A Bayesian Model Averaging Approach For Improving Catch Estimation Methods.

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Introduction

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 Sebastes), 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, current methods for speciating commercial landings provide ad-hoc point estimates of species compositions in unsampled strata by "borrowing" data across adjacent stratum in time and space. Due to complex interactions between biogeography and market category sorting dynamics, it is not possible to be certain about optimal a'priori pooling strategies. Here we introduce a Bayesian Model Averaging (BMA) method for discovering quantitatively justifiable pooling strategies by averaging across exhaustive sets of spatially partitioned models. In combination with Bayesian hierarchical modeling, these methods allow us to infer pooling strategies from port sampling data. Furthermore these methods allow for a complete statistical summary of several of the most important sources of uncertainty.

1. Model

Likelihood:

$$y_{ijklm\eta} \sim BB\big(\mu(\theta_{jklm\eta}),\ \sigma^2(\theta_{jklm\eta},\ \rho);\ n_{ijklm\eta}\big)$$

$$\theta_{jklm\eta} = \beta_0 + \beta^{(s)}_j + \beta^{(p)}_k + \beta^{(g)}_l + \beta^{(y:q)}_{m\eta}$$

Prior:

$$\beta_0 \propto 1 \qquad \beta^{(s,p,g)}_{j,k,l} \sim N(0, 32^2) \qquad \beta^{(y:q)}_{m\eta} \sim N(0, v)$$

$$logit(\rho) \sim N(0, 2^2) \qquad v \sim IG(1,\ 2x10^3)$$

2. Explore Spatially Pooled Models

Ways to Partition Ports:

$$\mathrm{B}_K = \sum_{\kappa=0}^{K} \frac{1}{\kappa!}\left(\sum_{j=0}^{\kappa}(-1)^{\kappa-j}\binom{\kappa}{j} j^K\right).$$

Spatial Constraints:

$\bar{\mathrm{B}}_K$: Groupings are small ($\leq$3 Ports)
$\hat{\mathrm{B}}_K$: Groupings are contiguous
$\hat{\bar{\mathrm{B}}}_K$: Groupings are small and contiguous

3. Bayesian Model Averaging

$$\omega_\iota = Pr(M_\iota|y) = \frac{p(y|M_\iota)p(M_\iota)}{\sum_\iota p(y|M_\iota)p(M_\iota)}$$

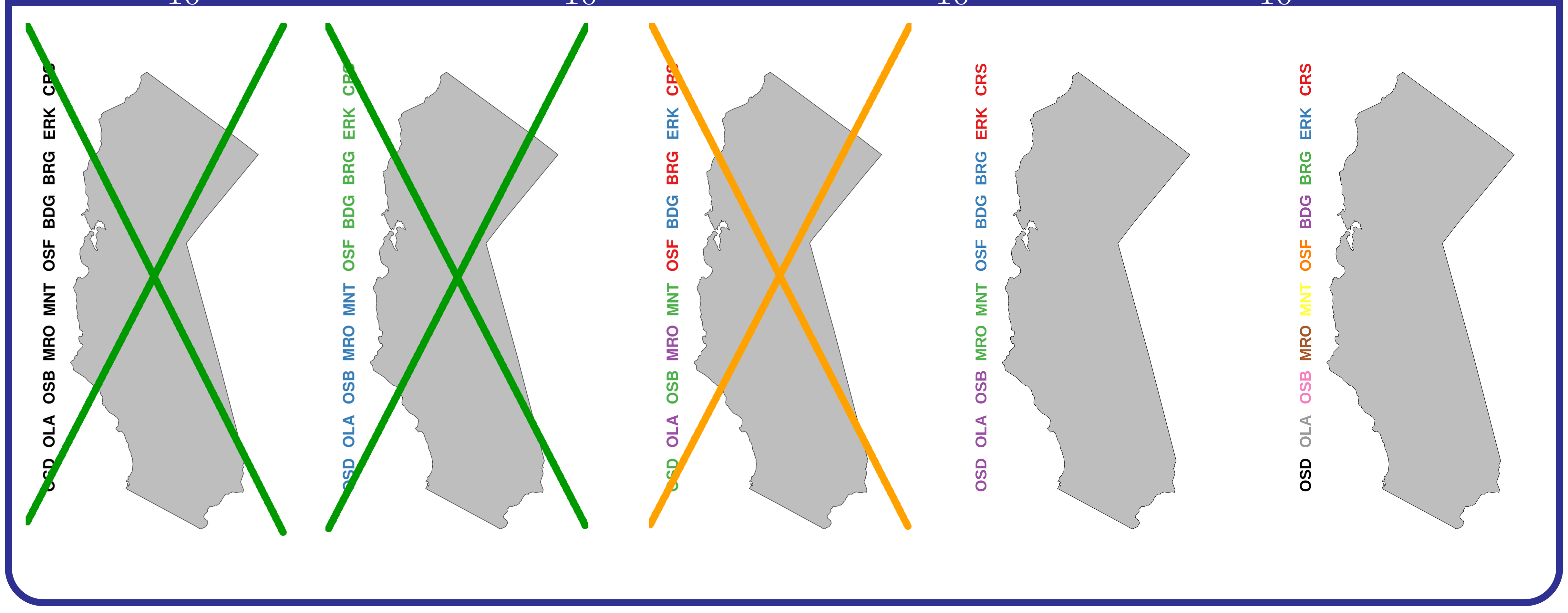
$$\bar{p}(\boldsymbol{\theta}|\boldsymbol{y}) = \sum_\iota \omega_\iota p(\boldsymbol{\theta}|\boldsymbol{y}, M_\iota)$$

$$\bar{p}(y^*|\boldsymbol{y}) = \int BB(y^*|\boldsymbol{\theta})\bar{p}(\boldsymbol{\theta}|\boldsymbol{y})\boldsymbol{d\theta}$$

Species Composition:

$$\pi^*_{jklm\eta} = \frac{y^*_{jklm\eta}}{\sum_j y^*_{jklm\eta}} \qquad y^*_{klm\eta} \neq 0.$$

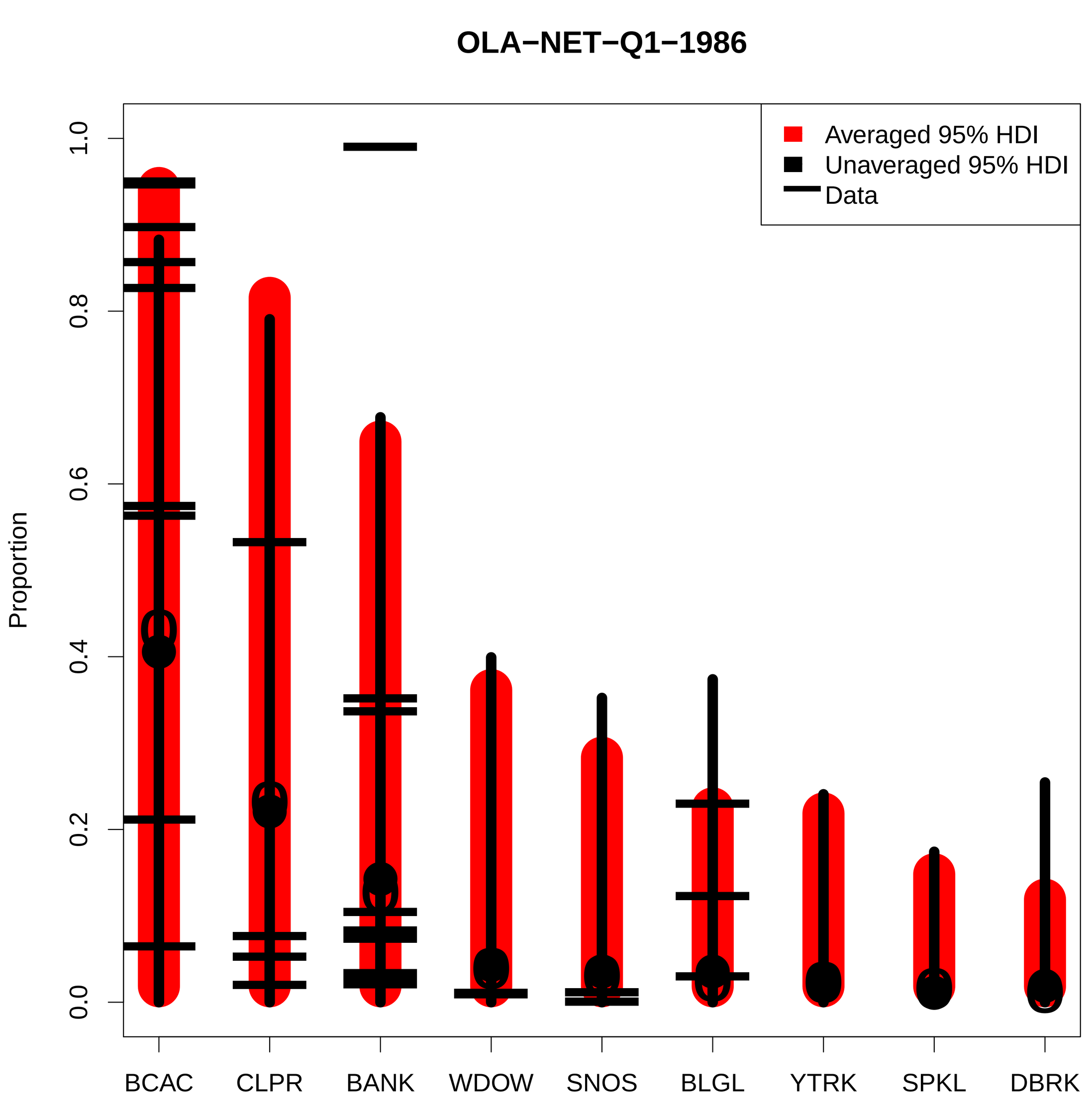
$\mathrm{B}_{10} = 115975$ $\bar{\mathrm{B}}_{10} = 61136$ $\hat{\mathrm{B}}_{10} = 512$ $\hat{\bar{\mathrm{B}}}_{10} = 274$

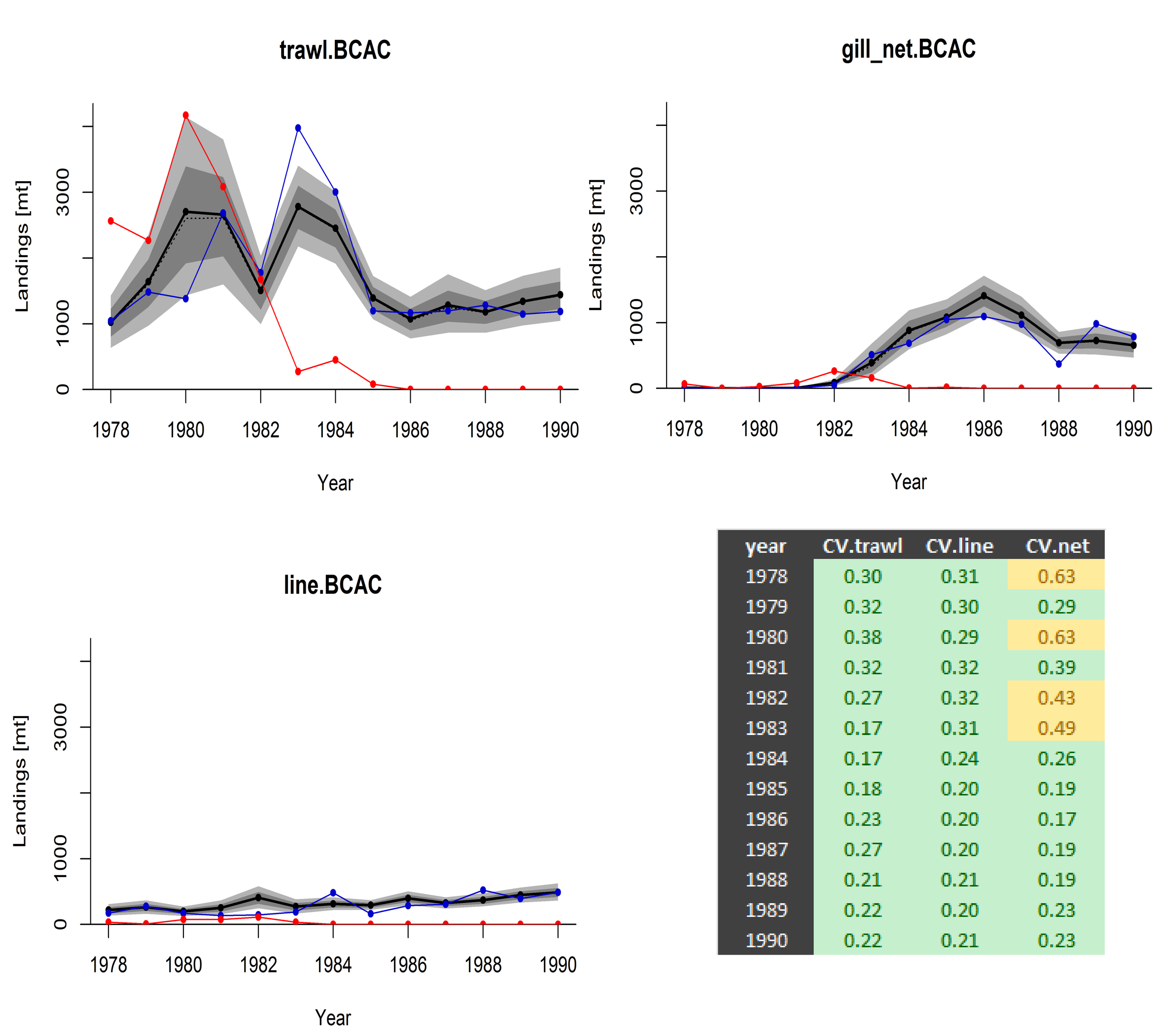


Group Bocaccio/Chili: 1983-1990

MCAT 956					
ω	0.26	0.21	0.19	0.11	0.10
CRS					
ERK					
BRG					
BDG					
OSF					
MNT					
MRO					
OSB					
OLA					
OSD					

Results





year	CV.trawl	CV.line	CV.net
1978	0.30	0.31	0.63
1979	0.32	0.30	0.29
1980	0.38	0.29	0.63
1981	0.32	0.32	0.39
1982	0.27	0.32	0.43
1983	0.17	0.31	0.49
1984	0.17	0.24	0.26
1985	0.18	0.20	0.19
1986	0.23	0.20	0.17
1987	0.27	0.20	0.19
1988	0.21	0.21	0.19
1989	0.22	0.20	0.23
1990	0.22	0.21	0.23

(Left) Species composition predictions from the ensemble model, along side predictions from the base model, and raw data from an example stratum in MCAT 956. (Right) Grey regions show the BMA landings 80% and 25% intervals for BCAC by gear from 1978-1990, current calcom estimates shown in blue, and nominal expansion shown in red. BMA CVs are shown in the bottom right.

Conclusion

A Bayesian model-based method for speciating commercial landings shows promise. BMA adds robustness to models by effectively integrating over modeling uncertainties.

Achievments of the Bayesian Approach:

- Model Overdispersion
- Robust Uncertainty Estimation
- Mechanisms for Pooling
- Out-of-Sample Predictions

Future Directions:

- Explore Additional Random Effects
- Possible Multivariate Likelihoods
- Dirichlet Process Models