

1 **A hierarchical modelling approach to estimating humpback whale abundance**
2 **from sand lance abundance**

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9 **Abstract**

10 The primary prey of humpback whales in the southwestern Gulf of Maine is sand lance.
11 Despite this established relationship, we lack models to further understand the influence
12 of sand lance on humpback whales or to predict humpback abundance or distribution in
13 response to climate-related changes in sand lance abundance or distribution. We used
14 a subset of long-term standardized survey data (2013-2019) from Stellwagen Bank
15 National Marine Sanctuary and a Bayesian hierarchical modelling approach to explore
16 the influence of sand lance on humpback whales at multiple spatial and temporal scales
17 while accounting for sampling variability and propagating uncertainty. We developed
18 zero-inflated Poisson mixed effects models for both sand lance and humpbacks, using
19 modelled sand lance abundance as a predictor in the whale model. Results showed a
20 statistically clear positive correlation between sand lance and humpback whales.
21 Regional mean abundances of both species increased from north to south, though site-
22 level variation within regions showed more variability. Results suggest annual variation
23 in abundance of both species, with potentially different influences. We demonstrate one
24 management application of our method by examining entanglement risk for humpback
25 whales. Whale aggregations were more likely to occur in a high density area of fixed
26 fishing gear that overlaps with an area of higher sand lance abundance. Our work
27 suggests that humpback whale distribution in the larger Gulf of Maine may be impacted
28 by climate-related fluctuations in sand lance abundance. Predicting future distributions
29 of humpback whales is important for ecosystem-based management, including
30 mitigation of human impacts, and our work serves as a foundation for further model
31 development.

32 **Keywords (6 max):** forage fish, predator-prey, Gulf of Maine, Bayesian, Stellwagen
33 Bank, habitat use, spatial overlap,

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38 **Introduction**

39 In the southwestern Gulf of Maine (GOM), the preferred prey of humpback whales
40 (*Megaptera novaeangliae*) is sand lance (*Ammodytes* spp.). Shifts in the abundance
41 and distribution of humpbacks into and out of the southwestern GOM have been linked
42 with fluctuations in the abundance of sand lance during several time periods since the
43 late 1970s. Steady increases in humpback whale densities from 1978-1982 correlated
44 with increased sand lance densities (Payne et al. 1986). Fluctuations in humpback
45 whale abundance followed fluctuations in sand lance abundance from 1982-1988
46 (Payne et al. 1990) and a decline in humpback whale abundance on Stellwagen Bank
47 from 1988-1994 was concurrent with a decline in presumed sand lance density and an
48 increase in humpback abundance on nearby Jeffrey's Ledge, where humpbacks feed
49 predominately on herring (Weinrich et al. 1998).

50 While the link between humpbacks and sand lance in the southwestern GOM is clear,
51 current evidence is limited to linear correlations. We lack statistical models to further
52 understand the strength of this relationship over time and space, or to predict changes
53 in the abundance and distribution of either species in response to climate change.

54 Here, we aimed to advance our understanding of the sand lance-humpback relationship
55 by using a Bayesian hierarchical modeling approach to account for: spatial and
56 temporal variability, uncertainty in the association of humpback abundance with latent
57 abundance of sand lance, and the observation process. We fit zero-inflated Poisson
58 mixed effects models to a subset of a unique, long-term dataset of humpback whale and
59 sand lance counts from seasonal standardized surveys in Stellwagen Bank National
60 Marine Sanctuary, a federal MPA in the southwestern GOM. The sanctuary is a critical
61 foraging area for humpbacks and in some years, hosts the highest sand lance densities
62 in the GOM (Richardson et al. 2014), providing an ideal location to further explore the
63 relationship between these species and to work toward building a predictive modeling
64 framework.

65

66 **Methods**

67 ***Data collection***

68 Field work was described in Silva et al. (2020). Briefly, 13 seasonal surveys for sand
69 lance and humpback whales were conducted from 2013 - 2019 (Fall: September –
70 November; n=5; Spring: April – June, n=6; Summer: July, n=2) in Stellwagen Bank
71 National Marine Sanctuary. The survey included 44 sites (~1 km apart in most areas) in

72 3 blocks (north, central, south) across Stellwagen Bank designed to sample all potential
73 sand lance habitat (Fig. 1A).

74 Sand lance are a benthopelagic species that spend time both in the water column and
75 in the sediment (Robbards 2000). We sampled sand lance in the sediment using the
76 U.S. Geological Survey Seabed Observation and Sampling System (SEABOSS)
77 (Blackwood & Parolski, 2001), equipped with a modified Van Veen benthic grab sampler
78 (0.1m²). At each site, the SEABOSS was deployed to the sea floor to sample sediment
79 and the number of sand lance in each sample was recorded. We assumed the number
80 of sand lance recorded in each grab sample was representative of the total number of
81 sand lance at each site (water column + sediment).

82 During each SEABOSS deployment, trained observers (typically 1 on either side of the
83 vessel) recorded the number of humpback whales in an 800 m radius around the vessel
84 for 10 minutes. We chose the sampling distance and observation period based on our
85 ability to reliably identify species and to limit the possibility of double counting
86 individuals (based on typical humpback dive durations of ~5 minutes, Wiley unpublished
87 data). Distances were estimated using a hand-held, fixed interval range finder calibrated
88 using laser range finders and a buoy at known distance in relation to the horizon
89 (Heinemann, 1981).

90 Some cruises resulted in no observations of sand lance or whales or very small total
91 species counts (two individuals). We excluded these data from analysis. We also
92 excluded summer data since there were only two cruises. Here we used data from five
93 cruises (n=164), with sampling effort spread over four years and fairly equally across
94 seasons and sites (Table 1, Table S1).

95 ***Modeling***

96 *Model structure*

97 Count data for sand lance and humpback whales contained mostly zeroes (Fig. 1B, C)
98 and preliminary models using Poisson and negative binomial distributions fit poorly. We
99 implemented a zero-inflated Poisson mixed effects model using a Bayesian hierarchical
100 framework. Several aspects of our study make it well suited for this approach. First, our
101 study design includes simple categorical covariates that are nested within several
102 spatial and temporal scales, inviting a hierarchical structure as well as random effects
103 (Hobbs & Hooten 2015). Second, this framework allows us to incorporate sampling
104 variability, which we believe is important given our data collection method (Pavanato et
105 al. 2017). Third, we can propagate uncertainty throughout prey and predator models.
106 Lastly, Bayesian methods allow for inference using true probability statements, which

107 better represent ecological data and are more useful for managers making decisions
108 (Wade 2000).

109

110 Sand lance sub-model

111 We modeled sand lance counts, sl_{ijk} , at site i in block j in year k , using a zero-inflated
112 mixture model,

113
$$sl_{ijk} \sim \begin{cases} 0 & f z_{ijk}^{sl} = 0 \\ ss (\lambda_{ijk}^{sl}) & f z_{ijk}^{sl} = 1 \end{cases}$$

114 where λ_{ijk}^{sl} is the mean number of sand lance per sediment sample at site i in block j in
115 year k ,

116 z_{ijk}^{sl} is a random variable describing seasonal zero-inflation in sand lance availability:

117
$$z_{ijk}^{sl} \sim Ber \text{ ull } (\phi_{m(ijk)}^{sl})$$

118
$$\phi_{m(ijk)}^{sl} \sim (0,1)$$

119 where $\phi_{m(ijk)}^{sl}$ is the probability of success (sand lance captured) for season m and $1 -$
120 $\phi_{m(ijk)}^{sl}$ is the probability of zero inflation. Sand lance in Stellwagen Bank National
121 Marine Sanctuary exhibit seasonal differences in behavior. In fall, sand lance spend
122 more time on or in the sediment in estivation prior to spawning (Suca et al. 2021). We
123 hypothesized that these seasonal differences in bottom time would influence the chance
124 of sand lance capture in sediment grabs. If $z = 0$, the mean number of sand lance
125 equaled zero. If $z = 1$, the number of sand lance in the count was distributed as a
126 Poisson random variable with mean λ_{ijk}^{sl} (Fig. 2).

127 We described λ_{ijk}^{sl} as a log linear function of block, site, and year,

128
$$\ln(\lambda_{ijk}^{sl}) = \beta_j^b + \beta_i^s + \beta_k^y$$

129
$$\beta_j^b \sim N(0, 10)$$

130
$$\beta_i^s \sim N(0, \sigma_{sl}^2)$$

131
$$\beta_k^y \sim N(0, \tau_{sl}^2)$$

132
$$\frac{1}{\sigma_{sl}^2} \sim Gamma(0.01, 0.01)$$

133
$$\frac{1}{\tau_{sl}^2} \sim Gamma(0.01, 0.02)$$

134 Data exploration suggested that sand lance counts differed substantially by block (Fig.
 135 1B, C). Our model structure assumed that each block had an overall mean number of
 136 sand lance, with site- and annual-specific effects. Site and year were treated as random
 137 effects to capture spatial and temporal variation in expected sand lance counts. We had
 138 no existing knowledge to inform choice of priors, therefore we used vague priors on all
 139 parameters. For site- and year- level variance, we used the conjugate gamma prior on
 140 the precision of normal distributions. After initial model runs, we chose to increase the
 141 precision (decrease variance) for $\frac{1}{\tau_{sl}^2}$ to 0.02 in order to decrease initial autocorrelation in
 142 MCMC chains.

143 Humpback whale sub-model

144 The humpback whale sub-model was similar to the sand lance model. We modeled humpback
 145 whale counts, w_{ijk} at site i in year k, using a zero- inflated mixture model,

146

147 $w_{ijk} \sim \begin{cases} 0 & f z_{ijk}^w = 0 \\ ss & (\lambda_{ijk}^w) \\ 1 & f z_{ijk}^w = 1 \end{cases}$

148
 149 where z_{ijk}^w is a random variable describing if whales were observed ($z=1$) or not ($z=0$) and λ_{ijk}^w is
 150 the mean number of whales at site i in year k (Fig. 2). We used a Bernoulli distribution with a
 151 uniform prior for z,

152 $z_{ijk}^w \sim Ber \quad ull (\phi_{m(ijk)}^w)$

153 $\phi_{m(ijk)}^w \sim (0,1)$

154 where $\phi_{m(ijk)}^w$ in season m represents the probability of success (whales observed) and $1 - \phi_{m(ijk)}^w$ is the probability of zero inflation. The annual migratory cycle of humpback whales
 155 consists of arrival on higher latitude feeding grounds (including the sanctuary) in spring and
 156 departure from feeding grounds to lower latitude breeding grounds in fall (Clapham et al. 1993).
 157 We hypothesized that whale presence in SBNMS, and therefore, sampling variability, may be
 158 influenced by their migratory cycle. If $z = 1$, the number of whales was distributed as a Poisson
 159 random variable with a mean, λ_{ijk}^w . If $z = 0$, the number of whales equaled zero.

161 Based on the established correlations between sand lance and humpbacks (Payne et al. 1986,
 162 Payne et al. 1990), we hypothesized that humpback whale counts were correlated with sand
 163 lance abundance and included expected sand lance abundance as a covariate in the humpback
 164 model. We described λ_{ijk}^w for each data point as a log linear function of expected sand lance
 165 abundance, site, and year (Fig. 2),

166 $\ln(\lambda_{ijk}^w) = \alpha_{sl} \ln(\lambda_{ijk}^{sl}) + \theta_i^s + \theta_k^y$, where

167 $\alpha_{sl} \sim N(0, 10)$

168 $\theta_i^s \sim N(0, \sigma_w^2)$

169 $\theta_k^y \sim N(0, \tau_w^2)$

170 $\frac{1}{\sigma_w^2} \sim Gamma(0.01, 0.01)$

171 $\frac{1}{\tau_w^2} \sim Gamma(0.01, 0.02)$

172 Since we assume humpback counts were correlated with sand lance counts, and the
 173 mean number of sand lance was assumed to vary by block, we did not include block as
 174 a covariate in the whale model. We included site and year as random effects to capture
 175 spatial and temporal variation in whale counts that may not be attributable to sand
 176 lance. We had no existing knowledge to inform choice of priors, therefore we used
 177 vague priors on all parameters as in the sand lance sub-model.

178 Model fitting and analysis

179 Models were implemented using Markov chain Monte Carlo (MCMC) algorithms in
 180 JAGS (Just Another Gibbs Sampler; Plummer 2003) called from R using the package
 181 *rjags* (Plummer 2011). We ran four chains with 1 million iterations, a burn-in of 50,000,
 182 adaptation period of 50,000 and a thinning parameter of 1/1000 to account for high
 183 autocorrelation in the chains. The total sample size consisted of 3800 draws (4 chains *
 184 ((1 million iterations – 50,000 burn-in) / 1000)).

185 We assessed convergence by inspecting trace plots to ensure well-mixed chains
 186 (Hobbs and Hooten 2015) and calculating Gelman-Rubin statistics (Rhat) (Gelman and
 187 Rubin 1992) for all parameters using the *MCMCvis* package (Youngflesh 2018). Rhat
 188 values close to 1 indicate convergence with values less than 1.2 acceptable (Gelman
 189 1996, Zuur et al. 2012).

190 We assessed model fit using posterior predictive checks, which evaluate the ability of a
 191 model to generate new observations that resemble our observed data. We simulated
 192 new data for sand lance and whale counts based on the posterior predictive
 193 distributions for the mean number of sand lance and whales. We defined the mean,
 194 variance and proportion of zeroes in our simulated datasets as test statistics. Goodness
 195 of fit was evaluated using Bayesian p values (P_B), the probability that the test statistic
 196 calculated from our simulated data is more extreme than the test statistic calculated
 197 from observed data. Very large or very small P_B (<0.1 or >0.9) indicate poor model fit.
 198 We conducted posterior predictive checks for each species and also summarized
 199 results by block, season and year.

200 Applications

201 We used model results to examine two applications that could have potential
 202 management implications: locating sand lance ‘hot-spots’ and exploring entanglement

203 risk to humpback whales. We used posterior probability distributions for the site
204 parameter to find the probability that a site had a greater than block average number of
205 sand lance. To explore entanglement risk, we estimated the probability of a whale
206 aggregation at each site and examined overlap between sites and fixed fishing gear
207 locations. To estimate site probabilities of whale aggregations, we used the new counts
208 of whales generated for posterior predictive checks and found the proportion of those
209 values that were greater than our arbitrarily chosen aggregation size (n=5). We explored
210 potential overlap between whale aggregations and fixed fishing gear by creating a
211 density map of trap-pot gear locations from 2014-2016 from Vessel Trip Report (VTR)
212 data (NOAA Fisheries) using the *spatstat* package (Baddeley et al. 2015).

213

214 **Results**

215 **Sand lance sub-model**

216 Trace plots and Gelman-Rubin statistics confirmed convergence of most parameters.
217 Twelve λ_{ijk}^{sl} values had Rhat values between 1.2 and 1.3. These values correspond to
218 sites that never had sand lance observations, suggesting the model could not separate
219 true vs. false zeroes for these data points. Two z_{ijk}^{sl} values also had Rhat > 1.2 & < 1.3.
220 For all fixed effects and variance components, Rhat values were <1.1 and effective
221 sample sizes (n.eff) were > 3200.

222 Overall posterior predictive checks for the mean, variance and proportion of zeroes for
223 sand lance showed no evidence of lack of fit (Bayesian p-values: mean = 0.53, variance
224 = 0.73, proportion of zeroes = 0.79; Fig. S2). Posterior predictive checks summarized by
225 block (Bayesian p-value range: 0.52 – 0.84), year (Bayesian p-value range: 0.38 –
226 0.90), and season (Bayesian p-value range: 0.50 – 0.82) also showed no obvious lack
227 of fit (Figs. S3 – S5).

228 Predicted sand lance abundance varied by block and increased from north to south,
229 with median estimates of 0.07 sand lance / block (north), 0.73 sand lance / block
230 (central), and 3.74 sand lance / block (south) (Fig. 3A, Table 2). Some annual
231 differences in abundance were observed (credible intervals overlapped in most years),
232 with the largest fluctuations in abundance occurring in the south. Median sand lance
233 estimates for the south in most years (2014, 2015, 2016) was greater than average,
234 while median estimates for the central block were at or below average in these years.
235 Highest abundances in all blocks occurred in 2016. Abundance estimates for the north
236 showed little to no difference by year with median annual estimates essentially the
237 same as the near-zero block average (Fig. 3A). In the south and central blocks, median
238 abundance estimates were below average in 2018 (Fig. 3A).

239 Parameter values suggested site-level variation in sand lance abundance (Fig. 4A,
240 Table 2). Above average sand lance abundance was predicted for one northern site,
241 two central sites, and one southern site (Fig. 4A). The 95% credible intervals of the
242 marginal posterior for three additional sites (one northern, 2 southern) were almost

243 entirely above zero. Southern and central blocks had mixtures of sites with median
244 estimates above and below average expected abundance, while all but three northern
245 median estimates were predicted to have below average abundance (Fig. 4A), which
246 was not surprising given that sand lance were only observed at 2 sites in the northern
247 block throughout the study period (Fig. S1).

248 The probability of sand lance availability was slightly greater in the fall (median = 0.42,
249 95% CI = 0.29 – 0.59) than the spring (median = 0.33, 95% CI = 0.17 – 0.56) (Table 2),
250 though overlapping credible intervals suggest little difference between seasons.

251 ***Humpback whale sub-model***

252 Trace plots and Gelman-Rubin statistics confirmed convergence of most parameters.
253 One λ_{ijk}^w value and seven z_{ijk}^w values had Rhat values between 1.2 and 1.3. For all fixed
254 effects and variance components, Rhat values were <1.1 and effective sample sizes
255 (n.eff) were > 3200.

256 Overall posterior predictive checks for the mean, variance and proportion of zeroes for
257 humpbacks showed no evidence of lack of fit (Bayesian p-values: mean = 0.51,
258 variance = 0.78, proportion of zeroes = 0.71; Fig. S2). Posterior predictive checks
259 summarized by block (Bayesian p-value range: 0.27 – 0.86), year (Bayesian p-value
260 range: 0.31 – 0.90) and season (Bayesian p-value range: 0.48 – 0.91) also showed no
261 obvious lack of fit (Figs. S3 – S5).

262 Humpback whales showed a statistically clear positive correlation with sand lance
263 (median = 0.35, 95% credible interval = 0.05 – 0.70; Fig. 4C, Table 2). Using this
264 relationship, estimated humpback abundance also increased from north to south, with
265 highest expected abundances in every year occurring in the south (Fig. 4B). Some
266 annual differences in humpback abundance were observed, but year-to-year variation
267 differed from sand lance. Median values for predicted humpback abundance in all sites
268 alternated from below average in 2014 and 2016, to at or above average in 2015 and
269 2018, respectively (Fig. 4B).

270 The posteriors for the parameter values suggested site-level variation in humpback
271 abundance (Fig. 4B). Above average humpback abundance was predicted for two
272 central sites and three southern site (Fig. 4B). The range of 95% credible intervals for
273 three additional sites (one central, two southern) were almost entirely above zero. No
274 northern sites showed clear differences in humpback abundance, though median and
275 50% Bayesian credible intervals were above average for two northern sites. Southern
276 and central blocks had mixtures of sites with median estimates above and below
277 average (Fig. 4B). Only one site (C6) showed clear, above average estimates for both
278 humpbacks and sand lance (Fig. 4A, B).

279 The probability of humpback availability was slightly greater in the fall (median = 0.53,
280 95% credible interval = 0.36 – 0.71) than the spring (median = 0.47, 95% credible
281 interval = 0.3 – 0.66) (Table 2), though overlapping credible intervals suggests little

282 difference between seasons. The median probability of observing whales was greater
283 than the probability of observing sand lance in both seasons (Table 2).

284

285 ***Applications***

286 Sites that were likely to have greater than average sand lance abundance, or sand
287 lance 'hot-spots', were identified in all blocks (Fig. 5). The probability that a site had
288 greater than block-average sand lance abundance was >0.75 for two northern sites,
289 four central sites, and five southern sites (Fig. 5).

290 Probabilities of at least 5 whales at a site ranged from 0 – 0.34, with whale aggregations
291 being most likely in the southern block at site S11 (Fig. 6). The three (S10, S11, S14)
292 sites with the highest probabilities of whale aggregations overlapped with a high density
293 area of trap-pot gear on the SW corner of Stellwagen Bank. The probability of >3
294 whales at sites was greater with sites S11 and S14 having probabilities of whale
295 aggregations ≥ 0.5 .

296

297 **Discussion**

298 ***Ecology***

299 We demonstrated a statistically clear, positive correlation between sand lance and
300 humpback whales, supporting findings from previous work and confirming persistence
301 of this relationship over time (Payne et al. 1986, Payne et al. 1990, Weinrich et al.
302 1998). While prior studies linked shifts in humpback distributions with fluctuations in
303 sand lance abundance at broad scales across large feeding areas, we showed
304 relationships at an intermediate (block) scale within a single feeding area. This result is
305 consistent with Silva et al. (2020) that applied spatial metrics to the same dataset and
306 found high spatial collocation between humpbacks and sand lance in southern
307 Stellwagen Bank.

308 The clear relationship between humpbacks and sand lance suggests that relative
309 effects of sites and year would vary similarly for both species, but this was not the case.
310 Only one site (C6) had a positive effect on both sand lance and humpback abundance.
311 Differences in site effects for sand lance and humpbacks are likely due to a combination
312 of scale mismatch and habitat selection by sand lance. Correlations between predators
313 and prey are often scale-dependent (Rose & Legget 1990, Fauchald et al 2000). Our
314 site-level observations of sand lance and humpbacks are collected at very different
315 spatial scales – 0.1 m² for sand lance and an 800 m radius for humpbacks. Further,
316 sand lance benthic distributions are highly patchy, ranging from 0 to 44 fish in a single
317 grab sample (Table S1). Humpback counts within 800 m are likely not reflective of sand

318 lance counts in 0.1 m² which may be further complicated by the patchy benthic
319 distribution of sand lance. While benthic habitat selection by sand lance is likely based
320 on preferred sediment grain size (coarse grain sand) and sufficient oxygen flow (Meyer
321 et al 1979, Robards 2000), the average patch size of sand lance on the bottom is
322 unknown. Identifying correlations between predators and prey at the scale of prey
323 patches would likely require observations at the scale of an individual humpback whale
324 (Redfern et al. 2006). Hazen et al. (2009) and Kirchner et al. (2018) associated
325 humpback foraging with individual pelagic sand lance schools using data from 3D
326 motion sensor tags on individual whales and prey data from echosounders.
327 Alternatively, conducting multiple sand lance grabs at a site, within an 800 m radius may
328 show better agreement between site effects for sand lance and humpbacks.

329 The complex behavior of sand lance could also contribute to differences in site
330 parameter estimates. We assumed that the number of sand lance in each grab sample
331 reflects the relative total number of fish at a site (water column + sediment), which may
332 not be true. Sand lance are generally thought to spend daytime periods feeding in the
333 water column and to return to the bottom at night, during periods of low light, during
334 estivation, and/or in response to predators (Robards 2000). While our findings of sand
335 lance in the sediment during the day provide evidence that diel behavior of sand lance
336 is actually more complex, it is likely that pelagic sand lance abundance is greater than
337 benthic sand lance abundance during the day. This may lead to observations of whales
338 at a site, but not of sand lance, even though sand lance may be present in the water
339 column. Sampling pelagic sand lance abundance may improve correlations at the site
340 level. Nevertheless, the site-level variation in abundance of humpbacks and sand lance
341 shown here suggest that scale considerations in future modeling or management
342 actions could be important.

343 Differences in year effects between species could reflect challenges with sampling, but
344 may also suggest true differences driven by different environmental factors. Our
345 sampling is conducted once per season in any year, capturing a small snapshot of
346 animal abundance. Counts used here and resulting parameter estimates may not be
347 representative of actual annual trends in abundance. For example, opportunistic
348 sightings data collected from whale watching and research cruises in the sanctuary
349 during this time period show that humpback whale abundance was relatively high in
350 2016 (Robbins, unpublished data), concurrent with the highest sand lance abundance in
351 our study. It is possible that whales were not present at the time of our survey, or that
352 they were present, but were outside our 800m observation radius. However, different
353 year effects between species could also reflect true differences in animal abundance.
354 Predicted sand lance abundance was lowest in 2018 when predicted humpback
355 abundance was highest. It is possible that humpbacks were targeting other prey during
356 this time. Humpbacks in the GOM also eat herring and mackerel (Hain et al. 1982,

357 Geraci et al. 1989). Without direct observations of surface feeding, it is not possible to
358 determine what whales were targeting as prey or if they were foraging at all during our
359 surveys. More frequent surveys or sampling for additional forage fish species may
360 better explain yearly differences.

361 We clarify here that because site and year were treated as random effects, it is a
362 common approach to only interpret differences between sites and years using only the
363 magnitude of their variance components and not the individual random effects.
364 However, it is also common for the values for the random effects themselves to also be
365 of interest, and our estimation approach also allows us to quantify the uncertainty
366 associated with their estimates via their credibility intervals. However, because the block
367 specific means vary, the relative effect of the same magnitude site effect on the sand
368 lance and whale densities will vary by blocks. We also fit a model with block-specific
369 variances for site effects. This had minimal influence on the results, but did lead to
370 decreased precision in site parameter estimates particularly for N sites where few sand
371 lance and whales were observed. We emphasize that the site comparisons we do
372 make, particularly in the identification of sand lance hot-spots in the application below,
373 are relative to block-specific mean abundances and are only relevant within their
374 respective blocks (not across blocks). We also note that based on the current model
375 and our approach to use random site effect values to identify hot-spots, there is little
376 reason to believe that these same sites will persist as hot-spots in the future.
377

Modeling

378 Our model performed well in predicting the overall mean counts of whales and sand
379 lance from our dataset, but tended to underestimate both the proportion of zeroes and
380 the variance in counts for each species (posterior predictive checks, Figs S2 - S5). The
381 underestimate of variance may be due to underestimation of zeroes. This may be
382 partially driven by fewer observations in the north or some northern sites with no sand
383 lance observations, leading to an overestimate of the mean in the northern block, while
384 underestimating the variance and proportion of zeroes.

385 A preliminary zero-inflated negative binomial model performed slightly better in
386 estimating the proportion of zeroes and variance for both sand lance and humpbacks
387 (Bayesian p value range: 0.35 – 0.54), but performed slightly poorer in estimation of
388 mean abundance (Bayesian p values: 0.43, 0.45). Results from the zero-inflated
389 negative binomial were similar to those presented here and given a marginally better
390 performance, we chose to present the simpler zero-inflated Poisson model.

391 We attempted to account for zero-inflation due to seasonal sampling variability by
392 including season as a covariate in the zero-inflation portion of the model. Successful
393 observation (whale presence) of whales and capture of sand lance was more likely in
394 the fall, though overlapping credible intervals and the tendency of the model to
395 underestimate zero-inflation suggests that additional factors may influence zero-
396 inflation.

397 ***Further model developments and extensions***

398 The current model structure is specific to Stellwagen Bank National Marine Sanctuary.
399 Our survey design and sampling method is neither directly applicable to other
400 geographic areas or methodologies, nor suited for future prediction or forecasting.
401 However, the current model demonstrates value in using simple geographic covariates
402 to gain understanding of species distributions and the utility of a Bayesian hierarchical
403 framework for representing ecological relationships. Model results here provide insight
404 into variation in abundance and distribution over several spatial and temporal scales
405 that can inform selection of environmental covariates to further model development. We
406 first discuss potential ways to extend the model for SBNMS based on our results, and
407 then briefly mention additional factors known to influence sand lance and humpback
408 abundance on broader scales that should be considered for model expansion to larger /
409 new geographic areas.

410 While we demonstrate a clear relationship between humpbacks and sand lance in the
411 sanctuary, data on the availability of alternative prey sources is necessary to fully
412 understand variation in humpback abundance and distribution and the threshold
413 abundance of various prey species that influence humpback movements into and out of
414 areas. There may years where sand lance abundance is low (such as 2018 here), but
415 alternative prey is able to support a small number of humpbacks.

416 The site-level variation in sand lance abundance seen here is likely partially driven by
417 preferred sediment grain sizes. The USGS has produced extensive, fine-scale sediment
418 data for SBNMS (Valentine 2019). Our survey sampled multiple sand types (very coarse
419 to medium sand), but grain size data suggest that fewer northern sites are classified as
420 coarse grain sand (0.5 – 1 mm), the preferred sediment size of sand lance, which may
421 contribute to decreased benthic sand lance abundance in the northern block (Robards
422 et al. 2000). Grain size should be incorporated into future models. Given the seasonal
423 behavioral changes exhibited by sand lance, grain size may be more important for sand
424 lance in the fall as they spend more time in the sediment, suggesting a need for an
425 interaction between season and grain size. Further, the distribution of sand lance likely
426 reflects a balance between suitable benthic habitat and prey availability (Van der Kooij
427 et al. 2008). Copepods, primarily of the genus *Calanus*, primarily compose sand lance
428 diets where they have been studied (Meyers et al. 1979, Danielsen et al. 2016,
429 Staudinger et al. 2020, Suca et al. 2021). On Stellwagen Bank, *Calanus finmarchicus*
430 was primary prey of sand lance during most months when feeding occurs (Suca et al.
431 2021). Sand lance abundance across the northeast Shelf was also correlated with
432 lagged *Calanus finmarchicus* abundance (Suca et al. 2021) Including *Calanus*
433 abundance in future models may help explain both site-level and block-level variation in
434 sand lance abundance.

435 Year to year and block-level variation in sand lance abundance suggests that additional
436 dynamic environmental covariates should be included in future models. One potential
437 factor is the strength of the Western Maine Coastal Current, a current driven by fresh
438 water runoff and local wind forcing that flows southwestward around the Gulf of Maine
439 with peak inputs during the spring (Bigelow 1927, Geyer et al. 1992). The Western
440 Maine Coastal Current is an important source of *Calanus* to Massachusetts Bay and
441 inter-annual variability in transport, combined with local wind forcing, can impact both
442 primary productivity and zooplankton abundance (Jiang et al. 2007, McManus et al.
443 2014, Suca et al. 2021). Metrics related to the strength of the Western Maine Coastal
444 Current may help explain changes in sand lance abundance.

445 In addition to prey abundance, hydrology and predation influence sand lance
446 abundance on broad scales (Suca et al. 2021). In the northwest Atlantic, sand lance
447 abundance oscillates out of phase with the abundance of herring and mackerel, which
448 are known to prey on larval sand lance (Staudinger et al. 2020, Suca et al 2021).
449 Lagged herring abundance and the proportion of warm slope water were linked in
450 declines in sand lance abundance (Suca et al. 2021). Other studies have found
451 correlations between sand lance and oceanographic variables such as bottom
452 temperature and salinity (Van der Kooij et al. 2008). Model adaptation for areas larger
453 should consider these variables.

454 One limitation to further study of sand lance abundance in general is lack of data. Sand
455 lance data collected in the Gulf of Maine are sparse (Richardson et al. 2014) and to our
456 knowledge, no data exists at a scale as fine as our survey. Given the importance of
457 sand lance to humpbacks, as well as commercial fishes and seabirds (Staudinger et al.
458 2020), collecting additional sand lance data throughout the Gulf of Maine should be a
459 priority, particularly given the push towards ecosystem based management (Koehn et
460 al. 2020).

461

462 ***Application***

463 We applied our results to examine overlap between humpback whale aggregations and
464 fixed gear to demonstrate one potential management application. Over 75% of GOM
465 humpbacks show scarring consistent with entanglement (Robbins 2012) and
466 entanglement remains a serious threat, including within the sanctuary (U.S. Department
467 of Commerce 2010). We show that sites more likely to have whale aggregations overlap
468 with an area of high density trap-pot gear on southern Stellwagen Bank. Wiley et al.
469 (2003) used standardized survey data to show that whales had the highest risk of
470 interaction with fixed fishing gear in the same location (southern Stellwagen Bank). Our
471 results show that the location of highest entanglement risk for humpbacks has remained
472 consistent for almost two decades, but also provides tangible probabilities that whale

473 aggregations are present in areas of high risk. Further, our hierarchical model structure
474 shows two potential spatial scales for management options, regional (block) and small
475 scale (~1km), based on a clear relationship between humpbacks and sand lance and
476 identification of both sand lance hotspots (where whales could be) and whale
477 aggregation sites.

478 **Conclusion**

479 We fit a Bayesian hierarchical model to a unique dataset to advance our understanding
480 of the sand lance - humpback whale relationship in the southwestern Gulf of Maine. Our
481 work explored this predator-prey relationship with a novel approach, extending our
482 knowledge past simple correlations and providing new insight into the abundance and
483 distribution of sand lance and humpbacks over multiple spatial and temporal scales that
484 can inform further model developments. Models to predict both sand lance and
485 humpback abundance in SBNMS and beyond will become crucial for understanding
486 potential changes to predator-prey dynamics and ecosystem structure due to climate
487 change. Sand lance appear especially vulnerable to increasing temperatures and ocean
488 acidification (Hare et al. 2016, Murray et al. 2019, Suca et al. 2021). Declines in sand
489 lance abundance and serious changes to the NE US forage fish complex are predicted
490 under current carbon emissions (Suca et al. 2021). Climate-induced shifts in the
491 abundance and distribution of sand lance will likely lead to shifts in the abundance and
492 distribution of humpbacks. Understanding how humpback whales will respond to
493 fluctuations in forage fish abundance is critical for predicting and mitigating human
494 impacts, like those from entanglement.

495

496 **Acknowledgements**

497 We thank P. Valentine and D. Blackwood for their invaluable contributions to this work
498 including time, expertise, and equipment. Thanks to Michael Thompson, Peter Hong
499 and Justin Suca for their instrumental efforts with field work and logistics. We are
500 grateful to Captains D. Slocum, A. Meloski and the R/V *Auk* crew for their efforts on this
501 project. We thank the many SBNMS volunteers and observers who helped collect these
502 data. Thanks to Les Kaufman, Joel Llopiz, and Hannes Baumann for their support and
503 involvement. This work was supported by the Bureau of Ocean Energy Management [IA
504 agreement M17PG0019], NOAA Stellwagen Bank National Marine Sanctuary, U.S.
505 Geological Survey, and the Volgenau Foundation. We thank two anonymous reviewers
506 for their thoughtful comments that greatly improved this manuscript.

507 The scientific results and conclusions, as well as any views or opinions expressed
508 herein, are those of the authors and do not necessarily reflect the views of the Office of
509 National Marine Sanctuaries, NOAA or the Department of Commerce.

510 **Data Accessibility Statement**

511 All data and code are available on github

512 (https://github.com/tammylsilva/sand_lance_humpback_bayesian_model).

513 **Conflict of Interest**

514 The authors have no conflicts of interest.

515 **Authors' Contributions**

516 Field research design & funding acquisition: DW, Data collection: DW, TS, Model
517 conceptualization & analysis: TS, GF, Writing – original draft: TS, Writing – review &
518 editing: TS, DW, GF.

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Table 1. Summary of data used in the model (n=164). The number of sites sampled and the total number of sand lance and humpback whales observed is given for each cruise. The number of sites with and without observations of sand lance and whales is shown to provide an idea of zero inflation.

Cruise	Total Sites sampled			Sites with observations / sites without observations							
	Sand lance	Whales	N	Sand lance			Whales				
				C	S	N	C	S	N		
Fall 2014	85	16	4	5	13	0 / 4	3 / 2	11 / 2	0 / 4	2 / 3	4 / 9
Spring 2015	30	11	12	14	7	0 / 12	5 / 9	2 / 5	0 / 12	1 / 13	2 / 5
Fall 2015	19	41	14	12	14	0 / 14	1 / 11	1 / 13	2 / 12	4 / 8	6 / 8
Fall 2016	124	23	9	9	12	2 / 7	0 / 9	7 / 5	1 / 8	1 / 8	7 / 5
Spring 2018	5	58	12	13	14	1 / 11	1 / 12	1 / 13	3 / 9	6 / 7	8 / 6

Table 2. Posterior medians, means, standard deviation and 95% credible intervals for selected model parameters. Posterior summaries for site effects were omitted here (shown in Fig. 4). Summaries for posterior distributions for other model parameters are included in the supplementary material.

Sand lance sub-model					
Parameter	Median	Mean	SD	Bayesian Credible Interval	
				2.50%	97.50%
$\beta_{central}^b$	-0.31	-0.36	1.12	-2.74	1.73
β_{north}^b	-2.6	-2.7	1.37	-5.69	-0.27
β_{south}^b	1.32	1.28	0.96	-0.73	3.15
β_{2014}^y	0.15	0.18	0.84	-1.44	1.98
β_{2015}^y	0.4	0.42	0.84	-1.21	2.2
β_{2016}^y	0.96	1	0.84	-0.6	2.81
β_{2018}^y	-1.43	-1.49	0.91	-3.46	0.12
σ_{sl}^2	2.49	2.89	1.77	0.82	7.33
τ_{sl}^2	1.47	3.38	8.91	0.25	16.87
$\phi_{fall(ijk)}^{sl}$	0.42	0.43	0.08	0.29	0.59
$\phi_{spring(ijk)}^{sl}$	0.33	0.34	0.1	0.17	0.56

Humpback whale sub-model					
Parameter	Median	Mean	SD	Bayesian Credible Interval	
				2.50%	97.50%
α_{sl}	0.35	0.36	0.16	0.05	0.70
Θ_{2014}^y	-0.5	-0.55	0.39	-1.4	0.12
Θ_{2015}^y	0.07	0.05	0.32	-0.64	0.62
Θ_{2016}^y	-0.56	-0.62	0.42	-1.58	0.06
Θ_{2018}^y	0.66	0.68	0.39	-0.02	1.51
σ_w^2	1	1.14	0.66	0.25	2.73
τ_w^2	0.42	0.86	2.46	0.05	3.91
$\phi_{fall(ijk)}^w$	0.53	0.53	0.09	0.36	0.71
$\phi_{spring(ijk)}^w$	0.47	0.47	0.09	0.3	0.66

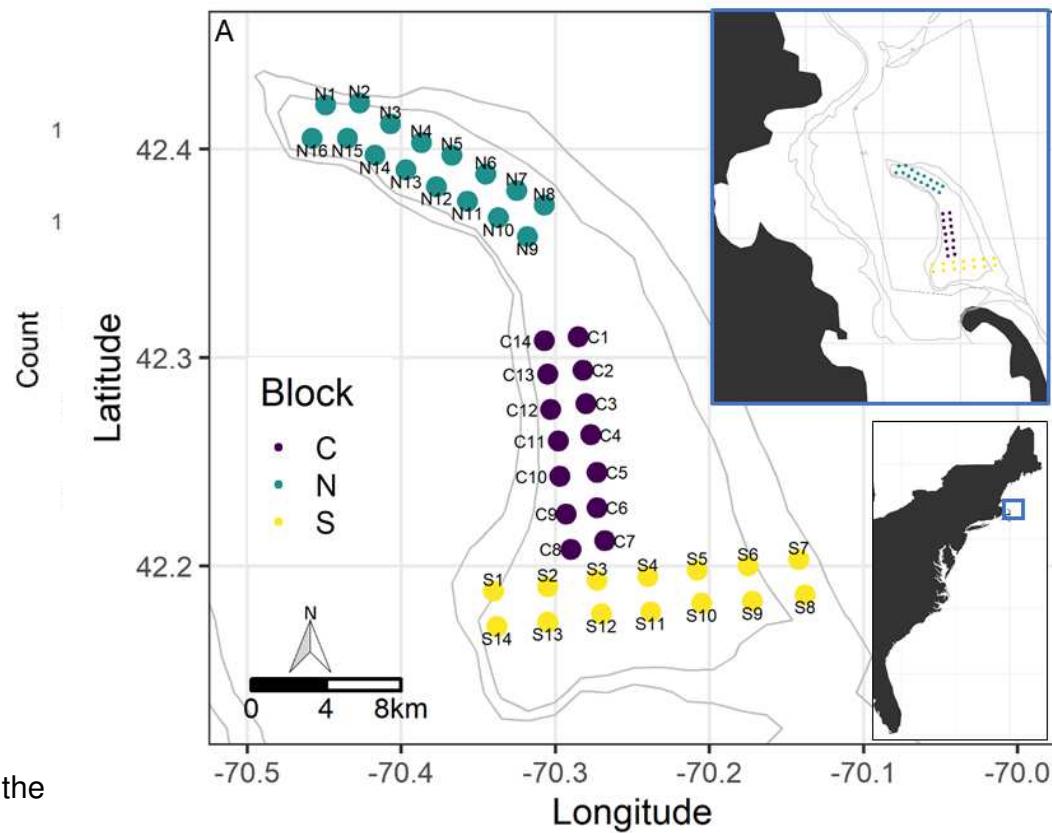
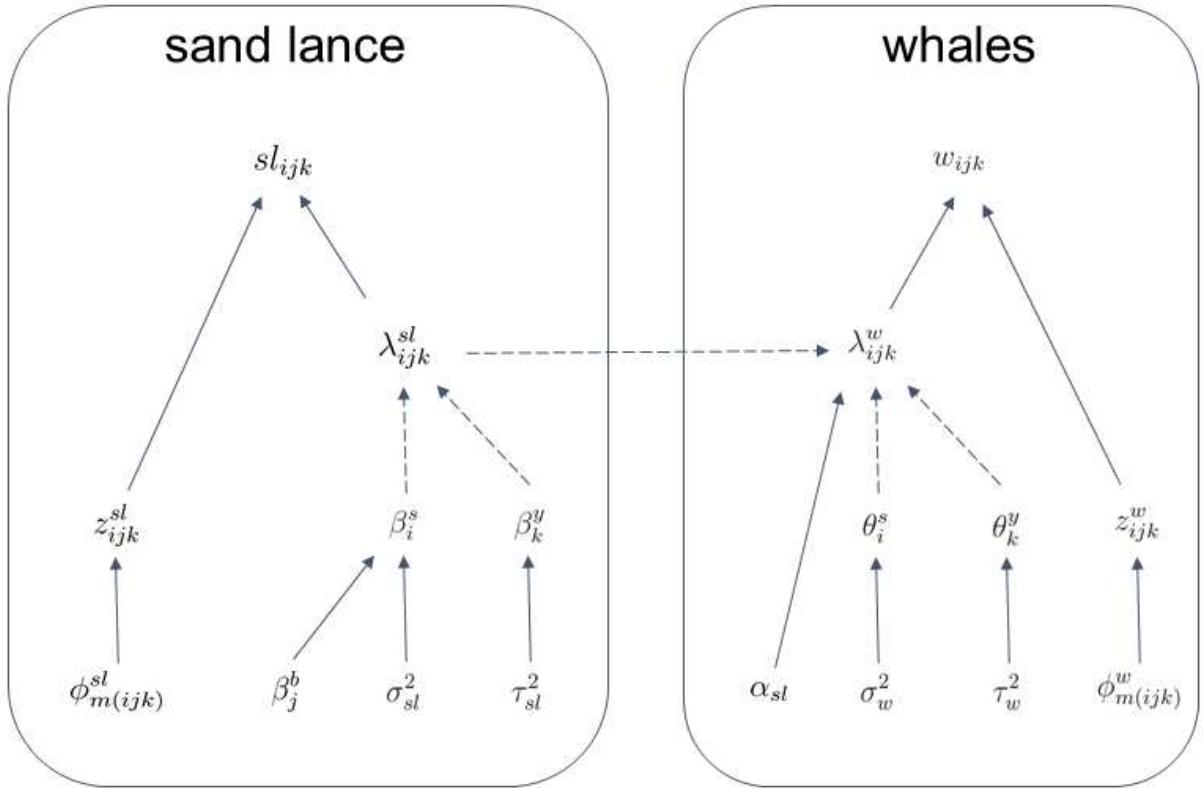


Figure 1.
Map of
survey
design

and

summary of data used in the model. A) Map shows Stellwagen Bank proper and the 44 sites included in the survey. Sites are organized into 3 blocks: North (N-green), Central (C-purple), and South (S-yellow). Sites within blocks were ~ 1km apart and were designed to sample all potential sand lance benthic habitat. Thin gray lines represent the 50m (outer) and 40m (inner) isobaths. Inset maps show the survey location within Stellwagen Bank National Marine Sanctuary (rectangular boundaries) off the coast of Massachusetts (top) and the location of the study site off the northeast U.S. B) Histogram of sand lance counts used in the model (n=164) colored by block. The inset shows counts equal to one between 17 and 44 that may be difficult to see. C) Histogram of humpback whale counts used in the model (n=164) colored by block.



$$\begin{aligned}
 & [z_{ijk}^{sl}, \beta_i^s, \beta_j^b, \beta_k^y, \sigma_{sl}^2, \tau_{sl}^2, \phi_{m(ijk)}^{sl}, z_{ijk}^w, \theta_i^s, \theta_k^y, \sigma_w^2, \tau_w^2, \phi_{m(ijk)}^w, \alpha_{sl} | sl_{ijk}, w_{ijk}] \propto \\
 & \prod_{n=1}^{164} [sl_{ijk} | z_{ijk}^{sl}] [z_{ijk}^{sl} | \phi_{m(ijk)}^{sl}] [\beta_i^s | \beta_j^b, \sigma_{sl}^2] [\beta_k^y | \tau_{sl}^2] [\phi_{m(ijk)}^{sl}] [\beta_j^b] [\sigma_{sl}^2] [\tau_{sl}^2] [w_{ijk} | z_{ijk}^w] [z_{ijk}^w | \\
 & \phi_{m(ijk)}^w] [\theta_i^s | \sigma_w^2] [\theta_k^y | \tau_w^2] [\phi_{m(ijk)}^w] [\sigma_w^2] [\tau_w^2] [\alpha_{sl}]
 \end{aligned}$$

Figure 2. Bayesian network and full expression for the posterior and joint distributions for hierarchical zero-inflated Poisson mixed effects model of sand lance and humpback whale abundance. Sand lance counts at site i in block j in year k , sl_{ijk} was modelled as a Poisson random variable with mean λ_{ijk}^{sl} . The mean number of sand lance, λ_{ijk}^{sl} was modeled as a log linear function of block β_j^b , site β_i^s , and year β_k^y . Site and year were treated as random effects with variance σ_{sl}^2 and τ_{sl}^2 , respectively. Seasonal zero inflation in sand lance availability was described by z_{ijk}^{sl} , where $\phi_{m(ijk)}^{sl}$ is the probability of zero inflation for season m . Humpback whale counts at site i in block j in year k , w_{ijk} , was modeled as a Poisson random variable with mean λ_{ijk}^w . The mean number of whales λ_{ijk}^w , was described as a log linear function of expected sand lance abundance λ_{ijk}^{sl} and its regression coefficient, α_{sl} , site θ_i^s and year θ_k^y . Site and year were treated

as random effects with variance σ_w^2 and τ_w^2 , respectively. Seasonal zero inflation in the observation of whales was described by z_{ijk}^w , where $\phi_{m(ijk)}^w$ was the probability of zero inflation for season m . Solid lines indicate stochastic relationships and dashed lines indicate deterministic relationships.

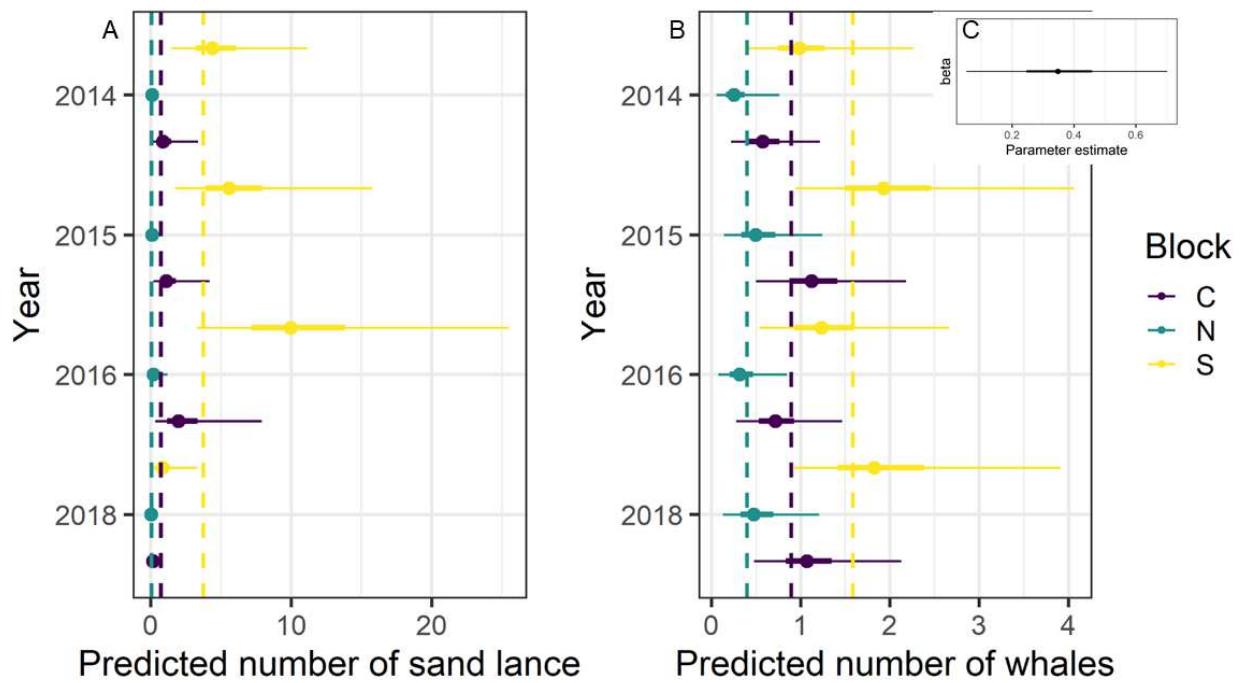


Figure 3. Predicted numbers of sand lance and humpback whales by block and year. Dashed vertical lines represent median abundance estimates for each block (N = green, C = purple, S = yellow). Points represent median abundance estimates for each block in each year. Thicker lines represent 50% Bayesian credible intervals and thinner lines represent 95% Bayesian credible intervals. A) Predicted numbers of sand lance. B) Predicted number of humpback whales. C) Parameter estimate for the influence of sand lance abundance on humpback abundance. This relationship was used to estimate block median abundance for humpbacks (dashed vertical lines) in (B).

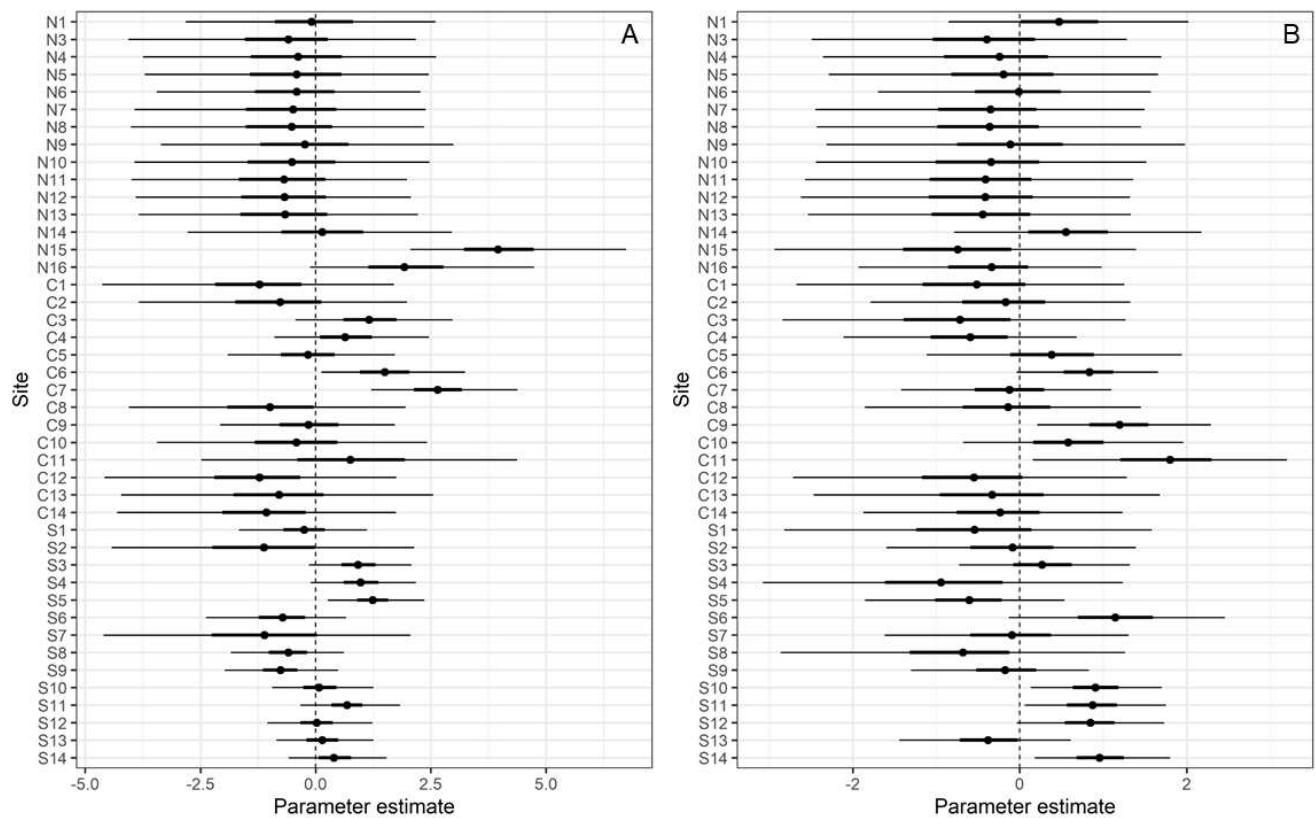


Figure 4. Summaries of posterior distributions for site effects for A) sand lance and B) humpback whales. Sites are ordered from north to south. Dashed vertical lines at 0 represent no deviation from the average abundance. Estimates greater than zero represent sites with greater than block average abundance while parameters below zero represent sites with less than block average abundance. Points represent posterior medians, thicker lines represent 50% credible intervals and thinner lines 95% credible intervals.

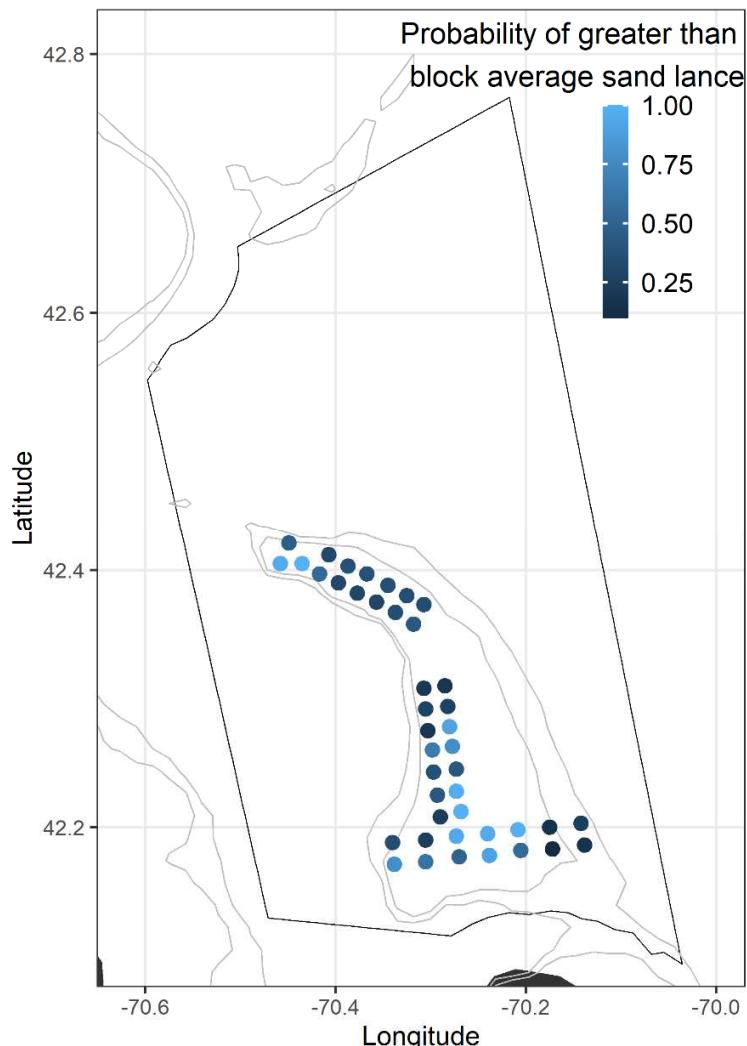


Figure 5. Probabilities that sites have greater than block average sand lance abundance. Predictions were based on an average year. Site N2 was never sampled in this subset of data and therefore, has no probability estimate and is missing in the map. Dark line represents Stellwagen Bank National Marine Sanctuary boundaries. Gray lines represent the 50 m (outer) and 40 m (inner) isobaths indicating Stellwagen Bank proper.

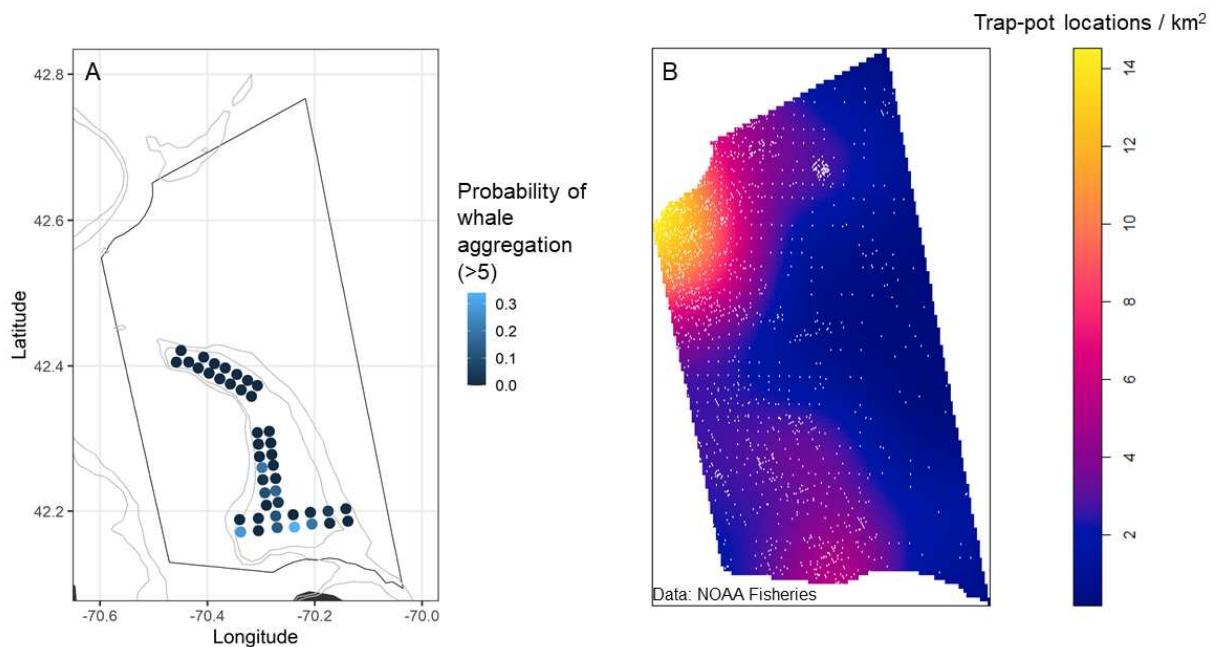


Figure 6. Assessment of humpback whale entanglement risk. A) Probability that whale aggregations (>5 whales) occur at sites. Predictions were based on an average year. Site N2 was never sampled in this subset of data and therefore, has no probability estimate and is missing in the map. Dark line represents Stellwagen Bank National Marine Sanctuary boundaries. Gray lines represent the 50 m (outer) and 40 m (inner) isobaths indicating Stellwagen Bank proper. B) Density of trap-pot fishing locations in Stellwagen Bank National Marine Sanctuary from 2014 – 2016. Data - NOAA Fisheries.