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MidFish: A harmonized freshwater fish survey data resource for fisheries research and management

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Minnesota Department of Natural Resources staff conduct annual seining survey on Lake Vermilion, Minnesota, USA. Photo credit: Gretchen Hansen.

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Abstract

Agencies across North America monitor freshwater fish populations to assess status and trends and to evaluate the effectiveness of management actions. Leveraging monitoring data across regions can improve the statistical power to detect change and evaluate management outcomes, but differences in sampling protocols, database structures, and terminology require integration of disparate data sources to enable effective use. We present MidFish, a publicly available data resource consisting of a harmonized database with reproducible and customizable workflows that integrates fish survey data from seven Midwestern states spanning 1937–2023. MidFish contains over 60 million individual fish records from 133,227 surveys across 8,431 water bodies, including over 21 million records with fish length measurements. Data were harmonized into a database of individual fish with fields containing information on individual fish characteristics, surveys, and lakes. Survey gear, effort, and purpose are included to enable calculation of relative abundances while accounting for differences in sampling methodologies. We provide customizable workflows that allow users to generate data sets or aggregated metrics tailored to specific analyses. Two example applications include generating standardized catch-per-unit-effort data sets for eight sport fish species and estimating time to harvestable size for Walleye *Sander vitreus* across lakes. MidFish provides a foundation for regional analyses of fish populations, growth, and size structure, and demonstrates how data sharing and harmonization can increase the scientific and management value of long-term fisheries monitoring programs more broadly.

Keywords: age and growth, FAIR data principles, Fish, fisheries, integrated data, lake, midFish, midwestern United States, monitoring data, recreational fisheries, relative abundance

Introduction

Lakes across the Midwestern United States support socioeconomically important, multispecies fisheries. To manage these resources, federal, state, local, and tribal natural resource management agencies devote significant resources to surveying fish populations and their habitats. Monitoring programs collect information on relative abundance, size, age, and species composition, which can be used to assess population status and trends, ecosystem responses to environmental change, and the effectiveness of management interventions (Bonar et al., 2024; Cooke et al., 2016; Radinger et al., 2019). Due to limited resources, agencies often cannot monitor at a sufficient spatio-temporal resolution to detect population or ecosystem responses on individual lakes at management relevant timescales (Wagner et al., 2013). In lake-rich regions, where monitoring efforts are spread across thousands of lakes, the lack of statistical power to detect responses on individual systems is even more problematic (Lester et al., 2003). As freshwater fisheries face increasing stress from global change (Reid et al., 2019), regional data sets that allow for assessing responses across broad environmental gradients and spatio-temporal scales are increasingly useful (Midway et al., 2016). Integrating and harmonizing data from disparate systems can improve the ability to detect change and support science-based fisheries management both by increasing sample size and statistical power and by examining responses over wider ranges of environmental conditions (Sievert et al., 2026).

Numerous efforts have compiled large freshwater fish data sets across regions and taxa (e.g., Comte et al., 2021; Embke et al., 2022; Lynch et al., 2021), but many remain limited by geography, standardization requirements, or challenges integrating data collected for different purposes (Midway et al., 2016; Sievert et al., 2026). In their foundational work to collate freshwater fish survey data from lakes in the Midwestern United States in the 1980s and 1990s, Beard et al. (1998) recognized that "Access to data sets that are temporally and spatially extensive would allow a more holistic description of the U.S. fisheries resources and facilitate the implementation of an ecosystem-based approach to decision making." This effort was an important step in collating freshwater fisheries data for this lake-rich region, but usage was low due to the challenges associated with harmonizing data and the database is no longer maintained. Recently, freshwater fish data collected using standardized methods from North America have been compiled and summarized (Tracy et al., 2023, 2024). However, the reliance on standardized methods means that lake-rich Midwestern states are massively underrepresented due to nonstandard sampling methodology employed in these states. Although standardized methods exist for monitoring freshwater fish populations (Bonar et al., 2024), sampling protocols for freshwater fish are not standardized across jurisdictional boundaries within North America (Bonar & Hubert, 2002; Cooke et al., 2016). Standardized monitoring programs are often cost prohibitive or impractical to implement consistently and are not always feasible (Bonar & Hubert, 2002; Smith & Blackwell, 2019). As an alternative, nonstandardized monitoring data can be integrated from diverse sources to form an ad hoc landscape level assessment (e.g., Sievert et al., 2026). In the absence of widespread adoption of standardized survey methodology, harmonizing data from disparate sources offers an alternative opportunity to leverage the vast amount of information contained in freshwater fish monitoring data to support fisheries management.

Although fish catch and effort data provide the foundation for inland fisheries management, harmonizing such data into a common structure that maximizes comparability between jurisdictional boundaries presents challenges (Kolb et al., 2013). Because inland fisheries monitoring and management is generally the purview of state agencies, sampling methods often differ across state lines. Within an agency, most states have fisheries monitoring protocols (e.g., Minnesota Department of Natural Resources, 2017), although protocols

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may vary even within a single agency over space and/or time for a host of logistical, financial, or cultural reasons (Hayes et al., 2003; Smith & Blackwell, 2019). Notable exceptions are community-level sampling programs (e.g., Bacigalupi et al., 2021) where the focus is on quantifying biodiversity and community-level metrics. Additionally, considerable variation between agencies exists in how (and whether) data are housed in a centralized database, the level of quality control applied to such databases, and the temporal window for which electronic data are available. As agencies are responsible for increasing amounts of data and multiple data requests, the time and resource burden for maintaining data quality and metadata is growing. Further, many fisheries professionals are reluctant to provide data for purposes that fall outside the original intent of the data collection to avoid erroneous inferences or misinterpretation of data collected for disparate purposes. Even when data are harmonized, quality control, maintenance of the database (staffing and funding), allowing extraction for a variety of user needs (often in the absence of staff support to field data requests), can be difficult to manage. Despite these challenges, harmonized data sets can be used to answer questions that span multiple scales and account for multiple drivers of change and their interactions (Cheruvelil & Soranno, 2018; Midway et al., 2016; Soranno et al., 2014). Fisheries monitoring data collected for different purposes by multiple agencies can be comparable, as long as assumptions are clearly articulated and statistical methods are employed that accommodate the complex data structures inherent in harmonized data sets (Sievert et al., 2026). Using FAIR (findable, accessible, interoperable, reusable) data and open science principles further enables flexible use of data for multiple purposes (Bayer et al., 2023; Wilkinson et al., 2016). Harmonizing monitoring data across jurisdictional boundaries requires substantial time and effort but remains a powerful tool for understanding and managing inland fisheries and aquatic systems under global change.

Here, we present MidFish, a comprehensive publicly available data resource, which aggregates fisheries survey data for tens of millions of fish from thousands of lakes from seven lake-rich states in the upper Midwestern United States. The motivations for this data harmonization were to facilitate research on the impacts of multiple broadscale stressors of fish populations in Midwestern Lakes, and to make freshwater fisheries data available and interpretable at broad spatial scales by creating a data resource following open science principles that are adaptable for various user needs and following FAIR data practices (Wilkinson et al., 2016). In this paper, we introduce MidFish, describe the data harmonization process, summarize the database contents, provide example workflows demonstrating its application, and discuss limitations and lessons learned to facilitate use of the resource by fisheries researchers and managers and future data integration efforts. By providing harmonized survey data from multiple states while preserving key information about sampling design, gear, and effort, MidFish enables new opportunities to examine ecological patterns and management outcomes for individual lakes at landscape scales.

Data aggregation

Data request

The study area included lakes in the upper Midwestern United States (Figure 1). We reached out to state agency contacts in Illinois, Indiana, Iowa, Michigan, Minnesota, North Dakota,

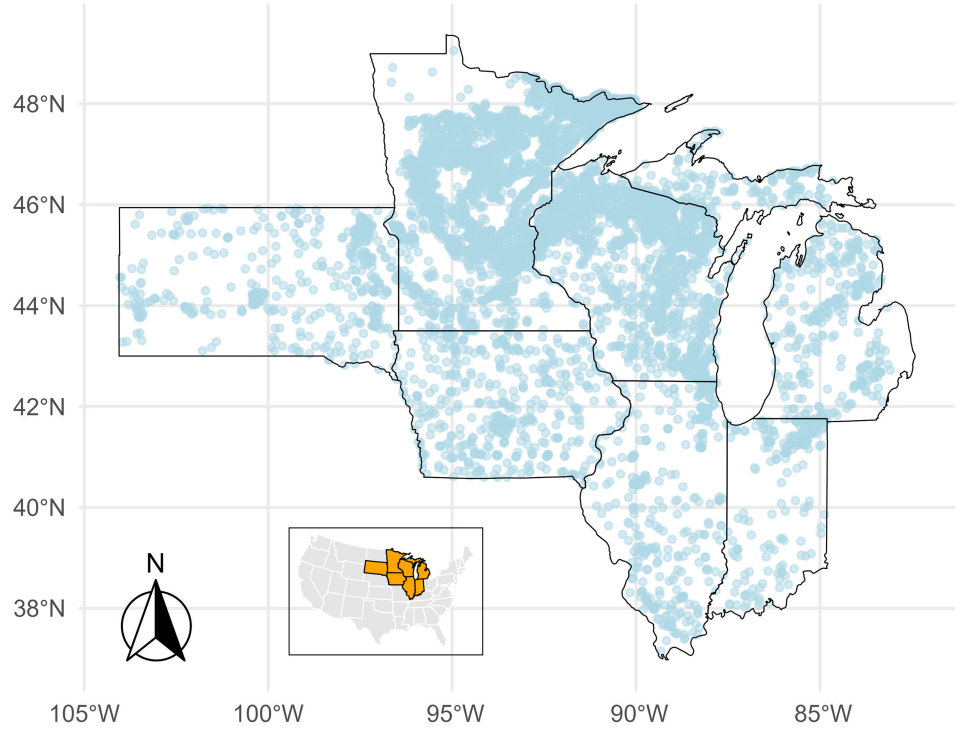


Figure 1 Geographical distribution of lakes in the study area for which at least one survey record is available. Blue dots indicate lake locations across multiple Midwestern states, with black lines denoting state boundaries.

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South Dakota, and Wisconsin. Initial communications included information on project goals, plans for publishing data, and requested data format, with an offer to follow up with a phone call at their convenience to clarify our request and answer questions. Fisheries survey data were requested from each state's natural resource agencies, including information on individual fish (species, length, weight, maturity, age, sex), number of fish caught, and survey details (e.g., survey method, location, sampling effort, date). We asked for data at the individual fish level (i.e., long format with one fish per row) but accepted aggregated counts. For aged fish, we also requested information on aging structures and age–length keys used. Initial requests focused on eight managed fish species: Black Crappie *Pomoxis nigromaculatus*, Bluegill *Lepomis macrochirus*, Cisco *Coregonus artedi*, Largemouth Bass *Micropterus nigricans*, Northern Pike *Esox lucius*, Smallmouth Bass *M. dolomieu*, Walleye *Sander vitreus*, and Yellow Perch *Perca flavescens*. These requests typically yielded multiple data products per state, often in different formats and structures. To streamline data harmonization, we subsequently requested entire fisheries databases (all species, all surveys), which reduced structural inconsistencies and facilitated more efficient integration. Data products varied by state, but, at a minimum, included survey- and fish-level information for the eight focal species, and in many cases encompassed complete statewide survey databases.

Data harmonization workflow

Architecture

We adopted a standardized data structure where each row represents a single fish observation, with columns containing both fish-level attributes (e.g., length, weight, age) and associated survey-level information (e.g., lake, gear, effort, date). Each row represents an individual fish observation; surveys with zero catch retain effort data with null fish values tagged to indicate that no fish of a given species were observed. This ensures that surveys with zero catch are retained. Survey and lake level information are also included for each row (fish record) to facilitate calculations of catch-per-unit-effort (CPUE) and other derived metrics, and support flexible queries based on fish, survey, and environmental attributes. MidFish contains 69 fields (columns) related to individual fish characteristics ($n = 18$), survey level characteristics ($n = 34$), lake identification and characteristics ($n = 10$), and data quality and integrity ($n = 7$). Full metadata and column descriptions can be found in Link et al. (2026).

Collating and cleaning data sets

State aggregation was prioritized first by standardizing each data product into a "fish-as-rows" format, linking individual fish records to associated effort data, expanding CPUE summaries into individual fish rows where necessary, and incorporating measured ages when available. To facilitate relative abundance comparisons, we defined an "effort grouping" variable representing a survey or sampling event (e.g., a specific gear deployed within a lake over a defined time period). Because sampling designs differed among states, temporal definitions of surveys varied (e.g., daily vs. annual aggregation). When effort data were reported at multiple resolutions (e.g., individual electrofishing transects or single nets within a multiday survey), we retained both the disaggregated and aggregated effort to enable flexible summaries. Survey records generally lacked specific location information beyond state level identifications, lake names, and counties. We standardized location information by assigning latitude–longitude coordinates and linking lakes to National Hydrography Dataset Plus High-Resolution identifiers (NHDPlus HR) using the "mwlaxeref" package in R (Frater, 2024) and supplemented by a crosswalk of spatially joined lake data and with spatial information (Corson-Dosch et al., 2023). This crosswalk links state-specific identifiers to other lake identifiers, enabling integration with broadscale spatial data sets that for the most part lack a linkage to state identifiers (Cheruvelil et al., 2021).

MidFish contains two broad types of quality-control "flags" to identify potential data issues or limitations at either the survey level or the individual fish level. At the survey level, we developed a binary indicator, *cpue_invalid*, to flag surveys that may not be suitable for relative abundance estimation. This field is derived from survey-level flags and is assigned a value of *y* when known issues are present that compromise relative abundance measures. Records with this flag include those where effort measures were negative, zero, or >10 standard deviations from the mean for that gear type, where two gears were reported for the same survey and at same effort, where agency provided data included unspecified flags related to CPUE estimation, where manual inspection of survey notes revealed survey issues that could affect CPUE estimation (e.g., "beaver chewed a hole in net"), and where no fish were reported for a given effort where we would expect fish to be caught (i.e., unreliable zero values, such as a multi-net gill net survey in Lake of the Woods that captured no fish). Fish that could not be linked to a specific effort were still retained as records that could be used for size or age analyses, but do not have an effort grouping identifier and were flagged to ensure they are not used in relative abundance calculations.

Flags were also created at the individual fish level to identify records with implausible lengths or weights (>10 standard deviations from the mean of that species), where length or weight was zero, or where agency records flagged the fish record as unreliable for unknown reasons. Original notes from agencies were retained in the database in the *flag* field to enable users to determine which data are suitable for their needs and resulted in 142 unique flags (Supplementary Table 1). We elected to flag the data rather than remove any records in recognition of the multiple potential uses of MidFish, and to enable users to implement different cutoffs and flagging criteria. For instance, surveys with questionable effort records may still provide individual fish data that could be valuable for size or age analyses. Quality-control flags provide a means by which users can make informed decisions about data inclusion based on their specific goals. These flag columns are intended to streamline the identification and filtering of problematic records. However, they should be used as an initial screening tool rather than a definitive filter. Users are encouraged to also consider other factors affecting comparability of abundance estimates, such as survey type, sampling method, timing, and effort relative to lake area.

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Table 1 Summary of unique observations for each variable in the database. Surveys represent unique total effort identification groupings, defined by a combination of lake, gear, and timing. Taxa represent unique values reported in surveys and in many cases includes hybrids, broad categories (e.g., "sunfish"), as well as non-fish taxa (e.g., crayfish, turtle). Gear counts are reported at the mid-level of the gear hierarchy.

State	Lakes	Surveys	Years	Taxa	Fish	Gears
Illinois	345	4,595	1984–2020	8	634,573	7
Indiana	239	792	2006–2022	95	148,942	5
Iowa	522	5,603	1973–2023	109	1,735,709	18
Michigan	464	2,307	2000–2019	8	527,184	6
Minnesota	4,148	63,800	1940–2022	164	33,846,047	39
South Dakota	420	5,773	1983–2023	122	2,177,057	27
Wisconsin	2,293	50,357	1937–2023	248	21,252,813	38
Total	8,431	133,227	1937–2023	358	60,322,325	102

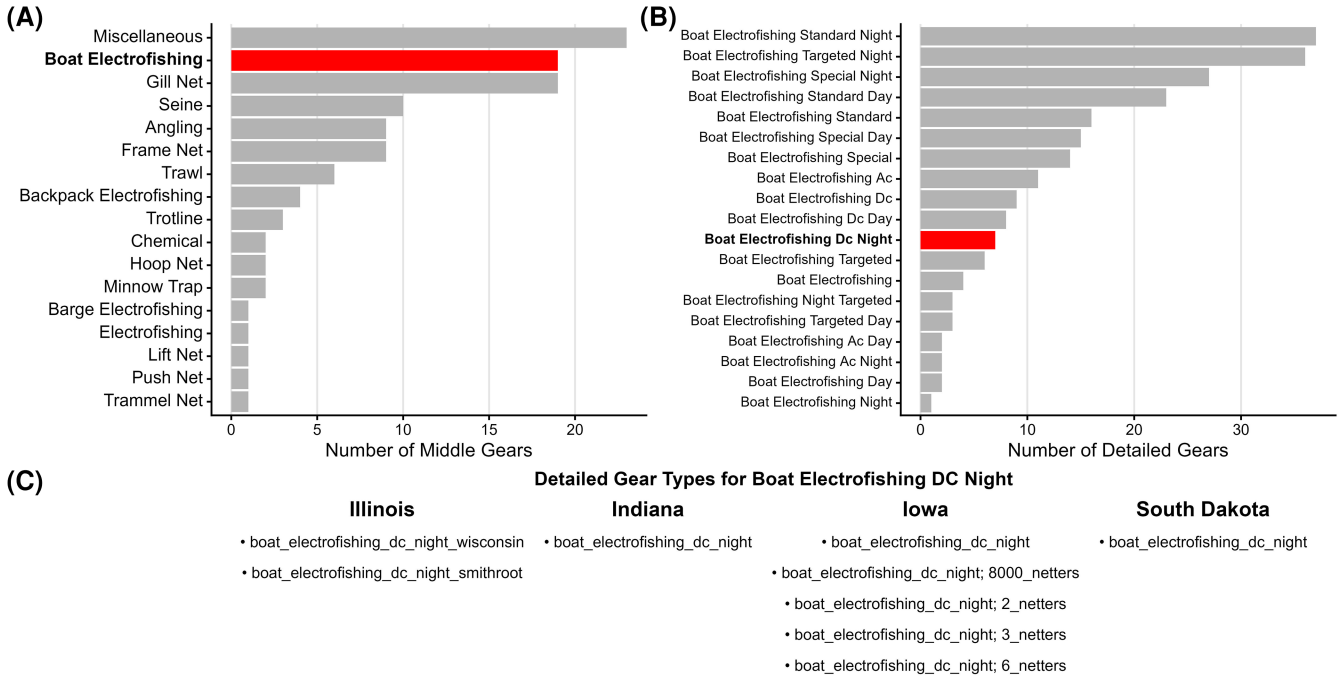


Figure 2 Hierarchical organization of sampling gear classifications. From panels (A–C), an example illustrates the progression from the total number of boat electrofishing gear types represented in the data set to the subset of gears classified as boat electrofishing DC night. Specifically, panel (A) shows the number of mid-level gear types for every simple gear in the data set, highlighting boat electrofishing. Panel (B) shows the number of detailed gears associated with the boat electrofishing simple gear, highlighting the number of boat electrofishing records at night with DC power. Panel (C) provides an example list of detailed gear types from boat electrofishing with DC power at night for the four states with survey data using this gear type.

To facilitate comparisons among different gear types, we classified sampling gear at three hierarchical levels, ranging from broad categories (e.g., gill nets, boat electrofishing, angling) to highly detailed descriptions (e.g., number of netters, power settings, net dimensions; Figure 2). Input from state agency personnel, combined with general fisheries knowledge, was used to aggregate detailed gear information into higher-level types common among states. Importantly, many records did not include detailed gear information, and entries at the most detailed level only reflect the attributes provided in the original data. Retaining three levels of specification provides users flexibility in selecting the level of gear aggregation that best suits their needs. Additional gear information that did not match information standardized across states was included in a gear notes column. Information included in the most detailed gear description may contain obvious errors (e.g., 8,000 netters for an electrofishing survey; Figure 2) but were retained as the original values without flag generation. This approach ensures transparency and facilitates filtering while preserving the fidelity of the original state agency gear descriptions.

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Following state-level collation, we standardized remaining differences among states (e.g., units of measure, field names), ensuring a consistent structure and standardized naming conventions. All standardizations were applied at the state level before merging into a harmonized, regional database, preserving traceability of modifications.

Age assignment

We assigned ages to fish with measured lengths using hierarchical age–length keys (HALKs; Frater et al., 2024), which combine data at various spatial scales to estimate ages for fish based on their length. Age–length keys were based on the most common aging structure within each of the eight focal species. Fish assigned a length-bin were given a random length from a uniform distribution between the minimum and maximum of their respective bin. We modified the approach of Frater et al. (2024) by restricting age assignments to fish within a buffer of observed length ranges used to construct keys, reducing potential bias when extrapolating beyond the range of the available data. Specifically, we only assigned ages to fish whose lengths fell within a buffer of 5% below the minimum and 5% above the maximum length used to build the key. Additionally, because the only requirement for building a key was the presence of at least five fish from five distinct (but not necessarily consecutive) age-classes, some intermediate ages could be missing and, in these cases, no ages were assigned to the missing classes. We provide assigned ages at all available hierarchical levels for a given fish (e.g., lake-year, lake, watershed, species); users should consider the scale of keys and associated uncertainty when determining whether assigned ages from various scales are useful for their specific analysis.

Database description

The MidFish database contains 60,322,325 individual fish records from 8,431 water bodies spanning 1937–2023 (Link et al., 2026). Data availability varied among the seven participating states, both in terms of species coverage and survey effort (Table 1). In total, the database includes 358 unique taxonomic groups (which includes unique fish species, hybrids, and genus-level records, and some non-fish taxa, including crayfish and turtles), ranging from 248 taxa in Wisconsin to 8 in Michigan and Illinois, which contributed data only for the originally requested sport fish. Survey effort is organized into 133,227 unique effort groupings (i.e., surveys), with Minnesota contributing the most (63,800) and Indiana the fewest (792). We were able to reliably assign latitude-longitude coordinates to 98% of lakes, and NHDPlus HRs to 92% of lakes. Bluegill are the most represented in the data in terms of number of lakes, surveys, and individuals, while Cisco are the least represented (Table 2).

At the coarsest level, the data set includes 17 gear types, while the intermediate level contains 102 distinct sampling methods. The most detailed level comprises 479 unique entries, providing the finest description of each sampling method, often specific to individual states (Figure 2). Minnesota contributed the most unique and detailed gear descriptions (341), many of which are distinguished by attributes such as the number of netters in electrofishing surveys. In contrast, Michigan, Illinois, and Indiana reported the fewest gear types at each level, reflecting the more standardized nature of the surveys conducted in and reported by these states.

Of the total individual fish records, 36% include measured length, 14% include measured weight, 4% include measured age, 25% include ages estimated via the HALK approach (Frater et al., 2024), 12% include sex, and 53% include coarse age-class designations (e.g., age 0 vs. adult). Age assignments derived from age–length keys account for 15,072,572 records, including 2,863,793 ages assigned using lake-year specific keys, representing the most detailed and accurate level in the hierarchy (Frater et al., 2024). Many of these percentages are influenced by the large number of fish records from Minnesota, which constitute ~50% of all data. Among fish missing length data, 65% originate from Minnesota, with most originating from CPUE surveys supplied without individual fish data. Similarly, 81% of fish with age-class designations are from Minnesota, primarily distinguishing between age 0 and adult fish.

Use case: Creation of a CPUE data set

To facilitate use of the MidFish database at multiple scales, we generated a CPUE data set for our eight target sport fish

Table 2 Summary of eight sport fish species representation in the MidFish database, including the number of unique lakes and surveys, minimum and maximum years of capture, number of sampling gears, number of states represented, and total number of fish records.

Species	Lakes	Surveys	Years	States	Fish	Gears
Bluegill	6,416	53,565	1940–2023	7	11,941,239	73
Yellow Perch	6,361	52,368	1940–2023	7	8,893,785	75
Walleye	4,347	55,137	1943–2023	7	4,780,058	72
Black Crappie	5,618	49,186	1940–2023	7	3,458,645	71
Largemouth Bass	5,999	53,224	1940–2023	7	2,275,592	72
Northern Pike	5,843	55,748	1940–2023	7	1,712,333	70
Smallmouth Bass	1,960	20,750	1946–2023	7	561,550	66
Cisco	855	5,567	1943–2022	4	404,846	36

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species from seven midwestern states. The MidFish database contains surveys that differ in gear, timing, purpose, and effort. To identify surveys that were suitable for indexing the relative abundance (CPUE) of our target species, we worked with data providers and fisheries professionals to determine which combinations of gear, season, and survey purpose reliably index abundance for each species within each state. These criteria were stored in an "inclusion table," which specified the survey conditions suitable for estimating CPUE for each species/state based on gear, time of year, minimum effort, and, in some cases, water temperature (Link et al., 2026). After selecting the appropriate surveys, fish count data for each survey was retrieved and aggregated. Using this method, we included surveys where zero fish of a species were caught (and, thus, CPUE = 0) only for instances where a suitable survey took place and no fish were caught. Because survey suitability varied by species and state, separate R scripts were developed for each state to apply tailored selection rules, extract the relevant fish records, and collapse them into standardized CPUE metrics. This workflow and CPUE data product are available at Link et al. (2026) and can be modified by other users to fit their needs.

We generated CPUE data sets for eight focal sport fish species (Figure 3A). In total, 391,144 CPUE records were generated. The number of unique water bodies with suitable survey methodology to measure relative abundance varied by species; Largemouth Bass CPUE was available for 6,403 lakes, while Cisco CPUE was available for 4,489. Notably, approximately 45% of all CPUE records are zero, reflecting our approach of identifying surveys suitable for indexing the abundance of a given species and retaining those surveys, even if no fish of that species were caught (which includes locations where the species does not exist). We emphasize that the zeros in the CPUE data set were created based on survey records and not necessarily a reflection of what was reported by agencies. We further emphasize that users should not assume species not reported in a lake should be imputed as zeros, as the lack of data in the CPUE data set reflects lack of appropriate survey for the species in that location. The highest proportion of zeros exist for species with limited distributions within our study region; 80% and 88% of CPUE values are zero for Smallmouth Bass and Cisco, respectively (Figure 3A).

Catch per unit effort can be compared among lakes or within lakes over time depending on user needs. While the majority of species and lakes in our data set are represented by only one survey (Figure 3A), a significant number of lakes have CPUE records across multiple years. In lakes with multiple surveys, CPUE data can be used to track relative abundance over time (Figure 3B). For example, Lake Wabedo, Minnesota (NHDHR ID = 72863809) has been surveyed using gill nets in 14 years from 1970–2022. In this lake, gill net CPUE suggests increasing relative abundance of several species and declines in others. These data could be used in a formal statistical analysis or to visualize patterns suggesting further exploration (e.g., Custer et al., 2024; Wagner et al., 2023). We caution that CPUE data are available for multiple gear types, and users can either focus on a single gear type (e.g., gill net catch rates shown in Figure 3B) or account for differences in catchability during statistical analysis (Custer et al., 2024; North et al., 2024)

Data on individual fish characteristics can also be extracted from surveys used for CPUE. For example, users may be interested in examining size structure of fish (Figure 3C), in which case, data from individual fish captured in surveys that have been aggregated to calculate must be retrieved from the full data set using the relevant effort ID(s). In this example, we visualized length distributions of Yellow Perch caught in standard gill nets from Lake Wabedo in the year where relative abundance was highest (2005) and the year where relative abundance was lowest (2021). We also visualize the mean length of the longest 15 fish as an index of female age at maturity (Holbrook et al., 2022) to further exemplify metrics that could be derived from MidFish

Use case: Estimating time-to-size of walleye

Estimating the time required for fish to reach a particular length provides insights into growth patterns. Here, we calculate the time (number of years) for Walleye to reach 15 inches as a surrogate for time to harvestable size, recognizing that size-based regulations vary by state and lake. We included Walleye with assigned ages derived from lake-year specific age–length keys to ensure the most accurate estimates (Frater et al., 2024). To minimize discrepancy based on aging structures, we only consider age assignments based on otoliths or spines. Because fish were sampled in a range of months within each year, we accounted for within-year growth by calculating a "decimal age" at capture relative to the day of year. Each fish's decimal age was determined assuming January 1 as day 1 of the year. Only fish of harvestable size (15 ± 0.5 inches) were included. For each lake-year, we calculated the mean decimal age, and when multiple years were available for a lake, we averaged across years. We did not constrain this analysis to any particular sampling gear.

The five states with available data for this analysis demonstrate variability in this metric (Figure 4). Following our criteria, Wisconsin contained the largest sample of fish with estimated ages ($n = 102{,}807$), representing 266 lakes and 545 lake-years. Michigan had the fewest individual fish ($n = 134$), while Iowa had the fewest lakes ($n = 7$) and lake-years ($n = 8$). Indiana and Illinois did not contain any records that met the age–length key or aging structure criteria.

Spatial trends in Walleye growth generally tracked gradients of temperature and productivity, with faster growth in warmer, more productive areas (Figure 4A) consistent with other studies (Massie et al., 2021; Pedersen et al., 2017). Still, considerable variability in time to harvestable size is observed even within small geographic areas and within individual lakes. Among individual lake-years, Cannon Lake (near Faribault, Minnesota; 2020) had the fastest growth to harvestable size, with Walleye reaching 15 inches in an average of 1.62 years. In contrast, Wheeler Lake (near Lakewood, Wisconsin; 2008) exhibited the slowest growth, requiring an average of 9.25 years for Walleye to reach 15 inches. Lakes varied in both the number of years represented and the number of fish sampled within each year. For example, Lake Winnibigoshish included 10 lake-years of data, with sample

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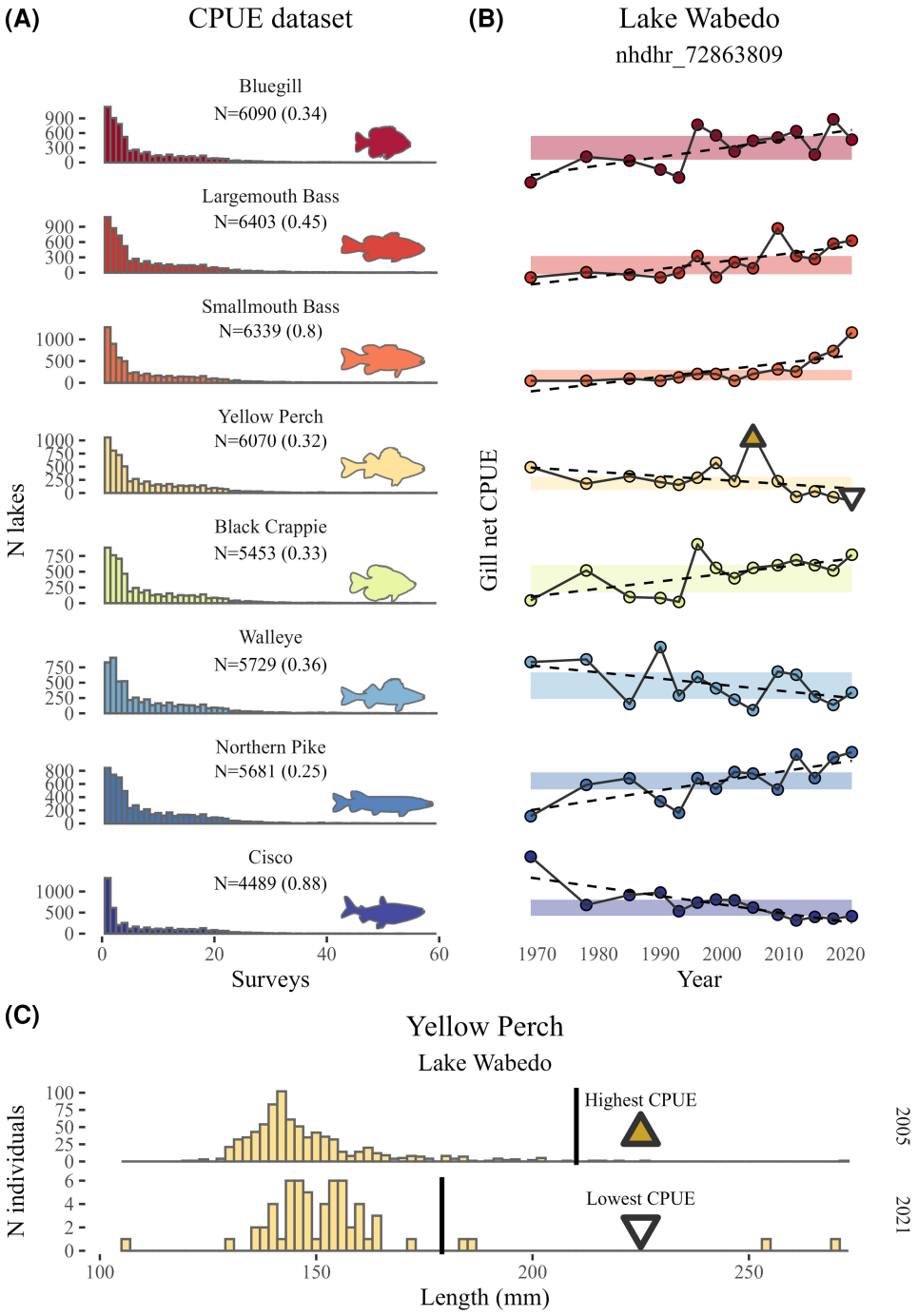


Figure 3 Example visualizations of catch per unit effort (CPUE) data across multiple scales from the MidFish Database. (A) Distribution of the total number of unique surveys (total_effort_idents) for each lake and species included in the filtered and aggregated CPUE data set (truncated at 60 for visual clarity, some lakes have up to 150 unique surveys). Text shows number of unique water bodies represented for each species, and the proportion of surveys that are zero catch in parentheses. (B) Catch per net night from standard gill net surveys by species from a single lake, Lake Wabedo (National Hydrography Dataset Plus High Resolution ID = 72863809), with linear trend lines and lake- and species-specific interquartile ranges. Gold and white triangles indicate the highest and lowest CPUE values for Yellow Perch in Lake Wabedo, respectively, which are expanded upon in (C). Length distributions of Yellow Perch caught in standard gill nets in Lake Wabedo from 2005 (year with highest CPUE) and 2021 (year with lowest CPUE) from Lake Wabedo, with black vertical lines representing the mean length of the largest 15 fish in the sample for each year as an index of fish maturity.

sizes within individual lake-years ranging from 19 to 50 fish (Figure 4B), illustrating the lake-year level variability in estimated time to size. These lake-year summaries are directly informed by the underlying age–length keys applied to fish within each year, as shown for the 2022 Winnibigoshish data (Figure 4C), linking individual-level age–length structure to the aggregated patterns observed at the lake-year scale. Annual variation in Walleye growth is observed in Lake Winnibigoshish over this time period (Figure 4B). Variation in growth within and among lakes provide an opportunity to

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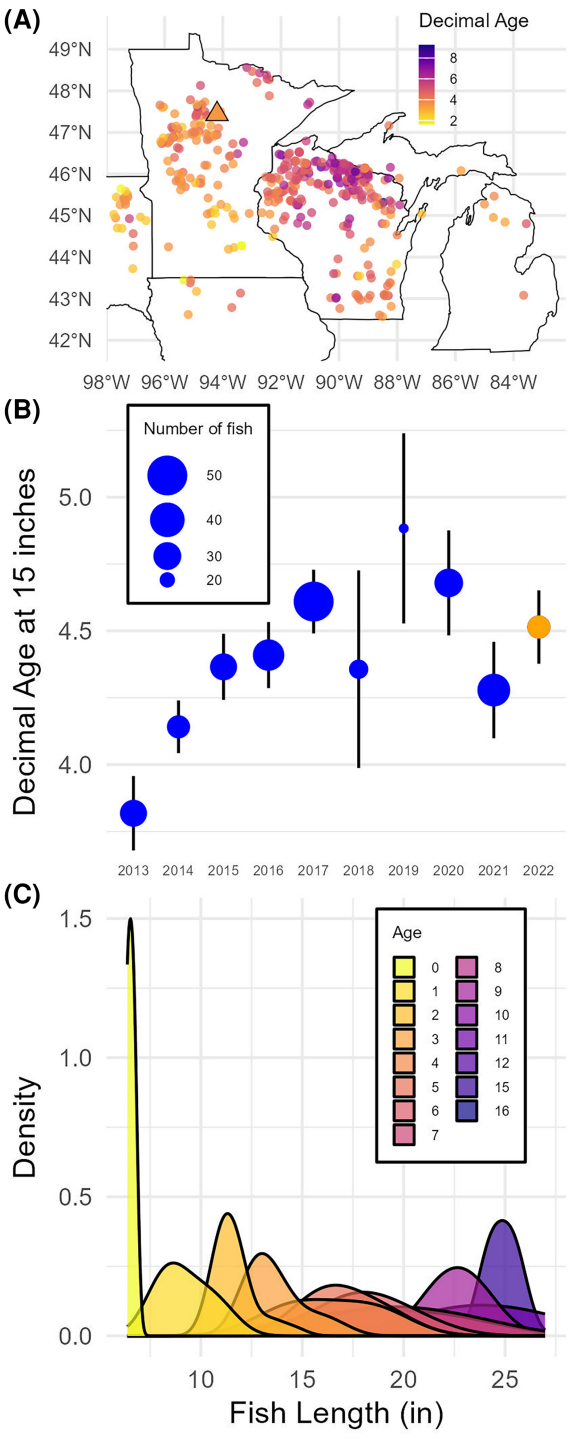


Figure 4 (A) The mean time (in decimal years) to reach 15 inches for Walleye within each lake. Ages were estimated using lake–year age–length keys derived from fish aged with otolith or spine structures. Cool colors indicate older average ages, while warm colors represent faster growth. Decimal ages account for the time of year each fish was caught by incorporating the Julian day of capture, assuming a January 1 start to the year. For lakes with data from multiple years, the mean age across years was used. (B) Temporal variation in growth within Lake Winnibigoshish, Minnesota, showing time to reach 15 inches across survey years. The size of the dot represents the number of fish used in the time to size calculation (C) Distribution of fish lengths by age-class, shown as a density plot filled by age for Lake Winnibigoshish in 2022. Warm colors represent younger age-classes.

examine environmental and density dependent effects on fish somatic growth (e.g., Huang et al., 2021; Matthias et al., 2018), as variation in growth provides more power to detect effects than measures of relative abundance such as CPUE (e.g., Carpenter et al., 1995).

Discussion

The MidFish database contains over 60 million individual fish records from 8,431 water bodies spanning 1937–2023 and is publicly available to support a variety of uses. Catch per unit effort data can be used to index relative abundance, which can be combined with water temperature data (Corson-Dosch et al., 2023) and other environmental data (e.g., Cheruvelil et al., 2021; Hanly et al., 2025; Meyer et al., 2024) to develop species distribution models and predict species abundance changes under future climate conditions (e.g., Custer et al., 2024). Relative abundance estimates could be used in trend analysis of single species (e.g., Wagner et al., 2016) or multiple species (e.g., Poulet et al., 2011). For some species, these data could be used to index recruitment based either on age-0 catch rates (e.g., Brandt et al., 2022) or using year-class strength estimates from age-specific catch rates (e.g., He et al., 2023). Aggregated data can also enable examination of responses to change at multiple scales. For example, MidFish could be used to assess fish abundance or growth responses to drivers such as climate change (e.g., Massie et al., 2021; Rounds et al., 2025), species invasions (e.g., Hansen et al., 2020), aquatic plant management activities (e.g., Olson et al., 1998), stocking effectiveness (e.g., Jennings et al., 2005), and more.

With over 21 million records of fish length, the MidFish database represents one of the largest compilations of fish size data at the individual organism level of which we are aware. The database contains more records and covers a larger geographical extent than databases on fish lengths for ~1.03 million fish from the Upper Mississippi River from 1993–2024 (U.S. Geological Survey, 1995), and fish length and weights from the north temperate lakes Long Term Ecological Research program with ~364,000 observations from 1981–2024 (Magnuson et al., 2024). Aggregated data from Tracy et al. (2024) covers a larger spatial extent with 1.8 million records from North America (Tracy et al., 2024), but data from Midwestern U.S. states are underrepresented or missing and individual fish data are not publicly available. By harmonizing fish survey data from thousands of lakes and multiple state agencies, MidFish provides a uniquely large and spatially extensive record of fish body sizes collected under real-world management programs. These data provide opportunities to investigate broad ecological patterns in fish size structure, growth, and life-history variation across environmental gradients, including responses to climate change and other stressors (e.g., Brooks et al., 2026). Length data could be used for size structure analysis (Miranda et al., 2024; Neumann & Allen, 2007), or combined with age data to analyze growth responses to environmental gradients (e.g., Massie et al., 2021). At the same time, the scale of the data set allows for questions that are difficult to address using single-agency monitoring programs alone, such as regional shifts in size structure,

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cross-jurisdictional comparisons of fisheries responses to environmental change, and synthesis of growth dynamics in diverse lake ecosystems. Importantly, these data arise from routine fisheries monitoring rather than targeted research programs, highlighting the potential of harmonized agency data sets to support macrosystem-scale fisheries science.

Although MidFish provides extensive information on freshwater fish in Midwestern U.S. lakes, it does not include all relevant fisheries data due to our focus on state agency data providers. Fish survey data collected by tribal natural resource agencies, local units of government, university researchers, or any other groups are not included unless those data were included in state agency databases. Because surveys represent diverse purposes and conditions, users must ensure that any data used for future work align with their analytical objectives and data constraints. Consideration of gear, timing, effort, and survey purpose is critical when generating derived data sets. We provide data in a minimally processed format and accompanying workflows to support flexible, transparent analyses, but users should evaluate survey suitability (e.g., gear, timing, effort) for their specific objectives. Additionally, users interested in length-at-age data should think critically about whether measured ages or ages assigned using an age–length key are most appropriate, and what level of the hierarchical age length key they are comfortable using given the increasing error rates associated with increased data borrowing from other systems as described in (Frater et al., 2024).

Harmonizing data from multiple sources with differing formats, nomenclatures, and data structures required an enormous amount of work. The creation of MidFish required substantial effort by multiple researchers and partners. In all cases, communication with data providers was critical for both sides to understand the uses and limitations of the data. Our team has learned many lessons along the way that may benefit future fisheries data harmonizers. First, devoting considerable time and energy into conversations with data providers to build trust and understanding among both parties is essential. Leading with goals and intended use for the data with requests for follow-up conversations with relevant agency staff prior to detailed data requests was effective for our team. Next, data requests should be as specific as possible in terms of both content and structure. Vague or open-ended data requests may lead to varying data formats and products even when requesting from the same organization. Specifying exactly what information is needed and for what purpose is helpful for both the requestor and the requestee. However, working with data with which one is unfamiliar makes it difficult to request the appropriate data without extensive engagement with data providers. To that end, we recommend that parties engaging in such efforts request metadata from agencies prior to submitting a data request. In the event that metadata are not available (a common situation in our experience), requesting a small subsample of data containing all possible columns to understand the data structure is helpful. When possible, we also recommend requesting specific filtering or SQL queries used to produce the data product to ensure it can be reproduced in the same format in the future.

Because maintaining and updating databases is a common problem in their longevity, we have designed the workflow for cleaning and collating to match the format in which agencies provided data and maintain records of how the data were originally provided as spreadsheets and in some cases, structured query language commands. In this way, it will be possible to keep this data set reasonably up to date with semi-regular updates of raw data from providers that can be collated and cleaned using the existing workflow. Identifying surveys suitable for CPUE estimation was also an extensive process requiring iterative feedback with partners and knowledge of fisheries sampling methodologies used in each state. Our team was able to accomplish this through existing and new partnerships with state agency personnel, and we provide the vetted CPUE data, filtering criteria, and customizable workflow for generating CPUE to enable future users to benefit from our work. Similarly, the application of age length keys to assign ages to fish has been vetted and applied for easy use and is modifiable for other purposes.

The MidFish database highlights the untapped potential of fisheries monitoring programs to support science and management beyond individual lakes or original purposes. Publicly funded agencies invest substantial resources in monitoring, generating vast quantities of data that are often used primarily for local management decisions and frequently not available publicly. By publishing both the database and the associated workflows, we aim to provide a flexible resource that researchers and managers can adapt to their own questions while maintaining transparency in how derived data products are created. By harmonizing survey data from multiple states while preserving information about sampling design, gear, and effort, MidFish enables new opportunities to examine ecological patterns and management outcomes across thousands of lakes. Such regional perspectives are increasingly needed as fisheries managers confront broadscale drivers of change that operate at the landscape scale. Furthermore, as funding for long-term environmental monitoring becomes increasingly constrained, maximizing the scientific and management value of existing data sets is more important than ever (Nelson, 2026). When linked with complementary environmental data sets describing lake conditions, climate, and watershed characteristics, harmonized fisheries data can help identify emerging patterns, evaluate management strategies, and anticipate future changes in freshwater fisheries. Future work could expand this effort to additional jurisdictions, incorporate newly collected data, or integrate fisheries observations with data sets describing habitat, angling pressure, or ecosystem change. Harnessing the collective value of existing monitoring programs offers a powerful path toward more informed and effective freshwater fisheries management.

Supplementary material

Supplementary material is available at *Fisheries* online.

Data availability

The data underlying this article are available in the U.S. Geological Survey ScienceBase repository at https://doi.org/10.5066/P1337ZQC. The data set can be cited as Link et al. (2026).

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Conflicts of interest

None declared.

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