Detectability of dolphins and turtles from Unoccupied Aerial Vehicle (UAV) survey imagery

Image by Amanda Hodgson

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Declaration:

I, Brooke Lloyd, declare that the research presented in this thesis is the product of my own work and that all works not created by myself are referenced appropriately. It is to my best knowledge that the work presented here has not been published previously or submitted for any degree at any tertiary institution.

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Abstract:

For many decades occupied aircraft with trained observers have conducted aerial surveys of marine megafauna to estimate population size and dynamics. Recent technological advances mean that unoccupied aerial vehicles (UAVs) now provide a potential alternative to occupied surveys, eliminating some of the disadvantages of occupied surveys such as risk to human life, weather constraints and cost. In this study, data collected from an occupied aircraft (at 500 ft) and a UAV (at 1400 ft) flown at the same time, deployed for counting dugongs, were compared for detecting dolphins and turtles within Shark Bay, Western Australia. The UAV images were manually reviewed *post hoc* to count the animals sighted and the environmental conditions (visibility, sea state, cloud cover and glare) had been classified by the occupied teams' data for each image. The UAV captured more sightings (174 dolphins and 368 turtles) than were recorded by the flight team (93 dolphins and 312 turtles). Larger aggregations (>10 animals) were also found in the UAV images (5 aggregations of dolphins and turtles) compared to the occupied teams sightings (0 dolphins and 3 aggregations of turtles). A generalised linear mixed model determined that turtle detection was significantly affected by visibility, while cloud cover, sea state and visibility significantly affected dolphin detection in both platforms. An expert survey of 120 images was also conducted to determine the image ground sampling distance (GSD; four levels from 1.7 to 3.5 cm/pixel) needed to identify dolphin and turtles to species. At 3 cm/pixel only 40% of the dolphins and turtles were identified to species with a reasonable level of certainty (>75% certainty). This study demonstrated that UAVs can be successfully deployed for detecting dolphins and turtles and that a GSD of 1.7 – 3cm/pixel is too low resolution to effectively identify dolphin and turtle species. Overcoming the limitations imposed on UAVs such as aviator regulatory bodies and payload capabilities will make UAVs a pivotal tool for future research, conservation, and management.

Table of Contents:

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Chapter 1. Introduction

Species seen as being at risk need to be studied and analysed to understand their population trends over time, whether they are decreasing, increasing or stable (IUCN, 2021). Monitoring animals in their natural habitat to determine population size and dynamics is challenging due to their complex behaviours and movements and is highly species dependant (Chabot & Bird, 2015). Methodologies for estimating the population size of a species date back decades, as animal surveys are a key component of ecology and understanding the abundance of a given population within an ecosystem (Cohen et al., 2003; Lindenmayer et al., 2012). Abundance and density measures have been noted as being the most important demographic measures of a population and constant monitoring of a given population, using surveying methods, aids in detecting changes within that group over time (Liebhold, 2002). Production of high-quality ecological information over extensive periods generates awareness of the changes to ecosystem structure, the key ecological processes involved, and the services that the ecosystem provides (Lindenmayer et al., 2012).

Large marine vertebrates that are long-lived, expansive in their range, and take years to mature, are the most susceptible to anthropogenic threats (Godley et al., 2010). Due to the consistent threat of climate change and the ever-increasing human population, anthropogenic stressors, such as fishing, marine debris, and vessel traffic, are affecting these marine vertebrate populations (Butterworth, 2017). These stressors, especially on coastal marine animal species, makes studying these human impacts a high priority (Lotze et al., 2006). Knowledge on the distribution of marine mammals and reptiles as well as their abundance, behaviour, and surrounding habitat, aids in their conservation and management, in particular allowing us to assess the anthropogenic impacts of co-occurring human activities (Broker et al., 2019). Data produced from surveys creates an understanding that is utilised to determine conservation status of a population and support evidence-based policy, management, and decision-making (Lindenmayer et al., 2012). Coastal marine mammals and sea turtles are seen as key organisms for marine conservation and management in Australia as they are concerns of 'National Environmental Significance' under the EPBC Act. They are among the species that most often 'trigger' the EPBC Act as they often occur in highly human-populated areas and are at greatest risk of human impact (IUCN, 2021).

Marine megafauna are large vertebrates that can be surveyed from the air such as whales, dolphins, sharks, rays, dugongs (*Dugong dugon*), and turtles (Preen et al., 1997). Marine megafauna are difficult to count and observe because they occur over large expanses, some having extensive migratory routes, as well as the time they spend submerged (Gray et al., 2019). These features of their biology and behaviour make it difficult to accurately estimate abundance (Cohen et al., 2003). Well-designed programs are fundamental to provide accurate and cost-effective estimates of abundance (Gray et al., 2019).

Both the IUCN and the International Whaling Commission (Paxton et al., 2011) rely on data from aerial surveys to estimate populations of some listed marine species to determine their status and monitor changes. The US Marine Mammal Protection Act (MMPA, 16 U.S.C. 1361 et seq) of 1972 also requires the monitoring of marine mammal populations, which for a number of species is conducted via aerial surveys (Maire et al., 2013).

Aerial surveys have been used to estimate the size of animal populations since the 1940s (Marsh & Sinclair, 1989a). In Australia, regular aerial surveys of dugongs have been conducted since the 1980s mainly in Queensland (Marsh et al., 2006) and the Torres Strait Islands (Marsh et al., 2004) and then later became a regular occurrence in the 1990s within Shark Bay and Exmouth, Western Australia (Preen et al., 1997; Gales et al., 2004). In the northern hemisphere, in both Europe (Hammond et al., 2002) and Canada (Kingsley & Reeves, 1998) aerial survey techniques are used to estimate the abundance of cetacean species such as harbour porpoises (*Phocoena phocoena*), bottlenose dolphins (*Tursiops* spp.), minke whales (*Balaenoptera* spp.) and humpback whales (*Megaptera novaeangliae*).

For the remainder of this introduction, I review the main methods used for marine megafauna surveys, specifically aerial surveys, and the emerging use of UAVs. I explore the broad necessity and use of marine animal surveys, the types of surveying methods that are used, as well as the marine megafauna that are targeted by these surveys, and the value of surveys in the world of conservation and monitoring.

1.1 Current land, vessel, and aerial-based techniques for detecting marine animals

Different survey methodologies are appropriate for different species, environmental conditions and also depends on the type of data being captured (Evans & Hammond, 2004). Each method has advantages and disadvantages according to species characteristics, environmental conditions, and the spatial and temporal scales of the survey, i.e. not one marine survey methodology is suitable for all uses (Evans & Hammond, 2004). In designing a survey, the following points should be considered:

the specific aims of the study, the behaviour of the target species, the budget, the time available for the study, morphology of the landscape, logistical support and the resources available for the study (Aragones et al., 1997). Most systematic marine animal surveys are conducted by human observers from high vantage points on land, or from a vessel or aircraft (Buckland et al., 2001). The strengths and weaknesses of land-based, vessel-based, and aerial-based survey methods are discussed below.

1.1.1 Land-based surveys

Land-based surveys are conducted by a team of observers recording sightings from a fixed location, limited to a certain range of observation (Giacoma et al., 2013). Land-based surveying requires a medium skill level of observation and is usually low cost because little equipment is needed (Giacoma et al., 2013). As observation is from a fixed point, from a distance, there is no interference with the animal being studied and hence no behavioural change (Giacoma et al., 2013). The large area being scanned at one time means land surveys are excellent at recording animal movements, interactions, group dynamics and anthropogenic elements (such as manoeuvring vessel traffic) (Papale et al., 2011). This also means that land surveys can be used to analyse sighting frequency over time as well as seasonal variation (Giacoma et al., 2013). Land-based surveys have been proven to produce adequate data and are effective in sampling for abundance, recording diving characteristics and behaviour at the surface for airbreathing marine organisms (Hawkins & Gartside, 2008). Particular locations such as Stradbroke Island, Queensland, Australia, which have ideal cliff-top viewing platforms, have been used to survey for humpback whales as they pass the coastline on their annual migration (Dudgeon et al., 2018). Most land-based surveys tend to focus on marine mammals because of their size and predictable migratory routes (Dudgeon et al., 2018). Therefore, land-based surveys are primarily advantageous in terms of their cost efficiency and ability to detect large migratory megafauna that travel close to the coastline.

However, land surveys are limited by their fixed position, limited range, and field of view. They are also very affected by conditions such as glare (Giacoma et al., 2013). As distance from the platform increases, detectability decreases because of the limitations of the visual field (Dudgeon et al., 2018). Land-based surveys are also limited to the detection of animals at the surface; they cannot be used to detect animals below the surface (Kelaher et al., 2020). Monitoring from a distance also means that some data, such as age, sex, body condition and precise location data cannot be collected and this type of survey only works for large marine megafauna (particularly whales) (Giacoma et al., 2013).

1.1.2 Vessel-based surveys

Vessel-based observations have also been a common method for marine megafauna surveying. Highly trained and skilful researchers are needed for boat-based surveys due to this type of surveying allowing for researchers to capture morphological data and even tissue sampling and tagging to better understand the genetic composition of that animal as well as its movements (Giacoma et al., 2013). Vessels are able to approach animals closely and thus collect more in-depth and detailed observations than land-based surveys e.g. photographic identification, social interaction, age determination, gender classification and even body condition (Giacoma et al., 2013). Vessel-based observations also produce high quality georeferencing data (Giacoma et al., 2013). Vessel-based surveys can be conducted from a range of boat types (catamarans, motorised vessels) with ranging speed capabilities (sailing or engines) based on the target animal being studied (Castelblanco-Martínez et al., 2019).

Complimenting boat-based surveys also include the use of sonar scanning to detect animals that are submerged or not visible in certain conditions (Castelblanco-Martínez et al., 2019).

Vessel-based surveys are also expensive because of the operating costs of the vessel and the need for highly trained individuals involved in the survey (Giacoma et al., 2013). The close proximity of vessels to the animals being studied and the fact that noise travels very well underwater means that vessel noise may disturb the focus animals. The noise disturbance created by vessels (even small boat-based surveys) means that the behaviour of some animals changes e.g. seabirds and dolphins can be attracted to the vessel, while some cetaceans can avoid the area (Würsig et al., 1998). This attractancy and avoidance to the research vessels may create biases in estimating abundance and distribution (Würsig et al., 1998), especially for marine mammals which are more sensitive to noise pollution than seabirds and sea turtles (Koski et al., 2011). Another limitation of boat-based surveys is that they can only observe animals at the water surface, limited to observing animals that are submerged (Thomson et al., 2013). There are also restrictions imposed on vessels, especially surrounding the distance that they are allowed to approach marine wildlife, so this and the boat's manoeuvrability also limits boat-based observations (Orbach et al., 2020).

1.1.3 Aerial surveys

Aerial surveys are another well-developed and used method within most coastal marine megafauna population assessments, as the height provides a larger field of view than possible from land or a vessel (Marsh & Sinclair, 1989a). Aerial surveys are recognised as being a valuable tool in wildlife management, this method mainly targets marine mammals and other air-breathing marine organisms (Jones et al., 2006). Aerial surveys are used for species that occur across large spatial scales and/or are too difficult to spot from land or a vessel. For example, dugongs do not present much of themselves at the surface for very long periods of time, so the aerial perspective allows observers to detect animals deeper in the water column (Hodgson et al., 2013). There are two commonly used ways of conducting aerial surveys, either in occupied vehicles (planes or helicopters) or unoccupied aerial vehicles (UAVs). The occupied aerial survey method consists of a pilot and a group of observers that fly in a light aircraft over a set flight path or transect at a low altitude (e.g., 500 ft for dugong surveys, Marsh & Sinclair, 1989a). The survey team usually has two observers on each side of the aircraft to minimise and quantify bias caused by observers missing sightings. The observers record the sightings perpendicular to the plane, in real-time. This method is known as line transect sampling (Buckland et al., 2004) and relies on three main assumptions:

1. All animals along the line are detected with certainty,
2. The perpendicular distance of the animal from the line is measured exactly, or all animals within a set distance from the line are counted with equal probability, and
3. Animals are detected in their initial location (Glennie et al., 2015).

The aerial advantage and overhead perspective maximizes the detection of animals that spend little time at the surface (Hodgson et al., 2013). Aerial surveys are also a good tool for surveying populations that are sparsely distributed over a large area (Quang & Becker, 1996) and for species with either predictable movements or habitats that are used regularly for activities such as resting, breeding, foraging, and socialising (Seymour et al., 2017).

Aerial surveys, however, do have their disadvantages. Aerial surveys are primarily conducted on air-breathing organisms because they rely on making observations of animals at the sea surface or just below (Marsh & Sinclair, 1989b). Air-breathing animals are defined as those that are obligated to come to the surface regularly and based on this behaviour researchers can determine an understanding of the probability of detecting them. Because aerial surveys are primarily conducted on air-breathing fauna, marine mammals (whales, dolphins and porpoises) and marine reptiles (alligators and turtles) are usually the main target species for aerial observation (Jones et al., 2006). They have also been applied to other species e.g., one aerial survey was conducted on whale sharks to better understand their temporal and spatial distribution as they seasonally aggregate around the islands of Seychelles (Rowat et al., 2009). However, relatively low numbers of whale sharks were sighted each month (varying from 0 to 14), and this highlights the problem of using aerial surveys to detect non-air-breathing fauna. Because aerial surveys rely on observations of animals at the surface, this factor too becomes a limitation as marine mammals and reptiles only spend a small portion of their time at the surface to breathe, rest or forage (Marsh & Sinclair, 1989b). Environmental conditions affect the observers' ability to detect animals and therefore need to be taken into consideration when estimating abundance (Pollock et al., 2006). Occupied aerial surveys have both functional and logistical limits, which leads researchers to search for other tools in surveying marine animals such as UAVs.

1.1.4 Satellite imagery

Satellite imagery, particularly in very high resolution (VHR) systems is now being utilised as an accessible and inexpensive alternative to aerial surveys, which researchers are hoping will aid in producing data on distribution, abundance, density, and population trends of animals for which we currently have large gaps in our understanding (Höschle et al., 2021). The objective of developing satellite imagery survey methodologies would be to have them as a supplement to current aerial and boat based surveys by helping researchers plan the field process (Höschle et al., 2021). However, this method is in its infancy, as satellite imagery tends to produce mid-to low-resolution images depending on the source of the data and the source determines the cost (Hyun et al., 2020). Satellite images also frequently have large areas of cloud cover and have limited repeatability due to the low number of orbits of a satellite per day currently (Anderson & Gaston, 2013).

1.2 Current UAV technology and its applications

Exploration of the ocean and its species and ecosystems is becoming more reliant on robotic systems (Fish, 2020). UAV technology is relatively new compared to land and occupied aerial surveys and ever-evolving in its use for monitoring wildlife (Bushaw et al., 2019). Derived from a military background (Anderson & Gaston, 2013), UAVs are able to produce both high spatial and temporal resolution data for a given area (Whitehead & Hugenholtz, 2014). UAVs have been successful in surveying both terrestrial (e.g. orangutan, elephant and cheetah) (Koh & Wich, 2012) and marine wildlife species (sea lions, dugong and whales) (Hodgson et al., 2013; Adame et al., 2017; Fiori et al., 2020). UAVs are defined as a vehicle containing a flying portion or unit, with at least one onboard camera, connected to a ground control station (GCS) and communicating with a launch and recovery system (Koski et al., 2009). UAV systems can range in cost from as little as $1000 into the millions (Koski et al., 2011) and in size from micro-craft no heavier the 250g to large aircraft over 150kg (CASA, 2021a). Recently, some UAVs have been improved to become waterproof, be cost-efficient, have a longer battery life, are able to travel greater distances (Fiori et al., 2017), and are built quieter than earlier UAVs, producing less noise disturbance (Christiansen et al., 2016a).

UAVs are used in a diverse range of scientific fields for oceanographic and meteorological studies to assess varying ocean temperatures (Inoue & Curry, 2004), ocean productivity (Elarab et al., 2015), the geomorphology of given coastlines, mapping of shoreline habitats, and studying the progression of coastal erosion (Mancini et al., 2013). They also have industrial applications such as equipment inspections and leak detection within the oil and gas sector (Budiyono, 2009). Broader tasks managed by UAV technology include surveillance (e.g. detecting sharks in swimming areas), military observation, and aiding in search and rescues (Valavanis, 2007). UAVs include an array of payload and sensor types, for example: photography, videography, thermal imaging, and telemetry (Jones et al., 2006). These sensors aid in collecting surrounding environmental data (Koski et al., 2011). Such data includes outside ambient temperature, sea ice movement, wind speed, and the given longitude and latitude of each still image (Koski et al., 2011).

UAVs are less invasive than some aircraft and boat based methods, cost-effective (content dependant), and accurate in wildlife and environmental monitoring (Gooday et al., 2018). Raoult et al. (2020) have developed operational protocols for the safe use of UAVs by the researchers and for the animals being studied.

Some ways to maximise the efficacy of UAVs include:

1. Understanding the common animal traits of your target species,
2. Understanding the information that can be produced from UAV research,
3. Picking the appropriate UAV for the survey type,

4. Understanding how the UAV may impact the target species,
5. Creating an appropriate flight pattern to optimize the data collected, and
6. Understand how the likely environmental conditions will affect the UAV in flight and the recording of data (Raoult et al., 2020)

Because of their success, UAVs have increased our capacity to observe many organisms, including both marine and terrestrial species, leading to a better understanding of their biology, physiology, ecology, and behaviours (Nowacek et al., 2016). Scientists are only just beginning to utilise the payload, media, sensory and mechanical capacity of UAVs (Torres et al., 2018).

1.3 Advantages and disadvantages of occupied and unoccupied aerial survey methods

Both occupied and unoccupied methods of aerial surveying have advantages and disadvantages, which are important to understand in order to determine which will be appropriate for the objectives of any study. Both occupied and unoccupied aerial surveys are conducted at altitude and hence similar factors affect the probability of detecting animals including water clarity, sun glare, sea state and observer error (Pollock et al., 2006; Hodgson et al., 2013; Lubow & Ransom, 2016;). Observer error may happen either in real-time or when reviewing images depending on the level of skill, training, and experience of the observer (Lubow & Ransom, 2016).

Occupied aerial surveys are particularly suited for use in dynamic conditions, collecting additional real-time data and have less imposed regulations when surveying than occupied aerial surveys (Table 1.1). They do however incur high risk to human lives, are expensive to operate and need highly trained individuals for observation

(Table 1.1). UAVs diminish the risk to human lives, are very manoeuvrable and the data captured creates permanent still image records that can be reanalysed (Table 1.1.). UAVs are however highly constrained by regulatory bodies and the image review process may be cost-prohibitive and time-consuming (Table 1.1).

Table 1.1. A summary of the advantages and disadvantages of occupied and unoccupied aerial methods for surveying marine animals.

Method	Advantage	Disadvantage
Occupied Aerial Survey	1. Better adapted to changing and dynamic conditions (Broker et al., 2019) 2. In some cases, an increased field of view at the front and sides of the aircraft leading to a larger area available for survey (Hodgson et al., 2013) 3. The ability to collect additional real time data that can become available for use in real time (Hodgson et al., 2013) 4. Currently less constrained by aviation regulations than UAVs (Colefax et al., 2018)	1. Aircraft crashes being one of the leading causes of infield marine mammal biologist fatalities (Hodgson et al., 2013) 2. Consisting of a pilot, a paid observer team and fuel costs, is highly expensive to operate (Hodgson et al., 2013) 3. Long flights within occupied surveys can result in observer fatigue and inaccurate detection (Hodgson et al., 2013) 4. Constrained by weather conditions (Goebel et al., 2015) i.e., need clear conditions such as good sea state, reduced sun reflectance and glare (Hodgson et al., 2013) 5. Specialised and experienced observer team required (Bayliss, 1986) 6. Limited in the capacity to identify the observed animal to species level due to high level of difficulty during real-time observation compared to that of still images (Colefax et al., 2018)
UAV Survey	1. Reduction in risk to human life (Hodgson et al., 2013) 2. Lower operational cost compared to aircrafts (depending on the drone	1. The need for this technology to be accepted by governing and regulating bodies, so UAVs aren't confined by aviation-

Method	Advantage	Disadvantage
UAV Survey	system used) (Goebel et al., 2015) 3. Still image analysis allows for the reduction in observer fatigue (Hodgson et al., 2013) 4. Increased location accuracy due to UAVs being fitted with internal GPS and flight telemetry payloads (Hodgson et al., 2013)	related restrictions (Koski et al., 2011) 1.1 UAVs cannot be flown out of sight from the operator, limiting their use over large distances (Colefax et al., 2018) 1.2 Common UAV airspace regulations limiting research include having a buffer distance to airports (Raoult et al., 2020)
	5. Little to no behavioural response from marine animals at altitude (Koski et al., 2009; Smith et al., 2016; Fiori et al., 2017) 6. Depending on the altitude, can be less constrained than aircrafts to environmental conditions, e.g., surveying in higher sea states (Hodgson et al., 2017) 7. Lower environmental footprint, producing less carbon and fuel emissions (Hodgson et al., 2013) 8. Very manoeuvrable, can be deployed in areas with limited take-off access (Hodgson et al., 2013) 9. Modest level of training required for image reviewing (Goebel et al., 2015) 10. Data can be reviewed by more than one observer making accounting for detection bias easier 11. Still images are a permanent record that can be shared and be reanalysed if necessary (Hodgson et al., 2013)	2. Image analysis can be cost-prohibitive and time-consuming, not delivering real time results like occupied surveys (Hodgson et al., 2013) 3. UAVs that are capable of flying long distances required for large-scale surveys are currently cost-prohibitive (Colefax et al., 2018)

1.4 Previous UAV studies of marine megafauna

UAV use for surveying marine wildlife studies has stemmed from its success in the terrestrial surveying field (Linchant et al., 2015). UAVs have been used for the study of large terrestrial animals such as deer (Israel, 2011), elephants (Ferreira & van Aarde, 2009) and rhinoceros (Mulero-Pázmány et al., 2014), as well as aquatic animals such as crocodiles (*Gavialis gangeticus*) (Thapa et al., 2018), whales (Christiansen et al., 2016a; Hodgson et al., 2017), dugongs (Hodgson et al., 2013) and even seabirds (Abd-Elrahman et al., 2005). The use of drones for survey marine fauna have increased greatly in recent years (Broker et al., 2019). Between 2015 and 2019 the percentage of UAV studies focussing on a particular taxon were as follows: 35% bird studies, 29% marine mammals, 19% terrestrial mammals, 12% reptiles (both aquatic and land), and 4% focussed on fish (Hyun et al., 2020).

The design of UAVs and the sensor technology currently available have enhanced their applicability to different types of marine surveys. The differing environmental conditions and depths of the ocean meant that UAVs are still under an “exploratory phase” for animal surveys in the marine environment (Broker et al., 2019). This “exploration” of UAVs technology has been applied to many different types of marine mammal studies such as:

1. Assessing the detection of large marine mammals (Koski et al., 2009; Hodgson et al., 2017)
2. Estimating abundance of pinniped breeding colonies (Adame et al., 2017)
3. Photo-identification of whales (Koski et al., 2015)
4. Assessing the body condition and population health of pinnipeds (Krause et al., 2017) and whales (Christiansen et al., 2019)

5. Estimating the energetic costs of reproduction in humpback whales (Christiansen et al., 2016b).
6. Understanding the copulatory behaviour and social construct of dusky dolphins (*Lagenorhynchus obscurus*) (Orbach et al., 2020).

The first cetacean UAV study was conducted in 2002 by the Office of Naval Research on Humpback whales and in 2006 Royal Dutch Shell Petroleum Development Company conducted a UAV study aiming to detect simulated whale targets in the marine environment (Koski et al., 2009). The study concluded that, in certain conditions, UAVs could easily detect either large cetaceans or large groups of cetaceans, and smaller animals would be harder to detect (Koski et al., 2009). In 2008, Shell joined with ConocoPhillips to use UAV technology to detect pinnipeds and cetaceans successfully but was hindered by restrictions from the US Federal Aviation Administration because of the cloud coverage in the area and having to remain within one nautical mile of the vessel (Koski et al., 2011). Another UAV study conducted by the National Marine Fisheries Service in 2009 used a *ScanEagle* UAV to identify and estimate population density on seals on pack ice (Cameron et al., 2009). This study confirmed that UAV technology had the ability to operate in difficult weather and still obtain high-quality images for identifying different species, ages, and even genders of seals (Cameron et al., 2009).

UAV technology has been utilised not only for marine mammals but also marine reptiles, such as turtles (Schofield et al., 2017a). Similar to marine mammal surveys, surveys of sea turtles are conducted to better understand their environment and population status to inform conservation approaches (Rees et al., 2018). One study in particular focussed on using UAVs for population assessments of loggerhead turtles (*Caretta caretta*) within Costa Rica (Sykora-Bodie et al., 2017). The smaller size of turtles and their deep diving and long breath-holding capabilities make them harder to detect than humpback whales or even Indo-pacific bottlenose dolphins (*Tursiops aduncus*) (hereafter referred to as bottlenose dolphins) (Hochscheid, 2014). Therefore, there is a need to better understand the implications of not only aerial surveying for marine mammals but also marine reptiles and how survey methods for the two taxa may differ.

1.5 Accounting for detectability bias

The imperfect detection of a target species can lead to a biased estimate of the population size (Buckland et al., 2004). The flight parameters of a survey, the environmental conditions, and the physical and behavioural characteristics of marine animals affect their successful and accurate detection (Linchant et al., 2015). As stated above, the method of line transect sampling used for most marine fauna species assumes all animals on the transect line (or within a set strip in the case of strip transect sampling) are detected with certainty (Marsh & Sinclair, 1989a). However, this is not possible because of varying depths at which marine fauna can occur, possible human error, and visibility issues (Marsh & Sinclair, 1989a). Therefore, these sources of variability need to be accounted for when counting individuals.

Visibility bias is relevant for animals that continuously dive and surface as they are only visible, sometimes, for short periods (Anderson, 2001). Visibility bias can lead to the underestimation of population sizes and has two main sources: availability and perception bias (Laake & Borchers, 2004). Firstly, availability bias occurs when an animal is missed as a result of being submerged and too deep to be viewed by an observer (Marsh & Sinclair, 1989a) or the surrounding environmental conditions concealing the animal (Hagihara et al., 2018). Secondly, perception bias occurs when an observer misses an available animal because of environmental conditions, the colouration of the animal, or observation fatigue (Boyd et al., 2019). A false negative error (i.e., no animal is recorded when an animal was present) occurs through either availability bias or perception bias (when an individual isn't detected within a given area) (Brack et al., 2018). While a false positive error arises from identifying the wrong individual or double-counting the same individual (Dénes et al., 2015).

As noted above, the probability of an animal being unavailable (availability bias) depends on that animal's diving behaviour (availability process) and the surrounding environmental conditions (Hodgson et al., 2017). Availability bias can be accounted for by determining the time that an animal has been "absent", which can be determined via time-depth recording (Pollock et al., 2006) or other tagging techniques (Schweder et al., 1991), or from human observation of surfacing and dive times (Barlow et al., 1988). Availability bias can be taken into account in the following ways:

1. Marsh and Sinclair (1989a) created an availability correction factor (ACF) for dugongs, by recording where they saw dugongs in the water column.
2. This ACF was later adapted by incorporating depth into their availability corrections. Using time-depth recorders (TDRs) and GPS satellite transmitters, they quantified the depth of dugongs. The instruments then measured the time the dugongs spent in "detection zones" in different environmental conditions, estimating probability of detection (Pollock et al., 2006; Hagihara et al., 2018).
3. Direct observations e.g., by using a drone (Hodgson et al., 2017).

One can account for perception bias onboard occupied surveys by having multiple independent observers and using mark-recapture techniques (Buckland et al., 2004; Pollock et al., 2006). Perception bias can be remediated in UAV imaging in a similar way, by having two people review the same images (Hodgson et al., 2017). Ongoing research is investigating whether multispectral imaging could improve availability bias (Shrestha & Hardeberg, 2013).

1.6 Diving and surfacing behaviour of cetaceans and sea turtles

Both marine mammals and sea turtles, have the interplay of needing to surface to breathe but dive for feeding and resting (Hochscheid, 2014). In the 1930s and 40s, physiologists and behavioural scientists began to investigate how air-breathing marine organisms dealt with the physical separation of food (in deep water) and oxygen (at the surface) (Hochscheid, 2014). Diving and surfacing intervals vary between taxa and within individuals of the same species and this variation in dive time creates heterogeneous patterns in observation which can cause bias (Kasamatsu & Joyce, 1995).

1.6.1 Dolphins

The distribution of cetaceans is linked to their surrounding habitat features, food availability and mating behaviours (Hastie et al., 2004). Cetaceans, especially dolphins, are very mobile animals that range over large distances, spending most of their time underwater (Hastie et al., 2004). The identification of dolphins during aerial surveys is difficult due to their agility and quick movements throughout the water column (Alves et al., 2013). Also, the small morphological variation between cetaceans makes it even more difficult to differentiate between species within occupied aerial surveys (Preen, 2004).

Odontocetes in particular, are known for having unpredictable surfacing patterns and behaviours (Raoult et al., 2020). Varying water depths (and associated foraging activities) and surfacing behaviours of dolphins determine the time available for detection during an aerial survey. It is thought that water depth acts as a factor for foraging efficiency, determining the time spent submerged at depth (Hastie et al., 2004). Therefore, if dolphins are spending large amounts of time at depth they become less ‘available’ for detection and the detection probability is thus lower in deeper water than shallower.

It is important to understand the diving mechanisms of dolphins, as dolphin pods will only be visible in times of surfacing or activities near the surface. Bottlenose dolphins and most dolphin species in general, utilise the whole water column to forage and consistently dive to depths of approximately 50 m to find food (Hastie et al., 2006). According to vocalisation records at 20-30 m, most feeding and socialising occurs within this area, with relatively little time spent above 10 m or near the surface (Hastie et al., 2006). Therefore, dives tend to be short and because they spend more time in 20-30 m of water, that means less time on the surface for observation. Observation of dolphins from above can be accomplished; an aerial survey, flown at 500 ft, was conducted in the Pilbara on bottlenose dolphins (*T. truncatus*) and was the first to estimate the abundance of an Australian pelagic dolphin community successfully (Allen et al., 2017). Dolphins can be seen from the air easily when they’re at the surface, but as mentioned this time is limited. Allen at al. (2017) did not use correction factors for availability bias of dolphins because there are no ACF currently determined for bottlenose dolphins. Thus, their estimate could not be corrected for availability bias, and was likely that they under estimated the number of dolphins in the area at that time.

1.6.2 Sea Turtles

The dive parameters of turtles are determined by the species of turtle, the turtle's size, ocean temperatures, and their surrounding habitat (Hochscheid, 2014). Sea turtles are exothermic and vary their diving and surfacing behaviour based on the surrounding environmental conditions (Table 1.2). The age of a sea turtle also affects their diving regime, as juvenile and adult sea turtles have different diving capacities (Table 1.2). In Shark Bay, Western Australia, both green turtles (*Chelonia mydas*) and loggerhead turtles (*Caretta caretta*) have varying dive time and depths according to the differing surface and water temperatures throughout the year (Thomson et al., 2012). Because sea turtles are exothermic, they tend to conduct short, frequent surfacing in warmer, shallower conditions and longer, infrequent surfacing intervals in colder, deeper conditions (Thomson et al., 2012).

A study conducted by Freitas et al., (2019) found that loggerhead turtles spend one-third of their time at the surface each day, with the minimum time one turtle spent at the surface in 24 h being 0.4 h. Loggerhead turtles are able to spend many hours beneath the surface, with one individual logging over 10 h submerged before surfacing (Hochscheid, 2014). Green turtles spend about half that time submerged, usually around 5 h during rest periods (Hochscheid, 2014). The biological attributes of sea turtles shown below should be considered when designing aerial surveys, whether occupied or unoccupied, and suggest that differing physiological and environmental conditions produce limitations as diving patterns are heterogeneous throughout different seasons and for different activities (Thomson et al., 2011).

Table 1.2. Summary of the key biological traits of sea turtles and how they influence detection probability.

Biological trait	Effect on detection probability during aerial surveys
- Exothermic, turtles rely on their surrounding environments temperature to regulate their bodily function and movements (Carr et al., 1978). This means that as temperatures change, so do the diving behaviour of sea turtles.	- As water temperature decreases, their diving capacity increases, meaning they spend longer time at depth, decreasing detection probability (Thomson et al., 2011).
- Sea turtles exhibit a behaviour known as basking, whereby they "bask" at the surface to thermoregulate via solar radiation (Boyer, 1965).	- This thermoregulatory behaviour also means turtles are more active and spend more time at the surface during the day (Hochscheid, 2014). This may increase detection probability, depending on what time during the day an aerial survey is conducted (Boyer, 1965).
- Surface time is negatively associated with wind speed due to less radiation penetration (Freitas et al., 2019).	- Strong winds and more wave activity means less surfacing time (Freitas et al., 2019).
- Juvenile sea turtles spend more time at the surface due to their decreased diving capacity compared to adults (Freitas et al., 2019).	- The age dynamics of the region needs to be considered, and whether it is a foraging ground or mating ground. This will determine whether the turtles are more mature and thus, can spend longer times at depth (Freitas et al., 2019).

Obtaining measures of relative and or absolute abundance is a high priority in sea turtle research worldwide (Hamann et al., 2010). Aerial line transect sampling has been used to estimate both the density and abundance of loggerhead turtle populations (Lauriano et al., 2011). However, over the past 40 years, biologging and biotelemetry (such as radio tracking, GPS, and satellite telemetry) have been used on sea turtles to understand both their movements and behaviours (Hussey et al., 2015). Mark-recapture methods (Chaloupka & Limpus, 2001), nesting beach monitoring (Broderick et al., 2002) and boat-based surveys (Seminoff et al., 2014) have also been useful abundance techniques for turtles. UAVs have the potential to advance the understanding of sea turtle population dynamics by allowing us to study and estimate the abundance of turtles at all developmental stages; nesting mothers, hatchlings, immature and adult turtles (both male and female) (Bevan et al., 2016). They have also provided information on the feeding, mating, and cleaning behaviours of turtles as well as their distributions and varying sex ratios within each species (Schofield et al., 2017b). UAV technology has provided even more avenues for understanding sea turtles, and this will enhance our knowledge about their detection probability and allow for better population assessments and benefit broad-scale conservation efforts (Sykora-Bodie et al., 2017).

1.7 Environmental conditions affecting sightings

Environmental factors play a huge role in the sighting rate and clear identification of the organisms being observed, as sea state (wind), water visibility, sun glare and cloud cover can hinder certainty in sightings from both occupied and still image observations (Lubow & Ransom, 2016). The sightability threshold (depth at which animal detection is not possible) becomes shallower as visibility declines (Pollock et al., 2006). A decline in water clarity also affects the ability to detect and make accurate taxonomic identification of an animal (Kelaher et al., 2020a). The error in sightability decreases in clearer and calm conditions (Pollock et al., 2006, Fuentes et al., 2015, Hodgson et al., 2017).

Rowat et al (2009) noted that during their whale shark (8-18 m in length) aerial survey, as the wind speed increased, wave height and sea state became visibly obstructive, and observers were unable to sight some whale sharks in the area. It is interesting to note that increased wind velocity and as a result, increased sea state, negatively affects sighting rate in occupied aerial surveys (Koski et al., 2009) but in some UAV surveys, these variables had no notable effects on sightability (Hodgson et al., 2013, Fiori et al., 2017, Hodgson et al., 2017). Mount (2005) found that winds speeds of 5-10 knots or above cause multiple scattering of sun glitter and glare across still images. Light interplay at the surface of water affects the quality of vertical observation from a given height (Mount, 2005). Sun angle, reflection, and refraction all play a role in affecting the amount of shadowing and subsurface illumination of the seafloor (Mount, 2005). Glare affects detectability and sightings of an animal and can produce false negatives (Guimarães Paiva et al., 2015).

1.8 Ground sample distance

Identifying species from the air is challenging as researchers aim to maximise spatial coverage while maintaining high resolution data (McClintock et al., 2015). The animal's body position, movements, and even the light conditions can affect the identification of an animal and a misidentification can bias the distribution and abundance of a given species (McClintock et al., 2015). Ground sample distance (GSD) is defined as the distance between pixel centre points that have been measured on the ground, e.g. in an image that has a 1 m GSD, the centre points of adjacent pixels within the image are located 1 m apart on the ground (Felipe-García et al., 2012). For a given GSD, the quality of the image depends on the exposure of the camera as well as other factors such as the blur caused by motion (Grenzdörffer, 2008). GSD ultimately is determined by the camera’s resolution, lens focal length and the altitude of the UAV (Kislik et al., 2018).

1.9 Conclusion: summary and major knowledge gaps

With advances in technology, the transition from occupied to unoccupied survey methods is likely, assuming regulations change. The question is whether the unoccupied platform can produce equal if not better results than the occupied platform. With issues such as risk to human lives, real time human error and environmental conditions in occupied flights, using the unoccupied technique may have more advantages then occupied. However, UAV technology is still relatively new and has some disadvantages.

The diving behaviour of dolphins and turtles, the environmental conditions of the survey (sea state, glare, visibility) and the given GSD of the images captured, will all affect the detectability of these two taxa. With dive characteristics and physiology varying between these two taxa, it is important to understand how environmental conditions affect observations and data recorded for each taxa and for each survey platform. Another gap in the knowledge of surveying both dolphins and turtles is the GSD required to identify each taxa to species level.

1.10 Thesis objectives and research aims

The objective of this Honours project is to compare the detectability of dolphins (*Tursiops* and *Sousa* spp.) and turtles (Cheloniidae) from an occupied aircraft with UAV images captured during concurrent surveys. I have also examined whether it is possible to identify different species of dolphins and turtles at varying GSDs and assess at what level of certainty these identifications were made. The data for this study were collected in 2012 from a trial UAV survey which assessed the detectability of dugongs in UAV images and compared these with the results from an occupied survey (Hodgson et al., 2013). That study was designed to optimise the detection of dugongs i.e., the flight altitude of 500 ft and resulting GSD were chosen for dugongs. Both dolphins and turtles were also clearly visible in the images from these surveys and were recorded by the observers in the occupied survey.

The specific objectives of my Honours research were to:

1. Compare the detection rates of dolphins and turtles in UAV images with those of real-time data collected from an occupied aircraft,
2. Investigate how detection rates of dolphins and turtles from the two survey platforms vary with environmental conditions (sea state, glare, visibility),
3. Determine whether is it possible for "expert researchers" (those who specialise in either dolphin or turtle research and are well versed in species identification of those taxa) to identify species of dolphins and turtles from the UAV images and the minimum GSD needed to identify species, and
4. Assess whether environmental conditions affect the "experts" ability to determine species at a given GSD.

Hypotheses:

Because UAVs provide high resolution, still images that can be reviewed, while occupied surveys only offer observers a few seconds to see and identify animals, I hypothesise that the UAV survey will provide a higher sighting rate of individuals than the occupied survey team.

Secondly, due to the clear and motionless analysis of images from the UAV, I predict that the environmental conditions of glare, sea state, visibility and cloud cover will affect the sighting rates of dolphins and turtles differently between the two platforms. With the four variables making detection of the two taxa more difficult within the occupied teams observations compared to the UAV images.

The third aim of this project is to determine the image GSD required to be able to identity dolphins and turtles to species level. I hypothesise that a lower GSD value image will capture clearer, more identifiable individuals than a high GSD value. Turtles are relatively small compared to their cetacean counterparts and previous aerial survey studies have suggested that the carapace width of a turtle needs to range from 30-75 cm to identify turtles to species level (Alves et al., 2013). Therefore, I also hypothesize that since dolphins are larger than turtles, a lower GSD will be needed to identify species of turtles than dolphins.

Likely, images with good environmental conditions (low glare, calm sea state) and low GSD will provide the best images for species identification. Therefore, I hypothesize that images with poor visibility and intense glare will affect the GSD required to identify species (meaning in harsher environmental conditions, the minimum GSD may need to be lowered to identify species of dolphins and turtles).

Chapter 2.1 Materials and Methods

The data used in this study were collected in 2012 from research primarily conducted to compare dugong detection rates between an occupied aircraft and a UAV (Hodgson et al., 2013). Data on dolphins and turtles were collected as secondary data during this study (see below *Detection of dolphins and turtles*). As the original research was focussed on dugong detection, this survey design was not the most appropriate design for dolphin and turtle detection. Here I describe the materials and methods of those trial flights and how the data I received were collected. Then in *Detection of dolphins and turtles*, I describe the methods specific to my aims and objectives.

2.1.1 Study site

Both occupied and unoccupied aerial surveys were conducted in Shark Bay, WA (25°30'S, 113°30'E) in 2012. The bay covers approximately 13,000 km^2 and is recognised for its high conservation values as it is a World Heritage Area (WHA) and a Marine Park. The Shark Bay WHA includes pristine, diverse seagrass ecosystems (Olson et al., 2012) with 12 different seagrass species (Walker et al., 1988). The Shark Bay region receives limited rainfall (average annual rainfall 197.1 mm) and has mean monthly temperatures ranging from 10.7-34.7°C (Meteorology, 2021). It supports large turtle populations and is important for both large and small cetaceans (Preen et al., 1997). Green turtles are the most common species within Shark Bay, with the loggerhead turtles also being present within the bay (Preen et al., 1997), while the two main delphinid species found here include a large population of bottlenose dolphins (Nicholson et al., 2012) and a lesser known population of humpback dolphins (*Sousa sahulensis)* (Parra & Corkeron, 2004).

2.1.2 Experimental design and flight details

The survey design followed that of five previous aerial surveys conducted within Shark Bay and consisted of a series of parallel line transects spaced 4.6 km apart (Gales et al., 2004; Preen, 2004; Holley et al., 2006;) . The 2012 survey focussed on detecting dugongs, so the transects flown were just in those areas where the highest density of dugongs were expected to occur. The two aircraft were flown at the same time over the same transects, at different altitudes (see below) and covered approximately similar sized strips (400 m each; a strip being a patch of ocean that the observations occurred within). However, the strips covered by each platform did not entirely overlap because the observers were looking at two 200 m strips either side of the aircraft while the UAV captured a 400m strip directly nadir (i.e., straight below the UAV). The flights took place between the 29th of August and the 3rd of September 2012. The correlated flight paths and dates of flying each transect are shown in Figure 2.1.

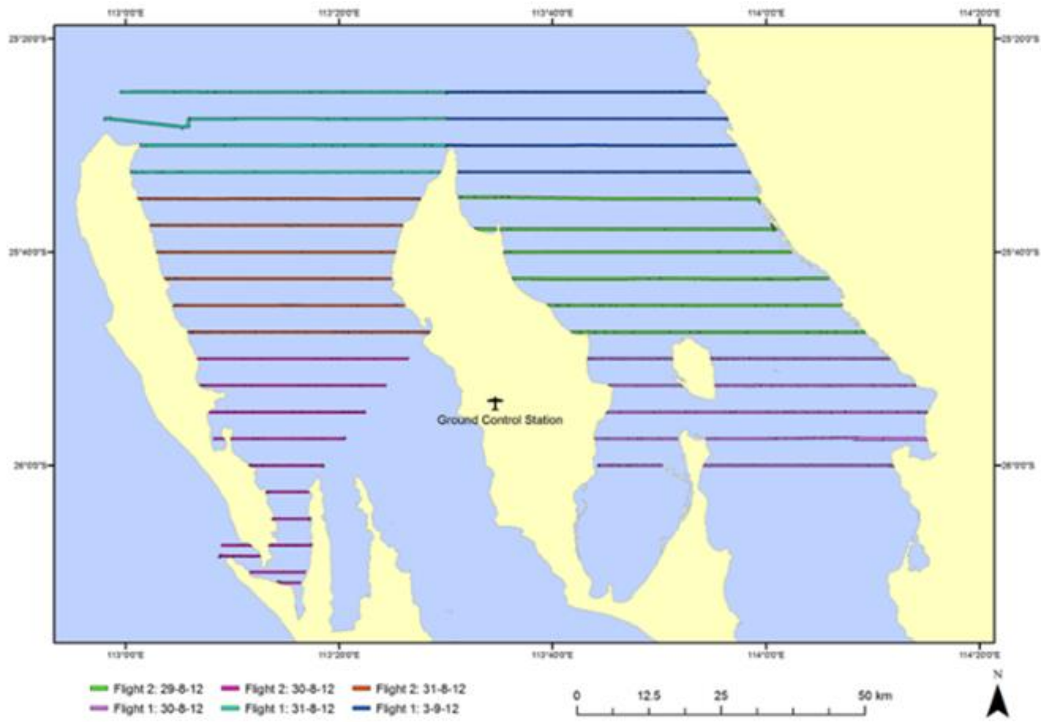

Figure 2.1. The combined footprint of the UAV images taken during the 2012 aerial survey of Shark Bay, WA, 29th August to 3rd September. Colours of flight paths identify each flight. Map provided by Amanda Hodgson.

2.1.3 Occupied aircraft observations

The aerial survey methods followed those described in Marsh and Sinclair (1989a). The aircraft used was a twin-engine Partenavia 68B which flew at 100 knots and at an altitude of 500 ft. The survey team consisted of a pilot, survey leader and four trained observers (two on each side of the aircraft). The ‘front seat’ and ‘back seat’ observers were isolated visually and acoustically so that their sightings were independent. This double-observer system maximised the probability of detecting dolphins and turtles and meant that the ‘perception bias’ could be calculated for the survey.

The observer team announced all dolphins and turtles within an approximately 200 m strip of ocean on each side of the aircraft. This 200 m strip was defined by rods attached to ‘pseudo wing struts’ (the exact widths were 206 m on the port side and 203 m on the starboard side).

2.1.4 UAV Surveys

i) ScanEagle UAV

The UAV used in this study was a fixed-wing *ScanEagle* (Figure 2.2). It was operated by Insitu Pacific Ltd and is described in detail in Hodgson et al. (2013, 2017). The *ScanEagle* was operated via a Ground Control Station (GCS) from Monkey Mia airport. The deployment of the UAV from the GCS was from a pneumatic catapult called a *Superwedge launcher* and was recovered using the *Skyhook* retrieval system (Hodgson et al., 2013).

ii) UAV Imaging System (payload)

As mentioned above, the primary goal of the data collected in 2012 was to maximise dugong detections and the altitude flown by the UAV was chosen on this basis. The GSD of 3.2-3.5 cm/pixel was achieved by flying at an altitude of 1300-1400 ft, which allows for the detection of dugongs (Hodgson et al., 2013).

Two SLR cameras (24-megapixel (6016 x 4000) Nikon D3200) were used to capture images from the UAV (Figure 2.2). Both cameras were fitted with a 50 mm lens and a polarising filter. Maximal coverage with minimal overlap of the two cameras was achieved by rotating each camera ~11.5º from vertical in opposite direction. The target image overlap along the transect line was 40% which previously was found to help account for sightings inhibited by glare (Hodgson et al., 2013). The overlap of 40% created an on-ground width ranging from 193.4 cm (3.2 cm/pixel GSD at 1300 ft) to 210.2 m (3.5 cm/pixel GSD at 1400 ft).

Figure 2.2. Pictures of the *ScanEagle* UAV (left), fitted with the two SLR cameras (right). Images by Amanda Hodgson.

2.1.5 Environmental conditions

Data on the environmental conditions were scored and compiled prior to my study. The process used is summarised below.

i) Visibility

The images captured by the UAV were used to determine the water visibility of the survey areas of both the occupied and unoccupied platforms. An image reviewer subjectively scored each image according to its dominant visibility category (Table 2.1) with 1 and 2 representing the differing visibility in waters where the seafloor is visible, and 3 and 4, where the water is deep.

Both the occupied and unoccupied transects were then broken into segments based on the visibility scores assessed within the UAV images. These segments had constant visibility but varied in length. All further analyses were then based on these segments.

Table 2.1. Summary of the visibility scale used to classify visibility from UAV images flown in Shark Bay between the 29th of August and 3rd of September 2012.

Visibility Category	Visibility of the Sea Floor	Water Quality
1	Clearly visible	Clear
2	Visible but unclear	Opaque
3	Not visible	Clear
4	Not visible	Opaque

ii) Sea state

The sea state score was based on the Beaufort scale which ranges from 0 (calm) to 6 (strong breeze with large waves) (Table 2.2). During the occupied surveys the team leader recorded the sea state data every 2 minutes, or when the conditions changed. A handheld GPS on board the occupied aircraft tracked the occupied survey flight path by recording a GPS location every second. Each GPS point was then assigned a sea state score based on the last record from the survey leader. The mean sea state was then calculated for each transect segment as the mean score of all GPS track locations that fell within the segment length.

Table 2.2. Summary of the Beaufort scale of wind force used to classify sea state for both occupied and unoccupied data collected in Shark Bay between the 29th of August and 3rd of September 2012 (Bureau of Meteorology, 1970). Note that the scale ranges from 0-6, even though there are 12 levels in the Beaufort scale, as sampling did not occur beyond a score of 6.

Force	**Description**	**Sea State**
0	Calm	Like a mirror
1	Light Air	Ripples, no foam
2	Light Breeze	Small wavelets, smooth crests with glassy appearance
3	Gentle Breeze	Large wavelets, some crests break, some white caps
4	Moderate Breeze	Small waves, frequent white caps
5	Fresh Breeze	Moderately long waves, many caps, some spray
6	Strong Breeze	Some large waves, extensive white foam crests, some spray

iii) Glare

Glare or ‘sun glitter’ was scored separately for the two platforms because glare was recorded differently on each platform (Hodgson et al., 2013). The occupied team noted down sun glitter for the north side of the plane (i.e., the direction in which sun glitter had the strongest effect). The estimate of sun glitter was subjective and scored as a percentage of the area observed that was affected. The scores were then applied to the GPS track locations (in the same way as for sea state) in order to determine the mean sun glitter for each occupied transect segment.

In the UAV images, glare (sun glitter) assessment was made by one image reviewer for all the images using the same ordinal scale as for the occupied surveys (Figure 2.3). The mean glare score for each UAV survey transect segment was calculated from the glare score of each north-facing image in the segment.

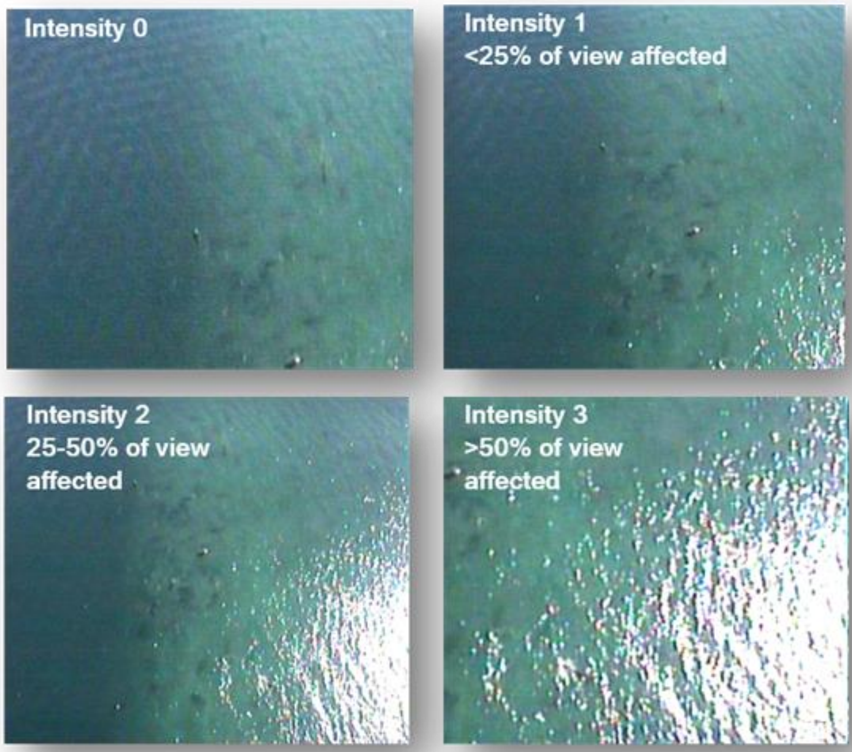

Figure 2.3. Examples of scores for the differing intensities of glare for selected UAV images obtained from Shark Bay. Western Australia. Images by Amanda Hodgson.

iv) Cloud cover

Cloud cover was recorded in oktas (ranging from 0 for completely clear sky to 8 for complete cloud cover) by the occupied survey leader at the beginning of each transect. Cloud cover was not scored within the UAV image review (as the clouds could not be seen) but was recorded by the occupied team. Cloud cover recordings were then applied to all occupied and UAV segments in that transect.

2.2 Detection of dolphins and turtles

2.2.1 Perception bias: UAV

In order to compare the manual image review detections of the main reviewer, a second reviewer was asked to review a subset of images from the same flight data set analysed by the main reviewer (n = 1968 images). This was done to calculate the UAV reviewer perception bias. The perception bias estimates were calculated via a mark-recapture model (Huggins model) using the program MARK. Then the perception probabilities used for each observer were provided by the model that best fit the data according to Akaike's Information Criterion (AIC), which corrects for small sample bias.

The occupied perception bias was calculated prior to my study following Pollock et al. (2006) using a generalised Lincoln-Petersen models within the program MARK (White & Burnham, 1999).

2.2.2 Image analysis and review

A total of 38,365 UAV images were analysed by both the author and Brooke Chester (who began reviewing UAV images during her bachelor's degree in marine biology) for turtle detection between 2019 and 2021. The analysis of images for dolphin detection had been conducted by three separate reviewers prior to this. The turtle reviewers recorded the time they started and completed reviewing each set of images as well as the number of images reviewed, to provide an estimate of the manual image review rate.

Reviewers searched each image for all turtles and dolphins present within the images and scored the environmental conditions within each image that contained a sighting. Reviewers also recorded the certainty of identification and whether the animals were resights. Certainty was scored as either uncertain or certain, with only certains being used in the final count. Resights of animals included those that were captured in multiple images and resights were subtracted from the final count. The images were all reviewed at 50% of their actual size to make the animals appear large and clear on the screen, and the reviewers used a standardised process to scroll around each image.

The image review process for detecting turtles was originally conducted using custom *ImageViewer* software, described in Cleguer et al., (2021) and then checked through the software *Dugong Detector* (DD; a custom software still under development). Within the *ImageViewer/*DD software, when an animal was sighted, a red box was drawn around the animal, creating a georeferenced footprint for that animal (Figure 2.4). The following information was recorded for each sighting:

- Taxa of the individual animal,
- Environmental state in the image i.e., sea state, glare, and visibility,
- Certainty of identification - certain (yes) or uncertain (no) for each sighting,
- First certains were selected only on the first instance of certainty (for individuals occurring in more than one image), these were used for the final counts of individuals, and
- If the sighting was a resight (yes or no, i.e., the same animal occurring within the overlap of successive images, they tend to be in the same position within the image just higher or lower in the plane of the image).

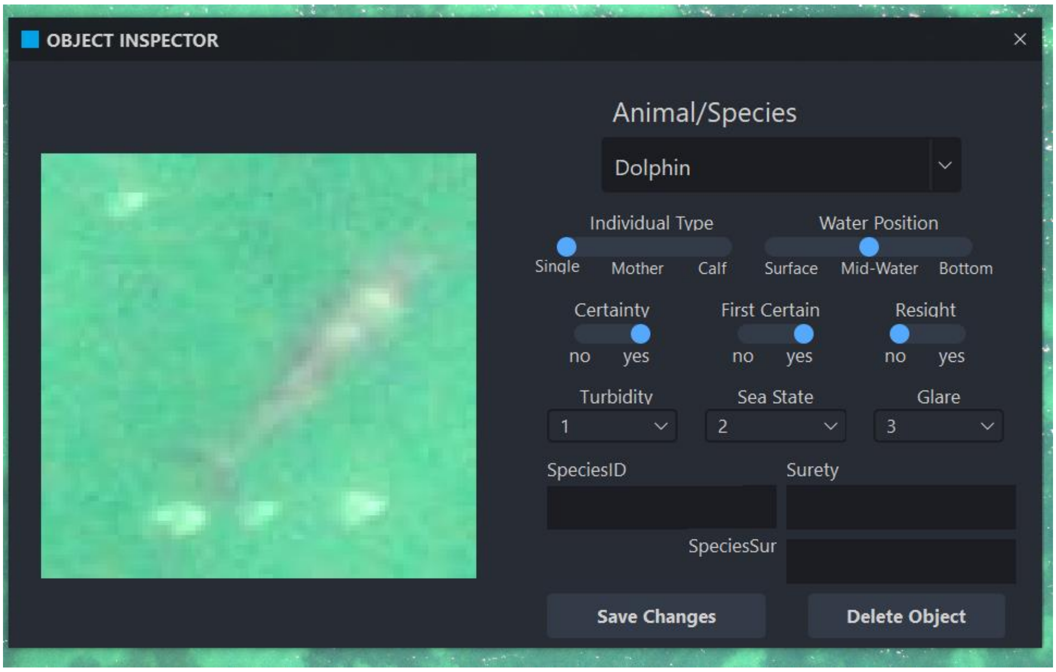

Figure 2.4. Example screen capture of the data recorded for each sighting within the *DugongDetector* program. Image of single dolphin.

The program DD georeferences each sighting which allows us to account for resights of dolphins and turtles that appeared in overlapping images (Figure 2.5). This is done within DD by the appearance of a green box next to an animal in a successive image. By clicking on the green box, reviewers can see what the animal looked like in the previous image and based on its offset position within the overall image and the position and orientation of the animal in the water, determine whether it was a resight, eliminating recounts. All images that were highlighted as containing animals were rechecked by the author to ensure the counts and associated scoring was correct and consistent.

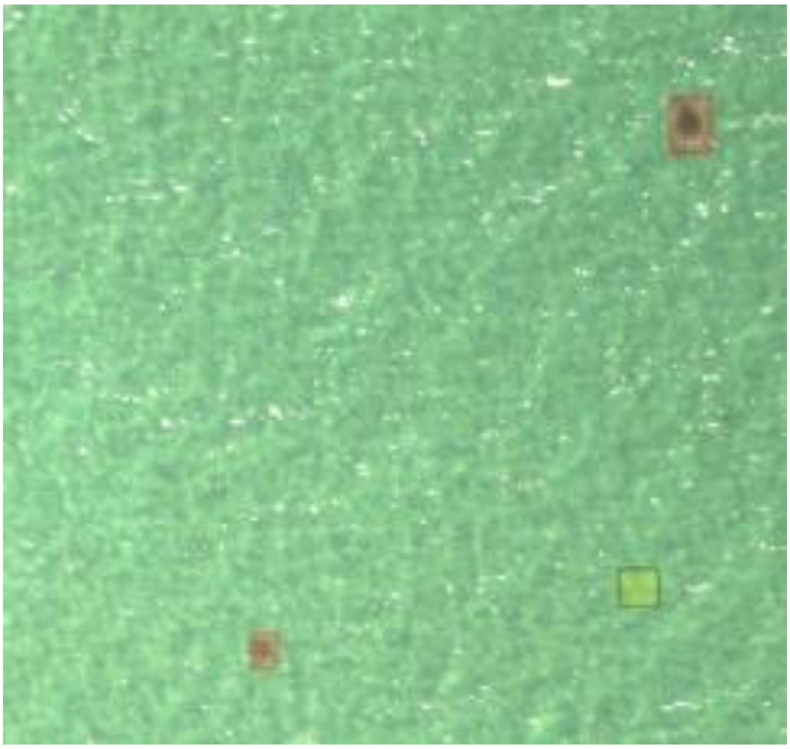

Figure 2.5. Example of a resight individual within the *DugongDetector* software. Red boxes indicate a new sighting; green boxes indicate a possible resighting from the previous image.

2.2.3 Mapping of sightings within ArcGIS

The area covered by the images and the occupied team had previously been mapped. When mapping the image footprints, the *ScanEagl*e's altitude, rotation, and orientation of the two cameras were accounted for. The transects had also already been split into segments of constant visibility. DD provided a georeferenced bounding box for each turtle and dolphin sighted which were exported as shapefiles and imported into ArcMap. The bounding boxes were polygons so were then transformed into points. The occupied turtle and dolphin sightings were mapped according to the GPS tracks of the aircraft by matching the time of the sighting with the closest track time (within 1 sec).

The main aim of using ArcGIS was to determine the counts of dolphins and turtles sighted within the UAV and occupied platforms per transect segment. I used the 'Spatial Join' tool to join both the UAV and occupied sightings to the transect segments. Then the tool "Join Field" combined the occupied and unoccupied data based on their common attributes, i.e., dolphin and turtle sightings within the same transect segment, to produce a total count per transect segment.

2.2.4 Assessing the influence of environmental conditions on detection

The effects of the four covariates (visibility, sea state, glare, and cloud cover) on the dolphin and turtle sighting rate were estimated assuming:

1. The number of dolphins and turtles available to be detected is equal relative to each of the covariates. However, visibility, which has a water depth factor, is correlated with turtle and dolphin distribution throughout the water column and thus detection. Due to the absence of data to properly model this relationship, we assumed that visibility had no effect on distribution;
2. The number of dolphins and turtles available to be detected during a single survey flight remained constant; and
3. Both dolphins and turtles were distributed randomly throughout the survey area and there are no systematic trends in the values of the four environmental covariates.

Of course, the consequences of these assumptions being incorrect would affect the fair evaluation of the data. Visibility may have an effect on detection and the chance of detection between a marine mammal and a reptile may differ due to their surrounding environmental factors, the same goes with the impact of distribution and the four covariates. There is also the chance that detection was not constant during a single flight, and this could have also led to more or less animals detected as the different platforms passed over.

The total number of dolphins and turtles sighted were tallied for each platform and within each transect segment as well as the associated four covariates within ArcGIS. A generalised linear mixed model (GLMM) was fitted to the number of dolphins and turtles detected per transect segment to determine the relationship between the ability to see the animals and the covariates. The response variable was assumed to be Tweedie distributed in order to account for any individuals forming groups. A Tweedie distribution is an exponential dispersion model often used in GLMMs. The R package cplm was used to fit the Tweedie GLMMs (Zhang, 2013).

Each flight and each transect was treated as a random effect to account for spatial and temporal autocorrelation. The covariates (glare, visibility, sea state and cloud cover) were treated as fixed effects. The Beaufort Sea state (0-6) was entered into the models as an ordinal value. Glare/sun glitter estimates of 0-50% and cloud cover oktas were also entered in the models as ordinal values. While visibility estimates were entered in the models as categorical values of 1, 2, 3 and 4 (with each row given a level e.g., Vis2, Vis3).

A backwards selection process (see example below) was used to determine the model of best fit for the fixed-effects components (the environmental covariates). Given that the data were non-normal and over dispersed, a one-sided t-test on the last main effect or interaction term to enter the model was used to decide whether that term was significant (at the 0.05 level of significance). The form of the equation fitted was:

Count (number of detections) ~ Platform*Sea state + Platform*Glare + Platform*Visibility + Platform*Cloud cover

Platform was the term to denote UAV as opposed to humans in an aircraft. The "main effects" (glare, visibility, sea state and cloud cover) apply to both platforms. Interactions are shown as e.g., Platform*Glare, where there is an interaction between the UAV and glare. The interaction term will put in the main effects as well (e.g., Platform*Sea_State will put terms Platform and Sea_State and Platforms:Seastate in the model).

If the interaction wasn't significant the interaction was dropped and the covariate re-fit into the equation e.g., if the cloud cover and platform interaction was not significant the equation would look like:

Count (number of detections) ~ Cloud cover + Platform*Sea state + Platform*Glare + Platform*Visibility

Once the last interaction term was dropped, platform would then have had to be re-added to the equation e.g.:

Count (number of detections) ~ Platform + Cloud cover + Sea state + Glare + Visibility

2.2.5 Expert surveys to test species identification

Emails were sent to people considered to be experts in either dolphin or turtle identification, asking them to participate in reviewing images where turtles and dolphins were present, to see if they could identify them to species level. Three dolphin and three turtle experts reviewed the 120 images each containing dolphins and turtles respectively. These surveys of experts were carried out under Human Ethics approval within Murdoch University.

The images were sent via Google Drive and the original images had been cropped to reduce the time of experts finding an animal within a full image. An accompanying excel spreadsheet was sent to the experts to document their response for each image. The experts were asked to review the images within approximately two weeks. The images were selected from a number of locations including Shark Bay and Ningaloo in Western Australia and the Northern Territory (see Table 2.3 for details of the images sent for expert identification).

Table 2.3. The details of each image dataset used in the human expert surveys and their specific altitudes and associated ground sampling distances (GSD).

Year	No. Dolphin Images	No. Turtle Images	Location	Altitude (feet)	GSD (cm/pixel)
2010	9	12	Shark Bay	500	1.7
2010	4	11	Shark Bay	750	2.5
2020	15	30	Ningaloo	250	3.0
2010	11	7	Shark Bay	1000	3.3
2012	41	30	Shark Bay	1400	3.5
2019	40	30	Northern Territory	500	3.5
Total	120	120			

The images sent for review by the experts had differing GSD, locality (Table 2.3) and environmental conditions of visibility, glare, and sea state. The experts were asked to record species, where possible, and the certainty of the species identification. Certainty values ranged from less than 50% to 100% (Table 2.4).

Table 2.4. Certainty categories assigned to species identification by dolphin and turtle experts

Certainty Category	Degree of Certainty
Unknown	0-49%
Guess	50-74%
Probable	75-99%
Certain	100%

When determining the final species agreement and the average certainty, the certainty scores were given a number (unknown = 0, guess = 1, probable = 2, certain = 3) and this was averaged across all three experts. Those results were then rounded appropriately to determine a certainty category for each species identified.

The experts also recorded the specific morphological features they used to identify species and had no prior knowledge of the location that the images came from or the GSD. Because the images ranged from Shark Bay to the Northern Territory a variety of dolphin and turtle species could have been present. The species available for detection were noted in the excel spreadsheet and may have included:

- Australian Snubfin Dolphin (*Orcaella heinsohni*)
- Spinner Dolphin (*Stenella longirostris*)
- Australian Humpback Dolphin (*Sousa sahulensis*)
- Indo-Pacific Bottlenose Dolphin (*Tursiops aduncus)*
- Green Turtle (*Chelonia mydas*)
- Loggerhead Turtle (*Caretta caretta*)
- Hawksbill Turtle (*Eretmochelys imbricata*)
- Olive Ridley Turtle (*Lepidochelys olivacea*)
- Leatherback Turtle (*Dermochelys coriacea*)
- Flatback Turtle (*Natator depressus*)

Chi-square test of independence was used to test whether the differing environmental variables of glare, visibility and sea state were related to the certainty of species identification (from unknown to certain). Each covariate was analysed separately using the significance level of 0.05. Categories were pooled when $n < 5$. The dataset of 3 cm/pixel provided no environmental information therefore only the GSDs of 1.7, 2.5, 3.3 and 3.5cm/pixel were assessed for effects of environmental conditions of species identification.

Chapter 3. Results

The total transect distance covered by the occupied aircraft and the UAV during the six survey flights was 991.59 km^2 (Table 3.1). The occupied observer team surveyed an estimated total area of 523.87 km^2 while the UAV images covered a total of 467.73 km^2 (Table 3.1).

A total of 44,941 images were captured from the UAV, with 38,365 being reviewed during this study. The total time to review all of these images was approximately 145 h with an average of 285 images reviewed per hour.

Table 3.1. Summary details of the flights, coverage, and sightings for each platform.

Flight	**UAV altitude** (feet)	**Transect segments**	**Occupied area** (km^2)	**UAV area** (km^2)	**Occupied count** Dolphins	Turtles	**UAV count** Dolphins	Turtles
29F2	1400	58	114.8	107.51	16	77	28	202
30F1	1300	62	91.49	82.21	5	29	14	30
30F2	1300	82	65.54	56.59	32	70	51	45
31F1	1400	35	83.34	76.64	14	63	34	19
31F2	1300	38	94.93	82.13	22	50	30	41
3F1	1300	21	73.77	62.65	4	23	17	31
Sub-total					**93**	**312**	**174**	**368**
Total		**296**	**523.87**	**467.73**	**405**		**542**	

3.1 Animals sighted

The UAV image reviewers were able to detect more dolphins (174) and turtles (368) within the image review process than the occupied aerial team (dolphins = 93; turtles = 312); i.e., nearly twice as many dolphins and 1.2 times as many turtles by the UAV (Table 3.1). When assessing the sightings per flight (Table 3.1), the UAV images captured more dolphins in every flight compared to the occupied survey.

The GLMM of best fit suggested that the number of dolphin sightings differed significantly between the occupied surveys and the UAV images with 2.15 times the number of dolphins (115% more) from UAV than the occupied (95% CI = [1.38, 3.39]) (Table 3.2). In contrast, the number of turtle sightings did not differ significantly between occupied flights and UAV (*P = 0.11*) (Table 3.2).

Table 3.2. Comparison of dolphin detection rates between the occupied and unoccupied platforms by GLMM analysis. Dolphin sightings were transformed by the Tweedie distribution to account for individuals forming groups. Platform term denotes the UAV as apposed to the occupied survey observations.

Dolphins						
	Estimate	**Std. Error**	**Point estimate**	**95% lower**	**95% upper**	**Significance**
Platform	0.77	0.23	2.15	1.38	3.39	<0.001

The UAV captured 10 or more dolphins in five segments and 10 or more turtles in five segments while the occupied survey did not record 10 or more dolphins in any segment and only 3 segments had ten or more turtles. In two segments, the UAV captured very large aggregations of turtles; one of 94 and another of 50 turtles while the occupied team recorded only 3 and 4 turtles respectively in the corresponding segments. These two large aggregations were removed from the GLMM analysis for the turtles as they were considered to be outliers and were swamping the more subtle effects.

In some cases, the larger segment counts for dolphins was also a result of larger groups being sighted in the UAV images compared to the occupied team. An example of a large group of dolphins is shown in Figure 3.1, where the red points indicate the UAV sightings (of individual animals), and the white dots indicate the occupied team's sightings (of groups). Zooming into transect 16, the single white dot for the occupied sightings represents a group of 5 dolphins, while the 10 individual red dots represent individual dolphins seen in the UAV images, i.e., a group of 10.

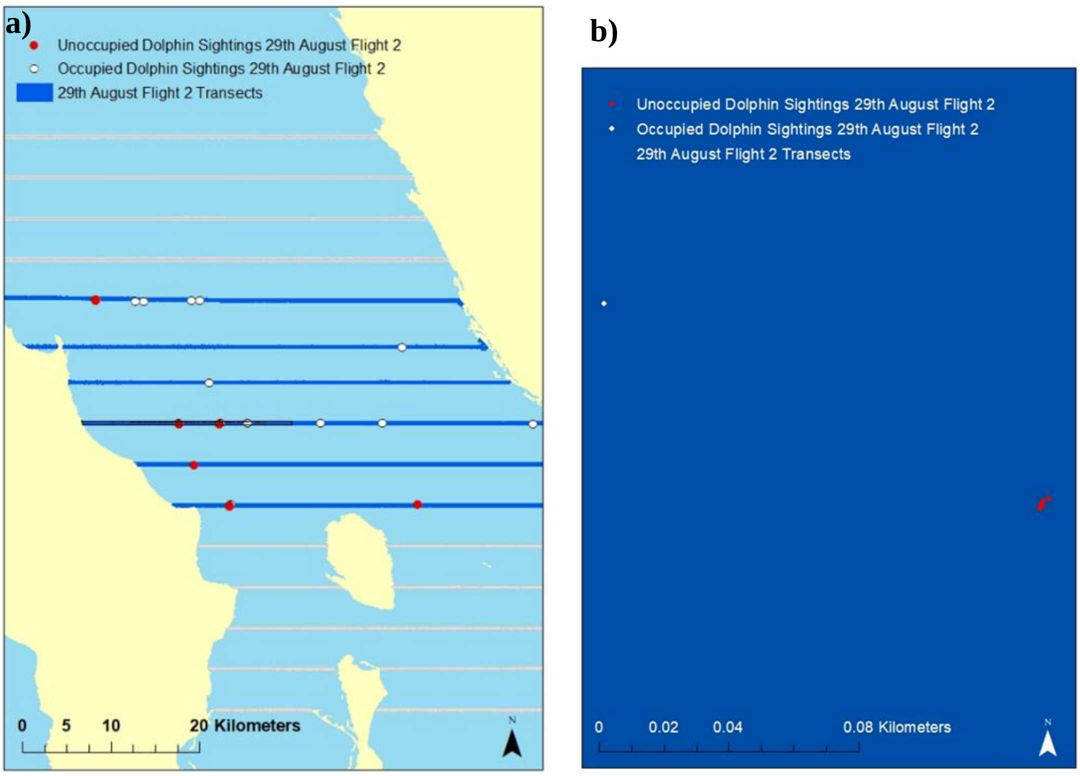

Figure 3.1. a) Map highlighting the transects flown on the 29th of August 2012, during flight 2, within Shark Bay, WA. The black outline represents transect 16 while the red dots indicate the UAV (unoccupied) sightings of individual dolphins, and the white dots indicate the occupied team's sightings of dolphin groups. *b)* Shows a zoomed in segment of transect 16 within the same flight. For the occupied data the single white dot represents a group of 5 dolphins, while red dots represent individual dolphins within the UAV data.

3.2 Influence of environmental conditions on detection

None of the interaction terms were significant, therefore the covariates affected both the UAV and occupied platforms in the same way. The detection of dolphins in both platforms was significantly influenced by visibility, sea state and cloud cover (Table 3.4).

The number of dolphins detected in both the occupied and UAV decreased by 12%, (95% CI = [0.79, 0.98]) with every unit (1 octa) increase in cloud cover (Table 3.3). The number of dolphins detected in Visibility 2 (where the sea floor is visible, but the water is opaque) was 4.4 times higher than in Visibility 1 (where the sea floor is visible, and the water is clear). Additionally, 4.8 times more dolphins were observed in Visibility 3 (where the see floor isn't visible but the water is clear) than in Visibility 2 (Table 3.3). The number of dolphins observed in the occupied aircraft and UAV decreased by 34%, (95% CI = [0.49, 0.9]) per unit increase in sea state (Table 3.3). Therefore, a reduction in sighting rates for dolphins was seen with an increase in sea state and cloud cover, while changes in visibility (i.e., as our category scores increased up to Visibility 3) meant an increase in detection for dolphins, in both occupied and unoccupied surveys.

For turtles, neither platform nor the platform interaction terms were significant. Therefore, visibility affected turtle detection the same way in both the occupied and UAV platforms. Significantly more turtles were detected in Visibility 1 than 3; 36% fewer in Visibility 3 (95% CI = [0.42-0.98]) (Table 3.3). Additionally, detection in Visibility 2 compared to Visibility 1 was 1.4 times (40%) higher however Visibility 2 was not significant in the analysis. Therefore, changes in visibility from category 1 to 3, meant turtle detection decreased.

Table 3.3. Summary of the results from GLMM analyses to test the influence of environmental variables on the detection of a) dolphins and b) turtles recorded from both observers and UAV. Response variable was Tweedie distributed to account for individuals forming groups. Alpha = < 0.05.

Variable	**Estimate**	**Std. Error**	**Point estimate**	**95% lower CI**	**95% upper CI**	**Significance (P =)**
a) Dolphins						
Intercept	-2.19	0.48				*7.26×10^{-6}*
Cloud Cover	-0.12	0.05	0.88	0.79	0.98	*0.024*
Visibility 2	1.47	0.43	4.37	1.87	10.2	*6.93×10^{-4}*
Visibility 3	1.57	0.43	4.81	2.06	11.2	*2.98×10^{-4}*
Sea State	-0.41	0.15	0.66	0.49	0.9	*0.008*

Variable	Estimate	Std. Error	Point estimate	95% lower CI	95% upper CI	Significance (P =)
b) **Turtles**						
	Estimate	**Std. Error**	**Point estimate**	**95%_lower**	**95%_upper**	**Significance (P =)**
Intercept	-0.71	0.34				*0.037*
Visibility 2	0.34	0.20	1.41	0.95	2.09	*0.09*
Visibility 3	-0.45	0.22	0.64	0.42	0.98	*0.041*

3.3 Perception bias

Perception bias previously calculated for the occupied observers was 0.95. The probability of the image reviewers detecting dugongs that were visible within the subset of images for all three reviewers ranged from 0.80 to 0.98 (previously calculated by Hodgson, Murdoch University, unpublished data). In this instance we are assuming that those three observers would have had a similar perception bias range for dolphins due to their similar morphology to sirenians.

The overall perception probability of the two image reviewers detecting turtles that were visible within the subset of images (n = 1968 total images; n = 33 images with certain turtles) was 0.94. The main reviewer who reviewed all the images detecting turtles for this thesis had a perception probability of 0.74 (±0.08) while the secondary reviewer had a perception probability of 0.77 (±0.08). Perception bias was unable to be calculated for dolphins due the main image reviewer only identifying turtles during their image review process.

3.4 Human expert surveys

3.4.1 Effect of GSD on species identification

i) Dolphin species identified

From the 120 images analysed by experts, three species of dolphin were identified: (*Tursiops aduncus*) the bottlenose dolphin, (*Orcaella heinsohni*) Australian snubfin dolphin and (*Sousa sahulensis*) the Australian humpback dolphin. Across all 120 images (pooled from all certainty levels) the percentage of dolphin species identified were 51% unidentifiable (Table 3.4), 32% bottlenose, 12% humpback and 5% were snubfin dolphins.

When evaluating the species identifications at different levels of GSD, the highest incidence of species identified (67%) was at 1.7 cm/pixel and the lowest was at 3.3 and 3.5 cm/pixel (45-46%) (Table 3.4).

Table 3.4. Summary of both turtle and dolphin total species identifications at different ground sampling distances (GSD) values from 1.7 cm/pixel to 3.5 cm/pixel.

GSD (cm/pixel)	Unknown Dolphin Identification	Dolphin Species Identified	N	Unknown Turtle Identification	Turtle Species Identified	N
1.7	33%	67%	9	58%	42%	12
2.5	50%	50%	4	45%	55%	11
3.0	40%	60%	15	20%	80%	30
3.3	55%	45%	11	43%	57%	7
3.5	54%	46%	81	87%	13%	60
Total			**120**			**120**

ii) GSD and certainty of dolphin species identified

Overall, across all 120 images reviewed, 51% had no certainty of dolphin identification, while 23% were a guess, 21% probable and 5% were certain. Thus, experts were 75-100% sure of their dolphin species identification in 26% of images.

When comparing the GSD with the certainty of identification, the GSD of 2.5 cm/pixel had the highest number of certain identifications (25%) (Figure 3.1). The lowest amount of no identifications (33%) was seen in a GSD of 1.7 cm/pixel. The GSDs of 3 and 3.3 cm/pixel had no certain identifications, while 3.5 cm/pixel had 5% certain identifications (Figure 3.1). GSDs of 3.3 cm and 3.5 cm/pixel produced the highest amount of no identifications (55%) (Table 3.4). While the GSD of 1.7 cm/pixel produced the second highest number of certain identifications (11%).

If considering experts were confident in their species identification where their classifications were probable or certain, 34% of the sightings at 1.7 cm/pixel were confident, which declined to 25% at 2.5 cm but the sample size for this GSD was very low (n = 4). The GSD of 3 cm had a 40% confidence of sighting (with 0% certains but high probable identifications of 40%). This declined to 9% confidence at 3.3 cm and 26% at 3.5 cm/pixel (Figure 3.1).

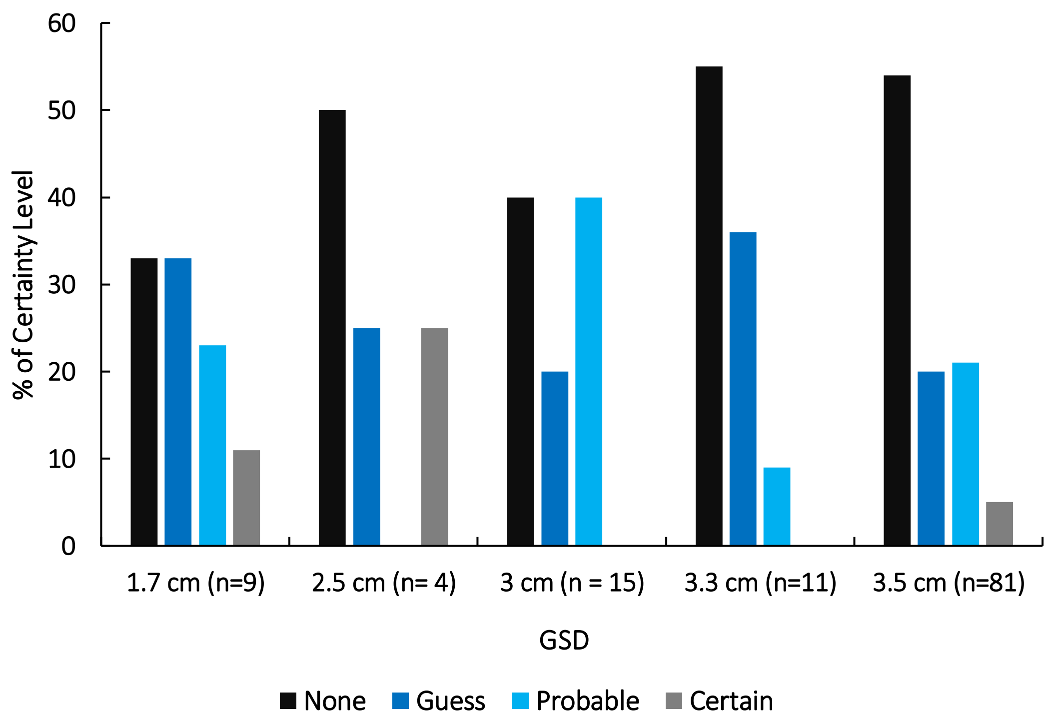

Figure 3.1. The percentage of mean certainty levels for dolphin species identified at different ground sampling distances (GSD) from 120 images sent to dolphin experts.

iii) Turtle species identified

Of the 120 images analysed by the three turtles experts, three species were identified: (*Chelonia mydas*) the green turtle, (*Caretta caretta*) loggerhead turtle and (*Natator depressus*) the flatback turtle. From the 120 images, including all certainty levels, 61% of turtles present could not be identified to species, 29% were green, 8% were loggerhead and 2% were flatback turtles.

The GSD of 3 cm had the highest rate of turtle species identification (80%) while the GSD of 3.5 cm had the lowest incidence of turtle species identification (13%) (Table 3.4).

iv) GSD and certainty of turtle species identified

From the 120 images reviewed for turtles, 61% had no certainty in identification, 22% were a guess, 15% probable and 2% certain. Meaning that experts were 75-100% sure of their identification in only 17% of images.

When comparing the differing GSD with the certainty of identification, the highest number of certain identifications were at GSDs of 3 cm (7%) which declined to 0% in all other GSD categories. The GSD of 3 cm also had the lowest number of no identifications (20%) (Figure 3.2).

If accepting both probable and certain outcomes, experts were confident in their species identification in 34% of the images at 1.7 cm GSD, at 2.5 cm/pixel they were 0% confident and 40% confident at 3 cm/pixel. This declined to 14% confidence at 3.3 cm/pixel and 5% confidence in species identification at 3.5 cm/pixel (Figure 3.2).

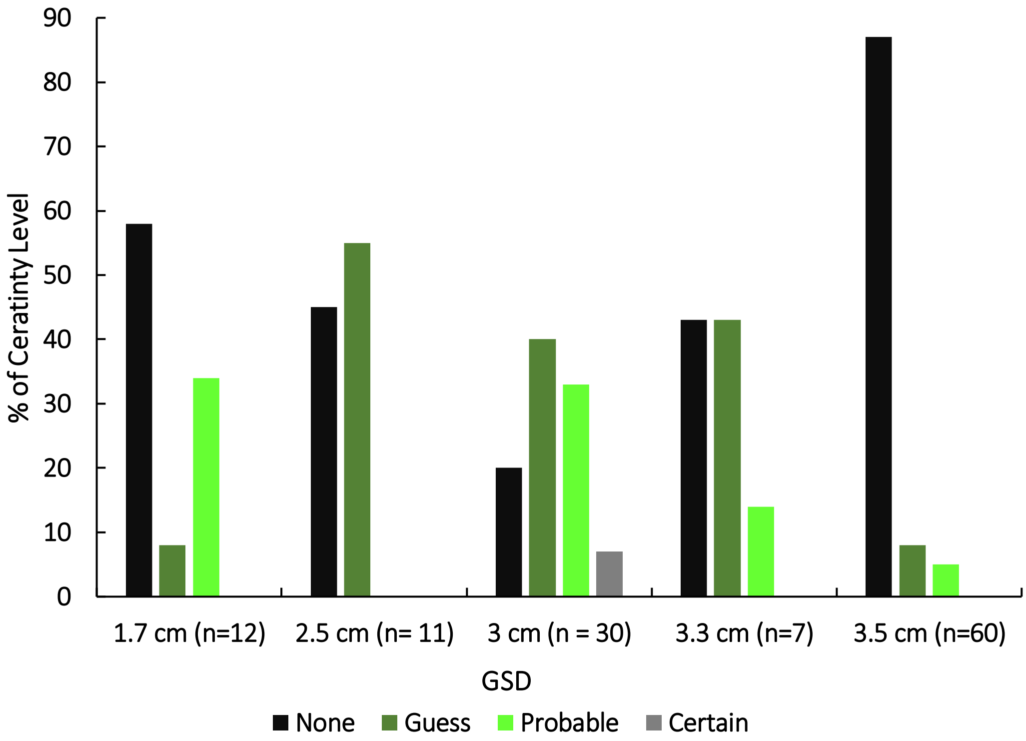

Figure 3.2. The percentage of mean certainty levels for turtle species identified at different ground sampling distances (GSD) from 120 images sent to turtle experts.

3.4.2 Effects of environmental conditions on species identification

i) Dolphins

The glare score of 0 produced the lowest number of certain dolphin identifications (0%) while the glare score of 3 had the highest number of certain identifications (15%) (Figure 3.3). Counterintuitively indicating that as glare increased, species identification certainty also increased ($X^2 = 19.37, P < 0.05, df = 9, n = 105$).

The visibility score of 4 had the highest number of certains (8%) and the second lowest number of no dolphin identifications (54%) (Figure 3.3). Note that a visibility score of 1 had no certain sightings but had a small sample size of 3 images, compared to the 31, 34 and 37 instances of visibility scores 2, 3 and 4 in the survey.

Because of the low sample sizes of some sea state categories, sea state categories were pooled to <=2 and >2. The overall trend seen for these two combined categories of <=2 and >2 was the same (Figure 3.3). The two categories had similar proportions of no identifications (51 and 54%) and the same proportion of certain identifications (6%) (Figure 3.3).

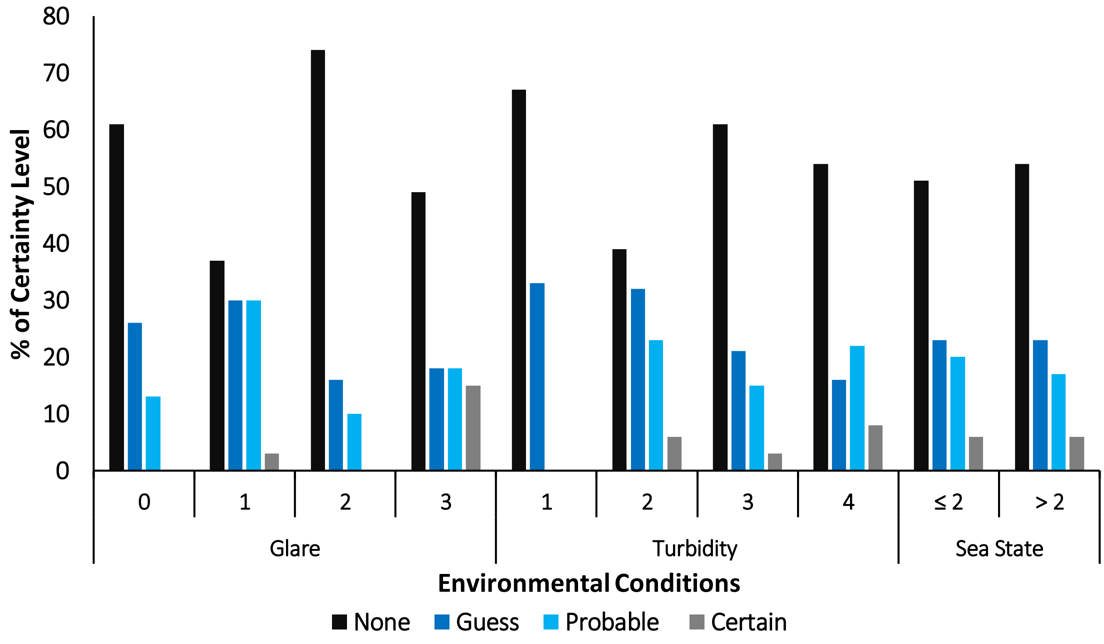

Figure 3.3. The percentage of mean certainty levels for dolphin species identifications under differing environmental conditions scored during the aerial survey.

ii) Turtles

As glare increased from a score of 0 to 3, probable turtle identifications remained the same (8%) while the proportion of no identifications declined from 88 to 54%) (Figure 3.4). There were no certain turtle identifications in any glare category.

For visibility the lowest proportion of no identifications (44%) were recorded in deep, clear water (visibility 3) as well as the highest proportion of probable identifications (18%) (Figure 3.4). The lowest proportion of probable identifications was recorded in visibility 2 (shallow opaque water) (4%). There were no certain identifications in any visibility category.

The sea state scores of 0, 4 and 5 had small sample sizes (n = 9, n = 1, n = 3 respectively), so results for turtles, like those for the dolphins, were pooled for sea states of <=2 and >2 (Figure 3.4). Unknowns decreased (from 82 to 50%) as sea state increased and while probable identifications remained the same (9%). Guesses increased from 9% to 41% from category <=2 to >2 (Figure 3.4). Therefore, there was a signifanct decline of unknowns and increase of guesses from <=2 to >2 ($X^2 = 12.61, P < 0.05, df = 3, n = 90$). Interesting to note that there were no certain identifications in this dataset because all the certain turtle identifications came from the GSD of 3 cm/pixel.

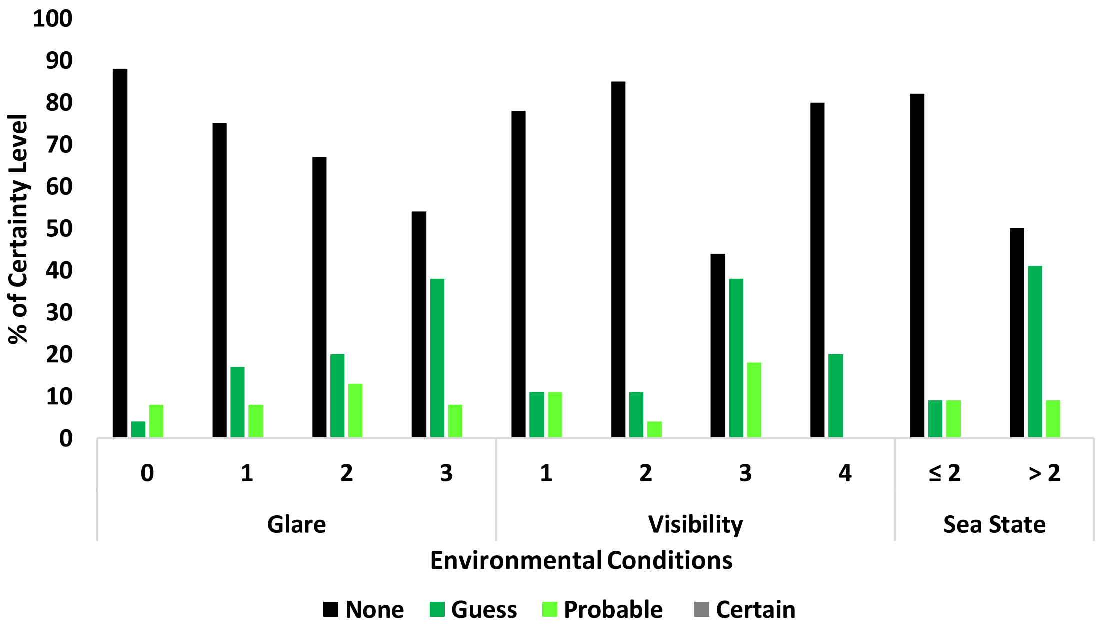

Figure 3.4. The percentage of mean certainty levels for turtles species identifications under differing environmental conditions scored during the aerial survey.

3.4.3 Agreement of species identification certainty among experts

There was little variation in certains from experts when all three identified the same species (when experts were certain in identifications all three had mentioned the same species). When two of the three experts had mentioned the same species more variation arose between guesses and probables. When the experts either could not identify the animal present in the image or all three experts identified a different species, variation in certainty was high (from unknowns to probables).

Chapter 4. Discussion:

In this study, data collected from synchronised flights of an occupied aircraft and a UAV during surveys designed to test the detection of dugongs, were used to test the detection of dolphins and turtles within Shark Bay, Western Australia. I also investigated the effect of the surrounding environmental conditions on the detection of both taxa. A human survey consisting of three turtle and three dolphin experts reviewed 120 images to determine the image ground sampling distance (GSD; four levels from 1.7 to 3.5 cm/pixel) needed to identify dolphin and turtles to species and the variation in identifying species with environmental conditions. Each of these findings is discussed in detail below.

4.1 Comparison of sighting rates

Large numbers of dolphins and turtles were detected from both occupied and unoccupied platforms during the aerial survey in Shark Bay. The results from the simultaneous surveys demonstrated that the UAV detected significantly more dolphins (~ twice as many) than the occupied survey, meaning that UAVs allowed for the detection of larger aggregations of individuals then the occupied survey (e.g., Figure 3.1). The number of turtles detected was similar for both platforms. A number of other studies have also found that the UAV platform produces a higher count of individuals for grey seals and seabirds than occupied surveying platforms (Johnston, 2019).

The higher detection rates in the UAV images is probably because during the image review process, the reviewer can scroll around the image, zoom in and out, and this extra search time makes finding individuals, that make up groups of taxa, much easier than collecting data during real time observation. In the image review process, often an animal was detected and then another next to it etc. making finding larger aggregations of individual dolphins possible.

The number of turtles detected in the two platforms was very similar and did not differ significantly, although it was slightly higher from the UAV images than the occupied team (368 compared to 312). However, there were two large aggregations of turtles observed from the UAV that were not detected from the occupied aircraft; one group of 94 and another of 50, while the occupied team spotted 3 and 4 respectively.

The 144 turtles missed from the occupied teams observation could be due to the fact that they could not differentiate between a turtle and possibly a reef bommie or other rounded formation. The blind zone of the aircraft (directly underneath the aircraft) could have also accounted for missing some of the large aggregations of turtles, but from the image review, these two large aggregations spanned over a wide range of ocean and would not have been entirely covered by the plane's blind zone during the whole flight path. It was clear in the UAV analysis that the 144 turtles detected were definitely turtles, so the occupied team definitely missed these individuals, however it is important to note that the removal of the two large aggregations of turtles from the UAV survey would mean that the occupied team spotted 312 turtles compared to 224 from the unoccupied.

The premise of being better able to detect larger groupings of animals by UAV than the occupied team is consistent for both dolphins and turtles. The size of a sea turtle is a lot smaller than a dolphin and their morphology (round with small flippers) may explain why the occupied observers were unable to spot as many aggregations as the UAV reviewers. The image review process also made it clear, in most instances, whether something was a turtle (noticeable head and flippers) or a rock or reef bommie.

4.2 Influence of environmental conditions on detection

4.2.1 Sea state

Sea state only affected dolphin detection within this study, not turtle detection. The number of dolphins detected in both the occupied and unoccupied platforms decreased per unit increase in sea state. Sea state is known to affect sighting rates in occupied aerial surveys for dugongs (Hodgson et al., 2013) but other previous marine megafauna drone surveys have suggested that sea state did not affect sighting rates of bottlenose dolphins, dugongs or humpback whales during their surveys (Fiori et al., 2017; Kelaher et al., 2020a). Sea state affects the detection for other marine species (e.g., dugong) as the motion and appearance of the waves and whitecaps draws the observers eye from possibly spotting an individual (Hodgson et al., 2013). Thus, still image review mitigates the issue of mobile white caps (Pollock et al., 2006), however, even in still image analysis, sea state can affect the detection of dolphins, as the water becomes rough and turbulent in the images.

So, the effect of sea state on dolphin detection within the UAV platform during my study, was contrary to expectations from other UAV studies using the same Beaufort Sea state scores. Dolphins may be affected by sea state because they occur in lower visibility (visibility 3 in deeper water) this deeper water may have more varying sea state conditions than shallower, high visibility locations. However, the number of turtles detected from the UAV images was not affected by sea state, which was consistent with other UAV studies (Fiori et al., 2017; Kelaher et al., 2020a).

4.2.2 Cloud cover

For dolphins, cloud cover also significantly affected detection, as the number of dolphins detected from both platforms decreased with every 1 octa increase in cloud cover. Cloud cover can be somewhat mitigated within the image review process as the brightness of the image can be changed, as well as the contrast (all images within this study were reviewed at 100% brightness). Cloud cover affects the amount of light penetrating the water column, which affects how deep one can see the animals. Previous drone surveys in fine weather and mild overcast conditions have concluded that cloud cover did not affect detectability of marine megafauna such as sharks, dolphins, rays and sea turtles (Kelaher et al., 2020b). It is possible that the detection of turtles was not affected by cloud cover because turtles usually come to the surface waters to bask, and in conditions where clouds are blocking UV, turtles remain deeper (Boyer, 1965).

4.2.3 Visibility

Detection of both dolphins and turtles in this study was affected by visibility for both platforms, but in different ways. For dolphins, sighting rate and detection increased in Visibility 3 compared to Visibility 1 and 2. These findings contrast with others in the literature: i.e. where visibility reduced the sightability threshold of dolphins and was negatively correlated with detection (Lin et al., 2021). However, dolphins probably occurred mostly in Visibility 3 because Visibility scores of 1 or 2 indicated quite shallow waters and were perhaps not their preferred habitat. Other studies have stated that the detection of dolphins may increase in turbid waters because their prey congregate in turbid zones to avoid visual predators (Moreno & Mathews, 2018).

Water clarity seemed to affect the sighting rate of turtles as the number of turtles observed in waters with higher visibility scores (i.e., less clear waters) declined compared to those in waters with lower visibility scores (i.e., clearer waters). The sighting rate of turtles decreased per unit increase in visibility, in both platforms (Table 3.3). This is a very common finding in the literature, as visibility accounts for detection into the water column (Samuel & Pollock, 1981). Many studies focussing on drone surveying found that low visibility affects the detectability and identification of marine megafauna negatively (; Pollock et al., 2006; Rowat et al., 2009; Kelaher et al., 2020a). The difficulty detecting megafauna in turbid waters is due to the fact that the sightability threshold is reduced, so under murky and opaque conditions the sightability in deeper water becomes shallower (Pollock et al., 2006).

Overall, there was no difference in the way the environmental conditions affected sighting rates from the two platforms. Therefore, both platforms showed the same effects, and thus UAVs and occupied surveys are comparable in their survey techniques.

4.3 Perception Bias

The perception probability calculated for both reviewers suggest that they saw 95% of the available dolphins and turtles for detection, meaning that of the dolphins (93) and turtles (312) detected by the occupied aircraft there would have been about 98 dolphins and 328 turtles available for detection.

The UAV dugong perception probability (assuming it would be the same for dolphins) on average was 89%, meaning that of the dolphins detected by UAV (174) they missed 11% of those available (193 dolphins). The perception probability for the main turtle reviewer, who had less training and experience then both the occupied observers and the UAV dugong observers, was 74%. Thus, of the turtles detected in the UAV, they missed 26% and the estimated number of turtles available was 464 turtles.

If the perception probability for UAV turtles was closer to the 89% of the UAV dolphin observers or 95% of the occupied team, there may have been a significant difference between the turtles detected in the two platforms (up to 328 turtles in the occupied observation compared to 464 detected in the UAV). The lower perception probability for the main turtle reviewer may also suggest that turtles are harder to find in the images (of which the GSDs were set for dugongs) compared to dugongs or dolphins.

4.4 Species identification and GSD

4.4.1 Dolphins

Three species of dolphin, i.e., bottlenose, humpback, and snubfin, were identified in 120 images from Shark Bay to the Northern Territory by three dolphin experts. These findings show that dolphin species can successfully be identified in UAV images. However, the unidentified dolphins made up 51% of the images.

If researchers were to accept both probable and certain identifications, experts were 75-100% sure of their identifications in 26% of the images, which was only just higher than the confidence for turtle identification (17%). The larger morphological features and the size of the dolphins compared to the turtles meant that even at the lowest GSD in the images tested, identification was more limited for the turtles. The main feedback from the experts was that when the dolphins occurred in pods (being mono-specific), identification was easier (multiple chances to capture morphological features) while a single dolphin made identification difficult. This may also be another explanation for the higher incidence of species identified for dolphins (behaviourally occurring in groups) compared to turtles which mainly appeared as a single animal in each image.

If accepting both probable and certain identifications, at 1.7 cm/pixel experts could confidently identify 34% of dolphins and at 3 cm/pixel they could identify 40%. This outcome of 40% species detection for dolphins is inadequate as researchers will not base a study on 40% identification rates. This means that for better dolphin species identification, either higher resolution cameras or the altitude needs to be lowered (<500 ft) to test GSD levels less than 1.7 cm/pixel.

The ability of the experts to identify dolphin species was affected by environmental conditions throughout the images. As glare increased from category 0 to 3, certainty in species identification of dolphins also increased. The reflection of light on the animals body within the image, created an "outline" of the dolphin. The sun reflectance made the identification of a fluke and pectoral fins very easy, helping to locate the animals during the image review process (Figure 4.1).

Figure 4.1 Dolphin identified by all three experts as *Tursiops aduncus* in a glare state of 3.

There was no real trend seen between dolphin species identification and changes in visibility states, however, all three experts commented that if the dolphins were not directly at the surface, depth made identification challenging. Sea state analysis indicated a slight decline in unknown identifications of dolphins in sea state of <=2 to >2, but nothing statistically significant.

4.4.2 Turtles

Three species of turtles, i.e., greens, loggerheads and flatbacks, were identified in the 120 images from Shark Bay to the Northern Territory reviewed by the three turtle experts. These findings show that the UAV imagery can be used to successfully identify turtles. However, the number of unidentified turtles was considerably higher (61%) than those that could be identified.

The certainty of turtle species identification was low, at all GSDs and environmental conditions, experts only able to provide species identifications (from guesses to certains) in 39% of the images. The expert feedback on turtle species identification from the UAV images ranged from seeing the turtles so clear that they could identify their gender (mainly males based on tail morphology) while in other instances they couldn’t distinguish whether the object was a turtle or a coral bommie. If we accept both probable and certain sightings, turtle species could only be identified in 17% of the images.

These findings clearly show that it is not possible to identify many turtles reliably at GSDs of 3.3-3.5 cm/pixel. If accepting the probable and certain identifications at 1.7 cm/pixel, only 34% of turtles were identified and at 3 cm/pixel 40% were confidently identified to species.

So similarly, to the dolphin species identification, the GSD values assessed need to be a lot lower then 1.7 cm/pixel (flown at lower altitude <500 ft and/or fitted with higher resolution cameras). Thus, with a species identification rate of approximately 40% ranging from a GSD of 1.7 to 3 cm, researchers have less than a one in two confidence in identifying species of turtles. My results are similar to that of another study that found no confidence in identifying turtles at GSDs from 2 to 4 cm/pixel (Sykora-Bodie et al., 2017).

To increase the chance of identifying species of turtles, UAVs could be flown at lower altitudes. The Ningaloo images provided reasonable certainty in species identification (40% probable and certain) with a GSD of 3 cm/pixel. However, it is important to note that the GSD may have been high (compared to 1.7 cm/pixel), but the images were all flown at the lowest altitude of 250 ft. As mentioned in Chapter 1 GSD is a combination of camera resolution, lens size and altitude. The lowest average height for UAV surveys of dugongs is 500 ft (Hodgson et al., 2013) therefore for better turtle species identification, flying at 200-400 ft may be more ideal. However, as camera resolution and lens size affects clarity, improving those two factors may also lower GSD for better species identification.

The identification of turtle species was also affected by environmental conditions throughout the images. As glare increased, the proportion of no turtle species identifications decreased, while certainty remained relatively the same. Although in some instances glare hinders detection and identification, some researchers have found that glare has a positive effect on the certainty of sightings (Aniceto et al., 2018). In my examination of the images for turtles, I found that under conditions with higher glare, the reflection of light from the turtle shell created a "bright outline" of the animal and can make the details of the head and flippers clearer.

Visibility had no clear influence on the certainty of turtle species identification. Overall, no clear pattern was seen in species identification certainty with visibility – it was 0%. Sea state saw a decrease in unknowns and increase in identifications in a sea state >2 compared to <=2. The effect of sea state was significant on turtle species identification, thus, unknowns significantly declined, and guesses increased with increasing sea state, this is contrary to my hypothesis. However, I would need a larger sample size to assess individual sea state categories on turtle species identification.

My results suggest that GSD levels of <1.7 cm/pixel is needed to be assessed to properly determine if lower GSDs are capable of better dolphin and turtle species identifications than just 40%. Assessing the impacts of the environmental covariates at a more suitable GSD for both species would create a clearer understanding of the influence of covariates on certainty of species identification.

4.5 Limitations

One major limitation to this study was the fact that the survey area/location used was done so to maximise the detection of dugongs. Areas with high seagrass densities were chosen as these are the foraging areas and are critical in the diet of dugongs (Anderson, 1998; Preen, 1995). Turtles are also herbivorous and relay on seagrass as a major dietary item (Garnett et al., 1985; Thomson et al., 2012; Heithaus et al., 2014). The selection of seagrass areas is thus likely to be appropriate for surveying turtles (Frazier, 1971). Also, the observers within the occupied aircraft would have mainly "trained" their eyes to focus on and pick up on dugong morphology (large wide body, flattened facial features, 3 m long) and the much smaller, rounded shape of a turtles (carapace length of 78 -112 cm) may easily have been missed.

Another limiting factor is the high altitude or GSD values used for species identification. For both the dolphin and turtle analysis, 3 cm/pixel provided the highest species identification rate but 40% is a poor indicator for success and not a good rate to base any type of study. Assessing GSD and environmental variables for dolphins and turtles needs to be assessed critically from <1.7 cm/pixel to provide better outcomes. This does come at a cost however, because aerial surveys are efficient at large spatial extents, lowering the GSD of the flight would increase the time needed to cover the same area.

Some of the experts who reviewed the still UAV images had also previously been observers in occupied aerial surveys. They stated that identifying species, particularly dolphins, was much easier during the real-time occupied flight than from still images because the observers were able to see the behaviours displayed and see the dolphins from multiple angles. Thus, UAV aerial surveys would probably benefit from video capture to enhance species identification (as this would capture similar motion of the animal as an occupied survey), followed by the examination of still images to count individuals. Some studies have already tested this by comparing three approaches for surveys; an occupied helicopter team, UAV video analysis and UAV still image analysis (Kelaher et al., 2020b). They found that all three approaches were able to detect turtles and dolphins reliably but identifying species was more difficult (Kelaher et al., 2020b). They suggested that the best method for identifying species was *post hoc* video analysis as fewer animals were missed due to the ability to replay the video (Kelaher et al., 2020b).

Turtle detection has the potential to be advanced by video analysis, using multirotor not fixed wing UAVs, the craft can follow individual and small aggregations of turtles, hovering at low altitudes (20-30 metres) (Bevan et al., 2015). This low hovering allows for detection of turtle species, following their behaviour in mating and copulation as well as even visualizing the dispersion of hatchlings from their nesting sites (Bevan et al., 2015). The multirotor, low flying, hover technique may indicate that turtle and dolphin UAV detection may need to be separate instead of surveyed simultaneously.

The final limitation of my study was that the sample size of 120 images was chosen to not impact the time and work hours of the experts who volunteered to review these images. Ideally, more images would have been made available for analysis, with more widely ranging environmental conditions and more images within the lower GSD categories.

Chapter 5. Conclusion and recommendations

5.1 Future implementations of UAV in megafauna surveys

The use of UAV technology in the future looks increasingly promising, as the technology improves as well as our understanding of how UAVs serve purpose in marine megafauna surveys. The past ten years alone has shown the benefits and reliable results that UAVs produce. UAVs are currently most frequently used in assessing the abundance and density of easily identifiable marine organisms, such as whales and dugong (Johnston, 2019), as my study has shown, it is highly difficult to identify others to species such as dolphins and turtles. Researchers can’t assess abundance without identifying the animals to species, hence the need to test what GSD is needed for species identification. UAVs are also able to fly in much smaller area than occupied flights, require fewer personnel, produce less visual and noise disturbance then aircraft and are safer (Kelaher et al., 2020b). One major future innovation of UAVs is the use of artificial intelligence to automate the detection of animals and reducing the time it takes to review the images captured, making UAVs an even more important tool for conservation and management (see 5.3 below).

5.2 Required changes to UAV regulations

The current rules and regulations surrounding drone and UAV flight make megafauna aerial surveys very difficult. By easing these restrictions, surveys and drone research in general will become a more straight-forward and simpler process. Some of the current UAV regulations imposed by CASA are discussed below, these restrictions can be addressed with the right permits and authorisation but makes organising the study site and surveying preparation a long, tedious task. Some restrictions include not being able to fly a drone out of visual line of sight, which means:

- Only flying during the day
- trying to avoid areas of limited visibility (e.g., cloud, fog, or smoke)
- the drone needs to be seen by the operators' own eyes
- not flying around obstacles that would restrict that visual line of sight

(CASA, 2021b).

Without proper permits and approvals drones cannot be flown above 120m (400ft) or within 5.5km of an airport (CASA requires a buffer distance to surrounding aerodromes) (CASA, 2021b). Using drones for work and research purposes, one must attain a remote pilot license (RePL) and operate for a business that holds a remotely piloted aircraft operators' certificate (ReOC) (CASA, 2021b). If CASA is able to ease these regulations under a research settings, or even make a simple application process for research applicants, researchers wanting to use drones and UAVs for surveying, detecting, and analysing will have a greater opportunity at doing so.

5.3 Automating detection

The future development of UAVs, especially for research on marine megafauna, will focus on automation of detection and rapid identification to provide detailed information for assessing population abundance and advice to management (Johnston, 2019). The image review process is very time consuming compared to real-time data collection, i.e., without automation this takes months and even years to produce estimates of numbers of individuals, depending on the number of images that need to be reviewed. Currently, the time taken to post-process the images form UAVs negates the time saved using them compared to traditional occupied aerial surveys (Cleguer et al., 2021).

Many researchers and programmers have been focussing on automating the detection process of fauna from UAV images, so this cost-prohibitive and time factor will be greatly reduced in the future. The use of neural networks has been tested for automating detections, specifically convolutional neural networks (CNN) which are *"deep learning computerisation, inspired by the brains neural networks to aid and teach the computer to discriminate and identify objects in complex conditions"* (Gray et al., 2019). Testing CNNs for marine megafauna surveys has been underway for several years and the results are promising, with one test detecting 8-9% more turtles compared to manual counts from images (Gray et al., 2019). This CNN approach is still in a "training" phase, as large datasets of images are needed to train the computer and to mitigate false positives i.e., recording the presence of an individual when none are present, picking up on glare, white caps, or breaking waves as fauna. The training of CNNs and mitigation of false positive are some of the biggest current issues facing the implementation of CNN for marine faunal surveys (Gray et al., 2019; Mejias et al., 2013).

Current research led by Dr Hodgson (Murdoch University) is examining the use of automated technology to detect marine megafauna from images using the program *Dugong Detector*. The images detected by myself and other reviewers are being used to train the software so that reviewers then only need to examine images where detections were identified, instead of reviewing the whole dataset, to mitigate false positives. Further improvements in CNN and automated detection software mean that the speed and accuracy of detection will be improved, possibly even permitting detection in real-time and identifying species with confidence (Gray et al., 2019).

5.4 Conclusion

From my study it is clear that UAV technology is capable of surveying both dolphins and turtles within a coastal environment as well as, if not better than traditional occupied flight surveys. The UAV payload and the image review process captured more dolphins and turtles in total than the occupied survey and detected significantly more dolphins (specially Indo-pacific bottlenose and Australian humpback dolphins) than the occupied flights. The image review process, which enabled still images to be captured and the time allowed to review images, meant that larger aggregations of both dolphins and turtles were detected in the unoccupied than occupied survey.

The three environmental variables that affected detection included cloud cover, visibility, and sea state. Cloud cover and sea state negatively affected sighting rates of dolphins from both UAVs and occupied surveys, while visibility affected dolphins and turtles in different ways. Dolphin detection was positively associated with the visibility state of 3 while turtle detection declined from visibility states of 1 to 4. The reasons behind why dolphins were more visible in visibility 3 could be based on their foraging behaviour in more turbid waters, as well as other behavioural mechanisms.

Increasing glare aided in the species identification of both dolphins and turtles. Species identification of dolphins and turtles improved up to visibility 2 and 3. Both the turtles and dolphins had better species identification and less unknown identifications in sea state score >2 compared to <=2 but due to occupied flights only being conducted in Beaufort Sea states of 3 or less, the >2 representation was poor for species identification comparison with <=2.

The GSD allowed species of dolphins and turtle to be detected at 3 cm/pixel with 40% confidence. A lower GSD will need to be investigated to provide evidence of better species identification at higher resolutions. Repeating the study but with high resolution video analysis instead of still image capture and increasing the sample size of images analysed within the species identification process would also be valuable.

The future of UAVs in marine megafauna surveying and research is very promising. Overcoming the limitations imposed on UAVs such as aviator regulatory bodies, platform endurance and payload capabilities will make UAVs a pivotal tool for future research, conservation, and management. Once automated detection algorithms are further developed and validated, the advances and uses of this technology will have global impacts on the study of wildlife species and conservation assessment and management.

Chapter 6. Bibliography

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*, *65*, 37-45.

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*(3), 913-925. https://doi.org/10.1111/mms.12403

Allen, S. J., Pollock, K. H., Bouchet, P. J., Kobryn, H. T., McElligott, D. B., Nicholson, K. E., Smith, J. N., & Loneragan, N. R. (2017). Preliminary estimates of the abundance and fidelity of dolphins associating with a demersal trawl fishery. *Scientific Reports*, *7*(1), 4995-4911. https://doi.org/10.1038/s41598-017-05189-0

Alves, M. D., Schwamborn, R., Borges, J. C., Marmontel, M., Costa, A. F., Schettini, C. A., & Araújo, M. E. (2013). Aerial survey of manatees, dolphins and sea turtles off northeastern Brazil: Correlations with coastal features and human activities. *Biological Conservation*, *161*, 91-100. https://doi.org/10.1016/j.biocon.2013.02.015

Anderson, D. R. (2001). The need to get the basics right in wildlife field studies. *Wildlife Society Bulletin*, *29*, 1294-1297.

Anderson, K., & Gaston, K. J. (2013). Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment*, *11*(3), 138-146. https://doi.org/10.1890/120150

Anderson, P. K. (1998). Shark bay dugongs (*Dugong dugon*) in summer. II: Foragers in a Halodule-dominated community. *Mammalia*, *63*, 409-425.

Aniceto, A. S., Biuw, M., Lindstrøm, U., Solbø, S. A., Broms, F., & Carroll, J. (2018). Monitoring marine mammals using unmanned aerial vehicles: quantifying detection certainty. *Ecosphere*, *9*(3), 1-15. https://doi.org/10.1002/ecs2.2122

Aragones, L., Jefferson, T., & Marsh, H. (1997). Marine mammal survey techniques applicable in developing countries. *Asian Marine Biology*, *14*, 15-39.

Barlow, J., Oliver, C. W., Jackson, T. D., & Taylor, B. (1988). Harbor porpoise, *Phocoena phocoena*, abundance estimation for california, oregon, and washington: II. aerial surveys. *Fishery Bulletin*, *86*(3), 433-444.

Bayliss, P. (1986). Factors affecting aerial surveys of marine aauna, and their relationship to a census of dugongs in the coastal waters of the northern-territory. *Wildlife Research*, *13*(1), 27-37. https://doi.org/10.1071/WR9860027

Bevan, E., Wibbels, T., Najera, B. M., Martinez, M. A., Martinez, L. A., Martinez, F. I., & Burchfield, P. M. (2015). Unmanned aerial vehicles (UAVs) for monitoring sea turtles in near-shore waters. *Marine Turtle Newsletter, 145*(1), 19-22.

Bevan, E., Wibbels, T., Navarro, E., Rosas, M., Najera, B., Sarti, L., Illescas, F., Montano, J., Pena, L., & Burchfield, P. (2016). Using umanned aerial vehicle (UAV) technology for locating, identifying, and monitoring courtship and mating behavior in the green turtle (*Chelonia mydas*). *Herpetological Review*, *47*, 27-32.

Boyd, C., Hobbs, R. C., Punt, A. E., Shelden, K. E. W., Sims, C. L., & Wade, P. R. (2019). Bayesian estimation of group sizes for a coastal cetacean using aerial survey data. *Marine Mammal Science, 35*(4), 1322-1346. https://doi.org/10.1111/mms.12592

Boyer, D. R. (1965). Ecology of the basking habit in turtles. *Ecology*, *46*(1/2), 99-118. https://doi.org/10.2307/1935262

Brack, I. V., Kindel, A., Oliveira, L. F. B., & Scales, K. (2018). Detection errors in wildlife abundance estimates from unmanned aerial systems (UAS) surveys: synthesis, solutions, and challenges. *Methods in Ecology and Evolution*, *9*(8), 1864-1873. https://doi.org/10.1111/2041-210X.13026

Broderick, A. C., Glen, F., Godley, B. J., & Hays, G. C. (2002). Estimating the number of green and loggerhead turtles nesting annually in the mediterranean. *Oryx*, *36*(3), 227-235. https://doi.org/10.1017/S0030605302000431

Broker, K. C. A., Hansen, R. G., Leonard, K. E., Koski, W. R., & Heide-Jorgensen, M. P. (2019). A comparison of image and observer based aerial surveys of narwhal. *Marine Mammal Science, 35*(4), 1253-1279. https://doi.org/10.1111/mms.12586

Buckland, S., Anderson, D., Burnham, K., Laake, J., Borchers, D., & Thomas, L. (2001). *Introduction to Distance Sampling: Estimating Abundance of Biological Populations.* (Vol. 15). Oxford University Press.

Buckland, S., Anderson, D., Burnham, K., Laake, J., Borchers, D., & Thomas, L. (2004). *Advanced Distance Sampling* (Vol. 89). Oxford University Press.

Budiyono, A. (2009). Advances in unmanned underwater vehicles technologies: modeling, control and guidance perspectives. *Indian Journal of Marine Sciences*, *38*, 282-295.

Bureau of Meteorology. (2021). *Climate statistics for Australian locations.* Commonwealth of Australia http://www.bom.gov.au/climate/averages/tables/cw_006105.shtml

Bushaw, J., Ringelman, K., & Rohwer, F. (2019). Applications of unmanned aerial vehicles to survey mesocarnivores. *Drones*, *3*(1), 28. https://doi.org/10.3390/drones3010028

Butterworth, A. (2017). *Marine mammal welfare: human induced change in the marine environment and its impacts on marine mammal welfare* (Vol. 17). Springer.

Cameron, M. F., Moreland, E. E., Walker, G., Hampton, D., & Bernard, M. (2009). *Ship-based unmanned aircraft system (UAS) surveys of the bering Sea pack ice from the NOAA Ship McArthur II: NOAA Cruise MC2-09-02, 13 May-11 June*. NOAA. https://repository.library.noaa.gov/view/noaa/12313

Carr, A. F., Carr, M. H., & Meylan, A. B. (1978). *The ecology and migrations of sea turtles. 7, the west caribbean green turtle colony.* (Vol. 162) Bulletin of the AMNH

Castelblanco-Martínez, D. N., Blanco-Parra, M. P., Charruau, P., Prezas, B., Zamora-Vilchis, I., & Niño-Torres, C. A. (2019). Detecting, counting and following the giants of the sea: a review of monitoring methods for aquatic megavertebrates in the Caribbean. *Wildlife Research*, *46*(7), 545-556.

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

Chaloupka, M., & Limpus, C. (2001). Trends in the abundance of sea turtles resident in southern Great Barrier Reef waters. *Biological Conservation*, *102*(3), 235-249. https://doi.org/https://doi.org/10.1016/S0006-3207(01)00106-9

Christiansen, F., Dujon, A. M., Sprogis, K. R., Arnould, J. P., & Bejder, L. (2016b). Noninvasive unmanned aerial vehicle provides estimates of the energetic cost of reproduction in humpback whales. *Ecosphere*, *7*(10), 1-18.

Christiansen, F., Rojano-Doñate, L., Madsen, P., & Bejder, L. (2016a). Noise levels of multi-rotor unmanned aerial vehicles with implications for potential underwater impacts on marine mammals. *Frontiers in Marine Science, 3*, 1-9. 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. (2019). Estimating body mass of free-living whales using aerial photogrammetry and 3D volumetrics. *Methods in Ecology and Evolution*, *10*(12), 2034-2044.

Civil Aviation Safety Authority. (2021b). *Drone rules.* Australian Government. https://www.casa.gov.au/knowyourdrone/drone-rules

Civil Aviation Safety Authority. (2021a). *Types of drones.* Australian Government. https://www.casa.gov.au/drones/drone-rules/drone-safety-rules/types-drones

Cleguer, C., Kelly, N., Tyne, J., Wieser, M., Peel, D., & Hodgson, A. (2021). A novel method for using small unoccupied aerial vehicles to survey wildlife species and model their density distribution. *Frontiers in Marine Science*, *8*, 1-17. https://doi.org/10.3389/fmars.2021.640338

Cohen, J. E., Jonsson, T., & Carpenter, S. R. (2003). Ecological community description using the food web, species abundance, and body size. *Proceedings of the National Academy of Sciences of the United States of America*, *100*(4), 1781-1786. https://doi.org/10.1073/pnas.232715699

Colefax, A. P., Butcher, P. A., & Kelaher, B. P. (2018). The potential for unmanned aerial vehicles (UAVs) to conduct marine fauna surveys in place of manned aircraft. *ICES Journal of Marine Science*, *75*(1), 1-8. https://doi.org/10.1093/icesjms/fsx100

Dénes, F., Silveira, L., & Beissinger, S. (2015). Estimating abundance of unmarked animal populations: accounting for imperfect detection and other sources of zero inflation. *Methods in Ecology and Evolution*, *6*, 543-556. https://doi.org/10.1111/2041-210X.12333

Dudgeon, C. L., Dunlop, R. A., & Noad, M. J. (2018). Modelling heterogeneity in detection probabilities in land and aerial abundance surveys in humpback whales (*Megaptera novaeangliae*). *Population Ecology*, *60*(4), 371-387. https://doi.org/10.1007/s10144-018-0631-8

Elarab, M., Ticlavilca, A., Torres-Rua, A., Maslova, I., & McKee, M. (2015). Estimating chlorophyll with thermal and broadband multispectral high resolution imagery from an unmanned aerial system using relevance vector machines for precision agriculture. *International Journal of Applied Earth*

Observation and Geoinformation, *43*, 32-42. https://doi.org/10.1016/j.jag.2015.03.017

Evans, P. G., & Hammond, P. S. (2004). Monitoring cetaceans in European waters. *Mammal Review*, *34*(1-2), 131-156. https://doi.org/10.1046/j.0305-1838.2003.00027.x

Felipe-García, B., Hernández-López, D., & Lerma, J. L. (2012). Analysis of the ground sample distance on large photogrammetric surveys. *Applied Geomatics*, *4*(4), 231-244. https://doi.org/10.1007/s12518-012-0084-2

Ferreira, S., & van Aarde, R. (2009). Aerial survey intensity as a determinant of estimates of african elephant population sizes and trends. *South African Journal of Wildlife Research*, *39*, 181-191. https://doi.org/10.3957/056.039.0205

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*(6), 1-13. https://doi.org/10.3390/rs9060543

Fiori, L., Martinez, E., Bader, M. K. F., Orams, M. B., & Bollard, B. (2020). 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*, *36*(1), 209-223. https://doi.org/10.1111/mms.12637

Fish, F. E. (2020). Advantages of aquatic animals as models for bio-inspired drones over present AUV technology. *Bioinspiration & Biomimetics*, *15*(2), 025001. https://doi.org/10.1088/1748-3190/ab5a34

Frazier, J. (1971). Observations on sea turtles at aldabra atoll. *Philosophical Transactions of the Royal Society of London. Biological Sciences*, *260*(836), 373-410.

Freitas, C., Caldeira, R., & Dellinger, T. (2019). Surface behavior of pelagic juvenile loggerhead sea turtles in the eastern north atlantic. *Journal of Experimental Marine Biology and Ecology*, *510*, 73-80. https://doi.org/10.1016/j.jembe.2018.10.006

Gales, N., McCauley, R. D., Lanyon, J., & Holley, D. (2004). Change in abundance of dugongs in shark bay, ningaloo and exmouth gulf, western australia: evidence for large-scale migration. *Wildlife Research*, *31*(3), 283-290.

Garnett, S. T., Price, I. R., & Scott, F. J. (1985). The diet of the green turtle, *Chelonia Mydas* (L.), in torres strait. *Wildlife Research*, *12*(1), 103-112.

Giacoma, C., Papale, E., & Azzolin, M. (2013). Are land based surveys a useful tool for managing marine species of coastal protected areas? *Diversity*, *5*(1), 15-25. https://doi.org/10.3390/d5010015

Glennie, R., Buckland, S. T., & Thomas, L. (2015). The effect of animal movement on line transect estimates of abundance. *PloS One*, *10*(3), 1-15. https://doi.org/10.1371/journal.pone.0121333

Godley, B. J., Barbosa, C., Bruford, M., Broderick, A. C., Catry, P., Coyne, M. S., Formia, A., Hays, G. C., & Witt, M. J. (2010). Unravelling migratory connectivity in marine turtles using multiple methods. *The Journal of Applied Ecology*, *47*(4), 769-778. https://doi.org/10.1111/j.1365-2664.2010.01817

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*(5), 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*(2), 100-108. https://doi.org/10.1139/juvs-2016-0029

Gray, P. C., Fleishman, A. B., Klein, D. J., McKown, M. W., Bézy, V. S., Lohmann, K. J., Johnston, D. W., & Gaggiotti, O. (2019). A convolutional neural network for detecting sea turtles in drone imagery. *Methods in Ecology and Evolution*, *10*(3), 345-355. https://doi.org/10.1111/2041-210X.13132

Grenzdörffer, G. (2008). Medium format digital cameras—a EuroSDR project. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *37*, 1043-1050.

Guimarães Paiva, E., Salgado-Kent, C., Gagnon, M. M., Parnum, I., & McCauley, R. (2015). An assessment of the effectiveness of high definition cameras as remote monitoring tools for dolphin ecology studies. *PloS One*, *10*(5), 1-21.

Hagihara, R., Jones, R. E., Sobtzick, S., Cleguer, C., Garrigue, C., & Marsh, H. (2018). Compensating for geographic variation in detection probability with water depth improves abundance estimates of coastal marine megafauna. *PloS One*, *13*(1), 1-15. https://doi.org/10.1371/journal.pone.0191476

Hamann, M., Godfrey, M. H., Seminoff, J. A., Barata, P. C. R., Bjorndal, K. A., Bolten, A. B., Broderick, A. C., Campbell, L. M., Carreras, C., Casale, P., Chaloupka, M., Chan, S. K., Coyne, M., Crowder, L. B., Diez, C. E., Dutton, P. H., Epperly, S. P., FitzSimmons, N. N., Formia, A., … & Godley, B. J. (2010). Global research priorities for sea turtles: informing management and conservation in the 21st century. *Endangered Species Research*, *11*(3), 245-269. https://doi.org/10.3354/esr00279

Hammond, P. S., Berggren, P., Benke, H., Borchers, D. L., Collet, A., Heide-Jorgensen, M. P., Heimlich, S., Hiby, A. R., Leopold, M. F., & Oien, N. (2002). Abundance of harbour porpoise and other cetaceans in the north sea and adjacent waters. *The Journal of Applied Ecology*, *39*(2), 361-376. https://doi.org/10.1046/j.1365-2664.2002.00713.

Hastie, G. D., Wilson, B., & Thompson, P. M. (2006). Diving deep in a foraging hotspot: acoustic insights into bottlenose dolphin dive depths and feeding behaviour. *Marine Biology*, *148*(5), 1181-1188. https://doi.org/10.1007/s00227-005-0143-x

Hastie, G. D., Wilson, B., Wilson, L. J., Parsons, K. M., & Thompson, P. M. (2004). Functional mechanisms underlying cetacean distribution patterns: hotspots for bottlenose dolphins are linked to foraging. *Marine Biology*, *144*(2), 397-403. https://doi.org/10.1007/s00227-003-1195-4

Hawkins, E. R., & Gartside, D. F. (2008). Social and behavioural characteristics of indo-pacific bottlenose dolphins (*Tursiops aduncus*) in northern new south wales, australia. *Australian Mammalogy*, *30*(2), 71-82. https://doi.org/https://doi.org/10.1071/AM08009

Heithaus, M. R., Alcoverro, T., Arthur, R., Burkholder, D. A., Coates, K. A., Christianen, M. J., & Fourqurean, J. W. (2014). Seagrasses in the age of sea turtle conservation and shark overfishing. *Frontiers in Marine Science*, *28*, 1-6.

Hochscheid, S. (2014). Why we mind sea turtles' underwater business: a review on the study of diving behavior. *Journal of Experimental Marine Biology and Ecology*, *450*, 118-136. https://doi.org/10.1016/j.jembe.2013.10.016

Hodgson, A., Kelly, N., & Peel, D. (2013). Unmanned aerial vehicles (UAVs) for surveying marine fauna: a dugong case study. *PloS One*, *8*(11), 1-15. 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*(4), 1253-1267. https://doi.org/10.1002/eap.1519

Holley, D. K., Lawler, I. R., & Gales, N. J. (2006). Summer survey of dugong distribution and abundance in Shark Bay reveals additional key habitat area. *Wildlife Research*, *33*(3), 243-250.

Höschle, C., Cubaynes, H. C., Clarke, P. J., Humphries, G., & Borowicz, A. (2021). The potential of satellite imagery for surveying whales. *Sensors*, *21*(3), 963. https://doi.org/10.3390/s21030963

Hundley, R., & Gritton, E. C. (1994). *Future Technology-Driven Revolutions in Military Operations: Results of a Workshop*. RAND Corporation.

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*(6240), 1255642. https://doi.org/10.1126/science.1255642

Hyun, C. U., Park, M., & Lee, W. Y. (2020). Remotely piloted aircraft system (RPAS)-based wildlife detection: a review and case studies in maritime antarctica. *Animals* , *10*(12), 1-17. https://doi.org/10.3390/ani10122387

Inoue, J., & Curry, J. (2004). Application of aerosondes to high-resolution observations of sea surface temperature over barrow canyon. *Geophysical Research Letters*, *31*, 1-4. https://doi.org/10.1029/2004GL020336

Israel, M. (2011). *A UAV-based ROE deer fawn detection system*. (Vol. 38) International Archives of Photogrammetry and Remote Sensing.

Johnston, D. W. (2019). Unoccupied aircraft systems in marine science and conservation. *Annual Review of Marine Science*, *11*(1), 439-463. https://doi.org/10.1146/annurev-marine-010318-095323

Jones, G. P., Pearlstine, L. G., & Percival, H. F. (2006). An assessment of small unmanned aerial vehicles for wildlife research. *Wildlife Society Bulletin*, *34*(3), 750-758. http://www.jstor.org/stable/3784704

Kasamatsu, F., & Joyce, G. G. (1995). Current status of odontocetes in the antarctic. *Antarctic Science*, *7*(4), 365-379. https://doi.org/10.1017/S0954102095000514

Kelaher, B. P., Colefax, A. P., Tagliafico, A., Bishop, M. J., Giles, A., & Butcher, P. A. (2020a). Assessing variation in assemblages of large marine fauna off ocean beaches using drones. *Marine and Freshwater Research*, *71*(1), 68. https://doi.org/10.1071/MF18375

Kelaher, B. P., Peddemors, V. M., Hoade, B., Colefax, A. P., & Butcher, P. A. (2020b). Comparison of sampling precision for nearshore marine wildlife using unmanned and manned aerial surveys. *Journal of Unmanned Vehicle Systems, 8*(1), 30-43. https://doi.org/10.1139/juvs-2018-0023

Kingsley, M. C., & Reeves, R. R. (1998). Aerial surveys of cetaceans in the gulf of st. lawrence in 1995 and 1996. *Canadian Journal of Zoology*, *76*(8), 1529-1550. https://doi.org/10.1139/z98-054

Kislik, C., Dronova, I., & Kelly, M. (2018). UAVs in support of algal bloom research: a review of current applications and future opportunities. *Drones, 2*(4), 35. https://doi.org/10.3390/drones2040035

Koh, L., & Wich, S. (2012). Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation. *Tropical Conservation Science*, *5*, 121-132. https://doi.org/10.1177/194008291200500202

Koski, W., Abgrall, P., & Yazvenko, S. (2011). An inventory and evaluation of unmanned aerial systems for offshore surveys of marine mammals. *Journal of Cetacean Research and Management*, *11*, 239-247.

Koski, W., Gamage, G., Davis, A., Mathews, T., Leblanc, B., & Ferguson, S. (2015). Evaluation of UAS for photographic re-identification of bowhead whales, *Balaena mysticetus*. *Journal of Unmanned Vehicle Systems*, *3*, 22-29. https://doi.org/10.1139/juvs-2014-0014

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*(3), 347-357. https://doi.org/10.1578/AM.35.3.2009.347

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*(11), 1-20. https://doi.org/10.1371/journal.pone.0187465

Laake, J., & Borchers, D. (2004). Methods for incomplete detection at distance zero. *Advanced Distance Sampling* (pp. 108-189). Oxford University Press

Lauriano, G., Panigada, S., Casale, P., Pierantonio, N., & Donovan, G. P. (2011). Aerial survey abundance estimates of the loggerhead sea turtle *Caretta caretta* in the pelagos sanctuary, northwestern mediterranean sea. *Marine Ecology. Progress series, 437*, 291-302. https://doi.org/10.3354/meps09261

Liebhold, G. (2002). Integrating the statistical analysis of spatial data in ecology. *Ecography*, *25*, 553–557. https://doi.org/10.1034/j.1600-0587.2002.250505.

Lin, M., Liu, M., Caruso, F., Rosso, M., Tang, X., Dong, L., Lin, W., Borroni, A., Bocconcelli, A., & Dai, L. (2021). A pioneering survey of deep-diving and off-shore cetaceans in the northern South China Sea. *Integrative Zoology*, *16*(4), 440-450.

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*(4), 239-252. https://doi.org/10.1111/mam.12046

Lindenmayer, D. B., Likens, G. E., Andersen, A., Bowman, D., Bull, C. M., Burns, E., Dickman, C. R., Hoffmann, A. A., Keith, D. A., Liddell, M. J., Lowe, A. J., Metcalfe, D. J., Phinn, S. R., Russell-Smith, J., Thurgate, N., & Wardle, G. M. (2012). Value of long-term ecological studies. *Austral Ecology*, *37*(7), 745-757. https://doi.org/10.1111/j.1442-9993.2011.02351.x

Lotze, H. K., Lenihan, H. S., Bourque, B. J., Bradbury, R. H., Cooke, R. G., Kay, M. C., Kidwell, S. M., Kirby, M. X., Peterson, C. H., & Jackson, J. B. C. (2006). Depletion, degradation, and recovery potential of estuaries and coastal seas. *Science (American Association for the Advancement of Science)*, *312*(5781), 1806-1809. https://doi.org/10.1126/science.1128035

Lubow, B., & Ransom, J. (2016). Practical bias correction in aerial surveys of large mammals: validation of hybrid double-observer with sightability method against known abundance of feral horse (*Equus caballus*) populations. *PloS One*, *11*, 1-15. https://doi.org/10.1371/journal.pone.0154902

Maire, F., Mejias, L., Hodgson, A., & Duclos, G. (2013). Detection of dugongs from unmanned aerial vehicles. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Tokyo, Japan, 2750–2756.

Mancini, F., Dubbini, M., Gattelli, M., Stecchi, F., Fabbri, S., & Giovanni, G. (2013). Using unmanned aerial vehicles (UAV) for high-resolution reconstruction of topography: the structure from motion approach on coastal environments. *Remote Sensing*, *5*, 6880-6898. https://doi.org/10.3390/rs5126880

Marsh, H., Lawler, I. R., Kwan, D., Delean, S., Pollock, K., & Alldredge, M. (2004). Aerial surveys and the potential biological removal technique indicate that the

Torres Strait dugong fishery is unsustainable. *Animal Conservation*, *7*(4), 435-443. https://doi.org/10.1017/S1367943004001635

Marsh, H., & Sinclair, D. F. (1989a). Correcting for visibility bias in strip transect aerial surveys of aquatic fauna. *The Journal of Wildlife Management*, *53*(4), 1017-1024. https://doi.org/10.2307/3809604

Marsh, H., & Sinclair, D. F. (1989b). An experimental evaluation of dugong and sea turtle aerial survey techniques. *Australian Wildlife Research*, *16*(6), 639-650.

McClintock, B. T., Moreland, E. E., London, J. M., Dahle, S. P., Brady, G. M., Richmond, E. L., Yano, K. M., & Boveng, P. L. (2015). Quantitative assessment of species identification in aerial transect surveys for ice-associated seals. *Marine Mammal Science, 31*(3), 1057-1076. https://doi.org/10.1111/mms.12206

Mejias, L., Duclos, G., Hodgson, A., & Maire, F. (2013). Automated marine mammal detection from aerial imagery. *Oceans*, 1-5. doi: 10.23919/OCEANS.2013.6741088.

Moreno, P., & Mathews, M. (2018). Identifying foraging hotspots of bottlenose dolphins in a highly dynamic system: a method to ehance conservation in estuaries. *Aquatic Mammals*, *44*(6), 694. https://doi.org/http://dx.doi.org/10.1578/AM.44.6.2018.694

Mount, R. (2005). Acquisition of through-water aerial survey images. *Photogrammetric Engineering & Remote Sensing*, *71*(12), 1407-1415. https://doi.org/10.14358/PERS.71.12.1407

Mulero-Pázmány, 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*(1), 1-10. https://doi.org/10.1371/journal.pone.0083873

Nicholson, K., Bejder, L., Allen, S. J., Krützen, M., & Pollock, K. H. (2012). Abundance, survival and temporary emigration of bottlenose dolphins (*Tursiops* sp.) off Useless Loop in the western gulf of Shark Bay, Western Australia. *Marine and Freshwater Research*, *63*(11), 1059-1068.

Nowacek, D. P., Christiansen, F., Bejder, L., Goldbogen, J. A., & Friedlaender, A. S. (2016). Studying cetacean behaviour: new technological approaches and conservation applications. *Animal Behaviour, 120*, 235-244. https://doi.org/https://doi.org/10.1016/j.anbehav.2016.07.019

Olson, E. L., Salomon, A. K., Wirsing, A. J., & Heithaus, M. R. (2012). Large-scale movement patterns of male loggerhead sea turtles (*Caretta caretta*) in shark bay, australia. *Marine and Freshwater Research*, *63*(11), 1-58. https://doi.org/10.1071/MF12030

Orbach, D. N., Eaton, J., Fiori, L., Piwetz, S., Weir, J. S., Würsig, M., & Würsig, B. (2020). Mating patterns of dusky dolphins (*Lagenorhynchus obscurus*) explored using an unmanned aerial vehicle. *Marine Mammal Science*, *36*(4), 1097-1110. https://doi.org/10.1111/mms.12695

Papale, E., Azzolin, M., & Giacoma, C. (2011). Vessel traffic affects bottlenose dolphin (*Tursiops truncatus*) behaviour in waters surrounding lampedusa island, south italy. *Journal of the Marine Biological Association of the UK, 92,* 1-9. https://doi.org/10.1017/S002531541100083X

Parra, G., & Corkeron, P. (2004). The indo-pacific humpback dolphin, *Sousa chinensis* (Osbeck, 1765), in australian waters: a summary of current knowledge. *Aquatic Mammals*, *30*, 1-10. https://doi.org/10.1578/AM.30.1.2004.197

Paxton, C., Hedley, S., & Bannister, J. (2011). Group IV humpback whales: their status from aerial and landbased surveys off western australia, 2005. *Journal of Cetacean Research and Management*, 223-234. https://doi.org/10.47536/jcrm.vi3.325

Pollock, K. H., Marsh, H. D., Lawler, I. R., & Alldredge, M. W. (2006). Estimating animal abundance in heterogeneous environments: an application to aerial surveys for dugongs. *The Journal of Wildlife Management*, *70*(1), 255-262. https://doi.org/10.2193/0022-541X(2006)70[255:EAAIHE]2.0.CO;2

Preen, A. (1995). Diet of dugongs: are they omnivores?. *Journal of Mammalogy, 76*(1), 163-171.

Preen, A. (2004). Distribution, abundance and conservation status of dugongs and dolphins in the southern and western arabian Gulf. *Biological Conservation*, *118*(2), 205-218. https://doi.org/https://doi.org/10.1016/j.biocon.2003.08.014

Preen, A. R., Marsh, H., Lawler, I. R., Prince, R. I. T., & Shepherd, R. (1997). Distribution and abundance of dugongs, turtles, dolphins and other megafauna in shark bay, ningaloo reef and exmouth gulf, western australia. *Wildlife Research*, *24*(2), 185-208. https://doi.org/10.1071/WR95078

Quang, P. X., & Becker, E. F. (1996). Line transect sampling under varying conditions with application to aerial surveys. *Ecology*, *77*(4), 1297-1302. https://doi.org/10.2307/2265601

Raoult, V., Colefax, A. P., Allan, B. M., Cagnazzi, D., Castelblanco-Martínez, N., Ierodiaconou, D., Johnston, D. W., Landeo-Yauri, S., Lyons, M., Pirotta, V., Schofield, G., & Butcher, P. A. (2020). Operational protocols for the use of drones in marine animal research. *Drones, 4*(64), 1-35. https://doi.org/10.3390/drones4040064

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., … & 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

Rowat, D., Gore, M., Meekan, M. G., Lawler, I. R., & Bradshaw, C. J. A. (2009). Aerial survey as a tool to estimate whale shark abundance trends. *Journal of Experimental Marine Biology and Ecology*, *368*(1), 1-8. https://doi.org/10.1016/j.jembe.2008.09.001

Samuel, M. D., & Pollock, K. H. (1981). Correction of visibility bias in aerial surveys where animals occur in groups. *The Journal of Wildlife Management*, *45*(4), 993-997.

Schofield, G., Katselidis, K. A., Lilley, M. K. S., Reina, R. D., & Hays, G. C. (2017b). Detecting elusive aspects of wildlife ecology using drones: New insights on the mating dynamics and operational sex ratios of sea turtles. *Functional Ecology*, *31*(12), 2310-2319. https://doi.org/https://doi.org/10.1111/1365-2435.12930

Schofield, G., Papafitsoros, K., Haughey, R., & Katselidis, K. (2017a). Aerial and underwater surveys reveal temporal variation in cleaning-station use by sea turtles at a temperate breeding area. *Marine Ecology*, *575*, 153-164. https://doi.org/10.3354/meps12193

Schweder, T., Øien, N., & Høst, G. (1991). Estimation of the detection probability for shipboard surveys of northeastern atlantic minke whales, based on a parallel ship experiment. *International Whaling Commisison*, *41*, 410-415.

Seminoff, J., Eguchi, T., J, C., Allen, C., D, P., R, R., Gilpatrick, J., Forney, K., & Peckham, S. H. (2014). Loggerhead sea turtle abundance at a foraging hotspot in the eastern Pacific Ocean: Implications for at-sea conservation. *Endangered Species Research*, *24*, 207-220. https://doi.org/10.3354/esr00601

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*(1), 1-10. https://doi.org/10.1038/srep45127

Shrestha, R., & Hardeberg, J. Y. (2013). Multispectral imaging using LED illumination and an RGB camera. *Color and Imaging Conference,* 8-13.

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 States. *Journal of Unmanned Vehicle Systems*, *4*(1), 31-44. https://doi.org/10.1139/juvs-2015-0017

Sykora-Bodie, S. T., Bezy, V., Johnston, D. W., Newton, E., & Lohmann, K. J. (2017). Quantifying nearshore sea turtle densities: applications of unmanned aerial systems for population assessments. *Scientific Reports*, *7*(1), 17690-17697. https://doi.org/10.1038/s41598-017-17719-x

Thapa, G. J., Thapa, K., Thapa, R., Jnawali, S. R., Wich, S. A., Poudyal, L. P., & Karki, S. (2018). Counting crocodiles from the sky: monitoring the critically endangered gharial (*Gavialis gangeticus*) population with an unmanned aerial vehicle (UAV). *Journal of Unmanned Vehicle Systems*, *6*(2), 71-82. https://doi.org/10.1139/juvs-2017-0026

Thomson, J., Cooper, A., Burkholder, D., Heithaus, M., & Dill, L. (2012). Heterogeneous patterns of availability for detection during visual surveys: spatiotemporal variation in sea turtle dive surfacing behaviour on a feeding ground. *Methods in Ecology and Evolution, 3,* 378-387.

Thomson, J. A., Cooper, A. B., Burkholder, D. A., Heithaus, M. R., & Dill, L. M. (2011). Heterogeneous patterns of availability for detection during visual surveys: spatiotemporal variation in sea turtle dive–surfacing behaviour on a feeding ground. *Methods in Ecology and Evolution*, *3*(2), 378-387. https://doi.org/10.1111/j.2041-210X.2011.00163.x

Thomson, J. A., Cooper, A. B., Burkholder, D. A., Heithaus, M. R., & Dill, L. M. (2013). Correcting for heterogeneous availability bias in surveys of long-diving marine turtles. *Biological Conservation*, *165*, 154-161. https://doi.org/10.1016/j.biocon.2013.06.005

Thomson, J. A., Heithaus, M. R., Burkholder, D. A., Vaudo, J. J., Wirsing, A. J., & Dill, L. M. (2012). Site specialists, diet generalists? isotopic variation, site fidelity, and foraging by loggerhead turtles in shark bay, western australia. *Marine Ecology Progress Series, 453*, 213-226.

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*, 1-14. https://doi.org/10.3389/fmars.2018.00319

Valavanis, K. (2007). *Advances in unmanned aerial vehicles: state of the art and the road to autonomy* (2007th). (33) Springer.

Walker, D., Kendrick, G., & McComb, A. (1988). The distribution of seagrass species in shark bay, western australia, with notes on their ecology. *Aquatic Botany, 30*(4), 305-317.

White, G. C., & Burnham, K. P. (1999). Program MARK: survival estimation from populations of marked animals. *Bird Study*, *46*, 120-139. https://doi.org/10.1080/00063659909477239

Whitehead, K., & Hugenholtz, C. (2014). Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: A review of progress and challenges. *Journal of Unmanned Vehicle Systems*, *2*, 69-85. https://doi.org/10.1139/juvs-2014-0006

World Meteorological Organization. (1970). *The Beaufort Scale of Wind Force:(technical and Operational Aspects)*. https://library.wmo.int/index.php?lvl=notice_display&id=5814#.YZBdDYZBy1s

Würsig, B., Lynn, S., Jefferson, T., & Mullin, K. (1998). Behavior of cetaceans in the northern Gulf of Mexico relative to survey ships and aircraft. *Aquatic Mammals*, *24*, 41-50.

Zhang, Y. (2013). Likelihood-based and bayesian methods for tweedie compound poisson linear mixed models. *Statistics and Computing*, *23*(6), 743-757.