1 A model-based approach to standardizing American lobster (*Homarus americanus*) 2 ventless trap abundance indices

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16 Highlights

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- Model-based approaches were used to remove variability in U.S. American lobster abundance indices.
- Accounting for site, day of year, and soak time in index construction provided insight on these factors' relation to catch.
- Model- and design-based indices provided similar trends in lobster abundance, with reduced variability in the indices and accounting for missing data.
- This advancement provides updated relative abundance indices for evaluation in future stock assessments.

26 Abstract

27 Fishery-independent ventless trap surveys are an integral component to assessing American lobster (Homarus americanus) population trends, as they can sample complex, heavily fished 28 29 habitats where most survey gear has difficulty accessing. U.S. American lobster stocks have been 30 assessed within state waters using a standardized ventless trap survey since 2006. However, 31 confounding survey attributes that may contribute to catch variability have not been investigated 32 and some discontinuity in sampling has resulted in missing estimates of abundance. We 33 constructed sex- and stock-specific generalized linear mixed models to discern the dynamics 34 between lobster catch and individual survey factors and removed these sources of variability 35 when producing continuous abundance indices. Soak time, day of year, and unique site had 36 measurable contributions to the variability in lobster catch per ventless trap. Generally, sex- and 37 stock-specific abundance indices from this model-based approach and a traditional design-based 38 approach exhibited similar trends. The two approaches' magnitudes and trends for the Gulf of 39 Maine were nearly identical. For Southern New England, model-based index trends were 40 smoother and lower in magnitude than the design-based estimates. The greatest difference in the 41 two approaches' trends for the Southern New England indices were in the early and terminal 42 years. This work serves as an example of how variability associated with fixed and random 43 effects of a survey can be accounted for when producing abundance indices used in stock

- 44 assessments.
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- 46 Key Words: ventless trap survey, American lobster, random effects, abundance indices
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48 **1. Introduction**

49 American lobster (*Homarus americanus*) supports the most valuable single-species 50 fishery in North America, with an ex-vessel value of \$US 1.7 billion in 2017 (DFO, 2020; 51 NOAA, 2020). Despite this economic significance, the species' dynamic life history can make it 52 difficult to infer population trends across life stages. Canadian lobster stock assessments 53 historically have relied on fishery-dependent data to derive catch per unit effort (CPUE) indices 54 for inferring population trajectories (DFO, 2013). However, using industry effort data may 55 provide misleading population trajectory signals given such CPUE data are derived primarily 56 from densely populated lobster areas where effort is concentrated, and do not necessarily include 57 the entirety of the population or stock bounds. Such dynamics have often led to hyperstability 58 when using CPUE to infer population abundance (Harley et al., 2001). Further, improvements in 59 fishing strategies and gear are constantly evolving and can influence CPUE (Smith and 60 Tremblay, 2003) yet are usually undocumented. While commercial CPUE can be useful in 61 assessing the performance of the fishery, these uncertainties have led to their exclusion as 62 abundance indices in U.S. American lobster stock assessments.

63 Historically, bottom otter trawl survey data from multi-species surveys have been used in 64 U.S. American lobster stock assessments as indicators of population trends (ASMFC, 2009; 65 ASMFC, 2015). Two of the greatest drawbacks for using otter trawl data to represent lobster 66 stock abundance are that (1) they typically do not sample in the preferable cobble or boulder 67 habitat of lobsters (Wahle and Steneck, 1991) in fear of entangling the trawl, and that (2) they cannot fish in areas or paths where fixed fishing gear exists (Smith and Tremblay, 2003). Trap 68 69 surveys have often been considered a better method of assessing the structure-oriented lobster 70 population (Tremblay et al., 2009). To address this concern for the U.S. lobster stocks, states

71 within the northeast U.S. initiated complementary lobster ventless trap surveys designed to target 72 sub-legal lobsters (or recruits) across various habitat types in state waters (0-3 nautical miles 73 from shore). The Coastwide Ventless Trap Survey (VTS) employs a random stratified sampling 74 design and gear modeled after the commercial fishing configuration of traps strung together over 75 trawl lines, but with the inclusion of ventless traps to retain sub-legal and legal sized lobsters. 76 The catch of lobsters per ventless trap (CPVT) is used to provide an estimate of the relative 77 abundance of lobsters through space and time. The VTS was designed with depth and NMFS 78 statistical areas defining the stratification based on pilot surveys and analyses (Pugh and Glenn 79 2020), which found that a stratification scheme based on depth provided the most accurate 80 estimates of relative abundance, as represented by reduced variability in CPVT. The NMFS 81 statistical area inclusion in survey stratification is intended to account for the latitudinal gradient 82 of environmental drivers on lobsters, such as temperature. Mean CPVT estimates in concert with 83 strata-specific weights based on the survey area domain are then used to derive annual 84 abundance indices. 85 Male and female CPVT indices were first used in 2015 as fisheries-independent assessment model inputs for the two U.S. stocks, Southern New England and the Gulf of 86 87 Maine/Georges Bank (ASMFC, 2015). This inclusion served as a major advancement for better 88 understanding the sub-legal lobster population and population trends in the summer, a season 89 that previously lacked relative abundance information. While the VTS abides by a standard set of

90 methods, unforeseen changes in sampling design can occur due to inclement weather and gear

91 loss. Many factors have been found to influence trap effectiveness and catchability for crabs and

92 lobsters (Miller, 1990; Tremblay and Smith, 2001; Smith and Tremblay, 2003; Geraldi et al.,

93 2009), but have been unaccounted for when constructing relative abundance estimates. Within

94 stock assessment models, survey indices are often scaled to the stock or population size using 95 non-linear, time-invariant relationships (Hilborn and Walters, 1992). While the estimated 96 parameters of these functions (i.e., catchability coefficients) capture the average magnitude of 97 survey catchability, process error in terms of time-varying catchability is often not considered. 98 Model-based approaches to standardizing fisheries-independent catch data have been 99 widely viewed as a useful tool in providing more accurate estimates of abundance indices 100 (Maunder and Punt, 2004). Utilizing these approaches provide several benefits, including an 101 understanding of the effects variables have on species observed abundance, reducing the 102 variance on the abundance predictions, corrected-abundance estimates for when these variables 103 deviate, a tool to help account for years with missed sampling, and a method to account for 104 random effects on observed abundances. This work aimed to understand the impact of several 105 covariates on lobster abundance trends for the inshore components of the Gulf of Maine (GOM) 106 and Southern New England (SNE) lobster stocks, and account for these sources of variability 107 when deriving abundance indices. Model-based approaches were utilized to derive sex- and 108 stock-specific annual abundance estimates from the lobster ventless trap surveys. Model-derived 109 male and female GOM and SNE CPVT indices were constructed and compared to those based 110 on the design-based approach to ascertain their differences and advantages, and ultimately the 111 significance of including factors documented to influence trap catchability in deriving abundance 112 estimates for the VTS.

113 **2. Methods**

114 2.1 Survey design

Beginning in 2006, the VTS has employed a random stratified survey design, using
NMFS Statistical Area (SA) and depth as the primary strata classifications. The SAs included in

117 the survey are 511, 512, 513, and 514 in the GOM region (no sampling is conducted in the 118 Georges Bank region of the stock), and 538, 539, and 611 in SNE. The survey is a cooperative 119 effort between state fisheries agencies and commercial lobstermen, in which lobstermen are 120 contracted to deploy and retrieve survey gear from their vessels with agency biologists aboard to 121 collect data (Pugh and Glenn, 2020). States that have or currently participate in the survey 122 include Maine, New Hampshire, Massachusetts, Rhode Island, and New York. The survey 123 design uses three depth strata that span the range of depths that lobsters are typically fished in 124 inshore waters: 1-20 m, 21-40 m, and 41-60 m.

125 Full description on the VTS can be found in ASMFC (2020). Briefly, all states have 126 sampled since 2006 but for three exceptions: New York sampled only from 2006-2009, New 127 Hampshire began sampling in 2009, and Massachusetts did not sample in 2013. All states except 128 Maine began sampling sites with one six-trap trawl lines, in which vented and ventless lobster 129 traps were alternated for three of each per trawl and spaced 60 feet apart (Table 1). Maine 130 deployed gear either as two three-trap trawls or as one six-trap trawl. Since 2015, Maine and 131 New Hampshire have exclusively fished ventless traps and abandoned sampling with vented 132 traps. Across states, sites are sampled twice per month with a targeted three-night soak time 133 (soak times have exceeded three nights when inclement weather delayed sampling). All traps are 134 baited when actively fishing, with bait type at the discretion of the contracted lobstermen. The 135 primary data stream from the survey is the number of lobsters caught in each trap, which is used 136 for estimating CPVT. However, for each lobster, several descriptors are also recorded: carapace 137 length to the nearest mm, sex, shell hardness, culls and other shell damage, external gross 138 pathology, mortality, the presence of extruded ova on females, and shell disease symptoms, with 139 bycatch similarly described where applicable.

140 2.2 Data processing

Samples considered for the model-based standardization included those whose sites
annual average position fell within the survey strata (Figure 1). All samples that fell out because
the sites have since been dropped from the survey domain were not included. This approach
resulted in a small portion of samples being dropped from Maine, New Hampshire,
Massachusetts, and Rhode Island, but also resulted in all samples from New York being
excluded.

147 Several data filters were also used to exclude samples from the modeling effort. Traps 148 that were not fishing effectively (e.g. torn netting, escape vent left open), and thus caught no or 149 few lobsters, were excluded from the analysis and considered as a missing trap given their 150 ineffective fishing. For ventless traps of this nature, their catch was not included in modeling 151 CPVT. Such vented and ventless traps were not incorporated into the total trap number in a 152 trawl. Further, only samples with soak times between one and six days were included. The 153 survey has traditionally targeted summer months (June, July, and August) for sampling; 154 however, due to occasional logistical or funding constraints, sampling timing sometimes varied. 155 Samples collected outside June-August were excluded from the analysis for consistency across 156 the survey domain. Lastly, only ventless trap catch was modeled; vented trap catch was excluded 157 from the analysis.

158 2.3 Modeling approach

Generalized linear mixed models were used to predict sex-specific lobster CPVT for both stocks. This statistical framework expands upon that of generalized linear models by allowing covariates to be modeled as fixed or random effects (Vidal et al., 2018). Random effects allow for assessing variability among factors of repeated measures, or when randomly selected

163 variables are part of a larger population of which the bounds are not completely sampled (Bolker 164 et al., 2009; Deroba, 2018). Four individual models were built to predict the desired CPVT 165 response variable: male CPVT in SNE, female CPVT in SNE, male CPVT in GOM, and female 166 CPVT in GOM. Catch data reflected lobsters 53mm and larger to match the data needs of the 167 lobster stock assessment model (ASMFC, 2020). Lobsters smaller than 53mm can be caught in 168 the survey; however, the proportion of the catch less than 53mm is often small, suggesting that 169 these smaller sizes are not selected by the traps (Appendix A). Lobster CPVT was modeled at the 170 trap level, and a negative binomial error distribution was used to model CPVT in each of the four 171 models given the overdispersion in the catch data. Further, the models included zero-inflation to 172 account for the high frequency of zero catch. The models were constructed using R package 173 'glmmTMB' (Brooks et al., 2017).

174 While the VTS collects many of the same data fields across states to derive lobster 175 abundance estimates, not all relevant data are collected by each state. Continuous, fine scale 176 sediment or bottom type data do not exist across the survey bounds to be included in the 177 standardization. Bathymetric slope was estimated for samples using NOAA's National 178 Geophysical Data Center (NGDC) depth data for the Northeast U.S. Shelf using R package 179 'raster' (Burrough and McDonnell, 1998), but corroboration between the associated depths and 180 those observed from the VTS was poor. Thus, bathymetry and slope data were not included in 181 the modeling. While bait type is believed to influence lobster catch rates, not all states have 182 consistently collected such data through time. Further, bait used in the SNE and GOM have been 183 primarily skate and herring, respectively, and may not provide enough variation in bait types for 184 the models to confidently assess catch variance associated with bait specifically. Lastly, position

of the trap within a trawl was not included based on the consistency of the information beingcollected through time by states.

187 Several covariates were tested for use in modelling lobster CPVT. Year was modeled as a 188 fixed effect, while unique site, day of year, and soak time were modeled as random effects. 189 Designating factors as random effects allowed for isolating their population-level effect 190 estimates and removed the effects that a given factor's variation in sampling data may have on 191 the fixed effect of annual CPVT. The natural log of the total number of traps used in each haul 192 was used as an offset term to account for varied effort when traps on a trawl were lost. In 193 instances where traps were lost or did not function properly (e.g. torn netting, escape vent 194 accidentally open), these traps were subtracted from the total number of traps in a trawl. Despite 195 modeling ventless catch only, all trap types (ventless or vented) fishing properly were counted as 196 a trap within the trawl. With CPVT modeled at the trap-level, ventless traps within a trawl had 197 the same covariate values, capturing the degree of CPVT variability associated within given 198 spatiotemporal conditions or soak time. Survey depth stratification was incorporated into the 199 model by weighting samples based in the model on the areal proportion that their strata 200 comprised of the SA-Depth-State stratification. The weight served as multipliers on the model 201 log-likelihood contributions. Variables' significance in predicting CPVT were evaluated for each 202 model using backward-stepwise comparison and removing covariates subsequently. The model 203 variants were constructed by removing them sequentially using backward stepwise selection, and 204 the model variant with lowest Akaike information criterion (AIC; Akaike, 1973) value was 205 selected to derive model-based indices.

Temperature can influence lobster life history (Fogarty et al., 2007) and has been
commonly used to describe lobster habitat, abundance, and distribution (Chang et al., 2010;

208 Tanaka and Chen, 2015; Tanaka and Chen, 2016). However, temperature and others habitat 209 variables were not incorporated into the models. The primary reason for their exclusion was that 210 for the current U.S. lobster stock assessment, environmental influence on fisheries-independent 211 indices are incorporated directly within the assessment model when estimating catchability 212 (ASMFC, 2020.) When relating the survey index to the total population within the assessment 213 model, catchability parameterization allows for directly estimating the influence of temporal 214 environmental changes within a survey area on the index's relation to the estimated population 215 size. This approach can account for changes in the availability of lobster to survey domains over 216 time driven by changes in the environment (ASMFC, 2020.) Thus, incorporating yearly 217 environmental effects in the model-based approach would distort the final impact of the 218 environment on the CPVT. Incorporating the environmental effects for seasonal or spatial 219 dynamics were considered, but consistently measured data at the needed resolution was not 220 available across the survey domain. Further, many of these environmental drivers that vary 221 spatiotemporally are inherently incorporated via the day of year, year, and site covariates. 222 Including other environmental variables in addition to these covariates could risk model 223 overfitting or double counting the effects of a given ecological factor. As such, this index work 224 focused on survey, temporal, and gear configuration concerns as opposed to interannual changes 225 in the environment.

226 *2.4 Design-based approach and comparisons*

The design-based abundance indices were constructed as used in the 2020 American
Lobster Stock Assessment (ASMFC, 2020), with brief description provided herein. The same
data sets generated from the data processing steps described previously were used for designbased calculations. Because Massachusetts did not run a survey in the GOM or SNE in 2013 and

the Massachusetts data can significantly influence the combined indices, design-based indiceswere not constructed for 2013 (ASMFC, 2015).

Survey sites were intended to not move within a year, so each survey site was treated as an effective replicate and samples within the year as repeated measures. Sites would only change slightly within a year if repeated gear loss threatened data collection. To get the yearly average CPVT for a survey site, catch in the ventless traps were first averaged across ventless traps within a trawl, then across trawls within a month, then across months in a year. Calculating the indices from the survey site averages then used a standard stratified-random sampling calculation, with the SA-Depth-State strata used in the survey design:

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$$Catch_{y} = \frac{\sum_{str} \frac{\sum_{s} Catch_{s,str,y}}{N_{str,y}} \times A_{str}}{\sum_{str} A_{str}}$$

241 where $Catch_{y,s,str}$ is the mean catch at site s in stratum str and year y, $N_{y,str}$ is the number of sites 242 in stratum str and year y, and Astr the area of a given stratum. As such, both the model and 243 design-based index units were CPVT, with the former using all traps in a predictive model, and 244 the latter arithmetically solving for weighted average CPVT. Both model-based and design-based 245 approaches were compared in terms of their magnitudes and relative trends. Trend differences 246 were examined after normalizing the indices by dividing each index by its time-series mean. The 247 resulting sex ratio for each stock and index type was also compared by dividing the male index 248 by the female index.

3. Results

250 *3.1 Model results*

251 When testing model variants, the models with the lowest AIC scores across sexes and 252 stocks were those excluding the number of traps offset (Table 2), of which all converged

253 successfully. Excluding the site effect resulted in the greatest difference in AIC scores and 254 weakened model fitness, suggesting that including site effect made the greatest improvement to 255 the model. Including the unique site effect improved model performance more for SNE models 256 than for GOM models, and for SNE females more than SNE males. The final models used to 257 derive abundance indices for all stocks and sexes included site, day of year, year, and soak time. 258 Random effect estimates indicated that in SNE, male and female CPVT were greater in 259 July than June and August (Figure 2). In the GOM, male lobster CPVT was greater in August 260 than June and July, whereas female lobster CPVT was similar in June and August, and slightly 261 lower in July (Figure 2). Random effect intercepts for SNE lobster CPVT did not suggest 262 discernible patterns with changes in soak time. Male CPVT indicated a slight positive effect with 263 increased soak time but was variable, and even more so for females (Figure 3). While SNE male 264 and female models shared similar patterns, the magnitudes were larger for females than males. 265 Soak time effects in the GOM CPVT suggested that for both males and females, catch increased 266 with increasing soak times. This pattern was more pronounced for males than females (Figure 3). 267 Random effects of site indicated spatial variability in its influence on CPVT for male and female 268 lobsters, but for SNE more than GOM. In SNE, both sexes' random effects for site were lower 269 inside the shallower estuaries (e.g. Buzzards Bay, Narragansett Bay) than in the deeper oceanic 270 environments (e.g. Block Island Sound, Rhode Island Sound) (Figure 4). In contrast to SNE, the 271 site effects were of smaller magnitude in GOM, and was less heterogeneous in the GOM survey 272 domain (Figure 4).

273 *3. 2 Abundance indices*

SNE model-based and design-based indices showed similar trends. Both SNE female and
 male abundance indices have declined since 2006, with the model-based declines smoother and

276 less variable over time than those from the design-based approach (Figure 5). Trends from the 277 model-based approach were more similar between sexes than those of the design-based 278 approach, albeit slightly different in magnitude. SNE indices using the design-based approach 279 were higher than those of the model-based approach (Figure 5). The greatest deviations between 280 the two approaches for SNE were in recent years; modeled-based indices declined from 2017 to 281 2018, whereas the design-based indices increased (Figure 5). Further, the 2019 terminal year 282 dropped from 2018 in the design-based approach, whereas it slightly increased in the model-283 based approach.

Corroboration in magnitude between model-based and design-based abundance indices for the GOM was stronger than in SNE. Design-based indices were modestly lower than the model-based indices throughout the time series. Both male and female GOM abundance indices increased from 2007 through 2012, with abundance variable but still high through 2019 (Figure 5). Standard errors were greater for GOM model-based indices than design-based, likely attributed to the processing of data at the individual trap level (i.e. model-based approach) opposed to the average site catch level (i.e. design-based approach).

Trends between model-based and design-based approaches were similar across sexes and stocks, except in the early and terminal years of the SNE indices (Figure 6). Corroboration in the sex ratios between the approaches varied by stock. For GOM sex ratios, both model-based and design-based approaches were similar, highlighting a trend towards female skewed catch (Figure 7). In SNE, the design-based approach also indicated a female skewed population in state waters; however, the model-based approach indicated a male-skewed community through time, with males up to 1.5 times more abundant than females (Figure 7).

4. Discussion

299 4.1 CPVT sources of variability

300 We have quantified several factors that influence catch rates of lobsters within the 301 Coastwide Ventless Trap Survey. Such confounding factors have long been suspected to 302 influence trap catch rates for crustacean species (Miller, 1990), and this work begins to assess 303 and account for these factors when deriving abundance indices by removing the variability in 304 catch associated with them. The year of sampling, day of year sampling occurred, unique site 305 sampled, and the soak time of the traps all influenced lobster CPVT. The site effect appeared to 306 have the greatest effect (Table 2), and more so in SNE than in the GOM (Figure 4). In SNE, we 307 hypothesize that the differences in site across the survey domain reflects differences in benthic or 308 thermal habitat. Narragansett Bay bottom temperatures have warmed significantly over the last 309 several decades (Fulweiler et al., 2015) and are consistently exceeding 20°C (ASMFC, 2020), a 310 temperature threshold believed to cause physiological stress and unsuitable conditions for 311 lobsters (Steenbergen et al., 1978; Dove et al., 2005). The SNE gradient of negative to positive 312 site effects moving away from the head of estuaries to oceanic environments may reflect lobster 313 preference for cooler oceanic waters than warmer estuarine waters. Wahle et al. (2015) noted that 314 bottom temperatures during this summer period were cooler at southern portions of Narragansett 315 Bay near Rhode Island Sound than the upper region of Narragansett Bay. Thermal habitat 316 suitability modeling for this species over the entirety of this survey domain, seasonality, and time 317 series would better test this hypothesis. While spatial differences in lobster settlement are 318 apparent within the GOM purportedly from differences in oceanography (Goode et al., 2019), 319 such differences are not strongly captured by the site effect for lobsters 53mm or greater. 320 Days in July in SNE corresponded to higher lobster CPVT rates, particularly for males. 321 Lobster CPVT in the GOM was greatest toward the end of August, with this pattern more

322 accentuated for males than females. The stock differences in temporal peak CPVT rates is likely 323 reflective of seasonal water temperature differences with latitude. Much of American lobster life 324 history and biological rates are influenced by temperature (ASMFC, 2020), and southern regions 325 like SNE generally warm seasonally earlier than northern regions such as the GOM. Soak time 326 effects indicated that there was either no discernible relationship between soak time and lobster 327 CPVT (e.g. SNE) or potential increases in CPVT at longer soaks (e.g. GOM) (Figure 3). While 328 our results did not provide a definitive relationship between lobster CPVT and soak time, they 329 were somewhat contrary to previous work. In the GOM, previous work has suggested lobster 330 CPVT increases logarithmically over a three-day soak, increasing over the first 24 hours and 331 then plateauing (Clark et al., 2015; Watson et al., 2019), thus perhaps the soak time effect 332 operates at a smaller time scale than targeted 3-day soak period in this monitoring program. The 333 effect of soak time on CPVT is also likely dependent on other factors, such as bait (Watson et al., 334 2019), stock size, and spatio-temporal factors. For example, these previously reported saturation 335 rates have been conducted in shallow waters compared to the range of depths that the VTS 336 samples. Any depth-specific relations between soak time and CPVT that may exist would be 337 aggregated in this analysis. Evaluating interaction effects between these and other covariates in 338 future studies or model developments would be worthwhile in elucidating these complexities. 339 Other variables may attribute to lobster CPVT and trap catchability that were not 340 accounted for in this analysis. The widely reported preference of cobble or boulder habitat for 341 lobsters (Wahle and Steneck, 1991) over low-relief (e.g. mud, sand) substrate is not explicitly 342 captured in the modeling. Previous studies have found mixed results regarding this; Tremblay 343 and Smith (2001) found that low-relief sites have lower lobster densities than boulder sites, 344 whereas Geraldi et al. (2009) found traps had higher counts on unstructured habitats then rocky

345 areas. The site effect may in part represent benthic habitat effects, but also likely includes other 346 components (e.g. bottom temperature, depth). Differences in end and middle traps of ventless 347 trap surveys have been found as a function of their distance apart; 1994 ventless trap sampling 348 off Cape Breton indicated middle traps had reduced lobster catch than end traps, but when 349 increasing the distance between traps in the trawl for the 1995 survey, no statistical differences 350 were found (Smith and Tremblay, 2003). Instances of lower catch in middle traps likely reflect 351 competition between the traps, whereas lack of differences may be indicative of non-overlapping 352 effective trap areas or trap saturation preventing detection of trap position differences. Bottom 353 temperature is likely manifested within the annual factor, which has been further examined via 354 the lobster stock assessment catchability parameterization (ASMFC, 2020).

355 Interspecific species interactions and behaviors can also influence lobster catch by 356 deterring them from entering the traps or being unable to because the traps have become quickly 357 saturated. Stocking experiments have indicated that the presence of American lobster in traps can 358 reduce the catch of *Cancer* sp. crabs, but the crabs' presence in traps does not significantly 359 impact lobster catch (Richards et al., 1983). However, a negative relationship between catch 360 rates of European lobster (Homarus gamarus) and Cancer pagurus for individual traps (Addison, 361 1995) suggests perhaps an antagonistic relationship between crabs and lobsters or a difference in 362 their local availability. Skerrit et al. (2020) further identified that lobster CPUE effects from 363 lobster-crab trap interactions can vary by the crab species. In the Coastwide Ventless Trap Survey, bycatch often includes *Cancer* spp., demersal fish, and other invertebrate species; 364 365 however, it is unclear the extent that high bycatch samples reflect areas of greater bycatch 366 abundance compared to lobster, or whether lobsters in the area are at higher number than 367 observed but are not reflected in the catch due to these species interactions. The true influence of

altered catch rates of a target species due to trap saturation from bycatch or species interactions
are variable across taxa and trap type (Robichaud et al. 2011, Kersey and Clark, 2011; Bacheler
et al., 2013). Future analyses should include disentangling these species interactions from
fisheries independent trap survey results by incorporating benthic habitat dependencies, as
evaluating the different species habitat needs in the context of observed habitat type would
provide better insight into these interactions.

374 Density-dependent factors and intraspecific interactions have also been speculated to 375 influence catch. Lobster catchability has been found to not necessarily be constant with density, 376 as pre-stocking traps with lobsters has been found to reduce the catch of lobsters (Richards et al., 377 1983). Similar findings were reported by Watson et al. (2019), where stocking lobsters before 378 deployment reduced catch and removing lobsters after 24 hours led to an increase in catch. Such 379 a phenomenon would have the potential to misrepresent an aggregated or highly abundant 380 species with lower and more uniform catch (Addison, 1995). Further, the intraspecies 381 interactions with American lobsters can vary with size; similar model standardization work for 382 sublegal and recruit lobsters per trap in Canadian surveys use the number of legal lobsters 383 observed to capture the behavioral dynamics between lobsters of different sizes (Cook et al., 384 2018). Work with rock lobsters (Jasus edwardsii) has shown that intraspecific interactions that 385 vary by sex and size effect trap catch and potentially inferences on abundance resulting from trap 386 CPUE (Frusher and Hoenig, 2001; Ihde et al., 2006). These complexities resulting from 387 intraspecies behavioral interactions and their influence on CPUE warrant further investigation 388 for ensuring non-biased indices used for stock assessment modeling. 389 4.2 Comparison of index methods

390 Both the model-based and design-based approaches capture the trends in American 391 lobster relative abundance for the two stocks over the sampled time period: increasing abundance 392 in the GOM and decreasing or stable, yet low, abundance in SNE (Figure 5). Except for 393 interannual differences, these trends are corroborated by several other survey trends over the 394 stock bounds and modeled population sizes (ASMFC, 2020). The differences in model-based and 395 design-based indices were greater for SNE than for GOM (Figures 5 and 6). The greater 396 similarity between the two approaches in the GOM may be attributed to the number of samples 397 for each model. GOM models had over 5.7 times more samples for model fitting than SNE, 398 perhaps providing more information to improve mean CPVT predictions. However, the greater 399 variability in catch in SNE also likely attributes to the reduced corroboration between the design 400 and model-based index approaches. The increased variability is highlighted in the standard error 401 estimates for both index types (Figure 5) and can partially be attributed to the factors included in 402 the model types. For example, the inclusion of the site in the SNE models appears to cause 403 substantial deviation in scale and trend differences between model-based and design-based 404 abundance indices (Appendix A).

405 The model-based approach of formulating abundance indices at the individual trap level 406 as opposed to aggregate means over a season in the design-based approach provided both 407 benefits and drawbacks. By constructing abundance indices at the trap-level, the inherent 408 variability within a trawl (as incorporated with multiple traps with varying CPVT having the 409 same covariate values) were better accounted for. Further, not averaging ventless trap catch over 410 a site in the model-based approach allowed for including more information on observed CPVT 411 for informing abundance index variance; averaging CPVT data within a trawl in the design-412 based approach may not account for this level of variability. As such, the variance in the model-

based estimates also increased as reflected in the standard error estimates (Figure 5). Despite theincrease in variance, index bias is generally reduced by accounting for factors affecting

415 catchability (Maunder and Punt, 2004).

416 One of the greatest benefits of the model-based approach is that it allows for estimating 417 abundances for 2013, where missing data from Massachusetts prevented the design-based 418 approach from calculating such data. GOM index estimates for 2013 indicated that year was one 419 of the top three years in abundance over the time series, where conversely, such estimates for 420 SNE indicated that year was either the lowest (females) or second lowest (male) abundance over 421 the time series (Figure 5). The model-based approach using random effects provides a solution 422 for estimating abundances for the stock unit in the event select state surveys are unable to be 423 conducted. The degree of missing data for a given year and stock should be evaluated prior to 424 relying on the model-based approach to estimate abundance.

425 Inferences on lobster population sex ratios are challenging with trap surveys as males and 426 females are not spatially uniform due to differences in biological needs (Jury et al., 2019). 427 Additionally, differences in catchability between sexes can create biases with trap surveys; 428 whereas in Canada, Tremblay and Smith (2001) reported females were less catchable than males. 429 Within SNE's Buzzards Bay, shallower areas tend to have warmer waters and lead to a male-430 skewed sex ratio, whereas deeper-cooler areas are reflective of a female-skewed ratio (ASMFC, 431 2010, Jury et al., 2019). The model-based approach for SNE captures this skewness, whereas the 432 design-based approach is reflective of a female-dominated catch (Figure 7). The difference does not appear to be influenced by the sample weighting in the model-based approach (Appendix A); 433 434 however, the large number of shallow strata samples in the models may account for this 435 discrepancy in sex ratios between the model- and design-based approaches. The SNE VTS strata

436 are predominantly shallow (0-20m), where the deeper (21-40m) strata are primarily located in437 the Rhode Island survey domain (Figure 1).

438 The model-based indices provided an alternative dataset for inclusion in stock assessment 439 model fitting (ASMFC, 2020). Understanding the influence of various factors on survey design 440 and catchability are paramount when trying to assess changes in abundance. Gear studies can 441 aim to test these factors through specific research and apply *post hoc* corrections (McManus et 442 al., 2020), but such efforts are often not possible due to funding and time constraints. This 443 modelling approach allows for testing these factor effects explicitly when deriving the abundance 444 estimates. Model-based approaches have become a favorable practice for several purposes, 445 including to account for survey variables introducing bias in observed abundance estimates 446 (Maunder and Punt, 2004; Venables and Dichmont, 2004), to incorporate environmental drivers 447 in abundance and distribution (Friedland et al., 2020), and to predict abundances through space 448 and time not sampled for a more complete understanding of population structure (Thorson et al., 449 2015). This work serves as an example of standardizing abundance indices for structure-oriented 450 species that require non-traditional sampling techniques. In the context of lobster, the 451 standardized approach also provides new insights on the catchability and life history for an 452 iconic and valuable species. With the additional year of data now available (i.e. 2013), and 453 smoother trends from removing variability associated with catchability and not population 454 changes, the intent is for these indices to improve the ability of U.S. American lobster stock 455 assessment models to accurately predict population trajectories.

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- Table 1. Description of Ventless Trap Survey by participating states.

State (Statistical Areas)	Operating Years	Trawl Configuration
Maine (511, 512, 513)	2006-2014	Single 6-trap trawls alternating vented and ventless traps or two 3-trap trawls with 3 vented traps on one trawl and 3 ventless traps on the other trawl
	2015-2019	One 3-trap trawl, all ventless traps
New Hampshire (513)	2009-2014	Alternating vented and ventless traps in single 6-trap trawls
	2015-2019	One 3-trap trawl, all ventless traps
Massachusetts (513, 538)	2006-2012, 2014- 2019	Alternating vented and ventless traps in single 6-trap trawls
Rhode Island (539)	2006-2019	Alternating vented and ventless traps in single 6-trap trawls
New York (611)	2006-2009	Alternating vented and ventless traps in single 6-trap trawls

- Table 2. Stepwise comparison of model fits using varying model covariates. Akaike informationcriterion (AIC) are provided for each model variant. Smaller values within a model type indicate
- better fit. Bold values indicate the model variant with the lowest AIC score.

Model	Variables	AIC
GOM Females	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)+offset(ln[Traps No.])	29263
	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)	28686
	fe(Year)+re(Day of Year)+re(Soak Time)	28697
	fe(Year)+re(Day of Year)	28695
GOM Males	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)+offset(ln[Traps No.])	26976
	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)	26463
	fe(Year)+re(Day of Year)+re(Soak Time)	26517
	fe(Year)+re(Day of Year)	26519
SNE Females	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)+offset(ln[Traps No.])	8276
	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)	8245
	fe(Year)+re(Day of Year)+re(Soak Time)	9619
	fe(Year)+re(Day of Year)	9637
SNE Males	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)+offset(ln[Traps No.])	8720
	fe(Year)+re(Day of Year)+re(Soak Time)+re(Site)	8692
	fe(Year)+re(Day of Year)+re(Soak Time)	9696
	fe(Year)+re(Day of Year)	9695



699 Figure 1. Survey domain and stratification for the lobster VTS within the Southern New England (SNE, left) and Gulf of Maine

700 (GOM, right) stock areas. Southern New England strata are 0-20m (dark red) and 21-40m (light red), whereas Gulf of Maine has 0-

20m (dark blue), 21-40 (blue) and 41-60m (light blue) strata. NOAA Statistical Areas are presented within each region. The insert

map of the Northeast United States in the right panel presents the geographical locations of SNE (dashed) and GOM (dotted) survey

703 domains.



Figure 2. Random effects intercepts for the day of year variable estimated for the male andfemale SNE and GOM catch per ventless trap (CPVT) models. Lines represent loess fits through

the day of year intercept values.



Figure 3. Random effects intercepts for the soak time variable estimated for the male and female

713 SNE and GOM catch per ventless trap (CPVT) models.





Figure 4. Random effect intercepts for the site variable estimated for the male (left column) and

female (right column) SNE (top row) and GOM (bottom row) catch per ventless trap (CPVT)

719 models. Effects are plotted spatially representing their location, with the size of points relative to

their value (more positive random effect intercepts correspond to larger points). Points within a

sex-specific figure are relative to that sex only. Inset histograms present the random effect

intercepts associated with the site variable for the respective catch per ventless trap (CPVT)

model.



Figure 5. Annual lobster catch per ventless trap (CPVT) indices by sex and stock. Model-based approach mean indices (solid lines) for males and females and their associated standard error are presented with mean design-based indices (dashed line).



Figure 6. Normalized male and female SNE and GOM CPVT indices using the model-based and design-based approach.



Figure 7. Annual sex ratios for indices using model-based and design-based approaches. The horizontal dotted line reflects where the sex ratio is 1:1.