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

Nick Grunloh, E.J. Dick, Don Pearson, John Field, Marc Mangel

# Abstract

# Introduction

Estimates of landed catch are a key component of many fishery management systems. Stock assessment models (referred to here as assessments) are often conditioned on time series of annual catch, usually under the assumption that catches are known without error. While some assessment models are able to incorporate uncertainty in catch (e.g. Stock Synthesis; Methot and Wetzel, 2013), reliable estimates of catch uncertainty are often unavailable. Without this information, assessment authors often rely on ad-hoc sensitivity analyses which may or may not be incorporated into management advice and/or fail to propagate catch uncertainty into quantities of interest to managers.

Over the past decade, the estimation of catch and associated uncertainty has become a focus for recreational fisheries in the United States (NAS, 2017). Commercial fisheries, on the other hand, are often assumed to have precise estimates of catch by species. This is due in part to the availability of landing receipts (aka fish tickets) which serve as a record of the weight of fish landed into various market categories (sort groups). As noted by Pearson et al. (2008), it is important to recognize that species and market categories are not synonymous. On the U.S. West Coast, for example, it is common for multiple species to be landed within a single market category (CALCOM 2017, PacFIN 2017). This is expected for categories that are clearly designated as mixed-species categories (e.g. “nearshore rockfish”, or species within a particular genus or family). However, in some states, categories that are named after a single species still contain several species, to varying degrees, even after regulations require sorting into a particular category (Pearson et al. 2008). As a result, estimation of landings for a single species based on landing receipt data alone may produce biased estimates of total catch.

Fishermen, dealers, or processors typically decide how to sort species into market categories on a landing receipt . Trained port samplers intercept vessels offloading catch or during subsequent processing in order to determine the species composition of catch landed in a given market category (Sen 1984, Crone 1995, Tsou et al. 2015). These species composition data are used to partition, or distribute, the weight of landed catch in a market category across species, a process commonly referred to as catch expansion (Pearson and Almany, 1995). To estimate total landings for a single species, the expanded catch is summed across all relevant market categories. Assuming that landing receipt data are a census of the landed catch, uncertainty in total catch for a given species reflects variability in the species composition among port samples. If information is available to estimate sources of bias in the landing receipt data, e.g. underreporting, then it is possible to also incorporate uncertainty in the bias correction factors as well (Bousquet et al. 2010). In this study, we quantify sampling uncertainty for estimates of landed catch, although the modeling framework could be extended to include uncertainty or bias in landing receipt data.

Within market categories, the species composition of landed catch can vary spatially, temporally, by fishing gear, and catch disposition (e.g. fish sold alive or dead). These differences are attributable to many factors, including market preference, fishing behavior, regulatory constraints, and biological/ecological characteristics (e.g. spatial distribution) of the landed species. As a result, estimates of species composition for a given market category are often stratified over time (e.g. quarterly) and across other relevant strata (e.g. ports, gears, catch disposition). Sampling programs often have limited funds, and attempts to reduce bias in species composition estimates through the introduction of additional strata comes at a cost, namely reduced precision (Cochran, 1977; Tomlinson, 1971).

On the U.S. West Coast, port sampling programs allocate effort both spatially and temporally, but many domains of interest (e.g. market category, gear type, catch disposition) remain unsampled or sparsely sampled due to a proliferation of categories over time, logistical constraints, and limited resources (Sen 1986; Crone 1995; Pearson et al. 2008; Tsou et al. 2015). In California, for example, commercial port sampling effort has changed over time and space (Pearson and Almany 1995). For example, regular sampling of California ports north of Point Conception (roughly 34° 27′ N. latitude) began as early as 1978, but the more southern ports were rarely sampled prior to 1983. This allocation of effort was largely based on the statewide distribution of landings, diffuse spatial distribution of southern commercial ports, and limitations in funding for port samplers.

When no port samples are collected for landed strata and domains, species composition estimates are ‘borrowed’ from other strata using deterministic algorithms based on expert opinion. These algorithms have unknown bias and precision. In contrast, model-based estimators are increasingly used to estimate quantities of interest for domains with small sample sizes and/or unsampled strata (sometimes referred to as small area estimation; Rao 2003). Shelton et al. (2012) developed a Bayesian hierarchical statistical framework for species composition data that pools information among sparsely sampled strata, predicts species compositions for unsampled strata, and can be combined with landing receipts to estimate total landings by species, across market categories and other strata, with associated estimates of uncertainty. Shelton et al. considered hierarchical pooling only among quarters within a single year, comparing generalized linear and hierarchical linear models to trawl data from a single port in California. The authors underscored the need to better understand performance of alternative models, and to overcome issues with computation time, particularly since commercial port sampling data sets often include hundreds of landed strata spanning decades, multiple ports, gear types, and other domains of interest.

Among the U.S. West Coast states, the challenge of estimating landings for sparsely-sampled mixed stock fisheries is perhaps greatest for California. Relative to Oregon and Washington, California has a greater number of commercial ports, market categories, and landed species, with greater species diversity among ports due to the geographical range of the coast. Of particular consequence to the estimation of species compositions is the proliferation of landed market categories over time, particularly during the 1990s (Figure 1). Sampling effort also leveled off in the mid-1990s, with a reduction in effort in the early 2000s. The net result of increased stratification and flat (or reduced) sampling effort over time is a decline in mean sample size per stratum (Figure 1). In this situation, it is critical to understand how efforts to reduce bias (e.g. increasing the number of landed market categories) affect precision of the expanded catch estimates.Models that take catch uncertainty into account are not new (c.f. Doubleday 1976), but most assessments on the U.S. West Coast assume catch is known without error (PFMC 2018). As a result, catch uncertainty is not propagated into management reference points. However, the implications of catch uncertainty are not limited to stock assessment efforts. In a management context, catch estimates with large (but unknown) uncertainty may cause managers to react to large, high-frequency deviations in estimated catch, and either impose unnecessary restrictions on a fishery, or mistakenly support excessive harvest. This is particularly an issue for prohibited and/or ‘choke’ species, for which information is limited and may be based solely on estimates of discarded catch.

In this study, we evaluate the model-based framework proposed by Shelton et al. (2012) using commercial port sampling data collected in California, U.S.A. We describe species composition data collected by the California Cooperative Groundfish Survey (CCGS, 2017) over the period 1978-1990. We then extend the Shelton et al. framework to address limitations of their approach. Specifically, we evaluate alternative likelihoods to address overdispersion, compare multiple hierarchical structures for pooling information through time, and integrate model predictions across uncertainties in the spatial model structure. Finally, we estimate landed catch by species for both sampled and unsampled strata, and summarize a general framework for quantifying uncertainty including an efficient database design for dissemination of results at any level of aggregation.



Figure 1: Number of commercial port samples per market category in California, 1978-2014 (upper panel), average sample size per stratum (middle panel), and number of market categories recorded on landing receipts (lower panel). [**add description of the smoothed lines in the lower two panels here**].

# Methods

## Data

As outlined in the data in are the result of a cluster sampling protocol across the many strata, in which each sample is intended to be composed of two fifty pound clusters from the selected stratum. Although port samplers do their best to follow protocol, in reality the port sampling environment does not always allow the exact protocol to be followed. Variations in the sampling protocol may result in only a single cluster being taken, or the size of clusters taken to vary, from stratum to stratum based on the particular challenges of sampling each stratum.

[add more detailed description of data here; e.g. samples are recorded as integer weights (pounds) by port samplers, number of market categories, range of years, gears, port complexes, ignoring live fish for now, etc.; show map of state with port complexes]

The model based methodology proposed here does not rely strongly upon the cluster sampling structure, but rather simply views each sample as independent and identically distributed () draws from a data generating model, conditional on a parameterization of the stratification system. So long as the parameterization and data generating model are sufficiently robust for handling the behavior of these data, the conditionally model of these data will be a practically useful model for producing predictions about the data generating system.

That said, for the purpose of modeling these data, it is enough to know which clusters were collected as part of which samples, and how big each cluster actually ended up being. This information is readily available from CALCOM,a database maintained by the California Cooperative Groundfish Survey (CALCOM 2018). Specifically, we aggregate all observed clusters across a unique sample so that the total weight sampled is the sum of all pounds in each unique sample. Similarly, the observed weight for a particular species in each unique sample is the sum of all of the observed weights, for that species, across each cluster of each unique sample.

Although model based data analysis has the potential to add significant structure to data, a judicious application of these methods must always confront the model with enough empirical information to adequately learn about the system. In this setting some market categories and time periods may not be well enough sampled to learn the parameters of the models presented here. For this reason, we refrain from modeling any period where the minimum number of possible parameters exceeds the number of samples for the modeled period. Rather than apply models inappropriately, these landings are speciated as the nominal species for their market category. We later demonstrate that due to the prioritization for sampling heavily landed, or otherwise commercially relevant categories, this sample size heuristic only leads to nominal speciation in market categories and time periods where total landings are low. Thus the expanded landings in these periods have a negligible effect on the overall expanded landings for species in these categories.

## Data Generating Model

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 parameter 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 ways in which cluster sampling itself 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 (NB) 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. The beta-binomial model is commonly used as an over-dispersed extension of the binomial model.

To discern between these discrete modeling options we considered Poisson, binomial, negative binomial, and beta-binomial models fit to a subset of the integer weight data from market category 250, in the Monterey port complex trawl fishery in 1982. This stratum was visited 32 times by port samplers, collecting a total of 59 cluster samples across 55 unique species. Each of the above mentioned models are fit to these data.

For each of the above mentioned models The predictive species composition distributions are visualized in Figure() as 95% Highest Density Intervals (HDI) , plotted on top of the predictive means for each model and the observed species compositions from the data in Figure(). For brevity we only consider the most prevalent six species in this example (CLPR, BCAC, WDOW, BLGL, ARRA, BANK). Additionally, the MSE, DIC, WAIC, and Bayesian marginal likelihood model probabilities are computed for each model as measures of model fit as seen in Table().

Table() show a clear preference for the overdispersed models, with the most overall support for the beta-binomial model. This initial result guideded the use of the beta-binomial data generating model for the purposes of building a model to apply at an operational scale.

### Operationalized Model

For a particular market category, is the sample of the species' weight, in the port, caught with the gear, in the quarter, of year . As supported by the preliminary results in Figure() and Table(), The are modeled as observations from a beta-binomial distribution conditional on parameters and ,

Where is the stratum level mean weight and is the stratum level residual variance. is related to a linear predictor, , via the mean function,

Here is the observed aggregate cluster size for each sample. Additionally, is related to and the overdispersion parameter, , via the following equation,

is the within-cluster correlation. The situation where represents identical information content among replicates within a cluster, with maximal overdispersion relative to the binomial distribution. The situation where represents totally independent information content among replicates within a cluster, and the beta-binomial model approaches the binomial model. explicitly models average overdispersion across all strata within a market category, while gives the model flexibility at the stratum level through the linear predictors,

Firstly, includes a reference level intercept (). Secondly, is factored among the many strata by additive offsets from for each of the species (), port-complexes (), and gear-groups (). Finally year and quarter parameters are indicated generally here inside the term. Several forms for are explored each implying a different prior and partial pooling strategies as described in the following section().

## Priors

To complete the Bayesian formulation of this model, priors are expressed in a largely diffuse manner.

Since the reference level is chosen arbitrarily, with no conception of which values it may take, no restrictions are placed on the value of the intercept. The species (), port-complex (), and gear-group () offsets are assigned diffuse normal priors. The large fixed values of the prior variance hyperparameters produce behavior similar to classical fixed effect models for species, port-complex, and gear- group parameters.

In returning to the time parameter model, , it is useful to consider how the inclusion of predictively superfluous parameters may cause overfitting and weaken model performance through the bias-variance dilemma (Ramasubramanian, K., & Singh, A., 2016). Simply put, the bias-variance dilemma means that model formulation is not simply a bias reduction task, but rather the goal is to formulate models which reduce bias, while jointly minimizing uncertainty. Janyes (2003, pg. 511) describes how the inclusion of estimation bias via the Bayesian methodology may produce better performing estimates, more quickly, than unbiased counterparts. Among the simplest ways to see the principle is in the structure of the MSE performance metric, and how it can be explicitly written to value both estimator bias and variance, as follows.

Furthermore a model can minimize bias, without regard for estimation uncertainty, by including one model parameter to be fit to each observation. These parameter estimates are totally unbiased, however such a model is also predictively useless since each estimated parameter is specifically bound to a particular observation, and thus such a model does not generalize.

For modeling we consider a spectrum of models which span a wide range of partially pooled models with several different predictive structures as seen below.

### (M1)

(M1) represents a fixed effects model for additive year and quarter parameters. Here each year and quarter are assigned totally independent and diffuse priors.

### (M2)

(M2) estimates two hierarchical variance parameters, and . has the effect of partially pooling information among year parameters, while partially pools information among quarter parameters (i.e. treats both year and quarter as “random effects”). The actual degree of pooling among each of the years and quarters is determined by the data. Depending on the posterior distributions of and , and may be shrunk back toward the common mean for small or allowed to take largely distinct values in the case of large estimates of the .

### (M3)

(M3) functions similarly as (M2), in that it has hierarchical partial pooling among both the and parameters, except that it introduces a two-way interaction term between year and quarter. This interaction term allows estimates for particular quarters to differ from year to year, as opposed to the previous models in which quarters within a year are assumed to be identical from year to year.

Furthermore the are also modeled hierarchically to introduce a single variance parameter, , shared among all of the time chunks. Although this interaction term adds many parameters to the model, the shared parameter functions to shrink extraneous estimates back toward the common stratum mean.

### (M4)

(M4) simplifies (M3) by excluding year and quarter main effects. This leaves all temporal information in the data to be modeled solely by the quarterly interaction terms. This model represents more opportunity for partial pooling through time than (M3), as fewer time parameters are introduced. Furthermore all of the are hierarchically pooled back toward a single common stratum mean via the single shared variance parameter, .

### (M5)

(M5) is largely the same as (M4), but it represents slightly less potential partial pooling through its hierarchical prior variances, , on . Here interaction terms are allowed to partially pool interactions across years, within a common quarter, but since each quarter is assigned a separate variance parameter no pooling is possible between quarters.

### (M6)

(M6) follows the same idea as (M5), however here interaction terms are allowed to partially pool interactions within a common year, across the quarters of that year, but not between years. (M6) often involves fitting slightly more parameters than (M5) because, at least in this setting, it is typical to model more than four years of data at once.

Historically, regulations have been enacted with the aim of isolating catch in a market category to a single species (“sort requirements”). This clearly affects the composition of the target market category, but these regulations also affect the species composition of other market categories in which the target species previously occurred. We incorporate this information into the model structure by treating time periods with relatively stable regulatory conditions as independent models. In other words, information is only shared among years in which regulations were similar. For example, a sort requirement for widow rockfish (*S. entomelas*) was initiated in 1983, which not only affected the composition of the “widow rockfish” market category (xxx), but also the composition of other categories, including the “unspecified rockfish” market category (250). We model the first five years of available data (1978-1982) independently from the years 1983-1990. In 1991, a sort requirement for bocaccio rockfish (*S. paucispinis*) was enacted, which is known to have affected the composition of other categories, including the Chilipepper rockfish market category (xxx) and the Chilipepper/Bocaccio market category (xxx).

Hierarchical variance parameters are estimated from the data. As the above models learn the posteriors of the hierarchical variance parameters, it affects the degree of shrinkage as well as the effective number of parameters held within the respective hierarchies (Gelman, 2014). To achieve this, each variance parameter must itself be assigned a prior to be estimated. For all of the hierarchical variance parameters included in the above models is assigned a diffuse inverse Gaussian (IG) prior, .

Finally the overdispersion parameter, , is assigned a diffuse normal prior on the logit scale, . The prior is indeed a symmetric, and far reaching, prior when back transformed to the unit interval. To notice this, it is helpful to realize that the central 95% interval for a (i.e. ), includes almost the entirety of the back transformed unit interval (i.e. ).

Table() shows a clear preference for model (M4). It is worth mentioning that among all of the models considered here, (M4) offers the largest potential for hierarchical partial pooling among the time parameters. For the duration of the methods we build upon this preliminary result.

## Species Composition Prediction

Bayesian estimation gives access to the full posterior distribution of all of the parameters of the model. It is useful to emphasize that in the Bayesian setting, these parameters have full distributions, and they are typically handled as a large number of samples from the joint posterior distribution of the parameters. Once the posterior sampling is complete, this simplifies parameter mean and variance estimation since the required moments are simply obtained by computing the desired moments from the posterior samples. Additionally the fact that the parameters are full distributions, means that any functions of those parameters are themselves random variables, with the function representing a transformation of those parameters.

To obtain predicted species compositions from this model, first consider the posterior predictive distribution of sampled weight for a particular stratum.

Here BB is the data generating beta-binomial distribution for a predictive observation and is the posterior distribution of the parameters given the observed data. Integration of the parameters, and , is done by Monte Carlo integration to obtain samples from the predictive distribution, , for sampled weights in the stratum.

Obtaining predictive species compositions from predictive weights amounts to computing the following transformation,

Here is the predicted proportion of species in the port, caught with the gear, in the quarter, of year .

## Model Exploration & Averaging

Presently, strata with diminishingly small sample sizes are managed by an ad-hoc "data borrowing" protocol, as outlined in Pearson and Erwin (1997). The protocol for "data borrowing" calls for pooling only when forced to fill holes brought about by unsampled strata. Naturally, such a pooling protocol introduces bias to fill in unsampled strata, however due to the mathematically unstructured way in which this bias is introduced, it is hard to quantitatively justify these "data borrowing" rules.

Model (M4) avoids temporal ad-hoc "borrowing" protocols described in Pearson and Erwin (1997) by making use of its hierarchical structure to fill temporal holes with a posterior predictive distribution for unseen time periods within the modeled period. This hierarchical structure uses the data to estimate the degree of pooling through time, rather than ad-hoc "data borrowing".

Despite the benefits of modeling these data as Bayesian hierarchical models, port sampling data still remains sparse. Given the degree of sparsity in these data it is certainly possible that models which consider an additional degree of data pooling between port complexes may offer predictive benefits. In exploring strategies for pooling data across space it is necessary to formalize the port complex pooling scheme in a way which provides a mathematically understandable and scalable structure to build upon.

Given the categorical nature of port complex variables, the typical hierarchical regularization priors among port complexes are not appropriate. Rather, we frame port complex pooling as a model uncertainty problem, in which we consider some degree of port complex pooling, but the exact degree of pooling, and the particular partitioning of the pooled port complexes are not known.

Port complex pooling is achieved by repeatedly fitting model (M4) with different partitionings of the port complex variables within a particular market category and modeling time period. This model exploration exercise explores the possible ways to produce groupings of the existing port complexes so as to discover predictively useful partitionings of the port complexes. Insisting that the port complex groupings be partitions of the available port complexes provides a well-defined mathematical structure for exploring the space of pooled port complexes.

The size of the space of possible pooled models is in the setting is well defined in terms of the size of the set of items to be partitioned, , as given by the Bell numbers (),

In the case of California the set of items to be partitioned is the set of port complexes in California, of which there are , implying a grand total of ways of partitioning the port complexes in California in each market category and modeled time period. The brute force model selection strategy of computing all 115975 of these partitionings strategies is computationally infeasible. However, not all pooling schemes represent biologically relevant models. For example, perhaps it is reasonable to pool only among adjacent ports (i.e. no discontinuities between port complex pooling in space), or perhaps it is reasonable to assert that similar regions can only extend across a small number of ports.

Here only adjacent port poolings are considered, such that the maximum size of a port complex grouping is three port complexes. These are the only two constraints that are enforced on port complex partitions here, although many other constraints may, in theory, be chosen. These constraints were chosen so as to mirror the currently accepted protocols in Pearson and Erwin (1997) within the context of this framework. When these two simple constraints are applied, the number of models to explore in each modeled period is reduced to a much more manageable 274 models.

An exhaustive search of the models in the constrained subspace of , allows for a concrete comparison of the relative predictive accuracy of each partitioning. Additionally the partitioned models provide a set of candidate models for use in Bayesian Model Averaging (BMA) (Hoeting et al., 1999). BMA, as applied here, essentially allows the model exploration strategy to average across all relevant port complex configurations and adds robustness to the final species composition estimates.

For the model in a set of candidate models , then the BMA weight for follows directly from Bayes Theorem as,

Where is the posterior probability that model is the true data generating model of the data, conditional on the subspace of candidate models and the observed data. is then straightforwardly used to average posteriors across all of the models, as

# Results

## Characteristics of the Landings Data

Figures X and X show the relative sampling effort and landings across the top percent of landed rockfish market categories for two modeled periods, 1978-1982 and 1983-1990. In the top panel of each figure the black line represents the proportion of landings in each market category, while the blue line represents the proportion of samples, by number, taken in each market category. In the bottom panel of each modeled period, colors represent the proportion of sampled weight of twelve commercially relevant species. Alternating dark and light grey panels fill in all other species. On the top of each bar the number of observed species in each market category is listed. Hatched regions indicated the nominal species of a market category where applicable.

In the two time periods we examine, commercial port sampling effort in California tracks both total landed weight as well as the number of species in each market category (Figures X and X; upper panels). These two factors are among the most important characteristics to prioritize in sampling for the sake of applying our model's results to a large proportion of landings .  
Furthermore given that port sampling effort increases with increasing landed weights, when sample sizes become too small to apply our model, the expanded landings tend to represent a negligible proportion of total landings.

The lower panels of Figures X and X demonstrate just how many different species are landed into commercially relevant market categories. Although market categories often carry names that label them with a nominal species, Figure makes it abundantly clear that these names can mislead our thinking about the purity, and consistency, of these categories through time. To drive this point home, consider market category 267. The nominal label for market category 267 is Brown Rockfish, while Brown Rockfish is only a small fraction of the sampled weight in that category. In fact, only Y% of the sampled weight in 1978-1982 consisted of Brown Rockfish. In 1978-1982 market category 267 might be better named ZZZ as ZZZ amounts to W% of sampled weight in this time period, however market category 267 is composed of Yhat% Brown and What% ZZZ in recent time periods (see Appendix X, Figure ?).

![](data:application/pdf;base64,) ![](data:application/pdf;base64,) ![](data:application/pdf;base64,)

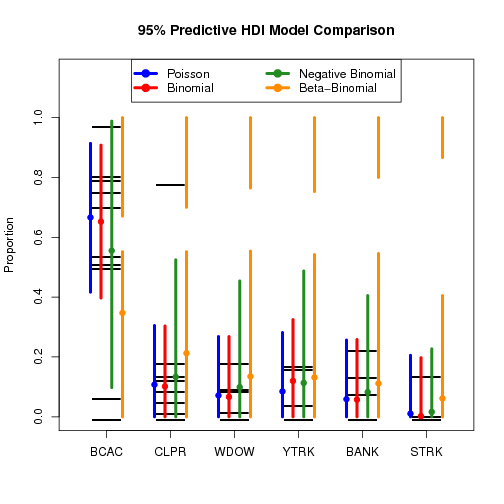
## Data Generating Model

### Example

Table(likelihood) shows model performance metrics for the previously described subset, market category 250 for the Monterey Trawl fishery in 1982. Here we consider Mean Squared Error (MSE; computed on the species composition scale), deviance information criterion (DIC), widely applicable information criterion (WAIC), and marginal Bayesian model probabilities (). These measures span a wide range of model selection philosophies and yet here they all consistently agree in ranking the likelihood models. Both of the overdispersion models considered here (NB and BB) outperform the more standard Poisson and binomial count models, with the most support being for the BB model and the Poisson model showing the least support.

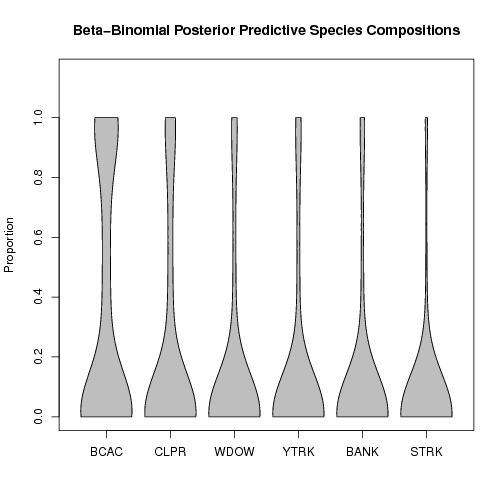
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Poisson | Binomial | NB | BB |
| MSE | 0.06412 | 0.06264 | 0.05171 | 0.04479 |
| DIC | 1342.27 | 1571.46 | 345.89 | 340.86 |
| WAIC | 1421.61 | 1665.41 | 345.09 | 341.66 |
|  |  |  |  |  |

Figure(likelihood) shows observed species compositions (black horizontal lines) plotted against Poisson, Binomial, NB, and BB predictive intervals (vertical lines). Here 95% highest density intervals (HDI) are shown to visualize the predictive accuracy of each model against the data.



Interval Plot

The large spread of the observed species compositions seen in Figure(1) visually demonstrate the degree of overdispersion present in port sampling data. The Poisson and binomial models disregard this overdispersion to prioritize fitting the data mean. The NB and BB models explicitly model overdispersion in the data, and as such they predict a larger subset of the data. Notably, only the intervals produced by the BB model include the low observed proportions of bocaccio (BCAC) and the high observed proportion of chilipepper rockfish (CLPR) in this example.



Violin Plot

The split beta-binomial intervals seen in Figure(1) reflect a large amount of residual variability to the unit interval. The beta-binomial is the only model considered here that estimates such a large degree of variability and thus it is the only model that produces predictive species composition distributions that effectively cover the range of observed species compositions. Figure(2) shows the beta-binomial predictive distributions as a violin plot demonstrating how the beta-binomial model distributes predictive density over the unit interval. The predictive intervals in Figure(1) are the smallest possible regions on each of these densities so that each intervals contain 95% probability. Species composition is bounded on [0, 1], thus in the presence of large variability predictive density may aggregate around the bounds. For the example of STRK, notice that although the predictive HDI is split, the vast majority of density lies directly atop the data.

## Predictor and Prior Selection

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | M1 | M2 | M3 | M4 | M5 | M6 |
| MSE | 0.127245 | 0.127042 | 0.126801 | 0.122373 | 0.127236 | 0.126573 |
| DIC | 39790.26 | 39491.64 | 39244.91 | 37231.70 | 39407.02 | 39406.41 |
| WAIC | 39745.58 | 39446.51 | 39192.25 | 37182.93 | 39354.11 | 39353.49 |
|  |  |  |  |  |  |  |

Table displays the relative support for the model structure on the time parameters. From M1 to M4 the models represent a spectrum of models with an increasing potential of shrinkage among time parameters. Models M5 and M6 represent models which build in complexity, from M4, via the inclusion of multiple hierarchical variance parameters among the interaction terms.

Across all of the time models, model M4 displays consistent support over all other candidate models considered here. Model M4 represents a model with maximal potential for pooling through time, while still maintain the ability to model differences in seasonality from year to year.

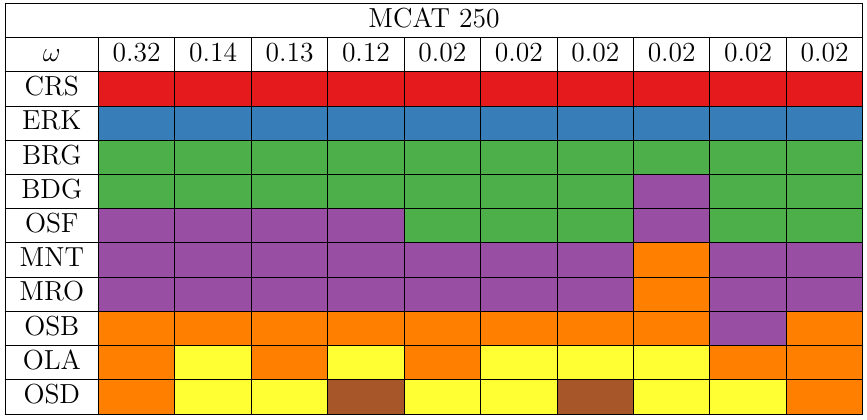
As a final check of the model structure and the implied prior information the prior predictive is considered. The prior predictive distribution summarizes the information that is intrinsic to the model structure itself, in the absence of data. The prior predictive of modeled weight is considered over a 100 pound cluster size, which is consistent with aggregating the two nominal 50 pound cluster samples described by Sen (1984) in the original sampling protocol.

![](data:application/pdf;base64,)

Prior Prediction

As seen in Figure the prior predictive of (M4) is both symmetric and quite diffuse over the 100 pound domain. The U shape of the distribution is a side effect of the diffusion of the selected prior. As data are added to the model, the indecisive U shape of this distribution collapses toward the data in the posterior.

## Model Exploration & Averaging



1978 to 1982

Figure shows the results of port complex model selection for the modeled period from 1978 to 1982 in market category 250. Along the top BMA weights, () for the top 10 models are displayed (each column is a distinct model). The following ten rows indicate the ten port complexes in California, and the colored cells indicate how port complexes are partitioned in each model.

Considering Figure, the best partitioned model (first column, ω=0.32) gives distinct parameters to CRS and ERK, while pooling BRG/BDG, OSF/MNT/MRO, and OSB/OLA/OSD. This model uses five parameters to model the ten ports complexes in California. Given the set of candidate models explained above, the BMA procedure weights this model at approximately 32% of the truth. Notice that the only difference among the top four models is in how the port complexes south of Point Conception are handled. In fact, the seven northerly port complexes are identically partitioned in the the top four models, , which also represent all of the possible partitionings of the southern three port complexes.

In this modeled period it is known that no species composition sampling was done south of Point Conception, thus it is not surprising that these models perform similarly. When no data is present, parameters simply represent place holders for out of sample prediction. Since the port complexes south of Point Conception are not informed by data, the predictions are identical in these categories. Since the first model makes identical predictions to the following three, and does so using the fewest parameters, it is correctly identified as the most parsimonious explanation among these data.

Considering how the top four model configurations share identical structure in the seven northerly port complexes, while exhaustively spanning the candidate partitions south of Point Conception, it is simple to see that BMA assigns approximately 71% marginal probability to the northerly model structure.

The results shown here only represent a single market category across the time period 1978-1982. Similar results for other market categories and time periods are provided in the appendix Figure.

* zero landings?

## Prediction

Repeatedly fitting model (M4) across port complex configurations and applying the BMA procedure, ultimately provides access to posterior predictive distributions of the species compositions () within a market category and time interval modeled period. A straight forward way to evaluate the performance of the model in each modeled period is to compare the predictions of the model in each modeled period with the actual observations of species compositions from port samplers.

We evaluated species composition posterior predictive distributions via HDI at three levels containing 68%, 95%, and 99% of posterior predictive probability. Table shows the proportion of observed species compositions which existed within the HDI across all strata, of each prediction level, in each modeled period. For example, observed species compositions for MC 250 in the 1978-1982 time period fell within the 68% HDI of the posterior predictive distribution 67.1% of the time (Table X).

* Should any of these be excluded?

### 78-82

|  |  |  |  |
| --- | --- | --- | --- |
|  | 68% | 95% | 99% |
| 250 | 67.1% | 96.1% | 98.7% |
| 253 | 67.3% | 96.3% | 98.9% |
| 262 | 67.4% | 93.8% | 95.3% |
| 265 | 69.6% | 96.0% | 97.8% |
| 269 | 68.2% | 88.8% | 90.2% |
| 270 | 68.6% | 93.6% | 96.7% |
| 956 | 68.3% | 96.7% | 99.2% |
| 959 | 68.5% | 96.3% | 98.1% |
| 961 | 69.3% | 93.2% | 95.3% |
| AVG | 68.3% | 94.5% | 96.7% |

### 83-90

|  |  |  |  |
| --- | --- | --- | --- |
|  | 68% | 95% | 99% |
| 245 | 60.8% | 94.9% | 97.7% |
| 250 | 68.1% | 96.0% | 99.0% |
| 253 | 69.3% | 97.1% | 98.9% |
| 259 | 83.8% | 91.9% | 92.9% |
| 262 | 68.5% | 95.1% | 95.9% |
| 269 | 68.6% | 94.2% | 94.7% |
| 270 | 67.9% | 94.2% | 96.7% |
| 663 | 68.1% | 94.1% | 96.3% |
| 667 | 69.4% | 92.5% | 93.5% |
| 956 | 67.5% | 96.2% | 99.0% |
| 959 | 67.4% | 96.4% | 99.0% |
| 960 | 68.0% | 96.1% | 98.6% |
| 961 | 68.6% | 94.6% | 97.8% |
| AVG | 68.9% | 94.9% | 96.9% |

Table largely shows that the observed proportion of predicted samples aligns appropriately with the predictions made by the model. Considering the average performance across market categories at each prediction level, it appears that prediction is mostly appropriate with the possible exception of the 99% prediction level. The 99% prediction level appears to slightly under-predict on average, indicating that predictive distributions are slightly lighter in the far tails than the data.

* tails lighter due to inla?
  + higher degree Laplace approximation will better capture higher moments of data and thus may better capture information in the tails

## Nuisance Parameters

### 78-82

#### 

#### 

### 83-90

#### 

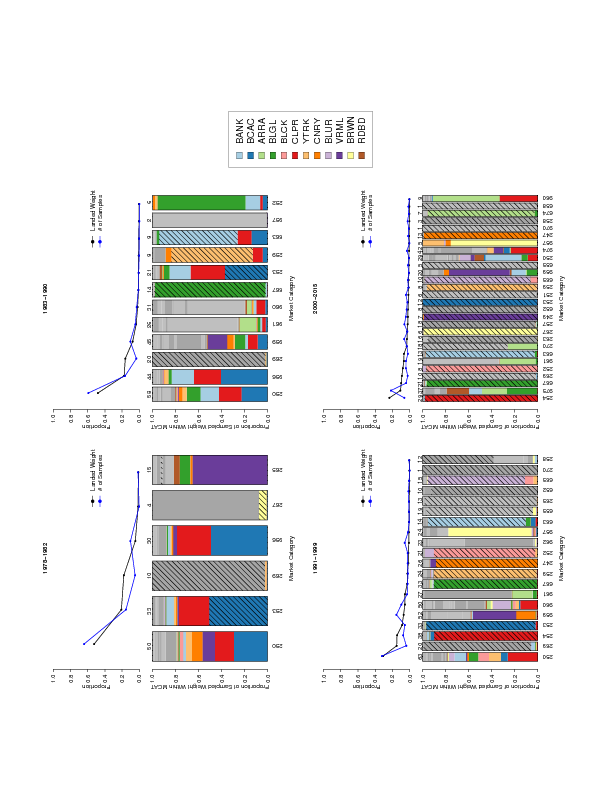
* high in 259 and over prediction in 259?
* lower rho might predict more appropriately?

#### 

* Degree of smoothing (hierarchical parameters, rho)
* Report mean/variance of example
* Add and tables across all runs

# Discussion

# Appendix



![](data:application/pdf;base64,) ![](data:application/pdf;base64,) ![](data:application/pdf;base64,) ![](data:application/pdf;base64,)

# Discussion

* Variance Estimates; Justify Model based statistics
* Biase/Variance trade off; hierarchical modeling
* Model averaging
* Looking Forward
  + forecasting/hindcasting
    - simple
    - time series models
  + more computation faster
    - broader model exploration
    - broader spatial expansion
  + Hierarchical Spatial Models
  + DP Models
* We treat the fish tickets as a census (total landed weight could be biased)
* Models that can incorporate catch uncertainty are not new (c.f. Doubleday 1976), but estimates of uncertainty in commercial landings are rarely made available, at least on the U.S. West Coast. Previous research has focused on discarded and biased (under- or over-reported) catch. Bousquet et al. (2010) developed a model-based framework for estimation of catch and associated uncertainty when underreporting is an issue. Their results included a reduction in precision of management quantities