**Echopype: A Python library for interoperable and scalable processing of water column sonar data for biological information**

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**ABSTRACT**

High-frequency sonar systems deployed on a wide array of ocean observing platforms are creating a deluge of water column sonar data at an unprecedented speed from all corners of the ocean. Efficient and integrative analysis of these data, either across different sonar instruments or with other oceanographic datasets, holds the key to understanding the response of marine ecosystems to the rapidly changing climate. Here we present Echopype, an open-source Python software library designed to address this need. By standardizing water column sonar data from diverse instruments following a community convention and utilizing the widely embraced netCDF data model to encode sonar data as labeled, multi-dimensional arrays, Echopype facilitates intuitive, user-friendly exploration and use of sonar data in an instrument-agnostic manner. By leveraging existing open-source Python libraries optimized for distributed computing, Echopype directly enables computational interoperability and scalability in both local and cloud computing environments. Echopype’s modularized package structure further provides a conceptually unified implementation framework for expanding its support for additional instrument raw data formats and incorporating new data analysis functionalities. We envision the continued development of Echopype as a catalyst for making information derived from water column sonar data an integrated component of regional and global ocean observation strategies.
1 INTRODUCTION

Active sonar systems are the workhorse for observing physical, biological, and geophysical features associated with the ocean due to their unique ability to collect data continuously at a wide range of resolution in time and space (Medwin and Clay, 1998). For measuring biological scatterers such as fish and zooplankton in the water column, decades of research since the 1970s have culminated in the regular use of scientific echosounder systems as a survey tool for fisheries and marine ecological research (Stanton, 2012).

The recent successful integration of active sonar systems on a wide variety of ocean observing platforms (e.g., Suberg et al., 2014; Moline et al., 2015; Chu et al., 2019) and the broader availability of broadband echosounders and multibeam systems (e.g., Colbo et al., 2014; Demer, et al., 2017) have created a deluge of ocean sonar data. From ships and moorings to autonomous surface and underwater vehicles, large volumes of data have been accumulating at an unprecedented speed from all corners of the ocean, including previously inaccessible remote regions and the deep sea. As an example, the volume of water column sonar data archived by the NOAA National Centers for Environmental Information (NCEI) in the U.S. (Wall et al., 2016) is over 280 TB at the time of writing (March 2024) and continues to grow at an accelerated rate. However, despite the dramatically expanded data collection capability, the fisheries acoustics and the broader ocean sciences communities are just at the early stages of unlocking the full potential of these extensive datasets.

A root cause of this problem is the lack of interoperable and scalable data workflows, which are key to handling the rapidly increasing data volume and enabling integrative use of sonar data in multidisciplinary oceanographic research. Across the broad spectrum of sonar systems, the highly heterogeneous binary data files are tedious to “wrangle” together to deliver a coherent observational dataset (Figure 1). Specifically, data storage formats differ significantly depending on the manufacturer and instrument model, signals used (e.g., broadband vs narrowband), and primary observation targets (e.g., fish in the water column vs seafloor). The processing and analysis workflow (e.g., Fleischer et al., 2012) typically involves a multi-stage procedure that requires transferring data across software systems designed to be used primarily through a Graphical User Interface (GUI) or via an Application Programming Interface (API). Different elements of a data workflow therefore can be hard to combine into a pipeline. In addition to issues with repeatability of the procedure and reproducibility of the results, the ingrained complexity and tedium has impeded efficient exploration of large datasets and increased cost associated with human resources and training. Furthermore, as the majority of commonly used software packages are closed-source or written in proprietary languages (Table 1), agile adjustments and rigorous verification of computational implementations remain challenging. While a number of open-source software packages were developed recently in the context of acoustics-based fisheries surveys (Perrot et al., 2018; Wall et al., 2018; Ladorit et al., 2020; open-ocean-sounding, 2021), none is currently able to interface directly with scalable data
storage formats or distributed computing resources that fully leverage the architecture of cloud computing platforms (Vance et al., 2019) and fully support community data conventions. These capabilities are crucial for broadening the use of sonar data beyond the immediate fisheries acoustics and ocean acoustics community.

In this paper we present Echopype, an open-source Python software library that is designed to enable interoperable and scalable processing of water column sonar data for extracting biological information. In Sec. 2, we discuss the design philosophy of Echopype, detail the advantages of our approach to standardizing data before performing computation, and describe the package structure and current functionalities. In Sec. 3, we present two use case examples as cloud-hosted executable Jupyter Notebooks using publicly available data sources. In Sec. 4, we discuss the current adoption of Echopype, its expansion flexibility, and the next stage of development goals. We conclude the paper by summarizing the contributions of Echopype to the fisheries acoustics, ocean acoustics, and broader oceanography community, both as an open-source software tool and as a community forum created through the publicly hosted online code repository.

Figure 1. A side-by-side comparison of data characteristics before (A) and after (B) the dramatic enhancement of data collection capability. Blocks of different colors represent data collected by different instruments.
Table 1. Comparison of Echopype with other popular software packages for processing water column sonar data.

| Software package | Echopype | EchoView | LSSS | ESP3 | Echolab/PyEcholab |
|------------------|----------|----------|------|------|-------------------|
| Language         | Python   | C++      | Java | Matlab (proprietary) | Matlab/Python |
| License          | Open source (Apache 2.0) | Proprietary | Proprietary | Open source (MIT) | Open source (MIT) |
| Operating system | Cross-platform | Windows | Windows, Linux | Cross-platform | Cross-platform |
| Primary user interface | Programmatic API | GUI | GUI | GUI | Programmatic API |
| Supported file types | Simrad .raw AZFP .01A Nortek .ad2cp | Simrad .raw AZFP .01A | Simrad .raw | Simrad .raw | Simrad .raw |
| SONAR-netCDF4 support | Read/Write* | Read/Write** | Read | No | No |
| Cloud-native data storage | Yes | No | No | No | No |
| Out-of-core computation | Yes | Unclear | Yes (memory mapping) | Yes (memory mapping) | No |

* Echopype reads and writes .nc files following an adaptation of SONAR-netCDF4 convention v1.0. See Sec. 2.2.2 for detail.
** Echoview currently supports reading .nc files from specific Simrad and Furuno omnisonars and a specific Furuno split-beam echosounder and exporting data derived from a specific Furuno omnisonar (Echoview, n.d.).

2 THE ECHOPYPE PACKAGE

2.1 Design philosophy

The goal of Echopype is threefold: 1) to democratize the access and analysis of water column sonar data through implementation and computation based on a community-defined, standardized data convention; 2) to liberate scientists from the tedium of data wrangling by providing a platform-independent, uniform programmatic interface; and 3) to directly interface with the vastly scalable computing power of the cloud. To achieve this goal, we develop a workflow that focuses first on standardizing data to the widely supported netCDF (Network Common Data Form, Rew and Davis, 1990; Unidata, n.d.) data model and related file formats. We then use the standardized data to build computation and visualization routines that leverage
open-source Python libraries maintained by the broad scientific computing community, especially those optimized for distributed computing (Figure 2). This design allows Echopype to adapt flexibly to both local and cloud computing environments (see Sec. 2.2.3 for detail) and ensures its natural continuing evolution with state-of-the-art computing technologies.

The netCDF data model is widely supported in the marine and earth sciences communities, which automatically enables Echopype’s capability to perform out-of-core computation on both local high-performance computing resources and the commercial cloud (Hoyer and Hamman, 2017; Abernathey et al., 2018). The self-describing and portable nature of this data model further promotes understanding and use of water column sonar data by the wider oceanography and geoscience community. To our knowledge, Echopype is currently the only software package that supports both reading from and writing to data files following the International Council for the Exploration of the Sea (ICES) SONAR-netCDF4 v1.0 convention (Macaulay and Peña, 2018) for scientific echosounder systems and directly interfaces with data access, storage and computation on the cloud (Table 1).

**Figure 2.** The Echopype workflow. Echopype generates standardized data represented in a netCDF data model by converting raw data collected by the sonar systems and incorporating metadata and other ancillary data following the SONAR-netCDF4 convention v1.0. The ancillary data include environmental parameters and platform position (e.g., GPS) and movements (e.g., roll, pitch, heave) that may not be included in the raw data files. Once the standardized data are calibrated into physical quantities (e.g., volume backscatter strength, or Sv), the data are represented as generic and flexible Xarray datasets.
2.2 Standardized data for interoperability and scalability

2.2.1 Data standardization

Echopype enables data interoperability across different sonar instruments and between the sonar data and other oceanographic datasets through the data standardization step at the first stage of its workflow (Figure 2). This involves parsing raw instrument files, organizing and converting the raw instrument-generated data to conform with the ICES SONAR-netCDF4 v1.0 convention (Macaulay and Peña, 2018). Similar to many data conventions in geosciences, the convention leverages the netCDF data model and the associated Climate and Forecast (CF) conventions (Hassell et al., 2017; CF Metadata Conventions, n.d.), including their standardized structures for multi-dimensional data, attributes, and logical groups of data and metadata. This “netCDF-CF” data model, file format and conventions have been widely embraced by the physical and biogeochemical ocean communities over the last two decades (Snowden et al., 2019; Tanhua et al., 2019).

Raw data encoded in a SONAR-netCDF4 dataset or file represent one sonar instrument on one platform, potentially encompassing an entire survey or deployment. The data are organized into seven netCDF4 groups, with components defined as mandatory, recommended or optional. SONAR-netCDF4 is a convention for the storage and exchange of fisheries sonar data and associated metadata, focused initially (v1.0) on raw backscatter and ancillary data from ship-mounted, omni-directional sonars. Additional data variables and changes were introduced in the recent v2.0 update to provide support for echosounder and ADCP data. Due to the timing mismatch that the majority of Echopype development on data standardization preceded the introduction of v2.0, the Echopype data structure primarily follows the v1.0 definitions but are augmented with modifications to enable a gridded data structure at the level of raw data (see Sec. 2.2.2) and adopting 2.0 names for data variables not present in v1.0. We anticipate continuing updates to the Echopype converted raw data structure as the convention evolves, and plan to develop converters between major versions in the future.

For processed data beyond the raw data level, such as volume backscattering strength (Sv, unit: dB re 1 m⁻¹) resulting from system calibration, Echopype currently uses netCDF data representations with sparser metadata and ancillary data, such as critical calibration and environmental parameters used to produce Sv. The Australia Integrated Marine Observing System (IMOS) Ships of Opportunity Bio-Acoustic (SOOP-BA) program has published a well described implementation of processed data (Kunnath et al., 2018). In the ICES community, a Gridded group was introduced in SONAR-netCDF4 v2.0 to accommodate processed data with specific dimension definitions. Even though processed datasets generated by Echopype do not strictly adhere to these definitions at the moment, the major data dimensions are similar and the differences are self-explanatory, due to the generality in water column sonar data use cases. Specifically, the v2.0 Gridded group data variable integrated_backscatter has coordinate dimensions (ping_axis, range_axis, frequency), which map to
Echopype coordinate dimensions \((\text{ping\_time}, \text{echo\_range}, \text{channel})\) in the calibrated \(Sv\) datasets. With the ongoing development of SONAR-netCDF4 and the possible emergence of new conventions for processed data, we plan to continue incorporating elements of the v2.0 definitions in the near future, and gradually update the processed data format in response to new developments.

Echopype leverages the functionality of the Xarray package (Hoyer and Hamman, 2017) to natively handle data structured following the netCDF data model as either in-memory objects or disk- or cloud-stored datasets. The in-memory form of the converted raw data is encoded in the \texttt{EchoData} object that enables convenient inspection and access of the tree-like group structure defined by the SONAR-netCDF4 convention (Figure 3). The processed data are standard Xarray datasets \texttt{(xr.Dataset)}. Both the \texttt{EchoData} object and the Xarray datasets can be serialized to netCDF4 or Zarr files directly on a local or remote (e.g., cloud) file system. Specifically, Zarr is a format for storing chunked, compressed, multi-dimensional arrays (Zarr, n.d.) that is compatible with the netCDF data model and optimized for cloud object storage and computation (Abernathy \textit{et al.}, 2018; The NetCDF NCZarr Implementation, n.d.). See Sec. 2.2.3 for more information about the Zarr and Xarray libraries and formats.
Figure 3. An example rendering of the EchoData object that makes it convenient to inspect and access converted raw data structured according to the Echopype adaptation of the SONAR-netCDF4 convention. The dataset rendered here was from a Kongsberg Simrad EK80 echosounder configured to collect both complex and power-angle samples. See the Echopype package documentation for other examples.
2.2.2 Structure of converted raw data

For converted raw data, Echopype implements a modification to the SONAR-netCDF4 convention v1.0 definitions to optimize data access and filtering (“slicing”) efficiency and usability by organizing potentially ragged data records into a gridded structure. This modification predated the development of the Gridded group in the v2.0 convention.

The v1.0 convention defines acoustic data variables, such as `backscatter_r`, based on a one-dimensional ragged array structure (Figure 4A) that uses a custom variable-length vector data type (sample_t) and ping_time as its coordinate dimension. While there is no direct match in the v1.0 definition for echosounder transducer channels, based on the definition that data from different beam modes of an omni-directional sonar are stored in subgroups (Beam_group1, Beam_group2, ...) under the Sonar group, a reasonable choice is to map each transducer channel to a separate subgroup.

Echopype restructures this multi-group ragged array representation into a single-group, multi-dimensional gridded representation (Figure 4B) by introducing two new coordinate dimensions, range_bin and channel. Data from different transducer channels are mapped along the new channel dimension, and data from each ping found in a sample_t vector in the convention are mapped along the new range_bin dimension. The potentially uneven number of samples along range across pings or different transducer channels is addressed by padding with NaN (Not a Number), resulting in a gridded structure across all dimensions. This data storage variant can be losslessly transformed into the contiguous ragged-array form defined in the convention and is equivalent to the CF convention's “incomplete multi-dimensional array” feature type (Eaton et al., n.d.). In practice, we have found that the NaN-padded data are compressed efficiently and do not incur substantially larger storage footprints.

In Echopype, the dimension and coordinate name channel is used rather than frequency to accommodate configurations in which multiple transducers of the same nominal frequency are used, because 1) duplicate values in a coordinate is not allowed, and 2) it is inaccurate to describe echo data from broadband transmissions using a single frequency. We added a new data variable `frequency_nominal` to capture the nominal operating frequency of a given transducer channel that is often referred to by fisheries acousticians.

Note that Echopype interprets the convention v1.0 definition of the coordinate dimension beam that represents different sonar beams as comparable to different sectors of split-beam transducers. Currently, this beam dimension is present only when such data are available, for example when complex samples are recorded for Kongsberg Simrad EK80 echosounder. In other cases, this dimension is implicit (not present). A new coordinate dimension subbeam was introduced in convention v2.0 to allow storing data from split-beam transducers, and its use is equivalent to the Echopype beam dimension described here.
Figure 4. Representation of multi-dimensional sonar backscatter data. (A) The SONAR-netCDF4 convention defines a one-dimensional contiguous ragged array structure with different transducers channels in different groups, ping_time as the dimension (different colors), and along-range values encoded using the custom sample_t variable-length vector data type. (B) Echopype uses the “incomplete multidimensional array” representation of the CF convention, with transducer channels mapped along the channel dimension and along-range values mapped along the range_bin dimension, in addition to the original ping_time dimension. Shorter pings are padded with NaN values (gray). Note that the beam dimension for split-beam transducers is not shown in the example sketched here. See text for details about the dimensions and CF array representations.

2.2.3 Interoperability and scalability

Echopype’s approach to standardizing raw and processed active acoustic data using the widely used, self-describing netCDF data model facilitates intuitive, user-friendly exploration and use of data in an instrument-agnostic manner. This standardization directly enables computational interoperability and scalability through leveraging three tightly-coupled open-source Python libraries for distributed computing: Zarr, a library that implements the cloud-optimized Zarr storage format (Zarr, n.d.); Xarray, a library for manipulating multi-dimensional labeled data (Hoyer and Hamman, 2017); and Dask, a library for parallel computing (Dask, n.d.). These libraries are designed such that code developed for local machines can be directly used with a scalable cyberinfrastructure, such as the commercial cloud, without the need to reorganize datasets or rewrite algorithms. Specifically, chunked and compressed Zarr datasets can be read and computed directly via Xarray, which transparently leverages Dask for distributed computation and task scheduling. The label-aware capability of Xarray significantly reduces the cognitive load for implementing algorithms that compute on multi-dimensional data with physically meaningful coordinates, such as frequency, time, range, and geographical location, all typical for sonar datasets.

We strive to implement all data interfacing and processing functions in Echopype to take advantage of the computational scalability offered by these libraries that allows researchers to
easily understand a given function. In practice, we have found that water column sonar data are often irregularly structured in time and space, and therefore require custom optimization beyond stock Xarray functions to parallelize efficiently across computing agents. The combination of using Dask to distribute pre-specified (“delayed”) computation on organized Zarr data that are loaded only when necessary (“lazy-loaded”) has been particularly powerful in enabling out-of-core computation of datasets that are larger than the immediately accessible system memory and for distributing computation to a cluster (Bednar and Durant, 2023).

2.3 Software engineering practices

The Echopype software package has been developed with software engineering best practices in mind to ensure robustness and maintainability of the software, including coding best practices, modular design, extensive tests, and continuous integration and deployment (CI/CD). Echopype follows the PEP8 style guidelines for writing Python code (PEP 8, n.d.), which enhances the codebase readability and cleanliness, making it easier for members of the community to understand and contribute. To ensure adherence to these guidelines, an automated framework using pre-commit and pre-commit.ci (pre-commit.ci, n.d.) are in place, which executes a set of validations before a new piece of code can be added to the codebase. The modular design of the Echopype package structure further makes it easily extensible to support additional instrument models and integrate new data processing functionalities. To ensure robustness of the software, an extensive number of tests have been written using both real instrument-generated data files and mock data (simulated data that mimics real data). The tests include both unit and integration tests that can be run locally as the codebase is being developed or within the Github Actions automated system as soon as changes to the codebase are uploaded to the online repository. This automated system also handles the building and distribution of the Echopype package to the Python Packaging Index (PyPI) (PyPI, n.d.) and on the conda-forge community channel (Conda-forge, n.d.) for use with the Conda package manager. Further, to support productive collaborative development, engagement of new contributors, and timely user updating, the project has adopted public milestones and issue tracking through Github’s project management tools, and a Development Roadmap page in the documentation.

2.4 Package structure and functionalities

The Echopype package is platform-independent and can be easily installed via PyPI or the Conda package manager via the conda-forge community channel. The package is hosted and continues to be actively developed in a GitHub repository (https://github.com/OSOceanAcoustics/echopype) under the open-source Apache 2.0 license. Current functionalities and usage examples are detailed in the package documentation.
Therefore, rather than providing a detailed enumeration of Echopype functionalities that will continue to change and expand, here we opt to provide conceptual groupings of functionalities that can be stacked to form an automated data processing pipeline. As the foundational data standardization components of Echopype mature, we plan to redirect our attention to focus on expanding downstream processing functionalities and computing scalability in the next stage of development (see details in Sec. 4).

2.4.1 Data conversion

The Echopype `convert` subpackage provides the functionality to parse and convert instrument-specific binary data files into a standardized representation, the `EchoData` object, consisting of both data and metadata following the Echopype adaptation of the SONAR-netCDF4 convention (see Sec. 2.2.1). The `EchoData` object can be readily serialized into netCDF4 or Zarr file formats, and also provides functions (through Python object methods) to incorporate ancillary information, such as geographical locations, if they do not already exist in the raw data files or require updates. The data read and write functionality are compatible with both local (e.g., hard drives) and remote file systems, including cloud object storage (e.g., Amazon Web Services S3).

Beyond the conversion of individual files, we devised a `combine_echodata` function that allows combining multiple `EchoData` objects, each from a raw data file, into a single combined `EchoData` object, making it possible to coalesce data from numerous individual raw files into larger, meaningful entities depending on the data collection mission. For example, thousands of raw files from a fishery survey can be organized into only tens of `EchoData` objects, each representing a single survey transect; long-term time series from a mooring can be organized into `EchoData` objects on a weekly or monthly basis. Similar to the use of EV files in Echoview to group and index raw data files, such organizational simplification can dramatically alleviate the burden of data wrangling, allowing researchers to focus on the analysis of logically grouped echo datasets.

At present, Echopype supports converting binary data files generated by the following systems: Kongsberg Simrad EK60, EK80, Kongsberg EA640 and similar echosounders (e.g., the ES family of echosounders), and ASL Environmental Sciences Acoustic Zooplankton and Fish Profiler (AZFP). Conversion is also possible for data from the Nortek Signature series ADCP, but the structure of the resulting `EchoData` object requires further changes to be fully consistent with those from other sonar models.

2.4.2 Calibration

Acoustic data recorded by sonar instruments typically requires additional unit conversion and calibration to arrive at physically meaningful quantities (e.g., Sv) that can be used directly in oceanographic and geophysical research (Simmonds and MacLennan, 2007; Demer et al., 2015). This procedure is non-trivial and highly instrument-specific, constituting a barrier for broad
access and understanding for water column sonar data. The calibrate subpackage provides the functionality to perform this procedure. After calibration, the previously heterogeneous data records from diverse instruments could be intuitively understood and used by a wider range of users beyond experts in acoustics. Echopype currently supports $S_v$ computation for both narrowband (AZFP, EK60, and EK80 “CW” mode transmission) and broadband data (EK80 “FM” mode transmission).

2.4.3 Data consolidation and alignment
The calibrated echo data are often the most useful when bundled together with ancillary information that are crucial for acoustic data interpretation and other quantities that can be derived from the raw acoustic data. Geospatial locations such as the latitude, longitude, and depth of the platform are examples of the former; phase information or split-beam angles that can be computed from EK80 complex samples are examples of the latter. Echopype provides functionalities through the consolidate subpackage to enhance the coherence and binding of these additional variables with the calibrated echo data at the raw data resolution. Additionally, the commongrid subpackage provides functionalities to bring data from all transducer channels onto the same specified temporal and spatial grid, which is desired for many downstream processing routines, including machine learning applications (Ordoñez et al., 2022). One common such operation is to compute the mean volume backscattering strength, or MVBS, across ping time and range, which are commonly used to reduce data variability (MacLennan et al., 2002).

2.4.4 Data filtering and selection
Data filtering and selection are important components of common water column sonar data processing pipelines. Data filtering typically includes quality control steps that detect and handle erroneous data entries or noisy data. For example, small timestamp reversals occur occasionally for data from Kongsberg Simrad echosounders and should be corrected or removed; influence of background noise that is specific for each system can be estimated and mitigated; impulsive noise spikes from transmissions of other acoustic instruments, such as the acoustic Doppler current profilers (ADCPs) and leakage from other transducer channels, should be removed (e.g., De Robertis and Higginbottom, 2007; Ryan et al., 2015). Data selection, on the other hand, typically involves classifying and selecting parts of the echo data that result from specific scattering sources. For example, an echogram can be segmented into regions where aggregations of a target fish species are located and regions that are below the seafloor, using manual or automatic procedures (e.g., Jech and Michaels, 2006; De Robertis et al., 2010; Brautaset et al., 2020). At present, Echopype offers a limited set of data filtering and selection functions in the qc (quality control), clean (noise characterization and removal), and mask (simple frequency-based echo classification and masking) subpackages. Efforts to include additional functionalities are ongoing.
2.4.5 Other functionalities

In addition to the above functionalities that mostly fall under the umbrella of data engineering to enable broader and more flexible usage of data, Echopype also includes other subpackages that are collections of data analysis or utility functions, such as the metrics, utils, and visualization subpackages. We anticipate that these subpackage groupings will change as more data analysis functionalities are added to Echopype in the future. At present, the metrics subpackage contains functions to compute ping-by-ping summary statistics of echoes that are useful for obtaining a quick overview of large echosounder time-series (Urmy et al., 2012). The utils subpackage contains utility functions, such as those used for logging, maintaining data provenance, handling local and cloud paths, and specifying variable encoding, etc. The visualize subpackage contains simple plotting functions for users to take a static, “quick look” of the data and the widely used echogram-specific “EK500” colormap. Note that this subpackage is intended to be lightweight and does not support elaborate interactive visualization. Instead, we have created and continue to develop a separate software package, Echoshader, to provide configurable, interactive “widgets” for adaptive dashboarding (Echoshader, n.d.).

3 USE CASE EXAMPLES

In this paper we provide two executable examples (as Jupyter notebooks hosted on https://github.com/OSOceanAcoustics/echopype-examples) that demonstrate usage of Echopype in processing water column sonar data collected from a ship and by a mooring (Figure 5A-C). We recommend that Echopype be imported as ep as shown in these examples for consistency.

In the example involving ship data (Figure 5A-C; ms_PacificHake_EK60_cruisetracks.ipynb), we demonstrate the power of label-aware data manipulation in exploiting the multi-faceted sonar data based on the standardized netCDF data model. We show the workflow to access, select, and plot sonar data within a particular geographic region along the survey transect during The 2017 Joint U.S. and Canada Pacific Hake Integrated Acoustic and Trawl Survey (Northwest Fisheries Science Center, Fishery Resource Analysis and Monitoring Division, 2019). The data conversion operations directly interact with raw data stored on the cloud and export data locally to the cloud-optimized Zarr format. The process of matching the ship’s geographic position with sonar data is straightforward and transferable to other scenarios requiring slicing. Here, multiple EchoData objects are calibrated and regridded individually, before being combined together for visualization.

In the example involving mooring data (Figure 5D-F; ms_OOI_EK60_mooringtimeseries.ipynb), we demonstrate the cross-instrument interoperability enabled by Echopype. We align sonar data collected by an upward-looking echosounder installed on a moored mid-water platform with shortwave irradiance measured by a surface mooring to observe the impact of a solar eclipse on
the vertical migration behavior of zooplankton. Both instruments are maintained by the US Ocean Observatories Initiative (OOI). In a workflow similar to the one involving ship data, we generate standardized sonar data by interacting directly with the OOI Raw Data Archive (an HTTP server) and match the heterogeneous datasets again based on the data labels along the time dimension in this case. Different from the ship data example, here the `combine_echodata` function is used to combine multiple `EchoData` objects together into a single `EchoData` object, on which calibration and regridding were performed.

These examples show the ease of accessing, processing, exploring, and visualizing water column sonar data by combining Echopype with other commonly used open-source Python libraries in a single computational environment (the Jupyter Notebook). Specifically, Echopype facilitates direct access of data hosted on a flexible range of sources and alleviates the tedium of data wrangling across different software systems and datasets.

![Figure 5](image-url)

**Figure 5.** Summary of the example Jupyter notebooks using ship data (panels A-C) and mooring data (panels D-F). (A) Data flow and functions used to process ship data. Note that each `EchoData` object is calibrated and regridded individual before being combined for
visualization. (B) Locations of the processed ship transect (red and black lines) and the mooring (yellow star) off the Oregon coast. (C) Multi-frequency echograms along the selected portions of the ship transect (black). (D) Data workflow and functions used to process mooring data. Note that multiple EchoData objects are combined into a single EchoData object before calibration and regridding operations. (E) Shortwave irradiance showing the timing of the eclipse. (F) Echogram showing the zooplankton response to the dimmed sunlight. In the annotation, \texttt{ep: Echopype, xr: Xarray}.

4 DISCUSSION

In this paper we present the Echopype package designed for enabling interoperable and scalable processing of water column sonar data for biological information. By taking the approach to first standardize data following a community convention before downstream analyses and visualization, Echopype provides not only a uniform interface to read and process measurements from diverse sonar instruments but also a clearly defined path toward broadening the understanding and use of water column sonar data.

Echopype is being adopted rapidly by the fisheries acoustics and the wider oceanography communities. Since the package’s first release in early 2019, we regularly received bug reports and feature requests both in our GitHub repository and through private emails. The majority of bug reports were data parsing errors due to the flexible and evolving data format of the Kongsberg Simrad EK80 echosounder, whereas the majority of feature requests are for expanding support for data collected by other sonar instruments or adding other echosounder data analysis functionalities. In addition to individual users, the US OOI cyberinfrastructure services has incorporated Echopype into their processing pipeline for serving bio-acoustic sonar data products (OOI-CGSN, n.d.). These data products were previously unavailable due to the complexities associated with the specialized echosounder raw data formats and calibration needs. The NOAA NCEI Water Column Sonar Data archive has also incorporated Echopype into the backbone of their pipeline to generate a cloud-hosted Zarr data lake (Wall \textit{et al.}, 2023), which also feeds into a web visualization app (Wall \textit{et al.}, 2020). These examples show the broader impacts of Echopype and its design philosophy to handle diverse water column sonar data through a standardized format and an instrument-agnostic programmatic interface.

Echopype is well positioned to expand its functionalities under the goals of interoperability and scalability. The package structure is modularized and provides a conceptually unified implementation framework for: 1) adding support for additional raw instrument-generated data formats from other echosounders, and 2) incorporating additional data processing and analysis methods downstream of the standardized data in a transparent manner, as instrument-agnostic function calls. With the maturation of the foundational data standardization components in Echopype, our goals in the next stage of development include: further optimize distributed
computing efficiency of existing functions, incorporate additional common data processing methods (e.g., noise masking, single target detection, bottom detection, etc.), add support for data from other echosounder models (e.g., Simrad EK500 and multi-beam data), improve data provenance tracking, and enhance adherence to newer versions of the SONAR-netCDF4 convention as well as other community conventions of metadata and processed data [e.g., the ICES AcMETA metadata convention (2016)]. These efforts will be accompanied by the continuing development of a set of data processing level definitions for echosounder data (Echolevels, n.d.), which will facilitate data pipelining and enhance data understanding and provenance tracking. At present, many Echopype functions generate data provenance and processing level information stored as variables or attributes, which are prototypes we plan to refine in the future.

The free and open-source nature of Echopype contributes directly to democratizing the access to and the analysis of water column sonar data. The package’s publicly hosted code repository provides an open forum centered around the standardization and processing of water column sonar data for a broad audience. It also creates an opportunity for the fisheries acoustics and ocean acoustics communities to incorporate best practices in data stewardship and an open, community-driven approach to technology development and scientific investigation. By providing a uniform, open-source, and cross-platform programmatic interface that liberates scientists from the tedium of data reading and wrangling, we envision the continued development of Echopype as a catalyst for making information derived from water column sonar data an integrated component of regional and global ocean observation strategies.

AUTHOR CONTRIBUTIONS

WJL initiated the package and conceptualized the manuscript. WJL and EM contributed significantly to the writing of this manuscript. LS and VS provided important suggestions. All authors contributed significantly to the design, code, testing and documentation of the package. All authors revised and approved the manuscript.

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