

# Improving Catch Estimation Methods in Sparsely Sampled Mixed-Stock Fisheries.

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## Abstract

## Introduction

### Context

### Data

- Collection issues
  - funding => nature of sparcity
- Lay down goal modeling goal
  - mean
  - uncertainty

## Methods

### Data Generating Model

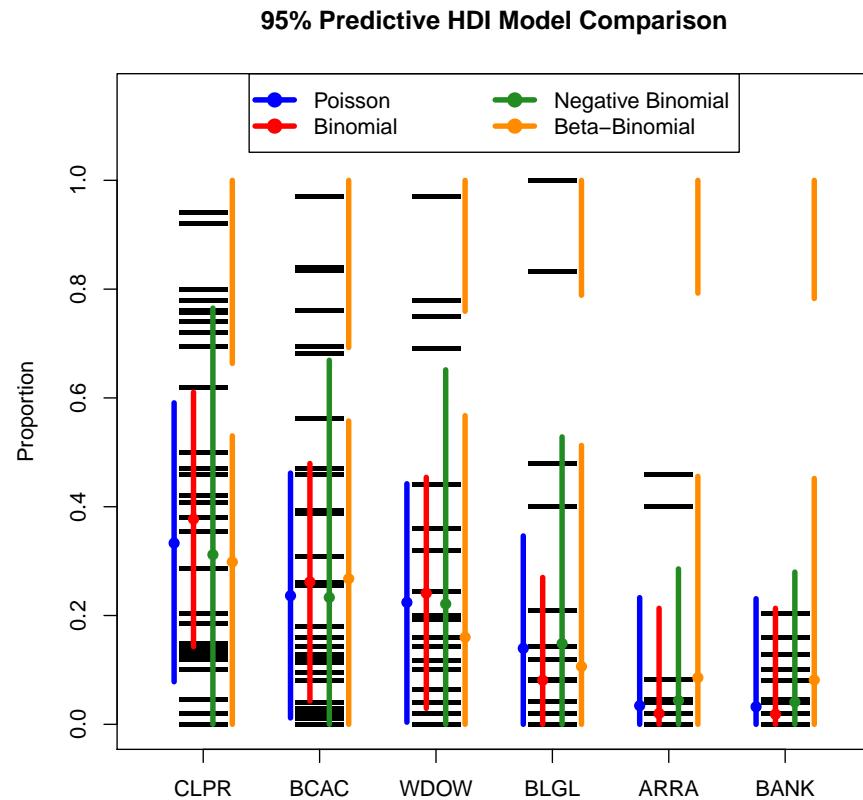
Something something heirarchical poisson model. Something something (Shelton, 2012).

For the purposes of accurately modeling not only species composition means, but also higher moments of the data, such as species composition variances, it is necessary to recognize model limitations with respect to over-dispersed data. Among the simplest models for count data are the poisson and binomial models. Both models are typically specified with a single degree of freedom for modeling all of the moments of the data, and thus they rely heavily on their respective data generating processes to accurately represent higher moments in the data. McCullagh and Nelder (1989, pg. 124) commiserate about the prevalence of

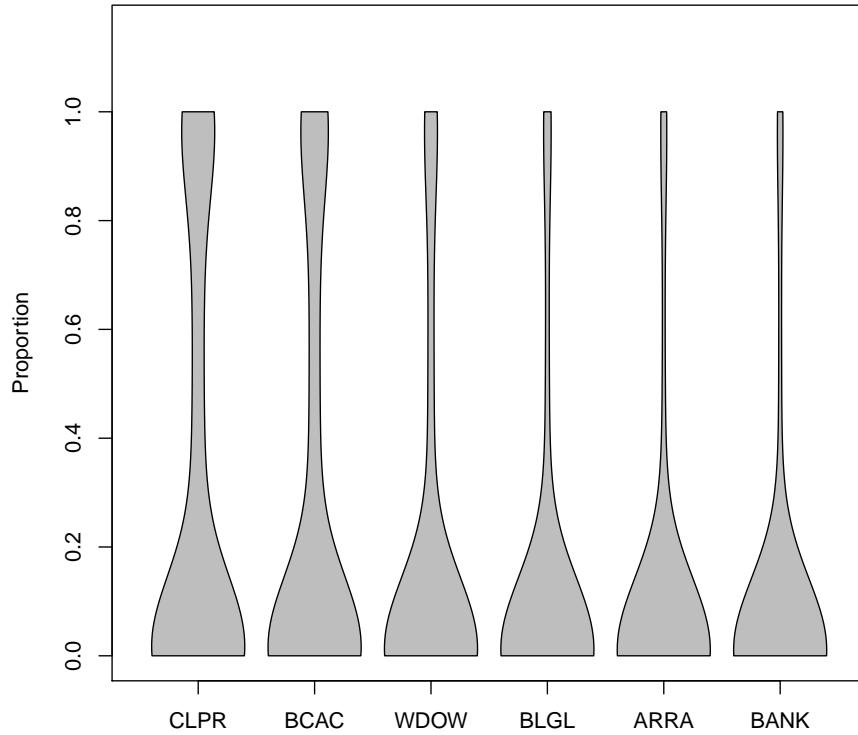
over-dispersed data in cluster sampling, and explain the numerous ways in which cluster sampling may result in over-dispersion.

Extending the Poisson and binomial models to deal with over-dispersion, typically involves adding additional parameters for the purpose of modeling higher moments of the data. The negative binomial distribution is often used as an over-dispersed extension of the poisson model, since it can be expressly written as an infinite mixture of poisson distributions. While the beta-binomial model is typically used to as an over-dispersed extension of the binomial model.

To discern between these models we consider a small scale example of the Poisson, binomial, negative binomial, and beta-binomial models fit to the port sampling integer weight data from market category 250, in the Monterey port complex trawl fishery in 1990. (any will work). This stratum was visited XX times by port samplers, collecting a total of YY cluster samples, resulting in ZZ observations, from each of the described models. These data contain 21 (at least; URCK) unique species, although for brevity we only consider for the top 6 species here.



### Beta–Binomial Posterior Predictive Species Compositions



- describe picture
- notice overdispersion
- improper variance model biases mean, beta-binomial is flexible to disentangles these effects.
- maths stuffs
  - mean function
  - variance; introduce  $\rho$
- justify linear predictor/transistion to priors

## Heirarchical Priors

## Prediction

## Model Exploration & Averaging

## Results

- General Products
- Degree of smoothing (heirarchical parameters)
- Posterior v. Current
  - Report degree of similarity
- Prediction v. Data
  - Report predictive accuracy

## Conclusions

- General Math/Science
- Database Stuff
- Looking Forward
  - forcasting/hindcasting
    - \* simple
    - \* timeseries models
  - more computation faster
    - \* broader model exploration
    - \* broader spatial expansion

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