DESIGN AND POWER ANALYSES FOR OFFSHORE WIND MONITORING SURVEYS

INTRODUCTION

Fisheries and benthic habitat monitoring plans are required actions for offshore wind developers in the United States designed to provide data and observations to answer targeted questions about possible effects of construction and operation. Considerable effort has been invested by organizations like the Bureau of Ocean Energy Management BOEM 2019a,b) and the Responsible Offshore Science Alliance (ROSA 2021), and individual researchers in developing guidelines and best practices for scientifically sound monitoring plans that fulfill stakeholder needs. As outlined in the existing guidelines, a common requirement for a robust sampling plan is the completion of a power analysis to estimate the number of samples required to detect a given change with a specified probability. Robust power analyses incorporate existing regional data derived from sampling gear and methods that are identical to the proposed survey and properly incorporate the survey design and hypotheses. Here we present a simple framework for standardizing the selection process of monitoring survey designs and provide methods for completing a BAG-style survey power analyses using simulations.

BACKGROUND

The process for selecting a survey design involves careful consideration of research questions important to the lease area and limitations of survey gear. A generalized approach for how to conduct this process can be completed by answering a series of yes or no questions (Figure 1). More detailed considerations can be found in ROSA 2021 and other literature. Although tools and methods for empirical relationships for completing a priori power analysis for ANOVA methodologies (e.g. gpower [Faul et al. 2009]) are present and at least one tool for using a hierarchical Bayesian approach to power analyses for GLMMs has been created (Fisher et al. 2019), the literature on statistical analyses and power analyses for BAG surveys is very limited. The unique problem with a BAG design is that the response variable is expected to vary spatially between pre- and post-impact sampling and the spatial response of this relationship is not well documented at this early stage of BAG survey implementation so application of both GLM and GAM family analyses are difficult. To avoid assumptions about the linearity of the effects in real data, a GAM or GAMM can be applied for the final statistical analysis of the survey, but test data modeled as part of power analysis simulations must make assumptions about the effects relationship to be conducted.

ACRONYM	DEFINITION
BACI	Before- After Impact-Control monitoring survey design employs sampling at control and impact sites both before and after an impact occurs (Green 1979) and can be expanded to have multiple control sites to be a 'beyond BACI" approach (Underwood 1994).
BAG	Before-After-Gradient design for monitoring surveys measure environmental variables before and after an impact occurs, but rather than select impact and control sites, BAG sampling occurs along a spatial gradient from the impact source (Ellis and Schneider 1997)
GLM	Generalized liner model, generalization of linear regression that allows for the response variable to have an error distribution other than the normal distribution.
GLMM	Generalized liner mixed model, an extension to GLMs in where the linear predictor comprises random effects in addition to fixed effects. See McDonald et al. (2000) or Fisher et al. (2019) for examples
GAM	Generalized additive model, generalized liner model where the linear response variable depends linearly on unknown smooth functions of some predictor variables see Brandt et al. (2018) for example
GAMM	Generalized additive mixed models, an extension to GAMs where the predictor comprises random effects in addition to fixed effects see Augustin et al. (2009) for example

Table 1. Acronyms and their definitions.

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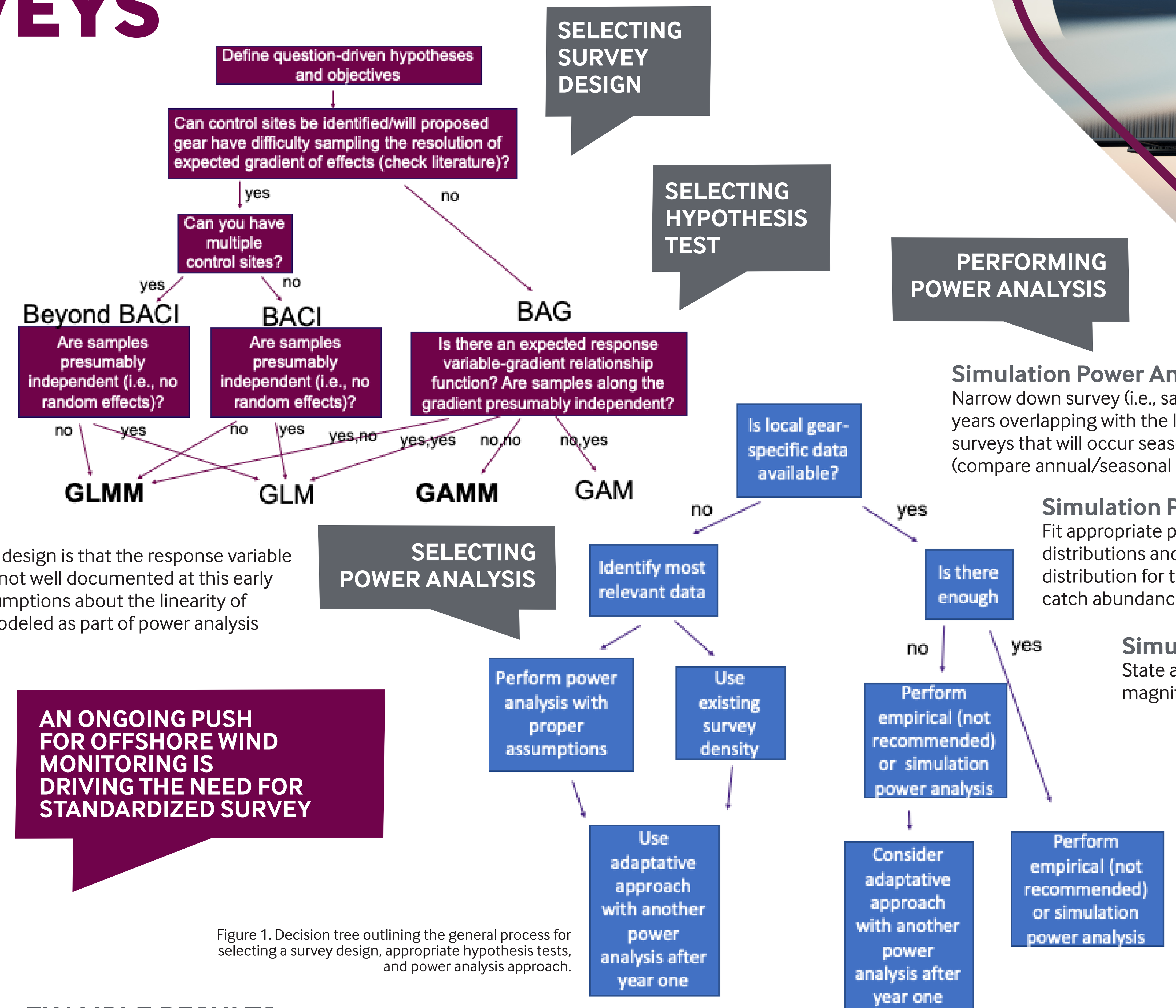

AN ONGOING PUSH FOR OFFSHORE WIND MONITORING IS DRIVING THE NEED FOR STANDARDIZED SURVEY

Figure 1. Decision tree outlining the general process for selecting a survey design, appropriate hypothesis tests, and power analysis approach.

Simulation Power Analysis Step 1.

Narrow down survey (i.e., sample) data to relevant spatiotemporal sets. For example, data from the previous 10 years overlapping with the lease area aggregated by season where appropriate (i.e., aggregate by season for surveys that will occur seasonally and by year for annual surveys such as bivalve dredge surveys). Explore data (compare annual/seasonal means and variances, perform bootstrapping, etc.)

Simulation Power Analysis Step 2.

Fit appropriate probability distributions to sample data and check fits. Some useful probability distributions and their applications are the normal distribution for trawl diversity data, lognormal distribution for trawl catch biomass data, and negative binomial distribution for ventless fish pot catch abundance (Figure 2)

Simulation Power Analysis Step 3.

State assumptions. Select desired power (usually 0.8 [Cohen, 1992]), range of sample sizes, magnitude(s) of effect size (check literature), and alpha level.

Simulation Power Analysis Step 4.

Identify independent variables from selected statistical analyses of final data (e.g., Equation 1). Create functions that will generate values of continuous independent variables (Equations 2 & 3). Create functions that will generate values for the dependent variable based on combinations of categorical variables that create a desired effect size (Table 2). Make sure that these functions incorporate the center and spread of the fitted distributions in Step 2.

Simulation Power Analysis Step 5.

Simulate data at chosen sample and effect sizes many times. Record each hypothesis test result and calculate average success of correctly rejecting the null hypothesis (aka power!) (Table 3).

EXAMPLE RESULTS

Below are examples of various fitted data, predictor and response variables of a GAM used to test a monitoring hypothesis, equations for simulating power analysis data, and power results as described in the simulation power analysis steps. The biggest assumptions for this power analysis are that a GAM could be used to approximate the power of this survey (though a GAMM may be applied for analysis depending on assumptions about random effects) and that the distance:treatment interaction term is realistic based on existing literature that fish aggregation effects are primarily limited to 100 m (Stanley and Wilson 2020; Griffin et al. 2016; Soldal et al., 2002; Lokkeborg et al., 2002; Valdemarsen, 1979).

Distance From Foundation	Before Impacts	After Impacts
~0 m	Spring: Negative binomial$(\mu = \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = \mu_{FA}, size = size_{FA})$	Spring: Negative binomial$(\mu = 2 * \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = 2 * \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = 2 * \mu_{FA}, size = size_{FA})$
~15 m		Spring: Negative binomial$(\mu = 1.5 * \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = 1.5 * \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = 1.5 * \mu_{FA}, size = size_{FA})$
~50 m		Spring: Negative binomial$(\mu = 1.33 * \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = 1.33 * \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = 1.33 * \mu_{FA}, size = size_{FA})$
~150 m		Spring: Negative binomial$(\mu = 1.25 * \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = 1.25 * \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = 1.25 * \mu_{FA}, size = size_{FA})$
~400 m		Spring: Negative binomial$(\mu = \mu_{SP}, size = size_{SP})$, Summer: Negative binomial$(\mu = \mu_{SU}, size = size_{SU})$, Fall: Negative binomial$(\mu = \mu_{FA}, size = size_{FA})$
~1,100 m		

Table 2. Matrix of functions to simulate dependent variable data based on distance from turbine and impact status.

Total Sample Size	72	144	216	288	360	432	504	**576**	**648**	**720**	**792**	**864**	**936**	**1008**	**1080**
Trawls Fished per Season	1	2	3	4	5	6	7	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Power	0.17	0.35	0.44	0.55	0.63	0.71	0.78	**0.84**	**0.88**	**0.9**	**0.93**	**0.95**	**0.96**	**0.97**	**0.98**

Table 3. Power at various samples sizes for a hypothetical power analysis. Values above 0.8 are bold.

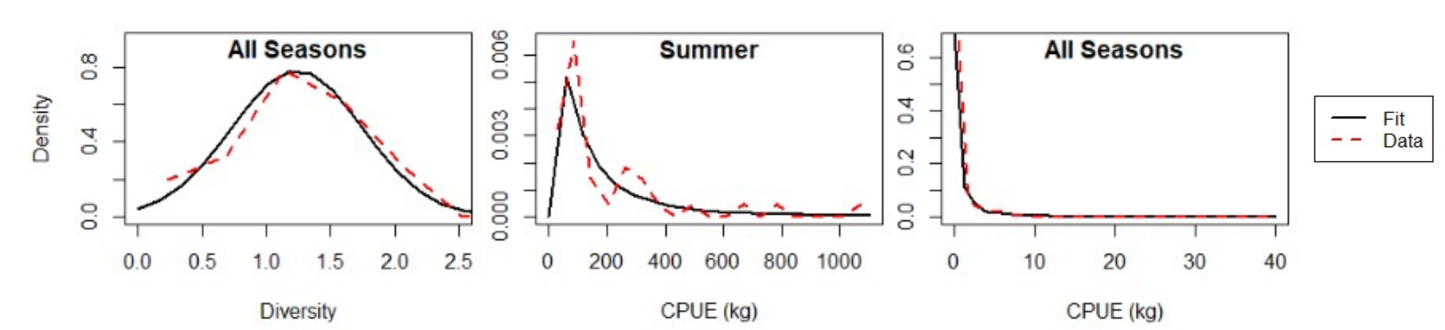

Figure 2. Sample distributions and fitted distributions or trawl catch diversity (left, normal distribution), trawl catch biomass (middle, lognormal distribution), and ventless trap catch abundance (right, negative binomial).

Before impact, After impact — Spring, Summer, Fall, Winter — Interaction between treatment and distance — Intercept

Equation 1: $CPUE = treatment + s(distance) + season + temp + treatment{:}s(distance) + treatment{:}temp + \beta 0$

Equation 2:

$N(\mu = 0, \sigma^2 = 0), N(\mu = 15, \sigma^2 = 2)$, $N(\mu = 50, \sigma^2 = 2), N(\mu = 150, \sigma^2 = 2)$, $N(\mu = 400, \sigma^2 = 25)$, or $N(\mu = 1{,}100, \sigma^2 = 25)$

Equation 3:

$N(\mu = 20°C\ , \sigma^2 = 2°C\ )$ designed to be insignificant for power analysis

Interaction between treatment and temperature

CONCLUSIONS

A power analysis is only as good as the survey design, research questions, input data, assumptions, and effect size(s) allow so vigorous examinations of each aspect are vital. Standard survey designs should become more apparent soon as more fisheries and benthic monitoring plans are approved but there is an immediate need for standardized surveys for developers to adapt to avoid incompatible data. Observed effect sizes (especially BAG effects) from large US developments will not begin to be collected until at least 2023 so many developers will have to design surveys and perform power analyses with the currently available information or any new European research.

Existing fisheries data can have large dispersion relative to center values making small effects difficult to detect.

MAKING COMPLEX EASY