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Using unmanned aerial vehicles and machine learning to improve sea cucumber density estimation in shallow habitats

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Sea cucumber populations around the globe are experiencing marked declines caused by overexploitation and habitat degradation. Fisheries-independent data used to manage these ecologically and economically important species are frequently collected using diver- or snorkeler-based surveys, which have a number of limitations, including small spatial coverage and observer biases. In the present study, we explored how pairing traditional transect surveys with unmanned aerial vehicles (UAVs) and machine learning could improve sea cucumber density estimation in shallow environments. In July 2018, we conducted 24 simultaneous snorkeler–UAV transects in Tetiaroa, French Polynesia. All UAV images were independently reviewed by three observers and a convolution neural network (CNN) model: ResNet50. All three methods (snorkelers, manual review of UAV images, and ResNet50) produced similar counts, except at relatively high densities ($\sim$75 sea cucumber 40 m^{-2}), where UAVs and CNNs began to underestimate. Using a UAV-derived photomosaic of the study site, we simulated potential transect locations and determined a minimum of five samples were required to reliably estimate densities, while sample variance plateaued after 25 transects. Collectively, these results illustrate UAVs' ability to survey small invertebrate species, while saving time, money, and labour compared to traditional methods, and highlights their potential to maximize efficiency when designing transect surveys.

Keywords: abundance estimation, convolution neural network, drone, fisheries-independent surveys, *Holothuroidea*, invertebrates, visual surveys

Introduction

Sea cucumbers (*Holothuroidea*) are marine benthic invertebrates that play an important role in coral reef ecosystems (Purcell *et al.*, 2014a). Their digestion of organic matter associated with ingested coral sand and rubble results in the dissolution of acidic $CaCO_3$ particulates and, consequently, increases local alkalinity in reef environments (Hammond, 1981; Schneider *et al.*, 2013; Purcell *et al.*, 2016). Importantly, this digestive process may help to buffer against the effects of increasing ocean acidification (Schneider *et al.*, 2013). As a digestive by-product, sea cucumbers also secrete ammonia (NH_3) that contributes to nutrient cycling and encourages productivity in coral systems (Uthicke and Klumpp, 1998; Uthicke, 2001). Furthermore, sea cucumbers directly increase oxygen levels in the sediment through bioturbation (Hammond, 1982). By implication, the presence of sea cucumbers may improve reef resilience and stability under future anthropogenic stressors (Schneider *et al.*, 2013), and it has been suggested that their removal can result in diminished ecosystem functionality (Purcell *et al.*, 2016).

Many species of tropical sea cucumbers are commercially valuable (Conand, 1998; Purcell *et al.*, 2014b), with the majority harvested to produce *bêche-de-mer* products for consumption in Asian markets (Anderson *et al.*, 2011; Eriksson and Clarke, 2015). Their ease of collection, low recruitment, slow growth, and high longevity make them particularly vulnerable to overfishing (Conand, 2001; Uthicke *et al.*, 2004). These factors coupled with high global demand for sea cucumber products have resulted in 70% of tropical sea cucumber species being listed as exploited, overexploited, or depleted (Anderson *et al.*, 2011; Purcell *et al.*, 2014b), with many local populations having already been extirpated (Purcell *et al.*, 2014b). To determine optimal harvest levels, stakeholders must be able to assess the spatio-temporal population dynamics from a variety of data sources including fisheries-independent surveys. To date, the majority of fisheries-independent surveys used to help sea cucumber management decisions comes from underwater visual censuses (UVCs), which provide density estimates over a small area using counts from SCUBA diver or snorkeler transects (e.g. Shepherd *et al.*, 2003; Léopold *et al.*, 2013; Rehm *et al.*, 2014; Idreesbabu and Sureshkumar, 2017). Though important tools, these surveys have a number of shortcomings, including high costs, errors and bias due to observer experience, and small spatial coverage (Shepherd *et al.*, 2003; Prescott *et al.*, 2013). They are also time-consuming and logistically impractical in many of the shallow sand flat habitats where sea cucumbers are abundant (Mercier *et al.*, 2000; Idreesbabu and Sureshkumar, 2017). Given the limitations of current survey methods and an increasing need for accurate sea cucumber abundance estimates, it is critical to develop tools and techniques to better monitor these ecologically and economically important populations.

Unmanned aerial vehicles (UAVs) have rapidly developed over the last decade and have been increasingly used by ecologists as a wildlife monitoring tool (Ivošević *et al.*, 2015). Their low cost, ease of use, relatively large spatial coverage, programmable flight paths, and ability to be deployed in remote locations have enabled UAVs to be applied to a wide range of studies in both terrestrial and marine environments (Anderson and Gaston, 2013; Colefax *et al.*, 2018). The majority of work in marine population monitoring has focused on the application of UAVs to replace traditional manned aerial surveys of large vertebrates such as dugongs (Hodgson *et al.*, 2013), cetaceans (Christiansen *et al.*, 2016), sea turtles (Rees *et al.*, 2018), and elasmobranchs (Kiszka *et al.*, 2016). More recently, UAVs have been used to examine aspects of species behaviour (Rieucau *et al.*, 2018) and to quantify changes in coral health (Parsons *et al.*, 2018). An as of yet unexplored potential application of UAVs is their ability to provide density estimates for shallow water invertebrate species, for which remote underwater vehicles or diver transects may be impracticable.

In this study, we evaluated the efficacy of UAVs as a means to supplement current data collection efforts for sea cucumbers in shallow water environments as well as their potential to overcome many issues associated with traditional diver-based surveys. Specifically, our objectives were to compare estimated counts and the time required to extract counts for sea cucumber transects using (i) *in situ* snorkeler observations, (ii) UAV data manually generated by observers, and (iii) UAV data generated using machine learning. Additionally, we explored how UAVs may be used to

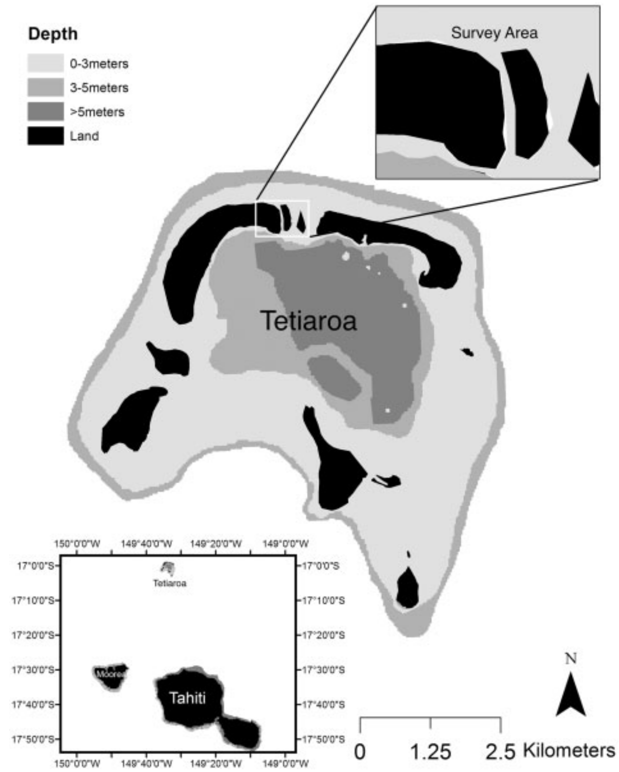

Figure 1. All UAV transects for this study were flown in sandflat habitats of Tetiaroa, French Polynesia of <2 m in depth, from 22 July 2018 to 24 July 2018. Lower inset depicts nearby islands of the Society Archipelago; Tahiti and Moorea. Upper inset highlights northern region of lagoon where UAV transects were flown.

improve survey design and quantify required survey effort for diver or snorkeler transects.

Methods

Data collection

We conducted sea cucumber transect surveys over shallow (<2 m) sandflats of Tetiaroa, French Polynesia, a small atoll in the Society Archipelago (Figure 1) from 22 July 2018 to 24 July 2018. In total, 24 paired snorkeler transects were conducted, with a random starting and heading selected for each. Prior to sampling, each survey location was verified using a Garmin eTrex 39x hand held Global Positioning System. Each transect covered a 4 m × 10 m area and occurred between 08:00 and 16:00 local time. Surveys were not restricted due to cloud coverage, wind speed, or the observed turbidity of the water. However, conditions were generally sunny with low turbidity due to wind. To aid in observer counts (i.e. reduce double counting), each transect was subdivided into 1 m × 10 m areas by connecting two grey 1-m PVC tubes covered in red electrical tape using weighted ¼″ black line, each at 10 m in length (Figure 2). Once the observers had deployed the transect grid, depth at both the starting and the end points of each transect was measured using a weighted Komelon 6622 open reel measuring tape. Following these measurements, observers waited until all sediment had settled before beginning transect surveys (60 s). Transects were conducted one at a time by two independent snorkelers, with all sea cucumbers seen by the observer recorded and aggregated across species, and times

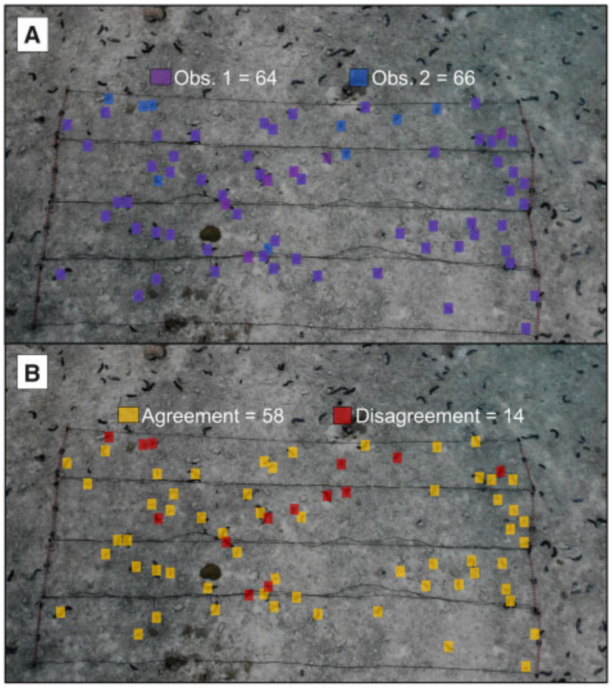

Figure 2. Example images of UAV data flown over snorkeler transects used in Tetiaroa, French Polynesia. Snorkeler transects are highlighted by weighted PVC and connected lines to ease comparison between divers and UAV. (a) Image after being processed by observers using Visual Counter software. Sea cucumbers identified by the observer 1 are represented by small purple squares, whereas observer 2 markings are indicated in blue. (b) Image of sea cucumber counts processed by two independent observers, with areas of agreement (represented by small orange squares) and disagreement (represented by small red squares) identified using MATLAB colour channel filtering in the L*a*b colour space.

required to complete each transect recorded in seconds. Once snorkelers completed their transects and cleared the area, each location was then surveyed using a DJI Mavic Air (168 mm × 83 mm × 49 mm; 430 g) with a 35 mm lens (85° field of view; 1/2.3″ COMS Sensor; 12 mega pixels) equipped with a polarizing lens to reduce issues with sun glare. The UAV was flown directly over the centre of the transect grid at an altitude of 7 m above sea level, and all videos were shot in 4k resolution (3840 × 2160) at 30 frames per second.

Manual review of UAV data

Counts from snorkelers were recorded *in situ*, whereas UAV video transects required additional steps to enumerate sea cucumbers. For each transect, a single image was selected from the video footage to be reviewed, using the ImageMagick package (version 6). Each image was then independently reviewed by two trained observers using the application Visual Counter (version 1.2; iVanya^{TM} 2015), with total time in seconds recorded for each observer to process an image. Visual Counter allowed observers to click on sea cucumbers present on an image and provided a total count of marked objects, relieving observers from self-tracking raw counts (Figure 2). After manual annotations of the sea cucumbers were completed by both observers, each pair of annotated images were compared to one another to by a third independent observer who provided the final count. To assist the third observer in comparing these two images, areas marked by both initial observers were converted to yellow, whereas areas of discrepancy (i.e. sea cucumbers marked by one observer but not the other) were converted to red. This colorization process was accomplished in MATLAB, by expanding the annotated pixel areas (to account for the same sea cucumber being marked in slightly different locations) and isolating marked pixels in the Commission Internationale de l'Eclairage (CIE) L*a*b colour space.

Automated UAV data review

To automate the process of identifying and enumerating sea cucumbers from UAV data, we elected to use ResNet50: a 50-layer convolution neural network (CNN) that supports residual learning (He *et al.*, 2016). CNNs are widely used for image classification and function by transforming an input image through a specified number of hidden layers. Each layer type serves a different function in the network, from feature extraction (convolution), to dimensionality reduction (pooling), and final feature aggregation (fully connected). ResNet50 was developed and trained using ImageNet: a large database of over 14 million annotated images (Russakovsky *et al.*, 2015). Using the pretrained ResNet50 architecture, we constructed a faster RCNN object detector for sea cucumbers. To train the faster RCNN detector, we used 72 augmented images taken from our UAV transects (flipped vertically, horizontally, and both). Each image was annotated for five separate classifiers as follows: small sea cucumbers, large sea cucumbers, rocks, detritus, and transect lines. Once trained, image classifiers were then used to predict the number of sea cucumbers present on the original (un-augmented) UAV transect images. Several different minimum validation criteria (MVC) were tested, defined as the minimum acceptable probability that an object is a sea cucumber for it to be counted as such (25, 50, 70, and 90%). For each MVC, we recorded the resulting F1 score (which strikes a balance between evaluating model precision and model recall) and selected MVC with the highest F1 value to be used for comparisons between snorkelers and UAV data generated using human observers.

Comparing count estimates

Counts generated from manually reviewing UAV images and from ResNet50 were compared to the maximum snorkeler count for each transect. The maximum snorkeler count was assumed to represent the most accurate sea cucumber count for each transect, as it is more likely for an observer to have a false negative (i.e. not see a sea cucumber) than a false positive (i.e. count a sea cucumber when it is not present; Andrew and Mapstone, 1987). Using this approach, we were able to compare the relative accuracy of each method to this standard. Counts of each method were compared to the maximum snorkeler count both visually and by using a Spearman's correlation test to measure the strength of the linear relationship between these paired data. The bias and percent bias of each method was also calculated for each transect, with the maximum snorkeler count again representing our standard for comparison. The minimum snorkeler counts were also included in these visual comparisons. It should be noted that these counts are inherently negatively biased compared to maximum snorkelers counts but were included to show how the discrepancy between snorkelers compares to counts derived from

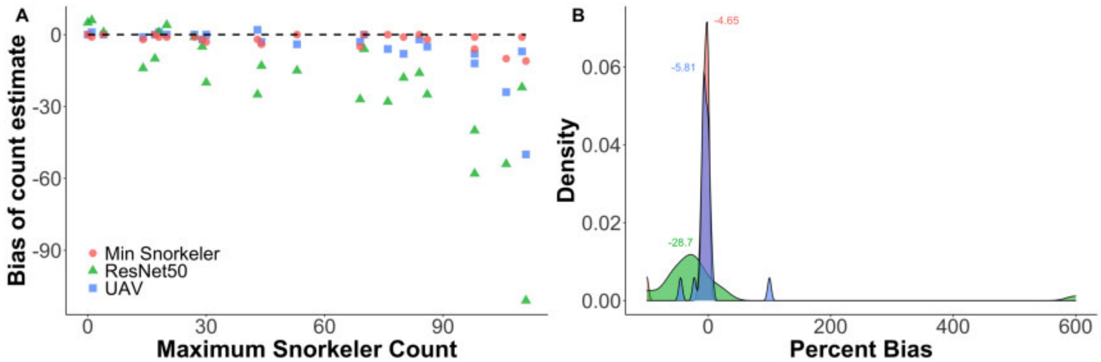

Figure 3. (a) Bias of the minimum snorkeler counts (red circles), images manually reviewed from UAV data (blue squares), and ResNet50 (green triangles) compared to the maximum snorkeler count for each transect (standardized to a value of zero, horizontal dashed line). (b) Density plot of the percent bias for each count method (same colour coding as panel a). Colour text corresponds to the median percent bias estimate for each method using on the same colour coding.

UAVs and from ResNet50. To determine if snorkelers or manual review of UAV data had significantly different time requirements, we used a Wilcoxon-signed rank test comparing the sum of the individual times of each observer for any one transect. All data were analysed in the R core environment (R Core Team, 2018), with significance accepted at a p value of ≤ 0.05.

UAVs to improve survey designs

Using the application Pix4DCapture (Version 4.6.0), we created a photomosaic of the entire study region from a series of 57 overlapping, geo-referenced images. The mosaic was then manually reviewed by a single observer using Visual Counter in the same manner as described for the manual review of UAV data, whereby all observed sea cucumbers were marked with a small, coloured square (e.g. blue). The XY coordinates of these marker positions were then extracted via the same colour channel filtering in CIE L*a*b colourspace as previously described. We then randomly selected a 4 m × 10 m representative section of the mosaic and provided the total number of marked sea cucumbers in this area. This procedure was then replicated for 2–100 simulated transects at a time and was then repeated 1000 times. Using these simulated samples, we then explored how total sample variance changed in relation to the simulated number of transects (1–100).

Results

The maximum sea cucumber count obtained by either snorkeler for each transect varied widely (range = 0–111), with a mean of 53.67 (±37.49; ±*SD*). Similar counts were generated by manually reviewing UAV data (48.21 ± 31.69), but ResNet50 tended to have lower estimates (33.21 ± 25.07). An MVC of 50% was selected as the best for ResNet50 (F1 = 0.81; see Supplementary Material for other MVC F1 scores), which had a 71.95% true positive detection rate (model recall) and a positive predictive value of 93.15% (model precision). Counts among snorkelers were relatively precise, averaging a difference of only 2.25 (±6.0) with a maximum difference of 11 and appeared greatest at higher densities. Counts among UAV reviewers were also relatively precise, though less so than snorkelers, with a mean difference of 9.71(±7.10).

Counts generating by manually reviewing UAV images tended to be negatively biased compared to the maximum snorkeler count, with a −5.81% median bias (±24.50; Figure 3b). This negative bias appeared minimal until transect densities reached 90 sea cucumbers and was similar to the bias of the minimum snorkeler count (−4.91% ± 20.40; Figure 3a). Counts generated by ResNet50 had a greater negative bias overall (−28.10% ± 135.90). Similar to manually reviewing UAV image, the negative bias of ResNet50 was inversely related to transect density (Figure 3a). The correlation between the maximum snorkeler counts and those generated by manually reviewing UAV images were highly significant ($p < 0.001$; $\rho = 0.95$), as were counts generated using ResNet50 ($p < 0.001$; $\rho = 0.70$).

Processing times for UAV images that were manually reviewed showed high variability from one image to another (range = 144–760 s), averaging 380.6 s (±156.10 s). The amount of time required to process any one image was strongly related to the number of sea cucumbers estimated to be present, but did not appear to be influenced by transect depth. Processing times required by snorkelers for each transect were significantly shorter than those by UAV review ($V = 274$, $p < 0.01$), with an average time required of 275.5 s (±238.40). However, times also varied greatly between transects for snorkelers (range = 92–456) and had a mean difference of <2 min compared to manual review of UAV images.

Pix4D proved capable of generating a photomosaic of the entire surveyed area (Figure 4). Furthermore, it was possible for observers to manually annotate sea cucumbers within these images using Visual Counter (Figure 4). Visual inspection of simulation results indicated that sample variance dramatically declined once sample size reached at least five transects, but that decreases in variance began to plateau at 25 transects for our surveyed area (Figure 5).

Discussion

In the present study, we have demonstrated how UAVs may be used in a new realm of marine research by highlighting their ability to survey invertebrate species, such as sea cucumbers, in shallow environments. Importantly, counts of sea cucumbers estimated using UAVs were similar to those obtained by snorkelers in the field. Although counts among UAV observers were relatively precise, they had greater variability than among snorkelers, highlighting the importance of using a third UAV reviewer to identify areas of agreement and disagreement between initial observations. In this regard, UAVs may have a distinct advantage over snorkelers or divers, as counts obtained can be archived and

Figure 4. Photomosaic map of study region in Tetiaroa, French Polynesia generated by stitching 57 overlapping, geo-referenced images using the application Pix4DCapture. Inset highlights a zoomed in portion of image with sea cucumbers manually marked using Visual Counter.

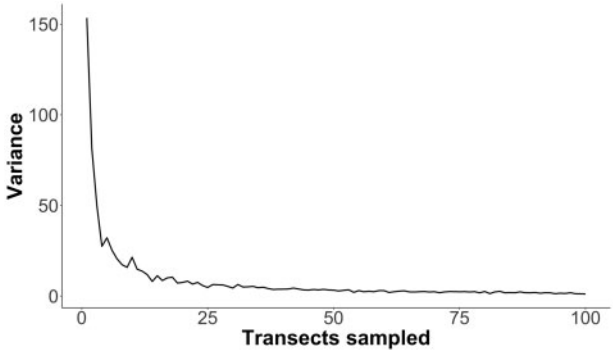

Figure 5. Sample variance from simulated transects (1–100) in relation to the number of transects sampled, based on sea cucumber locations taken from UAV generated photomosaic of the study region in Tetiaroa, French Polynesia. A total of 1000 simulations were run for each number of simulated transects sampled.

later reviewed by a number of experts until a consensus on the appropriate count is agreed upon. Furthermore, by individually marking sea cucumbers in images rather than aggregating counts across a transect (as is done with snorkelers and divers), researchers may be able to more accurately quantify survey detection probabilities and underlying factors that drive observer biases.

Though UAV counts were similar to snorkelers overall, it is important to note that this relationship did not hold under high-density conditions (i.e. >90 sea cucumbers). While the majority (79%) of sampled transects were below the 90 sea cucumbers 40 m^{-2} density threshold, this could still be cause for concern as it may result in a hyperstable index of relative abundance if not accounted for, whereby populations may be changing while indices remain stable (Hilborn and Walters, 1992). Fisheries-independent surveys frequently exhibit this type of density-dependent gear-efficiency, often referred to as "gear saturation" (Rago, 2005), including other visual survey methods (e.g. Campbell *et al.*, 2015; Kilfoil *et al.*, 2017). However, once detected, density-dependent gear efficiency can often be corrected for either statistically or through technological innovations and gear modifications (e.g. Kilfoil *et al.*, 2017). Although the exact reasons for underestimation of sea cucumbers at higher densities are unknown, it is possibly driven by sea cucumbers clustering under coral overhangs or on small coral heads, which makes counting using UAVs extremely difficult. Furthermore, the present study was conducted in an area well suited for surveying sea cucumbers using UAVs (e.g. contrasting colours of sea cucumbers on sandflats, relatively shallow water) and during favourable weather conditions (e.g. low wind, low surface turbidity). Accordingly, future research efforts should be conducted to examine the utility of UAVs across a gradient of depths, weather conditions, habitat types, and species of interest.

In addition to the relative accuracy of a method, researchers must consider the relative effort required to conduct a survey due to time and budgetary constraints. Although the time required to manually extract counts was higher for UAVs than for snorkelers, this extra time requirement could be allocated to periods when researchers are unable to be in the field (e.g. at night or during unfavourable weather conditions). Moreover, the additional time required to extract counts from images was driven by the increased number of observers (three) compared to snorkelers (two) and represents a relatively small increase in effort, particularly when considering other time constraints that we did not address in this study (e.g. time spent deploying and retrieving transects, time moving between site locations). This is in contrast to many other video survey platforms that are often rendered unusable for resource managers because of the elapsed time between collecting and extracting data (Harvey *et al.*, 2013). Furthermore, we were able to demonstrate that using CNNs, it may be possible to fully automate the process of extracting counts from UAV data, which could further reduce time requirements.

Our results indicate that using CNNs, such as ResNet50, can enable researchers to automate the process of identifying and counting sea cucumbers from UAV images. However, counts generated from ResNet50 did tend to be lower than those provided by manual reviews of these same images, particularly when many sea cucumbers were present. There are a number of factors that may have contributed to this lower than desired detection capability, but it was most likely driven by the small size of the dataset used to train the model. Numerous studies have shown that one of the most important factors for improving CNN model performance is to increase the size of the training dataset (Ozbulk *et al.*, 2016; Windrim *et al.*, 2016). As UAVs become more frequently used for this type of research, the amount of data available to develop these models will likely increase exponentially. Until that time, CNNs may be more suited as a "first pass" estimate, which can then be reviewed and corrected by human observers.

When considering the potential of CNNs to automatically enumerate sea cucumbers from image data, coupled with the relatively low cost of UAVs (~1000 USD) and their ability to be deployed in remote regions, UAVs become an obvious choice to supplement current UVC techniques as a research tool and may even facilitate the gathering of data where none currently exist. Though exact protocols for using UAVs will vary depending on laws and regulations of the site country (e.g. flying from higher altitudes and using zoom lenses to minimize interactions with humans and wildlife), these data would nonetheless improve our ability to monitor sea cucumber populations and could potentially be integrated using statistical approaches. The utility of UAVs may be particularly high in areas where UVCs are too expensive or logistically unrealistic to be implemented. Given the increasing popularity of UAVs in the public sector, it is also feasible that UAVs could be a source of large-scale citizen science data in the future. Though identifying sea cucumbers and other invertebrates from UAV data requires extensive training, it would be relatively simple to establish a repository where citizen scientists could contribute UAV images to be later reviewed by scientist, or ideally by machine learning methods such as CNNs. Similar citizen scientist image databases already exist, such as eBird (https://ebird.org/home), eMammal (https://emammal.si.edu), and Reef Vision (https://recfishwest.org.au/our-services/research/reef-vision-artificial-reef-monitoring/).

Importantly, our results build on previous work (e.g. Shepherd *et al.*, 2003) to indicate that sea cucumbers do not distribute uniformly or randomly throughout their environment, but instead cluster in groups. Therefore, UAVs may be particularly well suited to study these populations because they can cover a much larger area in a shorter time frame than is typical of UVCs. By mapping the study region ahead of deploying divers or snorkelers, researchers may be able to quantify the general spatial distribution of their target species and potentially identify what physical characteristics of the environment may be driving these observed distributions (e.g. distance to coral, tidal state). Furthermore, using photomosaic mapping could enable researchers to determine what survey effort is required to accurately and precisely estimate species densities. In the present study, we demonstrated how this technique could be used to determine the number of samples required to reliably estimate sea cucumber density within a study site. Using this same approach, researchers could determine at what spatial scales their samples become independent or how different sampling designs (random, stratified-random, systematic, or adaptive) and chosen transect sizes (i.e. better to have many small transects or fewer large transect) may impact their resulting count estimates prior to beginning their sampling efforts. This application of UAVs may be especially beneficial to researchers, as it would allow for the optimization of survey designs, provide justifications for the amount of survey effort required, and identify/designate areas for research priorities, all of which are increasingly important in the face of budgetary and personnel shortages. Furthermore, given the potential limitations of UAVs to identify sea cucumbers to the species level, coupled with depth restrictions of the technique, UAVs may be best served as a tool for improving diver and snorkeler transects until these limitations can be addressed.

As UAVs continue to advance and drop in price, they will undoubtedly be used increasingly by researchers and conservation managers. Here we have presented how this innovative technology can be used in the marine environment to enumerate invertebrates such as sea cucumbers. Given the ecological importance of sea cucumbers (particularly in the face of increasing ocean acidification due to climate change) as well as their massive global economic importance, it is imperative that we have reliable fisheries-independent data to help inform fisheries management as well as potential conservation measures. This data need is made all the more crucial by the fact that many sea cucumber species are undergoing dramatic declines in the face of overexploitation and other anthropogenic stressors (Purcell *et al.*, 2014a). Although UVCs such as diver and snorkeler transects will continue to play an important role in quantifying marine invertebrate communities, the reliability and numerous advantages of UAV surveys demonstrated in this study highlight their likely future role in describing spatio-temporal changes to populations in coral reef environments.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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Data availability statement

The data underlying this article will be shared on reasonable request to the corresponding author.

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