

Bayesian Modelling
of Direct and Indirect Effects of
Marine Reserves on Fishes

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Abstract

This thesis reviews and develops modern advanced statistical methodology for sampling and modelling count data from marine ecological studies, with specific applications to quantifying potential direct and indirect effects of marine reserves on fishes in north eastern New Zealand. Counts of snapper (*Pagrus auratus*: Sparidae) from baited underwater video surveys from an unbalanced, multi-year, hierarchical sampling programme were analysed using a Bayesian Generalised Linear Mixed Model (GLMM) approach, which allowed the integer counts to be explicitly modelled while incorporating multiple fixed and random effects. Overdispersion was modelled using a zero-inflated negative-binomial error distribution. A parsimonious method for zero inflation was developed, where the mean of the count distribution is explicitly linked to the probability of an excess zero. Comparisons of variance components identified marine reserve status as the greatest source of variation in counts of snapper above the legal size limit. Relative densities inside reserves were, on average, 13-times greater than outside reserves.

Small benthic reef fishes inside and outside the same three reserves were surveyed to evaluate evidence for potential indirect effects of marine reserves *via* restored populations of fishery-targeted predators such as snapper. Sites for sampling were obtained randomly from populations of interest using spatial data and geo-referencing tools in R—a rarely used approach that is recommended here more generally to improve field-based ecological surveys. Resultant multispecies count data were analysed with multivariate GLMMs implemented in the R package *MCMCglmm*, based on a multivariate Poisson lognormal error distribution. Posterior distributions for hypothesised effects of interest were calculated directly for each species. While reserves did not appear to affect densities of small fishes, reserve-habitat interactions indicated that some endemic species of triplefin (Tripterygiidae) had different associations with small-scale habitat gradients inside *vs* outside reserves. These

patterns were consistent with a behavioural risk effect, where small fishes may be more strongly attracted to refuge habitats to avoid predators inside vs outside reserves.

The approaches developed and implemented in this thesis respond to some of the major current statistical and logistic challenges inherent in the analysis of counts of organisms. This work provides useful exemplar pathways for rigorous study design, modelling and inference in ecological systems.

Preface

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Me, bombastically gesticulating to Marti's bemusement.
Poor Knights Islands. (Photo credit: Steve Hathaway).

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