1   **Accounting for space-time interactions in index standardization models**

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24 **Abstract**

25 Scientific survey data are used to estimate abundance trends for fish populations worldwide, and

26 are frequently analyzed using delta-generalized linear mixed models (delta-GLMMs). Delta-

27 GLMMs incorporate information about both the probability of catch being non-zero (catch

28 probability) and the expected value for non-zero catches (catch rates). Delta-GLMMs generally

29 incorporate year as a main effect, and frequently account for spatial strata and/or covariates.

30 Many existing delta-GLMMs do not account for random or systematic differences in catch

31 probability or rates in particular combinations of spatial strata and year (i.e. space-time

32 interactions), and do not recognize potential correlation in random space-time interactions

33 between catch probability and catch rates. We therefore develop a novel Bayesian delta-GLMM

34 that estimates correlations between catch probability and rates, and compare it with either (a)

35 ignoring year-strata interactions, (b) modeling year-strata interactions as fixed effects, or (c)

36 estimating year-strata interactions in catch probability or rates as independent random effects.

37 These four models are fitted to bottom trawl survey data for 28 species off the U.S. West Coast.

38 The posterior median of the correlation is positive for the majority (18) of species, including all 5

39 for which the posterior distribution has little overlap with zero. However, estimating this

40 correlation has little impact on resulting abundance indices or credible intervals. We therefore

41 conclude that the correlated random model will have a little impact on index standardization of

42 the West Coast bottom trawl dataset. However, we propose that the correlated model can

43 quickly identify correlations between occupancy probability and density, and that these identified

44 correlations can generate hypotheses for future research.

45

46 **Keywords** (5 max): index standardization, mixed-effects model, 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 in a design-based estimator) 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/credible intervals (Ye and Dennis 2009); (2) estimating the effects of and controlling for variables such as sampling vessel, season, and spatial location; (3) incorporating auxiliary information such as fishing hook depth (Bigelow and Maunder 2007); (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); and (5) accounting for highly non-normal catch rate distribution, e.g., as caused by fish schooling behaviors (Thorson et al. 2011, 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 biologically meaningful 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

70 stock range over time. The second component uses the catch rate for survey occasions where the

71 species was detected to estimate population density within its occupied range. Overall stock

72 abundance is then calculated as the product of stock range and densities within the occupied

73 range. Both model components are necessary because marine species will often undergo

74 changes in densities and stock range over time. Delta-GLMs approximate the expected value of

75 each model component as a function of covariates, and have been extended into a mixed-effects

76 modeling framework (delta-GLMMs), allowing model coefficients to also be treated as random

77 effects that differ among grouping variables (e.g., year and strata, Helser et al. 2004). Delta-

78 GLMMs used for index standardization always include a coefficient representing 'Year' for both

79 presence/absence and positive catch model components because the focus of inference during

80 index standardization is on changes in abundance from one year to the next. Standardization

81 models also frequently include 'Area' (a factor representing different sampling regions or strata),

82 for example, to account for consistent differences in stock density between on- and off-shore

83 habitats (Maunder and Punt 2004).

84   An interaction between year and area (Year×Area) can be included in the delta-GLMM to

85 represent abundance changes that differ among spatial areas in a random or systematic manner.

86 Systematic changes in abundance among areas, e.g., caused by different fishery exploitation

87 rates in different portions of stock range, are treated by including Year×Area as a fixed effect,

88 i.e. by estimating a separate parameter representing stock abundance in each year and area.

89 Random differences, e.g., caused by random annual changes in the distribution of total stock

90 abundance among multiple regions, are treated by including Year×Area as a random effect.

91 Treating Year×Area as a random effect requires estimating an additional coefficient (the variance

92 of random Year×Area deviations), and but is sometimes more parsimonious than treating

93   Year×Area as a fixed effect because random coefficients are 'shrunk' towards zero (Gelman and

94   Hill 2007). Random effects are appropriate when each random effect coefficient is exchangeable

95   (e.g., believed to arise from a 'random,' independent, and identical distribution) for each year-

96   area combination (Bolker et al. 2009). Treating Year×Area as random will explain some portion

97   of residual variance, likely resulting in tighter estimates of index credible intervals.

98   Delta-GLMMs generally treat random effects regarding the probability of non-zero catch and

99   the expected catch for non-zero catches in a given year-area combination as statistically

100   independent.   This assumption may commonly be violated.   As one example, random

101   environmental conditions may cause the target species to be more tightly aggregated in a given

102   year and area, thus causing fewer positive observations but greater expected catches for positive

103   catches.   In this case, the random effect for the catch rate component will be negatively

104   correlated with the random effect for presence/absence component, in violation of the common

105   delta-GLMM assumption that all random effects are exchangeable.   By contrast, random

106   environmental changes may cause a population to move into different strata than usual. For

107   strata into which they move, the probability of non-zero catch and the expected catch for non-

108   zero catches will both be increasing, causing a positive correlation between Year×Area

109   coefficients. This violation of random effect model assumptions can be rectified by estimating a

110   correlation between random effects within a given year-area combination, although we know of

111   no fisheries studies or models in other fields that have explored this.

112   In this manuscript, we pursue two related study goals.   First, we determine whether a

113   correlation between model components is supported by available data for West Coast species

114   and, if so, whether it is generally positive or negative. Second, we explore whether introducing a

115   correlation between model components affects estimated indices of abundance. To accomplish

116   these goals, we compare four alternative treatments of spatial and temporal interactions ('space-

117   time interactions') in delta-GLMM models: (1) not including any Year×Area interaction; (2)

118   treating Year×Area as fixed effects separately in both the presence/absence and catch rate model;

119   (3) treating Year×Area as independent random effects separately in both the presence/absence

120   and catch rate model; and (4) treating Year×Area as random effects that are correlated between

121   presence/absence and catch rate model components. We first apply all four models to bottom

122   trawl survey data for 28 species obtained from the Northwest Fisheries Science Center (NWFSC)

123   shelf and slope survey conducted annually by the National Oceanic and Atmospheric

124   Administration (NOAA) off the U.S. West Coast (e.g., 2003-2011, Bradburn et al. 2011). We

125   then assess the direction and magnitude of random effect correlations, to identify whether

126   correlations between presence/absence and positive catch components are likely to be positive,

127   negative, or indistinguishable from zero for these 28 species (goal 1). Next, we compare

128   resulting abundance indices and credible interval widths for each model to determine whether

129   including the correlation parameter affects the estimated abundance indices or the width of their

130   credible intervals (goal 2).

131   **2. Methods**

132   *2.1 Data availability*

133   As a case study, we use bottom trawl catch and effort data obtained from the NMFS NWFSC

134   shelf and slope survey off the U.S. West Coast (Keller et al. 2008, Bradburn et al. 2011). This

135   survey has operated with similar sampling protocols since 2003, and uses a stratified random

136   sampling design with six sampling strata composed of three depths categories (55-183 m., 184-

137   549 m., and 550-1280 m.) and two latitude categories (32-34.5, and 34.5-50 degrees latitude),

138   wherein sampling intensity is approximately equal to the area in each stratum. For the purposes

139   of this study, we adopted the default post-stratification used by the NWFSC (A. Hicks, pers.

140   comm. 2012), which uses the three depth categories from the sampling design and five latitudinal

141   categories (32-34.5, 34.5-40.5, 40.5-43, 43-47.5, and 47.5-50 degrees latitude). This results in

142   15 spatial strata.

143   We compiled data for 5756 sampling tows from 2003-2011 by the NWFSC shelf/slope

144   survey. We analyze data for 28 finfish species (Table 1) that were chosen because they either (a)

145   are flatfishes, (b) were assessed in 2011, (c) were likely to be assessed in 2013, or (d) had 200-

146   500 positive catches between 2003-2008 ('positive catches' representing occasions when the

147   species was detected on a sampling occasion), where this level was chosen to ensure that species

148   had information for estimating both presence/absence and positive catch rate model components.

149   These species range widely in the probability of occurrence from 84.1% (Dover) to 1.7%

150   (yelloweye), and in the average catch for positive tows from 1.6 kg. (cowcod) to 78.6 kg.

151   (chilipepper). Within each year, sampling for the NWFSC shelf/slope survey occurs in the same

152   time period (May-Oct.) and represents a snapshot of annual biomass that is comparable among

153   years.

154   *2.2 Model overview*

155   We first present the 'correlated model' because it represents the most complicated of the four

156   models. We then present in turn how each other model is derived from the correlated model.

157   We use a Bayesian hierarchical modeling framework, which specifies prior probabilities for

158   model parameters and the conditional probability of the data given parameters to define the

159   posterior distribution of model parameters. We use Bayesian methods to ease computation of the

160   biviariate integral used in the correlated model. This integral, while possible to compute in a

161   maximum likelihood statistical framework (e.g., Thorson et al. 2011), is computationally easier

162   using Bayesian Markov chain Monte Carlo methods.

163   *2.2.1 Correlated strata×year effects*

164   The probability of catch C (in weight, e.g., kilograms) being non-zero is approximated by a

165   logistic regression model:

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

167   where s_i and y_i are strata and year for tow i, $\omega^{(s)}$, $\omega^{(y)}$, and $\omega^{(sy)}$ are parameters representing the

168   effect of strata, year, and the strata×year interaction on the probability that C is non-zero, n_{strata}

169   and n_{year} are the number of strata and years, respectively, j and k are indices representing strata

170   and year, respectively, Φ is the logistic transformation $\Phi(X) = \exp(X)/(1+\exp(X))$, and $I(x=b)$ is

171   an indicator variable that equals one if $x = b$ and zero otherwise.

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

173   distribution:

174    $$p(C = c \mid C > 0, s_i, y_i, a_i) = \text{Gamma}(c \mid \alpha, \beta_i)$$
       (2)

175   where $\alpha = 1 / CV^2$, $\beta_i = 1 / (\mu_i \cdot CV^2)$, CV is the estimated coefficient of variation for C given that

176    $C > 0$, and μ_i is the expected value of catch for non-zero tow i. We parameterize this gamma

177   distribution such that the CV of all non-zero catches is constant (as represented by estimated

178   parameter CV). Other distributions may be appropriate (lognormal, inverse Gaussian, etc) but

179   for skewed distributions that occur in fishery data, the gamma distribution is well behaved

180   (Myers and Pepin 1990). The μ_i is in turn approximated by an exponential-transformed linear

181   model:

182 $$\mu_i = a_i \cdot \exp\left(\sum_{j=1}^{n_{strata}} \gamma_j^{(s)} I(s_i = j) + \sum_{k=1}^{n_{year}} \gamma_k^{(y)} I(y_i = k) + \sum_{j=1}^{n_{strata}} \sum_{k=1}^{n_{year}} \gamma_{j,k}^{(sy)} I(s_i = j) I(y_i = k) \right)$$

(3)

183 where a_i is the area swept (in hectares) for tow i, and $\gamma^{(s)}$, $\gamma^{(y)}$ and $\gamma^{(sy)}$ are parameters representing

184 the effect of strata, year and the strata×year interaction on the expected value of non-zero catch

185 C_i.

186   Strata×year interactions are treated as random effects, and specify that the random effect for

187 presence/absence $\omega^{(sy)}$ in strata s and year y is correlated with the random effect for positive

188 catch rates $\gamma^{(sy)}$ in strata s and year y:

189 $$p(\omega_{j,k}^{(sy)}, \gamma_{j,k}^{(sy)} \mid \Sigma_{sy}) = \mathrm{MVN}(0, \Sigma_{sy})$$

(4)

190 where MVN(μ, Σ) is a multivariate normal density function, and Σ_{sy} is the covariance among

191 strata×year random effects within a given strata-year combination:

192 $$\Sigma_{sy} = \begin{bmatrix} \sigma_\omega^2 & \rho_{sy} \sigma_\omega \sigma_\gamma \\ \rho_{sy} \sigma_\omega \sigma_\gamma & \sigma_\gamma^2 \end{bmatrix}$$

(5)

193 where σ_ω^2 and σ_γ^2 are the variance for positive catch rate and presence/absence random effects,

194 and ρ_{sy} is the estimated correlation between strata×year random effects for presence/absence and

195 positive catch rates model components. This correlated model therefore has a total of 320

196 estimated coefficients for each species, although the effective degrees of freedom may be less

197 than this number due to random effect shrinkage (Spiegelhalter et al. 2002).

198   The Bayesian model specification is completed by including prior distributions for all

199 parameters. We used a weakly-informative gamma prior on α, $p(\alpha) = $ Gamma(0.001,0.001), and

200 bounded uniform priors on all fixed-effect parameters $p(X) = $ 1/40 if -20 < X < 20 and zero

201 otherwise (the value 1/40 ensures that the integral of this prior is one), where X represents $\gamma^{(s)}$,

202 $\gamma^{(y)}$, $\omega^{(s)}$, and $\omega^{(y)}$. Because the correlated strata-year effects are treated as multivariate normal,

203 we used a standard conjugate inverse-Wishart prior on the covariance matrix (Gelman et al.

204 2003), which has a prior mean of zero (i.e. represents a prior assumption of no correlation). For

205 the simpler case of uncorrelated random effects, we used weakly-informative bounded uniform

206 priors on the standard deviation of strata×year random effects $p(X) = 1/20$ if $0 < X < 20$ and zero

207 otherwise, where X represents σ_ω or σ_γ (Gelman 2006). The posterior distribution for the model

208 is then defined as the product of all terms defined previously.

209 *2.2.2 Uncorrelated* Year×Area *effects*

210 As a second model, we consider allowing Year×Area effects in the presence/absence and

211 positive catch rate components to be independent ('uncorrelated Year×Area') by specifying that

212 correlations are zero ($c_{sy} = 0$). This has the result that Σ_{sy} is diagonal, and leaves 319 estimated

213 coefficients for each species.

214 *2.2.3 Fixed* Year×Area *effects*

215 As a third possible model, we specify that Year×Area effects are estimated as fixed effects. This

216 model eliminates Eqs. 4-5, and instead specifies bounded uniform priors on Year×Area effects,

217 $p(X) = 1/40$ if $-20 < X < 20$ and zero otherwise, where X represents $\gamma^{(sy)}$ and $\omega^{(sy)}$. It also requires

218 that all strata and year main effects are set to zero (i.e. $\gamma^{(s)} = \omega^{(s)} = \gamma^{(y)} = \omega^{(y)} = 0$), to prevent

219 confounding of main and interaction effects (where this parameterization additionally minimizes

220 parameter correlations). This leaves 271 estimated coefficients for each species, although the

221 number of effective degrees of freedom is likely higher than for the random Year×Area models

222 due to an absence of shrinkage of interaction coefficients (Spiegelhalter et al. 2002).

223 *2.2.4 Absent strata×year effects*

224   The fourth model we implement involves no estimation of Year×Area effects, but still retains the

225   fixed area and year effects. The model without Year×Area interactions again eliminates Eqs. 4-5,

226   and specifies that Year×Area effects are zero, $\gamma^{(sy)} = \omega^{(sy)} = 0$, leaving 47 estimated coefficients

227   per species.

228   *2.3 Estimating an index of abundance*

229   All four models (correlated, uncorrelated, fixed, and absent) are then used to estimate an index of

230   abundance for all 28 species. This index is calculated by multiplying the posterior distributions

231   for the probability of non-zero catch and the probability density of catch when non-zero, and

232   taking the sum weighted by strata area A_j for each stratum j:

233
$$p(B_k \mid c,s,y,a) = \sum_{j}^{n_{strata}} A_j \cdot p(C_{j,k} > 0 \mid c,s,y,a) \cdot p(\mu_{j,k} \mid C_{j,k} > 0, c,s,y,a)$$

(6)

234   where $p(B_k \mid c,s,y,a)$ is the probability density for random variable B_k representing abundance

235   (i.e., biomass) in year k given all available data (i.e., catch c, strata s, year y, and area swept a for

236   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

237     $p(\mu_{j,k} \mid C_{j,k} > 0, c,s,y,a)$ is the probability density of non-zero catches $\mu_{j,k}$ for that year and strata:

238
$$p(C_{j,k} > 0 \mid c,s,y,a) = \Phi\left(p(\omega_j^{(s)} \mid c,s,y,a) + p(\omega_k^{(y)} \mid c,s,y,a) + p(\omega_{j,k}^{(sy)} \mid c,s,y,a) \right)$$

(7)

239
$$p(\mu_{j,k} \mid c,s,y,a) = \exp\left(p(\gamma_j^{(s)} \mid c,s,y,a) + p(\gamma_k^{(y)} \mid c,s,y,a) + p(\gamma_{j,k}^{(sy)} \mid c,s,y,a) \right)$$

(8)

240   where $p(X \mid c,s,y,a)$ is the posterior distribution for parameter X. We use the median of $p(N_k \mid$

241     $c,s,y,a)$ as the index of abundance, and the standard deviation of $p(N_k \mid c,s,y,a)$ divided by its

242   median as a measure of precision for N_k.

243   *2.4 Estimation and convergence*

244   Samples from the posterior distribution are calculated using Markov chain Monte Carlo

245   (MCMC) methods as implemented in JAGS (Plummer 2003) and called from the R statistical

246   platform (R Development Core Team 2011) using the R2jags package (Su and Yajima 2012).

247   We used 3 chains, each obtaining 70,000 samples, the first 50,000 of which are used to adapt the

248   sampling algorithm and hence are discarded. The remaining 20,000 samples were then thinned

249   to obtain 4,000 samples per chain that were approximately independent.

250   All results that we present are made after checking for evidence of non-convergence.

251   Convergence checks include visual inspection of sampling chains for estimated parameters. We

252   additionally estimate the Gelman-Rubin R statistic, representing the ratio of variance within and

253   between chains, and the first-order autocorrelation for all derived parameters, i.e. the probability

254   of occurrence, density, and resulting abundance for each strata and year. For the total abundance

255   indices across all strata and years, for example, the median Gelman-Rubin R statistic was below

256   1.1 for nearly all species and models. For two species (cowcod, halfbanded), the median

257   Gelman-Rubin R statistic was less than 1.1 for the fixed effects model, but was in the range 1.2-

258   1.3 for all other models. Similarly, the median absolute autocorrelation across strata and years

259   was < 1.03 for all species and the first 3 models (no strata-year effects, fixed effects,

260   uncorrelated random effects). For the correlated model, which had slower mixing, approximately

261   half of the species had median lag-1 autocorrelations between 0.1-0.2.

262   **3. Results**

263   *3.1 The direction and importance of correlated random interactions*

264   We first address study goal #1, i.e. whether a correlation between model components is common

265   for West Coast species and, if so, whether it is generally positive or negative. Specifically, we

266   use the posterior distribution for the random-effect correlation c_{sy} to interpret whether the

267   correlation is likely to be non-zero. The posterior for c_{sy} is greater than 95% positive for Dover

268   sole, English sole, hake, rosethorn rockfish, and shortbelly rockfish. Inspection of the posterior

269   distribution for c_{sy} for each species individually (Fig. 1) suggests that other species (e.g. widow)

270   might be positive, although the length of the current dataset a not sufficient to be confident. This

271   positive correlation of Year×Area random effects between presence/absence and positive catches

272   could arise from random changes in spatial distribution among years which causes increased

273   (decreased) abundance in particular strata and years, in turn causing increased (decreased)

274   probability of detection and catches when detected.

275   *3.2 Comparing abundance index estimates and precision*

276   Next, we address study goal #2, i.e., whether introducing a correlation between model

277   components affects estimated indices of abundance. Comparison of the abundance indices for

278   the random and correlated models for those species where $\Pr[c_{sy} > 0] > 0.9$ (Fig. 2) shows that

279   there is little difference in the estimated indices or credible intervals.   However, minor

280   exceptions do occur, such as the 10% lower log-standard deviation for the "correlated" model

281   than the "random" model for shortbelly rockfish. Indices for all stocks and models (Supp. Fig.

282   1) similarly show little difference among index standardization methods. In general, the greatest

283   difference is seen for the model without any Year×Area interactions. This difference arises

284   because the "zero" model is unable to account for any space-time interaction, and is hence the

285   difference between the "zero" model and other models most pronounced for species such as

286   canary rockfish that have previously been shown to be susceptible to extraordinarily large

287   catches (Thorson et al. 2011).

288   **4. Discussion**

289   Simple survey analysis models for count data imply a linkage between the probability of

290   detection and the expected catch. For example, sampling locations with a greater expected value

291   for non-zero catches will also have a greater probability of non-zero catch when using a Poisson-

292   distributed GLM. This correlation between probability of detection and expected catch for count

293   data is also maintained for more-complex models, e.g., zero-inflated negative binomial GLMMs.

294   However, survey analysis models for continuous-valued data (e.g. catch weight per hectare as

295   often used in fisheries stock assessment) have not previously been developed that incorporate a

296   correlation between the probability of positive catch and the expected catch. We rectified this

297   absence by developing a novel delta-GLMM that estimates a correlation between random effects

298   affecting the positive and presence/absence model components. This model allows for greater

299   comparability with count-data models, and is also intended as a method to evaluate the strength

300   of evidence for such a correlation.

301   Overall, we find mixed support for a correlation between the probability of positive catch and

302   the expected value of non-zero catch. This correlation has a posterior distribution with little

303   (<10%) overlap with zero for only 5 of 28 species, but is positive for all five of these. A

304   noteworthy caveat is that the strength and magnitude of this correlation is likely affected by the

305   spatial strata stratification chosen *a priori* in any assessment, and the correlation might change if

306   strata were chosen at a more fine or coarse spatial scale. A positive correlation can arise when

307   environmental or anthropogenic factors cause random interannual changes in distribution among

308   spatial strata. Potential environmental factors include transient oceanographic effects, which

309   could cause a relocation of migratory species (e.g., Pacific hake) to suitable habitats (Methot and

310   Dorn 1994). Potential anthropogenic factors resulting in a correlation include changes over time

311   in the fishing intensity in different strata, which by decreasing total abundance in particular strata

312   will cause a synchronized decrease in the probability of detection and expected catch size when

313   detected in those strata.

314   For the NWFSC dataset analyzed here, the exact mechanism responsible for observed

315   correlations in Year×Area terms remains unclear, because the species for which it is supported

316   differ greatly in their distribution (e.g., Pacific hake are encountered throughout the bottom trawl

317   sampling strata while shortbelly rockfish is primarily encountered in S. California), degree of

318   fishing pressure (shortbelly has close-to-zero fishing mortality, the relative exploitation rate of

319   English sole is close to 2%, and the relative exploitation rate of hake is 10% in recent years;

320   Field et al. 2007, Stewart 2007, Stewart et al. 2011), migration (rockfish are sedentary, English

321   sole and Pacific hake are migratory) and age at maturity (English sole and Pacific hake have

322   lower age at maturity than most rockfish). As exploratory analysis, we plotted trends in the

323   CPUE-weighted center-of-mass of depth and latitude for each of the 28 species as a proxy for

324   spatial shifts in stock range. While no substantial trends in latitude were apparent, changes in

325   depth were apparent for Dover sole, hake, sablefish, and some rockfish species (rosethorn,

326   widow, and halfbanded). Thus, shifts in abundance among depths may explain the positive

327   correlation between the probability of non-zero catch and catch rates for Dover and rosethorn,

328   although this shift in depth distribution could itself be attributed to either environmental or

329   anthropogenic factors.

330   However, including the correlation between presence/absence and positive catch rate

331   components had very little effect on either the estimated indices or standard errors for any of

332   these species in our study. These species represent a diversity of data qualities (ranging from

333   easy to hard to detect) and life histories (migratory to sedentary). We therefore suspect the

334   correlated model will have little impact on index estimates for other species and study systems

335   with comparable data quantity and quality. The correlated model may still affect abundance

336   index estimates in study systems with less data within particular strata or years, e.g., surveys

337 before and after establishing no-take areas. In the latter case, continued collection of

338 presence/absence data may be feasible even when the total weight of catch cannot be measured

339 (i.e. because it is not brought onto a sampling vessel).

340 Despite the lack of difference in estimated indices between random and correlated models,

341 we believe that the correlated model provides one possible way additional to introduce

342 'biological realism' (Kuparinen et al. 2012) into conventional delta-GLMM index standardization

343 models. By biological realism, we mean that this correlation represents a fish behavior (i.e.

344 synchronized changes in local densities and the probability of occurrence) that is biologically

345 plausible for a wide variety of fishes. This definition applies to a general research trajectory in

346 fisheries (Bigelow and Maunder 2007, Zhou and Griffiths 2007, Thorson et al. 2011) and

347 ecological modeling (MacKenzie et al. 2005, Dail and Madsen 2011) that attempts to incorporate

348 biological processes and behaviors into survey analysis models using biologically interpretable

349 parameters and equations. Although the correlation explored in this study may or may not be

350 parsimonious for any given dataset or affect estimated indices of abundance, it allows

351 researchers to estimate and account for spatial processes such as localized depletion and/or

352 migration when analyzing survey data.

353 **5. Acknowledgements**

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461   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

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Table 2 – Comparisons among four candidate models for all 28 species, showing the posterior distribution for the random effect correlation parameter including the median estimate and the posterior probability that the correlation is positive.

Species	Median	5%	95%	$Pr(c_{sy}>0)$
Arrowtooth	-0.016	-0.403	0.373	0.471
Aurora	0.094	-0.381	0.518	0.653
Bocaccio	0.326	-0.343	0.758	0.840
Canary	0.255	-0.317	0.663	0.810
Chilipepper	0.059	-0.452	0.521	0.587
Cowcod	-0.044	-0.700	0.638	0.462
Darkblotched	-0.070	-0.471	0.334	0.374
Dover	0.421	0.154	0.641	**0.999**
English	0.480	0.129	0.726	**0.995**
Greenspotted	0.093	-0.441	0.556	0.626
Greenstriped	-0.043	-0.430	0.354	0.414
Halfbanded	0.001	-0.613	0.662	0.501
Hake	0.307	0.016	0.557	**0.981**
Longspine thornyhead (LST)	-0.075	-0.423	0.293	0.352
Petrale	0.041	-0.350	0.411	0.581
Pacific Ocean perch (POP)	-0.255	-0.682	0.338	0.193
Redbanded	-0.253	-0.684	0.345	0.210
Rosethorn	0.451	-0.068	0.756	**0.960**
Rougheye	-0.089	-0.601	0.526	0.387

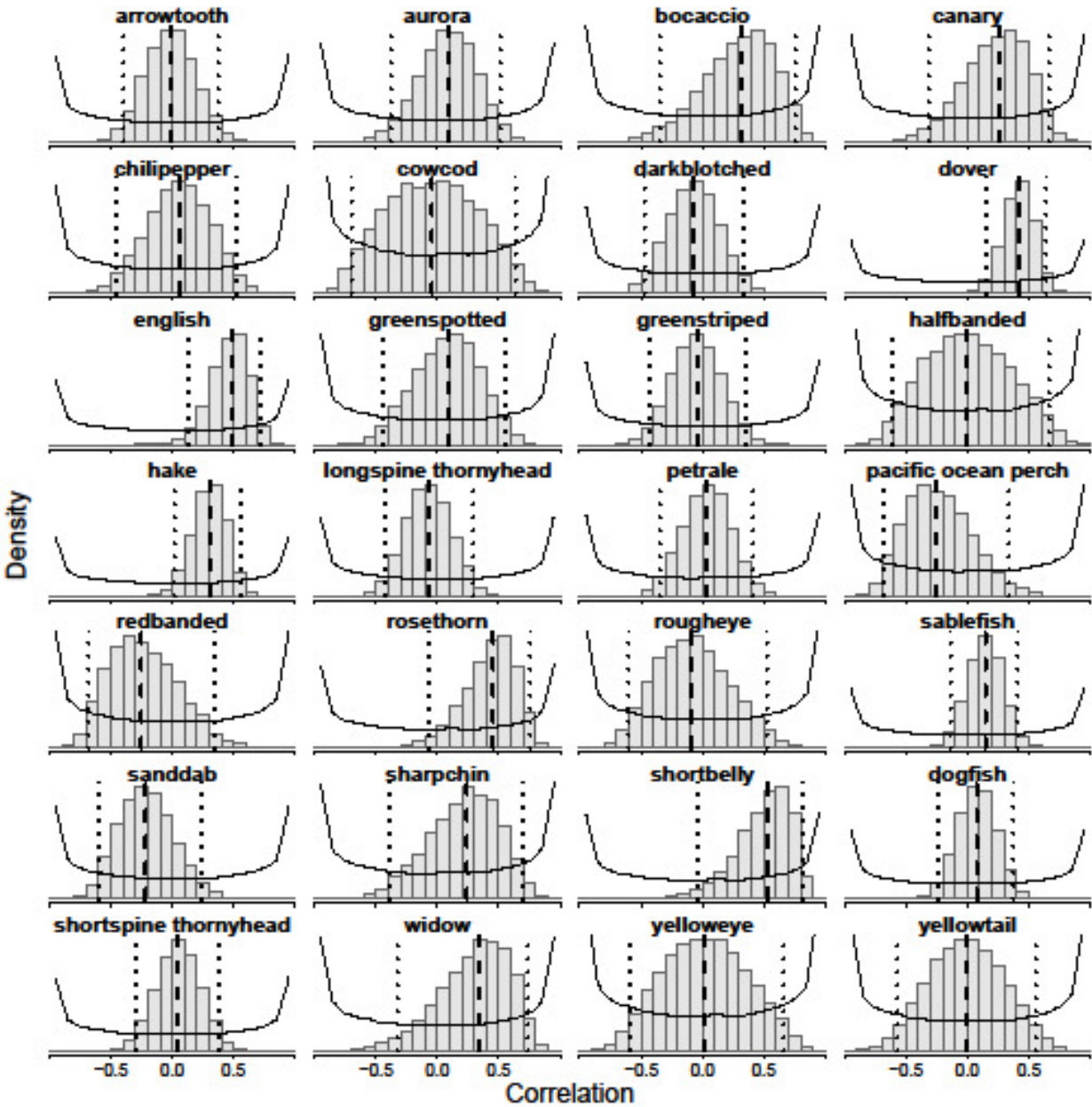|				
Sablefish	0.145	-0.135	0.410	0.842
Sanddab	-0.218	-0.597	0.243	0.177
Sharpchin	0.241	-0.386	0.698	0.772
Shortbelly	0.532	-0.038	0.823	**0.967**
Dogfish	0.079	-0.238	0.376	0.682
Shortspine thornyhead (SST)	0.050	-0.297	0.386	0.611
Widow	0.336	-0.327	0.739	0.851
Yelloweye	0.020	-0.593	0.664	0.522
Yellowtail	-0.008	-0.571	0.558	0.491

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Figure Captions

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472 Fig. 1 -- Posterior distribution for correlation c_{sy} between Strata×Year random effects for positive

473 catch $\gamma^{(sy)}$ and for presence/absence $\omega^{(sy)}$ model components, with median (dashed line) and 95%

474 credible interval (dotted lines) as well as the Wishart prior distribution (solid line).

475 Fig. 2 – Indices of abundance (lines, standardized) and +/- one posterior standard deviation for

476 those five species where the posterior distribution for correlations was significant ($\Pr[c_{sy} > 0] >$

477 0.9). Lines for are offset along the x-axis to improve legibility, and the fixed-effect Strata×Year

478 model is only included for those species that have at least one encounter in every strata-year

479 combination (e.g., Dover sole).

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482   Fig. 1

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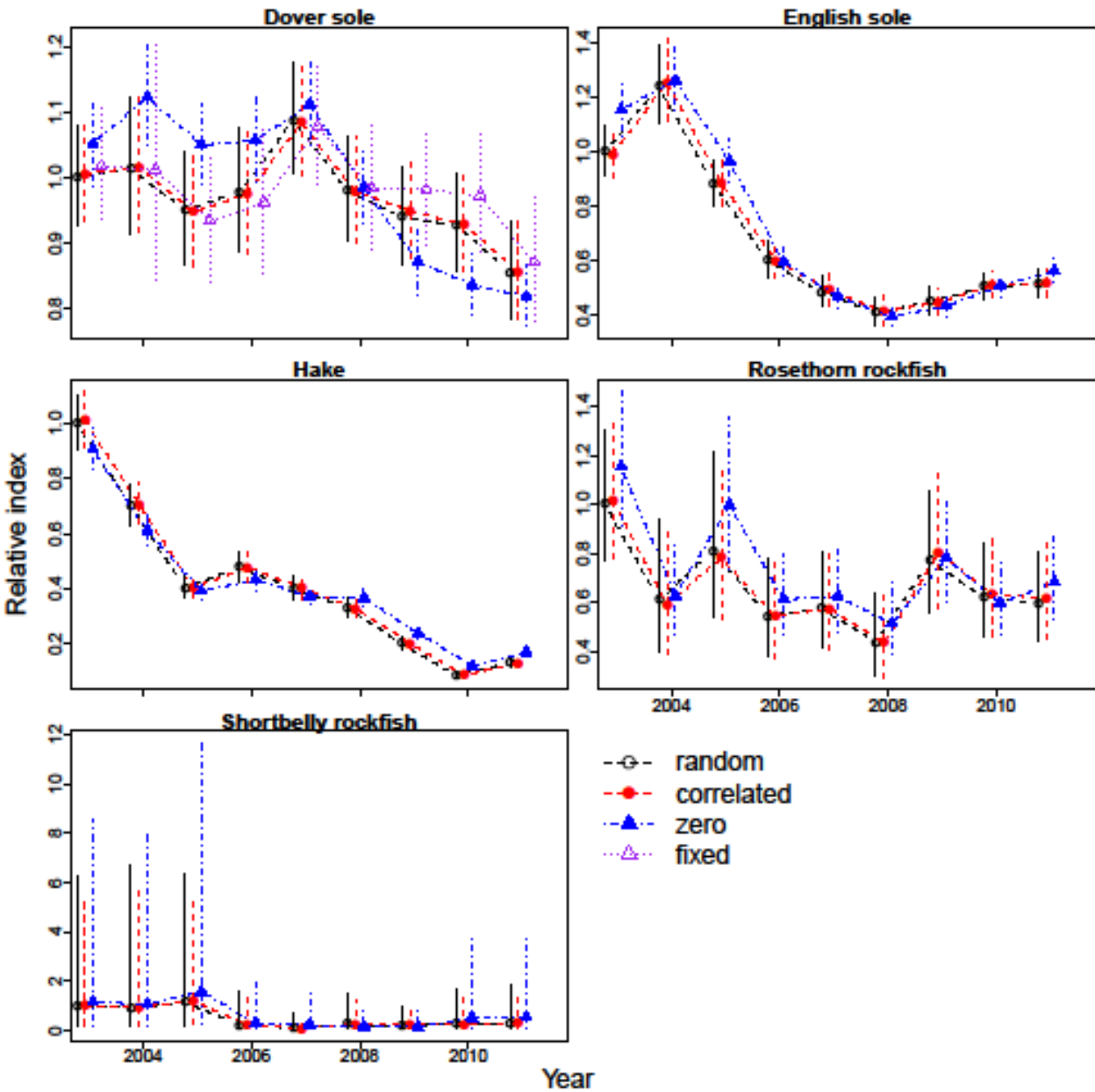
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Supplementary figure captions

Suppl. Fig. 1 – Panel figure showing the estimated indices (lines, standardized) and +/- one posterior standard deviation for indices estimated without Strata×Year interactions (blue filled triangle), with Strata×Year interactions as a fixed effect (purple hollow triangle), and with Strata×Year interactions as independent (black hollow circle) or correlated random effects (red filled circle), for each stock. Lines for are offset along the x-axis to improve legibility, and the fixed-effect Strata×Year model is only included for those species that have at least one encounter in every strata-year combination (e.g., Dover sole).

498   Fig. S1

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