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A Summary of Post-Cruise Data Loss in the North Pacific Observer Program from 2014 to 2023

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U.S. DEPARTMENT OF COMMERCE

National Oceanic and Atmospheric
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A Summary of Post-Cruise Data Loss in the North Pacific Observer Program from 2014 to 2023

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ABSTRACT

Fisheries observer programs represent a type of long-term ecological monitoring program (LTEM), and as such employ quality assurance and quality control methods (QA/QC) to ensure data vital to sustainable fisheries management is of the highest quality. In the North Pacific Observer Program (NPOP), a significant element of the QA/QC chain is the final debriefing, an interview between trained, knowledgeable staff (debriefers) and fisheries observers returning from deployment. The purpose of the interview is to review data and data collection protocols for compliance with collection requirements. To understand the impact of final debriefings on data quality in the NPOP, we summarized trends in how, where, and why debriefers deleted data during the interview stage from 2014 to 2023. We summarized deletions by calculating the percentage of data deleted by year, vessel-gear group, observer experience, the number of other observers on the same cruise, and reason for deletion. Our findings suggest debriefers in the NPOP rarely delete data. The value of debriefing becomes apparent through the removal of biased or incorrectly transcribed data, especially aboard vessels fishing pot gear, and for observers with little experience or when deployed as the sole observer on a trip. These summaries demonstrate how debriefing acts as a vital component of fisheries observer programs to maintain high data quality standards.

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INTRODUCTION

While fisheries globally provide various socioeconomic benefits, many have historically faced collapse or permanent closure due to overfishing (Hutchings 2000), often triggering management strategies that evaluate stock status, a process that relies heavily on both fishery-independent and fishery-dependent data collection (Beddington et al. 2007, Leblond et al. 2008, Bradley et al. 2019, Mangi et al. 2021, Ribera-Altimir et al. 2023). Scientific surveys provide fishery-independent data, whereas fishery observer programs are the most robust source of fishery-dependent data (Ewell et al. 2020, Mangi et al. 2021). Fishery observers are scientists who serve onboard commercial fishing vessels and collect data vital to fisheries management (Gilman et al. 2017, Stevenson 2018, McCracken 2019). Observers collect a variety of fishery-dependent data, including species composition of the catch, biological samples (e.g., lengths, weights, tissues), and fishing effort data. Observer programs have been critical in reducing overexploitation and maintaining healthy fish stocks globally, including those in the North Pacific (Worm et al. 2009).

The United States strives for fisheries sustainability through the enforcement of marine resource laws and regulations outlined by the Magnuson-Stevens Fishery Conservation and Management Act (MSA; Faunce et al. 2023). Originally passed in 1976 and reauthorized in 1996 and 2006, the MSA established management authority for the United States over fish resources within the U.S. Exclusive Economic Zone (EEZ) that extends from 3 to 200 nautical miles offshore. The MSA authorizes the use of fisheries observers serving onboard fishing vessels and at processing plants to collect the data necessary to manage fisheries sustainably (Porter 2010). Regional U.S. observer programs provide critical data for stock assessments that ensure the sustainability of fish stocks (Brooke 2015).

The North Pacific Observer Program (NPOP) is the most extensive regional U.S. observer program, deploying over 350 observers on more than 5,000 fishing trips annually (NMFS 2023). The NPOP collects fishery-dependent data for the North Pacific Fishery Management Council (NPFMC), which is responsible for managing fisheries within the 900,000 square mile EEZ off the Alaska coast. Alaska fisheries include some of the most commercially important fisheries in terms of landed volume

and value in the United States, mainly targeting groundfish such as walleye pollock (*Gadus chalcogrammus*), Pacific cod (*G. macrocephalus*), and Pacific halibut (*Hippoglossus stenolepis*) (NMFS 2024). Alaska fisheries are among the world's most well-managed fisheries partly because of rigorous fishery-dependent data collection protocols executed by observers (Worm et al. 2009, Faunce et al. 2023). However, data are only as good as the chain-of-custody, quality assurance (QA), and quality control (QC) protocols implemented during and after data collection. The NPFMC's reputation for sound management of Alaska groundfish fisheries is partly due to rigorous data management and QA/QC protocols, which are paramount to any successful ecological monitoring program.

The science of monitoring fisheries with observers is a form of long-term ecological monitoring (LTEM). Projects engaged in LTEM deploy some form of observation technology (e.g., people, electronic monitoring (EM), satellites, etc.) to evaluate the efficacy of management protocols and ecological system dynamics (Nussear and Tracey 2007, Dodds et al. 2012, Stein et al. 2013). Inherently operating over long time scales, LTEM projects generate large volumes of data that continuously update with new information, thus making data QA/QC challenging (Sutter et al. 2015). Many regulatory agencies and funding organizations therefore require data management plans from associated LTEM projects to ensure data quality, availability, and integrity for end-users (Dietrich et al. 2012, Smale et al. 2018, Tenopir et al. 2020). Despite these requirements, the literature describing fisheries monitoring programs often lacks comprehensive descriptions of data management practices (Kolb et al. 2013). Moreover, the LTEM literature, and fisheries monitoring studies specifically, presently lack evaluations of the impact of data quality procedures on the final data product. Because LTEM projects are often large, expensive, and comprise numerous trade-offs among objectives, assessing QA/QC procedures could improve workflows and operations as well as save time and money.

Data quality processes are critical to maintain the utility and integrity of the NPOP. The NPOP has a data management plan that includes a series of data QA/QC protocols that have been refined and improved upon over the 50-year history of the NPOP. (Stevenson et al. 2016, Observer Sampling Manual 2023, AFSC 2023b). However, the outcomes of the NPOP's QA/QC protocols, like those of most

fisheries monitoring programs, have rarely been subject to a transparent, comprehensive, and systematic evaluation.

We evaluated the last aspect of the NPOP's QA/QC protocols: deleting data deemed unsuitable during the post-deployment interview process, known as debriefing. The final debriefing interview is a critical step in the NPOP QA/QC process. We chose to focus on post-deployment deletions for two main reasons: (1) to limit the scope of the work and (2) to quantify the extent of deletions. Limiting the scope of the project was important because the QA/QC process is long and complex, and includes: data collection (e.g., collecting the correct data, following sampling protocols, recording and transcribing the data properly, ensuring data confidentiality, etc.); data entry (e.g., keypunch and error checks, validations); and in-season interviews, debriefing, and data quality checks implemented by data users for specific projects (Figure 1). By focusing on data deletions, we shine a light on data loss (as opposed to, e.g., data changes), narrowing the scope of work which can be readily quantified and potentially yield actionable insights that could have positive impacts along the QA/QC chain (e.g., improvements to training and debriefing). Furthermore, by evaluating the last step in the NPOP's QA/QC process, we simultaneously gain insight into the efficacy of prior steps in the process: errors present at this stage highlight shortcomings of prior data checkpoints, while other errors must have already been rectified.

Quantifying the extent of deletions helps put in perspective the costs and benefits of the large QA/QC investment and is important to provide assurance and transparency to observers, staff, end users, and the general public and to build trust that the data are of the highest quality. Robust and transparent QA/QC analysis also provides assurance that data quality issues, when identified, are addressed and handled in an objective manner. At times, deletions might potentially involve thousands of individual data points raising concerns that time and effort has been wasted on collecting bad data, or that some aspects of these deletions could have been prevented or some of these data retained. While deleting hundreds of rows of data containing thousands of data points might appear to be “large” and perhaps “unnecessary” without quantifying the scope of the problem the NPOP has no way to judge the overall impact. Thus, quantifying the magnitude of data deletions helps put the data loss into perspective.

We summarized trends in data deletions within the NPOP that occurred after an observer had returned from their deployment (referred to as post-cruise) during the debriefing process over a 10-year period (2014-2023). We compared trends in data deletions over time and among covariates that were likely to have a large impact on observer data collection and thus could result in deleting data. We also summarized reasons for data deletions which provide context as to why data were deleted. Summarizing the reasons for deleting data can provide insights into ways to improve training materials, observer in-season advising and support systems, and sampling strategies which will serve to increase overall data quality, minimize data loss, and maximize observer time and productivity. This study represents an important first step in assessing the effectiveness of data quality protocols and can act as a foundation for evaluating the entire QA/QC chain of the NPOP.

METHODS

The chief goal was to summarize data deletions in the NPOP. We confined our summaries to the period 2014-2023. In 2014, the NPOP added database functionality that allows for the reliable tracking of data changes and changed some data definitions, so this period represents the most consistent time series. We note that, in addition to conducting the post-cruise interview, debriefers and other NPOP staff often act as in-season advisors (ISA) during an observer's deployment. While we recognize that ISAs play a very large role in the QA/QC process while observers are at-sea collecting data, and because we focused on the post-cruise debriefing process, many errors had been identified and resolved in-season, reducing the effective number of errors that we were likely to see at the end of the cruise.

Covariates

We summarized data deletions within covariates that were likely to impact observer data collection: year, gear-vessel group, observer experience, and the number of observers present on the vessel during the same fishing trip. We quantified both retained and deleted data among our covariates and calculated standard percentages to compare deletion trends.

Years were defined by the particular edition of the Observer Sampling Manual being used, instead of the prototypical calendar sense. Each year, the NPOP updates the Observer Sampling Manual, a detailed operating manual for observer duties and sampling protocols (described further in 2.1.3.; AFSC 2023a). Updates and changes to observer duties and protocols are documented in the Observer Sampling Manual each year by the first week of December. Therefore, we defined years from the first week of December to the following year's first week of December.

Gear-vessel groups were made up of a single gear type and vessel class (see section 2.1.1 below) because, in tandem, gear-vessel groups dictate observer responsibilities aboard a vessel (AFSC 2023a). The NPOP typically uses gear-vessel groups to assign vessels to coverage categories that dictate observer deployment (AFSC 2024); observer sampling protocols and priorities also vary among gear-vessel groups (AFSC 2023a).

We used the number of prior cruises as a proxy to represent observer experience. With each fishing trip, observers gain experience which can be used and applied on subsequent deployments. However, many other factors might affect an observer's experience for which we have not accounted for in this study. Consider, for example, an observer deployed on their first pot vessel despite five prior deployments at processing plants. Observers are trained in general principles of random sampling and recording data, but the two situations are different and some adaptation and problem-solving would need to be applied. To simplify observer experience, we used the number of prior cruises (i.e., those completed prior to the cruise of data collection) as a simplified proxy for observer experience, which we term here as the number of prior cruises (PCs).

We labeled records as collected on either "solo cruises," where the observer collecting the data had no other observer present aboard the vessel, or "shared cruises," where the observer collecting the data had at least one other observer present on the vessel at the same time. When more than one observer was present on a fishing trip, observers could rely each other to verify data collection protocols and quality. For example, a less experienced observer might ask their partner observer to corroborate sampling methods or verify species identification.

We summarized the reasons for deleting records from the Debrief Editor Comment (DEC) database. During the post-cruise debriefing and data review process, debriefers must provide a rationale for deleting data. Reasons were selected from predetermined categories available within the DEC, but debriefers could also add written comments. We confined our summaries of DEC data to the predetermined categories within the DEC and limited the summaries to 2017-2023 when the DEC application first became available.

The North Pacific Observer Program

Before 1977, commercial fishing activity in Alaska waters was conducted by foreign vessels often sailing under the flags of Japan and the then-U.S.S.R. (Nelson et al. 1981). Starting in 1973, foreign nations voluntarily invited U.S. observers to monitor their fishing vessels operating in Alaska waters (Nelson et al. 1981, French et al. 1982, NMFS 2019). In 1976, passage of the MSA granted the United States authority over marine resources within 200 nautical miles of shore. In 1977, the first required observers were placed aboard foreign vessels, which marked the beginning of regulated observer coverage in the region. The subsequent domestication of Alaska fisheries culminated with the exclusion of foreign fishing vessels in the North Pacific groundfish fishery and establishment of the region's domestic observer program in 1991, now known as the North Pacific Observer Program (NPOP; Brooke 2015). The NPOP is administered by the Fisheries Monitoring and Analysis (FMA) Division of the Alaska Fisheries Science Center (AFSC), which is one of the regional science centers within the U.S. Department of Commerce's, NOAA, National Marine Fisheries Service (NOAA Fisheries).

Gear Types and Vessel Classes

Fishing vessels in the North Pacific deploy a variety of gear types, the majority of which can be categorized into three broad types: hook-and-line, trawl, and pot gear. Longline vessels use hook-and-line gear to set thousands of baited hooks along a groundline several miles long (NPFMC 2012). Trawl vessels operate by towing a large net behind the vessel, either in the pelagic or the benthic environment (non-pelagic trawl). Pot vessels deploy baited traps to the seafloor for later retrieval (NPFMC 2012).

While some vessels utilize other gear types (e.g., jig, seine) or multiple (referred to as mixed gear), they are uncommon in the North Pacific and were excluded from this study.

Regardless of gear type, most vessels can be defined as either a catcher vessel (CV) or a catcher processor/mothership (CP/MS). Catcher vessels store catch as whole fish in tanks until their delivery to processing plants or vessels that receive catch from several CVs for later delivery to a processing facility, known as tenders. Catcher vessels do not process their catch into a product. Catcher processors both fish and process and freeze either their own catch or catch delivered by another CV or tender vessel.

Motherships (MSs) are a less common vessel type that routinely take unsorted catch from other vessels but, unlike CPs, do not fish. Because observers sample MS operations identically to CP operations, we group CPs and MSs into a single category (CP/MSs). Catcher processors and mothership vessels tend to be larger than CVs because of their capacity to accept, freeze, and process catch.

We selected four gear types (pelagic trawl, non-pelagic trawl, hook-and-line, and pots) and two vessel classes (CV and CP/MSs) for data deletion summarization. Because these groups are interrelated, we combined one term from each to create eight gear-vessel groups. These gear-vessel categories represent the most observer deployments in any given year in the NPOP. We excluded data collected at shoreside processing plants because the volume of data collected during the study period was small in comparison to the amount of data collected on vessels. Furthermore, most data collection at processing plants occurs during pelagic trawl deliveries, thus data collected at plants largely reflect this gear type.

Observer Deployment

The NPOP deploys observers under regulations outlined by fishery management plans (FMPs), which vary by fishery, vessel size, and vessel class (Faunce et al. 2021). Observer service providers are private companies that employ, pay, and provide benefits to observers and support the logistics of observer deployments onto vessels. In general, providers deploy observers for up to 90 days (hereafter, a cruise). Within a cruise, an observer can be assigned to multiple vessels or plants (an assignment). In 2013, the NPOP restructured observer coverage guidelines to fall under three facets: vessels operating

under full coverage (100% of trips monitored), partial coverage (< 100% of trips monitored), or zero coverage (0% of trips monitored; Faunce et al. 2021).

In the full coverage sector, all vessels have at least one, but sometimes two or more, observers present on all fishing trips. In situations where two or more observers are present on a trip, one observer is designated to be the lead observer. The lead observer is typically more experienced and is responsible for overseeing all data collection and monitoring efforts, even those made by the other observers (hereafter, second observers) sharing the assignment. The full coverage sector includes most CP/MS vessels and CVs that participate in cooperatives (organizations that share catch quotas; NMFS 2024).

The partial coverage fleet includes the following: CVs greater than 40 feet length overall (ft LOA) that are not in the full coverage sector, often due to fishing individual fishing quotas (IFQ) or community development quotas (CDQ) for halibut; vessels targeting sablefish using hook-and-line, pots, or both; and vessels targeting groundfish using pot gear. The partial coverage fleet also includes longline CVs smaller than 46 ft LOA, CP/MSs that do not meet criteria for full coverage placement, and CVs of all gear types (NMFS 2024). In the partial coverage sector, trips logged by vessels are randomly selected to be monitored by a single observer; thus, unlike full coverage, not all trips are observed. The NPOP divides partial coverage vessels into strata defined by gear deployed and assigns expected observer coverage rates of trips to each stratum based on a statistically sufficient baseline that strives to balance competing priorities, logistics, and available funding (NMFS 2023, 2024). Selection rates establish observer deployment within the partial coverage fleet and, in that way, influence the volume of data collected across strata and thus may influence trends in data deletions.

We excluded the zero-coverage sector from our analysis because trips in this sector were not monitored. We also excluded data collected by electronic monitoring (EM) systems because EM data collection had different objectives than observer data collection, even though some vessels in both full and partial coverage fisheries carried EM systems.

Observer Sampling

Observer tasks followed a hierarchy based on gear type, vessel type, and predominant species, which is a proxy for the target fishery. Observers followed sampling guidelines detailed in the Observer Sampling Manual (AFSC 2023a). We provide a summary of these protocols here, but readers should consult the sampling manual for details.

In the full coverage sector, if two or more observers were on a single cruise, each instance of gear retrieval, referred to as a haul, was to be sampled. Trawl CVs targeting pollock retrieve only a few hauls per day, thus observers were expected to sample every haul. In cases where not all hauls were sampled, observers used a random sample table to determine which hauls to sample. Observers were instructed to use systematic random samples whenever possible to minimize sampling bias; however, alternative sampling designs were available if systematic random sampling could not be implemented. For a given sampled haul, a minimum of three samples was recommended. Sampling method varied by gear type due to discrepancies in access to catch. For example, on trawl vessels observers often sampled from catch dumped into the trawl alley, or, on CPs, catch was sent to the onboard factory where observers sampled from conveyor belts. During pre-defined periods of gear retrieval on longlines, observers sampled by tallying fish as they come out of the water attached to the hook. On pot vessels, observers could census the entire contents of single pots, although more commonly, the contents of multiple pots were combined and sampled.

For most samples within a haul, each fish was identified to the lowest possible taxonomic unit, typically species. The relative abundances of identified species within the sample comprised the species composition, and included count and weight data for each species. In some cases, observers collected subsamples to obtain count and weight data from species compositions. Within a species composition sample, observers collect paired sex - length measurements from a random subset of the species (AFSC 2024). From these sex-lengthed individuals, observers took a random subset of individuals for biological specimens (otoliths, scales, fin clippings, tissue samples, etc.). In sum, species compositions were nested within samples, lengths were nested within species compositions, and biological samples were nested within lengths.

Observers initially collected data on water-resistant paper forms which they subsequently entered into the ATLAS software system on-board each vessel. ATLAS allowed observers to remotely connect to the AFSC database (known as NORPAC) from sea and submit their data in near-real time. ATLAS (named after the mythological Titan that held up the sky) and NORPAC (for the North Pacific Observer Program) were built and are maintained by the AFSC FMA and are described in more detail in section 2.2 below.

Debriefing

The NPOP staff conducted both in-season advising and end of deployment interviews, known as debriefing. Staff advised observers in-season by providing guidance on sampling techniques and reviewing data error reports automatically generated by NORPAC upon receipt of data transmissions from ATLAS. Every completed cruise culminated in a final debriefing interview. Prior to the final debriefing, the observer ensured all data were submitted to NORPAC, addressed all in-season errors to the best of their ability, and completed a survey for each vessel assignment. Debriefers interviewed the observer and reviewed all submitted data including any unaddressed errors. Debriefers checked observer sampling methods, examined data for potential bias, and validated correct transcription from the paper forms to the database. During debriefing, observers and debriefing staff collaborated to fix errors. Any compromised data discovered during debriefing underwent one of three changes: (1) data were updated to a new value (which might include null); (2) data replaced null values; or (3) an entire data record (a row in a table) was deleted from the database to maintain high quality standards for data users. Data record deletions only occurred when errors could not be corrected based on all available information and thus the data became unsuitable for scientific purposes. Depending on the magnitude and extent of the error, the deletion itself may have been reviewed by other debriefers, the debriefing manager, or other knowledgeable staff. In 2017, debriefers began using the Debrief Editor Comments (DEC) application to record details about the deleted data and document the reason for the data changes and deletions. Final debriefings resulted in a deployment score for the observer; recommendations for future deployment; an anonymous survey completed by the observer, providing feedback for NPOP improvement; and checked,

error-free data remaining in the NORPAC database and ready for use by end-users (e.g., stock assessors, fisheries analysts, fisheries managers, etc.).

Data Infrastructure and Automated Data Checking

While observers are the first line of defense in the QA/QC chain, the NPOP also utilized automated data review procedures during and after an observer's deployment to ensure data quality.

Fishery data collected by observers and entered into ATLAS at-sea was transmitted electronically to the NORPAC database within NOAA Fisheries. The ATLAS infrastructure included 4 main components: (1) a free, Windows-exclusive Oracle XE relational database which stored observer data; (2) an Oracle Rest Data Service, a Java application that enabled browsers to operate ATLAS and users to perform data entry; (3) Application Express, an Oracle schema that served as the primary graphical interface of ATLAS; and (4) a REST API, embedded programming logic that transmitted data and communications to and from ATLAS (Glenn Campbell, AFSC-FMA, personal communication). NORPAC performed routine, automated data quality checks upon receipt of ATLAS data submissions including the following: comparing observer collected length and weight records to known, species-specific length and weight ranges; validating that the catch location of a species was within the known spatial range of that species; and flagging any anomalous data points for investigation by observers or staff (Stevenson et al. 2016). All observer data collected since 1996 have been stored and maintained in NORPAC.

NORPAC Database

NORPAC contained a wide variety of data including the following: fishing effort, catch, and biological data collected by observers and transmitted via ATLAS; logistical data from observer providers; vessel-specific information (e.g., lengths, name, etc.) from the U.S. Coast Guard and the Alaska Department of Fish & Game; and gear codes, species codes, and observer personnel information maintained in FMA data records. Data tables containing observer fishery data were updated daily via observer data transmissions from ATLAS. Data tables containing observer logistical data were relatively

static and only updated upon embarkation/disembarkation of vessels, certification of new observers, and other changes in observer logistical status (e.g., from “in-season” to “in-debriefing”). We utilized the logistical tables to join covariates (such as observer experience, see below) to observer fishery data.

Relational databases, such as NORPAC, intrinsically store data records that share relationships with other records and organize these in a parent-child hierarchy. The notion of a parent-child data relationship is straightforward: a child record is a record that cannot exist without the prior entry of another data record, known as the parent record. For example, a sample cannot be collected without the retrieval of a haul; thus, a sample record is the child of a parent haul record. We used several tables that exhibit a linear hierarchy of parent-child relationships, reflecting the hierarchical nature of observer data collections (Figure 2). Hauls were the ultimate parent record, as they defined the scope of observer data collection, including gear type, gear deployment and retrieval coordinates and times, catch volume and weight, and bottom depth fished. The first child of a haul was the sample, which served as a placeholder record for species composition. Some samples required the collection of sub-samples, which were children of samples (and thus children of hauls) and also served as placeholders for species composition records. Species compositions were children of samples for which each record was an individual species count and weight. Length records were usually children of species compositions. However, some length records were collected outside of a sample such that they were only children of the parent haul record from which they came. Finally, specimen records represented the lowest level in the hierarchy as the children of length records. In totality, we summarized six observer data tables that represent levels in the parent-child hierarchy depicted in Figure 2, and refer to them hereafter as hierarchy levels.

To exploit the relationships data records share across the hierarchy, relational databases use unique numeric sequences, called keys, stored in each related record. In NORPAC, every record was given the following keys: a key assigned to observers that reflects the deployment, called a cruise number; a key assigned to vessels by the Alaska Regional Office (AKRO) branch of NOAA, called a permit, and; a key assigned to the hierarchical level in which the record was collected (e.g., a haul record has a haul key). All child records were required to contain all parent keys within the child record so that the full hierarchy for the record was identified. For example, to match a sample record to its parent haul

record, each record shared the same cruise and permit keys, and the sample record contained the same haul key as the parent haul record. Because parent records had several child records, they did not contain their child keys (in the above example, the haul record did not contain a sample key). We utilized keys to join tables which produced the final datasets for summarization as explained in detail in 2.2.2.

NORPAC stored records in primary tables that contained the definitive version of the data and were organized by the hierarchical levels described above. NORPAC also stored any change to a record in history tables. Historical changes to both single data fields (e.g., a haul retrieval coordinate) and to entire records were recorded in these tables. A change to a record in a primary table triggered a copy of the prior state of that record to be added to the corresponding history table. This prevented data loss because changes or deletions could be reversed if needed. Every primary table in NORPAC had a corresponding history table; however, until this study, these had never been used to understand the scope of data changes in the NPOP.

Querying NORPAC

We queried data using the R package ‘*odbc*’ (Hester, Wickham, & Gjoneski 2024, R Core Team 2023) to link to and query the NORPAC database. First, we queried tables containing observer, gear, and vessel logistics. We filtered the observer logistics table to only include observers deployed from 2014 to 2023. We then queried the primary and history tables that corresponded to the hierarchy: haul, sample, sub-sample, species composition, length, and specimen. For all primary tables, we used the keys described above to join logistics tables and fishery data tables which produced finalized primary tables containing fisheries data collected by observers and their associated year, gear-vessel group, and observer experience (Figure 3a).

History tables store all changes made to primary tables, not just data deletions. After querying the history tables and using the keys to perform an inner join with logistics tables, we performed sequential filtering operations to obtain only those records that were deleted. We first removed any records in the history tables whose combination of cruise, permit, and hierarchy keys (e.g., haul key) were present in the corresponding primary table. This ensured that only records deleted from primary tables were included in

our history table dataset. Records can be deleted at several stages along the QA/QC chain (Figure 1); however, we are only interested in deletions made during debriefing. To ensure records represented deletions made during debriefing, for each observer's data set we filtered out any deletions that occurred before the "debriefing start date" recorded in the logistics data. To remove duplicated records, we retained only the most recent form of the deleted record. This reflected the record's final state upon deletion because a record cannot be changed after it is deleted. Finally, we queried and joined DEC data to corresponding records, thus attaching debriefer-recorded reasons for deletions. These queries, joins, and filters produced comprehensive datasets that reflected deletions made post-cruise with our selected covariates (Figure 3b). Hereafter, all references to history tables refer to these finalized datasets unless stated otherwise.

Deletion Summaries

Deletion of a child record does not affect the parent record; however, the deletion of a parent record often results in the deletion of all child records (exceptions can include length records that may still hold value despite a deleted parent sample). We define these instances of child record deletions caused by parent record deletions as *cascading deletions* and the hierarchical level of the parent record deletion as the source of the child record deletion.

Cascading deletions are important because the reason for deletion of the child record is independent of data quality of the child record. Rather, child record deletions caused by cascades were the result of data quality issues of one or more parent record. For example, a haul level deletion would result in the removal of all child records, even if child data (e.g., specimen data, etc.) were collected according to protocol and were perfectly valid data. History tables gave no indication if a deletion cascaded from a parent record deletion. We used a simple method to determine if a deletion was the result of cascading from a parent deletion. Deleted records could only result from a cascade effect if their parent record was also present in the history table -- in other words, if the parent record was also deleted. We labeled the highest hierarchical level (Figure 2) whose history table contained the deleted child record's keys as the deletion source.

To accurately summarize and compare data deletion trends in the NPOP across several covariates, we first calculated proportions of deleted records (deleted records/total records) within covariate groups, then converted these values into percentages. The numerator and denominator terms were indexed by the covariate group. We used the following equation to calculate total records, which is the sum of all records in both the history table (deleted records) and primary table (retained records):

$$(1) \quad T_G = d_G + r_G .$$

In equation 1, T represents the total number of records, d represents the number of deleted records, r represents the number of retained records, and G represents a given combination of the covariate terms h (hierarchical level), y (year), v (vessel class), g (gear type deployed), n (prior cruises), c (solo or shared cruise), and s (deletion source, only applicable to d). For example, G can reflect “hauls in 2020” (h and y) or “15 prior cruises” (n ; see Fig. 3 for examples of groups). We then calculated the proportion of records deleted in a given covariate group and converted the proportion into a percentage:

$$(2) \quad P_G = \frac{d_G}{T_G} * 100\% .$$

In equation 2, P represents the percent of total records deleted during debriefing within a particular group G (all other terms are as defined in equation 1). The reason for deletion obtained from the DEC application only applied to deleted records, therefore the percent of deleted records, D , was calculated as

$$(3) \quad D_{G,e} = \frac{d_{G,e}}{\sum d_{G,e}} * 100\% ,$$

where e represents the DEC reason, and all other terms are as defined in equations 1 and 2. The denominator in equation 3 represents all deletions within a given group, G , across all DEC records. The numerator reflects the number of deletions within the given group attributed to a specific DEC reason. All code used to produce these data and calculations are available on GitHub (<https://github.com/noaa-afsc> and search for the Observer-Data-Loss repository).

RESULTS

There were 23,127,381 total records collected by 1,425 observers from 2014 to 2023 in the NPOP. Species composition records constituted the majority of records during final debriefings (12,016,910 total records, 51.96%) and sub-sample records the least (232,741 total records, or 1.01%).

Debriefers deleted 251,415 records (1.09%) during final debriefings over the 10-year period. Of all records, across hierarchies, species compositions comprised the most deletions (104,313 records, 41.49%) while hauls comprised the fewest deletions (395 records, 0.16%). The percent of records deleted during debriefing, P , varied within hierarchies with specimen records deleted the most, proportionally (2.88% of all specimen records), and haul records deleted the least, proportionally (0.077% of all haul records).

Year

On average, 2,312,738 records were debriefed per year. The year with the most records was 2015 (2,719,683), while the year with the fewest records was 2023 (1,737,812). Over the 10-year period, records during debriefings decreased at a rate of 95,141 records per year. Species composition records constituted more than 49.3% of the total records in any given year. Conversely, sub-samples were less than 1.50% of the total records in any given year.

Debriefers deleted the fewest number and lowest percentage of records in 2020 (10,888 records, 0.51%), and the highest number and percentage of records in 2016 (48,564 records, or 1.85%; Figure 4a). Species composition, length, and specimen records collectively dominated types of deleted records in any given year, accounting for >90% of all deletions. Each year, debriefers deleted a higher percentage of species composition records and length records than any other hierarchical level. From 2017 to 2022, debriefers deleted roughly 1% or less of all records during final debriefings with no more than 25,300 records deleted in any given year. Greater resolution into trends of data deletions through time among hierarchy levels is available in the appendix (Appendix Figs. A1-6).

Attributing deletion sources to deleted records highlighted different annual trends. Most species composition deletions, which constituted the majority of deletions in most years, were cascaded from a parent sample deletion. In fact, for most years, most deletions cascaded from a parent sample or length deletion (Fig. 4b). For example, in 2016, debriefers deleted 2,597 parent samples, which cascaded into 33,871 child deletions. For species composition records specifically, over 80% of all deleted records cascaded from a parent sample deletion in most years (Appendix Fig. A4). Length record deletions also cascaded from parent sample deletions more often than any other type of parent record deletion (Appendix Fig. A5). Specimen deletions, alternatively, often cascaded from a parent length deletion, which accounted for roughly 15-20% of all specimen deletions in any given year (Appendix Fig. A6).

Gear Type and Vessel Class

Among gear types, both pelagic and non-pelagic trawl gear had the most records (5,774,200 and 10,876,958 records, respectively, cumulatively 72.00%), and pot gear had the fewest (794,045, 3.43%). The greatest P occurred on pot vessels (5.24%) and the lowest P occurred on trawl vessels (pelagic and non-pelagic collectively 0.75%). Among vessel types, observers collected 19,739,059 records (85.35%) on CP/MS vessels and 3,388,322 records (14.65%) on CVs. Debriefers deleted more records collected on CVs (2.84%) than CP/MSs (0.79%).

The distribution of records and P varied among gear-vessel groups. Overall, the majority of records were collected on non-pelagic trawl CP/MSs (10,279,918 records, or 44.45% of all records) while the fewest were collected on pot CVs (341,217 records, or 1.48% of all records; Fig. 2). The highest P occurred on pot CP/MSs (5.98% of records) and the lowest P occurred on pelagic trawl CP/MSs (0.25% of records).

Among gear-vessel groups, P varied temporally. While most gear-vessel groups' annual P rarely exceeded 5%, pot CP/MSs' P neared or exceeded 5% in three of the 10 years, and neared or exceeded 10% in three other years (Fig. 5). For all pot vessels, P peaked in 2014 (over 12.5% for CVs and CP/MSs; Fig. 5). Alternatively, pelagic trawl CP/MSs' P never exceeded 0.5% (Fig. 5). Annual P trends varied depending on the total number of records among gear-vessel groups. For example, gear-vessel groups

with comparatively few records collected, such as all pot vessels, longline CVs, and non-pelagic trawl CVs, had no consistent trend of P through time, sometimes increasing or decreasing year-over-year by up to 9% (Fig. 5). Gear-vessel groups that neared or exceeded one million records collected had generally static P from year to year. For example, annual P for non-pelagic trawl CP/MSs, the gear-vessel group with the most records collected, never exceeded 2% and only ranged year-over-year by up to 1.35% (Figure 5).

Annual gear-vessel group P trends varied among hierarchical levels. Species composition and length records dominated most deletions across gear-vessel groups and through time (Fig. 5a). Specimens were rarely deleted aboard longline and trawl CP/MSs in comparison to other gear-vessel groups (Fig. 5a). Deletion cascades changed these patterns; often, most deleted records in any given year across gear-vessel groups cascaded from a parent sample record deletion (Fig. 5b). Length record deletions were also responsible for cascaded deletions among gear-vessel groups, specifically over 75% of deletions on pot CP/MSs in 2023 (Figure 5b). While debriefers rarely deleted haul records (Fig. 5a and Appendix Fig. A1), over 26% of deletions on pot CVs in 2014 cascaded from haul record deletions (Fig. 5b). More figures detailing P trends through time among hierarchical levels and gear-vessel groups can be found in the appendix (Appendix Figs. A1-12).

Observer Experience

We approximated observer experience by quantifying the number of prior cruises (PCs) completed by the observer prior to data collection. Most observers deployed during the study period had few PCs, and records indicate that observers with fewer PCs collected proportionally more data than those with many PCs (Fig. 6). However, some observers did deploy with many PCs, with a few observers exceeding 80 PCs (maximum number of PCs for an observer = 88; Fig. 6). In fact, only 10 observers exceeded 24 PCs at the time of deployment. When observers have more PCs, the likelihood of an individual observer's performance to reflect the overall trend increases; however, more PCs likely reflect the performance of very few observers. The number of records collected by observers at each PC was concentrated among less experienced observers. Specifically, observers on their first cruise (0 PCs)

collected approximately 20% of all data records (Fig. 6). Indeed, record quantities scale consistently with the number of observers at each PC, given that every observer must have a first cruise, but not necessarily subsequent cruises. Across PCs, observer distributions mirror data quantity distributions: observers with three or fewer prior cruises collected 50% of the data and comprised 57% of all deployments; observers with six or fewer prior cruises collected 75% of the data and comprised 76% of all deployments; and observers with 16 or fewer prior cruises collected 95% of the data and comprised 94% of all deployments (Fig. 6). Given the distribution of data collection among PCs (Fig. 6), we confined this study to a maximum of 16 PCs. This reflects both the reality of observing and the data. Most observers only completed between one and three cruises, and above 16 PCs the noise of individual observers (very few observers = small sample sizes) overwhelms our ability to identify trends.

In general, P decreased with increasing observer experience up to 10 PCs (Fig. 7). Percentages of records deleted decreased from a high of 1.97% at 0 PC to a low of 0.30% at 10 PCs. However, beyond 10 PCs, deletions spiked at 11, 12, 14, and 15 PCs. These spikes are likely due to the low number of observers within each of those four PC levels as discussed above. Over ten-fold more observers were deployed at 0 PC (1,254 observers) than 11 PC (109 observers). At more PCs with fewer observers, deletions caused by a single observer become more likely to dictate trends than at PCs with more observers. In fact, at 11 PC, one observer was responsible for 98.60% of species composition deletions as well as 92.87% of length deletions; these comprised over 90% of deletions at 11 PC. Comparatively, the observer responsible for the most deletions at 0 PC only comprised 9.64% of all species composition deletions, 4.87% of all length deletions, and 2.59% of all specimen deletions at that PC level. Therefore, spikes in P with more PCs likely reflects isolated, individual observer deletion events.

Trends in P across prior cruises and among hierarchical levels reflected similar patterns found among gear-vessel groups over time. While debriefers deleted mostly species composition, length, and specimen records at most PCs (Figure 7a), the sources of these deletions varied (Fig. 7b). Indeed, most deletions cascaded from a parent sample record deletion at most PCs (Fig. 7b). Additionally, sub-samples were a dominant deletion source at 4 and 8 PCs, and lengths were often a second-leading source of

deletions across PCs (Fig. 7b). More figures detailing P trends across prior cruises among hierarchy levels are available in the appendix (Appendix Figs. A13-18).

Debriefers Editor Comments

The DEC application is relevant to 45.18% of the deletions in this study (113,595 of 251,415 deletions). We simplified DEC database categories for plotting (Table 1). Debriefers attributed a relatively small subset of available DEC categories to the majority of deletions. These categories included: “biased collection” (32.95%), “transcription error” (26.55%), and “other” (10.98%; Fig. 8). Debriefers rarely selected “snap gear sample change”, “inseason edit”, and “sample design change”, which collectively comprised only 0.11% of all attributable deletions (Fig. 8). Species composition and length records comprised the majority of deleted records among most DEC (Fig. 8a).

Among hierarchical levels, D was not always consistent. Debriefers did not delete any hauls due to biased collection, instead nearly 28% of haul deletions were due to “missing or illegible data” (Appendix Fig. A19). Conversely, debriefers deleted sample, sub-sample, species composition, and length records due to biased collection more than any other DEC reason (Appendix Figs. A20-23). “Specimen unusable or lost” was a unique reason only attributable to specimens, and debriefers deleted the most specimens for this reason (21.49% of specimen deletions; Appendix Fig. A24). As with our other covariates, attributing deletion sources revealed sample records were frequently responsible for child record deletions (Fig. 8b).

Debriefers’ attributions of DEC reasons varied with observer experience. For example, debriefers often attributed “biased collection” to record deletions for observers with less experience, whereas “other” explained more deletions of records collected by experienced observers (Fig. 9). Most DEC reasons applied to observers regardless of PCs as indicated by broad box plot distributions (Fig. 9). Debriefers’ editor comment reasons whose boxes were more narrowly distributed, such as “inseason edit” and “halibut calculation” tended to apply to relatively few records (on the order of hundreds).

Solo and Shared Cruises

Observers deployed on solo cruises (only one observer present on the cruise) had collected fewer records (8,201,949) than observers working alongside one or more other observers on the same vessel (14,749,195 records) during the study period. This is expected, given that vessels with two or more observers often fish with more effort (e.g., 24-hour fishing operations) and observers are expected to take shifts sampling (e.g., two observers $\sim 2\times$ data). Conversely, debriefers deleted over twice as many records from solo cruises (175,702 records, or 2.10%) than shared cruises (75,698 records, or 0.51%). This disparity is further magnified by observer experience. In general, P tapered off with increasing PC for solo observers; however, P for shared cruises were relatively static across PCs (Fig. 10). For solo cruises, P often exceeded 1% across PCs (Fig. 10a); for shared cruises, P consistently fell below 0.75%, although it exceeded 2% at 11 and 14 PCs (Fig. 10b). Furthermore, debriefers deleted a far greater percentage of data collected by observers with no prior experience on solo cruises (5.63% at 0 PC) than on shared cruises (0.71% at 0 PC), a nearly eight-fold difference (Fig. 10). This magnitude decreases as observer experience increases; however, it remains largely consistent among hierarchical levels (Appendix Figs. A25-30).

Debriefers' editor comments vary within solo and shared cruise record deletions. Recall the DEC application was available to debriefers in 2017; thus, only 113,281 deletions contain DEC reasons. Debriefers attributed "transcription error," "other," and "misidentified species" more often to deletions from shared cruises, whereas "biased collection," "scale failure," and "missing or illegible data" were more often deleted from solo cruises (Fig. 11). Debriefers attributed "transcription error" to proportionally more deletions from shared cruises than solo cruises by 18.29 percentage points, and "biased collection" to more deletions from solo cruises than shared cruises by 26.60 percentage points (Fig. 11). Debriefers' comments "snap gear sample change" and "haul not verified" were only attributed to solo cruises. We provide more insights to these differences in DEC reasons between solo and shared cruises among hierarchical levels in the appendix (Appendix Figs. A31-36).

DISCUSSION

Since 2014, the NPOP has deleted a relatively small amount of data during debriefing. Despite the limited number of deletions in debriefings, those deletions do warrant further investigation; data quality is a never-ending process, and there are benefits to be gained from understanding and reducing deletions further. Certain gear-vessel groups are more susceptible to deletion events than others (for example, Pot CP/MSs), which suggests that these gear-vessel groups might need extra attention during observer training and observers on these vessels might need extra help during deployment. While observers with less experience were more likely to have deleted data, only 2% of first-time observer data is deleted, suggesting that the NPOP's training program is overall successful at preparing observers for data collection at-sea. NPOP trainers and in-season advisors might consider improvements to training materials and in-season advice, especially for first-time observers, to help stem potential sampling bias or transcription errors. Our data also suggest that observers who share work and resources with other observers on the same fishing trip can potentially reduce the number and frequency of data deletions. Overall, the relatively low number and proportion of data deletions indicate a highly effective QA/QC chain that successfully addresses data issues throughout its operation and minimizes errors at the final stage. While this exploratory work describes trends and patterns, we feel that these explorations provide useful insights for improving the training, deployment, and debriefing processes and point toward more formal analyses to improve data quality in the long-term.

Our work is an important first step in evaluating effectiveness of QA/QC protocols in LTEM projects. The NPOP shepherds and manages millions of data records collected by observers and ultimately uses to make fisheries management decisions which carry implications for Alaska fisheries and northeastern Pacific marine ecosystems. This LTEM dataset is rich with information about how to improve data quality, and summarizing the quality of such an enormous dataset is challenging but critical for Alaska fisheries and ecosystem management in the northeastern Pacific Ocean. We present one, relatively small, view of these data, and while we evaluate but one step in the long NPOP QA/QC chain, it being the last stage provides insight into quality checks performed throughout the QA/QC chain. The

fact that such a narrow view produces interesting and useful insights into how both observers and debriefers ensure data quality is an example of how LTEM programs can leverage their data to quantify data quality efforts. Below, we emphasize how our summaries provide useful and actionable understanding of the NPOP and observer responsibilities.

Summary Findings

Yearly Trends

In any given year, the proportion of data deleted during debriefing was marginal (less than 2%) and has remained consistent since 2017. Because we define year not by the prototypical calendar, but rather the edition of the Observer Sampling Manual (see Methods), variability among years partially reflects annual changes to observer responsibilities. For instance, the NPOP significantly restructured operations in 2013. This included expanding observer responsibilities in the form of increased length and specimen quotas and more rigorous sampling methods. These added duties intensify an already demanding work environment at sea, making it particularly challenging for first-time observers to acclimate. Changes to observer responsibilities also impact more experienced observers by shifting their status quo, forcing them to modify familiar protocols and adapt to new responsibilities and sampling methods. We suggest that the large spike of deleted data in 2014 could reflect observers adapting to new responsibilities; substantially fewer deletions in 2015 suggests observers took 2 years to acclimate to the new NPOP protocols (Fig. 4). The impact of changing data collection requirements on data outcomes is not novel to the NPOP. Faunce et al. (2023) investigated temporal trends in observer reports of potential violations aboard fishing vessels in the North Pacific and concluded that new fishery regulations, which affect how observers perceive fishing operations, drove interannual variability of potential violations. Importantly, Faunce et al. (2023) detailed that variability in potential violations did not necessarily reflect an increase in fishing activity, but rather observers adapting to changing expectations. The NPOP always considers observer workload, trade-offs between different types of data collection and data quality, and management needs when asked to add to or alter the already demanding observer task list and data collection priorities. For example, all observer tasks are prioritized, with observer safety being the top

priority. Observers are trained to collect data in order of tasks, from highest to lowest priority, completing only those tasks that can be finished within the available time given.

Annual percentages of data deleted during debriefings might not reflect true observer performance. Debriefers are responsible for data deletion during debriefing and therefore serve as the final sentinels of data quality within the NPOP QA/QC chain. Debriefers' ability to evaluate data quality depends on their ability to detect errors. While NORPAC performs some automatic error detections and reports these to debriefers, other types of errors must be checked for manually by debriefers; for example, biased data collection, the most commonly attributed DEC reason by debriefers, would be challenging to code and detect within the NORPAC system. Bias can be difficult to detect in data, especially with large volumes of data (e.g., thousands to millions of data points). Rather, bias is usually acknowledged by observers during debriefing which relies on observer integrity and self-disclosure.

Debriefers deleted the fewest number of records in 2020, the year in which the COVID-19 pandemic began in the United States. While observers still monitored fishing activity aboard vessels, debriefers worked remotely and conducted video, rather than in-person, final debriefings. Interviews between debriefers and observers thus required a stable internet connection, which might not have always been possible. Regardless of internet stability, debriefing via a video call can complicate communication, for example, by masking or obscuring non-verbal communication. Though necessary, we suggest that these remote conditions might have impacted debriefers' ability to thoroughly question and understand observer sampling methods or challenges and might have fostered an environment where observers were less likely to self-disclose mistakes. Alternatively, a low deletion percentage during this time might have stemmed from fewer first-time observers deploying because fewer observer training sessions were held due to the pandemic. A more thorough investigation of the data deleted during 2020 deployments, and an understanding of debriefer perceptions while working remotely, is needed to better understand the cause of fewer data deletions during this year. Remote debriefings have continued into the post-pandemic years (2021-present) for a subset of observers that meet certain remote debriefing eligibility criteria. Future analyses could examine how remote and in-person debriefings compare to better understand the effect of remote debriefings on data quality.

Annual trends in percentages of data deleted during debriefings do not necessarily reflect all hierarchical levels we investigated. Species composition and length record deletions dominated most years' total deletions because they are the most frequently collected records. In a given haul, observers typically collected three samples. Each sample had an average of 8 species composition records, but, in rare cases, could have exceeded 100. Over a 10-year period, this amounts to over 12 million species composition records. However, while species composition deletions are numerous, proportionally few are deleted (never more than 2% in a given year, and less than 0.75% since 2018). Additionally, because samples and species compositions are explicitly tied to each other (a sample is a species composition of the catch, and species composition records are children of a sample record within NORPAC), it is reasonable that most species composition deletions are the result of the cascading effect of parent sample deletions. This is a critical insight: species composition deletions do not derive from problematic individual species composition records, rather they are the result of ineffective sampling methods that inherently impact associated species composition records.

Species composition and length records represent the greatest volume of data (collectively nearly 20 million of 23.1 million records), thus the overall annual trends in data deletions reflect annual trends of species composition and length deletions and thus mask deletion trends for less commonly collected hierarchical levels. For instance, in 2022, debriefers deleted the most haul records despite deleting the second-fewest records overall that same year. In 2014, specimens were deleted proportionally more than any other data type in all other years (over 5%). Overall, annual percentages of data deleted, both cumulatively and among hierarchical levels, are quite small and do not reflect significant data loss during debriefing.

Gear-Vessel Groups

Evaluating trends in percentages of data deleted among gear-vessel groups provides context to overall trends within the NPOP. Gear-vessel groups that generate the most data dictate the overall annual trend. Trawl and longline CP/MSs accounted for 83.39% of all data during the study period and collectively had more deletions than all other gear-vessel groups combined. Therefore, trawl and longline

CP/MSs likely explain the annual trends discussed above. Species composition record deletions, cascading from sample record deletions, comprise a significant majority of deletions aboard these vessel groups. The full coverage sector includes most CP/MSs, and observers deployed to these vessels typically sample every haul. In addition, many of these CP/MSs have more than one observer on board at any given time. Thus, these full coverage CP/MS vessels create far more sample and species composition records than other gear-vessel groups, explaining both the volume of data collected and hierarchical levels dominating total deletions. However, neither of these reasons explain markedly low percentages of data deleted overall in these gear-vessel groups; rather, we suggest this is a byproduct of deployment strategies. Because CP/MSs often fall in the full coverage sector, they must carry two or more observers under current fishery regulations. In cases where multiple observers are deployed to a vessel, the more experienced lead observer typically oversees all data collected during that trip. Lead observers are required to collaborate with second observers when conducting data checks and can offer guidance and advice to less experienced observers on the same trip. For example, by offering advice on sampling methods, lead observers might reduce confusion for lesser experienced individuals in establishing robust sample frames, thereby increasing data quality and resulting in fewer data deletions than if the less experienced observer were working alone. In the case of longline CPs, observer providers may deploy more experienced observers defined by having obtained additional certification for specific vessels (Federal Register 50 CFR § 679.53(a)(5)(v)(C)). Because more experienced observers tend to have fewer data deletions than less experienced observers (Fig. 7), observer deployments are a likely factor that can explain lower proportions of deletions aboard CP/MS trawls and longlines.

Other gear-vessel groups that we investigated show marked interannual variability in deletions. In most years, longline and trawl CVs deleted at least twice as many records than their CP/MS counterparts, nearing 5% on average in any given year, of which species composition and length record deletions are the majority of records deleted. As discussed above, CP/MSs in full coverage fishery are required by regulation to carry observers for all trips and, in most cases, all hauls must be sampled. This has fostered a culture aboard these vessels: vessel personnel are accustomed to observer presence and duties. Therefore, it is possible that the culture on full coverage CP/MSs could benefit observers, in that they face less

obstructions during data collection, whether those be mechanical (e.g., space allocation) or crew-derived (e.g., deck sorting of catch before sampling; AFSC 2023a). Catcher vessels, on the other hand, carry observers far less consistently, and may not possess the capacity to support observers as easily as CP/MSs (e.g., less space on smaller vessels). These issues might be exacerbated by well-documented negative perceptions held by fishers towards observers, which can create an unwelcoming or even hostile environment (Garcia, 2024) that could have significant negative impacts on an observer's ability to collect quality data. However, the extent to which this cultural difference is systematically encountered aboard CP/MSs compared to CVs in the North Pacific fleet is not clear.

Alternatively, we suggest that proportionally greater deletions aboard longline and trawl CVs may be a result of vessel size distributions. Catcher vessels tend to be smaller than CP/MSs because they do not have onboard processing facilities. Due to their smaller size, CVs have less available space for observers to conduct sampling duties, which could create a potential for sampling bias or faulty collection methods; for instance, hand-selecting (a form of bias) is a more convenient sampling method than random sampling, resulting in more errors and thus more data deletions on smaller CVs. Debriefers attributed over a third of length deletions to biased collection methods. However, the source of bias might not always reflect observer error; both crew practices and vessel conditions can also serve as sources of bias. For instance, the crew might pre-sort catch, making certain species or individuals unavailable for observer sampling (e.g., discarding overboard before sampling), resulting in the absence of species that would otherwise appear in the species composition. Size-sorting can also occur as fish move through an onboard processing facility; for example, larger individuals may get stuck on a conveyor belt and never make it to the sampling station (mechanical bias). Further investigation into the specific reasons attributed to deletions aboard longline and trawl CVs might provide more insight into an issue.

Both pot CP/MSs and pot CVs experienced the greatest proportions of deleted data for a given year. In 2014, nearly 15% of all collected data aboard pot vessels was deleted; in subsequent years, deletions varied considerably between 1% and 11% (Fig. 5). This trend also holds among hierarchical levels; for all summarized hierarchical levels, P was greatest aboard pot CP/MSs and pot CVs. While species composition and length records comprised the majority of record deletions for any given year on

pot CVs, specimens exhibited comparatively high P : over 40% of specimen data deleted in 2014. Deletions aboard these vessels likely stem from captains' decisions to selectively retrieve pots. Vessels fishing pot gear conduct fishing operations differently than other gear types in that they can leave gear deployed for extended periods of time, even returning to port while the gear is deployed. Observers might board pot vessels that have already deployed their gear, which can make it difficult for the observer to verify the number, placement, and length of deployment of pots. In these cases, through no fault of their own, observers might inadvertently set up incorrect sample frames and/or opportunistically sample pots as a solution, introducing bias. Additionally, bias is often present while sampling the catch from specific pots. Pots are retrieved one at a time and catch is dumped on a sorting table, where observers collect their sample. Hand-selection of organisms by observers for length and specimen collection is highly likely in these circumstances because observers do not always have equal access to all portions of the sorting table. Depending on the size and shape of the sorting table, as well as the mechanical sorting of large and small fish, observer samples can often end up being biased on pot vessels. As with longline and trawl CVs, further investigation into deletions from pot vessels might provide insight into corrective measures to avoid bias on pot vessels.

Observer Experience

For most people in most jobs, performance should improve with time as individuals gain experience and skill doing the work. Thus, it is unsurprising that observers with more PCs, our proxy for experience, deleted data less often than observers with fewer PCs. The general trend was for deletions to decrease with increasing experience. Most observers (76%) deployed with fewer than 6 PCs during the study period. Because higher numbers of PCs include far fewer observers than lower numbers of PCs, spikes in data deletions at higher PCs (above ~ 10 PCs) most likely reflect the influence of one or a few observers. Indeed, we found a majority of deleted records at 11 PCs derived from a single cruise (see 3.3. for details), though potential causes behind this data point are uncertain, as the deletions occurred prior to the use of Debrief Editor Comments system.

Of deletions with attributed DEC reasons, observers with more PCs often had “other” attributed to deleted data within the DEC because more common categories of data deletions did not apply in these circumstances (Figure 9). This could suggest the spikes in P with more PCs do not, in fact, reflect individual observer performance of duties, but rather the unpredictable and haphazard events that accompany working aboard these vessels in the northeast Pacific. Thus, the pattern of consistently decreasing deletions from few to more cruises, which then breaks down at higher PCs, might signal a switch in the cause of deletions from observer experience (few PCs) to random chance (many PCs). This work did not explore the specific mechanisms that caused deletions from experienced observers. Debriefers had the option to add additional comments (free-form writing) within the DEC application; these might clarify why deletions occurred. However, we did not explore written debriefer comments in this work. Future work could focus on mining these free-form written comments to investigate commonalities among deletions for experienced observers.

In contrast to more experienced observers, new, less experienced observers appeared to share similar data deletion problems. For instance, observers with less experience had biased data collection methods more often than more experienced observers. This is not unexpected: applying data collection protocols in a standardized, statistically rigorous manner can be very difficult for an inexperienced observer, as it often requires considerable problem-solving skills under conditions that could change depending on target species, catch size, catch composition, or vessel configuration. In addition, the rapid pace of retrieving gear, sorting catch, and deploying gear can result in an observer hand-selecting samples or otherwise inadvertently biasing their samples. Debriefers and in-season advisors heavily scrutinize how observers sample to ensure that sampling is unbiased, as this is a key requirement for downstream data uses such as fishery stock assessment models. More experienced observers have several debriefings under their belt, and thus they are likely more aware of where and how sampling problems arise and how to quickly adapt to reduce the likelihood of biased samples.

Experience is also critical when identifying fish. Species identification errors occurred more frequently for less experienced observers than more experienced observers, likely because less experienced observers have seen comparatively fewer fish species than more experienced observers.

Stevenson (2018) attempted to evaluate the accuracy of species identification by observers in the NPOP and found it to be quite high; however, he noted his population of observers did not include first-time observers. Stevenson highlighted the extensive feedback more experienced observers have received from debriefers compared to less experienced observers, which likely drove high correct identification rates among experienced observers (Stevenson 2018). This suggests that debriefer feedback might drive P among observer experience: the more experience, the more feedback, the less likely common errors, such as biased data collection and species misidentification, are to occur.

Despite our efforts, observer experience is not a straightforward metric. We simplified observer experience to a simple count of each observer's prior cruises. This assumes that all cruises are equal and offer observers equal opportunities to learn and grow, which might not always be the case. Several factors can differentiate cruises. Observer duties and responsibilities vary depending on the deployed gear type and associated vessel class, thus experience aboard one gear-vessel group does not reflect experience with another group. A new observer may deploy aboard several shared cruises before deploying aboard a vessel alone. An observer can have several cruises under calm sea conditions before experiencing perilous weather (for instance, an observer hired in the spring that completes several cruises before their first winter cruise). Numerous other factors (e.g., debriefing scores, variety of gear-vessel groups, number of solo versus shared cruises, etc.) could be factored in to obtain a better metric of observer experience. We recommend that future studies develop a better index of an observer's experience that includes multiple factors.

Solo Versus Shared Cruises

There is a large disparity in P on solo cruises and shared cruises. Observers on solo cruises can be deployed in either the full or partial coverage sector, whereas observers on shared cruises are always deployed in the full coverage sector. Therefore, distributions of P within shared cruises reflect observer experiences only in the full coverage sector, whereas distributions of P within solo cruises reflect experiences in both the full and partial coverage sector.

The magnitude of difference between P on solo cruises versus shared cruises is significant across observer experience. Debriefers delete data collected by first-time observers nearly eight-fold more frequently on solo cruises than shared cruises. Deletion trends suggest that observer resources on shared cruises, in contrast to those available on solo cruises, can explain this trend. Shared cruises by definition have multiple observers concurrently aboard a vessel, with an experienced observer present and designated as the lead observer. Lead observers must have completed several cruises, debriefings, and have received positive debriefing reviews, to be considered as a lead. Also, based on distributions of collected data by observer experience (Figure 6), it is fair to assume that these second observers are mostly new and likely have zero or few prior cruises. Observers with more experience (PCs) were less likely to use biased data collection methods (Figure 9). Furthermore, observers were far more likely to introduce bias in data collection aboard solo cruises than shared cruises (Figure 11). Therefore, it is possible that the presence of a lead observer might lower the likelihood of biased data collection by less experienced second observers, thereby reducing data deletions on shared cruises.

Other human resources are available to observers regardless of the presence of a lead observer. Upon deployment, observers are assigned in-season advisors (ISAs), which are FMA staff that have previously served as observers in the NPOP (and sometimes other observer programs) and often also serve as debriefers. ISAs have extensive knowledge of the NPOP and observer responsibilities. Observers are instructed to have daily communication with ISAs (via the ATLAS) to ask questions and upload data regularly so that automated error checks can be completed. However, some vessels within both full and partial coverage strata are unable to transmit information at-sea, which prevents observers from communicating with ISAs using ATLAS. In these cases, observers are instructed to communicate with the NPOP at port after completing an assignment. Without transmission capabilities at-sea, observers lose immediate access to a critical resource that would otherwise help observers maintain or increase data quality. Though it is unclear how frequently observers lack active ISA support within solo or shared cruises, investigating how deletions differ among observers with and without at-sea transmission capabilities may highlight how direct lines of communication between observers and the NPOP at-sea can boost overall data quality.

Debriefers tended to attribute the DEC reason “other” as a cause for data deletions more often in shared cruises than solo cruises (Figure 11) and for more experienced observers than less experienced observers (Figure 9). Inherent ambiguity in the term “other” prevents discussion into what drove deletions in this category; however, we assume, given other available DEC reasons, deletions attributed as “other” are unlikely to reflect bias, misidentification, or data transcription errors, which are relatively common (Figure 9). Instead, trends in deletions attributed to the DEC reason “other” likely reflect issues that are difficult to reconcile regardless of the presence of a lead observer, experience level, or communication with an ISA. For example, despite the fact that observers on shared cruises collected twice as many records than observers on solo cruises, debriefers deleted over twice as many records from solo cruises than shared cruises (Figures 10 and 11). Also, debriefers attributed more unique DEC reasons to deletions from solo cruises than shared cruises. Therefore, the DEC reason “other” may be diluted among solo cruise deletions that are also largely dominated by “Biased collection method”. This might incorrectly imply that observers on shared cruises face unique issues that are not common on solo cruises when, perhaps, observers on shared cruises simply do not encounter other DEC reasons as frequently. Further investigation into the reason “other” might help identify definable issues inherent to data collection in a hazardous environment such as fishing vessels in the North Pacific that are difficult to resolve regardless of observer or ISA support.

We have discussed deletions in the NPOP across several covariates, and have relied on debriefer-supplied reasons from the DEC to highlight issues observers face while collecting data. However, we stress caution in the interpretation of these trends due to inherent issues with attributing DEC reasons to deletions. While the DEC application is a powerful tool that enables debriefers to track common difficulties faced by observers during data collection, it is not used consistently by debriefers. DEC reasons (Table 1) were created with intended ambiguity (i.e., fewer categories with broad applicability) such that debriefers could streamline their workflow and not spend significant time searching for precise reasons to attribute to data changes. Interpreting DEC reasons as indicators of deletion causes can be challenging because two debriefers might attribute different DEC reasons to similar data changes. Additionally, deletions that cascaded from a parent record deletion do not automatically inherit their

parent record deletion’s DEC reason. In these circumstances, debriefers may simply apply the same DEC reason as the parent record deletion or they could apply a different DEC reason. Consider, for example, the DEC reason “sample deleted”. Despite the fact that a majority of deletions through time cascaded from a parent sample record deletion (Figure 4b), debriefers only attributed “sample deleted” to less than 7% of all deletions since 2017 (Figure 9). Moreover, many of these deletions were due to a parent haul, length, or specimen record deletion, in other words, not sample deletions (Figure 9b). We recommend some effort to standardize how DEC reasons apply to data changes in the future to reduce inherent variability in DEC attribution among users which would make the DEC application more robust and useful for improving data collection and quality in the NPOP.

Broader Implications

The fishery-dependent data collected by the NPOP is the critical foundation of sustainable fisheries management in waters off the Alaska coast. Therefore, maintaining and improving data quality is a paramount and on-going task. The NPOP data evaluation process begins the moment observers begin to collect data, data are recorded, and then uploaded to NORPAC from ATLAS transmissions. Key punch and error checks result in error messages and flags sent to the observer, the ISA, and the FMA IT group for human review. The data quality process continues when observers meet with an ISA during deployment (mostly virtual) and with a debriefer at the end of deployment (Figure 1). While several sources provide guidelines for best data management practices in LTEM projects (Sutter et al. 2015; Wilkinson et al. 2016; Tenopir et al. 2020; Ribera-Altimir et al. 2023), documentation of such within fisheries management programs is rare (Kolb et al. 2013; McManamay and Utz 2014). Furthermore, we have yet to identify an LTEM project that evaluates the efficacy of implemented QA/QC protocols and summarizes data loss. This work presents an important step toward this need by summarizing data deletions trends during the final step in the NPOP’s QA/QC chain.

The final QA/QC step, debriefing, is a critical control point for data quality in the NPOP. The NPOP requires this intensive review of data and validation of methods, in addition to a self-rating of performance by the data collector, are hallmarks of good data management (Sutter et al. 2015). Low

proportions of data deleted during the final debriefing suggest debriefers prioritize data retention and only completely delete a record after exhausting other options such as updating data records to values of lower resolution (e.g., a specific species identification to the genus level; moving a specimen sample to the haul level). Debriefers are held to high standards in the NPOP to ensure any data changes or deletions are well-informed. Similar to observers, debriefers follow specific protocols designed to maximize QA/QC during both in-season advising and final debriefing (AFSC 2023b, Stevenson et al. 2016). Setting high standards for data review promotes high data efficacy for end-user operations and elevates confidence in the data for end-users. In fisheries science, fishery-dependent data (i.e., observer-collected data) is vital to sustainable stock management (Gilman et al. 2017). Stock assessors and managers use observer data to monitor rates of catch, species mortality, and fleet-wide bycatch, as well as total catch accounting (Faunce et al. 2015, Gilman et al. 2017). The final debriefing ensures accurate, high-quality data for these uses. While the overall amount of data removal due to deletions was generally low, the next logical step would be to quantify the effect of data deletions on stock assessment and other end-user products.

Minimal deletions in the NPOP highlight effective QA/ QC protocols that enable success for all observers, even those being deployed for the first time. Observers with no prior experience had less than 2% of their data deleted during the final debriefing which reflects highly effective training that prepared the observer for data collection. The NPOP requires newly hired observers to complete a 3-week training class to obtain the necessary certification for observing. This class includes over 120 hours of instruction, covering sampling protocols for all vessel types and plants, communication with fishing personnel, and lab-guided exercises for identifying species, while continuously emphasizing safety practices and guidelines. Trainers assign observers daily take-home work and regularly assess their knowledge through exams. These efforts are effective: debriefers retain over 98% of data collected by first-time observers, whose only prior experience likely came from the NPOP training program.

High data retention during the last stage of the QA/QC process can indicate effective QC protocols throughout the process. NORPAC contains hundreds of automated checks which are run when data are uploaded to NORPAC, a hallmark of high QC standards and practices (Davison et al., 2024). NORPAC flags potentially erroneous data in-season and generates data reports for ISAs to review. ISAs

use these reports to evaluate observer performance during deployment including assessing the sampling methods employed (Stevenson et al., 2016). A mid-cruise debriefing is also required for first- and second-time observers. This is a dedicated time set aside for debriefers to communicate actively with each observer to review data collection methods. Few deletions after these QC protocols suggests their efficacy; most problematic data appear to be removed prior to the final debriefing. In this way, this study achieves an evaluation of the entire QA/QC process of the NPOP, and suggests it is highly effective at producing error-free, robust fisheries data. Further research is necessary to evaluate data deletions during these QC procedures to better understand the real impact of each QA/QC step.

A majority of NPOP data is collected by observers with relatively little experience. This reflects high observer turnover within the program: observers are not likely to return after one or, at most a few, deployments. This highlights the need for robust and thorough training, as described above, because first time observers collect the majority of NPOP data. The job of an observer is demanding, and even among the most dangerous in the U.S. (Case, Lincoln, & Lucas 2018; NOAA 2021; Garcia 2024). The presence of observers aboard vessels can create resentment between vessel crew and observers, which has manifested into forms of bullying, harassment, and assault against observers (Porter 2010, Drakopoulos 2022, Garcia 2024). Feelings of isolation and burnout from long, rigorous deployments can foster dissatisfaction among observers and reduce the likelihood of retention (NMFS 2021). We suspect that isolation is felt less frequently by observers on shared assignments than those on solo assignments, however little is known about observer perspectives aboard vessels. The NPOP requests observers to complete surveys of the time aboard each vessel at the end of each deployment. The data from these surveys however, have not been analyzed to understand what factors might encourage observers to deploy on subsequent cruises. A better understanding of observer perceptions, personal experiences, and emotions when aboard vessels might highlight new forms of bias that can further elevate data quality. The NPOP might benefit from understanding the factors that observers use to decide to whether or not to redeploy. Enticing observers to deploy on subsequent cruises would likely contribute to data quality enhancements. NPFMC (2024) explored possible causal links that might engage observer retention in the future, though these have not been investigated further.

We have summarized data deletions in the NPOP during the final debriefing and discussed potential causes and implications therein. However, we stress that this is only an initial effort, and far more must be done to better evaluate quality control efficacies in both the NPOP and LTEM projects writ large. For instance, our definition of data loss is intentionally constrictive. The NPOP collects even more data than what we described here, and data deletions are but one form of data loss. While we evaluate deletions of entire records, some records may be retained while specific fields within the record are deleted, which is also a form of data loss. Furthermore, data can be lost without being necessarily deleted, such as updating a species identification from a lower to a higher taxon. Quantifying these forms of data loss is not trivial and further analysis would require intensive effort. We have only presented data summaries of data deletions in the NPOP without any analysis of patterns. While our effort was substantial in scope and execution, a modeling approach would provide a more robust method to understand the factors that result in data deletions. A modeling approach would better highlight drivers of data deletions and inform improvements to NPOP data collection protocols. Although, as we mention here, a modeling effort would be strengthened by a robust definition of data loss that encapsulates the many ways data can be lost from collection to the moment debriefers approve it for scientific use. Furthermore, analyzing the efficacy of QA/QC measures promotes good data management as it ensures resources expended on data quality is well spent or otherwise could be better directed to other activities. In the case of the NPOP, debriefing is an excellent QA/QC protocol that minimizes total data loss and fosters trust in the ultimate data product.

Suggestions for Improvements

While we have provided evidence that the NPOP engages in successful, robust QA/QC protocols that elevate data quality by minimizing data deletions at one stage in the data management chain, we have also identified areas that may benefit from constructive feedback. The DEC application needs consistency among debriefers in how DEC reasons are applied to deletions. We recommend the development of a standardized protocol that outlines prerequisites and examples of specific reasons for each deletion category in the DEC. While some of the DEC reasons are adequate in presentation, others are either too

vague to parse reasonable information from or too specific to rare circumstances. The reasons supplied in DEC were created to provide debriefers with reasons diverse enough to cover a most issues observers face . With respect to this intention, we recommend reasons particularly ambiguous (such as transcription error and missing or illegible data) are split such that more information can be discerned from their attribution and reasons of greater specificity (snap gear sample change, inseason edit, and sample design change), which were rarely attributed to deletions (Figure 8), are condensed into other available reasons or removed entirely. Additionally, tracking data that NORPAC flagged as erroneous can help future studies expand analysis into other QA/QC protocols in the NPOP.

We also recommend the continued strong support of both new and experienced observers by ISAs and debriefers. Opportunities for debriefers to provide feedback to observers are not confined to final debriefings; as debriefers are also ISAs, they communicate with observers prior to any data collection aboard vessels. Providing debriefers additional resources that highlight individual observers' past struggles aboard vessels as well as struggles experienced more broadly by observers across the NPOP can help prepare observers for more difficult circumstances, whether those be unique to the individual observer or more pervasive to the program. For example, pot CVs experienced greater deletion percentages than any other gear/vessel group, suggesting observer data collection aboard these vessels may be difficult. We have discussed in 4.1.2. how pot vessels may board observers after deploying pots at-sea, which debriefers have identified as a potential cause for elevated bias rates because observers lack information vital to establishing sample frames. While we cannot coerce vessel operators to delay pot deployments for when observers are present, we can perhaps better prepare observers for these circumstances by improving the ISA data monitoring during deployment and creating robust sampling protocols unique to these situations.

Lastly, because observers with more experience tend to have fewer data deleted than observers with less experience, and because training new observers regularly introduces additional costs both fiscally and temporally for training staff whose time can be spent supporting currently deployed observers, the NPOP and observer providers should engage in practices that maximize observer retention.

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CITATIONS

- AFSC (Alaska Fisheries Science Center). (2023a). 2024 Observer Sampling Manual. Fisheries Monitoring and Analysis Division, North Pacific Groundfish Observer Program. AFSC, 7600 Sand Point Way N.E., Seattle, Washington, 98115. <https://www.fisheries.noaa.gov/resource/document/north-pacific-observer-sampling-manual>.
- AFSC (Alaska Fisheries Science Center). (2023b). Debriefing Continuity Guide [Unpublished Document], North Pacific Groundfish Observer Program. AFSC, 7600 Sand Point Way N.E., Seattle, Washington, 98115.
- AFSC (Alaska Fisheries Science Center). (2024). North Pacific Observer Program 2023 Annual Report. Fisheries Monitoring and Analysis Division, North Pacific Groundfish Observer Program. AFSC, 7600 Sand Point Way N.E., Seattle, Washington, 98115. <https://doi.org/10.25923/zbt1-v967>.
- Beddington, J.R., Agnew, D.J., and Clark, C.W. (2007). Current problems in the management of marine fisheries. *Science* 316(5832):1713-1716.
- Benaka, L. (editor). (2023). National Observer Program FY 2021 Annual Report. NOAA Tech. Memo. NMFS-F/SPO-241, 32 p. <https://doi.org/10.25923/pxe3-xg56>.
- Bradley, D., Merrifield, M., Miller, K.M., Lomonico, S., Wilson, J.R., and Gleason, M.G. (2019). Opportunities to improve fisheries management through innovative technology and advanced data systems. *Fish and Fisheries* 20(3): 564-583.
- Brooke, S.G. (2015). Federal fisheries observer programs in the United States: Over 40 years of independent data collection. *Marine Fisheries Review* 76(3): 1-38.
- Case, S.L., Lincoln, J.M., and Lucas, D.L. (2018). Fatal Falls Overboard in Commercial Fishing – United States, 2000-2016. *Morbidity and Mortality Weekly Report* 2018;67:465-469. <http://dx.doi.org/10.15585/mmwr.mm6721a7>.
- Dietrich, D., Adamus, T., Miner, A., and Steinhart, G. (2012). De-mystifying the data management requirements of research funders. *Issues in Science and Technology Librarianship* 70(1): 1-12.
- Dodds, W.K., Robinson, C.T., Gaiser, E.E., Hansen, G.J.A., Powell, H., Smith, J.M., Morse, N.B., Johnson, S.L., Gregory, S.V., and Bell, T. (2012). Surprises and insights from long-term aquatic data sets and experiments. *BioScience* 62(8): 709-721.
- Drakopoulos, L. (2022). Privatizing the fisheries observer industry: Neoliberal science and policy in the U.S. West Coast fisheries. *Geoforum* 131: 116-125.
- Ewell, C., Hocesvar, J., Mitchell, E., Snowden, S., and Jacquet, J. (2020). An evaluation of Regional Fisheries Management Organization at-sea compliance monitoring and observer programs. *Marine Policy* 115: 103842.
- Faunce, C., Moon, M., Packer, P., Campbell, G., Park, M., Lockhart, G., and Butterworth, N. (2021). The Observer Declare and Deploy System of the Alaska Fisheries Science Center. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-AFSC-426, 86 p. <https://doi.org/10.25923/wngg-9t31>.
- Faunce, C. H., Cahalan, J., Bonney, J., and Swanson, R. (2015). Can observer sampling validate industry catch reports from trawl fisheries? *Fisheries Research* 172: 34-43.

- Faunce, C. H., Smith, J., Kingham, A., and Jaszka, D. (2023). Fisheries observers as enforcement assets: 21 years of lessons from the North Pacific. *Marine Policy* 158: 105868.
- French, R., Nelson Jr., R., and Wall, J. (1982). Role of the United States Observer Program in management of foreign fisheries in the Northeast Pacific Ocean and Eastern Bering Sea. *North American Journal of Fisheries Management* 2(2): 122-131.
- Garcia, E.L. (2024). Fisheries observers: an overlooked vulnerability for crime and corruption within the global fishing industry. *Marine Policy* 161: 106029.
- Gilman, E., Weijerman, M., and Suuronen, P. (2017). Ecological data from observer programmes underpin ecosystem-based fisheries management. *ICES Journal of Marine Science* 74(6): 1481-1495.
- Hester, J., Wickham, H., and Gjoneski, O. (2024). *odbc: Connect to ODBC Compatible Databases (using the DBI Interface)*. R package version 1.4.2.
- Hutchings, J.A. (2000). Collapse and recovery of marine fishes. *Nature* 406(6798): 882-885.
- Kolb, T.L., Blukacz-Richards, E.A., Muir, A.M., Claramunt, R.M., Koops, M.A., Taylor, W.W., Sutton, T.M., Arts, M.T., and Bissel, E. (2013). How to manage data to enhance their potential for synthesis, preservation, sharing, and reuse—a Great Lakes case study. *Fisheries* 38(2): 52-64.
- Leblond, E., Daures, F., Berthou, P., and Dintheer, C. (2008). The Fisheries Information System of Ifremer: a multidisciplinary monitoring network and an integrated approach for the assessment of French fisheries, including small-scale fisheries. ICES 2008 Annual Science Conference, 22-26 September 2008, Halifax, Canada. <https://archimer.ifremer.fr/doc/00059/17002/>
- Mangi, S.C., Dolder, P.J., Catchpole, T.L., Rodmell, D., and de Rozarieux, N. (2015). Approaches to fully documented fisheries: practical issues and stakeholder perceptions. *Fish and Fisheries* 16(3): 426-452.
- McCracken, M.L. (2019). American Samoa longline fishery estimated anticipated take levels for Endangered Species Act listed species. PIFSC data report; DR-19-028. Pacific Island Fisheries Science Center, National Marine Fisheries Service, Honolulu. <https://doi.org/10.25923/b8gs-j441>.
- McManamay, R.A., and Utz, R.M. (2014). Open-access databases as unprecedented resources and drivers of cultural change in fisheries science. *Fisheries* 39(9): 417-425.
- Nelson Jr., R., French, R., and Wall, J. (1981). Sampling by U.S. observers on foreign fishing vessels in the eastern Bering Sea and Aleutian Island region, 1977-78. *Marine Fisheries Review* 43(5): 1-19.
- NMFS (National Marine Fisheries Service). (2019). A History of Federal Marine Fisheries Research in Alaska. National Oceanic and Atmospheric Administration, 709 West 9th Street. Juneau, Alaska 99802. <https://www.fisheries.noaa.gov/resource/outreach-materials/history-federal-marine-fisheries-research-alaska#:~:text=An%20eBook%20presenting%20historical%20timelines,as%20fisheries%20research%20in%20Alaska>.
- NMFS (National Marine Fisheries Service). (2023). 2024 Annual Deployment Plan for Observers and Electronic Monitoring in the Groundfish and Halibut Fisheries off Alaska. National Oceanic and Atmospheric Administration, 709 West 9th Street. Juneau, Alaska 99802. <https://www.fisheries.noaa.gov/resource/document/2024-annual-deployment-plan-observers-and-electronic-monitoring-groundfish-and>.

- NMFS (National Marine Fisheries Service). (2024). Fisheries of the United States, 2022. U.S. Department of Commerce, NOAA Current Fishery Statistics No. 2022. Available at: <https://www.fisheries.noaa.gov/national/sustainable-fisheries/fisheries-united-states>
- NPFMC (North Pacific Fishery Management Council). (2012). Fishing Fleet Profiles: April 2012. Anchorage, Alaska. Print. <https://www.npfmc.org/library/papers-and-pubs/>.
- NPFMC (North Pacific Fishery Management Council). (2024). Observer Availability Discussion Paper. September 2024. Anchorage, Alaska. Print. <https://meetings.npfmc.org/CommentReview/DownloadFile?p=9774a066-74cb-490d-b603-d0e9c7200c1b.pdf&fileName=D1%20Observer%20Availability%20Discussion%20Paper.pdf>
- Nussear, K.E., and Tracy, C.R. (2007). Can modeling improve estimation of desert tortoise population densities? *Ecological Applications* 17(2): 579-586.
- Porter, R.D. (2010). Fisheries observers as enforcement assets: lessons from the North Pacific. *Marine Policy* 34(3): 583-589.
- R Core Team (2023). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
- Ribera-Altimir, J., Llorach-Tó, G., Sala-Coromina, J., Company, J.B., and Galimany, E. (2023). Fisheries data management systems in the NW Mediterranean: from data collection to web visualization. *Database* 2023: 1-13.
- Smale, N., Unsworth, K., Denyer, G., and Barr, D. (2018). The history, advocacy, and efficacy of data management plans. *bioRxiv* 443499 <https://doi.org/10.1101/443499>.
- Stein, B.A., Staudt, A., Cross, M.S., Dubois, N.S., Enquist, C., Griffis, R., Hansen, L.J., Hellmann, J.J., Lawler, J.J., and Nelson, E.J. (2013). Preparing for and managing change: climate adaptation for biodiversity and ecosystems. *Frontiers in Ecology and the Environment* 11(9): 502-510.
- Stevenson, D.E. (2018). Documenting the reliability of species identifications in the North Pacific Observer Program. *Fisheries Research* 201: 26-31.
- Stevenson, D.E., Moon, M., Ricket, M., and Vechter, M. (2016). Species identification in the North Pacific Observer Program: Training, protocols, and data monitoring. AFSC Processed Rep. 2016-04, 37 p. Alaska Fish. Sci. Cent., NOAA, Natl. Mar. Fish. Serv., 7600 Sand Point Way NE, Seattle WA 98115 <http://doi.org/10.7289/V5/AFSC-PR-2016-04>.
- Sutter, R.D., Wainscott, S.B., Boetsch, J.R., Palmer, C.J., and Rugg, D.J. (2015). Practical Guidance for integrating data management into long-term ecological monitoring projects. *Wildlife Society Bulletin* 39(3): 451-463.
- Tenopir, C., Rice, N.M., Allard, S., Baird, L., Borycz, J., Christian, L., Grant, B., Olendorf, R., and Sandusky, R.J. (2020). Data sharing, management, use, and reuse: Practices and perceptions of scientists worldwide. *PLoS ONE* 15(3): e0229003.
- Wang, Y. and DiCosimo, J. (2019). National Observer Program 2016 fishery observer attitudes and experiences survey. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-F/SPO-186, 50 p. <https://spo.nmfs.noaa.gov/sites/default/files/TMSPO186.pdf>.

- Wilkinson, M.D., Dumontier, M., Aalbersberg, J.I., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J., Bonino da Silva Santos, L., Bourne, P.E., Bouwman, J., Brookes, A.J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C.T., Finkers, R., Gonzalez-Beltran, A., Gray, A.J.G., Groth, P., Goble, C., Grethe, J.S., Heringa, J., Hoen, P.A.C., Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S.J., Martone, M.E., Mons, A., Packer, A.L., Persson, B., Rocca-Serra, P., Roos, M., van Schaik, R., Sansone, S., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M.A., Thompson, M., van der Lei, J., van Mulligen, E., Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J., and Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data* 3(160018).
- Worm, B., Hilborn, R., Baum, J.K., Branch, T.A., Collie, J.S., Costello, C., Fogarty, M.J., Fulton, E.A., Hutchings, J.A., Jennings, S., Jensen, O.P., Lotze, H.K., Mace, P.M., McClanahan, T.R., Minto, C., Palumbi, S.R., Parma, A.M., Ricard, D., Rosenberg, A.A., Watson, R., and Zeller, D. (2009). Rebuilding global fisheries. *Science* 325(5940): 578-585.

Table 1. -- List of DEC terms presented in this summary and how they appear in the DEC application. Terms are organized alphabetically by the 'Modified DEC' column. * = term did not change for this summary.

Modified DEC	Original DEC
Biased collection	Biased collection method/crew/mechanical
Editor error*	Editor Error
Halibut calculation	Halibut auto calculation change
Haul not verified	Haul data not verified
Inseason edit	Inseason data edit
Missing or illegible data	Raw data missing/illegible/erasing present
Other*	Other
Sample deleted*	Sample deleted
Sample design change	Sample design/unit changed per observer collection method
Scale failure*	Scale failure
Snap gear sample change	Snap gear sample size changed per debriefing protocol
Species misidentified	Species ID error: verification/GIS/weight or length range
Specimen unusable or lost	Specimen lost or unusable
Tally error/rules*	Tally error/rules
Transcription error	Correction per Raw Data/Vessel Log/VMS/Fish Ticket/logistics notes/logbook/survey/interview

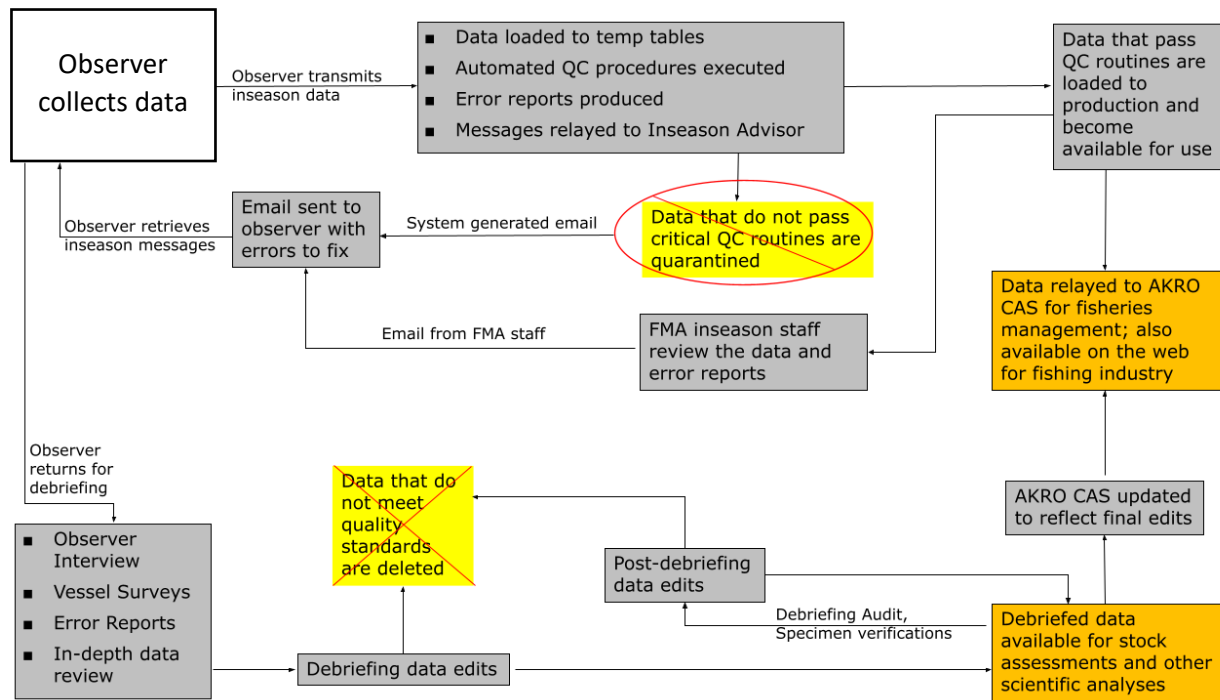


Figure 1. -- Flow chart of data management in the North Pacific Observer Program (NPOP). Flow of data begins in the upper left, where observers collect data as catch is retrieved or offloaded. AKRO = NOAA Fisheries Alaska Regional Office; CAS = Catch Accounting System; FMA = NOAA Alaska Fisheries Science Center Fisheries Monitoring and Analysis Division.

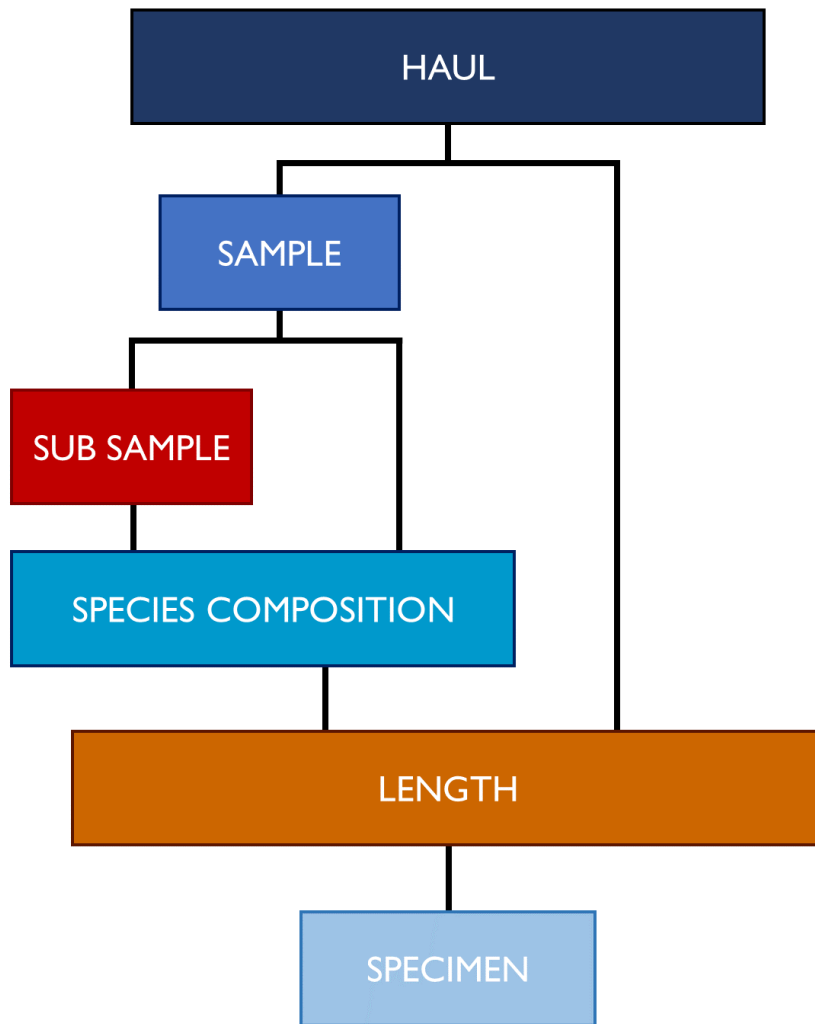


Figure 2. -- Cladogram of the data hierarchy within the NORPAC database. Here, a haul is considered the chief parent record, and a specimen the final child record, with black lines signifying direct parent-child relationships. For child boxes that directly connect to two parent boxes, that child can have either one or both of those boxes as its parent at once (e.g., a length record can either have a haul record as a parent, a species composition record as a parent, or both as parent records). Child boxes that indirectly connect to a parent box (i.e. its parent box connects to another parent box) are also considered children of that parent (e.g., a sub sample is a child of both sample and haul). Box sizes are arbitrary.

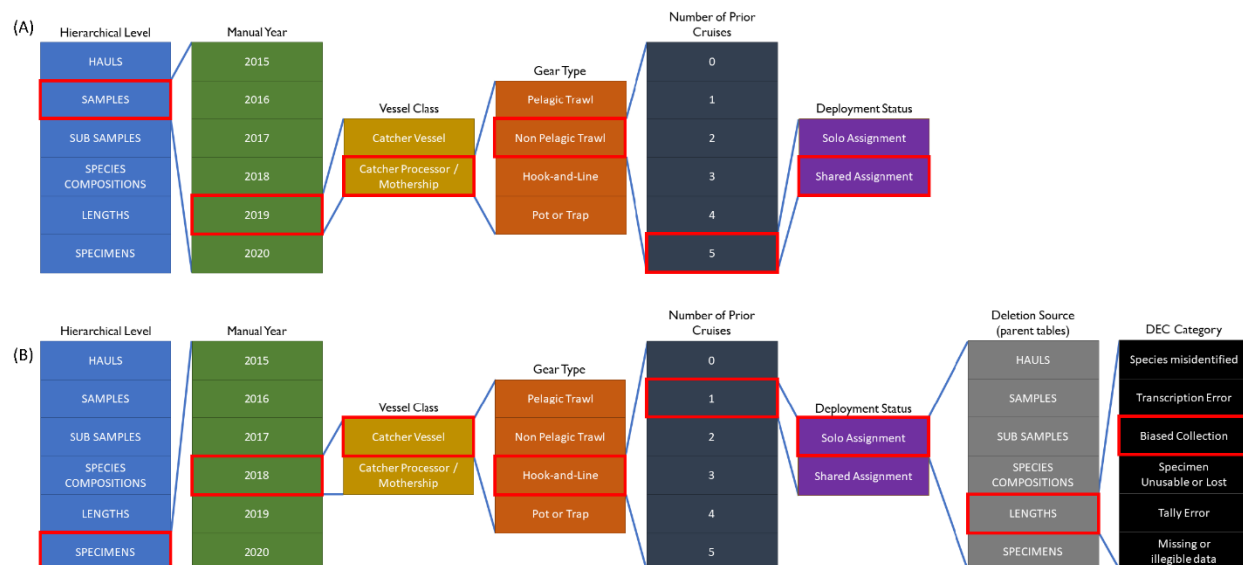


Figure 3. -- Flow chart of covariate hierarchies used in this study. Groups appear as stacked boxes of the same color, with labels sitting at the top of the stack. To follow an example flow of the covariate hierarchy, follow boxes outlined in red from left to right. (A) Covariate hierarchies within primary tables. (B) Covariate hierarchies within history tables.

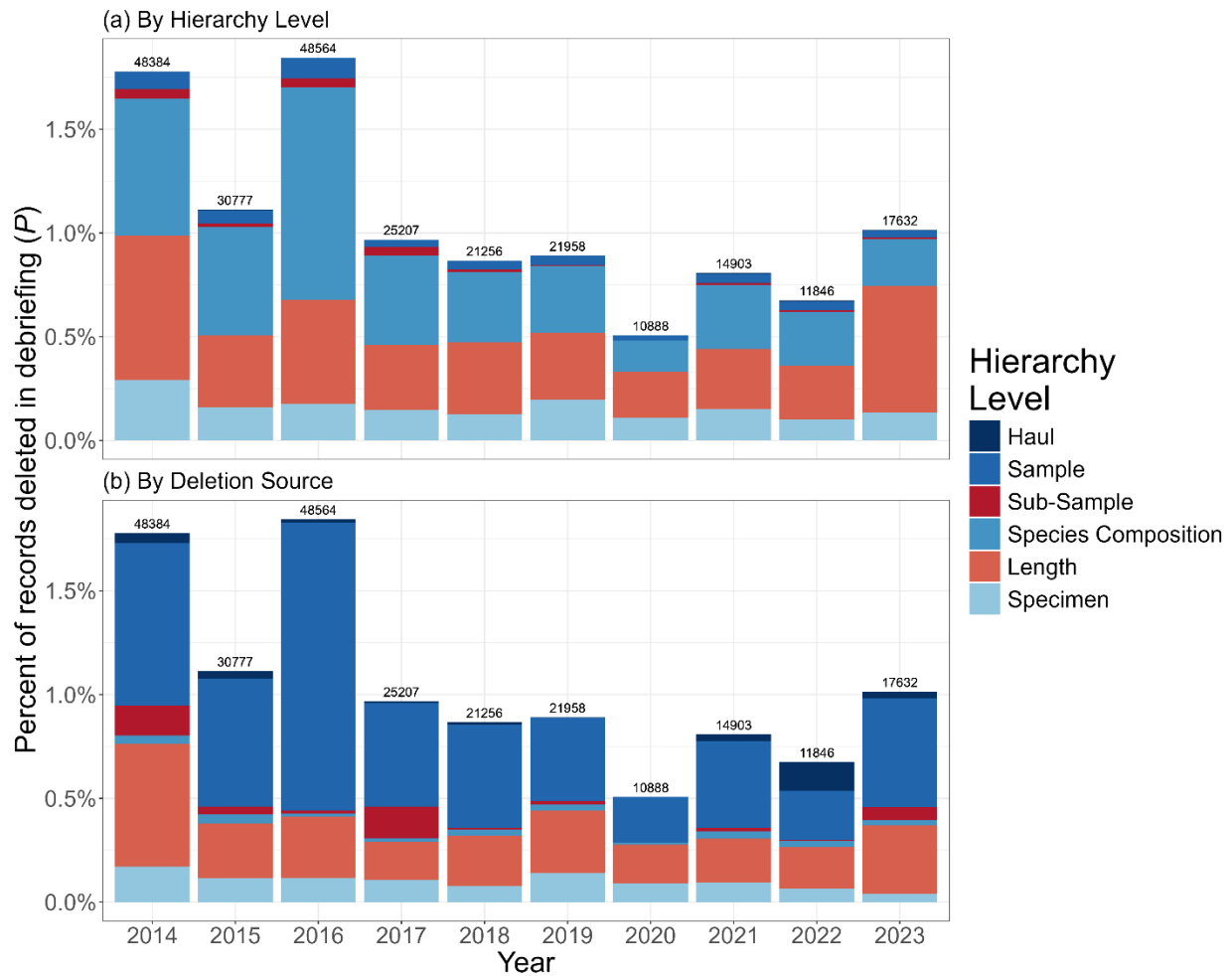


Figure 4. -- Percent of records deleted during debriefing (P) by year. Colors reflect (a) the hierarchy level of the data and (b) the deletion source. The area of respective colors on bars reflect deletion counts relative to other hierarchy levels or deletion sources (i.e., more color, more deletions). Number above the bar represents total deletions per year.

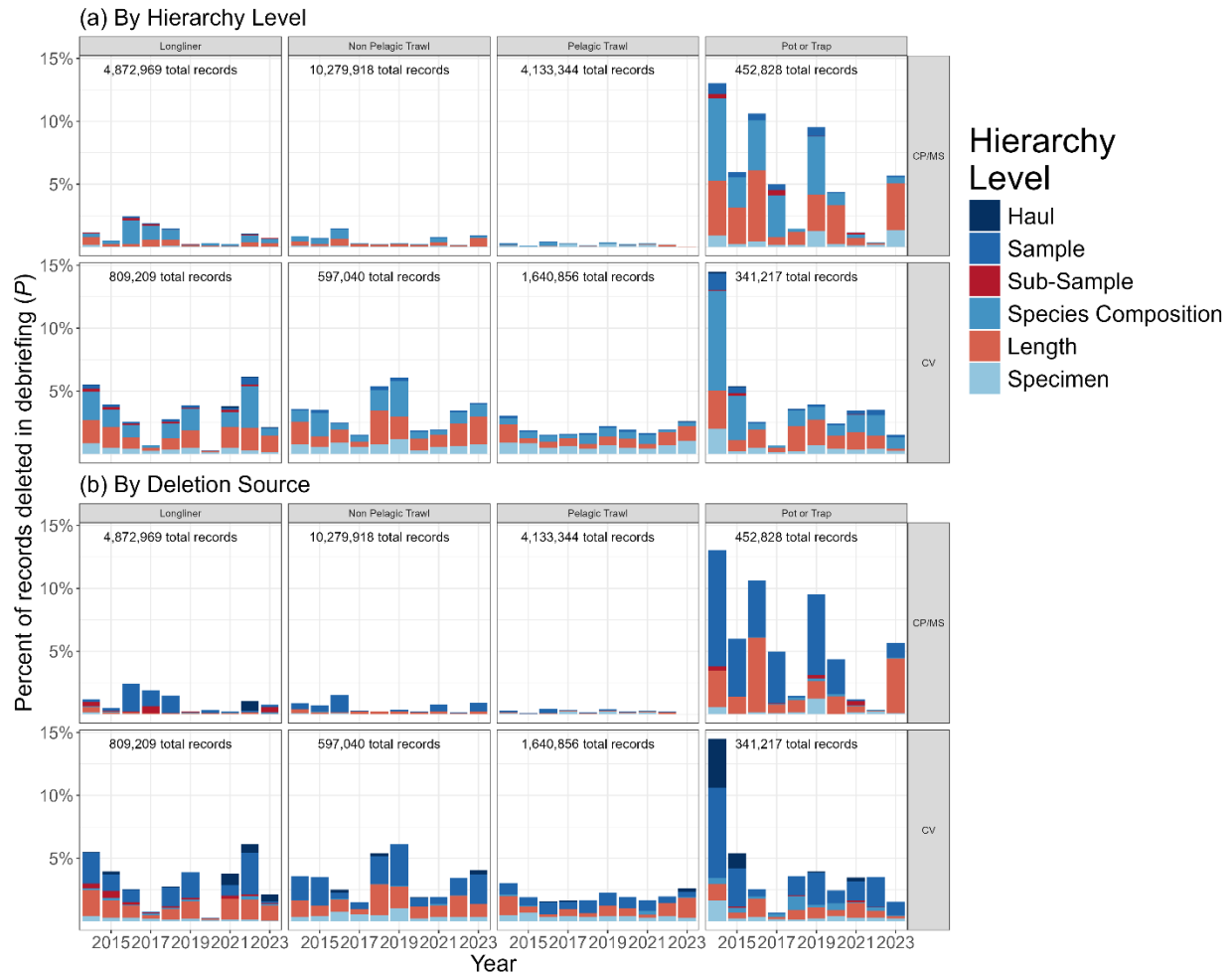


Figure 5. -- Percent of records deleted during debriefing (P) by year and faceted by gear type and vessel class. Colors reflect (a) the hierarchy level of the data and (b) the deletion source. The area of respective colors on bars reflect deletion counts relative to other hierarchy levels or deletion sources (i.e., more color, more deletions). Total sums of records collected per facet of gear type and vessel class (as a group) sit at the top of facet boxes.

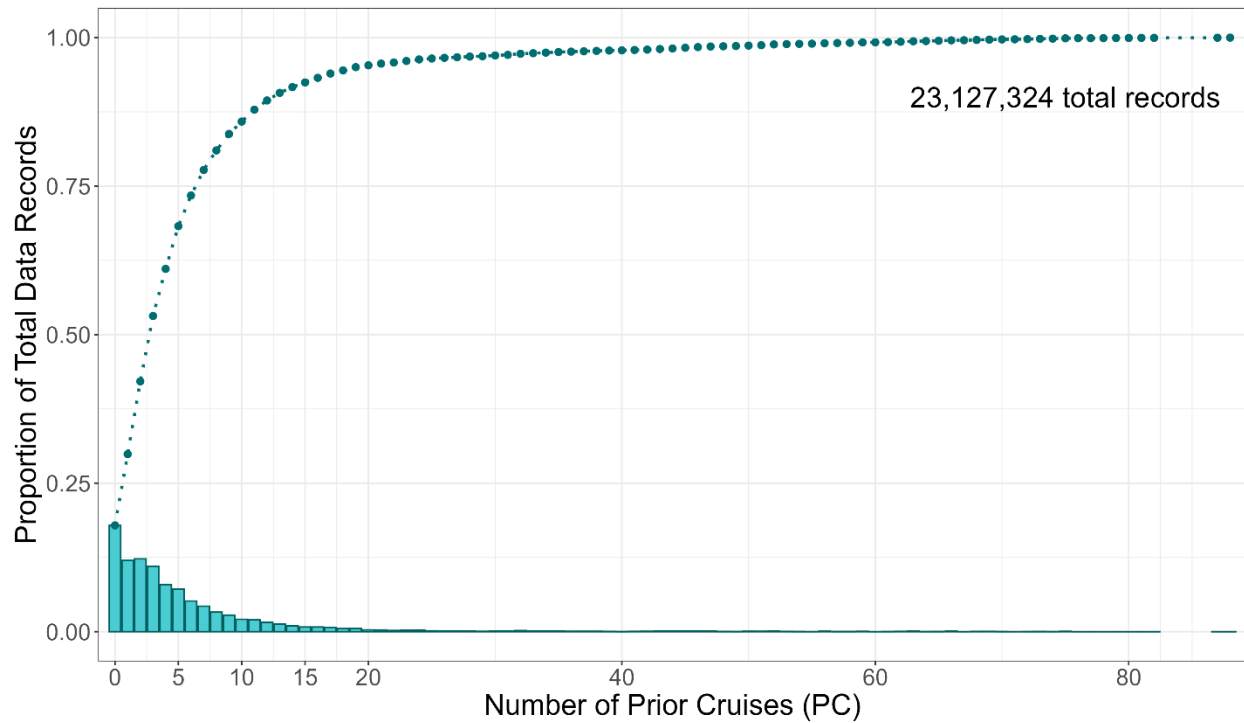


Figure 6. -- Pareto plot relating proportions of total data records collected to number of prior cruises (PC). Bars reflect the proportion of total data records collected by observers with the given amount of PC upon data collection. A dotted line connects dots that reflect the cumulative sum of proportions by each successive PC. The sum of data records for this plot sits in the upper right corner. The maximum PC is 88. Our data contains no records collected by observers with 83-86 PCs.

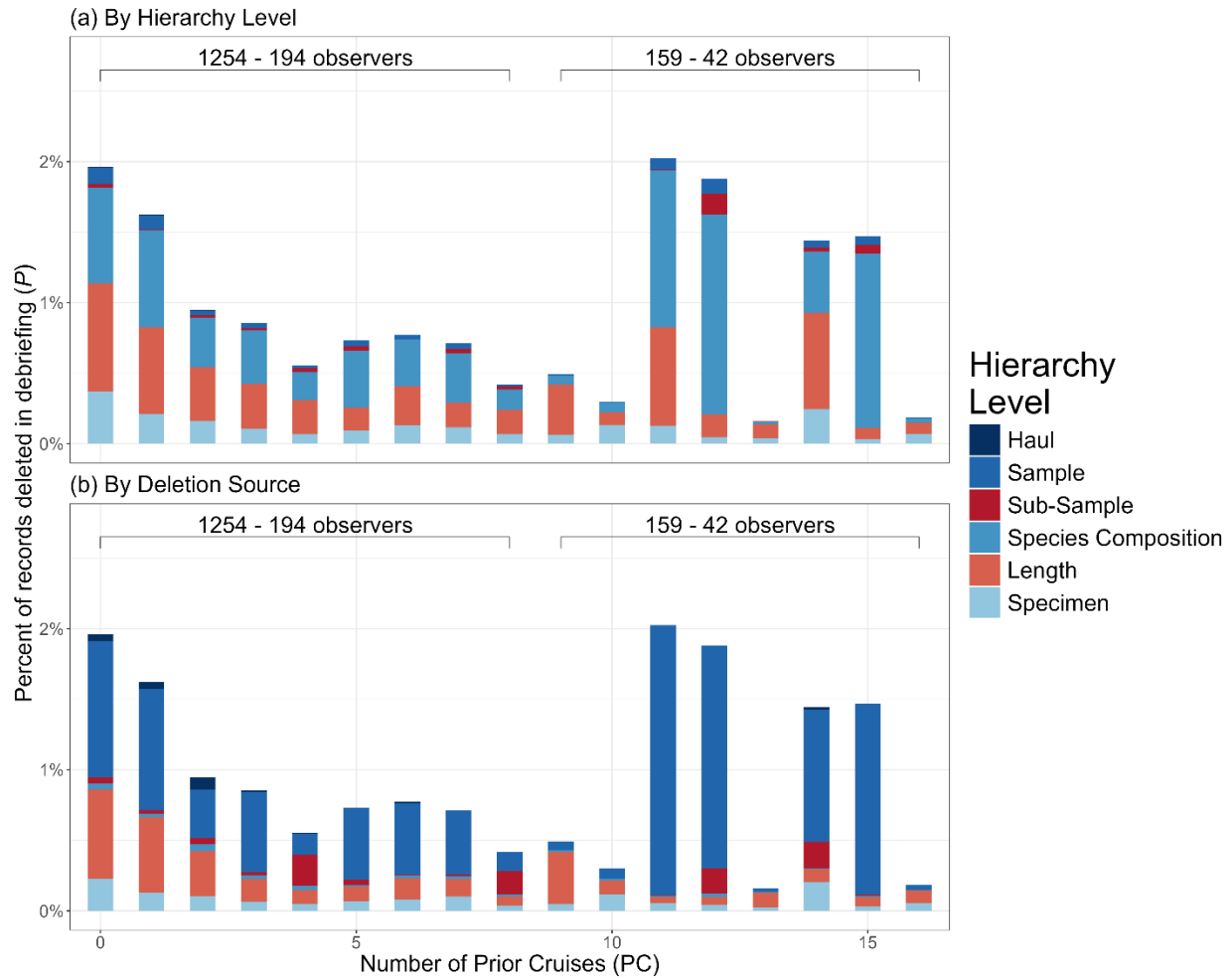


Figure 7. -- Percent of records deleted during debriefing (*P*) by number of prior cruises (PC). Brackets sit atop bars to encompass groups of prior cruises, with numbers above those brackets indicating the range of unique observers deployed within that range of PCs (i.e., the leftmost number is the amount of observers who deployed with the left-most PC in the bracket, and the rightmost number is the count of unique observers who deployed with the right-most PC in the bracket). Colors reflect (a) the hierarchy level of the data and (b) the deletion source. The area of respective colors on bars reflect deletion counts relative to other hierarchy levels or deletion sources (i.e., more color, more deletions). The plot omits data collected at PCs greater than 16.

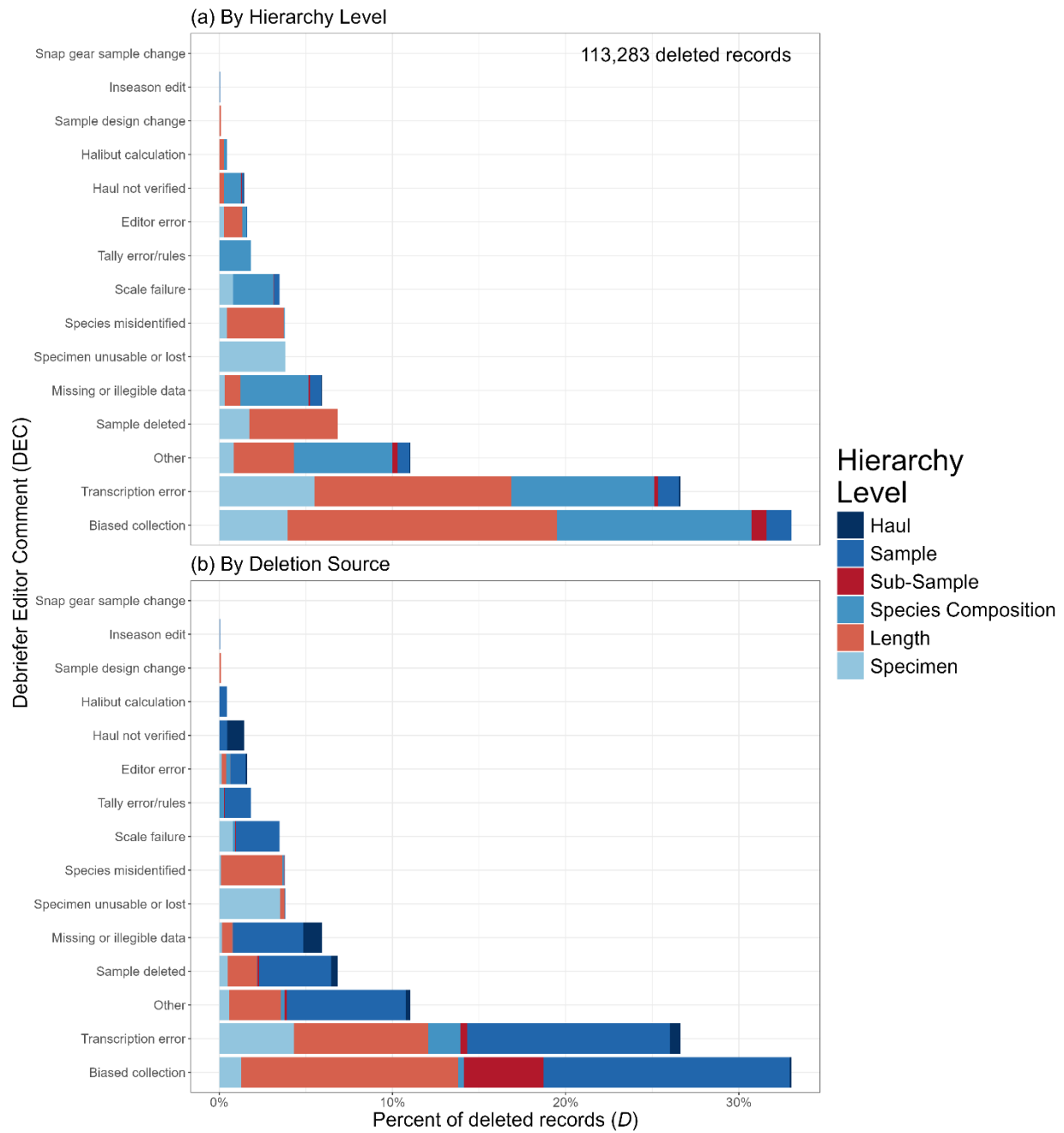


Figure 8. -- Percent of deleted records (*D*) by attributed DEC. Colors reflect (a) the hierarchy level the deletions represent and (b) the deletion source, and their area on bars reflect deletion counts relative to other hierarchy levels or deletion sources (i.e., more color, more deletions). The sum of deleted records* with attributed DEC reasons is in the top right corner of (a). *312 records were not attributed a DEC.

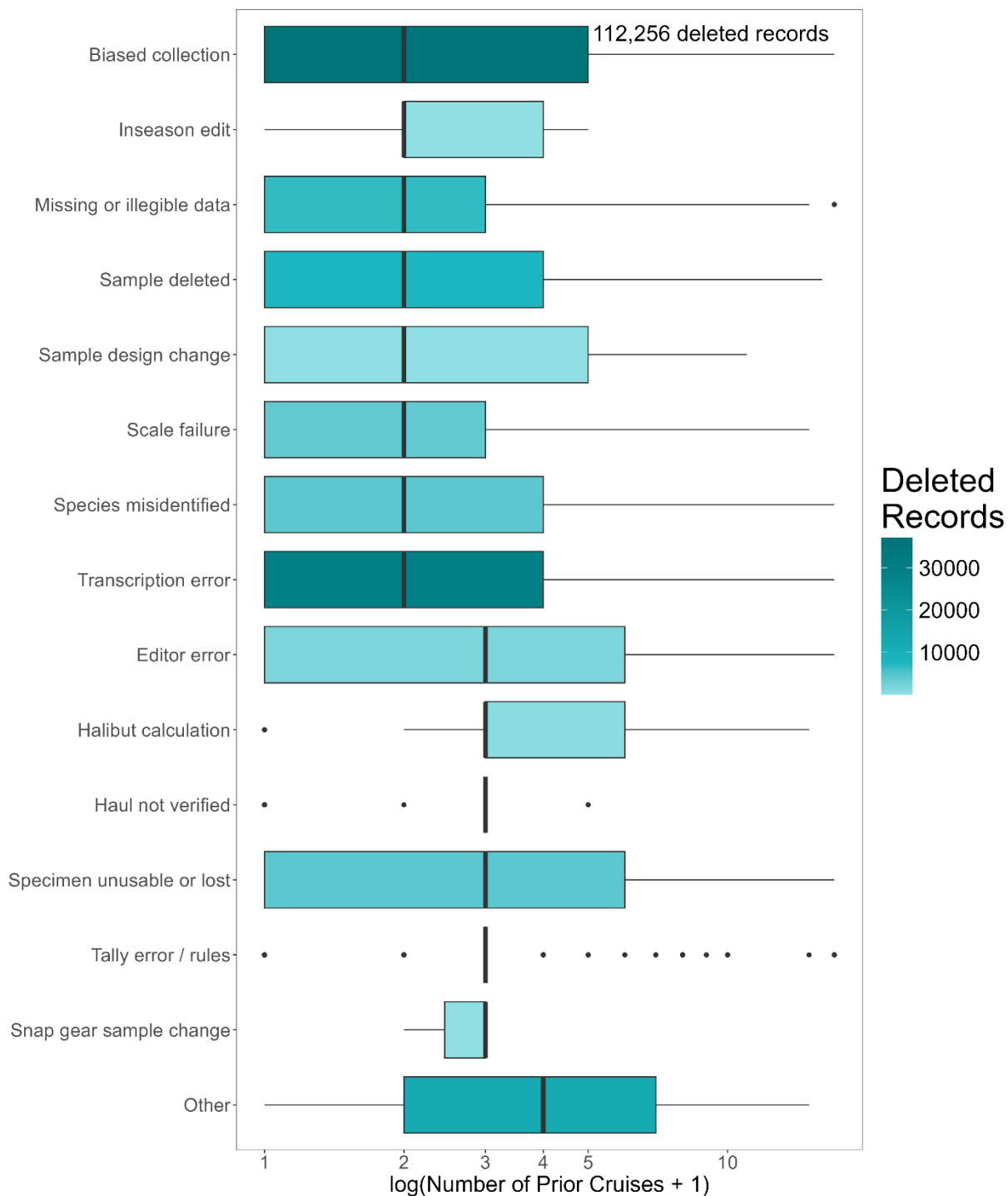


Figure 9. -- Boxplots of DEC reason counts as a function of the number of prior cruises by the observer upon data collection. Colors reflect the volume of deletions attributed to each DEC, with darker colors denoting larger volumes. The total number of deleted records for DEC reason is in the upper right of the panel.

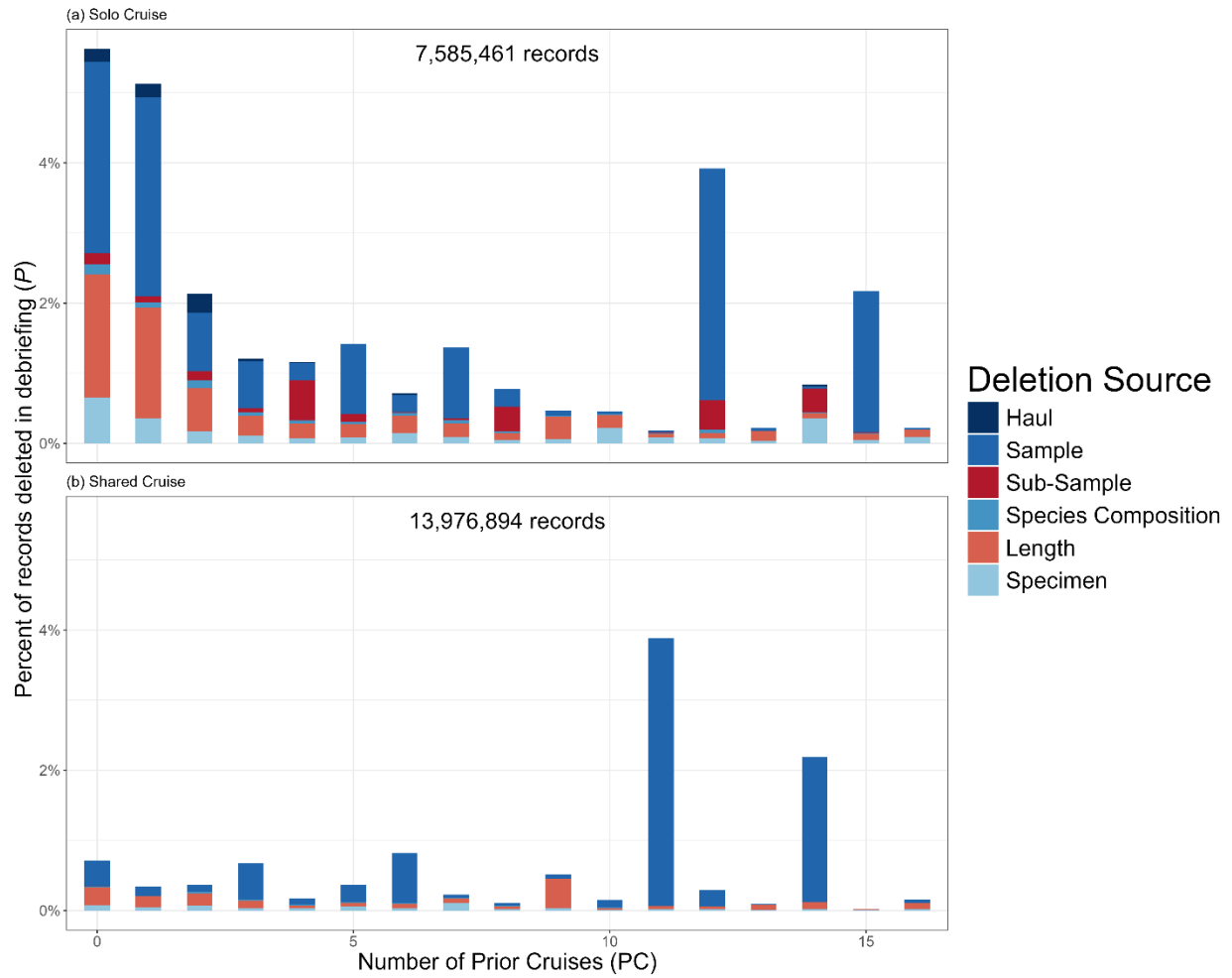


Figure 10. -- Percent of records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source, and their area on bars reflect deletion counts relative to other deletion sources (i.e. more color, more deletions). The sum of records within each cruise type is in the top of each panel.

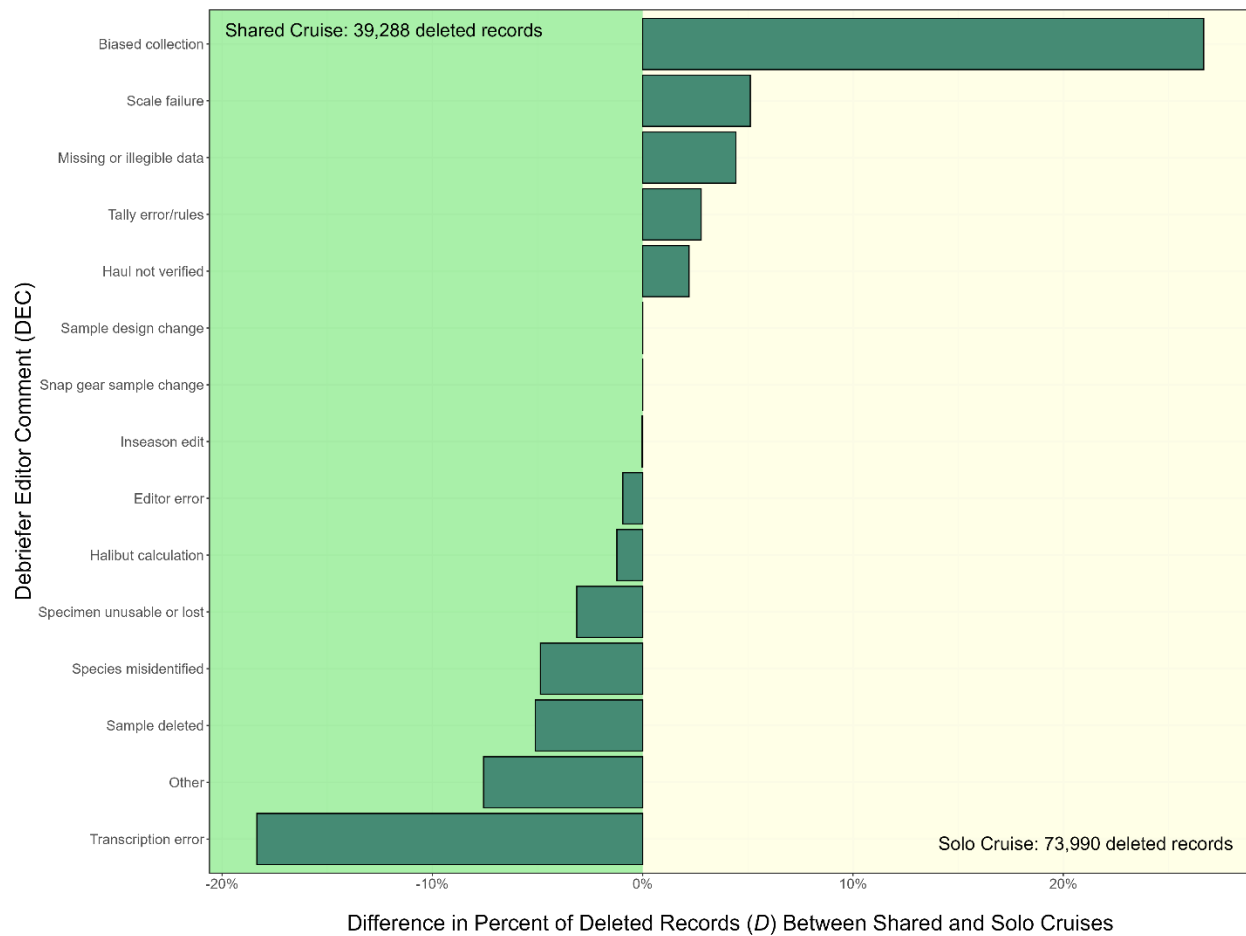
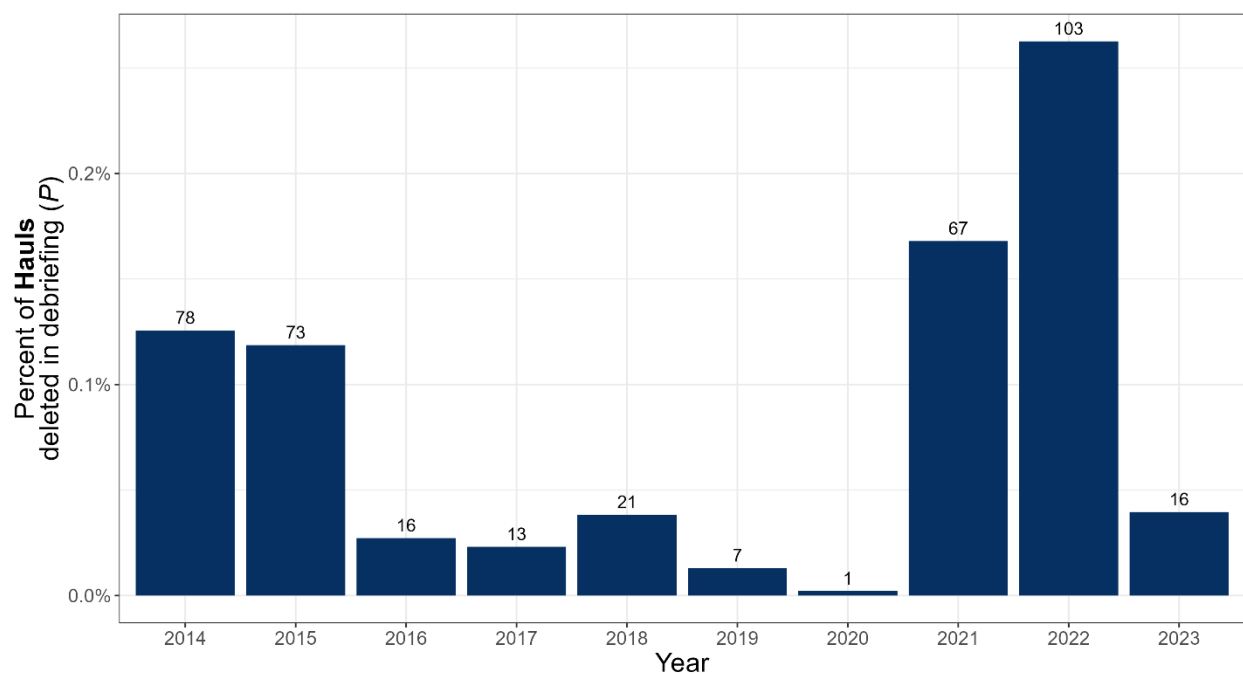
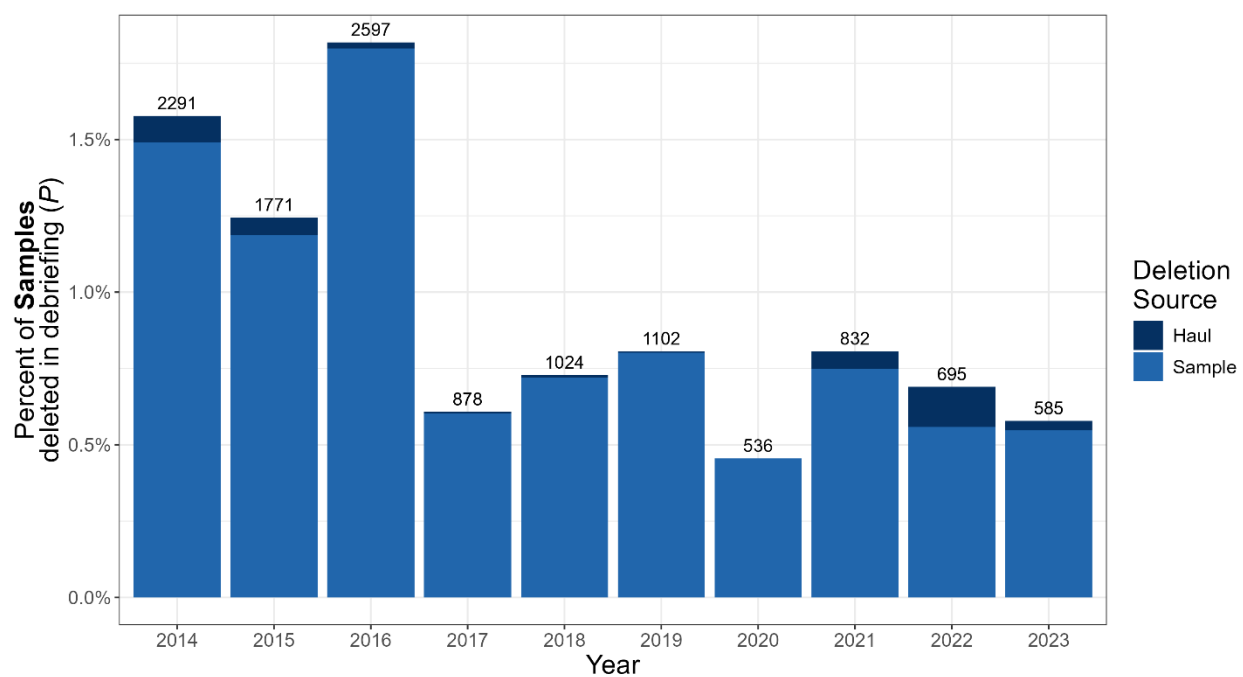


Figure 11. -- The difference in percent of deleted records (*D*) within DEC reasons between shared (negative values) and solo (positive values) cruises.

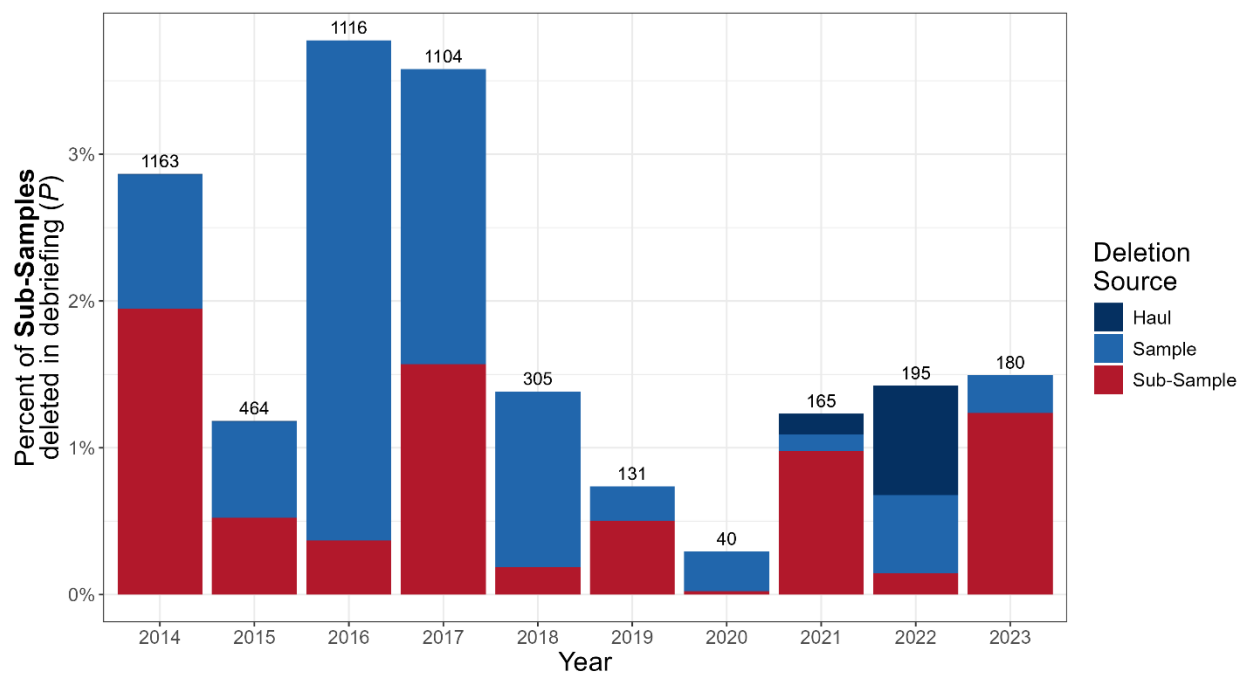
APPENDIX



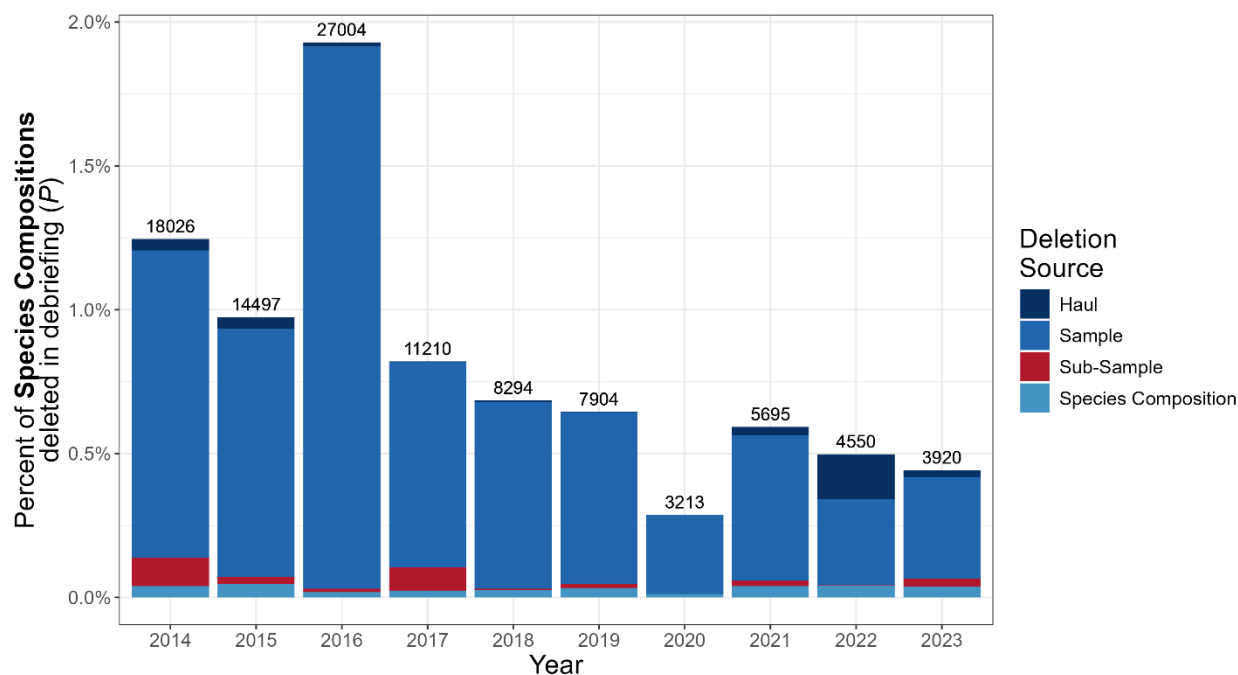
Appendix Figure A1. -- Percent of haul records deleted during debriefing (P) by year. Number above the bar represents the total deletions per year.



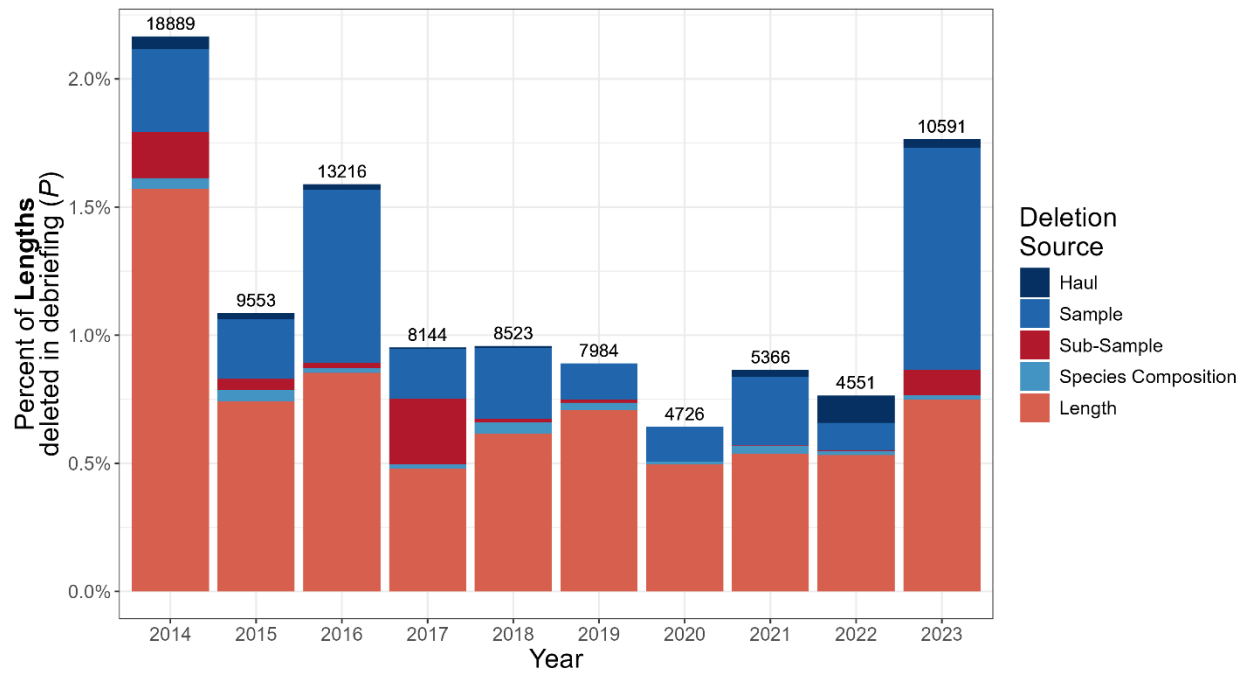
Appendix Figure A2. -- Percent of sample records deleted during debriefing (P) by year. Number above the bar represents the total sum of deletions per year. Colors reflect the deletion source. Number above the bar represents the total sum of deletions per year.



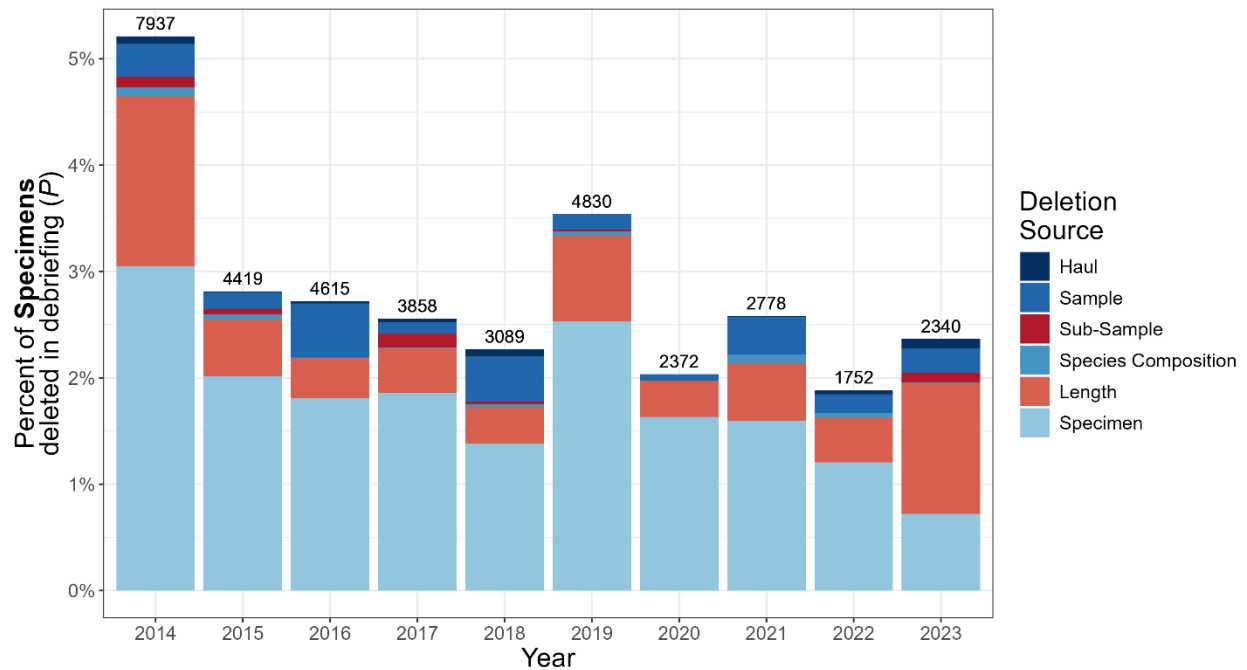
Appendix Figure A3. -- Percent of sub-sample records deleted during debriefing (P) by year. Number above the bar represents the total sum of deletions per year. Colors reflect the deletion source. Number above the bar represents the total sum of deletions per year.



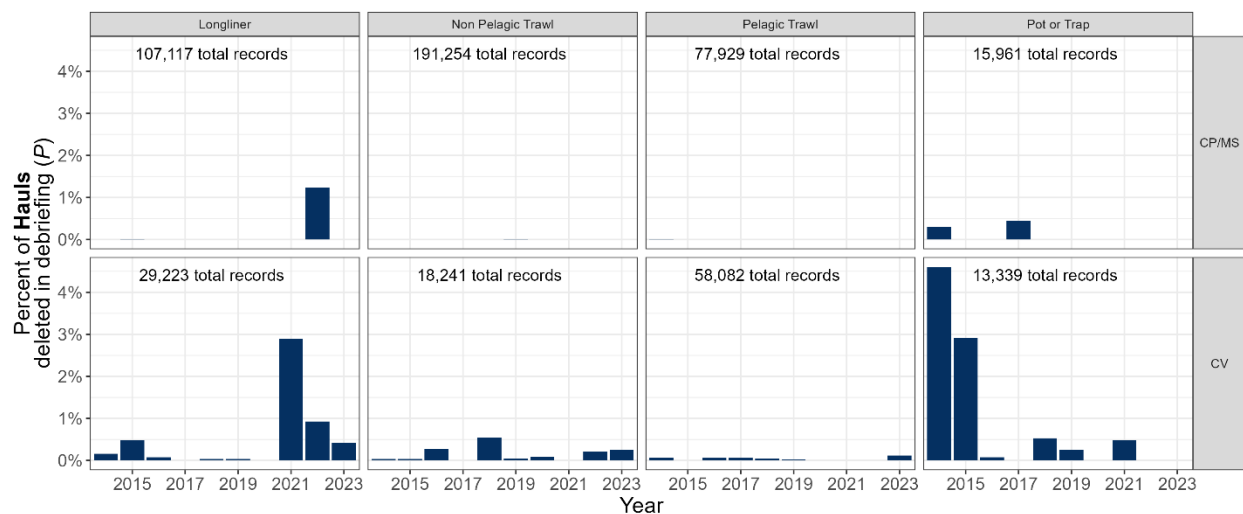
Appendix Figure A4. -- Percent of species composition records deleted during debriefing (P) by year. Number above the bar represents the total sum of deletions per year. Colors reflect the deletion source. Number above the bar represents the total sum of deletions per year.



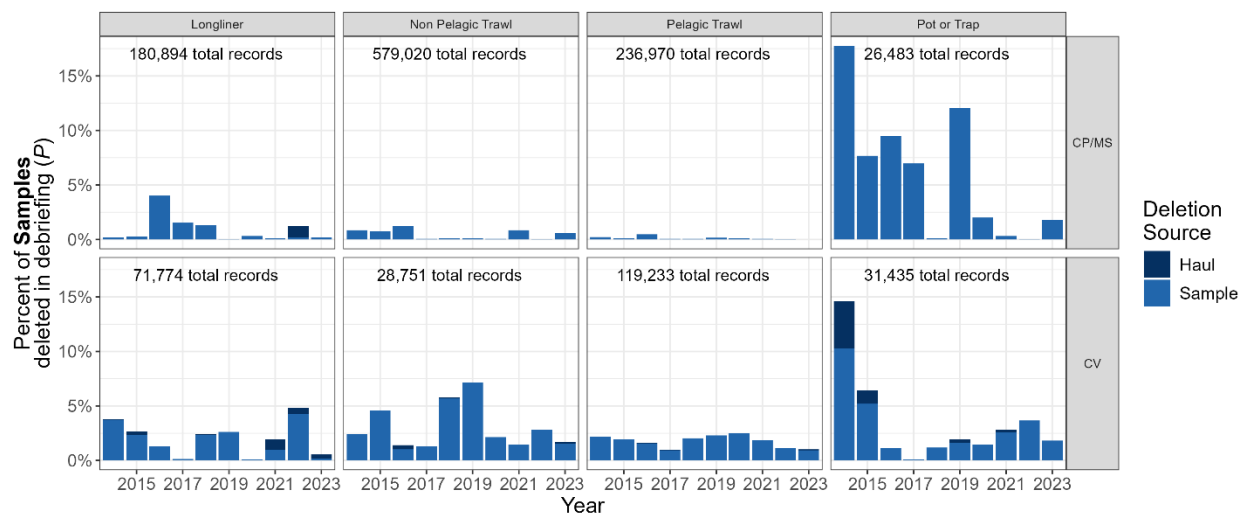
Appendix Figure A5. -- Percent of length records deleted during debriefing (P) by year. Number above the bar represents the total sum of deletions per year. Colors reflect the deletion source. Number above the bar represents the total sum of deletions per year.



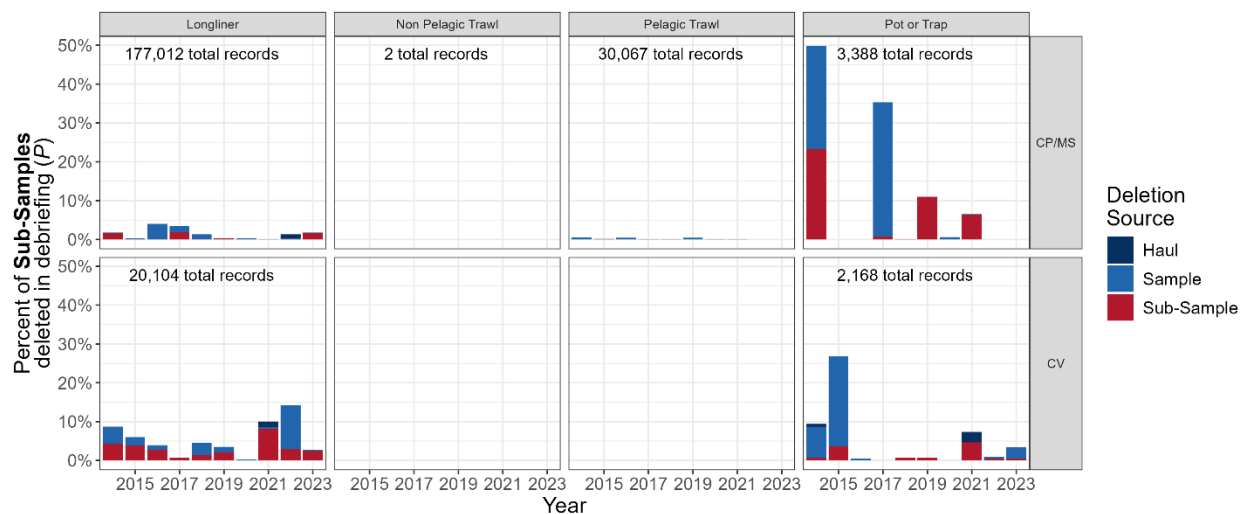
Appendix Figure A6. -- Percent of specimen records deleted during debriefing (P) by year. Number above the bar represents the total sum of deletions per year. Colors reflect the deletion source. Number above the bar represents the total sum of deletions per year.



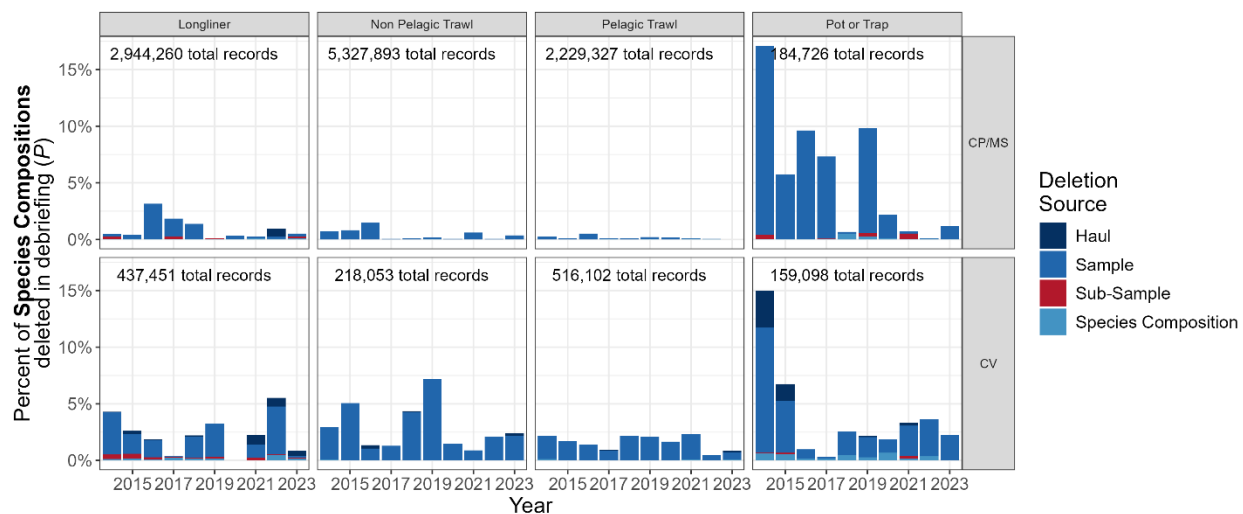
Appendix Figure A7. -- Percent of haul records deleted during debriefing (P) by year and faceted by gear type (top) and vessel class (right side). CP/MS = Catcher Processor/Motherships; CV = Catch Vessels



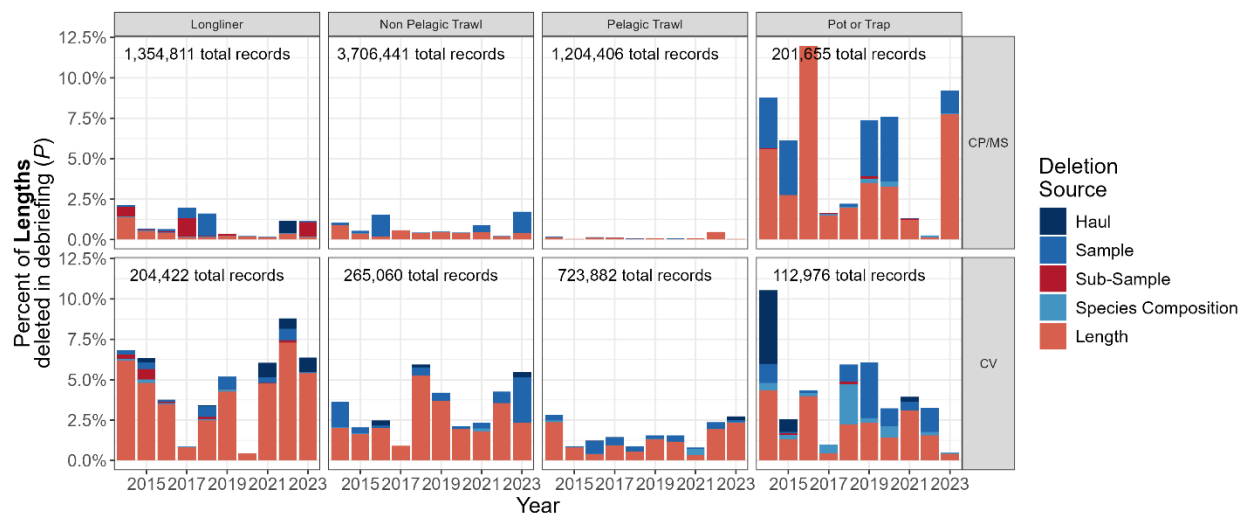
Appendix Figure A8. -- Percent of sample records deleted during debriefing (P) by year and faceted by gear type (top) and vessel class (right side). Colors reflect the deletion source. CP/MS = Catcher Processor/Motherships; CV = Catch Vessels.



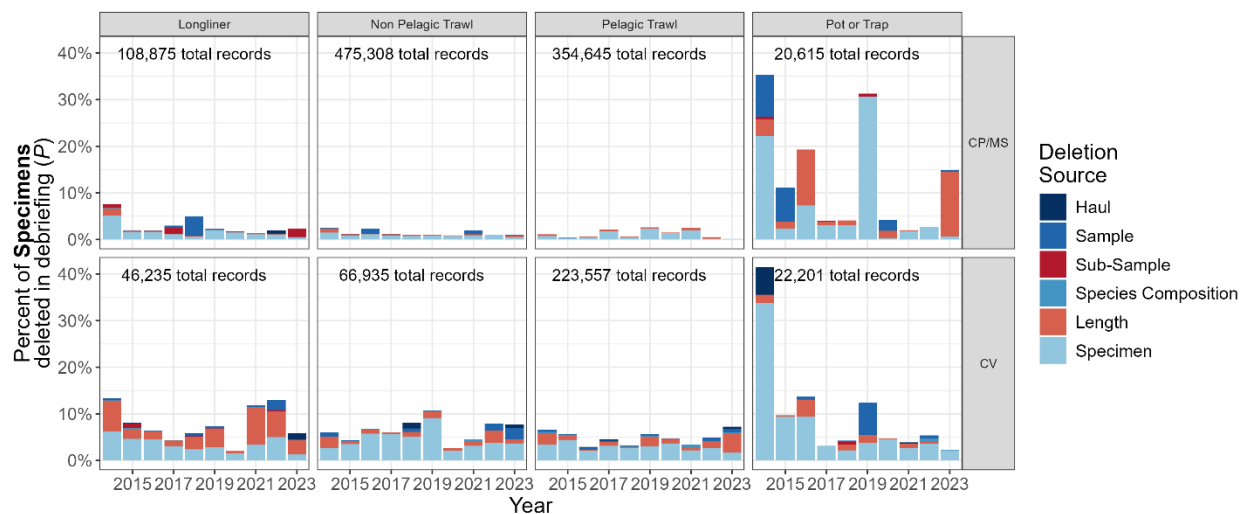
Appendix Figure A9. -- Percent of sub-sample records deleted during debriefing (P) by year and faceted by gear type (top) and vessel class (right side). Colors reflect the deletion source. Note: of trawl vessels, observers only collect sub-samples on CP/MSs equipped with flow scales if two predominant species are present in the sample (AFSC 2023a). CP/MS = Catcher Processor/Motherships; CV = Catch Vessels.



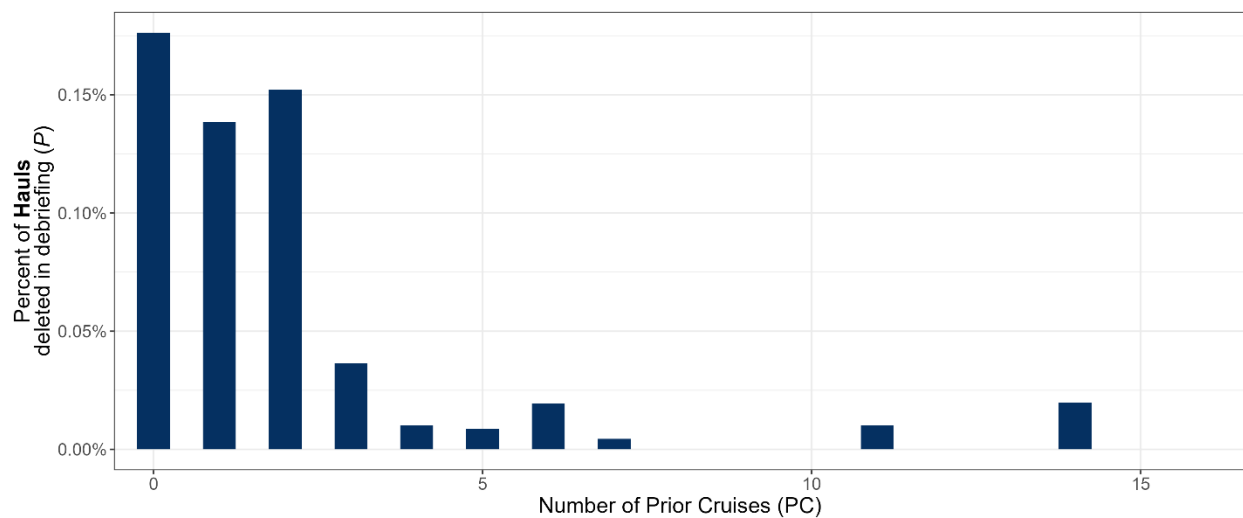
Appendix Figure A10. -- Percent of species composition records deleted during debriefing (P) by year and faceted by gear type and vessel class. Colors reflect the deletion source. CP/MS = Catcher Processor/Motherships; CV = Catch Vessels.



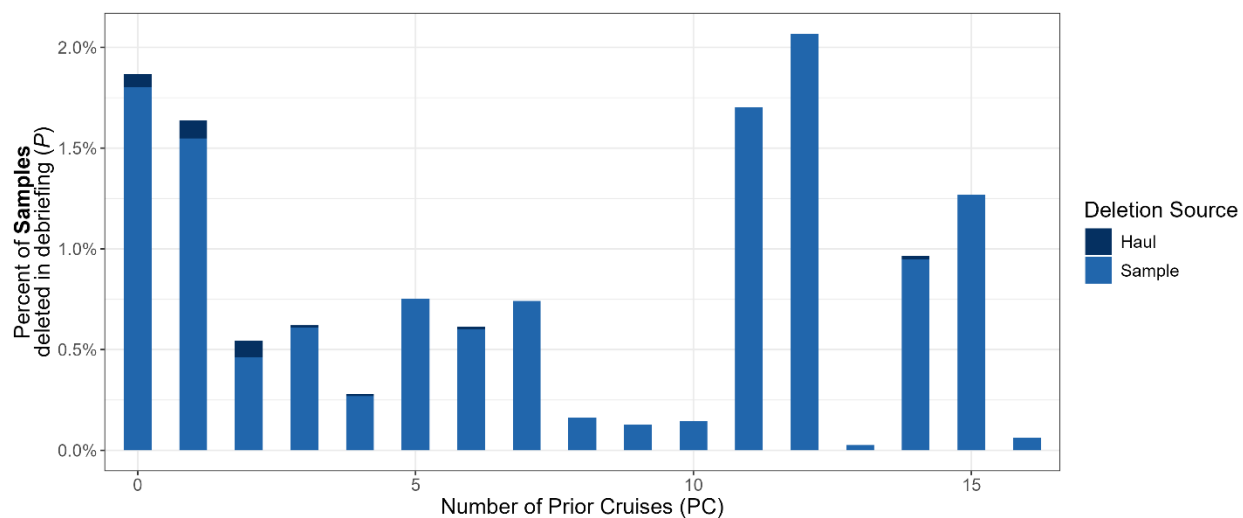
Appendix Figure A11. -- Percent of length records deleted during debriefing (P) by year and faceted by gear type and vessel class. Colors reflect the deletion source. CP/MS = Catcher Processor/Motherships; CV = Catch Vessels.



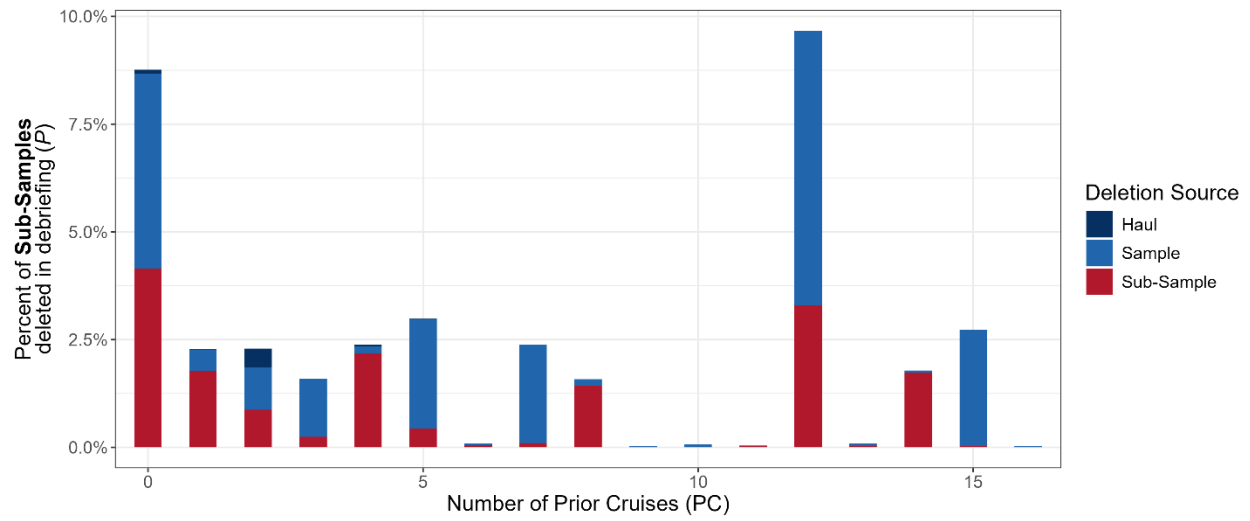
Appendix Figure A12. -- Percent of specimen records deleted during debriefing (P) by year and faceted by gear type and vessel class. Colors reflect the deletion source. CP/MS = Catcher Processor/Motherships; CV = Catch Vessels.



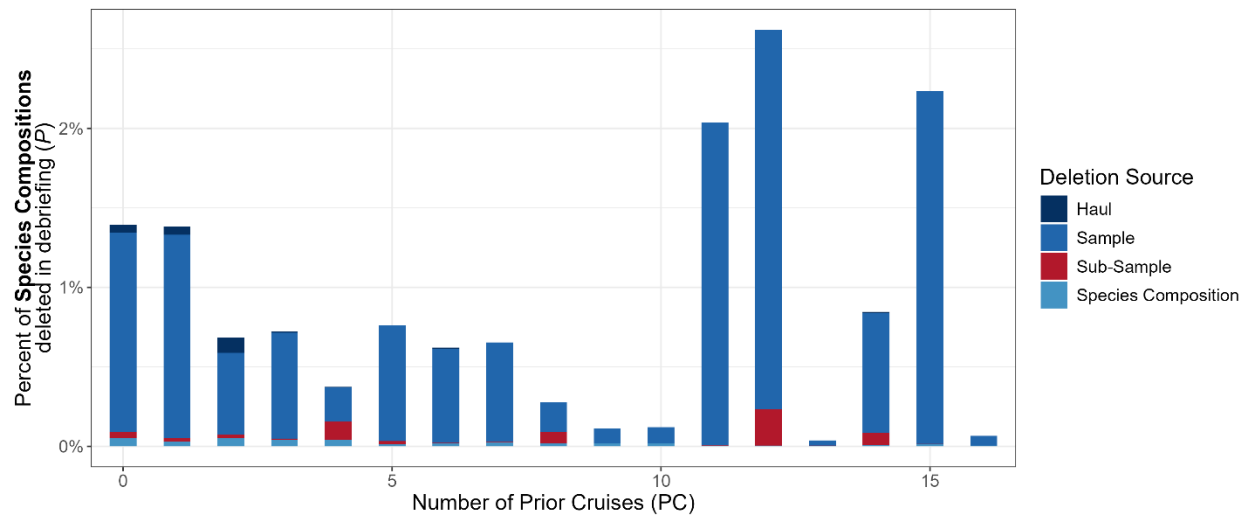
Appendix Figure A13. -- Percent of haul records deleted during debriefing (P) by number of prior cruises (PC).



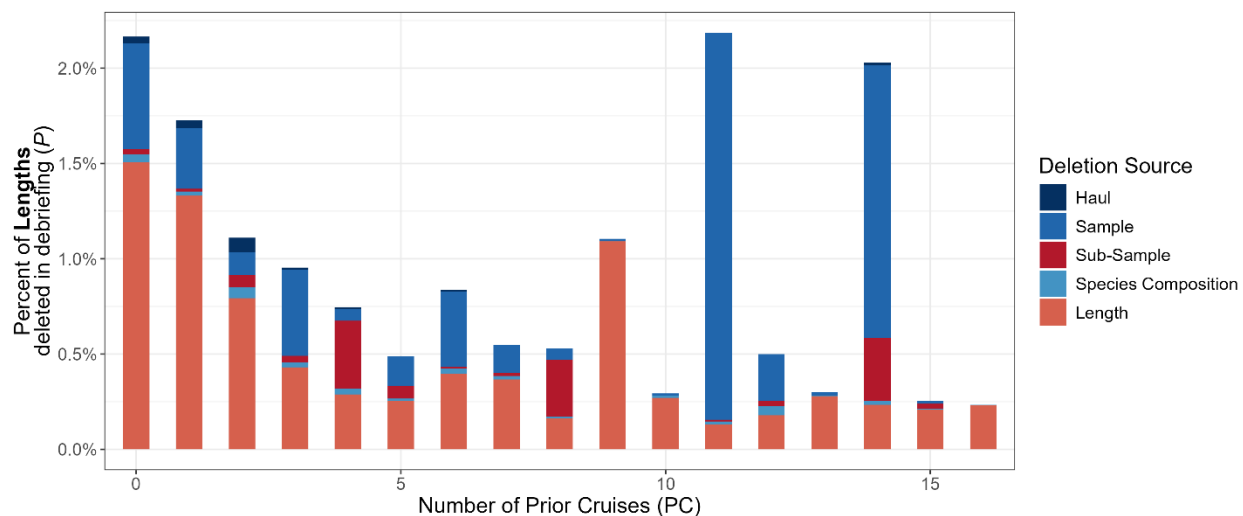
Appendix Figure A14. -- Percent of sample records deleted during debriefing (P) by number of prior cruises (PC). Colors reflect the deletion source.



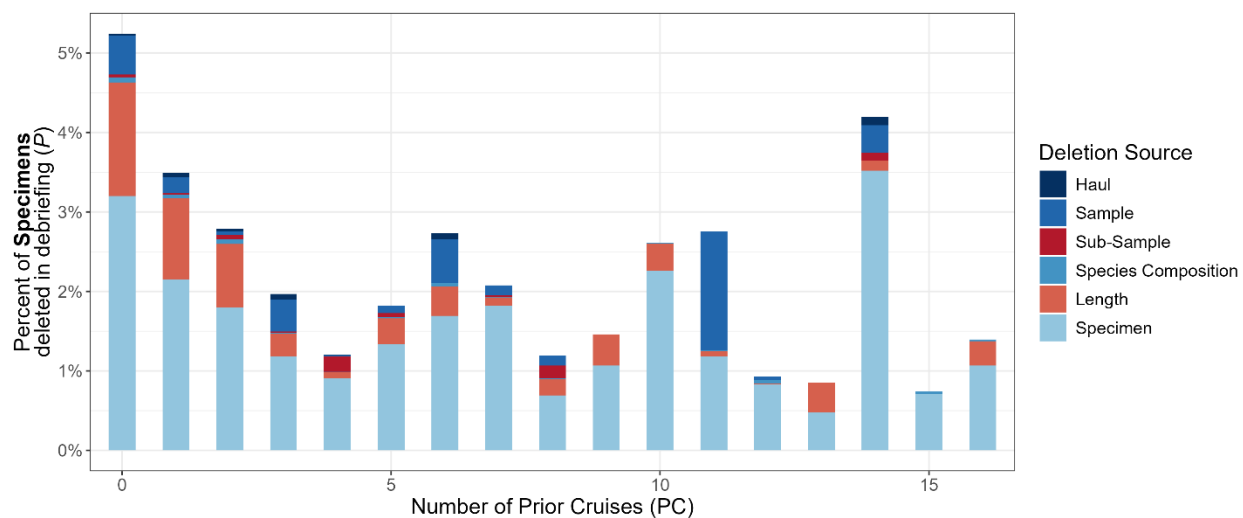
Appendix Figure A15. -- Percent of sub-sample records deleted during debriefing (P) by number of prior cruises (PC). Colors reflect the deletion source.



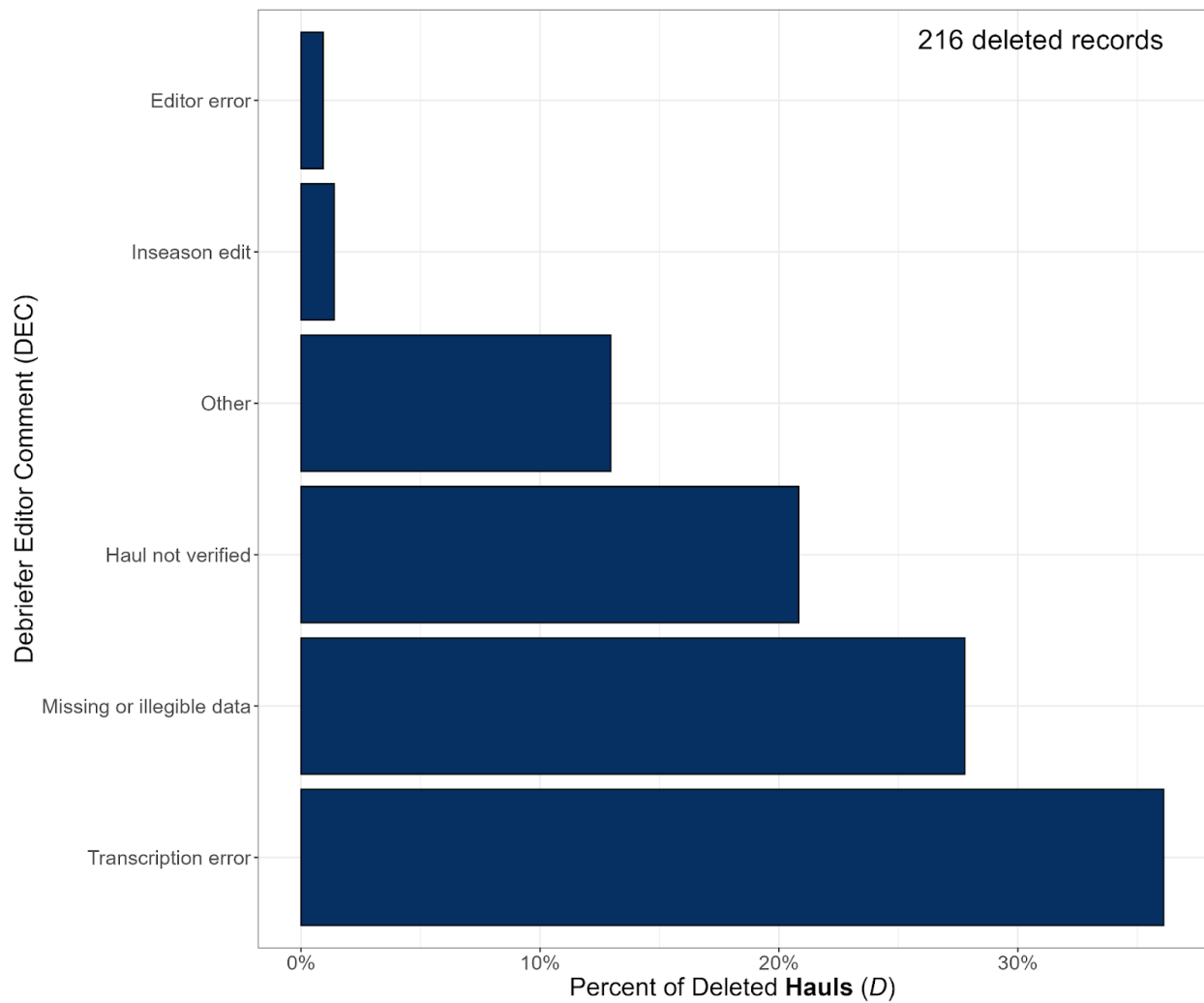
Appendix Figure A16. -- Percent of species composition records deleted during debriefing (P) by number of prior cruises (PC). Colors reflect the deletion source.



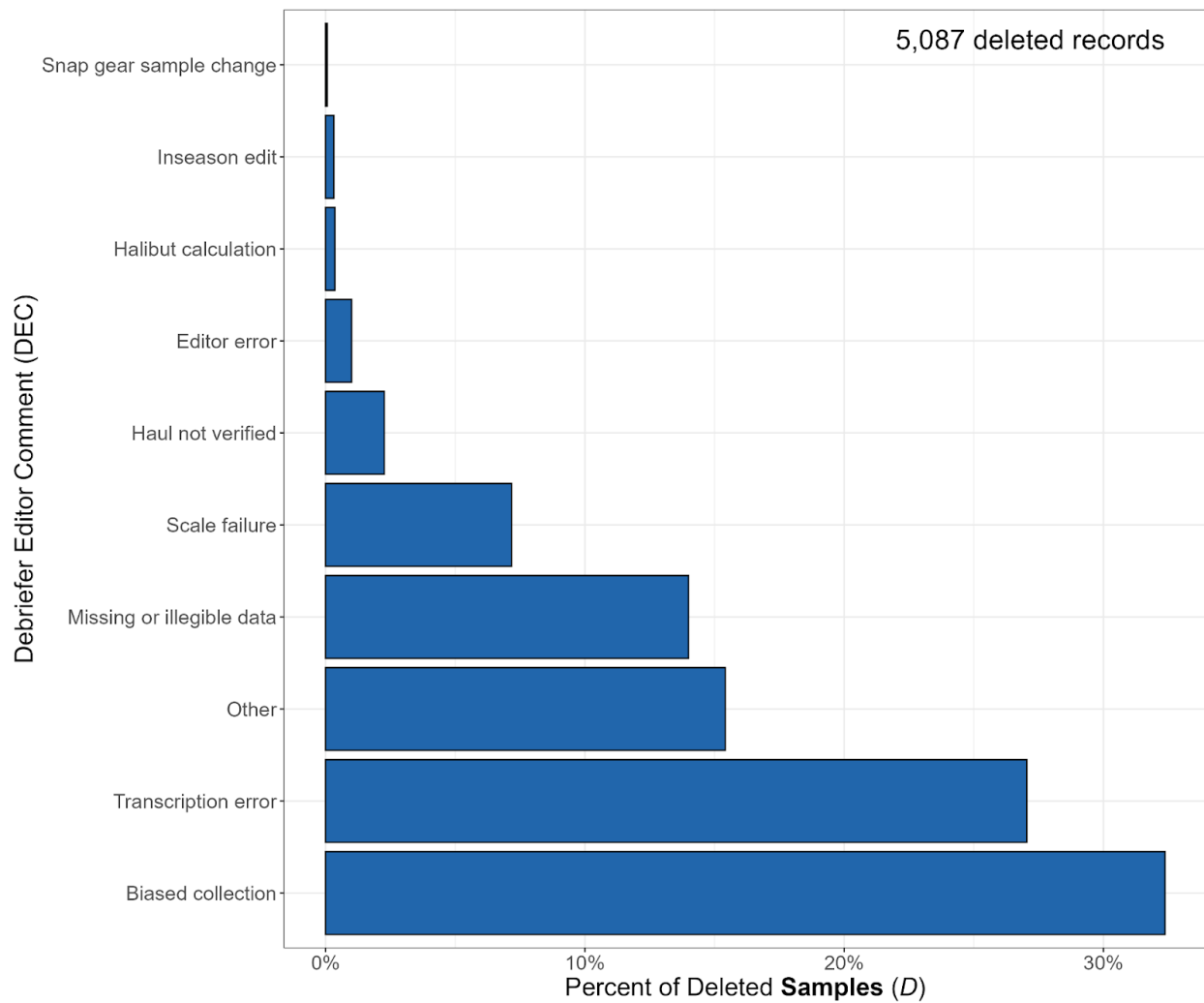
Appendix Figure A17. -- Percent of length records deleted during debriefing (*P*) by number of prior cruises (PC). Colors reflect the deletion source.



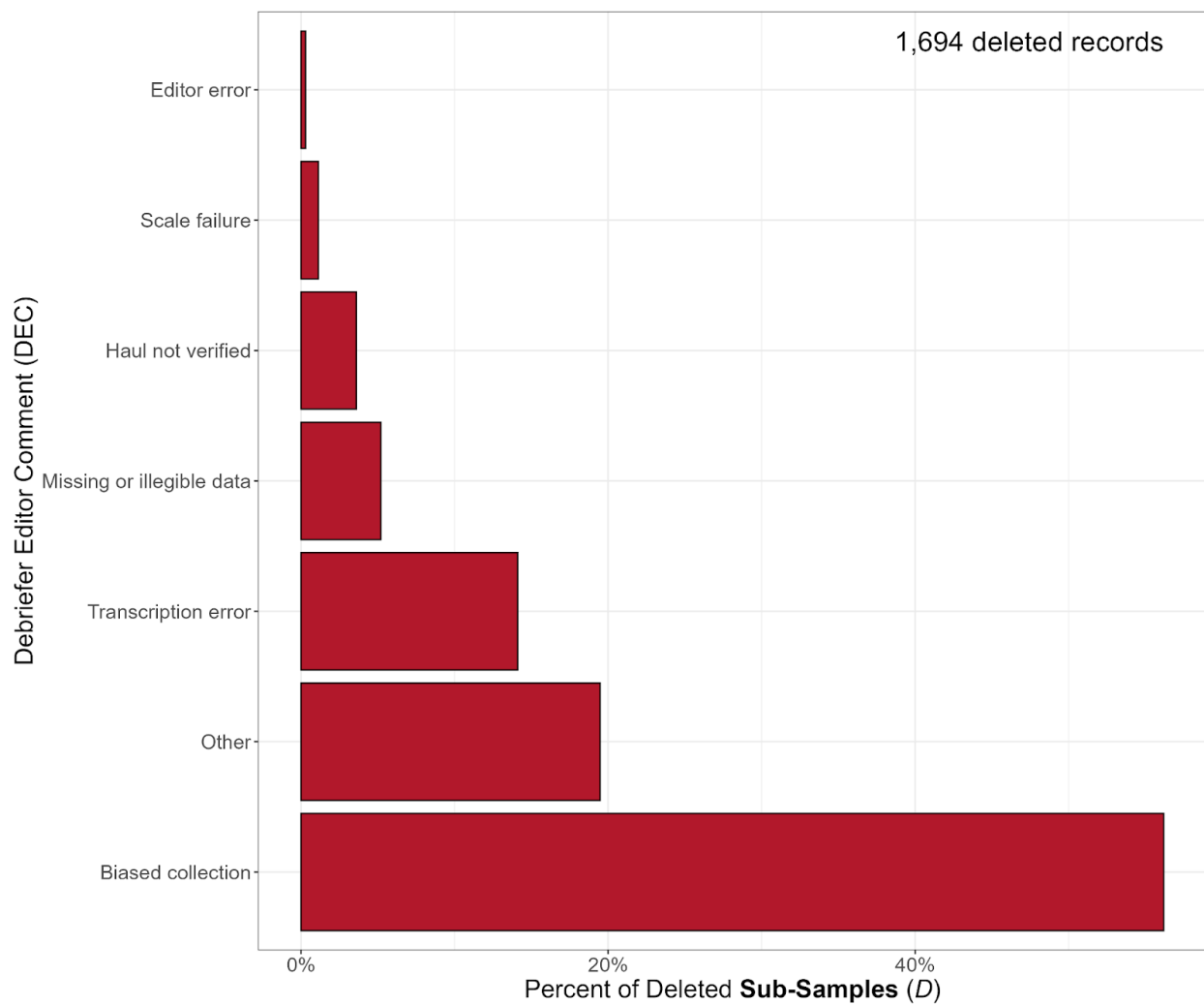
Appendix Figure A18. -- Percent of specimen records deleted during debriefing (*P*) by number of prior cruises (PC). Colors reflect the deletion source.



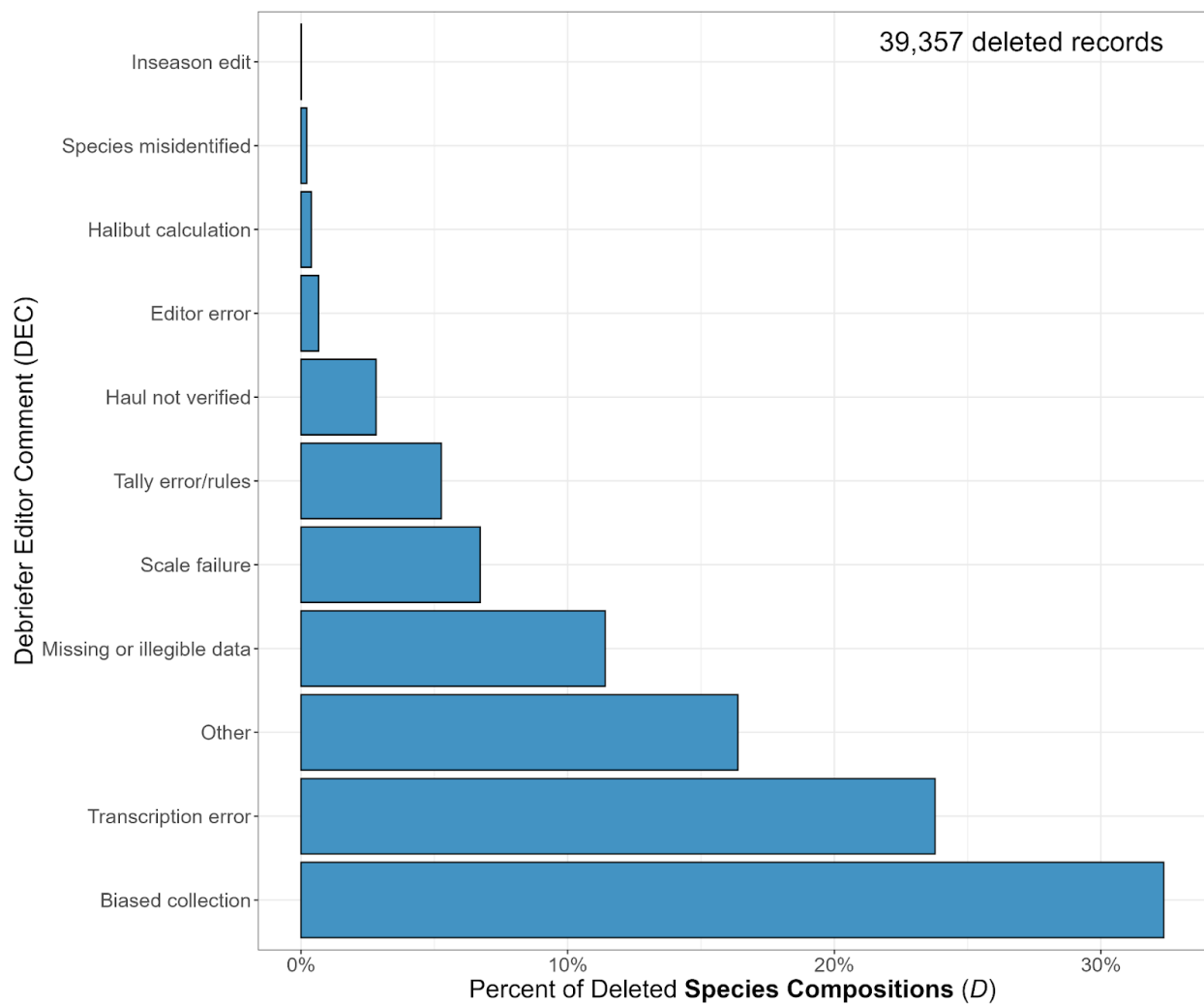
Appendix Figure A19. -- Percent of deleted haul records (*D*) by attributed DEC. The sum of deleted haul records with attributed DEC reasons is in the top right corner.



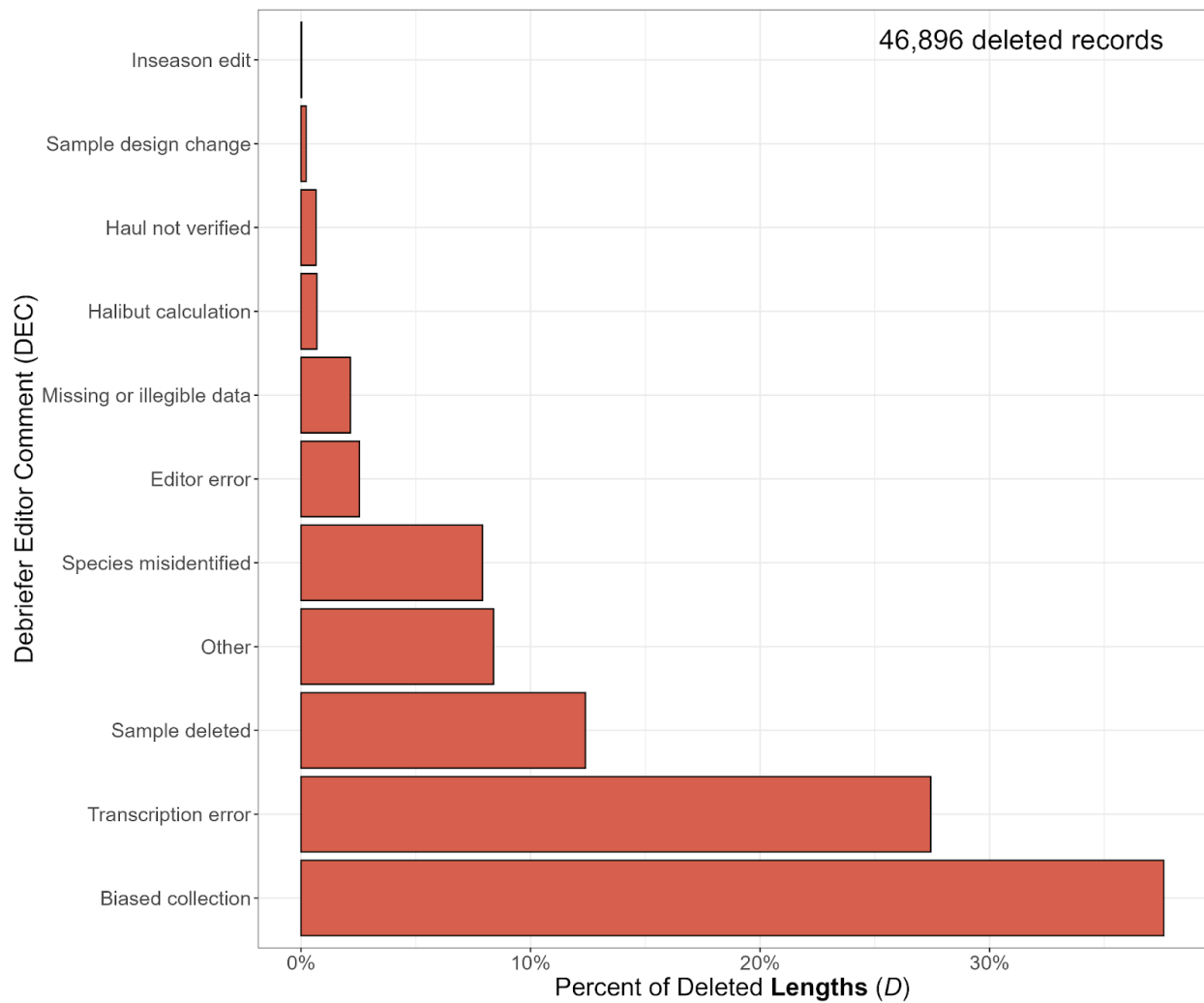
Appendix Figure A20. -- Percent of deleted sample records (*D*) by attributed DEC. The sum of deleted sample records* with attributed DEC reason is in the top right corner. *78 sample records were not attributed a DEC.



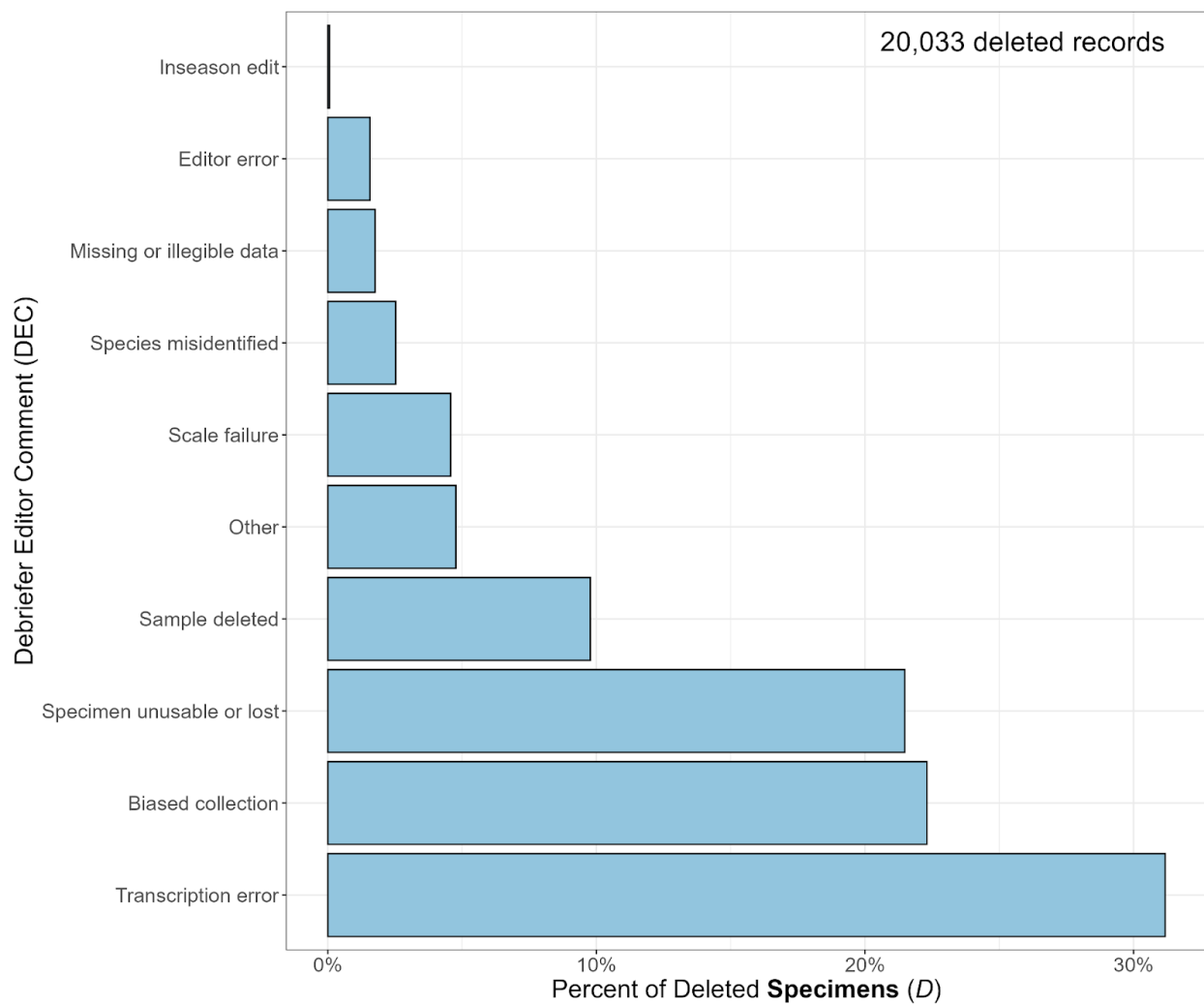
Appendix Figure A21. -- Percent of deleted sub-sample records (*D*) by attributed DEC. The sum of deleted sub-sample records with attributed DEC reason is in the top right corner.



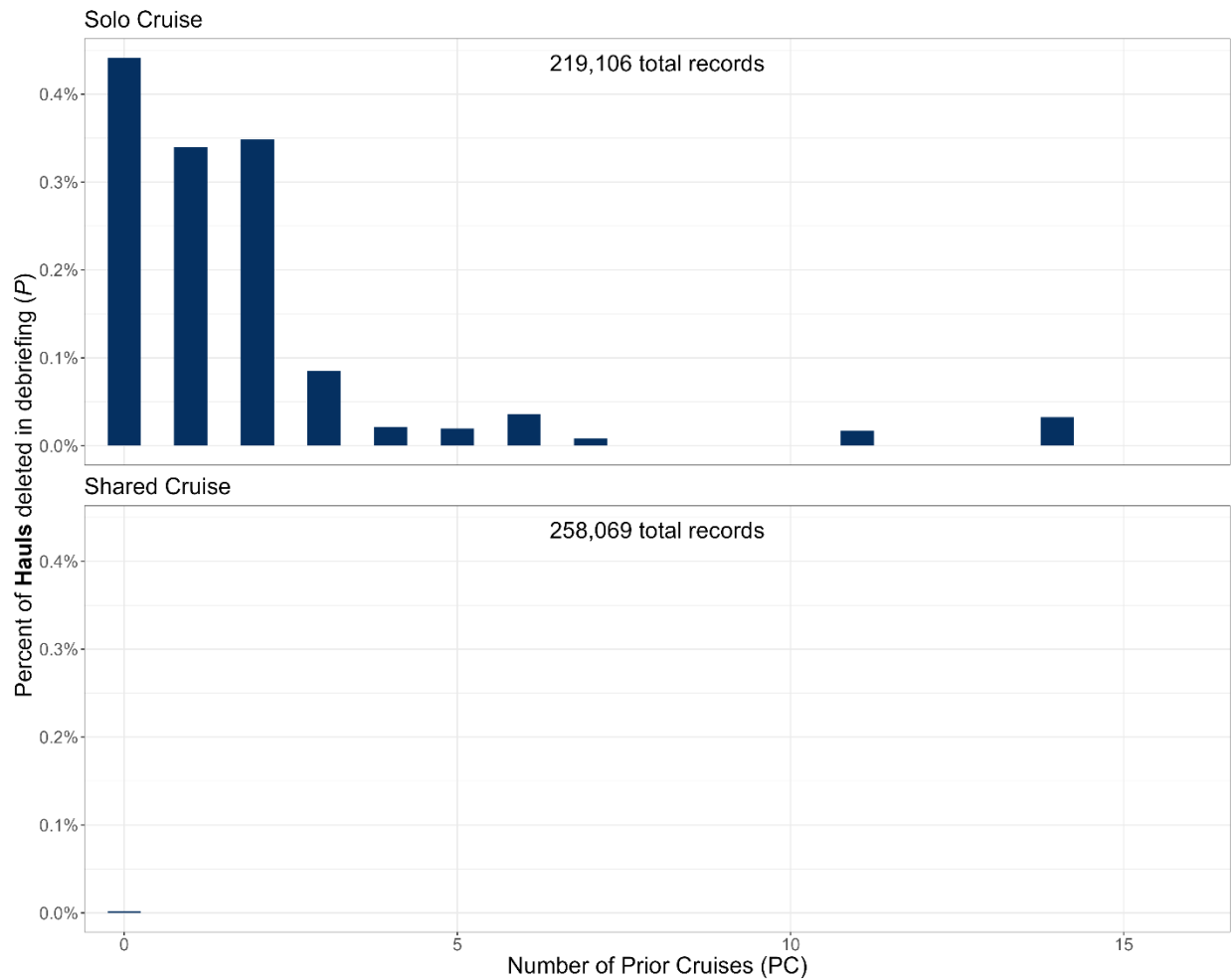
Appendix Figure A22. -- Percent of deleted species composition records (*D*) by attributed DEC. The sum of deleted species composition records* with attributed DEC reason is in the top right corner. *11 species composition records were not attributed a DEC.



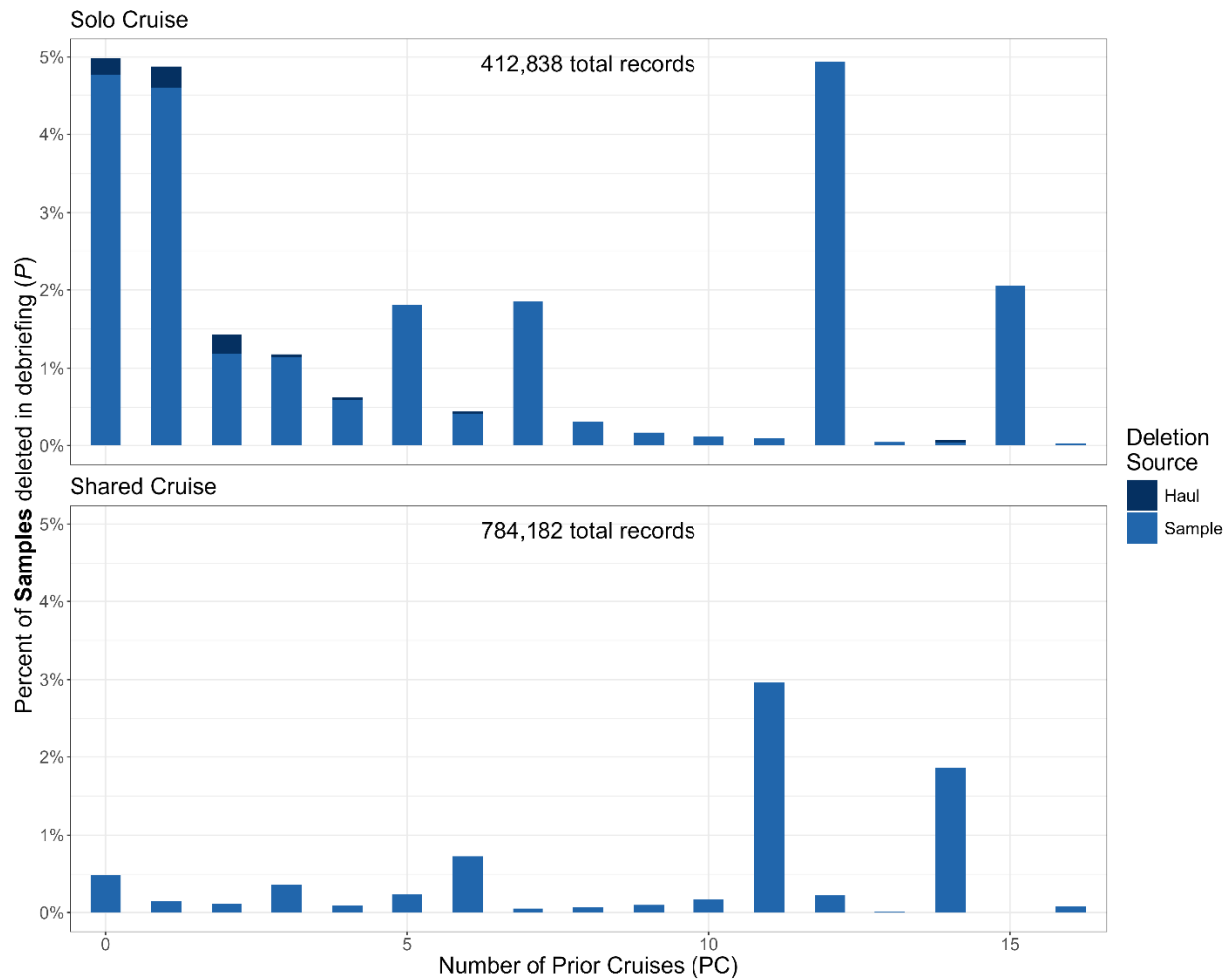
Appendix Figure A23. -- Percent of deleted length records (*D*) by attributed DEC. The sum of deleted length records* with attributed DEC reason is in the top right corner. *223 length records were not attributed a DEC.



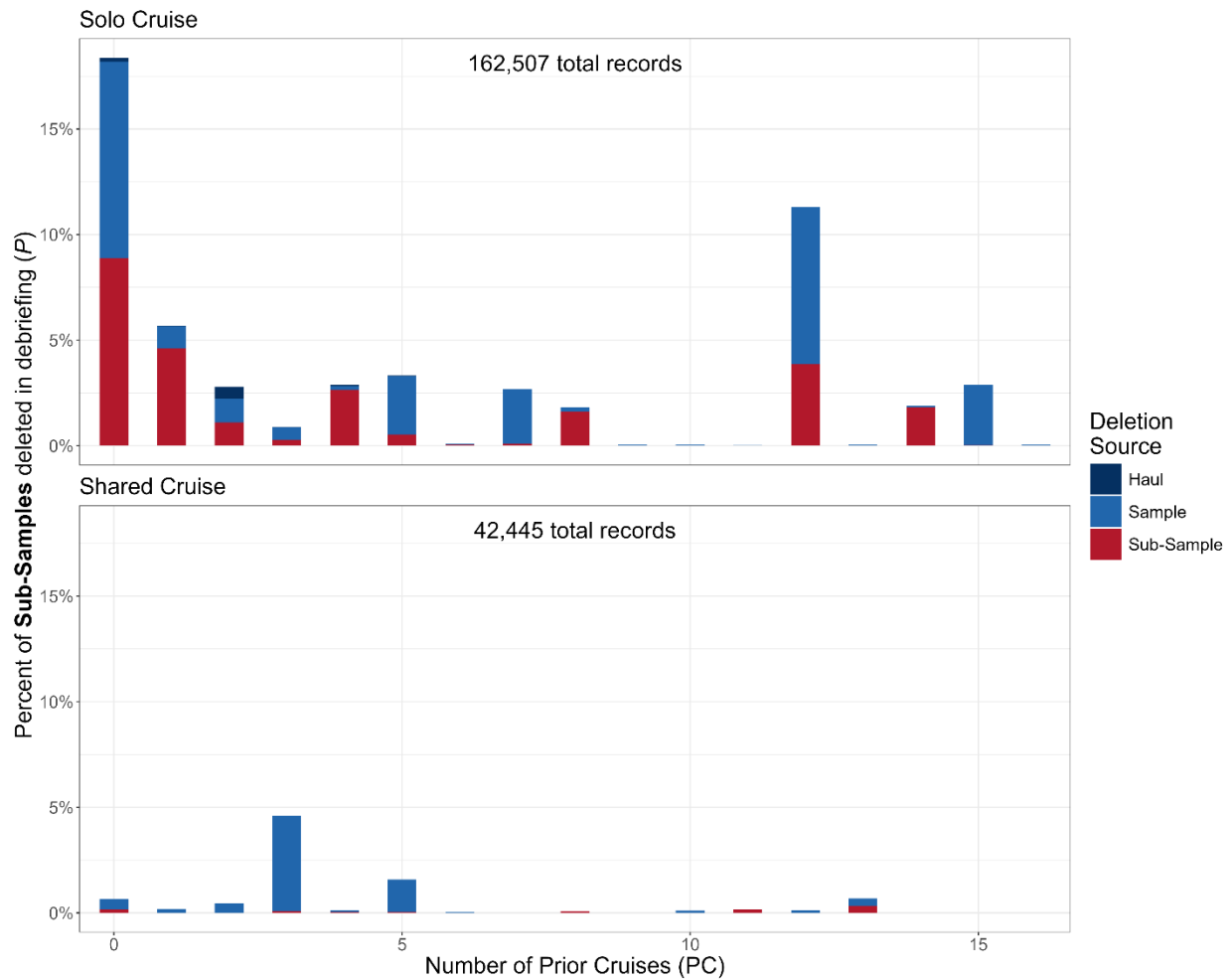
Appendix Figure A24. -- Percent of deleted specimen records (*D*) by attributed DEC. The sum of deleted specimen records with attributed DEC reason is in the top right corner.



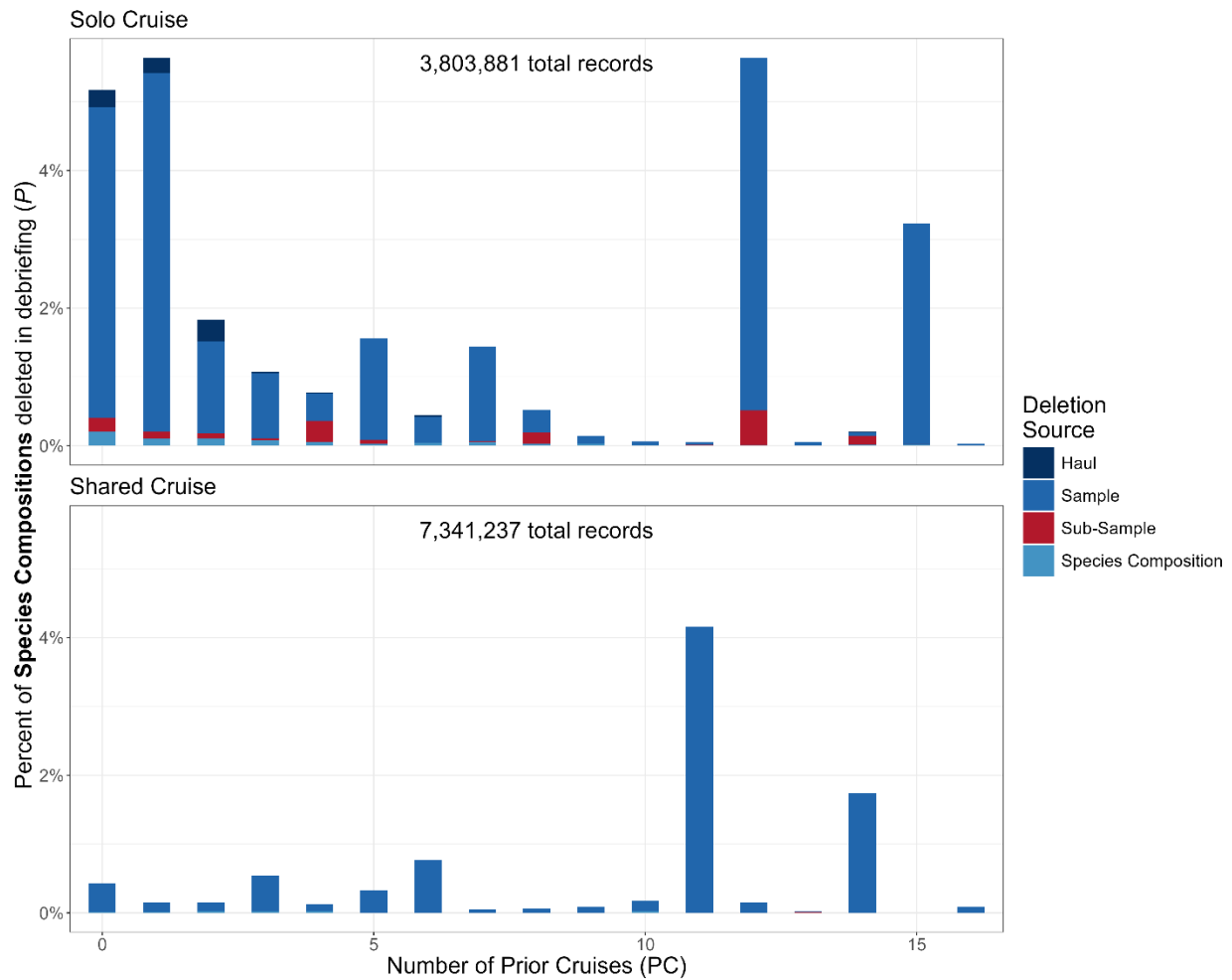
Appendix Figure A25. -- Percent of haul records deleted during debriefing (*P*) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. The sum of haul records within each cruise type is in the top of each panel.



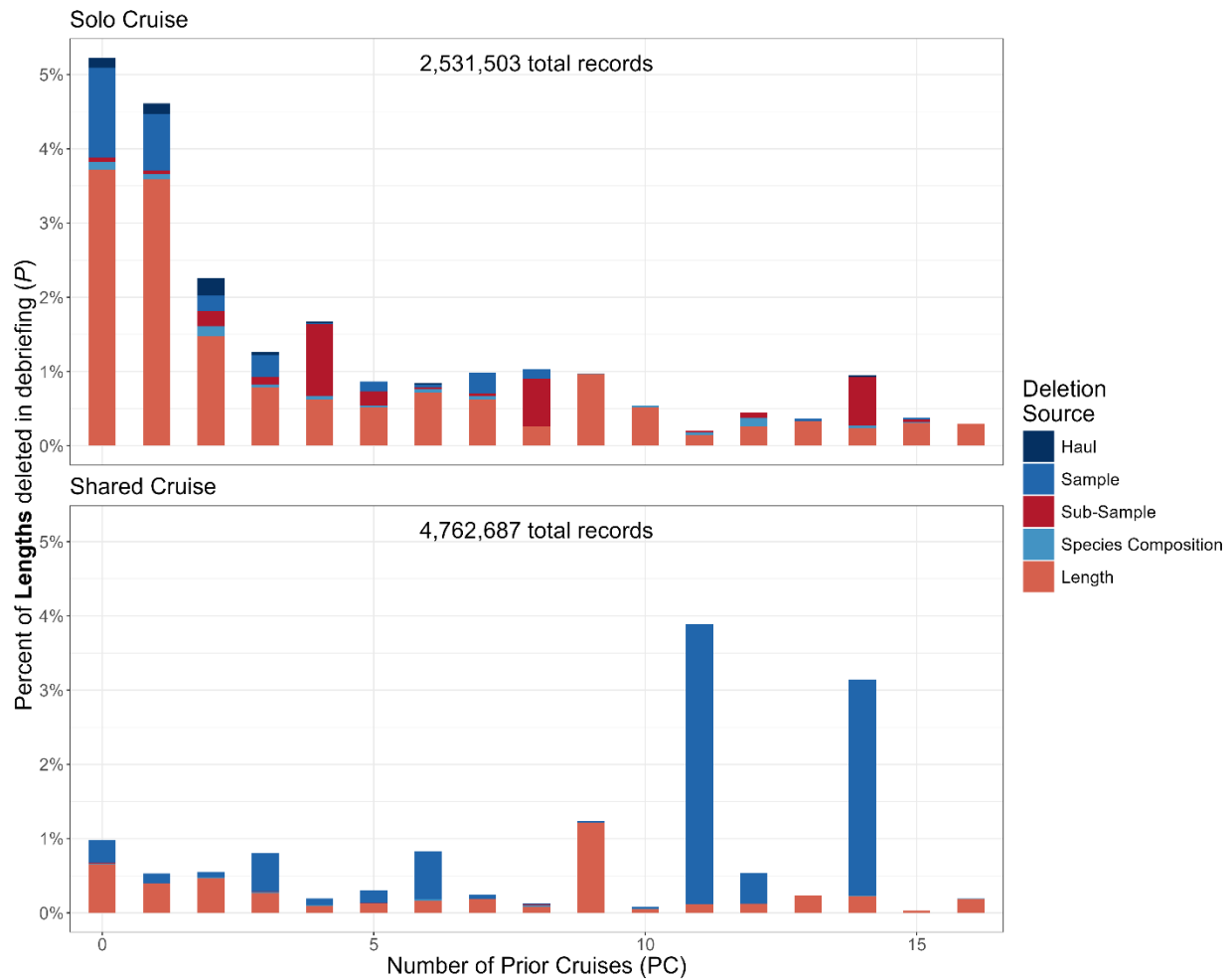
Appendix Figure A26. -- Percent of sample records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source. The sum of sample records within each cruise type is in the top of each panel.



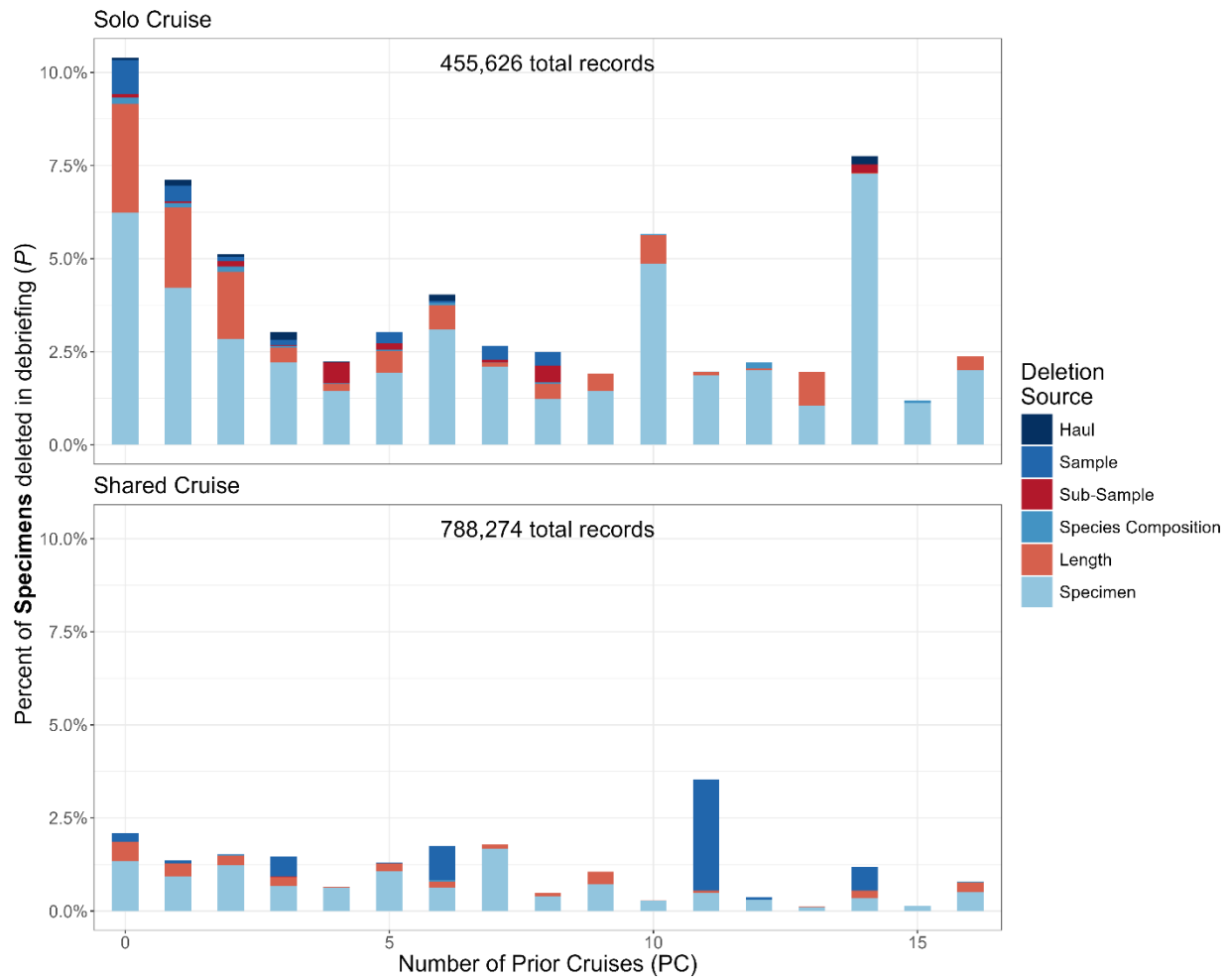
Appendix Figure A27. -- Percent of sub-sample records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source. The sum of sub-sample records within each cruise type is in the top of each panel.



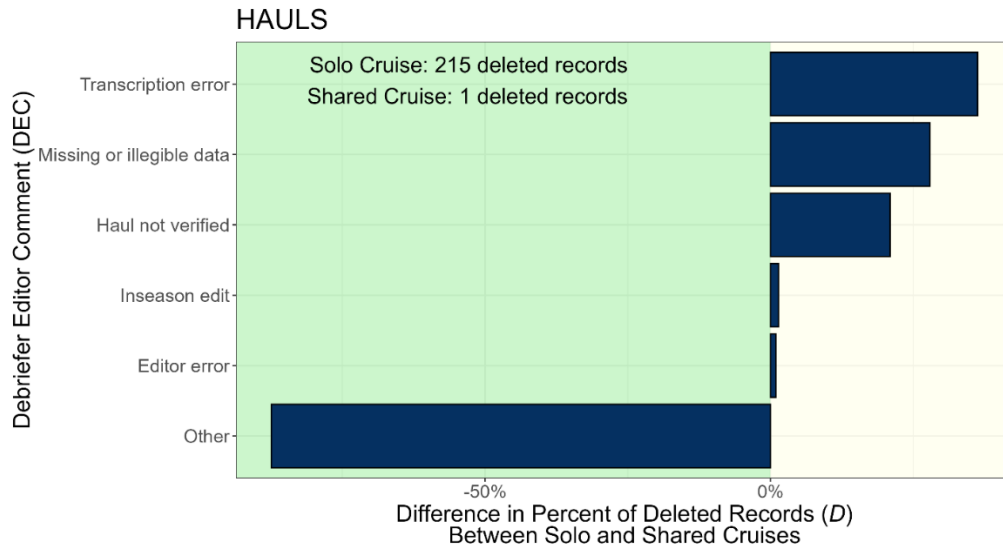
Appendix Figure A28. -- Percent of species composition records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source. The sum of species composition records within each cruise type is in the top of each panel.



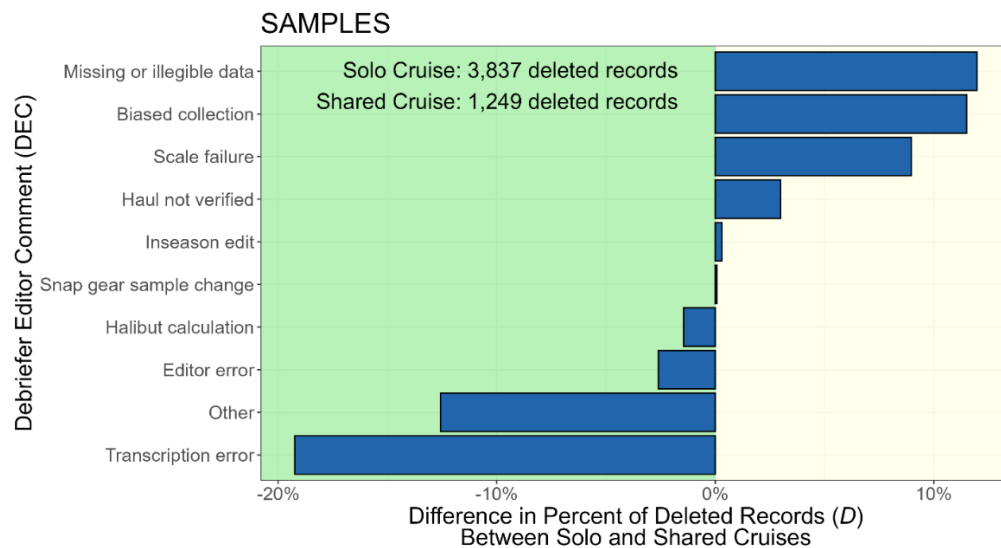
Appendix Figure A29. -- Percent of length records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source. The sum of length records within each cruise type is in the top of each panel.



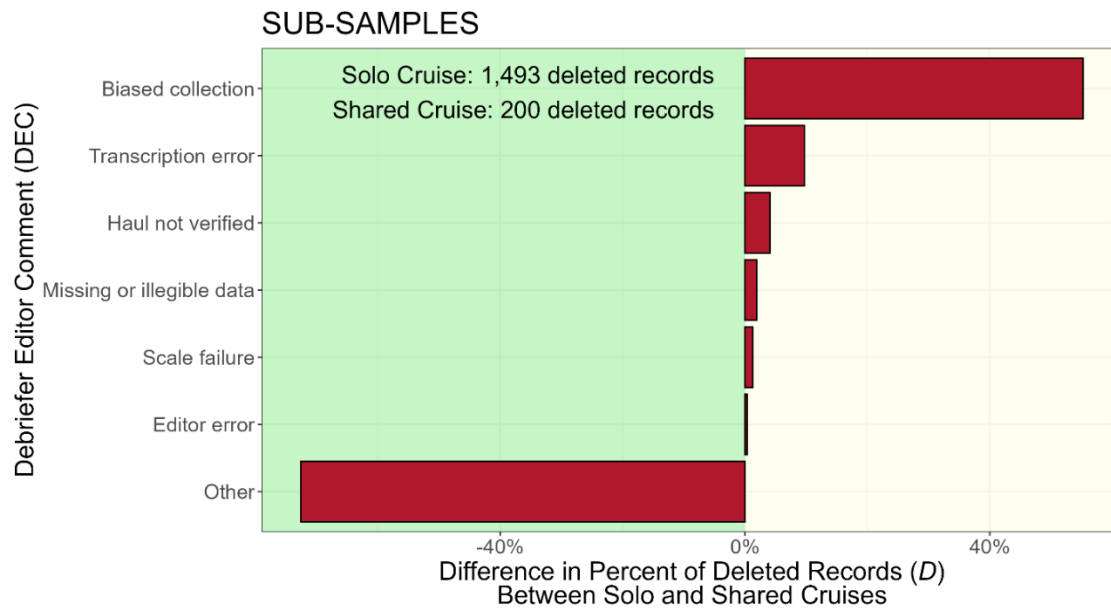
Appendix Figure A30. -- Percent of specimen records deleted during debriefing (P) by number of prior cruises (PC) split by whether the data was collected on (a) a solo cruise or (b) a shared cruise. Colors reflect the deletion source. The sum of specimen records within each cruise type is in the top of each panel.



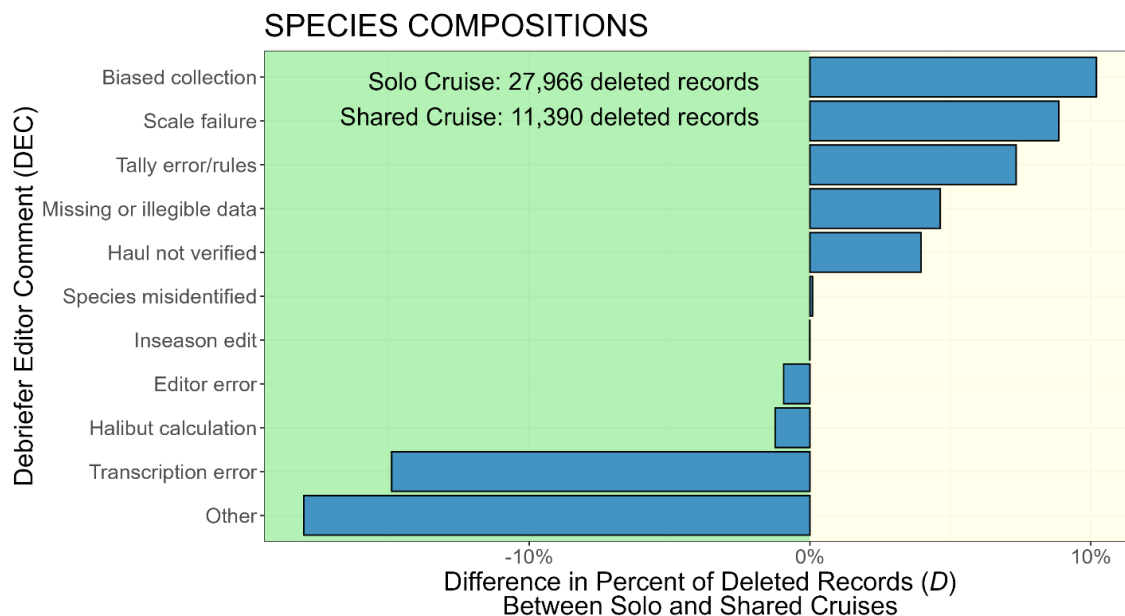
Appendix Figure A31. -- Difference in percent of deleted haul records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



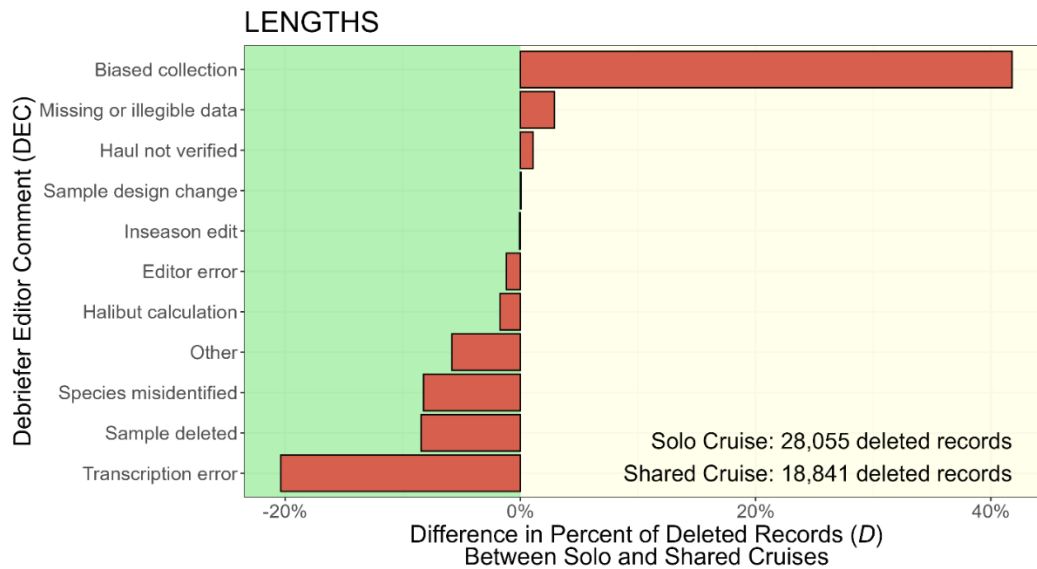
Appendix Figure A32. -- Difference in percent of deleted sample records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



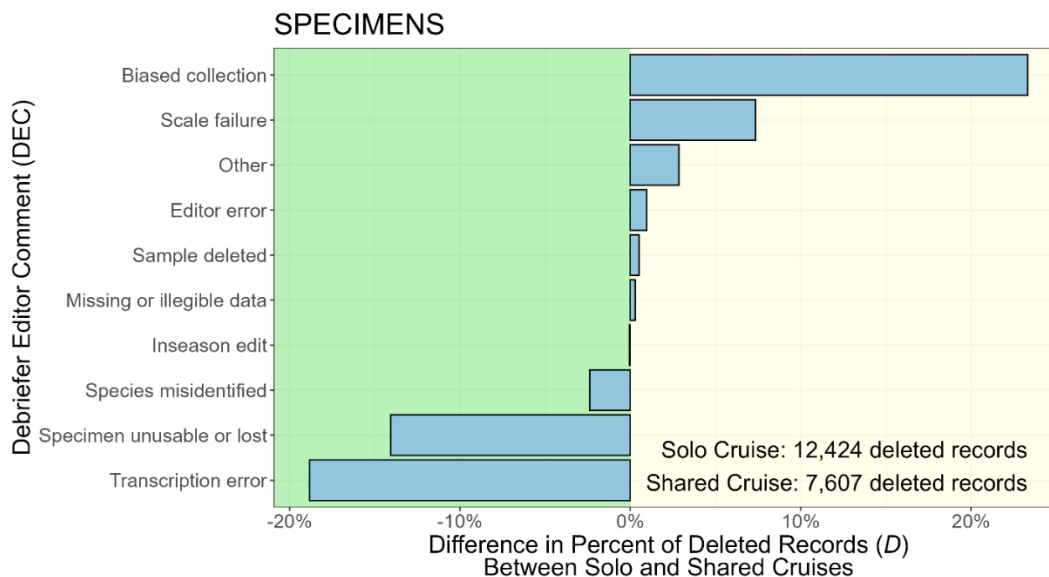
Appendix Figure A33. -- Difference in percent of deleted sub-sample records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



Appendix Figure A34. -- Difference in percent of deleted species composition records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



Appendix Figure A35. -- Difference in percent of deleted length records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



Appendix Figure A36. -- Difference in percent of deleted specimen records (*D*) among DEC reasons between solo and shared cruises. Bars extending to the left, appearing in the green-shaded region, indicate DEC attributed reasons proportionally more often on shared cruises than solo cruises. Bars extending to the right, appearing in the yellow-shaded region, indicate DEC attributed reasons proportionally more often on solo cruises than shared cruises.



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July 2025

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