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REVIEWS

Non-probabilistic surveys and sampling in the human dimensions of fisheries

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Abstract Fisheries management and conservation require consideration of fish, habitat, and people. In fisheries science, a growing body of research on human values, perspectives, and behaviours around fish—known as 'human dimensions' research—has emerged from the realization that management and conservation require a better understanding of people. Surveys are a common and versatile tool in human dimensions research, but not all surveys are equal. Large-scale, probabilistic surveys draw random samples from known populations (e.g., all license-holding recreational fishers in a jurisdiction) and represent the 'gold standard' in survey research. However, these surveys may fall short of this standard for various reasons. Surveys using non-probabilistic sampling are also common in human dimensions research. Non-probabilistic surveys are attractive to researchers facing time, cost, and other constraints, but differ notably from their probabilistic counterparts: data from non-probabilistic samples are typically unfit for population estimates and other inferences due their uncertain representativeness. Nonetheless, a wealth of research with non-probabilistic data within and outside of fisheries (e.g., in health sciences) suggests that these methods have valid applications and advantages in some contexts. We reviewed the literature on non-probabilistic surveys and sampling in the human dimensions of fisheries, and explored seminal literature from other thematic areas where such methods are common, to better understand their strengths, weaknesses, and applications relative to probabilistic methods. Here, we describe (1) how researchers have used non-probabilistic methods to study the human dimensions of fisheries, (2) how mismatching research questions, objectives, and methods can produce 'awkward surveys,' and (3) how researchers can use non-probabilistic surveys in ways that invoke their methodological strengths. While uncertain representativeness may limit the utility of non-probabilistic data in some contexts, non-probabilistic methods are time- and cost-effective, and have distinct advantages in studies of niche groups and phenomena, emergent or understudied phenomena, and in supplementary roles.

Keywords Non-probability · Nonprobabilistic · nonprobability · Sampling methods · Human dimensions · Natural resources · Wildlife

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Introduction

Fisheries management and conservation involve three primary considerations of fish, habitat, and people. Each consideration is complex, and efforts to manage and conserve fisheries must be flexible and cognisant of uncertainty (Walters and Hilborn 1978; Hilborn 1992; Hoggarth et al. 2006). Recently, greater appreciation of social complexity and uncertainty has led to the 'mainstreaming' of social science in this conventionally biological and ecological space (Sandlos et al. 2016; Bennett et al. 2017). A significant and growing literature on human values, thoughts, and behaviours around fish and wildlife use—known commonly as 'human dimensions' research—now exists to counter this imbalance (Ditton 1996; Manfredo et al. 2009; Jacobs et al. 2018). The human dimensions of fisheries encompass many subjects representing types and/or sources of uncertainty, such as diversity among fishers (Arlinghaus et al. 2008; Castello et al. 2013), non-compliance with regulations (Nielsen 2003; Jensen et al. 2017), variations in fishing activity across time and space (Hilborn 2007; Matsumura et al. 2019), and cryptic overfishing (Post et al. 2002). Greater understanding of fishers is needed (Hilborn 1992; Arlinghaus et al. 2013), such as where and when people fish (Hunt et al. 2011), or how aquatic invasive species may be spread by fishers (Drake and Mandrak 2010). Opportunities for human dimensions research to provide this understanding, and enhance fisheries management and conservation, are increasingly apparent.

Surveys are a staple in the study of fishers (e.g., creel surveys; Pollock 1994), and help to grasp what some managers regard as the "messy" human dimensions of fisheries (Hunt et al. 2013). Unlike a census, which derives information from a whole population, a survey derives information from a sample (i.e., population subset) which may or may not accurately represent the population. Surveys are versatile, and can be fitted to wide-ranging research questions and scenarios (Dillman 2011). Surveys also take diverse forms. For example, data may be reported by fishers via questionnaires, or recorded directly by researchers in aerial surveys. Data are also collected with less conventional methods (e.g., digital 'mining') not typically regarded as surveys. Our review considers sample data collected with wide-ranging methods, but focuses primarily on surveys due to their widespread application and utility in the human dimensions of fisheries (Pollock 1994).

Not all surveys are equal, and what inferences can be made with survey data depend on the sampling methods and survey instruments used to collect them (Rossi et al. 2013; Vaske et al. 2022). Sampling, coverage, measurement, and nonresponse errors are possible in all social surveys (Dillman 2011). Errors in data collection can be reduced with best practices (e.g., conducting pre-tests, increasing and diversifying contacts to survey participants, combining and/or diversifying survey modes, maximizing real and perceived benefits of participation; Dillman 2011; Greenberg and Dillman 2023), but these alone cannot resolve certain flaws in sampling. Coverage errors occur when certain elements of a population are missed in sampling (e.g., selecting a sample from cell phone numbers excludes people who do not possess cell phones), and the probability of selecting various elements is unknown. This is problematic in surveys aiming to make population-level inferences from sample data, in which case random sampling from a known population is necessary. Probabilistic surveys (i.e., surveys using probabilistic sampling) sample randomly, and, if necessary, across relevant strata in a population. This ensures that each individual in a population has an equal probability of being selected, resulting in a representative sample (i.e., population subset with similar demographic characteristics and proportions to the population). For this reason, probabilistic data are most suitable for population inferences, which are the goal of many surveys. Large-scale, probabilistic surveys in fisheries include the Survey of Recreational Fishing in Canada (Brownscombe et al. 2014), the National Survey of Fishing, Hunting, and Wildlife-Associated Recreation (United States; U.S. Fish and Wildlife Service and U.S. Census Bureau 2001), and the National Recreational Fishing Survey (Australia; Campbell et al. 2001). As these names suggest, much of the social surveying in fisheries focuses on recreational fishing, due to the heterogeneous, intense, and sometimes cryptic qualities of this activity (Fenichel et al. 2013; Hunt et al. 2013; Post et al. 2002).

Large-scale, probabilistic surveys are valued because they can provide statistically robust information on fishers. However, these surveys are time- and resource-intensive, and may be no more immune than non-probabilistic surveys (i.e., surveys using non-probabilistic sampling) to certain biases. Probabilistic creel surveys, for example, are susceptible to inaccurate reporting by fishers (i.e., measurement error; Alexiades et al. 2015) and often biased toward more active, older, and male individuals (i.e., nonresponse error; Vaske et al. 2022). Probabilistic surveys also face challenges in technological change (e.g., electronic communications, social media saturation) and declining response rates, which threaten the efficacy and even reliability of some surveys (Stern et al. 2014; Vehovar et al. 2016; Ferri-García and Rueda 2018; Stedman et al. 2019). Put simply, benefits of random and stratified sampling may be offset by errors and biases to which probabilistic surveys are equally prone. Bias may even result from poor execution of probabilistic sampling (e.g., stratified sampling without consideration of key demographic factors). For these reasons, probabilistic surveys must also be subject to basic scrutiny, and not blindly regarded as sources of 'gold standard' sample data.

Technological change has also created many new opportunities for social research. Online surveys are time- and cost-effective (Brickman Bhutta 2012; Lehdonvirta et al. 2021), social media platforms provide access to niche groups (Baltar and Brunet 2012), and smartphone applications allow for real-time data collection (Anderson 2012; Papenfuss et al. 2015). This has renewed interest in non-probabilistic methods (Brick et al. 2022) and other 'quasi-probabilistic' approaches (e.g., panels constructed with demographic quotas) which have been applied widely in fisheries and beyond. Non-probabilistic surveys involve non-random sampling from a population with unknown characteristics (e.g., academic surveys of Indigenous subsistence fishers; Nguyen et al. 2016). As such, non-probabilistic survey data are often biased by sampling and coverage errors which render them unfit for population inferences. In the human dimensions of fisheries, common biases such as avidity bias (i.e., overrepresentation of avid fishers in voluntary surveys) cast doubt on the inferential power of non-probabilistic data for research on whole populations. This does not mean that non-probabilistic surveys should be disregarded, as they provide many other valuable insights. Despite numerous applications of non-probabilistic sampling in fisheries, papers focusing on these methods and their applications are still rare. Recognizing this, we reviewed the literature on non-probabilistic surveys and sampling in the human dimensions of fisheries, describing past and current uses of these methods in this space (see Existing research). We then describe fundamental limitations, and opportunities for valid and insightful research in this space while drawing on key syntheses from outside of fisheries (see Discussion). Though fish and wildlife are often separated (for practical reasons) in management and elsewhere, these insights likely also apply to analogous questions and topics in wildlife (e.g., small-scale subsistence hunting) and other natural resources.

Review

We reviewed literature on non-probabilistic surveys and sampling in the human dimensions of fisheries to determine the extent and focus of research on this topic. An exploratory search revealed few papers focusing on non-probabilistic methods in fisheries and natural resources even though numerous studies employed some type of non-probabilistic method(s). We searched for "(non-probabilistic OR non-probability OR nonprobabilistic OR nonprobability) AND (fish* OR "natural resource*")" in Web of Science Core Collection (topics; 86 results) and Scopus (title, abstract, keywords; 121 results) on July 26th, 2022. Papers were deemed relevant if they focused on non-probabilistic methods in the human dimensions of fisheries, or if they utilized these methods to answer questions in this area. Our initial search yielded just six papers focusing on methods, and eight papers in which non-probabilistic methods were applied. We then broadened our review by searching for "(non-probabilistic OR non-probability OR nonprobabilistic OR nonprobability OR snowball* OR purposive OR convenien* OR "chain referral" OR chain-referral OR panel) AND (fish* OR natural resource*) AND (angler* OR recreational fisher*)" in the same databases, on the same date, using the same relevance criteria. Our second search included various new terms associated with non-probabilistic methods (e.g., 'snowball'), and captured additional papers that did not explicitly mention non-probabilistic methods. This yielded seven more methods papers and 21 empirical studies (see Table 1). Prominent lines of research that we identified in this area (e.g., social media research) were probed using cited reference searches, and a small number of additional relevant

Table 1 Non-probabilistic social surveys and/or samples in human dimensions research. Ordered chronologically from most recent (top), to least recent (bottom)

Author(s)	Topic(s)	Sampling Method(s)	Sample size (n)
Howarth et al. (2023)	Persistent challenges in freshwater fisheries management	Expert and respondent-driven sampling of hard-to-reach population of freshwater fisheries managers	50
Cascante et al. (2022)	Aquaculture technology adoption	Purposive sampling of key informants and experts from four fish farms	22
Dainys et al. (2022)	Estimating angler effort in a Lithuanian freshwater reservoir	Anonymous, non-probabilistic sonar device use data combined with aerial drone survey data to estimate angler effort	NA
Hook et al. (2022)	Impacts of COVID-19 on marine recreational angling	Online survey administered to panel of UK sea anglers recruited via email lists, in-person events, social media, print and electronic advertisements at tackle shops, charter boats, and sea angling organization and club meetings	559
Johansen et al. (2022)	Relationships between angler satisfaction and trip outcome(s)	Online angler app data used to collect data on sea trout fishing trips (i.e., trip outcome[s], angler satisfaction, other characteristics)	63
Sbragaglia et al. (2022)	Social and ecological impacts of bluefish distributional range shifts on recreational fisheries in Italy	Videos and related data mined from YouTube Data Application Program Interface to examine and characterize harvesting patters, social engagement, and sentiments of recreational anglers and spearfishers around invasive bluefish (*Pomatomus saltatrix*)	376 (videos)
Weir et al. (2022)	Angler-driven AIS proliferation	Angler app catch records used to map angler movements between waterbodies, identifying AIS proliferation risks across the contiguous United States	4,898,603 (records)
Howarth et al. (2021)	COVID-19 impacts on recreational fishing	Purposive and respondent-driven sampling (i.e., magazine and social media advertisements, email lists, link sharing) of recreational anglers in Ontario, Canada	789
Jeanson et al. (2021)	Drivers of pro-environmental behaviour of recreational anglers	Purposive and respondent-driven sampling (i.e., social media advertisements, email lists and newsletters, link sharing) used to recruit recreational anglers targeting rainbow trout (*Oncorhynchus mykiss*) in British Columbia, Canada	894
Kao et al. (2021)	Network connectivity and aquatic invasive species (AIS) transmission	Non-probabilistic data from > 1.3 million watercraft inspection surveys used to model lake connectivity and identify AIS transmission risks in Minnesota waterbodies	1,666,704 (reports)

Table 1 (continued)

Author(s)	Topic(s)	Sampling Method(s)	Sample size (n)
Akbar et al. (2020)	Impacts of provincial government policies on fishing communities	Purposive sampling of vocational fishers across key sites within the Central Indus Wetlands Complex	608
Becker et al. (2020)	Offshore marine fishing effort	Long-range camera used to estimate fishing effort at an artificial, offshore reef	NA
Fricke et al. (2020)	Angler-driven AIS proliferation	Anonymous, non-probabilistic sonar device use data used to identify and describe risks of angler-driven AIS transmission	10,768 (users) 66,918 (trips)
van der Hammen and Chen (2020)	Population size and demography of recreational anglers in The Netherlands	Stratified, quota sampling of a marketing company panel used to identify demographic predictors, and estimate participation rate and trends in recreational angling with records collected from 2009–17. Hard-to-reach subgroups were accessed and recruited from a purchased database, and by peer referral	> 500,000 (records)
Deely et al. (2019)	Utility of objective data for angler site choice analysis	Purposive and convenience sampling (i.e., interception at fishing sites, social media pages and angling clubs, newsletter advertisement) of 'coarse anglers.'	105
Fennel and Birbeck (2019)	Identity of female fly anglers	Purposive and respondent-driven sampling (i.e., contact with female fly fishing clubs, peer referral) of female fly anglers for an online survey	63
Curtis (2018)	Stocking preferences of Irish pike and brown trout anglers	Recruitment of pike and brown trout anglers to non-probabilistic panel via social media, newspapers, radio, tackle shops, and communications with angling clubs and organizations	341
Giovos et al. (2018)	Characterizing data-poor Mediterranean Sea recreational fisheries	Video records mined from social media to describe the species caught, locations fished, and techniques used by Mediterranean Sea recreational fishers in data-poor fisheries of European Union Mediterranean countries	1526 (video records)
Haryadi and Wahyudin (2018)	Conflict(s) between offshore fisheries and mining	Purposive and quota sampling of stakeholders belonging to local interest groups	70
Cavalcante et al. (2017)	Fishing-related injuries and stress in artisanal fishers	Purposive sampling of injured or previously injured artisanal fishers using information from local, supporting organizations	44

Table 1 (continued)

Author(s)	Topic(s)	Sampling Method(s)	Sample size (n)
Lerner et al. (2017)	Socio-economic characteristics of a niche recreational fishery	Purposive sampling of recreational swordfish anglers attending Southeast Swordfish Club and Hydro Glow Winter Swordfest meetings	38
Liu et al. (2017)	Estimating total catch for an unknown angler population	Non-probabilistic angler app data combined with probabilistic dockside data using a recapture design to estimate the total catch of red snapper for Texas coastal waters in the Gulf of Mexico	NA
Paukert et al. (2017)	Climate change impacts on inland fisheries	Expert panel used to identify questions and information gaps required for global assessment of climate change impacts on inland fisheries	NA
Shiffman et al. (2017)	Land-based shark angler perspectives and impacts on shark conservation	Content and discourse analysis of online discussion forum hosted by Florida's largest, land-based shark fishing club to identify noteworthy perspectives and practices of area shark anglers	1256 (posts)
Nguyen et al. (2017)	Data sharing in fish telemetry research	Purposive, convenience, and respondent-driven sampling of fish telemetry researchers to identify determinants of data sharing and describe associated benefits and risks	307
Fujitani et al. (2016)	Efficacy of lecture-based environmental education	Members of angling clubs engaged in self-organized stocking were selected and assigned randomly to a lecture treatment or control to determine the effect of fish stocking education on ecological knowledge and cognitions about stocking	201
Lauber et al. (2016)	AIS impacts in the Laurentian Great Lakes	Expert panel of aquatic ecologists and fisheries managers convened to develop invasion scenarios for five AIS	10
Androkovich (2015)	Recreational benefits of park use during dominant-year salmon run	Questionnaire distributed to convenience sample of park visitors intercepted at entrances to main viewing areas	409
Gallagher et al. (2015)	Risk perceptions and conservation ethics of specialized recreational anglers	Purposive and chain-referral sampling (i.e., website and magazine advertisements, link sharing) used to recruit recreational shark anglers to an online survey	158
Stratoudakis et al. (2015)	Outcomes of marine protected area establishment	Purposive sampling of skippers for fishing vessels operating in the study region	23

Table 1 (continued)

Author(s)	Topic(s)	Sampling Method(s)	Sample size (n)
Voyer et al. (2014)	Fisher resistance to marine protected area establishment	Purposive and respondent-driven sampling of key informants (i.e., recreational, professional, indigenous fishers) until theoretical saturation	53
Bracho-Espinoza et al. (2013)	Parasitism due to fish consumption	Purposive sampling used to obtain and test samples from trawl fishers in Médano Blanco, Falcon State, Venezuela	90
Pedroza (2013)	Small-scale marine fishery self-governance	Key informants (i.e., two government officials, six fishery inspectors) recruited to inform survey design. Purposive and chain-referral sampling used to access and interview hidden population of 'middlemen' (i.e., informal traders)	8 (key informants), 24 (middlemen)
Cooke et al. (2012)	Circle hook use in recreational fisheries	Respondent-driven sampling used to recruit North American anglers to an online survey about circle hook usage	1354
Dorow and Arlinghaus (2011)	Recreational fishing effort and demography in Northern Germany	Complementary phone, diary, and mail surveys using random and non-random sampling, quotas, and weighting used to estimate participation and landings in recreational fisheries of Northern Germany	648
Gren et al. (2009)	AIS proliferation	Panel data spanning 188 Swedish communities used to examine economic and attitudinal predictors of invasive crayfish occurrences	556 (observations)
Laitila and Palrud (2008)	Angler valuation(s) of dam removal	Visitor registers for two fishing sites used to obtain convenience samples of anglers for a mail-distributed choice experiment	1067
McOliver et al. (2008)	Risks of fishing-related *Cryptosporidium* exposure	Convenience samples of HIV/AIDS patients at outpatient clinic recruited and surveyed about participation in aquatic recreational activities	102 (preliminary), 153 (follow-up)
Knuth and Siemer (2007)	Aquatic stewardship education and promotion	Recommendations for advancing aquatic stewardship mined from a panel discussion by topic experts at the annual meeting of the American Fisheries Society	NA
Finley et al. (2003)	Design and implementation of a creel/angler survey	Expert panel convened to provide input on a proposed creel/angler survey for use in a human health risk assessment on the Passaic River	6

Table 1 (continued)

Author(s)	Topic(s)	Sampling Method(s)	Sample size (n)
Davis et al. (2000)	Research priorities for Australian freshwater fisheries	Purposive sampling (i.e., national survey of relevant organizations) and expert panels (i.e., topic experts, state representatives) used to identify key priorities	63 (organizations) 8 (first panel) 12 (second panel)

papers (n = 12) were added when we were notified of them (e.g., during peer review). Finally, we drew selectively from literature outside of fisheries and natural resources (e.g., health sciences, marketing) to identify key strengths and weaknesses of non-probabilistic methods, as well as opportunities for insightful research with these methods in the human dimensions of fisheries (see Boxes 1, 2, 3, 4). We searched for "(non-probabilistic OR non-probability OR non-probabilistic OR nonprobability) AND (survey* OR sampl* OR method*)" in the above-mentioned databases on July 28th, 2022. We selected papers which synthesized research and/or focused specifically on non-probabilistic surveys and sampling outside of fisheries. This included several key reviews (e.g., Cornesse et al. 2020), reports (e.g., Brick 2014), and other methods papers which capture this multidisciplinary literature, and contain guidance that we synthesize and apply to the human dimensions of fisheries (see Discussion). Though social surveys (i.e., studies where members of a population provide data via a survey instrument) are our primary focus, we also consider less-conventional forms of sampling (e.g., real-time and big data, digital 'mining') which provide a wider picture of what non-probabilistic methods can do in this context.

Existing research

Our review of the literature revealed that non-probabilistic survey and other methods are used for roughly four reasons in the human dimensions of fisheries: (1) understanding niche groups, (2) understanding niche phenomena, (3) understanding and/or applying novel technologies and/or citizen science, and (4) understanding general patterns in fishing. In their review of conceptual approaches and empirical evidence on probabilistic and non-probabilistic survey research, Cornesse et al. (2020) note that the rationale for many non-probabilistic surveys is not provided. Some surveys were likely missed in our review due to this lack of disclosure of survey methods and objectives, because papers that did not discuss non-probabilistic methods, or use associated terms like 'snowball' in their title, abstract, or keywords could not be captured. We revisit this issue in our Conclusion.

Niche groups

Recreational fishers

A total of 30 papers in our review involved recreational fishers. This is unsurprising, given the diversity and intensity of recreational fishing, as well as its primacy in many developed countries (Smith 1986; Arlinghaus et al. 2021). Angling (i.e., capturing fish with rod and reel) is a dominant method in recreational fishing, but other gear types (e.g., spear) are also used. Here, we use the terms 'angler' and 'angling' in reference to angling-specific cases and/or topics, and the terms 'fisher' and 'fishing' in reference to the full suite of fishers and gear types. Recreational fishing communities have many characteristics of hard-to-reach groups, meaning populations that are not easily surveyed due to their uncertain characteristics (i.e., lack of a sampling frame) and other barriers such as social stigma and language (Griffiths et al. 2010, 2013).

Non-probabilistic and quasi-probabilistic surveys of recreational fishers are relatively common (e.g., Papenfuss et al. 2015; Jiorle et al. 2016; Gundelund et al. 2020; Howarth et al. 2021; Jeanson et al. 2021; Johnston et al. 2021; Gundelund and Skov 2021; Fischer et al. 2021; Hook et al. 2022). Recreational fishers often differ by their specialization (Bryan 1977), which is a combined measure of avidity, skill, and centrality of fishing to one's life (Scott and Shafer 2001). Surveys in Cooke et al. (2012), Gallagher et al. (2015), Fujitani et al. (2016), Lerner et al. (2017), Shiffman et al. (2017), Gibson et al. (2019), Gundelund et al. (2021), and Johansen et al. (2022) targeted fishers engaging in such specialized activities as coastal sea trout fishing (Gundelund et al. 2021), pursuing such niche species as swordfish (Lerner et al. 2017), and participating in such unique initiatives as voluntary stocking (Fujitani et al. 2016). High specialization and relatively small population size make these groups very difficult to capture in large-scale, probabilistic surveys (Griffiths et al. 2013). Recreational fishers can also be spatially defined. For example, Laitila and Paulrud (2008), Dorow and Arlinghaus (2011), Voyer et al. (2014), Deely et al. (2019), Becker et al. (2020), and Dainys et al. (2022) surveyed recreational fishers about spatially confined issues (e.g., marine park establishment; Voyer et al. 2014), or surveyed fishing activity within defined areas (e.g., northern Germany; Dorow and Arlinghaus 2011). Other recreational fisher groups are defined by niche characteristics beyond specialization and/or location. For example, McOliver et al. (2008) sought HIV and AIDS patients in Baltimore, Maryland, given their vulnerability to *Cryptosporidium* exposure and related sickness (via fishing). Fennel and Birbeck (2019) surveyed a niche demographic in female fly anglers (fly fishing is a male-dominant pastime).

Some recreational fisher surveys are non-probabilistic by necessity (e.g., Howarth et al. 2021), while others serve very specific purposes (e.g., to assess the quality of citizen science data; Jiorle et al. 2016). Except where sampling frames are available to researchers, recreational fishers and their subgroups may be considered hard-to-reach. This alone is no justification for using scientifically unsound survey research in the human dimensions of fisheries. Instead, this highlights a need to determine what questions can be answered with data from various non-probabilistic samples.

Small-scale commercial and subsistence fishers

Like recreational fishers, small-scale commercial and subsistence fishers—particularly those in developing countries—often qualify as hard-to-reach groups. Non-probabilistic surveys of these fishers are common. Surveys by Pedroza (2013), Stratoudakis et al. (2015), Haryadi and Wahyudin (2018), Liao et al. (2019), Akbar et al. (2020), and Cascante et al. (2022) targeted spatially-defined groups (e.g., fish farmers in Colombia's southern Amazonian region; Cascante et al. 2022), often in relation to spatially confined issues (e.g., marine park spatial plan implementation; Stratoudakis et al. 2015). Other surveys focused on hard-to-reach groups for different reasons, such as human health risks of fish consumption and fishing (Bracho-Espinoza et al. 2013; Cavalcante et al. 2017). Surveys like these may also be non-probabilistic by necessity, due to the lack of a sampling frame for populations of interest.

Key informants

Just as some fishers can provide information on groups to which they belong, key informants (i.e., individuals possessing extensive knowledge on a topic) may provide valuable information on diverse and complex problems within their areas of expertise. Expert panels convened in Davis et al. (2000), Finley et al. (2003), Knuth and Siemer (2007), Lauber et al. (2016), and Paukert et al. (2017) provided insight on such complex problems and phenomena as climate change impacts on inland fisheries (Paukert et al. 2017), aquatic stewardship theory and practice (Knuth and Siemer 2007), and aquatic invasive species (AIS) in the Laurentian Great Lakes (Lauber et al. 2016). These studies offer guidance to researchers and practitioners in various forms (e.g., next steps, research questions, conservation priorities), and are distinctly forward-looking. These panels can be regarded as expert samples (i.e., purposive samples of key informants), which can be recruited and surveyed actively, and even opportunistically (e.g., at conferences). For example, Nguyen et al. (2017) surveyed fish telemetry researchers at conferences, then by phone and online, about data sharing in their professional networks. In Pedroza (2013), key informants (i.e., government officials) helped to design a survey of fishers. In all cases, key informants aggregate, organize, and convey information with great efficiency. Consequently, key informants are often a starting point when confronting complex problems that prove unconducive to structured and/or linear problem-solving (e.g., climate change impacts on inland fisheries; Paukert et al. 2017).

Niche phenomena

Documentation of niche phenomena

Investigations of niche groups may lead to investigations of niche phenomena (e.g., niche fisher groups may alter or create new instances of shark depredation; Box 4), or vice versa (e.g., range shifts in marine fish species may alter or create niche fisher groups; Sbragaglia et al. 2022). For example, surveys by McOliver et al. (2008) and Bracho-Espinoza et al. (2013) focused on unique parasite-host interactions in relation to fisheries, wherein niche groups were defined by niche phenomena. Androkovich et al. (2015) surveyed park visitors during a dominant year salmon run that provided an opportunity to estimate the net benefit of visits during such events. Gundelund et al. (2021) compared non-probabilistic citizen science data with probabilistic survey data and found them consistent under specific conditions (i.e., highly specialized fishery within a narrow spatiotemporal frame). Sbragaglia et al. (2022) mined data from YouTube videos to examine the social and ecological impacts of climate-induced range shifts in a marine fish species. Fennell and Birbeck (2019) used an online, chain-referral survey to document what was hypothesized as an emergent "habitus" among female fly anglers. Investigations of niche phenomena may simply document their occurrence in the real world, establishing new priorities in research, and even public health.

In-depth analyses

Many non-probabilistic surveys involving niche phenomena focus on the perspectives, attitudes, values, and other idiosyncrasies of fishers (e.g., Laitila and Paulrud 2008; Gren et al. 2009; Dorow et al. 2011; Cooke et al. 2012; Voyer et al. 2014; Gallagher et al. 2015; Haryadi and Wahyudin 2018; Liao et al. 2019). These affect management, exploitation of fish, and other activities. Fisher preferences are of particular interest (1) where certain behaviours have effects on fishery health (e.g., where anglers act as AIS vectors; Fischer et al. 2021), (2) in scenarios that involve trade-offs between conservation and socioeconomic benefits (e.g., marine protected areas; Stratoudakis et al. 2015), and (3) where preferences differ notably across fisher groups (e.g., rivalrous interactions between species-specific anglers; Curtis 2018). These studies often seek understanding of complex processes in human cognition and behaviour, which necessitate more in-depth study. Other complex processes that have been approached in this way include self-governance in small-scale fisheries (Pedroza 2013), environmental education in biodiversity conservation (Fujitani et al. 2016), physical injury and stress among artisanal fishers (Cavalcante et al. 2017), public policy impacts on fishery stakeholders (Akbar et al. 2020), novel technology adoption in aquaculture (Cascante et al. 2022), and large-scale freshwater fisheries governance (Howarth et al. 2023). What many non-probabilistic surveys lack in breadth may be offset by greater analytical depth, provided that research questions are conducive to this breadth versus depth trade-off. Questions about very complex processes, for example, may be better answered with detailed descriptions than precise numerical estimates.

Technologies and citizen science

Modern technologies

Modern technologies which are used to collect data (e.g., internet, smartphones) are somewhat synonymous with non-probabilistic methods because they are inexpensive, and can be implemented with relative speed and ease (Nayak et al. 2019). Convenience and self-administration are major, shared aspects of these methods and tools. As mentioned previously, modern technologies have also created new challenges (e.g., proliferation of spam) and opportunities (e.g., real-time data collection) for research. In fisheries, much of the discussion around non-probabilistic survey and other methods involves 'angler apps' (i.e., smartphone applications used by anglers, managers, and others to collect fisheries data). So far, researchers have used angler apps to study patterns in fishing along with the utility of apps as data sources. Examples of this include research on spatiotemporal patterns (Papenfuss et al. 2015; Fischer et al. 2021; Gundelund et al. 2021; Gundelund and Skov 2021; Johnston et al. 2021), catch data (Jiorle et al. 2016; Liu et al. 2017; Johnston et al. 2021), and sociodemographic characteristics of fishers (Gundelund et al. 2020, 2021; Gundelund and Skov 2021). Comparisons of app data to more conventional, probabilistic survey data reveal a mix of consistency and inconsistency for these two data types. Avidity bias, for example, is a very common result of voluntary reporting on apps (i.e., avid anglers are more likely to report). Other examples of technology-facilitated surveys include Howarth et al. (2021) and Fennell and Birbeck (2019), who deployed online surveys targeting recreational anglers in the province of Ontario and female fly anglers, respectively. Dainys et al. (2022) combined non-probabilistic data on sonar device use with data from an aerial drone survey to estimate angler effort for a reservoir in Lithuania, and Fricke et al. (2020) used similar data to identify AIS transmission risks associated with angler travel between waterbodies. Somewhat more unique, was the assessment and use of a long-range camera by Becker et al. (2020) to observe fishing effort at an offshore reef. Technology has created many new opportunities for data collection in the human dimensions of fisheries, but the role(s) of these data in fisheries management and science are still being decided.

Conducting and evaluating citizen science

Many of the above-mentioned studies focus on the utility of citizen science technologies (Jiorle et al. 2016; Gundelund et al. 2020, 2021; Gundelund and Skov 2021; Johnston et al. 2021). Validity is a primary concern when using data collected by unaffiliated and largely unknown individuals such as recreational anglers. The quality and characteristics of these data remain uncertain, though some studies suggest that citizen science data may be useful and reliable (e.g., Gibson et al. 2019; Taylor et al. 2022). The potential for fishers to contribute meaningfully in this capacity is undetermined, and the utility of non-probabilistic citizen science data will depend on how they are used, in addition to how they are collected.

Patterns in fishing

Preliminary inquiries and results

Many studies using non-probabilistic data in the human dimensions of fisheries are preliminary inquiries on relatively unknown or understudied phenomena (e.g., Anrokovich 2015). Examples of this include the socio-economic characteristics of niche fisheries (Lerner et al. 2017) and angler app data quality (Johnston et al. 2021). Often, preliminary inquiries focus on emergent phenomena that are significant, and expected to persist in the real world and/or as research priorities. One example of this is the COVID-19 pandemic and its effect(s) on all parts of society, including recreational fisheries (see Gundelund and Skov 2021; Howarth et al. 2021; Hook et al. 2022). Here, preliminary data on fishing effort and participation, catches and consumption, participant well-being, and sociodemographic characteristics of fishers were provided in advance of more intensive studies. Other emergent phenomena investigated preliminarily with non-probabilistic surveys include climate change and other future impacts on inland fisheries (Davis et al. 2000; Paukert et al. 2017), recreational angling for swordfish (Lerner et al. 2017), and AIS proliferation in the Laurentian Great Lakes (Lauber et al. 2016) and Sweden (Gren et al. 2009). Non-probabilistic data from these studies provided indications of important things to come—their implications for fisheries management, research, and use being highly uncertain.

General patterns

Concerns about non-probabilistic sampling arise primarily where research questions involve general phenomena (e.g., spatial dynamics, preferences, sociodemographics of large fisher populations). Yet, researchers have expressed interest in using angler apps to provide insight on certain fishing patterns. Papenfuss et al. (2015) and Johnston et al. (2021) used app data to study regional fishing patterns while making comparisons to conventional data, revealing consistencies that would support some specific uses of app data. Jiorle et al. (2016) compared catch data from the iAngler app to data from a large-scale, probabilistic survey, achieving a similar result. Kao et al. (2021) used data from watercraft inspection surveys to create a predictive model for AIS transmission in Minnesota, and Weir et al. (2022) used angler app data to map anthropogenic connectivity for waterbodies across the contiguous United States. Fischer et al. (2021) used app data to enhance a propagule transport model aiming to achieve more proactive management of AIS. These cases highlight the uncertain representativeness of non-probabilistic data, but also their utility when combined with and/or compared to more conventional, probabilistic data.

Gundelund and Skov (2021) used a platform like those mentioned above to provide preliminary data on changes in fishing activity and fisher sociodemographics in relation to COVID-19 pandemic lockdowns in 2020. Laitila and Palrud (2008) used non-probabilistic data to study angler site preferences and potential outcomes of dam removal. Similarly, Deely et al. (2019) used a purposive sample of anglers to compare objective and subjective data as predictors of site choice. In these examples, we also see non-probabilistic sample data being used to generate preliminary results, and compare and contrast methods for studying fishers.

In the absence of probabilistic data, researchers focusing on general patterns in fishing may favour 'quasi-probabilistic' samples (e.g., panels). These data are essentially non-probabilistic (i.e., are sampled non-randomly), but made to resemble probabilistic data using techniques such as demographic quotas. Studies by Gren et al. (2009), van der Hammen and Chen (2020), and Hook et al. (2022) used quasi-representative panels to study patterns in AIS proliferation (Gren et al. 2009), as well as fishing activity and demography in whole European countries (van der Hammen and Chen 2020; Hook et al. 2022). Panels differ notably from pure, non-probabilistic surveys (e.g., response rates can be determined in panel surveys), but they may be similarly biased toward avid individuals (Anderson 2012) or more panel-specific confounds such as professional respondents (Hillygus et al. 2014).

Discussion

Literature on non-probabilistic surveys and sampling in the human dimensions of fisheries and beyond reveals both limitations and opportunities associated with these methods—many of them identifiable in the above-mentioned studies. Here, we discuss both limitations and opportunities for non-probabilistic survey research in the human dimensions of fisheries (see Table 2), and provide guidance for those conducting such work.

Limitations

Non-probabilistic surveys and data have limitations related to representativeness, as well as the digital settings and modes which they tend towards. For example, research in a digital setting (e.g., on social media, smartphone applications) entails ethical concerns and risks beyond those seen in the 'real' world (Kosinski et al. 2015; Venturelli et al. 2017). These concerns and risks are not yet fully understood by institutions (e.g., ethical review boards; Monkman et al. 2018), and are beyond the scope of this paper. Here, we discuss more fundamental limitations of non-probabilistic surveys and data related to representativeness, and also the logistics of digital research.

Representativeness

The most fundamental limitation of results from non-probabilistic data is their uncertain, and, therefore, limited generalizability to the population of interest (Schillewaert et al. 1998; Brick 2014; Cornesse et al. 2020). Non-probabilistic sampling does not necessarily result in an unrepresentative sample, but non-probabilistic sampling methods lack certain safeguards against selection bias in larger populations

Table 2 Summarized strengths and weaknesses for probabilistic and non-probabilistic surveys

	Strengths	Weaknesses
Probabilistic	Statistical rigour—biases are minimized and can be estimated* Broad focus—robust data on large populations, general patterns	Costly and time consuming—not feasible in many research contexts
Non-probabilistic	Fast and frugal—feasible in many research contexts Acute focus—detailed information on complex processes, niche groups and phenomena	Biases—unknown, limited generalizability to populations
Quasi-probabilistic	Quasi-representativeness—samples can be curated using demographic quotas, weighting Known response rates	Quasi-representativeness—curation is arbitrary, does not guarantee representativeness Biases—source population and/or sample may have unique biases (e.g., professional respondents)

*Probabilistic data may lack statistical rigour in cases where measurement, nonresponse, and other execution errors are significant (see Introduction and Discussion)

(i.e., random sampling across relevant strata). However, some of the above-mentioned studies involve topics, and/or contain research questions and objectives that seem at odds with this fact. For questions requiring precise estimates or other population inferences, non-probabilistic survey data can only provide uncertain answers. Avidity, transiency, and volunteerism bias are common in non-probabilistic samples of fishers (Griffiths et al. 2013; Papenfuss et al. 2015; Jiorle et al. 2016). These selection biases can seriously affect conclusions based on non-probabilistic samples, such as estimates of total fishing effort for a population of recreational fishers. Quasi-probabilistic samples (e.g., panels) face similar, and also unique challenges such as misleading reports from so-called 'professional respondents' (Hillygus et al. 2014; Langer 2018). Online surveys, which tend to use non-probabilistic sampling (Revilla et al. 2015), are subject to additional biases (e.g., disparities in social media use; Stokes et al. 2019) and other complications (e.g., multiple responses, false reporting, algorithms; Kosinski et al. 2015; Topolovec-Vranic and Natarajan 2016). Estimates made with such data may be biased, and will also have unknown precision due to population size and other characteristics being unknown (Brick 2014). Tempting as non-probabilistic surveys may be, risks associated with unknown sampling, nonresponse, measurement, and other errors necessitate caution (Wardropper et al. 2021).

When no alternatives exist, one could argue that biased data are better than no data (e.g., in countries where large-scale, probabilistic surveys are not feasible). However, the opposite may be true if the risks of a misinformed decision are potentially severe (Brick et al. 2022). For example, convenience samples and activities with voluntary participation (e.g., angler consultation) may be biased toward a vocal minority whose interests do not represent most people, and/or align with ecologically sound courses of action (Hunt et al. 2010). Treating these data as representative could have negative social and ecological consequences. For certain activities and research questions, non-probabilistic data may not be powerful enough to justify their collection—researchers must know when *not* to conduct certain surveys, and how *not* to use certain data. Principally, researchers must avoid generalizing when their data are unfit for generalization (Langer 2018).

The representativeness of a non-probabilistic sample can be understood, and even enhanced by comparisons to benchmark data, as well as modifications of sampling and the data themselves. Research on this is far more common and advanced in fields such as health research and policy (Gallagher et al. 2015). Biases in non-probabilistic data can be identified by comparing them to probabilistic data (e.g., large-scale, probabilistic survey data). For example, Clegg et al. (2022) noted bias for some, but not all fish species after comparing non-probabilistic and probabilistic catch data in a commercial fishery. Typically, comparing non-probabilistic and probabilistic data reveals a mix of consistency and bias which is only clear in hindsight. However, inconsistencies may also result from measurement, nonresponse, and other errors in probabilistic data collection (see Introduction). Probabilistic surveys and data, therefore, must also withstand basic scrutiny (i.e., be properly executed, have minimal measurement and nonresponse errors) to serve effectively as benchmarks.

In some cases, measuring and accounting for bias in non-probabilistic data may be possible, and more effective than eliminating bias in sampling (e.g., contexts where probabilistic sampling is particularly costly and/or difficult to implement; Gundelund et al. 2023). This should be considered when assessing the fitness for use of non-probabilistic methods (see Opportunities and future research). Biases may also be reduced with techniques such as weighting, quota sampling, propensity score adjustment, and even machine learning (Elliot 2009; Szolnoki and Hoffman, 2013; Buelens et al. 2018; Ferri-García and Rueda 2018; Lamm and Lamm 2019). However, these methods are limited (Vehovar et al. 2016; Cornesse et al. 2020; Brick et al. 2022), and not advanced enough to render generalizable data from just any non-probabilistic sample. Combining and/or comparing methodologically dissimilar surveys can increase overall certainty and highlight biases in non-probabilistic data (Hartill and Edwards 2015; Midway et al. 2020), but representativeness will still be uncertain. For the foreseeable future, probabilistic data will be critical where accurate and precise population estimates, or other population-level inferences are needed.

As discussed in our Niche groups section, surveys using non-probabilistic methods such as chain-referral (also known as snowball) sampling are advantageous when investigating hard-to-reach groups (e.g., unlicensed recreational fishers). Yet, biased sampling within niche groups can result from group affiliation, refusal to participate, and 'seeding' (i.e., recruiting initial respondents prior to peer referral) too narrowly in a respondent-driven survey (Griffiths et al. 2010). Put simply, non-probabilistic samples may even be too narrow in groups that are already narrow and small. Coverage can be optimized with best practices (see Investigating niche groups), but the issue of uncertain representativeness will remain due to the lack of a sampling frame. This was the case for several studies mentioned in our Patterns in fishing section (e.g., Howarth et al. 2021), where non-probabilistic surveys with very wide coverage generated uncertain, and only preliminary answers to general questions. Uncertain representativeness is also limiting in research on niche phenomena, because non-probabilistic surveys may document the occurrence of a phenomenon, yet provide little or no indication of its frequency. For now, the best response to this type of limitation may be to ask different questions (e.g., questions not requiring population estimates).

Digital sprawl

Despite much interest, angler apps and other digital means of data collection are works in progress (Skov et al. 2021; Lennox et al. 2022). Barriers to using angler apps in fisheries management—beyond uncertain representativeness—include lack of standardization, data management incapacity, lack of validation, and potentially high developmental and administrative costs (Papenfuss et al. 2015; Venturelli et al. 2017; Bradley et al. 2019; Skov et al. 2021). Adding to the problem of digital sprawl is the challenge of surveying effectively across the full range of devices in a population (Wardropper et al. 2021). The utility of various platforms also depends on how widely and consistently they are used. If data are reported inconsistently, inaccurately, and by too narrow a segment of the population, they may provide very limited insight (Papenfuss et al. 2015; Venturelli et al. 2017; Johnston et al. 2021; Brick et al. 2022). As such, it is unlikely that these methods will provide statistically rigorous and/or census data on fishing in the near future (Brick et al. 2022).

For the above reasons, digital self-reports (e.g., angler apps, other platforms) represent a very large and promising, yet uncertain category of opportunities for research in the human dimensions of fisheries. There is evidence that these limitations can be overcome (Midway et al. 2020), and digital self-reporting has at least one major benefit in data collection and processing efficiency (Anderson 2012; Venturelli et al. 2017). Digital reporting may also facilitate research and management at finer spatiotemporal scales, provide windows into cryptic exploitation (e.g., fishing at private locations), strengthen relationships with fishers, and give revealed—as opposed to stated—preference and other data (Papenfuss et al. 2015; Venturelli et al. 2017; Midway et al. 2020; Skov et al. 2021). However, seizing these opportunities will require progress in key areas such as standardization, data management, and user retention (Venturelli et al. 2017).

Opportunities and future research

To maximize their utility, non-probabilistic social surveys should be applied to topics and research questions, and with objectives that reflect the strengths of non-probabilistic methods (e.g., depth of study, description, exploration, time-efficiency). In fisheries, this may take several forms. Brick (2014) advises that non-probabilistic sampling be considered where costs are lower, and where methods can be considered "fit for use." Fitness for use must be assessed case-by-case (Baker et al. 2013)—here, we offer guidance for those doing so (Fig. 1).

Investigating niche groups

Non-probabilistic surveys are advantageous, and even necessary to access some niche groups. For example, socially networked groups of specialized anglers can be accessed very effectively with respondent-driven sampling (Griffiths et al. 2010). Research in other disciplines has shown that social media can also dramatically increase access to niche groups (Baltar and Brunet 2012; Brickman Bhutta 2012; Topolovec-Vranic and Natarajan 2016; Stokes et al. 2019). In both management and research, niche groups may be of primary interest. Evolutions in recreational fishing have led to niche groups (e.g., highly specialized anglers) accounting for most of the effort for some species (Griffiths et al. 2010, 2013). Yet, these groups are often missed, or captured insufficiently by conventional surveys. Greater understanding of these groups is needed due to their differential impact(s) on fishery resources (Midway et al. 2020). These groups may also provide very valuable information to managers in certain decision-making contexts (Hunt et al. 2010; Mcclellan Press et al. 2016; Lennox et al. 2022). Coverage in niche groups can be maximized with best practices such as diverse 'seeding' and multi-wave recruitment (Kirchherr and Charles 2018), to where the resulting sample—narrow as it may be—captures a relatively narrow group. For research questions about said group, these data may be considered fit for use (Box 1).

Avid anglers are not the only notable subgroup in fisheries. Unlicensed anglers (e.g., poachers, anglers of a certain age or exceptional status, anglers pursuing certain species) are another subgroup that may only be reached with respondent-driven sampling due to their omission from sampling frames (Griffiths et al. 2010; Curtis 2018). In developing countries, small-scale subsistence and commercial fishers may be inaccessible due to the logistical impracticality of conducting large-scale, probabilistic surveys, or the absence of any sampling frame for these groups. Some niche groups may already exist in an online setting (e.g., Facebook groups; Baltar and Brunet 2012), or be assembled as part of one's study (Brickman Bhutta 2012). Non-probabilistic surveys aimed at deeply investigating these groups will be playing to their methodological strengths (e.g., identifying health risks associated with fishing activity; Bracho-Espinoza et al. 2013; Cavalcante et al. 2017). Recapture designs may even be used to estimate population size and proportion for undefined groups (see Griffiths et al. 2013). Often, license databases lack information (e.g., targeted species) needed to identify and understand niche groups (Griffiths et al. 2010), in which case knowledge gaps may be filled by well-planned, purposeful non-probabilistic surveys.

Investigating niche phenomena

Non-probabilistic data deemed insufficient for modeling may instead be fit for 'describing' (Groves 2005). Niche phenomena in the human dimensions of fisheries provide many opportunities for this kind of survey research. Complex processes, for example, may be best understood with more purposive, in-depth studies (e.g., small-scale fishery self-governance; Pedroza 2013). Purposive sampling and descriptive research are also suitable anywhere that gathered information are place-based and/or context-specific. Other non-probabilistic surveys may simply document noteworthy phenomena (Lehdonvirta et al. 2021), such as high retention rates for threatened species (Hammen et al. 2016), opportunities for parasite acquisition via fish consumption (Bracho-Espinoza et al. 2013), and AIS arrivals or "superhighways" (Lennox et al. 2022; Weir et al. 2022). Non-probabilistic data may even yield estimates of recreational value and demand for specific sites (Wallentin 2016). These are additional examples of non-probabilistic surveys playing to their methodological strengths (i.e., identification and description of issues not requiring generalization; Wardropper et al. 2021).

Non-probabilistic surveys around niche phenomena may lead to greater understanding of complex

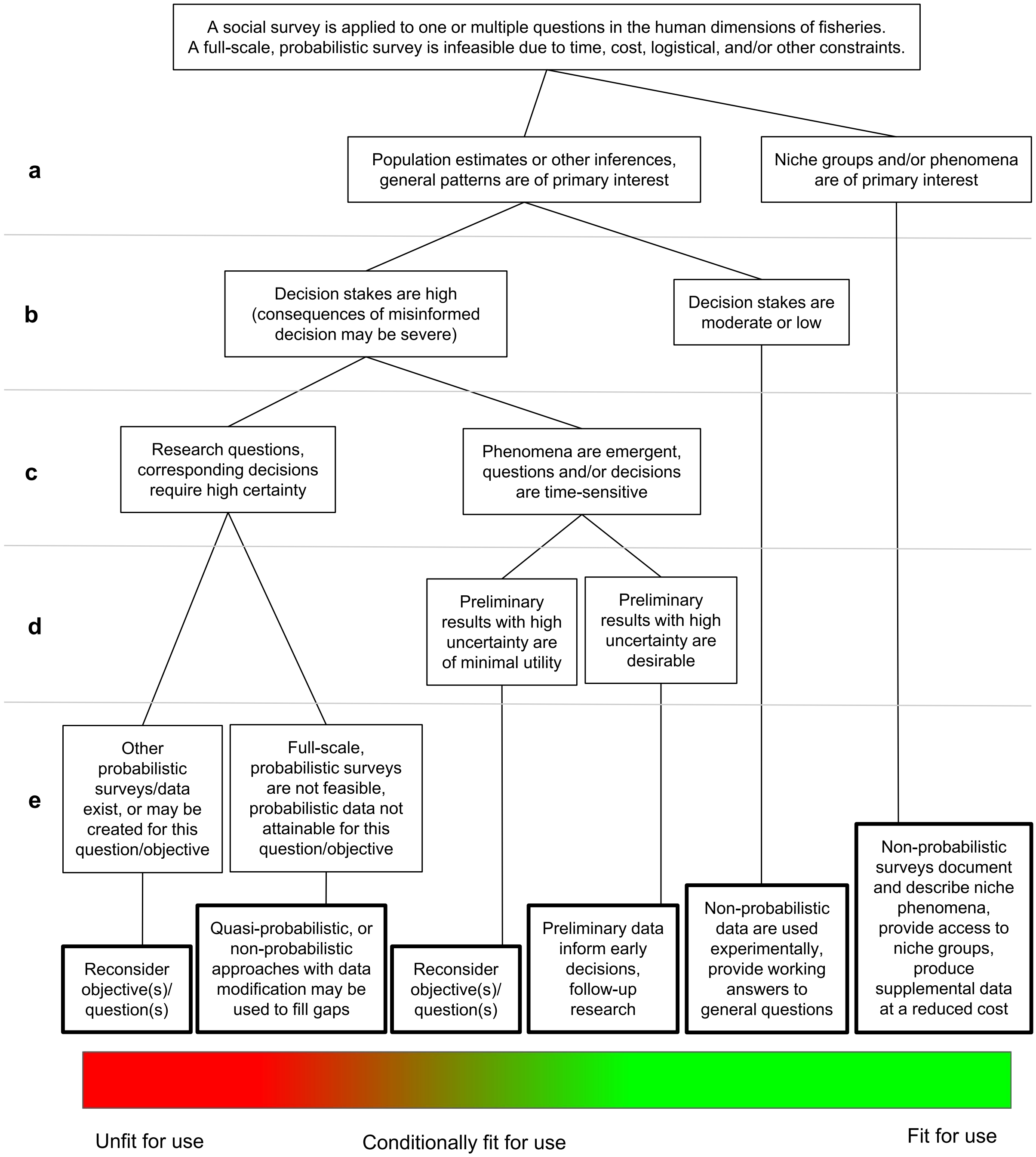
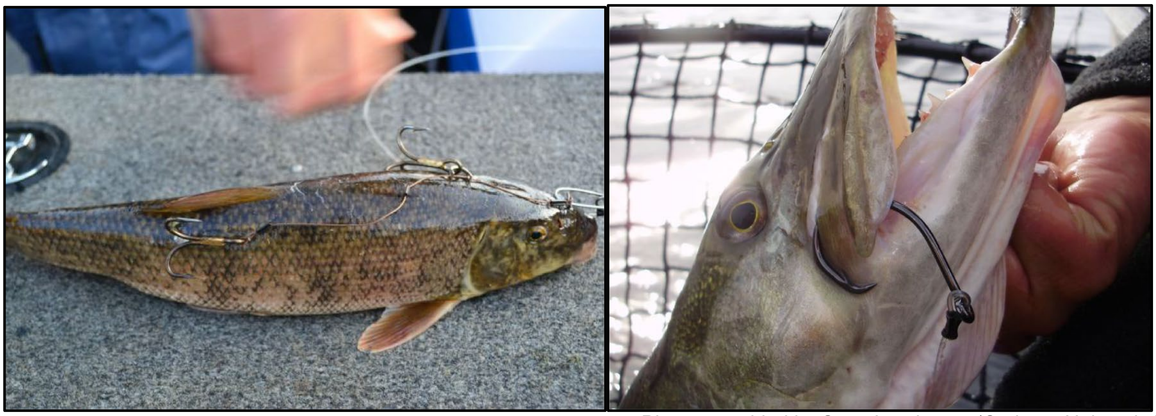


Fig. 1 Decision tree to assess the fitness of non-probabilistic methods for various social surveys in fisheries. We recommend that researchers consider—in this order—the scale of research objectives and questions (**a**), decision stakes (**b**), time constraints (**c**), the desirability of potentially biased data (**d**), and pre-existing surveys or data that may serve similar purposes (**e**). In short, non-probabilistic surveys are fit for use, and have advantages in fastness and frugality where biased data are acceptable and/or desirable (e.g., zooming in on niche groups, conducting time-sensitive research on emergent phenomena). Where accurate estimates and other inferences are required for larger populations, non-probabilistic methods are less fit for use (e.g., estimating recreational fishing impacts at a national level). Note that methodological decisions are subjective, context-dependent, and should be informed by—not based on—this visual

Box 1 Probing niche groups

Context. Niche subgroups have differential impacts on fisheries, but may be undefined and/or poorly understood (i.e., hard-to-reach). Avid, species-specific anglers using uncommon gear types and techniques (e.g., live bait fishing for muskellunge [*Esox masquinongy*])—though not captured in detail by large-scale, probabilistic surveys—may be of interest to fisheries managers (e.g., due to impacts on vulnerable species, potential transmission of AIS).



Photos provided by Sean Landsman (Carleton University)

Objective(s)/Question(s). Use purposive and respondent-driven sampling to access specialized angling subgroup(s). Survey anglers to determine (1) what species are used as bait, (2) if anglers can reliably identify baitfish species, (3) if live baitfish are transported, (4) if deep hooking occurs frequently, (5) what factors influence gear choice (e.g., hook type).

Next Steps. Documenting AIS threats in relation to this activity establishes new priorities in management and research. Suggestions of frequent, deep hooking may warrant follow-up research and/or gear restriction(s). Data on gear choice may inform campaigns aimed at circle hook adoption.

systems, or establish new priorities for researchers and managers. For example, these surveys may be used to describe detailed conflicts and/or document bycatch of keystone species in a multi-use fishery (Box 2). If the documented phenomenon is sufficiently concerning, it may then be prioritized in a full-scale survey, management discussion, or other follow-up study. Non-probabilistic methods may also be advantageous where data are affected by less common biases such as social desirability. Illegal and/or socially stigmatized activities (e.g., poaching) are another category of niche phenomena for which non-probabilistic methods (e.g., anonymous online surveys) may provide some opportunities (Lennox et al. 2022). An example of this is provided in Shiffman et al. (2017), where illegal fishing activity, defiant sentiments, and denial of negative impacts on conservation were distilled from an online discussion forum. Where non-probabilistic surveys are fit for use (e.g., where the objective is to describe a complex and/or niche phenomenon), they may also be preferred for their cost-effectiveness (Schillewaert et al. 1998).

Providing starting points

As we have already discussed, non-probabilistic data are fundamentally limited where research questions and objectives involve general (as opposed to niche) phenomena. This does not mean that all non-probabilistic surveys involving general phenomena are inappropriate, though failures to match research questions with research methods may lead to the creation of 'awkward surveys' (i.e., surveys with low inferential power). The lack of discussion around methods and objectives in non-probabilistic survey research may reflect a lack of methodological clarity in researchers who plan, design, and launch such surveys (e.g., non-probabilistic surveys aimed at population inferences).

Box 2 Zooming in on niche phenomena

Context. Some phenomena may be spatiotemporally confined and/or fishery-specific, yet significant to managers, conservationists, and fishers (e.g., due to a fishery's social, cultural, and economic importance). Fisher conflicts, for example, are major barriers to sustainability in multi-use fisheries. Conflicts are complex in and of themselves, and result from many complex, interacting group and individual thought processes.

Photos provided by Vivian Nguyen (Carleton University)

Objective(s)/Question(s). Use purposive, key informant sampling to document and describe in detail the perspectives and thought processes of key fisher groups (e.g., small-scale subsistence fishers), drivers of conflict, and niche occurrences such as at-risk species bycatch.

Next Steps. Management interventions are conceived and implemented with greater understanding of fisher groups (i.e., common interests, requisites for conflict resolution), and are less likely to exacerbate conflict or be met with non-compliance. Preliminary data on bycatch may establish this as a priority in management and research.

These 'awkward surveys' may also be motivated by cost and/or logistical constraints. Uprichard (2013) and Topolovec-Vranic and Natarajan (2016) note that non-probabilistic methods in some fields have gained momentum due to increasing research costs and competition for funding. For many purposes (e.g., informing a high-stakes decision), this rationale for the collection and use of biased data would be deemed insufficient. To avoid implementing awkward non-probabilistic surveys, researchers must consider and foresee what can *actually* be learned from the data they plan to collect—research questions, methods, and objectives should reflect this.

For general phenomena, non-probabilistic surveys may provide 'starting points' (e.g., preliminary data, hypotheses, research questions), as opposed to uncertain population estimates or other inferences. Just as qualitative data can inform the collection of quantitative data in a mixed-methods approach, non-probabilistic survey data may inform full-scale, probabilistic surveys conducted on much longer time scales. Similarly, in ecological fisheries research, exploratory environmental DNA surveys may detect species of interest which, again, prompt and/or inform full-scale, probabilistic surveys. Preliminary investigations of emergent phenomena are one example of how and where this might be accomplished in human dimensions research. Non-probabilistic surveys aimed at COVID-19 pandemic effects on fisheries (e.g., Gundelund and Skov 2021; Howarth et al. 2021; Hook

Box 3 Guiding active adaptive management experiments

Context. Some decisions need not, or cannot be based on 'gold standard' data (e.g., due to moderate or low decision stakes, time-sensitivity). For example, decisions about non-native fisheries may be based—at least preliminarily—on non-probabilistic data. Biased data may be acceptable, and even desirable in some cases (e.g., in fisheries maintained strictly for recreation).

Photos provided by Anthony McGrath (Victorian Fisheries Authority) and the lead author

Objective(s)/Question(s). Obtain preliminary data on angler stocking preferences (e.g., species, size, etc.) from a convenience sample of voluntary respondents.

Next Steps. Initial stocking strategies are determined by preference data from a sample of avid recreational anglers, and treated as deliberate management experiments. Stocking yields short-term benefits (e.g., recreation, sustenance), and data from subsequent probabilistic surveys (e.g., trips to stocked fisheries, self-reported satisfaction) provide experimental results.

et al. 2022) preliminarily identified trends in fishing activity worth researching more rigorously in subsequent months and years. Climate-induced range shifts in marine fish species are another kind of emergent phenomenon for which non-probabilistic methods have provided insight (Sbragaglia et al. 2022). Here, we see non-probabilistic surveys playing to methodological strengths in timeliness (Lehdonvirta et al. 2021) and hypothesis generation (Wardropper et al. 2021). While these surveys may not provide definitive answers to questions about general phenomena, they may instead determine what research questions are worth asking (e.g., in full-scale, probabilistic surveys). As mentioned in our Representativeness section, non-probabilistic data may also be preferable for some general queries where measuring and accounting for bias is more effective and less costly than avoiding it.

Quasi-representative panels are another potential starting point for research on general phenomena in the human dimensions of fisheries, particularly where probabilistic data are unavailable (e.g., in developing countries). Panels may be a reasonable alternative to full-scale surveys, and be sufficiently representative for some general purposes (Stern et al. 2014; Revilla et al. 2015). Arlinghaus et al. (2021) identified major gaps in worldwide recreational fishing data, and proposed panel research as a partial solution—an example of this is provided in van der Hammen et al. (2016). Quasi-probabilistic data may also be obtained with surveys that combine elements of probabilistic and non-probabilistic sampling (e.g., purposive sampling at randomly selected sites; Vehovar et al. 2016).

Box 4 Capturing and quantifying niche fisheries

Context. Large-scale, probabilistic surveys capture key aspects of fishing activity (e.g., catch rates, total participation), but miss others (e.g., specialized fishing, acute impacts). This may be problematic if the vast majority of effort for a species is attributable to uncaptured groups and/or activity.

Photos provided by Jessica Robichaud (Carleton University) and Dr. Ben Binder (Florida International University)

Objective(s)/Question(s). Intercept anglers at key sites (e.g., offshore reefs, boat ramps) and use RDS-recapture (see Griffiths et al., 2010) to estimate population size and total catch for a niche fishery. Anglers may also be surveyed about such acute impacts as shark depredation.

Next Steps. Supplementary data boost existing models, and regulatory decisions informed by more comprehensive and accurate estimates of fishing impacts. Preliminary data on depredation may prompt follow-up research.

Where they are attainable and fit for use, quasi-probabilistic data are both valid and useful.

As we have already discussed, non-probabilistic sampling should be limited to cases where it is deemed fit for use. At times, researchers may have to decide between modeling with biased data and not modeling at all—proceeding only if the corresponding limitations are acknowledged and deemed acceptable (Baker et al. 2013). In short, what some 'pure' statisticians may regard as invalid, other 'practical' statisticians may regard as "close enough for all practical purposes" (Vehovar et al. 2016). How common these scenarios are in fisheries is not clear, but cases where decision stakes are moderate or low provide opportunities to model, and/or investigate general phenomena with non-probabilistic data. Examples of this are provided in Barbini et al. (2015), where "opportunistic records" mined from a recreational fishing magazine served as proxy data for several shark species with no long-term population data, and in Giovos et al. (2018), where video records mined from social media helped to characterize data-poor Mediterranean Sea recreational fisheries. In fisheries management, non-probabilistic data could be used to make moderate- or low-stakes decisions, the outcomes of which could then be treated as results of adaptive management experiments (Walters and Hilborn 1978). When decision stakes are relatively low, non-probabilistic data may provide a working answer to some general questions (Box 3).

For some general questions, non-probabilistic methods may be highly fit for use. One example of this is expert sampling (i.e., purposive sampling of key informants; see Key informants), which may be used to create headway on the most urgent and complex fisheries issues (e.g., climate change impacts on inland fisheries, persistent challenges in freshwater fisheries management; Paukert et al. 2017; Howarth et al. 2023). Experts on a particular topic are a kind of niche group, and arguably the richest source of research priorities, questions, hypotheses, and other high-quality starting points. Here, non-probabilistic methods (e.g., expert sampling) have several advantages, such as the ability to make informed decisions despite significant, unmeasurable uncertainty (McCarthy 2014). Non-probabilistic data may also provide sound answers to some fundamental questions about fishery use. For example, van der Hammen et al. (2016) showed how an avidity profile might be established for populations of recreational fishers using quasi-probabilistic data. Griffiths et al. (2010) describe a combined respondent-driven sampling and recapture method (RDS-recapture) that may be used to estimate total catch for specialized recreational fisheries. These are just two more examples of how non-probabilistic data may be applied to general phenomena in valid and productive ways. What all of these opportunities have in common is their properly matched research questions and methods (i.e., playing to the methodological strengths of non-probabilistic sampling). This consideration is most important when the objective of a non-probabilistic survey is to learn about general phenomena.

Providing supplements

Where non-probabilistic methods are not sufficient on their own (e.g., for large population inferences), they may still provide useful supplementary information. For now, supplementary uses of non-probabilistic data alongside probabilistic data are more promising than basic substitutions of the former for the latter (Liu et al. 2017; Skov et al. 2021; Brick et al. 2022). For example, non-probabilistic data may be used to 'boost' models already fitted to probabilistic data (Fischer et al. 2021), or to increase estimate precision by combining non-probabilistic and probabilistic catch data via record linkage (Williams et al. 2022). Where conventional data are limited in space and time (e.g., creel data), non-probabilistic data (e.g., data from angler apps, respondent-driven surveys) may be used to fill various gaps. Information gaps that could be filled using non-probabilistic surveys include (1) population size and catch for specialized subgroups (Griffiths et al. 2010), (2) real-time shifts in fishing effort (Papenfuss et al. 2015), and (3) preliminary data on very specific fisheries (Skov et al. 2021). Clever combinations of probabilistic and non-probabilistic data may also prove more efficient than conventional methods of, for example, estimating angler effort (Liu et al. 2017; Dainys et al. 2022). Other times, non-probabilistic methods may simply be used to pose, and provide preliminary answers to questions that would otherwise not be asked (Lamm and Lamm 2019). Our review of the literature suggests that non-probabilistic sampling can answer many 'small' questions within, or peripheral to 'big' questions in the human dimensions of fisheries. For example, where large-scale, probabilistic surveys exist to answer so-called big questions (e.g., What is the population size for offshore permit anglers?), non-probabilistic surveys may be applied to so-called small questions which might inform, or follow up on certain aspects of the former survey type (e.g., Does shark depredation of hooked permit occur frequently?; Box 4). Providing supplementary information is yet another way that researchers may use non-probabilistic surveys in accordance with their methodological strengths.

Conclusion

Non-probabilistic and probabilistic methods have differing strengths and weaknesses—some of them practical (e.g., administrative costs) and others related to inference (e.g., sample representativeness; Table 2). Non-probabilistic surveys are most effective when research questions and objectives reflect their methodological strengths, which include depth of study (e.g., investigating niche groups, describing and/or documenting niche phenomena), low-cost preliminary investigation (e.g., providing starting points for research on and/or management of general phenomena), and supplementation (e.g., boosting models, answering peripheral questions; see Fig. 1). Many of the non-probabilistic studies that we reviewed (see Table 1) played to one or more of these strengths. Methodological innovations (e.g., RDS-recapture; Griffiths et al. 2010) have, and will continue to create opportunities for non-probabilistic survey research on more general phenomena, but probabilistic surveys will remain important where accurate population estimates and/or inferences are required. In short, non-probabilistic data are still limited in certain research contexts by their uncertain generalizability.

In the human dimensions of fisheries, opportunities to research niche groups are virtually endless. Recreational fisheries, for example, contain many avid, specialized, and impactful subgroups (Griffiths et al. 2010, 2013). Unlicensed recreational anglers and small-scale subsistence and/or commercial fishers may also be reached, and better understood with non-probabilistic surveys. The human dimensions of fisheries also contain many noteworthy, niche phenomena. Complex processes in governance, consumption of at-risk species, fishing-related health risks, and illegal or socially stigmatized activities are several examples of niche phenomena that may be worth documenting and describing in detail. For general phenomena, non-probabilistic surveys may provide starting points in the form of preliminary data, hypotheses, and research questions to help inform next steps in research and management (e.g., in relation to emergent or understudied phenomena). Similarly, expert sampling may create headway on highly complex fisheries issues. Non-probabilistic and quasi-probabilistic methods (e.g., panels) may also be fit for general use where decision stakes are moderate or low (e.g., in adaptive management experiments). Finally, non-probabilistic data may prove useful in supplementary roles, such as boosting models based on probabilistic data, and preliminarily answering questions not included in large-scale, probabilistic surveys.

Research with non-probabilistic methods should have a clear rationale that is reflected in research questions and objectives, and articulated in all presentations of the work (Cornesse et al. 2020). For example, where non-probabilistic sampling is used to ‘zoom in’ on a niche group, researchers should clearly state the underlying reasons (i.e., logistical constraints, methodological advantages) for their approach. As mentioned in our Existing research section, our review likely missed some papers that did not mention non-probabilistic methods or use associated terms up front, despite fitting the relevance criteria and the broad categories of opportunity in our Opportunities and future research section. Greater disclosure of these methods may highlight even greater possibilities for this kind of research.

In summary, there is no shortage of opportunity, in the human dimensions of fisheries, to use non-probabilistic methods in ways that invoke their strengths, and avoid conducting surveys that highlight their weaknesses. The same may be said for analogous science and management contexts involving wildlife and other natural resources. Compromises are virtually inevitable in survey research (Baker et al. 2013), and the fitness of non-probabilistic data and methods must be assessed case-by-case (see Fig. 1). Data are powerful, and researchers have a responsibility to collect, analyze, and present data in ways that inform, rather than mislead end-users (Langer 2018). Our review provides guidance for researchers looking to conduct valid and insightful research with non-probabilistic methods in the human dimensions of fisheries.

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Declarations

Conflict of interest The authors declare that there are no competing interests

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