Community occupancy models for deep sea coral distribution and richness

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Peter Etnoyer[2] and John Christensen[2]

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National Oceanic and Atmospheric Administration
U.S. Department of Commerce

Madrepora, Gulf of Mexico 2009 photolib.noaa.gov

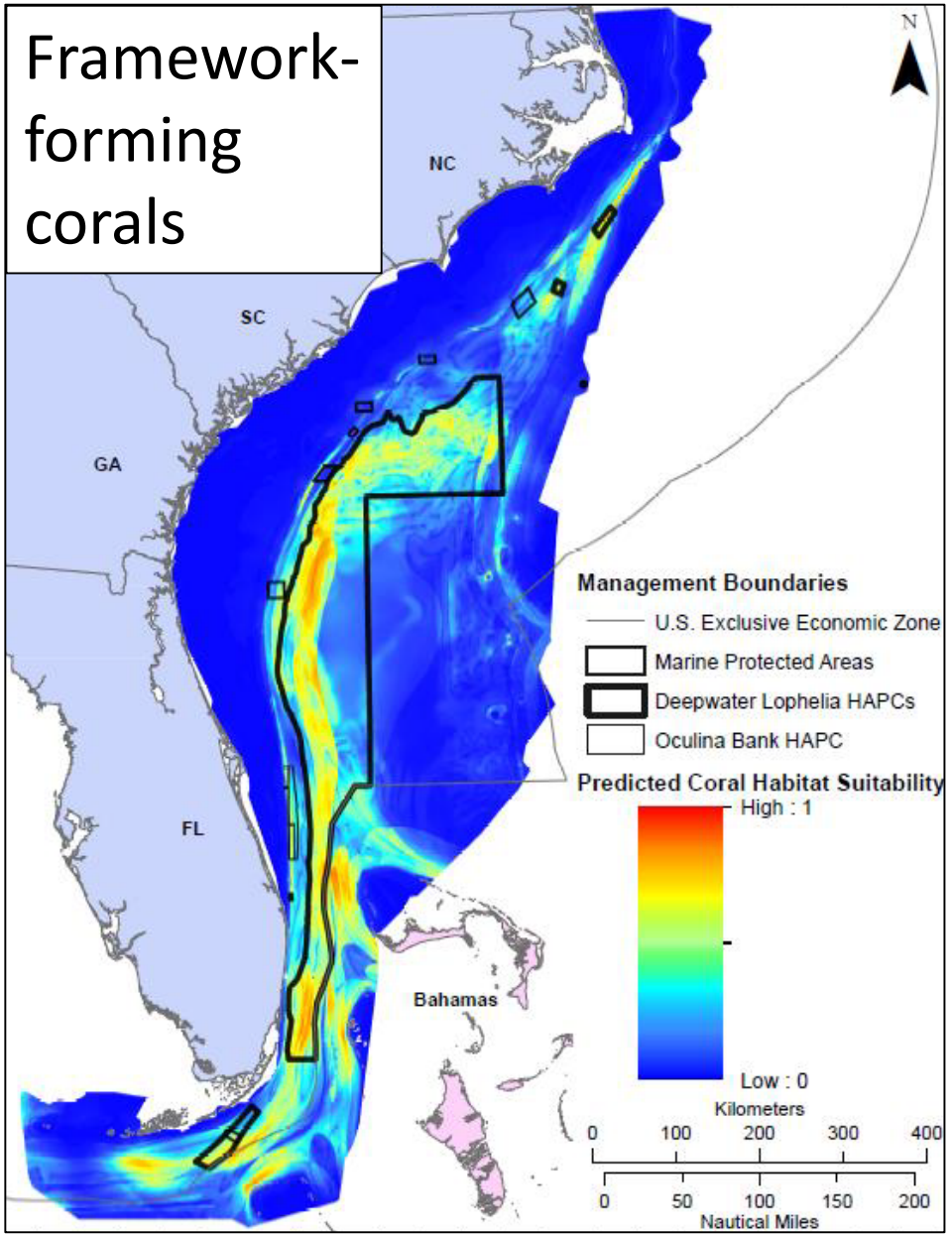
The state of deep-sea coral and sponge ecosystems of the US (2017): Ch. 8 Predictive habitat modeling

Guinotte JM, Georgian S, **Kinlan** BP, **Poti** M, Davies AJ.

NOAA Technical Memo. NMFS-OHC-4

Hourigan TF, **Etnoyer** PJ, Cairns SD (eds.)

deepseacoraldata.noaa.gov/library

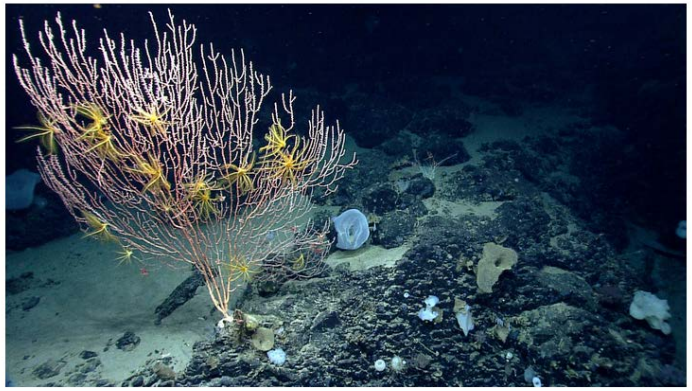


The New York Times

Vote Aids Deep Sea Corals in Much of Mid-Atlantic

By James Gorman

June 10, 2015



Coral like these will be protected from most bottom fishing because of a Mid-Atlantic Fishery Management Council vote. National Oceanic and Atmospheric Administration

Frank R. Lautenberg Deep-Sea Coral Protection Area

RI

CUT

DELAWARE

MARYLAND

VIRGINIA

Heezen Canyon

Nygren Canyon

Lydonia Canyon

Munson Canyon

Powell Canyon

Heel Tapper Canyon

Welker Canyon

Gilbert Canyon

Oceanographer Canyon

Veatch Canyon

Dogbody Canyon

Hydrographer Canyon

Block Canyon

Alvin Canyon

Atlantis Canyon

Nantucket Canyon

Ryan & McMaster Canyons

Emery & Uchupi Canyons

Jones & Babylon Canyons

Hudson Canyon

Mey-Lindenkohl Slope

Spencer Canyon

Wilmington Canyon

North Heyes & South Wilmington Canyons

South Vries Canyon

Baltimore Canyon

Warr & Phoenix Canyon Complex

Accomac & Leonard Canyons

Washington Canyon

Norfolk Canyon

BROAD ZONE

N

0 50 Miles

Map courtesy of
Chris Bruce, The Nature Conservancy

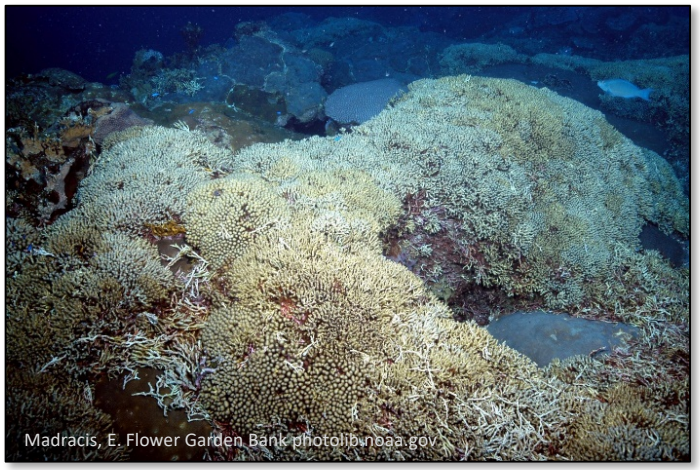
Discrete Zones
Other Canyons*
Broad Zone

*Map includes selected canyons; additional named canyons not shown due to space limitations.

Sources: MAFMC, NOAA, USGS, TNC

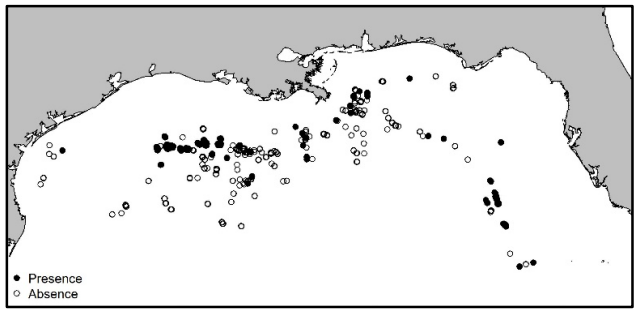
Project Goals and Objectives

- Goal 1: Rescue data
  - Compile presence and **absence** data from surveys
- Goal 2: Improve predictive models and maps
  - Develop and produce **predictive** spatial models to improve region-wide maps of the **distribution** of deepwater coral and chemosynthetic **communities**



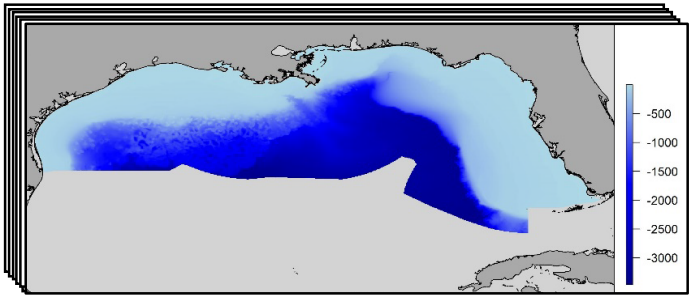
From Etnoyer et al. 2017 report to BOEM

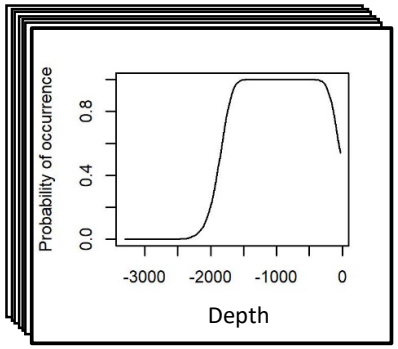
Spatial predictive modeling



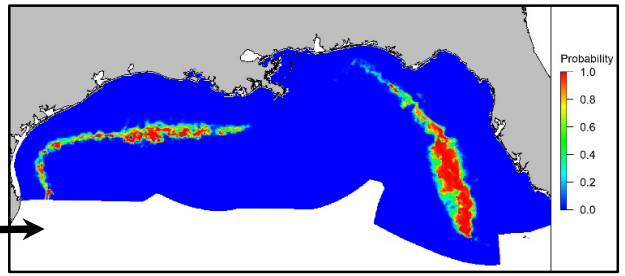
Presence/absence observations

Environmental predictors



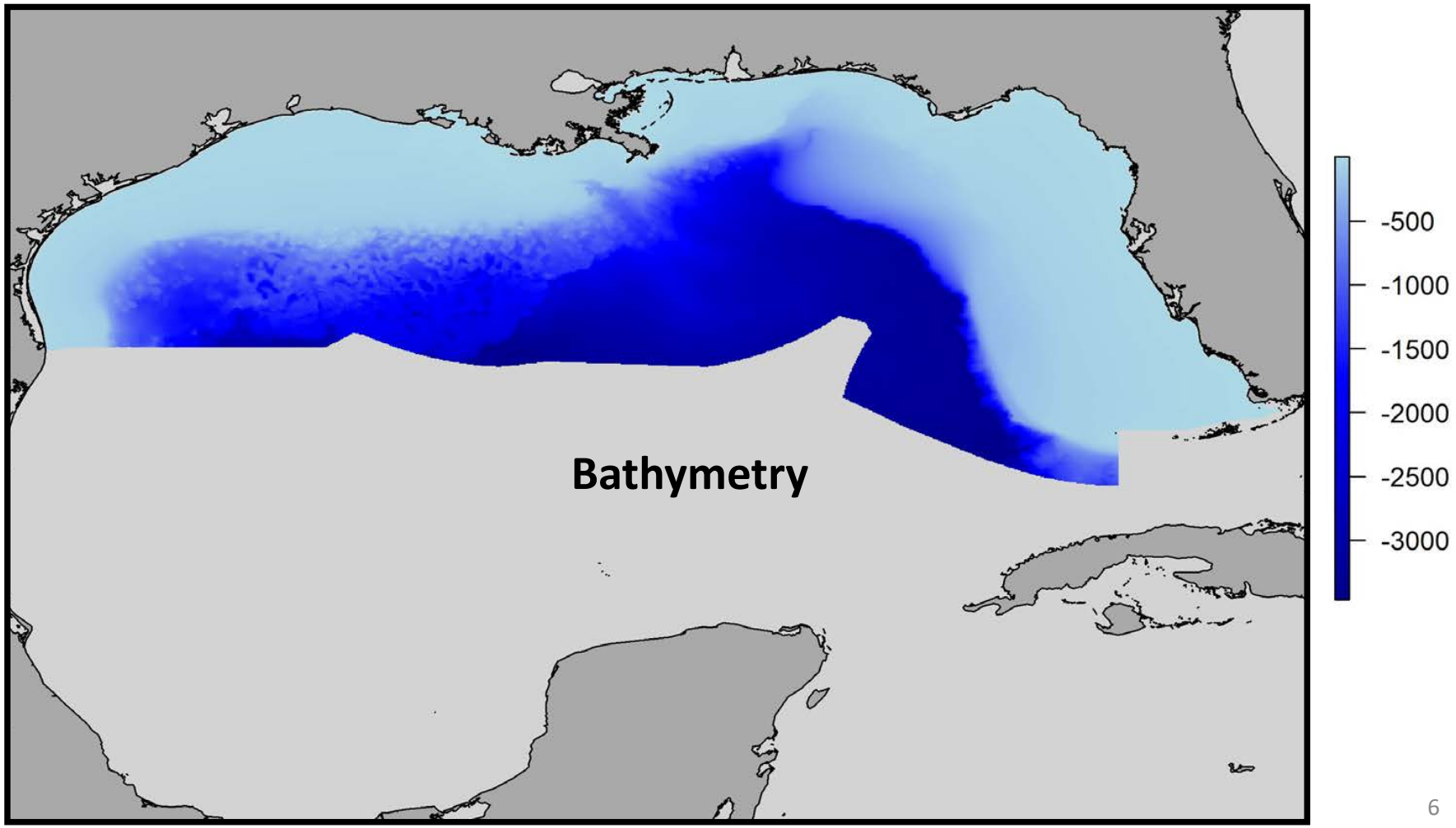


Functional relationships

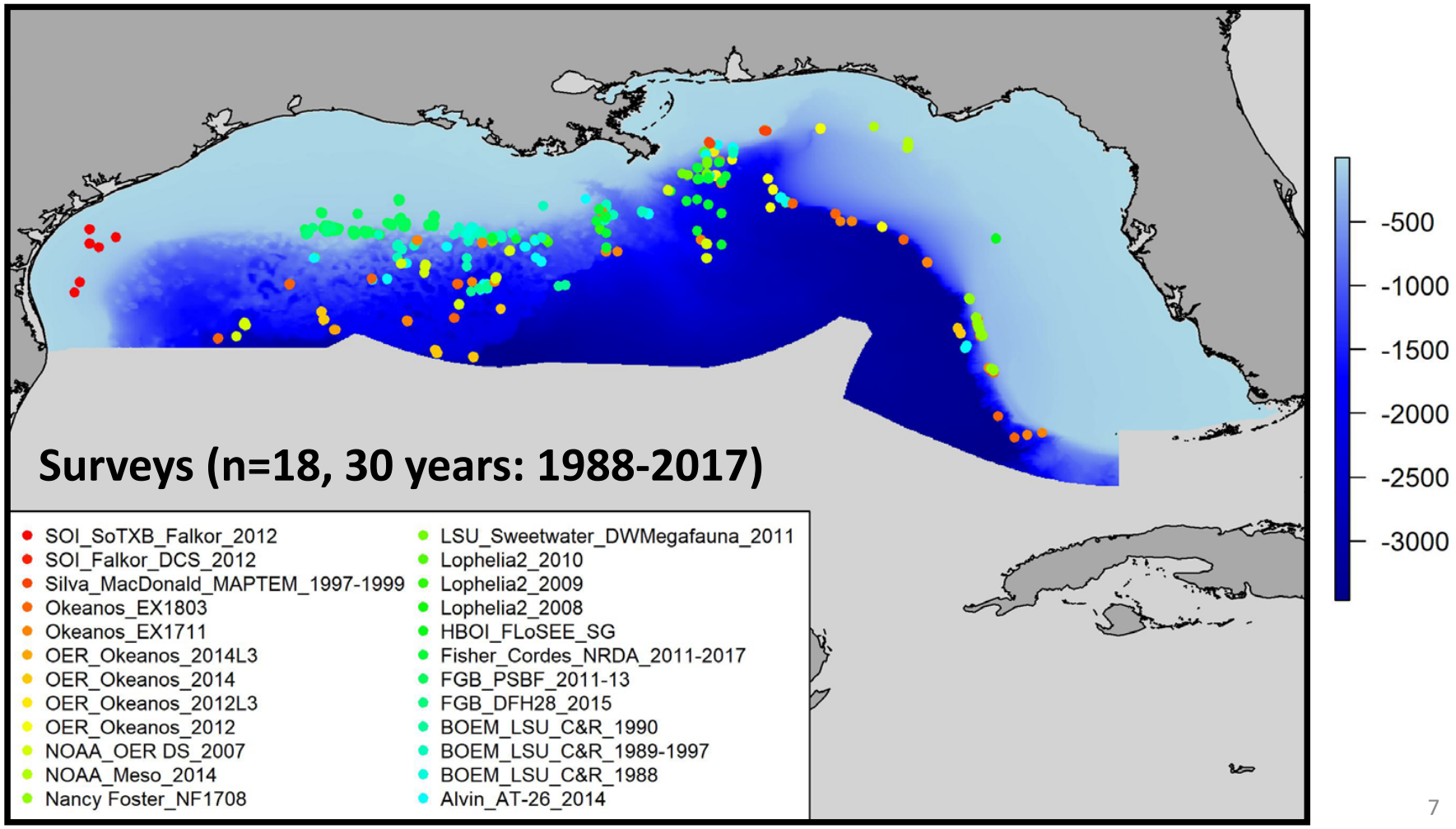


Predicted probability of occurrence

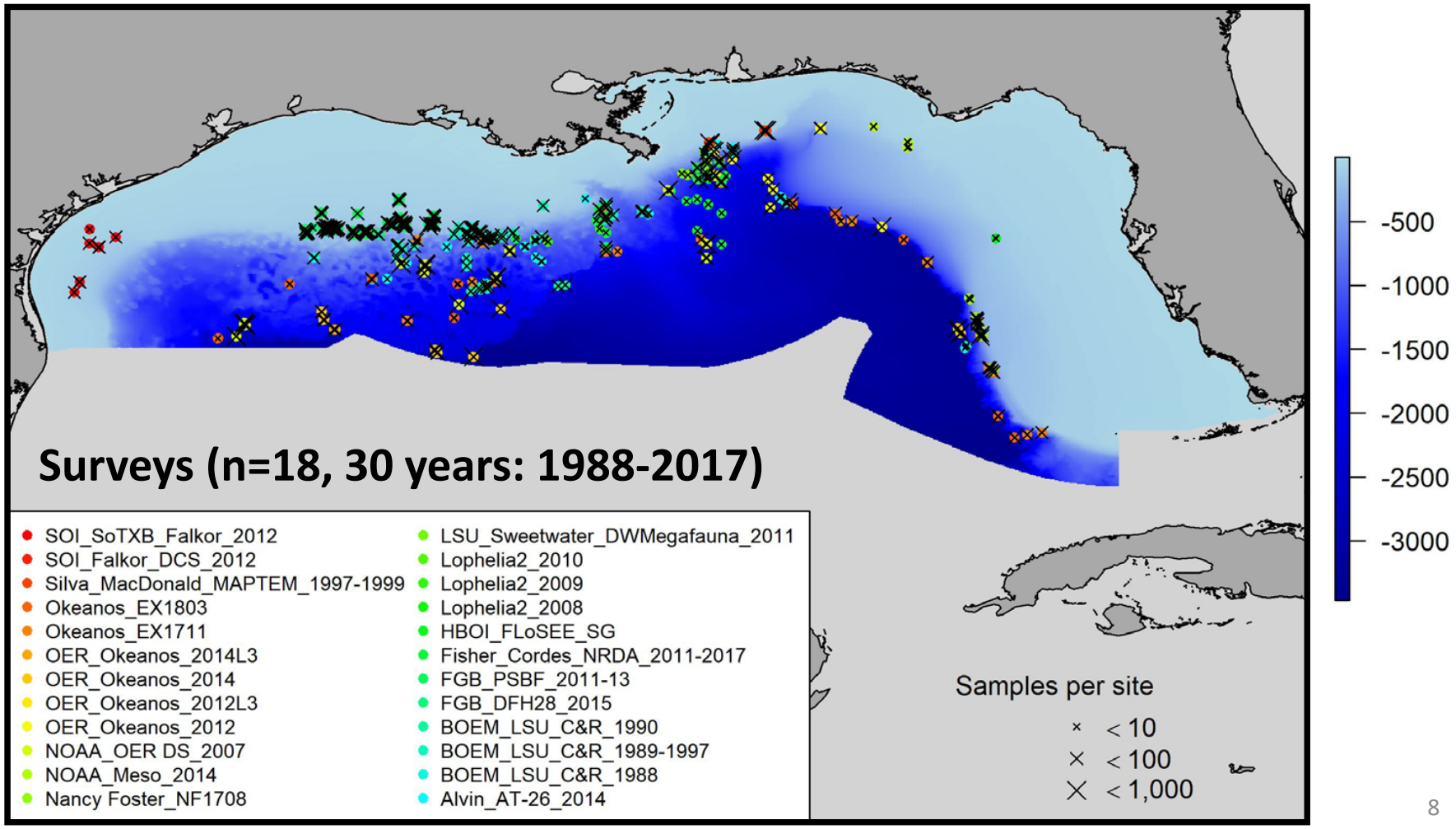
Survey effort



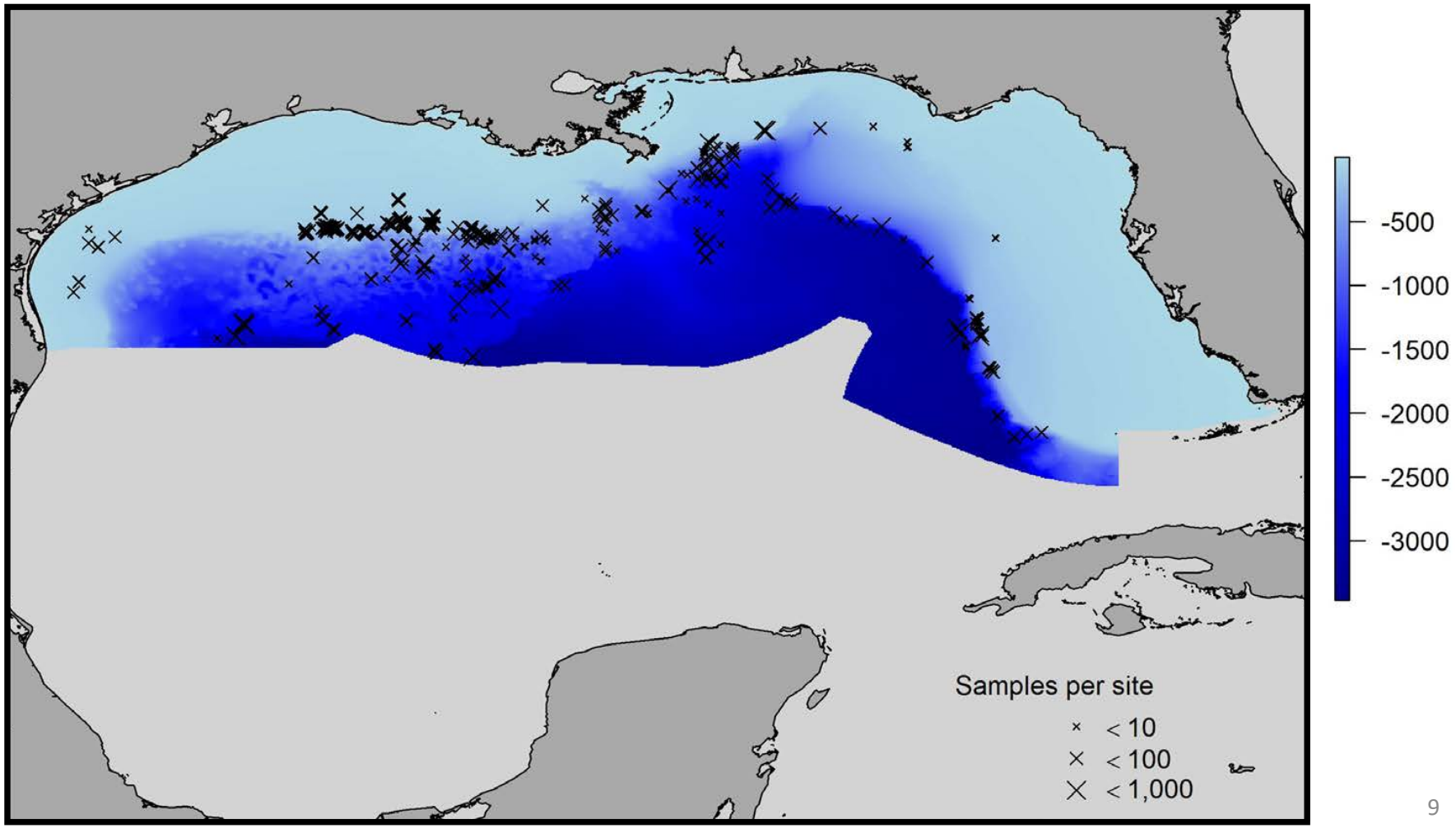
Survey effort



Survey effort



Survey effort



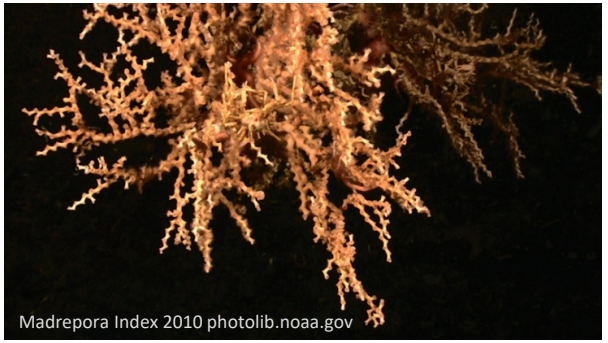
Statistical framework

Within-site variation → "**Detection** Probability" ("Availability Probability")

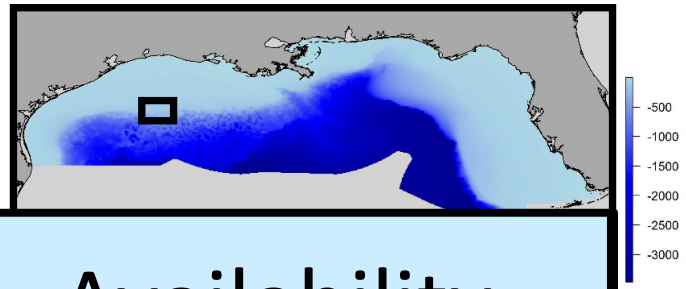
- "replicate" samples
  "space-for-time substitution"

Between-site variation → "**Occupancy** Probability"

- Habitat suitability



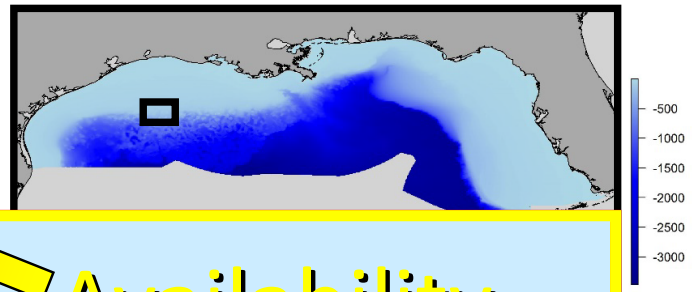
Detection probability



Availability

$$z_1 = 1 = z_2$$
$$y_1 = 0 = y_2$$

Detection probability



Availability

Occupancy probability


How confident are we
that observed absences
are "true" absences?
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Lophelia marinespecies.org

Assumptions of occupancy analysis

1. **No false positives**: species identified with confidence to lowest taxonomic level possible
2. **Closure**: sampling time window short relative to the system dynamics (static)
3. **Independence** of occurrence and detection probability across replicated visits
4. **Homogeneity** of detection probability: eliminate heterogeneity using observation-level covariate on detectability: effort offset

Conservative approach

"If we do not have a balanced design with the same number of replicates at each site, it is best if the number of surveys per site is **randomly allocated** to a site. If it depends instead on some site characteristics, biased estimates may result.

For instance, if multiple surveys are only undertaken at the "**better**" sites, where density and therefore detection probability (*p*) may be higher on average, the resulting estimate of ***p* will be biased high** with respect to all sites and therefore the **occupancy estimator will be biased low**".

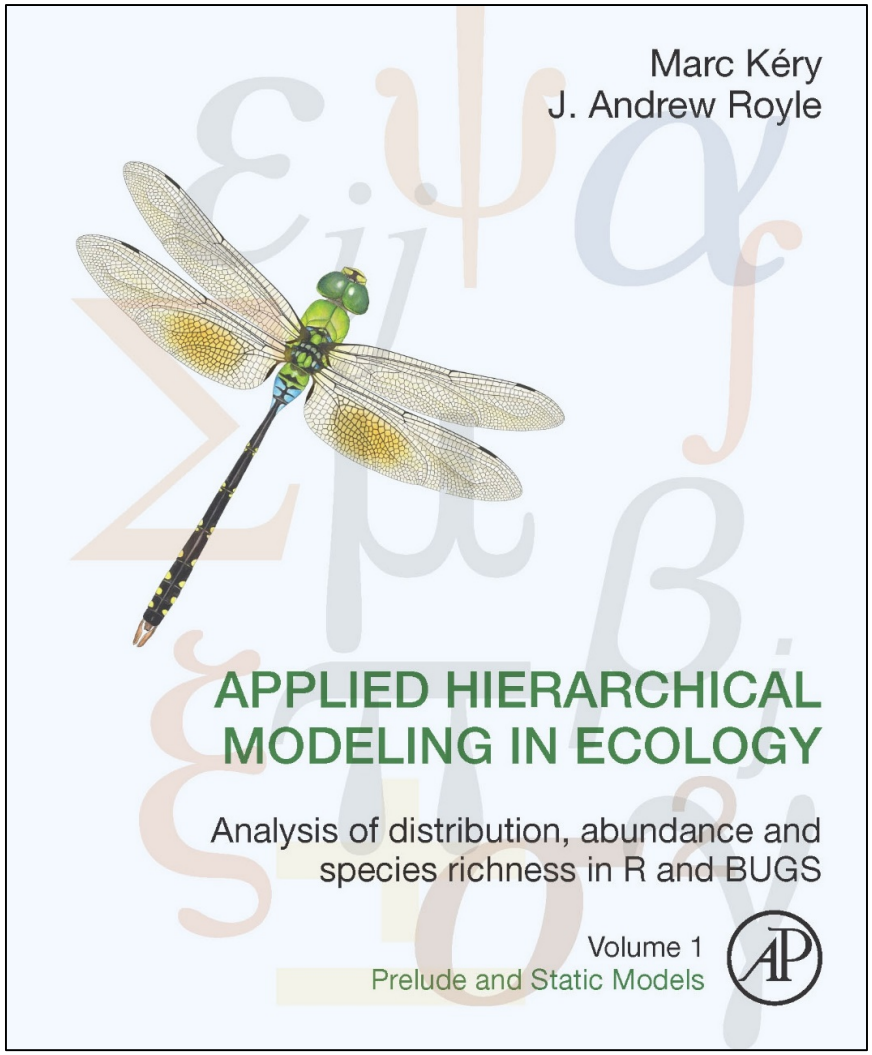
(Kery and Royle 2016, Applied Hierarchical Models in Ecology)

In a conventional model, **occurrence will be biased high**.

Why Occupancy analysis?

- Conservative approach ("false negative" analysis)
- Ability to estimate **true** distribution (standardized)
- Ability to estimate **community** species richness (multiple species/genera combined into single map)

Bayesian hierarchical approach



- Ch. 10 Modeling static occurrence and species distributions using site-occupancy models
- Ch. 11 Hierarchical models for communities

- Observation process (detection)

detection probability

presence/ absence data

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

$$cloglog\left(p_{ijk}\right) = alpha_{0,k} + offset_{ij}$$

detection intercept

effort (area)

i = site
j = occasion
k = species

- State process (occurrence)

occupancy probability

latent state

$$z_{ik} \sim Bernoulli\left(\Psi_{ik}\right)$$

$$cloglog\left(\Psi_{ik}\right) = beta_{0,k} + beta_{1,k} * bathy_i + \ldots$$

- Observation process (detection)

detection probability

presence/ absence data

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

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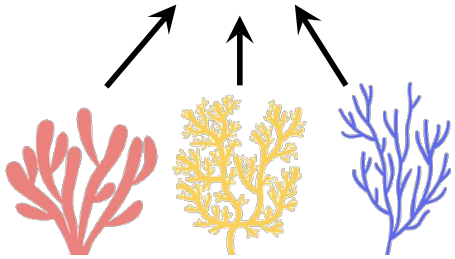
occupancy intercept

$$beta_{0,k} \sim Normal(u_{beta0}, \sigma^2_{beta0})$$



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$$cloglog(\Psi_{ik}) = beta_{0,k} + beta_{1,k} * bathy_i + \ldots$$

occupancy intercept

$$beta_{0,k} \sim Normal(u_{beta0}, \sigma^2_{beta0})$$

$$beta_{1,k} \sim Normal(u_{beta1}, \sigma^2_{beta1})$$

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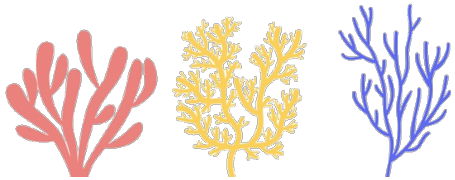
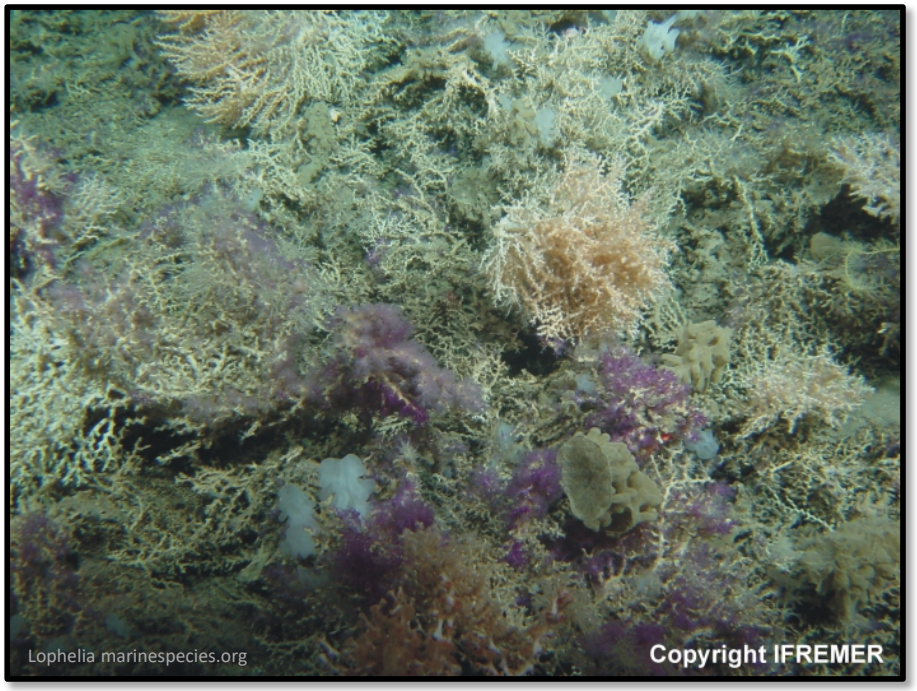


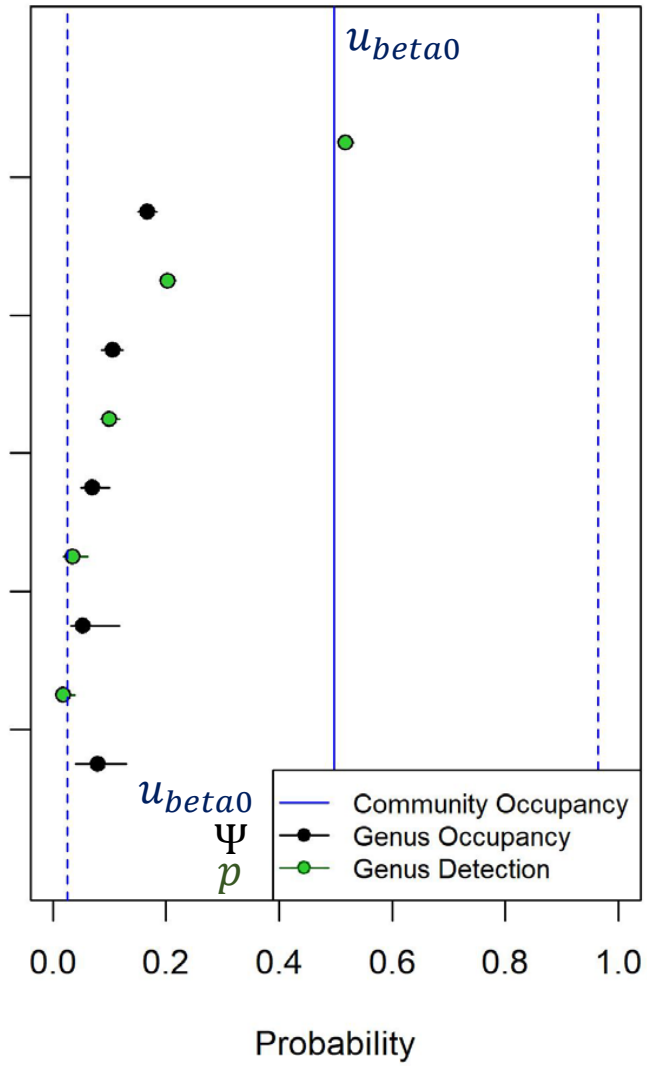
Example community

Branching stony corals: framework-forming Scleractinia

- Madracis
- Lophelia
- Madrepora
- Solenosmilia
- Enallopsammia



Occupancy & Detection Probability



Madracis n = 118 sites; 426 obs

Lophelia n = 84 sites; 347 obs

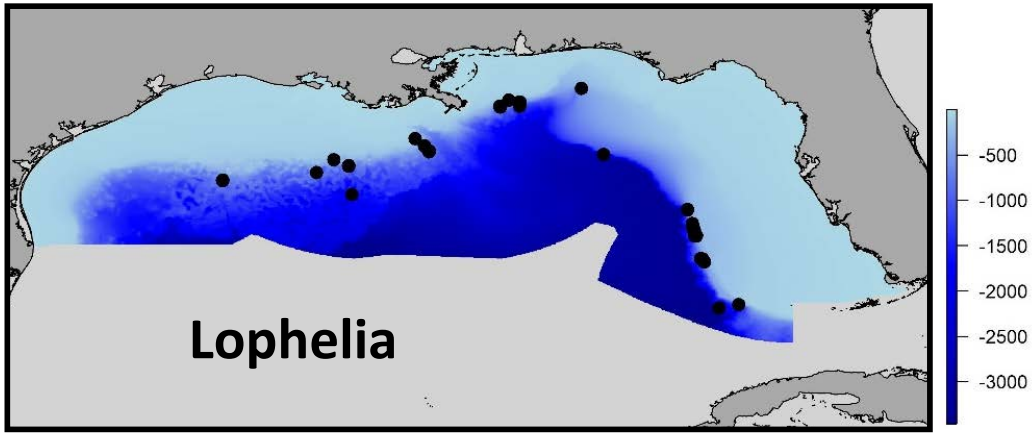
Madrepora n = 33 sites; 99 obs

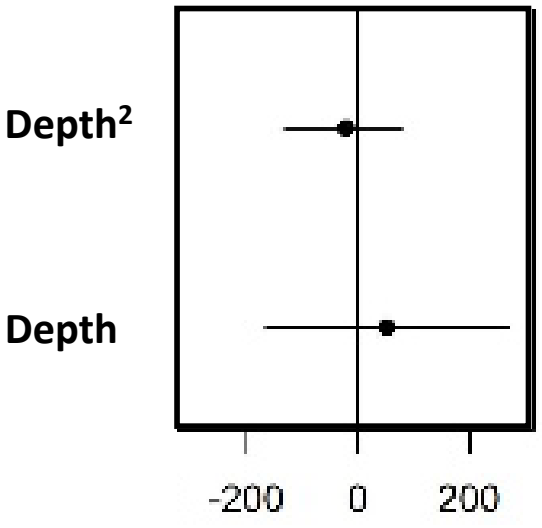
Solenosmilia n = 14 sites; 27 obs

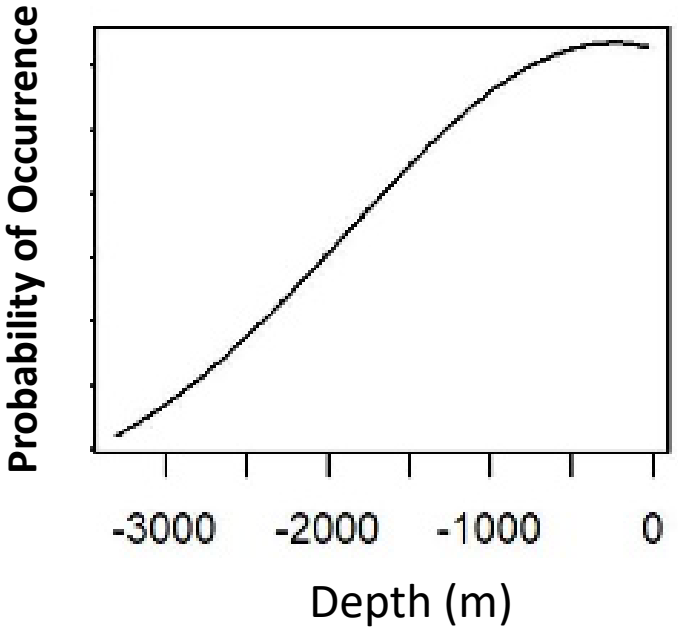
Enallopsammia n = 12 sites; 24 obs

N = 968 sites; 23,724 obs

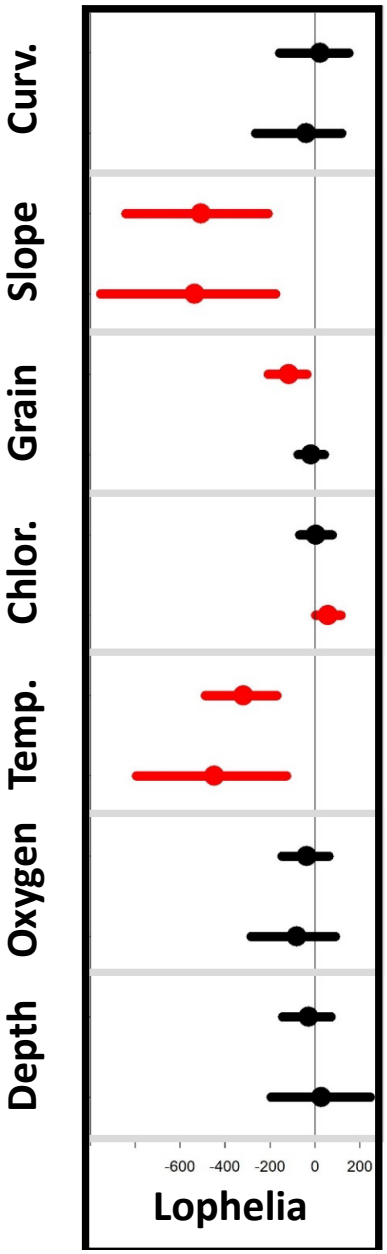
Covariate effects: genus-level

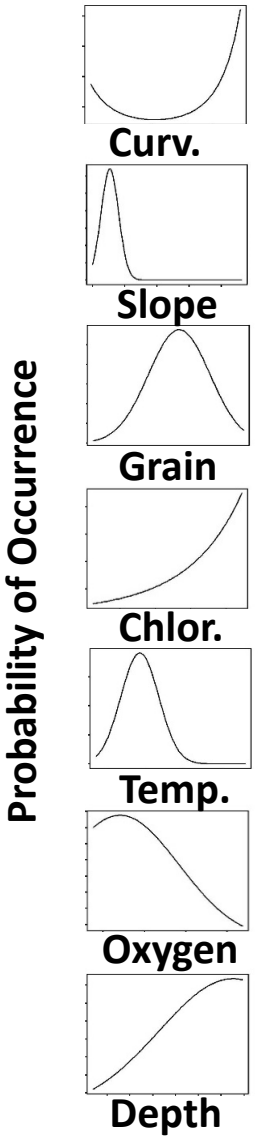


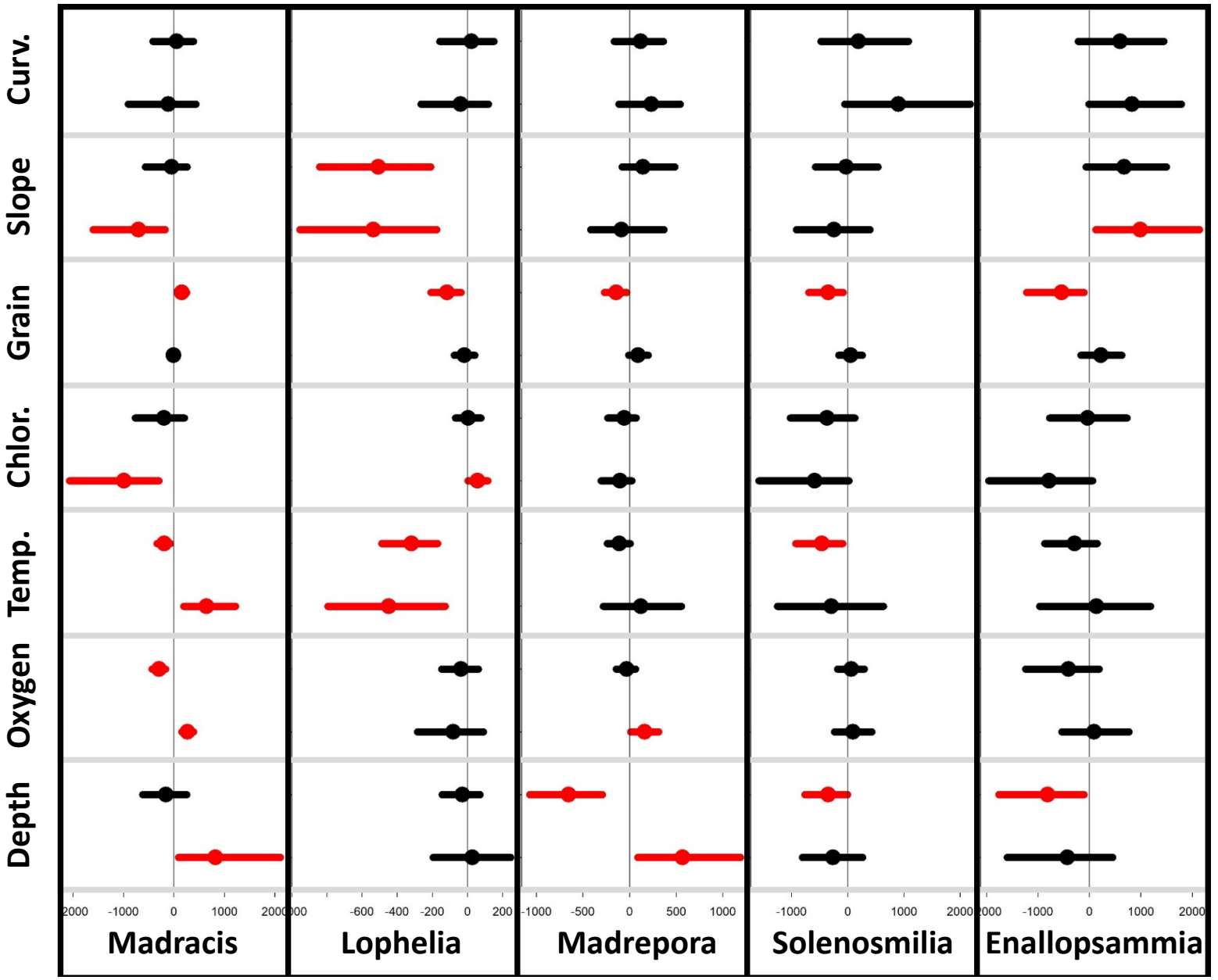




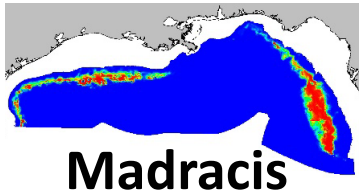
Covariate effects: genus-level



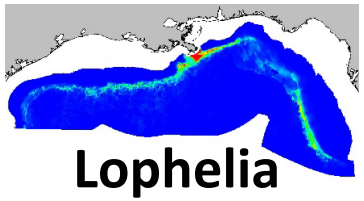



Curv.
Slope
Grain
Chlor.
Temp.
Oxygen
Depth
2000 -1000 0 1000 2000
000 -600 -400 -200 0 200
-1000 -500 0 500 1000
-1000 0 1000 2000
2000 -1000 0 1000 2000
Madracis
Lophelia
Madrepora
Solenosmilia
Enallopsammia

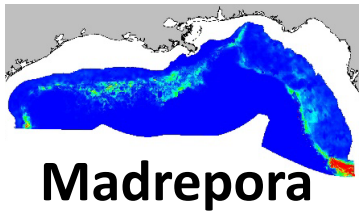
Framework-forming genus richness



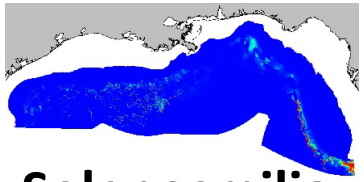
Madracis



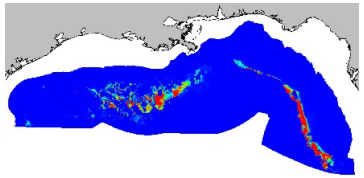
Lophelia



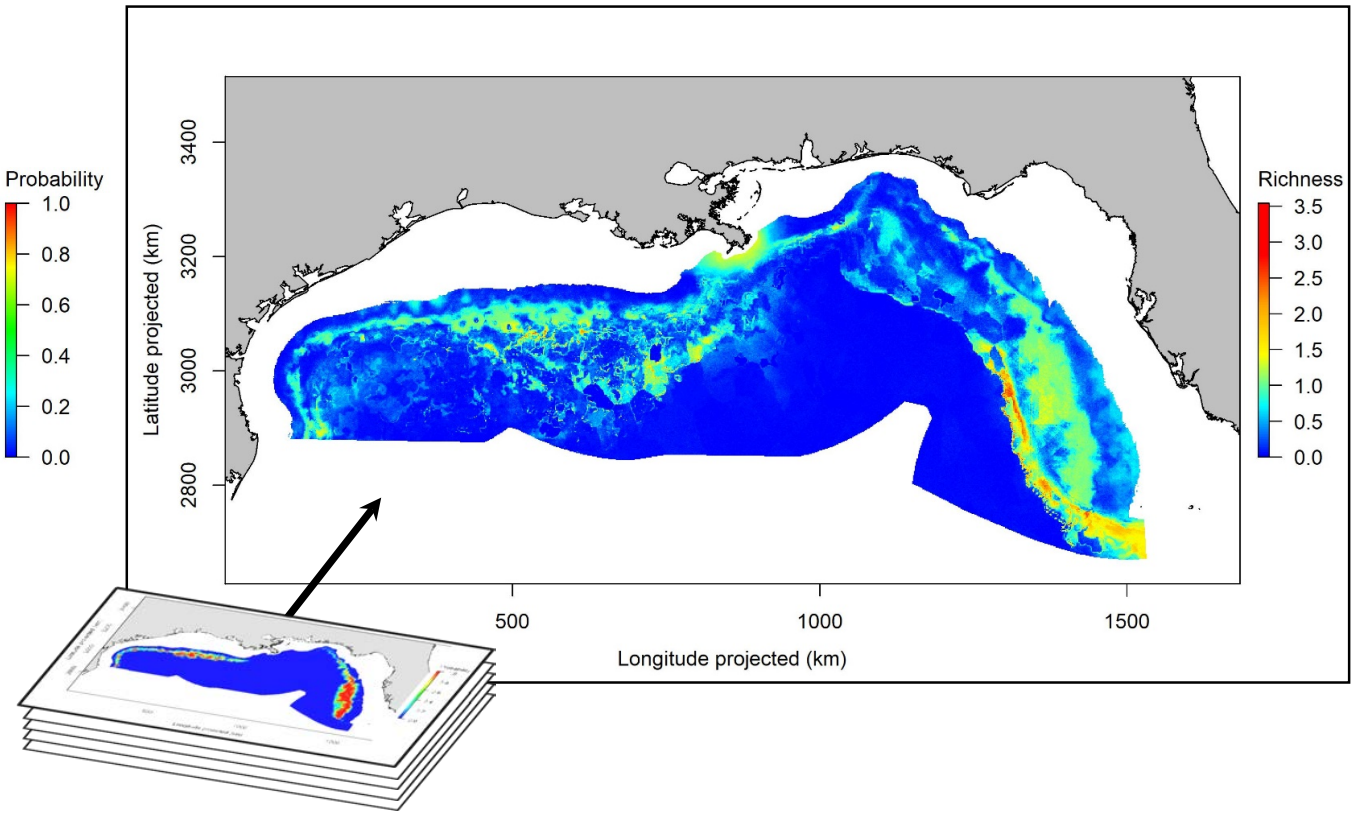
Madrepora



Solenosmilia

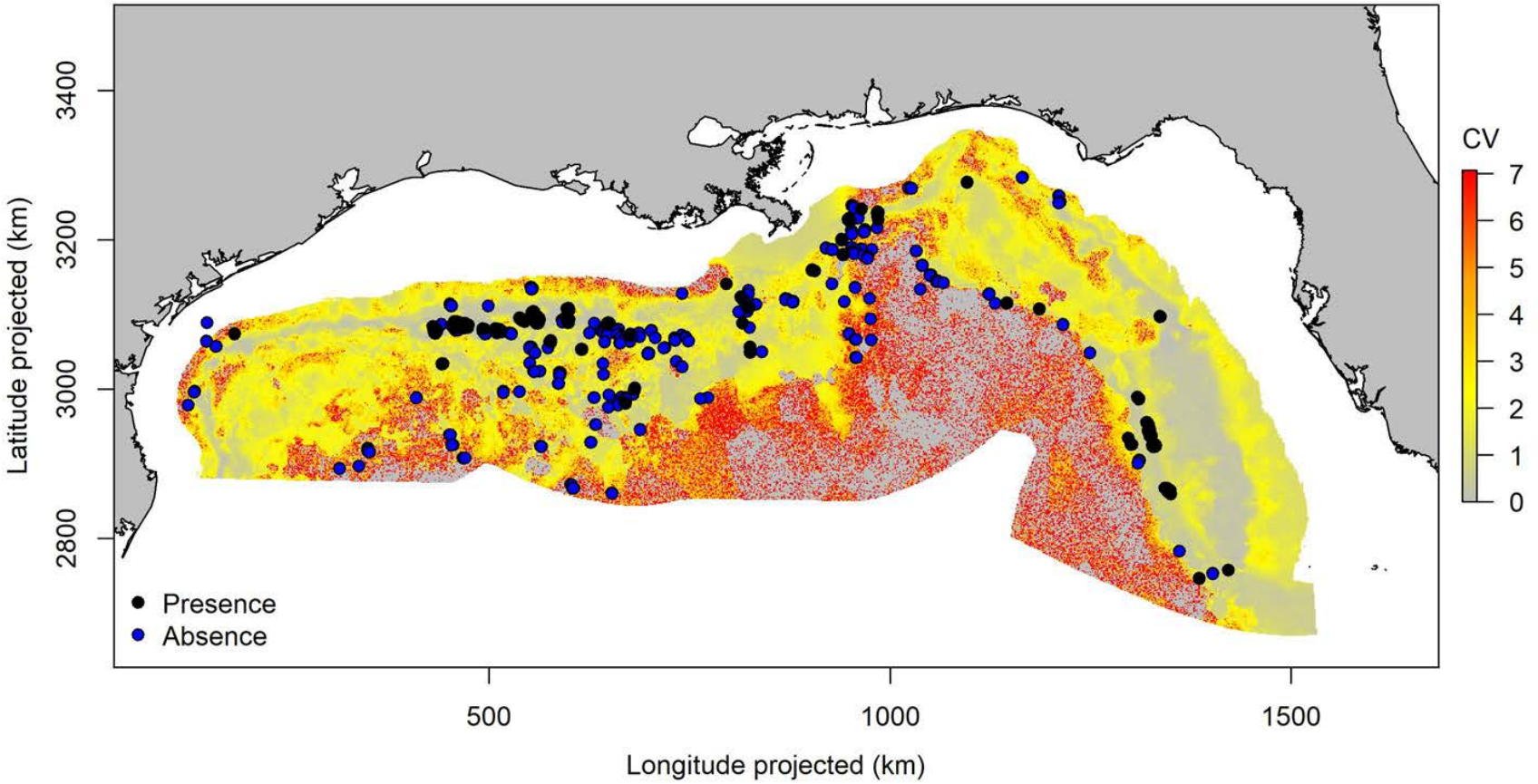


Enallopsammia

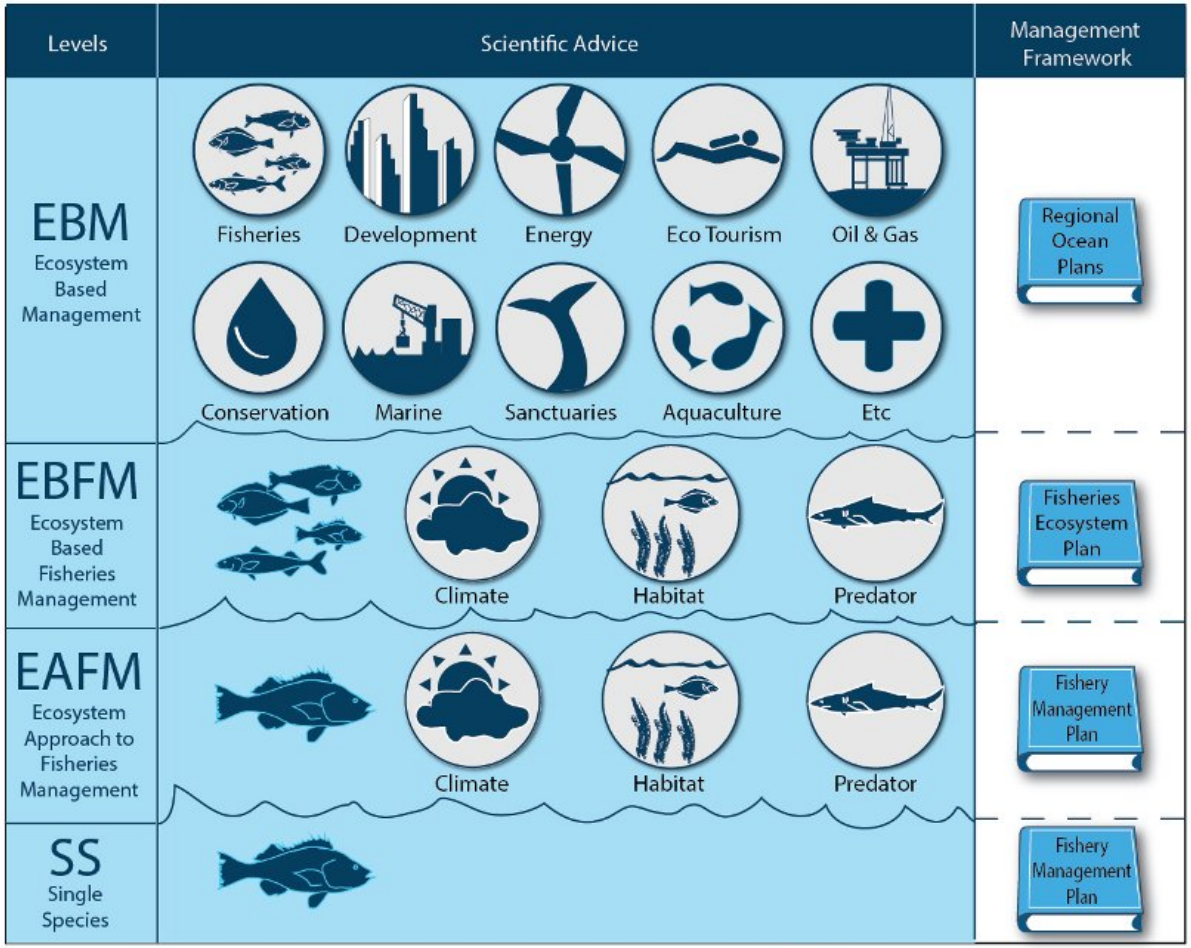


*Draft results for demonstration only

Uncertainty



Management applications



https://www.st.nmfs.noaa.gov/ecosystems/ebfm/ebfm-levels

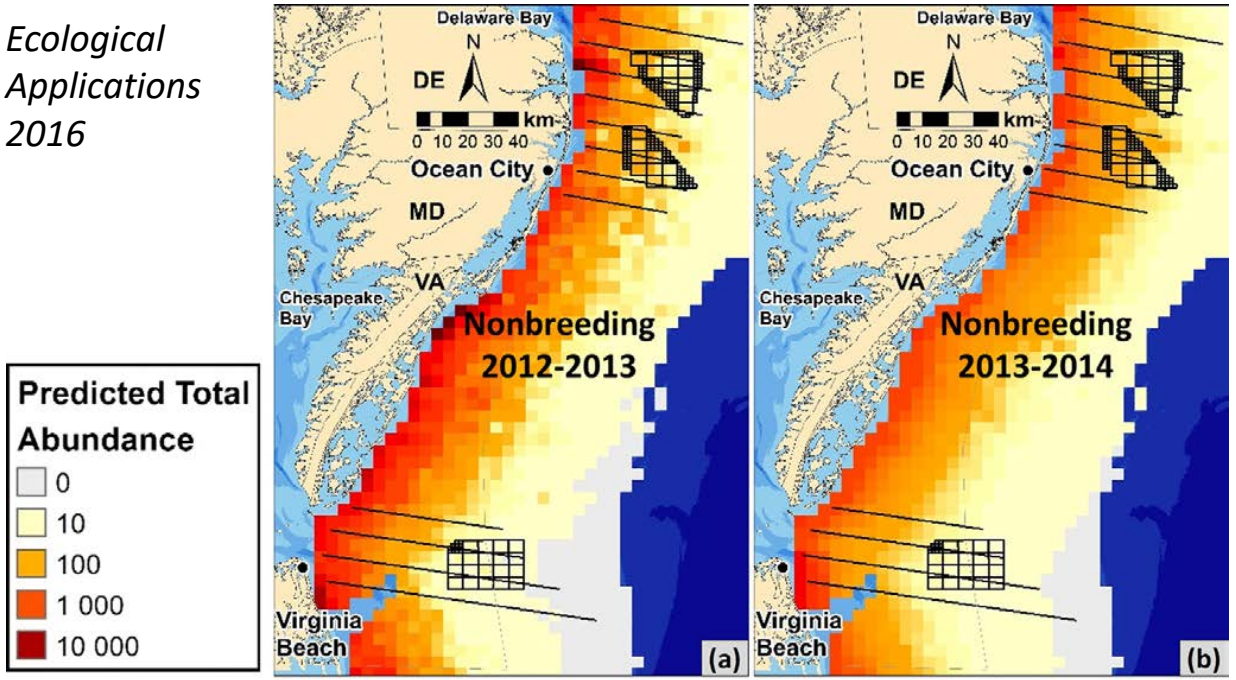
NOAA FISHERIES

Other management applications

Predicting the offshore distribution and abundance of marine birds with a hierarchical community distance sampling model

Holly F. Goyert,[1,4] Beth Gardner,[1] Rahel Sollmann,[1] Richard R. Veit,[2] Andrew T. Gilbert,[3] Emily E. Connelly,[3] and Kathryn A. Williams[3]

Ecological Applications 2016



Next steps

- Further model diagnostics
- Model selection/averaging


Lophelia coastalscience.noaa.gov/news/kinlan-tribute/

Acknowledgments

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BOEM Bureau of Ocean Energy Management

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Biogeography Branch

Chris Jeffrey
Michael Coyne
Bethany Williams
Brian Kinlan

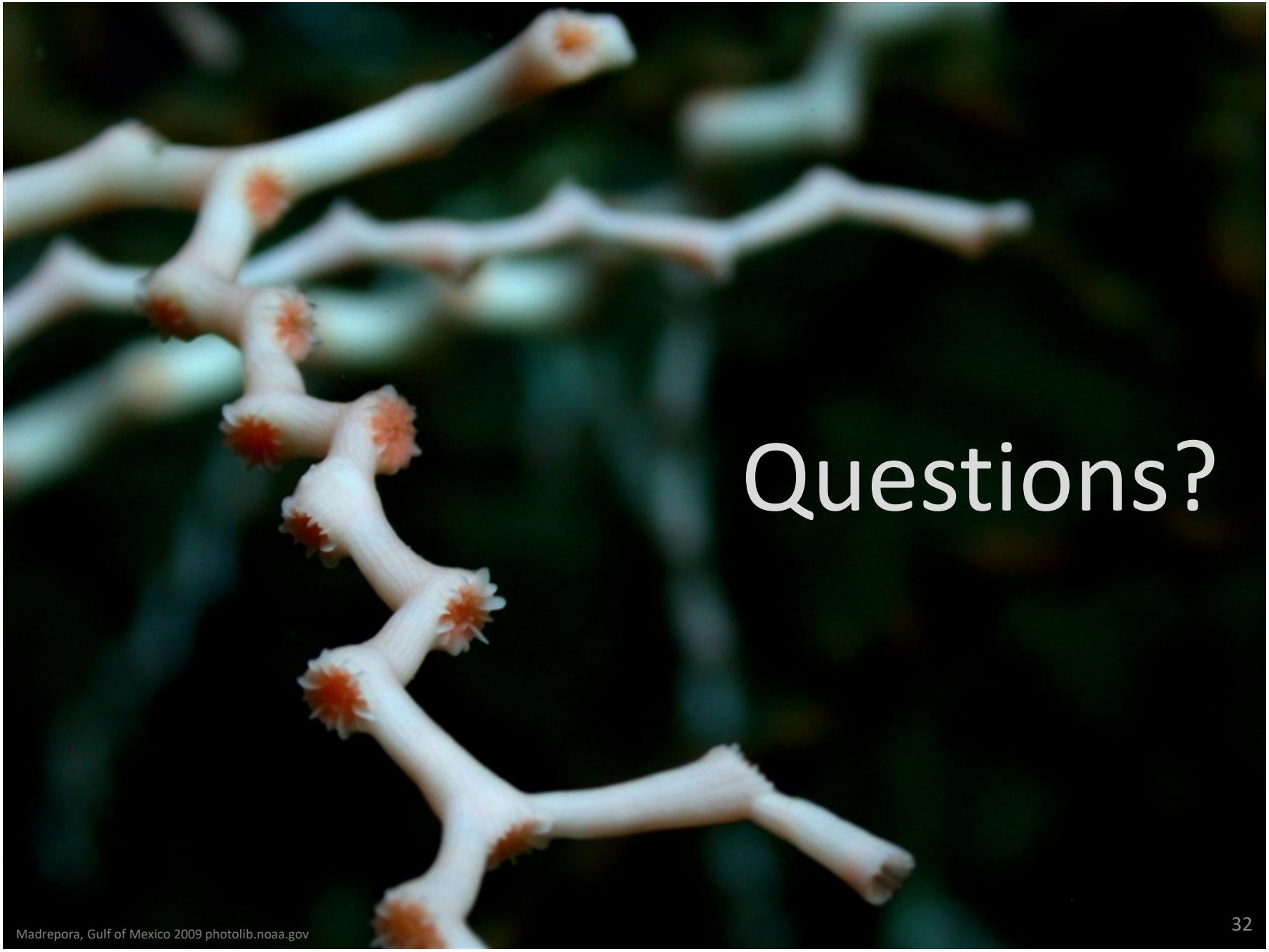
CSS 30 Years Our Future Is Bright

Deep Coral Research & Technology Program

Tom Hourigan
Heather Coleman

Dave Moran
Mark Mueller
Michelle Nannen


Solenosmilia, Lophelia, Oceanographer 2013 photolib.noaa.gov



Madrepora, Gulf of Mexico 2009 photolib.noaa.gov