

**Monitoring the UK's wild mammals: A new
grammar for citizen science engagement and
ecology**

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Declaration

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Pen-Yuan Hsing

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Abstract

Anthropogenic activities have imperilled not just global ecosystems, but also the ecosystem services they provide which are crucial for human livelihoods. To understand these changes, there is a need for effective monitoring over large spatial and temporal scales. This thesis will build on two proposed solutions. First, citizen science – defined here as the involvement of non-professionals in scientific enquiry – allows the crowdsourcing of data collection and classification to expand monitoring in ways that are logistically infeasible for ecologists alone. Second, motion-sensing camera traps can reduce the labour needed for monitoring since they can be deployed for long periods and provide continuous, relatively unbiased observations. In this thesis, I describe MammalWeb, a citizen science project in north-east England where I enlisted the aid of the local community in wild mammal monitoring. Motivated by the current unevenness of survey effort and data for mammals in Great Britain, MammalWeb involves citizen scientists in both the collection and classification of camera trap images, a novel combination. This is a multidisciplinary project, and in the following chapters I will begin, in Chapter 2, with a detailed reflection on the organisation of the MammalWeb citizen science project and approaches to evaluating its performance. I observe that the majority of contributions came from a small subset of citizen scientists. In Chapter 3, I develop an economical approach to deriving consensus classifications from the aggregated input of multiple users, which is a crucial part of many citizen science projects. This is followed in Chapter 4 by a case study of a partnership I initiated between MammalWeb and the local Belmont Community School, where we empowered a group of secondary school students to not only aid in collecting data for MammalWeb, but also design and deliver ecological outreach to their community. This is now the template for a wider network of school partnerships we are pursuing. Chapter 5 will examine common concerns around estimating species occupancy from camera trap data, including post-hoc discretisation of observations and effects of missing data. I also develop a resampling method to account for uncertain detections, a common issue when crowdsourcing data classifications. I show that, through resampling, the estimated parameters from occupancy models are robust against high uncertainty in the underlying detections. Lastly, Chapter 6 will discuss how my work on MammalWeb has laid the foundation for a wider citizen science camera trapping network in the United Kingdom and avenues for future work. Importantly, I show that MammalWeb citizen scientists have been empowered to be more than “mobile sensors” and act as independent researchers who have initiated ecological studies elsewhere.

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Chapter 1 - General introduction

1.1 Introduction

Global ecosystems are in the midst of rapid change and experiencing biodiversity loss at rates comparable to mass extinction events (Butchart et al. 2010, Dirzo et al. 2014). These changes are heavily influenced by anthropogenic activity (Corlett 2015, Svenning et al. 2016), and endanger ecosystem services crucial for human wellbeing (Millennium Ecosystem Assessment 2005, Díaz et al. 2006, Perrings et al. 2011a). The scale (both temporal and spatial) of these changes challenge existing methods for ecological monitoring, and camera trapping has been proposed as a solution with great potential (Burton et al. 2015, Steenweg et al. 2017) to enable quantities of data to be collected across wide spatial areas. Even then, large-scale ecological monitoring is costly and logistically challenging, and citizen science – the process of involving non-professionals in scientific enquiry – has become a popular way to scale up data collection and classification in ways ecologists cannot achieve on their own (Devictor et al. 2010, Amano et al. 2016). The combination of citizen science and camera trapping has been attempted in recent years with promising results (Swanson et al. 2015, McShea et al. 2015, Verma et al. 2016). Motivated by the above and a need for more comprehensive mammal monitoring in the United Kingdom (Croft et al. 2017), this thesis describes my research on implementing a citizen science camera trapping programme in north-east England: MammalWeb (<http://www.MammalWeb.org/>). In addition to tangible outcomes that will be discussed throughout this thesis, MammalWeb is novel for expanding the boundaries of citizen scientists where participants are not merely passive sensors, but empowered citizens who partake in other steps of the scientific method. This introductory chapter explores the general background to mammals, camera trapping and citizen science and includes the motivations for the MammalWeb project. Chapters 2 through 5 describe my work on organising MammalWeb; economically crowdsourcing data classification; partnering with a local school to enhance engagement; and exploring the potential of applying occupancy analysis to MammalWeb data. Chapter 6 is a general discussion reflecting on wider lessons learned from MammalWeb and their implications.

1.2 The need for ecological monitoring

Anthropogenic impacts on ecosystems are diverse and widespread. In a meta-analysis of global biodiversity loss, the majority of the 31 indicators studied showed steady declines since 1970 (Butchart et al. 2010). These declines were coupled with increases in measures of human influence such as invasive species, fish stock depletion, climate change (Butchart

et al. 2010), and increased land use (Foley et al. 2005). Human impacts are often just as large as natural processes, and the corresponding time period has received its own geological epoch called the Anthropocene (Corlett 2015, Svenning et al. 2016). In fact, the current rate of biodiversity loss is comparable to past mass extinction events and has been termed the “defaunation” of this planet (Dirzo et al. 2014).

Biodiversity loss impacts ecosystem services, which are functions provided by ecosystems that directly contributes to human livelihood such as food, water, air, or recreation (Millennium Ecosystem Assessment 2005, Perrings et al. 2011a). While there are concerns regarding the over-emphasis and monetisation of ecosystem services over nature’s intrinsic value (Kinzig et al. 2011, Silvertown 2015), it is nevertheless clear that anthropogenic impacts on ecosystems services can be detrimental to human wellbeing (Díaz et al. 2006). For example, light pollution from urban areas affects not only ecosystems (Longcore and Rich 2004, Gaston et al. 2012) including predator-prey relationships (Minnaar et al. 2014), but also the physical and mental wellbeing of humans living in that space (e.g. Karatsoreos 2012). Sometimes, human-wildlife interactions are mutually beneficial, and in one example, ecosystem engineers continued to maintain agricultural structures even after the departure of the humans who built them (McKey et al. 2010). In any case, there is a need for ecological monitoring to understand these complex interactions. It is important to note that biodiversity conservation often focuses on rare or endangered species, but common species – from the saiga antelope, cod, to certain grass species – are also of ecological importance (Gaston and Fuller 2008) and therefore they should be monitored as well.

Considering the global scale of biodiversity loss, there is now extensive literature examining the need for large-scale monitoring (Yoccoz et al. 2001, Fischer et al. 2010, Stephens et al. 2015), including the value of establishing long-term baseline data (Magurran et al. 2010), practical advice for designing effective monitoring programmes (Lindenmayer and Likens 2010, Sergeant et al. 2012, Schmeller et al. 2015), and frameworks for consolidating these efforts (Vos et al. 2000).

Methods for monitoring are diverse, such as direct counts, line transects (Sutherland 2006 p. 145), acoustic studies (Conway et al. 2004), dung counts (Eggert et al. 2003), hair and dung sampling for DNA (Piggott and Taylor 2003), aerial surveys (Krebs 1999), mark-recapture methods (Pollock et al. 1990), and many others. However, direct observations are limited to animals occurring in sufficiently high density in habitats with high visibility; tissue sampling requires expert lab work; aerial surveys are expensive and also limited by visibility; mark-recapture studies are time-consuming and intrusive; and acoustic studies are mainly

applicable to animals with loud and distinct vocalisations. In contrast, the use of motion-sensing camera traps has been proposed as an effective method for large scale ecological monitoring (Steenweg et al. 2017). In the following section, I will provide an overview of the development of camera trap technology and its ecological applications.

1.3 Camera trap ecology

1.3.1 History of camera trapping

Wildlife photography dates back to the beginnings of photographic technology itself. One of the earliest attempts was in 1863 by the German biologist Gustav Fritsch in South Africa (Guggisberg 1977). During the expedition of the *HMS Challenger* from 1872-1876, photography was used specifically for the study of wildlife such as rock-hopper penguins (*Eudyptes chrysocome*) and albatrosses (*Diomedea* spp.) (Kucera and Barrett 2011 p. 10). Animal-triggered photography first appeared in 1878, when British photographer Eadweard James Muybridge rigged a dozen cameras with fast shutters to photograph a galloping horse as it triggered trip wires, and showed that all four of a horse's feet are off the ground at certain times (Guggisberg 1977, Kucera and Barrett 2011 p. 10). Even at this early stage, photography aided the study of basic biology, in this case animal locomotion.

The first of what may be considered “camera trap” photography was developed by George Shiras in the 1890s (Cutler and Swann 1999, Kucera and Barrett 2011 p. 10). With a trip wire and flash system, Shiras documented the diversity of North American wildlife, from squirrels (*Sciurus carolinensis*) to moose (*Alces alces*). His works won the gold medal at the 1900 Paris World Exhibition and were published in National Geographic Magazine (Kucera and Barrett 2011 p. 10). This “flashlight trap photography” was used successfully across the world, and was given a detailed treatise by William Nesbit (1926).

By the mid-twentieth century, the use of camera traps in ecological studies had become widespread. Advances included portable power sources such as car batteries and using a light beam as a trigger (Buckner 1964). Cameras carried large 35 mm film magazines allowing hundreds of exposures (Abbott and Coombs 1964), and some operated in temperatures as low as -35°C (Diem et al. 1973). Even video cameras were used as early as the late 1950s to take advantage of the large number of exposures (Pearson 1959).

The subjects of camera trap studies were also diverse. In North America, Buckner (1964) used lightbeam triggered cameras to study mammals of Manitoba including, snowshoe hares (*Lepus americanus*), red squirrels (*Tamiasciurus hudsonicus*), and red-backed voles (*Clethrionomys gapperi*). Seydack (1984) estimated the population density for bushbuck (*Tragelaphus scriptus*), and tracked individual leopards (*Panthera pardus*) and honey badgers (*Mellivora capensis*) in South Africa, all with portable camera traps deployed in 100

ha survey blocks. Birds (Cowardin and Ashe 1965, Temple 1972, Diem et al. 1973) and Mediterranean monk seals (Hiby and Jeffery 1987, Kucera and Barrett 2011 p. 15) were studied, as were pollinators in Australia (Carthew and Slater 1991).

Camera traps were instrumental in the documentation of rare, endangered, or even presumed-extinct animals. Karanth's (1995) seminal camera trap study on tigers (*Panthera tigris*) in India not only provided insight into the ecology of this elusive carnivore, but also led to advances in the camera trap sampling design and downstream population estimation (Karanth and Nichols 2002, Karanth et al. 2004). In the Atlantic Forest of Brazil, the distribution of the critically endangered buff-headed capuchin monkey (*Cebus xanthosternos*) was characterised with camera traps (Kierulff et al. 2004). In another case, the Vietnamese saola (*Pseudoryx nghetinhensis*), dubbed the “Asian unicorn” (Callaway 2012) and previously only described by bone fragments, was rediscovered with camera traps (Whitfield 1998).

1.3.2 Contemporary camera traps

Modern camera traps take digital photos and generally fall into two categories (Swann et al. 2011): non-triggered and triggered.

Non-triggered cameras either take time lapse photography or videos, and have been used for studying animal behaviour and bird nests (Cutler and Swann 1999). By definition, they eliminate false triggers or cases where the trigger threshold is too high, but require more power, and reviewing the captured data is time-consuming (Swann et al. 2011 p. 31). However, non-triggered cameras have proliferated as webcams for realtime monitoring of animals not only for research, but also educational use (Animal Cameras 2014, MacRae 2014).

Triggered cameras were traditionally activated mechanically by trip wires or pressure pads (Swann et al. 2011 p. 31), and now commonly use active or passive infrared triggers. Active infrared cameras are triggered when an animal passes through a continuous beam from a transmitter to receiver, much like an invisible trip wire. These systems are very sensitive, but are more complicated to set up, have a narrow detection zone, and are known for frequent false triggers (Swann et al. 2011 p. 32).

Passive infrared triggered camera traps are by far the most common. Typically comprising two adjacent sensors that read background temperature, these cameras are triggered by the temperature change detected as an animal passes in front of the sensors (Swann et al. 2004). Practically all commercial models come in a single unit (as opposed to those with trip wires or an external power source), and are therefore easier to set up by just tying them to a tree or mounting on a tripod and arming them. While the size of detection

zones varies, they can generally monitor a much wider area than active infrared units. The cost of commercial camera traps ranges from less than US\$100 to more than US\$500 depending on feature set. “Trigger time”, the lag between detection of motion and release of the camera shutter, is a crucial consideration. Fast moving animals such as leopards may require trigger times as fast as 1/4 seconds to acquire an image of the whole animal. Other components to consider may include (1) housing, (2) software and recording options, (3) power source, and (4) lighting options.

Since camera traps operate without human intervention after deployment, they are often left in the field for months at a time, which underscores the importance of selecting a model with appropriate housing for the target environment. Sufficient weather proofing is critical for deployments in high temperature and/or high humidity environments. Placing a pack of silica gel within the camera housing, which changes colour from blue to red when moistened, is a good detector of water intrusion (Swann et al. 2011 p. 34). Appropriate camouflage is desirable to reduce visibility of the camera and the possibility of interfering with wildlife. Security measures are important to prevent theft and vandalism by humans, and also damage from animals. Most manufacturers such as RECONYX (<https://www.reconyx.com/>) and Cuddeback (<https://www.cuddeback.com/>) provide optional metal enclosures, cabling systems, and password software locks for these purposes.

Modern commercial camera traps offer a plethora of software and recording features, such as image resolution adjustment, audio and video recording, on board memory, built-in GPS, environmental data logging, time lapse options, or sensitivity settings. These features may comprise a large part of the camera trap's cost, so it is important to consider which ones are needed while balancing flexibility with cost when planning a project.

Electrical power outlets seldom exist in the field, and the majority of passive infrared camera traps operate on battery power (though most can be plugged into an outlet). Alkaline or lithium batteries are commonly used because of their low cost and uniform power output, but are not reusable and create waste. Rechargeable batteries may be a better option, since they are cost effective in the long run, and recent varieties such as nickel-metal-hydride (NiMH) or lithium ion batteries provide good performance.

Illumination is another important factor if night time photography is planned. Strobe flash can provide colour images, but may disturb animals and may be of particular concern for behavioural studies (Wegge et al. 2004, Swann et al. 2011 p. 38, Meek et al. 2014). Infrared illumination (approximately 850 nm) reduces the possibility of startling an animal, and recently manufacturers have released “black flash” or “no glow” illumination with 940 nm light emitting diodes (LEDs) which may further minimise disturbance.

The advantages of using camera traps for ecological monitoring over other methods such as direct observation, tagging, or indirect tracking are that they do not disturb the subject animals, can operate on their own for long periods without human intervention, and provide an auditable, unbiased dataset which can be reviewed by other researchers (Swann et al. 2011 p. 29).

The “set and forget” nature of camera traps is one of its greatest conveniences, but also one of the greatest risks to their use. When deployed in remote locales, equipment failures might go unnoticed for months, potentially an entire field season (Swann et al. 2011 p. 29). Most factors contributing to camera malfunction can be alleviated, however, through the selection of appropriate models (e.g. ones with weather proof housing), careful planning, and skilled set up. Additionally, theft or vandalism of field research equipment, including camera traps, is well documented (Bancroft 2010). Fortunately, simple solutions such as personal messages left on field equipment can reduce vandalism (Clarín et al. 2013). This is in addition to the use of security devices such as security posts (Meek et al. 2012) or manufacturer provided metal enclosures.

1.3.3 Ecological applications of camera traps

These benefits have contributed to the wide and varied use of camera traps in ecological research. In one review of more than 100 papers (Cutler & Swann 1999), camera traps were found to be used for studying nest predation, feeding ecology, nesting behaviour, animal activity patterns, population parameters, and the presence or absence of species. One exception is ectothermic animals, which proved to be a challenge for infrared camera traps to detect since their thermal signature often matches that of the background (Ariefiandy et al. 2013).

Methodologies for ecological monitoring with camera traps are diverse. On a basic level, they are effective for species inventories and measuring richness (Tobler et al. 2008, Si et al. 2014). Camera traps can also be used for distance sampling (Howe et al. 2017). If individual identification is possible, mark-recapture techniques have been adapted for camera traps and used extensively to monitor carnivores with unique fur patterns (Karanth 1995, Karanth and Nichols 2002). For most species, however, individual recognition is difficult, and one of the most widely used techniques in this case is occupancy modelling. At its most basic level, occupancy is defined as the probability of the target species being present at a site (MacKenzie et al. 2002), and is useful when absolute abundance is otherwise difficult to establish or not required. Occupancy is valuable when monitoring elusive species since it accounts for imperfect detection (missed detections of a species when it is present) and techniques have been developed to optimise survey effort as a trade-off between the number

of sites surveyed and the duration of those surveys (Eggert et al. 2003, Mackenzie and Royle 2005, Bailey et al. 2007). In addition, the standard occupancy model has been extended to multispecies studies, including interactions between species (Steinmetz et al. 2013) and tying community dynamics to human activity (Burton et al. 2012). Another important method is the random encounter model (REM), which provides a means of estimating abundance from camera trap data without individual recognition (Rowcliffe et al. 2008) and is based on physical theory regarding rates of collision between gas molecules and its comparisons to animal movement (Hutchinson and Waser 2007). Accompanying methods have been developed to estimate two critical terms in REM, the zone of detection around a camera (Rowcliffe et al. 2011), and the target species' movement rate (Rowcliffe et al. 2016). REM has been successfully applied, such as for estimating lion densities in Tanzania (Cusack et al. 2015). Concurrent with the development of camera trap ecological monitoring is the proliferation of software tools (Young et al. 2018), from image tagging and management (Krishnappa and Turner 2014, Ivan and Newkirk 2016, Niedballa et al. 2016, Nazir et al. 2017, Gerum et al. 2017) to R packages for occupancy modelling (Fiske and Chandler 2011) or rarefaction analysis (Hsieh et al. 2016).

As the popularity of camera traps grows, there is an increasing need for open standards on data sharing (Hampton et al. 2013, 2015, Forrester et al. 2016), and collating or coordinating studies to achieve large scale monitoring (Burton et al. 2015, Steenweg et al. 2017). Examples of large-scale camera trapping efforts include the Global Biodiversity Information Facility (GBIF; <https://www.gbif.org/>) or the Tropical Ecology Assessment and Monitoring Network (TEAM; <http://www.teamnetwork.org/>). Camera trap data from the TEAM network has been incorporated into the Wildlife Picture Index (O'Brien 2010), which was used for measuring proportional change in occupancy for mammals from Mongolia (Townsend et al. 2014) to Costa Rica (Ahumada et al. 2013). Large-scale camera trapping results in large image datasets, and ecologists are increasingly turning to crowdsourcing – and more broadly, citizen science – to meet the challenge of classifying these images (Steenweg et al. 2017).

1.4 Citizen science

Since the first use of the term in the 1990s (Irwin 1995), the definition of citizen science most commonly used today is the process of involving non-professionals in scientific enquiry (Cohn 2008, Silvertown 2009, Bonney et al. 2009). While not the focus of this thesis, it should be noted that the definition of citizen science can be fluid (Resnik et al. 2015), and major scientific discoveries were sometimes not made by those professionally employed as researchers. Indeed, Albert Einstein was a patent examiner and Gregor Mendel was an

Augustinian friar when their now-well-known scientific contributions were made (Silvertown 2009, Resnik et al. 2015). If we use the currently popular definition of involving non-professionals in science, then an early example of citizen science was the annual Christmas bird count held by the National Audubon Society in the United States since 1900, with over 60 million birds counted to date (Silvertown 2009). In fact, avian ecology has one of the longest histories of citizen science involvement, with thousands of annual participants collecting data since the mid-20th century via the North American (<https://www.pwrc.usgs.gov/bbs>) and United Kingdom (<https://www.bto.org/volunteer-surveys/bbs>) breeding bird surveys. This crowdsourcing of data collection is one of the most common forms of ecological citizen science, and covers diverse themes from tracking invasive insects (Pocock and Evans 2014), anuran call surveys (Weir et al. 2005), mapping coral reefs (Loerzel et al. 2017, Lucrezi et al. 2018), or plant phenology (Tansey et al. 2017). Crowdsourced data collection has also been employed in other scientific fields from astronomy (Willett et al. 2013) to meteorology (Hennon et al. 2014).

In addition to data collection, citizen scientists also aid in data classification (Kosmala et al. 2016). It began in the late 1990s with astronomy projects such as NASA Clickworkers (<http://nasaclickworkers.com/classic.php>) or the SETI@Home “volunteer computing” project (Anderson et al. 2002). In recent years, crowdsourced data classification has become a larger part of mainstream scientific discourse, likely due to the rapid development of digital tools which eased participation (Newman et al. 2012), and the requirement by many funding agencies for researchers to incorporate public outreach in their work (Silvertown 2009). A particularly successful example is Foldit (<https://fold.it/>) where citizen scientists are players in a game of modelling protein structures (Cooper et al. 2010) and the results of which have aided the design of antiretroviral drugs (Khatib et al. 2011b). There are now several online citizen science platforms such as Zooniverse (McMaster et al. 2014) or Scistarter (Cavalier et al. 2014) providing lists of projects volunteers can browse, participate in, or even fund. The current state-of-the-art is using user-contributed classifications to train machine learning and artificial intelligence algorithms for purposes ranging from protein folding (Khatib et al. 2011a), subcellular microscopy (Sullivan et al. 2018), to voice recognition (e.g., the Mozilla Common Voice project; <https://voice.mozilla.org/>).

Many data classification projects involve processing images, and they cover diverse subjects. An early web-based project, Galaxy Zoo (Schawinski and Lintott 2014), involved an online community in classifying stellar objects from telescope images. For ecological studies, there are successful projects on Zooniverse such as Invader ID for identifying non-native marine invertebrates (<https://www.zooniverse.org/projects/serc/invader-id>) or

Rainforest Flowers categorising images of flowers
(<https://www.zooniverse.org/projects/tomomi/rainforest-flowers>). Outside of Zooniverse, and with the rapid proliferation of cheap digital photography equipment such as mobile phones, even those with little scientific training can study the biodiversity of their surroundings. One notable example is iSpot (<https://www.ispotnature.org/>), where citizen scientists share photos they took of local wildlife and collaboratively identify and map them (Silvertown et al. 2015). A more recent project is BeeWatch, an online platform where citizen scientists submit and identify photos of bumblebees, and is notable for automated feedback that improves user accuracy and engagement (van der Wal et al. 2016). There is even research based on ecological data derived from tourist “selfies” taken at nature reserves (Richards 2014).

Perhaps most relevant to this thesis are citizen science projects involving the deployment and collection of camera traps such as the eMammal project in the United States (McShea et al. 2014), or the classification of animals from the obtained images such as Snapshot Serengeti (Swanson et al. 2015) or Instant Wild (Verma et al. 2016). It has been argued that citizen science is an important tool in addressing the challenges of large-scale ecological monitoring (Devictor et al. 2010, Conrad and Hilchey 2011, Amano et al. 2016), and camera trapping projects such as those mentioned above could play a crucial role (Steenweg et al. 2017). However, up to the time of my thesis research, there was no ongoing wildlife camera trapping project where citizen scientists were engaged in *both* the collection and classification of data. In addition, the loss of human-nature interactions in heavily developed landscapes – dubbed the “extinction of experience” (Soga and Gaston 2016) – is a strong reason for involving non-professional ecologists in ecology and conservation (Schuttler et al. 2018). It is with these considerations in mind that I now introduce MammalWeb, the citizen science project which is the focus of this thesis.

1.5 The MammalWeb project

The popular Zooniverse citizen science platform is based in the United Kingdom, which has a long history of citizen science and popular interest in natural history. At the beginning of the 20th century, there were already 500 local natural history societies with almost 100,000 members across the country (McIntosh 1986). Their thorough records of natural history provide a baseline from which one could evaluate changes in Great Britain’s biodiversity, and led to the formation of the government-supported Biological Records Centre in 1964 (Pocock et al. 2015). The Biological Records Centre currently coordinates the collection and archiving of biodiversity data from over 80 recording schemes, which is fed into the National Biodiversity Network (NBN; <http://www.nbn.org.uk/>) and the Global Biodiversity

Information Facility (GBIF; <https://www.gbif.org/>). Over the past decade, Open Air Laboratories (OPAL; <http://www.opalexplorenature.org/>), a network of academic institutions led by Imperial College London, has organised national citizen science biodiversity and environment surveys with great success (Davies et al. 2016, Lakeman-Fraser et al. 2016). In addition, ornithology-focused citizen science projects are very popular. In addition to the annual Breeding Bird Survey organised by the British Trust for Ornithology (BTO), there is also the Nest Records Scheme (NRS), whose citizen scientist-collected records since 1939 have provided valuable insight into long term ecological change (Crick et al. 2003) including the discovery that bird egg-laying has become earlier each year as a result of climate change (Crick and Sparks 1999).

In contrast with birds, data availability and survey effort for wild mammals are uneven across the UK (Battersby and Greenwood 2004, Croft et al. 2017). One aim of my research is to tackle this problem through developing a novel method for assessing the diversity and distribution of Britain's wild mammals, one which could be scaled up. Mammals are the focus not just for their ecological importance (Berger et al. 2001, Côté et al. 2004, Gill and Morgan 2010), but also their economic and cultural significance (Marboutin et al. 2003, Wardle and Bardgett 2004), conflict with human activities (Bruinderink and Hazebroek 1996), and disease transmission (Anderson and Trewhella 1985, Cassidy 2012, Stokstad 2017).

I have contributed to a significant degree to the production of MammalWeb, an ongoing project which partners with citizen scientists across north-east England (centred around County Durham) to deploy camera traps for monitoring wild mammals. The project begun as a collaboration between our research group at Durham University and the Durham Wildlife Trust (<https://durhamwt.com/>), citizen scientists can choose to participate as one or both roles of data collectors ("Trappers") or classifiers ("Spotters"). Informed by similar projects such as eMammal (McShea et al. 2015), Trappers are loaned (or can bring their own) camera traps and trained to deploy them following a standard protocol. They submit the camera trap images collected to our web platform (<http://www.MammalWeb.org/>) where registered Spotters collaboratively classify them using an interface similar to that of Zooniverse (Swanson et al. 2015), but designed to process entire sequences of images taken in quick succession. Since launching this project in mid-2015, more than 250,000 camera trap images have been submitted to MammalWeb from 234 sites mostly in the north-east of England. In the following section, I will outline the structure of the rest of this thesis with the summaries and aims of each chapter.

1.6 Thesis structure and aims

1.6.1 MammalWeb organisation

In addition to the challenges of large-scale ecological monitoring, the MammalWeb project was also faced with the task of recruiting, training, and sustaining a group of local citizen scientists to conduct effective camera trapping. In Chapter 2, I will describe the organisation of MammalWeb from pre-project-launch tests within Durham University; the logistics of initial and ongoing recruitment of citizen scientists; orchestrating the offline and online infrastructure of the project; metrics of project growth in terms of user activity; and reflections on evaluating project outcomes in terms of sustained engagement.

1.6.2 Economical crowdsourcing for camera trap image classification

As discussed above, there have been successful online citizen science projects which crowdsource data classifications including those for ecological monitoring. However, for projects that are more localised or monitoring less charismatic fauna, the demand for crowdsourced classifications (such as those for camera trap images) might surpass supply. On the MammalWeb website, our interface for classifying images is built such that the same sequence of camera trap images is shown to multiple Spotters. In Chapter 3, I develop a novel method for deriving consensus classifications from aggregated Spotter inputs for each image sequence via a logistic regression model. I discuss how these consensus classifications fit into an algorithm for prioritising which images to show classifiers, and its wider uses for citizen science-based wildlife monitoring.

1.6.3 School students conducting, contributing to and communicating ecological research — experiences of a school-university partnership

One goal of MammalWeb is to engage citizen scientists on a higher level, rather than the simple crowdsourcing of data collection. As part of that effort, I obtained funding from the British Ecological Society (BES) to pilot a partnership with our local Belmont Community School. This entailed working with a group of secondary school students so that they were not just MammalWeb citizen scientists, but also ecological ambassadors who deliver ecological outreach to their community. Chapter 4 describes this part of the MammalWeb project and discusses the lessons learned for pairing citizen science with education, including impact on the students which was documented in a professionally made video.

1.6.4 Handling uncertain detections and discretising data in camera trap-based occupancy modelling

Much of the effort since launching MammalWeb in 2015 has been organising citizen scientists, ensuring sustained monitoring across time and space, and economically working

with our userbase for crowdsourced data collection and classification. There is now a need to investigate the analytical tools with which we can use MammalWeb data. As noted earlier in this chapter, there are various methods for analysing camera trap data, of which occupancy is a frequently estimated parameter when direct measurements of abundance are not necessary. Modelling occupancy requires a dataset comprised of detection and non-detection records from surveys conducted across sampling sites within a region of interest. For citizen science projects that crowdsource data classification, uncertainty is introduced into these detections due to inaccuracies inherent across classifiers. In Chapter 5, I begin with simulations to examine this issue along with two others common to camera trapping studies: How to discretise continuous camera trap observations into discrete detection events for occupancy; and the impact of missing data on the accuracy of estimated occupancy. I then explore the incorporation of uncertain detections into occupancy modelling through a resampling approach.

1.6.5 General discussion

In the final chapter, I will put my work on the MammalWeb project in the wider context of citizen science and ecological monitoring. Specifically, I will focus on lessons learned that can be applied to sustaining citizen science engagement (such as the gamifying citizen science, partnering with libraries and museums, and further discussion on how to evaluate project outcomes), managing the crowdsourcing of data classification (such as A/B testing of different online user experiences and developing machine learning algorithms), and making ecological inferences from the results (such as the current limitations of, and ways to improve upon, the occupancy modelling I did, and the potential of using random encounter models). It concludes with a reflection on how MammalWeb is taking citizen science from a centralised to distributed topology where citizen scientists are empowered to do their own research and communicate results.

Chapter 2 - MammalWeb organisation

2.1 Introduction

Ecosystems across the world are experiencing rapid biodiversity loss strongly related to human activities (Butchart et al. 2010). The defaunation of the planet (Dirzo et al. 2014) has adverse impacts on ecosystem services, which are important for human livelihoods (Millennium Ecosystem Assessment 2005, Díaz et al. 2006, Perrings et al. 2011b). To understand these changes, there is a need for large-scale ecological monitoring (Fischer et al. 2010, Stephens et al. 2015). Of the solutions proposed, two are of particular interest in this chapter (and this thesis): The use of motion-sensing camera traps (Burton et al. 2015, Steenweg et al. 2017), and scaling up their reach by involving citizen scientists (Kosmala et al. 2016, Steenweg et al. 2017). Indeed, this has been attempted where citizen scientists have helped professional ecologists deploy camera traps (McShea et al. 2015) or classify images (Swanson et al. 2015). In the United Kingdom, there is a long history of citizen science projects for ecological monitoring (Pocock et al. 2015), including the highly successful annual Breeding Bird Survey and Nest Record Scheme (e.g., Crick and Sparks 1999). However, the monitoring effort for wild mammals remains uneven (Croft et al. 2017).

In this chapter, I will describe the organisation and management of the MammalWeb citizen science project (<http://www.MammalWeb.org/>) which I have been piloting since 2015. This project enlists the help of citizen scientists in the collection and classification of camera trap data (a rare combination), with an aim to develop a model that is suitable for large-scale monitoring of wild mammals in Britain while engaging citizen scientists on a level beyond the collection and classification of data. In the following sections, I will provide an overview of MammalWeb including the recruitment and organisation of citizen scientists; the online infrastructure of our web platform; and data outputs for downstream analyses and archiving. I believe documenting the organisation of citizen science projects is important but not well represented in literature, and the contents of this chapter will be of value to other citizen science practitioners.

In addition, I will explain the metrics used to measure project growth and citizen science engagement since the inception of MammalWeb through the end of 2018. This includes quantitative analyses on impacts to those metrics from “intervention” events such as public outreach events, talks, media coverage, competitions, or newsletters. I also explored the temporal patterns of this data in the form of a weekend versus weekday comparison. Qualitatively, I will characterise the email correspondence between us and citizen scientists

to derive practical recommendations on how to better understand participant needs to guide project development.

This chapter concludes with a discussion on the results of those efforts, possibilities for improving project evaluation, and improvements to the project “user experience” that we are implementing or could in the future.

2.2 Methods

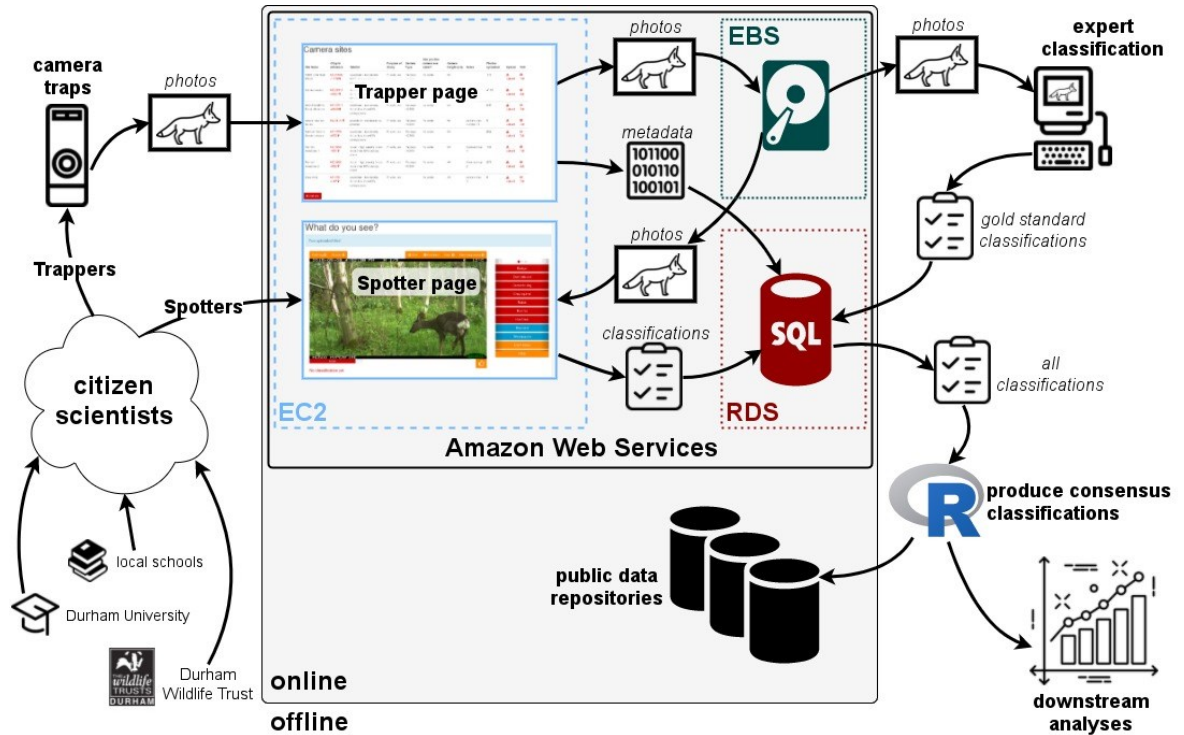


Figure 2.1. MammalWeb project organisation. Citizen scientists were recruited from Durham University, members of the Durham Wildlife Trust, and local schools. They could be one or both of Trappers, who deploy camera traps, and Spotters, who classify images MammalWeb. The web platform is hosted on the Amazon Web Services (AWS) Elastic Compute Cloud (EC2) with interfaces for camera trap image upload (Trappers page) and classifications (Spotter page). This is tied into image storage on AWS Elastic Block Store (EBS) while image classifications and other data are stored in a MySQL server on the AWS Relational Database Service (RDS). We provide an expert classified “gold standard” set of photos from which consensus classifications could be calculated from user classifications. These consensus classifications are used for downstream analyses and submission to public data repositories.

Before MammalWeb, there was a short-term trial organised in early 2014 where 30 students from Durham University were recruited to deploy camera traps. These students, in groups of three, were lent Reconyx HC500 camera traps for monitoring wildlife on university grounds. Through informal dialogue with the students, we derived qualitative guidance for MammalWeb, such as that camera traps deployed in the area need to have their batteries replaced and images downloaded at least once a month, or experience with the logistics of organising engagement meetings.

With this initial experience, we launched MammalWeb as a collaboration between us at Durham University with the local Durham Wildlife Trust. Partially funded by a United Kingdom Heritage Lottery Fund (grant Number: OH-14-06474) and my PhD scholarship

from Durham University, we began a full-scale roll-out of the project to those living in or near County Durham, England. In the following sections, I describe the process of recruiting MammalWeb citizen scientists, the roles of data collectors (“Trappers”) and classifiers (“Spotters”), the project web platform’s online infrastructure, and the data outputs from this process. The relationship between these project components is visualised in **Figure 2.1**. This section concludes with a description of the quantitative analyses performed on participant engagement metrics to gauge impacts from intervention events and temporal patterns.

2.2.1 Initial recruitment

Since its inception, the MammalWeb project has relied on citizen scientists for two tasks, the capture and classification of camera trap photos. Each citizen scientist can participate in one or both roles, which are called Trapper and Spotter, respectively (**Figure 2.1**).

Our first recruitment drive for Trappers and Spotters was in May 2015 when we advertised MammalWeb to members of the Durham Wildlife Trust and the Durham University community. Within the University, we posted a call for citizen scientists through the internal Dialogue Signposts (<https://www.dur.ac.uk/dialogue/signposts/>) and Greenspace sustainability newsletters (<https://www.dur.ac.uk/greenspace/>). These newsletters should reach all with a University email address. In these postings, we noted that anyone could participate as a Trapper, Spotter, or both.

2.2.2 Trappers

At Durham University, we received 45 responses to the initial call for participants, the majority of which were staff members in non-academic roles. Email was the primary means of communication with this group. I trained the University-based citizen scientists through two engagement meetings in June 2015. During each meeting, I began with a presentation on the operation of camera traps and its application to ecological monitoring where I emphasised the importance of closely following the camera trapping protocol (see supplementary material section 2.5 below). Each Trapper could select their own monitoring sites if they followed the protocol. The training sessions always included hands on tutorials where all participants could try setting up a camera trap and ask questions. They were reminded that for MammalWeb, a camera trap deployment is defined as any recorded time period during which a Trapper set up a camera trap to take photos. This means even if there was no wildlife presence at a site and subsequently no photos were obtained, this still counted as a valid deployment. This is important because the absence of detection during a deployment is itself useful data (such as for estimating occupancy, e.g., MacKenzie et al. 2002), and the length of a deployment is a measure of survey effort. At the end of the meeting, each citizen scientist was lent a camera trap and the appropriate locking mechanism. The

cameras included 20 Browning Strikeforce BTC-5, 17 Reconyx HC500, two Reconyx HC600, two Little Acorn Ltl-5211A, two Scoutguard SG550V-31B, and two Bushnell NatureView Cam HD. Citizen scientists could also use any camera traps they own to participate. For those who couldn't attend the engagement meetings or responded after the original call, we met with each individually and provided the same training.

The Durham Wildlife Trust loaned camera traps to 49 of its members whose primary means of communication was also email. Thirty-three of those attended group training sessions held at the Durham Wildlife Trust office in their Rainton Meadows reserve. The rest were trained through individual visits. The training process was the same as that at Durham University as described above. The camera traps loaned by the Durham Wildlife Trust include Bushnell Nature View, Bushnell Nature View Live, Bushnell HD Trophy, Ltl Acorn (Ltl 6310 MC), and Minox DTC-650. The MammalWeb project proved popular, and there was a waiting list for camera traps from the Durham Wildlife Trust during the two years examined in this chapter.

In addition to email, communication to citizen scientists was done through social media platforms including Twitter ([@MammalWeb](https://www.twitter.com/@MammalWeb) on <https://www.twitter.com/>) and Facebook (<https://www.facebook.com/MammalWeb>).

From email communications with the Trappers, we learned that once they have identified a deployment site, it was best to first set up the camera trap for just a few days and check it. If the photos obtained were level and taken at the desired angle, then the camera trap would be deployed for a longer time, usually up to a month.

At the end of each deployment, we asked Trappers to upload their camera trap photos to the MammalWeb website. Each registered Trapper on MammalWeb has access to a dedicated page where they could define camera trapping sites and upload photos (**Figure 2.2**).

Camera sites

Site Name	OS grid reference	Habitat	Purpose of Study	Camera Type	Can you/the camera see water?	Camera Height (cm)	Notes	Photos uploaded	Upload	Edit
SBBS Little High Wood	NZ 27602 41279	woodland - low density forest less than 60% canopy cover	Private use	Reconyx HC500	No water	65		770	Upload	Edit
Ustinov woods	NZ 26918 40527	woodland - low density forest less than 60% canopy cover	Private use	Reconyx HC500	No water	65		4113	Upload	Edit
near Josephine Butler allotment	NZ 27213 40283	woodland - low density forest less than 60% canopy cover	Private use	Reconyx HC500	No water	65		642	Upload	Edit
woods near my house	NZ 08 37	grassland - dominated by grasses	Private use	Reconyx HC500	No water	65	camera trap number 16	0	Upload	Edit
Durham Botanic Garden stream	NZ 2728 4072	woodland - low density forest less than 60% canopy cover	Private use	Reconyx HC500	No water	50		894	Upload	Edit
Rainton meadows 1	NZ 3259 4865	forest - high density forest more than 60% canopy cover	Private use	Reconyx HC500	No water	50	Camera trap 3	702	Upload	Edit
Rainton meadows 2	NZ 3262 4862	forest - high density forest more than 60% canopy cover	Private use	Reconyx HC500	No water	40	Camera trap 2	276	Upload	Edit
[New site]	NZ 2761 4147	woodland - low density forest less than 60% canopy cover	Private use		No water	30	camera trap 3	0	Upload	Edit

[+ Add site](#)

Figure 2.2. MammalWeb Trapper page for citizen scientists to define camera trap sites and upload photos.

When reaching this page for the first time, a registered MammalWeb Trapper would see an empty table. Their task when preparing photos to upload would be defining a camera trap site with the following attributes:

- Site Name – This is a unique name for the Trapper’s record and to distinguish it from others.
- OS grid reference – The user can use an embedded Google Maps view (reachable by clicking on the red pin icon) to specify the location of their camera trap at this site. It is recorded as an eight-digit United Kingdom Ordnance Survey Grid Reference. Alternatively, there is a text box with which the user can manually enter the grid reference at up to ten-digit resolution.
- Habitat – A list of habitat types for the Trapper to choose from. This refers to the camera trap’s immediate surroundings within 10 m. See **Table 2.1** for the list, accompanying definitions shown to users, and corresponding habitat types in other classification systems.
- Purpose of Study – This list includes “private use” (which applies to MammalWeb citizen scientists) or “part of scientific study”. The latter option is for cases where other camera trapping research projects wish to contribute to MammalWeb.
- Camera Type – For specifying the brand and model of the camera trap(s) used at this site. This list is occasionally updated when participants use camera traps that are not already on it.

- Can you/the camera see water? – This is for the Trapper to indicate whether a permanent body of water (stream, river, pond, or ocean) is visible in the camera trap’s field of view.
- Camera Height (cm) – Distance between the camera trap and the ground.
- Notes – Any additional notes by the Trapper.

Once defined, each site will be shown as a row in the Trapper page table.

Table 2.1. MammalWeb habitat types and corresponding types in other classification systems.

Habitat	Definition	LCM 2007 classes	LUCS categories	BTO Breeding Bird Survey
forest	High density forest >60% canopy cover.	Broadleaved woodland; Coniferous Woodland	Forestry and woodland	Woodland
woodland	Low density forest <60% canopy cover.	Broadleaved woodland; Coniferous Woodland	Forestry and woodland	Woodland
scrubland	Dominated by shrubs, i.e. small to medium woody plants <8 m high.	Heather	Rough grassland and bracken; Natural and semi-natural land	Scrubland
heath	A kind of scrubland characterised by open, low-growing woody plants < 2 m high.	Heather; Heather grassland	Rough grassland and bracken; Natural and semi-natural land	Heathland and bogs
grassland	Dominated by grasses.	Improved grassland; Rough grassland; Neutral grassland; Calcareous grassland	Rough grassland and bracken; Natural and semi-natural land	Semi-natural grassland/Marsh
marsh	A wetland dominated by herbaceous, i.e. non-woody plants.	Fen, Marsh and Swamp	Natural and semi-natural land	Semi-natural grassland/Marsh
bog	A wetland with few/no trees, some shrubs, with lots of peat accumulation.	Bog	Natural and semi-natural land	Heathland and bogs

Habitat	Definition	LCM 2007 classes	LUCS categories	BTO Breeding Bird Survey
swamp	A forested wetland.	Fen, Marsh and Swamp	Natural and semi-natural land	Semi-natural grassland/Marsh
rocky	Lots of bare rocks with little vegetation.	Inland rock	Natural and semi-natural land	Inland rock
coastal	Right on the coast, beach.	Salt water; Supra-littoral rock; Supra-littoral sediment; Littoral rock; Saltmarsh	Natural and semi-natural land; Water	Coastal
riverbank	Right on the riverbank.	Freshwater	Natural and semi-natural land; Water	Waterbodies
farmland	Pasture, etc.	Arable and horticulture	Agricultural land	Farmland
garden	Like a backyard garden, probably right next to a residence.	Urban; Suburban	Residential	Human sites
park	Recreational place.	Urban; Suburban	Leisure and recreational buildings	Human sites
residential	Houses, apartments, etc.	Urban; Suburban	Residential	Human sites
commercial	Stores and offices.	Urban; Suburban	Offices	Human sites
industrial	Factories and warehouses.	Urban; Suburban	Industry	Human sites

After a camera trap deployment, a MammalWeb Trapper will upload photos from the camera trap by clicking on the “Upload” button corresponding to the site of the deployment. This button takes the user to a page where they must enter the start and end timestamps of the deployment. These timestamps represent when the camera trap was set up and taken down, and are not for when the first and last images were taken. After entering the deployment time period, the Trapper can then upload the camera trap photos. Since the deployment time is a critical measure of sampling effort, the upload mechanism checks the timestamps of the uploaded photos fall within the deployment period. Photos taken outside of that time (if any) are rejected and would require manual review. After uploading photos, the corresponding entry for that site will display the number of photos uploaded for it thus far.

Approximately once every hour, the MammalWeb system will process new uploads and group photos into sequences. For MammalWeb, sequences are defined as photos with timestamps within 10 seconds of each other. Typically, this means that photos taken with a camera traps burst mode will fall within the same sequence. When registered users classify – or “Spot” – MammalWeb photos, they are shown an image sequence, by default, randomly drawn from the global pool, and are encourage to classify an entire sequence before moving to another. We believe that this design is of convenience to users since adjacent images within the same sequence may provide contextual information which aids classification.

2.2.3 Spotters

MammalWeb citizen scientists can also be Spotters by classifying the wildlife depicted in contributed camera trap images. Anyone with Internet access can register to be a Spotter, and don't have to be respondents to the initial call for participants.

After logging in, the user is presented with basic statistics on the total number of photos on MammalWeb, the number which the user has classified, number of animals classified, and the number of species they represent. Before proceeding, if the user has uploaded photos, they can choose to classify those first.

The MammalWeb Spotter page (**Figure 2.3**) is dominated by a camera trap image sequence randomly selected from the global pool or, if specified when logging in, the user's uploaded photos. This photo is always part of a sequence which the Spotter can move through with the navigation buttons (“Start”, “Previous”, “Next”, and “Next sequence”) above it (**Figure 2.3**). As of April 2018, in response to Spotter feedback, the interface has been updated such that arrows for moving backwards and forwards through a photo sequence are located on the two sides of an image, and the user only needs to provide a classification for the entire sequence rather than its individual constituent photos.

What do you see?

You uploaded this!

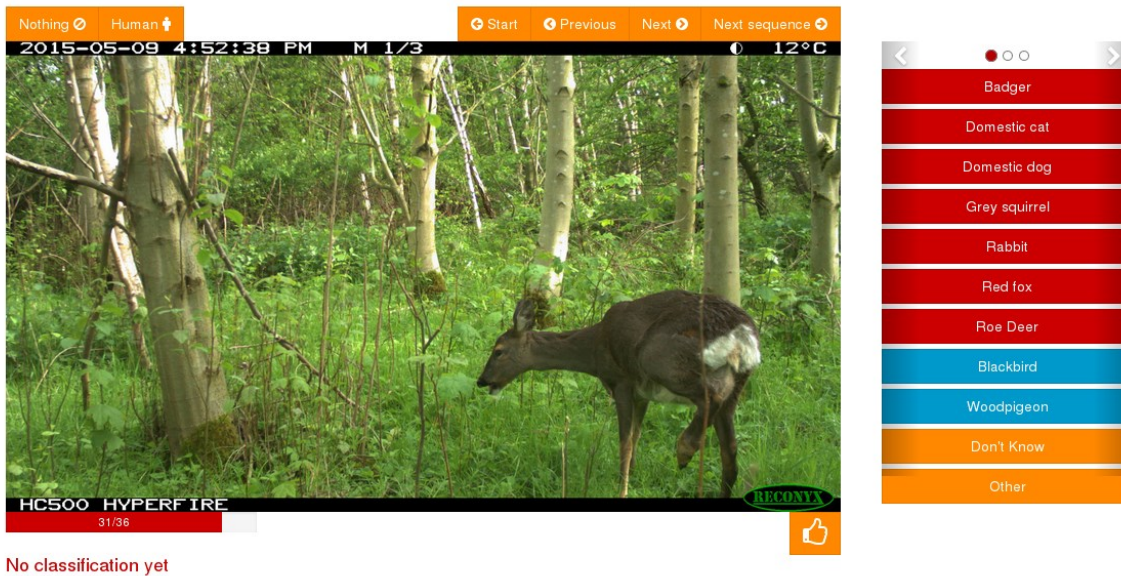


Figure 2.3. MammalWeb Spotter page for classifying camera trap photo sequences.

On the right is a three-page list of species the Spotter can choose from. For MammalWeb, a “species” could mean an individual species, a general group named “small rodent”, or “Don’t Know” and “Other”. Once the Spotter has identified the animal(s) depicted in the photo, they would click on the corresponding button in this list. This will open a popup window with example photos and a brief description of the animal. In this window, the Spotter will then specify the number of individuals of the species that are present, and their sex and age (juvenile or adult). Note that for cases where there is more than one “combination” of sexes and ages of the same species in a photo, the Spotter will need to classify them separately. For example, if there is one adult female roe deer and two juvenile roe deer in a photo, the user needs to click on the “Roe Deer” button twice: Once to specify one “Adult” “Female”, and the other to indicate two “Juvenile[s]” with “Unknown” sex. All animals currently classified for the image are listed on the bottom of the page.

Once a Spotter has classified all animals in an image, they can click on “Next” to move to the next photo in the sequence. Because the photos in a sequence are taken closely together, the list of animals classified in one image will carry over to the next. This way, if there are no changes in the composition of photos, the Spotter can simply click on “Next” again until they reach the end of the sequence.

The presence of the “Next” and “Previous” buttons allows Spotters to rapidly move back and forth through a sequence. While an individual photo may be difficult to classify (due to, for example, motion blur or only part of an animal being visible), contextual information provided by adjacent photos can aid classification.

At any point, the user can click on “Next sequence” to classify camera trap photos from another sequence. While this can be done even before all images in the current sequence are fully classified, we encourage Spotters to complete a sequence before moving to another.

Photo sequences with classifications are not removed from the global pool and will be presented again to other Spotters. This way, we can accumulate multiple classifications per photo (and sequence) from which to calculate consensus classifications as described in the next chapter. On 7 December 2018, MammalWeb was updated so that sequences without any classifications are prioritised for classification.

There are two additional buttons with a different behaviour: “Nothing” and “Human”. If a photo is “blank” and contains no wildlife, the Spotter can click on “Nothing” to classify it as such. This immediately takes the user to the next photo in the sequence without needing to click “Next”, but the “Nothing” classification will not carry over as with the other species. The “Human” button behaves the same way, except photos classified as “Human” will be taken out of the global pool of images so that they will not be displayed again for privacy.

2.2.4 Ongoing recruitment

MammalWeb was promoted several times during the span of the project. This included academic conferences such as the annual meetings of the British Ecological Society, the Ecological Society of America, the Society of Conservation Biology, the European Citizen Science Association, or the Ecological Society of Germany, Austria, and Switzerland. Non-academic outreach events included activities at local events – Belmont Community Fair and Celebrate Science – in March 2016 and October 2017 designed by school students with support from a British Ecological Society Outreach Grant. MammalWeb also had a dedicated tent for outreach during the June 2016 Glastonbury music festival in Somerset, England.

During the period covered in this chapter, we held two competitions to stimulate Spotter engagement. In April-May 2017, we held a competition for the most photos classified that month and best photo uploaded where winners received camera traps. The second competition was in November 2018, where each classification counted as one entry in a prize draw for vouchers redeemable on the online retailer Amazon.

The project was also promoted through social media during this time, and we disseminated printed flyers to local schools and wildlife groups. From these efforts, the number of MammalWeb Spotters continued to grow. And when we were contacted by prospective MammalWeb Trappers, we would train them individually. After the initial recruitment period, we also partnered with a local school in north-east England to not only involve students as Trappers and Spotters, but also as ecological ambassadors to their

community as a way to take citizen science engagement to the higher, “collaborative science” level as postulated by Haklay (2013). This will be discussed in Chapter 5.

2.2.5 Online infrastructure

The online infrastructure of the MammalWeb project is hosted on Amazon Web Services (AWS) (**Figure 2.1**). The primary user-facing frontend at <http://www.MammalWeb.org/> was built on top of the open source Joomla! 3.4.5 (The Joomla Project Team 2015) content management system (CMS), and includes the Trapper and Spotter pages previously described. This is run from on instance of the AWS Elastic Compute Cloud (EC2) (<https://aws.amazon.com/ec2/>). Photos uploaded through the Trapper page are stored in an AWS Elastic Block Store (EBS) (<https://aws.amazon.com/ebs/>) filesystem attached to the EC2 instance. All data, including photo metadata, user information, camera trap sites, deployment information, and photo classifications are stored in a MySQL 5.6 database (MySQL AB et al. 2015) (**Figure 2.4**) running on the AWS Relational Database Service (RDS) (<https://aws.amazon.com/rds/>) and administered with phpMyAdmin 4.0.10.20 (The phpMyAdmin Project 2015).

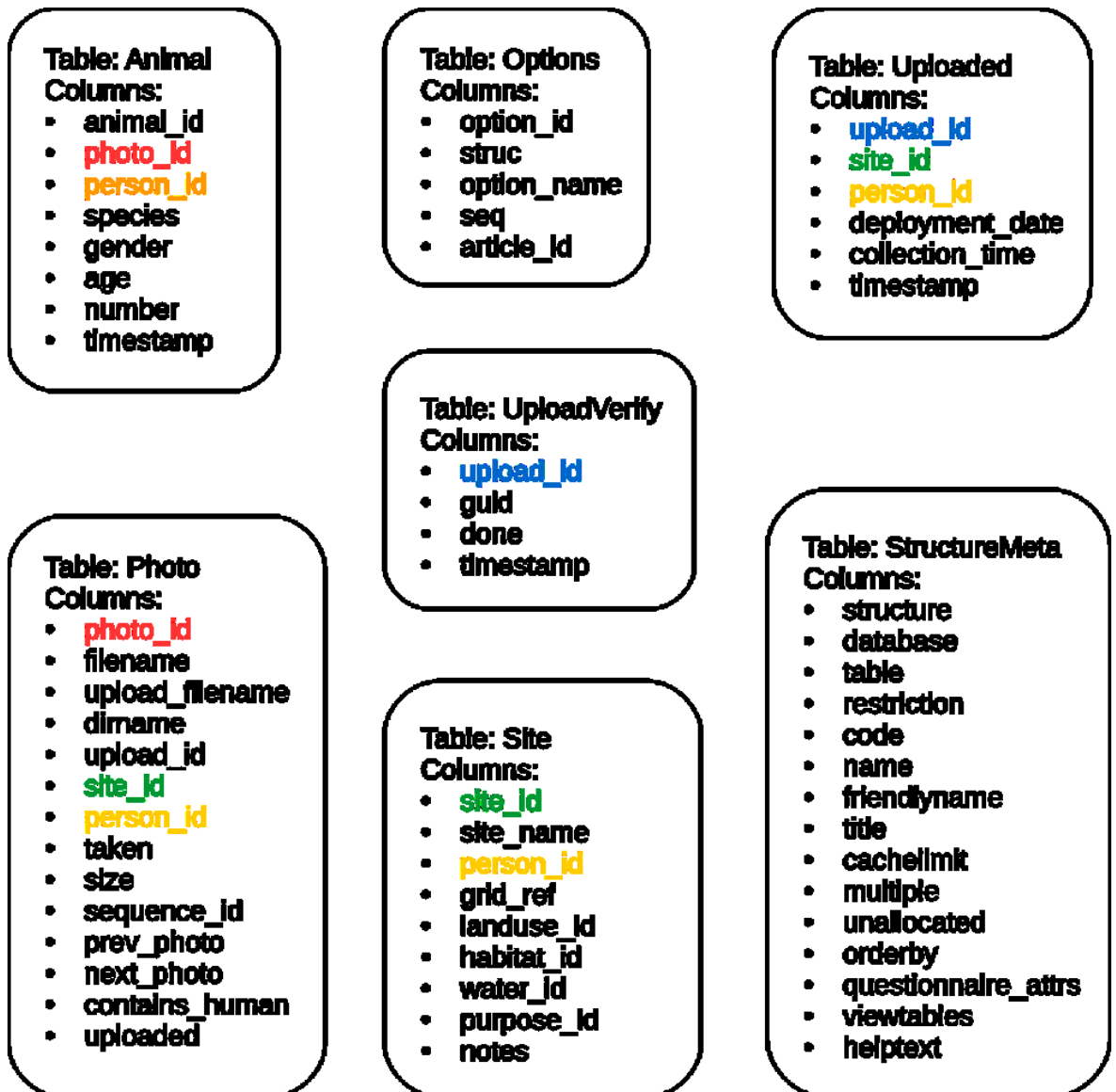


Figure 2.4. Primary tables in the MammalWeb MySQL database. Coloured columns are those shared by more than one table. The “Options” table stores values that other tables and the website interface can choose from, such as the list of species on the Spotter page, or list of habitat types on the Trapper photo upload page.

When a MammalWeb Trapper uploads camera trap photos to a defined site, the timestamps of when the photos were taken (“taken” in the database Photo table, **Figure 2.4**) are recorded in the database and associated with the photos. There are mechanisms to check that each uploaded file is indeed an image, and each photo is renamed to its checksum (e.g. c09038f027c64e1eb744dc6d37964734.jpg) in addition to being assigned a unique photo ID and sequence ID (“photo_id” and “sequence_id” in the database). A checksum is a piece of data (in this case, an alphanumeric string of characters) computationally derived from a file to uniquely identify it. With checksums acting as “fingerprints” for each image, duplicate uploads can be identified and prevented. A sequence is defined in MammalWeb as all photos taken within 10 seconds of each other. This was designed as a convenience for Spotters, so that by viewing images taken together, contextual information (such as the movement of an animal between images in the sequence) will aid classification.

When classifying photo sequences, the Spotter page pulls photos from the global pool which are stored on the EBS filesystem (a Spotter can also choose to classify their own photos first). Metadata collected with each classification from the Spotter page, including species, sex, age, and number of individuals (“species”, “gender”, “age”, “number”, and “timestamp” in the database) are stored in the MySQL database.

2.2.6 Analyses and data archiving

2.2.6.1 *Analysing citizen science engagement*

As described above, we have been promoting the MammalWeb project through various channels since launch. To understand the impacts of these “intervention” events on citizen science engagement, I collated the history of MammalWeb interventions of the following types: blog posts, competitions, events (such as outreach events or festival presences), news coverage, email newsletters, and public talks. For each intervention, I derived three engagement metrics from the MammalWeb MySQL database – the number of new users registered, number of active Spotters, and the median number of sequence classifications per Spotter (all three are per day) – for a period spanning from five days before to five days after the intervention. I then calculated the proportional change in these metrics before and after each intervention. This was based on the mean of the classifications metric and sums of the two Spotter metrics across the five-day before and after periods. For example, if the mean of the median daily classifications per Spotter was 4 before and 6 after an intervention, then the proportional change would be $6 \div 4 = 1.5$. Therefore, each intervention event would have one set of corresponding proportional changes in the three metrics. Of the interventions, the two competitions in 2017 and 2018 lasted more than a day, and their start times were used for the purpose of this analysis. I also created a group of 10 non-intervention events randomly selected such that their before and after periods would not overlap with any other intervention. Proportional changes in the three metrics were also calculated for this group. For each group (all interventions and the non-interventions group, total seven groups), I performed a one-sample Wilcoxon signed rank test with a null hypothesis of the data being centred around 1.0 (i.e., no proportional change before and after an event).

The two competitions we held (from 1 April to 15 May 2017, and from 12 to 26 November 2018) were substantially longer than other interventions, none of which lasted more than a day. Therefore, I conducted a separate analysis using the raw, daily values of the three metrics group into those from during the competition and the periods five-days and before the competition. The length of the before and after periods were chosen to minimise possible overlap with effects from other interventions. Here, I performed pair-wise tw-

sample Wilcoxon signed rank tests (null hypothesis of no difference) between the three groups of data to explore possible changes in engagement resulting from the competitions.

The final quantitative analysis was an exploration of temporal patterns in the three engagement metrics. This was done by grouping them into weekend and weekday categories where they were also compared with the two-sample Wilcoxon signed rank test (null hypothesis of no difference).

In addition to the above, and because email has been the primary form of communication because us and MammalWeb citizen scientists, I qualitatively reviewed the history of our email correspondence. I will characterise the primary types of these email exchanges and extract practical lessons learned on the broader impact of MammalWeb and considerations for running citizen science projects in general.

2.2.6.2 Gold standard and consensus classifications

Each camera trap photo (except those with humans) in MammalWeb's global pool are shown to multiple Spotters for classification. This acts as a voting system from which we can calculate consensus classifications on a sequence level. Once a confident consensus has been reached for a sequence, all of its constituent photos could be retired from the pool so that Spotter effort can be focused on those needing more classifications. The potential benefits of implementing this retirement scheme is discussed in the next chapter.

To determine what constitutes sufficient confidence in consensus classifications, we require expert classifications in addition to those by the citizen scientists. We did this through a combination of classifying photos as Spotters on MammalWeb and classifying photos downloaded manually. Photo sequences with consensus classifications that have confidence levels above a set threshold (e.g., 99%) can then be considered individual (though not necessarily independent, as discussed in Chapter 5) observations of wildlife. This is the set of data used for downstream analyses and archiving in public data repositories (see Chapter 3).

2.2.6.3 Data archiving and accessibility

All camera trap photos on MammalWeb are shared under the Creative Commons Attribution-ShareAlike 4.0 license (<https://creativecommons.org/licenses/by-sa/4.0/>). Chapter 3 describes the data that has been submitted to online repositories, which includes the UK's Environmental Records Information Centre (ERIC) North East (<http://www.ericnortheast.org.uk/home.html>) and the Open Science Framework (OSF; <https://osf.io/>).

2.3 Results

Since its inception in May 2015, MammalWeb has involved community members in north east England in monitoring local wildlife. This section describes measures of the project's growth and performance in terms of engagement with citizen scientists based on data as of 31 December 2018. I will also present analyses of impacts from intervention events on three of those metrics: the daily median number of sequence classifications per Spotter, the number of new users registered, and number of active Spotters. Possible temporal patterns were also examined, namely weekend versus weekday differences in the three metrics. Ecologically meaningful measures are based on consensus classifications, which will be addressed in Chapters 3 and 5.

2.3.1 Project growth

There were 489 active users registered on the MammalWeb website as of the end of 31 December 2018, of which 101 were Trappers who had uploaded camera trap images at least once (**Figure 2.5**). Most Trappers (>50) registered during the first six months of the project. While user growth has slowed since 2016, it has been steady including a major uptick in late 2018 comprised mainly of new Spotters. This uptick was concurrent with the second competition held among MammalWeb participants.

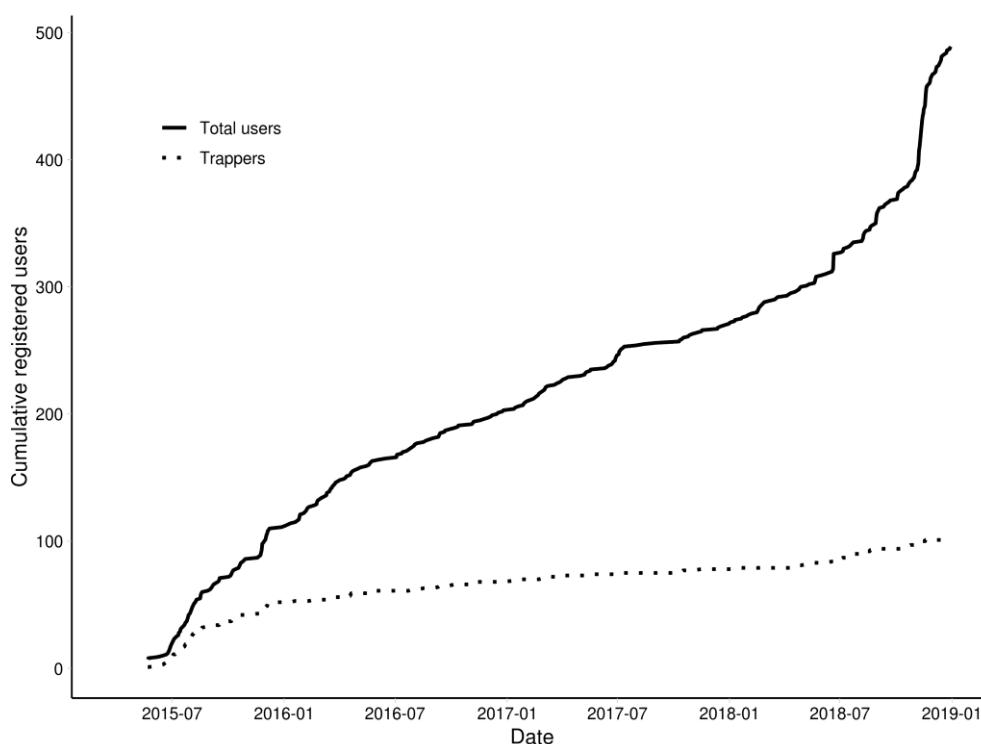


Figure 2.5. Registered MammalWeb users over time. Solid line is total number of users (Spotters and Trappers), dashed line is number of Trappers.

MammalWeb Trappers have uploaded 98,318 photo sequences of which 83,755 have been classified at least once (**Figure 2.6**). The growth in sequences has been largely steady

throughout the project. This is matched by the growth in the number of sequences that have been classified at least once, which is steady at about 70% (**Figure 2.7**). The large swings in the proportion of classified photos before 2016 is likely due to the relative dearth of photos in the system at that time.

Of note are two large step increases in the number of sequences uploaded (and associated decrease in proportion classified) in July and November 2018. The first was a contribution of images of the Highland Red Squirrel Project by the University of the Highlands and Islands based in Scotland, and the second was due to the incorporation of images from a systematic camera trap survey of County Durham conducted by us during the summer of 2018.

The proportion of sequences classified increased sharply at the end of 2018. This coincided with an upgrade of the MammalWeb backend infrastructure (on 7 December 2018) where sequences that have not received any classifications are now prioritised for Spotters.

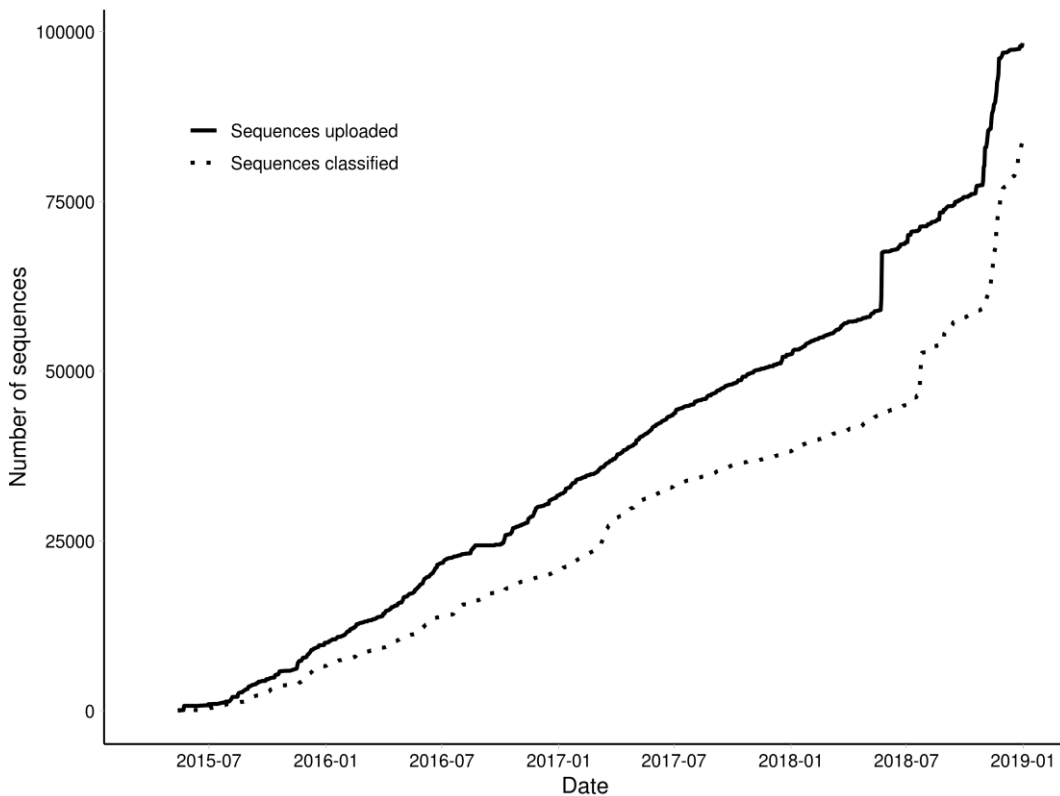


Figure 2.6. Photo sequences in the MammalWeb database by time. Solid line is number of contributed sequences, dotted line is the number that has been classified (Spotted) at least once.

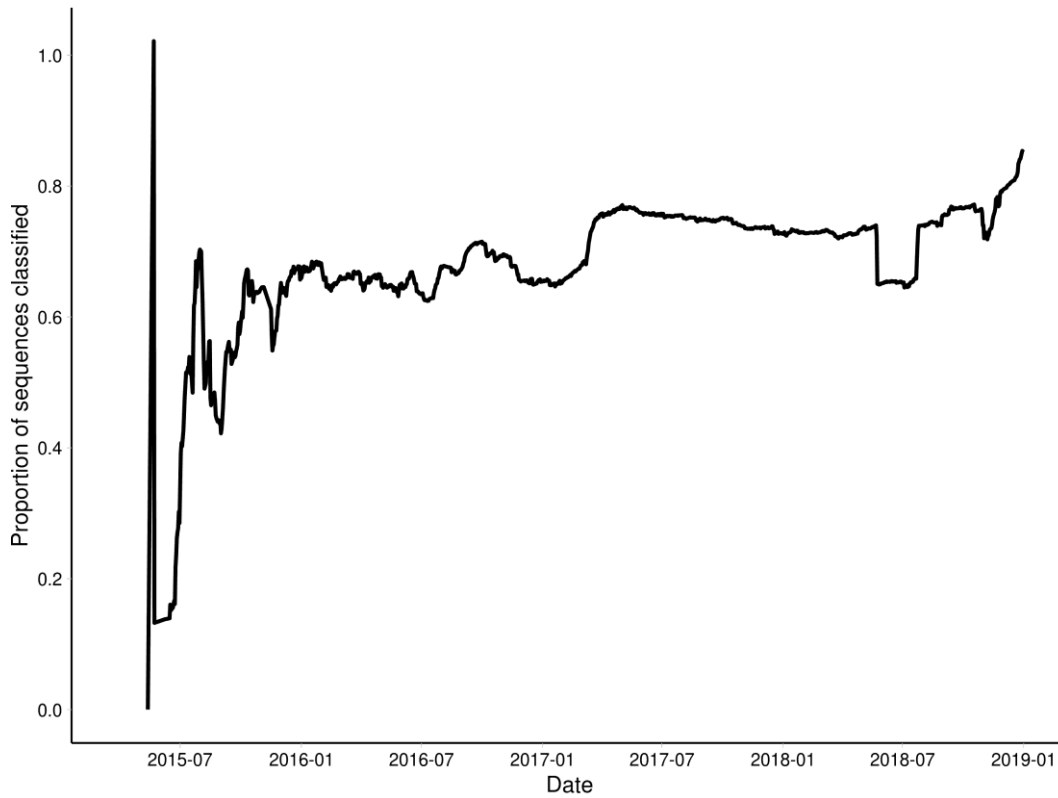


Figure 2.7. Proportion of MammalWeb sequences that have been classified (Spotted) at least once.

Since inception, the 101 MammalWeb Trappers have deployed camera traps at 427 sites (**Figure 2.8**). They are primarily in north east England, but also include relatively distant locations from south-west England to northern Scotland. These deployments have accumulated 23,778 days of observations, which on average produced 4.13 sequences per day.

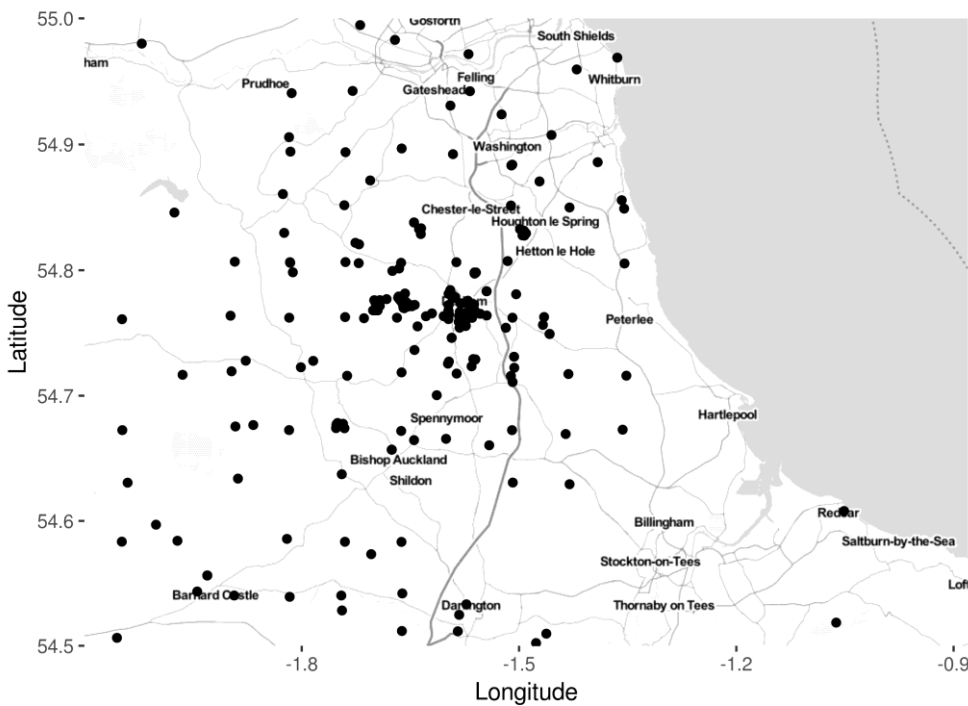


Figure 2.8. Most MammalWeb camera trap sites (black dots) are near County Durham, England.

2.3.2 Spotter efficiency

Of the 83,755 camera trap photo sequences on MammalWeb with at least one classification, the median number of classifications is 1 (mean: 1.99; interquartile range: 1-2; maximum: 35). Notably, 75.8% of classified sequences (63,505 sequences) have two or less classifications (**Figure 2.9**).

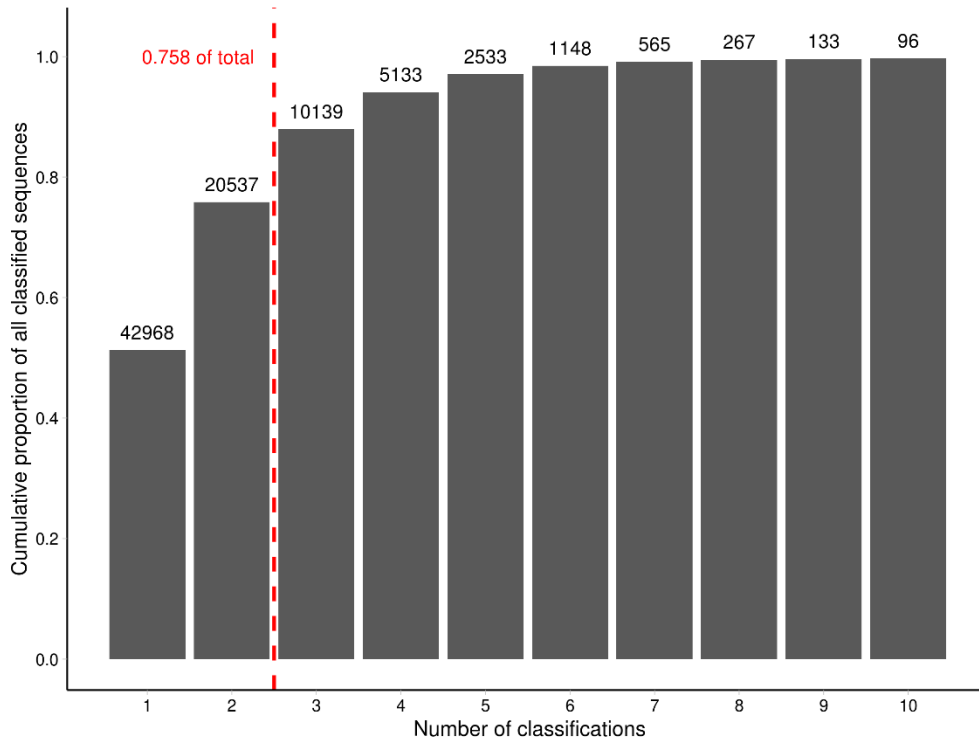


Figure 2.9. Cumulative proportions of all photo sequences that have been classified a certain number of times or less. The number over each bar is the number of sequence which have been classified that many times. Red vertical dashed line indicates that 75.8% of all classified sequences have been classified twice or less.

The majority of MammalWeb Spotters have contributed relatively few classifications while a small number have classified at a high intensity. This can be measured by the quantity and frequency of their contributions. Over half (69.6%) of registered Spotters have classified 100 or less sequences, while 7% have classified over 1000 (**Figure 2.10**). In terms of frequency, 83% have classified sequences on seven or less different days but a small but active minority (6%) have classified photos on 30 or more (**Figure 2.11**).

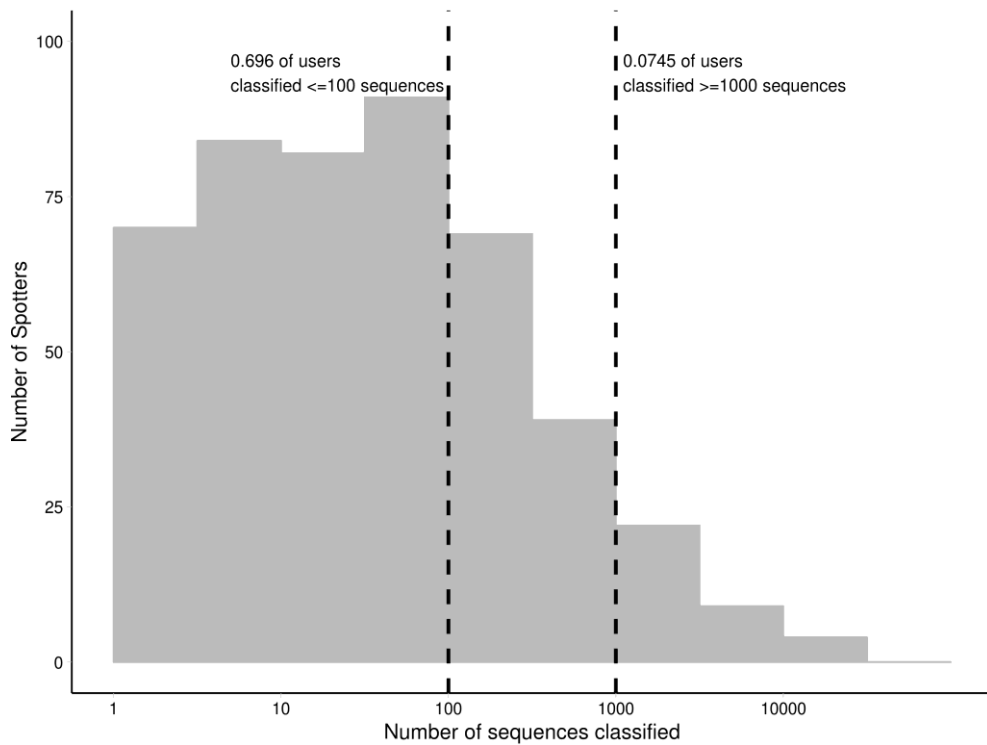


Figure 2.10. More than half (69.6%) of MammalWeb Spotters have classified <100 sequences while a minority (7.5%) have classified >1000.

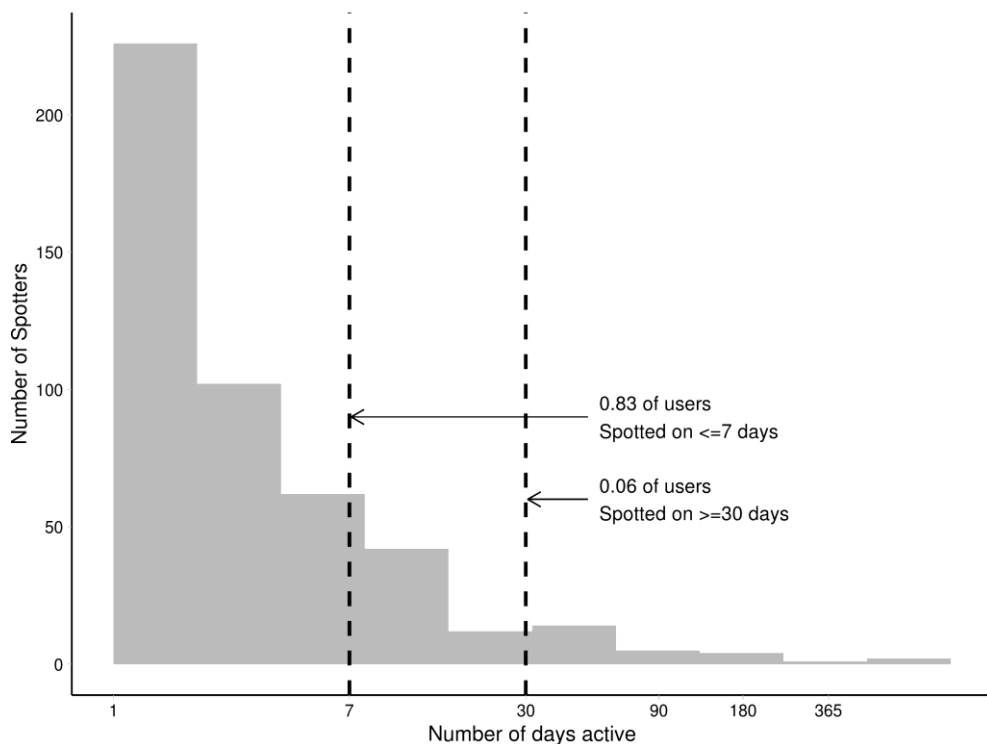


Figure 2.11. Most (83%) of Spotters have classified on <7 days, while 6% have classified on 30 or more.

From 2015 through 2018, the monthly number of Spotters who contributed classifications varied between 8 and 55, plus an exceptionally high number of 114 during November 2018 (**Figure 2.12**). Notably, the highest intensities (up to 147 classifications/day/Spotter in November 2016) occurred when relatively few Spotters logged in (November 2016 and September 2017).

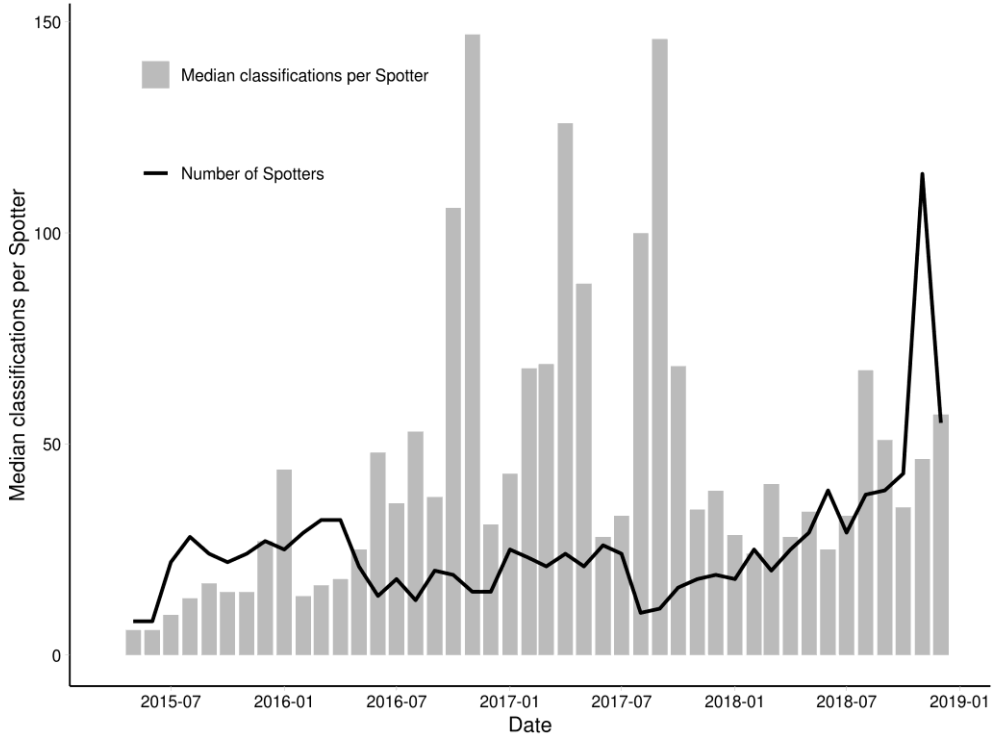


Figure 2.12. Monthly classification intensity (median classifications/day/user) and number of Spotters who classified each month (solid line).

2.3.3 Trapper efficiency

The median camera trap deployment duration is 2 days (mean 15.8 days). The monthly mean deployment duration varies between 3.2 and 18.9 days, appears to have decreased through 2017 but have since increased considerably (**Figure 2.13**).

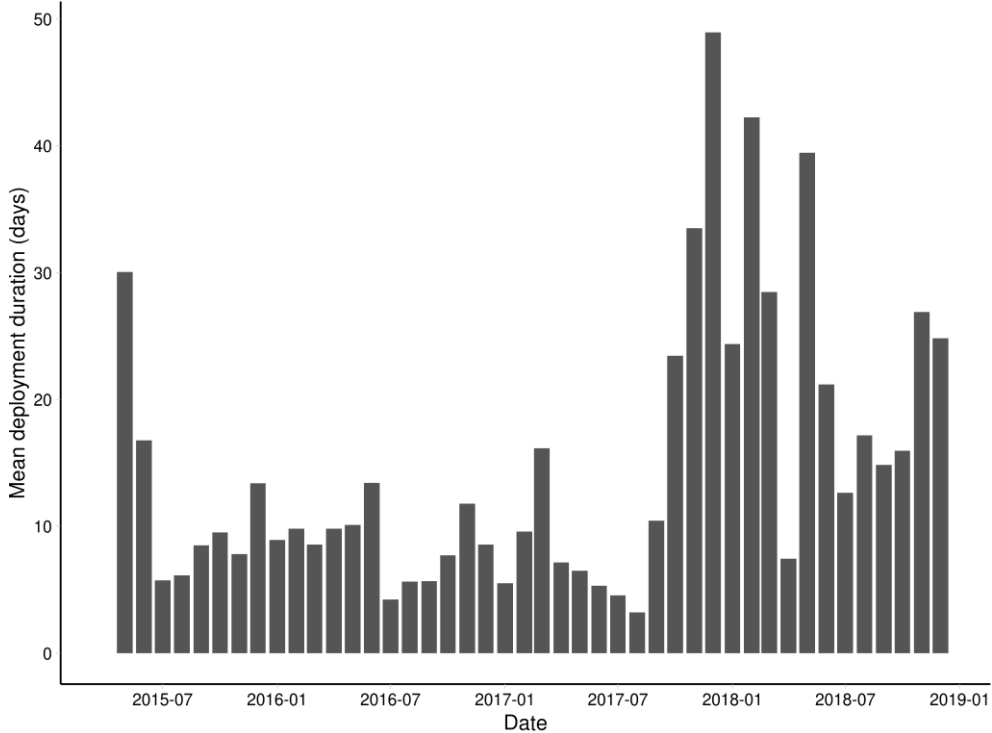


Figure 2.13. The monthly mean camera trap deployment durations for MammalWeb Trappers.

The number of Trappers who have uploaded photos decreased (**Figure 2.14**) from the peak of 23 in October 2015 to six in November 2017. This is matched by a small but overall decrease in the number of camera trapping sites from which they uploaded photos (**Figure 2.15**). However, the number of uploads per Trapper increased during the same period. These measures suggest that the number of monthly active Trappers has gone down, but those who remain upload photos more frequently even if their mean deployment durations are shorter. This trend has reversed since the beginning of 2018. The larger number of camera traps sites November 2018 was due to the upload of photos from our systematic survey across County Durham during the summer of that year.

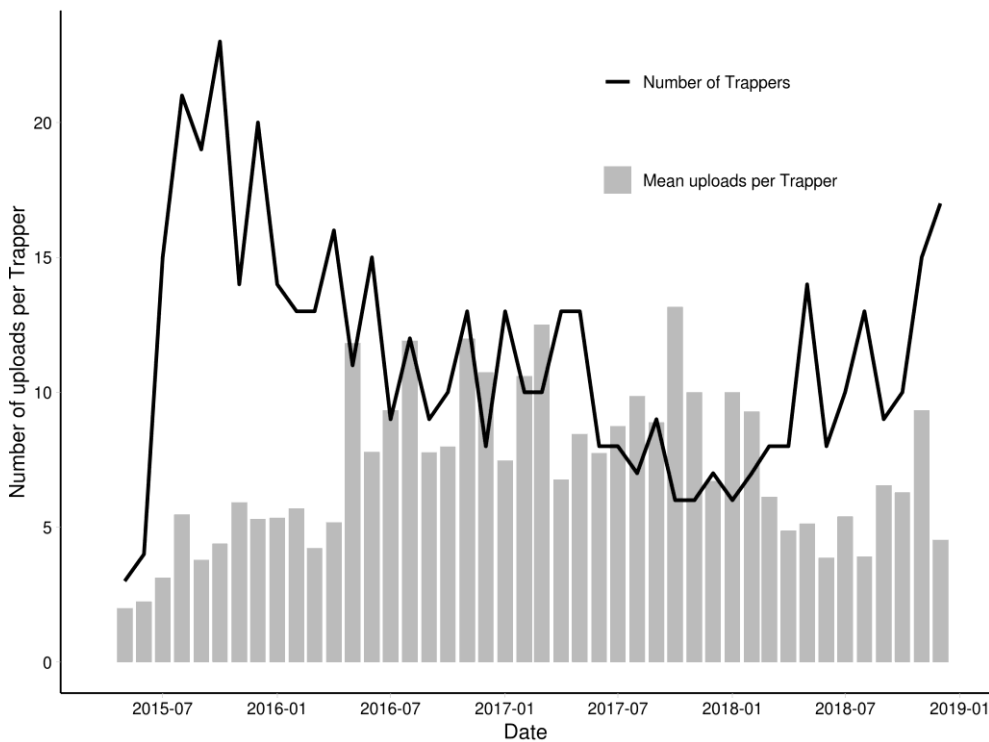


Figure 2.14. Monthly upload frequency per Trapper (uploads/month/user, grey bars) and number of Trappers who uploaded photos each month (solid line).

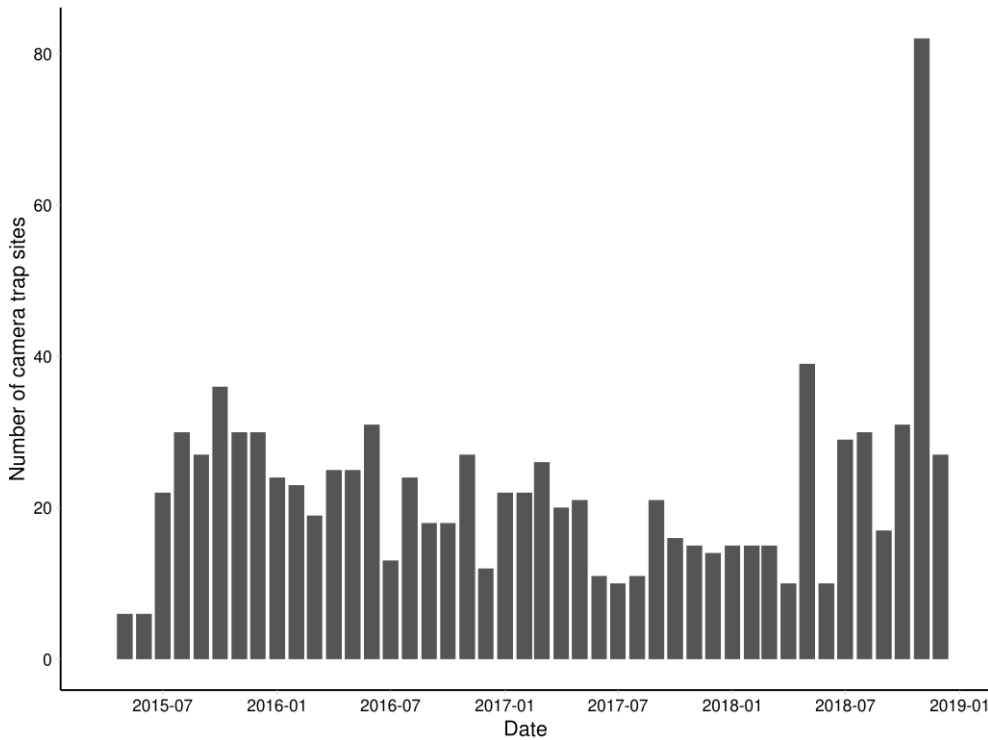


Figure 2.15. The monthly number of camera trapping sites monitored by Trappers over time. The large number of sites in November 2018 were from our systematic survey conducted earlier that year.

2.3.4 Effects of intervention events

For this analysis, I grouped MammalWeb intervention events since project launch until the end of 2018 into seven types (number of each type in parentheses): blog posts (8), competitions (2), public events (7), news coverage (7), email newsletters (10), and public talks (26). Data on the number of people reached for each intervention was not available. And as described, I added a non-intervention type of 10 randomly selected time periods which did not overlap with any other intervention event.

Relative to intervention events and regardless of their type, the random non-intervention group was consistently lower across all three engagement metrics (proportional change in the mean number of new users, number of active Spotters, and median number of classifications) (**Figure 2.16**). However, this difference was not statistically significant.

While the distribution of the three metrics were mostly above 1.0 for all intervention types, none of them were significantly so except the median number of classifications in response to blog posts ($p = 0.035$). Exceptionally, the median of the mean number of active Spotters was less than 1.0 in the news coverage group.

Also of note is that all types of interventions had a generally positive effect on the mean number of new users except for newsletters. The distribution of the other two metrics were more varied across intervention types and showed no clear pattern.

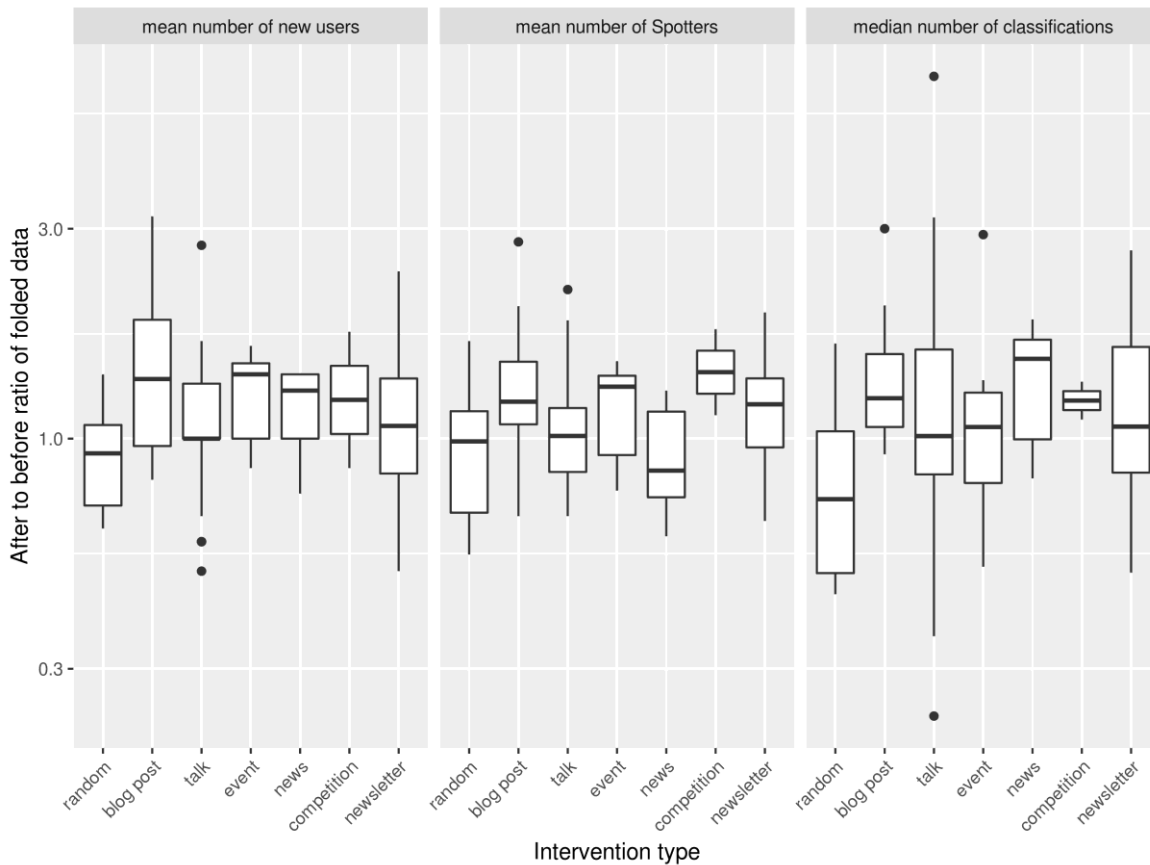


Figure 2.16. The distribution of three engagement metrics (before and after ratios of mean number of new users, mean number of active Spotters, and median number of classifications; data folded from daily values for five days before and five days after an intervention) from randomly selected time periods (which do not overlap with those of interventions) were consistently lower than that of intervention events regardless of type. None of the distributions were significantly different from 1.0 except median classifications in response to blog posts (one-sample Wilcoxon signed rank test, $p = 0.035$).

The number of active Spotters and their median number of classifications were visibly higher during the two competitions in 2017 and 2018 but not the number of new users (**Figure 2.17**). Of the pairwise comparisons between all groups, only the number of Spotters were significantly higher than before the beginning of the second competition ($p = 0.021$). Notably, the rate at which new users registered did not change and even decreased for the period immediately following competition two.

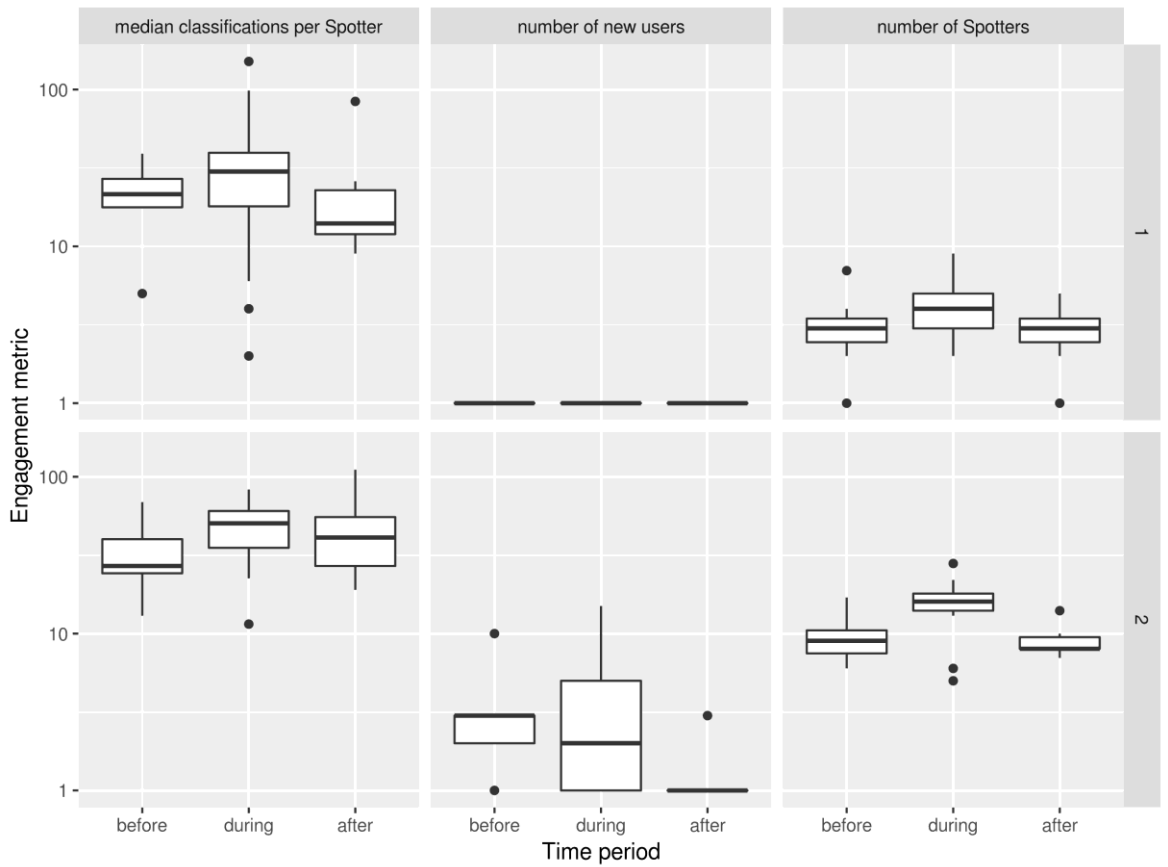


Figure 2.17. Engagement metrics increased significantly during competitions except the daily number of new users.

When these metrics were compared on weekdays versus weekends, the median number of classifications increased for weekend days ($p = 0.012$) (**Figure 2.18**). The other measures did not differ significantly in this case.

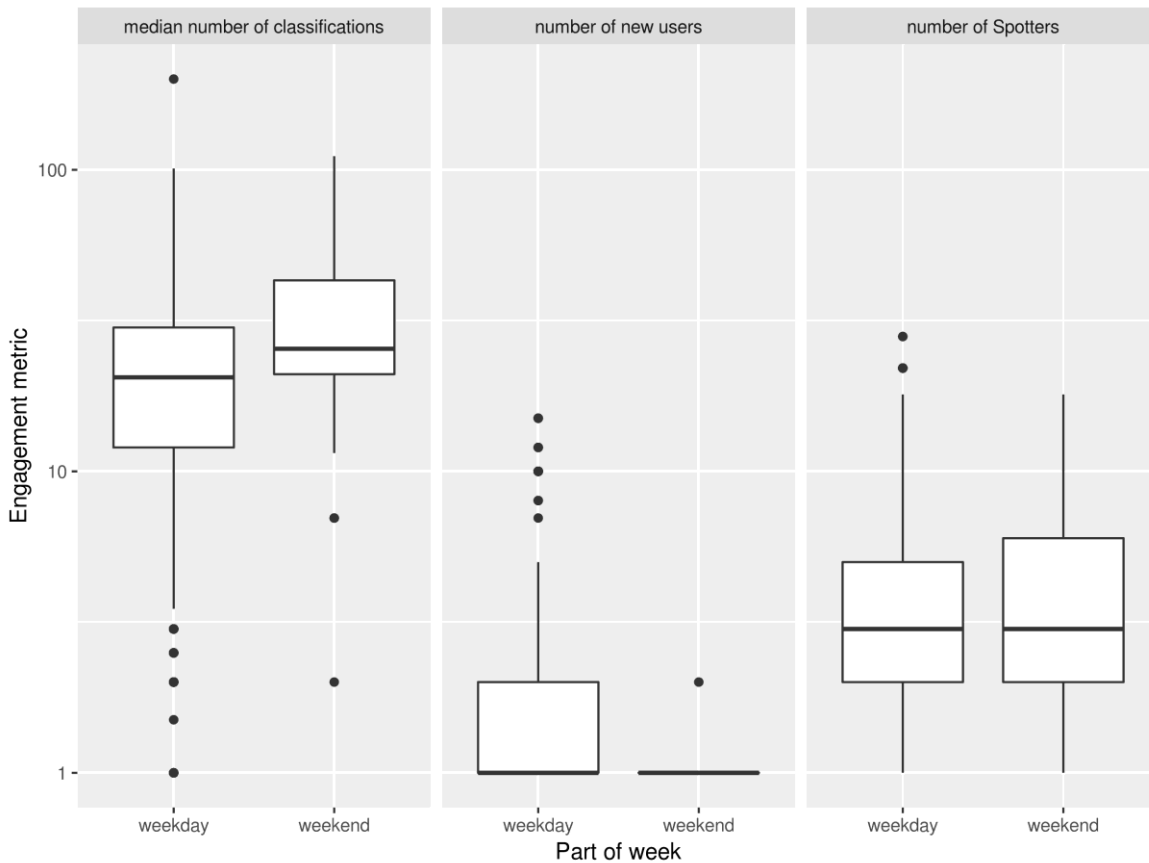


Figure 2.18. The volume of classifications increased during weekends (two-sample Wilcoxon signed rank test, $p = 0.012$), but not the number of new users or active Spotters.

2.3.5 Email interactions with citizen scientists

After recruiting citizen scientists, we maintain contact with them in ways from face-to-face engagement meetings, Twitter, Facebook, or email. Here I will focus on email correspondences as it has been the most consistent way in which we have communicated with participants, and they primarily consist of the following types.

First, a large volume of emails we receive were from those expressing interest in becoming MammalWeb Trappers or Spotters. This was especially true earlier during the project (2015 and 2016) when our social media presence was smaller. We were also contacted by school teachers (mostly from primary schools) who learned about MammalWeb through contacts with the Durham Wildlife Trust. An obvious gap in data revealed when reviewing these emails is that we did not explicitly record how each prospective citizen scientist heard about MammalWeb.

The second type of emails were feature requests for the MammalWeb website, and they were heavily focused on the Spotter page user experience. This feedback led directly to a more sequence-focused interface where buttons taking the user forwards and backwards through a sequence are placed directly on the sides of an image, and simplifying the process so that classifications apply to the entire sequence instead of its constituent photos.

The third group of correspondence was about technical issues, mostly centred around camera trapping. This could include questions on the specifics of deploying camera traps, such as clarifying the definition of a deployment, whether images depicting humans (or empty images) should be removed before upload, and other details. This process was important in refining the instructions we give to new Trapper during initial training. Existing Trappers also provide feedback on the online Trapper page user experience, such as a desire to more easily their camera trap deployment sites and manage the data and images associated with each upload. At this time, we have not had the resources to act on most of this feedback.

Lastly, we receive ad-hoc feedback from citizen scientists regarding notable or surprising observations and spin-off projects. For example, MammalWeb Trappers alerted us to the presence of non-native raccoons and coatis in north-east England, and with their help local authorities were able to track and capture those animals. We were also struck by citizen-initiated science such as independent camera trapping surveys for red squirrels in Galloway, Scotland and otters in Durham. In addition, we receive emails with general praise of the MammalWeb experience such as:

“...especially loved the squirrel fight and the fox’s in Deerness this year...”

Or, from a Spotter willing to be identified as Julia:

“Firstly, I can say what a delight and privilege I have found it; many of the species I have seen are normally so fleeting in the wild, and I have never so much as glimpsed a live badger. Ever. So these sometimes close-up, unguarded insights have been wonderful. Hard to choose favourites – perhaps the family groups of deer, or the stoats’ interactions. But, sadly, secondly, I really must apologise. Despite approaching the spotting conscientiously and armed with references, I very much fear to my embarrassment that I am guilty of misidentification of grey partridges on a number of occasions...”

Notably, no emails of complaint or negative feedback were received.

There were fewer emails outside of the above categories, but given the recent (late 2018) partnership with a local network of schools (described in Chapter 4), we now engage in considerably more email contact with teachers on how to integrate MammalWeb into the classroom.

2.4 Discussion

In this chapter, I described the process of launching and maintaining the MammalWeb citizen science project. In its current state, the organisation of the project and its online infrastructure achieves our aim of enabling citizen scientists to contribute and classify camera trap images of local wildlife. Because of this success, other UK-based wildlife organisations, including NatureSpy (<https://www.naturespy.org/>), Scottish Wildcat Action

(<http://www.scottishwildcataction.org/>), or the University of the Highlands and Islands (<https://www.uhi.ac.uk/>) have now partnered with us to expand this camera trapping network, which ties into our goal of large scale citizen science monitoring of wild mammals. In addition, as will be discussed in Chapter 4, we have successfully piloted a partnership with a local school. Students at Belmont Community School were not only involved as citizen scientists who deployed camera traps, but also empowered as ecological ambassadors who delivered outreach to their community. is now expanding into a wider network of schools mediated through the Great North Museum: Hancock in Newcastle (<https://greatnorthmuseum.org.uk/>). For the rest of this discussion, I will focus on the implications of the measures of project growth, the quantitative and qualitative analyses on engagement metrics, and a need to formally evaluate project outcomes.

2.4.1 Tracking project growth and sustainability

The MammalWeb citizen science project has experienced stable growth from 2015 through 2018 in terms of the number of photo sequences contributed by Trappers, and the number of sequences classified by Spotters. Our reach has expanded by the inclusion of other conservation projects such as the Highland Red Squirrels Project which corresponds with the increase in uploaded photos in autumn 2018. Recently, members of the MammalWeb team, through a partnership with the Great North Museum: Hancock in Newcastle, met with representatives from a network of 50 local schools. We are now actively building on our experience engaging one school (described in Chapter 4) and developing a partnership strategy with these schools. All of this will continue the growth of MammalWeb and aid in sustaining it. Effective monitoring requires a sustained effort, which in MammalWeb is analogous to maintaining a “minimum viable population” (MVP) of citizen scientists and investigating avenues for growth. However, despite the after-mentioned success, several challenges the sustainability of MammalWeb have become evident.

First, we are reliant on a core group of Trappers for camera trapping. These citizen scientists contribute photos to MammalWeb at a high intensity, but – at any given time – they deploy their cameras at a small number of sites, limiting the spatial and temporal coverage of the project’s monitoring effort. The implications of this for occupancy analysis will be discussed in Chapter 5.

A similar pattern can be seen in MammalWeb Spotters, where most classifications were contributed by a small group. And while the proportion of sequences with at least one classification has been stable and increased near the end of 2018, relatively few sequences have more than two classifications. This makes calculating consensus classifications, and the downstream analyses which rely on them, more difficult.

These observations are in line with what's observed in other citizen science projects (Sauermann and Franzoni 2015), but can be overcome with enhanced, sustained engagement. On the MammalWeb Spotter page, we have implemented a button to take the user back to the beginning of an image sequence. This simple change greatly eased navigation within a sequence, and was one of the most-requested features from user feedback. Other improvements to the Spotter page include an easier way to navigate between images within a sequence via left and right arrows on the currently shown image, and that the Spotter only needs to provide one classification for the whole sequence instead of for its constituent images individually (both implemented since April 2018). Another effective example was the MammalWeb competition in March-April 2017 for best uploaded photo and the most number of classifications by a Spotter. This likely led to the high monthly classification intensity (median 126 classifications/day/Spotter) during that time.

Since October 2016, we have partnered with the Smart Earth Network (<http://www.smartearthnetwork.com/>), a conservation non-profit organisation, and the web development firm Monterail (<https://www.monterail.com/>) to revamp the MammalWeb website with an improved user experience (UX) including interactive data visualisations. A new "Explore" page featuring an interactive map of MammalWeb-related camera traps and observations is now being tested. We hope this form of dynamic feedback can not only sustain motivation but also attract new participants.

2.4.2 Evaluating project performance

To track growth and maintain the sustainability of MammalWeb, there is a need to more formally study engagement metrics. In this chapter, I attempted this with the data available through the end of 2018.

For the three metrics used here (the number of new registered users, number of active Spotters, and median number of classifications), their proportional change before and after intervention events were – even if not statistically significant – visibly greater than 1.0 and considerably higher than that of randomly chosen periods outside of interventions. One limitation of this analysis is that the length of the before and after periods for an intervention (five days) was arbitrarily chosen. A separate analysis is needed to optimise the period length, which may also be a function of the type of intervention. Many interventions also overlap in time, and interactions between events and types of events will need to be modelled (as will be described below). The number of active Spotters and volume of classifications were visibly higher during the two competitions in 2017 and 2018. Strikingly, while the daily rate of new user registrations did not differ significantly from before and after competitions, the cumulative number of new Spotters increased considerably during the second competition.

With our current knowledge, I believe this is because the reach of MammalWeb communications (email, Twitter, and partner organisations) have grown greatly since the first competition. And while it was not statistically significant, classification rates were not maintained after the end of the competitions. To sustain engagement, we will need a better understanding of citizen scientists' motivations. Finally, higher volumes of classifications on weekends is reasonable given that users will likely have more disposable time to invest during days off. Future work should investigate temporal patterns on other levels, from diurnal to seasonal. A detailed understanding of these patterns will aid the timing of intervention events to maximise impact.

Email correspondence suggests that our interventions and outreach were at least partially successful in recruiting and motivating citizen scientists. In addition to the positive feedback, some participants actively provided suggestions on the user experience, and questions regarding the technicalities of camera trapping were valuable data on which we based improvements to the new Spotter and Trapper on-boarding process. Emails indicate that MammalWeb citizen scientists were engaged with their local environment in ways they previously would not have, and this is consistent with existing research on the need and benefits of such engagement in light of the “extinction of experience” in nature (Soga and Gaston 2016, Schuttler et al. 2018). However, shortcomings of how we manage communications were also revealed. First, we did not explicitly track how MammalWeb participants learned of the project and reached their level of engagement. We should, as part of a standard communications protocol, always ask for this information in all correspondence. Second, for most of the duration of the project, emails to us were often directed to our personal email accounts rather than the official MammalWeb email. As a result, it was exceedingly difficult for me to collate MammalWeb's email history for the current analysis. Starting in mid-2018, we have actively promoted MammalWeb's official lines of communication including the email info@mammalweb.org and the Twitter account [@MammalWeb](https://twitter.com/MammalWeb), and began sorting incoming email into several categories such as technical support, feedback, or school correspondence. Third, as could be seen in Julia's email, while they were positively impacted by the Spotting experience, there was concern about the accuracy of classifications. This highlights the importance of managing data quality (discussed in Chapter 3) and providing feedback to users in realtime to reinforce engagement. This feedback could take the form of automatically generated messages about accuracy and positive reinforcement, achieved through natural language generation algorithms (van der Wal et al. 2016). Finally, I noted a lack of specifically negative feedback or complaints received through email. I hypothesise that such sentiments may be present, but users are

more hesitant in actively communicating them. This is another reason for a more active approach to understanding our userbase through surveys or focus groups, as will be discussed later in this section.

The types of interventions examined in this chapter did not include MammalWeb's social media activity, such as that on Twitter. By the end of 2018, the [@MammalWeb](#) Twitter account has posted 907 Tweets which accumulated more than 1,000 likes from 523 followers. These Tweets were not included in the current analyses because they occurred on more than half of the days across MammalWeb's project lifetime and overlap greatly in time, therefore the before and after analysis performed on other types of interventions would not be practical. Rather than considering Tweets as "interventions", I believe Twitter and associated activities (from Tweets to re-Tweets, likes, or followers) can be considered as passive engagement based on outreach and dissemination of information.

Passive engagement takes on other forms such as visitors to the MammalWeb website (who may not register as users), newsletter readers or audiences at in-person outreach events and talks. Within the MammalWeb framework, I believe this is an intermediate level of engagement between interventions and scientific engagement, the latter being defined as the direct participation in citizen science. That is, many people engaged on this passive, intermediate level may be the recipient of outreach and stay informed on MammalWeb but not proceed to capturing or classifying photos. Therefore, there are two possible paths to citizen science from interventions to scientific engagement: Those who directly become Trappers or Spotters, or a subset of the passively engaged group who later decide to actively participate.

Even with the analyses described above, sustaining the growth of MammalWeb requires a more nuanced understanding of (1) how the two pathways to scientific engagement are related to interventions, (2) possible interaction effects between interventions in close temporal proximity, and (3) lag times between interventions and engagement metrics, which may be especially true for Trappers as there may be substantial time between a successful intervention and uploading photos. These understandings can be achieved through both quantitative and qualitative means.

Quantitatively, a modelling approach could be utilised in addition to the current method of deriving proportional changes in engagement data folded into those before and after interventions. For example, a generalised linear mixed effects model of the Poisson family can be fitted to engagement metrics such as the number of active Spotters. This model would include fixed effects such as the type of intervention (newsletter, talks, news coverage, etc.), week of day, or the total number of registered users at the time of intervention, and random

effects may be the intervention events and the dates on which they occurred. Importantly, generalised linear models can be used to discern interaction effects as well. In addition, more quantitative data should be gathered other than the three engagement metrics on which intervention impacts were examined. For interventions, useful data that can also be terms in this model may include the number of people reached and other measures of breadth of reach. In the future, we should also explicitly record related – that is, non-independent – interventions, such as blog posts and media coverage associated with a public talk. This information can then be a grouping variable included as an additional term in the model.

It will also be beneficial to implement web analytics for the MammalWeb website. Analytics software can be easily integrated with our existing IT infrastructure, and it records data such as the number of website impressions and even how “deep” a visitor explored the web platform. For example, analyses could be performed on the proportion of website visitors who browsed past the landing page and tried classifying photo sequences on the Spotter page. Privacy is of paramount importance, and proprietary services for web analytics such as Google Analytics need to be studiously avoided. Instead, a fully open source solution – inherently open to external scrutiny and under our control – such as Matomo (<https://matomo.org/>) or Open Web Analytics (<http://www.openwebanalytics.com/>) should be adopted. Social media analytics are also available for most platforms including those used by MammalWeb such as Twitter (<https://analytics.twitter.com/>) and others including Mastodon (<https://github.com/tootsuite/mastodon-api>).

For qualitative research, I believe there are two approaches which are applicable to MammalWeb and other citizen science projects. The more straightforward approach is the deployment of surveys to those (1) directly reached by intervention events, (2) engaged on the passive level (such as newsletter subscribers or Twitter followers), and (3) active Spotters or Trappers. At the first stage, the survey should assess changes in knowledge about MammalWeb and behaviour (such as interest in staying informed versus deciding to actively participate as a citizen scientist). Surveys on the second stage can track changes in engagement and act as reminders for those surveyed to participate. For Trappers and Spotters, we could learn about their motivations (which can inform the design of future interventions) and receive feedback on user experience. This is especially useful considering – as suggested by email correspondence – negative feedback is often not expressed unless specifically solicited. At all stages, surveys should ascertain how participants reached that level of engagement (e.g., “How did you hear about MammalWeb”, “Why did you follow us on Twitter?”, or “Why did you decide to become a Spotter?”). The second approach is organising focus groups and applying the Q methodology. This method has been used

extensively to measure stakeholders' beliefs and opinions on biodiversity conservation (Sandbrook et al. 2011, Rastogi et al. 2013, West et al. 2016, Hamadou et al. 2016). Q methodology is a qualitative technique for characterising patterns in subjective perspectives held by a group of interviewees on a given topic (Stephenson 1975). This is done by asking interviewees to sort a group of statements regarding a given topic, on a numbered grid, in order of how much they identify with each one. These rankings, called "Q sorts", are fed into a factor analysis (such as that implemented in the R package qmethod, Zabala 2014) which clusters the opinions into shared framings of the topic in question. This is a more intensive but comprehensive method for exploring the needs and motivations of MammalWeb citizen scientists, and may be especially important in understanding the temporal changes, with substantial lags after interventions, in Trapper activity such as that described in the results section. This method can also help explore the differences between the few, but very active "super users" who contribute at high intensity, and the majority of users who contribute relatively little. To my knowledge, Q methodology has not been used in a citizen science context and would be a novel avenue for further exploration.

However a citizen science project is executed, it needs robust measures of growth and performance. The results presented in this chapter – including those on project growth, Spotter and Trapper efficiency, and the analyses on quantitative and qualitative data – showed practical lessons learned which can be generalised to other citizen science projects, and highlight the challenges to be overcome.

On a broad level, performance measurement methodologies (e.g., "key performance indicators") have been developed specifically for businesses (Parmenter 2007), but they have not been successfully and widely applied to citizen science (or ecology and conservation) initiatives. Instead, a comprehensive evaluation framework for citizen science was recently proposed by Kieslinger et al. (2017). It was built upon an extensive review of evaluations for past citizen science projects, broad "expert" consultations, and informed by the quality criteria for Responsible Research and Innovation (Wickson and Carew 2014). This framework proposes evaluation criterion along three dimensions: scientific, citizen scientist, and socio-ecological/economic. Each criterion includes specific questions to guide the evaluation of a project. This framework would be useful for MammalWeb to identify gaps in the monitoring of performance and outcomes.

In summary, with the ongoing recruitment of citizen scientist Trappers and Spotters, the MammalWeb project has demonstrated stable growth with respect to the influx of camera trapping data (photos). An analysis on user engagement showed that the majority of contributions came from a minority of users, and that we are challenged to sustain a core

group of citizen scientists who can provide wide a representative temporal and spatial coverage for effective mammal monitoring. These challenges could be overcome with thoughtful, sustained engagement – informed by reflection on quantitative and qualitative insights from the analyses described above – while implementing a more comprehensive citizen science evaluation framework.

2.5 Supplementary material

The following is the camera trapping guidelines provided to each MammalWeb Trapper during the original engagement meetings and individual training in 2015:

When operating the camera trap, please:

- Turn the camera *off* before inserting or removing the memory card – failure to do so will corrupt valuable data!
- Double check that the time and date are correctly set on the camera – the *time and date format may be different depending on camera*, please be extra careful!
- Set the camera to take *three photos* every time it is triggered.

When picking a location for your camera trap, please:

- Avoid places with lots of human activity – the camera might be stolen, and we don't want countless photos of people walking by!
- Ensure the camera's field of view is unobstructed, and consider *future* plant growth.
- Make sure you attach the camera to something substantial like a tree trunk or fence post that will not wave around in the wind.
- Set the camera between 30 and 40 cm above ground – this is usually sufficient to photograph animals of all sizes, but please make a judgement based on the specific circumstances of your location. *Carefully record the height of your camera.*
- Do not place the camera too close to a track, hole, or fence. It should be at least 2 to 3 m away from where animals are likely to pass.
- Angle the camera *parallel* to the ground. You might need to wedge a stick or small rock behind the top of the camera.

- Do not angle the camera upwards!
- Avoid pointing the camera directly east or west so it won't get glare from the sun.
- Don't place the camera on the bank of a beck or river that may flood – the cameras are water-resistant against rain but not submersion!

Once you have set up the camera, before you leave please:

- Confirm fully charged batteries are used.
- Confirm the memory card is empty.
- Confirm the camera is active, and is not in motion test or walk test mode.
- Make sure all fastenings are tightly closed so water/moisture don't get in.
- Ensure the camera is fully secured/locked whenever possible.
- Carefully record the exact time and date when you deployed the camera. This is likely *not* when the first photo gets taken.

When you check on your camera, please:

- Take fully charged batteries and an empty memory card with you, so you can swap them on the spot and you won't have to make two trips.
- Double check that the time and date are still correct on the camera – the *time and date format may be different depending on camera*, please be extra careful!
- Carefully record the exact time and date you checked the camera and changed the memory card/batteries. This is likely *not* when the last photo was taken.

When downloading photos to your computer and uploading them to MammalWeb, please:

- Delete photos from the memory card *after* they have been transferred to your computer.
- Format your memory card regularly, but make sure you get all the photos first!
- Upload a maximum of a couple hundred photos at a time. You can upload more, but it might slow down your computer.

Chapter 3 - **Economical crowdsourcing for camera trap image classification**

Please note that this chapter (with the exception of this paragraph) has been published in the journal *Remote Sensing in Ecology and Conservation*. Full citation: Hsing, P.-Y., S. Bradley, V. T. Kent, R. A. Hill, G. C. Smith, M. J. Whittingham, J. Cokill, D. Crawley, and P. A. Stephens. 2018. Economical crowdsourcing for camera trap image classification. *Remote Sensing in Ecology and Conservation*. DOI: [10.1002/rse2.84](https://doi.org/10.1002/rse2.84)

3.1 Abstract

Camera trapping is widely used to monitor mammalian wildlife but creates large image datasets that must be classified. In response, there is a trend towards crowdsourcing image classification. For high-profile studies of charismatic faunas, many classifications can be obtained per image, enabling consensus assessments of the image contents. For more local-scale or less charismatic communities, however, demand may outstrip the supply of crowdsourced classifications. Here, we consider MammalWeb, a local-scale project in North East England, which involves citizen scientists in both the capture and classification of sequences of camera trap images. We show that, for our global pool of image sequences, the probability of correct classification exceeds 99% with about nine concordant crowdsourced classifications per sequence. However, there is high variation among species. For highly recognizable species, species-specific consensus algorithms could be even more efficient; for difficult to spot or easily confused taxa, expert classifications might be preferable. We show that two types of incorrect classifications – misidentification of species and overlooking the presence of animals – have different impacts on the confidence of consensus classifications, depending on the true species pictured. Our results have implications for data capture and classification in increasingly numerous, local-scale citizen science projects. The species-specific nature of our findings suggests that the performance of crowdsourcing projects is likely to be highly sensitive to the local fauna and context. The generality of consensus algorithms will, thus, be an important consideration for ecologists interested in harnessing the power of the crowd to assist with camera trapping studies.

3.2 Introduction

For several centuries (Greenwood 2007, Ratcliff 2008), citizen science projects have engaged non-professionals in the scientific process (Bonney et al. 2014). While ecological research has spearheaded the development of citizen science (Dickinson et al. 2010, Bonney et al. 2014), there are successful projects across a variety of disciplines from meteorology

(Hennon et al. 2014) to astronomy (Willett et al. 2013). Typically, these initiatives crowdsource data capture (i.e. volunteers as “sensors”, Goodchild 2007), data classification (interpreting collected data) or, occasionally, a combination of both (Kosmala et al. 2016). Some may even include citizen scientists in data analyses (Haklay 2013).

In the field of ecology, technological developments (Newman et al. 2012) and increasing recognition of the need for monitoring over large spatial and temporal scales (Conrad and Hilchey 2011, Stephens et al. 2015) have led to a proliferation of ecological citizen science projects (Kosmala et al. 2016). Concurrent with this is growing concern over “volunteer” skill and the resultant quality of data (Cohn 2008, Dickinson et al. 2010, 2012, Lukyanenko et al. 2016). Data capture can be improved through iterative protocol refinement or intensive training (Kosmala et al. 2016). In one case of community-managed resource monitoring, regular follow-up training for volunteers enabled them to produce data of quality comparable to that collected by professional scientists (Danielsen et al. 2014).

For data classification, quality can be improved by aggregating inputs from multiple users, especially when processing large datasets. For example Snapshot Serengeti is an ecological research project utilizing crowdsourced classifications to identify the contents of images taken by motion sensing camera traps deployed in Serengeti National Park. Researchers attracted over 28,000 online volunteers who, within 3 days, cast one million “votes” for what they thought was in the camera trap photos, equivalent to processing an 18-month backlog of images (Swanson et al. 2015). For each photo, a consensus classification was determined from votes cast by an average of 27 volunteers. They were then validated against almost 4,000 “gold standard” images, classified by experts, to show that consensus classifications typically had an accuracy exceeding 97% (Swanson et al. 2015, 2016).

The considerable success of Snapshot Serengeti might be due, in part, to project-specific factors. These include: (1) the presence in images of highly charismatic and diverse African megafauna which are novel to largely European and American audiences; (2) the low image to volunteer ratio (approximately 1.2 million images for 28,000 volunteers, or ~43:1); and (3) the long-established platform (<https://www.zooniverse.org/>) on which the project was hosted, with a large and dedicated international userbase.

In contrast, many citizen science projects focus on less charismatic faunas in areas of lower species diversity. Despite their lower diversity, focal communities may include species of conservation concern, as well as species that are locally common and, therefore, important contributors to ecosystem function (Geider et al. 2001, Gaston and Fuller 2008). The local relevance and lower charisma of these studies might make it harder to mobilize a large

international userbase. As a result, it may be necessary to determine image contents with fewer user classifications by crowdsourcing more economically.

An example of this is MammalWeb, a project in North East England that pilots the approach of involving local citizen scientists in monitoring mammals with camera traps. Participants engage in both data capture and data classification (camera trapping and classification of images) as defined by Kosmala et al. (2016). MammalWeb has a high image to classifier ratio (~550:1) and monitors mammals that are less diverse and may be considered less charismatic (Lorimer 2007) than their African counterparts. Preliminary indications from the pilot period are that the deployment of camera traps by MammalWeb's citizen scientists can yield useful data. Examples include the identification of a raccoon (*Procyon lotor*), an invasive non-native species, subsequently trapped and re-homed by the United Kingdom's (UK) Department for the Environment, Food and Rural Affairs (DEFRA) and the contribution of thousands of new mammal records to the Environmental Records Information Centre (ERIC) for the North East of England.

Using data collected in the MammalWeb study, we investigated economical approaches to aggregating user input into consensus classifications. This included analysing species-level variations in the number of classifications (including different combinations of correct and incorrect classifications) needed to achieve consensus at various confidence levels, and differentiating between two types of incorrect classifications: misidentification of a species or missing the presence of an animal altogether.

Relative to applying a generic consensus algorithm to all images, we showed that images of certain species could be retired more rapidly because (1) consensus was achieved with fewer classifications or (2) referral to expert classification may be preferable. Since MammalWeb combines data collection and classification in one citizen science project, we also examined whether this increased engagement affected the accuracy of classifications.

3.3 Methods

3.3.1 Project background and citizen scientist recruitment

MammalWeb focuses on North East England, addressing a general dearth of mammal monitoring in an area (Croft et al. 2017) with a relatively limited fauna (14 wild mammal species cf. 40 in the Snapshot Serengeti data base; Swanson et al. 2015). Between March 2015 and March 2018, we recruited 79 citizen scientists across the region (centred around County Durham) to deploy camera traps for the MammalWeb project. They consisted mainly of Durham University staff and members of the Durham Wildlife Trust (a local non-governmental organization focused on environmental conservation, education and

engagement). Recruiting and training citizen scientists from local community groups such as the Durham Wildlife Trust is comparable to projects such as eMammal (Forrester et al. 2017). Many participants were retirees, and most reported curiosity about local wildlife as their motivation for joining. A small number of contributors were local primary and secondary school teachers using camera traps in their teaching.

3.3.2 Camera trap data capture and classification

After training the citizen scientists to use a standard protocol, they were lent camera traps (primarily Browning Strikeforce, Reconyx Hyperfire and Bushnell cameras) and self-selected sites on which to deploy them. During deployment, all cameras were set to burst mode and would typically take three images in quick succession per trigger. By default, most cameras included a 30 second pause before the next trigger. Volunteers uploaded their camera trap images to the MammalWeb website (<http://www.MammalWeb.org/>), and also submitted metadata such as the deployment time period, location, make and model of camera trap and height of camera above ground.

Anyone with an Internet connection can register on MammalWeb to classify images (i.e. to be a “Spotter”), including those who deployed camera traps and uploaded photos (i.e. “Trappers”). Spotters were recruited through the same channels as Trappers, plus at public events and schools. Spotter classification effort varied from tens to thousands of images. Consequently, to characterize the distribution and skewness of classification intensity by individual Spotters, we calculated the proportions of those who classified fewer than 100 images and greater than 1,000 images. We also determined the relative contribution from the top 10% of Spotters in terms of classifications.

Uploaded camera trap photos taken less than 10 seconds apart were grouped into sequences, which typically (c. 84% of sequences) consisted of the three images taken in one burst (indeed, 94% of sequences are of length 2 or 3). The contextual information provided by adjacent images in a sequence should aid classifications that would otherwise be problematic (supplementary **Figure 3.6**). Therefore, MammalWeb's classification interface is such that the “next photo” button takes a Spotter to the next photo in the sequence rather than to another randomly selected one in the global pool of images (supplementary **Figure 3.7**). By going backwards and forwards through a sequence, Spotters may show greater accuracy in classifying the animals depicted since there is a greater chance of at least one clear image within the sequence. Users were encouraged to proceed only after they have classified all images in a sequence. Upon clicking “next sequence”, they were shown a randomly selected sequence from the global pool (or, optionally, the user's own pool of uploaded photo sequences).

The classifications for each image in a sequence were aggregated into the classification for that sequence. For example a three-image sequence where the images are sequentially classified as “blank”, “rabbit” and “grey squirrel” will have “rabbit and grey squirrel” as its classification. We treated each sequence as the base unit of animal detection, and all analyses for classification accuracy and consensus classifications were conducted at the sequence level.

3.3.3 Determining classification accuracy

We determined the accuracy of MammalWeb citizen scientists and assessed how the nature of a classification – correct and incorrect – may influence the calculation of a consensus. This was done by comparison with a “gold standard” set of classifications created by us, consisting of 10,483 sequences (35,417 images).

We calculated the probabilities of a user classification being correct for each species. For incorrect classifications, we examined, for each species, the proportions of classifications that were for another species or for the absence of any animal. With this information we also constructed a confusion matrix breaking down cases of mistaken identifications by species, and calculating false-negative (missing the presence of a species) and false-positive (stating a species is present when it is not) rates.

We also compared classification accuracies of citizen scientists who deployed camera traps and uploaded images (“Trappers”) and those who did not. Within the Trapper group, we also investigated whether they were more accurate when classifying their own images versus those uploaded by others. Both comparisons used generalized linear mixed effects models, with a binary response (correct or incorrect), spotter type (spotter or trapper, or uploader or other trapper) as a fixed effect, and spotter identity as a random effect.

3.3.4 Evaluating consensus classifications

For consensus classifications, we determined the following for each sequence, j : T_j (“total classifications”), the total number of unique classifications for the sequence; $P_{s,j}$ (“present”), the number of unique classifications indicating species s is present in one or more photos within the sequence; $O_{s,j}$ (“other”), the number of unique classifications indicating that species not including s are present in the sequence; B_j (“blank”), the number of unique classifications indicating that the sequence is devoid of animals. The total number of classifications for a sequence is thus: $T_j = P_{s,j} + O_{s,j} + B_j$. These numbers allowed us to determine the number of classifications indicating a species’ presence in a sequence ($P_{s,j}$) and the number indicating its absence (“absence”: $A_{s,j} = O_{s,j} + B_j$). We then used this information for four separate analyses.

First, using all sequences in our gold standard set that were identified as containing species s , we asked what proportion of classifiers (“Spotters”) agreed with this designation

$$\sum_j P_{s,j} / \sum_j T_j$$

This parameter, which we designate as $\text{Pr}(s)$ (the probability that species s is correctly identified in a sequence), serves as a crude indicator of which species are typically most (or least) readily identified within our focal fauna. For each gold standard species s , we also examined classifiers’ incorrect classifications to determine the relative proportions of those that were misclassifications (given by $O_{s,j}$) versus failed detections (given by B_j). This comparison serves to indicate how the potential for classifiers to overlook or misclassify varies among species.

Second, we used binary logistic regression to assess how the presence of a species in an image sequence is related to the number of classifications indicating its presence and absence. We conducted this analysis both for the full data set (across all species) and then separately for different species. Specifically, we determined whether the number of classifications indicating presence ($P_{s,j}$) and absence ($A_{s,j} = O_{s,j} + B_j$) of a given species (or no species at all) in a sequence was related to its true presence in, or absence from, the sequence. This model can be represented as $V_{s,j} \sim P_{s,j} + A_{s,j}$, where $V_{s,j}$ is a binomial indicator that species s is truly present in ($V_{s,j} = 1$) or absent from ($V_{s,j} = 0$) sequence j (and the error has a binomial distribution). Where multiple species have been identified to occur in sequence j , there may of course be multiple species in the image. This would not be a problem, as both users and gold-standard classifiers can classify multiple species in any image (and so, for two species a and b that occur in sequence j , $0 \leq P_{a,j} + P_{b,j} \leq 2T_j$). Far more commonly, however, where multiple species have been identified to occur in sequence j , one or more of those species has been designated in error. Here, using the entire data set would include non-independent data points (because, where species a and b are both identified as being in sequence j , even though only one of them is actually in the sequence, model $V_{a,j} \sim P_{a,j} + A_{a,j}$ is necessarily the converse of model $V_{b,j} \sim P_{b,j} + A_{b,j}$). To avoid this issue, we created 1,000 random bootstrap samples of the data set, stratified by sequence, in which all sequences were represented only once. We analysed each bootstrap sample as described above, and report mean and standard deviations of their Akaike information criteria (AICs; Akaike 1974). Analyses of the (bootstrapped) full data set suggested strong support (based on AIC scores; see Results) for an influence of the pictured species s on the relationship between confidence in classifications and P_s and A_s . To determine the effect of this variation

among species, we analysed data on the more commonly occurring species using only the subset of sequences for which at least one user has indicated the presence of the focal species.

Third, we investigated whether, for a given species s in sequence j , the impact on confidence of classifications for other species (“false positives”, $O_{s,j}$) differs from that of blanks (“false negatives”, B_j). This analysis recognises the fact that species differ in both their detectability and their recognisability; thus, classifications representing confusion over a species’ identity might reduce confidence in the species’ presence to a different extent to classifications suggesting that no animal species occurred in the sequence. This analysis used binary logistic regression, as described above; this time, the focus was on comparing the performance of the model $V_{s,j} \sim P_{s,j} + O_{s,j} + B_j$ with that of the simpler model $V_{s,j} \sim P_{s,j} + A_{s,j}$.

Fourth, we determined the rate at which we can retire sequences of species from the pool of sequences to be classified, given a target confidence threshold. This was based on two sources of information. Specifically, we used $\Pr(s)$ from our first analysis as an estimate of the probability that any new classification would be for the pictured species. We also used fitted models of the form $V_{s,j} \sim P_{s,j} + A_{s,j}$ to estimate the number of classifications needed (R) to achieve a given level of confidence C . For a given number of classifications indicating absence of a species in a sequence ($A_{s,j} = \{0,1,2,3\}$), it is possible to identify the number of classifications for the species’ presence ($P_{s,j}$) which would be required to give the desired confidence that the species is present:

$$R_{C,s,j} \sim P_{s,j} + A_{s,j}$$

The probability that this combination of classifications will be obtained is then:

$$\Pr(A_{s,j}, P_{s,j} | \Pr(s)) = \binom{A_{s,j} + P_{s,j}}{P_{s,j}} \Pr(s)^{P_{s,j}} (1 - \Pr(s))^{A_{s,j}}$$

The average number of classifications needed before a sequence containing a given species can be retired from the pool for classification is then given by the average sum of $A_{s,j} + P_{s,j}$ for $A_{s,j} = \{0,1,2,3\}$, weighted by the probability with which each is obtained, plus the probability that none of these criteria are satisfied, multiplied by the number of classifications we would accept before removing the sequence from the classification pool. We can then compare the implications of different approaches and target confidence thresholds for the speed at which sequences can be considered classified.

All data processing, analyses, and modelling was conducted in R 3.4.1 (R Core Team 2017) with the packages dplyr (Wickham et al. 2017), ggplot2 (Wickham 2016), lubridate (Grolemund and Wickham 2011), lme4 (Bates et al. 2015) and EnvStats (Millard 2013).

3.4 Results

As of 7 March 2018, MammalWeb citizen scientists had cumulatively deployed camera traps at 261 unique sites in North East England for 15,238 camera trap days. This yielded 173,315 images uploaded to our website. Since project inception, 265 Spotters (including those who deployed camera traps, i.e. Trappers) had contributed, via the MammalWeb website, 249,425 classifications of the content of 115,944 images (40,709 sequences). For the images with at least one classification, the median number of classifications was 2 (IQR: 1–3, maximum: 33). The majority of classifications were submitted by a small number of Spotters (supplementary **Figure 3.8**). More than half (58.9%) of MammalWeb users ($n = 156$) classified less than 100 photos, whereas 11.3% of the users ($n = 30$) each classified more than 1,000 photos (supplementary **Figure 3.8**). The top 10% of Spotters ($n = 27$, 15 of whom were Trappers) contributed 84.9% of all classifications.

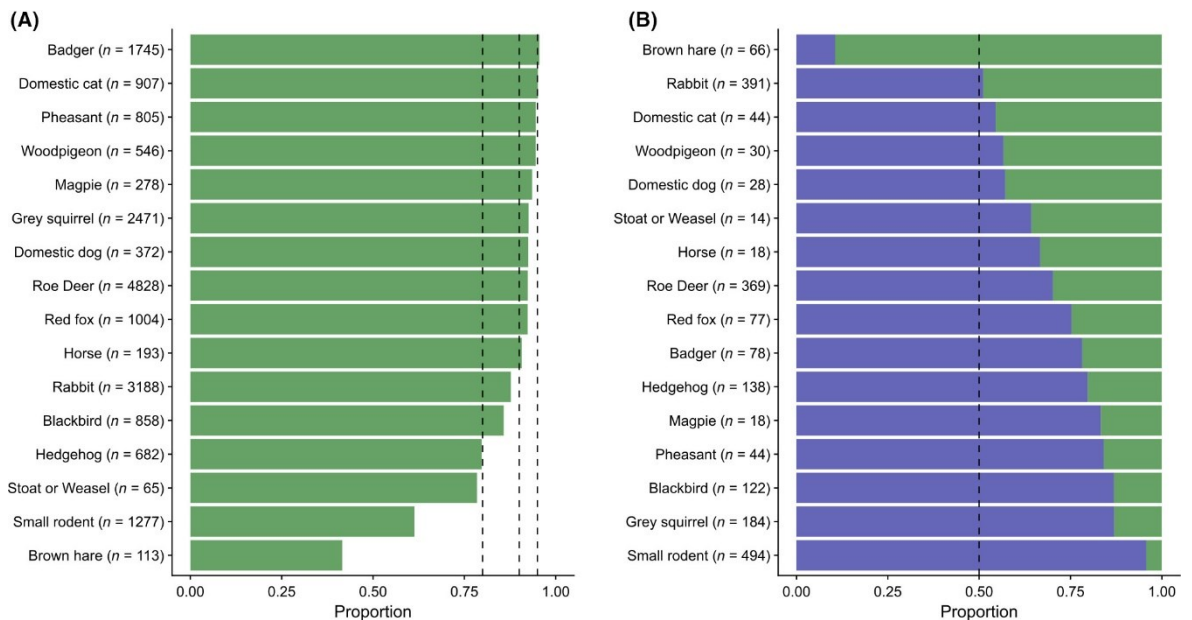


Figure 3.1. (A) Proportional accuracy of submitted classifications across the whole pool of sequences with gold standard classifications. Sample sizes (n) represent the number of classifications provided for sequences in which the gold standard indicates that the named species is present. Vertical lines show (from left to right) 80, 90 and 95% accuracy across all classifications of these sequences. (B) Proportions of incorrect classifications (classifications indicating absence of the true species in a sequence) that were for another species (green) or the absence of any animal (blue). Vertical line is 50%. Sample sizes (n) are the number of incorrect classifications.

At the sequence level, 21 species have been classified in our dataset. For most of the species in sequences with a gold standard, >90% of user-provided classifications were correct (**Figure 3.1A**). Badgers (*Meles meles*) were recognized by more than 95% of classifiers and only four species were correctly classified by <80% of users. Species vary markedly in whether incorrect classifications are due to missing the presence of an animal (B_j) or mistaking it for another species ($O_{s,j}$) (**Figure 3.1B**). For instance, most of the erroneous classifications of sequences containing brown hares (*Lepus europaeus*) were due

to mistaken identification (59 out of 66 incorrect classifications; **Figure 3.1**). In contrast, 96% of misclassifications of small rodents (a shared designation in MammalWeb for species of <500 g in body mass, principally rats, *Rattus norvegicus*; mice *Apodemus sylvaticus* and *Mus musculus*; and voles, *Microtus agrestis*) were due to them being missed altogether (473 out of 494 incorrect classifications where small rodents were present according to the gold standard; **Table 3.1**).

Table 3.1. Shaded cells are true positive rates representing the probability of a user classification being correct given an image of a certain species. False negative rates are the inverse (including stating there is nothing when an animal is present), and false positive rates are how often a species is identified when it is not there. Numbers of classifications are in parentheses. E.g. For badgers, there are 1,680 user classifications indicating their presence of which 0.8% are incorrect (false positives). There are 1,745 classifications where badgers are truly present, of which 95.5% were correct identified (true positives), and 4.5% where they were not identified (false negatives).

User classifications	Gold standard	Badger (1745)	Blackbird (858)	Domestic cat (907)	Grey squirrel (2471)	Hedgehog (682)	Pheasant (805)	Rabbit (3188)	Red fox (1004)	Roe Deer (4784)	Small rodent (1277)	Nothing (6353)	False positive rate
Badger (1680)		.955				.003		.001	.001	.001		.000	.008
Blackbird (773)			.858	.001	.000		.001	.001		.000	.001	.003	.048
Domestic cat (886)		.001		.951				.001	.007			.001	.026
Grey squirrel (2379)		.001	.005	.001	.926	.003	.004	.012			.002	.004	.039
Hedgehog (578)		.001		.006	.001	.798		.002			.008	.001	.059
Pheasant (773)							.945	.002				.001	.016
Rabbit (2905)		.002	.003		.003	.019	.002	.877	.003	.002	.001	.002	.037
Red fox (968)		.002	.001	.008	.000			.001	.923	.003	.002	.001	.042
Roe Deer (4513)		.002	.002		.000			.003	.004	.932		.003	.012
Small rodent (836)				.001	.001	.016		.003	.001		.613	.004	.063
Nothing (7770)		.035	.124	.026	.065	.161	.046	.063	.058	.054	.370	.975	.203
False negative rate		.045	.142	.049	.074	.202	.055	.123	.077	.068	.387	.025	

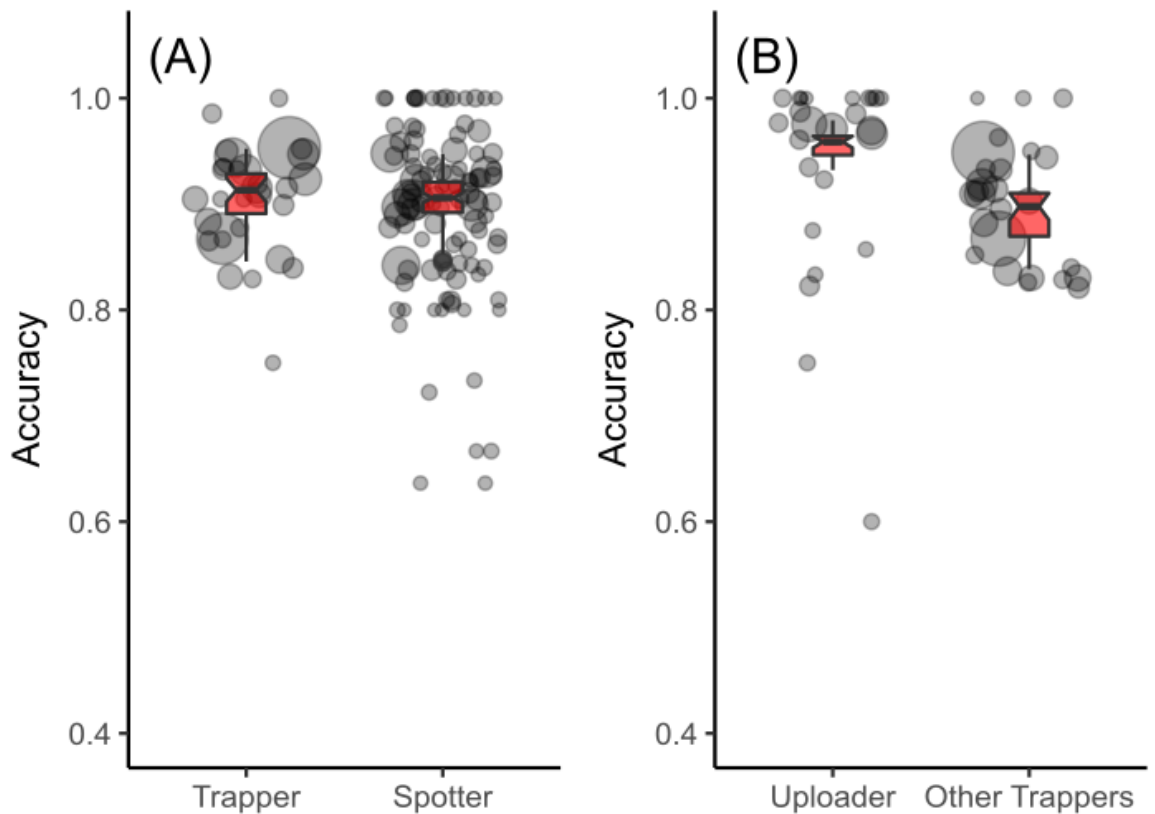


Figure 3.2. Of the citizen scientists who classified at least 10 sequences, (A) those who deployed camera traps (30 “Trappers”, 13,446 classifications) were marginally more accurate at image classification than those who did not (102 “Spotters”, 12,100 classifications) but this effect was not supported ($\Delta\text{AIC} = -1.49$, model weight = 0.32, relative to a model that did not account for the Spotter type). (B) There was strong support for the finding that 26 Trappers who classified images they uploaded (“Uploaders”, 2578 classifications) were more accurate than Trappers who classified images uploaded by other Trappers (“Other Trappers”, 10,136 classifications) ($\Delta\text{AIC} = 66.28$, model weight = 1.00, relative to a model that did not account for the Spotter type). In both panels, each data point represents a different individual; point size reflects relative numbers of classifications. Boxes and whiskers summarize predicted accuracy levels across individuals (line across each box indicates the median and the box boundaries indicate the interquartile range, IQR; whiskers identify extreme data points that are not more than 1.5 times the IQR on both sides; dots are more extreme outliers).

Among Spotters, those who also deployed camera traps and uploaded photos (“Trappers”) were slightly more accurate in their classifications (**Figure 3.2A**). In addition, Trappers were more accurate when classifying images they had obtained than those uploaded by other Trappers (**Figure 3.2B**).

Analyses of the data across species showed that both the number of classifications indicating presence and the number indicating absence of a species provide important information about the probability with which that species is actually in a sequence (**Figure 3.3**). On the global level, when a single classification has been submitted indicating a species’ presence, it is about 95% likely that the species in question does appear in the sequence. Predictably, more classifications for the species being present increase the likelihood that it is there, whereas more classifications for its absence have the opposite effect (**Figure 3.3**).

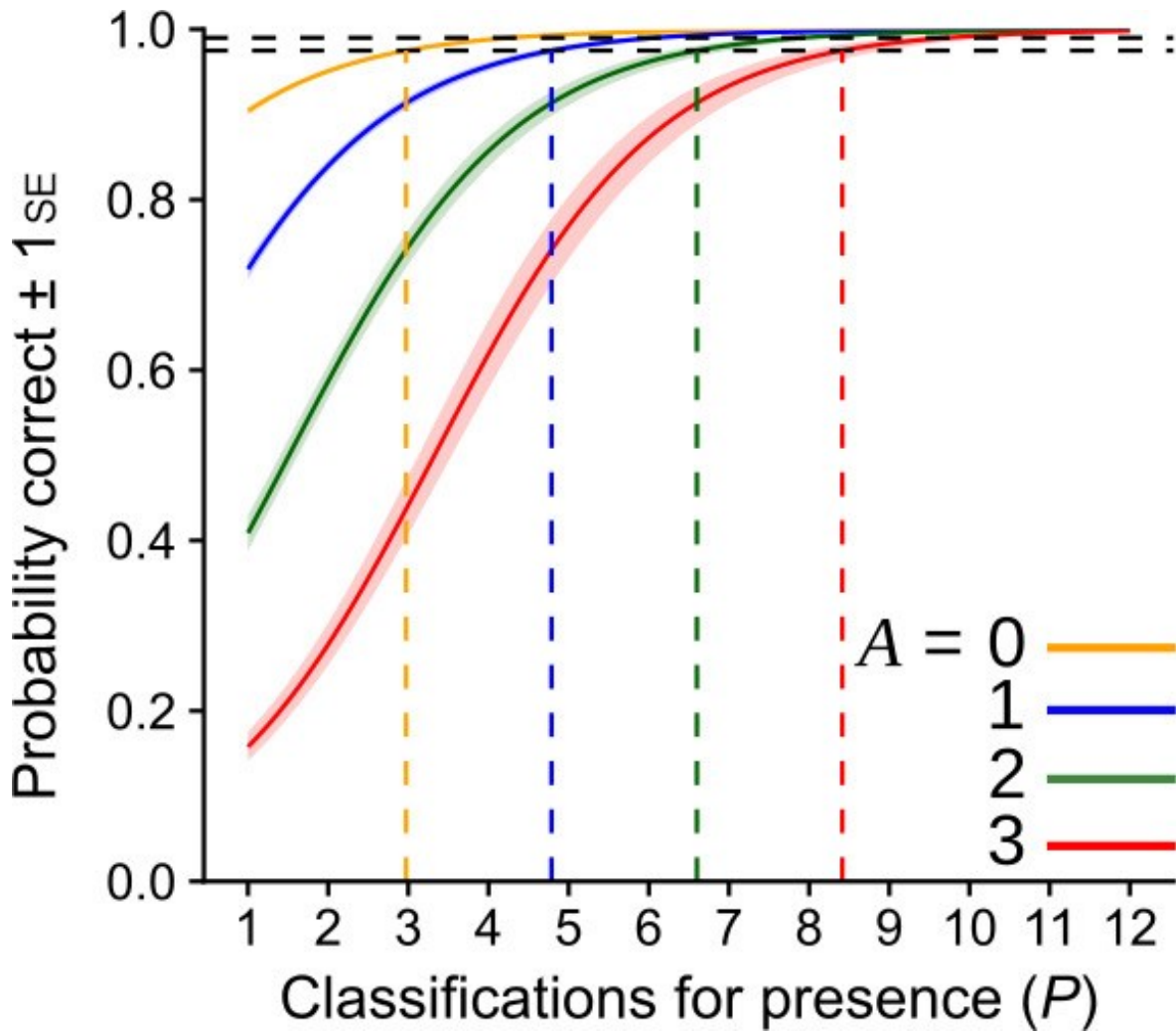


Figure 3.3. Global-level relationship between the number of classifications for the presence (P) and absence (A) of a given species in a sequence and the probability that it is indeed in the sequence. Solid lines show the mean relationship (over 1,000 bootstrapped samples) between the probability (predicted by the fitted model) that a species is present in the sequence and the number of classifications for that species (P), for 0 (orange line), 1 (blue line), 2 (green line) and 3 (red line) classifications indicating the species is absent (A). Polygons around the lines show \pm mean SE across the bootstrapped samples. Dashed horizontal lines show probabilities of 0.975 and 0.99. Corresponding dashed vertical lines show the number of classifications for the species required to give a confidence of 97.5%.

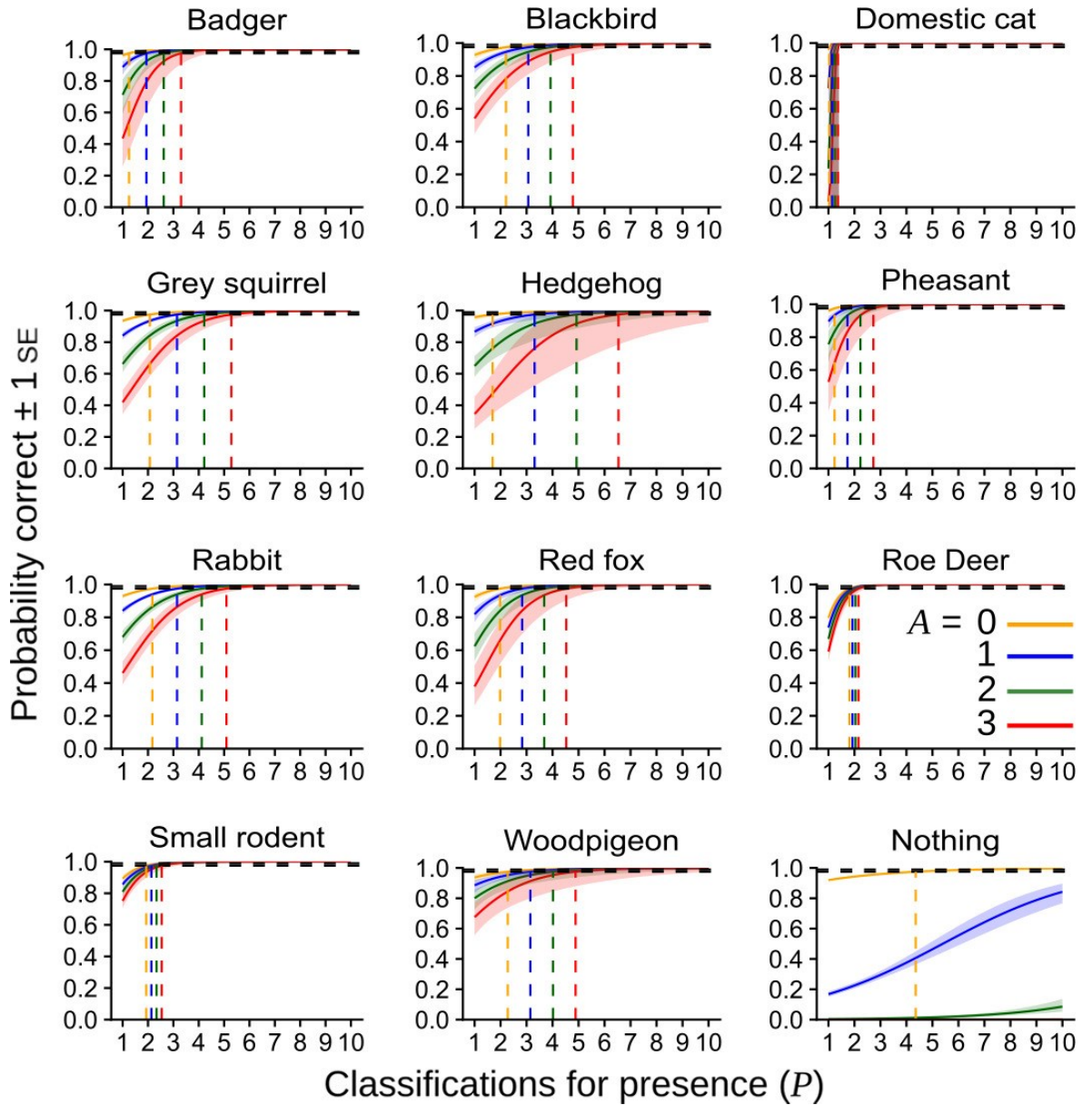


Figure 3.4. Species-level relationship between the number of classifications indicating the presence (P) and absence (A) of a given species, and the probability that it appears in a sequence. Solid lines show the mean relationship between the probability (predicted by the fitted model) that a species is present in the sequence and the number of classifications for that species, for 0 (orange line), 1 (blue line), 2 (green line) and 3 (red line) classifications indicating the species is absent. Polygons around the lines show \pm mean SE. Dashed horizontal lines show probabilities of 0.975 and 0.99. Corresponding dashed vertical lines show the number of classifications for the species that are required to give a confidence of 97.5%.

The above analysis is based on a model of the form $V_{s,j} \sim P_{s,j} + A_{s,j}$. However, models that included, also, the pictured species (s^*) as a fixed factor, outperformed the simpler model ($\Delta\text{AIC} = 196.74$, $\text{SD} = 19.99$). Consequently, we also analysed the relationship between image contents and numbers of classifications for individual species. Twelve species (including “nothing”, or blank (B), that is where no image in the sequence contained an animal) appeared in more than 200 gold standard sequences and so were analysed at the species level. For the different species, there was marked variation in the meaning of different combinations of classifications indicating presence and absence (**Figure 3.4**). In particular, some designations (e.g. small rodents) require larger numbers of classifications

for their presence to confer confidence in their appearance in the sequence (e.g. $P = 3$ for 97.5% confidence), but classifications for their absence (A) make relatively little difference (**Figure 3.4**). Other species, such as badgers, need few classifications for their presence to instil confidence that they are truly present but small numbers of differing classifications substantially undermine that confidence (**Figure 3.4**). Notably, increases in the number of classifications indicating that the sequence contains “nothing” do not materially increase the likelihood of consensus being correct (**Figure 3.4**). Even with 5 classifications indicating that the sequence contains “nothing”, the level of confidence does not rise above 97.5%. Any dissenting classifications, indicating that there is “something” in the sequence, have a very high impact on confidence that the sequence is indeed devoid of animals.

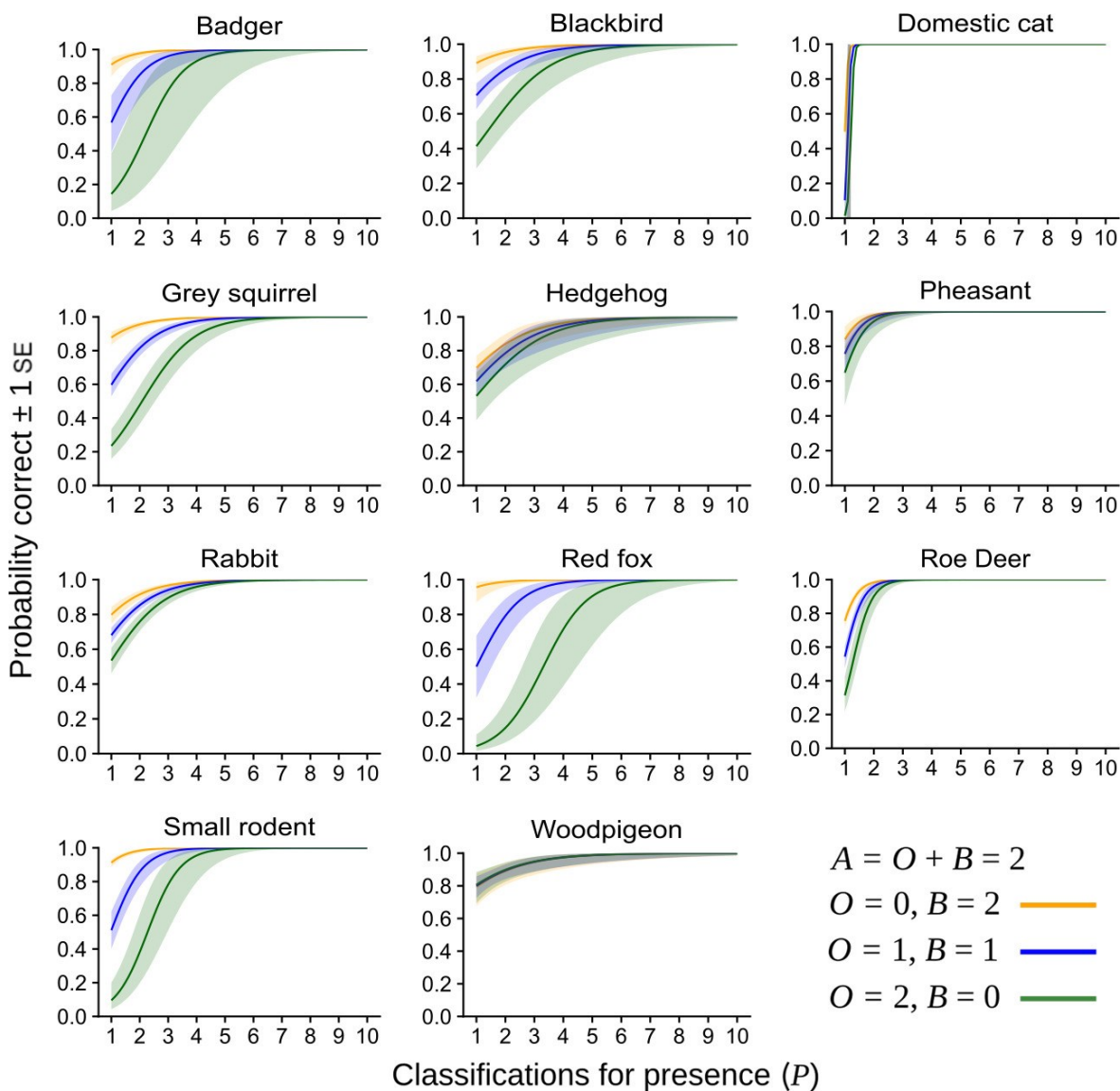


Figure 3.5. Implications of distinguishing between different types of classifications indicating that a species is absent (A). For some typically highly detectable species, such as the badger, classifications suggesting that no animal is present in the sequence (“false negatives”, B) are more damaging to confidence than are classifications suggesting that the pictured species is some other species (“false positives”, O). For visually distinctive species, such as the grey squirrel, the converse is true. For species that are seldom overlooked or misclassified, classifications indicating their absence count equally, regardless of whether they are for other species or no animals at all.

Models for individual species differed when separating classifications for absence (*A*) into those for other species (*O*) and those for no animals (*B*) (supplementary **Figure 3.9**). For eight species, doing so produced a better-supported model (supplementary **Table 3.2**). Coefficient values suggest the relative reduction in confidence resulting from classifications for no animals (*B*) and those for other species (*O*) (supplementary **Figure 3.10**). Classifications for other species (*O*) have a particularly strong effect on confidence for badgers, red foxes, and domestic cats (**Figure 3.5** and supplementary **Figure 3.10**).

Globally (without regard to specific species), 42.9% of sequences can be retired with 97.5% confidence after four classifications and a further 21.4% of sequences could be retired after seven (supplementary **Table 3.3**). At the 99% confidence level, 34.7% of sequences can be retired after five classifications (supplementary **Table 3.3**). The implication of these analyses is that, on average, 7.2 classifications would be needed per sequence to retire them with 97.5% confidence, while an average of 9.1 classifications are required for 99% confidence. If algorithms for sequence retirement are sensitive to the species most likely to be pictured, 88.1% or more of sequences containing highly recognizable species, such as badgers, could be retired after just two classifications (with 97.5% confidence) (supplementary **Table 3.4**). However, less recognizable species would need many more classifications to instil confidence (supplementary **Table 3.4**). For example, only about 85% of sequences classified as small rodents can be retired at 97.5% confidence even after six classifications (supplementary **Table 3.4**).

3.5 Discussion

There is a trend for citizen science projects to crowdsource data classification. The question of how proliferating projects can obtain confident classifications from a finite group of contributors suggests that more economic ways of utilizing user input would be beneficial. Data from the MammalWeb project suggest that individual classifiers are typically highly accurate and that a reliable consensus could be reached with approximately nine classifications per sequence. Moreover, we show that greater economy could be obtained by treating different species separately, and by discriminating between classifications that conflict over the identity of the pictured species, and classifications suggesting no species is present. Here, we discuss our results and their implications for crowdsourced image classification, increasing the classification rate and large-scale mammal monitoring.

3.5.1 Implications for crowdsourced image classifications

The majority of MammalWeb's camera trap image classifications originated from relatively few contributors (supplementary **Figure 3.8**), a pattern common among scientific crowdsourcing efforts (Sauermaun and Franzoni 2015). That the top 10% of MammalWeb

classifiers (“Spotters”) contributed 84.9% of all classifications is comparable to the average of 79% from a survey of seven projects on the Zooniverse citizen science platform (Sauermaun and Franzoni 2015).

Notably, Spotters who also helped to deploy camera traps (“Trappers”) were slightly more accurate in their classifications (**Figure 3.2A**). This might be assumed to occur because citizen scientists involved in both the data capture and classification stages of the project are engaged to a higher level (Haklay 2013) than those involved only in classification. Alternatively, it could reflect the fact that many Trappers are nature enthusiasts since they were recruited from a local nature-based organization (similar to Forrester et al. 2017). However, the data show that this difference arises principally because Trappers were more accurate in classifying images captured by themselves (**Figure 3.2B**). This is possibly due to direct access to those images on their own computers, where they can be scrutinized to a greater extent than on our website. It is also possible that these Trappers are simply more familiar with the fauna at sites where they deployed camera traps, although the vertebrate biota across North East England shows limited spatial variation.

We showed that the accuracy of volunteer-contributed classifications is generally high (**Figure 3.1**). With only one classification indicating the presence of a species, the likelihood is about 95% that the species is indeed present (**Figure 3.3**). For a given sequence where the species present is known, true-positive rates are generally high, which also suggests high accuracy (**Table 3.1**). In spite of this accuracy, to confer higher confidence in consensus classifications, multiple classifications are required per sequence. Specifically, without an algorithm that distinguishes between species, sequences in our dataset can be retired from the classification pool after an average of 7.2 classifications (for an accuracy of $\geq 97.5\%$) or 9.1 classifications (for $\geq 99\%$ accuracy) (supplementary **Table 3.3**). Given that there is some evidence that different types of classifications against the presence of a species may carry different weight (and, in particular, that classifications for the absence of any species of interest are generally less damaging to confidence than classifications for a different species; **Figure 3.5**), more elaborate approaches accounting for the nature of dissent might substantially improve these figures.

For some species, the number of classifications can be substantially reduced (e.g. 97.5% confidence with just two classifications indicating the presence of a badger, **Figure 3.4**); for other species, however, larger numbers would be required and an early transfer to expert classification might be preferable (supplementary **Table 3.4**). Species-level differences were also evident when differentiating the impacts from misidentification (i.e. the false-positive identification of a species) or mistakenly stating that no animal was present (i.e. false

negative) (**Figure 3.5**, supplementary **Figure 3.10**, and **Table 3.1**). A good example of the complications around false positives is given by brown hares. We found that brown hares are relatively poorly recognized in our dataset. In fact, they are commonly confused with rabbits (*Oryctolagus cuniculus*), the more frequently occurring lagomorph in the region. Although our analyses suggest that the majority of sequences containing rabbits could be removed after only three or four classifications (depending on the desired confidence level), this overlooks the possibility that brown hares might be of more interest, would need many more classifications to compel confidence, and could be overlooked if apparent rabbit sequences are retired rapidly. More data would be required to assess this problem, especially in relation to the specific probability with which hares are classified as rabbits (and the resultant probability that a sequence could achieve consensus on a rabbit being pictured, even if a hare is the actual subject).

With these analyses, we illustrated the importance of considering (1) the entire combination of classifications for the presence and absence of a species when calculating consensus classifications, and (2) the potential usefulness of a species-specific approach to doing so rather than applying a single algorithm to the entire dataset. An additional benefit is that even though an animal may be more or less evident in different images, achieving consensus for a sequence would let us retire all of its constituent images without needing consensus on each one.

One finding that might be very general to crowdsourced classifications is that far more classifications are required to classify with confidence a sequence having no subjects of interest, than to classify with confidence a sequence that does contain animals. Indeed, five or more uncontested classifications suggesting that a sequence is devoid of animals is needed to impart 97.5% confidence in that designation (**Figure 3.4**). That contrasts with the other species considered in **Figure 3.4**, which require between two and three uncontested classifications to give high confidence that they are actually present. As we noted above, more efficient algorithms for crowdsourcing reliable classifications should probably discriminate between the weight attributed to disagreements over whether a species is present and disagreements over the identity of a pictured species.

3.5.2 Increasing the classification rate

Our analyses suggest that a higher ratio of classifiers to images will be necessary before MammalWeb can be expanded and expected to contribute to timely and informative ecological analyses. In particular, our analyses suggest that, without distinguishing species, at least four or an average of 7.2 classifications will be required per sequence for 97.5% confidence in consensus. In the first 120 weeks of the project, we accumulated new

sequences at a rate of approximately 370 per week, and new sequence classifications at a rate of approximately 1,324 per week; this yields a ratio of approximately 3.6 classifications per sequence. This suggests that one option to ensure that classifications keep pace with accumulating image data is to increase our classifier pool by a factor of approximately 2.5, relative to the number of camera trappers. At present, we have approximately 3.5 classifiers to every trapper, so this would need to increase to approximately 9:1. Such an increase should inform any efforts to extend the reach of the MammalWeb project and can be built on existing work that seeks to understand citizen scientist motivations and to promote their continued involvement (Eveleigh et al. 2014, Jennett et al. 2016, Wald et al. 2016, Everett and Geoghegan 2016).

One alternative to increasing the relative size of the classifier pool is to encourage higher classification effort from existing users. Species-specific algorithms for sequence retirement could be problematic in this regard. For example some of the more recognizable species in our dataset are also some of the more charismatic. If these sequences are removed more rapidly than others, the dataset could rapidly become biased towards less charismatic species, more indistinct photos and images devoid of animals. Preliminary evidence from Snapshot Serengeti suggests that moderate numbers of images devoid of wildlife can actually increase classifier-engagement, by ensuring the relative rarity and novelty of wildlife images (Bower et al. 2015). In contrast, MammalWeb participants routinely cite animal-free images (about 41% of all sequences, based on gold standard classifications) as a deterrent to classification. It would be useful to investigate the source of this difference in the reported impacts of blank images on motivation. This may be related to the charisma of the animals being monitored, whether a project involves citizen scientists in both data capture and classification, user interface design or inaccuracies in self-reporting.

The importance of sequences devoid of animals is clear (**Figure 3.4**). Given the high proportion (31.4% according to the gold standard) of blank sequences in our dataset (and many other camera trap datasets), it is clear that the relatively low confidence with which blank sequences can be classified will have a major impact on the overall speed at which sequences can be retired without a species-specific classification algorithm. Options for reducing the proportion of blanks in the dataset include asking Trappers – who are more accurate at classifying their own images (**Figure 3.2**) – to pre-screen their data and remove blanks before upload, or using an automated algorithm to do so (see further below).

One further possibility for overcoming limitations to classification effort is to use the dataset to identify classifiers who have very high accuracy, giving a higher weighting to their votes, or preferentially tasking them with classifying more difficult images. User skill level

was accounted for in one of the Bayesian consensus models by Siddharthan et al. (2016), requiring 3.2 classifications per image to achieve 91% confidence. Some crowdsourcing platforms (e.g., van der Wal et al. 2016) include automated checking and training functionality with computer-generated structured feedback for volunteers, which could help to increase individual accuracy and reduce required numbers of classifications.

3.5.3 Implications for large-scale mammal monitoring

In contrast to some other taxa, mammals have not been routinely monitored at a community level in the UK (Battersby and Greenwood 2004, Croft et al. 2017). 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. 2016). However, given the nocturnal habits and generally low detectability of many mammals, the relatively short period during which the daytime-only BBS is carried out means that many species will be missed where they occur, and site-specific changes could be highly subject to stochasticity. Camera trapping would deliver a substantially richer picture of mammal occurrence in space and time and, ultimately, an approach like MammalWeb could be used to monitor mammals at a national level. In spite of this, MammalWeb was deliberately implemented at a local level to determine the feasibility of the approach. Our analyses suggest that the approach taken by MammalWeb should be feasible with modest efforts to increase the engagement or accuracy of existing classifiers, or the ratio of classifiers to images. The system could, consequently, be extended – but, at least given the current approach, it would be important to increase recruitment of classifiers to a greater extent than recruitment of camera trappers.

More generally, mammal monitoring using camera traps continues to grow globally (Rowcliffe and Carbone 2008), and there are increasing calls for more systematic and widespread approaches to the challenge (Steenweg et al. 2017). Crowdsourcing image classification is one solution to this challenge, and MammalWeb is one of several platforms that engages citizens for wildlife image classification. Others include Instant Wild (Verma et al. 2016), Zooniverse (Simpson et al. 2014), eMammal (McShea et al. 2015), iSpot (Silvertown et al. 2015) and BeeWatch (van der Wal et al. 2016). While our findings regarding accuracy for specific species might not generalize to other platforms, the approach to crowdsourcing classifications should.

There are several reasons why our approach might compare favourably to previous algorithms, especially on a species-by-species basis. As previously discussed, our classifiers are largely local to North East England and so are likely to be highly familiar with the small number of species commonly occurring on camera traps in the area. This can be seen in the

high accuracy of their classifications (**Figure 3.1**), especially from those who do the camera trapping (**Figure 3.2**). Moreover, classifiers on MammalWeb are shown entire sequences of images, potentially benefiting from contextual information across the sequence. Whether this provides a measurable benefit and, if so, to what extent, would be straightforward to determine with a platform that can easily be adjusted to show photos either individually or in sequence. Overall, our requirement for as few as four classifications per sequence for 97.5% confidence (if an animal is present) shows greater achievable efficiency than consensus algorithms employed where efficiency is not a strong requirement (Swanson et al. 2016).

Researchers frequently point to image classification as a major barrier to making best use of their camera trapping data. As camera trapping increases in scope, the demand for citizen scientists to assist with image classification is also likely to increase. Whether supply can keep pace with demand is unclear but it is likely that more and larger projects will compete for a finite pool of classifiers, with projects focused on less charismatic or conservation-relevant faunas struggling to meet demand. More refined approaches to training volunteers and making use of their data (e.g., van der Wal et al. 2016) should help. In addition, automated techniques to assist with image recognition may become necessary to alleviate the classification challenge. This need will be even more pronounced as those running camera trapping studies embrace more complex forms of analysis, such as those requiring animal speed and distance detection (Rowcliffe et al. 2016, Howe et al. 2017). Automated solutions are starting to emerge but, so far, have been proprietary (Kays *pers. comm.*), require manual image pre-processing (Yu et al. 2013), or yield very high false-positive rates (Price Tack et al. 2016). Whilst there is likely to be low transferability of species-detection algorithms among studies, experience at MammalWeb provides a strong motivation for change detection algorithms (Radke et al. 2005) simply to highlight (and remove) photos unlikely to contain wildlife; as discussed above, this process could substantially reduce the average number of classifications required to retire sequences. Knowing the presence and identity of wildlife within sequences could provide a dataset useful for training machine learning algorithms that are under development (Thom 2017, Norouzzadeh et al. 2018).

In summary, we believe MammalWeb has demonstrated the viability of a local citizen science camera trapping project that can sustainably monitor wildlife. Importantly, we have shown the benefits of considering species level differences when calculating consensus classifications including the relative impacts from false-positive and false-negative classifications. Our findings regarding the importance to retirement rates of reducing the proportion of “blank” sequences in the dataset are highly likely to generalize across projects.

Other differences from past citizen science projects, including involving citizen scientists in data capture and classification, the methods we used for crowdsourcing data classifications, and our insights into the use of sequence-level classifications to improve retirement rates of photos, are also of value to future monitoring initiatives.

3.6 Acknowledgements

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3.7 Data accessibility

The data (crowdsourced classifications and gold standard photos) used in this article are shared under the Creative Commons Attribution-ShareAlike 4.0 license in this repository (DOI: 10.17605/osf.io/znm6k/): <https://osf.io/znm6k/>

The code used for analysing consensus classifications and producing the relevant figures and tables is shared under the GNU GPLv3+ license in this git repository: https://gitlab.com/penyuan/consensus_classifications_MammalWeb/

3.8 Supplementary information



Figure 3.6. A sequence of camera trap images taken in burst mode of a red fox (*Vulpes vulpes*). When shown in isolation, the left-hand and middle images in this sequence might achieve high levels of consensus regarding their content. By contrast, the right-hand image would be hard to classify and might be subject to considerable uncertainty regarding its focal subject.

What do you see?

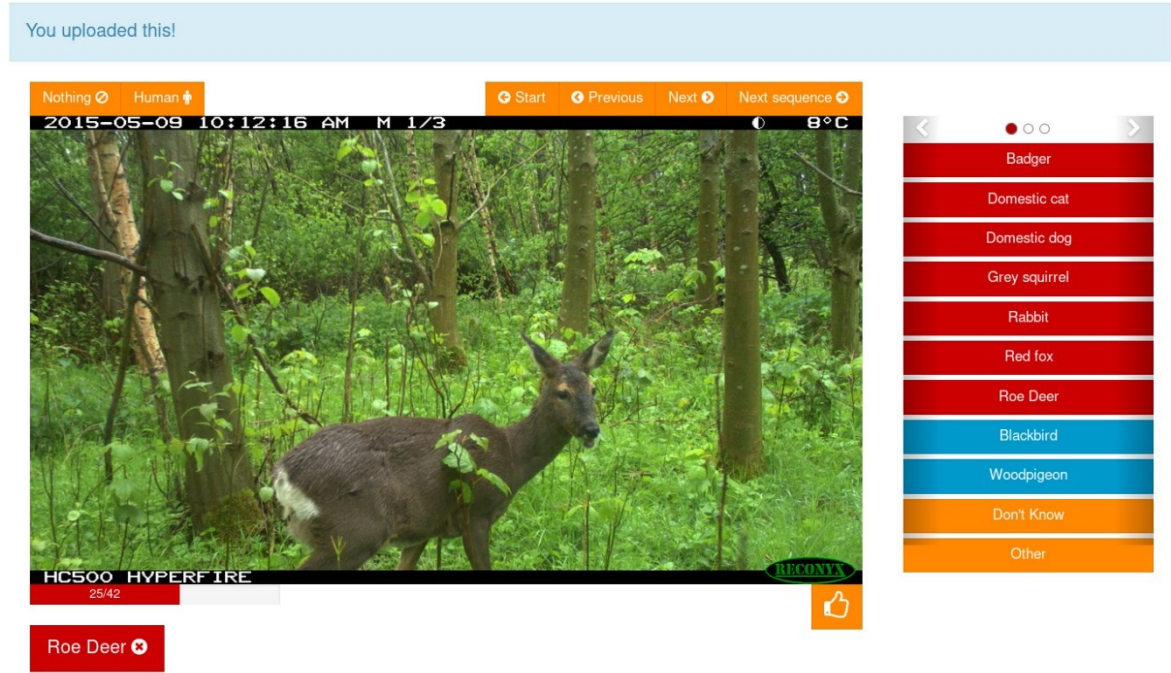


Figure 3.7. MammalWeb camera trap image classification (“Spotter”) interface.

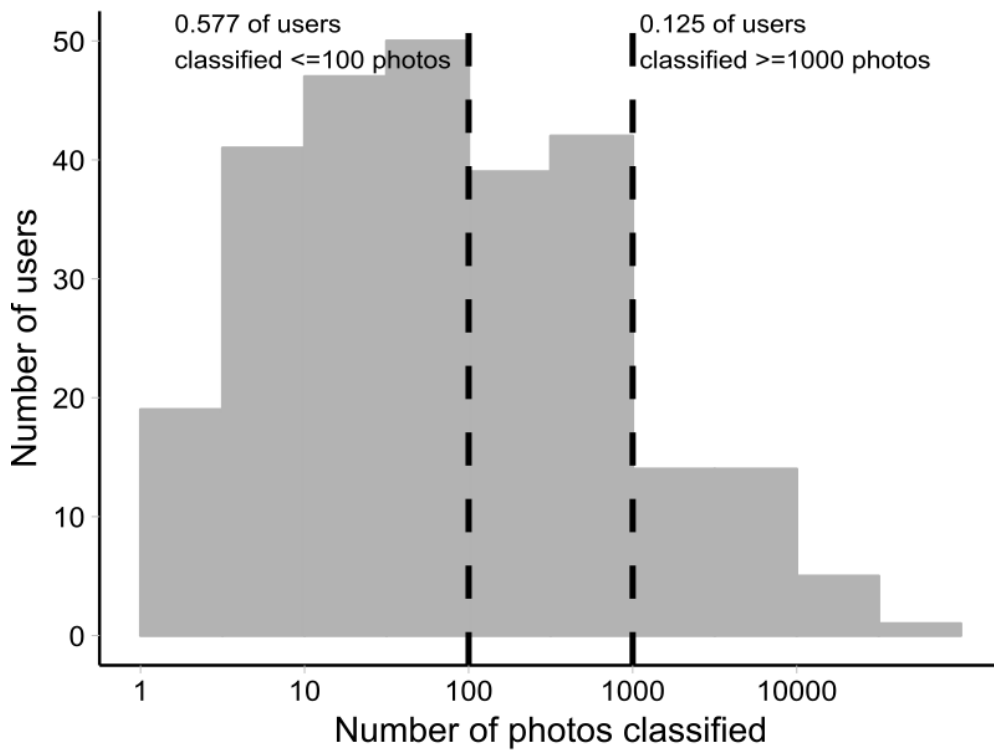
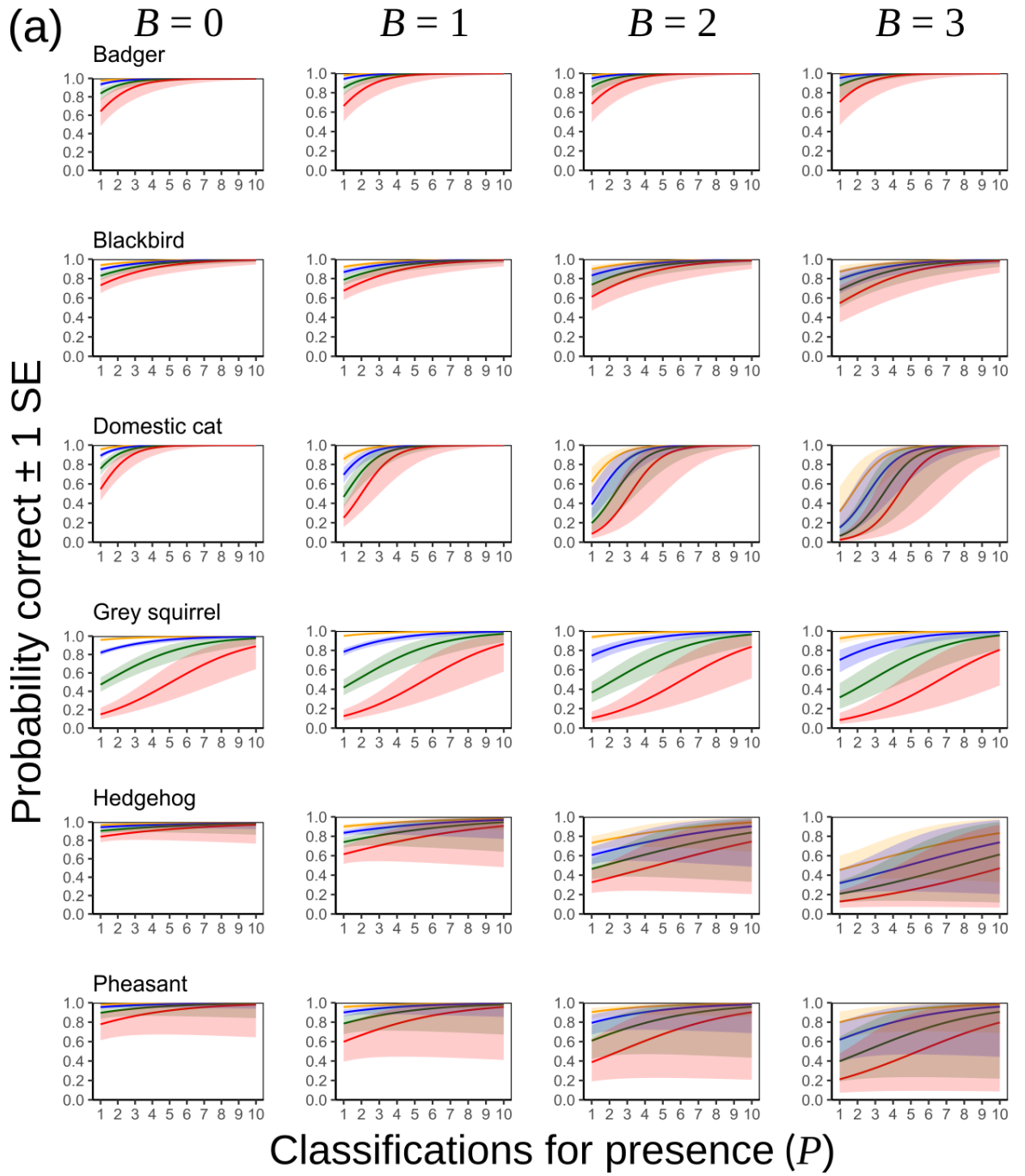


Figure 3.8. The majority of classification effort was contributed by relatively few users.



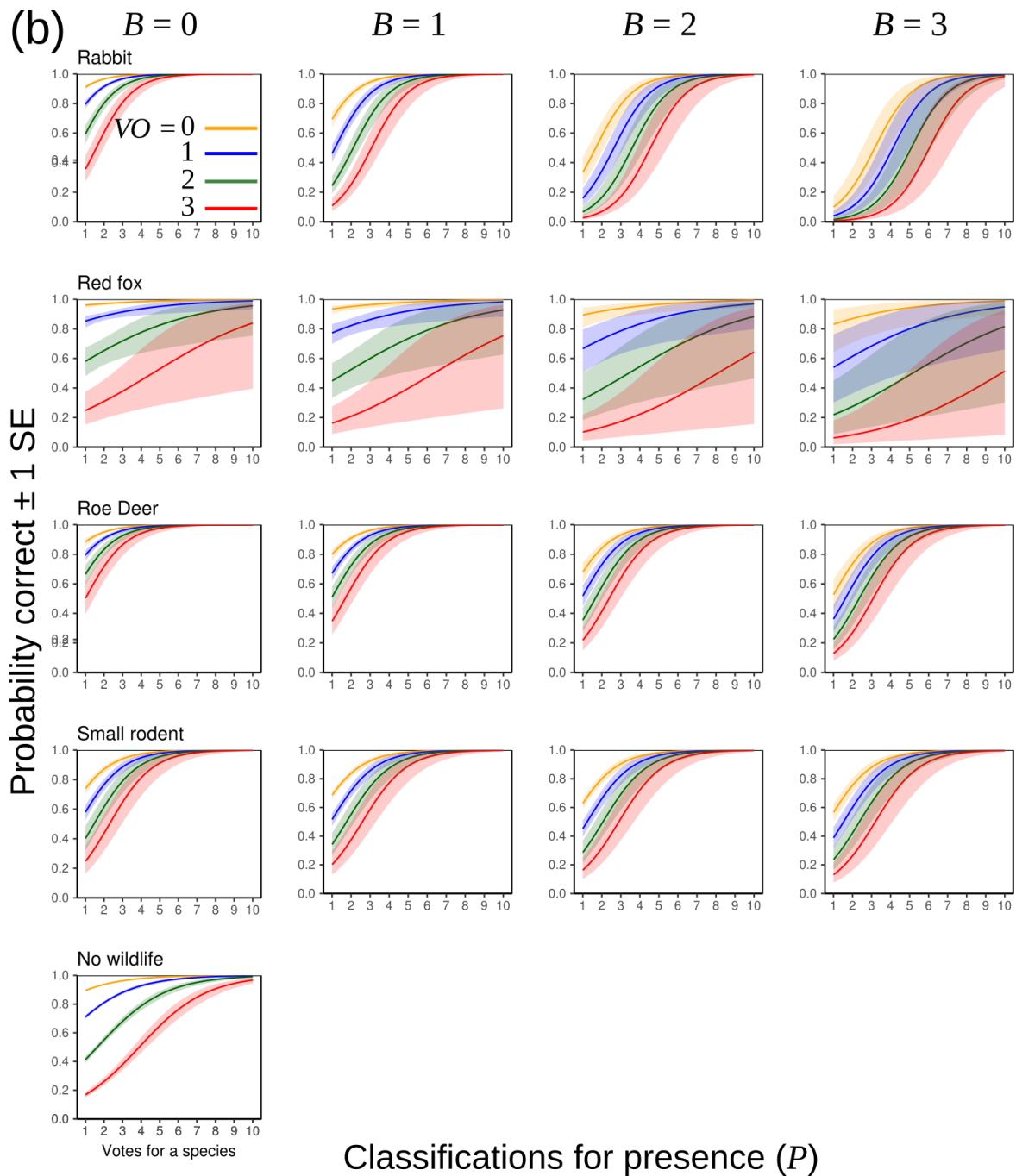


Figure 3.9. Relationship between classification confidence and the number of classifications for the presence (P) and absence (A) of certain species, with the classifications for absence split into those for other species (O) and blank (i.e. containing no vertebrates) (B).

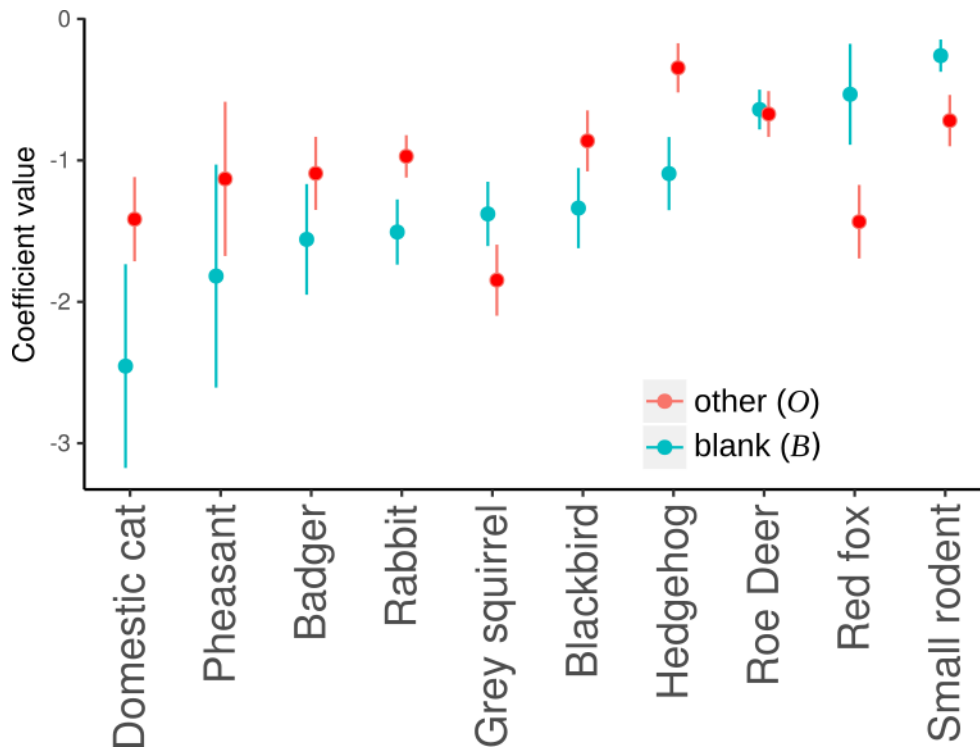


Figure 3.10. Coefficient values (\pm mean SE) for models that distinguish between the effects on classification confidence of those for “other species” (*O*) and “blank” (*B*).

Table 3.2. Impact of separating classifications for absence (*A*) model term into those for other species (*O*) and blank (*B*). Positive Δ AICs (bold font) indicate that increasing the number of parameters by having separate *O* and *B* terms is justified by the improved model fit.

model terms, Δ AIC			
Species	<i>P</i> + <i>A</i>	<i>P</i> + <i>O</i> + <i>B</i>	Δ AIC
Badger	68.22	59.61	8.61
Blackbird	151.82	140.13	11.69
Domestic cat	57.52	52.97	4.55
Grey squirrel	348.5	320.61	27.89
Hedgehog	134	134.94	-0.94
Pheasant	65.79	66.84	-1.05
Rabbit	418.04	411.34	6.69
Red fox	122.1	96.05	26.05
Roe Deer	213.79	197.37	16.43
Small rodent	277.19	221.14	56.05
Wood pigeon	71.29	73.28	-1.99

Table 3.3. Calculations for numbers of sequences-level classifications needed (*CN*) to achieve target confidence level across the global pool of image sequences.

Target confidence threshold	Classifications for absence (<i>A</i>)	Needed classifications for presence (<i>P</i>)	Total classifications needed (<i>CN</i>)	Expected proportion of sequences
0.975	0	4	4	0.429
	1	6	7	0.214
	2	7	9	0.149
	3	9	12	0.072
		Didn't match previous criteria	13	0.136
		Weighted average number of votes	7.2	
0.990	0	5	5	0.347
	1	7	8	0.217
	2	9	11	0.135
	3	10	13	0.109
		Didn't match previous criteria	14	0.192
		Weighted average number of votes	9.1	

Table 3.4. Calculations numbers of sequence-level classifications needed (*CN*) to achieve target confidence level for commonly-pictured species.

Species	Target confidence threshold	Classifications for absence (A)	Needed classifications for presence (P)	Total classifications needed (CN)	Expected proportion of sequences
Badger	0.975	0	2	2	0.881
		1	2	3	0.108
		2	3	5	0.009
		3	4	7	0.001
		Didn't match previous criteria		8	0.0002
		Weighted average number of votes		2.1	
Blackbird		0	3	3	0.488
		1	4	5	0.245
		2	4	6	0.157
		3	5	8	0.055
		Didn't match previous criteria		9	0.055
		Weighted average number of votes		4.6	
Domestic cat		0	2	2	0.827
		1	2	3	0.150
		2	2	4	0.020
		3	2	5	0.002
		Didn't match previous criteria		6	0.000
		Weighted average number of votes		2.2	
Grey squirrel		0	3	3	0.679
		1	4	5	0.217
		2	5	7	0.069
		3	6	9	0.023
		Didn't match previous criteria		10	0.012
		Weighted average number of votes		3.9	
Hedgehog		0	2	2	0.605
		1	4	5	0.163
		2	5	7	0.098
		3	7	10	0.043
		Didn't match previous criteria		11	0.090
		Weighted average number of votes		4.1	
Pheasant		0	2	2	0.845
		1	2	3	0.137
		2	3	5	0.015
		3	3	6	0.003
		Didn't match previous criteria		7	0.000

Species	Target confidence threshold	Classifications for absence (A)	Needed classifications for presence (P)	Total classifications needed (CM)	Expected proportion of sequences
Weighted average number of votes 2.2					
Rabbit		0	3	3	0.618
		1	4	5	0.234
		2	5	7	0.089
		3	6	9	0.035
			Didn't match previous criteria	10	0.025
Weighted average number of votes 4.2					
Red fox		0	2	2	0.595
		1	3	4	0.210
		2	4	6	0.093
		3	5	8	0.046
			Didn't match previous criteria	9	0.057
Weighted average number of votes 3.5					
Roe Deer		0	2	2	0.818
		1	2	3	0.156
		2	3	5	0.020
		3	3	6	0.005
			Didn't match previous criteria	7	0.001
Weighted average number of votes 2.2					
Small rodent		0	2	2	0.380
		1	3	4	0.180
		2	3	5	0.172
		3	3	6	0.119
			Didn't match previous criteria	7	0.149
Weighted average number of votes 4.1					
Weighted average number of votes 2.3					
Badger	0.990	0	2	2	0.881
		1	3	4	0.102
		2	4	6	0.015
		3	4	7	0.003
			Didn't match previous criteria	8	0.0003
Weighted average number of votes 2.3					
Blackbird		0	4	4	0.384
		1	5	6	0.257
		2	5	7	0.192
		3	6	9	0.078
			Didn't match previous criteria	10	0.089

Weighted average number of votes 6.0				
Domestic cat	0	2	2	0.827
	1	2	3	0.150
	2	2	4	0.020
	3	2	5	0.002
		Didn't match previous criteria	6	0.000
Weighted average number of votes 2.2				
Grey squirrel	0	4	4	0.597
	1	5	6	0.254
	2	6	8	0.095
	3	7	10	0.035
		Didn't match previous criteria	11	0.020
Weighted average number of votes 5.2				
Hedgehog	0	3	3	0.471
	1	5	6	0.190
	2	7	9	0.102
	3	8	11	0.081
		Didn't match previous criteria	12	0.157
Weighted average number of votes 6.2				
Pheasant	0	2	2	0.845
	1	3	4	0.126
	2	3	5	0.025
	3	4	7	0.003
		Didn't match previous criteria	8	0.001
Weighted average number of votes 2.3				
Rabbit	0	4	4	0.526
	1	5	6	0.266
	2	6	8	0.118
	3	7	10	0.051
		Didn't match previous criteria	11	0.040
Weighted average number of votes 5.6				
Red fox	0	3	3	0.459
	1	4	5	0.243
	2	5	7	0.128
	3	6	9	0.071
		Didn't match previous criteria	10	0.099
Weighted average number of votes 5.1				
Roe Deer	0	3	3	0.740

	1	3	4	0.212
	2	3	5	0.041
	3	3	6	0.006
		Didn't match previous criteria	7	0.001
		Weighted average number of votes	3.3	
<hr/>				
Small rodent	0	3	3	0.234
	1	3	4	0.270
	2	3	5	0.207
	3	4	7	0.081
		Didn't match previous criteria	8	0.208
		Weighted average number of votes	5.0	
<hr/>				

Chapter 4 - School students conducting, contributing to and communicating ecological research — experiences of a school-university partnership

Please note that this chapter (with the exception of this paragraph) has been submitted to the journal *School Science Reviews*, received two positive peer reviews, and is undergoing minor revisions. Full citation: Hsing, P.-Y., L. Coghill, J. Ryder, M. Austin, S. Dooley, A. Ellison, C. Fenwick, M. Garland, P. Humphrey, H. Proudlock, A. Robson, C. Steer, L. Turnbull, R. Ascroft, and P. Stephens. 2018. Citizen scientists: School students conducting, contributing to and communicating ecological research—experiences of a school-university partnership. *School Science Reviews*, in review.

4.1 Abstract

Started in north-east England in 2015, MammalWeb aims to improve our knowledge of British mammals through the use of motion-sensing “camera traps”. Fundamental to the project is the involvement of local communities and individuals who act as citizen scientists. They contribute to the collection and analysis of the camera trap photographic data. Here, we jointly describe our experiences as a partnership between Belmont Community School and Durham University. School students became citizen scientists and ecological ambassadors who took part in research and designed outreach materials for their local community. We discuss what we learned and the resulting mutual benefits.

4.2 Introduction

Providing opportunities for school students to experience authentic science in an academic research environment has been suggested to have positive impacts (Holman et al. 2016). They include developing students’ learning and research skills and other transferrable proficiencies such as independence, self-esteem, resilience, decision-making and communication skills (European Union and SOCIENTIZE Consortium 2014, Holman et al. 2016, Archer 2016). Students’ attitudes towards science are observed to improve and, as they become aware of STEM (science, technology, engineering, and mathematics) career options, more consider pursuing a science career (Jones et al. 2016, Holman et al. 2016). Such improvements are often more marked in students from traditionally under-represented groups (Jones et al. 2016, Holman et al. 2016). In addition, although practical work in general is not associated with any increase in science test scores (Organisation for Economic Co-

operation and Development 2016, Hamlyn et al. 2017), higher science test scores have been noted for students who reported doing more of their own design and execution of experiments than for their peers who had not engaged in such self-led experimentation (Jones et al. 2016, Hamlyn et al. 2017). As such, several organisations, including the Wellcome Trust (<https://www.wellcome.ac.uk/>), Nuffield Foundation (<https://www.nuffieldfoundation.org/>), and Research in Schools (<http://www.researchinschools.org/>), advocate such independent research programmes. In addition, a survey of 4,000 14-18 year-olds at state-funded schools in England identified that 58% would like to do more practical work (rising to 76% of those on a single science programme¹) and 53% would be interested in hearing more about scientists' research (Hamlyn et al. 2017). This suggests that there is also an appetite among students for more practical experiences.

Giving school students the opportunity to become citizen scientists, where they become involved in the scientific process and actually contribute to research, is a means of enabling people to become active participants in, and co-creators of, authentic science (Irwin 1995, Bonney et al. 2009, European Union and SOCIENTIZE Consortium 2014). Indeed, academic research is increasingly turning to citizen science for aid in data collection, classification, or even analyses (Kosmala et al. 2016). Crowdsourcing data collection is just one form of citizen science, but it could be a way of involving people, making research more democratic and potentially reducing the lag time between discovery and education (e.g., the Foldit project; Khatib et al. 2011).

Here, we present an example of school students as citizen scientists, who, through a collaborative partnership between Belmont Community School and Durham University (both in Durham in north-east England), contributed to real research while engaging their local community in the science. Belmont Community School (<http://www.belmontschool.org.uk/>) is a mixed-sex, state-funded secondary school for 11-16-years-olds, while Durham University (<https://www.durham.ac.uk/>) is a highly-selective collegiate research university, consistently ranked in the top 10 in the United Kingdom (UK), and top 100 worldwide.

North-east England has the lowest student participation in higher education in the UK (Higher Education Funding Council for England 2017), and we wanted this partnership to (1) expose students to real-world science at a university and become aware of STEM career options; (2) let teachers gain first-hand experience to reignite a passion for their subjects and

¹ In England and Wales, where students take an examined course (usually at around age 16) combining Biology, Chemistry and Physics and achieving one result at the end.

increase confidence and knowledge when discussing real research in the classroom; (3) allow researchers to crowdsource their science and broaden the impact of their work.

We believe our citizen science approach to a school-university partnership not only fulfils those goals, but also empowers students – through enhanced science learning and outreach – to be engaged citizens.

4.3 Citizen science ecological monitoring

The ecology-based citizen science project, MammalWeb (<http://www.MammalWeb.org/>), was founded in 2015 by a team of ecologists in the Department of Biosciences at Durham University and the local Durham Wildlife Trust (<https://www.durhamwt.co.uk/>). This was in response to gaps in the monitoring of British wild mammals (Croft et al. 2017) and as an investigation into whether the success of citizen science surveys for other taxa (such as the UK Annual Breeding Bird Survey: <https://www.bto.org/volunteer-surveys/bbs/>) could be replicated for mammals.

Mammals are elusive and often nocturnal, making them difficult to track. As such, the project uses motion-sensing “camera traps” to photograph different mammals as they pass. These cameras are set up and monitored by more than 70 citizen scientists, including members of the public and schools. The citizen scientists upload the resultant images to the online MammalWeb platform where anyone with an Internet connection can register to help classify the animals (**Figure 4.1**). As of March 2018, more than 250,000 images have been submitted from 230 sites in the region, representing 42 camera-years of cumulative monitoring. Of those, over 120,000 images have been classified at least once by the 273 active users on MammalWeb. We aim to aggregate input from multiple users for each image into consensus classifications on which further ecological analyses can be based (Hsing et al. 2018). These records are then also submitted to repositories including the Environmental Records Information Centre for the North-east of England (ERIC North-east: <http://www.ericnortheast.org.uk/>) and so contribute to national databases. MammalWeb’s growing dataset could enhance understanding of our natural heritage by allowing analyses of wildlife diversity and its changes across space and time, which is of critical importance in light of rapid global environmental change.

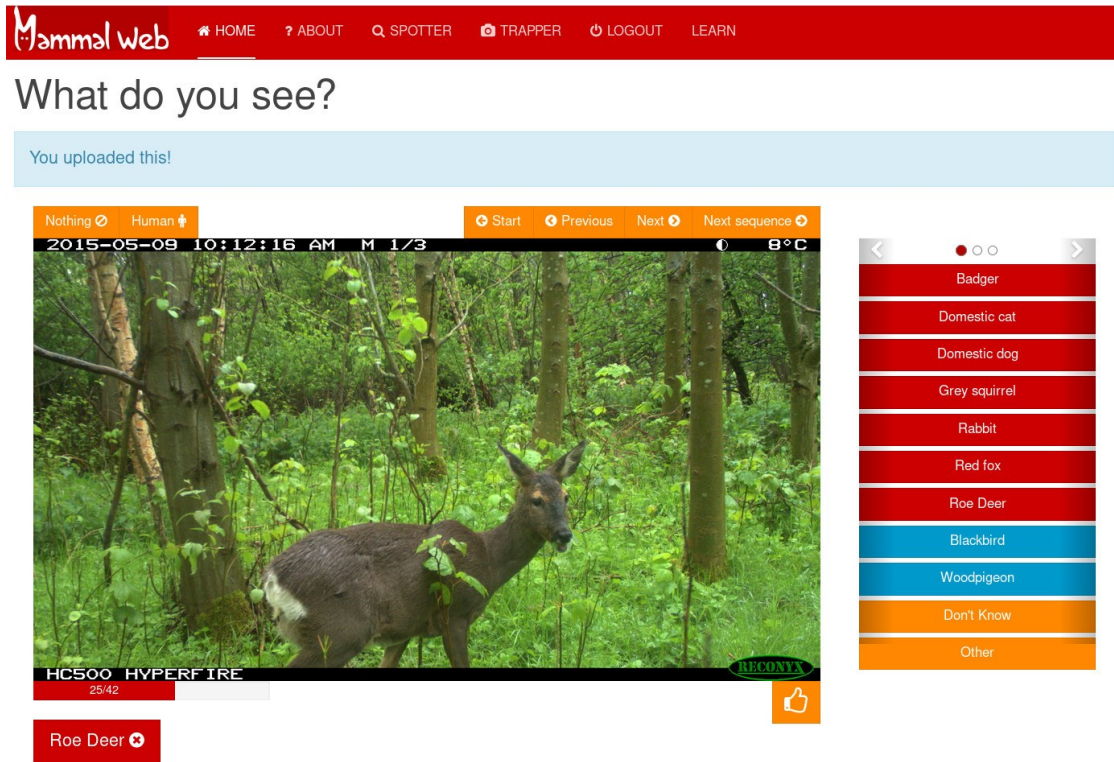


Figure 4.1. MammalWeb web interface for camera trap photo classification. Users choose from a scrollable list of options representing which animals they think are in each image.

In addition to quantitative analyses, the data (in the form of classified camera trap photos) collected by MammalWeb citizen scientists has led to civic engagement with tangible management outcomes. For instance, Mr Roland Ascroft used camera traps on a reclaimed colliery site at New Brancepeth (in County Durham, England), gathering over 20,000 images by the end of 2017. In addition to submitting these images to MammalWeb, he found 12 species of land mammals including roe deer (*Capreolus capreolus*). Camera-trap images showed that roe deer are present year-round and reproduce on the site. The site has been proposed as a Local Nature Reserve, and the camera-trapping results can inform its management.

On another occasion, a series of camera trap photos revealed the presence of a raccoon (*Procyon lotor*, which is not native to Britain) in nearby Sunderland (**Figure 4.2**). Since MammalWeb citizen scientists follow a specific camera trapping protocol that includes careful recording of metadata (such as the precise date, time, and location of camera deployments), the UK Department for Environment, Food and Rural Affairs (DEFRA) used MammalWeb data to locate the raccoon and transferred it to a local zoo.

Through the partnership between Belmont Community School and MammalWeb, we hoped that students would experience contributing to tangible scientific outcomes like these, and more importantly, take ownership of sharing this experience with their community.



Figure 4.2. A non-native raccoon (*Procyon lotor*) as imaged by a motion-sensing camera trap operated by a MammalWeb citizen scientist.

4.4 Student citizen scientists

Several schools across England worked with MammalWeb researchers in deploying camera traps and classifying photos. For example, the Durham Wildlife Trust engaged with several schools both at primary and secondary levels on the project and it was welcomed as an extremely valuable method of engagement for the students in terms of the natural environment and technology curriculum. However, in collaborating with Belmont Community School, we were able to build a deeper, sustained relationship both for long-term ecological monitoring, and in providing distinct experiential learning opportunities to a team of ten Year 9 students (aged 13–14). The goal was to train, support and empower the students as seed “ambassadors” who not only contributed to data collection, but also conducted their own ecological outreach within their community.

Throughout the academic year 2016, MammalWeb PhD student, Pen-Yuan Hsing (supported by Durham University’s outreach specialist, Dr Lorraine Coghill, and Belmont School’s science teacher and lead practitioner, Mrs Julie Ryder), made bi-weekly visits to the school. These after-school, extra-curricular sessions were initially focused on widening participation in the research, enabling the young people to gain an understanding of real-life science, including basic training on the deployment of camera traps for wildlife monitoring (**Figure 4.3**). Students were encouraged to consider factors including location, set-up and security, developing ownership over the trapping. In tandem, they researched local wildlife and investigated already-captured images on the MammalWeb platform. Support from a British Ecological Society Outreach Grant (<https://www.britishecologicalsociety.org/funding/outreach-grants/>) enabled the team to

visit a range of potential camera trapping sites beyond the school’s immediate location and broaden the students’ exposure to nature. This included the Durham Wildlife Trust’s Rainton Meadows Nature Reserve (County Durham) where, crucially, the students took control and ownership of camera trap deployment. Other field trips included one to camera trapping sites at the Durham University Botanic Gardens. A timeline of the above activities are shown in **Table 4.1**.

Table 4.1. Timeline of work with Belmont School students.

Dates	Activity
11 October 2015	Outreach Grant received from the British Ecological Society.
Late 2015 – end of spring 2016	Bi-weekly visits to Belmont School to work with student MammalWeb citizen scientists. Camera trap deployments occurred near the school during this time.
19 March 2016	Student-designed MammalWeb and ecology outreach activities delivered at the local Belmont Community Easter Fair.
4 – 5 July 2016	Field visits to the Durham Wildlife Trust Rainton Meadows nature reserve and the Durham University Botanic Garden.
May – July 2017	Multiple visits to Belmont School for further camera trapping. Filming of camera trapping work at Rainton Meadows (June – July 2017).
September 2017	Designing outreach activities for Celebrate Science Festival.
24 October 2017	Delivered outreach at Celebrate Science Festival.



Figure 4.3. Student citizen scientists deploying motion-sensing camera traps in Rainton Meadows nature reserve.

4.5 What the student citizen scientists learned

This section is an edited account written by the students – who are co-authors of this article – regarding their experiences deploying camera traps at the Rainton Meadows Nature Reserve where they obtained approximately 1,000 wildlife photos.

4.5.1 Finding a location for camera traps

During the first visit to Rainton Meadows, we scouted the reserve for suitable locations for deploying our two camera traps. To make sure scientifically useful photos can be obtained for MammalWeb, we set the following criteria for the environment in which we position the camera traps:

- Avoid places with substantial human activity which could disturb the monitoring and since thefts of cameras were known to occur.
- Consider which animals we were likely to observe in the area.
- Ensure the camera's field of view is not obstructed by foliage or low branches.

We selected a location in the woods near a stream and not viewable from the pedestrian paths. Animal tracks and remains were spotted nearby including bones, faeces, tracks and bird eggs. The cameras needed to be low to the ground because we believed most mammals here are small and the camera's limited range means placement is important. Although the camera is water resistant, we placed it under the canopy of trees to minimize exposure to the elements.

4.5.2 Setting up a camera traps

Camera traps require a strong and freestanding object to attach to (usually a tree or fence post). In our case this was a strong tree about 3 m from a stream. Considering the height of the animals likely to be in the environment, we placed our camera traps just below knee height.

To test the cameras' positioning, we initially set them to do a "walk test". While on this mode, a small red light on the camera flashes when an object moves in front of it — identifying when a picture would be taken. Once satisfied with the cameras' angles, we armed them to take real photos. We then attached the cameras with a cable lock to the tree trunk.

The camera traps we used (Reconyx HC500) employ an infrared motion sensor that triggers when an animal passes by. Upon each trigger, we set the camera traps to take three images in quick succession ("burst mode"). The camera resets within a minute after a trigger and is ready to take more pictures. We left the camera for three weeks between 13 June and 04 July 2017.

4.5.3 Expected findings

During the period of research in the weeks leading up to 13 June 2017 (the day in which the camera traps were set at Rainton Meadows), we used information from previous sightings and our knowledge of the type of environment found there (relating to the habitat certain species require to live) to predict what types of animals we would be able to photograph. Some examples of the species we predicted to find were: rabbits (*Oryctolagus cuniculus*), deer, hedgehogs (*Erinaceus europaeus*), grey squirrels (*Sciurus carolinensis*), and small rodents (e.g. rats, mice).

4.5.4 Collecting the camera traps

Upon collecting the cameras we uploaded their images onto a computer in order to observe our findings. We were delighted to discover that a large amount of animals had been photographed, some of which were predicted beforehand. Multiple photos of rabbits, hedgehogs and grey squirrels were captured on both of the cameras as well as some birds (**Figure 4.4**). In addition, we were excited to find that multiple images of a red fox cub (*Vulpes vulpes*) were taken on several different occasions (**Figure 4.4**). Even though it was known that red foxes lived in Rainton Meadows, it was surprising to find them captured on camera. The data can be used to predict the paths of the foxes, what times they use these routes and the activity they may be partaking in at these times.



Figure 4.4. Animals observed with camera traps set up by Belmont Community School students. Clockwise from top left: Rabbit, grey squirrel, red fox, and hedgehog. These photos have been uploaded to MammalWeb for classification by other citizen scientists. The greyscale images were taken at night or low-light conditions using the camera's infrared flash.

4.6 Students as ecological ambassadors

Crucial to the project was the ambition to encourage the students to become ambassadors for their research, engaging their own community. As such, later after-school sessions focused on facilitating the students' planning and design of ecological outreach. This took a student-led approach with school and university staff facilitating the process through a series of games, activities and training sessions that encouraged the students to develop their communication skills, taking consideration of different 'audiences', and exploring different engagement techniques.

The students decided to concentrate engagement efforts in three areas: (1) the development and delivery of interactive activities suitable for community events; (2) the development of educational materials for schools and public; and (3) the production of a short video to illustrate the project.

Commencing with the Belmont Easter Community Fair in March 2016 (**Figure 4.5**), the team (in self-designed t-shirts) ran a stall of activities aiming to engage visitors about their MammalWeb research and findings about local wildlife. The students demonstrated camera trapping and got people involved in classifying images on the MammalWeb platform. They found that an animal "poo" identifying game (with models of wildlife scat samples loaned from the British Ecological Society) was particularly successful in engaging people of different ages, whilst their mammal Easter egg hunt absorbed younger children and their peers. The team adapted their activities and have since contributed to several community events including engaging over 2,000 people in one day at Durham University's public Celebrate Science festival in October 2017 (**Figure 4.6**). In addition to demonstrating the use of camera traps and running the poo game at this festival, the students debuted an activity they developed where participants learned about animals through using stamps representing their tracks. Evaluation from the festival highlighted the students' contributions with several visitors naming it as their favourite activity, and multiple comments stating that it was "great to see young people who are so knowledgeable and enthusiastic about science".



Figure 4.5. Student ecological ambassadors at the March 2016 Belmont Easter Community Fair.



Figure 4.6. Student ecological ambassadors engaging visitors at the Celebrate Science festival in October 2017.

With support from the British Ecological Society, we worked with a local professional filmmaker to document these experiences, as well as illustrating the MammalWeb citizen science project to a wider audience. The resultant 10-minute video is shared in full (<https://vimeo.com/237565215/>) and 1.5-minute versions (<https://vimeo.com/237771257/>) under the Creative Commons Attribution-ShareAlike 4.0 license.

4.7 Lessons learned from citizen science collaboration between schools and universities

The core group of ten students who worked on the project were initially motivated by a general interest in wildlife and a desire to see them in their natural habitat. After nearly two years of working on MammalWeb-related outreach activities, the key outcomes reported by this group of students were:

- Considerable surprise about the diversity of wildlife that they were previously “oblivious” to.
- Excitement about participating in outdoors experiential learning, finally “learning outside the classroom”.
- Satisfaction from contributing to a real and on-going citizen science project with broad impact.
- Enjoyment from doing the above in their local community.

Through conversations with Mrs Julie Ryder, teachers at Belmont School noted:

- Involvement in the Mammal Web project has raised pupil awareness of the valuable contributions young people can make to research. The increased understanding of the distribution of animals in the local area has been shared with the school and the families of those involved, spreading the information through the local community and well beyond the core group of ten students.
- Links made with Durham University – allowing pupils to work alongside and contribute to research – has opened up the idea of education beyond school and the prospect of studying science at university.
- The pupils involved developed a real teamwork approach to solving problems, and showed that they are confident leaders and are able to interact with adults and students across the school and the wider community.
- Pupils have an increased enthusiasm to pursue science-related subjects beyond school, having broadened their experience of science related work. They feel confident to take an active part in a range of community projects.

- Involvement in projects linked with Durham University is a vital part of the extra-curricular provision they can provide for our students. Opening a window of opportunity for their students to work with the university is crucial if they are to increase the aspirations of their students.

From the perspective of researchers at Durham University:

- Crowdsourcing the collection and processing of data is just one form of citizen science, and it is very helpful to researchers whose time and resources are limited.
- When ecologists work with multiple schools, they can expand the geographical reach of their surveys. Also, if there is buy-in from teachers, then school partners can sustain ecological monitoring over longer periods of time when compared to individual volunteers, building long-term capacity.
- Citizen science projects such as MammalWeb – through education, outreach, and empowering citizen scientists – demonstrate the broader impact of research at universities.
- In the UK, universities are subject to evaluation by the Research Excellence Framework (REF; <https://www.ref.ac.uk/>) with broad implications for funding. Citizen science projects allow scientists to demonstrate the impact of their research outside academia, which is one of the criteria in REF, whilst simultaneously collecting important research information.
- Durham University has a stated goal of working more closely with the local community. MammalWeb is a successful case study of how Durham University researchers have achieved this with local citizens and students by joining them as co-creators of science.
- Working in partnership with young people and teachers provides a different perspective on the research, opening up new ideas and opportunities.

The project required a dedicated team to coordinate, and did experience delays and changes from the initial plans. From our experiences, we would advise the following if embarking upon a similar project:

- Identify dedicated key contacts from the school and the university. Many universities have outreach specialists which a teacher can contact to initiate this process.
- Take time to understand each other and get to know what everyone wants to achieve. Be honest and understand what can be achieved, including discussing barriers and limitations such as time, staffing, budget and resources (and possible solutions/ways to minimise).

- Agree how to communicate and maintain regular contact. Keeping each other updated and informed of changes to staffing and activities ensures that the programme can be adapted to suit all parties.
- Carefully consider time implications. Running something like this does take additional time. We deliberately arranged our activities as an alternative science club in order to reduce time/work pressures, and we were able to pre-provide all documentation (e.g., risk assessments) to facilitate field visits.
- Be aware of scheduling issues. The time pressures and academic schedules of schools and universities do not always align. Include substantial buffer time to deal with delays.
- Be flexible. New opportunities can arise (such as our participation in the Easter fair) and unforeseen circumstances (such as sickness) can hamper involvement.
- Think carefully about the how the project is set up - it is important that the students can take ownership of the project and feel confident and empowered to contribute to discussions and take action (within the limits of the project). It is important to emphasise regularly that the project is a collaboration between all participants, that it involves real-research and is not just a classroom exercise, and that their input is key. All involved adults should be made aware and supported with this too to prevent a more didactic approach, which alters the group dynamic and can impede full participation.
- For both the students and the wider group of citizen scientists contributing to MammalWeb, a major motivator is that they are conducting ecological research directly connected to their communities. This suggests that for a large-scale research project to involve schools, it is important to investigate and emphasise local relevance in order to sustain interest.
- Do consider what additional partners could contribute. For example, the British Ecological Society (BES) grant enabled the external visits by the school group (which we were not able to fund internally), but the BES was also keen to support through additional resources and training opportunities. Organisations like Research in Schools also promotes the integration of academic research in primary and secondary education.

4.8 Conclusion and future plans

We believe the MammalWeb citizen science project exemplifies the fruitful partnerships that can be formed between schools and universities. The mutual benefits and, in particular, the observed impact on the students as active, motivated, more confident learners, are felt to

outweigh the time and organisational commitment required. The students are already working on developing the project further and the school has activated new programmes for other groups with different organisations. Aspects of this project's findings have been presented at international conferences of the European Citizen Science Association, the British Ecological Society, and the Ecological Society of America. Insights gained from the crowdsourcing of data collection and classification have been published in peer-reviewed ecological journals (Hsing et al. 2018). In addition, MammalWeb has made contact with interested schools in other areas of the UK and is working with the Great North Museum: Hancock in Newcastle, England on a schools outreach partnership. We hope to develop the learning from this project into a wider educational network for ecological monitoring to fill the current gap in knowledge. Any school or teachers interested in this can contact us (email: info@mammalweb.org) and potentially borrow a camera trap for use with their students.

One challenge to tackle is how to integrate real-world science – such as the MammalWeb citizen science project – into the formal school curriculum if after-school, extracurricular activities are infeasible or not desired. This may involve a deeper discussion between researchers and teachers on where and how that science can fit in. In the case of MammalWeb, we believe it has the potential to complement the biology curriculum and possibly numerical skills (e.g., statistics) if data analyses are done as well. Through understanding the design of camera traps and MammalWeb platform there are also important technology and computing aspects to this work. We are currently developing activity guides for educators with this in mind.

This partnership has also prompted broader contact between other schools and Durham University. For example, the Ustinov Global Citizenship Programme at the University ran an engagement event between postgraduate researchers and local teachers to develop joint programmes for school pupils. This has already led to several Masters and PhD students (with subjects from psychology to social sciences) visiting those schools to engage young learners in the cutting-edge research being conducted at Durham University. The benefits of initial partnerships may thus be far reaching.

On the technical side, we are developing enhancements to the MammalWeb web platform to improve the user experience. One is the addition of interactive data visualisations allowing anyone to explore how observed wildlife changes over space and time. The other is a “project” feature allowing, for example, teachers to filter for and manage the photos and classifications contributed by their students. These features will be introduced from late-April 2018.

We hope the MammalWeb case study can serve as a template for implementation of other successful school-university partnerships.

4.9 Acknowledgements

We are grateful for generous support from the British Ecological Society for an Outreach Grant that made this work possible (<https://www.britishecologicalsociety.org/funding/outreach-grants/>). The video documenting this work was created by Ms Laura Degan, director of Writers' Block North East (<http://writersblockne.com/about/>). In addition, we would like to thank the staff at Belmont Community School, the Durham Wildlife Trust, and the Durham University Botanic Garden for their help. We also acknowledge support from the UK Heritage Lottery Fund for MammalWeb and Durham University for their Seedcorn Fund support and a Doctoral Scholarship for Pen-Yuan Hsing.

Chapter 5 - Handling uncertain detections and discretising data in camera trap-based occupancy modelling

5.1 Introduction

Reliably estimating animal populations is a key component of ecology and conservation (Kéry and Royle 2015). This often involves measures of abundance which are time and labour intensive to obtain, and may require the individual identification of animals (e.g., mark-recapture methods). For terrestrial mammals, measuring abundance can be difficult, since they are frequently elusive and nocturnal, and occur at low densities.

Occupancy is a measure defined as the proportion of an area or group of sampling sites in which a species is present (also defined as the *probability* that a site is occupied) (MacKenzie et al. 2002). The process of estimating occupancy is based on repeated surveys across multiple sites of interest where each survey determines the presence or absence of a target species. Occupancy can be useful when determining species richness and distribution, or as a surrogate for abundance for many research questions, such as when investigating changes in a population, or the relationship between populations and spatial or temporal covariates (e.g., Ahumada et al. 2013, Burton et al. 2015, Rovero and Spitale 2016, Rich et al. 2017). Occupancy models account for the imperfect detection of a species, defined as its probability of detection (or “detectability”) at a site given its presence or other covariates (MacKenzie et al. 2002, 2003). While the goal of many studies is to estimate occupancy, detectability is itself sometimes of biological interest with regards to factors such as changes in the physiological states of the animals, seasonal changes in behaviour (e.g., hibernation, when an animal is presence but hard to detect), or as a function of climate (Guillera-Aroita et al. 2010).

Data from camera trap surveys are frequently used for occupancy studies (Burton et al. 2015, Steenweg et al. 2017). This is because camera traps are non-invasive and can be deployed with relative ease across multiple sites and for long durations. It is generally assumed that the presence of a species can be confirmed as soon as a photo of it is captured, while its absence can be ascertained if no photos are obtained during the survey. Combining camera-trapping with occupancy estimation is especially useful for monitoring terrestrial mammals (McCallum 2013, Burton et al. 2015, Rovero and Spitale 2016, Rich et al. 2017, Bowler et al. 2017). This is because occupancy analysis does not require individual recognition of animals (which is highly problematic for many mammals), long camera trap

deployments can detect rare or elusive species, and occupancy analyses considers the possibility that an animal is not detected when present (which addresses the common assumption that non-detection means absence when camera trapping).

Citizen science projects have seen rapid growth as of late where, in their most common form, the collection and classification of data are crowdsourced to non-professionals (Silvertown 2009, Bonney et al. 2009). It has the potential to tackle large-scale ecological monitoring needs (Devictor et al. 2010), and there are now several citizen science camera-trapping projects targeting mammals (Swanson et al. 2015, McShea et al. 2015, Forrester et al. 2017). MammalWeb is one such project where I partnered with local communities near County Durham, England to deploy camera trap surveys to monitor wild mammals. As reported in Chapter 3, MammalWeb citizen scientists have, as of March 2018, classified about 116,000 images out of 250,000 collected over more than 15,000 camera trap days across 261 sites in the region. The MammalWeb project is notable of involving citizen scientists in both data collection and classification, while empowering them to design and deliver outreach (Chapter 4) or even start their own ecological surveys (Chapter 6).

Since MammalWeb began in mid-2015, the majority of my work has focused on recruiting and organising the citizen scientists to carry out camera trap deployments. In addition, I built on past work on crowdsourcing image classifications (Swanson et al. 2016) and developed a model which computes the probability a species is present in an image from aggregating user classifications (Hsing et al. 2018). These efforts have already produced tangible conservation outcomes – such as the capture of non-native species or informing the planning of a local nature reserve – there is a need to further explore the analytical tools to which we can apply these consensus classifications. Another important result is that we have taken citizen science participation to a higher level not just through school partnerships, but also members who have started their own ecological studies elsewhere in the country. Since MammalWeb data is essentially detection histories (absence and presence) for all the sites at which citizen scientists have deployed camera traps, in this chapter I will attempt to address issues arising from using MammalWeb data for occupancy analysis. They include how to discretise camera trap data into discrete sampling occasions and the handling of missing data in detection histories. Most importantly, I will explore the potential of utilising consensus classifications (as discussed in Chapter 3) as a measure of uncertain detection, an important topic when modelling occupancy (Miller et al. 2011, Clement 2016, Guillera-Arroita et al. 2017) and increasingly pertinent in light of the popularisation of crowdsourced data classification and machine learning algorithms. For the rest of this introduction, I will briefly expand on how I plan to address these three issues in this chapter.

First, occupancy models assume repeated discrete presence-absence surveys – called *sampling occasions* – across multiple sites during a *sampling season* (MacKenzie et al. 2002). Camera trap deployments are inherently continuous surveys, and there is no established guidance for dividing a deployment into discrete sampling occasions. While they are often 1-day long, some last for many weeks (Linkie et al. 2007, Ellis et al. 2014). Rovero and Spitale (2016) recommended that – as a general rule – discretising camera trap data into 1-day sampling occasions would be sufficient to achieve independence of detections. That is, within each 1-day sampling occasion, a detection is recorded as long as there is at least one photo of the target species. They tested discretising camera trap data collected by the TEAM Network (Rovero et al. 2014) by dividing 30-day-long surveys into sampling occasions between one and ten days long and fitting occupancy models to each one (Rovero and Spitale 2016). In this case, the estimated occupancy rates were not sensitive to different interval lengths. However, it remains to be seen how broadly this recommendation can be generalised. In addition, since MammalWeb camera trap detections are uncertain (i.e., the probability an animal is present derived from consensus classifications), discretising data into longer sampling occasions might be justified since aggregating multiple uncertain detections would increase the possibility that the species was indeed detected.

Second, large-scale camera trap studies can be financially burdensome and logistically complex (Mackenzie and Royle 2005, Gálvez et al. 2016). These practical limitations may require, among several strategies (reviewed in Mackenzie and Royle 2005), deploying camera traps in a temporally staggered fashion where only a subset of sites are surveyed at a time (van Berkel 2014 p. 51). This is true in the case of MammalWeb, where only a small subset (up to ~20) of the 261 sites have citizen scientist-deployed camera traps on a given day. This means that for each site in a given study area, there will be missing data during the sampling season, when no camera trap was deployed. The standard occupancy model (MacKenzie et al. 2002) anticipates the possibility of missing data as defined here, and simply discounts those sampling occasions in a site's detection history. Here I will explore its effects on estimated occupancy.

Third, uncertain detections – e.g., the possibility of incorrect species identification – during surveys may impact the reliability of downstream occupancy analysis (Guillera-Arroita et al. 2017). Uncertain detections might, for example, result from uneven observer expertise or identifying species from proxies (such as scat or tracks). To deal with this issue, in one case of utilising opportunistic, crowdsourced data for estimating wolf occupancy in France, the size of the area to which a detection applies is scaled by the corresponding observer's level of expertise (Louvrier et al. 2017). This way, wolf detections reported by

untrained observers were effectively weighted less in the occupancy model than those from trained park rangers. However, this approach does not apply to uncertain detections from camera-trapping which, at the simplest level, results from the often indistinct images of animals that need to be identified. In addition, current attempts to extend the standard occupancy model to account for uncertain detections describe them using a discrete, multi-state term (Miller et al. 2011). However, in the case of crowdsourced camera trap image classifications, uncertainty is measured as a continuous variable – the probability an animal is present – without an obvious, non-arbitrary way to discretise into an ordinal term. This is also true in light of recent advancements in machine learning algorithms for classifying camera trap images which gives probabilities for detection confidence (Norouzzadeh et al. 2018). In this chapter, I test an approach where detection histories are resampled according to their level of uncertainty (i.e., probability of correct classification) to construct confidence intervals around occupancy estimates. This was done with both simulated data and that from selected species observed as part of the MammalWeb project to estimate, for example, the number of camera trap days needed to confidently ascertain the presence or absence of a species.

5.2 Methods

5.2.1 Occupancy models

The analyses in this chapter are based on the standard, single-season, single-species occupancy model developed by MacKenzie et al. (2002) which I will briefly describe here. For a target species, we conduct an occupancy study across N sites, where each site is visited on T discrete *sampling occasions* where a given survey method is applied. The timespan encompassing all sampling occasions constitute the *sampling season* for occupancy analysis. The resulting *detection history*, \mathbf{h} , for each site, i , is recorded as a vector of 1s and 0s (e.g., 00101 for five sampling occasions with two detections and three non-detections), or more generally:

$$\mathbf{h} = \{h_{i,t}; t = 1, 2, 3, \dots, T\}$$

where $h_{i,t} = 1$ or 0 corresponding to detection or non-detection, respectively, on sampling occasion t . Note $h_{i,t}$ as defined in the standard occupancy model is a binary variable which does not account for uncertainty in detections.

It is assumed that true species presence or absence within each site does not change during the sampling season. That is, the sampling sites are closed to immigration, emigration, mortality, or reproduction. Additionally, it is assumed that the species is never erroneously detected (no false-positives) when absent, detections at one site are independent from those

at other sites, and detections *within* a site are also independent. Importantly, to account for possible non-detections of a species when it is present, its *probability of detection* (or “detectability”) is denoted by p .

With the above, the likelihood of a given detection history \mathbf{h} of the target species at site i can be represented as:

$$Pr(\mathbf{h} | O_i = 1) = \prod_{t=1}^T p_{i,t}^{h_{i,t}} (1 - p_{i,t})^{1-h_{i,t}}, \text{ for } i = 1, 2, 3, \dots, N$$

And:

$$Pr(\mathbf{h} | O_i = 0) = 1, h_{i,t} = 0 \text{ for all } i$$

where $O_i = 1$ or 0 depending on the true presence or absence of the species at site i .

The value of O_i is decided by the true occupancy ψ of the study area (encompassing all sites), which can be defined as the proportion of all sites occupied by the species, or the probability that site i is occupied. Since the presence and absence of the species is assumed to be fixed within each site during the season, ψ is therefore also assumed to be constant.

The goal of occupancy modelling is to compute *estimates* of occupancy (denoted by $\hat{\psi}$) and probability of detection (also referred to as detectability, denoted by \hat{p}) for the target species across N sites in the study area through T sampling occasions. For this purpose, the primary dataset to be derived from the raw data collected is a *detection matrix* where each row represents the detection history \mathbf{h} at site i .

Ecologically, it is reasonable that ψ and p can be a function of other physical and biological parameters. For occupancy analysis, they can be incorporated into the model as site-level (e.g., camera trap model, habitat type or distance to roads) and observation-level covariates (i.e., those which may vary between sampling occasions, such as temperature, precipitation, or the presence of other species) (MacKenzie et al. 2002). While important for certain ecological questions, they were not the focus of the current analyses.

5.2.2 Discretisation of camera trap data

To examine the effects of varying sampling occasion lengths when discretising data, I first simulated 200 detection matrices of 60 sampling occasions across 20 sites. During each simulation, I generated true occupancies at each site for three values of $\psi = \{0.1, 0.2, 0.4\}$ (e.g., if $\psi = 0.2$ then four out of the 20 sites would be chosen at random to be occupied) followed by generating detections across the 60 sampling occasions given three values of detectability ($p = \{0.05, 0.1, 0.2\}$). For example, a simulated detection matrix with $\psi = 0.2$, $p = 0.2$, 20 sites, and 30 sampling occasions would have approximately $20 \times 0.2 \times 30 \times 0.2 = 24$ detections.

Next, the 60 sampling occasions were discretised by aggregating detections into “reading frames” of different sizes. For example, a reading frame size of five means five consecutive sampling occasions (i.e., five camera trap days) were aggregated into one to infer whether the species had been detected ($h_{i,t}$ for the reading frame was 1; this occurred if the animal was recorded as present during one or more of the five consecutive camera trap days) or not ($h_{i,t}$ for the reading frame was 0, indicating that the animal was not recorded on any of the five consecutive days). The resulting discretised detection matrix would have $\frac{60}{5} = 12$ sampling occasions. This discretisation was done for reading frame sizes corresponding to all the positive factors of 60 excluding itself (i.e., 1, 2, 3, 4, 5, 6, 10, 12, 15, 20, and 30). This was applied to all 200 simulated detection matrices. Next, a single-species, single-season occupancy model (implemented by the `occu()` function provided by the “unmarked” package (Fiske and Chandler 2011) in R) was then fitted to each detection matrix to estimate $\hat{\psi}$ and \hat{p} . In other words, the nine combinations of ψ and p each had 200 simulated detection matrices (total 1,800 simulations) from which $\hat{\psi}$ and \hat{p} were calculated.

5.2.3 Effect of missing data on model estimates

To investigate the effect of temporally staggered camera trap deployments where only a subset of sites is sampled on a given sampling occasion, I introduced varying proportions of missing data (0.1 to 0.8) into a detection matrix of 60 sampling occasions across 20 sites with which to estimate $\hat{\psi}$. For each proportion, this was done for four combinations of $\psi = \{0.1, 0.2\}$ and $p = \{0.1, 0.2\}$ each with 200 simulated detection matrices (total 800 simulations).

5.2.4 Resampling from uncertain detections

As described earlier, uncertain detections for the purpose of estimating occupancy may arise from the indirect signs on which detections are based or, in the case of camera traps, crowdsourced classifications or ambiguity in images. For this analysis, uncertain detections were introduced by replacing 1s (detections) with probabilities of true detection (i.e., values between 0 and 1 representing probability of correct classification) within a simulated detection matrix given $\psi = 0.3$ and $p = 0.2$ across 60 sampling occasions at 20 sites. This was done four times (resulting in four “uncertain” detection matrices) where, each time, the probabilities of correct classification were drawn from normal distributions with mean $\bar{x} = \{0.4, 0.6, 0.8, 0.9\}$, standard deviation $\sigma = 0.072$, and capped at 1.0. The standard deviation was chosen to approximate the distribution of probabilities of correct species detections (derived from consensus of crowdsourced classifications) in the MammalWeb citizen science camera-trapping project (as described below and in Hsing et al. 2018).

Each of the four uncertain detection matrices was resampled 200 times where each uncertain detection (probability of correct classification) was the probability that it would be converted to a “1” (otherwise it would be converted to “0”). For example, for an uncertain detection of 0.9, it would be expected to be converted to “1” in 180 samples (and “0” in 20 samples). Occupancy model estimates of $\hat{\psi}$ and \hat{p} were computed for each sample.

This approach of resampling from uncertain detections was also applied to a real-world MammalWeb dataset. MammalWeb is an ongoing citizen science project in north-east England where participants deploy camera traps and submit the resultant photos to our web platform (<http://www.MammalWeb.org/>). We require citizen scientists who deploy camera traps to submit corresponding metadata indicating the time and location (among about 250 sites where they have deployed camera traps) at which images were taken. In a sense, the dataset of MammalWeb consensus classifications could be considered as a large occupancy detection matrix of 250 sites with a continuous sampling “season” from March 2015 to March 2018. However, this would likely violate the assumption of closure for occupancy models, a point to which I shall return in the discussion. Registered users on the website are shown sequences of these images (grouped as those taken within 10 seconds of each other) to classify. Each sequence of images is classified by multiple users. Between March 2015 and March 2018, 265 registered users contributed 249,425 classifications of 40,709 sequences (115,944 images). A subset of 10,483 sequences were classified by us as a “gold standard” to assess user accuracy for different species given the number of correct and incorrect (which includes false-positives and false-negatives) classifications for each sequence (Hsing et al. 2018).

These sequences (i.e., those with both user and gold standard classifications) were incorporated into a logistic regression model which was used to calculate consensus classifications from user classifications of 30,583 image sequences without a gold standard. Each consensus classification gives the probability that a certain species has been correctly detected in a sequence. “Nothing” (i.e., no animal present) is one of the possible “species”, and image sequences depicting the presence of more than one animal species were exceedingly rare and not included in this analysis (Hsing et al. 2018).

For the current analysis, consensus classifications were first discretised into 1-day sampling occasions. This meant that classifications from partial camera trap days were excluded (e.g., if a camera trap was first deployed on an afternoon, classifications from that time until midnight were excluded) so that each sampling occasion represented a complete calendar day. For a given species, all sequences with consensus classifications indicating its

presence were aggregated such that the uncertainty of its detection for that sampling occasion (i.e., camera trap day) is:

$$\Pr(\text{detection}) = 1 - \prod_{j=1}^J (1 - C_j)$$

where C_j is the consensus classification probability for image sequence j of J sequences taken during that day.

Next, I extracted ten 60-day detection matrices (i.e., 60-day long sampling seasons) where at least 20 camera trap sites were represented for three animals observed in MammalWeb: Grey squirrel (*Sciurus carolinensis*), red fox (*Vulpes vulpes*), and roe deer (*Capreolus capreolus*). These matrices were selected to avoid overlap in time and approximate the full duration for which MammalWeb classifications were available (March 2015 to March 2018). Each matrix was resampled 200 times to estimate mean $\hat{\psi}$ and \hat{p} using the method described above, with consensus classifications acting as the measure of uncertainty.

With the \hat{p} from each window and given that consensus classifications were discretised into 1-day-long sampling occasions, I also estimated the number of camera trap days needed to give a probability, $P = 0.95$, of detecting that species, given that it occurs in the area. This value can guide how long we ask MammalWeb citizen scientists to deploy camera traps, and was calculated by solving for the minimum number of days D such that:

$$1 - (1 - \hat{p})^D > P$$

To discern possible temporal patterns in MammalWeb data (which would suggest effects from temporal site-level covariates), I extracted 60-day detection matrices for badger (*Meles meles*) detections beginning from June and December in 2015, 2016, and 2017 (six matrices total). The spread of $\hat{\psi}$ and \hat{p} from 200 samples of each matrix were compared for this species, which is known to be less active (and, hence, presumably less detectible) during winter.

All analyses in this chapter were implemented in R 3.5 (R Core Team 2017) running in RStudio 1.1 (RStudio Team 2018) with the packages unmarked (for fitting occupancy models, Fiske and Chandler 2011), tidyverse (Wickham and RStudio Team 2017), lubridate (Grolemund and Wickham 2011), magrittr (Bache and Wickham 2014), and writexl (Ooms and McNamara 2018). The starting date, number of sites, and proportion of missing data for each window used for the above analyses on MammalWeb data can be found in supplementary **Table 5.2**.

5.3 Results

5.3.1 Discretisation of camera trap data

For each combination of simulation parameters (true ψ and p), the mean estimated occupancy ($\hat{\psi}$) from 200 simulated detection matrices was congruent with the true value. This was true across all discretisation frame sizes (**Figure 5.1**). In addition, the variance of $\hat{\psi}$ and \hat{p} increased with frame size *and* for low values of true ψ and p . Note that while \hat{p} appeared to diverge from p at larger frame sizes, it was not inaccurate *per se*. Instead, this was the result of aggregating p across many sampling occasions such that:

$$\hat{P} \cong 1 - (1 - p)^D$$

where \hat{P} is the estimated detectability for the reading frame and D is the number of pre-discretisation sampling occasions (e.g., camera trap days) that fall into each reading frame. Intuitively, this makes sense as the probability of detecting an elusive animal would be higher across many sampling occasions instead of one. For example, at $D = 10$ and $p = 0.05$, the simulation results in $\hat{P} \cong 0.4$ which is expected given the description above. Therefore, \hat{p} were accurate at each frame size.

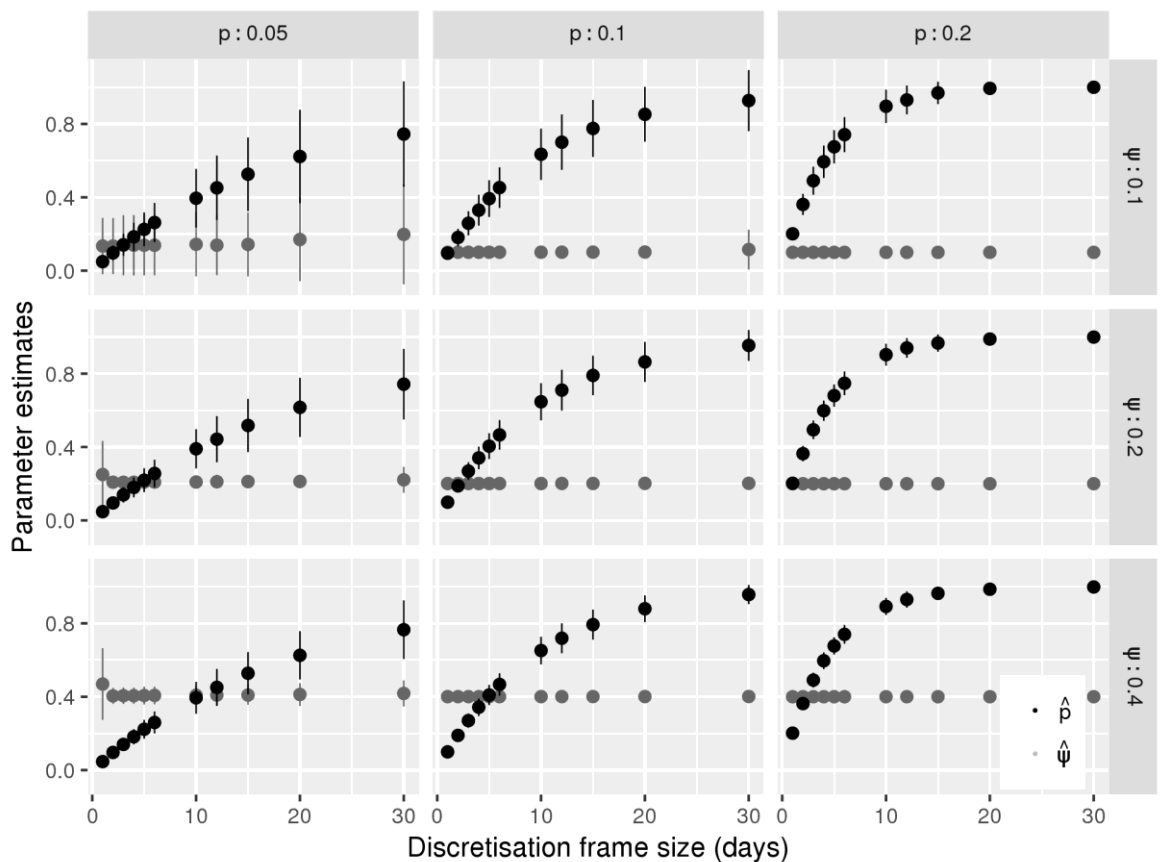


Figure 5.1. Mean estimated occupancies ($\hat{\psi}$ grey points) were robust against varying data discretisation frame sizes, while mean estimated detection probabilities (\hat{p} black points) increased with frame size in line with expectation. However, the variance of both estimates was greater for low values of true ψ and p (e.g., $\psi = 0.1$, $p = 0.05$) and increases with frame size. Vertical lines for each point are ± 1 standard deviation. Data from nine combinations of true ψ and p , each with 200 simulated detection matrices (total 1,800 simulations).

5.3.2 Effect of missing data on model estimates

After introducing varying proportions of missing data in a detection matrix, the accuracy and variance of estimated occupancies ($\hat{\psi}$) were positively related to true ψ and p (**Figure 5.2**). This was especially clear when true detection probability was low ($p = 0.1$), where $\hat{\psi}$ would substantially diverge from ψ with proportions of missing data higher than about 0.6. In cases where both ψ and p were greater than 0.1, $\hat{\psi}$ remained accurate even with up to 80% of data missing in the detection matrix.

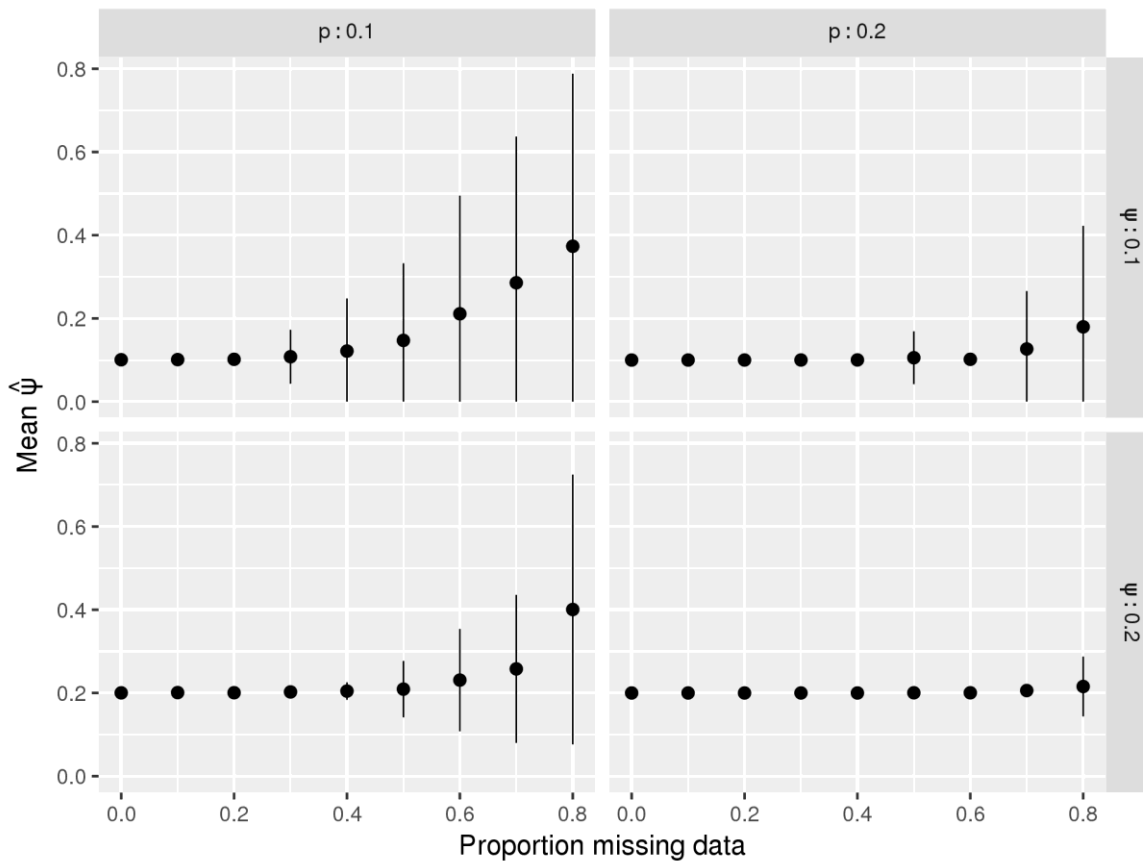


Figure 5.2. Mean estimates of occupancy ($\hat{\psi}$) were sensitive to high proportions of missing data when true occupancy and detection probability were low (e.g., $\psi = 0.1$, $p = 0.1$). Vertical lines crossing data points are ± 1 standard deviation. Data from 200 simulations of detection matrices for each proportion and combination of ψ and p (total 800 simulations).

5.3.3 Resampling from uncertain detections

Estimates of occupancy ($\hat{\psi}$) were clustered closely around the true value ($\psi = 0.3$) at all levels of uncertain detection in simulated data (**Figure 5.3**). However, there were more outliers when uncertainty was high (i.e., mean probability of correct classification is low). The variance of estimated detection probabilities (\hat{p}) was greater than that for $\hat{\psi}$ but decreased with higher mean probabilities of true detection (**Figure 5.3**). Similar to when discretising simulated data, \hat{p} were also accurate given how the resampling approach incorporates uncertain detections. For example, $\hat{p} \cong 0.18$ for when mean probability of

correct classification was 0.9 in **Figure 5.3**. Here, \hat{p} is, in effect, the true detectability ($p = 2.0$) multiplied by the mean probability of correct classification (0.9). Hence, the resampling method presented here was indeed accurate for \hat{p} given uncertain detections.

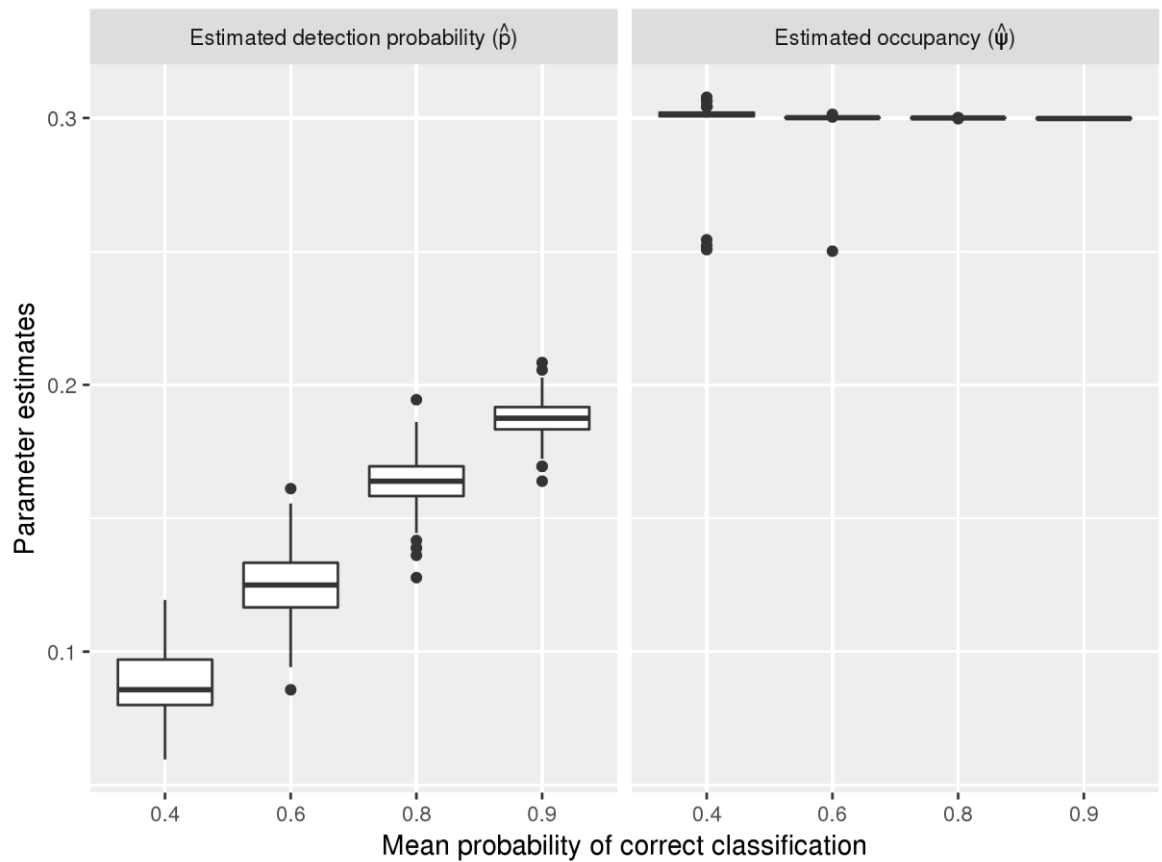


Figure 5.3. Both estimated occupancy ($\hat{\psi}$) and estimated detection probability (\hat{p}) were robust against uncertain detections. Each box plot represents parameter estimates from 200 resamples of a detection matrix (generated from $\psi = 0.3$ and $p = 0.2$) with detections replaced by uncertain detections (i.e., probabilities of correct classification) drawn from normal distributions with means $\bar{x} = \{0.4, 0.6, 0.8, 0.9\}$ and capped at 1.0.

When the resampling approach was applied to MammalWeb consensus classifications (which are measures of the probability of correct classifications) of three species, mean estimated occupancies ($\hat{\psi}$) largely fell between 0.5 and 0.6, but were highly variable for red fox (**Figure 5.4**). For all three species, mean estimated detection probabilities (\hat{p}) were lower than 0.3 and the variances of \hat{p} were low (with standard deviations $\sigma \leq 0.061$). The proportion of missing data for the detection matrices used here generally fell between 0.4 and 0.6 (supplementary **Table 5.2**).

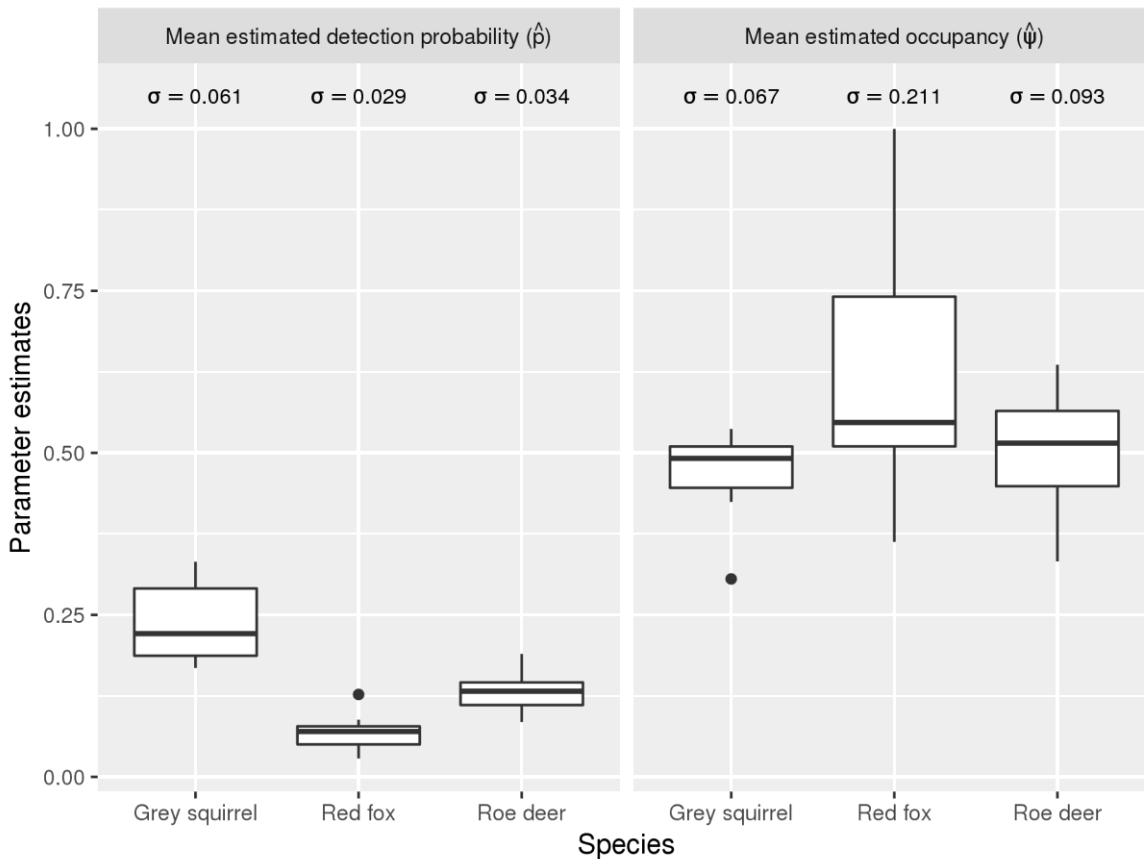


Figure 5.4. Box plots of mean occupancy model estimates of detection probability (\hat{p}) and occupancy ($\hat{\psi}$) for three species seen on MammalWeb. Each mean was derived from 200 resamples from an uncertain detection matrix made of MammalWeb consensus classifications. Ten detection matrices were drawn for each species across non-overlapping 60-day time windows. Standard deviations of the mean estimates (σ) are indicated above each box plot.

With mean \hat{p} for each species and a desired confidence level of $P = 0.95$, I calculated the number of days (D) needed for a camera trap to detect the three species (**Table 5.1**). Grey squirrels need, on average, only a 12.3 day camera trap deployment for detection, while the red fox requires almost two months ($D = 53.5$ days). In addition, the standard deviation of the estimate for red fox is 28.4 days, far greater than that of the other two species.

Table 5.1. Estimated mean number of camera trap days (D) needed to detect a species at a confidence level of $P = 0.95$. Derived from estimated mean detection probabilities (\hat{p}) from resampling MammalWeb consensus classifications from 10 60-day-long detection matrices.

Species	Mean time to detection (D)	Standard deviation
Grey squirrel	12.3	3.2
Red fox	53.5	28.4
Roe Deer	22.4	5.9

When comparing occupancy model estimates based on badger consensus classifications, the proportion of missing data for the June 2015 window was deemed too high (0.809, see supplementary **Table 5.2**) and was excluded from analysis. For the other five detection matrices (beginning December 2015, and June and December in 2016 and 2017), there was

no clear seasonal pattern to $\hat{\psi}$ (**Figure 5.5**). While estimated detection probabilities (\hat{p}) were slightly higher in June of 2016 and 2017 when compared to the winter months, all values of $\hat{\psi}$ and \hat{p} were generally low. Lastly, with the exception of $\hat{\psi}$ for December 2015, the variances of all \hat{p} (≤ 0.1) and $\hat{\psi}$ (mostly < 0.2) were very low after 200 resamples of their respective detection matrices. On average, the detection matrices of badger data represented 28 camera trapping sites (supplementary **Table 5.2**). However, the number of sites represented in each detection matrix did vary considerably, from 17 to 42.

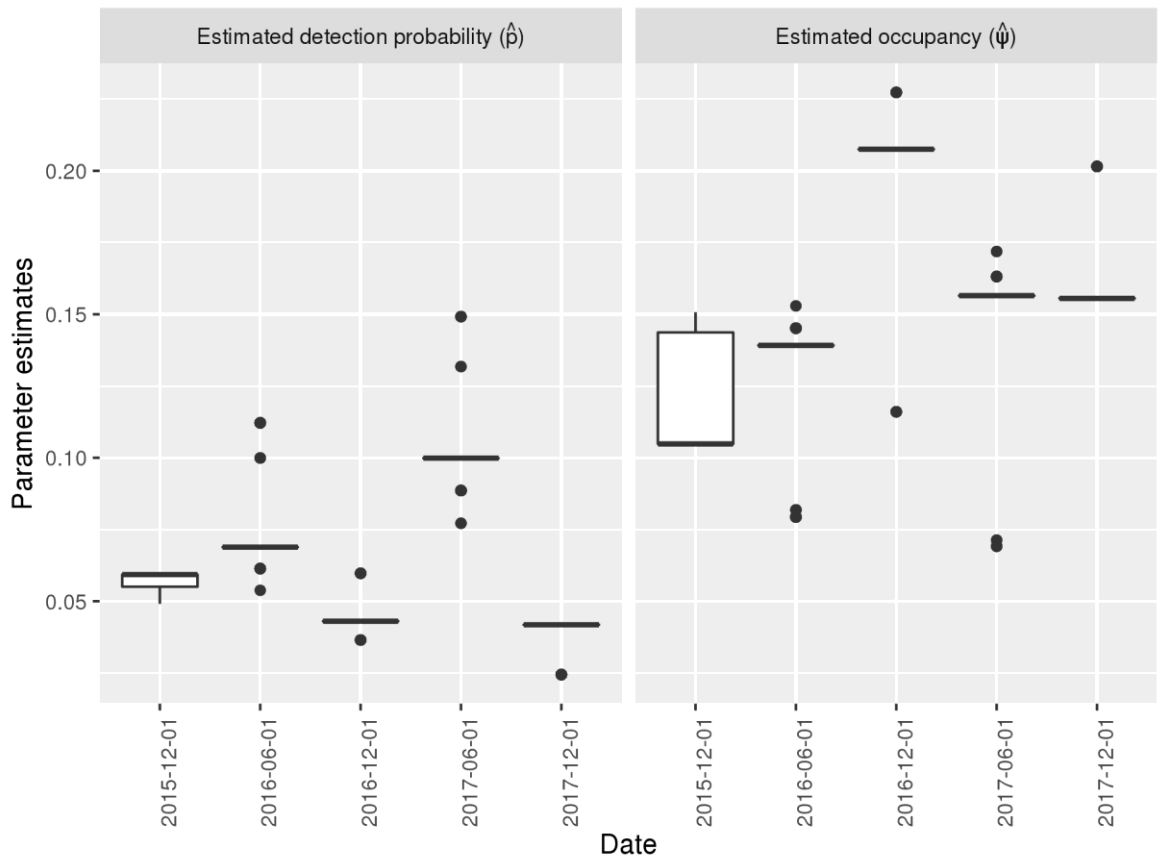


Figure 5.5. Estimates of badger occupancy and detection probability ($\hat{\psi}$ and \hat{p}) for detection matrices taken from 60-day windows starting in June and December of 2016, and 2017 plus December 2015. The horizontal axis is comprised of the starting dates (YYYY-MM-DD) of the six 60-day detection matrices from which 200 samples were drawn.

5.4 Discussion

Camera-trapping surveys are often deployed to provide data for estimating occupancy (e.g., Burton et al. 2015, Gálvez et al. 2016, Rich et al. 2017). This chapter investigated three issues common to such studies: a lack of well-established guidelines on how to discretise camera trap observations into discrete sampling occasions; possible effects of missing data on model estimates; and handling uncertain detections, specifically when crowdsourcing image classifications. Through simulations I performed, I showed that the accuracy of estimated parameters ($\hat{\psi}$ and \hat{p}) were generally robust against different discretisation frame

sizes and proportions of missing data, but their variances were not. I also showed that $\hat{\psi}$ and \hat{p} can be reliably estimated given uncertain detections via resampling, such as uncertainty arising from crowdsourced camera trap images classifications. In addition, I applied the resampling method to data collected by the MammalWeb citizen science project to estimate camera trap deployment times needed to confidently detect three species, plus observing a lack of clear seasonal variations in badger occupancy. For the rest of this chapter, I will discuss the findings with respect to occupancy modelling and practical considerations when conducting citizen science camera trapping. Specifically, (1) camera trap data should be discretised to 1-day long sampling occasions, which is especially important when there is a high proportion of missing data; (2) the resampling approach is useful for occupancy modelling especially when uncertainty in detections can be measured as a probability; and (3) citizen science camera trapping should, at least in the pilot phase, strive for longer deployments at fewer sites to more precisely estimate detectability, which would inform guidelines on minimum deployment durations for a wider roll-out.

5.4.1 Discretisation of camera trap data

There is currently a dearth of clear guidelines or studies on how to discretise continuous camera trap observations for occupancy modelling (Rovero and Spitale 2016). In this analysis, I simulated occupancy detection matrices using different input parameters (ψ and p) and discretised using a wide range of “reading frame” sizes from which model parameters ($\hat{\psi}$ and \hat{p}) were estimated. These simulations supported, and generalised, the pattern observed by Rovero and Spitale (2016) in a camera trap dataset collected by the TEAM network. Namely, the *precision* of both $\hat{\psi}$ and \hat{p} decreased with larger frames, and was especially pronounced when ψ and p were low (e.g., < 0.2). This result is reasonable because discretising data using larger reading frames reduces the effective number of sampling occasions on which estimates can be based.

In contrast to large reading frames (e.g., two weeks, Linkie et al. 2007), Guillera-Aroita et al. (2011) proposed treating detection history as a continuous, rather than discrete, process. They successfully piloted this approach on data collected from line transects, and suggested the possibility of its application to camera trap data. However, I am not aware of this being tested with camera trapping, and given existing concern that many animals move back and forth in front of a camera trap (Rovero and Spitale 2016), no discretisation at all might result in clusters of non-independent detections. In other words, reading frames which are too short may also be problematic. This can be a venue for future investigations.

Another motivation for this analysis was to explore the possibility of reducing uncertainty in detections – such as those from consensus crowdsourced image classifications – by

aggregating them into larger reading frames. In light of the above discussion, I do not recommend doing so. The probability of a consensus classification being correct is generally high for most species observed on MammalWeb (Chapter 3) and similar projects such as Snapshot Serengeti (Swanson et al. 2015, 2016). Throughout this thesis, I have discussed methods for increasing engagement to sustain crowdsourced classifications, including technical means, such as directing classifiers to image sequences needing more classifications (instead of randomly) to increase confidence (or to retire them for expert adjudication). I believe those methods would be more desirable than sacrificing the precision of $\hat{\psi}$ with larger (and fewer) reading frames. Therefore, given the current analysis, I believe it is reasonable to maintain the common practise of 1-day-long reading frames when discretising camera trap data.

5.4.2 Effect of missing data on model estimates

Past work has addressed the optimal design of camera trap surveys in light of limited resources (Mackenzie and Royle 2005, Gálvez et al. 2016), and one strategy is to deploy camera traps in a temporally staggered fashion such that only a subset of sites are surveyed on any sampling occasion (van Berkel 2014 p. 51). The current work builds on that strategy by examining the effect of missing data in the resultant detection matrices. The analysis here revealed that unless the true detection probability of a species is low (e.g., $p = 0.1$), estimates of mean occupancy ($\hat{\psi}$) remained largely accurate despite high proportions (i.e., up to 0.7 when $p \geq 0.2$) of missing data in a detection matrix. Effectively, missing data is analogous to reducing the number of camera trap days in a sampling season. For example, a 60-day sampling season might be reduced to 24 effective camera trap days if 60% of the detection matrix is missing data.

The reality of missing data, whether from temporally staggered camera trap deployments or other logistical constraints, has important implications for discretising camera trap data with large reading frames. This is because incomplete reading frames will need to be excluded from analysis when discretising data. For example, if a detection history of 00-110 (where “-” denotes a missed sampling occasion with no data) were to be discretised with a reading frame of size two, then the resulting detection history would be 0-1, and the detection on the original fourth sampling occasion would be excluded. This is another reason for keeping reading frames to one day for camera trap data.

5.4.3 Resampling from uncertain detections

The majority of existing work on using camera trapping data for occupancy analyses assumes detection as a binary variable: detection or non-detection. However, the reality is that detections are often uncertain and need to be addressed in order to produce unbiased

occupancy estimates (McClintock et al. 2010, Clement 2016, Guillera-Arroita et al. 2017). In this study, I built on the fact that data classification – specifically that of camera trap images – is now often crowdsourced (Swanson et al. 2016, Hsing et al. 2018). This process provides consensus classifications which can act as probabilities of true detection in an “uncertain” detection matrix. Resampling from these data enables fuller acknowledgement and utilisation of the uncertainty around estimated model parameters. In the simulations of this chapter, mean estimated occupancy rates ($\hat{\psi}$) remained accurate and precise even with low confidence in consensus classifications (i.e., low probability of correct classification). This is reassuring because even without calculating consensus classifications, the accuracy of MammalWeb user classifications is already above 90% for most species (Chapter 3). In addition, while estimated detectability (\hat{p}) has higher variances, they were also accurate given their corresponding levels of uncertainty.

One limitation of the current simulations is that the possibility of false positives was not considered, i.e., the incorrect detection of an animal when it is absent (which could be misidentification or true absence). This is important, because it has been demonstrated that false positives can significantly bias estimates of occupancy (Royle and Link 2006, McClintock et al. 2010). Future work could usefully assess this by introducing detections with varying false-positive rates into the existing implementation of the standard occupancy model. For instance, consider a simulated 1,200-element occupancy detection matrix consisting of 40 sampling occasions (e.g., camera trap days) across 30 sites with $n = 60$ true-positive detections of the target species. The false positive rate for this species is $f = 0.3$ (i.e., 30% of purported detections of the target species are incorrect). Of the 1,140 non-detections in the matrix, randomly convert u elements to possible detections where $u = nf = 60 * 0.3 = 18$. Therefore, the total number of “possible” detections (including possible false positives) in this detection matrix is $N = n + u = 78$. The value for each possible detection u would be drawn from the distribution of confidences in consensus classifications from n . With this detection matrix, one could then apply the resampling approach as described earlier. This way, the current simulations can be expanded to explore the impact of varying probabilities of false-positives. Fortunately, the logistic regression model used to compute consensus classifications for MammalWeb data already incorporates the possibility of false-positive detections (i.e., mistaken identification, see Chapter 3). Therefore, false-positives should not have had an additional impact on the accuracy of $\hat{\psi}$ in the analyses of MammalWeb data discussed below.

Miller et al. (2011) developed an extension to the standard occupancy model with an additional ordinal term representing observational states corresponding to different levels of

uncertain detection (including false positives). This model was successfully tested against real-world data collected from anuran call surveys. However, the sampling protocol of the anuran call survey specifically categorised observations into discrete classes that directly mapped to Miller et al.'s multiple detection states. For crowdsourced camera trap image classifications, uncertainty is measured as a continuous variable and there is no clear, non-arbitrary way to discretise it into discrete detection states. In comparison, the resampling approach studied here utilises the full range of uncertainty, and has the benefit of using just the standard occupancy model (MacKenzie et al. 2002).

With regards to the real MammalWeb data used in this analysis, it was noted earlier that it is essentially one large detection matrix encompassing all sites at which citizen scientists have deployed camera traps between 2015 and 2018. Treating it as such would almost certainly violate the standard occupancy model's fundamental assumption of site closure. However, this may be acceptable if the goal is to simply assess average occupancy across the region of interest (County Durham in the case of MammalWeb), allowing for changes in abundance, distribution, and behaviour within the region during that time period. Evidence for occupancy variations within this three-year dataset can be seen through the analysis (via resampling from uncertain detections) on the four species analysed.

One example suggesting a role for covariates is the red fox. Most of the 60-day detection matrices for red fox used in this analysis had proportions of missing data less than 0.5 (supplementary **Table 5.2**), which meant that the model estimates were generally reliable. These results showed that $\hat{\psi}$ was highly variable from less than 0.4 to 1.0, suggesting substantial variation between the detection matrices. To investigate this variation, the next steps would be to consider site- and observation-level covariates in the occupancy model. Fortunately, collecting this data has been required of MammalWeb citizen scientists since the beginning of the project (as described in Chapter 2). In contrast, the variance of $\hat{\psi}$ for the other three species, especially the grey squirrel, was small. This shows that even with these first steps towards applying MammalWeb data for occupancy analyses, we can already discern differences between species. Of these four species, I analysed badger data drawn from the summer and winter seasons between 2015 and 2017, but was unable to discern a clear temporal pattern despite very precise estimates of both $\hat{\psi}$ and \hat{p} . In this case, while $\hat{\psi}$ was not highly variable, the number of sites each detection represented varied greatly between 17 and 42, but I did not track how many times each site was represented in each detection matrix. The badger example suggests to me that, with the current analyses, it may be difficult to conduct species-specific analyses without considering – in addition to the site- and observation-level covariates mentioned above – which sites are represented in each

detection matrix, how many are repeated between the matrices, and whether these sites are representative of the wider region in the context of a specific ecological question.

One practical issue for a citizen science camera-trapping project such as MammalWeb is when the detectability of a species is very low. For the red fox, we can see that the standard deviation of the estimated number of days (D) needed to confidently ascertain its presence (or absence) is more than four weeks. This is likely because the relationship between the estimated number of days and \hat{p} is not linear. For small values of \hat{p} (such as the case with red fox), small changes will have a disproportionately large impact on D . Therefore, for low detectability species, a more targeted and systematic camera trap survey should provide a more precisely estimate \hat{p} . While \hat{p} is sometimes considered a “nuisance” parameter that is secondary to $\hat{\psi}$ (Rovero and Spitale 2016), it can be of practical value when designing surveys (Guillera-Arroita et al. 2010). For example, precise \hat{p} would allow us to provide guidance on minimum camera trap deployment durations when training citizen scientists. This is important for the MammalWeb project since, as discussed in Chapter 3, the currently highly localised reach of our monitoring and relatively non-charismatic nature of the species observed require more economical use of resources, which include camera trap deployment time. Ecologically, p may also be of interest as it could be a function of variables such as season, weather, or even reproduction (Best and Petersen 1982, Guillera-Arroita et al. 2010).

5.4.4 Broader implications

For the MammalWeb project, we can discern general occupancy statuses for the species analysed in this chapter on the level of Durham, England. For example, the mammal species in this region are not endangered or considered rare, which is reflected in $\hat{\psi}$ for grey squirrels, red foxes, and roe deer. However, $\hat{\psi}$ was lower for badgers, which is an important finding considering the long history of controversy regarding the badger’s role in the spread of bovine tuberculosis in Britain (e.g., Anderson and Trehwella 1985, Cassidy 2012, Stokstad 2017). Another result was that \hat{p} were low for all four species considered. We also know that some of the other species observed in MammalWeb, such as hedgehogs, are easily missed even when present in an image (i.e., common false-negative detections implying low p). This is of practical importance, since it suggests that MammalWeb citizen scientists should be guided to prioritise longer camera trap deployments over deployments at more sites, the data from which can be used to estimate \hat{p} more precisely. And since MammalWeb species are not rare species, this is in line with the established recommendation that for more common species, it is more efficient to survey fewer sites on more sampling occasions (Mackenzie and Royle 2005). In addition, a clear next step for applying occupancy analysis to MammalWeb data would be to consider covariates (which are recorded by citizen

scientists). I hypothesise that such analyses will provide insight into developing guidance on site selection in this developed and patchy landscape, or reveal limits to the proposed resampling method not observed in this chapter.

In addition to camera trapping, other survey methods also produce uncertain detections (Wilson and Delahay 2001, Sutherland 2011). This is especially true of methods relying on indirect signs. Species misidentification has been documented for approaches as diverse as detecting avian and anuran species from their calls (McClintock et al. 2010) to recording carnivore presence on the basis of scat samples (Karmacharya et al. 2012 p. 11). Thus, the analysis and proposed resampling approach described here could be more broadly applied to data collected via other means to incorporate uncertain detections into estimating occupancy. This would require methods to quantify uncertainty for a given survey method, such as by pairing it with another survey technique (Clare et al. 2017). Alternatively, the accuracy of indirect signs can be checked directly, such as through DNA sequencing of scat or hair samples (Eggert et al. 2003, Karmacharya et al. 2012, Clare et al. 2017). Once uncertainty has been determined as a continuous variable, then the resampling method described here could be applied.

In summary, in this chapter I conducted a series of simulations to explore three issues pertaining to applying occupancy analysis to camera trap data: data discretisation, missing data, and uncertain detections. The results show that a 1-day window is likely appropriate when discretising camera trap data, missing data should be considered in terms of the number of effective sampling occasions, and a resampling approach can be useful when uncertain detections are measured as a continuous variable. When applied to the MammalWeb citizen science projects, the analysis so far showed general trends in occupancy for the County Durham region in which the project takes place, and that species-level and finer-scale analyses will require the inclusion of site- and observation-level covariates in the occupancy model. Importantly, occupancy estimates were resilient to a wide range of uncertain detections and the resampling method has the potential to be more broadly applied to other crowdsourced camera trap image classification efforts. This method will also be useful considering the increasing popularity of applying machine learning algorithms to automatically classify images, which measures uncertainty on the same continuous scale (Norouzzadeh et al. 2018, Sullivan et al. 2018).

5.5 Supplementary information

Table 5.2. Occupancy detection matrices extracted from MammalWeb consensus classifications for four species. Each represents a 60-day window starting on a given date between March 2015 and March 2018. The number of sites indicate the number of citizen scientist monitored sites with camera trap deployments during

that time window. Proportion missing data represents the amount of camera trap days (across all sites) during which no camera was deployed.

Species	Window start date (YYYY-MM-DD)	Number of sites	Proportion missing data
Red fox	2015-12-25	36	0.517
	2016-02-28	31	0.452
	2016-05-02	39	0.522
	2016-07-09	28	0.521
	2016-09-15	31	0.472
	2016-11-19	22	0.485
	2017-01-19	33	0.432
	2017-04-13	27	0.623
	2017-09-14	23	0.387
Roe deer	2017-11-16	20	0.392
	2015-11-16	43	0.534
	2016-01-30	37	0.568
	2016-04-07	41	0.521
	2016-06-09	28	0.533
	2016-09-24	32	0.475
	2016-12-09	29	0.571
	2017-02-11	36	0.495
	2017-05-02	27	0.66
Grey squirrel	2017-07-08	22	0.692
	2017-09-13	23	0.388
	2015-11-03	48	0.58
	2016-02-05	36	0.567
	2016-04-07	41	0.521
	2016-06-10	28	0.536
	2016-09-14	31	0.475
	2016-11-24	22	0.498
	2017-02-01	37	0.477
Badger	2017-04-21	26	0.629
	2017-07-16	21	0.625
	2017-09-17	23	0.387
	2015-06-01	37	0.809
	2015-12-01	42	0.537
	2016-06-01	34	0.582
	2016-12-01	28	0.592
2017-06-01	17	0.604	
2017-12-01	20	0.454	

Chapter 6 - General discussion

As mentioned throughout this thesis, anthropogenic impact on global ecosystems (Butchart et al. 2010) have not only led to the defaunation of the planet (Dirzo et al. 2014), but also the loss of ecosystem services crucial to human livelihoods (Millennium Ecosystem Assessment 2005, Díaz et al. 2006, Perrings et al. 2011). Citizen science (Amano et al. 2016) and the use of motion-sensing camera traps (Burton et al. 2015, Steenweg et al. 2017) are two proposed methods to address the need for monitoring biodiversity on a large scale (Fischer et al. 2010, Stephens et al. 2015). Indeed, the combination of the two has been attempted where citizen scientists helped professional ecologists deploy camera traps (McShea et al. 2015) or classify images (Swanson et al. 2015). In the United Kingdom, a historically-prominent crowdsourced ecological data collection programme has been the Breeding Bird Survey organised by the British Trust for Ornithology (<https://www.bto.org/volunteer-surveys/bbs>, e.g., Harris et al. 2016). To our knowledge, there was no analogous initiative for monitoring wild mammals in Britain, but citizen science camera-trapping has been successfully trialled for that purpose in North America (e.g., the eMammal project, McShea et al. 2015). Motivated by examples such as these, we have been piloting – since 2015 – the MammalWeb citizen science project to crowdsource the collection and classification of camera trap data in north-east England. The ongoing influx of photographic data (more than 250,000 images) is collaboratively classified by registered users of our online platform (<http://www.MammalWeb.org>). This is not only to explore the potential of the MammalWeb model to achieve large-scale ecological monitoring, but also engaging citizen scientists in a larger part of the scientific process. The preceding chapters have highlighted some of the results, such as the capture of non-native species; developing a novel algorithm for more economically deriving consensus classifications from user input; empowering local students not as mere data collectors, but as ecological ambassadors to their community; and a resampling method that addresses uncertain detections in occupancy data, a common issue for camera trapping and crowdsourced data classification. Of the themes covered in this thesis, this chapter will discuss the following with consideration to lessons learned and how future work may proceed:

- Engagement, school partnerships, and evaluation
- Handling crowdsourced data classification
- Population estimates from crowdsourced camera trap data

6.1 Engagement, school partnerships, and evaluation

Chapter 2 described the organisation of the MammalWeb project. The number of registered users has been growing throughout the period examined, and the classification of camera trap images has kept up with its influx. As observed in Chapters 2 and 3, there are two types of contributors to MammalWeb: a small, dedicated group of “super users” who make most of the contributions, and a far larger group of users who were engaged for short durations and contributed relatively little. While this is consistent with other citizen science projects (Sauermann and Franzoni 2015), I believe the progress of MammalWeb mammal monitoring can be better sustained by more effectively engaging both groups.

To achieve the large-scale monitoring originally envisioned, I believe there is a need to attract more participants of the non-super user type. Since their retention rate is low for non-super users, recruitment has to be ongoing. Here I will reflect on – with consideration to lessons for other citizen science projects – (1) avenues for improving MammalWeb community engagement offline and online, (2) the potential of school, library, and museum partnerships, and (3) methods for evaluating project performance.

6.1.1 Improving community engagement

The most intensive engagement activities occurred at the inception of MammalWeb in mid-2015. With few exceptions, later engagement with citizen scientists took place through occasional email contact, social media, and one-on-one meetings. There is a need for periodic engagement campaigns to attract and retain citizen scientists. I expect at least three benefits can be derived from this approach.

First, regular engagement events may attract those who would eventually become super users, expanding the core group of dedicated contributors. Secondly, current super users can participate in regular refresher trainings, at which they will receive updates from us (such as updated protocols or presentations on the project’s ecological results) and aid the training of new citizen scientists. This point is important in light of the value of refresher trainings for maintaining citizen science data quality (Danielsen et al. 2014). Third, meeting existing citizen scientists can ease the introduction of new participants to MammalWeb, as social interaction is cited as one of the primary factors motivating citizen science participation (Reed et al. 2013). As of mid-2018, a monthly email newsletter has been used to update the MammalWeb userbase on project developments. It could be used to advertise these periodic meetings to increase engagement, among other lines of communication such as social media or partner organisations.

The MammalWeb online user experience should also be improved to stimulate engagement. Chapter 2 already covered some of the improvements being implemented for

MammalWeb, namely an upgraded Spotter page for classifying photos, the “Projects” feature for organising photos, and upcoming user-facing interactive data visualisations. There are further improvements which can be applied to MammalWeb, or more generally to other online crowdsourcing projects as well.

For example, the Spotter page could provide automated feedback. One embodiment of this is to “seed” the MammalWeb image pool with expert-classified gold standard images, which has been done for other crowdsourced image classification projects (Westphal et al. 2010). Feedback on classification accuracy can be automatically generated via natural language generation (van der Wal et al. 2016) whenever a user classifies a seeded image, which may encourage them to improve their accuracy (Kosmala et al. 2016).

Another possibility is a magnifying glass function, where the user would hover their mouse cursor over a camera trap image to zoom in on specific parts. This can be implemented with a simple combination of HTML (hypertext markup language), CSS (cascading style sheets), and Javascript (Rolich 2013, Refsnes Data 2018). Alternatively, the Chimp & See project (<https://www.chimpandsee.org/>) presents an image sequence as a grid of thumbnails, each of which can be clicked on for closer inspection to annotate chimpanzee camera trap photos collected in Cote d'Ivoire (McCarthy et al. 2018). A similar implementation may aid MammalWeb users in discerning animals as they move between images, and is worthy of future work.

As suggested in Chapter 3, one difference between MammalWeb and similar projects – such as Snapshot Serengeti – is that the wildlife monitored by MammalWeb are generally not considered “charismatic”. While exactly what constitutes a charismatic nonhuman species is not universally defined (Lorimer 2007), there is a term – “flagship species”- which refers to “a species used as the focus of a broader conservation marketing campaign based on its possession of one or more traits that appeal to the target audience” (Veríssimo et al. 2011). A global study has shown that African mammals, especially felids and primates, comprise most of the top ten highest regarded species worthy of being “flagships” (Macdonald et al. 2015). With the possible exception of primates, these are exactly the type of species often depicted in Snapshot Serengeti.

Another aspect of charisma is how it might cause sampling bias. In at least one study, observations from citizen scientists at the Olare Motorogi Conservancy in Kenya were strongly biased towards charismatic species such as gazelles, giraffes, lions and elephants (Steger et al. 2017). Camera traps avoid this bias to a large degree, since they are unbiased in their observations during deployment. The challenge for MammalWeb and other camera-trapping-based projects is avoiding this bias on the timing and site-selection levels. While

the protocol we asked our citizen scientists to follow was designed to avoid biases, the dearth of follow up engagement prevented us from knowing how closely those guidelines were followed. For example, informal conversations revealed that some MammalWeb citizen scientists – despite following our established protocol – strongly “hope” to catch certain species on camera or have placed cameras at sites where they “think” a certain species was present. This is another reason why periodic engagement events with refresher trainings would be of value.

In any case, while the wild mammal species being monitored by MammalWeb are generally not rare and less charismatic than their African relatives, even common species are ecologically important (Gaston and Fuller 2008). Therefore, it is imperative that a citizen science project such as MammalWeb characterise the motivations of its citizen scientists – including the role of animal charisma (if any) – and design engagement based on them.

One method of motivating citizen scientists to classify data is gamification. A noteworthy example is Foldit (<https://fold.it/>), where citizen scientists are players in a game of modelling protein structures (Cooper et al. 2010). The players collectively outperformed state-of-the-art computational methods (Khatib et al. 2011a), and their results have aided the design of antiretroviral drugs (Khatib et al. 2011b). More recently, a microscopy image classification “mini-game” was built into the long-running massively multiplayer online role-playing game (MMORPG) EVE Online (CCP Games 2003). Over one year, more than 320,000 players provided 33 million classifications to characterise subcellular protein distribution (Sullivan et al. 2018). In both examples, the crowdsourcing process was gamified because participants were incentivised with positive reinforcement: Score-based rankings on the Foldit website, and virtual credits to buy in-game items in EVE Online.

It may be possible to replicate a gamified citizen science project outdoors. Pokémon Go is an augmented reality (AR) game for mobile devices where players navigate through real-world landscapes to catch and battle game characters (Niantic and Nomura 2016). These characters are essentially virtual animals, and it has been proposed that a similar game could be developed to encourage players to engage with real-world nature including data collection (Dorward et al. 2017). By one estimate, the existing player effort invested in Pokémon Go is equivalent to 400 years of wildlife observations (August 2016).

Incentives may also lead to unintended consequences. In one experimental project, “spammers” gamed the system by classifying as many images as possible at the expense of accuracy (Bohannon 2011). This was because the reward was proportional to the number of images classified. While the reward in this example was a small monetary compensation (instead of points or virtual currency), it suggests that the incentive structure needs to be

carefully crafted if a citizen science project is to be gamified. In another study, Mekler et al. (2013) observed that points-based gamification increased the quantity of work done, while creating “meaning” for players increased the quality of classifications. This meaning could be a “[compelling] narrative, supporting users’ personal goals and interests, or having a purpose that is deemed valuable” (Mekler et al. 2013). To my knowledge, however, this line of enquiry (distinguishing between the rewards offered and the meaning of the work) has not been applied to the successful gamification examples I cited above. This may, in part, be due to a perception that gamification is not a “serious” science (Treuille and Das 2014).

If gamification were to be applied to MammalWeb or other ecological citizen science projects, the key would be to carefully develop an incentive system which ties the goals of the project with the motivations of citizen scientists. Since the objective of MammalWeb is to achieve sustainable monitoring of wild mammals across wide spatial and temporal scales, there is a need to attract and maintain citizen scientists outside of the super user group. I hypothesise that with gamification, MammalWeb will see the proportional distribution of effort (both in collection and classification of camera trap photos) move to a wider range of contributors, not just super users. Possible gamifications would be awarding points to those who deploy camera traps at under-recorded locations, or achievement badges for the cumulative number of days for which they have deployed cameras. In light of the above, I suggest investigating and implementing gamified elements into the MammalWeb user experience as a future step.

6.1.2 Potential of school and library partnerships

Chapter 4 described a successful partnership developed with Belmont Community School, where a group of students not only participated as citizen scientists in MammalWeb, but also acted as ecological ambassadors to their community. Tangible outputs included the 10 students designing and delivering outreach activities at community events, and the creation of a professionally-made project video notable for being almost completely unscripted yet impactful. In this section, I explore the potential of working with schools and libraries as a way of enhancing the engagement and reach of MammalWeb and other citizen science projects.

MammalWeb was not the first camera trap-based citizen science project to partner with schools. Successful partnerships have been established across the world, from Okinawa, Japan (OKEON: <https://okeon.unit.oist.jp/>) to North Carolina, United States (eMammal: <https://emammal.si.edu/>). In particular, the eMammal project has developed – in collaboration with local school teachers – a series of education materials adapted to the curriculum requirements of several US states (eMammal 2018). In one example, school

pupils deploy camera traps and are taught math skills to quantify their observations as required by state curriculum (Schuttler 2016). MammalWeb, however, was novel in that the students from Belmont School also acted as communicators of the science that they did.

Building on the successful pilot with Belmont School, MammalWeb also aims to create a network of partner schools. To do this, the project is working with a natural history museum, the Great North Museum: Hancock in Newcastle upon Tyne, England (<https://greatnorthmuseum.org.uk/>), and a charitable trust, The Institute for Research in Schools (<http://www.researchinschools.org/>), to leverage their existing school connections to bring MammalWeb into more classrooms. In general, school partnerships could increase the geographical reach of a citizen science project, and in the case of MammalWeb, the number of camera trap deployment sites. If there is buy-in from dedicated teachers, camera trap monitoring would be sustained over long periods because the same deployment activities can be repeated by a new group of students each year. A longitudinal study could be conducted on this scheme to measure not just scientific output, but also student learning outcomes and empowerment as citizen scientists.

In addition to schools, I believe partnering with libraries is another untapped opportunity. Local libraries often act as community centres with which residents are familiar, and libraries have experience organising events. In fact, Ignat et al. (2018) recently advocated for libraries to support citizen science by facilitating training, communication, recruitment, and acting as a repository of data and protocols. For a camera trap-based citizen science project such as MammalWeb, we could place camera traps at libraries. Visitors can loan the camera traps and “adopt” nearby sites that we have pre-selected for deployment. This scheme can be tied into a rewards system (i.e., gamified) where a citizen scientist receives recognition for adopting a camera trap and a monitoring site. Since MammalWeb already has a partnership with the Great North Museum: Hancock, I believe they can play a similar role.

Whether it’s a school, library, museum, or gallery, we can enlist the help of super users. These dedicated citizen scientists can act as “seed trainers” at schools and libraries to assist in the recruitment and training of new participants. By empowering super users in this way, we can take MammalWeb citizen science to higher levels of participation (Haklay 2013).

6.1.3 Evaluating project performance

The MammalWeb project has achieved tangible positive outcomes such as engaging a network of citizen scientists across north-east England for mammal monitoring, aiding the capture of a non-native species, school partnerships, and observation data which has been submitted to the Environmental Records Information Centre North East. However, there is need for formal evaluations to characterise the growth and performance of this project. For

example, there was no explicit measurement of changes in engagement after outreach events such as during the 2016 Glastonbury Festival, the 2017 camera trap photo competition, or those delivered by Belmont School students at community events. Nor did we measure the effects from user experience enhancements introduced to the MammalWeb Spotter page in mid-2018.

In Chapter 2, I discussed existing frameworks for measuring project performance. This included the key performance indicator (KPI) concept frequently used by businesses (Parmenter 2007), evaluation frameworks for conservation projects (Dickson et al. 2017), or newly proposed sets of criteria for citizen science projects (Chase and Levine 2016, Kieslinger et al. 2017). While these solutions would benefit MammalWeb, they are comprehensive and their implementation may be costly and time-consuming. Therefore, rather than attempting an exhaustive treatment of how to implement each element of a particular framework, here I will focus on a few specific methods for (1) characterising citizen scientist motivations, and (2) measuring engagement outcomes. I believe this can improve engagement in all of the areas described in the previous sections.

A simple method for evaluation is to deploy surveys for participants to complete after each engagement intervention. These interventions could be offline engagement events (such as follow up trainings, recruitment activities, or school lessons) or online changes such as the user experience improvements discussed previously. In addition, MammalWeb could also include a contact feedback form on its website for ad-hoc unsolicited feedback. Such surveys should at least aim to not only gauge the success of an intervention (e.g., whether a Spotter page upgrade has eased the classification of images), but also seek to understand a citizen scientist's motivations for participating.

More formally, the Q methodology has been applied extensively to measure stakeholders' beliefs and opinions on biodiversity conservation (Sandbrook et al. 2011, Rastogi et al. 2013, West et al. 2016, Hamadou et al. 2016). Q methodology is a qualitative technique for characterising patterns in subjective perspectives held by a group of interviewees on a given topic (Stephenson 1975). This is done by asking interviewees to sort a group of statements regarding a given topic, on a numbered grid, in order of how much they identify with each one. These rankings, called "Q sorts", are fed into a factor analysis (such as that implemented in the R package *qmethod*, Zabala 2014) which clusters the opinions into shared framings of the topic in question. I believe applying Q methodology to understand participant motivations is another avenue for future work that is not valuable just for MammalWeb, but citizen science in general.

Existing research provides a general view of what motivates citizen scientists. Positive motivators include interest in learning about a topic, an opportunity to contribute to science, enjoyment from the process, being part of a team, and being recognised (as extensively reviewed in Jennett et al. 2016). In contrast, negative motivations may include anxiety about making mistakes (Segal et al. 2015). However, as evidenced by informal conversations we have had with MammalWeb citizen scientists – such as a desire to explore “what’s near my garden”, hoping to see a rare species, or informing the planning of a nature reserve – there is value in identifying motivations specific to MammalWeb. To my knowledge, Q methodology has yet to be used in a citizen science context, and the need for understanding MammalWeb-specific motivators provide an opportunity to pilot this approach.

Once we have achieved a higher resolution understanding of the motivations of MammalWeb citizen scientists (instead of generalities such as a desire to contribute to science), there is the potential to tailor engagement interventions accordingly. For example, Segal et al. (2015) successfully used email interventions to increase participation in Zooniverse crowdsourcing projects. In addition, a better understanding the motivations of MammalWeb citizen scientists will aid in framing the meaning (as defined by Mekler et al. 2013) of this project if it is to be gamified. Communicating this meaning could be done in real time during the online image classification process (e.g., via natural language generation, van der Wal et al. 2016) or through our email newsletters.

In addition to understanding specific motivators, there is a need to better evaluate engagement outcomes. When measuring changes in knowledge or attitudes, the Q methodology (Stephenson 1975) or Likert-scale surveys (Likert 1932) could be performed before and after interventions such as recruitment drives or refresher trainings. For online interventions such as updates to the online user experience, A/B testing is commonly used (Kohavi et al. 2009). This is where two versions of the website are created, one with and one without the update. When visiting the website, a user is randomly directed to one of them. By soliciting feedback from all users (of which about half would have visited the updated site), a website administrator could understand the effect of the update.

The MammalWeb project also aims to partner with schools. Existing studies suggested that participation in citizen science increased students’ self-efficacy, i.e., a person’s belief in their ability to learn or perform (Hiller 2012), improved knowledge and deepened engagement with the natural environment (Zárybnická et al. 2017), or provided satisfaction from contributing to real scientific research (Silva et al. 2016). According to Schuttler et al. (2018), however, studies specifically looking at the impact of nature based citizen science on education outcomes are still very rare. In fact, learning outcomes are generally not

measured or unreported (Bela et al. 2016). This area of research could benefit from the MammalWeb experience if the evaluation of learning outcomes is incorporated into our upcoming school partnerships.

6.2 Handling crowdsourced data classification

Uncertainty is inherent to practically all scientific data. Crowdsourcing data classification is an increasingly popular way to process big data resulting from large scale scientific studies, including ecology. This has manifested in many online crowdsourcing platforms such as the Zooniverse (<https://www.zooniverse.org/>), SciStarter (<https://scistarter.com/>), Tomnod (specifically for digitising satellite imagery: <https://www.tomnod.com/>), or Amazon Mechanical Turk (<https://www.mturk.com/>). The crowdsourcing process introduces observation uncertainty (as defined by Milner-Gulland and Shea 2017) – such as the probabilities of false-positive or false-negative observations – resulting from the biases and errors of each user. It is therefore crucial to address observation uncertainty as part of any citizen science project (Cohn 2008, Dickinson et al. 2010, 2012, Kosmala et al. 2016).

For projects which crowdsource the classification of camera trap photos, handling observation uncertainty is done through expert validation or replication and calibration across users (Kosmala et al. 2016). In the former, domain experts manually validate each user-contributed classification (McShea et al. 2015), while the latter approach gathers multiple classifications per image which are combined into a consensus answer (Swanson et al. 2016). Starting with the Snapshot Serengeti project, and further developed by MammalWeb as described in Chapter 3, the current approach is to combine a subset of the data which are expert-classified as a “gold standard” by which user classifications are compared against. For MammalWeb, we developed a model that produces consensus classifications, which is a measure of the probability that a species is indeed present in an image (Hsing et al. 2018).

Now, we are running two studies to further investigate what may influence crowdsourced image classification performance. The first study is whether classifications of image sequences can more efficiently arrive at confidence consensus classifications and retire them, as opposed to classifying them individually. The second study is creating three versions of images, each at a different resolution. By randomly showing users, and asking them to classify images of different resolutions (and, hence, quality), we explore the practical issue of to what degree images can be downsampled to save storage space without sacrificing classification accuracy. Both of these studies are being trialled on the Zooniverse project beta test platform, and are being conducted similar to the A/B testing approach as described above.

The long-term potential of crowdsourcing data classifications is to use the classifications to train machine learning algorithms which can automate classification without any human input (LeCun et al. 2015, Krizhevsky et al. 2017). Initial results from applying such techniques to detecting and identifying animals in camera trap photos are promising (Thom 2017), and a deep neural network was able to, under certain conditions, classify Snapshot Serengeti images at close-to-human accuracy (Norouzzadeh et al. 2018). Machine learning algorithms require large training datasets (e.g., millions of classified images, Krizhevsky et al. 2017, Norouzzadeh et al. 2018), and I believe standard camera-trapping guidelines (Cadman and González-Talaván 2014, Wearn and Glover-Kapfer 2017) should include this as a need for increased data sharing from camera trap studies. Finally, the development of machine learning algorithms can itself be crowdsourced. The non-profit organisation, crowdAI (<https://www.crowdai.org/>), hosts competitions to develop machine learning solutions for data classification tasks. Classified camera trap photos from both MammalWeb and Snapshot Serengeti are available under open licenses, and could be hosted as a dataset on a platform such as crowdAI to solicit performant machine learning solutions.

6.3 Population estimates from crowdsourced camera trap data

Much of the work on the MammalWeb project has been focused on attracting and retaining a group of citizen scientists to monitor wild mammals in north-east England with motion-sensing camera traps. As discussed above and in Chapters 2 and 4, we have demonstrated the viability of a local-scale citizen science project while establishing the basis for large-scale monitoring through our web platform and growing organisational partnerships (including schools). Importantly, we developed a model (Chapter 3) which aggregates user-contributed classifications to form consensus classifications for camera trap photos. The bulk of my efforts since 2015 has been on achieving the above, and now we need to explore the most appropriate methods with which to derive ecological insights from the data that is our consensus classifications.

In Chapter 5, I attempted to address three issues likely to arise from conducting occupancy analysis on citizen science-collected camera trap data: discretisation of data, missing data, and uncertain detections. In the case of MammalWeb, the uncertain detections arise from uncertainty inherent to the consensus classifications we derive for each camera trap observation. Using a resampling approach, I showed that estimated occupancy rates remain accurate across different levels of uncertainty. One benefit of this method is the ability to incorporate uncertainty (which, in this case, can be measured as a continuous variable) into

the modelling process without modifying the underlying standard occupancy model as developed by MacKenzie (2002).

Whichever method is used to estimate populations using MammalWeb data, there is a need to ground truth the methodology with an independent population estimate. Unfortunately, the survey effort density for wild mammals is currently limited in north-east England (Croft et al. 2017), so a new survey will need to be conducted. With our existing set of camera traps, I believe there are two ways to achieve this.

The first would be a systematic occupancy survey across the area currently covered. This can be done for one species at a time, perhaps selected from the more commonly sighted mammals on our website (e.g., grey squirrels or roe deer). In practice, we could select an area where citizen scientist-deployed camera traps have detected that species, and conduct a systematic occupancy survey there. In addition, since MammalWeb does not target specific species, we could also utilise community-level multi-species occupancy models developed by Dorazio and Royle (2005).

To better estimate populations with camera traps without requiring individual recognition, there is the random encounter model (REM, Rowcliffe et al. 2008). Based on physical theory regarding rates of collision between gas molecules and its comparisons to animal movement (Hutchinson and Waser 2007), REM provides a factor which relates camera trapping rate to population density. Accompanying methods have been developed to estimate two critical terms in REM, the zone of detection around a camera (Rowcliffe et al. 2011), and the target species' movement rate (Rowcliffe et al. 2016). As REM methodology matures with further refinements – such as consideration for animal staying time (the duration for which an animal remains in a camera's field of view) (Nakashima et al. 2018) – it is becoming a practical and efficient approach for estimating animal density.

Camera trapping surveys need to be done systematically for occupancy modelling (Rovero and Spitale 2016) and population density estimation with REM (Rowcliffe et al. 2008). This was, in fact, the deployment strategy for collecting camera trap images for the Snapshot Serengeti citizen science project (Cusack et al. 2015). Specifically, camera traps should be randomly deployed along a regular grid of sites in the area of interest (Rovero et al. 2014). Since north-east England is a highly developed and patchy landscape (relative to, for example, Serengeti National Park), any survey (for occupancy or REM) could align and deploy the grid along a gradient of interest such as different habitat types or distance from roads.

6.4 Concluding remarks

Motivated by a need for larger scale wild mammal monitoring in Britain and a desire to engage citizen scientists on a higher level, the MammalWeb project was developed to partner with local communities in deploying motion-sensing camera traps. Since 2015, we have established a core group of citizen scientists (“super users”) who have consistently contributed and classified more than 250,000 camera trap images. Image classification is assisted on our web platform by almost 300 registered users. This effort has led to diverse, tangible outcomes from the capture of a non-native species; enriching the local biodiversity data archive (Environmental Records Information Centre for the North East of England: <http://www.ericnortheast.org.uk/home.html>); and the development of a consensus classification algorithm for crowdsourced data. We successfully piloted a school partnership which empowered learners not only as citizen scientists, but also ecological ambassadors to their community. Our efforts continue in terms of involving more partner organisations, including conservation groups such as Nature Spy (<https://www.naturespy.org/>), Scottish Wildcat Action (<http://www.scottishwildcataction.org/>), and a network of schools via the Great North Museum: Hancock and The Institute for Research in Schools; and further studies on the nuances of crowdsourcing methods on classifier accuracy (i.e., sequence- versus individual-based image classification or the effects of image resolution). For future work, this chapter has discussed:

- Enhancing the online user experience
- Introducing gamified elements
- Partnering not just with schools but also libraries and museums
- Formally evaluate engagement, motivations, and learning outcomes with the Q methodology
- Tying crowdsourced data classification into machine learning
- Applying the random encounter model to camera trap data to measure abundance and ground-truth MammalWeb data

I will end this discussion with an overview of general pitfalls to avoid and the potential of citizen science beyond crowdsourcing data collection or classification.

Major research funding bodies are increasingly requiring the research they support to demonstrate “broader” impacts (e.g., the European Union Horizon 2020 programme or the United States National Science Foundation), and citizen science projects fulfil this criterion (Silvertown 2009). While such requirements are strong motivators for academic researchers developing their research projects, they should not supersede the underlying ethical concerns regarding citizen science (Resnik et al. 2015). In particular, while the crowdsourcing of data

processing is a popular form of citizen science, it is especially prone to the exploitation of participants, which can manifest in at least two ways:

In an attempt to reduce spam and distributed denial of service attacks (DDOS), modern websites employ the reCAPTCHA system (Ahn et al. 2008) where a human visitor can be distinguished from a malicious, automated program by digitising a piece of scanned text or classifying photos. This proprietary program (which cannot be subject to external scrutiny) was acquired by Google and is now employed by the majority of websites on the Internet (Lung 2012). These crowdsourced classifications are used to train machine learning algorithms, the results of which are not shared; and there are legal and ethical concerns regarding reCAPTCHA since it effectively coerces Internet users into labourers without compensation or informed consent (Lung 2012). This form of exploitation should be avoided in citizen science projects.

The second issue is common in the social and behavioural sciences. Research projects in these fields frequently crowdsource data processing via the Amazon Mechanical Turk web platform where participants are provided with small financial incentives (e.g., Buhrmester et al. 2011, Crowston and Prestopnik 2013). As of 2016, more than 1,200 studies have been conducted with contributions from users of that platform (Bohannon 2016). One problem is how little users are paid (as low as USD\$0.15 per 10-minute commitment, Bohannon 2011), which raised concerns about labour exploitation (Fort et al. 2011) and objectification of users (Irani and Silberman 2013).

In addition to these examples, there is concern that participants will be exploited in other ways (Resnik et al. 2015), such as financial conflicts of interest (Bunch et al. 2014, Macey et al. 2014) or conflicting expectations of access to final research outputs (e.g., pharmaceutical patents derived from indigenous knowledge, Hellerer and Jarayaman 2000).

While some have been careful in distinguishing between paid “microtasking” (ala Amazon Mechanical Turk) versus “citizen science” (Tsueng et al. 2016), there is concern that the contribution of citizens is limited to a few narrowly defined tasks (del Savio et al. 2016). Indeed, there is a tendency to refer to citizen scientists as mobile sensors (Goodchild 2007) or even as “instruments” (Westphal et al. 2010). It is unlikely that such terms were used out of malice, but they reinforce the notion that citizen scientists are merely data collectors or processors, while neglecting the full potential of citizen science.

In contrast to fully centralised citizen science projects started by academics, MammalWeb has empowered citizen scientists to conduct their own ecological research. One citizen scientist, Anne Kelly, worked with local landowners to conduct camera trap otter surveys, and now delivers camera trapping workshops to wildlife enthusiast groups. Another

MammalWeb member, Roland Ascroft, developed and implemented a camera trap survey in southern Scotland to monitor the expansion of invasive grey squirrels. He also collected camera trap data to inform the planning of a Local Nature Reserve (LNR) near his town. Citizen scientists such as Kelly and Ascroft are the super users who could decentralise the MammalWeb project by (1) running their own research, and (2) being seed trainers for new citizen scientists. This form of empowerment is not common in citizen science projects, and is another example of the broader impacts of MammalWeb.

There is also a “distributed” form of citizen-initiated science. One example is the do-it-yourself biology movement of non-professional citizens who pooled resources to conduct their own biological research (Landrain et al. 2013, Seyfried et al. 2014). In one notable success, concerned citizens living along the Gulf of Mexico organised their own aerial surveys of the 2010 Deepwater Horizon oil spill, which severely impacted economically important fisheries (Muhling et al. 2012) as well as near-shore (Unified Area Command 2011) and deep-sea ecosystems (Hsing et al. 2013, Fisher et al. 2014). Now called Public Lab (<https://publiclab.org/>), this organisation develops their own research projects and facilitates citizen-initiated environmental studies in several countries.

Interestingly, the centralised, decentralised, and distributed topologies of citizen science described here are analogous to computer network topologies (Baran 1964, Peeters 2014). As described above, citizen science, in its decentralised or distributed forms, has the potential to contribute not only to science or education, but civic participation as well. This “collaborative science” (Dillon et al. 2016) is the highest level of participation as described by Haklay (2013), and I believe it should be a goal for citizen science projects such as MammalWeb.

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