



Original Articles

Effects of sample gear on estuarine nekton assemblage assessments and food web model simulations

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ABSTRACT

Long-term fisheries-independent sampling data inform population status and trends of species-specific biomass and are often used to drive biomass-based food web models such as the Comprehensive Aquatic Systems Model (CASM). Indicators such as total biomass and mean trophic level derived from these data and from CASM outputs inform management and facilitate assessments of on-going and predicted coastal change and restoration activities on fisheries, but rely on consistent sampling to enable comparisons across space and time. Changes in coastal estuarine gradients, combined with the availability of new sampling technologies, highlight a need to assess the potential consequences of changing sampling technologies on fisheries data and the cascading impact on model outputs. In Louisiana, USA, CASM models are used to inform coastal restoration projects, relying on 40 years of fisheries-independent data derived from 50' seine sampling. However, alternative use of electrofishers as a sampling method has been proposed to replace the seine sampling. In this study, we examine data from concurrent seine and electrofisher sampling in Barataria Basin, Louisiana, and compare biomass, assemblage data and CASM outputs related to species biomass, food web structure and energy cycling. In a paired comparison of data in 2018–2019, the electrofisher captured higher total catch and diversity compared to the seine. The electrofisher samples were dominated by shrimp (grass, white, brown) and larger bodied fish, while seine samples were dominated by smaller-bodied fish (i.e., anchovy, menhaden). Ecosystem indicators derived from running the CASM using biomass data from seine and electrofisher sampling separately in two different simulation exercises provide contrasting results. In Simulation Exercise 1, the use of different datasets (long-term CASM calibration, 2018–2019 seine, 2018–2019 electrofisher) to initialize the CASM biomasses did not result in large or long-running changes in the simulated biomasses over time. In contrast, in Simulation Exercise 2, CASM model outputs using adjusted gear ratios indicated changes in biomass structure when using electrofisher data, with a doubling of total food web biomass due to the increased shrimp count, and a 13% increase in total energy flow through the food web. Conversions based on area and gear efficiency for overall catch may be useful in maintaining the continuity of historical data. However, differences in species-specific catch due to gear selectivity could have large consequences for constructing and calibrating fish and ecosystem models and remain difficult to reconcile. These differences in assemblages, and estimated biomasses for key food web species, suggest careful consideration in changing gears.

1. Introduction

Long-term biological field data remain fundamental to informing management and conservation of natural resources (Rios-Saldaña et al.,

2018). Field data provide direct input into ecological indicators based on an assessment of trends and status of organisms and habitats but are also critical in the development of models to inform management decisions for the present, and for future scenarios (e.g., Ferreira et al.,

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2016, Brum et al., 2017, McClanahan et al., 2019). Despite the critical importance of field data, the cost and time required to support good field-based research or monitoring has resulted in a marked decrease in field-based studies and a concomitant increase in the use of machine learning, synthetic data, and modeling to inform natural resource management (Carmel et al., 2013, Rios-Saldaña et al., 2018). This trend continues even though these approaches to modeling and meta-analyses approaches rely on continued collection of observations and field experiments. Ensuring consistent, reliable, and comparable data through time and space remains a challenge as sampling methods and environmental conditions change. This challenge is especially relevant for fisheries management, which is dependent on status and trends assessment based on data derived from fish sampling techniques known to be selectively biased and varying in efficiency across habitats and environments (i.e., Rudstam et al., 1984, MacLennan, 1992, Chick et al., 1999, Mueller et al., 2017, Veiga-Malta et al., 2018).

Historically, single and multi-species assessments provided the basis for fisheries management decisions (Hilborn and Walters, 1992, Pitcher, 2001). The recognition that these assessments are based on simplified assumptions and incomplete pictures of the ecosystem in which the fisheries operate has led to increased reliance on food web models as more useful indicators for fisheries management (i.e., Pitcher, 2001, Martell et al., 2002, de Mutsert et al., 2017). Food web models quantify relationships between species and environments in terms of energy or biomass, ultimately forcing a reconciliation of field data that includes more than single species data (Rose et al., 2015, Walters et al., 2008). This approach has the additional advantage of providing bigger picture food web or ecological indicators of outcomes from restoration or management actions (i.e., Harvey et al., 2003, Bellmore et al., 2017, Lewis et al., 2021). However, studies have indicated that outcomes or indicators from these food web models can be sensitive to the structure of the food web and environmental forcing functions within the models (Watkins et al., 2016, Bellmore et al., 2017, Lewis et al., 2021). This concern is particularly relevant in fisheries as field sampling data are sensitive to both sampling gear used and the environment in which data are captured (e.g., Mueller et al., 2017, Hollweg et al., 2020). Changes in both the environment and technology result in introduction of new sampling and monitoring approaches (i.e., ICES, 1992, Nielsen et al., 2001, Raynie et al., 2020, Taylor et al., 2020), impacting the continuity and comparability of long-term field data used to calibrate or initialize food web models.

In shallow-water estuarine regions, field sampling occurs across highly variable habitats (i.e., mud, reef, vegetation) and conditions (i.e., salinity, turbidity, water depth). Gear selectivity and efficiency may vary significantly, not only between gear types, but within a gear type being used across spatial and temporal environmental gradients (Baker and Minello, 2011, Hollweg et al., 2020). For example, a study examining nekton biomass at oyster reef and mud bottom habitats using gill nets, seines and tray sampling presents significant differences in not just biomass estimates, but also in patterns across seasons, years and in species composition by gear type (Humphries and La Peyre, 2015). Managers setting restoration targets for American shad (*Alosa sapidissima*) used historic data but had to account for a change in gear types during the 50 years of sampling; without accounting for the change in gear, assessments of trends differed significantly (Maki et al., 2006). As such, within fisheries, attempts to change sample gears or update long-term monitoring programs necessitate the need to understand how gear efficiencies change for specific species, or across habitat types. Ultimately, these changes need to be analyzed in order to derive correction factors, and to understand how differently collected field data may influence food web model outputs and ultimately management or restoration assessments (Lewis et al., 2021).

The coastal region of Louisiana, USA consists of an extensive complex of shallow water estuaries and wetland areas supporting a highly productive recreational and commercial fishing industry (Orlando et al., 1993). To manage and conserve these valuable fisheries, a coast-wide

fisheries-independent monitoring program conducted by the Louisiana Department of Wildlife and Fisheries (LDWF) has provided data for over 40 years (Louisiana Department of Wildlife and Fisheries (LDWF), 2018). This monitoring program consists of sampling at over 500 established sites, approximately monthly, using different gear types, including 6', 16', and 20' trawls, 50' bag seines, and experimental gill nets and trammel nets, some of which target specific fisheries species and sizes while others target community assemblages. Data from this program have routinely informed stock assessments for key species (i.e., *Callinectes sapidus*), and for management recommendations related to harvest (i.e., Louisiana Department of Wildlife and Fisheries (LDWF), 2018).

These long-term fisheries-independent sampling data further inform decision-making related to coastal restoration and management projects in Louisiana by characterizing baseline or existing conditions within the estuaries, and have been used to initialize and calibrate existing water quality, habitat suitability index models, fish population, and food web models used to predict potential restoration or management action outcomes (de Mutsert et al., 2012, Watkins et al., 2016, Hijuelos et al., 2016, Lewis et al., 2016, de Mutsert et al., 2017, Baustian et al., 2018, Lewis et al., 2021). In particular, two food web models are used by Louisiana managers to inform water resource and coastal habitat restoration projects: the Comprehensive Aquatic Systems Model (CASM; Dynamic Solutions, 2016) and Ecopath with Ecosim (EwE, and Eco-space; de Mutsert et al., 2017). Both of these models are used together as an ensemble approach for evaluation of potential ecological impacts since they focus on the same estuarine fish and invertebrate species, have some similar environmental forcing functions that differently affect species production and food web interactions, and similarly use the LDWF sampling data to inform, calibrate, and validate the models (Lewis et al., 2021). CASM is more of a bottom-up approach based in water quality modeling, using daily bioenergetic growth equations describing biomass and production, with Type-II density-dependent consumption of prey by predators in the food web (DeAngelis et al., 1989, Bartell et al., 1999). EwE is more of a top-down fisheries-based approach describing production, standing stock biomass, and fishing mortality of species, with predator consumption of prey described by foraging arena theory (Walters and Juanes, 1993, Walters et al., 1997, Ahrens et al., 2012).

As the LDWF fisheries-independent data are used to calibrate the models, there is a recognized need to ensure consistency and standardization of field sampling through time and across studies to enable large-scale comparisons and meta-analyses to support fisheries assessments (Mills et al., 2008, Flaherty and Landsberg, 2011, Przeslawski et al., 2015, Kaller et al., 2013, Hollweg et al., 2020). Despite this need, new sampling technologies are often proposed, with questions as to how to reconcile catch of these new gear types with historic sampling data, and to better understand how changes in gear and baseline data may impact food web models used to inform restoration decision making.

Recent advances in electrofishing technology have resulted in the state of Louisiana testing this gear as a potential replacement to seine sampling. In other regions around the world, comparative studies of electrofishing and other gears generally conclude that electrofishing is most effective in sampling small fish and invertebrates within shallow water habitats, as measured by higher species richness, catch per unit effort (CPUE) and greater guild diversity as compared to multiple other sampling approaches (i.e., Miranda and Dolan, 2003, Mueller et al., 2017). In addition to differences in species assemblages resulting from potential gear bias or selectivity, results may be further influenced by environmental conditions during sampling including water depth, turbidity and salinity. Warry et al. (2013) found that electrofishing was less effective compared to nets as depth increased above 1.5 m, and as salinity increased above ~ 15. This is important within the rapidly changing Louisiana coast as climate change and riverine management impact estuarine water quality, including salinity and turbidity (Das et al., 2012). Further, as existing food web models currently used to

inform restoration and management decisions in this region have largely relied on data collected through the LDWF 50' bag seines (Watkins et al., 2016), understanding the potential impacts of changing gear types on not just assemblage and biomass data, but on indicators of food web structure and energy flow is critical.

Here, we use seine and electrofisher sampling from across Barataria Basin, Louisiana to compare species assemblages and biomass captured, and explore the potential impacts of differences in species assemblage and biomass reported on CASM-simulated biomass dynamics, and model-generated ecosystem indicators describing food web structure and energy cycling. Louisiana supports highly productive fisheries, however, this region is at the forefront of coastal change from a combination of anthropogenic and climate-related impacts (Orlando et al., 1993, Jankowski et al., 2017). Significant funding for restoration drives continued assessment of new technologies to support fisheries-independent monitoring, and managers rely on the use of ecosystem-based and food-web level indicators derived from models to help inform restoration planning, goal setting and species management (Coastal Protection and Restoration Authority of Louisiana (CPRA), 2017). Ensuring that monitoring programs build off historic data, but also adopt new technologies that can be related to the historic data and provide consistent results, is of primary importance to successful long-term monitoring of key aquatic species and nekton assemblages within estuaries.

2. Methods

This study compared species CPUE, total length, species richness, and assemblage across 12 long-term sampling sites within Barataria Basin, Louisiana, during monthly sampling carried out over 14 months using two gear types. The catch ratios and conversion factors between

the gear types were examined. We further used these data to explore how the monthly biomass data generated from the different gear types, when used in the initialization of species biomasses for the CASM food web model of Barataria Basin (Simulation Exercise 1), and when used to adjust CASM generated biomasses through gear specific catch ratios (Simulation Exercise 2), affected the simulated biomasses over time, and a suite of food web indicators representing trophic structure and energy cycling estimated from the CASM.

2.1. Study area

The lower Barataria Basin is located within southeast Louisiana, south of New Orleans, Lake Salvador, and the Gulf Intracoastal Waterway (Fig. 1). The larger basin complex was formed approximately 3,500–4,000 years ago as part of the Lafourche Delta complex of the Mississippi River and encompasses an area approximately 6,300 km² dominated by fresh to saline wetlands. The natural and artificial levees of the Mississippi River form the eastern border, and the abandoned Bayou Lafourche distributary lies along the western border of the basin. The lower basin consists of tidally influenced marshes, canals, bayous, bays, and lakes connected to a large bay system (Barataria and Caminada Bays) bordered by a chain of barrier islands, and to the Gulf of Mexico to the south. Freshwater inflow into Barataria Basin is derived largely from local precipitation, with the Davis Pond Freshwater Diversion, Naomi Siphon and West Pointe a la Hatche siphon serving as conduits into the basin for Mississippi River waters, and the Gulf Intracoastal Waterway serving as a conduit for Atchafalaya River waters into the system. Tides are diurnal and microtidal (0.3 m) with water levels largely dependent on wind. Salinity annual means typically range from fresh at the northern end of the basin to over 15 near the barrier islands, with salinity overall ranging from 0.3 to over 32 across study

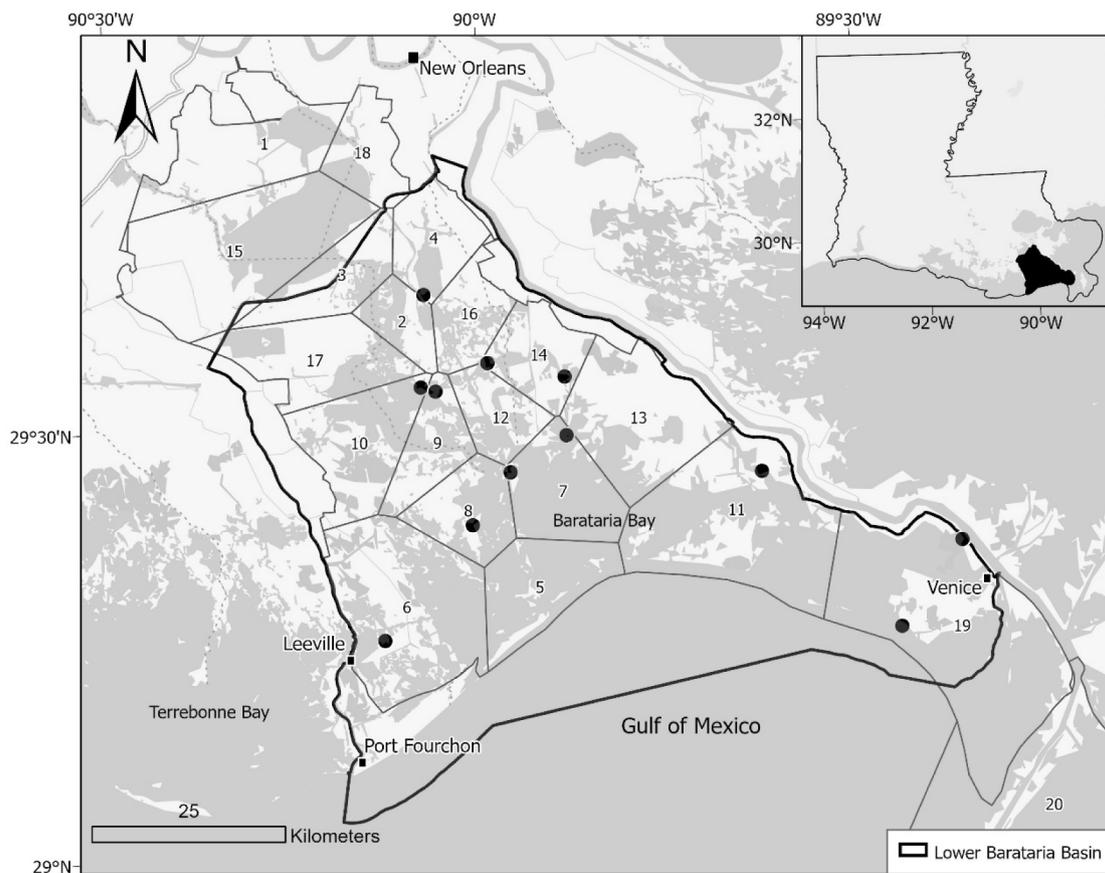


Fig. 1. Lower Barataria Basin, Louisiana with location of the 12 long-term fisheries-independent monitoring program seine sampling stations across the estuarine gradient. The model domain and 20 spatial polygons of the Barataria Basin Comprehensive Aquatic Systems Model (CASM) are indicated on the map.

sites over the last 10 years (Louisiana Department of Wildlife and Fisheries (LDWF), 2018). Salinities rarely exceed 10 along the river-dominated, southeastern region of the basin near Venice, Louisiana, yet can rise to over 20 in the marine influenced, southwest region of the basin near Leeville and Port Fourchon.

2.2. Nekton and environmental data

Biological and physical data collected from the LDWF Fisheries-Independent Monitoring Program (Louisiana Department of Wildlife and Fisheries (LDWF), 2018) were used to examine nekton data collected using 50' bag seines (15-m nylon bag seine; 6-mm mesh) and a boat-based electrofisher (Smith Root 9.0 GPP Electrofisher) within Barataria Basin, Louisiana. LDWF has conducted monthly sampling with the bag seines across Barataria Basin since 1986 (Fig. 1). This study selected 12 of these fixed long-term stations distributed across the basin to compare concomitant LDWF bag-seine and electrofisher samples across 14 months (May 2018-June 2019). Electrofishing is not part of the historic LDWF sampling and was implemented in early 2018 by LDWF to compare with seine samples in Barataria Basin only. Electrofishing consisted of triplicate sampling events with 90 s pulses each, following the shoreline. A total distance track was recorded in meters using a GPS receiver for each of the three 90 s pulses, which each followed along a unique track. After each 90 s pulse, nekton were bagged, placed on ice, and taken to LDWF facilities for processing. All nekton were processed by LDWF following their protocols (Louisiana Department of Wildlife and Fisheries (LDWF), 2018). All organisms from each gear type were identified to species and counted, with up to 30 randomly selected individuals of select species measured for biomass (g) and to the nearest total length (TL; mm). Prior to nekton sampling, discrete environmental variables of salinity, water temperature ($^{\circ}\text{C}$), dissolved oxygen (mg L^{-1}), and turbidity (NTU) were recorded.

2.2.1. Analyses of field survey data

Water quality data were examined to identify means and range of conditions captured. For each station, gear, and sample date, total CPUE, species richness, and species CPUE were calculated. As sampling consists of single seine hauls and triplicate electrofisher samples (~ 50 m/each), species CPUE for each gear and station was defined as the sum of the single or triplicate samples, respectively. Key species were defined as those historically highly abundant and ecologically or economically important: brown shrimp (*Farfantepenaeus aztecus*, Ives, 1891), white shrimp (*Litopenaeus setiferus*, Linnaeus, 1767), blue crab (*Callinectes sapidus*, Rathbun, 1896), bay anchovy (*Anchoa mitchilli*, Cuvier and Valenciennes, 1848), Gulf menhaden (*Brevoortia patronus*, Goode, 1878), Atlantic croaker (*Micropogonias undulatus*, Linnaeus, 1766), spotted and sand seatrouts (*Cynoscion* spp.), red drum (redfish; *Sciaenops ocellatus*, Gill, 1863), largemouth bass (*Micropterus salmoides*), striped mullet (*Mugil cephalus*), grass shrimp (*Palaemonetes* spp.), bluegill (*Lepomis macrochirus*), southern flounder (*Paralichthys lethostigma*), bay whiff (*Citharichthys spilopterus*), naked goby (*Gobiosoma bosc*), inland silver-side (*Menidia beryllina*, Cope, 1867), and pinfish (*Lagodon rhomboides*, Hobrooke, 1855).

CPUE and species richness of all organisms captured, and total length of dominant species (greater than 1% total catch) were analyzed by gear type, season (Winter: Jan-Mar; Spring: Apr-Jun; Summer: Jul-Sep; Fall: Oct-Dec), and blocked on station (random effects), using general linear mixed models (GLMMs; proc glimmix, SAS 9.2) with a Poisson (CPUE, species richness) or lognormal distribution (total length) to attain normality. When significant effects were found, post-hoc Tukey's HSD test was used.

Analysis of similarities (ANOSIM) and non-metric multidimensional scaling (NMDS) analyses were used to analyze differences in nekton assemblages by gear type within each season. The Bray-Curtis similarity measure was used to generate the distance matrix for NMDS, using log-transformed species abundance data. Analysis of similarities (ANOSIM;

Clarke, 1993) was performed on the Bray-Curtis matrix to determine similarities or differences based on the test statistic R (Clarke, 1993). If differences were found (R greater than 0.30), an analysis of similarity of percentages (SIMPER, R Package 'Vegan'; Oksanen et al., 2019) procedure was performed on nekton community abundance data using gear as a factor to determine species responsible for assemblage differences between gear types. We examined key species catch by examining the ratio of CPUE of electrofisher to the standard LDWF bag seine samples. A ratio of 1 indicated that both gear types collected a specific species.

2.2.2. Gear conversions

We examined gear comparisons for total CPUE using a gear conversion approach recently published in Hollweg et al. (2020). Specifically, this approach converts CPUE to a density corrected comparison by dividing the total area sampled by a gear efficiency conversion factor for the sampled habitat type. In this instance, seine area sampled (176.6 m^2) was divided by $0.4 (\pm 0.055)$, from Hollweg et al. (2020) to generate a gear-corrected density for the sample effort. Hollweg et al. (2020) does not provide a gear efficiency conversion for electrofisher, so a conservative value of 0.28 was used from Peterson et al. (2004), as there are no data for gear efficiency of electrofisher for the environment we were working in. We divided the linear area reported for each electrofisher run, assumed a 1 m width based on ability to collect samples, and divided it by the literature value to generate the electrofisher density conversion. These conversions were applied to CPUE, although we recognize that there may be selectivity in gear types. These gear-corrected nekton densities were then examined by gear type and season, following the same approach as described for the raw data-set above.

2.3. Barataria Basin Comprehensive Aquatic Systems model (CASM) description

The CASM for Barataria Basin was previously developed, calibrated and validated using LDWF field monitoring data (50' bag seines and 16' trawls) and U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service (NMFS) drop sampler data (Rozas and Minello 2011; 2015). The 16' trawl data were used for larger young of the year (YOY) and Age-1 + species, while the bag seine data were combined with drop sampler data to represent small YOY fish and invertebrate species biomasses within the shallow wetland habitats of the estuary (Watkins et al., 2016). The CASM describes daily biomass pools and flows among component taxa groups or populations (referred to as populations from hereon) in the modeled food web using a series of coupled differential equations, with one equation defined for each of the state variables. The CASM simulates the daily food web dynamics over multiple years, using daily inputs for salinity and temperature and the ratio of the estimated areal percent of marsh vegetation to open water habitat (marsh:open water), to differentially drive population growth for 20 spatial polygons (Fig. 1). Detailed model description is available in Watkins et al. (2016) for calibration and validation to existing conditions for Barataria Basin, but a brief description is provided here.

The Barataria Basin CASM includes phytoplankton, benthic algae, bacterioplankton, and particulate organic carbon (POC) in the water column and the sediments (i.e., detritus), as base prey biomass pools fueling consumption by the food web, and 32 consumer biomass pools or populations (Fig. 2). The consumer populations include several key coastal fish and invertebrate species important to Barataria Basin's ecology and economy. Some of the fish and invertebrate populations are divided into life stages (i.e., early or small YOY, late YOY, and Age-1 +) that exhibit different seasonal patterns, grow to the next life stage, and use the estuary habitats differently over the course of a year.

The fish and invertebrate consumer populations in the CASM are described by input-output bioenergetic rates that affect the daily growth rate (i.e., production, in $\text{g m}^{-2} \text{ d}^{-1}$). Daily consumption by the consumer

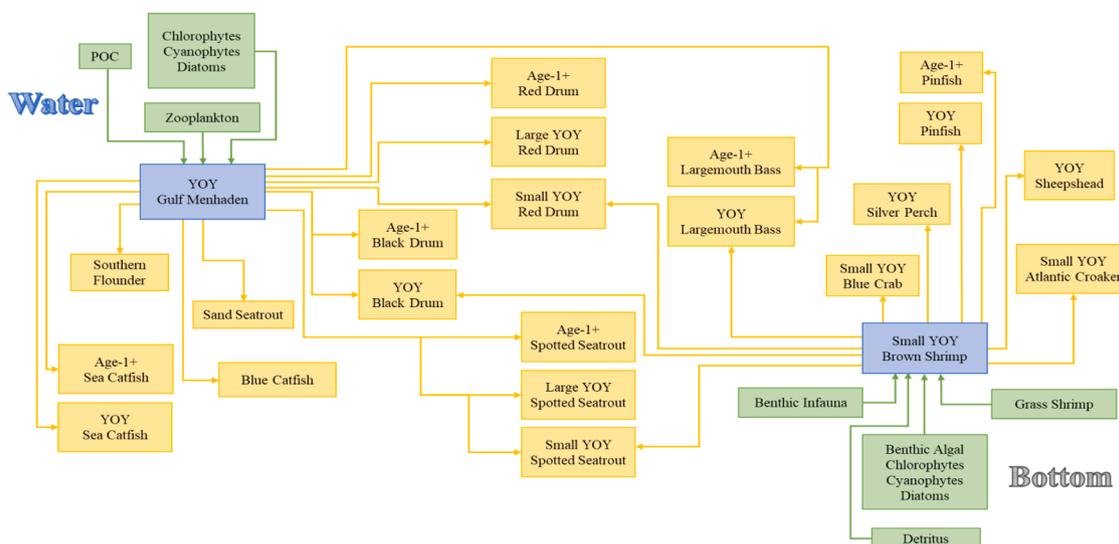


Fig. 2. Part of the Comprehensive Aquatic Systems food web model (CAS) centered on young of year (YOY) Gulf menhaden in the water column, and small YOY brown shrimp along the shallow and vegetated estuary bottom habitats. Specifically, from the top left, this depicts phytoplankton and particulate organic carbon (POC) in the water column as the energy source, and centered on YOY gulf menhaden using shallow estuarine waters and river mouths as nursery habitat. From the bottom right, this depicts benthic algae and detritus as the energy source, and centered around small YOY brown shrimp using the shallow shoreline and marsh edge habitat of the estuary as nursery grounds. In the CAS, the YOY biomass fluxes up to larger YOY or Age-1 + biomass pools for many of the species, with the flux rates based on the daily growth rates of the survivors from the smaller YOY pools.

populations on all available prey depend on the maximum consumption parameter (C_{max}) of each consumer, a prey selectivity coefficient (between 0 and 1) for all prey of each consumer, and the biomass of all available prey and their common predators within the food web (Watkins et al., 2016; Lewis et al., 2021). Daily maximum consumption (C_{max}) and respiration (r) estimates were based on parameters from available bioenergetics literature and fitted for the median-sized individual (in grams wet weight) from the field monitoring data (over all samples by gear type).

For the Barataria Basin CASM development and calibration (Watkins et al., 2016), LDWF 50' seine samples collected from 1995 to 2010 and NMFS drop sampler data collected from independent field studies were used to estimate the monthly biomass of the small YOY life stages caught by the gears while using the shallow shoreline and marsh edge habitats as nursery grounds (e.g., brown shrimp, white shrimp, blue crab, Gulf menhaden, Atlantic croaker, bay anchovy, pinfish), and the small marsh resident species (e.g., grass shrimp, killifish, silversides, gobies). These species and life stage biomass estimates were used to initialize the species biomass pools at the beginning of the CASM simulations starting January-1, and then used as observed monthly data to calibrate the daily predicted consumer biomasses generated by the CASM. The CASM was calibrated by adjusting a set of the species bioenergetic parameters (including C_{max} , respiration (r), and natural or background mortality (m)) to get the best fit between the predicted magnitude and seasonal pattern of population biomass with the observed biomass estimated from the seine and drop sampler data for an average climatic year (i.e., 1995–2010 data averaged by each of the 12 months, see Watkins et al., 2016, Lewis et al., 2021).

Biomass density ($g\ m^{-2}$) for YOY stages and resident marsh species was estimated using the seine and sampler data by dividing the biomass caught at each sampling event by an estimate of the area sampled. The area sampled for the LDWF seines was set to 461.8 m^2 . Note this area sampled by the LDWF seines was defined previously for the CASM development and calibration, and is based on the understanding of the seine sampling protocol outlined in the LDWF marine sampling manual (Louisiana Department of Wildlife and Fisheries (LDWF), 2018). For the CASM biomass estimates, area is equal to 15.24 m seine width \times 30.3 m haul distance from the water to the shoreline. This estimated area swept by the seines is larger than what is reported for the 2018–2019 LDWF

seine sample area estimated as 176.6 m^2 , that is based on the seine sampling protocol followed at that time where the 15-m seine begins with one post outstretched perpendicular to the anchored shore post, and then the outstretched seine end is swept in a quarter circle back to the shore to end 15-m parallel to the anchored shore post (i.e., area of a quarter circle = $\pi(15-m)^2 / 4$). The area sampled by drop samplers used in estimating the CASM biomasses are exactly 1 m^2 . The seine biomass was divided by a correction factor of 0.33 (Zimmerman et al., 1986). Biomass was estimated by converting the median length, from the length data, to weight using species-specific L-W equations (Appendix Table 1). In cases where no length data were available, all individuals captured were assigned the median weight estimated for that population (Table 1 in Watkins et al., 2016). The median weight of the species caught in each sample was multiplied by the CPUE (total species catch where effort was considered one sample) to estimate the species biomass per sample.

Table 1

Catch per unit effort (CPUE) of key species by gear type of seine and electrofisher, and overall. Other captures non-key species; none of the “other” accounted for more than 1% of total CPUE.

	Seine	Electrofisher	Total
Grass shrimp	9242	51,323	60,565
Bay anchovy	9337	1659	10,996
Gulf menhaden	6938	1022	7960
Brown shrimp	1549	6104	7653
White shrimp	670	6064	6734
Atlantic croaker	2027	25	2052
Striped mullet	343	1711	2054
Inland silverside	615	886	1501
Blue crab	743	148	891
Pinfish	115	357	472
Naked goby	97	108	205
Sand seatrout	148	126	274
Bay whiff	86	109	195
Redfish	9	210	219
Spotted seatrout	25	118	143
Largemouth bass	9	49	58
Southern flounder	1	41	42
Bluegill	13	28	41
Other	2280	4003	6283
Total Catch	34,247	74,091	108,338

2.4. CASM biomass Estimates, simulations and food web indicators using the seine and electrofisher sample data

Biomass density (g m^{-2}) of seven key species was estimated from the bag seine and electrofisher station samples from 2018 to 2019 using the same methods for estimating the initialization and calibration dataset from 1995 to 2010 for the Barataria Basin CASM (Watkins et al., 2016). The seven key species were sampled in high abundance and are also key mid-trophic level species in the estuary food web and include grass shrimp, brown shrimp, white shrimp, blue crab, Gulf killifish, bay anchovy, and Gulf menhaden. These mid-trophic level species primarily consume phytoplankton and zooplankton from the water column, or else benthic algae and infauna on the bottom, and serve as primary prey for most estuarine predators, including their larger conspecifics (e.g., croaker, blue crab) and red drum, spotted and sand seatrout, southern flounder, spot, largemouth bass, and catfish (Fig. 2). For each species, mean biomass was calculated over the 12 stations by month and gear type using data collected from January 2018–June 2019. For months with 2 years of data, the average from the two months was used. To generate biomass estimates, the median length was converted to weight using species-specific L-W relationships (Appendix Table 1; Appendix Fig. 1). To generate CPUE, gear conversions outlined above were used. The median weight was multiplied by the CPUE to get species biomass density (g m^{-2}). The mean monthly biomass density estimates from the CASM calibration dataset from 1995 to 2010, the 2018–2019 seine, and the 2018–2019 electrofisher were compared to identify differences in magnitude (biomass) and seasonal composition across a calendar year.

We used the calibrated CASM for Barataria Bay, Louisiana to examine if and how differences in assemblage and abundance data by gear type might impact model outputs using two different simulation exercises. While one approach for evaluating the effects of different sample data on CASM outputs would be to recalibrate the CASM based on the new species biomass data, this would take considerable effort and with only 18 months of data, likely does not reflect longer term mean existing conditions. Instead, using the originally calibrated CASM model, we explored the potential impacts of using monthly biomass data generated from different gear types in the CASM simulations using two

simulation exercises to evaluate impacts on predicted key species biomass, and food web indicators (Fig. 3). To run these two simulation exercises, we used the monthly areal biomass density estimates from our three datasets (CASM calibration: B_0 ; 2018–2019 seine: B_S ; 2018–2019 electrofisher: B_E , where B = areal biomass density, 0 = calibrated data set, S = seine, E = electrofisher) to calculate biomass ratios for the 2018–2019 seine and electrofisher compared to the original monthly calibration dataset estimated for the CASM (i.e., $R_S = B_S/B_0$; $R_E = B_E/B_0$, where R = ratio).

Simulation Exercise 1 evaluated how the use of different initial biomass values generated from different gear or timeframes affected the key species CASM-predicted biomass over time. Here, CASM was run and initialized using the biomass for the seven key species (Fig. 2; January 1, simulation day-1, Year 1) generated for each of three data sets in January (CASM calibration data-set: B_{0_Jan} ; Seine data, 2018–2019: B_{S_Jan} ; Electrofisher data, 2018–2019: B_{E_Jan}). The daily CASM-generated biomasses from the three data sets were compared for Year 2 of the simulation to explore if and how changes to these initial biomass values affected CASM biomass predictions over time. Year 2 of the simulation was used because the first year is much more variable and dependent on the initial conditions. By Year 2, effects of the other initial conditions set for the larger suite of species have worn off, but the adjustment to the CASM biomass on the seven key species still has an effect again on day 1 (simulated day 366) of Year 2 (and each subsequent simulated year) because a truncation rule in the CASM is applied which sets biomasses to $0.01 \times$ initial biomass if they are lower than that value.

Simulation Exercise 2 compared CASM model outputs (biomass, ecosystem, food web indicators) after running the CASM model with B_0 , then adjusting biomasses on May-15 (Year-2) using gear-specific (B_S, B_E) biomass ratios from May data to output food web model indicators. This simulation explored whether gear conversions could be applied after running the CASM model calibrated and initialized with B_0 .

Specifically, B_{CASM} for each of the seven key species generated by the CASM on May-15 in Year 2 was adjusted by the gear specific biomass ratio estimated from the data (seine: $B_{CASM} \times (B_{S_May}/B_{0_May})$; electrofisher: $B_{CASM} \times (B_{E_May}/B_{0_May})$, and the ecosystem indicators were

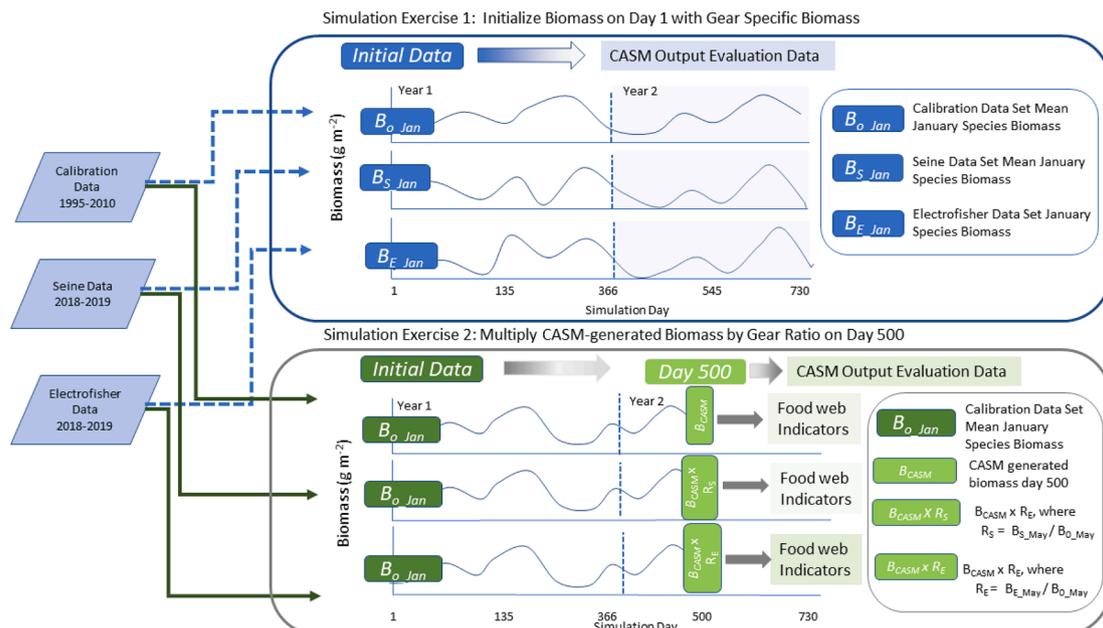


Fig. 3. Diagram showing how the mean monthly data from the original calibration dataset from 1995 to 2010 (B_0 ; from Watkins et al., 2016), the seine station data from 2018 to 2019 (B_S), and the electrofisher data from 2018 to 2019 (B_E) were used for two Comprehensive Aquatic Systems Model (CASM) simulation exercises to examine the impacts of different gear types on model outputs. Simulation Exercise 1 evaluated how the use of different initial biomass values, taken from B_0 , B_S , and B_E affected the CASM-predicted biomass over time. Simulation Exercise 2 evaluated how adjusting CASM-generated species biomasses (B_{CASM}) on day 500 using gear-specific May biomass ratios from the data (seine: $B_{CASM} \times (B_{S_May}/B_{0_May})$; electrofisher: $B_{CASM} \times (B_{E_May}/B_{0_May})$) affected the food web indicators.

calculated from the food web for that daily snapshot. The first set of indicators from the CASM used in this study describe the biomass structure for all species in the food web. Year 2 of the simulation was used because the first simulated year is much more variable and dependent on the initial conditions. By Year 2 the simulated daily species and life stage biomasses become more consistent and representative of the seasonal trends demonstrated by the observed biomass data used for the CASM calibration (Watkins et al., 2016). Ecosystem indicators of total biomass for the food web, the Shannon-Wiener evenness index (H'), and the Mean Trophic Level (MTL) of the food web were calculated for day 500. A change in the Shannon-Wiener H' value indicates a difference in the biomass distribution across all populations within the food web (Lewis et al., 2021). The MTL is the biomass-weighted average of all trophic levels for the component populations in the food web.

The second group of indicators focuses on how energy flows among the populations within the food web. The flow from phytoplankton through all consumers ($Flow_{PHYT}$), the flow from benthic algae through all consumers ($Flow_{ALG}$), the flow from detritus through all consumers ($Flow_{DET}$), and the total system throughput (TST) in the food web were estimated on day 500, and multiplied by 365 days, to explore how changes to the seven mid-trophic level population biomasses affect the food web. The first three indicators characterize the importance of phytoplankton from the water column, benthic algae on the estuary floor, and detritus as an energy source to the food web, and relative to each other, while TST is the sum of all energy flows in the food web and is a measure of the energy budget (Lewis et al., 2021). Specifically, the TST was calculated from the CASM as the sum of all consumption by predator_i on prey_j (ΣQ_{ij}), respiration (ΣR_i), egestion and mortality which flows to detritus (Σd_i), and migration or export out of the estuarine food web (Σe_i). The proportion of the flow from the two primary producers or detritus indicates how much of the overall energy budget is coming from each source in the modeled food web.

The daily CASM biomasses and the ecoindicators were compared specifically from spatial polygon 10 in the Barataria Basin model (Fig. 1), which had annual mean salinity concentrations around 12, and intermediate chl-*a* concentrations around 32 $\mu\text{g l}^{-1}$ (Lewis et al., 2021). The CASM spatial polygon 10 was used to be consistent in reporting results for the same subregion as Lewis et al. (2021); polygon 10 represents the typical estuarine conditions within Barataria Basin. Using a single spatial polygon from the Barataria CASM for the simulation exercises is easier to evaluate the differences than simulating changes and averaging the model outputs across all 20 polygons.

3. Results

3.1. Environmental variables and gear types

Salinity did not differ by gear types, but did differ significantly by station ($F_{11, 311} = 54.36$, $p < 0.0001$). Salinity ranged from 0.3 to 11.9 (mean \pm SE: 3.3 ± 0.9). The highest salinity site (2069) was significantly greater than all other sites; the lowest salinity site (2008) was significantly lower than all other sites. The remainder of the sites clustered into lower (2011, 2015, 2004, 2046, 2044) and upper salinity sites (2007, 2031, 2040, 2041, 2045). Temperature did not differ by gear, or station, but followed expected seasonal patterns, ranging from 25.1 to 29.4 °C (mean \pm SE: 26.9 ± 0.4). Turbidity and DO concentrations differed significantly between gear types ($F_{1,308} = 4.54$, $p < 0.0001$; $F_{1,308} = 8.12$, $p = 0.0047$) only. Turbidity ranged from 0.8 to 2.0 NTU (mean \pm SE: 1.4 ± 0.1) and was higher with electrofishing samples (1.7 ± 0.06 NTU), compared to seine (1.3 ± 0.06 NTU). DO concentrations ranged from 5.2 to 8.0 mg L^{-1} (mean \pm SE: 6.8 ± 0.2) and were also higher in electrofishing ($7.5 \pm 0.2 \text{ mg L}^{-1}$) than seine ($6.9 \pm 0.2 \text{ mg L}^{-1}$) samples. Linear mixed models with salinity, water depth and turbidity showed no significant relationships, regardless of gear type, between abundance, or nekton richness for the range of conditions sampled.

3.2. Nekton assemblages by gear type

A total of 108 338 individuals, consisting of 93 species, were collected. Of the total individuals captured, electrofisher samples captured 74 091, and seine samples captured 34 247. Key species accounted for 94% of the total catch, with grass shrimp accounting for 56% of the total catch. Of the remaining species, seven accounted for more than 1% of the overall catch, consisting of bay anchovy (10.0%), brown shrimp (7.0%), Gulf menhaden (7%), white shrimp (6%), Atlantic croaker (2.0%), striped mullet (1.9%), and inland silverside (1.4%) (Table 1). As grass shrimp were a dominant part of the catch, data were examined with and without grass shrimp.

CPUE differed significantly by gear type ($F_{1, 22} = 8.88$; $p < 0.0069$) and season ($F_{3, 308} = 4011.9$; $p < 0.0001$), but not the interactive effects. For gear, electrofishing had significantly higher CPUE (443.7 ± 42.8) as compared to seine (203.9 ± 28.1 ; $F_{1, 22} = 8.88$; $p = 0.0069$). For season, spring had the highest CPUE (490.6 ± 67.2), which was greater than summer CPUE (208.9 ± 27.8). Both were significantly greater than winter (283.9 ± 39.5) and fall (291.0 ± 58.7) CPUE, which did not differ from one another. Without grass shrimp, seine and electrofisher CPUE did not differ significantly, while season differed significantly ($F_{3, 308} = 2645$; $p < 0.0001$). Spring (231.1 ± 36.5) had the highest CPUE, followed by fall (137.0 ± 24.0), summer (112.2 ± 12.7) and then winter (70.4 ± 9.2).

Of the 92 total species captured across all gear types, the electrofisher captured 83 and the seine captured 80 different species. Species richness differed significantly by the interaction of gear by season ($F_{3,268} = 11.8$; $p < 0.0001$). Seine winter, spring, summer, fall and electrofisher winter were all similar and significantly lower than electrofisher spring, summer and fall richness. However, each gear type collected some unique species, with the electrofisher collecting 13 unique species, and seine 10 unique species (Table 2).

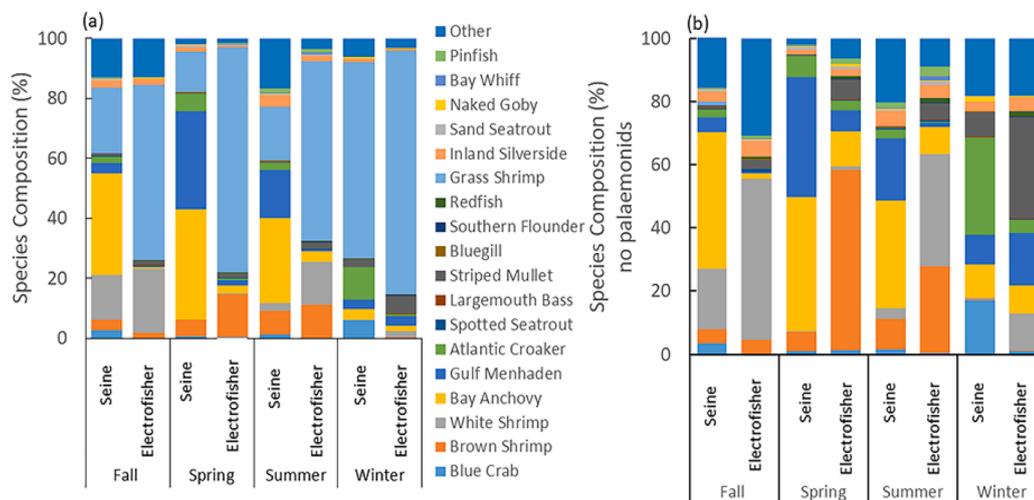
While the dominant species across all sampling was grass shrimp, accounting for 56% of the total catch, it composed only 26% of the seine catch, and 69% of the total electrofisher catch. The top three species from electrofishing accounted for over 85% of the total catch, and were grass shrimp (69%), brown shrimp (9%) and white shrimp (7%) (Fig. 4a). In contrast, the top three species collected using seines accounted for 74% of the total catch, and consisted of grass shrimp (26%), bay anchovy (28%) and Gulf menhaden (20%). Without grass shrimp, total catch consisted of 47 773 organisms, with 25 005 organisms captured by seine and 22 768 captured by electrofisher. For seine, bay anchovy and Gulf menhaden comprised 65% of the catch; for electrofisher, brown shrimp and white shrimp comprised 53% of total catch (Fig. 4b).

ANOSIM indicated differences in species assemblages by gear type for all seasons (stress values < 0.20 ; $p < 0.001$). SIMPER analysis

Table 2

Unique species captured by each gear type (seine and electrofisher) from May 2018 through June 2019.

Seine	Electrofischer
<i>enticirrhus littoralis</i> , Gulf kingfish	<i>Menippe mercenaria</i> , Stone crab spp.
<i>Sardinella aurita</i> , Spanish sardine	<i>Alpheus Euphrosyne</i> , Green snapping shrimp
<i>Peprilus burti</i> , Gulf butterfish	<i>Hypsoblennius hentz</i> , Feather blenny
<i>Portunus sayi</i> , Sargassum swimming crab	<i>Evorthodus lyricus</i> , Lyre goby
<i>Selene vomer</i> , Lookdown	<i>Mugil curema</i> , White mullet
<i>Farfantepenaeus duorarum</i> , Pink shrimp	<i>Micropterus punctulatus</i> , Spotted bass
<i>Scomberomorus maculatus</i> , Spanish mackerel	<i>Opsanus beta</i> , Gulf toadfish
<i>Pomatomus saltatrix</i> , Bluefish	<i>Alpheus heterochaelis</i> , Pistol shrimp
<i>Prionotus tribulus</i> , Bighead searobin	<i>Myrophis punctatus</i> , Speckled Worm Eel
<i>Chaetodipterus faber</i> , Atlantic spadefish	<i>Sphyrna guachancho</i> , Guaguanche
	<i>Trachinotus carolinus</i> , Florida pompano
	<i>Gambusia affinis</i> , Mosquito fish
	<i>Anguilla rostrata</i> , American eel



43

Fig. 4. Species composition (%) by gear type from the 14-month sampling effort (May 2018-June 2019). The panel on the left (a) shows composition of all samples and the panel on the right (b) shows the same data without grass shrimp (palaemonids).

however indicated minimal dissimilarity for all seasons, with shrimp and small-bodied fish species contributing most to dissimilarity between gear catches (Table 3).

Gear comparisons using the ratio of electrofisher to seine indicated that compared to seine catches, the electrofisher was more effective at capturing shrimp (grass shrimp, white shrimp, brown shrimp) and large fish species (redfish, spotted seatrout, largemouth bass and southern flounder; Fig. 5). Seines were only slightly more effective in collecting blue crab, and small bodied fish species (bay anchovy, gulf menhaden, Atlantic croaker).

3.3. Gear conversion

Using gear corrected densities, density differed by single effects only of gear ($F_{1,22} = 18.5$; $p = 0.0003$) and season ($F_{3, 308} = 39.7$; $p < 0.0001$). Specifically, electrofishing ($10.0 \pm 1.5 \text{ ind m}^{-2}$) had higher

Table 3

Results of similarity of percentages (SIMPER) analysis between gear types on log-transformed abundances by season.

Species	Contribution %	Cumulative %
Fall: Average dissimilarity = 30%		
Grass shrimp	12.3	12.3
White shrimp	10.6	22.9
Bay anchovy	8.1	31
Brown shrimp	6.2	37.2
Striped mullet	6.1	43.3
Winter: Average dissimilarity = 11%		
Grass Shrimp	10.5	10.5
Striped mullet	8.5	19
Atlantic croaker	6.2	25.2
Bay anchovy	5.7	30.9
Blue crab	5.7	36.6
Spring: Average dissimilarity = 37%		
Grass Shrimp	10.8	10.8
Brown shrimp	7.1	17.9
Bay anchovy	6.8	24.7
Gulf menhaden	6.5	31.2
Striped mullet	5.3	36.5
Summer: Average dissimilarity = 31%		
Grass Shrimp	11.5	11.5
White shrimp	8.4	19.9
Brown shrimp	7.6	27.5
Bay anchovy	6.7	34.2
Striped mullet	5.1	39.3

densities as compared to seine ($2.9 \pm 0.5 \text{ ind m}^{-2}$). For season, spring ($10.0 \pm 1.5 \text{ ind m}^{-2}$) was similar to fall ($6.5 \pm 1.4 \text{ ind m}^{-2}$) but was significantly greater than winter ($5.7 \pm 0.8 \text{ ind m}^{-2}$) and summer ($4.3 \pm 0.6 \text{ ind m}^{-2}$) densities. Fall did not differ significantly from any other season. Without grass shrimp, only season differed significantly ($F_{3, 308} = 6.4$; $p < 0.0001$). For season, spring ($4.0 \pm 0.5 \text{ ind m}^{-2}$) was significantly greater than fall ($2.9 \pm 0.6 \text{ ind m}^{-2}$), which was greater than summer ($2.1 \pm 0.2 \text{ ind m}^{-2}$), which was greater than winter ($1.3 \pm 0.2 \text{ ind m}^{-2}$).

3.4. CASM biomass Estimates, simulations and food web indicators using the seine and electrofisher sample data

Comparison of the monthly biomasses estimated for the seven species between the original CASM calibration data (Watkins et al., 2016) and the 2018–2019 seine and electrofisher data shows large differences in the magnitudes, composition, and timing of changes (Fig. 6a–c). For example, the monthly averaged biomass of Gulf menhaden estimated from the 2018–2019 seine samples was much higher with the CASM calibration dataset. The 2018–2019 seine samples also showed higher bay anchovy biomass with peaks in the spring months (March-May), compared to a later peak (June-Aug) in the CASM calibration dataset. Overall, the 2018–2019 electrofisher data had much higher grass shrimp, brown shrimp, and white shrimp biomass compared to the original CASM calibration dataset, and the seine data. In contrast, the calibration dataset had much more blue crab biomass and higher killifish biomass compared to the seine and electrofisher data for 2018–2019.

For Simulation Exercise 1 comparison, the CASM was minimally affected by adjusting the initial biomasses, with simulated daily biomasses in Year-2 (simulation days 366–730) showing similar seasonal species composition and biomasses of the seven key species over time (Fig. 6 d, e, f). Because the simulated biomasses of the seven populations were similar as Year 2 progressed, we knew a priori that large changes to the food web would not result.

For Simulation Exercise 2, differences in biomass were evident between the B_{CASM} , B_{S} , and B_{E} estimated for five of the seven key species (Appendix Table 1; Table 4). The grass shrimp biomass for day 500 was 16 times greater than the calibrated B_{CASM} for the 2018–2019 May seine data, and 663 times greater for the 2018–2019 electrofisher data. Biomass for brown shrimp, white shrimp, and Gulf menhaden in the 2018–2019 seine data were 1.5 to 2 times the magnitude of the generated day 500 calibrated B_{CASM} for the YOY species, but the YOY bay anchovy was nearly 6 times the biomass. Biomass for brown shrimp and

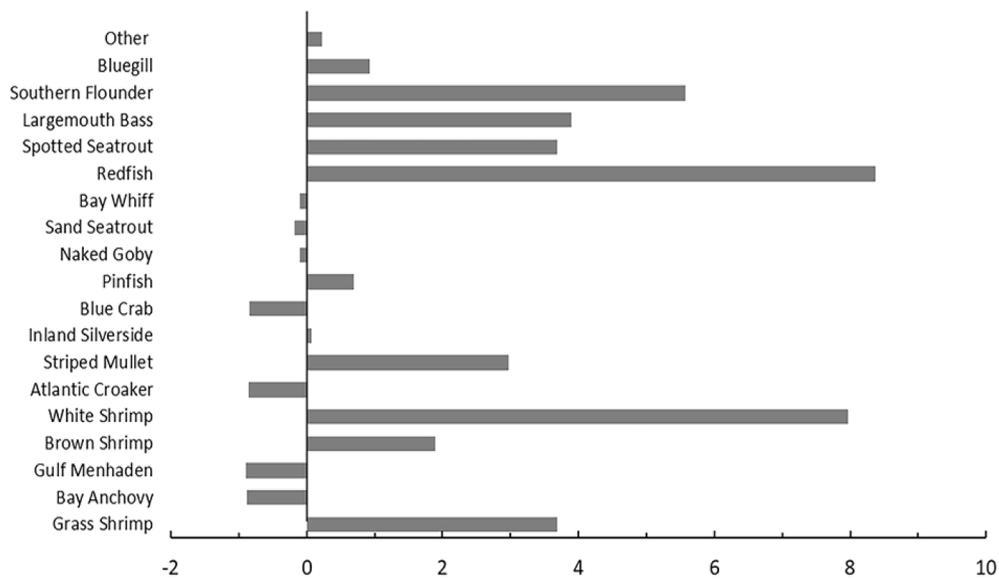


Fig. 5. Gear type ratio of electrofisher:seine for key species collected during the 14-month (May 2018- June 2019) sampling effort. For presentation purposes, the ratio was corrected such that a ratio of zero indicates equal catch per unit effort (CPUE) by gear type, whereas a ratio greater than zero indicates that the electrofisher is more likely to collect that species compared to the seine.

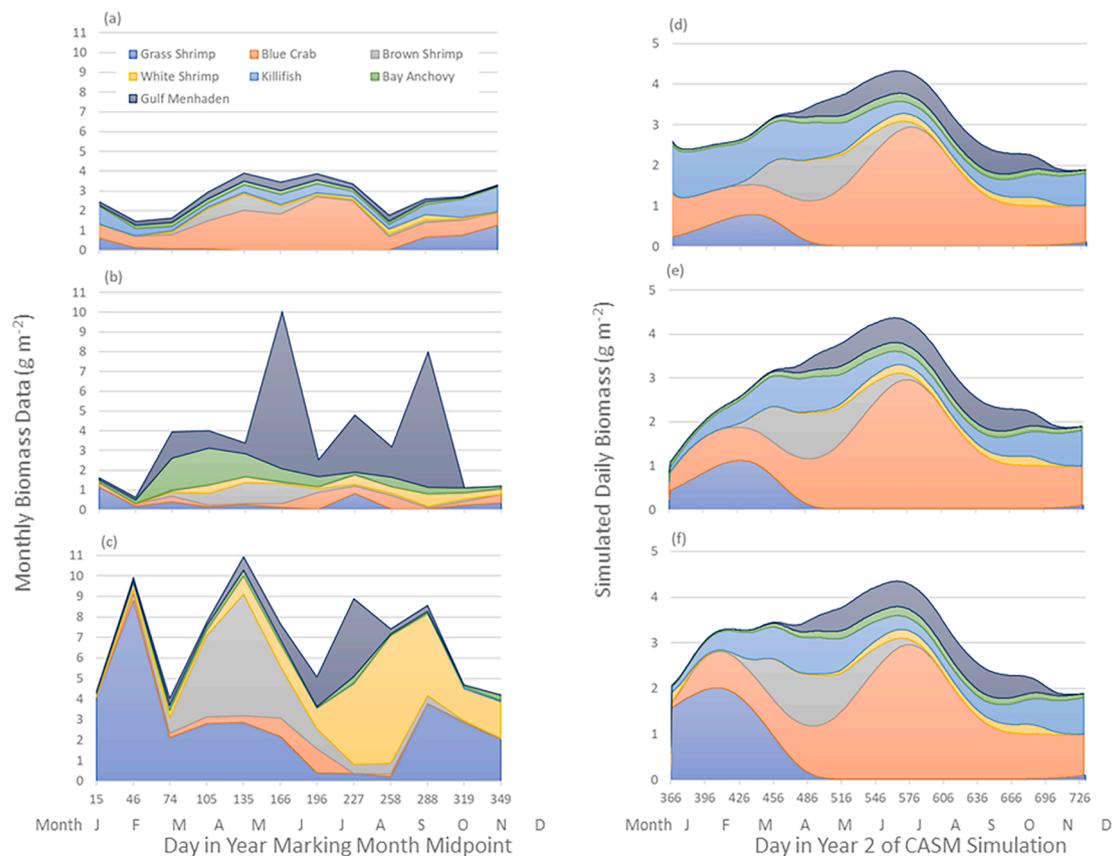


Fig. 6. Mean monthly biomass for seven key species in Barataria Estuary from the observed dataset from 1995 to 2010 used for Comprehensive Aquatic Systems Model (CASM) initialization and calibration (a), the seine station data from 2018 to 2019 (b), and the electrofisher station data from 2018 to 2019 (c). Model generated from simulation one of daily biomasses in Year 2 from the calibrated CASM using the calibration 1995–2010 dataset for Barataria Basin (d), the CASM run using the averaged January biomass from the seine data in 2018–2019 (e), and the CASM run using the averaged January biomass from the electrofisher data in 2018–2019 (f).

white shrimp were nearly 8 times higher for the electrofisher data, while Gulf menhaden biomass for day 500 was nearly 2 times higher than the B_{CASM} biomasses.

In contrast, B_{CASM} for blue crab and killifish were higher than either seine or electrofisher estimated biomasses. The biomass changes for the seven mid-trophic level YOY and resident species from the 2018–2019

Table 4

. Simulation Exercise 2 results of biomasses (g m^{-2}) for seven key species on day 500 (Year 2: May 15th) generated by the calibrated model (1st column), multiplied by the biomass ratio estimated from the 2018–2019 seine data (R_S ; 2nd column), and multiplied by the biomass ratio from the 2018–2019 electrofisher data (R_E ; 3rd column). The resulting daily total biomass ($\text{Total}_{\text{CBIO}}$), Shannon-Wiener Index (H'), Mean Trophic Level Index (MTL), and estimated annual summed consumption of phytoplankton ($\text{Flow}_{\text{PHYTO}}$), summed consumption of benthic algae (Flow_{ALG}), summed consumption of detritus (Flow_{DET}), Total system throughput (TST), and the daily ratio of predation mortality to natural mortality of all species within the food web. The food web indicators were estimated from spatial polygon 10 encompassing the mid-estuary region with intermediate salinities and base prey concentrations driving the food web. CASM = Comprehensive Aquatic Systems Model.

	Calibrated CASM	Seine	Electrofisher
Biomass (g m^{-2})			
Grass shrimp	0.023	0.377	15.25
Blue crab	1.551	0.109	0.245
Brown shrimp	1.155	1.498	8.362
White shrimp	0.027	0.055	0.204
Killifish	1.060	0.096	0.096
Gulf menhaden	0.677	0.961	1.164
Bay anchovy	0.177	1.021	0.238
CASM Food Web Indicators			
$\text{Total}_{\text{CBIO}}$ (t km^{-2})	18.33	17.78	39.23
H'	2.89	2.89	2.21
MTL	2.31	2.32	2.16
$\text{Flow}_{\text{PHYTO}}$ ($\text{t km}^{-2} \text{ yr}^{-1}$)	1468	1508	1532
Flow_{ALG} ($\text{t km}^{-2} \text{ yr}^{-1}$)	1335	1272	1293
Flow_{DET} ($\text{t km}^{-2} \text{ yr}^{-1}$)	571	529	526
TST ($\text{t km}^{-2} \text{ yr}^{-1}$)	5421	5285	6155
$M_{\text{Pred}}/M_{\text{Nat}}$	43.6	37.3	35.1

seine data applied to day 500 had minimal impact on food web indicators compared to the calibrated CASM (Table 4). The biomass differences across the seven species were not enough to result in changing the total daily biomass ($\text{Total}_{\text{CBIO}}$), the Shannon-Wiener Index (H'), or MTL of the food web. The increased biomass of bay anchovy and Gulf menhaden resulted in increased consumption of phytoplankton and zooplankton biomass in the food web, so that energy flow up the food web from phytoplankton ($\text{Flow}_{\text{PHYTO}}$) increased slightly. The large reductions in seine blue crab and killifish biomass compared to the calibrated CASM biomass affected consumption of benthic algae and detritus, and more than the increased consumption of benthic prey by the three shrimp biomasses. This difference resulted in slightly ($<10\%$) reduced flow up the food web from benthic prey sources (Flow_{ALG} and Flow_{DET}) compared to the calibrated CASM (Table 4). The total energy flow (TST) remained nearly the same for the CASM using the adjusted seine biomasses compared to the calibrated CASM (Table 4). The ratio of predation mortality versus the background or natural mortality ($M_{\text{Pred}}/M_{\text{Nat}}$) of all available biomass consumed by the food web was reduced to 85% of the calibrated CASM food web value on day 500. This reduction indicates that the changes in biomass for the seven mid-trophic level populations resulted in less overall consumption of available prey biomass by the food web.

In contrast, the biomass changes for the seven mid-trophic level YOY and resident species from the electrofisher data on day 500 changed the biomass structure from the calibrated CASM (Table 4). The total biomass ($\text{Biom}_{\text{TOTAL}}$) of the food web more than doubled with the large magnitude increases in grass shrimp, and YOY brown shrimp, white shrimp, and gulf menhaden biomass. The increased biomasses caused a reduction in the species or population evenness (H') of the food web, and MTL was also reduced. Interestingly, flow through phytoplankton ($\text{Flow}_{\text{PHYTO}}$) increased a bit more with increased Gulf menhaden biomass compared to both the calibrated CASM and the seine biomass. However, flow through benthic algal and detritus consumption by the larger biomass pools of the three shrimp species was still not enough to change the flow up the food web given the lower electrofisher biomass of blue crab and

Gulf killifish compared to the calibrated CASM model. The TST from the food web increased by about 13% over the TST of the calibrated CASM, but the ratio of predation mortality to natural mortality for all available prey biomass consumed in the food web on day 500 was reduced to 80% of the calibrated CASM. The total summed flows across all consumer population biomasses on day 500 (in $\text{g m}^{-2} \text{ yr}^{-1}$) were $\Sigma Q_{ij} = 3,937$, $\Sigma r_i = 418$, $\Sigma d_i = 1,049$, and $\Sigma e_i = 15.29$ for the calibrated CASM, compared to the increased $\Sigma Q_{ij} = 4,213$, $\Sigma r_i = 719$, $\Sigma d_i = 1,207$, and $\Sigma e_i = 15.25$ for the CASM using the adjusted electrofisher biomasses for the seven YOY and resident marsh species.

4. Discussion

Across coastal Louisiana, long-term fisheries-independent sampling provides critical data to support commercial and recreational fisheries management, water resource projects, and coastal restoration efforts. The combination of rapid coastal change and advances in sampling technologies affecting the efficiency and selectivity of sampling gear requires careful consideration of data interpretation when using some of these indicators. While improvements to electrofishing gear have enabled sampling across the estuarine (salinity) gradient in coastal Louisiana, potentially in place of the LDWF bag seines used for sampling small YOY transient species and resident marsh species, significant differences in species representation and CPUE by the two gears suggest changes in gear would impact data collected on species, food web and ecosystem indicators reliant on these data. Conversions based on area and gear efficiency for overall CPUE may be useful in maintaining the continuity of historical data. However, differences in species-specific catch due to gear selectivity could have large consequences for constructing and calibrating fish and ecosystem models and remain difficult to reconcile.

CPUE provides a broad comparison of habitat or ecosystem support for fisheries (i.e., Brandner et al., 2013; Mueller et al., 2017; Hollweg et al., 2019). In this study, differences in overall CPUE between gear types occurred consistently throughout the year and across the estuarine gradient; the electrofisher samples had higher CPUE and richness than seine samples, and also captured larger-bodied fish. Comparative studies of electrofishers and other gears, including seines, generally concur, finding that electrofishers are most effective in sampling within shallow water habitats, as measured by higher species richness, CPUE, biomass, and greater guild diversity (i.e., Wiley and Tsai, 1983; Ruetz et al., 2007; Warry et al., 2013; Mueller et al., 2017). In this study, the dominant catch in the electrofisher was grass shrimp, with catches consisting of greater than 50% grass shrimp across all samples, while seines captured less than half the number of grass shrimp. When CPUE was compared without grass shrimp, both gears had similar CPUE. Regardless, as grass shrimp are important prey items supporting higher trophic levels, this large difference in overall CPUE could have broad implications when considering food web or ecosystem models. Further, CPUE alone may not be a useful indicator as it measures only the component of the assemblage that is vulnerable to the selected sampling gear, which may not be representative of the overall assemblage (Hampton et al., 2005; Maunder et al., 2006; Walker et al., 2017).

Differences in species assemblages and the presence of unique species captured by each gear type present more difficult challenges when trying to reconcile catch from different sample approaches (Gibson-Reinemer et al., 2017). In this study, electrofishing tended to collect unique species that associate with structured habitat (i.e., gobies, blennies) as well as less common shrimp species (i.e., pistol shrimp, green snapping shrimp), and more large-bodied species. As all samples were taken adjacent to vegetated marsh, this likely reflects the effectiveness of this gear to shock individuals within this vegetated edge habitat. In contrast, unique species captured by seine were less easily categorized, although consisted of some species that could be more bottom-associated. Studies in other environments, including freshwater streams, have found similar results in terms of more unique species and

higher overall diversity when using electrofishers (i.e., Neebling and Quist, 2011, Mueller et al., 2017). For examining overall diversity or richness, electrofishing may be more effective across a broad range of habitats. However, regardless of gear used, the main challenge of fisheries sampling is that only a proportion of individual animals are caught by any specific sampling gear (Walker et al., 2017).

Long-term fisheries field data are used to inform management of dominant or key fishery species within an area. There were significant differences in catch with electrofishing being effective at capturing shrimp (i.e., grass, brown, and white shrimp), while seines were effective in capturing smaller-bodied prey fish (i.e. Gulf menhaden, bay anchovy). In a freshwater river study, a similar pattern occurred with higher numbers of juvenile fish captured using seines versus using electrofishers (Dewey, 1992). This result was hypothesized to be due to reduced ability to capture stunned fish in turbid, vegetated waters. As our study was conducted on the edge of vegetation, the structure did not likely impact the lower numbers of smaller fish, and it seems unlikely that turbidity was a factor in electrofisher sampling, as this would apply equally to all species.

In addition to differences in species assemblages resulting from potential gear bias or selectivity, study results may be further influenced by environmental conditions during sampling including water depth, turbidity and salinity (i.e., Miranda and Kratochvíl, 2008, Warry et al., 2013). Warry et al. (2013) found that electrofishing was less effective compared to nets as depth increased above 1.5 m, and as salinity increased above 15. In these coastal estuarine study sites, depths are not routinely measured, but the average depth across Barataria Basin is <2 m suggesting depth is not likely to be a factor. Similarly, Barataria Basin is consistently relatively turbid, and therefore turbidity is not likely a factor. However, salinity ranged up to 30, which may influence both the overall effectiveness of the electrofisher and the relative species selectivity as the effective conductivity of fishes may be species-specific; electrofishing may have been differentially effective in sampling a species across this salinity gradient (Miranda and Dolan, 2003). In examining species-salinity plots, we were unable to find a strong pattern suggesting an effect (Taylor et al., 2020). Given the multiple changing environmental factors, teasing out potential water quality effects remains challenging.

As meta-analyses and models based on long-term fisheries field data become more commonly used, the need to estimate relationships between reported catches using multiple gear types becomes increasingly important (Hollweg et al., 2020). Numerous approaches have been used in the past to create gear conversions, but often focused on single species (i.e., Robson, 1966, Wilderbuier et al., 1998, Kappenman, 1992, Lewy et al., 2004). Most recently, Hollweg et al. (2020) surveyed the literature across estuarine habitat types (i.e., mud bottom, vegetated marsh, oyster reef, submerged aquatic vegetation) to develop gear conversions based on area sampled, and estimated gear capture efficiencies, and applied them in a meta-analysis of multiple independent studies across estuaries in the northern Gulf of Mexico. While the gear efficiencies captured by Hollweg et al. (2020) tend to represent overall CPUE only, and are not species specific, to our knowledge, no such comparable data exist for electrofishing within an estuarine environment. As such, we used literature values from freshwater rivers to estimate total CPUE efficiency of the electrofisher as described in the methods for gear conversions which resulted in no change in the relative overall findings. However, this approach still fails to deal with species assemblage differences that are critical in informing both single species management and ecosystem or food web models. Specifically, conversions to compare overall CPUE rely on the assumption that there is no species selectivity by gear, and that catchability by species and habitat remain equal (Hampton et al., 2005, Maunder et al., 2006, Baker and Minello, 2011, Archaux et al., 2012, Zhou et al., 2014). For example, electrofishing may disproportionately sample different fish taxa based on species-specific conductivity, inadvertently biasing estimates of nekton assemblages across gradients (Dolan and Miranda 2003). Many other studies have examined

gear based abundance and size class selectively (Dembkowski et al., 2012), guild (i.e., feeding) or mobility (Baker and Minello, 2011). Bias by gear types remains essential to consider in light of the sampling goal (s), and the given habitat(s) to be sampled (Raposa and Roman, 2001).

While fisheries sampling often drives harvest management decisions, these data are increasingly being used to inform food web models and overall habitat management and restoration. Differences in both biomass capture and species composition may dictate a different model structure and/or provide very different biomass estimates that would impact food web model initialization and calibration, and ultimately food web model simulation runs. The first simulation exercise comparing seine and electrofisher biomass and species data indicated that the CASM is relatively robust to initial conditions. In this case, initial conditions were defined by the initial biomasses for the seven species at the start of the model run. The daily generated biomass of species in Year 2 were affected by the initial conditions for the first part of Year 2, but then the biomasses looked similar across the three CASM simulations for most of Year 2. The CASM robustness likely reflects that five of the seven species used also depend on the movement of migrating YOY into the system, and fluxing out of the YOY survivors to the next stage class (either larger YOY or Age-1 +) biomass pools for the conspecifics within the year. This is the case for many of the other key fish and invertebrates in the estuary that have two and three life stages with fluxing up to older life stages and migration out and then back into the estuary as small YOY which is required to complete the life cycle of the species over multiple-year simulations in the CASM. Gulf killifish and grass shrimp are represented by single biomass pools that remain in the estuary, but also show seasonal patterns corresponding with changing temperature and base prey biomass (i.e., benthic algae, detritus). Further, Gulf killifish and grass shrimp are affected by predation from the food web, so that their daily biomasses also remained similar over time (Fig. 6).

If the CASM was actually calibrated to fit the monthly averaged biomass data estimated from the 2018–2019 seine or electrofishing data, as compared to the original calibration dataset from 1995 to 2010 (Fig. 6a–c), the food web trophic structure and energy cycling would be different than what the calibrated CASM represents for Barataria Basin. Specifically, if based on the 2018–2019 seine data, the modeled food web would show more biomass concentration and flow through phytoplankton in the water column with higher biomasses of schooling species such as bay anchovy and Gulf menhaden. In contrast, if based on the 2018–2019 electrofisher data, the modeled food web would have more biomass concentration in the dominant shrimp species and would likely show a more benthic-driven food web. As a result, the long-term datasets used to calibrate and validate the models are critical in determining CASM outputs. As CASM represents more of a bottom-up approach, it would be interesting to examine whether the same results occur when explored using EwE, a more top-down fisheries-based approach.

Our findings show how differences in gear types used can affect data collected on CPUE and species composition. Our biomass estimates using the two separate sets of field data were largely different for the seven key mid-trophic level species that we substituted into the CASM. However, our application using the CASM was a conservative model exercise to demonstrate how changes in species data (in this case due to gear type changes) might affect fish population and food web model projections. Recalibrating the CASM generated biomasses to the monthly averaged field data would have given very different model results for species biomasses and food web indicators. Recalibrating food web models is difficult and not warranted for these datasets given the short amount of monthly data available from the paired seine and electrofisher data.

Providing robust and up to date data for collation and inclusion in species-specific, ecosystem, or food web models relies heavily on field data. Collection of these field data to inform status and trend assessments of species and ecosystems consists of trade-offs in gear efficiency, species-specific catchability, habitat changes and even logistics, but has

significant implications for management and restoration decision-making. Collection of these data remain essential through time, providing data to support fisheries management decisions, food-web modeling and meta-analyses.

CRedit authorship contribution statement

Megan K. La Peyre: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – original draft, Visualization, Project administration, Supervision, Funding acquisition. **Shaye Sable:** Conceptualization, Methodology, Formal analysis, Software, Validation, Investigation, Resources, Data curation, Writing – original draft, Visualization, Project administration, Supervision, Funding acquisition. **Caleb Taylor:** Formal analysis, Investigation, Data curation, Writing – review & editing, Visualization. **Katherine S. Watkins:** Methodology, Software, Validation, Formal analysis. **Erin Kiskaddon:** Writing – review & editing. **Melissa Baustian:** Visualization, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2021.108404>.

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