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To tag or not to tag: comparative performance of tagging and photo-identification in a long-term mark-recapture of Juvenile Green Turtles (*Chelonia mydas*)

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Abstract. Capture-mark-recapture (CMR) methods are widely used to estimate population parameters and to collect data on animal demography, migration, and life history. Sea turtle research programs generally use artificial tags, an invasive method. Photo-identification (PID) methods have become an important tool for animal identification. Herein, we assessed the effectiveness of a PID method for marking green turtles (*Chelonia mydas*) compared to traditional methods (artificial tags). As a part of a long-term CMR study, green turtles have been tagged and photographed since 2001. We analyzed 1917 captures with left and right side photographs of tagged turtles using Wild-ID software, these results were compared with tag-recapture data to assess error rates (false positives and negatives), and different effectiveness metrics. A combination of PID and tags (a match from either method was considered a recapture) was the most error-free and efficient criterion for identification of recaptures; however, it was the most time consuming and invasive criterion as well. We also assessed the effect of image quality indicators on the error rates of PID. We found that turtle cleanliness increases the similarity of images (indirectly related to false negatives), but we found no effect of sharpness, angle, light condition, or width and height in pixels of images on error rates. We could conclude that if image quality is improved, tags could be substituted by PID. However, we strongly recommend researchers to consider local situations (occurrence of by-catch or stranded dead turtles, for which tags are still necessary) before deciding to apply only PID.

Keywords: effectiveness metrics, error rates, Inconel tags, mark-recapture, photo-identification, sea turtles, Southwestern Atlantic.

Introduction

Marking individuals for population studies, through capture-mark-recapture (CMR) field methods, is one of the most accurate procedure to model survival rates, movement probabilities, and population sizes of wild populations. CMR-based models account for individual detection probabilities and thus provide more reliable inference for vital rates than alternative methods (Kéry and Schaub, 2011). Such population studies are essential for planning conservation efforts of several taxa, and sea turtles are not an exception, as estimates of vital rates have provided valuable insights for future actions on their populations (e.g., Colman et al., 2015; Kendall et al., 2019). Historically, captured individuals were artificially marked to conduct CMR population studies (Arntzen et al., 2004; Bardier et al., 2017; Suriyamongkol and Mali, 2018). Metal or plastic tags are the most widely used identification method in sea turtle programs worldwide (Reisser et al., 2008; Schofield et al., 2008; Carpentier et al., 2016). Recently, issues arose with artificial tags regarding animal welfare, such as suffering and reduced survival (Zemanova, 2017). There is no direct evidence of the impacts of Inconel tags themselves, but some plastic tags have been shown to increase by-catch probability (Nichols and Seminoff, 1998; Schofield et al., 2008). Considering these ethical drawbacks and that artificial marks are expensive (in terms of material and application time), a shift towards less invasive methods was favored by technological development of image processing, increasing the use of photo-identification (PID) as a marking method through diverse techniques. PID takes advantage of natural phenotypic patterns for the identification of individuals by finding recaptures through image matching; it has been applied to a wide variety of taxa, including sea turtles (Speed, Meekan, and Bradshaw, 2007; Bolger et al., 2012; Dunbar et al., 2014). Recent advances in digital photography and pattern recognition algorithms (Bolger et al., 2012) have allowed a quick and efficient analysis of large photographic databases (Dunbar et al., 2014). Software-assisted PID techniques reduce data processing time in comparison with visual PID techniques (Cruickshank and Schmidt, 2017; Bardier et al., 2020).

According to Bolger et al. (2012), the phenotypic pattern of an individual must be stable over the duration of the study period and should be unambiguously identified even when photographed under differing conditions. Thus, it is important to select wisely the phenotypic pattern for identification. For hard-shelled turtles, the lateral sides of the head are stable enough over time for their use as natural phenotypic markers (Carpentier et al., 2016). Indeed, PID techniques have been tested in several turtle species such as leatherback turtles (*Dermochelys coriacea*), hawksbill turtles (*Eretmochelys imbricata*) and green turtles (*Chelonia mydas*) with satisfactory results (Reisser et al., 2008; Dunbar et al., 2014; Araujo et al., 2016; Carpentier et al., 2016; Calmanovici et al., 2018). In these studies, a myriad of software-assisted PID tools have been applied, some of them specifically developed to analyze the scale patterns of turtles and tortoises (see supplementary table S1).

Despite the many advantages of PID, two types of error remain likely: matching two images of different individuals as if they were the same (equivalent to type I probabilistic errors), and false negatives: not matching two images of the same individual (equivalent to type II probabilistic errors) (Morrison et al., 2011; Cruickshank and Schmidt, 2017). Effectiveness metrics (Accuracy, Recall, Precision and F1) are performance metrics recently used for pattern recognition and classification (Aliev et al., 2019). These have been applied mostly in machine learning for herpetofauna tracking and recognition (Durso et al., 2021), including of turtles (Gray et al., 2019; Dujon et al., 2021), but they can also be applied to measure the performance of PID techniques (Pedersen and Mohammed, 2021). Poor quality images can reduce the capacity of individual recognition (Bendik et al., 2013); specifically, camera angle in relation to the objects, poor lighting, and the resolution of the image can influence error rates and effectiveness of the matching PID technique (Gates, 2004; Li and Jain, 2005).

It is important to validate estimated error and effectiveness of PID techniques for a given species because high error rates can bias population estimates (Morrison et al., 2011; Bardier et al., 2020). Hence, it is advisable to compare performance of different marking methods. When supplementing PID with tagging methods, both methods can be assessed in case of mistaken records, lost tags, or lack of recognition because of poor image quality. Performance should be assessed in terms of errors and effectiveness of both types of methods but also in terms of the time invested and invasiveness of each one (as handling for photo-taking can also be stressful for turtles). Individuals in nesting areas are easier to tag as they are on land, which is why nesting individuals are tagged more frequently than foraging individuals, although little is known about juveniles, males, and non-breeding females (Carpentier et al., 2016). A PID approach has been proposed to identify and track sea turtles of all ages and sexes over time (Reisser et al., 2008; Schofield et al., 2008; Chassagneux et al., 2013).

In the Southwestern Atlantic Ocean (SWAO), the Uruguayan coastal waters provide important developmental foraging grounds for green turtles (Vélez-Rubio et al., 2013). Juveniles of this species come from different rookeries around the Atlantic Ocean, forming a mixed genetic stock in Uruguayan waters that share some similarities with other stocks throughout the SWAO (Caraccio, 2008; Prosdocimi et al., 2012). The abundance of juvenile green turtles increases in the austral summer, probably due to a seasonal latitudinal migration along the coastal waters of the SWAO (González Carman et al., 2012; Vélez-Rubio et al., 2018). Metal tag recovery data showed a high site fidelity (76% of the turtles were re-captured at the same location) during the CMR project carried out since 2001 in Uruguay (López-Mendilaharsu et al., 2016). This turtle aggregation has been studied since 2000 by the local NGO Karumbé using in-water captures, biometrics, biopsies, PID, and tagging year-round.

The aim of this study is to determine whether the PID method is an effective alternative to tagging or whether both methods are complementary. For this, we addressed two specific objectives: 1) to assess performance in terms of time invested, error rates, and effectiveness metrics of the PID and tag methods (separately and combined); and 2) to assess the effect of image quality on error rates reported by PID method.

Materials and methods

Study area

The 710-km Uruguayan coast is part of a complex hydrological system that includes the frontal zone of the Rio de la Plata estuary and the Atlantic Ocean (Vélez-Rubio et al., 2018). Green turtles are found in the entire area, from Nueva Palmira (33°52′13.1″S, 58°24′42.3″W) to Barra del Chuy (33°45′ 54.7″S, 53°23′44.0″W), with the major foraging grounds being located in the rocky outcrops in Canelones, Maldonado, and Rocha departments (Vélez-Rubio et al., 2013). The long-term study on the abundance and habitat use of green turtles conducted by the local NGO Karumbé was carried out in the Rocha department, mainly in coastal-marine protected area of Cerro Verde e Islas de La Coronilla (fig. 1).

Data collection

Each turtle capture (see supplementary table S2 for glossary) consisted of [1] records of stranded animals from the Marine Turtle Stranding and Rescue Network and records from beach surveys conducted in Uruguay by the NGO Karumbé between 2001 and 2020 (Vélez-Rubio et al., 2013); and [2] turtles captured with set nets, a method for turtle capture and handling designed by technicians of the NGO Karumbé based on their experience of over two decades of studying the green turtle behavior. For this procedure the turtles were captured alive while feeding over rocky and sandy bottoms <5 m depth. Set nets (nylon monofilament, 50-m length × 3-m depth, 30-cm stretched mesh size) were deployed perpendicular to wave direction and were monitored constantly to avoid turtle drowning. After being captured, the turtles were located in the shade on an adequate surface for data collection (López-Mendilaharsu et al., 2016; Vélez-Rubio et al., 2018). Underwater photographs of turtles cannot be taken in Uruguayan coasts because of the turbidity of these waters.

Each captured turtle was measured (Curved Carapace Length, CCL notch to tip) using a flexible tape (accuracy = 0.1 cm). The Mean and the Standard Deviation of CCL are indicated as mean±SD. Turtles were photographed on both lateral sides of the head: each turtle was positioned dorsoventrally on a comfortable surface, the head was placed to expose the facial scales, epibionts were removed if present, and then the head was cleaned with sea water. Photographs were taken afterward of the sides of the head, taking on average 6 min per turtle. Given the time span of the data collection (19 years) and the nature of the volunteer work of the NGO Karumbé, 14 different photographic camera

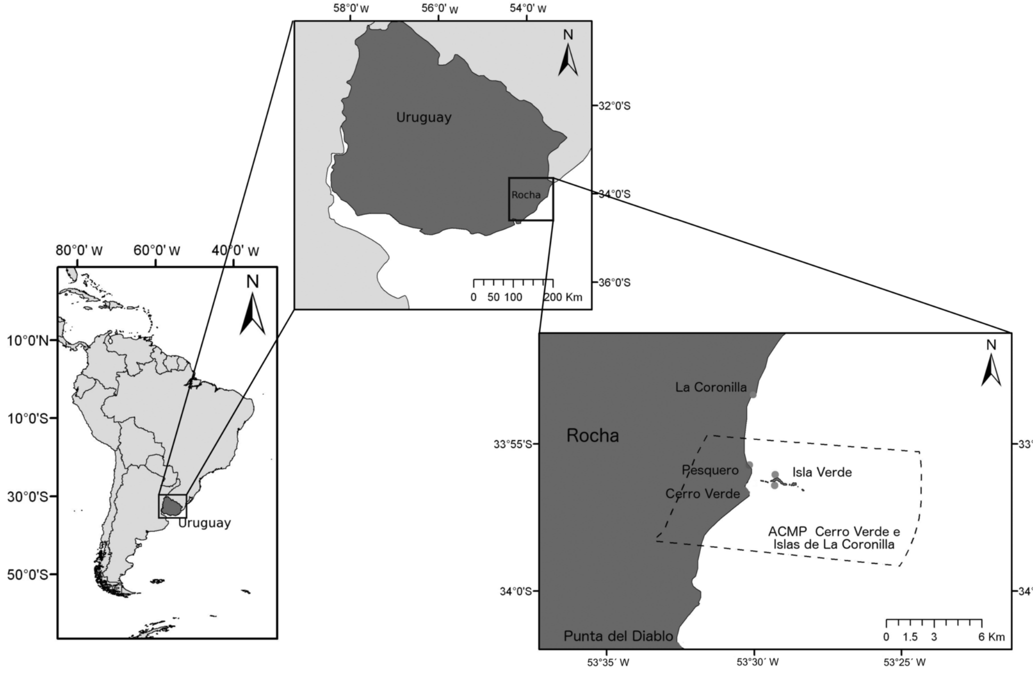

Figure 1. Map of Uruguay in South America. The study area included all the Uruguayan coast and the Coastal-Marine Protected Area of Cerro Verde e Islas de La Coronilla in Rocha, where captures of this study were performed.

models were used in the study (supplementary table S3). After photography, turtles were tagged with paired metal tags (Inconel) on their rear flippers, taking 4 min on average per turtle, unless the turtle was already tagged (then just the photographs were taken and tag codes were recorded). In the case of the presence of a tag scar (due to tag loss) we recorded this information and retagged the turtle. All turtles captured were in good condition after sampling and tagging and were released at the site of capture.

PID and tag data pre-processing

To match images through PID, we selected the best photograph obtained of each head side of each turtle (captured in [1] and [2]), and cropped it from the temporal scales to the lower margin of the mandible for correct visualization of the postorbital and tympanic scales (we adjusted brightness and contrast if necessary) using the software RawTherapee version 5.8 and Microsoft Office Picture Manager (fig. 2). Selection, cropping, and adjustment of images took on average 1 min per head side per captured turtle. We obtained a database consisting of one cropped image file per head side (left and right) per captured individual by surveyed day, the right and left image file names were recorded in spreadsheets.

We used an open-source software Wild-ID (Bolger et al., 2012) to process the cropped images because PID studies on herpetofauna successfully used it with fewer errors compared to other software tools (Suriyamongkol and Mali, 2018; Bardier et al., 2020). This software is based on the SIFT algorithm that recognizes and compares key points independent of the scale (Lowe, 2004) returning the 20 top-ranked potential matches for each focal image (Bolger et al., 2012). Then, the observer decides visually whether there is a match among these top 20 images. Wild-ID computes a matching score between the focal image and each of the 20 top-ranked images (quantifies the similarity between each pair), and ranks each of the 20 potential matches according to this score; these scores range from 0 (totally different pictures) to 1 (perfect match: exactly the same picture) (Bolger et al., 2012). Matching images through Wild-ID was conducted by three observers: C. Buteler, C. Bardier and Y. Gonzalez.

For tag data processing we recorded each tag number of each turtle (captured in [1] and [2]) in the same spreadsheet where the image file names for PID were recorded. This allowed us to keep track of the identity of each captured turtle with both PID and tag techniques. For further analysis we only considered records that had the complete set of information per turtle: left and right head side images and tag codes. If a turtle was already tagged when captured, matching tag code was simply conducted by manual search of tag codes within the spreadsheet (no time was accounted for in this search). Importantly, this implies that repeated tag codes of each turtle captured (i.e., tag matches) were available before PID processing; however, the search using PID was not biased by this information as observers that conducted PID through Wild-ID were blind to tag records.

Error and effectiveness metrics

We tested three criteria for regarding matches as recaptures: 1) PID regarded as recaptures only the matches recorded

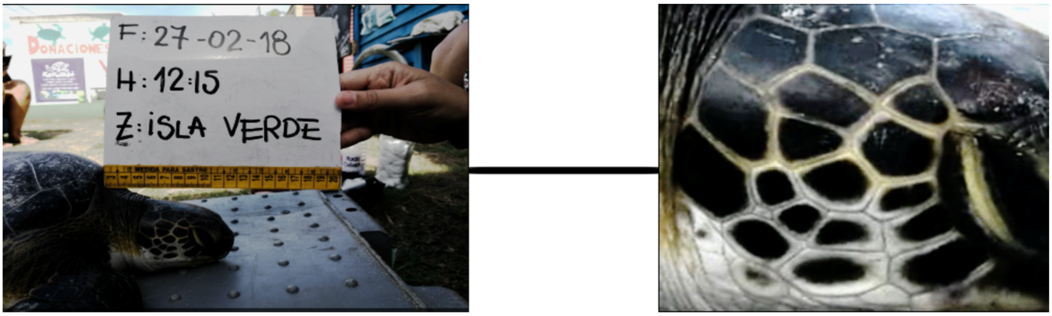

Figure 2. Example of cropping procedure of photographs of juvenile green turtle *Chelonia mydas* used in this study. Left: photograph of the turtle after a capture. Right: image resulting after manual cropping and adjustments for Wild-ID analysis.

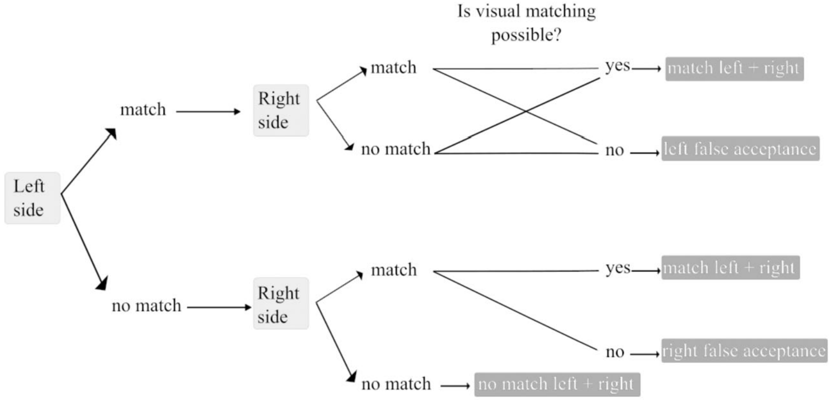

Figure 3. Diagram of decision-making for PID criterion that uses images from left and right sides of the head of juvenile green turtles *Chelonia mydas*.

through Wild-ID from left and right sides separately (see fig. 3 for details of the decision-making process when sides disagreed); 2) TAG regarded as recaptures the matches recorded only by metal tags; 3) PID OR TAG combined match information from Wild-ID from both head sides (PID) and tags (TAG): if there was a match using any criterion, then it was regarded as a recapture. We tested the last criterion as a combination of both techniques and not as more restrictive criterion (e.g., PID AND TAG: to regard as a recapture only those records for which both PID and TAG reported a match) because we can assume that the probability of false positives in both techniques is low and in the PID OR TAG criterion the false negatives of each technique can be detected, a more restrictive criterion would accumulate false negatives of both techniques.

We assessed the error rate metrics as the rate of misclassification of matches as recaptures of each criteria; for the following metrics zero indicates no error. For the three criteria, the false positive rate (FPR) and false negative rate (FNR) were calculated as follows (named false acceptance rate and false rejection rate in Cruickshank and Schmidt, 2017; Bardier et al., 2020):

$$FPR = \frac{N(false\ matches)}{N(non - matching\ comparisons)}$$

$$FNR = \frac{N(falsely - rejected\ matches)}{N(truly\ matching\ comparisons)}$$

where $N(false\ matches)$ is the number of matches between pairs (images or tags, according to the each of the three criteria described above) that were not true matching pairs, $N(falsely - rejected\ matches)$ is the number of matches that were true matching pairs but were not identified as such, $N(truly\ matching\ comparisons)$ is the number of true matches among all the comparisons. $N(non - matching\ comparisons)$ is the total number of comparisons that are not true matching pairs, defined as the total number of possible comparisons:

$$NMC = \frac{n!}{2 * (n-2)!} - TMC,$$

where n is the total number of images or tags to be compared (total captures), NMC is $N(non - matching\ comparisons)$, TMC is $N(truly\ matching\ comparisons)$. We compared the results of the three recapture criteria (PID, TAG, PID OR TAG) and identified situations in which there was a mismatch between criteria (i.e., a disagreement in the results regarding a given pair). In these cases, we conducted a posterior manual search of the images to decide whether a mismatch could be regarded as a recapture (Bendik et al., 2013). Based on this visual confirmation, we built a consensual record of all matching individuals, which we consider the definitive TRUE matching record. This consensus was used to calculate the $N(\textit{truly matching comparisons})$, and the recapture rate as follows:

$$\textit{Recapture rate} = \frac{N(\textit{truly matching comparisons})}{n}$$

Note that this recapture rate is based on how many photos or tags match out of the total number of photos or tags, which is not a modeled CMR recapture probability (i.e., the probability for a marked individual to be captured on any given sampling occasion). Additionally, we calculated this recapture rate using data available in previous studies of *C. mydas* (Reisser et al., 2008; Valdés et al., 2014; Chew, Liew and Joseph, 2015) for a standardized comparison of our results.

For each criterion we assessed effectiveness using metrics commonly used in PID studies: Accuracy, Recall, Precision, and F1 (Pedersen and Mohammed, 2021). Accuracy describes the proportion of the true positives and negatives detected by each criterion; Recall represents how well the criterion detected true positives, while Precision represents how well the criterion was able to detect positive cases. F1 is a good measure for the balance between Precision and Recall. According to these definitions from Pedersen and Mohammed (2021), we calculated effectiveness metrics as follows:

$$\textit{Accuracy} = \frac{N(CTP) + N(CTN)}{N(CTP) + N(CFP) + N(CFN) + N(CTN)}$$

$$\textit{Recall} = \frac{N(CTP)}{N(CTP) + N(CFN)}$$

$$\textit{Precision} = \frac{N(CTP)}{N(CTP) + N(CFP)}$$

$$F1 = \frac{2 * \textit{Recall} * \textit{Precision}}{\textit{Recall} + \textit{Precision}}$$

where $N(CTP)$ is the number of criterion true positives: i.e., how many of the $N(\textit{truly matching comparisons})$ were detected by each criterion; $N(CFN)$ is the number of criterion false positives: i.e., $N(\textit{falsely} - \textit{rejected matches})$; $N(CTN)$ is the number of criterion true negatives: i.e., how many of $(n - N(\textit{truly matching comparisons}))$ were regarded as without a match by each criterion; and $N(CFP)$ is the number of criterion false positives: i.e., $N(\textit{false matches})$. Notice that $N(CTP) + N(CFN) = N(\textit{truly matching comparisons})$; and $N(CTN) + N(CFP) = n - N(\textit{truly matching comparisons})$; thus, $N(CTP) + N(CFP) + N(CFN) + N(CTN) = n$.

Effect of image quality on PID

To assess the effect of image quality on the occurrence of false negatives and the matching score of images when using PID criterion, we evaluated image quality of a subsample of images composed by: 1) the true matches from TRUE, and 2) the *falsely-rejected matches* (see definition above) of the PID criterion. From each pair of images (of match types 1 and 2), we assessed the quality of each focal image: the image that was compared against the top 20 most similar images in Wild-ID. This subset of images was classified according to different quality indicators: angle of the photo (straight, oblique); light (good, poor); sharpness (good, poor); turtle cleanliness (dirty, clean); width and height in pixels (modeled separately). All indicators were measured using RawTherapee version 5.8.

We conducted two analyses to evaluate the effect of quality indicators on the occurrence of false negatives. First, we conducted a correspondence analysis using the match type of each image (true match (1), false negative (2)) and the quality indicators aforementioned as variables. Secondly, we ran a logit binomial generalized linear model using match type as a response variable and the quality indicators and width and height of the images as predictors.

We ran a logit binomial generalized linear model to evaluate the effect of quality indicators on the similarity of images using the matching score as the response variable (here we used a subsample restricted to match type 1: true matching images) and the quality indicators and width and height of the images as predictors. The matching score was square root transformed to approach normality.

The statistical analyses were performed using R version 4.0.2 (R Development Core Team, 2010) in the R Studio environment (R Studio, 2013) with a minimum significance level of $\alpha = 0.05$. A model simplification trough backward stepwise procedure was conducted using the built-in function step () in R. Whenever the data showed overdispersion (residual deviance/degrees of freedom > 2) we fitted quasibinomial family, and model simplification was achieved through backward stepwise procedure ANOVA contrasts using F-statistic (Crawley, 2007) in R.

Results

We recorded 1917 capture events with a complete set of left and right side photographs of tagged turtles, so we analyzed 1917 tag codes and 3834 cropped images through the software Wild-ID (fig. 4). These events represent 35% of turtles recorded (captured or stranded) by Karumbe over the 19 years of study ($N = 5436$). Of these 1917 events, 8% ($n = 153$) corresponded to stranded records [1], and 92% ($n = 1764$) corresponded to records of intentionally captured turtles [2]. The CCL of the turtles measured between 25.7-71.0 cm and 39.70 ± 5.70 cm ($n = 1917$). The Wild-ID matching score of images was variable: range = 0.0004-0.42, 0.09 ± 0.06. The longest period between capture and recapture identified by PID for one turtle was eight years. Five of the turtles possessed tags from Brazilian projects (unpublished data).

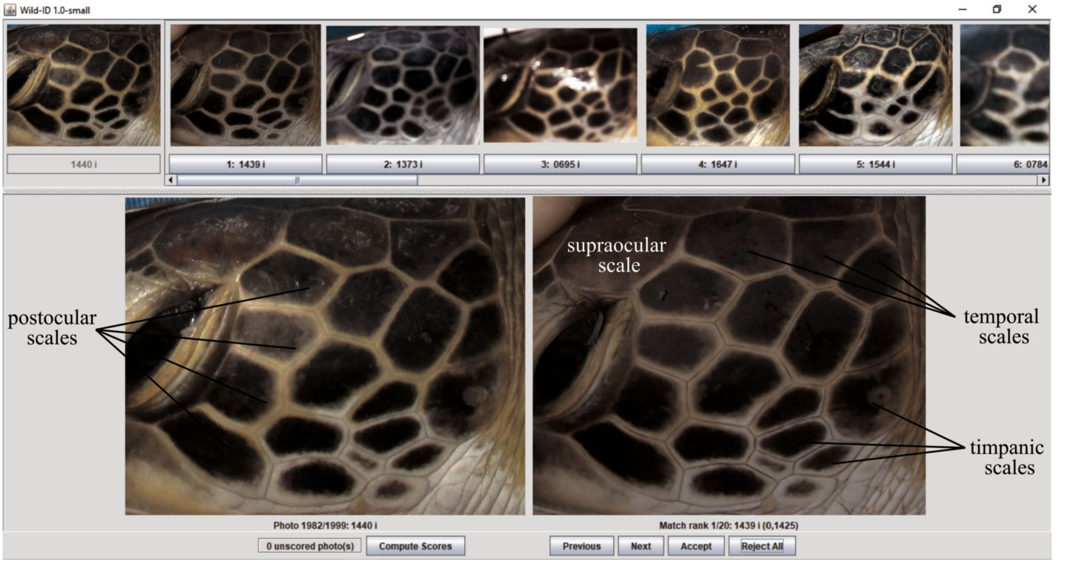

Figure 4. Example of PID technique using Wild-ID software: output of a matching comparison of two images of the left head side of a juvenile green turtle *Chelonia mydas*.

The time invested in turtle preparation for photographs (cleaning and manipulation) and photo taking was 192 hours. Afterwards, processing photographs into images to analyze them through Wild-ID, and Wild-ID analysis itself, took 128 hours. Thus, the total amount of time invested for PID was 320 hours. Tagging, accounting only for the time invested in placing both tags in the turtle fins (i.e., accounting only for untagged turtles) when the turtle was on land, took a total of 122 hours.

Error and effectiveness metrics

After analyzing the database of images and tags ($n = 1917$), we determined that the TRUE matching record was a sample that contained 1818 unique turtles, 99 of them were recaptured, with a resulting recapture rate of 0.05. Recapture rates in previous studies of *C. mydas* were: 0.22 (Reisser et al., 2008), 0.14 (Valdés et al., 2014), and 0.05 (Chew, Liew and Joseph, 2015). We captured 1838 animals once, 65 twice, 10 three times, 2 four times and 2 five times. The time interval between recaptures of individuals ranged between 4 and 2927 days (0 and 8 years). The combined approach of PID and TAG techniques allowed us to reconstruct the recapture history of 19 turtles that had lost the metal tags, while seven turtles were not detected by Wild-ID but were identified by tags (supplementary table S4).

Based on the TRUE record, the results of error rate assessments showed that PID was the criterion with the lowest FPR, but PID OR TAG was the criterion with the lowest FNR (table 1), TAG was the criterion with the highest error rates. Regarding effectiveness metrics, the three criteria had a good performance, since all metrics were above 80%; PID OR TAG had the highest Accuracy, Recall, and F1, while PID had the highest Precision (table 1).

Effect of image quality on PID

Of the total of the images analyzed ($n = 214$: 107 right and 107 left) according to match type, 175 were true matches (1), and 39 were PID false negatives (within sides, but were later resolved for PID criterion) (2). We classified 126 with high sharpness and 88 with low sharpness; 141 and 73 images showed straight and oblique angles, respectively; 130 and 84 images had good and poor light, respectively; and 166

Table 1. Error rates and effectiveness metrics for the three criteria to regard matches as recaptures for green turtles *Chelonia mydas* in Uruguay. Metrics: error and effectiveness metrics of each criteria (PID, TAG and PID OR TAG). PID: regarded as recaptures only the matches recorded through Wild-ID from left and right sides; TAG: regarded as recaptures the matches recorded only by metal tags; PID OR TAG regarded as recaptures if there was a match in either method. TRUE: is the true matching record. FPR: false positive rate; FNR: false negative rate. Accuracy describes the proportion of the true positives and negatives detected by each criterion; F1 is a good measure for the balance between Precision and Recall (both overall describe the capacity of the criterion to detect positives). Bold indicates the best criteria for each metric. Recaptures: is the number of recaptures according to each criteria and the TRUE. A detailed table of counts used in the formula of each metric is available in supplementary table S4.

Metrics	PID	TAG	PID or TAG	TRUE
FPR	**0.00**	<0.0001	<0.0001	–
FNR	0.07	0.19	**0.00**	–
Accuracy	0.9963	0.9896	**0.9995**	–
Precision	**1.00**	0.9877	0.99	–
Recall	0.9293	0.8081	**1.00**	–
F1	0.9634	0.8889	**0.9950**	–
Recaptures	92	81	100	99

were clean and 48 were dirty. Width range was 139-1425 pixels, 692.5 ± 252.9; height range was 131-1392 pixels, 538.0 ± 208.4.

Regarding the effect of quality indicators on the occurrence of false negatives, the correspondence analysis showed an association between the true match (1) and straight angle, as well as between clean conditions of turtle skin (fig. 5). However, the best model was the one that included the angle, cleanliness, and height as a predictor of true match, but no variable by itself was significant on the match type (Chi-squared ANOVA contrasts for binomial GLM: angle $Dev_{212} = 3.12$, $P = 0.07$; cleanliness $Dev_{211} = 2.25$, $P = 0.13$; height $Dev_{210} = 2.21$, $P = 0.14$). The best model to predict the effect of quality indicators on the similarity of images (Wild-ID score) was the one that included only turtle cleanliness (clean or dirty) and was significant ($F_{1,176} = 3.96$, $P < 0.05$).

Discussion

Our results show that the pattern of scales of both head sides remain unchanged for up to 8 years, as this is the longest time we recorded for a recapture using PID. Similar results were obtained by Carpentier et al. (2016) with recaptures of at least 11 years. CMR studies can be complex, involving capturing, handling, and tagging the individuals for further capture and identification in subsequent studies, or, in the case of highly migratory animals, they can only address a short period of the life stage (Bolger et al., 2012). PID techniques have a good performance in some CMR studies, for example in whale sharks, *Rhincodon typus* (Araujo et al., 2014) and spotted ragged tooth sharks, *Carcharias taurus* (Van Tienhoven et al., 2007), dolphins or whales (Weir et al., 2008).

Tagging is invasive because requires handling and restraining sea turtles (Janette et al., 2010), which may influence the behavior of the animal; in addition, tags have a short lifespan (Reisser et al., 2008; Dunbar et al., 2014). Time spent during manipulation for photo taking for PID technique (192 hours for PID criterion) was slightly longer than for tagging (122 hours for TAG criterion), as photo taking had to be accomplished on land (because of the difficulties of taking photographs underwater due to the high turbidity of Uruguayan coastal waters). Considering that either tagging or restraining the turtle out of the water for photo taking is stressful, both methods applied separately can be considered equally invasive in our study. Roberts et al. (2021) found that tagging in long-term studies can be up to five times more efficient than PID along time because tagged animals take less time to handle when recaptured. We did

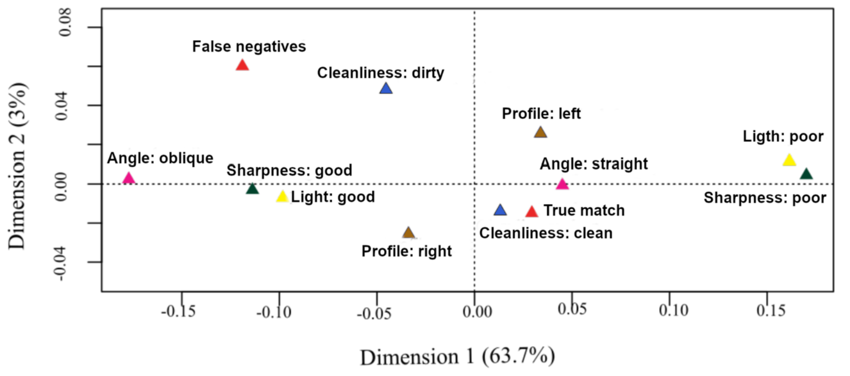

Figure 5. Correspondence analysis to explore the relation between quality indicators on the occurrence of false negatives using the PID technique for the study of juvenile green turtle *Chelonia mydas*.

not find such increase in efficiency, and therefore not such reduction in handling, because we had a low recapture rate and 19 turtles lost their tags (they had to be tagged again). Apart from invasiveness, PID took twice as long as TAG because after photography extra time was invested in processing photographs for matching analysis in search for recaptures. Then, applying PID OR TAG implied that time spent for marking and processing was the sum of all these times and, thus, PID OR TAG was the most time consuming and invasive criterion. In spite of that, and the fact that the effectiveness and error rates do favor the use of PID only, two arguments have to be claimed in favor of TAG: 1) a tagged turtle can be easily identified by fishers and, thus, they can rapidly report the by-catch to NGOs or research groups working locally; 2) a stranded turtle on the coast, when it is already dead and decomposition has started, it is more likely to be identified if a tag is present than by the facial scales (because they might be deformed or loose scales).

When comparing the error rates produced by PID, TAG and PID OR TAG criteria, we found that the FPR was very low for the three criteria, but PID had zero error. This likely happened because images of both head sides were taken into account for PID criteria, and a decision-making process for disagreement between sides was applied, whereas a false match was recorded by TAG and also was included in the PID OR TAG criterion. TAG had the highest FNR due to tag loss; indeed, in this study 19 turtles lost their tags but were identified as a recapture through Wild-ID, whilst seven turtles were not detected by Wild-ID but were identified by tag. Thus, the smallest false negative rates were recorded by PID OR TAG criterion, which took into account any match from either PID or TAG.

Our study is the first to assess these errors in sea turtles by comparing different marking methods. FPR and FNR violate the assumption that individuals are correctly identified (Yoshizaki et al., 2009). Small FPR seems to be frequent in studies, regardless of the species analyzed or the software used (Cruickshank and Schmidt, 2017). Errors found here for the PID OR TAG criterion (<0.0001 for FPR and 0.00 for FNR) were lower than values reported by Cruickshank and Schmidt (2017) using Wild-ID for the identification of the yellow-bellied toad (*Bombina variegata*). Studies reporting PID FNR for other marine animals are available, such as *Rhincodon typus* (FNR = 0.08, Arzoumanian, Holmberg and Norman, 2005; FNR = 0.07, Speed, Meekan and Bradshaw, 2007), with results similar to ours for PID. The highest FPR error reported in previous studies is 0.025 (Kelly, 2001), which is higher than our highest FPR (<0.0001 by TAG and PID OR TAG), which is unlikely to introduce substantial bias in population parameter estimates (Morrison et al., 2011). Our FNR (0.07) obtained by PID and for PID OR TAG (0) was below the minimum (0.10) to avoid bias in estimates of population parameters, according to Morrison et al. (2011). An example of how false negatives can bias population estimates is available in Suriyamongkol and Mali (2018). They found that the lack of recognition of four recaptures out of their 28 truly matching comparisons (FNR = 0.1428 according to our calculations), lead to an overestimation of 323 over 974 individuals when population size was modeled (Suriyamongkol and Mali, 2018).

Effectiveness metrics are becoming popular, yet to our knowledge no studies have measured them for marine turtles. Our results are similar to other effectiveness values recorded using under-water photographs and different PID criteria (Pedersen et al., 2021; Araújo et al., 2022) and to terrestrial vertebrates (Clapham et al., 2022). PID OR TAG accounted for the highest F1. As this metric is used to combine the precision and recall measurements into a single value, it aids the balanced comparison of their performance among marking methods. When comparing F1 for each single criterion, PID outperformed TAG: the effectiveness clearly indicates that PID is preferred. Indeed, PID OR TAG performs slightly better that PID in terms of F1, which can be argued in favor of using only PID, especially considering the drawbacks for animal welfare involved in tagging the turtles.

It is well documented that error rates of PID increase with decreasing image quality (Frasier et al., 2009; Barlow et al., 2011) because of the increased risk of making either false matches or to falsely reject matches. Although in this study there was no significant effect of angle or cleanliness on the probability of truly matching an image, correspondence analysis showed an association between true matches and either straight angle and clean conditions of turtle skin. Dunbar et al. (2021) assessed the software HotSpotter using images of hawksbill turtle (*Eretmochelys imbricata*) at a variety of angles to provide a description of successful match conditions. That software could identify individual turtles with differences in both horizontal and vertical angles. The matching power of the SIFT algorithm, used either by HotSpotter and Wild-ID, declines to 50% of match probability when images have 50 degrees of difference (Lowe, 2004), but this was sufficient tolerance for Dunbar et al. (2021), and likely it was in the case of our study. At nesting beaches, the presence of sand on the head of the turtles was identified as a cause of error in PID studies (Valdés et al., 2014; Steinmetz et al., 2018). Steinmetz et al. (2018) suggested that only photographs with less than 20% sand or reflection coverage in the area of interest should be used for matching and subsequent inclusion in a database. Sand should be removed from the area of interest with water, and the individual should be protected from the sun to reduce any reflection. In this study, the relationship of cleanliness with similarity of images that were true matching pairs was direct and significant: low scores due to dirty conditions imply low similarity and may indirectly lower efficiency of the method and, therefore, indirectly increase FNR. Thus, simply cleaning the turtle properly would improve the efficiency of the technique.

According to our calculations of recaptures, in Cuba, Valdés et al. (2014) recorded a recapture rate for nesting *Chelonia mydas* a value that may be higher than ours likely due to the permanence of individuals in nesting areas; nevertheless, Chew, Liew and Joseph (2015) found a rate in nesting areas in Malaysia similar to ours. Reisser et al. (2008) found a recapture rate markedly higher than ours in juvenile green turtles in Arvoredo Island, Southern Brazil. This difference could be due to the characteristics of the study areas. Our study was conducted on a coastline that offers many more feeding areas nearby, whereas probability of recapture can be higher in the archipelago because turtles move between islands that offer conditions for a longer residence time, with sea surface temperature around 22°C and not varying much throughout the year (Cantor et al., 2020).

Chelonia mydas is categorized as endangered by the IUCN (IUCN, 2004) and Vulnerable for Uruguay (Carreira and Maneyro, 2015), although more recent conservation efforts have considered the South Atlantic population as Least Concern (Broderick and Patricio, 2019). However, this last categorization was based mainly on information from nesting areas without taking into account the high risks and threats observed in feeding or developmental areas (Cantor et al., 2020). Long-term studies such as ours forge an essential baseline for further population studies at the regional level and for contribution to global knowledge on sea turtle stocks and associated threats in temperate regions.

In recent years, the NGO Karumbe has been tagging more turtles and we expect to have more recaptures in the coming years. We are tagging green turtles between 5 and 15 years old; after 10 years these individuals would be close to sexual maturity (green turtles reach reproductive age at 28 or 30 years, Zug et al., 2002) and therefore would be approaching nesting areas many kilometers away from Uruguay. Few studies have documented the stability of the head scale patterns for longer than a decade (Carpentier et al., 2016), because this is a highly migratory species and PID work in nesting areas is reduced due to restrictions on the use of flash at night (Valdés et al., 2014).

Because the tagging systems used in sea turtles have a short life span (Reisser et al., 2008), it is necessary to develop a technique with a long lifespan concordant with the long lifespan of these animals. The PID system facilitates identification of individuals throughout their lives because scale pattern is invariant despite the rapid growth in first years (Chew, Liew and Joseph, 2015). Hence, PID can act as a quantitative tool to reevaluate the conservation status of sea turtles at the local, regional, and global levels, and contribute to the development of policies towards the protection of coastal and marine areas used by sea turtles (Schofield et al., 2008; Su, Huang and Cheng, 2015). We agree with Su et al. (2015) that through the creation of cooperative databases, feeding and nesting areas could be identified (without the need of costly methods such as genetic or telemetry studies) and conservation strategies could be improved. Studies that photographed turtles underwater (e.g., Chassagneux et al., 2013; Araujo et al., 2016) indicate that physically capturing them can be avoided, decreasing the risk of injury and stress, while reducing methodology costs, although in Uruguay and other areas with turbid water this technique would be difficult to apply. In these areas the scientific and controlled capture of individuals is necessary to obtain population and health status information. These captures are an opportunity to photograph the turtles correctly, taking into account the insights from this and previous studies. Nevertheless, tags are still necessary in population studies of these turtles in Uruguay, given the high rates of by-catches by fishers and dead stranded turtles recorded in this country (Vélez-Rubio et al., 2013).

Conclusion

This study provides the first report of the use of PID methods for long-term data of juvenile sea turtles in feeding grounds of the SWAO, and the first to assess the comparative performance of PID and tagging methods in sea turtles. A combination of methods, PID OR TAG was the most efficient criterion for the correct identification of juvenile green turtles in Uruguay. However, the invasiveness of this criterion is the highest once the turtle is on land, as tagging and photo-taking have to be applied simultaneously. Considering: 1) that PID criterion had the lowest false positive rates, the best performance and a high effectiveness in general; and 2) that the relationship of cleanliness with similarity of images used for PID was direct and significant, we suggest that if the quality of images in future studies can be improved by properly cleaning the turtles before photo-taking, tags could be totally substituted by our PID criterion. We strongly recommend taking good quality pictures if PID is going to be applied either alone or as a complement to TAG (PID OR TAG). We also recommend considering the local situations (occurrence of by-catch or stranded dead turtles, for which tags are still necessary, like in Uruguay) before deciding to apply PID as the only marking method.

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