Quantifying local ecological knowledge to model past abundance of long-lived, heavily-exploited fauna (#42113)

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Quantifying local ecological knowledge to model past abundance of long-lived, heavily-exploited fauna

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Deriving robust historical population trends for long-lived species subject to human exploitation is challenging in scenarios where long-term scientific data are scarce or unavailable, as often occurs in small-scale fisheries and subsistence hunting. The importance of Local Ecological Knowledge (LEK) in data-poor scenarios is increasingly recognised in conservation, both in terms of uncovering past trends and engaging community stewardship of historic information. We propose a mixed socio-ecological framework to reliably document and quantify LEK to reconstruct historical population trends.

We demonstrate the validity of our approach by reconstructing long-term abundance data for the heavily-exploited East Pacific green turtle (*Chelonia mydas*). Using ethnographic methods (e.g., participant observation, semi-structured interviews), we documented LEK and obtained corroborated, qualitative data to understand the socio-environmental complexity of a green turtle fishery. We then established a framework to synthesise and quantify LEK data, in conjunction with Generalized Linear Models and Nonlinear Regression (NLR), to generate a standardised, LEK-derived Catch-Per-Unit-Effort (CPUE) time-series. This common index of abundance can be combined with ecological survey data for a holistic view of a species' historic and contemporary conservation status. Our data were validated by comparisons with fisheries statistics, and abundance trends prior to scientific monitoring were modelled by NLR.

As a case study, we used *C. mydas* in Baja California, Mexico, which was driven to near extinction by a largely unregulated fishery from the early 1950 to the 1980s. With no scientific baseline abundance data available for this time frame, we generated a statistically reliable, LEK-derived CPUE time-series back to the early 1950s in collaboration with local fishers. This approach generated a baseline abundance level not previously available, which revealed that the most critical (exponential) decline occurred between 1960 and 1980.

This robust integration of LEK data with ecological science is of critical value for conservation and management, and can be adapted by interdisciplinary teams to various long-lived taxa with a history of

human use.

Quantifying Local Ecological Knowledge to Model Past Abundance of Long-lived, Heavily-Exploited Fauna

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Abstract

Deriving robust historical population trends for long-lived species subject to human exploitation is challenging in scenarios where long-term scientific data are scarce or unavailable, as often occurs in small-scale fisheries and subsistence hunting. The importance of Local Ecological Knowledge (LEK) in data-poor scenarios is increasingly recognised in conservation, both in terms of uncovering past trends and engaging community stewardship of historic information. We propose a mixed socio-ecological framework to reliably document and quantify LEK to reconstruct historical population trends.

We demonstrate the validity of our approach by reconstructing long-term abundance data for the heavily-exploited East Pacific green turtle (*Chelonia mydas*). Using ethnographic methods (e.g., participant observation, semi-structured interviews), we documented LEK and obtained corroborated, qualitative data to understand the socio-environmental complexity of a green turtle fishery. We then established a framework to synthesise and quantify LEK data~~, in conjunction with~~ Generalized Linear Models and Nonlinear Regression (NLR), to generate a standardised, LEK-derived Catch-Per-Unit-Effort (CPUE) time-series. This common index of abundance can be combined with ecological survey data ~~for~~ a holistic view of a species' historic and contemporary conservation status. Our data were validated by comparisons with fisheries statistics, and abundance trends prior to scientific monitoring were modelled by NLR.

As a case study, we used *C. mydas* in Baja California, Mexico, which was driven to near extinction by a largely unregulated fishery from the early 1950 to the 1980s. With no scientific baseline abundance data available for this time frame, we generated a statistically reliable, LEK-derived CPUE time-series back to the early 1950s in collaboration with local fishers. This

approach generated a baseline abundance level not previously available, which revealed that the most critical (exponential) decline occurred between 1960 and 1980.

This robust integration of LEK data with ecological science is of critical value for conservation and management, and can be adapted by interdisciplinary teams to various long-lived taxa with a history of human use.

Introduction

Assessment of the current population status of long-lived species benefits from a firm understanding of historical baseline abundance (Pauly, 1995). For example, IUCN Red List criteria requires abundance trends over 3 generations, which, for long-lived species, may imply >100 years (Seminoff & Shanker, 2008; IUCN, 2019). However, deriving robust historical population trends is challenging when scientific monitoring data are scarce or unavailable (Pauly, 1995; Sáenz-Arroyo et al., 2005; Beaudreau & Levin, 2014). This is further aggravated in data-poor contexts, when a species is impacted by unquantified, unregulated and/or illegal exploitation, as is often the case in small-scale fisheries and subsistence hunting (Moller et al., 2004; Duffy et al., 2016; Selgrath, Gergel & Vincent, 2018). This has led to increased interest in Local Environmental Knowledge (LEK) to better understand long-term environmental change and human-environment interactions (Barrios-Garrido et al., 2018; Mason et al., 2019).

LEK data has been used in combination with official records and historical documentation to reconstruct historical abundance trends of exploited species (Jackson et al., 2001; Sáenz-Arroyo et al., 2005; Beaudreau & Levin, 2014). LEK also provides baseline data that fill gaps in knowledge that cannot be addressed through natural sciences alone (Mukherjee et al., 2018; Mason et al., 2019). Clear methodological guidelines, based on robust methods from social and natural sciences, are needed to reliably integrate LEK in conservation science (Mukherjee et al., 2018; Young et al., 2018; Moon et al., 2019). This includes developing approaches to collate and validate information from diverse knowledge sources, and forming interdisciplinary teams with expertise appropriate for the methods being used (St. John et al., 2014; Sutherland et al., 2018).

Local Ecological Knowledge (LEK) is defined as place-based empirical knowledge, held by a specific group of people about their surrounding environments and biota (Bélisle et al., 2018). LEK does not require that the population be indigenous, nor embedded in a broader shared culture, and thus can be applied to populations with relatively short histories of interactions with a specific environment (cf. Narchi et al., 2014). We present a case study of the East Pacific green turtle (*Chelonia mydas*, hereafter green turtle) in Baja California, Mexico to demonstrate a novel framework that can be adapted to long-lived, exploited taxa to evaluate abundance trends in data-poor scenarios. We used ethnography to document LEK, developed an *ad hoc* epistemological approach to synthesise and quantify LEK data, and used Generalised Linear Models (GLM) and nonlinear regression (NLR) to evaluate long-term *C. mydas* abundance trends. Our model describes historical declines, establishes baseline abundance, and helps to understand the role of human impacts.

Application Example: *C. Mydas* in Baja California, Mexico, a Case Study

To demonstrate our methods, we used the case of the green turtle in Bahía de los Ángeles (BLA), Baja California, Mexico (28°57'6.90"N, 113°33'44.76"W), an index foraging area in the Gulf of California (Seminoff et al., 2003, 2008). Green turtles have been a key food source in the arid Baja California peninsula since the earliest phases of human occupation at least 12,000 years ago (cf. Early-Capistrán, 2014). From the late 18th century until the early 1950s, green turtle harvests were primarily subsistence-oriented. Turtles were harpooned from small, wooden canoes propelled with oars or paddles. During the 1960s, the economic and demographic growth along the U.S.-Mexico border led to an increased market for green turtle meat in Mexican border cities. Within this trade, BLA was a key supplier, and was able to meet demands as the introduction of outboard motors, fibreglass vessels, and set-nets increased cargo volume and catch efficiency and improvement of highway infrastructure increased market access (Early-Capistrán et al., 2018). The fishery collapsed in the 1970s, green turtle licenses were suspended in 1983 as populations reached dangerously low levels, and all sea turtle fishing in Mexico was banned in 1990 (Márquez, 1996; Seminoff et al., 2008).

Green turtles are listed as Endangered by the IUCN and Mexican law (SEMARNAT, 2010; IUCN, 2019). Their populations in the Eastern Pacific ~~are currently increasing~~ thanks to decades of conservation efforts (Seminoff et al., 2015; Delgado-Trejo, 2016). However, abundance data and long-term trends ~~before~~ the commercial fishery are needed to contextualise current population levels (Seminoff et al., 2008; Early-Capistrán et al., 2018). This case-study demonstrates how LEK-data, compiled through ethnography, can be integrated with ecological modelling and conservation science.

Specific challenges of evaluating green turtle abundance

The complexity of the green turtle's life history makes it particularly challenging to evaluate its conservation status. Generation times are up to 50 years, and life stages occupy multiple habitats separated by hundreds or thousands of kilometres, often in different countries. Abundance data are skewed towards nesting beaches, which only quantify nesting females (Seminoff & Shanker, 2008; Godley et al., 2010). Important long-term data on nesting females have been generated since 1980 at the index nesting beach of Colola, Michoacán, Mexico (~1500 km from BLA) (Delgado-Trejo, 2016). However, to adequately evaluate population levels, further information is also needed on foraging areas where juveniles and adults of both sexes live (Seminoff & Shanker, 2008; Godley et al., 2010).

In-water scientific monitoring in BLA began in 1995, and these efforts use Catch-Per-Unit-Effort (CPUE) as a measure of abundance (Seminoff et al., 2008). Although CPUE is a crude measure of changes in exploited populations (López-Castro et al., 2010), we used it because (i) it is the only available metric of current abundance, and (ii) CPUE is an accepted proxy for abundance for IUCN Red Listing (O'Donnell, Pajaro & Vincent, 2010; IUCN, 2019).

Methods

We present flexible ~~guidelines~~ that can be modified for long-lived species with a history of human use. Our approach consists of four sequential phases: (1) background research and experimental design; (2) an iterative process of LEK documentation, synthesis, and quantification; (3) database standardisation and validation; and (4) statistical analysis and modelling of the standardised database (Figure 1). Interdisciplinary teams can ensure that quality, validity, and reliability standards are met across fields (Tengö et al., 2014; St. John et al., 2014; Sutherland et al., 2018). Detailed accounts of methods and tools are available in Supporting Information (Article S1).

Phase 1: Background Research and Experimental Design

1.1 Background research

Starting with an overarching research question (e.g., What was the baseline green turtle abundance, and how did it change over time, before scientific monitoring?), we carried out background research with natural and social science perspectives to gain a broad understanding of the research topic. Along with a review of scientific literature, we conducted historiographical research and preliminary site visits (Crandall et al., 2018).

Historiographical research situates biological questions in a socio-historical context, providing information on a species' past abundance which can be correlated with time-frames, social processes, or management regimes (details in Article S1) (Sáenz-Arroyo et al., 2005). Historiographical research helped us to understand human-green turtle interactions in BLA over centuries, and identify a time-frame for reconstructing baseline abundance before large-scale commercial exploitation (early 1950s) (Early-Capistrán et al., 2018).

We carried out preliminary site visits to (i) identify key local collaborators (knowledgeable community members who are willing to share their expertise on particular research topics); (ii) build rapport or working trust; and (iii) gain an understanding of social conditions and gather locally-relevant information for the definition of specific research questions and research design (Crandall et al., 2018). This research is part of an on-going collaborative process in BLA which began in 2012 (Early-Capistrán et al., 2018).

1.2 Experimental design

Background research helped define specific research questions and identify challenges in the study design and methods (Early-Capistrán et al., 2018; Crandall et al., 2018). Defining an approach to adequately estimate CPUE was a key challenge.

The skilled turtle fishers of BLA always targeted high-density locations (hot-spots) and aggregations, and thus maximised CPUE by optimising fishing patterns based on empirical knowledge of environmental conditions and green turtle behaviour (Early-Capistrán et al., 2018). Thus, adequate assessment of CPUE as a measure of abundance requires detailed understanding of the fishery and the variables that affected it (Moller et al., 2004). Furthermore, turtle fishers' expertise allowed for high CPUE events over time despite declining overall abundance (hyper-stability), underscoring the need to understand average CPUE trends (Maunder & Punt, 2004; Early-Capistrán, 2014) (Article S1, Figure S1). This scenario is challenging, as (i) interviewees' memory of "typical" events may be less accurate than that of salient events, and (ii) high variability in CPUE and changes in fishing efficiency can mask overall abundance trends (Maunder & Punt, 2004; Damasio et al., 2015; Sáenz-Arroyo & Revollo-Fernández, 2016). Thus, we designed our methodology to calculate CPUE based on multiple sources rather than individual recollections, and aimed to identify and account for sources of variation in CPUE that could bias proportionality with abundance (Maunder & Punt, 2004). Furthermore, we approached CPUE as a component of a holistic dataset on human-environment interaction.

We chose to calculate representative values for average CPUE (hereafter, CPUE) in one night of fishing during a specific year as the primary response variable, with the initial definition:

$$\text{CPUE} = \text{number of turtles caught} / \text{unit effort} \qquad \text{(eqn. 1)}$$

For initial inquiry, we used the working definition of one unit effort as one night (~12 hours) of fishing regardless of gear type (harpoon or net) (Maunder & Punt, 2004). In the following sections, we describe how this definition was refined continually as we gained further information on fishing technology, effort, and efficiency through the iterative feedback process between qualitative data, NLR, and GLM (Phase 2); and standardised to account for differences in gears and changes in efficiency (Phase 3).

Qualitative methodology

Ethnography was our primary data-gathering methodology. This holistic approach to the study of social systems uses a varied toolkit to generate qualitative and quantitative data (Table 1; Article S1; Table S1) (Bernard, 2011). Ethnography requires rapport, sensitivity to the cultural context, and developing an understanding of the social system on its own terms. Data are gathered broadly over topic areas, and new questions are developed continuously (Bernard, 2011; Early-Capistrán et al., 2018). Ethnography also helps identify biases by analysing data within a social and historical context (Drury, Homewood & Randall, 2011). Ethnographic data were systematised, cross-referenced, verified, and subject to analysis and meta-analysis (Bernard, 2011).

We chose ethnography because (i) the high degree of socio-environmental complexity required detailed information on diverse topics; (ii) sea turtle fishing is currently illegal in Mexico, and its inquiry requires working trust, long-term engagement, and confidentiality; and (iii) ethnography provides more detailed and reliable information on sensitive issues than questionnaires (Drury, Homewood & Randall, 2011; St. John et al., 2014). Research was designed in compliance with the ethical guidelines of the International Society of Ethnobiology (details in Article S1) (International Society of Ethnobiology, 2006), and approved by the Bioethics Committee of the Centro de Investigación Científica y de Educación Superior de Ensenada (Approval Number 2S.3.1).

We worked with the community at large including fishers' families, green turtle merchants, local authorities, commercial and sport fishers, and conservation workers to understand multiple perspectives. Using a deliberate hierarchical sampling method (Bernard, 2011), we identified a target population of fishers in the community who participated in legal sea turtle fishing before 1990. These fishers constitute a small sub-set (n=17) of the oldest fishers in the community, between 55 and 85 years of age. Expert LEK holders (hereafter, experts) were defined as community members recognised as experts by at least two peers, and whose empirical and specialised knowledge can be used as a basis for inferences and assessments about their surrounding environments and biota (cf. Bélisle et al., 2018). We interviewed experts and key local collaborators multiple times to gather specialised data (Tengö et al., 2014).

As fishers had varying degrees of expertise, we could not apply standardised questionnaires. We designed flexible interview guides for use in semi-structured and in-depth interviews based on previous ethnographic research on sea turtle use in BLA (Sáenz-Arroyo et al., 2005; Early-Capistrán et al., 2018). Interviewers used these guides as a roadmap for the interviews, allowing respondents to be thorough and make associations between questions, and to include new topics and questions according to interview progress (cf. Castro et al., 2014). Interview guides covered five main topic areas: (1) biographical profile and career history; (2) sea turtle consumption and commerce; (3) trends in sea turtle captures and sizes; (4) spatial distribution of sea turtle fishing; and (5) fishing effort and technology (Table 2). To prompt recollection of dates, questions were associated with important events in contributors' lives (details in Article S1). Questions were piloted with local fishers outside the target population (n=2) (Bernard, 2011; Young et al., 2018), and were constantly refined to ensure that they were locally contextualised and elicited meaningful answers (Drury, Homewood & Randall, 2011).

Quantitative methods

Throughout the iterative process, we used descriptive statistics for exploratory data analysis and to identify outliers (Zar, 2014). We chose NLR to describe CPUE trends over time (Ritz & Streibig, 2008), and GLM to identify significant predictor variables (cf. Maunder & Punt, 2004). We integrated residual analysis to ensure that model assumptions were met, and to evaluate goodness of fit and robustness for both GLM (Shapiro-Wilk $p>0.05$; $\mu\approx0$; Breusch-Pagan $p>0.05$) and NLR (Shapiro-Wilk $p>0.05$; $\mu\approx0$; F-test $p>0.05$) (Table 3) (Maunder & Punt, 2004;

Ritz & Streibig, 2008). Given the highly significant effect of time as a predictor variable in time-series data, residual autocorrelation was expected (Ritz & Streibig, 2008).

Phase 2: Recording, Synthesising, and Quantifying LEK

2.1 Data Gathering

M.M.E.C. and G.G.M. compiled ethnographic data over three field seasons (spring 2017, summer 2017, and spring 2018) and 57 working days, interviewing 94% (n=16) of living green turtle fishers, and community members who were not green turtle fishers (n=68). One fisher chose not to participate. Ethnographic research was conducted in accordance with the Code of Ethics of the International Society of Ethnobiology (International Society of Ethnobiology, 2006). Oral informed consent was obtained from all participants prior to the start of interviews. All participants were also asked if the consented to being recorded in audio and/or video, and if they consented to being photographed in addition to the interview (International Society of Ethnobiology, 2006). Oral consent was chosen as it was not deemed culturally appropriate to ask participants to sign a consent document, and because some participants were not comfortable with written language (International Society of Ethnobiology, 2006; Wedemeyer-Strombel et al., 2019).

We conducted semi-structured (n=11), in-depth (n=16), and informal (n=80) interviews; compiled field journals and technical photographs. When possible, interviews were recorded in audio or video with contributors' informed oral consent (Article S1; Tables S2, S3). Recorded interviews were transcribed in digital format. All interviews were conducted in Spanish, the researchers' and collaborators' primary language. We compiled field journals in digital format (.txt), recording all observations in detail.

Ethnographic data were validated through triangulation across data sources and methods to provide multiple forms of evidence rather than single data points (Creswell & Miller, 2000; Tengö et al., 2014). Once processed, data were confirmed by participants for reliability. Prolonged engagement in the field allowed us to compare interview data with observations, and helped build trust so that participants were comfortable disclosing information, increasing reliability in responses (Bernard, 2011).

2.2 Data Processing

All field journals and interview transcriptions were digitally processed and coded following a standardised protocol. Cryptic indicators ensured contributors' anonymity (Bernard, 2011). Footnotes were used to separate observations from analysis, and for cross-referencing. Cultural material codes (Murdock et al., 2008) were used to categorise ethnographic data, with customised codes for topics and themes specific to this research. Text entries were indexed using hashtags (#) to mark relevant topics (e.g., #fishing_gear), including ordinal codes (e.g., #max_cpue; #min_cpue) to classify information for data-binning (details in Article S1; Table S4). Along with data compiled in the 2017 and 2018 field seasons, ethnographic materials collected since 2012 were coded, indexed, and integrated into the qualitative database (Article S1; Table S2). Coding allowed us to break down qualitative data into analytical variables and raw values (Strauss & Corbin, 1994). Digital files allow for analysing large volumes of information by facilitating topic-specific searches. This process generated a corroborated, systematised, and cross-referenced qualitative database (Bernard, 2011).

2.3 Synthesis and quantification

Analysis ~~of qualitative data.~~

Qualitative textual analysis and discourse analysis were used to decipher the cultural, historical, and political dimensions of the research topic~~;~~ to identify potential sources of bias~~;~~ and to understand categories, processes, and connections (Crandall et al., 2018). We captured raw numerical data from interviews (Article S1; Table S4), and used Quantitative Textual Analysis tools in R 3.4 (*wordcloud*, *tm*, and *SnowBallC* packages) to identify themes and patterns (Bernard, 2011) (Article S1; Figures S2, S3).

Quantification of LEK data

We defined explanatory variables for CPUE based on qualitative data (Table 4). We generated initial indices for each variable based on the degree of detail and variation observed in interview responses, and defined standardisation and binning procedures (Figure 1).

We established four stages for the fishery, based on qualitative data and fisheries statistics (Early-Capistrán et al., 2018; Selgrath, Gergel & Vincent, 2018): (1) commercial development; (2) commercial fishing (harpoons); (3) commercial fishing (nets); and (4) collapse (Table 5). Qualitative data allowed for inferring that (i) fishing technology across the fleet was similar within each stage; (ii) at all stages, fishers would make trips of varying duration until reaching vessel capacity or exhausting food and water supplies; and, thus, (ii) CPUE could be calculated based on the knowledge of fisheries stages, trip duration, fishing gear type, displacement time, and vessel capacity (details Article S1). This framework allowed us to (i) bin data and standardise variations in expertise and response terms, (ii) systematically complement the knowledge of less experienced fishers with that of experts, and (iii) account for changes in fishing technology, effort, and efficiency over time (cf. Maunder & Punt, 2004).

We generated digital (.txt) files to summarise categorical, ordinal, and numerical data for each fisher (Article S1; Table S5). Using social network analysis (Bernard, 2011), we situated each fisher in relation to their fishing crew and extended family (Table 1). Ethnographic data provided us with numerical anchor values and limits for variables during each stage (Article S1).

2.4 CPUE calculation and preliminary database generation

To deal with variability, we used heuristic rules to make systematic inferences based on expert knowledge (Figure 2). This framework allowed us to calculate a central tendency based on collectively-generated knowledge rather than individual recollection, thus reducing individual cognitive bias (details in Article S1). Data points from fishers with less than one year of experience (n=3) were discarded.

Captures reported by weight were converted to number of turtles by dividing vessel capacity by mode of turtle mass (50 kg) reported by fishers and corroborated with monitoring data (Early-Capistrán et al., 2018) (details in Article S1). While turtle size was highly variable and likely declined in response to increasing fishing effort (Table 5), mixed juvenile/adult foraging groups with a slight juvenile bias —such as BLA, where ~56% of individuals are juveniles (Seminoff et al., 2003)— are present in green turtle foraging habitats worldwide (Seminoff et al., 2015). We consider our assumption regarding size distribution to be adequate given the nature of the data (Table 5) (details in Article S1).

2.5 Preliminary data evaluation

Evaluating statistical robustness

The estimation of CPUE and descriptor variables was an iterative process. Data were stored in .csv format, and all analyses were carried out in R 3.4 unless otherwise specified. We analysed descriptive statistics to evaluate statistical robustness by checking data distribution, evaluating normality (Shapiro-Wilk $p>0.05$), and identifying outliers (±2SD) (Zar, 2014). To evaluate CPUE trends, we serialised values for the independent variable "year" and used LABFit 7.2.49 to identify five preliminary models with best fit and starting values. We then ran NLR (*nlstools* and *easynls* packages) to choose the model that best described the data, and evaluated residuals (Table 3) (Ritz & Streibig, 2008).

We ran NLR at each round of the iterative process to (i) evaluate the general behaviour and performance of the data, (ii) identify outlier effects in residual analysis, and (iii) evaluate if the process was robust to these effects (Ritz & Streibig, 2008). Each data point was linked to a summary of qualitative and numerical data for a specific contributor, and outlying data could be contextualised and evaluated (Article S1, Table S5). Exponential decay models consistently showed the best fit.

Evaluating data treatment, variable, and parameter selection

We used GLM with a link function for Gaussian distributions to identify significant predictor variables for CPUE (*lmtest* and *car* packages). We used log-transformed values if CPUE distribution was non-normal (Zar, 2014). We ran models with each explanatory variable in the database, eliminating variables until we obtained a model with significant effects, a high percentage of explained deviance (D^2), a relatively low Akaike Information Criterion (AIC), and robust residuals (Table 3) (cf. Maunder & Punt, 2004).

These processes were adhered to throughout the methodological cycle. We ran a total of 36 NLR and 30 GLM on five different working databases. By integrating these analyses into the cyclical process, we are confident that we adequately identified confounding variables and sources of annual variation not attributable to abundance (Hilborn & Walters, 1992).

2.6 Feedback integration

Model-fitting feedback was integrated by identifying which variables and indices required further information or could be improved. We integrated feedback from community members during subsequent visits to the field by sharing preliminary results with them through narrative description, and asking for contributors' perspectives on validity and consistency. Contributors also identified gaps and provided further information (Huntington, 2000; Tengö et al., 2014). New questions were designed based on feedback (Figure 3). These procedures were repeated with each variable.

The cyclical process of data gathering, synthesis, and quantification was repeated until reaching topical saturation (similar instances were repeated and no additional data were found with which to develop new properties), thematic saturation (additional data did not produce new emerging themes), data saturation (new data repeated what was expressed in previous data) (Saunders et al., 2018), and until model fitting did not provide significant new information.

Phase 3: database standardisation

3.1 Raw CPUE Database Analysis

The result of the methodological cycle was a final, LEK-derived CPUE database with heterogeneous variables for unit effort (raw database). We carried out descriptive statistical analysis, NLR, and GLM analysis to evaluate the data and define standardisation procedures.

3.2 CPUE Database Standardisation

We standardised CPUE to (i) remove most of the annual variation not attributable to changes in abundance, and (ii) generate CPUE values that could be compared over time (Hilborn & Walters, 1992; Maunder & Punt, 2004). To choose predictor variables for standardisation, we ran GLM with log-transformed CPUE values. “Year” was removed as its high significance masked the effects of other variables.

We generated detailed definitions of unit effort based on the previous analyses. While fishers generally worked from dusk to dawn, fishing times on any given night with either gear type could be variable. For modelling purposes, values were simplified to 12hr blocks which reflect the vast majority of fishing effort (details in Article S1).

For set-nets, we matched unit effort with ecological monitoring data (100m net soaking for 12hr) (Koch, Brooks & Nichols, 2007):

$$C_{st} = (t \times R) / (n_r \times R \times 12hr) \quad \text{(eqn. 2)}$$

Where C_{st} is a standardised, representative value of average CPUE during a specific year (turtles $12hr^{-1}$); t is the number of turtles caught (turtles); n_r is the number of 100m nets (no units); R is net length (in multiples of 100m), which was simplified to short (~100m=R) or long (~200m=2R) (Table 4); and soaking time is 12hr.

For harpoon captures, we assigned a skill coefficient (*s,* percentage of success) (Table 4) to each harpooner through social network analysis (Table 1), based on colleagues’ assessment, such that:

$$C_{st} = t \times s^{-1} \times 12hr^{-1} \quad \text{(eqn. 3)}$$

The current ban on sea turtle fishing does not allow us to test for differences in susceptibility to fishing gears. However, harpoons and nets were not used simultaneously by any given fisher, and both were used over a roughly equivalent number of hours per night. Thus, we considered these values to be adequately standardised given the nature of the data. For years with multiple CPUE values, we calculated the mean after standardisation (Article S1; Figures S4, S5).

3.3 Evaluating statistical robustness

We evaluated reliability through comparison with fisheries statistics for BLA (annual landings in tonnes, 1962–1982) (Márquez cited in Seminoff et al., 2008). CPUE and total landings are both crude indicators of abundance, and comparative analyses have been used to assess the accuracy of LEK-derived data (Damasio et al., 2015; Sáenz-Arroyo & Revollo-Fernández, 2016). We compared the catch reduction rate and fitted an exponential decay model (QtiPlot 0.9.9.7**)** as an experimental process to evaluate trends in LEK-derived CPUE and annual landings (Sáenz-Arroyo & Revollo-Fernández, 2016) (details in Article S1). We then standardised both datasets to z-scores to avoid effects from differences in scales (Figure S6) (Zar, 2014) and used the Lin Concordance Correlation Coefficient (CCC) to assess agreement between paired values (*DescTools* package) (Lin, 1989; Altman & Altman, 1999) (Article S1; Figure S6).

Phase 4: Analysis of Standardised CPUE Data

We performed descriptive statistical analysis and NLR on the standardised database, following the procedures described in previous sections, to understand long-term abundance trends (Ritz & Streibig, 2008; Zar, 2014). We ran local sensitivity analysis (*easynls* package) by recomputing the model at intervals of ±0.1 relative to the starting values with best fit for both parameters, until the model reached a singular gradient (details in Article S1) (Zhou & Lin, 2017).

Case-study Synthesis

Results

We ~~obtained~~ a reliable, standardised green turtle CPUE time-series from 1952–1982 ~~(n=16)~~. GLM analysis of the raw database indicates that fishing gear type (p=0.000291), vessel capacity (p=0.00531), and number of nets (p=0.000652) were significant predictor variables for CPUE (Table 6). The model fit the data well (D^2=0.823), and residual analysis suggested that it is robust (Shapiro-Wilk, p=0.153; μ=-0.0699; Breusch-Pagan, p=0.0616). This implied that our standardisation procedure was robust (Hilborn & Walters, 1992). Comparative analysis with fisheries statistics confirmed reliability (Damasio et al., 2015; Sáenz-Arroyo & Revollo-Fernández, 2016): standardised CPUE and annual landings showed catch declines of 95% and 96%, respectively (Seminoff et al., 2008), and Lin CCC (ρ=0.726) shows strong agreement (Figure 4) (Altman & Altman, 1999; Zar, 2014).

NLR indicated that green turtle abundance declined exponentially during large-scale commercial exploitation ~~due to~~ increased fishing effort and efficiency (R^2=0.798) (Figure 5). Corroborating this, the declining trend during the fishery was consistently reported by all fishers. Residual analysis suggests that the model is robust for the data (Shapiro-Wilk, p=0.299; μ=-0.317; F-test, p=0.349). Local sensitivity analysis showed parameter values (α=24.112, β=-0.0829) and significance (α, $p=2.07 \times 10^{-6}$; β, $p=1.706 \times 10^{-5}$) remained unchanged for a range of starting values from -0.3 to +0.5 relative to the starting values for best fit, indicating that the model is robust over this range (Article S1, Table S6). Our results suggested that fishery-derived mortality exceeded replacement via reproduction or immigration rates into the feeding areas

(Chaloupka & Musick, 1996). Furthermore, increased fishing effort and efficiency could not compensate for overall abundance decline (Hilborn & Walters, 1992).

Previous research identified the early 1960s as a period when human impacts precipitated a major decline in green turtle abundance in BLA (Early-Capistrán et al., 2018). This suggests that CPUE values in the 1950s can be considered an adequate historical baseline abundance level, as green turtle captures in the Gulf of California in previous decades and centuries were relatively small and primarily subsistence-oriented (Márquez, 1996; Early-Capistrán et al., 2018).

Discussion

Understanding East Pacific green turtle population trends

Our LEK-derived data provide a baseline abundance of green turtles before large-scale commercial exploitation at a key feeding area in the Gulf of California, and describe population trends prior to ecological monitoring which are essential for establishing conservation and management goals (Seminoff et al., 2003; McClenachan et al., 2016). Our approach provides a historical reference point for the Bahía de los Ángeles foraging population. It enables us to better understand contemporary datasets and current population status in the area, especially in relation to green turtle ecological roles and carrying capacity (Seminoff et al., 2008).

When paired with contemporary in-water monitoring and nesting data, our LEK-derived estimates can provide fundamental insights for conservation status evaluations such as those conducted under the auspices of the IUCN Red List, which require a the three-generation time-span (Seminoff & Shanker, 2008; Mazaris et al., 2017). Such long-term perspectives are generally not attainable via scientific monitoring efforts alone, ~~of which~~ even the longest tenured sea turtle monitoring programs ~~didn't~~ start ~~until~~ the 1970s (Chaloupka & Limpus, 2001; Balazs & Chaloupka, 2004; Bjorndal, Bolten & Chaloupka, 2005).

While East Pacific green turtle populations are ~~known~~ to increase at both foraging areas and nesting beaches (Seminoff et al., 2015; Fonseca et al., 2018), information about small juveniles is still lacking, as green turtles < 50cm CCL are uncommon at this study site (Koch, 2013). Thus, future research that also integrates the smallest juvenile life stages and combines past trends with modern-day survey data is crucial for evaluating the overall conservation status of the East Pacific green turtle (Broderick et al., 2006; Seminoff & Shanker, 2008; Wildermann et al., 2018). Currently, the bulk of global abundance and trend data are generated at nesting beaches, with substantial knowledge gaps for foraging habitats that include pre-reproductive life stages (Wildermann et al., 2018). As immature individuals are the most abundant life stages in the population, expanding data on foraging habitats is of utmost importance for a holistic understanding of population status (Chaloupka et al., 2008; Mazaris et al., 2017; Wildermann et al., 2018).

Methodological innovation

By integrating LEK, social science, and natural science, we generated a robust, long-term database of the abundance of a long-lived, heavily-exploited marine species. The use of detailed, ethnographic data and an iterative approach are of particular value for documenting and quantifying LEK in scenarios of high socio-environmental and biological complexity, as they can allow for increased accuracy and reliability in comparison with data derived from structured questionnaire-based surveys or interviews alone (St. John et al., 2014; Crandall et al., 2018). Our approach is particularly useful in contexts where multiple and complex variables can affect or bias estimates of species abundance, as it allows researchers to understand and describe social, economic, technological, and environmental processes in detail. In the case of the green turtle, it allowed us to understand the trajectory of human impacts on green turtle abundance, and to account for the social, economic, and technological processes that affected the green turtle fishery (e.g., changes in fishing gear and displacement capacities, commercial demand, spatial dynamics, etc.) which we then quantified and integrated into our estimates, indices, and models. The reliability of this approach is corroborated by the concurrence of LEK-derived estimates with statistical data and robust model-fitting (Damasio et al., 2015; Sáenz-Arroyo & Revollo-Fernández, 2016).

We recognize that LEK data is epistemologically distinct from technical data, and have aimed to produce an approach that bridges epistemological gaps and produce a synergistic integration of LEK and biological science (cf. Brook & McLachlan, 2005; Tengö et al., 2014). As scientists, we recognize that our research is value-laden and that the inevitable differences between LEK and technical data are more often reflections of epistemological differences or methods of collection than inherent unreliability. Thus, LEK research requires trust-based collaboration between researchers and communities, a process that can necessitate years of commitment (Brook & McLachlan, 2005). In such contexts, when researchers can elicit and corroborate qualitative data derived from empirically-lived situations (Palmer & Wadley, 2007), synthesise and quantify this data, and submit quantified data to rigorous mathematical analysis, they can assure the reliability and robustness of LEK-derived estimates. Such information is of crucial importance for conservation and management, particularly in scenarios where there is a need for understanding long-term trends; where technical data are scarce or unavailable; or where species are impacted by illegal, unregulated or undocumented exploitation (Pauly, 1995; Duffy et al., 2016; Sáenz-Arroyo & Revollo-Fernández, 2016). Concomitantly, the use of LEK-derived estimates offers the possibilities of incorporating and empowering local conservation processes with peoples previously seen as deleterious agents for those same environments and species of which they hold a vast amount of LEK (cf. Berkes et al., 2005).

CONCLUSIONS

Our reconstruction revealed an exponential decline in green turtle abundance between 1960 and 1980 at one of the most important and productive green turtle commercial fishing areas in the eastern Pacific Ocean (Caldwell, 1963; Early-Capistrán et al., 2018). As scientific monitoring began only in 1994 after population collapse, no pre-exploitation baseline data were available to evaluate current abundance and conservation status (Seminoff et al., 2008). ~~This was remedied by o~~ur LEK-derived data ~~which~~ provide historical context and reliable baseline abundance for this population. We are confident that future studies integrating our LEK-derived estimates with current scientific monitoring data from both foraging habitats and nesting beaches will yield a more holistic, long-term ~~evaluation~~ of green turtle abundance, conservation, and population dynamics in the Eastern Pacific.

Beyond reconstructing green turtle abundance, our methodology may be exported to parallel cases dealing with the conservation and monitoring of other long-lived species as it can unravel complex phenomena by combining ethnographic data, LEK, and ecological modelling. By integrating knowledge systems, we provide a framework to overcome the challenges of documenting and quantifying LEK, and bridge practical and epistemological gaps (Mistry & Berardi, 2016; Mukherjee et al., 2018). This approach provides a way to deal with variation in individual memory through collectively-produced knowledge and corroborated data; to simplify and manage large volumes of qualitative information; and to translate qualitative data into a format compatible with ecological modelling (Bélisle et al., 2018). While we recognize the limitations of LEK-derived estimates, they nevertheless can provide a robust description of significant inflection points in abundance trends that would be less-resolved if analyses were limited to scantly-available technical data (Pauly, 1995; Sáenz-Arroyo & Revollo-Fernández, 2016).

LEK-based and integrative approaches provide long-term information where scientific monitoring data are scarce or unavailable, and contribute to the collaborative production of knowledge (Mistry & Berardi, 2016; Lee et al., 2018; Barrios-Garrido et al., 2018). While our methods are most readily adapted to marine fauna such as marine mammals, reptiles, teleost fish, and long-lived invertebrates, this approach can also be modified and applied to terrestrial and freshwater biota. We trust that future research that rigorously integrates social and ecological science can help address challenges for conservation and management in the context of global change and biodiversity loss (Mukherjee et al., 2018; Sutherland et al., 2018).

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Table 1 (on next page)

Methods used for data collection during ethnographic fieldwork

Method	Definition	Example of applications	Practical implications
Participant observation	Studying a social group through a combination of direct observation and immersion in group activities as an active participant	Participating in and documenting sport-fishing trips led by former green turtle fishers	All observations are compiled in field notes and journals, including, but not limited to research topics
Informal interviews	Interviews without structure or control, often conversations held during the course of fieldwork	Conversations with fishers or their family members recorded in written notes	Recorded in field notes and field journals
Semi-structured interviews	Interview based on a flexible list of written questions or topics that need to be covered. The interviewer maintains discretion to follow new leads.	Contributors were interviewed using an interview guide with recurring topics focused on the green turtle fishery	Recorded in audio or video with the contributors' consent
In-depth interviews	Aimed at obtaining detailed understanding of the topic of interest. Participants can communicate more freely and provide more detailed descriptions than with semi-structured interviews.	Experts and key local collaborators were interviewed in-depth on specific topics related to green turtle fishing or abundance (e.g.: fishing gear, green turtle commerce, etc.)	Recorded in audio or video with the contributors' consent
Focus groups	Moderated discussions with small groups (<10 people) on a particular topic	Focus group discussions with members of a fishing crew to discuss how green turtle abundance changed over the course of their careers	Recorded in audio or video with the contributors' consent
Oral histories	In-depth interviews about life stories, experiences, and eyewitness accounts	Interviewing experts on their life history and their experience as green turtle fishers	Recorded in audio or video with the contributors' consent
Participatory mapping	Contributors draw maps, locate key places on maps, or locate key sites together with researchers	Visiting key green turtle fishing spots and recording coordinates with GPS	Recorded in notes, digital maps, GIS or printed maps
Social network analysis	Identifying the structure of social relations	Documenting kinship and work relations among green turtle fishers and merchants	Recorded in notes and graphs
Discourse analysis	Analysis of communicative content and structure focused on how meaning is constructed and how power functions in a society	Analysing discourse on regulation or conservation to identify biases that could affect how fishers report on turtle catches	Analysis of ethnographic materials; feedback integrated into new questions

Sources: Bernard, 2011; Crandall, 2018; Early-Capistrán et al., 2018

1

Table 2(on next page)

Primary topic areas in interview guides

1. Biographical data and career history

Year of birth

Years as a fisher

Years in the green turtle fishery

Crew members and fishing merchants with whom they worked

2. Sea turtle consumption and commerce

Domestic sea turtle consumption dynamics (before 1990 ban)

Market dynamics for sea turtle sale (how, where, and how often turtles were shipped)

Commercial dynamics (how turtles were sold, prices, working relationships, etc.)

3. Sea turtle catches and sizes

Maximum and minimum catches

Frequency of aggregations and large catches

Average catches

Perceived changes in abundance

Size distribution (maximum and mode sizes, frequency of catching large turtles)

Sea turtle ethnobiology (effects of seasonality, tides, turtle behaviour, etc.)

4. Spatial distribution of fishing

Frequently used fishing grounds

Hot-spot and aggregation dynamics

Changes in use of fishing grounds across time

Distances and travel times to fishing grounds

5. Fishing effort and technology

Use and efficiency of different gear types/gear designs

Use of different vessels

Use of different propulsion systems

Table 3(on next page)

Tools and criteria for the model fitting and selection processes

Throughout the iterative process, we used Nonlinear Regression to describe Catch-Per-Unit-Effort trends over time , and Generalised Linear Models to identify significant predictor variables . Residual analysis were used to evaluate goodness of fit and ensure that model assumptions were met.

Process	Software	Model selection criteria	Residual analysis[a]
Preliminary model selection and initial values	LABFit 7.2.49	R^2 value	---
Nonlinear Regression (NLR)	R 3.4 (*nlstools* and *easynls* package)	R^2 value Robust residuals	Shapiro-Wilk $p>0.05$ $\mu \approx 0$ F-test $p>0.05$
Generalized Linear Model (GLM)	R 3.4 (*lmtest* and *car* packages)	$p<0.05$ D^2 value Low relative AIC Robust residuals	Shapiro-Wilk $p>0.05$ $\mu \approx 0$ Breusch-Pagan $p>0.05$

[a] Autocorrelation of residuals was expected due to the highly significant effect of time as a predictor variable in time-series data (Ritz & Streibig, 2008)

Table 4(on next page)

Variables, coefficients, and indices

Variable or coefficient	Type	Index	Source
Year of birth	Numerical	Date	Standard question in interviews
Dates working in the green turtle fishery	Range	Interval of dates	Standard question in interviews
Experience in the green turtle fishery	Ordinal	1 = 1-5 years 2 = 6-10 yeas 3 = 11-15 years	Binned from dates working in the fishery
Generation	Categorical	1 = Fishers who worked in commercial development and commercial fishing stages 2 = Fishers who worked during the collapse stage 3 = Fishers who worked through all stages	Category of cohorts of fishers defined based on the fishery stages in which the contributor worked
Fishery stage	Categorical	1 = Commercial development 2 = Commercial fishing (harpoon) 3 = Commercial fishing (nets) 4 = Collapse	Defined based on qualitative data on the fishery
Year	Numerical	Date for which the average CPUE is being described	Obtained directly from interviews (numerical value) or calculated based on heuristic rules (details in S.I.)
Fishing gear	Ordinal	1 = Harpoon 2 = Short set-net (☐100m) 3 = Long set-net (☐200m)	Binned from interviews or inferred based on heuristic rules
Harpooner skill coefficient	Percentage	Percentage of success (50-99%) [a]	Obtained from interview data and assigned to contributors based on social network analysis
Number of nets	Numerical	Number of nets used [b]	Obtained directly from interviews or inferred based on heuristic rules
Vessel type	Ordinal	Type of vessel used 1 = Wooden canoe (12-15 ft length) 2 = Fibreglass skiff (20-22 ft length) 3 = Boat (variable length)	Binned from interviews or inferred based on heuristic rules
Vessel capacity	Ordinal	Gross vessel tonnage 1 = Less than 1 tonne 2 = 1-1.5 tonnes 3 = Greater than 1.5 tonnes	Binned from interviews or inferred based on heuristic rules
Propulsion [c]	Categorical	1 = Oars 2 = Motor (5-10 horse-power) 3 = Motor (15-40 horse-power)	Obtained directly from interviews or inferred based on heuristic rules
Trip duration [c]	Numerical or interval	Number of days between leaving port and returning with a catch of turtles at vessel capacity Minimum limit: 1 day Maximum limit: 10 days	Obtained directly from interviews or inferred based on heuristic rules (S.I., Eqn. S1, S2)
Fishing time	Numerical	Number of nights spent fishing on a trip of regular duration	Obtained directly from interviews or inferred based on heuristic rules (S.I., Eqn. S1, S2)
Average CPUE	Numerical	Average number of turtles caught in one night during a specific year	Obtained directly from interviews (numerical value) or calculated based on heuristic rules

[a] Not assigned to captures with nets; [b] Not assigned to harpoon captures; [c] Proxies for spatial distribution of fishing

Table 5(on next page)

Fishery stages and characteristics

	Commercial development (1950-1959)	**Commercial fishing (harpoons) (1960-1965)**	**Commercial fishing (nets) (1966-1972)**	**Collapse (1974-1982)**
General characteristics	First years of the commercial fishery, with limited technology and fishing effort	Intense growth in demand leads to declining captures	Increasing fishing effort and efficiency, declining captures	Commercial collapse. Species abundance near extinction.
Regulation	Unregulated	Unregulated	Limited regulation: minimum size, permit restrictions, seasonal bans Temporary ban (1971)	Highly regulated: minimum size, permit restrictions, seasonal bans, nesting beach protection (1980-present) Green turtle licenses suspended (1983)
Gear type	Harpoons	Harpoons	Set-nets	Set-nets
Fleet conditions	Wooden canoes Oars or paddles	Wooden canoes 5-10 horse-power outboard motors	Canoes or skiffs 5-10 horse-power outboard motors	Fibreglass skiffs 15-45 horse-power outboard motors
Spatial distribution of fishing [a]	Overnight trips close to port are frequent	Motors allow faster displacement to farther fishing grounds Occasional trips >50 nautical miles	Trips >50 nautical miles are frequent Expeditions >100 nautical miles are frequent (canoes or skiffs off-loading to boats)	Trips >50 nautical miles are frequent
Size distribution [b]	Turtles □150 kg caught frequently (spans of weeks/months) Mode weight: 50 kg	Turtles □150 kg caught frequently (spans of weeks/months) Mode weight: 50 kg	Turtles 100-150 kg caught occasionally (spans of seasons/years) Mode weight: 50 kg	Turtles 100-150 kg caught rarely (spans of years) Mode weight: 50 kg
Fishing efficiency	Low	Low/Moderate	Moderate	High
Fishing effort	Low	High	High	Low
Commercial demand	Moderate	High	High/moderate	Moderate
Profitability	High	High	High/Declining	Not profitable

[a] Throughout the chronology, spatial distribution of fishing was highly variable due to the targeting of hot-spots and variations in the seasonal distribution of turtles

[b] Size distribution was highly variable throughout the chronology

Table 6(on next page)

Generalised Linear Model results for the raw Catch-Per-Unit-Effort database

Generalised Linear Models were used to identify significant predictor variables for CPUE. The most parsimonious model for the raw database suggests that fishing gear type, vessel capacity, and number of nets were significant predictor variables for CPUE.

Predictors	Estimate	Std. error	P-value
Gear type	0.447	0.109	0.00029
Vessel Capacity	0.324	0.108	0.00531
Number of nets	-0.319	0.083	0.00065
Model: logCpue ~ Gear + Vessel Capacity + Number of Nets; AIC: 34.744; D^2=0.823; *df*=29			

Figure 1

Overview of methodological processes to document, synthesise and quantify Local Ecological Knowledge.

The iterative process described in the upper box was repeated until reaching topical, thematic, and data saturation, and until model fitting did not provide significant new information. This iterative process generated a raw database with average, representative Catch-Per-Unit-Effort values for a given year, and heterogeneous descriptor variables.

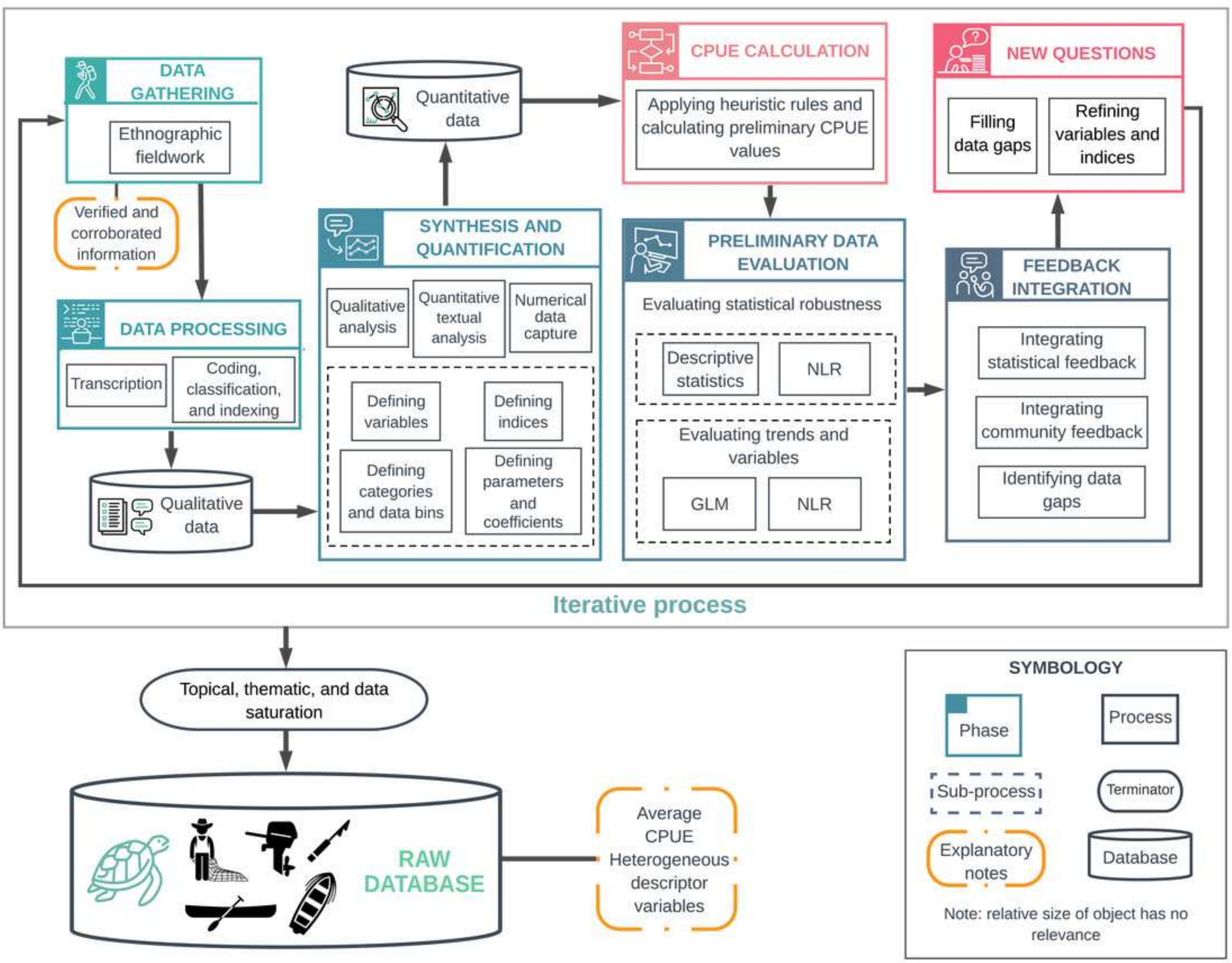


Figure 2

Heuristic rules used to to make systematic inferences based on expert knowledge and calculate raw Catch-Per-Unit-Effort values.

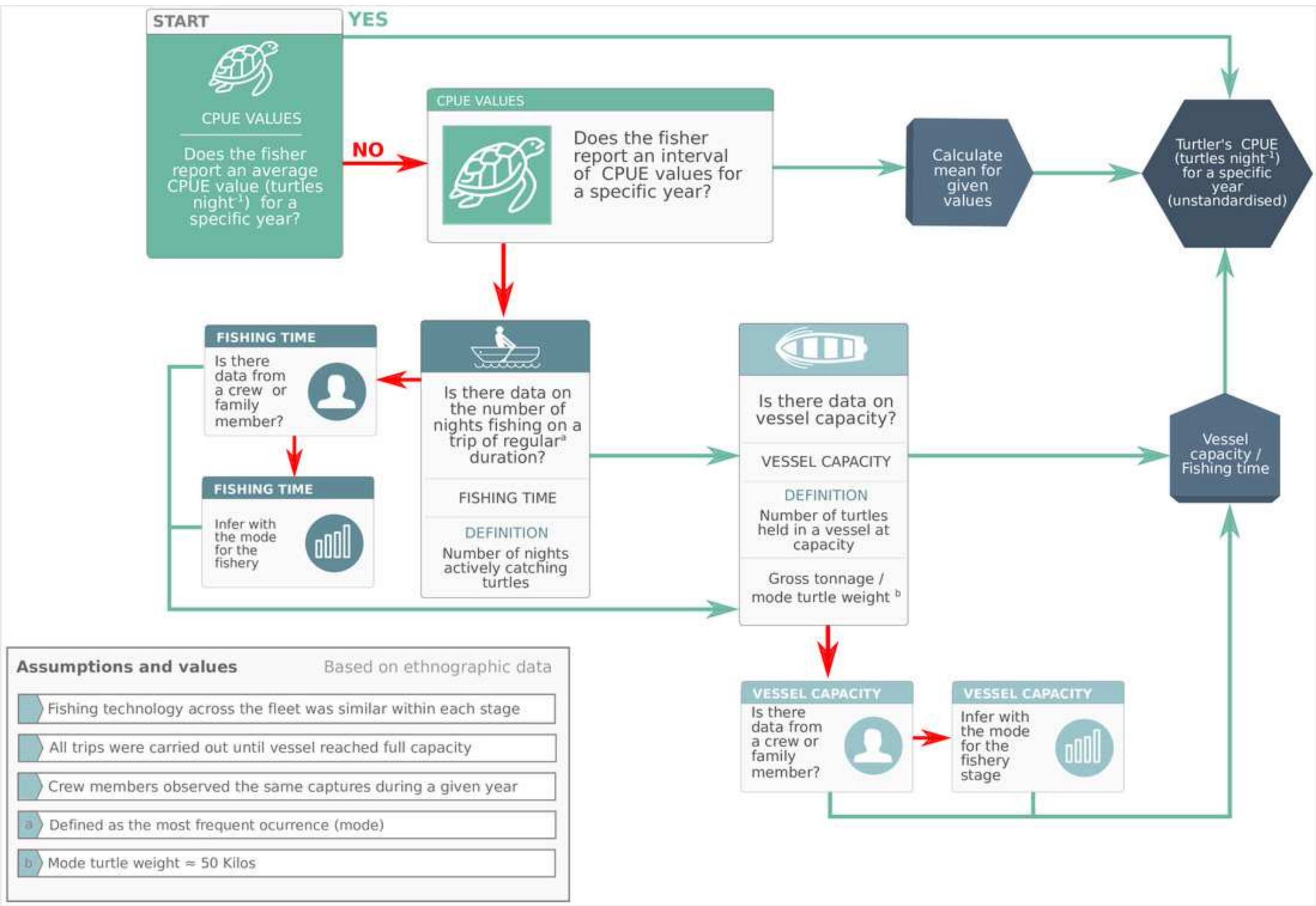


Figure 3

Cyclical process of index design and feedback integration.

Bold type shows numerical data from interviews. Indices and coefficients were revised and refined based on a cyclical process which used feedback from interviews, statistical analysis and modelling to design new questions. This process was repeated for each variable.

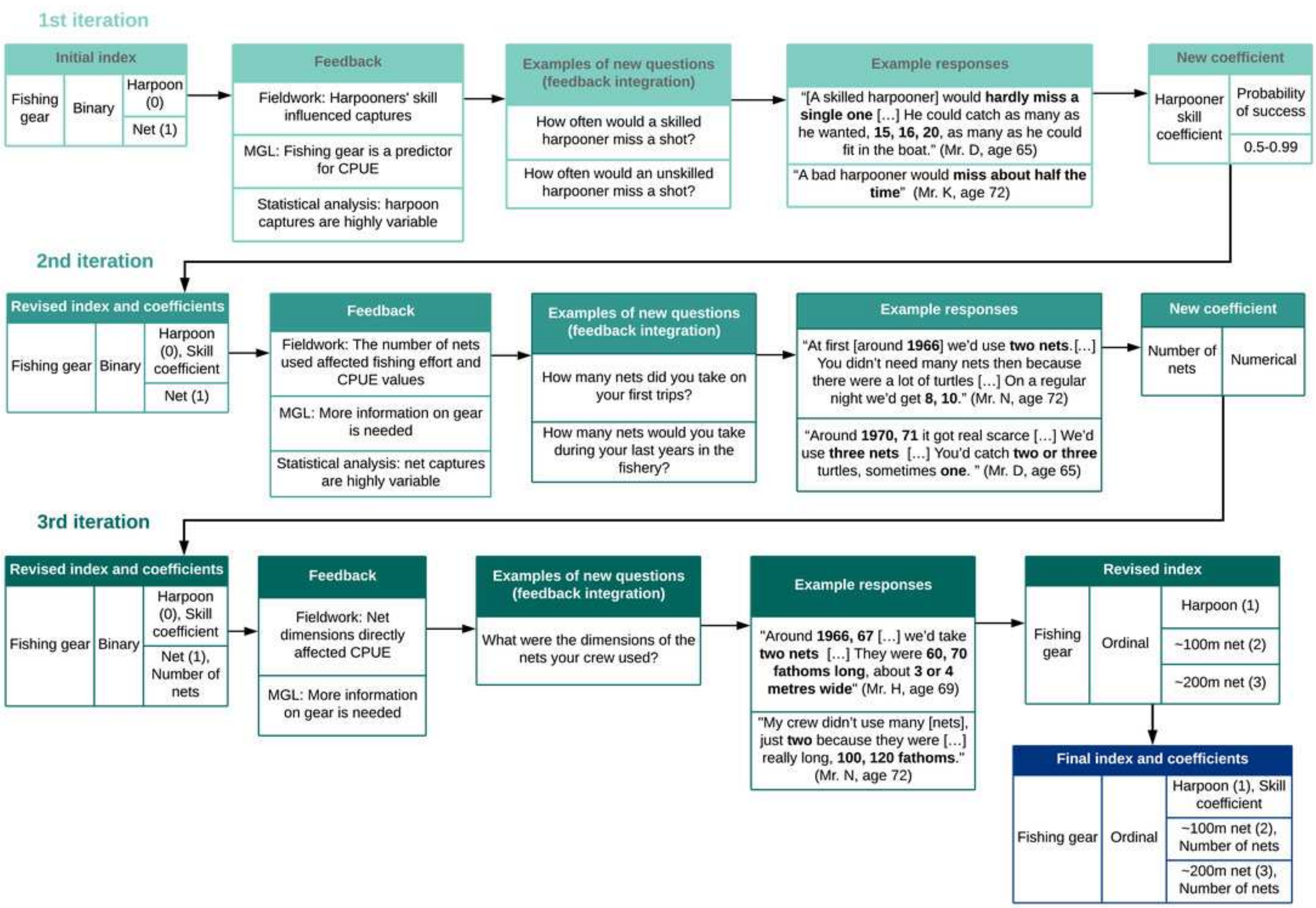


Figure 4

Comparative analysis of LEK-derived Catch-Per-Unit-Effort and total annual landings of *C. mydas* in Bahía de los Ángeles (1962-1982).

Data points are standardised, representative CPUE values for a specific year derived from Local Ecological Knowledge (red triangles and dotted line; left Y-axis) and total annual landings from available fisheries statistics for Bahía de los Ángeles (blue circles and dotted line; right Y-axis) (Márquez in Seminoff et al., 2008). Curves represent suggested trends based on an exponential decay model (details in Article S1). Lin Concordance Correlation Coefficient on paired z-scores suggests strong agreement between datasets.

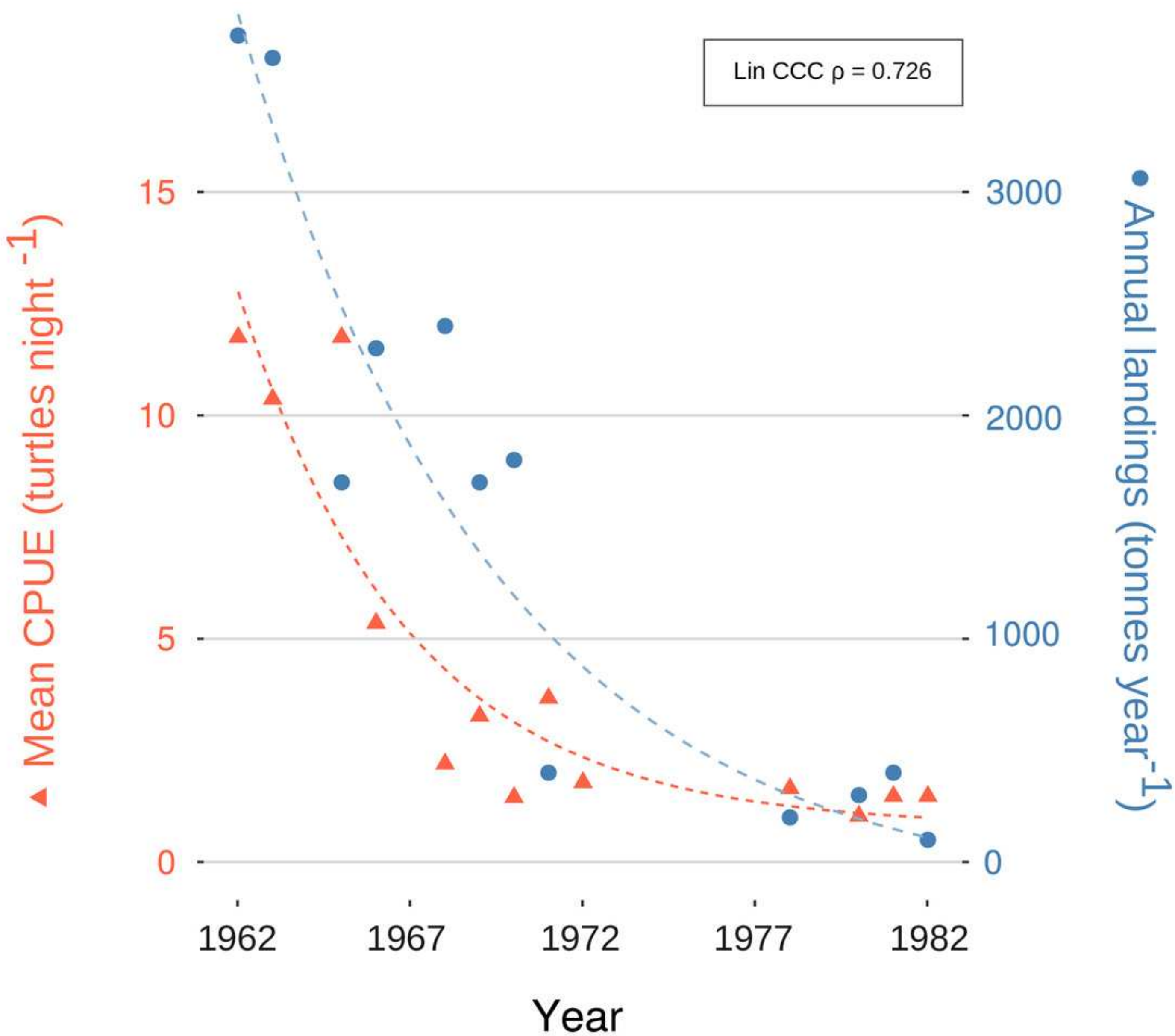
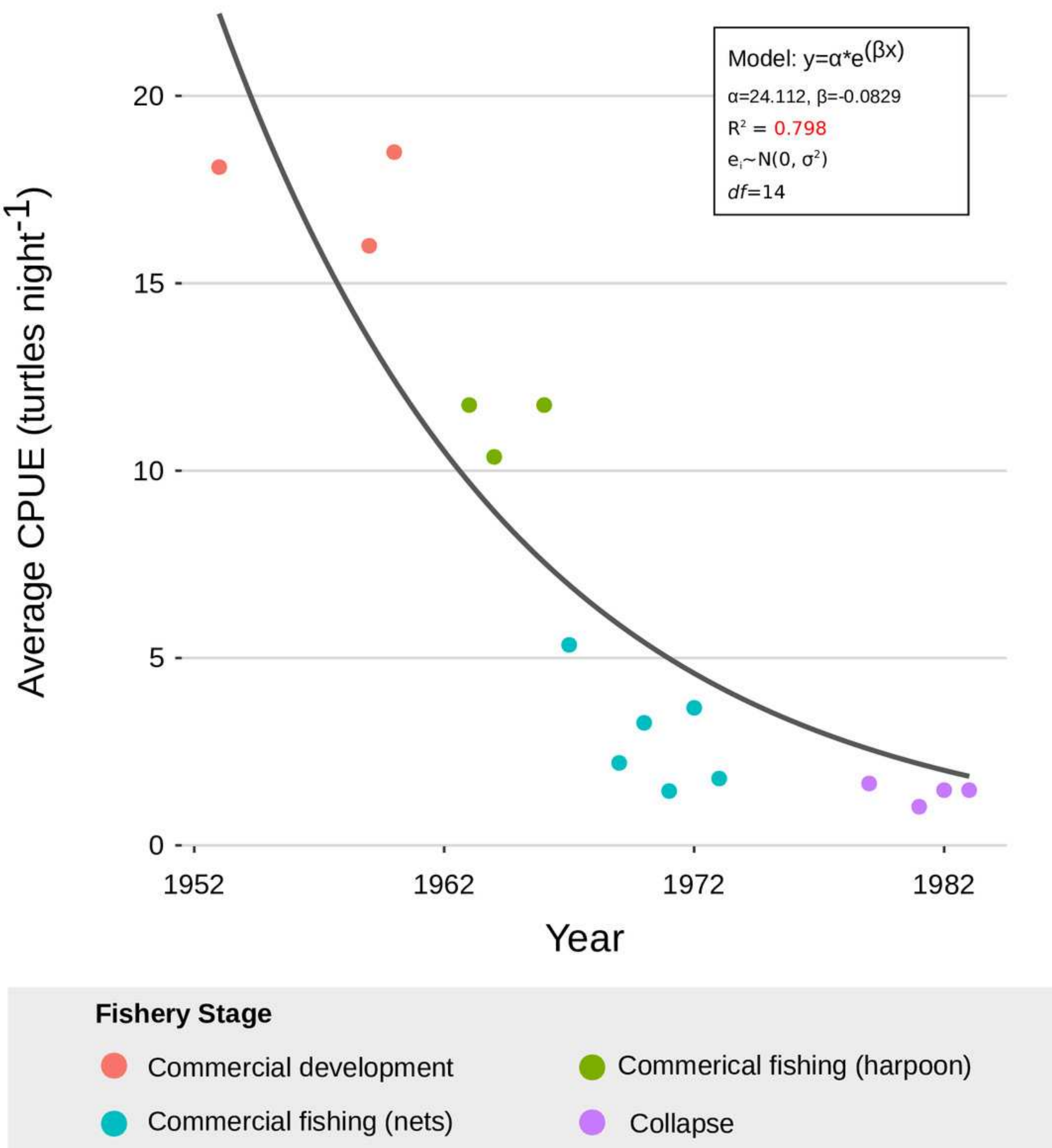

Lin CCC ρ = 0.726
▲ Mean CPUE (turtles night -1)
● Annual landings (tonnes year-1)
15
10
5
0
3000
2000
1000
0
1962
1967
1972
1977
1982
Year

Figure 5

Exponential decay model fitted to Catch-Per-Unit-Effort values derived from Local Ecological Knowledge.

Curve represents a fitted exponential decay model. Each data point is a representative Catch-Per-Unit-Effort value for a specific year, derived from Local Ecological Knowledge. Colours represent fishery stages (Table 5).


Model: y=α*e^(βx)
α=24.112, β=-0.0829
R² = 0.798
eᵢ~N(0, σ²)
df=14
Average CPUE (turtles night⁻¹)
20
15
10
5
0
1952
1962
1972
1982
Year
Fishery Stage
Commercial development
Commerical fishing (harpoon)
Commercial fishing (nets)
Collapse