

Modeling distributions of deep-sea corals offshore of the southeastern United States to guide efficient discovery and protection of sensitive habitats

Matthew Poti¹, Arliss Winship^{1,2}, Holly F. Goyert^{1,2}, Enrique J. Salgado^{1,2}, Rachel Bassett^{1,2}, Michael Coyne^{1,2}, Peter J. Etnoyer¹, Thomas F. Hourigan³, Heather Coleman³, John Christensen¹

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3. NOAA, NMFS, Deep Sea Coral Research and Technology Program

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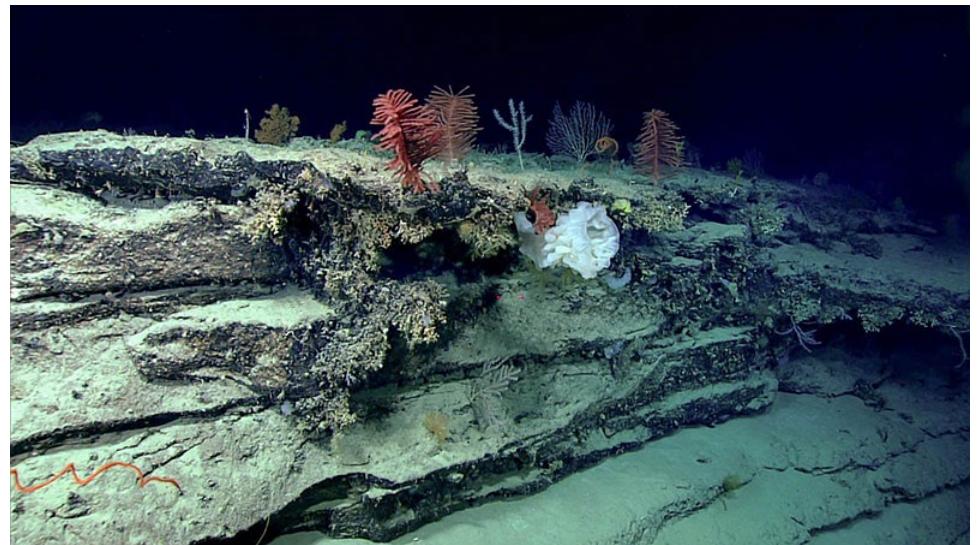


Background

- BOEM identified need for information on spatial distributions of sensitive benthic habitats offshore southeastern US
- Deep-sea corals can form complex 3-D structures that increase local biodiversity by providing microhabitats for other organisms
- Exposed hard substrate provides surface for attachment of sessile invertebrates and may be associated with increased diversity and abundance of large fish



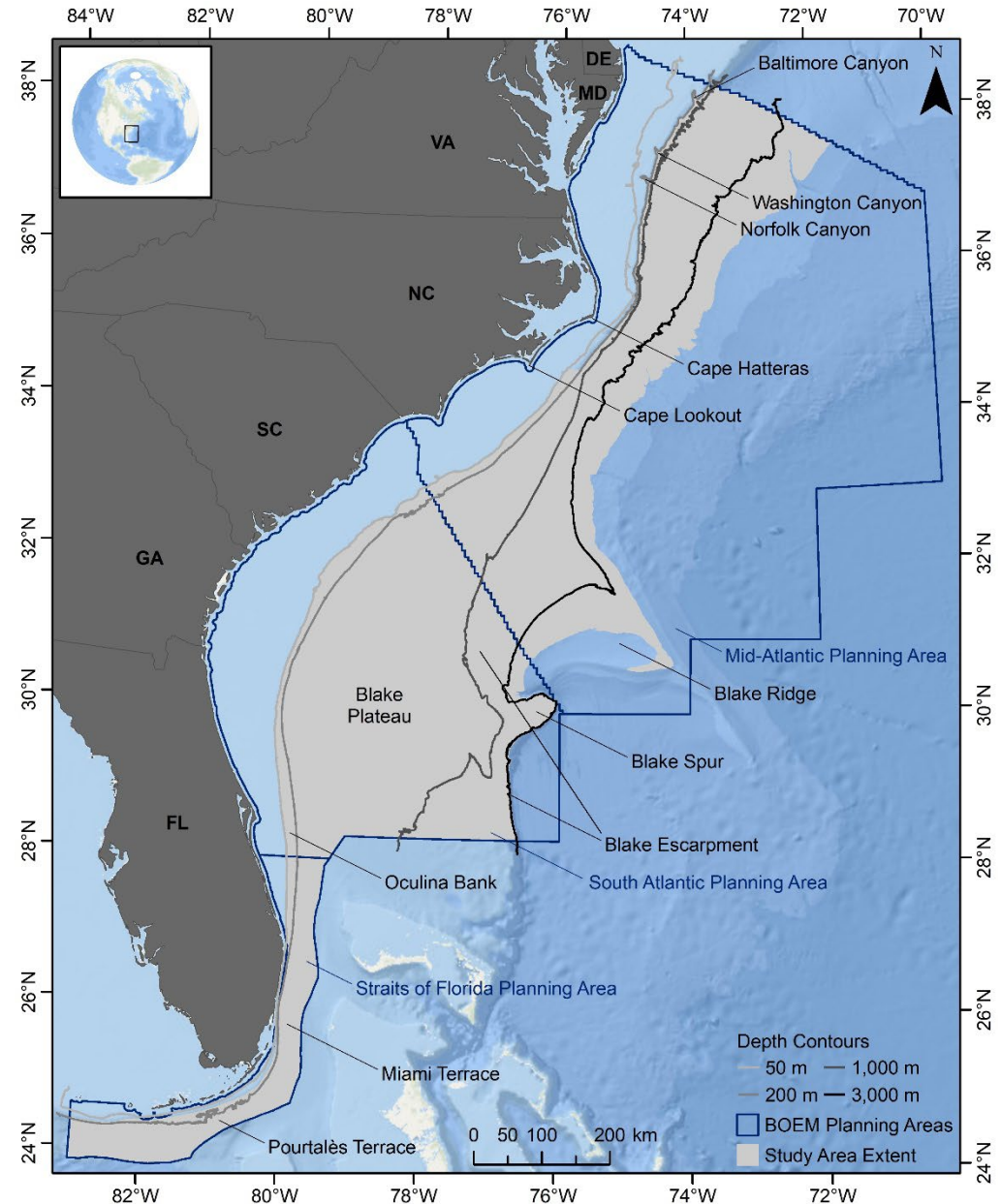
Credit: NOAA OER



Credit: NOAA OER

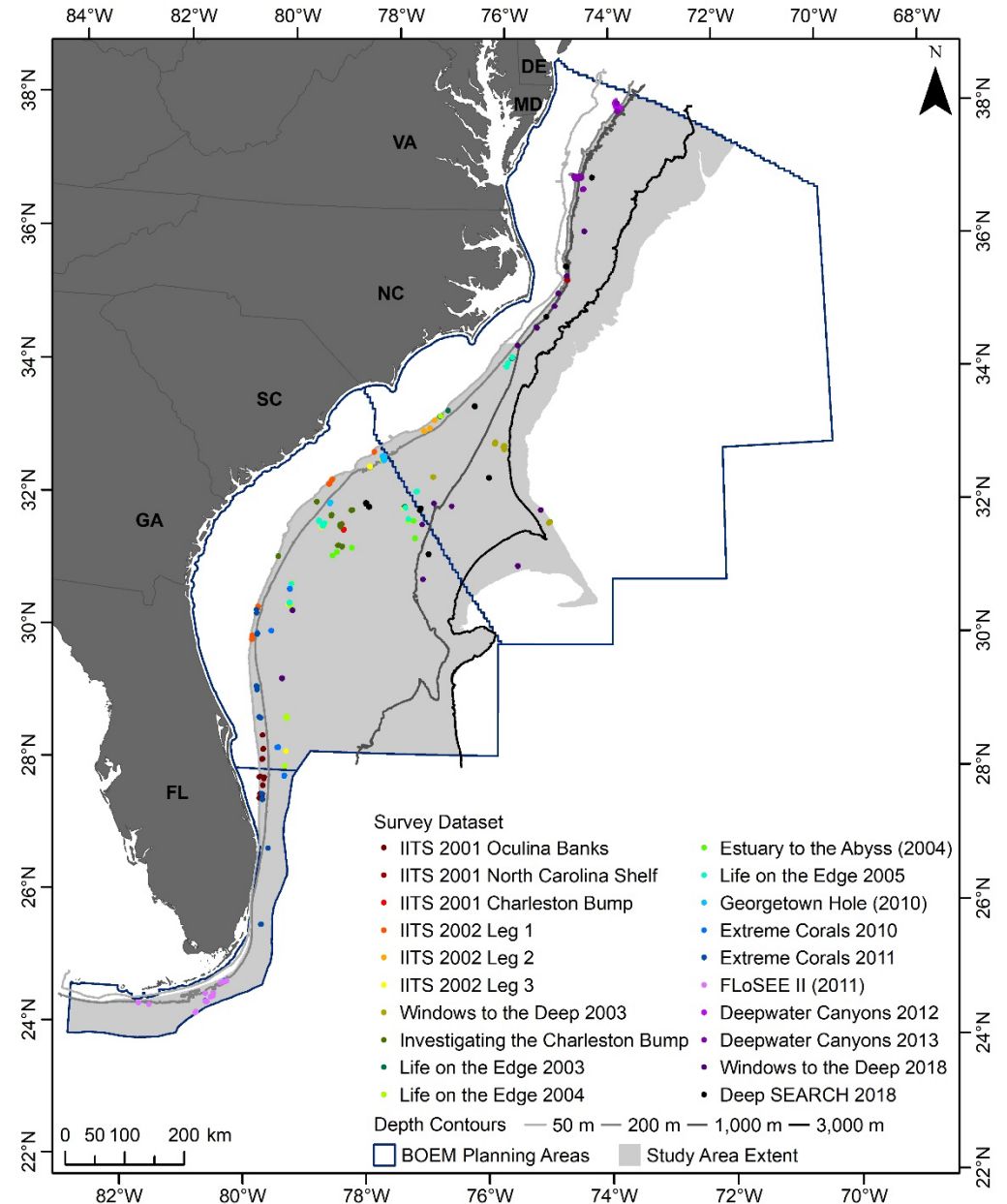
Background

- Hourigan et al. (2017) described four major concentrations of hardbottom habitats that support DSC communities
 1. Miami and Pourtalès Terraces
 2. *Oculina* coral mounds off FL
 3. continental shelf, shelf break
 4. continental slope, Blake Plateau
- Farther north, submarine canyons



Why Predictive Models?

- Although considerable research and exploration has been done, much of the region is still unmapped and unexplored
- Field surveys in the deep sea are logistically difficult and expensive
- Models can predict and map estimated occurrence to inform:
 - siting, environmental assessment
 - conservation, management decisions
 - selection of targets for mapping and exploration



Existing Predictive Models

- Unpublished regional scale models for group of structure-forming stony corals by Davies
- NCCOS regional scale models for 3 species and 1 genus of structure-forming stony corals, several other groups of DSCs
- Mienis et al. (2014) – two regional scale models for *Lophelia pertusa*
- Gasbarro et al. (2022) – models at multiple scales for *L. pertusa*

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Cold-water coral growth under extreme environmental conditions, the Cape Lookout area, NW Atlantic

F. Mienis^{1,2}, G. C. A. Duineveld³, A. J. Davies⁴, M. M. S. Lavaleye³, S. W. Ross⁵, H. Seim⁶, J. Bane⁶, H. van Haren⁷, M. J. N. Bergman³, H. de Haas¹, S. Brooke⁸, and T. C. E. van Weering¹

¹Royal Netherlands Institute for Sea Research, Department of Marine Geology, P.O. Box 59, 1790 AB Den Burg, the Netherlands

²MARUM, University of Bremen, Leobenerstrasse, 28253 Bremen, Germany

³Royal Netherlands Institute for Sea Research, Department of Marine Ecology, P.O. Box 59, 1790 AB Den Burg, the Netherlands

⁴School of Ocean Sciences, Bangor University, Isle of Anglesey, LL59 5AB, UK

⁵University of North Carolina-Wilmington, Center for Marine Science, 5600 Marvin Moss Lane, Wilmington, NC 28409, USA

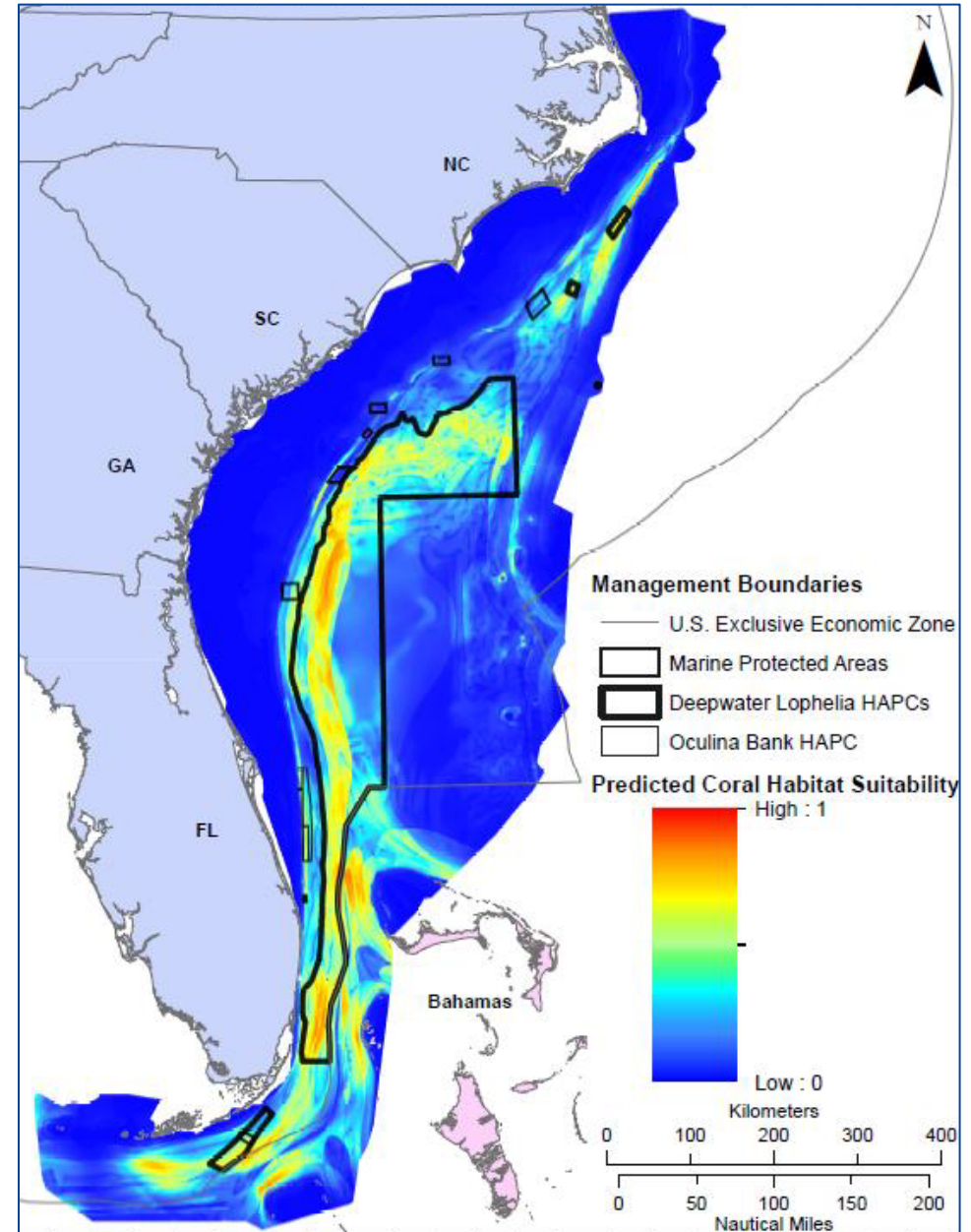
⁶University of North Carolina-Chapel Hill, Department of Marine Sciences, 3202 Venable Hall, Chapel Hill, NC 27599-3300, USA

⁷Royal Netherlands Institute for Sea Research, Department of Physical Oceanography, P.O. Box 59, 1790 AB Den Burg, the Netherlands

⁸Florida State University Coastal and Marine Lab, 3618 Coastal Highway 98, St. Teresa, FL 32358, USA

Why *New* Predictive Models?

- Earlier models used environmental predictors derived from regional bathymetry model
- Many of earlier models created for broad taxonomic groups that combined taxa with different habitat requirements
- Existing models were all presence-background models, fit using DSC presence data and randomly selected background locations rather than absence data

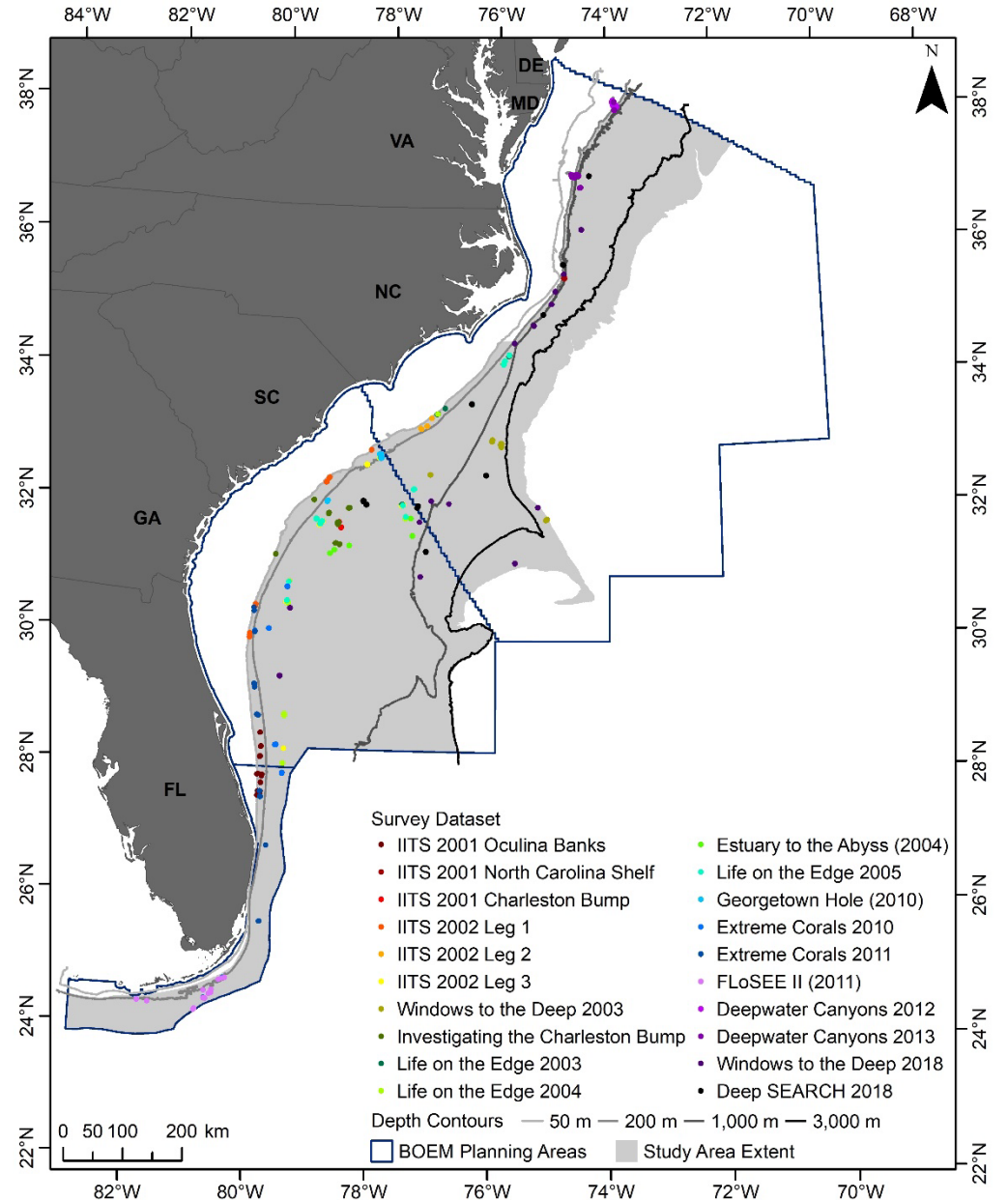


Objectives

- Data Synthesis: compile database of presence-absence records of DSC occurrence with associated measures of sampling effort and bottom type
- Predictive Modeling: develop predictive models that relate the occurrence of DSCs and hardbottom habitats to spatial environmental predictors in order to predict and map their potential spatial distributions across the study area

Methods (Data Synthesis)

- Inventory of available data from field surveys conducted by submersibles and ROVs used to compile a database of presence-absence records
- Each database record assigned a spatial position, estimate of survey area, DSCs observed, description of bottom type



Methods (Data Synthesis)

Table 1. Field survey datasets used to create the presence-absence database of deep-sea corals and hardbottom habitats

| Survey Dataset | Principal Investigator | Dives | Samples | Sites | Total Area (m ²) |
|--|------------------------------|-------|---------|-------|------------------------------|
| Islands in the Stream 2001 Oculina Banks | Shepard, Koeing | 16 | 41 | 33 | 8,110 |
| Islands in the Stream 2001 NC Shelf | Ross, Sulak | 10 | 28 | 16 | 3,987 |
| Islands in the Stream 2001 Charleston Bump | Sedberry | 3 | 62 | 36 | 9,987 |
| Islands in the Stream 2002 Leg 1 | Sedberry | 10 | 166 | 70 | 19,728 |
| Islands in the Stream 2002 Leg 2 | Ross, Sulak | 11 | 61 | 39 | 11,054 |
| Islands in the Stream 2002 Leg 3 | Pomponi, Reed | 23 | 209 | 106 | 37,728 |
| Windows to the Deep 2003 | Ruppel, Van Dover | 7 | 144 | 113 | 33,023 |
| Investigating the Charleston Bump (2003) | Sedberry, Stancyk | 13 | 193 | 80 | 25,114 |
| Life on the Edge 2003 | Ross, Baird, Sulak, Nizinski | 17 | 202 | 64 | 25,276 |
| Life on the Edge 2004 | Ross, Baird, Sulak, Nizinski | 25 | 202 | 100 | 27,675 |
| Estuary to the Abyss (2004) | Sedberry, Mitchell | 6 | 20 | 18 | 5,080 |
| Life on the Edge 2005 | Ross, Baird, Sulak, Nizinski | 18 | 302 | 122 | 36,960 |
| Georgetown Hole (2010) | Sedberry | 5 | 136 | 66 | 12,533 |
| Extreme Corals 2010 | Ross, Brooke | 8 | 356 | 89 | 13,800 |
| Extreme Corals 2011 | David, Reed | 9 | 72 | 65 | 20,705 |
| Florida Shelf-Edge Exploration II (2011) | Reed | 13 | 66 | 13 | 2,409 |
| Deepwater Canyons 2012 | Ross, Brooke | 20 | 3,673 | 438 | 64,470 |
| Deepwater Canyons 2013 | Ross, Brooke | 13 | 3,585 | 264 | 57,920 |
| Windows to the Deep 2018 | Morrison, Sautter | 17 | 86 | 84 | 16,300 |
| Deep SEARCH 2018 | Cordes | 10 | 219 | 132 | 29,056 |

Dives = number of submersible or remotely operated vehicle dives from the dataset that were used in this study.

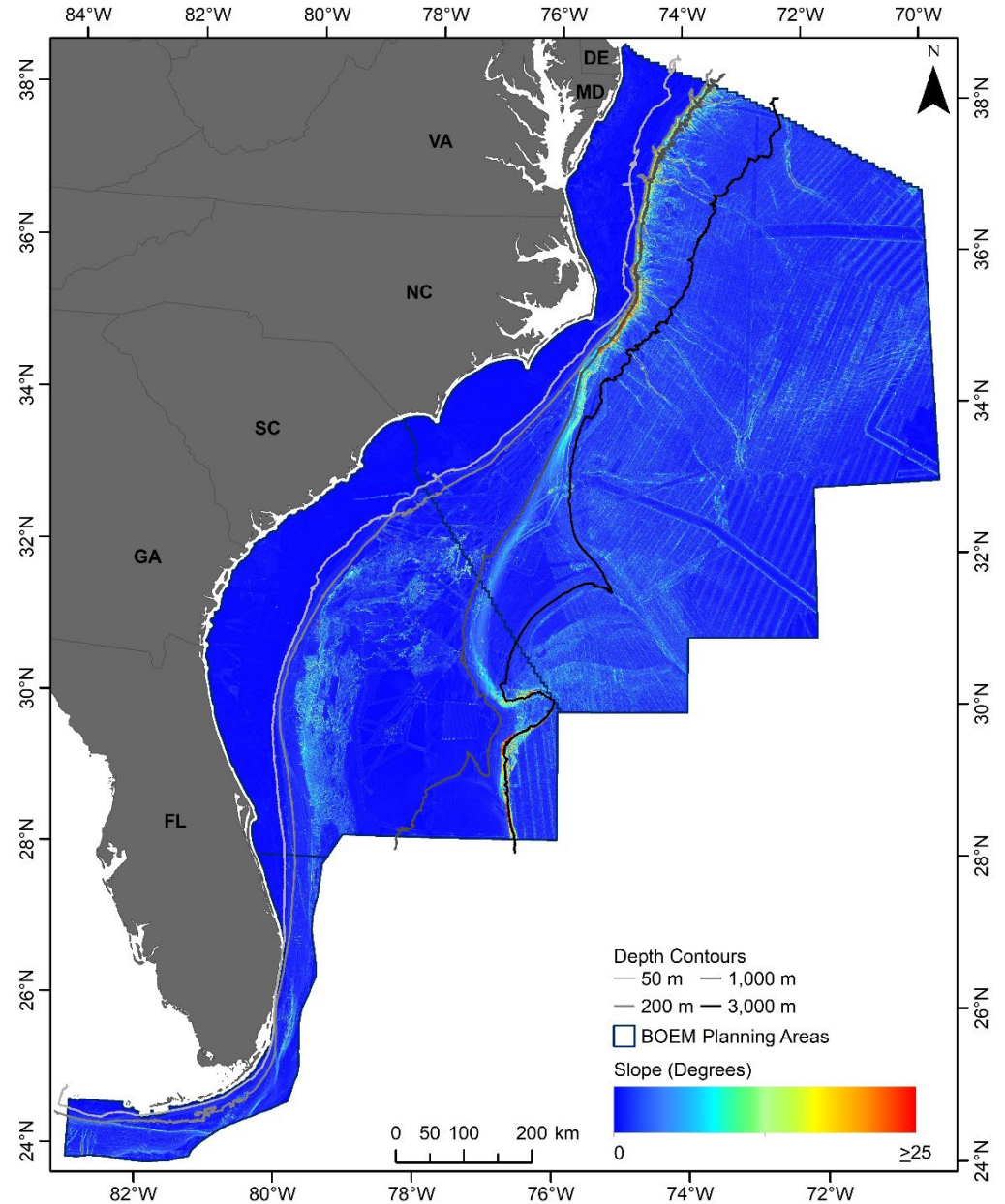
Samples = number of still images or video segments from the dataset that were analyzed to obtain deep-sea coral observations.

Sites = number of model grid cells containing samples from the dataset.

Total Area = sum of the survey area for all samples from the dataset.

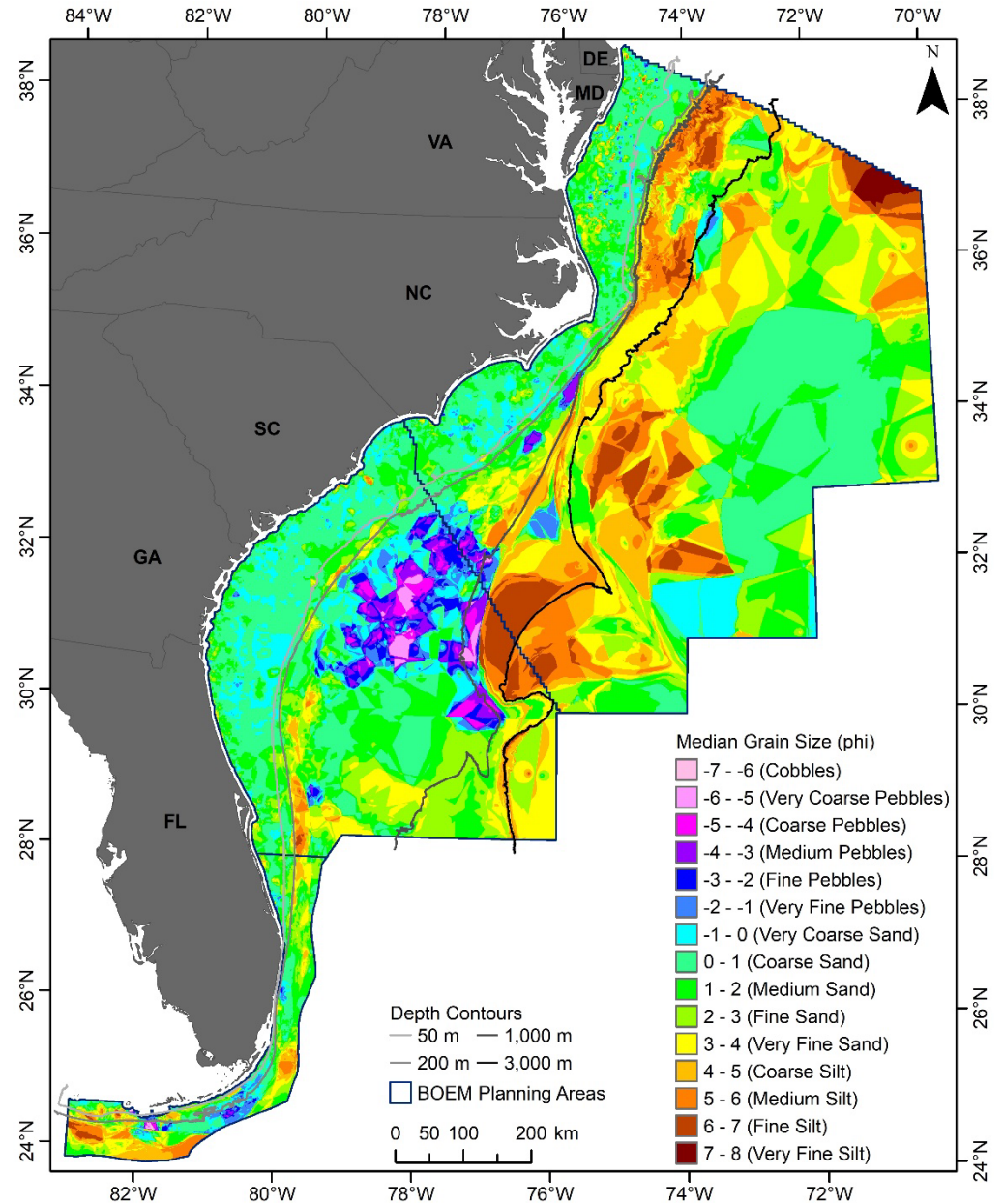
Methods (Predictive Models)

- Environmental predictors depicting:
 - depth and seafloor topography



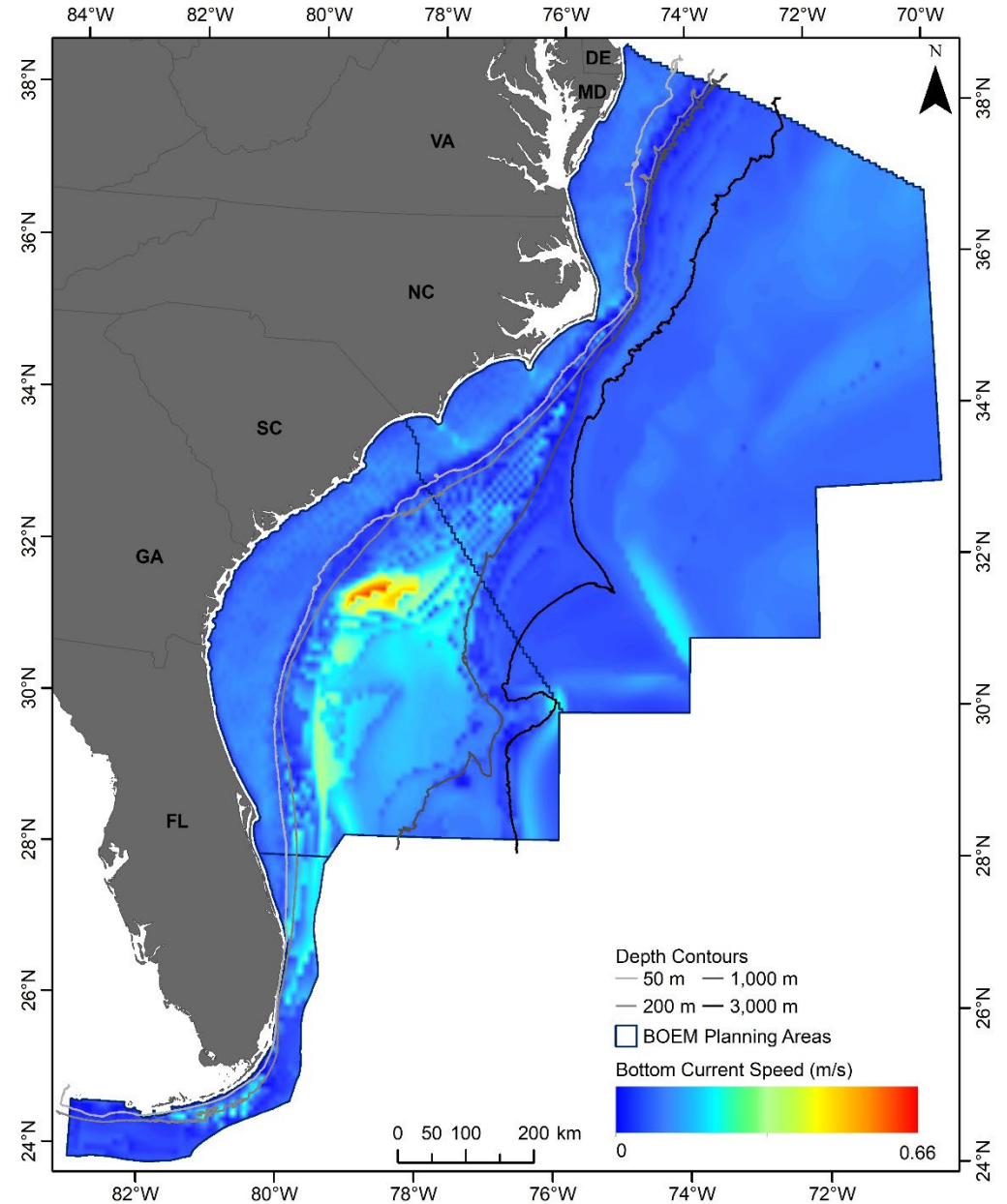
Methods (Predictive Models)

- Environmental predictors depicting:
 - depth and seafloor topography
 - substrate



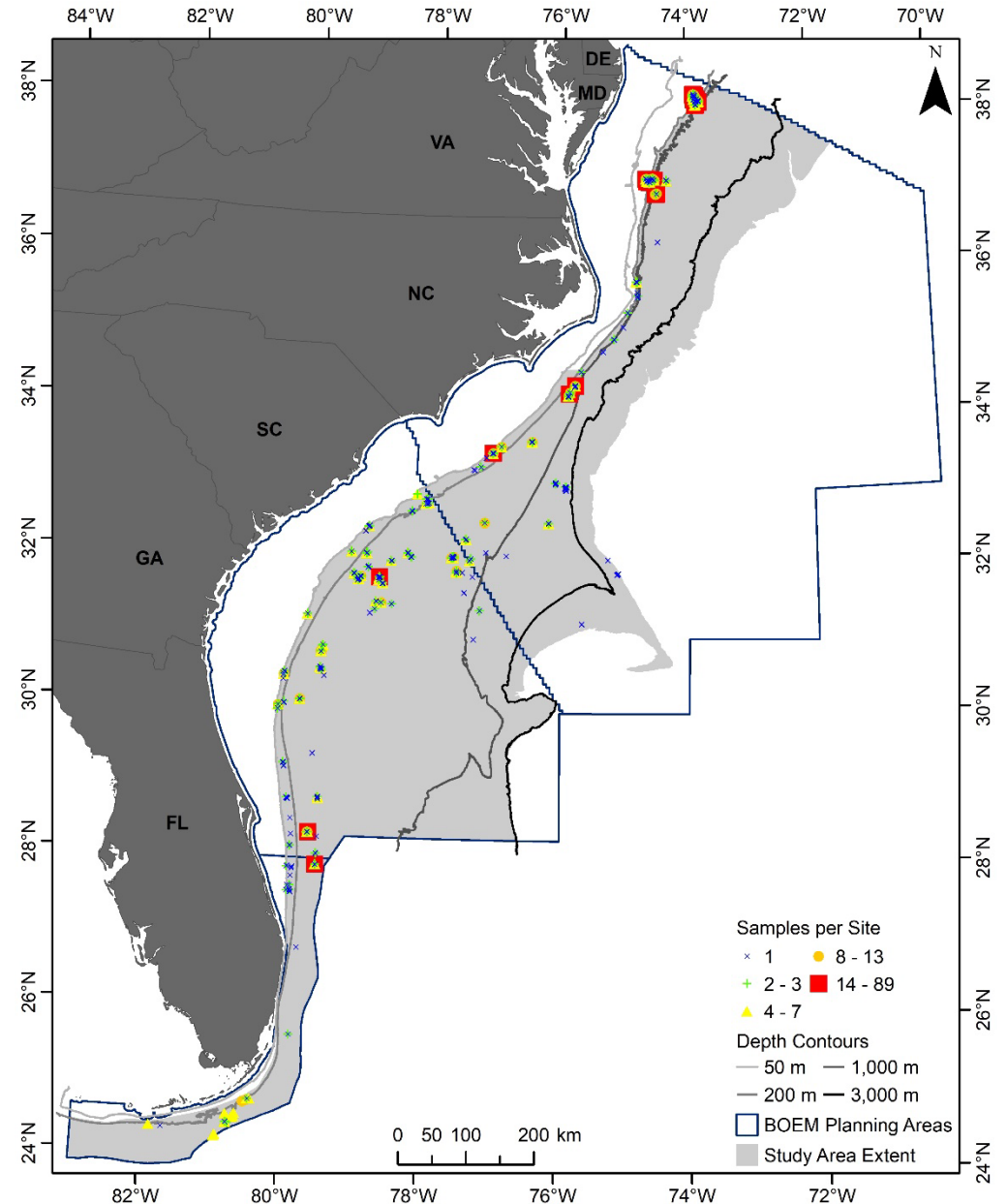
Methods (Predictive Models)

- Environmental predictors depicting:
 - depth and seafloor topography
 - substrate
 - oceanography
 - latitude/longitude
- Model grid at 100x100 m resolution

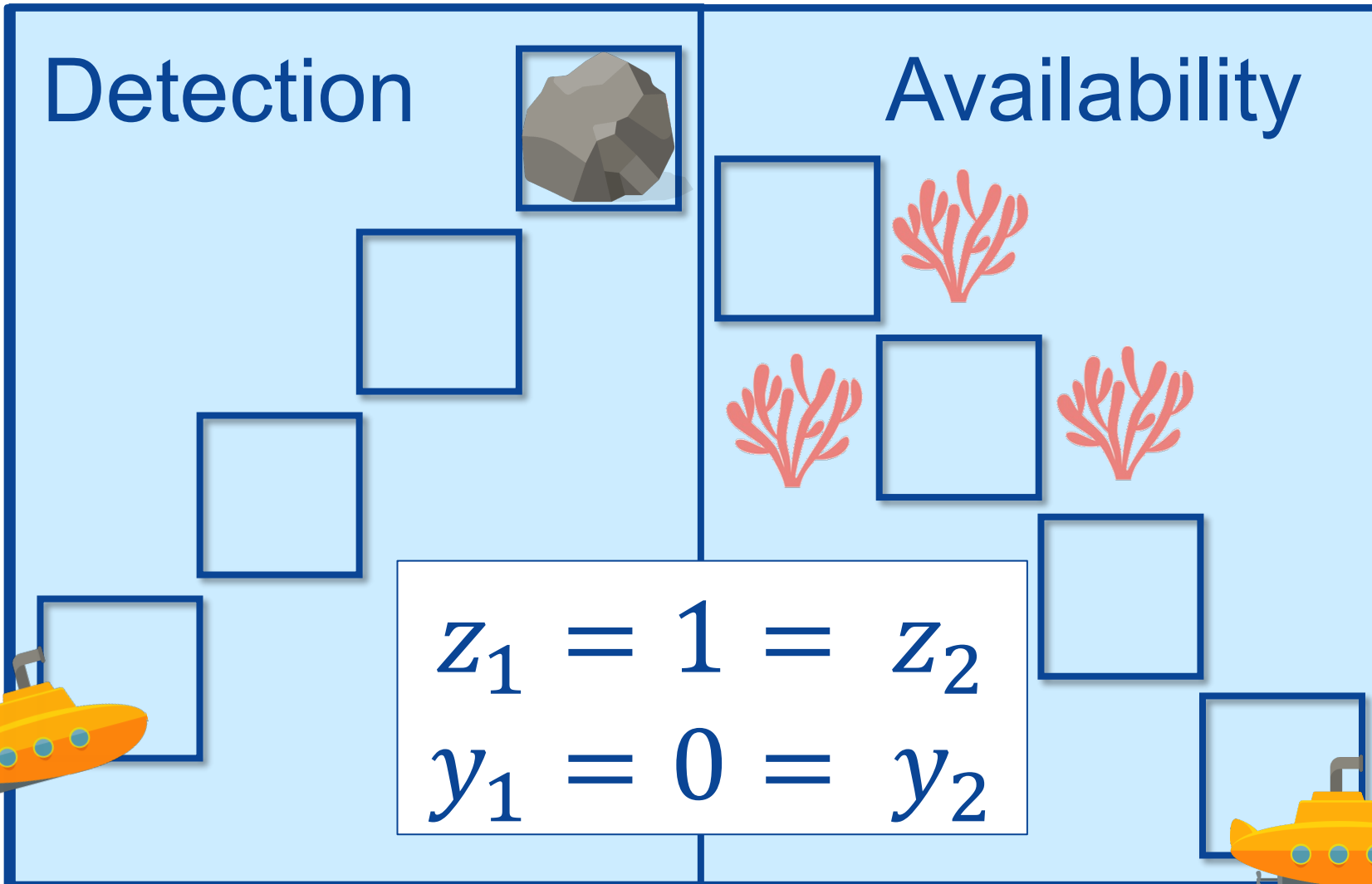


Methods (Predictive Models)

- Occupancy models – estimate both the probability of occurrence (occupancy probability) at a site (grid cell) and the probability of detecting an organism present at a site (detection probability)
- Space-for-time substitution using spatial replicates



Methods (Predictive Models)



Methods (Predictive Models)

- Occupancy analysis assumptions:
 1. Imperfect detection – sampled absences not treated as true absences
 2. No false positives – DSC observations only to finest taxonomic level for which observation could be identified with confidence
 3. Closure – sampling time frame short relative to system dynamics
 4. Independence of occupancy and detection probabilities
 5. Homogeneity of detection probability – assumption that detectability was consistent throughout study area unlikely to be met b/c of differences in survey data included; effort offset used to account for heterogeneity in detection probability; taxon- and site-level effects on detection probability also included

Methods (Predictive Models)

- Overall structure

$$y_{ijk} \sim \text{Bernoulli} (z_{ik} p_{ijk})$$

presence-absence data
 estimated occupancy state
 detection probability

i = site
j = occasion
k = genus
v = predictor
n = # predictors

- State process (occupancy)

$$z_{ik} \sim \text{Bernoulli} (\Psi_{ik})$$

occupancy probability

$$\text{cloglog}(\Psi_{ik}) = \text{beta}_{0k} + \sum_{v=1}^n f_{vk}(x_{vi}, \text{beta}_{vk})$$

genus-specific occupancy intercept
 natural cubic polynomial spline
 predictor-specific occupancy coefficients

$$\text{beta}_{0k} \sim \text{Normal}(u_{\text{beta}_0}, \tau_{\text{beta}_0})$$

$$\text{beta}_{vk} \sim \text{Normal}(u_{\text{beta}}, \tau_{\text{beta}})$$

Methods (Predictive Models)

- Observation process (detection)

$$\underset{\substack{\text{detection} \\ \text{probability}}}{\text{cloglog}(p_{ijk})} = \underset{\substack{\text{detection} \\ \text{intercept}}}{\alpha_0} + \underset{\substack{\text{site effect} \\ \text{on detection}}}{\alpha_{1,i}} + \underset{\substack{\text{genus effect} \\ \text{on detection}}}{\alpha_{2,k}} + \underset{\substack{\text{effort} \\ \text{(area)}}}{\log(\text{effort}_{ij})}$$

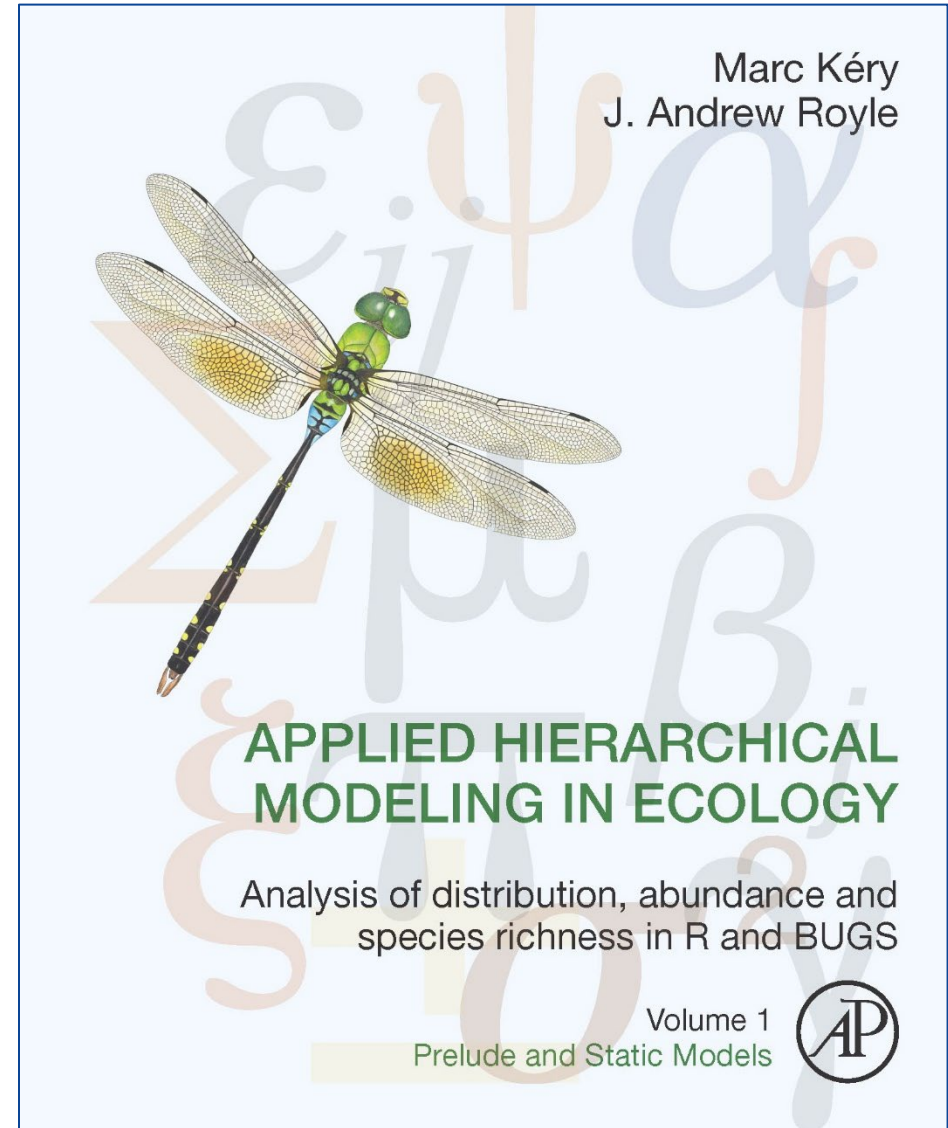
$$\alpha_{1,i} \sim \text{Normal}(0, \tau_{clp1})$$

$$\alpha_{2,k} \sim \text{Normal}(0, \tau_{clp2})$$

i = site
 j = occasion
 k = genus

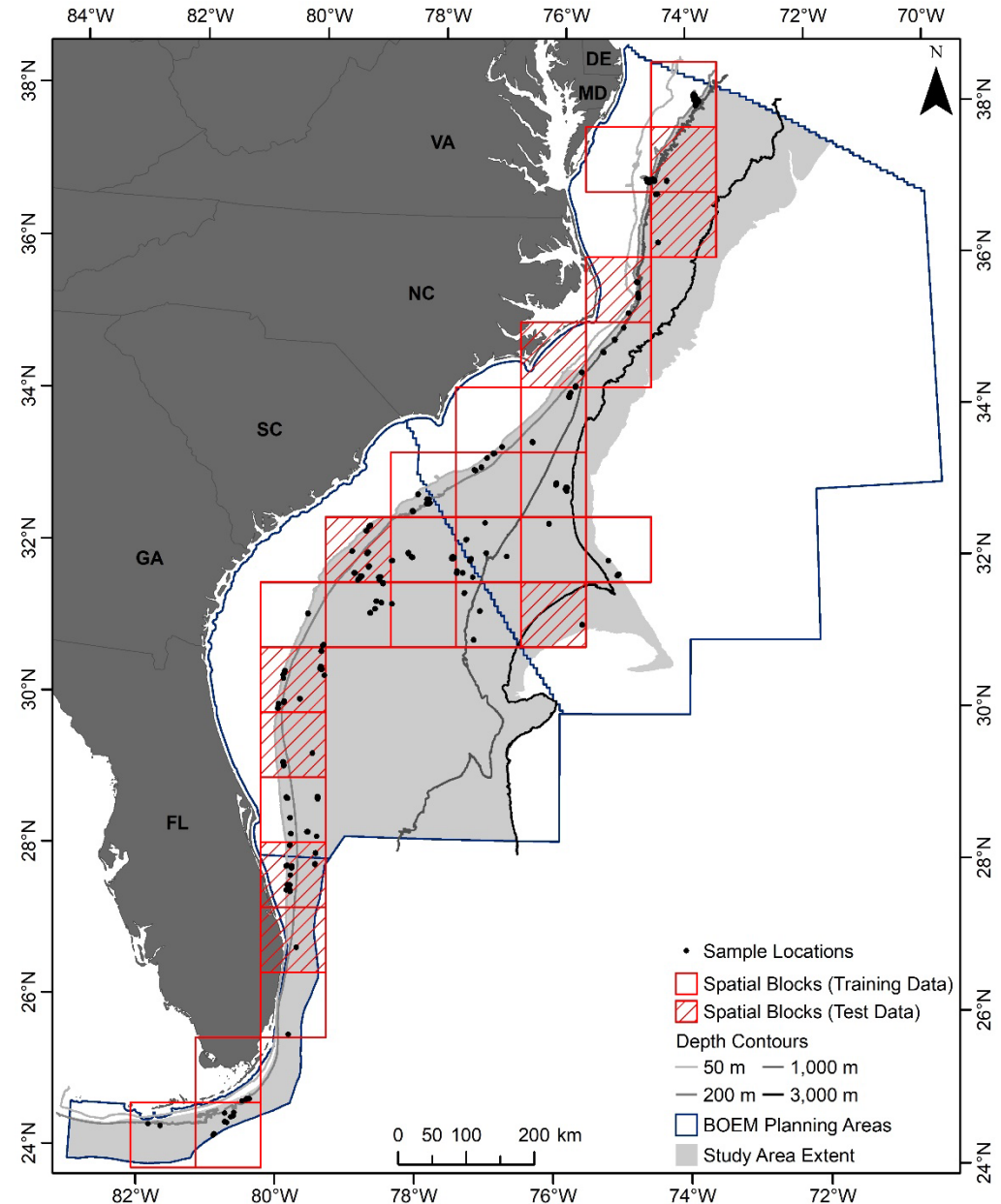
Methods (Predictive Models)

- Bayesian hierarchical approach
- Multi-taxon model – allowed estimate of richness
- 23 genera of DSCs:
 - 6 genera of stony corals
 - 5 genera of black corals
 - 12 genera of gorgonian corals
- 1 family – Stylasteridae
- Hardbottom habitats



Methods (Predictive Models)

- Model fit assessed using AUC, point-biserial correlation coefficient
- Model predictive performance from validation – spatial blocks used to define training and test subsets of the sample data



Results

- Model predictive performance
 - median correlation coefficient was 0.3
 - several genera >0.6 (including *Lophelia*, *Oculina*)
 - most test AUC values >0.9
 - a few genera had test AUC values <0.6

Results

Table 8. Assessment of model performance from validation

| Taxon | Samples (Training) | | Samples (Test) | | r_{pb} (Training) | | r_{pb} (Test) | AUC (Training) | | AUC (Test) |
|-----------------------|--------------------|---------|----------------|---------|---------------------|------|-----------------|----------------|------|------------|
| | Presence | Absence | Presence | Absence | P1 | P2 | P2 | P1 | P2 | P2 |
| <i>Lophelia</i> | 642 | 6,464 | 502 | 2,215 | 0.86 | 0.73 | 0.81 | 0.99 | 0.95 | 0.97 |
| <i>Solenosmilia</i> | 179 | 6,927 | 139 | 2,578 | 0.65 | 0.36 | 0.34 | 0.97 | 0.87 | 0.98 |
| <i>Oculina</i> | 70 | 7,036 | 90 | 2,627 | 0.84 | 0.69 | 0.80 | 1.00 | 0.99 | 1.00 |
| <i>Madrepora</i> | 66 | 7,040 | 66 | 2,651 | 0.45 | 0.26 | 0.30 | 0.97 | 0.93 | 0.97 |
| <i>Cladocora</i> | 8 | 7,098 | 17 | 2,700 | 0.85 | 0.57 | 0.61 | 1.00 | 1.00 | 1.00 |
| <i>Enallopsammia</i> | 15 | 7,091 | 7 | 2,710 | 0.87 | 0.36 | 0.24 | 1.00 | 0.99 | 0.99 |
| <i>Stichopathes</i> | 55 | 7,051 | 137 | 2,580 | 0.84 | 0.62 | 0.77 | 1.00 | 0.98 | 1.00 |
| <i>Leiopathes</i> | 97 | 7,009 | 49 | 2,668 | 0.61 | 0.29 | 0.17 | 0.98 | 0.91 | 0.96 |
| <i>Antipathes</i> | 46 | 7,060 | 44 | 2,673 | 0.46 | 0.31 | 0.70 | 0.99 | 0.97 | 1.00 |
| <i>Tanacetipathes</i> | 37 | 7,069 | 8 | 2,709 | 0.63 | 0.33 | 0.22 | 0.99 | 0.97 | 1.00 |
| <i>Bathypathes</i> | 25 | 7,081 | 19 | 2,698 | 0.49 | 0.14 | 0.08 | 0.99 | 0.93 | 0.96 |
| <i>Paragorgia</i> | 915 | 6,191 | 6 | 2,711 | 0.62 | 0.51 | 0.29 | 0.96 | 0.91 | 0.76 |
| <i>Plumarella</i> | 437 | 6,669 | 240 | 2,477 | 0.81 | 0.57 | 0.66 | 0.98 | 0.94 | 0.99 |
| <i>Anthothela</i> | 336 | 6,770 | 10 | 2,707 | 0.50 | 0.31 | -0.01 | 0.95 | 0.87 | 0.59 |
| <i>Acanthogorgia</i> | 173 | 6,933 | 122 | 2,595 | 0.66 | 0.35 | -0.02 | 0.97 | 0.88 | 0.58 |
| <i>Paramuricea</i> | 156 | 6,950 | 52 | 2,665 | 0.82 | 0.35 | 0.09 | 1.00 | 0.90 | 0.53 |
| <i>Eunicella</i> | 85 | 7,021 | 77 | 2,640 | 0.80 | 0.41 | 0.10 | 0.99 | 0.96 | 0.98 |
| <i>Muricea</i> | 57 | 7,049 | 69 | 2,648 | 0.65 | 0.48 | 0.84 | 0.99 | 0.98 | 1.00 |
| <i>Thesea</i> | 48 | 7,058 | 30 | 2,687 | 0.66 | 0.39 | 0.37 | 0.99 | 0.98 | 0.99 |
| <i>Callogorgia</i> | 52 | 7,054 | 0 | 2,717 | 0.58 | 0.11 | 0.02 | 1.00 | 0.95 | 0.90 |
| <i>Nicella</i> | 18 | 7,088 | 30 | 2,687 | 0.53 | 0.23 | 0.33 | 0.99 | 0.97 | 0.99 |
| <i>Chrysogorgia</i> | 22 | 7,084 | 5 | 2,712 | 0.67 | 0.21 | 0.17 | 1.00 | 0.95 | 0.97 |
| <i>Acanella</i> | 9 | 7,097 | 16 | 2,701 | 0.81 | 0.28 | 0.00 | 1.00 | 0.98 | 0.80 |
| Stylasteridae | 462 | 7,594 | 198 | 1,569 | 0.88 | 0.73 | 0.54 | 1.00 | 0.98 | 0.93 |
| Hardbottom | 4,287 | 3,397 | 1,851 | 288 | 0.88 | 0.64 | 0.40 | 0.98 | 0.87 | 0.78 |

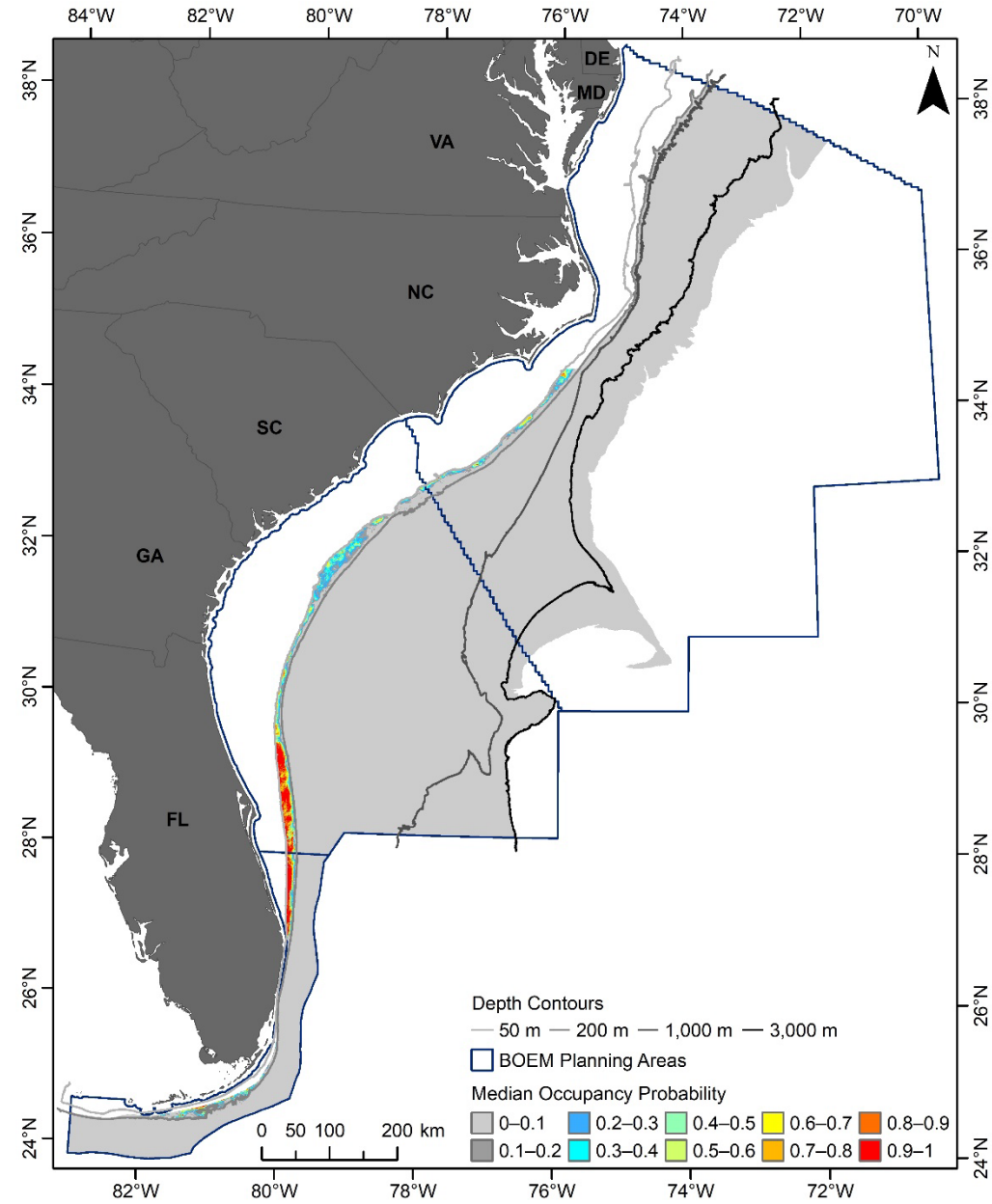
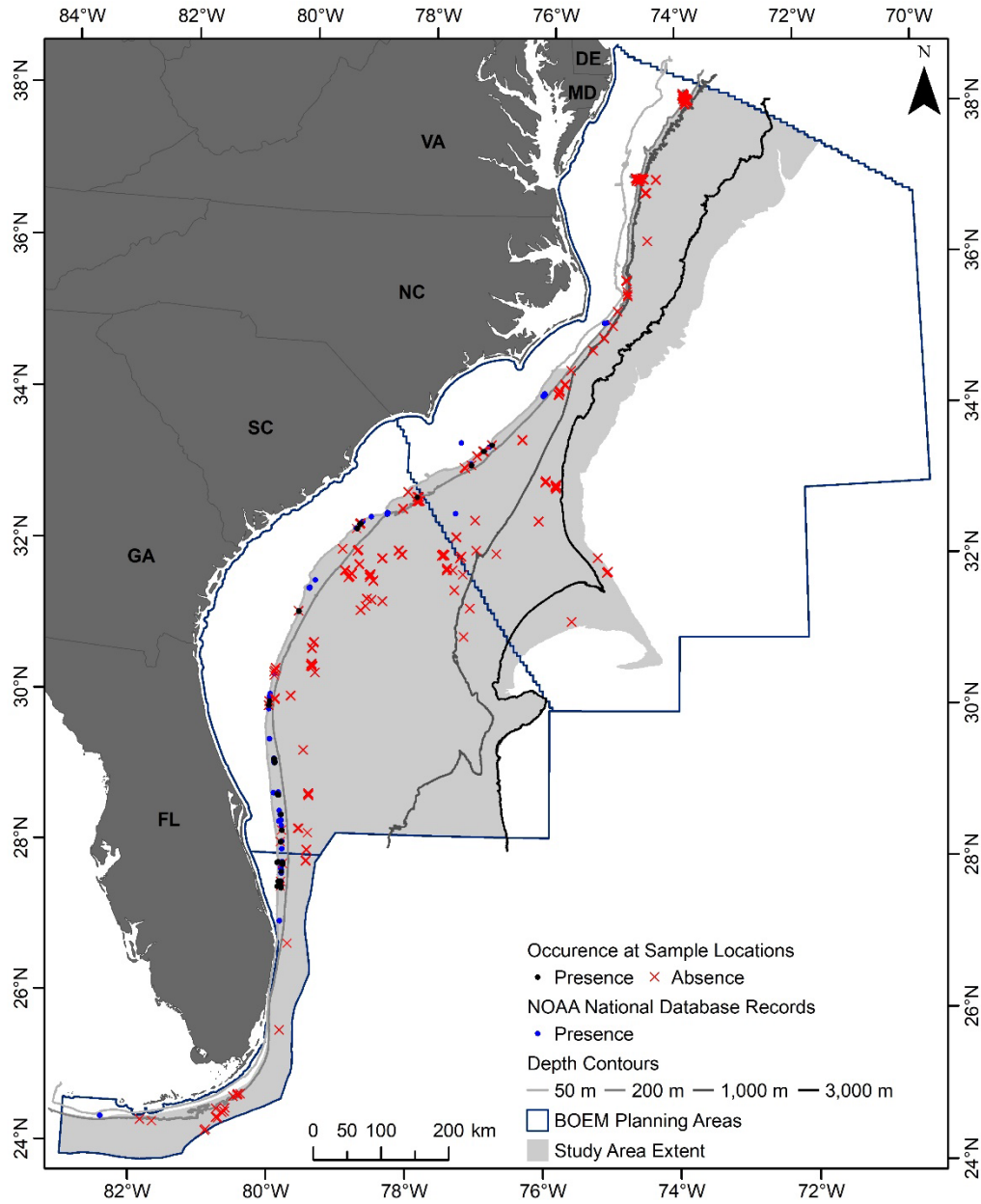
r_{pb} = point-biserial correlation coefficient.

AUC = area under the receiver operating characteristic curve.

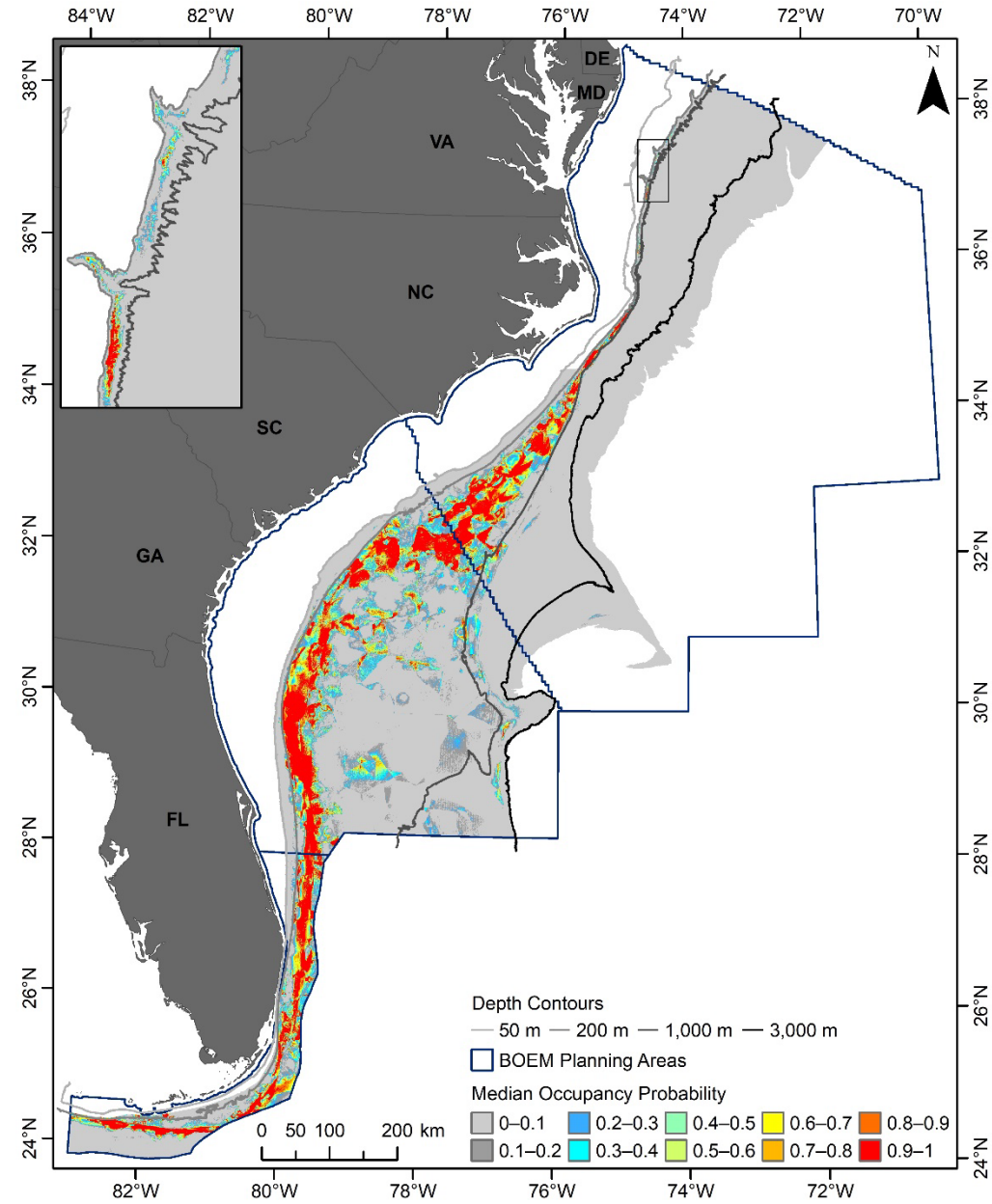
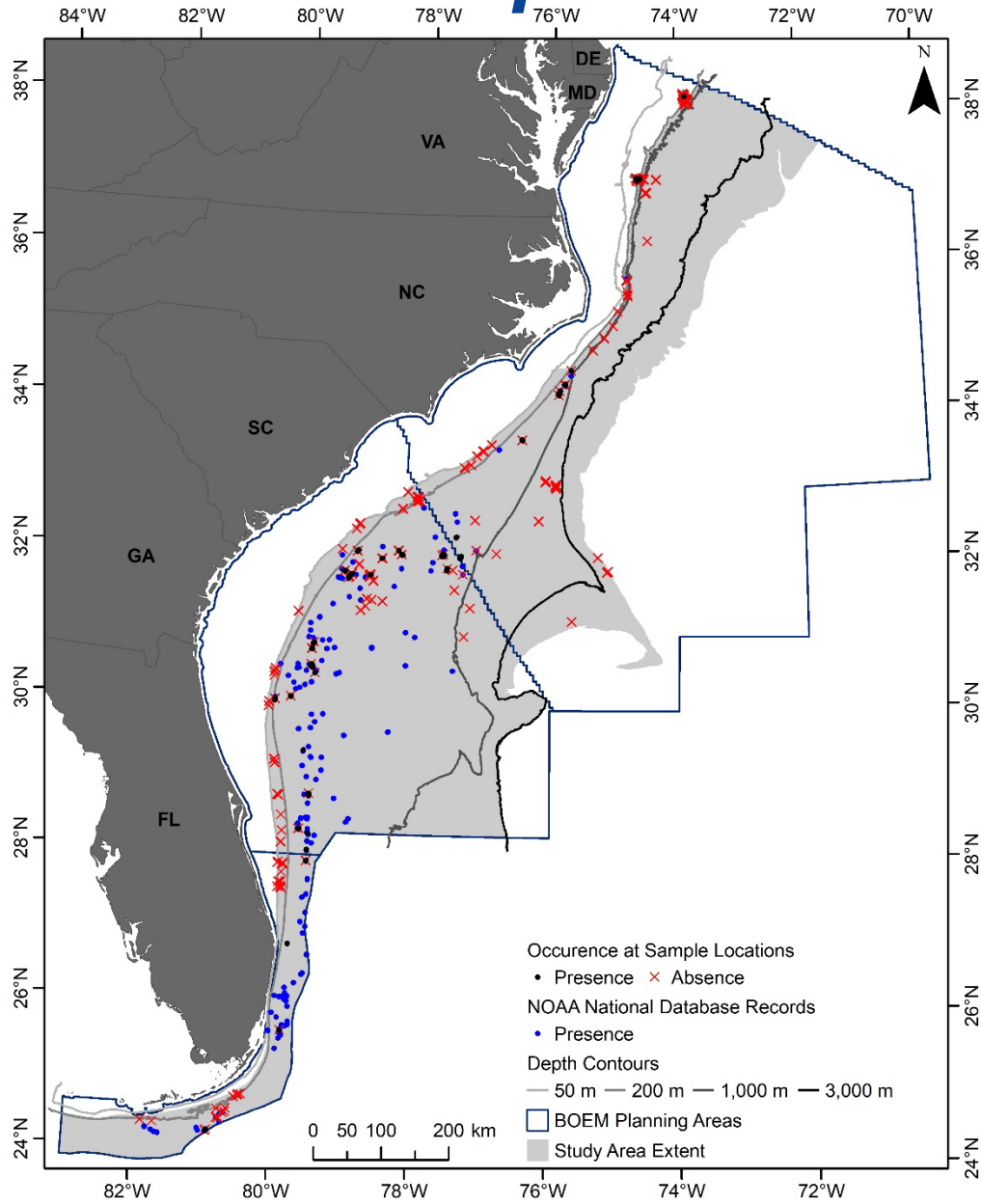
P1: predicted probabilities were calculated as the product of the estimated occupancy states (z_{ik}) and estimated detection probabilities (p_{ijk}); i.e., $z_{ik}p_{ijk}$.

P2: predicted probabilities were calculated by substituting the estimated occupancy probability (Ψ_{ik}) for z_{ik} and adjusting the estimated detection probability by setting the estimated site-level effect ($\alpha_{1,i}$) to zero.

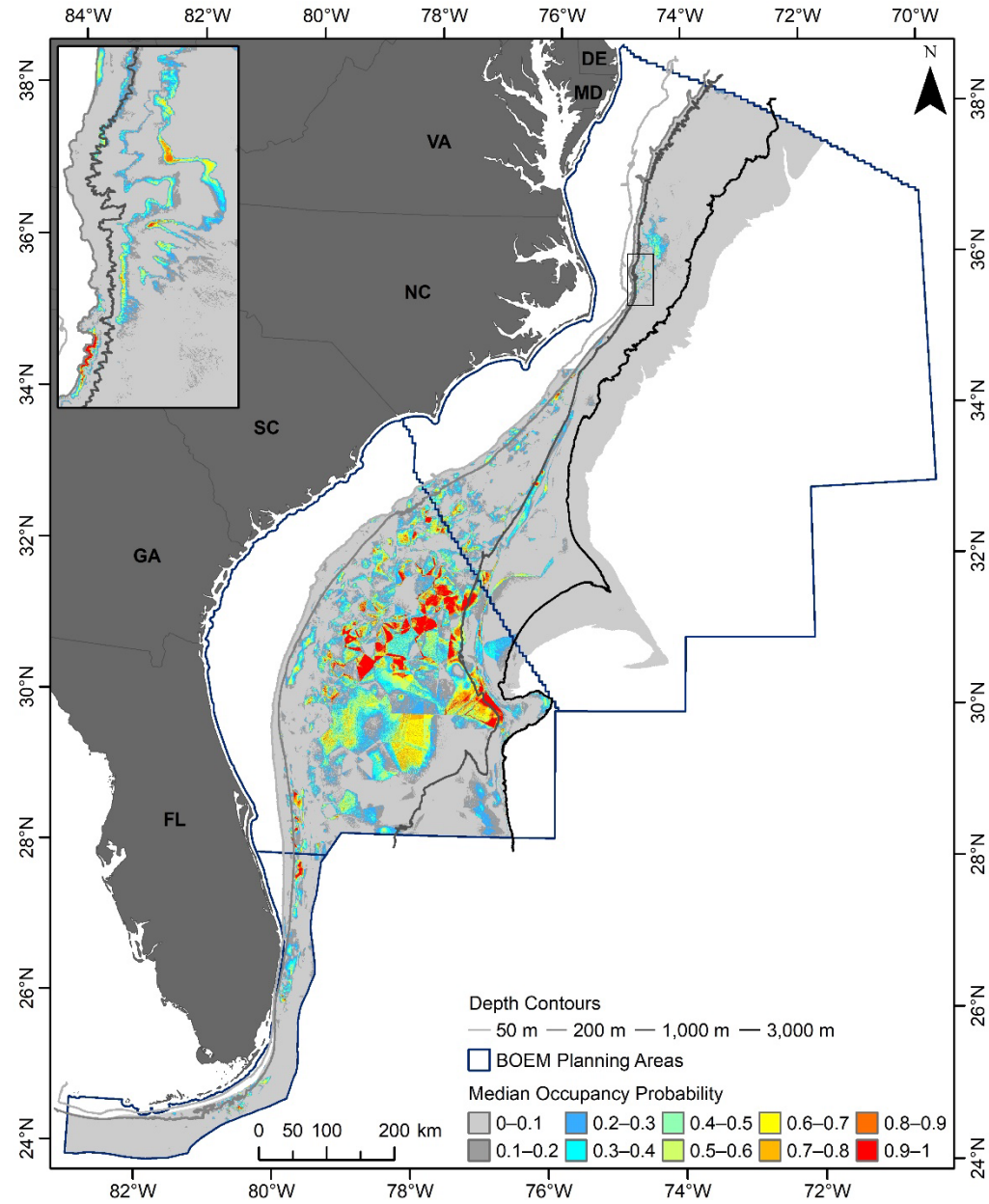
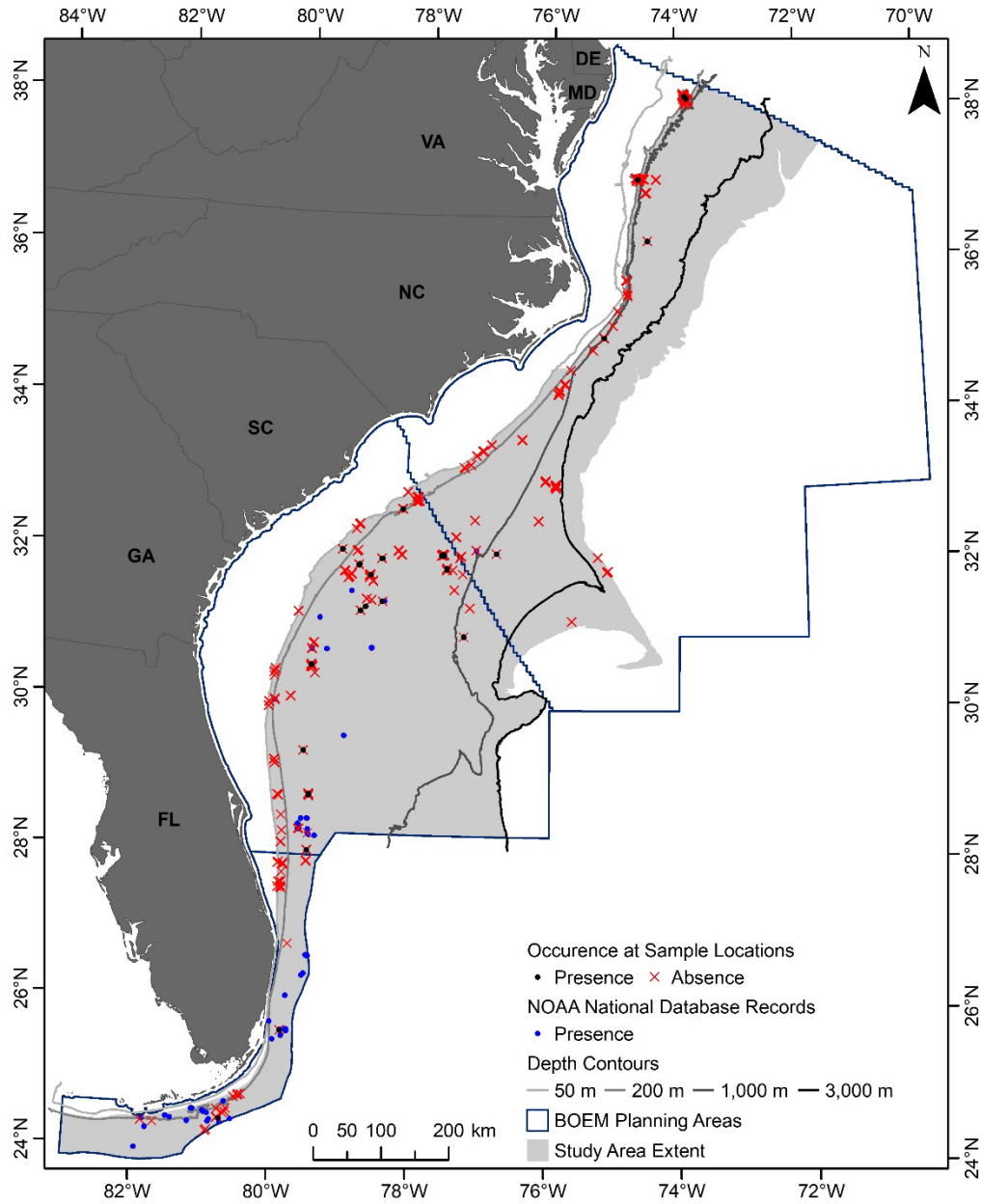
Results – *Oculina*



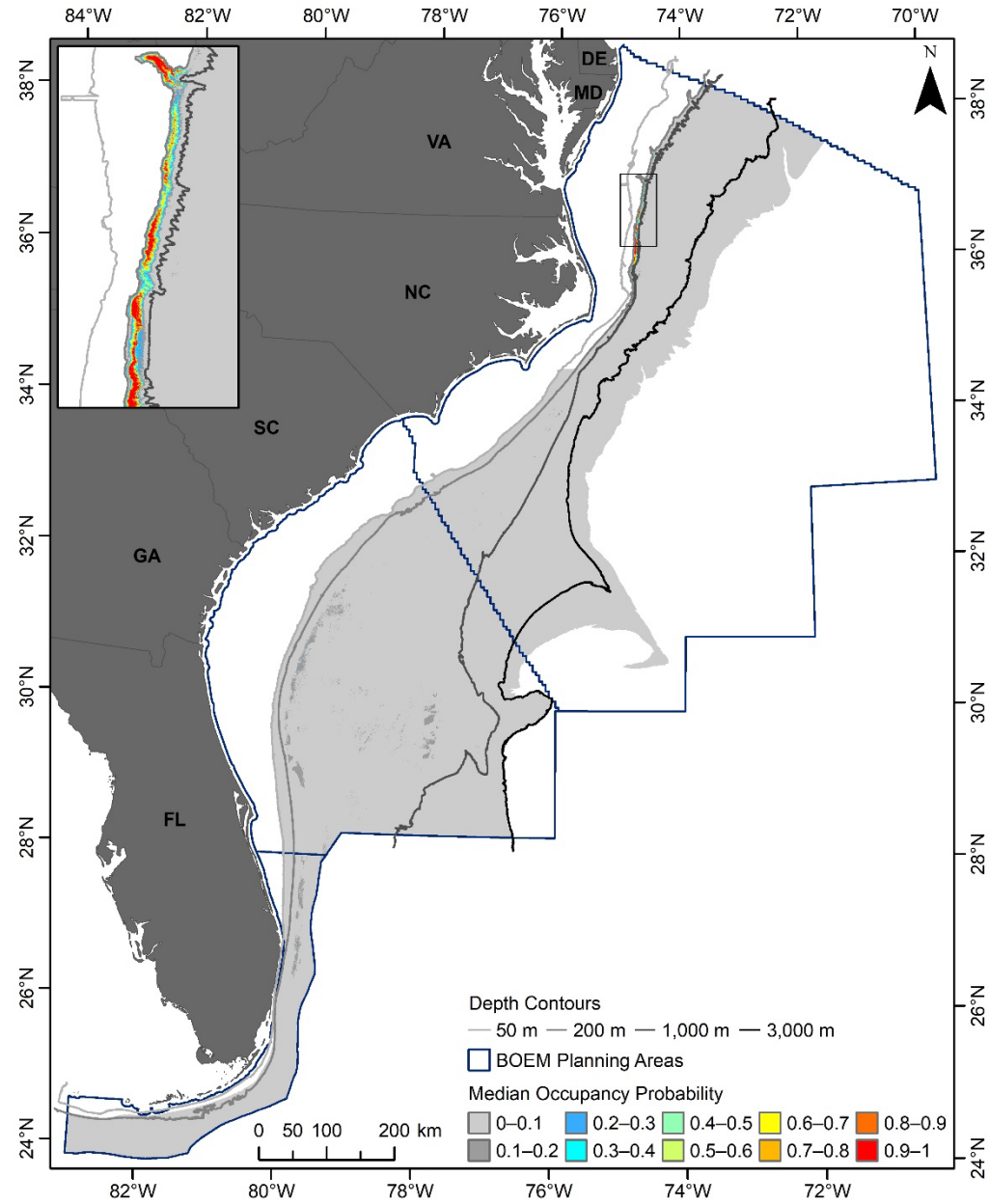
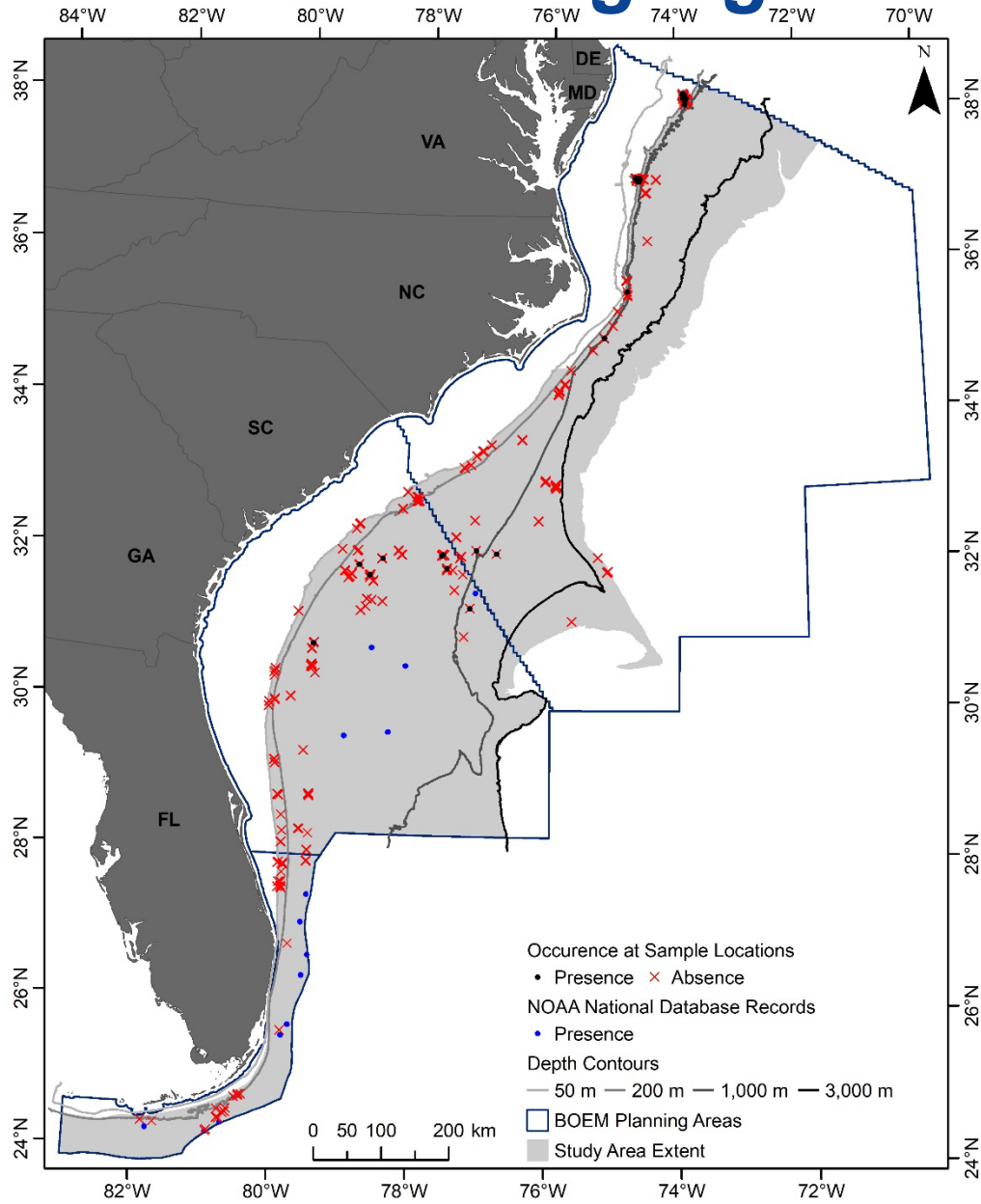
Results – *Lophelia*



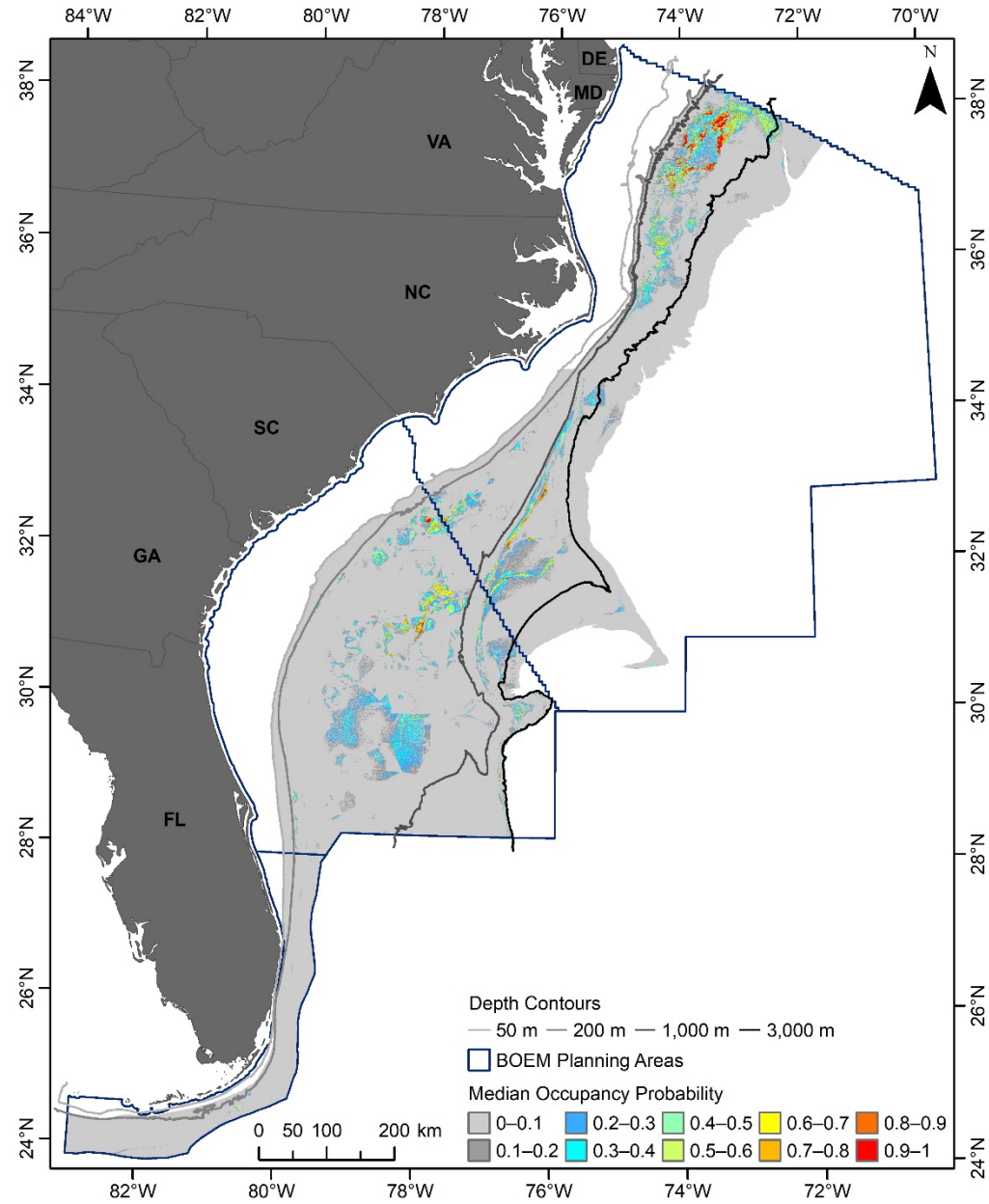
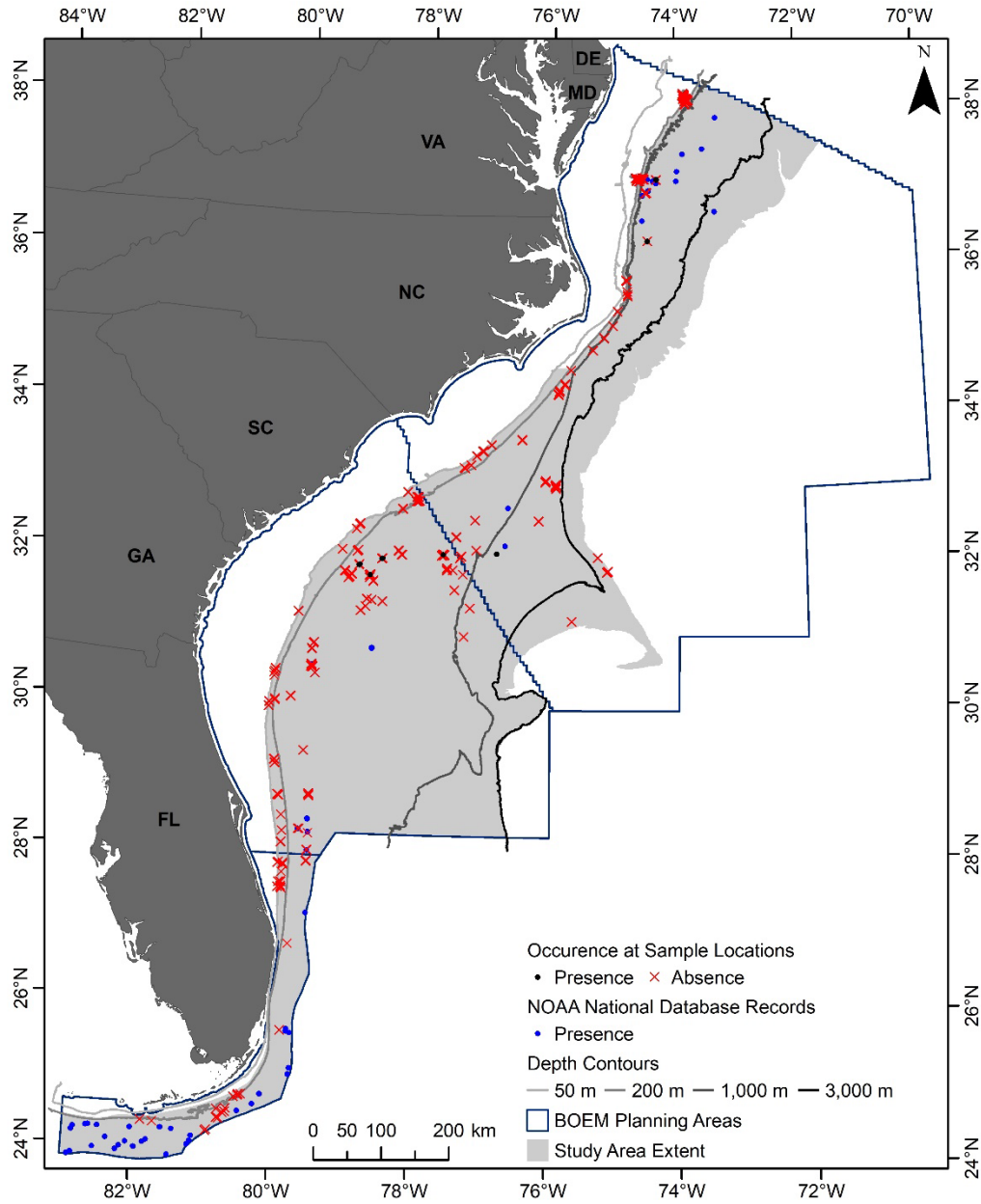
Results – *Paramuricea*



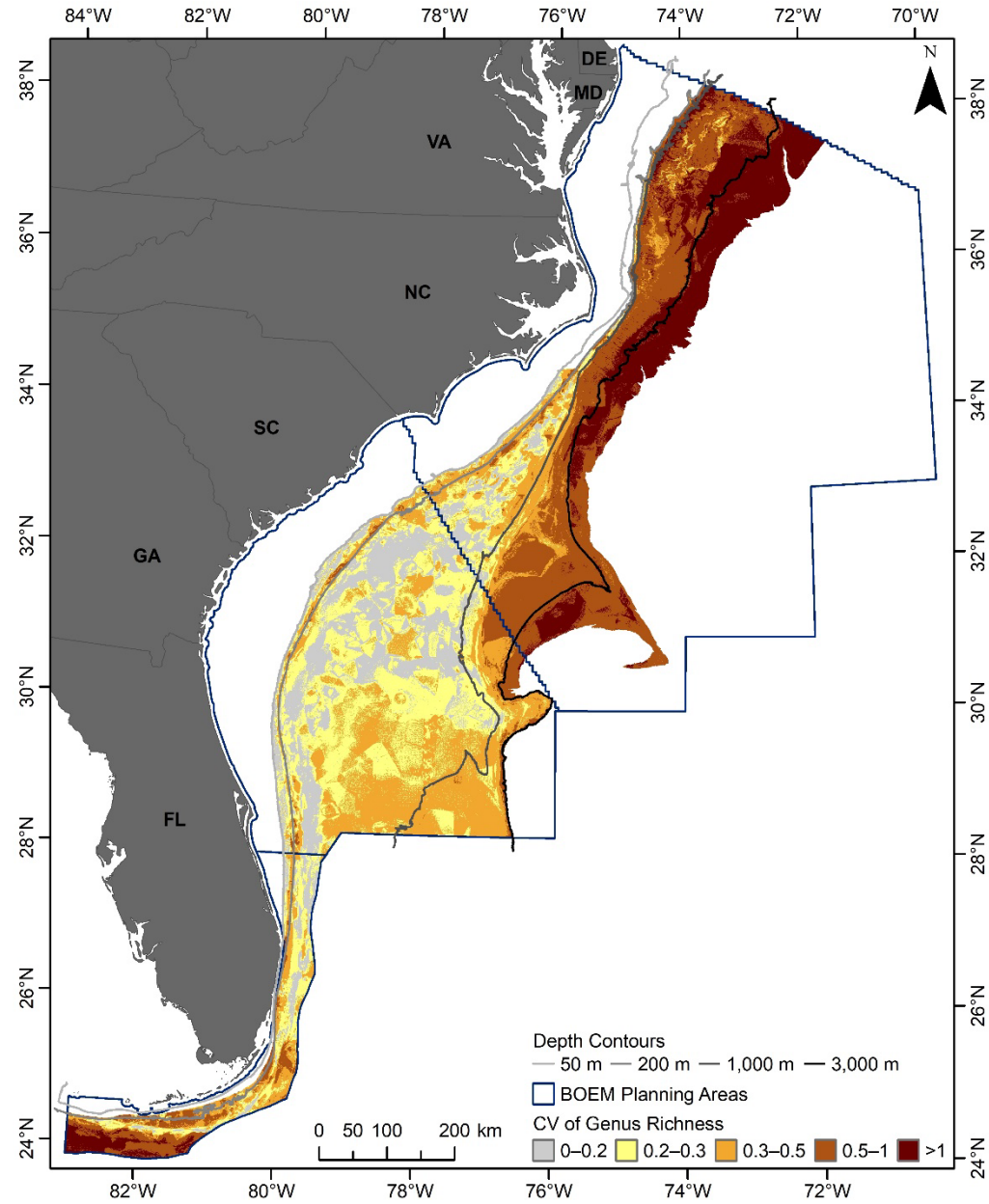
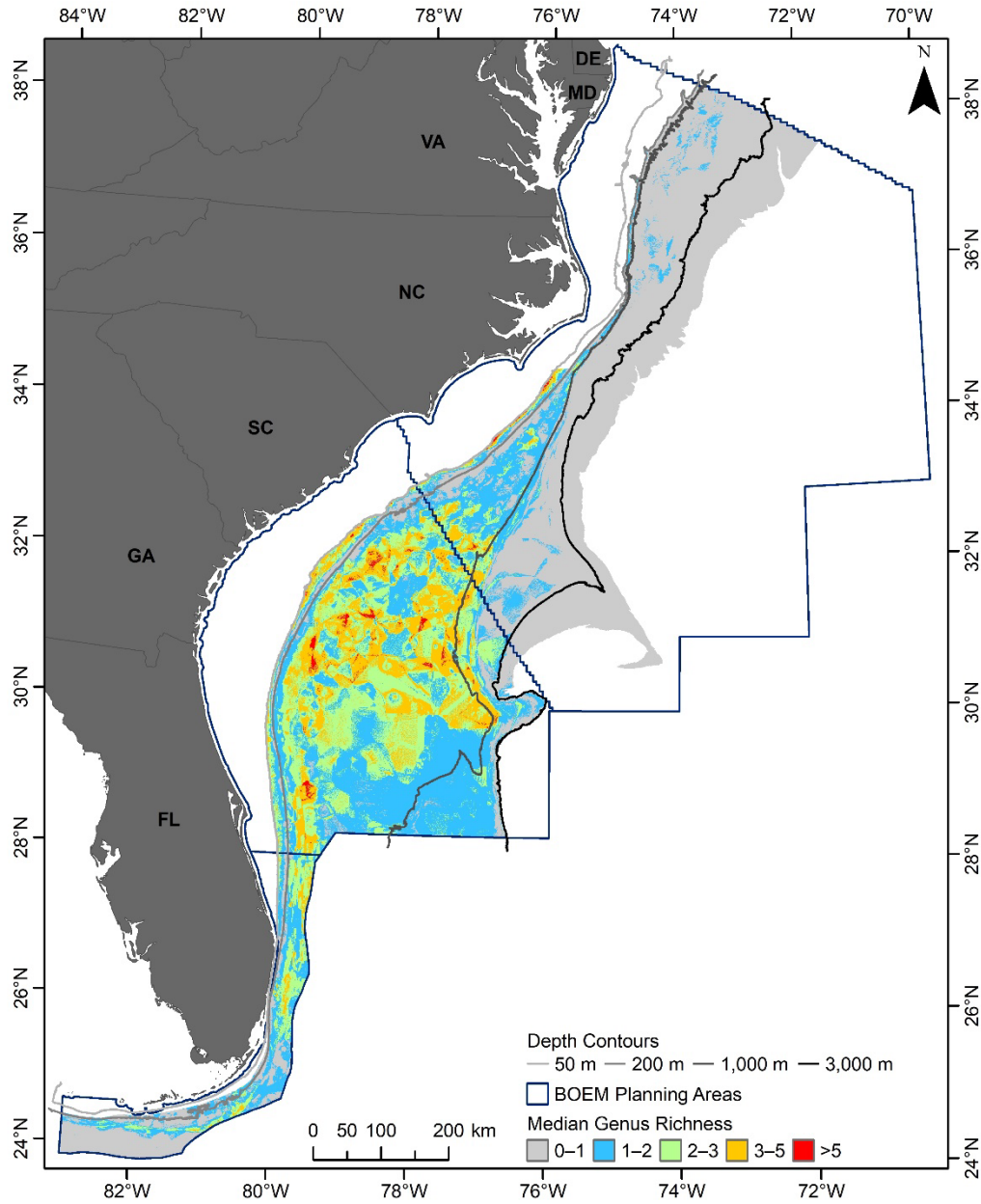
Results – *Paragorgia*



Results – *Acanella*



Results – Genus Richness



Data Products

- Data products include:
 - MS Access database of presence-absence records
 - maps and GIS data of model predictions
- Data products can be used to support environmental risk assessments, environmental impact statements, etc. related to review of proposed offshore activities
- Data products can also inform future research and exploration

Conclusions

- Improvements over existing models for DSCs in region:
 - incorporation of absence data with associated sampling effort
 - models attempted to distinguish true from false absences
 - incorporation of bathymetry data from multibeam mapping
 - incorporation of ocean current predictors
 - genus level models instead of broad taxonomic groups
 - joint modeling of multiple genera

Conclusions

- Limitations:
 - challenges of ‘opportunistic’ compilation of sample data
 - sample dataset unbalanced, not standardized
 - variability in # of observations, replicate samples at each site
 - missing environmental predictor variables
 - spatial scale and resolution
- Recommendation:
 - promote systematic sampling design intended to inform models of abundance/density

Acknowledgments

- Survey data provided by:
 - NOAA Central Library
 - Georgia Institute of Technology
 - College of Charleston
 - Gray's Reef NMS
 - Harbor Branch Oceanographic Institute
 - Florida State University
 - NOAA OER
 - Temple University
- Multibeam bathymetry provided by:
 - Jason Chaytor (USGS)
 - Scott Harris (College of Charleston)
- Surficial sediment data layers provided by:
 - Chris Jenkins (University of Colorado)
- Feedback on maps of model predictions:
 - Martha Nizinski (NOAA)
 - Sandra Brooke (FSU)

Questions?

For more information, see:

https://epis.boem.gov/final%20reports/BOEM_2022-038.pdf

<https://coastalscience.noaa.gov/project/characterizing-spatial-distributions-of-deep-sea-corals-and-hardbottom-habitats-in-the-u-s-southeast-atlantic/>

or contact: Matthew Poti, matthew.poti@noaa.gov

