# Local knowledge reconstructs historical resource use

**Leandro Castello[1*], Eduardo G Martins[2], Michael G Sorice[3], Eric Smith[4], Morgana Almeida[5], Gastao CC Bastos[6], Luis G Cardoso[7], Mariana Clauzet[8], Alisson P Dopona[9], Beatrice Ferreira[10], Manuel Haimovici[7], Marcelo Jorge[1], Jocemar Mendonça[6], Antonio O Ávila-da-Silva[6], Ana PO Roman[5], Milena Ramires[11], Laura V de Miranda[6], and Priscila FM Lopes[12]**

**Information on natural resource exploitation is vital for conservation but scarce in developing nations, which encompass most of the world and often lack the capacity to produce it. A growing approach to generate information about resource use in the context of developing nations relies on surveys of resource users about their recollections (recall) of past harvests. However, the reliability of harvest recalls remains unclear. Here, we show that harvest recalls can be as accurate to data collected by standardized protocols, despite that recalls are variable and affected by the age of the recollecting person and the length of time elapsed since the event. Samples of harvest recalls permit relatively reliable reconstruction of harvests for up to 39 years in the past. Harvest recalls therefore have strong potential to inform data-poor resource systems and curb shifting baselines around the world at a fraction of the cost of conventional approaches.**

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Information on the status and use of natural resources (such as wildlife) is vital for conservation. Yet such information is scarce in developing nations, which cover much of the world and often lack the human and financial capacity to collect and produce it (Castello 2023). An estimated 84% of harvested fish species—key sources of food and income—have not been formally assessed because most fall under the jurisdiction of developing nations (Ricard *et al*. 2012). This lack of information on a global scale affects many taxa, including species that are exploited and imperiled by extinction (Barlow *et al*. 2018). Deficient or absent information on resources hampers conservation efforts at a time when developing nations are undergoing rapid socioenvironmental change, creating conditions leading to an increasingly degraded natural world (Barlow *et al*. 2018; Soga and Gaston 2018).

*[1]Department of Fish and Wildlife Conservation, Virginia Tech, Blacksburg, VA [*](leandro@vt.edu); [2]Faculty of Environment, University of Northern British Columbia, Prince George, Canada; [3]Department of Forest Resources and Environmental Conservation, Virginia Tech, Blacksburg, VA; [4]Department of Statistics, Virginia Tech, Blacksburg, VA; [5]Laboratory of Fisheries Biology and Management of Aquatic Resources, Federal University of Pará, Belém, Brazil; [6]Fisheries Institute, Santos, Brazil; [7]Institute of Oceanography, Federal University of Rio Grande, Rio Grande, Brazil; [8]Public Policies, Strategies, and Development, Federal University of Rio de Janeiro, Rio de Janeiro, Brazil; [9]Institute of Research of Cananéia, Cananéia, Brazil; [10]Department of Oceanography, Federal University of Pernambuco, Recife, Brazil; [11]Laboratory of Human Ecology, University of Santa Cecília, Santos, Brazil; [12]Federal University of Rio Grande do Norte, Natal, Brazil*

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An emerging approach to generate information about resources relies on the local knowledge of resource users themselves, particularly their memories of past harvests (Sáenz-Arroyo *et al*. 2005). The idea is that if resource users can reliably recall their past harvests, then surveys with users could quickly produce historical time-series of resource use that would otherwise not exist and at considerably lower cost than conventional protocols (Tesfamichael *et al*. 2014). Surveys of harvest recalls are routinely used for agriculture in Africa (Beegle *et al*. 2012) and could be applied to many other resources and contexts. However, achieving the potential of this approach requires addressing skepticism and legitimate concerns about the accuracy of harvest recalls and their susceptibility to biases.

Self-reported recalls of everyday events, such as past harvests, are often thought to be unreliable because the retrieval of information from the human brain involves various factors and processes related to cognition and memory retention (Koriat *et al*. 2000). Research in psychology has identified important sources of bias associated with recalls of everyday events, including the age of individuals, which affects their cognitive abilities, and time elapsed since an event occurred (Sekeres *et al*. 2016; Diamond *et al*. 2020). As time elapses, people forget the details but remember the gist of events; people also tend to rely on information readily available in their minds to infer details (ie the "availability heuristic"), which can lead to biased recollection due to the rare events that stand out (Groome and Eysenck 2016).

Prior studies indicate that although harvest recalls approximate "true" harvests, their degree of reliability remains unclear. Recall accuracy can vary depending on the nature of events (eg seasonality) and cognitive processes that people rely on to recall (Aylesworth and Kuo 2018). Some studies have found general agreement between harvest recalls and the range or temporal trends of equivalent data collected using standardized monitoring protocols (hereafter, "observed harvest"; eg Gavin and Anderson 2005; Daw *et al.* 2011; Sáenz-Arroyo and Revollo-Fernández 2016). However, studies assessing recalled and observed harvests for statistical relationships have reported mixed results (Otero *et al.* 2005; Jones *et al.* 2008; Beegle *et al.* 2012; O'Donnell *et al.* 2012; Jones *et al.* 2020; Thurstan *et al.* 2016). Previous studies have also assessed different measures of recall, including "poor" and "good" harvests, which, unlike "typical" harvests, are thought to be more accurate due to their focus on rare or unique events; however, results from these studies have also been mixed (eg Daw *et al.* 2011; O'Donnell *et al.* 2012; Thurstan *et al.* 2016).

The potential use of harvest recalls in resource conservation is further complicated by variability. Researchers and managers usually need to estimate harvests at the level of entire resource systems (eg a fishery), which typically involves many individuals. However, harvesting skills, knowledge, and the technologies and practices used typically vary across resource users (Thurstan *et al.* 2016). Even if harvest recalls were accurate, variability in recall magnitude across individuals could limit the usefulness of recalls in reconstructing harvests for the past.

Here, we examined the reliability of harvest recalls using a comprehensive dataset of recalled and observed harvests for a range of fishers from distinct fisheries. We addressed three questions: Are harvest recalls affected by fisher age and elapsed time? Which measure of harvest recall (good, typical, or poor) is most suitable for historical reconstruction? And, can harvest recalls reconstruct historical harvests at the scale of entire resource systems?

## Methods

### Observed and recalled data

We selected 24 fisheries distributed across a latitudinal gradient along the coast of Brazil (Appendix S1: Figure S1). The fisheries included (i) multispecies artisanal fisheries in the 5–6°S region using a variety of gear types, (ii) a mix of single- and multispecies artisanal and industrial fisheries using gillnets and trawls in the 23–25°S region, and (iii) single- and multispecies industrial fisheries using gillnets and trawls in the 28–33°S region (Appendix S1: Table S1). These fisheries were chosen because they possessed reliable observed harvest data for which we could compare harvest recalls from fishers participating therein. In our analysis, the observed harvest data (i) were collected by trained personnel using standardized protocols; (ii) included all, or at least the bulk of, fishing trips landed; and (iii) derived from interviews with boat captains about their catch (in kilograms) and fishing effort (in days spent fishing, excluding travel time).

We standardized the observed harvest data as catch per unit effort (expressed as kilograms caught per days spent fishing [kg days-fishing$^{-1}$]) by calculating annual means per fishery; catch per unit effort is a widely used metric to assess fisheries status and trends (Hoyle *et al.* 2024). The observed dataset for all fisheries and years included 643,789 fishing trips with an average of 22 years of data per fishery, and 1248 fishing trips per year and fishery. The median annual coefficient of variation of the observed harvest data was only 5.3%, indicating the observed data are suitable to compare against recalled harvests (Appendix S1: Table S1).

In each fishery, we sought to interview as many fishers as possible using a structured survey (Appendix S1: Panel S1) applied in person and individually between January and December of 2018. The survey followed the guidelines of the Committee of Ethics at the Federal University of Rio Grande do Norte, Brazil (Approved Protocol #73739917.3.0000.5537). To minimize under- or overrepresentation of subgroups of the fisher population in each fishery, we used a two-pronged approach to recruit active and retired fishers. We approached fishers at landing sites and docks and relied on the snowball sampling method to ask them to refer potential interviewees. Using this approach, we obtained an 83% cooperation rate, and we interviewed a total of 396 fishers.

We used several prompts and cues to improve recall, because people often struggle to remember details of past events (Berney and Blane 1997). We began by asking fishers to recall their age, the year in which they started fishing, characteristics of their fishing activities (eg species targeted, gears used, fisheries engaged in), and when they last fished. This allowed us to construct a timeline of events (which, later in the interview, we relied on to help fishers recall their harvests) and identify the fisheries in which the fishers participated (so that, later in data analysis, we could compare recalled and observed harvest data for the same fisheries). We prompted fishers about their past fishing harvests by explaining that harvests in fishing trips are usually variable and that this variability serves as the basis for classifying harvests as good, typical, or poor, following the criteria described in Table 1. We then asked fishers to use the same criteria to elicit three distinct and continuous measures of harvest recall: one for good harvests, one for typical harvests, and one for poor harvests. We also asked fishers to elicit corresponding measures of fishing effort for each harvest recall (Table 1). Fishers recalled these three distinct measures of harvests (kilograms) and fishing effort (days-fishing) for two periods in their fishing careers, the first 3 years and the final 3 years they fished, thus eliciting six harvest recalls in total. We prompted fishers to elicit these recalls in 3-year periods to minimize uncertainty about the exact year (Tesfamichael *et al.* 2014).

Finally, we paired all recalled and observed data. We then standardized recalled harvests as kg days-fishing$^{-1}$ and estimated their respective years as the midpoints of each 3-year period. For example, if a fisher recalled harvests for the 1980–1982 period, we estimated its recall year as 1981. We

**Table 1. Variables of harvest recall, observed data, and candidate sources of effect in harvest recalls**

| Variable type | Name | Definition |
|---|---|---|
| Harvest recall (kg days-fishing$^{-1}$) | Typical harvest | Harvest in routine fishing trips |
| | Good harvest | Harvest in fishing trips where catches were larger than in typical fishing trips but were not the best ever |
| | Poor harvest | Harvest in fishing trips where catches were smaller than in typical fishing trips but were not zero |
| Observed data (kg days-fishing$^{-1}$) | Observed harvest | Fishery-level annual mean harvest |
| Candidate sources of effect | Age | Age of the individual (years) |
| | Time | Time elapsed since the recalled event (years) |

**Notes:** all variables are continuous; units of measure appear in parentheses.

paired by year the individual (fisher-level) recalled harvests to the mean (population-level) observed harvest of their respective fisheries. In this process, 426 datapoints of recalled harvests were excluded from the analysis due to a lack of corresponding observed data. The final dataset contained 1950 paired observations of recalled and observed data, 650 for each measure of harvest (good, typical, and poor), with a mean of 16 fishers (standard deviation [SD] = 13) per fishery. On average, fishers included in the paired dataset were 51 years of age (SD = 13 years) with 30 years of fishing experience (SD = 14 years) (Appendix S1: Table S1).

### Data analyses

Data were analyzed in two steps. First, we assessed if harvest recalls are affected by fisher age and elapsed time, and which recall measure (good, typical, or poor) is most suitable for historical reconstruction. We used a linear mixed model with a measure of recall accuracy as the response variable and with age, elapsed time, type of recall measure (good, typical, or poor), and their interactions as fixed effects (Appendix S1: Panel S2). Recall accuracy was calculated as:

$$y_{ijkl} = 100 - 100\left(\frac{h_{\mathrm{obs},kl} - h_{\mathrm{rec},ijkl}}{h_{\mathrm{obs},kl}}\right) \qquad \text{(Equation 1)},$$

where $y_{ijkl}$ is the accuracy of the recall (%) $i$ by fisher $j$ in fishery $k$ and year $l$; $h_{\mathrm{obs},kl}$ is the observed harvest in fishery $k$ and year $l$; and $h_{\mathrm{rec},ijkl}$ is the recalled harvest $i$ by fisher $j$ in fishery $k$ and year $l$.

In this measure of accuracy, 100% indicates a perfect recall, and values above or below 100% indicate overestimations or underestimations, respectively. Fishery and individual fisher identification codes were included as random effects to allow the intercept to vary randomly across both. Age and elapsed time were standardized and weakly correlated ($r$ = +0.2). We did not account for fishery gear (eg gillnet) or type (eg artisanal) in the model to avoid overfitting; however, exploratory analyses indicated fishery gear or type were unrelated to recall accuracy. We accounted for slight heterogeneity in the residuals by allowing residual variance to vary with type of harvest measure and recall accuracy. We fitted the global model and all models—including all possible subsets of predictor variables—using the restricted maximum likelihood estimation (REML) method in the R package *nlme*. We compared the models using the bias-corrected Akaike's information criterion (AICc) and averaged those comprising at least 95% of cumulative AICc weights using the *MuMIn* package in R.

We then assessed whether harvest recalls can reconstruct historical harvests at the scale of resource systems. We fitted additional similar models in which (fisher-level) recalled harvests were set as the response variable and (fishery-level) observed recalls were set as the predictor (Appendix S1: Panel S3). Recalled harvests were set as the response because they depend on observed harvests: that is, recalled harvests are estimates, not predictors, of observed harvests (Jones *et al.* 2008). We fitted two models using the recall measure that we had identified in the preceding analysis as being better suited for historical reconstruction. One of these models contained all datapoints of that recall measure, whereas in the other model, datapoints of the same measure were filtered to include only recalls with an accuracy of 100 ± 10%; hereafter, we refer to data from these two models as "unfiltered" and "filtered" recalls, respectively. The models accounted for slight heterogeneity in the residuals by allowing the residual variance to vary with observed harvest. We assessed the reliability of historical reconstruction by comparing the fitted regression lines to the 1:1 equivalence lines and using fivefold cross-validation, which evaluates model performance by comparing model predictions against observed data (using the *caret* package in R).

## Results

### Age and time effects

We found that recalls of harvests—good, typical, and poor—are affected by fisher age and elapsed time since harvest (Figure 1a). Recalls of good and poor harvests were larger than and smaller than observed harvests, respectively, in terms of magnitude (Figure 1b). Recalls of typical harvests were the most accurate of the three measures and were only slightly smaller than observed harvests (Figure 1b). Although the effects of age and elapsed time involved interactions among age, time, and type of recall measure (good,

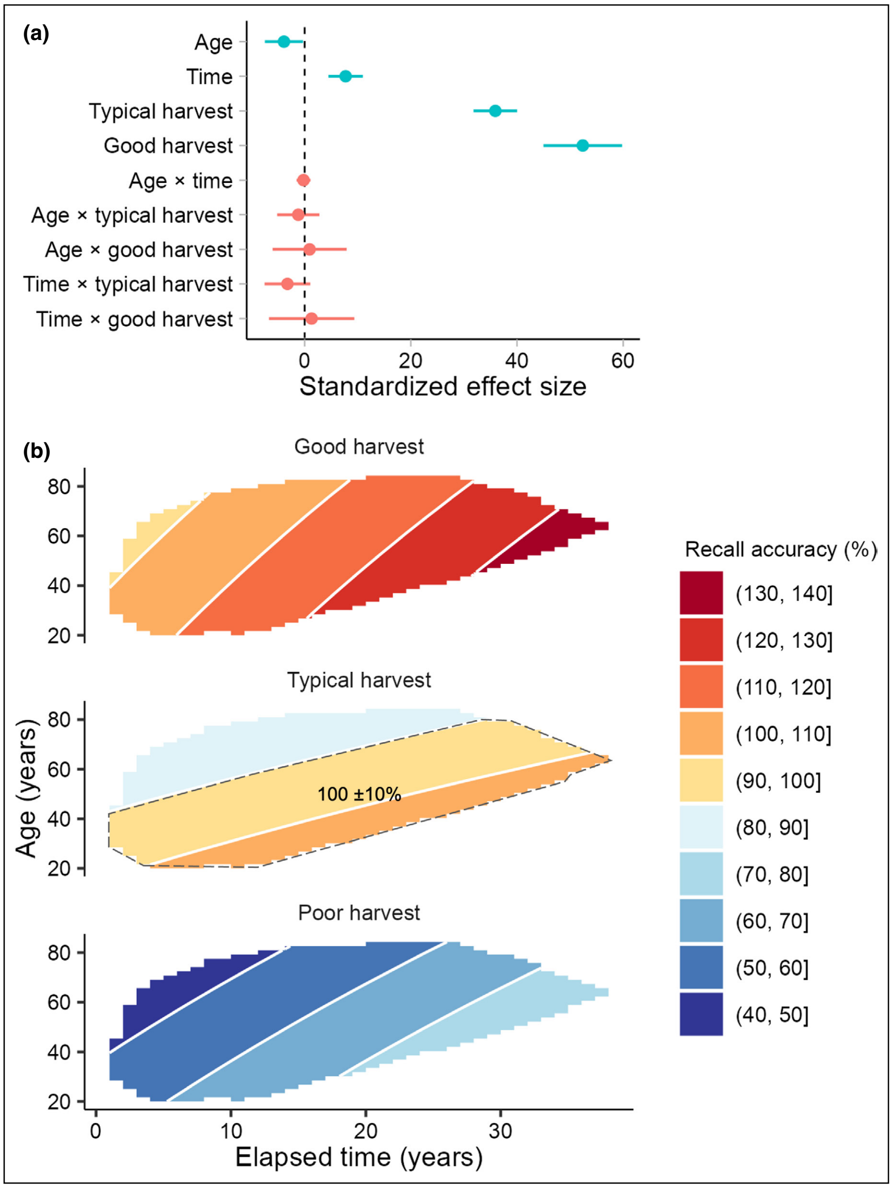


**Figure 1.** Effect of fisher age and elapsed time since harvest on the accuracy of three measures of harvest recall (good harvest, typical harvest, and poor harvest). (a) Model-averaged estimates of effect sizes (solid circles) and respective 95% confidence intervals (horizontal lines): red and turquoise indicate confidence intervals that cross zero and do not cross zero, respectively. Not shown: the intercept (57.7 [95% confidence interval: 50.9, 64.4]) represents values for poor harvests for the averages of age and elapsed time. (b) Model-averaged predictions presented as contour plots: values greater than 100% indicate recalls that overestimate (red shades) and values smaller than 100% indicate recalls that underestimate (blue shades). High accuracy (yellow and light orange shades): 100 ± 10%.

typical, and poor), two primary patterns emerged across the three recall measures: (i) harvests recalled by older fishers were smaller than those recalled by younger fishers and (ii) harvests recalled for recent years were smaller than those recalled for the distant past (Figure 1b). These results indicate that the magnitude of recalled harvests decreases with fisher age and increases with elapsed time.

Relative to recalls of good and poor harvests, recalls of typical harvests had the longest range of elapsed time with high accuracy (ie 100 ± 10%; Figure 1b), and therefore are better suited for reconstruction. For typical harvests, recalls by fishers 65 years old or younger for years early in their careers were quite accurate for up to 39 years in the past (accuracy 100 ± 10%). In contrast, for typical harvests, recalls by middle-aged fishers (45–65 years old) for recent years and by seniors (>65 years old) for all years underestimated harvests (accuracy 80–90%).

### Reliability of harvest recalls

Recalls of typical harvests reconstructed historical harvests regardless of whether they were filtered to minimize age and time effects. The regression line for unfiltered recalls had an intercept (16.73 [95% confidence interval {CI}: –6.33, 39.80]) that did not differ from zero and a slope (0.94 [95% CI: 0.88, 0.99], $n$ = 650) that barely differed from the 1:1 equivalence line, indicating that the recalled and observed harvests were nearly equal. However, and as expected, the regression line for filtered recalls was slightly closer to the 1:1 equivalence line (intercept = 13.87 [95% CI: –6.14, 33.89]; slope = 0.96 [95% CI: 0.88, 1.02]; $n$ = 383; Figure 2, a–c). This close match between observed and recalled data was characterized by substantial variability in fisher-level harvest recalls relative to fishery-level observed harvests, with a median absolute difference of 34.5% for unfiltered recalls and 33.2% for filtered recalls. Despite this variability, the median differences between observed and recalled harvests were only –4.9% for unfiltered recalls and –3.4% for filtered recalls (Figure 2d), because the positive and negative differences cancelled out one another. This indicates that recalls of typical harvests are 95–97% accurate.

## Discussion

Our results advance understanding of harvest recalls in three ways. First, they reveal that harvest recalls are affected by fisher age and elapsed time since the harvest. Our finding that fisher age reduces the magnitude of recalled harvests aligns with psychological studies showing that age increases error in recalls of everyday events (Sekeres *et al.* 2016; Diamond *et al.* 2020). This may occur because age lowers the richness of contextual information that people use to infer the details of past events (Devitt and Schacter 2016). Why such increases in error would lead to a systematic decrease in the magnitude of recalled harvests is unclear. Our finding that the magnitude of recalled harvests increases with elapsed time is similar to the finding of Thurstan *et al.* (2016) that recalled harvests increase by 0.65% per year of elapsed time. Availability heuristic could explain this effect if fishers' memories are influenced by large harvests in the "old days" (Thurstan *et al.* 2016). Further studies are needed to better understand age and time effects on harvest recalls; such work could build on decades of related psychological research, and be expanded to encompass other regions and resource systems (eg forests, bushmeat; Castello 2023).

Our results also show that the more reliable recall measure for historical reconstruction is typical harvest, which contrasts with prior findings that recalls of unique events (ie good and poor harvests) are more reliable (eg Daw *et al.* 2011; Thurstan *et al.* 2016). While availability heuristic may affect the accuracy of recalls of typical harvests, our results show that age and elapsed time have consistent effects on the magnitude of all three recall measures that must be considered in historical reconstruction. As compared to recalls of good and poor harvests, recalls of typical harvests have the advantage of being more informative, because resource assessments and management usually focus on prevailing conditions.

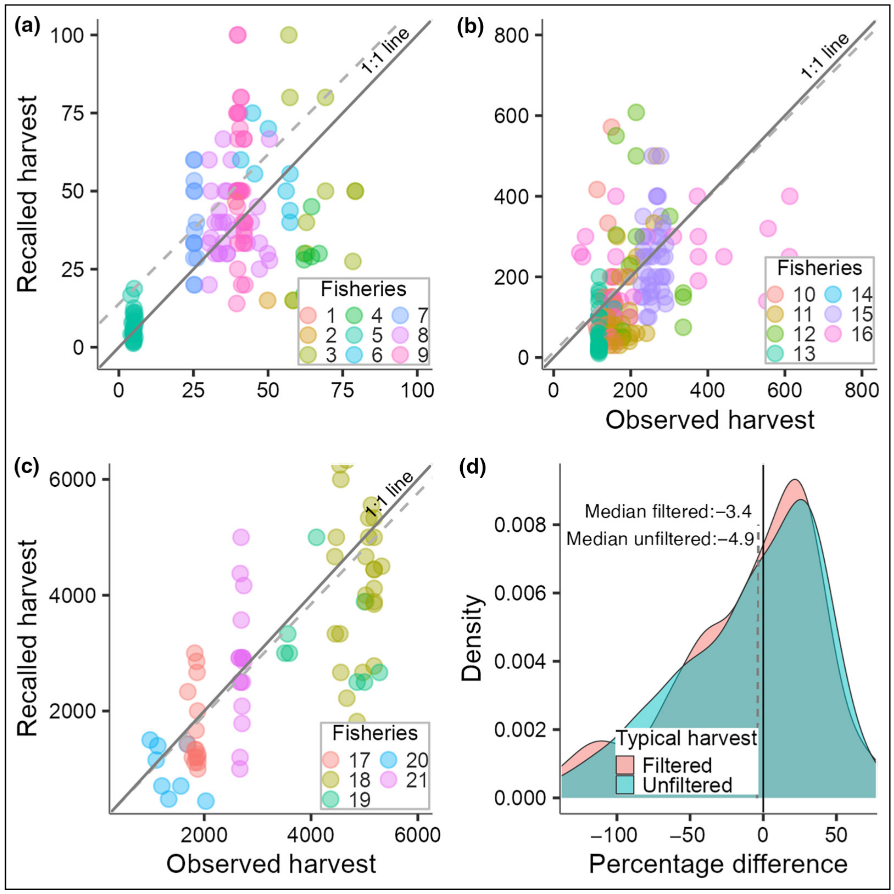


**Figure 2.** (a–c) Predicted relationship between recalled and observed harvests (expressed as kilograms of fish caught per days fishing) paired by year for 21 coastal fisheries in Brazil (Appendix S1: Table S1) using filtered recalls of typical harvests. Data are presented in three separate plots (fisheries 1–9 in [a], fisheries 10–16 in [b], and fisheries 17–21 in [c]) grouped by harvest magnitude, for visual clarity (note approximate order-of-magnitude differences in *x*- and *y*-axis values between plots). Solid lines depict 1:1 equivalence lines and dashed lines depict fitted regressions. (d) Reliability assessment of historical reconstructions, presented as percentage difference between recalled and model-predicted harvests.

Finally, our results suggest that recalls hold considerable promise for reconstructing historical harvests. Although individual-level recalls of typical harvests were variable relative to fishery-level harvests, just like individual-level observed harvests, they were accurate when aggregated, a result that corresponds with the findings of Aylesworth and Kuo (2018). This was the case regardless of whether recalls were filtered to minimize age and time effects, most likely because such effects were generally small. The validity of these results is demonstrated by application of recalls of typical harvests to reconstruct catches in three "data-less" fisheries in the Congo Basin (Castello *et al.* 2023), based on surveys of ~100 fishers per fishery. In the Congo Basin study, regression models that were fitted to unfiltered recalls of typical harvests revealed declines in catch on the order of 65–80% during the past half-century. Findings from Castello *et al.* (2023) in the Congo Basin demonstrate that, despite variability, samples of recalls can effectively produce historical resource-level information, and the results of the present study indicate that such information is almost as reliable as data collected from conventional fisheries monitoring.

To our knowledge, our results on the reliability of harvest recalls are based on the most comprehensive dataset to date; however, our analyses lack a "true" baseline and rely on the assumption that individual-level recalled harvests are comparable to the average of fishery-level observed harvests. To address this, we carefully selected the observed data to ensure they were robust, although fisheries datasets are never perfect (Pauly and Zeller 2016). We standardized harvests by effort and ensured that fishers' recalls were compared to observed data for the same fisheries. We also used a mixed modeling approach that leads to improved estimates for groups (eg fisheries) with small sample sizes through partial-pooling across fisheries. Therefore, we have no reason to question the assumption underlying our analyses. Measuring the true accuracy of harvest recalls usually requires experimental conditions that are difficult to implement over the time periods (typically decades) needed to reconstruct historical resource use.

Overall, our findings contribute to the development of a cost-effective approach to generate valuable information about numerous resource systems around the world that are in urgent need of monitoring and assessment data. Because recalls constitute one of the few sources of information that are relatively reliable and readily available, we suggest their use may help address the current dearth of conservation action, at least until higher-quality data become available. Harvest recalls could have myriad applications in many data-poor resources, including bushmeat species (Nasi *et al.* 2011); sharks, rays, and chimaeras (Dulvy *et al.* 2014); and most of the world's fisheries, which in numbers are artisanal fisheries (Pauly and Zeller 2016). Building on future studies, harvest recalls could be included as one of several types of knowledge that strengthen decision making, as has been advocated in several international arenas (eg UN Sustainable Development Goals, Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services; Díaz *et al.* 2019).

Harvest recalls could also be implemented within trial-and-error frameworks that inform management and support research initiatives. For resources in which little or no data are available, researchers and managers could use regression modeling on harvest recall data to assess historical trends (Early-Capistrán *et al.* 2020). The reconstructed data could underpin trend assessments, historical benchmarks, and various management decisions, including producing data useful to curb shifting baselines. Harvest recalls could also support periodic surveys, which would be cost-effective and would minimize time effects on the data while regularly generating actionable information for stakeholders.

Our study demonstrates that harvest recalls could boost the efforts of rural communities worldwide, which are increasingly responsible for managing the resources they depend on (Evans *et al.* 2011). Monitoring data produced by resource users at the community level have many advantages (Danielsen *et al.* 2022). As compared to data from scientific monitoring, data produced by resource users can be more relevant for management because such data can be more time- and place-specific (Eicken *et al.* 2021) and address problems that resource users think are important (Commodore *et al.* 2017). Moreover, it can enhance management responses through more rapid implementation of decisions (Danielsen *et al.* 2007). Local knowledge differs from equivalent scientific information in that it is better understood and hence more trusted by resource users, and as such can help promote compliance with rules and participation in conservation (Castello *et al.* 2009). Clearly, harvest recalls could help fill global gaps in resource data while harnessing the potential of community conservation where it is most needed.

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## Data Availability Statement

All data and analysis code needed to evaluate the conclusions presented here are provided in the article and available online at https://doi.org/10.5281/zenodo.8326397.

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## Supporting Information

Additional material can be found online at http://onlinelibrary.wiley.com/doi/10.1002/fee.2726/suppinfo