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QUANTIFYING CHANGE AND IMPACT THRESHOLDS FOR BIOLOGICAL MONITORING AT MARINE RENEWABLE ENERGY SITES

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INTRODUCTION

Marine hydrokinetic (MHK) energy is a renewable resource that helps meet growing energy demands, but potential environmental impacts due to site development and device operation have not been fully investigated [1]. Environmental monitoring is used to detect impacts caused by anthropogenic disturbances and is a mandatory requirement of operating licenses in the United States [2]. Because the number of operating sites is limited in the United States, studies describing environmental change due to the presence and operation of tidal and surface wave energy converters are scarce [3], restricting information that can be used to quantify regulatory thresholds.

A successful biological monitoring program provides data that will help developers and regulators make informed operational decisions and modifications to devices [4]. To achieve this goal, it is essential that monitoring programs detect changes that are biologically relevant, which we term impacts. To detect an impact, baseline data (data previous to change [5]) must be collected to facilitate comparison to any data collected during installation and operation [6]. Determining the maximum amount of change that constitutes an impact is a high priority when forming a monitoring plan [7]. Detection of change above a defined threshold may determine if a MHK project is allowed to continue operating [8]. Thus it is imperative to characterize relevant variables and potential impacts before operation and environmental monitoring begin at a MHK site [9].

Because little information exists that can inform impact characterization for MHK monitoring program development [10], regulators must model or estimate thresholds of biological change. Extreme value theory (EVT) is an approach used to model values that are infrequent but are potentially associated with impacts [11]. A distinct advantage of EVT is the ability to model outcomes of unobserved, rare values since the full range of outcomes may not be observed during baseline sampling. Results from EVT can be used by developers and regulators to characterize extreme but rare values associated with environmental impacts, and construct monitoring programs to include operational protocols for conditions under which these events occur. The goal of this study was to evaluate whether EVT is an appropriate method to characterize infrequent events that may result in biological impacts at a tidal MHK site. We tested the utility of EVT using a baseline, active acoustic dataset collected at a proposed turbine site in Admiralty Inlet, WA.

METHODS

Site Description

Admiralty Inlet is the site of the Snohomish Public Utility District's (SnoPUD) proposed tidal energy pilot project which received its project license from FERC on March 20th, 2014. The proposal was to deploy two OpenHydro turbines (http://www.openhydro.com/) approximately one kilometer off the coast of Whidbey Island.

To monitor changes in the densities and distributions of fish and macrozooplankton in the water column, data were collected using an upward-looking echosounder deployed on the seabed. Acoustic backscatter (i.e. ensemble reflected energy) data were recorded from May 9th to June 9th, 2011 using a BioSonics DTX echosounder operating at 120 kHz [12]. The echosounder was placed at 55 m depth about 750 m off Admiralty Head (Figure 1). The echosounder operated at 5 Hz for 12 minutes every 2 hours. For analysis, the data were constrained to 25 m from the bottom (2 x the proposed turbine height), thresholded at -75 dB re 1μPa to reduce noise and were vertically integrated over 12 minute sampling periods, yielding 361 datapoints.

FIGURE 1: STUDY LOCATION WITHIN PUGET SOUND, WASHINGTON (RIGHT) WITH LOCATIONS OF SNOPUD PROPOSED TURBINE AND ECHOSOUNDER (LEFT).

Extreme Value Theory

Extreme value theory [11,13,14] is a statistical approach for describing and modeling extreme values, which are statistically rare values in the tail of a distribution. A Peaks-Over-Threshold (POT) analysis is an EVT method that fits a generalized Pareto distribution (GPD) to values above a high threshold [11]. A quantity x follows a GPD:

$$G(x|\varepsilon,\sigma,u) = \begin{cases} 1-\left(1+\frac{\varepsilon(x-u)}{\sigma}\right)^{-1/\varepsilon} & if\ \varepsilon \neq 0 \\ 1-exp\left\{\frac{-(x-u)}{\sigma}\right\} & if\ \varepsilon = 0 \end{cases} \quad (1)$$

Where u is the threshold, σ is the scale parameter, and ε is the shape parameter.

To perform a POT analysis, first a threshold (u) is selected, then the scale (σ) and shape (ε) parameters are estimated with the data using MLE or Bayesian methods. The GPD threshold is usually defined visually [15] using mean residual life (MRL) and parameter stability plots. A MRL plot quantifies the mean number of values above a threshold as the threshold is increased. A parameter stability plot depicts the fit of the GPD scale or shape parameters as a function of threshold value. The optimal GPD threshold is identified where the plots stabilize or become linear. As this threshold detection is visual and subjective [16], we propose that an objective and automated way of selecting a threshold is to take the derivative of the slope of the MRL or parameter stability plot (Figure 3), and calculate the point where the derivative first equals zero. This point corresponds to the first inflection point and can be used as a threshold for extreme values.

The GPD can also be used to predict extreme value periodicity, termed return levels, including values that have not been observed [11,17]. These predictions should be of interest to both MHK regulators and developers as they predict the occurrence of conditions associated with high risk of impacts, such as extreme biomass concentrations near a device. Return levels are generated by inverting the GPD cumulative distribution function. We generated return levels using Markov chain Monte Carlo (MCMC) simulation [18], because it enables calculation of uncertainty in return levels by generating posterior distributions for the GPD shape and scale parameters.

The GPD was fit to two monitoring metrics (Figure 2) to characterize density (mean volume-backscattering strength, or mean Sv (unit: dB re 1 m^{-1})) and patchiness (aggregation index, AI (unit: 0 to 1, with 0 being evenly dispersed and 1 being aggregated)) of fish and zooplankton in the water column [19].

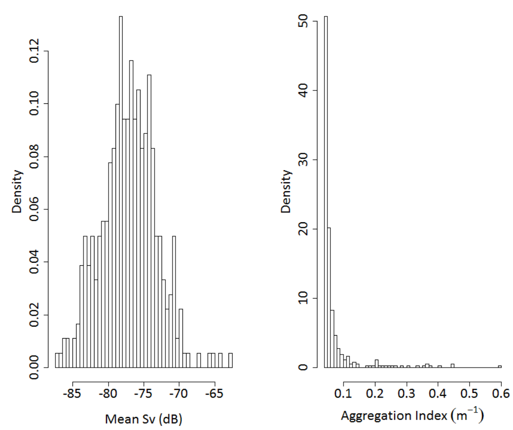

FIGURE 2: MEAN SV AND AGGREGATION INDEX DISTRUBITIONS.

RESULTS AND DISCUSSION

Threshold Choice

For the density metric (Mean Sv), the mean residual life plot was approximately linear between u ≈ -75 and u ≈ -71 (Figure 3). The scale parameter appears to be stable until about u ≈ -75, which is also the point where the variance sharply increased. After taking the derivative of both the MRL and parameter stability plots the first point where dY=0 for the mean residual life plot occurred at u = -74.58, and for the parameter stability plot at a value of u = -74.48. First dY=0 values for the Aggregation Index resulted in a threshold of u =0.135 for the mean residual life plot, and u =0.144 for the scale parameter stability plot.

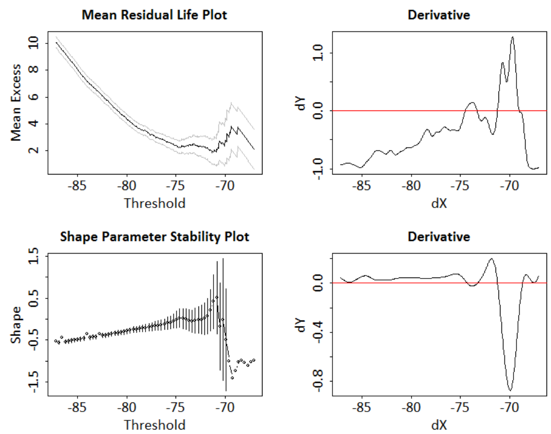

FIGURE 3: (LEFT SIDE) THE MRL PLOT AND SCALE PARAMETER STABILITY PLOT, (RIGHT SIDE) THE MATCHING DERIVATIVES WITH RED LINE SHOWING DY=0.

Using the first derivative to determine the threshold provides greater precision than visual estimation. Also, for both mean Sv and aggregation index metrics, the point estimates where the derivatives equaled zero were less than 0.1 units apart for the MRL and parameter stability plots. The proximity of the two sets of threshold estimates from the derivative method indicates the consistency of the method. Additional extreme value data are needed to determine if estimated threshold values remain constant and can be determined accurately.

Bayesian Analysis of Return Levels

For the Admiralty Inlet data, the spread of the 95% credible intervals of return levels showed that return level predictions have great uncertainty, even at low biomass density levels (Figure 4). Uncertainty could be decreased by collecting additional baseline data, but will increase baseline site characterization sampling. Data collected during project operation could supplement baseline data, with return levels used to inform project managers about conditions under which values exceeding thresholds are predicted to occur. This may be useful when large volumes of monitoring data will be collected, as more data will give better estimates for GPD parameters, which will decrease return level uncertainty.

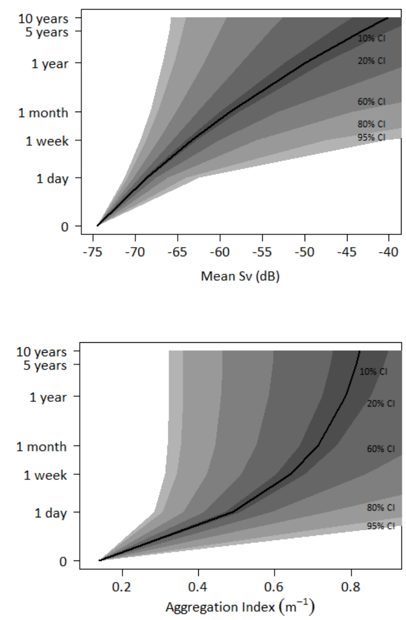

FIGURE 4: MEAN SV (TOP) AND AGGREGATION INDEX (BOTTOM) RETURN LEVELS FROM MEDIAN POSTERIOR ESTIMATE, WITH CREDIBLE INTERVAL GRADIENT. THE RETURN PERIOD IS ON A LOG10 SCALE.

Next Step

The general applicability of EVT to MHK projects is being investigated by applying the methods developed for Admiralty Inlet to another dataset. We will compare the results of two tidal energy sites to evaluate how sensitive GPD parameters are to data values and whether EVT results are unique to each site. Tidal energy sites, though they may contain different biological communities, are predicted to have similar physical characteristics and should have similar ranges of extreme values in biological monitoring variables. This comparison will enable us to determine the generality of the approach for MHK biological monitoring.

CONCLUSION

EVT provides an efficient tool to analyze baseline environmental monitoring data and can be used to establish statistically significant thresholds for rare and potentially high-impact events. EVT has many possible applications for biological monitoring; it can be used to infer conditions that result in impacts and be used to establish or refine regulatory thresholds used in monitoring programs.

Observations above a threshold are statistically rare and occur where high-risk events are likely to transpire [11]. Observing values above a threshold or an increase in the frequency of extreme values, could be used to indicate when an impact has occurred. Defining a threshold for extreme values will help MHK managers assess the risk of impacts as well as establish a baseline for expected extreme value periodicity. Data collected after a device begins operating can be used to supplement the EVA calculated using baseline data to refine return level and associated uncertainty estimates.

EVT will also be useful for understanding factors that cause environmental impacts. Extreme events can be correlated with biological or physical covariates such as biomass distribution or tidal speed. Patterns in these metrics may provide insight about the conditions under which impacts occur, which could then be used to adjust operating regulations and to increase vigilance during monitoring.

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