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

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Introduction

- I am Nick
- describe the california spp comps. port sampling data for modeling
- describe our modeling efforts for estimating ssp comps.

MCATs in Time

- **Top Panel:** Number of samples in rockfish market categories (1978-2015)
  - Colors represent different market categories
  - Thickness shows the number of samples
- **Bottom Panel:** Number of rockfish market categories
  - Count the colors
  - ~20 mcats in the late 70s
  - ~50 mcats in the recent times
- **Middle Panel:** Average number of samples per stratum
  - Find samples for each stratum (mcat, gear, port, year, qtr)
  - Average them
- 1978-1982
- 1983-1990

78-82 Bars

- **Top Panel:**
  - For each market category accounting for 99% of landings
    - (blue) Proportion landings by weight
    - (red) Proportion samples by #
- **Bottom Panel:** Aggregated Species Compositions
  - Colors represent 13 select species (others grey)
  - Number above is the # species present
  - Hatching is MCAT nominal species
- MCATs not pure
  - often nominal species is not even the major species
    - BCAC
    - BRWN
- Sampling Opportunistic
  - Sampling co-occurs with landings
  - Often as more species are present there are more samples
  - This is lucky for modeling
    - More samples than parameters (largely driven by spp)
    - Most landings are modeled (78-82: 96.8%)
- No sampling south of Conception

83-90 Bars

- Same picture but 83-90
  - (blue) Proportion landings by weight
  - (red) Proportion samples by #
  - Aggregated Species Compositions
- Top 99% of landings in more market categories
  - MCATs still largely impure
- 83-90: 98.3% of landings modeled

Likelihood Forms

- First modeling choice: Pick a Likelihood
- Shelton etal. 2012 Fit Multinomial via the Multinomial-Poisson trans.
  - Piece together independent Poissons
- We are not limited to Multinomial distribution
  - quantify uncertainty (residual variability)
  - consider modeling overdispersion
  - additional parameter (ϕ) to disentangle mean from variance
- y_{ij}: i^{th} sample of the j^{th} species' integer weight
- Remove all other modeling decisions by modeling a single stratum
  - MCAT 250
  - Montery
  - Trawl
  - 1982/Q2

Likelihood Graphs

- Fit models and look are how they predict
- **Left Pannel:** 95% HDI from each model along side observed sppComp data
  - black horizontal lines are observed species comps
  - blue is Possion (i.e. Multinomial) Model
  - red is Binomial
  - green is the Negative Binomial Model
  - yellow is the Beta-binomial Model
- **Right Panel:** Entire Beta-binomial predictive distribution
- Overdispersion is present (spp comps from [0,1])
- ~50 obsevations => 2.5 missing in 95% interval
  - Maybe NB missing a few to many, and BB missing a few to few
  - BB certaintly finding the most variance
  - split intervals but... very appropriate density

Likelihood Table

- Consider MSE, DIC, WAIC, and Marginal Likelihood Bayesian Model Prob.
- Varied model selection criterion (Nothing is perfect!)
- Consistent and large support for the Overdispersion Models
  - Most support for BB
- Moving forward I develop the BB model

Beta-Binomial Model

- A Full Operationalized Model!
- $y_{ijklm\eta}$: i^{th} sample of the j^{th} species' integer weight, in the k^{th} port, caught with the l^{th} gear, in the η^{th} quarter, of year m, for a particular market category.
- Stratum μ linked to θ and observed cluster size (n)
- Stratum σ^2 is largely a function of μ but with overdispersion ρ
  - $\rho \rightarrow 0$: Binomial variance
  - $\rho \rightarrow 1$: n times Binomial variance
- Modeling of θ (all predictors are categorical):
  - Intercept
  - Additive offsets for: Species, Port, Gear
  - Consider multiple time models

Time Models

- Bayesian Modeling
  - Heirarchical v. Random Effect Disclaimer
- (M1) Fixed main effect time model
  - No pooling
- (M2) Random main effect time model
  - years/quarter pool separately
- (M3) Random main effects + random interaction
- (M4) Random interactions jointly pooled
- (M5) Random interactions quarterly variances pooling across years
- (M6) Random interactions yearly variances pooling across quarters

Priors

- Very diffuse priors
- Main effects diffuse Normals
- ρ transformed to be a real number
  - $\text{logit}(\rho) \to (-3.91, 3.91)$
  - $\rho \to (0.02, 0.98)$
- Any heirarchical variance gets the same IG prior
  - Considered others:
    * $\sqrt{v} \sim \text{Half-Cauchy}(10^{-2})$
    * $\sqrt{v} \sim \text{Unif}(0, 10^5)$

Beta-Binomial Fits

- Fit model separately in 78-82 and 83-90 and compare model selection criterion
- 78-82:
  - Consistent support for more pooling
  - All measures point to (M4)
- 83-90:
  - Consistent support for interaction models
  - Uncertainty between (M3), (M4), and (M5)
  - Lesser support for (M6)
- We fit model (M4) everywhere
  - Stable and relatively fast model to fit
  - Given its support in 78-82, I am drawn to (M4)
    * Each time period seems to have a mind of its own

$$\begin{aligned}
\beta^{(t)}_{m\eta} &= \beta^{(y)}_{m} + \beta^{(q)}_{\eta} + \beta^{(y:q)}_{m\eta} \\
\beta^{(y)}_{m} &\sim N(0, 32) \\
\beta^{(q)}_{\eta} &\sim N(0, 32) \\
\beta^{(y:q)}_{m\eta} &\sim N(0, v)
\end{aligned}$$

?? LUNCH ??

Posterior Predictive Species Comps.

- Having settled on (M4) in both time periods, how do we build species comps?
- Inference results in samples from posterior distribution $P\Big(\mu_{jklm\eta}, \sigma^2_{jklm\eta}|y\Big)$
- Run samples back through BB likelihood to compute Monte Carlo integral and get posterior predictive distribution of sampled weight.
- Use draws from model posterior predictive weight to compute species comp. distribution
  - Plot shows average species compositions
  - Full distribution for y^* as well as π^*
  - Each sample sums to 1 and $\sum_j \mathbb{E}[\pi^*_j]$=1
- By adding an unobserved latent time period we can make out-of-sample predictions
  - (M4): unobserved $\beta^{(y)^*}$ and $\beta^{(q)^*}$

Single Quarter Hindcast

- Recall for 1978-1982 there was no sampling south of point conception.
- Adding an unobserved year and quarter
  - make predictions for each species in each combo of:
    - three observed gear groups
    - three southern port complexes

78-82 Prediction

- Modeled MCATs
- MCATs in the rows **(ordered by landings)** w/ 3 nominal HDI prediction levels
  - For each stratum of each MCAT compare data to prediction intervals
  - Observed level should match Nomial
  - Prediction higher than nominal => Overfitting
  - Prediction lower => Underfitting (not enough residual variance)
- Most do well
  - Average performance is reasonable
  - Note this is a unweighted, simple, average
  - More accurate would weight average by samples at each stratum
- Particularly well in heavily landed stratum
  - correlation of sampling effort w/ landings
- Widow is a wild child
  - only example that is off by more than 5% points at any level

83-90 Prediction

- Same Table
  - Modeled MCATs **(ordered by landings)** w/ 3 nominal pred. levels
- Again most do well
- Recall landings were spread across more MCATs in 83-90
  - Enough samples to also model more MCATs
- Blackgill, Yellowtail, Cowcod: off by 5% points at some level
  - Negligable Landings

Speciating Landings

- $\lambda_{\cdot klm\eta}$ is reported on landing reciepts
- $\lambda^*_{jklm\eta}$ stored in DB
- Aggregate to any level
  - across quarter, port complex, gear group
  - Also MCAT (I ran out of index variables :/)
- E.J. will show the speciated time series with predictive intervals
  - summed across MCAT
  - as it might be used in asessment

BMA Story

- Mentioned partial pooling thru time via heirarchical modeling
- But present system also pools in space
  - Given sparcity, it's entirely possible that we also need spatial pooling
- I show MSE to demonstrate the biase/variance trade off
  - Pooling directly exchanges sample size (postior variance) with bias
  - **Far Right** Least Bias
  - **Far Left** Most Bias, but most data for small posterior variance
  - A practicle solution is somewhere in between
- [Bell number] Idea: Try all partions of port complexes
- $\mathrm{B}_{10} = 115975$
  - Too many
  - add Spatial Modeling Constraints
  - Biogeography viewed through the lens of human behavior
    - sampling behavior
    - fisherman behavior
- $\bar{\mathrm{B}}_{10} = 61136$
  - Require partitions to be "small"
  - No super-grouping greater than 3 port complexes
  - points close in space behave similarly (smoothness)
- $\hat{\mathrm{B}}_{10} = 512$
  - Require continuous partitions (no leap frogging)
  - Like a GP continunity constraint
- $\hat{\bar{\mathrm{B}}}_{10} = 274$
  - Together we have "small" and "continuous" partitions
  - smoothness and continuity
  - a computationally manageable set of models to compute

BMA Math

- Defines a candidate model set
- We could just pick the single "best" model
  - defining "best" is hard
  - model selection criterion are imperfect
- Prediction results are averaged results

78-82 BMA Results

- Describe plot
- Recall no sampling in the south
  - All latent structure filled in by predictive distribution in the south
- 250:
  - Marginal model probability
    * N1: 32+14+13+12=71%
    * N2: 2+2+2+2=8%
- 253:
  - Central Block
  - BRG/BDG
  - Lump/Split CRS and ERK (among top 5 models; 58% model weight)
    * Split: 0.3448276
    * Lump: 0.6551724
- 269:
  - Sold on the BRG-BDG break

83-90 BMA Results

- Recall BRG-OSF Missing data
- 250:
  - Missing data story
    - Lump or
    - Quarantine
- 956:
  - Lump/Split CRS and ERK
  - A break at Cape Mendicino
  - BRG/BDG/OSF Quarantine os missing data
- 269:
  - Piont Conception Break
  - Cape Mendicino Break

Conclusions

- Using Bayesian models we have:
  - Account for overdispersion
  - Estimate uncertainty (full distribution)
  - Formal Mechanisms for pooling
  - provide structure for making out-of-sample prediction
- Future Modeling
  - Explore additional predictore in θ
    - Landing weighting
    - Vessel Effects
    - Speceies:Gear interactions
  - Overdispersion Multivate models
    - Dirichelette-Multinomial Model
  - Maybe Time Series Models
  - Cluster and integrate out spatial parameters via DP?