Innovative tools and technologies for improving biodiversity surveys using citizen science

Alan Stenhouse

School of Biological Sciences

Department of Ecology and Evolutionary Biology

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Cover Images: Koala image recorded by The Great Koala Count 2 participant ID e11db150-a010-4474-9619-e54ab6e129e4. Echidna image recorded by echidnaCSI participant ID 4301030b-2bec-408f-994d-f0cf91386093.

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ABSTRACT

This thesis advances knowledge of biodiversity monitoring using citizen science and demonstrates the potential of innovative tools and technology to improve the data generated by citizen science to inform species conservation and ecosystem management. Biodiversity around the world is in crisis and there are many challenges. Australian biodiversity is declining rapidly, with the worst mammal extinction rate in the world. Climate change, pollution, land clearing and other anthropogenic pressures are increasing and exacerbating pressures on ecosystems and wildlife. Biodiversity monitoring is crucial to inform us as to the current state and trends of ecosystems. Resources are limited for traditional scientific monitoring, thus other efficient and effective methods are being sought to augment biodiversity conservation research and management. Effective management solutions require stakeholder engagement, so community participation is one key part of solving this crisis. Citizen science is seen as part of the solution by engaging citizens in local actions that contribute to local and global improved outcomes. However, data contributed by citizen scientists are often seen as biased in space and time, and lacking in essential metadata, such as accurate effort data.

The aim of this thesis was to investigate and develop methods to enhance data collected by citizen scientists to improve wildlife monitoring. The objectives were to: 1. assess the potential of automatic collection of key monitoring metadata, such as species location and observer search paths, to enable more accurate assessments of observer effort and species absence; 2. increase knowledge on population distribution and abundance of an iconic Australian mammal species using citizen science and compare spatial coverage of this monitoring to traditional observations, using protected areas and geographic remoteness indicators; 3. assess how CS monitoring performed compared to other forms of monitoring when faced with major disruptions to community activities and movements caused by a global pandemic.

These objectives were addressed through three component studies. Firstly, a mobile app was developed which automatically recorded accurate metadata for each observation. Extra information about participants' search effort, including time taken and search path followed, was also automatically recorded. This app was used for a citizen science event to gather information about koala (*Phascolarctos cinereus*) populations and their habitats in South Australia. Results showed that recording of observations, search effort and search

path data was accurate and useful for both species population assessment and management of citizen science monitoring.

For objective two, a mobile app was developed to enable citizen scientists across Australia to record observational data and improve knowledge on the iconic short-beaked echidna (*Tachyglossus aculeatus*). Widespread participation over three years more than doubled observation counts across the continent compared to contemporary scientific observations from national and state repositories, while geographic coverage was similar, except for in some highly protected areas and very remote areas.

Finally, citizen science observational data for short-beaked echidna were compared to data from three biodiversity data repositories and demonstrated that citizen science monitoring was resilient to the effects of restrictions on community activities while other forms of monitoring were significantly reduced under harsh restrictions and more concentrated in highly protected areas than usual.

This thesis contributes towards efforts to understand and improve citizen science data for monitoring wildlife and biodiversity by enhancing data collection methods. The automatic collection of citizen scientist search paths and effort provides key information about where monitoring has occurred, even without observations being recorded. This is vital information for both modelling species populations and distribution and also for improved management of citizen science monitoring. Baseline echidna population distribution and abundance information has been improved across Australia and will help determine future population trends. This also contributes to our understanding of spatial biases of citizen science and scientific monitoring. Demonstrating the robustness of citizen science monitoring to disruptions caused by restrictions to community activity provides further important knowledge for assessing effective monitoring methods, particularly in light of the current pandemic and ongoing climate change effects. This knowledge will inform management of both CS and scientific biodiversity monitoring and further improve methods for biodiversity conservation in Australia and around the world.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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Alan Stenhouse
October 5, 2021

PUBLICATIONS ARISING FROM THIS THESIS

Journal Articles

Stenhouse, A., Roetman, P., Lewis, M., Koh, L.P., 2020. Koala Counter: Recording Citizen Scientists' search paths to Improve Data Quality. *Global Ecology and Conservation 24*, e01376. https://doi.org/10.1016/j.gecco.2020.e01376

Stenhouse, A., Perry, T., Grützner, F., Lewis, M., Koh, L.P., 2021. EchidnaCSI – Improving monitoring of a cryptic species at continental scale using Citizen Science. *Global Ecology and Conservation 28*, e01626. https://doi.org/10.1016/j.gecco.2021.e01626

Stenhouse, A., Perry, T., Grützner, F., Rismiller, P., Koh, L.P., Lewis, M., 2022. COVID restrictions impact wildlife monitoring in Australia. *Biological Conservation 267*, 109470. https://doi.org/10.1016/j.biocon.2022.109470.

Perry, T., **Stenhouse, A**., Wilson, I., Perfetto, I., McKelvey, M. W., Coulson, M., Ankeny, R. A., Rismiller, P. D., Grützner, F., 2022. EchidnaCSI: engaging the public in research and conservation of the short-beaked echidna. *PNAS 119* (5) e2108826119. https://doi.org/10.1073/pnas.2108826119.

Perry, T., West, E., Eisenhofer, R., **Stenhouse, A**., Wilson, I., Laming, B., Rismiller, P., Shaw, M., Grutzner, F., 2022. Characterising the Gut Microbiomes in Wild and Captive Short-beaked Echidnas Reveals Diet-Associated Changes. Accepted to *Frontiers in Microbiology.*

Conference Presentations

Stenhouse, A. (2018). Lessons Learned Developing Citizen Science Apps for Conservation. In *Ecological Society of Australia Conference 2018*, Brisbane, Australia.

Stenhouse, A., Roetman, P., Grützner, F., Perry, T., & Koh, L. P. (2018). Improving Data Quality in Citizen Science Apps for Conservation Biology. In *Biodiversity Information Standards (TDWG) Conference 2018, Dunedin, New Zealand.* Biodiversity Information Science and Standards, 2, e26665. DOI: http://doi.org/10.3897/biss.2.26665

Stenhouse, A., Roetman, P., Koh, L. P., Grutzner, F., & Perry, T. (2018). Developing Citizen Science Apps for Conservation Biology: Koala Counter and EchidnaCSI. In *Australian Citizen Science Conference 2018,* Adelaide, Australia.

Stenhouse, A., Koh, L. P., Roetman, P. (2017). Enhancing Citizen Science Technology to Improve Conservation Outcomes. The University of Adelaide. Poster. In *University of Adelaide Postgraduate Research Day*. https://doi.org/10.4225/55/59ed254f4fa85

Software

Apps on stores

Koala Counter

iOS - no longer available

Android: https://play.google.com/store/apps/details?id1⁄4com.scruffmonkey.koalacounter

echidnaCSI

iOS: https://itunes.apple.com/au/app/echidnacsi/id1260820816

Android: https://play.google.com/store/apps/details?id=com.scruffmonkey.echidnaCSI

Source code

Koala Counter: https://doi. org/10.25909/13239797

echidnaCSI: https://doi.org/10.25909/14528367

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Chapter 1. Introduction

Biodiversity around the world is in crisis with losses increasing (Butchart et al., 2010; Davis et al., 2018; Koh et al., 2004; Pimm and Raven, 2000). Habitat clearance and degradation from human activities combined with exotic pest species, both flora and fauna, have changed and continue to change our landscapes. More frequent and increasingly severe weather events such as droughts and floods, combined with long-term climatic changes, exacerbate the problems caused by landscape changes and result in increased pressures on remaining species (Bradshaw, 2012; Urban, 2015; Woinarski et al., 2019). Current rates of species' extinction are about 1000 times the background extinction rate and likely still underestimated as most species are probably still undescribed (Pimm et al., 2014). In Australia, at least 100 plant and animal species have become extinct since 1788 (Woinarski et al., 2019, 2015) and 580 extant plant and animal species are now classified as endangered or critically endangered (IUCN, 2020). Populations of many species are in decline while the status of many others remains unknown (IUCN, 2020). The need to reduce damage to global ecosystems and biodiversity has been recognised internationally by the Convention on Biological Diversity's Aichi Biodiversity Targets (Convention on Biological Diversity, 2020) and the United Nations' 2030 Agenda for Sustainable Development Goals SDG 14 and SDG 15 (United Nations, 2015).

Biodiversity and wildlife monitoring is crucial to inform us of the current state of ecosystems and how they are changing over time. Monitoring enables the evaluation of ecosystem responses to both external disturbances, such as invasive species, and to management actions taken to protect and restore biodiversity (Lindenmayer et al., 2012a). Longer-term studies are required to detect changes and determine trends (Lindenmayer et al., 2012b; Lindenmayer and Likens, 2010). Monitoring data may influence government policy and investments both directly, by providing evidence required for national and international agreements, and indirectly, by raising public awareness of important environmental issues (Possingham et al., 2012).

Monitoring of wildlife takes many forms, with traditional field monitoring often being highly structured in time and space, using varying methods suited to the target species and habitats. Structured monitoring aims to provide reliable data in forms that can be used for answering research questions of interest. Desirable monitoring characteristics include detailed descriptions of study sites, field protocols with standardised and calibrated methods, inclusion of appropriate reference sites and appropriate spatial and temporal scales (Lindenmayer and Likens, 2010). Conventional biodiversity field monitoring methods, particularly at large spatial and temporal scales, require significant resources and are still generally limited in extent, representativeness and frequency (Amano et al., 2016; Crawford et al., 2020; Neate-Clegg et al., 2020; Wal et al., 2015). In Australia, well-designed and long-term monitoring studies are lacking (Lindenmayer, 2012) which leads to an inability to reliably report on biodiversity trends (Cresswell and Murphy, 2017; Zichy-Woinarski, 2012). Few species have data at the spatial and temporal resolution necessary to provide confident determinations of current status and trends, while many species have little to no data recorded or are still undescribed or remain undiscovered (Cresswell and Murphy, 2017).

Monitoring data often suffer from multiple weaknesses, including limited taxonomic, temporal and spatial coverage, errors and inconsistencies including lack of standardisation in data formats, gaps in time series, and inaccurate or missing essential metadata such as survey method, search timing and effort (Bayraktarov et al., 2019; Boakes et al., 2010; Hughes et al., 2021; Meyer et al., 2016; Titley et al., 2017; Troudet et al., 2017). Additionally, many ecological datasets have been stored in data siloes and not widely shared, thus decreasing their utility as they cannot be easily combined and analysed with other datasets in a timely way (Boakes et al., 2010).

Consequently, new methods with improved efficiency are being sought to enhance biodiversity research and management. Improving the efficiency of reliable monitoring data collection may enable increased spatial and temporal replication, higher accuracy and faster progress from data collection to analysis, subsequently contributing to better conservation management outcomes (Zerger and McDonald, 2012). Achieving this may be possible by using appropriate technologies and methods together with greater community participation to provide data at the required temporal, spatial and taxonomic resolutions and representations.

1.1. CITIZEN SCIENCE

Public participation in scientific research is often called community-based science or citizen science (CS). It usually involves science-driven research with varying levels of public participation under three main categories – contributory projects, collaborative projects or co-created projects (Bonney et al., 2009). The participants are often volunteers with diverse ranges of experience and expertise whose contributions may range from the occasional and opportunistic recording of species observations to analysing and interpreting the resulting data, through to design or co-design of scientific research programs.

CS biodiversity monitoring has an extensive history (Miller-Rushing et al., 2012). Environmental monitoring has long been carried out by amateur natural historians interested in particular aspects of the natural world, often in their own locality, as local issues provided relevance and context. For example, in Kyoto, Japan, the annual cherry blossom appearance has great cultural importance and has been recorded for over 1200 years (Primack et al., 2009). This has enabled current scientists to use this phenological time series to better understand both regional climatic warming and urban heat island effects on biodiversity (Aono and Kazui, 2008). Historic phenological records from the 1850s onwards were combined with modern observations to study changes in flora and fauna species distribution, abundance, composition and movement (Primack and Miller-Rushing, 2012). Another long-term study is the annual Christmas Bird Count in the USA which has taken place since 1900 and informs strategies for protecting birds and their habitats, as well as identifying potential environmental issues (Audubon Society, 2021).

More recently, worldwide interest and participation in CS have greatly increased (Bonney et al., 2014; Pocock et al., 2018, 2017). Although concerns about human effects on the environment have been documented for centuries (Grove, 2002), wider community engagement in environmental issues increased with greater awareness of environmental problems around the world as anthropogenic effects on biodiversity were brought to public attention in the 1960s, helping to spur interest and concern for the environment (Dunn, 2012). The term "Citizen Science" first appeared in 1989 (Haklay et al., 2021) and then gained traction in the mid-1990s (Bonney, 1996; Irwin, 1995), coinciding with the development and rapid adoption of the World Wide Web (CERN, n.d.) which provided accessible, easy-to-use interfaces for entering and disseminating data and enabled further expansion of community-based projects. Improvements in electronic field data acquisition have been assisted by the subsequent development and rapid increase in availability of mobile devices, which now integrate multiple sensors for recording a variety of data, including images, audio, location and movement data.

While most CS projects begin through local, regional or national initiatives, some have increased their scope and now operate globally. As of August 2021, over four million citizen scientists from around the world have contributed more than 87 million observations of almost 170 thousand species to iNaturalist (https://www.inaturalist.org/stats). Interestingly, the primary goal of iNaturalist is to be a network for connecting people with nature, with the secondary goal of generating scientifically valuable biodiversity data (iNaturalist.org, 2021). One of the reasons for iNaturalist's popularity and success is its easy-to-use app which enables participants to quickly record and submit observations to the web portal, where they can be curated by other expert participants and shared. It also has a web portal providing an easy-to-use interface for all users to access the data and share results. eBird (https://ebird.org) is another globally popular citizen science program providing a mobile app and website with easy-to-use functionality. Over one billion bird observations of more than ten thousand species have been submitted by more than 700,000 participants since 2002. In 2021 alone, over 100 peer-reviewed publications have utilised data from eBird, with over 400 publications since 2010 answering questions ranging from bird distribution (Fink et al., 2010), to climate change effects on birds (Hurlbert and Liang, 2012), to global population estimates of 9,700 bird species (Callaghan et al., 2021). eBird's large dataset also contributes to a range of conservation outcomes including threatened species assessments, conservation planning, site and habitat management and protection, species management and policy development (Sullivan et al., 2017). These and other CS projects from around the world provide large amounts of data to the Global Biodiversity Information Facility (GBIF https://www.gbif.org/) which currently stores 1.8 billion species occurrence records. These data have been used by researchers worldwide in over 6100 peer-reviewed journal articles.

In Australia, CS provides an increasingly popular means of collecting and processing wildlife observational data and contributes to improving understanding of biodiversity status and trends (Cresswell and Murphy, 2017). Successful national CS programs include FrogId (https://www.frogid.net.au/), which provides a mobile app allowing the public to record and submit frog calls, enabling researchers to document species diversity and distributions with higher spatial and temporal coverage than previously possible. Over 400,000 frogs from 204 species have so far been identified (Australian Museum, 2020). Birdlife Australia (Birdlife Australia, 2021) runs multiple targeted programs with a large network of volunteers and partnerships with many governmental and non-governmental organisations. Their shorebird monitoring program (https://birdlife.org.au/projects/shorebirds) database goes back to 1981 for some areas and is the most complete shorebird count data in Australia. Volunteer contributions are highly significant, with up to ten times the support compared to governmental contributions (Garnett, 2012). Questagame (https://questagame.com) provides a gamified observational platform employing a variety of mechanisms, such as teams and competitions (or BioQuests), to motivate participants to submit sightings of biodiversity. Almost one million sightings have been submitted to date, with verified data contributing to regional, national and international biodiversity repositories.

For CS projects to deliver broad benefits, they need wide community participation and an effective means of sharing data with a diversity of end-users. In Australia, the Atlas of Living Australia (ALA - https://www.ala.org.au) provides an integrated platform for storing, finding, sharing and analysing biodiversity observations and contains over 100 million species occurrence records. It also provides a set of integrated tools, including the Australian Citizen Science Project Finder (https://biocollect.ala.org.au/acsa) which lists CS projects from around Australia as well as some international projects; BioCollect (https://www.ala.org.au/biocollect/) which enables organisations to establish their own biodiversity data collection projects such as CS monitoring; and the Spatial portal (https://spatial.ala.org.au) which provides easy access to mapping, visualisation and analysis of species occurrence and their environments. Over 50 peer-reviewed publications used ALA data or platforms in 2020 alone, illustrating the value of a national platform for biodiversity monitoring data. As the ALA provides good functionality in an integrated manner and is built on open-source software, it has been adopted internationally by GBIF as the Living Atlases platform (https://living-atlases.gbif.org/) and is currently being used in about 25 countries (Belbin et al., 2021).

Governments and organisations around the world view community participation in environmental monitoring as important, with many benefits of widespread inclusion and participation, such as accessing local knowledge (Alessa et al., 2015; Camino et al., 2020; Danielsen et al., 2021; Smith et al., 2018), increasing environmental awareness (Haywood et al., 2016; Johnson et al., 2014), educating and taking action on local and global issues (Danielsen et al., 2021, 2009; Haywood et al., 2016; Roetman et al., 2018). Australia's Strategy for Nature 2019-2030 (Commonwealth of Australia, 2019) includes CS contributions in two out of three goals. Progress measures for the first goal, "Connect all Australians with nature" include the number of contributions to CS programs. The third goal, "Share and build knowledge", also identifies the provision of robust data on Australia's nature to public information sets by CS programs as a progress indicator. Providing broad participation in CS biodiversity monitoring programs and ensuring the resulting data is robust is essential.

CS biodiversity monitoring surveys use a variety of methods and result in diverse forms of data. Some monitoring is highly structured and requires significant participant training to ensure data is collected at sufficient quality, such as the Breeding Bird Survey

(British Trust for Ornithology, 2018) and the Reef Life Survey (Edgar et al., 2020). Another method is to use temporally intensive biodiversity surveys – bioblitzes – which aim to intensively survey species and/or locations for a short time but at high intensity using multiple participants. Often these intend to repeat the process at regular intervals in order to collect more meaningful and useful data for research and may require expert participants to identify sightings or ensure protocols are followed. Other CS programs, such as iNaturalist, provide the opportunity for anyone to record opportunistic sightings of any species whenever they choose. While these opportunistic observations are often seen as being of lesser value, they can be useful for tracking the spread of invasive species, the presence of threatened species and for phenological studies, particularly for species that can be photographed (Di Cecco et al., 2021). Most programs are somewhere in between these examples and are designed to answer specific research questions. They are usually restricted to a small set of specific species or a particular region and collect a variety of information in addition to core species occurrence data such as location and date.

Desirable characteristics of the data collected by CS projects for biodiversity and wildlife monitoring include accuracy, completeness, timeliness, consistency and accessibility, and there are multiple other dimensions (Wang and Strong, 1996). Assessing data quality can be difficult, with one definition of data quality for CS being data of comparable accuracy to that produced by professionals (Bonney et al., 2014; Cooper et al., 2014; Kosmala et al., 2016; Theobald et al., 2015). Some report that CS data quality is already comparable to traditional monitoring (Kosmala et al., 2016). Evaluating data quality is also dependent on intended purpose – data of insufficient quality for one purpose may be usable for other purposes – thus fitness-for-use is a common method of assessment (Chapman et al., 2020; Kosmala et al., 2016; Wang and Strong, 1996)

A lack of standardisation can impact data usability in multiple ways. Paper-based form-filling is still often used in both traditional fieldwork and for CS observations. It is an error-prone and slow method for submitting data, as understanding text written by others can be difficult and lead to data entry errors and delays before data is available for use. Technology-based forms may avoid the requirement for transcription but can also lead to difficulties in using the data, as entries may require transformation from free-form text into formats usable for analysis. Standardised entries, using selection from a list of values, provide a much easier to use and efficient way of collecting data which avoids many of the problems inherent with free-text entries. Manual entry of location and date can also be problematic, for example, when users must select locations from a map, as this can lead to a lack of accuracy and precision. Manually entering latitude and longitude can lead to errors due to mistyping or lack of understanding of coordinate systems. Accuracy of observation date and time can also be problematic if manually entered.

Additionally, many biodiversity monitoring programs collect their data in isolation and are slow to share. This can lead to data siloes, which decrease the usage and value of data by limiting access to it. Using the Darwin Core Standard (Wieczorek et al., 2012) – an evolving biodiversity standard framework – may enable easier sharing, integration and understanding of some biodiversity and ecological data. Such mechanisms can help ensure community-run and public-funded projects follow the FAIR principles – that is, the resulting data are Findable, Accessible, Interoperable and Reusable (Wilkinson et al., 2016). This may ensure that CS project contributions are maximising their value as they are then rapidly available to the community and other researchers and can be more easily integrated with other datasets.

Data collected during environmental monitoring must be usable for the immediate research questions (Lindenmayer and Likens, 2010). However, possible future uses are not always clear (Possingham et al., 2012), so it is essential to also record key metadata. Information such as survey methods used should be included in overall project metadata, but there are also important metadata about each monitoring survey, such as search effort, and about each observation, such as location accuracy and precision (Bayraktarov et al., 2019). Search effort is usually not recorded at all or else is imprecise and recorded post-survey (Meyer et al., 2016). Observer search paths are rarely recorded or defined, except for highly structured CS projects that can require significant user training to ensure that the correct protocols are followed (Edgar et al., 2016). Such metadata are important when evaluating data for inclusion in other research (Kelling et al., 2019).

CS programs covering large temporal and spatial scales, with many thousands of participants, typically require substantial resources to ensure data is of sufficient quality for the required purposes. In some projects, such as eBird, automated data quality checks and filtering systems enable questionable data to be flagged and then checked by expert reviewers, who may also be volunteers (August et al., 2015; Sullivan et al., 2014). Photographs of sightings, when possible, enable easier validation in many projects and can help to prevent species misidentifications (Crall et al., 2011; Kosmala et al., 2016). User training can be an important tool in improving data quality, particularly for projects with special or complex requirements, such as when following strict monitoring protocols (Cooper et al., 2012; Lewandowski and Specht, 2015; Ratnieks et al., 2016). User-friendly software apps on mobile phones can provide automated validity checks to ensure that all required data has been supplied, as well as providing guidance on methodology and other contextual checks, if required, at the time of entry (Budde et al., 2017; van Berkel et al., 2018).

Despite these checks on data quality, there are particular errors and biases that may be present in CS monitoring (Boakes et al., 2010; Isaac and Pocock, 2015), though many of these biases and errors also occur with scientific monitoring (Boakes et al., 2010; Meyer et al., 2016; Titley et al., 2017; Troudet et al., 2017). Common concerns about CS monitoring data involve differences in observer skill levels and effort, uneven sampling in time and space and other issues that lead to bias and variability (Boakes et al., 2010; Cooper et al., 2012; Isaac and Pocock, 2015; Kosmala et al., 2016). Examples of spatial biases occur when CS participants survey known and favourite locations (Boakes et al., 2016), for example when they know that species of interest occur there. There can also be a bias towards observations close to roads or paths (Dissanayake et al., 2019; Geldmann et al., 2016) and towards populated areas, though this is also apparent with traditional monitoring (Pautasso and McKinney, 2007). Temporal biases may occur as people sample at preferred periods, such as weekends, school holidays or during fine weather (Courter et al., 2013). Taxonomic biases, such as personally favoured species, can also affect sampling (Huang et al., 2020; Hughes et al., 2021; Troudet et al., 2017), as does the skill level of the participant (Kelling et al., 2019), which can affect correct identification of species, individual and species counts, as well as the issue of only reporting species presence with no record of species absence (Cooper et al., 2012). Species detectability is also dependent on participant skill level (see Dickinson et al. (2010) for multiple examples from the literature). For example, many species are easily detectable by sound alone but only if the listener has the necessary expertise to recognise the call. Similarly, many plant and animal species can be visually recognised at the genus level, with individual species identification being more challenging. Skill levels usually improve with further experience and training (Dickinson et al., 2010) but can also deteriorate (Farmer et al., 2014).

Much research has been conducted aiming to reduce these sources of error, variability and bias during data collection, and also to reduce their effects, including enhanced statistical modelling techniques (Bird et al., 2014; Cunningham and Olsen, 2009; Isaac et al., 2014), CS project design methods (Cooper et al., 2012; Kelling et al., 2019; Sturm et al., 2017; Sullivan et al., 2014) and improved participant training and evaluation (Johnston et al., 2018; Kosmala et al., 2016). Improving the technology used in the field can also aid in reducing errors and bias. In-field guidance through the use of intelligent keys to aid species identification (Farnsworth et al., 2013) can help reduce taxonomic errors. Artificial intelligence/machine learning (AI/ML) is increasingly used to identify species using audio and/or visual samples, combined with important contextual ecological metainformation about location, date and time (Bonnet et al., 2018; Wäldchen and Mäder, 2018). Providing extra motivation to participants through gamification and other techniques is often used to increase engagement (Bowser et al., 2013; Deterding et al., 2011; Van Berkel et al., 2017), while supplying extra meta-information, such as asking if a complete list of species has been recorded, can aid later analysis (Cooper et al., 2012).

Improving the software used for CS wildlife and biodiversity monitoring on mobile devices has the potential to increase data quality in many ways (Newman et al., 2012; van Berkel et al., 2018). Software ease-of-use is important for ensuring user satisfaction and continued usage, which is important for increasing participation and thereby improving spatial and temporal coverage and intensity. Well-designed and easy-to-use mobile software can help ensure data collected is of sufficient quality, which requires that survey data is collected accurately with the necessary precision, and that survey and observational metadata are automatically collected, where possible. Fast sharing of survey data, to support timely analysis and increased data usability, can be enabled by direct integration with back-end regional or national biodiversity repositories.

Effective wildlife monitoring using CS is currently hampered by a lack of information regarding species absence and sampling effort in time and space (Cooper et al., 2012; Crall et al., 2011; Dickinson et al., 2010). There is a lack of understanding of the potential value of the automatic collection of CS monitoring metadata, such as search effort and path. Recording more accurate search metadata to improve the collection of species absence data has been suggested (Kelling et al., 2019; Sequeira et al., 2014), with other benefits of accurate search effort including improved understanding of sampling intensity and species detection probability leading to more robust inferences from modelling (Geldmann et al., 2016; Isaac et al., 2014). To confirm the significance of this, the eBird app recently included similar functionality to record observer search paths, to complement the use of complete lists and other techniques to assist in determining search effort, species detectability and observer skill levels (Cornell Lab of Ornithology, 2017).

There have been few studies in Australia that compare biases of CS and traditional observational data at continental scale and at high temporal and spatial intensity. Much of Australia is sparsely populated and inaccessible, so understanding similarities and differences of spatial aspects of CS and traditionally recorded observations is important to inform effective conservation management. A recent review of spatial bias in 646 studies of terrestrial reptile research in Australia (Piccolo et al., 2020), found that research effort was driven by accessibility, specifically proximity to universities. Lloyd et al. (2020) evaluated CS biodiversity project coverage in Australia against threatened species ranges to assess geographic and taxonomic coverage and found potential coverage of citizen science aligned relatively well with threatened species richness in terrestrial systems. A global study comparing CS bird observations to traditional monitoring found that CS data were not sufficient for monitoring most of the world's bird populations and even less in developing countries (Neate-Clegg et al., 2020). In the UK, CS monitoring data were less spatially biased than long-term scientific data but did display bias towards urban areas (Sumner et al., 2019). In addition, in just two weeks, CS provided comparable coverage to more than four decades of expert monitoring. A better understanding of biases in CS and traditional monitoring datasets can provide evidence for improving both.

Additionally, increasing our understanding of how resilient CS and conventional wildlife monitoring are to changed patterns of community activity is important to guide conservation management decision-making as societal disruptions continue to increase. Recent research overseas has provided conflicting evidence regarding changes to CS monitoring patterns during restrictions caused by the COVID-19 pandemic (Basile et al., 2021; Kishimoto and Kobori, 2021; Miller-Rushing et al., 2021; Rose et al., 2020). In Australia, biodiversity-related studies on pandemic effects relate to changes in species distribution and abundance (Gilby et al., 2021a) and human use of urban green space (Berdejo-Espinola et al., 2021) with no studies of changes to CS or traditional wildlife monitoring until now. Understanding these changes is important information as any data gaps or changes to sampling patterns in long-term monitoring datasets can affect future analyses. This knowledge may also allow better conservation management planning when faced with future disruptions.

1.2. RESEARCH AIMS AND OBJECTIVES

The overall aim of this thesis is to investigate and develop methods to enhance data collected by citizen scientists to improve wildlife monitoring. This aim is addressed through two sub-themes. The first is the development and trialling of improved mobile apps to improve CS wildlife monitoring data through two case studies of iconic Australian mammal species. The second is to explore aspects of data biases by comparing the CS data to data from official data sources, under normal conditions and also under exceptional circumstances. The objectives are thus:

1. to develop mobile applications for CS-based wildlife monitoring which enable: a. improved data collection through automatic recording of key metadata, including accurate observer effort data; and b. accurate, large-scale CS monitoring to improve species baseline knowledge through higher resolution spatial and temporal coverage than previously possible;

2. to compare spatial aspects of Australian CS wildlife monitoring data to traditional sources and assess possible biases of each;

3. to assess the resilience of CS data collection compared to traditional data sources when faced with disruptions caused by restrictions on community activities.

1.3. THESIS STRUCTURE

The remaining chapters of this thesis are presented as standalone papers which have been published or submitted for publication. Chapters two and three present two case studies that describe the development and application of novel mobile apps to citizen science projects for wildlife monitoring and how these may lead to improved results through the automatic collection of metadata to better understand biases around search effort and location. Chapters three and four compare data from one of these studies with data in official biodiversity repositories to provide insight into spatial biases of CS observations compared to data collected using traditional methods. Chapter four also compares how observations from CS and traditional sources are affected during periods of restrictions to community activity caused by a global pandemic. Chapter five summarises and discusses the overall research and presents conclusions that highlight key research contributions and opportunities for further research. The following presents a summary of the contents of each chapter.

Chapter two presents a new mobile app and analyses its use in a citizen science bioblitz-style project to collect koala population data for informing koala conservation and management in South Australia. The app uses mobile phone sensors to transparently and automatically record metadata such as species observation location and time, the search path the user takes, the time taken while searching and GPS location precision. Potential improvements to further increase the quality of collected data are suggested, along with recommendations for app development and the recording of important contextual metadata for CS projects. This chapter has been published as:

Stenhouse, A., Roetman, P., Lewis, M., Koh, L.P., 2020. Koala Counter: Recording Citizen Scientists' search paths to improve data quality. *Global Ecology and Conservation* 24, e01376.

Chapter three presents a custom mobile app and results from using it in a CS opportunistic monitoring program to improve baseline knowledge about short-beaked echidna population abundance and distribution across Australia. The data collected over three years were compared with existing traditional data sources in relation to coverage in protected areas and to geographic distribution using an index of accessibility and remoteness. This chapter has been published as:

Stenhouse, A., Perry, T., Grützner, F., Lewis, M., Koh, L.P., 2021. EchidnaCSI – Improving monitoring of a cryptic species at continental scale using Citizen Science. *Global Ecology and Conservation* 28, e01626.

Chapter four evaluates the effect of disruptions to wildlife monitoring caused by varying restrictions imposed on people's movement and compares these effects between CS and traditional sources. This chapter highlights the complementary nature of CS to scientific monitoring and the potential value of CS monitoring during times of social disruption. This chapter has been published as:

Stenhouse, A., Perry, T., Grützner, F., Rismiller, P., Koh, L.P., Lewis, M., 2022. COVID restrictions impact wildlife monitoring in Australia. *Biological Conservation 267*, 109470. https://doi.org/10.1016/j.biocon.2022.109470.

Chapter five highlights the key findings from these studies, outlines key contributions this work has made to improving the use of citizen science for wildlife monitoring and provides recommendations for future research and development.

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Chapter 2. Koala Counter: Recording Citizen Scientists' Search Paths to Improve Data Quality

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Principal Author

Name of Principal Author (Candidate)	Alan Stenhouse	
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Signature		Date: 01/10/2021

Co-author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
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iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Philip Roetman	
Contribution to the Paper	Conceptualisation, methodology, writing – review and editing.	
Signature		Date: 8 Oct 2021 Signed by Justin Brookes (Post-grad coordinator) on behalf of Philip Roetman

Name of Co-Author	Megan Lewis	
Contribution to the Paper	Methodology, writing – original draft preparation, writing – review and editing.	
Signature		Date: 05/10/2021

Name of Co-Author	Lian Pin Koh	
Contribution to the Paper	Methodology, writing – original draft preparation, writing – review and editing.	
Signature		Date: 04/10/2021

ABSTRACT

1. Biodiversity monitoring is key for developing informed solutions to the threats facing our environment, including habitat loss, increasing pollution, wildlife trafficking and climate change. Citizen science is increasingly used for collecting species observational data at wide spatial and temporal scales that are difficult and expensive to achieve using traditional means. Current apps used for citizen science biodiversity monitoring provide methods to record observational data on species' presence, including photos, location, date, time and an assortment of other data. However, data about species absences as well as automatically generated and accurate data on both search effort and search locations have been lacking.
2. Koala Counter is a free, cross-platform (Android & iOS), open-source app that was developed for a citizen science project to collect koala population data to inform koala conservation and management in South Australia. The app uses mobile phone sensors to transparently and automatically record metadata such as species observation location and time, the search path the user takes, the time taken while searching and GPS location precision. We tested this in the Citizen Science event "The Great Koala Count 2" in South Australia during November 2016.
3. Observations, paths and search effort data were accurate overall. Location accuracy was good, with some exceptions. Use of the app indicated a number of potential improvements that would further increase data quality.
4. Recording search paths offers a potentially valuable method of recording spatial and temporal components of search effort, improving on simple records of species observations and time taken, especially when no observations are made. These data may enable better ecological modelling by supplying accurate search effort data as well as enabling improved inference of species absence. Search paths also show locations that have not been searched, which is valuable information in management of citizen science monitoring programs.

2.1. INTRODUCTION

Citizen Science (CS) is increasingly used to assist with biodiversity monitoring, analysis and restorative services (Chandler et al., 2017; Edwards et al., 2018; Hesley et al., 2017). CS can often provide wider spatial and temporal coverage than is usually possible with traditional scientific projects (Dickinson et al., 2010; Hurlbert and Liang, 2012). Multiple sensors contained in mobile phones, combined with easy-to-use software apps and widespread internet accessibility (Bonney et al., 2014; Pimm et al., 2015) have been the primary enabling technologies behind the huge increase in numbers of CS projects. It is now easy to record observational data including photographs, video and audio as well as automatically recording other contextual information such as location, date and time. It is also easy to share this information by uploading data directly to national and international project data repositories.

There are multiple examples of CS biodiversity observational projects operating at local, national and global scales. iNaturalist had more than 13 million observations of almost 170 thousand species submitted in 2019 alone (https://www.inaturalist.org/stats/2019). By the end of 2019, over 737 million bird observation records had been submitted to eBird, a global citizen science program, from more than 500,000 participants over the previous 17 years (https://ebird.org/news/ebird-2019-year-in-review). Over 220 peer-reviewed publications (Wiggins et al., 2018) have utilised data from eBird to answer questions related to topics such as bird distribution (Fink et al., 2010) and climate change effects on birds (Hurlbert and Liang, 2012), contributing to a range of conservation outcomes including threatened species assessments, conservation planning, site and habitat management and protection, species management and policy development (Sullivan et al., 2017). CS also provides large amounts of data to the Global Biodiversity Information Facility (GBIF https://www.gbif.org/) which gathers and stores hundreds of millions of species occurrence records. These data have been used by researchers worldwide in over 1700 peer-reviewed journal articles (Chandler et al., 2017). CS data are contributing to monitoring progress on the United Nations Sustainable Development Goals (UN SDGs) and can complement official data sets by providing varying temporal and spatial data resolutions (Fritz et al., 2019).

However, with the increasing popularity of CS, there are concerns about the quality of data collected (Burgess et al., 2017; Lukyanenko et al., 2016). While some CS projects follow strict protocols requiring much user training (Edgar and Stuart-Smith, 2014), many projects collecting species observational data do not, particularly when aimed at the broader community, and often result in data with some form of bias – spatial, temporal and others (Boakes et al., 2010; Dickinson et al., 2010; Hugo and Altwegg, 2017; Isaac and Pocock, 2015). Spatial biases occur as observers follow known tracks or roads and ignore habitats which are harder to access or are further away, or when known areas of species occurrence are sampled rather than areas where the target species are less common. Temporal biases may occur as citizens prefer to record observations at times suitable to themselves, such as early morning or evening, or in the weekends. Often no accurate effort (time and distance) data is recorded and spatial coordinates can be inaccurate or lacking (Bayraktarov et al., 2019).

In current CS projects recording biodiversity observations, it is common to include photos of the target species which allow experts or data curators to confirm the observation, if necessary (Crall et al., 2011; Kosmala et al., 2016; Wiggins et al., 2011). When taking a photo, location is automatically recorded using the location services capabilities of mobile phones (utilising GPS, Wi-Fi and other subsystems as needed), thus accurately recording the location where species sightings have occurred. However, species absence data, which is important for species distribution modelling (Koshkina et al., 2017; Lobo et al., 2010; Václavík and Meentemeyer, 2009), is usually not recorded but often accounted for by ecologists by using environmental conditions to aid selection of random pseudo-absences (Barbet-Massin et al., 2012; Stokland et al., 2011; VanDerWal et al., 2009). Search effort and location are also important aspects of biodiversity monitoring (Crawford et al., 2020) and are often estimated by the observer after the fact, if at all, resulting in both imprecise effort data, as well as missing the possibility to discover where a species was not observed. Additional metadata about location – such as measures of how accurate the location data are – are not usually recorded and result in extra uncertainty when evaluating data quality (Meyer et al., 2016).

In the app presented here, we address these issues by gathering additional data transparently using the sensors that already exist on mobile phones. This may improve the accuracy of observer effort recordings, both spatially and temporally, by using the inbuilt sensors to automatically record search path and time. This may also improve the usability of the mobile app by eliminating the need to explicitly set location or calculate time taken. This could enable more accurate inference of species absence and thus improve the outcomes of CS-assisted biodiversity monitoring by improving contributions to species distribution and population abundance modelling (Dissanayake et al., 2019; Kelling et al., 2018; Pocock et al., 2018; Steen et al., 2019). Prior research suggested that the recording of accurate survey effort and search locations may enable better species absence data as well as improving detection probability (Sequeira et al., 2014). By actually recording the distribution of survey effort, it is possible to better identify sampling bias, which can improve species distribution modelling through more reliable selection of background environmental data used as pseudo-absences (Gomes et al., 2018; Guillera-Arroita et al., 2015; Phillips et al., 2009).

This paper describes an open-source, cross-platform mobile application we developed to record CS observations of an Australian native animal and its habitat, and also presents the results from use of the app in a weekend-long CS event. The app aimed to improve ecological data collected by Citizen Scientists by accurately and transparently recording search paths and effort as well as location metadata such as measures of horizontal accuracy. These data may be used to more accurately assess search effort as well as infer species absences as we can better determine the distribution and duration of searches. While developed specifically for this project, the app could be modified for use with other CS projects as the core functionalities of recording locations and species observations would remain the same, with project-specific questions and screens being added or adapted as desired.

2.2. MATERIALS AND METHODS

2.2.1. App Design & Implementation

The aim of the project was to gather information about koala (*Phascolarctos cinereus*) populations and their habitats in South Australia in order to guide their conservation and management and to assist development and understanding of monitoring protocols. More specifically, the project sought to gather new data about koala distribution, abundance and breeding, their habitat preferences and impacts on tree condition. We developed the Koala Counter app as an integral part of the project, with the specific information gathered designed by a collaborative team of CS practitioners and faunal ecologists.

The Koala Counter app was developed using LiveCode (version 6.7, www.livecode.org and www.livecode.com) – an open-source, multi-platform development environment enabling rapid application development using one source code base for multiple target devices. The app was compiled for both iOS and Android platforms in order to make it available to a wide user base. The app ran on both mobile devices which could provide location information, had a camera and had an Operating System (OS) that was compatible (Android version 2.3.3 and iOS 5.1.1 or later).

User registration requirements were kept to a minimum as they were regarded as a barrier to use (Jay et al., 2016; Martin et al., 2016). As the project was a short, intensive survey conducted over one weekend we wanted to enable anyone to take part without privacy concerns, particularly as their search paths were going to be recorded. Only an email address entry was required with few checks on validity – merely that the entry had the form of an email address – so that feedback to participants was possible. Each user was assigned a Unique User ID (UUID) that identified their uploaded data without any other link to their personal information. Data about the user's mobile device was also recorded to inform about possible device differences relating to data quality e.g. location accuracy (Kosmala et al., 2016; Wiggins and He, 2016).

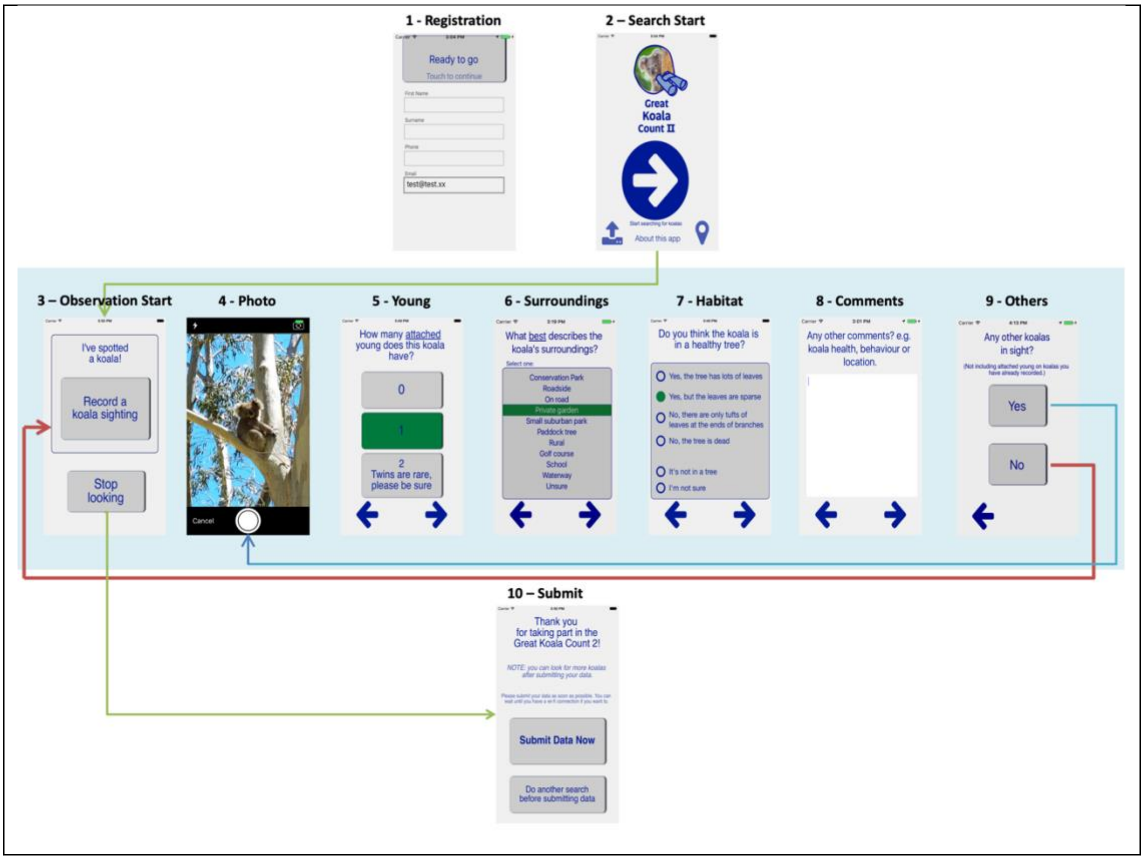

Figure 2-1 Screen flow of Koala Counter app. Location is recorded every 5 seconds while in the middle screens

The app screen flow is illustrated in Figure 2-1. In order to accurately record search effort and a user's search path, there were "Start" and "Finish" screens. Starting a search started recording the user's location every 5 seconds – resulting in the search path being recorded. In addition to the location (latitude, longitude and altitude), speed, compass heading, accuracy of horizontal and vertical locations and the GPS timestamp were also recorded, when available. The date and time from the mobile device clock were also recorded at the start and finish, as well as for each observation, as a check on the functioning of the device's Location Services subsystem.

To record an observation, the "Record a koala sighting" button was touched. This started the camera view, which enabled a photo to be taken immediately, while the subject was visible. Once the photo was taken, reviewed and accepted by the user, the participant answered a series of questions (Table S2-1) to gather ecological data related to koala population, breeding, habitat and tree condition.

Questions 1-3 were single-choice and must be answered before continuing to the next question. Question 4 was a free-form text entry answer enabling the user to provide any more details that they considered relevant. Question 5 was a simple branching question that enabled the user to make multiple observations from one location, in case there were multiple koalas visible. If "Yes" was selected then the app automatically returned to the camera, allowing the user to take a photo and then record details using Questions 1-5. If "No" was selected they returned to the "Record a koala sighting" screen and continued searching.

Multiple observations could be made from one location, using the steps above. Multiple observations could also be made during one search. Multiple searches were also possible – i.e. a user could start and stop a search in one area and then travel to another location and start another search – on the same day or another day.

On completion of a search, a participant could upload their data immediately or wait until later (when connected to Wi-Fi for example). It was not necessary to be connected to a mobile phone network to use the app, as all data were stored locally until they were uploaded. Data were uploaded to an intermediate server and from there processed periodically to upload observations to the project repository on BioCollect (https://www.ala.org.au/biocollect/), part of Australia's national biodiversity repository – the Atlas of Living Australia (ALA – https://www.ala.org.au/). Search path data were processed separately as it was not possible at the time of this project to store them on the ALA. Each participant's observations were identified only by their UUID to ensure privacy.

Data were recorded to a tab-delimited key-value pair text file with path locations interspersed with observations – one per line (Table S2-2). Location records were recorded by the app automatically every five seconds, starting when the participant initiated the search. Each path was started with a "Start" Event record and ended with a "Finished" Event record. Observation records were stored in sequence with the path.

The app "Koala Counter" was first released for Android (https://play.google.com/store/apps/details?id=com.scruffmonkey.koalacounter) and for iOS (https://itunes.apple.com/app/koala-counter/id1148857677) on October 13, 2016, with revision 1.09 released on November 21, 2016 on both platforms. This was used in the CS project "The Great Koala Count 2" in South Australia and we present results from this event to demonstrate the potential value of accurately recording Citizen Scientist search paths, species observations and effort.

2.2.2. App in Use - The Great Koala Count 2

The second South Australian Great Koala Count (GKC2) was held on Saturday 26th and Sunday 27th of November, 2016. This CS project followed the first South Australian Great Koala Count held during one weekend in November 2012 (Sequeira et al., 2014). A central project page on the University of South Australia's Discovery Circle website provided a central go-to point for project information including app download links and an instructional video on how to use the app (https://vimeo.com/192054563). Community participation was encouraged through the media, including social media, and the communication networks of the project partners (see Acknowledgements for details). The project repository on the ALA provided a web-based form interface to enter observations for participants without a mobile phone. We requested that volunteers download the app and then go outside and search safely for koala anywhere in South Australia during daylight hours.

2.2.3. Data Summary and Analysis

For this study we have selected all observation and path data submitted using the app during the weekend of the GKC2 and analysed it using RStudio version 1.2.5019 (R Core Team, 2019), R version 3.6.1 and the following packages: data cleaning and preparation for analysis with tidyverse (Wickham et al., 2019), graphs with ggplot2 (Wickham, 2016) and maps with ggmap3 (Kahle and Wickham, 2013) and QGIS 3.14 (QGIS Development Team, 2020).

To reduce their impact on effort and location accuracies, the following paths were removed: a) five long paths which occurred due to error or incorrect usage (such as not stopping the search and driving elsewhere); b) paths that contained only 2 rows, indicating an error or user test; c) paths with mean speed > 2 ms^{-1}, as determined from all location records for each path, as these indicated incorrect usage such as travelling to or from search areas by car or bicycle and this speed cut off is above normal walking speed while allowing some flexibility; d) paths with a duration < 1 minute, except those containing at least one observation. We calculated path duration from the start and finish times for each path. Durations for paths that were finished without an end time were derived from the number of location records multiplied by the recording frequency (5s). We calculated mean horizontal accuracy of locations for each path and provide summaries for overall horizontal accuracy by path and by participant. We calculated total observations by path and participant. We split observations into those with location data and those without and then calculated mean horizontal accuracy by path and participant. All observations were used for analyses.

2.3. RESULTS

2.3.1. Participants

Six hundred and twenty people downloaded the app (iOS: 387, Android: 233), of whom 549 registered it (Table S2-3). On the study weekend, 281 of these used the app and recorded at least one search path, while 232 participants made at least one observation and 49 recorded search paths with no observations. Forty-six participants recorded paths with observations but with no location data.

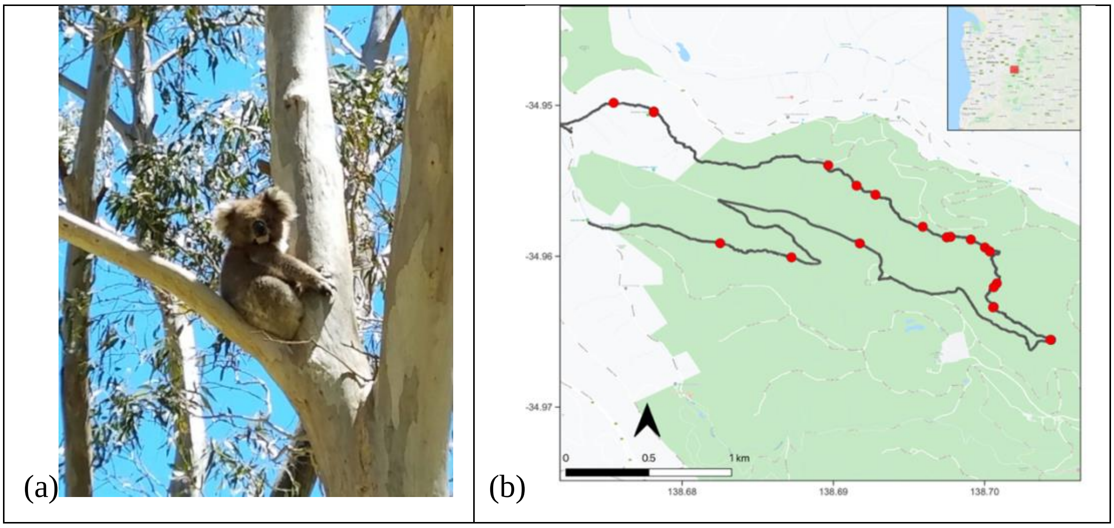

Figure 2-2 (a) Example observation photo of koala (from UUID 8d1ef5f6-c7ee-4ccf-8c12-ab715b293acb) and (b) Example path and observations for one participant, who followed established tracks between 11:00 am and 2:00 pm, with 22 koala observations recorded. Base map data: Google.

Figure 2-2(a) shows a sample koala observation photo taken during the study weekend and Figure 2-2(b) shows one participant's search path and observations as an example of the data collected using the app. The majority of searches and koala observations were in the conservation parks (Table S2-4) in the Adelaide Hills and Mount Lofty Ranges on the outskirts of Adelaide as shown on Figure 2-3(a), with three observations in Flinders Chase National Park on Kangaroo Island and others scattered within a 50km radius of Adelaide.

Observations and searches were concentrated around easily accessible roads and tracks, as illustrated in Figure 2-3(a). Figure 2-3(b) shows Cleland Conservation Park where most observations were on paths in the north of the park and some, mostly unsuccessful, searching in the South, with no searching in the middle.

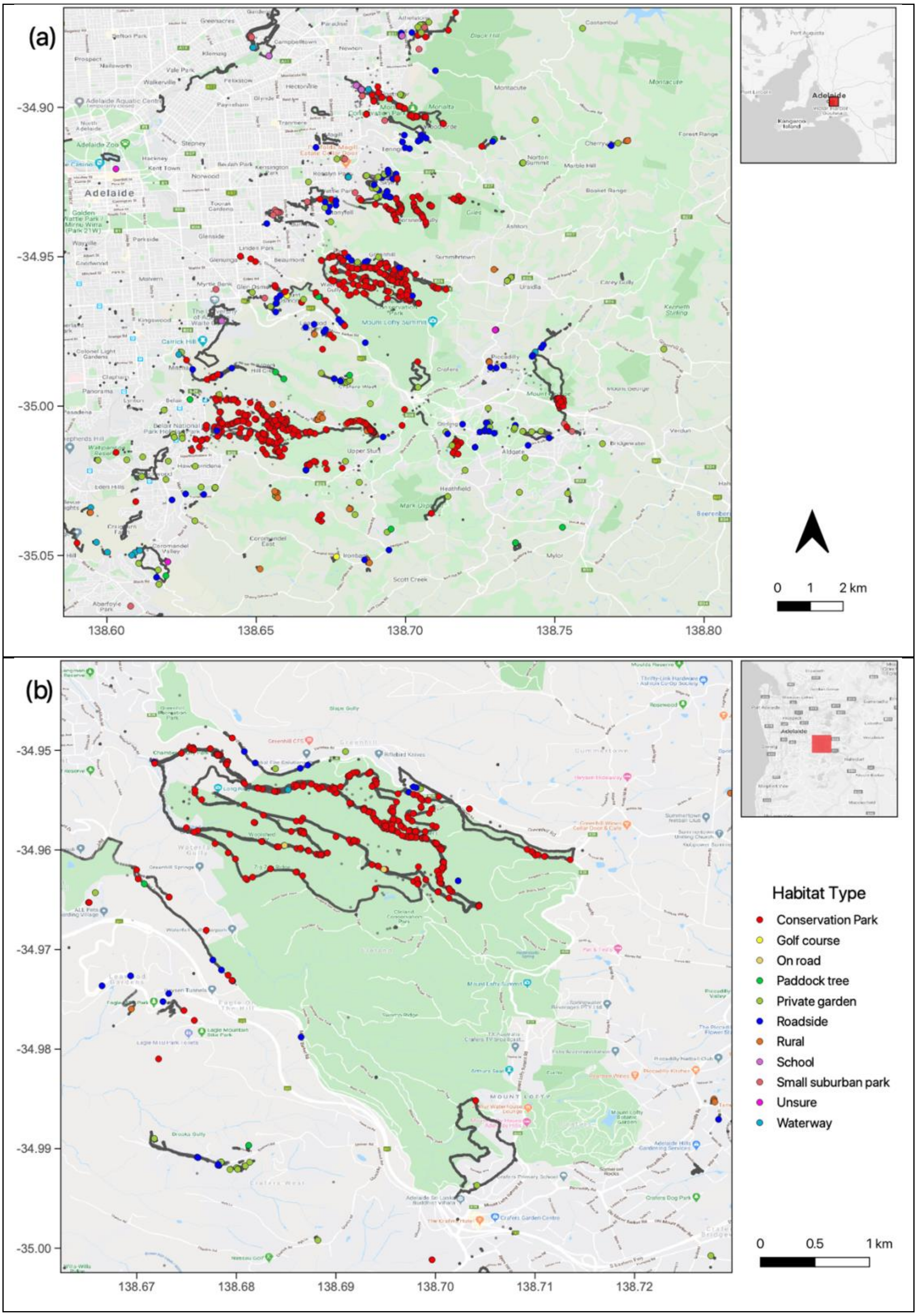

Figure 2-3 Maps showing search paths in grey and koala observations coloured according to habitat type. (a) Overview map for the Adelaide Hills and Mount Lofty Ranges on the outskirts of Adelaide in South Australia. (b) Search paths and observations in Cleland Conservation Park. Base map data: Google.

2.3.2. Search Paths

There were 774 paths recorded with a total time of 350.5 hours. The most paths completed by a single participant was 89. The mean number of paths per participant was 2.75 and the median was two. There were 692 paths (89.4%) with location data while 82 paths were recorded without. The maximum total search duration for one participant was 9.96 hours. See Table S2-5 for further details. The mean total search duration per participant was 74.85 minutes and the median per participant duration was 52.88 minutes. Twenty-five participants recorded no GPS locations during their searches which resulted in 82 paths without location data. The mean horizontal accuracy of locations per participant was 104.8 m, while the median was 12.2 m (Table S2-5).

The mean duration per search path was 27.17 minutes and the median duration was 9.85 minutes. The maximum total search duration for one path was 4.35 hours. The mean horizontal accuracy of locations per path was 111.5 m, while the median was 8.4 m (Figure 2-4). The maximum number of koala observations on one path was 36 (Table S2-6).

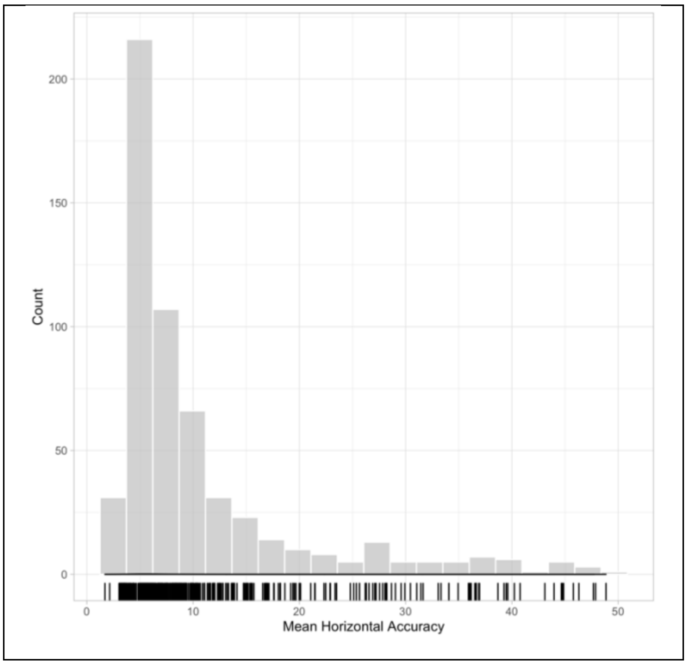

Figure 2-4 Distribution of paths mean horizontal accuracy, restricted to paths with mean horizontal accuracy <50m

2.3.3. Koala Observations

A total of 232 participants recorded 1604 observations of koala, 181 of which were described as “Attached young” including 3 sets of twins, resulting in 184 young and 1788 koala. Of these, 1394 observations were recorded with location data while 210 were recorded without location data (Table S2-7).

The mean observations per participant was 6.9, skewed particularly by one participant who made 124 observations; the median number of observations per participant was 3. One participant recorded 12 koala with attached young. The mean horizontal accuracy per user when recording observations was 80.84 m while the median was 6 m (Table S2-8). The mean number of observations per path was 2.85, with the maximum number for one path of 36 and the median observations per path was 1. The mean horizontal accuracy per path when recording observations was 58.95 m while the median was 5 m (Table S2-9).

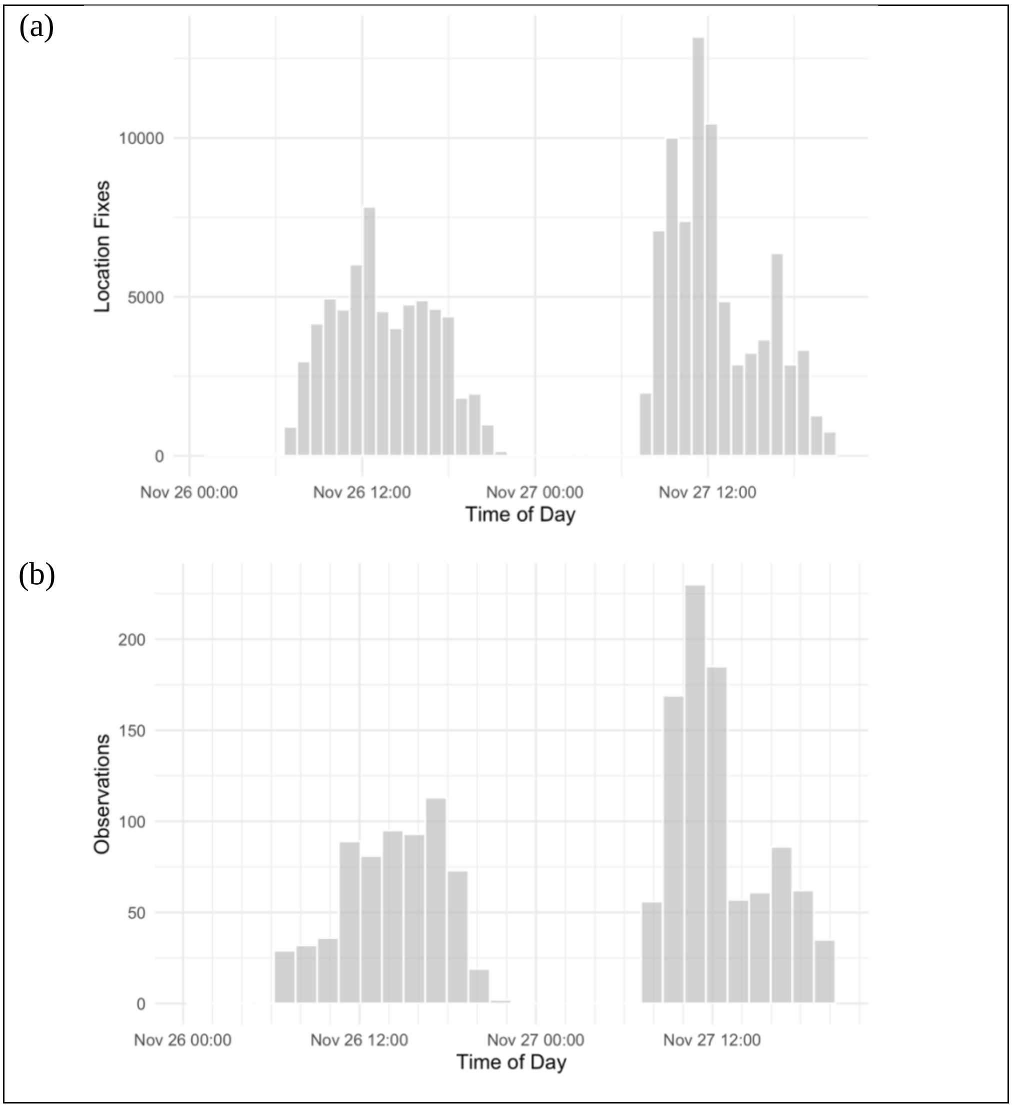

Figure 2-5 Temporal distribution of location fixes (a) and koala observations (b).

The temporal distribution of location fixes in Figure 2-5(a) is generally similar to the temporal distribution of observations in Figure 2-5(b). Most searches took place in the middle of the day with a smaller peak on late afternoon Sunday. It is noteworthy that there were more koala observations relative to the number of location fixes late in the day on

26th November, whereas the frequency of observations on 27th November more closely followed the timing of searches.

2.4. DISCUSSION

Using the app for this study provided a number of benefits which could aid other CS projects. The app provided accurate spatiotemporal observation data together with measures of location accuracy, and consistent and standardised observer responses. Effort data were also accurately recorded through the use of start and finish times for searches and a standardised location polling frequency. The path data that were recorded were generally very spatially accurate, with few exceptions, and show potential value for enabling inference of species absence. Trial of the app revealed some limitations which can be used to provide guidance for improving data gathered in future projects.

2.4.1. Benefits of this data

2.4.1.1 Accurate observation data

Recording location automatically when making observations resulted in accurate locations generally, with a few exceptions. Recording the extra location metadata, especially horizontal accuracy, enabled us to better evaluate the quality of these data and to identify outliers. The median horizontal accuracy for observations of 6 m and third quartile of 10 m indicates the good accuracy of the majority of observations, while some participants' observations were inaccurate, probably due to the location settings on their device. This extra metadata was essential for determining the level of error in these particular observations.

The difference between location and observation intensity on Saturday afternoon may be that the koala were more active on Saturday afternoon. Another possible reason may be incorrect usage of the app – it appears that some users started to initiate searches only after spotting a koala, which would lead to this discrepancy – possibly to prolong battery life of their device.

2.4.1.2 Accurate effort data

Effort data were generally accurate. By recording explicit start and finish events using the mobile device clock we could ensure a consistent and accurate measurement of search duration. By additionally recording the GPS timestamp and using a standard location polling frequency we could both cross-check this accuracy as well as calculate duration in case of error, for example when the user quit the app without explicitly finishing the search.

2.4.1.3 Assessing species presence and absence

Automatically recording participants' search paths offers some benefits. By documenting where searches have occurred, it may be possible to more accurately assess species absence. Without this search data, i.e. with only observation data, we would not know if an area had been searched and no koala were observed or if that area had not been searched at all. This could thus provide data about species absence as well as presence. In Figure 3(b) we can see areas such as the southern part of the park which have been searched with few observations.

2.4.1.4 Assessing monitoring coverage and spatial bias

We can also determine the spatial distribution and intensity of searching, both on an aggregate and individual level. This enables us to identify areas that have been adequately monitored and also where monitoring coverage is lacking as shown in Figure 2-3(b). Most participants followed easily accessible and established paths while searching. This spatial bias is often assumed for CS projects but the track data provided by our app can provide an objective basis to explicitly assess this bias. Search path data could also enable us to better target inadequately searched areas where additional monitoring should take place by identifying areas that have not been searched, such as the middle of Cleland Conservation Park in Figure 3(b), for example.

2.4.2. App Limitations

2.4.2.1 Location recording

Technical problems and incorrect usage led to some problems with recording location data. While most devices provided accurate readings, there were a few that had consistently poor accuracy, probably due to the location settings on their device or device hardware limitations. Some participants performed searches and made observations without location services being enabled on their phone or with inaccurate location services such as Wi-Fi only, despite being prompted on starting the app to ensure these were enabled. One solution to ensure this doesn't occur would be to disable access to the functionality of the app until location services are enabled.

To save battery life, we started the location tracking system only when beginning a search. As the location subsystem for a device takes some time to initialise, we usually did not get accurate location data at the start of a search. While this was not critical, a change to start the location services system on starting the app is desirable. We did record the start date and time from the device clock on starting a search, so this information was not lost, though a comparison of the device clock with the GPS timestamp is necessary when analysing the data.

2.4.2.2 Enhancing user feedback

Some participants proceeded without location services being activated on their device and some indicated they were uncomfortable with the idea of their mobile phone being used to track their location and thus always kept their location services turned off. This suggests that we could have provided better guidance to indicate the importance of location information being available and how it was being used. Another problem that occurred was that some users searched while travelling in a car or on a bicycle and only on sighting a koala would they stop and record their observation. This would also have been resolved with more training or preliminary information. A possible solution for this issue could be to provide in-app guidance so that if a certain threshold speed is exceeded then warnings or other action could occur. This could be another use for the automatically recorded metadata, as the current speed is one of the data items recorded.

Our original intention was to display the participant's path and observations on a map on the device. This would provide immediate feedback in an attractive way by showing their progress, as well as provide a history of their activity. This wasn't possible because of time constraints during development prior to the Great Koala Count weekend, but was subsequently added and would be beneficial in further projects using this app. All path and observational data were added as Javascript data to a template HTML file. Markers and paths were then displayed on a Google map in order to provide immediate feedback and visibility of observations and search paths in context. Each observation marker is selectable to display an information window showing observation details, including the photo that was taken. To display the map successfully does, however, require an internet connection, which may not always be available in the field.

2.4.2.3 Other variables

Species detectability and observer skill levels (Johnston et al., 2018) are important variables that are not addressed by this study but our data may assist in evaluating these. Repeated sampling may enable comparison between observers and evaluation of skill level changes over time. At the same time, this could assist with determining species detectability, which is particularly relevant when assessing species under decline (Burns et al., 2019).

2.4.3. Future App Development

Possible future enhancements to the app could include the following items.

2.4.3.1 Increased metadata usage

It may be beneficial to increase the amount of automatically recorded metadata using other sensors on mobile devices, such as the compass and accelerometer. Recording the compass heading at the time of taking an observation photo, might better enable us to determine possible duplicate animal observations or to clarify the status of apparent duplicate observations. For example, currently an observation records a point in space and time, but adding compass heading would allow us to differentiate between two observations from the same location but looking in different directions.

2.4.3.2 User ID integration

Data were uploaded to the ALA under a generic project identifier and a user's contributions can be identified by the user's UUID – a unique string. However, this means that the user cannot easily find the data they have contributed to the national database. A way to enable the user to easily register themselves on the ALA using the app would be desirable so that their contributions can be found as well as acknowledged, if they choose to do so. This can be important for participant motivation on a longer-term project (Preece, 2016).

2.4.3.3 Guided paths

A system to provide "guided paths" – structured or semi-structured surveys (Kelling et al., 2019) – to participants could be valuable. This might involve pre-recording a number of paths in different areas where monitoring is desired and then allowing participants to select paths of interest. The app would then assist the participant to follow the selected path while making observations as required. It would also be possible to provide further user guidance to indicate where, how and when to make observations and what to observe, so that more optimised CS sampling may be applied (Callaghan et al., 2019). This might significantly improve the usability of CS project data for conservation management.

2.4.4. Recommendations

From our experience in development of the Koala Counter app and its implementation in a CS project, we make the following recommendations in relation to app development for CS projects and to improve the data collected from these apps for ecological questions.

2.4.4.1 App development

- Ensure the app is dual platform to ensure the majority of participants can use it. We used LiveCode to save time and effort, but there are many possible options.
- Provide guidance inside the app on how to use it effectively. Supplement this by attempting to ensure that participants use the app correctly. For example, recognise if location services are not available and notify the user to correct the problem. If the speed while searching is too high, check with the user to see if they are actually still searching and guide them to the correct use.
- Ensure that the development platform supports the required sensor integrations. Can you take a photo and store it? Can you access location data including accuracy measures? What about other sensors like the compass and accelerometer?
- Don’t require participant registration but do enable registration to take place. A UUID should be used to uniquely (and anonymously) identify each participant. Allow the participants to decide if they want their name associated with their observations (to gain recognition, for example) and also allow them to edit their registration details.
- If possible, use an already existing system – though there are some advantages to having your own. If a project has a long timeframe then the costs of keeping software up-to-date may be significant, so cooperation with and support of existing systems, such as iNaturalist, may be a more sustainable project path.

2.4.4.2 Data and metadata

- Record the device timestamp with every location/observation to ensure accuracy of recording in case there are location issues and to check for any mismatch between device date and time compared to the location system reference timestamps.

- Record location changes as they occur. We recorded GPS data every n (5) seconds to try to reduce energy consumption. This is probably unnecessary in most cases, so relying on the device to provide location updates and recording them as provided may provide better information. It might also be useful to record a periodic time check (e.g. every minute) from the device itself, as a double-check on proper system function and with low energy requirement.
- Ensure a participant's own observations and paths are viewable on their own device. Ideally allow them to view where others have searched and made observations, though this may not be possible while in the field. This may allow them to better select routes that have not yet been searched.
- It may be useful to record device metadata (device type, OS version, etc.) with each observation. Participants often upgrade devices and OS versions change rapidly – some have more issues than others and it may be useful in future analyses if these metadata are available.
- Search path and effort data are valuable and can be automatically recorded. Recording metadata about locations, especially horizontal accuracy, is also valuable as it enables better quality assessment.
- Observation locations can be accurately and transparently recorded and observation metadata is also important for assessing data quality, particularly when Citizen Scientists use a wide range of devices with varying capabilities. Additional metadata such as compass heading may also prove useful in the future.

2.5. CONCLUSIONS

The Koala Counter app accurately recorded Citizen Scientists' search paths, search effort and species observations. It provided accurate spatiotemporal observation data together with a measure of location accuracy as well as consistent and standardised question responses. Effort data were also accurately measured through the use of start and finish times for searches as well as using a standardised location polling frequency. The path data that were recorded were generally very spatially accurate, with some exceptions, and show value for enabling inference of species absence. Recording species observations and time taken alone does not accurately reflect the spatial aspect of effort, especially when no observations are made. In addition to search paths and time, metadata such as location accuracy details and speed can also be automatically recorded and may prove useful for evaluating data quality, for on-the-fly user feedback and assistance, as well as in analysing user and device performance in context. In the future, as we accurately record citizen scientist search paths and effort, management of citizen science programs could be further enhanced by actively targeting locations where coverage has been lacking. Lastly, fast and easy uploading of data to national biodiversity repositories ensures that more timely and usable data is provided to global researchers.

In summary, the innovations implemented in this app provide a range of benefits which may enhance the quality of citizen science data by providing more information on the location and duration of searches. By recording metadata such as horizontal and vertical accuracy and speed, we provide more contextual information which may enable conservation practitioners to better understand the accuracy and limitations of the data. These methods may be used in other applications to improve the data used for conservation management and other ecological applications.

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DATA AVAILABILITY

Koala Counter is a free mobile app available for Android (https://play.google.com/store/apps/details?id=com.scruffmonkey.koalacounter) and previously available on iOS. Application code is available on FigShare at DOI: https://doi.org/10.25909/13239797 and GitHub at https://github.com/alanstenhouse/CitizenScience-KoalaCount-app.

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2.7. SUPPORTING INFORMATION

Table S2-1 Core observation questions and answer options in the app

1.	How many <u>attached</u> young does this koala have? 0 1 2 - Twins are rare, please be sure
2.	What <u>best</u> describes the koala's surroundings? Conservation Park Roadside On road Private garden Small suburban park Paddock tree Rural Golf course School Waterway Unsure
3.	Do you think the koala is in a healthy tree? Yes, the tree has lots of leaves Yes, but the leaves are sparse No, there are only tufts of leaves at the end of branches No, the tree is dead It's not in a tree I'm not sure
4.	Any other comments? e.g. koala health, behaviour or location.
5.	Any other koalas in sight? (not including attached young on koalas you have already recorded.)

2.7.1. Data file format

Each line is preceded by a type identifier: "L" for "Location", "O" for "Observation". There is also an identifier for the Start and Finish points for a search path, these are preceded by "E" for "Event" followed by a colon and then the type of Event - "Start" or "Finished". Each data value is preceded by its data identifier followed by a colon e.g. "latitude: -35.018088". Data items (identifier: value pairs) are separated from each other by tab characters (ASCII character 09).

Table S2-2 Data file format

Line Type	Identifier	Data item identifier
Observation	O	
		Latitude
		Longitude
		Altitude
		Course
		Speed

		Horizontal Accuracy
		Vertical Accuracy
		GPS Timestamp
		Device Date_Time
		Health
		Habitat
		Young
		Pic
		Notes
Location	L	
		Latitude
		Longitude
		Altitude
		Course
		Speed
		Horizontal Accuracy
		Vertical Accuracy
		GPS Timestamp
Event	E:Start	
		Latitude
		Longitude
		Altitude
		Course
		Speed
		Horizontal Accuracy
		Vertical Accuracy
		Device Date Time
		GPS Timestamp
	E:Finished	(as above for E:Start)

Table S2-3 Overview of records collected over the study weekend using the Koala Counter app. i = iOS, A = Android

Downloaded	620 (387^{i}, 233^{A})
Registered	549 (341^{i}, 208^{A})
Participants	281 (172^{i}, 109^{A})
- with observations	232 (140^{i}, 92^{A})
- without observations	49
- with observations but without location data	46
Total search paths	774 (556^{i}, 218^{A})
Total observations	1604 (976^{i}, 628^{A})

Table S2-4 Types of habitat in answer to the question “What best describes the koala’s surroundings?”

Habitat	All	With Location	No Location	With Young
Conservation Park	1109	985	124	120
Roadside	158	117	41	17
Private garden	141	122	19	22
Rural	73	65	8	7
Small suburban park	43	39	4	5
Paddock tree	34	20	14	4
Waterway	23	23	0	2
School	11	11	0	2
On road	5	5	0	0
Unsure	5	5	0	2
Golf course	2	2	0	0

Table S2-5 Search Paths Summary per User

	Min.	Q1	Median	Mean	Q3	Max.	NAs
Paths per user	1	1	2	2.75	3	89	
Mean Horizontal Accuracy [m]	1.9	7	12	105	44	1605	25
Koalas Observed	0	1	2	5.7	6	124	
Duration [s]	66	749	3173	4491	6784	35866	

Table S2-6 Search Paths Summary per Path

	Min.	Q1	Median	Mean	Q3	Max.	NAs
Mean Horizontal Accuracy [m]	1.7	5.3	8.4	111.5	27.6	4989.6	82
Koalas Observed	0	0	1	2	2	36	
Duration [s]	10	161	591	1630	2039	15672	

Table S2-7 Koala Observations Summary

	Adults	Young	Total	Notes
Observations with location data	1394	164	1558	3 sets of twins
Observations with no location data	210	20	230	No twins
TOTAL	1604	184	1788	

Table S2-8 Koala Observations per Participant

	Min.	Q1	Median	Mean	Q3	Max.	NAs
Observations per Participant	1	1	3	6.9	7.3	124	
Mean Horizontal Accuracy [m]	1.6	5.0	6.0	80.8	10.0	2700.0	24
Mean speed [m/s]	0	0	0.07	0.16	0.18	2.80	42
Young	0	0.0	0.0	0.8	1.0	12	

Table S2-9 Koala Observations per Path

	Min.	Q1	Median	Mean	Q3	Max.	NAs
Observations per path	1	1.0	1.0	2.8	3.0	36	
Mean Horizontal Accuracy [m]	1.6	5.0	5.0	58.9	9.1	2700.0	80
Mean speed [m/s]	0	0.0	0.0	0.12	0.14	5.02	115
Young	0	0.0	0.0	0.3	0.0	12	

Chapter 3. EchidnaCSI – Improving monitoring of a cryptic species at continental scale using Citizen Science

Statement of Authorship

Title of Paper	EchidnaCSI – Improving monitoring of a cryptic species at continental scale using Citizen Science	
Publication Status	☒ Published ☐ Submitted for Publication	☐ Accepted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
Publication Details	Stenhouse, A., Perry, T., Grützner, F., Lewis, M., Koh, L.P., 2021. EchidnaCSI – Improving monitoring of a cryptic species at continental scale using Citizen Science. *Global Ecology and Conservation 28*, e01626. https://doi.org/10.1016/j.gecco.2021.e01626	

Principal Author

Name of Principal Author (Candidate)	Alan Stenhouse	
Contribution to the paper	Conceptualization, Software development, Methodology, data curation, formal analysis, writing – original draft preparation, writing – review and editing.	
Overall percentage (%)	80%	
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.	
Signature		Date: 01/10/2021

Co-author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Tahlia Perry	
Contribution to the Paper	Conceptualisation, writing – review and editing.	
Signature		Date: 28/09/2021

Name of Co-Author	Frank Grützner	
Contribution to the Paper	Conceptualisation, writing – review and editing.	
Signature		Date: 01/10/21

Name of Co-Author	Megan Lewis	
Contribution to the Paper	Conceptualisation, Methodology, writing – review and editing.	
Signature		Date: 05/10/2021

Name of Co-Author	Lian Pin Koh	
Contribution to the Paper	Conceptualisation, Methodology, writing – review and editing.	
Signature		Date: 04/10/2021

ABSTRACT

1. Short-beaked echidna (*Tachyglossus aculeatus*) are a cryptic and iconic monotreme found throughout the continent of Australia. Despite observational records spanning many years aggregated in national and state biodiversity databases, the spatial and temporal intensity of sightings is limited. Although the species is of least conservation concern at the global level, a subspecies has been declared endangered on Kangaroo Island in South Australia. We need better population data over the whole continent to inform this species' conservation management.
2. To increase the temporal and spatial resolution of observations which may be used for more accurate population assessments, we developed a mobile app for citizen scientists to easily record echidna sightings and improve the quantity, quality and distribution of data collected for monitoring this species. EchidnaCSI is a free, cross-platform (Android & iOS), open-source app that we developed to collect echidna observational data around Australia. EchidnaCSI has been in use since September 2017 and uses mobile phone sensors to transparently and automatically record metadata, such as species observation location and time and GPS location precision.
3. We examine differences in spatial coverage between these observations and those in existing data repositories in the Atlas of Living Australia and state biodiversity databases, especially in relation to observations in protected areas and to an index of remoteness and accessibility.
4. EchidnaCSI has contributed over 8000 echidna observations from around Australia, more than recorded in all state systems combined, with similar spatial distribution. Although coverage was more limited in some protected areas than the reference data sources, numbers of observations in all remote areas were greater than the reference scientific data except for very remote regions.
5. EchidnaCSI has improved the spatial and temporal intensity of observations for this iconic species and provides a complement to scientific surveys, which might usefully focus on highly protected areas and very remote regions.

3.1. INTRODUCTION

Adequate assessment of the conservation status of many wildlife species in Australia and around the world is hampered by limited information on abundance and distribution (Joppa et al., 2011; Pimm et al., 2014; Woinarski et al., 2015). Biodiversity loss is increasing globally (Butchart et al., 2010) and on the Australian continent is likely worse than we currently realise (Wayne et al., 2017; Woinarski et al., 2019). Historical causal factors of decline such as habitat loss, introduced predators and a range of anthropogenic influences are now being exacerbated by changes to climate (Bradshaw, 2012; Urban, 2015; Woinarski et al., 2019). In Australia, there have been multiple species extinctions (Woinarski et al., 2019, 2015) and 580 extant plant and animal species are classified as endangered or critically endangered (IUCN, 2020). Many species' populations are in decline while the status of many others remains unknown (IUCN, 2020).

Short-beaked echidnas (*Tachyglossus aculeatus*) are an iconic yet cryptic monotreme found throughout Australia in a wide variety of habitats, ranging from coastal to mountain to desert (Brice et al., 2002; Grigg et al., 1989), with abundant and spatially varying primary food sources of termites and ants (Abensperg-Traun, 1994; Abensperg-Traun and Steven, 1997). The International Union for Conservation of Nature (IUCN) Red List rates the echidna as "Least Concern" as it is widely distributed in a broad range of habitats, has few major threats and the population appears to be stable, although estimates range from 5 to 50 million (Aplin et al., 2015). The IUCN status for widespread species is determined by historical trends in populations (IUCN, 2019), which for cryptic species can be difficult to determine, particularly when they are broadly distributed (Black, 2020).

However, population trends are hard to determine without significant effort in collecting monitoring data. It is expensive and difficult to survey and monitor wildlife species at large spatial scale (Crawford et al., 2020; Neate-Clegg et al., 2020). Echidnas are particularly difficult to locate in the wild (Rismiller and McKelvey, 2003) and are not attracted by lures (Rismiller and Grutzner, 2019). Additionally, their activity levels are affected by temperature – though usually diurnal, they tend to avoid activity in extreme heat, so are often active at night in warmer climates and seasons (Brice et al., 2002; Clemente et al., 2016).

Traditional wildlife surveys and monitoring have usually been carried out by national and state government agencies, research organisations, non-governmental organizations and community groups. Survey efforts often focus on particular species or groups of species which may act as ecosystem proxies or on particular, and often threatened, species or habitats. Long-term monitoring does occur but usually at smaller spatial scale, as funding is limited and has competing priorities which change over time.

There are few special efforts made to survey short-beaked echidna, and most observations are incidental, part of wider general surveys or as a by-product of other targeted species surveys, often consisting of signs of presence, such as tracks or scat, rather than actual species sightings. In addition, conducting formal surveys or obtaining sightings in remote areas is time-consuming and expensive. These factors lead to a patchwork of geographic coverage in monitoring as well as low temporal frequency, resulting in a lack of knowledge about current populations around Australia and thus difficulty in assessing how the population may be changing over time.

On Kangaroo Island in South Australia, long-term studies of the local sub-species (*Tachyglossus aculeatus multiaculeatus*) have shown population declines (Rismiller and Grutzner, 2019), resulting in the recent listing of this sub-species as “Endangered” under national biodiversity conservation legislation (Department for Environment and Water, 2017). The improved understanding of population status provided by more intensive studies raises questions about the IUCN classification of the species Australia-wide. Impacts from habitat modification, invasive species such as fox and cats, climate change and human population impacts combined with its low reproductive rate (Nicol and Andersen, 2007; Rismiller and McKelvey, 2000) may be contributing to more widespread decline.

Citizen Science (CS) has been suggested as a practical way to determine broad-scale population trends (Devictor et al., 2010; Dickinson et al., 2010; Hochachka et al., 2012) and has been rapidly expanding globally (Bonney et al., 2014; Follett and Strezov, 2015). This has been enabled by technological advances such as mobile phones with integrated cameras, GPS and easy-to-use apps (Baker, 2016; Silvertown, 2009). These provide a platform for non-specialists to quickly and easily record incidental observations that provide accurate and timely data. It is envisaged that CS contributions to biodiversity monitoring in Australia will continue to increase, as community engagement is one of the three goals of Australia's Strategy for Nature from 2019-2030 (Commonwealth of Australia, 2019) aiming to fulfil Australia's international commitments under the Convention on Biological Diversity (CBD or Aichi Biodiversity Targets) and the Sustainable Development Goals (SDGs) (United Nations Development Program, 2018).

There have been two community-based CS echidna monitoring projects in Australia, both called echidnaWatch – one in Queensland (https://wildlife.org.au/echidnawatch/) and one in South Australia (http://www.echidna.edu.au/monotremes/echidna_watch.html). Both have used paper-based collection mechanisms supplemented by phoned-in and email reports. However, these sometimes contain key metadata quality shortcomings, such as spatial inaccuracy, which can reduce its usability (Bayraktarov et al., 2019). In Queensland, these reports have been collated and uploaded to the State biodiversity repository but with delays, as no new records have been uploaded since 2016. The South Australian echidnaWatch recorded sightings to its own database though updates have been delayed due to the obsolescence of the software used – and it has now been superseded by our Echidna Conservation Science Initiative (echidnaCSI) project. For this study, we developed a mobile app – echidnaCSI – to enable the public to easily submit incidental observations of this iconic species, with accurate, automatically recorded metadata, such as location and date and time, and some additional observational details, such as size and activity.

One of the criticisms of CS data is that they are often biased (Mair et al., 2017; Silvertown et al., 2013), as citizen sightings and records do not follow structured surveys and that this introduces spatial and temporal biases, amongst others, into the data. While this may substantially affect the usability of CS data for some purposes, improved technology can enhance the quality of the data (Budde et al., 2017; Newman et al., 2012; Stenhouse et al., 2020). Scientific data can also be subject to biases, particularly when aggregated from different sources over broad temporal and geographic scales (Beck et al., 2014; Boakes et al., 2010; Piccolo et al., 2020). In this paper, we investigate some aspects of spatial bias by comparing our CS data to traditional sources from Australian national and state biodiversity repositories.

Our aims in this paper are to investigate specific questions about the abundance and distribution of our echidna CS records in relation to those from traditional sources stored in Australian national and state biodiversity repositories. 1: By using a mobile app, can CS using a dedicated mobile app intensify and expand spatial coverage of a cryptic, yet widespread, species? This could result in better baseline population information and enable improved assessment of population changes in the future. 2: Are there differences in coverage in protected areas (PA) and non-protected lands between our echidnaCSI observations and those from other data sources? PA are seen as a key solution for satisfying national and global commitments to conserve biodiversity (Buckley et al., 2008), especially as climate refugia become even more vital for biodiversity protection (Graham et al., 2019). Formal scientific surveys tend to focus on high-quality habitats that are often conserved in PAs. In contrast, we expect to record more CS observations than scientific data sources in non-protected areas and from PA where the general public is encouraged to visit and fewer from PA where access is more restricted. 3: Does geographic remoteness and accessibility affect observation counts? As CS observations are often biased, we examine the geographic remoteness of echidna observational records across Australia to assess differences between echidnaCSI and other sources. We expect to record fewer observations from remote locations than traditional scientific data sources and more from locations with easier access.

3.2. MATERIALS AND METHODS

3.2.1. App Development

The echidnaCSI app was developed using LiveCode (starting with version 8.1.5, www.livecode.org and www.livecode.com) – an open-source, multi-platform development environment enabling rapid application development using one source code base for multiple target devices. The app was compiled for both iOS and Android platforms and runs on mobile devices that can provide location information, have a camera and a compatible Operating System (currently Android version 4.2 or later and iOS 10.0 or later).

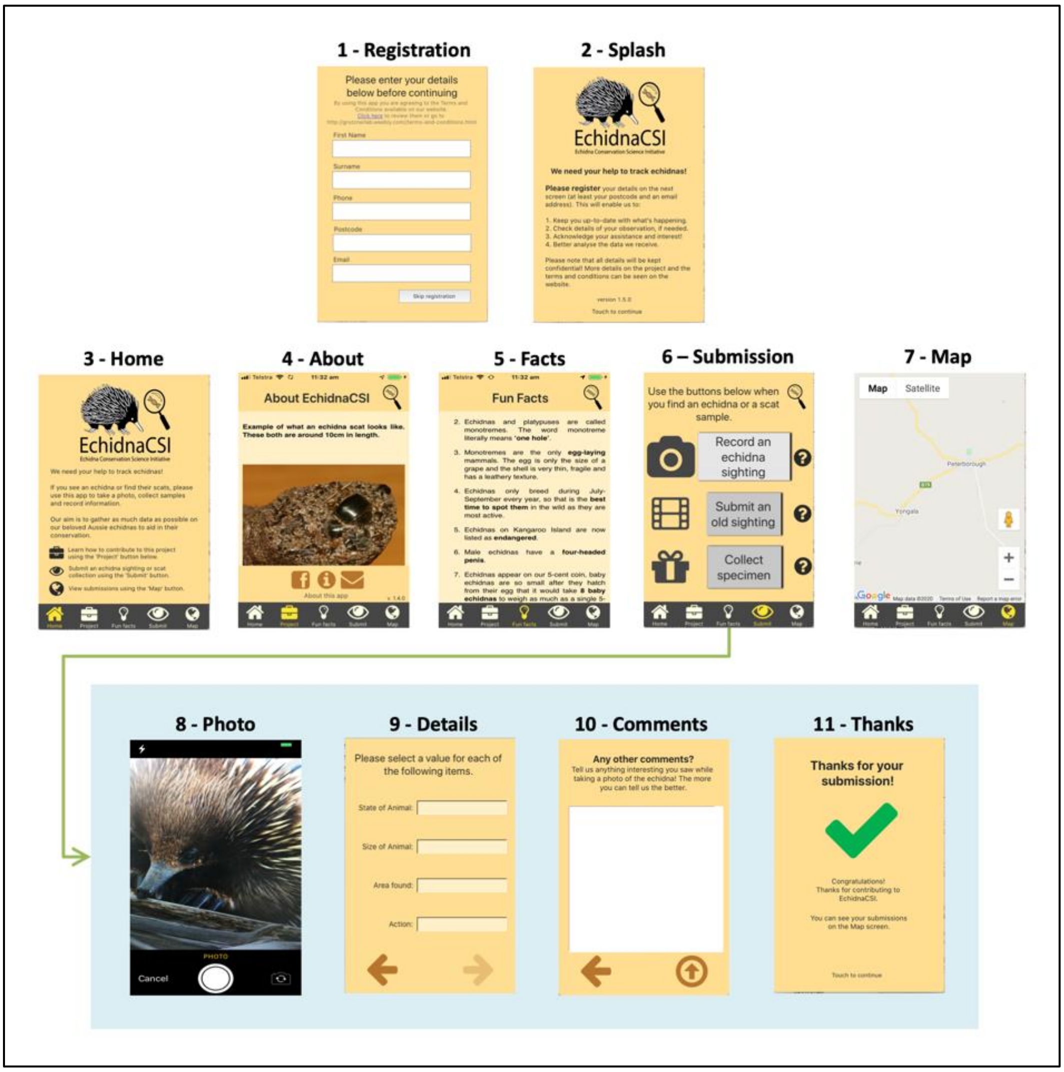


Figure 3-1 Screen flow of the echidnaCSI app. Submissions take place in the bottom screens

The app screen flow is illustrated in Figure 3-1. After the user arrives at the Home screen, they can submit data by navigating to the Submission screen and selecting one of three options: recording a current sighting, submitting a previously recorded photo and thirdly, collecting a physical specimen.

To record a current sighting, the “Record an echidna sighting” button is touched. This starts the camera view, which enables a photo to be taken immediately, while the echidna is in view. Once the photo has been taken, reviewed and accepted by the user, the participant answers a series of questions using a series of dropdown fields to constrain and standardise the responses (Table S3-1). These questions relate to this echidna's size, status (alive/dead), activity and location. Location data and date and time are automatically saved along with some measures of location accuracy. On completing the Details screen questions, the Comments screen allows the participant to enter free-text commentary to provide any further information that they deem relevant. On completion, the data is uploaded directly to the project data repository (https://biocollect.ala.org.au/acsa/project/index/8c3ae3b1-5342-40b4-9e72-e9820b7a9550) on the BioCollect portal at the Atlas of Living Australia (ALA). If network access is unavailable this may fail, but all data is stored in the app and the next upload attempt will include any data not previously successful. No network access is required to record an observation so remote use of the app is possible.

Photos taken at prior times and locations may also be submitted, provided they have accompanying location metadata. The same process as above is followed once the photo has been accepted. Collection of physical specimens such as scats is also possible and the participant is guided through the actual collection process after taking a photo to record location, date and time details. Each participant's observations are submitted to and identified in the ALA only by a Unique User ID (UUID) to ensure privacy. Data is recorded on the device to a tab-delimited key-value pair text file with one observation per line (Table S3-2).

3.2.2. App in Use - echidnaCSI

The echidnaCSI app was first released on 2 September 2017 and updated six times for iOS devices on the App Store and eight times for Android devices via the Google Play platform. The most recent release is version 1.4.0 which was released on August 11, 2019 for iOS devices and for Android devices on August 12, 2019. A project website (https://grutznerlab.weebly.com/echidna-csi.html) provides a central go-to point for project information including app download links. The project repository on BioCollect at the ALA provides a web-based form interface to enter observations made without the app.

Community participation has been continually encouraged through the media including national and regional TV, newspaper and radio stations, social media such as Facebook (EchidnaCSI) and Instagram (echidna_csi), email updates to registered participants and community outreach events (Perry et al., In review).

3.2.3. Data Summary

For this study, we have selected all echidna observations submitted to the echidnaCSI project between 01/09/2017 and 13/08/2020 using the echidnaCSI app or the project web interface on BioCollect. We also downloaded all other available echidna records from the ALA on 12/08/2020 (DOI: 10.26197/5f33a71948c4e) and all echidna records from the state governmental repositories for NSW (14/09/2020), Victoria (14/09/2020), South

Australia (09/09/2020), Queensland (11/09/2020), Western Australia (15/09/2020), Tasmania (12/09/2020) and the Northern Territory (09/09/2020). We restricted the external datasets to records from 01/09/2017 onwards to better compare to the data gathered in our project. Despite the difference in download dates, there is only one extra record from the state systems in the period described. Some records were removed as a result of data cleaning.

Some state systems share data with the ALA (and vice-versa) so these two data sources are not independent of each other, but the echidnaCSI data is independent of both, so we compare echidnaCSI data to ALA and then to state data separately. Further details on data sources and filtering of these records for use in this study are provided in Supplementary Information (S3.7.1 Methods).

To analyse coverage within PA, we downloaded the Collaborative Australian Protected Areas Database (CAPAD) 2018 (Australian Government Department of Agriculture, Water and the Environment, 2019) which provides spatial and textual information about national, state and private PA for Australia. This version includes 12,052 terrestrial PAs covering 151,787,501 ha (19.74 percent) of the Australian landmass (Department of Agriculture, Water and the Environment, 2019). For classification of PA, we used the IUCN categories (Table S3-3) which are an internationally recognised standard and classify PA according to their management objectives (Dudley et al., 2013).

To analyse the geographic distributions of observation locations we used the Accessibility and Remoteness Index of Australia 2016 Plus (ARIA+) (Hugo Centre for Population and Housing, 2020). ARIA+ is a continuously varying index of relative remoteness for Australian locations with values ranging from 0 (high accessibility) to 15 (high remoteness). A nationally recognised measure that has been used to derive the Australian Bureau of Statistics (ABS) Remoteness Area classification for Australia since 2001 (Taylor and Lange, 2016), the 1km^2 ARIA+ 2016 grid was used to assign ARIA+ scores to all of our observations. We subsequently classified our observation's ARIA+ scores into the ABS Remoteness Area categories (Australian Bureau of Statistics, 2018), as indicated in Table 3-1.

Table 3-1 ARIA+ (2016) categorised values

ARIA+ (2016) Category	ARIA+ (2016) Values
Highly Accessible	0 – 0.20
Accessible	> 0.20 – 2.40
Moderately Accessible	> 2.40 – 5.92
Remote	> 5.92 – 10.53
Very Remote	> 10.53 – 15.00

3.2.4. Analysis

We classified the origin of data from the ALA and state systems as Citizen Science or Science on the basis of several attributes (see Supplementary Info S3.7.1.1 for details). This resulted in five groups of data for analysis: echidnaCSI, which is all of CS origin; ALA-CS data; ALA-Science data; State-CS data and State-Science data. We analysed for differences between echidnaCSI and the other four groups in numbers of observations in PA and non-protected areas, and geographic distribution of observations, as measured by the ARIA+ remoteness/accessibility index.

We used the QGIS vector analysis tools (QGIS Development Team, 2020) to determine if observations were contained in PA and summarised and analysed the data using R. To test if source and science category groups had an effect on observation counts in the PA IUCN categories, we used Pearson's chi-squared test with Cramer's V for effect size (Howell, 2011). We removed the IUCN PA category "Not Assigned" as it contained too few observations. We compared observation counts for echidnaCSI to those of ALA-CS and ALA-Sci and then compared echidnaCSI to State-CS and State-Sci observations separately, as ALA and State observations are not completely independent – some data were shared between them.

We used the ARIA+ index to assess possible differences in geographic distribution between observations from our echidnaCSI CS project and observations from the ALA and state systems, each split into CS and scientific data as above. We first used the Shapiro-Wilk test of normality on each group. As all groups were not normally distributed, we used the non-parametric Kruskal-Wallis test (Dodge, Yadolah, 2008) and Dunn's pairwise post-hoc test with the Benjamini-Hochberg adjustment method to assess differences in distributions between the five observation groups.

Analyses were performed using RStudio version 1.2.5019 (R Core Team 2019) with R version 3.6.1 using the following packages: data cleaning and preparation for analysis with tidyverse (Wickham et al., 2019), statistical analysis and graphs with ggstatsplot

(Patil, 2018), graphs with ggplot2 (Wickham, 2016) and maps with ggmap3 (Kahle and Wickham, 2013). Final maps were prepared with QGIS 3.14 (QGIS Development Team, 2020).

3.3. RESULTS

3.3.1. Data Sources

3.3.1.1 EchidnaCSI

Observations were submitted using both the echidnaCSI app and the project web interface on BioCollect at the ALA. A total of 8859 users registered the app, of which 2718 (app 1943; web 775) have submitted a total of 7835 observations of echidna (app 6705; web 1130). The overall mean echidna observations per participant was 2.88 (app 3.45; web 1.46) and the median was 1 (app 2; web 1) (Table S3-4). The maximum total number of observations submitted by one participant over this study period was 115 using the app and 107 using the web.

There were 7538 observations of living echidnas (94%) and 297 of dead echidnas (4%). The majority were of medium (55%) to large (40%) size, with 130 (2%) young echidnas (puggles) recorded (Table S3-5). Most observations were made in bushland (34%), along the roadside (26%) or in farmland (23%), with 856 (11%) in urban/backyard areas and 242 (3%) in coastal areas or along waterways (Table S3-6). 83% (247 / 297) of dead echidna were recorded along the roadside. 54% were observed walking, 33% digging and only 0.5% (42) observations of echidnas mating (Table S3-7).

Observations were recorded from every state and territory in Australia, with higher concentrations, as expected, around more densely populated areas in NSW, Victoria and South Australia and fewer observations in sparsely populated areas.

3.3.1.2 ALA Data

A total of 4116 echidna observations were recorded in the biodiversity repository at the ALA for our study period. Of these, 2663 were from Scientific sources and 1453 of CS origin (Table S3-8), with the main CS sources being iNaturalist (169), Questagame (351) and individual uploads to BioCollect on the ALA. Most observations (2972) were recorded in NSW (Table S3-10).

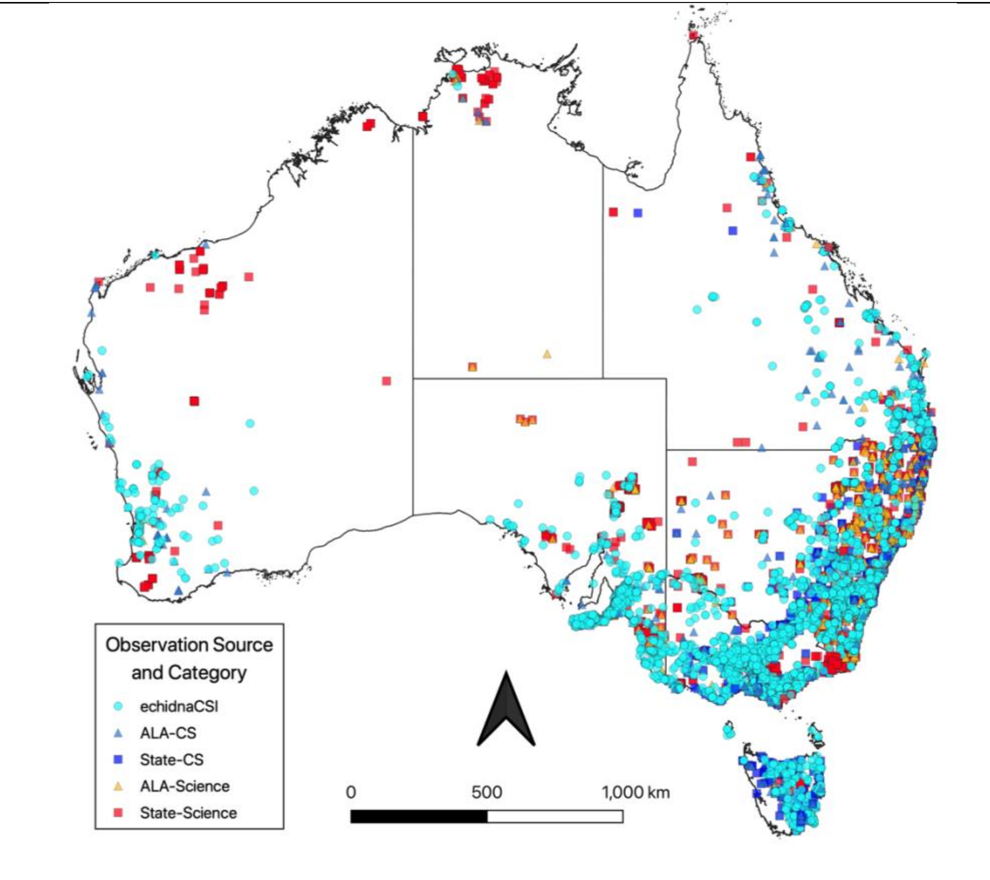
3.3.1.3 State Systems Data

A total of 5476 echidna observations were contributed to the State biodiversity repositories during our study period, with NSW and Victoria providing the majority (see Table S3-10 for details). Just over 50% (2786) were CS observations. Tasmania had a particularly high proportion of CS records (93% - 259/278), as numerous roadkills were reported as part of an existing CS project (Department of Primary Industries, Parks, Water and Environment, Tasmania, n.d.). A majority were also CS observations in NSW (66% - 2280/3438) where human-wildlife conflicts are recorded in the form of Wildlife rehabilitation records (New South Wales Department of Environment, Climate Change and Water, 2011).

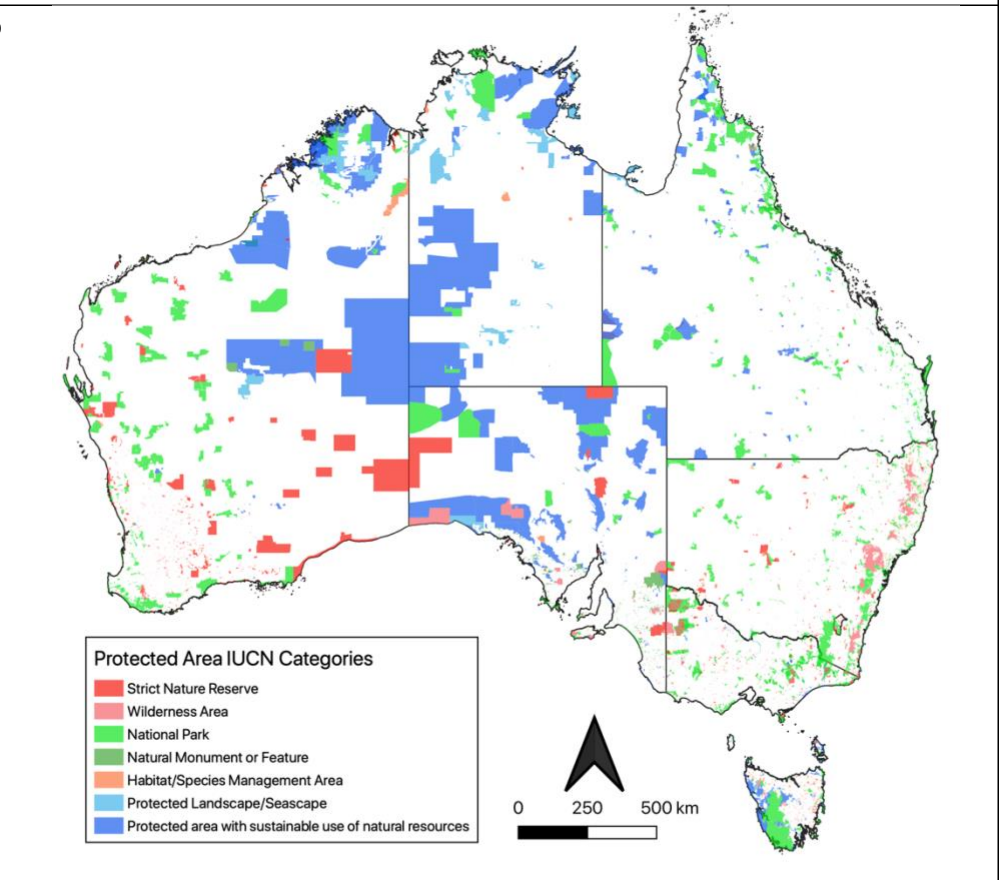
3.3.1.4 Data Summary

Combining data from all three data sources resulted in a total of 17427 echidna observations (eCSI: 7835; ALA: 4116; state: 5476), with 12074 (69%) from CS and 5353 (31%) from scientific sources (Table S3-8). There was much variation between States, both in numbers of observations and in contributions from CS and science sources. These included totals of 8645 (CS: 4924, 57%; Sci: 3721, 43%) in NSW, 4206 (CS: 3461, 82%; Sci: 745, 18%) in Victoria and 2352 (CS: 1757, 75%; Sci: 595, 25%) in South Australia (Table S3-9 and Table S3-10). See Figure 3-2 for overview maps of all observations (2a) with terrestrial protected areas (2b) and ARIA+ (2c) categorised regions.

a


Observation Source and Category
echidnaCSI
ALA-CS
State-CS
ALA-Science
State-Science
0
500
1,000 km

b


Protected Area IUCN Categories
Strict Nature Reserve
Wilderness Area
National Park
Natural Monument or Feature
Habitat/Species Management Area
Protected Landscape/Seascape
Protected area with sustainable use of natural resources
0
250
500 km

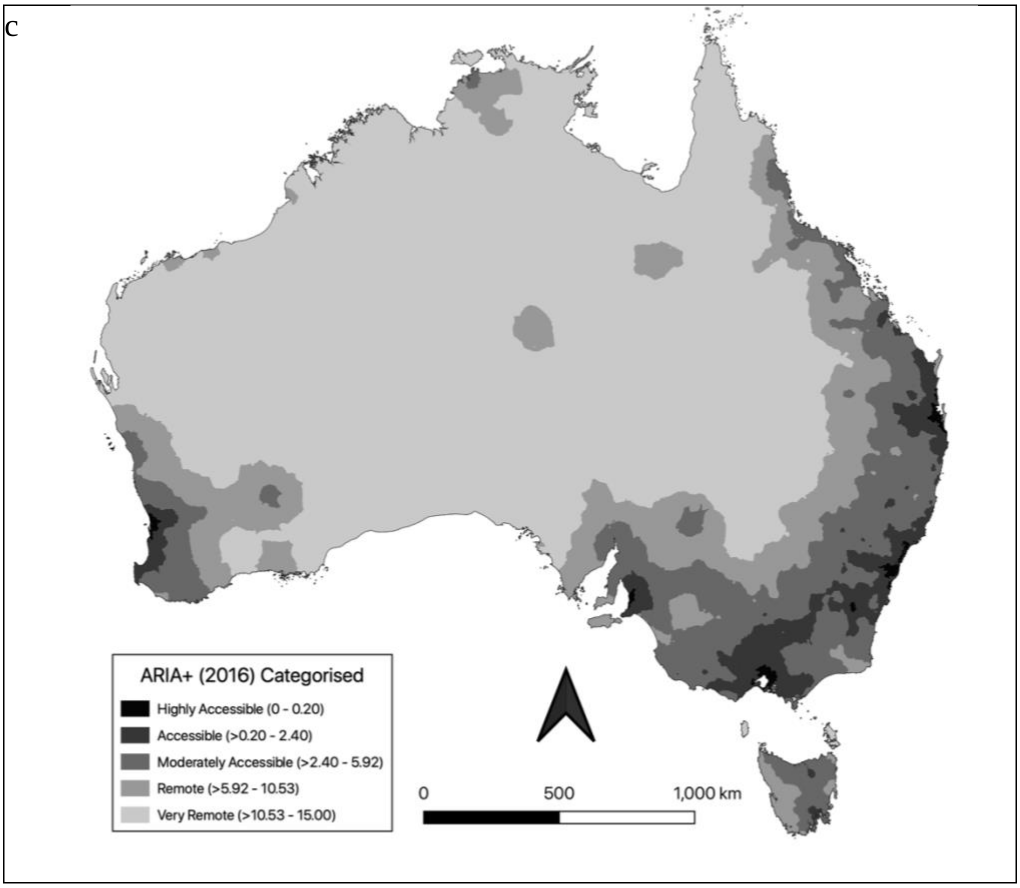


Figure 3-2 a) Echidna observations from all data sources; b) Protected Areas according to IUCN categories; c) Distribution of ARIA+ (2016) accessibility/remoteness categories across Australia.

3.3.2. Observations in Protected Areas

There were 4162 observations (23.9%) recorded inside PAs, of which 1599 (38.4%) were from Citizen Science and 2563 (61.6%) from Scientific sources (Table 3-2). EchidnaCSI provided 24.6% of these, compared to 36.2% from the ALA and 39.2% from the state systems. Citizen Science contributions inside PAs from the ALA were 9.7% of the total and from state systems just 4.1% of the total PA observations. There were 13265 observations (76.1% of all observations) recorded outside PAs, of which 10475 (79%) were from Citizen Science and 2790 (21%) from Scientific sources. Approximately 13% of echidnaCSI observations were made in PAs compared to over 36% of ALA and almost 30% of state system observations.

Table 3-2 Protected Area observations

Category	IUCN Description	eCSI	ALA		State		Total
			CS	Sci	CS	Sci	
IA	Strict Nature Reserve	77	40	167	9	311	604
IB	Wilderness Area	10	7	33	0	54	104

II	National Park	480	208	790	90	852	2420
III	Natural Monument or Feature	266	56	30	11	53	416
IV	Habitat/Species Management Area	120	63	68	39	55	345
V	Protected Landscape/Seascape	20	11	2	7	9	49
VI	Protected area with sustainable use of natural resources	51	19	12	15	124	221
NAS	Not Assigned	0	0	1	0	2	3
	Total PA	1024	404	1103	171	1460	4162
NA	Not Protected	6811	1049	1560	2615	1230	13265
	Total	8859	1857	3766	2957	4150	21589

When considering PA observations by IUCN category, the majority of observations were in "National Parks", followed by "Strict Nature Reserves", "Natural Monument or Feature" and "Habitat/Species Management Area". Of particular note are the large numbers of observations from Scientific sources in the state and ALA systems in the categories of "National Park" and "Strict Nature Reserve". Also noteworthy is the contribution from echidnaCSI in the "Natural Monument or Feature" and "Habitat/Species Management Area" categories and relatively poor contribution in the "Strict Nature Reserve" and "Wilderness Area" categories. There was much variation in PA observations between States, with only two States having observations in “Wilderness Areas”, where echidnaCSI provides only 10 observations out of a total of 104 across the whole country. For a detailed breakdown of observations by IUCN category per state and data source see Table S3-12, and for observation counts by IUCN category, State and CS/Science contributions to each see Table S3-13.

The results from testing the effect of data-source and science type on IUCN PA category using Pearson's chi-square test of independence and post-hoc test using Cramer's V are presented in Table 3-3. A statistically highly significant association with moderate effect is indicated overall for observation counts between echidnaCSI and ALA data sources (χ^2 (14, N = 11950) = 1516.71, p < .001, Cramer's V = 0.25) and with moderate-strong effect between echidnaCSI and state data sources (χ^2 (14, N = 13309) = 3237.78, p < .001, Cramer's V = 0.35).

Table 3-3 Pearson's chi-square test results for the independence of observation counts per PA category against data source

Data sources	DF	Statistic	p-value	Cramer's V	$CI_{95\%}$	N
eCSI, ALA-CS, ALA-Sci	14	1516.71	1.19 e-315	0.25	[0.23,0.26]	11950
eCSI, State-CS, State-Sci	14	3237.78	0	0.35	[0.33,0.36]	13309

When comparing data sources within each PA category, a statistically highly significant difference with moderate effect on observation counts is seen across all PA categories except for category V (Protected Landscape/ Seascape) when comparing echidnaCSI to ALA observations (Table S3-14) and all PA categories when comparing echidnaCSI to state observations (Table S3-15). This suggests that the observation method and PA category are not independent and that the strength of this association varies across PA categories. EchidnaCSI has markedly more observations in IUCN category III and non-protected areas, with noticeably fewer in IUCN category IA, IB and II, with smaller differences in the other categories.

3.3.3. Geographic Distribution of Observations

EchidnaCSI provided more observations in every ARIA+ category than both other data sources except for the "Very Remote" category, where state systems provided 167 observations compared to 77 from echidnaCSI and 46 from the ALA. Further splitting the data sources into Citizen Science and Science categories shows the significant contribution eCSI makes in all categories of accessibility (Table 3-4).

Table 3-4 Observation counts by ARIA+ (2016) Category, Source and Science category

ARIA+ (2016) Categories	**eCSI**	**ALA**		**State**		**Total**
	CS	**CS**	**Sci**	**CS**	**Sci**	
Highly Accessible (0.00 – 0.20)	1232	417	554	982	186	3371
Accessible (>0.20 – 2.40)	3656	483	931	1369	816	7255
Moderately Accessible (>0.24 – 5.92)	2017	429	497	383	939	4265
Remote (>5.92 – 10.53)	853	101	658	50	584	2246
Very Remote (>10.53-15.00)	77	23	23	2	165	290
Total	**7835**	**1453**	**2663**	**2786**	**2690**	**17427**

The ARIA+ values from echidnaCSI have a higher mean (2.41 ±2.43) than the other two CS groups but lower than the Science groups. The State Science data are the most widely dispersed and with a higher ARIA+ mean of 4.23 ±3.55 compared to 1.14 ±1.48 for State CS data, while ALA Science data have a mean of 2.81 ±2.71 compared with 2.23 ±2.58 for ALA CS data, with echidnaCSI remaining at 2.41 (Table 3-5). All group distributions are skewed with numerous outliers and bimodal characteristics are indicated in some groups (Figure 3-3).

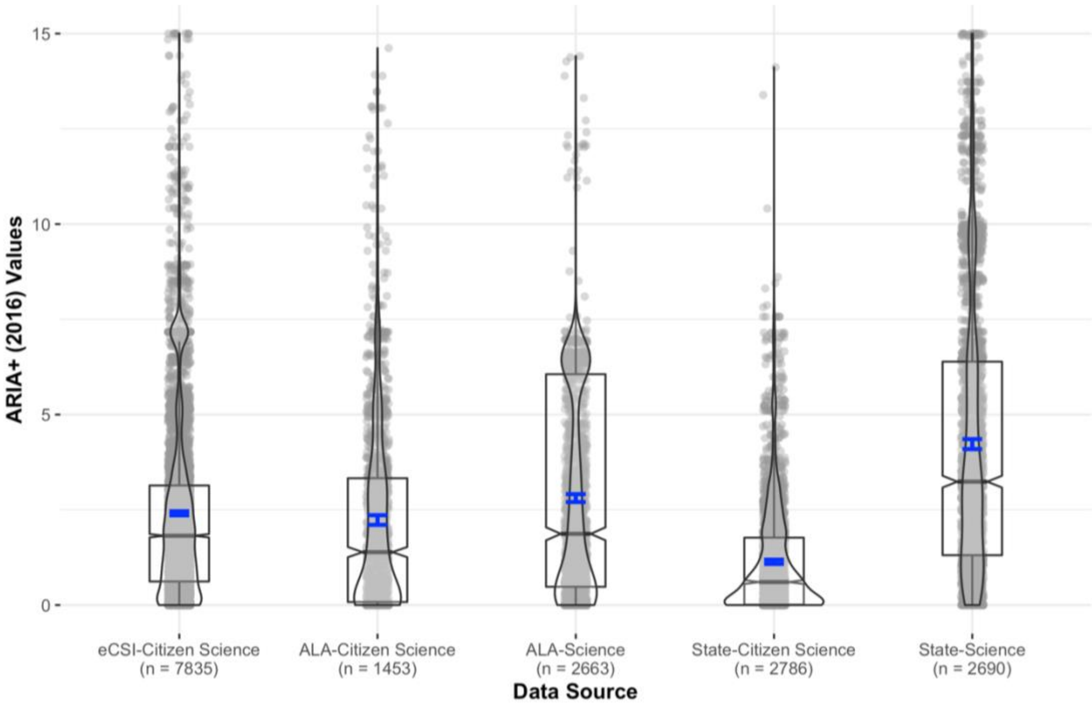


Figure 3-3 Distribution and summary statistics of ARIA+ (2016) index for observations for each data source and Citizen Science/Science category.

Table 3-5 ARIA+ value statistics by data source and category

Source	Category	Mean	Median	SD	Max	IQR	Count
eCSI	Citizen Science	2.41	1.82	2.43	15.00	2.52	7835
ALA	Citizen Science	2.23	1.39	2.58	14.62	3.25	1453
ALA	Science	2.81	1.87	2.71	14.41	5.58	2663
State	Citizen Science	1.14	0.61	1.48	14.12	1.76	2786
State	Science	4.23	3.24	3.55	15.00	5.08	2690

The data source group had a highly significant moderate effect on geographical distribution of observations as indicated by the Kruskal-Wallis test results (χ^2 (4, N = 17427) = 1789.40, p = 0.0, ε^2 = 0.10). There are highly significant differences in the geographic distribution of observations between echidnaCSI and the other four groups, except when comparing echidnaCSI to ALA-Sci (p = 0.03) as shown by the post-hoc Dunn test with Benjamini-Hochberg correction (Table 3-6).

Table 3-6 Statistical results from pairwise comparison of ARIA+ data by data source groups using the Kruskal-Wallis test with Dunn post-hoc test

Group 1	Group 2	Dunn Statistic	$p^{FDR\text{-}corrected}$	Sig
eCSI-Citizen Science	ALA-Citizen Science	6.04	1.68 e-9	***
eCSI-Citizen Science	ALA-Science	2.12	0.03	*
eCSI-Citizen Science	State-Citizen Science	27.38	2.54 e-164	***

eCSI-Citizen Science	State-Science	23.36	2.50 e-120	***
ALA-Citizen Science	ALA-Science	6.75	1.80 e-11	***
ALA-Citizen Science	State-Citizen Science	13.33	2.29 e-40	***
ALA-Citizen Science	State-Science	21.34	9.94 e-101	***
ALA-Science	State-Citizen Science	24.04	3.36 e-127	***
ALA-Science	State-Science	17.36	2.96 e-67	***
State-Citizen Science	State-Science	41.66	0	***

3.4. DISCUSSION

3.4.1. Mobile App Use

The echidnaCSI app has provided an easy-to-use tool for members of the public to quickly and easily record opportunistic sightings of echidna. A large number of participants have successfully submitted sightings, with some very enthusiastic participants using either the app or web interface regularly. This has resulted in almost doubling the number of echidna observations across Australia over the study period, which should considerably improve the accuracy of future population assessments by providing greater species presence data at wider spatial distribution than may be possible using traditional methods. The retention of regular participants should prove useful for providing improved longitudinal data, enabling better long-term analysis in certain areas.

Most observations from echidnaCSI were contributed by participants in the states of Victoria, New South Wales and South Australia, which is different from the other two data sources which were dominated by contributions from New South Wales (Table S3-10). This is probably due to the publicity that was generated for the project through both traditional and social media channels, which provided a focal point for interest in this particular species, supported by the use of a dedicated app. This resulted in echidnaCSI providing two to three times more observations than the other data sources in many states, apart from New South Wales, which recorded a similar number of observations to echidnaCSI. Much higher observation numbers are particularly noticeable in South Australia where the echidnaCSI project is based and more local events provided avenues for community engagement and interest which supplemented the other engagement channels.

Utilising the ALA as a biodiversity repository provides multiple benefits. It provides a stable, central portal for storage and access of observational data in standardised format which enables the wider use of these data for biodiversity research (Theobald et al., 2015).

It also provides a web interface that enables participants to supply observations recorded using devices other than mobile phones. In contrast to the app, the web interface to the ALA requires users to register before allowing contributions, which may be a barrier to use (Jay et al., 2016; Martin et al., 2016). The web interface does not automatically record location, date and time as the app does, and thus may introduce some errors when these are entered manually. It does record these from the metadata of an uploaded photo, if available, however. Nonetheless, it provides another very useful capability with little effort for the project team and resulted in a significant contribution in numbers of users and observations.

The app could be improved by better integration with the ALA. As participants using the app are assigned a Unique User Identifier (UUID) and are not automatically registered on the ALA, they cannot easily find their own observations on the ALA website. Ideally this should be improved so that the interface between systems is as seamless as possible, while preserving the low barrier-to-use of the app. Additionally, being able to see both their own and others' contributions from inside the app as well as online, and to be able to share these easily, would likely improve participants' engagement with the app and potentially increase the number of people using it.

3.4.2. Protected Areas

EchidnaCSI was successful in providing more observations in PA than from other CS sources as well as a large increase in observations in non-protected areas overall. There were significant differences in the number of observations in the varying PA IUCN categories. In "Strict Nature Reserves", human visitation, use and impacts are strictly controlled to ensure the protection of conservation values, so it is not surprising there were fewer CS observations in these PA. "Wilderness Areas" provide for restricted public access but aim to preserve the area's ecological integrity and should remain undisturbed by significant human activity, so CS observations in these areas are interesting, as visitor access is more limited and more likely to be confined to those with the skills and equipment to survive unaided (Dudley et al., 2013). PA where public access is encouraged, however, showed significantly higher numbers of observations from echidnaCSI, as might be expected. Contributing factors to this may include ease of access and the possibility that science-based studies prefer areas with less human disturbance. EchidnaCSI provided the majority of CS observations in all PA categories, which indicates how successful this project has been at attracting participation.

There was much variation in PA observations among States. For example, in the Northern Territory there were a total of 41 observations recorded in the State repository and these were all from camera traps. New South Wales had few PA observations provided by CS, whereas in Victoria and South Australia echidnaCSI provided almost as many sightings as were recorded by the State scientific sources, indicating the value of this project. This may be explained by the abundance of PA allowing public access, such as IUCN II-V, close to heavily populated areas of Adelaide in South Australia and Melbourne in Victoria. Population size probably also plays a role, which would also affect the numbers of governmental and other organisations monitoring biodiversity.

There are many challenges associated with managing PA for effective biodiversity conservation, both in Australia (Buckley et al., 2008; Watson et al., 2011; Woinarski et al., 2011) and worldwide (Cazalis et al., 2020; Gaston et al., 2006; Geldmann et al., 2019; Watson et al., 2014). Improving monitoring methods will surely involve utilising the public in recording incidental observations, as in echidnaCSI, complemented by using more structured methods performed by professionals and also by citizen scientists (Kelling et al., 2019; Pescott et al., 2015). Access to PA by the public can also be detrimental to biodiversity (Xavier da Silva et al., 2018) so care must be taken when assessing monitoring methods and conservation management.

3.4.3. Geographic Distribution by Remoteness Areas

EchidnaCSI provided more observations in all categories of remote areas of Australia than other sources except for Very Remote regions where State Scientific observations are most numerous. There are clear differences in remoteness between scientific and CS observations from State systems and this difference is less in ALA data. This smaller difference in ALA data may be due to possible misclassification of some data as CS, where it appears that data transfer between systems may have occurred without data sources being correctly recorded. The State systems included better indications of data sources enabling easier CS/Science classification which resulted in the clearer differences.

Except for Highly Accessible areas, the number of observations decreases with increased remoteness, both overall and for echidnaCSI. i.e. there are fewer observations in more remote areas. As Highly Accessible areas are very urbanised, it should not be too surprising that there are fewer observations in this category. The large increase in observations in Accessible areas may be explained by the availability of suitable habitat areas combined with their proximity to populated areas. Very large areas of Australia are classified as Remote or Very Remote and there are few observations in these areas. There is a need for more data from these remote areas and though some exist, these are often in siloed repositories where the data are slow to be shared more widely, if at all.

Small geographic clusters of scientific observations in Remote and Very Remote areas can be seen in NW, N and SE Australia (Figure 2a). These observations from the Western Australian, Northern Territory and Victorian state systems have observation type recorded and the majority of these are camera trap (CT) images. Automated recording technologies such as CT and audio recorders have great potential to increase species observations in remote areas. As they can operate throughout the day and night, they may increase the chances of recording echidna activity in warmer climates where echidna may be more active at night when other methods are less likely to detect them. This uninterrupted usage combined with their suitability for remote locations indicates CT to be a potentially complementary method to CS/echidnaCSI observations (Santangeli et al., 2020). As the climate continues to change, this may become a bigger issue as both humans and species such as the echidna adapt their behaviours to avoid temperature extremes (Graham et al., 2019; Heller and Zavaleta, 2009; Mackey et al., 2008; Synes et al., 2020).

EchidnaCSI has provided very good coverage of most regions apart from Very Remote areas. Given the lack of funding for environmental research in Australia and the expense of remote fieldwork, to increase coverage in these regions may require increased engagement with inhabitants of remoter regions, such as indigenous groups and others who temporarily visit these areas, such as mine workers and tourists. Payments for ecosystem services, which are increasingly used to reward landowners for preserving ecological-beneficial habitats and features, could be extended to cover payments for biodiversity monitoring services here in Australia (Rawlins and Westby, 2013; Tuanmu et al., 2016), though this should be used cautiously (Sommerville et al., 2011; van Berkel et al., 2018) as participants' continued engagement often stems from intrinsic science- and conservation-related motivations (Larson et al., 2020). The intensification of observations provided by echidnaCSI could also be used to stimulate CS activity in areas with fewer observations and would be made more useful by also recording CS search paths (Stenhouse et al., 2020). Gaps in desired observational coverage can then be prioritised for professional surveying, if necessary (Tulloch et al., 2013).

Disparate state data standards mean data usability is reduced. This could be overcome by ensuring data is uploaded to a national system that provides ease of use and access to consistent and standard format data for local and global researchers, enabling more rapid evaluations of current biodiversity. In Australia, the ALA provides a national biodiversity repository but it appears that some state systems are slow to integrate with it and that this integration sometimes lacks in detail, leading to difficulties in determining data sources. Though funding is limited and policy conflicts may exist, it would be highly beneficial to more fully utilise the services that the ALA provides (Salle et al., 2016). Its value is being increasingly recognised around the world as the increasing uptake of the ALA software by other countries shows (https://living-atlases.gbif.org/).

The integration of a variety of monitoring methods can lead to more effective monitoring with benefits for biodiversity and society. By utilising both scientific and community sources, program ownership and resilience may be broadened and societal benefits enhanced (Kühl et al., 2020).

3.5. CONCLUSIONS

The echidnaCSI app provided an easy-to-use system for citizen scientists to quickly provide accurate, vouchered data in a usable form to the project repository on the national biodiversity database. EchidnaCSI has substantially increased the spatial and temporal intensity of echidna observations around Australia since starting in September 2017. EchidnaCSI has provided comparable geographic distribution to other existing biodiversity surveys and databases at all levels of remoteness as measured by the ARIA+ index of accessibility, except for the Very Remote category. Some protected areas are also less covered by CS, indicating the value of professional surveys in these areas, particularly in PAs where public access is discouraged. While large gaps in geographic coverage for the Australian Short beaked echidna remain, this study indicates that CS programs can provide good observational data for a cryptic species at large scale and can highlight areas where scientific monitoring may provide even greater value. We plan to continue the refinement and promotion of the echidnaCSI project and app in order to increase the geographic and temporal extents of the data. This may enable further collaborative studies with ecologists and environmental scientists to address specific questions related to the ecology, distribution and conservation of this species and to detect the longer-term trends required to better evaluate the conservation status for this species on the Australian mainland.

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DATA AVAILABILITY

EchidnaCSI is a free mobile app available for Android (https://play.google.com/store/apps/details?id=com.scruffmonkey.echidnaCSI) and on iOS (https://itunes.apple.com/au/app/echidnacsi/id1260820816). Data is available for download from the DOIs and websites listed in Supplementary Information 3.7.2. Application code is available on FigShare at DOI: 10.25909/14528367 and Github at https://github.com/alanstenhouse/echidnaCSI-app.

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3.7. SUPPLEMENTARY INFORMATION

3.7.1. Methods

3.7.1.1 Data cleaning

We restricted ALA data to those records whose basisOfRecord column is "Human Observation" (23808) or "Image" (50) or "NA" (995) and removed those classified as "PreservedSpecimen" (720), "MaterialSample" (201), "FossilSpecimen" (1) and "MachineObservation" (1). We also excluded records with missing location data. Some records contained ambiguous event dates in the form of date ranges, for these the first date in the range was selected as the observation event date. Records with no observation year were also excluded (186).

To determine the source of ALA data and classify it as scientific or citizen science, we used a number of columns including "institutionCode", "provenance", "recordedBy" and "locality". This enabled us to more accurately determine which records were submitted by an official organisation – such as a government department or a scientific non-governmental organisation – and which were submitted by individuals or other groups, such as iNaturalist or Questagame.

Observations from camera traps in NSW were restricted to 1 observation per location per 30s as there were some sequences where each photo was recorded as an observation, some containing more than 10 per sequence. Other State data sources did not have this issue, though there were other issues such as temporal accuracy being only daily rather than including time, which limits the usability of the data for some purposes.

The ALA and some State systems include records from a variety of sources including CS programs like iNaturalist and Questagame. There are also records from wildlife rehabilitation centres and roadkill reports which result from human-echidna interactions. These records have been classified as CS records in order to better compare the contributions from CS to observations from scientific sources in order to show how much of a contribution CS already makes. The remaining data were classified as from scientific sources.

3.7.2. Data Sources

Datasets used in this study can be downloaded at the following sources.

Source	URL or DOI
echidnaCSI	https://biocollect.ala.org.au/acsa/project/index/8c3ae3b1-5342-40b4-9e72-e9820b7a9550

ALA	DOI: 10.26197/5f33a71948c4e
NSW	https://www.environment.nsw.gov.au/atlaspublicapp
NT	https://data.nt.gov.au/dataset/fauna-atlas-subset-mammals
QLD	https://apps.des.qld.gov.au/species-search/details/?id=838
SA	http://spatialwebapps.environment.sa.gov.au/naturemaps/?locale=en-us&viewer=naturemaps
TAS	https://www.naturalvaluesatlas.tas.gov.au/#SpeciesSearchPage
VIC	http://maps.biodiversity.vic.gov.au/viewer/?viewer=NatureKit
WA	https://naturemap.dbca.wa.gov.au/

3.7.3. Supplementary Tables

Table S3-1 Core observation questions and answer options in the app

Question	**Possible Answers**
State of Animal?	Alive Dead
Size of Animal?	Hold in one hand A small football A large basketball Unsure
Area found?	Roadside Urban / backyard Agricultural / farmland Bushland Coast / waterway
Action?	Walking Digging Mating Sleeping
Any other comments?	<free text entry>

EchidnaCSI data file format

Each line is preceded by a type identifier: “O” for “Observation”. Each data value is preceded by its data identifier followed by a colon e.g. “latitude: -35.018088”. Data items (identifier: value pairs) are separated from each other by tab characters (ASCII character 09).

Table S3-2 EchidnaCSI data file format

Line Type	Identifier	Data item identifier
Observation	O	
		Latitude
		Longitude
		Altitude
		Course
		Speed
		Horizontal Accuracy
		Vertical Accuracy
		GPS Timestamp
		Device Date_Time
		State
		Size
		Area
		Action
		Pic
		Notes

Table S3-3 IUCN Protected Area Categories (Dudley et al., 2013)

ID	**Category**	**Description**
Ia	Strict Nature Reserve	Category Ia are strictly protected areas set aside to protect biodiversity and also possibly geological/geomorphical features, where human visitation, use and impacts are strictly controlled and limited to ensure protection of the conservation values. Such protected areas can serve as indispensable reference areas for scientific research and monitoring.
Ib	Wilderness Area	Category Ib protected areas are usually large unmodified or slightly modified areas, retaining their natural character and influence without permanent or significant human habitation, which are protected and managed so as to preserve their natural condition.
II	National Park	Category II protected areas are large natural or near natural areas set aside to protect large-scale ecological processes, along with the complement of species and ecosystems characteristic of the area, which also provide a foundation for environmentally and culturally compatible, spiritual, scientific, educational, recreational, and visitor opportunities.
III	Natural Monument or Feature	Category III protected areas are set aside to protect a specific natural monument, which can be a landform, sea mount, submarine cavern, geological feature such as a cave or even a living feature such as an ancient grove. They are generally quite small protected areas and often have high visitor value.
IV	Habitat/Species Management Area	Category IV protected areas aim to protect particular species or habitats and management reflects this priority. Many Category IV protected areas will need

		regular, active interventions to address the requirements of particular species or to maintain habitats, but this is not a requirement of the category.
V	Protected Landscape/ Seascape	A protected area where the interaction of people and nature over time has produced an area of distinct character with significant, ecological, biological, cultural and scenic value: and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values.
VI	Protected area with sustainable use of natural resources	Category VI protected areas conserve ecosystems and habitats together with associated cultural values and traditional natural resource management systems. They are generally large, with most of the area in a natural condition, where a proportion is under sustainable natural resource management and where low-level non-industrial use of natural resources compatible with nature conservation is seen as one of the main aims of the area.

Table S3-4 EchidnaCSI Submissions by participant statistics

Source	**Mean**	**Median**	**SD**	**Max obs**	**# Participants**
app	3.45	2	6.19	115	1943
web	1.46	1	3.93	107	775
All	2.88	1	5.71	115	2718

Table S3-5 EchidnaCSI observations Size

Size	**Count**	**%**
Size of a small football	4377	54.6
Size of a large basketball	3206	40.0
Could hold in one hand	127	1.6
Unsure	125	1.6

Table S3-6 EchidnaCSI observations Area

Area	**Alive**	**Dead**	**Total**	**%**
Native vegetation / bushland	2684	15	2699	33.7
Roadside	1837	247	2084	26.0
Agricultural / farmland	1811	22	1833	22.9
Urban / backyard	851	5	856	10.7
Coast / waterway	240	2	242	3.0
NA	115	6	121	1.5

Table S3-7 EchidnaCSI observations Action

Action	**Count**	**%**
Walking	4328	54.0
Digging	2628	32.8
NA	568	7.1
Sleeping	225	2.8

Inactive	44	0.5
Mating	42	0.5

Table S3-8 Observation counts and percentage by source for Citizen Science and Science categories

Source	Citizen Science	Science	Total	CS %	Sci %
ALA	1453	2663	4116	35.3	64.7
eCSI	7835	0	7835	100	0
State	2786	2690	5476	50.9	49.1
Total	**12074**	**5353**	**17427**	**69.3**	**30.7**

Table S3-9 Observations by State for CS and Science

State	CS	Science	Total	CS %	Sci %
Australian Capital Territory	160	0	160	100.0	0.0
New South Wales	4924	3721	8645	57.0	43.0
Northern Territory	10	84	94	10.6	89.4
Other Territories	19	2	21	90.5	9.5
Queensland	698	64	762	91.6	8.4
South Australia	1757	595	2352	74.7	25.3
Tasmania	830	19	849	97.8	2.2
Victoria	3461	745	4206	82.3	17.7
Western Australia	175	120	295	59.3	40.7
NA	40	3	43	93.0	7.0
Total	**12074**	**5353**	**17427**	**69.3**	**30.7**

Table S3-10 All echidna observations by data source and State for CS and Science

Source	State	Citizen Science	Science	Total	CS %	Sci %
ALA	Australian Capital Territory	55	0	55	100.0	0
ALA	New South Wales	408	2564	2972	13.7	86.3
ALA	Northern Territory	8	7	15	53.3	46.7
ALA	Other Territories	6	1	7	85.7	14.3
ALA	Queensland	161	0	161	100.0	0
ALA	South Australia	181	90	271	66.8	33.2
ALA	Tasmania	126	0	126	100.0	0
ALA	Victoria	430	0	430	100.0	0
ALA	Western Australia	49	0	49	100.0	0
eCSI	Australian Capital Territory	105	-	105	100.0	-
eCSI	New South Wales	2237	-	2237	100.0	-
eCSI	Northern Territory	2	-	2	100.0	-
eCSI	Other Territories	13	-	13	100.0	-
eCSI	Queensland	519	-	519	100.0	-
eCSI	South Australia	1576	-	1576	100.0	-

eCSI	Tasmania	449	-	449	100.0	-
eCSI	Victoria	2804	-	2804	100.0	-
eCSI	Western Australia	126	-	126	100.0	-
State	New South Wales	2279	1157	3436	66.3	33.7
State	Northern Territory	0	77	77	0	100.0
State	Other Territories	0	1	1	0	100.0
State	Queensland	18	64	82	22.0	78.0
State	South Australia	0	505	505	0	100.0
State	Tasmania	255	19	274	93.1	6.9
State	Victoria	227	745	972	23.4	76.6
State	Western Australia	0	120	120	0	100.0

Table S3-11 State observations from 2017-2020 from scientific and citizen science sources

State	Citizen Science	Science	Total
NSW	2280	1158	3438
NT	0	77	77
QLD	18	66	84
SA	0	505	505
TAS	259	19	278
VIC	229	745	974
WA	0	120	120
Total	2786	2690	5476

Table S3-12 Protected Area observations by IUCN category, State and Source

IUCN	PA IUCN Category	State	ALA	eCSI	State	Total
IA	Strict Nature Reserve	New South Wales	177	20	117	314
IA	Strict Nature Reserve	Queensland	2	0	0	2
IA	Strict Nature Reserve	South Australia	4	7	13	24
IA	Strict Nature Reserve	Victoria	14	47	171	232
IA	Strict Nature Reserve	Western Australia	10	3	19	32
IB	Wilderness Area	New South Wales	36	7	47	90
IB	Wilderness Area	South Australia	4	3	7	14
II	National Park	Australian Capital Territory	2	2	0	4
II	National Park	New South Wales	835	133	438	1406
II	National Park	Northern Territory	0	0	33	33
II	National Park	Other Territories	5	10	0	15
II	National Park	Queensland	10	7	11	28
II	National Park	South Australia	42	98	250	390
II	National Park	Tasmania	35	56	36	127
II	National Park	Victoria	65	165	161	391
II	National Park	Western Australia	3	9	13	25

II	National Park	NA	1	0	0	1
III	Natural Monument or Feature	New South Wales	8	1	2	11
III	Natural Monument or Feature	Queensland	4	4	5	13
III	Natural Monument or Feature	South Australia	59	201	46	306
III	Natural Monument or Feature	Tasmania	2	12	3	17
III	Natural Monument or Feature	Victoria	13	48	8	69
IV	Habitat/Species Management Area	Australian Capital Territory	29	58	0	87
IV	Habitat/Species Management Area	New South Wales	72	17	51	140
IV	Habitat/Species Management Area	Other Territories	1	1	0	2
IV	Habitat/Species Management Area	Queensland	1	0	0	1
IV	Habitat/Species Management Area	South Australia	4	4	6	14
IV	Habitat/Species Management Area	Tasmania	1	2	5	8
IV	Habitat/Species Management Area	Victoria	23	37	32	92
IV	Habitat/Species Management Area	Western Australia	0	1	0	1
NAS	Not Assigned	New South Wales	1	0	2	3
V	Protected Landscape/Seascape	New South Wales	5	4	2	11
V	Protected Landscape/Seascape	Northern Territory	0	0	7	7
V	Protected Landscape/Seascape	Tasmania	8	8	5	21
V	Protected Landscape/Seascape	Victoria	0	8	2	10
VI	Protected area with sustainable use of natural resources	New South Wales	7	0	9	16
VI	Protected area with sustainable use of natural resources	Northern Territory	0	0	1	1
VI	Protected area with sustainable use of natural resources	Queensland	4	7	12	23
VI	Protected area with sustainable use of natural resources	South Australia	11	21	72	104
VI	Protected area with sustainable use of natural resources	Tasmania	8	14	17	39
VI	Protected area with sustainable use of natural resources	Victoria	1	9	27	37
VI	Protected area with sustainable use of natural resources	Western Australia	0	0	1	1

Table S3-13 Protected Area observations by IUCN category, State and Citizen Science/Science

IUCN	PA IUCN Category	State	CS	Science	Total	CS %	Sci %
IA	Strict Nature Reserve	New South Wales	33	281	314	10.5	89.5
IA	Strict Nature Reserve	Queensland	2	0	2	100	0
IA	Strict Nature Reserve	South Australia	10	14	24	41.7	58.3
IA	Strict Nature Reserve	Victoria	68	164	232	29.3	70.7
IA	Strict Nature Reserve	Western Australia	13	19	32	40.6	59.4
IB	Wilderness Area	New South Wales	10	80	90	11.1	88.9
IB	Wilderness Area	South Australia	7	7	14	50	50
II	National Park	Australian Capital Territory	4	0	4	100	0
II	National Park	New South Wales	200	1206	1406	14.2	85.8
II	National Park	Northern Territory	0	33	33	0	100

II	National Park	Other Territories	15	0	15	100	0
II	National Park	Queensland	19	9	28	67.9	32.1
II	National Park	South Australia	125	265	390	32.1	67.9
II	National Park	Tasmania	126	1	127	99.2	0.8
II	National Park	Victoria	276	115	391	70.6	29.4
II	National Park	Western Australia	12	13	25	48	52
II	National Park	NA	1	0	1	100	0
III	Natural Monument or Feature	New South Wales	7	4	11	63.6	36.4
III	Natural Monument or Feature	Queensland	8	5	13	61.5	38.5
III	Natural Monument or Feature	South Australia	232	74	306	75.8	24.2
III	Natural Monument or Feature	Tasmania	17	0	17	100	0
III	Natural Monument or Feature	Victoria	69	0	69	100	0
IV	Habitat/Species Management Area	Australian Capital Territory	87	0	87	100	0
IV	Habitat/Species Management Area	New South Wales	47	93	140	33.6	66.4
IV	Habitat/Species Management Area	Other Territories	2	0	2	100	0
IV	Habitat/Species Management Area	Queensland	1	0	1	100	0
IV	Habitat/Species Management Area	South Australia	5	9	14	35.7	64.3
IV	Habitat/Species Management Area	Tasmania	4	4	8	50	50
IV	Habitat/Species Management Area	Victoria	75	17	92	81.5	18.5
IV	Habitat/Species Management Area	Western Australia	1	0	1	100	0
NAS	Not Assigned	New South Wales	0	3	3	0	100
V	Protected Landscape/Seascape	New South Wales	7	4	11	63.6	36.4
V	Protected Landscape/Seascape	Northern Territory	0	7	7	0	100
V	Protected Landscape/Seascape	Tasmania	21	0	21	100	0
V	Protected Landscape/Seascape	Victoria	10	0	10	100	0
VI	Protected area with sustainable use of natural resources	New South Wales	0	16	16	0	100
VI	Protected area with sustainable use of natural resources	Northern Territory	0	1	1	0	100
VI	Protected area with sustainable use of natural resources	Queensland	11	12	23	47.8	52.2
VI	Protected area with sustainable use of natural resources	South Australia	27	77	104	26	74
VI	Protected area with sustainable use of natural resources	Tasmania	37	2	39	94.9	5.1
VI	Protected area with sustainable use of natural resources	Victoria	10	27	37	27	73
VI	Protected area with sustainable use of natural resources	Western Australia	0	1	1	0	100

Source v IUCN - eCSI, ALA-CS, ALA-Sci

Pearsons χ^2 (14) = 1516.71, p = 1.19e-315, Cramer's V = 0.25, $CI_{95\%}$=[0.23,0.26]

Table S3-14 Pearson χ^2 test results of Data source v PAs, for echidnaCSI and ALA data

IUCN	N	%	eCSI-CS	ALA-CS	ALA-Sci	Statistic	p	sig
IA	284	2.38	27.11	14.08	58.80	90.13	2.68 e-20	***
IB	50	0.42	20.00	14.00	66.00	24.28	5.34 e-6	***
II	1478	12.37	32.48	14.07	53.45	344.25	1.76 e-75	***
III	352	2.95	75.57	15.91	8.52	285.43	1.05 e-62	***
IV	251	2.10	47.81	25.10	27.09	23.82	6.73 e-6	***
V	33	0.28	60.61	33.33	6.06	14.73	6.34 e-4	***
VI	82	0.69	62.20	23.17	14.63	31.63	1.35 e-7	***
NotPA	9420	78.83	72.30	11.14	16.56	6479.27	0	***

Source v IUCN - eCSI, State-CS, State-Sci

Pearsons χ^2 (14) = 3237.78, p = 0 e+00, Cramer's V = 0.35, $CI_{95\%}$=[0.33,0.36]

Table S3-15 Pearson χ^2 test results of Data source v PAs, for echidnaCSI and state data

IUCN	N	%	eCSI-CS	State-CS	State-Sci	Statistic	p	sig
IA	397	2.98	19.40	2.27	78.34	379.30	4.32 e-83	***
IB	64	0.48	15.62	NA	84.38	77.38	1.58 e-17	***
II	1422	10.68	33.76	6.33	59.92	612.61	9.42 e-134	***
III	330	2.48	80.61	3.33	16.06	339.87	1.58 e-74	***
IV	214	1.61	56.07	18.22	25.70	51.60	6.25 e-12	***
V	36	0.27	55.56	19.44	25.00	8.17	0.017	*
VI	190	1.43	26.84	7.89	65.26	97.4	7.08 e-22	***
NotPA	10656	80.07	63.92	24.54	11.54	4755.27	0	***

Chapter 4. COVID restrictions impact wildlife monitoring in Australia

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Alan Stenhouse	
Contribution to the paper	Conceptualization, Methodology, formal analysis, writing – original draft preparation, writing – review and editing.	
Overall percentage (%)	80%	
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.	
Signature		Date: 01/10/2021

Co-author Contributions

By signing the Statement of Authorship, each author certifies that:

iv. the candidate's stated contribution to the publication is accurate (as detailed above);

v. permission is granted for the candidate in include the publication in the thesis; and

vi. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Tahlia Perry	
Contribution to the Paper	Conceptualisation, writing – review and editing.	
Signature		Date: 28/09/2021

Name of Co-Author	Frank Grützner	
Contribution to the Paper	Conceptualisation, writing – review and editing.	
Signature		Date: 01/10/21

Name of Co-Author	Peggy Rismiller	
Contribution to the Paper	Conceptualisation, writing – review and editing.	
Signature		Date: 24/09/2021

Name of Co-Author	Lian Pin Koh	
Contribution to the Paper	Conceptualisation, Methodology, writing – review and editing.	
Signature		Date: 04/10/2021

Name of Co-Author	Megan Lewis	
Contribution to the Paper	Conceptualisation, Methodology, writing – original draft preparation, writing – review and editing.	
Signature		Date: 05/10/2021

ABSTRACT

1. The global COVID-19 pandemic has imposed restrictions on people's movement, work and access to places at multiple international, national and sub-national scales. We need a better understanding of how the varied restrictions have impacted wildlife monitoring as gaps in data continuity caused by these disruptions may limit future data use and analysis.
2. To assess the effect of different levels of COVID-19 restrictions on both citizen science and traditional wildlife monitoring, we analyse observational records of a widespread and iconic monotreme, the Australian short-beaked echidna (*Tachyglossus aculeatus*), in three states of Australia. We compare citizen science to observations from biodiversity data repositories across the three states by analysing numbers of observations, coverage in protected areas, and geographic distribution using an index of remoteness and accessibility. We analyse the effect of restriction levels by comparing these data from each restriction level in 2020 with corresponding periods in 2018-2019.
3. Our results indicate that stricter and longer restrictions reduced numbers of scientific observations while citizen science showed few effects, though there is much variation due to differences in restriction levels in each state. Geographic distribution and coverage of protected and non-protected areas were also reduced for scientific monitoring while citizen science observations were little affected.
4. This study shows that citizen science can continue to record accurate and widely distributed species observational data, despite pandemic restrictions, and thus demonstrates the potential value of citizen science to other researchers who require reliable data during periods of disruption.

4.1. INTRODUCTION

The World Health Organization officially declared the novel coronavirus (2019-nCoV or COVID-19) a public health emergency of international concern on 30 January 2020 (World Health Organization, 2020a) and then declared a pandemic on 11 March 2020 (World Health Organization, 2020b). The impacts of the virus on global activity over the last year have been enormous and though the rapid development of vaccines have brought significant change and hope that it can be brought under control, the outlook for the future remains somewhat uncertain. Governmental policy responses around the world have varied greatly and change over time (Hale et al., 2021a) with accompanying variations in outcomes. Typical guidance for controlling the virus spread has included actions such as increased handwashing, personal distancing, tracking locations and contacts, wearing personal protective equipment, restricting personal movements and working from home. While these policies have been aimed primarily at human health, they have also affected our environment, biodiversity and conservation actions.

In Australia, the pandemic response has involved both the federal and state governments, with the Australian government declaring a Human Biosecurity Emergency on 18 March 2020 (Commonwealth Parliament of Australia, 2020) and subsequently closing the international borders, while leaving the states responsible for most other aspects of the pandemic response. This resulted in significant variations in state actions with restrictions being applied of varying duration and severity. At state level, South Australia (SA) was the least affected, Victoria (Vic) had long periods of severe restrictions due to COVID outbreaks, while New South Wales (NSW) was less officially restricted but dealt with some COVID spread.

The variations between states and over time resulted in varying degrees of travel and work limitations, with stay-at-home orders the highest degree of restriction. Non-essential travel and work were advised against and people were recommended to work or study from home, where possible. Many government departments, education and research organisations also restricted fieldwork and outreach activities and, as public safety could not be assured, parks and protected areas were often closed (Parliament of Australia, 2020).

These pandemic-related restrictions on people have produced the "anthropause" (Rutz et al., 2020), which has had a variety of impacts on biodiversity conservation research and practice. There have been positive impacts such as fewer disturbances to fauna and flora (Montgomery et al., 2020), reductions in wildlife roadkill (Bíl et al., 2021; Driessen, 2021; Manenti et al., 2020), improved legislation against wildlife consumption and trade (Koh et al., 2021) and changed activity patterns for some species (China et al., 2021; Manenti et al., 2020). Negative aspects include large increases in environmental pollution from personal protective equipment (PPE) such as masks and gloves (Hiemstra et al., 2021; Zhang et al., 2021), disruptions to field and lab work (Evans et al., 2020), reduced environmental monitoring and protection (Evans et al., 2020; IUCN, 2020b), interruptions to some management processes such as invasive species control programs (Manenti et al., 2020; Miller-Rushing et al., 2021), changes to distribution and abundance of some species (Gilby et al., 2021b), along with funding cuts curtailing existing projects (Rose et al., 2020).

Corlett et al., (2020) recently posed the question: what consequences will restrictions on field and lab work during the pandemic have for the species and ecosystems we are studying, monitoring, and protecting? Disruptions to scientific wildlife surveys and research caused by these restrictions may result in data gaps or other changes to long-term data collections which could impact later scientific analysis and affect our understanding of wildlife populations and biodiversity dynamics (Basile et al., 2021; Evans et al., 2020). As any successful conservation project requires local community cooperation and involvement (Koh and Sodhi, 2010), we extend this question by examining how pandemic restrictions on the general public disrupt biodiversity observations recorded by citizen scientists and then compare these to how observational data from scientific sources have been affected.

Citizen Science (CS) is increasingly used to augment scientific biodiversity monitoring by broadening the spatial and temporal coverage of species observations (Bonney et al., 2009b; Dickinson et al., 2010) and thereby enabling research that would be very difficult using formal scientific methods. In some parts of the world, CS projects have been severely impacted by COVID restrictions. Ad-hoc list submissions to the South African Bird Atlas project showed an approximate 50% decline during a strict lockdown in April 2020 while lists following a defined protocol declined 70% (Rose et al., 2020). In Japan, the CS-based City Nature Challenge recorded a greater than 60% decrease in participants and observations, also in April 2020 (Kishimoto and Kobori, 2021). There were mixed results in other projects, with CS bird observations from iNaturalist increasing in urban areas but decreasing in rural areas in Italy and Spain (Basile et al., 2021).

Although CS is often seen as spatially biased (Mair and Ruete, 2016; Silvertown et al., 2013), with CS participants recording observations in known and local locations (Dickinson et al., 2010), could this be an advantage during periods of restricted movements, so that such monitoring can still occur while other scientific fieldwork is impossible or severely reduced? Do movement restrictions affect CS observation numbers or where they are made? For example, are there changes to monitoring in protected areas (PA), which are considered vital for biodiversity conservation (Brooks et al., 2004; Buckley et al., 2008; Worboys et al., 2015) and often dominate traditional conservation efforts (Joppa and Pfaff, 2011)? In some countries, reduced income and fluctuating visitation patterns, particularly in tourism-dependent economies, resulted in reduced management activities such as species monitoring and protection, along with a range of other impacts (Hockings et al., 2020; Miller-Rushing et al., 2021). Does reduced access to PA also affect CS observations?

In this paper, we explore the effects of pandemic-related restrictions on wildlife monitoring by analysing observations of a widely distributed but cryptic monotreme in Australia, the short-beaked echidna (*Tachyglossus aculeatus*). This iconic species is found throughout Australia in a wide variety of habitats (Brice et al., 2002; Grigg et al., 1989; Rismiller, 1999) but is usually difficult to locate in the wild (Rismiller and McKelvey, 2003). Echidnas are opportunistic foragers, feeding on a wide variety of invertebrates, including ants and termites (Abensperg-Traun, 1994; Abensperg-Traun and Steven, 1997; Sprent et al., 2016). Current population estimates range from 5 to 50 million, indicating the uncertainty around the abundance of this species (Aplin et al., 2015).

Previous research (Stenhouse et al., 2021) showed that large numbers of observations of this species have been recorded through both CS and scientific sources, such as government departments and research organisations, and that these were well distributed geographically over long periods. There were some differences between CS and scientific observations (SO), especially related to relative contributions in PA and very remote areas, while CS has provided greater numbers of observations in recent years.

A successful CS program gathering data on short-beaked echidna in Australia is the Echidna Conservation Science Initiative (echidnaCSI). This has collected over 10 000 observations since September 2017 from around Australia using both a bespoke mobile app and a web portal (Perry et al., In review; Stenhouse et al., 2021). Using a mobile app provided several benefits including standardised responses and accurate data through utilising built-in sensors of mobile phones to automatically record location and time. The app uses the national biodiversity repository at the Atlas of Living Australia (https://www.ala.org.au) as the data repository, which enabled rapid upload and sharing. This had additional benefits of making the project easily discoverable and providing interoperable and reusable data according to the FAIR principles (Wilkinson et al., 2016). Widespread participation from around Australia has provided a large source of CS observations of echidna for augmenting scientific data from traditional sources.

We investigate how data from echidnaCSI compare to data recorded in three state-based biodiversity repositories. We look at how pandemic-related restrictions vary by Australian state and explore the effects of these restrictions on spatial and temporal aspects of echidna observations. We analyse for differences in restriction level effects on the location of CS and SO by comparing observation locations in different classes of protected areas, reserves and parks, as well as an index of remoteness and accessibility. We hypothesise that: 1. CS observations were reduced by COVID-19 restrictions, especially in states where restrictions were harsher; 2. SO were also reduced by pandemic restrictions due to limitations on fieldwork activity; 3. Observations in PA were reduced by COVID-19 restrictions, as many PA were closed; and 4. The geographic remoteness of observations was reduced by COVID-19 restrictions.

4.2. MATERIALS AND METHODS

4.2.1. Data Summary

For this study, we have selected all echidna observations submitted to the echidnaCSI project between 01/01/2018 and 31/12/2020. These observations contain accurate location information (latitude and longitude), accurate date and time, a photo, along with standardised responses to a small range of questions. We also downloaded all echidna records from the state governmental biodiversity data repositories for NSW (01/03/2021), Victoria (01/03/2021) and South Australia (04/03/2021) (Table S4-1). We selected these three states for analysis as they contain large numbers of echidna observations and had substantial differences in state pandemic responses. We selected state data from 01/01/2018 to 31/12/2020 to compare to the data gathered in the echidnaCSI project for the same period. Some records were removed as a result of data cleaning. Further details on data sources and filtering of these records for use in this study are provided in Supplementary Information (4.7.1.1 Data cleaning). For the purposes of this paper, the remaining data were classified as scientific observations (SO) as they have been curated and assessed as acceptable for state repositories.

COVID restrictions were collated from Australian federal and state government websites that provided official COVID-19 advice during 2020. From these announcements, information on restrictions was classified according to the criteria in Table 4-1. We included restrictions that were applied over large areas and not those that applied at fine geographic scale, such as suburb level. The resulting periods of restrictions for each state are in Table S4-2.

Table 4-1 Criteria for determining Australian COVID-19 restriction level classifications used in this study.

Level	Criteria
0	Effectively no or few restrictions - free to move and gather in larger groups. International and inter-state travel restrictions may be in place.
1	Some restrictions on gathering (< 500). Limits on some activities outside. Stay at home mostly guidance. Only essential work done outside home. Many public facilities closed. Schools open.
2	Restrictions on movement to some areas, probably movement limited to < 25km from home. Non-essential movement limited. Gathering limits at home < 10. Schools etc. closed.
3	No non-essential movement outside home. Limit to distance from home e.g. < 5km. Tight limitations on gatherings in public and private.
4	Very limited movement outside home allowed. Possible curfew. No gatherings in private or public.

To analyse how coverage within PA was affected by COVID restrictions, we used the Collaborative Australian Protected Areas Database (CAPAD) 2018 (Australian Government Department of Agriculture, Water and the Environment, 2019) which provides spatial and textual information about national, state and private PA for Australia. This version includes 12,052 terrestrial PAs covering 151,787,501 ha (19.74 percent) of the Australian landmass (Department of Agriculture, Water and the Environment, 2019). For classification of PA, we used the IUCN categories (Table S4-3) which are an internationally recognised standard and classify PA according to their management objectives (Dudley et al., 2013). We used the QGIS vector analysis tools (QGIS Development Team, 2020) to determine if observations were contained in PA.

To analyse how the geographic distributions of observation locations were affected by COVID restrictions, we used the Accessibility and Remoteness Index of Australia 2016 Plus (ARIA+) (Hugo Centre, 2018a). ARIA+ is a continuously varying index of relative remoteness for Australian locations with values ranging from 0 (high accessibility) to 15 (high remoteness). A nationally recognised measure that has been used to derive the

Australian Bureau of Statistics (ABS) Remoteness Area classification for Australia since 2001 (Taylor and Lange, 2016), the 1km^2 ARIA+ 2016 grid was used to assign ARIA+ scores to all of our observations.

4.2.2. Analysis

We classified the origin of data from the state systems as CS or SO based on several attributes (see Supplementary Information 4.7.1.1 for details). Each state records observations differently, as they originate from varying sources such as state government departments, non-governmental organisations and other groups and individuals. Apart from the filtering to remove records as described in S1.1, for the purposes of this analysis, we classify the remainder as scientific observations as they have been curated and accepted into the state repositories. This resulted in three groups of data for analysis: echidnaCSI (CS), which is all of CS origin; State-CS data and SO data. As there were only two records identified as State-CS data for 2020, this group was excluded from further analysis. Using the COVID restrictions data, we classified each observation into one of five levels according to state-level restrictions and the observation date. To determine if these restrictions resulted in differences between the COVID-affected 2020 and previous years, and to account for possible seasonal variations, we identified control periods for observations from 2018 and 2019 that corresponded to the restricted periods in 2020. To test if COVID restriction levels had an effect on observation counts between 2020 and prior years grouped by data source and state, we used Pearson's chi-squared test of independence with Cramer's V for effect size (Cohen, 1988; Howell, 2011).

To test for possible effects of COVID restrictions on observations in PA categories, we used Pearson's chi-squared test of independence with Cramer's V for effect size to test if there were differences in observation counts in 2020 between restriction levels for each data source, including and excluding non-PA. We then compared observation counts in PA categories for 2020 to prior years and compared these counts grouped by data source and restriction level.

We used the ARIA+ index to assess possible differences in geographic distribution between the CS and SO data sources and how they were affected by COVID restrictions. We first used the Shapiro-Wilk test of normality on each source. As all sources were not normally distributed, we used the non-parametric Kruskal-Wallis test (Dodge, Yadolah, 2008) and Dunn's pairwise post-hoc test with the Benjamini-Hochberg adjustment method to test for mean differences in ARIA+ values between restriction levels for each data source and then for each state. The effect size – rank Epsilon squared – is appropriate for non-parametric tests of differences between 2 or more samples. Values range from 0 to 1, with larger values indicating larger differences between groups.

We used Mann-Whitney tests to evaluate restriction level effects on geographic distribution, as represented by ARIA+ remoteness values, between 2020 and prior years broken down by state and data source. To do this, we compared the ARIA+ distributions, for each set of COVID restriction level periods in 2020, against the ARIA+ distributions for the same periods in 2018 and 2019. We performed these analyses for all CS and SO and also for each state.

Analyses were performed using RStudio version 1.4.1106 (RStudio Team, 2021) with R version 4.0.5 using the following packages: data cleaning and preparation for analysis with tidyverse (Wickham et al., 2019), statistical analysis and graphs with ggstatsplot (Patil, 2018) and statsExpressions (Patil, 2021), graphs with ggplot2 (Wickham, 2016) and maps with ggmap3 (Kahle and Wickham, 2013). Final maps were prepared with QGIS 3.16 (QGIS Development Team, 2021).

4.3. RESULTS

4.3.1. Observations

There were 12,164 short-beaked echidna observations in total from 2018 to 2020, spread over the three data groups and across three states - New South Wales (NSW) with 5280, South Australia (SA) with 2473 and Victoria (Vic) with 4411 (Table 4-2). There were differences in numbers recorded within states and within data groups, with a decline in 2019 and 2020 for state CS observations in NSW and Vic and in 2020 for SO in Vic. There was a small decline in CS observations in Vic from 2018 to 2020.

Table 4-2 Short-beaked echidna observation totals by data source, year and state.

Data source	Year	NSW	SA	Vic	Total
CS	2018	899	838	1266	**3003**
	2019	774	515	1059	**2348**
	2020	780	527	991	**2298**
State-CS	2018	684	0	115	**799**
	2019	265	0	73	**338**
	2020	0	0	2	**2**
SO	2018	520	117	411	**1048**
	2019	778	293	415	**1486**
	2020	580	183	79	**842**
Totals		**5280**	**2473**	**4411**	**12164**

Observations during 2020 stratified by data source, state and COVID restriction level show large differences in mean daily observation rates between levels, especially for both CS and SO in Vic level 0 and the other levels of restrictions (Table S4-4).

4.3.1.1 Temporal patterns

Figure 4-1 shows the overall numbers of observations separated by data source and by state, and varying temporal patterns by state. COVID restrictions are coloured by severity level with initial restrictions starting around mid-March 2020 in all states. Restrictions in NSW covered 108 days, with level 3 restrictions lasting 44 days. Vic had the longest and severest restrictions totalling 288 days, with level 3 and 4 restrictions in place for 151 days. Restrictions in SA totalled 102 days with only three days of severe restrictions. The observations are separated into those in PA and those in non-PA, which shows the large contribution that non-PA observations make to CS and the high proportion of PA observations from SO. During the three years of this study, CS observation counts display clear seasonal peaks from around September to January (spring-summer) in NSW and Vic, while in SA there are dual shorter and smaller peaks around April/May and September/October. All states show a trough in observations around May and June. SO show less seasonality with no repeating peaks. There is a notable decline in SO in Vic during 2020.

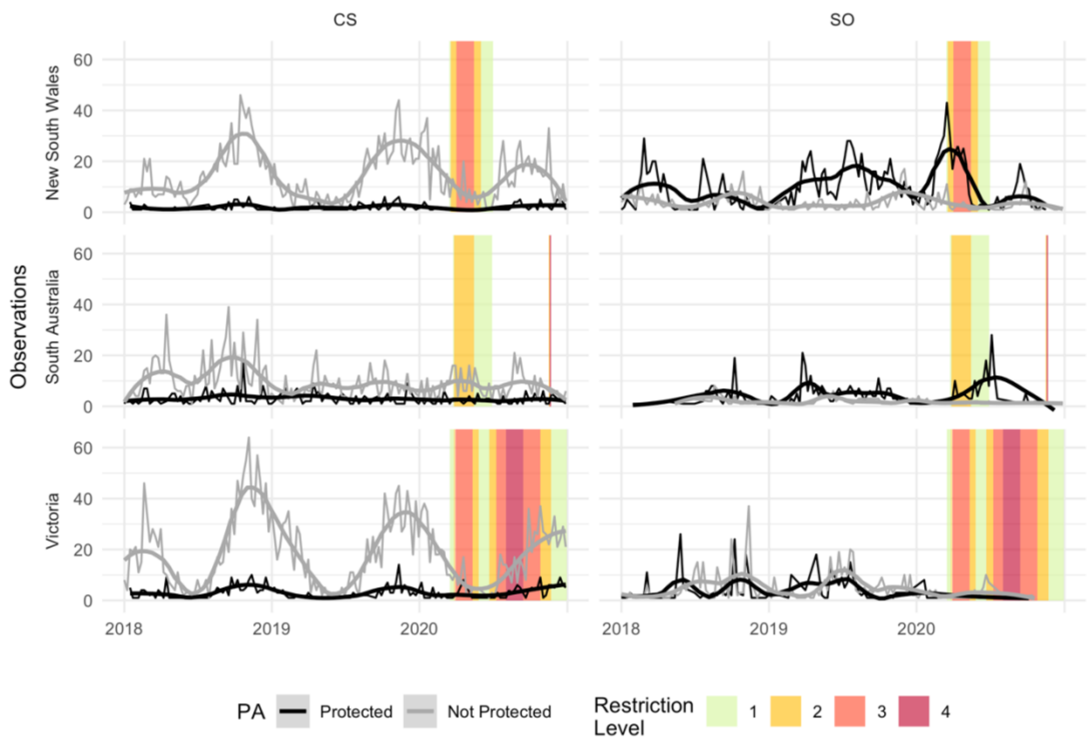

Figure 4-1 Weekly observation counts of short-beaked echidna in PA and non-PA from 2018-2020 with COVID-restriction level periods in 2020 shown, broken down by state and data source. Trend lines have been calculated using the loess method (Jacoby, 2000) and a smoothing window of approximately 9 months.

4.3.1.2 Spatial patterns

Figure 4-2 shows the spatial distribution of echidna observations, coloured by COVID restriction level, in southeastern Australia for 2020, with the base map showing ARIA+2016 categories of remoteness. There are many more CS observations (Figure 4-2a) than SO (Figure 4-2b), with similar geographic distributions. There is a sharp contrast in both the number and geographic distribution of observations in Vic during 2020. In Vic, CS provided 991 widespread observations in 2020 while there were just 79 SO, and in 2019, for comparison, there were 415 SO (Table 4-2).

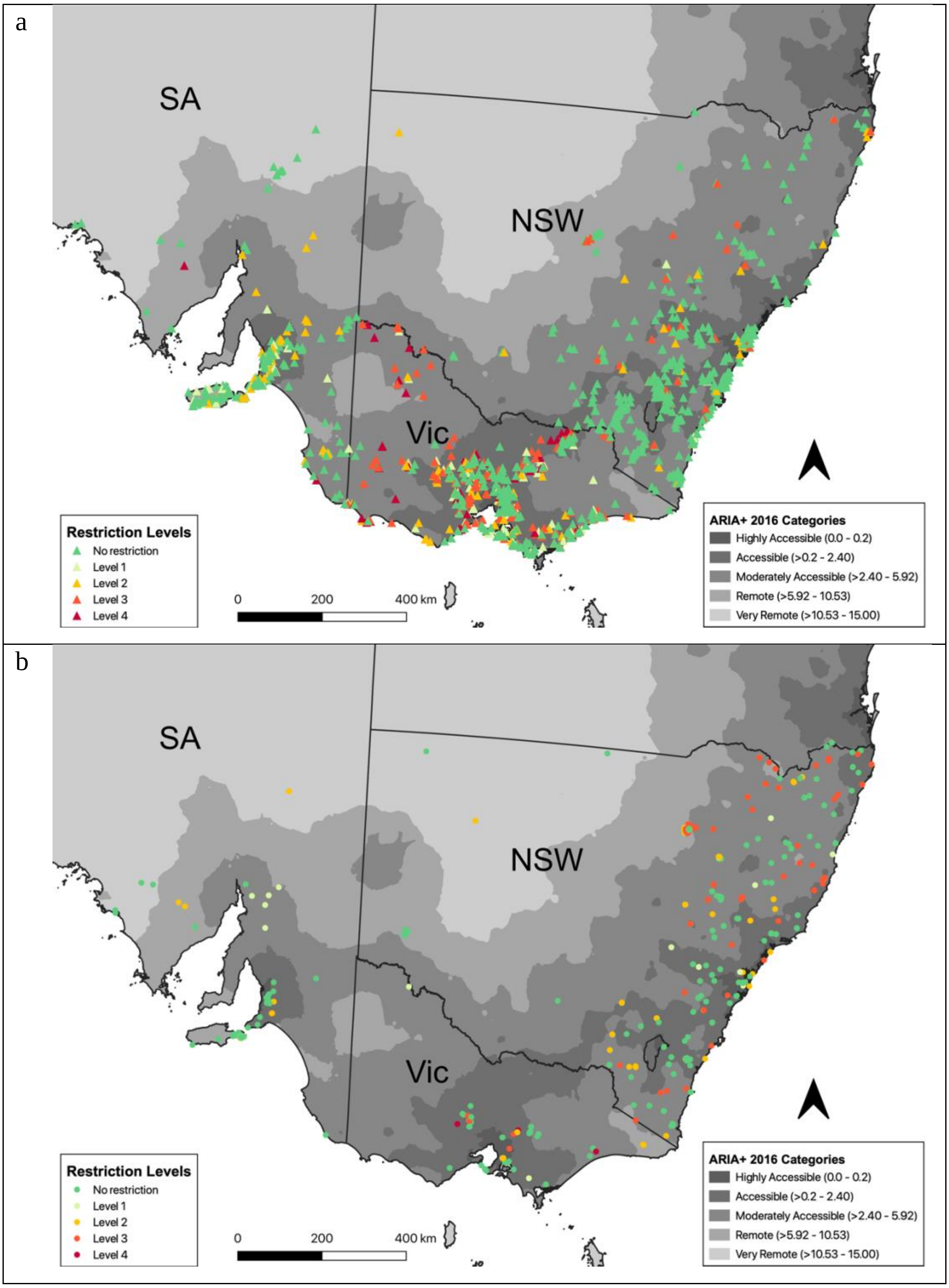

Figure 4-2 Distribution and number of 2020 short-beaked echidna observations coloured by lockdown level in south-east Australia, with ARIA+ (2016) remoteness categories (Hugo Centre, 2018b) indicated on the base map. **2a** All CS observations; **2b** All SO.

4.3.2. Effects of COVID-19 restrictions on observations

Observation counts for each restriction level, data source, State and period are detailed in Table 4-3. Note that the number of days varies between restriction level and State, which affects between-State and between-level comparisons. However, the number of days remains the same between periods for each restriction level and State.

Table 4-3 Short-beaked echidna observation counts per restriction level by data source, state and period.

			Restriction Level				
Data source	**State**	**Period**	**0**	**1**	**2**	**3**	**4**
CS	NSW	2018-2019	1460	32	79	102	0
	NSW	2020	675	12	35	58	0
	SA	2018-2019	973	127	241	-	12
	SA	2020	354	79	90	-	4
	Vic	2018-2019	542	521	459	611	192
	Vic	2020	290	205	140	260	96
SO	NSW	2018-2019	904	71	123	200	0
	NSW	2020	317	31	87	145	0
	SA	2018-2019	266	66	76	-	2
	SA	2020	89	61	33	-	0
	Vic	2018-2019	93	150	215	283	85
	Vic	2020	37	13	19	6	4

Numbers of CS observations were not affected by different COVID restriction levels. SA and Vic showed highly significant differences but with negligible effect and NSW showed no significant difference between restriction levels (Table S4-5). SO were affected by restriction levels. There were highly significant differences with small to moderate effects, with observation numbers in Vic being most affected by COVID restrictions (χ^2 (4, N = 3316) = 81.82, p < 0.001, Cramer's V = 0.29) followed by SA (χ^2 (3, N = 1880) = 24.04, p < 0.001, Cramer's V = 0.19) and NSW (χ^2 (3, N = 2452) = 44.88, p < 0.001, Cramer's V = 0.15). Interestingly, although SO in Vic decreased as restrictions were applied, in SA and NSW the results are more mixed, with some increases apparent in NSW.

4.3.3. Effects of COVID-19 restrictions on observations in protected areas

Observation counts for the periods of each level of restrictions by data source and PA status show clearly the differences between CS and SO in observations in PA and non-PA (Table S4-6). Observation counts by source, state, year and PA IUCN category also show large variations (Table S4-7), with an especially large reduction for SO in "Strict Nature Reserves" in Vic from 147 observations in 2018-2019 down to a single observation in this PA category in 2020.

CS observations in PA IUCN categories showed no significant differences in 2020 compared to 2018-2019 overall. However, SO showed a significant association between period and PA category, with small effects, when including non-PA (χ^2 (7, N = 3374) = 159.39, p < 0.001, Cramer's V = 0.21) and also when excluding non-PA (χ^2 (6, N = 2138) = 70.59, p < 0.001, Cramer's V = 0.17) (Table 4-4).

Table 4-4 Pearson's Chi-squared test results for comparing echidna observations in IUCN PA categories during COVID restrictions in 2020 with observations for the same periods during 2018–2019, separated by data source groups and including and excluding non-PA.

	Data source	Statistic	DF	p-value	Cramer's V (adj.)	95% CI	Sig
Including non-PA	CS	7.82	7	0.35	0.01	0-0	
	SO	159.39	7	<0.001	0.21	0.17-0.24	***
Excluding non-PA	CS	6.13	6	0.41	0.01	0-0	
	SO	70.59	6	<0.001	0.17	0.12-0.21	***

When comparing proportions of observations made in all PA IUCN categories and non-PA between COVID restriction levels in 2020 (Figure S4-2), CS observations were not significantly affected (χ^2 (28, N = 2297) = 46.81, p = .014, Cramer's V = 0.05). SO were moderately affected by COVID restriction levels, showing a highly significant association (χ^2 (24, N = 842) = 142.07, p < 0.001, Cramer's V = 0.19).

When non-PA are excluded from the analysis, the distribution of CS observations across PA IUCN categories showed no significant difference between COVID restriction levels (χ^2 (24, N = 324) = 28.32, p = .247, Cramer's V = 0.06). Distribution of SO in PA showed significant differences between levels, with moderate to strong effects (χ^2 (15, N = 642) = 112.41, p < 0.001, Cramer's V = 0.23).

4.3.3.1 Comparing effects of COVID-19 restrictions to prior years

No significant associations were found between COVID restriction levels and observations inside and outside PAs for CS observations. For SO, however, there were highly significant associations at each level of restriction, except for level 4, which had very few observations in 2020, all being in non-PA (Table 4-5 and Figure S4-3).

Table 4-5 Chi-square test results when comparing the effects of COVID restriction levels on observations in PA categories and non-PA during 2020 with observations during 2018–2019 for the same periods, separated into data source groups of CS and SO.

Data Source	Restriction Level	Statistic	DF	p-value	Cramer's V (adj.)	95% CI	Sig	N 2018-19	N 2020
CS	0	11.55	7	0.12	0.03	0-0.04		2975	1319
	1	11.2	6	0.08	0.07	0-0.11		680	296
	2	6.35	7	0.5	0	0-0		779	265
	3	6.49	7	0.48	0	0-0		713	318
	4	9.4	6	0.15	0.11	0-0.15		204	100
SO	0	79.12	7	<0.001	0.21	0.15-0.25	***	1263	443
	1	59.19	6	<0.001	0.37	0.25-0.45	***	287	105
	2	44.25	6	<0.001	0.26	0.16-0.33	***	412	139
	3	90.53	6	<0.001	0.37	0.27-0.43	***	483	151
	4	2.5	3	0.48	0	0-0		87	4

4.3.4. Effects of COVID-19 restrictions on geographic distribution of observations

COVID-19 restriction levels varied by location over time and we examined how these affected the geographic distribution of our observations. Aggregated overall, mean ARIA+ values ranged from 3.09 ±2.66 for level 0 observations to 1.76 ±1.75 for observations under level 4 restrictions (Table S4-8). A Kruskal-Wallis test showed highly significant but negligible effect of restriction level on mean remoteness values overall, as measured by ARIA+ (2016) (χ^2 (4, N = 3140) = 41.95, p < 0.001, ε^2 = 0.01). A post-hoc pairwise comparison using Dunn's test with Benjamini-Hochberg correction showed significant differences between level 0 (no restrictions) and all other levels. There were also significant differences between levels 1 to 3 and level 4 (Table S4-9).

4.3.4.1 By Data Source

When we analyse observations in 2020 by data source, restriction level shows a significant weak-moderate effect on mean geographic remoteness, as measured by ARIA+ (2016), indicated by the Kruskal-Wallis test results for both CS observations (χ^2 (4, N = 2300) = 61.2, p < 0.001, ε^2 = 0.03) and SO (χ^2 (4, N = 842) = 42.8, p < 0.001, ε^2 = 0.05) (Table S4-10). CS observations showed significant differences but with a small effect between groups at level 0 (no restrictions) and all restriction levels, as shown by the pairwise post-hoc Dunn test with Benjamini-Hochberg correction. SO showed more variation between groups, with significant differences between levels 0 and 3, also between level 1 and all other levels, and lastly between levels 2 and 3 (Table S4-11).

4.3.4.2 Within States

Restriction level shows little effect on the geographic distribution of observations within each state (Figure 4-3), though differences between states are clear. New South Wales shows a significant but weak effect between levels (χ^2 (3, N = 1360) = 27.9, p < 0.001, ε^2 = 0.02). There are negligible effects in both South Australia (χ^2 (3, N = 710) = 7.2, p = 0.06, ε^2 = 0.01) and Victoria (χ^2 (4, N = 1072) = 10.1, p = 0.04, ε^2 = 0.01) (Table S4-12). Pairwise comparisons between levels for each state showed small but significant differences between geographic distribution at level 0 (no restrictions) and all other restriction levels for NSW, with the median remoteness index surprisingly higher for all restriction levels than for level 0. This indicates that with no COVID-19 restrictions in place, more observations were made in accessible locations which is perhaps an indication of people being more active but still in proximity to populated or accessible areas. There were no significant differences between levels for SA or Vic (Figure 4-3 & Table S4-13).

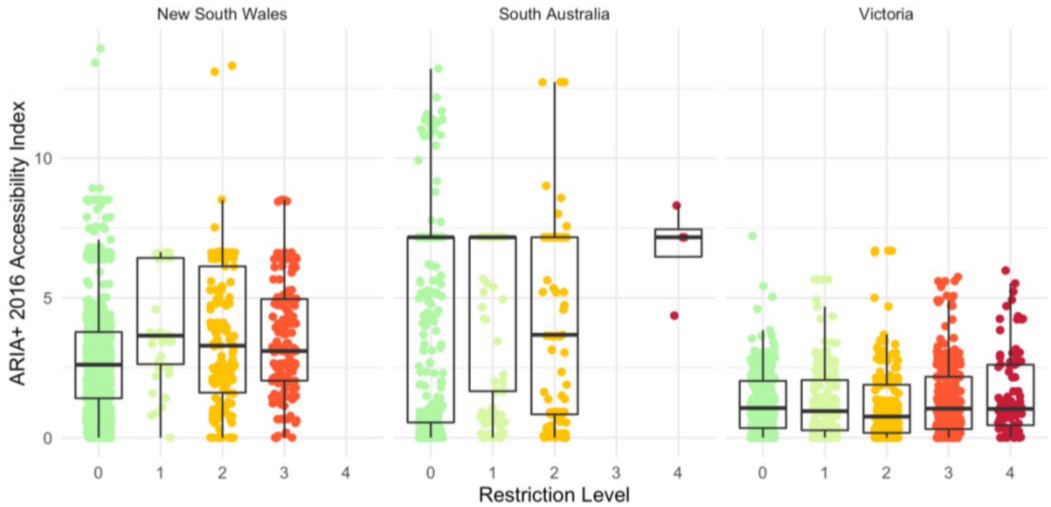

Figure 4-3 Comparison of COVID-19 restriction levels effect on ARIA+ 2016 remoteness values by state for observations in 2020. Boxplots for each state's restriction levels, showing median and inter-quartile range with outliers, are shown over observations coloured according to restriction level as in Figure 4-2. Note that New South Wales had no period of level 4 restrictions and South Australia no level 3 restricted period.

4.3.4.3 Between periods

Comparing ARIA+ values for remoteness between the same restriction periods in prior years to 2020 indicates no difference in geographic distributions for all restriction levels in CS observations (Figure 4-4a) except for level 2 which showed a small significant difference (Mann–Whitney U = 11.62, n1 = 779, n2 = 265, M1 = 1.32, M2 = 0.95, P < 0.05 two-tailed). The geographic distribution of SO was more affected by restrictions. ARIA+ remoteness distribution for SO (Figure 4-4b) showed significant increases at restriction levels 1, 2 and 3 in 2020 compared to the same periods in the previous two years (Table S4-14), while at level 4 there were very few SO.

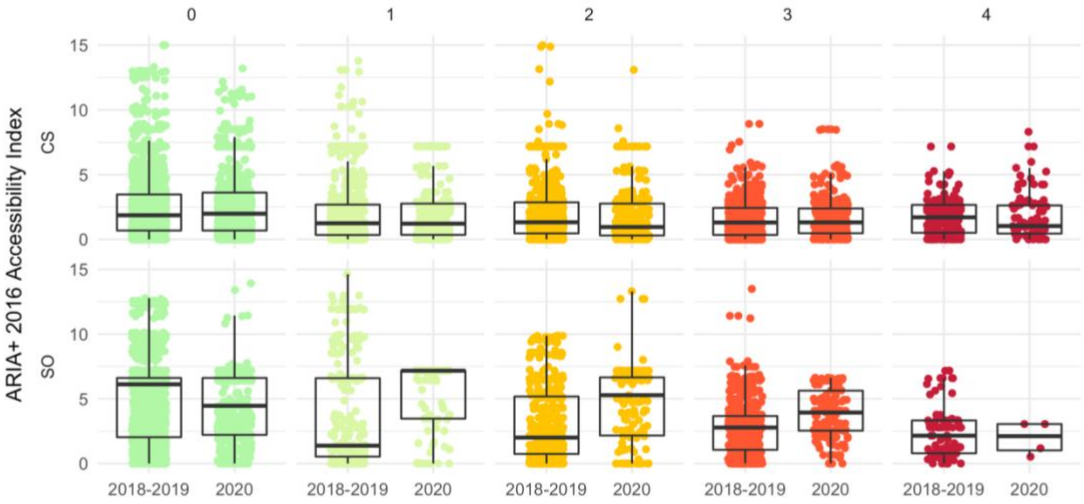

Figure 4-4 Effect of COVID-19 restrictions on ARIA+ (2016) remoteness index between COVID-affected 2020 and prior years (2018-2019). Boxplots show median and distribution of ARIA+ values plotted over observation points coloured by restriction levels as in Figure 4-2. Citizen science (CS) observations in the top row show a significant difference between periods in level 2 only, while scientific observations (SO) in the second row show significant differences between periods at restriction levels 1, 2 and 3.

To better evaluate the varied effects of restriction levels on the geographic distribution of observations, we then split the data by state (Figure S4-4). For CS observations, there were significant differences in the geographic distribution in NSW under restriction level 3 and in SA under levels 2 and 4, with no significant differences in Vic (Table S4-15). This is interesting as Victoria had the severest and longest restrictions but it appears this did not impact the distribution of observations. For SO, however, there are highly significant differences in geographic distribution in NSW under restriction levels 2 and 3, in SA under levels 0 and 1 and in Vic under levels 1 and 2. For summary statistics of ARIA+ by year, data source, state and restriction level see Table S4-16.

4.4. DISCUSSION

This study evaluated the impacts of COVID-related restrictions on observations of short-beaked echidna recorded using both CS and scientific methods in three states of Australia. There were many differences in COVID restrictions between states which led to variations in recording activity, though some interesting patterns are apparent. SO were most affected by restrictions, with significant reductions in Victoria where the restrictions were severest, while CS observations showed few impacts.

4.4.1. COVID-19 restrictions effects on observation counts

Somewhat surprisingly, our results show that observation counts from CS were not affected by COVID restrictions. While we had expected that observations would decrease, this did not occur, even in Victoria where restrictions were long and severe. One reason for this could be that echidnaCSI relies on opportunistic observations rather than formal or group surveys, thus the work-from-home restrictions may have contributed to more observations, as people remained at home and consequently explored local green spaces. This may have offset other negative effects, such as from reduced travelling and tourism. In addition, many echidna observations are in peri-urban areas where there is still abundant habitat, so people remaining at home have more opportunities to observe activity in their backyard and neighbourhood.

Numbers of SO were significantly affected by COVID restrictions, especially in Victoria, where there was a large decrease in SO overall, and the numbers of daily observations during each restriction level also decreased. This was expected due to the limitations on non-essential travel and fieldwork and in Victoria the restrictions were long and severe. In addition, it is possible that people contributing SO live in populated centres and were more affected by fieldwork restrictions. The other states had fewer restrictions and showed few effects. Of interest is the increase in observations per day in NSW under restriction levels two and three. It is unclear why this might be the case, but possibly due to later inclusion, after processing, of observations from camera traps, which continually record without human presence.

The variations apparent in Figure 4-1 are likely due to citizen scientists being more active at certain times of the year or in good weather (August et al., 2020; Boakes et al., 2010), as well as variable echidna activity. Echidnas are known for seasonal variations in activity which occur for several reasons, including breeding, weather patterns, particularly temperature, prey availability and periods of torpor and hibernation, all of which show regional variations (Abensperg-Traun and Boer, 1992; Brice et al., 2002; Clemente et al., 2016; Nicol and Andersen, 2007). Interestingly, CS observations in NSW and Vic show similar seasonal changes with large peaks corresponding to the warmer periods of the year while those in SA are flatter. These variations may be due to people being more active outside during summer months combined with longer daylight hours, or to seasonal changes in echidna activity, or, most likely, to a combination of these factors. The scientific data show more variations and again it is difficult to determine possible causes, though it is likely also due to variations in scientific fieldwork intensity and echidna activity.

4.4.2. COVID-19 restrictions effects on protected area observations

Observations from scientific sources in protected areas (PA) were significantly affected by COVID-19 restrictions while CS observations were not. This is interesting as we expected that both restrictions on personal movement and PA closures would most constrain CS observations but this was not the case. SO in Vic showed the biggest impact, as might be expected from a state with the most severe and long restrictions. This points to the probable classification of monitoring work as non-essential during a time of crisis, despite some PA being critical for ecosystem health and biodiversity preservation. In contrast, it appears that many CS participants remained active during periods of extreme restrictions and were in sufficient proximity to PA that they could still record wildlife observations.

SO in non-PA were significantly reduced for all periods of restriction in 2020, including under level 0, while CS showed a slight overall decline. This may be due to an increased focus on scientific monitoring and management in important conservation areas as a result of the varied restrictions placed on organisations due to the pandemic, while other non-essential work was postponed (Waithaka et al., 2021). This is reflected in the increased proportion of observations in highly protected IUCN PA categories "Strict Nature Reserve" and "Wilderness Area" in 2020 compared to prior years in NSW and SA. In Vic, however, observations in PA were severely reduced suggesting that even work in important conservation areas was restricted.

4.4.3. COVID-19 restrictions effects on geographic distribution of observations

With no restrictions (level 0), observations were more geographically remote overall than under all other restriction levels as was expected, as restrictions on movement impacted travel. When split by data source, this pattern was also apparent for CS observations but not for SO. When comparing remoteness values for 2020 against 2018 – 2019 for the same periods determined by restriction level (Figure 4-4), CS shows little difference between periods while SO are more impacted. This appears to be due to significant state variations in observations counts and remoteness values when we compare the same periods for each state (Figure S4-4). The higher population density of Vic than the other states, combined with few remote and no very remote regions, result in a reduced range of remoteness values for all echidna records in Vic compared to the other states. As SO in Vic were markedly reduced during restrictions in 2020, while the other states were not, the effect on geographic distribution is skewed upwards when combining all states data and comparing 2020 to 2018-2019, and thus shows an apparent increase in remoteness values in 2020 under restriction levels one to three.

Also interesting is the lack of significant difference in Vic CS observations between 2018-2019 and 2020 restricted level periods. Vic had the longest and strictest restrictions and despite this, the CS remoteness index values did not significantly change, which was not expected. This may be related to the regional characteristics of Vic, with many participants taking advantage of abundant green spaces in peri-urban and rural areas, which coincide with the echidna's habitat and dietary requirements. It highlights a strength of this CS program that it was able to continue to provide similar geographic coverage during varying levels of restrictions as in normal, unrestricted periods.

The major series of bushfires in 2019-2020 in Australia affected large areas within the study area and severely impacted the ecosystems and animals within them, the people who lived there and subsequently the conservation focus of many organisations. The impacts of the bushfires are many and varied (Khan, 2021; Wintle et al., 2020) and require a separate study, but a potential effect here is a decrease in monitoring activity in some areas during and after the fires, as activity by conservation and research organisations, other than wildlife emergency rescue and recovery, was often limited. At the same time, the general public was prohibited from these areas, which would have curtailed CS monitoring there.

We expected that the restrictions which curtailed travelling and tourism would have resulted in fewer CS observations, though this does not appear to be the case. Perhaps this is an indication of the strong interest in, and knowledge of, local areas by the participants as well as increased local activity due to the various restrictions, which included bans on international travel but offset by support for inter- and intra-state tourism. To evaluate one effect of restrictions on travel, comparing the numbers and locations of echidnas killed on roads may provide insights. Reduced travelling by car probably results in fewer animals being hit by vehicles, as well as fewer roadside observations. Reductions in wildlife roadkill due to reduced travelling have been detailed elsewhere (Driessen, 2021; Shilling et al., 2021) and it would be valuable to document these to further inform conservation management and transport planning.

This study has shown contrasting results to other international studies evaluating the effects of COVID-19 restrictions on biodiversity observations using CS. In 2020, our CS observation numbers were not significantly affected by the varying restriction levels, even under the severest restrictions, while other international studies reported declines from CS projects of 50-70% (Kishimoto and Kobori, 2021; Rose et al., 2020). Similarly, the geographical distribution of our CS observations showed little variation compared to prior years, in contrast to the changes to CS-based urban/rural bird observations in Italy and Spain (Basile et al. 2021) and in the USA (Crimmins et al., 2021), which decreased in rural areas but increased in urban areas. Echidnas are not as mobile nor commonly found in urban areas compared to birds and are more likely to be found in the peri-urban, rural and wilderness areas of Australia, thus it might be expected that the geographic distribution of these observations shows little change.

Our findings are influenced by the classification of levels of restriction on activity and movement of citizens and we acknowledge the reliance on human interpretation of government policy announcements to classify those restriction levels. A global database tracking COVID restrictions discusses some of the difficulties associated with classifying restrictions at varying scales (Hale et al., 2021b). Our interpretation and classification of the announcements might be done differently, though we believe the relative rankings of restriction severities would remain similar.

A strength of the echidnaCSI program is that it directly uploads observations to a national biodiversity repository, hence there are no delays in collating this data and it is immediately available for use. Scientific biodiversity monitoring is often slower to process and share observational data and thus it is possible that the state datasets did not reflect what had been recorded, but only what had been processed so far. Directly uploading data to a national or central repository also enables other activities to take place, such as data curation or classification, which can be performed both by experts and the public via crowdsourcing platforms. Such activities showed benefits of stay-at-home COVID-19 restrictions in some places (Crimmins et al., 2021) and illustrate another method where technology-supported CS can provide important contributions to biodiversity conservation research while fieldwork is disrupted. These tools will also be vital for scientific studies where disruptions to monitoring should be prevented, such as for threatened species.

We expect that traditional monitoring of other species will also have been affected and that it is important for researchers to be aware of the potential for temporal and spatial data gaps when analysing data from these timeframes in future. The distributed and consistent activities of the participants in the echidnaCSI project have demonstrated the potential value of CS to biodiversity and wildlife monitoring even under restrictions caused by a global pandemic.

4.5. CONCLUSIONS

The COVID pandemic has affected wildlife monitoring in Australia in varying ways. In this paper, using the iconic but cryptic short-beaked echidna as a case study, SO were most affected by restriction levels but the effects varied between states. Perhaps surprisingly, CS, through the echidnaCSI program, continued to provide numerous and widespread observations even during periods with severe COVID-related restrictions, while scientific monitoring was greatly reduced under the same restrictions. This highlights the value of CS, as widespread participation appears to be less affected by movement restrictions than scientific monitoring, which often involves remote fieldwork and fewer people. However, differences between CS and scientific monitoring remain, such as the lack of coverage in very remote regions and PA by CS. Thus, further research on alternative monitoring and detection methods to better cover these areas in the face of restrictions is vital to avoid gaps in monitoring coverage. Finally, this study illustrates the potential value of a national CS project for continued wildlife monitoring, even in times of crisis when other approaches may be more severely impacted.

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DATA AVAILABILITY

Data is available for download from the DOIs and websites listed in Supplementary Information S4.7.2.

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4.7. SUPPLEMENTARY INFORMATION

4.7.1. Methods

4.7.1.1 Data cleaning

Records from state biodiversity data repositories and the echidnaCSI project were selected for dates between 01 January 2018 and 31 December 2020. Observations from the state repositories were filtered to include physical sightings, such as from camera traps, direct observations, traps, roadkill or other similar direct evidence. Observations recorded using signs of presence, such as scats, diggings or other indirect evidence were omitted. Observations from camera traps in the NSW state dataset were restricted to 1 observation per location per 120s as there were some sequences where each photo was recorded as an observation, some containing more than 30 per sequence.

The state systems include records from a variety of sources including CS programs like iNaturalist and Questagame. There are also records from wildlife rehabilitation centres which result from human-echidna interactions. These records have been classified as state-CS records to better compare the contributions from CS to observations from scientific sources. For the purposes of this paper, the remaining data were classified as scientific observations (SO) as they have already been curated and assessed as acceptable for state repositories.

4.7.2. Data Sources

Datasets used in this study can be downloaded from the following sources.

Table S4-1 Echidna observations data sources

Source	URL or DOI
echidnaCSI	https://biocollect.ala.org.au/acsa/project/index/8c3ae3b1-5342-40b4-9e72-e9820b7a9550
NSW	https://www.environment.nsw.gov.au/atlaspublicapp
SA	http://spatialwebapps.environment.sa.gov.au/naturemaps/?locale=en-us&viewer=naturemaps
Vic	https://vba.dse.vic.gov.au/vba/index.jsp

4.7.3. Supplementary Tables

Table S4-2 State COVID-19 restriction level periods as determined through evaluation of official government releases. Dates are shown in YYYY-MM-DD format.

State	Level	Start	End
NSW	1	2020-03-15	2020-03-18

	2	2020-03-18	2020-04-01
	3	2020-04-01	2020-05-15
	2	2020-05-15	2020-06-01
	1	2020-06-01	2020-07-01
SA	1	2020-03-24	2020-03-27
	2	2020-03-27	2020-05-15
	1	2020-05-15	2020-06-29
	2	2020-11-16	2020-11-18
	4	2020-11-18	2020-11-21
Vic	1	2020-03-16	2020-03-26
	2	2020-03-26	2020-03-30
	3	2020-03-30	2020-05-11
	2	2020-05-11	2020-05-26
	1	2020-05-26	2020-06-22
	2	2020-06-22	2020-07-09
	3	2020-07-09	2020-08-02
	4	2020-08-02	2020-09-13
	3	2020-09-13	2020-10-26
	2	2020-10-26	2020-11-22
	1	2020-11-22	2020-12-30

Table S4-3 IUCN Protected Area Categories (Dudley et al., 2013).

ID	Category	Description
Ia	Strict Nature Reserve	Category Ia are strictly protected areas set aside to protect biodiversity and also possibly geological/geomorphical features, where human visitation, use and impacts are strictly controlled and limited to ensure protection of the conservation values. Such protected areas can serve as indispensable reference areas for scientific research and monitoring.
Ib	Wilderness Area	Category Ib protected areas are usually large unmodified or slightly modified areas, retaining their natural character and influence without permanent or significant human habitation, which are protected and managed so as to preserve their natural condition.
II	National Park	Category II protected areas are large natural or near natural areas set aside to protect large-scale ecological processes, along with the complement of species and ecosystems characteristic of the area, which also provide a foundation for environmentally and culturally compatible, spiritual, scientific, educational, recreational, and visitor opportunities.
III	Natural Monument or Feature	Category III protected areas are set aside to protect a specific natural monument, which can be a landform, sea mount, submarine cavern, geological feature such as a cave or even a living feature such as an ancient grove. They are generally quite small protected areas and often have high visitor value.

IV	Habitat/Species Management Area	Category IV protected areas aim to protect particular species or habitats and management reflects this priority. Many Category IV protected areas will need regular, active interventions to address the requirements of particular species or to maintain habitats, but this is not a requirement of the category.
V	Protected Landscape/ Seascape	A protected area where the interaction of people and nature over time has produced an area of distinct character with significant, ecological, biological, cultural and scenic value: and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values.
VI	Protected area with sustainable use of natural resources	Category VI protected areas conserve ecosystems and habitats together with associated cultural values and traditional natural resource management systems. They are generally large, with most of the area in a natural condition, where a proportion is under sustainable natural resource management and where low-level non-industrial use of natural resources compatible with nature conservation is seen as one of the main aims of the area.

Table S4-4 Observation totals and average per day during 2020 and 2018-2019 by COVID-19 restriction levels, data source and State.

			Observation Counts				Mean Observations / Day			
			CS		SO		CS		SO	
State	Level	Days	2018-19	2020	2018-19	2020	2018-19	2020	2018-19	2020
NSW	0	249	1460	654	904	315	2.93	2.71	1.82	1.27
	1	33	32	12	71	31	0.48	0.36	1.08	0.94
	2	40	79	56	123	89	0.99	0.88	1.54	2.17
	3	44	102	58	200	145	1.16	1.32	2.27	3.3
SA	0	264	973	354	266	89	1.84	1.34	0.50	0.34
	1	48	127	79	66	61	1.32	1.65	0.69	1.27
	2	51	241	90	76	33	2.36	1.76	0.75	0.65
	4	3	12	4	2	-	2	1.33	0.33	0
Vic	0	28	542	282	93	37	9.68	10.36	1.66	1.32
	1	93	521	198	150	13	2.8	2.2	0.81	0.14
	2	76	459	155	215	19	3.02	1.84	1.41	0.25
	3	127	611	260	283	6	2.41	2.05	1.11	0.05
	4	42	192	96	85	4	2.29	2.29	1.01	0.1

Table S4-5 Pearson's Chi-squared test results for comparing echidna observations during COVID-19 restrictions in 2020 with observations for the same periods of restrictions during 2018 and 2019, separated into State and data source of Citizen Science (CS) and Scientific Observations (SO).

Data Source	**State**	**Statistic**	**DF**	**p-value**	**Cramer's V (adj.)**	**95 % CI**	**Sig**
CS	NSW	1.97	3	0.58	0	0-0	
	SA	12.27	3	0.01	0.07	0-0.11	**
	Vic	24.51	4	< 0.001	0.08	0.04-0.11	***

SO	NSW	44.88	3	< 0.001	0.15	0.1-0.19	***
	SA	24.04	3	< 0.001	0.19	0.1-0.26	***
	Vic	81.82	4	< 0.001	0.29	0.22-0.35	***

Table S4-6 Observation counts in PA and non-PA for each restricted level period in 2020 and corresponding period totals for 2018-2019.

		2018-2019					2020				
Source	**PA**	**0**	**1**	**2**	**3**	**4**	**0**	**1**	**2**	**3**	**4**
CS	Not PA	2595	601	663	613	180	1152	242	227	276	76
	PA	380	79	116	100	24	167	54	38	42	24
SO	Not PA	429	143	184	227	53	122	26	30	18	4
	PA	834	144	230	256	34	321	79	109	133	0

Table S4-7 Observations counts in protected and non-protected areas by data source, State and period.

Source	State	Period	IA	IB	II	IV	V	III	NAS	VI	Not PA
CS	NSW	2018-2019	9	4	112	16	3	0	0	0	1529
		2020	2	6	45	8	2	2	1	0	714
	SA	2018-2019	2	2	82	4	0	180	0	15	1068
		2020	5	0	35	1	0	66	0	8	412
	Vic	2018-2019	38	0	146	35	7	39	0	5	2055
		2020	17	0	73	15	1	29	0	9	847
SO	NSW	2018-2019	89	40	730	21	2	2	2	6	406
		2020	62	30	374	5	0	0	0	0	109
	SA	2018-2019	7	1	219	6	0	39	0	53	85
		2020	84	0	5	0	0	54	0	11	29
	Vic	2018-2019	147	0	71	52	0	4	0	7	545
		2020	1	0	9	7	0	0	0	0	62

Table S4-8 ARIA+ statistics by COVID-19 restriction level for all observations from 2020.

Level	Mean	Median	SD	Max	IQR	N
0	3.09	2.5	2.66	13.92	3.7	1731
1	2.93	1.92	2.78	7.17	5.95	394
2	2.8	1.88	2.8	13.31	4.52	442
3	2.35	2.02	1.98	8.51	2.43	469
4	1.76	1.05	1.75	8.31	2.14	104

Table S4-9 Statistical results from post-hoc pairwise comparison of ARIA+ data by COVID-19 restriction level for 2020 using Dunn's all-pairs test with Benjamini-Hochberg correction.

group1 level	group2 level	Dunn statistic	p.value	sig
0	1	2.12	0.05	*
0	2	3.38	0.003	***
0	3	4.34	< 0.001	***
0	4	4.71	< 0.001	***

1	2	0.88	0.42	
1	3	1.58	0.14	
1	4	3.24	0.003	***
2	3	0.70	0.48	
2	4	2.71	0.01	**
3	4	2.30	0.04	*

Table S4-10 Kruskal-Wallis rank sum test for ARIA+ distribution by data source with epsilon2 rank effect size and 95% confidence levels.

Data Source	Statistic	DF	p-value	effect size	95 % CI
CS	61.2	4	< 0.001	0.03	0.01 – 0.04
SO	42.8	4	< 0.001	0.05	0.03 – 0.08

Table S4-11 Statistical results from post-hoc pairwise comparison of ARIA+ data by data source and level using Dunn's all-pairs test with Benjamini-Hochberg correction.

Data Source	Level A	Level B	Dunn Statistic	p-value	Sig
CS	0	1	4.37	< 0.001	***
	0	2	5.40	< 0.001	***
	0	3	5.63	< 0.001	***
	0	4	2.98	0.01	**
	1	2	0.74	0.76	
	1	3	0.84	0.76	
	1	4	0.22	0.92	
	2	3	0.08	0.93	
	2	4	0.31	0.92	
	3	4	0.37	0.92	
SO	0	1	4.38	< 0.001	***
	0	2	0.85	0.40	
	0	3	3.28	< 0.001	***
	0	4	1.93	0.07	
	1	2	3.05	< 0.001	***
	1	3	6.18	< 0.001	***
	1	4	2.83	0.01	**
	2	3	3.35	< 0.001	***
	2	4	2.07	0.05	
	3	4	1.3	0.22	

Table S4-12 Kruskal-Wallis rank sum test for ARIA+ distribution by restriction level and State with epsilon2 rank effect size and 95% confidence levels.

State	Statistic	DF	p-value	ε^2 Effect	95% conf.
NSW	27.9	3	< 0.001	0.02	0.01 – 0.04
SA	7.2	3	0.06	0.01	0 – 0.03
Vic	10.1	4	0.04	0.01	0 – 0.02

Table S4-13 Statistical results from post-hoc pairwise comparison of ARIA+ data by State and COVID-19 restriction level using Dunn's all-pairs test with FDR correction.

State	Level 1	Level 2	Dunn's Statistic	p-value	Sig.
NSW	0	1	3.31	< 0.001	***
	0	2	2.68	0.01	**
	0	3	3.90	< 0.001	***
	1	2	1.60	0.17	
	1	3	1.28	0.24	
	2	3	0.57	0.57	
SA	0	1	1.89	0.18	
	0	2	0.79	0.43	
	0	4	1.48	0.21	
	1	2	2.14	0.18	
	1	4	1.11	0.32	
	2	4	1.63	0.21	
Vic	0	1	1.08	0.38	
	0	2	2.13	0.11	
	0	3	0.38	0.70	
	0	4	1.15	0.38	
	1	2	1.03	0.38	
	1	3	1.38	0.33	
	1	4	1.87	0.15	
	2	3	2.39	0.08	
	2	4	2.65	0.08	
	3	4	0.85	0.44	

Table S4-14 Mann–Whitney U test results from comparing ARIA+ remoteness values for citizen science (CS) and scientific observations (SO) between COVID-affected 2020 and prior years (2018 – 2019) with r (rank biserial) for effect size.

Data source	Level	N (2018–19)	N (2020)	Median 2018-19	Median 2020	$\log_e$ U Statistic	p-val	sig	r (rank biserial)	95 % conf. levels
CS	0	2975	1319	1.86	1.98	14.46	0.19		-0.02	-0.06 – 0.01
	1	680	296	1.24	1.21	11.49	0.45		-0.03	-0.10 – 0.04
	2	779	265	1.32	0.95	11.62	0.04	*	0.08	0.00 – 0.15
	3	713	318	1.30	1.31	11.62	0.56		-0.02	-0.09 – 0.05
	4	204	100	1.70	1.03	9.29	0.42		0.06	-0.09 – 0.18
SO	0	1263	443	6.12	4.46	12.58	0.17		0.04	-0.018 – 0.12
	1	287	105	1.38	7.17	9.23	< 0.001	***	-0.32	-0.43 – -0.19
	2	414	139	2.00	5.28	9.92	< 0.001	***	-0.30	-0.40 – -0.21
	3	483	151	2.78	3.94	10.09	< 0.001	***	-0.34	-0.41 – -0.24
	4	87	4	2.15	2.11	5.15	0.98		-0.01	-0.44 – 0.58

Table S4-15 Mann–Whitney U test results from comparing ARIA+ remoteness values by State for citizen science (CS) and scientific observations (SO) between COVID-affected 2020 and prior years (2018 – 2019) with r (rank biserial) for effect size.

State	Data source	Level	N (2018 - 19)	N (2020)	Median 2018-19	Median 2020	U Statistic	p-val	sig	r (rank biserial)	95 % conf. levels
NSW	CS	0	1460	675	1.88	2.24	13	< 0.001	***	-0.11	-0.17 – -0.06
		1	32	12	2.61	3.65	4.87	0.1		-0.32	-0.69 – -0.03
		2	79	35	1.99	2.01	7.34	0.35		0.11	-0.12 – 0.34
		3	102	58	1.71	2.04	7.76	0.03	**	-0.21	-0.38 – -0.02
	SO	0	904	317	4.82	4.24	11.9	0.52		0.02	-0.05 – 0.08
		1	71	31	6.10	3.78	7.08	0.51		0.08	-0.13 – 0.26
		2	123	87	2.97	4.73	8.3	< 0.001	***	-0.25	-0.38 – -0.06
		3	200	145	2.88	4.08	9.25	< 0.001	***	-0.28	-0.39 – -0.18
SA	CS	0	973	354	4.31	5.16	12.05	0.89		-0	-0.06 – 0.07
		1	127	79	2.57	2.26	8.49	0.73		-0.03	-0.2 – 0.13
		2	241	90	2.30	1.15	9.42	0.05	*	0.14	0 – 0.25
		4	12	4	0.70	7.17	1.61	0.02	**	-0.79	-1 – -0.4
	SO	0	266	89	9.51	7.17	9.78	< 0.001	***	0.49	0.37 – 0.58
		1	66	61	9.78	7.17	8.12	< 0.001	***	0.67	0.47 – 0.82
		2	76	33	8.42	7.17	7.27	0.23		0.14	-0.09 – 0.34
Vic	CS	0	542	290	1.10	1.04	11.23	0.32		-0.04	-0.12 – 0.03
		1	521	205	1.15	1.00	10.91	0.57		0.03	-0.05 – 0.12
		2	459	140	1.15	0.73	10.47	0.08		0.1	0.01 – 0.2
		3	611	260	1.27	1.04	11.31	0.48		0.03	-0.05 – 0.11
		4	192	96	1.75	1.02	9.23	0.13		0.11	-0.03 – 0.25
	SO	0	93	37	1.08	1.19	7.45	0.98		0	-0.22 – 0.24
		1	150	13	1.06	0.00	7.2	0.02	**	0.37	0.11 – 0.65
		2	215	19	1.19	0.00	7.89	0.03	**	0.3	-0.02 – 0.59
		3	283	6	2.78	0.81	7.05	0.13		0.36	-0.12 – 0.71
		4	85	4	1.90	2.11	5.1	0.92		-0.03	-0.48 – 0.46

Table S4-16 ARIA+ (2016) summary statistics by year, data source and State.

Year	Source	State	Level	mean	med	sd	max	IQR	n
2018	CS	New South Wales	0	1.9	1.81	1.45	9.5	1.92	899
		South Australia	0	4.69	6.8	3.55	15	6.28	838
		Victoria	0	1.34	1.14	1.21	7.27	1.85	1266
	State-CS	New South Wales	0	0.93	0.61	1.03	6.1	1.22	684
		Victoria	0	1.03	0.86	1.1	5.66	1.23	115
	SO	New South Wales	0	3.13	2.92	2.13	13.49	2.89	520
		South Australia	0	7.86	9.78	4.1	12.98	4.11	117
		Victoria	0	1.71	1.13	1.72	6.85	2.21	411
2019	CS	New South Wales	0	2.3	2.12	1.76	13.04	2.02	774
		South Australia	0	2.91	1.05	3.27	15	4.9	515
		Victoria	0	1.38	1.31	1.14	5.93	1.84	1059
	State-CS	New South Wales	0	0.95	0.64	0.95	5.96	1.03	265
		Victoria	0	1.07	0.74	1.1	4.78	1.28	73
	SO	New South Wales	0	4.7	6.4	2.52	11.82	4.07	778
		South Australia	0	7.98	9.35	3.55	14.63	1.83	293
		Victoria	0	2.05	1.35	1.83	6.81	2.24	415
2020	CS	New South Wales	0	2.35	2.26	1.74	8.92	2.25	654
			1	3.11	3.65	0.92	3.67	0.91	12
			2	2.28	1.84	2.34	13.09	2.09	56
			3	2.56	2.04	2.1	8.51	1.51	58
		South Australia	0	4.18	5.16	3.54	13.2	6.86	354
			1	3.79	2.26	3.23	7.17	6.61	79
			2	2.99	1.15	2.95	8.58	6.78	90
			4	6.75	7.17	1.68	8.31	0.99	4
		Victoria	0	1.29	1.03	1.12	7.21	1.56	282
			1	1.32	1	1.31	5.66	1.78	198
			2	1.13	0.78	1.11	5	1.72	155
			3	1.41	1.04	1.31	5.75	1.87	260
			4	1.54	1.02	1.44	5.98	2.21	96
	State-CS	Victoria	0	0.06	0.06	0.08	0.11	0.06	2
	SO	New South Wales	0	4.31	4.22	2.31	13.92	3.93	315
			1	4.28	3.78	2.13	6.64	3.81	31
			2	4.45	4.79	2.33	13.31	3.85	89
			3	3.99	4.08	1.82	6.63	3.06	145
		South Australia	0	6.34	7.17	2.59	11.44	0	89
			1	6.83	7.17	1.18	7.17	0	61
			2	7.17	7.17	2.63	12.72	0	33
		Victoria	0	1.25	1.19	1.09	3.65	2.09	37
			1	0.56	0	1.27	4.34	0	13
			2	1.63	0	2.71	6.69	1.1	19
			3	1.43	0.81	2.12	5.6	1.19	6
			4	1.95	2.11	1.29	3.05	2.03	4

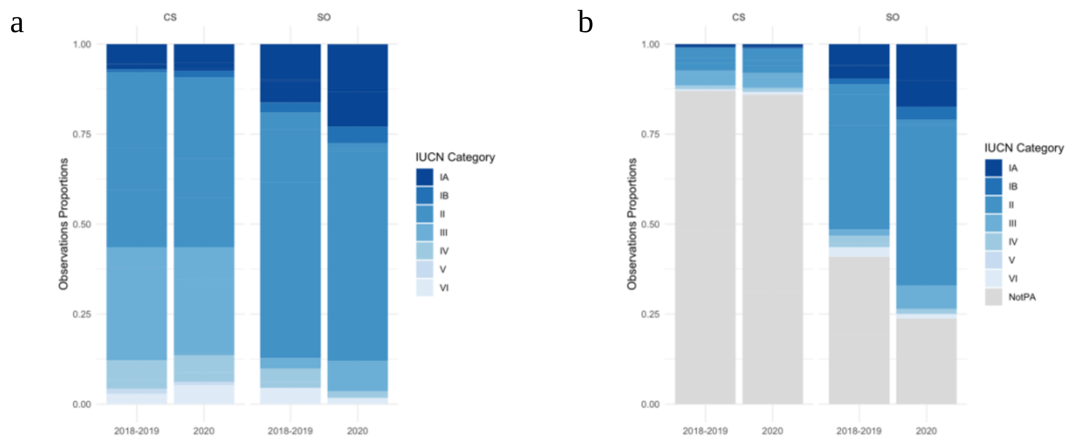

Figure S4-1 Protected areas distribution by IUCN category showing differences between 2020 and prior years, separated by data source. a. excluding non-protected areas and b. including non-protected areas.

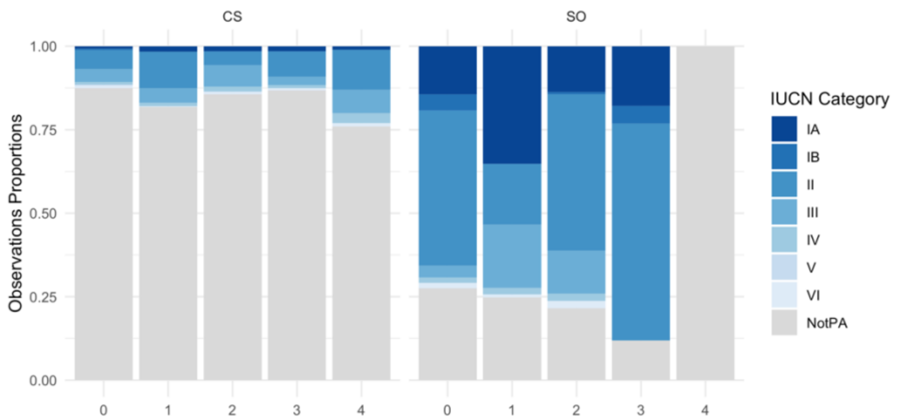

Figure S4-2 Protected areas observation counts distributions over COVID restriction level, compared by data source and IUCN PA category, including non-protected areas, for 2020 only.

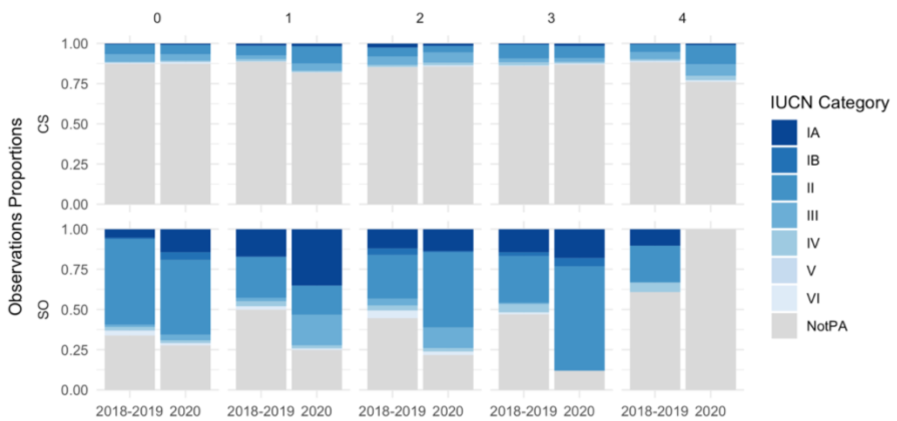

Figure S4-3 Comparing the distribution of observations between 2020 and 2018-2019 in protected and non-protected areas by IUCN category for each COVID-19 restriction level. Citizen Science (CS) observations are in the top row and scientific observations (SO) are in the bottom row.

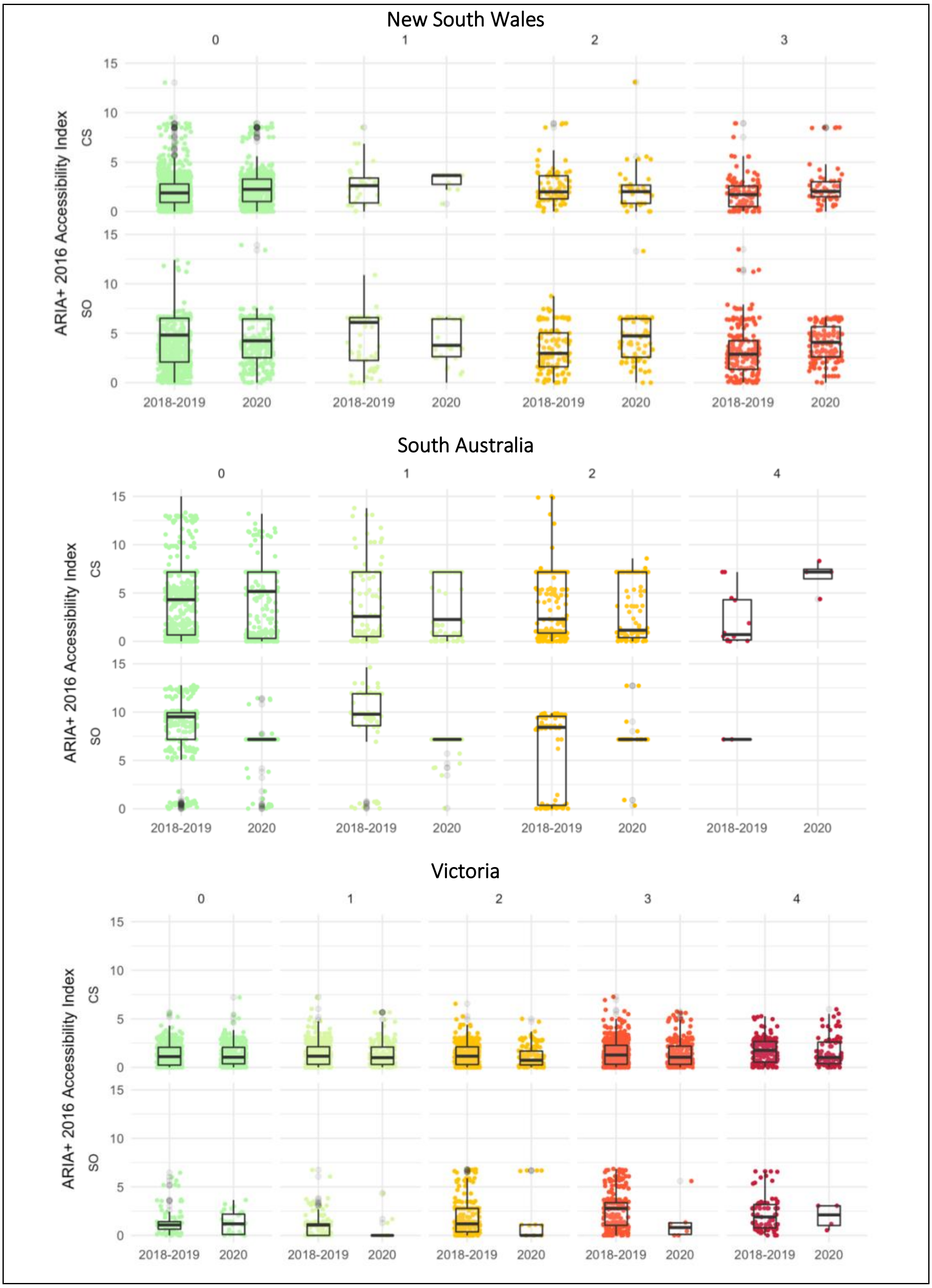

Figure S4-4 Comparison of geographic distribution of observations (using the ARIA+ 2016 Accessibility Index) between 2020 and 2018-2019 for each restriction level, broken down by State and data source. Boxplots show median and distribution of ARIA+ values plotted over observation points coloured by restriction levels (as in Figure 4-2).

Chapter 5. Discussion and Conclusions

Currently little is known about most of the world's biodiversity, yet this knowledge is key to understanding our environment and how it is changing over time (Wilson, 2000). Monitoring provides the data that allows us to gain this understanding by sampling the environment and recording physical and biological phenomena of interest, repeating this sampling at intervals in order to detect changes and patterns (Lindenmayer & Likens, 2010). There are many challenges to performing this effectively (Lindenmayer et al., 2012). Monitoring using traditional field methods is often resource-intensive and limited in geographic and temporal extent and frequency (Amano et al., 2016; Neate-Clegg et al., 2020; Wal et al., 2015), thus other techniques are being sought to supplement these. Citizen science has been increasingly used to provide wider spatial and temporal scales for wildlife monitoring and has been used throughout the world for birds (Sullivan et al., 2014), mammals (Parsons et al., 2018; Robbins et al., 2020), amphibians (Rowley et al., 2019), insects (Domroese & Johnson, 2017; Palmer et al., 2017; Sumner et al., 2019) and marine life (Edgar et al., 2020; Fulton et al., 2018; Simoniello et al., 2019). However, some reticence about the quality of CS monitoring remains, and there is scope for it to be improved, as it can suffer from errors, biases and other data deficiencies (Boakes et al., 2016; Isaac & Pocock, 2015).

The main aim of this thesis was to investigate and develop methods to enhance data collected by citizen scientists to improve wildlife monitoring. I developed two new mobile phone software apps with enhanced functions that were used in two case studies to record observations of iconic Australian mammal species. I examined how these data compare to that from traditional wildlife monitoring stored in national and regional biodiversity repositories and how aspects of biases from CS and traditional monitoring compared, under both common and exceptional conditions.

By automatically recording methodological and observational metadata, a better understanding of observer effort and observational precision can be obtained. Explicit and accurate observer effort can enhance species modelling, while recording metadata about observations allows for better evaluation of data quality when selecting records for proposed future uses. Improving our understanding of data biases and deficiencies in both CS and conventional monitoring can assist researchers in deciding which monitoring methods are suitable for their research and how these methods may be used to complement each other, where appropriate.

5.1. KEY FINDINGS AND OUTCOMES

I investigated and demonstrated methods of improving data from CS monitoring through the automatic recording of methodological and observational metadata including species observation location and time, observer search effort and path, and observation location accuracy (Stenhouse et al., 2020). A custom mobile app was developed and tested in a case study recording CS observations of koala in South Australia. This was the first time that this set of metadata had been recorded for an Australian CS project and this study provided a number of important insights. It showed that accurate data on observer search effort and search path could be recorded easily and transparently. This is key data for species distribution and abundance modelling as it enables improved inference of species absence by recording the distribution and duration of searches more accurately. Additionally, recording search path may improve management of CS monitoring by enabling the assessment of sampling bias and monitoring coverage. Recording search path provides evidence of where searches have occurred, even when no observations are recorded. Recording a measure of observation location accuracy also proved valuable by enabling better assessment of data quality, which is beneficial when determining fitness-for-use in future analyses.

Other CS projects have attempted to improve data quality by determining observer skill, species detectability and species' absence in different ways. A common approach for multi-species surveys is to check that a set of observations contains all species detected, so that absences can be inferred from a list of potential species possible in the same area (Sullivan et al., 2014; Szabo et al., 2010). It is also common, in addition, to specify a survey protocol, such as a specific area search, to assist with later definition of total search area (Birdlife Australia, 2021; British Trust for Ornithology, 2010). Adding the explicit and automatic recording of search path to this metadata can further improve data quality even for unskilled observers, as well as other uses as described above. The eBird mobile app has added this feature after the study in chapter two took place (Cornell Lab of Ornithology, 2017), confirming the value of this approach.

I provided insights and recommendations for others who are considering developing custom software for CS biodiversity monitoring. Limitations of the koala app were discussed with suggestions for possible solutions. Improved location recording would be possible using built-in checks, improved user guidance, and a small change to the process workflow which would be transparent to the participant. Enhanced user feedback which may reduce potential errors and improve participant motivation was also recommended.

I developed a new, purpose-designed CS mobile app for recording accurate observational data on short-beaked echidna, including guidance for the collection of physical samples (Stenhouse, Perry, Grützner, Lewis, et al., 2021). Continued and ongoing use over four years from 2017 through 2021 has resulted in over ten thousand echidna sightings being submitted by more than three thousand participants. This approximately doubled the observations recorded over the same period in the Atlas of Living Australia, thus greatly increasing the spatial and temporal intensity of sighting records.

Differences in spatial coverage were shown between these CS observations and those in existing data repositories in the Atlas of Living Australia and Australian state biodiversity databases, especially in relation to observations in protected areas and to an index of remoteness and accessibility. Coverage of CS records was more limited in some categories of protected areas than the other data sources. However, numbers of observations in all remote areas were greater than the reference scientific data, except for very remote regions. This provided insight into the spatial biases in these observation datasets and shows that CS provides good coverage in most areas. This is important information for Australian conservation management as previous studies demonstrate spatial biases according to human population density (Piccolo et al., 2020), but have not examined CS and traditional monitoring biases at continental scale in relation to categories of protected areas and non-protected areas, nor in relation to accessibility and remoteness. Comparing CS to traditional monitoring biases should assist conservation planning by demonstrating where each type of monitoring is most prevalent, thereby making more explicit where gaps in coverage occur. This information will allow more effective prioritisation of future CS and traditional surveying effort.

Although not included in this thesis, guidance provided by the mobile app around the collection and submission of scat samples resulted in citizen scientists contributing physical samples from across Australia. One hundred and fifty nine of these scats, with metadata submitted using the echidnaCSI app, were combined with samples from captive programs to discover new insights about the diet and gut microbiome of this species using a number of genetic analysis techniques (Perry, West, et al., 2022).

This thesis provided important information for conservation researchers and practitioners by demonstrating the resilience of CS monitoring to restrictions on community activities and movement caused by the COVID-19 pandemic (Stenhouse, Perry, Grützner, Rismiller, et al., 2022). There were fewer impacts on CS wildlife observations compared to scientific observations. CS observation counts remained robust, even under strict restriction levels, while observations from traditional monitoring in state biodiversity repositories (SO) were significantly reduced. In protected and non-protected areas, CS observations were not impacted by restrictions but SO were significantly affected, especially under severe restrictions. SO were concentrated even more than usual in PA, and were severely reduced in non-PA. There were significant impacts on the geographic distribution of SO but with great variation between states. The geographic remoteness of CS observations did not change significantly even under severe restrictions as occurred in the state of Victoria. These findings contrast with some international studies where CS observations were significantly reduced by pandemic-related restrictions on community activity and geographical distribution changed. This is important information for other researchers, and leads to greater confidence that CS monitoring in Australia may reduce data continuity problems, even during periods of societal disruption which can disturb other approaches.

5.2. SIGNIFICANCE OF THIS RESEARCH

Findings from this thesis demonstrate a number of ways to improve CS wildlife monitoring, how some biases compare between CS and traditional monitoring and, lastly, how CS monitoring is more robust to some disruptions than traditional monitoring methods.

Automatically recording CS search effort and search path in a CS program was a novel method and demonstrated the value of transparently recording metadata. Accurate observer effort is important for improved species population abundance and distribution modelling and recording observer search effort accurately was shown to be feasible and useful. Recording search paths offers a valuable method of recording spatial and temporal components of search effort, improving on simple records of species observations and time taken, especially when no observations are made. These metadata also increase the contextualisation of the observations (Brenton et al., 2018) and thus increase their value by allowing more informed evaluation of suitability for future analyses.

CS search paths provide key data for new methods of managing CS monitoring by clearly indicating what locations have not yet been searched as well as which locations have been searched, both with and without observations being recorded. This would allow both guided and self-directed monitoring improvements. Guided improvements are those provided by managers of CS monitoring efforts who may direct CS participants to areas where monitoring is desired, such as to repeat surveys in a previously surveyed area or to areas not yet surveyed. Self-directed monitoring improvements may occur when CS participants can select survey areas themselves using the extra information provided by prior CS search paths and times. Both successful and unsuccessful (i.e. those where no observations were recorded) searches provide important information to support these improvements. Additionally, fast access to this data is also required, highlighting the value of digital collection and direct uploading to a biodiversity repository.

The development and use of an easy-to-use mobile app available on both major mobile platforms, integrated with the national biodiversity repository and combined with continued engagement through a variety of means, ensured elevated awareness and wide participation (Perry, Stenhouse, et al., 2022). This enabled the collection of numerous and widespread CS observations of an iconic Australian monotreme, the short-beaked echidna (Stenhouse, Perry, Grützner, Lewis, et al., 2021) and greatly increased the spatial and temporal intensity of observations for this species. When combined with existing observations in national and state biodiversity repositories, these provide an important baseline for future population abundance, distribution and trends analyses, with higher accuracy than previously available. As the current short-beaked echidna population estimate is very broad at between 5 – 50 million (Aplin et al., 2015), these data will provide important input into future assessments, at both national and regional levels. This data may also be useful for more precise estimates and understanding of environmental preferences, especially when combined with other information such as increased knowledge of diet variability (Perry, West, et al., In press). The geographic similarities and differences of these CS contributions to scientific monitoring was demonstrated. This is of value for conservation management by indicating areas where scientific monitoring could be best utilised, for example in less accessible regions and highly protected areas, and where CS monitoring is providing sufficient coverage. Broader coverage may also allow particular areas of interest to be identified. For example, if unusual patterns are evident then more structured, traditional monitoring could be used to better understand the underlying drivers. CS monitoring gaps could also potentially be filled by CS using other motivational techniques, such as gamification, by informing participants where gaps exist or by targeting participant recruitment in less-covered regions.

This thesis also demonstrated that CS can continue to provide accurate and widespread contributions to biodiversity monitoring despite major community disruptions, even as traditional monitoring methods are being curtailed. This is valuable knowledge for conservation management and planning, as continuity of monitoring is essential to avoid data gaps which may limit future data analyses and thus highlights another valuable contribution from CS. Also significant was how varying regional community movement restrictions changed where traditional monitoring occurred, which is essential information for future analyses. These results contrasted to similar international studies which showed both dramatic reductions in observation numbers (Kishimoto & Kobori, 2021; Rose et al., 2020) and significant changes to geographic distributions (Basile et al., 2021; Crimmins et al., 2021). This highlights the regional differences in response to the pandemic and is critical to understand as communities respond to continued disruptions from the pandemic and increasing disturbances due to climate change, biodiversity loss and other major challenges.

5.3. FUTURE RESEARCH AND RECOMMENDATIONS

The following are areas of future research and recommendations for future development that emerge from the work presented in this thesis.

Further enhancements to mobile apps have been identified that could improve CS monitoring. These include: 1. enhancing integration with backend biodiversity repositories to improve participant motivation; 2. improving in-app checks to ensure participants are following required protocols, even when requirements are few, e.g. ensuring location tracking is activated on the device if this is required would reduce data losses through lack of understanding of requirements; 3. increasing automatically recorded metadata using other sensors available on mobile phones. For example, recording the compass heading at the time of taking an observation photo might better flag possible duplicate sightings during bioblitz-style events. This data could be used in phenological studies by using novel software to guide participants to both the correct location for making an observation as well as ensuring the correct orientation of the device when recording a new observation. Combining this with scheduled and automated reminders would allow more structured phenological monitoring to take place by providing technological support for repeated monitoring at fixed locations.

There is further potential for new tools to provide more rigour to the essentially unstructured and opportunistic methods that are often used to record species observations. Software tools to both define and follow guided monitoring paths at specified schedules would support more systematic CS monitoring. These require further investigation and trialling to gain more understanding on how participants and practitioners use them and to assess the results. Structured and semi-structured transects for CS have also recently been proposed by others (Callaghan et al., 2019; Kelling et al., 2019; McDonough MacKenzie et al., 2019) with the objective of providing extra assistance and scientific structure to previously unstructured CS monitoring, thereby improving the usability of these data for scientific purposes.

The lack of CS and traditional monitoring coverage in less accessible, remote and very remote areas of Australia remains problematic as these cover large portions of Australia. Finding effective means of monitoring these areas needs further investigation. Widening participation to include a variety of groups, especially local residents, would seem a priority, and this surely points to increased involvement of indigenous stakeholders. As discussed in Chapter three, scientific monitoring efforts could also usefully be concentrated in these remote regions, as well as in highly protected areas.

I recommend the development of software to build customised front-ends for apps and website portals which interact directly with national and international biodiversity repositories, such as the ALA or iNaturalist. Customisation and improved interfaces to allow selection of survey types, selection of order and presentation style of data collection items and languages used, custom branding and identity – all these may strengthen user motivation and retention through better localisation. This would allow community groups to more easily satisfy their local requirements and increase participation through local branding, while leveraging national and international infrastructure such as the ALA or iNaturalist which already provide a large range of useful features such as automatic data quality checks and data sharing facilities.

5.4. CONCLUSIONS

This thesis shows improvements to data collected in CS wildlife monitoring made possible by more effective application of mobile technology and purpose designed, easy-to-use software. Accurate and transparent recording of data and metadata combined with fast uploading to the national repository, where it is immediately available for curation and use, maximises the value of CS contributions to biodiversity conservation. These data, combined with novel and accurate metadata such as observer effort and search paths, provide new insights and potentially new tools by allowing more efficient directed and/or self-guided monitoring, through showing where has already been searched. In addition, these provide more comprehensive and representative data for better analyses for species monitoring and assessment.

Widespread participation has provided significantly improved monitoring coverage of an iconic and cryptic species in many regions of Australia and demonstrates the complementary nature of CS to other more traditional sources of monitoring data. CS continued to provide consistent monitoring data despite the varied restrictions due to COVID-19 and shows that CS can be resilient in disrupted times, which will become even more important as climate change and other anthropogenic disturbances increase their effects on our natural environments.

5.5. REFERENCES

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