor and Butts-Wilmsmeyer, 2020; van Dijk-Wesselius et al., 2018). Research also suggests that the ecological quality of green space is important for wellbeing (Knight et al., 2022). Through offering funding to each school and developing suggested activities to complete on the Encounters platform, the connecting schools to nature project aims to help schools either improve or increase the green space in their school grounds. Improving school grounds also means that schools that had low biodiversity at the time of entering the project can make changes to encourage more wildlife to visit their school grounds and monitor these changes with their camera traps and other techniques. This means that schools that might otherwise struggle to engage due to their lack of biodiversity (as discussed in Chapter 5) can still benefit from the project.

Another major component of the Encounters digital platform is a resource hub for teachers and volunteers. The resource hub has downloadable lesson plans, worksheets, and assemblies encouraging schools to spend time teaching outdoors and in nature. Although spending time outdoors is not a mandatory part of the National Curriculum for most age groups (Department for Education, 2015), outdoor learning and nature-based learning can be used to cover many different aspects of the curriculum in the UK (see https://nationalcurriculumoutdoors.com/). Within the schools project presented in this thesis, the workshops, teacher training sessions, and additional resources on the MammalWeb website were all designed to cover different aspects of the science curriculum listed on this page: https://www.mammalweb.org/en/community/schools. Furthermore, as mentioned in Chapter 5, I found that schools used the project to teach other areas of the curriculum such as English (through writing poems on species captured) and IT (through making PowerPoints of UK species). However, some teachers still view outdoor education as an unconventional way of teaching, which - particularly if those views are held by senior managers - can lead to barriers to leading lessons outdoors (Comishin et al., 2004; Waite, 2010). This could also have been one factor affecting longer-term use of the MammalWeb project to teach areas of the curriculum. The resource hub on the Encounters platform aims to offer more resources that explicitly link nature-based activities to all aspects of the National Curriculum. This is supported by in-person and digital teacher training sessions to build teachers' confidence with using the resources available. Re-framing outdoor and nature-based initiatives as an engaging tool for teaching the curriculum, rather than an extra-curricular activity or extra demand to be placed on teachers, will hopefully help to embed such projects into everyday teaching, long term.

The connecting schools to nature project is due to end in April 2023. Evaluation of this project will include how the project has impacted pupils' knowledge, appreciation, and willingness to conserve different UK species, as well as evaluation of the benefits and challenges for participating teachers. The Encounters platform will also go through a final stage of development, implementing new functionalities based on teacher feedback and making it appropriate to be rolled out more widely for schools to sign up nationally. Outcomes of the connecting schools to nature project, as well as findings presented in this thesis (e.g., the recommendations in Chapter 5), will help to guide future projects involving MammalWeb in schools.

6.2.2 Working with students with SEND

One area of work which could be explored is working specifically with students with special educational needs and disabilities (SEND). Research suggests that regular exposure to green spaces can be particularly beneficial for children with neurological disorders such as Attention Deficit Hyperactivity Disorder (ADHD) (Faber Taylor and Kuo, 2011). Parsons et al. (2018) worked with groups of high school students who deployed camera traps at a nature education centre and uploaded footage to the citizen science project eMammal. They describe one of the greatest benefits from the project was to a student with autism, who increased their communication and teamwork skills through field work with the cameras (Parsons et al., 2018).

The psychological benefits of spending time outdoors and connecting with nature are well studied (Bates et al., 2018; Chiumento et al., 2018; Harvey et al., 2020; van Dijk-Wesselius et al., 2018). From 2019 onward, I worked with a small group of students with SEND who, due to poor mental health, were educated outside of mainstream schools. The project involved the students designing their own scientific research questions which they then answered by deploying camera traps during various field trips and uploading footage to their own project on MammalWeb. Participation with MammalWeb had a positive impact on the students' wellbeing, with one student writing: "From a mental health perspective, it was beneficial to get outdoors and into nature, as well as giving us a very peaceful, strangely therapeutic, job of sorting through all of the images during lockdown" (Chapman, 2020).

The next stage of this project is for camera traps to be lent to other groups of students with SEND across County Durham. The students who have worked on the project, so far, have been designing leaflets and protocols which they will pass on to the new groups, mentoring them as they start their own camera trap investigations. Although this project appears to have had a positive impact on students, robust evaluation of the project has been difficult. This was partly due to the Covid-19 pandemic causing delays to the project and students not attending the centre but also because the small sample size of the group (< 10 students) means that traditional statistical methods (such as the ones used in Chapter 4) were not appropriate. Future work could not only expand on projects working with students with SEND but also complete thorough evaluations of the project to assess the benefits for participating students. This could perhaps include more in-depth qualitative approaches to explore impacts on students.

6.2.3 Expanding school networks whilst maintaining data quality

Since MammalWeb first started in 2015, it has worked with several schools, including those involved in the studies presented in this thesis, and those involved with the projects outlined above. In Chapter 3 of this thesis, I outlined the need for MammalWeb to expand its spatial coverage, including increasing the number of surveyed sites in under-represented habitats. In Chapter 5, I suggested that expanding networks of schools could be one way to help achieve this. Within the North-East region that much of this thesis has focussed on, it is evident that schools have already helped expand spatial coverage, particularly increasing coverage outside of the City of Durham where a lot of sites on MammalWeb are located (see map in Chapter 3) (Figure 1).

Moving forward, with everything that I have presented in this thesis in terms of benefits for participants and expanding spatial coverage, a logical next step for the MammalWeb project would be to continue to expand its schools network. So far, schools involved with the project have largely been based in North-East England, where MammalWeb was first established and where MammalWeb has a number of existing partnerships (e.g., The Great North Museum: Hancock) (Hsing et al., 2022). To expand coverage outside of this area, MammalWeb will need to establish partnerships with other organisations across the UK. This could include local authorities who manage education provision, as well as other organisations like universities and museums which often already have existing school networks with which they work.

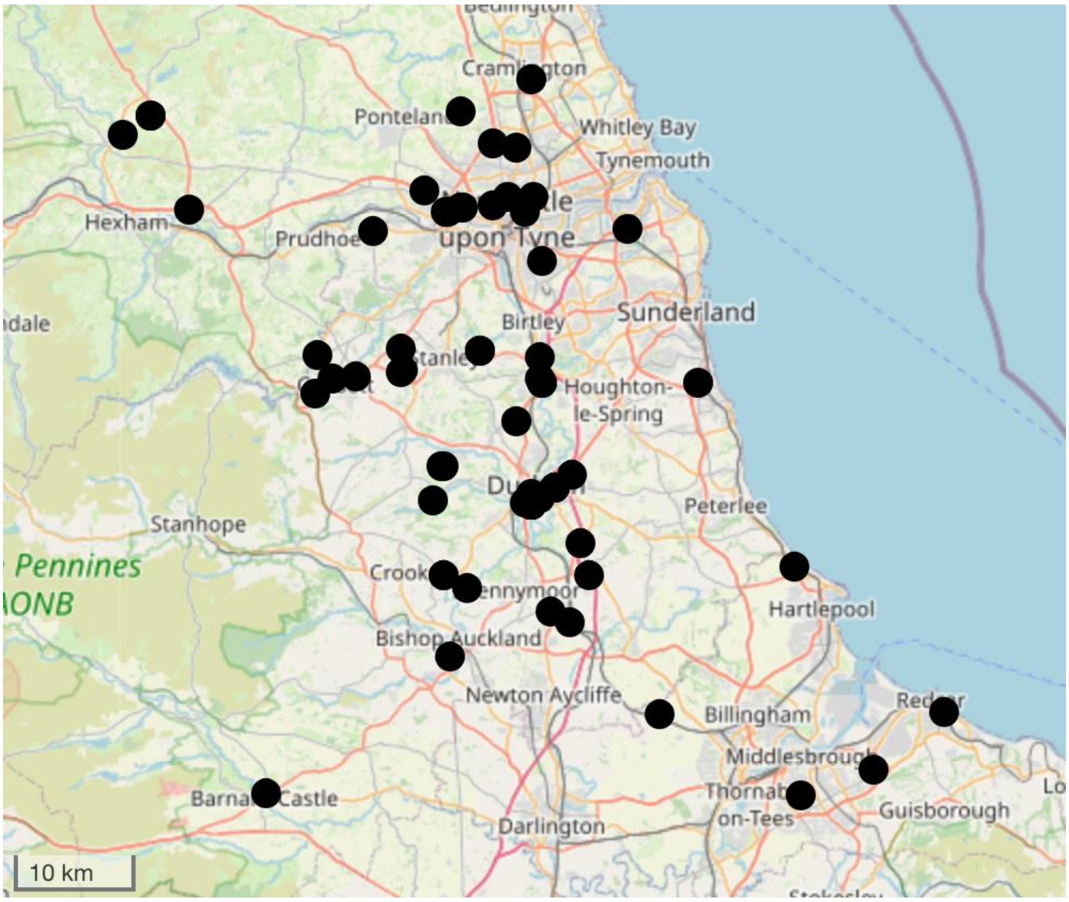

Figure 1. Distribution of sites where schools have deployed camera traps and uploaded footage to MammalWeb. Data is up to October 2022. Background map: © OpenStreetMap contributors licensed under CC BY-SA 2.0.

Expanding the network of schools with which MammalWeb works will increase the quantity of data on the platform. One challenge which may arise from this is ensuring that data quality is maintained. When schools have been involved in ecological citizen science projects, issues with data quality have been raised (Miczajka et al., 2015; Saunders et al., 2018; White et al., 2018). For the MammalWeb project, as footage is uploaded and can therefore be verified by others, this issue is somewhat alleviated. However, we do still find problems with either schools placing cameras in unsuitable locations or entering metadata (e.g., deployment or collection dates, or co-ordinates of sites) incorrectly. In Chapter 5, I documented that two schools set cameras either facing vegetation or facing the rising sun, resulting in false triggers. These two schools were in the pupil workshop intervention, which could suggest that the schools who attended teacher training were better equipped to set camera traps in appropriate places. For any school wishing to participate on MammalWeb, providing training and resources on how to set camera traps at appropriate sites before they upload footage would hopefully help to alleviate false trigger problems.

In Chapter 3, I found that data from 17 / 120 (14%) sites had incorrect information on deployment or collection dates, such as images that were uploaded outside of deployment dates, or collection dates set to the future. For the schools project, the proportion of sites with incorrect deployment dates attached to them was even larger (8 / 21; 38%). With a growing number of both school users and general users on the platform, it would be beneficial at this stage for MammalWeb to invest in implementing more data quality checks on the platform. For example, these could include error messages when collection dates are set to the future, or when footage uploaded is not from within the timeframe defined by the deployment and collection dates. Users on MammalWeb also provide information on where camera traps are placed, by either typing in coordinates or moving a marker on a map. It is likely that errors also occur here, although these are more difficult to track. Even a system to require that markers are moved from the default position before uploading footage would help to ensure that a valid location is entered. Furthermore, to make it easier for school teachers (who may not be familiar with finding coordinates of a site) to input site information it could be made possible to type in a postcode (so schools can find their rough location) and then a necessity to move the marker before uploading footage. Hopefully, implementing these checks will ensure that data uploaded by schools and other users can be used most effectively.

6.2.4 Outdoor learning and environmental education in UK policy

Driven by the growing evidence for the benefits of outdoor learning and connecting children with nature, several policy changes in this field have occurred over the past five years. In the Government's 25 year plan for the environment, it was announced that the Department for

Education will make funds available to enable children in England to increase their access to nature in and outside of school, in order to support their health and wellbeing (Department for Environment, Food & Rural Affairs, 2018). In 2022, the Department for Education outlined a new sustainability and climate change strategy for education (Department for Education, 2022). This strategy includes a new optional GCSE in natural history which will be taught in secondary schools from 2025 (Department for Education, 2022).

With these new governmental strategies come new opportunities for researchers to work with policy-makers to help shape what environmental education might look like in the future, for schools in the UK. To date, most schools that have used MammalWeb, including those presented in this thesis and those in the connecting schools to nature project, have been primary schools. There have, however, been a couple of projects involving secondary school students, including a project working with schools from Belmont Community School, County Durham, UK, where students co-authored a peer-reviewed publication reflecting on their experiences with MammalWeb (Hsing et al., 2020). Engaging with citizen science can have positive benefits for all age groups and, therefore, could be a powerful way of learning about local species and connecting to nature within the new natural history GCSE, as well as in other areas of the new sustainability strategy.

The new GCSE has been the focus of criticism, however, including the argument that many teachers are not currently equipped with the skills to run the course (Rushton and Dunlop, 2022). Although my study focussed on primary schools, this is consistent with my own experiences and findings of teachers not being confident enough, or having the skills necessary, to use the camera traps or the MammalWeb platform. In Chapter 5, I suggested that citizen science projects could work with universities to run sessions for student teachers. Indeed, a number of organisations are already offering training sessions for teachers to help prepare them for the new GCSE (e.g., https://www.nhm.ac.uk/schools/explore-urban-nature/teacher-training.html). Academics involved in ecological citizen science projects could support these training opportunities, giving teachers skills to use citizen science in their classrooms and contribute to species monitoring.

6.3 National-level camera trap citizen science networks: benefits for ecology and engagement

As shown throughout this thesis, citizen science is uniquely placed to foster connections between people and nature whilst also providing a means for long-term and large-scale data collection for data monitoring. It can be argued that the factors driving disconnection from nature highlighted in Chapter 4, are also driving the challenge of mammal monitoring discussed in Chapters 2 and 3. These include an increasing lack of opportunities to experience nature due to urbanisation and other factors (Neuvonen et al., 2007; Turner et al., 2004; Zhang et al., 2014), as well as a lack of knowledge about local species (Pilgrim et al., 2008); for mammals specifically, their elusive nature leads to a disconnect from nature but also a lack of mammal records being submitted (Figure 2). Citizen science can be a solution to tackling both of these challenges, simultaneously. Collecting records of mammals with camera traps opens opportunities for people to experience the nature local to them, whilst also collecting valuable data on mammal populations. These benefits should create a positive feedback cycle, with more mammal awareness increasing connection to nature, in turn meaning more mammal records are submitted (Figure 2).

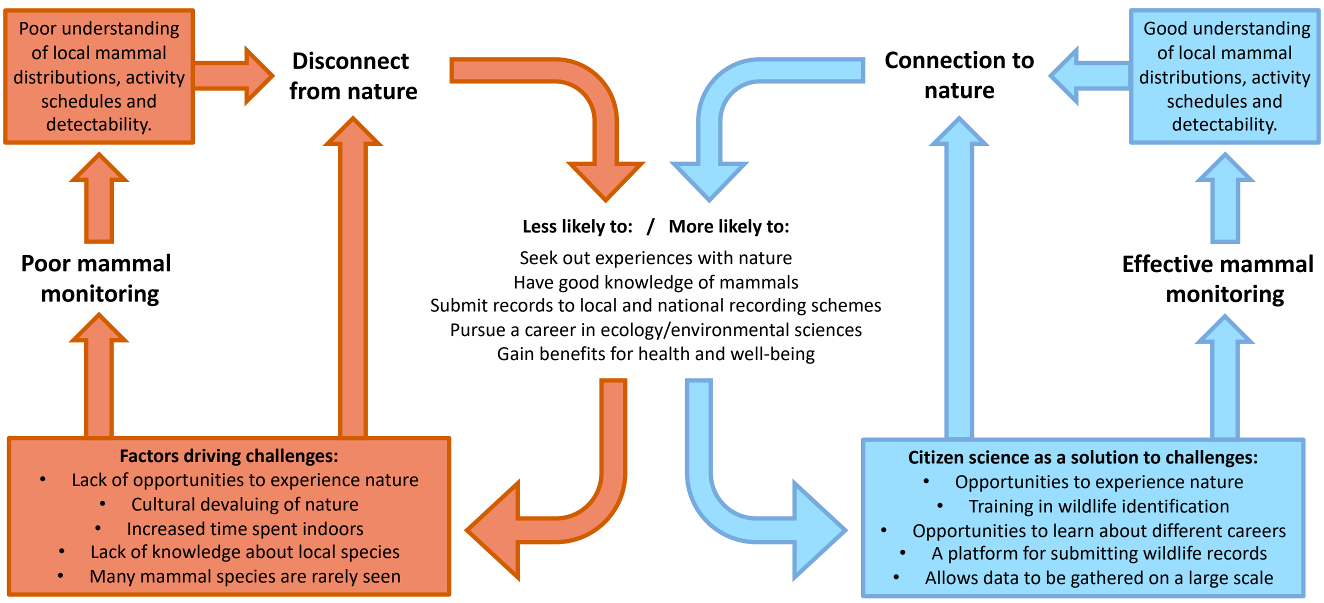

Figure 2. Schematic of the relationship between two challenges (poor mammal monitoring and disconnect from nature) and how citizen science can tackle both simultaneously.

This chapter has discussed several areas for future development, including: training citizen scientists in camera trap distance sampling methodologies; exploring integration of AI approaches; expanding spatial coverage through a site adoption scheme; exploring projects that work with students with SEND; and working with policy-makers to highlight the benefits of citizen science approaches for new education strategies. Whilst these have been discussed within two distinct sections of this chapter (ecological inferences and engagement), many of these pieces of work will be mutually beneficial for both ecology and engagement (see, also, Figure 6 in Hsing et al. 2022). For example, exploring the integration of AI approaches will help with citizen scientists collecting data for camera trap distance sampling, but will also allow for opportunities for automated feedback on classifications which can boost engagement (Baruch et al., 2016; van der Wal et al., 2016). Expanding school networks will help increase spatial coverage, and schools in grid cells not yet 'adopted' could be specifically targeted.

Advancing work in the areas of ecological monitoring and engagement will also be vital for helping to tackle ongoing biodiversity loss. Across the world, biodiversity is being lost at an unprecedented rate, heavily driven by human influence (Butchart et al., 2010). Early conservation interventions can make a positive difference to endangered species (Sodhi et al., 2011) but robust monitoring needs to be in place to detect trends in the first instance. Given the extent of biodiversity loss and the current lack of data on many wildlife populations, as highlighted throughout this thesis, efficient and robust monitoring schemes over large temporal and spatial scales are needed. Historically, citizen science has enabled the collection of vast quantities of biodiversity data (Chandler et al., 2017; Pocock et al., 2015; Silvertown, 2009); it is likely to continue to do so in the future. However, there is a need for projects to engage with both current and new participants. This thesis adds to a body of evidence that engaging children with ecological monitoring projects can have positive impacts for them as participants (Gustafsson et al., 2012; Harvey et al., 2020; Marchant et al., 2019; White et al., 2018). In an increasingly urbanised world, offering new opportunities for children to learn about and connect with nature can have positive benefits for them today, but could also empower them to grow up being more ecologically aware, helping to create a more sustainable future for our planet. Ultimately, therefore, any citizen science project should aim to expand its platform with consideration for both how the data can be used for ecological inferences and how to engage different audiences most effectively. With consideration for both aspects, citizen science projects like MammalWeb can maximise benefits for people and nature alike.

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