

<sup>1</sup> Estimation of survey efficiency and abundance for  
<sup>2</sup> commercially important species from industry-based  
<sup>3</sup> paired gear experiments

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**10 Abstract**

11 Fishery-independent surveys provide valuable information about trends in population abundance  
12 for management of commercially important fish stocks. A critical component of the  
13 relationship of the catches of the survey to the size of a fish stock is the catch efficiency  
14 of the survey gear. Using a general hierarchical model we estimated relative efficiency of  
15 chain sweep to the rockhopper sweep used by the Northeast Fisheries Science Center bottom  
16 trawl survey from paired-gear experimental tows carried out between 2015 and 2017 using  
17 a twin-trawl vessel. For 10 commercially important species, we fitted and compared a set  
18 of models with alternative assumptions about variation of relative efficiency between paired  
19 gear tows, size and diel effects on the relative efficiency, and extra-binomial variation of  
20 observations within paired gear tows. These analyses provided evidence of changes in relative  
21 efficiency with size for all species and diel effects were important for all but one species. We  
22 then used the bottom trawl survey data from surveys between 2009 and 2019 with the relative  
23 catch efficiency estimates from the best performing models to estimate annual and seasonal  
24 chain sweep-based swept area biomass for 17 managed stocks. We estimated uncertainty in  
25 all results using bootstrap procedures for each data component. We also assessed the effect  
26 of calibration on uncertainty of the biomass estimates and the degree of correlation of the  
27 annual biomass estimates.

**28 Keywords**

29 gear efficiency, abundance estimation, hierarchical generalized additive models,

30 **1 Introduction**

31 Ecosystem monitoring surveys such as fisheries-independent trawl surveys are used to obtain  
32 information on a range of species and are therefore not optimized with respect to sampling  
33 design or gear for any one species (Bijleveld et al., 2012; Wang et al., 2018). Gear and  
34 sampling protocols are designed to provide consistent and representative samples that allow  
35 indices of abundance at size and age to be developed for a suite of species (Azarovitz, 1981;  
36 Thiess et al., 2018). To provide indices of population abundance with minimal potential  
37 sources of bias, survey bottom trawl gear must be configured to be towed across as wide a  
38 variety of habitats as possible, including seafloor habitats with complex physical structures.

39 Indices of abundance at age and size derived from fisheries independent bottom trawl surveys  
40 are scaled to population size by the survey catchability ( $q$ ) parameter (Arreguín-Sánchez,  
41 1996). Catchability is typically estimated internally within stock assessment models that  
42 incorporate fisheries landings, indices of abundance, and life history parameters. However,  
43 the amount or quality of data and degree of contrast in the time series is often such that  
44 this parameter is difficult to estimate (Maunder and Piner, 2015). In such cases, estimates  
45 of survey catchability from auxilliary data can inform the stock assessment. These external  
46 estimates can be used as a direct input into the assessment model (Somerton et al., 1999),  
47 can serve as a diagnostic measure of model accuracy (Miller et al., 2019), or contribute to  
48 an alternate means of providing catch advice when an assessment model is not considered  
49 acceptable (Legault and McCurdy, 2017).

50 Catchability can be decomposed into two components, the proportion of the population  
51 available to the survey sampling frame and the efficiency of the survey gear given an  
52 individual is available to the gear (Paloheimo and Dickie, 1964). Here efficiency is the fraction  
53 of available fish retained by the gear, equivalent to availability-selection in Millar and Fryer  
54 (1999). Estimates of these components allow relative abundance indices to be converted into  
55 absolute abundance indices without a population model. As such, investigations of gear

56 mensuration (Kotwicki et al., 2011), species-specific gear efficiency (Thygesen et al., 2019;  
57 Jones et al., 2021), and availability of the stock to the survey design frame (Nichol et al.,  
58 2019) improve our understanding of catchability and therefore abundance of fish stocks.

59 Paired-gear studies where two gear are fished either concurrently or close together temporally  
60 and spatially have long been used to estimate the efficiency of one fishing gear relative to  
61 another (e.g., Gulland, 1964; Bourne, 1965). Of the two gears, one is often a reference gear  
62 that may be a gear currently used for annual surveys (e.g., Munro and Somerton, 2001).  
63 Typically neither of the gears is fully efficient and therefore the relative efficiency of gears  
64 is estimated (e.g., Miller, 2013; Kotwicki et al., 2017), but there are cases where one of the  
65 gears is assumed to be at least very nearly fully efficient (e.g., Somerton et al., 2013; Miller  
66 et al., 2019).

67 Whether or not full efficiency of one of the gears is assumed, paired-gear studies are essential  
68 for generating abundance time series from fishery independent surveys when there are changes  
69 in the vessel and(or) gears over time due to gear failures or improved technology (Pelletier,  
70 1998). These studies are also helpful for combining surveys conducted close together in space  
71 or time using alternative gears (Kotwicki et al., 2013).

72 Within the northeast US there has been a heightened focus on bottom trawl survey operations  
73 and gear efficiency. This focus has in part resulted from low quotas for a number of groundfish  
74 limiting fishing opportunities. To help provide clarity on the trawl operations and build  
75 trust in survey indies the New England and Mid-Atlantic Fisheries Management Councils  
76 developed a Northeast Trawl Advisory Panel. This panel is composed of members from  
77 industry, regional academics, as well as state and federal scientists. Together the group  
78 designed a set of experiments to better understand the efficiency of the bottom trawl survey  
79 gear for northeast US groundfish stocks.

80 In conducting paired-gear studies it is ideal to have the two gears deployed as close together  
81 spatially and temporally as possible to reduce variation between the gears in densities of the

species being captured. The twin-trawl rigging (Krag et al., 2015) where two trawls can be fished simultaneously approaches this ideal (ICES, 1996), and is the data-collection platform chosen by the Trawl Advisory Panel. The Panel decided to rig one of the twin trawls as the gear used by the bottom trawl survey which uses a rockhopper sweep. The other trawl was rigged similarly except with a chain sweep in an attempt to eliminate any escapement of fish under the gear. Assuming the chain sweep-based gear is fully efficient allows the efficiency of the rockhopper sweep-based gear used by the bottom trawl survey to be estimated from these experiments.

The analytical methods to estimate the efficiency of the bottom trawl gear are based on those used by Miller (2013) to estimate size effects on relative catch efficiency of the *Henry B. Bigelow* to the *Albatrosss IV* for a variety of commercially important species, but we extend the model to consider different size effects for tows conducted during the day or night since both the spring and fall bottom trawl surveys conducted in the Northeast US are 24-hour operations. We apply these methods to paired gear observations and estimate relative efficiency of the chainsweep and rockhopper sweep gears. We apply the estimated efficiency of the rockhopper gear to survey data to estimate spring and fall abundance indices from 2009-2019 for 17 commercially important fish stocks in the Northeast US (Table 1).

Often overlooked aspects of the application of relative catch efficiency estimates is the impact on the precision of abundance indices and the correlation among annual indices that the application induces. These indices are typically used as measures of relative abundance in stock assessment with the precision of the indices used to weight the observations within the assessment model. Furthermore, the sampling variability of the annual indices is typically assumed to be independent. Here we compare the precision of the calibrated and uncalibrated indices and measure the correlation of calibrated indices for each stock.

<sup>106</sup> **2 Methods**

<sup>107</sup> **2.1 Data collection**

<sup>108</sup> Data were collected during three field experiments carried out in 2015, 2016, and 2017,  
<sup>109</sup> respectively, aboard the *F/V Karen Elizabeth*, a 23.8m (78ft) stern trawler capable of towing  
<sup>110</sup> two trawls simultaneously side by side. However, red hake were only observed during the  
<sup>111</sup> 2017 field experiments. One side of the twin-trawl rig towed a NEFSC standard 400 x 12 cm  
<sup>112</sup> survey bottom trawl rigged with the NEFSC standard rockhopper sweep (Politis et al., 2014)  
<sup>113</sup> (Figure 1). The other side of the twin-trawl rig towed a version the NEFSC 400 x 12cm  
<sup>114</sup> survey bottom trawl modified to maximize the capture of flatfish. The trawl was modified  
<sup>115</sup> by reducing the headline flotation from 66 to 32, 20cm, spherical floats, reducing the port  
<sup>116</sup> and starboard top wing-end extensions by 50cm each and utilizing a chain sweep. The chain  
<sup>117</sup> sweep was constructed of 1.6cm ( $\frac{5}{8}$ in) trawl chain covered by 12.7cm diameter x 1cm thick  
<sup>118</sup> rubber discs on every other chain link (Figure 2). Two rows of 1.3cm ( $\frac{1}{2}$ in) tickler chains were  
<sup>119</sup> attached to the 1.6cm trawl chain by 1.3cm shackles. To ensure equivalent net geometry of  
<sup>120</sup> each gear, 32m restrictor ropes, made of 1.4cm ( $\frac{9}{16}$ in) buoyant, Polytron rope, were attached  
<sup>121</sup> between each of the trawl doors and the center clump. 3.4m<sup>2</sup> Thyboron Type 4 trawl doors  
<sup>122</sup> were used to provide enough spreading force to ensure the restrictor ropes remained taut  
<sup>123</sup> throughout each tow. Each trawl used the NEFSC standard 36.6m bridles. All tows followed  
<sup>124</sup> the NEFSC standard survey towing protocols of 20 minutes at 3.0 knots. In 2015, 108 (45  
<sup>125</sup> day, 63 night) paired tows were conducted in eastern Georges Bank and off of southern New  
<sup>126</sup> England (Figure 3). In 2016, 117 (74 day, 43 night) paired tows were conducted in western  
<sup>127</sup> Gulf of Maine and northern edge of Georges Bank. In 2017, 103 (61 day, 42 night) paired  
<sup>128</sup> tows were conducted in the western Gulf of Maine and off of southern New England. Paired  
<sup>129</sup> tows were denoted as “day” and “night” by whether the sun was above or below the horizon  
<sup>130</sup> at the time of the tow.

<sub>131</sub> **2.2 Paired-tow analysis**

<sub>132</sub> We employed the hierarchical modeling approach from Miller (2013) to estimate the efficiency  
<sub>133</sub> ( $\rho$ ) of the rockhopper sweep used by the NEFSC bottom trawl survey relative to the chain  
<sub>134</sub> sweep-based gear for ten species (Summer flounder, *Paralichthys dentatus*; American plaice,  
<sub>135</sub> *Hippoglossoides platessoides*; windowpane flounder, *Scophthalmus aquosus*; winter flounder,  
<sub>136</sub> *Pseudopleuronectes americanus*; yellowtail flounder, *Limanda ferruginea*; witch flounder,  
<sub>137</sub> *Glyptocephalus cynoglossus*; red hake, *Urophycis chuss*; goosefish, *Lophius americanus*; barn-  
<sub>138</sub> door skate, *Dipturus laevis*; thorny skate, *Amblyraja radiata*) from three separate research  
<sub>139</sub> trips carried out aboard a twin trawl vessel. We first fit and compared the same set of  
<sub>140</sub> 13 models as Miller (2013) with different assumptions about variation of relative efficiency  
<sub>141</sub> between paired gear tows, size effects on the relative efficiency, and extra-binomial variation  
<sub>142</sub> of observations within paired gear tows. The binomial (BI<sub>0</sub> to BI<sub>4</sub>) and beta-binomial (BB<sub>0</sub> to  
<sub>143</sub> BB<sub>7</sub>) models that were fitted for all species are described in Table 2 including pseudo-formulas  
<sub>144</sub> analogous to those used to specify and fit mixed or generalized additive models in R (R Core  
<sub>145</sub> Team, 2019; Wood, 2006). We then also included diel effects on relative catch efficiency and  
<sub>146</sub> interactions with size effects with the best performing model of the original 13 models for  
<sub>147</sub> each species. To fit these diel effects, we generalized the modeling framework somewhat in  
<sub>148</sub> that we allow multiple (cubic regression spline) smooth effects, differing by day and night,  
<sub>149</sub> on relative catch efficiency. We implemented the models using the Template Model Builder  
<sub>150</sub> package (Kristensen et al., 2016) in R and we used the “nlnminb” optimizer to fit the models  
<sub>151</sub> by maximizing the Laplace approximation of the marginal likelihood (R Core Team, 2019).

<sub>152</sub> If the best model included smooth length effects and the estimated smoothing parameter  
<sub>153</sub> implied a linear functions of length (on the transformed mean), then simple linear functions  
<sub>154</sub> (i.e., completely smooth) were assumed for further models that included diel effects on relative  
<sub>155</sub> efficiency. As such, there was one less (smoothing) parameter estimated for these models.

<sub>156</sub> We compared two alternative ways of estimating uncertainty in relative catch efficiency. The

157 first estimation approach uses the inverted hessian of the marginal log-likelihood and the  
 158 delta-method to estimate uncertainty in the predicted relative catch efficiency at size. The  
 159 second method, is a bootstrap method where we refit models to bootstrap resamples of the  
 160 paired station data. Specifically, we resampled the paired tows with replacement so that  
 161 the total number of paired tows was the same for a given species, but the total number  
 162 of length measurements varied depending on which of the paired tows entered the sample  
 163 for a particular bootstrap. We made 1000 bootstrap samples and estimated relative catch  
 164 efficiency at size from each bootstrap data set if the fitted model converged and the hessian  
 165 at the maximized log-likelihood was invertible.

166 For models BI<sub>4</sub>, BB<sub>6</sub>, and BB<sub>7</sub>, there are two fixed effects parameters associated with the  
 167 spline coefficients that are treated as random effects for station-specific smoothers and by  
 168 default the correlation of these pairs of random effects is estimated. For red hake, this  
 169 parameter was not estimable for BB<sub>6</sub> and assumed equal to zero.

### 170 2.3 Length-weight analysis

171 We fit length-weight relationships to the length and weight observations for each survey each  
 172 year. We assumed weight observation  $j$  from survey  $i$ , was log-normal distributed,

$$\log W_{ij} \sim N \left( \log \alpha_i + \beta_i \log L_{ij} - \frac{\sigma_i^2}{2}, \sigma_i^2 \right) \quad (1)$$

173 We used a bias correction to ensure the expected weight  $E(W_{ij}) = \alpha_i L_{ij}^{\beta_i}$ . We estimated  
 174 parameters by maximizing the model likelihood programmed in TMB (Kristensen et al.,  
 175 2016) and R (R Core Team, 2019) and generated predictions of weight at length

$$\widehat{W}(L) = \widehat{\alpha} L^{\widehat{\beta}}. \quad (2)$$

<sub>176</sub> Like the relative catch efficiency, we made bootstrap predictions of weight at length by  
<sub>177</sub> sampling with replacement the length-weight observations within each annual survey and  
<sub>178</sub> refitting the length-weight relationship to each of the bootstrap data sets.

## <sub>179</sub> 2.4 Biomass estimation

<sub>180</sub> For the 17 managed stocks that are populations of the species in the Northeast US where  
<sub>181</sub> we have estimated relative efficiency, we estimated stock biomass for each spring and fall  
<sub>182</sub> annual survey assuming 100% efficiency of the chainsweep gear by scaling the survey tow  
<sub>183</sub> observations by the relative efficiency of the chainsweep and rockhopper sweep gears. There  
<sub>184</sub> are single unit stocks for summer and witch flounders, American plaice, and barndoor and  
<sub>185</sub> thorny skates, but there are three stocks of winter and yellowtail flounders, and two stocks of  
<sub>186</sub> windowpane, red hake, and goosefish (Table 1). First, the tow-specific catches at length are  
<sub>187</sub> rescaled,

$$\widetilde{N}_{hi}(L) = N_{hi}(L) \widehat{\rho}_i(L) \quad (3)$$

<sub>188</sub> where  $N_{hi}(L)$  is the number at length  $L$  in tow  $i$  from stratum  $h$  and  $\widehat{\rho}_i(L)$  is the relative  
<sub>189</sub> efficiency of the chain sweep to rockhopper sweep at length  $L$  estimated from the twin trawl  
<sub>190</sub> observations that may depend on the diel characteristic of tow  $i$  if that factor is in the  
<sub>191</sub> best model fitted to the twin-trawl observations. Note that we have omitted any subscripts  
<sub>192</sub> denoting the year or season.

<sub>193</sub> The stratified abundance estimate is then calculated using the design-based estimator,

$$\widehat{N}(L) = \sum_{h=1}^H \frac{A_h}{an_h} \sum_{i=1}^{n_h} \widetilde{N}_{hi}(L) \quad (4)$$

<sub>194</sub> where  $A_h$  is the area of stratum  $h$ ,  $a$  is the average swept area of a survey station tow, and  
<sub>195</sub>  $n_h$  is the number of tows that were made in stratum  $h$ . The corresponding biomass estimate

196 is then

$$\hat{B} = \sum_{l=1}^{n_L} \hat{N}(L = l) \hat{W}(L = l) \quad (5)$$

197 where  $\hat{W}(L = l)$  is the predicted weight at length (Eq. 2) from fitting length-weight  
198 observations described above. Length is typically measured to the nearest cm so  $n_L$  indicates  
199 the number of 1 cm length categories that were observed during the survey.

200 We used the same criteria for survey station selection as those currently used to estimate  
201 indices of abundance or biomass for management of each stock. For Gulf of Maine winter  
202 flounder we also restricted the size classes in each tow to those  $\geq 30$  cm as the biomass of the  
203 population over this threshold is currently used for management of this stock. For some stocks  
204 there were certain years where some but not all of the set of survey strata used to define  
205 indices of abundances were sampled. In those years, the average catch per unit area was  
206 expanded to all of the stock strata proportionally to the areas of the sampled and unsampled  
207 strata. The fall 2017 survey was extremely restricted because of vessel mechanical failure and  
208 indices are not available for summer flounder, SNE-MA windowpane, and SNE-MA yellowtail  
209 flounder.

210 To estimate uncertainty in biomass, we used bootstrap results for the relative catch efficiency  
211 and weight at length estimates along with bootstrap samples of the survey data. Bootstrap  
212 data sets for each of the annual surveys respected the stratified random designs by resampling  
213 with replacement within each stratum (Smith, 1997). For each of the 1000 combined  
214 bootstraps, survey observations for bootstrap  $b$  were scaled with the corresponding bootstrap  
215 estimates of relative catch efficiency and predicted weight at length, using Eqs. 4 and 5.

216 We also used the bootstraps to summarize other aspects of the biomass estimates. First, we  
217 used the bootstraps to calculate the ratio of calibrated and uncalibrated biomass for each  
218 spring and fall annual survey which is the implicit relative catch efficiency in terms of biomass.  
219 The uncalibrated biomass estimate for bootstrap  $b$  uses the resampled survey data as the  
220 calibrated biomass estimate except that the bootstrap for the relative catch efficiency is not

221 used (i.e.,  $\hat{\rho}_i(L) = 1$  in Eq. 3). We also used the bootstraps to compare the coefficients of  
222 variation (CV) of the calibrated and uncalibrated biomass estimates. The CV for an annual  
223 biomass estimate for year  $y$  from either the spring or fall survey was calculated as

$$CV(\hat{B}_y) = \frac{SD(\hat{B}_y)}{\bar{\hat{B}}_y}$$

224 where

$$SD(\hat{B}_y) = \sqrt{\frac{\sum_{b=1}^K (\hat{B}_{y,b} - \bar{\hat{B}}_y)^2}{K-1}},$$

225

$$\bar{\hat{B}}_y = \frac{\sum_{b=1}^K \hat{B}_{y,b}}{K},$$

226 and  $K$  is the number of bootstraps.

227 For summmer flounder it was necessary to omit one of the 1000 bootstraps of relative catch  
228 efficiency at length due to an extremely large value which the standard deviation and mean of  
229 the bootstraps was sensitive to. Finally, we calculated correlation of annual biomass estimates  
230 for years  $y$  and  $z$  using the bootstrap estimates of biomass

$$Cor(\hat{B}_y, \hat{B}_z) = \frac{Cov(\hat{B}_y, \hat{B}_z)}{SD(\hat{B}_y) SD(\hat{B}_z)}$$

231 where the covariance is

$$Cov(\hat{B}_y, \hat{B}_z) = \frac{\sum_{b=1}^K (\hat{B}_{y,b} - \bar{\hat{B}}_y)(\hat{B}_{z,b} - \bar{\hat{B}}_z)}{K-1}.$$

232 We summarized the relative precision of the calibrated and uncalibrated biomass estimates  
233 as the average of the annual ratios of the CVs for the calibrated and uncalibrated estimates

$$\frac{1}{n_y} \sum_{y=1}^{n_y} \frac{CV(\hat{B}(\rho))}{CV(\hat{B})}.$$

<sup>234</sup> We summarized the correlation of biomass estimates as the mean correlation of all annual  
<sup>235</sup> calibrated biomass estimates

$$\overline{Cor} = \frac{1}{n_y(n_y - 1)/2} \sum_{y=2}^{n_y} \sum_{z=1}^y Cor(\hat{B}_y, \hat{B}_z).$$

## <sup>236</sup> 3 Results

### <sup>237</sup> 3.1 Paired-tow observations

<sup>238</sup> In terms of paired tows and total numbers of fish, flatfish were the most well sampled species,  
<sup>239</sup> but goosefish was observed in the most paired-tows and red hake was the most prevalent  
<sup>240</sup> in terms of total numbers caught (Table 3). Witch flounder was the most prevalent flatfish  
<sup>241</sup> species caught while yellowtail flounder was the most frequently observed flatfish in terms of  
<sup>242</sup> paired tows. For all species but summer flounder, and barndoor and thorny skates, only a  
<sup>243</sup> subsample of all of the fish that were caught were measured for length, but nearly all winter  
<sup>244</sup> flounder and goosefish were measured.

### <sup>245</sup> 3.2 Relative catch efficiency

<sup>246</sup> As measured by AIC, the best performing models for all 10 species included size effects on  
<sup>247</sup> the relative efficiency of the chain and rockhopper sweep gears and between-pair variability  
<sup>248</sup> in relative catch efficiency (Table 4). Extrabinomial variation (i.e., beta-binomial) in relative  
<sup>249</sup> catch efficiency at size within pairs was also important for American plaice, yellowtail flounder,  
<sup>250</sup> witch flounder, red hake, and thorny skate. Model convergence was an issue for all species,  
<sup>251</sup> particularly for the most complex models with pair-specific smooth functions of length (BI<sub>4</sub>)  
<sup>252</sup> and smooth effects of size on the beta-binomial dispersion parameter (BB<sub>3</sub>, BB<sub>5</sub>, and BB<sub>7</sub>).  
<sup>253</sup> Including diel effects on relative catch efficiency improved model performance for all species

<sup>254</sup> except American plaice (Table 5). For those species with diel effects on relative catch  
<sup>255</sup> efficiency, the ratio of the efficiencies was generally greater for daytime observations, when  
<sup>256</sup> fish are typically more closely associate with the sea floor, than those for nighttime tows,  
<sup>257</sup> with the exception of large winter flounder (Figure 4). The largest differences in efficiency  
<sup>258</sup> was estimated for smaller barndoor skate. For most of the species, the difference in efficiecies  
<sup>259</sup> between the gears was generally greater for smaller individuals.

<sup>260</sup> All 1000 bootstrap fits of the paired tow data provided estimates of relative catch efficiency  
<sup>261</sup> at size for summer, windowpane, and yellowtail flounder, and red hake, goosefish, and thorny  
<sup>262</sup> skate. All but 2 of the bootstraps for winter flounder and 3 for barndoor skate provided  
<sup>263</sup> estimates of relative catch efficiency. For witch flounder, 817 bootstraps provided estimates  
<sup>264</sup> and only 386 provided estimates for American plaice. One bootstrap fit for summer flounder  
<sup>265</sup> was excluded due to an extremely high relative efficiency of the chainsweep gear which  
<sup>266</sup> impeded estimation of standard errors from the bootstrap fits.

<sup>267</sup> We see that generally where data are prevalent the bootstrap and hessian-based confidence  
<sup>268</sup> intervals are similar across all species. However, sometimes substantially different perceptions  
<sup>269</sup> of confidence ranges exist at the extremes of the length range for particular species where  
<sup>270</sup> there are fewer data and asymptotic properties of estimators can be less applicable.

### <sup>271</sup> 3.3 Biomass estimation

<sup>272</sup> Total biomass estimates calibrated to the chain sweep gear were variable across years for most  
<sup>273</sup> stocks and without strong trend (Figure 5). However, declining trends exist for the George  
<sup>274</sup> Bank and southern New England-Mid-Atlantic yellowtail flounder stocks and an increasing  
<sup>275</sup> trend for northern goosefish. Biomass estimates were greatest on average for northern red  
<sup>276</sup> hake and least for Gulf of Maine winter flounder, although this biomass estimate excludes fish  
<sup>277</sup> less than 30 cm in length. Fall and spring biomass estimates were similar in scale for most  
<sup>278</sup> stocks, except that southern New England winter flounder and northern goosefish estimates

<sup>279</sup> were typically greater in the fall than the spring.

<sup>280</sup> The efficiency of the rockhopper sweep in terms of biomass relative to that calibrated to the  
<sup>281</sup> chainsweep gear varies across survey years and seasons due primarily to differences in size  
<sup>282</sup> composition, but also variation in estimated length-weight relationship parameters (Figure  
<sup>283</sup> 6). The efficiency of the bottom trawl survey gear was greatest for the winter flounder stocks  
<sup>284</sup> and American plaice (0.6 to 0.9) and least for red hake, witch flounder, windowpane, and  
<sup>285</sup> yellowtail flounder stocks (0.2 to 0.4). Precision of the estimated annual biomass efficiencies  
<sup>286</sup> was worst for Georges Bank winter flounder and the skate stocks. For Gulf of Maine winter  
<sup>287</sup> flounder, southern red hake, and barndoor skate, the average fall biomass efficiencies were  
<sup>288</sup> typically greater than the fall than the spring although the differences were small relative to  
<sup>289</sup> the confidence intervals.

<sup>290</sup> Comparing the average of estimated coefficients of variation for annual calibrated and  
<sup>291</sup> uncalibrated biomass estimates showed large increases for summer flounder in the fall  
<sup>292</sup> (> 50%), southern New England winter flounder in the spring (77%), Georges Bank winter  
<sup>293</sup> flounder (more than 200% for spring and fall), northern red hake (95% for spring and 178%  
<sup>294</sup> for fall), northern goosefish in the fall (93%), and barndoor skate (> 100% for both spring and  
<sup>295</sup> fall) induced by the variability in the estimation of the relative catch efficiency of the gears  
<sup>296</sup> using chain and rockhopper sweep gears (Table 6). Effects of calibration on the precision of  
<sup>297</sup> the biomass estimates was relatively minor for other stocks.

<sup>298</sup> We observed little correlation of annual biomass estimates induced by the relative catch  
<sup>299</sup> efficiency estimation for most of the stocks (Table 7). However, the biomass estimates were  
<sup>300</sup> highly correlated for George Bank winter flounder in the spring (65%) and barndoor skate  
<sup>301</sup> (> 70% on average). Estimates for Georges Bank winter flounder in the fall, both red hake  
<sup>302</sup> stocks, northern goosefish, and thorny skate were greater than 20% on average.

303 **4 Discussion**

304 The data that we used to estimate bottom trawl survey catch efficiency came from an  
305 experiment using a twin trawler and many of the standard tow protocols for the NEFSC  
306 survey on the *R/V Henry B. Bigelow*. The experimental net used on one side of the twin  
307 trawl was the same as the standard survey trawl used on the *Bigelow* except that it contained  
308 roughly half number of floats and the sweep was modified to optimize flatfish catch by  
309 minimizing the ability of flatfish to pass under the net. The other side of the twin trawl was  
310 essentially identical to the standard gear used on the *Bigelow*. The towing of the standard  
311 survey bottom trawl on the twin trawl experiment differed in a few ways from its deployment  
312 on the spring and fall bottom trawl surveys, but we believe that these differences did not  
313 have a significant effect on the results. The use of larger doors and the restrictor rope served  
314 to fix the net geometries which may be the biggest source of variability in comparative trawl  
315 catches. This setup also allowed us to avoid many of the potential problems due to the large  
316 differences in size of the *Bigelow* and the *F/V Karen Elizabeth*. We do not suspect that the  
317 use of the restrictor rope would influenced flatfish behavior in front of the trawl because  
318 flatfish have been shown to generally not react to trawling induced stimuli until they are in  
319 very close proximity or even contacted by the fishing gear (Ryer et al., 2010). The spread  
320 data indicated that the restrictor rope remained taut throughout the towing process (setting,  
321 towing, hauling back), so we believe it likely that the restrictor rope was almost always at  
322 least 1 m off the bottom.

323 Herding is a known phenomena for flatfish and many other species when certain types of gear  
324 are used (Ramm and Xiao, 1995; Somerton and Munro, 2001; Somerton et al., 2007; Rose  
325 et al., 2010). Somerton and Munro (2001) considered two factors of bridle herding effects on  
326 efficiency. The first factor was the size of the bridle path where the bridle is off the ground  
327 ( $W_{\text{off}}$ ) and the second factor, the herding efficiency ( $h$ ) was fraction of fish in the bridle  
328 contact path that are moved into the path of the net path. The former is a function of gear

329 design, and controllable, whereas the latter is a function of fish behavior with regard to the  
330 bridle when it is in contact with the substrate. The bridle configuration on the bottom trawl  
331 survey are designed to minimize contact with the bottom (reference) and lack of abrasion of  
332 painted bridles used during one of the twin trawler research trips provided evidence of little  
333 or no bridle contact during the paired tow experiments used to collect the data used in this  
334 study. Furthermore, studies have consistently found that herding behavior occurred during  
335 the daytime (Glass and Wardle, 1989; Somerton and Munro, 2001; Ryer and Barnett, 2006;  
336 Bryan et al., 2014; Ryer et al., 2010; Dean et al., 2021) with some studies indicating high  
337 herding coefficients ( $h$ ) along the sections of the bridles in contact with the bottom. Studies  
338 that have evaluated herding at night or in low light conditions did not find evidence for a  
339 directional herding response (Glass and Wardle, 1989; Ryer and Barnett, 2006; Ryer, 2008;  
340 Ryer et al., 2010). The minimal bridle contact with the substrate and the large fraction of  
341 nighttime tows during the bottom trawl survey suggests flatfish herding is unlikely to be an  
342 important factor in catch efficiency based on net spread-based swept area.

343 On the other hand, the biomass estimates assume that the chain sweep gear is fully efficient,  
344 but it is likely at least some small fraction of fish, that may depend on size, are not captured  
345 by the gear. The biomass estimates also implicitly assume that the entire stock is available  
346 to the bottom trawl survey, but many of these stocks extend somewhat outside of the survey  
347 strata used to define the indices either throughout the year or seasonally due to migration.  
348 If either of these assumptions do not hold this method of biomass estimation would be  
349 negatively biased (expected value of biomass estimates would be lower than the true value).  
350 However, estimation using the data from these paired-gear studies and these assumptions is  
351 less biased than those made without them.

352 Treating the chain-sweep based abundance estimates implicitly assumes that the chainsweep  
353 provides complete capture efficiency and that the stock resides completely within the strata  
354 that are used to generate the abundance indices. It is unlikely that the chainsweep gear is

355 completely efficient for all sizes of fish of a particular species over all substrate types that are  
356 sampled. It is also typical for many of these stocks to extend somewhat outside of the survey  
357 strata used to define the indices either throughout the year or seasonally due to migration.

358 These analyses treat the amount of daylight as binary effect (day/night) on the relative catch  
359 efficiency. However, behavior of the fish with respect to the gear is likely to change more  
360 gradually with the amount of light. A continuous measure of light that uses the angle of  
361 the sun, the depth of the tow and light attenuation with depth, might prove to be a better  
362 explanatory variable for changes in relative catch efficiency and perhaps improve estimation  
363 of abundance from the bottom trawl survey (Jacobson et al., 2015; Kainge et al., 2017).

364 Aside from the direct impact of estimated catch efficiency of the NEFSC trawl survey gear on  
365 biomass estimation. Our analyses show more subtle impacts of using independent estimates of  
366 efficiency with survey tow data to generate the abundance indices. Without the independent  
367 efficiency estimates, the sampling variability of each of the seasonal and annual relative  
368 abundance indices is independent of the others. The bootstrapping methods we employed  
369 illustrated the including estimates of catch efficiency affects the variability of the resulting  
370 abundance estimates and their independence from each other. For some stocks there was a  
371 substantial effect of the relative catch efficiency estimation on the precision of the biomass  
372 indices. Similarly, we found high correlation of annual indices ( $> 0.6$ ) for Georges Bank  
373 winter flounder and barndoor skate. In these cases, the decrease in precision and increased  
374 correlation may have an impact on bias and precision of important estimates from the  
375 assessment model such as stock size and fishing mortality. As such, future work should  
376 evaluate effects of incorporating this information in an assessment model.

377 The estimates of absolute abundance produced using the sweep comparison experiments have  
378 already been informative to assessments and management of many stocks in the Northeast  
379 U.S. Chainsweep-based abundance estimates have been used directly in the age-structured  
380 assessment model for summer flounder and northern and southern goosefish stocks (NEFSC,

<sup>381</sup> 2019, 2020c). Abundance estimates for southern New England-Mid-Atlantic winter flounder,  
<sup>382</sup> both Cape Cod-Gulf of Maine and southern New England- Mid-Atlantic yellowtail flounder  
<sup>383</sup> stocks, and American plaice were used to validate the abundance estimates produced by  
<sup>384</sup> the assessment models (NEFSC, 2020b). The abundance estimates have also been used  
<sup>385</sup> directly in assessments for witch flounder, Gulf of Maine winter flounder, Georges Bank  
<sup>386</sup> yellowtail flounder, northern and southern red hake stocks, which are all assessed using  
<sup>387</sup> simpler index-based assessment methods (Legault and McCurdy, 2017; NEFSC, 2020b,a).  
<sup>388</sup> These estimates can be especially valuable for index-based methods where the scale of the  
<sup>389</sup> stock is assumed known. The abundance estimates have also been used in a supporting  
<sup>390</sup> fashion for fall-back assessments of both Gulf of Maine-Georges Bank and southern New  
<sup>391</sup> England-Mid-Atlantic windowpane stocks (NEFSC, 2020b).

<sup>392</sup> Typically, research surveys provide only a relative index of abundance rather than an absolute  
<sup>393</sup> estimate of abundance. Stock assessment models then integrate these observations with  
<sup>394</sup> time series of catch and other data sources to determine the scale of the population. However,  
<sup>395</sup> various factors can make for imprecise and inaccurate scaling of population levels including  
<sup>396</sup> inaccurate catch data (Cadigan, 2016), time-varying catchability (Wilberg et al., 2009),  
<sup>397</sup> low fishing mortality rates over the time series (Adams et al., 2020), and uncertain and  
<sup>398</sup> time-varying natural mortality (Stock et al., 2021). In these cases, external information such  
<sup>399</sup> as those produced by studies such as ours, can be particularly useful in estimating the size of  
<sup>400</sup> of the stock, the status of the stock relative to optimal levels and ultimately making catch  
<sup>401</sup> advice for commercially important fish stocks.

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Fig. 1. Diagram of the standard Northeast Fisheries Science Center rockhopper sweep center and wing sections.

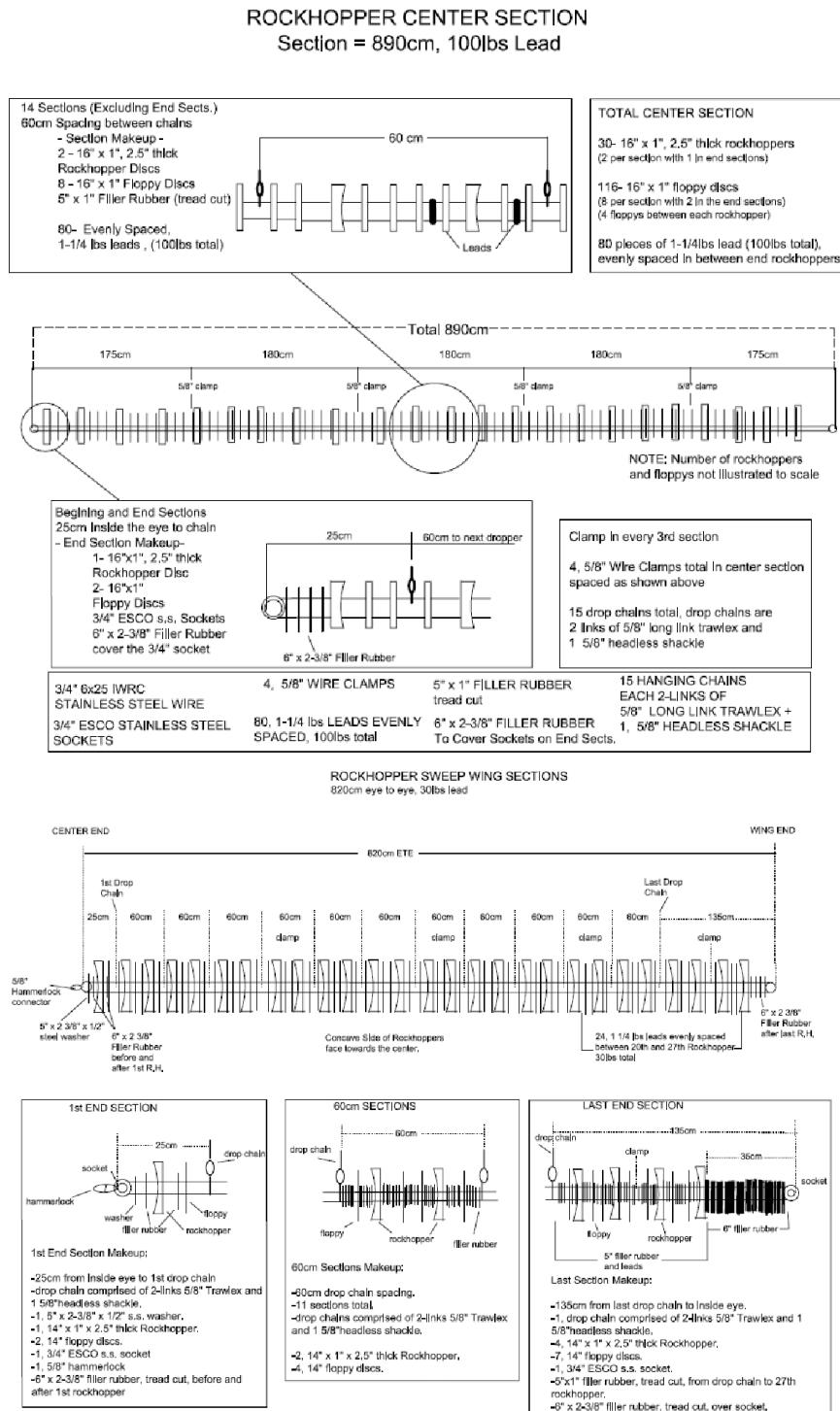


Fig. 2. Diagram of the chain sweep designed maximize bottom contact and flatfish capture.

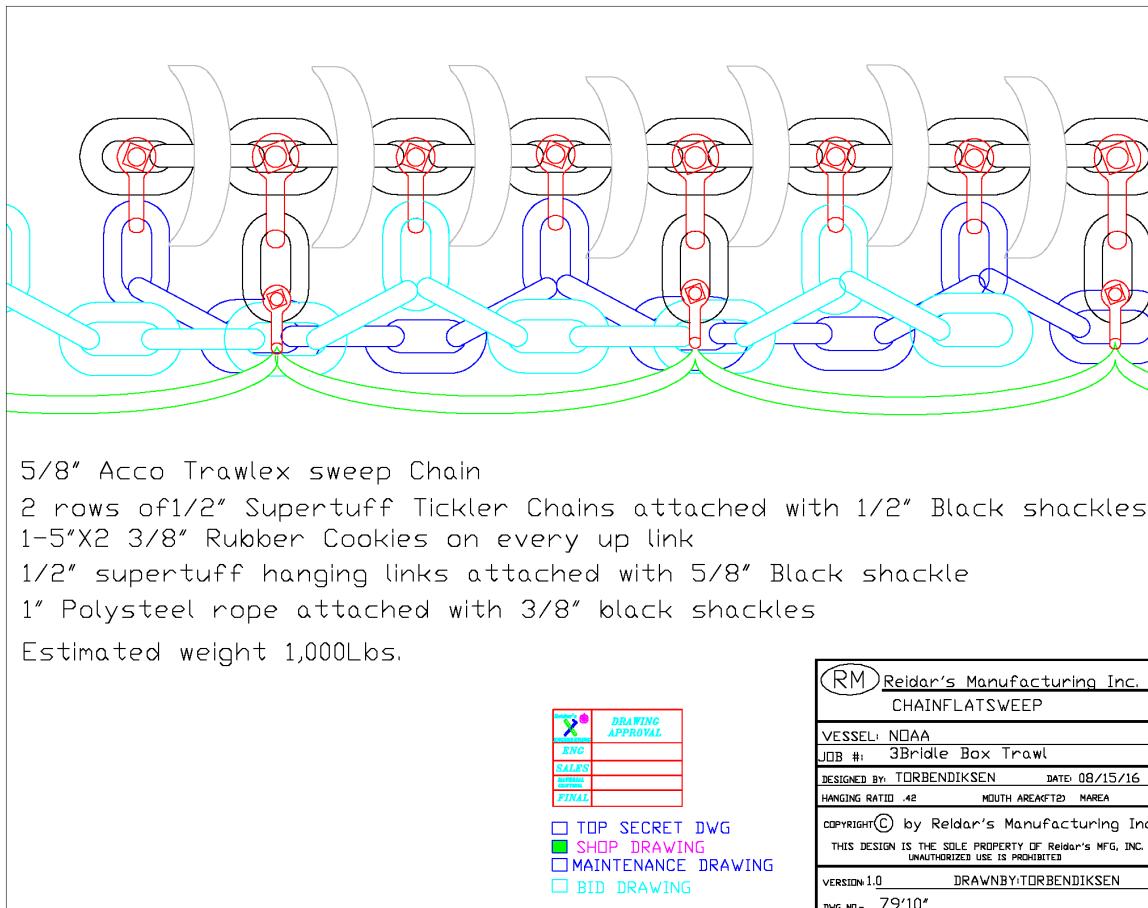


Fig. 3. Annual locations of stations during where the F/V Karen Elizabeth conducted twin-trawl sets with the standard bottom trawl gear and the gear with a chain sweep instead of the rockhopper sweep.

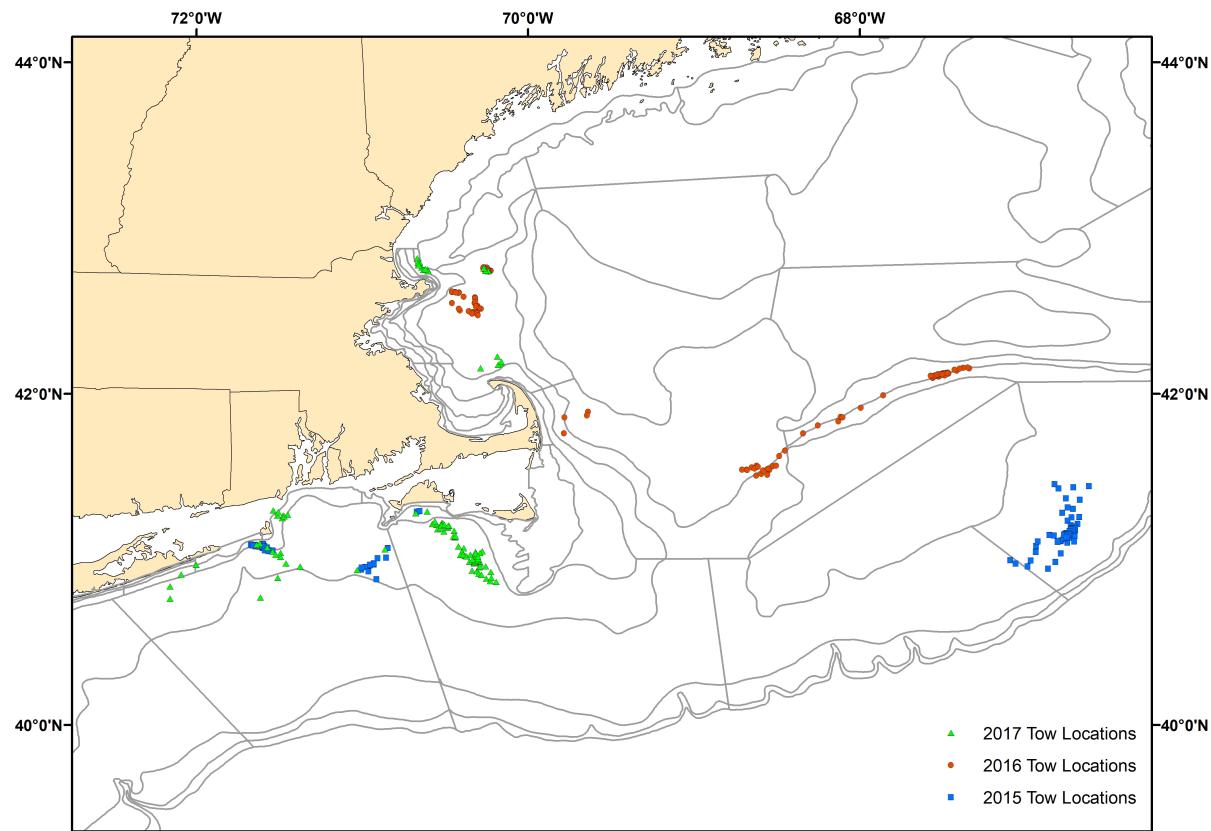


Fig. 4. Relative efficiency of gears using chain and rockhopper sweeps from the best performing model for each species (Table 5). Blue and red denote results for day and night data, respectively, and thick and thin lines represent overall and paired-tow specific estimates of relative catch efficiency, respectively. Points represent empirical estimates of relative efficiency for paired observation by length and paired tow. Polygons and dashed lines represent hessian-based and bootstrap-based 95% confidence intervals, respectively.

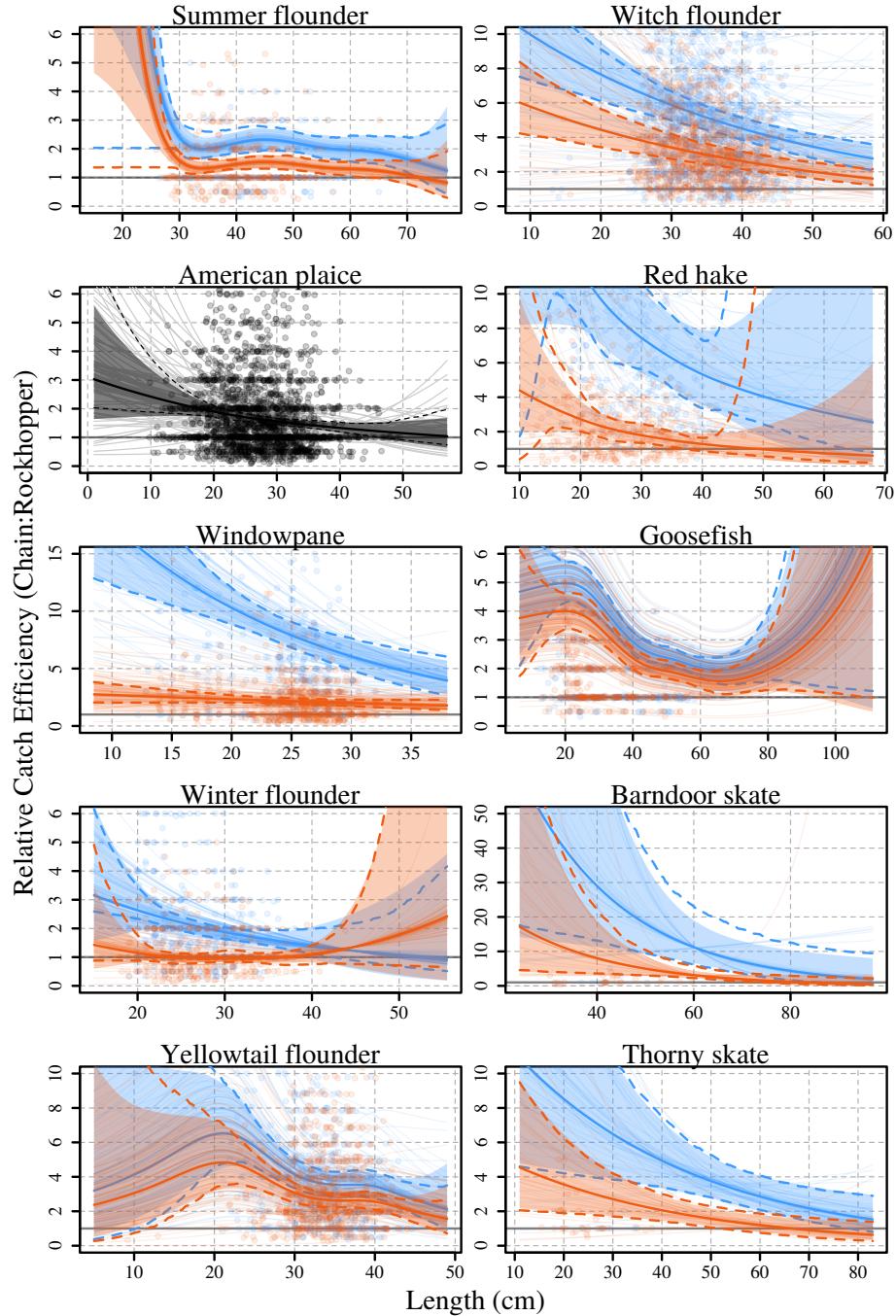


Fig. 5. Annual spring (blue) and fall (red) biomass estimates for each managed stock assuming 100% efficiency for chainsweep gear with shaded polygons representing bootstrap-based 95% confidence intervals. Relative catch efficiency at size estimates and bootstraps are from the best performing model for each species (Table 5).

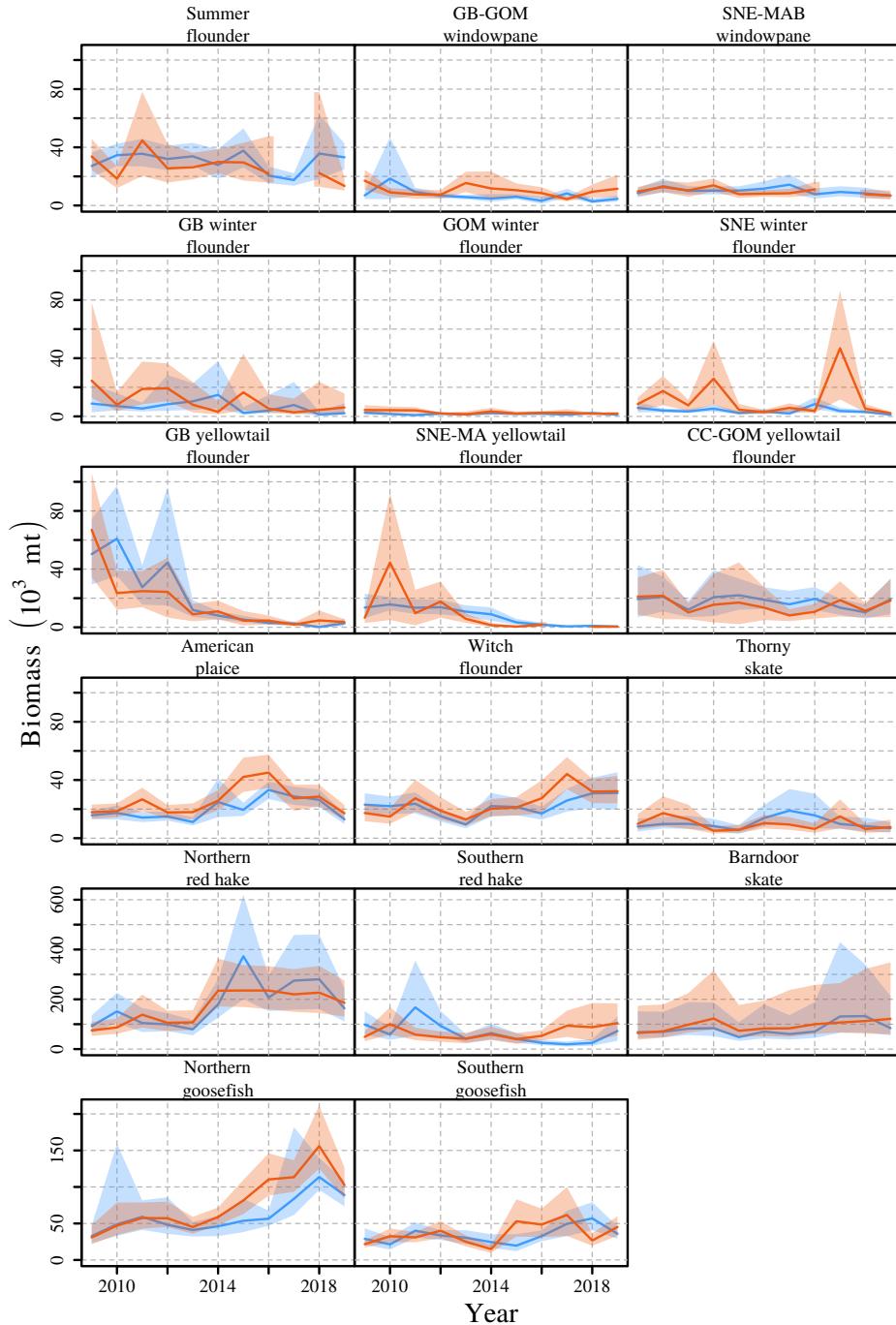


Fig. 6. Implied efficiency of annual spring (blue) and fall (red) bottom trawl survey biomass estimates for each managed stock assuming 100% efficiency for chainsweep gear with shaded polygons representing bootstrap-based 95% confidence intervals. Relative catch efficiency at size estimates and bootstraps are from the best performing model for each species (Table 5).

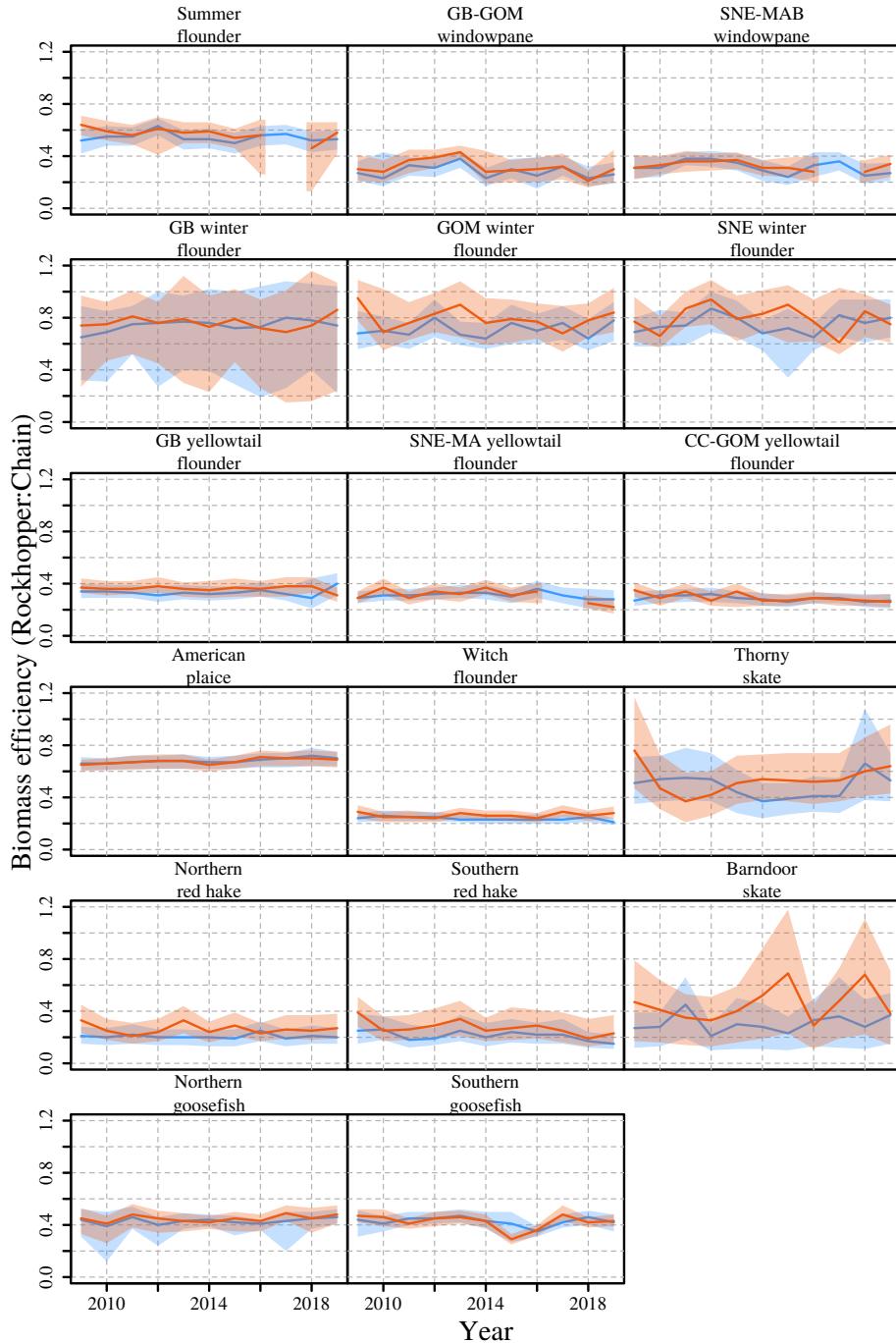


Table 1. Managed stocks associated with the species for which relative catch efficiency was estimated.

Stock
Summer flounder
American Plaice
Georges Bank-Gulf of Maine (GB-GOM) windowpane
Southern New England-Mid-Atlantic Bight (SNE-MAB) windowpane
Georges Bank (GB) winter flounder
Gulf of Maine (GOM) winter flounder
Southern New England (SNE) winter flounder
GB yellowtail flounder
Southern New England-Mid-Atlantic (SNE-MA) yellowtail flounder
Cape Cod-Gulf of Maine (CC-GOM) yellowtail flounder
Witch flounder
Northern red hake
Southern red hake
Northern goosefish
Southern goosefish
Barndoor skate
Thorny skate

Table 2. Description of relative catch efficiency ( $\rho$ ) and beta-binomial dispersion ( $\phi$ ) parameterizations for binomial and beta-binomial models and number of marginal likelihood parameters ( $n_p$ ) for the 13 base models from Miller (2013) and fit to paired chainsweep and rockhoppersweep tow data for each species.

Model	$\log(\rho)$	$\log(\phi)$	$n_p$	Description
BI <sub>0</sub>	$\sim 1$	—	1	population-level mean for all observations
BI <sub>1</sub>	$\sim 1 + 1 pair$	—	2	population- and random station-level $\rho$
BI <sub>2</sub>	$\sim s(length)$	—	3	population-level smooth size effect on $\rho$
BI <sub>3</sub>	$\sim s(length) + 1 pair$	—	4	population-level smooth size effect and random station-level intercept for $\rho$
BI <sub>4</sub>	$\sim s(length) + s(length) pair$	—	7	population-level and random station-level smooth size effects for $\rho$
BB <sub>0</sub>	$\sim 1$	$\sim 1$	2	population-level $\rho$ and $\phi$
BB <sub>1</sub>	$\sim 1 + 1 pair$	$\sim 1$	3	population-level and random station-level intercept for $\rho$ and population-level $\phi$
BB <sub>2</sub>	$\sim s(length)$	$\sim 1$	4	population-level smooth size effect on $\rho$ and population-level $\phi$
BB <sub>3</sub>	$\sim s(length)$	$\sim s(length)$	6	population-level smooth size effect on $\rho$ and $\phi$
BB <sub>4</sub>	$\sim s(length) + 1 pair$	$\sim 1$	5	population-level smooth size effect and random station-level intercept for $\rho$ and population-level $\phi$
BB <sub>5</sub>	$\sim s(length) + 1 pair$	$\sim s(length)$	7	population-level smooth size effect on $\rho$ and $\phi$ and random station-level intercepts for $\rho$
BB <sub>6</sub>	$\sim s(length) + s(length) pair$	$\sim 1$	8	population-level and random station-level smooth size effects on $\rho$ and population-level $\phi$
BB <sub>7</sub>	$\sim s(length) + s(length) pair$	$\sim s(length)$	10	population-level and random station-level smooth size effects on $\rho$ and population-level smooth size effects on $\phi$

Table 3. Number of paired tows where fish were captured and the number of fish captured and measured for lengths for each species in total and by day or night.

Species	Paired Tows			Captured			Both Gears Measured			Chainsweep Measured			Rockhopper Measured			
	Total	Day	Night	Total	Total	Day	Night	Total	Day	Night	Total	Day	Night	Total	Day	Night
Summer flounder	141	75	66	4,154	4,154	1,770	2,384	2,616	1,195	1,421	1,538	575	963			
American plaice	134	84	50	31,983	19,245	13,619	5,626	10,982	7,775	3,207	8,263	5,844	2,419			
Windowpane	195	100	95	15,310	13,014	6,221	6,793	9,854	5,443	4,411	3,160	778	2,382			
Winter flounder	171	97	74	6,586	6,449	3,605	2,844	3,805	2,385	1,420	2,644	1,220	1,424			
Yellowtail flounder	192	101	91	18,545	14,134	6,849	7,285	10,065	5,297	4,768	4,069	1,552	2,517			
Witch flounder	132	83	49	57,133	23,927	13,899	10,028	14,899	9,271	5,628	9,028	4,628	4,400			
Red hake	73	40	33	47,275	12,585	6,614	5,971	8,587	4,908	3,679	3,998	1,706	2,292			
Goosefish	302	165	137	8,798	8,541	3,985	4,556	6,409	3,053	3,356	2,132	932	1,200			
Barndoor skate	62	33	29	502	502	219	283	397	198	199	105	21	84			
Thorny skate	90	56	34	907	907	399	508	648	311	337	259	88	171			

Table 4. Difference in AIC for each of the 13 models described in Table 2 from the best model (**0**) by species.

	BI <sub>0</sub>	BI <sub>1</sub>	BI <sub>2</sub>	BI <sub>3</sub>	BI <sub>4</sub>	BB <sub>0</sub>	BB <sub>1</sub>	BB <sub>2</sub>	BB <sub>3</sub>	BB <sub>4</sub>	BB <sub>5</sub>	BB <sub>6</sub>	BB <sub>7</sub>
Summer flounder	27.96	13.53	8.9	<b>0</b>		28.64	15.45	10.59					
American plaice	821.11	546.54	743.34	494.92	415.63	179.48	71.76	141.44		37.06	0.71	<b>0</b>	
Windowpane	1045.06	38.51	1029.72	17.03	<b>0</b>	585.7	32.22	572.73		15.27			
Winter flounder	216.47	15.73	200.33	3.02	<b>0</b>	163.31	16.63	151.66	151.01	4.21	6.78	1.41	
Yellowtail flounder	727.15	97.93	727.36	51.84	10.96	394.94	70.2	391.13	371.13	31.85	<b>0</b>	3.33	
Witch flounder	1424.17	212.64	1372.66		35.33	881.28	142.53	844.47		81.37		<b>0</b>	
Red hake	1884.51	295.85		170.75		627.33	166.43	590.92		95.8	59.31	<b>0</b>	0.83
Goosefish	227.67	87.23	80.37	<b>0</b>		219.13		76.54					
Barndoor skate	36.51	10.01	31.34	2.72	<b>0</b>	36.23	11.99	29.03		4.6			
Thorny skate	39.04	8.57	32.65	3.44	1.15	22.38	5.84	18.66		1.38	5.19	<b>0</b>	

cc

Table 5. Best performing models from Table 4 and extended models that include diel effects on relative catch efficiency for each species with the number of parameters for each model ( $n_p$ ) and the differences in AIC ( $\Delta\text{AIC}$ ) from the best of the three models (**0**) by species.

	Model	$\log(\rho)$	$\log(\phi)$	$n_p$	$\Delta\text{AIC}$
<b>Summer flounder</b>					
	BI <sub>3</sub>	$\sim s(\text{length}) + 1 \text{pair}$	–	4	22.92
	BI <sub>3a</sub>	$\sim dn + s(\text{length}) + 1 \text{pair}$	–	5	<b>0</b>
	BI <sub>3b</sub>	$\sim dn * s(\text{length}) + 1 \text{pair}$	–	7	1.74
<b>American plaice</b>					
	BB <sub>7</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	$\sim s(\text{length})$	10	<b>0</b>
	BB <sub>7a</sub>	$\sim dn + s(\text{length}) + s(\text{length}) \text{pair}$	$\sim s(\text{length})$	11	1.43
	BB <sub>7b</sub>	$\sim dn * s(\text{length}) + s(\text{length}) \text{pair}$	$\sim s(\text{length})$	13	2.95
<b>Windowpane</b>					
	BI <sub>4</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	–	7	152.1
	BI <sub>4a</sub>	$\sim dn + \text{length} + s(\text{length}) \text{pair}$	–	7	4.06
	BI <sub>4b</sub>	$\sim dn * \text{length} + s(\text{length}) \text{pair}$	–	8	<b>0</b>
<b>Winter flounder</b>					
	BI <sub>4</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	–	7	50.68
	BI <sub>4a</sub>	$\sim dn + s(\text{length}) + \text{length} \text{pair}$	–	7	0.3
	BI <sub>4b</sub>	$\sim dn * s(\text{length}) + \text{length} \text{pair}$	–	9	<b>0</b>
<b>Yellowtail flounder</b>					
	BB <sub>6</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	8	3.84
	BB <sub>6a</sub>	$\sim dn + s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	9	<b>0</b>
	BB <sub>6b</sub>	$\sim dn * s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	11	3.48
<b>Witch flounder</b>					
	BB <sub>6</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	8	19.68
	BB <sub>6a</sub>	$\sim dn + \text{length} + s(\text{length}) \text{pair}$	$\sim 1$	8	<b>0</b>
	BB <sub>6b</sub>	$\sim dn * \text{length} + s(\text{length}) \text{pair}$	$\sim 1$	9	1.52
<b>Red hake</b>					
	BB <sub>6</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	8	32.35
	BB <sub>6a</sub>	$\sim dn + s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	8	<b>0</b>
	BB <sub>6b</sub>	$\sim dn * s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	10	3.18
<b>Goosefish</b>					
	BI <sub>3</sub>	$\sim s(\text{length}) + 1 \text{pair}$	–	4	5.44
	BI <sub>3a</sub>	$\sim dn + s(\text{length}) + 1 \text{pair}$	–	5	<b>0</b>
	BI <sub>3b</sub>	$\sim dn * s(\text{length}) + 1 \text{pair}$	–	7	6.8
<b>Barndoor skate</b>					
	BI <sub>4</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	–	7	15.57
	BI <sub>4a</sub>	$\sim dn + \text{length} + \text{length} \text{pair}$	–	5	<b>0</b>
	BI <sub>4b</sub>	$\sim dn * \text{length} + \text{length} \text{pair}$	–	6	1.83
<b>Thorny skate</b>					
	BB <sub>6</sub>	$\sim s(\text{length}) + s(\text{length}) \text{pair}$	$\sim 1$	8	15.51
	BB <sub>6a</sub>	$\sim dn + \text{length} + \text{length} \text{pair}$	$\sim 1$	7	<b>0</b>
	BB <sub>6b</sub>	$\sim dn * \text{length} + \text{length} \text{pair}$	$\sim 1$	8	1.38

Table 6. Average of annual (2009-2019) ratios of coefficients of variation for calibrated and uncalibrated biomass indices for each stock by seasonal survey. Coefficients of variation are based on bootstrap resampling of paired tow observations, survey station data and associated length and weight observations. Annual indices for fall 2017 were not available for summer flounder, SNE-MA windowpane, and SNE-MA yellowtail flounder.

Stock	Average CV Ratio	
	Calibrated:Uncalibrated	
	Spring	Fall
Summer flounder	1.13	1.51
American plaice	1.07	1.02
GB-GOM windowpane	1.03	1.07
SNE-MAB windowpane	1.06	0.90
GB winter flounder	3.19	3.89
GOM winter flounder	1.05	1.07
SNE winter flounder	1.77	0.99
GB yellowtail flounder	1.06	0.98
SNE-MA yellowtail flounder	1.05	0.99
CC-GOM yellowtail flounder	1.01	1.02
Witch flounder	1.12	1.11
Northern red hake	1.95	2.78
Southern red hake	1.28	1.28
Northern goosefish	1.93	1.34
Southern goosefish	1.18	1.04
Barndoor skate	2.47	2.78
Thorny skate	1.14	1.20

Table 7. Average correlation of annual (2009-2019) calibrated biomass indices for each stock by seasonal survey. Annual indices for fall 2017 were not available for SNE-MA windowpane and SNE-MA yellowtail flounder.

Stock	Spring	Fall
Summer flounder	0.16	0.14
American plaice	0.09	0.06
GB-GOM windowpane	0.06	0.04
SNE-MAB windowpane	0.06	0.05
GB winter flounder	0.65	0.45
GOM winter flounder	0.05	0.05
SNE winter flounder	0.07	0.03
GB yellowtail flounder	0.05	0.04
SNE-MA yellowtail flounder	0.07	0.02
CC-GOM yellowtail flounder	0.05	0.04
Witch flounder	0.10	0.10
Northern red hake	0.42	0.34
Southern red hake	0.25	0.21
Northern goosefish	0.21	0.30
Southern goosefish	0.10	0.07
Barndoor skate	0.74	0.81
Thorny skate	0.29	0.25