Aquatic Mammals 2025, *51*(3), 281-296, DOI https://doi.org/10.1578/AM.51.3.2025.281

Innovative Machine Learning and Stakeholder Method to Assess Bycatch of *Tursiops truncatus* in the Southern Gulf of Mexico

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Abstract

The assessment and mitigation of bycatch, currently identified as the most significant threat to marine mammals, represents a substantial challenge for society. This issue is particularly acute in developing countries, where data on small-scale fisheries are scarce, and knowledge gaps exist regarding the distribution and abundance of various marine mammal species. Artisanal fisheries, particularly in developing countries, have been linked to significant mortality levels of marine organisms due to bycatch. The magnitude of this phenomenon reveals alarming figures. Notably, there is a high incidence of interactions between the bottlenose dolphin (*Tursiops truncatus*) and nearshore gillnets, where the overlap in their coastal distribution creates high-risk zones. The imperative to assess bycatch is driven not only by conservation principles but is also essential for sustainability in developing countries due to U.S. government regulations on imports of fishery products aimed at reducing bycatches worldwide. This study proposes an innovative methodology to investigate marine mammal bycatch in the southern Gulf of Mexico. This methodology is based on the development of artificial intelligence models, the integration of stakeholder input, and the use of habitat suitability models. This approach utilizes 11 years of sighting records and 1,654 spatial-temporal fishing effort data points collected through interviews with fishers. Additionally, the study develops artificial intelligence models, specifically Random Forest algorithms in *Python*, to enhance the analysis and prediction of bycatch risk. This research identified monthly variations in high-risk zones for marine mammal bycatch in the southern Gulf of Mexico, highlighting regions with a higher likelihood of interaction with gillnets. This pioneering work of applying artificial intelligence to marine mammal bycatch provides a complementary analysis for areas with limited economic and data resources.

Key Words: bycatch, artificial intelligence, machine learning, Geographic Information System, *Python*

Introduction

Bycatch is a significant problem for the conservation of various marine organisms, leading to the extinction of different species around the world (Casey & Myers, 1998; Lewison et al., 2004; Northridge, 2009; Taylor et al., 2017). It arises from direct interaction with fishing activities and refers to the unintentional capture of non-target species (Hall et al., 2000; Davies et al., 2009). Bycatch stands as the primary threat currently faced by marine mammals and is responsible for the death of hundreds of thousands of individuals annually (Read et al., 2006; Reeves et al., 2013; Avila et al., 2018). This issue significantly impacts demographic and genetic aspects of cetaceans, resulting in elevated mortality rates and population declines (Mendez et al., 2010; Mannocci et al., 2021). In particular, the viability of the common bottlenose dolphin (*Tursiops truncatus*) is affected by several bycatch events, with numerous records of interactions between different fishing methods and this species in various regions of the world (Díaz-López, 2006; Zappes et al., 2016; Byrd & Hohn, 2017). This species exhibits coastal and oceanic ecotypes throughout its extensive distribution, which encompasses tropical and temperate oceans worldwide. Coastal ecotypes are characterized by forming smaller groups of females with offspring, juveniles of both sexes, or solitary male subgroups (Wells & Scott, 2009). The survival of coastal dolphins is significantly endangered by their interaction with gillnets (D'Agrosa et al., 2000; Slooten et al., 2006; Rojas-Bracho & Reeves, 2013). The incidence of bycatch events has increased markedly since the 1970s due to the growing demand for resources and the expansion of fishing activity driven by population growth (Breen et al., 2017;

Cruz et al., 2018). Despite recognising the problem, more comprehensive assessments of the impact of marine mammal bycatch, such as *Tursiops truncatus*, in regions where data are scarce or non-existent are needed.

To address bycatch internationally, in 2017, the U.S. government issued regulations requiring countries exporting fishery products to implement marine mammal bycatch assessment and mitigation measures equivalent to those set forth in the Marine Mammal Protection Act as a fundamental requirement for access to the U.S. market (Williams et al., 2016; Johnson et al., 2017). Developing comparable measures represents a significant challenge for countries with limited resources. Even though import regulations aimed at mitigating bycatch primarily target commercial fisheries, their objective is to assess and reduce this issue on a broader scale, with each country responsible for implementing them. This need is even more pressing in small-scale fishing, where limited information and high marine mammal mortality due to bycatch underscore the urgency of mitigation and evaluation efforts (Moore et al., 2010).

Small-scale fisheries are typified by the utilization of smaller vessels and a paucity of sophisticated technologies, representing the most prevalent modality among the different types of fisheries (Allison & Ellis, 2001; Muallil et al., 2011). Artisanal fishing is an essential livelihood for the well-being of coastal communities worldwide, providing food, employment, and food security (Garcia & Rosenberg, 2010; Jentoft et al., 2011). Despite their pivotal role in sustaining millions of individuals, small-scale fisheries are deficient in management plans and projects due to restricted access to public resources (Kosamu, 2015; Teh et al., 2015). Management deficiencies result in a lack of spatio-temporal information on fishing efforts, in contrast to the situation observed in commercial fisheries (Salas et al., 2007; Stewart et al., 2010; Metcalfe et al., 2017). Small-scale fishing is a highly important economic activity in the state of Yucatán, Mexico. It directly supports more than 16,930 people and contributes 14.69% to the regional GDP (CONAPESCA, 2022). Therefore, it is crucial to develop new methodologies for bycatch analysis to protect marine mammals and promote the sustainability of coastal communities and countries worldwide.

Complementary data is a potential solution to the challenges associated with acquiring information regarding bycatch (Peltier et al., 2016; Murphy et al., 2019). Integrating artificial intelligence and machine learning tools has made it easier to address challenges in scientific research (Adam et al., 2017; Gakhar et al., 2024). The use of these tools has made it possible to infer patterns that traditional analytical methods had not previously identified through the extraction and management of large volumes of data. The use of these methodologies in marine research is relatively recent and is scarce in the bycatch study (Salman et al., 2020; Long et al., 2024). Furthermore, integrating geographic information systems and participatory mapping, in conjunction with the involvement of stakeholders, allows for addressing information gaps in data-limited contexts through local expertise.

The state of Yucatán is in southeastern Mexico. Along with Campeche and Quintana Roo, it forms the Yucatán Peninsula, a vast karstic plain that separates the Gulf of Mexico from the Caribbean Sea. The Campeche Bank, an extensive continental shelf surrounding the Yucatán Peninsula, expands seaward up to 300 km from the north coast of the Yucatán Peninsula. This extensive continental shelf is rich in marine resources supporting many key species for artisanal fishing. The high diversity of species in the area has driven the implementation and development of a range of artisanal fishing techniques. The fishing methods implemented in Yucatán include gillnets, longlines, bottom longlines, handlines, harpoons, and a selective method called Jimba, which utilises a 7.5-m bamboo pole for the capture of octopuses. The artisanal fleet consists of fibreglass vessels ranging in length from 8 to 12 m, equipped with outboard motors ranging from 50 to 75 hp (Fernández-Méndez et al., 2011). Yucatán state consists of 12 coastal municipalities, including 14 fishing communities, along 378 km of coastline. For the study, the Yucatán coastline is analysed among three regions—Western, Central, and Eastern—based on hydrological characteristics (Merino, 1997; Herrera-Silveira et al., 2004). The Western region is composed of the communities of Sisal and Celestún; the Central region includes the towns of Dzilam de Bravo, Telchac, and Progreso; and the Eastern region encompasses the fishing communities of San Felipe and El Cuyo.

Processes aimed at reducing marine mammal bycatch require the participation and integration of the various stakeholders involved in this issue, including fishers, government authorities, and the scientific community. The present research, developed in three phases, proposes a novel, low-cost methodology that integrates multiple tools such as machine learning and diverse data sources for the spatio-temporal characterization of marine mammal bycatch in the southern Gulf of Mexico. The first stage involved estimating the habitat suitability of *Tursiops truncatus* through an exhaustive analysis of 8 y of sighting records, complemented with data from literature on the study area. The next phase focused on estimating the spatio-temporal fishing effort by gathering data from interviews, scientific publications, and government sources. Finally, a Random Forest machine learning model identified areas at risk of monthly bycatch based on habitat suitability and fishing effort, categorized by the type of fishing gear used in the region.

Methods

Habitat Suitability Modelling

The habitat model for *Tursiops truncatus* covered a larger area than the study region due to the species' high mobility and the absence of geographical barriers limiting its distribution. The modelling area covered the Gulf of Mexico and extended from the Northwestern Atlantic region, bounded by the coast of the South American continent, including the maritime areas of the Greater and Lesser Antilles, to the warm-temperate oceanic provinces of the Northwestern Atlantic.

The Autonomous University of Yucatan's Marine Mammal Research and Conservation Program (PICMMY-UADY) has conducted monitoring efforts over 11 y, aiming to record marine mammal sightings in the southern Gulf of Mexico. Unlike the northern Gulf, where abundant information exists, the southern region shows a significant lack of data on sightings of these species. The data obtained during the navigational process encompass comprehensive information, including the geographic location (as determined by GPS), time, date, sampling effort, and the marine mammal species identified. In the interest of focusing the present study on a single species, only the records of *Tursiops truncatus* were utilized.

Additionally, an exhaustive search for species presence-only data was conducted in the scientific literature, including peer-reviewed articles, government reports, and theses. To avoid a negative correlation between presence records and environmental variables, which could be attributed to areas with higher record density, the data were filtered using the 'spThin' package in *R* software. Using a random approximation algorithm, the "thin" function filtered the geographic points corresponding to the sighting records, based on a distance of 35 km, which reflects the estimated average movement range for *Tursiops truncatus* (Irvine et al., 1981).

Environmental Predictors

According to the previous work, five predictors were selected for analysis, two oceanographic and three bathymetric, associated with the occurrence of marine mammals (Praca et al., 2009; Fernandez et al., 2018; Ramírez-León et al., 2021). The oceanographic predictors were sea surface temperature (SST, °C) and chlorophyll-a (Chl-a) concentration (mg/m^3). Chl-a concentration is an indirect indicator of phytoplankton presence, reflecting the abundance of primary producers. This relationship allows for the inference of the distribution and abundance of higher trophic levels, such as *Tursiops truncatus*, through bottom-up trophic processes (Ware & Thomson, 2005; Huot et al., 2007). Data corresponding to a 12-y period from 2011 to 2023 were downloaded and averaged, including metrics for maximum, minimum, and mean values obtained using the MODIS-Aqua sensor from the Ocean Color portal (https://oceancolor.gsfc.nasa.gov). The information has a spatial resolution of approximately 0.041° (equivalent to about 4 km) with a processing level of L3. The bathymetric variable predictors included bathymetry (D, m), bottom slope (B, degrees), and distance to the 200-m isobath (D_{200}, m). Bathymetric data were obtained from the General Bathymetric Chart of the Oceans (GEBCO; https://www.gebco.net). A custom computational routine was developed using the 'Rasterio' and 'GDAL' packages in *Python* to perform multiple processing steps on the downloaded bathymetric data. 'Rasterio' was employed to read and manipulate the raster data, and 'GDAL' was utilized to calculate the seabed slope and the distance to the 200-m isobath. This process was achieved through functions that facilitated raster reprojection, resampling, and spatial analysis operations. The collinearity among the analyzed variables was assessed using Pearson's correlation coefficient, employing the 'corrplot' package in *R*. This package allows for the visualization of the correlation matrix, making it easier to identify relationships between variables. Additionally, the 'mecofum' package in *R* facilitated the selection of uncorrelated predictors by establishing a correlation threshold of 0.7.

We used the 'ENMeval' package in *R* to model habitat suitability and then employed *MAXENT* software to predict this suitability. Based on previous studies, we constructed a model using a random sample of 10,000 geographic points spatially distinct from the records catalogued in the previous stage. We fitted the *MAXENT* algorithm to linear, quadratic, and hinge features.

We performed cross-validation of the model using a block methodology, dividing the dataset into four groups. The *MAXENT* algorithm evaluated one of the blocks while using the other three to train the algorithm. The performance of each model generated from the different MaxEnt runs, resulting from the combinations of selected linear, quadratic, and hinge features, was evaluated using the area under the curve (AUC) and the omission rate (OR). These indicators measure, respectively, the discriminatory ability of the models and the proportion of test locations that fall within cells not predicted as suitable (Elith et al., 2006; Phillips et al., 2006). The logistic model output was employed to ascertain habitat suitability within a raster with a resolution of 0.04°, encompassing the entirety of the study area. The suitability values are expressed on a scale from 0 to 1, with 0 representing low habitat suitability and 1 indicating high habitat suitability.

Spatio-Temporal Fishing Effort

This research used a rapid interview tool commonly employed to obtain data on fishing efforts and bycatch of marine organisms. The interview was modified to align with the local context to facilitate its implementation (Moore et al., 2010). The questionnaire was divided into two main sections. The first focused on identifying the marine mammal species sighted by fishers and their frequency of this success. The second section of the study was designed to collect data on the various fishing gears employed in the region, with particular attention paid to the frequency and seasonal patterns of their utilisation. A map of the maritime regions surrounding the interview locations was created. The marine area adjacent to each locality was divided into 6-km-wide hexagons. The objective of the map was to enable fishers to identify the areas in which they conducted their fishing activities, indicating the month and type of fishing gear employed.

The interviews were conducted over 2 y, from 2022 to 2024, at the landing ports. The objective was to conduct 50 interviews per port; however, the degree of receptiveness exhibited by the fishers varied across the different study areas, resulting in some locations meeting the proposed target. While few efforts have been made in the study area, this work provides valuable insights into the available information. An additional 30 interviews in each site were conducted in the various study ports to assess the spatial correspondence of the selected hexagons with the information gathered at the beginning of the research to validate the collected data. The analysis demonstrated the consistency of the hexagons with the designated fishing areas.

The data obtained from the maps utilized in the interviews was digitized employing *QGIS* software. A vector layer was created, comprising all the collected data and arranged in accordance with the hexagonal grid. The fishing effort was estimated in square metres for gillnets; in thousands of hooks for longlines; and in fishing units for Jimbas, fishing line, and traps, based on the information provided by the fishers. We calculated fishing effort means and standard deviations by gear type, with the results broken down monthly by location and represented in the generated map.

Analysis of Fishing Effort and Density Using Python

We used a geospatial data processing approach to analyse fishing effort and its spatio-temporal density. The process employed specialized *Python* libraries for spatial analysis and large-scale data management, including NumPy, Pandas, and 'Rasterio.' We also developed personalized computational routines incorporating the "Haversine" function for distance calculations. The methodology consisted of loading a CSV file with the information obtained in the previous stage using the Pandas library. A cell size of 0.04° was defined, which would be used to create a grid over the study area, and this size was selected to obtain adequate resolution. Grid boundaries were then established using the "np.arange" function, generating a range of values from the minima and maxima of the coordinates. A function was developed to assign each fishery record to a grid cell using "np.arange" to sort the values into predefined ranges. The centre of each cell was then calculated, allowing the location of the records to be more accurately represented by adding half the cell size to the cell index position. The number of records in each cell was counted using the Pandas library, generating a new DataFrame showing the density of records per cell. Finally, the relevant columns were selected and saved in a new CSV file. To facilitate the interpretation of the data, the calculated densities were normalised by dividing each value by the maximum, allowing the density to be displayed on a scale of 0 to 1. The values were classified into four ranges, from 1 to 4, based on their density and fishing effort, where level 4 corresponds to high, level 3 to medium, level 2 to low, and level 1 to null. Bathymetric data and the distance to the nearest fishing port were added to the information obtained from the generated cells. We designed a computational routine using *Python* to convert decimal coordinates into raster file indices using the "raster index" function. Next, linear interpolation was applied to the four nearest pixels to enhance the spatial precision of the center of each grid. Finally, a function was developed to extract the depth values corresponding to each geographic point. The obtained values were assigned to the corresponding spatial analysis cells within a DataFrame.

The distance between each cell and the fishing locality was determined using a *Python* script that implements the "Haversine" formula. A function named "Distance" was created, which takes the longitudes and latitudes of the cells and the localities of interest as parameters. This function calculated the distance in kilometres for each studied cell during the analysed period. The calculated distances were organised into a NumPy array and incorporated as a new column in the original DataFrame. We assessed the differences in fishing effort among months using a non-parametric analysis of variance test (Kruskal-Wallis H). This methodology provides a clear and systematic framework for analysing monthly fisheries data, allowing for effectively identifying geographical patterns and concentrations.

Bycatch Risk Assessment Using Artificial Intelligence

The marine mammal bycatch risk assessment was conducted by developing and implementing a machine learning model in *Python* designated as a random forest. Random Forest is a supervised machine-learning model that uses decision rules to classify data based on independent variables. The analysis is performed by recursively identifying patterns across multiple decision trees. The algorithm divides the data into subsets based on the independent variables evaluated in each tree. The result is obtained through a statistical exercise, which calculates the mode of the classifications made by all the trees.

The dependent variable obtained corresponds to the marine mammal bycatch risk classification, categorized into five levels ranging from 0 to 4, ordered from lowest to highest. Level 0 represents no risk, while level 1 covers a risk range of 1 to 25%, level 2 from 26 to 50%, level 3 from 51 to 75%, and level 4 from 76 to 100%. The independent variables included in the Random Forest model, based on findings from previous stages of the investigation, are habitat suitability of *Tursiops truncatus*, fishing density, fishing effort, fishing gear types, latitude, longitude, distance to the fishing port, bathymetry, month, region, and the geographic locations of bycatch events, determined over an 11-y study developed by PICMMY in the region using oceanographic models. All information was geospatially structured in a 0.04° grid for analysis using the artificial intelligence model.

A custom *Python* routine was developed to build a Random Forest model using the "scikit-learn" machine learning library. Data collected in earlier stages were incorporated into the methodological stage. The model was designed to include the SMOTE (Synthetic Minority Over-sampling Technique) method. This strategy creates synthetic instances of the minority class, enhancing the model's ability to detect representative patterns.

Spatio-Temporal Maps of Marine Mammal Bycatch Risk

A Random Forest Classifier was built with 1,000 estimators and a maximum depth of 20, training the model on the balanced dataset. The model's performance was evaluated using standard metrics such as the confusion matrix, classification report, and accuracy, calculated with "scikit-learn" functions. Additionally, the importance of the model's features was analysed to identify the most influential variables in the predictions. Cross-validation was performed using StratifiedKFold to ensure the model's robustness. Finally, the model's performance was visualised using the matplotlib and seaborn libraries, producing ROC (receiver operating characteristic) curves and precision-recall graphs. These visualisations allowed for evaluating the validity of all analysed categories of incidental marine mammal bycatch risk.

The geospatial visualization of marine mammals' probability of incidental catch by month in the southern Gulf of Mexico was conducted by generating a *Python* script that loaded incidental catch risk files in CSV format. The data were transformed into point geometry for representation in the spatial coordinate system. Next, the probability of incidental catch of marine mammals was classified into four levels to facilitate analysis: the first level ranges from 0 to 25%; the second from 25 to 50%; the third from 50 to 75%; and the fourth from 75 to 100%. The resulting file was exported in shapefile format for manipulation and presentation using *QGIS* software.

Results

A total of 268 interviews were conducted across the seven study locations, resulting in 1,654 data points (geospatial records) of fishing efforts in Yucatán state. At least 30 interviews were carried out in each location. Additionally, 38% of the interviewed fishers reported sightings of marine mammals. The greatest concentration of gillnet fishing effort was observed in January and July. The non-parametric annual variance analysis identified differences in fishing efforts between months (H_{11} = 68.5; $p < 0.05$). The change in the dynamics of fishing gear coincides with the beginning of the octopus fishing season (*Octopus maya, Octopus vulgaris*) which uses Jimbas. This fishing method does not negatively impact marine mammals. However, despite the frequent use of Jimbas from August to December, a remnant of gillnet fishing persists, representing less than 10% of fishing activity.

The artificial intelligence model developed allowed the monthly identification of marine mammal bycatch risk areas with an accuracy of 82.63%. The variable that contributed the most to the model, as measured by the reduction in mean squared error, was the fishing gear, with 15.98%. Next, fishing effort contributed 14.79%, followed by habitat suitability with 12.08%. The month explained 11.84% of the variability, while latitude and longitude contributed 10.12 and 10.09%, respectively. Distance, region, and bathymetry contributed 9.48, 7.01, and 7.25% in that order. Finally, the locality variable accounted for 1.35% of the Random Forest model.

A comprehensive evaluation of the model was conducted. First, the ROC, precision recall, and learning curves were analysed to assess its overall performance. Additionally, potential errors, including hallucinations, were investigated through cross-validation and a systematic evaluation in which the obtained results were compared with spatio-temporal information on bycatch zones extracted from an 11-y study based on Lagrangian models conducted by our research group. Finally, the results were validated by regional experts in marine mammals and fishery resources. The cross-validation process yielded an average value of 0.84 with a standard deviation of 0.03. The machine learning model generated for bycatch analysis demonstrates an accuracy greater than 0.98 (Figure 1). The cross-validation curve exhibits significant fluctuations when using fewer than 800 data points. However, both the training and cross-validation curves tend to stabilize and converge once 1,000 training data points are reached. This behaviour suggests the absence of overfitting and good performance of the generated model.

The relationship between the true positive rate and the false positive rate (Figure 2) highlights the model's ability to differentiate the spatio-temporal probabilities of risk of marine mammal bycatch in the study area. The model demonstrates a high predictive capacity for risk levels 0, 1, 2, and 4, whose curves show excellent behaviour, approaching the upper left corner. In contrast, the curve for class 3 shows slightly erratic behaviour indicating good performance, albeit with some false positives and negatives. The model

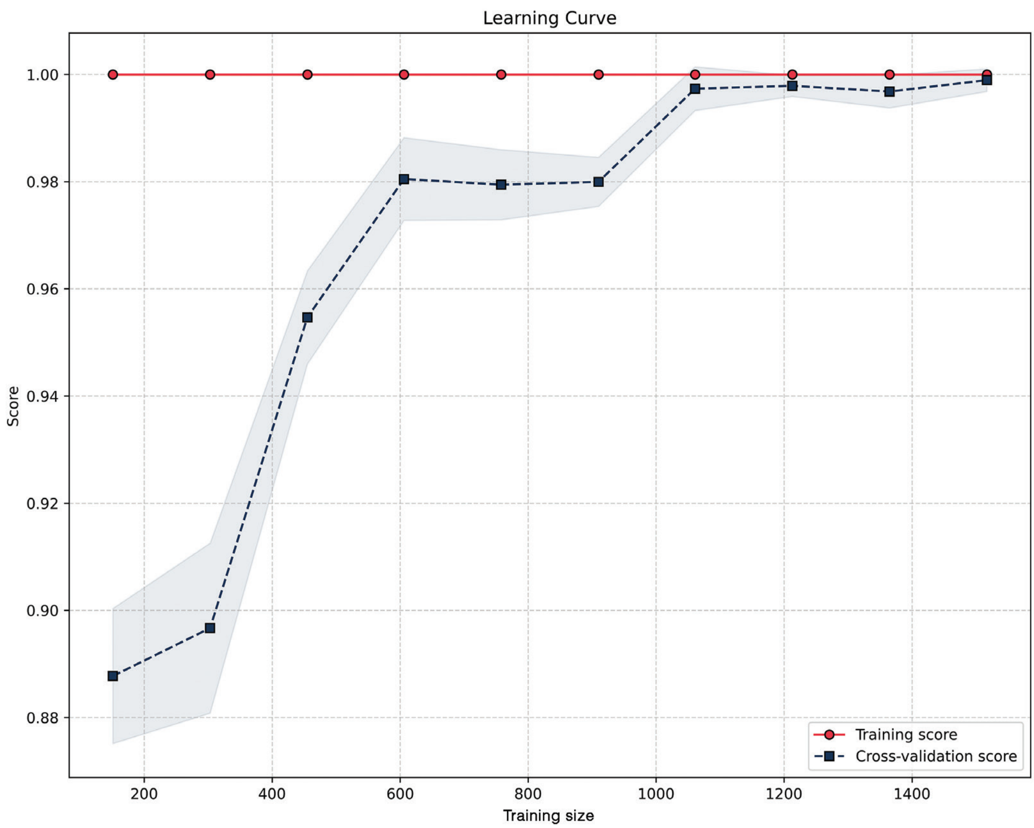

Figure 1. The learning curve of the artificial intelligence model for spatio-temporal assessment of bycatch risk using 1,654 supporting data points. Training and cross-validation curves are included.

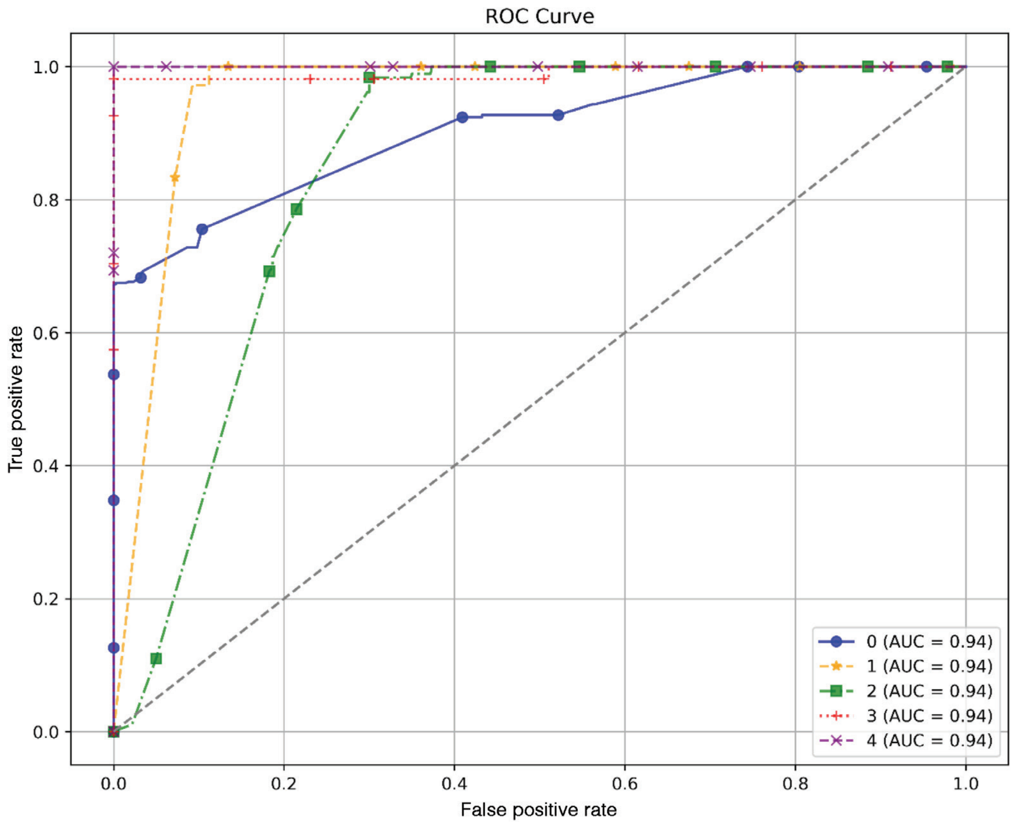

Figure 2. The ROC (receiver operating characteristic) curve showing the relationship between the true positive rate and the false positive rate in the prediction of the following five bycatch risk levels in the study area: 0% (class 0), 1 to 25% (class 1), 26 to 50% (class 2), 51 to 75% (class 3), and 76 to 100% (class 4).

predicts with high accuracy areas with bycatch risk between 0 and 50%, as well as between 76 and 100%, while it performs less consistently when predicting areas with risks between 51 and 75%. This behaviour can be explained by the difficulty in identifying areas of intermediate risk in contrast to those areas where there is a marked incidence of bycatch or no bycatch at all. All risk levels have an area under the curve greater than 0.94, showing a good fit for the model.

The relationship between precision (the accuracy of positive predictions) and recall (true positive rate) allows for the evaluation of the model's high performance (Figure 3). Classes 0, 1, and 2, representing risks between 0 and 50%, demonstrate optimal performance, exhibiting high precision and recall values. The model accurately predicts areas with a bycatch risk below 50%. However, in classes 3 and 4, corresponding to regions with risks between 51 and 100%, more significant variability is observed, as evidenced by a slight decrease in precision as recall increases. This pattern suggests that as the model attempts to capture more true positives, it generates a reduced proportion of false positives.

Despite this variability, the model maintains a high capacity to predict areas at risk of marine mammal bycatch. Its performance is consistent across different risk levels, with high scores in the ROC curve indicating good generalisation and the absence of overfitting as the validation data exhibit behaviour consistent with the training data.

The confusion matrix heatmap demonstrates an adequate capacity for assigning risk levels within the training partitions (Figure 4). The model accurately predicts bycatch risk levels between 0 and 50%. The accuracy of risk level prediction in areas with risk levels between 76 and 100% is slightly diminished, with a misclassification rate of 8%. In contrast, class 3, corresponding to risk predictions between 51 and 75%, demonstrates a lower degree of consistency, with 50% of correct assignments, 22% classified as a higher risk level, and 57% classified as one risk level lower. Despite the overall

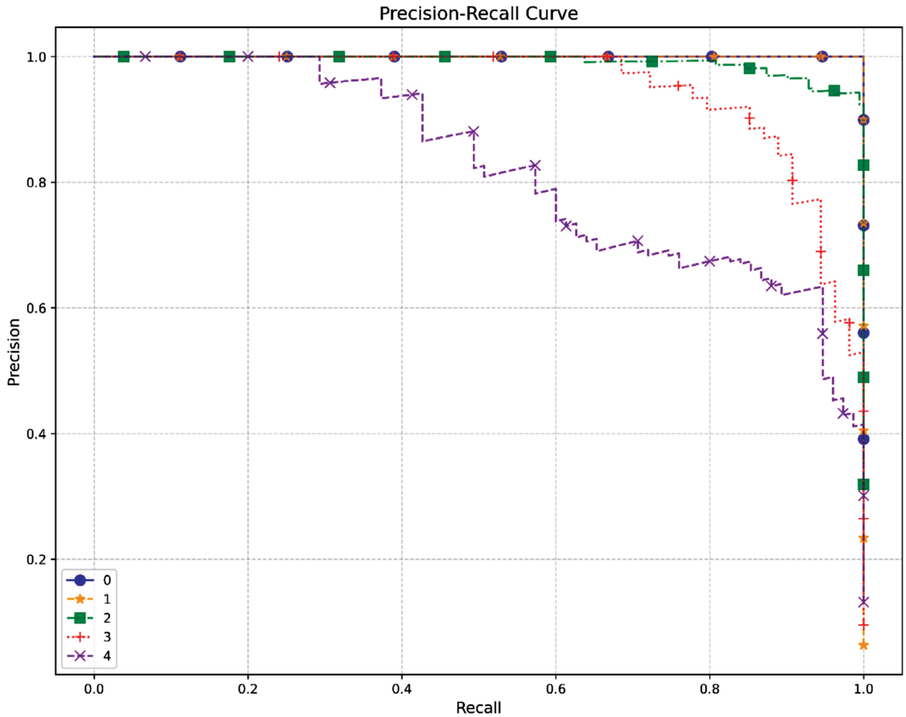

Figure 3. A precision-recall curve illustrating the relationship between precision (accuracy of positive predictions) and recall (rate of true positives) in determining the following five levels of marine mammal bycatch risk in the study area: 0% (class 0), 1 to 25% (class 1), 2 to 50% (class 2), 51 to 75% (class 3), and 76 to 100% (class 4).

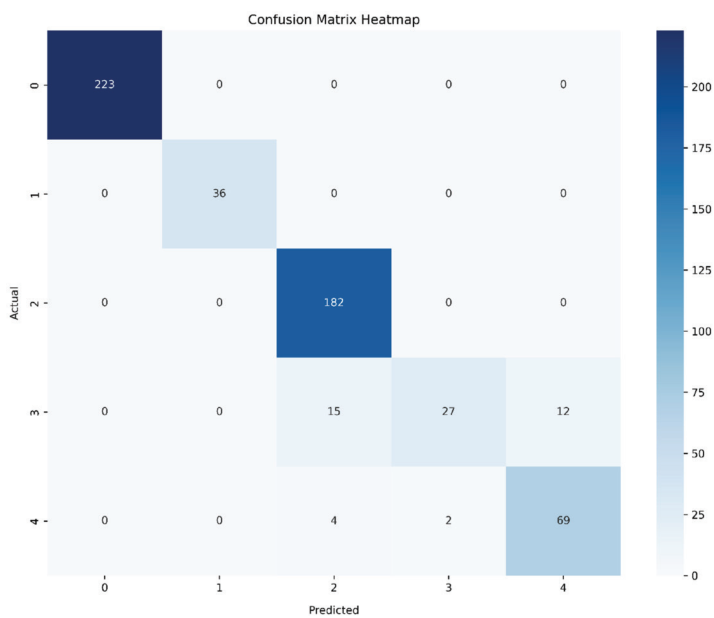

Figure 4. A confusion matrix heatmap shows the classification of five levels of marine mammal bycatch risk in training partitions: 0% (class 0), 1 to 25% (class 1), 26 to 50% (class 2), 51 to 75% (class 3), and 76 to 100% (class 4). Values on the diagonal represent correct predictions, while values outside the diagonal indicate misclassification errors between classes.

good model performance, it is worth noting that the assignments tend to occur in adjacent risk levels, suggesting that predictions remain close to the actual value, limiting large-scale errors in determining bycatch risk areas for marine mammals.

Spatio-Temporal Maps of Marine Mammal Bycatch Risk

In January, areas with a high bycatch risk are observed across all three study regions. However, the highest risk zones are concentrated in the central region, particularly in the localities of Progreso and Dzilam de Bravo (Figure 5). These areas are located between 8 and 15 km from the coastline. The distance from the shore pattern is consistent throughout the study area. This phenomenon can be attributed to competition with other fishing gear, such as line and longline fishing, which has the effect of excluding other maritime regions. In the eastern region, specifically in the locality of El Cuyo, a considerable extent of areas at risk of incidental catch of marine mammals has been identified. Additionally, a spatial association between the risk areas and the central fishing localities in the region is evident. A limited interaction zone between fishing activities and the habitat of *Tursiops truncatus* characterizes the locality of Celestún, located in the western region. However, in this restricted area, there is a high risk of bycatch (75 to 100%), suggesting an intensified use of gillnets in a confined maritime region.

Spatio-temporal analysis of the probability of *Tursiops truncatus* bycatch along the Yucatán coast revealed clear temporal patterns. The distribution of marine mammal bycatch risk exhibits seasonal variations throughout the year (Figure 6). During the initial 2-mo period, the areas exhibiting the highest risk levels are primarily concentrated in the central region, between Progreso and Dzilam de Bravo. In contrast, the western and eastern regions exhibit fewer risk zones, with Celestún and San Felipe emerging as the areas with the lowest concentration of critical points. Although the concentration of high-risk areas (red and yellow points) persists in March, their extent is diminished in comparison to previous months. From April to June, there is an increase in interactions between fishing activities and *Tursiops truncatus*, resulting in the expansion of high-risk zones from the central region eastward, reaching locations such as San Felipe and El Cuyo. In the

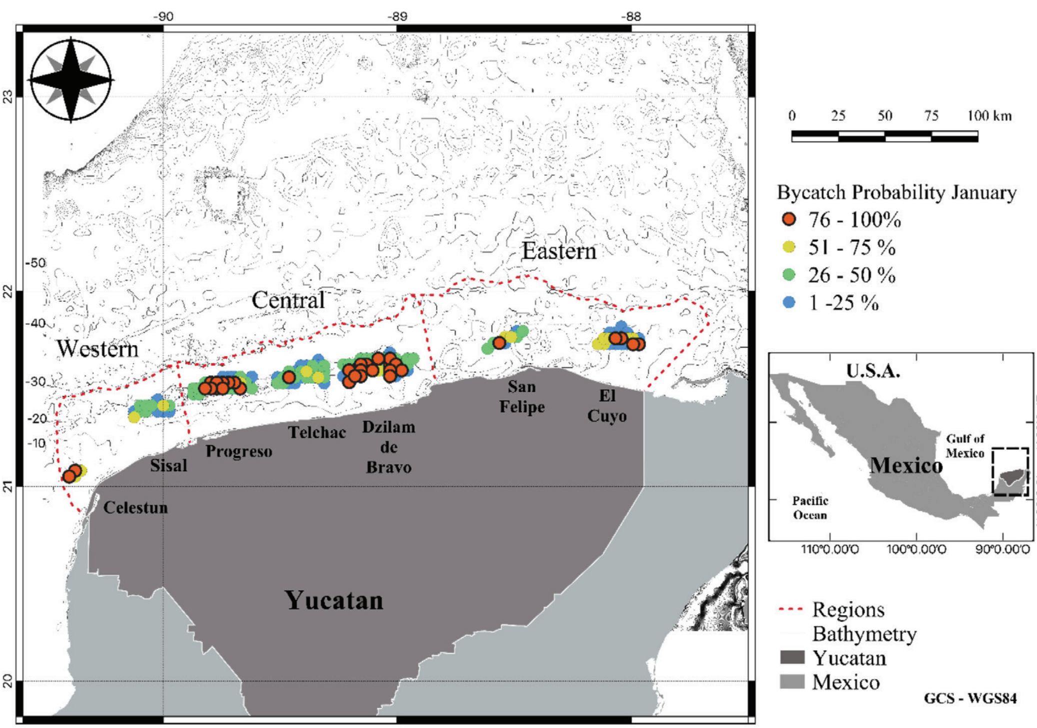

Figure 5. Spatial-temporal assessment of bycatch probability for *Tursiops truncatus* in the southern Gulf of Mexico. Red areas indicate high risk (76 to 100%), orange areas indicate moderate-high risk (51 to 75%), green areas indicate moderate-low risk (26 to 50%), and blue areas indicate low risk (1 to 25%).

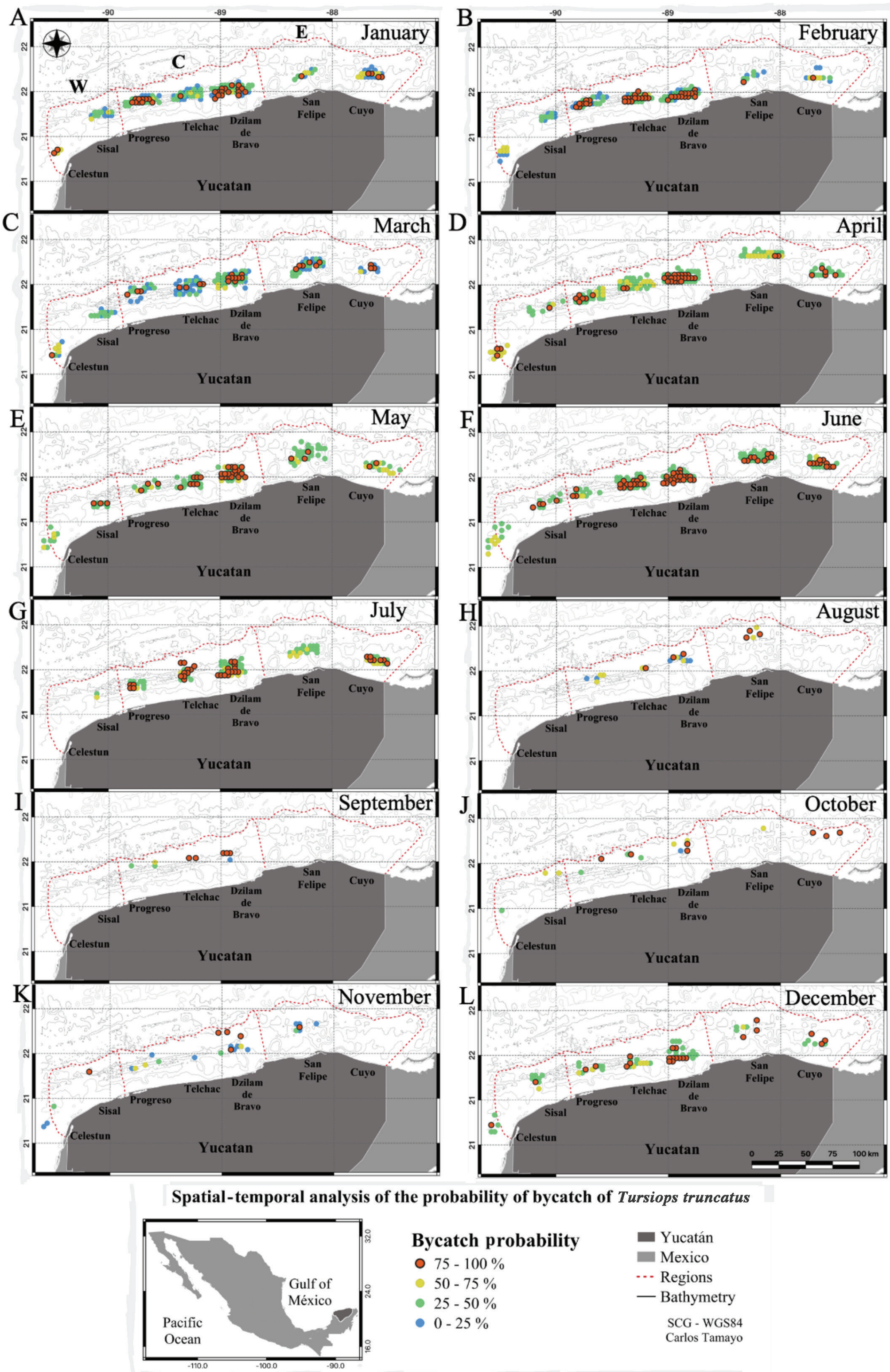

Figure 6. Annual spatial-temporal assessment of bycatch probability for *Tursiops truncatus* in the southern Gulf of Mexico. Red areas indicate high risk (75 to 100%), orange areas indicate moderate-high risk (50 to 75%), green areas indicate moderate-low risk (25 to 50%), and blue areas indicate low risk (0 to 25%).

western region, the expansion is less uniform, with most new high-risk areas concentrated around the fishing community of Sisal. In July, a general reduction in risk areas was observed across all locations except Telchac, Dzilam de Bravo, and El Cuyo, where high-risk zones persisted.

During the first 7 mo of the year, all locations demonstrated some level of bycatch risk. Between February and July, the spatial distribution of risk areas was dispersed, covering distances ranging from 14.816 to 27.978 km from the coastline, underscoring the widespread nature of the issue.

In August and November, there is a notable decline in the probability of incidental capture of *Tursiops truncatus*, with low (0 to 25%) and moderate (25 to 50%) risk levels becoming more prevalent. In December, however, there was a notable increase in incidents of capture risk, which resembles the pattern observed earlier in the year. Scattered points and concentrations near the coastal zone characterise this pattern. All locations subjected to analysis exhibited at least one region where the risk of incidental capture exceeded 75%. The areas with the most elevated concentration of high-risk zones were observed in the central zone, particularly in Telchac and Dzilam de Bravo, where numerous red and yellow dots were identified near the coastline. This pattern suggests that the possibility of high-risk interactions may increase towards the end of the year, potentially due to changes in fishing activity.

Discussion

The analysis of bycatch, recognised as the primary threat to marine mammals, requires the development of novel methodologies to supplement conventional techniques for data acquisition, particularly in contexts where data are scarce. Although it was identified in the 1970s, unresolved issues still make it difficult to understand and address (Hall et al., 2000; Cox et al., 2007; Davies et al., 2009). This phenomenon, which interacts synergistically with other threats, can devastate several stocks, even with only a few entanglement cases yearly (Jaaman et al., 2008; Minton et al., 2011; Halpern et al., 2015). The lack of data specific to small-scale fisheries, coupled with events often taking place in remote locations with minimal regulatory oversight and public scrutiny, generates a complex scenario for analysing and mitigating this threat (Read, 2008). This research presents a novel complementary analysis of marine mammal bycatch. The proposed methodology integrates artificial intelligence tools, stakeholder knowledge, Lagrangian particle models, and habitat suitability models to determine the spatiotemporal risk of bycatch for *Tursiops truncatus*. To achieve this, environmental and oceanographic numeric models and variables are integrated with information obtained through participatory mapping, ultimately feeding a machine learning model designed to categorize areas of bycatch risk.

Implementing programs to assess marine mammal bycatch equivalent to those established by the Marine Mammal Protection Act in the United States poses a significant economic and logistical challenge for developing countries (Williams et al., 2016). Moreover, this challenge is exacerbated in small-scale fisheries, where traditional monitoring methods are limited by the large number of vessels, dispersed landing sites, and inadequate regulatory measures (Briscoe et al., 2014; Moore et al., 2021). The import provisions outlined in Section 101(a)(2) of the Marine Mammal Protection Act, enacted by the National Oceanic and Atmospheric Administration in 2017, are primarily targeted at commercial fisheries. However, bycatch assessment and mitigation goals could be addressed in a broader framework that addresses all types of fishing activities. The need to evaluate this is particularly relevant in small-scale fisheries, where access to information on fishing activity is limited. The methodology proposed in this study is versatile as it can be applied to different types of fishing activities, offering easily accessible and low-cost alternatives to comply with the regulations imposed. This contributes to the conservation of marine mammals and to the sustainability of developing countries. To address both bycatch analysis and fishery product export requirements, complementary data and the implementation of alternative approaches have been proposed to overcome the barriers to marine mammal bycatch monitoring in data-limited scenarios (Murphy et al., 2019).

In this study, we propose an alternative that incorporates newer methods such as machine learning. While the use of artificial intelligence tools in marine research is somewhat limited, it is even rarer in the field of bycatch (Mannocci et al., 2021; Lopez et al., 2024). Previous studies have employed various strategies, including image analysis, echo-sounding, habitat suitability assessment, environmental variables, and fisheries information (Poisson et al., 2022; Goikoetxea et al., 2024; Long et al., 2024). However, our pioneering work in integrating artificial intelligence into the study of marine mammal bycatch integrates stakeholder knowledge with traditional analytical methods and artificial intelligence techniques in a data-limited region.

The typical approach to bycatch monitoring is to employ onboard observers to obtain robust catch estimates (Moore et al., 2021). However, this methodology may have limitations and might not accurately assess the issue (Peltier et al., 2016; Hines et al., 2020). This phenomenon is due to changes in fishing activity dynamics when an observer is present. In artisanal fisheries, small vessels that limit the number of crew members, the large number of boats, the dispersion of landing ports, and scarce financial resources exacerbate the challenges of implementing onboard observers (Lewison et al., 2004; Clarke et al., 2014; Gilman et al., 2014). The integration of stakeholders, as proposed in this study (fishers, government agencies, and the scientific community), has the potential to address issues arising from a lack of local information and contribute to the development of more robust theoretical frameworks for evaluating and mitigating bycatch on a global scale.

The analysis identified a spatio-temporal variation in areas with the highest risk of incidental catch of marine mammals throughout the year. This behaviour is related to changes in the dynamics of fishing activity in the region. For example, from 1 August to mid-December, the octopus fishing season is open; octopus fishing is the leading fishing resource in the area and does not conflict with the capture of marine mammals. This phenomenon, along with the moratorium on grouper fishing during February and March, increases the use of gillnets, creating a higher risk scenario during the first 7 mo of the year.

The incorporation of diverse fishing gear types into the bycatch assessment enabled the delineation of spatially disparate risk zones through the exclusion of areas of competition based on the specific gear utilized. This approach facilitated the identification of spatial risk patterns in the central region, particularly along a strip between Progreso and Dzilam de Bravo. This finding can be explained by the higher density of fishing fleets and the proximity to Mérida, which provides easy transport and access routes (Monroy-García et al., 2019).

The results are consistent with the unique previous study conducted in the region on bycatch, which focused on sea turtles. This concurrence may be because cetaceans and sea turtles face conflicts with gillnets. Although the highest mortality rates of mega vertebrates are associated with gillnets, other fishing gear types may also negatively interact with species such as *Tursiops truncatus* (Werner et al., 2006; Forney et al., 2011; Hamer et al., 2012). The overlap between the distribution of organisms and the high fishing activity intensity in coastal areas could explain the high mortality rates resulting from bycatch associated with artisanal fisheries, where *Tursiops truncatus* is particularly vulnerable. It is essential to include various types of fishing gear and to extend the analysis to longer time periods to assess interannual variations in fishing dynamics.

The analysis revealed alterations in the maritime zone's scope and the distance from fishing grounds in areas with a high probability of bycatch. The gradual increase in the extent of these high-risk areas, observed between February and July, is associated with meteorological factors and the rise in fishing activity. From December to February, the intensification of "Norte" winds impedes fishing activity, limiting the distance covered and the search for new operational areas for the fleet (Santamaría et al., 2023). Subsequently, an expansion of probable risk areas is observed from March to July, which aligns with previous studies in the region that have suggested increased resource-seeking efforts due to declining catches and growing food demand driven by continuous population growth (Fernández-Méndez et al., 2011; Salas et al., 2011; Selgrath et al., 2018; Torres-Irineo et al., 2021).

This analysis proposes a complementary methodology at the global level and represents a first step at the regional level to address marine mammal bycatch. It offers insights regarding the sustainability of fishing communities and the evaluation of this phenomenon. The risk assessments presented in this study strengthen management and conservation plans by estimating the likelihood of such events (Hobday et al., 2011; Williams et al., 2011; Samhouri & Levin, 2012; Briscoe et al., 2014; Gibbs & Browman, 2015; Verutes et al., 2020). However, in small-scale fisheries, management plans are often ineffective due to the lack of data to accurately determine this issue's extent. This challenge highlights the need to seek complementary data for more precise estimates (Stelzenmüller et al., 2015). Participatory mapping and stakeholder engagement effectively solve this problem through a two-way approach. First, they facilitate access to large amounts of local information and allow results to be effectively communicated to fishing communities and regulators (Wiber et al., 2004; Alfaro-Shigueto et al., 2010; Samhouri & Levin, 2012; Trimble & Berkes, 2013; Bradbury et al., 2014; Rosenthal et al., 2015; Cominelli et al., 2019). Integrating artificial intelligence tools complements traditional methods, strengthens management plans, and helps reduce bycatch, even in contexts of limited resources and information, such as in many developing countries.

Acknowledgments

We acknowledge the personnel of the Autonomous University of Yucatan's Marine Mammal Research and Conservation Program (PICMMY-UADY) for their valuable participation during data collection. We are grateful to M. C. Isis Coral Hernández-Herrera for her help in obtaining the interviews as well as to the fishing community of Yucatán for the information provided. Carlos Tamayo-Millán was awarded a scholarship supported by CONAHCYT to pursue his PhD studies. All data were collected according to Mexican laws and regulations (SEMARNAT: SGPA-DGVS-06508-12, SGPA-DGVS-08256-13, SGPA-DGVS-00267-15, SGPA-DGVS-02797-16, SGPA-DGVS-00403-17, SGPA-DGVS-007603-18, SGPA-DGVS-06727-19, SGPA-DGVS-02143-22, and SPARN-DGVS-03199-23).

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