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Modeling baseline conditions of ecological indicators: Marine renewable energy environmental monitoring

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ABSTRACT

Ecological indicators are often collected to detect and monitor environmental change. Statistical models are used to estimate natural variability, pre-existing trends, and environmental predictors of baseline indicator conditions. Establishing standard models for baseline characterization is critical to the effective design and implementation of environmental monitoring programs. An anthropogenic activity that requires monitoring is the development of Marine Renewable Energy sites. Currently, there are no standards for the analysis of environmental monitoring data for these development sites. Marine Renewable Energy monitoring data are used as a case study to develop and apply a model evaluation to establish best practices for characterizing baseline ecological indicator data. We examined a range of models, including six generalized regression models, four time series models, and three nonparametric models. Because monitoring data are not always normally distributed, we evaluated model ability to characterize normal and non-normal data using hydroacoustic metrics that serve as proxies for ecological indicator data. The nonparametric support vector regression and random forest models, and parametric state-space time series models generally were the most accurate in interpolating the normal metric data. Support vector regression and state-space models best interpolated the non-normally distributed data. If parametric results are preferred, then state-space models are the most robust for baseline characterization. Evaluation of a wide range of models provides a comprehensive characterization of the case study data, and highlights advantages of models rarely used in Marine Renewable Energy environmental monitoring. Our model findings are relevant for any ecological indicator data with similar properties, and the evaluation approach is applicable to any monitoring program.

1. Introduction

Statistical models are commonly fit to ecological indicator data to detect and measure change in environmental monitoring programs, but observed patterns are potentially affected by the choice of model used to analyze data (e.g., Jones-Farrand et al., 2011; Olden and Jackson, 2002; Thomas, 1996). Ecological indicators characterize ecosystem attributes such as structure, composition, and function (Niemi and McDonald, 2004; Noss, 1990) that vary over time or location. An indicator can be measured directly or derived from metrics to serve as proxies for indicators (e.g., counts, concentrations, rates). Statistical models can then be applied to indicator or metric data to characterize baseline conditions, which includes estimation of pre-disturbance variability, data trends, and relationships between biotic and abiotic components of the environment (Treweek, 1996, 2009). Quantifying baseline conditions enables the design of operational monitoring programs that measure change caused by known disturbances (Schmitt and Osenberg, 1996; Treweek, 2009). By standardizing indicators and models used to analyze ecological baseline data, uncertainty in assessment of environmental change is reduced and sites can be compared across time and locations.

In terrestrial and aquatic ecosystems, ecological indicators are used to quantify ecosystem change in response to disturbances. Examples include climate change (Ainsworth et al., 2011), resource harvest (e.g. commercial fisheries; Large et al., 2013), and human activity − ranging from population growth to acoustic disturbances (Andrews et al., 2015). For monitoring programs, indicators need to be evaluated with models to develop standards for quantifying anthropogenic effects on the environment. Anthropogenic disturbances to ecosystems result from the addition or cessation of human activity with positive or negative effects. One example of an anthropogenic activity that may impact aquatic ecosystems is marine renewable energy (MRE; see Table A1 for the list of defined abbreviations) technologies, including offshore wind turbines, surface wave energy convertors, and tidal stream turbines.

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With the exception of offshore wind operations, current MRE development is largely demonstration scale (e.g., 1–2 devices installed for testing and validation), rather than commercial enterprises that are grid connected. In the United States, the lack of commercial scale MRE projects is partially attributed to the uncertainty associated with environmental effects of MRE development. At this time, there are no standard monitoring requirements for baseline or operational monitoring of MRE sites within the United States and other nations (Copping et al., 2016).

In an effort to ensure efficient, comparable, and informative monitoring programs, initial guidelines have been developed for MRE monitoring study design and data collection. These guidelines emphasize the use of ecological indicators to assess change caused by MRE development (Boehlert et al., 2013; Klure et al., 2012). Indicators recommended for measuring change include abundance, distribution, diversity, and behavior (Niemi and McDonald, 2004; Noss, 1990) of ecosystem components that may be affected by development, including marine mammals, birds, fish, and habitat (Boehlert et al., 2013; Klure et al., 2012; McCann, 2012). Common methods to collect metrics that serve as proxies for indicators, such as abundance counts, diversity indexes, location measurements, include trawl, acoustic, and optical surveys (Klure et al., 2012; McCann, 2012; Polagye et al., 2014). Despite recommendations of indicator use, current guidelines lack best practices for analyzing indicator or metric data. Previous efforts to analyze MRE monitoring data have been narrow in scope, usually restricted to generalized regression models. We define generalized regression models to include linear regressions (e.g., Hammar et al., 2013; ORPC, 2014), semi- or parametric generalized linear (mixed) models (GLMMs) (e.g., Bergström et al., 2013; Embling et al., 2013; Stenberg et al., 2015), and generalized additive (mixed) models (GAMMs) (e.g., Benjamins et al., 2016; Mackenzie et al., 2013). These models have been used to characterize baseline conditions and to predict effects of MRE development on those conditions (e.g., Duck et al., 2006; Tollit and Redden, 2013; Viehman et al., 2015). The use of semi- and full parametric models for monitoring is constrained due to the limited range of error distribution assumptions, and a required parametric relationship between predictors and response variable.

An evaluation of a wider range of model classes is needed to establish best practices when analyzing environmental data to establish baselines for ecological indicators. Time-series and nonparametric models differ from generalized regression models, and yet are equally capable of fitting indicator data, predicting environmental effects, and measuring change. Evaluating the ability of generalized, time series, and nonparametric regression models to characterize ecological time series data is necessary to recommend best practices. We use data from a proposed MRE site as a case study for model evaluation, but because this framework is general, the models and methods presented here are applicable to a wide range of monitoring programs and indicators. Establishing best practices for characterizing baseline conditions decreases site characterization and operational monitoring costs, enables comparison among sites, and reduces uncertainty in environmental assessments.

2. Methods

2.1. MRE baseline case study

The case study baseline data was collected at a tidal turbine pilot project site proposed by the Snohomish County Public Utility District No. 1 from May 11 to June 8, 2011 (Horne et al., 2013). The site is located ~1 kilometer off Admiralty Head, Puget Sound Washington (48.18° N, −122.73° W), at a depth of ~60 m (Public Utility District No. 1 of Snohomish County, 2012). The project would deploy two, 6 m Open Hydro turbines (http://www.openhydro.com/). Active acoustic backscatter data recorded using a 120 kHz BioSonics DTX echosounder mounted on a Sea Spider platform is assumed representative of a primary monitoring method that would be deployed throughout the life of an MRE project. Acoustic backscatter is representative of nekton (i.e., macro-invertebrates and fish that move independently of fluid motion) density within the water column (Maclennan et al., 2002). The echosounder sampled at 5 Hz for 12 min every 2 h, and a −75 dB re 1m^{-1} threshold was applied to the data to remove noise (Horne et al., 2013). Data values were constrained to 25 m from the bottom, a height corresponding to twice that of the proposed OpenHydro tidal turbine.

A suite of metrics derived from the acoustic backscatter data are available to quantify nekton density and vertical distribution in the water column (cf. Burgos and Horne, 2007; Urmy et al., 2012). Two metrics were chosen to represent MRE monitoring data: mean volume backscattering strength (Sv) (dB re 1 m^{-1}) and an aggregation index (AI) (m^{-1}). Both metrics are continuous, display periodic autocorrelation (Jacques, 2014), and are trend-stationary (i.e., statistical data properties are constant over time, assuming that the periodicity and trend in the data are associated with deterministic environmental variables). These two metrics serve as proxies of abundance and behavior, which are indicators of nekton structure and function (cf., Niemi and McDonald, 2004; Noss, 1990; Wiesebron et al., 2016). Sv data serves as a proxy for nekton density and are normally distributed. The AI data measures animal patchiness, are non-normal, right-skewed, and composed primarily of low aggregation values with spikes of high aggregation (Fig. 1). The terms *low state* and *high state* will be used to refer to the two magnitudes of AI values. These metrics are considered representative of MRE baseline data, because MRE monitoring guidelines consider fish a primary receptor (i.e., ecosystem component that responds to change) of MRE environmental stressors (i.e., external events or features associated with MRE development) (e.g., Boehlert et al., 2013; Klure et al., 2012; McCann, 2012).

Ancillary environmental measurements collected during Admiralty Inlet surveys (cf. Jacques, 2014) were used as potential covariates in the candidate models. Daily tidal range (m), tidal speed (m/s), and Julian day of year were matched to each time stamp from May 11th through June 8, 2011. Tidal range was calculated as integrated tidal speed through the day (Jacques, 2014). A Fourier series defined by a 24 h period was also included as an environmental variable to represent time-of-day.

2.2. Evaluation approach

We developed an evaluation to assess the ability of statistical models to characterize baseline environmental conditions that identify potential effects of MRE development and to accurately measure effects during operations. The approach is intended to evaluate data variability, trends, and relationships between components of the environment. We used cross-validation as a model selection tool to quantify interpolation accuracy (i.e., ability to predict data within the range of the empirical data) (Hastie et al., 2009). This approach ensured an equal assessment of model accuracy across all statistical model classes (parametric v. non-parametric), while at the same time, parameterized all candidate models to have the greatest probability of success in accurately characterizing the data. Residual diagnostics were used to assess the validity of model error distribution and autocorrelation structure assumptions. The 10-fold cross validation model selection and residual diagnostics provide estimates of model fit accuracy and residual variability. Patterns in selected covariates among models were interpreted as trends and important predictor variables of the indicator data. Results from the evaluation were then used to recommend model (s) most capable of characterizing normally and non-normally distributed monitoring data. All analyses were conducted using the R v.3.1.2 statistical software environment (R Core Development Team, 2014).