Elsevier Editorial System(tm) for Fisheries Research
Manuscript Draft

Manuscript Number:

Title: Accounting for space-time interactions in index standardization models

Article Type: Research Paper

Keywords: index standardization; mixed-effects model; posterior predictive score; deviance information criterion; Bayesian model

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Manuscript Region of Origin: USA

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Included is a manuscript entitled “Accounting for space-time interactions in index standardization models.” Drs. Ward and I have all contributed to the work, accept responsibility for it, and agree to its submission to Fisheries Research. We do not have any extended abstracts, related articles, or reports submitted or published elsewhere related to it.

Indices of abundance derived from scientific survey data are perhaps the single most important data input in stock assessment models. For at least ten years, these indices are primarily estimated using a class of index standardization model called delta-generalized linear mixed models (delta-GLMMs). In this time, however, no study has attempted a review of methods accounting specifically for statistical interactions between spatial (e.g., strata) and temporal (e.g., year) variables in these models (a.k.a. space-time interactions), or of correlations in these interactions between presence/absence and positive catch rate model components. We therefore developed a novel delta-GLMM model that incorporates correlations between different delta-GLMM model components, and tested this and other space-time interaction models using data for 28 species off the U.S. West Coast. We find that random space-time interactions are supported in most cases, and that correlations between presence/absence and positive catch rates are positive for the few cases where the correlation is statistically significant. However, accounting for this correlation has little impact on resulting indices of abundance.

Index standardization models are widely used in fisheries science and stock assessment, and often require some treatment of space-time interactions. We therefore believe that this manuscript will have a wide audience and will be well cited. Additionally, we note that Fisheries Research has published many of the foundational papers in index standardization, including Maunder and Punt (2004) "Standardizing catch and effort data: a review of recent approaches" *Fish. Res.* **70**: 141–159. We therefore believe that Fisheries Research is the most appropriate journal for this research.

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Graphical Abstract (for review)

Highlights (3-5, 85 char. incl. spaces each):

- Interactions between spatial strata and year are important in index standardization
- Model selection supports strata-year interactions for many Pacific fish species
- Correlated strata-year interactions are important and positive for several species
- Correlated and uncorrelated strata-year interactions yield similar abundance indices

Accounting for space-time interactions in index standardization models

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Abstract

Scientific survey data are used to estimate abundance trends for fish populations worldwide, and are frequently analyzed using delta-generalized linear mixed models (delta-GLMMs). Delta-GLMMs incorporate information about both the probability of catch being non-zero (catch probability) and the expected value for non-zero catches (catch rates). They generally incorporate year as a main effect, and frequently account for spatial strata and/or covariates. Many existing delta-GLMMs do not account for random or systematic differences in catch probability or rates in particular combinations of spatial strata and year (i.e. space-time interactions), and do not recognize potential correlation in random space-time interactions between catch probability and catch rates. We therefore develop a novel Bayesian delta-GLMM that estimates correlations between catch probability and rates, and compare it with either (a) ignoring year-strata interactions, (b) modeling year-strata interactions as fixed effects, or (c) estimating year-strata interactions in catch probability or rates as independent random effects. These four models are fitted to bottom trawl survey data for 28 species off the U.S. West Coast. Model selection using posterior predictive scores indicates that random strata-year interactions are supported for the majority (22) of species. The posterior median of the correlation is positive for the majority (19) of species, including all 5 for which the posterior distribution is significantly different from zero. However, estimating this correlation has little impact on resulting abundance indices or confidence intervals. We therefore propose that this model is useful in distinguishing spatial patterns in survey data, particularly for datasets longer than our case study (9 years), but do not believe that is will have a large impact on index standardization of the West Coast bottom trawl dataset.

Keywords (5 max): index standardization, mixed-effects model, posterior predictive score, deviance information criterion, Bayesian model

1. Introduction

Scientific surveys are conducted worldwide and are an important source of information about abundance trends in marine species. Indices of annual stock abundance obtained from survey data are generally incorporated into population dynamics models to estimate stock productivity, current stock status, and allowable catch levels (Quinn and Deriso 1999). These outputs are then used to inform fisheries management policy such as annual catch and/or fishing effort levels.

Scientific survey data usually include catch and effort statistics for each survey occasion, and catch per unit effort (CPUE) is commonly treated as a measure of local densities. CPUE data can be summarized using simple statistics (i.e. mean CPUE) or complex standardization models to provide an index of stock abundance. Index standardization models provide several benefits over simple summary statistics when analyzing survey data, including: (1) improving estimates of indices and confidence intervals (Ye and Dennis 2009); (2) controlling for variables such as sampling vessel, season, and spatial location; (3) incorporating auxiliary information such as fishing hook depth (Bigelow and Maunder 2007); and (4) accounting for stratified and unbalanced sampling designs, i.e. where particular areas and/or years are sampled more or less heavily than others due to intentional sampling design or random chance (Wiedenmann and Essington 2006). Index standardization models may also explicitly account for species biology, e.g., fishing schooling behaviors (Thorson et al. 2012).

Delta-generalized linear models (delta GLMs) have become widely used in fisheries and other fields for index standardization because they allow separation of the model into two components (Pennington 1983, Stefansson 1996). The first component uses the detection or non-detection of the species at each survey location to estimate changes in species range over time. The second component uses the catch rate for survey occasions where the species was detected to estimate population density within its occupied range. Overall stock abundance is then calculated as the product of stock range and densities within the occupied range. Both model components are necessary because marine species will often undergo changes in densities and stock range over time. Delta-GLMs approximate the expected value of each model component as a function of covariates, and have been recently extended into a mixed-effects modeling framework (delta-GLMMs), allowing grouping variables (year, strata, vessel) to also be treated as random effects. Delta-GLMMs used for index standardization always include a coefficient representing 'Year' for both presence/absence and positive catch model components because the focus of inference is on changes in abundance from one year to the next. Standardization models also frequently include 'Area' (a factor representing different sampling regions or strata), for example, to account for consistent differences in stock density between on- and off-shore habitats (Maunder and Punt 2004).

An interaction between year and area (Year×Area) can be included in the delta-GLMM to represent abundance changes that differ among spatial areas in a random or systematic manner. Systematic changes in abundance among areas, e.g., caused by different fishery exploitation rates in different portions of stock range, are treated by including Year×Area as a fixed effect, i.e. by estimating a separate parameter representing stock abundance in each year and area. Random differences, e.g., caused by random annual changes in the distribution of total stock abundance among multiple regions, are treated by including Year×Area as a random effect. Treating Year×Area as a random effect only requires estimating a single parameter (the variance of random Year×Area deviations), and is in some cases a more parsimonious treatment of random distributional changes than treating Year×Area as a fixed effect. Random effects are appropriate when each random effect coefficient is exchangeable (believed to arise from a 'random,' independent, and identical distribution) for each year-area combination (Gelman and Hill 2007). Treating Year×Area as random will explain some portion of residual variance, likely resulting in tighter estimates of index confidence intervals.

Delta-GLMMs generally treat random effects regarding the probability of non-zero catch and the expected catch for non-zero catches in a given year-area combination as statistically independent. This assumption may commonly be violated. As one example, random environmental conditions may cause the target species to be more tightly aggregated in a given year and area, thus causing fewer positive observations but greater expected catches for positive catches. In this case, the random effect for the catch rate component will be negatively correlated with the random effect for presence/absence component, in violation of the common delta-GLMM assumption that all random effects are exchangeable. By contrast, random environmental changes may cause a population to move into different strata than usual. For strata into which they move, the probability of non-zero catch and the expected catch for non-zero catches will both increasing, causing a positive correlation between Year×Area coefficients. This violation of random effect model assumptions can be rectified by estimating a correlation between random effects within a given year-area combination, although we know of no fisheries studies or models in other fields that have explored this.

In this manuscript, we compare four alternative treatments of spatial and temporal interactions ('space-time interactions') in delta-GLMM models: (1) not including any Year×Area interaction; (2) treating Year×Area as fixed effects separately in both the presence/absence and catch rate model; (3) treating Year×Area as independent random effects separately in both the presence/absence and catch rate model; and (4) treating Year×Area as random effects that are correlated between presence/absence and catch rate model components. We apply all four models to bottom trawl survey data obtained from 2003-2011 for 28 species off the U.S. West Coast, and use model selection to identify which of these models are parsimonious for each species. We also compare resulting abundance indices and confidence interval widths for each model, as inclusion of another parameter is likely to result in less precise estimates of abundance. Last, we explore the direction and magnitude of random effect correlations, to identify whether correlations between presence/absence and positive catch components are likely to be positive or negative for these 28 species. We hypothesize that positive correlations would be caused by changes in distribution among strata, while negative correlations would be caused by changes in distribution within strata.

2. Methods

2.1 Data availability

As a case study, we use bottom trawl catch and effort data obtained from the NMFS NWFSC shelf and slope survey off the U.S. West Coast (Keller et al. 2008, Bradburn et al. 2011). This survey uses a stratified random sampling design with six sampling strata composed of three depths categories (55-183 m., 184-549 m., and 550-1280 m.) and two latitude categories (32-34.5, and 34.5-50 degrees latitude), wherein sampling intensity is approximately equal to the area in each stratum. For the purposes of this study, we adopted the default post-stratification used by the NWFSC (A. Hicks, pers. comm. 2012), which uses the three depth categories from the sampling design and five latitudinal categories (32-34.5, 34.5-40.5, 40.5-43, 43-47.5, and 47.5-50 degrees latitude). This results in 15 spatial strata.

We compiled data for 5756 sampling tows from 2003-2011 by the NWFSC shelf/slope survey. We analyze data for 28 finfish species (Table 1) that were chosen because they either (a) are flatfishes, (b) were assessed in 2011, (c) were likely to be assessed in 2013, or (d) had 200-

500 positive catches between 2003-2008 (‘positive catches’ representing occasions when the species was detected on a sampling occasion), where this level was chosen to ensure that species had information for estimating both presence/absence and positive catch rate model components. These species range widely in the probability of occurrence from 84.1% (Dover) to 1.7% (yelloweye), and in the average catch for positive tows from 1.6 kg. (cowcod) to 78.6 kg. (chilipepper). Within each year, sampling for the NWFSC shelf/slope survey occurs in the same time period (May-Oct.) and represents a snapshot of annual biomass that is comparable among years.

2.2 Model overview

We first present the 'correlated model' because it represents the most complicated of the four models. We then present in turn how each other model is derived from the correlated model. We use a Bayesian hierarchical modeling framework, which specifies prior probabilities for model parameters and the conditional probability of the data given parameters to define the posterior distribution of model parameters. We use Bayesian methods to ease the calculation of confidence intervals for the index of abundance that is calculated from presence/absence and positive catch rate components, and because it eases computation of the bivariate integral necessary for the correlated model.

2.2.1 Correlated strata×year effects

The probability of catch C being non-zero is approximated by a logistic regression model:

$$p(C>0\,|\,s_i,y_i)=\Phi\left(\sum_{i=1}^{n_{strata}}\omega_j^{(s)}I(s_i=j)+\sum_{i_{year}=1}^{n_{year}}\omega_k^{(y)}I(y_i=k)+\sum_{i_{strata}=1}^{n_{strata}}\sum_{i_{year}=1}^{n_{year}}\omega_{j.k}^{(sy)}I(s_i=j)I(y_i=k)\right) \quad (1)$$

where s_i and y_i are strata and year for tow i, $\omega^{(s)}$, $\omega^{(y)}$, and $\omega^{(vs)}$ are parameters representing the effect of strata, year, and the strata×year interaction on the probability that C is non-zero, n_{strata}

and n_{year} are the number of strata, years, and vessels, respectively, j and k are indices representing strata and year, respectively, Φ is the logistic transformation $\Phi(X)$ = $\exp(X)/(1+\exp(X))$, and $I(x=b)$ is an indicator variable that equals one if $x = b$ and zero otherwise.

The probability density for catch C given that catch is non-zero is approximated by a gamma distribution:

$$p(C=c\,|\,C>0,s_i,y_i,a_i)=\mathrm{Gamma}(c\,|\,\alpha,\beta_i) \qquad (2)$$

where $\alpha = 1 / CV^2$, $\beta_i = 1 / (\mu_i \cdot CV^2)$, CV is the estimated coefficient of variation for C given that $C > 0$, and μ_i is the expected value of catch for non-zero tow i. We assume that the CV of all non-zero catches is the same (and therefore do not use a sub-script for α). Other distributions may be appropriate (lognormal, inverse Gaussian, etc) but for skewed distributions that occur in fishery data, the gamma distribution is well behaved (Myers and Pepin 1990). The μ_i is in turn approximated by an exponential-transformed linear model:

$$\mu_i = a_i \cdot \exp\left(\sum_{j=1}^{n_{strata}} \gamma_j^{(s)} I(s_i=j) + \sum_{k=1}^{n_{year}} \gamma_k^{(y)} I(y_i=k) + \sum_{j=1}^{n_{strata}} \sum_{k=1}^{n_{year}} \gamma_{j,k}^{(sy)} I(s_i=j) I(y_i=k)\right) \qquad (3)$$

where a_i is the area swept (in hectares) for tow i, and $\gamma^{(s)}$, $\gamma^{(y)}$ and $\gamma^{(vs)}$ are parameters representing the effect of strata, year and the strata×year interaction on the expected value of non-zero catch C_i.

Strata×year interactions are treated as random effects, and specify that the random effect for presence/absence $\omega^{(sy)}$ in strata s and year y is correlated with the random effect for positive catch rates $\gamma^{(sy)}$ in strata s and year y:

$$p(\omega_{j,k}^{(sy)}, \gamma_{j,k}^{(sy)}\,|\,\Sigma_{sy}) = \mathrm{MVN}(0, \Sigma_{sy}) \qquad (4)$$

where MVN(μ,Σ) is a multivariate normal density function, and Σ_{sy} is the covariance among strata×year random effects within a given strata-year combination:

$$\Sigma_{sy} = \begin{bmatrix} \sigma_\omega^2 & \rho_{sy}\sigma_\omega\sigma_\gamma \\ \rho_{sy}\sigma_\omega\sigma_\gamma & \sigma_\gamma^2 \end{bmatrix} \tag{5}$$

where σ_ω^2 and σ_γ^2 are the variance for positive catch rate and presence/absence random effects, and ρ_{sy} is the estimated correlation between strata×year random effects for presence/absence and positive catch rates model components.

The Bayesian model specification is completed by including prior distributions for all parameters. We used a weakly-informative gamma prior on α, $p(\alpha)$ = Gamma(0.001,0.001), and bounded uniform priors on all fixed-effect parameters $p(X) = 1/10$ if $-5 < X < 5$ and zero otherwise, where X represents $\gamma^{(s)}$, $\gamma^{(y)}$, $\omega^{(s)}$, and $\omega^{(y)}$. Because the correlated strata-year effects are treated as multivariate normal, we used a standard conjugate inverse-Wishart prior on the covariance matrix (Gelman et al. 2003). For the simpler case of uncorrelated random effects, we used weakly-informative bounded uniform priors on the standard deviation of strata×year random effects $p(X) = 1/20$ if $0 < X < 20$ and zero otherwise, where X represents σ_ω or σ_γ (Gelman 2006).

The posterior distribution for the model is then defined as the product of all terms defined previously. Samples from the posterior distribution are calculated using Markov chain Monte Carlo (MCMC) methods as implemented in JAGS (Plummer 2003) and called from the R statistical platform (R Development Core Team 2011) using the R2jags package (Su and Yajima 2012).

2.2.2 Uncorrelated Year×Area *effects*

As a second model, we consider allowing Year×Area effects in the presence/absence and positive catch rate components to be independent ('uncorrelated Year×Area') by specifying that correlations are zero (c_{sy} = 0). This has the result that Σ_{sy} is diagonal.

2.2.3 Fixed Year×Area *effects*

As a third possible model, we specify that Year×Area effects are estimated as fixed effects. This model eliminates Eq. 4-5, and instead specifies bounded uniform priors on Year×Area effects, $p(X) = 1/10$ if $-5 < X < 5$ and zero otherwise, where X represents $\gamma^{(sy)}$ and $\omega^{(sy)}$.

2.2.4 Absent strata×year effects

The fourth model we implement involves no estimation of Year×Area effects (but still retains the fixed area and year effects, as in all of the above models). The model without Year×Area interactions again eliminates Eq. 4-5, and specifies that Year×Area effects are zero, $\gamma^{(sy)} = \omega^{(sy)} = 0$.

2.3 Estimating an index of abundance

All four models (correlated, uncorrelated, fixed, and absent) are then used to estimate an index of abundance for all 28 species. This index is calculated by multiplying the posterior distributions for the probability of non-zero catch and the probability density of catch when non-zero, and taking the sum weighted by strata area A_j for each stratum j:

$$p(N_k \mid c,s,y,a) = \sum_{j}^{n_{strata}} A_j \cdot p(C_{j,k} > 0 \mid c,s,y,a) \cdot p(\mu_{j,k} \mid C_{j,k} > 0, c,s,y,a) \tag{6}$$

where $p(N_k \mid c,s,y,a)$ is the probability density for random variable N_k representing abundance in year k given all available data (i.e., catch c, strata s, year y, and area swept a for all tows), $p(C_{j,k} > 0 \mid c,s,y,a)$ is the probability that catch $C_{j,k}$ in strata j and year k is positive, and $p(\mu_{j,k} \mid C_{j,k}>0, c,s,y,a)$ is the probability density of non-zero catches $\mu_{j,k}$ for that year and strata:

$$p(C_{j,k} > 0 \mid c,s,y,a) = \Phi\left(p(\omega_j^{(s)} \mid c,s,y,a) + p(\omega_k^{(y)} \mid c,s,y,a) + p(\omega_{j,k}^{(sy)} \mid c,s,y,a) \right) \tag{7}$$

$$p(\mu_{j,k} \mid c,s,y,a) = \exp\left(p(\gamma_j^{(s)} \mid c,s,y,a) + p(\gamma_k^{(y)} \mid c,s,y,a) + p(\gamma_{j,k}^{(sy)} \mid c,s,y,a) \right) \tag{8}$$

where $p(X|c,s,y,a)$ is the posterior distribution for parameter X. We use the median of $p(N_k \mid c,s,y,a)$ as the index of abundance, and the standard deviation of $p(N_k \mid c,s,y,a)$ divided by its median as a measure of precision for N_k.

2.4 Comparisons among models

We compare the performance of models with correlated, uncorrelated, fixed, and absent strata×year interactions using several performance metrics. We explored two versions of the Deviance Information Criterion (DIC, Spiegelhalter et al. 2002, Sturtz et al. 2005) for model selection, although we found that DIC generated spurious results in many cases (e.g., selected a correlated model when the posterior distribution for the correlation c_{sy} was centered at zero) and also generating conflicting advice depending upon the form of DIC used. This is unsurprising, given that DIC is unreliable for models where the posterior distribution is bimodal, as will often occur for mixed-effects models such as ours. We therefore used posterior predictive scores (Gneiting et al. 2007, Shelton et al. 2012) to evaluate which of these models is most parsimonious for each of the 28 species:

$$S = -\ln\left(\prod_{i=1}^{n_{samples}} \frac{1}{n_{mcmc}} \sum_{l=1}^{n_{mcmc}} \Pr(C_i \mid \boldsymbol{\beta}_l) \right) \tag{9}$$

where $n_{samples}$ is the total number of survey sample observations, n_{mcmc} is the number of thinned MCMC samples from the posterior distribution, and $\boldsymbol{\beta}_l$ is the l-th MCMC sample from the vector of model parameters. ΔS (the difference between S for each model and the lowest S) is reported for each model and, although there is no theoretical guidance on how to interpret ΔS, we found that $\Delta S < 2$ was able to discriminate between models that had good and poor model fit and parsimony.

We report the estimated random-effect correlation for each species. We also compare indices of abundance and credible interval width arising from all species, to explore whether (a) different treatments of Year×Area interactions results in appreciable differences in estimated indices and (b) whether correlated models generally increase or decrease confidence interval width compared with other methods.

3. Results

3.1 Model selection

Comparison of ΔS among models for each species (Table 2) shows that the model without Year×Area interactions is selected 6/28 times, and the model with Year×Area interactions as a fixed effect is only selected 1/28 times. There is no obvious pattern in terms of probability of occurrence of average positive catch for those species where Year×Area interactions are not selected. ΔS identifies support for Year×Area as a random for 22/28 species (shortspine thornyhead has $\Delta S < 2$ for both the random and the absent interactions). Thus, the majority of species have support for some random space-time interaction. For those species where $\Delta S < 2$ for both the random and correlated models, we use the posterior distribution for the random-effect correlation c_{sy} to interpret whether the correlated model is supported. Of these species, the posterior for c_{sy} is greater than 95% positive for English sole, hake, rosethorn rockfish, and shortbelly rockfish. The posterior for c_{sy} is also greater than 90% positive for widow rockfish. Inspection of the posterior distribution for c_{sy} for each species (Fig. 1) suggests that other species (e.g. canary and bocaccio) might be positive, although the length of the current dataset a not sufficient to be confident. The correlation is positive for all five species where the posterior substantially differs from zero, and the median correlation is positive for 19/28 species. This generally positive correlation of Year×Area random effects between presence/absence and positive catches could arise from random changes in spatial distribution among years which causes increased (decreased) abundance in particular strata and years, in turn causing increased (decreased) probability of detection and catches when detected.

3.2 Comparing abundance index estimates and precision

Comparison of the abundance indices for the random and correlated models for those species where $\Delta S < 2$ for these models and where $\Pr[c_{sy} > 0] > 0.9$ (Fig. 2) shows that there is little difference in the estimated indices or confidence intervals. However, minor exceptions do occur, such as the 10% greater log-standard deviation for shortbelly rockfish in 2003 for the random effect model (0.59) than the correlated model (0.54). By contrast, the correlated model has a greater standard deviation than the random model in other years (e.g., shortbelly 2005). One interesting computational result was that even when the posterior correlation of the Year×Area effects was estimated to be closed to zero, generating MCMC samples using JAGS is considerably faster (by >2 fold) for the correlated than the random model. Exploratory analysis indicates that this is likely due to the improved speed of joint sampling from a multivariate normal distribution (used by the correlated model), rather than two independent normal distributions (used by the random model).

4. Discussion

Simple survey analysis models for count data imply a linkage between the probability of detection and the expected catch. For example, sampling locations with a greater expected value for non-zero catches will also have a greater probability of non-zero catch when using a Poisson-distributed GLM. This correlation between probability of detection and expected catch for count data is also maintained for more-complex models, e.g., zero-inflated negative binomial GLMMs. However, survey analysis models for continuous-valued data (e.g. catch weight per hectare as often used in fisheries stock assessment) have not previously been developed that incorporate a correlation between the probability of positive catch and the expected catch. We rectified this absence by developing a novel delta-generalized linear mixed model that estimates a correlation between random effects affecting the positive and presence/absence model components. This model allows for greater comparability with count-data models, and is also intended as a method to evaluate the strength of evidence for such a correlation.

Overall, we find mixed support for a correlation between the probability of positive catch and the expected value of non-zero catch. This correlation is significant for only 5 of 28 species, but is positive for the majority. A positive correlation can be caused by either environmental or anthropogenic causes that cause random interannual changes in distribution among spatial strata. Potential environmental causes include transient oceanographic effects, which could cause a relocation of migratory species (e.g., Pacific hake) to suitable habitats (Methot and Dorn 1994). Potential anthropogenic causes for a correlation include changes over time in the fishing intensity in different strata, which by decreasing total abundance in particular strata will cause a synchronized decrease in the probability of detection and expected catch size when detected in those strata.

For the NWFSC dataset analyzed here, the exact mechanism responsible for correlations in Year×Area terms remains unclear, because the species for which it is supported differ greatly in their distribution (e.g., Pacific hake are encountered throughout the bottom trawl sampling strata while shortbelly rockfish is primarily encountered in S. California), degree of fishing pressure (shortbelly has close-to-zero fishing mortality, the relative exploitation rate of English sole is close to 2%, and the relative exploitation rate of hake is 10% in recent years; Field et al. 2007, Stewart 2007, Stewart et al. 2011), migration (rockfish are sedentary, English sole and Pacific hake are migratory) and age at maturity (English sole and Pacific hake have lower age at maturity than most rockfish). As exploratory analysis, we plotted trends in the CPUE-weighted center-of-mass of depth and latitude for each of the 28 species as a proxy for spatial shifts in stock range. While no substantial trends in latitude were apparent, changes in depth were apparent for Dover sole, hake, sablefish, and some rockfish species (rosethorn, widow, and halfbanded). Therefore, we believe that shifts in abundance among depths may explain the positive correlation between the probability of non-zero catch and catch rates for Dover, rosethorn, and widow rockfish, although this shift in depth distribution could itself be attributed to either environmental or anthropogenic factors.

Including the correlation between presence/absence and positive catch rate components had very little effect on either the estimated indices or standard errors for any of these species in our study. These species represent a diversity of data qualities (ranging from easy to hard to detect) and life histories (migratory to sedentary). We therefore believe that our result is applicable to other species and regions. The flexible nature of this model is also applicable to other types of delta-distributed data, both for fish and other taxa, and estimating a correlation between presence/absence and positive catch rate components may have a bigger effect on resulting indices of abundance for datasets with less information about abundance in each spatial strata.

Finally, we believe that the correlated model represents additional 'biological realism' (Kuparinen et al. 2012) in conventional delta-GLMM index standardization models. By biological realism, we mean that this correlation represents a fish behavior (i.e. synchronized changes in local densities and the probability of occurrence) that is biologically plausible for a wide variety of fishes. This definition applies to a general research trajectory in fisheries (Bigelow and Maunder 2007, Zhou and Griffiths 2007, Thorson et al. 2011) and ecological modeling (MacKenzie et al. 2005, Dail and Madsen 2011) that attempts to incorporate biological processes and behaviors into survey analysis models using biologically interpretable parameters and equations. Although the correlation explored in this study may or may not be parsimonious for any given dataset and/or affect estimated indices or abundance, it allows researchers to estimate (or place priors on) biological processes when analyzing survey data. We hope that these 'biologically realistic' index standardization models will allow researchers to characterize fish behaviors when analyzing survey data, and will therefore cast new light on old research questions such as spatial and temporal changes in fish distributions.

5. Acknowledgements

This work was improved by discussions with I. Stewart, I. Taylor, J. Wallace, A. Hicks, O. Hamel, O. Shelton, E.J. Dick, and J. Cope. We are grateful to the NMFS NWFSC survey team that collects the shelf/slope survey data, including (among others) J. Buchanan, K. Bosley, and D. Kamikawa. Data was provided by B. Horness and J. Wallace, and editorial help was provided by I. Taylor.

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Table 1 – List of species

Common name	Scientific name	Proportion with positive catch	Average positive catch (kg.)
Arrowtooth	*Atheresthes stomias*	0.315	24.306
Aurora	*Sebastes aurora*	0.145	5.411
Bocaccio	*Sebastes paucispinis*	0.044	10.398
Canary	*Sebastes pinniger*	0.054	39.471
Chilipepper	*Sebastes goodie*	0.114	78.603
Cowcod	*Sebastes veils*	0.021	1.613
Darkblotched	*Sebastes crameri*	0.167	12.403
Dover	*Microstomus pacificus*	0.841	55.004
English	*Parophrys vetulus*	0.326	10.780
Greenspotted	*Sebastes chlorostictus*	0.050	5.956
Greenstriped	*Sebastes elongates*	0.214	11.159
Halfbanded	*Sebastes semicintus*	0.058	22.722
Hake	*Merluccius productus*	0.530	33.669
Longspine thornyhead	*Sebastolobus alascanus*	0.429	46.886
Petrale	*Eopsetta jordani*	0.333	8.395
Pacific Ocean perch	*Sebastes alutus*	0.069	29.355
Redbanded	*Sebastes babcocki*	0.084	1.828
Rosethorn	*Sebastes helvomaculatus*	0.076	6.738
Rougheye	*Sebastes aleutianus*	0.047	5.272

Sablefish	*Anoplopoma fimbria*	0.712	20.426
Sanddab	*Citharichthys sordidus*	0.245	34.733
Sharpchin	*Sebastes zacentrus*	0.059	70.163
Shortbelly	*Sebastes jordani*	0.070	53.779
Dogfish	*Squalus acanthias*	0.289	42.247
Shortspine thornyhead	*Sebastolobus alascanus*	0.599	11.999
Widow	*Sebastes entomelas*	0.034	11.395
Yelloweye	*Sebastes ruberrimus*	0.017	7.070
Yellowtail	*Sebastes flavidus*	0.050	63.554

Table 2 – Comparisons among four candidate models for all 28 species, showing differences in posterior predictive scores (Eq. 9) where supported models have $\Delta S < 2$ (shown using italic and bold typsetting), as well as the posterior distribution for the random effect correlation parameter including the median estimate and the posterior probability that the correlation is positive.

	Strata×Year interaction				Random effect correlation c_{sy}	
Species	None	Fixed	Random	Correlated	Median	$\Pr(c_{sy} > 0)$
Arrowtooth	***0.0***	40.5	7.8	8.8	-0.005	0.49
Aurora	6.0	58.5	***1.4***	***0.0***	0.086	0.63
Bocaccio	10.5	69.2	***0.4***	***0.0***	0.300	0.80
Canary	27.1	50.5	***0.0***	***0.5***	0.275	0.83
Chilipepper	36.1	34.0	***0.0***	***1.7***	0.030	0.55
Cowcod	***0.0***	112.1	23.4	16.6	-0.040	0.46
Darkblotched	63.8	63.6	***0.0***	***1.2***	-0.073	0.38
Dover	***0.0***	190.5	145.6	149.0	0.424	***1.00***
English	34.8	27.3	***0.0***	***1.1***	0.502	***0.99***
Greenspotted	19.8	68.8	***0.4***	***0.0***	0.009	0.52
Greenstriped	37.8	48.8	***0.0***	***1.4***	-0.030	0.45
Halfbanded	19.5	85.7	***0.0***	2.5	-0.001	0.50
Hake	59.2	12.9	***0.0***	***0.4***	0.302	***0.98***
Longspine thornyhead	***0.0***	34.5	4.0	18.6	-0.066	0.36
Petrale	11.5	20.0	***0.3***	***0.0***	0.074	0.62
Pacific Ocean perch	15.2	77.4	***0.0***	***0.7***	-0.257	0.19

Redbanded	0.4	81.9	***0.0***	***1.3***	-0.239	0.22
Rosethorn	24.5	67.6	***0.0***	***0.6***	0.462	***0.97***
Rougheye	3.7	82.9	***0.0***	***0.8***	-0.098	0.40
Sablefish	***0.0***	144.2	133.4	133.6	0.149	0.85
Sanddab	10.8	45.1	***0.0***	2.8	-0.214	0.19
Sharpchin	16.5	43.0	***0.0***	***1.6***	0.215	0.75
Shortbelly	43.7	68.2	***0.0***	***1.0***	0.574	***0.99***
Dogfish	109.6	***0.0***	14.2	14.2	0.160	0.82
Shortspine thornyhead	***0.0***	21.0	***1.2***	5.2	0.054	0.62
Widow	24.7	61.7	***0.0***	***0.4***	0.395	***0.92***
Yelloweye	5.5	74.3	***0.3***	***0.0***	0.046	0.55
Yellowtail	3.9	66.5	***0.0***	***1.4***	0.192	0.75

Figure Captions

Fig. 1 -- Posterior distribution for correlation c_{sy} between Strata×Year random effects for positive catch $\gamma^{(sy)}$ and for presence/absence $\omega^{(sy)}$ model components, with median (dashed line) and 95% credible interval (dotted lines).

Fig. 2 – Indices of abundance (lines) and +/- one standard error (standardized to have mean of one) for those five species where model selection indicated support for the correlated and random models ($\Delta S < 2$ for both) and the posterior distribution for correlations was significant ($\Pr[c_{sy} > 0] > 0.9$)

Figure 1
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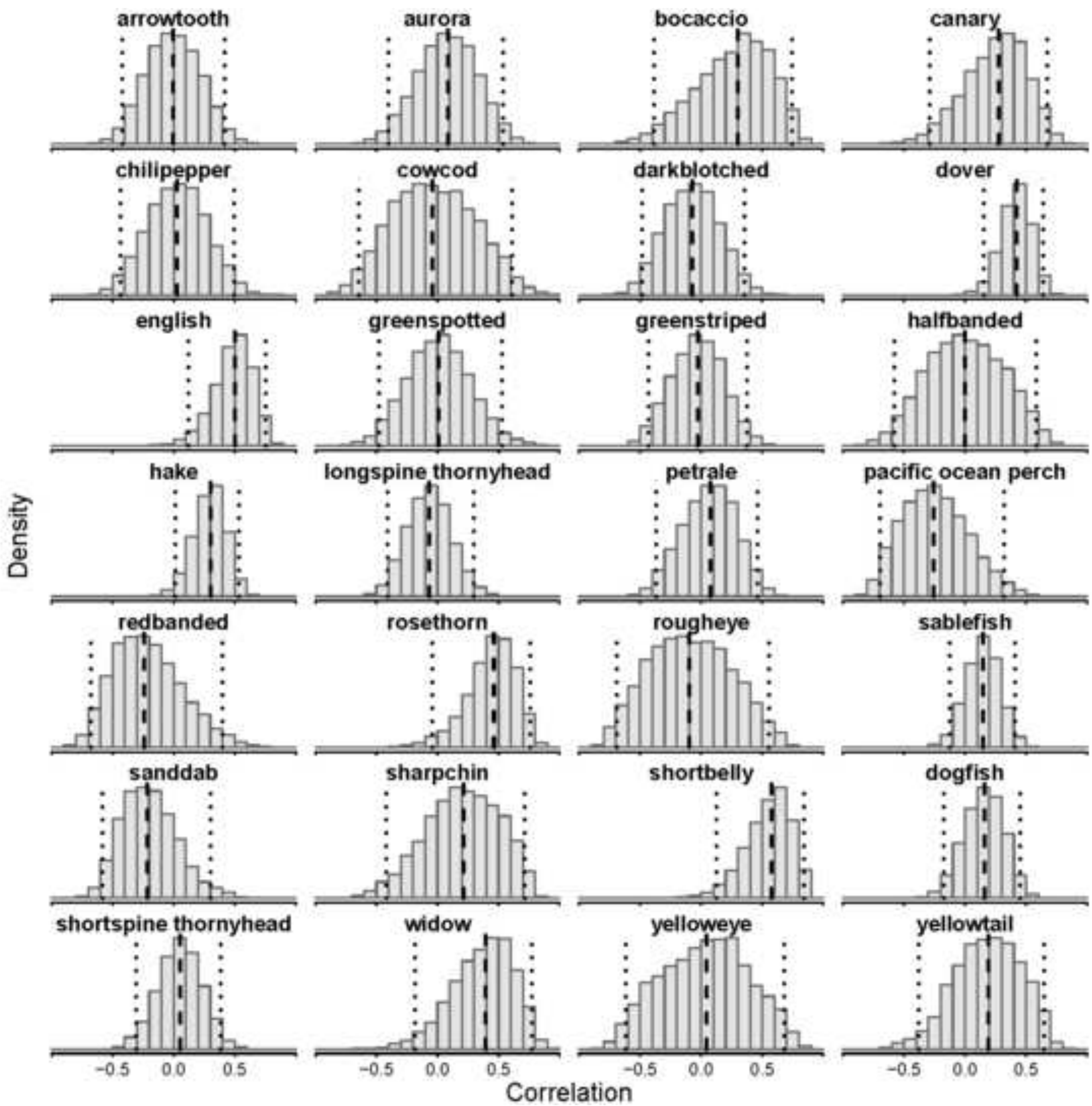

Figure 2
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