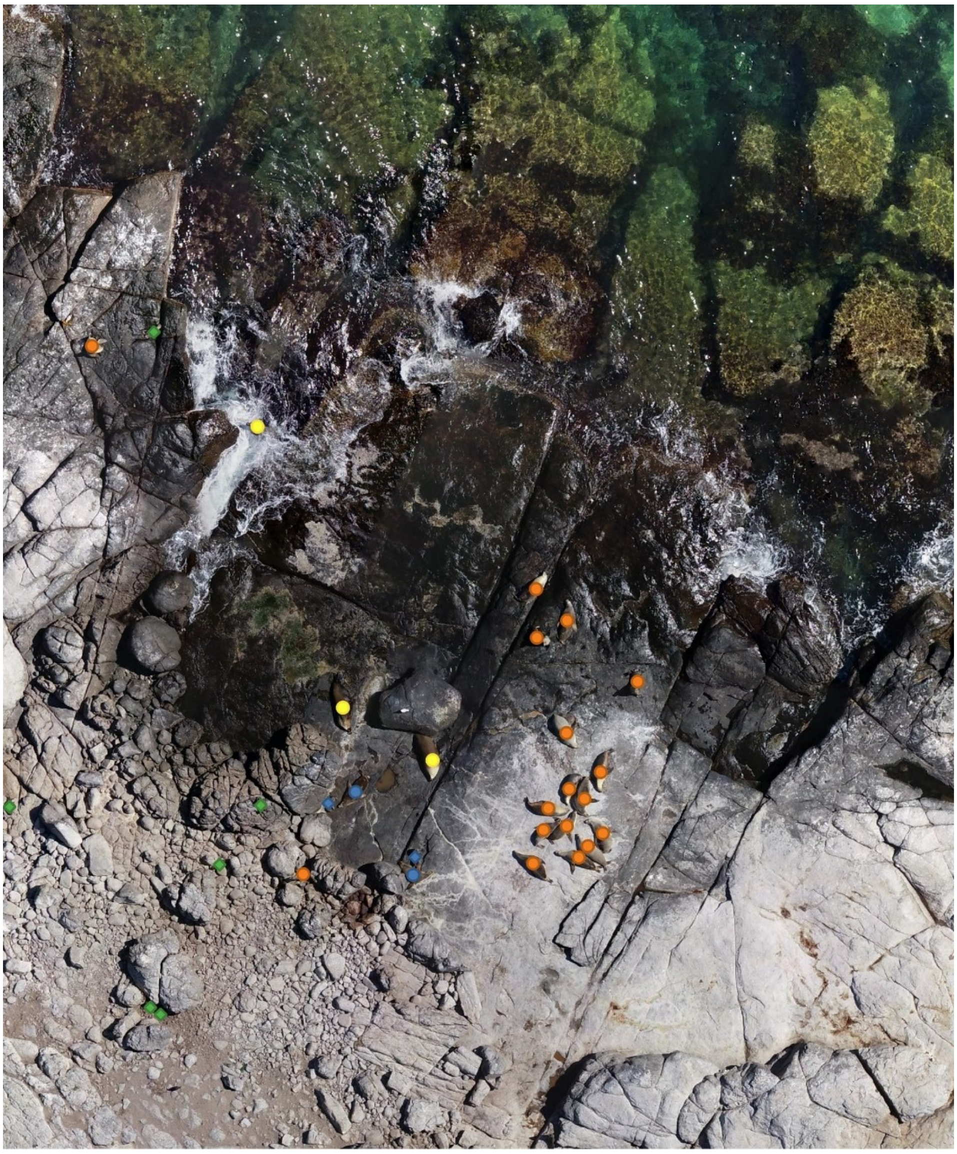

A pilot study assessing Australian sea lion *Neophoca cinerea* pup abundance at Dangerous Reef using ground and drone-facilitated counting approaches

A report prepared for the Department for Environment and Water

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1. Introduction

Monitoring the breeding activity of Australian sea lions (ASL; *Neophoca cinerea*) provides an estimate of the breeding effort and success of the species. These data can be used to estimate population status and trends, as well as to investigate the drivers of changes in ASL abundance (Goldsworthy et al. 2021). However, collecting breeding data of ASL presents a number of challenges. Variations in colony sizes, densities and timing of breeding as well as the accessibility of sites mean a suite of monitoring techniques that reduce survey error may be more effective than relying on one approach across all breeding sites. In combination, these techniques could provide increased statistical power to detect changes in population trends of this endangered pinniped.

Ground-based surveys are commonly used to estimate pinniped breeding effort and success. In the ASL context, standard ground counts of pups is the most universal method used to monitor pup production. Such surveys are conducted by a small team of observers who locate and tally all pups via a systematic search of a site. If undertaken at the end of the breeding season, ground counts can provide a good estimate of pup abundance in small- to medium-sized populations with a 4-5 month breeding season, where the maximum count of pups occurs at the very end of the breeding season (Goldsworthy et al. 2021). However, in the largest breeding colonies (>150 pups), the duration of the breeding season can last 6-9+ months, and it is usual for fully moulted pups to be present alongside newborn pups. In these breeding sites, the peak in pup numbers usually occurs well before the end of the breeding season, and multiple within season surveys may be needed in order to ensure a count occurs during this 'peak' window (Goldsworthy et al. 2021). For these larger breeding sites, multiple capture-mark-resight (CMR) surveys can improve estimates of pup production as they seek to account for availability and detectability biases, as well as pup survival, so that net-pup production between surveys can be estimated. However, these surveys require considerably more investment in time and effort as a sizeable proportion of pups in an isolated and distinct colony need to be temporarily marked and allowed to mix freely within the colony. Multiple, independent observations are then made of a haphazard sub-sample of pups to assess the abundance and ratio of marked to unmarked pups. Both these ground-based techniques are most effective with experienced field personnel and can pose risks to animals and researchers.

As many pinniped species aggregate to breed in relatively open habitats that are largely unobstructed from above (e.g. rocky islands, beaches), there has been an increasing interest in using remotely sensed data to complement ground-based surveys. Observations from traditional aircraft and using satellite and drone-derived imagery have yielded beneficial results. For example, high-resolution satellite imagery has been shown to provide abundance estimates of southern elephant seals (*Mirounga leonina*) that are comparable to concurrent ground counts (McMahon et al. 2014). While satellite imagery is extremely useful, it can lack the spatial resolution needed to monitor most small- to medium-sized pinniped species. It can also be compromised by local weather conditions such as cloud cover. Drone-derived imagery can overcome these limitations, which has resulted in many researchers adopting this technology to monitor pinnipeds in recent years. For example, research on grey seals (*Halichoerus grypus*) has demonstrated that drone-derived abundance estimates are comparable to traditional aircraft surveys (Johnston et al. 2017), automating the detection of the species in drone-acquired thermal imagery is possible (Seymour et al. 2017) and entangled individuals can be identified at known haul-outs (Martins et al. 2019). Similar research has shown the suitability of drones as a research and monitoring platform for a variety of other species including Stellar sea lions (*Eumetopias jubatus*) (Sweeney et al. 2016), Antarctic fur seals (*Arctocephalus gazella*) (Goebel et al. 2015), Australian fur seals (*A. pusillus doriferus*) (Allan et al. 2019; McIntosh et al. 2018; Sorrell et al. 2019), and New Zealand fur seals (*A. forsteri*) (Gooday et al. 2018). In combination, these studies demonstrate that remotely sensed imagery is very useful for monitoring marine mammals.

Australian sea lion researchers have capitalised on the utility of observing the coastal pinniped from above for some time. For example, helicopter-facilitated observations have: a) provided useful demographic insights of sites that can be overflown but where shore-based landings are problematic, b) yielded rapid insights into the breeding stage of colonies, as well as c) the opportunistic discovery of new breeding and haul-out sites across a large spatial extent. More recently, drones have been used to make opportunistic observations of breeding at a number of sites (e.g. Seal Bay, Nuyts Reef, Olive Island, Bunda Cliffs) and develop a non-invasive technique to assess body condition (Hodgson et al. 2020). Notably, drone-facilitated monitoring of ASL along the Bunda Cliffs has provided breeding data of sites that are essentially unavailable for ground survey. The promising results achieved across these diverse sites suggest that drone-facilitated monitoring of ASL could be viable and useful, particularly at large breeding sites.

The objective of this pilot study was to investigate the suitability of monitoring breeding activity of ASL using drone-acquired imagery at Dangerous Reef. The University of Adelaide in collaboration with the Department for Environment and Water, conducted approximately monthly surveys at Dangerous Reef (ex-Port Lincoln) during the 2018-19 breeding season. Drone-acquired imagery was collected on each survey, with ground counts completed when possible. Using the data collected at Dangerous Reef, this study sought to:

1. Investigate the best parameters for processing the digital photographs to create outputs that could be used for estimating abundance (e.g. orthomosaics, which are geo-referenced maps that are free of distortion)
2. Process all imagery using the best parameters
3. Develop a protocol for detecting and counting animals, concentrating on the pup cohort
4. Based on these findings, evaluate the utility of drone-facilitated monitoring of ASL relative to other methods and provide recommendation for next steps.

Dangerous Reef was considered an ideal location to develop a drone counting approach and compare the results with ground collected abundances given the large size and high density of the ASL colony. We hypothesised that pup detection probability using the drone-facilitated approach would be higher at Dangerous Reef compared to many other breeding sites, as the main island is relatively flat, almost devoid of vegetation and has less complex terrain than other colonies. Prior to this study, the suitability of using drone imagery to estimate pup abundance at Dangerous Reef was not known.

2. Methods

2.1 Study site

Fieldwork was completed at Dangerous Reef (-34.82ºS, 136.21ºE) which is part of the Sir Joseph Banks Group Conservation Park in the Spencer Gulf, South Australia. The main, rocky island of the reef was the focus of the study as it supports one of the largest breeding colonies of ASL (Goldsworthy et al. 2021). Researchers accessed the island by small boat opportunistically ex-Port Lincoln to monitor the 2018-19 breeding season. Public access to the island is prohibited.

2.2 Ground counting approach

Counts of pups were made on foot when weather conditions allowed safe landing on the main island. A small team which consisted of the same two personnel experienced in ASL population monitoring (JH, DH) conducted each survey and were assisted by one to three additional observers. Counts were completed using a standard technique employed across the ASL range (Goldsworthy et al. 2021). The team walked in a line and maintained as even a spacing as possible while navigating the rocky terrain and avoiding causing unnecessary ASL disturbance. A circuit adjacent to the perimeter was searched first, followed by one to two additional smaller concentric circuits. Care was taken to ensure all areas of the island, including in small caves and between boulders, were searched systematically to reduce the likelihood of missing pups, double counting or causing pups to move long distances. Observers used visual, acoustic (e.g. pups calling) and behavioural (e.g. mate-guarding) cues to aid detection of individuals. Handheld VHF radios were used to ensure clear communication was maintained between surveyors.

A scribe recorded all pups that were detected by the survey team. Each pup was assigned to a pelage category to provide an indication of the survey timing relative to the stage of the breeding season. The categories utilised in this study adopt those in Goldsworthy et al. (2021) except the ‘moulting’ class. The five pup age-classes were defined as:

1. Black mate-guarded – a young pup (~0-10 days) who is accompanied by their mother who herself is being mate-guarded by an adult male. These pups typically have poorly developed motor-skills and have a darker, sometimes almost black or grey, appearance.
2. Black – post mate-guarded pups (1-4 weeks). The mother may or may not be present.

3. Brown – noticeably older (~4-20 weeks), stronger and larger pups with a brown appearance. The mother may or may not be present.
4. Moulted – pups who have moulted (>20 weeks). These pups are highly mobile and capable of dispersing from their birth location (e.g. swimming to rock outcrops and nearby islands).
5. Dead – dead pups were recorded and semi-permanently marked (using biodegradable spray paint in attempt to make them visible in subsequent drone surveys) when possible.

2.3 Drone-facilitated counting approach

a. Drone flight protocol

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

For each survey, the same automated mission was flown to collect digital photographs at nadir. The missions were planned and subsequently executed using Maps Made Easy. The mission had an intended height of 40 m above surface level using 'terrain awareness'. This height was selected as a balance between sufficient ground sample distance (~9-10 mm/px) and mitigating any potential disturbance to wildlife. Front and side overlap were both set to 85%, with photographs (jpeg format, 5472 x 3648 px) captured using the 'at equal distance interval' mode which produced an intended flight speed of 4.0 m/s and a capture interval of approximately 2 seconds. The aircraft was launched from a stationary boat, anchored near the shore on the lee side of the island so that the pilot could maintain visual line of sight with the aircraft at all times. Drone-derived imagery was always captured prior to personnel landing on the island, and as close to solar noon (± 2 hours) as possible. One opportunistic survey was flown late in the day (~1700 hrs) and resulted in long shadows – these prevented consistent detection of individuals and so the survey was omitted from the dataset. Flights were in accordance with local regulations and permits, and flown by the same licensed pilots.

b. Data processing

Digital photographs were grouped by survey. Each group was visually reviewed and unsatisfactory images (e.g. overexposed photographs due to light reflecting on water) were omitted. Datasets were then batch processed using a python script in the photogrammetry pipeline software Agisoft Metashape Professional (version 1.5.2, Agisoft, LLC, St. Petersburg, Russia)(Appendix 1). After initial processing, a selection of the same, discrete natural features from each survey were labelled and used as ground control points (GCPs) for co-registration of survey products (e.g. to ensure each orthomosaic was in approximately the same position in 2-dimensional space; Figure 1, Appendix 2 and 3). Ground control could be automated if coded targets of known positions were placed in the study site (e.g. see Supplementary Information in Hodgson et al. (2020)), although this would likely require island access before each survey which could cause unwanted colony disturbance. Then, batch processing was resumed to generate a variety of products at medium to high quality (see Appendix A4 for processing parameters).

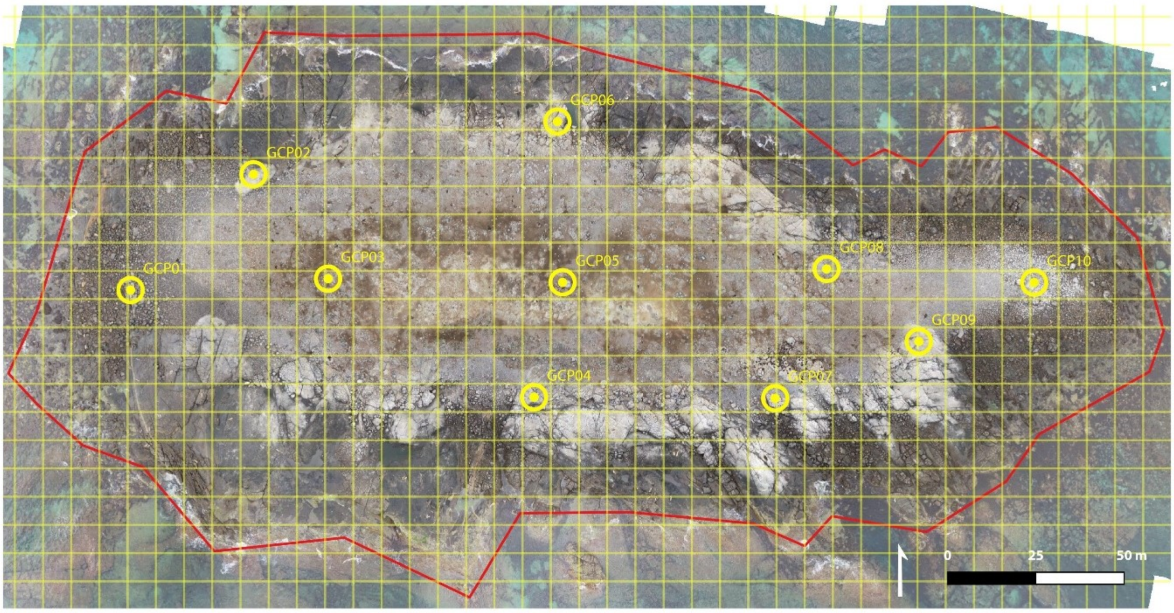

Figure 1. Processing drone-derived imagery and developing a standardised counting approach. Imagery was co-registered using discrete natural features for ground control points (yellow circles; Appendix 2 and 3). This was a key part of the processing as it ensured each survey's outputs (e.g. orthomosaics) were in the same spatial dimension. An 8 m square grid (yellow grid) was overlaid to aid counting all individuals within a standardised area of the main island (red polygon).

c. Digitising individuals

Orthomosaics (n = 8) were imported as raster layers into an open-source geographical information system application, QGIS (version 3.16.0, QGIS Development Team). After ensuring orthomosaics were free of processing artefacts, a protocol was developed to estimate the abundance of ASL for each survey.

To do this, an 8 m grid was overlaid on the orthomosaics (Figure 1) and individuals were manually detected and digitised using a point shapefile (one file per class, per survey). Points were located as close to the centre of the torso as possible, in line with the fore flippers. Two experienced observers independently annotated all surveys by moving cell-by-cell (left-to-right, top-to-bottom) across the island and zooming as needed to error check detections. When necessary, the annotator toggled between sequential surveys to differentiate ASL from other features (e.g. a rock) and to assist categorisation (e.g. dead versus live animals). The brightness tool was utilised to investigate areas of shadow as needed. The search area was standardised for each survey to approximately the extent of ground surveys, being all land and some areas of water (red polygon; Figure 1).

By categorising pups into age-classes, ground surveys are useful for quickly determining how progressed a colony is through a breeding season. This information can be used to infer if a count was completed before, during or after the optimum survey time (i.e. when pup abundance was at a maximum). It would be advantageous if a similar indication could be achieved with the drone-facilitated approach, especially if a drone-only survey was completed or if only part of the season was surveyed (this distinction between classes though valuable, is less important if surveys are conducted at regular intervals over the entire season). Accordingly, we trialled categorising pups into the same age-classes used for ground counts. While some individuals could be differentiated confidently into these classes, we found it to be subjective and considered it would be very problematic for inexperienced observers. We were also keen to establish classes that were non-subjective, thereby increasing the likelihood of accurate categorisation by non-experienced personnel (e.g. citizen scientists) or via an automated approach (e.g. machine learning) should this be desirable in the future. After a structured process of trial and error, we defined two key pup classes differentiated by the presence and proximity of the assumed mother. We also digitised and categorised all other animals into one of another five classes. The classes used in this study were (Figure 2):

1. Accompanied pup – a pup with an adult female (i.e. an ‘attendant female’) within 1.5 m, measured using the shortest horizontal distance between the two animals.
2. Unaccompanied pup – a pup with no adult female within a proximity of 1.5 m.
3. Attendant female – an adult female with a pup (i.e. an ‘accompanied pup’) or juvenile (i.e. an ‘accompanied juvenile’) within 1.5 m. If multiple adult females were present, the closest female to the pup was categorised as the attendant female.
4. Adult male – an individual that could be confidently considered an adult male (e.g. by a visible blonde ‘cap’, considerably larger with darker pelage than adult females).
5. Other – all other ASL individuals. This included juveniles not in the proximity of an attendant female, females not attending a pup or juvenile, sub-adult males and any other individual who could not be confidently categorised into another class.
6. Dead – dead animals of any age or sex.
7. Accompanied juvenile – juveniles within a 1.5 m proximity of an adult female (i.e. an ‘attendant female’).

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

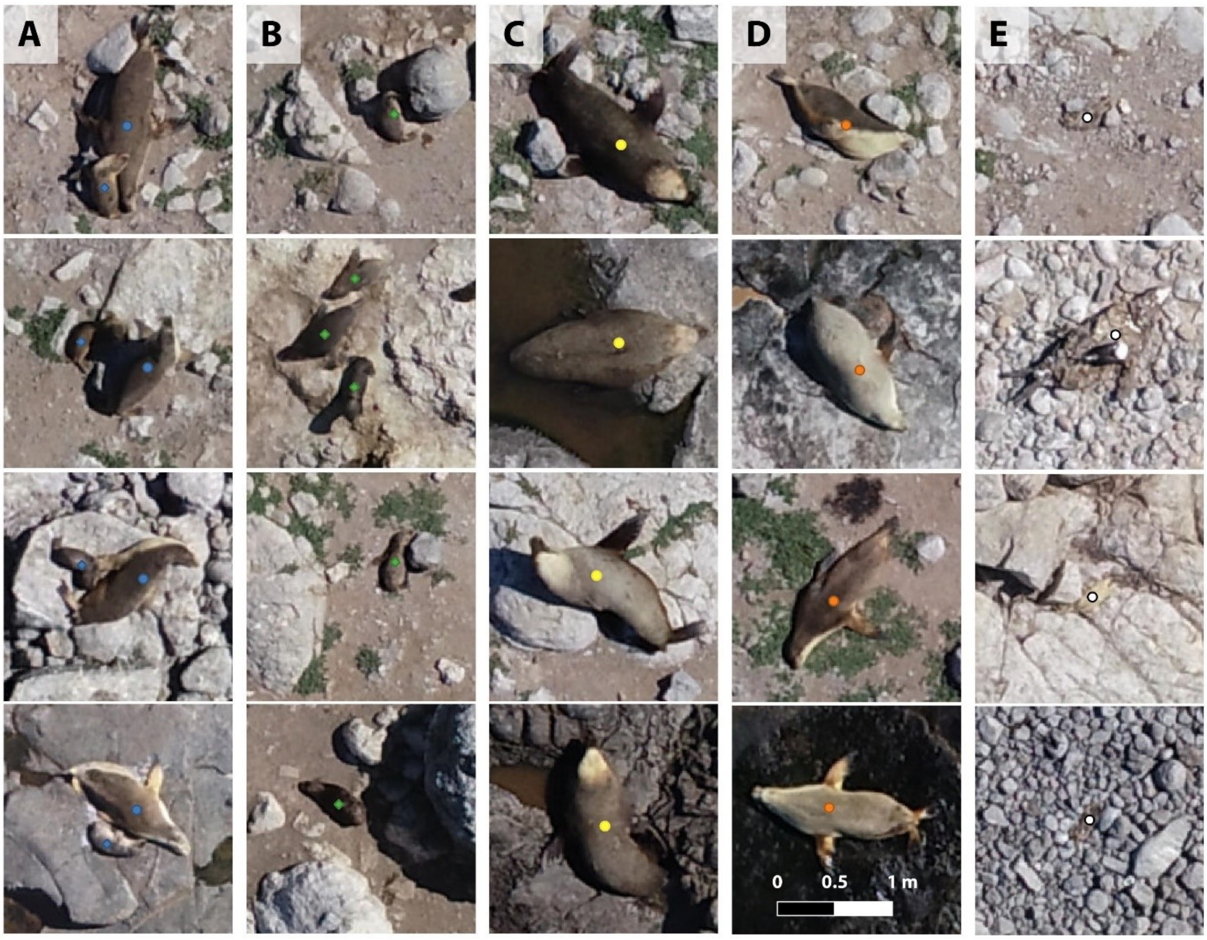

Figure 2. Examples of individuals from one survey (T05) categorised into six different classes. a) *Accompanied pups* and *attendant females*, b) *unaccompanied pups*, c) *adult males*, d) *other* and e) *dead*. All insets are at the same scale.

2.4 Analysis

We were interested in determining how a) ground counts of pups compare to those made using the drone counting approach and b) the similarity (precision) between counts of animals in orthomosaics by independent, experienced observers. Accordingly:

a. To compare count approaches, we calculated the percentage difference between the counting approaches' estimated total live pup abundance for each time point with concurrent surveys. We also calculated the percentage difference between the two maximum counts for each approach. For the ground surveys, pups from all age-classes were pooled to give an estimate of total live pups. For the drone surveys, the mean (rounded up to an integer) of the two independent counts per survey was taken to be the approaches' best estimate. The two observers' detections were not compared on an individual animal basis to maintain the independence of the detections (e.g. avoiding the subjectivity of comparing detections where one observer disagrees that the detection is accurate).

b. To assess the precision of independent counts made using the drone-facilitated counting approach for each time point, we calculated percentage differences between observers for counts of total animals, as well as the subset categories of *pups* and *non-pups*.

Counts of dead pups were omitted from analyses. The ground count of 'dead' pups was opportunistic and therefore was not suitable as a metric of cumulative dead. Similarly, due to the mobility and density of animals on the island, marked carcasses moved or disappeared throughout the drone surveys preventing a digital metric. The problematic nature of consistently categorising dependent juveniles meant they were also excluded from analyses.

3. Results

Dangerous Reef was surveyed approximately monthly between July 2018 and February 2019 (Table 1). Of the eight visits to the site, drone-derived imagery was collected on all visits, however, ground counts were only performed when environmental conditions allowed safe island access and when adequate personnel were available (n = 5; Table 1).

On average, drone surveys captured 413.6 ± 35.1 digital photographs per survey. Processing resulted in a mean of 380.4 ± 40.3 of these images being utilised (i.e. being 'cameras') in orthomosaics due to the area of water sampled during surveys. The ground sample distance averaged 1.03 ± 0.07 cm/px.

3.1 Estimated pup abundance

Ground counts estimated peak pup abundance in December 2018 (327 pups; Table 1). The concurrent drone survey estimated a similar number with a negligible percentage difference between the estimates (3.31%; Table 1). The drone-facilitated approach, however, observed the highest number of pups 61 days later in the final survey (T08). The absolute percentage difference between the two maximum counts was 12.88% (Table 1).

Table 1. Pup abundance at Dangerous Reef across the 2018-19 breeding season estimated from ground and drone-derived counting approaches.

Survey	Date	Ground count	Mean drone count[1] (min – max)	% diff. (G:D)
T01	2 July 2018	-	2 (2 – 2)	-
T02	16 August 2018	-	24 (23 – 24)	-
T03	20 September 2018	-	97 (95 – 99)	-
T04	10 October 2018	192	184 (179 – 189)	4.26
T05	16 November 2018	261	257 (247 – 266)	1.54
T06	21 December 2018	327	338 (335 – 341)	-3.31
T07	17 January 2019	263	344 (344 – 344)	-26.69
T08	20 February 2019	299	372 (371 – 373)	-21.76

[1] This is the mean of two independent counts of the drone imagery, rounded up to an integer.

Of the five time points with both ground and drone counts, the first three shared relatively similar pup abundance estimates (4.26, 1.54 and -3.31% difference; Table 1). On the next two surveys, however, the approaches had dissimilar abundance estimates with the drone approach estimating 81 and 73 more pups respectively (Table 1).

3.2 Pup classes for each counting approach

The ground surveys demonstrate the progression of the breeding season at Dangerous Reef (Figure 1a). The first ground survey (T04) observed predominantly black pups, with similar numbers each of black mate-guarded and brown pups. The third ground survey (T06) recorded mainly brown pups with fewer recent births than previous surveys. Moulted pups were in the largest proportion in the final survey (T08).

The drone approach also provided an insight into the progression of the breeding season (Figure 1b). Estimated pup abundance increased steadily over the first six surveys, before plateauing in the final three surveys. Accompanied pups were more common in the first four surveys (between 50 – 77.3 % of observed pups), while unaccompanied pups were in higher numbers for the last four surveys (between 57.3 – 62.9 % of observed pups).

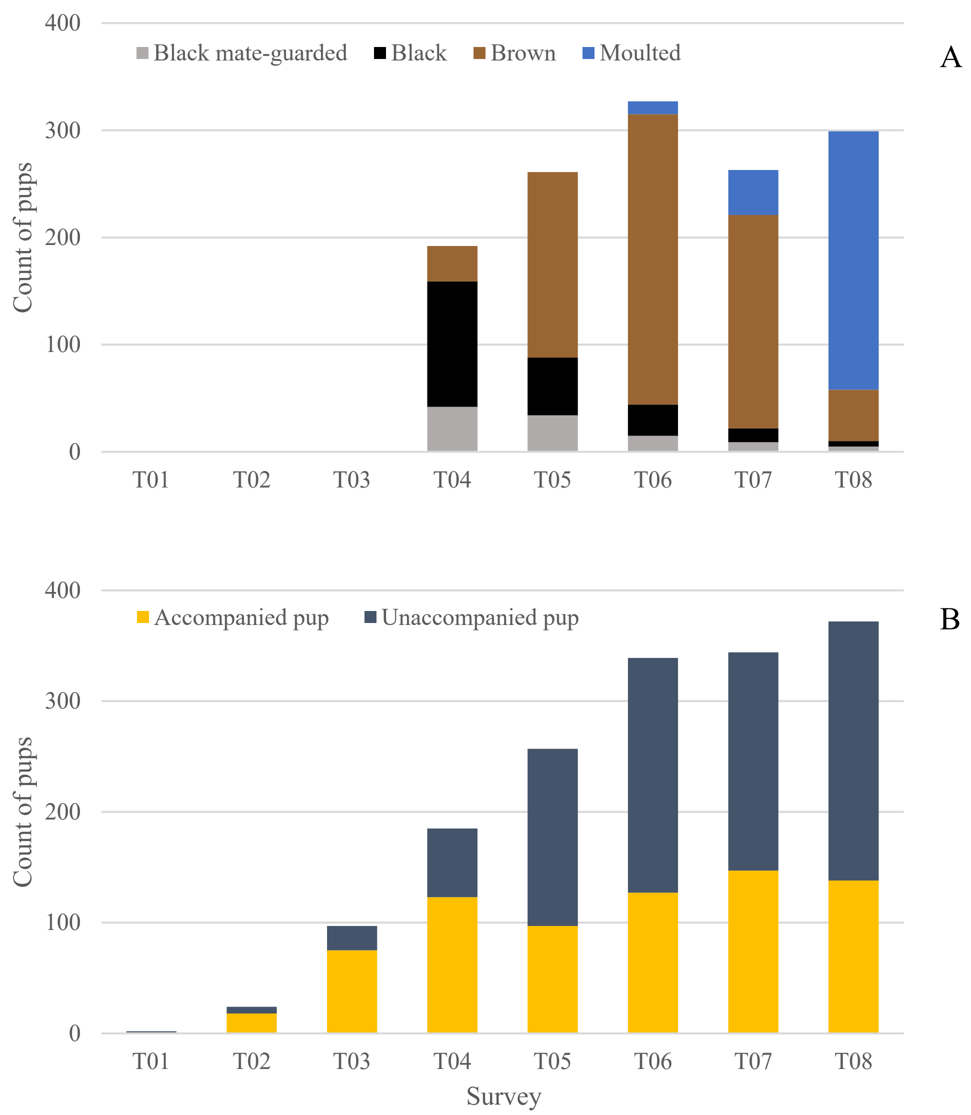

Figure 1. Pup abundance at Dangerous Reef across the 2018-19 breeding season estimated from a) ground and b) drone-derived counting approaches.

3.3 Drone-derived colony demographics

While ground counts were constrained to pups, the drone approach estimated the number of animals in several other age and sex classes (Figure 2). Pups increased in proportion each survey, starting at 3% and progressing to 53.4% of all animals by T08 (Figure 2b).

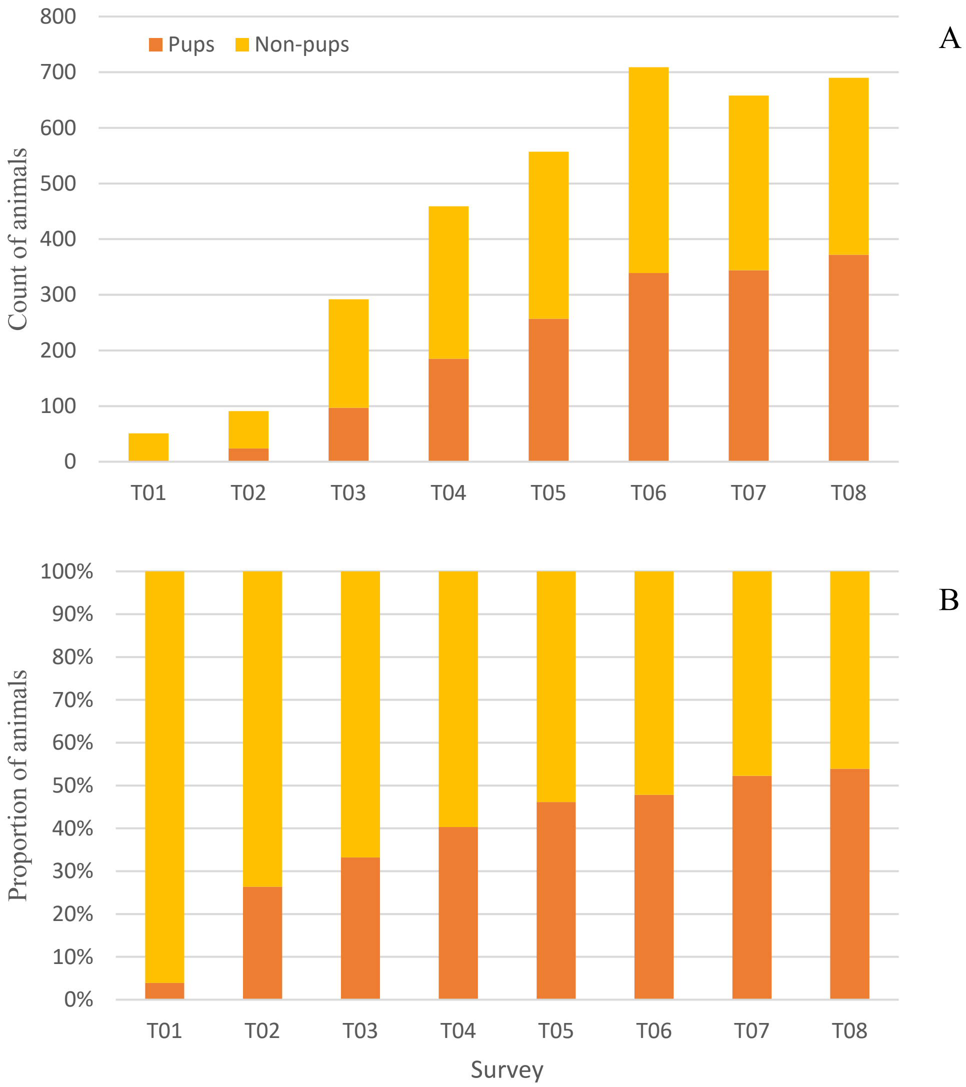

Figure 2. Drone-derived estimates of pup and non-pup abundance at Dangerous Reef across the 2018-19 breeding season. Data are presented as a) counts and b) proportions. 'Pups' includes the classes of *accompanied pup* and *unaccompanied pup*, while 'non-pups' includes *attendant female*, *adult male* and *other*.

3.4 Precision of independent drone-derived counts

Independent estimates of ASL abundances in drone imagery were relatively precise (Table 2). Pup abundance estimates were slightly more variable than non-pup estimates (mean percentage difference: 2.94 vs 1.79%; Table 2).

Table 2. Absolute percentage difference between the estimates of abundance made by two independent observers. 'Pups' includes the classes of *accompanied pup* and *unaccompanied pup*, while 'non-pups' includes *attendant female*, *adult male* and *other*.

Survey	Pups	Non-pups	Total animals
T01	0.00	6.19	5.41
T02	4.26	1.50	0.00
T03	4.12	0.00	2.05
T04	5.43	0.00	2.40
T05	7.41	1.67	4.45
T06	1.78	0.54	2.25
T07	0.00	0.64	0.45
T08	0.54	3.79	0.72
Mean	2.94	1.79	2.22

4. Discussion

4.1 Estimated pup abundance

The negligible percentage difference between the maximum ground count (T06) and the comparable drone estimate suggests there is a level of similarity between the approaches at this point in the breeding season. Interestingly, although our dataset is constrained to just five time points with concurrent surveys, the relationship between the estimates is not linear over time or consistently biased. Early in the breeding season, drone counts were marginally below ground counts (T04 and T05). For the subsequent three time points, drone counts increasingly exceeded ground estimates. This is likely attributable to differences in the detection probability of pups for each technique, and the variation in this probability over time for each technique. We expected ground counts to have a higher rate of detection than drone counts early in the season. This is because black mate-guarded and black pups are more likely to be obscured from above (e.g. by their mother, stashed under a rock ledge), making them unavailable for drone detection but still able to be detected by ground counters. After a certain age, it is likely that the probability of detection of pups decreases for ground counts, principally resulting from their increased mobility. This can make ground counting difficult, especially if pups are disturbed and enter the water, move into areas already surveyed or cause animals well ahead of the search team to move. For drone counts, detection probability at this point in the season is likely to be greater as pups are less obscured (e.g. reduced 'hiding' behaviour), larger and at times have a greater contrast to the background. At this point in the breeding season, drone counts are also at an advantage as the technique itself is not known to initiate behavioural responses meaning that considerably more pups are resting in the open when captured in photographs.

The accuracy of ASL pup abundance estimates is dependent on survey timing (Goldsworthy et al. 2021). Surveys conducted too early in the season typically return underestimates as a considerable number of pups are born after the survey. Experience also indicates that surveys completed too late in the season are confounded by the increased mobility of pups who are harder to detect (e.g. more aquatic) or are not available for observation (e.g. have dispersed to nearby islands). However, ground counts remain ideal for small to medium colonies, which accounts for the majority of breeding sites. But for those few sites with large numbers of pups (i.e. >100 pups, n = 4), the optimum window is relatively small, it varies between colonies and can be hard to predict for colonies that are infrequently visited. It is likely that drone-facilitated monitoring is most useful for improving estimates of pup production at these sites.

In this study, the changes in the proportions of pups in each age-class over the five surveys demonstrates that ground sampling was well timed. This provides the opportunity to contrast the level of susceptibility of drone surveys to timing in the breeding season. The maximum ground count was observed in December 2018 (T06) at which time the drone survey estimate was just 11 pups more (3.3% difference). In the next and final two time points, ground counts were less than this maximum, however, drone counts continued to increase. Interestingly, drone-derived counts in the final three surveys were relatively consistent, increasing by 34 pups. This may suggest the drone-facilitated approach has a longer window during which reliable abundance estimates can be collected – a considerable advantage on a practical level, especially for sites that cannot be visited regularly throughout the breeding season. While timing ground counts at some sites is relatively easy (e.g. at Dangerous Reef through reports of animals returning to the colony), timing just one or two visits within the optimum survey window is difficult for the vast majority of colonies.

4.2 Drone-facilitated monitoring

Overall, the drone-facilitated approach developed in this study was highly successful. High-quality imagery was captured for all time points and at sufficient ground sample distance for confident detections of individuals across the ASL size range. The co-registration process produced orthomosaics that were highly correlated spatially, allowing observers to toggle between time points to clarify detections (e.g. confirm if a potential pup was a rock). This was an excellent result given ground control was limited to natural features.

This study presents a number of other benefits and limitations of the drone-facilitated counting approach, including:

- Drone surveys can be completed without landing on islands/entering an ASL colony – this reduces potential disturbance to ASL, reduces the number of personnel required and mitigates in-colony risks.
- Drone-only surveys can be collected by personnel with less ASL experience
- Imagery and data (e.g. detections of animals) are reviewable – this is particularly useful for reanalysing data, investigating questions retrospectively, obtaining expert review of imagery post survey and at a convenient time etc.

- Drone survey success will vary across sites due to changes in the detection probability of ASL – for example, at sites with complex habitat (e.g. caves, boulders, thick vegetation) it is likely that the approach will detect a lower proportion of animals. Similarly, for colonies with very few animals, the effect of low detection probability could have a considerable negative influence on the abundance estimate. While it may be possible to calibrate for detection probability on site level, this would likely require a considerable number of concurrent counts per site.
- Ground counts allow on island observations which cannot be achieved with a drone (e.g. detecting young pups that are stashed via their calls; these are unavailable for drone detection)
- Drone surveys may still be possible from a vessel nearby the island even when ocean conditions prevent boat-facilitated landing (N.B. access to ASL sites via helicopter overcomes the difficulties of boat-facilitated island landings).
- Presently, drone counts take longer to complete – there is a potential for machine learning or citizen science to reduce this investment, although this would likely need experienced personnel input to establish the protocol and error-check detections.

Automating drone-facilitated monitoring is key to unlocking the technique's full potential and implementation on a larger scale. Data collection is already achievable with minimal user-input thanks to stable and advanced flight programming software and, regulations permitting, this step could be fully automated (e.g. a remotely deployed drone that docks at a base to recharge from a self-sustaining power source and upload data). Similarly, image processing can be completed without user input (e.g. to create products of interest such as geo-referenced orthomosaics). However, the automatic and accurate extraction of required data, such as the detection and counting of pups, is a challenge yet to be fully resolved (Hollings et al. 2018). An array of studies have reported semi-automated approaches using 'off-the-shelf' object-based image analysis and supervised classifications (Afán et al. 2018; Chabot et al. 2018) through to more advanced machine learning approaches with promising results (Francis et al. 2020; Gray et al. 2019; Kellenberger et al. 2018; Lyons et al. 2019). Dujon and Schofield (2019) reviewed manuscripts in ecology that used drones (n = 213), reporting that 42% used machine learning to assess the visual data. They concluded that while drone use has recently rapidly increased in ecology studies, with 93% of the manuscripts that were reviewed being published between 2012 and 2018, the uptake of machine learning to process imagery has been slower. Fully harnessing artificial intelligence, including machine learning (Lamba et al. 2019), will be key to overcoming manual processing and thereby creating a truly powerful tool for ASL monitoring and ecological science more broadly.

4.3 Recommendations

1. Future surveys of Dangerous Reef should complete both survey approaches whenever possible. This will provide a more extensive dataset to analyse the relationship between the count approaches at this site. This calibration is essential so that data continuity between the approaches can be ensured (see Hodgson et al. (2016) for an indication of the number of duplicate counts of colonial birds needed to achieve a given margin of error between counting approaches). The collection of drone imagery typically adds 60-90 minutes at the site, and processing and analyses can be completed later if resources are limited.
2. Ground counting approach
    a. Due to the size and complexity of the Dangerous Reef colony especially at peak-breeding, it is recommended that a minimum of two people complete ground counts including at least one experienced observer. Ideally, the survey team would consist of three to four capable observers.
3. Drone counting approach:
    a. Consider redefining the 'dependent juvenile' age-class. This class was included primarily to differentiate nursing juveniles present in the first few surveys and in the event that naïve observers were completing counts (i.e. to reduce the likelihood of nursing juveniles from the preceding breeding season being classified as 'accompanied pups'). However, we noticed that the accompanied juvenile class can be problematic in late season surveys as there were instances of animals that could be arguably considered an 'accompanied pup', 'accompanied juvenile' or 'other'.
    b. Developing a semi- or automated counting technique would improve the efficiency of this technique. Machine learning may provide a solution and/or a citizen science approach may be beneficial.
    c. Investigate if other classes of animals provide an indication of breeding timing, or correlate with pup abundance or similar. A larger dataset would be useful for these types of investigations.

4. Trialling drone surveys at other suitable ASL colonies (e.g. The Pages – which can also be accessed via boat with boat launched drones) and near-shore/coastal colonies where drones can be launch from the mainland (e.g. Nicolas Baudin Island, Point Labatt). Larger colonies should be prioritised.

5. Acknowledgements

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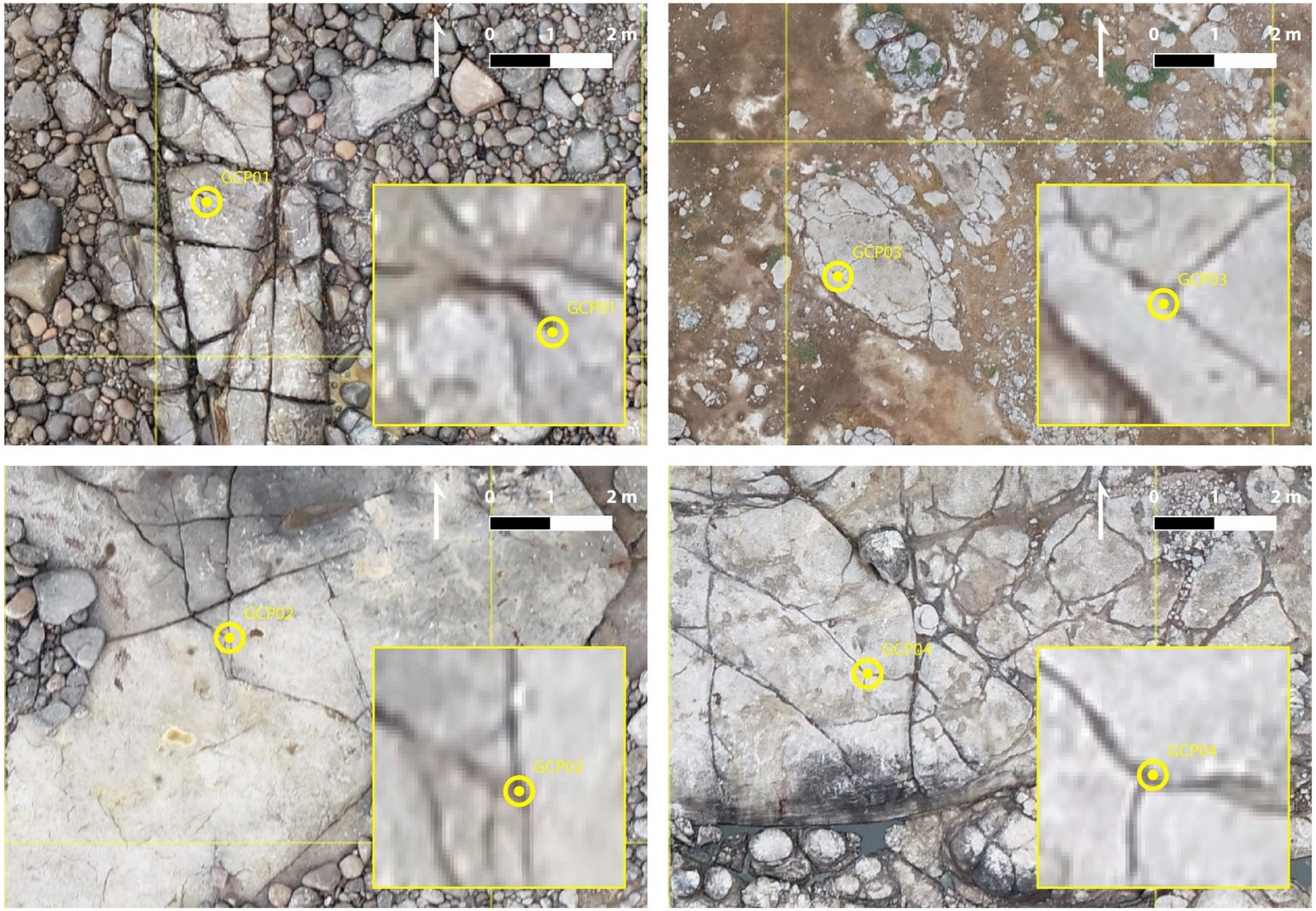
Appendix 1. Agisoft Metashape processing script

```
import os
import Metashape

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

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

paths = os.listdir(main_path)

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

print(lstpaths)

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

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

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

def process(input_path):

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

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

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

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

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

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

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

   #LOAD IMAGES

   print("Script started")

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

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

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

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

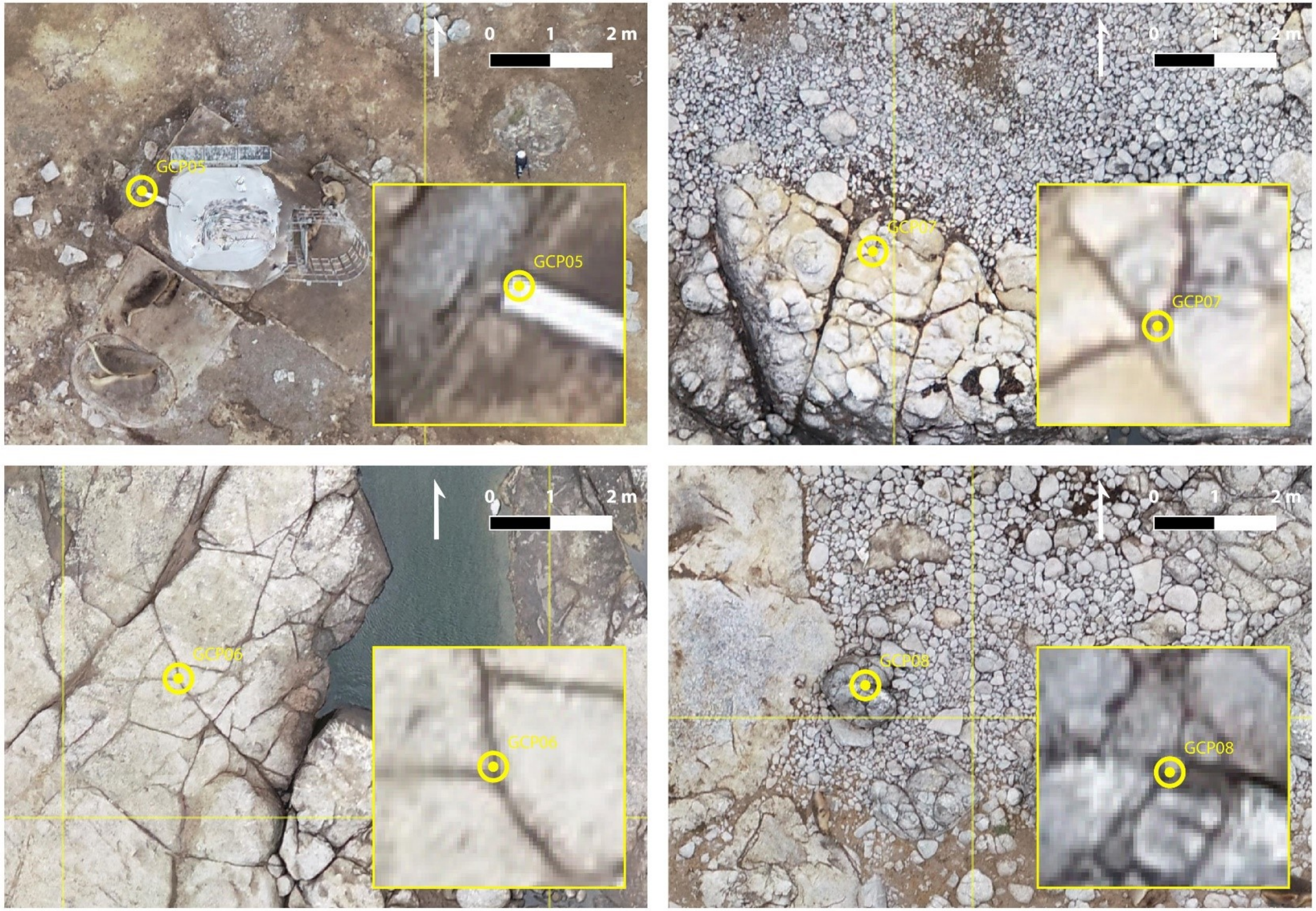
```
	#####################################################################
####################################

	#CALCULATE AND OUTPUT IMAGE QUALITY
    chunk.estimateImageQuality()

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


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

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


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

	##COREGISTER HERE IF NEEDED

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

	#BUILD PRODUCTS AND EXPORT

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

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

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

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

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

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

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

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

    Metashape.app.update()

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

    #EXPORT PRODUCTS

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

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

    print("Script finished")

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


for path in lstpaths:
    process(path)

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



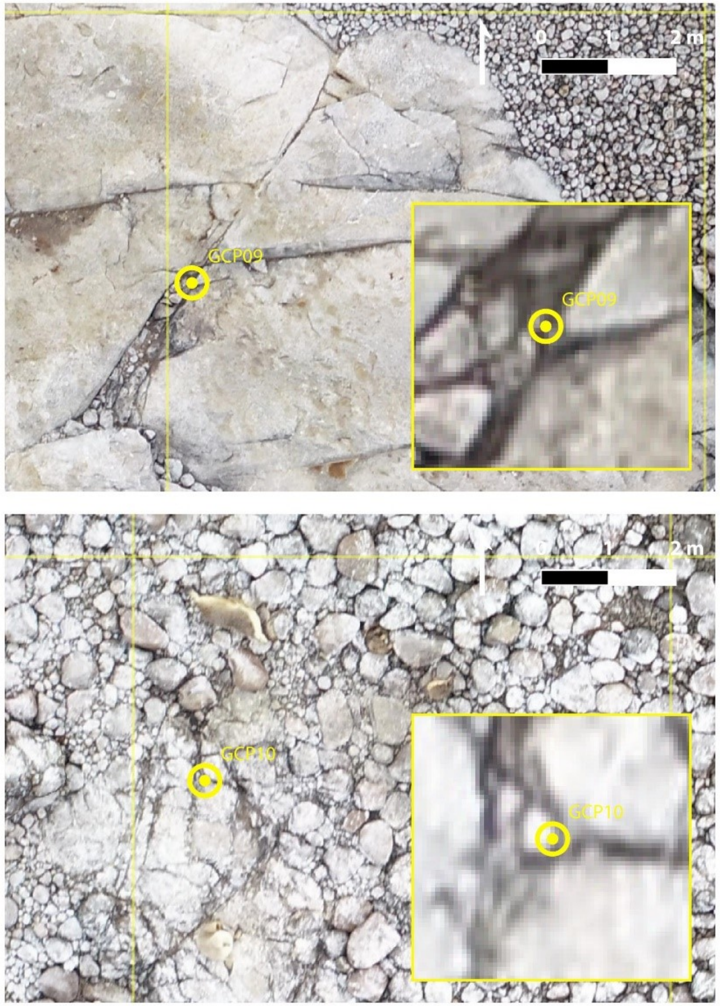
Appendix 2a. Natural features on main island used as ground control points (GCPs) during drone imagery processing.

Ground control points 1 – 4. Refer to Appendix 2 for GCP co-ordinates.



Appendix 2b. Natural features on main island used as ground control points (GCPs) during drone imagery processing.

Ground control points 5 – 8. Refer to Appendix 2 for GCP co-ordinates.



Appendix 2c. Natural features on main island used as ground control points (GCPs) during drone imagery processing.

Ground control points 9-10. Refer to Appendix 2 for GCP co-ordinates.

Appendix 3. Co-ordinates of the ground control points on main island, Dangerous Reef.
This is formatted as input code for Agisoft Metashape.

```
GCP05,136.212606,-34.815143,5.094273,0.005000
GCP02,136.211667,-34.814830,3.028042,0.005000
GCP01,136.211270,-34.815110,2.637009,0.005000
GCP03,136.211882,-34.815105,4.438187,0.005000
GCP04,136.212501,-34.815432,2.760357,0.005000
GCP06,136.212614,-34.814733,2.943722,0.005000
GCP08,136.213424,-34.815141,2.864223,0.005000
GCP07,136.213246,-34.815464,2.126972,0.005000
GCP09,136.213698,-34.815337,2.373287,0.005000
GCP10,136.214063,-34.815201,1.364697,0.005000
```

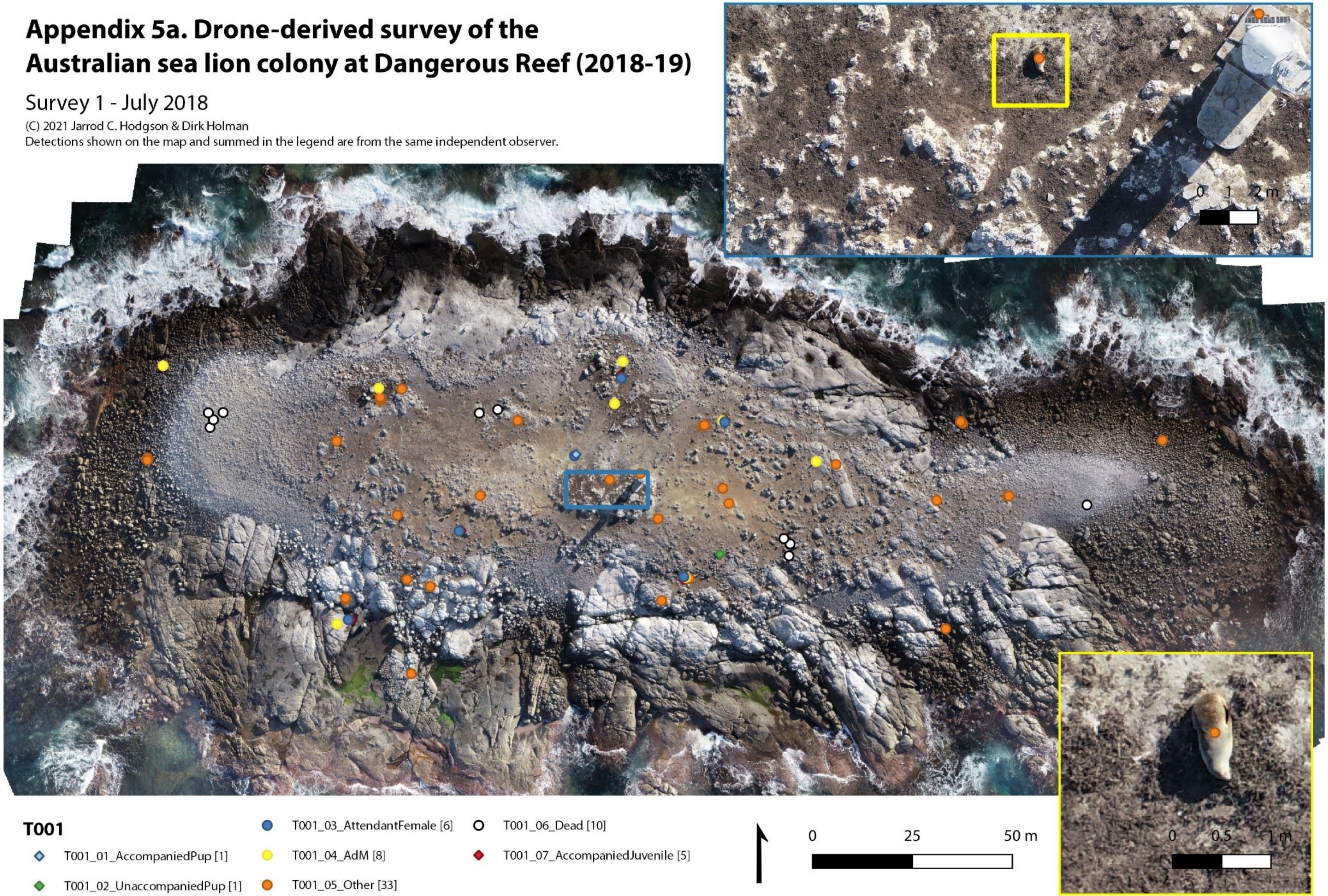
Appendix 4. Agisoft Metashape processing parameters. Parameters for initial (prior to co-registration) and final batch processing of imagery.

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

Appendix 5a. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 1 - July 2018

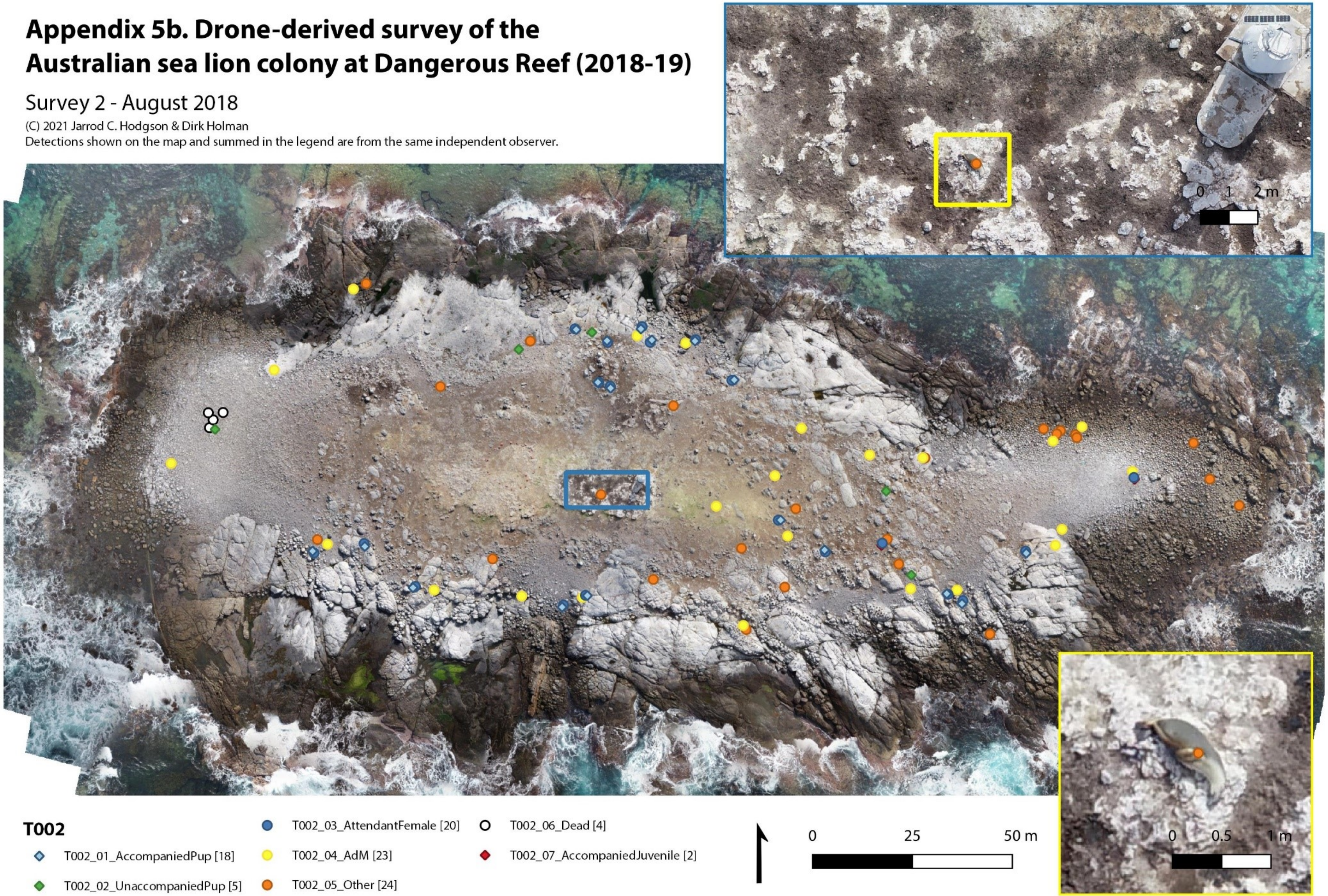
Detections shown on the map and summed in the legend are from the same independent observer.



Appendix 5b. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 2 - August 2018

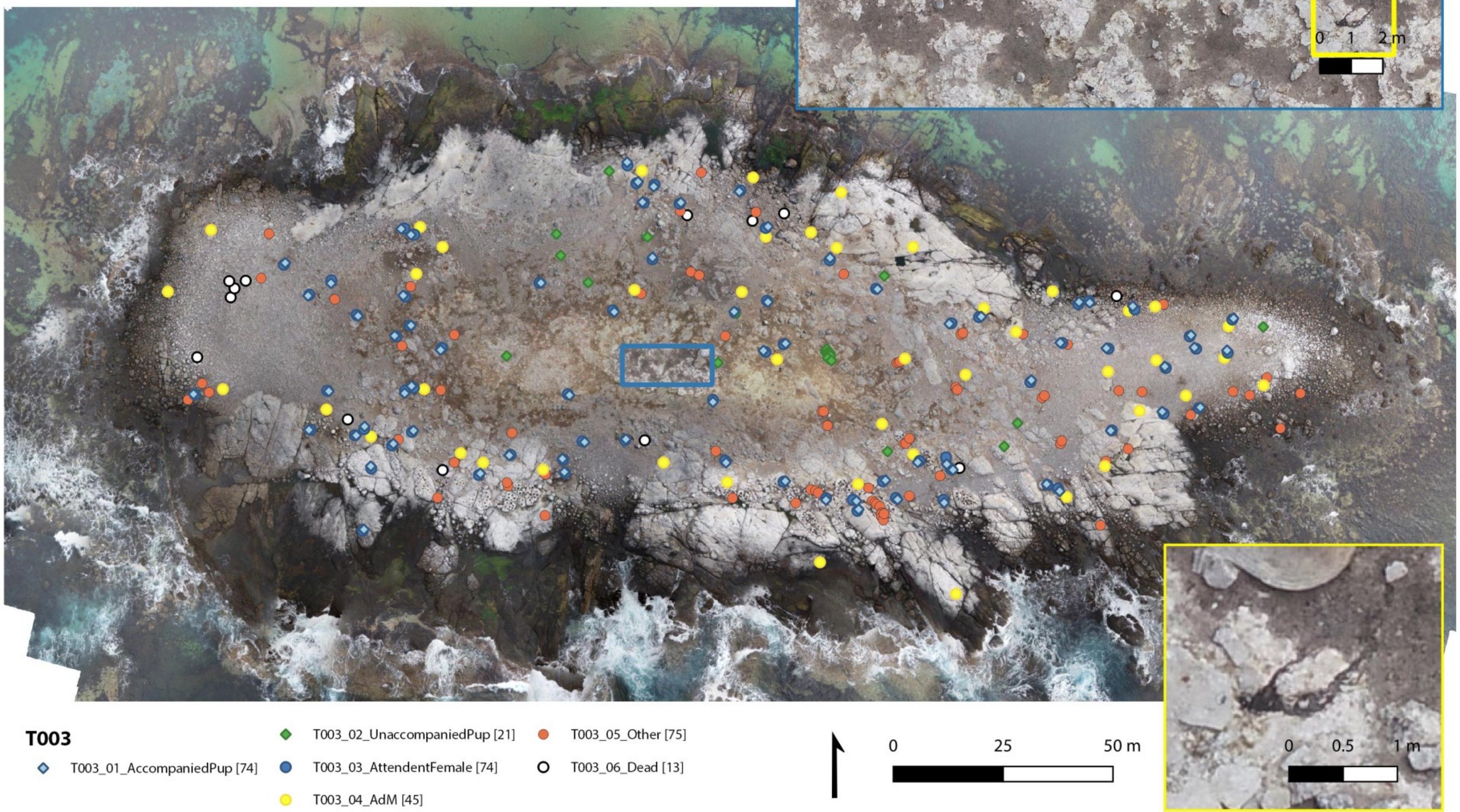
Detections shown on the map and summed in the legend are from the same independent observer.



Appendix 5c. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 3 - September 2018

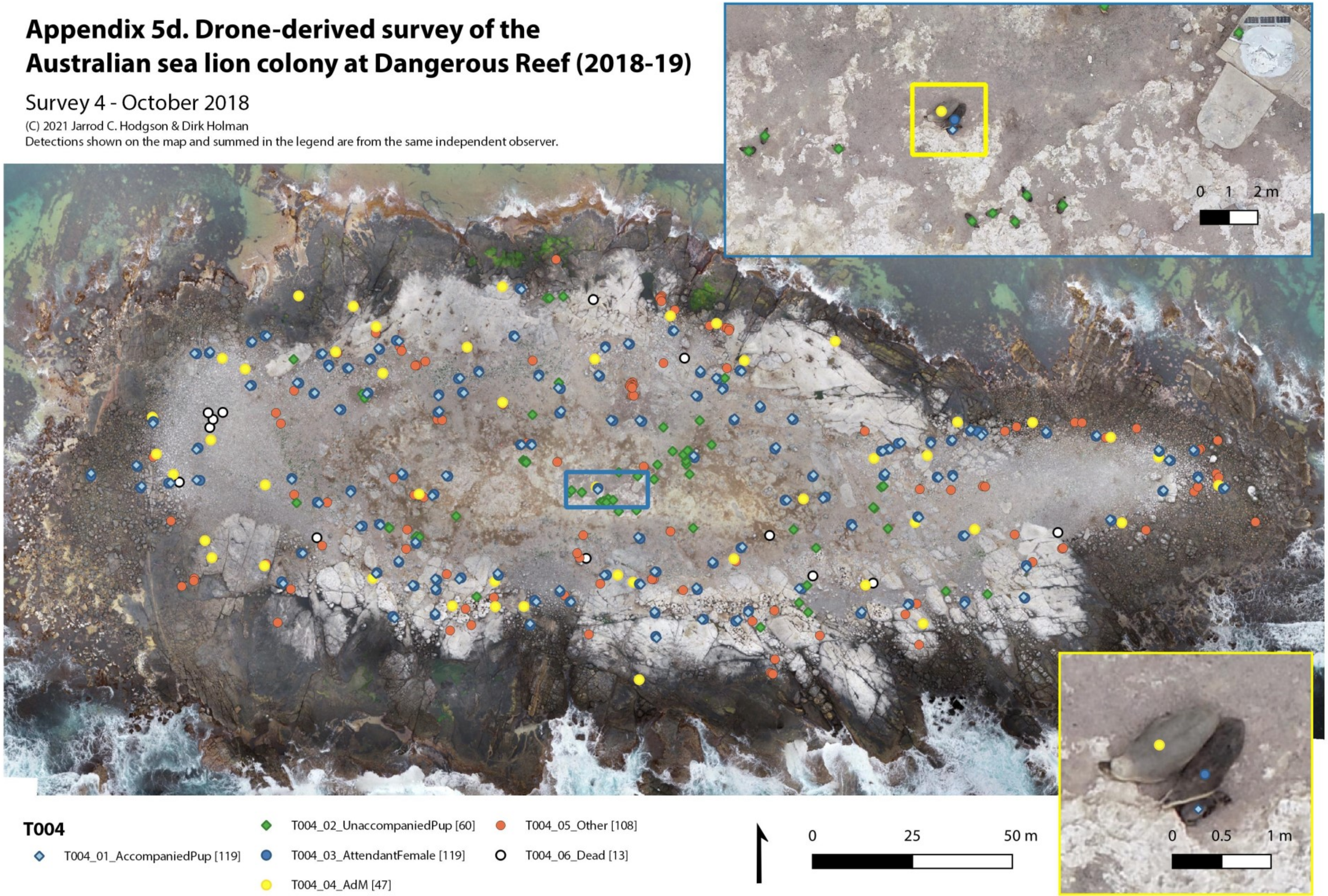
Detections shown on the map and summed in the legend are from the same independent observer.



Appendix 5d. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 4 - October 2018

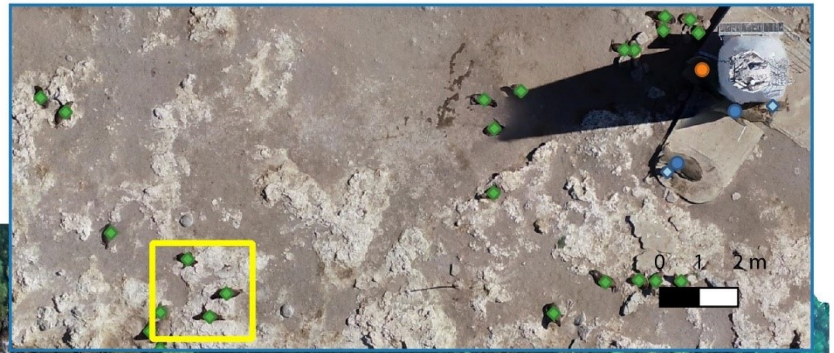
Detections shown on the map and summed in the legend are from the same independent observer.

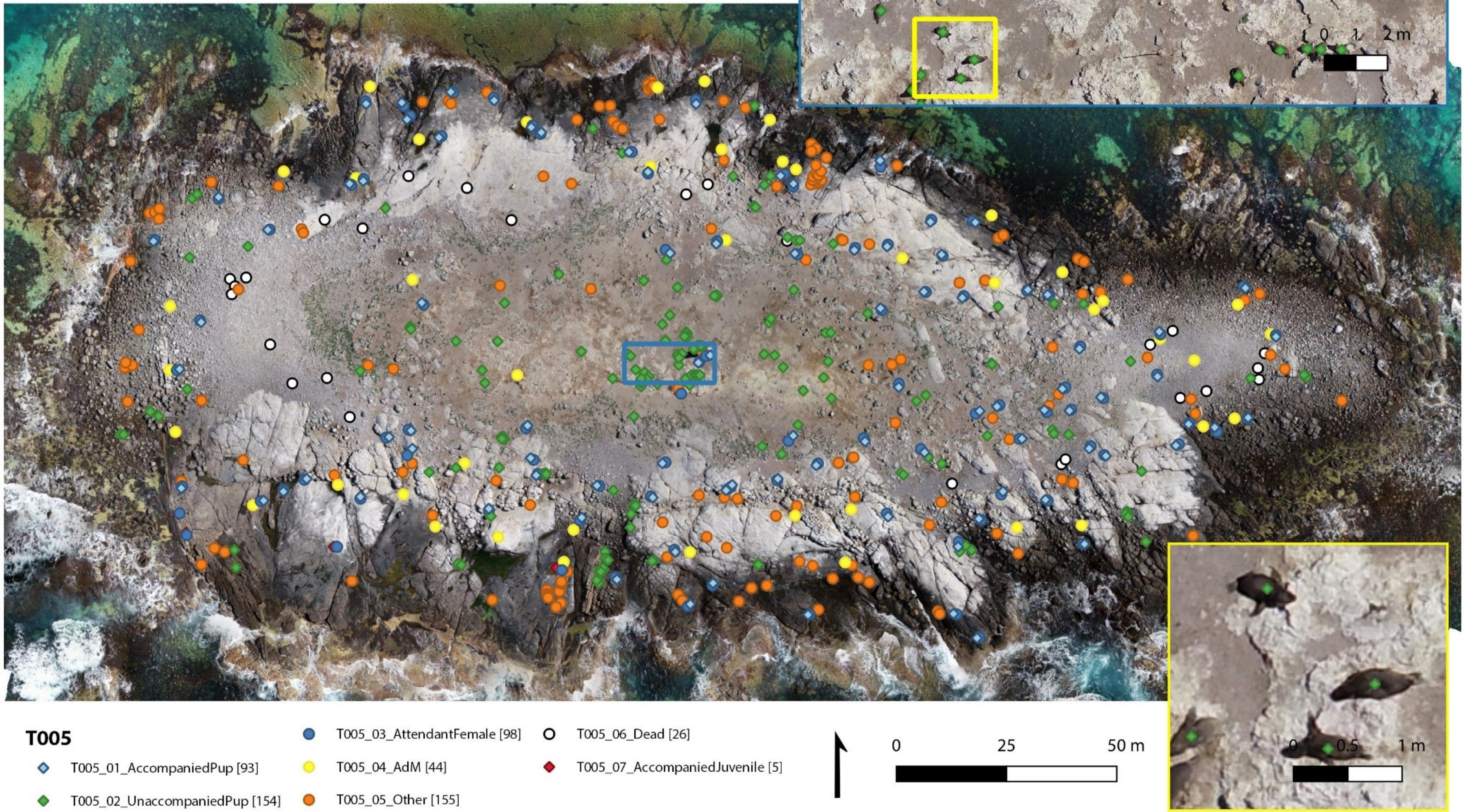


Appendix 5e. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 5 - November 2018

Detections shown on the map and summed in the legend are from the same independent observer.





T005

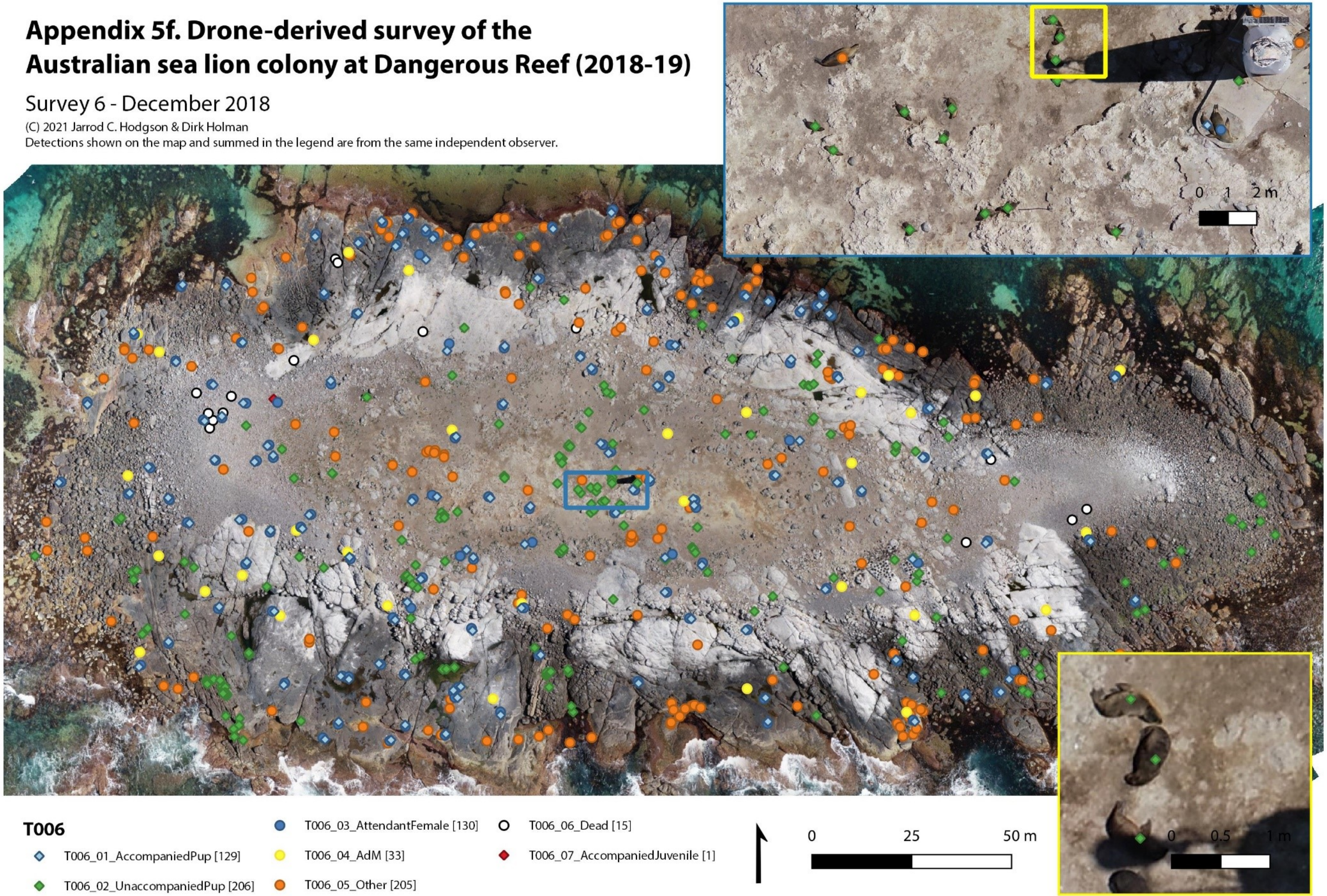
- T005_01_AccompaniedPup [93]
- T005_02_UnaccompaniedPup [154]
- T005_03_AttendantFemale [98]
- T005_04_AdM [44]
- T005_05_Other [155]
- T005_06_Dead [26]
- T005_07_AccompaniedJuvenile [5]

0 25 50 m

Appendix 5f. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 6 - December 2018

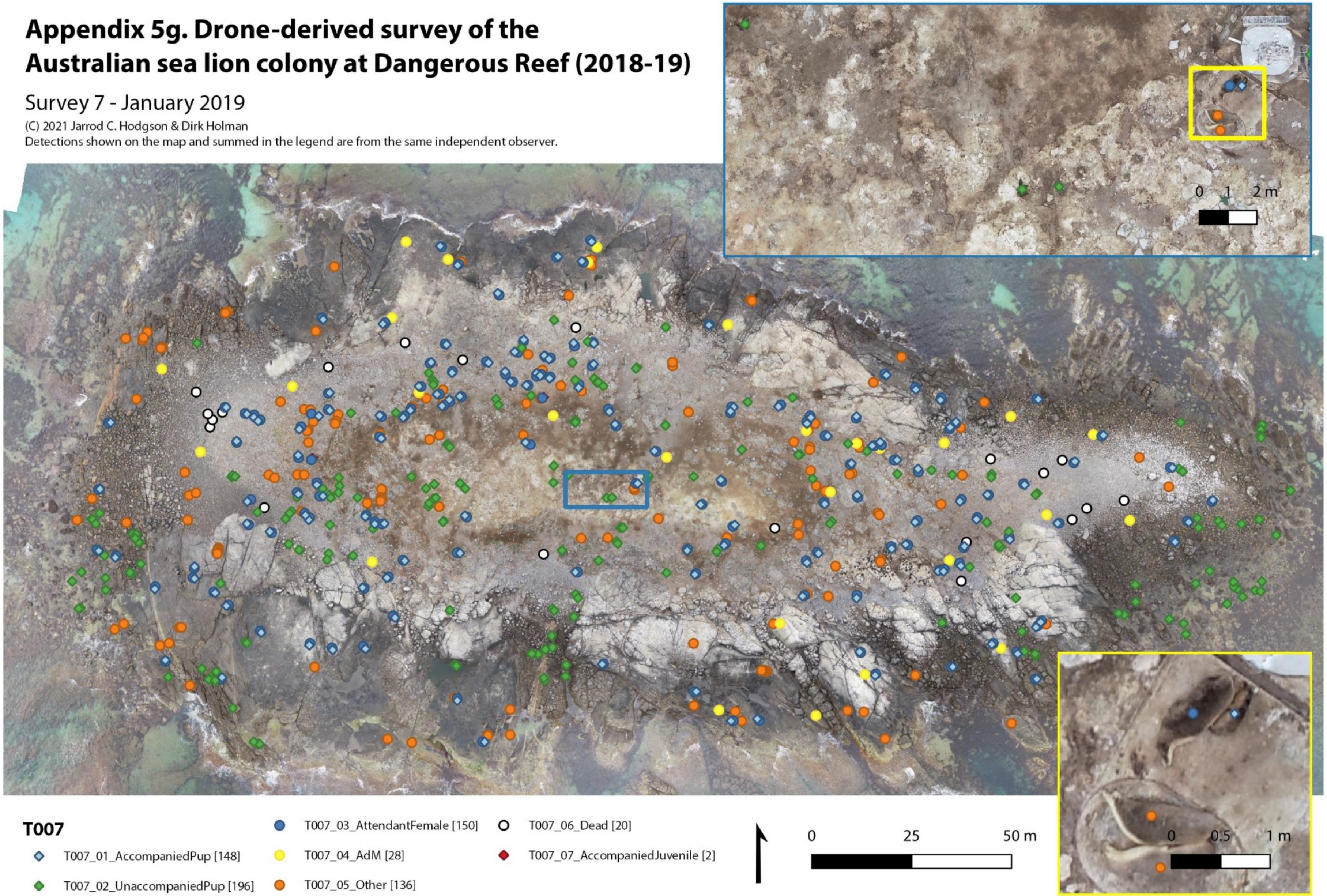
Detections shown on the map and summed in the legend are from the same independent observer.



Appendix 5g. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 7 - January 2019

Detections shown on the map and summed in the legend are from the same independent observer.



Appendix 5h. Drone-derived survey of the Australian sea lion colony at Dangerous Reef (2018-19)

Survey 8 - February 2019

Detections shown on the map and summed in the legend are from the same independent observer.