Using drones to improve wildlife monitoring in a changing climate

Jarrod C. Hodgson

A thesis submitted in fulfilment
of the requirements for the degree of
Doctor of Philosophy

at The University of Adelaide, Australia
within the School of Biological Sciences

December 2020

Table of contents

List of figures

List of tables and code

Publications arising from this thesis[1]

Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology*, 26, R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution*, 9, 1160-1167. https://doi.org/10.1111/2041-210x.12974

Hodgson, J.C., Holman, D., Terauds, A., Koh, L.P. & Goldsworthy, S.D. (2020) Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics. *Biological Conservation*, 242, 108402. https://doi.org/10.1016/j.biocon.2019.108402

---

[1] Published manuscripts as of December 2020.

Summary

This thesis advances knowledge of wildlife monitoring techniques and demonstrates the potential of high-resolution, remotely sensed data to inform species conservation, improve ecosystem management and assess mitigation strategies for biodiversity loss. Drones can easily collect systematic, high spatial and temporal resolution data to detect fluctuations in key parameters such as abundance, range and condition of some species. Advances in drone-facilitated wildlife monitoring of sentinel species will provide rapid, efficient insights into ecosystem-level changes. This thesis focused on resolving knowledge gaps within three key areas of wildlife drone-ecology: disturbance, population monitoring and body condition.

From the outset, we recognised drones might have undesirable or unforeseen behavioural and physiological effects on wildlife. To address this, I led a time-critical publication that advocated researchers adopt a precautionary approach given the limited understanding of the impacts. It also provided recommendations for conducting drone-facilitated research around wildlife as the basis for a code of best practice.

Then, using colonial birds as a study group, we tested the utility of drone-derived data for population monitoring. First, life-sized, replica seabird colonies containing a known number of fake birds were used to robustly assess the accuracy of our intended approach compared to the traditional ground-based counting method. Drone-derived abundance data were, on average, between 43% and 96% more accurate, as well as more precise, than estimates from the traditional approach. Our open-source, semi-automated detection algorithm estimated abundance 94% similar to manual counts from the remotely sensed imagery. To apply this in the field, we collected drone-derived abundance data by repeatedly surveying representative, wild colonial birds (a tern, cormorant and pelican species). We used these data to develop a transferable technique requiring minimal user-input for adaptable and high spatiotemporal population monitoring.

Finally, to investigate the use of drone-facilitated photogrammetry, we used a representative pinniped species to test if non-invasively acquired, morphometric data could infer body condition. Drone-derived measurements of endangered Australian sea lions (*Neophoca cinerea*) of known size and mass were precise and without bias. These two- and three-dimensional measurements from orthomosaics and digital elevation models were highly correlated with animal mass and body condition indices and not significantly different to those generated from ground-collected data.

This work addresses and informs a range of issues arising from human activity in the Anthropocene, including rapid habitat loss, species extinctions and an altered climate. We have shown that using technology for wildlife monitoring enables timely, proactive environmental and conservation management.

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.

I acknowledge that copyright of published works contained within this thesis resides with the copyright holder(s) of those works.

I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

Jarrod Hodgson
December 2020

Acknowledgements

Firstly, I would like to thank my supervisors: Lian Pin Koh, Aleks Terauds and Simon Goldsworthy. I met each of you through our shared passions for discovery and ecology: learning to fly a drone just before heading off for remote fieldwork, chatting on a heli-deck in the sub-Antarctic and after answering a last minute call for a compatible drone controller! I am grateful for the freedom you have each given me, as well as the helpful guidance along the way. You have been sage mentors and friends. Lian Pin – thank you for your ongoing support and understanding. You have always generously offered me opportunities and guided me to becoming a better scientist. Aleks – despite us not being able to access the remote sites envisaged for much of this thesis, you have continually supported me and my research. Thanks for always being there. Simon – thank you for your generosity and care. Our days and nights in the field will always be memorable; may they continue.

I would like to thank my co-authors who contributed to, and improved, the science within this thesis. I especially acknowledge Rowan Mott and Shane Baylis – you both helped make the #EpicDuckChallenge the fun and valuable science it was. Similarly, this project benefited from the many volunteers who gave their time.

I acknowledge the Unmanned Research Aircraft Facility (URAF) at The University of Adelaide. The URAF has provided me the opportunity to easily and compliantly take to the skies, access equipment and incubate ideas. In particular, thank you to Lian Pin Koh, Adam Kilpatrick, Ken Clarke, Ramesh Raja Segaran, Po-yun Wong, Molly Hennekam, Steve Andriolo, Mitch Bannink and Dillon Campbell.

During the years of my PhD in Adelaide, I have been fortunate to work with numerous groups and people. I acknowledge the Department for Environment and Water (DEW) and Primary Industries and Regions South Australia (PIRSA) for their interest in and support of my research. Special thanks to Sandy Carruthers, Simon Bryars, Dan Rogers, Adrienne Rumbelow, Kirsty Wedge, Danny Brock and Alana Binns. I also thank Greg Johnston and Diane Colombelli-Negrel for their support on various bird projects.

To my South Australian pinniped family, thank you. From fieldwork to social events, it was always a pleasure. Special thanks to Simon Goldsworthy, Sarah-Lena Reinhold, Peter Shaughnessy, Dirk Holman, Kristian Peters, Mel Stonnill and Tanya Rosewarne.

Thanks to all the Olifolks (or whatever term the group is using this week!): Tasya, Alan, Sreekar, Bowie, Aakash, Sabine, Kylie, Joshua, Amelie, Hannah, Alicia, Boone, Andrew, Claire, Brooke, Ingrid, Mike, Angus, Molly, Dot, Ken, Ramesh, Bertram and Megan.

The research presented in this dissertation occurred during, and has been part of, the rapid evolution of using drone-acquired data in ecological science. The research has provided some

timely publishable answers, but it has also been a journey of technological failures, encountering systems not ready for change and discoveries best suited to lengthy discussions on remote islands rather than the pages of a journal. For all these experiences, and many more, I am the richer.

Finally, thank you to my friends and family who have supported me throughout my studies and related endeavours, especially Mum, Dad and Brendan.

1 General introduction

1.1 Wildlife monitoring in a changing climate

The intensification of human activities in the Anthropocene has transformed ecosystems and it continues to threaten global biodiversity (Steffen *et al.* 2006; Waters *et al.* 2016). Fauna are under pressure from climate change, habitat loss and degradation, overexploitation and the spread of invasive species (Pereira *et al.* 2010). Current animal extinction rates are estimated at hundreds to thousands of times faster than the rates that prevailed in the last tens of millions of years (Pimm *et al.* 2014; Ceballos *et al.* 2015). This has resulted in a sixth mass species extinction, which is accelerating (Ceballos, Ehrlich & Raven 2020). There is also evidence that beyond global species extinctions, the Earth is experiencing a huge episode of vertebrate population declines and extirpations – a 'biological annihilation' (Ceballos, Ehrlich & Dirzo 2017). These impacts will have negative, cascading consequences on ecosystem functioning, ecosystem services and human wellbeing. Accordingly, there is an urgent need to intensify conservation efforts to reduce the rate of biodiversity loss (Tilman *et al.* 2017).

Ecological data are vital for understanding ecosystem responses to a changing climate, and ultimately, conserving biodiversity. Data are used to assess risks, identify change and predict future scenarios. Data also provide feedback on the effectiveness of management actions. Historical species presence data have been used to quantify extinction rates and to model this risk into the future. These estimates focus on the irreversible impacts of biodiversity change and, while important, they fail to capture changes on finer scales (e.g. a significant contraction in a species' range) which are necessary to inform management actions (Pereira *et al.* 2010). Of the four broad types of biodiversity scenario metrics (Pereira *et al.* 2010), species abundance change derived analyses are particularly useful. These metrics draw on wildlife population variability using demographic data such as species presence, abundance and distribution (Couvet *et al.* 2011). Over time, these data reveal population trends.

Sentinel species are defined as those that respond to ecosystem variability and/or change in a timely and measurable way (Hazen *et al.* 2019). By definition, these species can indicate an otherwise unobserved change in ecosystem function (Hazen *et al.* 2019). In the marine environment, top predators (including certain species of seabirds and marine mammals) that are conspicuous and integrate information from the bottom to the top of the food web are ideal candidates (Piatt & Sydeman 2007; Hazen *et al.* 2019; Velarde, Anderson & Ezcurra 2019). They offer the ability to collect multiple measurements, sometimes from a single population, that provide information over multiple scales about ecological processes that can be hard to observe directly. For example, demography can be measured using population counts over multiple breeding seasons, diet can be sampled on smaller scales through scat analysis or over broader and longer scales using stable isotope analysis. Changes in these parameters by sentinel species like seabirds and pinnipeds can help to identify thresholds or tipping points when physical processes (e.g. an increase in temperature) translate to broad-scale implications for the ecosystem (Hazen *et al.* 2019). An example of this is Cassin's auklet (*Ptychoramphus aleuticus*) colony abandonment and juvenile California sea lion (*Zalophus californianus*) die-offs in response to the 2013–16 marine heatwave in the Northeast Pacific Ocean which depleted prey for both species (Cavole *et al.* 2016). This demonstrates how monitoring sentinel species of wildlife can provide very efficient insights into complex environmental processes. However, in a time of limited conservation funding (Waldron *et al.* 2013) and pressing time constraints for researchers (Fischer, Ritchie & Hanspach 2012), innovative approaches that improve the quality, speed and cost-effectiveness of data collection for these species are invaluable.

1.2 Technology in wildlife ecology

Technology, the application of scientific knowledge for practical purposes, is increasingly being adopted for wildlife monitoring. Emerging tools and techniques can facilitate improved data collection, as well as obtain novel data, while minimising ecosystem disruption (Moll *et al.* 2007; Hebblewhite & Haydon 2010; Pimm *et al.* 2015). For example, animal-borne telemetry devices have revolutionised our understanding of animal movements, including their interactions with the environment and species distribution (Hussey *et al.* 2015; Kays *et al.* 2015). Camera traps and acoustic recorders have become established tools for determining whether a species is present at a site and estimating population density (Rowcliffe & Carbone 2008; Marques *et al.* 2013; Rowcliffe *et al.* 2016; Pfeffer *et al.* 2018). Remote sensing has provided researchers with spatiotemporal datasets that have been used to discover mega-colonies of seabirds in remote and hard to access locations (Borowicz *et al.* 2018). Similarly, artificial intelligence is assisting the automation of data extraction from an increasing number of data-rich collection techniques, including drone imagery and soundscapes (Lamba *et al.* 2019). These examples demonstrate the utility of harnessing technology for wildlife monitoring, yet there may be limitations that need addressing for these techniques to be applied more broadly.

Despite advances in conservation technology, conventional field techniques are commonplace in ecology. A meta-analysis using 348 papers randomly selected from publications across the top 30 ecology-themed journals between 2004 and 2014 found that 80% of sampled observations were collected using conventional field methods, with just

6.9% utilising remote sensing (Estes *et al.* 2018). Furthermore, observational durations and resolutions within that period were largely unchanged compared to those in studies from preceding years, although intervals had become finer and extents larger (Estes *et al.* 2018). While the perceived slow uptake of technology may be influenced by publishing timeframes, the results suggest that modern ecology's observational domains are fairly narrow and methods are not keeping pace with new sampling techniques. The need for greater utilisation of technology is recognised in the literature. A recent call advocated for international leadership and coordination to realise the potential of conservation technology (Lahoz-Monfort *et al.* 2019). Others have advocated a "lean start-up" based approach to bring conservation into the innovation era (Iacona *et al.* 2019), as well as fostering interdisciplinary collaborations to assist uptake of 'technoecology' (Allan *et al.* 2018). Even though publications since 2014 reporting the use of technology for wildlife monitoring are plentiful, it is apparent that more needs to be done to realise the effective integration of technologies for scalable ecology and conservation (Marvin *et al.* 2016) – especially those technologies that demonstrate considerable promise.

1.3 Advancing ecological understanding with remote sensing

Earth observation data, perhaps more than ever before, can play a critical role in supporting conservation science and environmental management (Buchanan *et al.* 2009). Satellite remote sensing is a common source of such data, offering repeatable, standardised and verifiable information on long-term trends of biodiversity indicators (Pettorelli *et al.* 2014; Turner 2014). Recently, a group of leading remote sensing scientists identified ten questions in conservation that they considered analyses of Earth observation data could help to resolve (Rose *et al.* 2015). Not surprisingly, two questions specifically involved the use of these data to increase understanding of species distributions and abundances, as well as species movements and life stages. It was considered that remote sensing data on extrinsic environmental drivers (e.g. land cover, elevation and bathymetry) could be integrated with analyses of intrinsic biological factors and historical and current species distributions and abundances (Rose *et al.* 2015). While extremely valuable, this indicates that data at global extents (even very high-resolution satellite data) is not currently of sufficient resolution to quantify wildlife distributions and abundances directly (Turner 2014).

The desire for spatial data at very high resolution led ecologists to use drones. Formative studies at the turn of the twenty-first century documented the potential of small remote controlled aircraft for ecological research of wildlife (Thome & Thome 2000). Building on the lessons learnt from monitoring wildlife from traditional aircraft, these studies targeted species that could be seen from above, such as many species of waterbirds and seabirds. In 2002 and 2003, Jones, Pearlstine and Percival (2006) built a custom fixed-wing drone equipped with autonomous control and video equipment to test the potential usefulness of such an aircraft for wildlife research applications in Florida, USA. They were particularly interested in assessing populations of midsize vertebrates and their habitats. After conducting more than 30 flights, Jones, Pearlstine and Percival (2006) concluded that “although new technical and operational challenges were discovered in our prototype UAV system for wildlife research, we still are confident in the utility of this tool…We encourage further experimentation with airframe and electronic design, types of sensors, and practical field applications”. Although the authors conceded they were unable to collect georeferenced imagery and that their aircraft was difficult to deploy in complex areas (e.g. heavily vegetated), theirs was a seminal study. It paved the way for the use of drones in ecological and conservation science in years to come (Watts *et al.* 2010; Anderson & Gaston 2013; Marris 2013; Chabot & Bird 2015; Linchant *et al.* 2015). Compared to traditional remote sensing, researchers had realised that drones offered the potential for scale-appropriate measurement of ecological phenomena, delivering fine spatial resolution at user-controlled revisit periods.

1.4 Using drones to quantify key wildlife parameters

As aircraft and sensor technology became more affordable and more reliable, ecologists increasingly recognised the utility of drone-facilitated wildlife population monitoring across various taxonomic groups and ecosystems. For example, Koh and Wich (2012) demonstrated the use of a prototype drone, dubbed a ‘Conservation Drone’, for surveying and mapping tropical forests. The inexpensive prototype was capable of flying pre-programmed missions autonomously using open-source software. Importantly, this work highlighted the potential for drones to directly survey for the presence of large arboreal mammals such as the Sumatran orang-utan (*Pongo abelii*), and indirectly by detecting their nests (constructed of decaying vegetation). Since this discovery other studies have compared drone-facilitated nest surveys to traditional ground-based nest surveys of orang-utans (Wich *et al.* 2016), as well as for other ape species (van Andel *et al.* 2015; Bonnin *et al.* 2018). However, given the difficulty of detecting nests from above using cameras operating at visible wavelengths, especially in complex forest structures, more recent efforts have focused on the use of thermal-infrared imagery to directly detect primates (Longmore *et al.* 2017; Kays *et al.* 2018; Spaan *et al.* 2019) and other arboreal mammal species (Corcoran *et al.* 2019; Hamilton *et al.* 2020).

Other large taxa have been the subject of novel drone-facilitated research and monitoring. For instance, imagery collected using drones has been used to study rhinoceros species and inform poaching mitigation endeavours (Mulero-Pazmany *et al.* 2014), survey elephants (*Loxodonta africana*) (Vermeulen *et al.* 2013) and hippopotamus (*Hippopotamus amphibius*) (Inman *et al.* 2019), and quantify the social interactions of migrating barren-ground caribou (*Rangifer tarandus groenlandicus*) (Torney *et al.* 2018). Drone imagery has also been used to detect individuals and estimate the nest density of a variety of crocodilian species (Evans *et al.* 2016; Ezat, Fritsch & Downs 2018; Scarpa & Piña 2019) and measure the spectral signature and behaviour of polar bears (*Ursus maritimus*) (Barnas *et al.* 2018; Chabot, Stapleton & Francis 2019). Typically, study species have been those that can be consistently observed from above (i.e. unobstructed), thereby minimising detectability issues. The size of such animals has also meant that image resolution has not normally been a limiting factor for accurate detection and/or observation. However, as many large terrestrial animals have extensive ranges and can occur at very low density, careful consideration needs to be given to the availability of these animals relative to the sampling effort that can be realistically achieved with a given drone setup.

In the marine context, monitoring sentinel species, such as seabirds and pinnipeds, is particularly efficient. As the majority of species in both of the groups aggregate on land or ice to breed within distinct breeding sites, their amenability to drone-facilitated monitoring was quickly realised.

1.4.1 Colonial birds

Birds, particularly colonial species including many seabirds and waterbirds, are highly suited to drone-facilitated monitoring. As these species aggregate to breed, researchers can sample them at their regular or opportunistic breeding sites, benefiting from collecting data when the species are at higher density and during times of reproduction. This increases sampling efficiency and provides the opportunity to collect data on key life stage metrics, including breeding effort and breeding success. Owing to their flight requirements, many colonial birds also tend to breed at sites with no to minimal overhead obstructions that simplifies their detection in aerial imagery. Similarly, non-flying seabirds (e.g. penguins) often utilise breeding sites that have simple, low-lying vegetation communities or that are highly substrate-dominated (e.g. rocky shorelines, ice-dominated ecosystems). Drone-facilitated monitoring of colonial birds can also overcome the need to enter colonies and allow the observation of areas that are hard to access on foot or view from traditional aircraft or using satellite imagery. This presents the opportunity to minimise wildlife disturbance (e.g. investigator disturbance) (Borrelle & Fletcher 2017), mitigate access-related damage to the surrounding environment (e.g. fragile flora) and for an alternative sampling technique that may be suitable for culturally sensitive locations (e.g. sacred sites).

Not surprisingly, since Jones, Pearlstine and Percival (2006) surveyed white ibis (*Eudocimus albus*) and early attempts to automate the detection of birds in drone imagery (Abd-Elrahman, Pearlstine & Percival 2005), a plethora of bird species have been surveyed using an ever evolving drone-facilitated technique. Chabot and Bird (2012) presented initial comparisons of drone-derived photographic counts to visual ground counts of staging Canada geese (*Branta Canadensis*) and snow geese (*Chen caerulescens*). Drone-derived counts varied in precision, likely attributable to the differences in contrast between the different species and substrates, and shortcomings related to the unsophisticated imaging system. Using an improved aircraft and sensor to survey a large common tern (*Sterna hirundo*) colony, Chabot, Craik and Bird

(2015) found a strong correlation between photographic tern counts and ground nest counts. Then, Hodgson *et al.* (2016) demonstrated that drone-derived counts of colony nesting birds are an order of magnitude more precise than traditional ground counts and, importantly, proposed a method for ensuring compatibility with historic datasets. Concurrently, drones were being used to monitor Tristan albatross (*Diomedea dabbenena*) (McClelland *et al.* 2016) through to black-vented shearwater (*Puffinus opisthomelas*) (Albores-Barajas *et al.* 2018), gentoo penguin (*Pygoscelis papua*) (Goebel *et al.* 2015; Ratcliffe *et al.* 2015) and Antarctic shag (*Leucocarbo bransfieldensis*) (Oosthuizen *et al.* 2020). In combination, these studies demonstrated that drone-facilitated monitoring was now not only viable but was also an effective technique across a broad spectrum of species and biomes. Further research was needed to better understand the accuracy of drone-derived data relative to the spatial resolution and how it compares to more traditional monitoring methods (see Aim 2). The data collection, processing, analysis and interpretation workflow also needed to be further refined to ensure it could be reliably and cost-effectively integrated into both existing monitoring regimes and to establish new monitoring programs.

In the previous decade of drone-facilitated bird monitoring, there has been increasing improvement of techniques to extract larger scale, more in-depth ecological insight. As is common across remote sensing, being able to process imagery to produce mosaics that are undistorted, geo-referenced and scaled is ideal. Sarda-Palomera *et al.* (2012) used repeated surveys of black-headed gull (*Chroicocephalus ridibundus*) to demonstrate that basic geo-referencing of drone imagery could provide locational data on individual nests without causing colony disturbance. Sarda-Palomera *et al.* (2017) extended this work using the same manual geo-referencing technique in an attempt to unravel spatial and temporal factors affecting the dynamics of colony formation and nesting success in the species, although these conclusions were met with some objection (Callaghan *et al.* 2018; and responded to by Sardà-Palomera *et al.* 2018). More advanced geo-referencing methods have been used to stitch drone-acquired imagery into seamless geo-referenced images, namely orthomosaics, using a photogrammetry technique called ‘structure from motion’. This process identifies points in overlapping digital photographs to reconstruct the landscape in three dimensions. Orthomosaics have been used to quantify the abundance and distribution, as well as conduct habitat analysis, for a variety of bird species (Chabot, Carignan & Bird 2014; Afán, Máñez & Díaz-Delgado 2018; Albores-Barajas *et al.* 2018; Borowicz *et al.* 2018; Lyons *et al.* 2019). These studies have shown tremendous promise, however, the robustness of the technique for large scale monitoring within and across species, sites and years is limited (see Aim 3).

1.4.2 Marine mammals

Population and habitat use monitoring for large marine mammals, particularly cetaceans, has traditionally been conducted using aerial line-transect surveys. The low density of these animals, coupled with the proportion of time they are detectable from above and their potential to move long distances quickly, creates a suite of considerations necessary for effective sampling (Fewster *et al.* 2008). Transects surveys from conventional aircraft are ideal, as surveys can sample large areas relatively quickly while ensuring that parallel transects are sufficiently spaced to avoid the possibility of double counting. However, like any technique, there are limitations including the need for experienced observers and an inability to review observations, as well as safety risks to personnel involved in light aircraft operations. This had led to consistent interest in the suitability of drone technology for these type of surveys, and related spatially explicit occupancy and distribution modelling (Martin *et al.* 2012). Initial studies investigated the influence of environmental variables such as sea state and turbidity on detection rates, as well as operational parameters such as altitude (Koski *et al.* 2009; Hodgson, Kelly & Peel 2013). The promising results prompted further work, including to quantify the availability of specific species and observer perception biases (Koski *et al.* 2013; Hodgson, Peel & Kelly 2017; Ferguson *et al.* 2018), as well as ship based surveys (Moreland *et al.* 2015). Owing to the sampling effort needed for line transect surveys, these studies relied upon relatively large, long endurance, fixed-wing drones (e.g. Boeing Insitu ScanEagle) that are typically highly priced and their usage is generally subject to more stringent civil aviation regulation (Fiori *et al.* 2017).

Similar to colonial birds, many marine mammal species make use of predictable habitats for social activities such as mating and feeding young, as well as resting. This aggregating behaviour provides an opportunity to collect remotely sensed data when animals are at high density, facilitating the efficient calculation of abundance estimates for sentinel species. This is particularly useful for species that are otherwise largely cryptic and unavailable for ground-based or remotely sensed detection, including many pinnipeds. For example, high-resolution satellite imagery has been shown to provide abundance estimates of southern elephant seals (*Mirounga leonina*) that are comparable to concurrent ground counts (McMahon *et al.* 2014). While satellite imagery is extremely useful, it can lack the spatial resolution needed to monitor most small- to medium-sized pinniped species. It can also be compromised by local climate conditions such as cloud cover. Drone-derived imagery can overcome these limitations, which has resulted in many researchers adopting this technology to monitor pinnipeds in recent years. For example, research on grey seals (*Halichoerus grypus*) has demonstrated that drone-derived abundance estimates are comparable to traditional aircraft surveys (Johnston *et al.* 2017), automating the detection of the species in drone-acquired thermal imagery is possible (Seymour *et al.* 2017) and entangled individuals can be identified at known haul-outs (Martins *et al.* 2019). Similar research has shown the suitability of drones as a research and monitoring platform for a variety of other species including Stellar sea lions (*Eumetopias jubatus*) (Sweeney *et al.* 2016), Antarctic fur seals (*Arctocephalus gazella*) (Goebel *et al.* 2015), Australian fur seals (*A. pusillus doriferus*) (McIntosh, Holmberg & Dann 2018; Allan *et al.* 2019; Sorrell *et al.* 2019), and New Zealand fur seals (*A. forsteri*) (Gooday *et al.* 2018). In combination, these studies demonstrate that drones are a powerful tool for the collection of data to monitor marine mammals.

1.5 Main aims

Drones have become a powerful addition to the ecologist's toolkit. The suitability of drone-derived data for a diverse array of ecological science is well documented by literature reviews (Anderson & Gaston 2013; Chabot & Bird 2015; Linchant *et al.* 2015; Christie *et al.* 2016; Fiori *et al.* 2017; Rees *et al.* 2018; Johnston 2019; Joyce *et al.* 2019). In a relatively short time, the technology has evolved from primitive remote controlled devices using film photography (Thome & Thome 2000) to aircraft with considerable endurance, autonomy and capable of carrying high-quality, miniaturised sensors. The technology has also become more accessible, reliable and affordable, although there remain some challenges influencing their broader implementation (Duffy *et al.* 2018). Drones can provide researchers with a tool to sample at spatial and temporal resolutions that were not easily attained using existing remote sensing methods (e.g. space borne satellites and traditional aircraft). This has provided extensive new research opportunities within the field of wildlife ecology, as well as highlighted opportunities for improvement (Hollings *et al.* 2018) and gaps in our knowledge.

Broadly, this thesis explores the utility of drone-derived data for wildlife monitoring at a variety of scales. Focusing on two groups of sentinel species, colonial birds and pinnipeds, we sought to develop workflows that used drone-acquired imagery for robust abundance surveys as well as more focal studies. The goal was to address gaps in knowledge within this area of important and evolving ecological science, thereby improving on traditional techniques in a time of drastic ecosystem change and species extinctions. To achieve this goal, four main aims have been addressed:

> **Aim 1: recognise potential disturbance issues when using drones around wildlife**
>
> Despite a rapid gain in the momentum of drone-facilitated wildlife monitoring between 2010 and 2015 (Anderson & Gaston 2013; Linchant *et al.* 2015; Christie *et al.* 2016), there were limited quantitative studies investigating the behavioural or physiological responses of wildlife to drone operations. Anecdotal evidence indicated that there would be a high degree of intra- and inter-species variability in responses, and the lag before substantive insight would be disseminated in the scientific literature was a concern. To raise awareness of this potential issue, we provided timely recommendations for conducting scientific research around wildlife using drones. These recommendations adopted a precautionary approach and aimed to provide the basis for best practice guidelines that would evolve as new research was completed.

Aim 2: quantify the accuracy of drone-facilitated wildlife abundance estimates, using manual detections of digital imagery and a semi-automated approach, relative to the traditional approach.

Using colonial birds as a study group, we investigated the accuracy of drone-facilitated monitoring and traditional ground-based monitoring. To do this, we constructed replica colonies of a common seabird, the Greater Crested Tern (*Thalasseus bergii*), so that the true number of individuals was known, unlike in natural colonies. This robust experimental design allowed thorough testing of the two statistical components of accuracy, bias and precision, for each monitoring approach. A semi-automated detection algorithm was also developed, and the results were compared with manual human counts derived from the same imagery.

Aim 3: develop a transferrable workflow for large-scale, drone-facilitated abundance monitoring and spatiotemporal analyses of aggregated wildlife.

Given the demonstrated accuracy of drone-facilitated monitoring, we developed a workflow to collect and process drone-acquired imagery for abundance monitoring at user-specified spatial and temporal resolutions. To ensure the workflow was generalisable across different species and habitats, we applied it to repeated field surveys of three colonial bird species of varying size and nesting across a spectrum of habitat: crested tern (*Thalasseus bergii*), black-faced cormorant (*Phalacrocorax fuscescens*) and Australian pelican (*Pelecanus conspicillatus*). Subsequently, concentrating on a large breeding colony of pelicans in South Australia, we refined the approach so that it could be executed with minimal user-input to answer tailored spatiotemporal questions (e.g. flux in breeding effort).

Aim 4: use drone-derived photogrammetry to estimate non-invasively the body condition of marine mammals.

Using Australian sea lions (*Neophoca cinerea*) as a case study, we measured the size and mass of a subset of post-breeding individuals and compared these to measurements derived from high-resolution aerial photogrammetry. We assessed the variability in drone-derived dimensions and tested for bias in each measuring technique. Then we built and evaluated models to predict animal mass using straight-line distances and area measured from orthomosaics, as well as the 3-dimensional measurement of volume determined from digital elevation models (DEMs). Based on our findings, we contrasted body condition indices developed from each of the datasets (ground, 2D and 3D measurements).

Over the next four chapters, we address these aims using a combination of techniques. Given the pace at which high-resolution remote sensing has and will continue to evolve, this thesis aimed to address pressing questions in this area of rapidly evolving ecological science, while also informing wildlife monitoring beyond the aircraft, sensors and software used. In the final part of this thesis, the findings of each chapter are synthesised and their implications for wildlife monitoring and future research are discussed.

For the benefit of readers of this thesis, it is worth noting:

1. The research chapters have been written concisely as manuscripts for publication and therefore there is some unavoidable repetition, particularly in each introduction. Statements of authorship precede each chapter clarifying the manuscript's publication status at the time of thesis submission.
2. There is inconsistency in the terminology used to refer to drones in the following chapters. 'Drone' is used wherever possible, with exceptions arising in Chapters Two and Three that were published with alternative terms. I have chosen to use drone as it is simple, inclusive (i.e. free of gendered terminology) and now widely used in both the scientific community and general populous (Chapman 2014; Granshaw 2018). Alternative descriptors include unmanned aerial vehicle (UAV), unmanned aerial system (UAS) and remotely piloted aircraft (RPA), although there are regional differences in the popularity of these terms.
3. Science communication accompanied each of the published manuscripts in this thesis, including articles released by Creative Commons licence in *The Conversation*. These articles are available online, and are reproduced as Appendices to this thesis.

1.6 References

Abd-Elrahman, A., Pearlstine, L. & Percival, F. (2005) Development of pattern recognition algorithm for automatic bird detection from unmanned aerial vehicle imagery. *Surveying and land information science: journal of the American Congress on Surveying and Mapping*, pp. 37-46. American Congress on Surveying and Mapping, ACSM.

Afán, I., Máñez, M. & Díaz-Delgado, R. (2018) Drone Monitoring of Breeding Waterbird Populations: The Case of the Glossy Ibis. *Drones,* **2,** 42. https://doi.org/10.3390/drones2040042

Albores-Barajas, Y.V., Soldatini, C., Ramos-Rodriguez, A., Alcala-Santoyo, J.E., Carmona, R. & Dell'Omo, G. (2018) A new use of technology to solve an old problem: Estimating the population size of a burrow nesting seabird. *PloS One,* **13,** e0202094. https://doi.org/10.1371/journal.pone.0202094

Allan, B.M., Ierodiaconou, D., Hoskins, A.J. & Arnould, J.P.Y. (2019) A Rapid UAV Method for Assessing Body Condition in Fur Seals. *Drones,* **3,** 24. https://doi.org/10.3390/drones3010024

Allan, B.M., Nimmo, D.G., Ierodiaconou, D., VanDerWal, J., Koh, L.P. & Ritchie, E.G. (2018) Futurecasting ecological research: the rise of technoecology. *Ecosphere,* **9**. https://doi.org/10.1002/ecs2.2163

Anderson, K. & Gaston, K.J. (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment,* **11,** 138-146. https://doi.org/10.1890/120150

Barnas, A.F., Felege, C.J., Rockwell, R.F. & Ellis-Felege, S.N. (2018) A pilot(less) study on the use of an unmanned aircraft system for studying polar bears (Ursus maritimus). *Polar Biology,* **41,** 1055-1062. https://doi.org/10.1007/s00300-018-2270-0

Bonnin, N., Van Andel, A., Kerby, J., Piel, A., Pintea, L. & Wich, S. (2018) Assessment of Chimpanzee Nest Detectability in Drone-Acquired Images. *Drones,* **2,** 17. https://doi.org/10.3390/drones2020017

Borowicz, A., McDowall, P., Youngflesh, C., Sayre-McCord, T., Clucas, G., Herman, R., Forrest, S., Rider, M., Schwaller, M., Hart, T., Jenouvrier, S., Polito, M.J., Singh, H. & Lynch, H.J. (2018) Multi-modal survey of Adelie penguin mega-colonies reveals the Danger Islands as a seabird hotspot. *Scientific Reports,* **8,** 3926. https://doi.org/10.1038/s41598-018-22313-w

Borrelle, S.B. & Fletcher, A.T. (2017) Will drones reduce investigator disturbance to surface-nesting seabirds? *Marine Ornithology,* **45,** 89-94.

Buchanan, G.M., Nelson, A., Mayaux, P., Hartley, A. & Donald, P.F. (2009) Delivering a global, terrestrial, biodiversity observation system through remote sensing. *Conservation Biology,* **23,** 499-502. https://doi.org/10.1111/j.1523-1739.2008.01083.x

Callaghan, C.T., Brandis, K.J., Lyons, M.B., Ryall, S. & Kingsford, R.T. (2018) A comment on the limitations of uavs in wildlife research - The example of colonial nesting waterbirds. *Journal of Avian Biology*. https://doi.org/10.1111/jav.01825

Cavole, L., Demko, A., Diner, R., Giddings, A., Koester, I., Pagniello, C., Paulsen, M.-L., Ramirez-Valdez, A., Schwenck, S., Yen, N., Zill, M. & Franks, P. (2016) Biological Impacts of the 2013–2015 Warm-Water Anomaly in the Northeast Pacific: Winners, Losers, and the Future. *Oceanography,* **29**. https://doi.org/10.5670/oceanog.2016.32

Ceballos, G., Ehrlich, P.R., Barnosky, A.D., Garcia, A., Pringle, R.M. & Palmer, T.M. (2015) Accelerated modern human-induced species losses: Entering the sixth mass extinction. *Sci Adv,* **1,** e1400253. https://doi.org/10.1126/sciadv.1400253

Ceballos, G., Ehrlich, P.R. & Dirzo, R. (2017) Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *Proceedings of the National Academy of Sciences of the United States of America,* **114,** E6089-E6096. https://doi.org/10.1073/pnas.1704949114

Ceballos, G., Ehrlich, P.R. & Raven, P.H. (2020) Vertebrates on the brink as indicators of biological annihilation and the sixth mass extinction. *Proceedings of the National Academy of Sciences of the United States of America,* **117,** 13596-13602. https://doi.org/10.1073/pnas.1922686117

Chabot, D. & Bird, D.M. (2012) Evaluation of an off-the-shelf Unmanned Aircraft System for Surveying Flocks of Geese. *Waterbirds,* **35,** 170-174. https://doi.org/10.1675/063.035.0119

Chabot, D. & Bird, D.M. (2015) Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in?1. *Journal of Unmanned Vehicle Systems,* **3,** 137-155. https://doi.org/10.1139/juvs-2015-0021

Chabot, D., Carignan, V. & Bird, D.M. (2014) Measuring Habitat Quality for Least Bitterns in a Created Wetland with Use of a Small Unmanned Aircraft. *Wetlands,* **34,** 527-533. https://doi.org/10.1007/s13157-014-0518-1

Chabot, D., Craik, S.R. & Bird, D.M. (2015) Population census of a large common tern colony with a small unmanned aircraft. *PloS One,* **10,** e0122588. https://doi.org/10.1371/journal.pone.0122588

Chabot, D., Stapleton, S. & Francis, C.M. (2019) Measuring the spectral signature of polar bears from a drone to improve their detection from space. *Biological Conservation,* **237,** 125-132. https://doi.org/10.1016/j.biocon.2019.06.022

Chapman, A. (2014) It's okay to call them drones. *Journal of Unmanned Vehicle Systems,* **02,** iii-v. https://doi.org/10.1139/juvs-2014-0009

Christie, K.S., Gilbert, S.L., Brown, C.L., Hatfield, M. & Hanson, L. (2016) Unmanned aircraft systems in wildlife research: current and future applications of a transformative technology. *Frontiers in Ecology and the Environment,* **14,** 241-251. https://doi.org/10.1002/fee.1281

Corcoran, E., Denman, S., Hanger, J., Wilson, B. & Hamilton, G. (2019) Automated detection of koalas using low-level aerial surveillance and machine learning. *Scientific Reports,* **9,** 3208. https://doi.org/10.1038/s41598-019-39917-5

Couvet, D., Devictor, V., Jiguet, F. & Julliard, R. (2011) Scientific contributions of extensive biodiversity monitoring. *C R Biol,* **334,** 370-377. https://doi.org/10.1016/j.crvi.2011.02.007

Duffy, J.P., Cunliffe, A.M., DeBell, L., Sandbrook, C., Wich, S.A., Shutler, J.D., Myers-Smith, I.H., Varela, M.R., Anderson, K., Pettorelli, N. & Horning, N. (2018) Location, location, location: considerations when using lightweight drones in challenging environments. *Remote Sensing in Ecology and Conservation,* **4,** 7-19. https://doi.org/10.1002/rse2.58

Estes, L., Elsen, P.R., Treuer, T., Ahmed, L., Caylor, K., Chang, J., Choi, J.J. & Ellis, E.C. (2018) The spatial and temporal domains of modern ecology. *Nat Ecol Evol,* **2,** 819-826. https://doi.org/10.1038/s41559-018-0524-4

Evans, L.J., Jones, T.H., Pang, K., Saimin, S. & Goossens, B. (2016) Spatial Ecology of Estuarine Crocodile (Crocodylus porosus) Nesting in a Fragmented Landscape. *Sensors,* **16**. https://doi.org/10.3390/s16091527

Ezat, M.A., Fritsch, C.J. & Downs, C.T. (2018) Use of an unmanned aerial vehicle (drone) to survey Nile crocodile populations: A case study at Lake Nyamithi, Ndumo game reserve, South Africa. *Biological Conservation,* **223,** 76-81. https://doi.org/10.1016/j.biocon.2018.04.032

Ferguson, M.C., Angliss, R.P., Kennedy, A., Lynch, B., Willoughby, A., Helker, V., Brower, A.A. & Clarke, J.T. (2018) Performance of manned and unmanned aerial surveys to collect visual data and imagery for estimating arctic cetacean density and associated uncertainty. *Journal of Unmanned Vehicle Systems***,** 1-27. https://doi.org/10.1139/juvs-2018-0002

Fewster, R.M., Southwell, C., Borchers, D.L., Buckland, S.T. & Pople, A.R. (2008) The influence of animal mobility on the assumption of uniform distances in aerial line-transect surveys. *Wildlife Research,* **35,** 275. https://doi.org/10.1071/wr07077

Fiori, L., Doshi, A., Martinez, E., Orams, M.B. & Bollard-Breen, B. (2017) The Use of Unmanned Aerial Systems in Marine Mammal Research. *Remote Sensing,* **9,** 543. https://doi.org/10.3390/rs9060543

Fischer, J., Ritchie, E.G. & Hanspach, J. (2012) Academia's obsession with quantity. *Trends in Ecology & Evolution,* **27,** 473-474. https://doi.org/10.1016/j.tree.2012.05.010

Goebel, M.E., Perryman, W.L., Hinke, J.T., Krause, D.J., Hann, N.A., Gardner, S. & LeRoi, D.J. (2015) A small unmanned aerial system for estimating abundance and size of Antarctic predators. *Polar Biology,* **38,** 619-630. https://doi.org/10.1007/s00300-014-1625-4

Gooday, O.J., Key, N., Goldstien, S. & Zawar-Reza, P. (2018) An assessment of thermal-image acquisition with an unmanned aerial vehicle (UAV) for direct counts of coastal marine mammals ashore. *Journal of Unmanned Vehicle Systems,* **6,** 100-108. https://doi.org/10.1139/juvs-2016-0029

Granshaw, S.I. (2018) RPV, UAV, UAS, RPAS … or just drone? *The Photogrammetric Record,* **33,** 160-170. https://doi.org/10.1111/phor.12244

Hamilton, G., Corcoran, E., Denman, S., Hennekam, M.E. & Koh, L.P. (2020) When you can't see the koalas for the trees: Using drones and machine learning in complex environments. *Biological Conservation,* **247,** 108598. https://doi.org/10.1016/j.biocon.2020.108598

Hazen, E.L., Abrahms, B., Brodie, S., Carroll, G., Jacox, M.G., Savoca, M.S., Scales, K.L., Sydeman, W.J. & Bograd, S.J. (2019) Marine top predators as climate and ecosystem sentinels. *Frontiers in Ecology and the Environment,* **17,** 565-574. https://doi.org/10.1002/fee.2125

Hebblewhite, M. & Haydon, D.T. (2010) Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences,* **365,** 2303-2312. https://doi.org/10.1098/rstb.2010.0087

Hodgson, A., Kelly, N. & Peel, D. (2013) Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PloS One,* **8,** e79556. https://doi.org/10.1371/journal.pone.0079556

Hodgson, A., Peel, D. & Kelly, N. (2017) Unmanned aerial vehicles for surveying marine fauna: assessing detection probability. *Ecological Applications,* **27,** 1253-1267. https://doi.org/10.1002/eap.1519

Hodgson, J.C., Baylis, S.M., Mott, R., Herrod, A. & Clarke, R.H. (2016) Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports,* **6,** 22574. https://doi.org/10.1038/srep22574

Hollings, T., Burgman, M., van Andel, M., Gilbert, M., Robinson, T., Robinson, A. & McPherson, J. (2018) How do you find the green sheep? A critical review of the use of remotely sensed imagery to detect and count animals. *Methods in Ecology and Evolution,* **9,** 881-892. https://doi.org/10.1111/2041-210x.12973

Hussey, N.E., Kessel, S.T., Aarestrup, K., Cooke, S.J., Cowley, P.D., Fisk, A.T., Harcourt, R.G., Holland, K.N., Iverson, S.J., Kocik, J.F., Mills Flemming, J.E. & Whoriskey, F.G. (2015) Aquatic animal telemetry: A panoramic window into the underwater world. *Science*, **348,** 1255642. https://doi.org/10.1126/science.1255642

Iacona, G., Ramachandra, A., McGowan, J., Davies, A., Joppa, L., Koh, L.P., Fegraus, E., Game, E., Guillera-Arroita, G., Harcourt, R., Indraswari, K., Lahoz-Monfort, J.J., Oliver, J.L., Possingham, H.P., Ward, A., Watson, D.W., Watson, J.E.M., Wintle, B.A. & Chadès, I. (2019) Identifying technology solutions to bring conservation into the innovation era. *Frontiers in Ecology and the Environment*. https://doi.org/10.1002/fee.2111

Inman, V.L., Kingsford, R.T., Chase, M.J. & Leggett, K.E.A. (2019) Drone-based effective counting and ageing of hippopotamus (Hippopotamus amphibius) in the Okavango Delta in Botswana. *PloS One*, **14,** e0219652. https://doi.org/10.1371/journal.pone.0219652

Johnston, D.W. (2019) Unoccupied Aircraft Systems in Marine Science and Conservation. *Annual Review of Marine Science*, **11,** 439-463. https://doi.org/10.1146/annurev-marine-010318-095323

Johnston, D.W., Dale, J., Murray, K., Josephson, E., Newton, E. & Wood, S. (2017) Comparing occupied and unoccupied aircraft surveys of wildlife populations: Assessing the gray seal Halichoerus grypus breeding colony on Muskeget Island, USA. *Journal of Unmanned Vehicle Systems*. https://doi.org/10.1139/juvs-2017-0012

Jones, G.P., Pearlstine, L.G. & Percival, H.F. (2006) An assessment of small unmanned aerial vehicles for wildlife research. *Wildlife Society Bulletin*, **34,** 750-758. https://doi.org/10.2193/0091-7648(2006)34[750:aaosua]2.0.co;2

Joyce, K.E., Duce, S., Leahy, S.M., Leon, J. & Maier, S.W. (2019) Principles and practice of acquiring drone-based image data in marine environments. *Marine and Freshwater Research*, **70,** 952-963. https://doi.org/10.1071/mf17380

Kays, R., Crofoot, M.C., Jetz, W. & Wikelski, M. (2015) Terrestrial animal tracking as an eye on life and planet. *Science*, **348,** aaa2478. https://doi.org/10.1126/science.aaa2478

Kays, R., Sheppard, J., McLean, K., Welch, C., Paunescu, C., Wang, V., Kravit, G. & Crofoot, M. (2018) Hot monkey, cold reality: surveying rainforest canopy mammals using drone-mounted thermal infrared sensors. *International Journal of Remote Sensing*, **40,** 407-419. https://doi.org/10.1080/01431161.2018.1523580

Koh, L.P. & Wich, S.A. (2012) Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science*, **5,** 121-132.

Koski, W.R., Allen, T., Ireland, D., Buck, G., Smith, P.R., Macrander, A.M., Halick, M.A., Rushing, C., Sliwa, D.J. & McDonald, T.L. (2009) Evaluation of an Unmanned Airborne System for Monitoring Marine Mammals. *Aquatic Mammals*, **35,** 347-357. https://doi.org/10.1578/am.35.3.2009.347

Koski, W.R., Thomas, T.A., Funk, D.W. & Macrander, A.M. (2013) Marine mammal sightings by analysts of digital imagery versus aerial surveyors: a preliminary comparison. *Journal of Unmanned Vehicle Systems*, **01,** 25-40. https://doi.org/10.1139/juvs-2013-0015

Lahoz-Monfort, J.J., Chadès, I., Davies, A., Fegraus, E., Game, E., Guillera-Arroita, G., Harcourt, R., Indraswari, K., McGowan, J., Oliver, J.L., Refisch, J., Rhodes, J., Roe, P., Rogers, A., Ward, A., Watson, D.M., Watson, J.E.M., Wintle, B.A. & Joppa, L. (2019) A Call for International Leadership and Coordination to Realize the Potential of Conservation Technology. *Bioscience*, **69,** 823-832. https://doi.org/10.1093/biosci/biz090

Lamba, A., Cassey, P., Segaran, R.R. & Koh, L.P. (2019) Deep learning for environmental conservation. *Current Biology*, **29,** R977-R982. https://doi.org/10.1016/j.cub.2019.08.016

Linchant, J., Lisein, J., Semeki, J., Lejeune, P. & Vermeulen, C. (2015) Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review*, **45,** 239-252. https://doi.org/10.1111/mam.12046

Longmore, S.N., Collins, R.P., Pfeifer, S., Fox, S.E., Mulero-Pázmány, M., Bezombes, F., Goodwin, A., De Juan Ovelar, M., Knapen, J.H. & Wich, S.A. (2017) Adapting astronomical source detection software to help detect animals in thermal images obtained by unmanned aerial systems. *International Journal of Remote Sensing***,** 1-16. https://doi.org/10.1080/01431161.2017.1280639

Lyons, M.B., Brandis, K.J., Murray, N.J., Wilshire, J.H., McCann, J.A., Kingsford, R.T. & Callaghan, C.T. (2019) Monitoring large and complex wildlife aggregations with drones. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210x.13194

Marques, T.A., Thomas, L., Martin, S.W., Mellinger, D.K., Ward, J.A., Moretti, D.J., Harris, D. & Tyack, P.L. (2013) Estimating animal population density using passive acoustics. *Biological Reviews of the Cambridge Philosophical Society*, **88,** 287-309. https://doi.org/10.1111/brv.12001

Marris, E. (2013) Fly, and bring me data. *Nature*, **498,** 156-158.

Martin, J., Edwards, H.H., Burgess, M.A., Percival, H.F., Fagan, D.E., Gardner, B.E., Ortega-Ortiz, J.G., Ifju, P.G., Evers, B.S. & Rambo, T.J. (2012) Estimating distribution of hidden objects with drones: from tennis balls to manatees. *PloS One*, **7,** e38882. https://doi.org/10.1371/journal.pone.0038882

Martins, M.C.I., Sette, L., Josephson, E., Bogomolni, A., Rose, K., Sharp, S.M., Niemeyer, M. & Moore, M. (2019) Unoccupied aerial system assessment of entanglement in Northwest Atlantic gray seals (Halichoerus grypus). *Marine Mammal Science*. https://doi.org/10.1111/mms.12590

Marvin, D.C., Koh, L.P., Lynam, A.J., Wich, S., Davies, A.B., Krishnamurthy, R., Stokes, E., Starkey, R. & Asner, G.P. (2016) Integrating technologies for scalable ecology and conservation. *Global Ecology and Conservation*, **7,** 262-275. https://doi.org/10.1016/j.gecco.2016.07.002

McClelland, G.T.W., Bond, A.L., Sardana, A. & Glass, T. (2016) Rapid population estimate of a surface-nesting seabird on a remote island using a low-cost unmanned aerial vehicle. *Marine Ornithology*, **44,** 215-220.

McIntosh, R.R., Holmberg, R. & Dann, P. (2018) Looking Without Landing—Using Remote Piloted Aircraft to Monitor Fur Seal Populations Without Disturbance. *Frontiers in Marine Science*, **5**. https://doi.org/10.3389/fmars.2018.00202

McMahon, C.R., Howe, H., van den Hoff, J., Alderman, R., Brolsma, H. & Hindell, M.A. (2014) Satellites, the all-seeing eyes in the sky: counting elephant seals from space. *PloS One*, **9,** e92613. https://doi.org/10.1371/journal.pone.0092613

Moll, R.J., Millspaugh, J.J., Beringer, J., Sartwell, J. & He, Z. (2007) A new 'view' of ecology and conservation through animal-borne video systems. *Trends in Ecology & Evolution*, **22,** 660-668. https://doi.org/10.1016/j.tree.2007.09.007

Moreland, E.E., Cameron, M.F., Angliss, R.P. & Boveng, P.L. (2015) Evaluation of a ship-based unoccupied aircraft system (UAS) for surveys of spotted and ribbon seals in the Bering Sea pack ice1. *Journal of Unmanned Vehicle Systems*, **3,** 114-122. https://doi.org/10.1139/juvs-2015-0012

Mulero-Pazmany, M., Stolper, R., van Essen, L.D., Negro, J.J. & Sassen, T. (2014) Remotely piloted aircraft systems as a rhinoceros anti-poaching tool in Africa. *PloS One*, **9,** e83873. https://doi.org/10.1371/journal.pone.0083873

Oosthuizen, W.C., Krüger, L., Jouanneau, W. & Lowther, A.D. (2020) Unmanned aerial vehicle (UAV) survey of the Antarctic shag (Leucocarbo bransfieldensis) breeding colony at Harmony Point, Nelson Island, South Shetland Islands. *Polar Biology*. https://doi.org/10.1007/s00300-019-02616-y

Pereira, H.M., Leadley, P.W., Proenca, V., Alkemade, R., Scharlemann, J.P., Fernandez-Manjarres, J.F., Araujo, M.B., Balvanera, P., Biggs, R., Cheung, W.W., Chini, L., Cooper, H.D., Gilman, E.L., Guenette, S., Hurtt, G.C., Huntington, H.P., Mace, G.M., Oberdorff, T., Revenga, C., Rodrigues, P., Scholes, R.J., Sumaila, U.R. & Walpole, M. (2010) Scenarios for global biodiversity in the 21st century. *Science*, **330,** 1496-1501. https://doi.org/10.1126/science.1196624

Pettorelli, N., Laurance, W.F., O'Brien, T.G., Wegmann, M., Nagendra, H., Turner, W. & Milner-Gulland, E.J. (2014) Satellite remote sensing for applied ecologists: opportunities and challenges. *Journal of Applied Ecology*, **51,** 839-848. https://doi.org/10.1111/1365-2664.12261

Pfeffer, S.E., Spitzer, R., Allen, A.M., Hofmeester, T.R., Ericsson, G., Widemo, F., Singh, N.J., Cromsigt, J.P.G.M., Rowcliffe, M. & O'Brien, T. (2018) Pictures or pellets? Comparing camera trapping and dung counts as methods for estimating population densities of ungulates. *Remote Sensing in Ecology and Conservation*, **4,** 173-183. https://doi.org/10.1002/rse2.67

Piatt, I.J.F. & Sydeman, W.J. (2007) Seabirds as indicators of marine ecosystems. *Marine Ecology Progress Series*, **352,** 199-204. https://doi.org/10.3354/meps07070

Pimm, S.L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R. & Loarie, S. (2015) Emerging technologies to conserve biodiversity. *Trends in Ecology & Evolution*, **30,** 685-696. https://doi.org/10.1016/j.tree.2015.08.008

Pimm, S.L., Jenkins, C.N., Abell, R., Brooks, T.M., Gittleman, J.L., Joppa, L.N., Raven, P.H., Roberts, C.M. & Sexton, J.O. (2014) The biodiversity of species and their rates of extinction, distribution, and protection. *Science*, **344,** 987-+. https://doi.org/10.1126/science.1246752

Ratcliffe, N., Guihen, D., Robst, J., Crofts, S., Stanworth, A. & Enderlein, P. (2015) A protocol for the aerial survey of penguin colonies using UAVs. *Journal of Unmanned Vehicle Systems*, **3,** 95-101. https://doi.org/10.1139/juvs-2015-0006

Rees, A.F., Avens, L., Ballorain, K., Bevan, E., Broderick, A.C., Carthy, R.R., Christianen, M.J.A., Duclos, G., Heithaus, M.R., Johnston, D.W., Mangel, J.C., Paladino, F., Pendoley, K., Reina, R.D., Robinson, N.J., Ryan, R., Sykora-Bodie, S.T., Tilley, D., Varela, M.R., Whitman, E.R., Whittock, P.A., Wibbels, T. & Godley, B.J. (2018) The potential of unmanned aerial systems for sea turtle research and conservation: a review and future directions. *Endangered Species Research*, **35,** 81-100. https://doi.org/10.3354/esr00877

Rose, R.A., Byler, D., Eastman, J.R., Fleishman, E., Geller, G., Goetz, S., Guild, L., Hamilton, H., Hansen, M., Headley, R., Hewson, J., Horning, N., Kaplin, B.A., Laporte, N., Leidner, A., Leimgruber, P., Morisette, J., Musinsky, J., Pintea, L., Prados, A., Radeloff, V.C., Rowen, M., Saatchi, S., Schill, S., Tabor, K., Turner, W., Vodacek, A., Vogelmann, J., Wegmann, M., Wilkie, D. & Wilson, C. (2015) Ten ways remote sensing can contribute to conservation. *Conservation Biology*, **29,** 350-359. https://doi.org/10.1111/cobi.12397

Rowcliffe, J.M. & Carbone, C. (2008) Surveys using camera traps: are we looking to a brighter future? *Animal Conservation*, **11,** 185-186. https://doi.org/10.1111/j.1469-1795.2008.00180.x

Rowcliffe, J.M., Jansen, P.A., Kays, R., Kranstauber, B., Carbone, C. & Pettorelli, N. (2016) Wildlife speed cameras: measuring animal travel speed and day range using camera traps. *Remote Sensing in Ecology and Conservation*, **2,** 84-94. https://doi.org/10.1002/rse2.17

Sarda-Palomera, F., Bota, G., Padilla, N., Brotons, L. & Sarda, F. (2017) Unmanned aircraft systems to unravel spatial and temporal factors affecting dynamics of colony formation and nesting success in birds. *Journal of Avian Biology,* **48,** 1273-1280. https://doi.org/10.1111/jav.01535

Sardà-Palomera, F., Bota, G., Sardà, F. & Brotons, L. (2018) Reply to "a comment on the limitations of UAVs in wildlife research - the example of colonial nesting waterbirds". *Journal of Avian Biology*. https://doi.org/10.1111/jav.01902

Sarda-Palomera, F., Bota, G., Vinolo, C., Pallares, O., Sazatornil, V., Brotons, L., Gomariz, S. & Sarda, F. (2012) Fine-scale bird monitoring from light unmanned aircraft systems. *Ibis,* **154,** 177-183.

Scarpa, L.J. & Piña, C.I. (2019) The use of drones for conservation: A methodological tool to survey caimans nests density. *Biological Conservation,* **238,** 108235. https://doi.org/10.1016/j.biocon.2019.108235

Seymour, A.C., Dale, J., Hammill, M., Halpin, P.N. & Johnston, D.W. (2017) Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery. *Scientific Reports,* **7,** 45127. https://doi.org/10.1038/srep45127

Sorrell, K.J., Clarke, R.H., Holmberg, R. & McIntosh, R.R. (2019) Remotely piloted aircraft improve precision of capture–mark–resight population estimates of Australian fur seals. *Ecosphere,* **10**. https://doi.org/10.1002/ecs2.2812

Spaan, D., Burke, C., McAree, O., Aureli, F., Rangel-Rivera, C.E., Hutschenreiter, A., Longmore, S.N., McWhirter, P.R. & Wich, S.A. (2019) Thermal Infrared Imaging from Drones Offers a Major Advance for Spider Monkey Surveys. *Drones*, **3,** 34. https://doi.org/10.3390/drones3020034

Steffen, W., Sanderson, R.A., Tyson, P.D., Jäger, J., Matson, P.A., Moore III, B., Oldfield, F., Richardson, K., Schellnhuber, H.-J. & Turner, B.L. (2006) *Global change and the earth system: a planet under pressure*. Springer Science & Business Media.

Sweeney, K.L., Helker, V.T., Perryman, W.L., LeRoi, D.J., Fritz, L.W., Gelatt, T.S. & Angliss, R.P. (2016) Flying beneath the clouds at the edge of the world: using a hexacopter to supplement abundance surveys of Steller sea lions (Eumetopias jubatus) in Alaska1. *Journal of Unmanned Vehicle Systems***,** 1-12. https://doi.org/10.1139/juvs-2015-0010

Thome, D.M. & Thome, T.M. (2000) Radio-controlled Model Airplanes: Inexpensive Tools for Low-Level Aerial Photography. *Wildlife Society Bulletin,* **28,** 343-346.

Tilman, D., Clark, M., Williams, D.R., Kimmel, K., Polasky, S. & Packer, C. (2017) Future threats to biodiversity and pathways to their prevention. *Nature,* **546,** 73-81. https://doi.org/10.1038/nature22900

Torney, C.J., Lamont, M., Debell, L., Angohiatok, R.J., Leclerc, L.M. & Berdahl, A.M. (2018) Inferring the rules of social interaction in migrating caribou. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences,* **373**. https://doi.org/10.1098/rstb.2017.0385

Turner, W. (2014) Conservation. Sensing biodiversity. *Science*, **346,** 301-302. https://doi.org/10.1126/science.1256014

van Andel, A.C., Wich, S.A., Boesch, C., Koh, L.P., Robbins, M.M., Kelly, J. & Kuehl, H.S. (2015) Locating chimpanzee nests and identifying fruiting trees with an unmanned aerial vehicle. *American Journal of Primatology*. https://doi.org/10.1002/ajp.22446

Velarde, E., Anderson, D.W. & Ezcurra, E. (2019) Seabird clues to ecosystem health. *Science,* **365,** 116-117. https://doi.org/10.1126/science.aaw9999

Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P. & Bouche, P. (2013) Unmanned aerial survey of elephants. *PloS One,* **8,** e54700. https://doi.org/10.1371/journal.pone.0054700

Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., Roberts, J.T. & Gittleman, J.L. (2013) Targeting global conservation funding to limit immediate biodiversity declines. *Proceedings of the National Academy of Sciences of the United States of America*, **110,** 12144-12148. https://doi.org/10.1073/pnas.1221370110

Waters, C.N., Zalasiewicz, J., Summerhayes, C., Barnosky, A.D., Poirier, C., Galuszka, A., Cearreta, A., Edgeworth, M., Ellis, E.C., Ellis, M., Jeandel, C., Leinfelder, R., McNeill, J.R., Richter, D., Steffen, W., Syvitski, J., Vidas, D., Wagreich, M., Williams, M., Zhisheng, A., Grinevald, J., Odada, E., Oreskes, N. & Wolfe, A.P. (2016) The Anthropocene is functionally and stratigraphically distinct from the Holocene. *Science*, **351,** aad2622. https://doi.org/10.1126/science.aad2622

Watts, A.C., Perry, J.H., Smith, S.E., Burgess, M.A., Wilkinson, B.E., Szantoi, Z., Ifju, P.G. & Percival, H.F. (2010) Small unmanned aircraft systems for low-altitude aerial surveys. *Journal of Wildlife Management*, **74,** 1614-1619. https://doi.org/10.2193/2009-425

Wich, S., Dellatore, D., Houghton, M., Ardi, R. & Koh, L.P. (2016) A preliminary assessment of using conservation drones for Sumatran orang-utan (Pongo abelii) distribution and density. *Journal of Unmanned Vehicle Systems*, **4,** 45-52. https://doi.org/10.1139/juvs-2015-0015

Statement of authorship

Title of paper	Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research
Publication status	☑ Published ☐ Accepted for publication ☐ Submitted for publication ☐ Unpublished and unsubmitted work written in manuscript style
Publication details	Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. Current Biology, 26, R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Principal Author

Name of principal author (candidate)	Jarrod Hodgson		
Contribution to the paper[2]	Conceptualisation, methodology, investigation, writing – original draft, writing – review and editing.		
Overall percentage (%)	95		
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	25/07/2020

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	Lian Pin Koh		
Contribution to the paper	Conceptualisation, writing – review and editing, supervision.		
Signature		Date	25/07/2020

---

[2] As per the CRediT (Contributor Roles Taxonomy) authorship contribution statement guidelines

2 Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research[3]

The use of unmanned aerial vehicles (UAVs), colloquially referred to as 'drones', for biological field research is increasing (Watts *et al.* 2010; Anderson & Gaston 2013; Chabot & Bird 2015). Small, civilian UAVs are providing a viable, economical tool for ecology researchers and environmental managers. UAVs are particularly useful for wildlife observation and monitoring as they can produce systematic data of high spatial and temporal resolution (Linchant *et al.* 2015). However, this new technology could also have undesirable and unforeseen impacts on wildlife, the risks of which we currently have little understanding (Ditmer *et al.* 2015; Pomeroy, O'Connor & Davies 2015; Vas *et al.* 2015). There is a need for a code of best practice in the use of UAVs to mitigate or alleviate these risks, which we begin to develop here.

Different wildlife populations can respond idiosyncratically to a UAV in proximity depending on a variety of factors, including the species, environmental and historical context, as well as the type of UAV and its method of operation. While we do not presently have sufficient information on how these factors might affect wildlife to develop prescriptive policies for UAV use, we could draw from existing guidelines for ensuring the ethical treatment of animals in research (Sikes, Gannon & Mammalogists 2011; National Health and Medical Research Council 2013). For example, the ARRIVE (Animals in Research: Reporting In Vivo Experiments) guidelines detail the minimum information all scientific publications reporting research using laboratory animals should include (Kilkenny *et al.* 2010), which may serve as a good starting point for the UAV context.

Considering the growing popularity of UAVs as a tool among field biologists, we advocate for the precautionary principle to manage these risks. Specifically, we provide a suite of

---

[3] Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology,* **26,** R404-405. https://doi.org/10.1016/j.cub.2016.04.001

recommendations as the basis for a code of best practice in the use of UAVs in the vicinity of animals or for the purpose of animal research, which supplement current standards in animal field research and reporting.

> **Adopt the precautionary principle in lieu of evidence.** When researchers cannot make informed decisions about minimum wildlife disturbance flight practices for their environment or study species, they should exercise caution, particularly if endangered species or ecologically sensitive habitats are involved. While reported observations of animal responses to UAVs are increasing, there is a need for more empirical evidence across a range of animals and environments. Experiments that ethically quantify disturbance using captive and wild animals to fill this knowledge gap are necessary to inform minimum wildlife disturbance practices. As an interim measure, expert advice on species and UAV monitoring should be obtained for operations involving taxa whose responses to UAVs are poorly quantified or unknown.
>
> **Utilise the institutional animal ethics process to provide oversight to UAV-derived animal observations and experiments.** UAV monitoring that involves animals will benefit from ensuring all UAV methods are in accordance with approved institutional ethics permits. We encourage UAV users to seek this approval when appropriate and explain the anticipated benefit of using UAV technology in their situation. Ethics committees should evaluate these claims relative to comparative traditional techniques (e.g. ground surveys or remotely sensed data from an alternative, higher altitude platform such as manned aircraft or satellites).
>
> **Adhere to relevant civil aviation rules and adopt equipment maintenance and operator training schedules.** UAV operations need to comply with all relevant civil aviation rules which may include restrictions on flying beyond visual line of sight, above a defined altitude, at night and near people or in the vicinity of important infrastructure and prohibited areas. In countries where rules are not present or are still evolving, operators are encouraged to exercise caution. UAV equipment should be regularly serviced to ensure good working order, and maintenance recorded appropriately. Experienced operators should be utilised for UAV operations (formal accreditation is necessary in some countries). Where appropriate, approval for flight should be sought from indigenous communities.
>
> **Select appropriate UAV and sensor equipment.** UAVs should be selected to minimise visual and audio stimulus to target and non-target organisms, while remaining capable of satisfying study objectives. Consideration should be given to the way different units move (e.g. the gliding motion of a fixed-wing unit) as well as their shape, volume and colour relative to the study environment. In some cases, it may be beneficial to modify UAVs to mimic non-threatening wildlife, e.g. a bird that is not a

predator of the target species. Sensors should be optimised (e.g. focal length) to enable collection of suitable data from a UAV operated, typically, as high or as far as possible from the subjects.

Exercise minimum wildlife disturbance flight practices. Particular attention should be given to siting launch and recovery sites away from animals (out of sight if possible) and maintaining a reasonable distance from animals at all times during flight. Potentially threatening approach trajectories and sporadic flight movements should be avoided. Species-specific protocols, including optimum flight altitude, should be developed and implemented wherever possible.

Cease UAV operations if they are excessively disruptive. Animal responses should be measured during UAV operations (and before and after if possible). Monitoring stress response at a physiological level is encouraged, as is the use of tracking technology to quantify potential displacement. Operations should be aborted if excessive disturbance results, especially in cases when quantification of UAV disturbance is not a research interest. The methods for such studies should be reviewed and only resumed with a refined protocol if justifiable.

Detailed, accurate reporting of methods and results in publications. UAV specifications and flight practices should be reported accurately and in full. Thorough results should be reported to ensure findings can be integrated in future research. Notes of animal responses (see above) should be included in published studies to generate an evidence base for refined guidelines. We encourage authors to be proactive in sharing suggestions for improving UAV best practices in biological field research and also to guide the regulation of recreational use. Importantly, such reports should include both positive and negative observations, including accidents during operations and incidents of excessive disturbances to animals. Publishers may wish to consider minimum reporting requirements for manuscripts that involve UAV operations.

Promoting the awareness, development and uptake of a code of best practice in the use of UAVs will improve their suitability as a low impact ecological survey tool. We consider this code to be a first and guiding step in the development of species-specific protocols that mitigate or alleviate potential UAV disturbance to wildlife.

2.1 Author contributions

J.C.H. and L.P.K. conceived and wrote the paper.

2.2 References

Anderson, K. & Gaston, K.J. (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment*, **11,** 138-146. https://doi.org/10.1890/120150

Chabot, D. & Bird, D.M. (2015) Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in?1. *Journal of Unmanned Vehicle Systems*, **3,** 137-155. https://doi.org/10.1139/juvs-2015-0021

Ditmer, M.A., Vincent, J.B., Werden, L.K., Tanner, J.C., Laske, T.G., Iaizzo, P.A., Garshelis, D.L. & Fieberg, J.R. (2015) Bears Show a Physiological but Limited Behavioral Response to Unmanned Aerial Vehicles. *Current Biology*, **25,** 2278-2283. https://doi.org/10.1016/j.cub.2015.07.024

Kilkenny, C., Browne, W.J., Cuthill, I.C., Emerson, M. & Altman, D.G. (2010) Improving bioscience research reporting: the ARRIVE guidelines for reporting animal research. *PLoS Biology*, **8,** e1000412. https://doi.org/10.1371/journal.pbio.1000412

Linchant, J., Lisein, J., Semeki, J., Lejeune, P. & Vermeulen, C. (2015) Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review*, **45,** 239-252. https://doi.org/10.1111/mam.12046

National Health and Medical Research Council (2013) Australian code for the care and use of animals for scientific purposes. National Health and Medical Research Council, Canberra.

Pomeroy, P., O'Connor, L. & Davies, P. (2015) Assessing use of and reaction to unmanned aerial systems in gray and harbor seals during breeding and molt in the UK1. *Journal of Unmanned Vehicle Systems*, **3,** 102-113. https://doi.org/10.1139/juvs-2015-0013

Sikes, R.S., Gannon, W.L. & Mammalogists, A.S. (2011) Guidelines of the American Society of Mammalogists for the use of wild mammals in research. *Journal of Mammalogy*, **92,** 235-253. https://doi.org/10.1644/10-Mamm-F-355.1

Vas, E., Lescroel, A., Duriez, O., Boguszewski, G. & Gremillet, D. (2015) Approaching birds with drones: first experiments and ethical guidelines. *Biology Letters*, **11,** 20140754. https://doi.org/10.1098/rsbl.2014.0754

Watts, A.C., Perry, J.H., Smith, S.E., Burgess, M.A., Wilkinson, B.E., Szantoi, Z., Ifju, P.G. & Percival, H.F. (2010) Small unmanned aircraft systems for low-altitude aerial surveys. *Journal of Wildlife Management*, **74,** 1614-1619. https://doi.org/10.2193/2009-425

Statement of authorship

Title of paper	Drones count wildlife more accurately and precisely than humans
Publication status	☑ Published ☐ Accepted for publication ☐ Submitted for publication ☐ Unpublished and unsubmitted work written in manuscript style
Publication details	Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. Methods in Ecology and Evolution, 9, 1160-1167. https://doi.org/10.1111/2041-210x.12974

Principal Author

Name of principal author (candidate)	Jarrod Hodgson		
Contribution to the paper	Study design, data collection, development of the semi-automated detection technique, data analysis, manuscript writing and editing.		
Overall percentage (%)	60		
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**	25/07/2020

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	Rowan Mott		
Contribution to the paper	Study design, data collection, data analysis, manuscript writing and editing.		
Signature		**Date**	25/07/2020

Name of co-author	Shane Baylis		
Contribution to the paper	Study design, data collection, data analysis, manuscript writing and editing.		
Signature		**Date**	02/08/2020

Name of co-author	Trung Pham		
Contribution to the paper	Development of the semi-automated detection technique and manuscript editing.		
Signature		**Date**	02/08/2020

Name of co-author	Simon Wotherspoon		
Contribution to the paper	Data analysis and manuscript editing.		
Signature		**Date**	02/08/2020

Name of co-author	Adam Kilpatrick		
Contribution to the paper	Study design assistance, data collection and manuscript editing.		
Signature		**Date**	02/08/2020

Name of co-author	Ramesh Raja Segaran		
Contribution to the paper	Data collection and manuscript editing.		
Signature		**Date**	29/07/2020

Name of co-author	Ian Reid		
Contribution to the paper	Development of the semi-automated detection technique and manuscript editing.		
Signature		**Date**	27/7/2020

Name of co-author	Aleks Terauds		
Contribution to the paper	Study design, data analysis, manuscript writing and editing.		
Signature		**Date**	27/07/2020

Name of co-author	Lian Pin Koh		
Contribution to the paper	Study design, data collection, development of the semi-automated detection technique, data analysis, manuscript writing and editing.		
Signature		**Date**	25/07/2020

3 Drones count wildlife more accurately and precisely than humans[4]

3.1 Abstract

Knowing how many individuals are in a wildlife population allows informed management decisions to be made. Ecologists are increasingly using technologies, such as Remotely Piloted Aircraft (RPA; commonly known as "drones", Unmanned Aerial Systems or Unmanned Aerial Vehicles), for wildlife monitoring applications. Although RPA are widely touted as a cost-effective way to collect high-quality wildlife population data, the validity of these claims is unclear.

Using life-sized, replica seabird colonies containing a known number of fake birds, we assessed the accuracy of RPA-facilitated wildlife population monitoring compared to the traditional ground-based counting method. The task for both approaches was to count the number of fake birds in each of 10 replica seabird colonies.

We show that RPA-derived data are, on average, between 43% and 96% more accurate than the traditional ground-based data collection method. We also demonstrate that counts from this remotely sensed imagery can be semi-automated with a high degree of accuracy.

The increased accuracy and increased precision of RPA-derived wildlife monitoring data provides greater statistical power to detect fine-scale population fluctuations allowing for more informed and proactive ecological management.

---

[4] Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution,* **9,** 1160-1167. https://doi.org/10.1111/2041-210x.12974

3.2 Introduction

Human activities are creating environmental conditions that pose threats and present opportunities for wildlife. In turn, this creates challenges for conservation managers. Some species have benefited from anthropogenic actions. For example, many invasive species profit from human-assisted dispersal (Hulme 2009; Banks *et al.* 2015), and mesopredators may thrive following human-driven loss of top predators (Ritchie & Johnson 2009). However, in many cases, wildlife populations are undergoing alarming declines, and extinction rates are now as high as 100-fold greater than the background extinction rate (Ceballos *et al.* 2015). Ecological monitoring is essential for understanding these population dynamics, and rigorous monitoring facilitates informed management. The effectiveness of management decision-making is often dependent on the accuracy and timeliness of the relevant ecological data upon which decisions are based, meaning that improvements to data collection methods may herald improved ecological outcomes from management actions.

Emerging technologies are increasingly being adopted by ecologists to improve data collection and capture novel data (Moll *et al.* 2007; Hebblewhite & Haydon 2010; Pimm *et al.* 2015). Advances in genetic techniques have resulted in the cost-effective application of environmental DNA sampling to the detection of endangered species and invasive species (Sigsgaard *et al.* 2015; Smart *et al.* 2015; Smart *et al.* 2016). Camera traps and acoustic recorders have become established tools for determining whether a species is present at a site, and estimating population density (Rowcliffe & Carbone 2008; Marques *et al.* 2013). Furthermore, animal-borne telemetry devices have revolutionised our understanding of animal movements, including their interactions with the environment, and species distributions (Hussey *et al.* 2015; Kays *et al.* 2015). Such technologies have been vital in advancing our understanding of wildlife and answering fundamental questions, such as how many individuals are in a population and whether that population trajectory is increasing or decreasing.

Remotely Piloted Aircraft (RPA; commonly known as “drones”, Unmanned Aerial Systems or Unmanned Aerial Vehicles) have seen a rapid uptake by ecologists for data collection. This surge in popularity has arisen largely due to their ability to carry remote sensing instruments that collect data at scales highly suited to monitoring ecological phenomena (Anderson & Gaston 2013). Compared to remote sensing instruments mounted to spacecraft and conventional aircraft, RPA are more suited to collecting extremely fine spatial and temporal resolution data at the discretion of the user. These benefits have led many practitioners to label RPA as a powerful tool for wildlife ecology (Jones, Pearlstine & Percival 2006; Watts *et al.* 2010; Chabot & Bird 2015; Linchant *et al.* 2015; Christie *et al.* 2016). Consequently, RPA are being used for data collection in an increasingly diverse suite of ecological applications, including transect counts of African Elephants *Loxodonta africana* (Vermeulen *et al.* 2013), monitoring for poaching activities (Mulero-Pazmany *et al.* 2014), detecting reptile and arboreal mammal nests (Evans *et al.* 2016; Wich *et al.* 2016), and estimating the body condition of cetaceans and pinnipeds (Christiansen *et al.* 2016; Krause *et al.* 2017).

Many bird species are highly suited to RPA-facilitated population monitoring. RPA have been used to assess the breeding status of the canopy-breeding Hooded Crow *Corvus cornix* (Weissensteiner, Poelstra & Wolf 2015) and to take a census of multi-species assemblages of songbirds (Wilson, Barr & Zagorski 2017). They have also been a useful tool in collecting valuable datasets of species which congregate and/or those that frequent known sites to breed. For example, RPA have been used to estimate the size of staging flocks of geese (Chabot & Bird 2012), take population censuses of colony nesting species of gull, tern and penguin (Sarda-Palomera *et al.* 2012; Chabot, Craik & Bird 2015; Ratcliffe *et al.* 2015; Sarda-Palomera *et al.* 2017), and also make a rapid population estimate of the Tristan Albatross *Diomedea dabbenena* at a remote island where nests are at low density (McClelland *et al.* 2016). While some studies have investigated the variability of RPA surveys compared to traditional methods (Chabot, Craik & Bird 2015; Hodgson *et al.* 2016a), to date, rigorous quantification of the accuracy of RPA-derived data has been limited.

We assessed the accuracy of RPA-facilitated wildlife population monitoring compared to the traditional ground-based counting method. The task for both approaches was to count the number of fake birds in each of 10 replica seabird colonies. Each replica colony had a different known number of life-sized individuals. Although the replica colonies lacked the flying or moving individuals of real colonies, the stationary decoys provided a realistic representation of the nesting seabird stimuli that observers encounter in the field. We hypothesised that counts from RPA-derived imagery would be more accurate and more precise than those generated using the traditional approach, confirming that RPA technology is a significant advance for ecological monitoring.

3.3 Materials and methods

3.3.1 Study site and simulated colony set-up

Fieldwork (#epicduckchallenge) was completed at a metropolitan beach in South Australia (Port Willunga, 35°15'33 S, 138°27'41 E). The beach comprised pale cream to golden-coloured sand, natural debris and was largely devoid of rocks. The terrain was representative of a low-lying sand cay, gently sloping from the high water mark up to a small (0 – 1.5 m), natural, vegetated embankment. The experimental design, including the majority of anticipated statistical analyses, was pre-registered (Hodgson *et al.* 2016b).

Ten simulated Greater Crested Tern *Thalasseus bergii* breeding colonies were constructed using commercial, life-sized, plastic duck decoys (~ 25.5 x 11.3 cm, 185 cm^{-2} footprint).

Colonies were situated separately on the beach, above the high water mark, in sandy areas that were analogous to nesting habitat. These areas had minimal topographic variation, and were typically devoid of vegetation but often contained natural beach debris.

As the interactions of individuals are thought to influence colony layout, a model of nesting pressure was applied to an underlying hexagonal grid to generate unique, unbiased colony layouts (Hodgson *et al.* 2016b). The hexagonal grid was re-created in the field using a wire mesh, upon which grid cell centres were marked (mean density: 11.39 m^{-2}). Pre-counted wooden skewers were placed one per cell at a random location within all cells identified as occupied in the colony layout map. The mesh was removed and each skewer was replaced with a decoy facing approximately into the wind. One individual was placed in each occupied cell. The number of skewers retrieved was taken to be the true number of individuals in the colony. Colony sizes were between 463 and 1017 individuals.

3.3.2 Ground counting approach

Ground-based counts (ground counts) were made using a standard field technique (Hodgson *et al.* 2016a). All observers were ecologists with experience observing and counting birds, primarily in a professional or academic capacity. Counters used tripod-mounted spotting scopes or binoculars as required. Hand-held tally counters were used to assist counting. For each colony, the observation viewpoint (Figure 3.1e) was selected because it provided the optimum vantage, was at a similar altitude to the colony and was 37.5 m from the nearest bird. This distance is a biologically plausible minimum approach distance as it is the flight initiation distance of the Caspian tern *Hydroprogne caspia* (Moller *et al.* 2014), a similar species to that being replicated. Counts (n = 61) were 7 ± 2.65 min (SD) in duration. Each of the four to seven counters made a single blind count of the number of individuals in each colony. The numbers of counters were selected based on a preliminary power analysis (Hodgson *et al.* 2016b) which investigated the sample sizes necessary to detect small (~ 10%) differences in mean counts and count variances between ground and counts from RPA-derived imagery to high (80%, 90%, and 95%) power. Counters had no knowledge of the true number of individuals in the colonies or the colony set-up technique. Counts were made between 0930 and 1645 on one day in late autumn, resulting in variation in illumination and shadows. During this period, wind speed was low to moderate (~ 5 – 20 kt), cloud cover varied (15% – 75%) and visibility was high (> 500 m).

3.3.3 RPA description, flight characteristics and data collected by RPA

A small, off-the-shelf quadcopter (Iris+, 3D Robotics) was used as a platform to image each colony. After positioning the RPA in the centre of the colony at 15 m above ground level, it was piloted in ‘altitude hold’ mode to make a vertical ascent without movement in other axes. The RPA was loitered for short periods (~ 10 seconds) at 30 m, 60 m, 90 m and 120 m above ground level (sample heights) to enable the capture of several photographs at each height.

Sampling was restricted to a height of 120 m as this is a common maximum limit for standard RPA flight. Ground control station connection (Mission Planner, planner.ardupilot.com) was utilised and total flight time for missions was 5 to 7 min. All missions were in accordance with local regulations and flown by the same licenced pilot. Samples were collected within 40 min of the completion of ground counts.

Imagery was captured using a compact digital camera (Cyber-shot RX100 III, Sony – resolution: 5,472 x 3,648 px; sensor: CMOS; sensor size: 13.2 x 8.8 mm; lens: ZEISS Vario-Sonnar T). Exposure time was set at 1/2000 seconds using "shutter priority" mode. Photographs were captured successively (~ 1 sec intervalometer) using the Sony PlayMemories Time-lapse application in jpeg format and at a focal length of 8.8 mm for all sample heights. The camera was mounted facing downward using a custom vibration dampening plate. The footprint of a single image at each height encompassed the colony for all replicates. For analysis, only the image captured closest to the middle of the loiter time period for each sample height was used. These images (scenes; $n = 40$) were cropped (colony area < 50% of footprint) so that the image footprint was identical for each sample height for a given colony. High-quality imagery was obtained for six of the ten colonies. Imagery for the remaining four colonies was affected by vibration-blur caused by a failure of the sensor attachment, likely due to wind speeds near the limit of the capability of the RPA platform. Scenes are archived online (https://doi.org/10.5061/dryad.rd736).

The ground sample distance (GSD), being the distance between adjacent pixel centres on the ground, for sample heights were 0.82 cm, 1.64 cm, 2.47 cm and 3.29 cm (Figure 3.1). When photographed at nadir, this approximated to 275, 69, 30 and 17 pixels per individual respectively. The variance in GSDs was intended to represent the resolutions commonly achieved in wildlife monitoring applications, which result from sensor and sampling height variations.

3.3.4 Manual counting approach for RPA-derived imagery

Manual counts of perceived individuals in digital imagery were completed following a technique previously implemented for RPA-facilitated monitoring of living seabirds (Hodgson *et al.* 2016a). Systematic counts were made using the multi-count tool within an easy-to-use, open source, java-based scientific image processing program (ImageJ, http://imagej.net/). This tool is used by manually placing a mark on each object to be counted and then computing a tally of the number of marks placed. A grid plugin was used to overlay a square matrix (cell sizes: 70,000, 15,000, 8,000 and 4,000 pixels for each sample height) and counters were instructed to view the colony sequentially (gridcell by gridcell: left to right, top to bottom). Counters were encouraged to zoom in to each cell as they progressed and, upon completion, review their count at different levels of zoom until they were satisfied they had counted all individuals. For each sample height, seven to nine individuals counted each colony. Counters had no knowledge of the experimental setup and only one had experience in ground counting colonial birds.

3.3.5 *Semi-automated counting approach for RPA-derived imagery*

In each scene, digital bounding boxes were used to manually delimit a percentage of individual birds (Figure 3.2a). Four larger areas of background without birds were also delimited. These data were used to train a linear support-vector machine (a discriminative classifier; Cortes & Vapnik 1995), which predicted the likelihood of each pixel being a bird or background when applied to the corresponding scene (Figure 3.2b). Instead of relying on colour intensities, for each pixel used in the training processes, we computed rotation-invariant Fourier histogram of oriented gradient (Liu et al. 2013) features. This resulted in the classifiers being trained to determine which features distinguished birds from the background. The predicted likelihood (score) maps indicated the approximate locations of birds in the scenes, and detections were generated by applying a threshold to the score maps. This process unavoidably resulted in redundant bird proposals (Figure 3.2c) and so the final detection results were obtained by suppressing redundant proposals by minimising an energy function (Pham *et al.* 2016; Figure 3.2d). This function encoded the spatial distribution of objects and was informed by our knowledge of how the birds nest (e.g. two birds cannot occupy the same location). The source code and dataset are archived online (https://doi.org/10.4225/55/5a57f969d82e0).

To determine the minimum amount of training data required for accurate detections relative to manual image counts, we varied the percentage of individual birds used as training data from 1% to 30% for each scene.

3.3.6 *Statistical methods*

All analyses were carried out in *R* version 3.2.2 (R Core Team 2016). Pre-registered analyses were designed to investigate how within-colony absolute count error, within-colony variability of counts and within-colony bias of counts differed between count techniques (Hodgson *et al.* 2016b). For analyses of count error, we consider our contrasts of experimental conditions to be conservative compared to typical field conditions. In the field, ground counters contend with the movement of live birds while counters of RPA-derived imagery use static images. Our use of decoys, therefore, removes a potential source of error for ground counters, whereas that source of error is minor or non-existent for counts made from RPA-derived images.

For each test, a generalised linear mixed model was fit between the response (e.g. absolute count error) and the technology used to make the count (e.g. ground count, manually counted RPA-derived image captured at 30 m height, semi-automatically counted RPA-derived image captured at 30 m height), with colony included in the model as a random effect. To investigate effects of counting technique on absolute count error, we defined the response as the absolute difference between the true number of birds in a colony and the counted number of birds. To investigate effects of counting technique on count variability, we defined the response as the absolute difference between each count and the mean of counts of the same colony taken using the same method. Count variability was not estimated for semi-automated counts as there was only a single semi-automated count per colony. To investigate the effect of counting technique on relative count bias, we defined the response as the difference between the true number of birds in the colony and the counted number of birds. For the absolute count error model we used a Poisson distribution with quasi-likelihood estimation, and for the variability and bias models we used a Gaussian distribution. For each model, post-hoc Tukey tests were used to test for differences in the response between all pairs of treatment levels.

Semi-automated count data were added to the experimental design after our pre-registration of the analysis, and caused minor changes to the planned analysis. The addition of semi-automated count data, with a single replicate per colony, required fitting colony as a random effect instead of as a fixed effect in each model.

Statements comparing the accuracy of counts from RPA-derived imagery to ground counts are based on the mean within-colony Root Mean Squared Error (RMSE) of that counting approach, standardised as a proportion of the true count within each colony. For instance, a statement that counts from RPA-derived imagery are '95% more accurate than ground counts' means that, within-colony, the RMSE for counts from RPA-derived imagery is 5% of the RMSE for ground counts, representing a 95% reduction in RMSE.

To compare the semi-automated counts to that of the people counting the images, we first took the semi-automated count after 10% of training data had been used for each scene. Ten percent of training data was consistently identified as a threshold over which little improvement in counts occurred for all scenes. We compared this count to each of the manual counts of the same image using ANOVA for all scenes, and also for those scenes of high quality. We also used log-linear models with a Poisson distribution to make more quantitative comparisons of the two approaches.

3.4 Results

3.4.1 *Manual counts from RPA-derived imagery versus ground counts*

On average across all colonies, counts from RPA-derived imagery were between 43% and 96% more accurate than ground counts, depending on the sample height (between 92% and 98% for the colonies with high-quality imagery; Table S3.1). The mean absolute error was significantly smaller for counts from RPA-derived imagery at all heights compared to ground counts (all $P < 0.001$; Figure 3.3a).

No significant increase in count accuracy was achieved by obtaining imagery from heights lower than or equal to 90 m. Using data only from colonies with high-quality imagery, there was no significant change in count accuracy across the range of heights. The lower accuracy of ground counts was due to significant underestimations of the true number of individuals in colonies (Figure 3.3b). Counts from RPA-derived imagery obtained at 30 m and 60 m did not significantly under- or over-estimate the true number of individuals in a colony, and there was no evident bias in counts from RPA-derived imagery at any height for colonies with high-quality imagery (Figure 3.3b).

Counts from RPA-derived imagery were more precise (i.e. had lower inter-counter variability) than ground counts, regardless of the height at which imagery was obtained ($t_{4,560}$ -10.21 to -13.37, all $P < 0.001$; Figure S3.1). Counts from RPA-derived imagery were more precise for imagery obtained at 30 m compared to those obtained from 120 m ($P = 0.01$), however, there were no significant differences in precision among counts from RPA-derived imagery at different heights for colonies with high-quality imagery (all $P > 0.98$).

3.4.2 *Semi-automated counts from RPA-derived imagery*

By increasing the percentage (from 1% to 30%) of individuals used as training data for the image-analysis algorithm, 10% training data was consistently identified as a threshold above which little improvement in count accuracy was achieved (Figure S3.2). There was no significant difference between counts that were made with 10% training data and those made by manual counting from RPA imagery across all scenes. The semi-automated results were 94% similar to manual counts across all scenes (98% for the colonies with high-quality imagery; see also Table S3.1).

3.5 Discussion

RPA-derived data were more accurate and more precise than the traditional data collection method, validating claims that RPA are a highly beneficial tool for ecologists. By facilitating accurate census data, RPA can provide ecologists with more confidence in population estimates from which management decisions can be made. Furthermore, the superior precision of counts from RPA images increases statistical power to detect population trends, owing to the lower type II error rate in statistical analysis that comes with comparing measures with smaller variance (Gerrodette 1987). The improved precision of completing wildlife population censuses using RPA has been demonstrated for free-living seabird colonies (Hodgson *et al.* 2016a), suggesting our results are generalisable to natural settings. Differences in accuracy and precision between RPA-facilitated and traditional survey methods can be attributed to the sources and magnitudes of variance for each method, which are strongly affected by the different vantages (Hodgson *et al.* 2016a).

Manual counting from RPA-derived imagery returned high-quality data. We estimate that a reasonable detection rate for manual counting is at least 72 birds per minute (unpublished data), demonstrating the suitability of this approach for colonies of less than a few thousand individuals. However, when the number of individuals is high, or repeat counts of colonies are required at different time points, the labour investment needed for manual counting can be substantial, so image-analysis techniques have been increasingly employed to streamline the detection process (Chabot & Francis 2016). Our semi-automated image-based object detection algorithm required the manual delineation of a proportion of birds and four areas of background without birds to be used as training data. Delineations were comfortably made at a rate of 30 birds per minute, and user intervention was not required once processing started. Accordingly, given 10% training data was sufficient for accurate counts, our semi-automated approach reduced user time investment without diminishing data quality compared to the manual, RPA-derived census. While processing time will vary with computing power, we still consider employing the algorithm and inputting training data a more efficient use of user time. This will be of particular interest in today’s research environment where funding for conservation is limited (Waldron *et al.* 2013) and researchers are under ever more pressing time constraints (Fischer, Ritchie & Hanspach 2012).

The capture quality and resolution of RPA-derived imagery heavily influenced the results of both human and semi-automated detection. Consequently, ecologists should determine the minimum required GSD for their context and optimise their sensor accordingly (e.g. resolution, focal length) relative to sample height. When determining an appropriate sample height, best practice protocols should be considered to minimise potential disturbance to wildlife (Hodgson & Koh 2016), while complying with relevant local aviation legislation and achieving an acceptable sample area within the possible survey time period.

The ability to collect data with higher accuracy, higher precision and less bias than the existing approach confirms that RPA are a scientifically rigorous data collection tool for wildlife population monitoring. This approach produces a permanent record, providing the unique opportunity to error-check, and even recount with new detection methods, unlike ground count data. RPA-facilitated monitoring also presents the opportunity to collect population data without entering breeding grounds or ecologically sensitive areas, thereby avoiding the disturbance associated with ground surveys. Furthermore, as RPA platforms, sensors and computer vision techniques continue to develop, it is likely that the accuracy and cost-effectiveness of RPA-based approaches will also continue to improve.

3.6 Acknowledgements

We particularly thank those who assisted with this study including Po-yun Wong, the ground support team and the numerous volunteers who made counts from the ground or RPA-derived imagery. We acknowledge the South Australian Department of Environment, Water and Natural Resources and the City of Onkaparinga for granting permits for this work (M26523-1 and 4138 respectively). J.C.H. is supported by an Australian Government Research Training Program Scholarship. L.P.K. is supported by the Australian Research Council and Conservation International.

3.7 Authors' contributions

J.C.H., R.M., S.M.B., A.T. and L.P.K. designed the study, analysed the data and wrote the manuscript. A.D.K. assisted with designing the study. J.C.H., R.M., S.M.B., A.D.K., R.R.S. and L.P.K. collected the data. S.W. contributed to the analyses. T.T.P., J.C.H., L.P.K. and I.R. developed the semi-automated detection technique. All authors contributed to drafting the manuscript.

3.8 Data accessibility

The pre-registered experimental design is available via the Open Science Framework: https://doi.org/10.17605/osf.io/a6n3b (Hodgson *et al.* 2016b). The count data, scenes, semi-automated aerial image counting approach source code and dataset, and *R* script are available on the Dryad Digital Repository: https://doi.org/10.5061/dryad.rd736 (Hodgson *et al.* 2018).

3.9 References

Anderson, K. & Gaston, K.J. (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment*, **11,** 138-146. https://doi.org/10.1890/120150

Banks, N.C., Paini, D.R., Bayliss, K.L. & Hodda, M. (2015) The role of global trade and transport network topology in the human-mediated dispersal of alien species. *Ecology Letters*, **18,** 188-199. https://doi.org/10.1111/ele.12397

Ceballos, G., Ehrlich, P.R., Barnosky, A.D., Garcia, A., Pringle, R.M. & Palmer, T.M. (2015) Accelerated modern human-induced species losses: Entering the sixth mass extinction. *Sci Adv*, **1,** e1400253. https://doi.org/10.1126/sciadv.1400253

Chabot, D. & Bird, D.M. (2012) Evaluation of an off-the-shelf Unmanned Aircraft System for Surveying Flocks of Geese. *Waterbirds*, **35,** 170-174. https://doi.org/10.1675/063.035.0119

Chabot, D. & Bird, D.M. (2015) Wildlife research and management methods in the 21st century: Where do unmanned aircraft fit in?1. *Journal of Unmanned Vehicle Systems*, **3,** 137-155. https://doi.org/10.1139/juvs-2015-0021

Chabot, D., Craik, S.R. & Bird, D.M. (2015) Population census of a large common tern colony with a small unmanned aircraft. *PloS One*, **10,** e0122588. https://doi.org/10.1371/journal.pone.0122588

Chabot, D. & Francis, C.M. (2016) Computer-automated bird detection and counts in high-resolution aerial images: a review. *Journal of Field Ornithology*, **87,** 343-359. https://doi.org/10.1111/jofo.12171

Christiansen, F., Dujon, A.M., Sprogis, K.R., Arnould, J.P.Y. & Bejder, L. (2016) Noninvasive unmanned aerial vehicle provides estimates of the energetic cost of reproduction in humpback whales. *Ecosphere*, **7,** e01468. https://doi.org/10.1002/ecs2.1468

Christie, K.S., Gilbert, S.L., Brown, C.L., Hatfield, M. & Hanson, L. (2016) Unmanned aircraft systems in wildlife research: current and future applications of a transformative technology. *Frontiers in Ecology and the Environment*, **14,** 241-251. https://doi.org/10.1002/fee.1281

Cortes, C. & Vapnik, V. (1995) Support-vector networks. *Machine Learning*, **20,** 273-297.

Evans, L.J., Jones, T.H., Pang, K., Saimin, S. & Goossens, B. (2016) Spatial Ecology of Estuarine Crocodile (Crocodylus porosus) Nesting in a Fragmented Landscape. *Sensors*, **16**. https://doi.org/10.3390/s16091527

Fischer, J., Ritchie, E.G. & Hanspach, J. (2012) Academia's obsession with quantity. *Trends in Ecology & Evolution*, **27,** 473-474.

Gerrodette, T. (1987) A power analysis for detecting trends. *Ecology*, **68,** 1364-1372. https://doi.org/10.2307/1939220

Hebblewhite, M. & Haydon, D.T. (2010) Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, **365,** 2303-2312. https://doi.org/10.1098/rstb.2010.0087

Hodgson, J.C., Baylis, S.M., Mott, R., Herrod, A. & Clarke, R.H. (2016a) Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports*, **6,** 22574. https://doi.org/10.1038/srep22574

Hodgson, J.C., Baylis, S.M., Mott, R. & Koh, L.P. (2016b) A comparison of the accuracy of simulated animal counts using traditional and UAV-assisted methods. *Open Science Framework*. https://doi.org/10.17605/osf.io/a6n3b

Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology*, **26,** R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Raga Segaran, R., Reid, I., Terauds, A. & Koh, L.P. (2018) Data from: Drones count wildlife more accurately and precisely than humans. *Dryad Digital Repository*. https://doi.org/10.5061/dryad.rd736

Hulme, P.E. (2009) Trade, transport and trouble: managing invasive species pathways in an era of globalization. *Journal of Applied Ecology*, **46,** 10-18. https://doi.org/10.1111/j.1365-2664.2008.01600.x

Hussey, N.E., Kessel, S.T., Aarestrup, K., Cooke, S.J., Cowley, P.D., Fisk, A.T., Harcourt, R.G., Holland, K.N., Iverson, S.J., Kocik, J.F., Mills Flemming, J.E. & Whoriskey, F.G. (2015) Aquatic animal telemetry: A panoramic window into the underwater world. *Science*, **348,** 1255642. https://doi.org/10.1126/science.1255642

Jones, G.P., Pearlstine, L.G. & Percival, H.F. (2006) An assessment of small unmanned aerial vehicles for wildlife research. *Wildlife Society Bulletin*, **34,** 750-758. https://doi.org/10.2193/0091-7648(2006)34[750:aaosua]2.0.co;2

Kays, R., Crofoot, M.C., Jetz, W. & Wikelski, M. (2015) Terrestrial animal tracking as an eye on life and planet. *Science*, **348,** aaa2478. https://doi.org/10.1126/science.aaa2478

Krause, D.J., Hinke, J.T., Perryman, W.L., Goebel, M.E. & LeRoi, D.J. (2017) An accurate and adaptable photogrammetric approach for estimating the mass and body condition of pinnipeds using an unmanned aerial system. *PloS One*, **12,** e0187465. https://doi.org/10.1371/journal.pone.0187465

Linchant, J., Lisein, J., Semeki, J., Lejeune, P. & Vermeulen, C. (2015) Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. *Mammal Review*, **45,** 239-252. https://doi.org/10.1111/mam.12046

Liu, K., Skibbe, H., Schmidt, T., Blein, T., Palme, K., Brox, T. & Ronneberger, O. (2013) Rotation-invariant HOG descriptors using fourier analysis in polar and spherical coordinates. *International Journal of Computer Vision*, **106,** 342-364. https://doi.org/10.1007/s11263-013-0634-z

Marques, T.A., Thomas, L., Martin, S.W., Mellinger, D.K., Ward, J.A., Moretti, D.J., Harris, D. & Tyack, P.L. (2013) Estimating animal population density using passive acoustics. *Biological Reviews of the Cambridge Philosophical Society*, **88,** 287-309. https://doi.org/10.1111/brv.12001

McClelland, G.T.W., Bond, A.L., Sardana, A. & Glass, T. (2016) Rapid population estimate of a surface-nesting seabird on a remote island using a low-cost unmanned aerial vehicle. *Marine Ornithology*, **44,** 215-220.

Moll, R.J., Millspaugh, J.J., Beringer, J., Sartwell, J. & He, Z. (2007) A new 'view' of ecology and conservation through animal-borne video systems. *Trends in Ecology & Evolution*, **22,** 660-668. https://doi.org/10.1016/j.tree.2007.09.007

Moller, A.P., Samia, D.S., Weston, M.A., Guay, P.J. & Blumstein, D.T. (2014) American exceptionalism: population trends and flight initiation distances in birds from three continents. *PloS One*, **9,** e107883. https://doi.org/10.1371/journal.pone.0107883

Mulero-Pazmany, M., Stolper, R., van Essen, L.D., Negro, J.J. & Sassen, T. (2014) Remotely piloted aircraft systems as a rhinoceros anti-poaching tool in Africa. *PloS One*, **9,** e83873. https://doi.org/10.1371/journal.pone.0083873

Pham, T.T., Rezatofighi, S.H., Reid, I. & Chin, T.-J. (2016) Efficient point process inference for large-scale object detection. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).*

Pimm, S.L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R. & Loarie, S. (2015) Emerging technologies to conserve biodiversity. *Trends in Ecology & Evolution*, **30,** 685-696. https://doi.org/10.1016/j.tree.2015.08.008

R Core Team (2016) R: A language and environment for statistical computing. Vienna, Austria. *http://www.R-project.org*.

Ratcliffe, N., Guihen, D., Robst, J., Crofts, S., Stanworth, A. & Enderlein, P. (2015) A protocol for the aerial survey of penguin colonies using UAVs. *Journal of Unmanned Vehicle Systems*, **3,** 95-101. https://doi.org/10.1139/juvs-2015-0006

Ritchie, E.G. & Johnson, C.N. (2009) Predator interactions, mesopredator release and biodiversity conservation. *Ecology Letters*, **12,** 982-998. https://doi.org/10.1111/j.1461-0248.2009.01347.x

Rowcliffe, J.M. & Carbone, C. (2008) Surveys using camera traps: are we looking to a brighter future? *Animal Conservation*, **11,** 185-186. https://doi.org/10.1111/j.1469-1795.2008.00180.x

Sarda-Palomera, F., Bota, G., Padilla, N., Brotons, L. & Sarda, F. (2017) Unmanned aircraft systems to unravel spatial and temporal factors affecting dynamics of colony formation and nesting success in birds. *Journal of Avian Biology*, **48,** 1273-1280. https://doi.org/10.1111/jav.01535

Sarda-Palomera, F., Bota, G., Vinolo, C., Pallares, O., Sazatornil, V., Brotons, L., Gomariz, S. & Sarda, F. (2012) Fine-scale bird monitoring from light unmanned aircraft systems. *Ibis*, **154,** 177-183.

Sigsgaard, E.E., Carl, H., Moller, P.R. & Thomsen, P.F. (2015) Monitoring the near-extinct European weather loach in Denmark based on environmental DNA from water samples. *Biological Conservation*, **183,** 46-52. https://doi.org/10.1016/j.biocon.2014.11.023

Smart, A.S., Tingley, R., Weeks, A.R., van Rooyen, A.R. & McCarthy, M.A. (2015) Environmental DNA sampling is more sensitive than a traditional survey technique for detecting an aquatic invader. *Ecological Applications*, **25,** 1944-1952. https://doi.org/10.1890/14-1751.1

Smart, A.S., Weeks, A.R., van Rooyen, A.R., Moore, A., McCarthy, M.A. & Tingley, R. (2016) Assessing the cost-efficiency of environmental DNA sampling. *Methods in Ecology and Evolution*, **7,** 1291-1298. https://doi.org/10.1111/2041-210x.12598

Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P. & Bouche, P. (2013) Unmanned aerial survey of elephants. *PloS One*, **8,** e54700. https://doi.org/10.1371/journal.pone.0054700

Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., Roberts, J.T. & Gittleman, J.L. (2013) Targeting global conservation funding to limit immediate biodiversity declines. *Proceedings of the National Academy of Sciences*, **110,** 12144-12148. https://doi.org/10.1073/pnas.1221370110

Watts, A.C., Perry, J.H., Smith, S.E., Burgess, M.A., Wilkinson, B.E., Szantoi, Z., Ifju, P.G. & Percival, H.F. (2010) Small unmanned aircraft systems for low-altitude aerial surveys. *Journal of Wildlife Management*, **74,** 1614-1619. https://doi.org/10.2193/2009-425

Weissensteiner, M.H., Poelstra, J.W. & Wolf, J.B.W. (2015) Low-budget ready-to-fly unmanned aerial vehicles: an effective tool for evaluating the nesting status of canopy-breeding bird species. *Journal of Avian Biology*, **46,** 425-430. https://doi.org/10.1111/jav.00619

Wich, S., Dellatore, D., Houghton, M., Ardi, R. & Koh, L.P. (2016) A preliminary assessment of using conservation drones for Sumatran orang-utan (Pongo abelii) distribution and density. *Journal of Unmanned Vehicle Systems*, **4,** 45-52. https://doi.org/10.1139/juvs-2015-0015

Wilson, A.M., Barr, J. & Zagorski, M. (2017) The feasibility of counting songbirds using unmanned aerial vehicles. *Auk*, **134,** 350-362. https://doi.org/10.1642/Auk-16-216.1

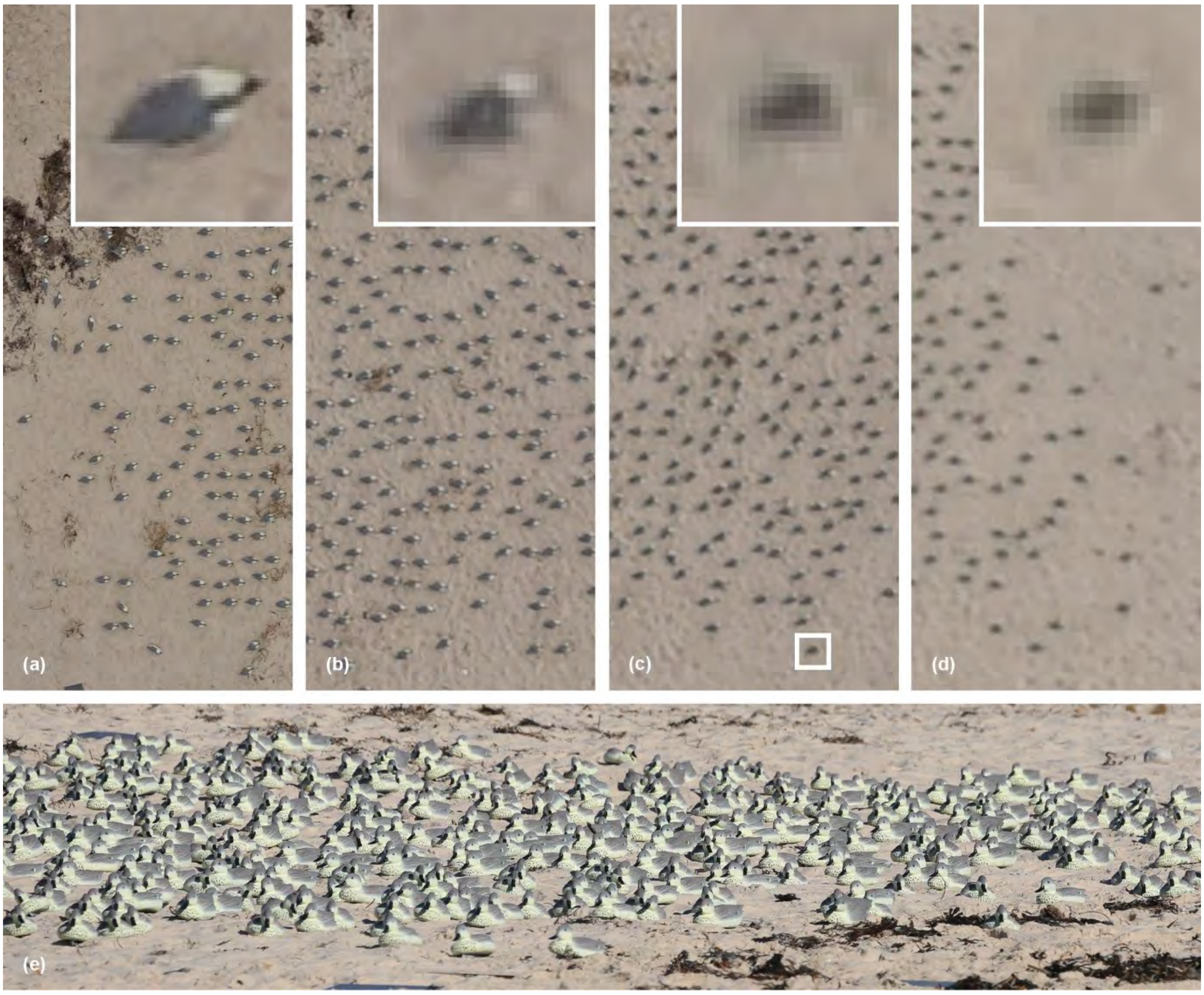


Figure 3.1: Aerial vantage of a replica seabird colony compared with the ground counter's viewpoint. One colony represented by a mosaic of images (a-d) photographed from an RPA-mounted camera at varying heights (30 m, 60 m, 90 m and 120 m) and resulting ground sample distances (GSD; 0.82 cm, 1.64 cm, 2.47 cm and 3.29 cm). Insets are of the same individual (square; c) at each height, displaying the decrease in resolution relative to an increase in GSD. (e) View of the colony from a ground counter's standing position.

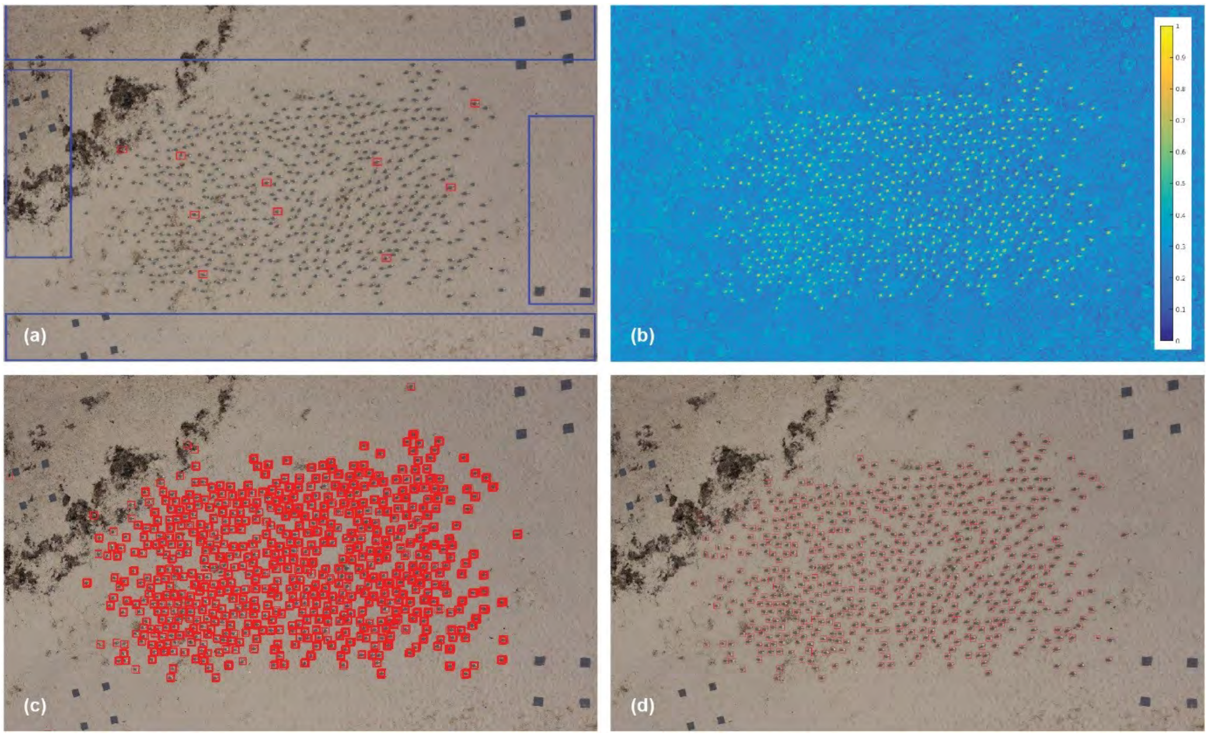


Figure 3.2: Semi-automated detection and counting of wildlife using computer vision techniques. (**a**) User annotation of perceived target objects (red) and background (blue). (**b**) Predicted likelihood (score) map generated by the trained classifier which has automatically determined which image features distinguish objects from background, independent of scale and orientation. Warmer colours indicate increasing likelihood of the pixel being a target object. (**c**) Target object proposals (red) computed by thresholding the score map. Object size is estimated from the annotations. (**d**) Final output (which includes a total count and detection co-ordinates) where detected individuals are delineated (red) after redundant detections have been automatically suppressed.

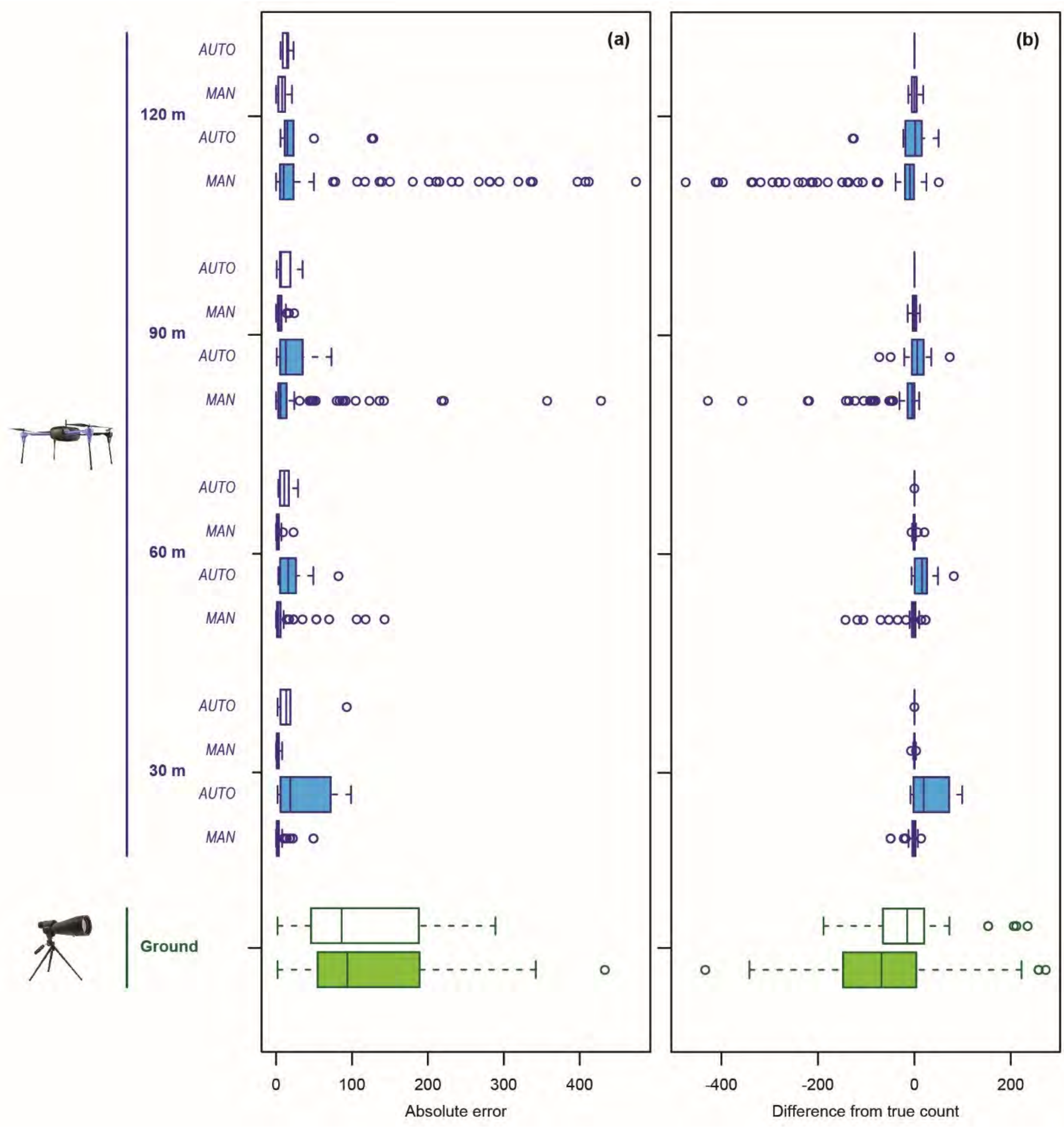


Figure 3.3: Accuracy and bias of RPA and traditional wildlife monitoring approaches. The absolute error (**a**) and difference from the true count (**b**) of each method. Data from all colonies (*n* = 10; shaded) and also for the subset of colonies with high-quality imagery (*n* = 6; unshaded) are presented for manual counts from RPA-derived imagery (blue) and ground counts (green). Manual (Man) and semi-automated (Auto) counts from RPA-derived imagery are displayed and data are grouped by height, which reflects ground sample distance (GSD; 30 m height = 0.82 cm GSD, 60 m = 1.64 cm, 90 m = 2.47 cm, 120 m = 3.29 cm).

Table S3.1: Mean percentage increase in accuracy of RPA wildlife monitoring approaches compared with the traditional ground count approach. Percentages are calculated for manual (*Man*) and semi-automated (*Auto*) counts from RPA-derived imagery using data from all colonies (n = 10) as well as the subset of colonies with high-quality imagery (n = 6). Data are grouped by height, which reflects ground sample distance (GSD; 30 m height = 0.82 cm GSD, 60 m = 1.64 cm, 90 m = 2.47 cm, 120 m = 3.29 cm).

Height (m)	**All colonies (%)**		**Colonies with high-quality imagery (%)**	
	Man	*Auto*	*Man*	*Auto*
30	96	77	98	88
60	90	84	97	88
90	74	80	94	89
120	43	77	92	85

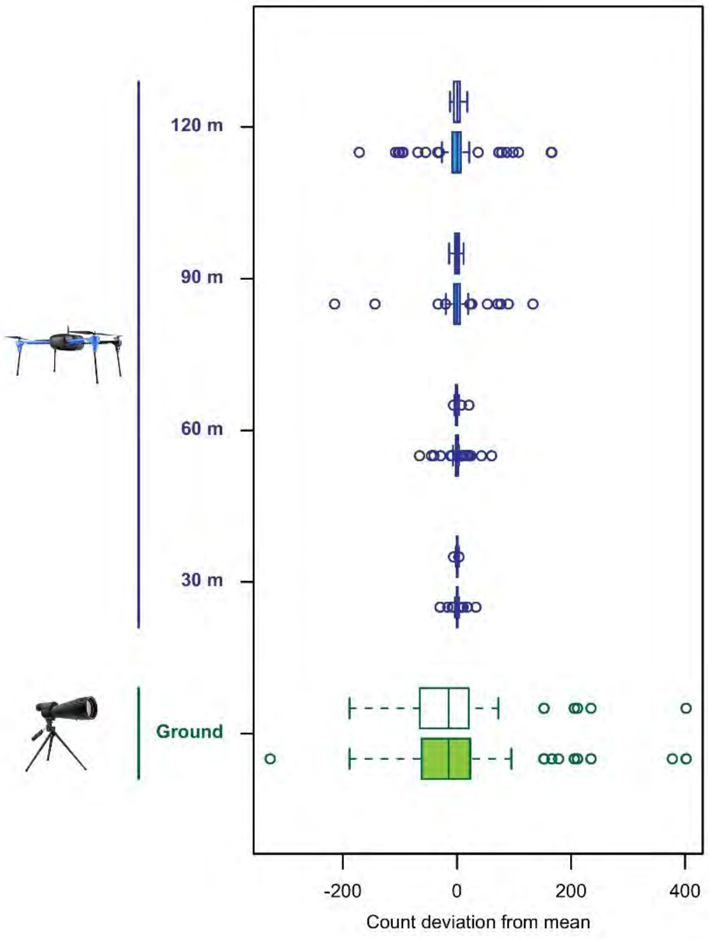


Figure S3.1: Precision of RPA and traditional wildlife monitoring approaches. Data from all colonies (*n* = 10; shaded, lower box in each course) and also for the subset of colonies with high-quality imagery (*n* = 6; unshaded, upper box in each course) are presented for manual counts from RPA-derived imagery (blue) and ground counts (green). Data are grouped by height, which reflects ground sample distance (GSD; 30 m height = 0.82 cm GSD, 60 m = 1.64 cm, 90 m = 2.47 cm, 120 m = 3.29 cm).

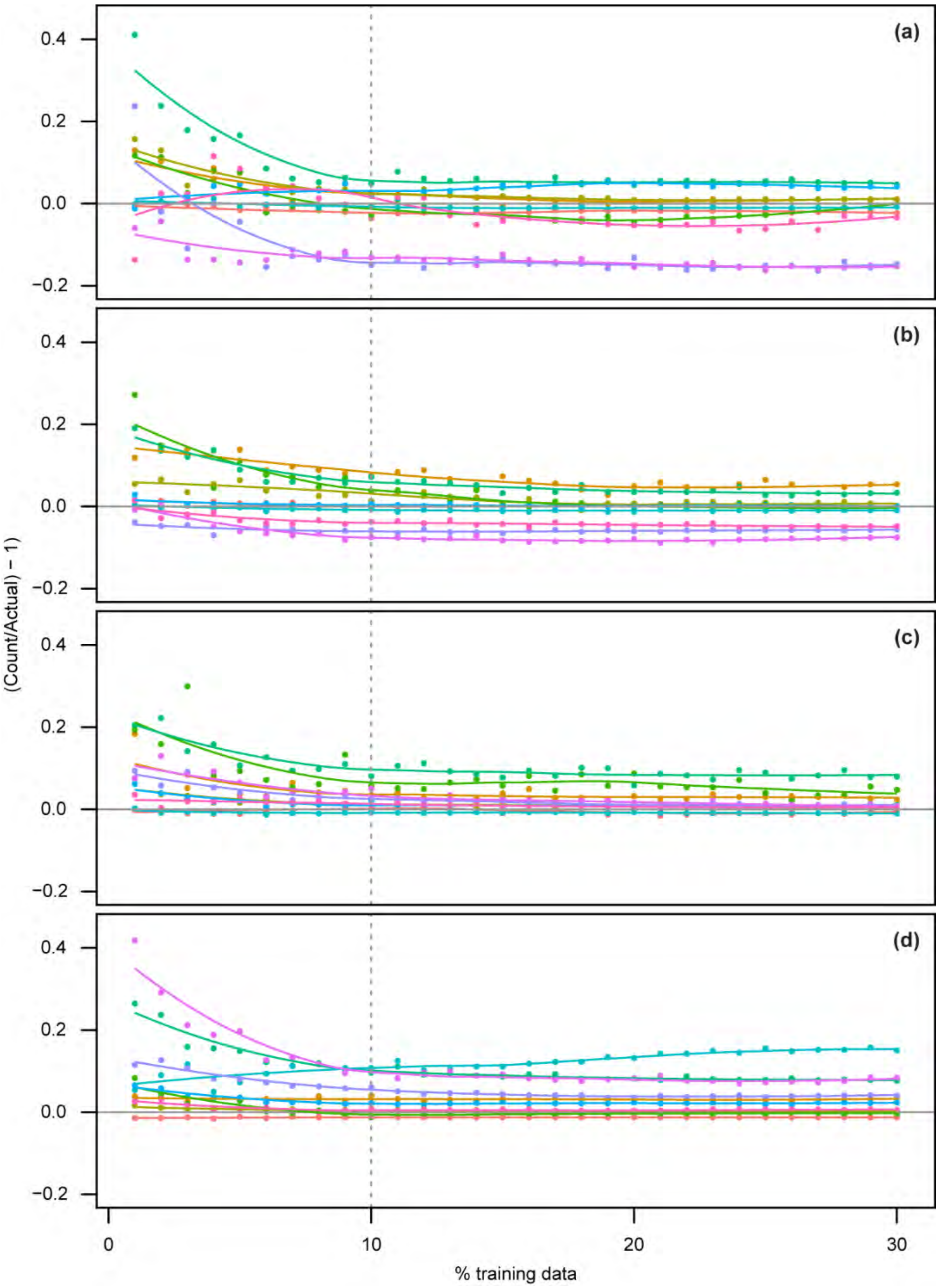


Figure S3.2: Accuracy of semi-automated counts from RPA-derived imagery with varied amounts of training data. Colonies (*n* = 10) are represented by individual colours at each height, which reflects ground sample distance (GSD; 120 m height = 3.29 cm GSD (**a**); 90 m = 2.47 cm (**b**); 60 m = 1.64 cm (**c**); 30 m = 0.82 cm (**d**)). Lowess smoothed trendlines are displayed. Analyses were computed using count estimates generated from 10% training data (dashed line).

Statement of authorship

Title of paper	Improving spatiotemporal monitoring of aggregated sentinel species with drones
Publication status	☐ Published ☐ Accepted for publication ☐ Submitted for publication ☑ Unpublished and unsubmitted work written in manuscript style
Publication details	Prepared for submission to Nature Ecology and Evolution (brief communication format)

Principal Author

Name of principal author (candidate)	Jarrod Hodgson		
Contribution to the paper	Conceptualisation, data collection, processing workflow, data analysis and writing.		
Overall percentage (%)	95		
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**	05/08/2020

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	Aleks Terauds		
Contribution to the paper	Supervision		
Signature		**Date**	05/08/2020

Name of co-author	Simon Goldsworthy		
Contribution to the paper	Supervision		
Signature		**Date**	05/08/2020

Name of co-author	Lian Pin Koh		
Contribution to the paper	Supervision		
Signature		**Date**	05/08/2020

4 Improving spatiotemporal monitoring of aggregated sentinel species with drones[5]

4.1 Abstract

As climate change continues to alter the global environment, more species will become extinct and species not currently of high conservation concern will become vulnerable. The ability to efficiently identify changes in wildlife abundance and distribution is essential to stem drastic increases in biodiversity loss, as well as to track the performance of climate change mitigation strategies. To do this, we present a generalisable drone-derived remote sensing technique requiring minimal user-input. Our approach achieves spatially accurate population monitoring of colonial birds, ideal sentinel species given their conspicuous breeding aggregations at all latitudes and timely amplification of trophic information.

4.2 Main text

Monitoring ecosystem sentinels can reveal changes in ecosystem function (Hazen *et al.* 2019). In the marine environment, the population trends and phenology of top predators such as seabirds are ideal for detecting variability and changes in ocean processes over multiple timescales. Conveniently, as most seabirds aggregate to breed along coastlines, on islands and on ice, remotely sensed data collected from air- and space-borne instruments can be used to estimate changes in their abundance. If imagery of sufficient spatiotemporal resolution can be collected of these colonies, and population data can be extracted automatically, there is the potential to rapidly detect ecosystem changes over large-scales.

While satellite imagery can be valuable for estimating the extent of large colonies of seabirds, drones are currently better suited to collecting higher spatial resolution data needed for monitoring the trajectories of these populations (Borowicz *et al.* 2018). The sub-centimetre image resolution that can be achieved with drones allows individual birds that can be seen

---

[5] Prepared for submission to *Nature Ecology and Evolution* (brief communication format)

from above to be readily delineated. Drone-facilitated monitoring also results in accurate abundance estimates which exceed those achieved using traditional ground-based methods (Hodgson *et al.* 2016; Hodgson *et al.* 2018). It also overcomes many of the difficulties of sampling hard to access sites and is likely to mitigate the disturbance impacts that can result from on-ground monitoring (Hodgson & Koh 2016; Borrelle & Fletcher 2017). Despite these benefits, drone-facilitated population monitoring of these sentinel species is not yet fully realised. Research in recent years has improved each part of the process, from data collection to analysis. What is lacking is a robust demonstration of the approach, with intra- and inter-seasonal and site replication. Such an example is needed to better convey the benefits of this remote sensing technique and facilitate broader uptake by practitioners.

Here, we validate drone-facilitated population monitoring for colonial birds. We used a small, affordable multirotor drone to fly autonomous missions to capture overlapping digital photographs of breeding sites. Our primary objective was to develop a transferable process to generate abundance estimates from the imagery with minimal user-input. Additionally, we sought to generate positional information for each bird of sufficient relative accuracy across the surveys to infer which birds made a breeding attempt.

We monitored a range of small to large colonial bird species over time. Drone-derived photographs of each survey (n = 46) were processed with a batch script (Figure S4.2) using a photogrammetry technique called ‘structure from motion’. For each survey, this process automatically reconstructed the environment using 3-dimensional point cloud that allowed the photographs to mosaicked into a single image that was free of distortion. These orthomosaics were co-registered with high precision using natural features (n = 4 – 8), which facilitated spatiotemporal analyses as each mosaic was located in the same, relative position in space. Repeated surveys were conducted at a tern (n = 11), cormorant (n = 4) and pelican (n = 31) breeding site. The suite of species provided variation in bird size (0.28 – 6.8 kg), nest-density (0.32 – 0.93 m mean nearest-neighbour distance) and habitat (Figure 4.1). The approach was successful for all three species, demonstrating it generalises across colonial birds and the different habitats in which they breed.

To investigate reproducibility of the survey technique and spatial accuracy over time, we focused on one of the species (Australian pelican, *Pelecanus conspicillatus*). An island in South Australia on which pelicans consistently breed was regularly sampled from the adjacent shore year-round, and at higher frequency during the breeding season (n = 31 surveys over 29 months). Pelicans were present for the majority of the surveys (68%) and abundance during each breeding season peaked in October. However, maximum abundance reduced considerably over the three breeding seasons (2017 = 3,953 individuals, 2019 = 305 individuals; Figure S4.1). This was reflected in the number of chicks detected on the island, with abundance peaking in December in each year (Figure S4.1).

We also developed a technique to use drone-derived imagery to infer the traditionally ground-collected parameter of breeding effort. Breeding attempts were defined as adults detected in the same location (< 40 cm) in consecutive surveys. Using data from the first two seasons, we found breeding effort decreased by 41.8% (Figure 4.2). We observed that colony sites between the two years rarely overlapped and also that vegetation growth patterns appear to be spatiotemporally associated with bird breeding (Figure 4.2). Our results demonstrate that drone-facilitated population monitoring of colonial birds that can be seen from above is not only robust across seasons and sites, but that the spatiotemporal insights exceed those achievable with traditional, ground-based techniques.

The precise co-registration of imagery across surveys shows this technique can be adapted for broad scientific inquiry at user-defined spatial and temporal resolution. Drone-facilitated monitoring provides a tremendous opportunity to extend understanding of the more specific breeding ecology of colonial birds, through to the environmental drivers influencing their demography and phenology. The technique is also suitable for other taxa who are not constrained to a nest. For example, imagery of aggregations of pinnipeds (e.g. elephant seals) could be processed with an adapted method. Larger buffers around individuals could be used to automatically delineate breeding harems and there is also potential for concurrent body condition monitoring (Alvarado *et al.* 2020; Hodgson *et al.* 2020).

It is conceivable that this approach could be fully automated if the manual detection of birds can be overcome. Researchers are continually refining computer vision and machine learning techniques to automate this process (Chabot & Francis 2016; Lyons *et al.* 2019), and ongoing advances in artificial intelligence may soon provide a solution. Once this step is automated with sufficient accuracy, the entire processing workflow presented here could be coded into a pipeline, benefitting from our co-ordinate derived metrics (e.g. breeding effort). This would provide drastic time- and cost-efficiencies.

Flexible monitoring techniques that can be applied to new areas will be vital as the range and trends in abundance of species continue to change in response to a changing climate. Birds, particularly those that aggregate to breed, are ideal indicators of the health and changes in the ecosystems that support them. We contend our technique is suitable for targeted data collection of unconcealed colonial birds at a global scale. Current consumer-grade drones can capture suitable resolution imagery at low cost. This means authorised local researchers and drone operators can work collaboratively to rapidly document the range and abundance of species at large scales. This technique could also be used to process other remotely sensed data of birds. With access to super-high resolution (e.g. < 10 cm) satellite data, the population trends of sentinels species could be quantified on an unprecedented, global scale.

While remotely collected data will not provide some of the detail possible through ground census techniques (Callaghan *et al.* 2018), the benefits eclipse the limitations for monitoring suitable colonial birds. Anderson and Gaston’s (2013) prediction that drone-derived data would revolutionise spatial ecology can now be realised for marine sentinels. Now, more than ever before, we need to harness technological solutions to collect and extract the data needed to improve our understanding of global ecosystem change and, ultimately, conserve biodiversity.

4.3 Materials and methods

4.3.1 Study sites

Three colonial bird species were monitored in South Australia. Australian pelicans (*Pelecanus conspicillatus*) on North Pelican Island, in the Coorong, (-36.043771, 139.558515) were sampled routinely (n = 31) between October 2017 and February 2020, encapsulating three breeding seasons. A crested tern (*Thalasseus bergii*) colony that formed on the same island was repeatedly surveyed (n = 11) during the 2017-18 summer. Black-faced cormorant (*Phalacrocorax fuscescens*) data was collected (n = 4) on a rock outcrop during routine drone-facilitated monitoring of pinnipeds in 2018 at Dangerous Reef, Spencer Gulf (-34.816993, 136.206227).

4.3.2 Drone flight protocol

A small, off-the-shelf quadcopter drone (Phantom 4 Pro, DJI) was used as a platform to collect high resolution, digital imagery of all colonies. Imagery was captured using the aircraft's integrated, gimballed sensor and lens (sensor: CMOS; sensor size: 13.2 x 8.8 mm; lens focal length (35 mm equivalent): 24 mm). The aircraft, including remote controller with tablet (iPad Mini 2, Apple) and hood, was prepared and calibrated for flight prior to each survey.

For each site, the same automated mission/s were flown each survey to collect digital photographs at nadir. The missions were planned, and subsequently piloted, using Ground Station Pro (GS Pro, DJI) at a height of 60 m above surface level. This height resulted in an intended ground sample distance of 1.6 cm/px. Front and side overlap were both set to 85%, with photographs (jpeg format, 5472 x 3648 px) captured using the 'at equal distance interval' mode which produced an intended flight speed of 4.5 m/s and a capture interval of approximately 2 seconds. The aircraft was launched from the shore adjacent the island (Coorong) or from a boat (Dangerous Reef). All flights were in accordance with local regulations and permits, and flown by the same licensed pilot.

4.3.3 Image processing

Digital photographs were grouped by survey. Each group was manually reviewed and unsatisfactory images (e.g. overexposed photographs due to light reflecting on water) were removed. Datasets were then batch processed using a python script in the photogrammetry pipeline software Agisoft Metashape Professional (version 1.5.2, Agisoft, LLC, St. Petersburg, Russia)(Appendix Code A1). After initial processing, a selection of the same, discrete natural features from each survey were labelled and used as ground control points for co-registration of survey products (i.e. to ensure each orthomosaic was in approximately the same position in 3-dimensional space). Ground control could be automated if coded targets of known positions were placed in the study sites (for Supplementary Information in Hodgson *et* *al.* 2020). Then, batch processing was resumed to generate a variety of products at medium-high quality (see Appendix Table A2 for processing parameters).

4.3.4 Detecting individual birds

Orthomosaics were imported as raster layers into an open-source geographical information system application, QGIS (version 3.8.3, QGIS Development Team). After ensuring orthomosaics were free of processing artefacts, the abundance of birds for each survey was determined using a standardised technique (Hodgson *et al.* 2016; Hodgson *et al.* 2018). To do this, a 15 m grid was overlayed and individuals were manually detected and digitised using a point shapefile (one file per class, per species, per survey). The same person completed all annotations by moving cell-by-cell (left-to-right, top-to-bottom) across the island and zooming as needed to error-check detections. When necessary, the annotator toggled between sequential surveys to differentiate birds from other features (e.g. a rock versus a small, down-covered chick). Only non-flying individuals above the high-water line were digitised (white polygon; Figure 4.2). For pelicans, individuals were categorised into two classes using standard features and behavioural characteristics:

- Adult: individuals of mature size in adult plumage. This class included courting birds (which, for pelicans, could often be differentiated by their gular pouch colouring and ‘pairing’ behaviour), incubating individuals which were at a consistent density and adult birds of unknown breeding status. Dead birds were excluded.
- Chick: this class ranged from small, down-covered chicks to fledglings. As chicks are altricial and naked when the hatch, they are restricted to the nest and are covered by their parents until they can independently thermoregulate. The period chicks are restricted to the nest typically lasts for 10 days (Johnston 2016). Additionally, given pelicans usually lay multiple eggs but ultimately raise a maximum of one to fledging, dead chicks were not digitised.

Shapefiles were exported to provide a total count of each class per survey.

4.3.5 Automating the estimation of breeding effort

When pelicans were breeding, surveys were completed at a frequency less than their incubation period. This meant there were multiple opportunities to image a given breeding attempt, which has a duration greater than the incubation period given at least one bird is present in that location for nest preparation and hatchling incubation if the attempt is successful. Breeding effort (nests) were defined as an adult bird in the same position in two or more consecutive surveys. To automate this classification, a series of steps were completed using a processing model (Figure S4.2). The script took all shapefiles of adult detections (e.g. 12) during one breeding period (< 12 months) as inputs. These were merged into a single layer reprojected in the appropriate coordinate system, with every point then buffered by 0.2

m. This value was selected by trial and error to encapsulate variability in: bird position on the nest, the position of the detection on the bird and the co-registration of the orthomosaics. Resulting vectors that were overlaying were dissolved and separated into individual parts (yellow polygons; Figure 4.1A). Then, by iterating through the input shapefiles, the individual bird detections (points) were added to the 'parts' that had been created (points in the insets; Figure 4.1A). This resulted in birds that had been detected within 0.2 m through the sampling period being grouped together as a 'nest'. Conveniently, this meant any partners resting next to the incubating bird were 'absorbed' into that nest. A centroid was generated for each group to create a new point shapefile and metadata (i.e. bird presence/absence for each nest across time points) written into the attribute table. To remove any instances where birds in the same position in non-consecutive surveys had been falsely deemed a 'nest', the attribute data was processed using an R script which calculated the length of time (days) each 'nest' persisted in consecutive surveys (using the greatest length in the unlikely case of a nest having two periods with consecutive detections) (R Core Team 2018). These cleaned data were reimported to QGIS to visualise nests (Figure 4.2).

4.4 Acknowledgements

We recognise the support of Ramesh Raja Segaran and the Unmanned Research Aircraft Facility.

4.5 Funding

This study received partial funding and logistical support from the Department for Environment and Water. J.C.H. is supported by an Australian Government Research Training Program Scholarship.

4.6 Author contributions

J.C.H. conceived the study. J.C.H and L.P.K. designed the study. J.C.H. collected the field data. J.C.H led analysing the data and drafting the manuscript with contributions from all authors.

4.7 References

Alvarado, D.C., Robinson, P.W., Frasson, N.C., Costa, D.P. & Beltran, R.S. (2020) Calibration of aerial photogrammetry to estimate elephant seal mass. *Marine Mammal Science*. https://doi.org/10.1111/mms.12714

Anderson, K. & Gaston, K.J. (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment,* **11,** 138-146. https://doi.org/10.1890/120150

Borowicz, A., McDowall, P., Youngflesh, C., Sayre-McCord, T., Clucas, G., Herman, R., Forrest, S., Rider, M., Schwaller, M., Hart, T., Jenouvrier, S., Polito, M.J., Singh, H. & Lynch, H.J. (2018) Multi-modal survey of Adelie penguin mega-colonies reveals the Danger Islands as a seabird hotspot. *Scientific Reports,* **8,** 3926. https://doi.org/10.1038/s41598-018-22313-w

Borrelle, S.B. & Fletcher, A.T. (2017) Will drones reduce investigator disturbance to surface-nesting seabirds? *Marine Ornithology,* **45,** 89-94.

Callaghan, C.T., Brandis, K.J., Lyons, M.B., Ryall, S. & Kingsford, R.T. (2018) A comment on the limitations of uavs in wildlife research - The example of colonial nesting waterbirds. *Journal of Avian Biology*. https://doi.org/10.1111/jav.01825

Chabot, D. & Francis, C.M. (2016) Computer-automated bird detection and counts in high-resolution aerial images: a review. *Journal of Field Ornithology,* **87,** 343-359. https://doi.org/10.1111/jofo.12171

Hazen, E.L., Abrahms, B., Brodie, S., Carroll, G., Jacox, M.G., Savoca, M.S., Scales, K.L., Sydeman, W.J. & Bograd, S.J. (2019) Marine top predators as climate and ecosystem sentinels. *Frontiers in Ecology and the Environment,* **17,** 565-574. https://doi.org/10.1002/fee.2125

Hodgson, J.C., Baylis, S.M., Mott, R., Herrod, A. & Clarke, R.H. (2016) Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports,* **6,** 22574. https://doi.org/10.1038/srep22574

Hodgson, J.C., Holman, D., Terauds, A., Koh, L.P. & Goldsworthy, S.D. (2020) Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics. *Biological Conservation,* **242,** 108402. https://doi.org/10.1016/j.biocon.2019.108402

Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology,* **26,** R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution,* **9,** 1160-1167. https://doi.org/10.1111/2041-210x.12974

Johnston, G.R. (2016) Breeding Biology of Australian Pelicans (Pelecanus conspicillatus) on the Coast of South Australia. *Waterbirds,* **39,** 300-305. https://doi.org/10.1675/063.039.0310

Lyons, M.B., Brandis, K.J., Murray, N.J., Wilshire, J.H., McCann, J.A., Kingsford, R.T. & Callaghan, C.T. (2019) Monitoring large and complex wildlife aggregations with drones. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210x.13194

R Core Team (2018) R: A language and environment for statistical computing. Vienna, Austria. *http://www.R-project.org*.

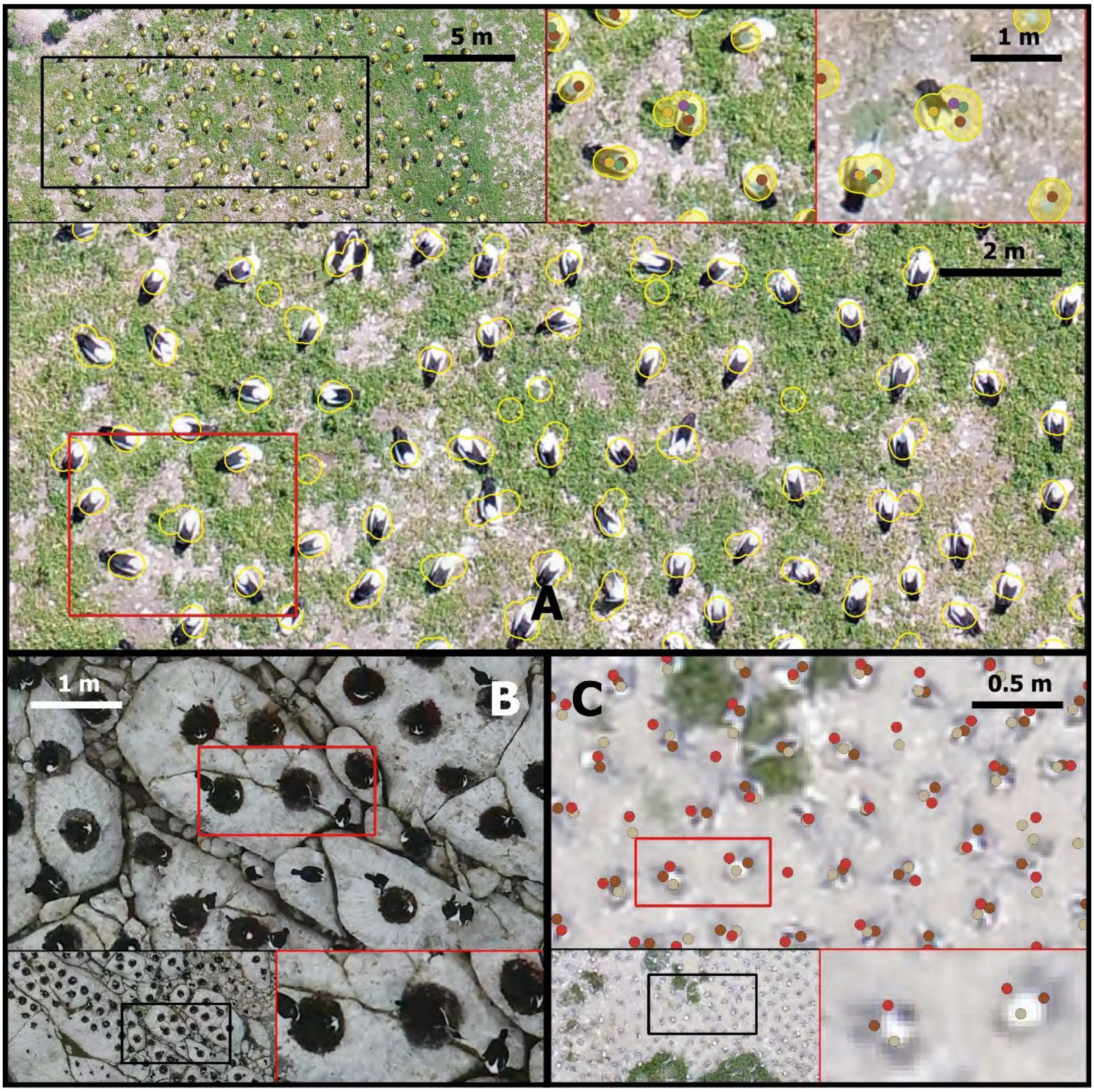


Figure 4.1. Drone-facilitated population monitoring generalises across colonial bird species. A – Australian pelican (*Pelecanus conspicillatus*), a large colonial waterbird species, were repeatedly monitored at one site over three breeding seasons. The yellow polygons delineate ‘nests’, defined as areas where adult birds that have been detected within 40 cm over consecutive surveys. Coloured circles represent the position of detection on each survey, which demonstrates the precision of the imagery co-registration. See Figure 4.2.
B – a black-faced cormorant (*Phalacrocorax fuscescens*) breeding colony on a rock outcrop. These are a medium sized species.
C – an example of a small seabird species being monitored, the crested tern (*Thalasseus bergii*).

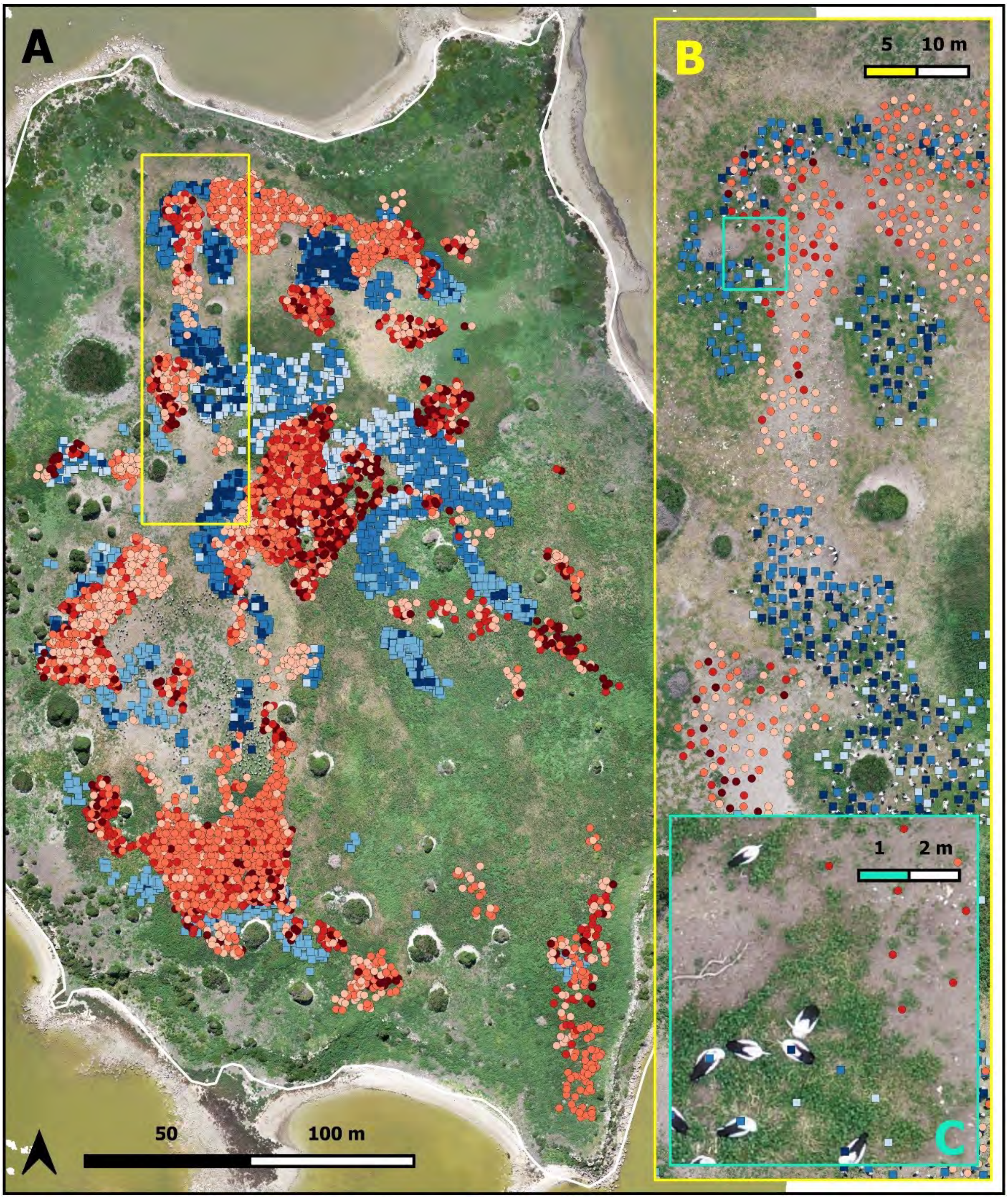


Figure 4.2. Drone-facilitated wildlife surveys (n = 25) are spatially accurate over time. Breeding effort of Australian pelican (*Pelecanus conspicillatus*) at a key site over two breeding seasons (2017-18 = red circles, 2018-19 = blue squares). Drone-derived geo-located nests (2017-18 = 3,965; 2018-19 = 2,308) are defined as point locations where an adult bird was present (within 0.2 m) in two or more consecutive surveys. Colour intensity of symbols represents nesting duration (i.e. darker shades = nest occupied for more consecutive surveys). The orthomosaic displayed is of the same survey (T16, September 2018). **A** – the extent of breeding at the site. Detections were constrained within the island perimeter (white polygon). **B** – colony locations in opposing years depicting pelican nest-site choice and vegetation

response to nesting impacts. **C** – examples of the technique detecting two nests with partner birds present, and one bird assumed not to have made a breeding attempt at that location (i.e. the unmarked birds).

Appendix Table A4.1. Agisoft Metashape processing parameters. Chosen parameters for initial (prior to co-registration) and final batch processing of imagery.

Parameters	**Processing parameters**	
	Initial stage	Final stage
Point cloud – alignment		
Accuracy	Highest	Highest
Generic preselection	Yes	Yes
Reference preselection	No	No
Key point limit	40,000	40,000
Tie point limit	4,000	4,000
Adaptive camera model fitting	Yes	Yes
Dense point cloud		
Depth map quality	High	Ultra high
Depth map filtering mode	Mild	Mild
Model – reconstruction		
Surface type	Height field	Height field
Source data	Dense cloud	Dense cloud
Interpolation	Enabled	Enabled
Strict volumetric masks	No	No
Texturing		
Blending mode	Mosaic	Mosaic
Enable hole filling	Yes	Yes
Enable ghosting filter	Yes	Yes
DEM		
Source data	Dense cloud	Dense cloud
Interpolation	Enabled	Enabled
Orthomosaic		
Blending mode	Mosaic	Mosaic
Surface	DEM	DEM
Enable hole filling	Yes	Yes

Appendix Code A4.1. Agisoft Metashape processing script

```
import os
import Metashape

#path where images are stored
main_path = r"D:\Data"  # Alter this as needed

#path where the scalebars.csv file is stored
#scalebar_path = r"D:\Data\Scalebars\scalebars.csv"

paths = os.listdir(main_path)

lstpaths = [os.path.join(main_path, x) for x in paths]

print(lstpaths)

basedir, imagedir = os.path.split(main_path)
print(basedir)

if not os.path.exists(basedir + r"\Projects"):
    os.makedirs(basedir + r'\Projects')

if not os.path.exists(basedir + r"\Exports"):
    os.makedirs(basedir + r"\Exports")

def process(input_path):

    print(input_path)
    project_name = os.path.basename(input_path)
    print(project_name)
    project_path = basedir + r"\Projects\\" + os.path.basename(os.path.normpath(input_path))
    global doc
    doc = Metashape.app.document
    doc.save(project_path + "_project.psx")

    #app = QtGui.QApplication.instance()
    #parent = app.activeWindow()

    #path to photos
    path_photos = input_path
    path_export = basedir + r"\Exports\\" + os.path.basename(os.path.normpath(input_path))
    #print(path_export) diagnostic

        ####################################################################
####################################

    #processing parameters
    accuracy = Metashape.Accuracy.HighAccuracy  #align photos accuracy
    #preselection = Metashape.Preselection.GenericPreselection
```

```
    keypoints = 40000 #align photos key point limit
    tiepoints = 4000 #align photos tie point limit
    source = Metashape.DataSource.DenseCloudData #build mesh source
    surface = Metashape.SurfaceType.HeightField #build mesh surface type
    quality = Metashape.Quality.HighQuality #build dense cloud quality
    filtering = Metashape.FilterMode.MildFiltering #depth filtering
    interpolation = Metashape.Interpolation.EnabledInterpolation #build mesh interpolation
    face_num = Metashape.FaceCount.HighFaceCount #build mesh polygon count
    mapping = Metashape.MappingMode.AdaptiveOrthophotoMapping #build texture
mapping
    surface1 = Metashape.DataSource.ElevationData #build ortho surface type
    pointformat = Metashape.PointsFormat.PointsFormatLAZ
    rasterformat = Metashape.RasterFormat.RasterFormatTiles
    tiff_compression = Metashape.TiffCompression.TiffCompressionNone
    #cref = Metashape.CoordinateSystem
    #projection = Metashape.CoordinateSystem("EPSG::4326")
    #atlas_size = 8192
    blending = Metashape.BlendingMode.MosaicBlending #blending mode
    color_corr = False
    #elevation_data = Metashape.

        ####################################################################
####################################

    #LOAD IMAGES

    print("Script started")

    #remove existing chunk
    chunk = doc.chunk
    doc.remove(chunk)
    #creating new chunk
    doc.addChunk()
    chunk = doc.chunks[-1]
    chunk.label = input_path
    #chunk.crs = Metashape.CoordinateSystem("EPSG::4326")

        #camera.label = camera.path.rsplit("/",1)[1]

    #loading images
    image_list = os.listdir(path_photos)
    photo_list = list()
    for photo in image_list:
        if ("jpg" or "jpeg" or "JPG" or "JPEG") in photo.lower():
            photo_list.append(path_photos + "\\" + photo)

    chunk.addPhotos(photo_list)
    chunk.addSensor()
    doc.save(chunks = [doc.chunk])
    sensor = chunk.addSensor()
```

```
            ##########################################################################
####################################

            #CALCULATE AND OUTPUT IMAGE QUALITY
    chunk.estimateImageQuality()

    file = open(path_export + "_Cameras.txt", "wt")
    for camera in chunk.cameras:
        if "Image/Quality" in camera.meta.keys():
            file.write(path_export + ", " + project_name + ", " + camera.label + ", " +
camera.meta["Image/Quality"]+ "\n")
        else:
            file.write("There are no camera quality values to export - why not?")
    file.close()


##########################################################################
##############################

            #ALIGN PHOTOS
    #align photos
    chunk.matchPhotos(accuracy = accuracy, generic_preselection = True,
reference_preselection = False, filter_mask = False, keypoint_limit = keypoints,
tiepoint_limit = tiepoints)
    chunk.alignCameras(adaptive_fitting = True)


##########################################################################
##############################

            ##COREGISTER HERE IF NEEDED

            ##########################################################################
####################################

            #BUILD PRODUCTS AND EXPORT

    #building dense cloud
    Metashape.app.gpu_mask = 1  #GPU devices binary mask
    Metashape.app.cpu_enable = True
    chunk.buildDepthMaps(quality = quality, filter = filtering)
    chunk.buildDenseCloud(point_colors = True)

    doc.save(chunks = [doc.chunk])

            #building mesh
    chunk.buildModel(surface = surface, source = source, interpolation = interpolation,
face_count = face_num)
```

```
    #build texture
    chunk.buildUV(mapping = mapping, count = 1)
    chunk.buildTexture(blending = blending)

    doc.save(chunks = [doc.chunk])

        #build DEM
    chunk.buildDem(source = source, interpolation = interpolation)

    #Build Orthomosaic
    chunk.buildOrthomosaic(surface = surface1, blending = blending, fill_holes = True)

    doc.save(chunks = [doc.chunk])

    Metashape.app.update()

        ######################################################################
####################################

    #EXPORT PRODUCTS

    chunk.exportPoints(path_export + ".laz", source = source, format = pointformat, colors =
True, projection = projection)
    chunk.exportOrthomosaic(path_export + "_Ortho.tif", format = rasterformat,
tiff_compression = tiff_compression)
    chunk.exportDem(path_export + "_DEM.tif", format = rasterformat)
    chunk.exportReport(path_export + "_Report.pdf", title = project_name)

    doc.save(chunks = [doc.chunk])

    print("Script finished")

    #Metashape.app.addMenuItem("Process #", process)


for path in lstpaths:
    process(path)

print('Congratulations, all projects have finished! The script is complete')
```

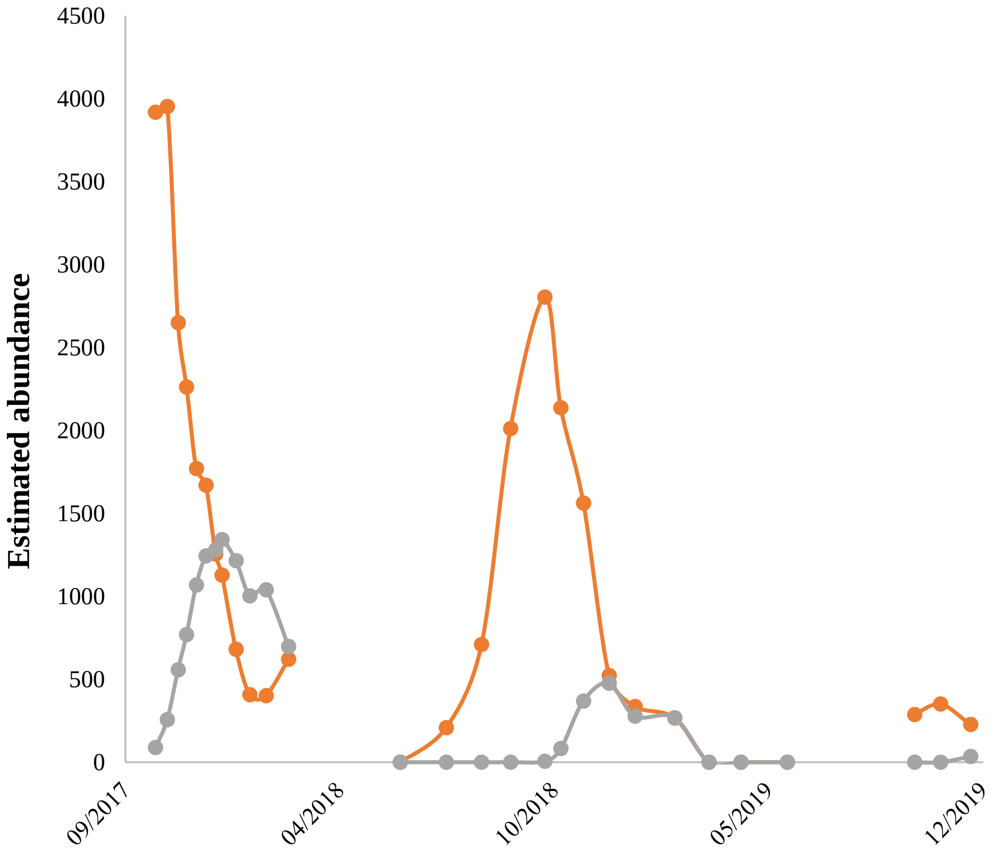


Figure S4.1. Estimated abundance from drone-facilitated population monitoring of Australia pelican (*Pelecanus conspicillatus*) on North Pelican Island, South Australia. Individuals (adults = orange, chicks = grey) were detected in orthomosaics using repeated surveys (n = 31) over three breeding seasons.

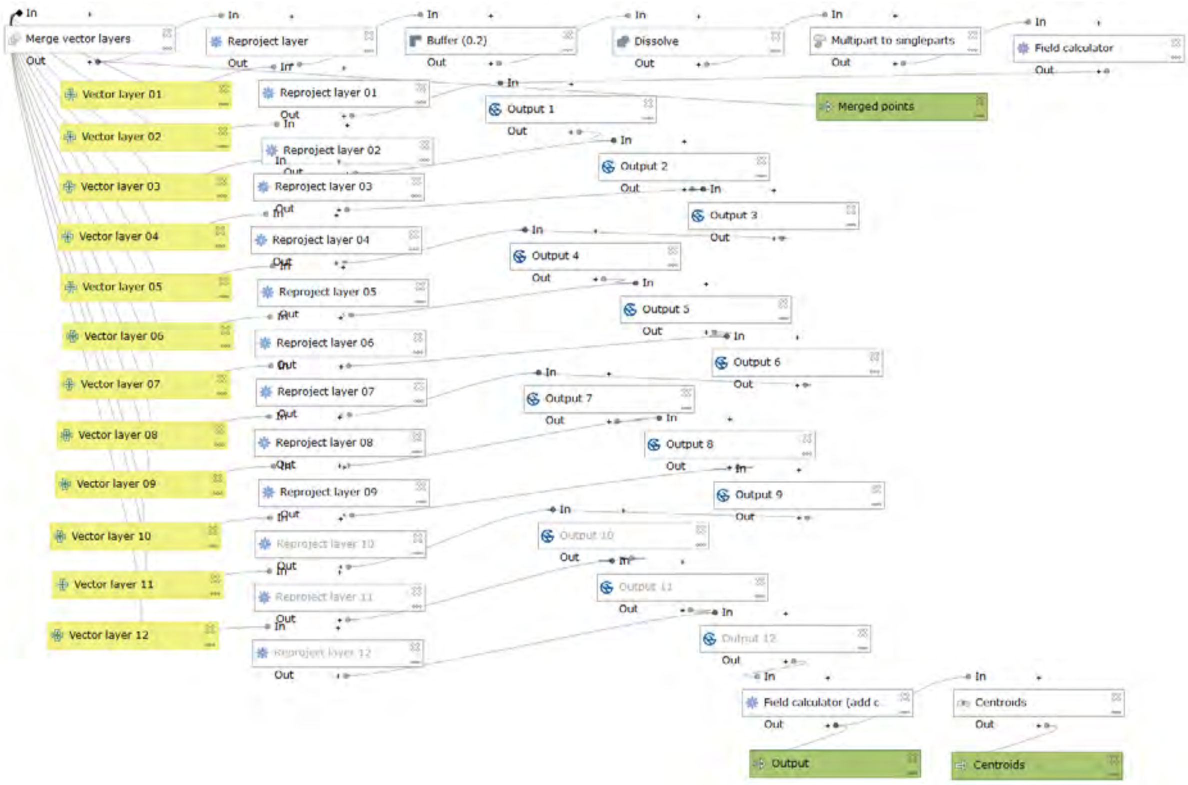


Figure S4.2. Geographic Information System (GIS) processing model used to automate the estimation of breeding effort.

Statement of authorship

Title of paper	Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics
Publication status	☑ Published ☐ Accepted for publication ☐ Submitted for publication ☐ Unpublished and unsubmitted work written in manuscript style
Publication details	Hodgson, J.C., Holman, D., Terauds, A., Koh, L.P. & Goldsworthy, S.D. (2020) Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics. Biological Conservation, 242, 108402. https://doi.org/10.1016/j.biocon.2019.108402

Principal Author

Name of principal author (candidate)	Jarrod Hodgson		
Contribution to the paper[6]	Conceptualisation, methodology, software, validation, formal analysis, investigation, resources, data curation, writing – original draft, writing – review and editing, visualisation, project administration, funding acquisition.		
Overall percentage (%)	70		
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**	25/07/2020

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	Dirk Holman		
Contribution to the paper	Investigation, writing – review and editing.		
Signature		**Date**	27/07/2020

---

[6] All contributions are described using the CRediT (Contributor Roles Taxonomy) authorship contribution statement guidelines

Name of co-author	Aleks Terauds		
Contribution to the paper	Writing – review and editing, supervision.		
Signature		**Date**	27/07/2020

Name of co-author	Lian Pin Koh		
Contribution to the paper	Methodology, writing – review and editing, supervision.		
Signature		**Date**	25/07/2020

Name of co-author	Simon Goldsworthy		
Contribution to the paper	Methodology, investigation, data curation, writing – review and editing, supervision, project administration, funding acquisition.		
Signature		**Date**	28/07/2020

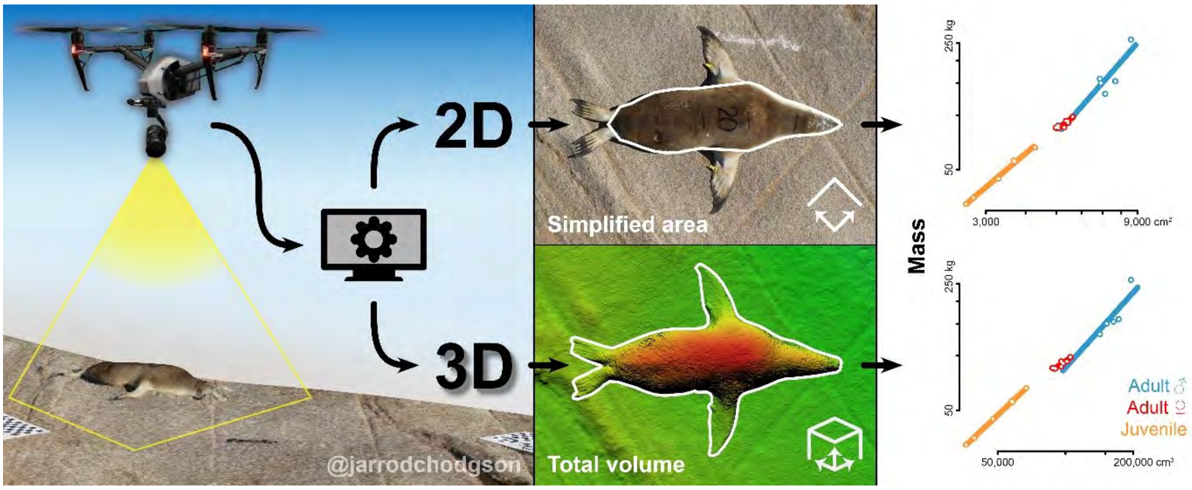


Figure 5.0. Graphical abstract.

5 Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics[7]

5.1 Abstract

Understanding causes of population change is critical for conservation. Quantifying them can be difficult, especially for hard to sample animals like marine vertebrates (e.g. pinnipeds). One solution is to investigate spatiotemporal differences in a species' body condition by measuring body size and mass. Collecting traditional morphological measurements is risky and labour intensive, making less invasive and more efficient techniques desirable. Using Australian sea lions (*Neophoca cinerea*) of known size and mass as a case study, we tested the suitability of using drone-derived photogrammetry to estimate morphological measurements and assess body condition. Drone-derived measurements were precise and without bias. Animal mass was highly correlated with the 2-dimensional and 3-dimensional measurements of simplified area and volume, explaining > 77% and > 84% (all $P < 0.01$) of the variation in mass, depending on the age-sex class. The juvenile class exhibited the strongest associations (both 2D and 3D $R^2 > 0.99$). Using each measurement as a proxy for mass, we calculated body condition indices for each class by standardising the variables by animal length. Photogrammetric indices ranked individuals comparably to those generated from ground-collected data ($r_s = 0.77 – 1$, depending on age-sex class). Our technique provides a workflow for the non-invasive collection of morphometric data to quantify animal condition, which is transferrable to other pinniped species with species-specific calibration. It will also facilitate the efficient collection of morphometric data of vertebrates from remotely sensed imagery.

---

[7] Hodgson, J.C., Holman, D., Terauds, A., Koh, L.P. & Goldsworthy, S.D. (2020) Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics. *Biological Conservation,* **242,** 108402. https://doi.org/10.1016/j.biocon.2019.108402

5.2 Introduction

Wildlife are threatened by anthropogenic impacts. Human activities have changed the global climate and biodiversity at unprecedented rates (Steffen *et al.* 2006). Analyses of time-series species data indicate that the animal extinction rate in the last century is up to 100 times higher than the background rate (Ceballos *et al.* 2015), and possibly even higher (Pimm *et al.* 2014). Estimates indicate that a sixth mass extinction is already underway (Ceballos, Ehrlich & Dirzo 2017), reinforcing the need for intensified conservation efforts to reduce the rate of biodiversity loss.

While measuring spatial and temporal change at the community level (e.g. species richness) is important, understanding the impact of threats at the population level is critical to mitigating extinctions. For example, detecting changes in abundance, and quantifying distribution and reproductive success over time are fundamental to effective conservation. However, estimating absolute values (e.g. absolute abundance) is often difficult and cost prohibitive where conservation funding is limited (Waldron *et al.* 2013). In many cases, relative measurements (e.g. an index of abundance) that are statistically robust and cost effective can be employed (e.g. Hopkins & Kennedy 2004). Such metrics provide the opportunity to detect spatial and temporal variations at the population scale, which can be used to better understand the mechanisms underlying change. In the case of population trajectories, understanding the underlying causes is important for informed conservation management (Krebs 1991; Keith *et al.* 2015).

Body condition can be used to investigate drivers of population change. Although terminology and definitions vary, body condition indices (BCIs) have been used by ecologists as a surrogate for fitness or fitness-related traits (Stevenson & Woods 2006). Specifically, many BCIs seek to non-destructively estimate the nutritional state of an animal (i.e. relative fat reserve), based on the assumption that this is a likely indicator of factors such as past foraging success and ability to cope with environmental pressures, which may ultimately impact fitness (Jakob, Marshall & Uetz 1996). Generally, BCIs use a measure of body mass standardised by a linear measure of body size to help differentiate individuals of the same length but different masses. Two main techniques for calculating a BCI are: a simple ‘ratio index’ (e.g. body mass divided by length) or a ‘residual index’ (i.e. body mass regressed on body size after appropriate transformations) where the residual distances of individual points from the regression line serve as the estimators of condition (Jakob, Marshall & Uetz 1996; Schulte-Hostedde *et al.* 2005). While some limitations of BCIs have been identified (Green 2001; Peig & Green 2010; Cox, Calsbeek & Blanckenhorn 2015; Wilder, Raubenheimer & Simpson 2016), when implemented appropriately they provide a useful metric for rapidly investigating the health of a population (e.g. Bradshaw *et al.* 2000). This may be especially valuable for monitoring indicator species (Siddig *et al.* 2016; Hazen *et al.* 2019), such as many marine mammals, as geographical variation in condition may reflect regional variation in the health of the ecosystems that support them (Zacharias & Roff 2001). Collecting morphometric data that underpin BCIs of marine mammals is challenging, as they are often highly mobile, have large ranges and spend limited or no time ashore. Sampling can also require complex, risky techniques (e.g. anaesthesia). For these reasons, time and cost-efficient data collection techniques that mitigate the risks of invasive sampling are desirable.

Photogrammetry, the science of making measurements through the use of photographs (Baker 1960), has been used to estimate a variety of morphological measurements in mammals (Postma *et al.* 2015). Once calibrated, this technique can remove the need for animal handling, reduce disturbance and provide field efficiency, resulting in greater sample sizes. The technique has been used for marine vertebrates that can be observed at the surface, such as cetaceans (Cheney *et al.* 2018; Noren *et al.* 2019), and taxa that congregate on land to breed or rest, including pinnipeds (Sweeney *et al.* 2015). Techniques that provide scale to ground-acquired photographs, such as placing an object of known size near to the animal, have been used to estimate the size and mass of a variety of seal species (Haley, Deutsch & Leboeue 1991; Bell, Hindell & Burton 1997; Ireland *et al.* 2006; McFadden, Worthy & Lacher 2006; Beltran *et al.* 2018). Scaling in single-photograph studies has also been achieved by measuring the distance between the sensor and the focal individual with a laser distance metre (Meise *et al.* 2014). Multiple ground-acquired photographs captured either synchronously (Steller sea lions (Eumetopias jubatus);Waite *et al.* 2007) or sequentially (southern elephant seals (Mirounga leonina); de Bruyn *et al.* 2009) have been used to create three-dimensional reconstructions of pinnipeds. These techniques have overcome some of the constraints of single-photograph approaches, which typically require specific animal postures and camera orientations.

Recent advances in drone (also known as remotely piloted aircraft, RPA) technology have provided researchers with a powerful tool for robust, marine mammal photogrammetry (Joyce *et al.* 2019). Compared to remote sensing instruments mounted to spacecraft and conventional aircraft, drones are well suited to collecting fine spatial resolution data needed for morphometric analyses (Johnston 2019). For example, single images have been used to measure whales (Durban *et al.* 2015; Christiansen *et al.* 2019; Gray *et al.* 2019), provide estimates of the mother-calf energy transfer in southern right whales (Eubalaena australis; Christiansen *et al.* 2018), and predict the mass of adult female leopard seals (Hydrurga leptonyx; Krause *et al.* 2017). Allan *et al.* (2019) used mosaicked, geo-referenced imagery (i.e. an orthomosaic) to estimate the length and auxiliary girth of Australian fur seals (*Arctocephalus pusillus doriferus*). These recent studies demonstrate the tool's diverse utility for ecological research applications beyond estimating pinniped presence and abundance (e.g. Koski *et al.* 2009; Hodgson, Kelly & Peel 2013; Adame *et al.* 2017; Johnston *et al.* 2017; McIntosh, Holmberg & Dann 2018). However, as the accuracy of drone-derived photogrammetry has only been directly tested for one age-sex class of a single species of pinniped (Krause *et al.* 2017), the technique requires broader validation.

We investigated the ability of using drone-acquired imagery and photogrammetry to quantify the morphology and condition of the Australian sea lion (ASL; *Neophoca cinerea*), which is classified as endangered by the International Union for the Conservation of Nature (IUCN; Goldsworthy 2015). The species is endemic to Australia and breeds primarily on islands off the southern and south-western coasts (Gales, Shaughnessy & Dennis 1994; Shaughnessy *et al.* 2011). Sealing in the 18th and early 19th centuries by European colonists reduced distribution and population size to an unknown extent (Ling 1999). Although now protected, the cumulative impact of localised threats such as bycatch from demersal gillnet fisheries and pollution, as well as global-scale threats such as entanglement in marine debris and impacts related to climate-change, ASL in South Australia have declined by an estimated 78% over the past three generations (ca 38 years; Page *et al.* 2004; Goldsworthy & Page 2007; Goldsworthy *et al.* 2010; Australian Government 2013; Goldsworthy *et al.* 2015). The species' low abundance, rapid decline, genetically-fragmented range and complex life history (e.g. non-annual and temporally asynchronous breeding), mean enhanced understanding is needed to inform conservation and management measures. As drone-derived morphometric data can be collected non-invasively, a robust and scalable technique can provide time-critical quantification of animal size across subpopulations without subjecting animals to the considerable risks of anaesthesia traditionally required to collect measurements. If this study generates accurate morphometric data, the techniques outlined could be used to investigate spatial and temporal variations in body condition across the ASL range to better inform conservation and management.

Using ASL individuals of known size and mass, we compared high resolution aerial photogrammetric and ground measurements to: 1) quantify the variability of 2-dimensional (2D) measurements in post-processed, drone-acquired imagery, 2) quantify biases in measurements of each technique, and 3) build and evaluate models to predict animal mass using straight-line distances and area measured from orthomosaics, as well as the 3-dimensional (3D) measurement of volume determined from digital elevation models (DEMs). Based on our findings, we contrast BCIs developed from each of the datasets (ground, 2D and 3D measurements) and discuss its utility for providing a relative index of body condition in otariid seals, as well as the applicability for this approach to provide accurate morphometric information for pinnipeds in general.

5.3 Materials and methods

5.3.1 Study site

Fieldwork was completed over six days in April 2019 on the north coast of Olive Island, South Australia (32.72°S, 133.97°E) at the end of the ASL breeding season. Research was conducted in accordance with wildlife research (Department for Environment and Water: A2468-20) and animal ethics (The University of Adelaide and Primary Industries and Regions South Australia Animal Ethics Committees: S-2018-062 and 32-12 respectively) permits.

5.3.2 Ground capture and measurement protocol

We selected focal individuals that were on or near flat terrain and in a relaxed state. To minimise disturbance to surrounding animals, we targeted individuals that were isolated or in areas of low ASL density. Juveniles were captured using a custom hoop net. Adults were immobilised using Zoletil® (~1.3 mg/kg, range 0.8 to 1.6, Virbac, Sydney, Australia), administered intra-muscularly using remote syringe darts (1.5 ml capacity) fired from a dart gun (MK24c, Paxarms, Cheviot, New Zealand). Dosages were determined using a visual weight estimation of each individual prior to darting. Animals were maintained under gas anaesthesia during data collection using Isoflurane® (Veterinary Companies of Australia, Artarmon, Australia), administered via a purpose-built gas anaesthetic machine with a Cyprane Tec III vaporiser (Advanced Anaesthetic Specialists, Sydney, Australia).

Various morphometric measurements were collected while each animal was anaesthetised (Table 5.1). Prior to taking measurements, animals were placed in a standard and natural position (i.e. prone position, ensuring the animal was not stretched along the longitudinal axis, with fore flippers outstretched). The dorsal standard length (GSL; linear distance from nose tip to end of tail) was measured using a caliper (custom made using ‘T-track’ and Lexan scales; Incra, Dallas, USA), while a tape was used to measure the curvilinear distance between the same points (GCL). Width (GW1 – GW4) and girth (GG1 – GG4) were measured at 20% intervals along the GSL and also on the head at the base of the ears (GWE, GGE) using calipers (60 cm anthropometer; Cescorf, Porto Alegre, Brazil) and a tape measure respectively. Auxiliary girth (GAG) was also recorded. Mass (GMA) was measured using a 300 kg x 0.1 kg digital hanging scale (WS603, Wedderburn, Australia). The majority of animals were weighed in a stretcher suspended from a pole held at shoulder height by two people. Large males were placed in a cargo net and lifted using a block and tackle system attached to a safety tripod (TM-9, Zero, Christchurch, New Zealand). To aid monitoring recovery, and to ensure animals were not recaptured, a temporary identification number was placed on the centre of the back using bleach or permanent marker. Tags were also placed on the trailing edge of both fore flippers. Finally, the animal was placed in the prone position and orientated toward the sun when possible, with fore flippers outstretched. Recovery was monitored from nearby.

5.3.3 Drone flight protocol

A quadcopter drone was used as a platform to collect high resolution, digital imagery (Inspire 2, DJI, Shenzhen, China). Imagery contained objects of known size for scaling (see following paragraphs) and was captured using an integrated, gimballed sensor (Zenmuse X7, DJI – sensor: CMOS (Super 35), sensor size: 23.5 x 15.7 mm) fitted with a standard range, prime lens (DL 50 mm F2.8 LS ASPH, DJI) angled at nadir. The aircraft, including remote controller with tablet (iPad Mini 2, Apple, California, USA) and hood, was prepared for flight prior to each animal capture, with calibration completed as necessary.

Upon the completion of the ground protocol for each animal, the aircraft was launched away from the focal individual (> 75 m) at a site of the same elevation. After launching, the drone was manually piloted to 20 m above surface level and then positioned directly above the individual using the sensor’s live feed. A small number of photographs (jpeg and RAW format) were immediately captured at 20 m as a precaution in case the animal recovered before subsequent mapping missions were completed. An automated mission was then planned in situ using Ground Station Pro (GS Pro, DJI) to map the animal and its immediate surroundings by creating a region of interest (~ 15 m square) centred on the animal. Front and side overlap were set to 80% and 60% respectively, with photographs (jpeg format, 6016 x 4008 px) captured using the ‘hover and capture at point’ mode. Parameters, including survey height and overlap, were selected to optimise drone sampling. Upon mission completion, it was repeated at a perpendicular course angle. All missions (mean flight time = 9 ± 1 mins) were in accordance with local regulations and flown by the same licensed pilot. As ASL were recovering from anaesthesia during drone flights, behavioural response data were not collected (Hodgson & Koh 2016).

Prior to each flight, custom calibration boards (n = 3-5) were positioned approximately 1-5 m from the animal. Boards were placed in level locations as close as possible to the elevation on which the animal was lying. Each board contained a unique pair of coded targets (diameter: 22 cm) to provide scale references for image processing (Appendix 5.2).

5.3.4 Image processing and measurement protocol

Digital photographs were grouped by animal. Each group was manually reviewed and unsatisfactory images (e.g. overexposed photographs) were removed. Data were then batch processed using a Python script in the photogrammetry pipeline software, Agisoft Metashape Professional (version 1.5.2, Agisoft LLC, St. Petersburg, Russia). In the initial processing, the coded targets on the calibration boards were automatically detected and scale bars were created using the known distance between target pairs (0.5515 m) before a variety of outputs were produced at medium-high quality (Table A5.1). Adding scale bars enhanced the dimensional accuracy of the projects, ensuring later-collected measurements were absolute. To standardise the spatial extent of the outputs and minimise processing, a marker was manually placed on the spine of each animal at the GW3 position. A variation of the batch script was then executed which duplicated the initial processing (i.e. the ‘chunk’), resized the horizontal plane of the bounding box from encapsulating the entire project to a 7 m square centred on the manually inserted marker and subsequently completed all steps as per the initial script but at maximum quality (Table A5.1). The mean ground sample distance (GSD or the distance between adjacent pixel centres on the ground) for the orthomosaics and DEMs was 1.6 ± 0.11 mm.

Using the shape tool, the perimeter of each animal was manually delineated (mean vertices = 99.1 ± 10.1) in the DEM. Shapes were reviewed in the corresponding model and orthomosaic, with individual vertices moved as necessary. The orthomosaics were then updated by assigning only the highest ranked photograph for each shape to ensure there was minimal photograph mosaicking of the animal. A batch script was used to export the final .tif orthomosaics including world files for georeferencing.

To make 2D measurements of animals, the orthomosaics were imported into Autodesk AutoCAD 2019 (version P.46.0.0, Autodesk Inc, California, USA) and georeferenced using the LISP utility, GeoRefImg (Figure 5.1A). Independent observers (n = 10) then measured standard length (PSL) by drawing a straight line from the nose tip to the end of the tail. A subset of observers’ lengths (n = 3) were segmented into 5% intervals by automatically inserting nodes. In Ortho mode, observers then drew perpendicular width lines (PW01 – PW16) at each node excluding those positioned in line with the fore flippers (45, 50 and 55% increments). The endpoints of all lines were joined using a polyline; the polyline length provided a simplified perimeter (PSP), while the area within the polyline provided a standardised simplified area (PSA). All measurements were extracted via a Data Extraction Table. Three-dimensional measurements were extracted within Metashape by selecting the shape delineating the perimeter of each animal in the DEM (Figure 5.1B) and using the ‘measure shape’ tool. The planar perimeter (PPE) and area (PAR) as well as the total volume (PVO; using the ‘best fit plane’) were recorded. For simplicity, these three measurements were grouped as 3D as they were all extracted from an output containing 3D information. See Table 5.1 for an overview of all measurements.

To investigate the need to have known scale when sampling free-ranging animals, the processing steps were repeated without detecting the coded targets. The unscaled orthomosaics and DEMs were used to generate a second dataset (non-scaled dataset) of the key morphometric measurements (i.e. relative measurements of PSL, PSA and PVO).

5.3.5 Statistical methods

We were interested in the accuracy of the drone approach, so we postulated four key questions. The aim of the first two was to quantify (1) variability and (2) bias. We then developed and assessed models to (3) estimate mass and (4) quantify differences in BCI animal ranking using ground, 2D and 3D data, as well as the influence of using unscaled imagery.

1. *Photogrammetric variability*: how similar are photogrammetric measurements made by independent, naïve observers? We compared the precision of our photogrammetric observers using measurements of PSL (n = 10 per animal) by fitting a linear mixed-effects model with *Animal* and *Observer* as random effects using *lme4* (Bates *et al.* 2015). Given that the vast majority of the random variation in PSL was due to among-animal variability, in order to identify the relative magnitudes of the other random effect of interest (i.e. *Observer*), we fitted a second linear mixed-effects model which we conditioned on the sampled set of animals by fitting *Animal* as a fixed effect. Then we assessed observer bias by testing the level of repeatability (i.e. the intra-class correlation coefficient, ICC) of *Observers* to measure PSL (Nakagawa & Schielzeth 2010). We estimated confidence intervals (95%) and standard errors by completing parametric bootstrapping (n = 1000) using the *rptR* package (Stoffel, Nakagawa & Schielzeth 2017).
2. *Bias between techniques*: how similar were the 2D photogrammetric observations compared to the ground measurement? We used measures of standard length to test this as they were common to both techniques. Given the repeatability of individuals to measure PSL, we used the multi-observer mean PSL for each animal. However, as we only had one ground measurement, which is unlikely to be free of error, we did not assume it to be 'true' (Sokal 2012). Accordingly, we completed a standardised major axis estimation (SMA, or Model II regression) between mean PSL and GSL using the *smatr* package (Warton *et al.* 2012). This procedure was chosen as it did not assign dependence to a given variable and because we were interested in summarising the relationship between the two variables rather than predicting Y from X (Warton *et al.* 2006; Sokal 2012). In this way, as is common in morphometric studies, we estimated the line best describing the bivariate scatter of the two variables. We evaluated the slope of the SMA against a null hypothesis of isometry (i.e. a slope of 1) by using a slope test (Warton *et al.* 2006).
3. *Mass estimation*: how strong is the relationship between GMA and a) 2D and b) 3D photogrammetic measurements (see Table 5.1), such that a given candidate variable could be used as a proxy for (i.e. estimate) GMA? Given our interest in summarising the relationship between candidate photogrammetric variables and GMA, and that the same conditions applied in terms of measurement error and variable dependence, we again completed SMA estimation using the *smatr* package (Warton *et al.* 2012). GMA

ranged 229.5 kg across animals but less within age-sex classes, particularly within adult females (Table 5.2), so we fitted models for each class separately. Although slope tests found no difference between many of the age-sex classes, we consider the grouping to be necessary for interpreting results given the biological differences between the age-sex classes. The juvenile class included both sexes, while sub-adult males (n = 2) were pooled with adult males. Measurements were log-transformed as necessary. Models were evaluated based on the strength of the association (R^2) between GMA and candidate variables.

4. *Body condition indices*: to what extent are BCIs derived from 2D and 3D photogrammetric measurements comparable to indices calculated from ground-collected data? Our aim was not to make a direct assessment of the condition of the sampled animals nor were we seeking to validate a specific BCI (Hayes, Shonkwiler & Speakman 2001). Rather, we wanted to test the suitability of BCIs derived solely from photogrammetric measurements compared to those from ground measurements. Due to the small sample sizes of each cohort, we present the simplest BCI which is a ratio of sizes, namely mass divided by length (i.e. BCI = GMA/GSL). For photogrammetric BCIs, we used the best 2D and 3D proxies for GMA (i.e. PSA and PVO), divided by PSL. We assumed ranks of condition derived from ground data to be the best estimates of condition and so we compared these ranks with those derived from photogrammetric data using Spearman's rank correlation coefficient (r_s). We used this non-parametric approach as each format's BCI was on a different scale and we were interested in the ranking of animals in each cohort per format rather than the absolute BCI values. We used the same method to compare the 2D and 3D BCIs with those indices computed from the non-scaled dataset.

All analyses were completed using data from animals with both ground and photogrammetric measurements, unless otherwise indicated. The level of significance used for all tests was $p < 0.05$. Confidence intervals were set at 95%. All values are listed as mean ± standard deviation (s.d.) unless otherwise indicated. Analyses were carried out in *R* version 3.5.0 (R Core Team 2018).

5.4 Results

Twenty-one free-ranging animals were surveyed over six consecutive days. Weather conditions were consistent, with all flights conducted in low winds (< 10 knots) and partly-cloudy skies across a spectrum of light conditions. Ground morphometric measurements were recorded for all animals (n = 21; Table 5.2), while suitable drone-acquired imagery was collected for 20 animals (95.2%).

5.4.1 Photogrammetric variability

The mean range in animal PSL was very low (1.19 ± 0.67 cm), particularly given this translated to a mean variation of 7.4 pixels (based on the mean GSD). Due to the differences in animal length (range: GSL = 109.3-193.1 cm, PSL = 111.3-195.6 cm; Table 5.2), animal identity accounted for 99.97% of the observed variation in PSL. After controlling for this effect, residual error accounted for the majority of variation in PSL (84.8%, SE = ± 7.9%, CI = 66.9% - 97.6%) while observer had a negligible effect (15.2%, SE = ± 7.9%, CI = 2.4% - 33.1%).

5.4.2 Bias between techniques

There was a highly significant, positive, linear relationship between GSL and mean PSL ($R^2 = 0.99$; $p < 0.001$; Figure 2). The estimated regression coefficient (1.02, CI = 0.98-1.07) was not significantly different from 1, indicating that measures of length are isometric, which suggests that neither technique is biased.

5.4.3 Mass estimation

Of the 2D measurements, PSA was most correlated with GMA for each age-sex class ($R^2 = 0.77 – 0.99$; Figure 3,Table 3). Within the 3D measurements, PVO was most correlated with GMA for each cohort ($R^2 = 0.83 – 0.99$; Figure 5.3,Table 5.3). The strength of the correlation was highest in the juvenile cohort, followed by the adult male and then adult female age-sex classes for both 2D and 3D datasets (Figure 5.3, Table 5.3).

5.4.4 Body condition indices

Photogrammetric-derived BCI ranks of individuals for each age-sex class were comparable to BCI ranks derived from ground data (Table 5.4). The 3D-derived index ranks were more similar to ground-ranks than those from 2D data (Table 5.4). The juvenile cohort was ranked in the same order irrespective of approach, however, the two adult cohorts varied in their correlation strength and significance across the approaches. Non-scaled BCI ranks were also comparable to those derived from scaled data for both 2D and 3D indices (Table 5.4).

5.5 Discussion

5.5.1 Photogrammetric variability and bias between techniques

Drone-derived morphological measurements were precise and without bias. Independent measurements of PSL exhibited low variability and were highly repeatable, as demonstrated by the extremely small proportion of total error attributable to observer. Additionally, across all animals, there was no significant bias in either technique, however, larger deviations in length were observed among the adult males. These deviations may be explained by 1) the time of day when these animals were sampled, 2) the increased height of this age-sex class which produced longer shadows and reduced the probability of observers to identify the extremities of the animals, and 3) a potential allometric scaling effect whereby small differences in the position of larger animals between the two sampling events causes greater differences in length compared to smaller-sized animals. To minimise these differences, we suggest sampling when shadows are at their minimum (i.e. solar noon), sampling individuals who are orientated so that their shadow is adjacent to areas of the body least important for measuring (e.g. if measuring PSL is of primary interest, an animal whose sagittal plane is perpendicular to the direction of the sun would be optimum), using experienced observers, and/or adjusting the orthomosaic (e.g. altering contrast) to increase the likelihood of detecting edges of interest. In combination, the high precision and lack of bias in the technique demonstrates that the drone sampling and data processing procedures produced orthomoasics and DEMs that accurately represented the animals and associated environment.

In general, photogrammetry reduces several sources of observer error. Unlike ground-based measurements, the location of drone-derived measurements can be more effectively standardised across animals. For example, width measurements can be automatically located at desired increments of PSL and made at exactly perpendicular to PSL (i.e. PW01:PW16). On the ground, the repeatability of making these measurements between semilandmarks (non-discrete anatomical loci; Zelditch, Swiderski & Sheets 2012) is lower. Also, in the case of repeat, independent measurements, observers are utilising identical data, free of animal movement and changes in environmental conditions. A related advantage is that drone-derived measurements can be error-checked – actual measurements can be reviewed to interrogate the reason for statistical outliers. Although field restrictions prohibited multiple, independent ground measurements in this study, the high precision and high repeatability of our drone-derived morphometrics support the conceptual advantages of the technique that have been observed for other pinniped species (Krause *et al.* 2017).

5.5.2 Mass estimation and condition indices

Variation in the strength of the relationship between photogrammetric measurements (i.e. PSA and PVO) and GMA for age-sex classes could be attributed to several related factors. Firstly, there were considerable differences in the size variation among the age-sex classes, with a range of 174.1 kg in adult males compared to just 13.3 kg across adult females. While these differences were expected given the sexual dimorphism exhibited by ASL, they resulted in some data points being highly influential on model fits. Secondly, the relatively small sample sizes per age-sex class (n = 6 – 8) compounded the influence of particular individuals on the analyses. Despite these inherent constraints, the consistent relationship between the size measurements provides good evidence of a strong relationship, which would possibly strengthen with larger sample sizes.

Given PSA and PVO correlated strongly with GMA, they were used as proxies for GMA to calculate separate ratio BCIs of ASL. Similar to the mass estimations, the small sample sizes and the spread of individuals within each age-sex class likely resulted in conservative BCI comparison estimates. For example, these factors meant some individuals of relatively similar size were ranked differently in each BCI, despite only minor differences in actual BCI scores. From a population monitoring perspective, subtle differences in BCI ranking are of minor interest relative to detecting significant spatiotemporal differences in body condition.

The suitability of BCI monitoring has been debated in recent years. Using residuals from a regression of body mass on a linear measure of body size to calculate a BCI is a common method employed in vertebrate studies that has attracted some criticism. Green (2001) argued that mass/length residual indices have a suite of underlying statistical assumptions which are likely to be violated in some or all studies. However, proponents maintain, through analyses of small mammal data and simulations, that with appropriate caution, residual based indices are legitimate (Schulte-Hostedde *et al.* 2005). Another criticism has been that many traditional BCIs fail to account for the scaling relationship between different size measures (Kotiaho 1999), although an alternate index has been shown to successfully overcome this issue (i.e. scaled mass index; Peig & Green 2009; Peig & Green 2010). More broadly, BCIs have been criticized for the lack of consensus in the definition of ‘condition’ and the best index (Wilder, Raubenheimer & Simpson 2016), the limited quantification of the relationship between observed ‘condition’ and fitness (Cox, Calsbeek & Blanckenhorn 2015) and their susceptibility to inter-observer bias (Krebs & Singleton 1993). However, when implemented and documented appropriately, BCIs can yield useful data without the cost or invasive procedures associated with many alternative methods (Wilder, Raubenheimer & Simpson 2016).

A benefit of BCIs is that they can be useful for rapid and non-invasive insight at the population level. For example, our workflow could be used to complete a non-destructive, preliminary assessment of the variation in condition across the ASL range. Given the marked variation in trends in abundance among ASL populations across their range (Goldsworthy *et al.* 2015), determining whether there is any geospatial correlation between population trends in abundance and BCIs could provide critical insights into how environmental variability is mediating anthropogenic impacts across the species range. Photogrammetric-only condition assessments could be completed at key representative colonies with known trends in abundance, and with consideration of ecological (e.g. colony size, foraging strategy and range), environmental (e.g. likelihood of impacts of threats) and sampling practicality factors. Any observed spatial variation in condition, calculated using the most appropriate index formula, could be investigated relative to the possible genotypic and environmental drivers (e.g. population sub-structure, prey availability, habitat suitability, proximity and risk to threatening processes) to inform future conservation and research efforts. Such an assessment benefits from its ability to target age-sex classes of interest (e.g. juveniles, who had the strongest associations and are not subject to possibly confounding variables of pregnancy and the marked breeding season related changes in mass composition present in adult males), and the capacity to add additional ground-measurements at any time to increase the robustness of mass estimation analyses. In turn, this presents the opportunity to rapidly acquire more frequent species level insights, and with considerably lower risk to animals and researchers, than by solely collecting on-ground measurements. The insights provided by such an assessment would be formative in determining the need and best approach for more detailed measures of animal body composition or fitness-related traits (Wilder, Raubenheimer & Simpson 2016).

5.5.3 Considerations for future drone-derived pinniped morphometrics

Despite 2D and 3D measurements having similar relationships to GMA for each age-sex class, consideration should be given to the relative benefits and limitations of each format. As expected, our 3D measurement of animal size (PVO) had the highest correlation with mass. This indicates that the drone sampling technique (i.e. the total number of images and their GSD, which result from the mission parameters, and the sensor and lens specifications and their sampling height, respectively) and image processing parameters yielded robust 3D models. The quality and resolution of the 3D information is evident from visual examination of animals of similar length but with variation in mass (Figure 5.4). However, generating 3D data requires subjects to remain stationary, which may not be a practical requirement for free-ranging animals. A potential solution to this issue would be to use a swarm of drones (e.g. > 5 small multirotor aircraft operating synchronously) that capture photographs simultaneously, thereby rendering animal movement inconsequential. Controlled experiments could be used to determine the optimum number of drones for this approach. On the other hand, while orthomosaic-derived, 2D measurements contain less dimensional information than 3D measurements of size, they provide several benefits over single-photograph approaches. Such approaches assume that images are sampled at nadir, even in windy conditions, and that images are free of distortion. While these assumption may be satisfied in some circumstances, the orthorectification process overcomes these strict requirements. Additionally, animal movement artefacts can be overcome by selecting just one photograph to be used in the orthomosaic for the entire area of the animal. In this way, and similar to previous 3D solutions (e.g. de Bruyn *et al.* 2009), the surrounding area (i.e. stationary surfaces) provides sufficient detail to generate an accurate point cloud which will be used to correct any distortions in the photograph selected to express the subject.

In transitioning to exclusively capturing photogrammetric data of pinnipeds, there are a variety of relevant considerations and research opportunities for future studies:

1. All data in this study were sampled from anaesthetised individuals at a similar time in their breeding cycle, with the assumption that an anaesthetised animal is analogous to a resting individual exhibiting the same posture. Imagery was sampled at a low height (20 m), resulting in a very high GSD. While lower resolution imagery may achieve comparable results (Krause *et al.* 2017), the sampling height could be increased while maintaining the GSD by utilising a larger sensor and/or a greater focal length. Flying at an increased height is desirable for free-ranging animals as a precaution to avoid disturbance, particularly for species where behavioural and physiological response data are lacking (Hodgson & Koh 2016).
2. Although the prone position is a common posture in free-ranging ASL that are resting, care should be exercised in extrapolating the results to other postures. The PSA measurement process attempts to provide redundancy for posture variation, particularly fore flipper orientation, by being unconstrained by animal width in that region (i.e. width >40% and <60% of PSL). For concave postures, the technique could be modified so that PSL curved with the shape of the spine. In the 3D context, the very high correlation between PVO and GMA suggests that animal density is relatively constant, indicating that estimates may not be significantly influenced by small to moderate variations in body posture (e.g. prone position with fore flippers parallel and adjacent to the body rather than outstretched).
3. Drone sampling was optimised by placing anaesthetised individuals on relatively level, rock planes, orientating them in the direction of the sun to minimise shadows and avoiding areas with nearby vertical interferences (e.g. another animal, protruding rocks). It is assumed that these practices reduced the likelihood of orthomosaic and DEM artefacts, thereby increasing the accuracy of photogrammetric data derived from these sources. Individuals satisfying these criteria could be selected when sampling in free-ranging colonies.
4. Our results suggest using non-scaled imagery is adequate for BCI monitoring, however, if absolute measurements are needed, the use of a scaling technique is recommended.
5. When possible, we recommend collecting ground measurements for species-specific calibration. This is likely important for studies that need to summarise the relationship between mass and photogrammetric measurements.
6. Morphometric data sampling can be completed concurrently with colony-level abundance monitoring of pinnipeds (McIntosh, Holmberg & Dann 2018; Sorrell *et al.* 2019), as well as accurate and precise estimates of other, co-located indicator species

such as seabirds (Hodgson *et al.* 2016; Hodgson *et al.* 2018). Such broadened surveys will provide time and cost efficient data with the potential to provide multi-species ecosystem insights.

5.6 Conclusion

We have developed a non-invasive, practical technique to make accurate body measurements of an otariid seal species. Drone-derived measurements were highly repeatable and not dissimilar to traditional, ground-collected data. This means that morphometric data can be collected without the risks involved with anaesthetising and handling animals. It also presents considerable time and cost efficiencies when imagery can be processed easily and quickly. Importantly, both 2D and 3D measurements (PSA and PVO, respectively) were highly correlated with ASL mass, particularly for juveniles. We have shown these measurements can be used to develop condition indices comparable to those from ground-collected data. While these indices should be interpreted carefully, they could be used to make rapid, preliminary assessments of the spatial and temporal variation in the condition of this endangered, marine indicator species relative to environmental fluctuations. With species-specific calibration, we anticipate that our technique will be transferrable to other pinniped species.

5.7 Funding

This study received funding from the Department for Environment and Water, Government of South Australia. J.C.H. is supported by an Australian Government Research Training Program Scholarship.

5.8 CRediT authorship contribution statement

Jarrod C. Hodgson: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing. **Dirk Holman:** Investigation, Writing - review & editing. **Aleks Terauds:** Supervision, Writing - review & editing. **Lian Pin Koh:** Methodology, Supervision, Writing - review & editing. **Simon D. Goldsworthy:** Data curation, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing - review & editing.

5.9 Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.10 Acknowledgements

We thank those who made photogrammetric measurments, and Dillon Campbell, Emma Sherratt and Steven Delean for providing considered input to the experiment. We appreciate the support of Ramesh Raja Segaran and the Unmanned Research Aircraft Facility, as well as Darren Guidera for his professional service during vessel transit. We thank Simon Bryars and other Department for Environment and Water staff for facilitating the study.

5.11 References

Adame, K., Pardo, M.A., Salvadeo, C., Beier, E. & Elorriaga-Verplancken, F.R. (2017) Detectability and categorization of California sea lions using an unmanned aerial vehicle. *Marine Mammal Science,* **33,** 913-925. https://doi.org/10.1111/mms.12403

Allan, B.M., Ierodiaconou, D., Hoskins, A.J. & Arnould, J.P.Y. (2019) A Rapid UAV Method for Assessing Body Condition in Fur Seals. *Drones,* **3,** 24. https://doi.org/10.3390/drones3010024

Australian Government (2013) Recovery Plan for the Australian Sea Lion (Neophoca cinerea). (ed. E. Sustainability, Water, Population and Communities.).

Baker, W.H. (1960) *Elements of photogrammetry*. Ronald Press, New York.

Bates, D., Machler, M., Bolker, B.M. & Walker, S.C. (2015) Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software,* **67,** 1-48. https://doi.org/10.18637/jss.v067.i01

Bell, C.M., Hindell, M.A. & Burton, H.R. (1997) Estimation of body mass in the southern elephant seal, Mirounga leonina, by photogrammetry and morphometrics. *Marine Mammal Science,* **13,** 669-682. https://doi.org/DOI 10.1111/j.1748-7692.1997.tb00090.x

Beltran, R.S., Ruscher-Hill, B., Kirkham, A.L. & Burns, J.M. (2018) An evaluation of three-dimensional photogrammetric and morphometric techniques for estimating volume and mass in Weddell seals Leptonychotes weddellii. *PloS One,* **13,** e0189865. https://doi.org/10.1371/journal.pone.0189865

Bradshaw, C.J.A., Davis, L.S., Lalas, C. & Harcourt, R.G. (2000) Geographic and temporal variation in the condition of pups of the New Zealand fur seal (Arctocephalus forsteri): evidence for density dependence and differences in the marine environment. *Journal of Zoology,* **252,** 41-51. https://doi.org/DOI 10.1111/j.1469-7998.2000.tb00818.x

Ceballos, G., Ehrlich, P.R., Barnosky, A.D., Garcia, A., Pringle, R.M. & Palmer, T.M. (2015) Accelerated modern human-induced species losses: Entering the sixth mass extinction. *Sci Adv,* **1,** e1400253. https://doi.org/10.1126/sciadv.1400253

Ceballos, G., Ehrlich, P.R. & Dirzo, R. (2017) Biological annihilation via the ongoing sixth mass extinction signaled by vertebrate population losses and declines. *Proceedings of the National Academy of Sciences of the United States of America,* **114,** E6089-E6096. https://doi.org/10.1073/pnas.1704949114

Cheney, B., Wells, R.S., Barton, T.R. & Thompson, P.M. (2018) Laser photogrammetry reveals variation in growth and early survival in free-ranging bottlenose dolphins. *Animal Conservation,* **21,** 252-261. https://doi.org/10.1111/acv.12384

Christiansen, F., Sironi, M., Moore, M.J., Di Martino, M., Ricciardi, M., Warick, H.A., Irschick, D.J., Gutierrez, R., Uhart, M.M. & Iossa, G. (2019) Estimating body mass of free-living whales using aerial photogrammetry and 3D volumetrics. *Methods in Ecology and Evolution,* **10,** 2034-2044. https://doi.org/10.1111/2041-210x.13298

Christiansen, F., Vivier, F., Charlton, C., Ward, R., Amerson, A., Burnell, S. & Bejder, L. (2018) Maternal body size and condition determine calf growth rates in southern right whales. *Marine Ecology Progress Series,* **592,** 267-281. https://doi.org/10.3354/meps12522

Cox, R.M., Calsbeek, R. & Blanckenhorn, W. (2015) Survival of the fattest? Indices of body condition do not predict viability in the brown anole (Anolis sagrei). *Functional Ecology,* **29,** 404-413. https://doi.org/10.1111/1365-2435.12346 de Bruyn, P.J.N., Bester, M.N., Carlini, A.R. & Oosthuizen, W.C. (2009) How to weigh an elephant seal with one finger: a simple three-dimensional photogrammetric application. *Aquatic Biology*, **5,** 31-39. https://doi.org/10.3354/ab00135

Durban, J.W., Fearnbach, H., Barrett-Lennard, L.G., Perryman, W.L. & Leroi, D.J. (2015) Photogrammetry of killer whales using a small hexacopter launched at sea. *Journal of Unmanned Vehicle Systems*, **3,** 131-135. https://doi.org/10.1139/juvs-2015-0020

Gales, N.J., Shaughnessy, P.D. & Dennis, T.E. (1994) Distribution, Abundance and Breeding Cycle of the Australian Sea Lion Neophoca-Cinerea (Mammalia, Pinnipedia). *Journal of Zoology*, **234,** 353-370. https://doi.org/DOI 10.1111/j.1469-7998.1994.tb04853.x

Goldsworthy, S.D. (2015) Neophoca cinerea. The IUCN Red List of Threatened Species 2015: e.T14549A45228341.

Goldsworthy, S.D., Mackay, A.I., Shaughnessy, P.D., Bailleul, F. & Holman, D. (2015) Maintaining the monitoring of pup production at key Australian sea lion colonies in South Australia (2014/15). Final Report to the Australian Marine Mammal Centre. South Australian Research and Development Institute (Aquatic Sciences), Adelaide. SARDI Publication No. F2010/000665-5. SARDI Research Report Series No. 871.

Goldsworthy, S.D. & Page, B. (2007) A risk-assessment approach to evaluating the significance of seal bycatch in two Australian fisheries. *Biological Conservation*, **139,** 269-285. https://doi.org/10.1016/j.biocon.2007.07.010

Goldsworthy, S.D., Page, B., Shaughnessy, P.D. & Linnane, A. (2010) Mitigating Seal Interactions in the SRLF and the Gillnet Sector SESSF in South Australia. Report to the Fisheries Research and Development Institute. South Australian Research and Development Institute (Aquatic Sciences), Adelaide. SARDI Publication No. F2009/000613-1. SARDI Research Report Series No. 405.

Gray, P.C., Bierlich, K.C., Mantell, S.A., Friedlaender, A.S., Goldboge, J.A. & Johnston, D.W. (2019) Drones and convolutional neural networks facilitate automated and accurate cetacean species identification and photogrammetry. *Methods in Ecology and Evolution*, **10,** 1490-1500. https://doi.org/10.1111/2041-210x.13246

Green, A.J. (2001) Mass/length residuals: Measures of body condition or generators of spurious results? *Ecology*, **82,** 1473-1483. https://doi.org/Doi 10.2307/2680003

Haley, M.P., Deutsch, C.J. & Leboeue, B.J. (1991) A Method for Estimating Mass of Large Pinnipeds. *Marine Mammal Science*, **7,** 157-164. https://doi.org/DOI 10.1111/j.1748-7692.1991.tb00562.x

Hayes, J.P., Shonkwiler, J.S. & Speakman, J.R. (2001) Morphological indicators of body condition: useful or wishful thinking? **,** 8-38. https://doi.org/10.1017/cbo9780511551741.003

Hazen, E.L., Abrahms, B., Brodie, S., Carroll, G., Jacox, M.G., Savoca, M.S., Scales, K.L., Sydeman, W.J. & Bograd, S.J. (2019) Marine top predators as climate and ecosystem sentinels. *Frontiers in Ecology and the Environment*, **17,** 565-574. https://doi.org/10.1002/fee.2125

Hodgson, A., Kelly, N. & Peel, D. (2013) Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PloS One*, **8,** e79556. https://doi.org/10.1371/journal.pone.0079556

Hodgson, J.C., Baylis, S.M., Mott, R., Herrod, A. & Clarke, R.H. (2016) Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports*, **6,** 22574. https://doi.org/10.1038/srep22574

Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology*, **26,** R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution,* **9,** 1160-1167. https://doi.org/10.1111/2041-210x.12974

Hopkins, H.L. & Kennedy, L.L. (2004) An assessment of indices of relative and absolute abundance for monitoring populations of small mammals. *Wildlife Society Bulletin,* **32,** 1289-1296. https://doi.org/Doi 10.2193/0091-7648(2004)032[1289:Aaoior]2.0.Co;2

Ireland, D., Garrott, R.A., Rotella, J. & Banfield, J. (2006) Development and application of a mass-estimation method for Weddell seals. *Marine Mammal Science,* **22,** 361-378. https://doi.org/10.1111/j.1748-7692.2006.00039.x

Jakob, E.M., Marshall, S.D. & Uetz, G.W. (1996) Estimating fitness: A comparison of body condition indices. *Oikos,* **77,** 61-67. https://doi.org/Doi 10.2307/3545585

Johnston, D.W. (2019) Unoccupied Aircraft Systems in Marine Science and Conservation. *Annual Review of Marine Science,* **11,** 439-463. https://doi.org/10.1146/annurev-marine-010318-095323

Johnston, D.W., Dale, J., Murray, K., Josephson, E., Newton, E. & Wood, S. (2017) Comparing occupied and unoccupied aircraft surveys of wildlife populations: Assessing the gray seal Halichoerus grypus breeding colony on Muskeget Island, USA. *Journal of Unmanned Vehicle Systems*. https://doi.org/10.1139/juvs-2017-0012

Joyce, K.E., Duce, S., Leahy, S.M., Leon, J. & Maier, S.W. (2019) Principles and practice of acquiring drone-based image data in marine environments. *Marine and Freshwater Research,* **70,** 952-963. https://doi.org/10.1071/mf17380

Keith, D., Akcakaya, H.R., Butchart, S.H.M., Collen, B., Dulvy, N.K., Holmes, E.E., Hutchings, J.A., Keinath, D., Schwartz, M.K., Shelton, A.O. & Waples, R.S. (2015) Temporal correlations in population trends: Conservation implications from time-series analysis of diverse animal taxa. *Biological Conservation,* **192,** 247-257. https://doi.org/10.1016/j.biocon.2015.09.021

Koski, W.R., Allen, T., Ireland, D., Buck, G., Smith, P.R., Macrander, A.M., Halick, M.A., Rushing, C., Sliwa, D.J. & McDonald, T.L. (2009) Evaluation of an Unmanned Airborne System for Monitoring Marine Mammals. *Aquatic Mammals,* **35,** 347-357. https://doi.org/10.1578/am.35.3.2009.347

Kotiaho, J.S. (1999) Estimating fitness: comparison of body condition indicies revisited. *Oikos,* **87,** 399-400.

Krause, D.J., Hinke, J.T., Perryman, W.L., Goebel, M.E. & LeRoi, D.J. (2017) An accurate and adaptable photogrammetric approach for estimating the mass and body condition of pinnipeds using an unmanned aerial system. *PloS One,* **12,** e0187465. https://doi.org/10.1371/journal.pone.0187465

Krebs, C.J. (1991) The Experimental Paradigm and Long-Term Population Studies. *Ibis,* **133,** 3-8. https://doi.org/DOI 10.1111/j.1474-919X.1991.tb07663.x

Krebs, C.J. & Singleton, G.R. (1993) Indexes of Condition for Small Mammals. *Australian Journal of Zoology,* **41,** 317-323. https://doi.org/Doi 10.1071/Zo9930317

Ling, J.K. (1999) Exploitation of fur seals and sea lions from Australian, New Zealand and adjacent subantarctic islands during the eighteenth, nineteenth and twentieth centuries. *Australian Zoologist,* **31,** 323-350.

McFadden, K.W., Worthy, G.A.J. & Lacher, T.E. (2006) Photogrammetric Estimates of Size and Mass in Hawaiian Monk Seals (<I>Monachus schauinslandi</I>). *Aquatic Mammals,* **32,** 31-40. https://doi.org/10.1578/am.32.1.2006.31

McIntosh, R.R., Holmberg, R. & Dann, P. (2018) Looking Without Landing—Using Remote Piloted Aircraft to Monitor Fur Seal Populations Without Disturbance. *Frontiers in Marine Science*, **5**. https://doi.org/10.3389/fmars.2018.00202

Meise, K., Mueller, B., Zein, B. & Trillmich, F. (2014) Applicability of single-camera photogrammetry to determine body dimensions of pinnipeds: Galapagos sea lions as an example. *PloS One*, **9,** e101197. https://doi.org/10.1371/journal.pone.0101197

Nakagawa, S. & Schielzeth, H. (2010) Repeatability for Gaussian and non-Gaussian data: a practical guide for biologists. *Biological Reviews of the Cambridge Philosophical Society*, **85,** 935-956. https://doi.org/10.1111/j.1469-185X.2010.00141.x

Noren, S.R., Schwarz, L., Chase, K., Aldrich, K., McMahon-Van Oss, K. & St Leger, J. (2019) Validation of the photogrammetric method to assess body condition of an odontocete, the shortfinned pilot whale Globicephala macrorhynchus. *Marine Ecology Progress Series*, **620,** 185-200. https://doi.org/10.3354/meps12971

Page, B., McKenzie, J., McIntosh, R., Baylis, A., Morrissey, A., Calvert, N., Haase, T., Berris, M., Dowie, D., Shaughnessy, P.D. & Goldsworthy, S.D. (2004) Entanglement of Australian sea lions and New Zealand fur seals in lost fishing gear and other marine debris before and after Government and industry attempts to reduce the problem. *Marine Pollution Bulletin*, **49,** 33-42. https://doi.org/10.1016/j.marpolbul.2004.01.006

Peig, J. & Green, A.J. (2009) New perspectives for estimating body condition from mass/length data: the scaled mass index as an alternative method. *Oikos*, **118,** 1883-1891. https://doi.org/10.1111/j.1600-0706.2009.17643.x

Peig, J. & Green, A.J. (2010) The paradigm of body condition: a critical reappraisal of current methods based on mass and length. *Functional Ecology*, **24,** 1323-1332. https://doi.org/10.1111/j.1365-2435.2010.01751.x

Pimm, S.L., Jenkins, C.N., Abell, R., Brooks, T.M., Gittleman, J.L., Joppa, L.N., Raven, P.H., Roberts, C.M. & Sexton, J.O. (2014) The biodiversity of species and their rates of extinction, distribution, and protection. *Science*, **344,** 987-+. https://doi.org/10.1126/science.1246752

Postma, M., Tordiffe, A.S.W., Hofmeyr, M.S., Reisinger, R.R., Bester, L.C., Buss, P.E. & de Bruyn, P.J.N. (2015) Terrestrial mammal three-dimensional photogrammetry: multispecies mass estimation. *Ecosphere*, **6,** art293. https://doi.org/10.1890/Es15-00368.1

R Core Team (2018) R: A language and environment for statistical computing. Vienna, Austria. *http://www.R-project.org*.

Schulte-Hostedde, A.I., Zinner, B., Millar, J.S. & Hickling, G.J. (2005) Restitution of mass–size residuals: validating body condition indices. *Ecology*, **86,** 155-163.

Shaughnessy, P.D., Goldsworthy, S.D., Hamer, D.J., Page, B. & McIntosh, R.R. (2011) Australian sea lions Neophoca cinerea at colonies in South Australia: distribution and abundance, 2004 to 2008. *Endangered Species Research*, **13,** 87-98. https://doi.org/10.3354/esr00317

Siddig, A.A.H., Ellison, A.M., Ochs, A., Villar-Leeman, C. & Lau, M.K. (2016) How do ecologists select and use indicator species to monitor ecological change? Insights from 14 years of publication in Ecological Indicators. *Ecological Indicators*, **60,** 223-230. https://doi.org/10.1016/j.ecolind.2015.06.036

Sokal, R.R. (2012) *Biometry : the principles and practice of statistics in biological research*, 4th ed. edn. W.H. Freeman, New York.

Sorrell, K.J., Clarke, R.H., Holmberg, R. & McIntosh, R.R. (2019) Remotely piloted aircraft improve precision of capture–mark–resight population estimates of Australian fur seals. *Ecosphere*, **10**. https://doi.org/10.1002/ecs2.2812

Steffen, W., Sanderson, R.A., Tyson, P.D., Jäger, J., Matson, P.A., Moore III, B., Oldfield, F., Richardson, K., Schellnhuber, H.-J. & Turner, B.L. (2006) *Global change and the earth system: a planet under pressure*. Springer Science & Business Media.

Stevenson, R.D. & Woods, W.A., Jr. (2006) Condition indices for conservation: new uses for evolving tools. *Integrative and Comparative Biology,* **46,** 1169-1190. https://doi.org/10.1093/icb/icl052

Stoffel, M.A., Nakagawa, S. & Schielzeth, H. (2017) rptR: repeatability estimation and variance decomposition by generalized linear mixed-effects models. *Methods in Ecology and Evolution,* **8,** 1639-1644. https://doi.org/10.1111/2041-210x.12797

Sweeney, K.L., Shertzer, K.W., Fritz, L.W. & Read, A.J. (2015) A novel approach to compare pinniped populations across a broad geographic range. *Canadian Journal of Fisheries and Aquatic Sciences,* **72,** 175-185. https://doi.org/10.1139/cjfas-2014-0070

Waite, J.N., Schrader, W.J., Mellish, J.A.E. & Horning, M. (2007) Three-dimensional photogrammetry as a tool for estimating morphometrics and body mass of Steller sea lions (Eumetopias jubatus). *Canadian Journal of Fisheries and Aquatic Sciences,* **64,** 296-303. https://doi.org/10.1139/F07-014

Waldron, A., Mooers, A.O., Miller, D.C., Nibbelink, N., Redding, D., Kuhn, T.S., Roberts, J.T. & Gittleman, J.L. (2013) Targeting global conservation funding to limit immediate biodiversity declines. *Proceedings of the National Academy of Sciences of the United States of America,* **110,** 12144-12148. https://doi.org/10.1073/pnas.1221370110

Warton, D.I., Duursma, R.A., Falster, D.S. & Taskinen, S. (2012) smatr 3-an R package for estimation and inference about allometric lines. *Methods in Ecology and Evolution,* **3,** 257-259. https://doi.org/10.1111/j.2041-210X.2011.00153.x

Warton, D.I., Wright, I.J., Falster, D.S. & Westoby, M. (2006) Bivariate line-fitting methods for allometry. *Biological Reviews of the Cambridge Philosophical Society,* **81,** 259-291. https://doi.org/10.1017/S1464793106007007

Wilder, S.M., Raubenheimer, D. & Simpson, S.J. (2016) Moving beyond body condition indices as an estimate of fitness in ecological and evolutionary studies. *Functional Ecology,* **30,** 108-115. https://doi.org/10.1111/1365-2435.12460

Zacharias, M.A. & Roff, J.C. (2001) Use of focal species in marine conservation and management: a review and critique. *Aquatic Conservation-Marine and Freshwater Ecosystems,* **11,** 59-76. https://doi.org/DOI 10.1002/aqc.429

Zelditch, M.L., Swiderski, D.L. & Sheets, H.D. (2012) *Geometric morphometrics for biologists: a primer,* Second edition edn. Academic Press.

Table 5.1. Abbreviations of the ground and photogrammetric measurements made for each individual. Ground measurements (abbreviations starting with a 'G') were made in the field, while photogrammetric measurements (abbreviations starting with a 'P') were derived from orthomosaics (2-dimensional; 2D) and digital elevation models (3-dimensional; 3D). The numbers in square parentheses indicate the number of independent measurements per animal.

Measurement (scale)	**Ground**	**Photogrammetric**	
		2D	3D
Mass (kg)	GMA [1]	-	-
Standard length (cm)	GSL [1]	PSL [10]	-
Curvilinear length (cm)	GCL [1]	-	-
Width at ears (cm)	GWE [1]	-	-
Girth at ears (cm)	GGE [1]	-	-
Width at 20% intervals (cm)[a]	GW1 – GW4 [1]	-	-
Girth at 20% intervals (cm)	GG1 – GG4 [1]	-	-
Auxiliary girth (cm)	GAG [1]	-	-
Width at 5% intervals, excluding 45%, 50% and 55% (cm)[a]	-	PW01 – PW16 [3]	-
Simplified area (cm^2)	-	PSA [3]	-
Simplified perimeter (cm)	-	PSP [3]	-
Perimeter (cm)	-	-	PPE [1]
Area (cm^2)	-	-	PAR [1]
Volume (cm^3)	-	-	PVO [1]

[a] Ground width interval positions were calculated relative to ground standard length (GSL) and photogrammetric intervals were positioned automatically from photogrammetric standard length (PSL). Therefore, 20% interval measurements for each individual are not necessarily at identical locations (e.g. GW1 versus PW04).

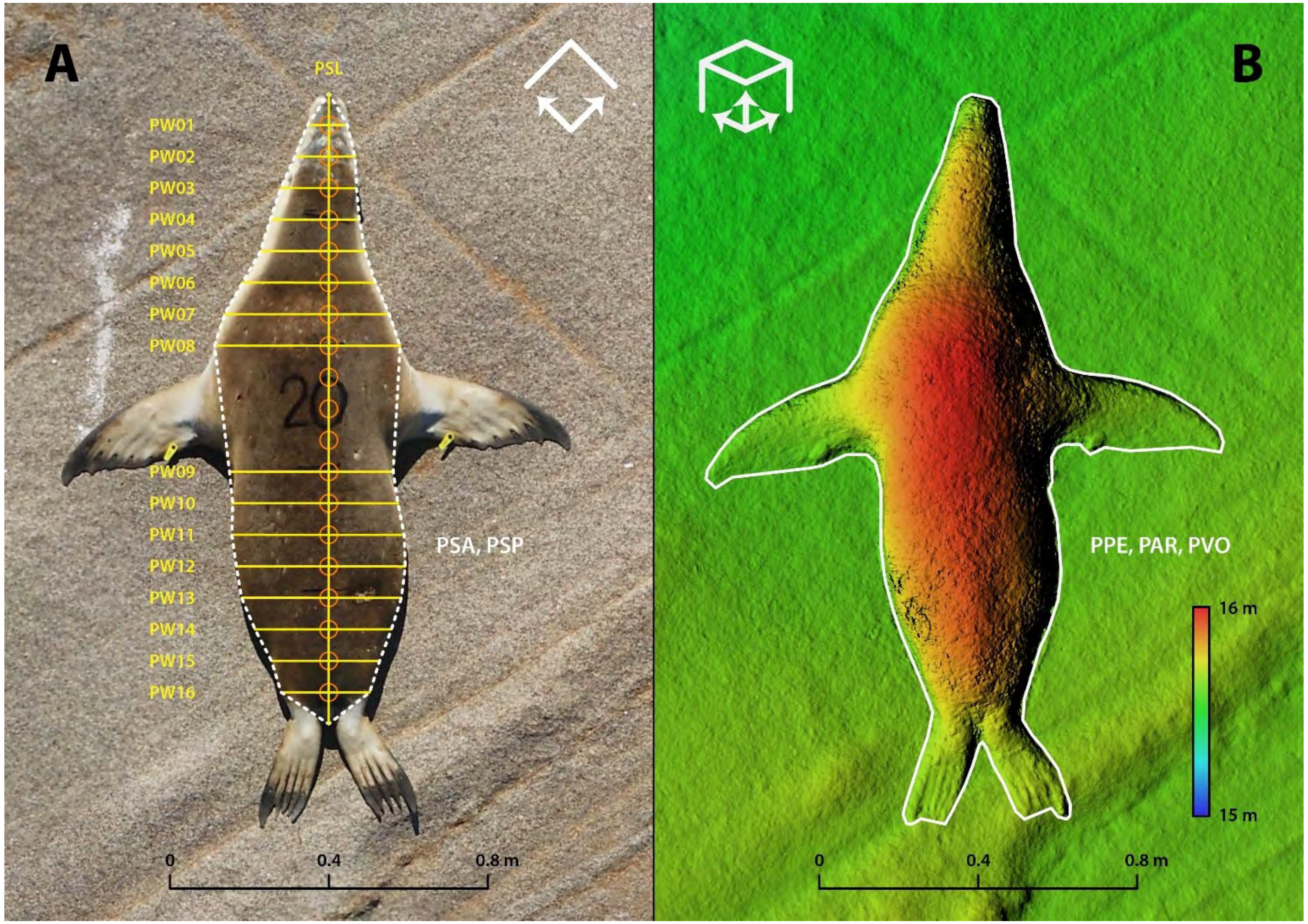


Figure 5.1. An example of photogrammetric measurements of an adult female Australian sea lion. Two-dimensional measurements were made in geo-referenced orthomosaics (A) and digital elevation models (DEMs; shown with 'hillshading' on) were used to calculate measurements such as volume (i.e. 'PVO'; B). Open orange circles (A) depict 5% intervals of photogrammetric standard length (PSL). The colour gradient (B) represents height above mean sea level. See Table 1 for descriptions of abbreviated labelled measurements.

Table 5.2. Mean ground and photogrammetric measurements (± s.d.) for juvenile and adult Australian sea lions at Olive Island, South Australia. Measurement ranges (minimum – maximum) are displayed in square parentheses.

Age-sex class	**Ground**					**Photogrammetric**		
	n	Mass (GMA; kg)	Standard length (GSL; cm)	Curvilinear length (GCL; cm)	Auxiliary girth (GAG; cm)	n	Simplified area (PSA; cm^2)[a]	Volume (PVO; cm^3)
Juvenile (male and female)	6	48.4 ± 13.3 [32.3 – 66.3]	124.1 ± 12.7 [109.3 – 139.6]	132.9 ± 12.8 [118.2 – 149.8]	87.2 ± 8.6 [73.0 – 96.8]	6	3,377.8 ± 635.5 [2,596.7 – 4,279.7]	51,040 ± 11,972 [36,214 – 66,963]
Adult female	8	89.7 ± 4.8 [84.9 – 98.2]	158.1 ± 3.2 [154.3 – 162.4]	169.2 ± 3.8 [163.3 – 173.8]	106.0 ± 3.2 [102.7 – 110.5]	8	5,281.0 ± 226.8 [4,975.3 – 5,621.3]	95,341 ± 6,098 [87,577 – 105,072]
Adult male	7[b]	164.2 ± 55.4 [87.7 – 261.8]	179.1 ± 11.9 [155.0 – 193.1]	192.3 ± 13.4 [165.8 – 207.8]	128.4 ± 13.7 [105.2 – 142.9]	6[b]	7,036.3 ± 1,163.9 [5,062.0 – 8,590.3]	153,065 ± 34,397 [93,311 – 195,102]

[a] Calculated using the mean PSA (n = 3) of each individual.

[b] Two sub-adult males are included in this group.

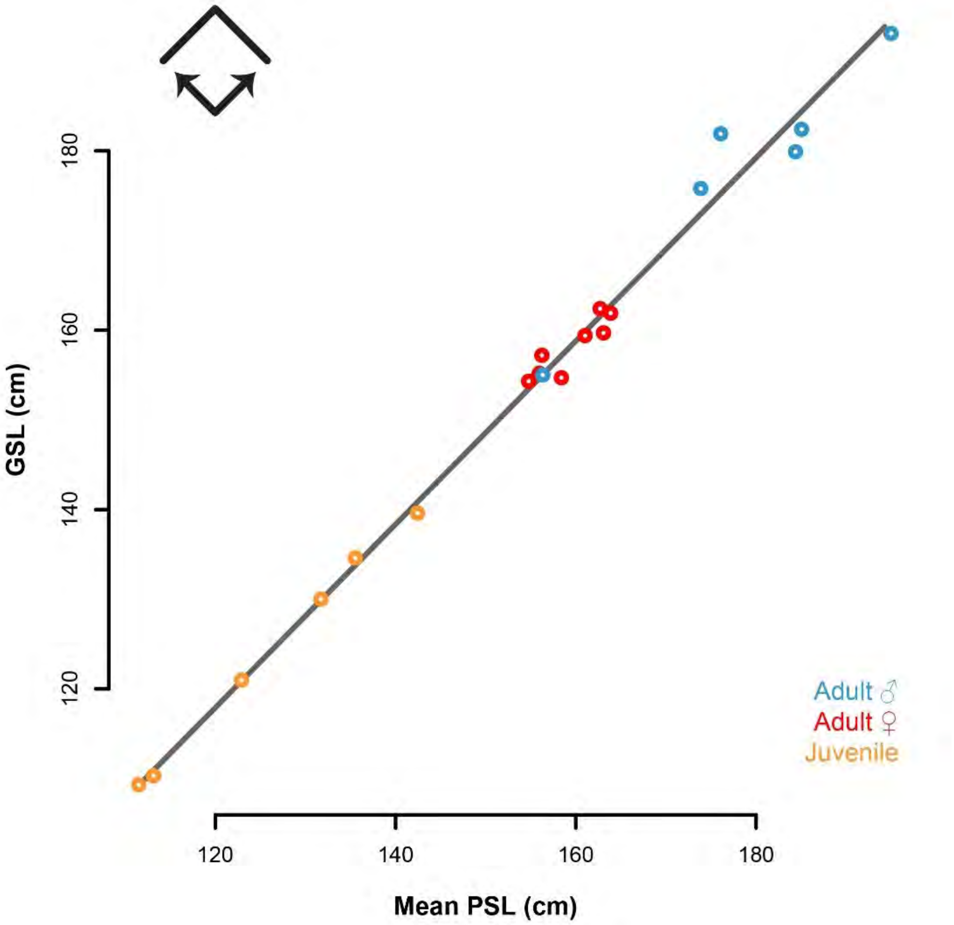


Figure 5.2. Measurement technique bias. Standardised major axis estimation (SMA, or Model II regression) of mean photogrammetric standard length (PSL, n=10 measurements; 2-dimensional) to ground-measured standard length (GSL, n=1 measurement)(R^2 0.99 and $P < 0.001$). The estimated regression coefficient (1.02, CI = 0.98-1.07) indicated that measures of length are isometric. Age-sex classes are indicated by the colours of the data points (see legend).

Table 5.3. Standardised major axis estimation (SMA, or Model II regression) parameters and results for the models which best summarise the relationship between 2-dimensional (simplified area, PSA) and 3-dimensional (volume, PVO) photogrammetric measurements and mass (GMA). Models were fitted for each age-sex class.

Equation	**Age-sex class**	**n**	**Slope (95% CI)**	**Intercept (95% CI)**	**R^2**	***p***
log(GMA) ~ log(PSA)	Juvenile	6	1.49 (1.32 – 1.68)	-3.58 (-4.22 – -2.95)	0.992	<0.001
	Adult female	8	1.23 (0.77 – 1.95)	-2.61 (-4.82 – -0.41)	0.766	0.004
	Adult male	6	1.99 (1.19 – 3.34)	-5.48 (-9.60 – -1.37)	0.850	0.009
log(GMA) ~ log(PVO)	Juvenile	6	1.18 (1.13 – 1.23)	-3.88 (-4.12 – -3.62)	0.999	<0.001
	Adult female	8	0.83 (0.56 – 1.23)	-2.17 (-3.85 – -0.49)	0.834	0.002
	Adult male	6	1.38 (0.86 – 2.23)	-4.99 (-8.52 – -1.46)	0.874	0.006

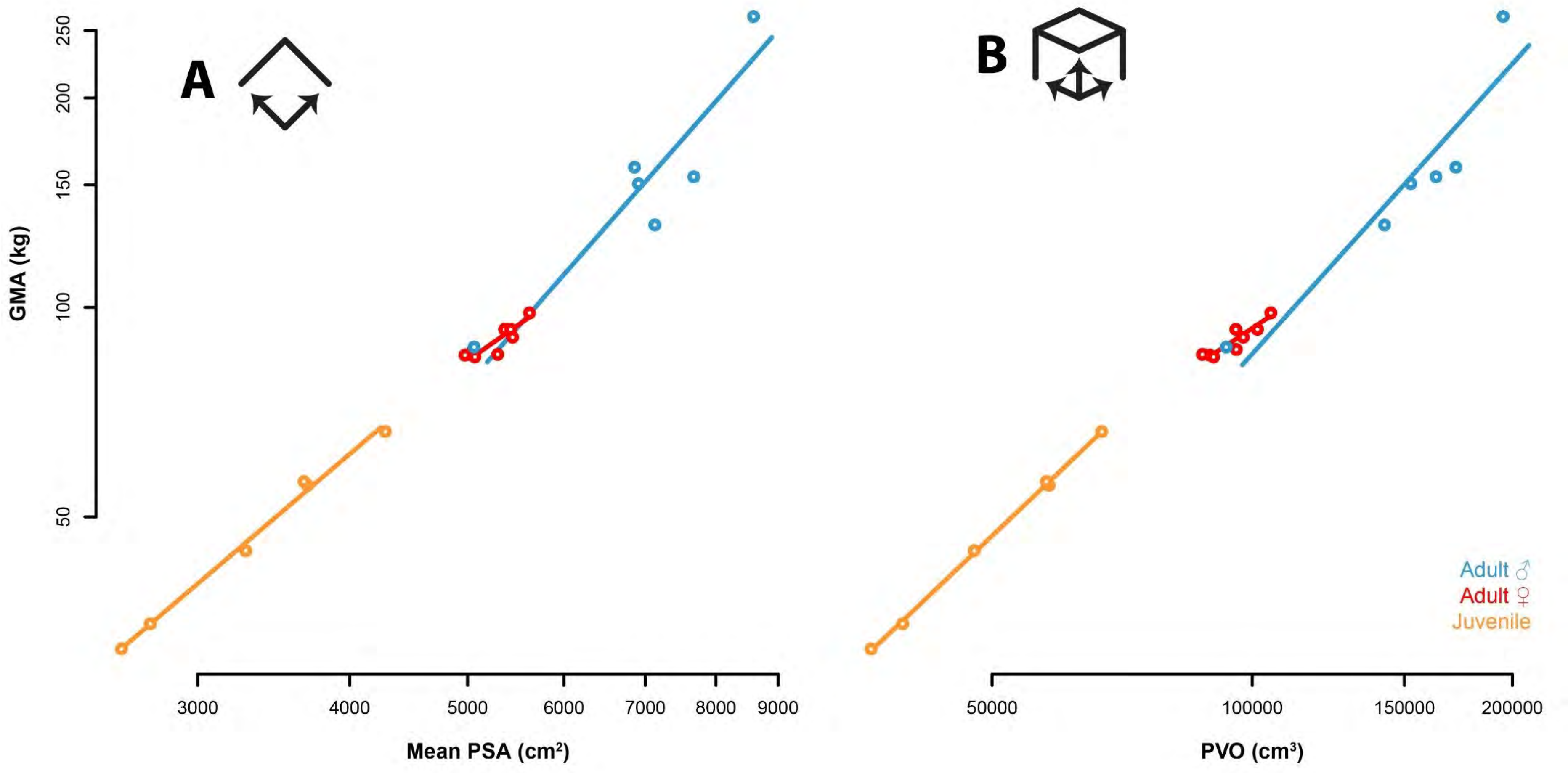


Figure 5.3. Mass estimation. Standardised major axis estimation (SMA, or Model II regression) for mean photogrammetric simplified area (PSA; A) and volume (PVO; B) by animal age-sex class. Parameter estimates and presented in Table 3. Axes are log transformed and displayed using true values. Age-sex classes are indicated by the colours of the data points (see legend).

Table 5.4. Comparisons of the ranking of individuals by body condition indices (BCI) calculated using ground and photogrammetric measurements. Ranks derived from ground-data were compared to 2-dimensional and 3-dimensional ranks using Spearman's rank correlation coefficient (r_s). Within each photogrammetric type, scaled and non-scaled derived ranks were also compared.

Age-sex class	**n**	**Types of BCI data used in rank comparison**[a]			
		Ground to 2D (scaled)	Ground to 3D (scaled)	2D (scaled) to 2D (non-scaled)	3D (scaled) to 3D (non-scaled)
Juvenile (male and female)	6	$r_s = 1$, p = 0.003	$r_s = 1$, p = 0.003	$r_s = 1$, p = 0.003	$r_s = 0.943$, p = 0.017
Adult female	8	$r_s = 0.86$, p = 0.01	$r_s = 0.88$, p = 0.007	$r_s = 0.90$, p = 0.004	$r_s = 0.905$, p = 0.005
Adult male[a]	6	$r_s = 0.77$, p = 0.1	$r_s = 0.94$, p = 0.02	$r_s = 0.829$, p = 0.058	$r_s = 0.943$, p = 0.017

[a] Scaled = datasets with scale bars added during processing to give absolute measurements, non-scaled = datasets with no scale bars added during processing which resulted in measurements considered to be relative.

[b] Two sub-adult males are included in this class.

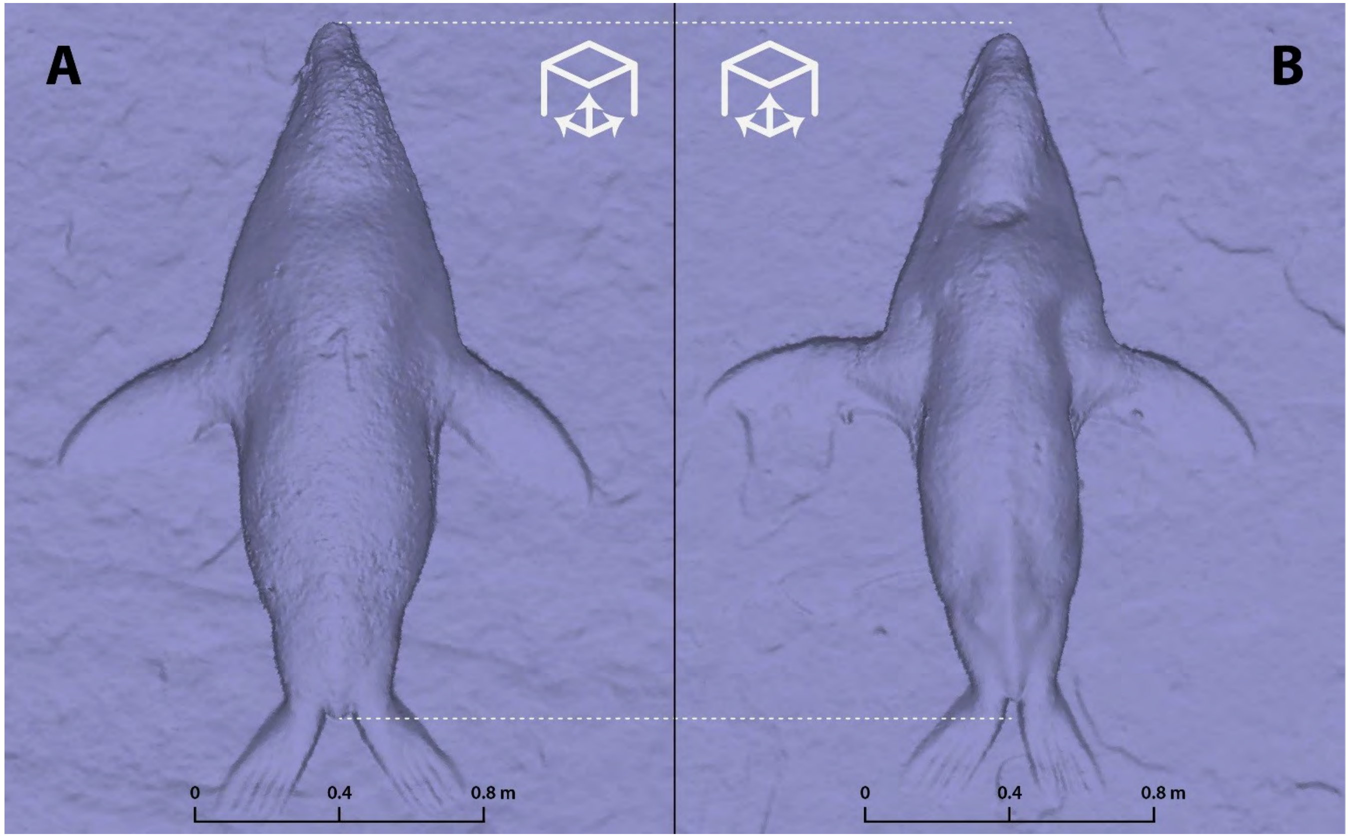


Figure 5.4. Polygonal meshes (models, in ‘solid’ view mode) of two adult male Australian sea lions constructed using Agisoft Metashape. The animals are of similar length (5.7 % difference; A = 193.1 cm, B = 182.4 cm) but vary in their mass (66.3 % difference; A = 261.8 kg, B = 131.4 kg). The difference in mass is visually noticeable, particularly in the neck, shoulder and pelvic regions. The larger individual has a higher body condition index score across all input measurement datasets (i.e. ground and photogrammetric). The white hashed lines represent the standard length extremities of the larger individual (A).

Appendix Table A5.1. Agisoft Metashape processing parameters. Chosen parameters and summary statistics for initial and final batch processing of imagery.

Parameters	**Processing parameters**	
	Initial stage	Final stage
General		
RMS	0.26 ± 0.07	0.37 ± 0.49
Mean coverage (m^2)	441.65 ± 60.49	48.37 ± 10.96
Point cloud – alignment		
Accuracy	Highest	Highest
Generic preselection	Yes	Yes
Reference preselection	No	No
Key point limit	40,000	40,000
Tie point limit	4,000	4,000
Adaptive camera model fitting	Yes	Yes
Dense point cloud		
Mean points (x 1,000,000)	49.3 ± 8.6	20.5 ± 3.7
Depth map quality	High	Ultra high
Depth map filtering mode	Mild	Mild
Model – reconstruction		
Surface type	Height field	Height field
Source data	Dense cloud	Dense cloud
Interpolation	Enabled	Enabled
Strict volumetric masks	No	No
Texturing		
Blending mode	Mosaic	Mosaic
Enable hole filling	Yes	Yes
Enable ghosting filter	Yes	Yes
DEM		
Source data	Dense cloud	Dense cloud
Interpolation	Enabled	Enabled
Mean resolution (mm/pix)	3.23 ± 0.22	1.6 ± 0.11
Orthomosaic		
Blending mode	Mosaic	Mosaic

Surface	DEM	DEM
Enable hole filling	Yes	Yes
Mean resolution (mm/pix)	1.62 ± 0.11	1.6 ± 0.11

Appendix 5.2. Digital file (.pdf) containing unique pairs of coded targets to provide scaling. Coded targets can be automatically detected during Agisoft Metashape processing.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2019.108402.

6 General conclusions

This thesis examined how we can use drones to monitor sentinel species of wildlife more efficiently. Using a multi-faceted approach (including a robust experiment to test the quality of drone-derived abundance data, drone-facilitated monitoring of three species of colonial birds and in-field photogrammetric calibration of a representative pinniped) this research resolved knowledge gaps within three key areas of wildlife ecology: disturbance, population monitoring and body condition. The findings within each of these areas built on previous research to provide timely contributions within the quickly evolving field of wildlife drone-ecology and, more broadly, the integration of technologies for scalable ecology and conservation (Marvin *et al.* 2016).

6.1 Wildlife disturbance

From the outset, we recognised that drones might have undesirable or unforeseen effects on wildlife and encouraged researchers to adopt a precautionary approach (Chapter 2; Hodgson & Koh 2016). It was important to recognise this potential issue, especially because wildlife may display no, or limited, behavioural responses, while still experiencing physiological impacts that can be difficult to quantify (e.g. Vas *et al.* 2015). This was highlighted by an initial study on free-roaming American black bears (*Ursus americanus*) who all had an increase in heart rate when overflown by a drone but rarely exhibited a detectable behavioural response (Ditmer *et al.* 2015). Later, a similar response pattern was also shown by adult King Penguins (*Aptenodytes patagonicus*) (Weimerskirch, Prudor & Schull 2017). Our timely contribution raised awareness of the potential disturbance issues when very few quantitative studies had investigated wildlife responses to drone operations.

Since the publication of the correspondence, the body of literature on wildlife responses to drones has increased considerably. In 2017, a systematic review of the available literature attempted to identify the factors influencing the probability and magnitude of wildlife reactions to drones (Mulero-Pazmany *et al.* 2017). Using data extracted from 36 published studies and 17 unpublished field campaigns, Mulero-Pazmany *et al.* (2017) concluded that wildlife reactions depended on both the drone attributes (flight pattern, engine type and size of aircraft) and the characteristics of the animals themselves (type of animal, life-history stage and level of aggregation). Unsurprisingly, these findings supported the authors' hypothesis but importantly also provided evidence the authors used to inform the development of the best practice guidelines for which we had garnered awareness. Others have refined them for specific regions (e.g. Antarctica; Leary 2017; Harris, Herata & Hertel 2019), integrated them into procedures for standardising methodological reporting (Barnas *et al.* 2020) and discussed them in the policy arena (Wallace, Martin & White 2017).

Given the suitability of many colonial bird species to drone-facilitated monitoring, their responses to drones are of ongoing interest (e.g. Lyons *et al.* 2018; Collins, Giffin & Strong 2019; Irigoin-Lovera *et al.* 2019; Barr *et al.* 2020). Findings to date have used an array of experimental designs with vastly different approach paths and flight heights but in combination they continue to suggest that responses are species- and status-specific. For example, Vas *et al.* (2015) approached unaffected birds to within 4 m during 80% of flights (n = 204). McEvoy, Hall and McDonald (2016) also found little or no obvious disturbance effects on wild, mixed species flocks of waterbirds. Bevan *et al.* (2018), however, reported that Crested Terns (*Thalasseus bergii*) displayed disturbance behaviours when overflown at 60 m, although this was limited to repeated overflights of the same colony. Brisson-Curadeau *et al.* (2017) reported an average of 8.5% of Common Murres (*Uria aalge*) flew off in response to the drone, but >99% of those birds were non-breeders. The authors did not detect any impact of the drone on breeding success of murres, except at a site where aerial predators were abundant and several birds lost their eggs to predators following drone flights. Initial findings by Weston *et al.* (2020) suggest that the flight-initiation distance varies between species (n = 22), although the flight heights tested (4 and 10 m) were not representative of those used during population monitoring. Regardless of the species- and status-specific differences that have been observed and quantified, the limited evidence available encouragingly suggests that drones reduce disturbance to surface-nesting birds compared with traditional in-colony data-collection methods (Borrelle & Fletcher 2017).

There has been increasing interest in the effects of drone operations on marine mammals (Smith *et al.* 2016; Erbe *et al.* 2017). For cetacean research, the utility of drones for data collection is extensive (e.g. Christiansen *et al.* 2016a; Fiori *et al.* 2017; Pirotta *et al.* 2017; Christiansen *et al.* 2018; Torres *et al.* 2018; Christiansen *et al.* 2019; Fiori *et al.* 2019; Horton *et al.* 2019; Christiansen *et al.* 2020a). Evidence also suggests the technique poses minimal disturbance risk. Given that sound stimulus is the most likely factor to cause disturbance, Christiansen *et al.* (2016b) recorded the in-air and in-water noise from two commonly used multi-rotor drones to assess the potential for negative noise effects on marine mammals. They concluded that while some marine mammals may hear drone noise underwater at close range (e.g. baleen whales and pinnipeds but not toothed whales), it is implied that the underwater noise effect is small, even for animals close to the water surface (Christiansen *et al.* 2016a). Behavioural response studies have reported that southern right whales (*Eubalaena australis*)

(Christiansen *et al.* 2020b) are not disturbed by drones, however low altitude flights have caused responses in dolphins (Ramos *et al.* 2018; Fettermann *et al.* 2019). For pinnipeds that are ashore (e.g. in breeding colonies), it is generally considered that the sound caused by drone overflight is also the stimulus most likely to elicit a response. This means the variability in the level of the background noise at colony sites, due to intra- and inter-site differences in wind and sea conditions, is likely to influence the ability of pinnipeds to detect drones aurally for a particular flight. While surveying Australian fur seals (*Arctocephalus pusillus doriferus*), McIntosh, Holmberg and Dann (2018) reported that a large multirotor drone flying at 80 m caused low disturbance to a small number of animals, but flying at 60 m caused unacceptable disturbance. However smaller drones (DJI Phantom 4 and Phantom 4 Pro) were undetected by the seals and did not cause observable disturbance. This is consistent with observations of long-nosed fur seals (*Arctocephalus forsteri*) and Australian sea lions (*Neophoca cinerea*) which have rarely been observed responding to small multirotor overflight at or above 40 m (J. Hodgson, unpublished data). More research is needed to robustly quantify the influence of different factors (e.g. drone sound versus size stimulus) on pinniped response, however, the anecdotal evidence suggests that small drones flying at or above 40 m cause less disturbance at the colony level than on-ground surveys.

6.1.1 Future research

Understanding the effects of drone-facilitated research on wildlife is in its infancy. Further research is required to understand potential short- and longer-term behavioural and physiological impacts, the latter of which we have very limited knowledge. Obtaining physiological response data can be difficult, however innovative approaches may negate confounding factors and avoid unnecessarily invasive techniques (e.g. using a microphone inside a replica egg to record the heart rate of an incubating bird; Howard, Hodgson & Koh 2018). Results will continue to inform research best practice, as well as assisting wildlife managers and regulators when issuing permits and setting guidelines for drone operations. Concerted effort is needed to continue to establish an informed and standardised overarching code of best practice for drone operations in the vicinity of wildlife. This should be freely available and integrate previous recommendations (e.g. Ratcliffe *et al.* 2015; Vas *et al.* 2015; Hodgson & Koh 2016; Smith *et al.* 2016; Mulero-Pazmany *et al.* 2017; Bevan *et al.* 2018; Lyons *et al.* 2018; Harris, Herata & Hertel 2019). It is important that the code not only recognises and endeavours to mitigate disturbance to subject animals, but also to wildlife that may be encountered incidentally during drone operations (e.g. raptors).

While advancing knowledge of wildlife responses to drone-facilitated monitoring is a recommended research priority, it is worth recognising this in a broader and progressive light, specifically:

- The drone stimulus (e.g. flight path, flight height) used in a considerable number of studies is not representative of the stimulus that wildlife would be exposed to during drone-facilitated population monitoring (e.g. Rümmler *et al.* 2015; Weimerskirch, Prudor & Schull 2017; Weston *et al.* 2020). This has largely resulted from the worthy intention of researchers to quantify the proximity at which wildlife respond (e.g. flight initiation distance; Weston *et al.* 2020) to establish safe operating distances. These results should be interpreted with care, and unnecessary extrapolations avoided, to ensure permitting bodies have a quantitative evidence base to inform their regulatory duties rather taking an overly precautionary approach. Ideally, in addition to testing for the effect of drone proximity on wildlife responses, the actual stimulus encountered by wildlife when conducting monitoring should be quantified (as this may be completed from a considerably greater distance from the subject animals).

- Few studies have contrasted the effects of drone-facilitated monitoring with the disturbance which can result from obtaining the same data using traditional approaches, as commented by Borrelle and Fletcher (2017). Although traditional techniques are often more easily accepted (e.g. by institutional ethics committees), it is not uncommon for the disturbance caused by these practices to be unquantified. Although drones have a potential to cause disturbance they may mitigate many of the commonly accepted impacts of traditional techniques (Zemanova 2020).
- Little attention has been given to quantitatively investigating the benefit of engineering solutions with the potential to mitigate disturbance (e.g. propellers that create less sound). Similarly, factors such as the visual appearance may influence the responses of some species and taxonomic groups and these options should also be investigated as potential mitigation strategies (e.g. Klug *et al.* 2020).
- As wildlife response data continue to be collected, it will be important to investigate longer-term effects and the potential for animals to habituate to the presence of drones (e.g. Ditmer *et al.* 2019) and related monitoring technologies.
- Finally, with the increasing quality and miniaturisation of aircraft and their sensors, it is increasingly feasible to collect data of satisfactory quality from a flying position of a sufficient distance from wildlife to remove any potential disturbance. This requires researchers to understand the spatial resolution (e.g. ground-sample distance, GSD) that is required for their use-case. Quantifying this is relatively straightforward and can often be completed with simulated data (e.g. Hodgson *et al.* 2018) prior to field data collection. This allows the selection of an appropriate sensor and lens combination to achieve the required GSD from a ‘safe’ flight height/distance. Given this reality, the benefits of response studies that are heavily invasive should be evaluated carefully on a case-by-case basis.

6.2 Wildlife population monitoring

The #EpicDuckChallenge (Chapter 3; Hodgson *et al.* 2018) provided unique insight into the bias and precision of drone-derived abundance estimates as well as those obtained using the traditional ground approach. Prior to this, the quality of the data derived from drone-facilitated wildlife population monitoring had not been as robustly quantified, nor had that of the traditional, accepted approach. This may have been because in wild populations the true population size is unknown and so it is not possible to assess the accuracy of any count method. This meant previous studies were limited to assessing precision (Hodgson *et al.* 2016), defined as the variance between replicated counts by different counters attempting to count the same sample (Gregory, Gibbons & Donald 2004), or simple contrasts between estimates (e.g. the correlation between the two count types; Chabot, Craik & Bird 2015). We overcame this issue using life-sized, replica seabirds in 'colonies' where the true numbers of individuals was known. The research demonstrated that drone-derived abundance estimates of colonial birds were more accurate and more precise than ground counts. We consider these benefits will generalise to other aggregations of wildlife than can be detected in drone-imagery; a notion which is supported by the tests of precision which have been completed in natural settings for birds and seals (Hodgson *et al.* 2016; Sorrell *et al.* 2019). This means that drone-derived wildlife monitoring data provides greater statistical power to detect fine-scale population fluctuations allowing for more informed and proactive ecological management.

Despite the numerous studies that have used drones to monitor populations of aggregated animals, few have done so on large scales (Hollings *et al.* 2018). We demonstrated this is readily achievable with inexpensive drones by monitoring across different species, sites and years (Chapter 4). Our study sites were hard to access (islands). Drone-facilitated monitoring minimised researcher risks by avoiding island landings and the drone overflights were likely to have caused considerably less disturbance to the wildlife compared to on-island surveys.

Automating drone-facilitated monitoring is key to unlocking the technique's full potential and implementation on a large scale. Data collection is already achievable with minimal user-input thanks to stable and advanced flight programming software and, regulations permitting, this step could be fully automated (e.g. a remotely deployed drone that docks at a base to recharge from a self-sustaining power source and upload data). Similarly, image processing can be completed without user input (e.g. to create products of interest such as geo-referenced orthomosaics; Chapter 4). However, the automatic and accurate extraction of required data, such as the detection and counting of a target species, is a challenge yet to be fully resolved (Hollings *et al.* 2018). The open-source computer vision technique we developed (Chapter 3; Hodgson *et al.* 2018) demonstrated a semi-automated solution which advanced earlier methods (Chabot & Francis 2016) although it did not process particularly quickly and may not generalise across all habitats (Lyons *et al.* 2019). Since then, an array of studies have reported semi-automated approaches using 'off-the-shelf' object-based image analysis and supervised classifications (Afán, Máñez & Díaz-Delgado 2018; Chabot, Dillon & Francis 2018) through to more advanced machine learning approaches with promising results (Kellenberger, Marcos & Tuia 2018; Gray *et al.* 2019; Lyons *et al.* 2019; Francis *et al.* 2020). Dujon and Schofield (2019) reviewed manuscripts in ecology that used drones (n = 213), reporting that 42% used machine learning to assess the visual data. They concluded that while drone use has recently rapidly increased in ecology studies, with 93% of the manuscripts that were reviewed being published between 2012 and 2018, the uptake of machine learning to process imagery has been slower. Fully harnessing artificial intelligence, including machine learning (Lamba *et al.* 2019), will be key to overcoming manual processing and thereby creating a truly powerful tool for ecological science.

6.2.1 Future research

While this thesis complements existing research to advance drone-facilitated wildlife population monitoring, there remains a plethora of research opportunities in this area, including:

- Using geo-referenced orthomosaics for comprehensive spatiotemporal analyses. As our orthomosaics co-registered well (Chapter 4) individual nests could be identified over time. These data are suitable for many analyses including demography. Habitat information from ground flora surveys to data extracted from drone-derived 3-dimensional digital ecosystems (e.g. D'Urban Jackson *et al.* 2020; Oosthuizen *et al.* 2020) could be added to analyses to discern, for example, what factors drive nest-site choice. This would benefit the prediction of suitable nesting habitat that could be managed accordingly, especially for sensitive species or those of conservation concern in need of refugia. We expect the same method could be employed to collect similar information for other taxonomic groups.
- Further investigation into the use of non-visual spectrums, as well as sampling concurrently in multiple spectrums. The use of thermal imagery for wildlife detection has long been of interest and recent improvements in sensor resolution have led to the technology being highly useful for drone-facilitated wildlife monitoring (Seymour *et al.* 2017; Corcoran *et al.* 2019; Beaver *et al.* 2020; Hamilton *et al.* 2020; Santangeli *et al.* 2020). We predict that if the sampling and processing barriers associated with multispectral sampling can be overcome, the benefits to drone-facilitated wildlife monitoring will be considerable.
- Calibrating coarser resolution imagery collected by other platforms (e.g. satellite imagery). This technique has tremendous potential for wildlife detection and monitoring. It was validated recently by combining Landsat medium resolution satellite imagery with drone and ground surveys to discover a major hotspot of Adèlie penguin (*Pygoscelis adeliae*) abundance in the Danger Islands off the Antarctic Peninsula (an estimated 751,527 nesting pairs of penguins; Borowicz *et al.* 2018). Similarly, Bowler *et al.* (2020) demonstrated that large seabirds can be detected solely from very high resolution satellite imagery; however, adding drone imagery to this workflow is likely to improve results as it would provide better

ground truth data. This process may also allow sufficient calibration for satellite imagery-only detections of smaller individuals.

- Developing statistical models to account for imperfect detection. Modelling could improve machine learning abundance estimates by accounting for overall probability of detection, false detection and duplicate detection (Martin *et al.* 2012; Brack, Kindel & Oliveira 2018; Corcoran, Denman & Hamilton 2020; Williams, Schroeder & Jackson 2020).
- Developing and testing a fully autonomous wildlife population monitoring system with an integrated processing and analysis pipeline. Such a system could be contained in a suitably robust equipment structure with a drone entering and exiting to complete missions as programmed. A self-sustaining power supply (e.g. via solar electricity on the drone itself or via battery storage at a ground station) could recharge the drone batteries when not in operation as well as facilitate wireless data transfer to the cloud. This setup would be particularly useful in remote locations where human visitation is difficult or undesirable. The system could also take the form of a small satellite, such as a cubesat (Pimm *et al.* 2015). The goal would be to collect data over large areas, at required spatial and temporal resolutions, that is rapidly processed and analysed via a pipeline to provide near-real time insights. The processing side of such a system could be advanced as needed for automated change detection through to predictive modelling of areas not sampled at a given time point.

6.3 Wildlife body condition

The final data chapter in this thesis demonstrated that accurate morphometrics of an eared seal (otariid) can be collected non-invasively using drones (Chapter 5; Hodgson *et al.* 2020). While using photogrammetry to measure mammals is not new (Bell, Hindell & Burton 1997; McFadden, Worthy & Lacher 2006; de Bruyn *et al.* 2009; Postma *et al.* 2015), using aerial drones as a platform to capture the data has only occurred in recent years. Initial attempts that focused on marine mammals relied on single photograph approaches but, given they investigated free-living cetaceans, they either lacked calibration with animals of known size and mass (Durban *et al.* 2015; Gray *et al.* 2019) or, inventively, used a proxy for these measurements (i.e. historical catch records; Christiansen *et al.* 2019). As pinnipeds haul-out to rest and breed, morphometric data obtained from photogrammetry can be more easily ground-truthed. Allan et al. (2019) were able to use historical length and auxiliary girth measurements of a colony of Australian fur seals (*Arctocephalus pusillus doriferus*) to compare with their estimates from mosaicked, geo-referenced imagery (i.e. an orthomosaic). However, Krause *et al.* (2017) appear to be the first to have tested the accuracy of drone-derived photogrammetric data using adult female leopard seals (*Hydrurga leptonyx*) of known body size and mass. Our research extended on these studies by sampling Australian sea lion (*Neophoca cinerea*) individuals from all age-sex classes (juvenile, adult female and adult male) and estimating both 2-dimensional and 3-dimensional measurements of our study species. Drone-derived measurements were highly repeatable and not dissimilar to traditional, ground-collected data, as has been reported for similar techniques on other pinnipeds (Krause *et al.* 2017; Alvarado *et al.* 2020).

Our investigation ultimately sought to develop and test a technique that used our accurate drone-derived morphometrics to quantify the body condition of a sentinel species of marine mammal. The plight of our endangered study species provided extra motivation to develop a non-invasive technique without the considerable risks involved with anaesthetising and handling animals. Our technique produced body condition indices that ranked animals comparably to those generated from ground-collected data. While these indices should be interpreted carefully, they have great potential to be used in the rapid assessment of the spatial and temporal variation in the condition of this indicator species relative to environmental fluctuations. Two recent cetacean studies provide examples of such spatial and temporal investigations into a species' condition. Christiansen *et al.* (2020a) conducted a population estimate of right whale body condition, showing that critically endangered juvenile, adult and lactating female North Atlantic right whales (*Eubalaena glacialis*) were all in poorer body condition than those from three seemingly healthy (i.e. growing) populations of southern right whales (*E. australis*). Similarly, Soledade Lemos *et al.* (2020) investigated the temporal variation in body condition of eastern North Pacific gray whales (*Eschrichtius robustus*) over three consecutive years. They documented improvement in body condition with the progression of the feeding season in all three years, but discovered significantly better body condition in the first year which they correlated with a difference in prey availability and/or quality using upwelling patterns from a six year period (Soledade Lemos *et al.* 2020). The spatial and temporal ecosystem insights from these studies exemplifies the utility of drone-derived morphometrics for body condition analyses. They demonstrate the potential for this type of research to inform marine mammal conservation efforts and, importantly, the use of these sentinel species to understand the impacts of climate change on marine ecosystems at a global scale.

6.3.1 Future research

The use of drone-derived morphometrics is an exciting and quickly evolving area of drone-ecology. In addition to those already discussed (see 5.5.3), future research opportunities include:

- Using the technique we developed to investigate spatial and temporal variation in the body condition of Australian sea lion (*N. cinerea*) populations across the species' range, which spans more than 3,000 km of southern Australian coastline (Gales *et al.* 1992; Shaughnessy *et al.* 2011) within the 'Great Southern Reef' (Bennett *et al.* 2016). This could provide valuable insight into the relationship between individual health and colony trends in abundance. For example, if a colony is in decline and its members are in poor condition, it could be that factors such as food availability or disease are driving the decline. However, if there is no difference in the condition of animals from declining and recovering colonies, then declines may be due to direct human impacts such as bycatch in commercial fisheries, entanglement in marine debris or impacts from climate change. Results would be beneficial for identifying the most likely threats to the species' survival, thereby contributing to informed conservation strategies.

- Refining the technique we developed with additional calibration sampling, especially if applying it to other species. This would increase confidence in the relationship between mass and photogrammetric variables (e.g. area and volume); however, the need for increasing this confidence for Australian sea lions (*N. cinerea*) should be carefully balanced against the risks of anaesthetising and handling animals. It is also possible that photogrammetric-only data are sufficient as scale independent indicies can be employed (i.e. relative measurements) to compare animals. Any future sampling should embrace advances in technology to improve the technique while maintaining compatibility with existing datasets.
- Developing an automated processing workflow. This could be accomplished using artificial intelligence, such as deep learning using convolutional neural networks which have shown considerable potential in similar studies (e.g. Gray *et al.* 2019). A robust workflow would provide time and cost efficiencies, and possibly reduce error, thereby allowing researchers to scale-up their data inputs and increase statistical power.
- Integrating body condition research into broader scale drone-facilitated wildlife monitoring. For example, morphometric data sampling could be completed concurrently with colony-level abundance monitoring of pinnipeds and other, co-located indicator species (e.g. seabirds) (Hodgson *et al.* 2016). Such broadened surveys will provide time and cost-efficient data, particularly if processed automatically, with the potential for more powerful, multi-species ecosystem insights.

6.4 Summary

This thesis highlights the utility of drones for monitoring sentinel wildlife species. The findings resolve knowledge gaps in three key areas of wildlife drone-ecology: disturbance, population monitoring and body condition. A time-critical publication recognised that drones might have undesirable or unforeseen behavioural and physiological effects on wildlife and provided important recommendations for conducting drone-facilitated research around wildlife as the basis for a code of best practice. The wildlife population monitoring component of the thesis quantified the accuracy benefits of using drone-derived data to estimate the abundance of aggregated animals. Then, using wild colonial birds, we developed a generalisable and repeatable technique requiring minimal user input for adaptable and high spatiotemporal population monitoring. Finally, we used drone-facilitated photogrammetry to acquire accurate morphometric data to infer body condition in pinnipeds. Together, these findings improved drone-facilitated wildlife monitoring. Multi-faceted monitoring approaches that utilise ground, drone and Earth observation data, as well as those from innovative techniques yet to be realised, will be vital for continuing to detect the ecological impacts of climate change and informing conservation.

6.5 References

Afán, I., Máñez, M. & Díaz-Delgado, R. (2018) Drone Monitoring of Breeding Waterbird Populations: The Case of the Glossy Ibis. *Drones*, **2,** 42. https://doi.org/10.3390/drones2040042

Alvarado, D.C., Robinson, P.W., Frasson, N.C., Costa, D.P. & Beltran, R.S. (2020) Calibration of aerial photogrammetry to estimate elephant seal mass. *Marine Mammal Science*. https://doi.org/10.1111/mms.12714

Barnas, A.F., Chabot, D., Hodgson, A.J., Johnston, D.W., Bird, D.M. & Ellis-Felege, S.N. (2020) A standardized protocol for reporting methods when using drones for wildlife research. *Journal of Unmanned Vehicle Systems*, **8,** 89-98. https://doi.org/10.1139/juvs-2019-0011

Barr, J.R., Green, M.C., DeMaso, S.J. & Hardy, T.B. (2020) Drone Surveys Do Not Increase Colony-wide Flight Behaviour at Waterbird Nesting Sites, But Sensitivity Varies Among Species. *Scientific Reports*, **10,** 3781. https://doi.org/10.1038/s41598-020-60543-z

Beaver, J.T., Baldwin, R.W., Messinger, M., Newbolt, C.H., Ditchkoff, S.S. & Silman, M.R. (2020) Evaluating the Use of Drones Equipped with Thermal Sensors as an Effective Method for Estimating Wildlife. *Wildlife Society Bulletin*. https://doi.org/10.1002/wsb.1090

Bell, C.M., Hindell, M.A. & Burton, H.R. (1997) Estimation of body mass in the southern elephant seal, Mirounga leonina, by photogrammetry and morphometrics. *Marine Mammal Science*, **13,** 669-682. https://doi.org/DOI 10.1111/j.1748-7692.1997.tb00090.x

Bennett, S., Wernberg, T., Connell, S.D., Hobday, A.J., Johnson, C.R. & Poloczanska, E.S. (2016) The 'Great Southern Reef': social, ecological and economic value of Australia's neglected kelp forests. *Marine and Freshwater Research*, **67,** 47. https://doi.org/10.1071/mf15232

Bevan, E., Whiting, S., Tucker, T., Guinea, M., Raith, A. & Douglas, R. (2018) Measuring behavioral responses of sea turtles, saltwater crocodiles, and crested terns to drone disturbance to define ethical operating thresholds. *PloS One*, **13,** e0194460. https://doi.org/10.1371/journal.pone.0194460

Borowicz, A., McDowall, P., Youngflesh, C., Sayre-McCord, T., Clucas, G., Herman, R., Forrest, S., Rider, M., Schwaller, M., Hart, T., Jenouvrier, S., Polito, M.J., Singh, H. & Lynch, H.J. (2018) Multi-modal survey of Adelie penguin mega-colonies reveals the Danger Islands as a seabird hotspot. *Scientific Reports*, **8,** 3926. https://doi.org/10.1038/s41598-018-22313-w

Borrelle, S.B. & Fletcher, A.T. (2017) Will drones reduce investigator disturbance to surface-nesting seabirds? *Marine Ornithology*, **45,** 89-94.

Bowler, E., Fretwell, P.T., French, G. & Mackiewicz, M. (2020) Using Deep Learning to Count Albatrosses from Space: Assessing Results in Light of Ground Truth Uncertainty. *Remote Sensing*, **12,** 2026. https://doi.org/10.3390/rs12122026

Brack, I.V., Kindel, A. & Oliveira, L.F.B. (2018) Detection errors in wildlife abundance estimates from Unmanned Aerial Systems (UAS) surveys: Synthesis, solutions, and challenges. *Methods in Ecology and Evolution*, **9,** 1864-1873. https://doi.org/10.1111/2041-210x.13026

Brisson-Curadeau, E., Bird, D., Burke, C., Fifield, D.A., Pace, P., Sherley, R.B. & Elliott, K.H. (2017) Seabird species vary in behavioural response to drone census. *Scientific Reports*, **7,** 17884. https://doi.org/10.1038/s41598-017-18202-3

Chabot, D., Craik, S.R. & Bird, D.M. (2015) Population census of a large common tern colony with a small unmanned aircraft. *PloS One*, **10,** e0122588. https://doi.org/10.1371/journal.pone.0122588

Chabot, D., Dillon, C. & Francis, C.M. (2018) An approach for using off-the-shelf object-based image analysis software to detect and count birds in large volumes of aerial imagery. *Avian Conservation and Ecology*, **13**. https://doi.org/10.5751/ace-01205-130115

Chabot, D. & Francis, C.M. (2016) Computer-automated bird detection and counts in high-resolution aerial images: a review. *Journal of Field Ornithology*, **87,** 343-359. https://doi.org/10.1111/jofo.12171

Christiansen, F., Dawson, S.M., Durban, J.W., Fearnbach, H., Miller, C.A., Bejder, L., Uhart, M., Sironi, M., Corkeron, P., Rayment, W., Leunissen, E., Haria, E., Ward, R., Warick, H.A., Kerr, I., Lynn, M.S., Pettis, H.M. & Moore, M.J. (2020a) Population comparison of right whale body condition reveals poor state of the North Atlantic right whale. *Marine Ecology Progress Series*, **640,** 1-16. https://doi.org/10.3354/meps13299

Christiansen, F., Dujon, A.M., Sprogis, K.R., Arnould, J.P.Y. & Bejder, L. (2016a) Noninvasive unmanned aerial vehicle provides estimates of the energetic cost of reproduction in humpback whales. *Ecosphere*, **7,** e01468. https://doi.org/10.1002/ecs2.1468

Christiansen, F., Nielsen, M.L.K., Charlton, C., Bejder, L. & Madsen, P.T. (2020b) Southern right whales show no behavioral response to low noise levels from a nearby unmanned aerial vehicle. *Marine Mammal Science*. https://doi.org/10.1111/mms.12699

Christiansen, F., Rojano-Doñate, L., Madsen, P.T. & Bejder, L. (2016b) Noise Levels of Multi-Rotor Unmanned Aerial Vehicles with Implications for Potential Underwater Impacts on Marine Mammals. *Frontiers in Marine Science,* **3**. https://doi.org/10.3389/fmars.2016.00277

Christiansen, F., Sironi, M., Moore, M.J., Di Martino, M., Ricciardi, M., Warick, H.A., Irschick, D.J., Gutierrez, R., Uhart, M.M. & Iossa, G. (2019) Estimating body mass of free-living whales using aerial photogrammetry and 3D volumetrics. *Methods in Ecology and Evolution,* **10,** 2034-2044. https://doi.org/10.1111/2041-210x.13298

Christiansen, F., Vivier, F., Charlton, C., Ward, R., Amerson, A., Burnell, S. & Bejder, L. (2018) Maternal body size and condition determine calf growth rates in southern right whales. *Marine Ecology Progress Series,* **592,** 267-281. https://doi.org/10.3354/meps12522

Collins, S.A., Giffin, G.J. & Strong, W.T. (2019) Using flight initiation distance to evaluate responses of colonial-nesting Great Egrets to the approach of an unmanned aerial vehicle. *Journal of Field Ornithology*. https://doi.org/10.1111/jofo.12312

Corcoran, E., Denman, S. & Hamilton, G. (2020) New technologies in the mix: Assessing N-mixture models for abundance estimation using automated detection data from drone surveys. *Ecology and Evolution*. https://doi.org/10.1002/ece3.6522

Corcoran, E., Denman, S., Hanger, J., Wilson, B. & Hamilton, G. (2019) Automated detection of koalas using low-level aerial surveillance and machine learning. *Scientific Reports,* **9,** 3208. https://doi.org/10.1038/s41598-019-39917-5

D'Urban Jackson, T., Williams, G.J., Walker-Springett, G. & Davies, A.J. (2020) Three-dimensional digital mapping of ecosystems: a new era in spatial ecology. *Proceedings: Biological Sciences,* **287,** 20192383. https://doi.org/10.1098/rspb.2019.2383 de Bruyn, P.J.N., Bester, M.N., Carlini, A.R. & Oosthuizen, W.C. (2009) How to weigh an elephant seal with one finger: a simple three-dimensional photogrammetric application. *Aquatic Biology*, **5,** 31-39. https://doi.org/10.3354/ab00135

Ditmer, M.A., Vincent, J.B., Werden, L.K., Tanner, J.C., Laske, T.G., Iaizzo, P.A., Garshelis, D.L. & Fieberg, J.R. (2015) Bears Show a Physiological but Limited Behavioral Response to Unmanned Aerial Vehicles. *Current Biology*, **25,** 2278-2283. https://doi.org/10.1016/j.cub.2015.07.024

Ditmer, M.A., Werden, L.K., Tanner, J.C., Vincent, J.B., Callahan, P., Iaizzo, P.A., Laske, T.G. & Garshelis, D.L. (2019) Bears habituate to the repeated exposure of a novel stimulus, unmanned aircraft systems. *Conserv Physiol*, **7,** coy067. https://doi.org/10.1093/conphys/coy067

Dujon, A.M. & Schofield, G. (2019) Importance of machine learning for enhancing ecological studies using information-rich imagery. *Endangered Species Research*, **39,** 91-104. https://doi.org/10.3354/esr00958

Durban, J.W., Fearnbach, H., Barrett-Lennard, L.G., Perryman, W.L. & Leroi, D.J. (2015) Photogrammetry of killer whales using a small hexacopter launched at sea. *Journal of Unmanned Vehicle Systems*, **3,** 131-135. https://doi.org/10.1139/juvs-2015-0020

Erbe, C., Parsons, M., Duncan, A.J., Osterrieder, S. & Allen, K. (2017) Aerial and underwater sound of unmanned aerial vehicles (UAV, drones). *Journal of Unmanned Vehicle Systems*. https://doi.org/10.1139/juvs-2016-0018

Fettermann, T., Fiori, L., Bader, M., Doshi, A., Breen, D., Stockin, K.A. & Bollard, B. (2019) Behaviour reactions of bottlenose dolphins (Tursiops truncatus) to multirotor Unmanned Aerial Vehicles (UAVs). *Scientific Reports*, **9,** 8558. https://doi.org/10.1038/s41598-019-44976-9

Fiori, L., Doshi, A., Martinez, E., Orams, M.B. & Bollard-Breen, B. (2017) The Use of Unmanned Aerial Systems in Marine Mammal Research. *Remote Sensing*, **9,** 543. https://doi.org/10.3390/rs9060543

Fiori, L., Martinez, E., Bader, M.K.F., Orams, M.B. & Bollard, B. (2019) Insights into the use of an unmanned aerial vehicle (UAV) to investigate the behavior of humpback whales (Megaptera novaeangliae) in Vava'u, Kingdom of Tonga. *Marine Mammal Science*. https://doi.org/10.1111/mms.12637

Francis, R.J., Lyons, M.B., Kingsford, R.T. & Brandis, K.J. (2020) Counting Mixed Breeding Aggregations of Animal Species Using Drones: Lessons from Waterbirds on Semi-Automation. *Remote Sensing*, **12,** 1185. https://doi.org/10.3390/rs12071185

Gales, N.J., Cheal, A.J., Pobar, G.J. & Williamson, P. (1992) Breeding Biology and Movements of Australian Sea-Lions, Neophoca-Cinerea, Off the West-Coast of Western-Australia. *Wildlife Research*, **19,** 405-416. https://doi.org/Doi 10.1071/Wr9920405

Gray, P.C., Bierlich, K.C., Mantell, S.A., Friedlaender, A.S., Goldboge, J.A. & Johnston, D.W. (2019) Drones and convolutional neural networks facilitate automated and accurate cetacean species identification and photogrammetry. *Methods in Ecology and Evolution*, **10,** 1490-1500. https://doi.org/10.1111/2041-210x.13246

Gregory, R.D., Gibbons, D.W. & Donald, P.F. (2004) Bird census and survey techniques. *Bird ecology and conservation* (eds W.J. Sutherland, I. Newton & R. Green). Oxford University Press, Oxford.

Hamilton, G., Corcoran, E., Denman, S., Hennekam, M.E. & Koh, L.P. (2020) When you can't see the koalas for the trees: Using drones and machine learning in complex environments. *Biological Conservation*, **247,** 108598. https://doi.org/10.1016/j.biocon.2020.108598

Harris, C.M., Herata, H. & Hertel, F. (2019) Environmental guidelines for operation of Remotely Piloted Aircraft Systems (RPAS): Experience from Antarctica. *Biological Conservation,* **236,** 521-531. https://doi.org/10.1016/j.biocon.2019.05.019

Hodgson, J.C., Baylis, S.M., Mott, R., Herrod, A. & Clarke, R.H. (2016) Precision wildlife monitoring using unmanned aerial vehicles. *Scientific Reports,* **6,** 22574. https://doi.org/10.1038/srep22574

Hodgson, J.C., Holman, D., Terauds, A., Koh, L.P. & Goldsworthy, S.D. (2020) Rapid condition monitoring of an endangered marine vertebrate using precise, non-invasive morphometrics. *Biological Conservation,* **242,** 108402. https://doi.org/10.1016/j.biocon.2019.108402

Hodgson, J.C. & Koh, L.P. (2016) Best practice for minimising unmanned aerial vehicle disturbance to wildlife in biological field research. *Current Biology,* **26,** R404-405. https://doi.org/10.1016/j.cub.2016.04.001

Hodgson, J.C., Mott, R., Baylis, S.M., Pham, T.T., Wotherspoon, S., Kilpatrick, A.D., Segaran, R.R., Reid, I., Terauds, A. & Koh, L.P. (2018) Drones count wildlife more accurately and precisely than humans. *Methods in Ecology and Evolution,* **9,** 1160-1167. https://doi.org/10.1111/2041-210x.12974

Hollings, T., Burgman, M., van Andel, M., Gilbert, M., Robinson, T., Robinson, A. & McPherson, J. (2018) How do you find the green sheep? A critical review of the use of remotely sensed imagery to detect and count animals. *Methods in Ecology and Evolution,* **9,** 881-892. https://doi.org/10.1111/2041-210x.12973

Horton, T.W., Hauser, N., Cassel, S., Klaus, K.F., Fettermann, T. & Key, N. (2019) Doctor Drone: Non-invasive Measurement of Humpback Whale Vital Signs Using Unoccupied Aerial System Infrared Thermography. *Frontiers in Marine Science,* **6**. https://doi.org/10.3389/fmars.2019.00466

Howard, C.Q., Hodgson, J.C. & Koh, L.P. (2018) Heart rate measurement of nesting birds using a microphone in a plastic egg. *Proceedings of ACOUSTICS,* **7**.

Irigoin-Lovera, C., Luna, D.M., Acosta, D.A. & Zavalaga, C.B. (2019) Response of colonial Peruvian guano birds to flying UAVs: effects and feasibility for implementing new population monitoring methods. *PeerJ,* **7,** e8129. https://doi.org/10.7717/peerj.8129

Kellenberger, B., Marcos, D. & Tuia, D. (2018) Detecting mammals in UAV images: Best practices to address a substantially imbalanced dataset with deep learning. *Remote Sensing of Environment,* **216,** 139-153. https://doi.org/10.1016/j.rse.2018.06.028

Klug, P.E., Fernández-Juricic, E., Blackwell, B.F. & Egan, C.C. (2020) Testing a key assumption of using drones as frightening devices: Do birds perceive drones as risky? *The Condor,* **122**. https://doi.org/10.1093/condor/duaa014

Krause, D.J., Hinke, J.T., Perryman, W.L., Goebel, M.E. & LeRoi, D.J. (2017) An accurate and adaptable photogrammetric approach for estimating the mass and body condition of pinnipeds using an unmanned aerial system. *PloS One,* **12,** e0187465. https://doi.org/10.1371/journal.pone.0187465

Lamba, A., Cassey, P., Segaran, R.R. & Koh, L.P. (2019) Deep learning for environmental conservation. *Current Biology,* **29,** R977-R982. https://doi.org/10.1016/j.cub.2019.08.016

Leary, D. (2017) Drones on ice: an assessment of the legal implications of the use of unmanned aerial vehicles in scientific research and by the tourist industry in Antarctica. *Polar Record***,** 1-15. https://doi.org/10.1017/s0032247417000262

Lyons, M., Brandis, K., Callaghan, C., McCann, J., Mills, C., Ryall, S. & Kingsford, R. (2018) Bird interactions with drones, from individuals to large colonies. *Australian Field Ornithology,* **35,** 51-56. https://doi.org/10.20938/afo35051056

Lyons, M.B., Brandis, K.J., Murray, N.J., Wilshire, J.H., McCann, J.A., Kingsford, R.T. & Callaghan, C.T. (2019) Monitoring large and complex wildlife aggregations with drones. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210x.13194

Martin, J., Edwards, H.H., Burgess, M.A., Percival, H.F., Fagan, D.E., Gardner, B.E., Ortega-Ortiz, J.G., Ifju, P.G., Evers, B.S. & Rambo, T.J. (2012) Estimating distribution of hidden objects with drones: from tennis balls to manatees. *PloS One*, **7,** e38882. https://doi.org/10.1371/journal.pone.0038882

Marvin, D.C., Koh, L.P., Lynam, A.J., Wich, S., Davies, A.B., Krishnamurthy, R., Stokes, E., Starkey, R. & Asner, G.P. (2016) Integrating technologies for scalable ecology and conservation. *Global Ecology and Conservation*, **7,** 262-275. https://doi.org/10.1016/j.gecco.2016.07.002

McEvoy, J.F., Hall, G.P. & McDonald, P.G. (2016) Evaluation of unmanned aerial vehicle shape, flight path and camera type for waterfowl surveys: disturbance effects and species recognition. *PeerJ*, **4,** e1831. https://doi.org/10.7717/peerj.1831

McFadden, K.W., Worthy, G.A.J. & Lacher, T.E. (2006) Photogrammetric Estimates of Size and Mass in Hawaiian Monk Seals (<I>Monachus schauinslandi</I>). *Aquatic Mammals*, **32,** 31-40. https://doi.org/10.1578/am.32.1.2006.31

McIntosh, R.R., Holmberg, R. & Dann, P. (2018) Looking Without Landing—Using Remote Piloted Aircraft to Monitor Fur Seal Populations Without Disturbance. *Frontiers in Marine Science*, **5**. https://doi.org/10.3389/fmars.2018.00202

Mulero-Pazmany, M., Jenni-Eiermann, S., Strebel, N., Sattler, T., Negro, J.J. & Tablado, Z. (2017) Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review. *PloS One*, **12,** e0178448. https://doi.org/10.1371/journal.pone.0178448

Oosthuizen, W.C., Krüger, L., Jouanneau, W. & Lowther, A.D. (2020) Unmanned aerial vehicle (UAV) survey of the Antarctic shag (Leucocarbo bransfieldensis) breeding colony at Harmony Point, Nelson Island, South Shetland Islands. *Polar Biology*. https://doi.org/10.1007/s00300-019-02616-y

Pimm, S.L., Alibhai, S., Bergl, R., Dehgan, A., Giri, C., Jewell, Z., Joppa, L., Kays, R. & Loarie, S. (2015) Emerging technologies to conserve biodiversity. *Trends in Ecology & Evolution*, **30,** 685-696. https://doi.org/10.1016/j.tree.2015.08.008

Pirotta, V., Smith, A., Ostrowski, M., Russell, D., Jonsen, I.D., Grech, A. & Harcourt, R. (2017) An Economical Custom-Built Drone for Assessing Whale Health. *Frontiers in Marine Science*, **4**. https://doi.org/10.3389/fmars.2017.00425

Postma, M., Tordiffe, A.S.W., Hofmeyr, M.S., Reisinger, R.R., Bester, L.C., Buss, P.E. & de Bruyn, P.J.N. (2015) Terrestrial mammal three-dimensional photogrammetry: multispecies mass estimation. *Ecosphere*, **6,** art293. https://doi.org/10.1890/Es15-00368.1

Ramos, E.A., Maloney, B., Magnasco, M.O. & Reiss, D. (2018) Bottlenose Dolphins and Antillean Manatees Respond to Small Multi-Rotor Unmanned Aerial Systems. *Frontiers in Marine Science*, **5**. https://doi.org/10.3389/fmars.2018.00316

Ratcliffe, N., Guihen, D., Robst, J., Crofts, S., Stanworth, A. & Enderlein, P. (2015) A protocol for the aerial survey of penguin colonies using UAVs. *Journal of Unmanned Vehicle Systems*, **3,** 95-101. https://doi.org/10.1139/juvs-2015-0006

Rümmler, M.-C., Mustafa, O., Maercker, J., Peter, H.-U. & Esefeld, J. (2015) Measuring the influence of unmanned aerial vehicles on Adélie penguins. *Polar Biology*. https://doi.org/10.1007/s00300-015-1838-1

Santangeli, A., Chen, Y., Kluen, E., Chirumamilla, R., Tiainen, J. & Loehr, J. (2020) Integrating drone-borne thermal imaging with artificial intelligence to locate bird nests on agricultural land. *Scientific Reports*, **10,** 10993. https://doi.org/10.1038/s41598-020-67898-3

Seymour, A.C., Dale, J., Hammill, M., Halpin, P.N. & Johnston, D.W. (2017) Automated detection and enumeration of marine wildlife using unmanned aircraft systems (UAS) and thermal imagery. *Scientific Reports*, **7,** 45127. https://doi.org/10.1038/srep45127

Shaughnessy, P.D., Goldsworthy, S.D., Hamer, D.J., Page, B. & McIntosh, R.R. (2011) Australian sea lions Neophoca cinerea at colonies in South Australia: distribution and abundance, 2004 to 2008. *Endangered Species Research*, **13,** 87-98. https://doi.org/10.3354/esr00317

Smith, C.E., Sykora-Bodie, S.T., Bloodworth, B., Pack, S.M., Spradlin, T.R. & LeBoeuf, N.R. (2016) Assessment of known impacts of unmanned aerial systems (UAS) on marine mammals: data gaps and recommendations for researchers in the United States1. *Journal of Unmanned Vehicle Systems***,** 1-14. https://doi.org/10.1139/juvs-2015-0017

Soledade Lemos, L., Burnett, J.D., Chandler, T.E., Sumich, J.L. & Torres, L.G. (2020) Intra- and inter-annual variation in gray whale body condition on a foraging ground. *Ecosphere*, **11**. https://doi.org/10.1002/ecs2.3094

Sorrell, K.J., Clarke, R.H., Holmberg, R. & McIntosh, R.R. (2019) Remotely piloted aircraft improve precision of capture–mark–resight population estimates of Australian fur seals. *Ecosphere*, **10**. https://doi.org/10.1002/ecs2.2812

Torres, L.G., Nieukirk, S.L., Lemos, L. & Chandler, T.E. (2018) Drone Up! Quantifying Whale Behavior From a New Perspective Improves Observational Capacity. *Frontiers in Marine Science*, **5**. https://doi.org/10.3389/fmars.2018.00319

Vas, E., Lescroel, A., Duriez, O., Boguszewski, G. & Gremillet, D. (2015) Approaching birds with drones: first experiments and ethical guidelines. *Biology Letters*, **11,** 20140754. https://doi.org/10.1098/rsbl.2014.0754

Wallace, P., Martin, R. & White, I. (2017) Keeping pace with technology: drones, disturbance and policy deficiency. *Journal of Environmental Planning and Management***,** 1-18. https://doi.org/10.1080/09640568.2017.1353957

Weimerskirch, H., Prudor, A. & Schull, Q. (2017) Flights of drones over sub-Antarctic seabirds show species- and status-specific behavioural and physiological responses. *Polar Biology*, **41,** 259-266. https://doi.org/10.1007/s00300-017-2187-z

Weston, M.A., O'Brien, C., Kostoglou, K.N., Symonds, M.R.E. & McKenzie, A. (2020) Escape responses of terrestrial and aquatic birds to drones: Towards a code of practice to minimize disturbance. *Journal of Applied Ecology*, **57,** 777-785. https://doi.org/10.1111/1365-2664.13575

Williams, P.J., Schroeder, C. & Jackson, P. (2020) Estimating Reproduction and Survival of Unmarked Juveniles Using Aerial Images and Marked Adults. *Journal of Agricultural, Biological and Environmental Statistics*. https://doi.org/10.1007/s13253-020-00384-5

Zemanova, M.A. (2020) Towards more compassionate wildlife research through the 3Rs principles: moving from invasive to non-invasive methods. *Wildlife Biology*, **2020**. https://doi.org/10.2981/wlb.00607

Appendices

Hodgson, J. & Koh, L.P. (2016). A guide to using drones to study wildlife: first, do no harm. *The Conversation.* https://theconversation.com/a-guide-to-using-drones-to-study-wildlife-first-do-no-harm-57069

Hodgson, J., Terauds, A. & Koh, L.P. (2018). ‘Epic Duck Challenge’ shows drones can outdo people at surveying wildlife. *The Conversation*. https://theconversation.com/epic-duck-challenge-shows-drones-can-outdo-people-at-surveying-wildlife-90018

Hodgson, J., Koh, L.P. & Goldsworthy, S. (2020). Australian sea lions are declining. Using drones to check their health can help us understand why. *The Conversation*. https://theconversation.com/australian-sea-lions-are-declining-using-drones-to-check-their-health-can-help-us-understand-why-127523

THE CONVERSATION
Academic rigour, journalistic flair

A UAV's perspective of southern elephant seals (*Mirounga leonina*) on Australia's sub-Antarctic Macquarie Island. J. Hodgson, Author provided

A guide to using drones to study wildlife: first, do no harm

May 24, 2016 5.35am AEST

Technological advances have provided many benefits for environmental research. Sensors on southern elephant seals have been used to map the Southern Ocean, while tracking devices have given us a new view of mass animal migrations, from birds to zebras.

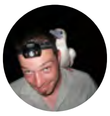
Miniaturisation of electronics and improvements in reliability and affordability mean that consumer drones (also known as unmanned aerial vehicles, or UAVs) are now improving scientific research in a host of areas. And they are growing more popular for wildlife management, as well as research.

Wildlife drones can be used in many different ways, from small multi-rotor units that can scare invasive birds away from crops, to fixed-wing aircraft that fly above rainforests to spot orangutan nests. UAVs have also been shown to provide more precise data than traditional ground-based techniques when it comes to monitoring seabird colonies.

Other industries, from mining to window-cleaning, are looking at using drone technology. Some forecasts predict that the global market for commercial applications of UAVs will be valued at more than US$127 billion. Given their usefulness in the biologist's toolkit, the uptake of UAVs for environmental monitoring is likely to continue.

But this proliferation of drones raises questions about how best to regulate the use of these aircraft, and how to ensure that wildlife do not come to harm.

Authors



Jarrod Hodgson
PhD Candidate, University of Adelaide

Lian Pin Koh
Associate Professor, University of Adelaide

Wildlife disturbance

Biologists carrying out field studies are typically interested in animals' natural state, or how their behaviour changes when conditions are altered. So it is important to know whether the UAVs disturb the animals and, if so, exactly how.

Of course, different species in different environments are likely to have very different responses to the presence of a UAV. This will also depend on the type of UAV and how it is used. Our current understanding of wildlife responses is limited.

A team of French and South African biologists observed the reaction of semi-captive and wild birds to UAVs. They found that the approach angle had a significant impact on the birds' reaction, but approach speed, UAV colour and flight repetition did not.

In polar regions, where UAVs may be particularly useful for sampling inaccessible areas, researchers found that Adélie penguins were more alert when a UAV was in range, particularly at low altitudes.

These studies, and similar observational studies on other animals besides birds, provide an initial understanding of wildlife behaviour. But the animals' behaviour is only one aspect of their response – we still need to know what happens to their physiology.

A UAV-mounted camera provides an aerial view of a Sumatran elephant (*Elephas maximus sumatranus*) in North Sumatra. L. P. Koh

Cardiac bio-loggers fitted to a small number of free-roaming American black bears in northwestern Minnesota have shown that UAV flights increased the bears' heart rates by as much as 123 beats per minute. Even an individual in its winter hibernation den showed stress responses to a UAV flying above.

Interestingly, the bears rarely showed any behavioural response to the drones. This shows that just because animals do not appear visually disturbed, that doesn't necessarily mean they're not stressed.

A code of practice

We have developed a code of best practice, published today in the journal Current Biology, which seeks to mitigate or alleviate potential UAV disturbance to wildlife. It advocates the precautionary principle in lieu of sufficient evidence, encouraging researchers to recognise that wildlife responses are varied, can be hard to detect, and could have severe consequences.

Jarrod Hodgson launches a fixed-wing UAV on Macquarie Island. J. Hodgson

It also provides practical recommendations. The code encourages the use of equipment that minimises the stimulus to wildlife. Using minimum-disturbance flight practices (such as avoiding threatening approach trajectories or sporadic flight movements) is advised. The code also recognises the importance of following civil aviation rules and effective maintenance and training schedules, and using animal ethics processes to provide oversight to UAV experiments.

The code isn't just food for thought for biologists. It is relevant to all UAV users and regulators, from commercial aerial videographers to hobbyists. Unintentionally or otherwise, such users may find themselves piloting drones close to wildlife.

Our code urges the UAV community to be responsible operators. It encourages awareness of the results of flying in different environments and the use of flight practices that result in minimum wildlife disturbance.

Low-impact conservation

As researchers continue to develop and refine UAV wildlife monitoring techniques, research that quantifies disturbance should be prioritised. This research will need to be multi-faceted, because responses could vary between species or individuals, as well as over time and in different environments. Greater knowledge could help us to draw up species-specific guidelines for drone use, to minimise disturbance on a case-by-case basis.

UAVs are a useful wildlife monitoring tool. We need to proactively develop and implement low-impact monitoring techniques. Doing so will expand our technological arsenal in the battle to manage Earth's precious and increasingly threatened wildlife.

THE CONVERSATION

Academic rigour, journalistic flair

A drone image of a breeding colony of Greater Crested Terns. Researchers used plastic bird decoys to replicate this species in an experiment that compared different ways of counting wildlife. Jarrod Hodgson, CC BY-ND

‘Epic Duck Challenge’ shows drones can outdo people at surveying wildlife

February 14, 2018 12.11am AEDT

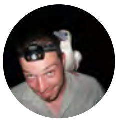
Ecologists are increasingly using drones to gather data. Scientists have used remotely piloted aircraft to estimate the health of fragile polar mosses, to measure and predict the mass of leopard seals, and even to collect whale snot. Drones have also been labelled as game-changers for wildlife population monitoring.

But once the take-off dust settles, how do we know if drones produce accurate data? Perhaps even more importantly, how do the data compare to those gathered using a traditional ground-based approach?

To answer these questions we created the #EpicDuckChallenge, which involved deploying thousands of plastic replica ducks on an Adelaide beach, and then testing various methods of tallying them up.

As we report today in the journal Methods in Ecology and Evolution, drones do indeed generate accurate wildlife population data – even more accurate, in fact, than those collected the old-fashioned way.

Authors



Jarrod Hodgson
PhD Candidate, University of Adelaide

Aleks Terauds
Senior Research Scientist / Section Head, Australian Antarctic Division

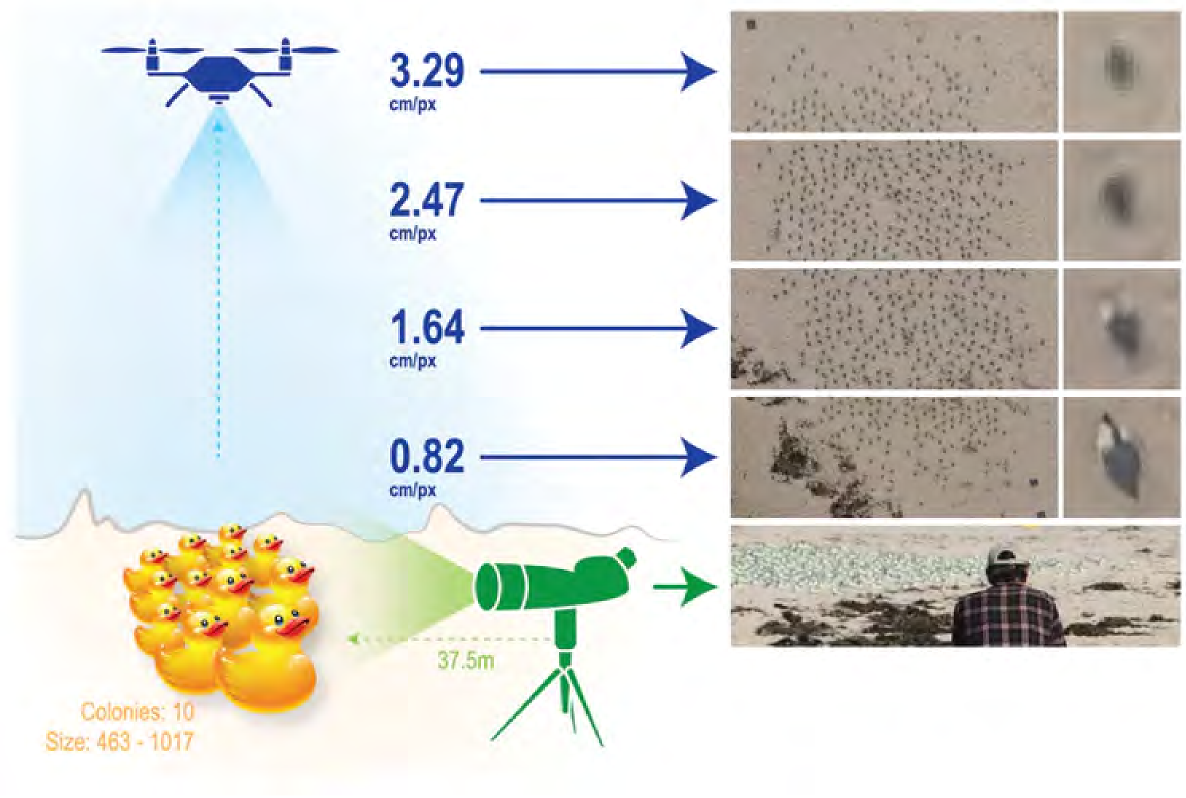
Lian Pin Koh
Professor, University of Adelaide

Jarrod Hodgson standing in one of the replica colonies of seabirds constructed for the #EpicDuckChallenge. S. Andriolo

Assessing the accuracy of wildlife count data is hard. We can’t be sure of the true number of animals present in a group of wild animals. So, to overcome this uncertainty, we created life-sized, replica seabird colonies, each with a known number of individuals.

From the optimum vantage and in ideal weather conditions, experienced wildlife spotters independently counted the colonies from the ground using binoculars and telescopes. At the same time, a drone captured photographs of each colony from a range of heights. Citizen scientists then used these images to tally the number of animals they could see.

Counts of birds in drone-derived imagery were better than those made by wildlife observers on the ground. The drone approach was more precise and more accurate – it produced counts that were consistently closer to the true number of individuals.



Comparing the vantages: drone-derived photographs and the ground counter’s view. J. Hodgson

The difference between the results was not trivial. Drone-derived data were between 43% and 96% more accurate than ground counts. The variation was due to how many pixels represented each bird, which in turn is related to the height that the drone was flown and the resolution of the camera.

This wasn’t a surprise. The experienced ground counters did well, but the drone’s vantage point was superior. Observing photos taken from above meant the citizen scientists did not have to contend with obscured birds that often occur during ground counts. The imagery also benefited the citizen scientists as they could digitally review their counts as many times as they needed. This reduced the likelihood of both missing an individual and counting an individual more than once.

The scientists were assisted by many volunteers, without whom the #EpicDuckChallenge would not have been possible. J. Hodgson

However, even though it proved to be more accurate, making manual digital counts is still tedious and time-consuming. To address this, we developed a computer algorithm in the hope that it could further improve efficiency without diminishing data quality. And it did.

We delineated a proportion of birds in each colony to train the algorithm to recognise how the animal of interest appeared in the imagery. We found that using 10% training data was sufficient to produce a colony count that was comparable to that of a human reviewing the entire scene.

This computerisation can reduce the time needed to process data, providing the opportunity to cut the costs and resources needed to survey wildlife populations. When combined with the efficiencies drones provide for surveying sites that are hard to access on foot, these savings may be considerable.

Using drone monitoring in the field

Our results have important implications for a range of species. We think they are especially relevant to aggregating birds, including seabirds like albatrosses, surface nesting penguins and frigatebirds, as well as colonial nesting waterbirds like pelicans.

Other types of animals that are easily seen from above, including hauled-out seals and dugongs, are highly suited to drone monitoring. The nests or tracks of animals, such as orangutans and turtles, can also be used to infer presence.

Additional experiments will be useful to assess the ability of drones to survey animals that prefer to stay hidden and those within complex habitats. Such assessments are of interest to us, and researchers around the globe, with current investigations focused on wildlife such as arboreal mammals and cetaceans.

We are still learning about how wildlife react to the presence of drones, and more research is required to quantify these responses in a range of species and environments. The results will help to refine and improve drone monitoring protocols so that drones have minimal impact on wildlife. This is particularly important for species that are prone to disturbance, and where close proximity is not possible or desirable.

***Read more:* How drones can help fight the war on shark attacks**

The world is rapidly changing, with many negative outcomes for wildlife. Technology like drones can help scientists and managers gather data fast enough to enable timely assessment of the implications of these changes.

When monitoring wildlife, increasing the accuracy and precision of animal surveys gives us more confidence in our population estimates. This provides a stronger evidence base on which to make management decisions or policy changes. For species and ecosystems threatened with extinction or irreparable damage, such speedy action could be a literal lifeline.

THE CONVERSATION
Academic rigour, journalistic flair

Australian sea lions (Neophoca cinerea) are one of the rarest pinnipeds in the world and they are declining. Jarrod Hodgson, CC BY-ND

Australian sea lions are declining. Using drones to check their health can help us understand why

January 17, 2020 2.19pm AEDT

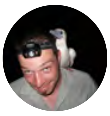
Australian sea lions are in trouble. Their population has never recovered from the impact of the commercial sealing that occurred mainly in the 19th century.

Currently, the Australian sea lion is a threatened species (listed as endangered by the International Union for Conservation of Nature or IUCN) with the population estimated at 10,000 – 12,000. More than 80% of these animals live in the coastal waters of South Australia, where their numbers are estimated to have fallen by more than half over the past 40 years.

The sea lions' survival is threatened by many factors, including bycatch in commercial fisheries, entanglement in marine debris and impacts related to climate change.

With time running out, the sea lions' survival depends on informed management. One important step is to establish a low-risk way of quickly assessing the health of the current population. The results could help us identify how to stop the population declining.

Authors



Jarrod Hodgson
PhD Candidate, University of Adelaide

Lian Pin Koh
Professor, University of Adelaide

Simon Goldsworthy
Principal Scientist, Ecosystem Effects of Fishing & Aquaculture, South Australian Research and Development Institute, and Affiliate Professor, University of Adelaide

Low-lying rock islands and outcrops make important breeding sites for Australian sea lions but many are threatened by sea-level rise. J. Hodgson

---

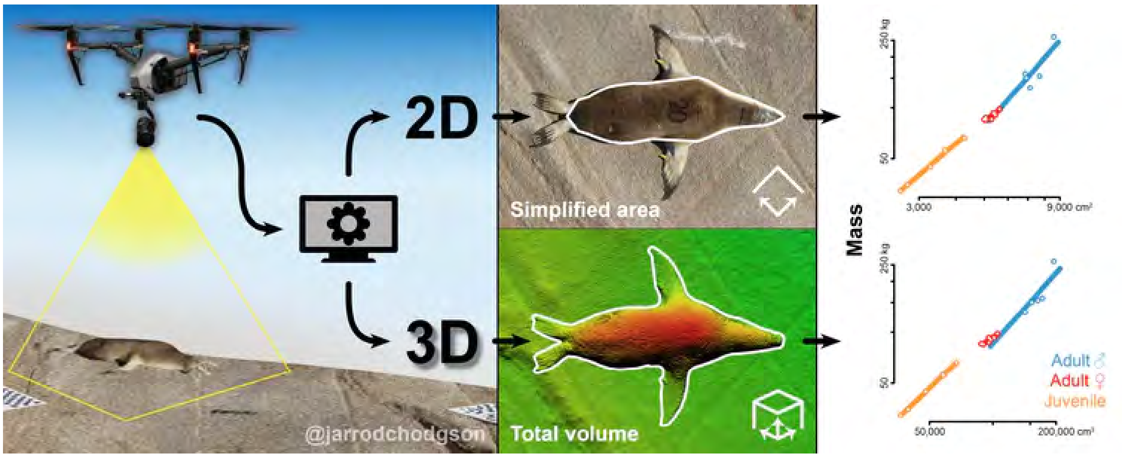
***Read more:* Australia's 'other' reef is worth more than $10 billion a year - but have you heard of it?**

Technological insight

One common way to get a quick idea of an animal's health is to assess its body using a measure equivalent to the body mass index (BMI) for humans, which is calculated from a person's mass divided by the square of their height. But using a tape measure and scales to obtain the size and mass of Australian sea lions is time consuming, costly and involves risky anaesthesia of endangered animals.

With our colleagues Dirk Holman and Aleks Terauds, we recently developed a technique to non-invasively estimate the body condition of Australian sea lions by using a drone to collect high-resolution photos of sedated sea lions. We then used the photos to digitally reconstruct a 3D model of each animal to estimate its length, width and overall volume – and compared these to physical measurements.

The technique, recently published in *Biological Conservation*, worked better than expected.



Drone-captured photographs were processed to create 2D mosaics of images and 3D models. These were used to measure area and volume, both of which approximated animal mass. J. Hodgson

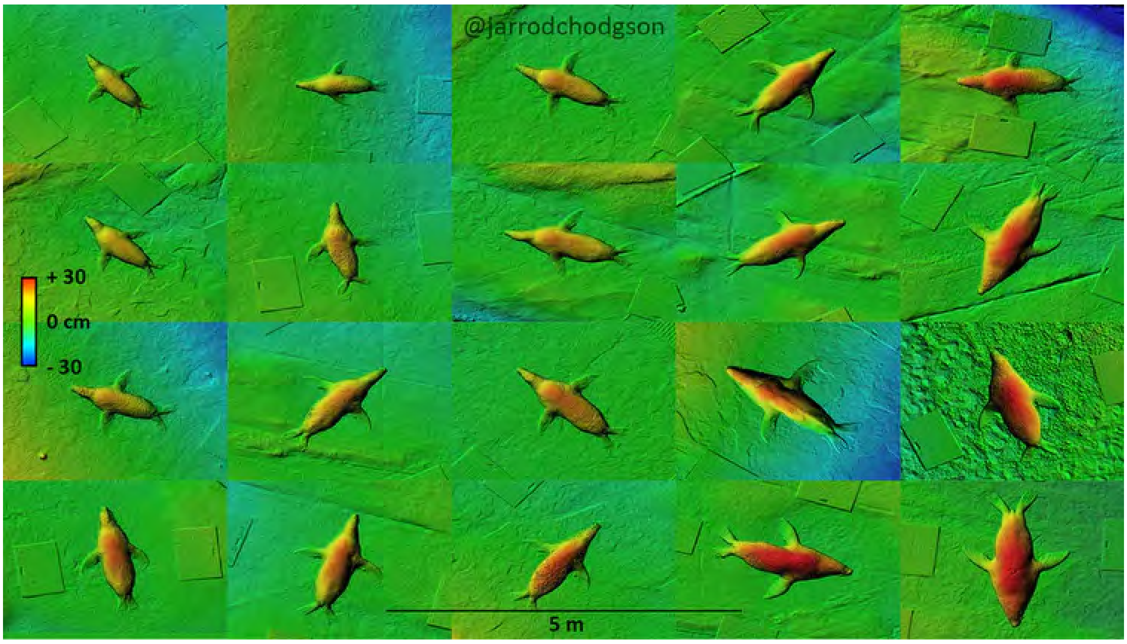
The measurements were accurate, and we found a strong correlation between the mass of an individual and the area and volume measurements derived from the drone pictures. These are the key ingredients needed to assess sea lion condition without handling animals.

Conserving an iconic species

While simple body condition measurements have limitations, they are useful for conservation because they provide rapid health insights across a species' range.

Australian sea lions breed at around 80 known sites spanning more than 3,000 km of southern Australian coastline within the Great Southern Reef.

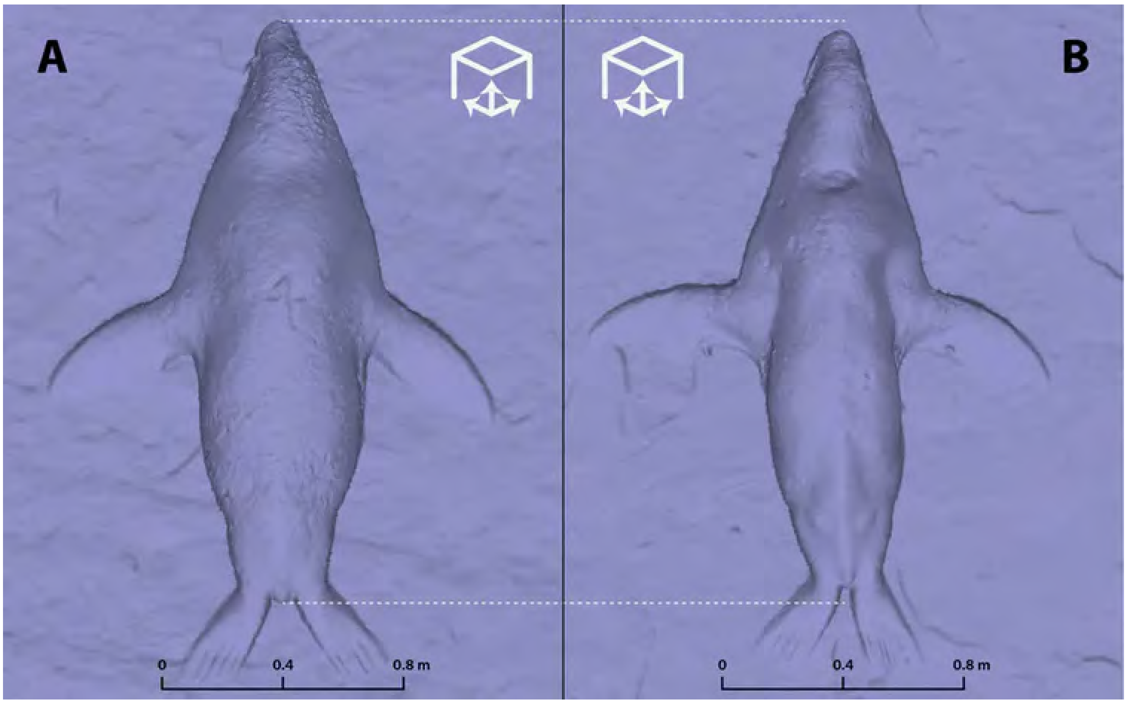
Our technique can be used to study free-ranging animals at colonies across this range, from Kangaroo Island in South Australia to the Houtman Abrolhos Islands in Western Australia, and test for differences in condition.



3D models of animals measured in the study. J. Hodgson

This can give us valuable information about how individual health and colony trends in abundance are related. For example, if a colony is in decline and its members are in poor condition, it could be that factors such as food availability and disease are driving the decline.

However, if there is no difference in the condition of animals from declining and recovering colonies, then declines may be due to direct human impacts such as bycatch in commercial fisheries and entanglement in marine debris. We could then target the most likely threats identified using this technique to better understand their impact and how to protect the sea lions against them.



These two adult male Australian sea lions differed by just 11 cm in length but more than 130 kg in mass. J. Hodgson

This technique could be used to complete a population-wide survey of Australian sea lion condition and help ensure the species' survival. It would build on past mitigation measures which include successfully reducing by-catch from gillnet fishing along the sea floor.

It will also complement current initiatives, including a trial to control a parasite that may improve pup survival.

Australian sea lions are an icon of Australia's Great Southern Reef. As an important top-order predator in these coastal waters, they are indicators of ocean health. Understanding and mitigating the causes of their decline will not only help the species recover, but it will also help to ensure the unique coastal ecosystems on which Australian sea lions depend remain intact and functional.