

1 **Online Appendix**

2 3 **Forecasting the Dynamics of a Coastal Fishery Species Using a Coupled Climate-** 4 **Population Model.**

5
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- 8 **1. Background on global climate models**
- 9 **2. Choice of a Stock Recruitment Function**
- 10 **3. Distribution model based on logistic regression**
- 11 **4. Results for NCAR CCSM 3.0 model runs**
- 12 **5. References**

13 14 15 **1. Background on global climate models**

16 Minimum winter air temperatures were derived from two prominent global climate
17 models: the NCAR Community Climate System Model (CCSM) 3.0 (Collins et al. 2006, Meehl
18 et al. 2007), and the GFDL Climate Model (CM) 2.1 (Delworth et al. 2006, Meehl et al. 2007).
19 The resolution of atmosphere in the CCSM is 1.4° latitude and 1.4° longitude with 25 levels. The
20 resolution of the atmosphere in the CM2.1 is 2.0° latitude by 2.5° longitude with 34 levels. The
21 resolution of the ocean in both models is approximately 1° longitude; the resolution in latitudes
22 varies between 1° in the extratropics to ~1/3° in the tropics to resolve equatorial waves
23 associated with El Niño. The influence of subgrid scale processes (e.g., turbulence in the

24 boundary layer, thunderstorms and ocean eddies) are parameterized based on large-scale
25 conditions, i.e., variables that are simulated on the model's coarse grid. Even at coarse
26 resolution, the models are run on super computers as the temperature, moisture, salinity, winds,
27 ocean currents, etc., are predicted at hundreds of thousands of grid boxes.

28 Global coupled models can be verified by comparing their output to the recent past, e.g.,
29 how simulated and observed temperatures changed over the 20th century. An exact match
30 between observations and model simulations in a given period is not expected because of random
31 fluctuations in the climate system. However, these models should simulate the statistics of
32 natural variability, replicate the long-term trends driven by greenhouse gases and other external
33 forcing, and reproduce the spectral properties of observations. To overcome the influence of
34 random fluctuations in climate, the output of an ensemble of model runs (as opposed to a single
35 model run) is generally compared to observations. Nine NCAR CCSM3.0 and three GFDL
36 CM2.1 simulations were conducted for the 20th century. Minimum winter temperature for the
37 grid cell over southern Chesapeake Bay was extracted from the ensemble model runs and
38 compared with observed minimum winter temperatures for Virginia. The GFDL CM2.1 mean
39 was about 0.5°C lower and the standard deviation was slightly greater than observed (Fig. A1).
40 The NCAR CCSM3.0 had a +3.0°C bias but the standard deviation was nearly identical to
41 observations (Fig. A1). These mean differences between the climate models and observations
42 were used to bias correct the minimum winter air temperatures estimated in the GFDL CM2.1
43 and NCAR CCSM3.0 climate models. The smoothed observations indicate a long-term cycle in
44 minimum winter air-temperature with high temperatures in the 1940's and low temperatures in
45 the 1970's; these warm and cool periods have been linked to the Atlantic Multidecadal
46 Oscillation. (Kerr 2000, 2005). The modeled temperatures do not match this long-term trend in

47 observed temperature, but the modeled temperatures due seem to exhibit a cycle of similar
48 duration and magnitude as observed. A comparison of spectral properties indicates that
49 variability in observations generally matched variability in the simulations (Fig. A2). At the
50 longer periods, there is good agreement between the models and observations. At shorter periods,
51 the GFDL model exhibited higher variability at 3-4 year periods and lower variability at 5-7 year
52 periods than the observations. Confidence intervals (CI) from the NCAR CCSM3.0 model
53 included the observations at all frequencies, but there were more ensembles, so it is likely that
54 with more GFDL ensembles, the CI would enclose the observations. Based on these comparisons
55 of historical model runs and observations, the GFDL CM2.1 and NCAR CCSM3.0 appear to
56 capture the long-term dynamics of minimum winter temperature in the mid-Atlantic region.

57 Prior studies have also shown that climate models, including CCSM3 and CM2.1,
58 generally reproduce the continental-scale trends (Randall et al. 2007) and some regional trends
59 (Knutson et al. 2006, Seager et al. 2007). The CM2.1 reproduces the observed warming over the
60 20th century in the subtropical North Atlantic and continental U.S. when anthropogenic forcing
61 is included, but over-estimates warming for the southeast US (Knutson et al. 2007). All climate
62 models have biases and several factors may lead to model-data differences including model
63 error, inadequate representation of regional processes (e.g., aerosol loading,
64 deforestation/reforestation, irrigation), and natural variability (i.e., the atmospheric circulation
65 over the southeast United States is influenced by El Nino and the Atlantic Multidecadal
66 Oscillation). While there are differences between the CM2.1 and the observed annual
67 temperature trends in the southeast U.S., there is general agreement between the simulated and
68 observed minimum winter temperature in the mid-Atlantic region (Fig. A1 and A2).

69 Although, the analyses above suggest that the climate models reasonably capture the
70 minimum winter air temperatures in coastal Virginia, a potential concern is that the coupled
71 climate-population model results are specific for this model grid cell. However, there is strong
72 concordance in the time series of minimum winter air temperature over the eastern seaboard of
73 the United States (Fig. A3) in historical observations, climate model hindcasts, and climate
74 model forecasts (Table A1). This concordance is expected since prior studies have documented
75 strong concordance in interannual winter air temperature over the eastern U.S. (Joyce 2002),
76 estuarine water temperatures in the mid-Atlantic (Hare and Able 2007), coastal water
77 temperatures (Nixon et al. 2004), and sea surface temperature in the western North Atlantic
78 (Friedland and Hare 2007). Additionally, minimum winter air temperature is closely related to
79 minimum winter water temperature in estuaries along the mid-Atlantic coast (Hettler and Chester
80 1982, Hare and Able 2007) owing to the efficient heat exchange between atmosphere and water
81 in these shallow systems (Roelofs and Bumpus 1953). Thus, minimum winter air temperatures
82 from Virginia can serve as a proxy for coast-wide variability in minimum winter water
83 temperatures.

84

85 **2. Choice of a stock-recruitment function**

86 A number of functions have been used historically to model the relationship between fish
87 population size and subsequent recruitment (Hilborn and Walters 2004). There also are a number
88 of extensions of these functions that include the effect of the environment on recruitment
89 (Hilborn and Walters 2004). We evaluated two common stock recruitment functions (Beverton-
90 Holt and Ricker) and several extensions of these functions that include environmental effects
91 (Table A2). The Akaike Information Criterion (AIC) was used to choose the best formulation to

92 use in the coupled climate-population model. Spawning stock biomass and recruitment data were
93 obtained from a recent stock assessment of Atlantic croaker (ASMFC 2005) and minimum
94 winter air temperature in Virginia
95 (http://www.sercc.com/climateinfo_files/monthly/Virginia_temp.html) was used as a proxy for
96 water temperature during the estuarine juvenile stage (Hare and Able 2007).

97 The stock-recruitment functions were initially fit with non-linear algorithms, but these
98 algorithms rarely converged. As a result, linear forms of the stock recruitment functions (model 1
99 and 4, see Table A2) were fit using least-squares regression. The environmental extensions of the
100 Ricker stock-recruitment model are easily linearized (models 5-11, see Table A2) and these
101 models were also fit using least-squares. The environmental forms for the Beverton-Holt model
102 (models 2 and 3) are not easily linearized. To fit these models, the standard Beverton-Holt terms
103 (a and b) were estimated using the linearized version of the model (model 1), and then a non-
104 linear fitting algorithm was used to estimate the environmental parameter (c) with the standard
105 parameters (a and b) fixed at the appropriate values. Because the linearized forms of the models
106 used different dependent variables ($1/R$ for Beverton and Holt and $\ln[R/S]$ for Ricker), AIC was
107 estimated based on the models predictions of R using the non-linearized forms of the equations,
108 with the terms derived from the linearized models. In this way, AIC was calculated based on the
109 residual sums of squares of estimated R and observed R . The strength of evidence of the
110 alternative models was calculated following (Burnham and Anderson 1998).

111 The Ricker stock-recruitment model with a temperature term was the best-supported
112 model evaluated (Table A2), with the highest strength of evidence ($w=0.619$). The models with
113 environmental terms were far superior to the standard stock-recruitment models. The relative
114 likelihood of the environmental Beverton and Holt model (model 2) compared to the standard

115 Beverton and Holt model was ~ 6000 to 1 ($w_{\text{model 2}} / w_{\text{model 1}}$). For the environmental Ricker
116 (model 5) compared to the standard Ricker (model 4), the relative likelihood was ~ 10000 to 1.
117 Based on these results, model 5 was chosen for use in the population model. Temperature-
118 dependent Ricker models with higher order terms (model 8 and 9) had moderate strengths of
119 evidence ($w=0.137$ and $w=0.181$). These models potentially create non-linearities that could
120 amplify the effect of climate at higher minimum winter temperatures. However, over the range of
121 temperatures forecasted in the climate models, the higher order models predict very similar
122 recruitment compared to the linear model, so non-linear effects are minimal, and thus these were
123 not included in the final model.

124

125 **3. Distribution model based on logistic regression**

126 As an alternative approach to multiple regression for modeling distribution, a logistic
127 regression was developed that used the presence / absence at individual trawl stations. First,
128 trawl stations were screened to remove stations that sampled deeper than 45 m; this value was
129 based on the 5% level of a logistic regression of catch on depth. The logistic regression model
130 was used in a form similar to the average distance model. Catch at station s in year Y was
131 modeled as the distance of station s in year Y , spawning stock biomass (S) in year Y , and
132 minimum winter temperature in year Y :

$$133 \quad \text{catch}_{sY} = a + b \cdot \text{dist}_{sY} + c \cdot \text{SSB}_Y + d \cdot T_Y + e \cdot \text{SSB}_Y^2 + f \cdot T_Y^2 \quad (6)$$

134 The model was fit using the `glm [family=binomial(link="logit")]` function in R ([http://www.r-](http://www.r-project.org/)
135 [project.org/](http://www.r-project.org/)) and an Akaike multi-model inference was used to determine the model parameters.
136 The model was then used to forecast Atlantic croaker distribution estimating the distance to the
137 50% and 10% catch probability. The results were qualitatively similar to those from the average

138 distance approach, with distances decreasing with increasing F and increasing with increasing
139 CO₂ emissions; we choose to present the results of the multiple regression model.

140

141 **4. Results for NCAR CCSM 3.0 model runs**

142 The NCAR CCSM3.0 climate model provided qualitatively similar results as the GFDL
143 CM2.1 model. The most striking difference was that the NCAR CCSM3.0 B1 and A1B runs
144 predicted similar long-term minimum winter temperatures, which resulted in similar spawning
145 stock forecasts (Fig. A4) and distribution forecasts (Fig. A4). However, the relative effect of
146 climate compared to fishing was similar between the NCAR CCSM3.0 and GFDL CM2.1 (Fig.
147 A4). Similarly, the overall forecasts of Atlantic croaker distribution were very similar between
148 the NCAR CCSM3.0 and the GFDL CM2.1; the NCAR CCSM3.0 predicted less change
149 between the B1 and A1B scenarios (Fig. A4). Owing to the similarity between the temperature
150 forecasts for the NCAR CM3.0 between the B1 and A1B scenarios, the predicted effects of
151 climate on fishery benchmarks were less for the A1B scenario than predicted under the GFDL
152 model (Fig. A5, Table A3).

153

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212

213

214 Table A1. Kendall's concordance (W) for time series of minimum winter air temperatures from
 215 locations indicated in Fig. A3. Calculations were made for each of the models considered.
 216 Kendall's concordance is a non-parametric test that measures the degree of agreement between
 217 multiple series of data.: 0 indicates no agreement; 1 indicates perfect agreement

Model	W	p	Year
GFDL 20 th Century	0.63	p<0.001	1861-2000
NCAR 20 th Century	0.75	p<0.001	1870-1999
NCEP Reanalysis	0.73	p<0.001	1948-2006
GFDL Commit	0.74	p<0.001	2001-2100
GFDL B1	0.69	p<0.001	2001-2200
GFDL A1B	0.74	p<0.001	2001-2200
NCAR Commit	0.79	p<0.001	2000-2099
NCAR B1	0.73	p<0.001	2000-2349
NCAR A1B	0.74	p<0.001	2000-2349

218

219 Table A2. Akaike Information Criteria values for various models fit to stock (S) and recruitment
 220 (R) data for the mid-Atlantic stock of Atlantic croaker. Values provided for corrected Akaike
 221 Information Criteria (AIC_c), number of parameters in the model including the error term (k), the
 222 delta-AIC_c, which is scaled to the minimum observed AIC_c, and the model weights (w), which
 223 range from 0 to 1.

No.	Model	Linearized Model	AIC _c	k	ΔAIC _c	W
1	$R = \frac{S}{b + aS}$	$\frac{1}{R} = a + \frac{b}{S}$	309.1	3	24.6	0.000
2	$R = \frac{e^{cT} S}{b + aS}$	Not linearized	291.5	4	7.0	0.019
3	$R = \frac{S}{b + e^{cT} aS}$	Not linearized	294.6	4	10.1	0.004
4	$R = Se^{a+bS}$	$\ln\left(\frac{R}{S}\right) = a + bS$	303.4	3	18.9	0.000
5	$R = Se^{a+bS+cT}$	$\ln\left(\frac{R}{S}\right) = a + bS + cT$	284.5	4	0.0	0.619
6	$R = Se^{a+bS+dT^2}$	$\ln\left(\frac{R}{S}\right) = a + bS + dT^2$	306.2	4	21.7	0.000
7	$R = Se^{a+bS+eST}$	$\ln\left(\frac{R}{S}\right) = a + bS + eST$	293.4	4	8.9	0.007
8	$R = Se^{a+bS+cT+dT^2}$	$\ln\left(\frac{R}{S}\right) = a + bS + cT + dT^2$	287.5	5	3.0	0.137
9	$R = Se^{a+bS+cT+eST}$	$\ln\left(\frac{R}{S}\right) = a + bS + cT + eST$	287.0	5	2.5	0.181
10	$R = Se^{a+bS+dT^2+eST}$	$\ln\left(\frac{R}{S}\right) = a + bS + dT^2 + eST$	295.8	5	11.3	0.002
11	$R = Se^{a+bS+cT+dT^2+eST}$	$\ln\left(\frac{R}{S}\right) = a + bS + cT + dT^2 + eST$	290.5	6	6.0	0.031

224

225 Table A3. Maximum sustainable yield (*MSY*) and fishing rate at maximum sustainable yield
 226 (F_{MSY}) based on three CO2 emission scenarios simulated with two global climate models. Also,
 227 provided are the values based on the most recent stock assessment; the values presented here are
 228 slightly different than those presented in the assessment for Atlantic croaker (37) because the
 229 model form used here (an environmentally-explicit Ricker stock-recruitment function) is
 230 different than that used in the stock assessment (a standard Beverton-Holt function)

Scenario	F_{MSY}	Yield (<i>MSY</i>) (kg)
A1B	0.81	3.36×10^7
B1	0.75	3.08×10^7
Commit	0.59	2.41×10^7
Observed	0.48	1.87×10^7

231

232

233 **Figure Legends**

234

235 Fig. A1. Time series of observations and ensemble predictions from GFDL CM2.1 and NCAR
236 CCSM3.0 climate models (top row). Distributions of observed and modeled reanalysis minimum
237 winter air temperatures and comparison of observed and predicted means and standard deviations
238 of temperature (middle row). Smoothed observations and predictions, with the predictions
239 corrected by the mean difference between model and observations (bottom row). The climate
240 model forecasts coupled with the population model were also adjusted by the mean difference. In
241 all cases, temperature as an axis label refers to minimum winter air temperature in Virginia.

242

243 Fig. A2. Spectral analysis of observations and model reanalysis ensembles. In top panels,
244 shading indicates the 95% confidence intervals of model runs calculated from the ensemble runs.
245 In bottom panel, results for each model run are presented.

246

247 Fig. A3. Time series of minimum winter air temperatures from the NCEP Reanalysis for grid
248 cells nearest the locations indicated on the map. These data were significantly concordant: the
249 pattern of interannual variability was coherent across the time series.

250

251 Fig A4. Forecasts of the effects of climate change on Atlantic croaker abundance and distribution
252 along the mid-Atlantic coast of the United States based on the NCAR CCSM3.0 global climate
253 model. A) Forecast mean spawning stock biomass (2010 to 2100) for three climate scenarios
254 (commit, B1, and A1B) and a range of fishing mortality rates. Spawning stock biomasses are

255 significantly different among climate scenarios at most levels of fishing mortality rate. B)
256 Contours of the ratio of the partial derivatives of S to F ($\frac{\partial S}{\partial F}$) and S to temperature ($\frac{\partial S}{\partial T}$); this
257 ratio is a measure of the relative effect of climate compared to fishing. The average minimum
258 winter air temperature from 2010 to 2100 for climate model scenario is shown by the colored
259 triangles on the left of panel B. C) Forecasts of mean population location, D) northern extent of
260 the range (mean + 2 standard deviations), and E) percent of years when northern extent of the
261 population is north of the New York apex (distance 600). Inset shows location of various
262 distance marks along the continental shelf. The historical values (1972-2004) of mean location
263 (~240 km), northern extent (~420 km), and proportion of years with the measure of northern
264 extent exceeding 600 km (0.09) are shown as grey contours in C, D and E. Arrows along the x-
265 axis indicate the level of current fishing mortality rate. The average minimum winter air
266 temperature from 2010 to 2100 for climate model scenario is shown by the colored triangles on
267 the left of panel E.

268

269 Fig. A5. Yield curves based in the temperature dependent Ricker stock recruitment model and
270 three climate scenarios using the NCAR CCSM3.0 climate model. The current management
271 benchmark (based on a Ricker function) of the fishing rate to maintain the maximum sustainable
272 yield is 0.48. This benchmark is calculated for the three climate scenarios

Figure A1

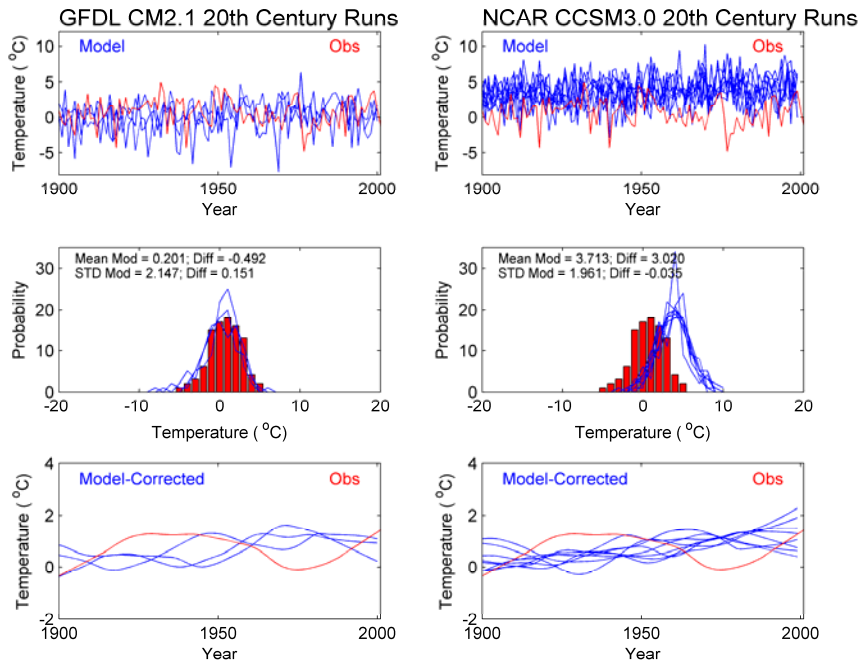


Figure A2

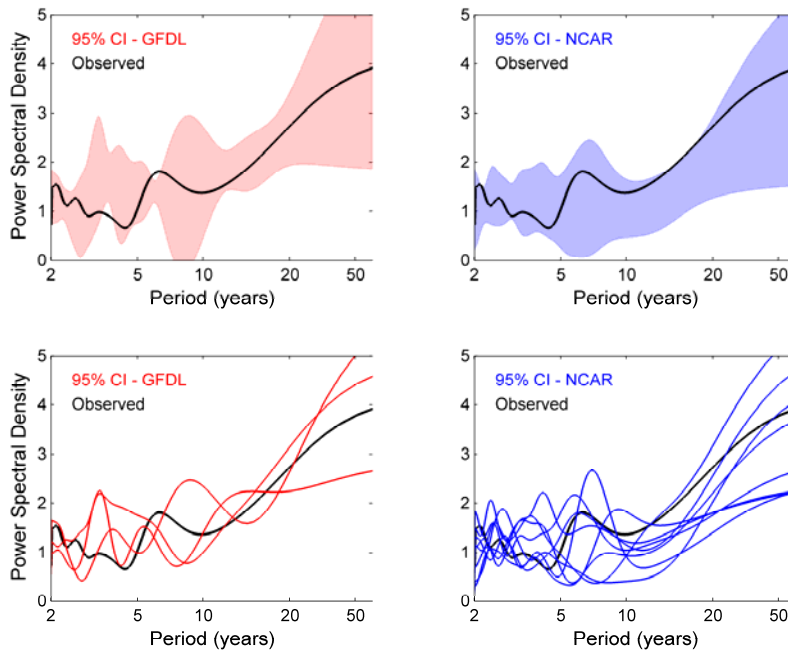


Figure A3

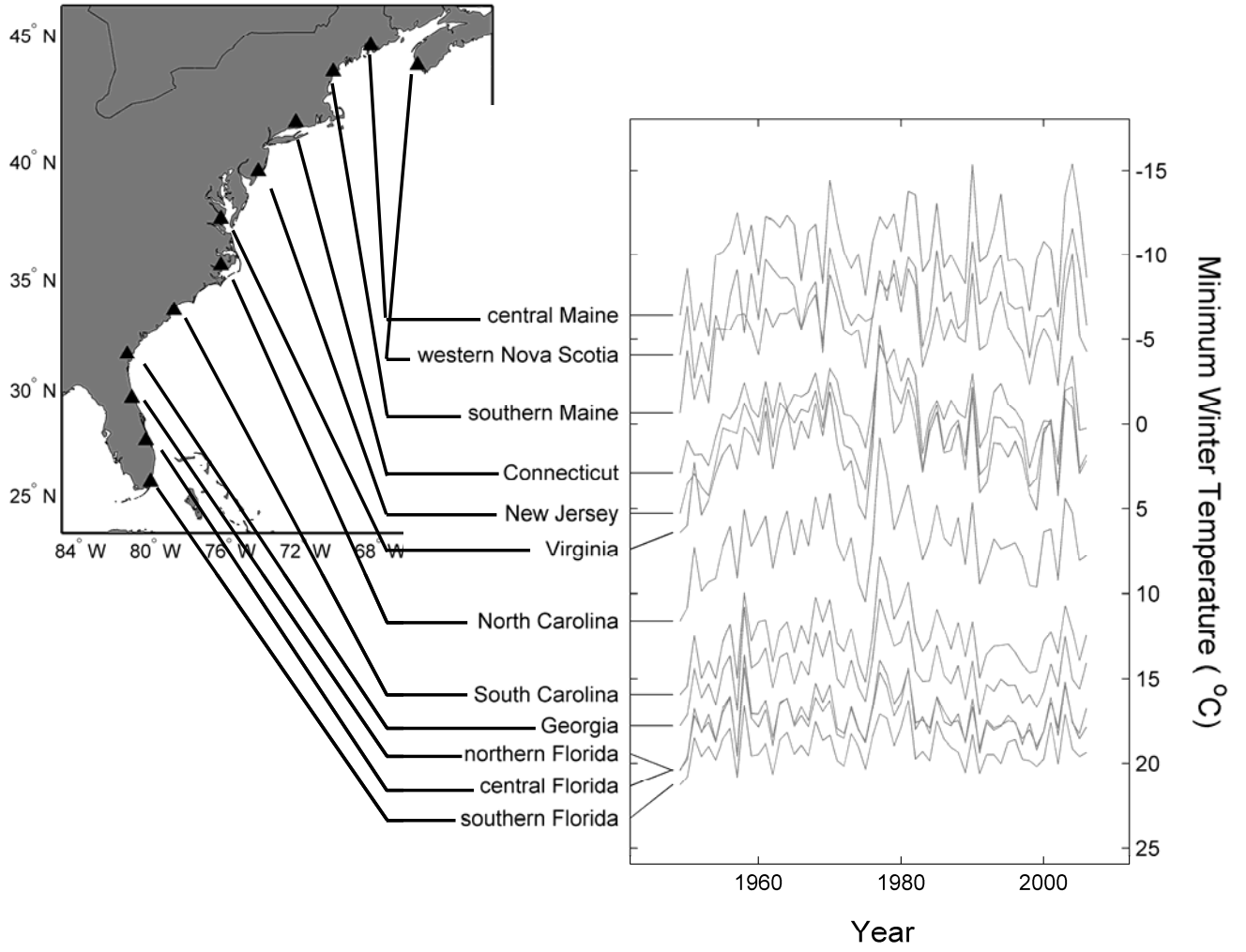


Figure A4

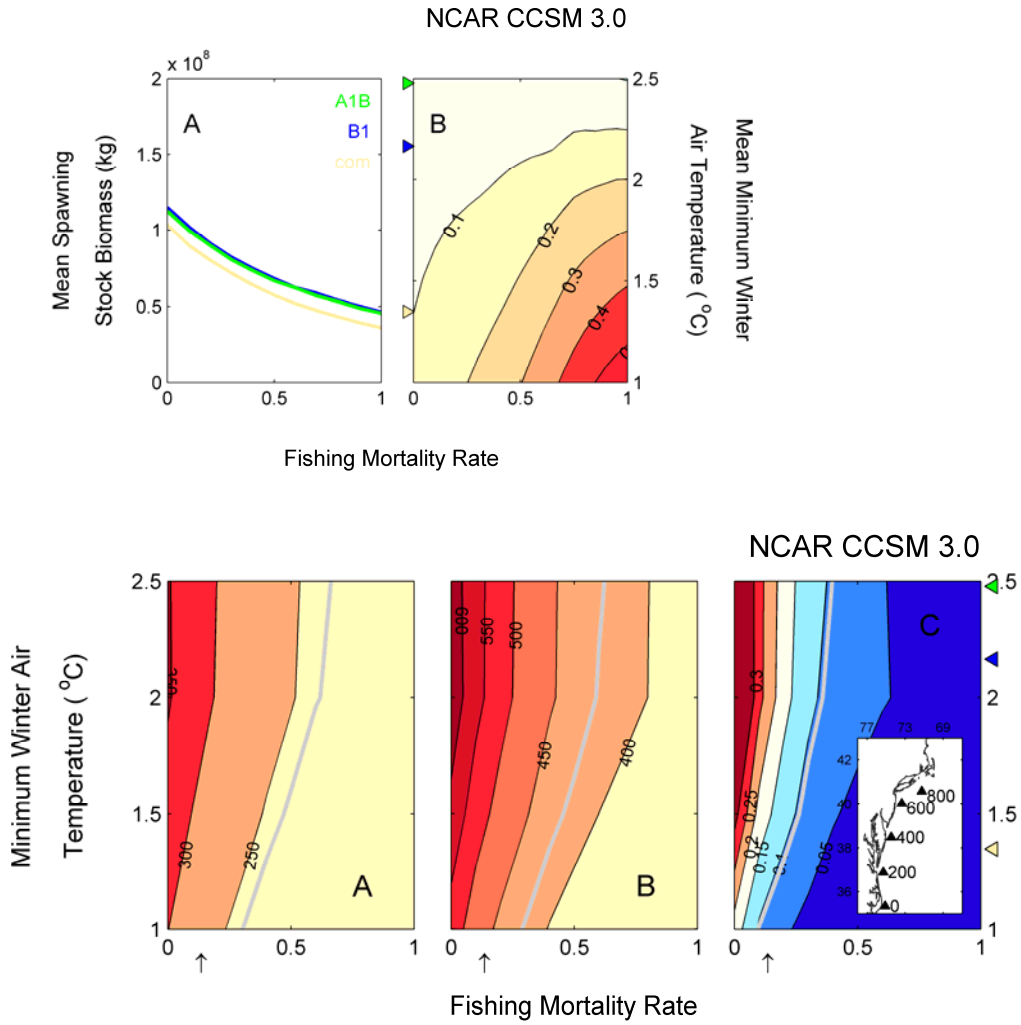


Figure A5

