



# A Bayesian Model Averaging Approach For Improving Catch Estimation Methods.



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## 1. 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 combining Bayesian hierarchical models with BMA allows for a complete statistical summary of the major sources of uncertainty in species composition estimates.

## 2. Model

### Likelihood:

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

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

### Prior:

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

$$\text{logit}(\rho) \sim N(0, 2^2) \quad v \sim IG(1, 2 \times 10^3)$$

## 3. Model Exploration

### Number of Partitioned Models:

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

### Spatial Constraints:

$\bar{B}_K$ : Groupings are small (<3 Ports)

$\hat{B}_K$ : Groupings are contiguous

$\hat{\hat{B}}_K$ : Groupings are small and contiguous

## 4. Bayesian Model Averaging

$$\omega_i = Pr(M_i|y) = \frac{p(y|M_i)p(M_i)}{\sum_i p(y|M_i)p(M_i)}$$

$$\bar{p}(\theta|y) = \sum_i \omega_i p(\theta|y, M_i)$$

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

### Species Composition:

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

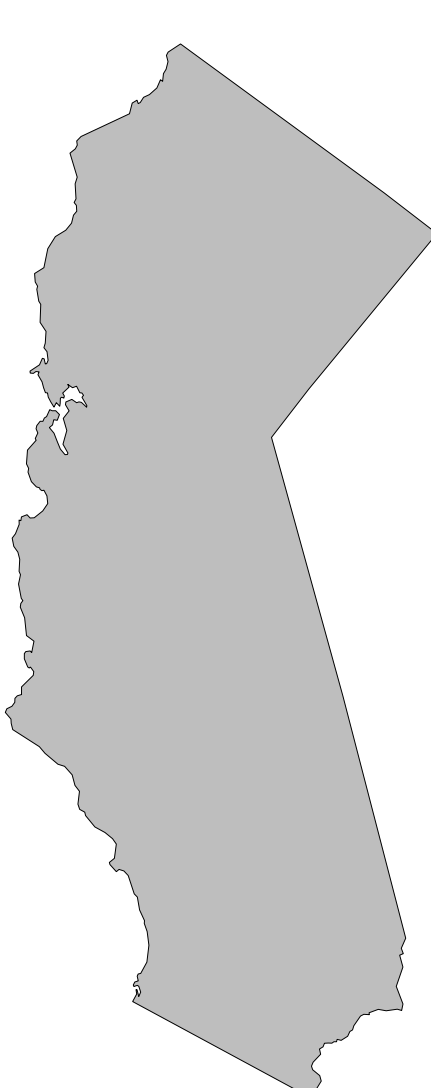
$B_{10} = 115975$

$\bar{B}_{10} = 61136$

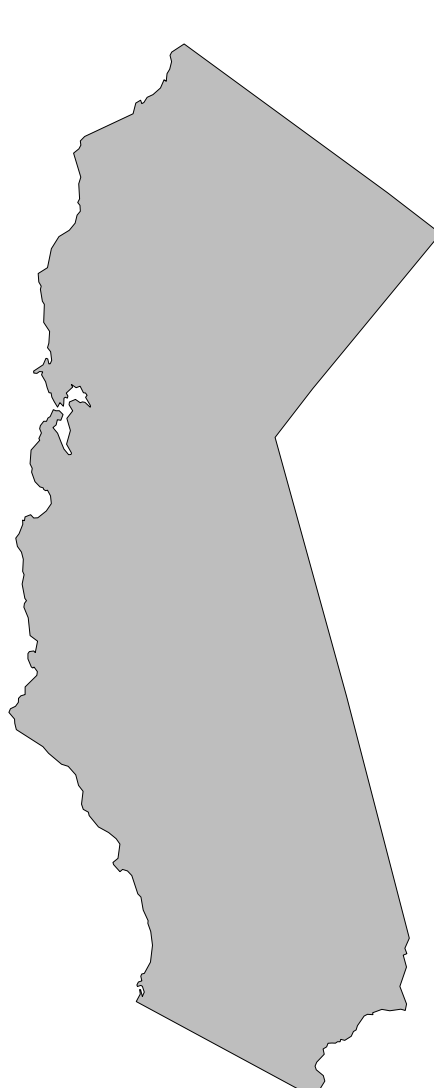
$\hat{B}_{10} = 512$

$\hat{\hat{B}}_{10} = 274$

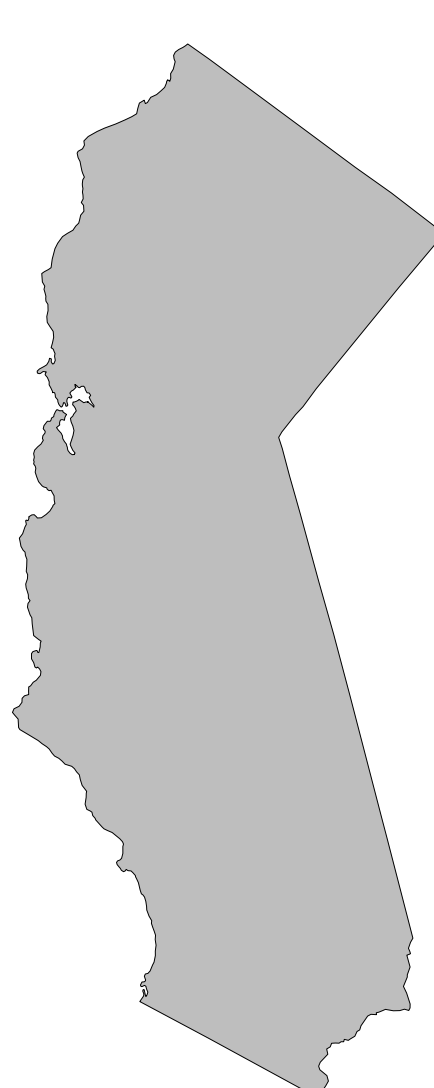
OSD OLA OSB MRO MNT OSF BDG BRG ERK CRS



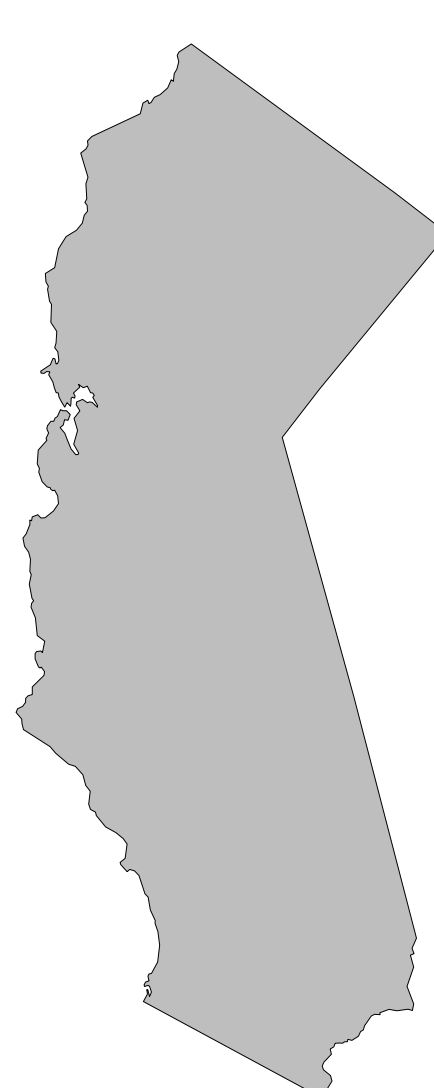
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