The Verification of Ecological Citizen Science Data

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The Verification of Ecological Citizen Science Data

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Declaration

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

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Abstract

In the current climate and nature crisis, biodiversity and ecosystems are experiencing irreversible losses. In response to these threats, increasingly ambitious targets are being set to conserve and protect nature by 2030. Widespread and up-to-date data are required to understand the extent of losses and to ensure we are on track to meet these targets for nature. Citizen science datasets, based on records of species observations made by volunteers, are the primary sources of data at the geographical scale required to analyse large-scale trends in species abundances and distributions. Due to the unstructured nature of data collection by many individuals, there are concerns around data quality, inaccuracy, and bias in these datasets. Verification is an essential process for ensuring data quality but, as the volume of data being collected by citizen scientists grows, bottlenecks in data processing can arise. This thesis details my research into the verification of ecological citizen science data.

I start by reviewing current approaches to verification within ecological citizen science schemes whose data features in scientific literature. The results from this review identify three distinct approaches to verification: expert, community consensus and automation. This research highlights that expert verification has been the default approach for many schemes and proposes that alternative approaches should be considered more widely to deal with growing data volumes. Alongside identifying verification approaches, this review identifies the information that is used to inform the verification of citizen science data. This information typically comprises one or more of three types of data: attributes of the species, the environmental context, and attributes of the observer. I then outline an idealised system for verification, recommending that all information should be considered when verifying citizen science observations and identifying the meta-data that can be used in the verification process.

Informed by the results from the review of citizen science approaches, Chapters 3 and 4 outline my research into alternative frameworks for verification that use Bayesian Classification models that account for contextual information. In the first instance, I include the attributes of the species and the environmental context to verify citizen science records by using past data to quantify identification mistakes made by citizen scientists and

considering when and where a species is more likely to be observed. I apply this approach to two contrasting citizen science schemes: MammalWeb, a scheme that uses community consensus verification to classify camera trap images; and iRecord, a scheme that uses expert verification for ad-hoc opportunistic species observations collected by field-based citizen scientists. The results show that for MammalWeb, including contextual information improved the accuracy of verification; for iRecord, including attributes of the species improved verification, but including contextual information provided little advantage. The framework outlined in Chapter 3 assumes all observers have the same expertise; therefore, in Chapter 4 I expand on this framework by exploring how observer variability can be integrated into approaches to verification. The results show that including observer traits makes minimal difference to the accuracy of verification, owing to low contributions by most individual observers, making it difficult to quantify observer variability. The results from Chapters 3 and 4 also highlight that citizen science identifications pre-verification are generally very accurate (90% or higher), bringing into question the need for developing highly accurate and intensive verification processes.

Given the human and technical effort that is channelled into verification, Chapter 5 of this thesis presents my research into the extent to which accurate verification matters in a conservation policy and management context. I simulate inaccuracies in a citizen science dataset of UK butterflies, to explore how data accuracy might impact estimates of the coverage provided by protected areas, and the consequences of these estimates for decisions that could be made using this analysis. The results show that, for more ubiquitous species, errors can be tolerated; however, for species with restricted ranges, inaccurate datasets tended to over-estimate the area of occupancy and therefore over- or under-estimate protected area coverage, depending on whether coverage was actually low or high, respectively. The results presented here indicate that, for some species, highly accurate verification may not be necessary and, moving forward, citizen science schemes should consider whether there is really a need to verify every record.

As data volumes grow, addressing bottlenecks to ensure that data are up-to-date and available for analysis increasingly requires more efficient approaches to verification. The results from this thesis explore how verification can evolve to meet the current needs of those who run and manage citizen science schemes, as well as end users of the data, without compromising the decisions that are made using citizen science data. By addressing issues within this foundational process on which citizen science data is reliant, this thesis aims to emphasise the valuable role that citizen science plays in addressing the biodiversity crisis and further strengthen its place within ecological research.

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1. General Introduction

1.1 Introduction

Globally, biodiversity and ecosystems are experiencing irreversible losses caused by pervasive and ubiquitous anthropogenic threats (Hayhow et al., 2019; IPBES, 2019; WWF, 2022). Species are being lost at an unprecedented rate, causing degradation to ecosystem functioning and services (WWF, 2022). To address these overarching threats to nature, ecological research efforts are focused on understanding widespread losses to biodiversity and changes in ecosystems (Cooke et al., 2019; Eddy et al., 2021; Soroye et al., 2020; Strassburg et al., 2020). Such research can then determine the extent of these impacts and inform policy and management responses to instigate action to protect biodiversity, conserve species populations (Cazalis et al., 2022a; Chowdhury et al., 2023; Hoveka et al., 2022), and evaluate future scenarios for nature recovery (Duarte et al., 2020; Nicholson et al., 2019; Powers and Jetz, 2019). Addressing these research questions relies on large volumes of accurate and up-to-date data covering a wide geographical and temporal scale (Groom et al., 2017; Hassani et al., 2021; Hochkirch et al., 2021; Nathan et al., 2022).

Alongside research, efforts need to be focused on education and outreach, to raise awareness for these issues, which in turn can increase bottom-up action and environmental stewardship, as well as democratise the fields of ecology and conservation (Davis et al., 2022; Salomon et al., 2018; Strickland et al., 2021). Citizen Science, which broadly encompasses all volunteer contributions to science, is a key tool and research approach for gathering the data required to address large-scale research questions, as well as engaging the public in environmental issues (Adler et al., 2020; Dickinson et al., 2010, 2012; Fraisl et al., 2022; Kobori et al., 2016). The development of citizen science initiatives and the use of citizen science data has increased in recent decades (Fraisl et al., 2022; Kobori et al., 2016; Pocock et al., 2015; Silvertown, 2009). As more individuals have contributed to citizen-led ecological datasets and data volumes have grown, concerns have been expressed within the ecological research community around the quality of this data (Johnston et al., 2023; Pocock et al., 2017). To ensure data is of a known quality, citizen science records are verified to check for correctness (Pocock et al., 2015). With an increase in the volume of ecological data being collected by citizen scientists, verification is becoming an increasingly time-consuming process (Bonter and Cooper, 2012; Sutherland et al., 2015).

Here, I chronicle the evolving role of citizen science within the field of ecology. I describe the benefits of using citizen science approaches, as well as the concerns that have arisen from the wider use of citizen science datasets within ecological research. Detailing issues of data quality in citizen science schemes, I then examine the position of verification within citizen science datasets and concerns that have been highlighted with the verification process as data volumes grow. I then outline how the research described in this thesis informs future directions for the verification of ecological citizen science data to address the current issues within the verification process.

1.2 Citizen science in ecology

Within the field of ecology, volunteers have been contributing to species datasets for centuries (Dickinson et al., 2010; Fraisl et al., 2022; Pocock et al., 2015; Silvertown, 2009). These volunteer-collected datasets are valuable long-running time-series datasets that allow us to understand species abundances, distributions (Dennis et al., 2017; Horns et al., 2018), and phenology (Fuccillo et al., 2015; McDonough MacKenzie et al., 2017), and therefore, investigate changes in ecological processes in response to anthropogenic drivers (Cooper et al., 2014; Crimmins and Crimmins, 2022). Historically, these contributions have come from volunteer naturalists recording observations of species (Pocock et al., 2015). More recently, these volunteer contributions have been labelled as citizen science and encompass a broad range of initiatives and approaches that make use of technological advancements to diversify how citizen scientists can contribute (Fraisl et al., 2022; Johnston et al., 2023; Pocock et al., 2017). These contributions have now extended beyond collecting species observations, with citizen scientists now being involved in classifying images (Hsing et al., 2022), digitising specimens (Sforzi et al., 2019), and informing the research process and project design (Cox et al., 2015). Increased availability of, and access to, technology is allowing more people to contribute to these projects than ever before, allowing individuals to encounter and learn about species from across the globe (Callaghan et al., 2021; Larson et al., 2020).

Using citizen science approaches in the ecological research process yields a range of benefits. Large-scale citizen science datasets have a spatial coverage that is unmatched by traditional data collection methods, making them the primary datasets for modelling large-scale global trends for species across the globe (Altwegg and Nichols, 2019; Johnston et al., 2020a). Furthermore, by relying on citizen scientists for data collection and processing, time and resources can then be directed to other areas within the research process. Engaging citizen scientists can also benefit and progress research, as by engaging individuals with regional knowledge and expertise, there is the potential to gain insight into local knowledge and value systems (Kimura and Kinchy, 2016). By engaging the public in the research process through citizen science, there is potential to create long-term sustained public engagement, which is effective in creating behavioural change (NCCPE, 2016).

Despite the tangible benefits of using citizen science, a range of challenges are faced when developing and implementing citizen science initiatives, as well as using the datasets that come from citizen science schemes. Although several citizen science schemes are self-sustaining, many others are constrained by funding and resources and therefore have limited capacity to maintain the running of a scheme (Fraisl et al., 2022; Pocock et al., 2014). The limitations that many citizen science schemes face can reduce engagement with a project (Callaghan et al., 2019; Fraisl et al., 2022; Poisson et al., 2020), reducing the amount of data that can be collected by a scheme. Alongside these challenges, a primary concern that can limit the use of citizen science data in the field of ecological research is that of data quality. Many schemes revolve around unstructured monitoring and are set up without specific aims or hypotheses in mind, or with the broad aim to collect more data, which presents challenges when analysing large volumes of data (Isaac et al., 2014; Isaac and Pocock, 2015). The unstructured nature of data collection and the contributions of many non-experts to datasets raises questions about bias and accuracy of these datasets (Crall et al., 2011; Cruickshank et al., 2019; Hunter et al., 2013; Kosmala et al., 2016a; Wiggins et al., 2011). In the following section, I will discuss in more depth the concerns and issues of data quality in ecological citizen science datasets.

1.3 Data quality in citizen science

Data being collected by volunteers globally is increasing (Johnston et al., 2023). Although some schemes may aim to recruit citizen scientists with some expertise in biological recording (Van Strien et al., 2011), many schemes encourage contributions from as many individuals as possible, regardless of their expertise or prior experience with species identification (Sutherland et al., 2015). Furthermore, to keep involvement straightforward, submitting records often requires minimal effort, with many schemes consisting of ad-hoc opportunistic species sightings with limited meta-data (Terry et al., 2020). The unstructured nature of data collection can lead to biases in these datasets (Boakes et al., 2016; Callaghan, et al., 2021; Johnston et al., 2023), and the variability in experience and expertise of the hundreds or thousands of citizen scientists contributing to these datasets raises concerns about their accuracy (Feldman et al., 2018; Fuccillo et al., 2015; Gorleri et al., 2022).

Data collected by citizen scientists can have spatial, temporal, and data content biases (August et al., 2020). For example, species observations can be centred around more populated areas, or areas that are more accessible to the public, such as public parks, gardens, or roads (Geldmann et al., 2016; Mair and Ruete, 2016). Citizen science records are also biased towards weekends and summer months, with inconsistent recording through time (Bird et al., 2014). These biases generally affect schemes that rely on field-based citizen scientists. However, biases that relate to the species that are recorded can affect both field-based and desk-based citizen science projects. For field-based citizen science schemes, records can be biased towards easily recognisable species or species that are less affected by human presence (Callaghan, et al., 2021; Farmer et al., 2014). Alternatively, field-based citizen scientists that contribute large volumes of species records may choose to submit only observations of unusual or rare species (Johnston et al., 2023). For desk-based citizen science schemes, where individuals may classify images or species, these observations could be biased towards more easily recognisable, charismatic species (Kosmala et al., 2016a). Inaccuracies can arise when species are difficult to identify based on visual traits alone (Morris, 2019), or when species pairs have similar traits (Hsing et al., 2018). Often, a range of factors must be considered when identifying a species, including the habitat or region in which it was observed, and the phenology and traits of the species; therefore, recorder experience and expertise can also impact the accuracy of observations (Johnston et al., 2018).

A range of evidence highlights issues of data quality within citizen science datasets. However, in many cases, these datasets are the only available data that has the level of geographical coverage required to investigate large-scale ecological questions. Therefore, it is necessary to understand the level of data quality in these datasets and address these concerns to strengthen the place of citizen science within ecological research.

1.4 Verification of ecological citizen science data

Concerns around data quality within citizen science are addressed by ensuring the data undergo a series of checks for data completeness and correctness. These processes can be categorised as validation and verification. Validation is the process by which the records are checked to ensure the information has been submitted correctly (Tweddle et al., 2012). These checks can include identifying incorrectly entered dates, grid references or species name spelling. This process can be carried out automatically by setting rules for online data entry forms or by tools such as the National Biodiversity Network Record cleaner (Dean, 2013; Tweddle et al., 2012). Verification is the process by which the species identification is checked for correctness based on the information provided with that observation (Tweddle et al., 2012). This process is typically carried out by experts with specific taxonomic or regional expertise (Pocock et al., 2015; Pocock et al., 2014). If a photo, recording, or specimen is provided with an observation, this can be used to confirm the species identification. If no evidence is provided, species identify can only be considered correct based on the plausibility of the observation given the reported location, date, and observer (Baker et al., 2021; Kosmala et al., 2016a; Wiggins et al., 2011). An observation may be considered incorrect if an observation is outside of the species spatial or temporal range, if a species is typically confused with another species or if the expertise of the observer is unknown to the verifier (Baker et al., 2021; Kosmala et al., 2016a; Wiggins et al., 2011). An expert may ask for more information or photos to confirm the identification, informing whether they accept the observation or provide an alternative species identification. If a relevant expert is not available, records can go unchecked and unverified (Bonter and Cooper, 2012; Sutherland et al., 2015). There may also be a backlog of records to verify, leading to long delays between the submission and verification of a citizen science record (Bonter and Cooper, 2012; Pocock et al., 2015). This can exclude large volumes of citizen science records from being included in analyses, due to a lack of confidence in the observations.

Although some citizen science schemes do require photos or specimens to be submitted with an observation, the majority of citizen science records require minimal information for an observation to be submitted, typically this is: species name, location and date (Baker et al., 2021). Many citizen science observations are not accompanied by photos, and even if photos are provided, many species cannot be identified from photos alone (Morris, 2019). As a result, verification does not guarantee complete accuracy of citizen science data. However, it is a necessary process of quality assurance that ensures errors within the data are reduced.

As global connectivity has increased due to advancements in, and increased access to, technology and the internet, community-based verification is now being used for some citizen science schemes (Hsing et al., 2022; Siddharthan et al. 2016; Swanson et al., 2016). This is when individuals submit observations to a website or forum and then other members of an online community can verify them. Members of the community may have expert status (Silvertown et al., 2015) or verification is based on a consensus identification by several individuals (Di Cecco et al., 2021). This approach to crowdsourcing verification draws on a larger pool of individuals to confirm observations and can increase the efficiency of verification (Hsing et al., 2022). However, a lack of taxonomic or regional expertise can still lead to gaps in data, with portions of records remaining unverified (Barbato et al., 2021).

Having a large proportion of unverified or inaccurate records can impact recorders and end users of the data. Failing to provide timely feedback to citizen scientists regarding the records they have submitted can impact engagement and reduce the retention of volunteers (van der Wal et al., 2016). This reduces the potential positive impact of citizen science schemes through outreach and engagement, as well as reducing potential species observations that can be collected by citizen scientists in the future. For end users of the data, inaccurate species occurrence information can limit the inferences and decisions that can be made using citizen science datasets. The large spatial coverage and temporal scale of citizen science datasets provide a key resource for a range of ecological research, policy and conservation management uses (Powney and Isaac, 2015). Citizen science datasets are often used within ecological research to explore trends in species abundance and distributions through species distribution or occupancy modelling (Boyd et al., 2023). An incorrect observation that was within the known range of species would have minimal impact on modelling outputs, however, incorrect observations outside of the known range could be more impactful on the analysis. Inaccurate estimates of species abundances and distributions (Sutherland et al., 2015) can have subsequent impacts on conservation management and policy (Adler et al., 2020; McKinley et al., 2017; Vann-Sander et al., 2016), due to a lack of robust evidence that can be used to inform decision making.

Verification remains an essential process for the range of scientific applications of citizen science data, however as data volumes grow it is becoming an increasing time-consuming process that is leading to a lack of up-to-date data. Timely and efficient verification remain a challenge for many citizen science schemes.

1.5 Moving towards automated verification

As the global community of citizen scientists grows, and the volumes of data being collected by citizen scientists increase, there is a focus in the field of ecological research and data science on how to manage data effectively and process it efficiently (Fraisl et al., 2022; McClure et al., 2020; Wang et al., 2015). In turn, this has prompted exploration of approaches to automated verification (Bonter and Cooper, 2012; Kelling et al., 2011; Yu et al., 2011). These approaches can include data filters, statistical models, or computer vision techniques (McClure et al., 2020; Wang et al., 2015). Chapter 2 of this thesis reviews some specific approaches to automated verification for various citizen science schemes. Particularly for larger citizen science schemes, relying solely on expert review is no longer feasible, compelling a focus on integrating more efficient approaches to verification. However, many citizen science schemes lack the time and resources to develop these approaches independently. In this thesis, Chapters 3 and 4 present a Bayesian approach to verification that uses past data to assess the confidence that we can have in a citizen science record based on species confusions, the environmental context of the observation (Chapter 3), and information about the data recorders (Chapter 4).

1.6 Thesis structure and aims

Motivated by the need to increase efficiency in the verification process and understand issues of data quality within citizen science, this thesis describes my research into the verification of ecological citizen science data. In addition to understanding the process of verification within ecological citizen science data and exploring ways in which we can increase the efficiency of the verification, I explore the impacts of inaccurate data in the research context. Chapter 2 describes the current approaches to the verification of ecological citizen science data and provides guidance on how the process can be improved. Chapters 3 and 4 outline frameworks for verification that use the environmental context (Chapter 3) of a citizen science record and recorder expertise (Chapter 4) to assess confidence in citizen science records using Bayesian classification models, and present how this can be integrated into the verification process. Chapter 5 explores the extent to which accurate verification matters by using citizen science datasets of different accuracies to explore policy and management questions. Finally, Chapter 6 is a general discussion that reflects on the future of verification within citizen science and the implications of this research.

1.6.1 The verification of ecological citizen science data: current approaches and future possibilities

Initially, I review ecological citizen science schemes that feature in published research to provide an overview of the breadth of verification methods that are currently used. This research can then be used as a benchmark for monitoring future progress and the evolution of verification methods. Here, I examine approaches to verification, the factors that may influence choice of verification approach and the information that is used to verify citizen science data. The results from reviewing 259 citizen science schemes found that expert verification was used most widely amongst citizen science schemes, followed by community consensus and automation. Expert verification, although highly accurate, is time-consuming, and can lead to a lag between the submission and verification of an observation. Therefore, I propose an idealised system for data verification, that implements a hierarchical approach to verification where the bulk of records are verified by automated or community consensus approaches, and any flagged records are verified by experts. The results from this review also explore the range of information that is used to verify observations, which can be categorised under attributes of the species, the environmental context, and the observer. The idealised system for verification outlines how each category of information can be considered and the associated meta-data that can be used to verify an observation.

1.6.2 Verifying citizen science biodiversity data: accounting for contextual information within a Bayesian framework

Informed by the idealised system for verification outlined in Chapter 2, I then present a framework for automated verification that, in the first instance, considers attributes of the species and the environmental context. Attributes of the species that can be considered in the verification process include ease of identification, rarity, or confusion with other species. Considerations regarding the environmental context include the known geographical range, the phenology, diurnal activity, or habitat preferences of a species. Here I outline how this information can be accounted for using a Bayesian Classification Model that makes use of the meta-data associated with each record, as well as the historical data submitted to a scheme, to estimate the probability of a record being of a given species. This framework harnesses the species confusion matrix that quantifies mistakes made by citizen scientists, as well as when and where a species is most likely to be observed. I demonstrate how this approach can be applied to MammalWeb, a citizen science scheme that crowdsources the classification of camera trap images, and iRecord datasets that comprise ad-hoc, opportunistic records collected by field-based citizen scientists. For MammalWeb the results presented show that models including contextual information improved on the models that did not include contextual information, but for iRecord, including context showed little improvement in verification accuracy.

1.6.3 Using observer metrics in the verification of ecological citizen science data

The framework presented in Chapter 3 assumed that all observers have the same expertise and therefore are included in the same confusion matrix. Individuals contributing to citizen science schemes vary in terms of their experience with species identification, taxonomic expertise and encounters with nature. Considering the variability between observers that contribute to citizen science schemes, here I examine how traits of the observer can be integrated into verification frameworks and the impact on verification accuracy. I detail how the framework outlined in Chapter 3 can be expanded upon and how observer ID can be used to inform the probability of a record being correct by assigning a confusion matrix to each observer. I then show a variation of this model that uses past data to categorise observer traits, which can be used to assess confidence in an observation. This approach was applied to MammalWeb and iRecord datasets. The results show that accounting for user accuracy and other observer traits provides minimal improvement when verifying citizen science records. For many citizen science schemes, most observers submit very few records, and volunteer retention within citizen science schemes is low. This can limit the effectiveness of the approach presented here as observer expertise cannot be estimated effectively for most citizen scientists. The research conducted here and in Chapter 3 also highlights that in the datasets used, accuracy of the citizen science observations is generally 90% or higher prior to verification.

1.6.4 Does accurate verification of ecological citizen science data matter? The impact of data accuracy on protected area coverage for biodiversity indicators

Large amounts of time and resources are continuing to be directed to ensuring citizen science data is as accurate as possible, through expert verification and the development of automated verification approaches. Given the high accuracy that can be observed in citizen science datasets, or achieved through automated verification approaches it is timely to explore the extent to which accurate verification matters in ecological analysis to examine whether there is a need to verify every citizen science record. Here, I investigate this question by assessing protected area coverage for UK Butterflies with datasets with different levels of simulated inaccuracy (20%, 10%, 5% and 2%). Using these datasets, I estimated the area of occupancy and compare percentage overlap with protected areas for inaccurate datasets and the original data. The results presented here highlight that for more ubiquitous species, the small amounts of error introduced into the data can be tolerated, but for species with constricted ranges, the consequences of inaccurate verification are greater. Before considering the need for every record to be verified, the costs of inaccurate verification should be considered in the context of the end uses of the data. For species where pinpointing the exact location is essential, every record should be verified. However, for many species where identifying specific occurrences is not necessary, the need for verifying every record should be reconsidered to ensure efficient data processing.

1.6.5 General discussion

The research conducted in this thesis explores how the verification of ecological citizen science data can evolve in response to increased data volumes and the need for up-to-date data, to benefit both those who manage citizen science schemes and end users of the data.

The rationale for much of this research is based on concerns around data quality in citizen science. However, for the datasets used here, the accuracy prior to verification is already high. Here, I discuss how, moving forward, confidence in citizen science data can grow through increased transparency in verification approaches, as well as through developing alternative frameworks for dealing with imperfect data. Furthermore, I outline how the posterior probabilities that are calculated using the Bayesian Framework outlined in Chapters 3 and 4 could be used as confidence metrics to inform analysis using citizens science datasets. I discuss how using confidence metrics can provide an alternative for assessing data quality, over simply categorising species observations as correct or incorrect. End users of citizen science data can then make informed decisions about how to analyse and interpret the results based on confidence within a dataset. Chapter 6 also discusses the valuable role that citizen science has to play in our progress towards the global 2030 targets for nature, and how engaging citizen scientists across the globe in all aspects of ecological conservation can ensure widespread action is taken to protect nature.

2. The Verification of Ecological Citizen Science Data: Current Approaches and Future Possibilities

2.1 Abstract

Citizen science schemes enable ecological data collection over very large spatial and temporal scales, producing datasets of high value for both pure and applied research. However, the accuracy of citizen science data is often questioned, owing to issues surrounding data quality and verification, the process by which records are checked after submission for correctness. Verification is a critical process for ensuring data quality and increasing trust in such datasets but verification approaches vary considerably between schemes. Here, we systematically review approaches to verification across ecological citizen science schemes that feature in published research, aiming to identify the options available for verification, and to examine factors that influence the approaches used. We reviewed 259 schemes and were able to locate verification information for 142 of those. Expert verification was most widely used, especially among longer-running schemes, followed by community consensus and automated approaches. Expert verification has been the default approach for schemes in the past, but as the volume of data collected through citizen science schemes grows and the potential of automated approaches develops, many schemes might be able to implement approaches that verify data more efficiently. We present an idealised system for data verification, identifying schemes where this system could be applied and the requirements for implementation. We propose a hierarchical approach, where the bulk of records are verified by automated or community consensus approaches, and any flagged records can then undergo additional levels of verification by experts.

2.2 Introduction

In the current polarised political and media environment (Iyengar and Massey, 2019), with public access to a vast choice of information sources (Huber et al., 2019; Iyengar and Massey, 2019), there is an increasing need for effective public engagement and science communication. There is, therefore, an argument for the democratisation of science, to make information accessible to everyone, to engage the public in scientific issues, and to involve them in scientific research endeavours (Mason and Garbarino, 2016; Salomon et al., 2018). Democratizing science in ecology and conservation has the potential to increase understanding of environmental issues and scientific research methods, catalysing bottom-up action, greater environmental stewardship, and ecological conservation. Furthermore, scientists can involve the public in the research process through gaining insight into local knowledge and value systems, and through volunteer contributions to data collection and interpretation (Kimura and Kinchy, 2016). Involving the public in research can be a highly effective means of public engagement and science communication, as it involves sustained, longer-term engagements. Also, there is often a two-way dialogue in which both the public and researchers can provide input and feedback, consulting and collaborating on the research (Pace et al., 2010; NCCPE, 2016). One way that public engagement is increasingly embedded in ecological research is through data collection by members of the public. For ecology and conservation, specifically, the public can contribute to species monitoring and biological recording, documenting species' occurrences to track species' distribution, abundance, and/or phenology (Sutherland et al., 2015).

Volunteers play a key role in biological recording and have been contributing to ecological datasets for centuries (Silvertown, 2009; Dickinson et al., 2010; Miller-Rushing et al., 2012; Pocock et al., 2015). This process falls under the overarching term citizen science which broadly encompasses any volunteer involvement in science (Roy et al., 2012). The term was coined in the 1990s as a strategy for improving public trust and understanding in science (Woolley et al., 2016). More recently, the term has been adopted to describe a range of initiatives and research endeavours across disciplines (Woolley et al., 2016), with citizen science now featuring more in published literature (Kullenberg and Kasperowski, 2016). Within the field of ecology, in addition to biological recording, citizen science schemes can also include tasks such as identifying species from photographic records or digitising data associated with specimen collections (Roy et al., 2012).

Citizen science recording schemes have collected some of the longest-running time-series datasets of species populations (Devictor et al., 2010). Such datasets play a key role in assessments of species' changes in relation to pervasive anthropogenic pressures such as climate change, pollution, invasive species, and urbanisation (Sutherland et al., 2015). Biological recording benefits from contributions by volunteers because those contributions increase the geographical range and temporal span over which species can be recorded, providing long-term species-distribution datasets that can be used to assess and compare ecological trends (Pocock et al., 2015). These recording schemes typically rely on ad hoc, opportunistic records, although there are examples of hypothesis-led citizen science schemes, as well as schemes that have set up standardized monitoring protocols (Sewell et al., 2010; Flower et al., 2016; Smale et al., 2019).

Data quality is a concern with citizen science data, as generally unstructured sampling protocols can introduce bias and noise (Isaac et al., 2014; Kamp et al., 2016; Pescott et al., 2015). This can present challenges when analysing citizen science datasets and can limit the scientific questions that can be addressed (Isaac et al., 2014). The accuracy of citizen science data has also been questioned, owing to issues surrounding validation and verification (Kosmala, et al., 2016a). Validation is a process through which records are checked to ensure the data have been submitted correctly. Verification is the process of checking records for correctness; within ecological citizen science schemes, this generally means confirming species identity (Tweddle et al., 2012). Verification is a critical process for ensuring data quality of, and trust in, citizen science datasets (Gilfedder et al., 2019), enabling those datasets to be used in environmental research, management, and policy development (Tweddle, et al. 2012).

In this review, we initially aim to explore different approaches to verification across citizen science schemes whose data feature in published research. We review citizen science scheme attributes, as well as verification approaches, and identify the information used to verify each record. We use this information to examine the different ways citizen science schemes verify data and the citizen science scheme attributes that may influence choice of verification approach. We then aim to understand whether citizen science schemes are using the most suitable verification approach to maximise confidence in, and validity of, the data, whilst also ensuring efficient verification of records.

2.3 Systematic Review Method

2.3.1 Literature search

To survey the verification approaches across existing citizen science schemes, we conducted this review based on the systematic review protocol developed by the Collaboration for Environmental Evidence (2018). The search terms we used were replicated from a review of the diversity and evolution of citizen science programmes carried out by Pocock et al. (2017). These terms were “citizen science,” “take part AND (nature OR environment),” “volunteer-based monitoring,” “public participation in scientific research,” and “participatory science.” We also used the search term “volunteer.” Searches were carried out in October and November 2019 using Web of Science, and were filtered by “ecology,” “zoology,” “entomology,” and “ornithology.” To ensure that our keyword searches in Web of Science were not missing large components of the literature that might be found elsewhere, additional searches for the terms “ecology AND (volunteer OR citizen science)” were carried out using Google Scholar, and the first 100 results were reviewed.

We excluded papers if there were no mentions of a specific citizen science scheme, or if volunteers had been recruited to assist with the research but the contributions did not continue beyond the study and were not linked to a particular scheme. For example, Flaherty and Lawton (2019) requested, using various media outlets, information on grey squirrel, red squirrel, and pine marten sightings by the general public; public sightings were used alongside hair tube and live trapping surveys to assess species distributions. In another example, data were collected from recreational anglers to combine with mark-recapture data to estimate populations of fish species (Lyon et al., 2019). These volunteer contributions were only for the duration of the study and were not linked to any particular scheme. We also excluded review papers, or results that discussed citizen science from a theoretical point of view. Finally, we excluded papers if the citizen science scheme focused on collecting data solely on the abiotic environment. These schemes included those collecting data on water quality (Brooks et al., 2019; Křeček et al., 2019) or on soil quality (Bone et al., 2012). Where papers had used data from multiple schemes, we recorded all of the schemes included in the research. Citizen science schemes nested within a larger citizen science initiative or repository were considered separately if the paper identified the specific scheme. For example, Snapshot Serengeti (Swanson et al., 2015), Penguin Watch (Jones et al., 2018), and Season Spotter (Kosmala, et al., 2016b) were referenced specifically, even though they all fall under the Zooniverse citizen science community, and therefore we recorded them as separate schemes. By contrast, Torney et al. (2019) referenced only the Zooniverse, and therefore the Zooniverse was also recorded. The search yielded 434 papers (see Appendix A.1 for full reference list), which drew on 259 citizen science schemes (see Appendix A.2 for full list of schemes).

The search strategy aimed to encompass a broad range of citizen science programmes, including recording schemes that do not identify as a citizen science scheme but do fit the definition of citizen science. It is, of course, likely that schemes will have been overlooked by the searches—most notably, schemes that have not led to published outputs. The term citizen science has been widely used only in recent decades, although volunteers have been contributing to ecological datasets for centuries (Silvertown, 2009; Dickinson et al., 2010; Miller-Rushing et al., 2012; Pocock et al., 2015), and therefore such volunteer contributions may not be linked to a specific volunteer recording scheme and are not referenced in literature. Furthermore, schemes may not provide information on the citizen science scheme attributes or verification approach publicly, and therefore would not be included in the results of this literature review. Although these searches did identify some schemes from non-English-speaking communities and regions, the search strategy is inherently biased towards schemes that operated in English (Pocock et al., 2017). These biases in the search methodology should not systematically impact the conclusions of the review.

2.3.2 Identifying verification approaches and citizen science scheme attributes

Verification approaches used by citizen science schemes were not always documented in the paper itself. Therefore, we carried out searches to obtain information on verification approaches and the information used to verify records, as well as citizen science scheme attributes, in both academic and non-academic search engines. We obtained this information from either the published literature in which the scheme featured or the scheme's public online platform, which may be a website specifically for a scheme, or a web page embedded within a larger website (see Appendix A.2 for full list of schemes, attributes, and sources).

For each citizen science scheme, we identified the following attributes: number of species recorded through the scheme, number of occurrence records collected through the scheme, data type, number of participants, geographical extent, and duration in years. Data type refers the amount of information or evidence needed to submit an occurrence record to a scheme. For example, some schemes require photos, recordings, or physical specimens to be submitted before an occurrence can be confirmed. Other schemes allow indirect or direct sightings to be submitted without further evidence. Indirect sightings include observations such as mammal tracks or dung at a given location. Direct sightings refer to a species being observed but the minimum information required for an occurrence to be submitted is species name, location, and date.

2.3.3 Data analysis

We performed simple analyses to investigate two questions. First, we asked what attributes of schemes influence whether we were able to find information on their approaches to verification. Second, using those schemes for which we were able to find information on approaches to verification, we asked which attributes of the schemes influenced the approaches that were used.

Some attribute categories included very few schemes. Therefore, we aggregated some categories for our analysis. Specifically, we classified numbers of participants as either ≤ 1,000 or > 1,000; numbers of records as either ≤ 1 million or > 1 million; and data type as either "No evidence" (for reports of direct or indirect sightings without physical evidence) or "Evidence available" (for those data points associated with specimens, photographs, or recordings).

To assess whether scheme attributes influence whether or not we were able to find information on verification approaches, we focused on schemes for which all scheme attributes were available. Inevitably, this biased the data towards schemes with more complete and accessible information. However, this was necessary for a complete investigation of which scheme attributes seemed most predictive of whether verification information could be identified, and still resulted in reasonable sample sizes of schemes with and without verification information. Using this focused dataset, we ran a binary logistic regression including the main effects of geographic scale, participant numbers, record numbers, species numbers, data type (all categorical), and scheme duration (continuous). To compare models and identify which effects were informative when determining whether schemes reported their verification approach or not, we used the dredge function from package MuMIn (Barton 2020) for model selection by comparing ΔAIC_c between all subsets of effects within this global model.

To assess which scheme attributes appear to influence verification approach, we used multinomial regression (function multinom from package nnet; Venables and Ripley 2002). Specifically, we modelled the probability that expert, automated, community consensus, or other verification approaches would be used as a function of the same scheme attributes included in the saturated binary logistic regression. Once again, we focused on only those schemes for which all attributes were available. Some schemes used more than one approach, in which case those schemes appeared in our data set once for each approach used. The dredge function was used again for model selection, to determine which attributes were most informative in determining which verification approach was used, considering main effects only.

2.4 Results

2.4.1 Summary of citizen science recording schemes

Of the 259 citizen science schemes, the focal taxa were birds (N = 97), invertebrates (N = 67), mammals (N = 24), plants and fungi (N = 17), and amphibians and reptiles (N = 8). As well, there were schemes that allowed any taxa to be recorded (N = 27) and schemes that focused on marine taxa (N = 9). There were also schemes that recorded invasive species (N = 6) and schemes that recorded roadkill (N = 4). There was substantial variation in the number of species recorded through the schemes. Where this information was available (N = 203), 68 schemes had recorded 1–10 species, 50 schemes had recorded 11–100 species, 59 had recorded 101–1,000 species, 15 had recorded 1,001–10,000 species, and 11 had recorded more than 10,000 species.

Of the schemes for which record number was available (N = 140), 12 schemes had fewer than 1,000 records, 95 schemes had between 1,000 and 1 million records and 33 had more than 1 million records. The data type submitted with each record varied across schemes: 18 allowed indirect sightings to be submitted, 165 required direct sightings to be submitted, 51 required photo submissions, 10 required recordings, and 15 required specimens to be submitted.

To determine the number of citizen scientists involved in each scheme, we included both those who collected data and registered users who may verify data. Of the schemes for which this information was available (N = 165), 76 had between 1 and 1,000 participants, 86 had between 1,000 and 1 million participants, and 3 had more than 1 million participants.

In terms of geographical extent, 17 schemes collected data at a global, cross-continental scale. Across the remaining schemes, 34 operated across multiple countries within the same continent, 125 schemes collected data at a country level, and 83 schemes operated at a regional level (i.e., the level of a region within a country). There were schemes operating on every continent besides Antarctica, with 106 in Europe, 96 in North America, 17 in Oceania, 10 in Asia, 8 in Africa, and 5 in South America.

The schemes we reviewed spanned a wide range of ages. Of schemes where duration was available (N = 225), 90 schemes had been running for less than 10 years, 64 had been running for between 10 and 20 years, 34 had been running between 20 and 30 years, and 37 schemes had been running for longer than 30 years.

2.4.2 Approaches to data verification in citizen science schemes

Across the 259 citizen science schemes, no information was found on verification approach for 117 of the schemes. Within the schemes for which verification information was found, 118 schemes relied on expert verification, 24 verified data through community consensus, and 14 used automated approaches, which encompassed algorithmic approaches without human classification. Several of the schemes used multiple verification approaches, and all of the schemes that used automation to verify data used at least one other method of verification on a subset of the data. Most commonly, automation was used alongside expert verification. Other verification approaches included using existing independent (West, 2012) or expert (Hof and Bright, 2016) datasets to confirm the likely accuracy of citizen-submitted records and carrying out follow-up surveys in a subset of locations (Kabat et al., 2012).

The information used to verify citizen science data refers to the record-level information that is used by citizen science schemes when carrying out data verification of species occurrences. This was categorised as species, environmental context, and recorder expertise. Species information is based on ease of identification (Pocock et al., 2015), confusion with other species (Siddharthan et al., 2016), rarity, and co-occurrence with other species. Environmental context takes into account the time, date, and location of the observation and, therefore, whether the species' occurrence was likely given the time of day, season (Dennis et al., 2016), habitat (Pocock et al., 2015; Sutherland et al., 2015), documented range of the species (Terry et al., 2020), and phenology (Chapman et al., 2015; Roy and Sparks, 2000). Attributes of the recorder that are of interest could include the experience and expertise of the individual submitting the record. This can be considered qualitatively when submitting the record, by asking the recorder to state their confidence in identification (Desaegher et al., 2019; Waetjen and Shilling, 2017) or experience with biological recording (Bates et al., 2015). Recorder expertise can also be quantified after record submission, using metrics such as how long the individual has been participating in the scheme, volume of records submitted, and accuracy of previously submitted records (Yu et al., 2010; Horns et al., 2018; August et al., 2020). Schemes can also use novel approaches to account for recorder expertise. One example of this is iSpot, in which recorders develop a taxon-specific reputation via points earned once records they have submitted are verified as correct by other participants (Silvertown et al., 2015).

Schemes were allocated to one or more of these categories based on information provided by the scheme on its verification approach. For many schemes, these details were not publicly available. Furthermore, individual expert verifiers may take into account all, or a combination, of these factors on a record-by-record basis, using their regional and taxonomic expertise as well as their personal knowledge of individual contributors' abilities to identify species correctly. Therefore, it is unlikely that we were able to catalogue for our analysis all of the information considered by schemes and verifiers. Across the schemes for which the required information was available, 105 used information on the species itself, 86 considered the environmental context, and 13 used information on recorder expertise. The majority of schemes used species information and environmental information together.

2.4.3 Citizen science scheme attributes and verification approach

We restricted our analysis to 103 schemes with complete information on scheme attributes. As expected, this biased schemes towards those with available verification information (all data: schemes with verification information = 142, schemes without = 117; complete attribute data: schemes with verification information = 73, schemes without = 30; Fisher's test, p = 0.006). Nevertheless, we were still able to model the propensity for verification information to be found. The best-performing model (based on Akaike Information Criterion) included data type, number of records, and scheme duration (Figure 2.1). Only more complex versions of the same model had $\Delta AIC_c < 6$, and ΔAIC_c for the null model was > 8.

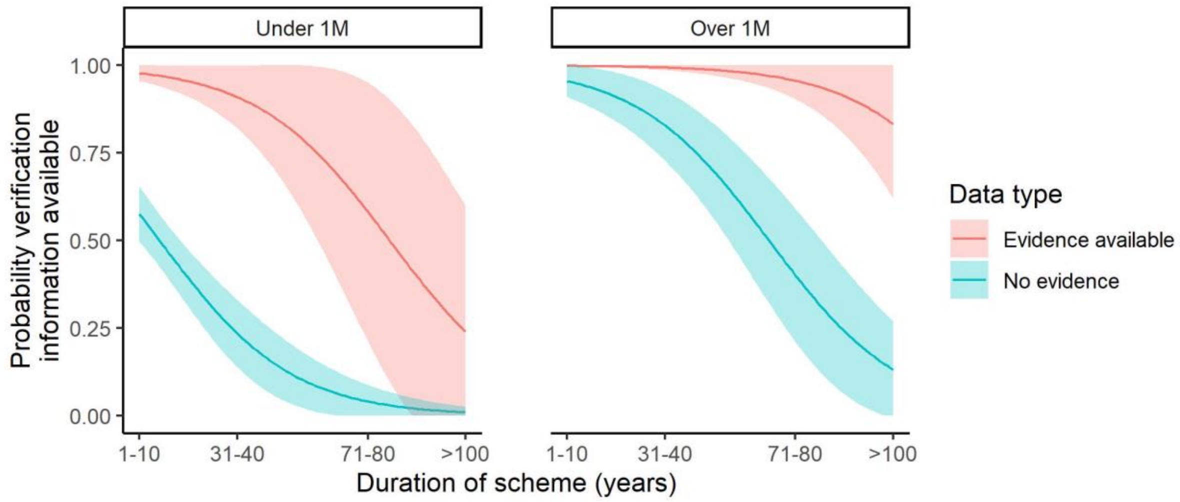

Figure 2.1: The probability of verification information being found given the numbers of participants (left panel, ≤ 1 million [M]; right panel, > 1 million [M]), duration of schemes, and data type. Fitted probabilities (lines) and standard errors (filled polygons) are estimated using the best-performing binary logistic regression model.

Using the 73 schemes for which scheme attributes and verification approach were found, we modelled the factors that best predicted the verification approaches used. Among the schemes we considered, 61 used expert approaches, 7 used automated approaches, 12 used community consensus approaches, and 8 used other approaches. Given the low sample sizes, there was limited evidence of clear predictive effects of scheme attributes. Among the models examined, only those including number of participants, data type, or both, performed better than the null (ΔAIC_c for the null model was 1.9). Recognising that these are weakly supported effects, we nonetheless note that a model including both number of participants and data type suggests that: (i) automated approaches are used only for schemes with more participants and are slightly more common for schemes without physical evidence; (ii) community consensus approaches are more common for schemes with more participants and for which evidence is available; (iii) expert approaches are more common in schemes with fewer participants, but for schemes with more participants, they are more common when no physical evidence is available; and (iv) other approaches are most common for schemes with a smaller number of participants and for which no tangible evidence is available (Figure 2.2).

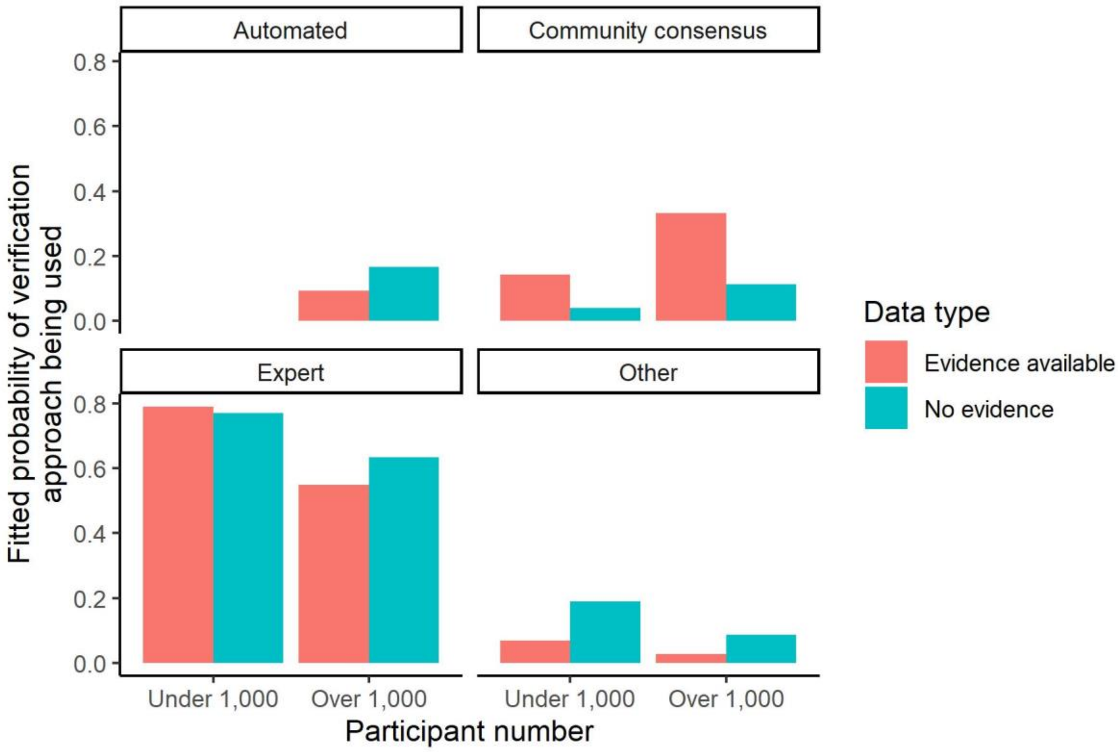

Figure 2.2: The probability of each verification approach (see panel headings) being used for schemes with different numbers of participants and different data types. Fitted probabilities (filled columns) are estimated using the best-performing parameters in multinomial regressions.

2.5 Discussion

With data quality as a key concern across citizen science datasets, there is a need to ensure validity and increase trust of these data through verification. This review identifies patterns in approaches to data verification among citizen science schemes. By identifying the range of approaches available and by considering scheme attributes that appear to contribute to choices in verification approach, we demonstrate the options available to both new and existing schemes. Here, we also present an idealised system for data verification, identifying where and how such a system could be implemented within citizen science schemes.

2.5.1 Existing patterns in verification of citizen science data

No information on data verification was found for over 40% of the schemes we reviewed. Our analyses suggest that information on verification was less likely to be found for older schemes, schemes with fewer participants, and schemes that do not require the contribution of physical evidence (specimens, photos, or recordings). Lack of available verification information does not mean that no verification is carried out; for schemes that lack a web presence and do not report verification methods in publications, verification methods are simply not publicly available or therefore are hard to identify. There may, however, be schemes that do not consider verification, trusting the recorders' abilities to report species correctly (Wiggins et al., 2011). This may be justifiable if schemes specifically recruit knowledgeable volunteers (Gardner, 2019) or provide training to volunteers before surveying (Smale et al., 2019). Some citizen science schemes focus recording effort on selected days annually (Chase and Levine, 2016). In these cases, volunteers may be joined and led by an expert (Chase and Levine 2016) and therefore errors could be identified and corrected, in person, during the data collection. Smaller-scale citizen science schemes may focus on collaborative, community-based approaches with small numbers of participants (Tweddle et al., 2012). In these cases, there may be an established trust amongst members, or verification may happen more informally between participants. Acknowledging this, there is still an imperative to report on verification methods to increase trust in the dataset and to benefit end users of the data. Arguably, this imperative is even more pronounced for those schemes that do not require physical evidence, for which verification information is currently harder to find. If there is transparency in verification approach, then the data quality can be better understood, and potential error or bias can be quantified and accounted for in analyses of the data (Pocock et al., 2014; Burgess et al., 2017).

Where verification information was available, expert verification was the most common approach. Verification by experts, although not flawless (McBride et al., 2012), has a high accuracy (Yu et al., 2012), and therefore may be a more suitable approach to obtain the level of data quality required for published research outputs (Bonter and Cooper, 2012; Miller-Rushing et al., 2012). Furthermore, schemes that monitor rare (Donnelly et al., 2014) or invasive species, for which accuracy of individual records is crucial to guide management actions (Crall et al., 2011; Pusceddu et al., 2019), require expert verification to pinpoint occurrences and ensure high-quality data. Expert verification can be time consuming for large datasets (Kelling et al., 2011; Yu et al., 2012), and schemes that operate at a large geographic scale rely on extensive networks of taxonomic and regional experts (Sutherland et al., 2015). A lack of verifiers in certain regions or with particular specialisms can lead to gaps in verified data (Bonter and Cooper, 2012). As a result, there can be a significant time lag between submission and verification of records (Bonter and Cooper, 2012).

Community consensus was the second most common verification approach. It was more common among schemes with a larger number of participants and for schemes that required evidence to be submitted with each record. Community consensus may be preferable for schemes with sufficient participants, as crowdsourcing the assessment of physical evidence spreads the task of verification across a greater number of individuals and can be particularly useful when verifying camera trap datasets, which can rapidly grow to very large sizes (Hsing et al., 2018; Swanson et al., 2016). Community consensus approaches can also be used alongside automated approaches in a hierarchical verification system (Green et al. 2020). Once multiple users have classified a record, consensus algorithms can be applied to analyse classifications and to categorise confidence in a record (Siddharthan et al., 2016; Hsing et al., 2018). Community consensus approaches also have the potential to enhance public engagement and community development. Diversifying the tasks in which citizen scientists can be involved can make the scheme more accessible to those who do not have the access or mobility to go to areas where they can record species (Borden et al., 2013). When using community consensus approaches, expert verification may still be required if datasets contain species that are less straightforward to identify, such as commonly confused species pairs (Hsing et al., 2018). This approach relies on a large number of citizen scientists investing time in the scheme (Hsing et al., 2018; Swanson et al., 2016), and therefore may not be suitable for schemes with smaller numbers of users. Furthermore, if community consensus approaches are used for schemes that operate on a global scale and record many species, the community may not have the local knowledge required to verify records for species that are less straightforward to identify or are less well known amongst the general public (Swanson et al., 2015). As a result, the verified data in these schemes may be skewed toward widely recognised, charismatic species.

Perhaps unsurprisingly, owing to their recent emergence, automated approaches were not widely used among the subset of citizen science schemes reviewed. Schemes that used automation, did so in conjunction with other methods including, most frequently, expert verification. Automation is typically the first step in the verification process, with records being checked for a range of attributes. These include whether they are in the expected geographical and temporal range, if the species is particularly rare, or for schemes that ask for the number of individuals of a species recorded, whether that number is unusually high (Bonter and Cooper, 2012; Kelling et al., 2011; Pocock et al., 2015; Yu et al., 2012). Any records that do not meet set criteria are flagged and then sent to expert verifiers (Bonter and Cooper, 2012; Kelling et al., 2011; Yu et al., 2012). Automation reduces the burden on expert verifiers by decreasing the volume of records that require verification. Automated approaches are widely applicable across citizen science schemes and can be applied to records for a huge diversity of taxa (Pocock et al., 2015). Automation is the most time-efficient way of verifying citizen science data, allowing data to be reviewed in real time as records are submitted, as well as—potentially—providing citizen scientists with immediate feedback on their submissions (Bonter and Cooper, 2012; Kelling et al., 2011; van der Wal et al., 2016; Yu et al., 2012). From the perspective of participant involvement, having rapid feedback on submitted records has the potential to strengthen engagement and to increase motivation to continue recording (Rotman et al., 2014). Although automation can reduce the number of records that require expert review, careful consideration of the verification rules is required to reduce the burden on experts without leading to classification errors (Yu et al., 2012).

With the distributions and abundances of many species changing rapidly in response to persistent anthropogenic environmental change, timely and accurate verification is important to ensure the availability of up-to-date biodiversity information (Sutherland et al., 2015). Verification by experts has perhaps been the default approach for citizen science schemes in the past (Kosmala et al., 2016a; Silvertown, 2009). With the growing volume of citizen science data that has been and will continue to be collected, there is an argument for schemes to explore and implement other verification approaches that allow large quantities of data to be verified more efficiently. The most appropriate verification approach may vary from scheme to scheme, and research may be required to assess the risks or rewards of alternative approaches. Expert verification is likely always to be required for a subset of the data, but given the emergence of community consensus and automated verification in recent decades (Newman et al., 2012), these approaches should be carefully considered for schemes moving forward. As the position of citizen science in ecological research evolves, with new schemes continually being established, verification approaches must evolve to suit the needs of schemes whilst also ensuring data quality and accuracy of records.

2.5.2 Recommendations for verification of citizen science data

Our review highlights the range of verification methods used by different citizen science schemes. In some cases, this variation might reflect deliberate and informed choices based on what works best given the attributes of different schemes. In others, it is likely that choices reflect historical contingency, or cost and ease of implementation. Some schemes may be limited to a certain approach due to available resources, time, or personnel. Others may feel bound to a verification approach in order to maintain consistency over time. In those situations, retrospective application of new methods, or calibration by running two systems in tandem, might provide reassurance to enable the implementation of new approaches.

Whilst a range of factors may influence choice of, or lack of, verification approach, transparency of documentation of verification approaches is required to increase confidence in citizen science as a means of collecting reliable data. Therefore, we recommend that citizen science schemes publicly report their verification approach. Schemes that lack a platform on which this information can be made readily available should ensure that published research clearly identifies whether and how the data were verified.

2.5.2.1 An idealised system for verification

Considering the options available for verification and the attributes that may contribute to the choice of verification approach, we have outlined a hierarchical system for verification (summarised in Figure 2.3). This approach considers the data that can be used to verify records, where automated and community consensus approaches can be implemented, and when expert verification may still be required.

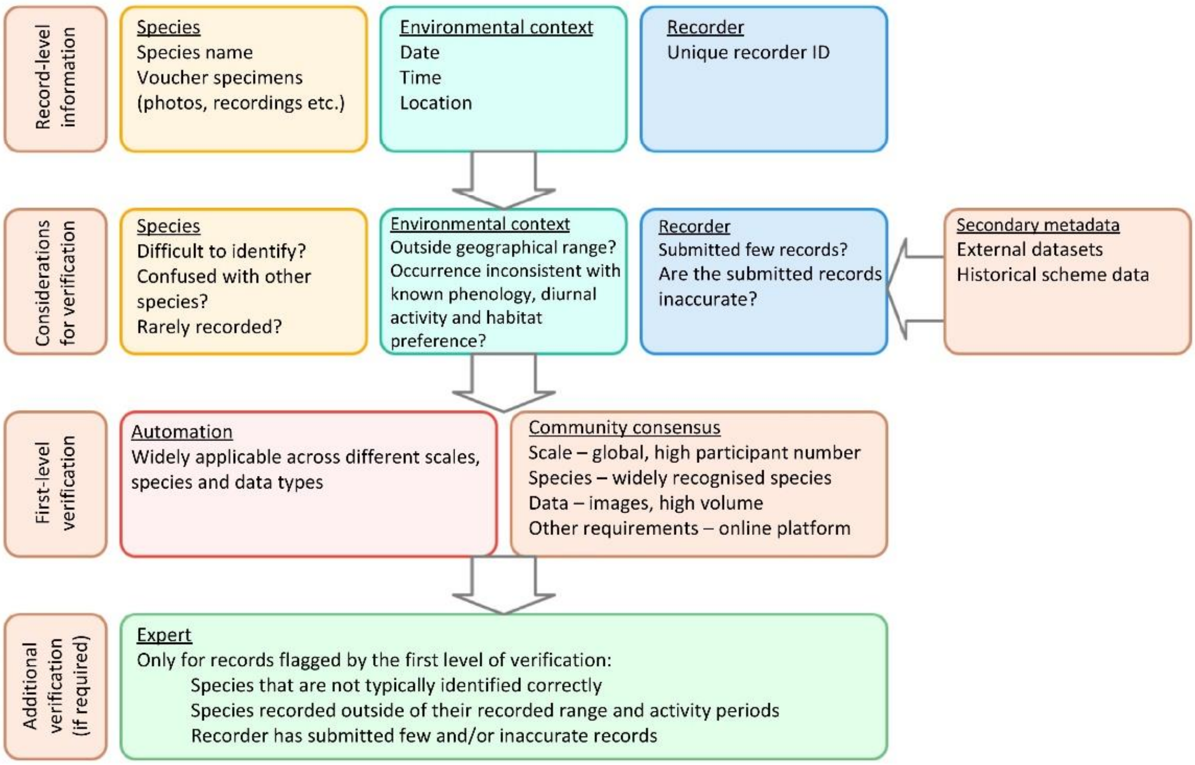

Figure 2.3: Summary of recommendations for an idealised system for verification of ecological citizen science data. Considerations for verification highlight some of the questions that can be answered using the record-level information and secondary metadata. If the answer to these questions is yes, then we propose further levels of verification may be required. First-level verification indicates the attributes of schemes that could use community consensus and automated approaches. Additional verification highlights the kinds of records that may be flagged and therefore will need to be reviewed by experts.

When verifying records, schemes should consider the breadth of information available to improve verification, making use of all data that accompanies each record (Figure 2.3). Ideally, recorders should submit the maximum available evidence with each record, such as photos or recordings, assuming the user interface through which volunteers submit records is fit for purpose. Submitting photos or other evidence may not be possible for every scheme, particularly those centred around annual count events, such as the Batumi Raptor

Count (Wehrmann et al., 2019) or Christmas Bird Count (Meehan et al., 2019), where large numbers of species are recorded during a constrained period. Furthermore, requiring more information to be submitted with every species record may discourage volunteers from taking part, creating a trade-off between data completeness and data volume. For many schemes, the minimum amount of information required is date, location, and species name. For other schemes, indirect sightings can be submitted, particularly those recording mammal species, which are often less abundant, frequently nocturnal, and less likely to be observed directly. Verification approaches need to be developed and applied in view of the minimum amount of information that typically comes with each record. Even with the limited record-level information that may accompany each record, verification approaches can still take into account information on the species, the environmental context, and the recorder (Figure 2.3). This can be done through input from expert verifiers, or by using secondary metadata such as historical data recorded through the scheme or external datasets. These data can then be used to cross-reference the metadata with each record (Terry et al., 2020). If schemes have large volumes of data across many species and records with varying amounts of information, a hierarchy of approaches could be implemented. This allows the bulk of records to be verified by automated and community approaches, and then flagged records undergo additional levels of verification (Figure 2.3).

Automated verification approaches are flexible and—resources for implementation permitting—could be used more widely across citizen science schemes to verify large quantities of data efficiently. Automation can be implemented within schemes that already have large quantities of historic data, as these can be used to inform algorithms and develop filters for the datasets (Kelling et al., 2011). To account for verification metrics for the species, environmental context, and recorder expertise (Figure 2.3), automated approaches can incorporate record-level information and secondary metadata (Terry et al., 2020), as well as expert knowledge (Kelling et al., 2011). For automated approaches to account for environmental factors, location, date, and time are required, as well as prior knowledge of the species' geographical and temporal range (Sutherland et al., 2015). Using contextual information is most useful for schemes that focus on monitoring species' phenology, or when there are no photos or recordings submitted with a record. However, it is associated with the risk that sightings could be rejected if the species displays novel activity patterns or range shifts. To account for recorder expertise, individual recorders require a unique ID. It is important to consider that as individuals submit more records, their accuracy when identifying species may improve. When accounting for environmental context or recorder expertise in automated verification approaches, it is essential to retain flexibility, with rules being dynamically updated as unexpected sightings accumulate or as recorder expertise improves.

Another approach that can be used as the first level of verification is community consensus (Figure 2.3). This approach is less widely applicable than automated verification and typically requires an online platform that connects recorders and verifiers, and large enough numbers of volunteers to verify the volume of records (Hsing et al., 2018; Siddharthan et al., 2016; Silvertown et al., 2015; Swanson et al., 2016). Community consensus approaches are more suitable for species that are more widely recognised by the public and where there is photographic evidence with each record (Swanson et al., 2016), as this means that the record can be verified based on visual attributes of the species, and no prior knowledge of the environmental context is required.

If automated and community approaches cannot verify records with an appropriate level of certainty, experts can provide additional levels of verification (Figure 2.3). It is important, therefore, for schemes to decide on their required level of certainty, which may vary depending on the species and the purpose for which the data will be used. For most schemes, a proportion of the data will ultimately need to be referred to experts for verification. A key aim of automated approaches is to minimise the proportion of the data that require expert verification. This additional verification is likely to be required for species that have not been recorded before through the scheme, for rarer species, for invasive species for which pinpointing the exact location of individuals is necessary (Lagoze, 2014), and for species that are recorded beyond their typical range or habitat. If a scheme is focusing exclusively on these kinds of species, expert verification may be the most appropriate approach. Expert insight can also be used to inform automated verification approaches, by providing information on the species and environmental context that can be accounted for in data filters. Furthermore, if a scheme is considering recorder expertise when verifying data, expert insight could also be beneficial to identify trusted recorders, allowing their submissions to be used in place of a gold standard when verifying and analysing data.

2.6 Conclusions

We reviewed approaches to data verification across ecological citizen science datasets, and assessed factors that appear to influence the choice of verification approach. Alongside this, we highlighted that the verification approaches of many citizen science schemes are not readily available to the public. We recommend how citizen science schemes can approach verification and make appropriate choices to ensure data quality. Citizen science plays an important role in data collection at a geographical and temporal scale unmatched by other data collection methods and is a valuable means of engaging the public in scientific endeavours. By developing improved verification approaches and using the full range of information available, issues of data quality within citizen science datasets can be addressed, thereby increasing trust in citizen science approaches, and strengthening the place of citizen science within ecological research.

3. Verifying Citizen Science Biodiversity Data: Accounting for Contextual Information Within a Bayesian Framework

3.1 Abstract

Citizen science schemes are continuing to grow in scope and scale, as the volume of data collected by citizen scientists increases. To ensure citizen science records are of a known quality, they need to be verified. Currently, verification is predominantly carried out by experts, but automated approaches are continuing to emerge, allowing for more efficient data processing and a reduced burden on expert verifiers. Here, we show how readily-available contextual information can be harnessed in a generalised Bayesian framework for verifying ecological citizen science data. We demonstrate how this approach can be applied to both crowdsourced classifications of camera trap images, and ad-hoc, opportunistic records collected by field-based citizen scientists. We present classification models which make use of the meta-data associated with each record, as well as the historical data submitted to a scheme, to incorporate information on the species and the environmental context into the probability of a record being of a given species. We present two variations of model, a species-only model that uses the species confusion matrix to quantify identification mistakes made by citizen scientists and an environmental context model that uses a contextual matrix that quantifies when and where species are observed. We then present a cross-validation approach to model selection, formalising the process of determining which contextual variables help to verify the record. For the crowdsourcing example, the environmental context model improved accuracy of species classification compared with the species-only model; by contrast, contextual information did not improve the accuracy of inference from ad-hoc records. We then present how setting probability thresholds for acceptance can improve the accuracy of verification models and outline how the approaches applied here can be incorporated into the verification process to reduce the burden on expert verifiers.

3.2 Introduction

Volunteer contributions have underpinned ecological research endeavours for centuries, with many long-term species occurrence datasets being collected by non-professional scientists (Miller-Rushing et al., 2012; Pocock et al., 2015, 2017). More recently, these volunteer efforts have been defined as 'citizen science', encompassing a range of initiatives in which volunteers contribute to, and collaborate on, research into a vast array of ecological questions (Kullenberg and Kasperowski, 2016; Miller-Rushing et al., 2012). Computing and technological advances mean that contributing to citizen science schemes has become increasingly straightforward (Di Cecco et al., 2021; Luna et al., 2018; Newman et al., 2012), allowing projects to grow in scope and scale (Pocock et al., 2017). The volume of data being collected by these schemes is continuing to increase (Di Cecco et al., 2021), and the tasks in which citizen scientists can be involved are diversifying. Some schemes now involve citizen scientists in data processing tasks or data analysis (Brown and Williams, 2019; Graham and Smith, 2021; Haklay, 2013; Pocock et al., 2017), whilst other schemes collaborate and co-create projects with volunteers (Wiggins and Crowston, 2011).

Citizen science datasets that consist of species occurrence records can span large spatial and temporal scales, making them a key resource in advancing our understanding of changes in species distributions, abundances, and phenology in response to pervasive anthropogenic threats (Sutherland et al., 2015). Citizen science is also a valuable tool in outreach, providing opportunities to engage the public in the research process, and raise awareness of ecological issues (Dickinson et al., 2012). To encourage as many individuals as possible to participate, as well as to collect large volumes of data, citizen science schemes often aim to keep involvement straightforward, allowing ad-hoc, opportunistic records to be submitted with minimal information (Baker et al., 2021). This can lead to citizen science data being spatially (Geldmann et al., 2016) and temporally (Knape et al., 2022) biased, favouring more common, widely recognised species (Boakes et al., 2016; Isaac and Pocock, 2015; Robinson et al., 2018). The biases that arise from data collection by citizen scientists, and the lack of meta-data associated with each species record, can lead to questions and concerns around data quality (Kosmala et al., 2016). This can also limit the research questions that can be explored using citizen science datasets (Brown and Williams, 2019; Clare et al., 2019; Isaac et al., 2014), because modelling large-scale ecological trends relies on accurate and high-quality data (Clare et al., 2019; Isaac et al., 2014).

Verification is an essential process for ensuring that citizen science records are as accurate as possible (Baker et al., 2021; Tweddle, et al., 2012). Currently, the majority of citizen science schemes rely on experts to verify species records (Baker et al., 2021). This can be problematic, particularly when every record must be checked by experts, potentially creating bottlenecks in data processing. Furthermore, for schemes that collect data at a large geographic scale, a greater number of experts is required to ensure there is sufficient taxonomic and regional expertise to verify the range of submitted records. As a result, a large proportion of records can remain unverified for long periods (Bonter and Cooper, 2012; Sutherland et al., 2015). More recently, alternatives to expert verification have been developed. Examples include community consensus, where records are classified by citizen scientists and then verified based on majority classification (Hsing et al., 2018; Swanson et al., 2015), and automation (Bonter and Cooper, 2012; Kelling et al., 2011; Yu et al., 2012). As the volume of data being collected by citizen scientists increases, automated verification becomes particularly attractive, allowing more efficient data processing and reducing the burden on expert verifiers (Baker et al., 2021). In turn, this ensures species datasets are up-to-date and available rapidly for research and analysis. Automated verification has been approached in several ways by different citizen science schemes (Baker et al., 2021). Some schemes pass records through a series of data filters and set rules that flag unusual observations for that species, given the location and date (Bonter and Cooper, 2012; Kelling et al., 2011; Yu et al., 2012). For schemes that have large volumes of photographic observations, artificial intelligence algorithms, neural networks and computer vision tools can be used for automated image recognition and classification (Gomez Villa et al., 2017; Green et al., 2020; Norouzzadeh et al., 2018; Terry et al., 2020; Willi et al., 2019). Community consensus verification approaches can be used alongside novel statistical approaches that quantify confidence and certainty in classifications, which can then be integrated into classification algorithms for verification (Mugford et al., 2021; Siddharthan et al., 2016; Swanson et al., 2016).

A range of information can be used to verify a citizen scientist's species record. The information available will depend on the meta-data associated with each record (Baker et al., 2021; Terry et al., 2020). For many schemes, the minimum amount of information required to submit a species record is species name, date, and location, with other fields such as habitat and time being optional (Baker et al., 2021). Submitting evidence such as photos, videos or recordings with records is also often optional (Baker et al., 2021). Therefore, those verifying records will rely on the contextual information of the observation, such as the observer who submitted the record, the environmental context of the observation and the attributes of the species itself (Terry et al., 2020). Various modelling approaches for assessing observer expertise and verifying citizen science data have been developed. For example Santos-Fernandez and Mengersen (2021) used Bayesian item response models to quantify citizen scientists' ability based on task difficulty for Snapshot Serengeti data; De Lellis et al. (2019) used a Bayesian classification algorithm that accounts for citizen scientist demographics; Saoud et al. (2020) incorporated user features into machine learning approaches to detect misidentifications; and Mugford et al. (2021), applied a modified version of Kim and Ghahramani's (2012) Independent Bayesian Classifier Combination Model (IBCC) to classify observations based on user accuracy in the iNaturalist New Zealand dataset.

Incorporating attributes of the species itself is valuable, particularly for species that are hard to identify (Falk et al., 2019; Gorleri et al., 2022) or often confused with similar species (Hsing et al., 2018). Accounting for contextual environmental information may be important in determining the accuracy of species records, as many species have specific habitat associations (Oliver et al., 2009), and are more active during certain seasons (Dennis et al., 2016; Roy and Sparks, 2000) or at certain times of day (Refinetti, 2008). Accounting for these environmental factors becomes particularly important where records lack photographic evidence, for rarer species or for species that are often misidentified (Siddharthan et al., 2016). Consequently, it is important to ensure that verification approaches make use of the meta-data provided and account for when and where a species is observed. Previous approaches that have used species attributes include: Swanson et al. (2016), who used a plurality algorithm that incorporated species false-positive and false negative error rates to calculate measures of confidence for each observation in the Snapshot Serengeti dataset, achieving a 97.9% accuracy overall; Siddharthan et al. (2016), who presented an incremental Bayesian model for classifying observations for BeeWatch data, accounting for ease of species identification and user ability, delivering 91% accuracy on unseen data, outperforming majority vote; and Hsing et al. (2018), who evaluated consensus classifications for MammalWeb data by calculating probabilities of user classifications being correct for each species.

Here, in the first instance, we will look at attributes of the species itself and the environment, by using past data from citizen science schemes to examine the mistakes that are made when identifying, and the context in which species observations occur, to inform the confidence we can have in a citizen science observation. We present how this information on the species itself and the context of an observation can be harnessed in a simple, generalised Bayesian framework for verifying ecological citizen science data, which can be applied both to schemes that crowdsource the classification of species records, and schemes that comprise ad-hoc, opportunistic records. We present two variations of this framework. The first is applied and used for community consensus classifications by using the species confusion matrix to quantify how frequently the species is correctly identified, and an environmental context matrix that quantifies where and when it is most frequently observed. The second variation of the framework is used for expert-verified observations by evaluating how likely an expert is to accept or reject a record based on the species and the context. We then present a k-fold cross validation approach to model selection, where we apply the model to 100 iterations of randomly selected training and test data; formalising the process of determining which contextual variables help to verify the record. The approach outlined here can assess and quantify accuracy for large volumes of records, streamlining and increasing efficiency within the verification process, by directing resources and expertise towards records having a greater level of uncertainty. Our approach has the potential to address issues of data quality within citizen science schemes and allow data to be available for use more rapidly.

3.3 Methods

This framework applies an adapted version of Kim and Ghahramani's (2012) Independent Bayesian Classifier Combination Model (IBCC). We present two separate adaptations of the model. The first model we present is a community consensus classification model, that can be applied to citizen science schemes that use community consensus verification. For schemes that use community consensus verification, a citizen science record consists of one or more species classifications by citizen scientists. We apply this model to MammalWeb data, a citizen science scheme that monitors mammals using camera traps. The second model we present is an expert behaviour model for expert verified citizen science schemes, where a citizen science record consists of a single species identification from a field-based citizen scientist that is either verified as correct by an expert or redetermined to another species. We apply the expert behaviour model to iRecord Coleoptera and Diptera data, where ad-hoc opportunistic species observations are submitted by citizen scientists through an online platform or app. Within each framework we have two types of models, a species-only model, that uses the species confusion matrix to quantify how frequently a species is correctly identified by citizen scientists; and an environmental-context model that incorporates contextual meta-data using a matrix quantifying how frequently a species was observed in each environmental context. These models output a probability for every species that could be observed within the dataset. This set of probabilities is then used to inform the classification of that observation as a given species. We then detail how cross-validation across 100 iterations of randomly split training and test data and model performance metrics can be used to compare models to determine which contextual environmental variables are most useful in identifying the correct species within each citizen science dataset.

3.3.1 Community consensus classification model

In the community consensus model, a citizen science record consists of an observation with species classifications by one or more citizen scientists, with the observation process being independent of the classification process. For each citizen science record, hereafter an instance, we calculate a vector of probabilities, each one relating to a species that could be observed within the model. This set of probabilities is then used to classify the instance as a particular species. Each probability calculated can be represented as $P(S \mid R, H, D, K)$, which denotes the probability of an instance being species S, given: the set of (one or more) reported species that arises from citizen scientist classifications, R; the environmental context (hereafter, context) of the instance, H; the previous data D; and other prior knowledge K. The environmental context relates to categorical variables where the instance was observed, i.e., habitat, season, and time. Here, the previous data is referring to the confusion matrix, such that $D = \{(r_i, h_i, s_i)\}$, with $i \in [1..n]$ indexing the previous instances in the data where true species s_i, was classified by citizen scientists as reported species r_i and observed in environmental context h_i.

We introduce parameters π that capture the relevant information in the data D, such that:

$$P(S \mid R, H, D, K) \propto \int d\pi \; P(R \mid S, H, \pi_1) \; P(S \mid H, \pi_2) \; P(\pi \mid D, K) \qquad (1)$$

where we have split $\pi = (\pi_1, \pi_2)$ into two components that represent different processes that influence $P(S \mid R, H, D, K)$. The first factor, $P(R \mid S, H, \pi_1)$, relates to the species classification process, denoting the probability that an instance will be classified as a particular species given the true species and the context. This is the theoretical counterpart of the empirical confusion matrix that quantifies the number of instances where a true species has been identified correctly, or as another species in each environmental context. The second factor, $P(S \mid H, \pi_2)$, describes the observation process, denoting the probability of the true species given the environmental context. This is the theoretical counterpart to a second matrix, hereafter referred to as the context matrix, that quantifies the frequency with which the true species appear in each context. The final factor, $P(\pi \mid D, K)$, describes what the previous data tell us about the parameters. Thus, Equation (1) describes how prior information from the past data D propagates via π to tell us about a new instance, where we integrate over possible values of the parameters, weighted by the evidence for each value from the previous data captured by the species confusion matrix and the context matrix.

Here, we apply two versions of the model to calculate $P(S \mid R, H, D, K)$. Firstly, a species-only model that uses the species confusion matrix to calculate the first factor, $P(R \mid S, H, \pi_1)$. The species-only model assumes that all species are equally likely to be observed in each context, and therefore excludes the context matrix, making the second and third factors constants. The second model type is the environmental context model, where we calculate the second factor using the context matrix that quantifies the number of previous instances where the true species has been observed in each context. The null model here is the species with the highest number of classifications, i.e., the modal species.

3.3.1.1 Choice of parameters and prior

To integrate prior knowledge from the confusion and context matrices into Equation (1), we use Bayes' theorem to invert the final factor in the equation, such that the information regarding previous instances described by D is integrated into the first and second factors. In doing so, we introduce prior probabilities for π. As citizen scientists are unable to see reports made by other citizen scientists for any instance, we can assume that identifications made by citizen scientists are independent of each other, given the true species and environmental context and π_1. Knowledge of π_2 renders true species in different instances independent, given the environmental context. The result from integrating previous instances data is that:

$$P(S \mid R, H, D, K) \propto \int d\pi \ \prod_{i=0}^{n} P\left(r_i \mid s_i, h_i, \pi_1\right) P(s_i \mid h_i, \pi_2)\ P(\pi \mid K) \tag{2}$$

where:

- $P(r_i \mid s_i, h_i, \pi_1)$ describes the probability of reported species r for instance i, given the true species s, the environmental context h from the previous instances and any other information we might have, π;
- $P(s_i \mid h_i, \pi_2)$ describes the probability of true species s for instance i given the environmental context h from the previous instances and any other information we might have, π;
- $P(\pi \mid K)$ describes any additional information regarding the instance.

The final factor represents additional information that we might have regarding the types of errors that may arise and the distribution of prior data across species and environmental context types. Here, we assume that in the absence of previous data, all possible combinations of reported species, true species, and environmental contexts are equally likely and therefore the third factor is a constant within the model.

We take $\pi_1 = \{\pi_{1,rsh}\}$, where r represents citizen science species classifications, s is the true species, and h is the contextual environmental variables in the previous instances; and $\pi_2 = \{\pi_{2,sh}\}$, which represents the true species s and the contextual environmental variables h in the previous instances; and set $P(r \mid s, h, \pi_1) = \pi_{1,rsh}$ and $P(s \mid h, \pi_2) =$

$\pi_{2,sh}$. Therefore, the probabilities are calculated using the corresponding values from the matrix that relates to each factor, with $\pi_{1,rsh}$ relating to the species confusion matrix and $\pi_{2,sh}$ relating to the context matrix.

The task of defining a prior then depends only on the restrictions we place on these matrices. The context variable, h, consists of a combination of context types, such as habitat, season, and time of day. The prior can restrict the dependence of π_1 and π_2 on h to subsets of these context types (including all or none of them), which may be applicable if there are combinations of context types that are implausible. Here, we are assuming that all context types are equally likely, and therefore we do not place any restrictions on the matrices, meaning that the confusion matrix includes all combinations of reported species, true species, and context types, and the context matrix includes all combinations of true species and context types. The only constraint we then impose on the probabilities is that they sum to one, which requires normalisation. Thus, given p context types, the choice of prior above generates $2^p \times 2^p = 2^{2p}$ possible models, consisting of the choices of dependence on all possible subsets of the context types in π_1 and π_2. Once these constraints are specified, we simply place constant (i.e., Dirichlet with all parameters equal to 1) priors on each independent $\pi_{1,\cdot sh}$ and $\pi_{2,\cdot h}$.

Once the prior is specified, we can perform the integration above (Equation 2). The result is that:

$$P(S \mid R, H, D, K) \propto \frac{B(\{n_r + n_{rSH} + 1\}_{r \in \mathcal{S}})}{B(\{n_{rSH} + 1\})} \; B(\{n_{SH} + 2, \{n_{sH} + 1\}_{s \neq S}\}) \tag{3}$$

where:

- n_r is the number of reports of species r for the current instance;
- n_{rsh} is the total number, across all instances in the training data, of reports of species r when the true species is s and the context is h;
- n_{sh} is the number of instances in the training data which the true species is s in context h;
- B is the beta function, defined for integer arguments as:

$$B(\{z_i\}) = \frac{\prod_{a \in A} (z_a - 1)!}{\sum_a (z_a - 1)!} \tag{4}$$

3.3.1.2 Species classification for community consensus model

The expression for $P(S \mid R, H, D, K)$ in Equation (3) gives a vector of probabilities for each possible species (i.e. the species in the previous data) being the true species. These probabilities can be used to inform the classification of an instance as a certain species. This classification could be dependent on the probabilities assigned to each species or prior knowledge of the species. For example, classification rules can be set, such that an instance is only classified as a species if the probability exceeds a given confidence threshold. Higher thresholds can be set for specific species that are known to be rare or frequently misidentified.

Classification is a decision problem and, as such, needs a loss function that encodes the 'cost' associated with classifying as species s when the true species is species s' (which may or may not be equal to s); minimising the expected loss provides the optimal classification according to this loss function. The choice of loss function will depend on the level of error that is acceptable and the risks of misidentifications within the model. Specific ecological scenarios might justify particular choices of loss function. For more common species, a misclassified citizen science record may have little impact on the citizen science data. However, if a rare species is misclassified and the record flows to a database, this could impact interpretation of the data held for that species. In the examples shown here, we initially use a simple correct/incorrect loss function, where each citizen science record is classified as the species with the highest probability. We then explore the impacts on model accuracy of setting probability thresholds.

3.3.2 Expert behaviour classification model

For datasets that are verified by experts, the probability of true species s might depend on factors that differ from those that matter for community consensus verified data. When an expert makes a decision about whether the reported species is correct or not, they are likely to couple their knowledge of the reported species with the environmental context of the instance. Therefore, we present a variation of this Bayesian framework that can be applied to expert verified data. In this variation of the framework, instead of calculating $P(S \mid R, H, D, K)$ using two probabilities dependent on the confusion and context matrices, we model $P(S \mid R, H, D, K)$ directly based on a single confusion matrix that n_{sk}, which quantifies from the past data D, all possible combinations of true species s and context k, that includes both the environmental context h and reported species, r. The confusion matrix n_{sk} is quantified using past instances in the dataset. We can then calculate the probability that the expert classifies true species, $\tilde{s}$, using the following:

$$P\left(\tilde{s} \middle| \tilde{k}, D\right) = \frac{n_{\tilde{s}\tilde{k}}+1}{n_{\tilde{k}}+|S|} \tag{5}$$

where:

- $n_{\tilde{s}\tilde{k}}$ is the number of instances in the training data with true species $\tilde{s}$ and context $\tilde{k} = (\tilde{r}, \tilde{h})$, where $\tilde{r}$ is the reported species in that instance and $\tilde{h}$ is the environmental context,
- $n_{\tilde{k}}$ is the number of instances in the training data with context $\tilde{k}$, which is equal to the sum over the true species $\tilde{s}$ in the $n_{\tilde{s}\tilde{k}}$ matrix,
- $|S|$ is the total number of species.

In this classification model, the prior is the mean value of the probability parameters for each expert classified species; i.e., π_{sk} for each k, are all $\frac{1}{|S|}$ where $|S|$ is the number of species. As a result, when $|S| > 2$, there is more prior probability on the rest of the expert classified species than on the one reported; thus, in the absence of data, the probability of a species identification being changed from the reported species to another species by an expert is higher than the probability of the reported species being accepted by the expert. Note that the effect of the number of species is only important when the number of species and number of data points are of the same order. Here, the null model is accepting the initial species observation as correct.

3.3.2.1 Species classification for expert behaviour model

Equation 5 provides a probability for every species that could be observed in the model. When evaluating these probabilities for expert verified datasets, we can classify instances in two ways. Firstly, as we have described for the community consensus classification model, we can classify the expert-predicted true species by selecting the species that has the highest posterior probability. Secondly (and alternatively), we can use the probability of the reported species to classify whether a record is accepted as correct, or redetermined (i.e., the reported species is considered incorrect, and the record should be changed to another species).

If choosing the latter classification method, the probability of the reported species being redetermined to another species is expressed as the following:

$$P\left(\tilde{c} = 1 \middle| \tilde{k}, D\right) = \frac{(n_{\tilde{k}} - n_{\tilde{r}\tilde{k}}) + |S| - 1}{n_{\tilde{k}} + |S|} \tag{6}$$

$$P\left(\tilde{c} = 0 \middle| \tilde{k}, D\right) = \frac{n_{\tilde{k}} + |S| - 1}{n_{\tilde{k}} + |S|} \tag{7}$$

where:

- $\tilde{c}$ is a binary variable that describes whether the reported species is accepted ($\tilde{c} = 1$) or redetermined ($\tilde{c} = 0$),
- $\tilde{k}$ is the environmental context, including single reported species $\tilde{r}$ and environment $\tilde{h}$,
- D is the previous data.

These expressions give us two probabilities. We can then set a threshold for whether the instance can be accepted as correct or redetermined. If the probability of the reported species (calculated in Equation 6) does not meet the threshold value and is redetermined, it can then undergo additional levels of expert verification to determine the true species. The threshold set will depend on the species and the costs of incorrectly classifying a species. However, here to ensure consistency with comparing approaches, we apply the same approach as the community consensus classification model and classify the instance as the species with the highest posterior probability.

3.3.3 Model selection

When applying these frameworks to citizen science data, k-fold cross-validation can be used to select between models and determine which context types are most effective at estimating the true species (Gelman et al., 2014; Hooten et al., 2015; Link and Sauer, 2015). To apply cross-validation we use data for which there are expert assessments of the species in each instance, as proxies for the 'truth'. This expert assessed data is used to validate the model species classifications and calculate the accuracy of each of the models that are being compared.

The data for which we have expert assessments is divided randomly, using an 80/20 partition, into training and test data. From the training data, we obtain the n_{rsh} and n_{sh} matrices for the community consensus classification model, and the n_{sk} matrix for the expert behaviour classification model. The classification methods for each model are then applied to the test data to classify the true species for each instance in the test data. The resulting classifications are then validated against the expert assessments of the true species using several metrics, as follows. Using the validated classifications, we calculate several metrics to compare and assess model performance. For both the community consensus classification model and the expert behaviour model, we calculate: the (negative) log likelihood across instances; the proportion of instances for which the classification is correct; and the squared error (where the error is the difference between the probability assigned to a species and 1, if it is the correct species, or zero, otherwise). This process is repeated for 100 random splits and the mean of each metric is taken across repeats.

Proportion of correct instances is perhaps the most important metric for model selection for these classification models because, when verifying instances using these models, the aim is to maximise the number of correct instances to ensure accurate verification of the true species by the model. However, additional metrics were calculated to evaluate how well the model fits the data and to quantify the overall level of error in the model predictions. Including these additional metrics may be most useful when comparing models in which the proportion correct is similar.

3.4 Data

To demonstrate how these frameworks can assist in the verification process we applied the classification models to two types of citizen science datasets focused on different taxa and representing contrasting approaches to data collection and verification. For the community consensus classification model, we used data collected through MammalWeb, a citizen science project that monitors mammals using camera traps, and in which citizen scientists classify what they believe to be in the photos or videos on the MammalWeb online platform (Hsing et al., 2022; Hsing et al., 2018). For the expert behaviour classification model, we used Diptera and Coleoptera reports collected through iRecord. These data comprise ad hoc, opportunistic observations collected by citizen scientists, held by the Biological Records Centre (BRC), and published through the National Biodiversity Network (NBN) Atlas. These data, which may optionally include photographic evidence, are submitted to iRecord by individual citizen scientists, or through the national, volunteer-led recording schemes; they are verified by experts (Pocock et al., 2015).

3.4.1 MammalWeb

The data, collected between April 2015 and May 2021, consist of species observation instances and citizen scientist classification reports from the MammalWeb citizen science project (Hsing et al., 2022). Although MammalWeb has collected 630,644 (as of February 2022) sequences of photos through the project, we only used sequences that had been checked by experts. MammalWeb allows users to set up their own projects to investigate specific hypotheses and questions (Hsing et al., 2022); therefore, we limited the data to include only observations collected for MammalWeb Britain, a project with the broad aim of cataloguing mammalian biodiversity in Britain.

Observations of humans were removed from the dataset and, for our purposes, small rodents and birds were grouped and categorised as ‘Other’. The resulting dataset consisted of 66,635 classifications of 24,850 sequences, comprising 25 true species. This included ‘Don’t Know’ reports, in which the species could not be identified from the camera trap image, as well as ‘Nothing’ reports, where the camera had been triggered without vertebrate wildlife being pictured in the resultant footage.

The contextual environmental variables that we included in the model were habitat, season, and time (of day). These variables were categorised based on the time and date in the photographs’ EXIF data, and habitat information provided by the individual deploying the camera trap. The dataset included 13 habitat categories, including null, which arose when habitat was not reported. Season was categorised using the dates submitted with the records, the cut-off for the seasons being the winter and summer solstices, and the spring and summer equinox for the year of the report. Time was categorised into 'day' or 'night' based on the time the photo was taken and using the Suncal package (Thieurmel and Elmarhraoui, 2019) to get the sunrise and sunset times for the location and date of each sequence. We have three context types, and saturated $\pi_{1,osh}$ and $\pi_{2,sh}$, modelling dependence on all combinations of habitat, season, and time for both probability parameters. For the species-only model we include all combinations of habitat, season, and time, as well as a model that excludes all contextual variables from the species confusion matrix. Therefore, species-only scenarios tested 8 possible models. For the environmental context model, we tested against all possible combinations of habitat, species, and time. Therefore, we tested the global model, which included all possible context types, and 63 possible sub-models.

3.4.2 iRecord

We applied the expert behaviour classification model to Coleoptera and Diptera records submitted to iRecord between January 2000 and March 2022. Each record had been verified by experts and either accepted as correct or redetermined to another species.

The original Coleoptera and Diptera datasets consisted of 285,731 and 344,104 records. We limited the datasets to observations that were identified to species level and removed any species that had occurred only once in the dataset. We also removed any records that had no evidence, such as photos, videos, or specimens, submitted with the observation because, in these cases, there was no basis on which to determine whether or not the species was correct (N Coleoptera records = 142,336; N Diptera records = 199,209). We removed families that had a redetermination rate of less than 0.03 because, in these cases, the lack of prior data on redeterminations prevents useful modelling of the process. Within the Diptera data, the majority of records belonged to the hoverfly family, Syrphidae, which were predominantly submitted to the UK Hoverfly Recording Scheme. For the Coleoptera dataset, the majority of records belonged to the ladybird family, Coccinellidae, which were mainly submitted through the UK Ladybird Survey. We therefore separated these families from the rest of the species records and analysed them separately. This resulted in four separate datasets to which we applied the classification model (Table 3.1).

Table 3.1: Number of records, species and redetermination rate of iRecord datasets to which we applied the expert behaviour verification model.

Dataset	Number of records	Number of species	Redetermination rate
Syrphidae	83,585	229	0.0400
Diptera (without Syrphidae records)	13,762	204	0.0612
Coccinellidae	82,758	51	0.0427
Coleoptera (without Coccinellidae records)	33,107	442	0.0527

The contextual variables included in the model were habitat, season, sample method and "data cleaner" result; these attributes are explained, as follows. Habitat was not reported consistently; therefore, we grouped habitats into UK Habitat Classifications (Butcher et al., 2020) based on the information provided with each record. This resulted in 23 habitat categories for the Coleoptera Data and 25 for the Diptera data. We categorised season using the dates reported with each record, again using the solstice and equinox dates for the year in which the species was reported. Sample method describes how the data were collected in the field; this might include, for example, whether a trap or net was used when surveying. Data cleaner result refers to whether the observation passed the NBN data cleaner, which is the first step in the validation and verification process once a record has been submitted to iRecord. The NBN Record Cleaner is software that carries out automated validation checks to flag dates, grid references and species names that have been incorrectly entered. The software also carries out verification checks that flag species records that are observed outside of the typical spatial or temporal range, are particularly rare, or difficult to identify (Dean, 2013). This variable was categorised as 'true' for species that passed the record cleaner, and 'false' for records that were flagged. We could not include time as a contextual variable for the iRecord data, because records do not have an exact time submitted with the meta-data.

We saturated $n_{s\tilde{k}}$, imposing no constraints, modelling dependence on all combinations of the four context types. Therefore, we tested 16 models.

3.5 Results

3.5.1 MammalWeb

The null model, where we classified species based on choosing the modal species (i.e., the species with the most reports) for each instance, had an accuracy of 0.896.

The species-only community consensus classification model that included no contextual environmental variables and relied solely on the relative abundances of misidentifications within the species confusion matrix improved very slightly on simply accepting the modal species (proportion correct = 0.9002, squared error=0.0095, negative log likelihood = 0.661). For the environmental -context models that included environmental information within the species confusion matrix, π_1, and context matrix, π_2, the model that performed best across the three metrics included time in π_1; i.e., the model confusion matrix depended on time, but not habitat or season. The same model included all three of habitat, season, and time in π_2; i.e., all three were deemed relevant to determining whether a species was likely to be captured by a camera trap (proportion correct = 0.919, squared error = 0.0056, negative log likelihood = 0.402). See Appendix B.1 for the cross-validation results from all models.

If we set a probability threshold for whether we accept the model classification (i.e., the species with the highest posterior probability), the proportion of correct instances (N instances = 4970) for both the species-only model and the best performing model in cross validation increases, with the model that includes contextual environmental variables performing better at thresholds below 0.6 (Figure 3.1A). By setting thresholds for acceptance, a proportion of the instances are removed from the pool that need to be verified. More instances are removed at lower thresholds for the best performing contextual model (Figure 3.1B), meaning that the contextual model is classifying instances with higher confidence.

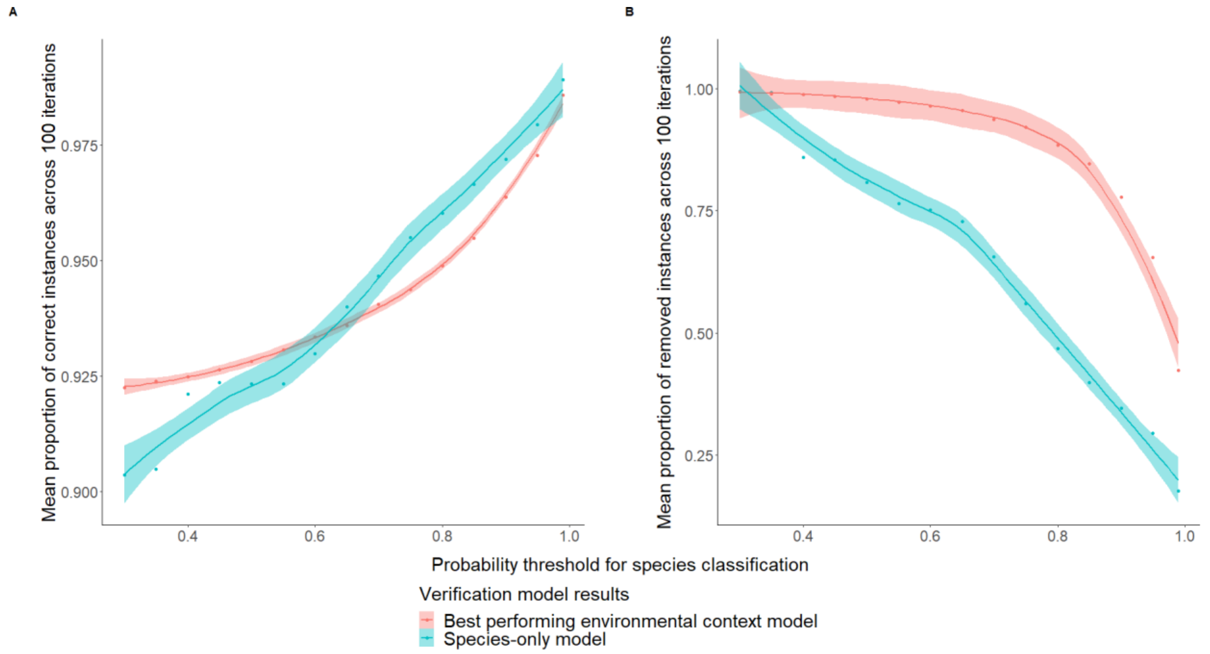

Figure 3.1: The proportion of correct instances for MammalWeb data across 100 cross-validation iterations when applying the species-only community consensus classification model and the best performing environmental context model (which included the contextual variables habitat, season and time), when we only classified instances if the maximum species probability is above a certain threshold (A); and the proportion of instances removed (i.e. accepted and verified as the classified species) for a given threshold for the species-only model and best performing model (B). Trendline and standard errors (filled polygons) fitted from a locally estimated scatterplot smoothing function (LOESS).

To examine the impacts of the number of classifications on the model selection metrics, we compared the species-only model and the best performing contextual model. We limited the minimum number of citizen science classifications per instance by selecting the first 1-5 classifications for each instance and removed sequences which had below the minimum number of classifications. We then applied the species-only and best performing environmental-context community consensus classification model to each subset of classifications. Models performed better when the minimum number of citizen science reports was increased, with the best performing environmental-context model outperforming the species-only model when the classification number was limited to between 1 and 5 (Figure 3.2).

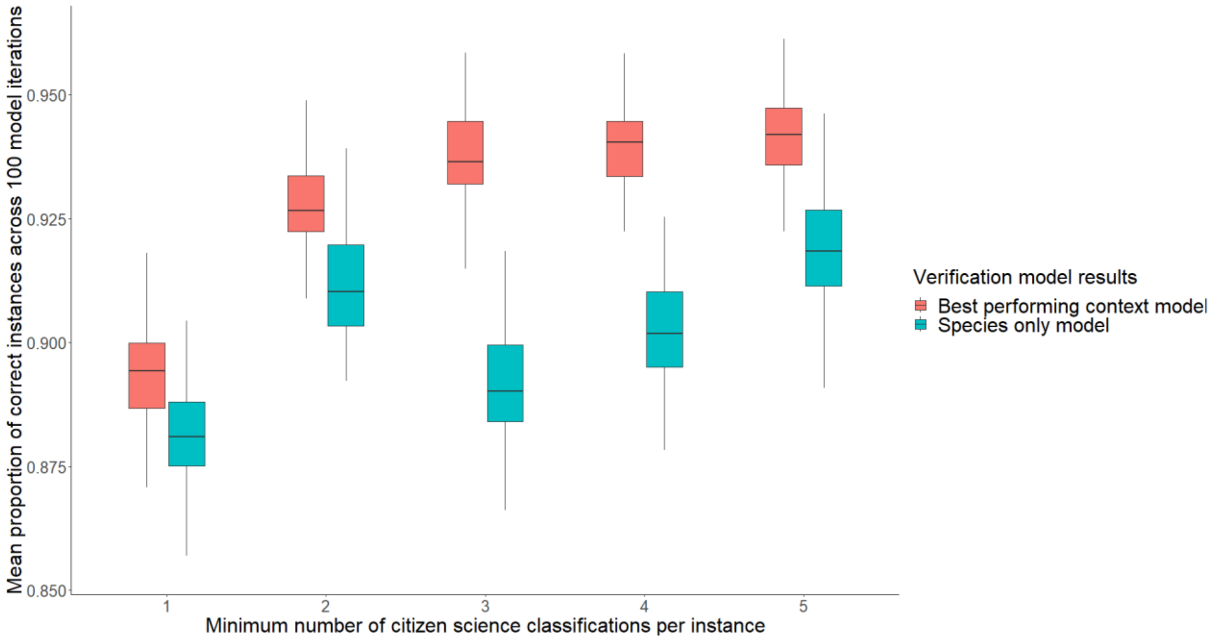

Figure 3.2: Proportion of correct instances across 100 model iterations when we limit the minimum number of citizen science classifications to 1-5 for each instance for the species-only model and best performing context model.

The model that included contextual environmental variables improved on the species-only model for some species but not others (Figure 3.3). The best model generally outperformed the species-only model for commoner species, such as Grey squirrel, Rabbit and Roe deer, but performed worse for rarer species such as American mink, Red squirrel and Stoats (Figure 3.3).

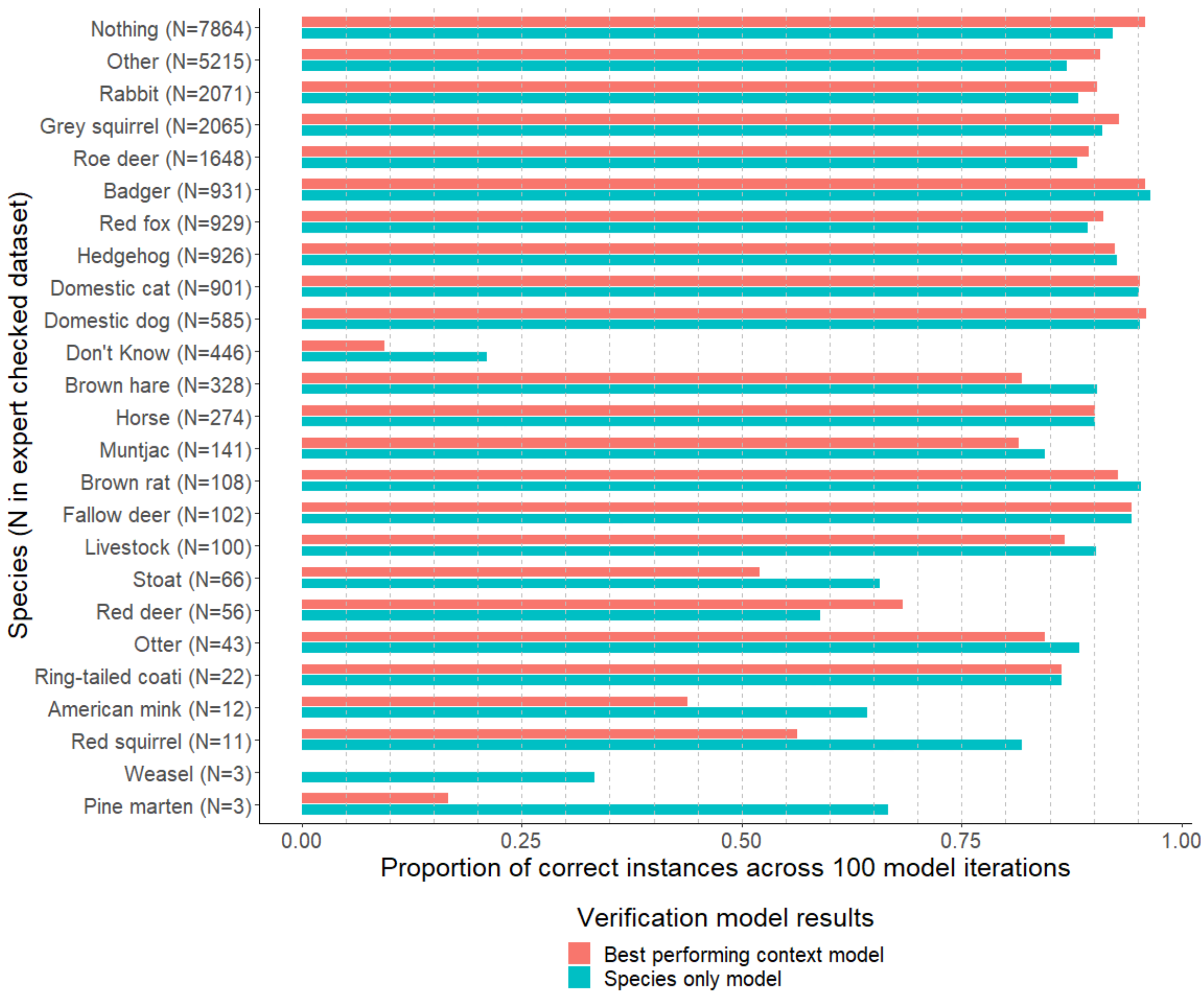

Figure 3.3: Proportion of correct instances across 100 model iterations for the species-only model and best performing context model by species, with the frequency with which each species appears in the dataset.

3.5.2 iRecord

3.5.2.1 Coleoptera records

If we accept as correct the initial reported species, i.e., the species report submitted by the recorder, the proportion correct for the Coccinellidae family would be 0.957, and for the remaining Coleoptera records, 0.947.

For the Coccinellidae records, the model that included season, performed marginally better in terms of proportion correct (accuracy) and negative log likelihood (certainty). This contextual model improved on the species-only model that did not include any contextual variables and relied solely on the matrix that describes the frequency with which species are redetermined (See Table 3.2). For the remaining Coleoptera records the species-only model performed best overall (See Table 3.2). See Appendix B.2 for full cross validation results summary.

Table 3.2 iRecord Coleoptera data results summary for the null model, species-only model and the best performing contextual model (that included season)

Dataset	Model	Proportion Correct	Squared Error	Negative Log Likelihood
Coccinellidae records	Null	0.957	-	-
Coccinellidae records	Season	0.959	0.0082	0.245
Coccinellidae records	Species-only	0.958	0.005	0.203
Remaining Coleoptera records	Null	0.947	-	-
Remaining Coleoptera records	Species-only	0.957	0.0019	1.55

3.5.2.2 Diptera records

For the Syrphidae family, the proportion correct would be 0.959, and for the remaining Diptera records, 0.938.

For both the Syrphidae records and the remaining Diptera records, the species-only model performed best overall (See Table 3.3). See Appendix B.3 for full cross validation summary.

Table 3.3 iRecord Diptera data results summary for the null model and species-only models (that did not include contextual information)

Dataset	Model	Proportion Correct	Squared Error	Negative Log Likelihood
Syrphidae records	Null	0.959	-	-
Syrphidae records	Species-only model	0.969	0.0032	0.394
Remaining Diptera Records	Null	0.938	-	-

Remaining Diptera Records	Species-only model	0.953	0.0037	1.261

The species-only classification model that used the species confusion matrix improved on simply accepting the initial reported species as correct; however, in these examples, including contextual information did not improve on the species-only classification model. Although none of the contextual variables included in these models were deemed relevant, the species-only model proved informative in predicting whether or not an expert would redetermine a species.

3.6 Discussion

We present a general Bayesian framework for verifying citizen science data. The models we present integrate contextual meta-data associated with citizen science records, and historical data submitted to citizen science schemes. This historic data is used to quantify the probability that a citizen science record is a particular species for the community consensus classification model, and that the species identity provided by the recorder is correct for the expert behaviour model. Importantly, the information we use to improve on the null model where we accept the modal species or the initial observation as correct is all readily obtainable from past data from any scheme. This means that our approach is likely to be applicable to any scheme for which historic, verified data are already available. We show how this framework can be applied to community-classified citizen science data and adapted for the case of expert-verified citizen science data. We also outline model performance metrics that can be used to compare models, and to assess which variables are most useful in verifying the true species.

For MammalWeb, an example of a community consensus-based citizen science scheme, our framework for verification improved the proportion of correct instances relative to simply accepting the modal species as the true species. Furthermore, cross validation showed that including contextual environmental variables improved the performance of the verification framework. The best performing model included time in describing the probability that a species was classified correctly, given the true species, indicating that whether a photo was taken during the day or night influences the accuracy of a citizen scientist's identification. If images are taken at night by camera traps then the quality can be lower (Swanson et al., 2015), the image may be too dark to see the species clearly (Egna et al., 2020), or the flash may 'white out' the animal captured in the photo (Willi et al., 2019); all of these issues could influence whether a citizen scientist accurately reports what is in that image (Westworth et al., 2022). Additionally, the best performing model included habitat, season, and time in describing the probability of the true species given the environmental context in which that species was observed, indicating that all of these variables influence whether a given species is recorded at all. Given what is known about habitat preferences (Coomber et al., 2021; Mathews et al., 2018), and specific diurnal or seasonal patterns of mammals (Hart et al., 2022; Helm et al., 2013), it is unsurprising that these factors assist us in verifying the true species for this dataset. Considering the improvement in model performance when integrating contextual variables into the models applied here, citizen science schemes should make use of the information available with a citizen science record and consider incorporating such information into automated approaches to verification.

Setting thresholds for confidence in species records before verifying the species for that instance can improve the accuracy of the models, but high thresholds mean that only a small proportion of records can be accepted. The thresholds set will depend on the level of accuracy required. For example, if an accuracy of 95% is considered suitable, then we can set the probability threshold to between 0.7 and 0.8 and remove 80% of instances. If a higher accuracy is required then the threshold needs to be higher, but we can still potentially halve the number of instances that require further classification (Figure 3.1). For more common species a lower threshold may still achieve a high accuracy, but for rarer species, however, where errors impose greater risks to interpretation and use of the data, a higher threshold may be required.

If we limit the number of citizen science reports per instance for MammalWeb, we can use cross-validation to track how the proportion correct changes in relation to the number of citizen science reports. The best performing model in cross validation achieved similar proportions of correct instances for 3 citizen science reports and above (Figure 3.2), indicating that incorporating contextual variables into classification models can reduce the number of classifications that are required to verify an observation as a certain species. This means that the true species can be accepted with fewer citizen science reports, and volunteers can be directed to those instances that remain unverified. Of course, the number of classifications required before an instance can be verified will depend on the species, and how recognisable or easily identifiable it is. For example, Hsing et al. (2018) found that for the MammalWeb dataset, instances containing badgers could be retired after two classifications with a 97.5% confidence, whereas other, less well recognised species required more classifications before they could be retired with the same confidence.

When comparing the accuracy of identification of different species in the MammalWeb dataset, it is clear that the model performed well for the most common species, such as Grey Squirrel, Rabbit and Roe Deer, and for highly recognisable species, such as Red Fox and Badger (Figure 3.3). The model performed poorly for rarer species, such as American Mink, Pine Marten, and Stoat. For species such as Pine Marten of which there were only 3 observations in the dataset, the poor model performance results from a lack of training data. However, for species such as stoats that use a range of habitats (Sainsbury et al., 2019), the poor model performance may be due to a lack of clear habitat preferences meaning that for this particular species contextual information is not useful in verifying species identity.

To highlight the generality of this approach to a range of schemes, we applied it to iRecord data, which currently rely on expert verification. The approach presented here has the potential to identify species that can be accepted as correct without expert checks, and those that will need additional expert verification, allowing expert verifiers to focus attention on citizen science reports in which we have less confidence. In this case, applying our framework to the expert-verified iRecord datasets improved on simply accepting the initial citizen science report as correct, with the species-only model that did not include any contextual information performing best overall. This indicates that for these iRecord datasets, contextual information was not deemed important, but the species confusion matrix was useful in verifying the true species. This may be due to species' traits being used in preference to the environmental context when assessing whether or not a record is correct (Ratnieks et al., 2016). For example, Morris (2019) found that within the iRecord Hoverfly Record Scheme, common misidentifications were often due to confusion between two similar species or species requiring examination under a microscope before they could be identified to species level. Therefore, for identifying Diptera, the physical attributes of the species are more important than where the species was observed. This reflects the ubiquitous and cosmopolitan nature of many of the species in these datasets, which means that their distribution may not be influenced by habitat preferences or seasonal patterns (Terry et al., 2020); rather, their distributions may be better explained by host plants or prey distributions (Comont and Ashbrook, 2017), and experts are more likely to consider the distributions of these interacting species, as opposed to broad contextual variables such as habitat or season. Although, in this case, the contextual variables were not deemed important in verifying the true species, other meta-data associated with records may be important in assessing confidence in, and verifying, species records (Terry et al., 2020). For example, observers can vary in their contributions to schemes, motivations, and encounters with wildlife (August et al., 2020; Di Cecco et al., 2021); all of these attributes might affect an observer's ability to identify species correctly. Consequently, models that consider observer attributes or identities might improve discrimination in this context (De Lellis et al., 2019; Mugford et al., 2021; Santos-Fernandez and Mengersen, 2021; Saoud et al., 2020). Our framework is straightforward to adapt to include recorder information, accounting for variance in recorder ability and expertise, as well as including any other contextual variables that citizen science schemes may consider important when assessing the accuracy of citizen science records.

For some citizen science datasets, experts rarely redetermine records to other species, which presents the question of whether experts need to verify every record. Low rates of redetermination could be due to a lack of evidence, such as photos or specimens; such evidence might be necessary to identify a record as any species other than the reported species (Pocock et al., 2015). Furthermore, if the record is of a widely recognised species or from a trusted recorder, expert verifiers are likely to accept the record as correct without additional evidence. It could also be the case that citizen scientist reports are simply very accurate. Accuracies of records amongst citizen scientists have been shown to be high in certain cases (Austen et al., 2016; Kallimanis et al., 2017; Kosmala et al., 2016a). This is particularly relevant for iRecord datasets that are often associated with National Recording Schemes; many citizen scientists contributing to such schemes are experts (Boakes et al., 2016; Pocock et al., 2015). Moreover, providing training and identification support to citizen scientists can improve accuracy (Perry et al., 2021; Ratnieks et al., 2016). Therefore, whether expert verification of every record is needed is highly questionable within many schemes. This could be examined by evaluating historical data to identify which species are most frequently reported correctly, or by experts deciding on the species that they know are difficult to identify. This means records of more easily identified species could be automatically accepted, enabling experts to focus their efforts on verifying records of species that are more often misidentified.

As the volume of data collected through citizen science schemes grows, verification is becoming an increasingly intensive process (Baker et al., 2021; Dickinson et al., 2012; Johnston et al., 2022; Pocock et al., 2015). For both kinds of schemes that we looked at, our framework – drawing on readily available data – could reduce the time taken to verify the bulk of instances, which typically consist of uncontroversial records of common species. This means that new species reports can be processed more efficiently and made available for research and analysis more rapidly. How citizen science schemes choose to use this framework may depend on the information required from the scheme and the species that are recorded. Importantly, cross validation identifies sources of error in these classification models, which can provide insight into whether model classifications should be accepted. In the case of MammalWeb, the model performed poorly for rarer species. Therefore, if the model classifies an instance as a rare species, it is unlikely that we can accept this classification without further human verification. Once the sources of error, i.e. which species the model is classifying incorrectly, have been identified, the costs associated with inaccurate species verification can be evaluated. Citizen science data can be used to inform conservation management decisions regarding rare or threatened species (Callaghan et al., 2020; Hyder et al., 2015; Young et al., 2019), or detect and monitor invasive species (Crall et al., 2011, 2015; Maistrello et al., 2016). In these cases, appropriate policy and management decisions are often contingent on pinpointing exact locations of species. For citizen science schemes from which data are used for research into overarching ecological trends and processes, the probabilistic outputs from the classification model's outputs could be integrated into modelling species abundances and distributions. The posterior probabilities reflect the probability of a species report being correct, allowing modelling approaches to integrate metrics of the accuracy of the data and account for records in which we have less confidence (Bird et al., 2014; Isaac et al., 2014; Van Eupen et al., 2021).

The approaches presented here have the potential to support verification in any recording scheme for which some previously verified data are available. For schemes that rely on community consensus verification, Bayesian classification models can reduce the number of classifications required for each instance. For schemes in which experts verify every record, this general framework can be used to prioritise records that may need additional levels of verification, reducing the number of records that need to be checked. By integrating these approaches into the verification process, data can be assessed and processed more efficiently, allowing the data to be verified in real-time. This ensures citizen science data are both accurate and up to date, providing robust and reliable datasets for research and analysis.

4. Using Observer Metrics in the Verification of Ecological Citizen Science Data.

4.1 Abstract

Citizen science approaches within ecology are an effective means of collecting widespread species data and engaging the public in environmental issues. However, concerns around accuracy and bias have been raised. Citizen scientists can vary in terms of their ecological knowledge, contributions to citizen science schemes and motivations for joining the schemes, which can impact their ability to correctly identify a species. Here, we present a method that uses observer metrics to inform verification approaches and account for variability among citizen scientists. The verification approach outlined in this chapter builds on the classification models presented in Chapter 3 to show how observer ID can be used to inform the probability of a record being correct by assigning a confusion matrix to each observer. We then show a variation of this model that uses past data to categorise observer traits, which are then used to assess confidence in an observation. As outlined in Chapter 3, we apply these approaches to MammalWeb and iRecord datasets. We show that, for the datasets used here, accounting for user accuracy and other observer traits improves verification accuracy minimally. For many citizen science schemes, the majority of contributors submit very few records, and volunteer retention is low. This limits the effectiveness of the approach because we cannot effectively estimate observer expertise for most citizen scientists. We suggest that where observer information is not available, or a new observer submits to a scheme for the first time, the species confusion matrix is most effective for helping to verify the observation. Furthermore, we consider whether intensive verification approaches are required to achieve highly accurate verification, given the already high accuracy of citizen science observations that are accepted to be correct in datasets such as MammalWeb and iRecord.

4.2 Introduction

Citizen science has been used extensively within ecology to collect large volumes of data and to engage the public in environmental issues (Adler et al., 2020; Brown and Williams, 2019; Dickinson et al., 2010, 2012; Pocock et al., 2017; Silvertown, 2009). Ecological citizen science schemes vary in their approaches and aims (Pocock et al., 2017), with volunteers contributing to, and collaborating on, scientific research through data collection, interpretation, and analysis (Johnston et al., 2022; Kobori et al., 2016). Advances in, and increased access to, technology mean that – in many cases – contributing to citizen science schemes is now more accessible. This has enabled more people to contribute to citizen science schemes (Anhalt-Depies et al., 2019; August et al., 2015; Kelling et al., 2019), leading to larger volumes of data being collected using citizen science approaches (Clare et al., 2019; Crimmins et al., 2021; Johnston et al., 2020a). Advances in data processing, AI, and high-performance computing mean that these increased volumes of data can be stored and processed, and the capabilities of citizen science data to address a range of ecological research questions and hypotheses can continue to be explored (Green et al., 2020; Johnston et al., 2019; McClure et al., 2020). Alongside being used as a research tool, citizen science is also used as a means of outreach and public engagement to increase awareness of ecological and environmental issues as well as to allow participants to learn about the research process (Dickinson et al., 2012; Johnston et al., 2022). This has additional benefits that can lead to enhanced protection and conservation of species and ecosystems by the public (Pocock et al., 2023; Von Gönner et al., 2023).

The two aims of citizen science schemes, to collect data and engage the public, often create a trade-off between data quality and mass participation (Anhalt-Depies et al., 2019). To encourage as many individuals as possible to submit data, contributing to citizen science schemes is often kept as simple as possible with minimal information required when submitting a species record (Sutherland et al., 2015; Terry et al., 2020). Although this leads to large volumes of data being collected, citizen scientists' motivations for joining a scheme (Ganzevoort et al., 2017; Hobbs and White, 2012), and the amount they contribute to a scheme may vary (Boakes et al., 2016; Di Cecco et al., 2021), which can lead to differences in experience and expertise with species identification. This influences data quality and introduces biases and inaccuracies into citizen science datasets. For example, species records collected by citizen scientists can lack precision (Forrester et al., 2015), have false-positive or false-negative errors (Gorleri et al., 2022; Johnston et al., 2022) or be incomplete (Kallimanis et al., 2017). Observers may also prefer to record certain species, leading to taxonomic bias in datasets; for example, some observers record more detectable species (Callaghan et al., 2021; Farmer et al., 2014), whilst others record a species because it is an interesting or unusual observation (Johnston et al., 2022). Citizen science datasets can also be biased towards more charismatic species (Troudet et al., 2017), or species about which there is greater public awareness (Boakes et al., 2016). Observer efforts can also be temporally biased towards the summer months (Di Cecco et al., 2021) and weekends (Courter et al., 2013). The unstructured nature of many citizen science schemes also means that observers often choose where they record species, leading to spatially biased datasets (Johnston et al., 2022; Mair and Ruete, 2016). Such variation in observers can negatively impact data quality and reduce confidence in citizen science datasets. To assure the quality of the data, citizen science records need to be verified to ensure the species' identification is correct (Baker et al., 2021; Kosmala et al., 2016a; Lotfian et al., 2021; Pocock et al., 2015; Wiggins et al., 2011). This process is typically carried out by experts, with some schemes using community consensus or automated approaches to verify data (Baker et al., 2021).

Given the range of factors that can lead to biases and inaccuracies in citizen science datasets, verification could be improved by considering all the available information associated with a citizen science observation (Baker et al., 2021; Terry et al., 2020). In Chapter 2 of this thesis, we reviewed the current approaches to verification and presented an idealised approach to verification. This idealised approach categorised the information that can be used to inform verification under attributes of the species, the environmental context of a record and the observer. Chapter 3 of this thesis presented a verification approach that accounted for attributes of the species and the environmental context, which was applied to MammalWeb and iRecord data. We presented two models, the species-only model which assessed confidence in citizen science observations based only on the species confusion matrix, and the environmental context model, which included contextual meta-data submitted with records to quantify where and when species were most likely to be observed. These models assumed that all observers made similar mistakes and therefore were included in the same confusion matrix. The results from this chapter showed that contextual information can assist with automated verification. For MammalWeb, including contextual information improved on the performance of the species-only model. For iRecord, the species confusion matrix improved on the null model where we accepted the initial observation as correct, but including contextual information provided little advantage. We aim to build on Chapter 3 by exploring verification approaches that account for observer variability, to examine whether this impacts on the performance of the models and improves the accuracy of verification.

Here, we present how observer metrics can be used to account for variability among citizen scientists and inform the verification of citizen science records in two ways. Firstly, we outline how observer ID can be used to inform the probability of a record being correct by assigning a species confusion matrix to each observer that quantifies mistakes made in their previous observations. The second approach uses observer traits that describe each individual's contributions to a scheme, such as time contributing to a scheme, accuracy of previous records or number of records contributed, to inform the verification of an observation. Both of these approaches are applied to citizen scientist datasets from the same two schemes used in Chapter 3, to which citizen scientists contribute in different ways. Specifically, we apply verification models to MammalWeb, a citizen science scheme in which volunteers classify camera trap images, and iRecord, in which field-based citizen scientists submit ad-hoc, opportunistic species observations. We use cross-validation to compare models, assess the effectiveness of the verification approach and examine the extent to which information about the observer matters when verifying citizen science data in these examples. We aim to present a simple approach that is widely applicable across schemes, and that incorporates observer variation without intrusive requests for additional information from citizen scientists.

4.2.1 Current approaches to accounting for observer variability in citizen science schemes

Citizen science schemes may ask contributors for a range of information that can be used to assess and quantify observer variation; for example, some schemes ask citizen scientists for personal details regarding their profession (Pusceddu et al., 2019), age (Bates et al., 2015) or prior knowledge of the study species (Meentemeyer et al., 2015), others ask citizen scientists to categorise their confidence in the submitted identification (Desaegher et al., 2019; McDonough et al., 2017; Sun et al., 2018; Waetjen and Shilling, 2017), or ask for information about the data collection process, such as sampling effort over space and time (Kelling et al., 2019; Sequeira et al., 2014). Citizen science schemes also quantify observer variability using novel computational and statistical approaches. For example, iSpot has designed a novel reputation system for citizen scientists (Silvertown et al., 2015). Other examples include Kelling, et al. (2015), who propose an approach for eBird that indexes observers' ability to create expertise scores for individuals; Evolution MegaLab, which weights observations based on scores from a quiz in which citizen scientists have to answer species identification questions before submitting records (Worthington et al., 2012); and August et al., (2020), who present a data-derived approach for understanding recording patterns in observers for opportunistic data. Citizen science schemes may also increase confidence in the data by trying to mitigate inaccuracies associated with observer variation. This has been approached in a range of ways; for example, some citizen science schemes provide training in identification and survey methods (Earp et al., 2022; Feldman et al., 2018), provide online identification tools and quizzes (Perry et al., 2021; Sharma et al., 2019; Worthington et al., 2012), or recruit expert volunteers (Van Strien et al., 2011) or citizen scientists with a particular interest in the area being monitored (e.g., recruiting hikers to record species in national parks or along trails, Sun et al., (2018), or divers to monitor marine wildlife, Meschini et al., (2021).

Various modelling approaches have been developed to assess observer expertise and verify citizen science data. Santos-Fernandez and Mengersen, (2021) present an approach that uses item response models to define observer ability for Snapshot Serengeti Data and De Lellis et al., (2019) introduce a classification algorithm that uses Bayesian approaches to integrate citizen scientist demographics into the verification process. Mugford et al. (2021), use a modification of an Independent Bayesian Classifier Combination to assess user ability and classify observations that generate user accuracies from a multinomial distribution instead of using a confusion matrix. Machine learning approaches (Crowston et al., 2020; Saoud et al., 2020) have also been used to assess user ability, detect misidentifications, and then classify observations for crowdsourced image classifications. Machine learning approaches achieve high accuracies and have been effective but are computationally intensive, making them inaccessible for citizen science schemes that do not have the resources or expertise to develop such verification approaches. Furthermore, these approaches are generally applicable to datasets where citizen scientists contribute primarily through image classification, which limits the applicability of machine learning approaches to a smaller number of citizen science schemes. Here, by contrast we present a simple statistical approach that makes use of past data submitted to a scheme to assess confidence in citizen science observations using the confusion matrix, that can be applied to both classification- and field-based citizen science schemes.

4.3 Methods

Our framework builds on the methodology outlined in Chapter 3, which uses an adapted version of the Independent Bayesian Classifier Combination (IBCC) model described by Kim and Ghahramani (2012). As in Chapter 3, we outline two separate adaptations of the model, a community consensus classification model which we apply to MammalWeb data, and an expert behaviour classification model which we apply to iRecord data. In the community consensus classification model, a citizen science record, hereafter described as an instance, consists of a species observation that has ben classified by one or more citizen scientists. For the expert behaviour model, an instance is referring to a single species identification made by a citizen scientist that has been submitted to a scheme and verified by an expert. Building on the species-only model and environmental-context models presented in Chapter 3, here, we outline an observer-expertise model that accounts for observer variability by incorporating information on the observer into the species confusion matrix. We account for observer variability in two different ways. Firstly, we use observer ID to create a species confusion matrix for each observer, accounting for the mistakes individuals made. Secondly, we categorise observer traits such as time contributing to a scheme, number of records submitted and role within the scheme, which we incorporate into the confusion matrix. As described in Chapter 3 these models output probabilities for every species that is then used to classify an instance as a given species. We use cross-validation to compare models and determine which information is most useful when verifying species observations.

4.3.1 Classification model

For each instance, we calculate a set of probabilities, each one representing a species that could be observed within the model. Each probability can be denoted as $P(S \mid R, O, H, D, K)$ which refers to the probability of an observation being species S, given the reported species R, which may be a set of one or more citizen science classifications, or a single report of a species, the observer, O, which represents the citizen scientist(s) reporting the species they believe to be in that instance, the context of the instance e.g. the habitat, season or time, H, other prior knowledge K, and previous observations D. Here, $D = \{(r_i, o_i, h_i, s_i)\}$, where $i \in [1..n]$ labels an instance that consists of a citizen science classification r_i, by an observer or observers o_i, the environmental context h_i of the instance and the true species s_i that gave rise to the classification.

We calculate $P(S \mid R, \mathrm{O}, H, D, K)$ using two factors that describe different components the probability. The first factor, $P(R \mid S, \mathrm{O}, \pi_1)$, which we label as π_1, describes the classification process, denoting the probability of an instance being reported as a particular species given the true species and the observer classifying that instance. If there are multiple reports by different observers for a given instance, then we calculate $P(R \mid S, O, \pi_1)$ for each observer. As in Chapter 3, we incorporate contextual environmental information using a second parameter $P(S \mid H, \pi_2)$, which we label as π_2, that describes the observation process, denoting the probability of an instance being the true species S, given the environmental context H.

This can be denoted as:

$$P(S \mid R, H, D, K) \propto \int d\pi \; P(R \mid S, O, \pi_1) \; P(S \mid H, \pi_2) \tag{1}$$

If we only want to include species and observer information when calculating $P(S \mid R, \mathrm{O}, H, D, K)$, then we calculate the first factor $P(R \mid S, O, \pi_1)$ using the species confusion matrix and set the second factor to be a constant. However, if we wish to incorporate contextual information such as habitat, season, or time, then we calculate second parameter, $P(S \mid H, \pi_2)$, using the context matrix. Here, the species-only model excludes observer information in the first factor and the observer-expertise model includes observer information in first factor. The environmental-context model uses the context matrix to calculate a probability for the second factor, instead of keeping it as a constant. The null model is the species with the highest number of citizen science classifications.

Each factor is calculated using a confusion matrix, which is obtained from the training data. Here, π_1 is calculated using confusion matrix n_{sro}, which describes the number of instances where observer, o, identifies true species, s, as reported species, r. This, therefore, quantifies the number of mistakes that each observer has made previously when identifying all the species that could be observed in the model. We calculate π_2 using the matrix n_{sh}, which is the number of instances in which the environmental context is h and the true species is s. Each probability is calculated using a categorical distribution for reported species r in instance i.

When introducing prior probabilities for π, for π_1 we assume citizen science reports are independent of each other, which is appropriate in this case because, on MammalWeb, citizen scientists cannot see classifications made by previous observers. For π_2 we assume that the true species in different instances are independent of one another. We place constant Dirichlet priors with all parameters equal to 1 on each independent π_1 and π_2. We then calculate the posterior probability of the unknown true species S, given the known classifications for each reported species R, the observer or observers that provided those classifications, O, the observed environmental context H and the training data D, using:

$$P(S|R,O,H,D)\ \alpha\ \left[\prod_o \frac{B(\{\tilde{n}_{ro}+n_{ro\tilde{s}\tilde{h}}+1\}R)}{B(\{n_{ro\tilde{s}\tilde{h}}+1\})}\right] B(\{n_{SH}+2,\{n_{sH}+1\}_{s\neq S}\}) \tag{2}$$

Where:

- $\tilde{n}_{ro}$ is the number of classifications by observer o of reported species r for the current instance
- $n_{ro\tilde{s}\tilde{h}}$ is the total number of species reports r by observer o when the trues species is s across all instances in the training data
- n_{sh} is the number of instances in the training data where the true species is s in context h
- B is the beta function defined as:

$$B(\{z_i\}) = \frac{\prod_{a\in A}(z_a-1)!}{\sum_a (z_a-1)!} \tag{3}$$

Equation (2) provides a posterior probability for every species that could be the true species, i.e. every species that has been observed in the dataset. Therefore, the final step in this classification framework is estimating the true species based on the array of posterior probabilities provided by the model. The approach that could be taken will depend on the cost of incorrect classification. If an incorrect classification is costly and comes with high risks, then thresholds could be imposed before estimating the true species. For now, however, we use the same approach as in Chapter 3, classifying the true species as the species that has the highest posterior probability.

4.3.1.1 Expert behaviour variant of the classification model

As outlined in Chapter 3, the decision for an expert to determine whether the reported species is correct or not differs from the citizen science classification process for community consensus datasets. Therefore, the posterior probabilities of species for expert-verified datasets do not need to be weighted by the number of times the expert has selected the true species when the reported species was different, i.e., π_1 in the classification model. This means that we vary the calculation of the posterior probability slightly so that $P(S \mid R, \mathrm{O}, H, D, K)$ is modelled based on the confusion matrix n_{sk}, where s describes the true species and k is the context from the training data which, in this case, includes the reported species r and the observer o. The probability of the true species is then calculated using:

$$P(\tilde{s}|\tilde{k}, D) = \frac{n_{s\tilde{k}}+1}{n_{\tilde{k}}+|S|} \tag{4}$$

Where:

- $n_{s\tilde{k}}$ is the number of instances with true species s and context $k = (r, o)$, where r is the reported species and o is the observer,
- $n_{\tilde{k}}$ is the number of instances with context k, which is equal to the sum of true species s in $n_{s\tilde{k}}$ matrix,
- $|S|$ is the total number of species.

Here, the null model is accepting the initial citizen science identification as correct. As with the model described above, this provides a posterior probability for every possible species that has been observed in the data and, in this variant of the model, instances are also classified by taking the species with the highest posterior probability to be the estimated true species.

4.3.2 Data

Firstly, we applied the community consensus classification model to MammalWeb data collected between April 2015 and June 2022. MammalWeb is a citizen science scheme that collects data using camera traps across the UK and areas of mainland Europe and verifies data using the community consensus approach, where citizen scientists, or ‘spotters’, classify an instance based on what they believe is in that sequence of photos or videos (Hsing et al., 2022). We only used classifications for instances for which we had a 'gold standard', where an expert had identified the species that were captured in that photo sequence. This dataset consisted of 48,692 instances with 145,582 citizen science classifications. A total of 1086 citizen scientists, or 'spotters', had contributed classifications to this dataset, with 577 contributing more than 10 classifications.

We applied the expert behaviour model to iRecord Coleoptera and Diptera data collected between January 2000 and March 2022. These datasets consisted of reports of ad-hoc, opportunistic observations by citizen scientists. The Coleoptera dataset consisted of 115,865 records, and the Diptera dataset consisted of 97,347 records. Within the Coleoptera records, the majority of records were Coccinelidae observations (N=82,758) which were predominantly submitted to the UK Ladybird survey, and within the Diptera records, the majority of records were Syrphidae observations (N=83,585) which were mainly submitted to the UK Hoverfly Recording Scheme. Therefore, these records were separated from the main dataset, and we applied the model to them separately. The datasets varied in the number of observers who had submitted records, and the proportion of observers with more than 10 observations (Table 4.1).

Table 4.1: Number of observers contributing to iRecord datasets.

Dataset	**Total number of observers**	**Number of observers with more than 10 observations**
Syrphidae	6799	862
Diptera (without Syrphidae records)	1942	281
Coccinellidae	14893	1,009
Coleoptera (without Coccinellidae records)	5778	577

4.3.3 Observer metrics

We used two different ways of quantifying observer expertise to inform the posterior probability of the true species. Firstly, observer IDs (MammalWeb) or usernames (iRecord) enabled us to create a confusion matrix for each individual contributor. Many observers had classified very few images on MammalWeb or submitted only a small number of species observations to iRecord (Table 4.1). Therefore, we categorised any citizen scientists who had fewer than 10 classifications/observations as new observers. When applying the model, new observers had one shared confusion matrix, derived from grouping all new observers, and any observer with 10 or more classifications/reports had an individual confusion matrix. This assumes that all new observers have the same expertise, which is unlikely to be the case. However, when a new observer joins a scheme, there is little information available to quantify their expertise; using a more general confusion matrix is the best available information regarding common errors.

The second approach we took to quantifying observer expertise was to categorise observers based on metrics that quantified their contributions to the focal scheme, and which relate to the probability with which they would correctly identify species. We used number of classifications and number of records submitted to MammalWeb and iRecord, respectively. We also calculated the time contributing to the scheme, in years, and the accuracy of previously submitted records. In addition, we considered the different roles that contributors could adopt. For MammalWeb, this meant categorising observers as either 'spotters' who only classify camera trap images, 'trappers' who put out camera traps to record observations as well as classifying images, and 'own camera', where trappers are classifying the records captured by their own camera trap. For iRecord, we categorised contributors as 'observers' or 'verifiers' where verifiers are individuals who are experts who check the records of others to ensure they are correct, as well as submitting them.

These observer metrics can be used alongside contextual environmental information. Chapter 3 shows that contextual information assists in verification for MammalWeb but not for iRecord. Therefore, we included contextual information alongside observer metrics for MammalWeb but not for iRecord. The contextual variables included for MammalWeb were habitat, season, and time.

4.3.4 Model selection

As outlined in Chapter 3, we carried out model selection using cross-validation to identify which observer metrics and context types are most effective when identifying the true species.

For MammalWeb, when using observer ID, we saturated π_2 using all possible context types and estimated parameters for all possible combinations of variables. Therefore, we ran 16 models. For the observer traits model we saturated both π_1 and π_2 and ran for all possible combinations of variables, running 128 models in total. For iRecord, we ran the model to include only observer ID, and then for all combinations of observer traits. Therefore, we ran 17 models in total.

For 100 repeats, we divided the data randomly using an 80/20 training and test partition. Using the training data, we acquired the relevant matrices, which we then used to apply the classification model to the training data. We then validated the model classification against the expert assessments to calculate the proportion of correct instances, the negative log-likelihood of instances and the mean squared error. These metrics were used to compare models to determine which was most suitable for verifying the true species for each dataset. We also compared the performance of these models to the null model which, for MammalWeb, is simply accepting the modal species as the true species and, for iRecord, is accepting the reported species as the correct one. For each dataset, we calculate the proportion correct and the squared error for the null model to compare with the classification model.

4.4 Results

4.4.1 MammalWeb

The null model, where we accept the modal species as the true species, had a proportion correct of 0.917 and a squared error of 0.0047. The result here is higher because the Chapter 3 dataset was restricted to MammalWeb Britain, whereas here we used a larger dataset, including data from other projects.

The model where each observer had an individual confusion matrix (proportion correct = 0.929, negative logged likelihood = 0.637, squared error = 0.0069) improved on both the null model and species-only classification model (proportion correct = 0.918, negative logged likelihood = 0.65, squared error = 0.0073). Models that included both observer ID and environmental context performed worse overall (Figure 4.1). However, models that included only environmental context performed better than the observer ID models with the model that saturated π_2, i.e., included habitat, season, and time, performing best overall (proportion correct = 0.934, negative logged likelihood = 0.354, squared error = 0.0036). This result was seen in Chapter 3 with the most saturated environmental context model performing best overall. See Appendix C.1 for the full cross-validation summary.

Models that included one observer trait in π_1 improved on the species-only classification model, and performed better than models that included a combination of observer traits (Figure 4.1). The models that included observer accuracy, as well as environmental context, performed best overall (proportion correct = 0.936, negative logged likelihood = 0.351, squared error = 0.00354), and the models that included observer role generally performed similarly to the environmental context only models (observer role best-performing model: proportion correct = 0.934, negative logged likelihood = 0.355, squared error = 0.0036). See Appendix C.2 for the full cross-validation summary.

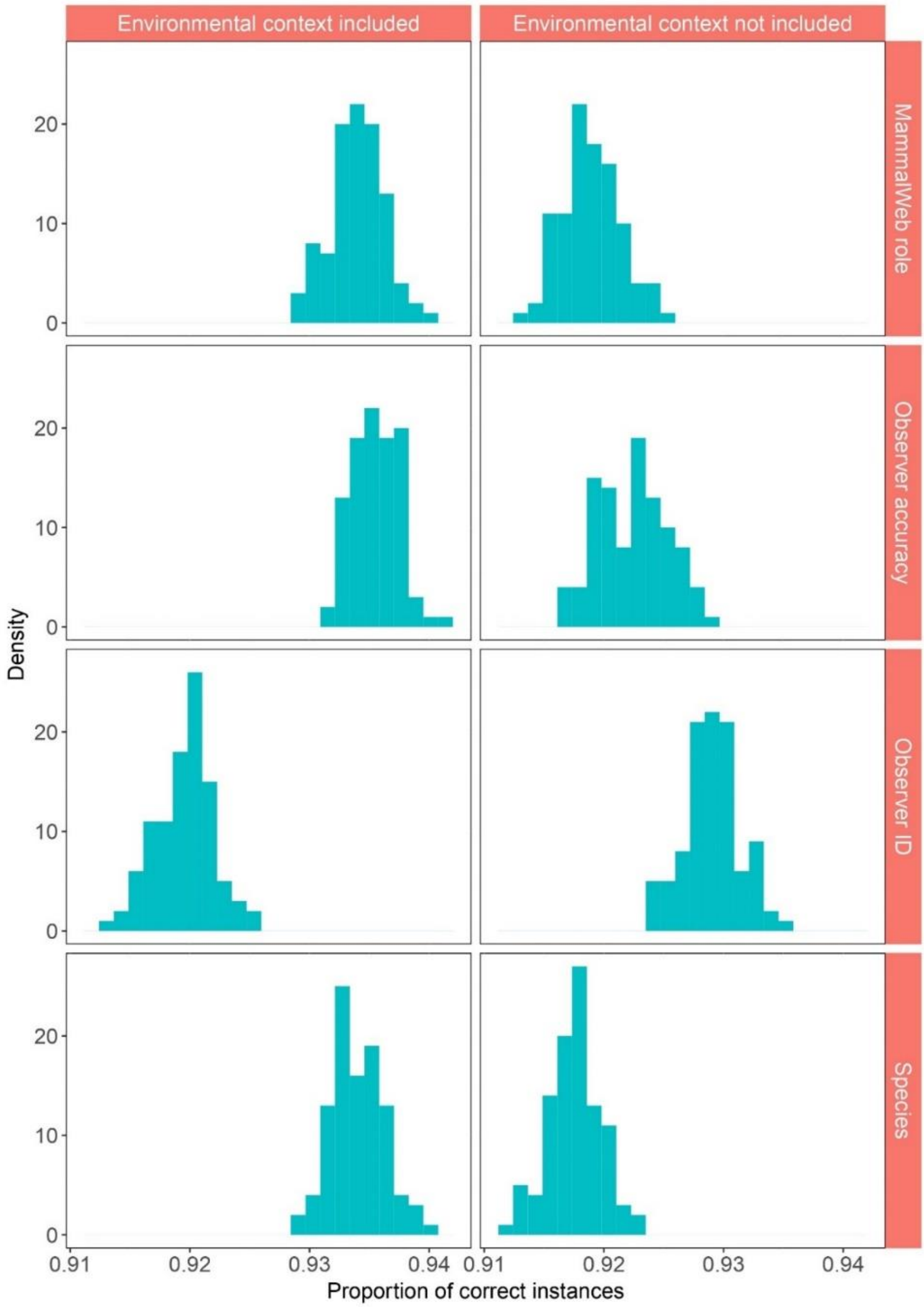

Figure 4.1: Model performance for proportion of correct instances across 100 iterations of cross-validation for MammalWeb classification models.

For MammalWeb spotters, accuracy did not improve with time classifying or with classification number (Figure 4.2). The majority of observers submitted very few observations, but those who submitted a large number of observations generally had high accuracy. Some spotters classified images sporadically and with large gaps between classifications (Figure 4.2C).

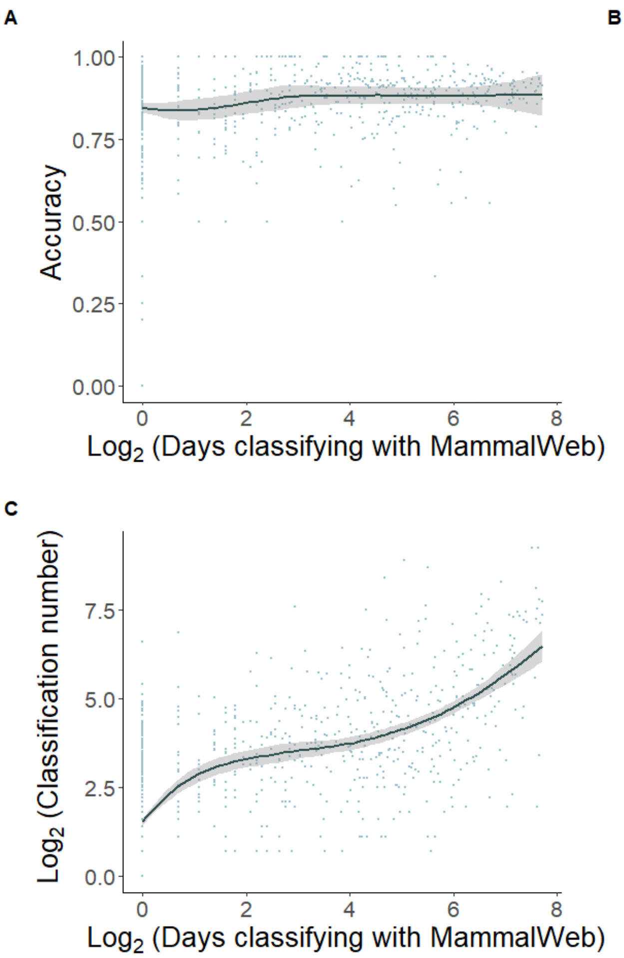

Figure 4.2: The accuracy of spotters in relation to (A) the number of days between their first and last classification and (B) the total number of classifications. (C) The relationship between days classifying (quantified as the number of days between their first and last classification) and classification number. Trendlines and standard errors fitted from a locally estimated scatterplot smoothing function (LOESS).

The mean accuracy for those who classified and uploaded images to MammalWeb (Trappers) was 89.6%, for those who only classified images (Spotters) the average accuracy was 85.3% (Figure 4.3A). Trappers classifying images that were captured by their own camera trap had a mean accuracy of 92.1% (Figure 4.3B). Trappers classifying images that were not captured by their own camera trap had a mean accuracy of 87.7% (Figure 4.3B).

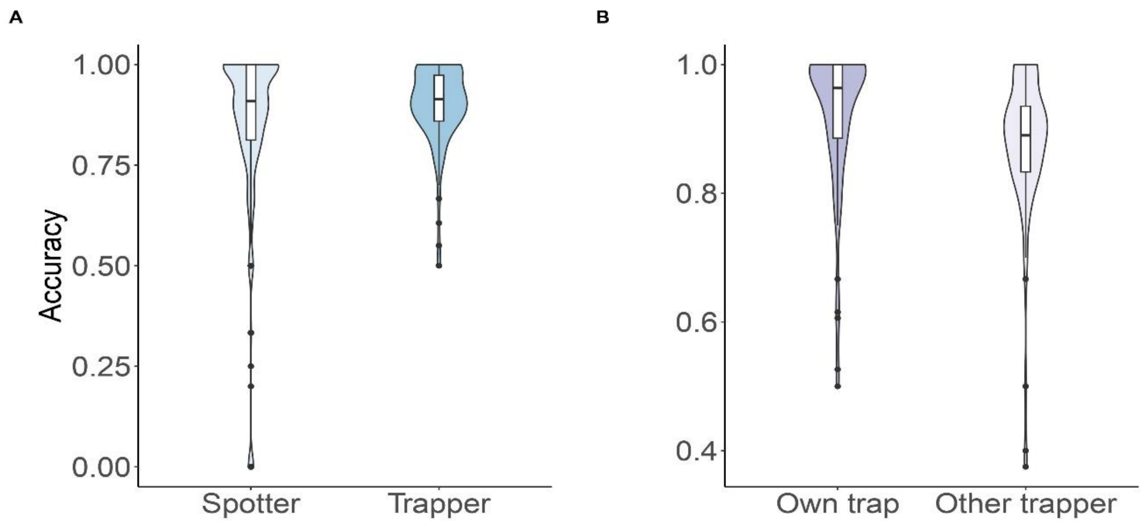

Figure 4.3: The accuracy of MammalWeb spotters in relation to whether they are (A) a trapper as well as a spotter, and (B) spotting for their own trap or not. The lines within each box display the means from each group.

4.4.2 iRecord

4.4.2.1 Coleoptera

If we accept the initial citizen science observation as the true species (the null model), then the proportion of correct instances for Ladybirds was 0.957 and for the remaining Coleoptera records was 0.947.

The observer ID models did not improve on the null model or the species-only model for the Ladybird records (species-only model: proportion correct = 0.958, negative log likelihood = 0.313, squared error = 0.109; observer ID model: proportion correct = 0.925, negative log likelihood = 0.932, squared error = 0.0133) or the remaining Coleoptera records (species-only model: proportion correct = 0.957, negative log likelihood = 1.551, squared error = 0.0019; observer ID model = 0.756, negative log likelihood = 3.64, squared error = 0.0022).

Models that included observer traits performed similarly or worse than the null model and the species-only model for both the Ladybird records and the remaining Coleoptera records.

The models that included observer role and observer accuracy performed most similarly to the species-only model (Figure 4.4). See Appendix C.3 for the full cross-validation results.

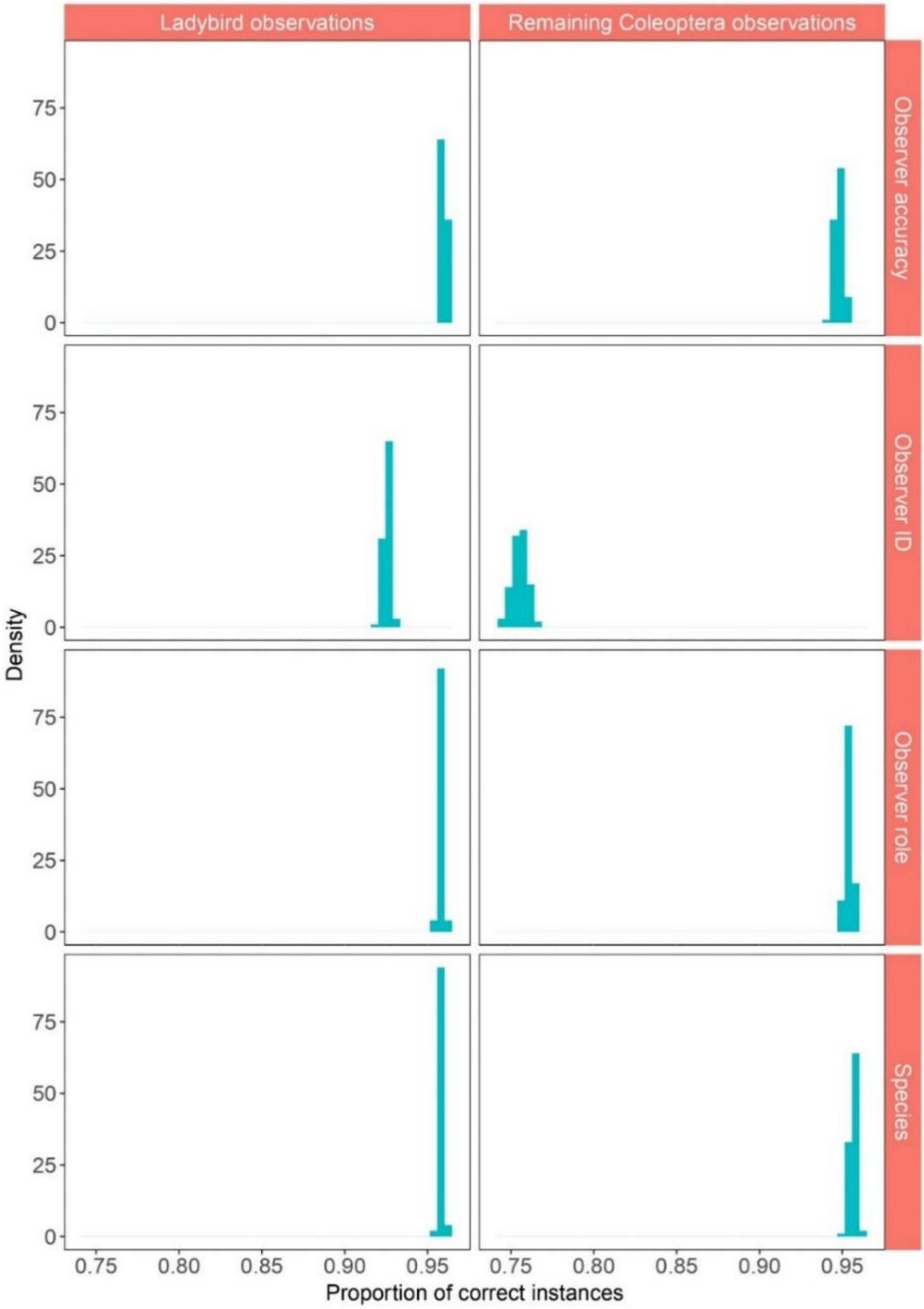

Figure 4.4: Model performance for proportion of correct instances across 100 iterations of cross-validation for iRecord Coleoptera classification models.

Accuracy did not improve with time recording through iRecord but did improve with record numbers for both the Ladybird observers and the observers for the remaining Coleoptera records. The number of observations was also uneven through time, with increased time as an iRecord observer not necessarily leading to increased observation numbers (Figure 4.5).

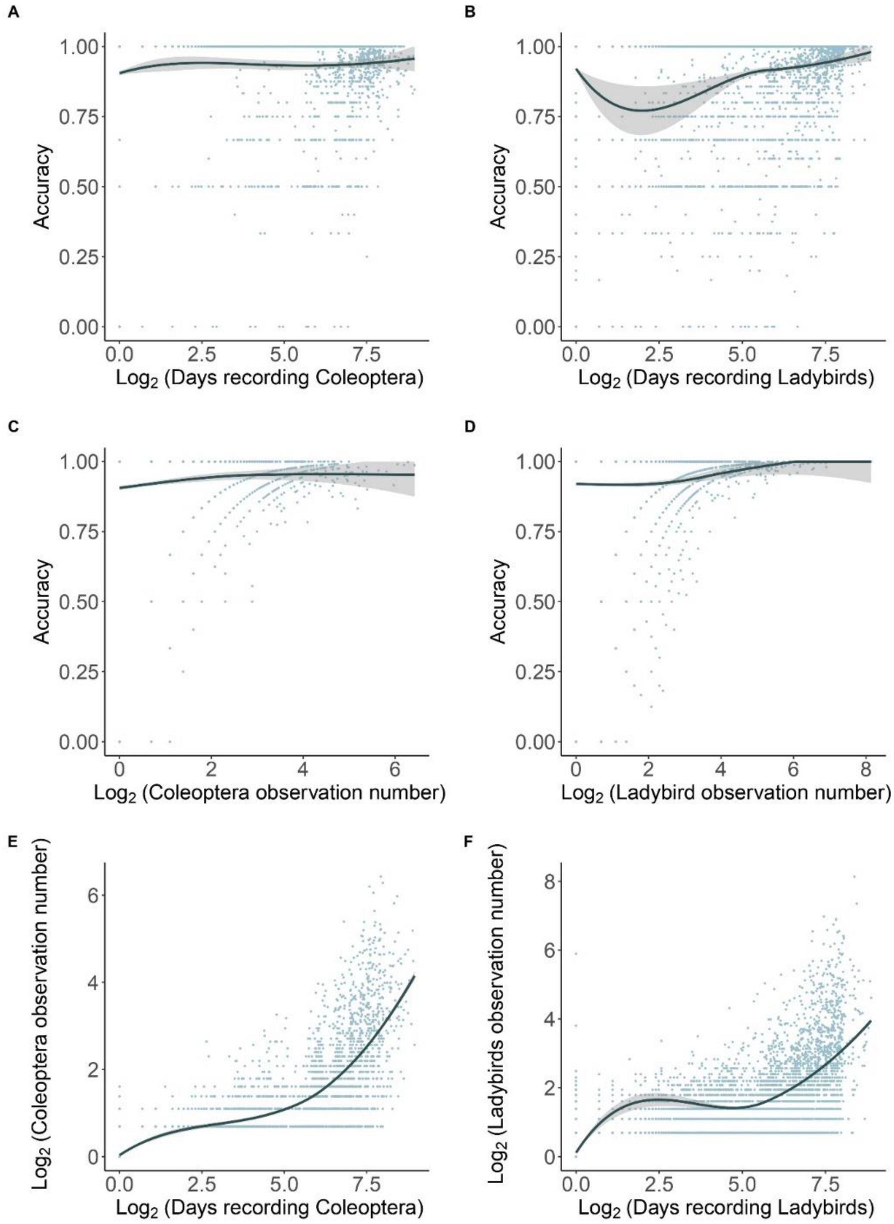

Figure 4.5: The accuracy of iRecord Coleoptera observers in relation to the number of days between their first and last observation (A & B), the total number of classifications (C & D) and the relationship between days classifying (quantified as the number of days between their first and last observations) and classification number (E & F). Trendlines and standard errors fitted from a locally estimated scatterplot smoothing function (LOESS).

4.4.2.2 Diptera

If we accept the initial observation as correct (the null model), the proportion correct for Hoverfly records is 0.960, and for the remaining Diptera records is 0.938.

The observer ID models did not improve on the null model or the species-only model for the Hoverfly records (species-only model: proportion correct = 0.969, negative logged likelihood = 0.395, squared error = 0.0032; observer ID model: proportion correct = 0.864, negative log likelihood = 2.607, squared error = 0.0047), or the remaining Diptera records (species-only model: proportion correct = 0.953, negative logged likelihood = 1.26, squared error = 0.0037; observer ID model: proportion correct = 0.786, negative log likelihood = 3.23, squared error = 0.0045).

Several of the observer traits models improved slightly on the null model for the Hoverfly dataset, and even more so for the remaining Diptera records. None of the observer traits models improved on the species-only model. For the Hoverfly data, the models that included the observer role only (proportion correct = 0.968, negative logged likelihood = 0.424, squared error = 0.0032) and the observer accuracy only (proportion correct = 0.967, negative logged likelihood = 0.592, squared error = 0.0036) performed similarly to the species-only model. For the remaining Diptera records, the species-only model outperformed all the models that included observer traits (Figure 4.6). See Appendix C.4 for the full cross-validation results.

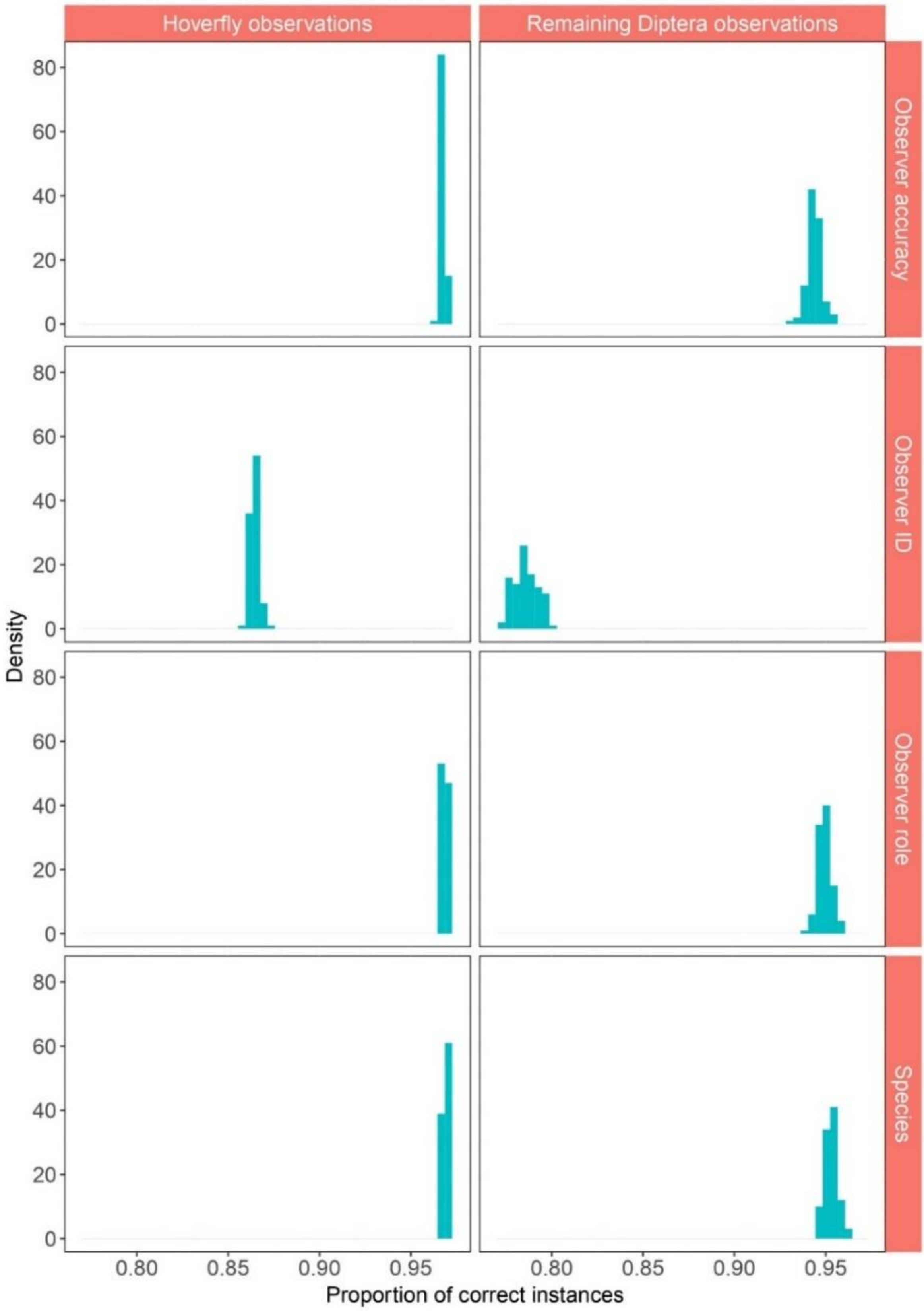

Figure 4.6: Model performance for proportion of correct instances across 100 iterations in cross-validation for iRecord Diptera classification models.

Accuracy remained consistent in relation to time recording with iRecord. Accuracy did, however, improve slightly with record numbers for Hoverfly observers (Figure 4.7). Hoverfly and Diptera datasets exhibited similar patterns to MammalWeb and iRecord Coleoptera records, with most citizen scientists submitting very few observations (Figure 4.7).

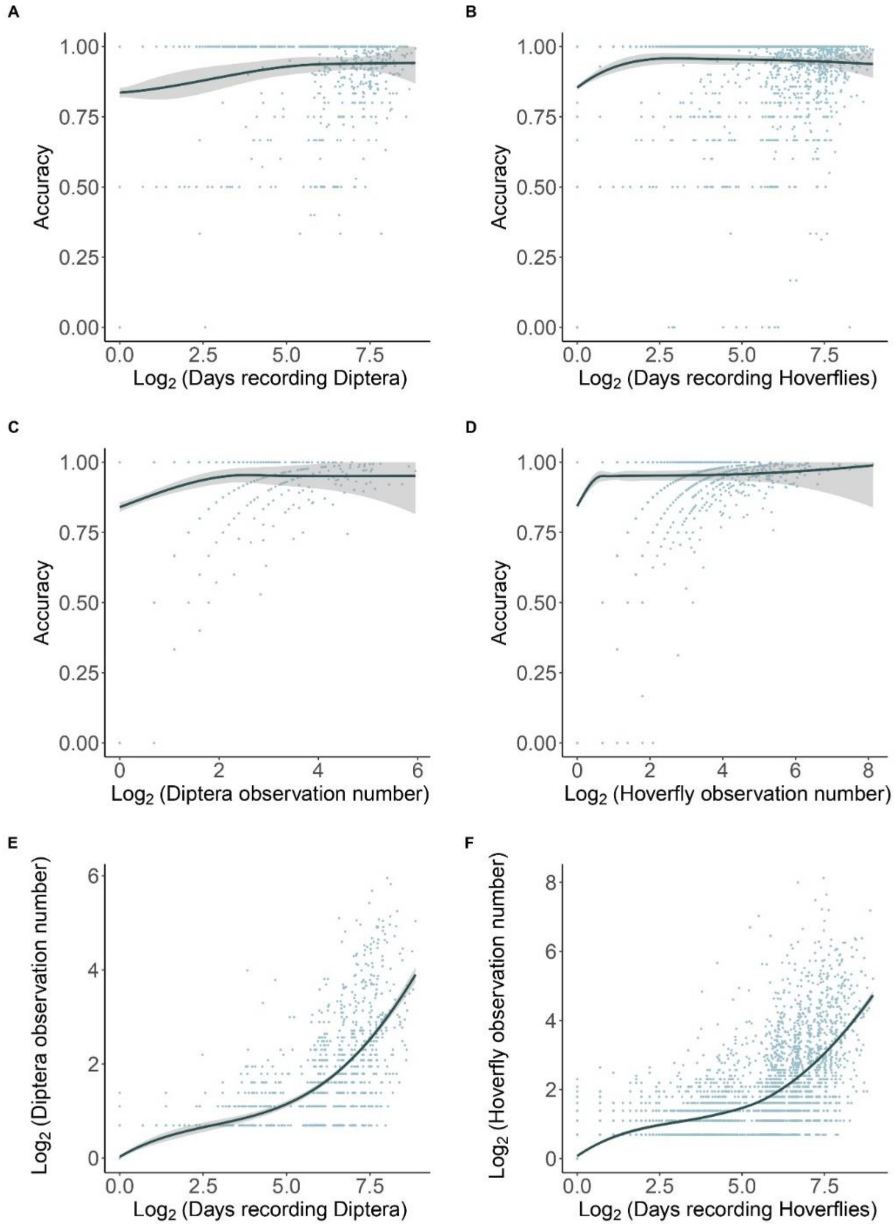

Figure 4.7: The accuracy of iRecord Diptera observers in relation to the number of days between their first and last observation (A & B) and the total number of classifications (C & D). As well as the relationship between days classifying (quantified as the number of days between their first and last observations) and classification number (E & F). Trendlines and standard errors fitted from a locally estimated scatterplot smoothing function (LOESS).

4.5 Discussion

We explored whether integrating information on the experience and expertise of citizen scientists into classification models can assist in verifying citizen science records. The approaches outlined here can be applied to schemes where the only information available on citizen scientists contributing to schemes is observer ID. However, we go beyond that to consider how observer ID can be used to categorise observer traits and be integrated into verification approaches.

For MammalWeb, a scheme in which citizen scientists classify what they believe to be in camera trap images, including observer ID improved on the null model and the species-only model but did not improve on the environmental context model. As MammalWeb monitors mammals across the UK and parts of mainland Europe (Hsing et al., 2022; Smith et al., 2023), it is possible that citizen scientists may be asked to classify a sequence of images of a species that they have not previously encountered. This can lead to differences in species-specific confusion by observers, which will not be captured in the species-only classification model. However, the observer ID model did not improve on the environmental context model, indicating that, in this instance, environmental factors were more useful for verifying the true species. Chapter 3 of this thesis discusses why contextual information may be beneficial in identifying the true species in the case of MammalWeb. When incorporating observer traits into the classification models, including the accuracy of the observers' previous classifications improved slightly on the environmental context model. Unsurprisingly, therefore, an observer's previous accuracy can indicate their likely future accuracy. Furthermore, as citizen scientists contribute more to a scheme, their accuracy can improve with greater experience in species identification (Falk et al., 2019; Greving et al., 2022; Kelling, et al., 2015). Within MammalWeb, there was greater variation in the accuracy of citizen scientists who submitted very few records, with citizen scientists who had submitted a greater number of records generally having a higher accuracy (Figure 4.2). If an individual has classified a large number of images, then they are more likely to have encountered the same species multiple times, allowing them to develop their identification skills. In this example, time classifying with MammalWeb did not assist in estimating the true species. MammalWeb classifiers do not contribute classifications at a steady rate through time, with some classifiers submitting very few observations, with large gaps between their first and last classifications (Figure 4.2). This pattern is found widely in online citizen science schemes, with many schemes experiencing low retention rates of citizen scientists, and a small proportion of citizen scientists accounting for the majority of citizen science records (Crall et al., 2017; Kaplan Mintz et al., 2023; Segal et al., 2015).

Models of iRecord data that included observer ID or observer traits did not improve on the species-only classification model. As was observed with MammalWeb, the majority of iRecord observers submit few observations and contribute for only a short time. This means that insufficient information is captured by the confusion matrix to differentiate between observers and, therefore, observer metrics are not useful in verifying the true species in these examples. Although expert verifiers may be familiar with some trusted observers within iRecord (Baker et al., 2021), due to the high volume of contributors that submit records to the scheme, it is unlikely that verifiers are familiar with all observers. If an expert is unfamiliar with the observer and their expertise is based on observer ID, they are likely to use a range of information when verifying a record (Terry et al., 2020). Although degrees of participation do vary, both in terms of time recording and number of observations, these factors do not seem to influence accuracy to a great extent (Figures 4.5 and 4.7).

We previously suggested that efficient verification of citizen scientists' data should make use of all available information, including species attributes, environmental context and observer attributes (Baker et al., 2021, Chapter 2). Overall, however, in the examples we explored here, integrating observer attributes made marginal or no difference to the accuracy of the verification approaches, primarily due to the low contributions of most individual citizen scientists and their generally high initial accuracy. Quantifying previous mistakes made by observers using the confusion matrix or by categorising observer traits could still help inform verification, either by determining how many more classifications are required or by informing expert-made decisions. If a record comes in from an observer who has a high accuracy and a high number of previous classifications, then this could be accepted automatically, directing effort towards those submitted by observers with a historically lower accuracy. In the cases where a new observer or an observer characterised by low contributions submits an observation, then these approaches can still be applied using the overall species confusion matrix and the species-only classification model, which for both MammalWeb and iRecord has shown improvements on the null models.

The results presented here and in Chapter 3 show how a range of information can be incorporated into verification approaches for two contrasting citizen science schemes. For MammalWeb, each individual category of information - the species, environmental context, and observer - shows improvement on the null models. However, for iRecord, only attributes of the species proved useful when verifying observations. For both MammalWeb and iRecord, including all the available information when using these approaches to verify species records makes little or no difference to the overall accuracy of verification. Should schemes choose and apply the approach presented here, consideration should be given to the meta-data available and the factors that may influence the accuracy of records. Furthermore, where information is not available, using the simplest approach and considering only the species confusion matrix can assist in verification and achieve high accuracies. Given the initial high accuracies of the records accepted to be correct in the schemes presented here, the value of intensive, highly accurate verification for exploring research questions and trends in species abundances and distributions is debatable.

5. Does accurate verification of ecological citizen science data matter? The impact of data accuracy on protected area coverage for UK butterflies.

5.1 Abstract

In the current nature and climate crisis, large-scale citizen science datasets are being used in a range of contexts to understand trends in species abundances and distributions in response to widespread anthropogenic threats. Concerns are often raised regarding biases and inaccuracy in citizen science datasets, and verification is often required to promote confidence in those data. Verification is becoming an increasingly intensive and time-consuming process for many citizen science schemes as data volumes grow. Here, we explore the extent to which accurate verification matters when examining the protected area coverage for UK butterfly species. To examine this, we simulated different levels of inaccuracy (20%, 10%, 5% and 2%) for National Biodiversity Network butterfly records. We then compared the percentage overlap between protected areas and estimated areas of occupancy for the inaccurate datasets and compared those with the same metrics derived from the original data. The consequences of inaccurate data varied between species. For more ubiquitous species, inaccuracy had minimal impacts on analytical outputs. For species with restricted ranges, inaccurate data overestimated the area of occupancy relative to the original data, leading to differences in protected area overlap; however, the direction of differences depended on the original extent of overlap. The need to verify every record is dependent on the costs of inaccuracy and the end use of the data. In some cases, locating specific species occurrences is necessary for targeted conservation efforts. However, for most species, this is unnecessary, and if inferences are robust to low levels of inaccuracy, then citizen science schemes should reevaluate the need for continued improvements in the accuracy of verification approaches for all species.

5.2 Introduction

The global climate and biodiversity crises are impacting species' populations and functioning of global ecosystems (Hayhow et al., 2019; IPBES, 2019; WWF, 2022), and ambitious global targets are being set to improve the outlook for nature by 2030 (Nicholson et al., 2019; Buchanan et al., 2020; Joly, 2023). Quantifying the rate of biodiversity loss and tracking species abundances and distributions in response to widespread threats is vital in assessing progress towards these targets (Joly, 2023); in particular, monitoring is essential for highlighting the scale of the problem, galvanising political and public support to mitigate and reverse biodiversity loss, and protecting, conserving, and promoting species populations (Mace et al., 2008; Akçakaya et al., 2018; Heilpern et al., 2018; Bolam et al., 2021; Grace et al., 2021). Monitoring is also essential to predict future scenarios for nature (Di Marco et al., 2019; Leadley et al., 2022; Nicholson et al., 2019; Powers and Jetz, 2019). Investigating large-scale ecological questions typically requires large volumes of up-to-date species occurrence data, collected across great spatial and temporal scales (Hassani et al., 2021; Hochkirch et al., 2021; Nathan et al., 2022). This level of data coverage is most frequently found in datasets collected by volunteers and through crowdsourced observations (Groom et al., 2017), the contributions of which can broadly be categorised as 'citizen science'. Projects that mobilise citizen scientists to collect data are continuing to grow in scope and scale (Baker et al., 2021; Pocock et al., 2017). Technological advancements are leading to novel methods for data collection (Biggs et al., 2015; Newson et al., 2015; van Klink et al., 2022) and increased access to technology mean that more people are contributing to citizen science schemes than ever before (Callaghan et al., 2019b; Di Cecco et al., 2021a). As data volumes increase, and data processing and storage capabilities progress, citizen science data have been used to explore a range of research questions and hypotheses, to expand our understanding of ecological processes in response to biodiversity loss and climate change (Brown and Williams, 2019; Crimmins and Crimmins, 2022; Soroye et al., 2018).

Ecological data collected by citizen scientists typically consist of ad-hoc, opportunistic records (Baker et al., 2021; Dickinson et al., 2012; Fraisl et al., 2022; Kobori et al., 2016; Pocock et al., 2017), and the data quality of these volunteer collected datasets is often questioned, due to concerns around unstructured sampling methods (Callaghan et al., 2021; Isaac et al., 2014; Kamp et al., 2016; Kelling et al., 2018), bias (Callaghan et al., 2019;

Johnston et al., 2020b; Kosmala et al., 2016a) and inaccuracies of species identifications by non-experts (Barbato et al., 2021; Crall et al., 2011; Gardiner et al., 2012; Vantieghem et al., 2017). Various studies have reviewed and examined the accuracy of citizen science data. A taxon-specific example assessed identification errors of passerine species on eBird, and found that 97% of the photo observations were correctly identified but accuracy varied from species to species and depended on the ease of identification (Gorleri et al., 2023). Identification accuracy is lower for some other taxa; for example, assessing two UK-based bumblebee citizen science schemes, Falk et al., (2019) found an overall citizen science accuracy of 49% for BeeWatch and 44% for Blooms for Bees. Although this highlights wide discrepancies between taxa in the accuracy of citizen identification, citizen science identification has been shown to be generally accurate. For example, Aceves-Bueno et al. (2017) reviewed studies that compared citizen-collected with expert-collected datasets and found that over half of these studies had an agreement of 80% or more between citizen scientists and experts. These findings also align with Kosmala et al., (2016a), whose assessment of data quality in citizen science stated that between 70 and 95% accuracy is typical for species identification tasks within citizen science schemes. The level of accuracy that may be considered acceptable is dependent on the risks associated with inaccurate data and how the data is going to be used. In large-scale analysis of species abundances and distributions, models can account for some level of inaccuracy, reducing the impact of incorrect observations. However, if data is being used at a local or regional level to inform policy and management decisions, inaccuracies have a greater impact on the interpretation of the data.

Concerns around data quality have led to large volumes of human and technical resources being focused on mitigating, quantifying, and correcting for inaccuracies in citizen science data. Pre-record submission, citizen science schemes can aim to prevent inaccurate species identification by providing training and ID support, either in-person (Feldman et al., 2018) or online (Perry et al., 2021; Sharma et al., 2019). Post-submission, resources are focused on verifying data to ensure they are of a known quality (Baker et al., 2021). For the majority of citizen science schemes, this process is carried out by experts, which can be time-consuming and relies on large networks of volunteers with taxonomic and regional expertise (Baker et al., 2021). More recently, technical resources have been focused on developing statistical machine learning and artificial intelligence (AI) approaches for automating verification (Green et al., 2020; Mugford et al., 2021; Siddharthan et al., 2016; Terry et al., 2020; Willi et al., 2019). These approaches can have a high accuracy overall, but this is dependent on the volume of training data available (Green et al., 2020); classification accuracy is generally lower for rarer, or less frequently recorded species (van Klink et al., 2022; Willi et al., 2019). Furthermore, limited funding or technical expertise may pose barriers to the implementation of these approaches, due to intensive and costly technical requirements (Baker et al., 2021).

An example of an AI verification approach includes Terry et al. (2020), who integrated automated image identification with the meta-data associated with each image to verify ladybird images automatically; the top-1 (i.e. choosing the species with the highest probability) accuracy of the model was 69%. Palmer et al. (2021) composed an AI algorithm that eliminated empty images and then identified the species in images that are not empty for Snapshot Safari data. The first step that identified whether an image was empty or not had a 95% accuracy, and the species identification had an 89% accuracy. Statistical approaches to verification also exist. For example, Swanson et al., (2016) applied a plurality algorithm to Snapshot Serengeti data that had a 97.9% agreement with expert identifications and Siddharthan et al., (2016) developed a Bayesian incremental model for BeeWatch data that achieved a 91% accuracy. Chapters 3 and 4 of this thesis applied a variation of the Independent Bayesian Classifier Combination model that harnesses aspects of the species, environmental context (Chapter 3) and the recorder (Chapter 4) to assess confidence in and classify MammalWeb and iRecord data; this achieved a 92-97% accuracy, depending on the dataset and the meta-data included. Despite this, even the null models (taking citizen-submitted classifications at face value) achieved high accuracies (89-96%), prompting the question of whether elaborate statistical approaches to yield incremental improvements in accuracy are likely to be worthwhile.

Overall, given the generally high accuracy of citizen science observations, and the effort that goes into ensuring that citizen science data are as accurate as possible, it is timely to explore to what extent accurate verification matters when using these datasets to explore real-world questions and hypotheses. Ecological citizen science data is used in a range of contexts in research, policy development and environmental management. This can include species distribution modelling (Feldman et al., 2021), tracking progress towards targets for nature (Fraisl et al., 2020) or managing the spread of invasive species (Larson et al., 2020). Here, we aim to address whether accurate verification matters by assessing the extent to which butterfly species are represented by protected areas in the UK. We explore these questions by repeating the analytical frameworks for the same dataset where we have simulated different levels of accuracy to see how this impacts the analytical outputs and interpretation of the data.

5.3 Methods

To compare the extent to which accurate verification matters in an environmental policy and conservation management context, we carried out a national version of a recent global analysis carried out by Chowdhury et al., (2023) that assessed protected area coverage for insect populations. The primary objective of protected areas is to conserve nature by reducing anthropogenic threats and pressures within the designated area (Schulze et al., 2018). Protected areas are therefore a primary focus of the 2030 targets for nature, with many countries across the globe committing to protect 30% of the earth's land and oceans by 2030 (Dinerstein et al., 2019). Protected area coverage for species populations provides an index to inform conservation efforts, making it a suitable metric to examine and directly compare between datasets with different levels of inaccuracy, allowing us to evaluate the potential impacts of data quality on policy and management responses. For our assessment of the impacts of data accuracy in citizen science data, we focused on butterflies in the UK. Butterflies are a charismatic species group that are well monitored and studied, and for which there is generally a large volume of citizen science data in the UK (Fox et al., 2022). Butterflies have short life cycles, are often reliant on a specific plant species as hosts or for food and can be restricted to particular habitats (Brereton et al., 2011). Therefore, butterfly species can be sensitive to changes in habitats or environmental conditions, making them a key taxon indicator for assessing environmental quality and overall biodiversity (Brereton et al., 2011). Many butterfly species in the UK have seen significant declines in recent decades (Warren et al., 2021), and many species are considered at risk of extinction by the IUCN Red List for Threatened Species (Fox et al., 2022). Butterflies are therefore a focus in policy and management decisions. Analysing trends in butterfly abundances and distributions can influence landscape-scale habitat management (Ellis et al., 2019), policies regarding agricultural practices (Stewart et al., 2022; Threadgill et al., 2021) or conservation efforts within protected areas (Ashe-Jepson et al., 2022; Hetherington et al., 2022).

5.3.1 Data

The verified citizen science dataset we used as the baseline analysis against which to compare inaccurate date was the National Biodiversity Network (NBN) Atlas records for UK butterfly species. The NBN Atlas is the UK's largest repository for biodiversity data, which holds over 208 million occurrence records from 170 data partners including conservation organisations, local environmental records centres, and research institutions (National Biodiversity Network, 2022, 2023). NBN butterfly records from the last 10 years were downloaded in May 2023. We removed records for which the grid reference location accuracy was greater than 1-km² and that had not been identified to species level. We also removed records that were categorised as 'unconfirmed'. The NBN Atlas aggregates data from multiple data sources provided by a range of organisations each with different processes for verification. Confirmed records could be verified as 'correct', if evidence such as photos or videos were provided with the observation, or 'considered correct' if there is no other information with which to determine whether an observation is anything other than the reported species. Although, confirmed records may not be completely accurate, here we assume that the NBN data is correct. The remaining dataset included 4,053,121 records of 58 species.

5.3.2 Simulating inaccuracies

Inaccuracies were simulated in two different ways. Firstly, we simulated inaccuracies in a 'guessing' scenario. For a randomly selected proportion of the whole dataset, we randomly changed each record to another species that had been observed in the dataset. Each record had an equal chance of being reclassified. This meant that each inaccurate record could be misidentified as 1 of 57 species. The probability of each mistake was proportional to the frequency with which the species was observed within the dataset. Therefore, those species that were more common were more likely to be 'guessed'. This decision was based on the assumption that citizen scientists who were unsure of the species' identity would be more likely to guess more common species.

The second scenario for inaccurate records was based on empirical species confusions. To simulate this scenario, we used the species confusion matrix from iRecord redetermination data for butterfly records. The butterfly records had been submitted through the iRecord online platform or app and verified by experts. Each record had either been accepted as correct, or redetermined to another species. This redetermination data was then used to create a frequency matrix, quantifying the number of times that each species had been redetermined to another species by expert verifiers. We converted this frequency matrix to a proportional confusion matrix (See Appendix D.3 for the proportional species confusion matrix). We then simulated inaccuracies by changing a proportion of the records to another species based on the relative proportion of times that specific mistake was made. In this scenario, the number of potential species that a record could be changed to was smaller, as a record would only be changed to a species that the original species had been incorrectly identified as in the iRecord confusion matrix. The probability of each mistake was weighted based on the proportional confusion matrix; therefore, more common mistakes within the confusion matrix would be reflected in the inaccurate data.

For each scenario, we simulated four levels of inaccuracies, such that we had four inaccurate datasets for each scenario. Many citizen science schemes and automated verification approaches achieve an accuracy of 80% or more (Aceves-Bueno et al., 2017; Kosmala et al., 2016a). We therefore set four levels of inaccuracy: 20%, 10%, 5% and 2%. Including the original NBN Atlas dataset, this yielded 9 datasets with which to carry out the analysis.

5.3.3 Protected area coverage

To assess the level of protected area coverage for butterfly species in the UK, we replicated the analysis carried out by Chowdhury et al. (2023). The analysis was carried out in QGIS (QGIS Development Team, 2023). For each species within the dataset, we estimated occupancy using an alpha-concave hull. This is a variation of the convex hull which encompasses all species records within the minimum bounding geometry (Asaeedi et al., 2017; Chowdhury et al., 2023). The alpha-concave hull removes links between occurrence points based on the mean nearest neighbour, with individual outliers being removed if they are more than twice the mean distance of the nearest neighbour. This means the occupancy can be divided into several polygons (Asaeedi et al., 2017; Chowdhury et al., 2023) and distributions are typically a spatial subset of the minimum bounding geometry of the convex hull. This was calculated using the concave hull plugin in QGIS (QGIS Development Team, 2023).

Once the area of occupancy had been estimated using the alpha-concave hull, we then calculated the percentage overlap with the protected areas of the UK. The protected areas dataset was downloaded through the World Database on Protected Areas, a comprehensive global database of marine and terrestrial protected areas that is updated monthly (UNEP-WCMC and IUCN, 2023). The UK dataset included, but was not limited to, Areas of Outstanding Natural Beauty, Areas of Species Scientific Interest, National and Local Nature Reserves. We downloaded the dataset for the UK terrestrial protected areas in May 2023. Using the Overlap Analysis plugin in QGIS (QGIS Development Team, 2023), we calculate the percentage overlap between the area of occupancy and the protected areas for the UK for each butterfly species.

We carried out this analysis for the original dataset to provide the baseline outputs. We then repeated this process for the 8 datasets containing simulated inaccuracies, so that we could compare the outputs with those from the original analysis.

5.3.4 Data analysis

To examine the impact of inaccuracies on the protected area coverage analysis for different species, we explored two questions. Firstly, we assessed the impact of errors on species with limited ranges, to understand the extent to which verification may be necessary for certain species. To explore this question, we analysed the relationship between change in area of occupancy and the original area of occupancy. Secondly, we explored the extent to which inaccurate data leads to the over or under-estimation of protected area coverage for different species, to understand the potential consequences of inaccurate verification on interpretation of the data and potential impacts on policy and management responses. This was explored by modelling the relationship between error and protected area overlap.

We explored the impact of error on area of occupancy by modelling logged proportional change in area of occupancy (in km^2) between the original and inaccurate data using a Gaussian linear regression. We included the predictors of error type (guessing or species confusions), logged number of observations in the original dataset, logged area of occupancy for the original dataset and extent of error (0.02, 0.05, 0.1, 0.2). Change in area of occupancy, number of observations and original area of occupancy were logged to normalise the data. To determine which predictors were most informative within the model, the dredge function (package MuMln, Barton, 2020) was used to compare all combinations of variables within the global model. To analyse the relationship between error and protected area overlap, we modelled proportional change in protected area overlap between the original data and the inaccurate data, again using a Gaussian linear regression. We included the same predictors as the previous analysis as well as the logged original protected area overlap, to examine how the over and under-estimation of protected area coverage related to the original extent of coverage. The dredge function was used again to evaluate models.

5.4 Results

The overlap between the protected areas of the UK and the area of occupancy for the whole butterfly dataset, i.e., the aggregated ranges of all species, was 16%. For the original NBN occurrence records, the protected area coverage of the estimated area of occupancy ranged from 5% for the Black Hairstreak (*Satyrium pruni*) and Heath Fritillary (*Melitaea athalia*) to 95% for the Lulworth Skipper (*Thymelicus acteon*). The majority of species had a 15-20% overlap with protected areas (Figure 5.1).

Neither the guessing nor the species confusion scenarios captured the range of protected area overlap seen in the original dataset. As with the original dataset, the majority of species had a 15-20% overlap (Figure 5.1). Generally, the more inaccurate datasets had a narrower range of overlap between areas of occupancy and protected areas.

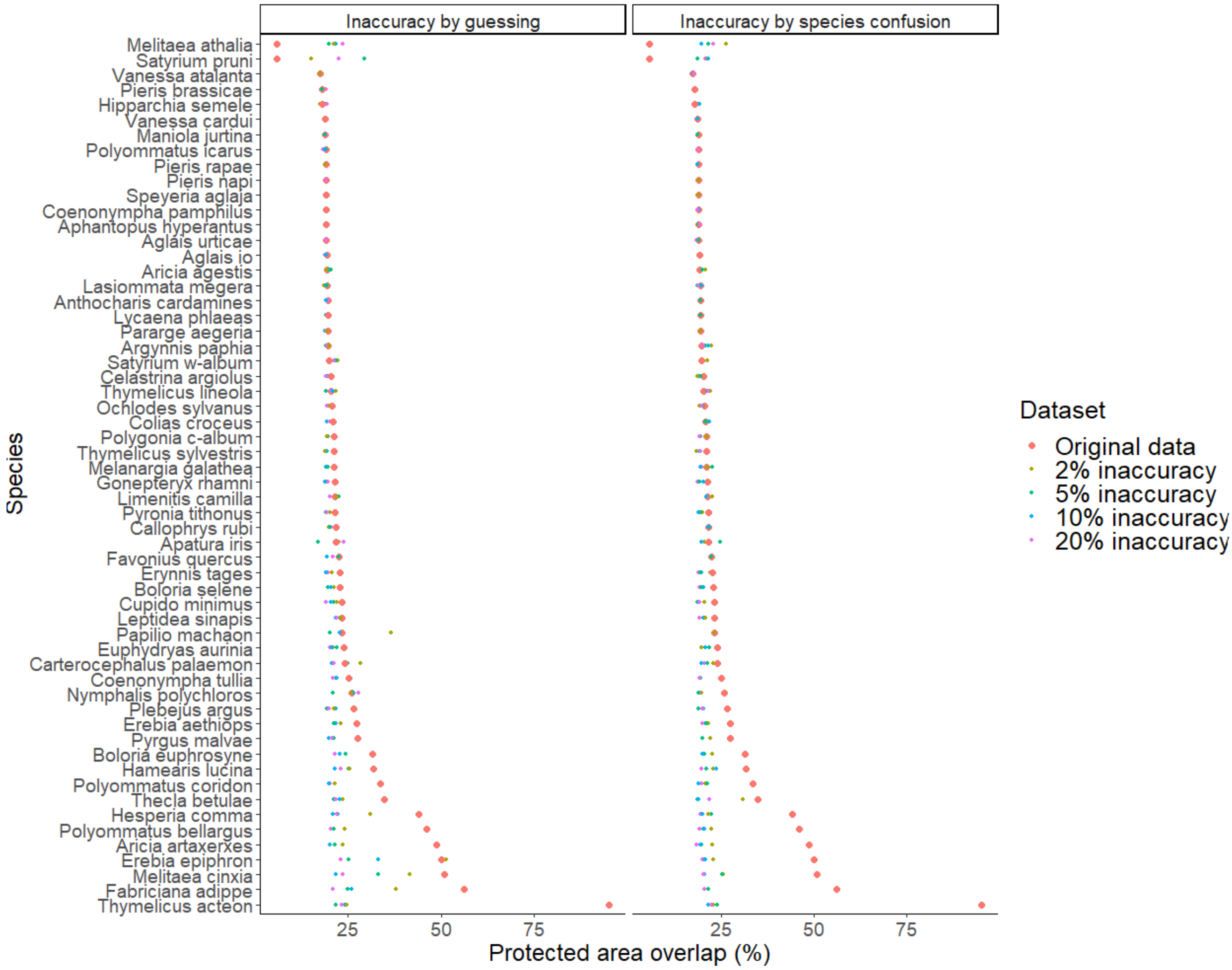

Figure 5.1: Percentage overlap between protected areas and estimated occupancy of UK butterfly species for the original NBN dataset and datasets where inaccuracies were introduced.

Species with fewer observations generally had a higher overlap with protected areas in the original data (Figure 5.2). When inaccuracy was introduced, percentage overlap varied less with the number of observations (Figure 5.2). See Appendix D.1 for the results by species for the guessing scenario and Appendix D.2 for the results by species for the species confusion scenario.

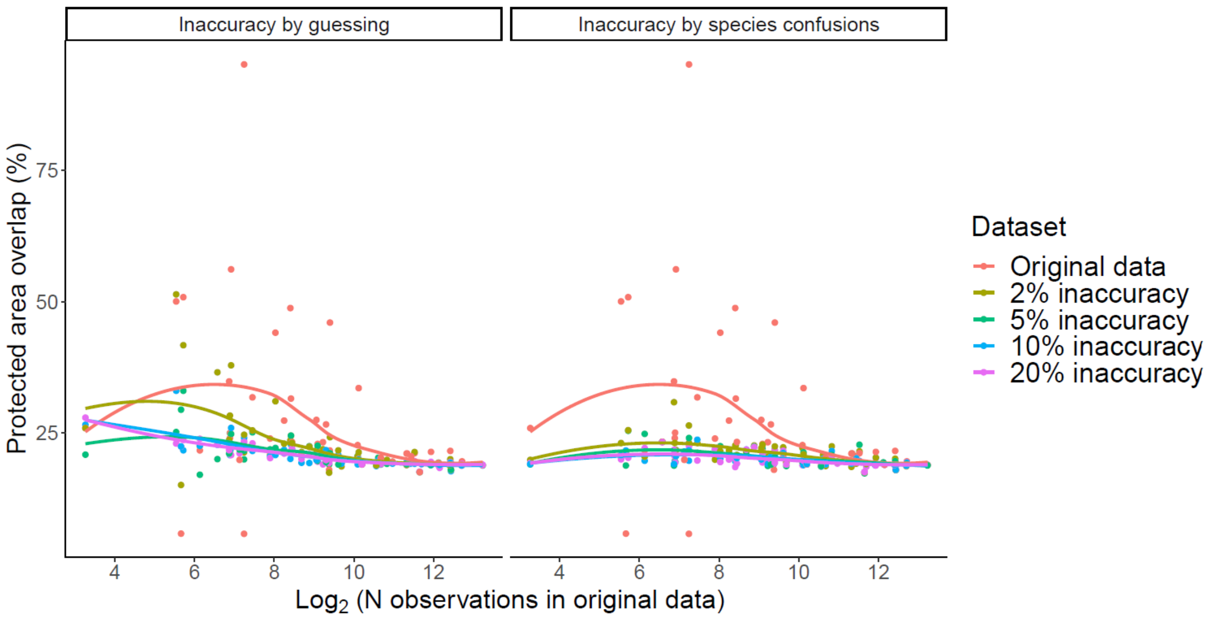

Figure 5.2: Protected area overlap in relation to the logged number of observations in the original dataset for inaccuracies by guessing and inaccuracies by species confusions. Trendlines fitted from a locally estimated scatterplot smoothing function (LOESS).

As more inaccuracy was introduced, the estimated area of occupancy increased relative to the original dataset (Figure 5.3). The area of occupancy was generally higher for datasets with frequency-weighted random inaccuracies (Figure 5.3).

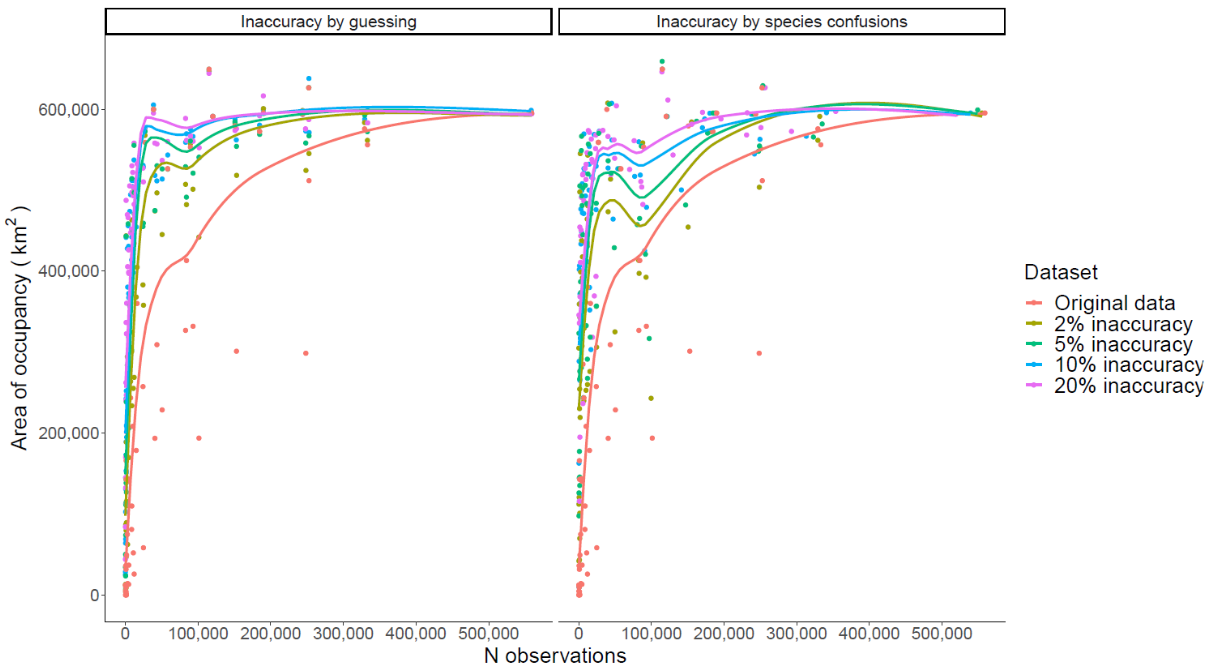

Figure 5.3: Estimated area of occupancy by number of observations in each inaccurate dataset. Trendlines fitted from a locally estimated scatterplot smoothing function (LOESS).

5.4.1 Impacts of error on analysis outputs

Proportional change in area of occupancy was significantly related to the extent of inaccuracy (*estimate* = 2.24 ± 0.384 SE, t = 5.83, $p < 0{\cdot}05$), logged number of observations in the original data (*estimate* = 0.12 ± 0.017 SE, t = 6.79, $p < 0{\cdot}05$), logged original area of occupancy (*estimate* = -0.85 ± 0.018 SE, t = -47.083, $p < 0.05$) and inaccuracy type (*estimate* = -0.17 ± 0.052 SE, t = -3.31, $p < 0.05$). For species with smaller ranges in the original dataset, the proportional change in area of occupancy was generally higher and more ubiquitous species showed little change in area of occupancy (Figure 5.4).

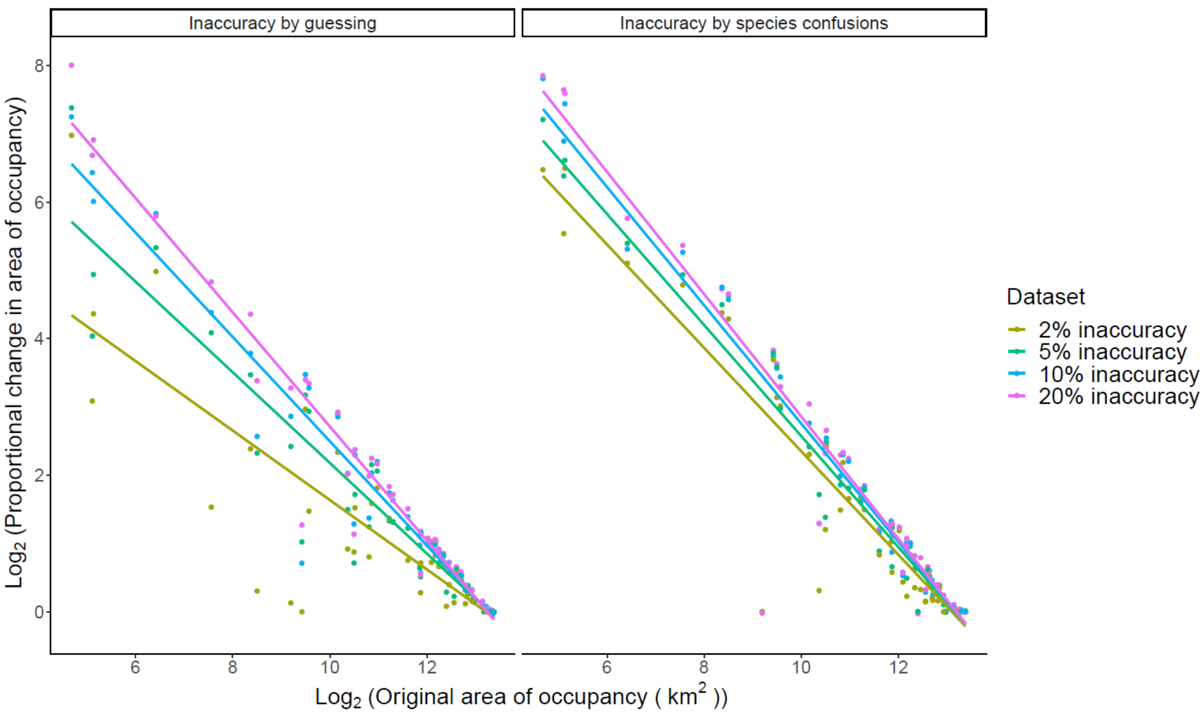

Figure 5.4: Logged proportional change in area of occupancy by logged original area of occupancy for inaccurate datasets. Trendlines fitted from a general linear regression.

Proportional change in protected area overlap was significantly related to the logged number of observations per species in the original data (*estimate* = 0.017 ± 0.005 SE, t = 3.37, $p < 0.05$), logged original area of occupancy (*estimate* = -0.149 ± 0.005 SE, t = -27.97, $p < 0.05$) and logged original protected area overlap (*estimate* = -1.28 ± 0.018 SE, t = -68.74, $p < 0.05$). Species with low protected area coverage in the original dataset saw an overestimation of protected area coverage when both types of inaccuracies were introduced (Figure 5). The species that had the highest protected area coverage saw an under-estimation of the protected area coverage for inaccurate datasets (Figure 5.5).

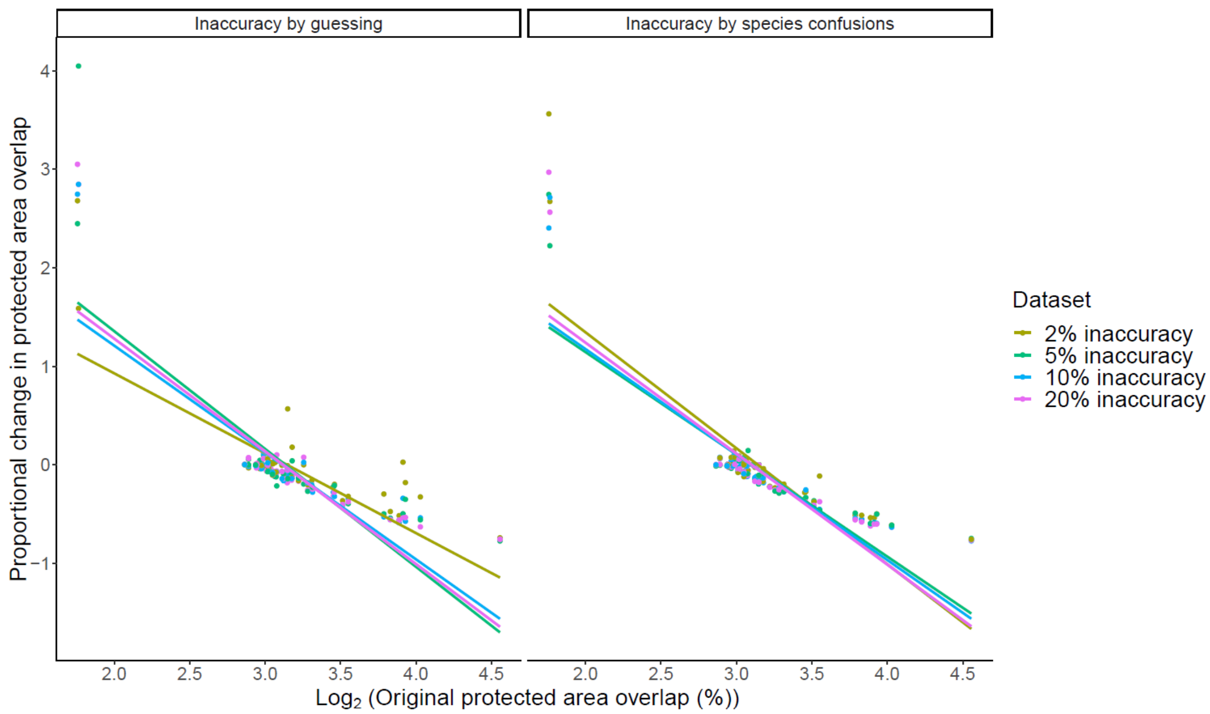

Figure 5.5: Proportional change in protected area coverage by original protected area overlap for each inaccurate dataset. Trendlines fitted from a general linear regression.

5.4.2 Species results

The consequences of inaccuracy on the analysis varied between species. Species with limited ranges such as the Lulworth Skipper (See 5.4.2.1) showed a greater difference in estimated area of occupancy and protected area overlap between the original data and the inaccurate data, with the inaccurate data leading to an under-estimation of protected area coverage. For more widespread species such as the Large Skipper (See 5.4.2.2) and the Painted Lady (See 5.4.2.3) the results here show less difference in protected area coverage between the original and inaccurate data.

5.4.2.1 Thymelicus acteon

The Lulworth Skipper has a small range in the South of Dorset, where it is found in large numbers (R. Jones et al., 2023). It is considered near threatened on the most recent red list assessment for UK Butterflies (Fox et al., 2022). The confusion matrix (Table 5.1) shows that citizen scientists more often submit an observation of another species, erroneously identified as the Lulworth Skipper (false positives), than they submit an observation labelled as another species that is the Lulworth Skipper (false negative). The number of observations in the original dataset was 1400. The numbers of observations in the guessing scenarios were similar to the original dataset (20% inaccuracy: N = 1417; 2 % inaccuracy: N = 1411), but the datasets where inaccuracies were introduced using species confusions led to an increase in observations in the more inaccurate dataset (20% inaccuracy: N = 1865; 2% inaccuracy N=1450). When simulating inaccuracies, the data overestimated the range, because observations were spread farther beyond the restricted range of this species, thus leading to an under-estimation of protected area coverage; the estimated area of occupancy, and difference between actual and estimated protected area coverage, was larger for the guessing scenario data (Figure 5.6).

Table 5.1: The proportional confusion matrix for the Lulworth Skipper.

	True species				
Citizen science identification	Callimorpha dominula	Macroglossum stellatarum	Ochlodes sylvanus	Thymelicus acteon	Thymelicus sylvestris
Thymelicus acteon	0.1	0.1	0.6	0	0.2
Thymelicus sylvestris	0	0	0	1	0

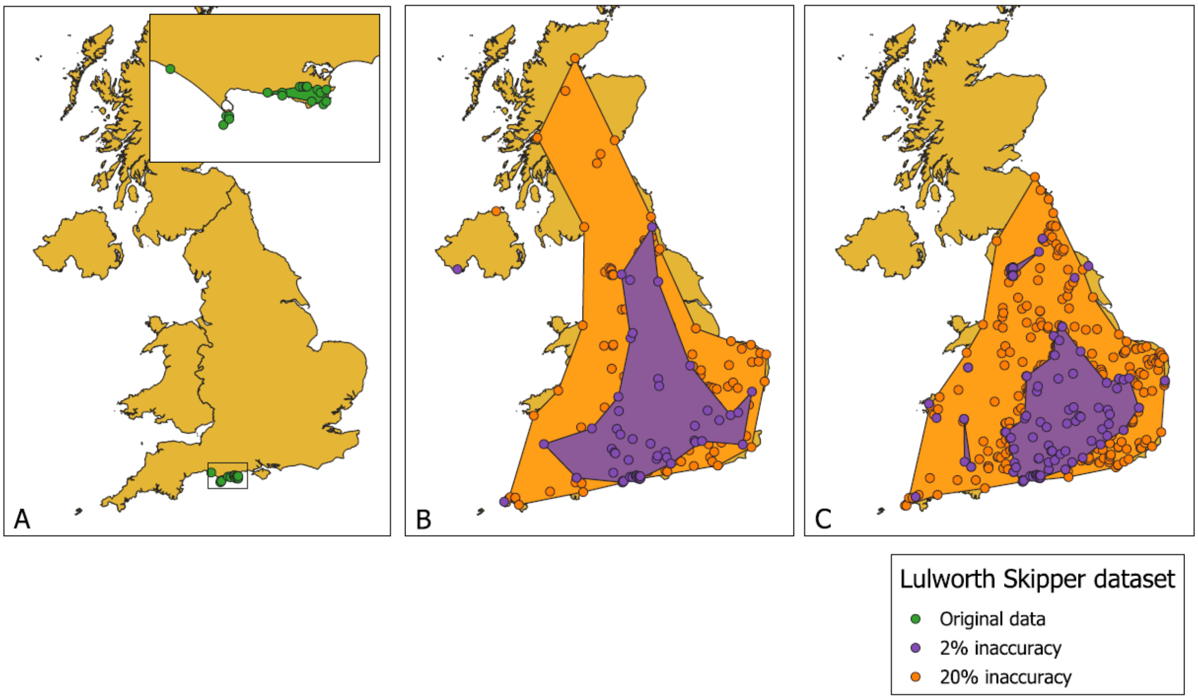

Figure 5.6: Map to show the estimated area of occupancy for the Lulworth Skipper in the original NBN data (A) and for the datasets where inaccuracies were simulated by guessing (B) and by species confusions (C).

4.4.2.2 Satyrium pruni

The Black Hairstreak has a small range in central England and is only found in Blackthorn scrub on clay soils (Tilley et al., 2023). This species is considered endangered in the most recent red list assessment (Fox et al., 2022). The iRecord confusion matrix (Appendix D.3) showed that the Black Hairstreak was only subject to false-positive errors. The number of observations in the original dataset was 287, and the protected area coverage was 5%. The inaccurate datasets over-estimated the area of occupancy for the Black Hairstreak, which led to an over-estimation of the protected area coverage. Although the difference in estimated area of occupancy compared to the original dataset was greater for the guessing scenario (Figure 5.7), the level of overestimation in protected area coverage was similar for both the guessing (20% inaccuracy = 22% overlap; 2% inaccuracy = 15% overlap) and species confusion scenarios (20% inaccuracy = 20% overlap, 2% inaccuracy = 21% overlap).

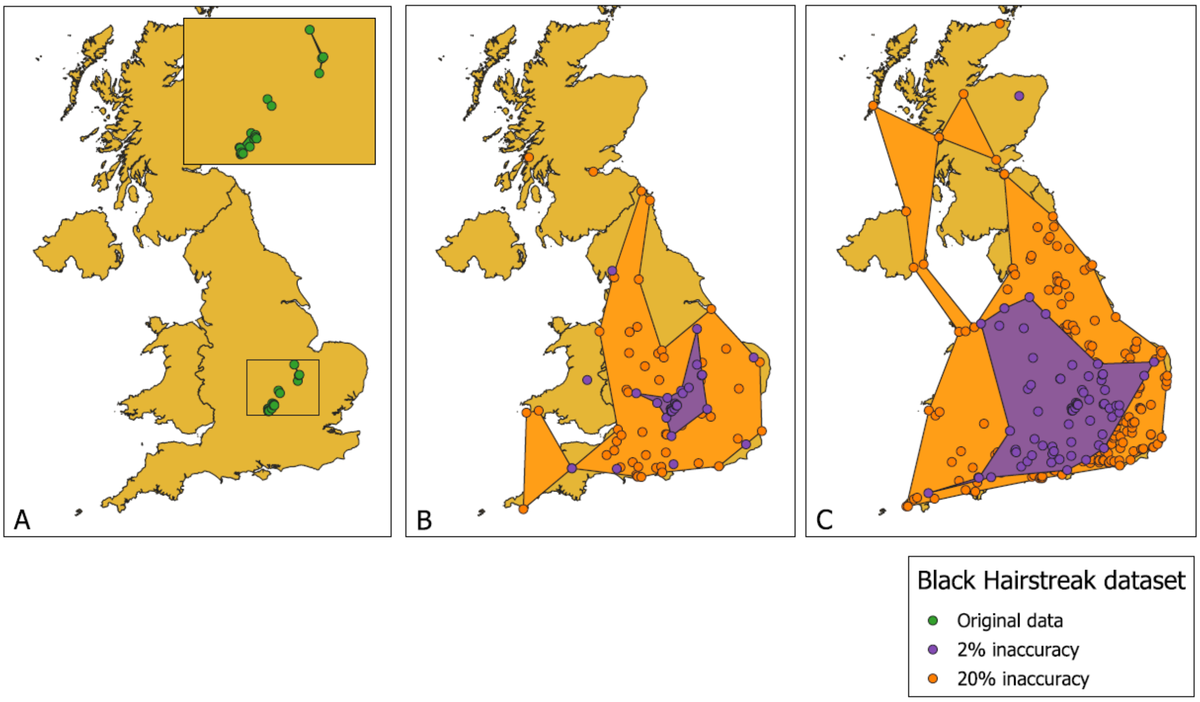

Figure 5.7: Map to show the estimated area of occupancy for the Black Hairstreak in the original NBN data (A) and for the datasets where inaccuracies were simulated by guessing (B) and by species confusions (C).

5.4.2.3 Ochlodes sylvanus

The Large Skipper is found throughout most of England and is categorised as least concern in the most recent red list assessment (Fox et al., 2022). The original dataset had 93,119 records with a 20% overlap with protected areas. The iRecord confusion matrix (Appendix D.3) showed a range of false positive and false negative errors.

Increases in the area of occupancy were larger for the datasets where inaccuracies were introduced by guessing (Figure 5.8). This did not result in a difference in protected area overlap for either the guessing (20% inaccuracy = 19% overlap; 2% inaccuracy = 20% overlap), or the species confusion (20% inaccuracy = 19% overlap; 2% inaccuracy = 19% overlap) scenarios.

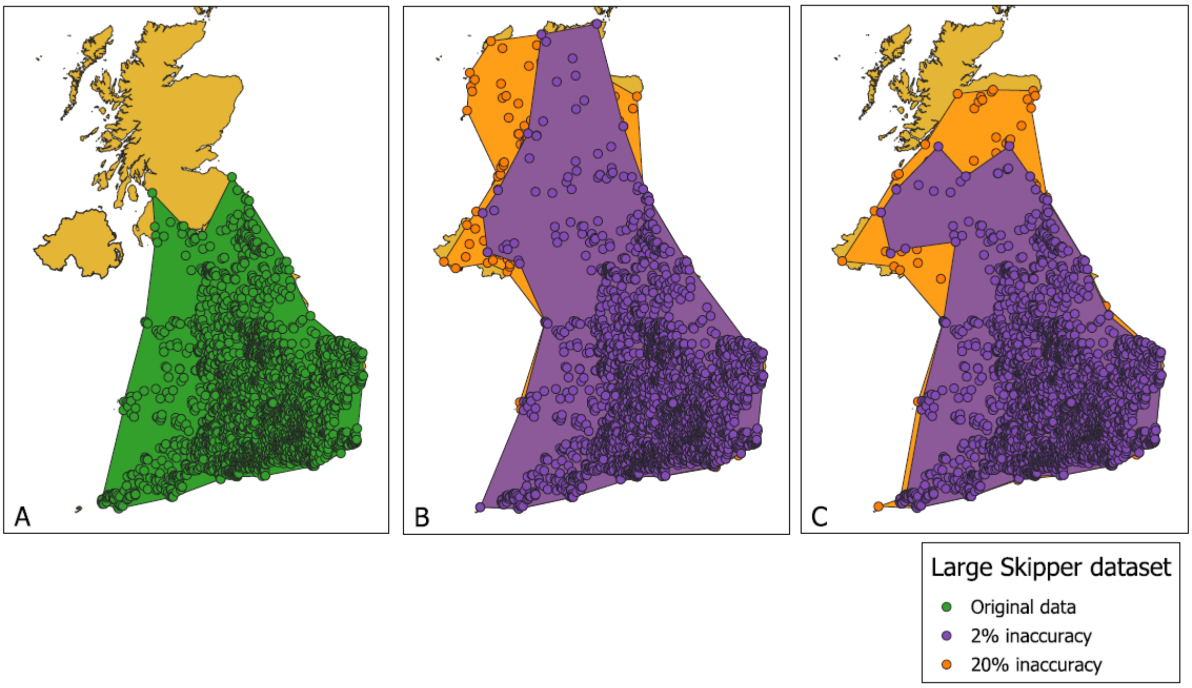

Figure 5.8: Map to show the estimated area of occupancy for the Large Skipper in the original NBN data (A) and for the datasets where inaccuracies were simulated by guessing (B) and by species confusions (C).

5.4.2.4 Vanessa cardui

The Painted Lady is a ubiquitous species found across much of the UK and is categorised on the Red List as of least concern (Fox et al., 2022). The original dataset had 38,709 records and an 18% overlap with protected areas. Introducing inaccuracies for this species showed little change in the area of occupancy and protected area overlap compared to the original data (Figure 5.9).

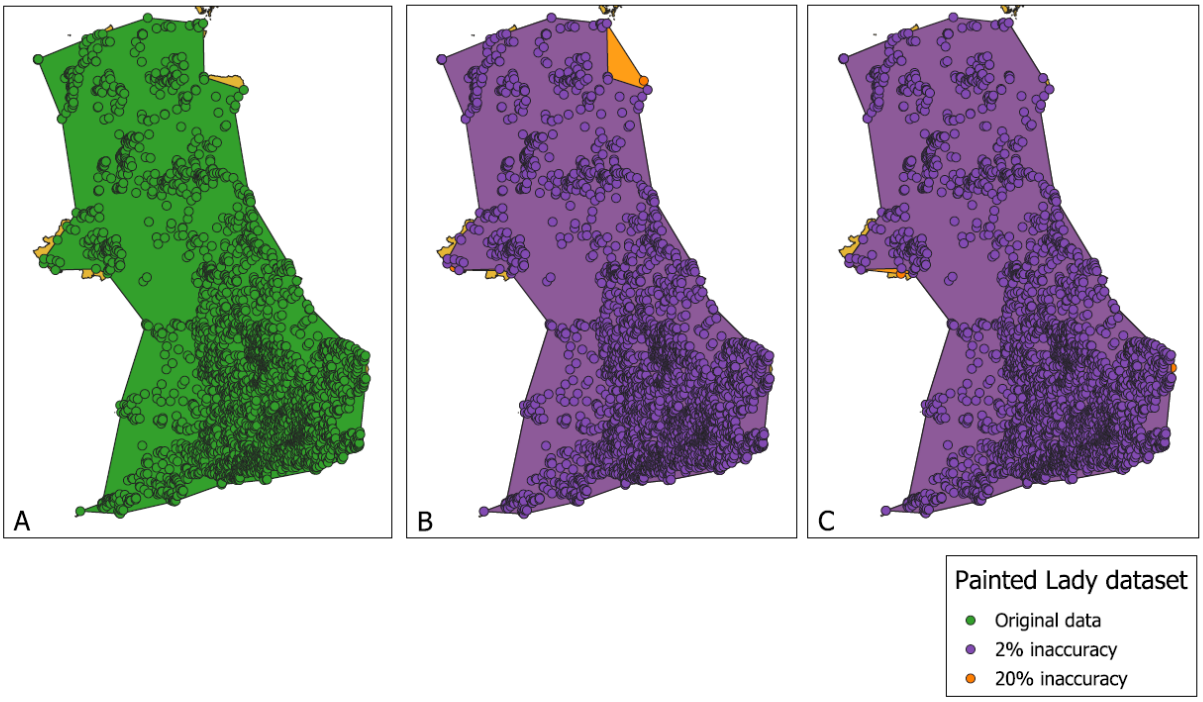

Figure 5.9: Map to show the estimated area of occupancy for the Painted Lady in the original NBN data (A) and for the datasets where inaccuracies were simulated by guessing (B) and by species confusions (C).

5.5 Discussion

We explored the extent to which accurate verification of ecological citizen science datasets matters in the context of protected area coverage of UK butterfly species, by applying the same analytical framework to datasets with different levels of accuracy. We simulated inaccuracies for two different scenarios: inaccuracies due to random errors and inaccuracies based on empirical species confusions. We aim to examine the impact of these inaccuracies on the outputs of this analysis, the inferences that can be made using these results, and the implications for policy and management responses that these might prompt. Our findings show that inaccurate data have the potential to increase the estimated area of occupancy for butterfly species (Figure 5.4). This has consequences for assessing protected area coverage, particularly for species that have restricted geographic ranges (Figure 5.6), with this analysis severely over- or under-estimating protected area coverage for these species. For species that have ubiquitous distributions and large volumes of observations, our analyses indicate that some error can be tolerated when estimating occupancy and making inferences with the outputs of the analysis, because inaccurate data has little impact on the analysis output. For species with large ranges, introducing error did not to lead to high levels of over- or under-estimation of range sizes, with little difference between 20% inaccuracy and 2% inaccuracy (Figure 5.9).

In the analysis presented here, the observation densities are lower in areas that are outside of the range of the original data than areas within the range of the original data (Figures 5.6 - 9). As alpha-hulls are based on nearest neighbour distances, if there are enough observations that are within the mean nearest neighbour distance to one another they will be included in the distribution regardless of the density of observations. Alpha-hulls have been used in a range of contexts to estimate species distributions (Meyer et al., 2018; Pena et al., 2014; Rivers et al., 2010). However, given the varied density in observations between the original data and inaccurate data, the alpha-hull approach may not be an appropriate approach, especially for analysing inaccurate datasets. Rather, approaches that account for variability in densities of observations, such as kernel density estimation may be a more suitable method of analysis (Fleming and Calabrese, 2017; Pena et al., 2014; Zhang et al., 2018). Kernel densities can be applied by identifying biases in observations of presence-only data, by weighting points with fewer neighbours. In some cases, up-weighting observations with fewer neighbours may be more appropriate, for example when accounting for sampling bias (Brown, 2014). Here, where observations with fewer neighbours are more likely to be inaccurate, observations could be down-weighted to provide more accurate estimated occupancies. In the context of the verification process, random errors in occurrence data could be picked up by automated tools such as the NBN Record Cleaner, which run checks to identify records that are out of range (Dean, 2013).

Given the high levels of accuracy that can be observed in citizen science datasets pre-verification, as well as how demanding it can be to implement accurate verification, there is an argument for evaluating how verification can evolve and adapt to growing data volumes and the demand for up-to-date data. The results here question whether every record needs to be verified, and suggest which species should be prioritised for verification and which records could be accepted as correct without time-consuming verification approaches. For widespread species with large numbers of citizen science observations, verifying every citizen science record is perhaps unnecessary, as errors in individual records will make little difference to the overall spread of the data. A small proportion of records could still be verified, to monitor inaccuracies and ensure data quality. For species that are known to be threatened, vulnerable, or range-restricted, verifying every record is more important, because analysis of trends will be more sensitive to errors. Another consideration for evaluating the need for verification should be species-specific accuracies. For example, if citizen science identification accuracy is high for a given species, then verifying every record is less necessary, but for species that are frequently misidentified, verification is more important to correct for errors in citizen science observations.

Before evaluating approaches to verification, and whether there is a need to verify every record, the costs of errors should also be considered. If species' ranges are over or underestimated, this can have consequences for policy and management decisions that are developed in response to analysing trends in species populations (Gardiner et al., 2012; Kamp et al., 2016; Soroye et al., 2018). For example, when managing the spread of invasive species, underestimating the distribution of a species could lead to delays in control measures being implemented, potentially allowing the species to disperse further (Andow et al., 2016; Maistrello et al., 2016). This could, in turn, lead to more time and resources being needed to manage the species in the future (Epanchin-Niell, 2017). In the case of invasive species, inaccurate observations can be costly both via environmental impacts, and in the contact of the time and resources that may be directed to control the species' spread. When assessing the conservation status of rare, threatened, or declining species, the implications of inaccurate verification may also be costly. Accurate species occurrences and distributions are necessary to assess, evaluate and implement site-specific habitat management practices to promote and conserve specific species (Johnston et al., 2020a; Robinson et al., 2018). If the species' data are inaccurate, this can lead to resources being directed to where they are not needed, potentially to the detriment of areas where habitat management would be most beneficial (Gill et al., 2023; Zurell et al., 2022). If a citizen science scheme is monitoring these species, efforts should be focused on ensuring observations of these species are as accurate as possible (Baker et al., 2021). For more ubiquitous species, data inaccuracy might conceal range contractions or population decreases; in turn, this could lead to underestimates of the species' vulnerability. In the context of the datasets used here, many butterfly species are experiencing declines. A 2022 red list assessment showed that 41% of UK butterfly species were considered threatened under IUCN red list criteria, which was a 26% increase in threatened species since the last assessment in 2006 (Fox et al., 2022). This is a pattern that can be seen in other invertebrate groups, due to climate change (Harvey et al., 2020), agricultural intensification (Outhwaite et al., 2022) and habitat loss (Kehoe et al., 2021). Due to the rapidly changing conservation status of many species, the costs of inaccurate verification should be assessed dynamically. If a species' conservation status changes, or if declines in abundance and distribution are observed, then accurate verification may become more necessary for species that were formerly considered ubiquitous.

Here, we explore the impacts of inaccurate verification on ecological analysis, and the inferences that can be made using the outputs. In this context, we show that inaccurate verification can overestimate the area of occupancy of some species, specifically for those with limited geographical ranges, but, for more ubiquitous species, small amounts of error (≤20% inaccuracy) make minimal difference to spatial inferences. For some species, therefore, verifying every record may be unnecessary; verification should be focused on species where highly accurate data are needed to pinpoint exact locations of species. Given how time- and resource-intensive verification can be this research signposts a way forward for how verification can evolve to deal with large volumes of data without compromising inferences that can be made in analysis.

6. General Discussion

6.1 Synthesis

Citizen science has underpinned ecological data collection for centuries (Mesaglio et al., 2021; Pocock et al., 2015, 2017; Sutherland et al., 2015). As volunteer-collected datasets are being used more widely in ecological research to explore a range of research questions (Fraisl et al., 2022; Poisson et al., 2020), data quality and accuracy of citizen science data remain at the forefront of the discourse around their use (Johnston et al., 2023). Verification is a necessary and essential process for ensuring data quality (Gilfedder et al., 2019; Tweddle, et al. 2012), but the large volumes of citizen science records submitted to schemes can create bottlenecks in data processing (Baker et al., 2021). A range of scheme-specific verification approaches have aimed to address verification bottlenecks (Bonter and Cooper, 2012; Siddharthan et al., 2016; Swanson et al., 2016; Yu et al., 2011). However, there has not been a large-scale examination of the verification of ecological citizen science data.

This thesis contributes to our understanding of the role that verification currently plays in ecological citizen science schemes by examining how approaches to verification should evolve in response to increased data volumes, presenting alternative approaches to verification and exploring the impacts of inaccurate verification on inferences that can be made using citizen science data. Chapter 2 of this thesis presents the first review of verification approaches within ecological citizen science schemes. In this chapter, I reviewed 259 citizen science schemes that record species data across the globe to provide a current examination of the verification approaches of citizen science data. The results from this research highlighted that verification by experts has tended to be the default approach, but alternative approaches such as community consensus and automation are being adopted by more recent schemes. I discuss the issues that may arise from relying on expert verification and present an idealised approach for verification. This idealised system outlined a hierarchical approach to verification that suggested using community consensus or automation as the first level of verification and only using expert verification for anomalous observations. Furthermore, I outline the range of information that can be used to verify citizen science observations, which we broadly categorise as attributes of the species, the environmental context, and the observer.

Based on the idealised approach to verification outlined in the previous chapter, Chapter 3 shows the implementation of an automated verification approach that incorporates species attributes, using existing information on species confusions, and environmental context, using relative frequencies with which species appear in different contexts. I illustrate how this approach can be applied to both schemes that crowdsource image classification tasks and schemes that rely on field-based citizen scientists to collect species data. In the crowdsourcing example, including contextual information improved verification accuracy by 1-3%, but for ad-hoc records, context provided little advantage in verifying records. I discuss why meta-data can sometimes be useful in assessing confidence in citizen science observations, and how setting thresholds for confidence can improve accuracy. Chapter 4 presents how variation in observer expertise can be used to inform automated verification approaches and shows that, in the examples presented, accounting for observer expertise does not necessarily improve the accuracy of verification. Strong skews in observer contributions lead to difficulties in quantifying observer variability when, for the majority of observers, little data is available to assess expertise. This problematic attribute is likely to be common to many citizen science schemes, suggesting that it might often be difficult to make use of information on observers. Chapters 3 and 4 highlight that citizen science observations are already highly accurate pre-verification (89-96% for the datasets analysed in this thesis), and that automated verification approaches provide marginal improvements in verification accuracy. I, therefore, discuss the extent to which accurate verification is necessary, and whether it is worthwhile to continue to develop intensive automated verification approaches that provide minimal improvements in verification accuracy.

Given the difficulties of using contextual data to improve the accuracy of verification, particularly for schemes that consist of ad hoc records, in Chapter 5 I examine the extent to which accurate verification matters by exploring the impacts of inaccurate data on spatial analysis that informs policy and management responses. Specifically, I examined the impact of inaccurate data when examining protected area coverage for UK Butterfly species. I explored this by simulating different levels of inaccuracy (20%, 10%, 5%, 2%) in NBN butterfly occurrences, then estimated occupancy and calculated percentage overlap with UK protected areas. The results from this chapter show that the impacts of inaccurate verification vary from species to species. For more ubiquitous, widespread species, the spatial inferences showed little variation with different levels of inaccuracy. However, for species with restricted ranges, inaccurate datasets tended to increase the estimated area of occupancy. This resulted in a misrepresentation of protected area coverage for these species, leading to under- or over-estimations of protected area coverage for species that originally had either high or low protected area overlap, respectively. I discuss these results in the context of evaluating the need to verify every record, and the costs and consequences of using inaccurate data in different contexts. For example, for some rare or threatened species, pinpointing the exact location of occurrences is necessary for implementing effective conservation and habitat management. However, for species where pinpointing individual occurrences is not necessary, small amounts of error, such as the 2-20% range presented in this thesis, can potentially be tolerated, and the need for intensive and highly accurate verification approaches should be evaluated.

This research contributes to our understanding of verification within ecological citizen science data and explores how citizen science schemes should evaluate approaches to verification. Furthermore, this thesis signposts a way forward for verification approaches to evolve in the future, to ensure data are processed efficiently and effectively, benefiting both those who run and manage citizen science schemes and end users of the data.

6.2 Confidence in citizen science approaches within ecological research

Citizen science initiatives have collected large volumes of data that provide insight into species abundances (Callaghan et al., 2021), distributions (Johnston et al., 2020b), and phenology (Soroye et al., 2018). These citizen science datasets have proven to be a key resource that can be used in ecological research, conservation management and environmental policy development (Adler et al., 2020; Fraisl et al., 2022). However, data quality remains a concern when using citizen science data in ecological research (Johnston et al., 2023), and resources are continuing to be focused on improving the accuracy of citizen science data through verification (Baker et al., 2021; McClure et al., 2020). Despite these efforts to increase verification accuracy, all datasets will inevitably have some amount of error (Freitas et al., 2020; Grenié et al., 2023; Valdez et al., 2023). Given the increased use of citizen-collected data in a range of research, policy, and management contexts, there is a need to address issues around confidence in citizen science data and examine how to deal with imperfect citizen science data.

6.2.1 Transparency within citizen science data

Verification is the primary way in which data quality is assessed and inaccuracies are corrected (Baker et al., 2021; Tweddle et al., 2012). However, as Chapter 2 of this thesis highlighted, many citizen science schemes whose data are used in ecological research provide no information as to how the data are verified (Baker et al., 2021). Transparency in verification approaches can be increased by reporting how the data are verified (i.e., expert, community consensus or automation), who verifies the data and the information used to verify data. Furthermore, it would be beneficial to report on the decision-making framework that is used to evaluate whether a record could be accepted or not, and the percentage of records that are redetermined to another species. End users of the data can then be aware of the potential issues in data quality and can then account for this in research and analysis (Anhalt-Depies et al., 2019; Wang et al., 2015).

If verification approaches are reported more widely, concerns around confidence and data quality can be directly addressed on a case-by-case basis when they arise and ensures citizen science schemes are accountable for the quality of their data. For example, some schemes allow records to be submitted without evidence such as photos or videos. If there is transparency in the fact that a proportion of the data is not backed by photographic evidence, then end users may choose to filter out all records without photos or selectively remove instances for hard to identify species with no photographic evidence. More broadly, if redetermination rates are shared, as they have been in Chapters 3 and 4 of this thesis, then this could highlight the already high accuracy of citizen science observations prior to verification, further bolstering confidence in citizen science data.

Increased transparency has the potential to catalyse movement towards better data standards and best practices for data collection and management within citizen science. This then can improve the reputation of, and confidence in, citizen science data, leading to the wider use of citizen science approaches within the ecological research community.

6.2.2 Dealing with imperfect data

All data, irrespective of how they are collected and verified are subject to errors (Barré et al., 2019; Bird et al., 2014; Simões and Peterson, 2018). Research efforts, including those presented in this thesis, are continuing to be focused on understanding data quality and striving for verification approaches that, in many cases, only marginally improve verification accuracy (Chapter 3, Chapter 4, Mugford et al., 2021; Siddharthan et al., 2016; Terry et al., 2020). Therefore, citizen science schemes and end users of the data should consider alternative frameworks for managing, processing, and analysing imperfect data.

As citizen science schemes grow, verification becomes a more intensive and time-consuming process (Baker et al., 2021). The research presented throughout this thesis highlights that verification approaches should adapt to meet the needs of citizen science schemes and discusses two considerations for citizen science schemes when evaluating verification approaches. Firstly, Chapter 2 of this thesis questions whether expert verification should be the default approach to verification and recommends that citizen science schemes explore alternative approaches to verification. Secondly, Chapter 5 of this thesis questions the need for continuing to develop intensive verification approaches and suggests that citizen science schemes should evaluate the need for every record to be verified. Moving forward, schemes should consider alternative frameworks for processing citizen science records, that not only evaluates the most suitable approach to verification, but also whether the verification of every record is necessary.

When designing a verification framework, initially citizen science schemes should aim to understand data quality, determining the overall level of inaccuracy and identifying where inaccuracies are within the data. Furthermore, citizen science schemes should evaluate the specific costs of inaccurate verification for a given dataset. This will identify species where highly accurate verification matters and whether the end use of the data can tolerate the inaccuracies present within the dataset. This process will identify two groups of data, citizen science records where the level of inaccuracy within the data can be accepted, and observations where highly accurate verification is essential. If inaccuracy can be tolerated then citizen science schemes can choose to accept those observations at face value, and resources can be focused on striving for higher accuracy for records where highly accurate verification is necessary.

6.2.2.1 Confidence metrics when using citizen science data

Bayesian approaches provide a useful framework with which to assess whether a citizen science observation is correct by incorporating prior information and data to estimate likelihood, i.e., the probability of a species observation being correct or not (Siddharthan et al., 2016). Additionally, Bayesian models have the flexibility to incorporate past data and prior knowledge to inform the posterior probability and can be updated when new evidence becomes available. This thesis contributes to, and builds on, a growing body of research that uses Bayesian approaches to assess confidence in, and verify, citizen science data (De Lellis et al., 2019; Mugford et al., 2021; Santos-Fernandez and Mengersen, 2021; Siddharthan et al., 2016). Given the flexibility of Bayesian approaches, such frameworks have the potential to be a valuable tool for evaluating imperfect data and using citizen science data within ecological research.

In Chapters 3 and 4 of this thesis, a variation of the Independent Bayesian Classifier Combination was used to provide a likelihood value for each species that could be observed, which was then used to classify a record as a given species using top-1 accuracy, i.e., the species with the highest probability. Chapters 3 and 4 show that using this approach improves the accuracy of verification by 1-3%. Accuracy can be further increased if thresholds are set, i.e., where records are only accepted if the likelihood exceeds a certain value. For example, in Chapter 3, verification accuracy for MammalWeb data increased from 91.9% to 96.3% when the probability threshold was set to 0.9. However, setting higher thresholds mean that more of the data remains unverified and will either require additional classifications by citizen scientists or expert review. In Chapter 3, a threshold of 0.9 removed 77% of instances, leaving 23% requiring further verification. Beyond being used in the verification process, probability metrics have the potential to be used as a measure of confidence and could be an alternative to records either being categorised as ‘correct’ or ‘incorrect’. This means that end users of the data can avoid removing large proportions of the data and allows inaccuracies in the data to be accounted for in analysis. Confidence metrics could be used as an indicator for data quality, or when developing modelling approaches, with analysis integrating probability metrics to account for potential inaccuracies or varying likelihoods in the data.

Probability metrics can be calculated and assigned to individual species occurrence records using the methods presented in Chapters 3 and 4 of this thesis. If a citizen science scheme is collecting more than species occurrence data, such as behaviour or life stage, the methods presented in this thesis for calculating confidence metrics would need to be expanded to account for the additional levels of data that end users may analyse. This could be achieved by expanding the confusion matrix to account for categorical factors such as behaviour, assigning a single probability to the species and the behaviour, i.e., the probability of that certain species behaviour being observed given the contextual information included in the model. Alternatively, more complex item response models (Santos-Fernandez and Mengersen, 2021) or Bayesian hierarchical models (Hertzog et al., 2021) could calculate separate probabilities for the species and the behaviour observed.

Prior to analysis, confidence metrics could be used as an indicator of overall data quality, and as an identifier for subsets of the dataset where confidence is low. If, within a dataset, probability metrics are showing low confidence in specific species, then this could be accounted for by pooling data from other sources to fill in data gaps (Callaghan et al., 2019; Fithian et al., 2015), either by compiling data from expert-collected sources (Robinson et al., 2020) or other citizen science datasets (Crall et al., 2010). When analysing citizen science datasets, confidence metrics could be incorporated into models that explore species distributions and temporal trends in species populations. For example, records could be weighted based on confidence, which has been shown to be an effective approach when accounting for bias and uneven sampling in occupancy models when estimating species distributions (Dennis et al., 2017; Johnston et al., 2020b). Correction factors, where bias and inaccuracy are corrected for based on observed patterns, could be used to account for variability in confidence when analysing trends in species abundances through time (Belt and Krausman, 2012; Cretois et al., 2021; Isaac et al., 2014; Stuber et al., 2022).

Although a range of known inaccuracies and biases affect citizen-collected datasets, citizen science datasets continue to be used in ecological research to expand our knowledge of species and ecological processes. By assessing confidence in citizen science observations and assigning confidence metrics to species identifications, end users of the data can make informed decisions about how to account for data quality in the analysis. By using metrics to quantify confidence, issues of data quality can be identified, and concerns around data quality can be challenged, further highlighting the value of, and increasing confidence in citizen science datasets and their use in ecological research. In the future, research could be focused on exploring how these confidence metrics influence inferences that could be made using citizen science data to address ecological questions.

6.3 Citizen science and targets for nature

As the severity of the nature and climate crises increase, ambitious targets are being set to mitigate climate change and protect biodiversity to improve the global outlook for nature (Dinerstein et al., 2019; Roberts et al., 2020; Waldron et al., 2020). Some of the most notable targets include the sustainable development goals, which were agreed upon by the global community at the 2015 UN Summit (Locke et al., 2019), and committed to meet a range of social, economic, and environmental goals by 2030, which included stopping biodiversity loss (Opoku, 2019; Visseren-Hamakers et al., 2021). More recently, nature conservation organisations across the globe have committed to the target of conserving at least 30% of land by 2030 (Dinerstein et al., 2019). To track our progress toward reaching these targets, as well as assess the effectiveness of conservation efforts that are being developed to meet these targets, dynamic assessments of the state of nature are required at a global scale (Buchanan et al., 2020; Green et al., 2019; Shepherd et al., 2016). Furthermore, engagement and collaboration between scientists, policymakers, and citizens is required to mobilise and empower communities across the world to take action for nature, improving the outlook for biodiversity across the globe (Devictor et al., 2010; Fritz et al., 2019; Pocock et al., 2019). Citizen science has proven to be a powerful tool for both large-scale data collection and engagement within the fields of ecology and conservation (Fraisl et al., 2022; Von Gönner et al., 2023). By engaging citizen scientists in different levels of the research and decision-making process we can collect large volumes of data with which to assess the state of nature, as well as catalyse environmental stewardship, conservation management and protection of biodiversity, ensuring we are on track to meet these targets for nature. Verification is a fundamental process that is intrinsic to the collection, processing, and use of citizen science data, and therefore is key to considering the wider use of citizen science approaches in research and policymaking associated with meeting global targets for nature.

Connecting with citizen scientists more widely through knowledge sharing has the potential to provide insight into local knowledge and values systems, filling critical data gaps for species or geographical regions where data are currently deficient (Fontaine et al., 2021; Hochkirch et al., 2021; Tauginienė et al., 2020; Tengö et al., 2021). This could be particularly beneficial when assessing rare or threatened species. The IUCN Red List for Threatened Species is the largest database for the assessment of the extinction risk of species, globally, and has assessed over 150,000 species (IUCN, 2023). However, these species assessments are generally biased towards terrestrial ecosystems and animal species (Bachman et al., 2019; Cazalis et al., 2022; Harfoot et al., 2021; IUCN, 2023; Miqueleiz et al., 2020). Plants and fungi, freshwater and marine species, and invertebrates are currently underrepresented in Red List assessments (IUCN, 2023). Failing to identify species that are at risk of extinction can lead to the loss of species and impact assessments that are made regarding the global state of biodiversity change (Betts et al., 2020). By striving to target and fill these gaps in data through citizen science and community initiatives, we can identify the species and taxonomic groups most at threat and target resources to those most at risk from extinction. Many of the underrepresented species' groups are more difficult to identify (Barbato et al., 2021; Mesaglio et al., 2023; Newcomer et al., 2019), and therefore, verification will be necessary to ensuring that this data is accurate. As highlighted in Chapter 5, accurate verification is necessary for rare or threatened species, and therefore, verification efforts should be focused on the species that are identified as at risk from extinction by Red List assessments. Verification will also be essential in engaging citizen scientists, as providing timely feedback enhances engagement and provides support that could lead to continued contributions by citizen scientists towards data collection. Furthermore, efficient verification will be necessary to ensure that the state of nature is accurately assessed, filling in data gaps and providing more robust evidence to inform decision-making around conservation and the protection of biodiversity, as well as assess our progress towards nature targets.

Aside from data collection, engaging citizen scientists in conservation policy and management decisions can catalyse bottom-up action for nature locally, which can amount to positive cumulative impacts for nature at a greater geographic scale (Devictor et al., 2010; McKinley et al., 2017). Involving communities in conservation management democratises the decision-making process and can inspire public involvement in the implementation of conservation measures for habitats and species (Devictor et al., 2010; McKinley et al., 2017; Newman et al., 2017). Furthermore, by maintaining long-term engagement with citizen scientists and providing efficient and timely feedback through verification, local communities can effectively maintain and evaluate the effectiveness of conservation efforts (Newman et al., 2017). Engaging with citizen scientists can increase the community of people across the globe concerned for and working to protect nature. This has the power to influence policymaking and hold decision-makers accountable to protect and conserve nature (Adler et al., 2020; Hollow et al., 2015; Young et al., 2019). This could lead to top-down decision-making to establish legal obligations to protect nature, designate protected areas and outline mitigation measures to reduce the impact of infrastructure development (Dinerstein et al., 2019; Maxwell et al., 2020).

Citizen scientists can play a key role in working towards these bold and necessary targets to protect nature and halt biodiversity loss by 2030. Citizen science can continue to play a role in data collection to fill in gaps and data deficiencies, but we can move beyond data collection to engage citizen scientists further in the implementation of conservation measures, with verification providing the foundation for the data and information collected through these schemes. Just as citizen science has been proven to collect data at a scale unmatched by traditional data collection methods, if we engage citizen scientists in conservation actions, we can have a greater positive impact on the protection of nature at a global scale.

6.4 Conclusions

This thesis contributes to and builds upon the range of research that examines issues of data quality within ecological citizen science data by examining approaches to verification, exploring ways in which we can increase efficiency within verification, and assess the impacts of inaccurate verification. The research conducted here includes the first review of verification approaches within ecological citizen science schemes, which highlights the reliance on experts in the verification process and the need to move towards more efficient ways of verifying data. In pursuit of that greater efficiency, I explore how attributes of the species, the environmental context and the observer can be used to inform automated verification approaches. The key findings here show the usefulness of the species confusion matrix in verifying citizen science data, and how the environmental context and observer variability can be captured using the confusion matrix. However, in some situations the environmental context provided little advantage when verifying data, and for all the examples presented here, accounting for the observer did not improve the accuracy of verification. I then explore the impacts of inaccurate data on spatial analysis in an environmental policy and management context, discussing the costs of inaccurate verification when conserving species and habitats. The overarching findings of this thesis highlight the need to evaluate approaches to verification within ecological citizen science schemes to verify records efficiently without compromising data quality and downstream decision-making. Moving forward, there should be a focus on increasing confidence in citizen science data within ecological research. Increased trustworthiness of citizen science data could be achieved through more transparency regarding data quality and verification within citizen science schemes, and by exploring alternative approaches for dealing with imperfect data, including the use of confidence metrics in the analysis of citizen science data. The scientific community should move beyond only involving citizen scientists in data collection and consider engaging them further in the decision-making process and implementation of conservation efforts. This can lead to widespread efforts to conserve nature and ensure we are on track to meet the current targets for halting and reversing biodiversity loss.

Appendices

Appendix A

Chapter 2

Table A.1: References for 434 papers that were reviewed, and the citizen science schemes that featured in each paper.

Literature search references DOI: *https://doi.org/10.5334/cstp.351.s1*

Table A.2: Names, attributes, verification approaches and references for each of the 259 citizen science schemes that were reviewed.

Citizen Science Scheme Data DOI: *https://doi.org/10.5334/cstp.351.s2*

Appendix B

Chapter 3

Table B.1: Cross-validation summary from the community consensus classification model that was applied to MammalWeb data. Cross validation was used to compare models and determine which contextual variables were most useful in verifying species correctly. Variables included in π_1 refer to the contextual information that was included in the confusion matrix to calculate $P(R \mid S, H, \pi_1)$, the probability of a species being classified as a particular species given the true species and the context. Variables included in π_2 refer to the context information that was included in the context matrix to calculate $P(S \mid H, \pi_2)$, the probability of the true species given the environmental context. Model selection metrics included proportion of correct instances (i.e. citizen science records where the species was correctly classified by the model), the negative log likelihood across instances and the squared error (where the error is the difference between the probability assigned to a species and 1, if it is the correct species, or zero, otherwise).

Variables included in π_1			Variables included in π_2			Model selection metrics		
Habitat	Season	Time	Habitat	Season	Time	Proportion correct	Mean squared error	Log likelihood
0	0	0	0	0	0	0.900219673	0.009479838	-0.661323428
1	0	0	0	0	0	0.903396169	0.009495696	-0.669377363
0	1	0	0	0	0	0.904645783	0.009504704	-0.671655858
1	1	0	0	0	0	0.907533899	0.009564245	-0.67353931
0	0	1	0	0	0	0.902316403	0.009880948	-0.694896237
1	0	1	0	0	0	0.906690052	0.009704785	-0.686010163
0	1	1	0	0	0	0.907983497	0.009591541	-0.681210756
1	1	1	0	0	0	0.907802148	0.009927646	-0.703395597
0	0	0	1	0	0	0.916587019	0.005713633	-0.406526627
1	0	0	1	0	0	0.913848987	0.005915473	-0.419613022
0	1	0	1	0	0	0.915754259	0.005822821	-0.412873125
1	1	0	1	0	0	0.907834396	0.006323705	-0.448277425
0	0	1	1	0	0	0.916038713	0.00577987	-0.422165492
1	0	1	1	0	0	0.910537985	0.006128597	-0.444106639
0	1	1	1	0	0	0.911404185	0.00609931	-0.440716718
1	1	1	1	0	0	0.900159198	0.006923735	-0.49160144
0	0	0	0	1	0	0.915790179	0.005765215	-0.413200584
1	0	0	0	1	0	0.910559452	0.006115711	-0.44087924
0	1	0	0	1	0	0.916709242	0.00584177	-0.414408154
1	1	0	0	1	0	0.90378241	0.00661069	-0.468547352
0	0	1	0	1	0	0.914163017	0.005929787	-0.431852691
1	0	1	0	1	0	0.905445276	0.006485935	-0.473055698
0	1	1	0	1	0	0.910183338	0.00615888	-0.446115094
1	1	1	0	1	0	0.893349069	0.007238995	-0.519513653
0	0	0	1	1	0	0.915298355	0.005702828	-0.404691683
1	0	0	1	1	0	0.916549628	0.005770379	-0.411135301
0	1	0	1	1	0	0.918115218	0.005639771	-0.400859476
1	1	0	1	1	0	0.911546913	0.006140079	-0.4362837
0	0	1	1	1	0	0.917606032	0.005751333	-0.417751287
1	0	1	1	1	0	0.912102452	0.006059448	-0.435379318
0	1	1	1	1	0	0.915354902	0.005877223	-0.422951189
1	1	1	1	1	0	0.901867549	0.006745126	-0.476071255
0	0	0	0	0	1	0.913785955	0.00583828	-0.417213776

1	0	0	0	0	1	0.909486919	0.00617104	-0.443449286
0	1	0	0	0	1	0.915586962	0.005931154	-0.421546
1	1	0	0	0	1	0.902328194	0.006630053	-0.470982215
0	0	1	0	0	1	0.916561879	0.005757097	-0.414836746
1	0	1	0	0	1	0.908427406	0.006296439	-0.454369631
0	1	1	0	0	1	0.913991473	0.00602421	-0.431212118
1	1	1	0	0	1	0.896855973	0.007015649	-0.496689542
0	0	0	1	0	1	0.914635656	0.005776557	-0.406473696
1	0	0	1	0	1	0.914237161	0.005890909	-0.41663583
0	1	0	1	0	1	0.914618986	0.005850193	-0.41476603
1	1	0	1	0	1	0.907627734	0.006309331	-0.443686592
0	0	1	1	0	1	0.917328405	0.005671997	-0.405760229
1	0	1	1	0	1	0.914100388	0.005915184	-0.421745991
0	1	1	1	0	1	0.914068524	0.005924598	-0.42138084
1	1	1	1	0	1	0.901982394	0.006723614	-0.471775099
0	0	0	0	1	1	0.914907258	0.005800663	-0.413791842
1	0	0	0	1	1	0.909541655	0.006160757	-0.439332931
0	1	0	0	1	1	0.917164846	0.005803008	-0.410744493
1	1	0	0	1	1	0.903412976	0.00653075	-0.457012329
0	0	1	0	1	1	0.91788653	0.005694175	-0.411983455
1	0	1	0	1	1	0.910158947	0.006212238	-0.443570296
0	1	1	0	1	1	0.916786491	0.005848515	-0.417121258
1	1	1	0	1	1	0.899390184	0.006840629	-0.485131083
0	0	0	1	1	1	0.914350161	0.005785407	-0.407763102
1	0	0	1	1	1	0.916704315	0.005780615	-0.409678793
0	1	0	1	1	1	0.9172162	0.005715107	-0.403292335
1	1	0	1	1	1	0.911703361	0.006133681	-0.429583591
0	0	1	1	1	1	0.918709002	0.005612251	-0.402947986
1	0	1	1	1	1	0.91619043	0.005855489	-0.417356553
0	1	1	1	1	1	0.917979888	0.005733235	-0.407534988
1	1	1	1	1	1	0.907486624	0.006455964	-0.456437853

Table B.2: Cross-validation summary for the expert behaviour model that was applied to iRecord Coleoptera data. Contextual information included in model refers to the information included in the overall matrix to calculate $P(S \mid R, H, D, K)$, the probability of true species S, given the recorded species, R, and contextual information H. Model selection metrics are as described in Appendix B.1.

Contextual information included in the model				**Coccinellidae records model selection metrics**			**Remaining Coleoptera records model selection metrics**		
Data cleaner result	**Sample method**	**UK Habitat category**	**Season**	**Proportion correct**	**Mean squared error**	**Log likelihood**	**Proportion correct**	**Mean squared error**	**Log likelihood**
0	0	0	0	0.958561888	0.005885833	-0.20323671	0.95716056	0.001964051	-1.54886
1	0	0	0	0.958522749	0.007156035	-0.22507814	0.95279529	0.001991753	-1.71446
0	1	0	0	0.957860631	0.00614	-0.21222723	0.95165188	0.001975957	-1.62934
1	1	0	0	0.958536648	0.007338604	-0.23258588	0.94853	0.002001884	-1.78859
0	0	1	0	0.957625733	0.01033926	-0.32274299	0.91684015	0.00214959	-2.73416
1	0	1	0	0.954917244	0.011495869	-0.38039354	0.90700444	0.002164674	-2.88654
0	1	1	0	0.957162621	0.010484671	-0.33645744	0.90959692	0.002156643	-2.80324
1	1	1	0	0.954221755	0.011567159	-0.39136671	0.9007186	0.002171178	-2.95241
0	0	0	1	0.959079067	0.008250348	-0.24489323	0.94738757	0.002084606	-2.11454
1	0	0	1	0.958778207	0.009711029	-0.29061822	0.93991374	0.002101324	-2.28373
0	1	0	1	0.958560699	0.008437243	-0.25609015	0.94110286	0.002090978	-2.18907
1	1	0	1	0.95818753	0.009869617	-0.30286919	0.9337774	0.00210919	-2.35579
0	0	1	1	0.954053094	0.012978718	-0.4852712	0.8685586	0.002201057	-3.29081
1	0	1	1	0.947099837	0.0139786	-0.56301311	0.85657478	0.002209989	-3.43551
0	1	1	1	0.952748919	0.013070308	-0.50200266	0.86067767	0.002203216	-3.35486
1	1	1	1	0.946226957	0.014052059	-0.57887767	0.84931468	0.00221454	-3.49302

Table B.3: Cross-validation summary for the expert behaviour model that was applied to iRecord Diptera data. Contextual information included in model refers to the information included in the overall matrix to calculate $P(S \mid R, H, D, K)$, the probability of true species S, given the recorded species, R, and contextual information H. Model selection metrics are as described in Appendix B.1.

Contextual information included in the model				**Syphidae records**			**Remaining Diptera records**		
Data cleaner result	**Sample method**	**UK Habitat category**	**Season**	**Proportion correct**	**Mean squared error**	**Log likelihood**	**Proportion correct**	**Mean squared error**	**Log likelihood**
0	0	0	0	0.969175	0.003241	-0.39449	0.953008	0.003707	-1.26141
1	0	0	0	0.96903	0.003448	-0.53116	0.949598	0.003755	-1.33797
0	1	0	0	0.968441	0.003264	-0.42317	0.949116	0.003788	-1.39444
1	1	0	0	0.967846	0.003472	-0.56345	0.945864	0.003833	-1.47054
0	0	1	0	0.962148	0.004063	-0.94674	0.945249	0.004016	-1.61674
1	0	1	0	0.955393	0.004216	-1.16719	0.941376	0.004051	-1.69072
0	1	1	0	0.960628	0.004079	-0.97908	0.939279	0.004081	-1.7536
1	1	1	0	0.95378	0.004229	-1.19962	0.933201	0.004118	-1.83195
0	0	0	1	0.968353	0.003578	-0.56692	0.90525	0.004493	-2.56036
1	0	0	1	0.966415	0.00378	-0.75623	0.899659	0.004515	-2.62201
0	1	0	1	0.967224	0.003599	-0.60116	0.890805	0.004531	-2.69443
1	1	0	1	0.965136	0.003798	-0.79223	0.886308	0.004555	-2.75274
0	0	1	1	0.953107	0.004303	-1.28348	0.863595	0.004618	-2.93938
1	0	1	1	0.94144	0.004439	-1.5309	0.855272	0.004637	-2.99973
0	1	1	1	0.951476	0.004316	-1.31922	0.846562	0.00465	-3.06485
1	1	1	1	0.938838	0.004453	-1.5679	0.8399	0.004673	-3.1207

Appendix C

Chapter 4

Table C.1: Full cross-validation results for observer ID models applied to MammalWeb data using the community consensus verification model. Variables included in π_1 refer to the contextual information that was included in the confusion matrix to calculate $P(R \mid S, O, \pi_1)$, the probability of a species being classified as a particular species given the true species and the observer. As described in Appendix B.1, Variables included in π_2 refer to the context information that was included in the context matrix to calculate $P(S \mid H, \pi_2)$, the probability of the true species given the environmental context. Model selection metrics are as described in Appendix B.1.

Variables included in π_1	Variables included in π_2			Model selection metrics		
Observer ID	Habitat	Season	Time	Proportion correct	Mean squared error	Log likelihood
0	1	1	0	0.934781537	0.003576593	-0.353810084
0	1	1	1	0.934582977	0.003588988	-0.354605015
0	1	0	1	0.934771878	0.003634319	-0.360105823
0	1	0	0	0.934734316	0.003619812	-0.362087377
0	0	1	1	0.932842565	0.003688106	-0.370366107
0	0	1	0	0.932936159	0.003691745	-0.373848182
0	0	0	1	0.932536506	0.003734691	-0.374542189
0	0	0	0	0.917713526	0.007357774	-0.659816714
1	1	1	1	0.919595249	0.00429944	-0.411861073
1	1	1	0	0.917190652	0.004419336	-0.42561421
1	1	0	1	0.917074746	0.00441696	-0.426726839
1	1	0	0	0.915340203	0.004534782	-0.444592947
1	0	1	1	0.913403067	0.004680195	-0.456495006
1	0	0	1	0.912471655	0.00474525	-0.468580855
1	0	1	0	0.91254877	0.004794747	-0.471413388
1	0	0	0	0.92904671	0.006896607	-0.636739642

Table C.2: Full cross-validation results for observer traits models applied to MammalWeb data using the community consensus verification model. Variables included in π_1 refer to the contextual information that was included in the confusion matrix to calculate $P(R \mid S, O, \pi_1)$, the probability of a species being classified as a particular species given the true species and the observer traits. MammalWeb role refers to whether the observer was a spotter (only classifies photos) or a trapper (also records observations using camera traps). As described in Appendix B.1, Variables included in π_2 refer to the context information that was included in the context matrix to calculate $P(S \mid H, \pi_2)$, the probability of the true species given the environmental context. Model selection metrics are as described in Appendix B.1.

Variables included in π_1				**Variables included in π_2**			**Model selection metrics**		
MammalWeb role	**Classification number**	**Years classifying**	**Accuracy**	**Habitat**	**Season**	**Time**	**Proportion correct**	**Mean squared error**	**Log likelihood**
0	0	0	0	0	0	0	0.917564707	0.007358504	-0.658950527
1	0	0	0	0	0	0	0.918951344	0.007320674	-0.656694909
0	1	0	0	0	0	0	0.920274825	0.00718009	-0.648804134
1	1	0	0	0	0	0	0.922433704	0.007141178	-0.647804469
0	0	1	0	0	0	0	0.918861991	0.007367266	-0.66527163
1	0	1	0	0	0	0	0.922268586	0.007276476	-0.654326661
0	1	1	0	0	0	0	0.922066815	0.007133541	-0.649175039
1	1	1	0	0	0	0	0.924785958	0.00710279	-0.647117403
0	0	0	1	0	0	0	0.922395633	0.006886964	-0.625157406
1	0	0	1	0	0	0	0.924804766	0.006924103	-0.628412877
0	1	0	1	0	0	0	0.924834925	0.006743164	-0.619348751
1	1	0	1	0	0	0	0.927367324	0.006782604	-0.624618871
0	0	1	1	0	0	0	0.924344014	0.006952251	-0.631302329
1	0	1	1	0	0	0	0.927802102	0.006996318	-0.635089732
0	1	1	1	0	0	0	0.926592227	0.006808449	-0.627836032
1	1	1	1	0	0	0	0.928355896	0.007011132	-0.643942551
0	0	0	0	1	0	0	0.93454631	0.003629007	-0.362863369
1	0	0	0	1	0	0	0.933623027	0.003672955	-0.362944598
0	1	0	0	1	0	0	0.933295468	0.003687094	-0.366649852
1	1	0	0	1	0	0	0.930553416	0.003822554	-0.376711807
0	0	1	0	1	0	0	0.933121905	0.003705449	-0.368448843
1	0	1	0	1	0	0	0.929891953	0.003887442	-0.380498849
0	1	1	0	1	0	0	0.930931881	0.003833796	-0.38085235
1	1	1	0	1	0	0	0.925648967	0.004112994	-0.401000157
0	0	0	1	1	0	0	0.935591677	0.003583606	-0.359626467
1	0	0	1	1	0	0	0.932698705	0.003715782	-0.367826948
0	1	0	1	1	0	0	0.933051048	0.003688044	-0.369265997
1	1	0	1	1	0	0	0.929158588	0.003922897	-0.387711587
0	0	1	1	1	0	0	0.933552223	0.003726766	-0.372006478
1	0	1	1	1	0	0	0.926856579	0.004019707	-0.393622333
0	1	1	1	1	0	0	0.930203155	0.003908693	-0.387799804
1	1	1	1	1	0	0	0.919840139	0.004323169	-0.422511153
0	0	0	0	0	1	0	0.933033589	0.003692323	-0.371262978
1	0	0	0	0	1	0	0.931549686	0.003754004	-0.377357437
0	1	0	0	0	1	0	0.931790894	0.00377484	-0.381252394
1	1	0	0	0	1	0	0.928958244	0.003942289	-0.393750394
0	0	1	0	0	1	0	0.931997464	0.003778655	-0.378199386
1	0	1	0	0	1	0	0.928294067	0.003996779	-0.399382214

0	1	1	0	0	1	0	0.930106094	0.003904378	-0.391774257
1	1	1	0	0	1	0	0.923425084	0.004288074	-0.423971361
0	0	0	1	0	1	0	0.935065083	0.003627299	-0.36848418
1	0	0	1	0	1	0	0.930845978	0.003825762	-0.384685163
0	1	0	1	0	1	0	0.932538417	0.003769282	-0.38244908
1	1	0	1	0	1	0	0.926923731	0.004076171	-0.406937241
0	0	1	1	0	1	0	0.932616617	0.003820711	-0.386141899
1	0	1	1	0	1	0	0.925080619	0.004201672	-0.418024422
0	1	1	1	0	1	0	0.929128069	0.004019761	-0.40607704
1	1	1	1	0	1	0	0.918331309	0.004505875	-0.446323713
0	0	0	0	1	1	0	0.934522299	0.003598079	-0.355622916
1	0	0	0	1	1	0	0.934280798	0.003609708	-0.354827561
0	1	0	0	1	1	0	0.933696396	0.003636815	-0.357415045
1	1	0	0	1	1	0	0.931441442	0.00376141	-0.366920163
0	0	1	0	1	1	0	0.933078298	0.003683874	-0.363339486
1	0	1	0	1	1	0	0.931355244	0.003796275	-0.36743363
0	1	1	0	1	1	0	0.931756037	0.003766331	-0.369612717
1	1	1	0	1	1	0	0.926946214	0.004038669	-0.390966259
0	0	0	1	1	1	0	0.935851095	0.003542111	-0.351578131
1	0	0	1	1	1	0	0.934133734	0.003630669	-0.358558512
0	1	0	1	1	1	0	0.933407064	0.003649556	-0.361634827
1	1	0	1	1	1	0	0.930364394	0.003845014	-0.37789275
0	0	1	1	1	1	0	0.933677737	0.003708975	-0.365432456
1	0	1	1	1	1	0	0.929585301	0.00390918	-0.381737971
0	1	1	1	1	1	0	0.930852947	0.003847149	-0.377600011
1	1	1	1	1	1	0	0.923153084	0.004197168	-0.406722244
0	0	0	0	0	0	1	0.933041799	0.003710203	-0.372451689
1	0	0	0	0	0	1	0.932347613	0.00379135	-0.379638653
0	1	0	0	0	0	1	0.932156584	0.003775395	-0.380930085
1	1	0	0	0	0	1	0.928840287	0.003966323	-0.395137767
0	0	1	0	0	0	1	0.930877954	0.003818932	-0.382881643
1	0	1	0	0	0	1	0.928066068	0.004018023	-0.399287981
0	1	1	0	0	0	1	0.929514458	0.00393438	-0.392469066
1	1	1	0	0	0	1	0.923720297	0.004301412	-0.426827345
0	0	0	1	0	0	1	0.93372798	0.003687009	-0.372817992
1	0	0	1	0	0	1	0.93061695	0.003844491	-0.38410271
0	1	0	1	0	0	1	0.93205594	0.003794846	-0.383318531
1	1	0	1	0	0	1	0.926503754	0.004090775	-0.408088495
0	0	1	1	0	0	1	0.930949702	0.003854998	-0.388899408
1	0	1	1	0	0	1	0.925212935	0.004179027	-0.415630491
0	1	1	1	0	0	1	0.928424649	0.004027889	-0.404070858
1	1	1	1	0	0	1	0.918466875	0.004498978	-0.445706958
0	0	0	0	1	0	1	0.935104291	0.003607736	-0.356106409
1	0	0	0	1	0	1	0.933902029	0.00365357	-0.358308595
0	1	0	0	1	0	1	0.933763936	0.003682427	-0.366324582
1	1	0	0	1	0	1	0.931297135	0.003798522	-0.370121566
0	0	1	0	1	0	1	0.933020768	0.003709782	-0.365392332
1	0	1	0	1	0	1	0.930925057	0.003828682	-0.372691204
0	1	1	0	1	0	1	0.931593725	0.003799612	-0.373630616

1	1	1	0	1	0	1	0.926224333	0.004061356	-0.393114728
0	0	0	1	1	0	1	0.935131582	0.003598431	-0.356818869
1	0	0	1	1	0	1	0.932561137	0.003708265	-0.363742073
0	1	0	1	1	0	1	0.932906639	0.003697224	-0.365509391
1	1	0	1	1	0	1	0.929304665	0.003895273	-0.38045828
0	0	1	1	1	0	1	0.933230843	0.003714918	-0.367182192
1	0	1	1	1	0	1	0.927974646	0.00397166	-0.387718571
0	1	1	1	1	0	1	0.929736183	0.003904289	-0.384047409
1	1	1	1	1	0	1	0.922071163	0.004218629	-0.40662219
0	0	0	0	0	1	1	0.933236859	0.003668507	-0.367625759
1	0	0	0	0	1	1	0.932077373	0.003736713	-0.371969547
0	1	0	0	0	1	1	0.932031283	0.003762779	-0.377962723
1	1	0	0	0	1	1	0.929362006	0.003910034	-0.388181747
0	0	1	0	0	1	1	0.931502376	0.003772163	-0.376754166
1	0	1	0	0	1	1	0.928334998	0.003945084	-0.391572844
0	1	1	0	0	1	1	0.929267839	0.003898862	-0.390459257
1	1	1	0	0	1	1	0.924415454	0.00420606	-0.411160877
0	0	0	1	0	1	1	0.934774372	0.003630824	-0.364955199
1	0	0	1	0	1	1	0.931191049	0.003802648	-0.37972936
0	1	0	1	0	1	1	0.932053954	0.00375671	-0.378265003
1	1	0	1	0	1	1	0.927038825	0.004030543	-0.399068079
0	0	1	1	0	1	1	0.931802949	0.0038167	-0.382446609
1	0	1	1	0	1	1	0.925380575	0.004108666	-0.405934202
0	1	1	1	0	1	1	0.928099955	0.003992551	-0.400371927
1	1	1	1	0	1	1	0.919178251	0.004411259	-0.433625497
0	0	0	0	1	1	1	0.934077284	0.003605565	-0.355635559
1	0	0	0	1	1	1	0.934003029	0.003615383	-0.35510421
0	1	0	0	1	1	1	0.933634286	0.003634908	-0.357941622
1	1	0	0	1	1	1	0.932000891	0.003727748	-0.362068638
0	0	1	0	1	1	1	0.933158435	0.003666838	-0.361301385
1	0	1	0	1	1	1	0.931171557	0.003784368	-0.367546017
0	1	1	0	1	1	1	0.932029112	0.003734446	-0.36348234
1	1	1	0	1	1	1	0.927142791	0.003969128	-0.379826523
0	0	0	1	1	1	1	0.935570929	0.003526881	-0.347094995
1	0	0	1	1	1	1	0.934334914	0.003620694	-0.354674172
0	1	0	1	1	1	1	0.934244933	0.003624485	-0.356317676
1	1	0	1	1	1	1	0.931191677	0.003800675	-0.371225049
0	0	1	1	1	1	1	0.933954641	0.003666063	-0.362144578
1	0	1	1	1	1	1	0.929814713	0.003883742	-0.376215198
0	1	1	1	1	1	1	0.930833865	0.003817377	-0.373418985
1	1	1	1	1	1	1	0.924214399	0.004129651	-0.396141729

Table C.3: Cross-validation summary for the expert behaviour model that was applied to iRecord Coleoptera data. Contextual information included in model refers to the information on the observer that was included in the overall matrix to calculate $P(S \mid R, O, D, K)$, the probability of true species S, given the recorded species, R, and observer information O. Model selection metrics are as described in Appendix B.1.

Contextual information included in the model					**Coccinellidae records**			**Remaining Coleoptera records**		
Observer role	**Record number**	**Accuracy**	**Time recording**	**Observer ID**	**Proportion correct**	**Mean squared error**	**Log likelihood**	**Proportion correct**	**Mean squared error**	**Log likelihood**
0	0	0	0	0	0.958400328	0.005916235	-0.20454766	0.956513547	0.001964184	-1.55154
0	0	0	0	1	0.925473144	0.01337201	-0.932646985	0.755551916	0.002191741	-3.64908
0	0	0	1	0	0.958262942	0.010907045	-0.313444825	0.92089759	0.002187975	-2.96522
0	0	1	0	0	0.959876106	0.006926567	-0.216294223	0.947841719	0.002087983	-2.14929
0	0	1	1	0	0.956451928	0.011692266	-0.388982186	0.87395402	0.002208283	-3.40952
0	1	0	0	0	0.959148616	0.008630034	-0.235595831	0.950771853	0.002105004	-2.17699
0	1	0	1	0	0.956172124	0.012772738	-0.438310251	0.869050435	0.002210341	-3.42572
0	1	1	0	0	0.959604319	0.008723994	-0.245889302	0.941825964	0.002124321	-2.36389
0	1	1	1	0	0.95499869	0.012877946	-0.468670128	0.845154463	0.002213257	-3.5553
1	0	0	0	0	0.958274868	0.006448005	-0.215040838	0.954014929	0.00197218	-1.60707
1	0	0	1	0	0.957689559	0.011331486	-0.337466115	0.913711803	0.002188495	-3.01743
1	0	1	0	0	0.95973402	0.007464868	-0.230549518	0.943671705	0.002092453	-2.2031
1	0	1	1	0	0.9553966	0.012105523	-0.414028274	0.866575461	0.002208587	-3.45044
1	1	0	0	0	0.959093806	0.009184715	-0.257435205	0.946575065	0.002108899	-2.23082
1	1	0	1	0	0.954485109	0.013103999	-0.466288861	0.861624481	0.002211339	-3.46801
1	1	1	0	0	0.95939465	0.009275153	-0.267725856	0.937742218	0.002127574	-2.41437
1	1	1	1	0	0.95348425	0.013195706	-0.495419418	0.83746658	0.002214662	-3.59338

Table C.4: Cross-validation summary for the expert behaviour model that was applied to iRecord Diptera data. Contextual information included in model refers to the information on the observer that was included in the overall matrix to calculate $P(S \mid R, O, D, K)$, the probability of true species S, given the recorded species, R, and observer information O. Model selection metrics are as described in Appendix B.1.

Contextual information included in the model					**Syphidae records**			**Remaining Diptera records**		
Observer role	**Record number**	**Accuracy**	**Time recording**	**Observer ID**	**Proportion correct**	**Mean squared error**	**Log likelihood**	**Proportion correct**	**Mean squared error**	**Log likelihood**
0	0	0	0	0	0.969031	0.003242	-0.39521	0.953077	0.003705	-1.26129
0	0	0	0	1	0.864507	0.004793	-2.607	0.785866	0.004586	-3.23074
0	0	0	1	0	0.964051	0.004303	-1.04257	0.918029	0.004572	-2.64313
0	0	1	0	0	0.967191	0.003573	-0.59219	0.943892	0.004159	-1.83904
0	0	1	1	0	0.953398	0.004482	-1.37013	0.868947	0.004669	-3.11698
0	1	0	0	0	0.967747	0.003905	-0.69396	0.948643	0.004206	-1.83868
0	1	0	1	0	0.953856	0.004643	-1.59773	0.864895	0.004668	-3.10178
0	1	1	0	0	0.966006	0.003999	-0.80748	0.940021	0.004288	-2.0379
0	1	1	1	0	0.945002	0.004687	-1.75532	0.842062	0.004688	-3.25467
1	0	0	0	0	0.96858	0.003268	-0.42356	0.9494	0.003752	-1.31506
1	0	0	1	0	0.962487	0.004314	-1.08117	0.909339	0.004579	-2.68149
1	0	1	0	0	0.966242	0.003597	-0.62334	0.938029	0.004189	-1.89042
1	0	1	1	0	0.951374	0.004495	-1.40627	0.860483	0.004676	-3.1431
1	1	0	0	0	0.966338	0.003925	-0.72931	0.941455	0.00423	-1.88867
1	1	0	1	0	0.951801	0.004653	-1.63421	0.858801	0.004673	-3.12919
1	1	1	0	0	0.964578	0.004017	-0.84243	0.932414	0.004309	-2.08807
1	1	1	1	0	0.942541	0.00469	-1.79195	0.833521	0.004695	-3.28439

Appendix D

Chapter 5

Table D.1 Full results for the protected area coverage analysis of 58 UK Butterfly species where inaccuracies have been introduced into the data by a random guessing scenario.

Species	N	Estimated area of occupancy (km²)	Protected area overlap (%)	Inaccuracy
Aglais io	184707	580267.2	19.12416	10% inaccuracy
Aglais io	184598	572504.4	19.27975	2% inaccuracy
Aglais io	184728	591825.6	18.81213	20% inaccuracy
Aglais io	184760	568884.5	19.35305	5% inaccuracy
Aglais io	184715	572504.4	19.27975	Original data
Aglais urticae	120334	591036.8	19.10815	10% inaccuracy
Aglais urticae	120334	591036.8	19.10815	2% inaccuracy
Aglais urticae	120193	590895.7	19.10302	20% inaccuracy
Aglais urticae	120477	591036.8	19.10815	5% inaccuracy
Aglais urticae	120364	591036.8	19.10815	Original data
Anthocharis cardamines	89625	575282.9	19.13195	10% inaccuracy
Anthocharis cardamines	89466	557321.2	19.37706	2% inaccuracy
Anthocharis cardamines	89491	566896.3	19.5337	20% inaccuracy
Anthocharis cardamines	89465	560652.3	19.46824	5% inaccuracy
Anthocharis cardamines	89445	553120.1	19.47996	Original data
Apatura iris	479	130913.9	22.56293	10% inaccuracy
Apatura iris	461	87024.2	22.55752	2% inaccuracy
Apatura iris	448	112853.2	23.88931	20% inaccuracy
Apatura iris	462	74055.94	17.04851	5% inaccuracy
Apatura iris	460	36266	21.69369	Original data
Aphantopus hyperantus	252859	571152.8	19.21959	10% inaccuracy
Aphantopus hyperantus	252669	545205.2	19.15039	2% inaccuracy
Aphantopus hyperantus	252820	597408.3	18.80014	20% inaccuracy
Aphantopus hyperantus	252726	567042.3	19.28167	5% inaccuracy
Aphantopus hyperantus	252681	511745.2	19.08535	Original data
Argynnis paphia	50588	513720.9	19.72636	10% inaccuracy
Argynnis paphia	50545	445231.1	19.87316	2% inaccuracy
Argynnis paphia	50624	536735.6	19.31373	20% inaccuracy
Argynnis paphia	50638	526272.1	19.1363	5% inaccuracy
Argynnis paphia	50559	228682.5	19.72489	Original data
Aricia agestis	40631	518168.9	19.80213	10% inaccuracy
Aricia agestis	40622	474339.3	19.24526	2% inaccuracy
Aricia agestis	40546	558154.9	19.30584	20% inaccuracy
Aricia agestis	40669	474806.3	20.27512	5% inaccuracy
Aricia agestis	40601	193606.8	19.3958	Original data
Aricia artaxerxes	4441	430669.6	20.07352	10% inaccuracy
Aricia artaxerxes	4492	259289.6	23.60662	2% inaccuracy
Aricia artaxerxes	4473	398625.3	21.41258	20% inaccuracy
Aricia artaxerxes	4487	318591.7	21.41253	5% inaccuracy
Aricia artaxerxes	4471	13335.5	48.81071	Original data
Boloria euphrosyne	4516	372381.8	22.79499	10% inaccuracy
Boloria euphrosyne	4534	274388.1	24.46554	2% inaccuracy

Boloria euphrosyne	4477	426212.8	21.5285	20% inaccuracy
Boloria euphrosyne	4537	266121.3	24.51068	5% inaccuracy
Boloria euphrosyne	4539	140640	31.56002	Original data
Boloria selene	8854	512057.4	20.41815	10% inaccuracy
Boloria selene	8861	463282.2	21.21362	2% inaccuracy
Boloria selene	8947	530045.8	19.54113	20% inaccuracy
Boloria selene	8867	514296.9	19.6842	5% inaccuracy
Boloria selene	8870	370303.5	22.91718	Original data
Callophrys rubi	12017	512040.2	20.11945	10% inaccuracy
Callophrys rubi	12007	499689.7	19.90418	2% inaccuracy
Callophrys rubi	12004	503593.8	20.31442	20% inaccuracy
Callophrys rubi	12028	497079.6	20.15744	5% inaccuracy
Callophrys rubi	12025	434081.1	21.67565	Original data
Carterocephalus palaemon	995	189483.5	20.79537	10% inaccuracy
Carterocephalus palaemon	974	46820.82	28.32762	2% inaccuracy
Carterocephalus palaemon	968	336633.6	21.28313	20% inaccuracy
Carterocephalus palaemon	983	138478.9	24.99984	5% inaccuracy
Carterocephalus palaemon	980	4305.853	24.02542	Original data
Celastrina argiolus	43299	511440.4	19.55033	10% inaccuracy
Celastrina argiolus	43411	496621.6	19.46255	2% inaccuracy
Celastrina argiolus	43433	556965.1	19.09569	20% inaccuracy
Celastrina argiolus	43459	530169.6	18.9925	5% inaccuracy
Celastrina argiolus	43396	309212.3	20.29071	Original data
Coenonympha pamphilus	150852	587448	19.01243	10% inaccuracy
Coenonympha pamphilus	150935	582364.2	18.94145	2% inaccuracy
Coenonympha pamphilus	150848	573695.7	19.2863	20% inaccuracy
Coenonympha pamphilus	150764	584226.6	18.9122	5% inaccuracy
Coenonympha pamphilus	150917	579226.5	19.01562	Original data
Coenonympha tullia	991	441729	21.89376	10% inaccuracy
Coenonympha tullia	993	443665.2	21.00485	2% inaccuracy
Coenonympha tullia	988	487370.6	20.91237	20% inaccuracy
Coenonympha tullia	994	443104.5	21.65862	5% inaccuracy
Coenonympha tullia	988	166060.1	25.05485	Original data
Colias croceus	5941	473752.5	19.32954	10% inaccuracy
Colias croceus	5947	325501	21.37831	2% inaccuracy
Colias croceus	5853	505260.3	20.05763	20% inaccuracy
Colias croceus	5923	357149.5	21.02878	5% inaccuracy
Colias croceus	5916	285079.9	20.85504	Original data
Cupido minimus	10127	504380.9	20.44323	10% inaccuracy
Cupido minimus	10113	403725	21.90506	2% inaccuracy
Cupido minimus	10118	521946.3	19.02589	20% inaccuracy
Cupido minimus	10159	426961.9	21.18411	5% inaccuracy
Cupido minimus	10137	208370.3	23.25082	Original data
Erebia aethiops	3838	456147.8	21.79722	10% inaccuracy
Erebia aethiops	3800	293984.8	22.97063	2% inaccuracy
Erebia aethiops	3759	466131.6	21.08858	20% inaccuracy
Erebia aethiops	3820	458530.7	21.30083	5% inaccuracy
Erebia aethiops	3823	143656.3	27.36644	Original data
Erebia epiphron	261	64242.74	33.05098	10% inaccuracy

Erebia epiphron	256	6679.372	51.41869	2% inaccuracy
Erebia epiphron	247	145077	23.00595	20% inaccuracy
Erebia epiphron	246	50299.81	25.18593	5% inaccuracy
Erebia epiphron	254	4928.171	50.07188	Original data
Erynnis tages	24239	530726.5	19.02268	10% inaccuracy
Erynnis tages	24180	383028.2	20.56461	2% inaccuracy
Erynnis tages	24128	527169.6	19.5622	20% inaccuracy
Erynnis tages	24211	455125.2	20.61803	5% inaccuracy
Erynnis tages	24235	257483.9	22.68824	Original data
Euphydryas aurinia	2662	427915	20.57538	10% inaccuracy
Euphydryas aurinia	2696	294270.6	20.84907	2% inaccuracy
Euphydryas aurinia	2684	469690.8	20.22976	20% inaccuracy
Euphydryas aurinia	2694	283868.6	21.87723	5% inaccuracy
Euphydryas aurinia	2689	75002.82	23.94571	Original data
Fabriciana adippe	1020	153578.5	25.97098	10% inaccuracy
Fabriciana adippe	1001	8880.089	37.89653	2% inaccuracy
Fabriciana adippe	1008	240901.1	20.81203	20% inaccuracy
Fabriciana adippe	1019	114251.1	24.80987	5% inaccuracy
Fabriciana adippe	1009	1919.403	56.18406	Original data
Favonius quercus	7171	494405.6	19.29038	10% inaccuracy
Favonius quercus	7212	263778.2	22.36014	2% inaccuracy
Favonius quercus	7183	447504.7	20.94946	20% inaccuracy
Favonius quercus	7194	324408.3	22.47103	5% inaccuracy
Favonius quercus	7201	243452.8	22.45568	Original data
Gonepteryx rhamni	152644	562065.3	18.89022	10% inaccuracy
Gonepteryx rhamni	153042	518290.4	19.17758	2% inaccuracy
Gonepteryx rhamni	152840	575785.5	19.48622	20% inaccuracy
Gonepteryx rhamni	152903	554088	18.92714	5% inaccuracy
Gonepteryx rhamni	152874	301129.9	21.40257	Original data
Hamearis lucina	1715	195040.2	21.58459	10% inaccuracy
Hamearis lucina	1725	110465.6	25.49609	2% inaccuracy
Hamearis lucina	1706	360393.5	23.01643	20% inaccuracy
Hamearis lucina	1734	171476.9	25.12821	5% inaccuracy
Hamearis lucina	1725	49440.83	31.79749	Original data
Hesperia comma	3116	380286.9	20.81265	10% inaccuracy
Hesperia comma	3065	62603.98	31.04548	2% inaccuracy
Hesperia comma	3067	405568.4	21.97746	20% inaccuracy
Hesperia comma	3069	269804.8	22.15256	5% inaccuracy
Hesperia comma	3073	14340.94	44.11636	Original data
Hipparchia semele	11846	537280.2	19.11098	10% inaccuracy
Hipparchia semele	11838	493436.6	17.44317	2% inaccuracy
Hipparchia semele	11915	558125.2	19.31844	20% inaccuracy
Hipparchia semele	11867	555342.5	19.00218	5% inaccuracy
Hipparchia semele	11841	380289.5	17.99586	Original data
Lasiommata megera	16165	492464.3	19.17182	10% inaccuracy
Lasiommata megera	16166	404848.5	18.63638	2% inaccuracy
Lasiommata megera	16149	532493.1	19.34892	20% inaccuracy
Lasiommata megera	16184	506728.9	19.36787	5% inaccuracy
Lasiommata megera	16142	360128.5	19.40038	Original data

Leptidea sinapis	4609	367225.7	21.84757	10% inaccuracy
Leptidea sinapis	4655	169779.2	23.09522	2% inaccuracy
Leptidea sinapis	4727	397201.8	22.04229	20% inaccuracy
Leptidea sinapis	4643	206110.1	22.6975	5% inaccuracy
Leptidea sinapis	4665	36998.11	23.2966	Original data
Limenitis camilla	8798	442236.6	20.01368	10% inaccuracy
Limenitis camilla	8831	233808.8	21.97837	2% inaccuracy
Limenitis camilla	8935	497228.2	20.0353	20% inaccuracy
Limenitis camilla	8895	373745	22.57429	5% inaccuracy
Limenitis camilla	8866	110015.7	21.46816	Original data
Lycaena phlaeas	58271	543420.6	19.16345	10% inaccuracy
Lycaena phlaeas	58233	526411.2	19.5166	2% inaccuracy
Lycaena phlaeas	58107	560091.5	19.44748	20% inaccuracy
Lycaena phlaeas	58250	526001.3	19.47797	5% inaccuracy
Lycaena phlaeas	58182	526387.3	19.5166	Original data
Maniola jurtina	558418	598558	18.80892	10% inaccuracy
Maniola jurtina	558937	595271.4	18.89715	2% inaccuracy
Maniola jurtina	559380	594309.1	18.94868	20% inaccuracy
Maniola jurtina	558747	595260.9	18.89745	5% inaccuracy
Maniola jurtina	559031	595271.4	18.89715	Original data
Melanargia galathea	101482	539940.4	19.14766	10% inaccuracy
Melanargia galathea	101136	441955.9	21.37446	2% inaccuracy
Melanargia galathea	101515	552375.7	19.64238	20% inaccuracy
Melanargia galathea	101376	540767.8	19.49451	5% inaccuracy
Melanargia galathea	101230	193855.1	21.15487	Original data
Melitaea athalia	1405	209301.1	21.70823	10% inaccuracy
Melitaea athalia	1395	89501.22	21.32245	2% inaccuracy
Melitaea athalia	1431	201423	23.46738	20% inaccuracy
Melitaea athalia	1389	127061.7	19.97687	5% inaccuracy
Melitaea athalia	1397	613.577	5.792878	Original data
Melitaea cinxia	314	102896.4	21.70263	10% inaccuracy
Melitaea cinxia	308	3624.379	41.73114	2% inaccuracy
Melitaea cinxia	305	132419.6	23.69195	20% inaccuracy
Melitaea cinxia	286	9377.883	33.04715	5% inaccuracy
Melitaea cinxia	304	165.526	50.88322	Original data
Nymphalis polychloros	30	25281.38	26.58232	10% inaccuracy
Nymphalis polychloros	27	12406.22	25.93525	2% inaccuracy
Nymphalis polychloros	26	44227.47	27.92332	20% inaccuracy
Nymphalis polychloros	27	34510.52	20.87399	5% inaccuracy
Nymphalis polychloros	26	12406.22	25.93525	Original data
Ochlodes sylvanus	92965	566232.5	19.22556	10% inaccuracy
Ochlodes sylvanus	93018	501178.7	19.90576	2% inaccuracy
Ochlodes sylvanus	93199	560399.6	19.39396	20% inaccuracy
Ochlodes sylvanus	93118	521032.9	19.58077	5% inaccuracy
Ochlodes sylvanus	93119	331934.2	20.54358	Original data
Papilio machaon	713	172876.1	22.74707	10% inaccuracy
Papilio machaon	721	11245.13	36.5678	2% inaccuracy
Papilio machaon	713	262355.4	22.82244	20% inaccuracy
Papilio machaon	711	111238.7	20.02756	5% inaccuracy

Papilio machaon	716	9883.109	23.32231	Original data
Pararge aegeria	333157	598103.9	18.80824	10% inaccuracy
Pararge aegeria	333091	561483.4	19.46321	2% inaccuracy
Pararge aegeria	333438	583122.7	19.14517	20% inaccuracy
Pararge aegeria	333016	572202.9	19.25658	5% inaccuracy
Pararge aegeria	333167	556020	19.59625	Original data
Phengaris arion	19	28880.72	14.89035	10% inaccuracy
Phengaris arion	34	84229.81	24.23934	20% inaccuracy
Pieris brassicae	252572	637942	17.72104	10% inaccuracy
Pieris brassicae	252363	626389.9	17.99511	2% inaccuracy
Pieris brassicae	252411	587161.8	19.17775	20% inaccuracy
Pieris brassicae	252373	626568.6	17.99149	5% inaccuracy
Pieris brassicae	252318	626389.9	17.99511	Original data
Pieris napi	243764	593721.1	18.98957	10% inaccuracy
Pieris napi	243823	598408.9	18.86283	2% inaccuracy
Pieris napi	244168	593607.9	18.98695	20% inaccuracy
Pieris napi	243492	593954.8	18.99149	5% inaccuracy
Pieris napi	243700	593954.8	18.99149	Original data
Pieris rapae	329340	587581.3	18.88044	10% inaccuracy
Pieris rapae	329076	583463.9	18.86445	2% inaccuracy
Pieris rapae	328835	596608.8	18.80166	20% inaccuracy
Pieris rapae	329307	592519.6	18.85259	5% inaccuracy
Pieris rapae	329145	575697.6	18.98081	Original data
Plebejus argus	11010	398239.4	21.73574	10% inaccuracy
Plebejus argus	10931	255261.3	21.25389	2% inaccuracy
Plebejus argus	10841	493139.6	19.8803	20% inaccuracy
Plebejus argus	10966	449240.7	19.47266	5% inaccuracy
Plebejus argus	10958	52139.32	26.63524	Original data
Polygonia c-album	84052	569614.7	19.38516	10% inaccuracy
Polygonia c-album	84098	482170.3	19.41387	2% inaccuracy
Polygonia c-album	84178	561595.3	19.38339	20% inaccuracy
Polygonia c-album	84006	491360.1	19.568	5% inaccuracy
Polygonia c-album	84073	413094.2	21.09203	Original data
Polyommatus bellargus	12147	451034	20.49276	10% inaccuracy
Polyommatus bellargus	12065	268860.9	24.20511	2% inaccuracy
Polyommatus bellargus	12048	482511.5	20.38153	20% inaccuracy
Polyommatus bellargus	12117	470728.7	21.13587	5% inaccuracy
Polyommatus bellargus	12087	25977.4	46.03947	Original data
Polyommatus coridon	24780	528379.7	19.76921	10% inaccuracy
Polyommatus coridon	24905	357952.2	21.33836	2% inaccuracy
Polyommatus coridon	24740	510217.9	20.01637	20% inaccuracy
Polyommatus coridon	24748	459214.6	19.93156	5% inaccuracy
Polyommatus coridon	24848	58473.54	33.56056	Original data
Polyommatus icarus	189850	598903.1	18.90898	10% inaccuracy
Polyommatus icarus	189942	600713.9	18.87974	2% inaccuracy
Polyommatus icarus	189819	616435.8	18.36697	20% inaccuracy
Polyommatus icarus	190177	594701	19.0513	5% inaccuracy
Polyommatus icarus	189957	595248.7	18.96352	Original data
Pyrgus malvae	8625	413897.3	19.85558	10% inaccuracy

Pyrgus malvae	8605	300547.3	21.08182	2% inaccuracy
Pyrgus malvae	8573	451844.8	20.73644	20% inaccuracy
Pyrgus malvae	8601	302725.3	21.21454	5% inaccuracy
Pyrgus malvae	8604	81074.33	27.49584	Original data
Pyronia tithonus	248284	572853.7	19.34106	10% inaccuracy
Pyronia tithonus	248470	524336.7	20.00781	2% inaccuracy
Pyronia tithonus	247875	575764.4	19.43236	20% inaccuracy
Pyronia tithonus	248186	558217.3	18.95115	5% inaccuracy
Pyronia tithonus	248325	298644.9	21.59251	Original data
Satyrium pruni	295	69063.95	22.44257	10% inaccuracy
Satyrium pruni	295	13330.01	15.095	2% inaccuracy
Satyrium pruni	280	170182.4	22.43635	20% inaccuracy
Satyrium pruni	284	23687.94	29.44517	5% inaccuracy
Satyrium pruni	287	169.526	5.832583	Original data
Satyrium w-album	1237	252159.6	22.0745	10% inaccuracy
Satyrium w-album	1239	188896.6	22.21277	2% inaccuracy
Satyrium w-album	1249	246913.4	21.1448	20% inaccuracy
Satyrium w-album	1239	238484.6	21.83155	5% inaccuracy
Satyrium w-album	1247	142876.6	19.88425	Original data
Speyeria aglaja	26940	576766.3	18.99892	10% inaccuracy
Speyeria aglaja	27001	567593.1	19.16546	2% inaccuracy
Speyeria aglaja	26960	573616.4	19.06895	20% inaccuracy
Speyeria aglaja	27062	572407.6	19.06954	5% inaccuracy
Speyeria aglaja	27011	559013.4	19.00846	Original data
Thecla betulae	953	242592.1	22.87095	10% inaccuracy
Thecla betulae	961	79858.85	23.67109	2% inaccuracy
Thecla betulae	947	239809	21.75134	20% inaccuracy
Thecla betulae	960	142392.3	21.08711	5% inaccuracy
Thecla betulae	961	31878.1	34.83758	Original data
Thymelicus acteon	1417	151675.9	24.09002	10% inaccuracy
Thymelicus acteon	1411	115666	24.66895	2% inaccuracy
Thymelicus acteon	1417	322739.5	23.24783	20% inaccuracy
Thymelicus acteon	1429	173048.6	21.63541	5% inaccuracy
Thymelicus acteon	1400	107.808	95.22837	Original data
Thymelicus lineola	14983	454515.8	20.83915	10% inaccuracy
Thymelicus lineola	14891	368028.7	21.69349	2% inaccuracy
Thymelicus lineola	14822	500804.8	20.33795	20% inaccuracy
Thymelicus lineola	14798	479042.8	19.00826	5% inaccuracy
Thymelicus lineola	14913	178630.6	20.4294	Original data
Thymelicus sylvestris	82864	559139.5	19.42371	10% inaccuracy
Thymelicus sylvestris	82829	507183	18.89909	2% inaccuracy
Thymelicus sylvestris	82800	588576.5	18.91295	20% inaccuracy
Thymelicus sylvestris	82790	528962.2	19.06233	5% inaccuracy
Thymelicus sylvestris	82809	326860	21.0936	Original data
Vanessa atalanta	115241	646943.8	17.59217	10% inaccuracy
Vanessa atalanta	115149	646971	17.59158	2% inaccuracy
Vanessa atalanta	115076	644184	17.64731	20% inaccuracy
Vanessa atalanta	115119	649329.3	17.53759	5% inaccuracy
Vanessa atalanta	115136	649352.1	17.53708	Original data

Vanessa cardui	38653	605224.8	18.69949	10% inaccuracy
Vanessa cardui	38768	600028.7	18.86607	2% inaccuracy
Vanessa cardui	38627	595111.8	18.97675	20% inaccuracy
Vanessa cardui	38664	599522.9	18.86675	5% inaccuracy
Vanessa cardui	38709	599662.9	18.86351	Original data

Table D.2 Full results for the protected area coverage analysis of 58 UK Butterfly species where inaccuracies have been simulated using the species confusion matrix.

Species	N	Estimated area of occupancy (km²)	Protected area overlap	Inaccuracy
Aglais io	170196	577127.2	19.21465	10% inaccuracy
Aglais io	181864	572327.3	19.28294	2% inaccuracy
Aglais io	155597	581305.7	19.34193	20% inaccuracy
Aglais io	177420	570437.5	19.39726	5% inaccuracy
Aglais io	184715	572504.4	19.27975	Original data
Aglais urticae	121689	590974	19.11004	10% inaccuracy
Aglais urticae	120635	591036.8	19.10815	2% inaccuracy
Aglais urticae	122760	611352.3	18.57464	20% inaccuracy
Aglais urticae	121073	591036.8	19.10815	5% inaccuracy
Aglais urticae	120364	591036.8	19.10815	Original data
Anthocharis cardamines	82823	559688.8	19.52574	10% inaccuracy
Anthocharis cardamines	88092	558341.7	19.56753	2% inaccuracy
Anthocharis cardamines	76261	561018.6	19.53886	20% inaccuracy
Anthocharis cardamines	86202	554411.4	19.45477	5% inaccuracy
Anthocharis cardamines	89445	553120.1	19.47996	Original data
Apatura iris	1109	406650.6	19.71332	10% inaccuracy
Apatura iris	600	120769.1	20.49265	2% inaccuracy
Apatura iris	1727	368511.5	22.1113	20% inaccuracy
Apatura iris	759	144597	24.83716	5% inaccuracy
Apatura iris	460	36266	21.69369	Original data
Aphantopus hyperantus	241894	544636.2	18.69703	10% inaccuracy
Aphantopus hyperantus	250447	551078.9	18.8437	2% inaccuracy
Aphantopus hyperantus	231033	568161.4	19.26431	20% inaccuracy
Aphantopus hyperantus	247356	547925.7	19.09934	5% inaccuracy
Aphantopus hyperantus	252681	511745.2	19.08535	Original data
Argynnis paphia	47365	464289.9	21.55584	10% inaccuracy
Argynnis paphia	49901	325079.6	22.46543	2% inaccuracy
Argynnis paphia	44381	519231.3	20.35725	20% inaccuracy
Argynnis paphia	49006	428881.6	20.80706	5% inaccuracy
Argynnis paphia	50559	228682.5	19.72489	Original data
Aricia agestis	40415	527358.4	20.09344	10% inaccuracy
Aricia agestis	40493	473372.8	20.84717	2% inaccuracy
Aricia agestis	40267	566291.5	19.08381	20% inaccuracy
Aricia agestis	40521	536269.7	19.93773	5% inaccuracy
Aricia agestis	40601	193606.8	19.3958	Original data
Aricia artaxerxes	5135	471942.2	19.6082	10% inaccuracy
Aricia artaxerxes	4588	307596.3	22.61376	2% inaccuracy
Aricia artaxerxes	5850	503461.2	18.529	20% inaccuracy
Aricia artaxerxes	4767	481057.4	19.83163	5% inaccuracy
Aricia artaxerxes	4471	13335.5	48.81071	Original data
Boloria euphrosyne	7222	526650.7	20.00017	10% inaccuracy
Boloria euphrosyne	5062	391911.8	22.68663	2% inaccuracy
Boloria euphrosyne	10108	531860.4	19.96632	20% inaccuracy
Boloria euphrosyne	5888	502714.2	20.65396	5% inaccuracy
Boloria euphrosyne	4539	140640	31.56002	Original data
Boloria selene	9361	492762.2	20.21557	10% inaccuracy

Boloria selene	8996	435141.8	22.64105	2% inaccuracy
Boloria selene	10015	513167.3	19.38583	20% inaccuracy
Boloria selene	9113	505920.2	19.89516	5% inaccuracy
Boloria selene	8870	370303.5	22.91718	Original data
Callophrys rubi	11380	436740.2	21.73271	10% inaccuracy
Callophrys rubi	11896	434081.1	21.67565	2% inaccuracy
Callophrys rubi	10856	433767	21.7077	20% inaccuracy
Callophrys rubi	11755	430657.2	21.79873	5% inaccuracy
Callophrys rubi	12025	434081.1	21.67565	Original data
Carterocephalus palaemon	4068	499297.1	19.66535	10% inaccuracy
Carterocephalus palaemon	1601	343077.3	23.08817	2% inaccuracy
Carterocephalus palaemon	7147	486770.3	20.55188	20% inaccuracy
Carterocephalus palaemon	2558	386927.2	21.36974	5% inaccuracy
Carterocephalus palaemon	980	4305.853	24.02542	Original data
Celastrina argiolus	45829	561849.6	19.03638	10% inaccuracy
Celastrina argiolus	43848	513594.4	18.71533	2% inaccuracy
Celastrina argiolus	48588	562081.9	19.43698	20% inaccuracy
Celastrina argiolus	44741	521083.7	19.53467	5% inaccuracy
Celastrina argiolus	43396	309212.3	20.29071	Original data
Coenonympha pamphilus	173339	587945.5	18.8755	10% inaccuracy
Coenonympha pamphilus	155387	584207.4	18.92997	2% inaccuracy
Coenonympha pamphilus	195787	587872	18.83504	20% inaccuracy
Coenonympha pamphilus	162262	585152.4	18.91923	5% inaccuracy
Coenonympha pamphilus	150917	579226.5	19.01562	Original data
Coenonympha tullia	7153	569413.2	19.42472	10% inaccuracy
Coenonympha tullia	2115	545122.8	19.57172	2% inaccuracy
Coenonympha tullia	13234	573584	19.33415	20% inaccuracy
Coenonympha tullia	3989	566548.1	19.47852	5% inaccuracy
Coenonympha tullia	988	166060.1	25.05485	Original data
Colias croceus	14905	379845.6	21.84076	10% inaccuracy
Colias croceus	7644	329596.7	21.36452	2% inaccuracy
Colias croceus	23804	393570.8	21.83806	20% inaccuracy
Colias croceus	10344	332705.8	20.77923	5% inaccuracy
Colias croceus	5916	285079.9	20.85504	Original data
Cupido minimus	21372	568778.4	19.10732	10% inaccuracy
Cupido minimus	12447	480891.6	20.49756	2% inaccuracy
Cupido minimus	33282	573787.9	19.26051	20% inaccuracy
Cupido minimus	15873	545132.9	18.72906	5% inaccuracy
Cupido minimus	10137	208370.3	23.25082	Original data
Erebia aethiops	4857	507973.1	20.81932	10% inaccuracy
Erebia aethiops	4019	437924.4	21.67232	2% inaccuracy
Erebia aethiops	5866	519799.6	19.95144	20% inaccuracy
Erebia aethiops	4364	492856.2	21.17567	5% inaccuracy
Erebia aethiops	3823	143656.3	27.36644	Original data
Erebia epiphron	2987	476591.5	20.79249	10% inaccuracy
Erebia epiphron	778	359249.6	23.09308	2% inaccuracy
Erebia epiphron	5514	518818.9	19.98662	20% inaccuracy
Erebia epiphron	1581	505260.9	20.3965	5% inaccuracy
Erebia epiphron	254	4928.171	50.07188	Original data

Erynnis tages	23875	475892.1	19.76234	10% inaccuracy
Erynnis tages	24207	356522.6	22.12397	2% inaccuracy
Erynnis tages	23778	568045.3	18.87535	20% inaccuracy
Erynnis tages	24130	483779	19.41798	5% inaccuracy
Erynnis tages	24235	257483.9	22.68824	Original data
Euphydryas aurinia	3027	433509	20.75334	10% inaccuracy
Euphydryas aurinia	2751	398931	19.92935	2% inaccuracy
Euphydryas aurinia	3247	450677.3	21.85417	20% inaccuracy
Euphydryas aurinia	2862	373563.5	21.86825	5% inaccuracy
Euphydryas aurinia	2689	75002.82	23.94571	Original data
Fabriciana adippe	1763	371829.5	20.60386	10% inaccuracy
Fabriciana adippe	1161	230280.3	21.74826	2% inaccuracy
Fabriciana adippe	2494	410862.2	20.66363	20% inaccuracy
Fabriciana adippe	1377	266924.2	21.74048	5% inaccuracy
Fabriciana adippe	1009	1919.403	56.18406	Original data
Favonius quercus	6557	243707.6	22.44132	10% inaccuracy
Favonius quercus	7086	239978.6	22.62907	2% inaccuracy
Favonius quercus	5875	236530	22.29716	20% inaccuracy
Favonius quercus	6878	243707.6	22.44132	5% inaccuracy
Favonius quercus	7201	243452.8	22.45568	Original data
Gonepteryx rhamni	141329	500311.7	20.21795	10% inaccuracy
Gonepteryx rhamni	150616	454402.1	20.32325	2% inaccuracy
Gonepteryx rhamni	129808	543427.4	18.83036	20% inaccuracy
Gonepteryx rhamni	147159	481662.2	19.15309	5% inaccuracy
Gonepteryx rhamni	152874	301129.9	21.40257	Original data
Hamearis lucina	2740	360774.7	23.7213	10% inaccuracy
Hamearis lucina	1939	219367.6	23.09687	2% inaccuracy
Hamearis lucina	3753	491163.8	19.75918	20% inaccuracy
Hamearis lucina	2251	317276.9	21.23761	5% inaccuracy
Hamearis lucina	1725	49440.83	31.79749	Original data
Hesperia comma	4144	447534.9	20.15035	10% inaccuracy
Hesperia comma	3298	291884.2	21.53325	2% inaccuracy
Hesperia comma	5117	387300.5	19.46791	20% inaccuracy
Hesperia comma	3649	280825.7	22.49548	5% inaccuracy
Hesperia comma	3073	14340.94	44.11636	Original data
Hipparchia semele	14668	553971	19.36784	10% inaccuracy
Hipparchia semele	12397	543230.1	19.27888	2% inaccuracy
Hipparchia semele	17336	563099.3	19.17778	20% inaccuracy
Hipparchia semele	13265	556861.9	19.09747	5% inaccuracy
Hipparchia semele	11841	380289.5	17.99586	Original data
Lasiommata megera	17682	516245.6	19.71458	10% inaccuracy
Lasiommata megera	16471	475731.5	19.46105	2% inaccuracy
Lasiommata megera	19305	534518.6	19.00354	20% inaccuracy
Lasiommata megera	16967	470991.9	18.70698	5% inaccuracy
Lasiommata megera	16142	360128.5	19.40038	Original data
Leptidea sinapis	6867	471160.5	20.21015	10% inaccuracy
Leptidea sinapis	5086	417652.9	20.79943	2% inaccuracy
Leptidea sinapis	8894	526833.1	19.18426	20% inaccuracy
Leptidea sinapis	5745	444759.4	20.80708	5% inaccuracy

Leptidea sinapis	4665	36998.11	23.2966	Original data
Limenitis camilla	15204	352041.4	21.11182	10% inaccuracy
Limenitis camilla	10095	252902.4	22.7763	2% inaccuracy
Limenitis camilla	21534	369418.2	21.01268	20% inaccuracy
Limenitis camilla	12118	267671.9	21.99348	5% inaccuracy
Limenitis camilla	8866	110015.7	21.46816	Original data
Lycaena phlaeas	53829	526464.6	19.52355	10% inaccuracy
Lycaena phlaeas	57268	526411.2	19.5166	2% inaccuracy
Lycaena phlaeas	49487	539376.7	19.18882	20% inaccuracy
Lycaena phlaeas	56137	526387.3	19.5166	5% inaccuracy
Lycaena phlaeas	58182	526387.3	19.5166	Original data
Maniola jurtina	539181	595271.4	18.89715	10% inaccuracy
Maniola jurtina	555185	595271.4	18.89715	2% inaccuracy
Maniola jurtina	519324	593844.8	18.94562	20% inaccuracy
Maniola jurtina	549030	599003.2	18.81256	5% inaccuracy
Maniola jurtina	559031	595271.4	18.89715	Original data
Melanargia galathea	93287	478882.9	19.64957	10% inaccuracy
Melanargia galathea	99638	243046	21.51977	2% inaccuracy
Melanargia galathea	85485	510678.5	19.67875	20% inaccuracy
Melanargia galathea	97080	316812.8	22.76471	5% inaccuracy
Melanargia galathea	101230	193855.1	21.15487	Original data
Melitaea athalia	1511	124439.3	19.7206	10% inaccuracy
Melitaea athalia	1422	101113	26.43204	2% inaccuracy
Melitaea athalia	1663	195030.6	23.00139	20% inaccuracy
Melitaea athalia	1442	135350.6	21.6912	5% inaccuracy
Melitaea athalia	1397	613.577	5.792878	Original data
Melitaea cinxia	361	162950.2	20.63175	10% inaccuracy
Melitaea cinxia	313	42042.58	25.54045	2% inaccuracy
Melitaea cinxia	383	345797.7	20.2926	20% inaccuracy
Melitaea cinxia	318	97858.68	25.42067	5% inaccuracy
Melitaea cinxia	304	165.526	50.88322	Original data
Nymphalis polychloros	7277	521180.5	19.09956	10% inaccuracy
Nymphalis polychloros	1517	497794.3	19.87934	2% inaccuracy
Nymphalis polychloros	14612	571373	19.31154	20% inaccuracy
Nymphalis polychloros	3657	548846.8	19.01545	5% inaccuracy
Nymphalis polychloros	26	12406.22	25.93525	Original data
Ochlodes sylvanus	90758	425164.7	20.1891	10% inaccuracy
Ochlodes sylvanus	92715	392477.7	19.15741	2% inaccuracy
Ochlodes sylvanus	88268	482347	19.68937	20% inaccuracy
Ochlodes sylvanus	91851	420888.3	19.96378	5% inaccuracy
Ochlodes sylvanus	93119	331934.2	20.54358	Original data
Papilio machaon	644	9883.109	23.32231	10% inaccuracy
Papilio machaon	704	9883.109	23.32231	2% inaccuracy
Papilio machaon	553	9689.663	23.23783	20% inaccuracy
Papilio machaon	678	9883.109	23.32231	5% inaccuracy
Papilio machaon	716	9883.109	23.32231	Original data
Pararge aegeria	313200	566582	19.3293	10% inaccuracy
Pararge aegeria	329191	561510.8	19.47873	2% inaccuracy
Pararge aegeria	292822	572566.2	19.39376	20% inaccuracy

Pararge aegeria	323025	565568.7	19.35304	5% inaccuracy
Pararge aegeria	333167	556020	19.59625	Original data
Phengaris arion	748	402006.9	20.75285	10% inaccuracy
Phengaris arion	152	305017.9	21.9686	2% inaccuracy
Phengaris arion	1539	454360.6	19.87734	20% inaccuracy
Phengaris arion	370	323280.3	22.26566	5% inaccuracy
Pieris brassicae	254424	626389.9	17.99511	10% inaccuracy
Pieris brassicae	252565	626691.8	17.99023	2% inaccuracy
Pieris brassicae	256582	626568.5	18.07226	20% inaccuracy
Pieris brassicae	253415	628998.1	17.92178	5% inaccuracy
Pieris brassicae	252318	626389.9	17.99511	Original data
Pieris napi	237936	593644.3	18.99968	10% inaccuracy
Pieris napi	242621	593916	18.9926	2% inaccuracy
Pieris napi	231907	595524.1	18.93918	20% inaccuracy
Pieris napi	240790	593820.1	18.99579	5% inaccuracy
Pieris napi	243700	593954.8	18.99149	Original data
Pieris rapae	340995	595614.4	18.78562	10% inaccuracy
Pieris rapae	331693	591106.1	18.67354	2% inaccuracy
Pieris rapae	353695	597199.3	18.82389	20% inaccuracy
Pieris rapae	335102	581743.6	19.06188	5% inaccuracy
Pieris rapae	329145	575697.6	18.98081	Original data
Plebejus argus	14577	532110.7	20.43997	10% inaccuracy
Plebejus argus	11678	464278.8	19.99366	2% inaccuracy
Plebejus argus	18194	537946.4	19.93151	20% inaccuracy
Plebejus argus	12765	519920	18.98219	5% inaccuracy
Plebejus argus	10958	52139.32	26.63524	Original data
Polygonia c-album	77023	517058.4	19.19437	10% inaccuracy
Polygonia c-album	82664	413210.1	21.09379	2% inaccuracy
Polygonia c-album	70094	525565.6	19.25102	20% inaccuracy
Polygonia c-album	80599	457426.1	19.61461	5% inaccuracy
Polygonia c-album	84073	413094.2	21.09203	Original data
Polyommatus bellargus	12087	25977.4	46.03947	Original data
Polyommatus bellargus	12051	259989.8	22.45132	2% inaccuracy
Polyommatus bellargus	11847	411662.4	20.68344	10% inaccuracy
Polyommatus bellargus	11941	291286.5	20.40414	5% inaccuracy
Polyommatus bellargus	11574	546230.5	19.35125	20% inaccuracy
Polyommatus coridon	24024	529596	18.88325	10% inaccuracy
Polyommatus coridon	24686	306129.5	20.9296	2% inaccuracy
Polyommatus coridon	23194	551308.7	19.75849	20% inaccuracy
Polyommatus coridon	24444	356900.7	21.31082	5% inaccuracy
Polyommatus coridon	24848	58473.54	33.56056	Original data
Polyommatus icarus	180483	594943.4	18.96534	10% inaccuracy
Polyommatus icarus	188157	595248.7	18.96352	2% inaccuracy
Polyommatus icarus	170370	596118	18.92641	20% inaccuracy
Polyommatus icarus	185024	595230.1	18.96412	5% inaccuracy
Polyommatus icarus	189957	595248.7	18.96352	Original data
Pyrgus malvae	14168	500131.7	19.95731	10% inaccuracy
Pyrgus malvae	9677	361683.7	22.11907	2% inaccuracy
Pyrgus malvae	19491	514289.6	20.0079	20% inaccuracy

Pyrgus malvae	11275	483562.1	20.03156	5% inaccuracy
Pyrgus malvae	8604	81074.33	27.49584	Original data
Pyronia tithonus	249449	562774	19.0457	10% inaccuracy
Pyronia tithonus	248552	503618.4	20.10166	2% inaccuracy
Pyronia tithonus	250792	577300.7	19.26487	20% inaccuracy
Pyronia tithonus	248805	554572	19.6217	5% inaccuracy
Pyronia tithonus	248325	298644.9	21.59251	Original data
Satyrium pruni	287	169.526	5.832583	Original data
Satyrium pruni	399	126228.6	18.80619	5% inaccuracy
Satyrium pruni	856	335824.1	20.79249	20% inaccuracy
Satyrium pruni	341	112242.1	21.429	2% inaccuracy
Satyrium pruni	573	288778	21.66953	10% inaccuracy
Satyrium w-album	2002	342418.7	21.47241	10% inaccuracy
Satyrium w-album	1373	254410.4	21.42585	2% inaccuracy
Satyrium w-album	2737	443619.2	19.98083	20% inaccuracy
Satyrium w-album	1614	276270.5	21.38887	5% inaccuracy
Satyrium w-album	1247	142876.6	19.88425	Original data
Speyeria aglaja	28370	572930.8	19.09476	10% inaccuracy
Speyeria aglaja	27263	559041.9	19.00417	2% inaccuracy
Speyeria aglaja	29155	572422	19.09426	20% inaccuracy
Speyeria aglaja	27620	570255.6	19.15991	5% inaccuracy
Speyeria aglaja	27011	559013.4	19.00846	Original data
Thecla betulae	968	115969.7	19.086	10% inaccuracy
Thecla betulae	973	43489.57	30.87228	2% inaccuracy
Thecla betulae	1009	115986	21.78681	20% inaccuracy
Thecla betulae	981	177453.5	18.79657	5% inaccuracy
Thecla betulae	961	31878.1	34.83758	Original data
Thymelicus acteon	1400	107.808	95.22837	Original data
Thymelicus acteon	1531	145800.2	24.04745	5% inaccuracy
Thymelicus acteon	1450	69971.35	23.09578	2% inaccuracy
Thymelicus acteon	1865	277161.5	22.47116	20% inaccuracy
Thymelicus acteon	1622	265103.2	21.68828	10% inaccuracy
Thymelicus lineola	16896	303117	21.1885	10% inaccuracy
Thymelicus lineola	15362	276137.5	22.2702	2% inaccuracy
Thymelicus lineola	18879	318374.9	21.59723	20% inaccuracy
Thymelicus lineola	15895	318417.5	21.32531	5% inaccuracy
Thymelicus lineola	14913	178630.6	20.4294	Original data
Thymelicus sylvestris	84737	518660.6	19.19506	10% inaccuracy
Thymelicus sylvestris	83137	397243.3	18.54589	2% inaccuracy
Thymelicus sylvestris	86773	503809.2	19.53498	20% inaccuracy
Thymelicus sylvestris	83845	465056.2	19.18316	5% inaccuracy
Thymelicus sylvestris	82809	326860	21.0936	Original data
Vanessa atalanta	114858	649352.1	17.53708	10% inaccuracy
Vanessa atalanta	115033	649352.1	17.53708	2% inaccuracy
Vanessa atalanta	114518	646039.7	17.59355	20% inaccuracy
Vanessa atalanta	114882	659086.6	17.31243	5% inaccuracy
Vanessa atalanta	115136	649352.1	17.53708	Original data
Vanessa cardui	45360	607314.6	18.63469	10% inaccuracy
Vanessa cardui	39998	607543.7	18.63044	2% inaccuracy

Vanessa cardui	51900	604124.4	18.72709	20% inaccuracy
Vanessa cardui	42100	606233.9	18.68432	5% inaccuracy
Vanessa cardui	38709	599662.9	18.86351	Original data

Table D.3 The proportional confusion matrix for UK Butterfly species from iRecord that was used to simulate inaccuracies for the species confusion scenario (see Appendix D.2 for the results from the species confusion analysis).

True species	**Citizen science identification**	**Proportion of redeterminations**
Aglais io	Aglais urticae	0.333333333
Aglais io	Anthocharis cardamines	0.041666667
Aglais io	Boloria euphrosyne	0.020833333
Aglais io	Erebia aethiops	0.020833333
Aglais io	Euphydryas aurinia	0.020833333
Aglais io	Limenitis camilla	0.020833333
Aglais io	Maniola jurtina	0.020833333
Aglais io	Nymphalis polychloros	0.020833333
Aglais io	Pieris napi	0.020833333
Aglais io	Polygonia c-album	0.020833333
Aglais io	Pyronia tithonus	0.0625
Aglais io	Vanessa atalanta	0.3125
Aglais io	Vanessa cardui	0.083333333
Aglais urticae	Aglais io	0.084444444
Aglais urticae	Anthocharis cardamines	0.004444444
Aglais urticae	Aphantopus hyperantus	0.004444444
Aglais urticae	Carterocephalus palaemon	0.004444444
Aglais urticae	Erynnis tages	0.004444444
Aglais urticae	Hipparchia semele	0.008888889
Aglais urticae	Limenitis camilla	0.004444444
Aglais urticae	Lycaena phlaeas	0.013333333
Aglais urticae	Maniola jurtina	0.004444444
Aglais urticae	Nymphalis polychloros	0.324444444
Aglais urticae	Ochlodes sylvanus	0.004444444
Aglais urticae	Pararge aegeria	0.004444444
Aglais urticae	Pieris brassicae	0.013333333
Aglais urticae	Polygonia c-album	0.013333333
Aglais urticae	Pyronia tithonus	0.004444444
Aglais urticae	Vanessa atalanta	0.257777778
Aglais urticae	Vanessa cardui	0.244444444
Anthocharis cardamines	Aglais urticae	0.016666667
Anthocharis cardamines	Celastrina argiolus	0.033333333
Anthocharis cardamines	Gonepteryx rhamni	0.033333333
Anthocharis cardamines	Leptidea sinapis	0.033333333
Anthocharis cardamines	Maniola jurtina	0.016666667
Anthocharis cardamines	Melanargia galathea	0.016666667
Anthocharis cardamines	Pieris brassicae	0.1
Anthocharis cardamines	Pieris napi	0.233333333
Anthocharis cardamines	Pieris rapae	0.5
Anthocharis cardamines	Pyrgus malvae	0.016666667
Apatura iris	Limenitis camilla	0.9
Apatura iris	Pararge aegeria	0.1
Aphantopus hyperantus	Coenonympha pamphilus	0.019230769
Aphantopus hyperantus	Coenonympha tullia	0.019230769
Aphantopus hyperantus	Cupido minimus	0.230769231
Aphantopus hyperantus	Erebia aethiops	0.019230769

Aphantopus hyperantus	Erebia epiphron	0.096153846
Aphantopus hyperantus	Maniola jurtina	0.346153846
Aphantopus hyperantus	Ochlodes sylvanus	0.019230769
Aphantopus hyperantus	Pararge aegeria	0.211538462
Aphantopus hyperantus	Phengaris arion	0.019230769
Aphantopus hyperantus	Thymelicus sylvestris	0.019230769
Argynnis paphia	Aphantopus hyperantus	0.012987013
Argynnis paphia	Boloria euphrosyne	0.168831169
Argynnis paphia	Fabriciana adippe	0.103896104
Argynnis paphia	Polygonia c-album	0.012987013
Argynnis paphia	Speyeria aglaja	0.701298701
Aricia agestis	Aricia artaxerxes	0.085714286
Aricia agestis	Cupido minimus	0.028571429
Aricia agestis	Plebejus argus	0.057142857
Aricia agestis	Polyommatus coridon	0.042857143
Aricia agestis	Polyommatus icarus	0.785714286
Aricia artaxerxes	Aricia agestis	1
Boloria euphrosyne	Argynnis paphia	0.166666667
Boloria euphrosyne	Boloria selene	0.666666667
Boloria euphrosyne	Lasiommata megera	0.166666667
Boloria selene	Boloria euphrosyne	0.818181818
Boloria selene	Euphydryas aurinia	0.060606061
Boloria selene	Hamearis lucina	0.03030303
Boloria selene	Speyeria aglaja	0.090909091
Callophrys rubi	Aphantopus hyperantus	0.5
Callophrys rubi	Gonepteryx rhamni	0.5
Celastrina argiolus	Aphantopus hyperantus	0.005076142
Celastrina argiolus	Cupido minimus	0.304568528
Celastrina argiolus	Phengaris arion	0.020304569
Celastrina argiolus	Pieris brassicae	0.005076142
Celastrina argiolus	Plebejus argus	0.010152284
Celastrina argiolus	Polyommatus bellargus	0.010152284
Celastrina argiolus	Polyommatus coridon	0.015228426
Celastrina argiolus	Polyommatus icarus	0.624365482
Celastrina argiolus	Pyronia tithonus	0.005076142
Coenonympha pamphilus	Coenonympha tullia	0.209302326
Coenonympha pamphilus	Maniola jurtina	0.395348837
Coenonympha pamphilus	Pieris rapae	0.023255814
Coenonympha pamphilus	Pyronia tithonus	0.348837209
Coenonympha pamphilus	Thymelicus sylvestris	0.023255814
Colias croceus	Gonepteryx rhamni	0.75
Colias croceus	Maniola jurtina	0.25
Cupido minimus	Celastrina argiolus	0.333333333
Cupido minimus	Plebejus argus	0.333333333
Cupido minimus	Polyommatus icarus	0.333333333
Erebia aethiops	Aricia agestis	0.285714286
Erebia aethiops	Erebia epiphron	0.285714286
Erebia aethiops	Hipparchia semele	0.142857143
Erebia aethiops	Maniola jurtina	0.285714286

Erynnis tages	Pararge aegeria	0.5
Erynnis tages	Pyrgus malvae	0.5
Fabriciana adippe	Speyeria aglaja	1
Favonius quercus	Apatura iris	0.130434783
Favonius quercus	Cupido minimus	0.043478261
Favonius quercus	Satyrium pruni	0.043478261
Favonius quercus	Satyrium w-album	0.695652174
Favonius quercus	Thecla betulae	0.086956522
Gonepteryx rhamni	Aglais io	0.038461538
Gonepteryx rhamni	Callophrys rubi	0.038461538
Gonepteryx rhamni	Colias croceus	0.576923077
Gonepteryx rhamni	Pieris brassicae	0.038461538
Gonepteryx rhamni	Pieris napi	0.153846154
Gonepteryx rhamni	Pieris rapae	0.153846154
Hamearis lucina	Melitaea athalia	1
Hesperia comma	Argynnis paphia	0.2
Hesperia comma	Coenonympha tullia	0.2
Hesperia comma	Ochlodes sylvanus	0.6
Hipparchia semele	Maniola jurtina	0.4
Hipparchia semele	Pararge aegeria	0.2
Hipparchia semele	Vanessa cardui	0.4
Lasiommata megera	Aphantopus hyperantus	0.076923077
Lasiommata megera	Coenonympha pamphilus	0.076923077
Lasiommata megera	Coenonympha tullia	0.153846154
Lasiommata megera	Erebia epiphron	0.076923077
Lasiommata megera	Hipparchia semele	0.153846154
Lasiommata megera	Lycaena phlaeas	0.076923077
Lasiommata megera	Pararge aegeria	0.230769231
Lasiommata megera	Pyronia tithonus	0.153846154
Limenitis camilla	Apatura iris	0.5
Limenitis camilla	Melanargia galathea	0.5
Lycaena phlaeas	Aphantopus hyperantus	0.142857143
Lycaena phlaeas	Celastrina argiolus	0.142857143
Lycaena phlaeas	Coenonympha pamphilus	0.428571429
Lycaena phlaeas	Pyronia tithonus	0.142857143
Lycaena phlaeas	Thymelicus sylvestris	0.142857143
Maniola jurtina	Aglais io	0.006825939
Maniola jurtina	Aphantopus hyperantus	0.126279863
Maniola jurtina	Aricia agestis	0.003412969
Maniola jurtina	Aricia artaxerxes	0.003412969
Maniola jurtina	Celastrina argiolus	0.006825939
Maniola jurtina	Coenonympha pamphilus	0.464163823
Maniola jurtina	Coenonympha tullia	0.020477816
Maniola jurtina	Erebia aethiops	0.010238908
Maniola jurtina	Erynnis tages	0.003412969
Maniola jurtina	Gonepteryx rhamni	0.003412969
Maniola jurtina	Hipparchia semele	0.013651877
Maniola jurtina	Lasiommata megera	0.003412969
Maniola jurtina	Ochlodes sylvanus	0.003412969

Maniola jurtina	Pararge aegeria	0.020477816
Maniola jurtina	Pieris napi	0.003412969
Maniola jurtina	Polygonia c-album	0.003412969
Maniola jurtina	Pyronia tithonus	0.283276451
Maniola jurtina	Satyrium pruni	0.003412969
Maniola jurtina	Satyrium w-album	0.006825939
Maniola jurtina	Thymelicus sylvestris	0.003412969
Maniola jurtina	Vanessa atalanta	0.003412969
Maniola jurtina	Vanessa cardui	0.003412969
Melanargia galathea	Limenitis camilla	0.666666667
Melanargia galathea	Pararge aegeria	0.333333333
Melitaea athalia	Argynnis paphia	0.5
Melitaea athalia	Euphydryas aurinia	0.5
Nymphalis polychloros	Aglais urticae	1
Ochlodes sylvanus	Carterocephalus palaemon	0.008097166
Ochlodes sylvanus	Celastrina argiolus	0.004048583
Ochlodes sylvanus	Coenonympha pamphilus	0.004048583
Ochlodes sylvanus	Coenonympha tullia	0.008097166
Ochlodes sylvanus	Erynnis tages	0.024291498
Ochlodes sylvanus	Hesperia comma	0.064777328
Ochlodes sylvanus	Lycaena phlaeas	0.004048583
Ochlodes sylvanus	Maniola jurtina	0.004048583
Ochlodes sylvanus	Polygonia c-album	0.004048583
Ochlodes sylvanus	Pyronia tithonus	0.008097166
Ochlodes sylvanus	Thymelicus acteon	0.024291498
Ochlodes sylvanus	Thymelicus lineola	0.137651822
Ochlodes sylvanus	Thymelicus sylvestris	0.700404858
Ochlodes sylvanus	Vanessa atalanta	0.004048583
Pararge aegeria	Aphantopus hyperantus	0.148648649
Pararge aegeria	Boloria euphrosyne	0.013513514
Pararge aegeria	Carterocephalus palaemon	0.081081081
Pararge aegeria	Celastrina argiolus	0.013513514
Pararge aegeria	Coenonympha pamphilus	0.013513514
Pararge aegeria	Coenonympha tullia	0.013513514
Pararge aegeria	Erynnis tages	0.027027027
Pararge aegeria	Gonepteryx rhamni	0.013513514
Pararge aegeria	Hamearis lucina	0.027027027
Pararge aegeria	Hesperia comma	0.013513514
Pararge aegeria	Hipparchia semele	0.067567568
Pararge aegeria	Lasiommata megera	0.081081081
Pararge aegeria	Maniola jurtina	0.162162162
Pararge aegeria	Melanargia galathea	0.040540541
Pararge aegeria	Pieris brassicae	0.013513514
Pararge aegeria	Pieris napi	0.027027027
Pararge aegeria	Pieris rapae	0.013513514
Pararge aegeria	Pyrgus malvae	0.148648649
Pararge aegeria	Pyronia tithonus	0.054054054
Pararge aegeria	Thymelicus sylvestris	0.013513514
Pararge aegeria	Vanessa atalanta	0.013513514

Pieris brassicae	Aglais urticae	0.008130081
Pieris brassicae	Colias croceus	0.016260163
Pieris brassicae	Gonepteryx rhamni	0.024390244
Pieris brassicae	Hipparchia semele	0.008130081
Pieris brassicae	Ochlodes sylvanus	0.008130081
Pieris brassicae	Pararge aegeria	0.008130081
Pieris brassicae	Pieris napi	0.130081301
Pieris brassicae	Pieris rapae	0.796747967
Pieris napi	Aglais io	0.002808989
Pieris napi	Anthocharis cardamines	0.033707865
Pieris napi	Gonepteryx rhamni	0.002808989
Pieris napi	Leptidea sinapis	0.030898876
Pieris napi	Melanargia galathea	0.002808989
Pieris napi	Pieris brassicae	0.219101124
Pieris napi	Pieris rapae	0.707865169
Pieris rapae	Aglais urticae	0.004385965
Pieris rapae	Anthocharis cardamines	0.01754386
Pieris rapae	Celastrina argiolus	0.00877193
Pieris rapae	Colias croceus	0.00877193
Pieris rapae	Gonepteryx rhamni	0.030701754
Pieris rapae	Leptidea sinapis	0.048245614
Pieris rapae	Melanargia galathea	0.004385965
Pieris rapae	Pararge aegeria	0.004385965
Pieris rapae	Pieris brassicae	0.587719298
Pieris rapae	Pieris napi	0.280701754
Pieris rapae	Pyronia tithonus	0.004385965
Plebejus argus	Celastrina argiolus	0.076923077
Plebejus argus	Cupido minimus	0.153846154
Plebejus argus	Hesperia comma	0.076923077
Plebejus argus	Polyommatus icarus	0.692307692
Polygonia c-album	Aglais io	0.00990099
Polygonia c-album	Aglais urticae	0.158415842
Polygonia c-album	Anthocharis cardamines	0.01980198
Polygonia c-album	Aphantopus hyperantus	0.00990099
Polygonia c-album	Argynnis paphia	0.158415842
Polygonia c-album	Boloria euphrosyne	0.01980198
Polygonia c-album	Carterocephalus palaemon	0.00990099
Polygonia c-album	Coenonympha pamphilus	0.00990099
Polygonia c-album	Fabriciana adippe	0.00990099
Polygonia c-album	Gonepteryx rhamni	0.00990099
Polygonia c-album	Hamearis lucina	0.02970297
Polygonia c-album	Hesperia comma	0.01980198
Polygonia c-album	Lasiommata megera	0.00990099
Polygonia c-album	Lycaena phlaeas	0.04950495
Polygonia c-album	Maniola jurtina	0.00990099
Polygonia c-album	Melitaea athalia	0.00990099
Polygonia c-album	Nymphalis polychloros	0.277227723
Polygonia c-album	Ochlodes sylvanus	0.00990099
Polygonia c-album	Pararge aegeria	0.01980198

Polygonia c-album	Polyommatus icarus	0.00990099
Polygonia c-album	Pyronia tithonus	0.02970297
Polygonia c-album	Speyeria aglaja	0.00990099
Polygonia c-album	Vanessa atalanta	0.02970297
Polygonia c-album	Vanessa cardui	0.069306931
Polyommatus bellargus	Plebejus argus	0.125
Polyommatus bellargus	Polyommatus coridon	0.375
Polyommatus bellargus	Polyommatus icarus	0.5
Polyommatus coridon	Plebejus argus	0.142857143
Polyommatus coridon	Polyommatus bellargus	0.142857143
Polyommatus coridon	Polyommatus icarus	0.714285714
Polyommatus icarus	Aricia agestis	0.163265306
Polyommatus icarus	Aricia artaxerxes	0.030612245
Polyommatus icarus	Celastrina argiolus	0.214285714
Polyommatus icarus	Coenonympha tullia	0.010204082
Polyommatus icarus	Cupido minimus	0.265306122
Polyommatus icarus	Lycaena phlaeas	0.010204082
Polyommatus icarus	Pararge aegeria	0.020408163
Polyommatus icarus	Phengaris arion	0.010204082
Polyommatus icarus	Plebejus argus	0.183673469
Polyommatus icarus	Polyommatus bellargus	0.030612245
Polyommatus icarus	Polyommatus coridon	0.051020408
Polyommatus icarus	Pyronia tithonus	0.010204082
Pyrgus malvae	Carterocephalus palaemon	0.25
Pyrgus malvae	Erynnis tages	0.5
Pyrgus malvae	Polygonia c-album	0.25
Pyronia tithonus	Aglais urticae	0.012345679
Pyronia tithonus	Aphantopus hyperantus	0.024691358
Pyronia tithonus	Coenonympha pamphilus	0.314814815
Pyronia tithonus	Coenonympha tullia	0.012345679
Pyronia tithonus	Erynnis tages	0.012345679
Pyronia tithonus	Hipparchia semele	0.00617284
Pyronia tithonus	Lasiommata megera	0.00617284
Pyronia tithonus	Lycaena phlaeas	0.00617284
Pyronia tithonus	Maniola jurtina	0.580246914
Pyronia tithonus	Ochlodes sylvanus	0.012345679
Pyronia tithonus	Pararge aegeria	0.00617284
Pyronia tithonus	Pieris brassicae	0.00617284
Satyrium w-album	Satyrium pruni	0.5
Satyrium w-album	Thecla betulae	0.5
Speyeria aglaja	Argynnis paphia	0.170731707
Speyeria aglaja	Boloria euphrosyne	0.195121951
Speyeria aglaja	Boloria selene	0.414634146
Speyeria aglaja	Euphydryas aurinia	0.024390244
Speyeria aglaja	Fabriciana adippe	0.097560976
Speyeria aglaja	Pararge aegeria	0.024390244
Speyeria aglaja	Vanessa cardui	0.073170732
Thecla betulae	Favonius quercus	0.4
Thecla betulae	Maniola jurtina	0.4

Thecla betulae	Satyrium pruni	0.2
Thymelicus acteon	Thymelicus sylvestris	1
Thymelicus lineola	Ochlodes sylvanus	0.137931034
Thymelicus lineola	Polygonia c-album	0.017241379
Thymelicus lineola	Thymelicus sylvestris	0.844827586
Thymelicus sylvestris	Carterocephalus palaemon	0.008928571
Thymelicus sylvestris	Coenonympha pamphilus	0.017857143
Thymelicus sylvestris	Lycaena phlaeas	0.044642857
Thymelicus sylvestris	Ochlodes sylvanus	0.625
Thymelicus sylvestris	Pieris rapae	0.017857143
Thymelicus sylvestris	Thymelicus acteon	0.017857143
Thymelicus sylvestris	Thymelicus lineola	0.267857143
Vanessa atalanta	Aglais io	0.14084507
Vanessa atalanta	Aglais urticae	0.338028169
Vanessa atalanta	Apatura iris	0.014084507
Vanessa atalanta	Hipparchia semele	0.014084507
Vanessa atalanta	Maniola jurtina	0.014084507
Vanessa atalanta	Nymphalis polychloros	0.028169014
Vanessa atalanta	Pararge aegeria	0.014084507
Vanessa atalanta	Pieris brassicae	0.028169014
Vanessa atalanta	Polygonia c-album	0.014084507
Vanessa atalanta	Vanessa cardui	0.394366197
Vanessa cardui	Aglais io	0.052631579
Vanessa cardui	Aglais urticae	0.315789474
Vanessa cardui	Boloria euphrosyne	0.01754386
Vanessa cardui	Erynnis tages	0.01754386
Vanessa cardui	Hesperia comma	0.01754386
Vanessa cardui	Hipparchia semele	0.01754386
Vanessa cardui	Maniola jurtina	0.01754386
Vanessa cardui	Melitaea cinxia	0.01754386
Vanessa cardui	Nymphalis polychloros	0.087719298
Vanessa cardui	Pararge aegeria	0.070175439
Vanessa cardui	Polygonia c-album	0.035087719
Vanessa cardui	Pyronia tithonus	0.01754386
Vanessa cardui	Vanessa atalanta	0.315789474

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