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

Nick Grunloh, Edward Dick, Don Pearson, John Field, Marc Mangel

Abstract

Introduction

Context

Data

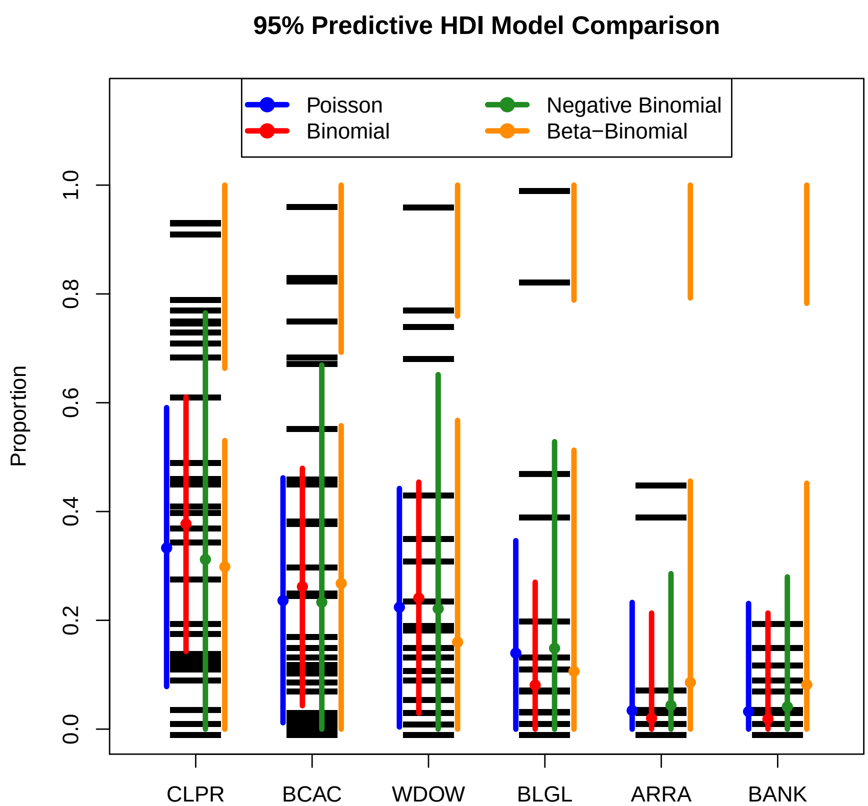
```
* Collection issues
    * funding => nature of sparcity
* Lay down goal modeling goal
    * mean
    * uncertainty
```

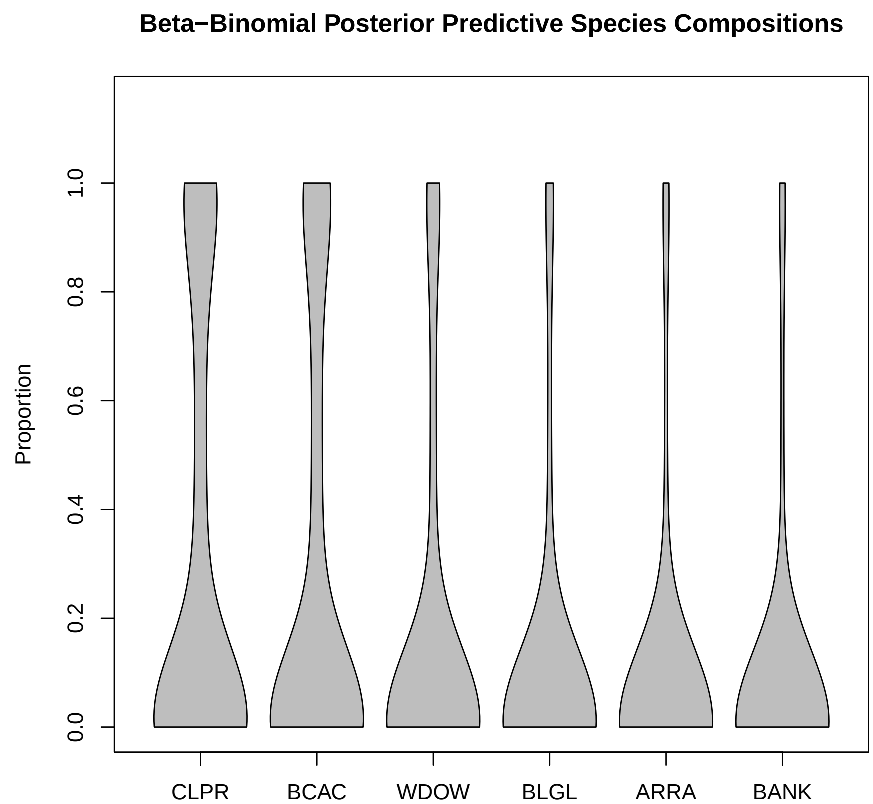
Methods

Data Generating Model

For the purposes of accuratly modeling not only species composition means, but also higher moments, such as species composition variances, it is neccisary to recognize model limitations with respect to over-disperse data. Amoung the simplest models for count data are the poisson and binomial models. Both models are typically specificed with a single degree of freedom for modeling the mean, and thus rely heavily on their respective data generating processes to accuratly represent higher moments in the data. This is a well understood issue with modeling count data of the sort. McCullagh & Nelder (1989, pg. 124) writes, "Over-dispersion is not uncommon in practice. In fact, some would maintain that over-dispersion is the norm in practice and nominal dispersion the exception."

Adding


95% Predictive HDI Model Comparison
Poisson
Binomial
Negative Binomial
Beta−Binomial
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
CLPR
BCAC
WDOW
BLGL
ARRA
BANK




```
* maths stuffs
    * mean function
    * variance; introduct $\rho$
* justify linear predictor/transistion to priors
```

Heirarchical Priors

Prediction

Model Exploration & Averaging

Results

Prediction Experiment

Conclusions

General Math/Science

Database Stuff

Looking Forward

```
* forcasting/hindcasting
    * simple
    * timeseries models
* more computation faster
    * broader model exploration
    * broader spatial expansion
```

References

[1] Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2014). Bayesian data analysis (Vol. 2). Boca Raton, FL, USA: Chapman & Hall/CRC.

[2] Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: a tutorial. Statistical science, 382-401.

[3] Pearson, D.E., and Erwin, B. (1997). Documentation of California's commercial market sampling data entry and expansion programs. NOAA Tech Memo. NOAA-TM-NMFS-SWFSC-240.

[4] R Core Team (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

[5] Rue H., Martino S., Lindgren F., Simpson D., Riebler A. (2013). R-INLA: Approximate Bayesian Inference using Integrated Nested Laplace Approximations. Trondheim, Norway. URL http://www.r-inla.org/.

[6] Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. Journal of the royal statistical society: Series b (statistical methodology), 71(2), 319-392.

[7] Sen, A.R. (1984). Sampling commercial rockfish landings in California. NOAA Tech Memo. NOAA-TM-NMFS-SWFSC-45.

[8] Sen AR. (1986). Methodological problems in sampling commercial rockfish landings. Fish Bull. 84: 409-421 .

[9] Shelton, A. O., Dick, E. J., Pearson, D. E., Ralston, S., & Mangel, M. (2012). Estimating species composition and quantifying uncertainty in multispecies fisheries: hierarchical Bayesian models for stratified sampling protocols with missing data. Canadian Journal of Fisheries and Aquatic Sciences, 69(2), 231-246.