SUPPORTING INFORMATION

Integrating local ecological knowledge, ecological monitoring, and computer simulation to evaluate conservation outcomes

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1. LEK-derived catch-per-unit-effort (CPUE) estimates

We compiled data in an on-going transdisciplinary research process with the BLA community initiated in 2012. We documented, corroborated, and classified LEK through ethnography; synthesized through coding, indexing, and heuristics; and integrated feedback processes with statistical analyses. We standardized all CPUE estimates to one 12-h in-water set for a single 100m net. Standardization (i) removed most variation not attributable to abundance changes (e.g., fishing gear types, fleet characteristics, spatial dynamics); and (ii) generated estimates compatible with monitoring data. To evaluate central tendencies, we used annual mean CPUE for all analyses (Figure S1, Table S1). LEK data were shown to be statistically reliable and generated robust models of population change (Early-Capistrán et al. 2020a). See Early-Capistrán and collaborators (2020a) for full theoretical framing and detailed methodological processes. See Early-Capistrán and collaborators (2020b) for data and code.

2. LEK-derived CPUE standardization

LEK-derived CPUE estimates were standardized as follows:

> "We standardized CPUE to (i) remove most of the variation not attributable to changes in abundance by accounting for variables such as gears, fleet characteristics, fishers' experience, etc.; and (ii) generate CPUE values that could be compared over time (Hilborn & Walters 1992; Maunder & Punt 2004). To choose predictor variables for standardization, we ran GLMs (*nlme, car, dplyr*, and *DescTools* packages) (Early-Capistrán et al. 2020b) with log-transformed CPUE values and a residual correlation structure based on an auto-regressive model of order 1 (AR-1) structured by the variable 'year' (Zuur 2009). We chose predictor variables for standardization using models with significant effects, high percentage

of explained deviance (D^2), relatively low Akaike Information Criterion (AIC), and robust residuals (cf. Maunder & Punt 2004). We generated detailed definitions of unit effort based on these analyses, to obtain comparable values for turtles caught in one night. While fishers generally worked from dusk to dawn, fishing times on any given night with either gear type could be variable. For modelling purposes, we simplified values to 12 h blocks which reflect the vast majority of fishing effort. For set-nets, we standardized unit effort to approximate ecological monitoring data (100 m net soaking for 12 h) (Koch, 2013; Seminoff et al., 2003):

$$C_{st} = {(t \cdot R)}\Big/{(n_r \cdot R \cdot 12hr)} \qquad \text{(eqn. S1)}$$

Where C_{st} is a standardized, representative value of CPUE during a specific year (turtles 12 h^{-1}); t is the number of turtles caught (turtles); and n_r is the number of 100 m nets (no units). R is net length (in multiples of 100 m), simplified to short (~100 m = R) or long (~200 m = $2R$). Soaking time is 12h. For harpoon captures, we assigned a skill coefficient (s, percentage of success) to each harpooner through social network analysis, based on colleagues' assessment, such that:

$$C_{st} = t \cdot s^{-1} \cdot 12hr^{-1} \qquad \text{(eqn. S2)}$$

The current ban on sea turtle fishing does not allow us to test for differences in susceptibility to fishing gears. 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 standardized given the nature of the data." (Early-Capistrán et al. 2020a)."

Further details are available in Early-Capistrán et al. (2020a), Supporting Information.

3. Monitoring procedures and standardization

During scientific monitoring, turtles were captured using entanglement nets with the same depth (8m) and mesh size (0.8m) as those used by commercial turtle fishers. Nets were set and checked every 0.5-12hr, and captured turtles were measured, weighed, and released (Seminoff et al. 2003; Santacruz López 2012). Nets are set for periods of 12-24 hr, and monitoring occurs monthly, with some variation due to weather conditions, logistics, and funding availability (Seminoff et al. 2003; Santacruz López 2012).

Monitoring data were provided by author J.A. Seminoff (2003; NOAA, Unpublished raw data) for 1995–2005 and Comisión Nacional de Áreas Naturales Protegidas (CONANP) & Grupo Tortuguero de Bahía de los Ángeles (Unpublished raw data) for 2005–2018.

All monitoring data were standardized to one 12-h in-water set for a 100m net to allow for comparison across time (Seminoff et al. 2003). Mean values for each year were calculated after standardization and used for all analyses.

4. Mean values for analyses

Analyses of commercial green turtle fishing revealed that high CPUE events occurred throughout the chronology despite overall declines in abundance (hyper-stability) (*sensu* Hilborn & Walters 1992), as expert fishers consistently targeted high-density locations or aggregations of turtle by relying on detailed empirical knowledge of green turtle behavior and local environmental and oceanographic conditions (Early-Capistrán et al. 2020a). Thus, methods for compiling LEK data focused on estimating central trends rather than high catch events, and we used mean, standardized CPUE values to obtain representative estimates (Early-Capistrán et al. 2020a). We used the same approach to evaluate monitoring data, (i) to maintain consistency throughout the time series, and (ii) to reduce the effects of high variability in catch rates, likely due to green turtle grouping behavior (Figure S2).

5. Commercial Fishing and Conservation phases

For MICE analyses and calculations of population growth rates, we grouped data into two processes: Commercial Fishing (1952-1983) and Conservation (1978-2018) (Figures 2, 3). For Conservation, we appended LEK values from 1978-1982 to the monitoring dataset. These values correspond to the fishery collapse stage (Figures 2, 3) (Early-Capistrán et al. 2020a). We consider this to be an adequate modification, as conservation and research efforts began in the late 1970s and regulation increased over time, culminating in the permanent ban on all sea turtle capture and use in Mexico, declared in 1990 (Figure 1). Integrating LEK and monitoring values for the early years of conservation processes allowed us to interpolate values in the temporal gap between the end of commercial fishing (1983) and the start of in-water monitoring (1995) using MICE. Commercial Fishing is described with the LEK dataset, to which no data were appended.

6. Analyses with Multiple Imputation by Chained Equations (MICE)

6.1 Imputation model selection

We selected the imputation model by comparing three methods: predictive mean matching (pmm), weighted predictive mean matching (wpmm), and Bayesian linear models (van Buuren 2018). Both pmm and wpmm implement a Markov Chain Monte-Carlo algorithm to sample subsets of observed values (van Buuren 2018). For each imputation model, we generated *m* datasets equivalent to the percentage of missing data (Bodner 2008). We first observed imputed values directly, and discarded Bayesian linear models as they generated implausible negative values. We then conducted descriptive evaluation of (i) plots of the density distribution of observed and imputed values; (ii) one-dimensional scatterplots of observed and imputed values; and (iii) two-dimensional scatter plots (cpue ~ year) of observed and imputed values (van Buuren & Groothuis-Oudshoorn 2011; van Buuren 2018).

We fitted datasets imputed with pmm and wpmm to the analysis model (eqn. 1) and ran multiply imputed repeated analyses separately. We compared pooled parameter, R^2 values, and residuals ($e_i \sim N(0, \sigma^2)$) between imputation models, and also compared these results with the model fitted analysis for the observed values only. The results suggest that values from weighted predictive mean matching (wpmm) were more plausible than those obtained from predictive mean matching (pmm), as they had greater concordance with observed values, pooled parameter estimates were closer to estimates from observed values, and pooled residuals were robust. We selected wpmm as the imputation model for both LEK and monitoring datasets. Additionally, wpmm is robust to non-normal data distributions (Jia 2016).

6.2 Analysis model selection

We used a nonlinear model to describe both Commercial Fishing and Conservation processes:

$$Y \sim \alpha \cdot e^{(\beta x)} \quad \text{(eqn. S3)}$$

Where Y is the response variable (CPUE), α and β are fitted constants, and x is the independent variable (year), which was serialized for all analyses. We then used *R 4.0.4* to run nonlinear least squares regression (NLR) (Table S3) (Early-Capistrán et al. 2020a). Model performance was ratified with residual analyses ($e_i \sim N(0, \sigma^2)$).

6.3 Starting value selection

We used a quasi-Newton method to optimize starting values for NLR, both for observed values and for the analysis model in MICE. We obtained initial approximate starting values by linearizing the nonlinear analysis model (eqn. S1) to the form:

$$ln(Y) \sim ln(\alpha) + \beta x \quad \text{(eqn. S4)}$$

We ran a linear regression with observed values, extracted parameter values, and transformed ln(α) to α. These values were used as starting values for NLR, which were then run iteratively by extracting parameter values and plugging them back in as starting values for the next iteration until parameter estimates stabilized. With MICE, we used parameter estimates from the *m* pooled models as new starting values.

6.4 Residual analysis of MICE models

We evaluated model performance through residual analyses ($e_i \sim N(0, \sigma^2)$) with two complementary approaches. We first extracted and analyzed residuals from each of the *m* model fittings separately (Nguyen et al. 2017). We then averaged residuals across all *m* models to ratify the fit of the pooled model.

6.5 Confidence intervals for MICE models

Graphic representation of results generated by MICE represents a unique challenge, as this method generates *m* "complete" datasets in which missing data are replaced by plausible simulated values and, afterward, the analysis model (eqn. 1 in main text) is fitted separately to each of the *m* datasets and then pooled using Rubin's Rules to generate pooled parameter estimates with standard errors that (i) account for variance within and between imputed models, and (ii) allow for the uncertainty of the missing data (Dong & Peng 2013; Nguyen et al. 2017). If performed under appropriate conditions, pooling preserves the relations between the data, preserve the uncertainty about these relations, and generate results that are unbiased and have valid statistical properties (van Buuren & Groothuis-Oudshoorn 2011; van Buuren 2018). However, MICE does not generate a singular model or regression, but rather describes the distribution of the parameters generated by the *m* multiply imputed models (Bodner 2008; Nguyen et al. 2017).

We used an *ad hoc* method to (i) visualize a trend line (broadly equivalent to a regression line) that reflects the pooled predicted values across all *m* multiply imputed models, (ii) pool values for the upper and lower bounds according to Rubin's Rules to account for both within-model and between-model variance across the m multiply imputed models, and (iii) draw 95% confidence intervals describing the upper and lower bounds for all points of the pooled trend line (Dong & Peng 2013; Nguyen et al. 2017). The process in R (4.0.4) consisted of the following steps (see also Data and Code):

- Calculate predicted values across all *m* multiply imputed models to generate *m* vectors of predicted values for each year
- Obtain pooled predictions by calculating the mean predicted value for each year across the *m* multiply imputed models, to obtain the trend line.
- Calculate within-model variance for each of the *m* multiply imputed models with the following equation:

$$Vw = \frac{1}{m}\left(\sum_{i=1}^{m} SE^2\right) \quad \text{(eqn. S5)}$$

  - Where m is the number of imputed datasets and SE is the estimated standard error of each of the imputed datasets.

- Calculate between-model variance of the *m* multiply imputed models with the following equation:

$$Vb = \frac{\sum_{i=1}^{m}\left(\theta-\overline{\theta}\right)^2}{(m-1)} \quad \text{(eqn. S6)}$$

- Where θ is the parameter of interest (the mean of each of the *m* vectors of predicted values) and $\overline{\theta}$ is the mean parameter value (in this case, the mean of the means).

- Calculate total variance with the following equation:

$$Vtotal = Vw + Vb + 1/Vb \qquad \text{(eqn. S7)}$$

- Calculate the pooled standard error with the following equation:

$$SEpooled = \sqrt{V}total \qquad \text{(eqn. S8)}$$

- Calculate 95% confidence intervals of ± 1.96 standard errors from the mean, given the normal distribution of errors verified in residual analysis.

6.6 Degrees of freedom in multiple imputation

Degrees of freedom in multiple imputation must account for the effects of missing data, generating adjusted degrees of freedom for each parameter (van Buuren 2018). The *mice* package in *R* (van Buuren & Groothuis-Oudshoorn 2011) uses Barnard-Rubin's adjustment (Barnard & Rubin 1999) to calculate degrees of freedom for the pooled parameter estimates, *v*, using the degrees of freedom of a hypothetically complete dataset, $\bar{Q}$, and λ, which describes the proportion of variation due to missing data (van Buuren 2018). Here we provide a brief conceptual overview. Full mathematical and computational details are available in van Buuren (2018), Chapter 2.

Let m be the number of imputed datasets. Rubin's (1987) original equation for degrees of freedom is as follows:

$$v_r = \frac{(m-1)}{\lambda^2} \qquad \text{(eqn. S9)}$$

Estimated degrees of freedom for observed data which account for the effects of missing data, v_{obs}, are calculated as follows:

$$v_{obs} = \frac{(v_{com}+1)}{(v_{com}+3)} v_{com}(1-\lambda) \qquad \text{(eqn. S10)}$$

v_{com} are the degrees of freedom of a hypothetical complete dataset, $\bar{Q}$. For a model with k parameters and a sample size n, v_{com} can be defined as $v_{com} = n - k$ (van Buuren 2018). Barnard and Rubin's (1999) adjusted degrees of freedom for use in tests with multiple imputation are calculated as follows:

$$v = \frac{v_r \cdot v_{obs}}{v_r + v_{obs}} \qquad \text{(eqn. S11)}$$

The adjusted value v is always less than or equal to v_{com} (van Buuren 2018). To broadly describe the effect of the variance ratios, consider that λ occupies values between 0 and 1. If $\lambda = 0$, then $v = v_{com}$; that is to say, there is no variation due to missingness. Conversely, λ = > 0.5 suggests substantial effects due to imputation (van Buuren 2018).

7. Population growth rates

We calculated population growth rates for the processes of Commercial Fishing (1952-1983) and Conservation (1978-2018) by modifying the analysis model (eqn. 1) to the form:

$$N = N_0 \cdot e^{(rt)} \qquad \text{(eqn. S12)}$$

Where N is the end value, N_0 is the starting value, r is the rate of change, and t is the elapsed time. This equation is solved for r such that:

$$r = ln(N/N_0)/t \qquad \text{(eqn. S13)}$$

We then calculated population growth rates using values for the first and last observed values for each process. To verify results, we integrated values for r, t, and N_0 to eqn. S7 and compared results to observed values for N (Table S4).

8. Catch rate analyses

We compared catch rates, measured as mean annual CPUE, in commercial fishing (1952-1982; LEK data) and scientific monitoring (1995-2018; Monitoring data). We used a Mann-Whitney U test, as neither dataset was normally distributed (Table S5).

9. Size distribution analyses

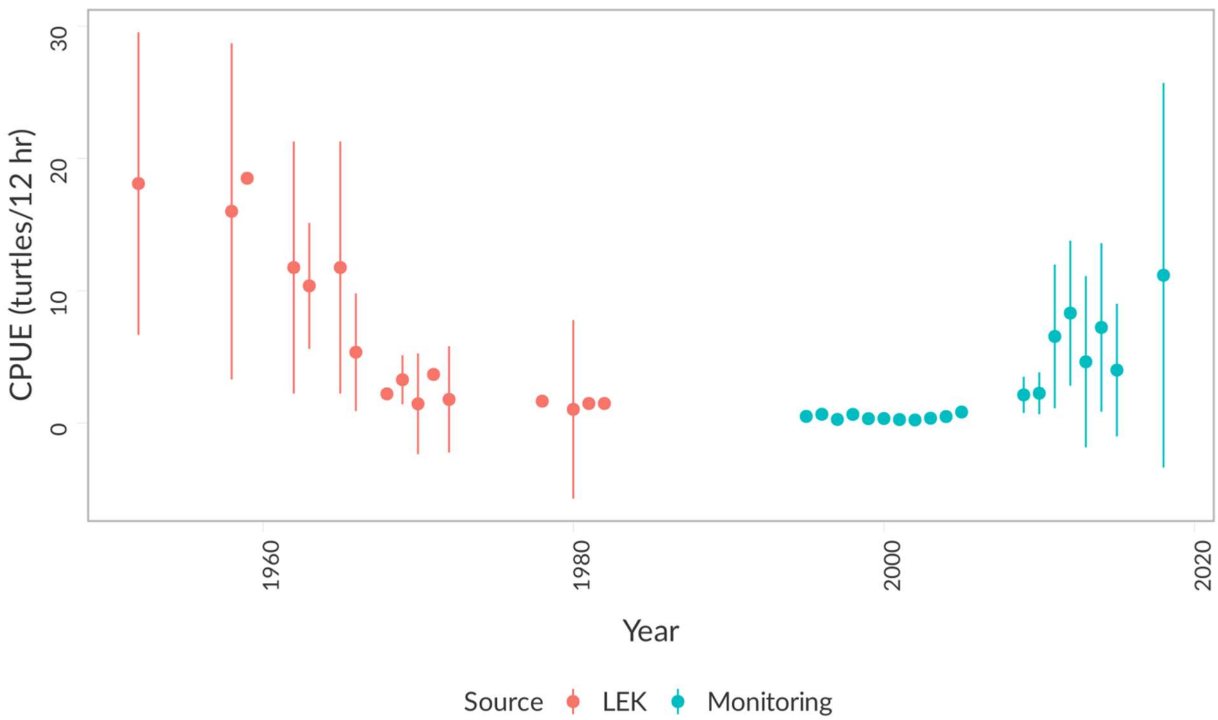
We analyzed size distribution by evaluating Curved Carapace Length (CCL, cm), and by grouping juveniles and adults using the mean CCL of nesting females at Colola (82.0 cm) (Alvarado Díaz & Figueroa cited in Seminoff et al. 2015). We divided monitoring data into two groups according to data availability: Period 1 (1995-2005) and Period 2 (2009-2018). We obtained descriptive statistics of CCL in both periods (Table S6). Given the non-normal distribution of CCL values in Period 2, we used a Mann-Whitney U test ($\alpha = 0.05$) to compare size composition between periods and found significant differences (Table S7).

Figures

Figure S1: Map of the study area

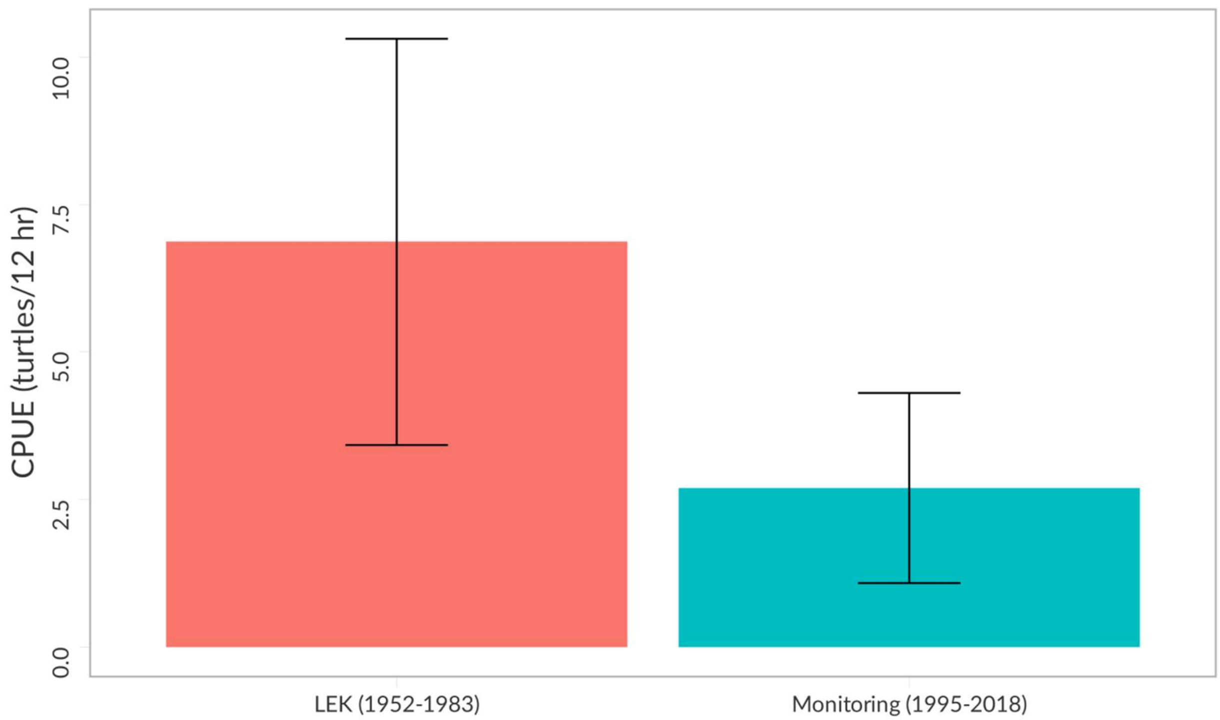
Map showing the location of the study site at Bahía de los Ángeles, Baja California, Mexico (orange circle) and Ensenada, Baja California, Mexico (yellow circle), the primary market for green turtle catches during the historical commercial fishery (see Figure 1). The green square in the inset map shows the index nesting site in Colola, Michoacán. At the time of this study, the village of Bahía de los Ángeles had a population of ~500 people, with economic activity centered on small-scale fishing and seasonal tourism. Map produced in Qgis using Stamen Terrain Basemap (CC BY 3.0) and data from OpenStreetMap (ODbL).

Figure S2: All CPUE values from LEK and Monitoring datasets.



All CPUE values from LEK (1952-1982) and Monitoring (1995-2018) datasets, with means (points) and 95% Confidence Intervals. Note that some years had only one observation. Mean annual CPUE values were used for all analyses. See also Tables S1, S2.

Figure S3: Mean annual CPUE values grouped by dataset



Mean annual catch-per-unit-effort (CPUE) values grouped by dataset (LEK and Monitoring), with error bars showing 95% Confidence Intervals. See also Table S5.

Figure S4: Diagram of methodological pipeline used for Multiple Imputation by Chained Equations (MICE).

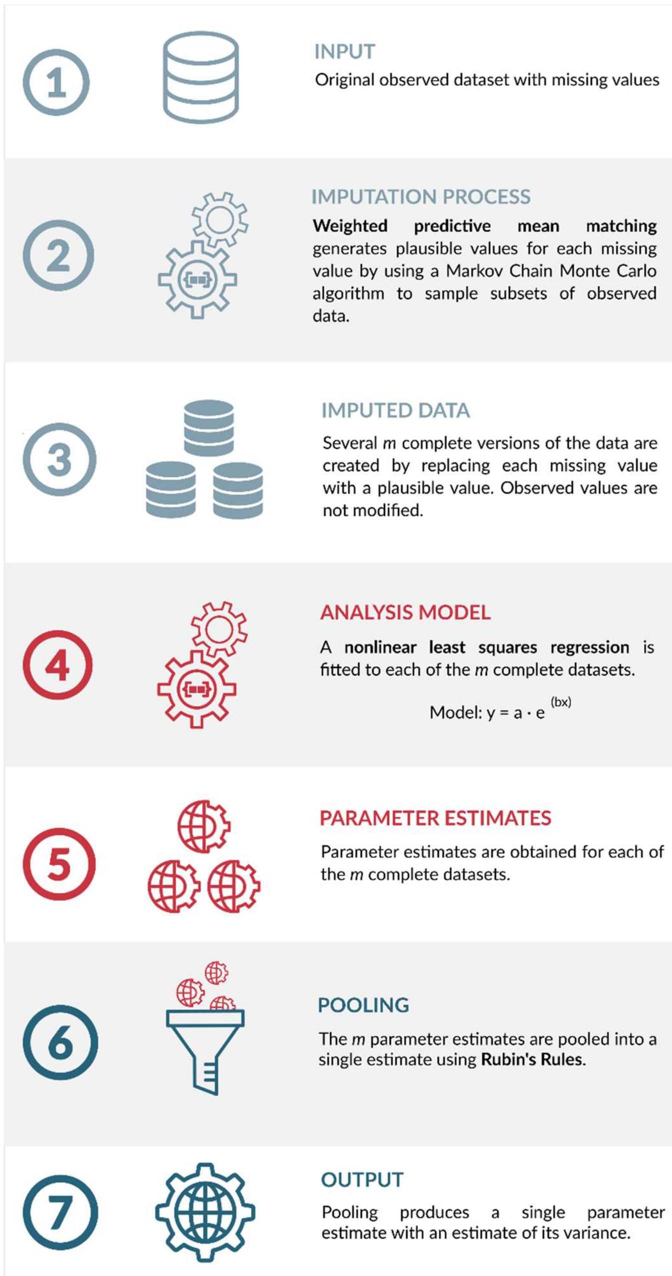
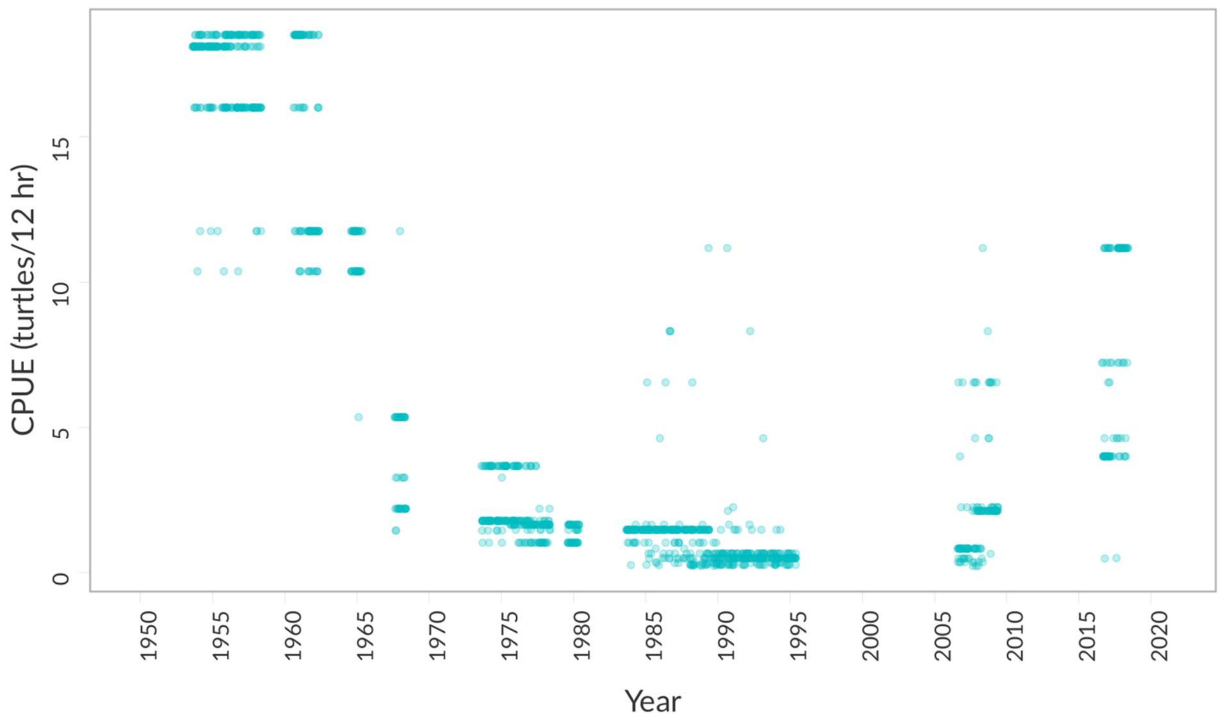


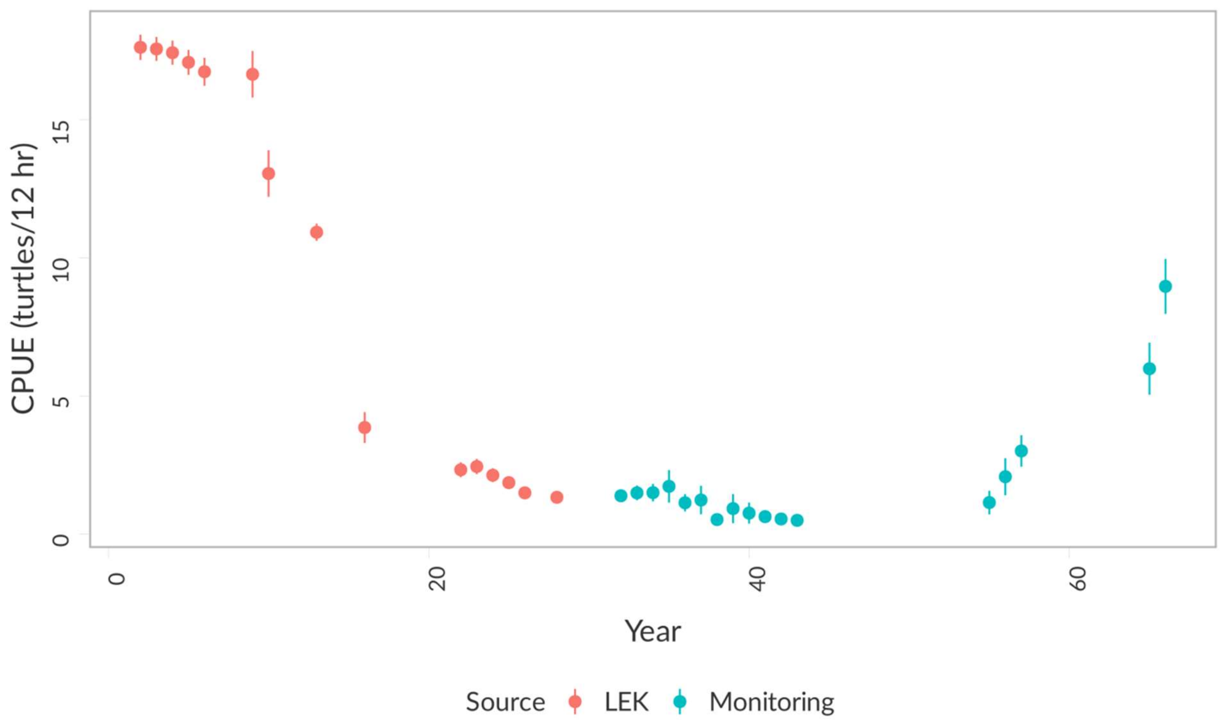
Diagram of methodological pipeline used for Multiple Imputation by Chained Equations (MICE). Models and rulesets are shown in bold.

Figure S5: Scatterplot of all imputed values



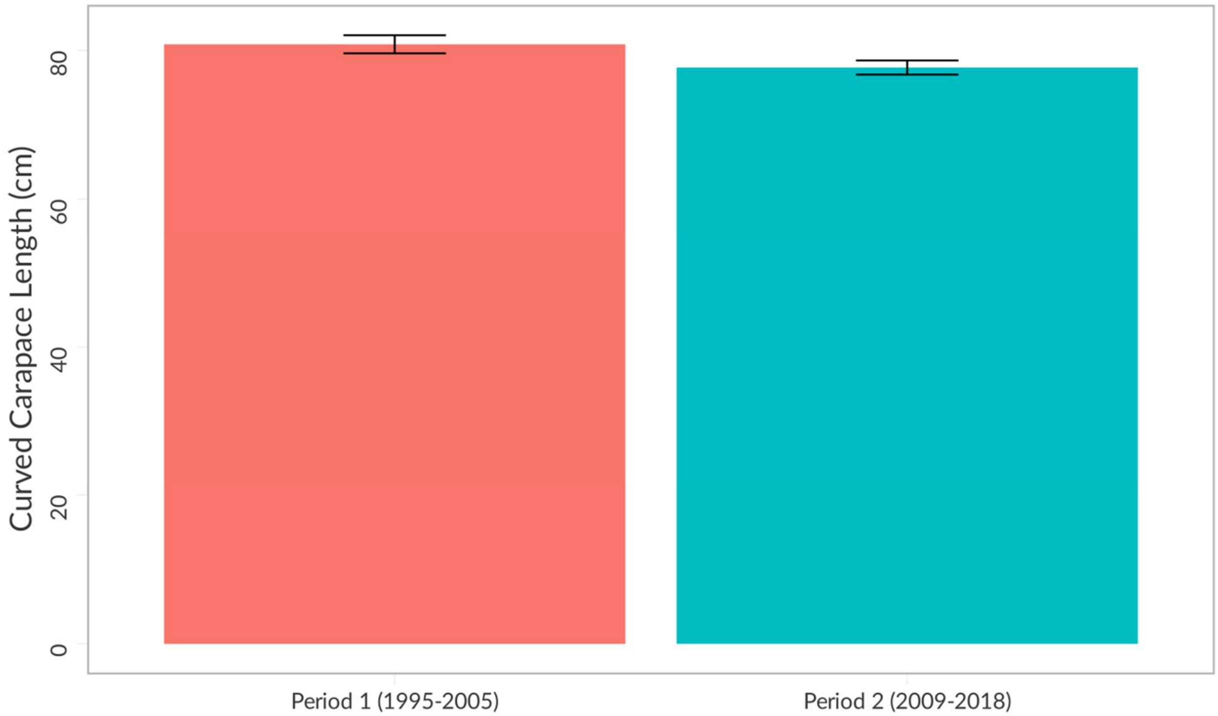
All values imputed for missing data from LEK and Monitoring datasets (N = 1446).

Figure S6: Mean multiply imputed CPUE values



Mean multiply imputed CPUE values (points) with 95% Confidence Intervals. Note that narrow confidence intervals are due to the large number of imputed data points per year, sampled from subsets of observed data. See also Figure S5.

Figure S7: Curved Carapace length grouped by period



Curved Carapace Length (CCL, cm) in Monitoring data, grouped by period, with error bars showing 95% Confidence Intervals. See also Table S7.

Tables

Table S1: Descriptive statistics of all catch-per-unit-effort (CPUE) values

Dataset	N	Mean	Median	Standard deviation	Minimum	Maximum
LEK data (1952-1982)	32	6.68	3.91	6.04	0.5	19
Monitoring data (1995-2018)	148	3.21	1	6.45	0	36

Table S1: Descriptive statistics of all CPUE values

Table S2: Descriptive statistics of mean annual catch-per-unit-effort (CPUE) values

Dataset	N	Mean	Median	Standard deviation	Minimum	Maximum
LEK data (1952-1982)	16	6.86	3.47	6.46	1.03	18.5
Monitoring data (1995-2018)	19	2.69	0.66	3.34	0.23	11.17

Table S2: Descriptive statistics of mean annual CPUE values

Table S3: Results of nonlinear regression for mean annual catch-per-unit-effort. Italics indicate significant results at $\alpha = 0.05$.

Parameter	Estimate	Std. Error	95% C.I.	*t*-value	P-value	R^2
LEK data: commercial fishing (1952-1982), nonlinear regression; Model: $y \sim \alpha^{(\beta \cdot x)}$; $df = 14$; $e \sim N(0, \sigma^2)$						
α	24.112	3.124	[17.413 -30.812]	7.719	*2.07e-06*	0.798
β	-0.0829	0.0130	[-0.111 to -0.0551]	6.382	*1.71e-05*	
Monitoring data: conservation (1978-2018*), nonlinear regression; Model: $y \sim \alpha^{(\beta \cdot x)}$; $df = 21$; $e \sim N(0, \sigma^2)$						
α	5.40e-04	8.22e-04	[-0.00117 - 0.00225]	0.657	0.518	0.780
β	0.148	0.0238	[0.0985 - 0.198]	6.212	*3.67e-06*	

* LEK values from 1978-1982 were appended to interpolate for the temporal gap between the end of commercial fishing (1983) and the start of in-water monitoring (1995).

Table S3: Results of non-linear regression for mean CPUE

Results of nonlinear regression for mean annual catch-per-unit-effort (CPUE). Italics indicate significant results at $\alpha = 0.05$.

Table S4: Annual population growth rates during commercial fishing and conservation

Phase	Start year	End year	Annual growth rate	Predicted value	Observed value
Commercial Fishing (LEK data)	1952	1982	-8.4%	1.456	1.475
Conservation (LEK and Monitoring data)	1978*	2018	4.8%	11.075	11.167

* As in MICE analyses, LEK values from 1978-1982 were appended to interpolate for the temporal gap between the end of commercial fishing (1983) and the start of in-water monitoring (1995). See also Figure 1.

Table S4: Annual population growth rates

Annual population growth rates during Commercial Fishing and Conservation. Growth rates were calculated using mean annual catch-per-unit-effort (CPUE) values.

Table S5: Results of Mann-Whitney U test for mean annual catch-per-unit-effort (CPUE) values in LEK and monitoring datase. Italics indicate significant result ($\alpha = 0.05$).

Variable	Period	N	U	p	95% C.I.
CPUE (turtles/night)	LEK (1952-1982)	16	232	*0.008*	0.81 – 7.75
	Monitoring (1995-2018)	19			

Table S5: Mann-Whitney U test for CPUE values

Results of Mann-Whitney U test for mean annual catch-per-unit-effort (CPUE) values in LEK and Monitoring datasets. Italics indicate significant result ($\alpha = 0.05$).

Table S6: Descriptive statistics of size distribution (Curved Carapace Length, cm) in monitoring data

Period	N	Mean	Median	Standard deviation	Minimum	Maximum
Period 1 (1995-2005)	289	80.85	80.8	10.51	51.1	104.5
Period 2 (2009-2018)	414	77.72	75.5	9.83	54.5	109

Table S6: Descriptive statistics for Curved Carapace Length

Descriptive statistics of size distribution (Curved Carapace Length, cm) in monitoring data.

Table S7: Results of Mann-Whitney U test for Curved Carapace Length (CCL) in monitoring data. Italics indicate significant result ($\alpha = 0.05$).

Variable	Period	N	U	p	95% C.I.
Straight Carapace Length (cm)	Period 1 (1995-2005)	282	71406	*1.228e-05*	1.99 – 5.20
	Period 2 (2009-2018)	414			

Table S7: Mann-Whitney U test for Curved Carapace Length.

Results of Mann-Whitney U test for Curved Carapace Length (CCL) in monitoring data. Italics indicate significant result ($\alpha = 0.05$).

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