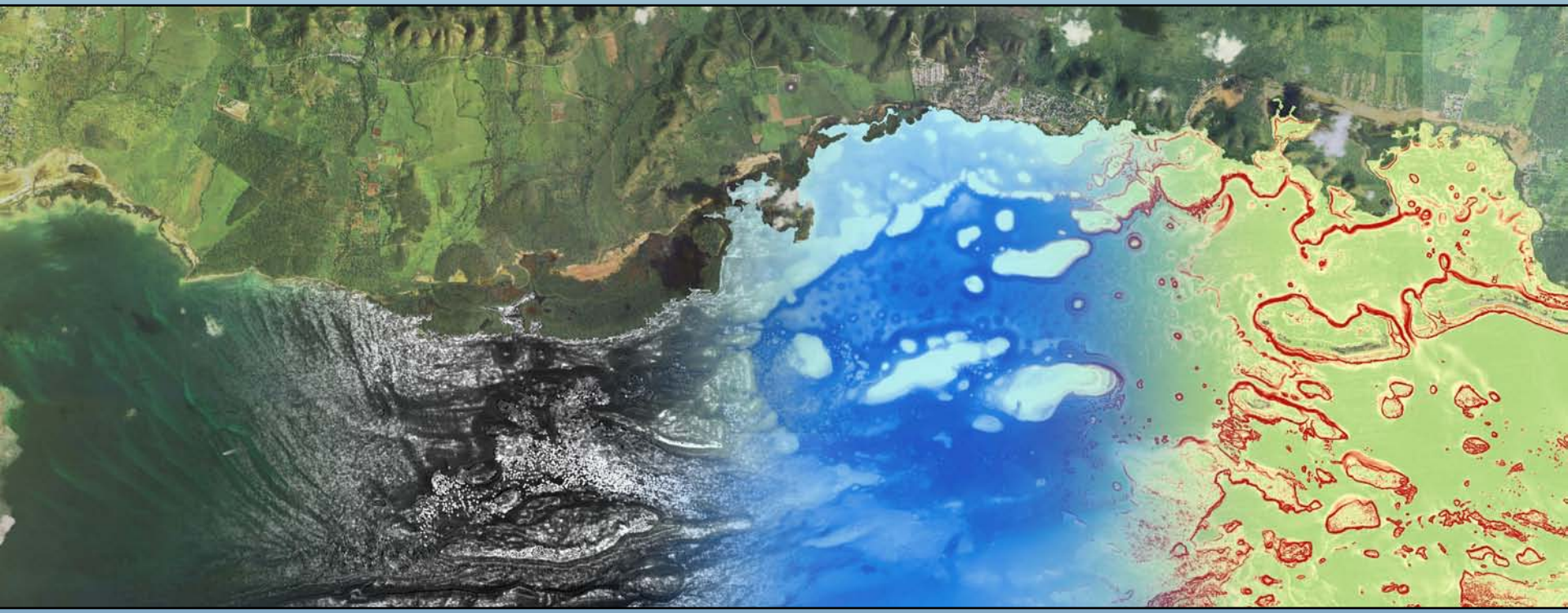
Measuring the rough with the smooth:

Using LiDAR bathymetry to predict fish & coral distributions



Bryan Costa, Simon Pittman & Tim Battista
NOAA CCMA Biogeography Branch

http://ccma.nos.noaa.gov/about/biogeography/

AGENDA

Part 1 - Background

- Explain how bathymetric LiDAR is acquired
- Describe study area
- Discuss importance of study

Part 2 - Methods

- Integration of biological & physical datasets

Part 3 - Analysis

- Summarize key results
- Provide concluding remarks

Part 1

What is LiDAR?

Light Detection And Ranging

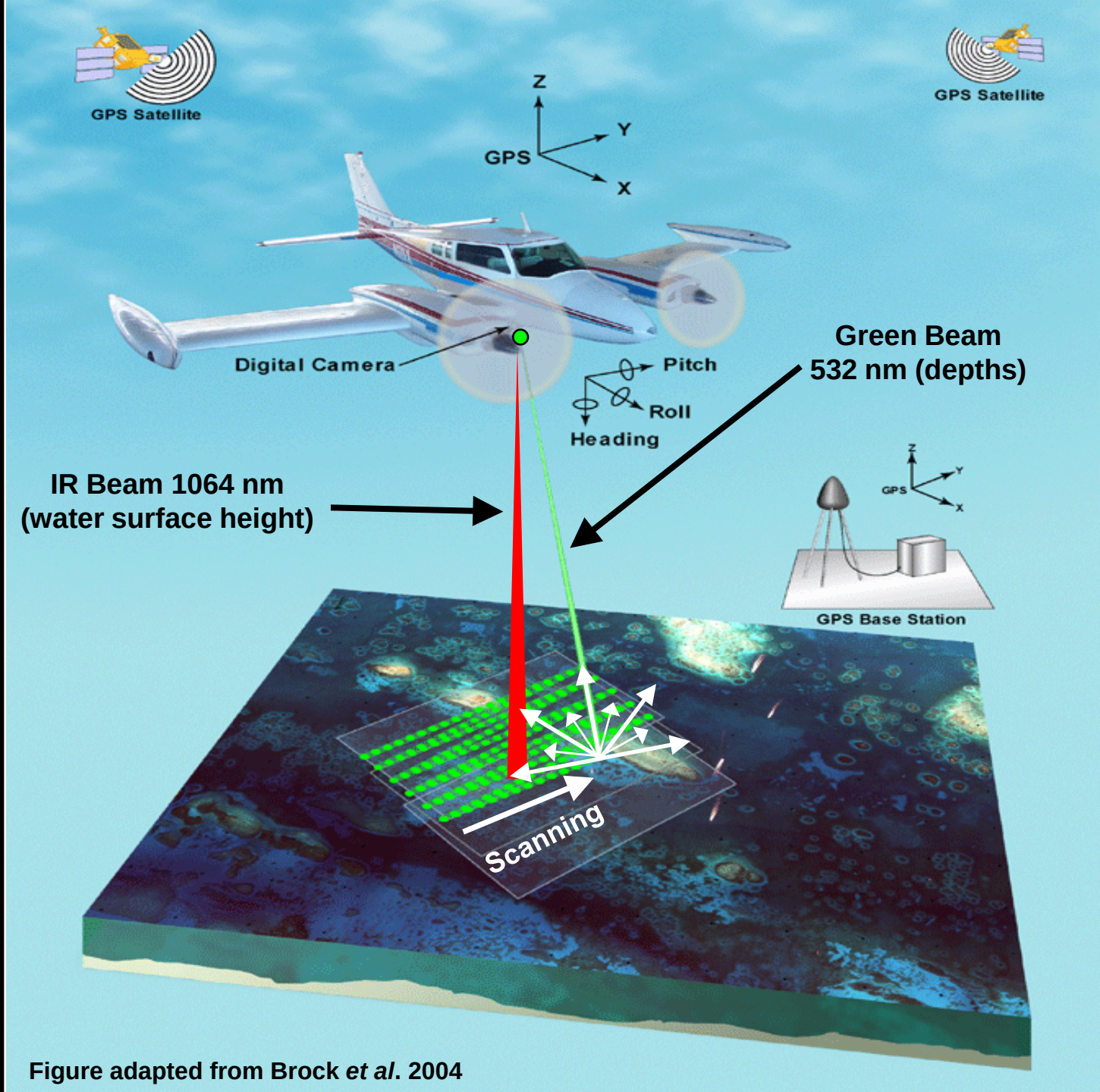
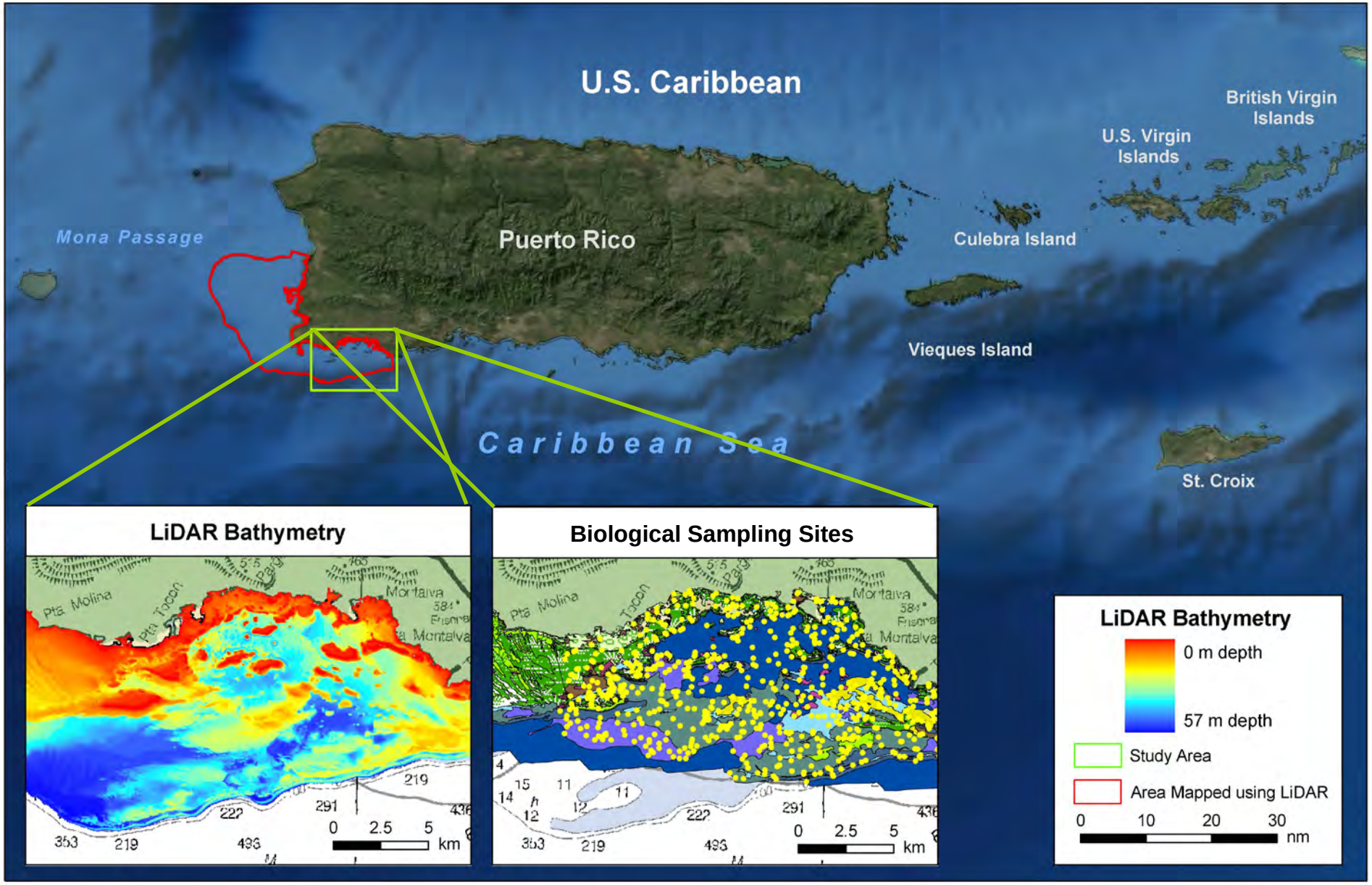


Figure adapted from Brock *et al*. 2004

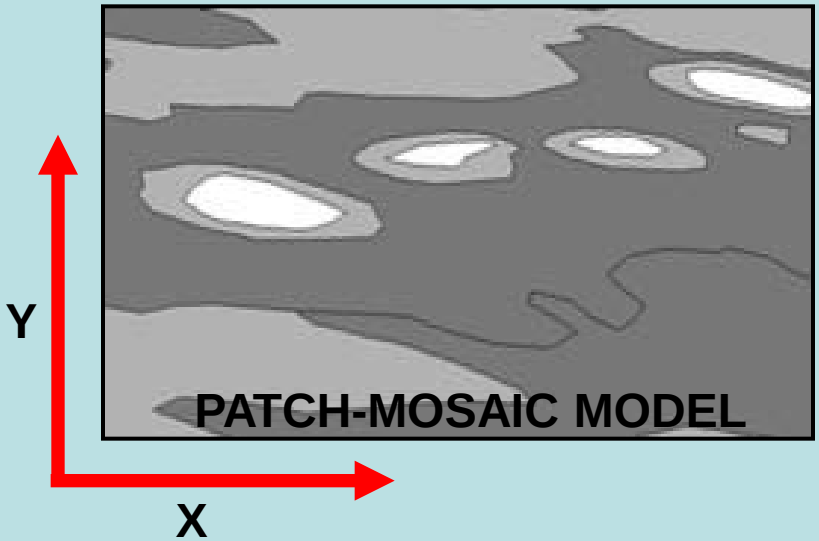
Part 1 : Study Area (SW Puerto Rico)

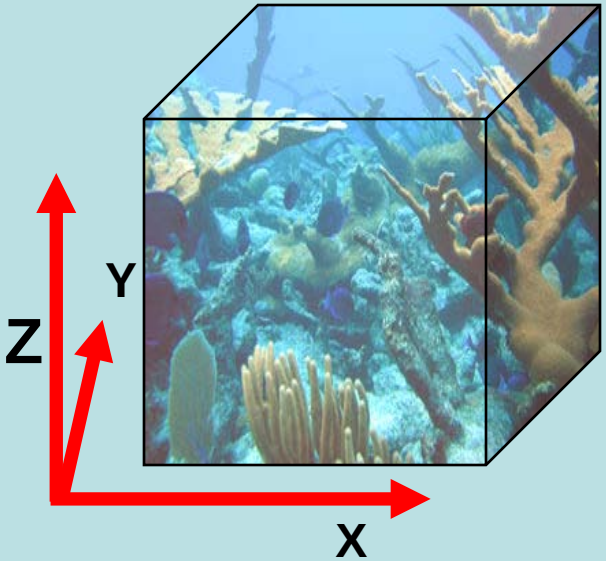


PART 1 : Mapping Seascapes for Ecological Studies

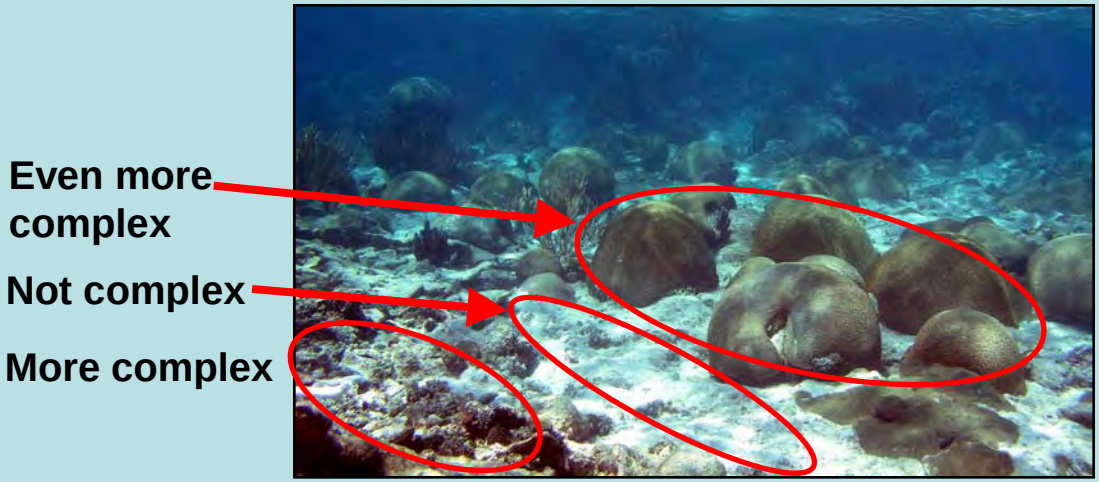
A.) CONVENTIONAL 2D APPROACH

- Passive optical sensors
- 2D thematic map
  - Homogeneous patches
  - Discrete patch boundaries
- Ecologically meaningful?





Vertical heterogeneity important



Habitat gradients important

PART 1 : Mapping Seascapes for Ecological Studies

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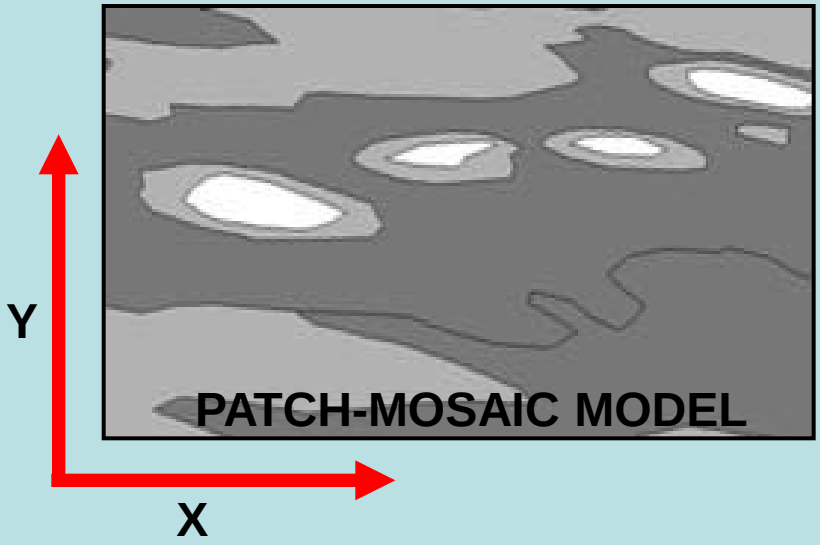
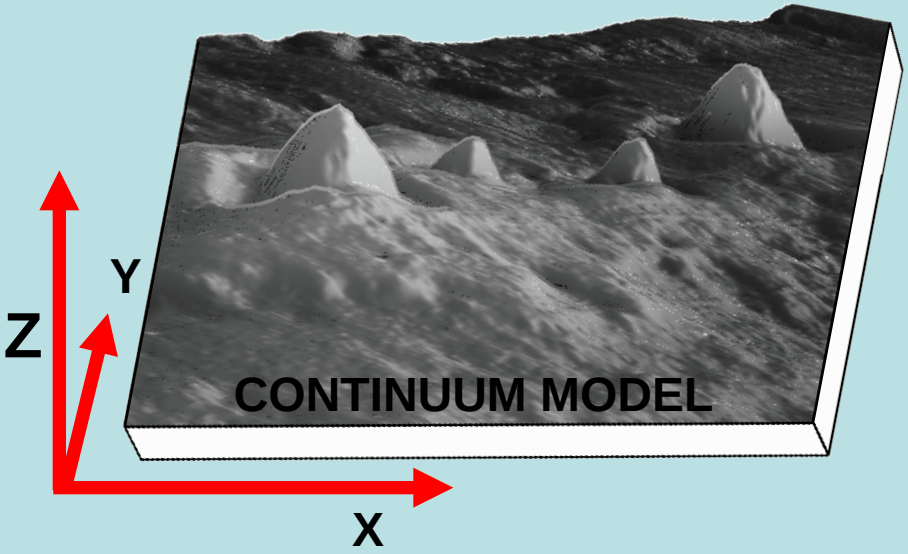
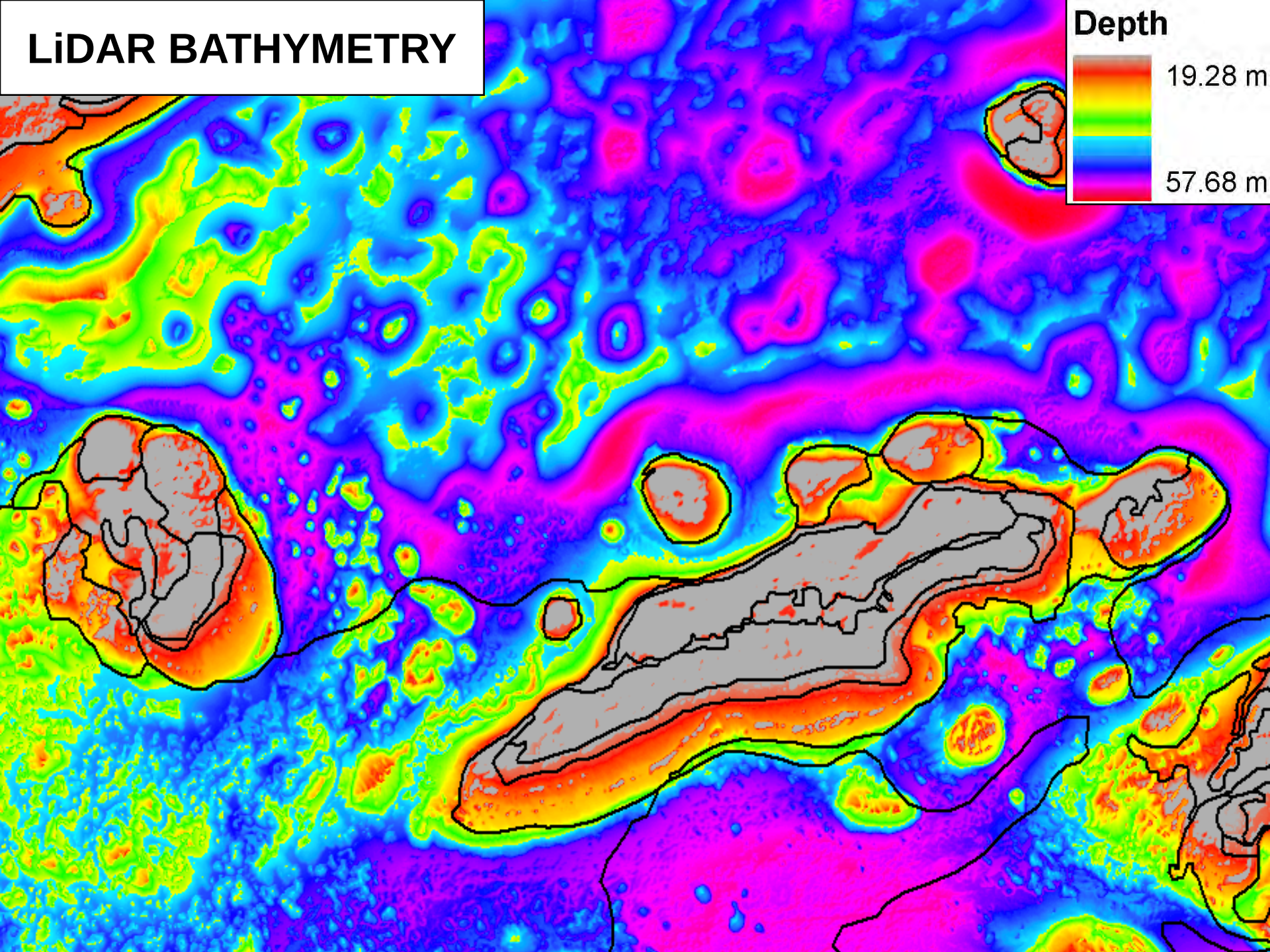


B.) 3D SPATIAL GRADIENTS

- Active optical & acoustic
- Continuous topography
- No patch boundaries
- cm - meters resolution
- Ecologically meaningful?



LiDAR BATHYMETRY

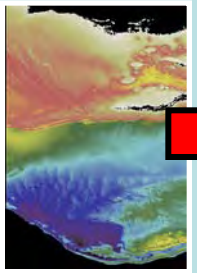


Part 1 : Research Questions

- Is LiDAR bathymetry useful for predicting the diversity & abundance of fish & corals?
- Which morphometric(s) are the best predictors for fish & corals?
- Which spatial scales are most influential?

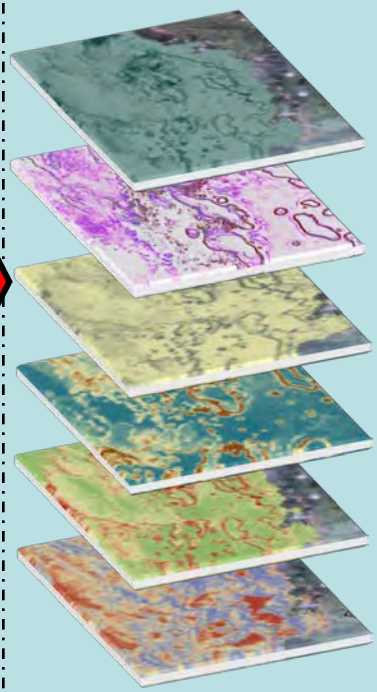
PART 2 : Quantifying Substratum Morphology

LiDAR Bathymetry



4 x 4 m

1. Apply morphometrics



SD of depth

Rugosity

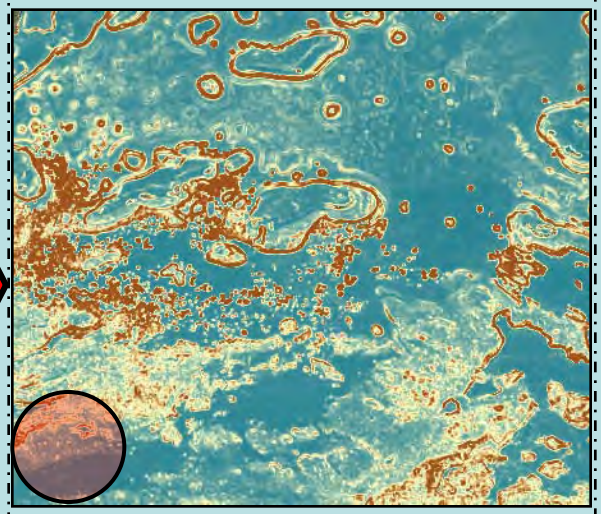
Slope

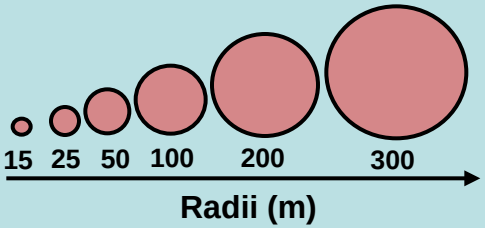
Slope of slope

Fractal *D*

Curvature

2. Quantify metrics at multiple spatial scales

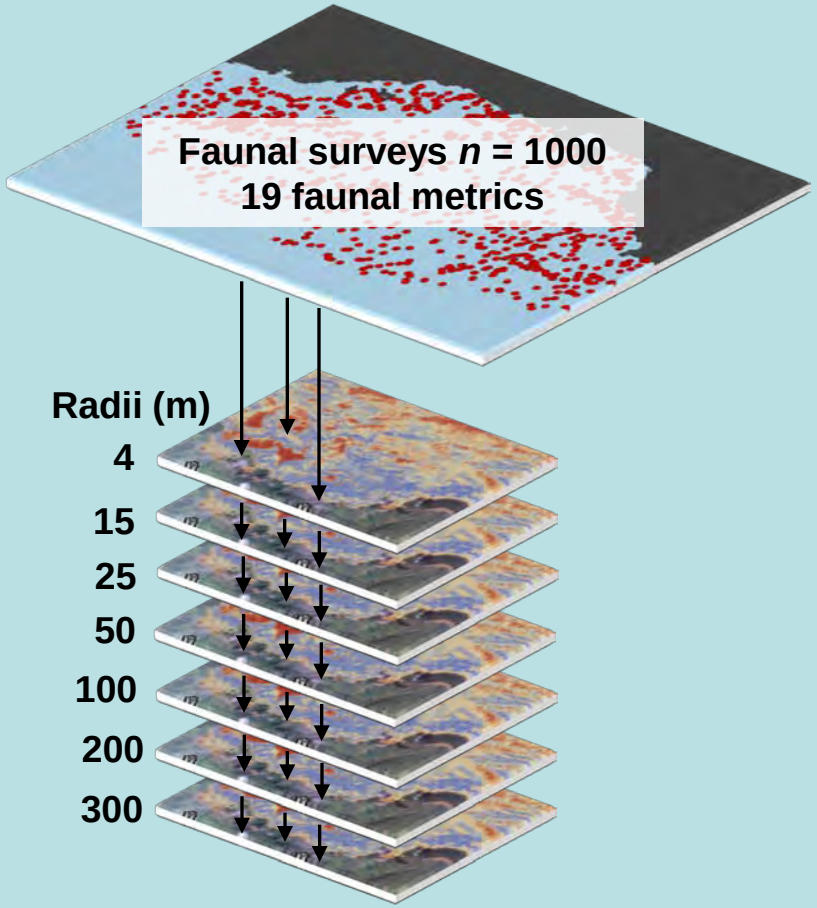




= 42 Spatial predictors

Pittman *et al*. 2007, Ecological Modeling 204, 9-21

Part 2 : Assembling response/predictor variables



Multiscale morphometric surfaces n=42

Fish assemblages

Species richness
Abundance
Biomass

Herbivores & piscivores

Species richness
Abundance
Biomass

Parrotfish & grouper

Biomass

Coney, three spot damsel & blue tang

Abundance
Biomass

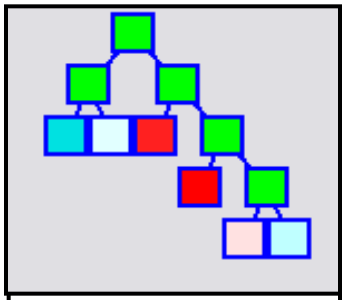
Scleractinian corals

Species richness
Abundance

Part 2 : Predictive modeling using TreeNet™
(Boosted Regression Trees)

- **New nonparametric, non-linear approach to machine learning**
- **Lots of small trees (100s - 1000s) grown sequentially**
- **New tree learns from failings of previous tree to boost final model**

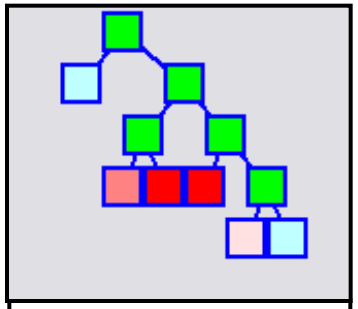
Tree 1



First tree intentionally "weak"

+

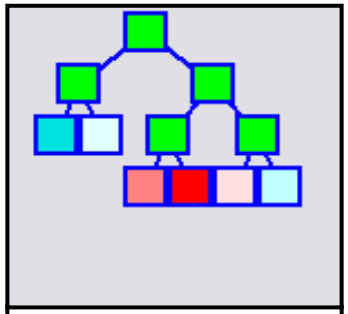
Tree 2



2nd tree predicts residuals from first tree

+

Tree 3



3rd tree predicts residuals from Tree 1 & 2

+?

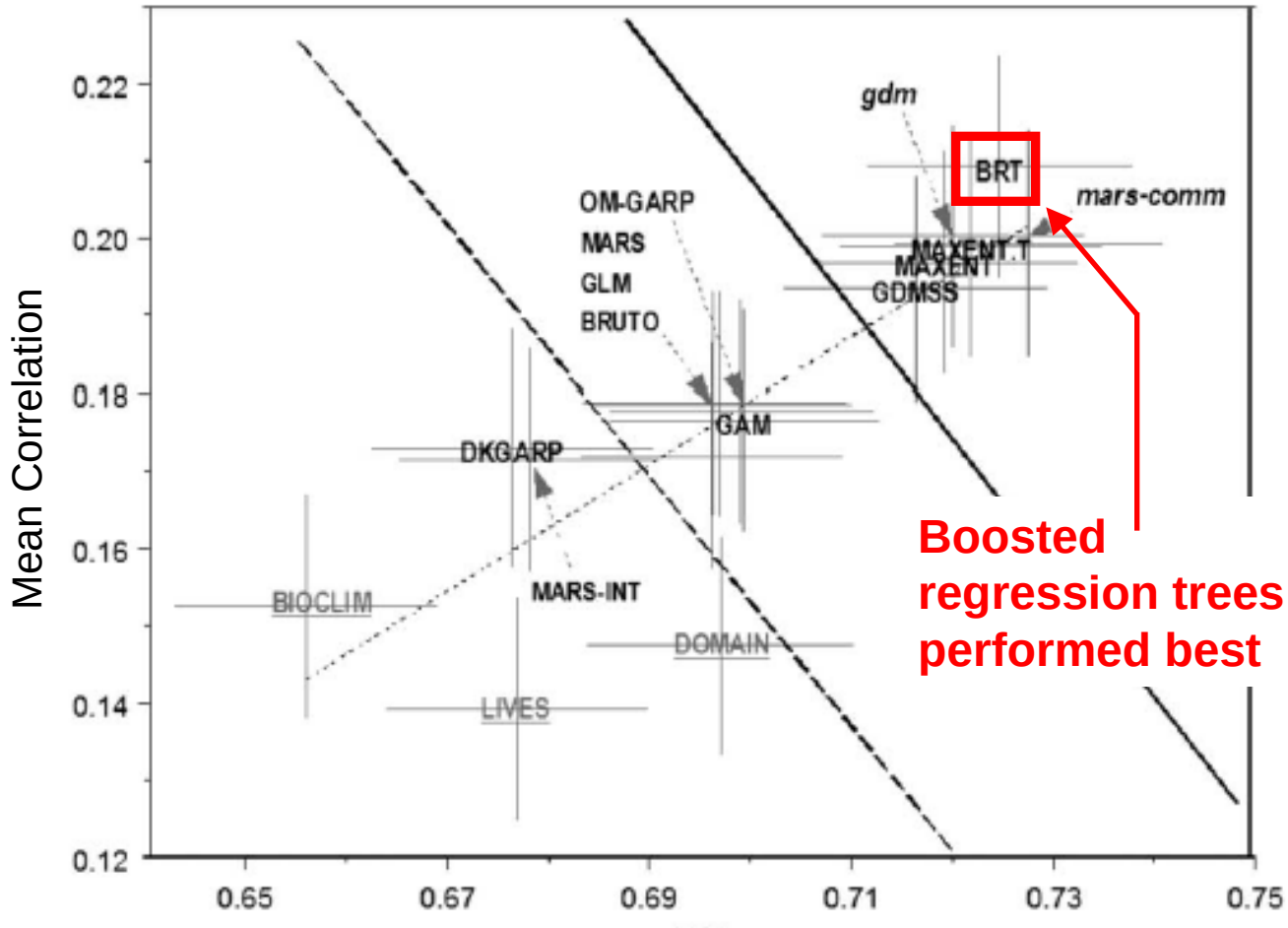
Tree ensemble method of boosting

TreeNet™ developed by Jerry Friedman, 1999 (Stanford University)

Part 2: Comparing Models

Compared 16 modeling techniques using 226 species from 6 regions

Elith et al. 2006. Ecography. 29:2



(AUC) Area Under the Receiver Operating Characteristic Curve

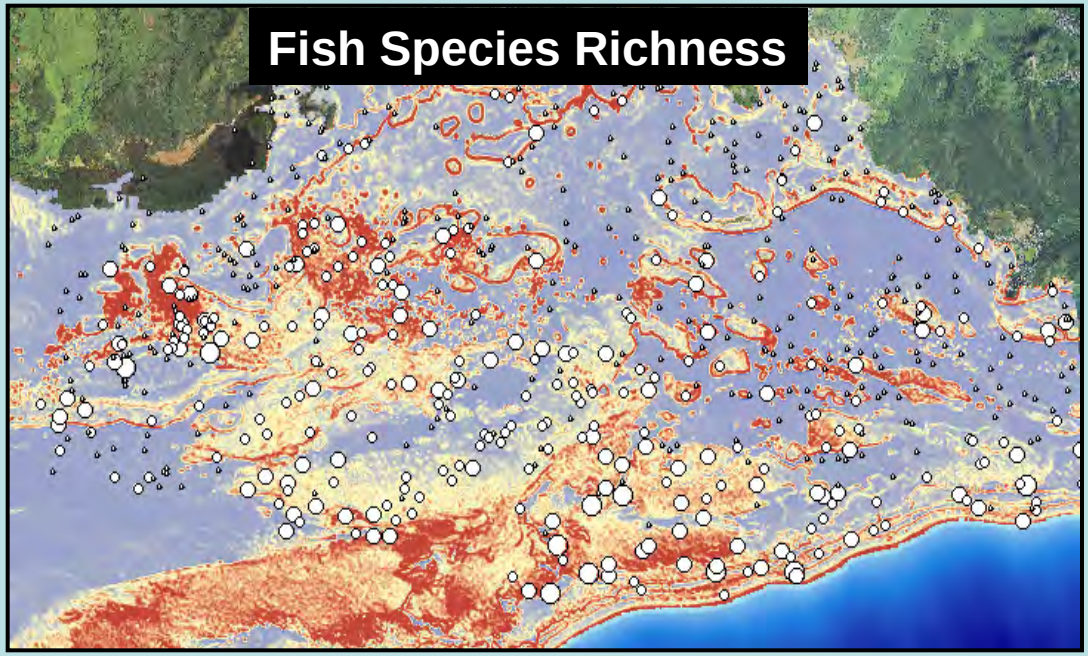
Part 3 : Which morphometric was most important?

Best TreeNet models (R^2)	
Herbivore biomass	0.72
Parrotfish biomass	0.68
Coral sp. richness	0.65
Fish sp. richness	0.64

1. **<u>Slope of slope</u> - best predictor for :**
   - **coral species richness & abundance**
   - **13 out of 17 fish metrics**

2. **<u>Rugosity</u> - best predictor for 3 metrics**

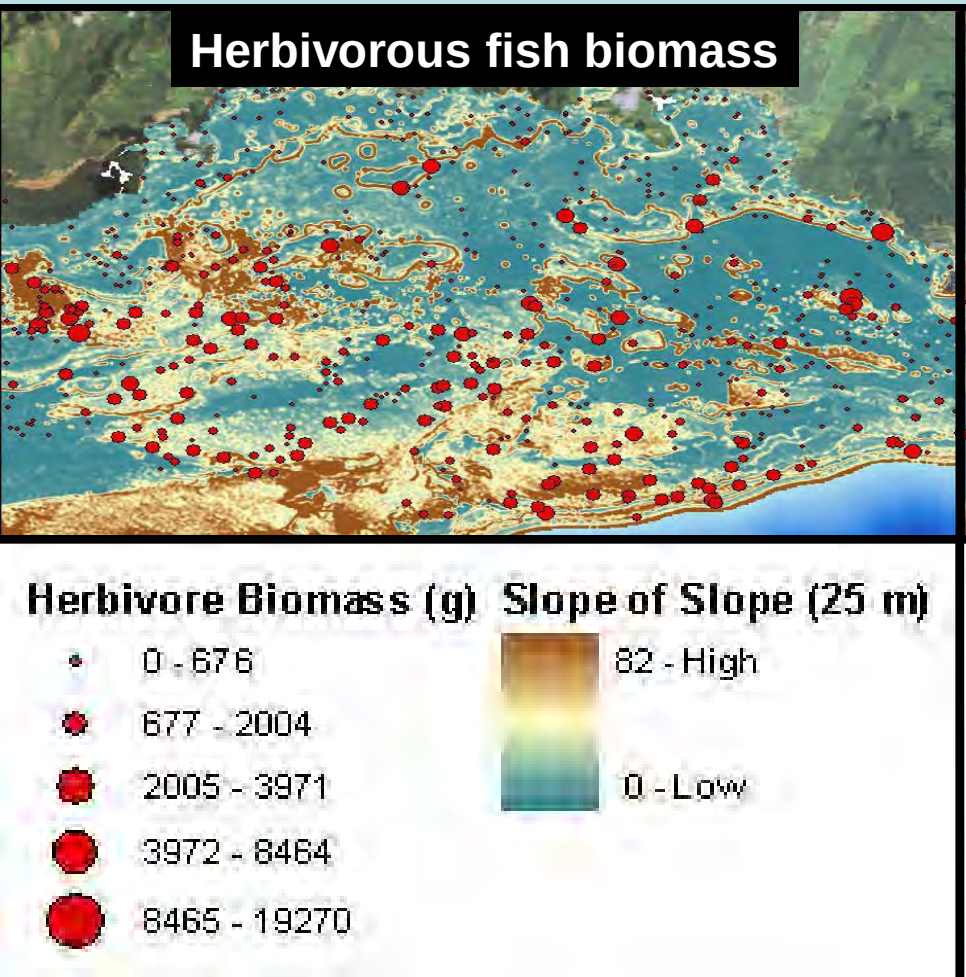
3. **<u>Curvature</u> - best predictor for 1 metric**

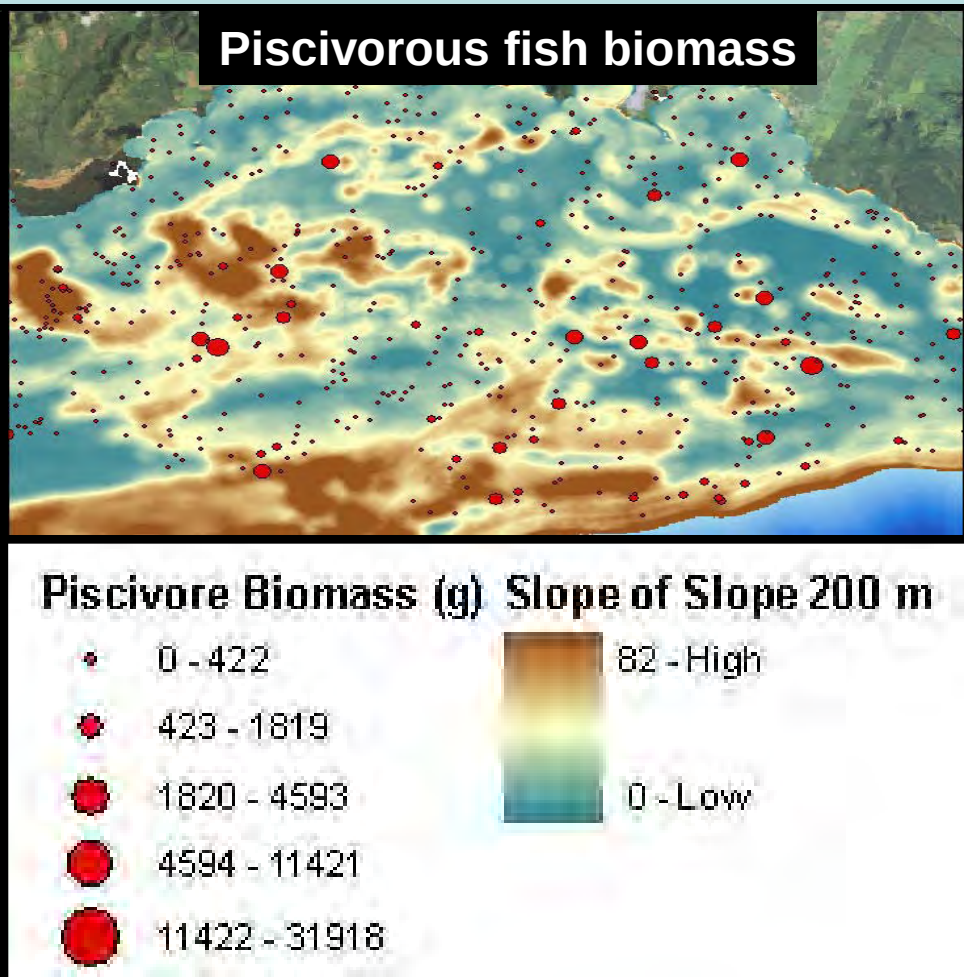


Fish Sp. Richness	Slope-Slope (15 m)
0 - 10	84 - High
11 - 21	
22 - 31	0 - Low
32 - 41	

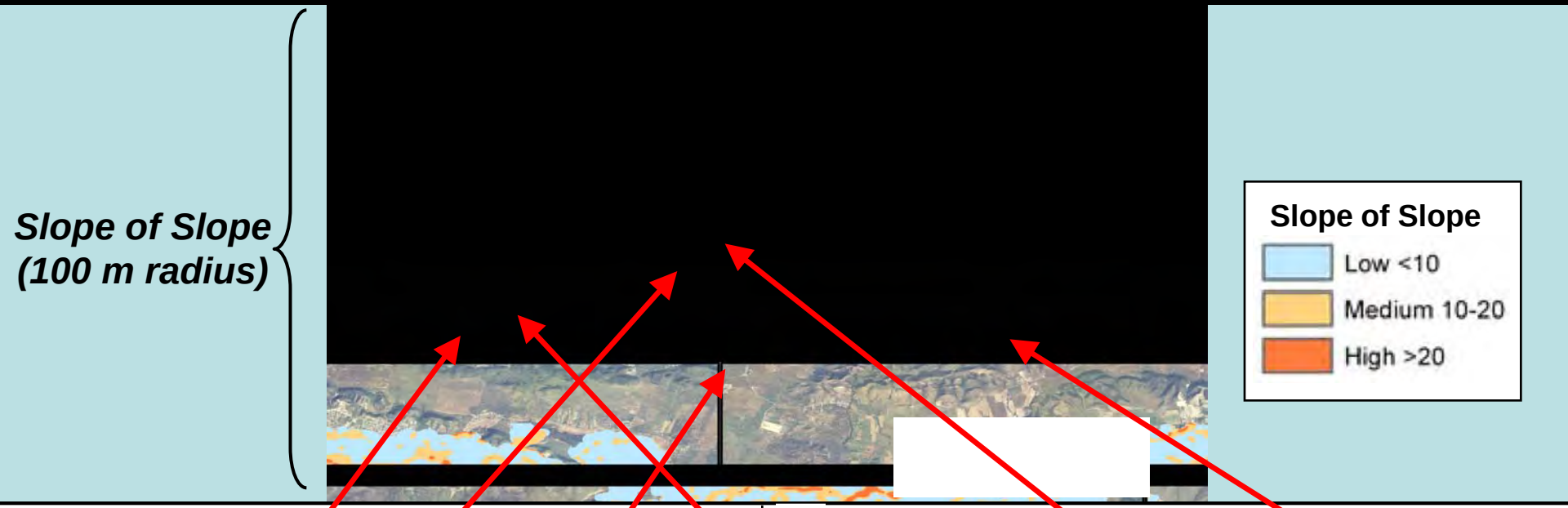
Part 3 : Which spatial scales were most important?

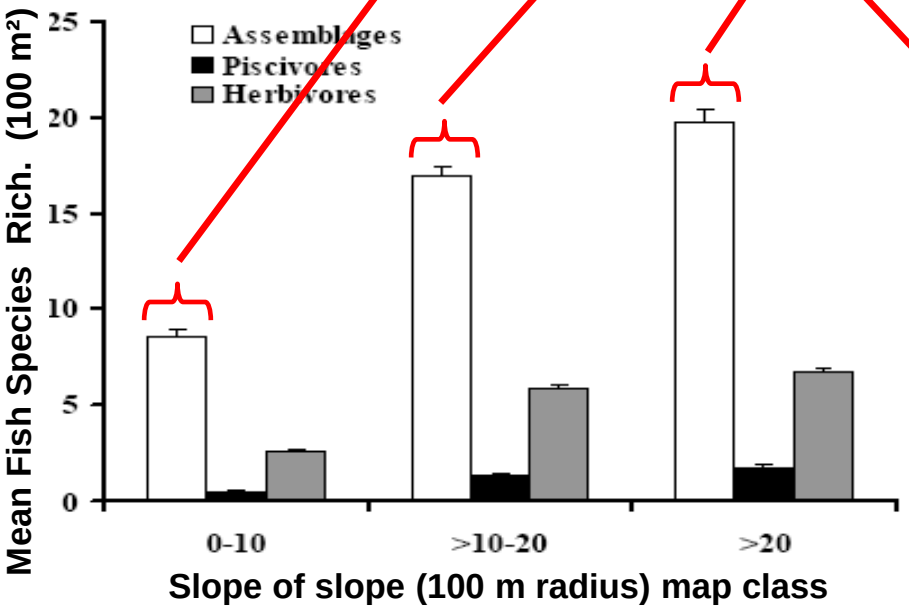
- **65% of metrics influenced by more local variability (≤ 25 m radius)**
- **Piscivores responded to structure at broader scales than herbivores**

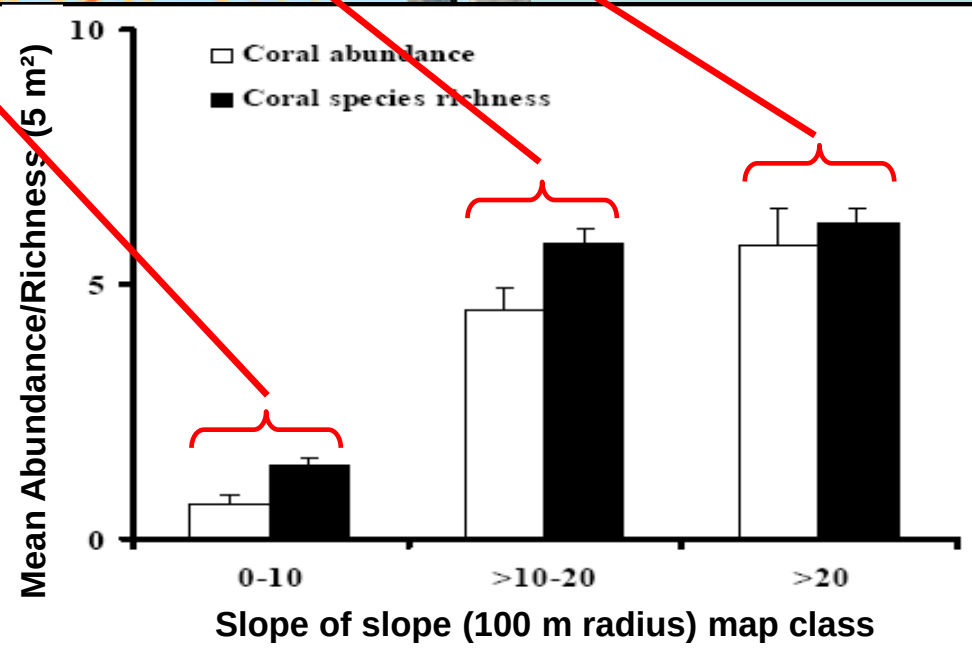




Part 3 : Using classes of complexity as predictors







Part 3 : The End / Just the Beginning

Conclusions:

1. LiDAR morphometrics useful predictors

- Offer great potential to support EBM decisions

2. Surface complexity should be integrated with 2D maps

- Studies linking surface patterns to ecological processes needed

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Future Directions:

1. Development of spatial predictions

2. Explore additional predictive metrics

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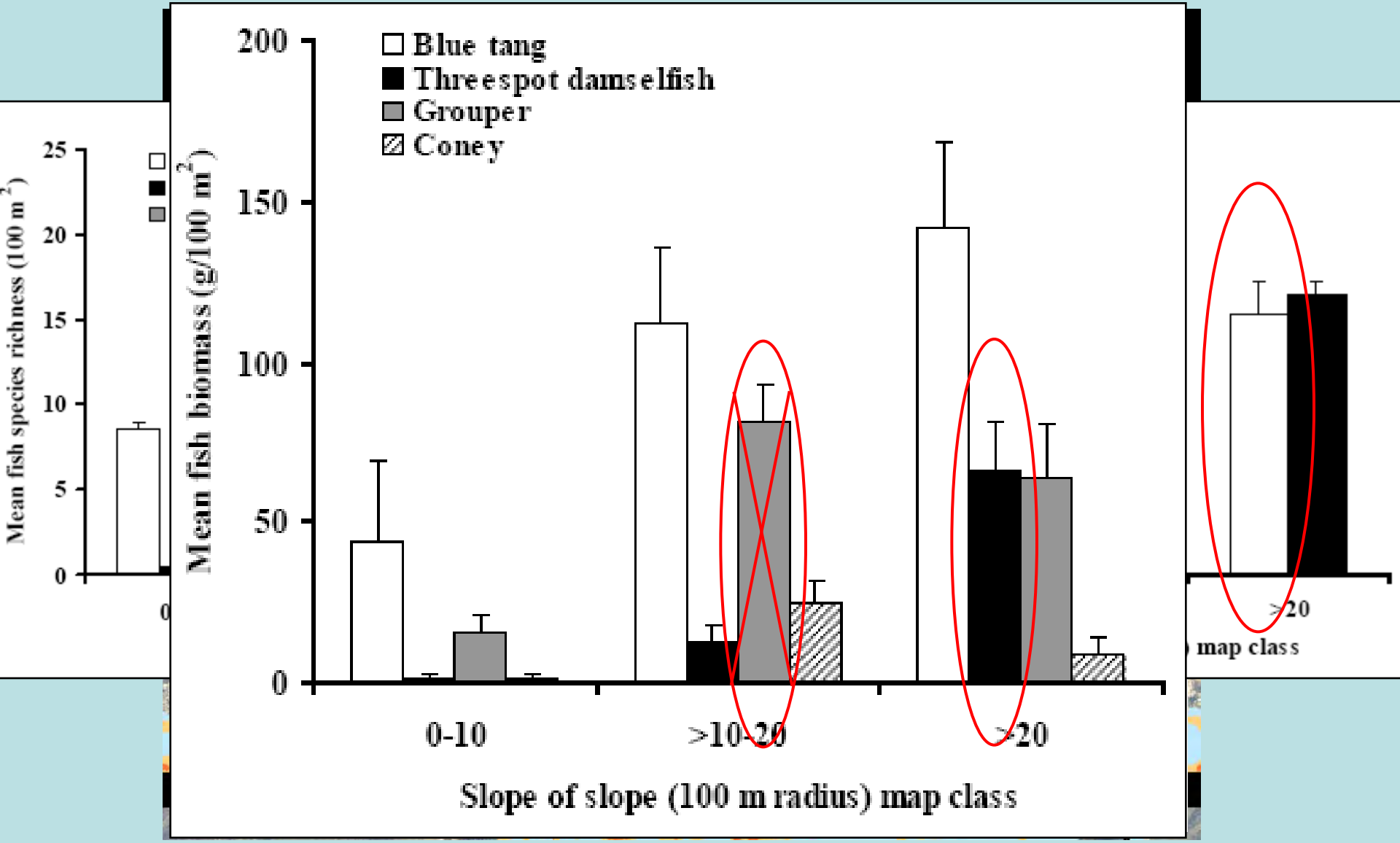
Datasets Publically Available:

http://ccma.nos.noaa.gov/about/biogeography/

END

Part 2 : Using classes of complexity as predictors



RESULTS: Which *technique* produced the best predictor(s) of fish/coral species richness & abundance?

Pearson Correlation: LiDAR surfaces may be better predictors of fish/corals than *in situ* measures

Response | ***In situ*** | **LiDAR**

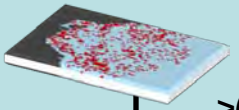
Response variables	Correlation coefficient		Max. r (variable, scale [m])	
Fish metrics (100 m^2)	Log chain rugosity	Log depth variance	Hardbottom only	Hard and softbottom
Assemblage				
Species richness	**0.36**	**0.26**	**0.29** (slope/slope 50)	**0.57** (slope/slope 100)
Biomass (g)	**0.17**	0.12	**0.22** (slope 50)	**0.51** (slope/slope 100)
Abundance	**0.3**	<0.01	**0.11** (depth 100)	**0.34** (slope/slope 100)
Trophic group				
Piscivore abundance	0.08	<-0.01	**0.26** (depth 200)	**0.31** (slope/slope 100)
Piscivore biomass (g)	0.05	0.02	**0.24** (slope/slope 100)	**0.34** (slope/slope 0.34)
Piscivore richness	**0.28**	**0.16**	**0.28** (slope/slope 100)	**0.4** (slope/slope 100)
Herbivore abundance	**0.36**	-0.03	**0.13** (plan curve)	**0.44** (slope/slope)
Herbivore biomass (g)	**0.12**	0.07	**0.26** (slope 50)	**0.56** (slope/slope)
Herbivore richness	**0.32**	**0.16**	**0.27** (slope 50)	**0.56** (slope/slope 100)
Family/Species groups				
Grouper biomass (g)	0.05	0.02	**0.27** (depth 300)	**0.34** (slope-slope 100)
Parrotfish biomass (g)	**0.12**	0.07	**0.29** (slope-slope 100)	**0.56** (slope-slope 100)
Species				
Coney abundance	0.03	-0.03	**0.15** (depth 100)	**0.13** (depth 300)
Coney biomass (g)	-0.06	0.02	**0.14** (depth 100)	**0.12** (depth 300)
Threespot damselfish abundance	**0.25**	**0.24**	**0.53** (slope 50)	**0.52** (slope 50)
Threespot damselfish biomass (g)	**0.25**	**0.19**	**0.53** (slope 50)	**0.52** (slope 50)
Blue tang abundance	0.07	0.02	**-0.18** (depth 15)	**0.32** (slope 50)
Blue tang biomass (g)	0.05	0.06	**0.2** (slope-slope 100)	**0.41** (slope-slope 100)
Coral metrics (5 m^2)				
Scleractinian coral species richness	**0.45**	**0.25**	**0.26** (slope-slope 200)	**0.54** (slope-slope 100)
Scleractinian coral cover	**0.62**	**0.38**	**0.39** (slope-slope 100)	**0.59** (slope-slope 100)

RESULTS : Which *morphometric* was the most important predictor of fish/coral species richness & abundance?

Response variables	No. trees used	Best predictors (>70 % contrib.) (Hard & softbottom)	Best model R^2
Fish metrics (100 m^2)			
Assemblage			
Species richness	875	slope-slope 15, 25 & 100	0.64
Biomass (g)	593	slope-slope 25, 200 & 15	0.46
Abundance	614	slope-slope 15	0.27
Trophic group			
Piscivore abundance	174	slope-slope 25, water depth 300, slope 25	0.16
Piscivore biomass (g)	195	slope-slope 200, plan curv. 25, SD water depth 100	0.18
Piscivore richness	277	slope-slope 200, slope-slope 100, rugosity 25	0.32
Herbivore abundance	586	slope-slope 15 & 25	0.57
Herbivore biomass (g)	1000	slope-slope 25 & 15	0.72
Herbivore richness	485	slope-slope 15 & 25	0.64
Family/Species groups			
Grouper biomass (g)	173	plan curv. 25, slope-slope 100, water depth 300	0.22
Parrotfish biomass (g)	613	slope-slope 25 & 15	0.68
Species			
Coney abundance	1000	plan curve 300	0.21
Coney biomass (g)	993	plan curve 300, fractal dimension 200	0.12
Threespot damselfish abundance	904	rugosity 50, slope 50, slope-slope 100	0.48
Threespot damselfish biomass (g)	943	slope-slope 100, rugosity 50, slope 50	0.41
Blue tang abundance	871	slope-slope 25, water depth 15, plan curv. 25	0.2
Blue tang biomass (g)	694	slope-slope 25, 15 & 100	0.24
Coral metrics (5 m^2)			
Scleractinian coral species richness	917	slope-slope 25	0.65
Scleractinian coral cover	258	slope-slope 200	0.54

Boosted Reg. Trees
1. Slope-slope exhibited strongest & most frequent significant correlations
2. More variance explained by non-linear functions

Target = Fish species richness



Soft-bottom sites — ***<0.12*** | ***>0.12*** — **Hard-bottom sites**

Rugosity

<1.8 | ***>1.8***

SD of depth

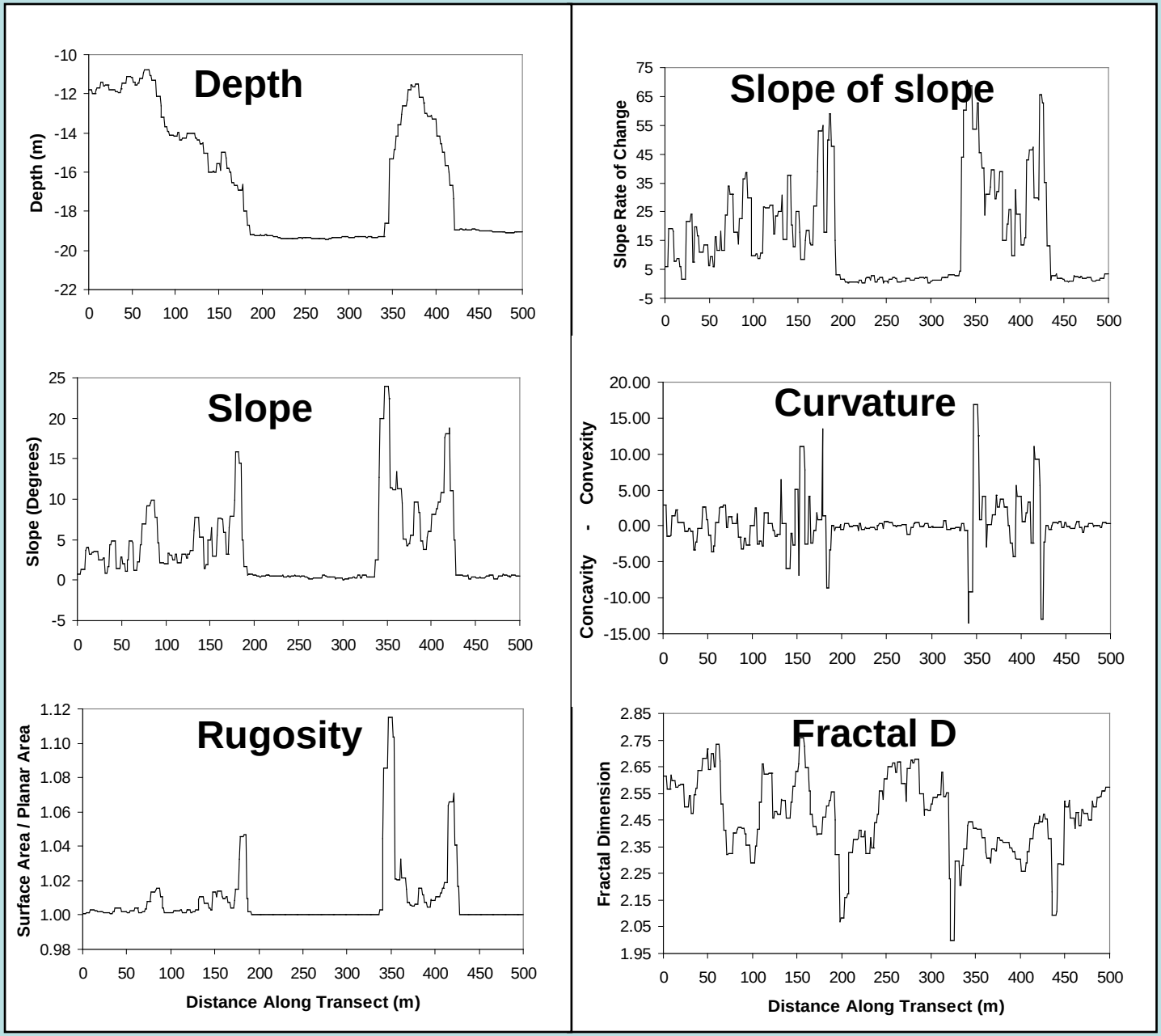
<0.43 | ***>0.43***

SD of Depth

Predicted Fish species richness

Lower complexity	Higher complexity	Lower complexity	Higher complexity
7.3	15	13	19

Morphometric profiles



METHODS: *Morphometrics*

Slope

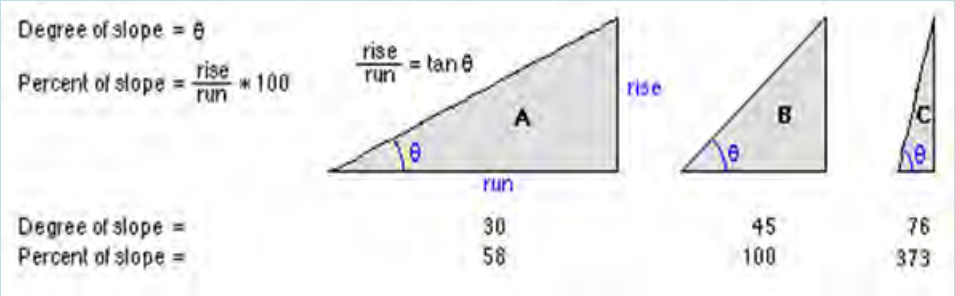
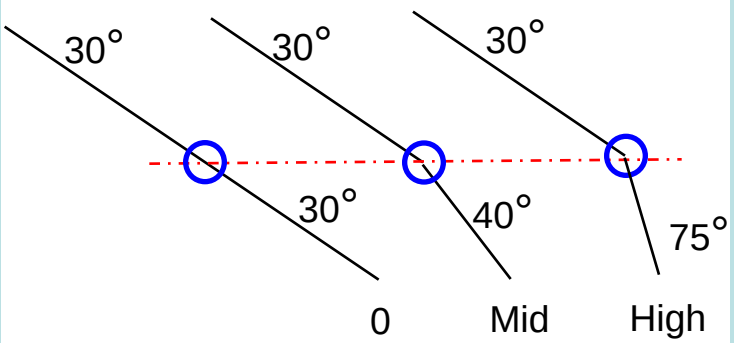
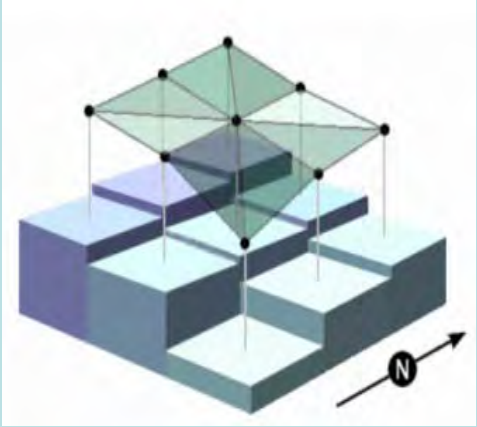


Fig. Adapted from ESRI, 2008

Slope of Slope



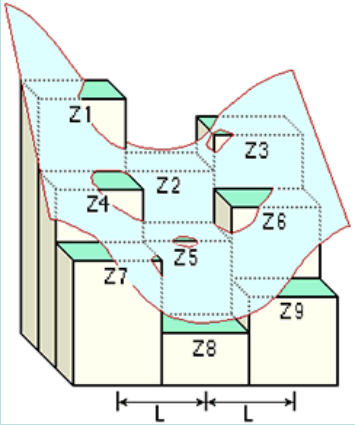
Rugosity



= Surface Area / Planar Area

Fig. Adapted from Jenness, 2002

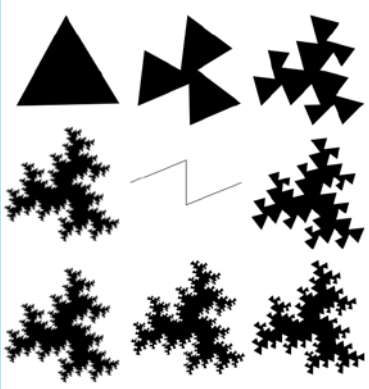
Curvature



= Convexity or Concavity
(4th order polynomial fit)

Fig. Adapted from ESRI, 2008

Fractal Dimension



FD = - [log (n1/n2)/ log(L1/L2)]
n = # elements
L = linear size

Mandelbrot, 1967