

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

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Abstract

Effective management of exploited fish populations, requires accurate estimates of commercial fisheries catches to inform monitoring and assessment efforts. In California, the high degree of heterogeneity in the species composition of many groundfish fisheries, particularly those targeting rockfish (genus *Sebastodes*), leads to challenges in sampling all potential strata, or species, adequately. Limited resources and increasingly complex stratification of the sampling system inevitably leads to gaps in sample data. In the presence of sampling gaps, ad-hoc species composition point estimation is currently obtained according to historically derived “data borrowing” (imputation) protocols which do not allow for uncertainty estimation or forecasting. In order to move from the current ad-hoc “data-borrowing” point estimators, we have constructed Bayesian hierarchical models to estimate species compositions, complete with accurate measures of uncertainty, as well as theoretically sound out-of-sample predictions. Furthermore, we introduce a computational method for discovering consistent “borrowing” strategies across over-stratified data. Our modeling approach, along with a computationally robust system of inference and model exploration, allows us to start to understand the effect of the highly stratified, and sparse, sampling system on the kinds of inference possible, while simultaneously making the most from the available data.

Significance

In order to understand how fish populations respond to fishing, it is critical to obtain accurate estimates of how many fish are removed from the ocean (catch) and to quantify the precision of those estimates. Traditionally, population dynamics models used to measure this response to fishing (“stock assessments”) are conditioned on a time series of annual catches. These catch estimates are often treated as being known without error, despite the fact that they are derived

from sampling programs that estimate the proportion of different species found within multiple sampling strata. Sampling error introduces uncertainty into estimates of the catch, and unsampled strata must be “filled in” through a process sometimes referred to on the U.S. West Coast as “borrowing” (i.e. data imputation). Historically, methods used to “borrow” information among strata have been ad-hoc in nature and driven by expert opinion of local managers (Sen et al. 1984, 1986) (Pearson and Erwin 1997). We seek to improve upon this practice through development of a model-based approach that provides estimates of catch and associated uncertainty, as well as an objective, defensible framework for model selection and data imputation. Although the theoretical basis for a model based estimation of species composition in mixed stock fisheries has been advanced (Shelton et al., 2012), it has not yet been implemented successfully using actual historical or contemporary data.

The difficulties associated with the existing ad-hoc approach are magnified by an increase in the number of sampling strata over time, specifically the number of “market categories,” into which fishermen and dealers sort their catch (Figure 1, Bottom). The increase in the number of market categories (sampling strata) has not been matched by increases in sampling effort, resulting in a decline in the average number of samples per stratum (Figure 1, Middle). In other words, data are becoming more sparse, increasing our uncertainty in estimates of catch. Since the data are also stratified over a number of ports, fishing gear types, years, and quarters, inference is not possible without some sort of stratum pooling. Rather than rely so heavily on the previous, ad-hoc pooling rules which change based on the availability of samples, we hope to standardize any necessary pooling through an exhaustive search of the space (possible configurations) of pooled models. Pooling (and partial pooling) among strata is achieved using Bayesian hierarchical statistical models and model averaging (Gelman et al., 2014).

Methods

Model

For a particular market category, $y_{ijklm\eta}$ is the i^{th} sample of the j^{th} species’ weight, in the k^{th} port, caught with the l^{th} gear, in the η^{th} quarter, of year m . The $y_{ijklm\eta}$ are said to be observations from a Beta-Binomial distribution (BB) conditional on parameters θ and ρ .

$$y_{ijklm\eta} \sim BB(y_{ijklm\eta} | \theta, \rho).$$

Given observed overdispersion relative to the Poisson and Binomial distributions, the Beta-Binomial model makes use of a correlation parameter, ρ , to better model uncertainties. The linear predictor parameters, θ , are then factored as follows among the many strata,

$$\theta_{jklm\eta} = \beta_0 + \beta_j^{(s)} + \beta_k^{(p)} + \beta_l^{(g)} + \beta_{m\eta}^{(y:q)}.$$

Our priors are largely diffuse, representing relatively little prior information, producing behavior similar to classical fixed effect models on species ($\beta_j^{(s)}$), port ($\beta_k^{(p)}$), and gear ($\beta_l^{(g)}$) parameters. Our priors on time parameters ($\beta_{m\eta}^{(y:q)}$) are normal distributions centered at zero with a hierarchical variance shared among all year-quarter interaction terms. In recent years, inference on these models has become faster and easier to compute through the use of computational Laplace approximations (Rue et al., 2009); we compute inferences on the above model in R (R Core Team, 2015) using the R-INLA package (Rue et al., 2013).

Species Composition

Applying the Bayesian predictive framework to the above model gives the following expressions for predicted weight in each stratum,

$$p(y_{jklm\eta}^*|y) = \iint \text{BB}\left(y_{jklm\eta}^*|\theta_{jklm\eta}, \rho\right) P\left(\theta_{jklm\eta}, \rho|y\right) d\theta_{jklm\eta} d\rho.$$

$p(y_{jklm\eta}^*|y)$ is computed via monte carlo integration and represents the model's full predictive distribution for the j^{th} species' weight, in the k^{th} port, caught with the l^{th} gear, in the η^{th} quarter, of year m . The following joint transformation of the species' predictive weights result in predictive species compositions,

$$\pi_{jklm\eta}^* = \frac{y_{jklm\eta}^*}{\sum_j y_{jklm\eta}^*} \quad y_{jklm\eta}^* \neq 0.$$

Because the y^* are random variables, and π^* is nothing more than a transformation of the y^* , π^* is also a random variable. Furthermore once inference is complete, we can easily sample these distributions and compute any desired moments from the samples.

Model Exploration & Averaging

The straight-forward spatial model implied by the typical categorical port-complex variables do not adequately make in-sample predictions at the observed sample sizes. Presently the vanishingly small within-stratum sample sizes are managed by an ad-hoc “borrowing” protocol outlined by Pearson and Erwin (1997).

We aim to formalize the idea of “borrowing” via an exhaustive search of spatially pooled models among port-complexes. We combine this exhaustive search of the set of possible pooled models, with the formalized process of Bayesian Model Averaging (BMA) (Hoeting et al., 1999), to integrate model uncertainty about port groupings into species composition estimates. BMA both captures the model uncertainty around port pooling into species composition estimates, while pinning the relative predictive accuracy of each model against other models, in the set of possible pooled models, to discover optimal port super-complexes in each market category.

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