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# Evaluation and optimisation of underwater visual census monitoring for quantifying change in rocky-reef fish abundance

Timothy Jones [a,*], Robert J. Davidson [b], Jonathan P.A. Gardner [a], James J. Bell [a]

[a] School of Biological Sciences, Victoria University of Wellington, PO Box 600, Wellington 6140, New Zealand
[b] Davidson Environmental Ltd, PO Box 958, Nelson, New Zealand

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ABSTRACT

Monitoring is essential for effective conservation and management but the ability of monitoring to deliver accurate and precise measures of changes in abundance is often not evaluated, particularly in marine studies. Here we use long-term datasets from three New Zealand marine reserves to evaluate the capacity of underwater visual census monitoring to quantify trends in abundance for four reef-fish species. Simulations parameterized by the observed data were used to evaluate multiple monitoring configurations based on statistical power and trend-estimate precision and accuracy. These results were then used to identify optimal monitoring designs that maximized power, precision or accuracy within budgetary constraints. Power and trend-estimate accuracy and precision were highest for abundant species and lowest for species exhibiting low and/or highly variable abundances. For the least abundant species, trend estimates were less accurate and precise for negative compared to positive trends, highlighting a reduced ability to identify ongoing declines in depleted populations. Optimal monitoring configurations varied amongst species, locations and whether assessments were based on power, precision or accuracy. In general, higher within-site replication was required for the least abundant species, whereas greater site replication was required for more spatially heterogeneous species/locations. In addition, we found that for some species the optimal monitoring approach changes through time, highlighting the need for an adaptive approach to monitoring. Finally, we recommend that future monitoring evaluations focus on assessing precision and accuracy, rather than power, as this places greater emphasis on the assessment of biological rather than statistical significance.



## 1. Introduction

Monitoring of marine and terrestrial ecosystems is essential for effective conservation and management (Lindenmayer and Likens, 2010; Reynolds et al., 2011). Monitoring can provide information on long-term changes in abundance, demographic parameters and ecosystem condition (Seavy and Reynolds, 2007; Lindenmayer and Likens, 2010) and can inform successful conservation and management strategies (Bart et al., 2004). For a monitoring program to be effective it should provide both accurate (small bias) and precise (low uncertainty) estimates of trends in the monitored metric. However, estimating change (e.g. in population abundance) from survey data poses several logistical and statistical challenges (McDonald-Madden et al., 2010; Molloy et al., 2010). Because quantifying trends in ecological studies is so influenced by temporal and spatial variability (Sims et al., 2006; Molloy et al., 2010) designing monitoring programs to maximize their capability to quantify these trends requires considerable planning, field testing and statistical evaluation before implementation (Reynolds et al., 2011; Lebuhn et al., 2012). However, *a priori*, researchers rarely know the degree of variability that affects abundance measures, which is important considering that decisions pertaining to the distribution of sampling effort depend on the relative magnitudes of the different components of variation (Urquhart et al., 1998; Sims et al., 2006). In many cases, resource limitations (e.g. time, cost, and availability of trained observers) may lead to survey designs that meet some of the requirements of an effective monitoring program by emphasising replication on specific spatial or temporal scales to the detriment of other monitoring requirements. For example, resources used to achieve high spatial coverage may mean that monitoring can only be carried out infrequently, thus giving a poor indication of changes through time (Field et al., 2005). Given the limited resources dedicated to monitoring and the expense of performing large-scale surveys, particularly in marine habitats, there is a danger that sub-

* Corresponding author.
*E-mail address:* timothy.t.jones@gmail.com (T. Jones).

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optimal monitoring may be performed (McDonald-Madden et al., 2010; Reynolds et al., 2011; Guillera-Arroita and Lahoz-Monfort, 2012).

Underwater visual census (UVC) methodologies are used extensively in marine studies for assessing the abundance of invertebrates, macroalgae and reef fish (Samoilys and Carlos, 2000; Denny and Babcock, 2004; Stuart-Smith et al., 2008; Edgar and Barrett, 2012; Eddy et al., 2014). Fish abundance data collected by UVC are typically characterised by high variability (Samoilys and Carlos, 2000; Willis et al., 2003). However, few studies have examined the effectiveness (in terms of accuracy and precision) of monitoring data collected by UVC to determine long-term trends in fish abundance, let alone to optimise monitoring designs (however, see Molloy et al., 2010), something that is vital considering the reliance on these techniques globally when quantifying the status of fish populations (Denny and Babcock, 2004; Babcock et al., 2010; Eddy et al., 2014). This may be due to the perceived complexity of performing assessments for data types that are not suited to simple statistical tests (Reynolds et al., 2011). Nonetheless, the widespread use of the UVC methodology makes such assessments a valuable resource for researchers and will help to better inform management decisions.

In this study we describe an approach that may be used to design optimum monitoring programs to identify abundance trends of reef fish species as assessed by UVC. Monitoring should provide accurate and precise measures of changes in abundance. Although power analysis (and by proxy analyses of precision, as power and precision are directly related) is commonly used in monitoring assessments (Seavy and Reynolds, 2007) it does not guarantee that monitoring will be accurate (Bart et al., 2004; Nakagawa and Cuthill, 2007) and so we directly incorporate analyses of monitoring accuracy, as well as assessments of power and precision. Using the example of four temperate New Zealand reef fish species we quantify the power of statistical tests for trends, in addition to trend-estimate accuracy and precision, for multiple monitoring configurations incorporating different numbers of sites, transects within sites and monitoring frequencies. We also quantify the financial costs of each design and identify the most cost-effective approaches by identifying the best-performing designs for specific monetary budgets. We aim to evaluate the current monitoring configuration and to determine optimal monitoring designs for different locations and for species that display different characteristics in terms of abundance and spatio-temporal variability and whether this varies amongst assessments of power, precision and accuracy. Finally, we aim to provide a general methodology for the identification of a cost-effective monitoring design and provide results and recommendations that could be applied to temperate reef fish species with similar characteristics (abundance and variability) in other locations.

## 2. Methods

Here is given a brief description of the methods and for more details see Appendices A–D of the Supplementary Material.

### 2.1. Datasets

Datasets from three New Zealand marine reserves were examined: Long Island-Kokomohua Marine Reserve (established 1993, hereafter LIMR), Tonga Island Marine Reserve (established 1993, hereafter TIMR) and Horoirangi Marine Reserve (established 2005, hereafter HMR) (Fig. 1). Datasets consisted of the observed abundance of reef fish collected using the same UVC protocol and set of trained divers (three divers were responsible for collecting the data over the entire study period at each reserve). Sites were characterised by boulder or rocky reef substratum devoid of a macroalgal canopy (i.e. rocky barrens), in a depth range of 5–12 m. At each site, pairs of divers swam along 30 m transects haphazardly placed at the same designated sites and recorded all fish in a 2 m wide and 2 m high corridor. In addition to fish abundance, size was visually estimated by the divers, trained in fish size estimation, in order to classify individuals into legal and sub-legal size classes. Underwater visibility was at least 4.5 m horizontal distance to ensure that visibility did not affect data collection. Twelve transects were performed at each site with five sites at LIMR, seven at TIMR and eight at HMR surveyed annually (see Davidson et al., 2014).

We limited our analysis to four species that were observed at all three MRs; blue cod (*Parapercis colias*), spotty (*Notolabrus celidotus*), blue moki (*Latridopsis ciliaris*) and tarakihi (*Nemadactylus macropterus*). Legal-sized (length > 30 cm) blue cod abundance was also analysed as it has been used as an indicator of a MR effect (Pande et al., 2008) and because it allows a comparison between analyses based on total versus legal-sized abundance. To aid with comparing these results with other species/systems, a range of summary statistics related to abundance and variability are included in Supplementary Material.

### 2.2. Modelling and parameter estimation

Monitoring designs are evaluated using a Monte-Carlo simulation methodology with simulations parameterized such that they are representative of the observed data, but with a known trend through time for assessment purposes (Sims et al., 2006). A total of 15 initial datasets (five species/size classes' $\times$ three reserves) were collated. Three of the initial datasets displayed non-linear trends through time; total blue cod and legal-sized blue cod at LIMR and spotty at TIMR (Appendix B – Supplementary Material). However, for these datasets trends were approximately linear either side of an inflection point at 1999/2000 for legal-sized blue cod at LIMR, 2003/2004 for total blue cod at LIMR and 2005/2006 for spotty at TIMR. Because we are interested in monitoring efficacy for estimating linear trends in abundance and to avoid fitting a linear model to non-linear trend data, these datasets were split into two time periods (legal-sized blue cod – 1993–1999, 2000–2010; total blue cod – 1993–2003, 2004–2010; spotty – 1999–2005, 2006–2010). This also allows us to examine whether power and trend-estimate accuracy and precision of monitoring designs changes through time.

To estimate abundance and variance parameters to inform simulations, poisson generalized linear mixed effects models (GLMMs) and negative-binomial GLMMs (both with log-link function), were fitted to each dataset using the lme4 package in R (Bates et al., 2014). Four variance components were identified as potential contributors to the overall variance of the fish counts: (1) between-site; (2) within-site; (3) synchronous temporal variation (same across sites); and (4) temporal variability unique to each site (survey-specific variation). Consequently, random effects of site, year and survey were trialled to model potential between-site, synchronous, and survey-specific variation, respectively. To account for potential overdispersion relative to the poisson distribution and to model within-site variation, an observation-level random effect was trialled in the poisson GLMMs. This was not necessary for negative-binomial models because overdispersion is inherently modelled by a dispersion parameter, $v$. All possible combinations of random-effects plus a fixed effect for modelling continuous trends through time were fitted for poisson (32 model combinations) and negative-binomial GLMMs (16 model combinations) and model parameter estimates (intercept, slope and random effects standard deviations) and Akaike Information Criterion (AIC) were extracted from each model. The observed data and