ICES Journal of Marine Science, 2025, Vol. 82, Issue 3, fsaf022
https://doi.org/10.1093/icesjms/fsaf022
Received: 15 November 2024; **revised:** 10 February 2025; **accepted:** 11 February 2025
Food for Thought

ICES CIEM
International Council for the Exploration of the Sea
Conseil International pour l'Exploration de la Mer

Effect size as a measure of biological relevance for offshore wind impact studies

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Abstract

There is an urgent need to translate the outcomes of offshore-wind-fisheries research and monitoring into information that is useful to decision-makers. Papers published in peer-reviewed journals typically report whether or not results are significant based on a statistical test and an associated *P*-value which is compared to a threshold (e.g. $P < 0.05$). However, statistical significance cannot tell us whether or not the observed results hold any biological relevance. The lack of a clear connection to biological relevance makes it difficult for decision-makers to interpret research findings and understand how a given study fits into the larger picture of offshore wind interactions with the ecosystem. Toward addressing this challenge, this paper makes the following recommendations to translate the outcomes of research and monitoring studies into information that is useful to scientists, fisheries managers, and other stakeholders: (i) report effect size(s) and associated confidence intervals associated with outcomes for research and monitoring studies alongside the results of conventional statistical tests of significance; (ii) consider the biological relevance of research and monitoring outcomes using scientific reasoning to assess the magnitude and direction of the effect size, the width of the confidence intervals, and the factors that may have affected them; (iii) advance cumulative science by reporting the components used to calculate effect sizes, namely the mean, standard deviation, and sample sizes for individual studies; (iv) publish raw data to new or existing open access data repositories following the FAIR guiding principles of data stewardship and management, i.e. data should be Findable, Accessible, Interoperable, and Reusable; and (v) conduct periodic meta-analyses of existing research to evaluate the mean, magnitude, and direction of the effect size to evaluate the overall mean effect of offshore wind development across studies.

Keywords: renewable energy; statistics; uncertainty; cumulative science; meta-analysis; open science

Introduction

The science of fish and fisheries interactions with offshore wind is advancing quickly as offshore wind developments (OWDs) continue to be constructed in marine ecosystems around the world (Galpasoro et al. 2022, Hogan et al. 2023, Gill et al. 2024). An international scientific community is emerging to address questions of fisheries resource interactions with OWDs as evidenced by the existence of multiple ICES (International Council for the Exploration of the Sea) working groups addressing offshore wind issues and the release of the ICES Roadmap for Offshore Renewable Energy (ICES 2024). Multi-modal approaches, including field, laboratory, and modeling methodologies are being applied as researchers grapple with a wide range of questions, including how habitat change, energy emissions, and altered physical oceanography affect biomass, abundance, and distribution; whether these changes translate to population level effects; and what these changes mean for fisheries socio-economics (Galpasoro et al. 2022, Hogan et al. 2023, Gill et al. 2024). The recent advancement of research efforts has yielded an accelerated rate of peer-reviewed research on these topics which will provide the basis of much needed scientific advice for regulators and fisheries managers (Fig. 1).

The need for actionable science to support fisheries management decisions with regard to OWD cannot be overstated. Although research efforts are advancing, they still lag behind the pace of OWD due to the immediacy of society's critical need for renewable energy, and the reality that economics and infrastructure development occur on a much more rapid timetable than empirical science. Therefore, there is an immediate need to translate the outcomes of research and monitoring into information that is useful to decision-makers (Wilding et al. 2017).

The majority of published papers report results that are significant based on the statistical tests used, and often results are characterized as having a positive, adverse, or neutral effect on the indicator(s) measured (e.g. Gill et al. 2024). Many compelling effects of OWD on fisheries species have been described (Galpasoro et al. 2022, Gill et al. 2024). These include, e.g. the effects of electromagnetic fields and low frequency noise on the movement and behavior of cod larvae (*Gadus morhua*) and haddock larvae (*Melanogrammus aeglefinus*) (Cresci et al. 2022, 2023); the effect of enhanced food availability for European plaice (*Pleuronectes platessa*) due to the colonization of epibenthos on structures and scour protection (Buyse et al. 2023); the effect of wind farm presence on black sea bass abundance (*Centropristis striata*) (Wilber et al. 2022); and the temporary effect of fishing cessation during construction on the size and abundance of European lobster (*Homarus gammarus*) (Roach et al. 2018, 2022).

As the outcomes of empirical research are published in peer-reviewed literature, the scientific community is beginning to piece together the complex puzzle of interactions between OWD and the structure and function of marine ecosystems.

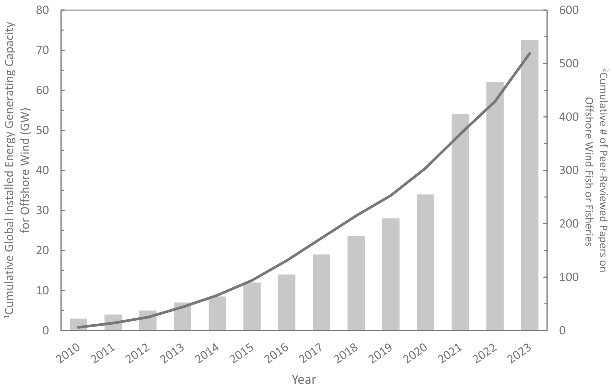

Figure 1. Temporal trend from 2010 to 2023 in the cumulative global installed energy capacity for offshore wind (bars) and in the cumulative number of peer-reviewed papers on the broad topic of offshore wind and fish or fisheries (line). Sources: [1]Statista (2024); [2]Web of Science search by year for papers containing the terms and "offshore wind" and "fish" or "fisheries."

While the puzzle pieces continue to emerge, the question of how to evaluate biological relevance is coming to the fore. The purpose of this paper is to provide researchers with resources, concepts, and best practices to evaluate the biological relevance of their findings, and facilitate the advancement of the cumulative science of offshore wind and fisheries. Although this paper focuses on offshore wind research outcomes for fisheries species, the concepts presented could be extended and applied to other marine species and other anthropogenic activities.

The issue: statistical significance is not equivalent to biological relevance

Research that gets published in peer-reviewed journals often presents results that use a threshold test such as $P < 0.05$ for statistical significance. Results with a *P*-value below this threshold tend to get published while those above the threshold often get placed in the "file drawer" of research (*sensu* Rosenthal 1979). Statisticians have long noted many caveats with the $P < 0.05$ approach, namely that that *P*-values are often misused, misunderstood, and misinterpreted (Wasserstein and Lazar 2016); that with a sufficient level of replication, a statistical test will almost always find a significant difference (Sullivan and Feinn 2012); and that *P*-values cannot tell us about the strength of an effect or its biological relevance. This approach to data analysis and interpretation persists, despite early calls to move away from this approach in the sciences at large (Wilkinson et al. 1999) and in the ecological sciences specifically (Martinez-Abrain 2008, Halsey 2019). The American Statistical Association (ASA) felt so strongly about this issue that in 2016, it was compelled to publish a list of principles underlying the proper use and interpretation of the *P*-value (Table 1; Wasserstein and Lazar 2016) which was later supported by a note published by Amrhein et al. (2019) that had more than 800 signatories from across the sciences. The official ASA statement spurred the publication of numerous papers making a variety of recommendations on this topic. Some suggested reducing the standard *P*-value to 0.005 (Benjamin et al. 2018 cited in McShane et al. 2019). Others recommended halting the practice of dichotomizing results into those that are significant vs. those that are not (McShane et al. 2019). The statement published by the ASA, however, was

Table 1. American Statistical Association principles underlying the proper use and interpretation of the *P*-value (as stated in Wasserstein and Lazar 2016).

Principle 1: "*P*-values can indicate how incompatible the data are with a specified statistical model."
Principle 2: "*P*-values do not measure the probability that the studied hypothesis is true, or the probability that the data were produced by random chance alone."
Principle 3: "Scientific conclusions and business or policy decisions should not be based only on whether a *P*-value passes a specific threshold."
Principle 4: "Proper inference requires full reporting and transparency."
Principle 5: "A *P*-value, or statistical significance, does not measure the size of an effect or the importance of a result."
Principle 6: "By itself, a *P*-value does not provide a good measure of evidence regarding a model or hypothesis."

not intended to eliminate the *P*-value approach; rather it was focused on informing scientists on the proper use and interpretation of *P*-values. Still, many of us, myself included, continue this practice because this is the method for analysis and interpretation we learned in graduate school, and because "significant" results are what get published in peer-reviewed journals. Given the context of the rapidly advancing field of offshore wind and fisheries science and the urgent need for actionable research to underpin scientific advice, how then can biological relevance be evaluated? This is a vexing question and one that is faced across the sciences.

A potential solution: effect sizes with confidence intervals and scientific reasoning

Effect Size—Current best practices call for reporting more informative quantities such as the effect size and confidence intervals around the effect size, while continuing to report, although de-emphasizing, *P*-values (Popovic et al. 2024). An effect size is a quantitative measure of the difference between two groups (when comparing discrete groups such as a treatment and a control) or the association between two groups (when comparing the relationship between two continuous variables). Some common examples are provided in Table 2. One statistical authority in the USA, the American Psychological Association (APA), has been recommending the routine reporting of effect size since 1994 (Wilkinson et al. 1999). The benefits of reporting effect sizes are multiple. First, effect sizes are straightforward to calculate. There are many textbooks, online resources, and existing statistical packages available to calculate them (e.g. Borenstein et al. 2009, Viehtbauer et al. 2010, Wallace et al. 2016). Second, effect sizes are straightforward to understand (Table 2; Fig. 2). For example, a Cohen's *d* of 0.8 indicates that the average sample from the impact site was 0.8 standard deviations greater than an average sample from the control site (Table 2; Fig. 2; Cohen 1988). Third, effect size can be calculated for any response variable. Fourth, effect sizes put studies examining similar questions using different designs or methods on equal footing for comparison. Fifth, understanding effect sizes can inform power analysis and the design of future research and monitoring.

Precision and confidence intervals—Precision of the effect size can be estimated with either the variance (S^2) or the standard error (SE) of the effect size. The equations for variance and SE are unique for each effect size metric (Borenstein et al. 2009). Larger confidence intervals around an estimated effect

Table 2. Examples of common measures of effect size and their attributes.

Measure of effect size	Equation for effect size	Variable definitions	Effect size definition	Benchmarks of relative magnitude
Measures for comparison of groups				
Cohen's d	$d = \frac{(\bar{X}_{impact} - \bar{X}_{control})}{s}$	$\bar{X}_{impact}$= Mean at the impact site; $\bar{X}_{control}$ = Mean at the control site; s = standard deviation	Standardized mean difference between the impact group and the control group (Cohen 1988)	Small 0.2 Medium 0.5 Large 0.8 Very large 1.3
Hedges' g	$g = d * 1 - (\frac{3}{4df - 1})$	d = Cohen's d; df = degrees of freedom used to estimate the standard deviation	Standardized mean difference between the impact group and the control group; Corrects for bias due to small sample sizes (Hedges and Olkin 1985)	Small 0.2 Medium 0.5 Large 0.8 Very large 1.3
Log response ratio (L_{RR})	$RR = \frac{\bar{X}_{impact}}{\bar{X}_{control}}$ $L_{RR} = ln(\bar{X}_{impact}) - ln(\bar{X}_{control})$	RR = response ratio; $\bar{X}_{impact}$= mean at the impact site; $\bar{X}_{control}$ = mean at the control site	The natural log of the ratio of the response in the impact location to the response in the control location (Hedges et al. 1999, Sullivan and Feinn 2012)	Small 0.7 Medium 1.1 Large 1.4
Measures of association				
Pearson's correlation (r)	$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$	x_i= value of the ith x-variable; y_i = value of the ith y-variable; $\bar{\bar{x}}$ = mean of the x-variables; $\bar{y}$ = mean of the y-variables; r ranges from −1 to 1	Measure of the strength and direction of the relationship between two sets of continuous data (Nakagawa and Cuthill 2007, Borenstein et al. 2009)	Small: ± 0.2 Medium: ± 0.5 Large: ± 0.8
Coefficient of determination (r^2)	$r^2 = \frac{SS_{Residuals}}{SS_{Total}}$	$SS_{Residuals}$= sums of squares of the residuals; SS_{Total}= total sums of squares; r^2 ranges from 0 to 1	Proportion of variance in one variable explained by another variable (Nakagawa and Cuthill 2007, Sullivan and Feinn 2012)	Small: 0.04 Medium: 0.25 Large: 0.64
eta squared (η^2)	$\eta^2 = \frac{SS_{Effect}}{SS_{Total}}$	SS_{Effect}= sums of squares of the effect; SS_{Total}= total sums of squares; η^2 ranges from 0 to 1	Proportion of variance in a dependent variable explained by group membership of the independent variable (Lakens et al. 2013)	Small: 0.01 Medium: 0.06 Large: 0.14

Adapted from Table 1 in Sullivan and Feinn (2012), Table 1 in Lakens et al. (2013); draws on information from Ferguson (2009).

size indicate lower precision and greater uncertainty in the estimate, i.e. that there is less confidence in the estimated effect size. Many factors may affect the precision of the estimated effect size (ES), and many of these are described in Table 3. Among these is the number of samples. Notably, several effect sizes offer corrections for small sample size bias such as Hedges g, an alternative to Cohen's d which corrects for bias in studies in which sample size is <20; and omega squared, a less biased alternative to eta squared (Table 2; Lakens et al. 2013). These factors should be considered when evaluating the precision of a given estimate, and in attempting to reduce uncertainty in future studies.

Interpreting effect size with scientific reasoning—Small, medium, and large effect size ranges have been defined for some specific measures of effect size (Table 2) but these categories have been described as arbitrary even by those who developed them (e.g. Cohen 1988). Figure 2 shows the difference in the distribution between a hypothetical control (mean = 14, standard deviation = 3) and impact site for a normally distributed response variable under scenarios in which Cohen's d is considered to be small, medium, and large. From a biological perspective, although these are useful benchmarks, they still require scientific reasoning to interpret (Bakker et al. 2019). An effect size defined as "small" may have important biological consequences for some response variables. For example, a "small" change in primary production could have important consequences for the overall productivity of an ecosystem (Friedland et al. 2012); likewise, a "small" increase in water temperature could make a habitat inhospitable for some species but more welcoming to others (Mills et al. 2024). On the other hand, there may be instances where we may interpret that an effect size is biologically relevant only when it is medium or large, such as an increase in abundance of an already abundant species. These considerations may extend beyond the biological context to the effects on human dimensions. While a 10% change in fish abundance may seem like a relatively small change for some species, such a change may have strong downstream effects for the fishing community and socio-economic indicators (Livermore et al. 2023, Willis-Norton et al. 2024).

Determining the biological relevance (i.e. practical significance) of an effect size requires scientific reasoning rooted in a deep understanding of existing scientific evidence. There is no boiler plate, one-size-fits all approach for defining the

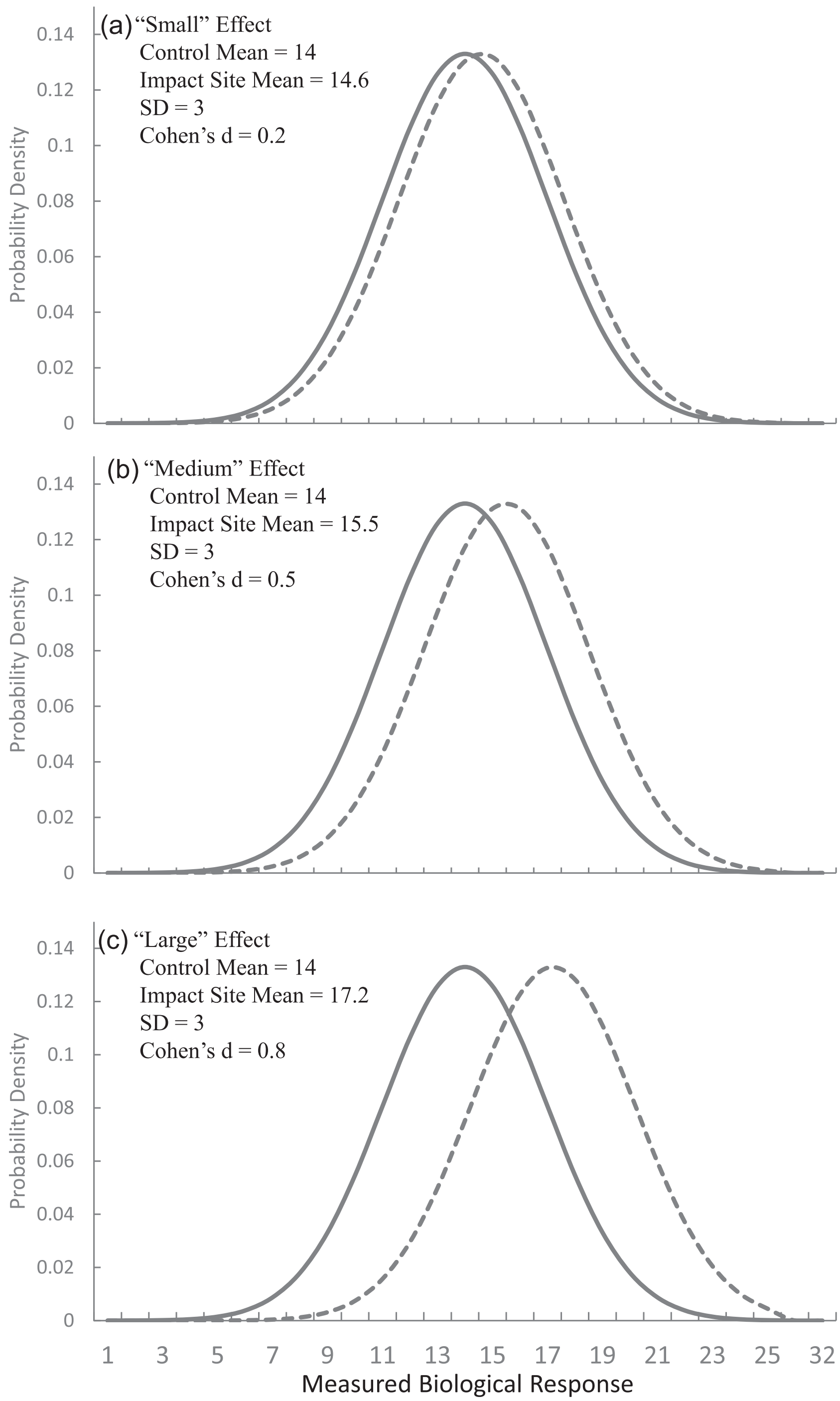

Figure 2. Distributions under the scenarios in which Cohen's *d* shows (a) "small" effect; (b) "medium" effect; and (c) "large" effect, given the effect size benchmarks in Cohen (1988). Solid line = control site; Dotted line = impact site. The biological relevance of an effect size of a given magnitude can be evaluated with scientific reasoning.

biological relevance of an effect size for an individual study. However, there are logical questions that can be asked of individual studies that can facilitate a scientific reasoning process to draw such inferences. Table 3 describes several factors and questions that influence effect size and its precision which should be considered when evaluating the biological relevance for the outcome of offshore wind research and monitoring studies. Applying scientific reasoning provides context for comparing an effect size from an individual study to other effect sizes reported in the literature for similar studies (Lakens 2013, Bakker et al. 2019). The research community is working to identify meaningful indicators for ecosystem responses to OWD including those associated with individual size, condition, trophic dynamics, aggregate biomass, sensitive species, ecosystem function, migration, distribution, and socio-economics (Raoux et al. 2019, Baulaz et al. 2023, Friedland et al. 2023, Methratta 2024, NEFSC 2024, Secor et al. 2024, Willis-Norton et al. 2024). The concepts of scientific

Table 3. Considerations for interpreting effect size and applying scientific reasoning to infer biological relevance of an ES for a given study (adapted from Bakker et al. 2019).

1. Research or monitoring question—What question does the study address? What are the spatial and temporal scales relevant to the question?
2. Magnitude and direction of effect size—How big is the effect size (ES)? Does the ES evaluate differences between groups or measures of association? Is the metric appropriate for the study design?
3. Width of the confidence intervals around the effect size.—What is the level of precision for the ES, i.e. how much confidence do we have in the effect size? Larger confidence intervals around an estimated effect size indicate lower precision and greater uncertainty in the estimate.
4. Biological response(s) measured to address the question—What aspect of biology is the effect size assessing: abundance, density, size, condition, egg production, etc.
5. Consequences of change in the biological response(s) measured—Would the magnitude of effect measured in the study have a commensurate, disproportionate, or neutral effect on an individual, the population, the ecosystem? How would these changes affect fisheries, fishing communities, and other ecosystem uses/functions?
6. Study design.—What study design was used? For example, is it a Before-After-Control-Impact (BACI), Before-After-Gradient (BAG) design, or a Before-After (BA) design? Was it a field or laboratory study? Is the effect size metric used appropriate for the study design?
7. What is the effect size comparing?—ES is a relational measure, which means by definition it is used for comparisons. Does the ES compare before vs. after, control vs. treatment, BACI contrasts, different treatment levels, or some other comparisons in an experimental design?
8. Sample size—What is the level of replication? Increased precision is expected in a study with larger sample sizes.
9. Potential covariates—What other un-controlled variables might have contributed to the magnitude and direction of the ES and associated estimates of precision, and how might these differ among similar studies? Covariates may include the number/size/placements of turbines, distance from shore, season/time of year, time since intervention began, habitat types, depth, water temperature, focal species, gear type, differences in gear deployment (e.g. soak time), etc.
10. Status of the population being studied—What is the status of the species/stock/population? Is the population experiencing an increasing, decreasing, or neutral trend and what are the causes (if known) of the trend? Is the species endangered? Is there active fishing in the area for the focal species? What other stressors is the population currently exposed to or vulnerable to? Baseline data collection and analysis can inform many of these questions.

reasoning in Table 3 provide a path toward understanding when changes in these indices are biologically meaningful.

This raises the question of what should be done when a change is found to be biologically relevant, i.e. *to what end are we monitoring*? Reference points, thresholds, and decision criteria are needed to engender purpose for offshore wind research and monitoring programs, and to connect outcomes to the decision-making process (Link 2005, Wilding et al. 2017, Methratta et al. 2023, Cresci et al. 2024). Such decision criteria would be invaluable in informing when an impact mitigation action should be triggered, where to site future wind farms, and in the evaluation of cross-sector trade-offs in an integrated ecosystem assessment framework (Samhouri et al. 2014, 2017, Wilding et al. 2017, RODA 2023, Cresci et al. 2024). Thresholds for unacceptable levels of change can be determined through expert elicitation and agreed upon by relevant stakeholders and regulatory agencies prior to the initiation of a monitoring program (Wilding et al. 2017). For example, Wilding et al. (2017) proposed that exceedance of the upper confidence level of the pre-determined threshold of unacceptable change should trigger a precautionary mitigation response.

Routine reporting of effect sizes could accelerate cumulative offshore wind and fisheries science

Cumulative science (*sensu* Lakens 2013), or an aggregation of existing pieces of information into a cohesive, well-supported, widely accepted scientific knowledge/concept/paradigm, can be advanced through quantitative meta-analysis. Quantitative meta-analysis is a method by which a standardized estimate of the mean effect (i.e. the mean effect size) can be calculated for a group of similar studies so that they are comparable (Hedges and Olkin 1985, Borenstein et al. 2009, Gurevitch et al. 2018). Synthesizing the results of similar studies conducted by multiple investigators in a quantitative manner holds the potential to reveal emergent patterns across studies. Used in ecology and fisheries science since the early 1990s, meta-analytic methods have been valuable in developing cumulative science across topic areas including marine protected areas (Hollitzer et al. 2023), ocean acidification (Cattano et al. 2018), and offshore wind (Methratta and Dardick 2019). Thorson et al. (2015) describes some of the challenges and solutions associated with meta-analytic techniques and provides a guide to best practices for applying these methods in fisheries science. Cumulative science is also needed to underpin cause–effect relationships in order to advance cumulative effects models (Willsteed et al. 2018). Conducting meta-analyses can be time consuming, primarily because of the time it takes to acquire the data to include in analyses. Routine and consistent reporting of effect sizes in individual papers would make conducting meta-analysis of offshore wind impacts (and other impacts to the marine ecosystem) much more time and cost efficient. This could bypass or at least minimize the effort needed to comb the literature, extract the elements needed from individual papers, contact authors for data, digitize figures to estimate means, etc. and would be particularly valuable in an area of science where information is urgently needed. By extension, the publishing of data and meta-data to open-access, virtual repositories following FAIR data stewardship and management principles (i.e. data that are Findable, Accessible, Interoperable, and Reusable) (Wilkinson et al. 2016) would likewise advance open and transparent science. This could hasten the delivery of science-based information to fisheries managers and advance the development of cumulative science for offshore wind and fisheries.

Routine reporting of effect sizes could inform future research studies

Power analysis is commonly used to estimate the number of samples needed to detect an effect and thus correctly reject the null hypothesis (Cohen 1988). Many of the questions being asked in offshore wind and fisheries science are new, and particularly for *in-situ* field studies, there are many variables that cannot be controlled which increase the variance around estimated means. Power analysis for the purpose of sample size determination can therefore be a powerful tool in designing offshore wind research and monitoring programs (Franco et al. 2015, South Fork Wind, LLC, and INSPIRE Environmental 2020, Livermore et al. 2023). The four elements of a power analysis are the desired level of statistical power, the acceptable level of significance, the effect size (often unknown and thus estimated based on best professional judgement), and sample size (often the value we are trying to determine).

Knowing effect sizes that are specific to the region, species, and biological response(s) being measured would enable more accurate estimates of the sample size needed to determine expected effects in future studies (Lakens 2013).

Conclusions and recommendations

The science of offshore wind and fisheries is advancing rapidly as is the development of offshore wind installations around the world. There is an urgent need to translate the outcomes of research and monitoring into information that is useful to decision-makers. This requires an evaluation of the biological relevance (i.e. the practical significance) of research and monitoring findings. To facilitate this, the following recommendations are offered: (i) report effect size(s) and associated confidence intervals associated with outcomes of research and monitoring studies alongside the results of conventional statistical tests of significance; (ii) consider the biological relevance of research and monitoring outcomes using scientific reasoning to assess the magnitude and direction of the effect size, the width of the confidence intervals, and the factors that may have affected them; (iii) advance cumulative science by reporting the components used to calculate effect sizes, namely the mean, standard deviation, and sample sizes for individual studies; (iv) publish raw data to new or existing open access data repositories following the FAIR guiding principles of data stewardship and management; and (v) conduct periodic meta-analyses of existing research to evaluate the mean, magnitude, and direction of the effect size across studies to evaluate the overall mean effect of OWD.

Although this paper focuses on offshore wind and fisheries species, the concepts presented here are applicable to other marine species and other anthropogenic activities. For example, there is a growing body of knowledge describing the effects of offshore wind on marine mammals, seabirds, zooplankton, and phytoplankton (e.g. Wang et al. 2018, Galpasoro et al. 2022, Hestetun et al. 2023). Marine species may also encounter a variety of other point-source pressures brought about by existing and emerging human activities such as oil and gas developments, pollution, other marine renewables, and seabed mining (Fowles et al. 2018, Fraser et al. 2018, Miller et al. 2018, Hooper et al. 2021, Fortune et al. 2024). Regardless of the taxa or activity evaluated, evaluating the biological relevance for an observed effect is necessary for informed decision-making.

Acknowledgments

I would like to express my gratitude to the members of the Marine Development and Ecology Branch (MDEB) at the Northeast Fisheries Science Center (NEFSC), the broader northeast regional wind team of NOAA Fisheries, our regional science partners, and the ICES Working Group on Offshore Wind Development and Fisheries (WGOWDF) for many excellent conversations about the science of fish, fisheries, and offshore wind. I would also like to thank Andy Jones (NEFSC) and the anonymous reviewers whose comments improved this manuscript. The views expressed herein are those of the author and do not necessarily reflect the views of the U.S. Department of Commerce or its sub-agencies.

Conflict of interest: None declared.

Data availability

No new data were generated or analyzed in support of this manuscript.

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Handling Editor: Howard Browman