

UNLOCKING A FISH FINDER FOR BENTHIC HABITAT CHARACTERIZATION

By Michael P. Scherer and Val Schmidt

ABSTRACT. Single beam sonars can provide valuable acoustic information on the structure of benthic habitats and the contents of the water column. Nominally, acoustic sensors that provide water column data in scientific applications can cost tens or hundreds of thousands of dollars. In contrast, consumer grade fish finders that are mass produced are very inexpensive, costing only tens or hundreds of dollars. Unlocking a fish finder for scientific use could increase access to low-cost sensing methods for coastal communities that are historically underserved. The principal challenge with using a fish finder for benthic habitat classification is that the sonars are generally not interoperable and are often limited to visualization on a display or chart plotter made by the sonar manufacturer. This vendor lock prevents the sonar data, and in particular water column data, from being stored and processed to create mapping products. In this project, “SonarPhony” was developed to provide interoperability software to enable the real-time visualization and logging of water column data from a low-cost fish finder. A machine learning approach was used to demonstrate that the logged data could be used to estimate bottom type and identify the presence of seagrasses. This solution thus provides a low-cost means for both benthic habitat classification and bathymetric mapping.

INTRODUCTION

Understanding the location and character of benthic habitats is critical for people to understand their fisheries. US laws such as the Magnuson–Stevens Fishery Conservation and Management Act (2007) require the definition and management of essential fish habitat, such as seagrasses, which in turn requires sensing that can be deployed on large scales to manage fisheries (Federal Register, 2013). Coastal communities around the world depend on fish stocks whose habitats are easily misunderstood for lack of visibility without expensive tools (Harden-Davies and Snelgrove, 2020). These economic barriers to entry prevent local, distributed, independent access to ocean data.

Existing data pipelines for crowdsourced bathymetry using low-cost sensors have been proven to expand access and detect changes to charted bathymetry, in particular, after natural disasters (Gilbert et al., 2025). Low-cost fish finders have been used for bathymetric studies and habitat mapping to create gridded digital elevation models (DEM; Gomes et al., 2025). Benthic acoustic classification has been thoroughly studied, but largely with significantly more expensive sensor systems (Anderson et al., 2008; Gumusay et al., 2019). Commercial solutions exist for processing higher end consumer grade fish finder data that rely on licensing models (Helminen et al., 2019). Underwater video has been used to relate seafloor characteristics to acoustic data (Rooper and Zimmermann, 2007; Sánchez-Carnero, 2023). With added open interface water column data, consumer fish finders could be used to map beyond bathymetry to include seafloor and habitat characterization, at a cost that is accessible for citizen science.

Small uncrewed systems also benefit from low-cost sensing with open interfaces. Sensors incorporated on an uncrewed platform can cost as much or more than the vehicle itself. Because no people are on board, and uncrewed systems may operate completely over the horizon (Scherer and Chance, 2023; Cross et al., 2025), an open interface is required to collect and visualize data remotely.

To address this gap, we introduce SonarPhony, an open-source interoperability software that unlocks an off-the-shelf fish finder for data logging, remote or autonomous operation, and collection of water column data. The usefulness of these data is further demonstrated with the development of a machine learning classifier of benthic habitat type from the SonarPhony software.

MATERIALS AND COST

The benthic characterization system consists of three subsystems: the sonar itself, a GPS and sonar data logger, and a drop camera (Table 1). The Vexilar SP100 sonar is an off-the-shelf product that can be operated from any computer with the SonarPhony software. The data logger was based on a Raspberry Pi running SonarPhonyD. The integrated Wi-Fi on the Pi connects to the sonar. A USB GPS receiver was used to georeference the soundings. The drop camera was used to validate the bottom type.

ASSEMBLY

SOFTWARE. Two applications were created. SonarPhony has a graphical user interface that can be used to drive and visualize the sonar data (see Figure 1) or to play back log files. SonarPhonyD is a daemon that can log the water column data and output

NMEA0183 sentences. The NMEA0183 output is useful for interfacing with a chart plotter or other data acquisition system. An alternate daemon was also developed to control and transmit over ROS2 for robotics applications.

SONAR. The sonar was installed as specified by the manufacturer. When submerged in water, the sonar created a Wi-Fi access point for computer connection. The SonarPhony software was run to visualize and record the data. The T-Pod (SP100) model used for this study operates at 125 kHz and 30° beam, pinging 28–29 times per second with 302 samples per ping. The SP200 could reduce uncertainty due to its fixed mounting, though it operates at different frequencies.

DATA LOGGER. The portable charger was plugged into the input USB power port of the Raspberry Pi. Raspberry Pi OS Lite was installed on the Pi. A daemon version of SonarPhony, called SonarPhonyD, was initiated by a systemd script to run on the Pi to log sonar data. In addition to logging sonar data, it published a NMEA0183 string of the depth to a configured network port. OpenRVDAS (Agarwal and Cohn, 2020) was installed to log the GPS data and validate the logging of the sonar data, reading the NMEA0183 strings from both.

DROP CAMERA. The GoPro used for this study was chosen because it was on hand. With the waterproof enclosure, the camera is rated to 60 m of water depth. The light was attached to the base

of the camera using the provided mount. The end of the diving reel line was then tied to the combined system. Additional weight could be added for a faster descent rate.

CODE

The sonar, which also acts as the Wi-Fi access point, always assigns itself the IP of 192.168.1.1, and accepts UDP traffic on port 5000. The client first issues a handshake message to establish itself as the leader. Upon acceptance by the sonar, the client can then begin issuing commands to direct the sonar to begin transmitting pings and to select the requested range of the water column data. The commands are issued once per second to keep the sonar alive. If the commands stop, the sonar will cease transmitting after several seconds. Each returned ping contains the battery voltage, state of charge, water temperature, range of the water column (minimum and maximum), detected depth, and water column data that is a raster array of intensities with values between 0 and 255. Altering the gain had no effect on the returned raster intensities, so it is assumed that the gain is for visualization. The source code can be [found on Github](#).

FIELD APPLICATION EXAMPLE

The usefulness of the sensor for bottom type characterization was assessed. Data were collected at Bonita Bayou in St. Petersburg, Florida, USA, on December 1, 2024, and March 2, 2025. The bay has a largely sandy seafloor with patches of seagrass, rocks, and fan corals. A third dataset was collected in Lake Martin, Louisiana, on November 17, 2024. Lake Martin is a freshwater lake with a silted mud bottom. The data logger was fixed to a kayak, and the sonar was towed by a short, fixed line behind it. A cell phone was used to connect to the OpenRVDAS instance running on the data logger to verify that the sonar and GPS were both collecting data. For the purposes of this study, a fixed sonar range of 0–9 ft was used at all times to reduce variability, making each sample in the

TABLE 1. Material costs for the SonarPhony acquisition system.

ITEM	COST
SONAR	
Vexilar SP100 or SP200	\$59.95
Total	\$59.95
DATA LOGGER	
Raspberry Pi 3 model B	\$35.00
USB Wi-Fi Dongle	\$20.00
USB GPS	\$20.00
Portable USB Charger	\$10.00
Watertight Enclosure	\$10.00
Total	\$95.00
DROP CAMERA	
Diving Reel (or thin line)	\$20.00
GoPro HERO11 Black	\$299.99
GoPro Enclosure	\$49.99
Light – Movo LED-WP	\$29.95
Total	\$399.93
TOTAL COST	\$554.88

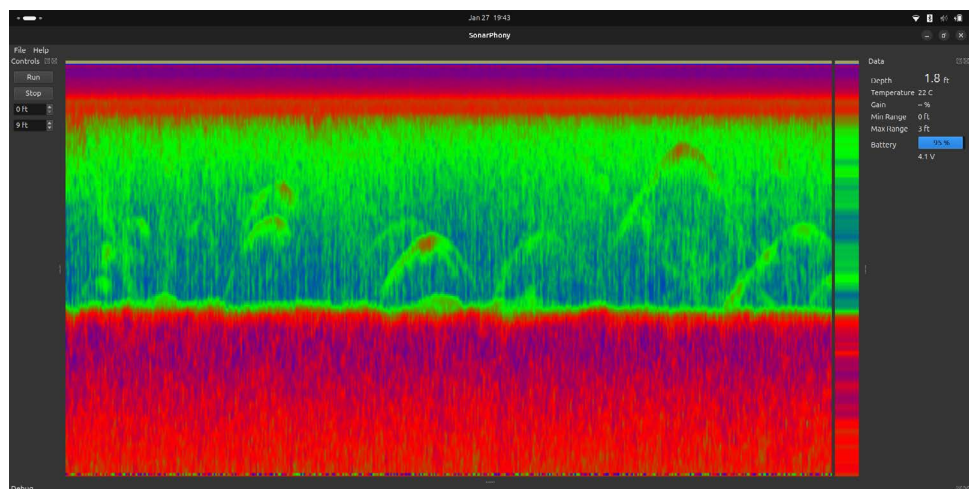


FIGURE 1. This image shows the SonarPhony app displaying a waterfall of water column data collected in Lake Martin, Louisiana.

water column approximately 7 cm high. Periodically, the camera was dropped from the kayak, logging the time of each deployment, shown in Figure 2.

The data logs were converted from NMEA0183 data and raw sonar data, respectively, into Python pickle format. Time was corrected by comparing the offset between GPS time and the system clock in the logs, and the corrected timestamps were used thereafter.

Each drop camera video segment was reviewed to determine the bottom type at the drop location. The timestamp recorded in the handwritten log for each camera drop was then used to associate the bottom type with a GPS coordinate. Training and test data were then extracted by first selecting the soundings within a 5-second neighborhood of each drop camera location and tagging those soundings based on the bottom type. Within each

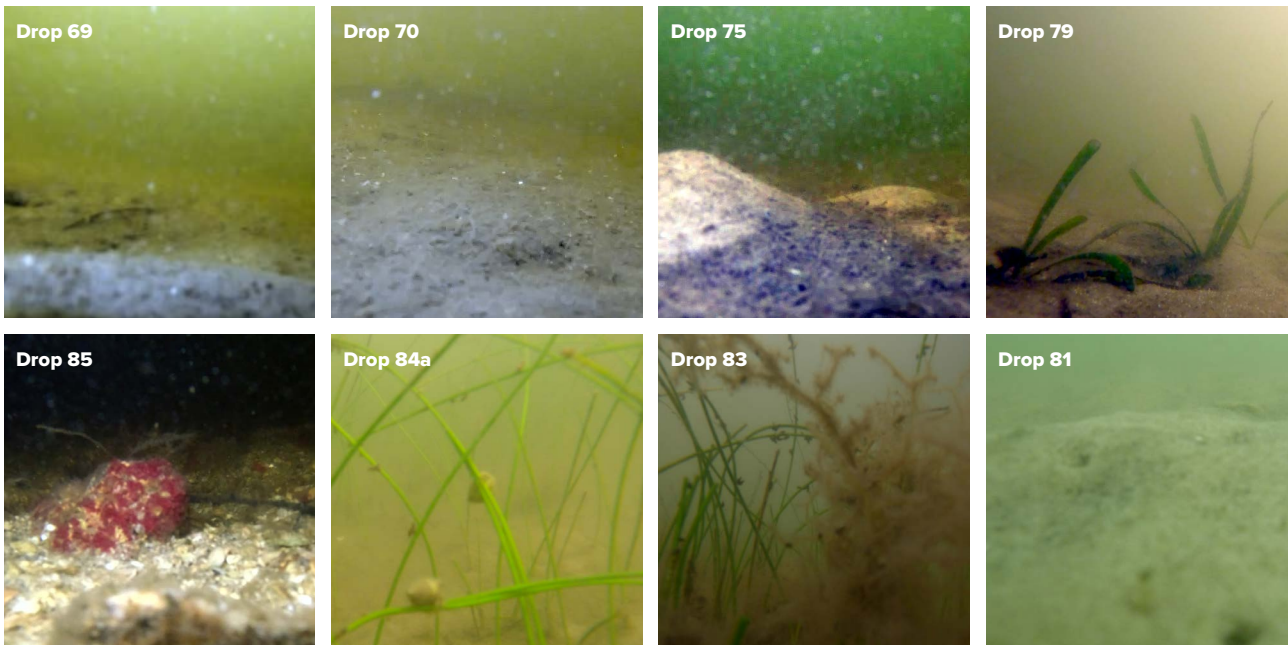
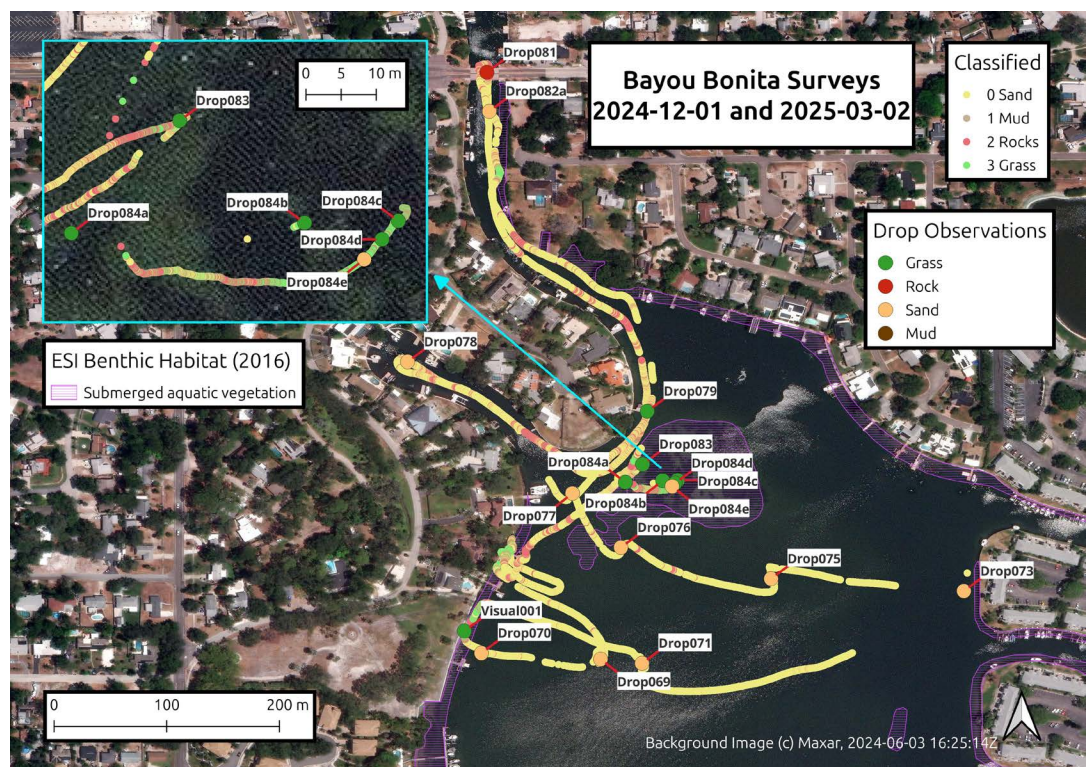


FIGURE 2. Imagery obtained from the drop camera at selected sites in Bonita Bayou, FL. Drop locations are shown in Figure 3.

FIGURE 3. Survey region in Bayou Bonita, drop camera locations, and resultant classification of bottom type using sonar data. Detail shows classified seagrass correlated over the region where seagrass can be seen in a satellite image from six months prior. Background image source: Maxar 2024-06-03



sounding's water column data, the 16 samples on either side of the detected hard bottom were extracted, including the center sample at the hard bottom, resulting in a window of 33 samples. All other samples in the water column for each sounding were discarded to focus on bottom type classification. Thirty-three percent of the tagged and extracted soundings, randomly selected, were allocated to test data, and the remainder were used for training.

To increase model accuracy and generalization (Bishop, 2006), a set of basic statistical and power spectra features were extracted from each sounding's sample window (Preston et al., 2001). Basic features included mean, standard deviation, skew, and kurtosis. Power spectra features were quantified using the periodogram method from SciPy (Virtanen et al., 2020). Features were calculated on both the entire window and on the samples directly above the hard bottom to increase the discriminating ability of seagrass.

Many implementations use unsupervised clustering algorithms to detect bottom type (Gumusay et al., 2019), so initial trials were done with K-Means. Unsupervised learning methods are capable of discovering categorizations of data that might not be known a priori; however, these clusters may have no physical meaning (Mitchell, 1997). Thus, it was difficult to validate that the clusters were correlated to any particular bottom type.

Because the target classes (bottom types) were known for this study, a supervised learning algorithm was chosen. AdaBoost was selected after trialing a selection of supervised learning algorithms implemented in scikit-learn (Pedregosa et al., 2001). AdaBoost is an ensemble method that uses many so-called "weak" classifiers whose results are combined to get a more accurate result (Freund and Schapire, 1997). The AdaBoost classifier was trained on the data using 200 estimators, because additional estimators did not appreciably increase the accuracy of the model. When only considering classes of sand, mud, and rocks, the classifier performed very

well with 96% accuracy and a Matthews correlation coefficient of 0.92. Considering all four classes of sand, mud, rocks, and seagrass, the quantitative scores reduced to 87% accuracy and a Matthews correlation coefficient of 0.79 (Figure 4). The greatest confusion in classification was between sand and grass. Because the identified grass lived in sand, it is reasonable that a broad swath would have poor discriminating ability between the two bottom types. As a notable example, location 79 was sparse in seagrass compared to locations 83 and 84, as shown in Figure 2. The results of the classification on the dataset can be found in Figure 3, demonstrating correlation of seagrass presence with both satellite imagery from 2024 and from NOAA Environmental Sensitivity Index (ESI) Benthic Habitats established in 2016. The machine learning code can be [found on Github](#).

FUTURE DEVELOPMENT

Machine learning models could be improved by collecting training datasets with higher data density, such as by collecting persistent camera data during the entire collection process.

Further experimentation could be done using the SP300 model of sonar, which supports higher frequencies of 200 kHz that may have better discriminating ability for thin seagrasses. The SP300 also supports 80 kHz operation, so multiple frequencies could be collected to better characterize bottom type. Of additional interest is full characterization of the acoustic properties of the sonar, such as target strength calibration, which might allow the sonar to be used in more traditional processing pipelines for biomass estimation or classification.

A practical limitation in this solution is that it provides a fixed number of samples for any range setting. Therefore, increasing the range of the sensor reduces the resolution of the water column data. A future study could evaluate the reasonable maximum range

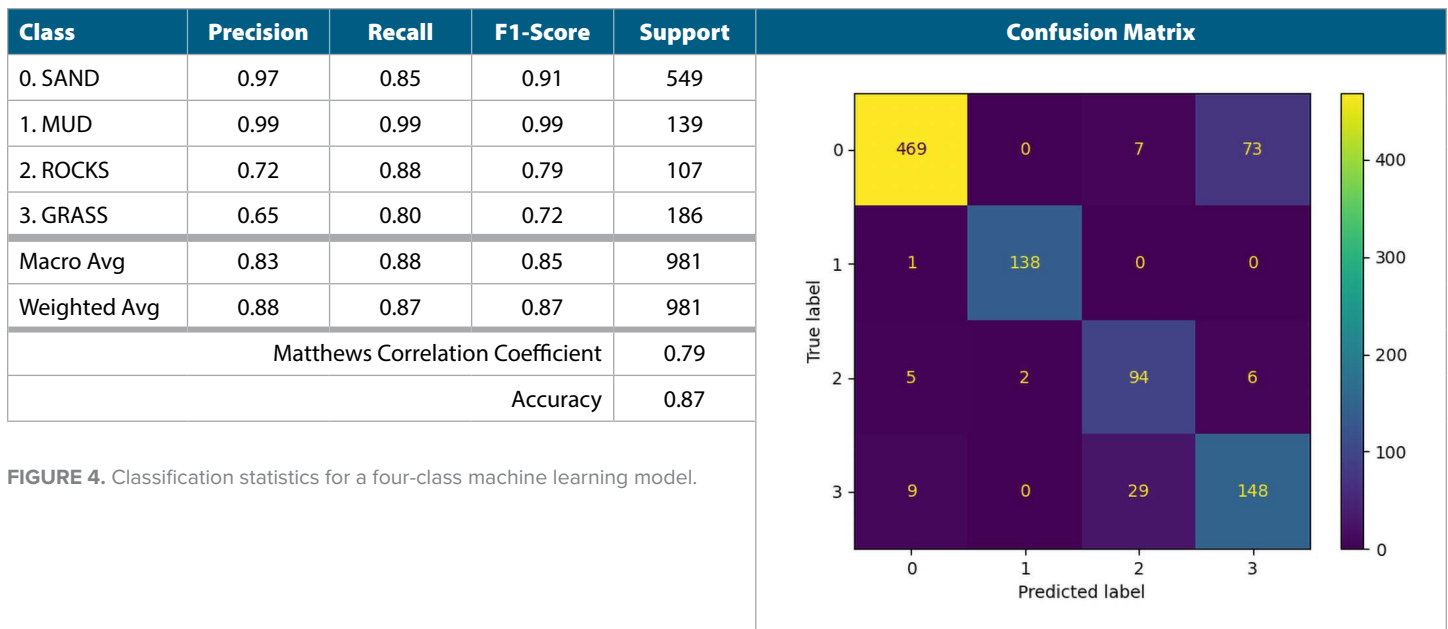


FIGURE 4. Classification statistics for a four-class machine learning model.

of the sonar, or if the minimum range could be modified to move the window of water column data to a region of interest without losing resolution.

CONCLUSION

Seafloor classification, and in particular seagrass identification, is valuable for communities where seagrasses are measured and protected. Low-cost tools for measuring seagrass abundance enable citizen scientists to track changes to essential fish habitat. SonarPhony was shown to be effective in a region for characterizing bottom type, and it was stable over two data collection excursions. Bottom type classification of sand, mud, and rocks was demonstrated in addition to identification of seagrasses, which could serve as a useful tool for understanding habitat. This low-cost methodology further enables crowdsourcing of seafloor classification.

REFERENCES

- Agarwal, A., and D. Cohn. 2020. A novel data acquisition solution to expedite global oceanographic research. Pp. 1–6 in *Global Oceans 2020: Singapore–US Gulf Coast*. Biloxi, MS, USA, October 5–30, 2020, <https://doi.org/10.1109/IEEECONF38699.2020.9389328>.
- Anderson, J.T., D. Van Holliday, R. Kloser, D.G. Reid, and Y. Simard. 2008. Acoustic seabed classification: Current practice and future directions. *ICES Journal of Marine Science* 65(6):1,004–1,011, <https://doi.org/10.1093/icesjms/fsn061>.
- Bishop, C.M. 2006. *Pattern Recognition and Machine Learning*. Springer, New York, New York, USA, 738 pp.
- Cross, R., D.R. Neff, and M.P. Scherer. 2025. Mission capable: A contrasting analyses of an uncrewed surface vehicle for extended duration offshore hydrographic survey. Pp. 1–5 *OCEANS 2025 - Great Lakes*, Chicago, IL, USA, September 29–October 2, 2025, <https://doi.org/10.23919/OCEANS59106.2025.11245139>.
- Federal Register. 2013. Amendment 4 to the Fishery Management Plan for Corals and Reef Associated Plants and Invertebrates of Puerto Rico and the US Virgin Islands: Seagrass Management. NOAA (National Oceanic and Atmospheric Administration), <https://www.federalregister.gov/documents/2013/03/06/2013-05067/amendment-4-to-the-corals-and-reef-associated-plants-and-invertebrates-fishery-management-plan-of>.
- Freund, Y., and R.E. Schapire. 1997. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of Computer and System Sciences* 55(1):119–139, <https://doi.org/10.1006/jcss.1997.1504>.
- Gilbert, S., S.A. Murawski, M.E. Luther, A. Silverman, M. Hommeyer, R. Vistocci, S. Chernoch, H. Clark, S. Grasty, and K. Erickson. 2025. Partnering with the “Crowd”: Development of a Community Bathymetry Program in Tampa Bay, Florida, USA. *Marine Technology Society Journal* 59(2), pp. 51–61, <https://doi.org/10.4031/MTSJ.59.2.9>.
- Gomes, P.T., R. Henriques, M. Rubal, D. Azevedo, and D. Carreira-Flores. 2025. Assessing the potential of consumer-grade fish finders to improve coastal habitat mapping in data-poor areas. *Continental Shelf Research* 296:105590, <https://doi.org/10.1016/j.csr.2025.105590>.
- Gumusay, M.U., T. Bakirman, I. Tuney Kizilkaya, and N.O. Aykut. 2019. A review of seagrass detection, mapping and monitoring applications using acoustic systems. *European Journal of Remote Sensing* 52(1):1–29, <https://doi.org/10.1080/22797254.2018.1544838>.
- Harden-Davies, H., and P. Snelgrove. 2020. Science collaboration for capacity building: Advancing technology transfer through a treaty for biodiversity beyond national jurisdiction. *Frontiers in Marine Science* 7:40, <https://doi.org/10.3389/fmars.2020.00040>.
- Helminen, J., T. Linnansaari, M. Bruce, R. Dolson-Edge, and R.A. Curry. 2019. Accuracy and precision of low-cost echosounder and automated data processing software for habitat mapping in a large river. *Diversity* 11(7):116, <https://doi.org/10.3390/d11070116>.
- Mitchell, T.M. 1997. *Machine Learning*. McGraw Hill, New York, New York, USA, 432 pp.
- Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, and others. 2011. Scikit-learn: machine learning in Python. *Journal of Machine Learning Research* 12:2,825–2,830.
- Preston, J.M., A.C. Christney, S.F. Bloomer, and I.L. Beaudet. 2001. Seabed classification of multibeam sonar images. Pp. 2,616–2,623 in *MTS/IEEE Oceans 2001: An Ocean Odyssey. Conference Proceedings*, Honolulu, HI, USA, November 5–8, 2001, (IEEE Cat. No. 01CH37295), <https://doi.org/10.1109/OCEANS.2001.968411>.

- Rooper, C.N., and M. Zimmermann. 2007. A bottom-up methodology for integrating underwater video and acoustic mapping for seafloor substrate classification. *Continental Shelf Research* 27(7):947–957, <https://doi.org/10.1016/j.csr.2006.12.006>.
- Sánchez-Carnero, N., D. Rodríguez-Pérez, S. Llorens, V. Orenes-Salazar, A. Ortolano, and J.A. García-Charton. 2023. An expeditious low-cost method for the acoustic characterization of seabeds in a Mediterranean coastal protected area. *Estuarine, Coastal and Shelf Science* 281:108204, <https://doi.org/10.1016/j.ecss.2022.108204>.
- Scherer, M.P., and T.S. Chance. 2023. Enabling over the horizon operation on a line-of-sight uncrewed surface vehicle. Pp. 1–5 in *OCEANS 2023 - MTS/IEEE U.S. Gulf Coast*. Biloxi, MS, September 25–28, 2023, <https://doi.org/10.23919/OCEANS52994.2023.10337131>.
- Virtanen, P., R. Gommers, T. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, and others. 2020. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods* 17:261–272, <https://doi.org/10.1038/s41592-020-0772-5>.

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