Ocean and Coastal Management 211 (2021) 105750

Contents lists available at ScienceDirect

Ocean and Coastal Management

journal homepage: www.elsevier.com/locate/ocecoaman

Primary Research Article

Quantifying human use of sandy shores with aerial remote sensing technology: The sky is not the limit

Euan J. Provost[a,*], Melinda A. Coleman[b], Paul A. Butcher[b], Andrew Colefax[c], Thomas A. Schlacher[d], Melanie J. Bishop[e,f], Rod M. Connolly[g], Ben L. Gilby[d], Christopher J. Henderson[d], Alan Jones[h], Mariano Lastra[i], Brooke Maslo[j], Andrew D. Olds[d], Brendan P. Kelaher[a]

[a] Southern Cross University, National Marine Science Centre and Marine Ecology Research Centre, Coffs Harbour, NSW, Australia
[b] New South Wales Department of Primary Industries, National Marine Science Centre, Coffs Harbour, NSW, Australia
[c] Sci-eye, Lismore, NSW, Australia
[d] School of Science and Engineering, University of the Sunshine Coast, Maroochydore DC, 4558, Queensland, Australia
[e] Dept of Biological Sciences, Macquarie Univ., North Ryde, NSW, 2109 Australia
[f] Sydney Inst. of Marine Science, Mosman, NSW, 2088, Australia
[g] Australian Rivers Institute - Coast & Estuaries, School of Environment & Science, Griffith University, Gold Coast, 4222, Queensland, Australia
[h] Marine Ecology, Australian Museum, 6 College Street, Sydney, NSW, Australia
[i] Estación de Ciencias Marinas de Toralla (ECIMAT), Universidade de Vigo, 36331, Vigo, Spain
[j] Department of Ecology, Evolution and Natural Resources, Rutgers, The State University of New Jersey, 14 College Farm Road, New Brunswick, NJ, 08901, USA

ARTICLE INFO

Keywords:
Beach use
Beach management
Coastal management
Unmanned aerial vehicle
Drone
UAV
Aerial image.

ABSTRACT

Understanding the use of sandy beaches underpins strategies for effective management of this valuable ecosystem. In this context, remote-sensing platforms and aerial imagery could, theoretically, provide novel and cost-effective solutions to identify and map beach visitor use. Recreational beach use patterns were examined using data collected via an established drone-based method and from commercial orthomosaic images collected via crewed aircraft to assess the practicality of these methods. Our study encompassed ~780 km of east Australian coastline and assessed 73,021 beach visitors to find similar participation rates in sunbathing (46.3 vs 47.7%), walking (21.8 vs 18.6%), swimming (20.9 vs 19.5%), surfing (10.7 vs 14.0%) and fishing (0.3 vs 0.1%) when measured by drones or crewed aircraft, respectively. The larger spatial coverage of crewed aircraft was a distinct advantage that allowed mapping of geographic patterns in beach use for thirteen sites separated by 100s of kilometres. Beach visitation was significantly influenced by season, weekend/public holidays, temperature, solar radiation, beach area, size of households adjacent to beaches, and time of day. Both drones and crewed aircraft are practicable tools for sandy shore management, providing complementary solutions to generate visitor-use data at multiple scales that can be used to optimise recreational service provisions and better support environmental conservation strategies.

1. Introduction

Sandy beaches dominate many coastlines and contribute measurably to coastal economies (Lucrezi et al., 2016; Rodella et al., 2020). The high social and environmental value of beaches creates a formidable management challenge – balancing expectations for recreation against conserving sensitive habitats and wildlife (McLachlan et al., 2013; Pérez-Maqueo et al., 2017; Schlacher et al., 2014). As beach management is often limited by resource availability (i.e. staff, equipment, access and infrastructure), data on the spatial distribution and temporal patterns of visitor numbers are essential to efficiently deploy services that enhance the user experience and protect the environment. Accurately identifying the patterns of recreational beach use can facilitate a better understanding of the impacts of human activity on wildlife (Christiansen and Lusseau, 2015; Ciuti et al., 2012; Meager et al., 2012; Schlacher et al., 2011; Schlacher et al., 2013), inform management

* Corresponding author.
E-mail address: euanjprovost@gmail.com (E.J. Provost).

https://doi.org/10.1016/j.ocecoaman.2021.105750
Received 8 November 2020; Received in revised form 20 May 2021; Accepted 28 May 2021

decisions regarding the placement of conservation zones, and limit access to protect sensitive species from human disturbance (Maslo et al., 2018).

Recreational beach visitation and use is most commonly quantified using direct, on-ground observations (Dwight et al., 2007; King and McGregor, 2012). As a result of recent technological advances, remote-sensing techniques are being used increasingly for cost-effective monitoring in coastal areas (Guillén et al., 2008; Ouellette and Getinet, 2016; Turner et al., 2016). Common platforms include remotely piloted aerial vehicles, hereafter called drones (Butcher et al., 2019; Provost et al., 2019), and fixed cameras (Guillén et al., 2008; Jiménez et al., 2007; Kammler and Schernewski, 2004). While remote monitoring techniques can collect large volumes of high-resolution data (Splinter et al., 2018; Wood et al., 2016), some platforms may not be suitable in certain locations (Andriolo and Elena, 2019). For example, small commercially available drones can establish recreational beach use patterns (Provost et al., 2019), but are often limited by airspace restrictions (e.g. controlled airspace), regulations (e.g. restricted to visual line of sight, not in populous areas), and current technology (e.g. battery life and range, Colefax et al., 2018; Doukari et al., 2019; Duffy et al., 2018). In contrast to drones, crewed aircraft (i.e. aircraft flown by an on-board pilot) can capture data over larger spatial scales with fewer airspace restrictions, but are generally more expensive (Colefax et al., 2018), disruptive (Scobie and Hugenholtz, 2016) and risk the safety of the on-board observers (Kelaher et al., 2020; Watts et al., 2010; Wiegmann and Taneja, 2003). Despite clear benefits of using different monitoring techniques (Donaire et al., 2020), there is no published research comparing the relative strengths and weaknesses of available aerial monitoring platforms to assess patterns of visitor use on sandy beaches.

Advances to sensor technology has increased the availability of high-resolution imagery from aerial remote-sensing platforms (e.g. satellites, crewed aircraft and drones). Existing high-resolution image databases may provide a cost-effective method for monitoring recreational beaches. Although publicly available satellite imagery does not generally have enough resolution to enumerate recreational beach use (Themistocleous et al., 2019), recent advances in large-scale orthomosaic mapping created via low-flying crewed aircraft may be useful. For example, the Nearmap Limited image database contains high-resolution images at regular intervals (up to six times a year) from 2007 to the present for coastal areas within Australia, USA, and New Zealand. These orthomosaic maps provide imagery at 6–7 cm pixel resolution, which is substantially better than satellite data and generally less constrained by cloud cover (Joyce et al., 2018). While the Nearmap database is primarily used for urban planning, mapping vegetation, and development assessments (Davis et al., 2015; Scott et al., 2019), theoretically, it could also be a practical tool for mapping recreational beach use.

Here, we evaluate the use of high-resolution, aerial, orthomosaic imagery to map visitor numbers and the types of recreational activities. We extracted data on visitor numbers and the types of recreational activity for every individual that could be distinguished in aerial images obtained from crewed aircraft (Nearmap covering 2010 to 2020) and compared these to images obtained by small drones. Imagery from crewed aircraft encompasses large swathes of sandy beaches on the east coast of Australia, at scales of 100s–1000s of kms, so has the potential to reveal regional variation in visitor numbers and use types. Current legislation in Australia requires drone operations to be within line of sight, so the utility of drones is generally limited to areas under ~5 km depending on the aircraft and conditions. Imagery collected via crewed aircraft also typically includes different seasons and weather conditions, creating the possibility to investigate temporal changes in visitor numbers and identify the factors shaping beach use. Using the orthomosaic imagery from crewed aircraft, we also test hypotheses about geographic variation and temporal patterns of beach use and identify the environmental and socio-economic factors influencing beach visitation. Our assessment covered ~780 km of coastline, included 500 survey days, and involved 73,021 individual beach visitors.

2. Methods

2.1. Drone-based sampling methods

We sampled five popular recreational beaches with drones (DJI Phantom 4, 1.4 kg quadcopter) in New South Wales Australia (Fig. 1) during the 2017 austral summer (27 Dec '16 to 29 Jan '17), winter (30 Jun '17 to 17 July '17), and spring (23 Sep 17 to 8 Oct '17; usage data was collected in conjunction with a shark surveillance program, see Provost et al., 2019 for further details). Drones operated daily except during inclement weather (e.g. rain or winds over 35 km/h). The beaches surveyed during summer included Seven Mile (Lennox Head), Shelly/Lighthouse (Ballina), Surf/Kendalls (Kiama), and Redhead beach (Redhead). The beaches surveyed during winter and spring were Main/Clarks (Byron Bay), Seven Mile (Lennox Head), and Shelly/Lighthouse beach (Ballina) (Table S1).

Drone flights began at 10:30 a.m. and surveyed ~2 km of beach (including the water section seaward of the surf zone) situated adjacent to the main beach access point (the local Surf Life Saving club of each beach was approximately the mid-point: Table S1). At each beach, a commercially licensed pilot manually flew the drone at a speed of 8 m.s-1 alongshore over the inner surf zone at 60 m altitude, with the camera facing towards the beach to capture people between the foot of the dunes to the swash zone. The drone was then maneuvered further seaward and flew a parallel flight path to capture the in-water users. This generated a U-shaped flight path with the camera facing the same direction. Although there was some video overlap between the two transects, the footage was analysed to ensure there was no double counting. Video data were recorded in UHD resolution (3840 × 2160) at 25 frames per second. Cameras were equipped with circular polarising filters (ND4) to reduce glare.

Videos were all analysed by a single researcher who counted all individual beach goers and classified the activities of each beach user into one of the following categories: 'sunbathing' (people sitting, lying, standing, and engaged in beach games), 'walking' (walking, running, dog walking), 'swimming' (standing, wading, or swimming in the water without a wave-riding board), 'surfing' (surfing, stand-up paddle boarding, bodyboarding, kite surfing), and 'fishing' (holding a rod, bait collection).

2.2. Crewed aircraft imagery methods

High-resolution aerial orthomosaic images from crewed aircraft, supplied by Nearmap Pty Ltd, were also used to quantify people on beaches. Images were captured during overflights and typically had a resolution (GSD 5.8–7.5 cm or better) that was high enough to visually detect shorebirds. As there were only three orthomosaic time points available during the period of drones sampling, we used all the 10 years of sampling to generate appropriate precision. The same individual who analysed the drone footage visually scored all images available before March 2020 using the same categories as in the drone-based methods. Orthomosaic imagery was used to quantify beach use for thirteen locations in NSW: Main/Clarkes (Byron Bay), Seven Mile (Lennox Head), Shelly/Lighthouse (Ballina), Park (Coffs Harbour), Jetty (Coffs Harbour), Sawtell (Sawtell), Flynns/Nobbys (Port Macquarie), Newcastle (Newcastle), Merewether (Newcastle), Redhead (Redhead), City (Wollongong), Surf/Kendalls (Kiama), and Chinamans/Hyams Beach (Hyams Beach) (Fig. 1, Table S1). These thirteen beaches included the five beaches where drone footage was collected to allow the precision of the two methods to be directly compared. All of the beaches in our study were relatively similar, as they are relatively clean, free and well-maintained access, have basic amenities (i.e. toilets and parking), and homogenous morphological attributes (i.e. medium grain sand, reflective and wave dominated from the south-east, see Short, 2006). For

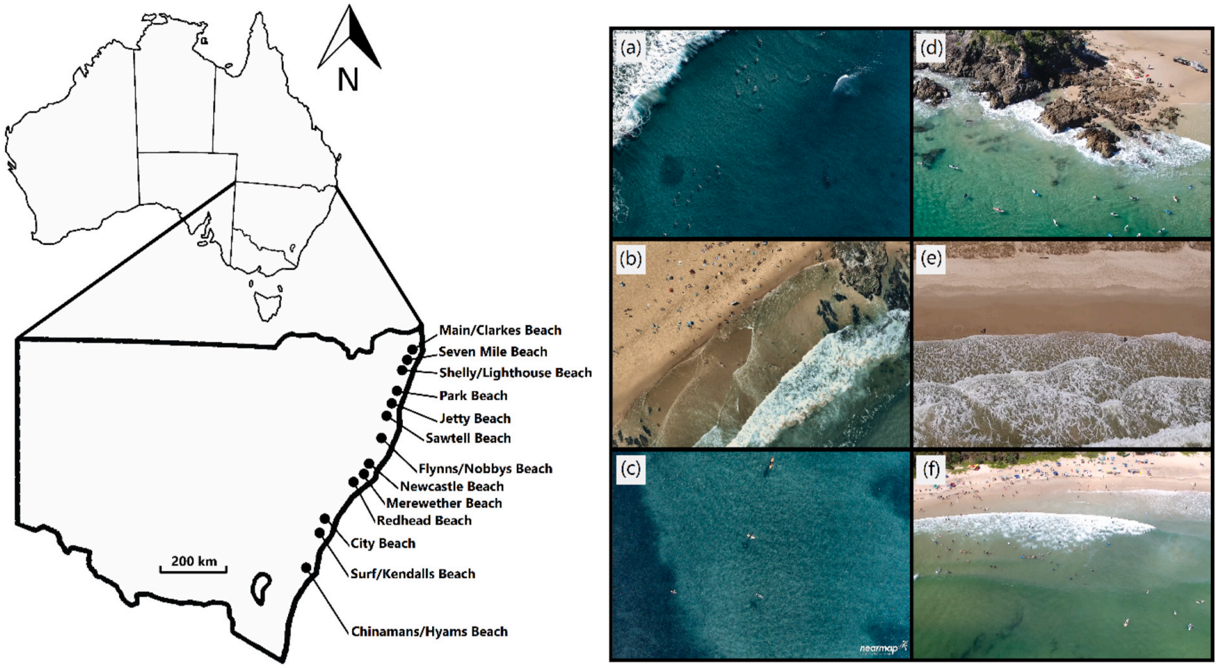

Fig. 1. Beaches where visitation and usage were investigated in NSW Australia. Examples of crewed aircraft (Nearmap Pty Ltd) orthomosaic images (a, b & c). Examples of drone-based survey data (d, f & e).

beaches investigated by both drones and crewed aircraft the same length of beach was surveyed. For the additional beaches, the length of beach sampled was determined by geographical boundaries (i.e. headlands), or for the case of very long beaches (over 2.5 km) the 1 km of beach in front of the local Surf Life Saving club was sampled.

Using the images from crewed aircraft, we evaluated potential drivers of beach visitor numbers and their activities, by testing hypotheses about the relationships between beach user response variables in the crewed-flight imagery and environmental and socio-economic predictors. For each of the thirteen beaches we extracted from the orthomosaic images the time the image was collected, the number of public beach access points, and the beach area (ha) from the foot of the dune to the edge of wet sand within the north and south mark (Table S1). We sourced weather information, daily maximum temperature, rainfall, and solar radiance, from the Australia Bureau of Meteorology using the closest weather station to each beach (http://www.bom.gov.au). We obtained data on median weekly income, and the average number of people, per household for areas abutting beaches from the 2016 census of the Australian Bureau of Statistics (https://www.abs.gov.au). The General Hazard Rating for each beach was obtained from Surf Life Saving Australia (https://beachsafe.org.au). We also included categorical predictors, such as the inclusion of a beach in a Marine Park (y/n), the dominant land use of the adjacent towns (urban vs rural), and whether an image was captured on the weekend or a public holiday (y/n).

2.3. Statistical analyses

We used permutational analyses of variance (PERMANOVA, Anderson, 2017) to compare visitor numbers among the beaches sampled (random factor) using two separate tests with the drone-based survey dataset, and the orthomosaic images dataset limited to these same beaches. We did not compare the two methods within the same PERMANOVA analysis because images from entire temporal series Nearmap data over 10 years was required to obtain a reasonable level of precision. All PERMANOVAs were based on 4999 permutation and Euclidean Distance resemblance measures. We transformed overall visitation (all user groups) data with a Log (x+1) function before analysis to reduce any variance heterogeneity in analyses. To compare the precision of mean estimates between the drone and crewed aircraft images, we calculated the relative standard error (RSE $=$ SE/mean $\times$ 100) for replicate images on the same beach. Additionally, we calculated the Spearman's rank correlation coefficient to assess the relationship between the total visitation data collected via the two methods.

To determine the influence of environmental conditions and socio-economic factors on beach attendance extracted from crewed-flight imagery, we constructed a Generalized Linear Mixed Model (GLMM) in R (RStudio Team, 2020). The predictor variables we used for the analysis were beach, season, time of day, weekends & public holidays vs weekday, beach General Hazard Rating category (safe 1–3, moderate 4–6, hazardous 7–8), number of public access points, daily maximum temperature (°C), daily solar radiation (MJ/m2), rainfall (measured at 9 a.m. recording the past 24 h), beach area (ha), rural or urban, median household income ($AUD), average number of persons per household, within marine park, and the time of day (24 h transformed to sine and co-sine scale). The factors used in this study were limited to those which can be determined retrospectively or by using remote sensing. To account for inherent variation in beach attendance at the beach level, we used a random intercept for beach in each model. We used these predictor variables to assess the influence on i) total beach attendance, and ii) the portion of participants in key user activities: sunbathing, walking, swimming, and surfing. We did not undertake a GLMM for fishing as the participation in this activity was infrequent.

To assess the influence of each of the covariates on the total beach visitation, we used a GLMM using the package 'glmmTMB' (Brooks et al., 2017). The distribution of data fit a negative binomial model structure. We used a backward selection process, where one variable was removed at a time, based on Akaike Information Criterion, for each subsequent model iteration until a final model comprising variables considered potentially influential was reached. We checked the assumptions of homoscedasticity and linearity of the model and undertook a sensitivity analysis using Cooks Distance with the 'Influence.ME package' (Nieuwenhuis et al., 2012). To assess the significance of fixed-effects coefficients, we used the 'car' package (Fox and Weisberg, 2019) to construct Analysis of Deviance tables using Type II Wald Chi-square tests. We conducted further pairwise comparisons (Tukey) using the 'emmeans' package (Lenth, 2020) to assess differences of within-factor groups retained in the final model and deemed significant.

To assess the proportions of total participants engaging in each of the key user activities, we converted the number of people in each activity to a percentage relative to the total number of beach users present across all activities. We constructed Separate Linear Mixed Effects Models using the 'lme4' package (Bates et al., 2015) for each of the user activities. For these models, we used similar backwards selection processes, model checking, and post-hoc analysis, as described for the model assessing total beach user attendance.

3. Results

3.1. Variation in beach visitor numbers

Imagery from 500 survey days (306 orthomosaic and 194 drone) was analysed and 73,021 individual beach users quantified. Visitor numbers varied spatially, and both sampling techniques produced the same rankings among beaches: the most populous beach was Byron Bay, the least number of visitors were at Ballina, with the rest being intermediate (Spearman's correlation; $r_s = 1$, $p = 0.02$, $N = 5$, Table S2). Compared to images from crewed aircraft, the estimates of mean visitor numbers we obtained with drones were more precise for three beaches (Lennox Head, Kiama, Ballina), but similar for Redhead, and more variable for Byron Bay (Table 1). The precision of mean visitor numbers obtained from replicate orthomosaic imagery had RSE values < 0.2 for all but three beaches and was <0.3 for all beaches in our data set (Table S3). The higher precision is possible due to the greater sampling frequency of drone surveys.

At the state-wide scale, thirteen beaches repeatedly surveyed with crewed aircraft with over 700 km between the northern- and southern-most beach sampled, we found large spatial variation in beach visitor numbers, ranging from relatively few at Park Beach, Coffs Harbour to Byron Bay where mean visitor numbers were 15 times higher (Tables S3 and S4; Fig. S1). We observed seasonal patterns in beach visitation, with average daily attendance ($\pm$SE) increasing from winter (47.4 visitors $\pm$ 6.6), to autumn (110.7 $\pm$ 16.6) and spring (122.1 $\pm$ 16.7), and then to summer (182.0 $\pm$ 21.2).

3.2. Patterns in visitor activities

We identified 33,931 beach visitors in the orthomosaic images obtained via crewed aircraft. Most people were sunbathing (48%), followed by swimming (20%), walking (19%), surfing (14%), and fishing (0.1%). A very similar pattern was found in the drone data that yielded 41,189 visitors with 46%, 22%, 21%, 11%, and 0.3% involved in sunbathing, walking, swimming, surfing, and fishing, respectively (Table S5).

The beaches analysed with orthomosaic imagery from crewed aircraft fall into four broad groups based on the frequency of which recreational activities were undertaken by beach visitors (Fig. 2):

1) 'surfing and swimming beaches'; dominated by people riding waves (mainly in-water users with and without boards, e.g. Lennox Head and Ballina).
2) 'walking beaches'; where most beach users engaged in exercising by walking, running, or appreciation of nature (e.g. Port Macquarie, Sawtell and Park Beach, Coffs Harbour);
3) 'sun and fun beaches'; used mostly for sunbathing and swimming (e.g. Byron Bay, Jetty Beach, Coffs Harbour).
4) 'multi-use and fishing beaches'; whilst all beaches are used for multiple types of activities, only a few showed a reasonable proportion of beach users engaging in recreational fishing (e.g. Kiama). Those groups are not fixed categories in the sense that patterns of beach use change seasonally and, in the sense that all beaches support a diversity of uses.

3.3. What factors influence beach use?

There were significant relationships between total beach visitation and season, weekend/public holidays versus weekdays, daily temperature, solar radiation, beach area, persons per household, and time of day (Table 2, Table S4). Visitor counts showed a strong seasonal change with a reduction from summer to winter by 74% (Fig. 3). Season altered the pattern of beach use, where during the cooler months a considerably higher proportion of people walked and fewer sunbathed or swam. Conversely, sunbathing and swimming dominated activity patterns in spring and summer (Fig. 3). Visitor numbers increased by 27% on weekends/public holidays, with these times impacting upon participation in key user groups (Fig. 4). On weekends a greater proportion of visitors swam (average daily swimmers: weekday 20 vs weekend 25) and sunbathed (average daily sunbathers: weekday 48 vs weekend 64). Conversely, relatively fewer people surfed and walked on the weekend. Of all the variables tested, solar radiation was the only variable that was included in every model. Beach visitor counts were positively related to sunshine, as was sunbathing and swimming. The model found for every 1 unit increase in solar radiation, beach visitation was predicted to increase by 4.98 $\pm$ 1.44%, and for every 1° increase in temperature, an increase of 3.36 $\pm$ 1.49% was expected (Fig. 5). There was also greater predicted visitation around midday than during the morning and afternoon periods.

The participation in key activities was influenced by a limited number of factors (Table 2). Sunbathing was found to be greatest on days with increased solar radiation and was more prevalent at urban beaches compared to rural beaches (Table S7, Fig. 5). In contrast to sunbathing, more people walked on less sunny days. Interestingly, on beaches bordered by households with a higher income, fewer people were observed walking (Table S8). The beaches rated least hazardous had the greatest percentage of swimmers, followed by the most hazardous beaches, with the lowest percentage of swimmers at the beaches rated moderately safe (Table S9). Swimming was also positively influenced by solar radiation and daily temperature. Participation in swimming was significantly greater on weekend/public holidays than weekdays (Fig. 4). The percentage of surfers was significantly higher at beaches rated as hazardous, with less participation as the safety rating decreased (Table S10).

Table 1
Spatial variation of beach visitors on five beaches surveyed with both drones and crewed aircraft-sourced imagery. Beaches are ranked (from most to least populous) for each survey method separately (Relative standard error RSE = SE/mean x 100). n = the number of sample days at these locations.

	Crewed Aircraft				Drone			
Beach	Mean	SD	RSE	N	Mean	SD	RSE	n
Main/Clarkes Beach, Byron Bay	309.5	137.9	10.8	17	430.3	315.1	12.9	32
Redhead Beach, Redhead	139.6	115.5	13.3	39	241.5	168.8	13.2	28
Seven Mile Beach, Lennox Head	70.6	41.5	14.7	16	194.2	104.3	7	59
Surf/Kendalls Beach Kiama	41.1	63.6	29.3	28	103	57.2	11.1	25
Shelly/Lighthouse Beach, Ballina	37.9	27.9	17.9	17	90.5	58.6	9.1	50

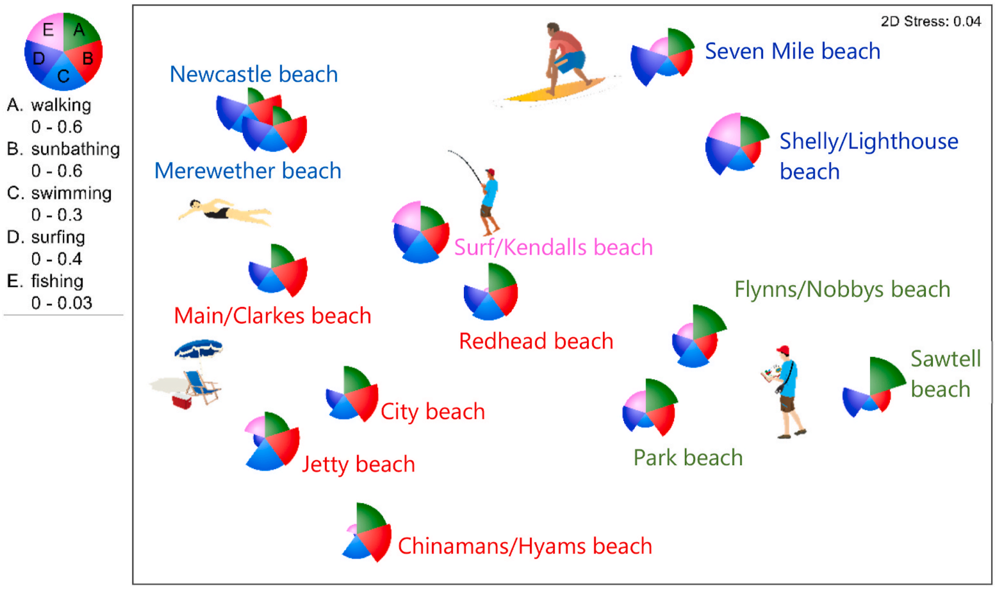

Fig. 2. Variation in recreational activity frequencies between beaches where visitor activity participation was classified from aerial images obtained with crewed aircraft. The figure is an ordination (non-metric multidimensional scaling) based on the resemblance (Bray Curtis coefficient) of beaches with respect to the relative frequencies of recreation types (i.e. beaches that have similar patterns of use are closer). The size of the segments is proportional to the percentage of beach visitors engaged in that particular recreational activity. Beach names are coloured by predominant activity, which is also indicated by an activity symbol for each cluster.

Table 2
Summary of GLMMs analyses relating patterns in beach visitor numbers and types of activity to a range of putative predictors. (NA indicates that the variable was eliminated from the model during backwards selection, where one non-influential variables were eliminate based on Akaike Information Criterion for each subsequent model iteration until a final model comprising variables considered potentially influential was reached. * - P < 0.05, ** - P < 0.01, *** - P < 0.001).

Predictor	Total Visitation	Sunbathing	Walking	Swimming	Surfing
Season	**	***	***	NA	NA
Weekend/ Public Holiday	***	**	NA	***	0.089
Access Points	0.096	NA	NA	0.232	0.058
Urban/Rural	0.078	*	NA	NA	NA
Temperature	*	NA	NA	***	NA
Solar Radiation	***	***	***	***	***
Area	**	0.105	NA	NA	NA
Median Household Income	0.072	NA	***	NA	NA
People per Household	**	NA	NA	0.075	NA
Time (sine)	0.652	***	NA	NA	***
Time (co-sine)	*	***	***	0.144	**
Marine Park	NA	0.096	NA	0.163	NA
Safety rating	NA	NA	NA	*	***

4. Discussion

Sandy beaches are valuable but vulnerable ecosystems that require evidence-based management to ensure sustainable use and development (Jones et al., 2017; Schlacher et al., 2008). Data describing the types of activities and the number of people participating can underpin beach management strategies; however, monitoring programs that gather such information can be time-consuming and expensive. Technological advances may offer efficient and cost-effective methods for monitoring; however, any new or innovative technique must be thoroughly compared against existing conventional methods which are understood to be reliable (Beckmann et al., 2019). We showed that analysing an existing database of orthomosaic imagery (Nearmap) is a cost-effective method for quantifying seasonal and site-specific patterns of recreational beach use and enumerating visitation. At current levels of image acquisition, the orthomosaics had adequate resolution and sampling frequency to reliably detect and classify beach users, giving results comparable to a proven drone-based methodology (Provost et al., 2019). We contend that the methods used in this study provide a cost-effective solution to monitor the behaviours of beach attendees, and to facilitate the provision of adequate services and zoning to safeguard users and the environment.

The analysis of the sporadically collected Nearmap orthomosaic images from crewed aircraft in this study resulted in observations of beach usage patterns comparable to those found using drone-based methodology (Provost et al., 2019). The study found that beach visitation was highest during warmer periods, which is consistent with similar investigations using traditional methods (Balouin et al., 2014; Dwight et al., 2007). This increased attendance corresponded to greater numbers of people engaged in sunbathing and swimming. Walking was an important and persistent year-round activity so ample access to promote this activity, and limit impacts to sensitive habitats (i.e. dunes, headlands), should be maintained year-round. Knowing that greater beach visitation is expected on weekends and public holidays (Dwight et al., 2007) assists the planning of services, suggesting that more resources will be required during these high-use times to protect beach users (e.g. times lifeguards patrolling beaches or wildlife monitoring, Butcher et al., 2019; White and Hyde, 2010; Zielinski et al., 2019). Understanding how and when beaches are used also aids the conservation of coastal wildlife by indicating times when additional monitoring or protections (i.e. restricting access) may be required to lessen impacts to sensitive beach areas (Schlacher et al., 2013; Travaille et al., 2015). Consequently, semi-regular large-scale monitoring using imagery collected by crewed aircraft with 6–7 cm per pixel resolution can reliably quantify beach usage patterns on the east coast of Australia.

Recreational beach use is influenced by numerous factors, such as culture, geomorphology, environmental variables, and current management practices (James, 2000; Lucrezi et al., 2016; Rodella et al., 2017; Semeoshenkova and Newton, 2015). Our results suggest that the social-economic factors included in our analyses (e.g. medium household income) were not as important for predicting beach use than environmental variables (e.g. temperature and time of day). One consideration for this study was the difficulty in obtaining comprehensive social and demographic data that were comparable to environmental information, and perhaps other analyses of socio-economic data are needed to better understand how such factors impact beach usage (Elliott et al., 2018; Schuhmann et al., 2019). However, on face value, it

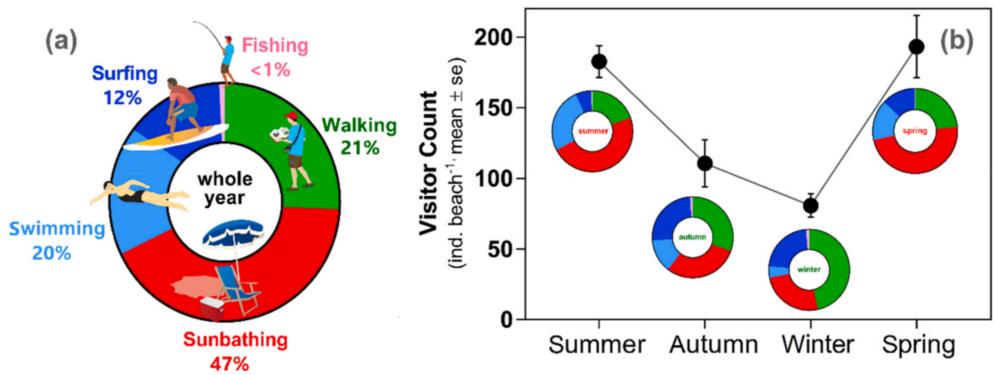

Fig. 3. Frequency of the key recreational activity types (a) and their seasonal change in relation to variation in the total daily visitor count per beach (mean ± SE) (b) from aerial images obtained with crewed aircraft.

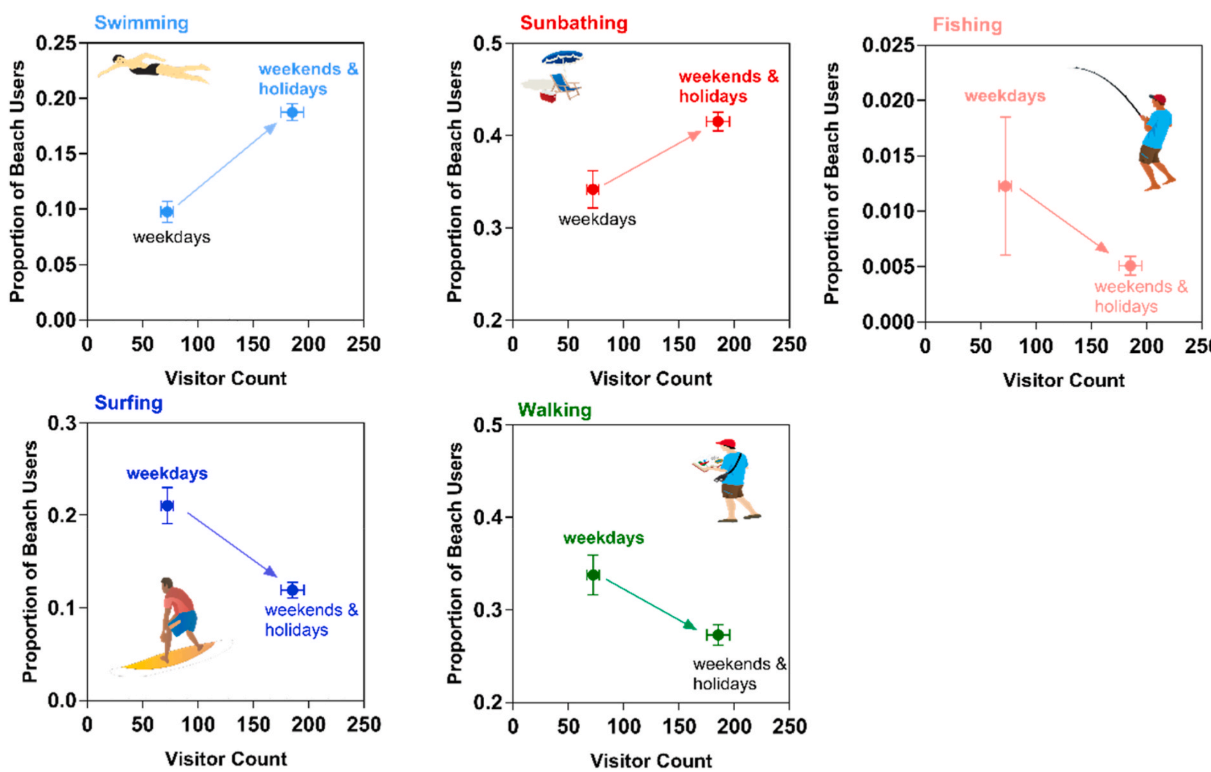

Fig. 4. Mean frequency of participation (±SE) in key recreational activity types in relation to the activity occurring on the weekend and public holidays compared to weekdays from aerial images obtained with crewed aircraft.

appears that environmental changes associated with season and beach conditions are important drivers of beach use. For example, temperature and solar radiation clearly increased overall visitation and participation in sunbathing and swimming (Balouin et al., 2014; Dwight et al., 2007). Beach specific factors, such as beach safety rating, was related to participation in surfing with a preference for beaches rated more hazardous. The variation in recreational use among beaches suggests there is value in tailoring specific management arrangements and service provisions to each beach. Understanding beach-specific drivers of use provides an opportunity to enhance the beach-going experience by promoting popular activities in places where high participation already exists (e.g. facilitating surfing events on popular surfing beaches, Barbieri and Sotomayor, 2013; Gray and Gray, 2017; Morgan, 2019; White and Hyde, 2010). This data also ensures the protection of local sensitive species and habitats from human disturbance, as key activities can be limited to certain sections of coastline and effectively monitored for compliance (Maslo et al., 2018; Desfosses et al., 2019).

The advantages of using of crewed aircraft for collecting orthomosaic imagery are fewer airspace restrictions than drones, and an increased capacity to collect data over larger spatial scales (Table 3) (Colefax et al., 2018; Kelaher et al., 2020). However, to obtain appropriate accuracy and precision it was necessary to include all sampling times within the 10 years of the Nearmap database. This made direct comparisons of both methods unfeasible as there were only three sampling dates that overlapped, which shifted the focus of this study to compared usage patterns. However, the large temporal period between sampling limits the capacity of existing image databases, such as Nearmap, to assess short-term trends in beach visitation. While it may be cost-effective to quantify beach use with existing high-resolution orthomosaic imagery from crewed aircraft, a drone-based approach is more appropriate when fine temporal scale (e.g. hourly or daily) monitoring is required. For example, to determine the peak times for certain activities (i.e. assessing when fishing occurs to optimise compliance activities, see Smallwood et al., 2012; Taylor et al., 2018), regular sampling by drones or fixed

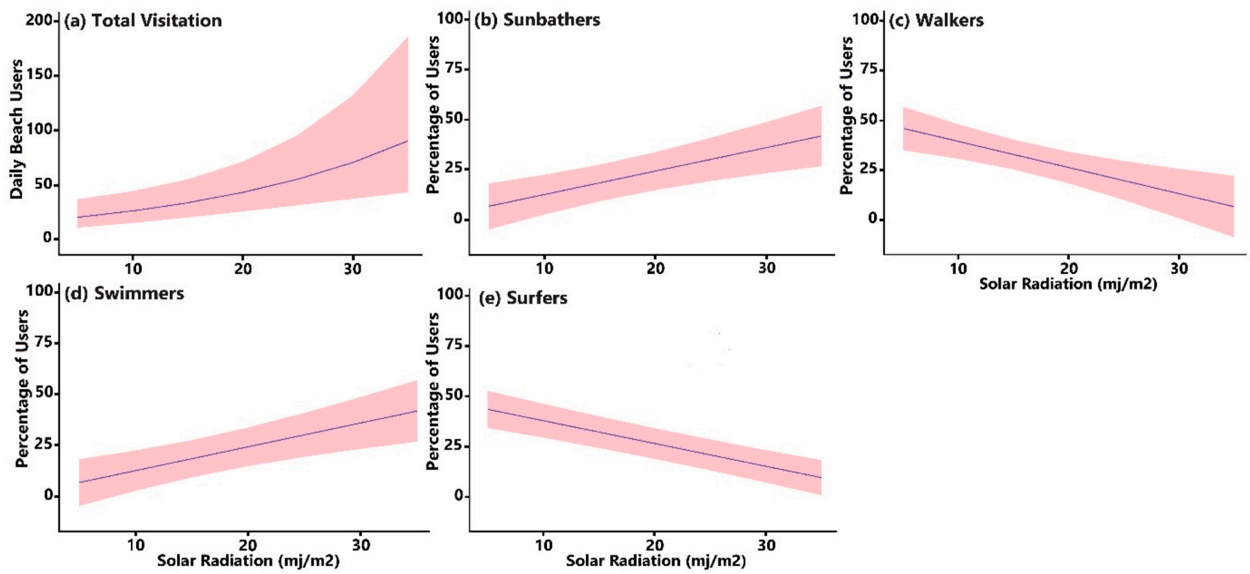

Fig. 5. The effect of max daily solar radiation on the mean daily beach visitors and the participation in key user activities, for all beaches combined from aerial images obtained with crewed aircraft. Plots show mean ± 95% confidence intervals.

Table 3
Common methods used to directly measure beach visitation and usage.

Technique	Digital	Scale	Advantages	Limitations
Lifeguard counts/ estimates	No	<2 km	Affordable, sampling flexibility, unaffected by cloud cover/weather conditions	Not precise, possible bias, no possibility for reanalysis, limited spatial coverage
Fixed camera	Yes	<2 km	Affordable, continuous monitoring, unaffected by cloud cover	Limited location, low-resolution, data needs post analysis
Drones	Yes	<5 km	Affordable, sampling flexibility, high-resolution video data	Small flight times, data needs post analysis, airspace restrictions, rain and wind can impact collection
Crewed aircraft	Yes	Up to 100s of km	Large coverage, good resolution	Infrequent, costly, requires a runway, cloud coverage may impact collection

video cameras operating throughout the day would be more beneficial than orthomosaic images from crewed aircraft flights that generally occur on monthly to yearly time scale (Windle et al., 2020). Additionally, the visual resolution capacity of drones can easily be tailored by altering flight patterns depending on the investigators monitoring needs, for example, to detect whether dogs were on-leash, if attendees are following local regulations, or the type and location of plastic pollution (Kane et al., 2021; Martin et al., 2018; Zielinski et al., 2019). Drone-based monitoring would be fitting when flexibility is required regarding the frequency and timing of beach sampling, such as before and after a planned or natural impact (i.e. development, extent of storm erosion: Turner et al., 2016). In such situations, imagery obtained from specifically chartered crewed aircraft is likely to be more expensive than monitoring using small drones (Colefax et al., 2018; Kelaher et al., 2019). Nonetheless, using a complimentary approach of digital aerial image acquisition (e.g. crewed aircraft, drones and satellites) can improve the overall monitoring of coastal areas by overcoming the limitations of each method.

Understanding the factors that drive beach attendance, or participation in key activities, is important for cost-effective provision of services and for minimising environmental impacts (Jiménez et al., 2007; Zhang and Wang, 2013). The development of novel remote-sensing techniques will improve the capacity for comprehensive data collection to inform evidence-based management of natural systems (Nyman, 2019; Mahrad et al., 2020), by increasing data availability and the frequency of collection. The availability of high-resolution aerial imagery from crewed aircraft will likely expand in the future and cost of analysis will decrease, as object-based image analysis and deep-learning neural networks automate data processing (Dujon and Schofield, 2019; Gray et al., 2019). Additionally, the use of aerial techniques to collect digital beach use data that can be imported into a GIS framework will further benefit beach through the visualisation of user distributions that can better inform effective zoning decisions (Donaire et al., 2020; Fung and Wong, 2007). Providing the data collected is freely available and easily integrable, there may be long-term benefits from very little initial investment into digital aerial imagery (Allan et al., 2018; Marvin et al., 2016).

5. Conclusion

The use of aerial orthomosaic imagery to enumerate beach visitation and identify key recreational activities was evaluated with promising results. The resolution and temporal coverage of Nearmap aerial orthomosaic imagery was sufficient to quantify beach use on the east coast of Australia. In our study region, beach visitation and use varied among locations and was significantly influenced by season, weekends, public holidays, daily temperature, solar radiation, beach area, and time of day. Our study supports the contention that orthomosaic images can provide information on patterns of beach use, with an existing stockpile of images available allowing for rapid assessments to be possible. A current limitation of this database includes the restricted sampling frequency in regional areas, although there was greater sampling frequency in densely populated places. In the future, the direct comparison of techniques helps to precisely compare the data gathered by multiple methods (Scholten et al., 2019; Themistocleous et al., 2019). Overall, digital aerial orthomosaic images from drones or crewed aircraft can provide reliable estimates of beach usage, with enough detail to determine specific usage groups. This aerial imagery can benefit the effective management of beaches by providing cost-effective monitoring and data informing how sandy beaches are used, and to predict how patterns change over time and under different climatic conditions.

Declaration of competing interest

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

Acknowledgements

The project idea was originally developed at the inaugural GLOBE (Global Ocean Beaches) workshop at USC (University of the Sunshine Coast, Australia), of which Michael A. Weston, Jenifer E. Dugan and David M. Hubbard also participated. This project was supported by Southern Cross University and the New South Wales Department of Primary Industries. The project used equipment provided by ARC LIEF Grant (LE170100007) to BPK, PAB and MAC.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ocecoaman.2021.105750.

References

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

Anderson, M.J., 2017. In: Permutational Multivariate Analysis of Variance (PERMANOVA). Wiley StatsRef: Statistics Reference Online, pp. 1–15. https://doi.org/10.1002/9781118445112.stat07841 pp.

Andriolo, U., Elena, S., 2019. Operational use of surfcam online streaming images for coastal morphodynamic studies. Rem. Sens. 11, 1–21. https://doi.org/10.3390/rs11010078.

Balouin, Y., Rey-Valette, H., Picand, P.A., 2014. Automatic assessment and analysis of beach attendance using video images at the Lido of Sète beach, France. Ocean Coast Manag. 102, 114–122. https://doi.org/10.1016/j.ocecoaman.2014.09.006.

Barbieri, C., Sotomayor, S., 2013. Surf travel behavior and destination preferences: an application of the Serious Leisure Inventory and Measure. Tourism Manag. 35, 111–121. https://doi.org/10.1016/j.tourman.2012.06.005.

Bates, D., Martin, M., Ben, B., Steve, W., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Software 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Beckmann, C., Tracey, S., Murphy, J., Moore, A., Cleary, B., Steer, M., 2019. Assessing new technologies and techniques that could improve the cost-effectiveness and robustness of recreational fishing surveys. In: Proceedings of the National Workshop. South Australian Research and Development Institute, Adelaide, South Australia, 10-12 July 2018.

Brooks, M.E., Kristensen, K., Benthem, K. J. van, Magnusson, A., Berg, C.W., Nielsen, A., Skaug, H.J., Maechler, M., Bolker, B.M., 2017. glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. R J. 9, 378–400.

Butcher, P., Piddocke, T., Colefax, A., Hoade, B., Peddemors, V., Borg, L., Cullis, B., 2019. Beach safety: can drones provide a platform for sighting sharks? Wildl. Res. 46, 701–712.

Christiansen, F., Lusseau, D., 2015. Linking behavior to vital rates to measure the effects of non-lethal disturbance on wildlife. Conservat. Lett. 8, 424–431. https://doi.org/10.1111/conl.12166.

Ciuti, S., Northrup, J.M., Muhly, T.B., Simi, S., Musiani, M., Pitt, J.A., Boyce, M.S., 2012. Effects of humans on behaviour of wildlife exceed those of natural predators in a landscape of fear. PloS One 7, e50611. https://doi.org/10.1371/journal.pone.0050611.

Colefax, A.P., Butcher, P.A., Kelaher, B.P., 2018. The potential for unmanned aerial vehicles (UAVs) to conduct marine fauna surveys in place of manned aircraft. ICES (Int. Counc. Explor. Sea) J. Mar. Sci. 75, 1–8. https://doi.org/10.1093/icesjms/fsx100.

Davis, T.R., Gallen, C., Laird, R., Harasti, D., 2015. Mapping Sub-tidal Habitats in the Eastern Port of Port Stephens. Final Report to the Hunter Local Land Services. Project ID: HCR13 820, 1–48.

Desfosses, C., Taylor, S., Adams, P., Blight, S., 2019. The Feasibility of Using Remotely Piloted Aircraft Systems (RPAS) for Recreational Fishing Surveys in Western Australia. Fisheries Occasional Publication No, p. 137.

Donaire, J.A., Galí, N., Gulisova, B., 2020. Tracking visitors in crowded spaces using zenith images: drones and time-lapse. Tour. Manag. Perspect. 35 https://doi.org/10.1016/j.tmp.2020.100680.

Doukari, M., Batsaris, M., Papakonstantinou, A., Topouzelis, K., 2019. A protocol for aerial survey in coastal areas using UAS. Rem. Sens. 11 https://doi.org/10.3390/rs11161913.

Duffy, J.P., Cunliffe, A.M., DeBell, L., Sandbrook, C., Wich, S.A., Shutler, J.D., Myers-Smith, I.H., Varela, M.R., Anderson, K., 2018. Location, location, location: considerations when using lightweight drones in challenging environments. Rem. Sens. Ecol. Conserv. 4, 7–19. https://doi.org/10.1002/rse2.58.

Dujon, A.M., Schofield, G., 2019. Importance of machine learning for enhancing ecological studies using information-rich imagery. Endanger. Species Res. 39, 91–104. https://doi.org/10.3354/esr00958.

Dwight, R.H., Brinks, M.V., SharavanaKumar, G., Semenza, J.C., 2007. Beach attendance and bathing rates for Southern California beaches. Ocean Coast Manag. 50, 847–858. https://doi.org/10.1016/j.ocecoaman.2007.04.002.

Elliott, L.R., White, M.P., Grellier, J., Rees, S.E., Waters, R.D., Fleming, L.E., 2018. Recreational visits to marine and coastal environments in England: where, what, who, why, and when? Mar. Pol. 97, 305–314. https://doi.org/10.1016/j.marpol.2018.03.013.

Fung, T., Wong, F.K.K., 2007. Ecotourism planning using multiple criteria evaluation with GIS. Geocarto Int. 22, 87–105. https://doi.org/10.1080/10106040701207332.

Fox, J., Weisberg, S., 2019. An {R} Companion to Applied Regression, third ed. https://socialsciences.mcmaster.ca/jfox/Books/Companion/.

Gray, G.M.E., Gray, C.A., 2017. Beach-user attitudes to shark bite mitigation strategies on coastal beaches; sydney, Australia. Hum. Dimens. Wildl. 22, 282–290. https://doi.org/10.1080/10871209.2017.1295491.

Gray, P.C., Bierlich, K.C., Mantell, S.A., Friedlaender, A.S., Goldbogen, J.A., Johnston, D. W., 2019. Drones and convolutional neural networks facilitate automated and accurate cetacean species identification and photogrammetry. Methods. Ecol. Evol. 10, 1490–1500. https://doi.org/10.1111/2041-210X.13246.

Guillén, J., García-Olivares, A., Ojeda, E., Osorio, A., Chic, O., González, R., 2008. Long-term quantification of beach users using video monitoring. J. Coast Res. 24, 1612–1619. https://doi.org/10.2112/07-0886.1.

James, R.J., 2000. From beaches to beach environments: linking the ecology, human-use and management of beaches in Australia. Ocean Coast Manag. 43, 495–514. https://doi.org/10.1016/S0964-5691(00)00040-5.

Jiménez, J.A., Osorio, A., Marino-Tapia, I., Davidson, M., Medina, R., Kroon, A., Archetti, R., Ciavola, P., Aarnikhof, S.G.J., 2007. Beach recreation planning using video-derived coastal state indicators. Coast. Eng. 54, 507–521. https://doi.org/10.1016/j.coastaleng.2007.01.012.

Jones, A.R., Schlacher, T.A., Schoeman, D.S., Weston, M.A., Withycombe, G.M., 2017. Ecological research questions to inform policy and the management of sandy beaches. Ocean Coast Manag. 148, 158–163. https://doi.org/10.1016/j.ocecoaman.2017.07.020.

Joyce, K.E.A., Duce, S.A., Leahy, S.M.A., Leon, J.B., Maier, S.W.C., 2018. Principles and practice of acquiring drone-based image data in marine environments. Mar. Freshw. Res. 70, 952–963. https://doi.org/10.1071/MF17380.

Kammler, M., Schernewski, G., 2004. Spatial and temporal analysis of beach tourism using webcam and aerial photographs. Coastline Rep. 2, 121–128. HYPERLINK. http://www2010.eucc-d.de/plugins/coastline_reports/pdf/cr2/Kammler_Schernewski.pdf. http://www2010.eucc-d.de/plugins/coastline_reports/pdf/cr2/Kammler_Schernewski.pdf. http://www2010.eucc-d.de/plugins/coastline_reports/pdf/cr2/Kammler_Schernewski.pdf.

Kane, B., Zajchowski, C.A.B., Allen, T.R., McLeod, G., Allen, N.H., 2021. Is it safer at the beach? Spatial and temporal analyses of beachgoer behaviors during the COVID-19 pandemic. Ocean Coast Manag. 205, 105533. https://doi.org/10.1016/j.ocecoaman.2021.105533.

Kelaher, B.P., Colefax, A.P., Tagliafico, A., Bishop, M.J., Giles, A., Butcher, P.A., 2019. Assessing variation in assemblages of large marine fauna off ocean beaches using drones. Mar. Freshw. Res. 71, 68–77. https://doi.org/10.1071/mf18375.

Kelaher, B., Peddemors, V., Hoade, B., Colefax, A., Butcher, P., 2020. Comparison of sampling precision for nearshore marine wildlife using unmanned and manned aerial surveys. J. Unmanned Veh. Syst. 8, 30–43. https://doi.org/10.1139/juvs-2018-0023.

King, P., McGregor, A., 2012. Who's counting: an analysis of beach attendance estimates and methodologies in southern California. Ocean Coast Manag. 58, 17–25. https://doi.org/10.1016/j.ocecoaman.2011.12.005.

Lenth, R., 2020. Emmeans: estimated marginal means, aka least-squares means. R Package Version 1.4.8. https://cran.r-project.org/package=emmeans.

Lucrezi, S., Saayman, M., Van der Merwe, P., 2016. An assessment tool for sandy beaches: a case study for integrating beach description, human dimension, and economic factors to identify priority management issues. Ocean Coast Manag. 121, 1–22. https://doi.org/10.1016/j.ocecoaman.2015.12.003.

Martin, C., Parkes, S., Zhang, Q., Zhang, X., McCabe, M.F., Duarte, C.M., 2018. Use of unmanned aerial vehicles for efficient beach litter monitoring. Mar. Pollut. Bull. 131, 662–673. https://doi.org/10.1016/j.marpolbul.2018.04.045.

Marvin, D.C., Koh, L.P., Lynam, A.J., Wich, S., Davies, A.B., Krishnamurthy, R., Stokes, E., Starkey, R., Asner, G.P., 2016. Integrating technologies for scalable ecology and conservation. Glob. Ecol. Conserv. 7, 262–275. https://doi.org/10.1016/j.gecco.2016.07.002.

Maslo, B., Leu, K., Pover, T., Weston, M.A., Schlacher, T.A., 2018. Managing birds of conservation concern on sandy shores: how much room for future conservation actions is there? Ecol. Evol. 8, 10976–10988. https://doi.org/10.1002/ece3.4564.

Mahrad, B. El, Newton, A., Icely, J.D., Kacimi, I., Abalansa, S., Snoussi, M., 2020. Contribution of remote sensing technologies to a holistic coastal and marine environmental management framework: a review. Rem. Sens. 12, 2313. https://doi.org/10.3390/rs12142313.

Meager, J.J., Schlacher, T.A., Nielsen, T., 2012. Humans alter habitat selection of birds on ocean-exposed sandy beaches. Divers. Distrib. 18, 294–306. https://doi.org/10.1111/j.1472-4642.2011.00873.x.

McLachlan, A., Defeo, O., Jaramillo, E., Short, A.D., 2013. Sandy beach conservation and recreation: guidelines for optimising management strategies for multi-purpose use. Ocean Coast Manag. 71, 256–268. https://doi.org/10.1016/j.ocecoaman.2012.10.005.
Morgan, D., 2019. Development of a method to estimate and predict beach visitation. Tourism Mar. Environ. 12, 69–77.
Nieuwenhuis, R., Grotenhuis, M. te, Pelzer, B., 2012. influence.ME: tools for detecting influential data in mixed effects models. R J. 4, 38–47.
Nyman, E., 2019. Techno-optimism and ocean governance: new trends in maritime monitoring. Mar. Pol. 99, 30–33. https://doi.org/10.1016/j.marpol.2018.10.027.
Ouellette, W., Getinet, W., 2016. Remote sensing for marine spatial planning and integrated coastal areas management: achievements, challenges, opportunities and future prospects. Rem. Sens. Appl.: Soc. Environ. 4, 138–157. https://doi.org/10.1016/j.rsase.2016.07.003.
Pérez-Maqueo, O., Martínez, M.L., Cóscatl Nahuacatl, R., 2017. Is the protection of beach and dune vegetation compatible with tourism? Tourism Manag. 58, 175–183. https://doi.org/10.1016/j.tourman.2016.10.019.
Provost, E.J., Butcher, P.A., Colefax, A.P., Coleman, M.A., Curley, B.G., Kelaher, B.P., 2019. Using drones to quantify beach users across a range of environmental conditions. J. Coast Conserv. 23, 633–642. https://doi.org/10.1007/s11852-019-00694-y.
Rodella, I., Madau, F., Mazzanti, M., Corbau, C., Carboni, D., Simeoni, U., Parente, L., 2020. Carrying capacity as tool for beach economic value assessment (case studies of Italian beaches). Ocean Coast Manag. 189, 105130. https://doi.org/10.1016/j.ocecoaman.2020.105130.
RStudio Team, 2020. RStudio: integrated development environment for R. RStudio. PBC. http://www.rstudio.com/.
Scholten, C.N., Kamphuis, A.J., Vredevoogd, K.J., Lee-Strydhorst, K.G., Atma, J.L., Shea, C.B., Proppe, D.S., 2019. Real-time thermal imagery from an unmanned aerial vehicle can locate ground nests of a grassland songbird at rates similar to traditional methods. Biol. Conserv. 233, 241–246. https://doi.org/10.1016/j.biocon.2019.03.001.
Schlacher, T.A., Schoeman, D.S., Dugan, J., Lastra, M., Jones, A., Scapini, F., Mclachlan, A., 2008. Sandy beach ecosystems: key features, sampling issues, management challenges and climate change impacts. Mar. Ecol. 29, 70–90.
Schlacher, T.A., de Jager, R., Nielsen, T., 2011. Vegetation and ghost crabs in coastal dunes as indicators of putative stressors from tourism. Ecol. Indicat. 11, 284–294. https://doi.org/10.1016/j.ecolind.2010.05.006.
Schlacher, T.A., Nielsen, T., Weston, M.A., 2013. Human recreation alters behaviour profiles of non-breeding birds on open-coast sandy shores. Estuar. Coast Shelf Sci. 118, 31–42. https://doi.org/10.1016/j.ecss.2012.12.016.
Schlacher, T.A., Schoeman, D.S., Jones, A.R., Dugan, J.E., Hubbard, D.M., Defeo, O., Peterson, C.H., Weston, M.A., Maslo, B., Olds, A.D., Scapini, F., Nel, R., Harris, L.R., Lucrezi, S., Lastra, M., Huijbers, C.M., Connolly, R.M., 2014. Metrics to assess ecological condition, change, and impacts in sandy beach ecosystems. J. Environ. Manag. 144, 322–335. https://doi.org/10.1016/j.jenvman.2014.05.036.
Schuhmann, P., Skeete, R., Waite, R., Bangwayo-skeete, P., Casey, J., Oxenford, H.A., Gill, D.A., 2019. Coastal and marine quality and tourists' stated intention to return to Barbados. Water 11, 1–19. https://doi.org/10.3390/w11061265.
Scobie, C.A., Hugenholtz, C.H., 2016. Wildlife monitoring with unmanned aerial vehicles: quantifying distance to auditory detection. Wildl. Soc. Bull. 40, 781–785. https://doi.org/10.1002/wsb.700.
Scott, J.K., Batchelor, K.L., Webber, B.L., 2019. Long term monitoring of recruitment dynamics determines eradication feasibility for an introduced coastal weed. NeoBiota 50, 31–53. https://doi.org/10.3897/neobiota.50.35070.
Semeoshenkova, V., Newton, A., 2015. Overview of erosion and beach quality issues in three Southern European countries: Portugal, Spain and Italy. Ocean Coast Manag. 118, 12–21. https://doi.org/10.1016/j.ocecoaman.2015.08.013.
Short, A.D., 2006. Australian beach systems—nature and distribution. J. Coast. Res., 2006 (211), 11–27. https://doi.org/10.2112/05A-0002.1.
Smallwood, C.B., Pollock, K.H., Wise, B.S., Hall, N.G., Gaughan, D.J., 2012. Expanding aerial-roving surveys to include counts of shore-based recreational Fishers from remotely operated cameras: benefits, limitations, and cost effectiveness. N. Am. J. Fish. Manag. 32, 1265–1276. https://doi.org/10.1080/02755947.2012.728181.
Splinter, K.D., Harley, M.D., Turner, I.L., 2018. Remote sensing is changing our view of the coast: insights from 40 Years of monitoring at Narrabeen-Collaroy, Australia. Rem. Sens. 10, 1744. https://doi.org/10.3390/rs10111744.
Taylor, M.D., Gaston, T.F., Raoult, V., 2018. The economic value of fisheries harvest supported by saltmarsh and mangrove productivity in two Australian estuaries. Ecol. Indicat. 84, 701–709. https://doi.org/10.1016/j.ecolind.2017.08.044.
Themistocleous, K., Mettas, C., Evagorou, E., Hadjimitsis, D.G., 2019. The use of satellite remote sensing and UAV for the mapping of coastal areas for the use of marine spatial planning. Proc. SPIE 11156, Earth Resourc. Environ. Rem. Sens./GIS Appl. X 1115610. https://doi.org/10.1117/12.2533064.
Travaille, K.L., Salinas-de-León, P., Bell, J.J., 2015. Indication of visitor trampling impacts on intertidal seagrass beds in a New Zealand marine reserve. Ocean Coast Manag. 114, 145–150. https://doi.org/10.1016/j.ocecoaman.2015.06.002.
Turner, I.L., Harley, M.D., Drummond, C.D., 2016. UAVs for coastal surveying. Coast. Eng. 114, 19–24. https://doi.org/10.1016/j.coastaleng.2016.03.011.
Watts, A.C., Perry, J.H., Smith, S.E., Burgess, M.A., Wilkinson, B.E., Szantoi, Z., Ifju, P.G., Percival, H.F., 2010. Small unmanned aircraft systems for low-altitude aerial surveys. J. Wildl. Manag. 74, 1614–1619. https://doi.org/10.2193/2009-425.
White, K.M., Hyde, M.K., 2010. Swimming between the flags: a preliminary exploration of the influences on Australians' intentions to swim between the flags at patrolled beaches. Accid. Anal. Prev. 42, 1831–1838. https://doi.org/10.1016/j.aap.2010.05.004.
Wiegmann, D.A., Taneja, N., 2003. Analysis of injuries among pilots involved in fatal general aviation airplane accidents. Accid. Anal. Prev. 35, 571–577. https://doi.org/10.1016/S0001-4575(02)00037-4.
Windle, A.E., Poulin, S.K., Johnston, D.W., Ridge, J.T., 2020. Rapid and accurate monitoring of intertidal Oyster reef habitat using unoccupied aircraft systems and structure from motion. Rem. Sens. 11 https://doi.org/10.3390/rs11202394.
Wood, G., Lynch, T.P., Devine, C., Keller, K., Figueira, W., 2016. High-resolution photo-mosaic time-series imagery for monitoring human use of an artificial reef. Ecol. Evol. 6, 6963–6968. https://doi.org/10.1002/ece3.2342.
Zhang, F., Wang, X.H., 2013. Assessing preferences of beach users for certain aspects of weather and ocean conditions: case studies from Australia. Int. J. Biometeorol. 57, 337–347. https://doi.org/10.1007/s00484-012-0556-4.
Zielinski, S., Botero, C.M., Yanes, A., 2019. To clean or not to clean? A critical review of beach cleaning methods and impacts. Mar. Pollut. Bull. 139, 390–401. https://doi.org/10.1016/j.marpolbul.2018.12.027.