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Dynamic changes in American lobster suitable habitat distribution on the Northeast U.S. Shelf linked to oceanographic conditions

Running Title: Change in American lobster suitable habitat

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Abstract

American lobster (*Homarus americanus*) supports one of the most valuable regional fisheries in the United States, with its abundance and distribution profoundly influenced by environmental conditions. To explain how lobster distribution has changed over time and assess the role of environmental variables on these changes, we used random forest classification and regression trees models to estimate occupancy and biomass in two seasonal periods. The occupancy models were fit to static and dynamic variables, which yielded model fits with AUC scores of 0.80 and 0.78 for spring and fall, respectively. Biomass models were fit with the same data and resulted in models explaining 61 and 63% of the spring and fall biomass variance, respectively. Significant variables scored in the formation of the regression trees were secondary productivity (i.e. zooplankton), bathymetry characteristics, and temperature. American lobster suitable habitat has changed regionally; habitat has increased in the Gulf of Maine and declined in Southern New England. There is also evidence of declining habitat along the inshore margin of the Gulf of Maine, which has been accompanied by a shift in occupancy probability offshore. Habitat suitability results from the random forest models provide insights on the structure and function of lobster habitat and context to understand recent population trends.

Key words: American lobster, Random Forest, suitable habitat, temperature, secondary productivity, front, Northeast U.S. Shelf

Introduction

57 American lobster (*Homarus americanus*) is widely distributed over the Northeast U.S.
58 Continental Shelf (hereafter referred to as the Northeast U.S. Shelf) where it supports the most
59 valuable single-species fishery in the United States (NOAA, 2017). A recent assessment
60 highlighted the disparity between the two separate lobster stocks, with the Gulf of Maine-
61 Georges Bank (GOM/GBK) stock reaching record high abundances while the Southern New
62 England (SNE) stock declining to all-time low abundances (ASMFC, 2015). While commercial
63 harvest has influenced population abundances through time, environmental and ecosystem
64 changes have contributed to the recent stock dynamics (ASMFC, 2015). A combination of
65 conservation measures and favorable environmental conditions lead to dramatic increases in
66 landings in the GOM/GBK lobster fishery, but deficient conservation measures and unfavorable
67 environmental conditions led to a collapse of the SNE lobster fishery (Le Bris et al. 2018). To
68 effectively provide advice on sustaining lobster populations and maintaining the viability of the
69 commercial lobster fishery, understanding the environmental impacts on American lobster and
70 its habitat are imperative.

71 Temperature is perhaps the most prominent environmental forcing factor on American
72 lobster and in defining its habitat. American lobster migration has been linked to water
73 temperatures, which contributes to a lobster's ability to successfully molt, mate, and extrude eggs
74 (Cooper & Uzmann, 1971; 1980). Increased temperatures have been associated with more
75 frequent molts, reduced intermolt increments, smaller sizes to reach sexual maturity (Little and
76 Watson, 2005; McMahan et al., 2016), and faster and earlier egg development and hatching
77 (Goldstein and Watson, 2015). Lobsters partition spatially by size and sex (Karnofsky et al.,
78 1989; Campbell, 1990), with these segregations attributed to their differing responses to
79 environmental factors such as temperature and depth (Chang et al., 2010).

80 In the Northeast U.S. Shelf, ocean temperatures have increased significantly over the last
81 several decades (Friedland and Hare, 2007; Pershing et al., 2015; Kavanaugh et al., 2017). The
82 change in temperature is associated with changes in American lobster population size and
83 distribution, with both centers of lobster biomass and fisheries landings shifting northeast since
84 the 1970s (Pinsky and Fogarty, 2012). Projections of increasing temperatures over the next
85 century (Saba et al., 2016) suggest that temperature will continue to have an impact on critical
86 American lobster life history traits and the anticipated distribution of thermal habitat for lobster
87 (Fogarty et al., 2007; Chang et al., 2010; Tanaka and Chen, 2015; Tanaka and Chen, 2016;

88 Georgas et al., 2016; Rheuban et al., 2017; Goode et al., 2019). Warming water conditions may
89 have a disproportionate effect on lobster at the southern end of their latitudinal range due to
90 impacts on their life history. At temperatures nearing 20°C, increased physiological stress,
91 increased prevalence of lobster epizootic shell disease, and decreased immune function can lead
92 to increased rates of natural mortality (Steenbergen et al., 1978; Dove et al., 2005; Pearce and
93 Balcom, 2005; Glenn and Pugh, 2006; Wahle et al., 2009; Steneck et al., 2011; Barris et al.,
94 2018).

95 Several other environmental and oceanographic factors affect lobster life history and
96 contribute to the definition of lobster habitat. Lobsters are associated with benthic structure
97 including rocks, cobble, boulders, and ledge that they use to shelter, particularly during larval
98 settlement and following life stages (Lawton and Lavalli, 1995). Suitable settlement habitat has
99 often been considered a significant contributor to recruitment success and may impose
100 limitations on year class size (Wahle and Steneck, 1991; Wahle and Steneck, 1992).

101 Productivity variables, which are not often accounted for in habitat evaluations, may also
102 serve an important role in defining lobster habitat and influence recruitment. The Northeast U.S.
103 Shelf ecosystem has undergone decadal changes in zooplankton community composition and
104 spatial structure (Pershing et al., 2010; Morse et al., 2017), with zooplankton abundance
105 variability linked to finfish stocks' recruitment (Perretti et al., 2017) and larval habitat suitability
106 (McManus et al., 2018). For adult marine fauna, correspondence between their abundance and
107 zooplankton often highlight the reliance on productive regions and the oceanographic conditions
108 that support them (Sheldon et al., 1977). Ocean fronts associated with water temperature and
109 density may play an important role in structuring lobster habitat (Belkin et al., 2014) through
110 defining regions of enhanced productivity and pelagic to benthic coupling that support
111 increased growth and foraging opportunities (Bakun, 2006). Fronts likely contribute to suitable
112 habitat for a range of species and subsequently increasing prey-predator interactions and feeding
113 opportunities for lobster (Mugo et al., 2014). This interaction may be reflected in the diet of adult
114 lobsters, which includes prey such as mussels, gastropods, macroalgae, polychaetes, and
115 amphipods (Sainte-Marie and Chabot, 2001). To date, food availability for older lobsters has not
116 been considered a limiting factor in their abundance and distribution.

117 Species distribution models (SDMs) have been useful tools for identifying an organism's
118 potential habitat range, prioritizing areas for conservation and management decisions, and

119 evaluating survey designs (Guisan & Thuiller, 2005; Elith and Leathwick, 2009; Bachelier et al.,
120 2016). American lobster life history and habitat have been the subject of hindcast and forecast
121 models for various portions of the Northeast U.S. Shelf using bioclimate envelope models,
122 generalized additive models, and additional analytics (Chang et al., 2010; Tanaka and Chen,
123 2015; Tanaka and Chen, 2016; Kleisner et al., 2017; Tanaka et al., 2017; Morley et al. 2018;
124 Tanaka et al., 2018). However, previous studies have evaluated a rather narrow scope of
125 variables and, aside from Kleisner et al. (2017) and Morley et al. (2018), isolated their inferences
126 to fine scale areas that do not evaluate change over the entire Northeast U.S. Shelf. Furthermore,
127 prior studies have not provided a comparative analysis of variable contribution.

128 We implemented random forest (RF) ensemble models (Cutler et al. 2007) to identify the
129 environmental factors that correspond to lobster presence and abundance. The RF models were
130 then used to predict spatio-temporal lobster distribution to understand how lobster suitable
131 habitat has changed through time for both U.S. stocks. The resulting time series habitat indices
132 describe changes in the lobster abundance through time and help guide future ecosystem
133 considerations for lobster fishery management. Using a suite of marine ecosystem descriptors,
134 we aimed to help form hypotheses for future studies focusing on mechanistic relationships
135 between lobsters and their habitat.

136 **Methods and Materials**

137 This study is based on a series of SDMs, created with RF models, for dominant species in
138 the U.S. Northeast Shelf (Friedland et al. 2020). Details for sources of variables in this study are
139 provided in the respective sections below.

140 Data collection

141 *Lobster data*

142 The response variables were occurrence and catch-per-unit-effort of American lobster
143 from the Northeast Fisheries Science Center's (NEFSC) fishery-independent bottom trawl survey
144 within federal waters of the Northeast U.S. Shelf. The survey has been conducted in the spring
145 since 1968 and the fall since 1963 using a stratified random design, which provides both spatial
146 and temporal depictions of fish and macroinvertebrate abundances (Grosslein, 1969). Catches
147 were standardized for various correction factors related to vessels and gears used in the time
148 series (Miller et al. 2010), following the methods of Friedland et al. (2020). These data are from

149 the NEFSC fishery-independent bottom trawl survey available from the InPort NMFS Data
150 Management Program (<https://inport.nmfs.noaa.gov/inport/>).

151 *Explanatory variables*

152 The independent or explanatory variable set included bathymetry, productivity, and
153 climate variables (Table A1). Several explanatory variables were used to describe lobster habitat
154 and develop hypotheses that can be tested in future studies focusing on mechanistic relationships
155 in lobster habitat. Static variables were kept constant over all years, whereas dynamic variables
156 varied annually. Station data included observations made contemporaneously to survey stations.

157 Prior to fitting the models, the independent variable set was first tested for
158 multicollinearity among the explanatory variables (R package rfUtilities, version 2.1-3), and
159 strongly correlated covariates were removed from the analysis (threshold: $p=0.1$), following the
160 methods of Murphy et al. (2010). From the reduced set of explanatory variables, the final model
161 variables were selected utilizing the model selection criteria of Murphy et al. (2010) as
162 implemented in 'rfUtilities'. This includes removing multivariate redundant variables using qr
163 matrix decomposition. Removing redundant variables improves the biological interpretability
164 and predictive power.

165 *Climate*

166 Surface and bottom water temperature and salinity were used as dynamic abiotic
167 variables in the analysis. These data were collected contemporarily to each tow with
168 Conductivity/Temperature/Depth (CTD) instruments. The data are from the NEFSC survey
169 temperature and salinity data from the National Center for Environmental Information
170 (https://www.nodc.noaa.gov/oads/stewardship/data_assets.html). Temperature and salinity data
171 for model predictions were based on an interpolation procedure described in Friedland et al.
172 (2019). This procedure combines a kriged interpolation of the annual data with climatological
173 data to estimate complete temperature and salinity fields. This approach was favorable since it
174 preserved the observational nature of the data and kept it as close as possible to the data used in
175 the habitat model fits.

176 Sea surface temperature (SST) from remote sensing sources were summarized as monthly
177 means with their associated gradient magnitude or frontal fields, and applied in the habitat
178 models as static variables. There are many methods used to identify oceanographic fronts (e.g.
179 Belkin and O'Reilly, 2009) that often apply a focal filter to reduce noise and then identifies

180 gradient magnitude with a Sobel filter. These calculations were conducted in R using the raster
181 package (version 2.6-7) by applying a three by three mean focal filter and a Sobel filter to
182 generate x and y derivatives, which were then used to calculate gradient magnitude. This indexes
183 the annual cycle, and all the available monthly variables, after removing collinear and redundant
184 variables, were used in each of the seasonal models. These monthly variables were averages of
185 the monthly concentrations or fronts from all years in the time series. Monthly SST fields were
186 based on the 4 km MODIS Terra sensor data. These data are from the Ocean Color website
187 (<https://oceancolor.gsfc.nasa.gov/>).

188 *Bathymetry*

189 Bathymetry variables represented a series of static variables that reflect the shape and
190 complexity of the benthic environment. Depth of the station (in meters) was used as a static
191 variable in the analysis. The observed depth made with each survey tow was used in model
192 fitting, whereas model predictions were based on depths from the ETOPO1
193 (<https://www.ngdc.noaa.gov/mgg/global/>) dataset, which provided Northeast U.S. Shelf
194 bathymetry at a resolution of 0.0167° (Fig A1).

195 Most of the other bathymetry variables were based on depth measurements, including the
196 complexity, bathymetry position index (BPI), vector ruggedness measure (VRM), profile
197 curvature at 2, 10, and 20 km, slope at 2, 10, and 20 km, slope of the slope at 2, 10, and 20 km,
198 rugosity, and seabed topography variables (Table A1). Complexity represented the difference in
199 elevation values from a center cell and the eight cells immediately surrounding it. Each of the
200 different values were squared and then averaged. The index was the square root of this average
201 (Riley et al., 1999). BPI was a second order derivative, which compares the depth and slope
202 values at a location to those at neighboring locations, of the bathymetry using the Nature
203 Conservancy Northwest Atlantic Marine Ecoregional Assessment (NAMERA) data with an inner
204 radius of 5 and an outer radius of 50 (Lundblad et al., 2006). VRM measured terrain ruggedness
205 as the variation in three-dimensional orientation of grid cells within a neighborhood based on the
206 TNC NAMERA data (Hobson, 1972; Sappington et al., 2007). Rugosity measured small-scale
207 variation of amplitude in the height of a surface, the ratio of the real to the geometric surface area
208 (Friedman et al., 2012). Seabed topography is a measure that combines seabed position and slope
209 (Anderson et al., 2010). Benthic profile curvature, slope, and slope of slope at 2 km, 10 km and
210 20 km spatial scales were also derived from depth data (Winship et al., 2018). The vorticity

211 variable was based on benthic current estimates and is at a 1/6 degree (approximately 19 km)
212 spatial scale (Kinlan et al., 2016). Soft sediment was based on grain size distribution from the
213 USGS usSeabed: Atlantic coast offshore surficial sediment data (Anderson et al., 2010). Aside
214 from the bathymetry variables derived from depth, these variables' data were from Northeast
215 Ocean Data (<http://www.northeastoceandata.org/>), or National Centers for Coastal Ocean
216 Science (<https://coastalscience.noaa.gov/project/statistical-modeling-marine-bird-distributions/>).

217 *Productivity*

218 Productivity was incorporated into the model as both primary and secondary levels of
219 production in the marine ecosystem. Chlorophyll concentration from remote sensing sources
220 were summarized as monthly means with their associated gradient magnitude or frontal fields
221 and applied in the habitat models as static variables. These chlorophyll concentration and frontal
222 field variables represented seasonal primary productivity cycles. After removing collinear and
223 redundant variables, all the available monthly chlorophyll variables were tested in each of the
224 seasonal models. Chlorophyll concentration measurements were based on the 4 km data from the
225 Sea-viewing Wide Field of View Sensor (SeaWiFS), Moderate Resolution Imaging
226 Spectroradiometer on the Aqua satellite (MODIS), Medium Resolution Imaging Spectrometer
227 (MERIS), and Visible and Infrared Imaging/Radiometer Suite (VIIRS) sensors during the period
228 1997-2016. These data represented a merged product using the Garver, Siegel, Maritorena Model
229 (GSM) algorithm obtained from the Hermes GlobColour website. These four sensors provided
230 an overlapping time series of chlorophyll concentration during the period and were combined
231 based on a bio-optical model inversion algorithm (Maritorena et al., 2010). From these data,
232 mean monthly fields were generated for chlorophyll. Gradient magnitudes of these data were
233 calculated in the same manner as with the habitat data as described above. These data are from
234 the Hermes GlobColour website (<http://hermes.acri.fr/index.php>).

235 Zooplankton abundance was used as a dynamic variable measured by the NEFSC
236 Ecosystem Monitoring Program (EcoMon), which conducts shelf-wide bimonthly surveys of the
237 Northeast U.S. Shelf ecosystem (Kane, 2007), and the MARine Resources Monitoring,
238 Assessment, & Prediction program (MARMAP), which conducted similar surveys before
239 EcoMon (data available at <https://accession.nodc.noaa.gov/0187513>). Zooplankton and
240 ichthyoplankton were collected throughout the water column to a maximum depth of 200 m
241 using paired 61-cm Bongo samplers equipped with 333-micron mesh nets. Sample location in

242 this survey was based on a randomized strata design, with strata defined by bathymetry and
243 along-shelf location. Plankton taxa were sorted and identified. In this study, zooplankton
244 represents a proxy for secondary productivity as opposed to representing a direct relationship
245 between zooplankton and adult and juvenile lobsters. This is because lobsters at the life stages
246 represented in the trawl survey catch do not feed on zooplankton, because they are not in early
247 life stages. We used the log of the abundance (number per 100m³ of water filtered) of each of the
248 18 most abundant taxonomic categories as potential explanatory variables, and we also used the
249 total bio-volume of all taxa (displacement volume in ml per 100m³ of water filtered) as a
250 potential explanatory variable. Biovolume is the settled volume of plankton per water volume
251 sampled (mm³/m³). It is measured by estimating the total volume of plankton in the sample jar.
252 The zooplankton sample time series had some missing values which were ameliorated by
253 summing data over five-year time steps so that the current year is centered and interpolated into a
254 complete field using ordinary kriging, following the methods from Friedland et al. (2020). For
255 example, the data for spring 2000 would include the available data from 1998-2002 tows.

256 Data analysis

257 *Random forest approach*

258 RF is an ensemble model approach based on combinations of large sets of decision trees
259 (Breiman et al., 1984). Tree models such as RF provide powerful predictive power with many
260 explanatory variables (Cutler et al., 2007), yet perhaps the greatest benefit of these models is
261 they largely ignore non-informative predictors, but predictor selection is still important given
262 redundant predictors increase variance and reduce model performance (Elith et al., 2008). Other
263 benefits of tree models include resistance to overfitting, ability to identify interactions, and
264 overall flexibility (Elith et al., 2008). In this technique, the learning sample is divided in two by
265 maximizing the homogeneity in the two resulting child nodes, which is done with an algorithm
266 known as binary recursive partitioning. RF trees are grown by selecting a random bootstrap
267 subset of the original dataset and a random set of explanatory variables (Liaw and Wiener,
268 2002), which is different from the process in standard decision trees, where all explanatory
269 variables are used. Within the subset, the partitioning starts with the most important variable and
270 ends with the least important variable.

271 *Occupancy and biomass habitat models*

272 Occupancy and biomass habitats for lobster were estimated with RF decision tree models
273 using the aforementioned static and dynamic explanatory variables. The effect of bathymetry,
274 productivity, and climate factors on variation in species presence or absence and biomass were
275 tested. Models were constructed separately for spring and fall seasons. The spring and fall
276 seasons were based on the timing of the offshore survey, which varied slightly over time. The
277 modeling domain focused on the Northeast U.S. Shelf and upper slope, latitudinally extending
278 from the states of North Carolina to Maine. Occupancy models were fit as two-factor
279 classification models (absence as 0; presence as 1) using the ‘randomForest’ R package (version
280 4.6-14). Biomass models were also fit using the same package with \log_{10} transformed biomass-
281 per-unit-effort plus one (fall biomass: mean=0.228, sd=0.4, spring biomass: mean=0.180,
282 sd=0.353) as the response variable and the same starting set of explanatory variables as in the
283 occupancy models. The number of trees was set to 200, and the number of variables randomly
284 sampled as candidates at each split was the square root of the total number of variables for the
285 occupancy models, and the total number of variables divided by three for the biomass models.

286 Habitat was estimated from the model fits over a standard 0.1° grid, which circumscribes
287 the range of ecosystem assessment areas in the region (Figure 1) and a wide range of habitats
288 with varying oceanographic conditions (Townsend et al., 2006). The grid represented limited
289 extrapolation into the inshore areas of the Northeast U.S. Shelf not exceeding one grid cell
290 beyond the observed data. The length of the time series of model fits was constrained by the
291 shortest dynamic variable time series to meet the requirement of complete cases in the RF fitting.
292 As such, the fitting time series was constrained to 1992 – 2017, corresponding to the length of
293 the station salinity data.

294 *Model selection criteria and variable importance*

295 The habitat models were evaluated for fit based on out-of-bag classification accuracy. For
296 occupancy model accuracies, AUC (Area Under the Receiver Operating Characteristic Curve)
297 and Cohen’s Kappa were calculated using the “irr” R package (version 0.84) (Gamer et al.,
298 2012). The AUC assumes a threshold of classification probability of 0.5. For biomass models,
299 the variance explained by the model, mean absolute error, root mean square error, and bias were
300 calculated using the “Metrics” R package (version 0.1.3). To evaluate variable importance in
301 both occupancy and biomass models, the number of times a variable was the root variable, or the
302 variable at which the whole sample is divided into two (the first variable in the tree), were

303 plotted against the mean minimum node depth for the variable, highlighting the top 10 important
304 variables (“randomForestExplainer” R package, version 0.9). For occupancy models, Gini index
305 decreases were plotted against accuracy decreases, whereas node purity increases versus MSE
306 increases were plotted for the biomass models, highlighting the top 10 most important variables.
307 These presentations allowed for calculating and visualizing variable importance under different
308 criteria.

309 *Visualizations*

310 Three types of visualizations were created from the model output. The first visualization
311 provided the average probability of occupancy over the ecosystem, accompanied by the rate of
312 change in occupancy probability as a Sen slope, which represented the median of the slopes of
313 all lines through pairs of points. The nonparametric Sen slope is less vulnerable to single values.
314 The second visualization provided the gradient magnitude of occupancy probability over the
315 ecosystem, or frontal strength of this habitat measure, also accompanied by the rate of change in
316 occupancy gradients as a Sen slope. Gradient magnitudes of these output data were calculated in
317 the same manner as with the habitat data as described above. The third visualization provided
318 average biomass habitat over the ecosystem, also accompanied by the rate of change in biomass
319 habitat as a Sen slope. Trends in total occupancy habitat area in each ecoregion (GOM, GBK,
320 and SNE), delimited by threshold occupancy probabilities of 0.25, 0.50, and 0.75 over time, were
321 calculated, as well as the sum of the area with occupancy probabilities above each probability
322 during each year.

323 **Results**

324 *Model diagnostics*

325 Although both occupancy models were accurate, the spring model was better fitting than
326 the fall model (Table 1). The AUCs indicated that all models performed better than random
327 classifications. The spring model had a better rate of successful classification than the fall model.
328 The Kappa statistics indicated that spring and fall occupancy models showed substantial and
329 moderate agreements, respectively. For biomass, the RF models explained between 60.9% to
330 63% of the variance (Table 2). The spring biomass model had a smaller error and bias than the
331 fall biomass model.

332 *Variable importance*

333 A variety of climate, bathymetry, and productivity variables were significant and
334 included in the spring and fall models (Table A1). Bottom water temperature, BPI, depth, several
335 secondary productivity variables, and SST fronts were important variables (Figure 2; Figure 3).
336 Bottom water temperature was a highly important variable for fall, and more for the occupancy
337 model than for the biomass model. In the spring, SST fronts were more important than in the fall,
338 especially for occupancy (Figure 2 a and b and Figure 3 a and b). Bathymetry variables were
339 more important for occupancy in the spring than in the fall. Chlorophyll fronts were more
340 important than SST fronts in the fall, and SST fronts were more important than chlorophyll
341 fronts in the spring. Zooplankton taxa Chaetognaths, *Centropages typicus*, *Paracalanus parvus*,
342 and *Calanus finmarchicus* were particularly important for occupancy and biomass models in the
343 spring, followed by bathymetry variables (Figure 2 c and d). Secondary productivity was
344 consistently more influential and significant than primary productivity in the spring. Secondary
345 productivity variables were also important in the fall occupancy model, followed by bathymetry
346 variables (Figure 3 a and b). *Metridia lucens*, Appendicularians, *Pseudocalanus spp.*, and
347 *Centropages hamatus* had especially strong influences in the fall. Productivity variables were
348 also very important for fall biomass, while bathymetry variables were not as important for fall
349 biomass as they were for fall occupancy (Figure 3 c and d).

350 Of the most important variables, lobster occupancy was negatively related to depth, slope
351 at 2 km, and *Metridia lucens*. Lobster occupancy had nonlinear relationships and optimal ranges
352 with values of November SST front, December SST front, BPI, March chlorophyll
353 concentration, Chaetognatha, *Paracalanus parvus*, *Calanus finmarchicus*, *Pseudocalanus spp.*,
354 Gastropoda, Appendicularians, and bottom water temperature. Lobster occupancy was positively
355 related to *Centropages typicus* and Salpa (Fig. A1 - A10; A21- A29). Lobster biomass decreased
356 with SST, December SST front, Chaetognatha, *Paracalanus parvus*, *Calanus finmarchicus*,
357 Appendicularians, and *Centropages typicus*. Lobster biomass had nonlinear relationships and
358 optimal ranges with values of November SST front, December SST front, BPI, September
359 chlorophyll concentration, *Penilia spp.*, and Gastropoda. Lobster biomass increased with depth,
360 June chlorophyll concentration, July chlorophyll concentration, October chlorophyll front,
361 *Temora longicornus*, *Centropages hamatus*, and *Pseudocalanus spp.* Lobster biomass increased
362 and then decreased with bottom water temperature (Fig. A11- A20; A30- A41). Values of these
363 important dynamic variables varied overtime (Fig. A42- A54).

364 *Predicted area occupied and biomass*

365 Lobster distribution varied across space, with greater occupancy and biomass predicted
366 for GOM and GBK than SNE. Lobster habitat occupancy probabilities were greatest (probability
367 > 0.50) for inshore GOM, off the coast of southern Nova Scotia, and offshore SNE (Figure 4 a
368 and c). All models predicted low occupancy in offshore southern GOM. In the fall, the
369 occupancy was concentrated near inshore areas, whereas it was more diffused into offshore areas
370 in the spring. However, the occupancy probability area in offshore SNE was higher in the fall
371 than in the spring. Off the coast of Massachusetts, more areas were predicted to be found with
372 lobster in the fall than in the spring as well.

373 Occupancy habitat scores increased through time in most of the offshore GOM and some
374 portions of SNE and declined in the inshore GOM and most of SNE (Figure 4 b and d). The
375 greatest negative change in occupancy was in the northern and inshore region of SNE. The
376 greatest positive change in occupancy was in the offshore GOM. In the spring, there was more of
377 a positive change in the center of the GOM than in the fall. The greatest negative change in
378 occupancy for the fall was in the northern part of SNE and GBK. More of the inshore GOM had
379 a negative change in occupancy in the fall than in the spring.

380 The total area with 25% or greater probability of occupancy varied over time and regions
381 (Figure 5 a and b). In the GOM, the total area with 25% or greater probability of occupancy
382 increased in the fall and varied with no trend in the spring. In GBK, the total area with 25% or
383 greater probability of occupancy varied with no noticeable trend. In SNE, the total area with 25%
384 or greater probability of occupancy varied with no noticeable trend in the spring and decreased in
385 the fall. The total area with 50% or greater probability of occupancy increased greatly over time
386 in the GOM and increased slightly in GBK (Figure 5 c and d). In SNE, the total area with 50% or
387 greater probability of occupancy varied with no trend in the spring and decreased in the fall. At
388 the beginning of the time series, the total area with 50% or greater probability of occupancy was
389 lowest in the GOM compared to the other regions, but by the end of the time series, the total area
390 was highest in the GOM. The total area with 75% or greater probability of occupancy increased
391 greatly in the GOM but declined in recent years (Figure 5 e and f). In GBK and SNE, the total
392 area with 75% or greater probability of occupancy varied over time in the spring and slightly
393 decreased in the fall.

394 Habitat frontal strength, or occupancy gradient magnitude, was large off the inshore
395 GOM, around GBK, and in offshore SNE near the shelf break (Figure 6 a and c). In the fall in
396 SNE, there was a larger shift in habitat front towards offshore near the shelf break than in the
397 spring. The linear trend in the occupancy fronts was most positive in the offshore GOM and the
398 most negative in the inshore GOM, indicating that the habitat front was moving offshore (Figure
399 6 b and d).

400 Spatial predictions of the models highlighted strikingly area-specific differences in
401 biomass (Figure 7 a and c). Lobster biomass was predominantly concentrated near inshore GOM,
402 including off the coast of southern Nova Scotia, and most of the predicted lobster biomass was
403 off mid-coast Maine. The predicted biomass of the inshore GOM was much higher than the
404 predicted biomass in any other area, with the highest predicted biomass in other areas being
405 almost half of that in the inshore GOM. Biomass was much less in the offshore GOM and the
406 whole area of SNE, although in SNE much of the lobster biomass was predicted to be offshore
407 near the shelf break. There was more biomass in the offshore GOM in the spring than in fall, and
408 biomass off Cape Cod and in GBK was greater in the fall than the spring.

409 Changes in biomass were not necessarily aligned with changes in occupancy. Positive
410 changes in biomass were pervasive in the GOM, especially off mid-coast Maine, and most of the
411 negative change in biomass was in SNE (Figure 7 b and d). There were also some patches of
412 positive changes in biomass in the southern region of SNE. In the spring, the most positive
413 change in biomass was off midcoast Maine. In the spring, the rate of change was more similar
414 over space in the GOM than it was in the fall. The most positive change the fall biomass was off
415 the coast of Maine and Nova Scotia. There were also some negative changes in biomass on GBK
416 and in some parts of the inshore GOM in the fall, as well as positive changes in biomass in the
417 greater GOM region. These changes differ from the spring, in which there was less negative
418 change on GBK and positive change in most of the inshore GOM.

419 Habitat fronts produced from spatial predictions of the occupancy and biomass models
420 corresponded to SST fronts (Figure 8). Strongest SST front probabilities in the spring and fall
421 were most pronounced along the shelf break in SNE, followed by the inner shelf regions of SNE
422 and GOM, and southwest GBK. Habitat fronts were strongest in the inner GOM and SNE, and
423 offshore SNE, but spatially mismatched with SST front probabilities in GBK.

424 **Discussion**

425 *Trends in lobster habitat suitability*

426 The RF models accurately described the changes in American lobster habitat over the
427 Northeast U.S. Shelf. The models provide information on both lobster distribution and the
428 environmental conditions associated with lobster occupancy. The habitat trends estimated for
429 ecoregions corresponded to the declining and increasing population trends for the SNE and
430 GOM-GBK stocks, respectively (ASMFC, 2015). Separating the GOM and GBK into two
431 regions, as opposed to the unified stock region, allowed for acknowledging the oceanography
432 differences between the two areas, as well as their differences in habitat suitability trends. Since
433 1992, lobster habitat has declined and shifted offshore in SNE, and shifted offshore into deeper
434 water in GOM-GBK. These patterns agree with previously reported decreasing habitats in SNE
435 (Rheuban et al., 2017; Tanaka and Chen, 2015), offshore transitioning thermal habitats in the
436 GOM-GBK (Rheuban et al., 2017), increased habitat suitability in the GOM (Tanaka and Chen,
437 2016; Chang et al., 2010), and regional landings increasing in the north (NMFS, 2018).

438 Occupancy and biomass patterns differed in both the spring and fall, possibly indicating
439 density-dependent habitat selection of American lobster. Both occupancy and biomass were
440 highest off the coast of the GOM, peaking off the coast of the mid-Maine region, but there was a
441 greater change in occupancy in the offshore GOM and even a negative change in occupancy in
442 the inshore GOM, unlike the change in biomass. Lobsters are moving into areas that were
443 previously less occupied or unoccupied, which may be attributed to the increase in biomass in
444 the inshore GOM or an offshore shift in optimal thermal conditions (Tanaka and Chen, 2016),
445 causing lobsters to spread out into more offshore areas. It has been repeatedly demonstrated that
446 the spatial distribution of marine species expands with increases in abundance (Marshall and
447 Frank, 1994; Petitgas, 1998; Anderson and Gregory, 2000), indicating density-dependent habitat
448 selection where increases in population size lead to increases in competition, reduced habitat
449 suitability and ultimately an expansion of occupied area (Fretwell and Lucas, 1970; MacCall,
450 1990). The ideal free distribution theory describes that mobile individuals will select habitats that
451 maximize their fitness (Fretwell and Lucas, 1970). Population abundance can affect demographic
452 and life history characteristics of populations, such as dispersal (Fauchald et al., 2006), survival
453 (Bjornstad et al., 1999; Hails and Crawley, 1992), and reproductive success (Burgess et al.,
454 2011). Future research should consider including a density-dependent variable into analyses of
455 spatial distributions of lobster.

456 *Environmental drivers in predicted habitat*

457 Although American lobster distribution has been extensively studied, the RF models
458 provided additional insight on the effects of environmental factors on lobster abundance and
459 distribution. Spatial-temporal variability in lobster abundance and distribution corresponded to
460 both biological and physical oceanographic conditions. Although climate variables were
461 important drivers of American lobster habitat, productivity and bathymetry variables had the
462 greatest significance on lobster presence and biomass. These results suggest that productivity
463 fronts, which correspond with SST fronts, are important for lobster habitat. To date, biotic
464 variables such as chlorophyll concentration and zooplankton have not been included in lobster
465 habitat models. Additionally, bathymetry variables have largely not been included.

466 *Environmental drivers*

467 *Climate drivers*

468 Exact mechanisms driving habitat occupancy change are unclear but have been
469 associated with increasing ocean temperatures. Ocean warming has led to a northward center of
470 biomass shifts for many taxa (Pinsky et al., 2013), and the results for lobster biomass in this
471 study agrees with this. Increased prevalence and severity of epizootic shell disease in the
472 warming habitats of SNE (Steneck et al., 2011; Castro et al., 2006) have contributed to the
473 collapse of southern lobster populations, which suggests that temperature has a large effect on
474 habitat.

475 The influence of temperature was stronger and significant in the fall, with secondary
476 productivity variables relevant in both seasons. Temperature's profound impact on lobster life
477 history makes it surprising that it was not the leading contributor to habitat suitability in the RF
478 models in the spring. However, this finding should not negate or lessen the impact of
479 temperature on lobster behavior, physiology and distribution, as temperature is anticipated to
480 have further ramifications for the population in the future (Fogarty et al., 2007; Pinsky et al.,
481 2013). The variability of temperature during the spring trawl surveys may contribute to the
482 model results. Additionally, during the timeframe of the spring trawl surveys, lobsters may not
483 be actively migrating or moving since temperature may not have increased enough to stimulate
484 movement.

485 *Bathymetry drivers*

486 Bathymetry, especially depth and BPI, played a large role in lobster habitat. However, the
487 importance of bathymetry variables was often less than that of productivity and climate
488 variables. Although shelter is important for lobsters, bathymetry may play a role more for
489 smaller lobsters for refuge from predators than larger lobsters. As lobsters grow larger, they
490 become more active and use shelter less often (Lawton and Lavalli, 1995).

491 *Productivity drivers*

492 Although zooplankton taxa have been found to directly impact larval survival and
493 recruitment for several fish stocks in the study region (Peretti et al., 2017), the importance of
494 zooplankton taxa for lobster likely represents another important environmental condition that
495 also relates to zooplankton. This study focuses on juvenile and adult lobster and not earlier life
496 stages that may feed directly on zooplankton. Zooplankton biomass varies dynamically during a
497 given year, which makes it difficult to relate zooplankton biomass collected at the time of the
498 zooplankton surveys to lobsters in the spring and fall. However, averaging zooplankton biomass
499 can be a proxy for productivity over time, as the chlorophyll variables were static. The
500 zooplankton variables represent overall ocean productivity as opposed to a true predator-prey
501 relationship. The relationship between adult and juvenile lobsters and zooplankton is probably
502 not a direct relationship but lobster habitat is most likely dictated by productivity and
503 oceanography. For example, ocean fronts are key components to the ecosystem within the
504 Northeast U.S. Shelf through vertical mixing of nutrients that can affect the onset and duration of
505 phytoplankton blooms (Mann and Lazier, 2006). Ocean fronts occur over various spatial and
506 temporal scales (Belkin et al., 2014) and support multiple trophic levels and fisheries (Tseng et
507 al., 2014).

508 We hypothesize that the significance of zooplankton in describing lobster habitat is
509 associated with the role of physical oceanography, specifically frontal transition zones, in
510 creating these productive, ecologically rich features, as has been described for other species (Le
511 Fevre et al., 1986). The link between water column productivity in supporting demersal fish and
512 invertebrate species via benthic-pelagic coupling has been noted within the Northeast U.S. Shelf
513 (Friedland et al., 2008), and may serve as a major mechanism in providing lobster habitat in
514 these dynamic regions. Broad changes in the GOM may be reflected by changes in zooplankton
515 abundances (Pershing et al., 2005). Zooplankton community composition has undergone distinct
516 regime shifts over the previous decades (Morse et al., 2017). In this study, breaking zooplankton

517 into small taxonomic levels was beneficial, because individual taxonomic levels are spatially
518 varied. Plankton biovolume was not used in any of the models, probably because it is not as
519 spatially varied as individual taxonomic levels. Some individual taxonomic levels tend to line up
520 with production zones and fronts, which further supports our hypothesis that productive waters
521 are important for lobster habitat. Some plankton species are more dominant within fronts,
522 whereas others are more dominant outside of fronts (Moisander et al. 1997; Taylor et al. 2012;
523 Roy et al. 2015). In Georges Bank, different taxonomic levels are associated with different water
524 mass types (Ashjian et al. 2001). In the Northeast U.S. Shelf, anomalies of several copepod taxa
525 are associated with changes in frontal zones (Pershing et al. 2010). Therefore, the model results
526 are most likely suggesting general correlations among organisms within high productivity
527 waters.

528 Nonetheless, these results can be used to develop hypotheses to test in future studies that
529 focus on the role of zooplankton in lobster habitat. Another future research topic can be the
530 effect of broad scale changes in productivity on American lobster. This study suggests
531 productivity has a large effect on lobster distribution, even more so than temperature.

532 *Modelling limitations*

533 The results from this modeling effort are limited by both the survey design and the
534 covariate data available. The trawl survey data capture the broader population movements and
535 abundance trends through time; trawl surveys are unable to sample near rocky bottom or ledge or
536 where fixed gear is set (Smith and Tremblay, 2003), a known habitat preference and high
537 abundance regions of lobsters (Wahle, 1992; Lawton and Lavalli, 1995). The significance of
538 bathymetry and ruggedness in the RF models suggests that this preference for lobsters is at least
539 partially accounted for, but both sampling in these areas and covariate information at finer scales
540 and descriptions (e.g. cobble, rock, ledge, boulder) may improve results.

541 The NEFSC trawl survey also occurs in federal waters offshore and samples larger
542 lobsters, while a notable portion of the population, particularly smaller lobsters, reside within
543 inshore waters from spring through fall. Additionally, the large proportion of adult lobsters in the
544 trawl survey data may be a result of exploitation of the young lobsters. Thus, these results are
545 specific to larger lobsters, and may not represent the habitat requirements of younger, pre-recruit
546 lobsters. Other trawl surveys that cover inshore waters should be considered. Once catchability
547 differences between the NEFSC and states' trawl surveys are calibrated, other trawl data sources

548 can be included to allow for fully modeling the regions. Additionally, although correction factors
549 were applied, changes in vessels and gears in the trawl survey can introduce biases.

550 A key assumption in this study is that relationships between lobster and environmental
551 variables are stationary across space and time. Li et al. (2018) modeled lobster spatial
552 distribution allowing relationships to vary among space and found that the relationships
553 between lobster and environmental variables were different in the western and eastern GOM.
554 Similarly, the relationship between bathymetry variables and lobster may have changed
555 overtime with fluctuations in the abundance of predators and therefore, the need for sheltered
556 habitat.

557 In this study, the RF models were used to describe American lobster realized niche using
558 bottom-up forcing covariates, and do not account for top-down controls on the population.
559 Predation on lobsters also influences their spatial distribution, most prominently at the extreme
560 ends of the range of lobsters (Boudreau et al., 2015). Changes in top-down controls related to
561 ground fish predation have been postulated to have influenced lobster abundance in the coastal
562 GOM area. Following intense fishing on cod and haddock in the coastal GOM during the 1930s,
563 lobster abundance and landings increased in the following decades with the contemporary
564 increased abundance consistent with a predation release effect (Acheson and Steneck, 1997;
565 Steneck, 2006; Steneck and Wahle, 2013). Predators, notably cod, have long been noted to
566 influence lobster abundance and distribution (Boudreau et al., 2015). The decline in cod
567 abundance has been thought to explain part of the increase in lobster abundance (Hanson &
568 Lanteigne, 2000). Li et al. (2018) found a significant relationship between temperature and
569 lobster habitat in the eastern GOM, but not in the western GOM, with the operating hypothesis
570 that predators may have a greater effect on lobsters than temperature in the western GOM.
571 Predation risk on lobsters is lower in the GOM than in SNE, which may affect lobster habitat
572 (Wahle et al., 2013). Changes in top down controls (i.e. predators) may have also allowed
573 lobster to persist on previously unsuitable substrates (i.e. mud). Other top down controls,
574 including fishing pressure, may also contribute to discrepancies between our predictions and
575 empirical observations and should be further evaluated.

576 Additionally, RF models have limitations. Interpreting the relationships between the
577 response and explanatory variables can be difficult with many decision trees. Furthermore,
578 variable importance from RF models tend to be biased towards correlated variables, continuous

579 variables, and variables with many categories (Strobl et al. 2007; 2008).

580 *Conclusions*

581 These habitat suitability results advanced current understanding on lobster habitat
582 distribution, change, and the various environmental factors influencing American lobster
583 presence and biomass. Of note, the role of lower trophic level productivity appears to be an
584 important consideration in defining lobster habitat, which previous studies have not
585 investigated. Furthermore, previous studies have examined finer spatial scales for lobsters
586 (Chang et al., 2010; Tanaka and Chen, 2015; Tanaka and Chen, 2016; Tanaka et al., 2017;
587 Tanaka et al., 2018), whereas this work provides a more holistic view of the changes in lobster
588 habitat since 1992 that better correspond to the migratory species' stock bounds.

589 These results may prove valuable as inputs to the lobster stock assessment (i.e. tuning
590 recruitment deviations). Furthermore, these results can provide insights into the environmental
591 variables that have strong influences on distribution, and hence, population dynamics. Including
592 such estimates and information in the stock assessment model may better account for ecosystem
593 changes that have impacts on lobster life history and abundance, a common call often included in
594 assessments' terms of references. As these results suggest, a holistic approach using various
595 levels of oceanography should be incorporated into the assessment and management of American
596 lobster to ensure sustainable harvests. With the marine ecosystem expected to continue changing,
597 understanding of the environmental drivers for America's largest fishery are imperative now
598 more than ever.

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604 **Conflict of interest statement**

605 There is no conflict of interests to state in this research.

606 **Data sharing statement**

607 The data that support the findings of this study can be available upon reasonable request from the
608 corresponding author.

609 **Author Contribution Statement**

610 M.D.M. wrote the manuscript along with K.D.F., M.C.M., and A.G.G. K.D.F. conceived the
611 presented idea and performed the random forest modelling. M.D.M. and K.D.F. analyzed the
612 modelling results. All authors discussed the results and contributed to the final manuscript.

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908

909 **Tables**

910 Table 1. Diagnostics for occupancy models including accuracy, area under the curve (AUC) and
911 Cohen's Kappa.

Season	Accuracy	AUC	Cohen's Kappa
Spring	0.85	0.80	0.62
Fall	0.79	0.78	0.56

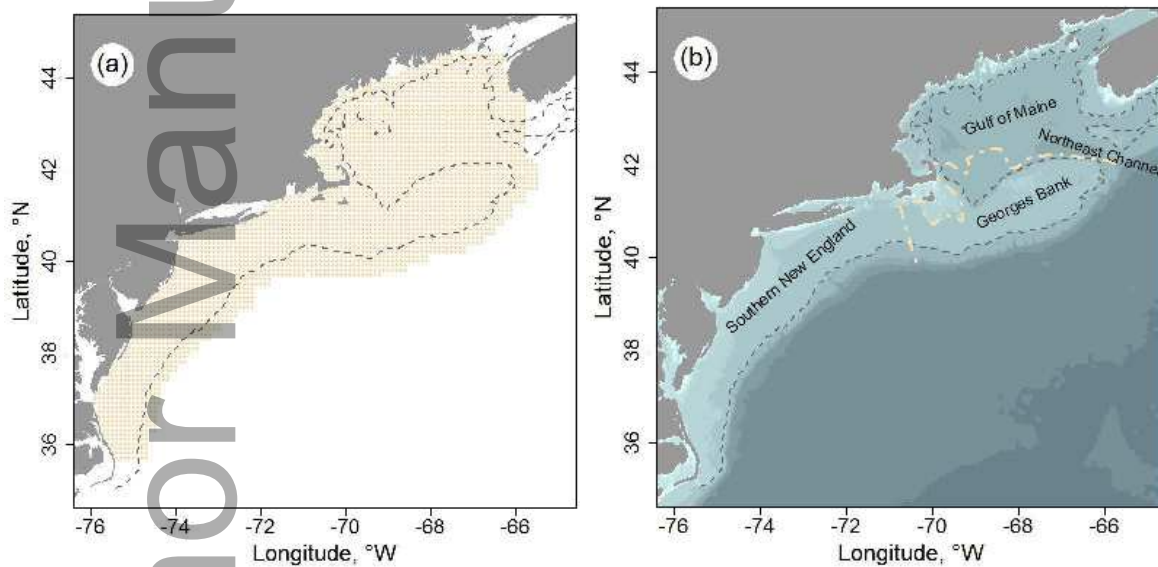
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913 Table 2. Diagnostics for biomass models including variance explained, Mean Absolute Error
 914 (MAE), Root Mean Squared Error (RMSE), and bias (logarithmic scale).

Season	Variance explained	MAE	RMSE	Bias
Spring	60.9	0.059	0.15	-0.0048
Fall	63.0	0.096	0.17	-0.0054

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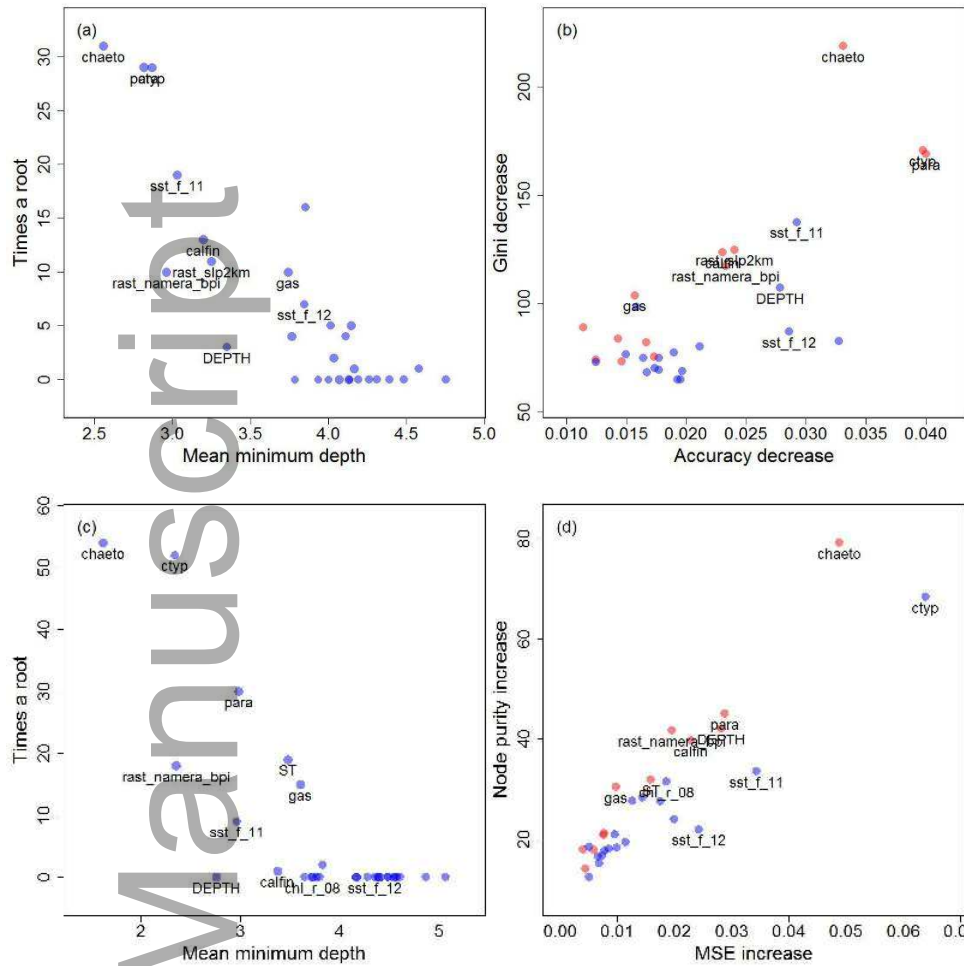
916 **Figures**



917

918 Figure 1. Northeast U.S. shelf with the estimation grid (a). Boundaries between Gulf of Maine,
 919 Georges Bank and Southern New England regions demarcated with yellow lines (b). Grey dashed
 920 lines denote 100 m depth contour.

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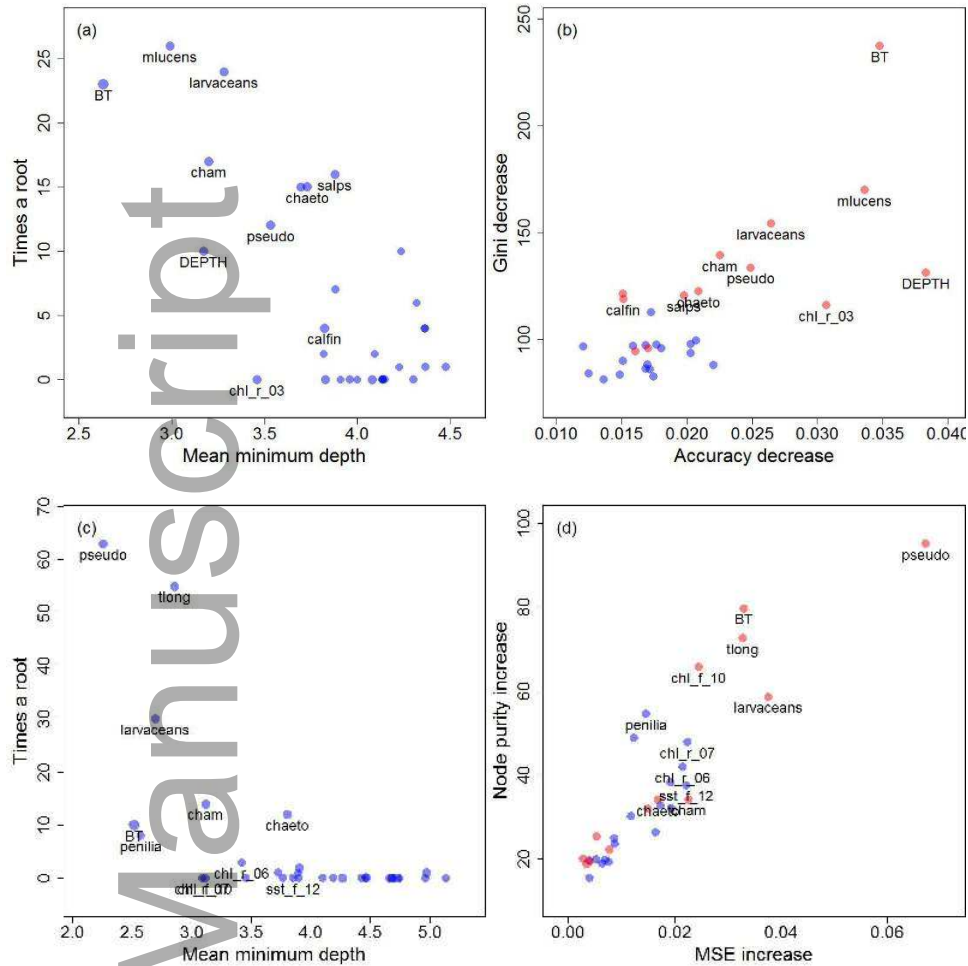


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924 Figure 2. The number of times a variable was the root node variable versus the mean minimal
 925 depth of a variable in a tree in spring occupancy (a) and biomass (c) models. The mean decrease
 926 in the Gini index of node impurity by a variable versus the mean accuracy decrease if a variable
 927 were to be removed from the spring occupancy model (b); red circles indicate that the variable is
 928 significant. The mean node purity increase by a variable versus the mean increase of mean
 929 squared error (MSE) if a variable were to be removed from the spring biomass model (d); red
 930 circles indicate that the variable is significant. The variables are significant if the number of
 931 nodes in which the variable was used for splitting is greater than the theoretical number of
 932 successes if they were random. The explanations of the abbreviations are in Table A1.

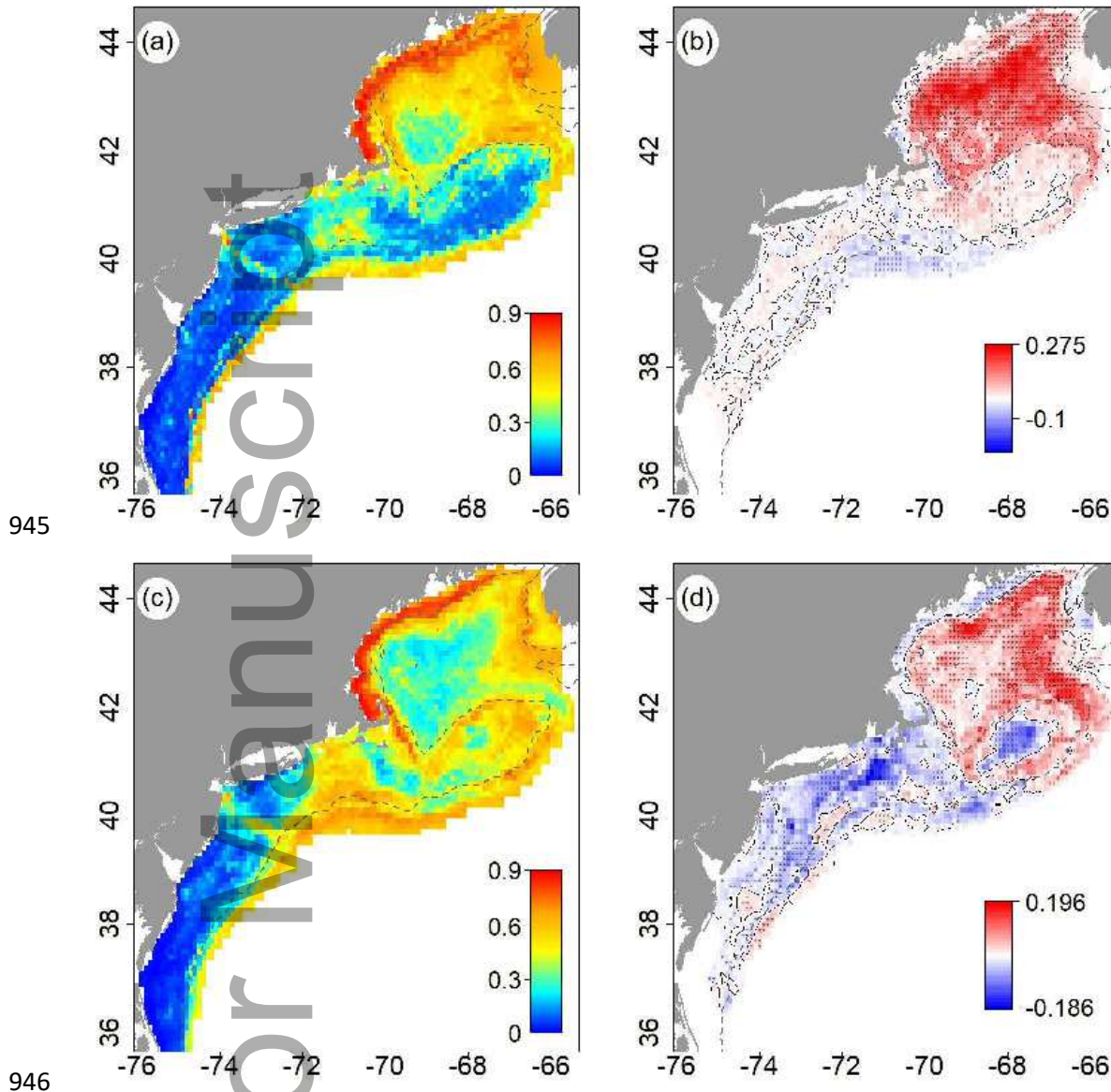
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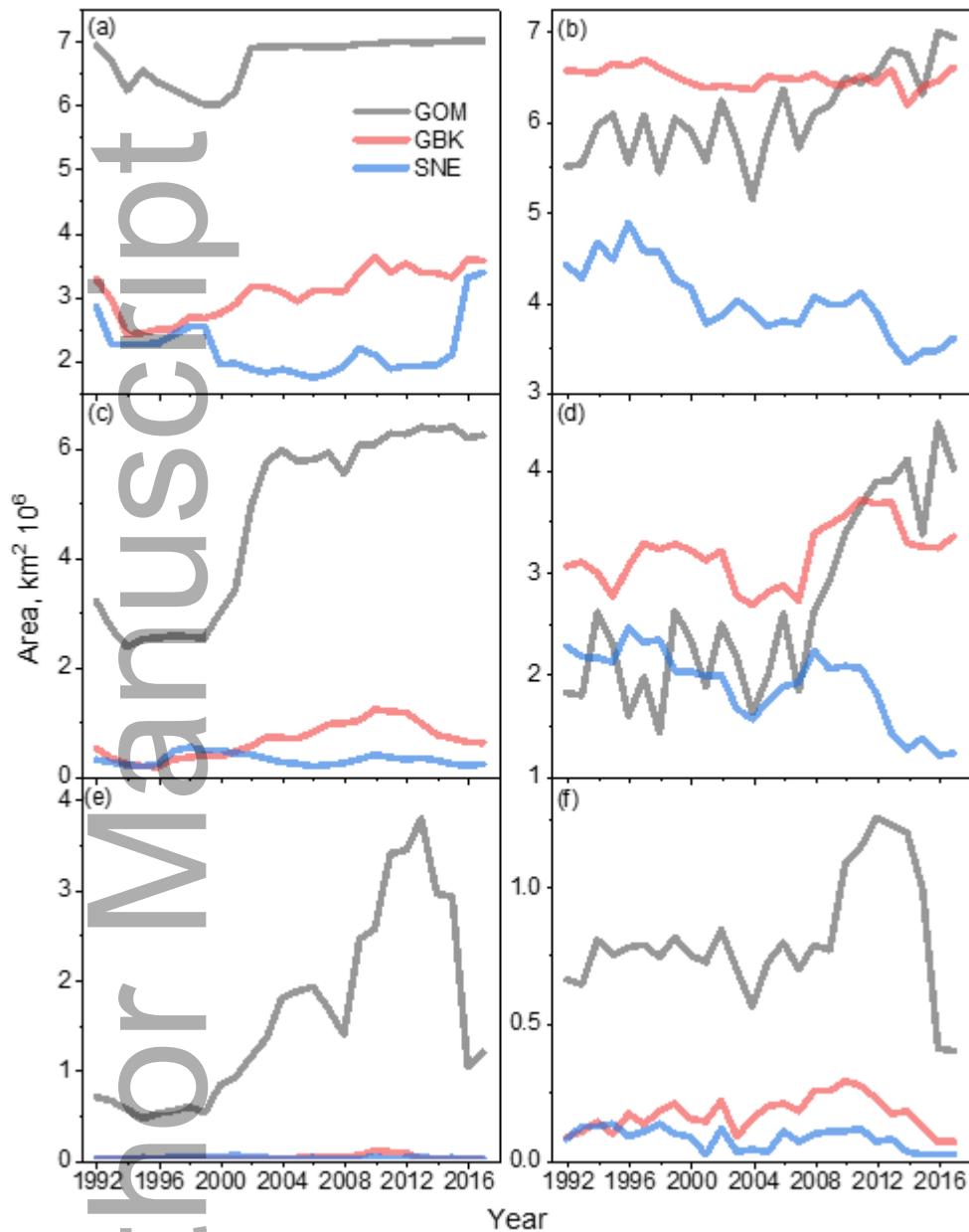
936 Figure 3. The number of times a variable was the root node variable versus the mean minimal
 937 depth of a variable in a tree in fall occupancy (a) and biomass (c) models. The mean decrease in
 938 the Gini index of node impurity by a variable versus the mean accuracy decrease if a variable
 939 were to be removed from the fall occupancy model (b); red circles indicate that the variable is
 940 significant. The mean node purity increase by a variable versus the mean increase of mean
 941 squared error (MSE) if a variable were to be removed from the fall biomass model (d); red
 942 circles indicate that the variable is significant. The variables are significant if the number of
 943 nodes in which the variable was used for splitting is greater than the theoretical number of
 944 successes if they were random. The explanations of the abbreviations are in Table A1.



945

946

947 Figure 4. Time series mean predicted occupancy probability for American lobster in the spring
 948 (a) and fall (c) using the RF model with the annual rate of change (Sen slope) in occupancy
 949 probability (b and d, spring and fall, respectively). Black crosses in rate of change panels indicate
 950 significant slopes ($p < 0.01$).



951
 952 Figure 5. Habitat areas in each region (Gulf of Maine, Georges Bank, and Southern New
 953 England) with minimum occupancy probabilities of 25%, 50%, and 75% for spring (a, c, and e,
 954 respectively) and fall (b, d, and f, respectively) for the years 1992 to 2017 predicted from the RF
 955 models.

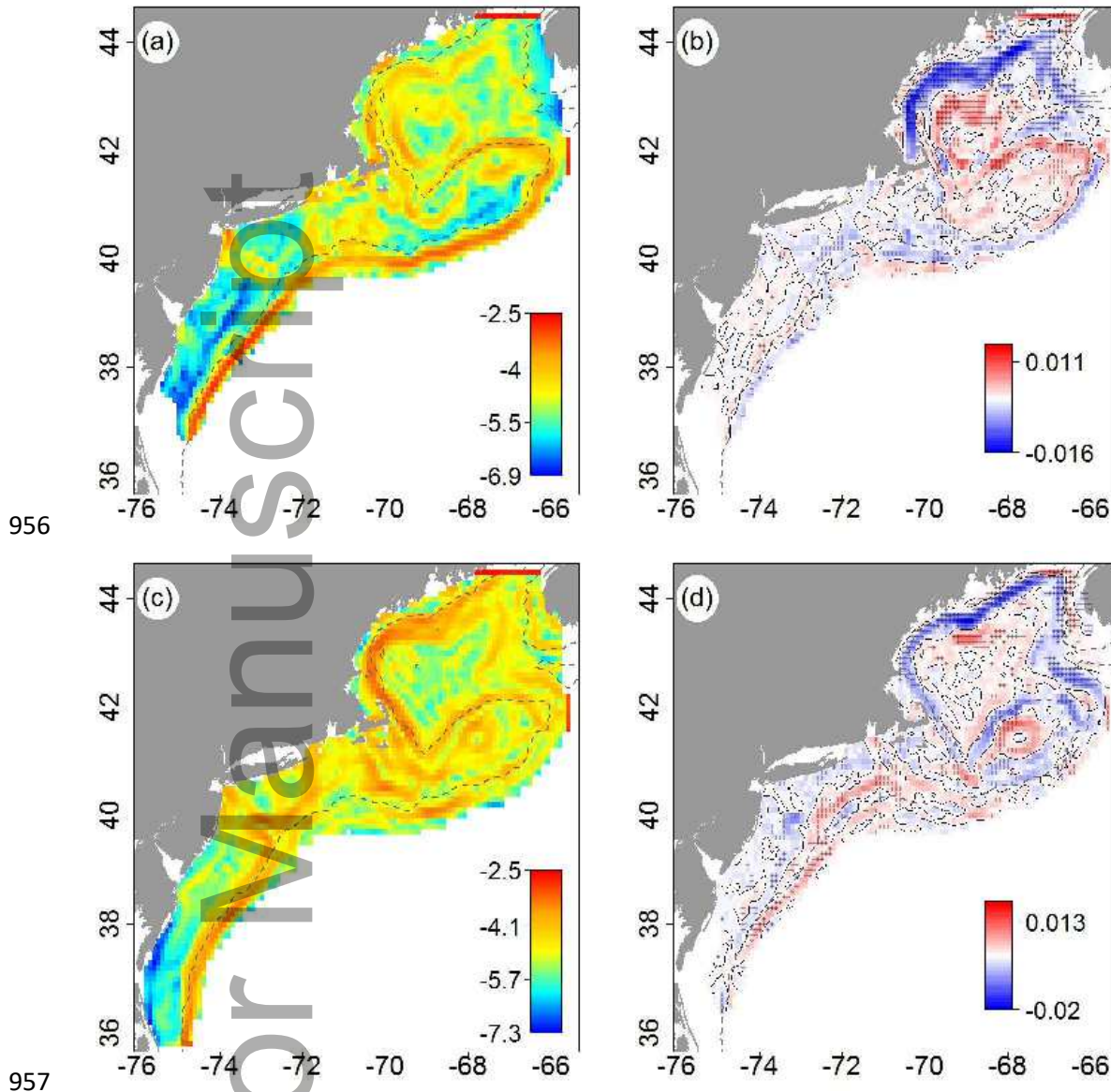
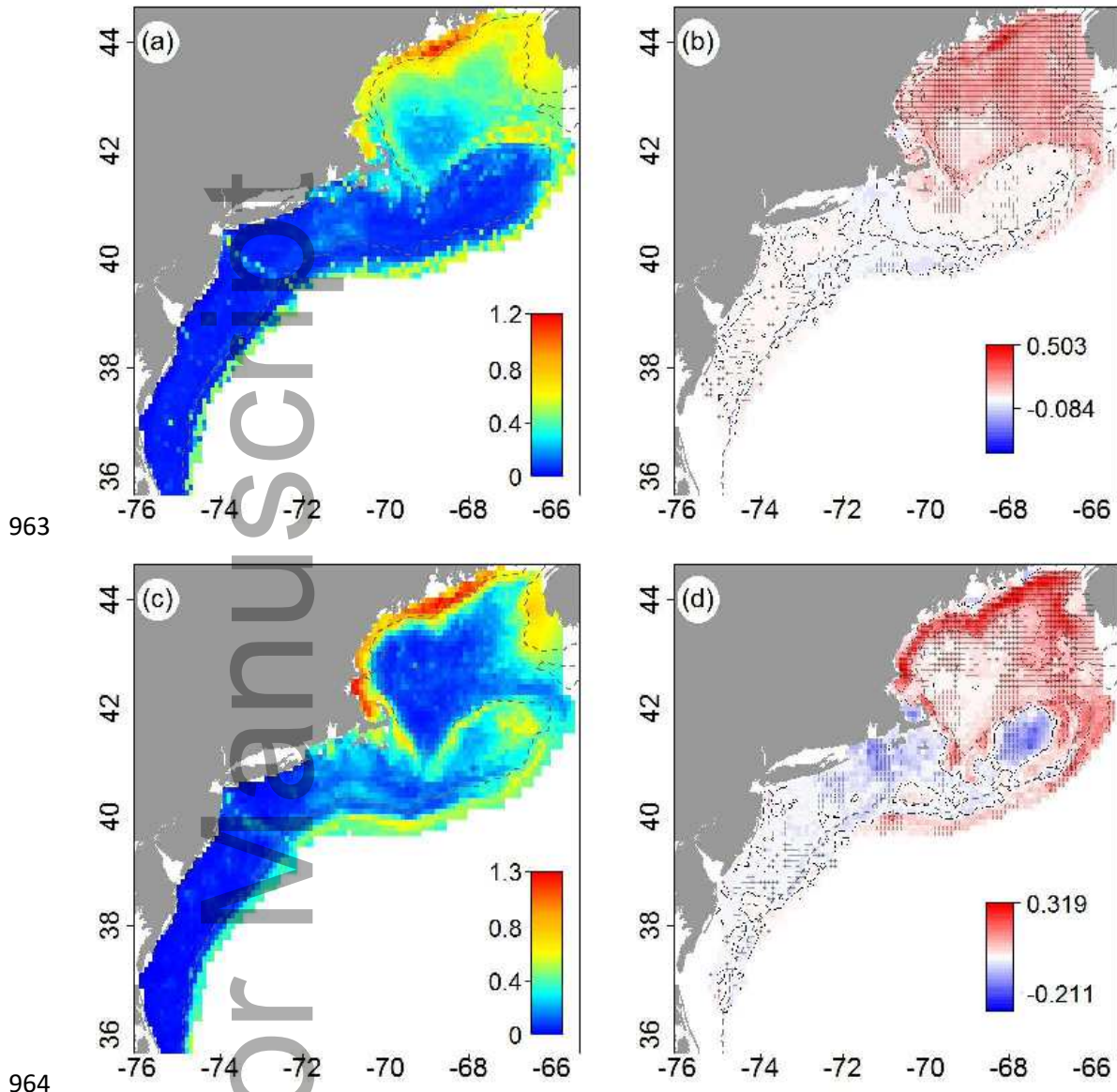


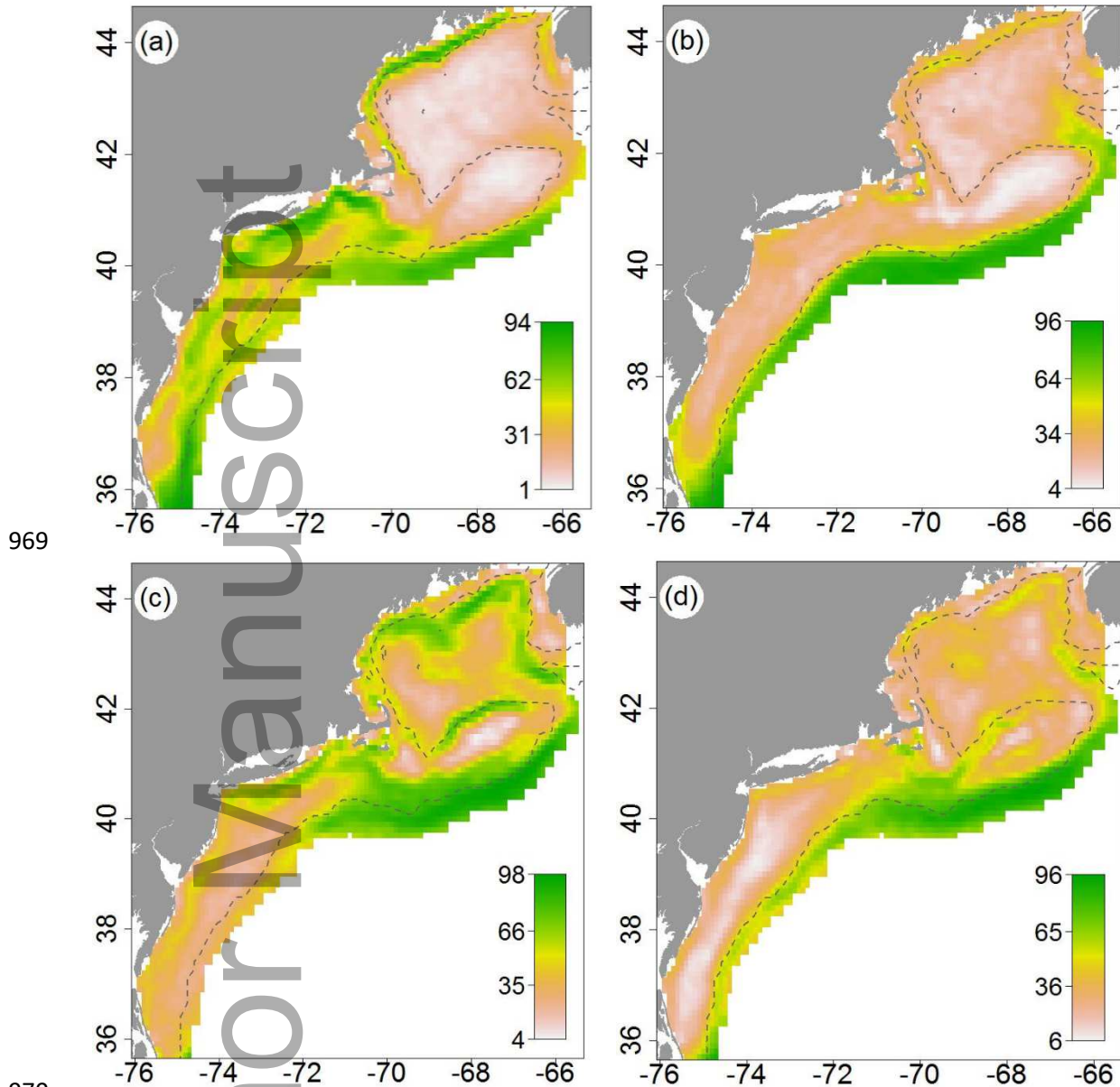
Figure 6. Time series mean occupancy probability gradient magnitudes (frontal strengths) predicted in the spring (a) and fall (c) with the rates of change (Sen slope) in occupancy gradient magnitudes (b and d, spring and fall, respectively). Black crosses in rate change panels indicate that the slopes are significant ($p < 0.01$).



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964

965 Figure 7. Time series mean predicted biomass for American lobster in the spring (a) and fall (c)
 966 using the RF model with the annual rates of change (Sen slope) in biomass (b and d, spring and
 967 fall, respectively). Black crosses in rate of change panels indicate significant slopes ($p < 0.01$).
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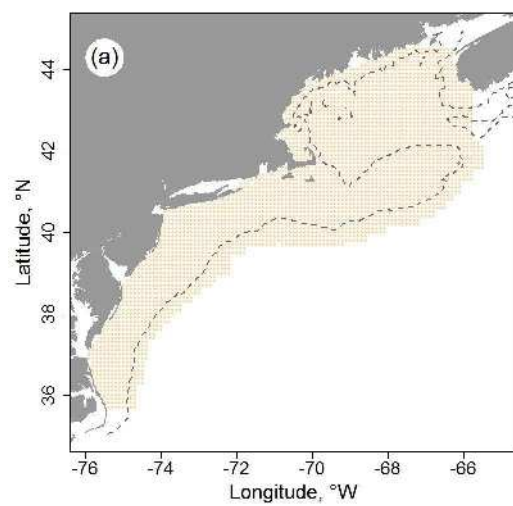


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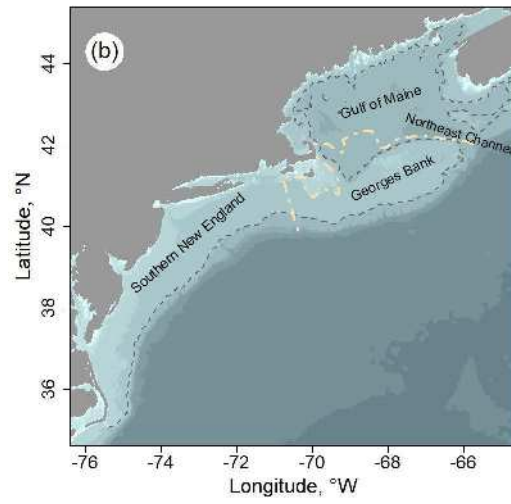
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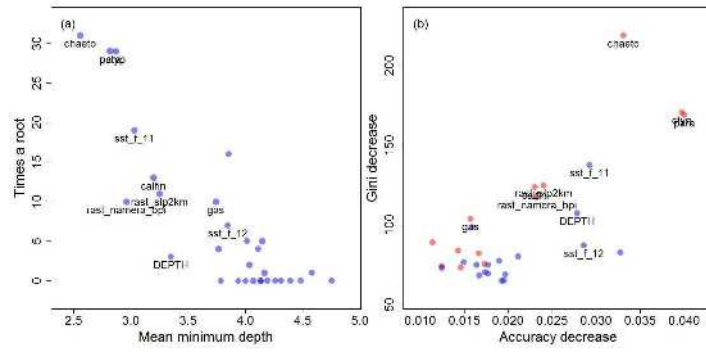
972 Figure 8. Sea surface temperature frontal probabilities (expressed as percent) for winter (a),
 973 spring (b), summer (c), and fall (d). Sea surface temperature frontal probabilities were taken
 974 from Winship et al. (2018) and represent the likelihood of a front forming during the four
 975 seasonal time periods.



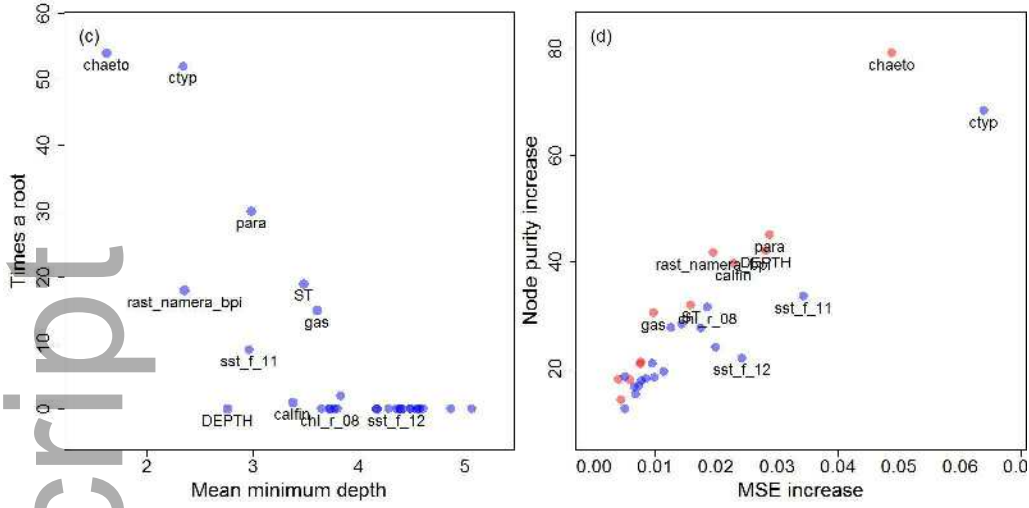
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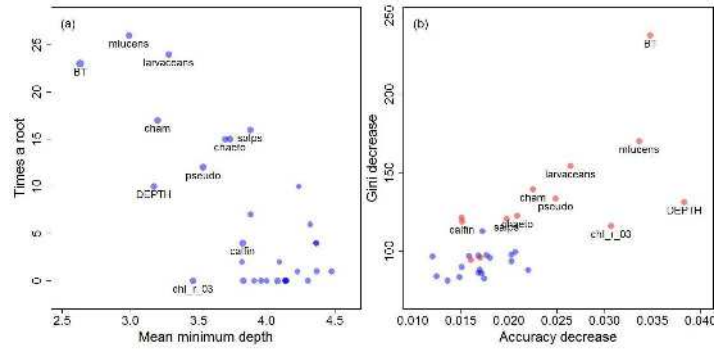
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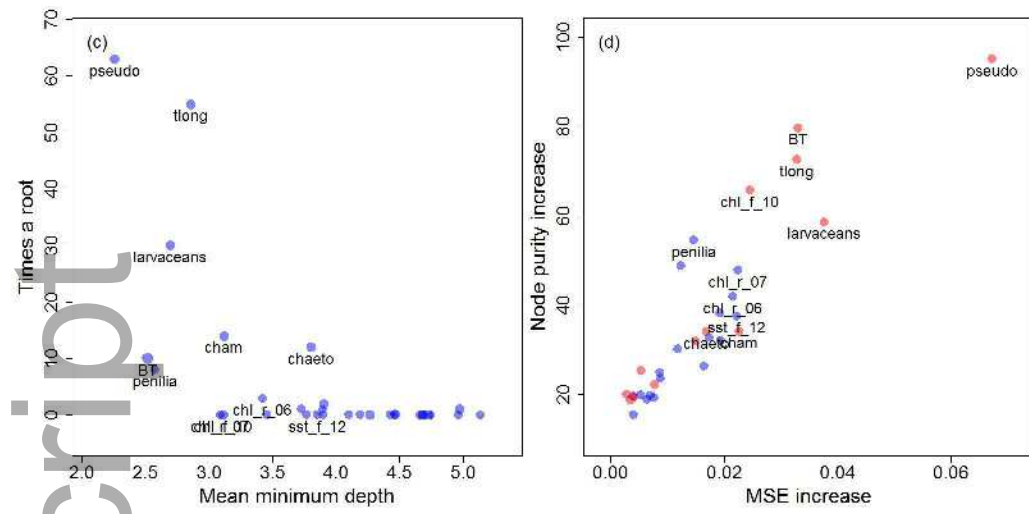
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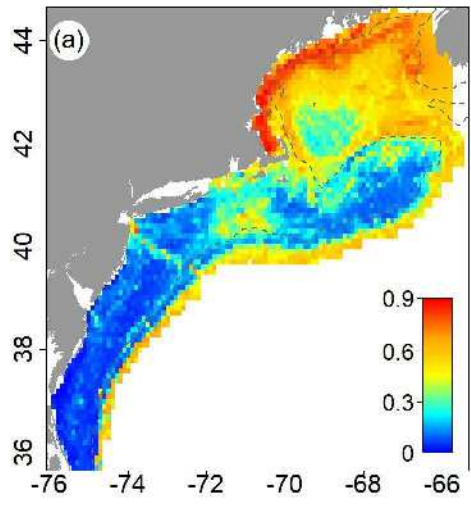
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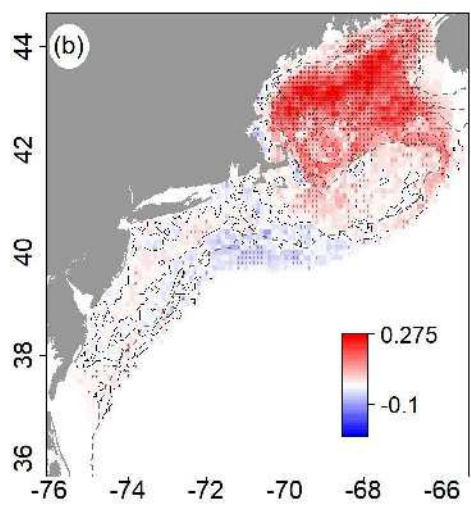
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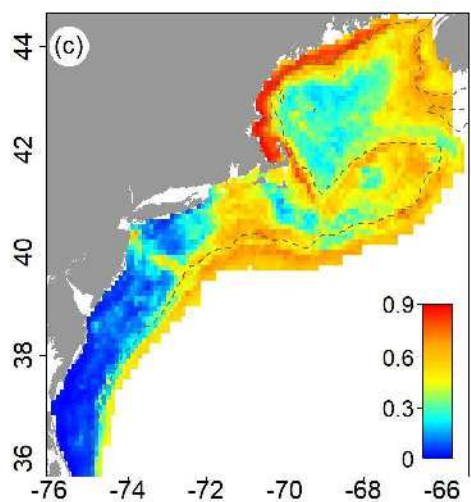
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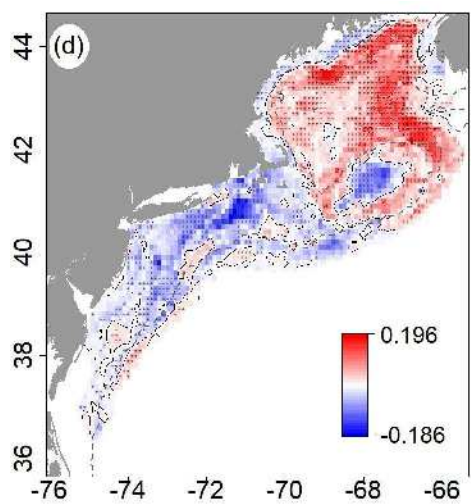
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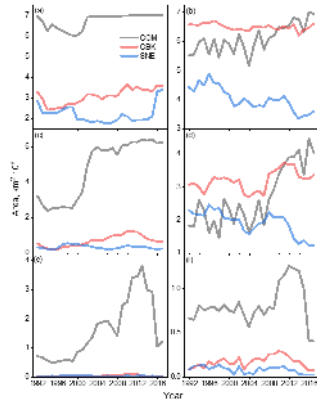
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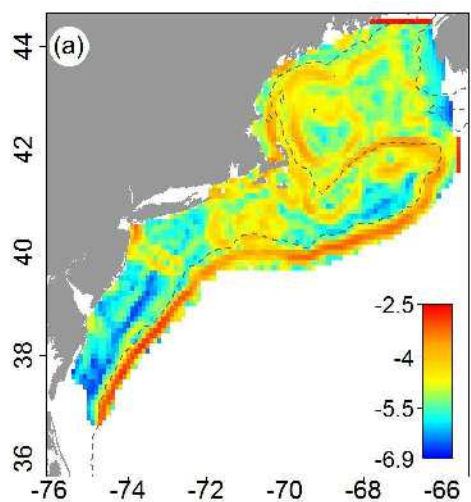
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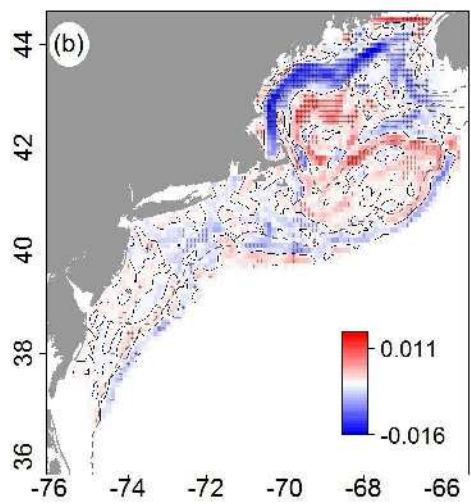
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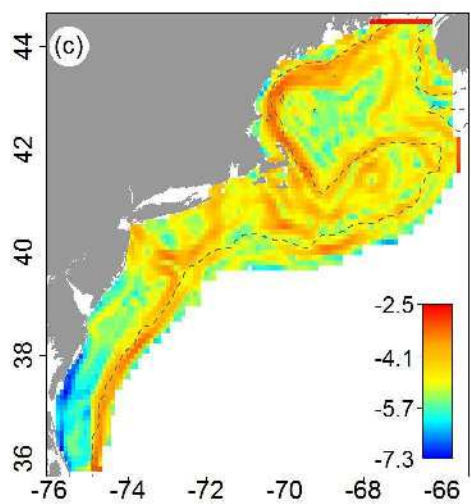
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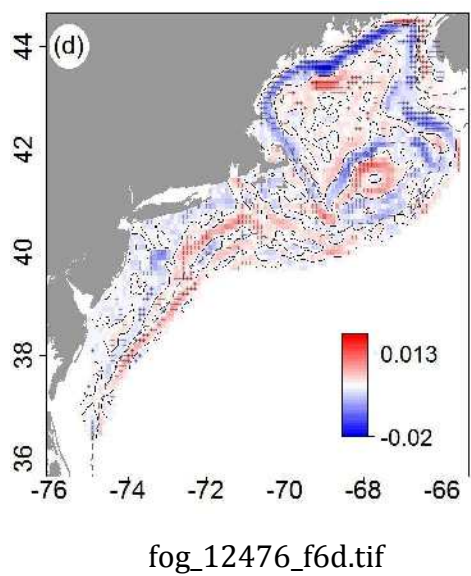
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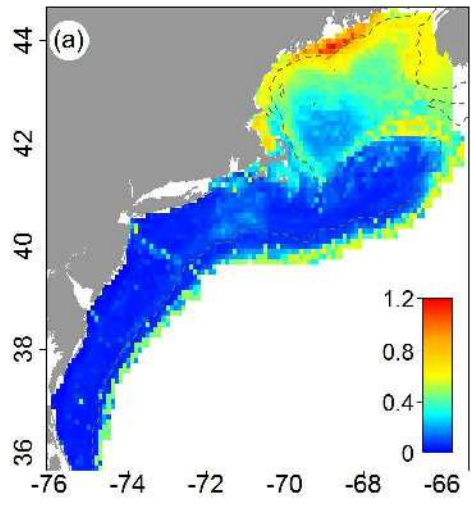


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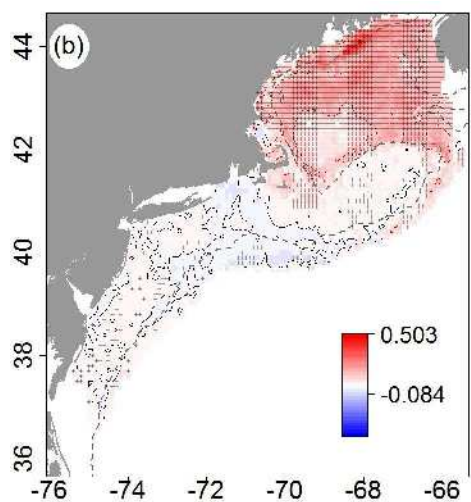


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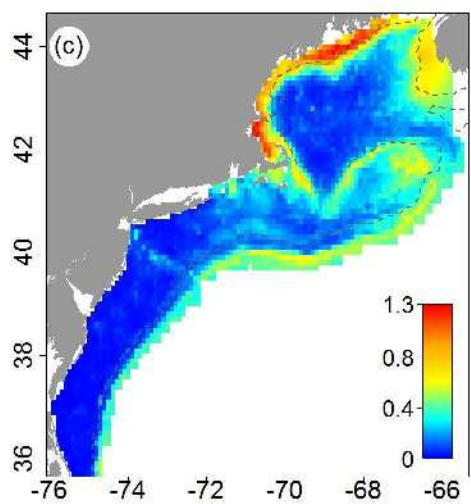




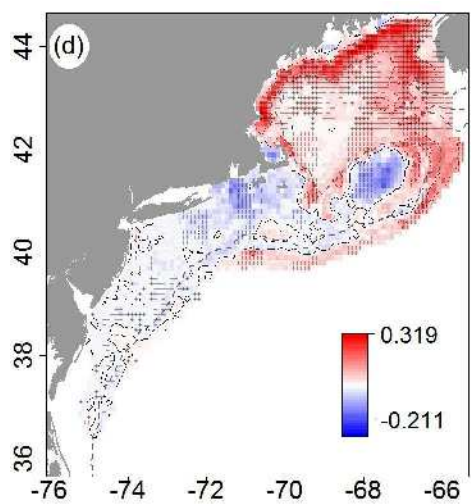
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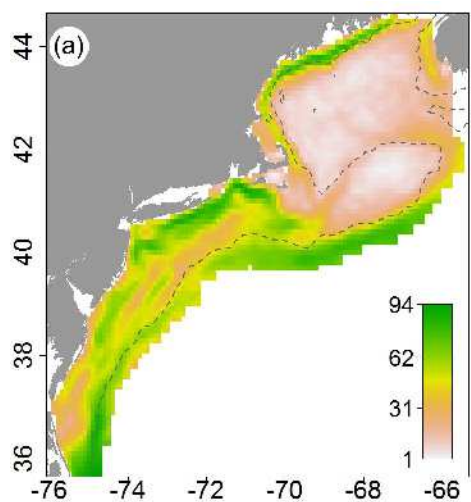
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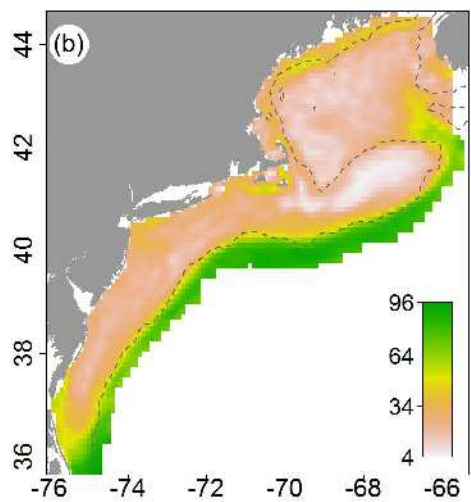
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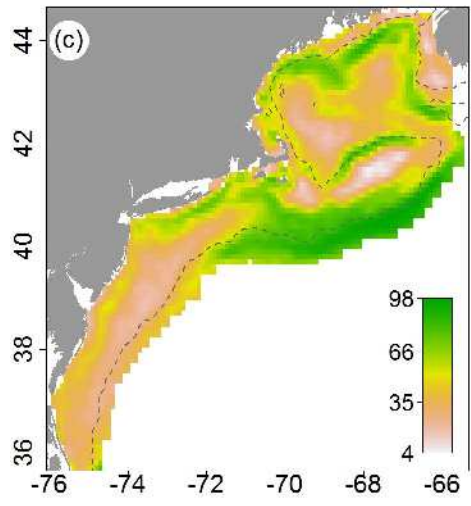
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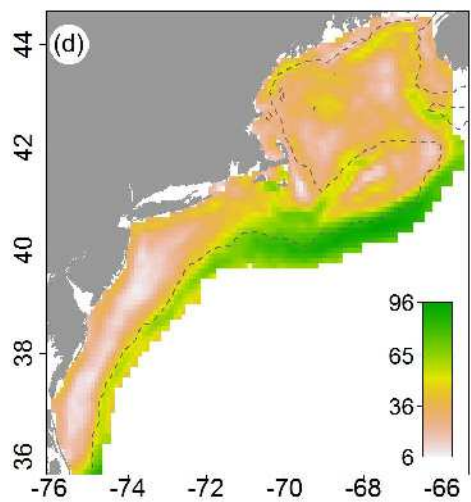
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fog_12476_f8b.tif



fog_12476_f8c.tif



fog_12476_f8d.tif