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Comparison of Conventional, Rake, and Sonar-Based Biophysical Habitat Measurements in a Shallow Ontario River

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ABSTRACT

Knowledge of habitat availability is critically important for the management and recovery of freshwater species. Quantifying habitat availability often requires fine-scale sampling at point-based locations across a large geographic extent, which can be laboursome. Technological advancements and lower costs make sonar approaches increasingly attractive for quantifying habitat availability, but uncertainty remains about their accuracy and precision in shallow ecosystems. The objective of this study was to determine how well sonar-derived indices aligned with conventional point-based measurements for habitat variables that influence the distribution and life-history functions of freshwater biota (water depth, submerged aquatic macrophyte volume, substrate composition) in a shallow river in Ontario, Canada. Sonar-derived measurements indicated that 98.5% of the surveyed area was <2 m depth (mean = 0.74 m ± 0.33 SD) while kriging interpolation of conventional depth measurements indicated the entire survey area was <2 m depth (mean = 0.97 m ± 0.12 SD). A regression slope of conventional and sonar-derived depth measurements was not significantly different than one ($t_{117} = -0.33$, $p = 0.74$) but conventional measurements were greater than sonar-derived estimates at 88% of the sites, reflecting consistent differences in identifying the bed elevation. Weak ($R^2 < 0.4$) positive correlations were observed between sonar-derived hardness and biovolume with conventional measurements. Differences between conventional and sonar-derived metrics related to measurement scale and the error associated with both conventional and sonar results. Overall, decisions about which approach to use for measuring habitat availability will depend on the specificity required for management decisions.

1 | Introduction

Freshwater species are among the most globally imperiled taxa (Collen et al. 2014; Böhm et al. 2021). Most approaches to protect and recover these species require information about habitat requirements and availability, considering different life-stages when appropriate (Cooke et al. 2012; Castañeda et al. 2020; Drake et al. 2021). Habitat availability can be described and estimated at multiple scales, which will be species and context-dependent (Anderson et al. 2009; Mollenhauer et al. 2019). For example, the availability of habitat for a small-bodied riverine fish species could be examined within a single stream, across multiple streams, or across whole and multiple watersheds depending on the objectives (Dextrase et al. 2014). Quantifying habitat availability at larger scales requires a balance in the level of resolution to be achieved and the amount of effort required for different measurement approaches. For habitat specialists, fine-scale measurements of abiotic variables may be needed to accurately represent habitat availability for the species, but achieving this resolution can be laborious, particularly when sampling is performed at point-based locations across a large geographic extent.

Sonar technology can help overcome the challenges of measuring some aquatic habitat variables at larger spatial scales. While once used solely in marine ecosystems or large freshwater lakes (Fornshell and Tesei 2013), sonar technology is now being used to quantify habitat conditions in a variety of freshwater ecosystems such as shallow beaver ponds (Bradbury et al. 2023) and rivers (Kaeser et al. 2013). This includes quantifying physical habitat structure (e.g., water depth) along with estimates of substrate hardness (Buscombe 2017) and biovolume of aquatic plants (Bennett et al. 2020). The ability to use sonar to monitor freshwater ecosystems is in part due to technological advancements for recreational angling (Cooke et al. 2021; Ridgway et al. 2024); recreational fish finders are now available that use a combination of sonar technologies with complex algorithms to provide live, detailed maps of the underwater environment. Although present-day fish finders can now be used at far shallower depths than was historically possible, there remain uncertainties about sonar performance in shallow ecosystems.

A variety of factors can make habitat sampling in shallow aquatic ecosystems challenging. From a conventional standpoint, substrate can be too soft to effectively navigate the waters by foot, or in turbid urbanized systems, sampling may need to be performed from a boat to ensure crew safety (e.g., danger due to anthropogenic waste). Sonar technology could be particularly helpful in these situations when sampling cannot be performed by wading. However, shallow depths can limit the effectiveness of sonar technology due to the increased frequency of multipath propagation (Kandi et al. 2024). Multipath propagation describes the situation when acoustic waves have multiple reflections or refractions, or scatter prior to being received, which reduces image quality (Kandi et al. 2024). Few studies have quantified the magnitude of error when mapping shallow ecosystems using recreational sonar, and therefore studies evaluating the relationship between sonar-derived outputs from recreational fish finders with point-based measurements can improve our understanding of the ability to use sonar technology to map fish habitat (Winfield et al. 2015; Botrel et al. 2023).

The objective of this study was to undertake aquatic habitat mapping in the Canard River, Ontario, Canada and compare sonar-derived habitat measurements with data collected using conventional, point-based habitat surveys. The Canard River functions as a shallow wetland throughout its downstream reaches and supports a diverse fish and mussel community, with records of at least six freshwater taxa (five fishes, two mussels) protected under the Canadian *Species at Risk Act* (SARA 2002). We first investigated the spatial distribution of, and relationship between, sonar-derived depth, substrate hardness, and biovolume of aquatic macrophytes using a Lowrance HDS 9 Live Sonar Unit. Next, we evaluated how site-specific conventional habitat measurements and rake-based vegetation surveys compared to sonar-derived metrics. Finally, we developed habitat classes based on sonar-derived depth and biovolume estimates to provide a spatial habitat surface that can inform freshwater species monitoring programs in the Canard River. Overall, the results of this study provide insight into the relationship between conventional habitat measurements and sonar-derived estimates, and an example of the use of sonar-based methods in a large, shallow, vegetated riverine habitat.

2 | Materials and Methods

2.1 | Study Area

The Canard River is a tributary of the Detroit River located in Essex County, Ontario. Land use in the Canard sub-watershed is primarily agricultural; more than half of the sub-watershed area is under tile drainage with corn, winter wheat, and soybeans being the major crops (Singh 2014). Water quality in the Canard River is relatively poor, with frequent exceedances of provincial guidelines for nitrates, nitrites, ammonia, total phosphorus, and suspended solids (Essex Region Conservation Authority 2015; Morris et al. 2020). Despite water quality concerns, the river supports over 40 freshwater fish species (Leslie and Timmins 2005) and eight mussel species (Morris et al. 2020). The Canard River was surveyed between July and September 2023 using a multimethod approach, where habitat characteristics considered important for supporting freshwater fishes (Jackson et al. 2001) were measured, including both biological (e.g., vegetation cover) and physical measurements (e.g., depth). Measurement approaches, which are described below, included (1) conventional habitat sampling, (2) rake-based sampling, and (3) sonar sampling.

2.2 | Conventional Habitat Sampling

Conventional habitat sampling occurred at randomly selected point locations (i.e., sites) across the navigable portion of the river, with 124 sites being within the area surveyed using sonar (Figure 1). Conventional habitat sampling consisted of point-based measurements of turbidity (Nephelometric Turbidity Units; NTU), water temperature (°C), dissolved oxygen (mg/L), and water depth (m). Three depth measurements were recorded per site, one from the bow, stern, and port side of the boat, and were averaged. Water quality variables were measured using a YSI EX02 multiparameter sonde, and depth was measured using a telescopic push pole. A visual assessment of the areal percent cover of emergent, submerged, and floating vegetation, or open water at a site was also recorded. Substrate composition was quantified by obtaining a handful of bed material within the center of the site, or with a Petite Ponar dredge, and describing the sample based on median particle diameters derived from Bain's (1999) modified Wentworth scale, a scale common for characterizing substrate composition for assessing fish-habitat associations (e.g., Gáspárdy, Goguen, et al. 2021; Gáspárdy et al. 2025). Substrate composition at a site was described as the proportional representation of clay (<0.005 mm), silt (0.005–0.05 mm), sand (0.05–2 mm), gravel (2–65 mm), cobble (65–250 mm), rubble (broken manmade material), and organic material (plant and animal material, excluding mussels). Finally, we summed the proportional representation of clay and silt, and refer to that sum as the proportional representation of soft substrate.

2.3 | Rake-Based Vegetation Sampling

A rake-based method was used to sample aquatic vegetation at sites with conventional sampling ($n = 124$ sites) that was adapted from Wagner and Mikulyuk (2012). The method

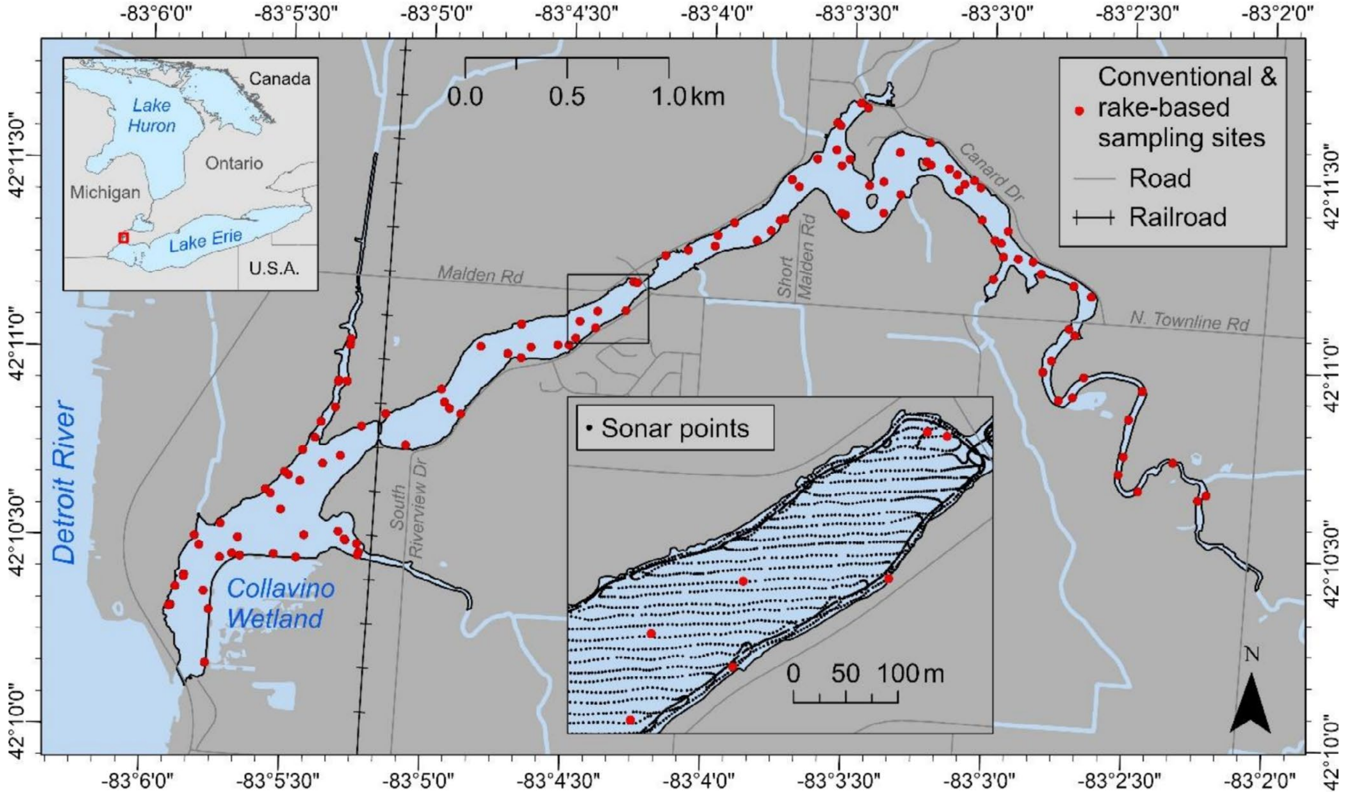

FIGURE 1 | Location of conventional and rake-based habitat sampling (red points) in the Canard River, Ontario, Canada (July–September 2023). The bottom inset map is an example of the sonar transects performed across the entirety of the outlined river section. [Color figure can be viewed at wileyonlinelibrary.com]

involved submerging a garden rake (50-cm head width) to the river bottom, spinning the rake 360°, pulling it up vertically, and recording information on the collected vegetation (Gáspárdy, Barnucz, et al. 2021). Vegetation collected by rake was bagged at each site and brought back to the laboratory, frozen, and subsequently thawed for processing. In the laboratory, thawed specimens were separated by taxa, identified to the species or genus level, gently dried via a salad spinner, and weighed (g; White et al. 2026). Displacement volume, which describes the volume of water displaced after submerging the aquatic vegetation in a known volume of water, was measured per taxa as a proxy for site biomass using a graduated cylinder. Further methodological details on vegetation sampling can be found in White et al. (2026).

2.4 | Sonar Data Collection and Preparation

Down-scan sonar data were collected from a 5.7-m aluminum jon boat using a Lowrance HDS 9 Live Sonar Unit equipped with a 3-in-1 transducer between July 18–26, 2023. Down-scanning was performed as opposed to side-scan as down-scan produces finer resolution maps, and due to the shallow water, it was expected to experience less backscatter. The transducer was mounted to the vessel on the starboard side of the gunwale near the bow, 5 cm below the water surface. A Lowrance Point-1 external GPS antenna was used to improve accuracy for vessel navigation and sonar data collection. The Wide Area Augmentation System was enabled on the GPS, which led to an accuracy of 1–2 m. Prior to sampling, a mapping grid was developed using the search and rescue feature within the sonar unit to provide operators with a trail to navigate during sampling; 10 m between trails was chosen for this project (Figure 1 inset), which provided suitable habitat coverage while allowing for efficient vessel navigation.

Sonar measurements were recorded by first performing a shoreline transect, navigating as close to the shoreline as possible (Figure 1). Once the shoreline transect was complete, the vessel operator proceeded to follow the 10-m mapping grid. Vessel speed was maintained at 4.5–6.5 km/h to achieve optimal data quality during recording; vessel speed was reduced to approximately 2.5 km/h while turning at the end of each mapping grid transect. Care was taken to ensure that mapping grid lines and shoreline transect lines overlapped along the edges of the mapped area to ensure data quality during times of reduced vessel speed during turns and in shallow habitats. As well, the transducer was monitored during sampling to avoid macrophyte interference with data collection. Data files were downloaded at the end of each survey day for archiving. Finally, downloaded file outputs were uploaded to BioBase, which is a proprietary cloud-based webtool that automates sonar and GPS signal processing to extract measures of substrate hardness, depth, and percent biovolume at points within the transects.

Kriging interpolation of substrate hardness, depth, and percent biovolume was performed in ArcGIS Pro Version 2.9.8 at a 10-m resolution within the spatial extent of the Canard River, which was based on the Ontario Hydro Network waterbody polygons (OMNRF 2018). Previous research has demonstrated

Kriging approaches outperform other interpolation methods when describing trends in spatially dynamic landscapes (Valley et al. 2005). A point grid was extracted from each of the surfaces using the ArcGIS Conversion Toolbox. Locations of conventional habitat measurements were spatially joined to the substrate hardness, depth, and biovolume grids to extract interpolated estimates, where the mean value of points within 10 m of the conventional habitat survey location was calculated and extracted for analysis. Three observations were excluded from the conventional data set as they were not within 10 m of the sonar recordings. In addition, kriging interpolation was performed for conventional and rake-based metrics to produce maps comparable to the sonar-derived estimates.

K-means clustering was used to develop a map of general aquatic habitat classes across the Canard River. The approach was designed to divide multivariate data sets into K clusters by minimizing the within-cluster sum of squares (Hartigan and Wong 1979); $K = 2$, 3, 4, and 5 clusters were considered that were based on sonar-derived estimates of biovolume and depth. Substrate hardness was not included in the clustering as there was limited variation observed across the system. The elbow method was used to select the best K for the data, which is a visual test evaluating the difference in sum-of-square error for each K cluster. Clustering was performed using the 'kmeans' function from the R "stats" package (R Core Team 2024) and mapped in ArcGIS Pro Version 2.9.8.

2.5 | Comparisons Between Conventional, Rake, and Sonar-Derived Metrics

Generalized additive models (GAMs) were used to evaluate the relationship between sonar-derived and conventional depth measurements to account for nonlinear relationships. Given the imperfect relationship, we evaluated whether the inclusion of the proportion of soft substrate cover (conventional measure) would improve model performance. We hypothesized that differences in depth measurements could be influenced by the presence of unconsolidated benthic material or other soft substrates. Conventional measurements could infer deeper habitats in areas with high coverage of soft substrate as the telescopic push pole used to measure depth may break the top layer of the substrate when lowered to the bottom, whereas sonar-based methods may better capture the depth to the top of the substrate layer.

GAMs were fit using the 'gam' function from the 'mgcv' package in R (Wood 2011; R Core Team 2024), where a Gaussian family was used to model depth and covariates were incorporated as linear predictors or thin plate regression splines (Wood 2003). Prior to modeling, 0.05 m was added to sonar-derived depth measurements to account for the depth of the transducer. Chi-square tests were used to determine whether the inclusion of smoothing variables (thin plate regression splines) and/or linear predictors improved model performance at a significance level $\alpha = 0.05$. Model diagnostics were evaluated using the "plot" function in base R and the "gam.check" function in "mgcv" (Wood 2011, R Core Team 2024). Based on diagnostic plots, we suspected that there may be spatial autocorrelation in model residuals and therefore we considered a smooth interaction term of UTM-coordinates to better fit model assumptions of independence between sites.

A t-test was used to determine if the modeled slope and intercept of conventional depth on sonar-derived depth was significantly different than one and zero, respectively. In addition to the regression-based approach, a Kolmogorov–Smirnov test was used to compare the cumulative distribution functions of sonar-derived depth measurements with interpolated conventional depth measurements. Statistically significant differences in distribution would indicate that the two measurement approaches produce values that differ more than expected from random sampling variation alone.

Comparisons of substrate hardness and biovolume with conventional measures were less direct than for depth but followed a similar analysis procedure. Substrate hardness estimates are derived based on the reflectivity of the river bottom; acoustic signals reflect more off hard than soft surfaces. Sonar-derived estimates of substrate hardness are on a relative scale with values of 0.00–0.25 representing soft bottoms, 0.25–0.30 representing medium hardness bottoms, and 0.30–0.50 representing hard bottoms (BioBaseMaps 2019). Previous research has demonstrated a negative correlation between substrate hardness and sediment depth measured using sediment cores and with visual assessments (Winfield et al. 2015). Here, we evaluated the relationship between sonar-derived substrate hardness and the proportion of a site composed of soft substrate. We compared models where the proportional cover of soft substrate was included as a linear or smoothed effect and evaluated model residuals with and without a spatial parameter. This was under the hypothesis that hardness would be negatively related to the proportion of soft substrate cover, and to consider potential spatial relationships in model residuals. GAMs were fit for sonar-derived hardness using a quasibinomial family due to its proportional structure.

Sonar-derived biovolume describes the percentage of the water column occupied by aquatic vegetation. It is estimated by dividing the mean plant height (m) recorded in the water by mean water depth (m) averaged over 5–30 pings bound to each GPS location along a traveled path multiplied by 100. We compared biovolume estimates with the total displacement of vegetation measured at a site from rake collections using GAMs. Previous research suggested a correlation between percent biovolume at a site and the frequency of occurrence of aquatic plants from point surveys (Valley et al. 2015). As such, we also considered the proportion of a site with aquatic vegetation in our model. Like the hardness models, GAMs were fit for biovolume using a quasibinomial family, and covariates were incorporated as linear effects or thin plate regression splines (Wood 2003). All model predictions were plotted using "ggplot2" functions in R (Wickham 2016; R Core Team 2024).

3 | Results

3.1 | Conventional Habitat Sampling

Water temperature ranged between 18.9°C–29.3°C during the sampling period (Figure 2a). Mean dissolved oxygen was 6.31 mg/L ± 2.99 SD (Figure 2b). Turbidity varied from clear to

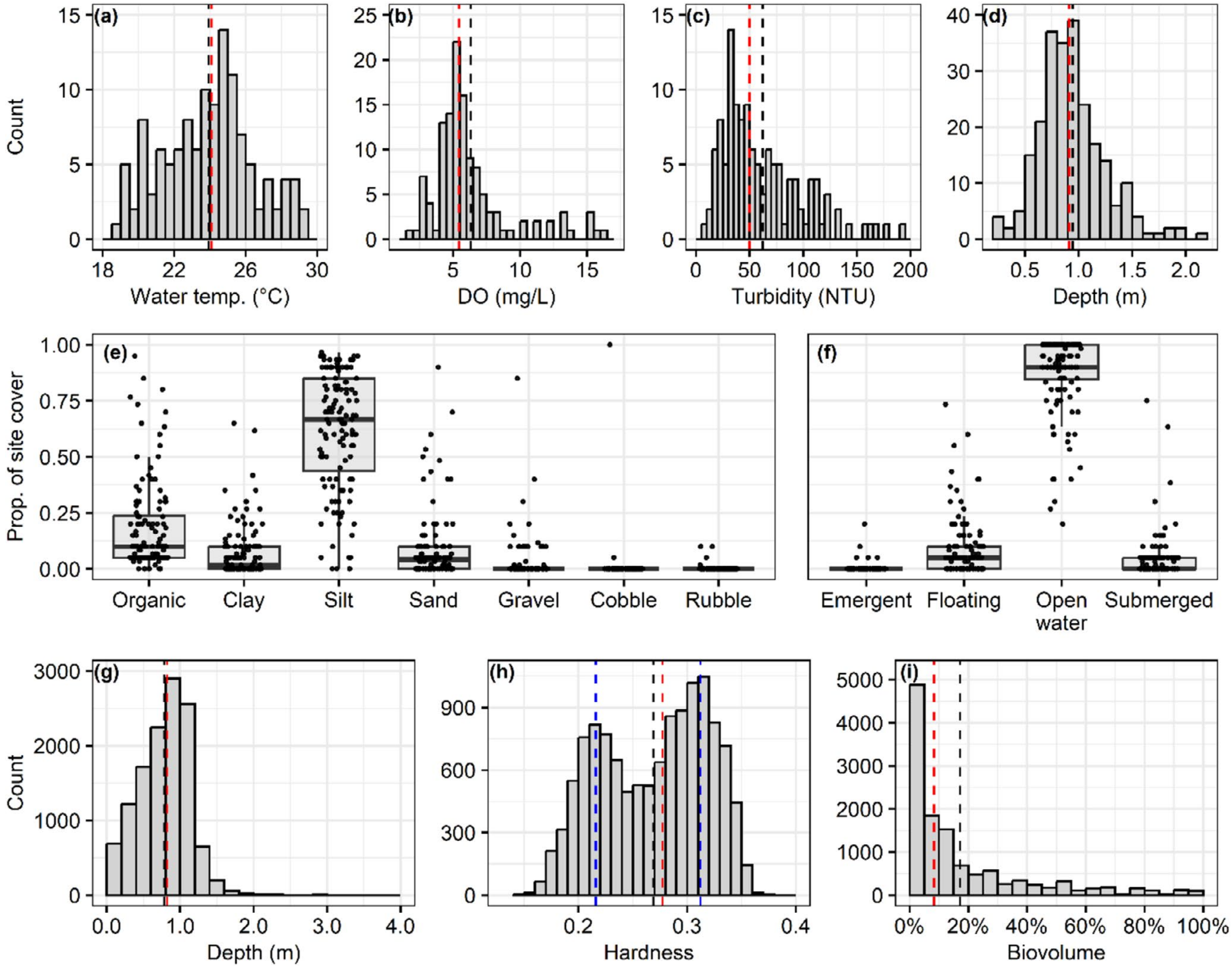

FIGURE 2 | Histograms of (a) water temperature (°C), (b) dissolved oxygen (DO; mg/L), (c) turbidity (NTU), and (d) water depth (m) measurements collected using a conventional sampling approach from the Canard River. Also shown are boxplots of the proportional cover of (e) sediment and (f) vegetation classes at a site, and histograms of sonar-derived (g) water depth (m), (h) substrate hardness, and (i) biovolume. Red dashed lines indicate medians, black dashed lines indicate means, and blue dashed lines indicate two modes for substrate hardness. [Color figure can be viewed at wileyonlinelibrary.com]

turbid, with measurements ranging between 5.26 and 192.96 NTU (Figure 2c). Measured water depth at conventional habitat site locations averaged 0.95 m ± 0.31 SD (Figure 2d). Substrate was primarily composed of silt (median = 66.67% cover), followed by organic material (10.00%), sand (4.17%), and clay (1.67%); minimal large-grain substrates were observed (Figure 2e). Most survey sites were characterized by open water (median = 90%), followed by different proportions of floating, submerged, and emergent vegetation (Figure 2f).

3.2 | Rake-Based Vegetation Sampling

Seventy-four sites (60%) had no vegetation collected on the rake. Four submerged taxa were collected: Coontail (*Ceratophyllum demersum*), *Naiad* sp., Sago Pondweed (*Stuckenia pectinatus*), and Water Celery (*Vallisneria americana*). Similarly, three floating taxa (filamentous algae, Duckweed *Lemna* sp., Pondweed *Potamogeton natans*) and three emergent taxa (Lotus *Nelumbo lutea*, Yellow Pond Lily *Nuphar variegate*, White Water Lily *Nymphaea* sp.) were collected. Of the 13,791 mL of total displacement measured in the laboratory, American Lotus and White Water Lily were the most dominant, with a total displacement of 6754 mL (49%) and 4888 mL (35%), respectively. Coontail (965 mL; 7%), *Naiad* sp. (504 mL; 4%), Yellow Pond Lily (300 mL; 2%), Pondweed (floating leaves; 180 mL; 1%), and Duckweed (113 mL; 1%) were the other taxa with a total displacement greater than 100 mL.

3.3 | Sonar-Derived Habitat Characteristics

Sonar-derived habitat measurements indicated that 98.5% of the surveyed area in the Canard River was < 2 m depth (mean = 0.74 m ± 0.33 SD; range = 0.00–3.73 m) with relatively low biovolume (mean = 0.17 ± 0.22 SD; range = 0–1) and medium substrate hardness (mean = 0.27 ± 0.05 SD; range: 0.14–0.38; Figure 2g–i). There was limited variation in sonar-derived depth across the river, with the deepest locations associated with road and railroad crossings (Figure 3a). Sonar-derived estimates of substrate hardness showed a bimodal distribution with modes of

0.22 and 0.31 (Figure 2h). The softest substrates were observed downstream of Short Malden Rd. (Figure 3b). Biovolume estimates across the sampled area were right skewed, with 72.6% of estimates below 0.20 (Figure 2i). Biovolume was patchy, with the greatest biovolume observed upstream of Short Malden Rd. along Canard Dr. and west of the railroad tracks (Figure 3c). Biovolume was greatest at locations with moderate substrate hardness (Figure 4a); 62.2% of the surveyed area of the Canard River had substrate hardness > 0.25. The shallowest locations had the greatest biovolume (Figure 4a); 99.9% of the area with biovolume ≥ 25% was < 1 m depth. A strong negative correlation was observed between biovolume and depth (Figure 4b), and hardness was greatest in the shallower locations (< 0.5 m; Figure 4c).

Three clusters were derived based on sonar-derived depth and biovolume estimates, interpreted as: (1) shallow depth (mean = 0.25 m), high biovolume (0.59); (2) medium depth (0.68 m), medium biovolume (0.13); and (3) deep depth (1.10 m), low biovolume (0.05; Figure 5). Approximately 16.88%, 40.45%, and 42.67% of the surveyed area was classified as Clusters 1, 2,

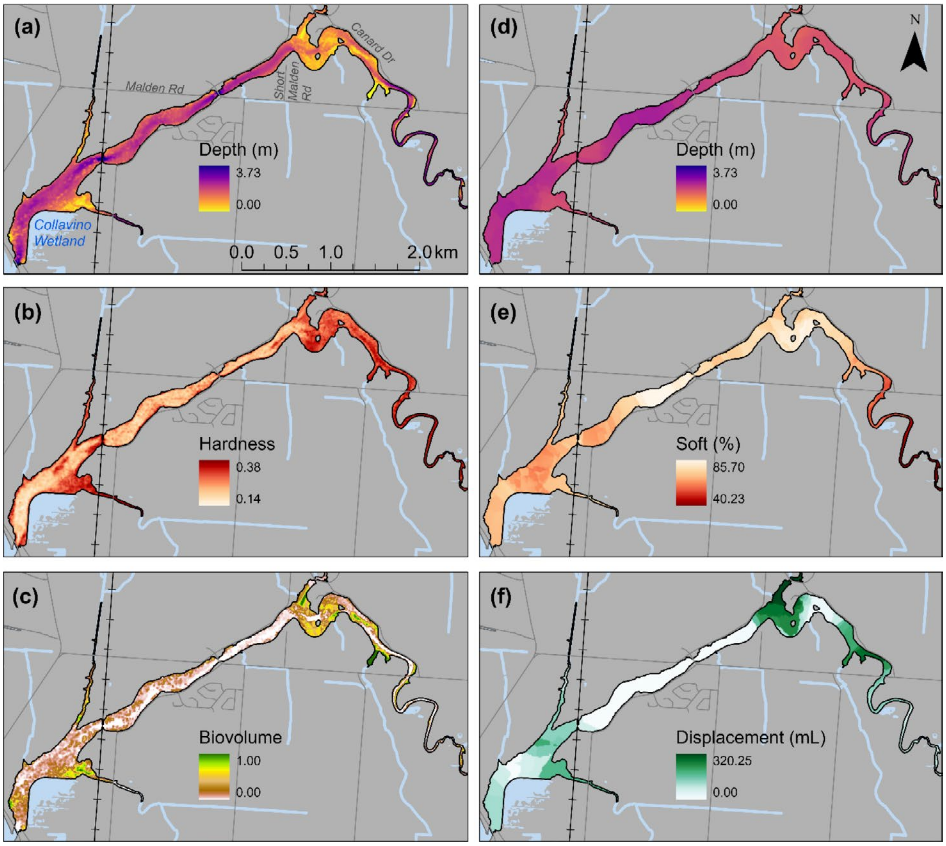

FIGURE 3 | Kriging interpolations of sonar-derived (a) water depth (m), (b) substrate hardness, and (c) aquatic plant biovolume, and conventional and rake-based metrics including (d) water depth (m), (e) percent soft substrate cover, and (f) total aquatic vegetation displacement (mL). [Color figure can be viewed at wileyonlinelibrary.com]

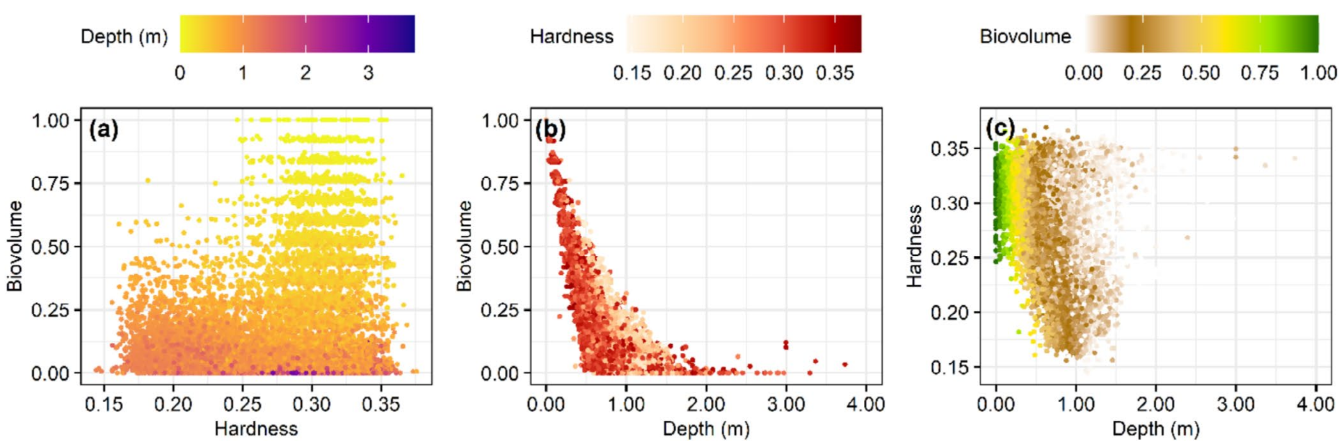

FIGURE 4 | Relationships between sonar-derived variables. Color scales match Figure 3's maps. [Color figure can be viewed at wileyonlinelibrary.com]

and 3, respectively (Figure 5a). The shallowest areas with the greatest biovolume (Cluster 1; Figure 5b) were mostly found along the shoreline, while the mid-channel areas had greater depths but less biovolume (Clusters 2, 3; Figure 5a).

3.4 | Comparisons Between Conventional, Rake, and Sonar-Derived Metrics

A positive linear relationship was observed between sonar-derived (d_s) and conventional (d_c) measurements of water depth ($d_s = 0.98 \times d_c - 0.18$), with an adjusted $R^2 = 0.603$ (Figure 6a). The slope of this relationship was not significantly different from 1 ($t_{117} = -0.33$, $p = 0.74$) while the intercept was significantly different than 0 ($t_{117} = -2.57$, $p = 0.01$); mean depth was significantly different between the conventional (mean ± SD = 0.95 m ± 0.31) and sonar-derived methods (0.74 m ± 0.33; $t_{225.61} = 5.69$, $p < 0.001$). The mean difference between methods at sites with conventional habitat sampling was 0.21 m ± 0.20 SD. Approximately 88% of the conventional measurements were greater than corresponding sonar-derived estimates, which is shown in Figure 6a as points below the 1:1 line. A Kolmogorov–Smirnov test indicated that the distribution of sonar-derived depth measurements was significantly different than the distribution of depths interpolated from the conventional depth measurements ($D = 0.42$, $p < 0.001$; Figure S1). Interpolation using the conventional measurements led to more uniform depth across the entirety of the sampling frame (Figure 3d), lacking the fine-scale differences observed through sonar recordings (Figure 3a).

The final depth model included a linear effect of the proportion of a site with soft substrate, which was negatively related to sonar-derived depth (Figure 6b). Modeled residuals were determined to be non-random based on a normal Q–Q plot; a smooth interaction term of UTM-coordinates eliminated residual

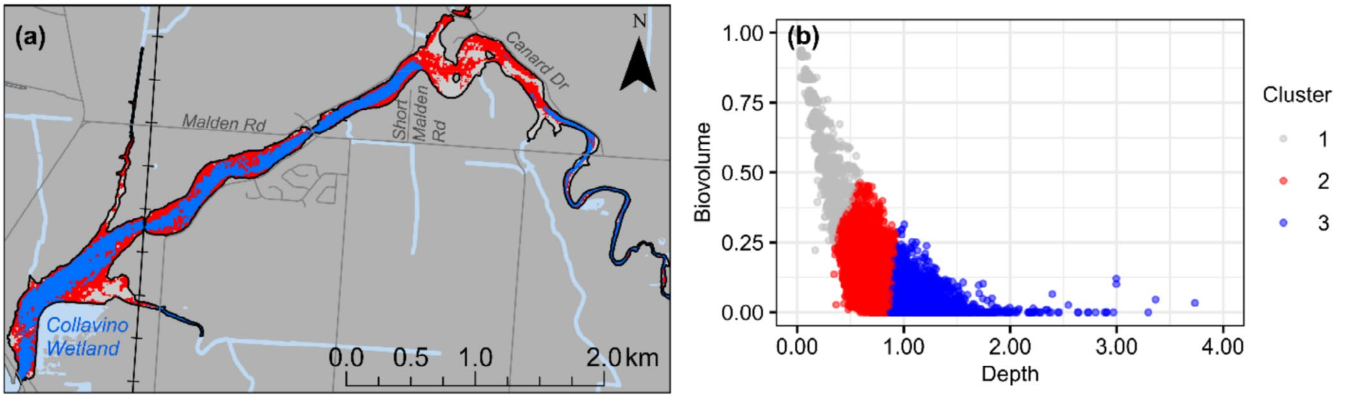

FIGURE 5 | (a) Map of habitat clusters (colours) of the Canard River built based on sonar-derived estimates of biovolume and depth. (b) Sonar-derived biovolume as a function of site depth (m) based on cluster assignment. [Color figure can be viewed at wileyonlinelibrary.com]

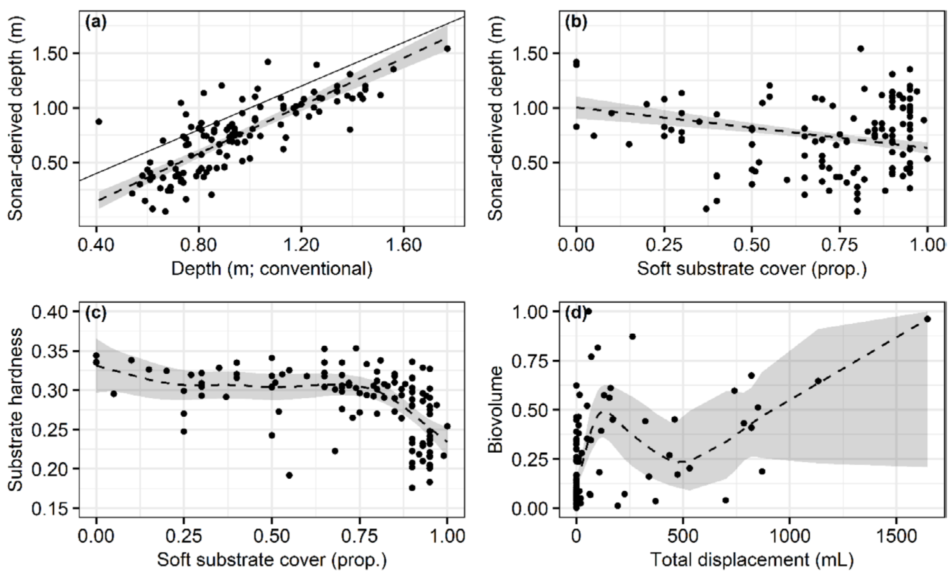

FIGURE 6 | Generalized additive model (GAM) effects plots. Partial effects are displayed as black dashed lines with 95% credible intervals (grey ribbon) for (a) conventional depth and (b) soft substrate cover with sonar-derived depth. Effects plots are also presented for (c) soft substrate cover with sonar-derived hardness, and (d) total vegetation displacement (mL) with sonar-derived biovolume. The solid black line in (a) indicates 1:1 relationship. [Color figure can be viewed at wileyonlinelibrary.com]

patterns and improved model fit (χ^2 deviance = 1.12, df = 7.99, $p < 0.001$; adjusted $R^2 = 0.713$). Even after accounting for measured depth and soft substrate cover, sonar readings were consistently deeper in the upstream section (Figure S2).

A nonlinear, negative relationship was observed between sonar-derived hardness and the proportion of soft substrate at a site (adjusted $R^2 = 0.199$; Figure 6c). The negative relationship between hardness and soft substrate cover was particularly evident at sites where the proportional cover of soft substrates measured greater than 0.75 (Figure 6c). Inclusion of a smoothed spatial covariate improved model performance (adjusted $R^2 = 0.533$); in general, sonar-derived hardness was predicted to be firmer than what is expected in upstream and nearshore habitats based on the measurements of soft substrate cover, and softer in the main channel (Figure S2). Interpolation of the percent soft substrate at a site (Figure 3e) broadly aligned with the distribution of sonar-derived hardness (Figure 3b), where the softest substrates were found in the middle section of the river.

The relationship between biovolume and the total vegetation displacement at a site was non-linear, but generally positive (adjusted $R^2 = 0.375$; Figure 6d). Inclusion of the percent cover of aquatic vegetation at a site as a linear (χ^2 deviance = 0.19, df = 0.38, $p = 0.12$) or smoothed effect (χ^2 deviance = 0.92, df = 1.37, $p = 0.054$) did not significantly improve model performance, but a spatial variable did (χ^2 deviance = 10.82, df = 28.14, $p < 0.001$; Figure S2). The relationship between biovolume and vegetation displacement was considered insignificant ($p = 0.079$) when sites with zero vegetation on the rake were removed ($n = 24$ remaining sites; adjusted $R^2 = 0.291$). Interpolation of aquatic vegetation displacement was successful at delimiting the areas with the greatest density of aquatic vegetation but failed to capture the fine-scale patterns such as in nearshore areas (Figure 3f).

4 | Discussion

Quantifying habitat composition for freshwater species is important for management, but collecting spatially expansive habitat data can be difficult. Recent advancements have made sonar technology more accessible and affordable, offering an effective way to map freshwater habitat features. However, its application in shallow systems presents unique challenges. In particular, shallow water increases the likelihood of multipath propagation, which can degrade image quality relative to deeper water. Our results suggested a strong positive correlation between conventional and sonar-derived depth estimates in the Canard River, but the two measurement techniques resulted in different means and overall distributions. Less strong were the relationships for measurements of substrate composition and biovolume between conventional and sonar-derived metrics.

Although the slope of the relationship between conventional and sonar-derived depth was not significantly different from one, conventional measurements were greater than sonar-derived estimates at most surveyed sites. This discrepancy may be partly explained by the methods used to collect and compare the depth data. Conventional depth measurements were recorded from the bow, stern, and port side of the boat using a telescopic push pole and averaged, while we averaged sonar-based estimates within 10 m of the conventional site coordinates. The averaging procedures themselves may have contributed to the imperfect relationship, as they involved comparing spatially distinct and methodologically different measurements. Additionally, the soft river bottom likely introduced error in the conventional measurement; the push pole may have penetrated the soft substrate resulting in greater depth readings than those captured by sonar. This was supported by the partial effects plots of the top GAM, which indicated that sonar-derived depth was reduced with increasing proportional cover of soft substrate, assuming conventional depth was fixed at its mean.

A weak positive relationship was observed between metrics derived from rake-based surveys with sonar-derived biovolume, which corresponds with previous research in other freshwater ecosystems (Valley et al. 2015; Howell and Richardson 2019; Helminen et al. 2019). For example, Valley et al. (2015) compared the frequency of occurrence of submerged and floating aquatic vegetation with sonar-derived estimates of biovolume. Their results suggested a weak positive relationship ($R^2 = 0.43$), albeit slightly stronger than what was observed in this study between biovolume and vegetation displacement. Botrel et al. (2023) evaluated the interchangeability of quadrat, rake, and echosounding techniques for quantifying the biomass of submerged aquatic vegetation in Lac Saint-Pierre, Québec. Their results suggested that biovolume estimates were underestimated in shallow habitats (< 1 m) but outperformed point estimate sampling in deeper habitats (> 3 m). The imperfect relationship between biovolume and total displacement in this study was likely caused by challenges with interpretation of sonar readings at shallow depths as the majority of the Canard River is < 1 m depth, along with error associated with an imperfect approach to measuring aquatic vegetation (i.e., rake-based survey).

We observed a weak negative relationship between sonar-derived hardness and the percent soft substrate cover at a site. Previous research suggests that hardness scores can be biased high due to the challenges of interpreting sonar returns in shallow (< 0.74 m) or densely vegetated habitats (BioBaseMaps 2017), which may explain some of the discrepancies observed in this study. Brownscombe et al. (2024) noted that interpretation of substrate hardness using down-scan sonar can be challenging, citing that higher hardness values can represent different scenarios, from simple bare rock substrate to intermixed substrates that cannot be distinguished. An additional challenge for this study was that the conventional approach to measuring substrate size consisted of a single grab sample which suffers from in-field interpretation and can fail to accurately represent the variation of the surrounding area. Nevertheless, the interpolated trends from conventional measurements broadly showed similar patterns to the sonar-derived metrics, where the middle section of the river contained the softest substrates relative to sampled areas up- and down-stream.

Clustering of the sonar-derived metrics allowed for the creation of broad habitat classes that can be used for multiple purposes, including site selection for monitoring or identifying ecologically significant areas for species life-history. Previous research has linked sonar-derived habitat characteristics with ecologically significant habitat of rare fishes. Schooley and Neely (2018) compared sonar-derived estimates of hardness with the results of substrate grab sampling and visual assessments to understand Paddlefish (*Polyodon spathula*) spawning habitat availability in two southern United States rivers; areas of potential spawning habitat were characterized as sites with hardness ≥ 0.386 (Schooley and Neely 2018). Winfield et al. (2015) found a moderate correlation between sonar-derived hardness estimates and a visual habitat suitability index for Arctic Charr (*Salvelinus alpinus*) spawning habitat ($R^2 = 0.48$; Winfield et al. 2015). Fish species monitoring in the Canard River could benefit from a habitat-stratified sampling design informed by the sonar-derived habitat clusters. For example, Cluster 1 (shallow depth, high biovolume) may be considered ecologically significant habitat for species such as Longnose Gar (*Lepisosteus osseus*; Holm et al. 2009) that occupy densely vegetated areas, and therefore sampling efforts could be prioritized within these clusters.

5 | Conclusion

The general alignment with conventional measurements and increased spatial coverage of sonar-based methods suggests that sonar technology can be used as a tool to quantify certain habitat features that influence the distribution and life-history functions of freshwater fish species. Nevertheless, there are advantages and disadvantages of relying on this technology. Generally, sonar derived data are quicker to collect and result in significantly more data for selected variables across a greater geographic area than conventional measurements; for example, conventional sampling in this study required 28 days of sampling whereas sonar data collection was completed in six days. And because of the increased sample size, there are fewer assumptions about interpolation across the surveyed region. Alternatively, at present, sonar-derived data do not capture information about the composition of vegetation or water quality conditions that can be important life-history requirements of particular species. Moreover, expertise is required to assemble and operate the sonar equipment to ensure accurate data collection, and during processing. Significant preparation was undertaken prior to field sampling that included installation of the unit, configuring the settings, and anticipating potential challenges. Finally, whereas conventional sampling and analysis of the data could be performed by trained biologists using open-source software (e.g., R Core Team 2024), mapping the river using the down-scan sonar required the use of proprietary software to extract the data that now requires licensing.

Ultimately, the decision on what to measure and how to measure it (e.g., conventional, rake, sonar) should be guided by the species of interest and specific research objectives under consideration. Each method applied in this study offers different strengths, and in most situations, using a combination of approaches will provide the most reliable and ecologically meaningful information. A multi-method design captures a broader range of habitat characteristics and allows sonar-derived measurements to be continually validated against conventional techniques. Future work will focus on integrating sonar more fully into fish species monitoring programs by not only mapping habitat types, but also linking those habitat patterns to full fish community composition data. Ultimately, integrating a multi-method approach to habitat assessments will help refine habitat classifications, improve calibration across sampling techniques, and, when paired with fish sampling, strengthen our understanding of how species interact with shallow freshwater habitats.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support this study are stored in the Biodiversity Science Database at Fisheries and Oceans Canada and can be obtained through the following weblink or by contacting the Great Lakes Laboratory for Fisheries and Aquatic Sciences.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** rra70120-sup-0001-Supinfo.docx.