PING-Mapper: open-source software for automated benthic imaging and mapping using recreation-grade sonar

This is a Preprint and has not been peer reviewed.

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Key Points:

- We developed an open-source software for exporting benthic datasets and georeferenced imagery from Humminbird side scan sonar systems.
- Software provides automated and reproducible approach to processing sonar data with minimal interaction from the user.
- Three case studies are presented to highlight use cases of processed benthic datasets.

June 13, 2022

Associated software, PING-Mapper: `https://github.com/CameronBodine/PINGMapper`

PING-Mapper: open-source software for automated benthic imaging and mapping using recreation-grade sonar

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June 13, 2022

Abstract

The characterization of benthic habitats is essential for aquatic ecosystem science and management, but is frequently limited by waterbody visibility and depth. Recreation-grade side scan sonar systems are increasingly used to aid scientific inquiries in shallow water due to their relative low-cost, ease of operation, low-weight, and ease of mounting on a variety of vessels. However, existing procedures and software for post-processing these data are either limited, closed source, or fail on data from new sonar models; limiting development of reproducible workflows. Here we present PING-Mapper, an open source and freely available side scan sonar post-processing toolset for processing and mapping sonar recordings from popular Humminbird instruments. The modular software automatically: 1) decodes sonar recordings from any Humminbird system; 2) exports ping attributes from every sonar channel; 3) uses sonar sensor depth for water column removal; and 4) exports sonogram tiles and georectified mosaics. Sonar channels are processed in parallel for quick decoding and metadata extraction. Workflows for major processing workflows including georectification and image export scale with computing resources. The software has been extensively tested using data from several river distributaries of varying character and distribution of depths, but could also be used in estuarine and lacustrine environments. Usage of PING-Mapper is illustrated in three case studies focused on mapping large woody debris, bathymetric mapping, and visual interpretation and mapping of substrates for select reaches of the Pearl and Pascagoula river systems in Mississippi.

Keywords– Acoustic remote sensing, Sidescan sonar, Benthic habitat

Plain Language Summary

Side scan sonar instruments provide a way to survey and visualize the bottom of rivers, lakes, or oceans. Since the early 2000s, companies catering predominantly to anglers have manufactured recreation-grade side scan sonar systems to aid fishermen in locating fish and identifying potential hazards. Scientists seeking to understand and manage aquatic habitats soon found use in these systems to create grayscale images of water bottoms because they are inexpensive, are easy to operate, and require minimal mounting equipment on the boat. Software has been created by companies to process these data, but the underlying processing workflow and computer code are not publicly available, which makes it difficult to reproduce and compare results among multiple scientists and studies. Other publicly available approaches and software are either outdated, not maintained, or not free. That is why we made PING-Mapper. This software is built using a programming language called Python, an increasingly popular language used by many scientists. All the code of PING-Mapper is made freely available. We designed the software to work on any computer with minimal hardware specifications, to export the desired datasets as quickly as possible. We demonstrate the use of the exported datasets with three case studies focused on common scientific usages, locating and mapping targets (specifically large trees and branches), creating depth maps, and visually discerning the distributions of common substrates such as sand and cobble.

1 Introduction

Our understanding of the Earth's surface and atmosphere has benefited from large investments in air and space-borne observation systems, such as NASA's Earth Observation System (EOS) (Murphy, 2021), providing unparalleled ability to model the climate (Yang et al., 2013), track landcover changes (Weiers et al., 2004; Bock et al., 2005), or map species-specific habitat availability (Kerr & Ostrovsky, 2003). In comparison, the spatial and temporal extent of our knowledge of aquatic environments, particularly shallow freshwater habitats, remains limited. This leaves scientists and managers with less information to address threats to species that depend on freshwater systems (Barnosky et al., 2011; Tickner et al., 2020). Shallow waterbodies are ubiquitous; 85% of the world's 3.5M rivers have an average depth of 1m (Andreadis et al., 2013), and the average depth of the world's 27M lakes is 41.8m, with 99% of lakes less than 10m in depth (Cael et al., 2017). Shallow water, particularly small waterbodies (Biggs et al., 2017), are disproportionately important for aquatic biodiversity including macrophytes (Fu et al., 2014), bacteria, diatoms and chironomids (Zhao et al., 2019); macrobenthos (Musale & Desai, 2010); plankton (Longhurst, 2007); pelagic fish (Smith & Brown, 2002); and assemblages of marine meiofauna, macrofauna, and megafauna (Danovaro et al., 2010).

Techniques available for mapping in-stream habitat depend on the species of interest, type of system, parameters of interest, and spatial scale (Myrvold & Dervo, 2020), however traditional techniques for collecting these parameters are limited in space and time. Side scan sonar (SSS) is an effective technology for efficiently collecting large swaths of benthic imagery (Chesterman et al., 1958; Klein & Edgerton, 1968; Singh et al., 2000; Brown et al., 2011). Sonar images are geographically rectified (i.e., georectified), converting time and slant-range distance data into a regular Cartesian grid positioned accurately in space using geographic positioning system (GPS) coordinates. Survey-grade systems popular for imaging marine ecosystems are relatively expensive and require substantial technical expertise. It is also more difficult and dangerous to operate hydrographic survey vessels in shallow water. Recreation, or consumer-grade sonar systems (e.g., Humminbird, Lowrance, and Garmin) offer an alternative and are increasingly popular for scientific research (Kaeser & Litts, 2010; Schmidt et al., 2020; Scholl et al., 2021). These systems are comparatively low-cost, portable, and easy to operate and deploy; require minimal power and experience; and can be launched from small watercraft. However, extracting and processing data from these systems remains a major challenge. Leveraging the transformative potential of these systems for scientific research thus requires free and open-source software implementations of scientifically defensible processing workflows that have been tested on a variety of data.

The first method to extract data from Humminbird Side Imaging systems to map shallow water habitat features was a sonar screen snapshot approach (Kaeser & Litts, 2008, 2010). In this method, concurrent overlapping snapshots are captured at regular intervals via live feed imagery on the control head screen. Snapshots can be inadvertently missed, leaving gaps in resulting sonar mosaics. Snapshot image resolution is determined by the control head's screen size, necessitating larger and more expensive systems. After data collection, tools developed by the authors require time-consuming manual post-processing steps to generate georectified mosaics, limiting batch processing options. The tools are written in Visual Basic for Applications (VBA) and run in potentially cost-prohibitive

ESRI ArcGIS software; however, current ArcGIS versions no longer support VBA, effectively rendering this approach obsolete.

Many of the limitations of the snapshot approach can be overcome by recording sonar intensity and metadata directly to file, but format and structure are not provided by the manufacturer. Currently, options for processing these files are limited. Decoding recordings from early Humminbird models was first demonstrated with PyHum (Buscombe et al., 2016; Buscombe, 2017); an open-source Python toolbox for decoding sonar recordings, exporting ping metadata (e.g., vessel position, heading, and speed), applying sonar intensity corrections, classifying bed textures, and exporting georectified imagery. The software is limited in application because it only works for older Humminbird models, is difficult to install due to underlying dependencies, and has poor computational efficiency. Alternatives to this toolbox have additional limitations. For example, HumViewer (Johansen, 2013) permits users to view the recording but offers limited export functionality. HumConverter (Parnum et al., 2017) is a free software for decoding sonar recordings but requires MATLAB (> 1,000 USD) to work with file exports. Low-cost (< 500 USD) commercial software such as SonarTRX (Leraand Engineering Inc., 2022) and ReefMaster (ReefMaster Software Ltd., 2021) offer interfaces and tools for viewing, correcting, and exporting sonar data. However, source-code for these programs are not housed on public-repositories, limiting opportunities for collaboration, scientific applications requiring reproducibility, and modifications or extensions to functionality.

This article describes PING-Mapper, a new modular processing engine written in Python 3 that is open-source and free to use. It is similar in scope to PyHum, but works with data from all Humminbird models, is easier to install and maintain, and is more computationally efficient. We have also significantly improved the algorithms for depth detection, and image rectification, and have tested on a larger variety of environmental conditions. The software provides many advantages to the software and methodologies referenced here including: 1) decoding any Humminbird sonar recording, regardless of model (at the time of writing, there are 14 Humminbird side imaging models available); 2) batch processing of sonar recordings; 3) export of ping metadata to comma separated value or CSV format files; 4) export of non-rectified imagery; 5) export of georectified imagery; and is 6) publicly hosted in a repository, ensuring workflow transparency, and inviting contributions from the community.

2 Implementation

The following sections describe PING-Mapper's processing workflow (Figure 1) for decoding and exporting benthic datasets from Humminbird SSS systems.

2.1 Decode Humminbird Files

Sonar recording files from a Humminbird sonar instrument are written in a proprietary format of ASCII-encoded hexadecimal values. Each sonar scan creates a single DAT file. The DAT file stores metadata when a recording is initialized, including the selected water type (of which there are three; fresh, shallow saltwater, deep saltwater), the Unix time (epoch) in seconds, Easting and Northing in World Geodetic System 1984 (WGS 84) World Mercator coordinate reference system, name of the recording, number of pings , initial range setting (i.e., number of ping returns), and length of the recording in milliseconds.

Along with the DAT file, each active sonar channel, or beam, has an associated SON and IDX file. The SON file stores the pings while the IDX file stores the byte index (the location in the file of the start of each ping) and time elapsed of each ping in the SON file. A ping has two components: 1) ping attributes (termed here as ping header, or sim-

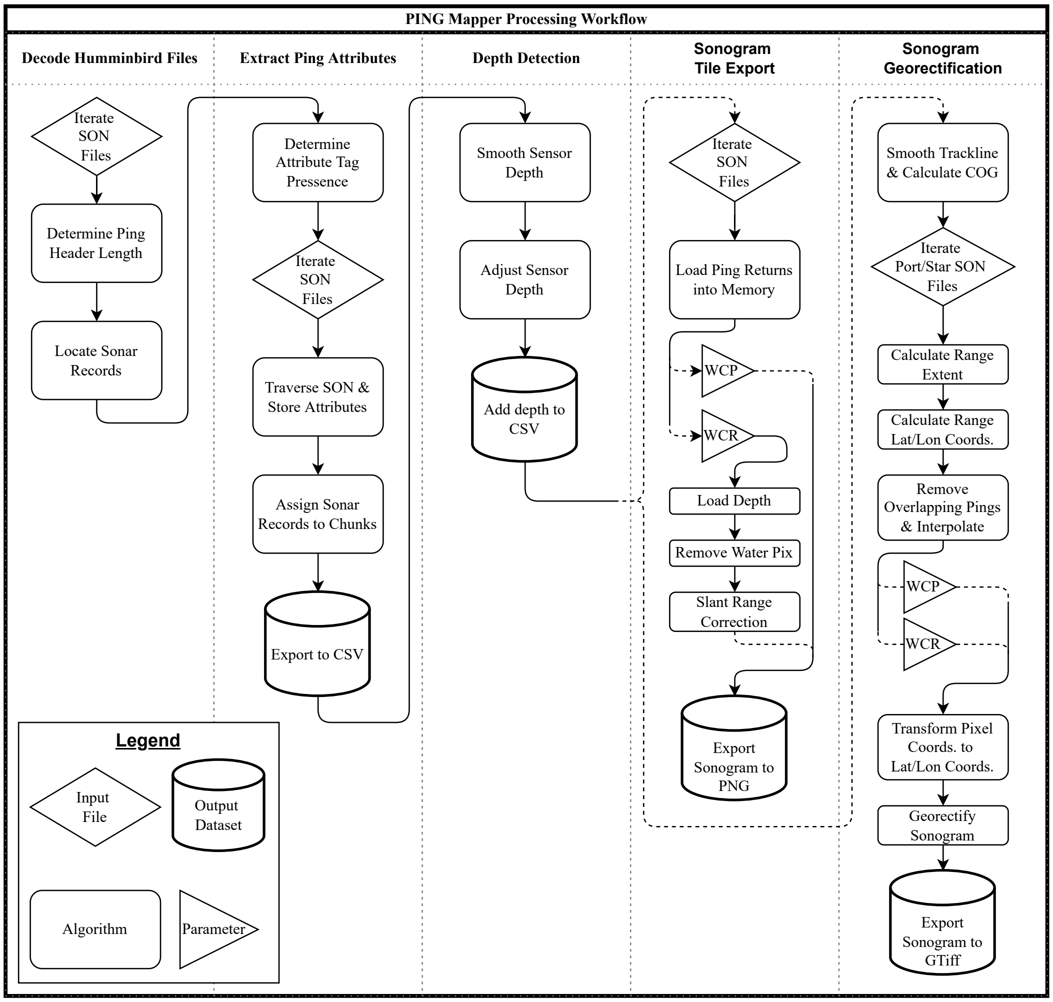

Figure 1. Overview of PING-Mapper processing workflow as described in Section 2. Acronyms are defined as: SON (Humminbird sonar file); CSV (comma-separated values file); WCP (water column present); WCR (water column removed); PNG (portable network graphics); COG (course over ground, i.e., heading); Lat (latitude); Lon (longitude); and GTiff (geospatial tag image file format).

ply header); and 2) ping returns, or acoustic backscatter intensity values, stored in 8-bit [0-255] encoding (Buscombe, 2017).

The number of bytes in a ping vary in two ways. First, the length of the header is dependent on the Humminbird model, with each model storing a varying number of ping attributes (see Supporting Information Table 1). Regardless of the header contents, each starts and ends with the same values, allowing PING-Mapper to automatically determine header length. Second, the ping length (in milliseconds) varies with the number of returns following the header, determined by the range setting at the time of the survey, which in turn dictates the sonar pulse length (Buscombe, 2017). The last attribute in the header indicates the number of returns that follow. The next ping immediately follows the last return of the previous ping, and so on. The IDX file allows quick navigation to the beginning of each sonar record, but these files can become corrupt due to, for example, power failure during the survey. If the IDX file is corrupt or missing, PING-Mapper locates pings based on the header length and number of returns.

2.2 Extract Ping Attributes

For each ping in a SON file, the header stores a series of attributes relating to that ping's returns. Each attribute is tagged with a unique identifier, or name, followed by the attribute's value. All sonar models use consistent naming of a given attribute, but may have additional unused attribute slots. Once pings are located, PING-Mapper decodes each header and exports the attributes to a CSV for each sonar beam. Attributes with valid data contain positional information, time elapsed, depth at nadir, heading, and speed. A list of all attributes and their location based on sonar model is provided in Table 1. These data are used in subsequent georectification procedures, which convert the raw data into a regular spatial grid that can be viewed as a map (see section 2.5).

2.3 Depth Detection

Water depth is a fundamental variable governing river hydraulics, morphologies, sediments, and habitats and is also used to make the necessary geometric corrections to the sonar imagery to recreate continuous planform imagery of the bottom (see sections 2.4-2.5). SSS systems are equipped with down-facing sonar beam(s) that imprecisely estimate the depth at nadir for each sonar record. These data are stored in the SON files for each ping. The estimates are often error-prone due to various mechanical and environmental factors (Yan et al., 2021). Therefore, options to smooth noisy estimates and uniformly adjust the depth to account for sonar transducer offset are provided.

2.4 Sonogram Tile Export

Once ping attributes have been extracted, non-rectified sonar imagery of ping returns, or sonograms, are optionally exported to tiles. PING-Mapper loads ping returns into memory in batches based on chunk size (see Section 2.6). Sonograms can be exported with the water column present (WCP) or water column removed (WCR). WCP images show the water column at nadir, making them suitable for applications of locating and counting fish (Flowers & Hightower, 2013) as well as measuring height of submerged vegetation (Sánchez-Carnero et al., 2012). WCP images require no additional post-processing and can be directly exported to standard image formats. Alternatively, WCR images are most suitable for accurate spatial positioning of the bed as presence of the water column introduces geometric distortions which affect of the bed pixels in the near-field (Cobra et al., 1992), necessitating additional post-processing to generate these sonograms.

A two-step geometric correction to the sonogram is required to remove the water column pixels then relocate the bed pixels horizontally across the track, known as slant range correction (Cobra et al., 1992). The sonar system cannot measure depth across track, preventing precise calculation of across track distance, or range, to each pixel. Therefore, a naïve assumption that the bed is flat across the track allows the range to be approximated using the slant range and depth at nadir. This flat-bed assumption applies only to the useful portion of riverbed scanned, which is approximately 10-20 times the water depth as a rule-of-thumb. The flat-bed assumption is calculated piecewise across the width of the waterbody and bed pixels are redistributed across the track. Gaps in the data are then filled using a one-dimensional piecewise linear interpolation method. Non-rectified SRC sonogram tiles can then be exported to standard image formats.

2.5 Sonogram Georectification

Recreation-grade sonar systems often have an autonomous internal GPS receiver in the sonar control head. Ports are available to add an external GPS that might have better positional accuracy. Each sonar record has a single geographic coordinate and the heading from the GPS. These data are used to warp the sonogram to the vessel track and geographically locate each pixel, termed here georectification.

In a typical side scan survey, the vessel is constantly moving to image the bed. However, the GPS refresh rate is typically slower than the ping rate, resulting in multiple sonar records sharing identical coordinates despite the constant movement of the vessel. PING-Mapper performs several corrections to recalculate the coordinates for each sonar record along the track. First, ping coordinates are filtered to ensure unique coordinate pairs. Next, coordinates are filtered to decrease point density and speed the next step of fitting a third-degree piecewise affine spline to the filtered coordinates. The spline is parameterized using the sonar record's unique id and the time elapsed. Finally, new coordinates are then predicted for each sonar record using the spline, resulting in sonar records with unique coordinate pairs along the smoothed vessel course spaced assuming a constant speed. These steps further improve rectification of sonograms along sinuous river reaches.

2.6 Processing Large Recordings

The duration of a sonar survey and the range setting dictate the size of the sonar recording file, which can become prohibitively large for a typical computer to process. Therefore, PING-Mapper was designed to process sonar recordings in chunks. The chunk size sets the number of ping returns that will be read into memory for each sonar beam. A value of 500 is found to be appropriate in most scans but can be altered by users based on available computing resources. This any modern computer to process sonar recordings of any size.

Another advantage to processing sonar recordings in chunks is that multiple chunks can be processed concurrently. PING-Mapper supports multi-threaded processing to extract ping attributes, export non-rectified imagery, and sonogram georectification and export, resulting in decreasing overall processing time. Tests were conducted on a 01h:00m:06s sonar recording to determine speed of processing and data export. PING-Mapper is able to process and export all possible data products in 00h:41m:14s on a typical computer. Assuming a typical day in the field can result in upwards of 8h of sonar recordings, PING-Mapper could be set to process the data over night with datasets ready for analysis the next morning. Additional information is provided in Supplement Information Section Computational Performance and Table 2.

3 Case Studies

The following three case studies illustrate some analyses that can be undertaken with outputs from PING-Mapper. First, WCP sonar mosaics are used to locate and map

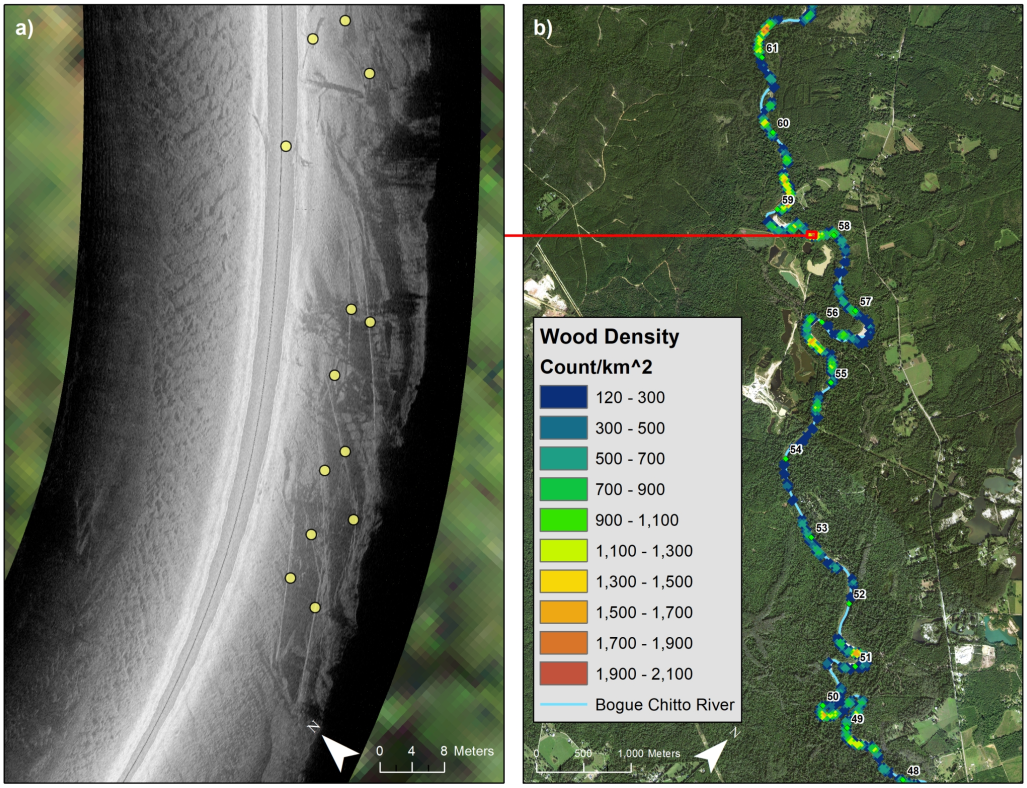

Figure 2. Example of locating and mapping large woody debris in the Bogue Chitto River in Mississippi. Panel (a) shows a georectified sonogram with water column present, with yellow points indicating location of large woody debris. Panel (b) shows wood density count per square kilometer.

large woody debris distribution in the Bogue Chitto River, MS. Second, sonar depth estimates from two survey transects on the Pearl River, MS allow creation longitudinal depth profiles and basic bathymetric surfaces. Finally, WCR sonar mosaics are visually interpreted to identify and delineate substrates on the Leaf River, MS. All sonar data were collected with a Humminbird Solix Chirp Mega SI+ sonar instrument operating at a nominal central frequency of 1.2 MHz with unknown frequency bandwidth; however, similar results are expected from any modern Humminbird model.

3.1 Mapping Large Woody Debris

Large woody debris present in aquatic environments serve important ecological functions for various species (Dolloff & Warren, 2003). Surveying rivers with SSS has proven successful in locating large-woody debris (Holcomb et al., 2020; Kaeser & Litts, 2008). SSS data were collected on the Bogue Chitto River, MS approximately 54 to 63 river kilometers (RKM) upstream of the confluence with the Pearl River on March 2, 2021. The sonar data were post-processed using PING-Mapper and georectified sonograms with the water column present were exported. Large woody debris were visually identified in a GIS by their distinguishing characteristic of long, linear edges and the shadows that they cast. Points were then placed on identified wood throughout the survey reach (Figure 2a). Finally, mapping the density of these points illustrates variation in wood presence across river reaches (Figure 2b).

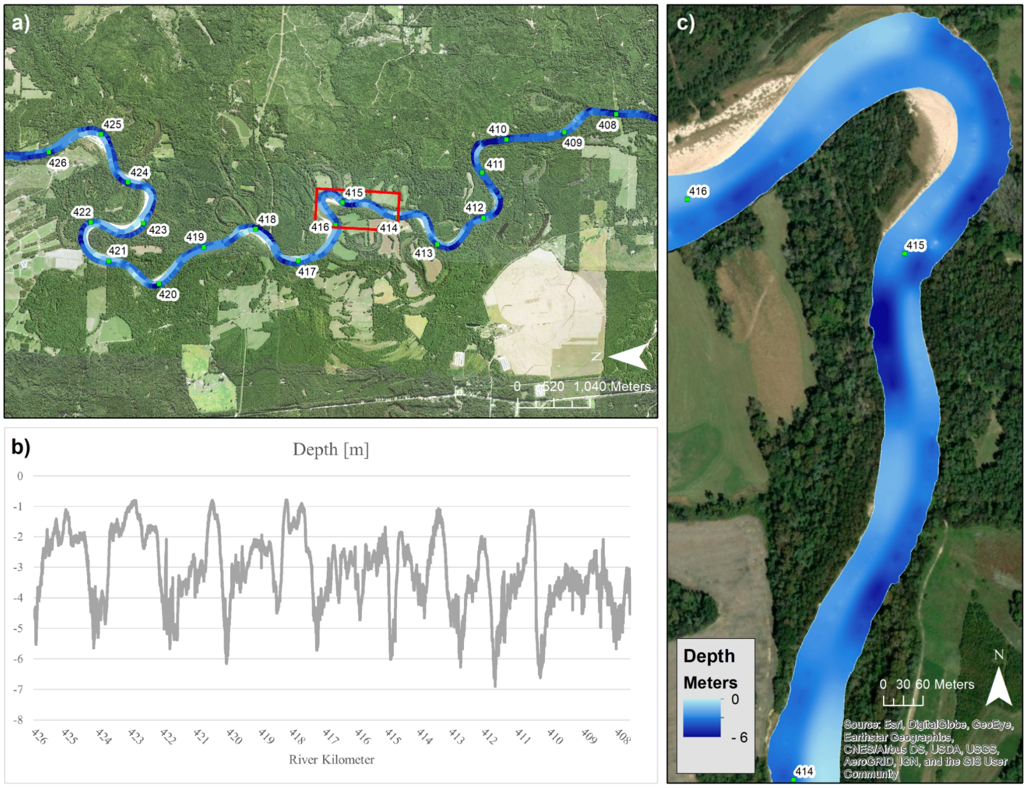

Figure 3. Example of mapping depth with SSS. Panel (a) shows sonar depths from two adjacent survey transects across 18 river kilometers on the Pearl River in Mississippi, surveyed upstream (RKM 426) to downstream (RKM 408). Panel (b) shows depth readings from the transect on the right side of the channel. Panel (c) shows an interpolated surface derived from the two transects and constrained by manually digitized banklines. To digitize the banklines, WCR georectified mosaics were exported and brought into a GIS where they were visually interpreted to determine the location of the bank, and a polyline was digitized along the bank.

3.2 Mapping Bathymetry

Two SSS survey transects from two vessels spaced to reduce interference were conducted on the Pearl River, MS on March 4, 2021, from RKM 426 to 408. One vessel surveyed the left side of the channel and the other right, moving upstream to downstream. Sonar depth estimates from down-facing beams are shown for two transects (Figure 3a) and a longitudinal profile for the river-right transect (Figure 3b) shows that our software is able to position and map the sonar data to capture the complex bathymetry in the sequence of riffles and pools. The sonogram mosaics and satellite imagery were used to delineate channel bank lines in a geographic information system (GIS). The bank lines constrained an inverse distance weighting (IDW) interpolation of the two transects to generate a bathymetric surface (Figure 3c).

3.3 Mapping Substrate

Scanning a waterbody with SSS results in imagery with tones and textures that can be associated with different types of substrate (Kaeser & Litts, 2010). Once georectified, the sonograms are brought into a GIS for visual interpretation and manual delin-

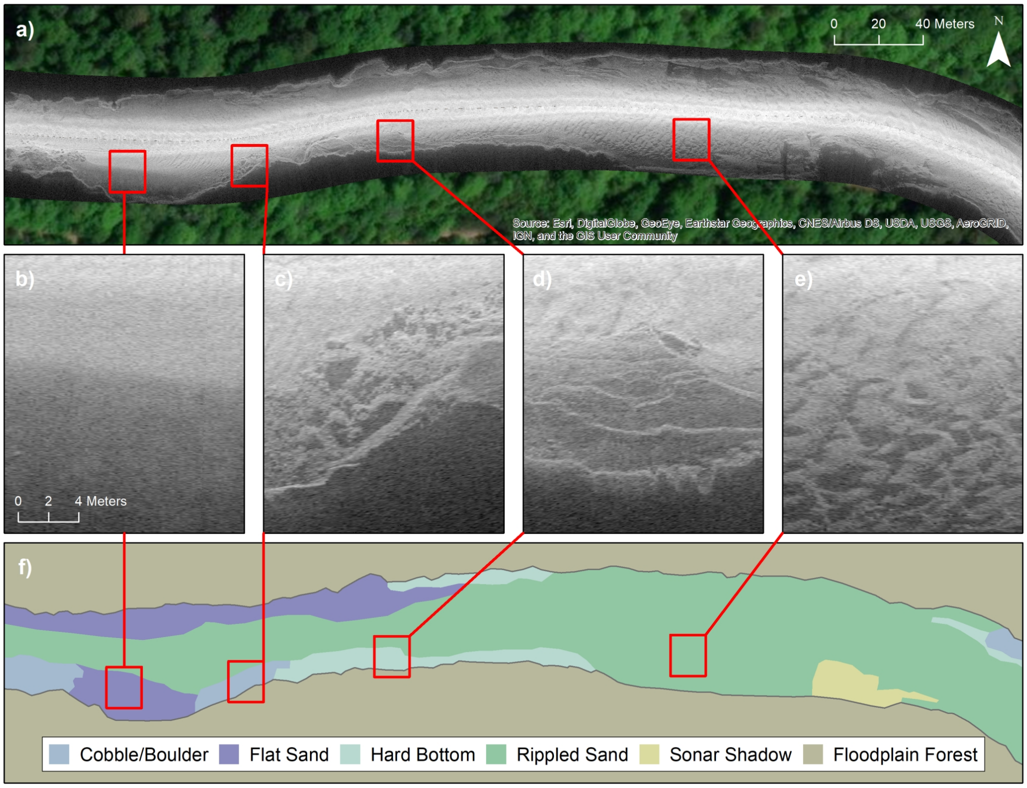

Figure 4. Example of delineating and classifying substrate on the Leaf River, MS. Panel (a) shows georectified sonograms with the water column removed. Detail views of the sonagrams show (b) flat sand; (c) cobble/boulder; (d) hard bottom; and (e) rippled sand. Panel (f) shows a map of the substrate boundaries visually identified and manually delineated in a GIS.

eation of polygons, resulting in maps showing coverage and distribution of substrates at large spatial extents. The Leaf River, MS, was scanned 138 RKM upstream of the Pascagoula River confluence on May 6, 2021. The sonar recordings were processed with PING-Mapper and georectified sonograms with the water column removed were exported (4a). Different substrate types were visually identified and polygons were manually digitized in a GIS to delineate substrate boundaries. Smooth, homogeneous textures are associated with flat sand bedforms (4b); blocky textures with shadows are associated with boulder and cobble (4c); sharp edges indicating terracing are associated with hard bottom (4d); and wavy, chevron textures with shadows are associated with rippled sand (4e). Portions of the sonogram with the same substrate characteristics were delineated with a polygon, resulting in a map of substrate distribution (4f).

4 Discussion

PING-Mapper is a new Python toolbox for decoding and exporting benthic datasets from Humminbird SSS instruments. It builds and improves upon previous algorithms (Buscombe, 2017) for depth detection and georectification, and speeds processing and export. The software is designed to 1) decode sonar recordings from any Humminbird system; 2) export ping attributes from every sonar channel; 3) use sonar sensor depth for water column removal; and 4) exports sonogram tiles and georectified mosaics. The software are hosted in a public repository to ensure equitable access.

Aquatic scientists are increasingly using SSS to inform a range of research efforts. This includes mapping essential habitats (Kaeser & Litts, 2008; Cheek et al., 2016; Walker & Alford, 2016; Holcomb et al., 2020), informing invasive species competition for discrete habitat patches (Goclowski et al., 2013; Prechtel et al., 2018), enhancing habitat modeling for aquatic species (Smit & Kaeser, 2016; Kaeser et al., 2019), and mapping aquatic vegetation (Gumusay et al., 2019). Studies like these depend on the ability to easily convert output from recreation-grade sonar systems into reproducible datasets with minimal expertise in data processing. PING-Mapper provides a suite of algorithms to facilitate this conversion. More importantly, these tools generate large datasets quickly which allow scientific studies to be conducted at increasing spatial and temporal scales relevant to numerous disciplines in ecological, environmental, and physical sciences concerned with the form and character of benthic environments and the life they support.

The creation of a recreation-grade sonar processing pipelines allows opportunities for future research, analysis, and applications of datasets generated by PING-Mapper. For example, a primary use of side scan sonar image mosaics is to locate and map substrate distributions throughout aquatic systems. Visual identification and manual digitization is common practice (Kaeser et al., 2013) but automated machine learning approaches such as Buscombe and Goldstein (2022) show promise. Future work will focus on developing and integrating automated substrate segmentation and classification workflows to inform landscape-level aquatic studies. Reliable depth measurements are necessary to ensure accurate spatial positioning and coverage of automated substrate maps generated from sonogram mosaics, therefore automated depth detection routines such as Zheng et al. (2021) will be incorporated in the future. Potential improvements for the marine environment include implementing attitude adjustment (i.e., pitch, yaw and roll) and incorporating salinity to better locate the bed (Blondel, 2009).

The goal of this software is to address the growing and evolving data processing needs of the aquatic research community by including recreation-grade sonar datasets in their research. Particular emphasis has been placed on making PING-Mapper an open source tool for benthic applications and research. The code is designed to be modular and object oriented to facilitate contributions, modifications, and new applications from the community. This software is the first of its kind in that it allows any engaged citizen or researcher working in any aquatic waterbody to image their system with zero software costs and full reproducibility.

Data Availability Statement

The code for PING-Mapper and test sonar recordings are available on Zenodo and GitHub via Bodine and Buscombe (2022).

Acknowledgments

This study was made possible by a partnership between the U.S. Fish and Wildlife Service and Northern Arizona University. Funding for this work was provided by the Open Ocean Restoration Area Trustee Implementation Group of the Deepwater Horizon Trustee Council as part of their Final Restoration Plan 1 for birds and sturgeon. The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the U.S. Fish and Wildlife Service. Thanks to Channing St. Aubin (USFWS), Mike Andres (USM), Eric Haffey (USM), Kasea Price (USM), and Katherine Wright (USM) for data collection and planning, and to Daniel Haught (USGS) for testing.

Supporting Information

Computational Performance

The software is designed to speed processing and dataset export through multi-threaded processing. Export of plots, tiles and rectified sonograms account for the largest proportion of the total processing time, therefore running these algorithms in parallel result in significant decrease in total processing time. Algorithms which were parallelized include decoding and export of SON ping metadata, export of bedpick plots, export of sonogram tiles, and export of rectified sonogram GeoTiffs. Portions of the software that run sequentially (e.g., non-parallelized) include decode and export of DAT metadata, determining SON file structure, depth processing, trackline smoothing, and mosaic rectified sonograms.

The computational performance of PING-Mapper was tested with a sonar recording from a Humminbird Helix with Mega imaging. Sonar recording includes high-frequency down image (200 kHz), very high-frequency down image (1.2 MHz), and two very high-frequency side scan images (1.2 MHz). Total duration of the recording is 01:00:06 (hh:mm:ss). Total ping count is 279,916. Range setting is 1,398 returns per ping, or 26.6m. Chunk size is set to 512 pings, resulting in the following exports: 547 WCP sonograms; 274 WCR sonograms; 137 bedpick plots; 274 WCP rectified GeoTiffs; 274 WCR rectified GeoTiffs; and mosaics for WCP and WCR.

Tests were run on a Windows 10 laptop with Intel i7-8650U 1.90 GHz CPU, 16 GB of memory, and 500 GB solid state hard drive. Each test was run with an increasing number of processing threads (t), including t =1, 2, 4, 6, and 8 threads. All other parameters remained the same. Processing time, in seconds, are shown for the main components of the software in Table 2. Total processing time is reported in seconds as well as hours, minutes, and seconds (hh:mm:ss) for reference. Sequential algorithm processing time remained approximately constant with varying number of process threads. The algorithm for decoding SON scales with number of threads until the number of threads is equal to the number of beams, then remains roughly constant for $t > 4$. The algorithms to export bedpick plots, sonogram tiles, and rectify sonograms had decreasing processing time with increasing t.

Table 1. Humminbird SON file structure for specified sonar models: 9xx series, 11xx series, Helix, Onyx, and Solix. Other models presumably follow a similar pattern. The Name and Description indicate the type of data available for each ping in a Humminbird sonar recording. The Hex Tag is the 8-bit hexadecimal value preceding the data value. For each of the Humminibird models, the offset from the beginning of the recording is given for the respective data type. This pattern repeats for each ping for the duration of the sonar recording.

			Data Offset (by model)		
Name	Description	Hex Tag	9xx	11xx; Helix; Onyx	Solix
Ping #1	Beginning of ping #1	C0	+0	+0	+0
Header Start	Beginning of ping header	21	+3	+3	+3
Record Number	Unique ping ID	80	+5	+5	+5
Time Elapsed	Time elapsed (msec)	81	+10	+10	+10
UTM X	EPSG 3395 easting coord.	82	+15	+15	+15
UTM Y	EPSG 3395 northing coord.	83	+20	+20	+20
Heading Quality	Quality flag[1]	84	+25	+25	+25
Heading	Heading (1/10 deg)	-	+27	+27	+27
Speed Quality	Quality flag[1]	85	+30	+30	+30
Speed	Vessel speed (cm/sec)	-	+32	+32	+32
NA	Unknown data contents	86	-	+35	+35
Depth	Sonar depth (cm)	87	+35	+40	+40
NA	Unknown data contents	-	-	-	+44-83
Sonar Beam	Sonar beam ID[2]	50	+40	+45	+85
Voltage	Voltage scale (1/10 volt)	51	+42	+47	+87
Frequency	Sonar beam frequency (Hz)	92	+44	+49	+89
NA	Unknown data contents	-	+48-60	+53-65	+89-145
Return Count	Number ping returns (n)	A0	+62	+67	+147
Header End	End of ping header	21	+66	+72	+152
Ping Returns	Sonar intensity [0-255]	21	+67	+73	+153
Ping #2	Beginning of ping #2	21	+67+n+1	+73+n+1	+152+n+1
...[3]	...	...	...	...	...

[1] 0=bad; 1=good.

[2] 0=Down Scan Low Freq.; 1=Down Scan Hi Freq.; 2=Side Scan Port-side; 3=Side Scan Starboard; 4=Down Scan Megahertz.

[3] Pattern repeats for duration of sonar recording.

Table 2. Computation time for sequential and multi-threaded algorithms on a test dataset[c].

Threads (t)	Sequential Algorithms[b]	Decode SON[c]	Bedpick Plots[c]	Sonogram Tiles[c]	Rectify Sonograms[c]	Total (s)	Total (hh:mm:ss)
1	367.3	52.8	423.3	1158.6	4349.0	6351.0	01:45:51
2	363.4	35.3	261.0	723.2	3197.1	4580.0	01:16:20
4	361.5	25.7	186.7	531.2	1960.9	3066.0	00:51:06
6	359.0	23.9	179.6	533.7	1451.8	2548.0	00:42:28
8	363.2	24.0	175.8	522.1	1388.9	2474.0	00:41:14

[a] Test dataset from a Humminbird Helix with Mega imaging. Sonar recording includes high-frequency down image (200 kHz), very high-frequency down image (1.2 MHz), and two very high-frequency side scan images (1.2 MHz). Total duration of the recording is 01:00:06 (hh:mm:ss). Total ping count is 279,915. Range setting is 1,398 returns per ping, or 26.6m.

[b] Sequential (e.g., non-parallel) algorithms include decoding DAT file, determining SON file structure, depth processing, trackline smoothing, and generating rectified mosaics.

[c] Multi-threaded processing algorithm.

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