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RESEARCH ARTICLE

Drone photogrammetry reveals contrasting body conditions of dugongs across the Indo-Pacific

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Abstract

The monitoring of body condition, reflecting the state of individuals' energetic reserves, can provide early warning signals of population decline, facilitating prompt conservation actions. However, environmental and anthropogenic drivers of body condition are poorly known for rare and elusive marine mammal species over their entire ranges. We assessed the global patterns and drivers of body condition for the endangered dugong (*Dugong dugon*) across its Indo-Pacific range. To do so, we applied the body condition index (BCI) developed for the related manatee based on the ratio of umbilical girth (approximated as maximum width times), to straight body length measured in drone images. To cover the entire dugong's range, we took advantage of drone footage published on social media. Combined with footage from scientific surveys, social media footage provided body condition estimates for 272 individual dugongs across 18 countries. Despite small sample sizes relative to local population sizes, we found that dugong BCI was better, that is, individuals were 'plumper', in New Caledonia, the United Arab Emirates, Australia and Qatar where populations are the largest globally. Dugong BCI was comparatively poorer in countries hosting very small dugong populations such as Mozambique, suggesting a link between body condition and population size. Using statistical models, we then investigated potential environmental and anthropogenic drivers of dugong BCI, while controlling for seasonal and individual effects. The BCI decreased with human gravity, a variable integrating human pressures on tropical reefs, but increased with GDP per capita, indicating that economic wealth positively affects dugong energetic state. The BCI also showed a dome-shaped relationship with marine protected area coverage, suggesting that extensive spatial protection is not sufficient to maintain dugongs in good state. Our study provides the first assessment of dugong body condition through drone photogrammetry, underlining the value of this non-invasive, fast and low-cost approach for monitoring elusive marine mammals.

Introduction

Animal populations are traditionally monitored by estimating their abundance and population changes over time (Finn et al., 2023). However, the monitoring of abundance is often costly, infrequent and prone to uncertainty, leading to low statistical power and limited ability to detect trends in population size (Andersen & Steidl, 2020). Body condition provides another valuable metric for monitoring populations. Body condition reflects the state of individual energetic reserves, an individual in good condition having higher energy reserves and being 'plumper' than one in poor condition (Schulte-Hostedde et al., 2001). Body condition is strongly linked to survival, reproductive success and fitness (Castrillon & Bengtson Nash, 2020) and has direct consequences on population dynamics (Stevenson & Woods, 2006). Because body condition fluctuates on relatively short time scales (Fuentes-Allende et al., 2023; Lemos et al., 2020), its monitoring can allow the early detection of population changes (Carroll et al., 2024). Understanding body condition is thus crucial for the management and conservation of long-lived and slow-reproducing species that are vulnerable to extinction. Among such species, marine mammals represent an increasingly threatened taxonomic group (Pimiento et al., 2020).

The monitoring of body condition has gained increasing attention in marine mammals as a way to provide early warning signals of population decline (e.g. Carroll et al., 2024; Harwood et al., 2015; Serres et al., 2024). Variations in body condition have been observed over time (de Oliveira et al., 2023; Harwood et al., 2015; Lemos et al., 2020), geographic gradients (Castelblanco-Martínez et al., 2021; Lemos et al., 2020; Russell et al., 2023) and species ranges (Torres et al., 2022). However, the potential drivers of these variations are more rarely investigated. Previous studies highlighted the effect of environmental processes such as climate variability and upwelling dynamics (Akmajian et al., 2021; Lemos et al., 2020; Torres et al., 2022; Wachtendonk et al., 2022) but also human pressures, including direct exploitation and depletion of food resources (Serres et al., 2024) on marine mammals' body condition. Body condition may also be genetically inherited, reflecting local adaptations to specific environments (Christiansen et al., 2020; Torres et al., 2022). To date, few studies have simultaneously tested the effects of environmental and human drivers on the body condition of a marine mammal across its entire geographic range.

Monitoring the body condition of marine mammals is challenging because of their high mobility and elusive nature (Castrillon & Bengtson Nash, 2020). Traditionally, body condition assessments have relied on carcasses obtained from strandings, direct harvesting, and fisheries bycatch (Evans et al., 2003; Harwood et al., 2015; Read, 1990). Methods for deriving body condition in marine mammals have included blubber measurements (Zeng et al., 2015), body composition analyses (McLellan et al., 2006), biochemical marker identifications (Bengtson Nash et al., 2013) and morphometric measurements (Kershaw et al., 2017). Recently, advances in drone photogrammetry have offered a non-invasive alternative to manual morphometric measurements. Drones, due to their small size and reduced noise, can provide high-resolution images of individuals with minimal disturbance (Torres et al., 2018). Drone photogrammetry has been applied to derive body condition for mysticetes (Christiansen et al., 2020; Lemos et al., 2020; Russell et al., 2023) and odontocetes (de Oliveira et al., 2023; Kotik et al., 2023; Serres et al., 2024), but also for pinnipeds (Carroll et al., 2024; Hodgson et al., 2020; Krause et al., 2017). However, using drones to assess the body condition of globally rare and elusive sirenians is challenging, and studies have been limited to the Antillean manatee (*Trichechus manatus manatus*) (Castelblanco-Martínez et al., 2021; Ramos et al., 2022). To date, drone photogrammetry has never been applied to study the body condition of the dugong (*Dugong dugon*), a particularly vulnerable and sparsely detected species (Marsh et al., 2011). The only existing body condition studies focused on dugongs relied on the capture and out-of-water measurements of individuals in Australia (Burgess et al., 2013; Lanyon et al., 2010). Although this capture-based approach remains applicable to large populations, drone assessments better comply with ethical standards for ensuring the welfare of dugongs, especially in fragmented populations.

Dugongs, as seagrass-dependent marine mammals (Marsh et al., 2011), are particularly sensitive to anthropogenic pressures throughout their Indo-Pacific range. Major contemporary threats to dugongs include incidental and deliberate capture in artisanal fisheries (Briscoe et al., 2014; Hines et al., 2020), loss of seagrass habitats due to coastal development and pollution (Ng et al., 2022; Zhang et al., 2023) but also climate change and extreme weather (Marsh et al., 2022). The dugong is globally assessed as Vulnerable by the International Union for Conservation of Nature (IUCN) (Marsh & Sobtzick, 2019) but different statuses have been assigned to local populations in New Caledonia (Endangered, Hamel et al., 2022), continental East Africa (Critically Endangered, Trotzuk, Allen, et al., 2022) and Japan (Critically Endangered, Brownell et al., 2019). Australia hosts the largest population (~165,000 individuals), followed by the Persian Gulf (~5000 individuals), while other populations are small and fragmented (Marsh et al., 2024), challenging monitoring and body condition studies. Furthermore, many small populations are located in developing countries where conservation efforts are lagging and over-exploitation of marine resources negatively impact dugongs (Trotzuk, Findlay, et al., 2022). Thus, new data sources and non-invasive methods are urgently needed to provide accurate assessments of body condition for dugongs.

The objective of our study is twofold. We first describe the global patterns of dugong body condition throughout the Indo-Pacific region. To cover the dugong's entire geographic range, we combine drone footage derived from scientific surveys with footage published on social media, an under-explored yet invaluable source of data for rare but emblematic species (Mannocci et al., 2021). We then use statistical models to investigate environmental and anthropogenic drivers of dugong body condition at the Indo-Pacific scale.

Material and Methods

Video footage collection

Drone videos of dugongs were manually searched on social media platforms (YouTube, Instagram and Facebook) using the keywords 'dugong', 'drone' and 'aerial.' Social media users were contacted to obtain additional information (e.g. date and geographic location) not specified in the publication, also leading to the acquisition of additional (unpublished) videos. Videos were downloaded manually. Duplicate videos published by the same user on different social media platforms were removed. When videos were re-shared by different users, the original user's video was retained. Additionally, aerial videos of dugongs were gathered from scientific surveys through direct interactions with academics, members of non-governmental organisations (NGOs) and companies conducting these surveys. Videos from scientific surveys were all collected by drone except in New Caledonia where a GoPro camera fitted under a microlight airplane was used (Mannocci et al., 2024). Scientific surveys varied in purpose (e.g. abundance estimation and behaviour observations) and were not specifically dedicated to body condition assessment. In scientific surveys, drone models used included DJI Phantom 4, DJI Mavic 2 PRO, DJI Mavic 3E, DJI Air 2S and WingtraOne and flight altitude ranged from 20 to 250 m. For each video, metadata included location (latitude/longitude), date, owner category (photographer, amateur, academic, media, tourism operator, NGO, environmental consultant, government and company), owner name and social media platform, when applicable.

Data processing

The quality of each video was first assessed. Videos characterised by low resolution (lower than 1280 × 720 pixels), excessively tilted angles, high distortion, low contrast, overly small dugongs (subjectively evaluated), or videos where dugongs were only underwater were excluded (Table S1, Fig. S1), as they would lead to inaccurate morphometric measurements. The number of unique individuals was determined, considering that videos recorded by the same person may show the same individual(s). If videos recorded by the same pilot were collected on the same day at a similar time, individuals were considered as replicates between these videos. If videos from the same pilot were recorded on the same day but at distant times, their background imagery (i.e. substrate such as sand or seagrass) was compared: if backgrounds were similar, individuals were considered as replicates; if not, they were considered different individuals. If videos from the same pilot were recorded on different days, individuals were considered different.

Each individual was categorised as adult female, juvenile or unidentified individual. Juvenile dugongs are known to remain with their mothers for up to 1.5 years (Marsh et al., 1984), swimming less than 2 m apart or in direct contact (Marsh et al., 2022). When two individuals, one significantly smaller than the other, exhibited this behaviour, the larger was categorised as an adult female and the smaller as a juvenile (potentially being a calf, here included within the 'juvenile' category). In the absence of distinctive features between males and females, an individual observed alone was categorised as 'unidentified'.

Images were extracted from each selected video at a rate of 5–10 frames per second using the FFmpeg software (https://ffmpeg.org/). The frame rate was adjusted to capture each individual in an optimal position for subsequent measurements. Each image's quality was evaluated using a scoring system developed for the Antillean manatee (Landeo-Yauri et al., 2020). Scores were assigned based on resolution (sharpness), distortion (portion of the body distorted by water movement), contrast (range of tones), visible portion of the individual (coverage of body parts by turbidity and/or light reflection, termed 'partial') and angle (camera angle) (Fig. S2). The scores were summed to obtain an overall quality score for each image (higher values indicating lower quality). Images with an overall score ≥ 17 were excluded (Table S2, Fig. S3).

Body condition index

Body condition is a proxy of individuals' energetic reserves. Individuals with good body condition have higher energy reserves (appearing 'plumper'), leading to higher survival and reproductive success (Schulte-Hostedde et al., 2001). In marine mammals, body condition has been inferred from drone photogrammetry using body surface area indices calculated from parabolic models (e.g. Lemos et al., 2020), three-dimensional volumetric models (e.g. Christiansen et al., 2019) and ratios of body measurements (e.g. Serres et al., 2024). Only the latter approach has been applied to sirenians (the Antillean manatees) (Ramos et al., 2022). In the absence of prior drone-based body condition assessments for dugongs, we applied the body condition index (BCI) based on body ratios derived for related manatees, currently representing the only validated index for sirenians:

$$\mathrm{BCI} = \mathrm{UG}/\mathrm{SL}$$

where UG is the umbilical girth, considered as the maximum waist circumference in sirenians (Harshaw et al., 2016), while SL is the straight-line body length from the tip of the snout to the median notch of the caudal fin (Fig. 1). Assuming that sirenians' bodies approximate an ellipsoid with maximum circumference at the umbilicus (Erdsack et al., 2018), UG is obtained by multiplying the maximum body width (MW) by (Harshaw et al., 2016; Ramos et al., 2022):

$$\mathrm{UG} = \mathrm{MW} \times \pi$$

Leading to:

$$\mathrm{BCI} = (\mathrm{MW} \times \pi)/\mathrm{SL}$$

To provide evidence that the BCI is applicable to dugongs, we digitised physical measurements data available in Burgess et al. (2013) for dugongs and Harshaw et al. (2016) for manatees, and we regressed SL against UG, including species as an interaction term before comparing species slopes using a t test.

SL and MW were measured on drone images in pixels using the ImageJ software (https://imagej.net/ij/) by a single analyst. Although SL and MW were originally measured in metres by Ramos et al. (2022), BCI is a unit-less relative index that can be calculated from measurements in any units. To confirm this, we compared BCIs calculated from relative and absolute measurements (in pixels and metres, respectively) for all individuals where altitude was available, allowing conversion of pixels to metres based on ground sampling distance.

To increase accuracy, only individuals that were fully elongated and near image centres were measured to minimise distortion effects (Burnett et al., 2019) (examples in Fig. S4). For each individual, 2–15 replicate measurements (SL and MW) were made on subsequent images, proportional to the number of images where it was in an optimal position. Measurement variability among replicates was quantified by deriving the coefficient of variation (CV) around mean BCI. A basic sensitivity analysis was conducted to assess the impact of SL and MW variations on the calculation of BCI. Specifically, SL or MW were incremented by 1 and the differences between newly obtained and original BCI were calculated.

All individual measurements with their associated image quality score, unique identifier and individual class were compiled in R (version 4.3.3). The mean and standard deviation of BCI were then calculated per individual based on its replicates. Video metadata were appended to the measurements based on the video identifier. The general workflow of the methodology is illustrated in Figure 2.

Body condition predictors

Environmental and anthropogenic predictors known for their potential to explain dugong body condition (Table 1) were collected from global remotely sensed and socio-economic datasets (detailed in Tables S3 and S4). Predictors included mean water temperature, the human gravity index (herein 'gravity'), an integrated proxy of human pressures on tropical reefs estimated as a ratio between human population density and the proximity of these populations to reefs (Cinner et al., 2018), gross domestic product (GDP) per capita and the percent coverage by marine protected areas (MPAs). Though seagrass is a potential driver of dugong body condition, we did not include it because reliable seagrass data are still lacking at a global scale. To associate predictors with dugong body condition, a buffer was created around the location of each dugong observation. The buffer radius was set to 26 km, corresponding to the maximum average distance travelled by a dugong from its capture site compiled from multiple telemetry studies (Marsh, 2022). All predictors were compiled within this buffer, except GDP per capita that was directly assigned based on the province of observation (Table S3).

Statistical analyses

Statistical tests

To test for the effects of individual class, geographic location, country and genetic cluster (Srinivas et al., 2021) on dugong BCI, non-parametric Kruskal–Wallis tests were implemented in R, considering subgroups with at least 10 observations. Dunn post-hoc tests with Bonferroni correction were further performed to identify significant variations in body condition between the modalities of these factors. The association between the BCIs of females and

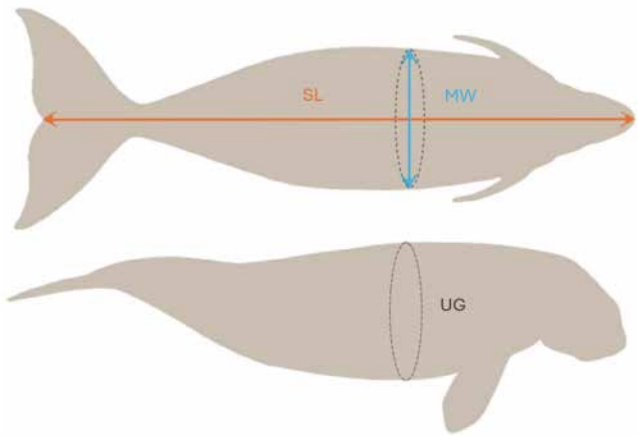

Figure 1. Illustration of morphometric measurements to derive the body condition index of dugongs. (A) Straight-line body length (SL) and maximum width (MW) were measured for each dugong in dorsal view on drone images. (B) Umbilical girth (UG) (not measured on drone images) is related to MW through multiplication by π. Images adapted from Encyclopedia Britannica 2001 (https://www.britannica.com/animal/sirenian).

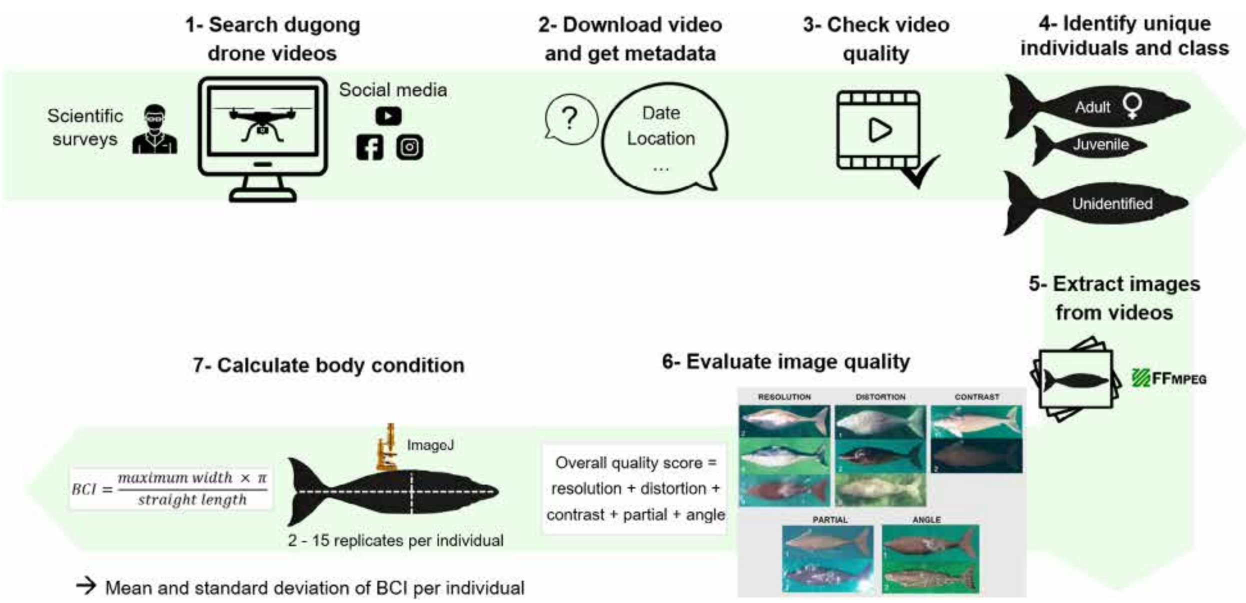

Figure 2. General workflow to determine the body condition index (BCI) of dugongs from drone images.

their offsprings was tested by computing the R-square of their linear regression.

Statistical modelling

Generalised linear mixed-effects models (GLMMs) were built to relate dugong BCI to environmental and anthropogenic predictors (Table 1). GLMMs were run in R using the glmmTMB package (Brooks et al., 2017). Dugong BCI was log-transformed to achieve normality and modelled with a Gaussian distribution. Candidate models with all possible combinations of non-collinear predictors were fitted. Predictor collinearity was assessed by calculating Pearson correlation coefficients between all pairs of predictors (Zuur et al., 2010). When the correlation coefficient exceeded |0.7|, only one predictor from the pair was included at a time in the same model. Collinearity was further assessed by calculating the variance inflation factor (VIF) for each predictor, a VIF below 5 indicating low correlation, a VIF between 5 and 10 indicating moderate correlation, and a VIF above 10 indicating a high correlation (Zuur et al., 2010). Both linear and second-order polynomial relationships were tested for all predictors. Individual class and month were included as

Table 1. Main rationale and expected relationships for environmental and anthropogenic predictors used to model dugong body condition.

Predictor (abbreviation)	Unit	Rationale	Expected relationship with dugong body condition
Mean water temperature (temperature)	Celsius degree	Temperature affects sirenians' body condition via thermoregulation, with individuals from cooler environments exhibiting better body condition (Harshaw et al., 2016; Lanyon et al., 2006; Zeh et al., 2018). Water temperature also affects the growth and quality of seagrass (Danaraj et al., 2021), with indirect effects on dugong foraging success and thus body condition	Decreasing temperature leads to *increasing* body condition
Mean human gravity (human_grav)	Inhabitants/minute^2	Areas with high human gravity have degraded seagrass and polluted waters (Lincoln et al., 2021), Degraded seagrass habitats lead to decreased foraging success and ultimately poorer condition of dugongs	Increasing human_grav leads to *decreasing* body condition
Gross domestic product per capita (gdp_per_capita)	US Dollars	Low GDP per capita is representative of less developed countries where coastal communities use gillnets that are harmful for dugongs (Trotzuk, Findlay, et al., 2022) or directly predate dugongs for food (Moore et al., 2018). Fishing-induced population decline can lead to a decrease in population fitness mediated by an Allee effect, that can be reflected in the poorer body condition of animals (Nagel et al., 2021)	Decreasing gdp_per_capita leads to *decreasing* body condition
Coverage of marine protected areas (perc_mpa)	Percentage	Areas with low proportions of MPAs are more likely to have unregulated human activities, for example, construction, ship traffic, fishing that degrade seagrass habitats, disturb dugongs or kill them. Degraded seagrass habitats lead to decreased foraging success and poorer condition of dugongs. Disturbances caused by ship traffic or other activities increase energy expenditures of animals, leading to poorer body condition (Serres et al., 2024). Population decline due to excessive mortality may lead to a decreased fitness, which can be reflected in poorer body condition (Nagel et al., 2021)	Decreasing perc_mpa leads to *decreasing* body condition

categorical factors to account for individual and seasonal variations in body condition. The individual identifier was included as a random effect to account for repeated measurements of individuals (Carroll et al., 2024).

A forward and backward variable selection procedure based on Akaike Information Criterion (AIC) was implemented using the stepAIC function from the MASS package (Ripley et al., 2024). All candidate models were ranked according to their AIC, and the lowest AIC model was selected as the best model. Residual diagnostics of the best model were produced using the DHARMa package (Hartig & Lohse, 2022), which uses a simulation-based approach to derive interpretable residuals for GLMMs. Three tests were performed: a Kolmogorov–Smirnov test to evaluate the conformity of the residuals' distribution, a dispersion test to evaluate if the simulated dispersion matched the observed dispersion and an outlier test to check if there were more outliers than expected in the simulation. The presence of spatial autocorrelation in residuals was tested by calculating the Moran's I Autocorrelation Index using the ape package (Paradis et al., 2024).

Results

Overview

Two hundred and twenty-eight videos of dugongs were collected in total, of which 131 (59%) passed the quality check (see Table S1 and Fig. S1). Videos were recorded in 70 different geographic locations originating from 18 countries out of the 34 with confirmed resident dugong populations (i.e. 53%) (Fig. 3A). The most represented countries were Australia (22.6%), Indonesia (20.9%) and Saudi Arabia (9.7%). The majority of videos (77.6%) came from social media (39.5% from Instagram, 23.9% from YouTube and 11.2% from Facebook), while the remaining videos (22.4%) originated from scientific surveys. For some countries, all videos originated from social media (e.g. India and Palau), while for others (e.g. Seychelles, Saudi Arabia and Malaysia) all videos came from scientific surveys (Fig. 4). Three countries (Mozambique, Indonesia and New Caledonia) had videos from both sources. Videos were collected by various users, including amateurs (26.9%), NGOs (18.7%), photographers (17.9%) and

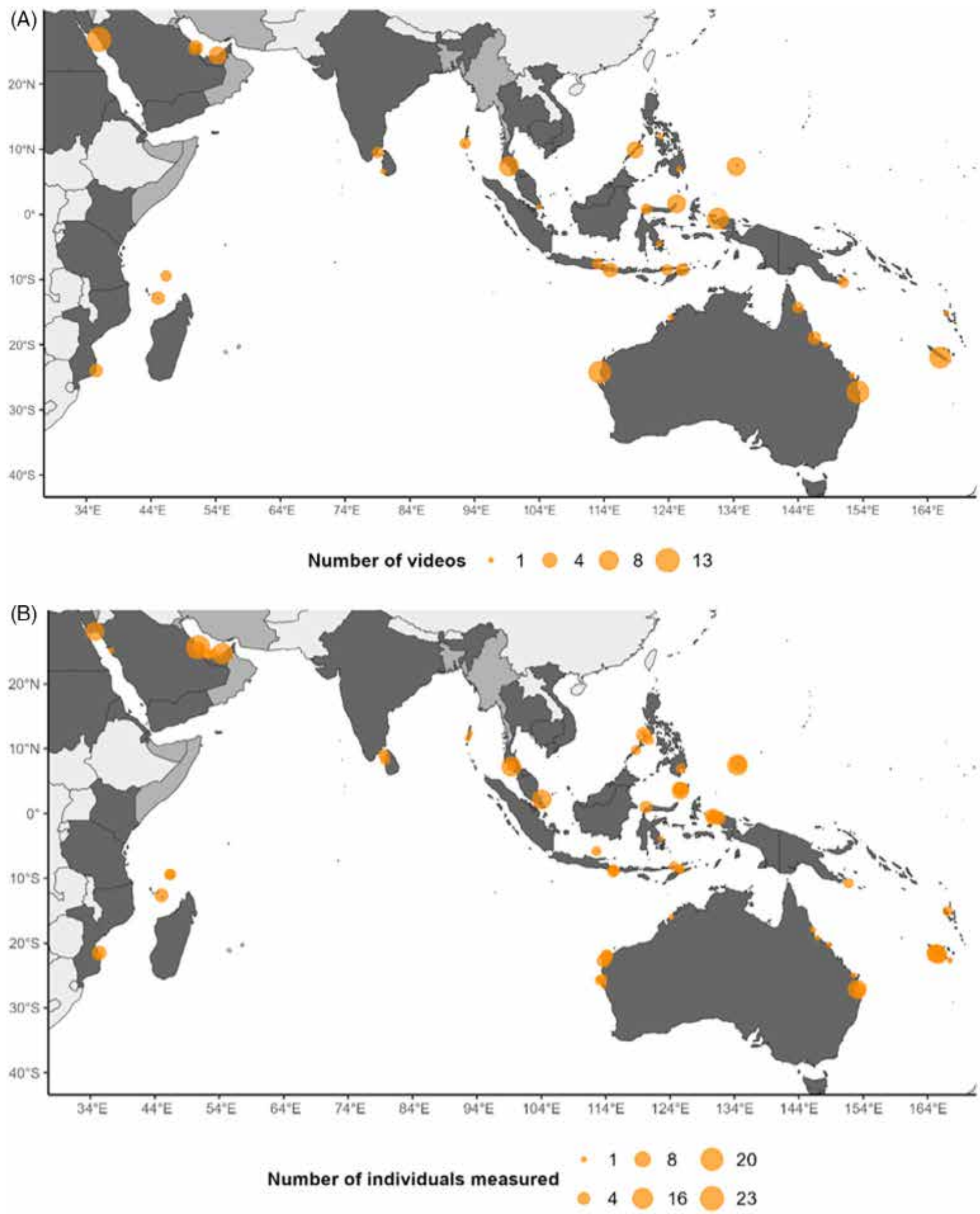

Figure 3. Geographic locations of dugong observations depicting (A) the number of available videos and (B) the number of individual dugongs measured (circle size scaled to quantity). To avoid overlapping circles, locations were mapped at the scale of administrative provinces rather than based on their specific geographic coordinates. Countries with confirmed resident populations ($n = 34$) and unconfirmed populations ($n = 7$) (Marsh et al., 2024) are shown in dark grey and light grey, respectively. Countries where the dugong is not present are shown in very light grey.

academics (11.2%). Videos contained on average 6 individual dugongs (SD = 13, range = 1 to 100 in Qatar).

A total of 949 dugong images were extracted from these videos, of which 23 (2.5%) were excluded due to low overall quality scores (≥17), resulting in 926 dugong images (mean quality score = 9.9, SD = 2.8) (e.g. Table S2; Fig. S3). There was no significant difference in quality between images derived from social media and scientific surveys (Kruskal–Wallis test: $\chi^2 = 2.04$, P-value = 0.15). In this study, 1200 measurements (SL and MW) were taken from the 272 individual dugongs (mean replicates = 4.4, SD = 1.5, range = 2–15) (Fig. 3B) of which 11 were assumed to be the same based on drone pilot and date. In total, 21.3% of the measured

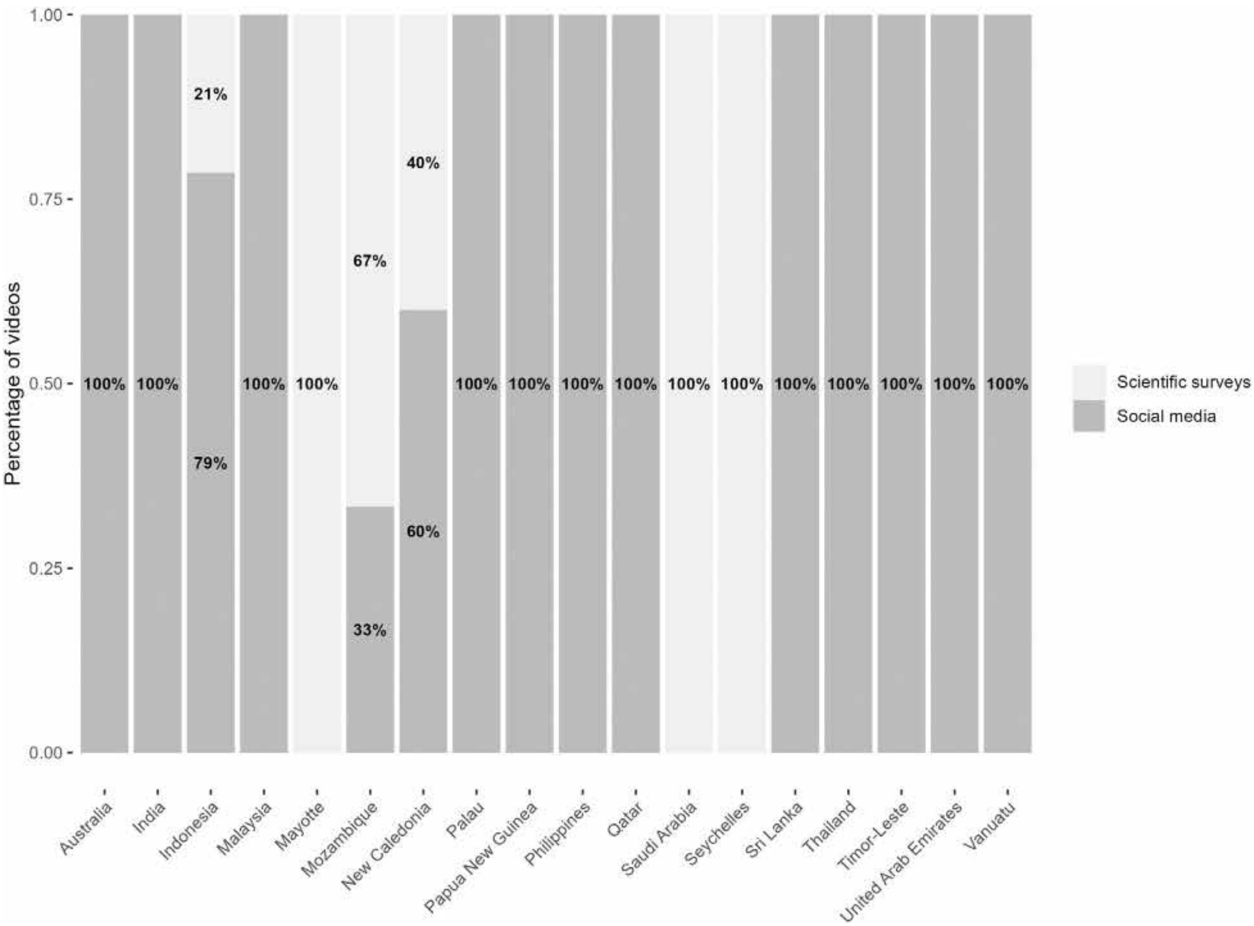

Figure 4. Data origin of videos per country.

individuals were adult females, 20.2% were juveniles and 58.5% were unidentified.

Dugong BCI ranged from 0.54 to 0.97 across individuals (mean = 0.75, SD = 0.08, CV = 0.10). The regression slopes of SL against UG were non-significantly different between dugongs and manatees (Fig. S5) (P-value = 0.19), indicating that the BCI model is applicable to dugongs. BCIs calculated from absolute and relative measurements yielded nearly identical values (R^2 of linear regression = 0.999; Fig. S6), confirming that the index was independent of the measurement unit. Variability from repeated measurements of individuals had limited effects on mean BCI (CV = 0.05). The sensitivity analysis indicated that BCI was four times more sensitive to MW than to SL. BCI did not significantly differ between images from social media and scientific surveys (Kruskal–Wallis test: $\chi^2 = 0.01$, P-value = 0.93). Overall image quality and resolution had no significant effects on BCI (Kruskal–Wallis test: $\chi^2 = 16.7$, P-value = 0.08 and $\chi^2 = 4.09$, P-value = 0.77, respectively).

Global patterns of dugong body condition

BCI significantly differed between countries (Kruskal–Wallis test: $\chi^2 = 76.39$, P-value < 0.01). Dugongs from New Caledonia, the United Arab Emirates and Australia exhibited the best body conditions (mean BCI ≥ 0.80) (Fig. 5). Those from Qatar, Vanuatu, Mayotte (France), the Philippines, Malaysia (peninsular side), Saudi Arabia (Red Sea coast), Seychelles, Thailand, India and Indonesia were in intermediate condition (mean BCI between 0.7 and 0.8). In contrast, dugongs from Palau, Mozambique, Papua New Guinea, Sri Lanka and Timor-Leste had the poorest body conditions (mean BCI ≤ 0.7), though sample sizes were very low in the latter three countries. Within countries, BCI was not significantly different between sampled geographic locations except in Palau (Kruskal–Wallis test: $\chi^2 = 7.98$, P-value < 0.01) (Fig. S7). Overall, the magnitude of differences in BCI between countries (0.19 units) was similar to or higher than differences within countries (e.g. New Caledonia = 0.14 units, Palau = 0.12 units, Qatar = 0.08 units), except for Indonesia

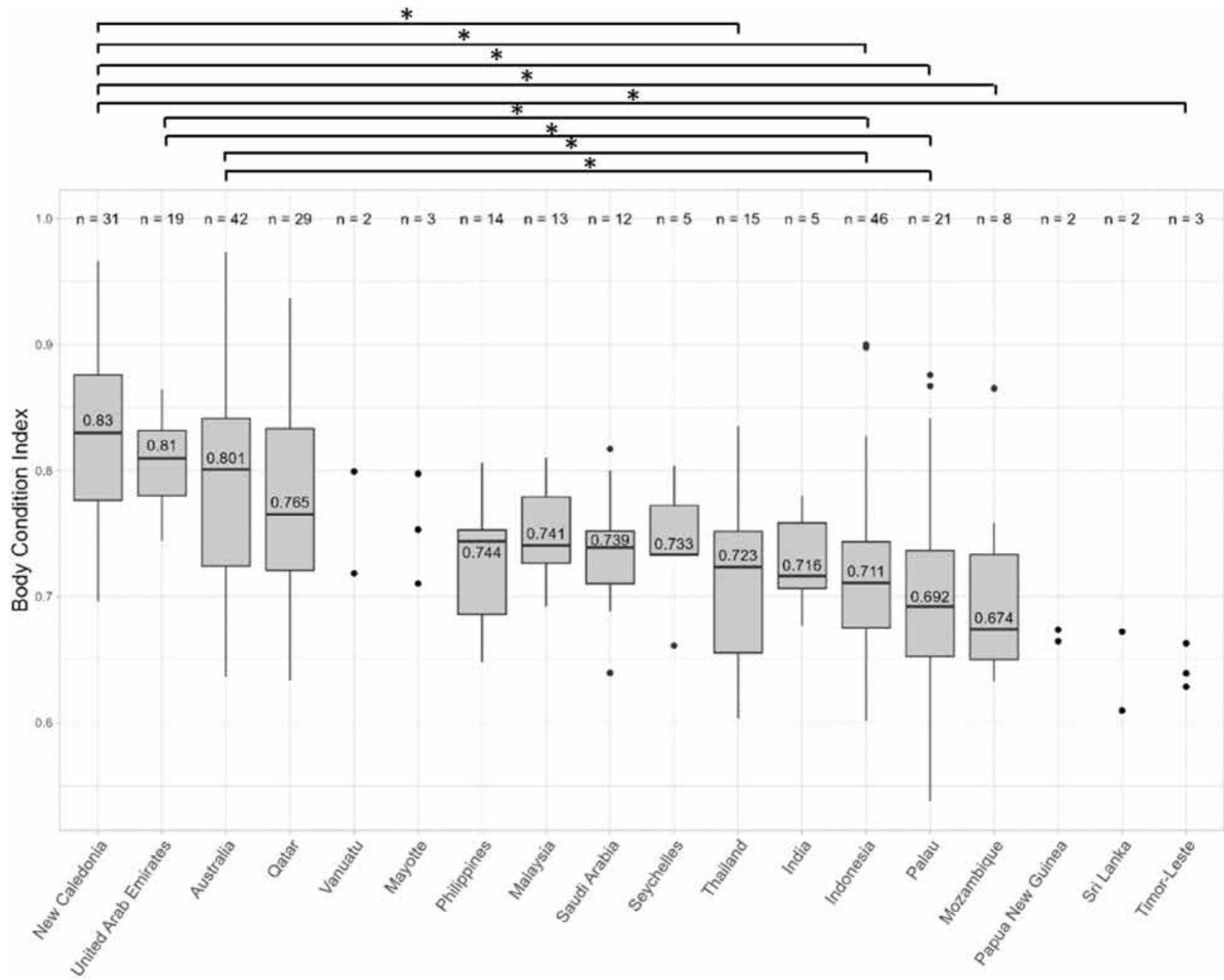

Figure 5. Variability of body condition index across countries (n: number of individuals measured). Each boxplot represents the 1st and 3rd quartiles; the dark line inside each box is the median (associated value); vertical bars indicate the range of data excluding outliers represented by black dots; the height of the box indicates the interquartile range. Results of significant (*P*-value <0.01) Dunn post hoc tests between countries are indicated by asterisks. When the sample size is ≤ 4, boxplots are not drawn and individual values are represented as dots.

(0.29 units). BCI also significantly differed between genetic clusters (Kruskal–Wallis test: $\chi^2 = 38.39$, *P*-value <0.01), being highest in the Pacific cluster and lowest in the South Asia cluster (Fig. S8).

BCI significantly differed between classes of individuals (Kruskal–Wallis test: $\chi^2 = 14.66$, *P*-value <0.01). Juveniles had the highest BCI (mean = 0.79, SD = 0.07) followed by adult females (mean = 0.75, SD = 0.07) and unidentified individuals (mean = 0.74, SD = 0.08). Moreover, higher BCI in females appeared to be associated with higher BCI in juveniles (Fig. S9; R^2 of linear regression = 0.41).

Drivers of dugong body condition

Temperature and GDP per capita were collinear (Pearson correlation coefficient = −0.73) so they could not be included in the same model. Therefore, four candidate models of dugong body condition were fitted. The model including GDP per capita, percent coverage of MPAs and human gravity as polynomial terms was selected as the best model (marginal and conditional R^2 of 0.318 and 0.791, respectively) (Table 2, Fig. S10). Residual diagnostics revealed no anomalies regarding normality, dispersion, homoscedasticity, geographic distribution (Fig. S11) or spatial autocorrelation (Moran's I autocorrelation test: *P*-value = 0.22).

All model predictors exhibited significant relationships with BCI (Fig. 6). BCI was highest for juveniles and for months spanning from June to October. BCI increased with GDP per capita in the core range of the data, reaching a plateau around 70,000 US dollars before showing a highly uncertain decrease supported by a single data

Table 2. Ranking of generalised linear mixed-effects models for log-transformed body condition index (BCI).

Model name	Model formula	AIC	ΔAIC	Marginal R^2	Conditional R^2
2poly	log(BCI) ~ poly(gdp_per_capita, 2) + poly(perc_mpa, 2) + poly(human_grav, 2) + month + indiv_class + (1lindiv_id)	−2598.98	0	0.318	0.791
1poly	log(BCI) ~ poly(temperature, 2) + poly(perc_mpa, 2) + poly(human_grav, 2) + month + indiv_class + (1lindiv_id)	−2588.80	10.2	0.281	0.791
2linear	log(BCI) ~ gdp_per_capita + perc_mpa + human_grav + month + indiv_class + (1lindiv_id)	−2571.72	27.3	0.249	0.790
1linear	log(BCI) ~ temperature + perc_mpa + human_grav + month + indiv_class + (1lindiv_id)	−2569.59	29.4	0.227	0.790

AIC, Akaike Information Criterion; ΔAIC, difference in AIC with to the best model; Marginal R^2, coefficient of determination for variance explained by fixed effects; Conditional R^2, coefficient of determination for variance explained by fixed and random effects; poly(predictor, 2), second-order polynomial function of given predictor; 1lindiv_id, random effect on individual id. Model '2poly' was selected as the best model (its model coefficients are shown in Fig. S10).

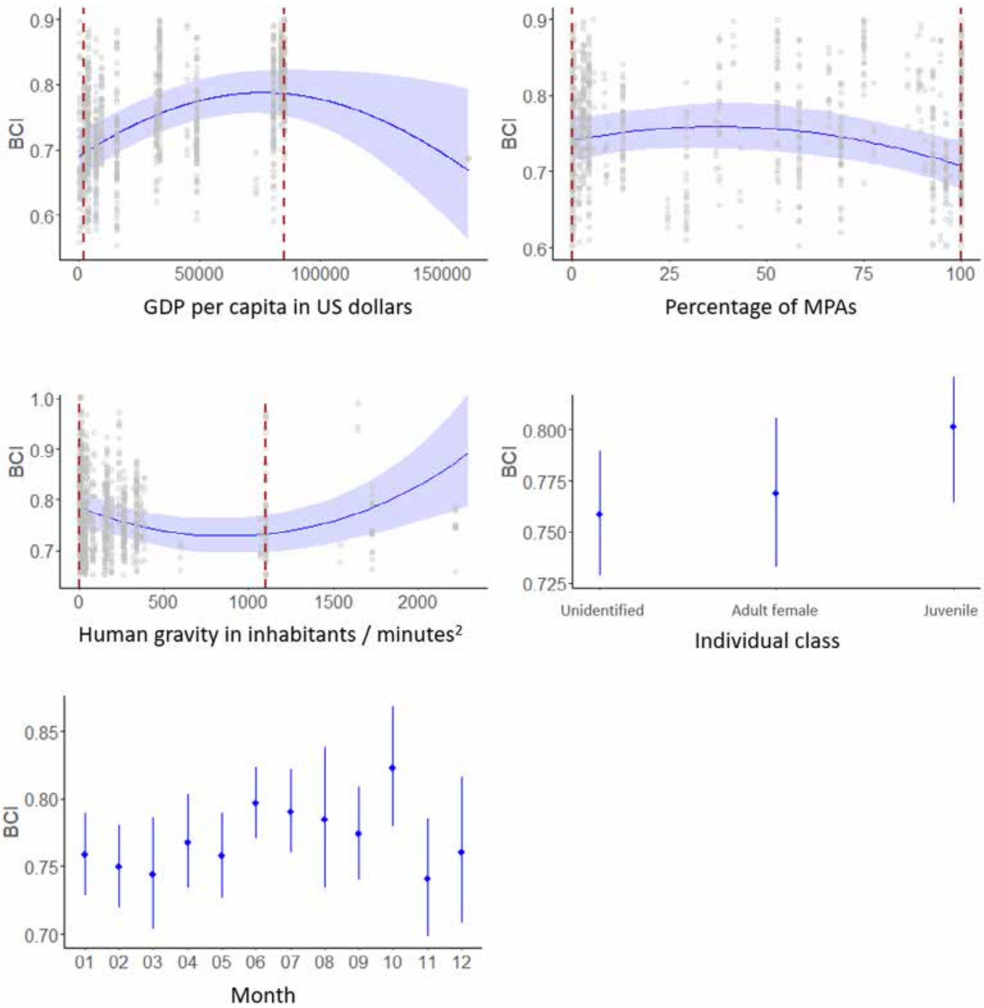

Figure 6. Estimated relationships between dugong body condition index (BCI) and significant predictors from the best model. For continuous predictors, the shaded blue area represents the 95% confidence intervals around the estimated mean (solid blue line), grey dots are the data points and brown vertical dashed lines are the 5th and 95th quantiles. Wider confidence intervals beyond the 95th quantile for GDP per capita and human gravity indicate high uncertainty in the estimated relationships. For categorical predictors, the dots and the vertical lines represent the mean and the 95% confidence intervals, respectively.

point. BCI showed a dome-shaped relationship with percent coverage of MPAs, peaking around 40%. BCI decreased with human gravity up to values of c. 800 inhabitants/minutes^2 within the core range of our data, then showed an uncertain increase supported by little data. We further added country as an interaction term with human gravity to investigate country-specific differences (Fig. S12). In the United Arab Emirates, BCI exhibited a U-shaped relationship, with an increase in BCI despite high human gravity. In contrast, the relationship was dome-shaped in New Caledonia and the Philippines, indicating negative impacts of high human gravity on BCI. Other countries had weaker relationships with human gravity.

Discussion

We present the first global evaluation of dugong body condition, highlighting the value of drone photogrammetry for monitoring this elusive and endangered species. The collection of drone footage from both scientific surveys and social media allowed us to measure 272 dugongs in countries spread over the species' entire range, from easternmost Mozambique to westernmost Vanuatu. Our study is also the first to explicitly model the effects of environmental and anthropogenic drivers on the body condition of the dugong. While previous studies on marine mammals modelled potential drivers of body condition (e.g. Akmajian et al., 2021; MacMillan et al., 2023; Wachtendonk et al., 2022), mostly environmental drivers were investigated. Here, we highlight new potential anthropogenic drivers like marine protected area coverage, gross domestic product and human gravity.

Methodological considerations

Our study pioneers the use of social media as a source of data to assess the body condition of marine mammals globally when scientific surveys are scarce. Yet, a rigorous selection process is required to ensure social media data's quality aligns with that of scientific surveys (Tables S1 and S2). Marine mammals, as charismatic species, generate significant activity on social media (Otero et al., 2024). The growth of ecotourism, affordable drones and high-speed internet have increased the sharing of marine mammal footage online. While social media footage has been used to derive species occurrences, mortality, traits and behaviour (Cranswick et al., 2022; Sullivan et al., 2019; Węgrzyn et al., 2023) or training datasets for deep learning models (Mannocci et al., 2021), it remains an under-explored data source for body condition studies. Combined with scientific surveys, social media provided a substantial number of images (n = 926) for deriving morphometric measurements of dugongs.

Among the 34 countries with confirmed resident dugong populations (Marsh et al., 2024), many host very small populations (e.g. Comoros, Kenya and Cambodia), making sightings difficult to record for social media users and scientists alike. Some countries, such as Egypt and Saudi Arabia, prohibit drone use or have very strict drone regulations while others (e.g. Sudan and Timor-Leste) have limited tourism and research efforts, leading to geographic gaps in our sampling. Scientific surveys were crucial for filling gaps in areas where tourism is limited, such as in Aldabra, where access is restricted. Despite our effort to expand the geographic coverage, the number of collected images in each location was limited. In locations where the dugong is relatively abundant (e.g. Australia and Persian Gulf), the ratio of sample size to population size was low. In locations where the species is rare but significant field efforts led to observations, the ratio was higher. This is the case of Mayotte where the three recorded individuals represent nearly one third of the estimated local population (c. 10 individuals) (Marsh et al., 2024). Overall, caution is needed to interpret these findings due to low sample sizes and continuing data collection is necessary for better generalisation.

Several drawbacks arise from the opportunistic nature of social media footage. Social media images lack altitude data, leading us to use measurements in pixels to derive BCI. Nevertheless, BCI is a unit-less relative index that can be derived from both metric and pixel measurements (Kotik et al., 2023; Lemos et al., 2020; Vermeulen et al., 2023). Our comparison of BCIs calculated from absolute and relative measurements confirm the negligible impact of measurement unit (Fig. S6). The absence of altitude data also prevents quantifying measurement errors related to altitude (Bierlich et al., 2021). Nevertheless, the variability from repeated measurements of individuals on different images (potentially taken at different altitudes) has limited effects on mean BCI (CV = 0.05). We explicitly account for this measurement variability in our GLMM as part of the random effect. Our sensitivity analysis further indicates that BCI is four times more sensitive to MW than to SL, highlighting the importance of accurate MW individual measurements. Camera lens distortion and animal body position are important sources of measurement uncertainty (Burnett et al., 2019). We sought to minimise them by measuring only individuals that were fully flat and elongated near image centres. Finally, though we accounted for individual replicates based on drone pilot and video collection date, we cannot rule out the possibility of having counted individuals more than once, leading to pseudo-replication.

One important limitation is the lack of a validated BCI for the dugong, as the only sirenian drone-based assessment was conducted on captive Antillean manatees (Ramos et al., 2022). Unlike manatees, dugongs rarely survive in captivity, preventing the rectification of drone measurements with actual physical measurements. Physical measurements may be carried out through capture and release of wild dugongs, but such studies are challenging and invasive as they need to be lifted out of water (Burgess et al., 2013; Lanyon et al., 2010). For these reasons, we could not obtain physical measurements for comparison with our drone measurements. Nevertheless, we provide some evidence that the BCI model developed for manatees is also applicable to dugongs (Fig. S5). A relative BCI derived for wild dugongs based on umbilical girth and straight body length (Burgess et al., 2013) also stressed the value of such measurements for assessing body condition. Alternatively, body condition could be derived by estimating a body surface area index, as done for whales (Burnett et al., 2019; Kotik et al., 2023; Torres et al., 2022), though this technique has never been applied to sirenians. To ultimately validate our application of the BCI model to dugongs, drone measurements should be compared with physical measurements of wild animals in relatively high abundance areas (e.g. Australia and Persian Gulf), proceeding with care and strict compliance with ethical rules.

Global geographic patterns of dugong body condition

Our study demonstrates significant variability in dugong body condition among countries (Fig. 5), which can be related to the size of putative populations. Countries with relatively high BCI have large, relatively healthy populations (Australia $\sim$165,000 individuals; Persian Gulf encompassing United Arab Emirates and Qatar $\sim$5400 individuals (Marsh et al., 2024)), though our sample sizes are small relative to population sizes. In the Red Sea coast of Saudi Arabia that hosts an estimated population of $\sim$1800 individuals (Preen, 1989), dugongs exhibit intermediate body conditions. In Mozambique where the population counts around 400 individuals (Trotzuk, Findlay, et al., 2022), dugongs have one of the poorest body conditions. In most other countries with small populations (e.g. India, Indonesia and Seychelles), body condition is relatively low, although the lack of data on population size precludes further interpretation. One exception is New Caledonia where individuals show the highest BCI despite a modest population of $\sim$1200 individuals (Cleguer et al., 2017). While our analysis was conducted per country, additional studies are warranted at the population level, as one country may host several populations (e.g. Australia; Seddon et al., 2014) with significant body condition variations between them.

Similar connections between body condition and population size have been suggested in other marine mammals. For example, body condition is poorer in declining populations of Indo-Pacific humpback dolphins impacted by cumulative anthropogenic pressures than in apparently stable populations (Serres et al., 2024). Similarly, exposure to anthropogenic pressures likely contributes to the low body condition of individuals from the depleted population of North Atlantic right whales compared to healthier southern right whales (Christiansen et al., 2020). One study also shows that pinnipeds from a small breeding colony have poorer body conditions compared to those from a larger adjacent colony, possibly reflecting an Allee effect, that is, a decrease in fitness as population density declines (Nagel et al., 2021). Both intrinsic factors (e.g. Allee effect) and extrinsic factors (anthropogenic and environmental) may contribute to the poorer body condition of dugongs observed in smaller populations. Whether declining populations lead to poorer body condition or poorer body condition is symptomatic of populations decline remains an open question. Variations in dugong body condition may also be due to genetic differences between populations, as dugongs exhibit considerable genetic diversity across their geographic range (Srinivas et al., 2021). We show that body condition significantly differs between dugongs from putative genetic clusters, with the highest BCI for the Pacific cluster and the lowest BCI for the South Asia cluster (Fig. S5). Genetic dissimilarity between marine mammal populations can manifest through morphological disparities (e.g. Foote et al., 2009), potentially inducing differences in body condition. Although morphological differences between dugong genetic clusters have not been studied, they may play a role in observed body condition variations.

Finally, our study demonstrates variability in body condition between individual classes, highlighting higher BCI in juveniles than in adult females. Juveniles may have greater energy reserves to meet their thermoregulation needs, as seen in harbour porpoises (McLellan et al., 2006), leading to higher BCI than in adults. The energetic investment of females in parental care may also explain their relatively poorer body condition. In right whales, female in better condition invest more resources in parental care and lactation, ultimately leading to juveniles in better condition (Christiansen et al., 2018). This pattern seems to hold true for dugongs (Fig. S9). However, the lack of sex and age class identification for individuals observed alone (lumped into the 'unidentified' category) prevents interpretations on sex ratios or size structures of populations. While sex can only be identified by visual examination of genitalia visible on the ventral surface (Lanyon et al., 2009), age class may be derived from absolute size measurements in drone images combined with age information obtained from captured individuals (Vivier et al., 2023).

Potential drivers of dugong body condition

Marine protected areas can improve the health state of seagrass (Daru & le Roux, 2016), potentially leading to improved foraging success and better condition of dugongs. The implementation of MPAs can also lead to the reduction or ban of harmful gillnets (Trotzuk, Findlay, et al., 2022), reducing the risk of population decline that may lead to poorer body condition through an Allee effect (Nagel et al., 2021). Along these lines, we find an increasing BCI up to 40% of MPA coverage followed by a decrease, suggesting that extensive spatial protection is not sufficient to maintain dugongs in good energetic state. Future studies should address the effects of MPA coverage in more details, as multiple types of MPAs could affect dugong condition in multiple ways.

In locations with higher GDP per capita, coastal communities are less likely to heavily depend on marine resources and to use harmful fishing gear (MacNeil et al., 2020), reducing the risk of population decline and induced body condition decrease. We highlight a positive relationship between BCI and GDP per capita at the core range of the data (indicated by the 5th and 95th quantiles in Fig. 6). The subsequent decrease is highly uncertain as it is associated with a single data point (from the Whitsunday province in Australia), making interpretations difficult and urging the need for additional data collection in wealthier provinces. With increasing economic wealth, other usages like vessel traffic and tourism may intensify, with potential negative effects on dugong condition. Quantification of the presence of boats and surface gillnets through satellite-based monitoring (Zucchetta et al., 2025) would allow incorporating these more direct predictors into the models.

Human gravity reflects human pressures on tropical reefs, influenced by population density and reef remoteness (Cinner et al., 2018). We hypothesised that areas with high human gravity were more likely to have degraded seagrass beds and polluted habitats (Lincoln et al., 2021), leading to decreased foraging success and thus poorer condition of dugongs. In accordance with this hypothesis, BCI decreases with human gravity at the core range of the data (Fig. 6). The subsequent uncertain increase beyond 1000 inhabitants/minutes^2 appears supported by little data (from Indonesia and the Philippines). We also stress differing relationships between countries (Fig. S12). We find an increasing relationship with higher human gravity values in the United Arab Emirates but decreasing relationships in New Caledonia and the Philippines. This apparent inverted pattern may be due to stronger dependence on marine ecosystems in small insular states like New Caledonia and the Philippines (Selig et al., 2019) where human pressures on tropical reefs may be more detrimental to dugongs.

Conclusions

We provide the first assessment of dugong body condition at the Indo-Pacific scale, underlining the value of drone photogrammetry as a non-invasive, fast and affordable approach for monitoring populations and investigating the pressures affecting them. Our country-level analysis shows that dugongs from smaller populations are in relatively poorer condition than dugongs from larger, less threatened populations. Our study also unlocks the potential of social media as a rich and underused source of footage for evaluating marine mammal body condition globally. Our statistical models further reveal that MPA coverage, GDP per capita and human gravity are potential drivers of dugong body condition. Continuing data collection in already sampled but also in new locations will be key to assess the generalisation of these findings. Future studies should be conducted at finer spatial scales to investigate local drivers of dugong body condition and examine subpopulation effects that can undermine correlations with predictors at the larger scale. Assessing seasonal effects will also be important, as season was found as a predictor of body condition in marine mammals (de Oliveira et al., 2023; Lemos et al., 2020; Serres et al., 2024), stressing the need for continuous monitoring.

As many dugong populations remain unassessed, a perspective of this study is to develop a novel indicator of conservation status based on body condition measurements by drone. This indicator would provide a proxy and early warning signal for population health on shorter time scales than traditional abundance surveys, facilitating prompt conservation actions. Finally, the assessment of dugong body condition could be further accelerated by using deep learning techniques to automate measurements, as recently done for whales (Bierlich et al., 2024).

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Author Contributions

LM, CG and DM conceived the ideas and designed the methodology; CG, LB, TB, CB, HC, RH, AK, AJM, DN, MRN, LP, AS, MS, ET, NAZ and LM collected the data; LM and CG analysed the data; LM and CG led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Conflict of Interest

Authors have no conflicts of interest to declare.

Data Availability Statement

The tabular data (excluding sensitive geographic locations) and R code to reproduce the analysis is available at https://github.com/LauraMannocci/dugong_condition. Original videos are accessible from their corresponding URLs available in the tabular data for those extracted from social media and through requests to co-authors for those derived from scientific surveys.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Data S1. Supporting information.

