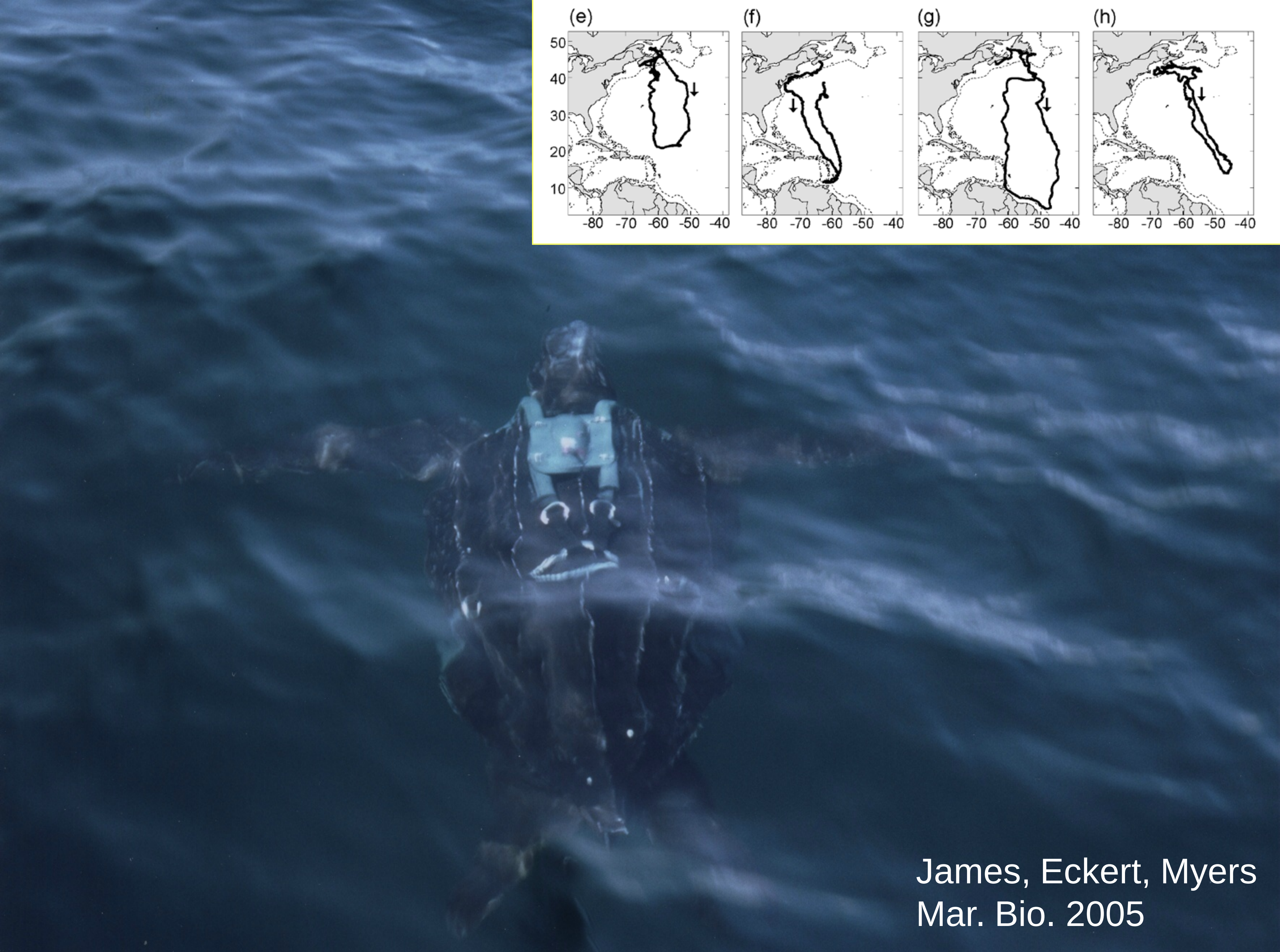
Ransom A. Myers (RAM)
Ian Jonsen, Joanna Flemming
Greg Breed, Chris Field
Mike James
Don Bowen

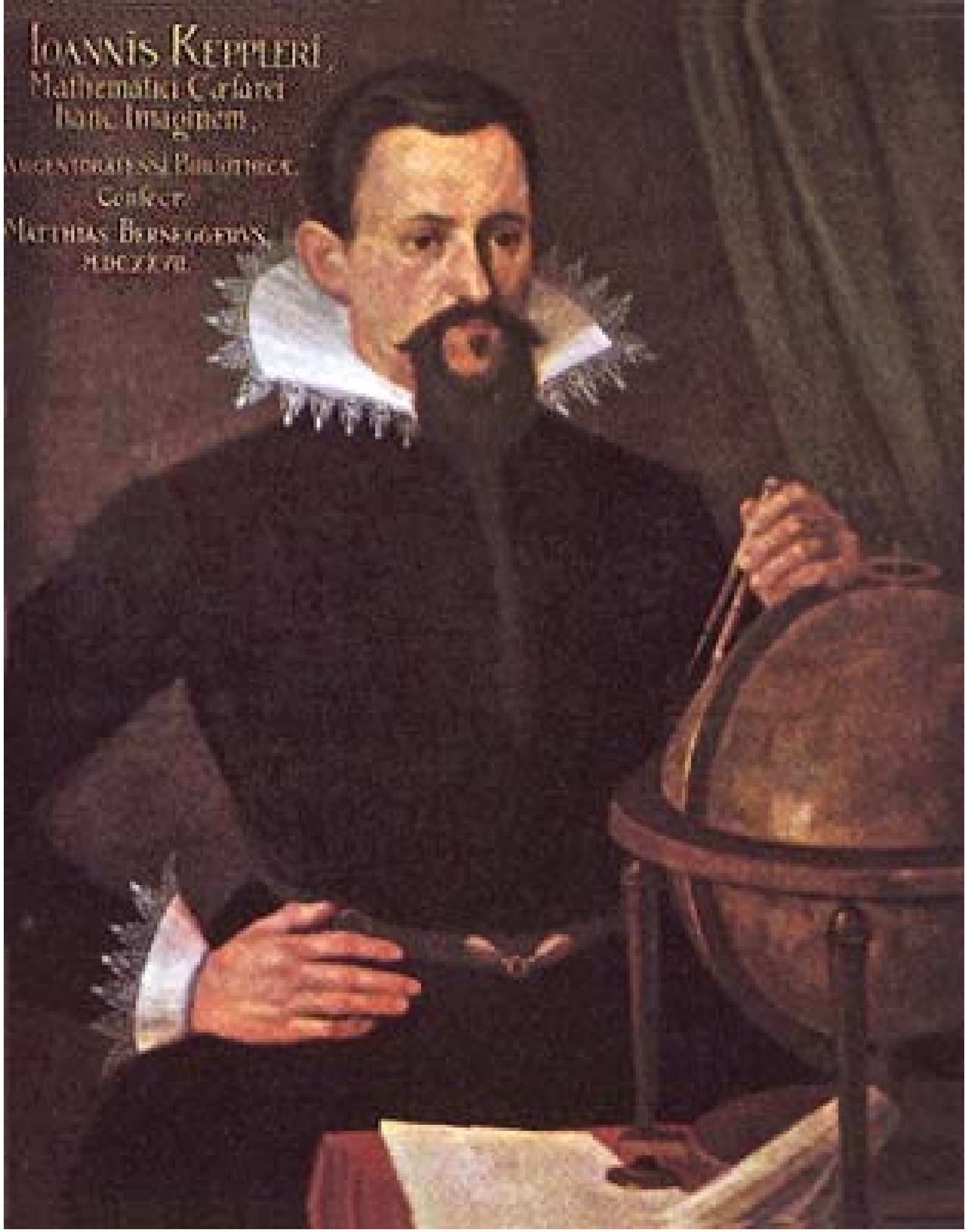
State-Space Models for Movement and Habitat Use

FMAP (Future of Marine Animal Populations)
http://fish.dal.ca

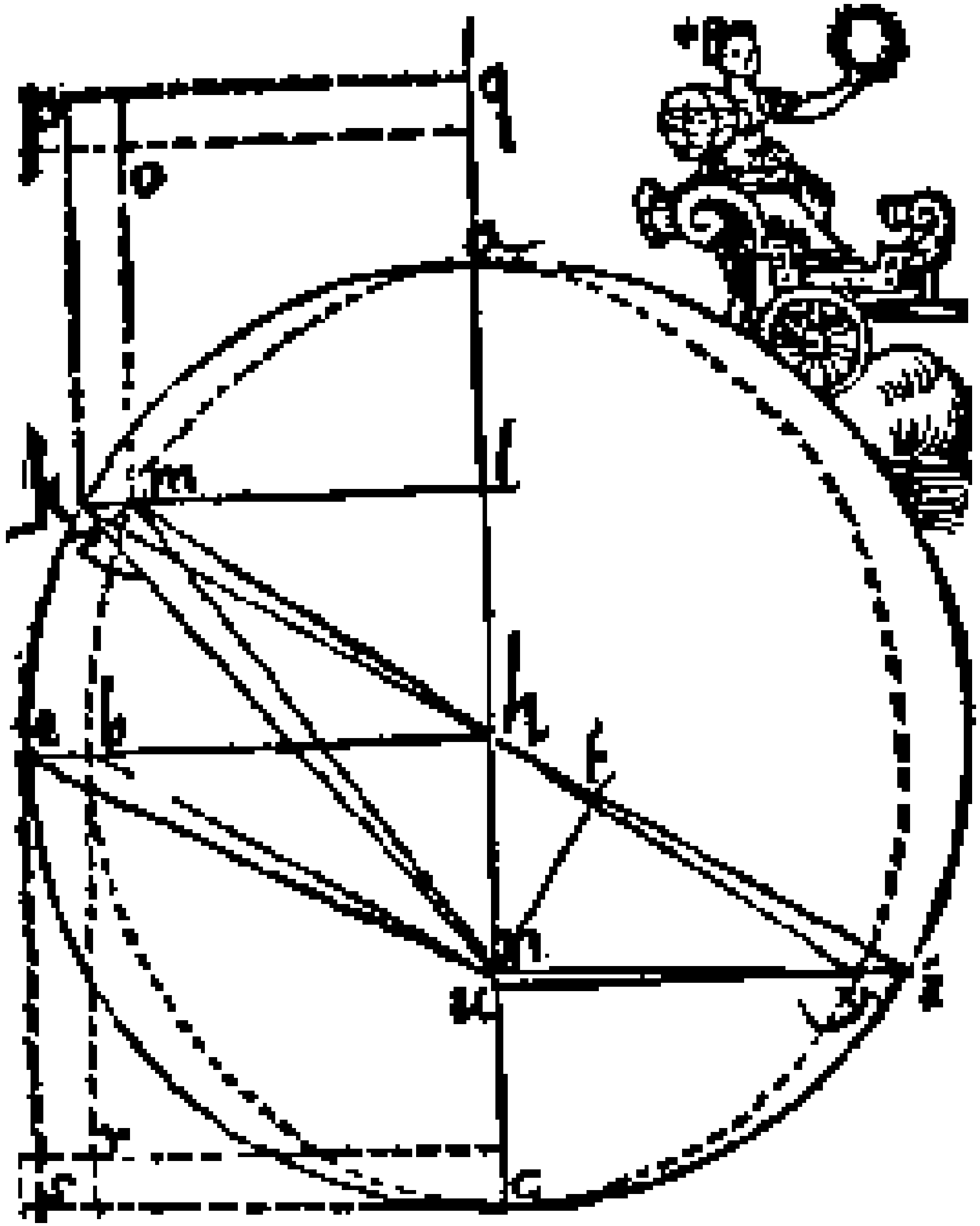
Dalhousie University
Halifax, Canada



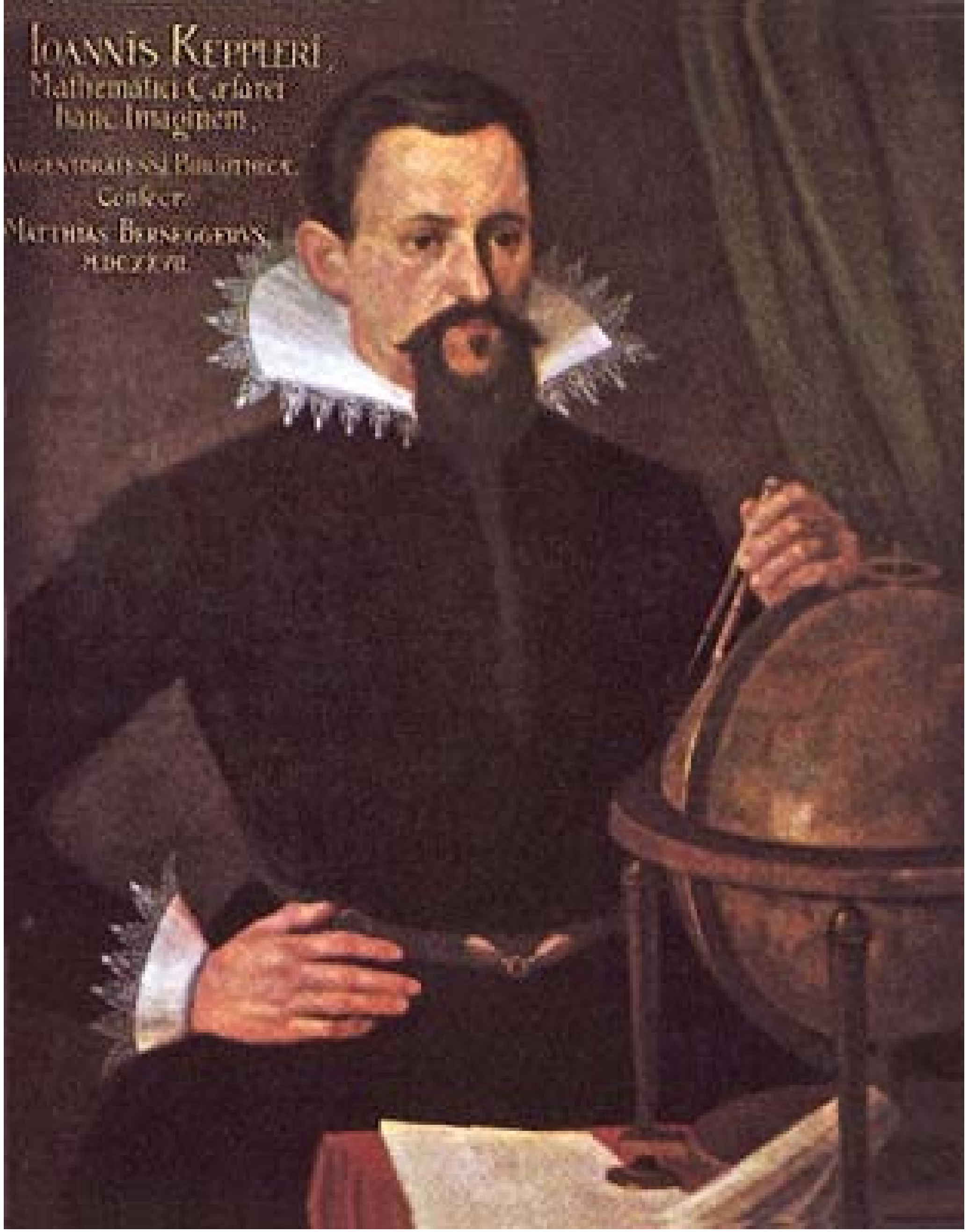
James, Eckert, Myers
Mar. Bio. 2005



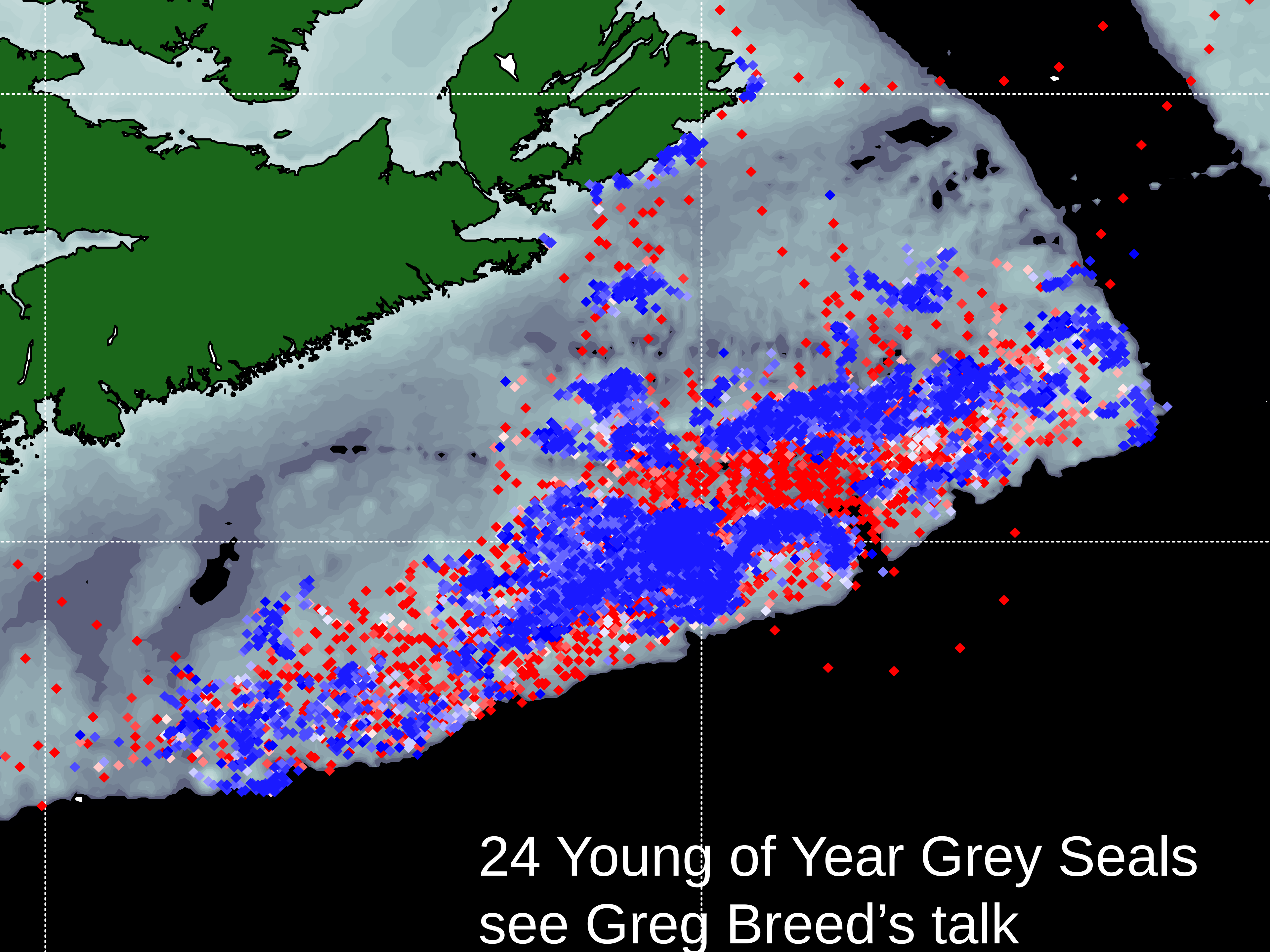
Imperial Mathematician



Kepler's elliptical orbit for Mars..



Imperial Mathematician

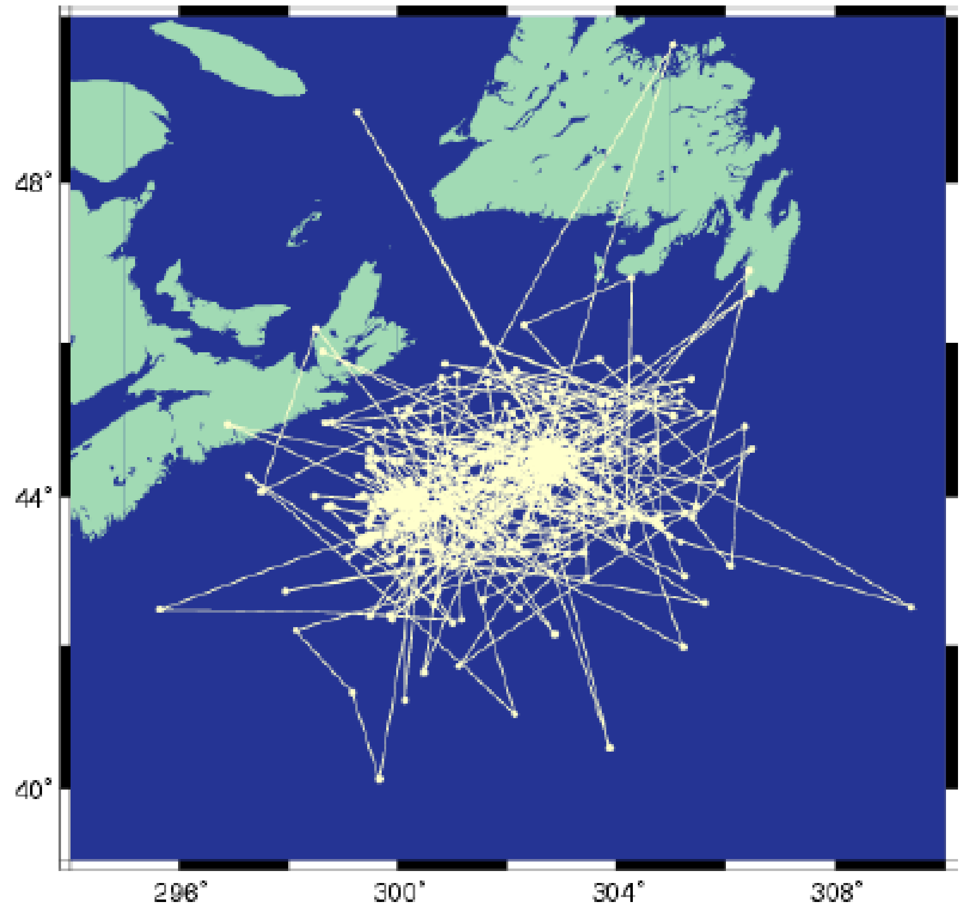


24 Young of Year Grey Seals
see Greg Breed's talk

Argos Satellite Telemetry Data
Getting more out of the data

Goals of State-Space analysis

- Infer true locations from noisy data
- Account for error w/out loss of information
- Infer behaviour, test hypotheses



Argos Satellite Telemetry Data

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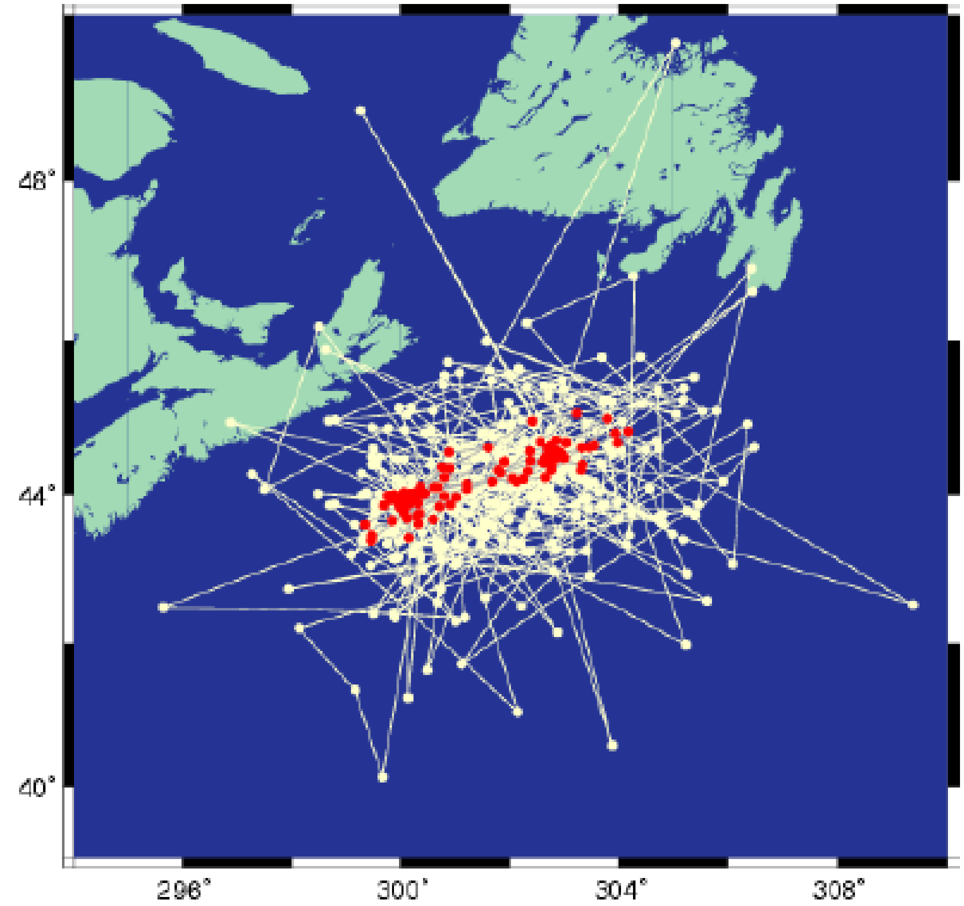
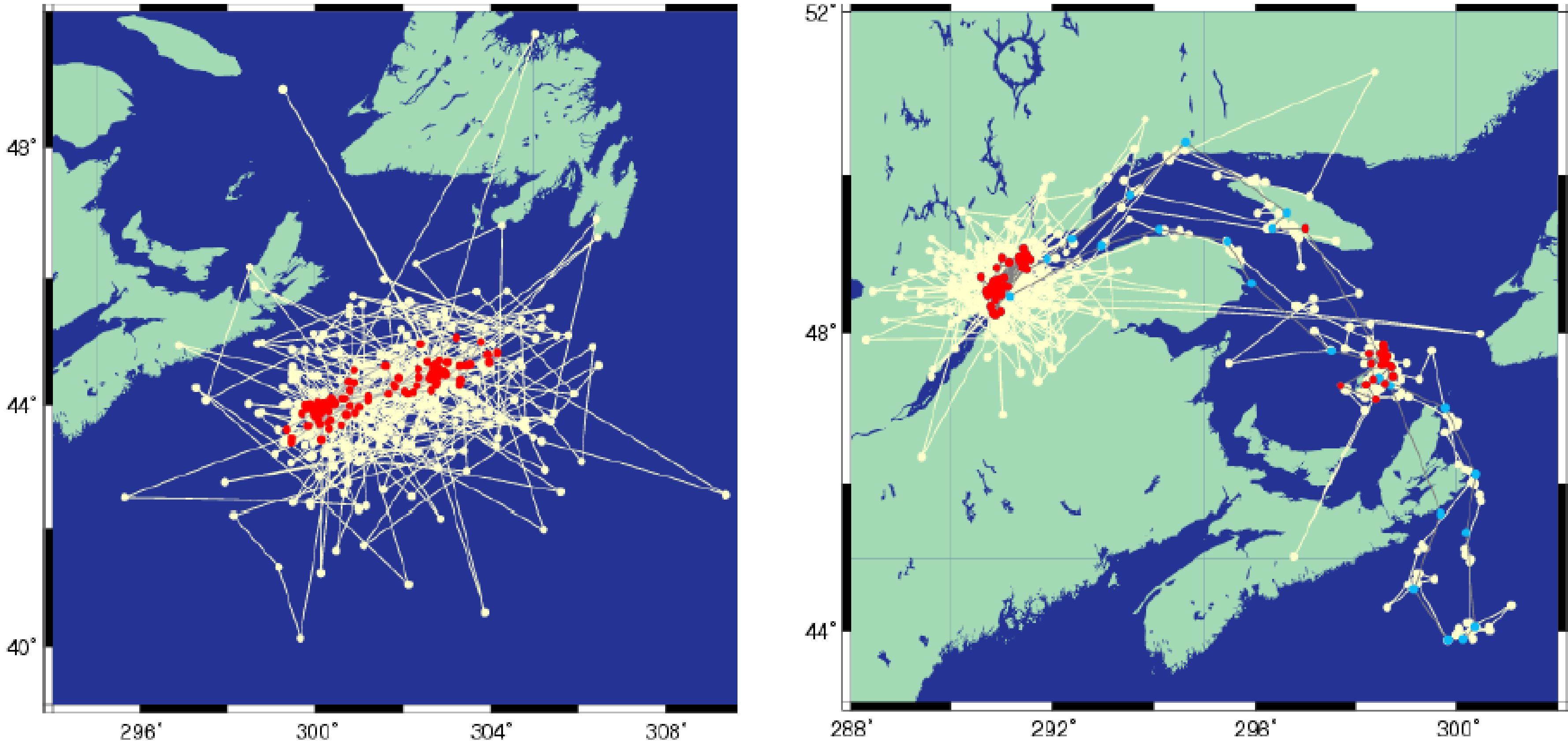


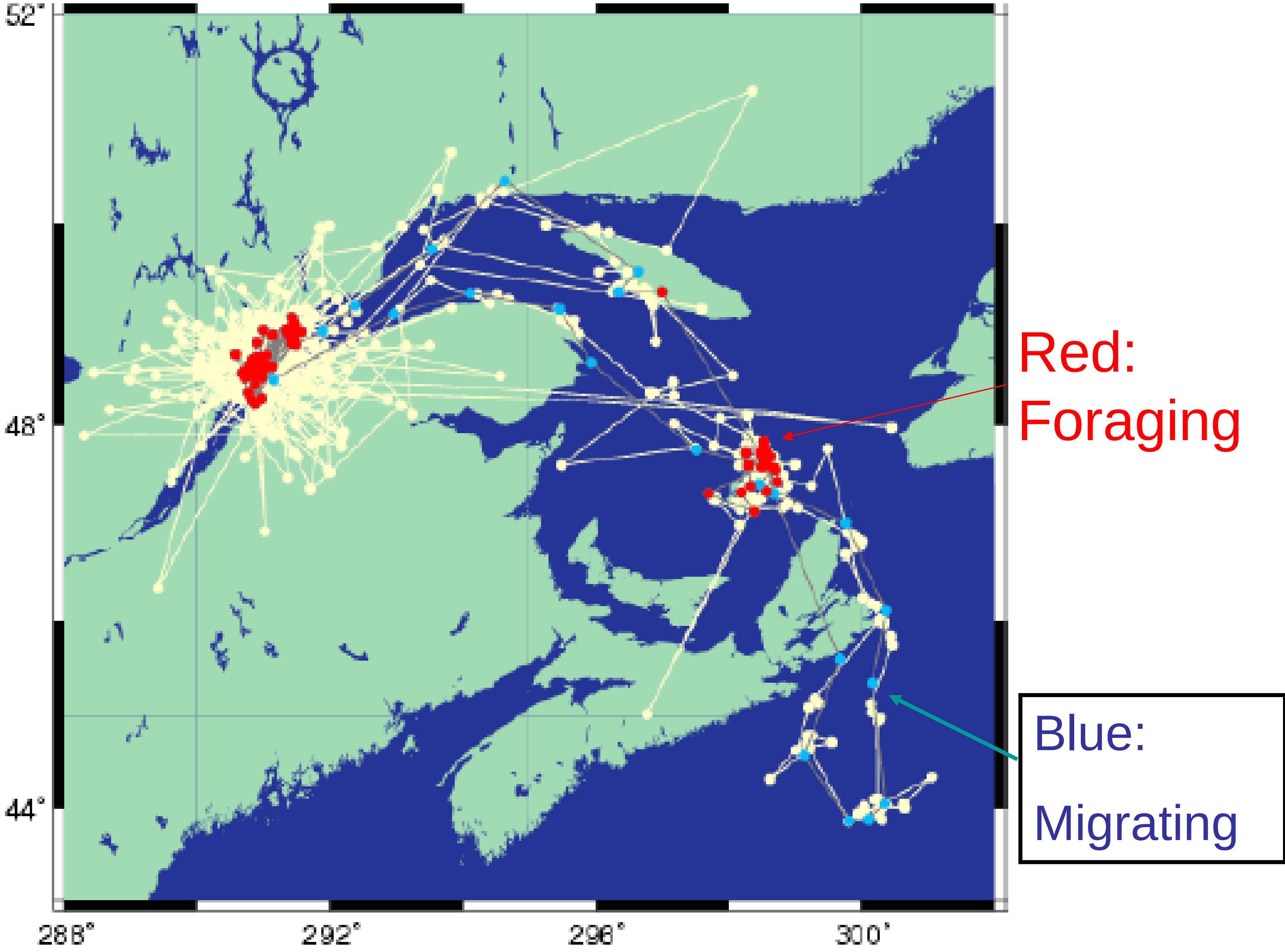
Jonsen, Flemming and Myers (2005) Ecology 86: 2874-2880

Data Filtering & State Estimation

Jonsen et al. 2005. Ecology 86:2874-2880



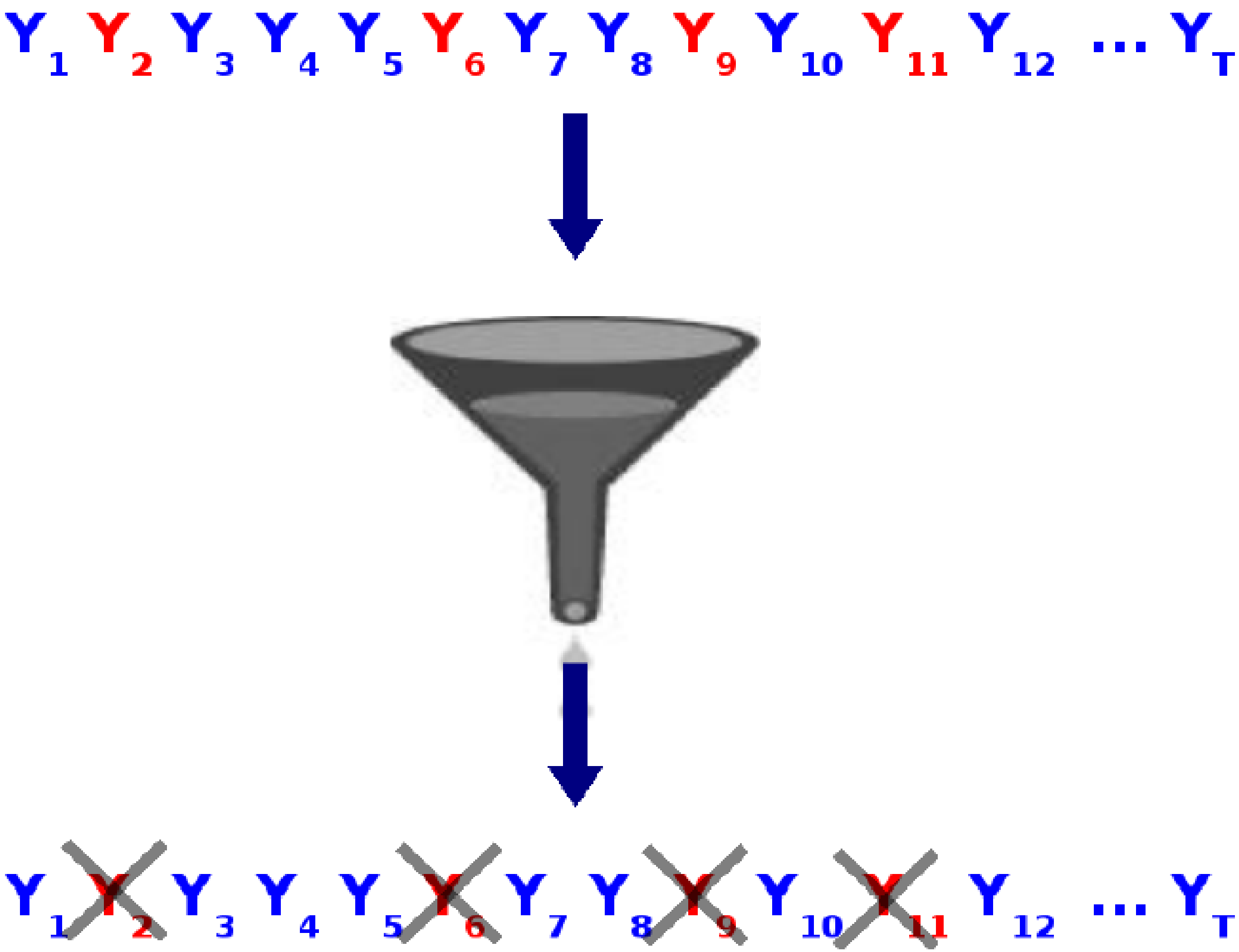
Jonsen, Flemming and Myers (2005) Ecology 86: 2874-2880



52°
48°
44°
288°
292°
296°
300°
Red: Foraging
Blue: Migrating

Noisy Data: ad-hoc Filtering

Extreme values removed prior to analysis



State-Space Filtering is Fundamentally Different

Location estimates w CIs & parameter estimation

$$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \ldots\ Y_T$$

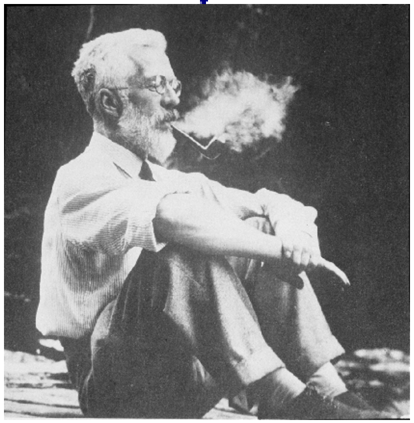

Rev. Thomas Bayes

$$\alpha_1\ \alpha_2\ \alpha_3\ \alpha_4\ \alpha_5\ \ldots\ \alpha_T\ ;\ \gamma\ ,\ \sigma\ ,\ \tau$$

State-Space Filtering is Fundamentally Different

Location estimates w CIs & parameter estimation

$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \dots\ Y_T$



We also carried out likelihood analysis

This is Sir Ronald Fisher

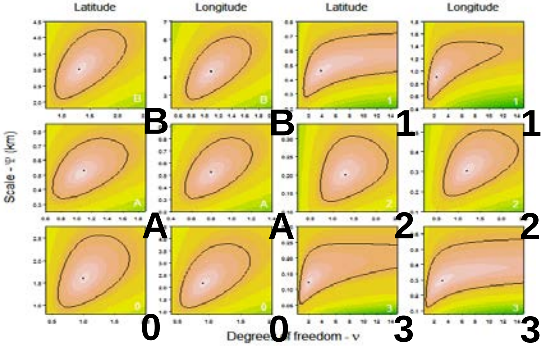
$\alpha_1\ \alpha_2\ \alpha_3\ \alpha_4\ \alpha_5\ \dots\ \alpha_T\ ;\ \gamma\ ,\ \sigma\ ,\ \tau$

State-Space Filtering is Fundamentally Different

Location estimates w CIs & parameter estimation

$$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \dots\ Y_T$$

Priors



Rev. Thomas Bayes

Meta-analysis of data from other animals

$$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \dots\ Y_T$$

$$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \dots\ Y_T$$

$$Y_1\ Y_2\ Y_3\ Y_4\ Y_5\ Y_6\ Y_7\ Y_8\ Y_9\ Y_{10}\ Y_{11}\ Y_{12}\ \dots\ Y_T$$

$$\alpha_1\ \alpha_2\ \alpha_3\ \alpha_4\ \alpha_5\ \dots\ \alpha_T\ ;\ \gamma\ ,\ \sigma\ ,\ \tau$$

What are State Space Models

- Analysis of sequential data observed with error
- Estimate unobservable states from error-prone observations
- Simultaneously deal with process variability & estimation error
- Accomodates non-Gaussian errors, nonlinear dynamics, and other complexities in the data
- Accomodates missing observations

Why State Space Models?

- Simply one of the key “right ways” to think about many modern problems
- Engineers, Economists, Oceanographers use this approach
- State-space models used for:

    Tracking moving objects

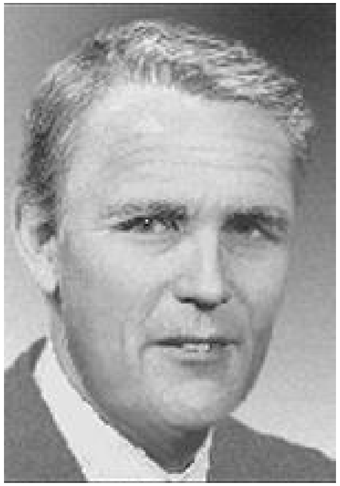
    Shooting down missiles

    Predicting stock market trends

    Predicting global circulation patterns

    Speech recognition

The First State-Space Model: the Kalman Filter

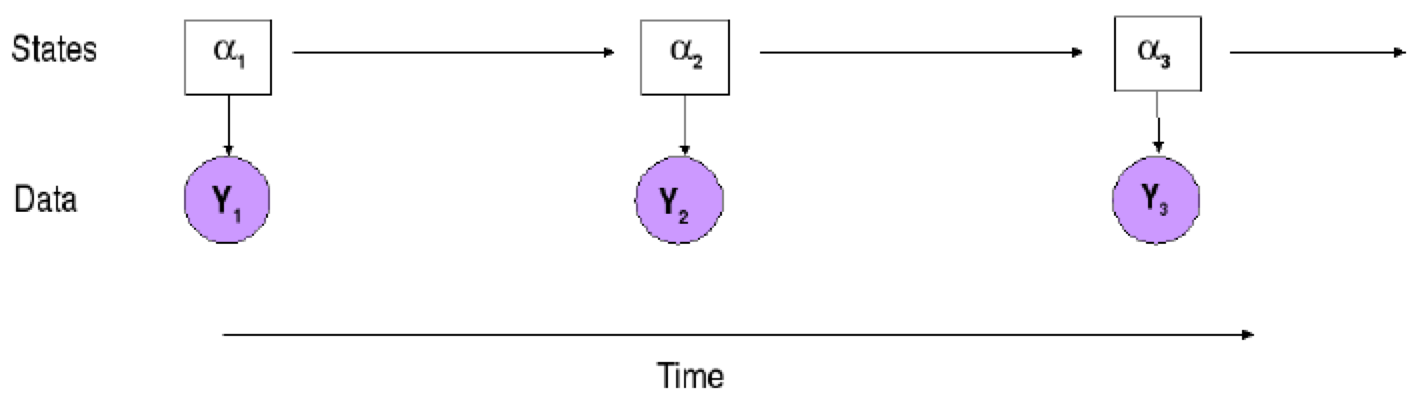


Process Model : $y_{k+1} = A_k y_k + u_k$

Measurement Model : $x_k = M_k y_k + v_k$

- Used to estimate state variables, not dynamical parameters
- Can be applied to non-stationary processes.
- Measurement noise and process noise are white and Gaussian.
- Dynamics are linear.

State-Space Concept



State Space Models

Error function

$$y_t = h\,(\alpha_t\,,\,\varepsilon_t)$$

observed location

true location

Measurement Equation

- Relates imperfect observations to true position

- Estimate ARGOS error with ε

Transition Equation

$$\alpha_t = f\,(\alpha_{t\text{-}1},\,\eta_t\,;\,\gamma)$$

movement function

parameters

- Predicts next position from behavioral model

What is important about the transition equation?

$$\alpha_t = f\,(\alpha_{t\text{-}1},\ \eta_t\ ;\ \gamma)$$

The state variable is random variable, and should NOT be thought of as a simple number. The above equation can be better interpreted as the probability of a given state value $\alpha_{t.}$ Thus, we write the state as a Greek letter, α_t. Consider the simplest model where the mean for the next time period is a simple multiple of this years state.

$$p(\alpha_t |\ \alpha_{t\text{-}1}) = \mathcal{N}\,(\alpha_{t\text{-}1}\,\gamma\,,\sigma)$$

What is important about the state equation?

$$\alpha_t = f\ (\alpha_{t\text{-}1},\ \eta_t\ ;\ \gamma)$$

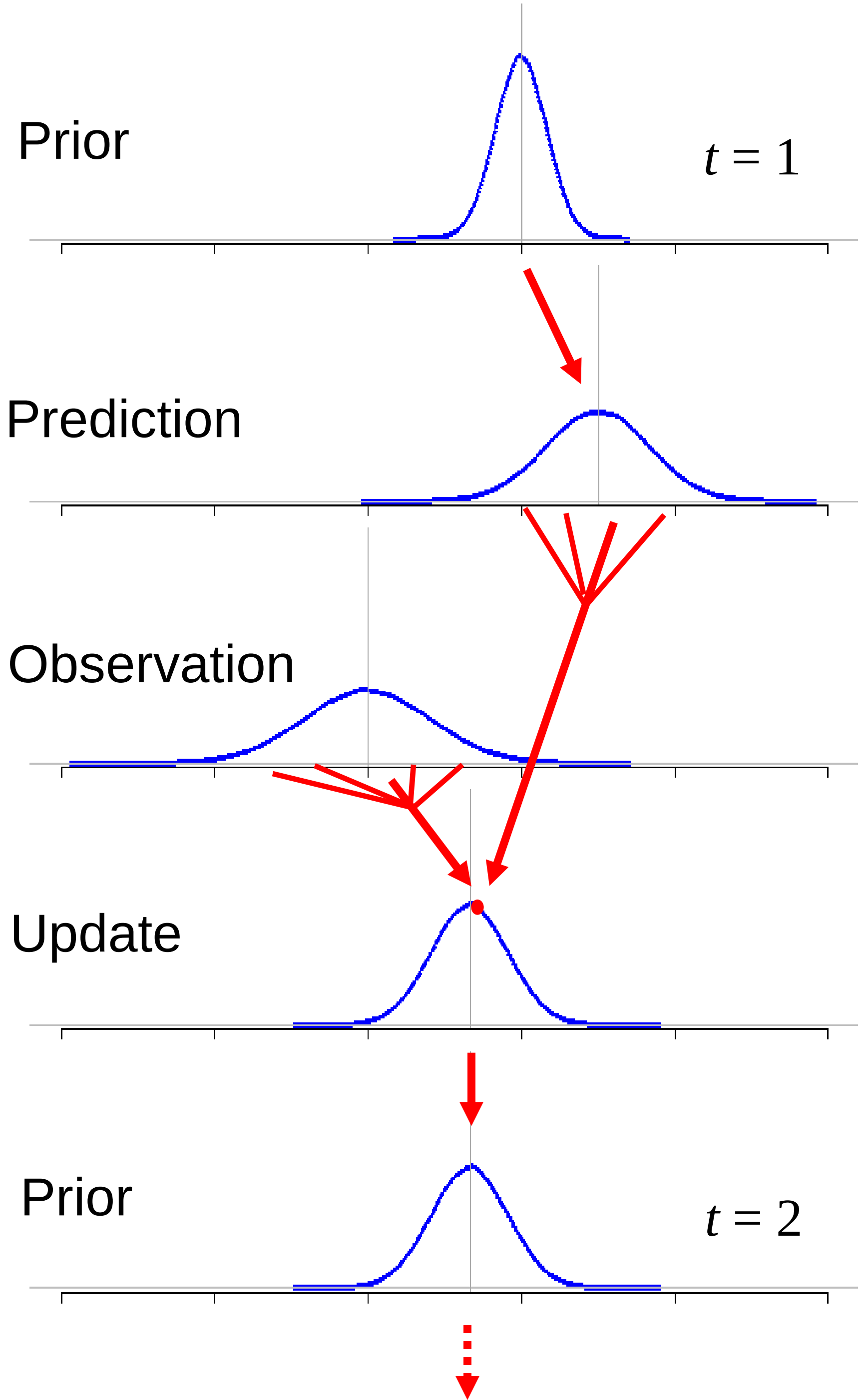
The state variable is random variable, and should NOT be thought of as a simple number. We write the state as a greek letter, α_t

How is this programmed with BUGS

mean[t] <- *f*(*alpha[t-1]* ; γ)

alpha[t] ~ dlnorm (*mean[t]*, *sigma*)

This symbol means "is distributed as", and implies that alpha[t] is a random variable.



1[st] location = release point

eg. release location estimated with GPS

Apply dynamics (transition eqn)

Observe a location with error

Integrate over predicted & observed densities (Bayes Rule)

Updated prediction becomes prior for next time step

Software

WinBUGS: Bayesian Analysis Using Gibbs Sampling

Bayes Rule

$$p(\alpha_t \mid Y_t;\gamma) = \frac{p_y(\mathbf{y}_t \mid \alpha_t)\, p(\alpha_t \mid Y_{t-1};\gamma)}{\int p_y(\mathbf{y}_t \mid \alpha_t)\, p(\alpha_t \mid Y_{t-1};\gamma)\, d\mathbf{x}_t}$$

This is the innovation likelihood

Movement (Transition) Equation

- First difference correlated random walk

$$d_t \;=\; \gamma T(\theta) d_{t-1} \;+\; N_2(0,\Sigma)$$

$$\alpha_t = \alpha_{t-1} + d_t$$

Observation Equation

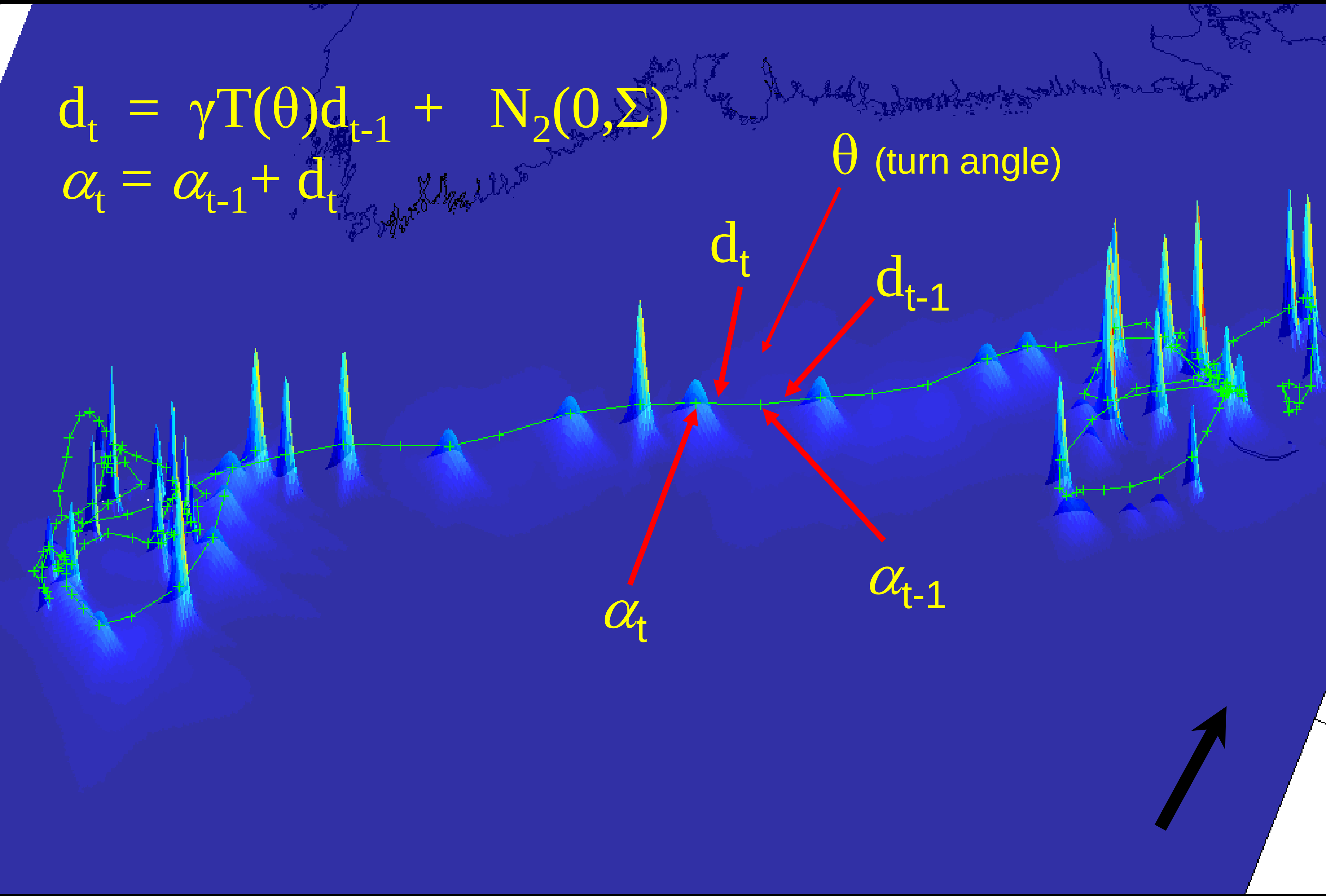
y_t = *t-distribution* $(\alpha_t\,,\ \sigma_{t,}\ \upsilon_t\,)$

Plus an algorithm to regularize estimated locations in time

Movement (Transition) Equation

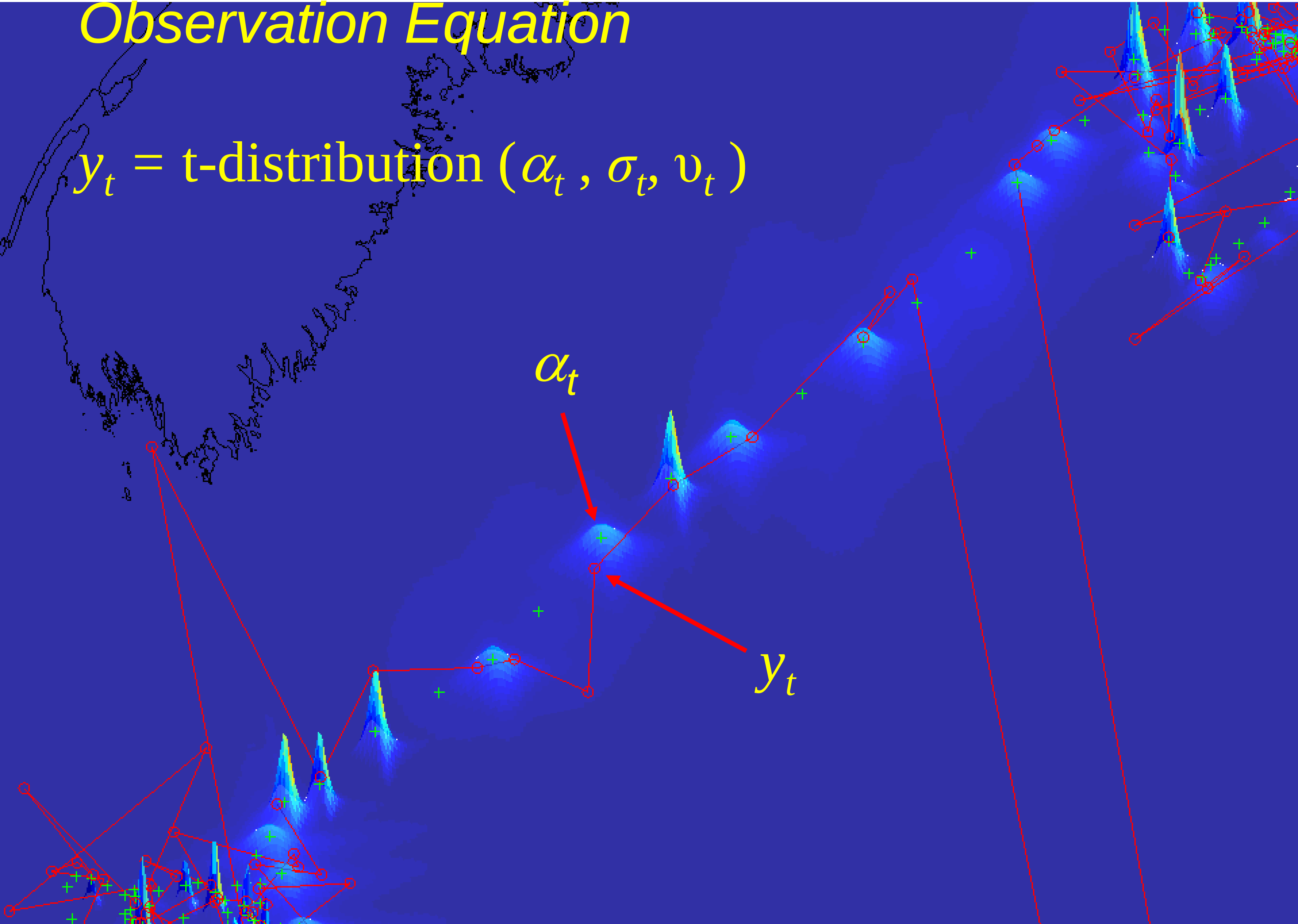
$$d_t = \gamma T(\theta) d_{t-1} + N_2(0,\Sigma)$$

$$\alpha_t = \alpha_{t-1} + d_t$$



Observation Equation

$$y_t = \text{t-distribution}\,(\alpha_t\,,\,\sigma_t,\,\upsilon_t\,)$$

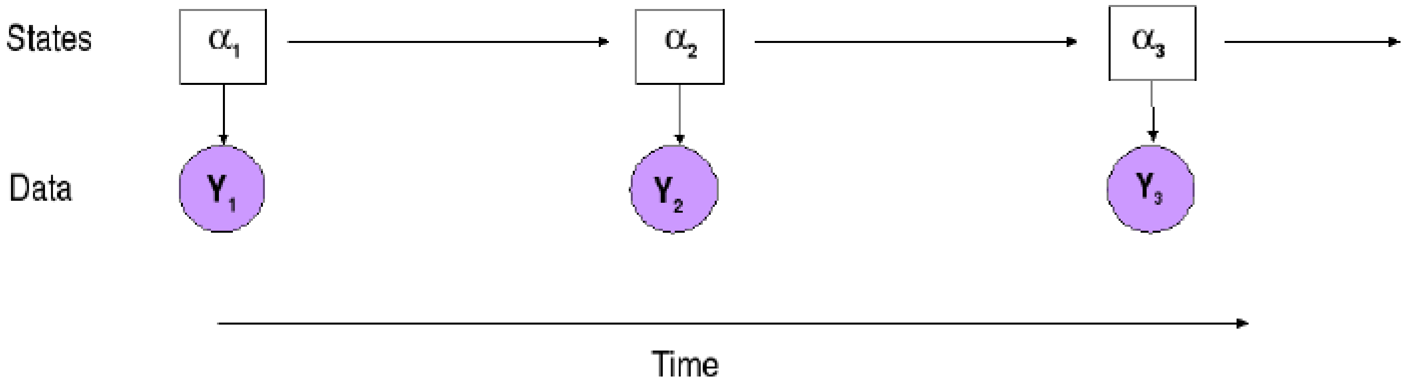


Dealing with Complex Data
Argos telemetry data

- Observations made irregularly through time
- Observation errors non-Gaussian (extreme values)
- Observation errors vary through time

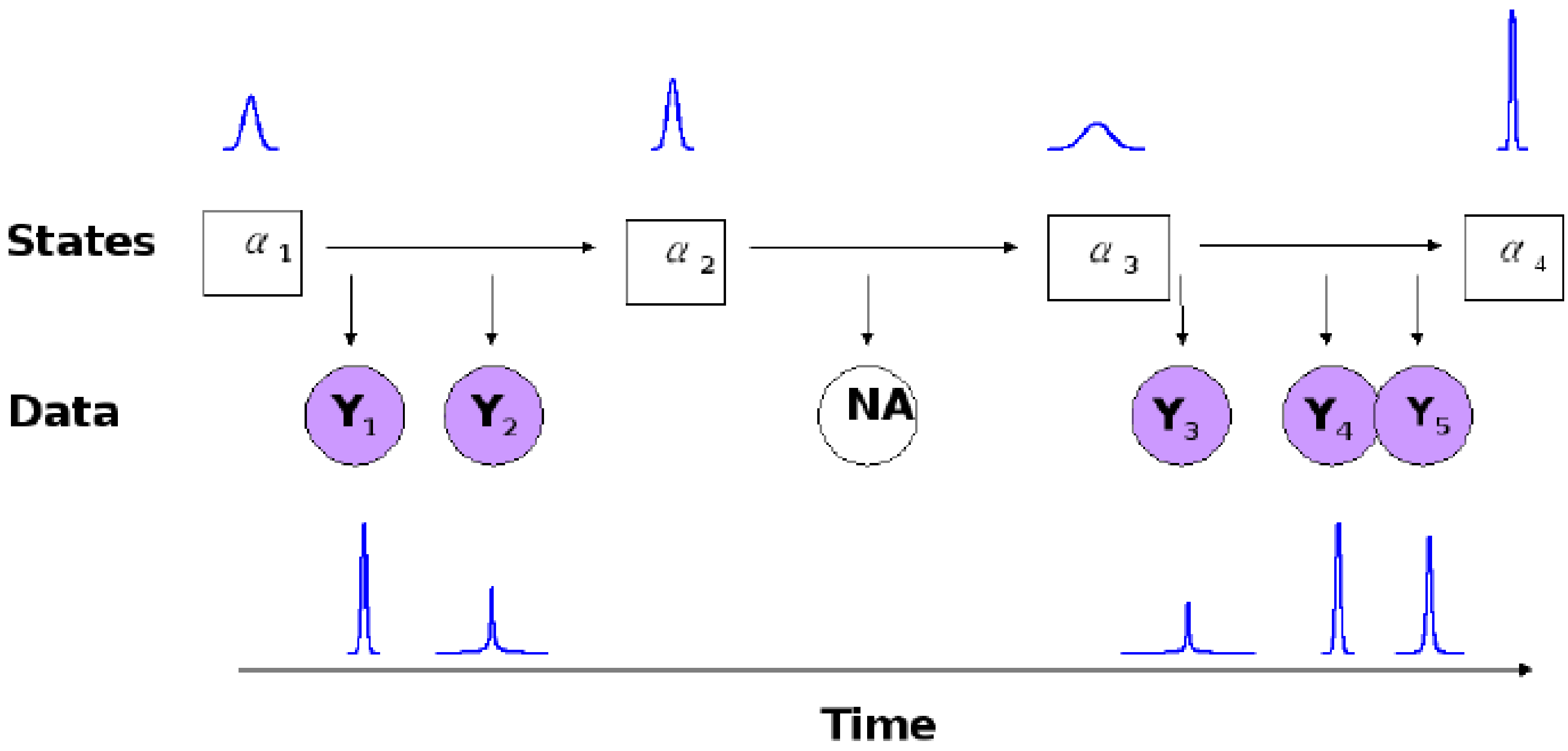
"Ideal" Data

Regular time intervals with constant Gaussian errors, & no missing data



"Real" Data

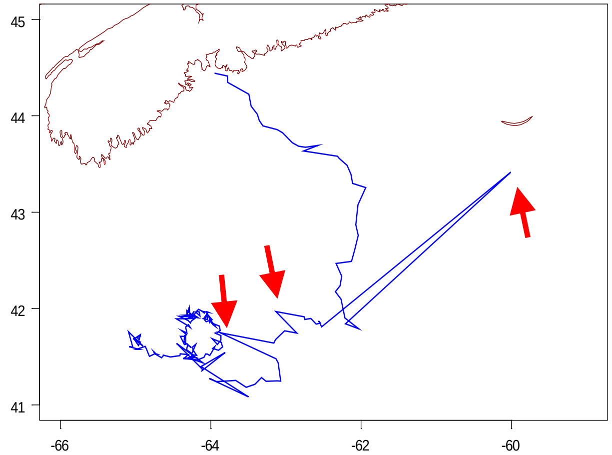
Irregular time intervals with varying non-Gaussian errors, & missing data

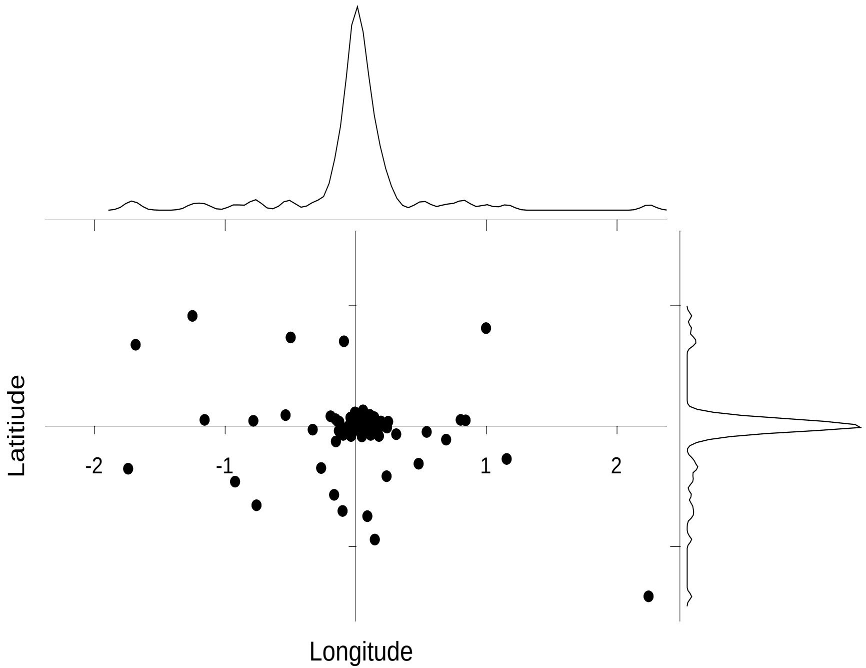


Sources of Uncertainty

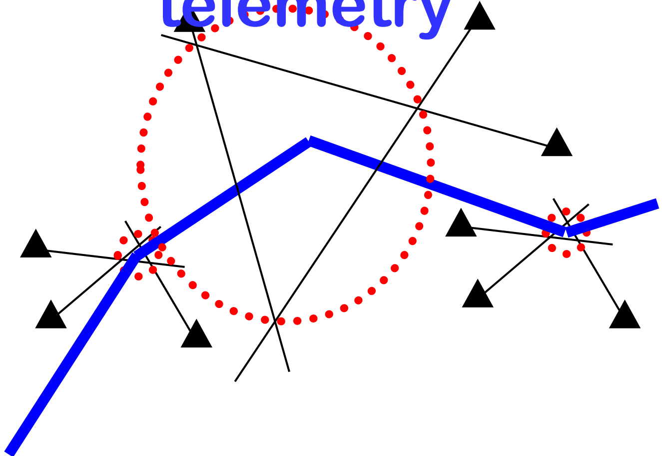
- Estimation error
  - Data observed with error
  - Errors can be non-Gaussian

Satellite telemetry

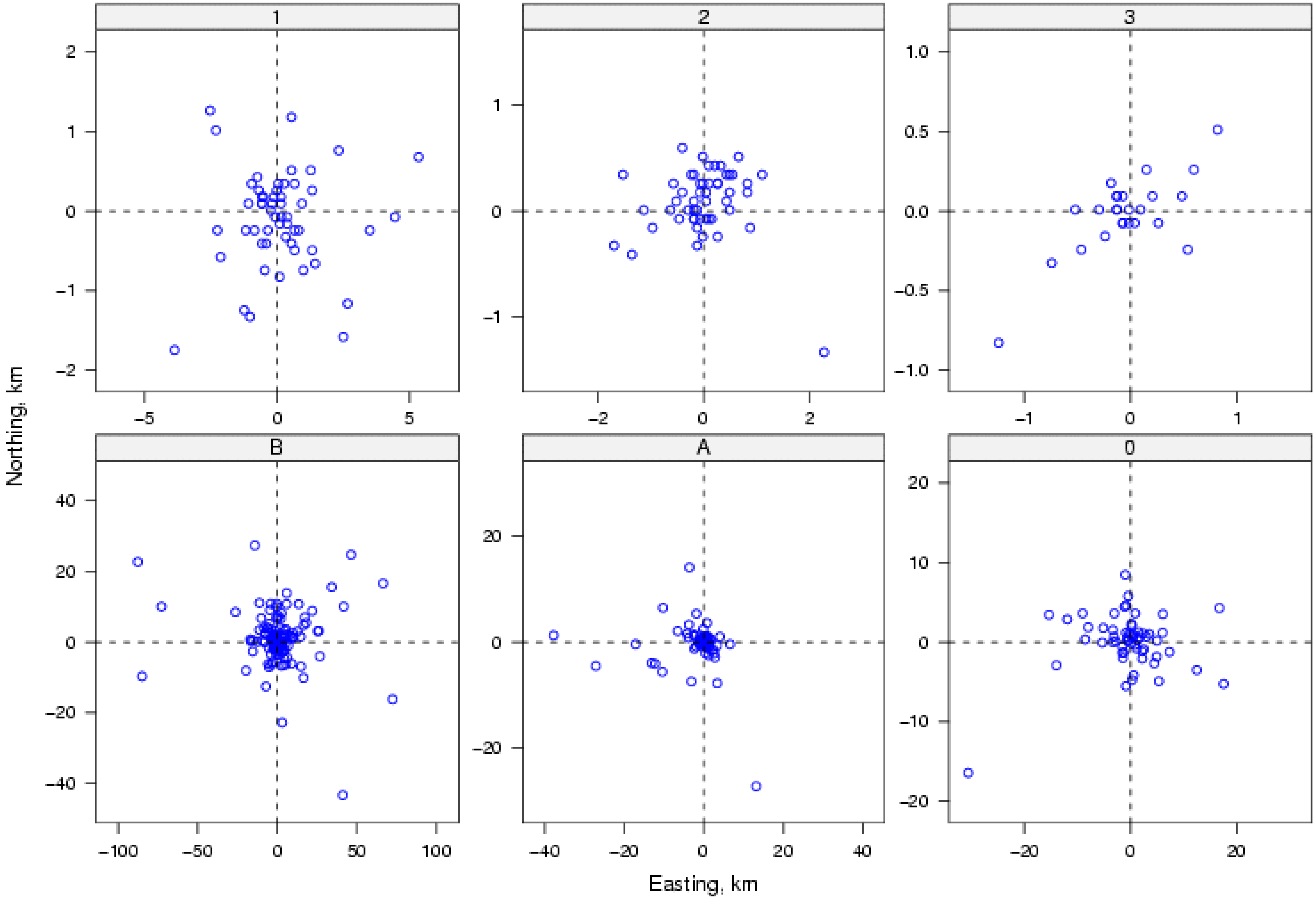




Radio or acoustic telemetry

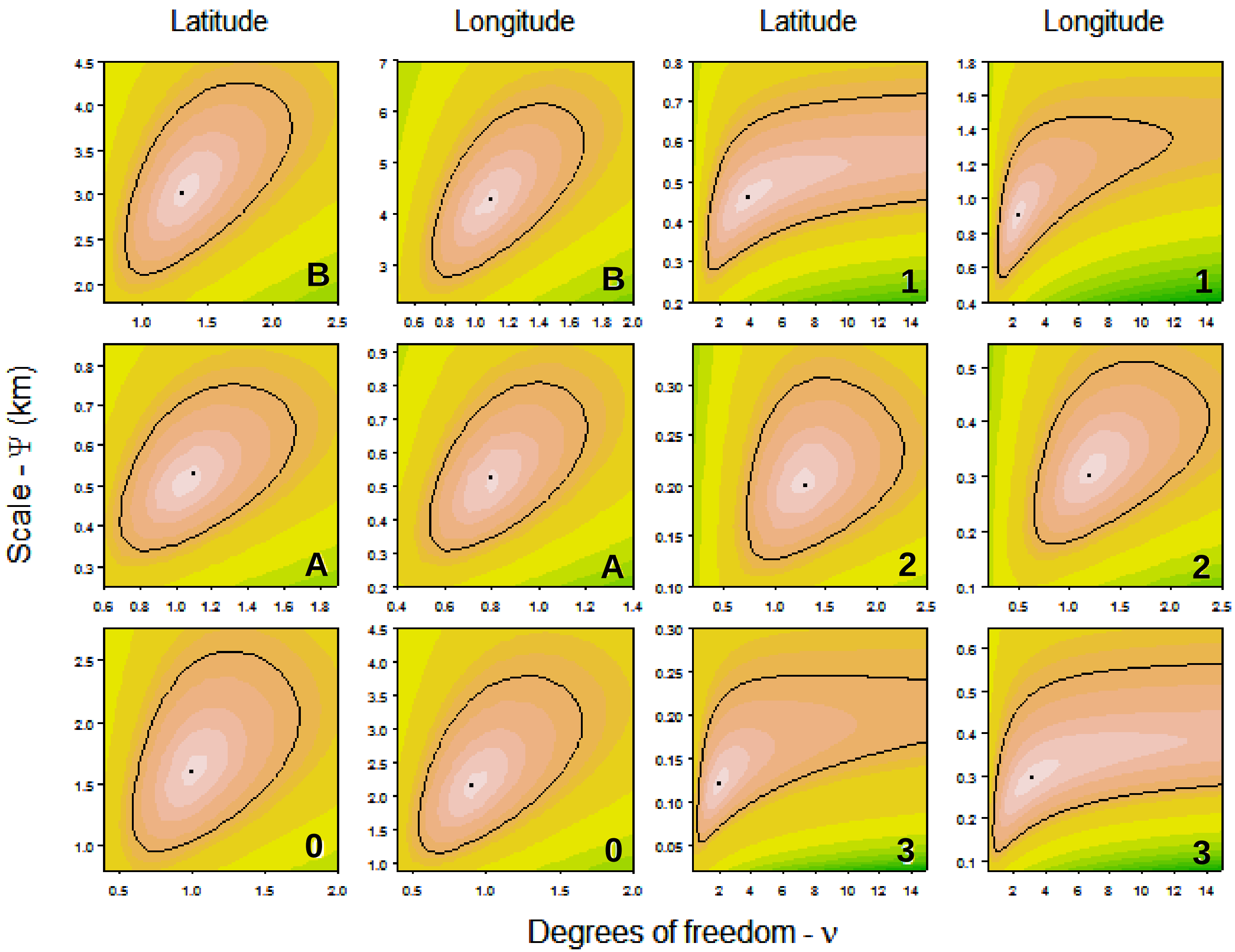


Argos location errors

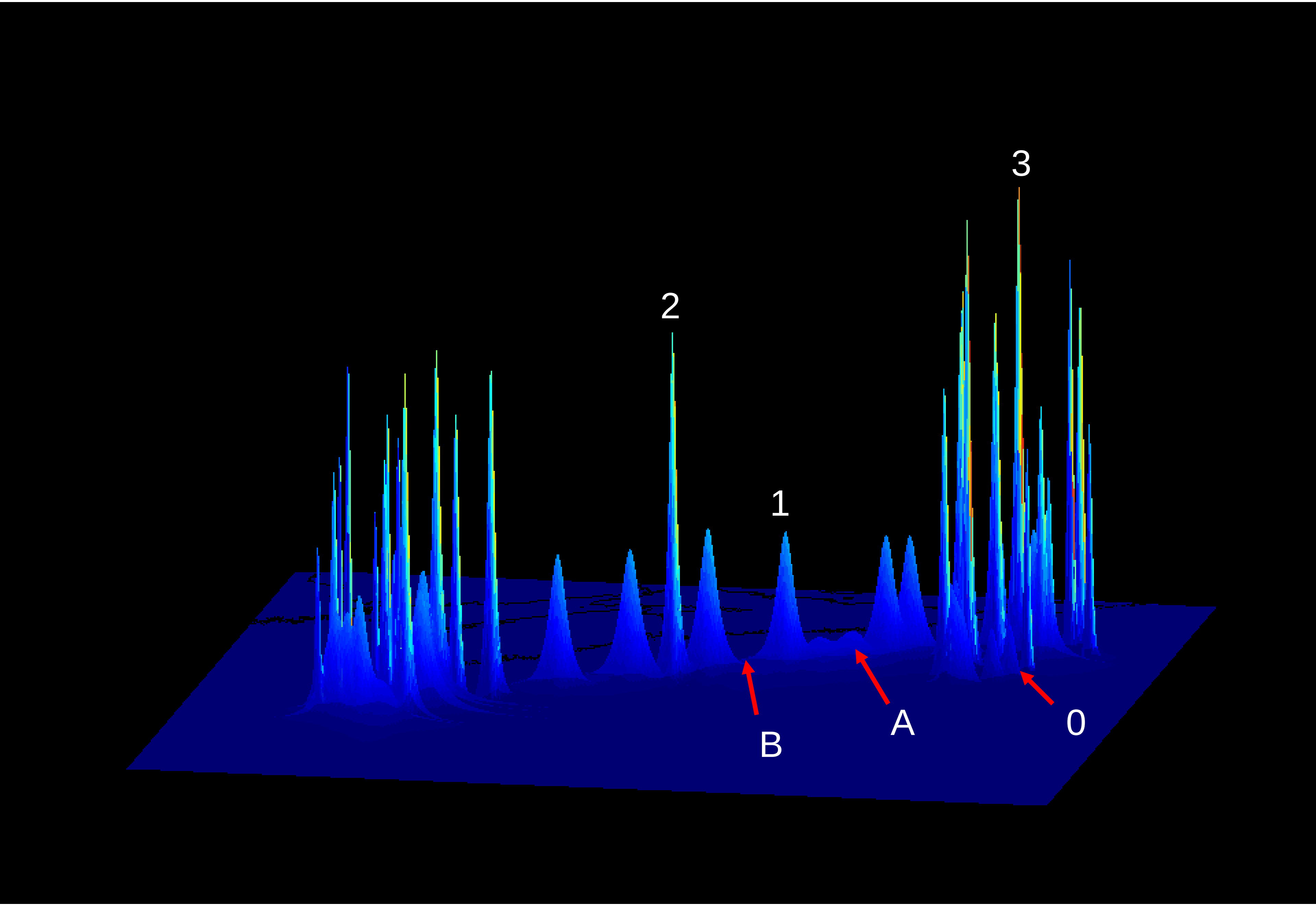


data from Vincent et al. 2002

Argos errors follow *t*-distributions:



Jonsen, Flemming, Myers, Ecology, 2005


3
2
1
B
A
0

Tag Precision

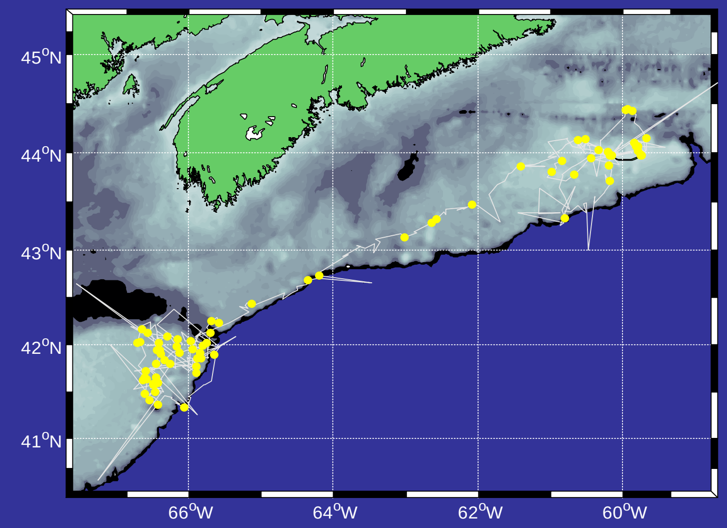
$$y_t = \text{t-distribution}\,(\alpha_t\,, c\sigma_t, \upsilon_t\,)$$

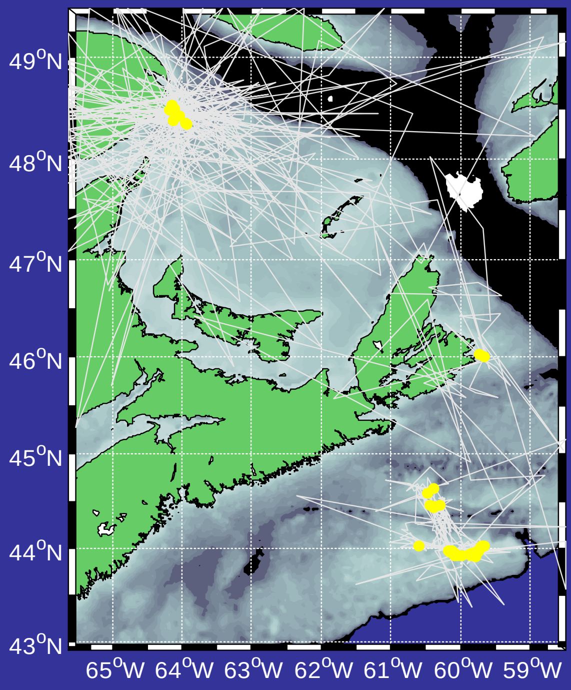
σ for each location class is assumed known (Vincent et al. 2002, Jonsen et al 2005)

c is an estimated parameter that scales the variance to each tag

Best tags are **1000's** of times more precise than the worst tags

Best tags in a single lot can be **100's** of times more precise than worst tags from a lot

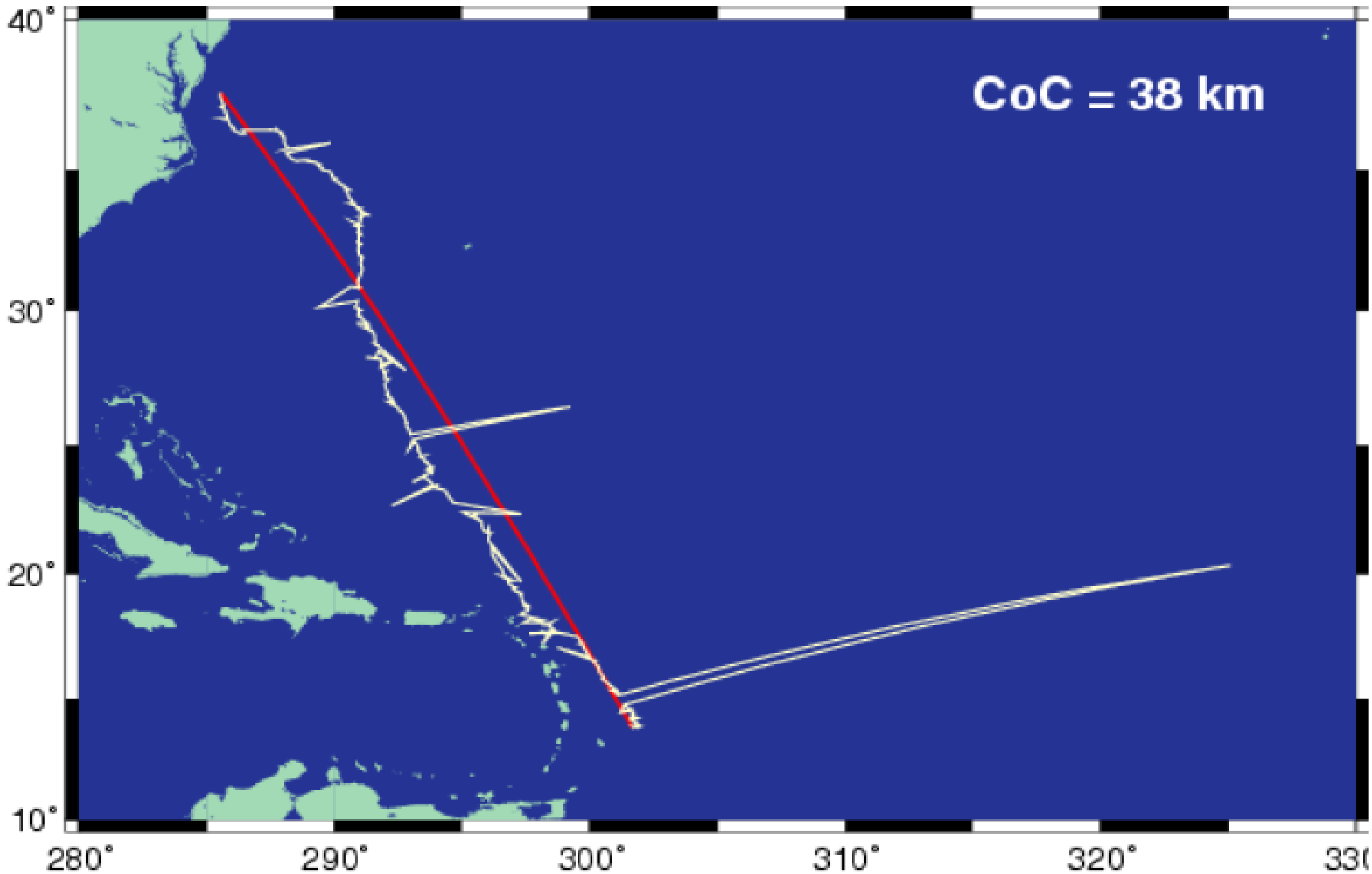


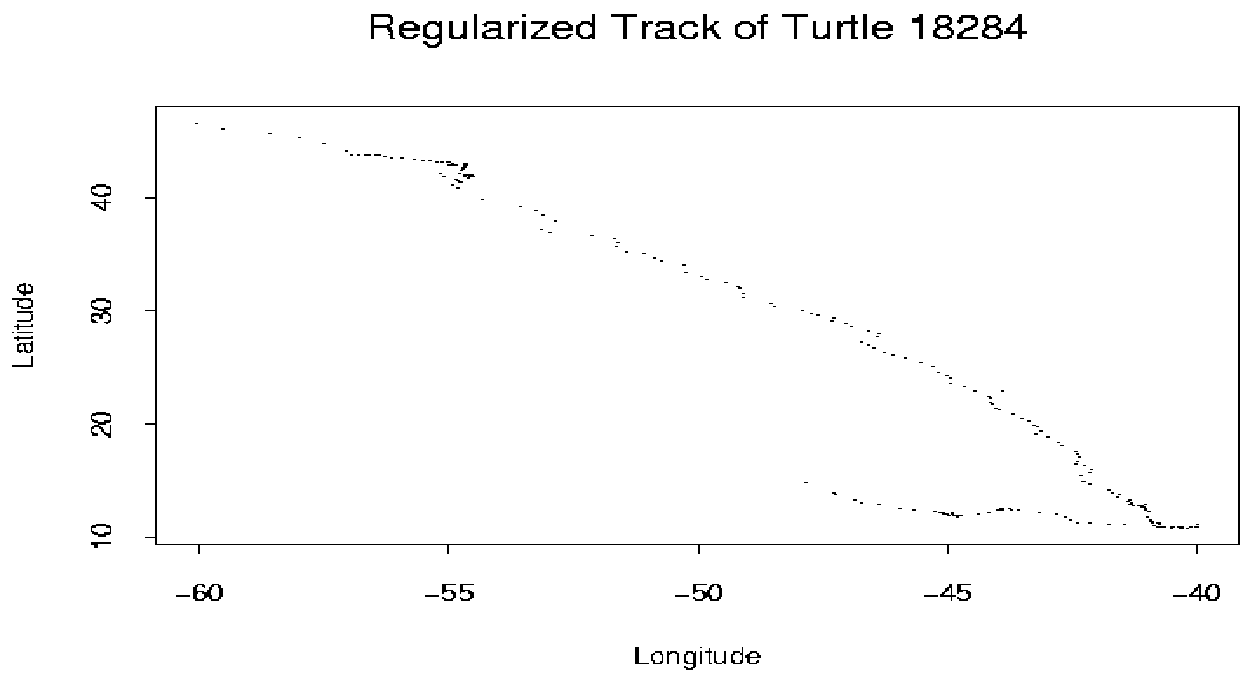


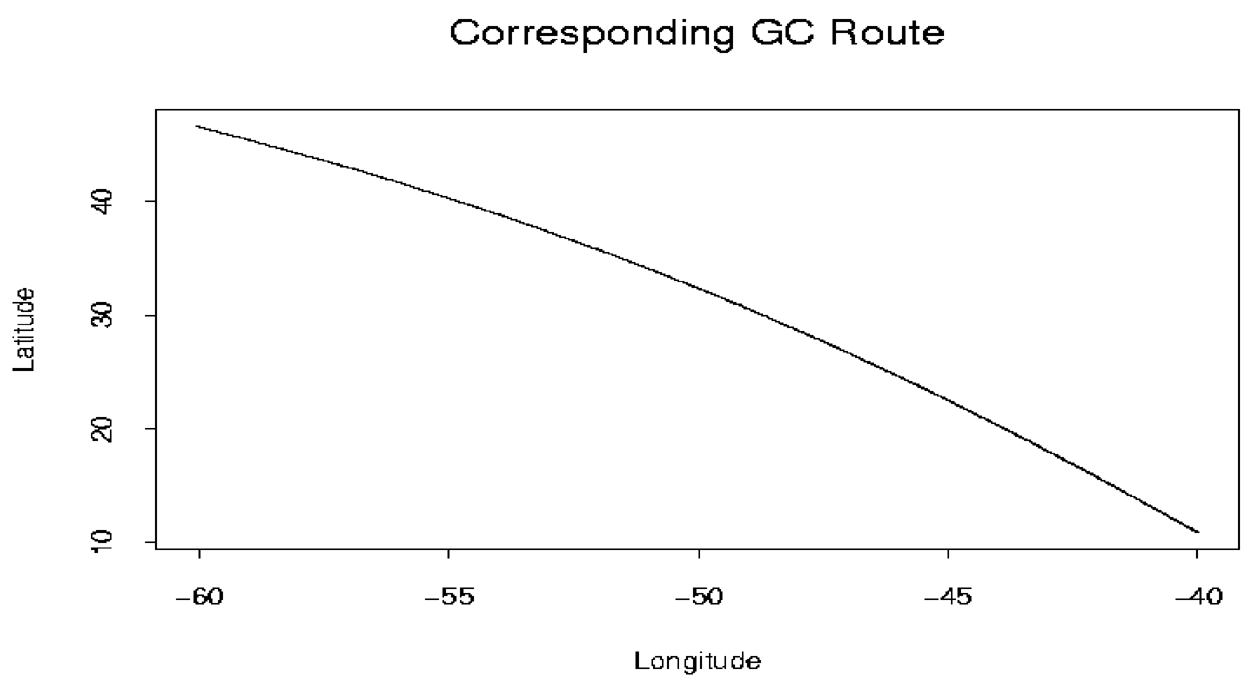
State-space models allow you to think about things, that it is very difficult to think about otherwise

Navigation: Estimating the "Circle of Confusion"

Flemming et al. in press. Environmetrics

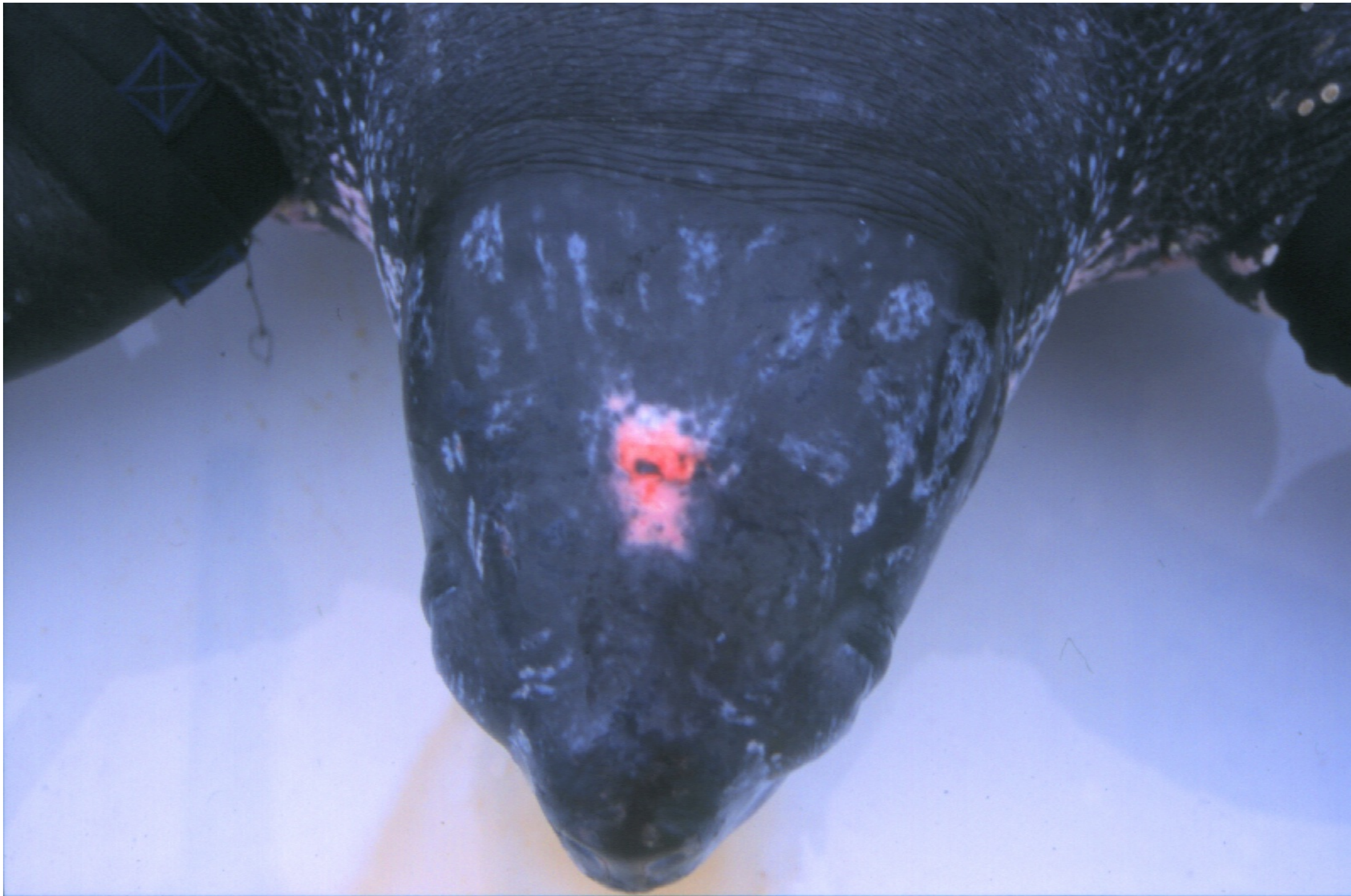



Regularized Track of Turtle 18284
Latitude
Longitude
10
20
30
40
−60
−55
−50
−45
−40

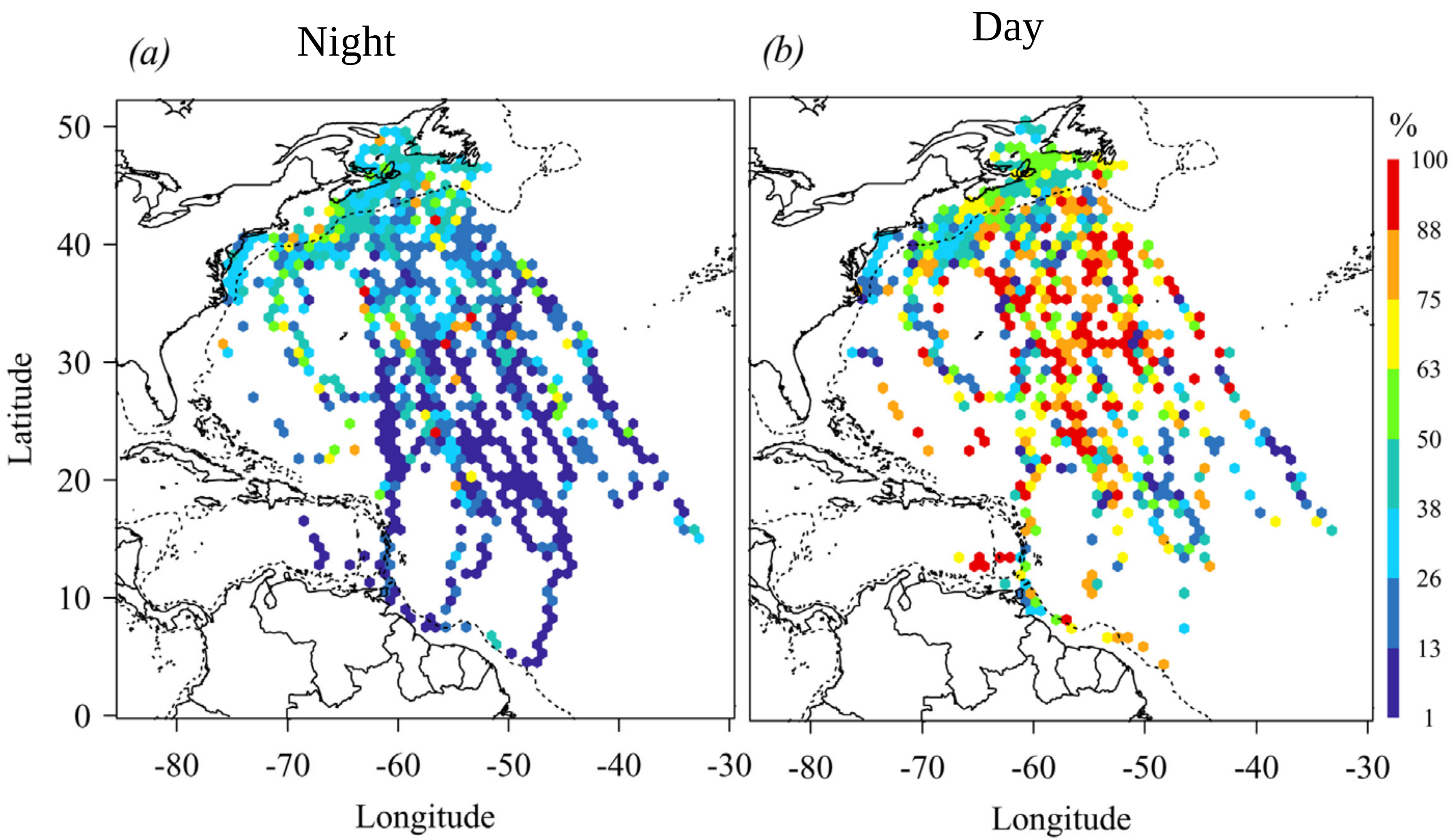

Corresponding GC Route
Latitude
Longitude
10
20
30
40
−60
−55
−50
−45
−40

It is essential to treat groups of animals simultaneously for maximum utility of the data.

Leatherback turtles are unique in that they expose their pineal spot to sunlight.

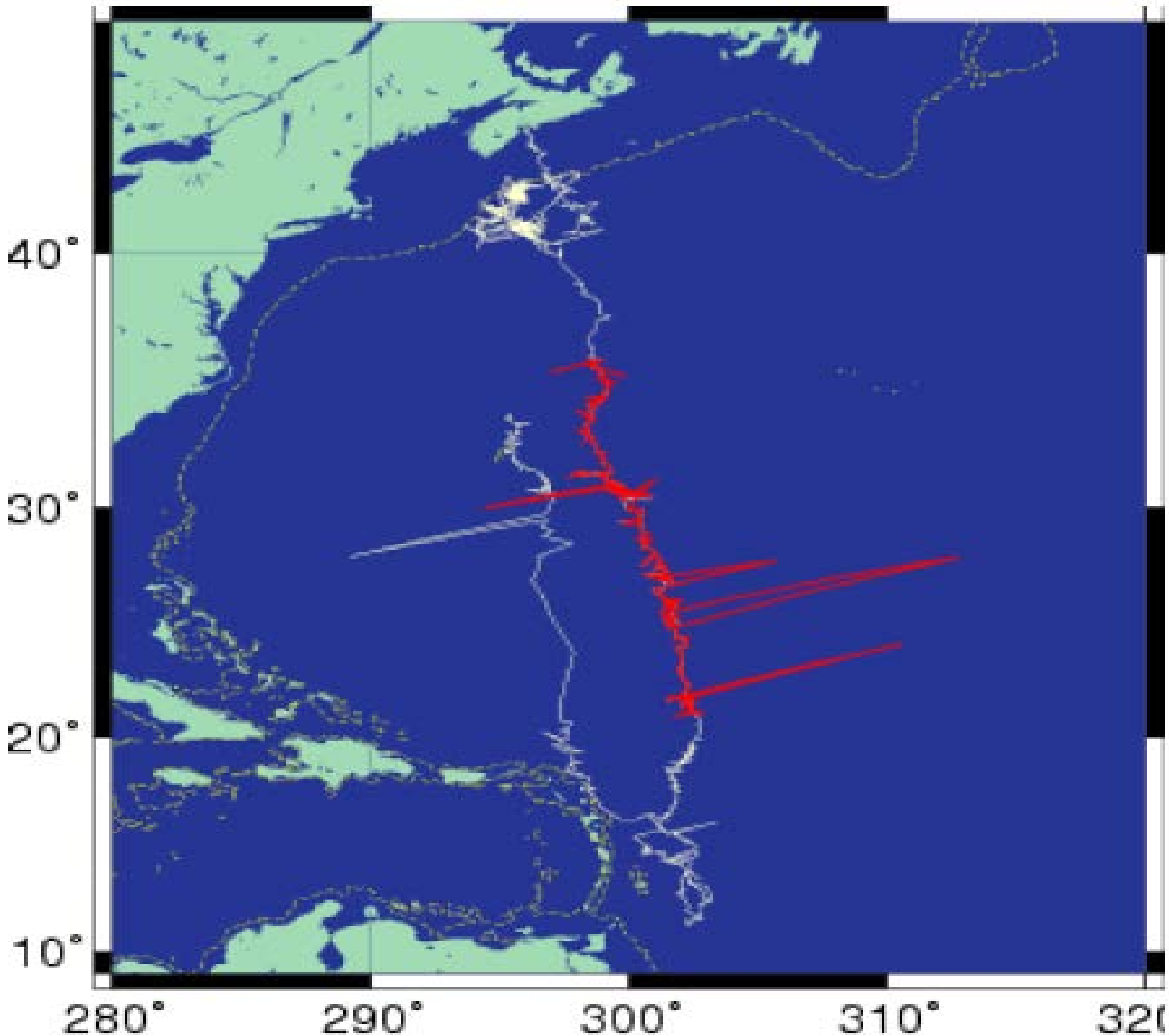


Turtles are close to the surface during the day during migration

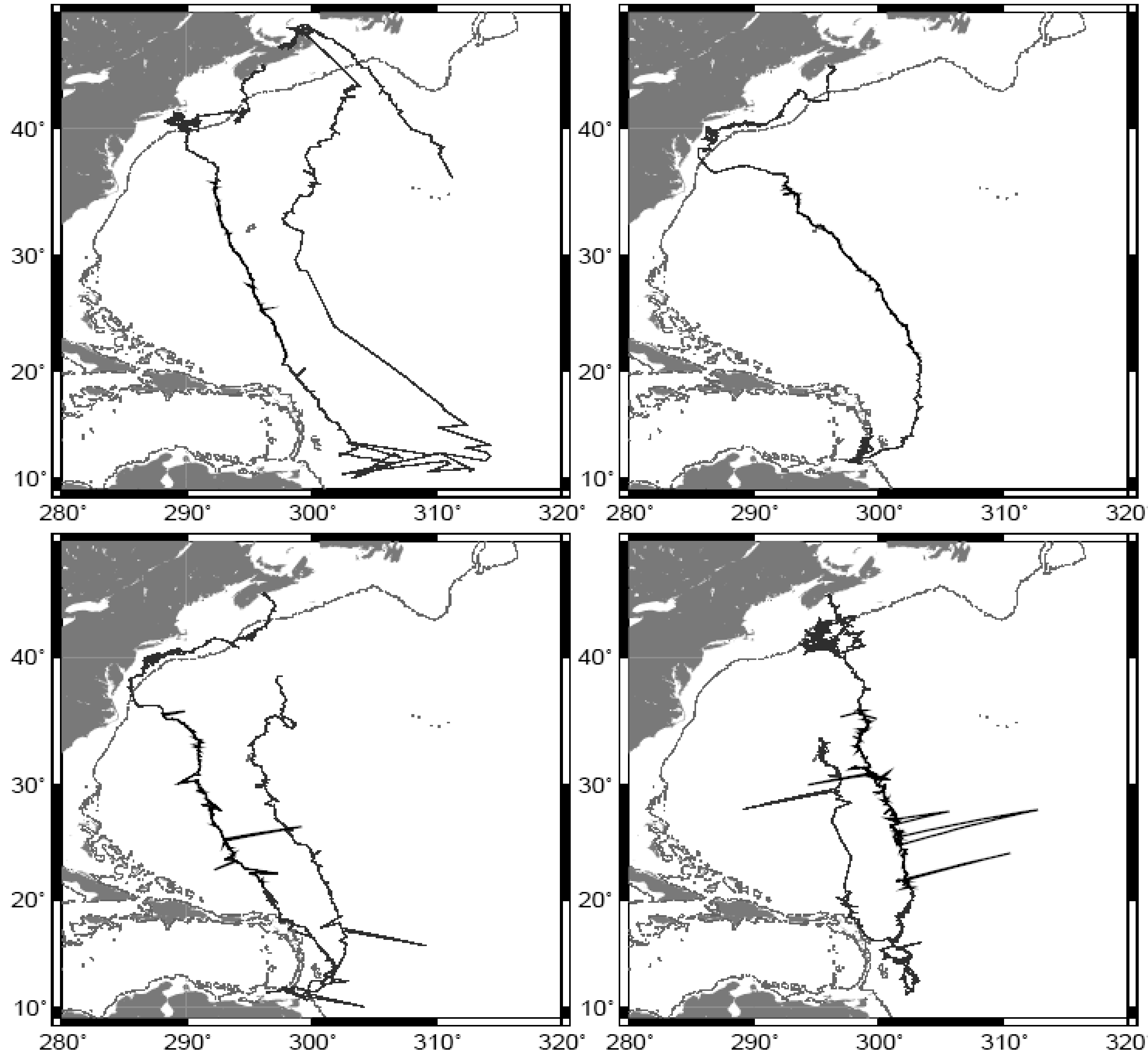


James et al. in review

Examining Diel Migration Behaviour in Leatherbacks



Jonsen, James Myers. in review. Journal of Animal Ecology


40°
30°
20°
10°
280°
290°
300°
310°
320°

Hierarchical Bayes State-Space Model (HB SSM)

$\mu_{\beta_1} \sim \mathrm{N}(0, 10^4)$ $\quad$ $\sigma_{\beta_1} \sim \mathrm{U}(0, 1)$ **Hyper-priors**

μ_{β_1} $\quad$ σ_{β_1} **Hyper-parameters**

$\pi(\beta_1) \sim \mathrm{N}(\mu_{\beta_1}, \sigma^2_{\beta_1})$ **Prior**

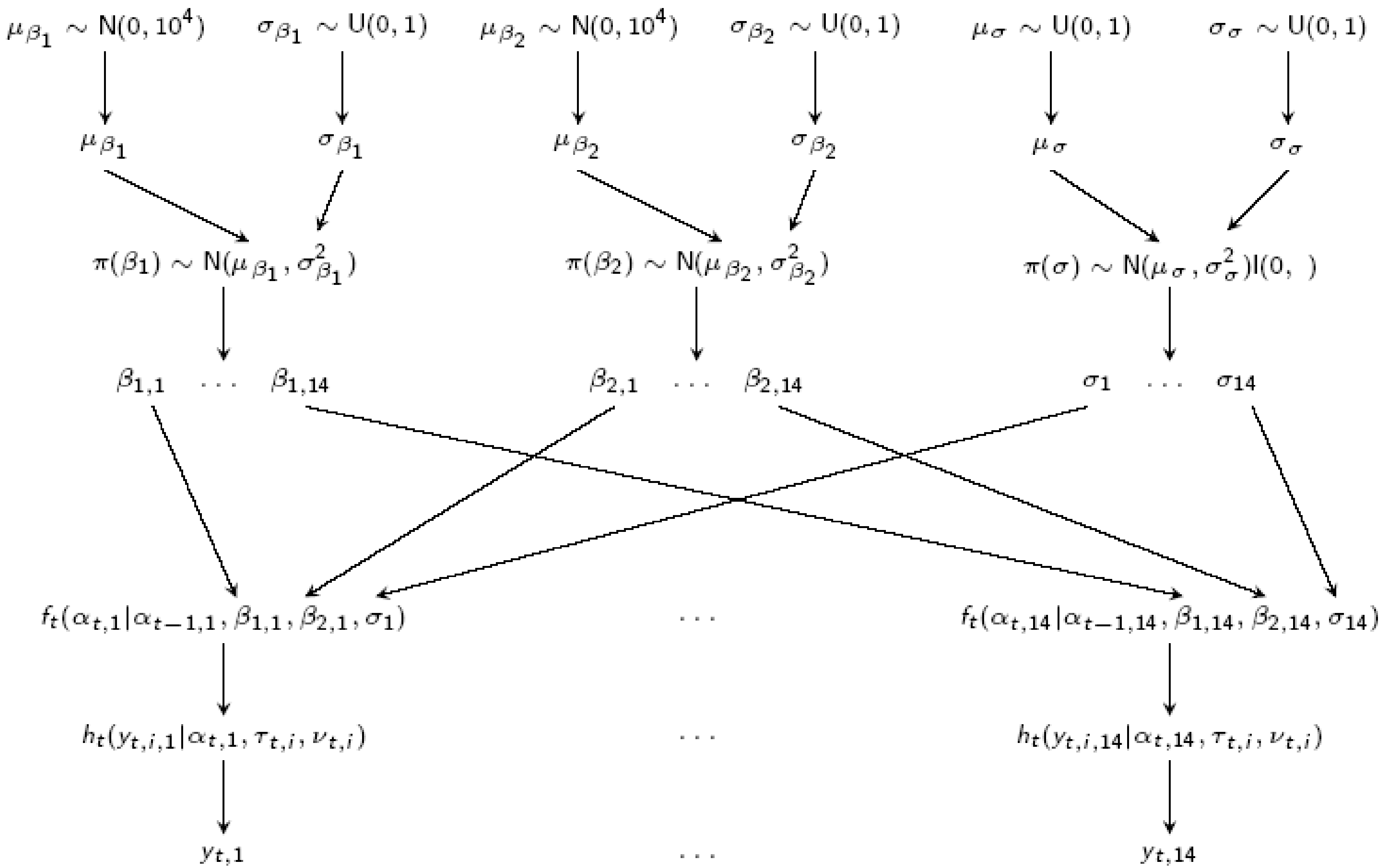
$\beta_{1,1} \quad \cdots \quad \beta_{1,14}$ **Parameters**

$f_t(\alpha_{t,1} | \alpha_{t-1,1}, \beta_{1,1}, \beta_{2,1}, \sigma_1)$ ... **Process sampling densities** ... $f_t(\alpha_{t,14} | \alpha_{t-1,14}, \beta_{1,14}, \beta_{2,14}, \sigma_{14})$

$h_t(y_{t,i,1} | \alpha_{t,1}, \tau_{t,i}, \nu_{t,i})$ ... **Observation sampling densities** ... $h_t(y_{t,i,14} | \alpha_{t,14}, \tau_{t,i}, \nu_{t,i})$

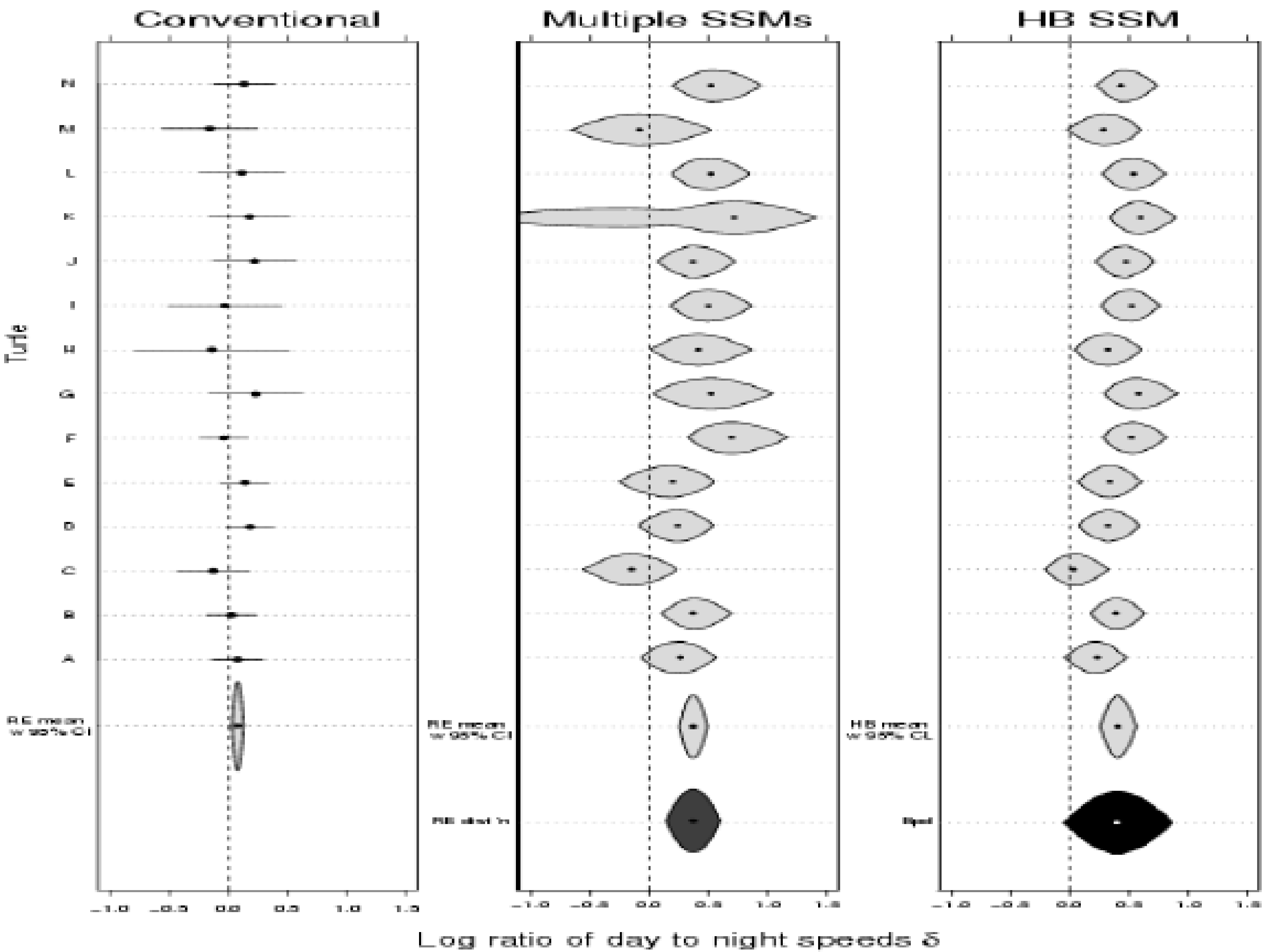
$y_{t,1}$ ... **Data** ... $y_{t,14}$

HB SSM

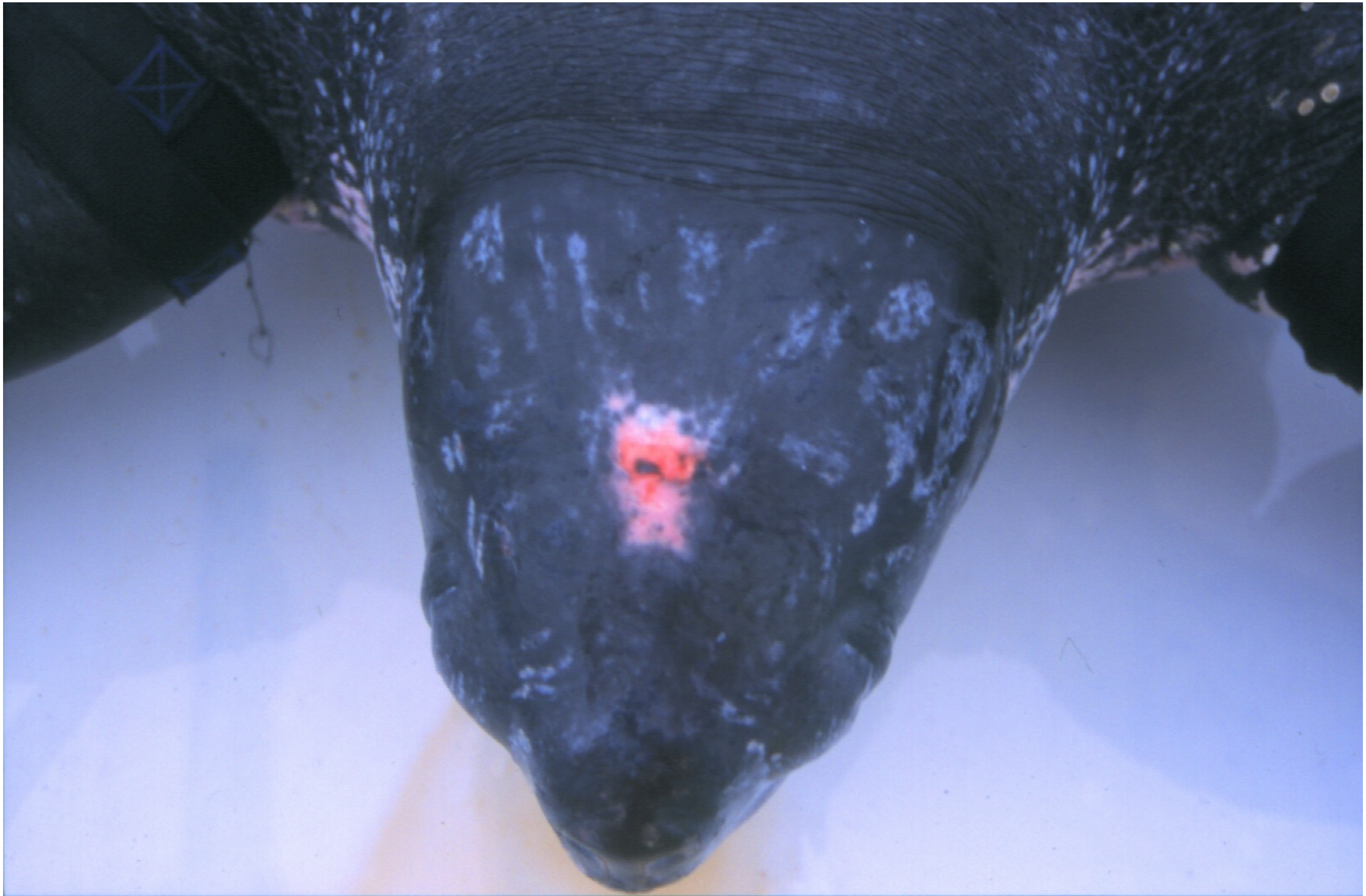


$\mu_{\beta_1} \sim N(0, 10^4)$
$\sigma_{\beta_1} \sim U(0, 1)$
$\mu_{\beta_2} \sim N(0, 10^4)$
$\sigma_{\beta_2} \sim U(0, 1)$
$\mu_\sigma \sim U(0, 1)$
$\sigma_\sigma \sim U(0, 1)$
μ_{β_1}
σ_{β_1}
μ_{β_2}
σ_{β_2}
μ_σ
σ_σ
$\pi(\beta_1) \sim N(\mu_{\beta_1}, \sigma^2_{\beta_1})$
$\pi(\beta_2) \sim N(\mu_{\beta_2}, \sigma^2_{\beta_2})$
$\pi(\sigma) \sim N(\mu_\sigma, \sigma^2_\sigma)I(0, \ )$
$\beta_{1,1} \cdots \beta_{1,14}$
$\beta_{2,1} \cdots \beta_{2,14}$
$\sigma_1 \cdots \sigma_{14}$
$f_t(\alpha_{t,1}|\alpha_{t-1,1}, \beta_{1,1}, \beta_{2,1}, \sigma_1)$
$\cdots$
$f_t(\alpha_{t,14}|\alpha_{t-1,14}, \beta_{1,14}, \beta_{2,14}, \sigma_{14})$
$h_t(y_{t,i,1}|\alpha_{t,1}, \tau_{t,i}, \nu_{t,i})$
$\cdots$
$h_t(y_{t,i,14}|\alpha_{t,14}, \tau_{t,i}, \nu_{t,i})$
$y_{t,1}$
$\cdots$
$y_{t,14}$

Conventional Approaches Do Not Work



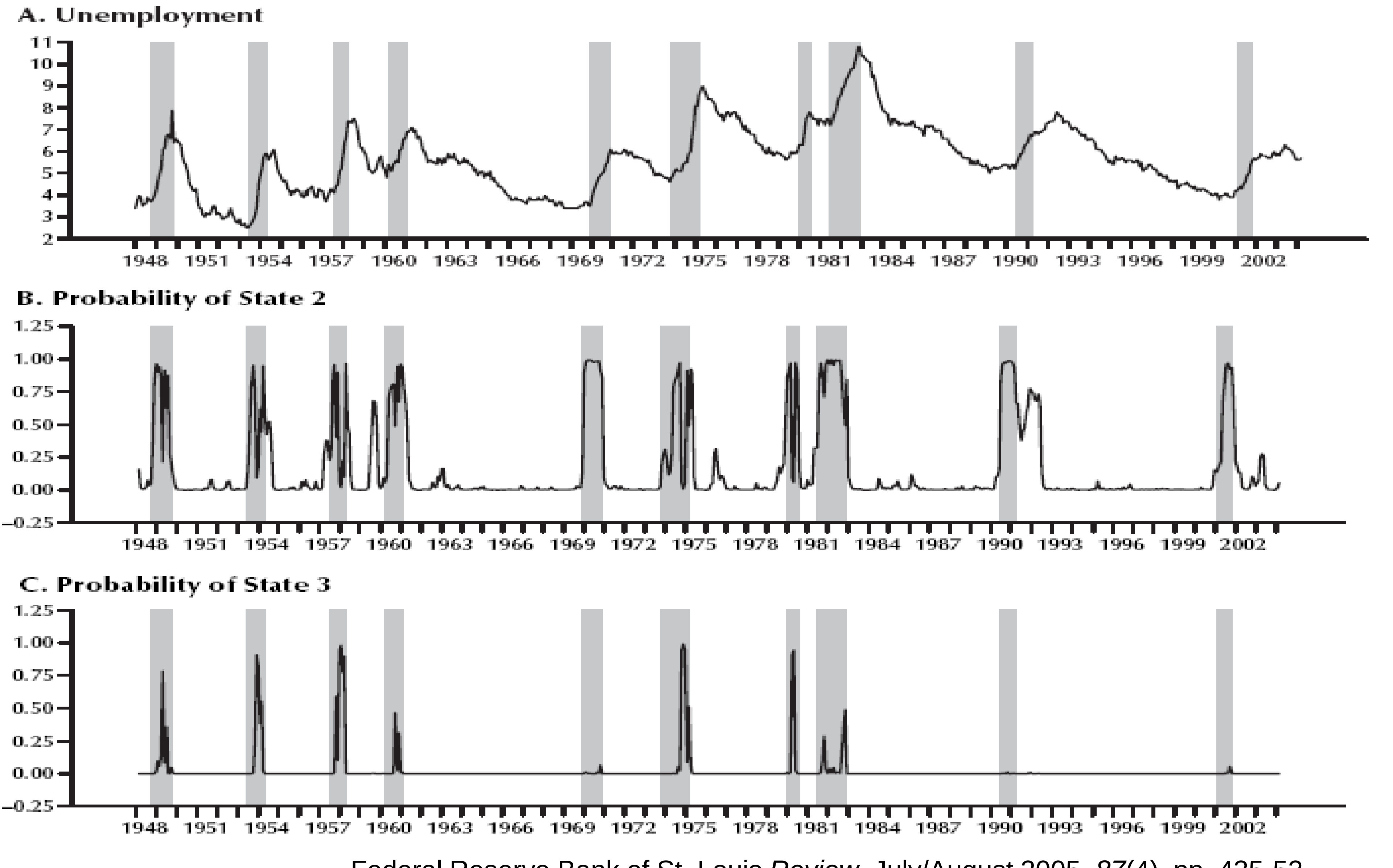
Results are consistent with the hypothesis that the pineal spot improves navigation.



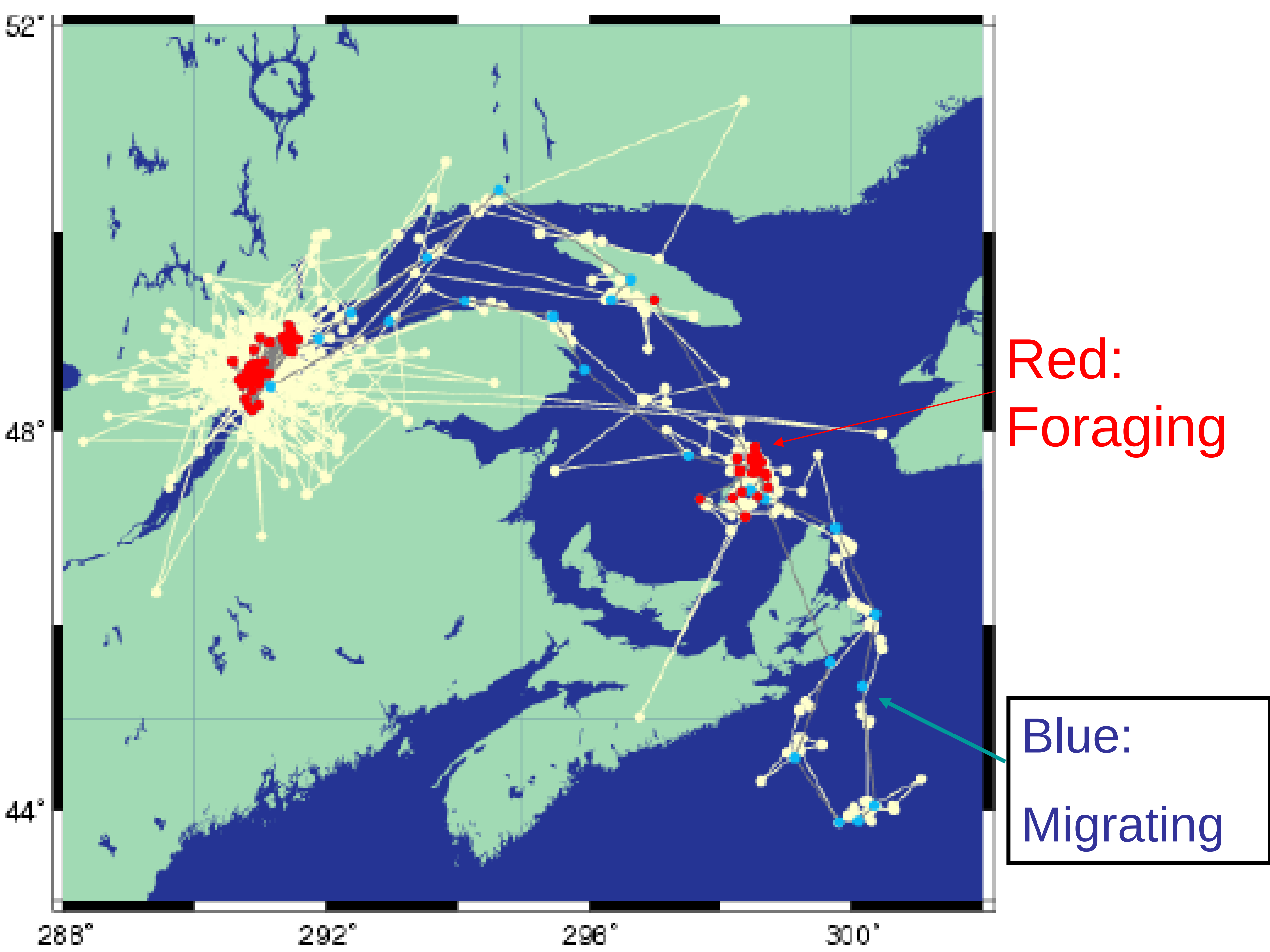
Dynamics of behavior is very nonlinear, to determine hot spots and foraging

- Solution: Markov switching models between behavioral modes
- Dynamics within a behavioral mode is linear

State-Space Switching Models



Federal Reserve Bank of St. Louis *Review*, July/August 2005, *87*(4), pp. 435-52.


52°
48°
44°
288°
292°
296°
300°
Red:
Foraging
Blue:
Migrating

Summary

- State-space models allow you to think about problems which have no conventional solution
- Fundamentally different approach to analysis of complex, error-prone data emphasis on estimation of “true” states, biological parameters and uncertainty
- Models can be fit to other types of sequential movement data (GPS, Archival tags)

The Future

- Better incorporation of oceanographic data
- Model testing, statisticians do NOT know how to compare models with non-Gaussian errors
- More “user friendly” (i.e. less “user angry” methods). This would include an easy to use library with a variety of possible behaviour.

Critical Spatial/Temporal Models Tools

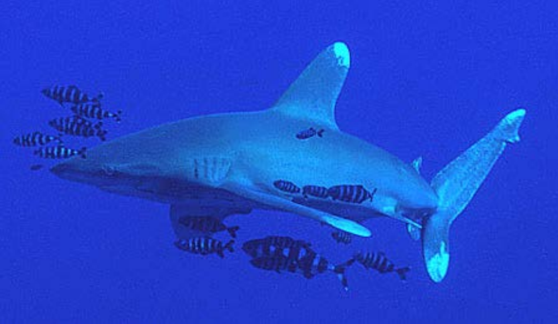
Ransom A. Myers (RAM)
Dalhousie University, Canada

Pew Global Sharks Assessment

http://fish.dal.ca

FMAP (Future of Marine Animal Populations)
Lenfest Foundation
Sloan Census of Marine Life

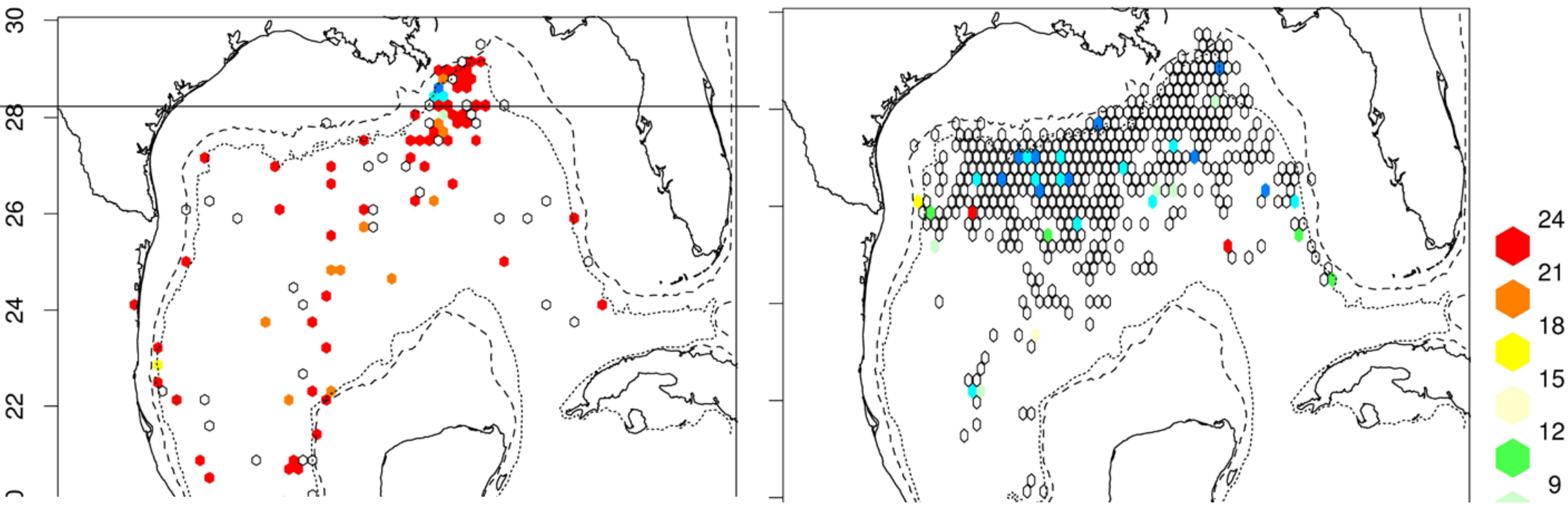
What was the most common large animal in the world? (perhaps this one was)



Loss of sharks in the Gulf of Mexico

300 fold decline – no one noticed

[redacted]



1950's 1990's

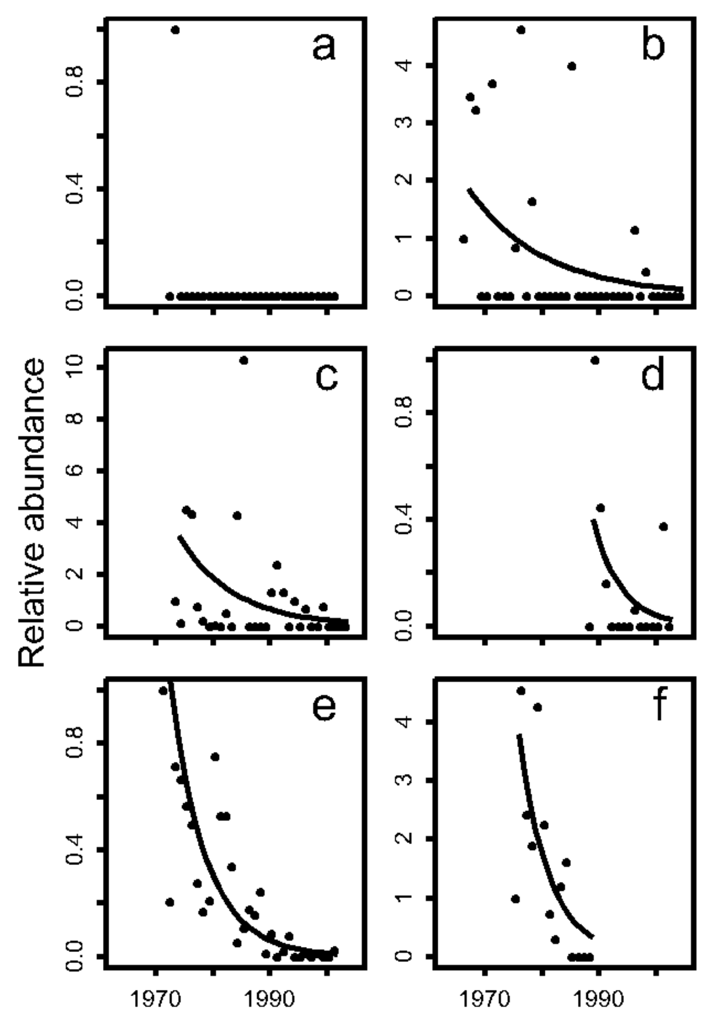
Oceanic Whitetip captures per 10,000 hooks

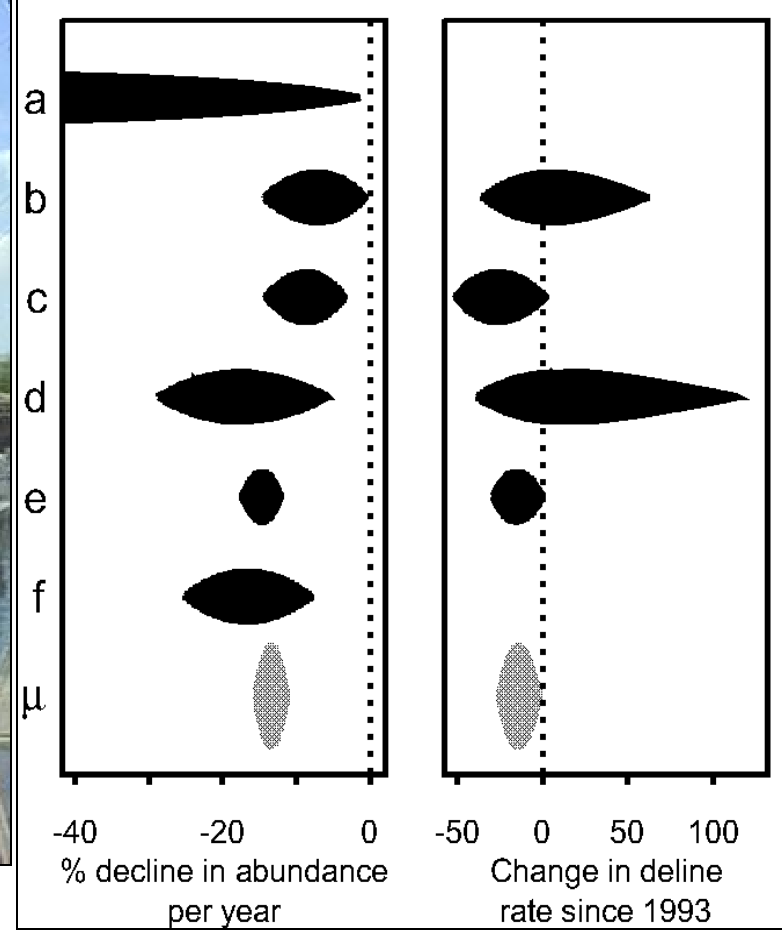
Baum and Myers, 2004 Ecology Letters

Circumstantial evidence of oceanic whitetip sharks being common in the Gulf of Mexico

Critical Modeling Tools

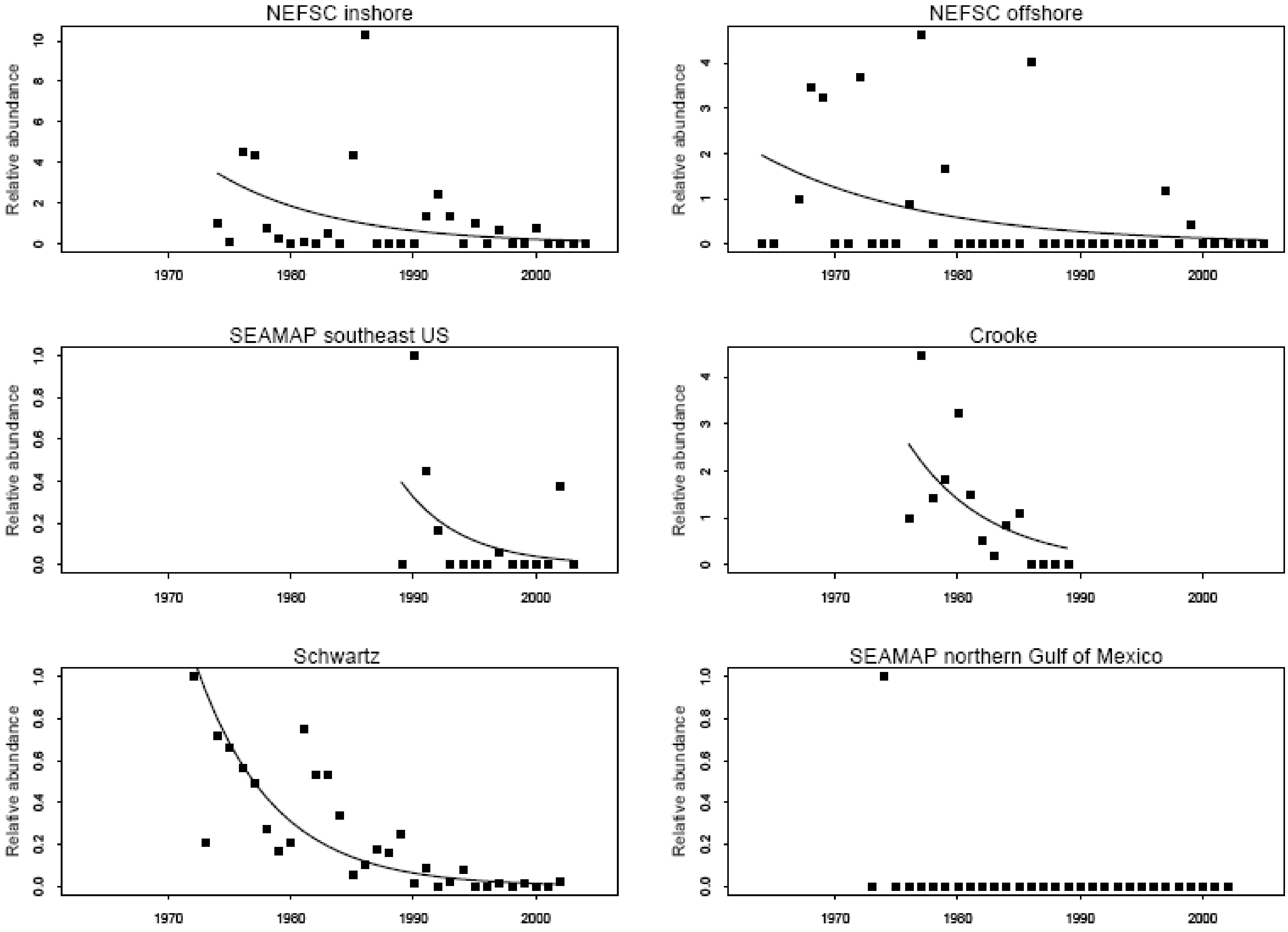
- Generalized linear models with negative binomial error
- Generalized linear mixed effects models to standardize old and new surveys



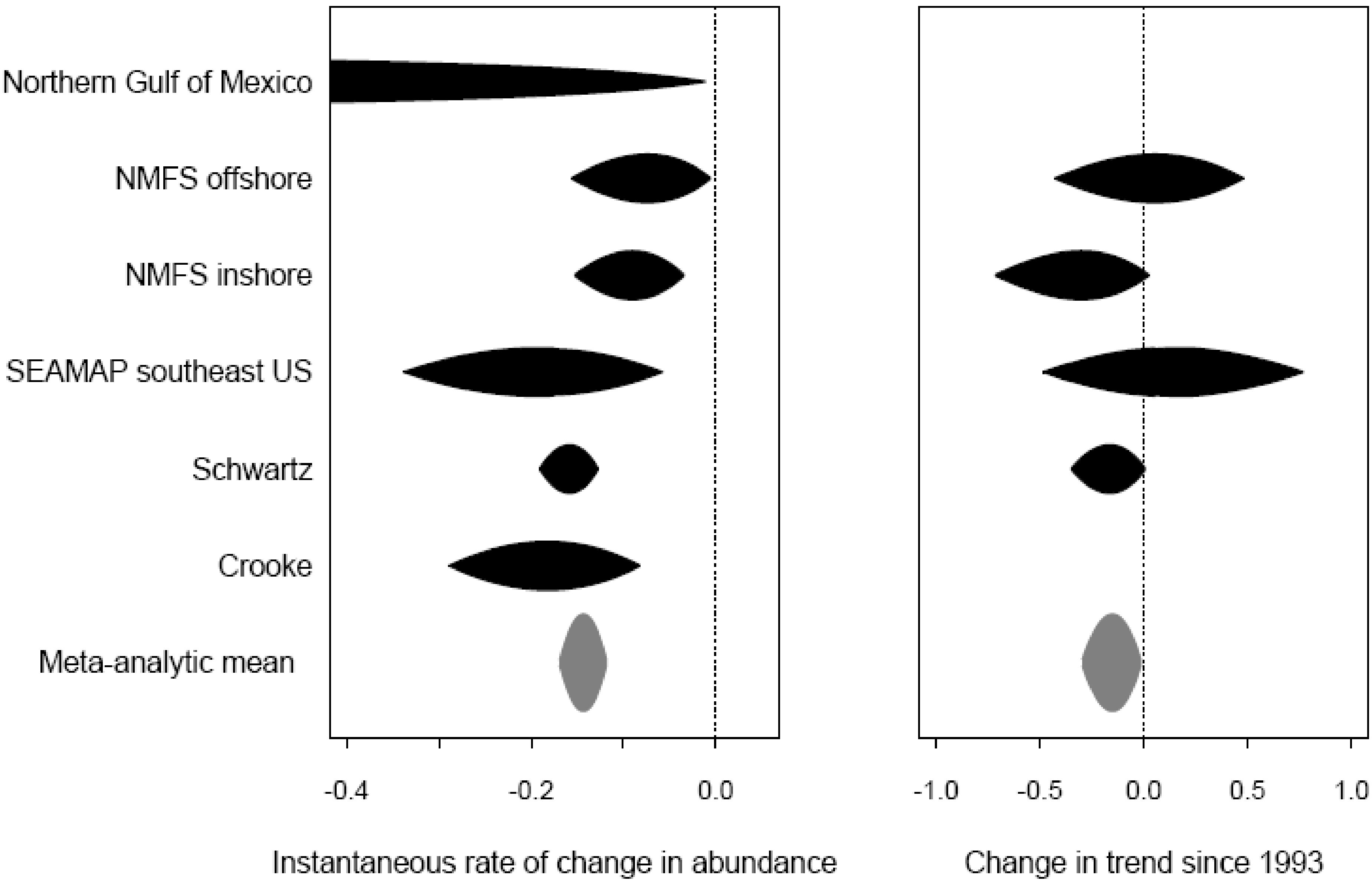


a. Northern Gulf of Mexico bottom shrimp trawl survey
b. NMFS offshore bottom trawl survey
c. NMFS inshore bottom trawl survey
d. Southeast U.S. SEAMAP bottom shrimp trawl survey
e. North Carolina Institute of Marine Sciences longline survey
f. Crooke commericial longline data
μ. Meta-analytic mean

Loss of Dusky Sharks in the Eastern US



Consequences of "protection" since 1993: Rate of decline has increased:

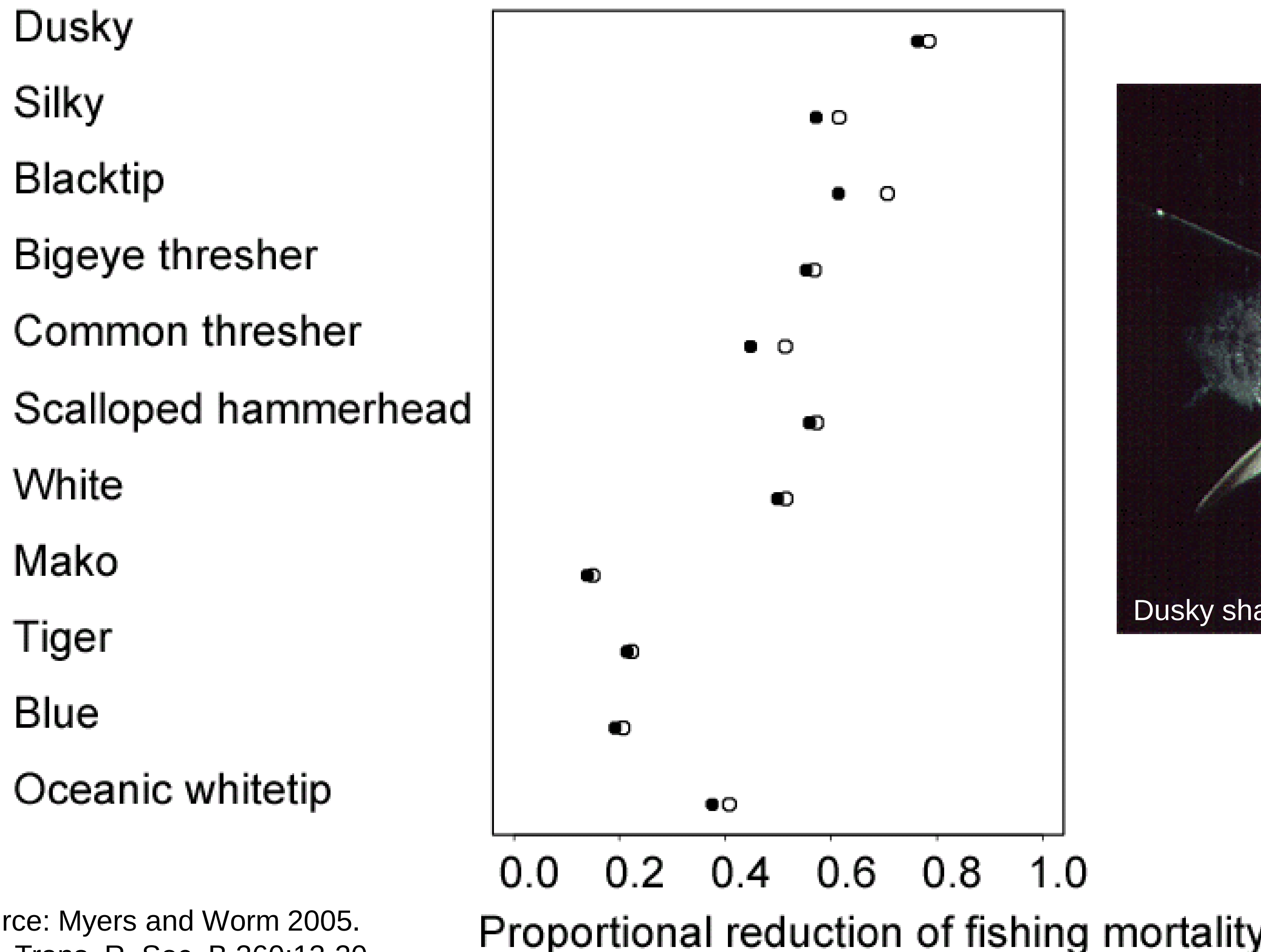


Critical Modeling Tools

Surveys vary in time, and the sharks move seasonally up and down the coast

We used a generalized linear mixed effect model with negative binomial errors to describe the seasonal movement up and down the coast by allowing the seasonal harmonics to be an interaction, i.e. latitude and harmonics.

Reduce fishing mortality for sensitive species for survival of the species




Dusky shark. Source: NMFS

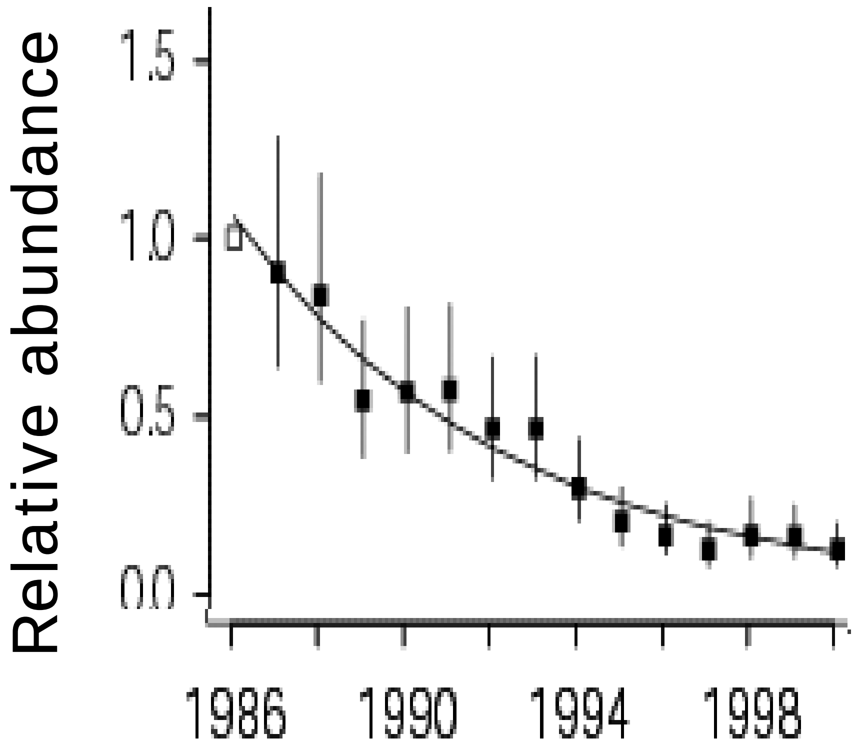
Source: Myers and Worm 2005.
Phil. Trans. R. Soc. B 360:13-20

Critical Modeling Tools

- Calculus
- Generalized linear models

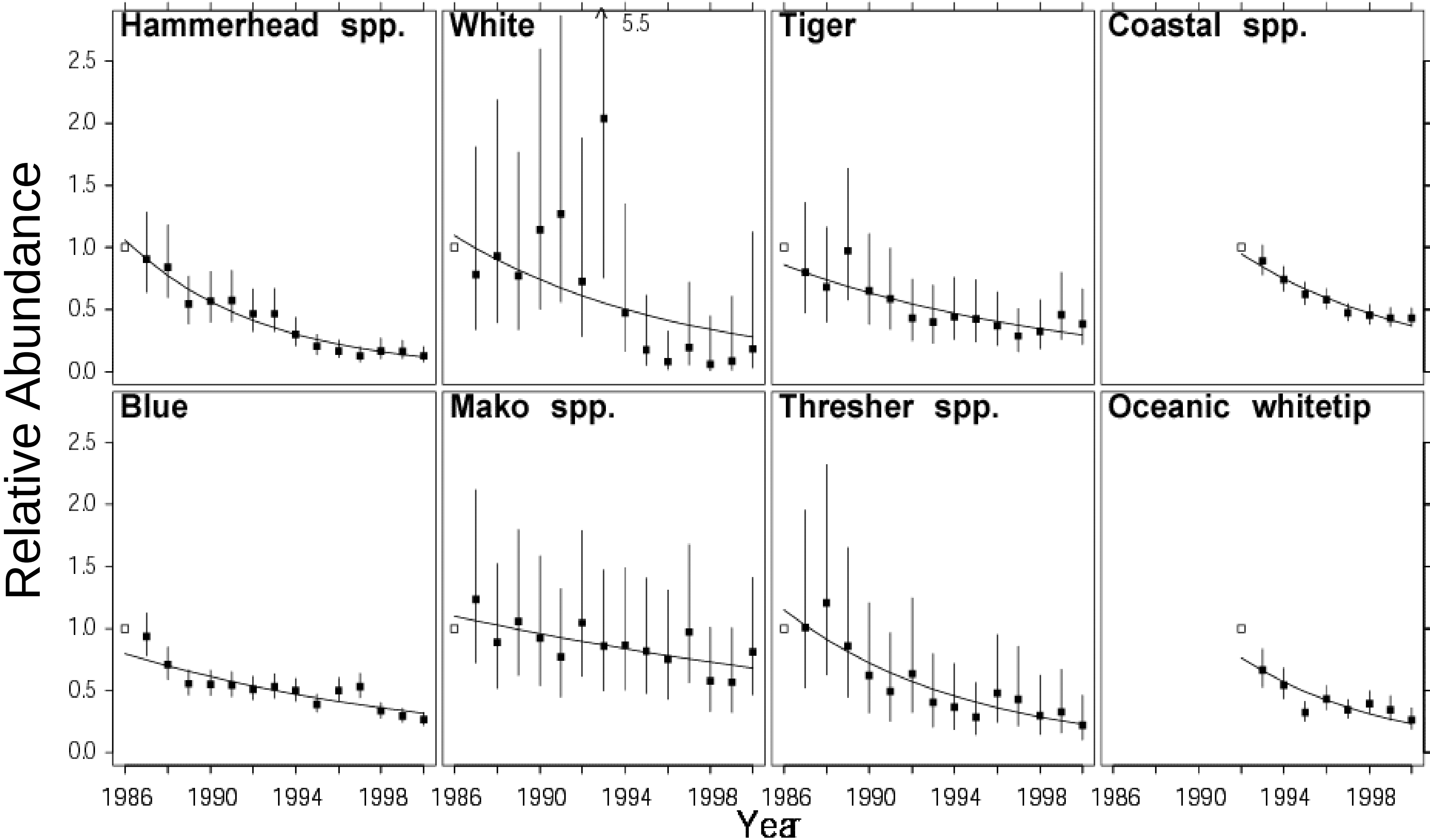
Hammerhead sharks

Sphyrna lewini



Science. Jan. 2003. J.K. Baum, R.A. Myers, D.G. Kehler, B. Worm, S.J. Harley, P.A. Doherty

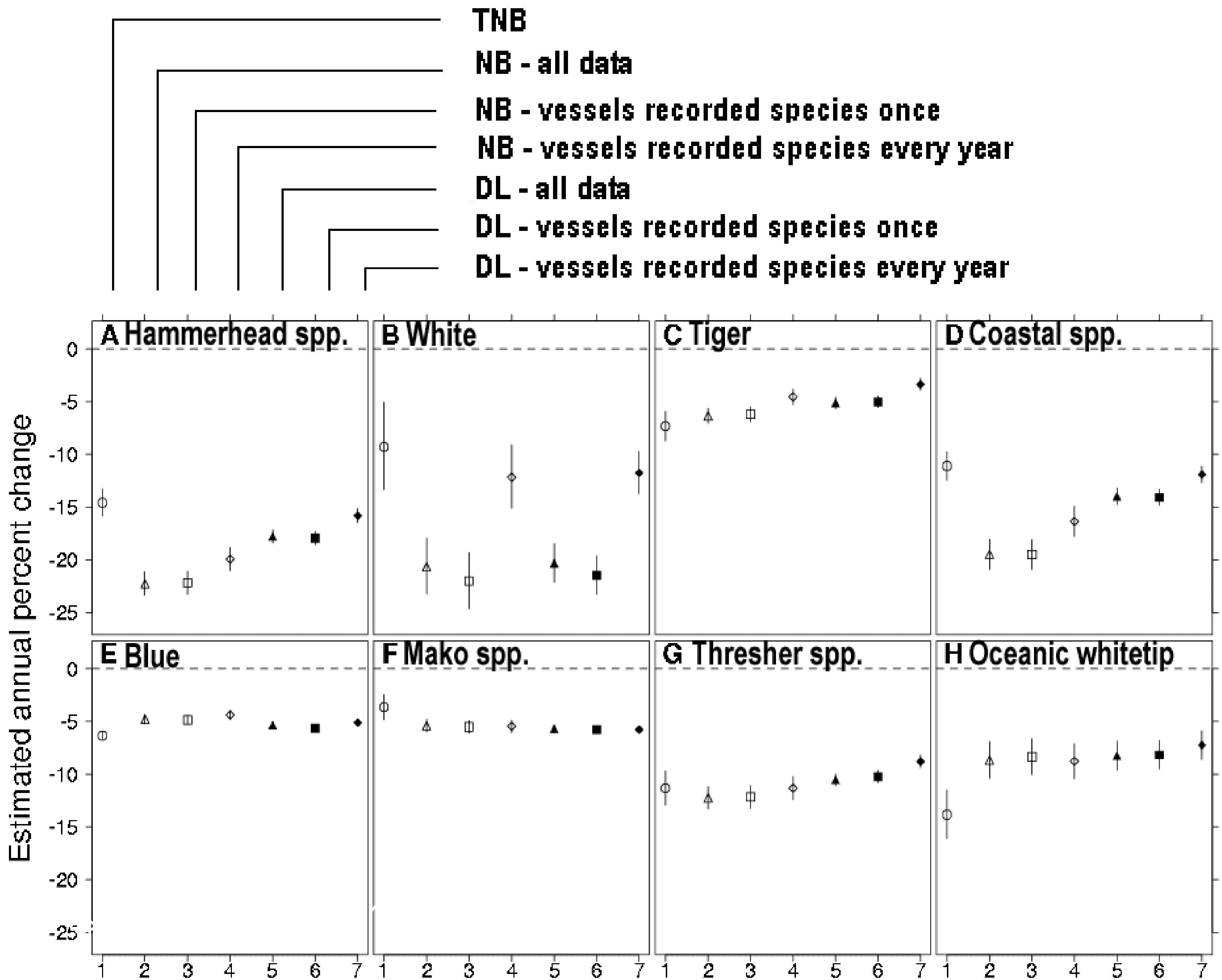
Results



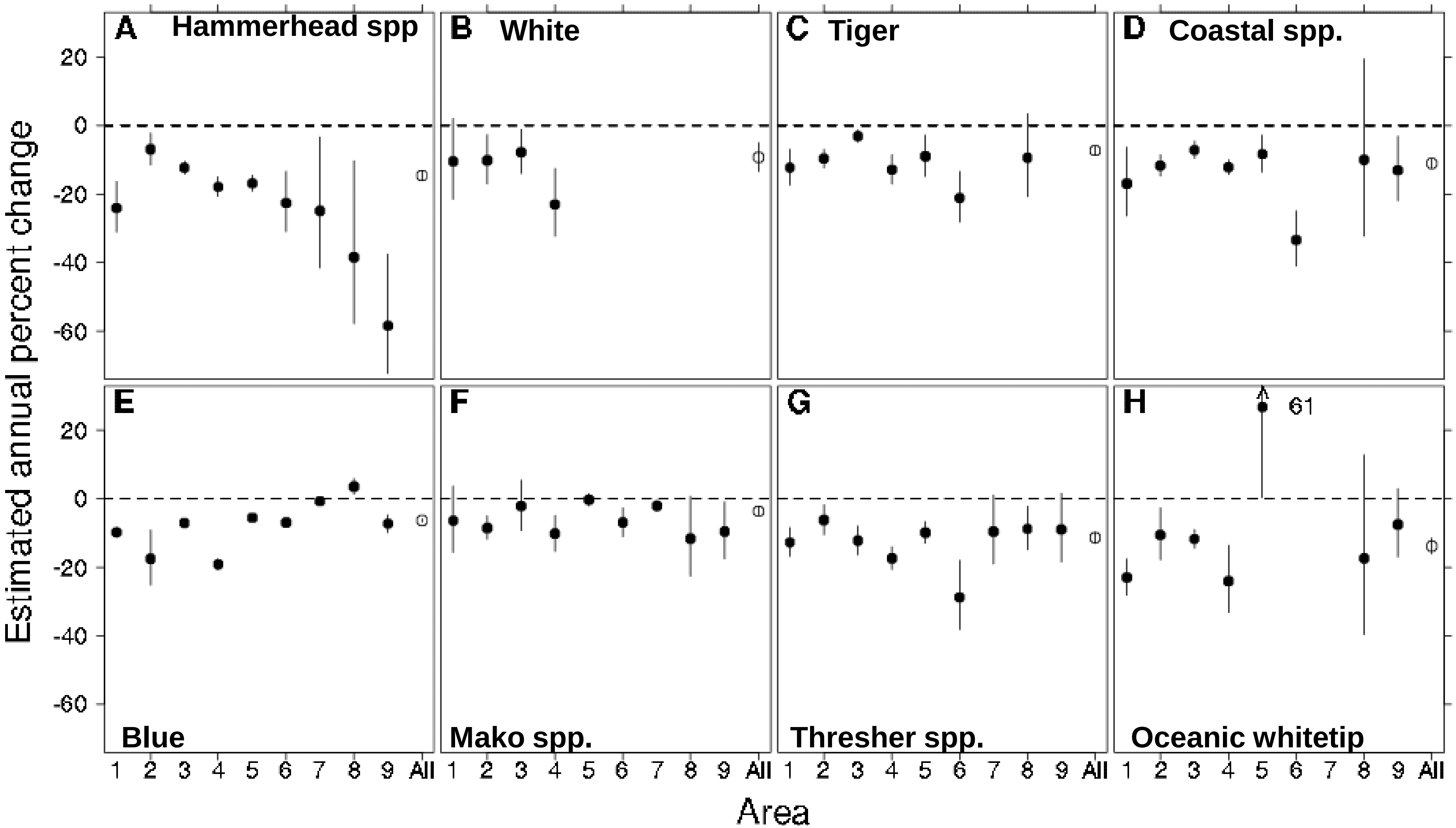
Hammerhead spp.
White
5.5
Tiger
Coastal spp.
Blue
Mako spp.
Thresher spp.
Oceanic whitetip
Relative Abundance
0.0
0.5
1.0
1.5
2.0
2.5
1986
1990
1994
1998
Year

Critical Modeling Tools

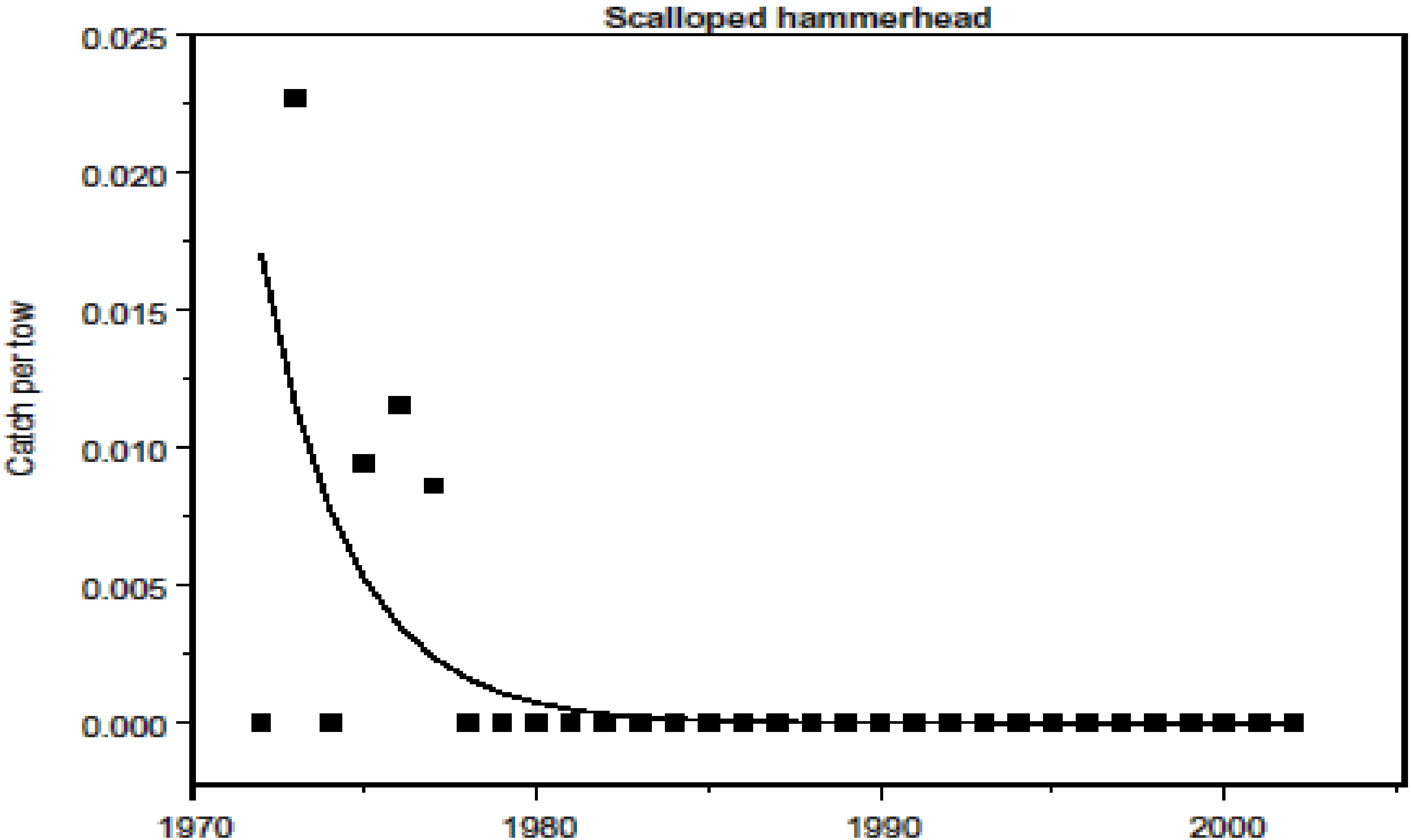
- Development of a new regression model that does not use “zeros” (we believe the fishermen sometimes lie).
- Robustness analysis that show results are robust to alternative assumptions


TNB
NB - all data
NB - vessels recorded species once
NB - vessels recorded species every year
DL - all data
DL - vessels recorded species once
DL - vessels recorded species every year
A Hammerhead spp.
B White
C Tiger
D Coastal spp.
E Blue
F Mako spp.
G Thresher spp.
H Oceanic whitetip
Estimated annual percent change
0
-5
-10
-15
-20
-25
1
2
3
4
5
6
7

1 Caribbean
2 Gulf of Mexico
3 Florida
4 S Atlantic Bight
5 Mid Atlantic Bight
6 NE Coastal
7 NE Distant
8 Sargasso
9 S America

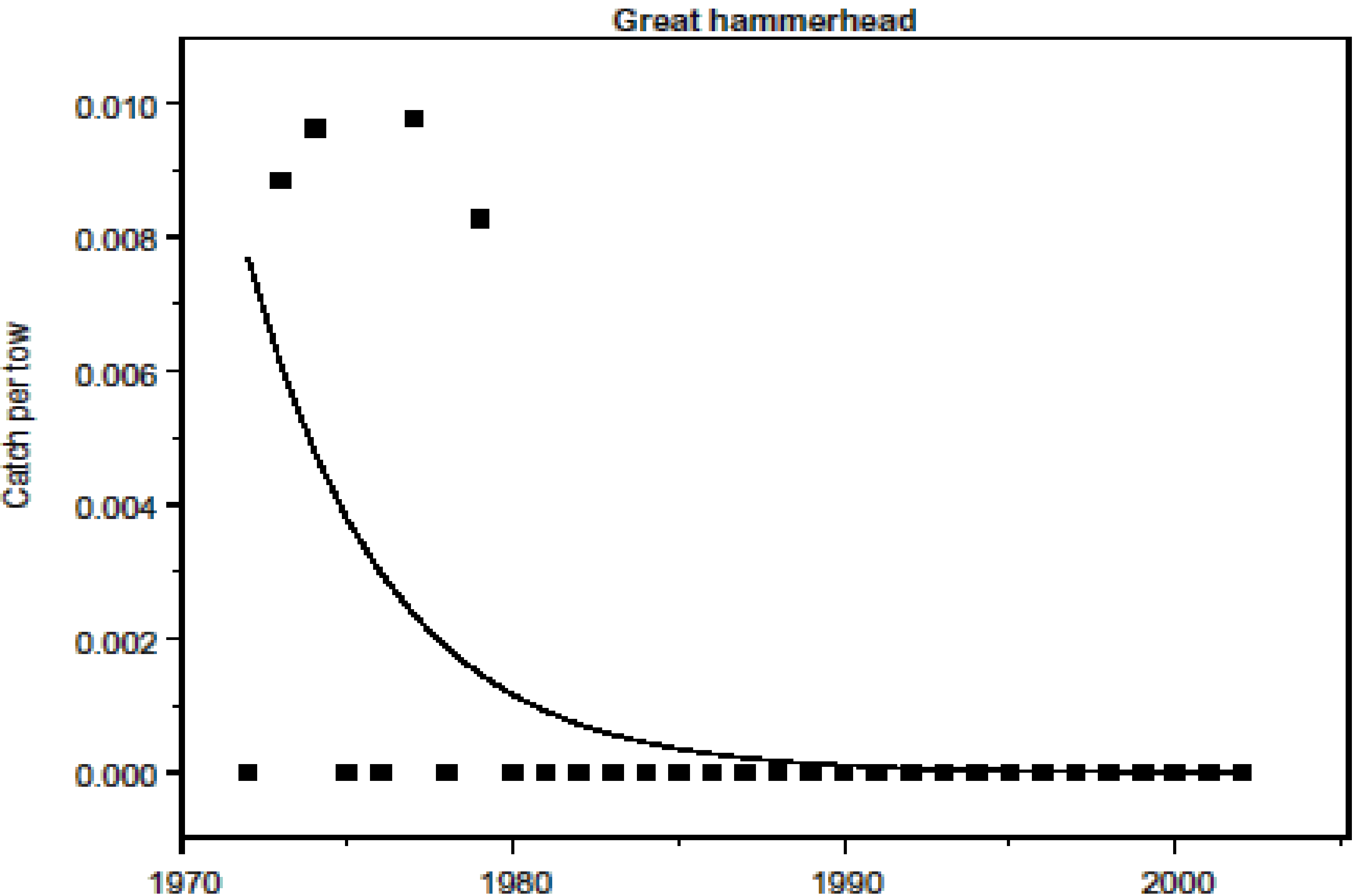


Same results for trawl surveys in Gulf of Mexico



Shepherd and Myers Ecology Letters 2005

Same results for trawl surveys in Gulf of Mexico



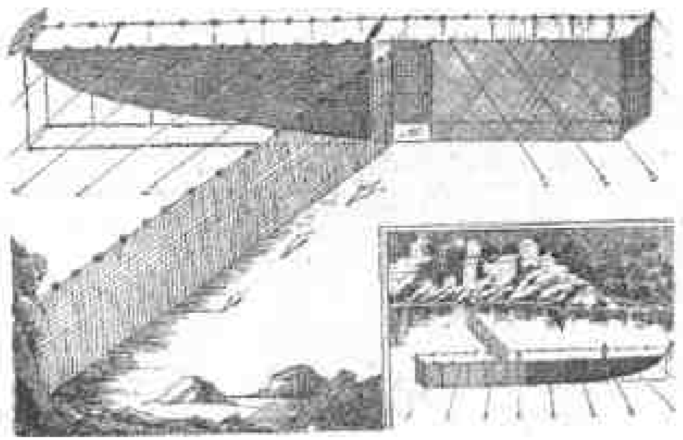
Shepherd and Myers Ecology Letters 2005

Decline of Mediterranean Sharks

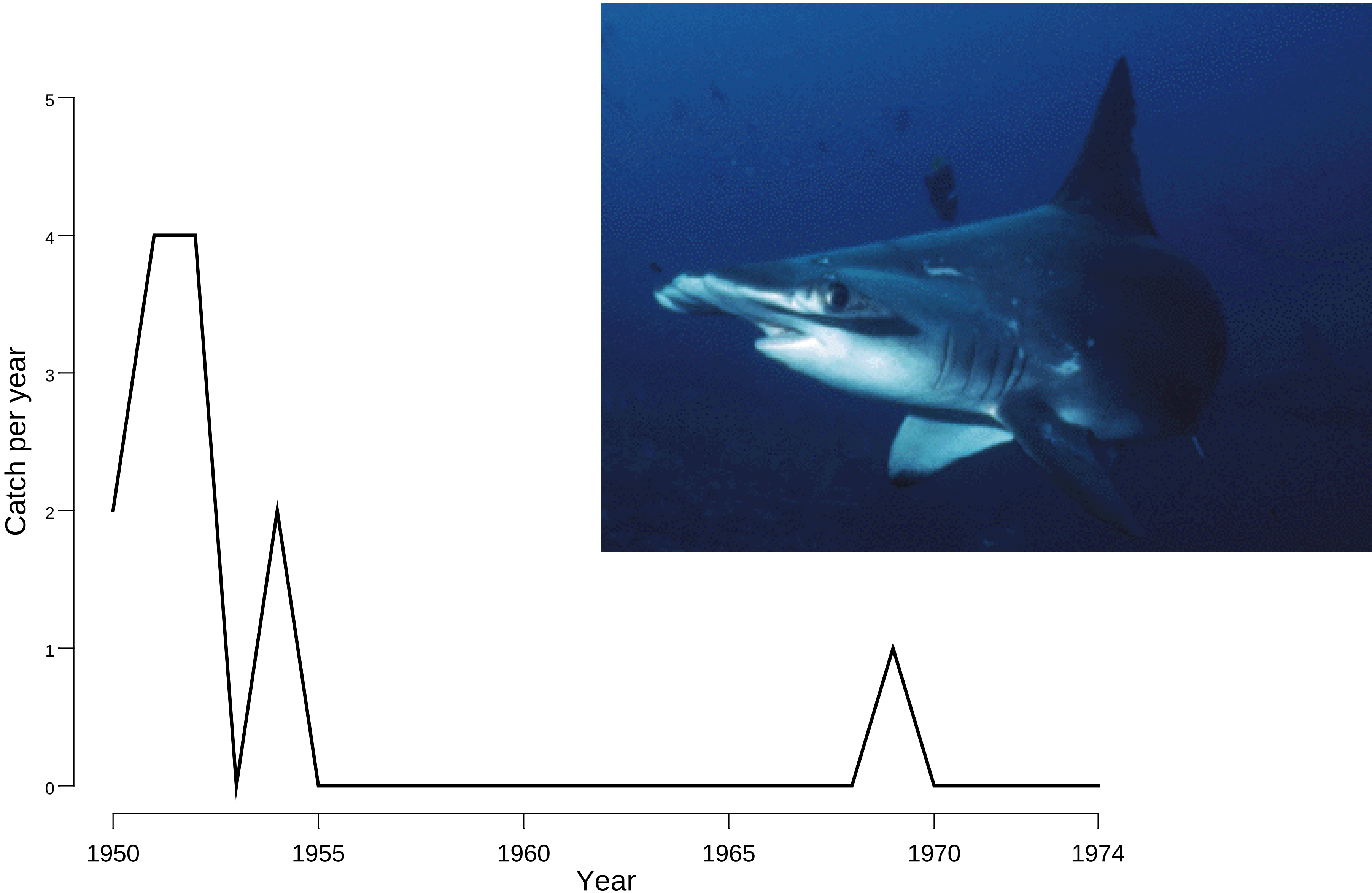
By catch associated with a Tuna Trap

In Ligurian Sea

"Tonnara di Camogli"



Decline of Hammarhead sharks

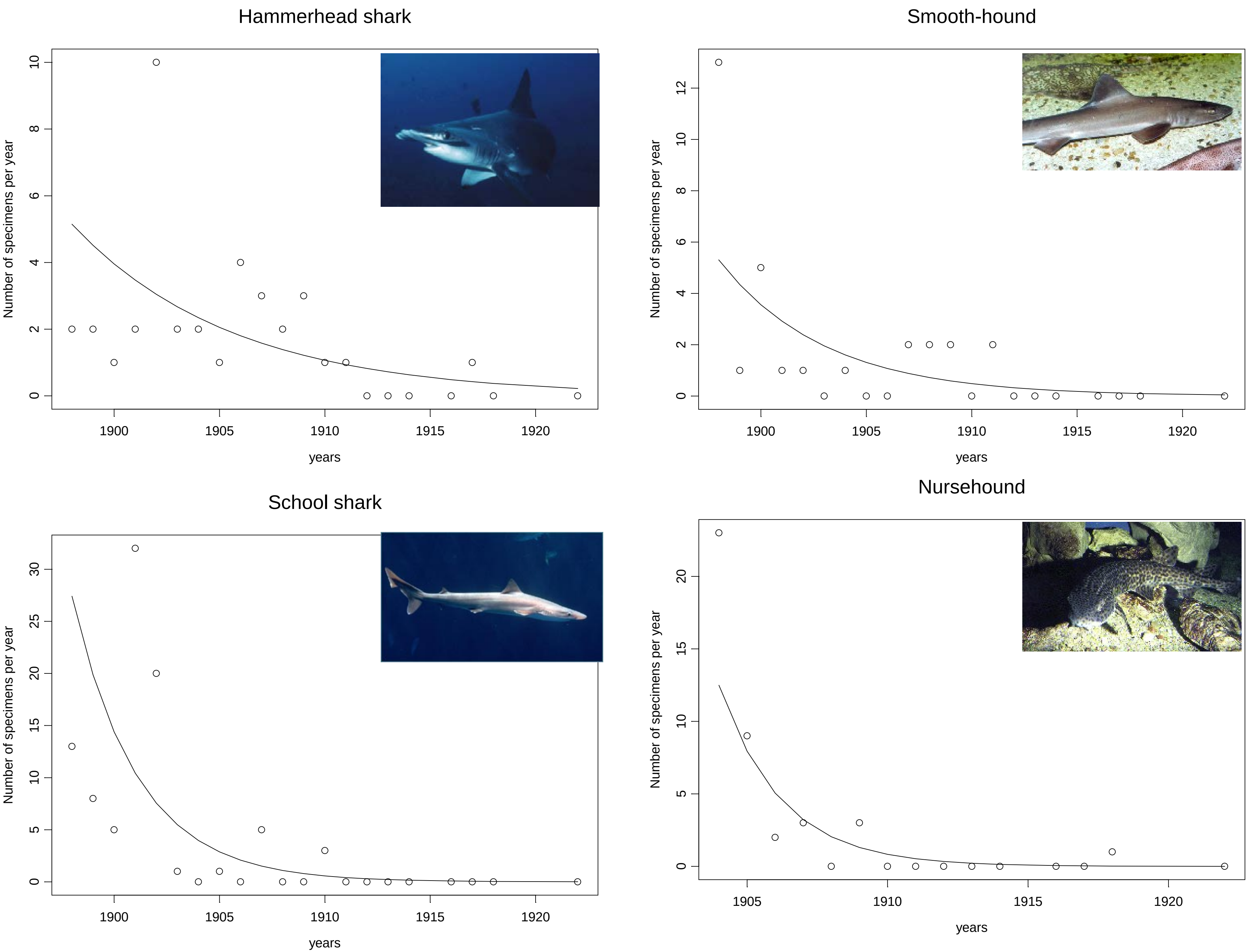


Boero F. & A. Carli 1979 – Boll. Mus. Ist. Biol. Univ. Genoa (47)

Decline of Mediterranean Sharks

By catch associated with a Tuna Trap
In Tirrenian Sea

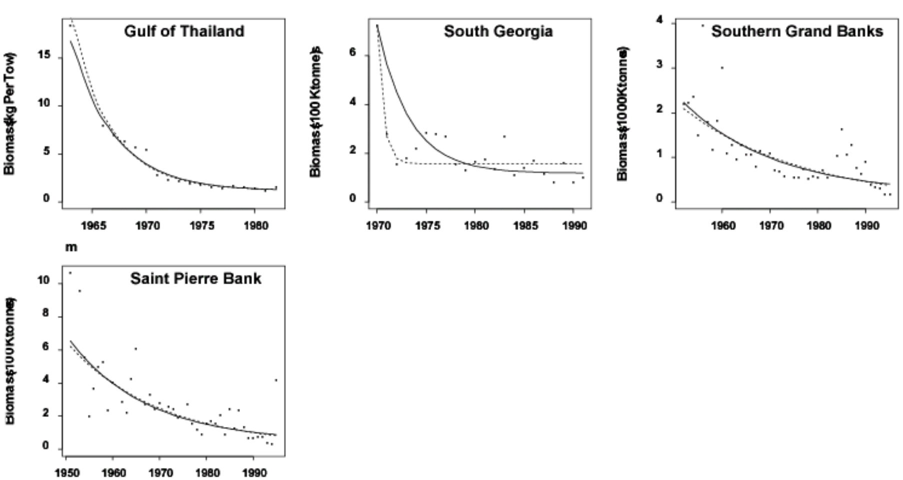
“Tonnarella di Baratti”

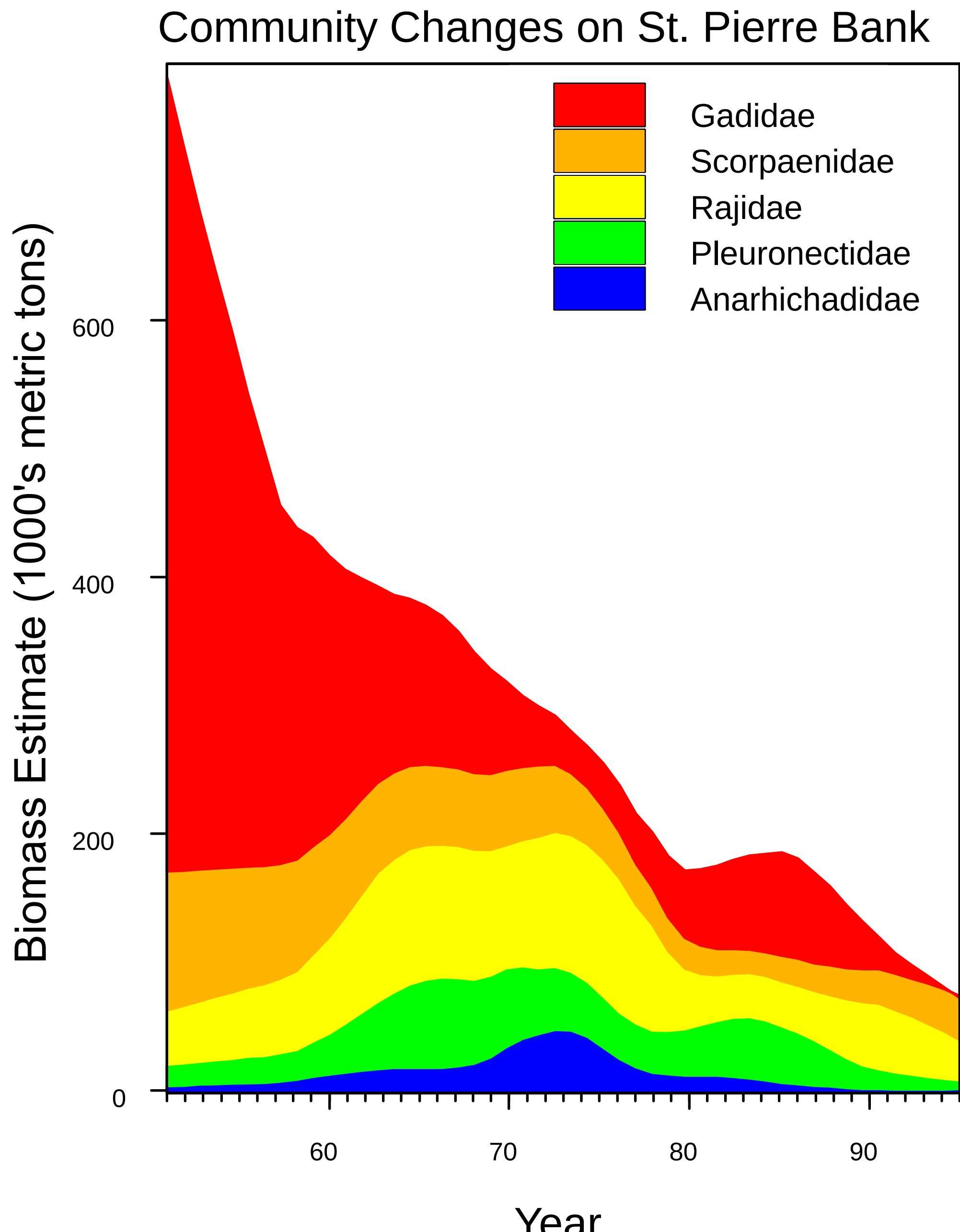

Hammerhead shark
Smooth-hound
School shark
Nursehound
Number of specimens per year
years
1900
1905
1910
1915
1920

Critical Modeling Tools

- Repeat analysis world wide using a meta-analytic approach


15 May 2003
International weekly journal of science
nature
www.nature.com/nature
Net losses
Industrialized fishing hits fish stocks
Financial markets
You can't buck the physics
Jupiter's moons
Headed for a hundred
Functional genomics
The power of comparison
naturejobs Heidelberg — Europe's molecular biology capital

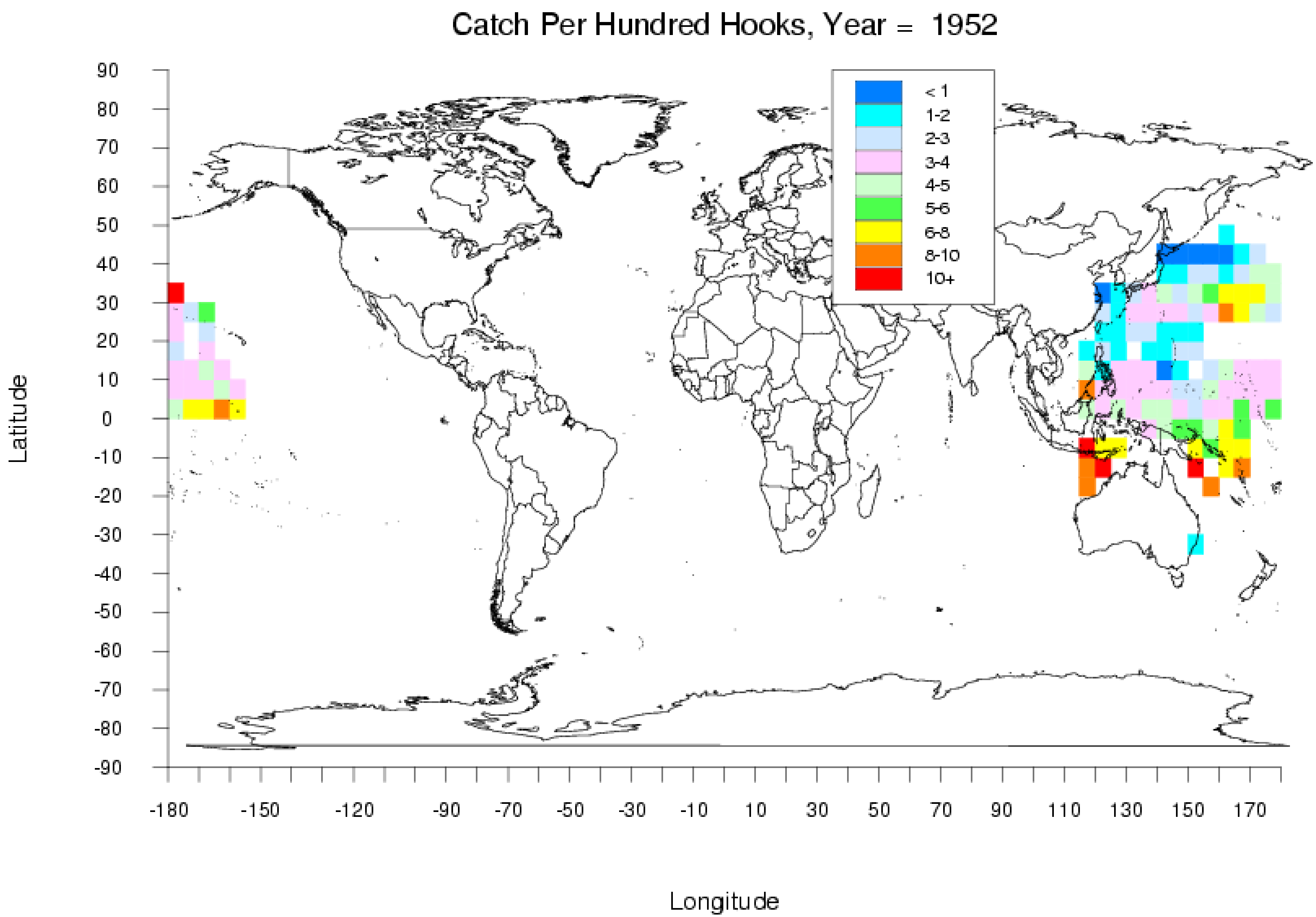

Gulf of Thailand
Biomass(kg Per Tow)
0
5
10
15
1965
1970
1975
1980
South Georgia
Biomass(100 Ktonne)
0
2
4
6
1970
1975
1980
1985
1990
Southern Grand Banks
Biomass(1000Ktonne)
0
1
2
3
4
1960
1970
1980
1990
Saint Pierre Bank
0
2
4
6
8
10
1950
1960
1970
1980
1990

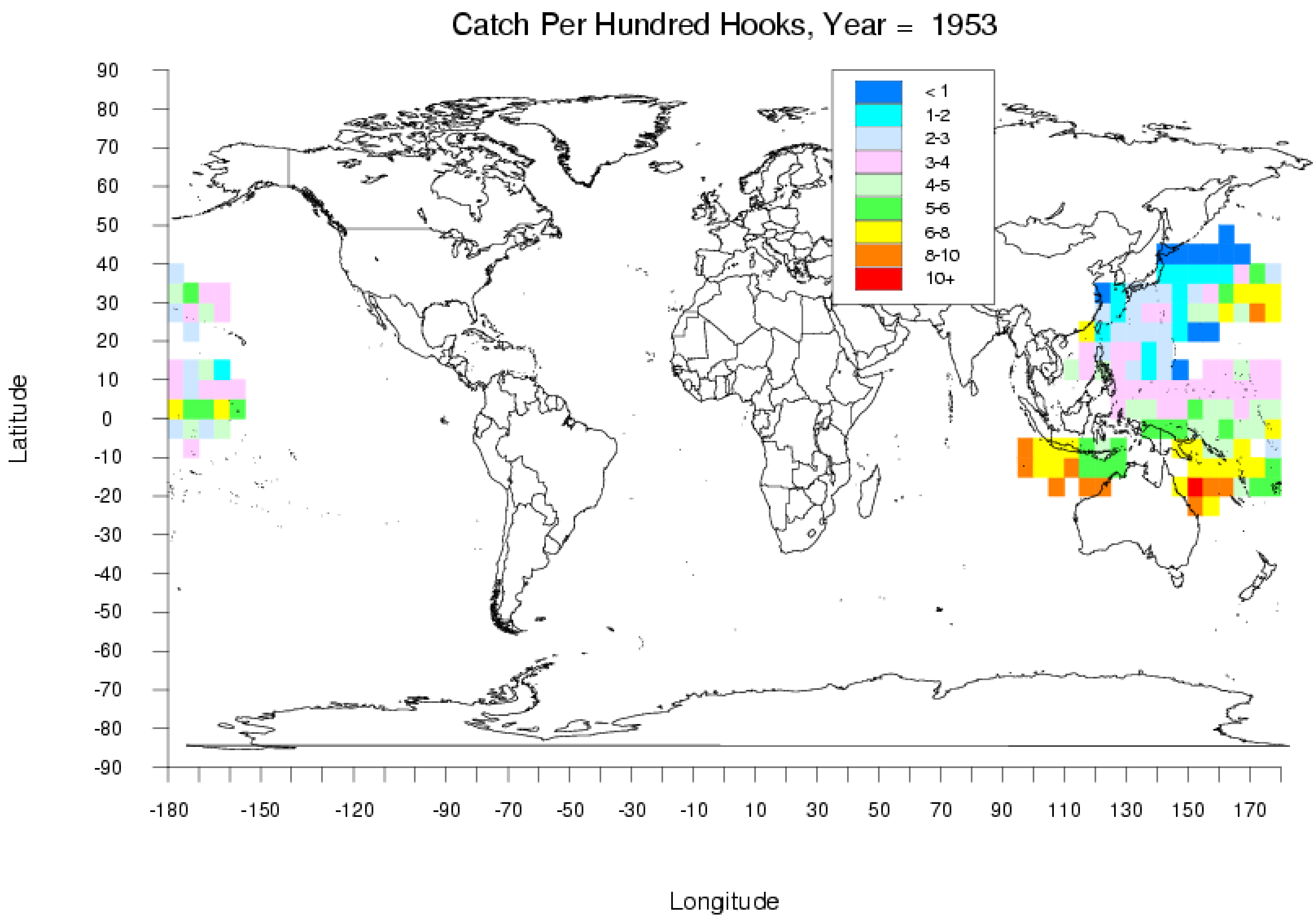

Community Changes on St. Pierre Bank
Gadidae
Scorpaenidae
Rajidae
Pleuronectidae
Anarhichadidae
Biomass Estimate (1000's metric tons)
0
200
400
600
60
70
80
90
Year

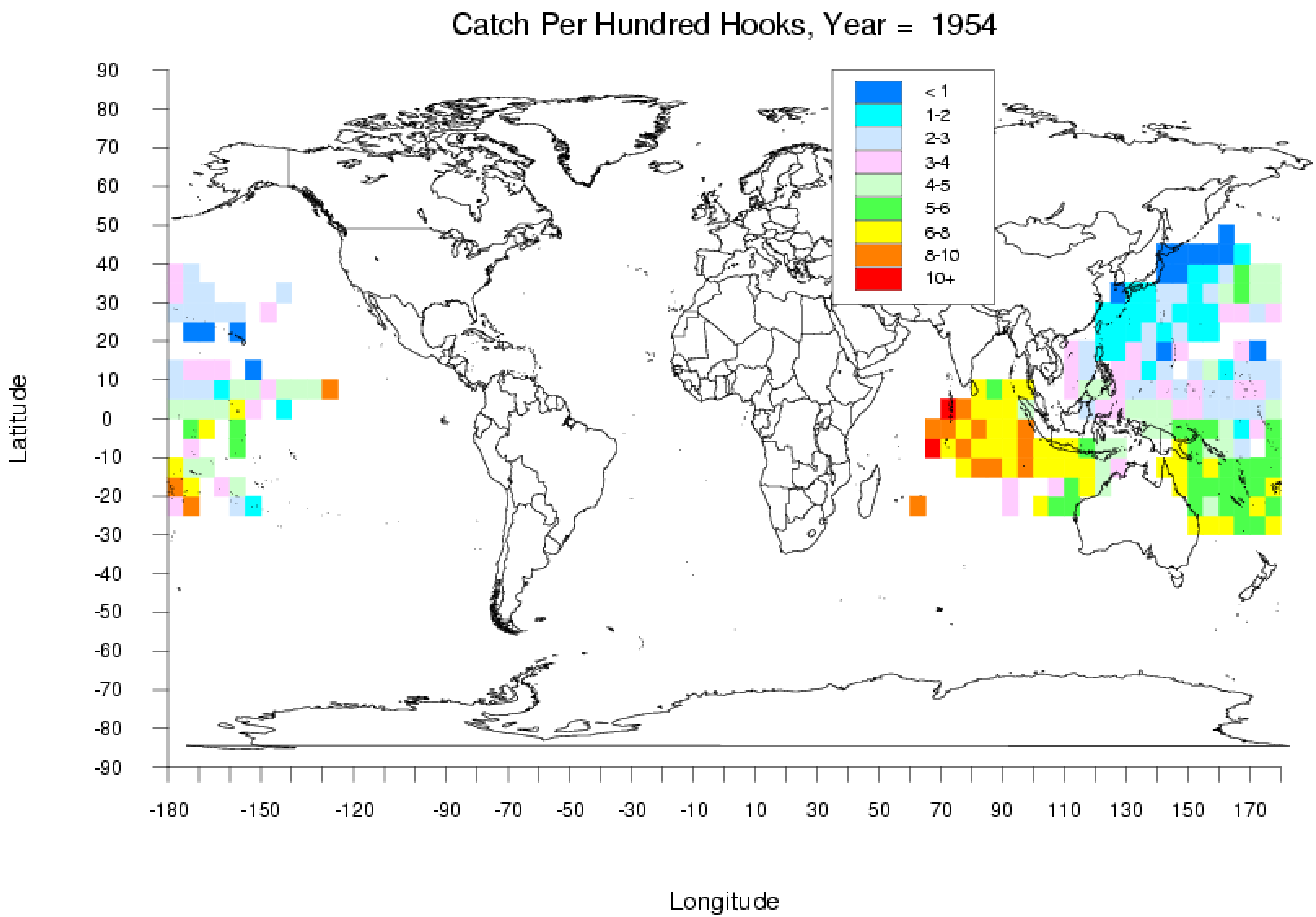
Critical Modeling tools:

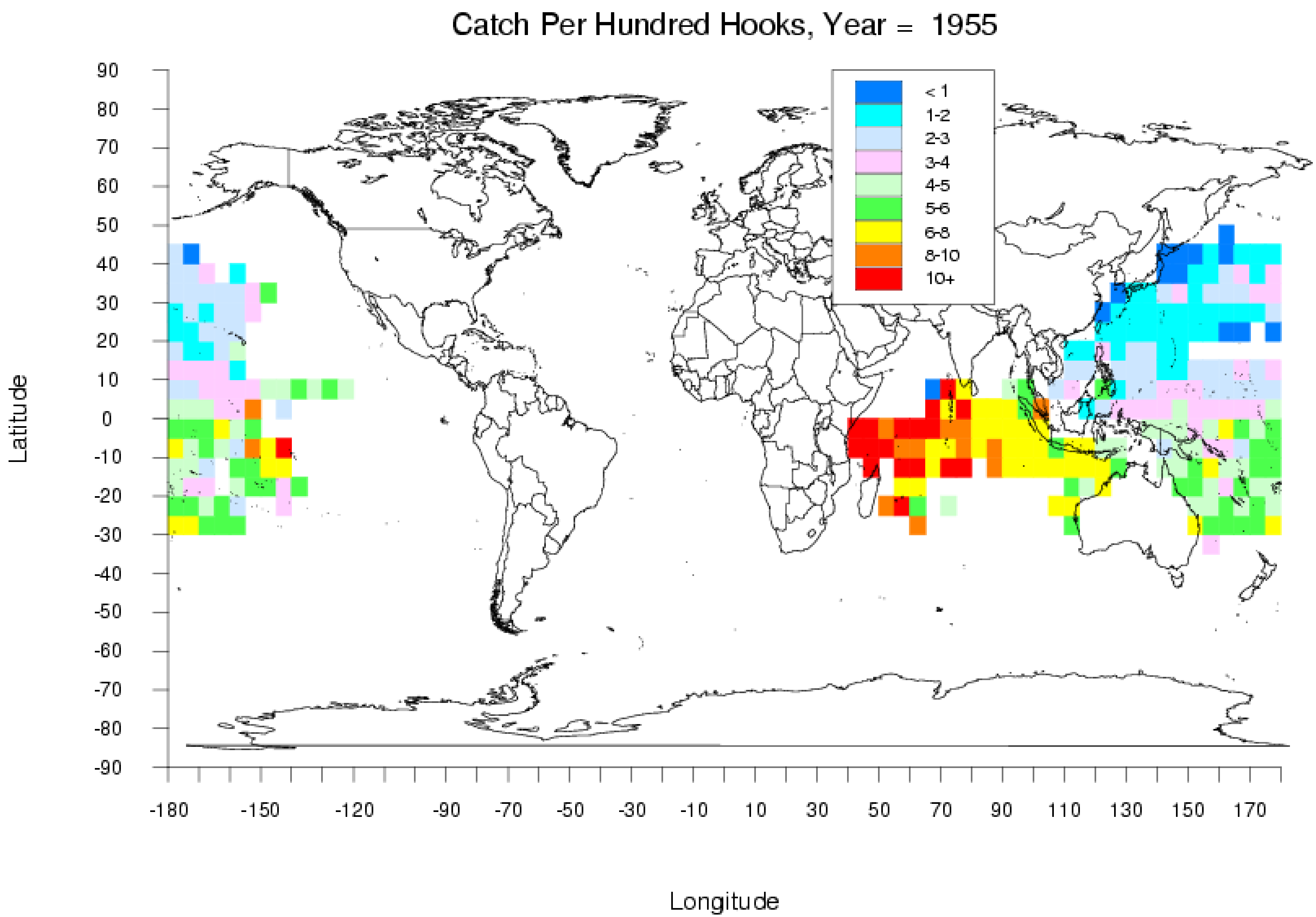
- Generalized linear models to standardize historical surveys, e.g. diurnal differences
- Mapping historical surveys on recent Stratified Random design


555
lbs.
Cabo Blan
LBS.
1135
CABO
BLANCO

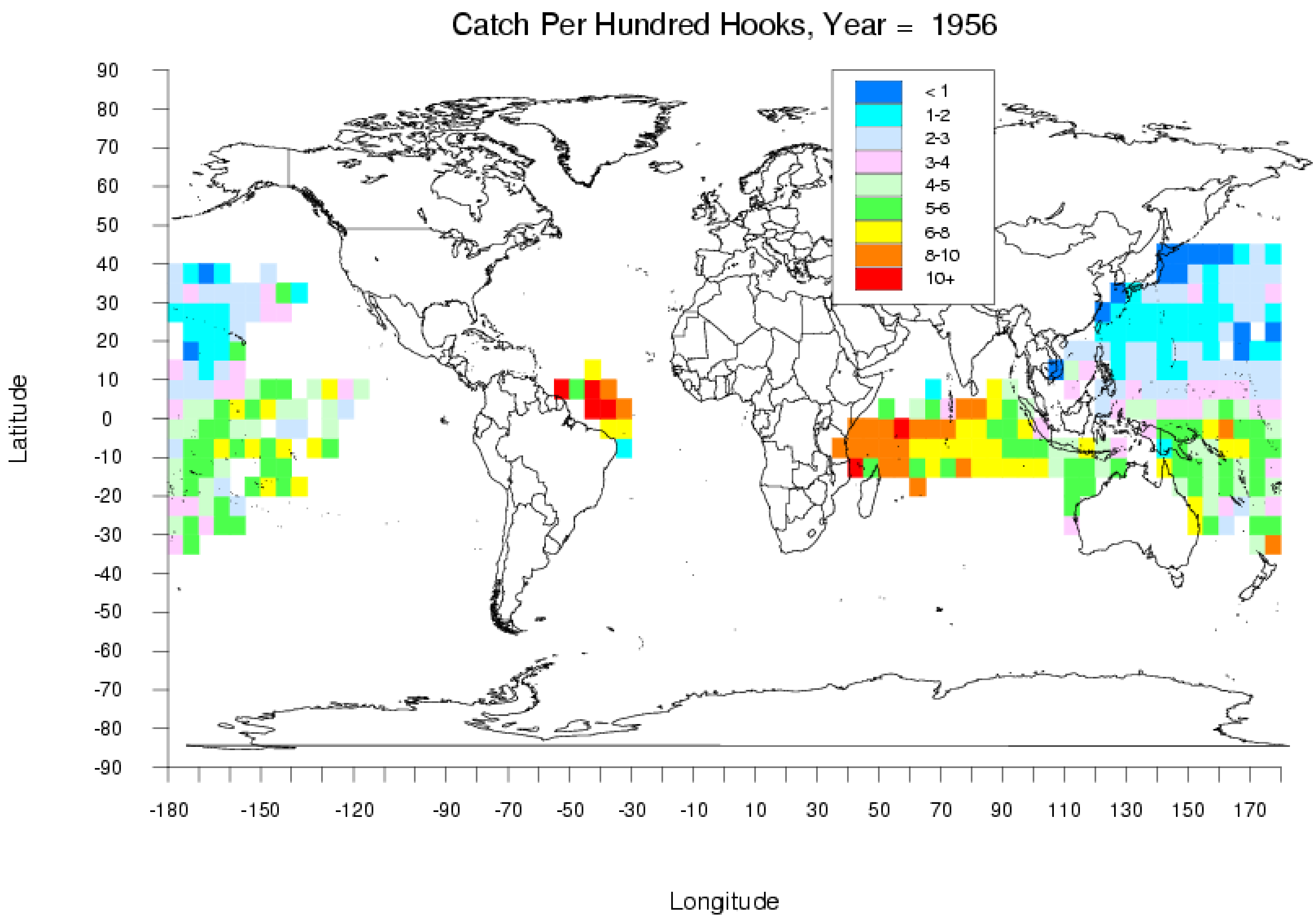

Catch Per Hundred Hooks, Year = 1952
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1953
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170

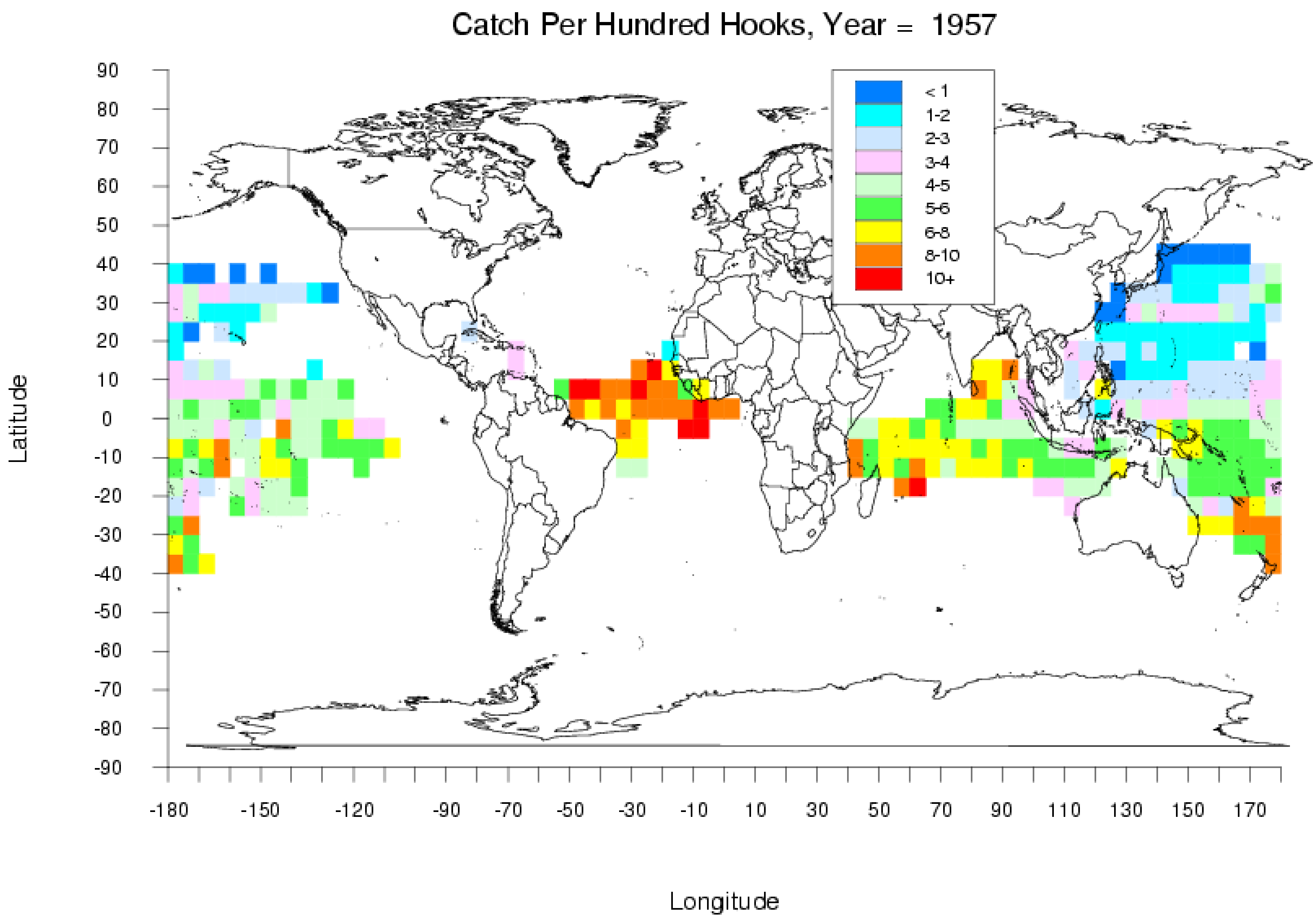

Catch Per Hundred Hooks, Year = 1954
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170

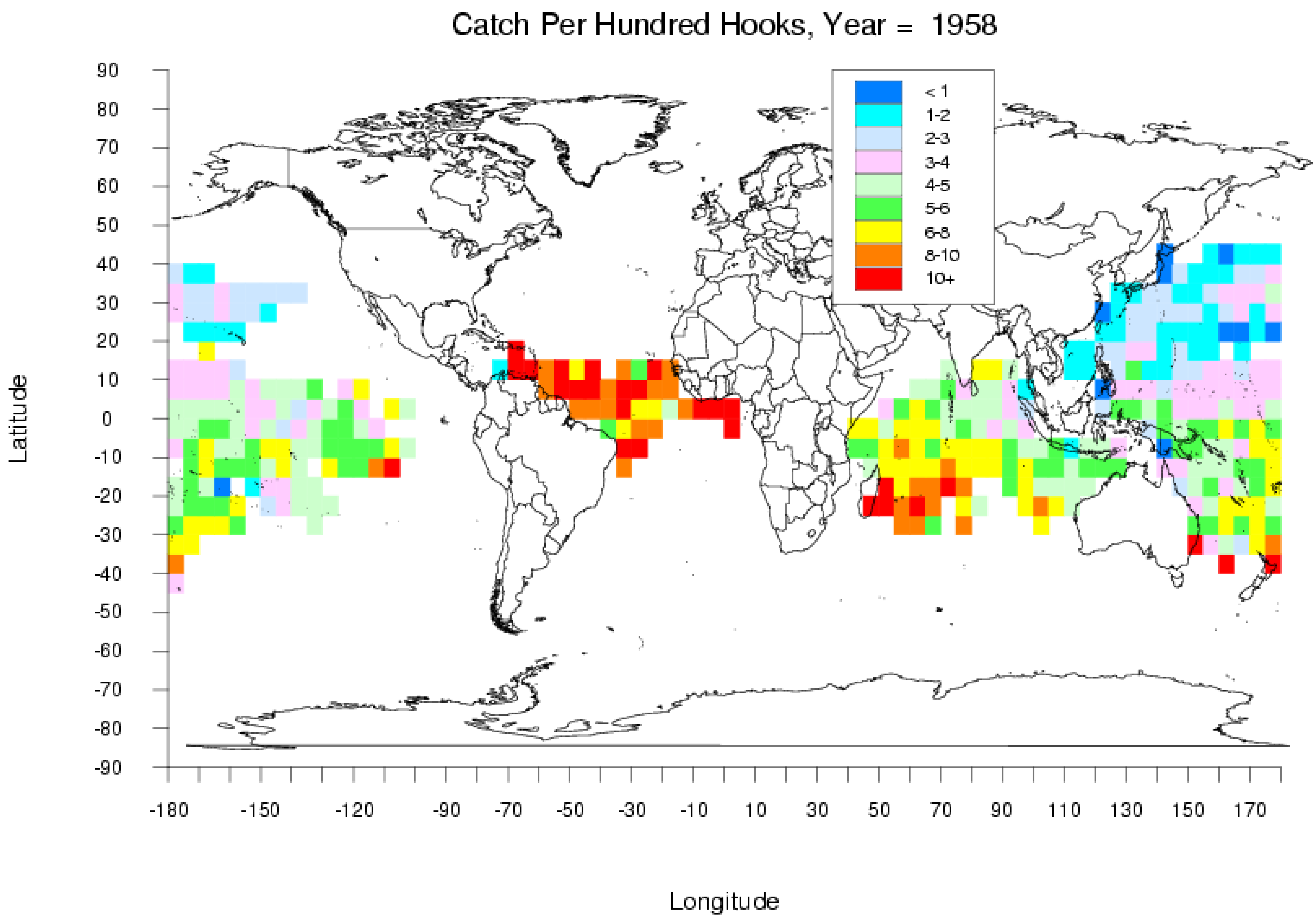


Catch Per Hundred Hooks, Year = 1955
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Longitude

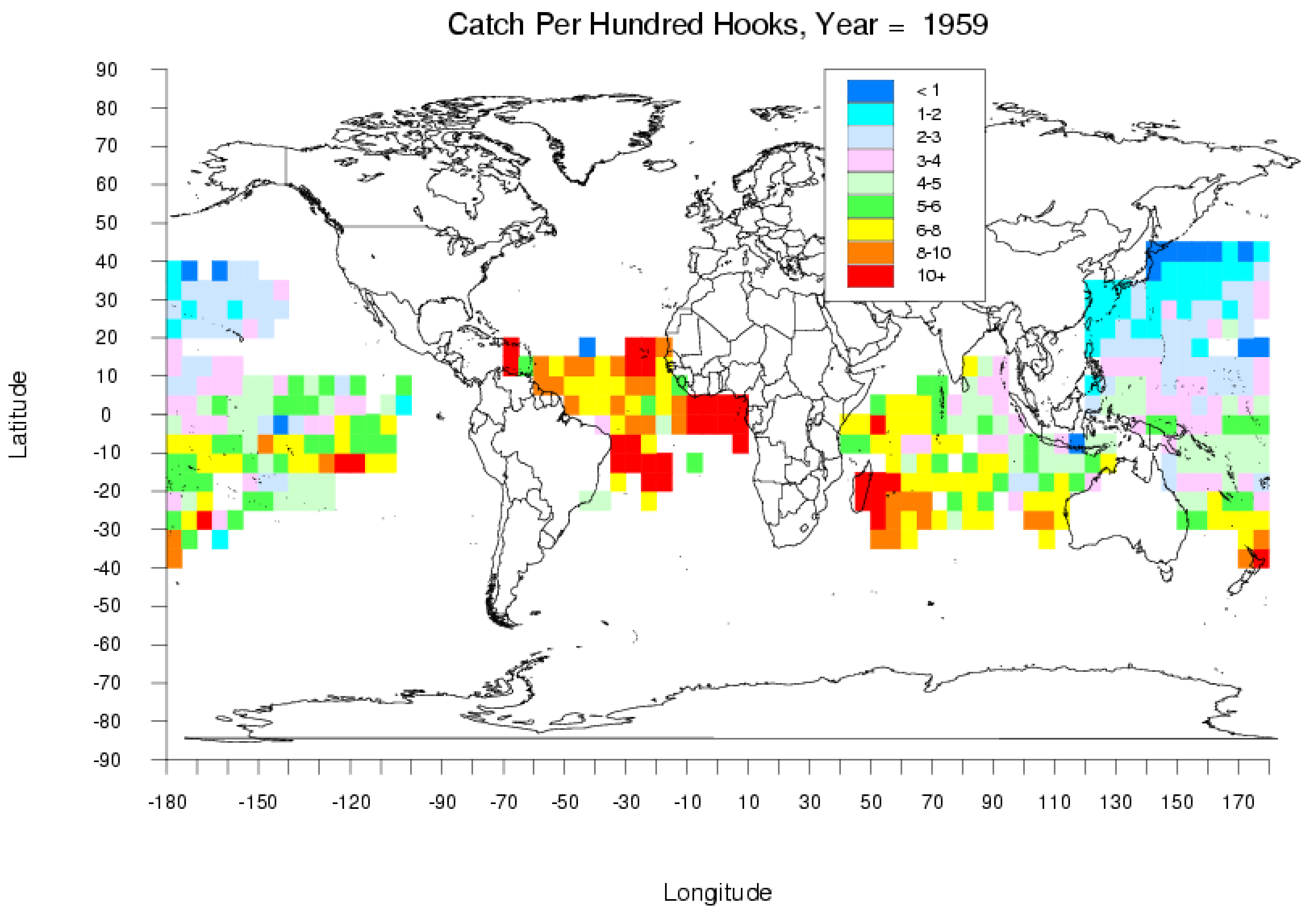


Catch Per Hundred Hooks, Year = 1956
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1957
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Longitude



Catch Per Hundred Hooks, Year = 1958
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1959
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
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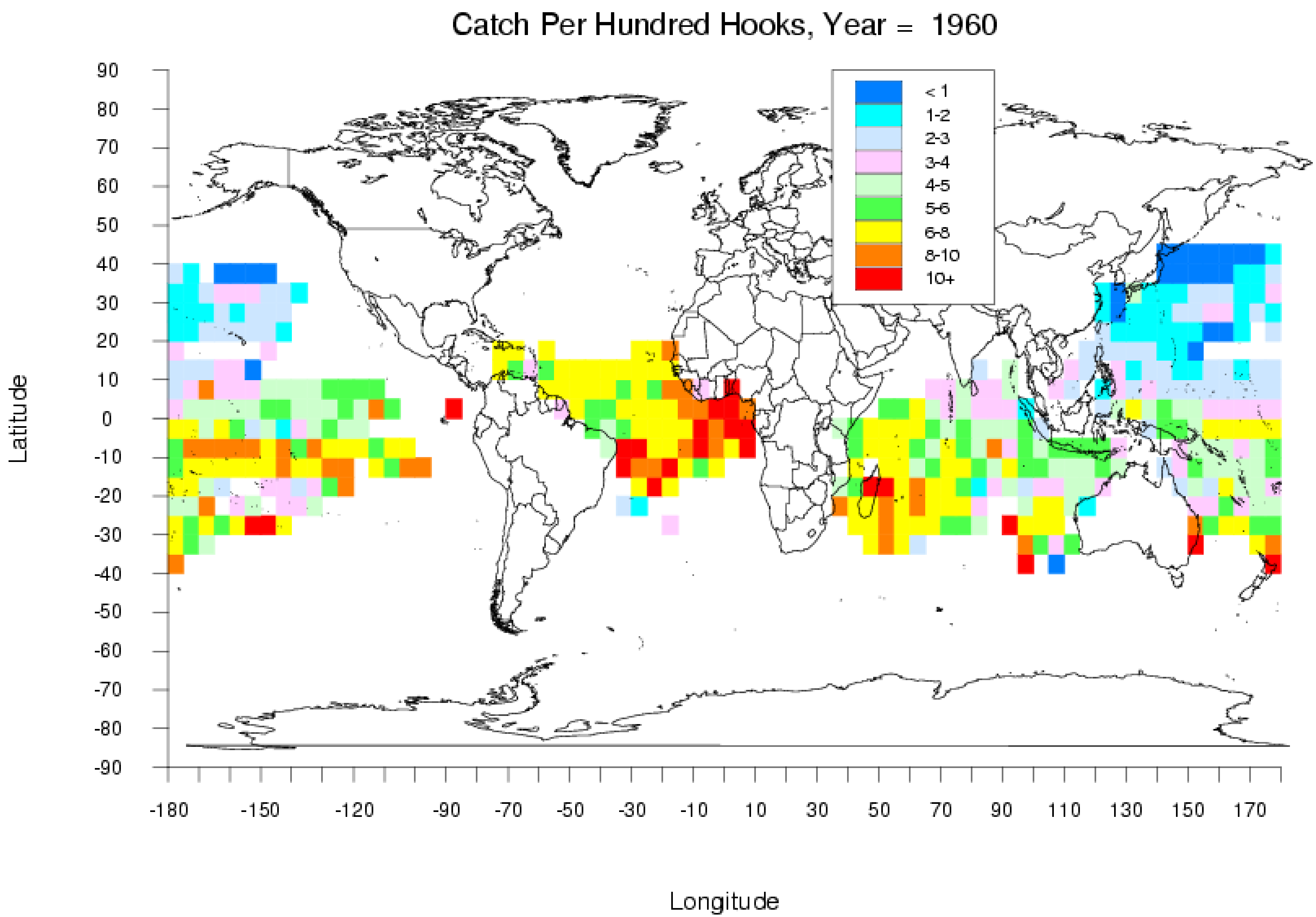
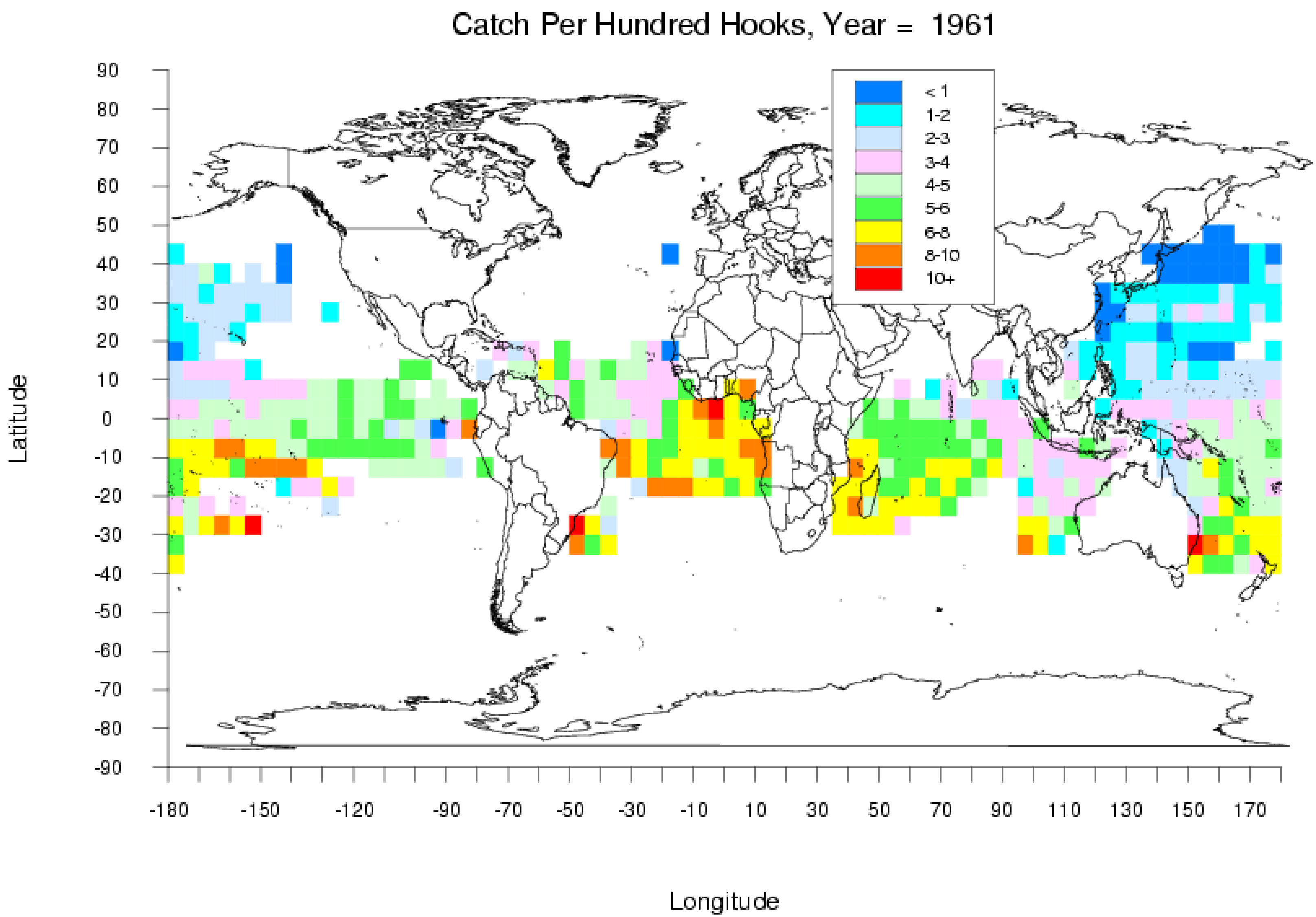
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1960
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Longitude



Catch Per Hundred Hooks, Year = 1961
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
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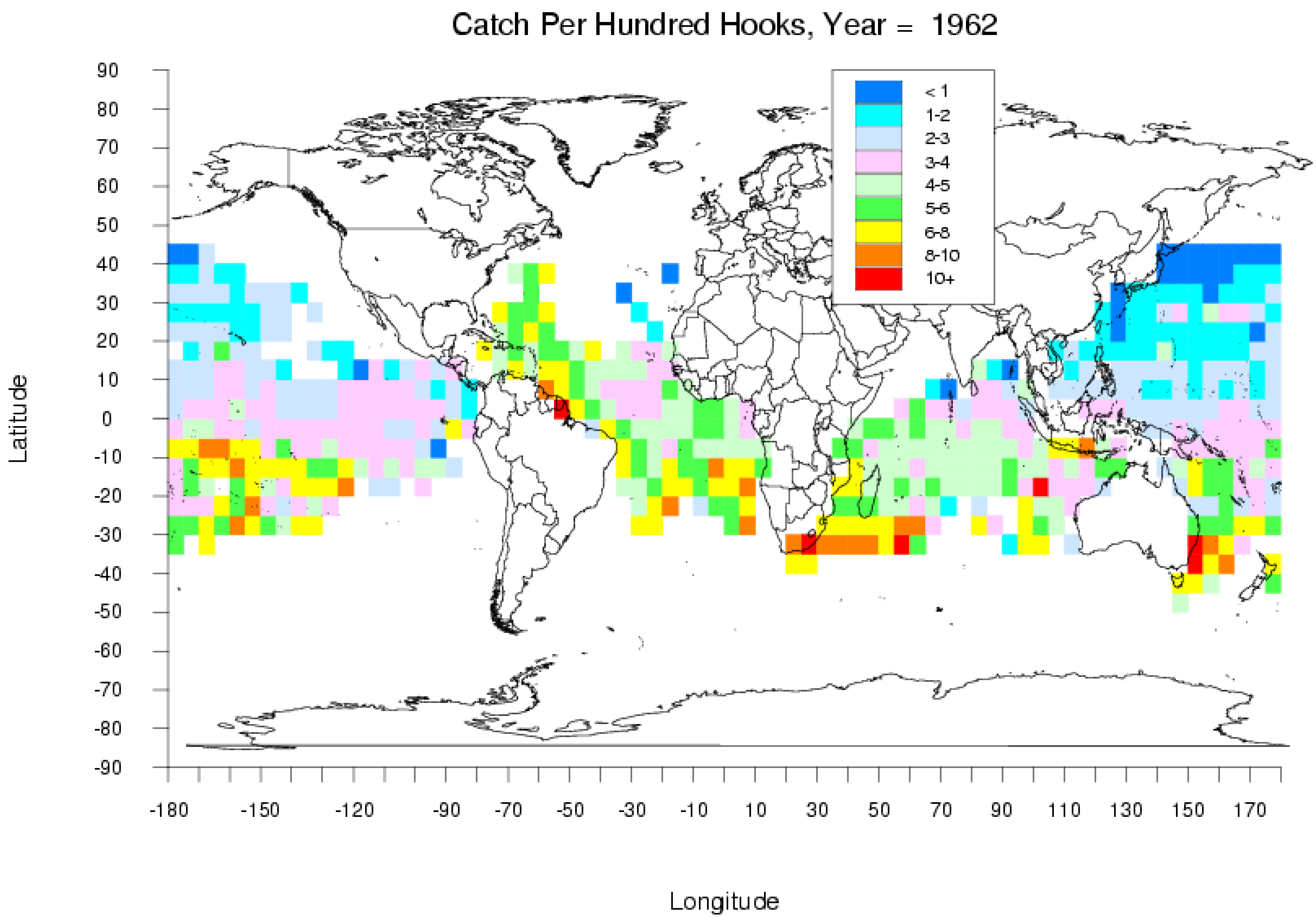
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1962
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
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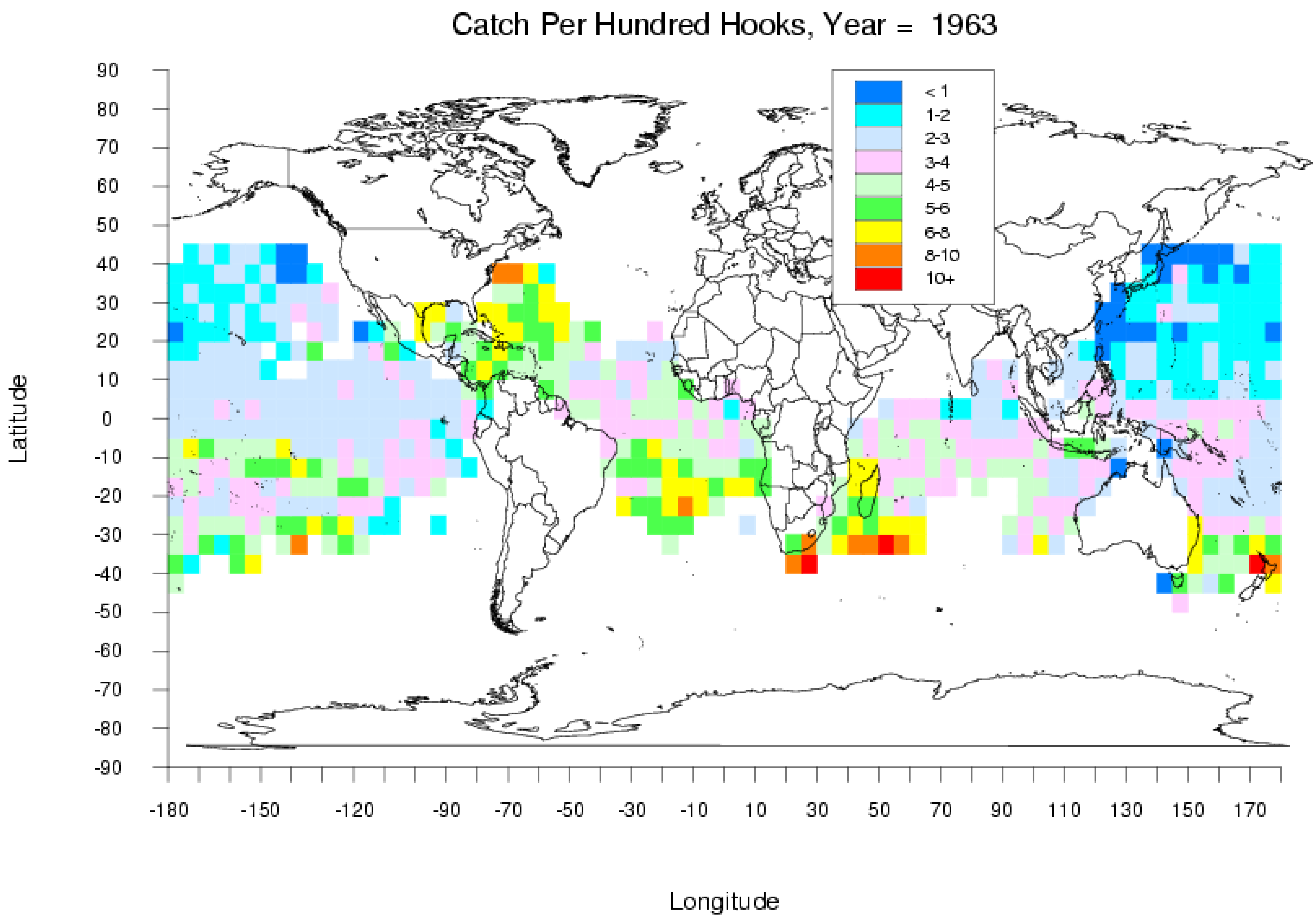
70
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1963
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
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30
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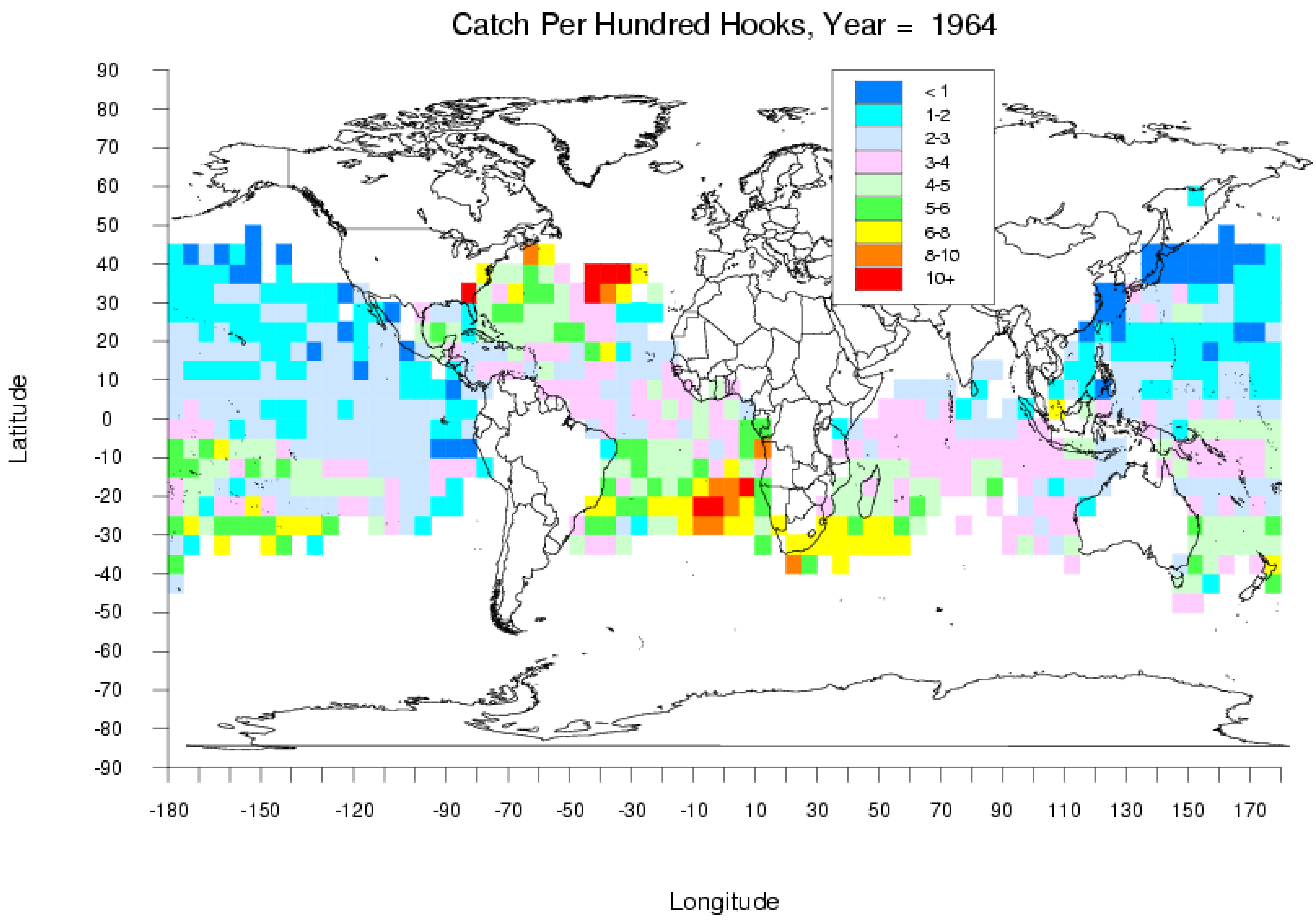
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1964
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
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-10
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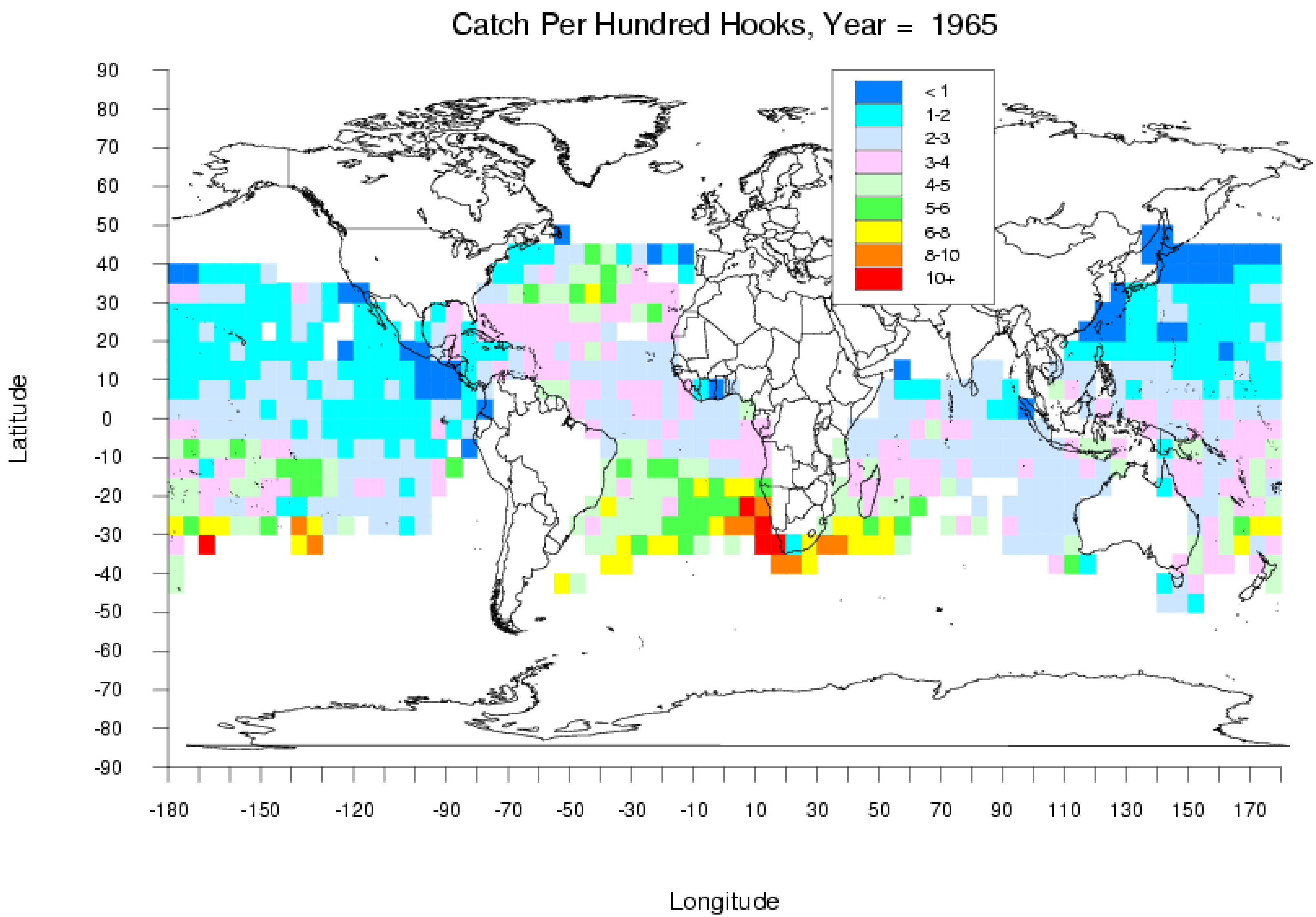
70
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1965
Latitude
Longitude
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
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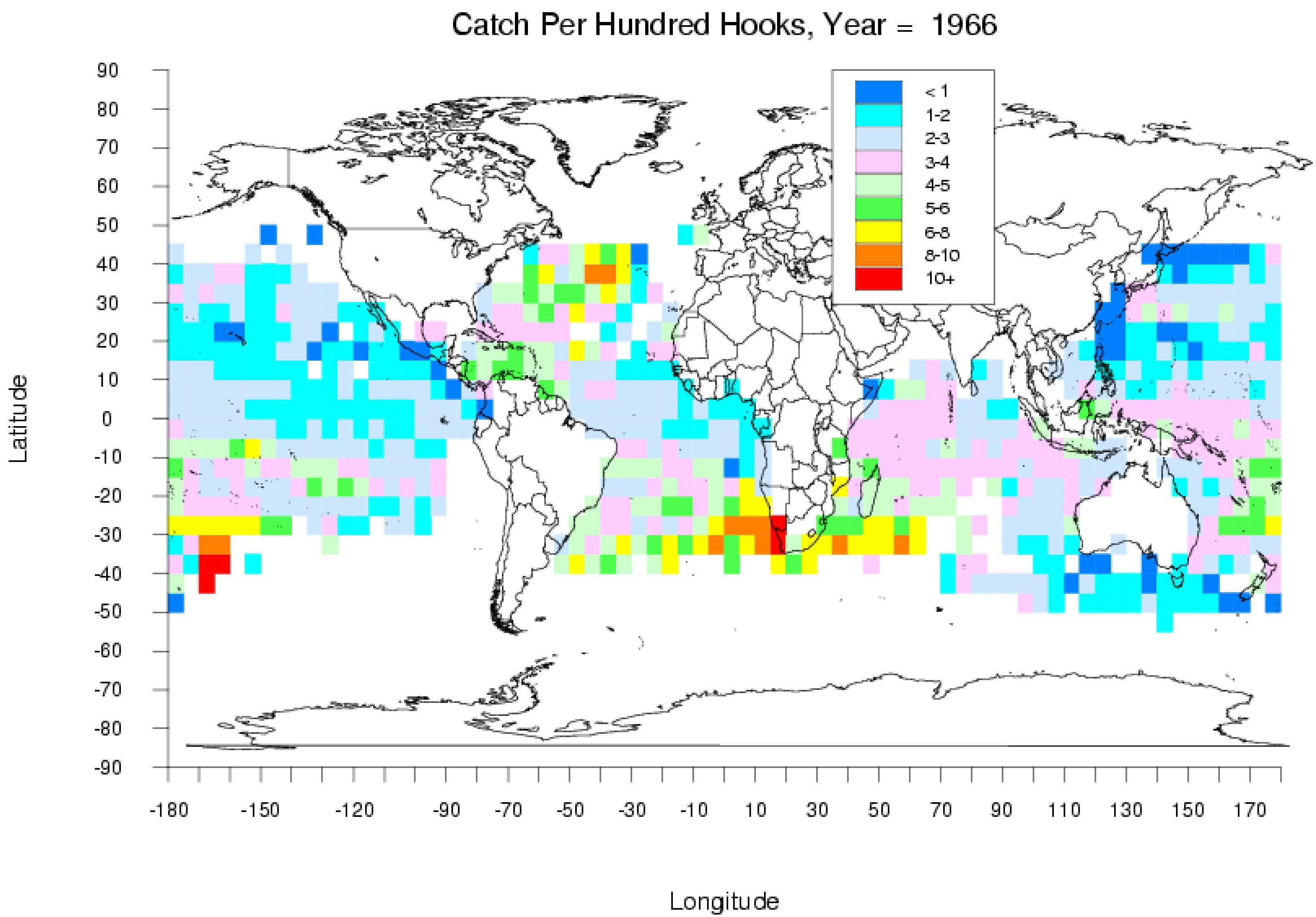
70
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1966
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
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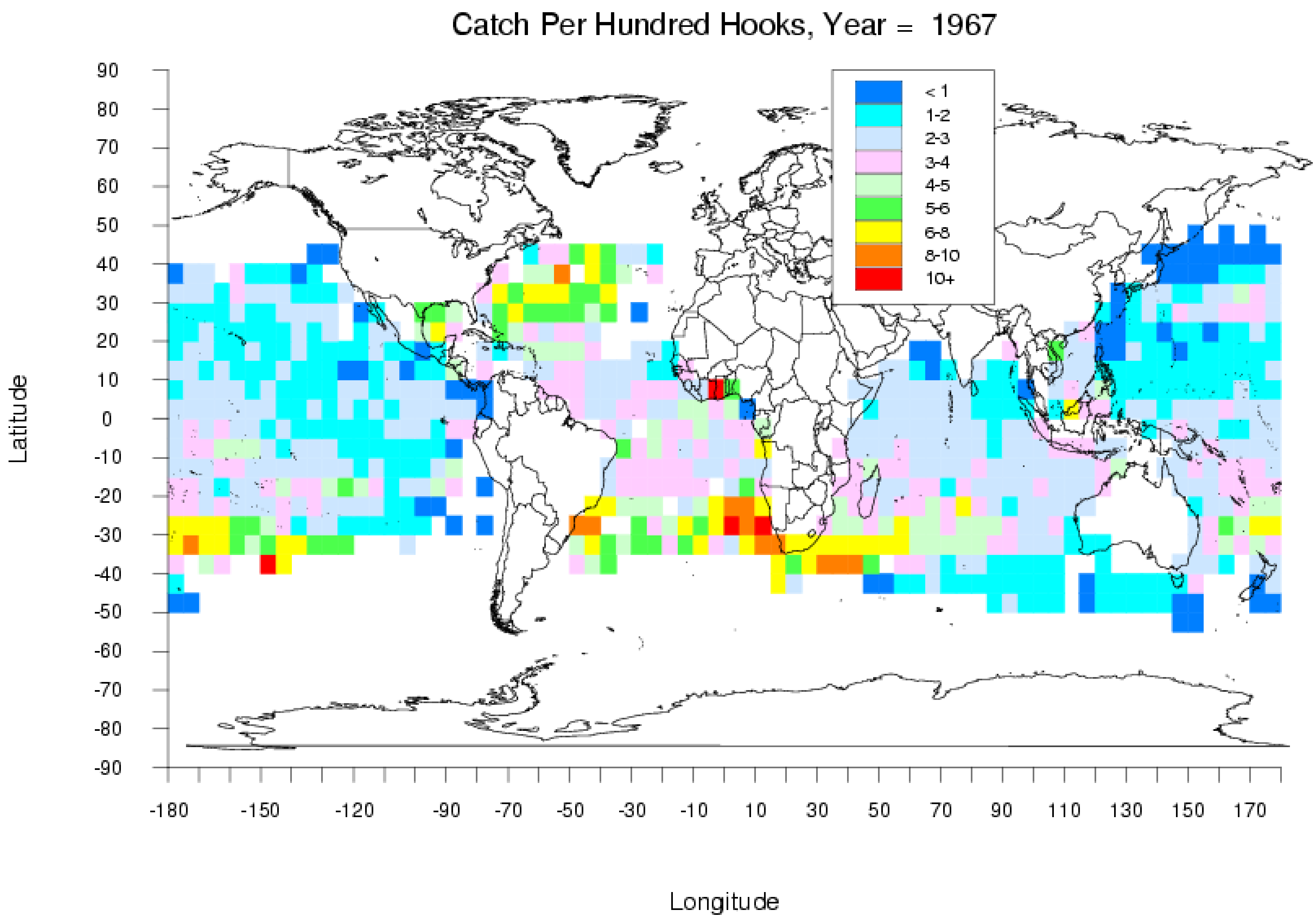
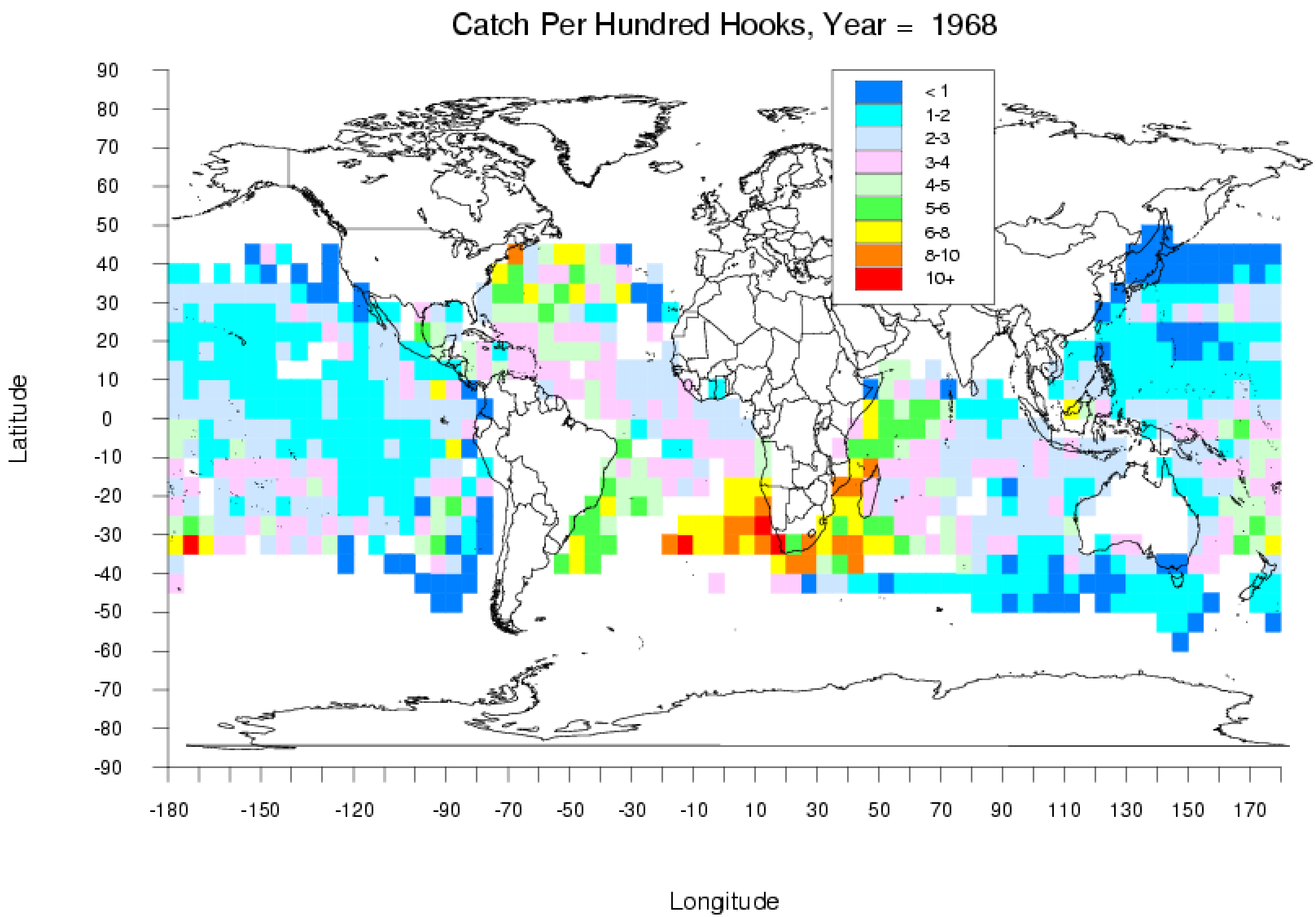
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1967
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+



Catch Per Hundred Hooks, Year = 1968
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
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-10
10
30
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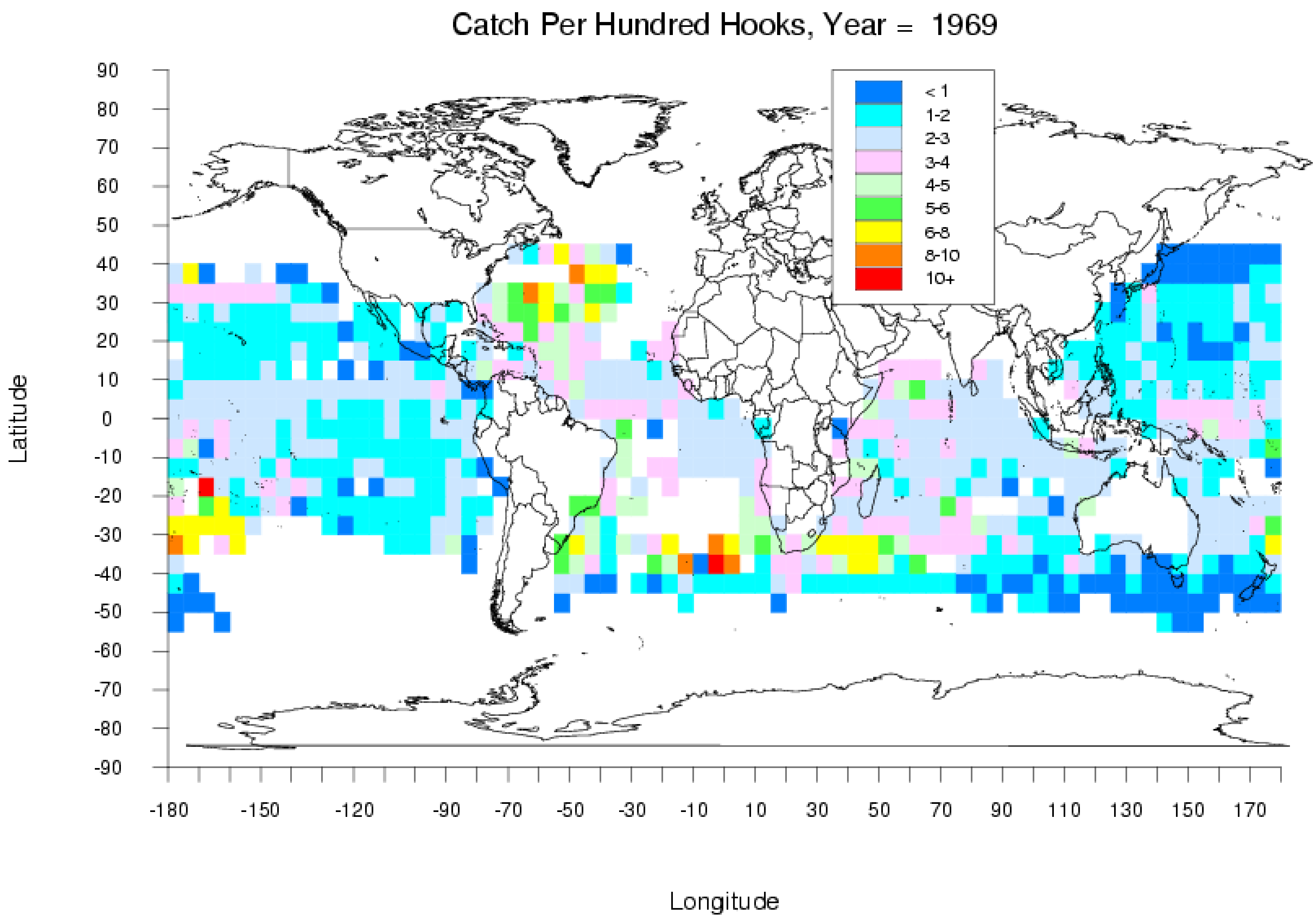
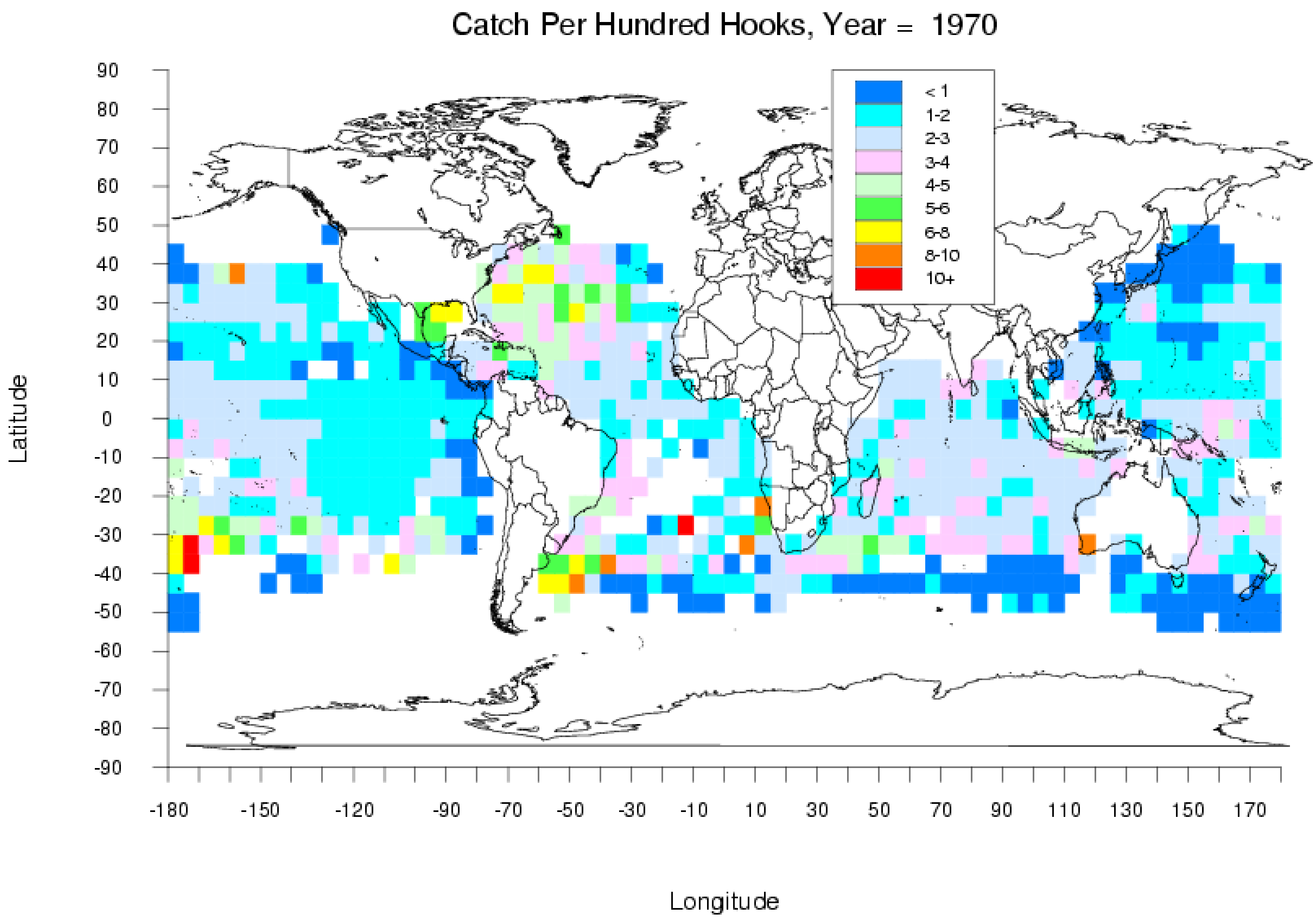
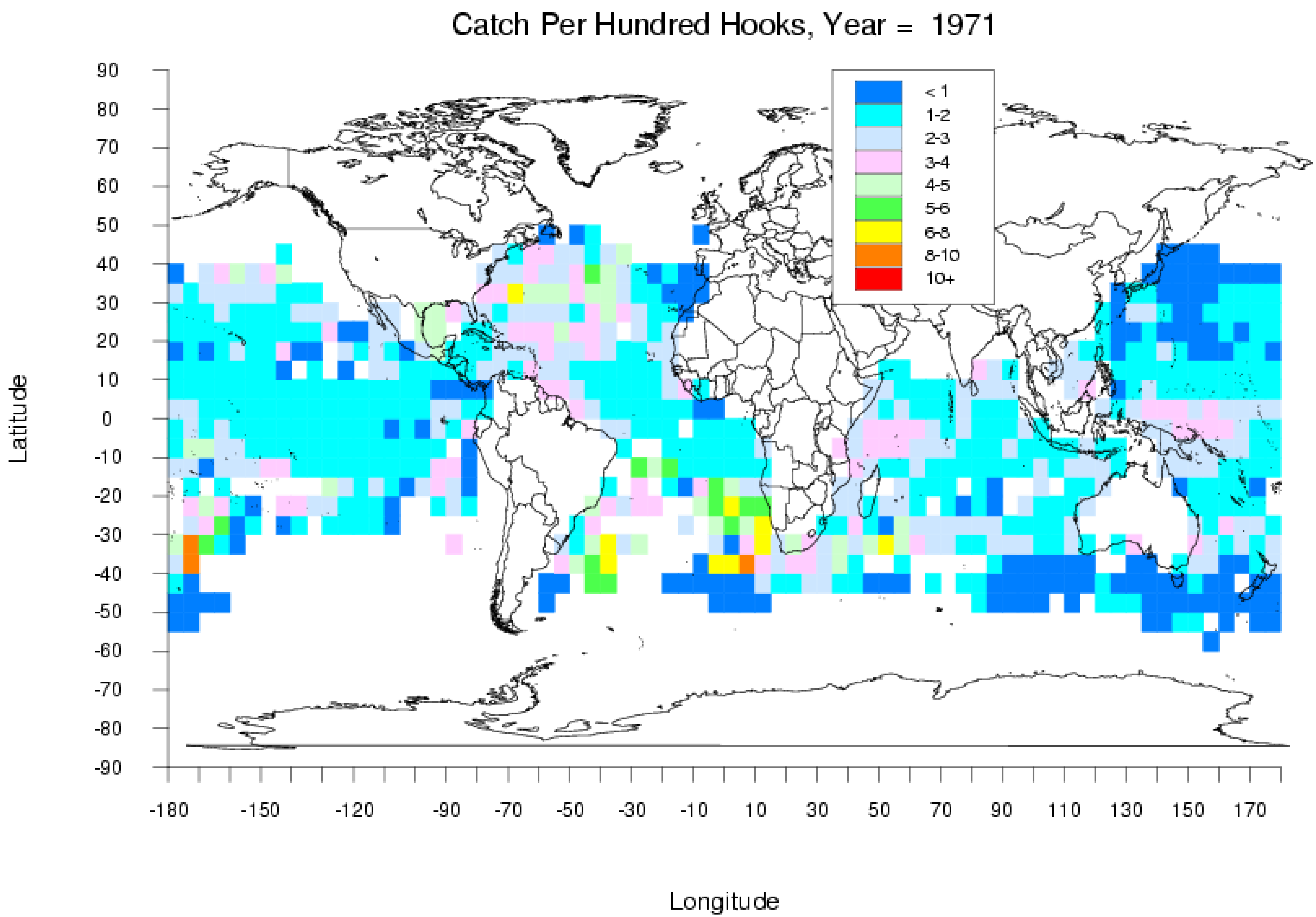
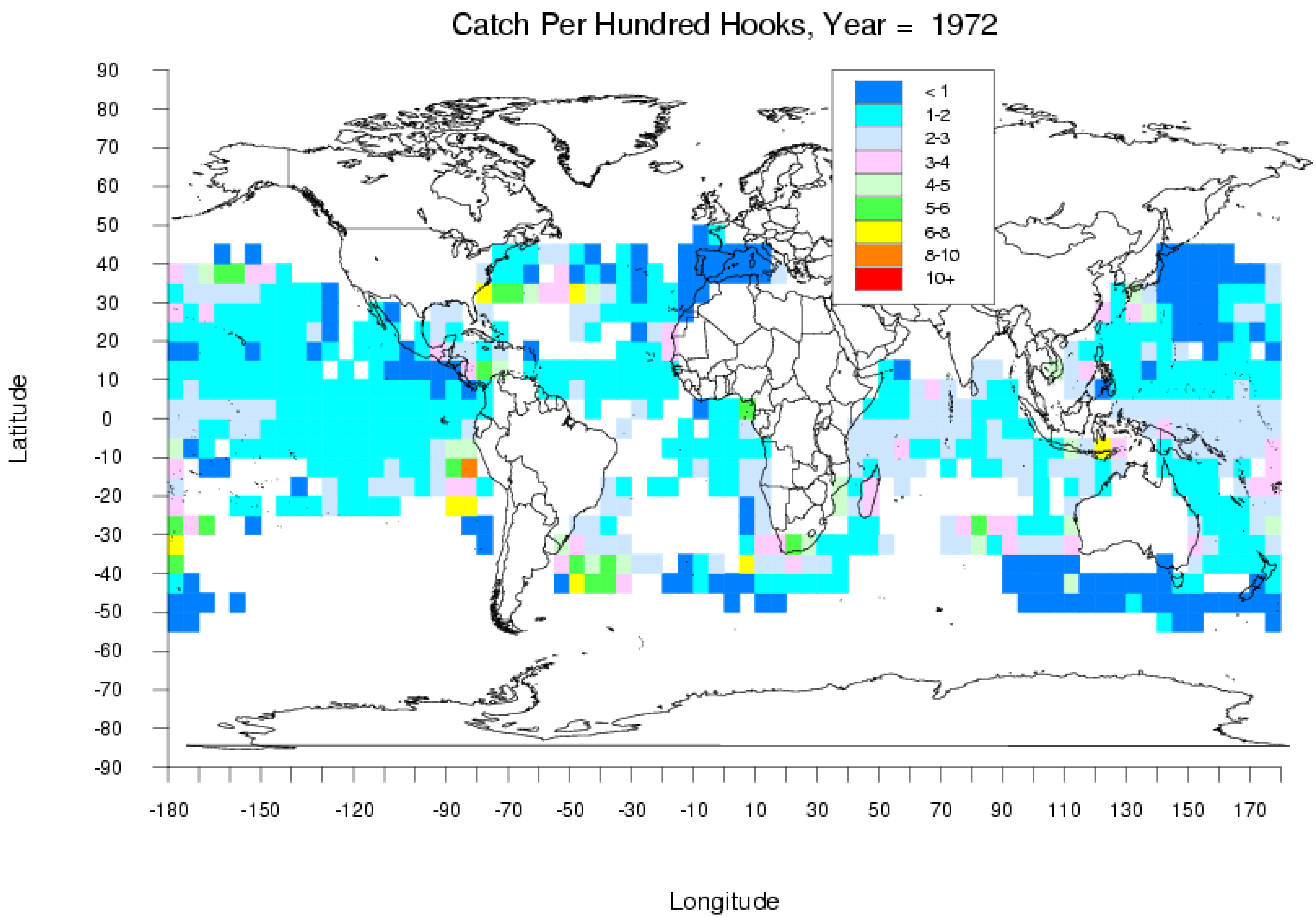
70
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1969
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Latitude
Longitude


Catch Per Hundred Hooks, Year = 1970
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+


Catch Per Hundred Hooks, Year = 1971
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1972
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
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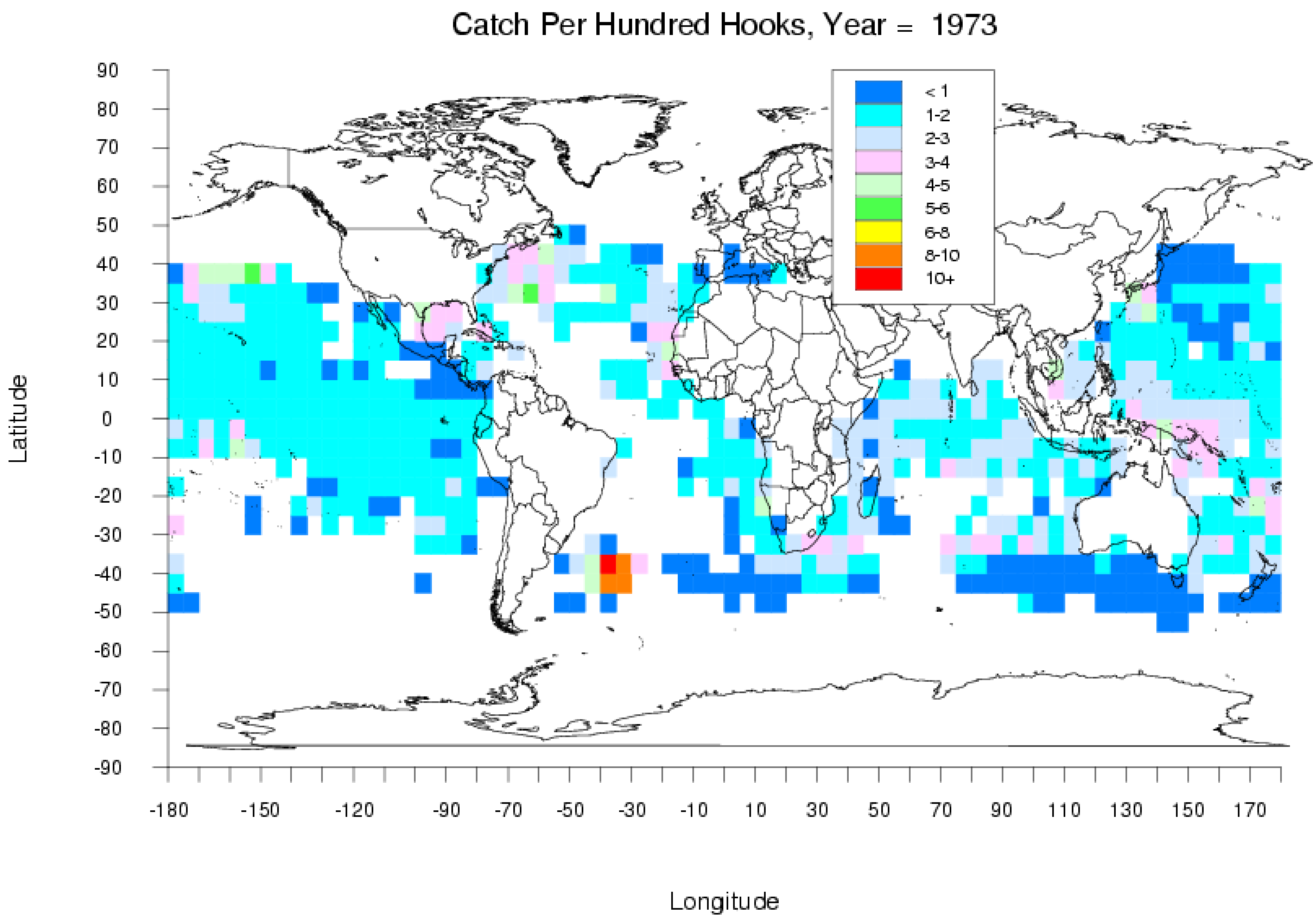
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Latitude
Longitude



Catch Per Hundred Hooks, Year = 1973
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
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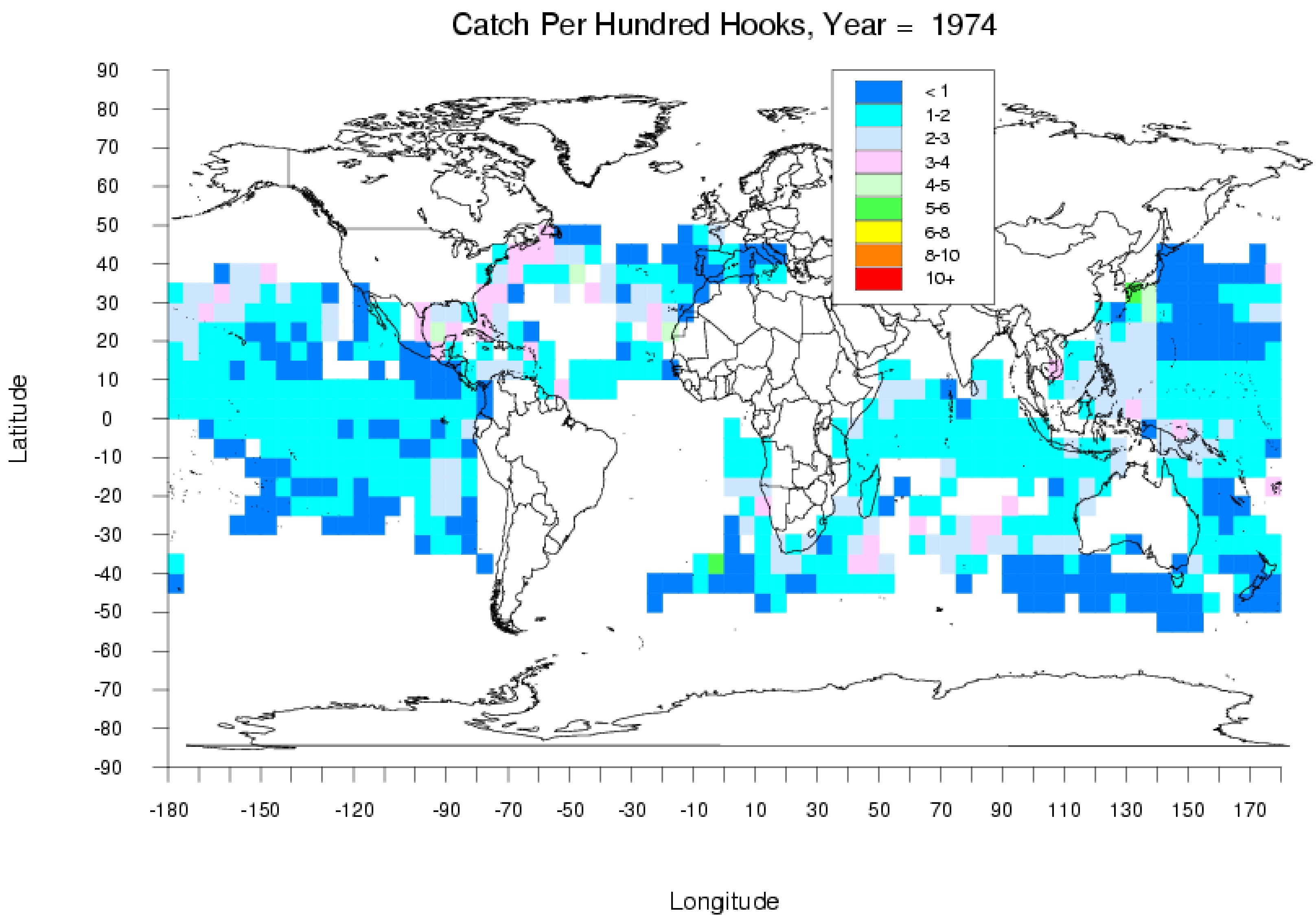
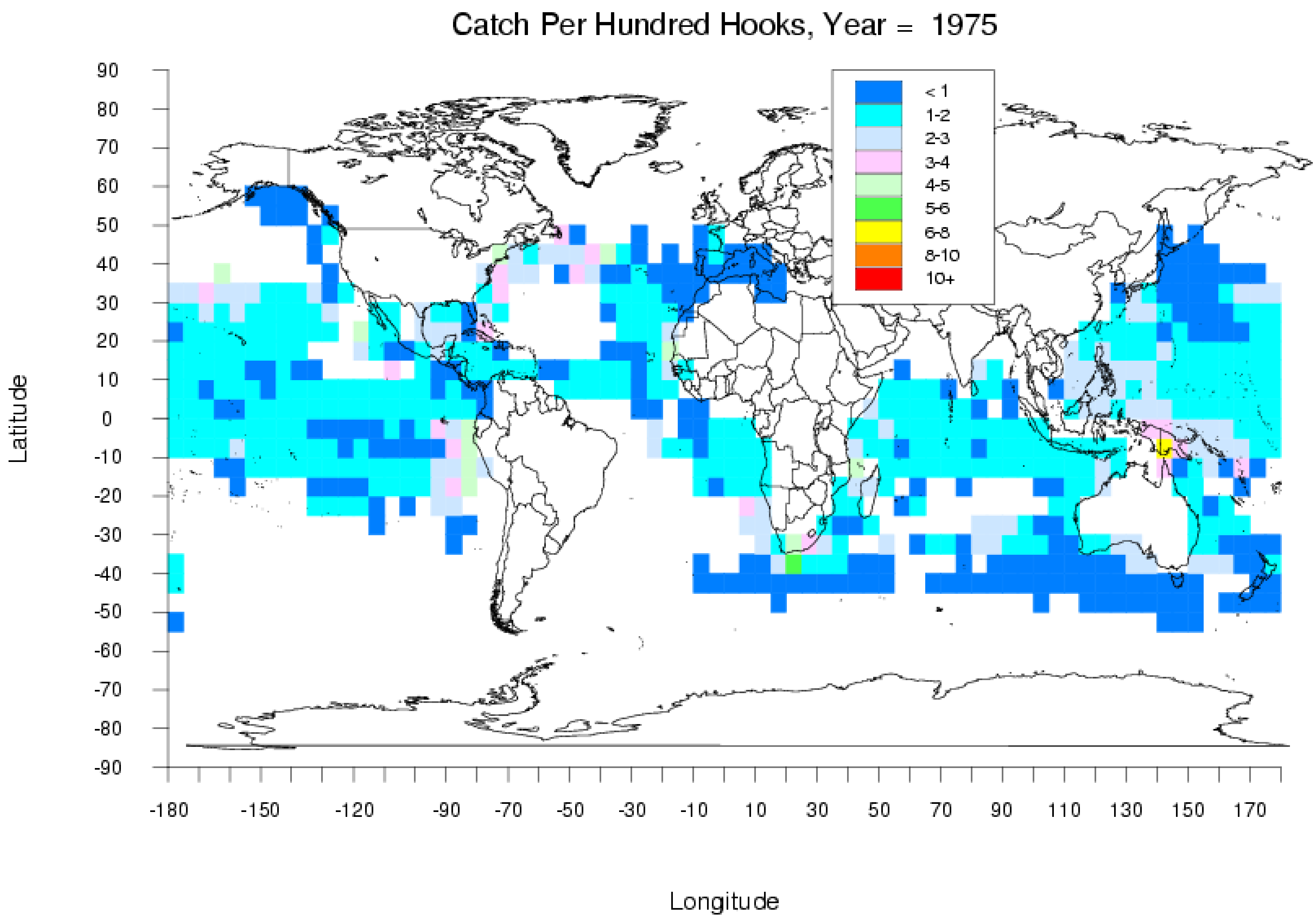
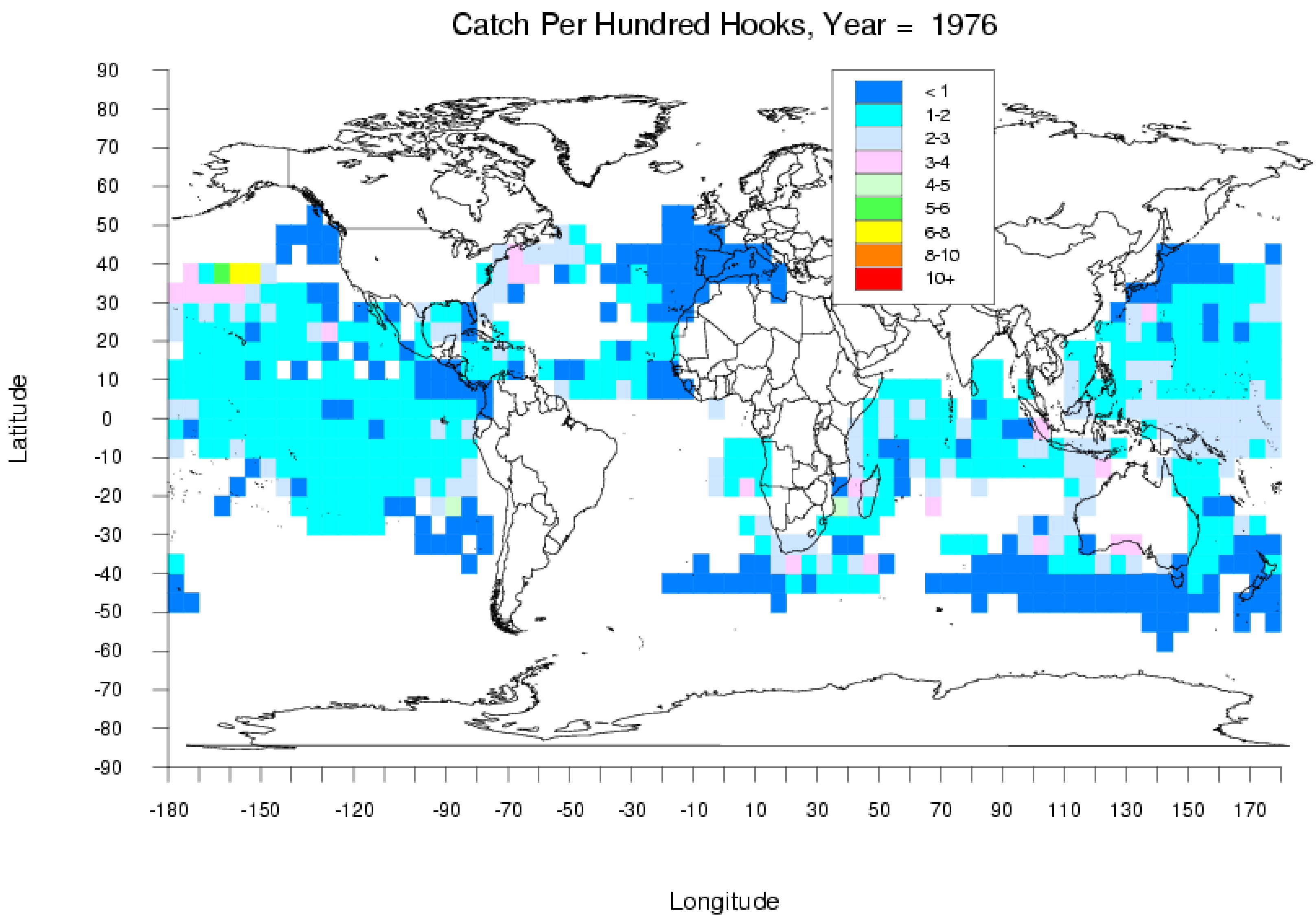
90
110
130
150
170



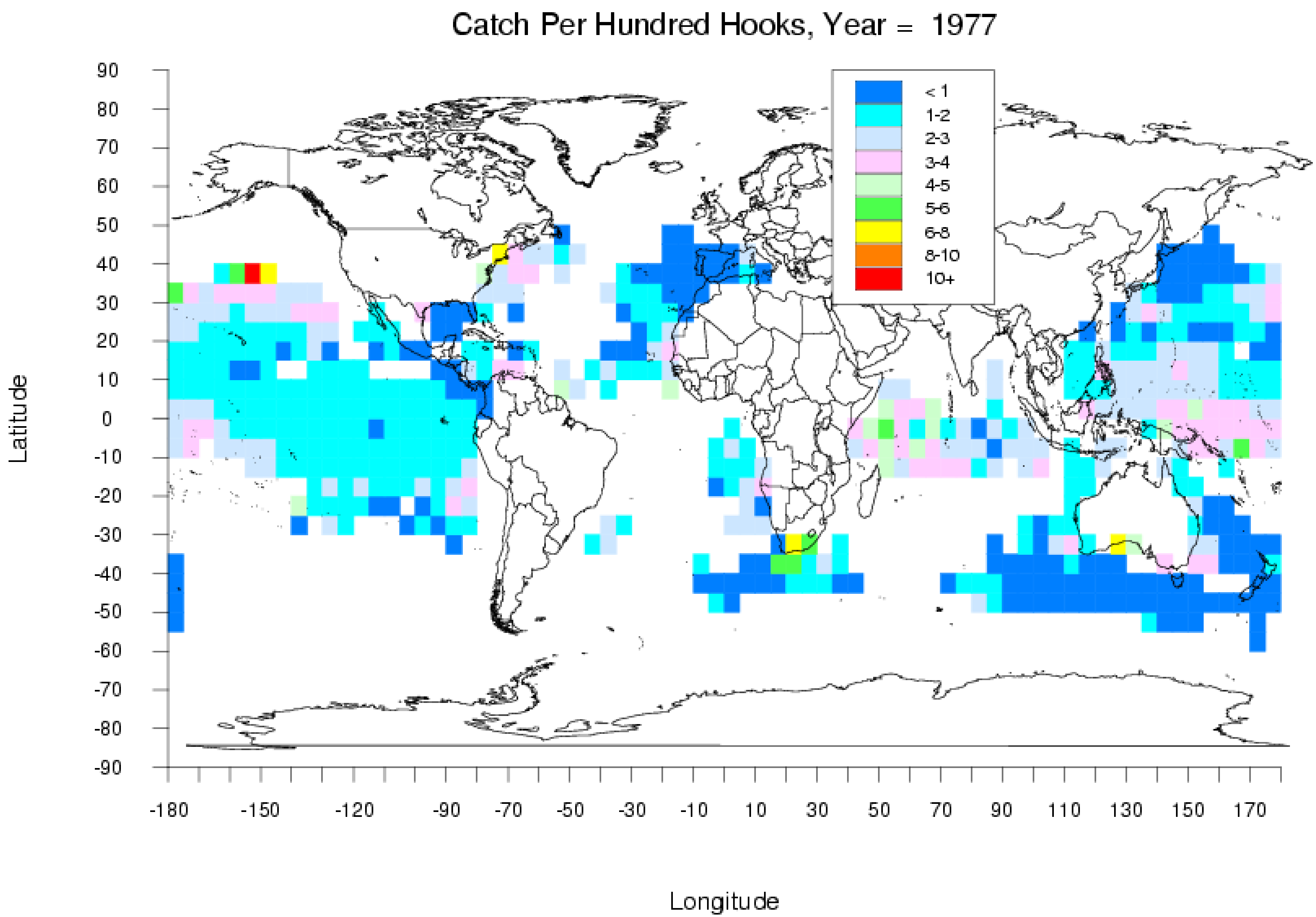
Catch Per Hundred Hooks, Year = 1974
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Latitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Longitude



Catch Per Hundred Hooks, Year = 1975
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170



Catch Per Hundred Hooks, Year = 1976
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170
Longitude


Catch Per Hundred Hooks, Year = 1977
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
-10
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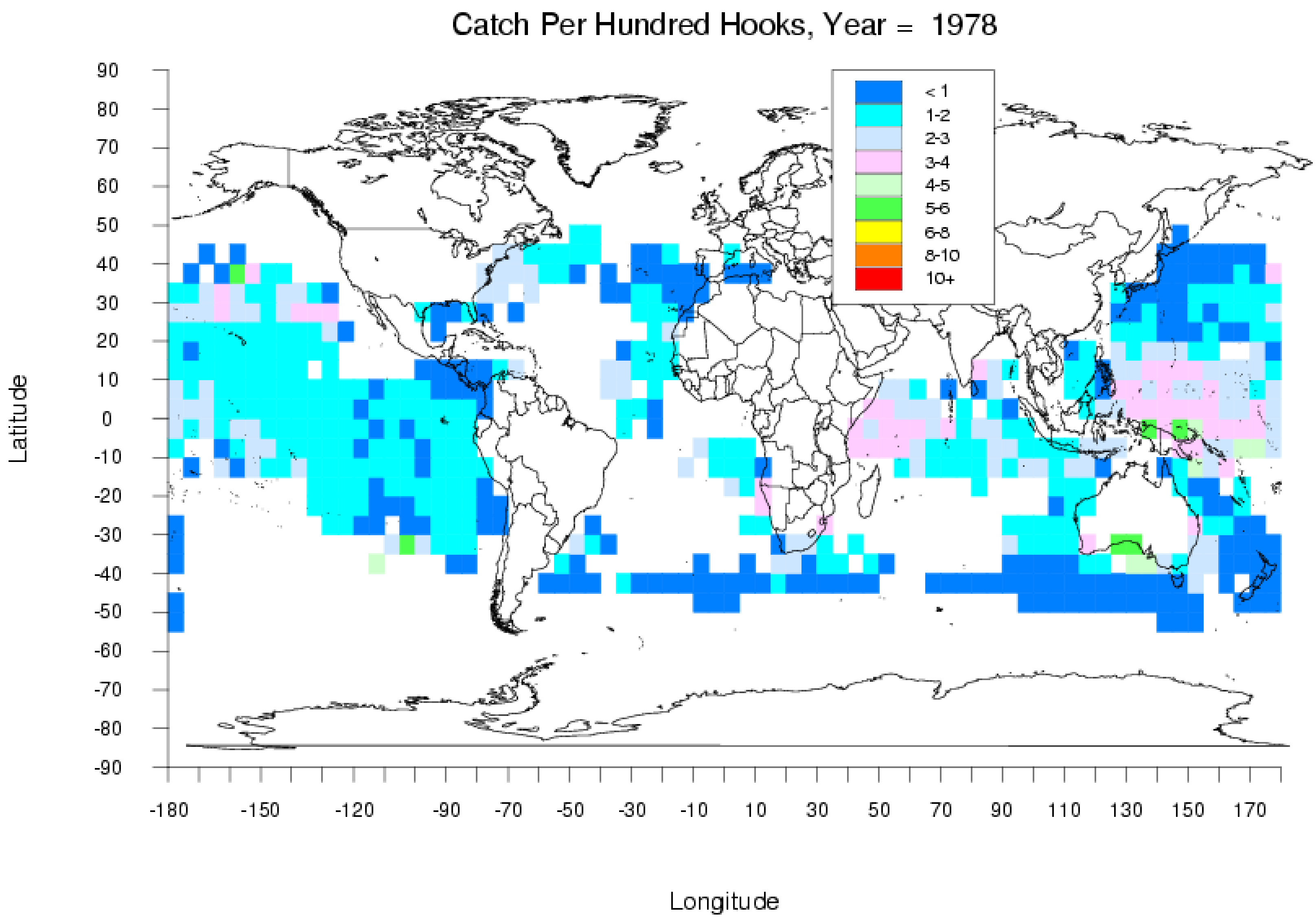
30
50
70
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1978
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
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-70
-50
-30
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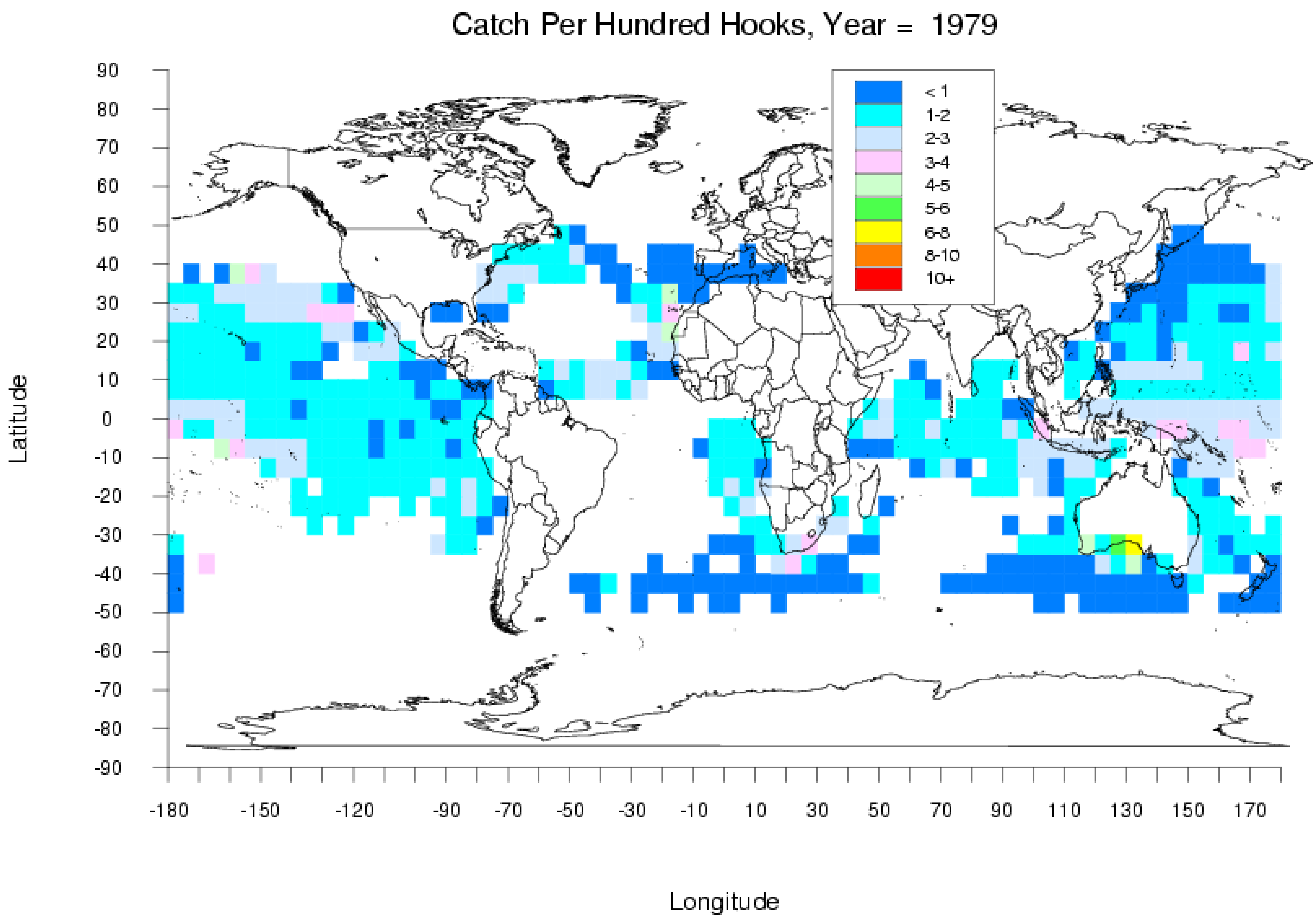
90
110
130
150
170


Catch Per Hundred Hooks, Year = 1979
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
Longitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-180
-150
-120
-90
-70
-50
-30
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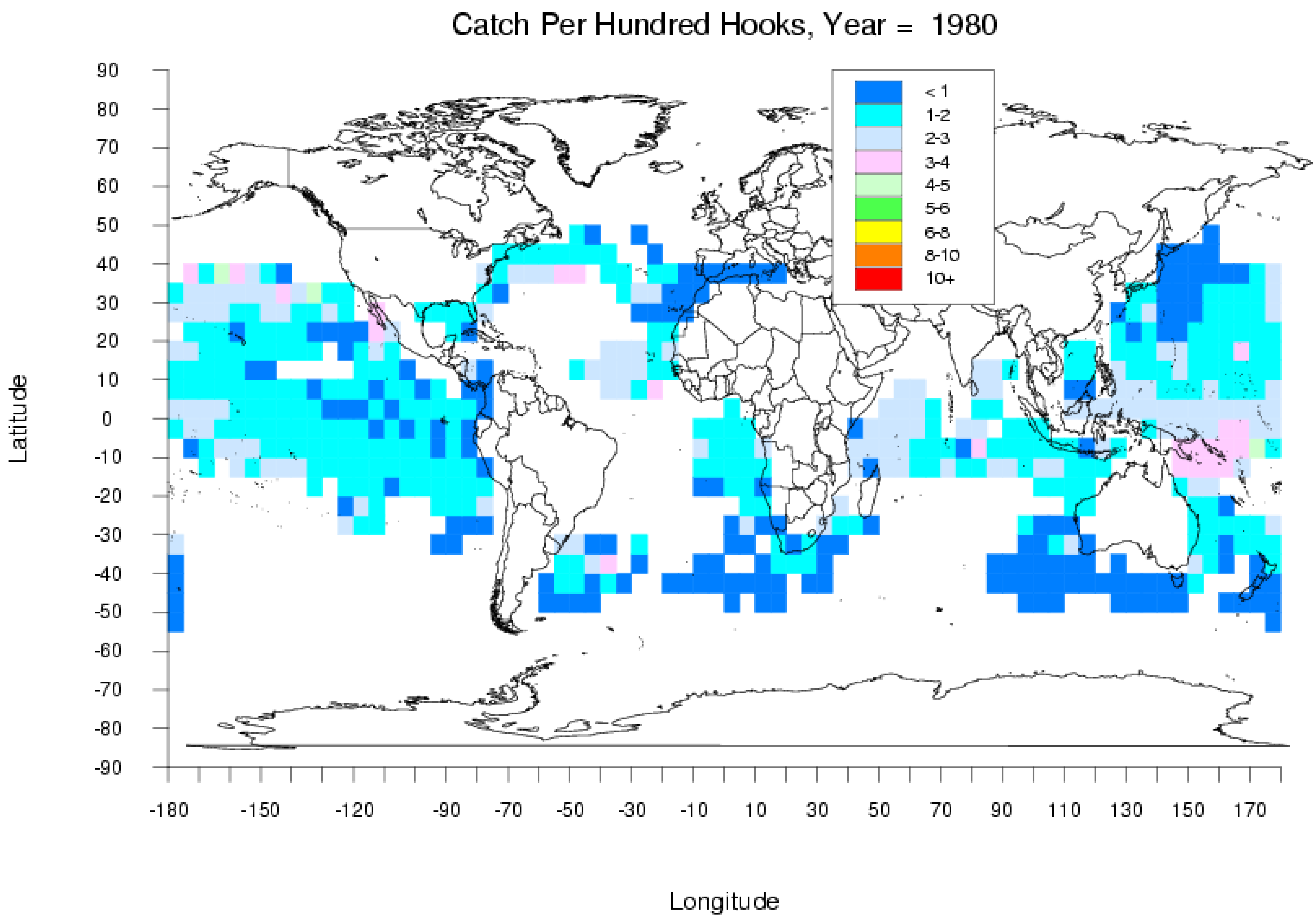
90
110
130
150
170

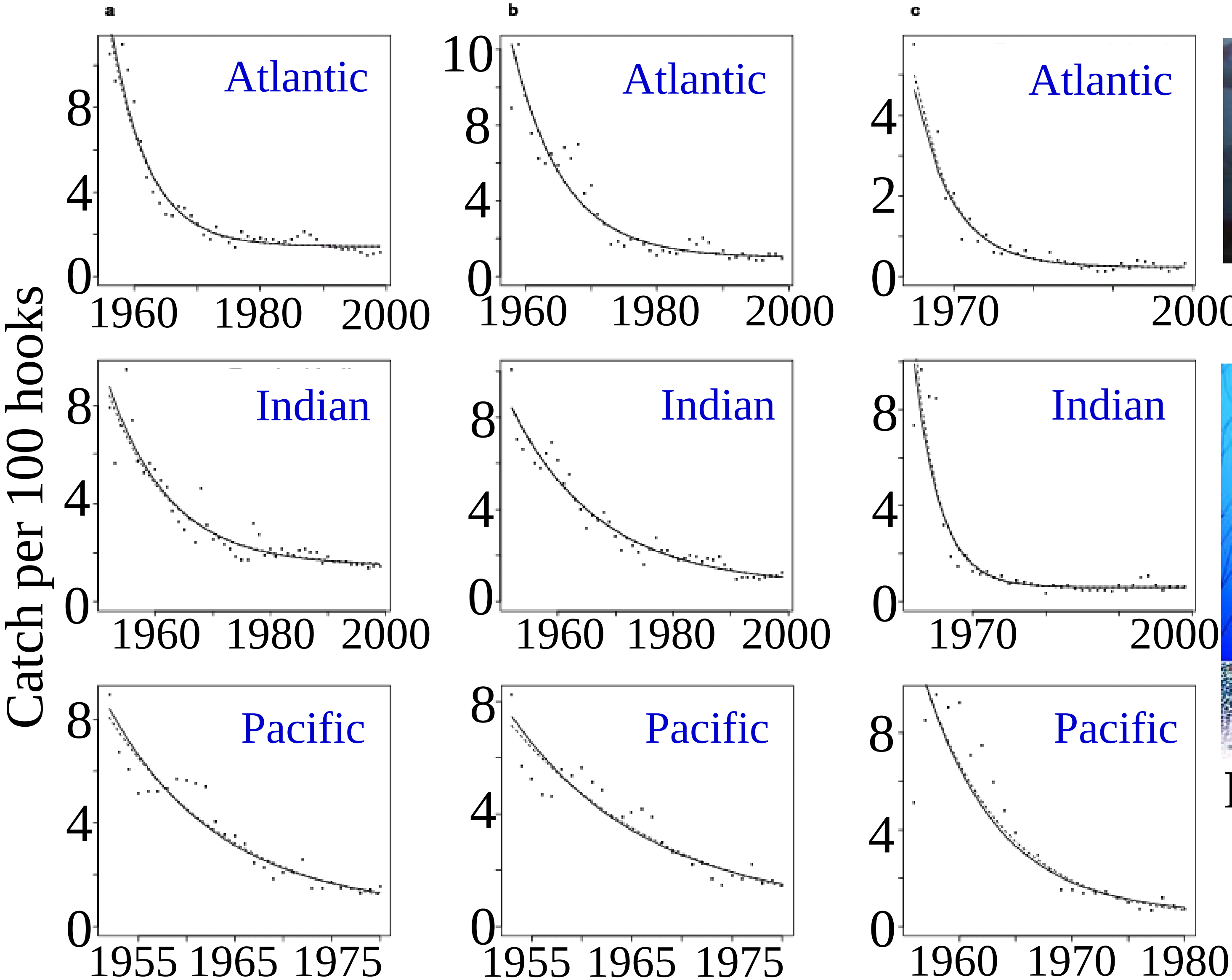


Catch Per Hundred Hooks, Year = 1980
< 1
1-2
2-3
3-4
4-5
5-6
6-8
8-10
10+
Latitude
90
80
70
60
50
40
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
Longitude
-180
-150
-120
-90
-70
-50
-30
-10
10
30
50
70
90
110
130
150
170

Critical Modeling Tools

- Plot the data and think for yourself

Common patterns of decline



Myers and Worm (2003)

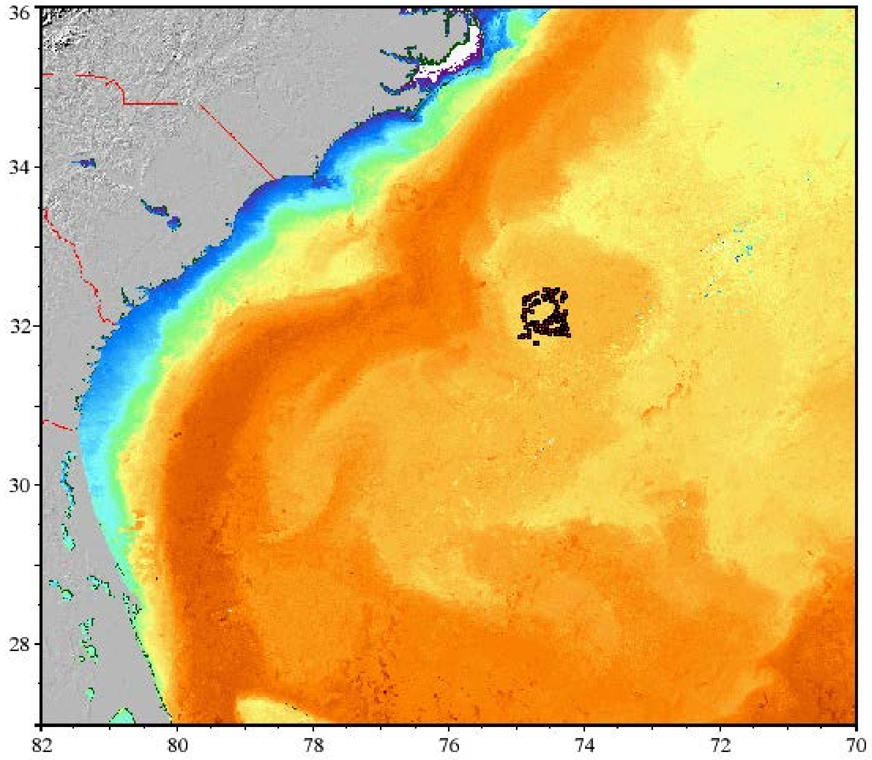
Critical Modeling tools:

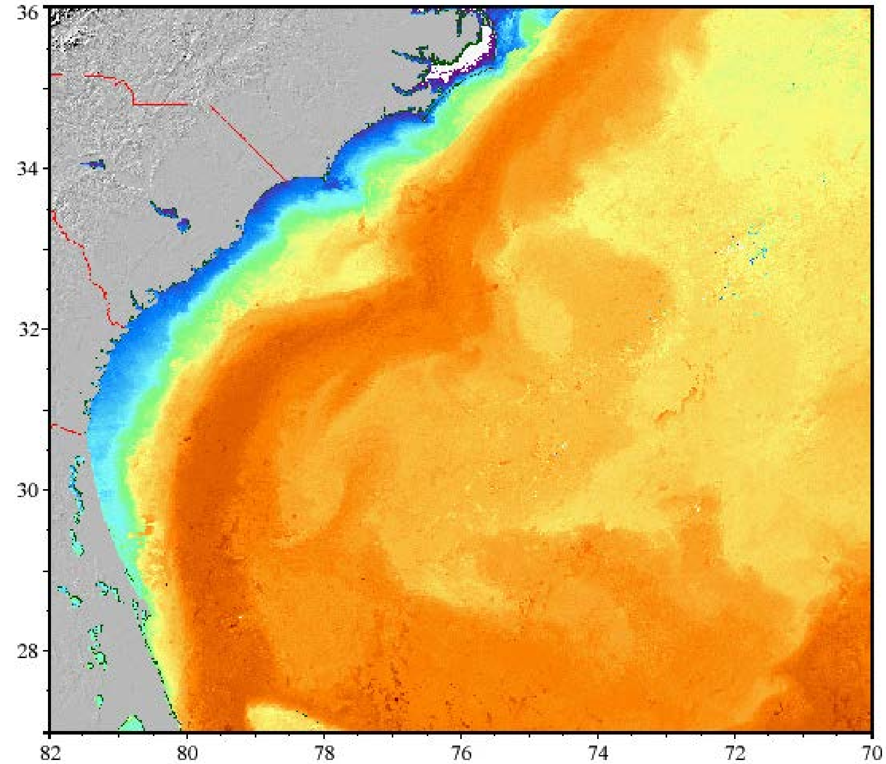
- Nonlinear Mixed Effect Models to Describe Common Patters

Totally Stupid Reasons for not Believing the Obvious

- You ignore research surveys.
- Removing Large Predators Couldn’t Possibly Affect Survival of Other Fish.
- Fishing Couldn’t Possibly Affect the Size of Tuna.
- Fishermen are so stupid they cannot use satellite data to find tuna.
- Fishermen are so stupid that they don’t improve their gear.

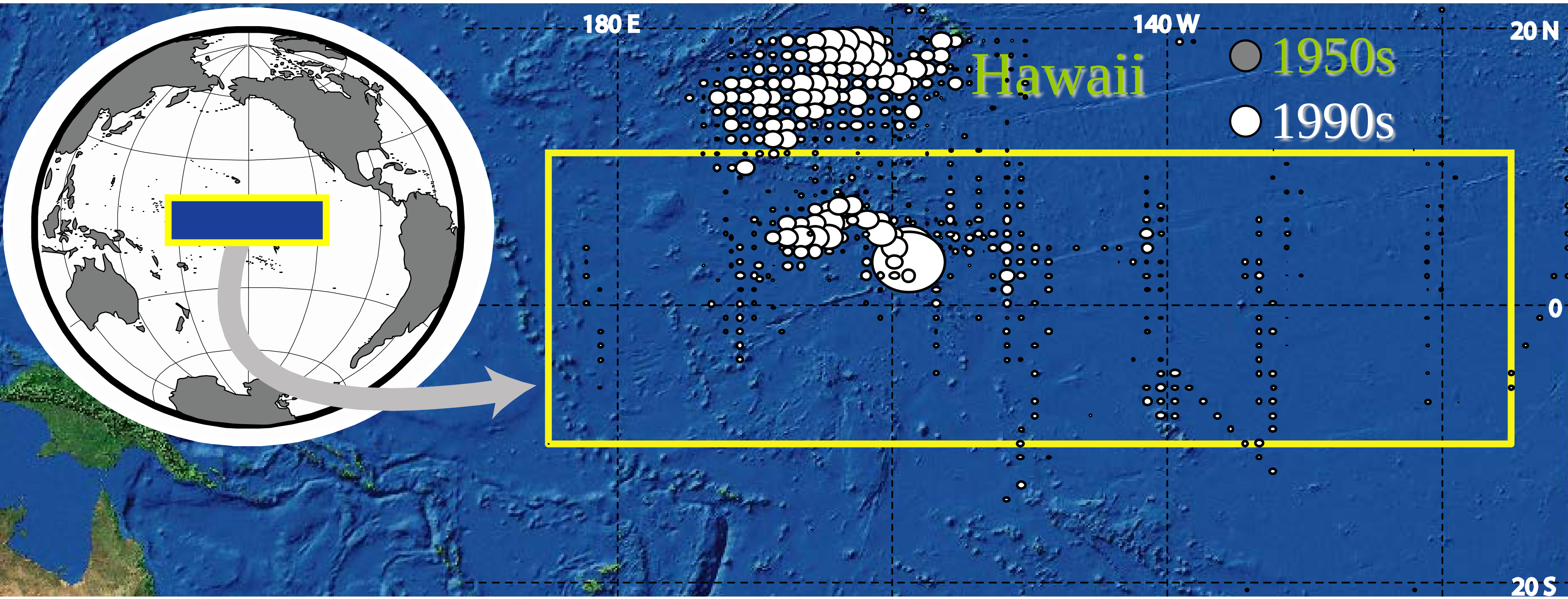
These estimates are conservative: Fishermen are smarter (GPS, satellite information, **ACDP** (Acoustic Current Doppler Profiler)).



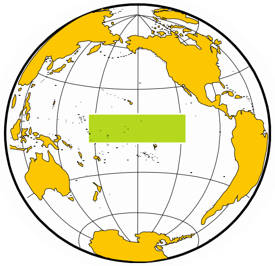


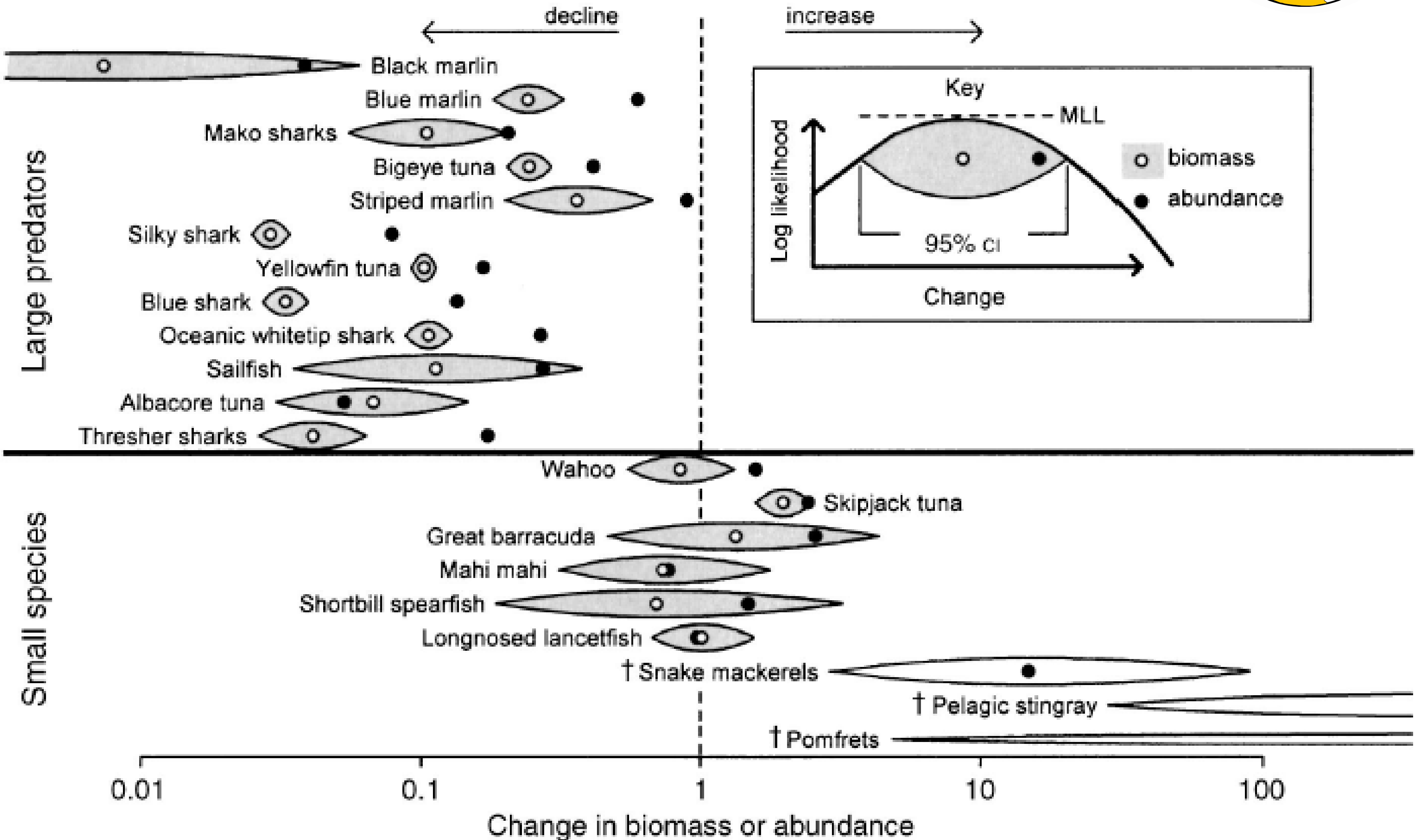
Locations of a leatherback turtle over a two week period tagged by my student Mike James that maintains its position within a cold core ring (somehow).

Study area



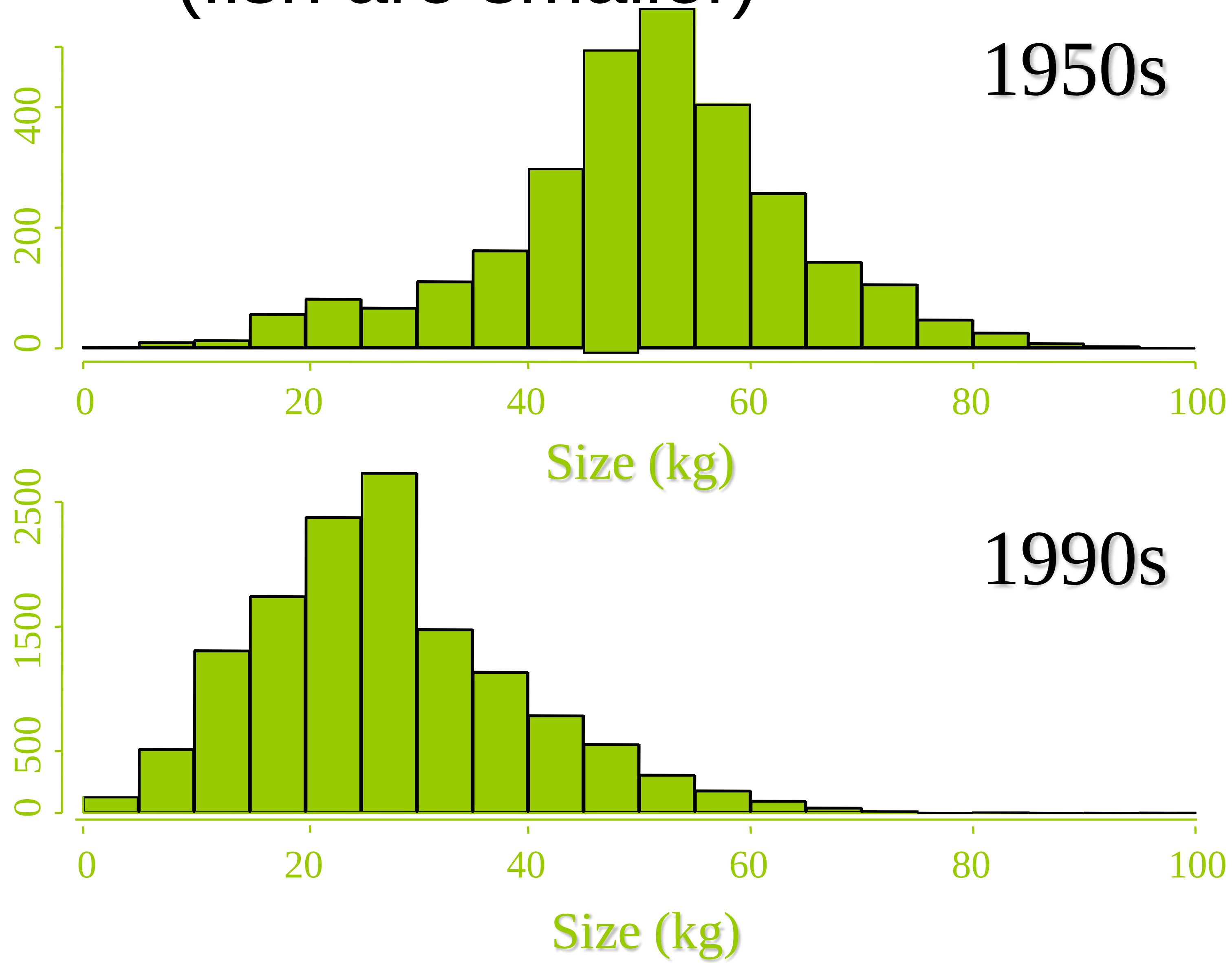
Analysis repeated using independent research data





Ward and Myers 2005 Ecology

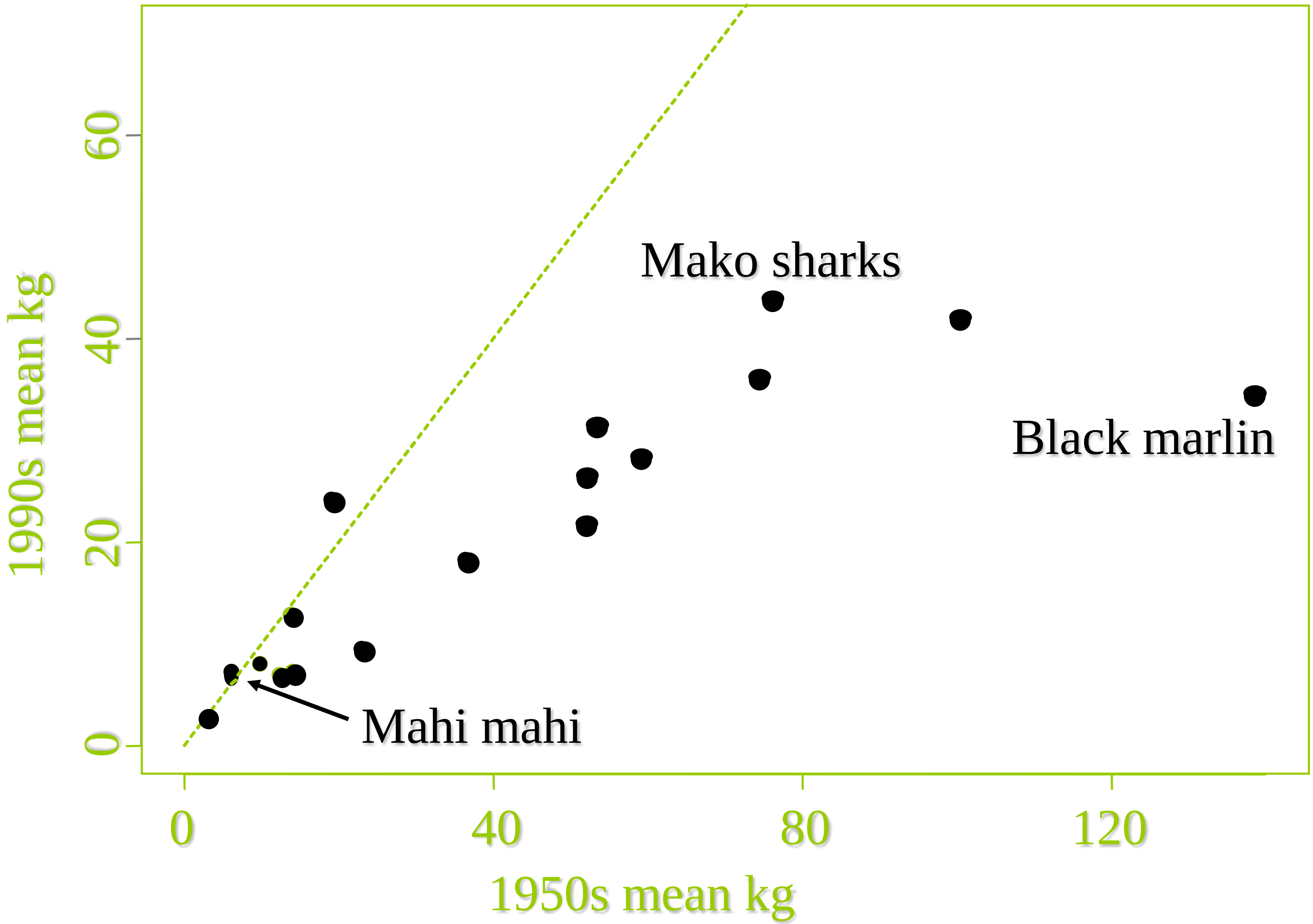
These estimates are conservative: (fish are smaller)



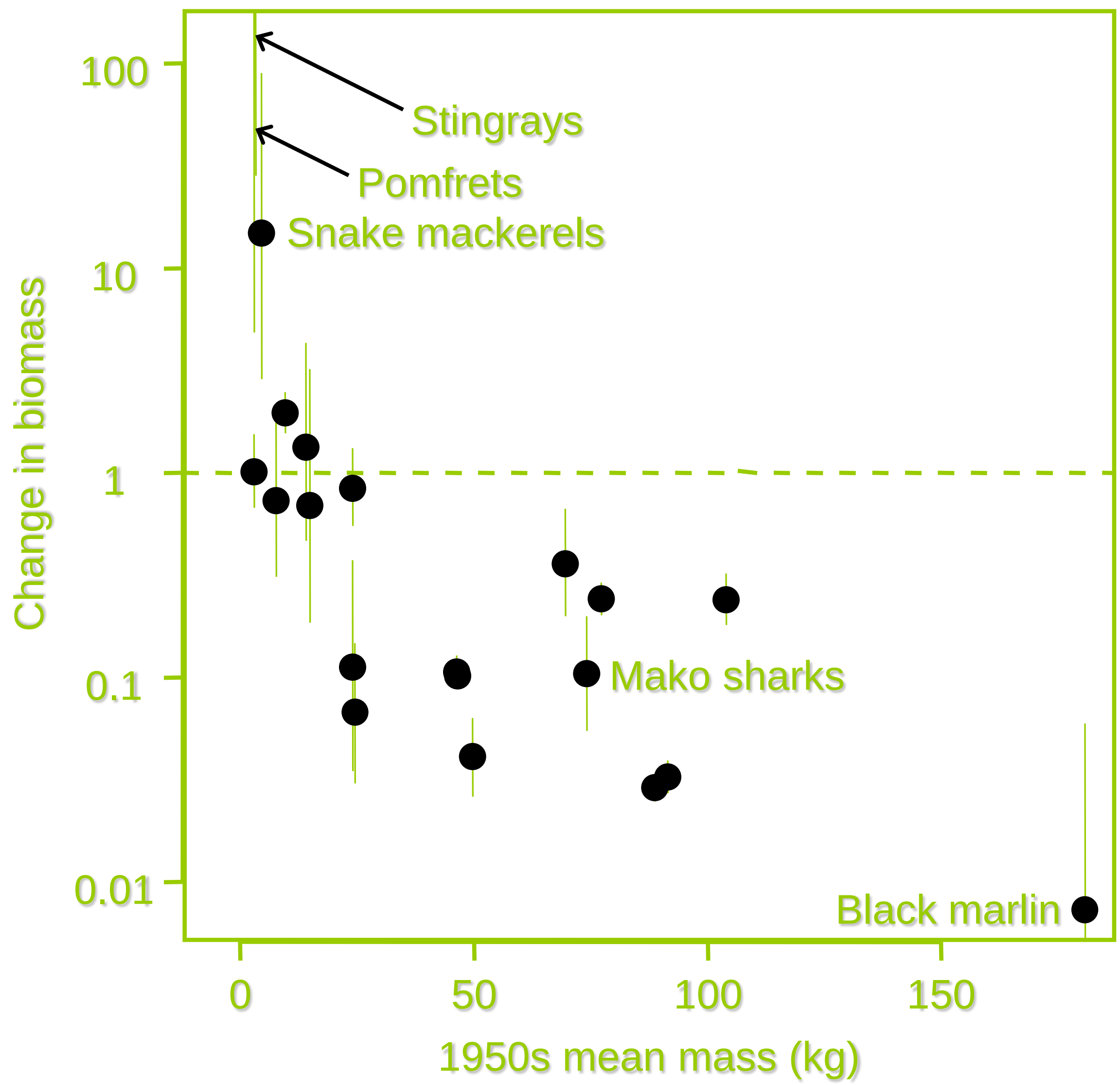
Yellowfin tuna – equitorial Pacific

Ward and Myers 2005 Ecology

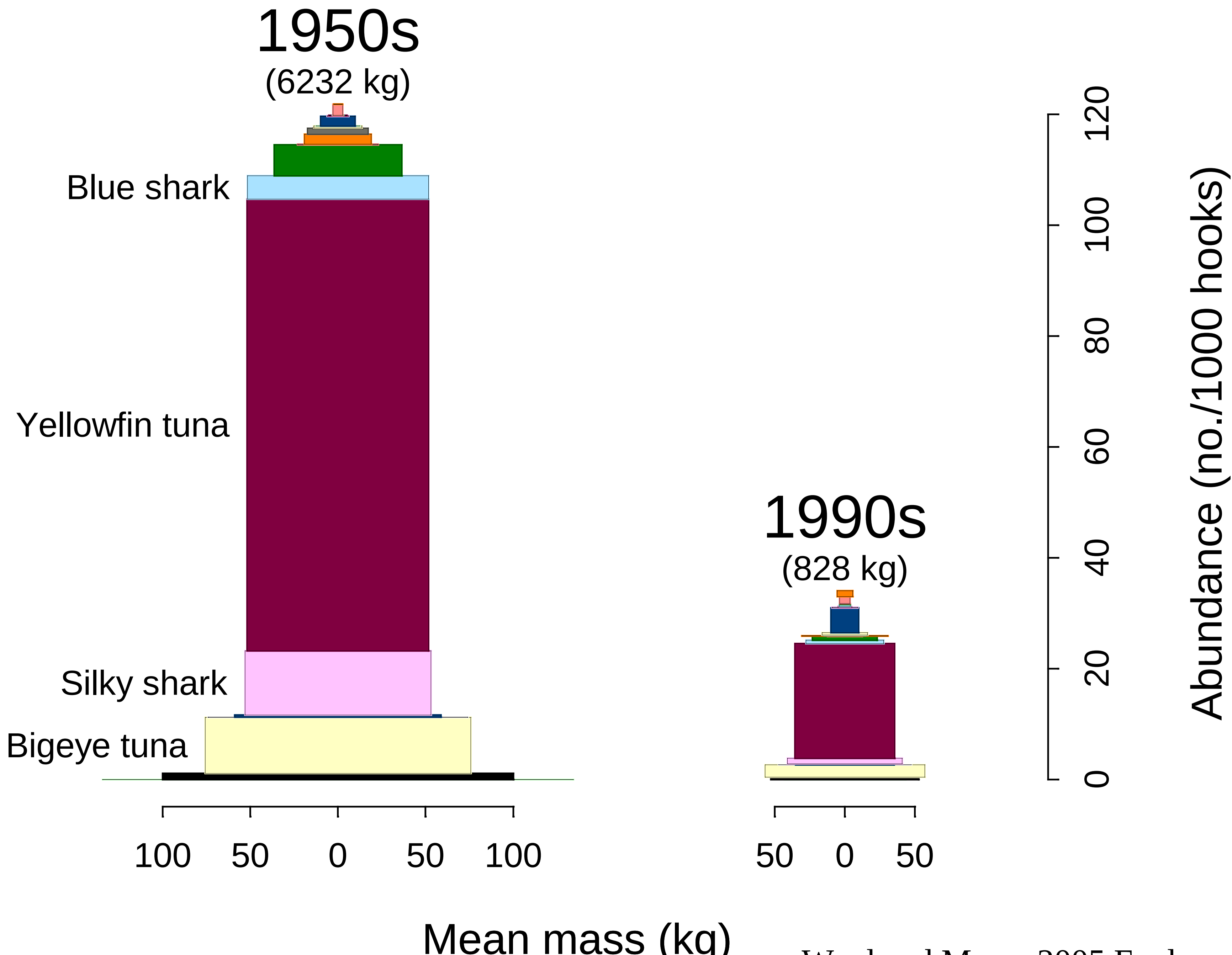
Change in body size



Ward and Myers 2005 Ecology



Ward and Myers 2005 Ecology



Ward and Myers 2005 Ecology

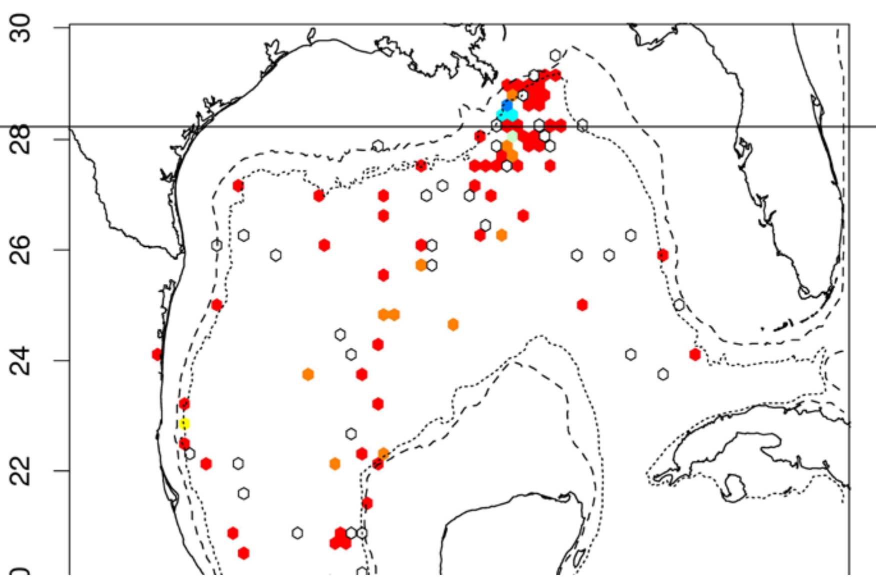
Critical Modeling tools:

- Generalized linear mixed effects models to standardize historical surveys for depth and soak time

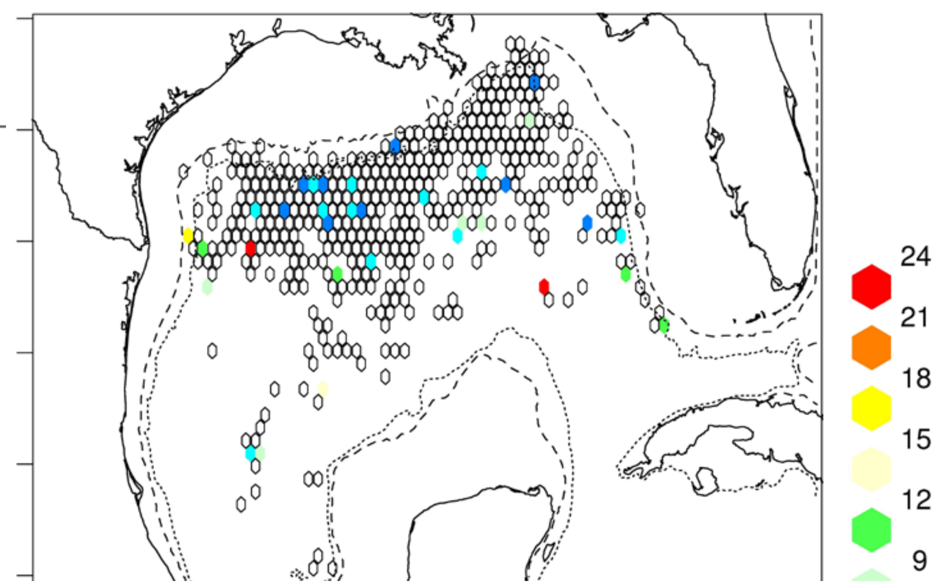
Loss of sharks in the Gulf of Mexico

300 fold decline – no one noticed

[redacted]



1950's

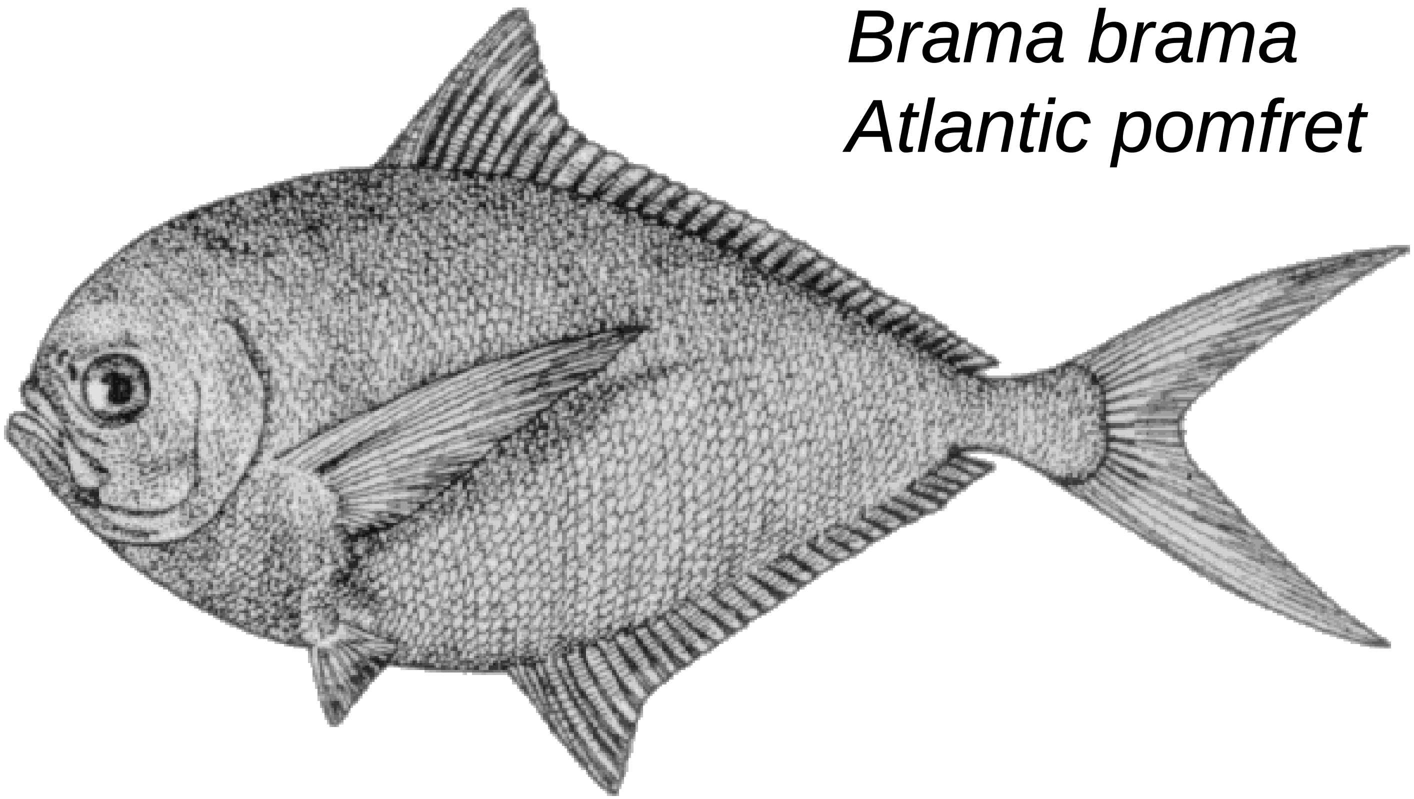


1990's

Oceanic Whitetip captures per 10,000 hooks

Many thanks to NMFS for data and advice

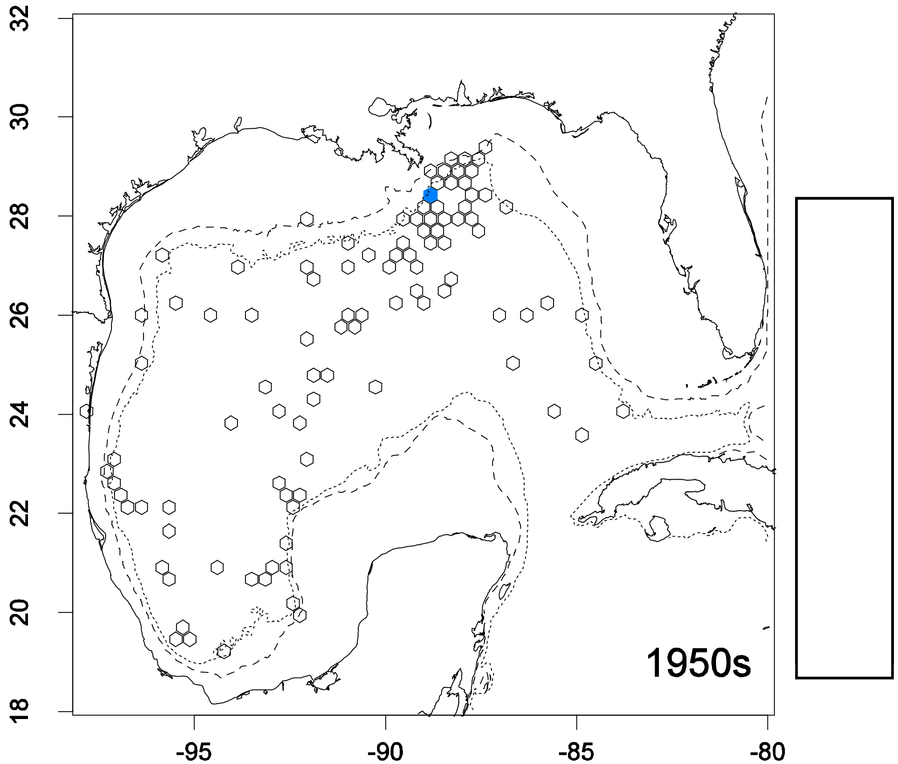
What about prey fish?

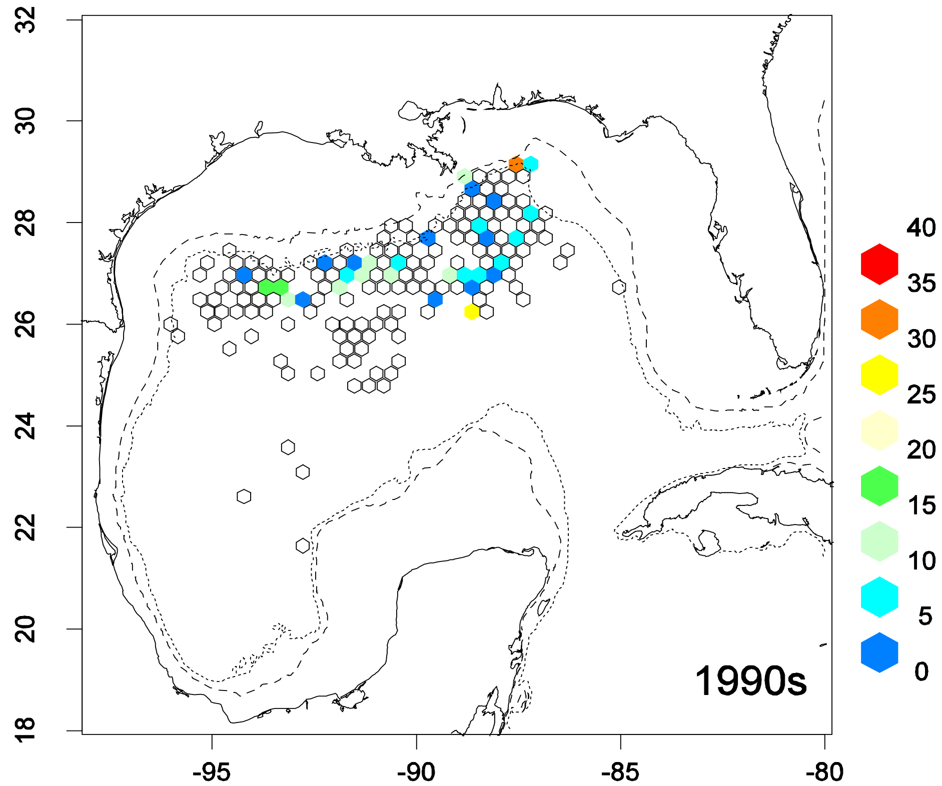


Brama brama
Atlantic pomfret

Illustration taken from the book "Encyclopedia of Canadian Fishes" by Brian W. Coad with Henry Waszczuk and Italo Labignan, 1995,

Explosion of Pomfrets in the Gulf of Mexico
~1000 fold increase – no one noticed





1950's

1990's

Pomfret captures per 10,000 hooks

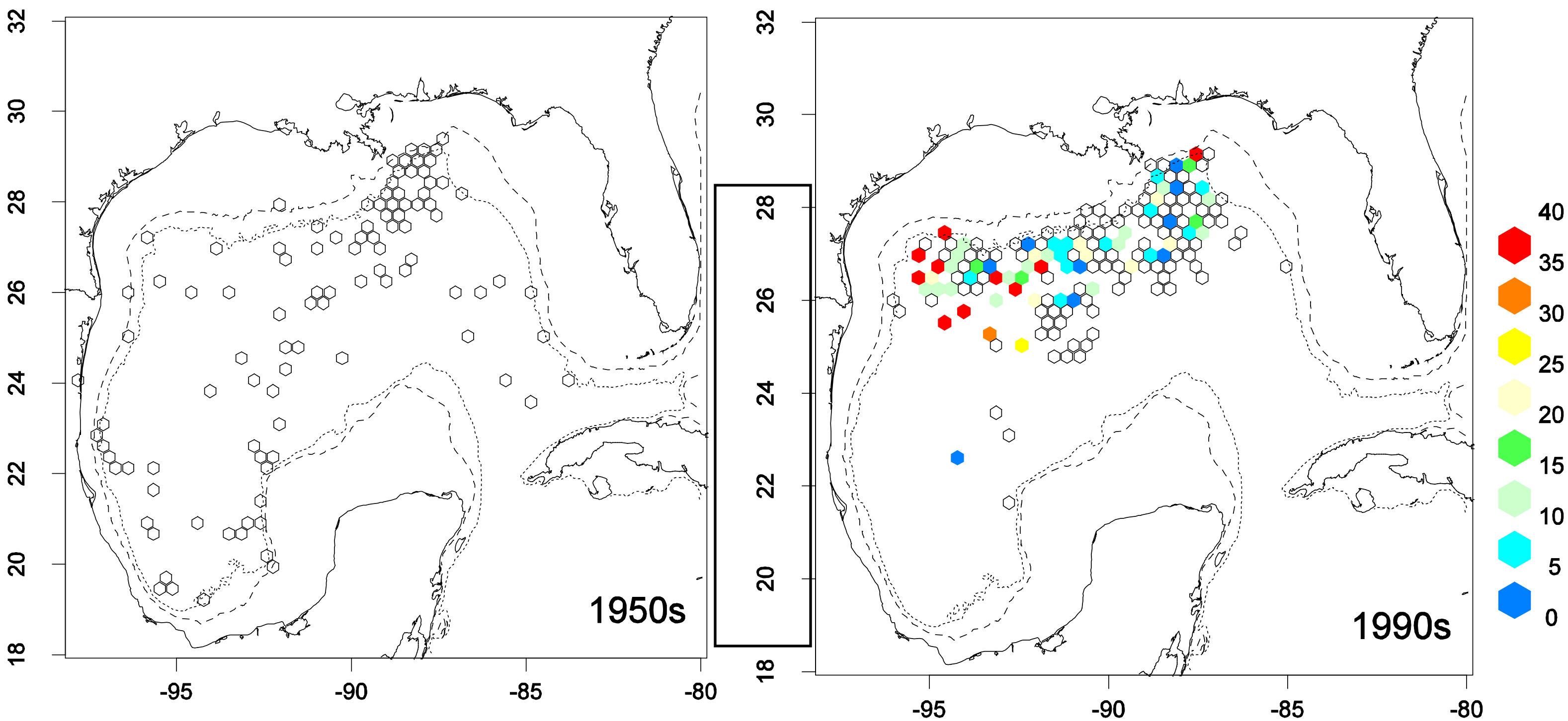
Many thanks to NMFS for data and advice

The Rise of the Marine Mesopredators

Pelagic Sting Ray
Pteroplatytrygon violacea

Photos from Phillip Colla, photography

Explosion of Pelagic Stingrays in the Gulf of Mexico
~1000 fold increase – no one noticed

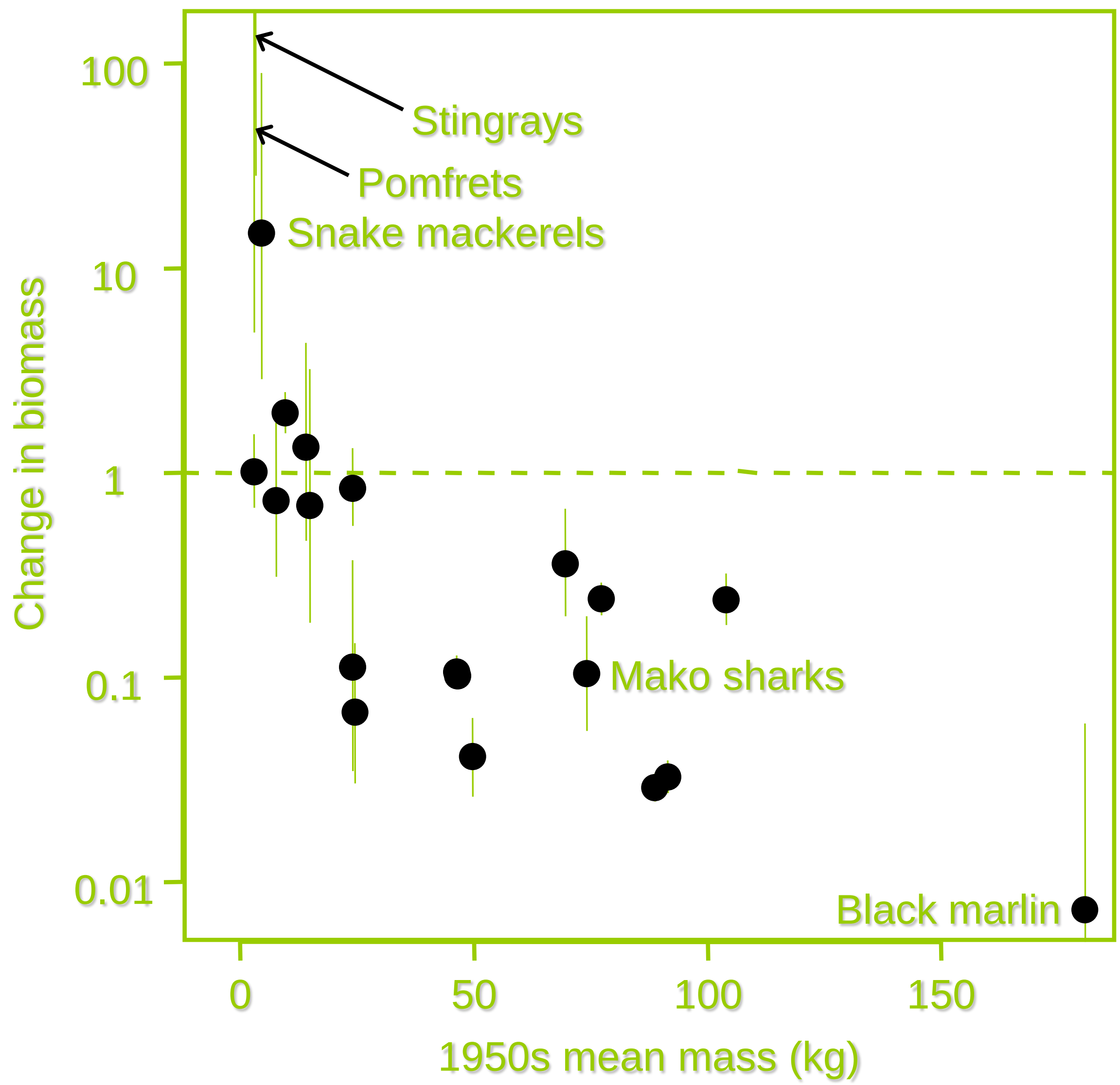


1950's

1990's

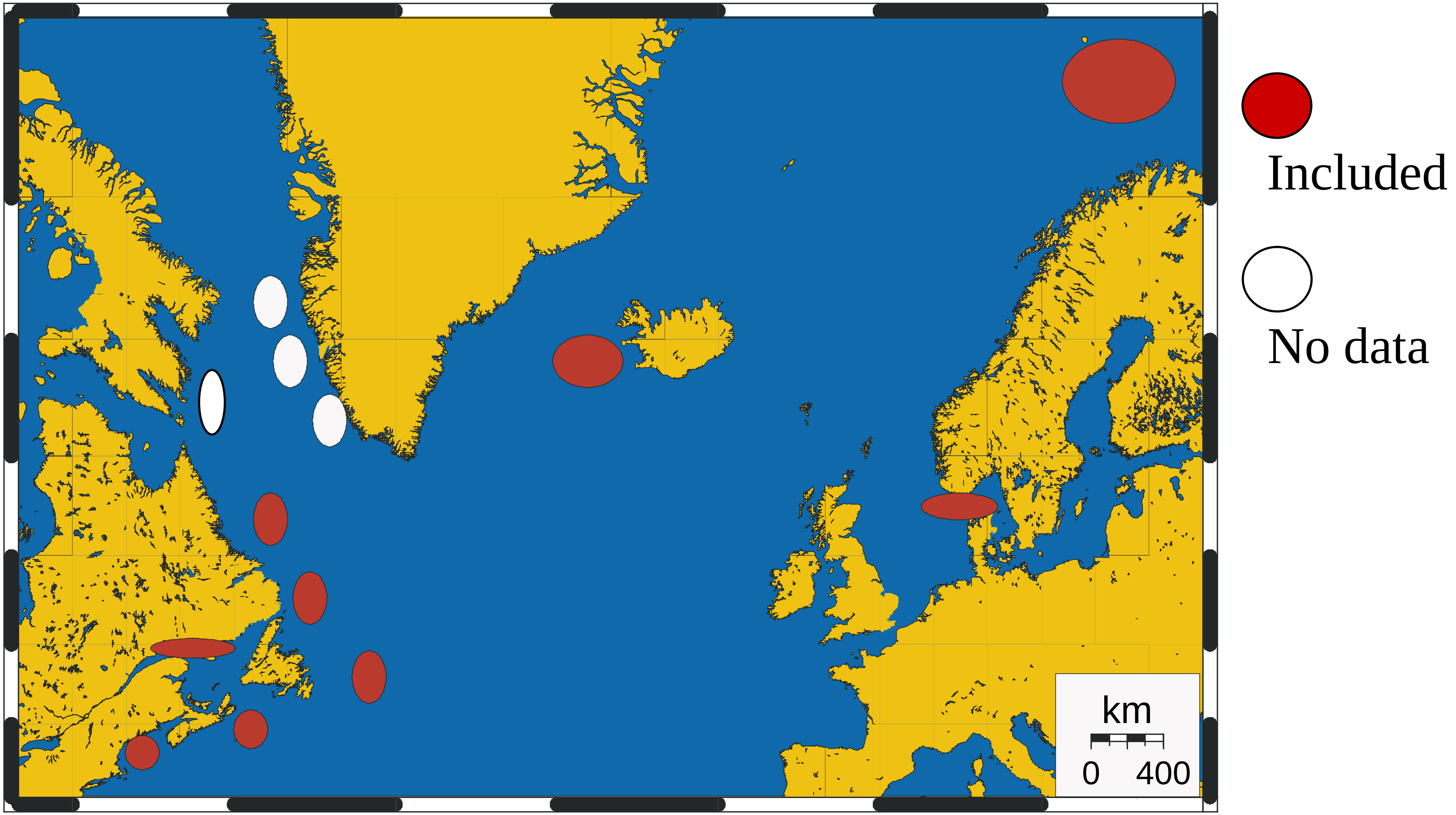
Pelagic stingray captures per 10,000 hooks

Many thanks to NMFS for data and advice

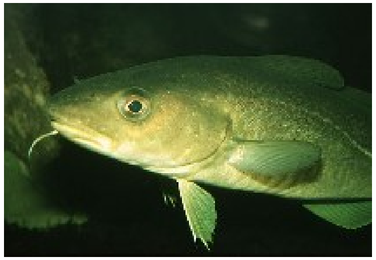


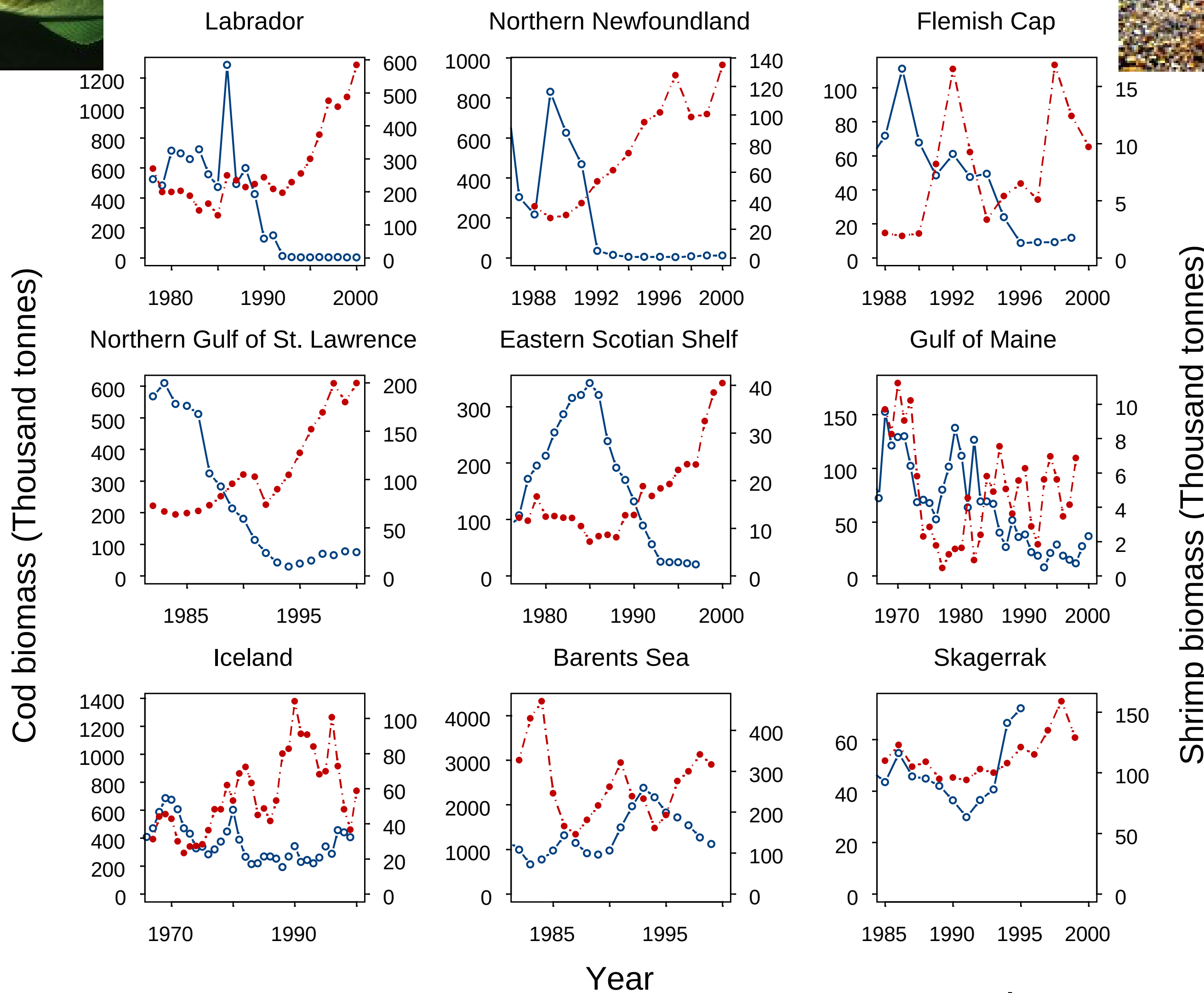
Stingrays
Pomfrets
Snake mackerels
Mako sharks
Black marlin
100
10
1
0.1
0.01
Change in biomass
0
50
100
150
1950s mean mass (kg)

Major shrimp stocks in the North Atlantic



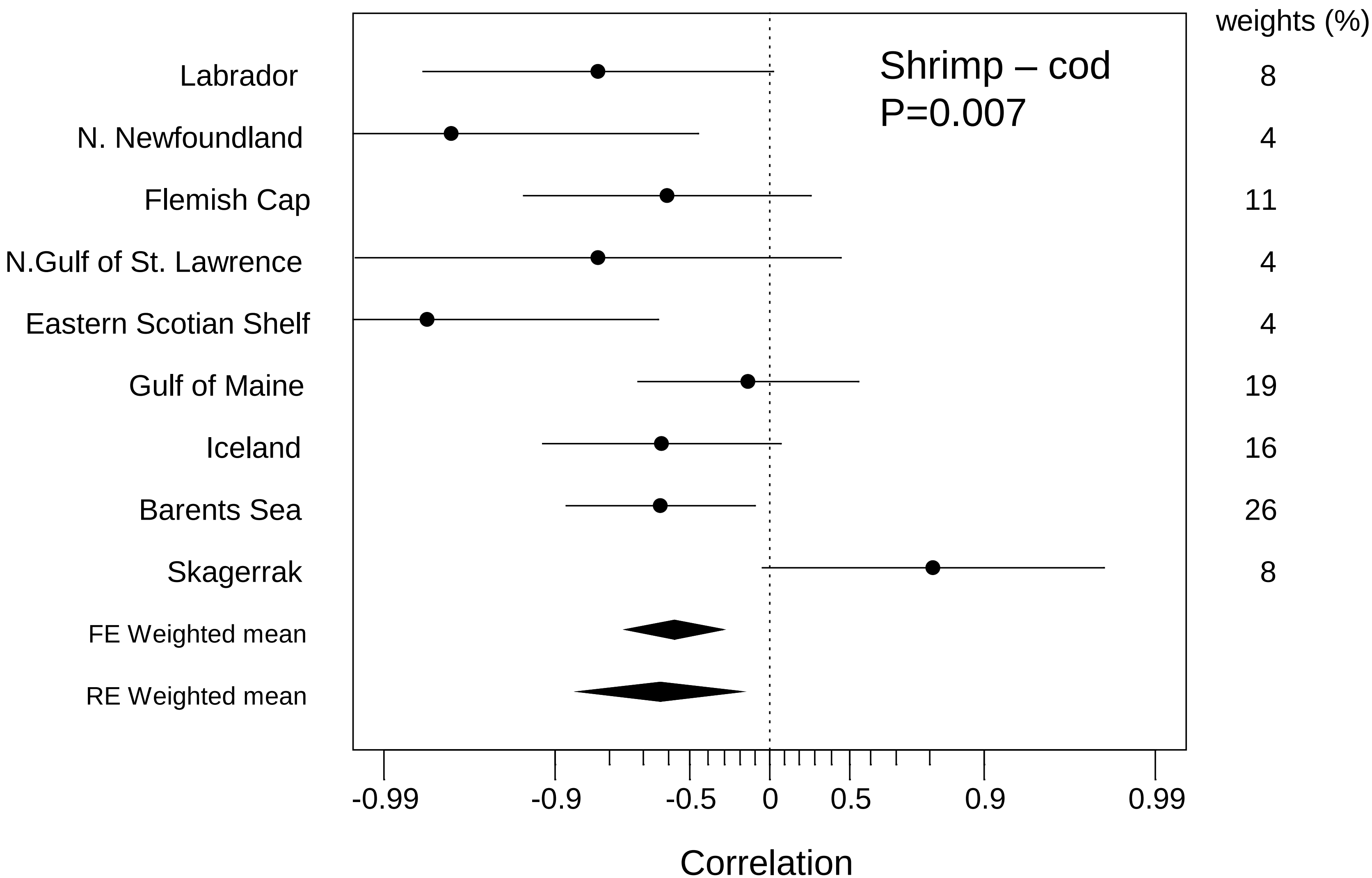
Cod and shrimp biomass in the North Atlantic: time series





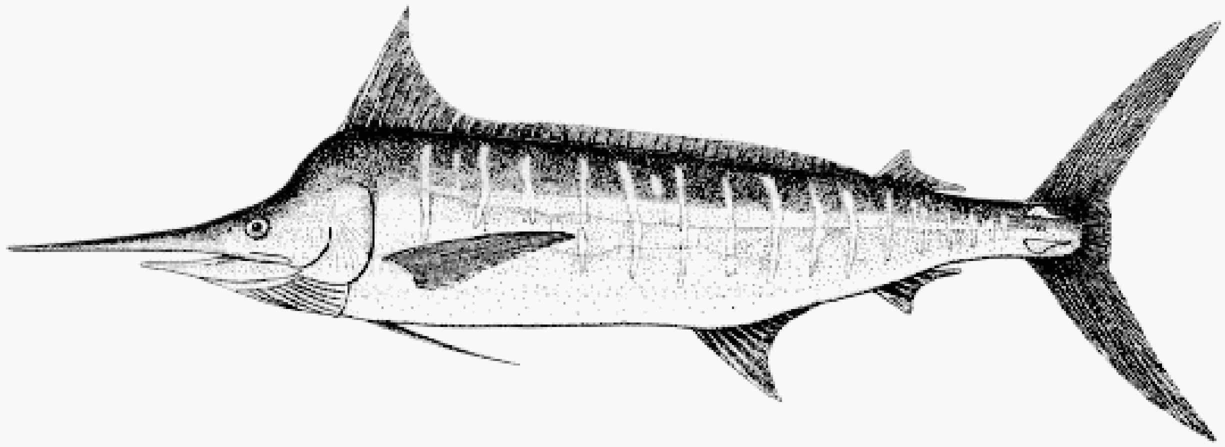
Worm and Myers, Ecology 2003

Step 2: Random-effects meta-analysis



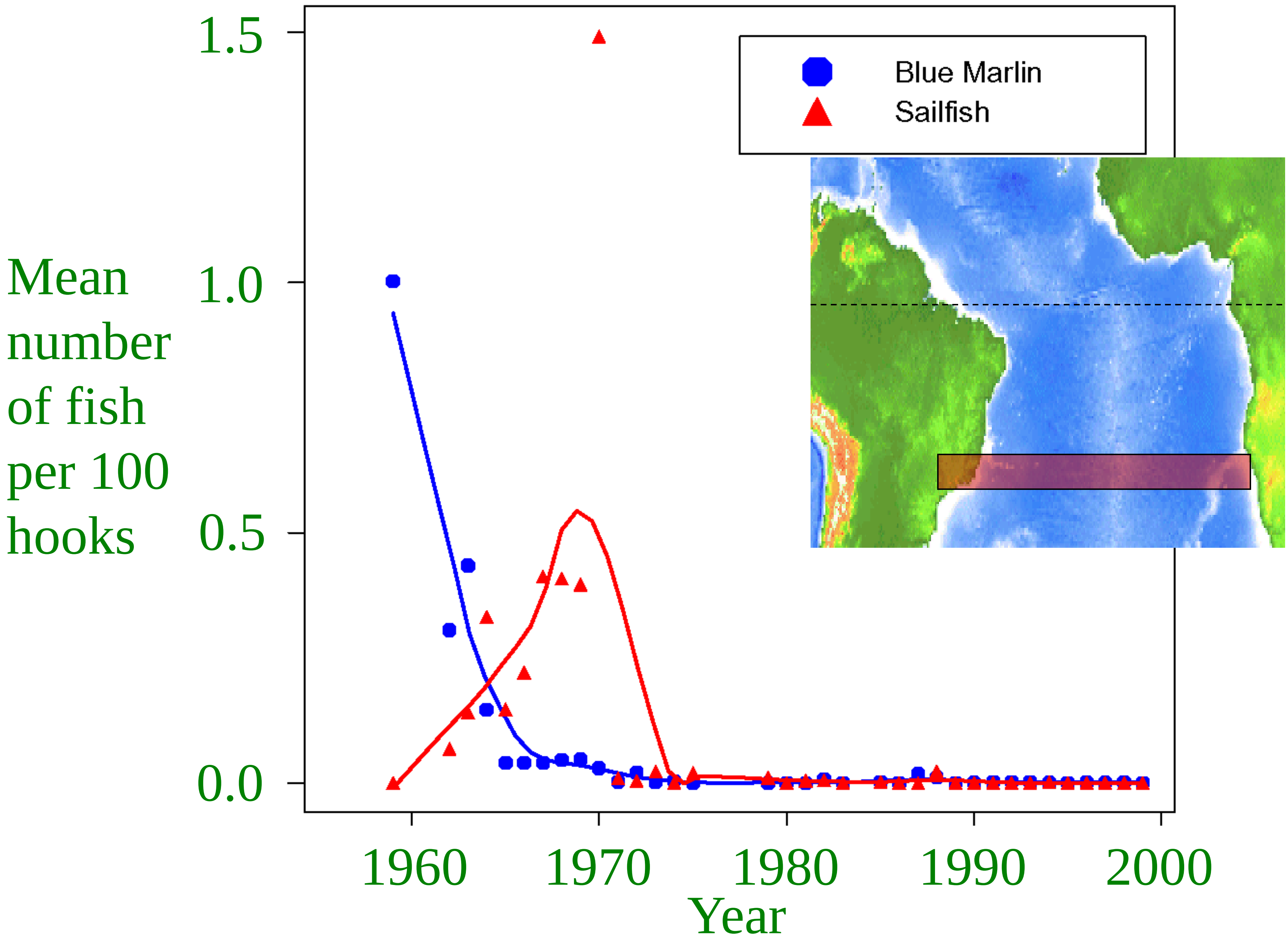
Critical Modeling Tools

- Random effects meta-analysis
- Corrections for temporal autocorrelations
- Corrections for spatial autocorrelaitons
- Modeling of environmental (bottom up) effects

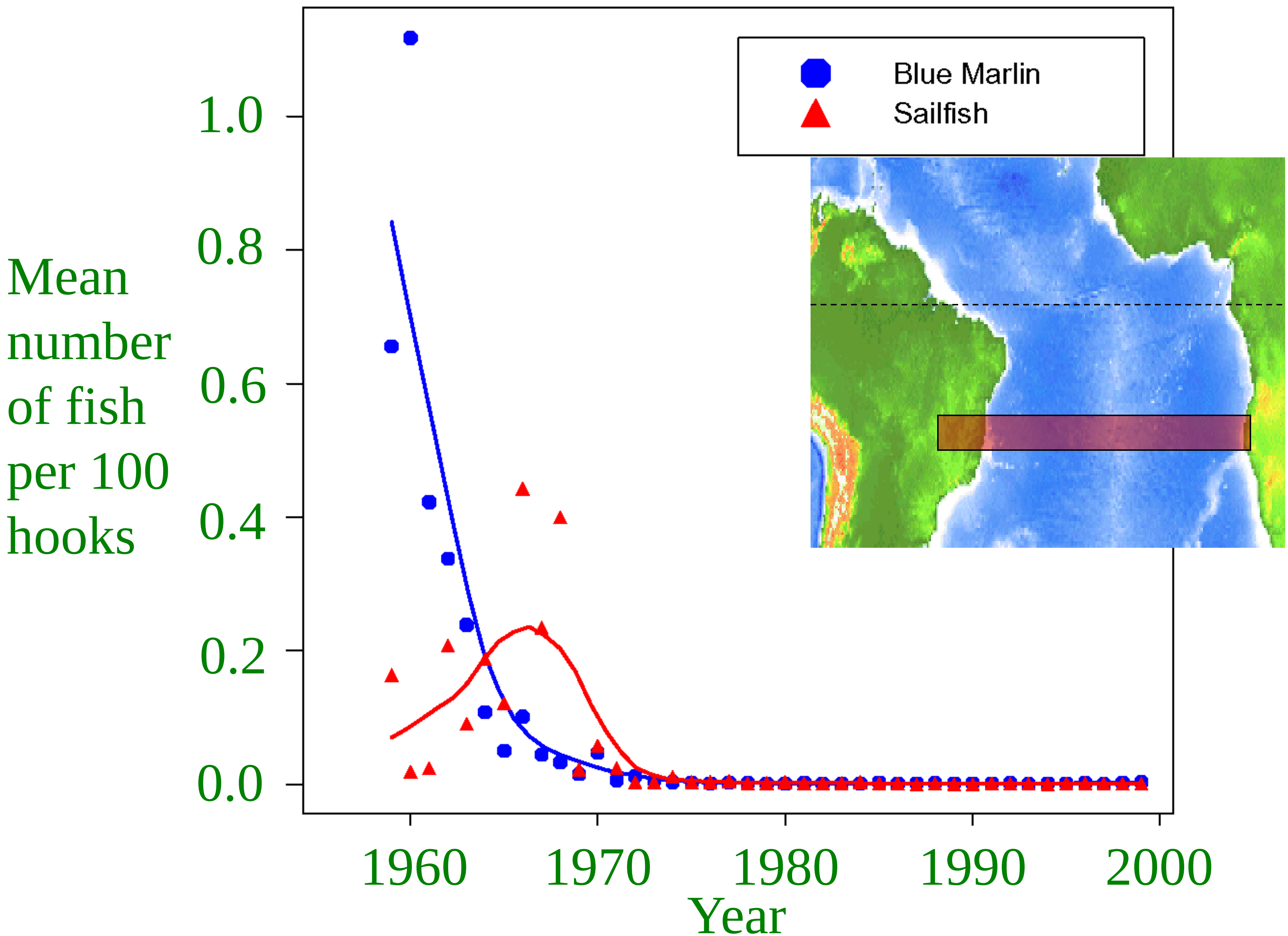


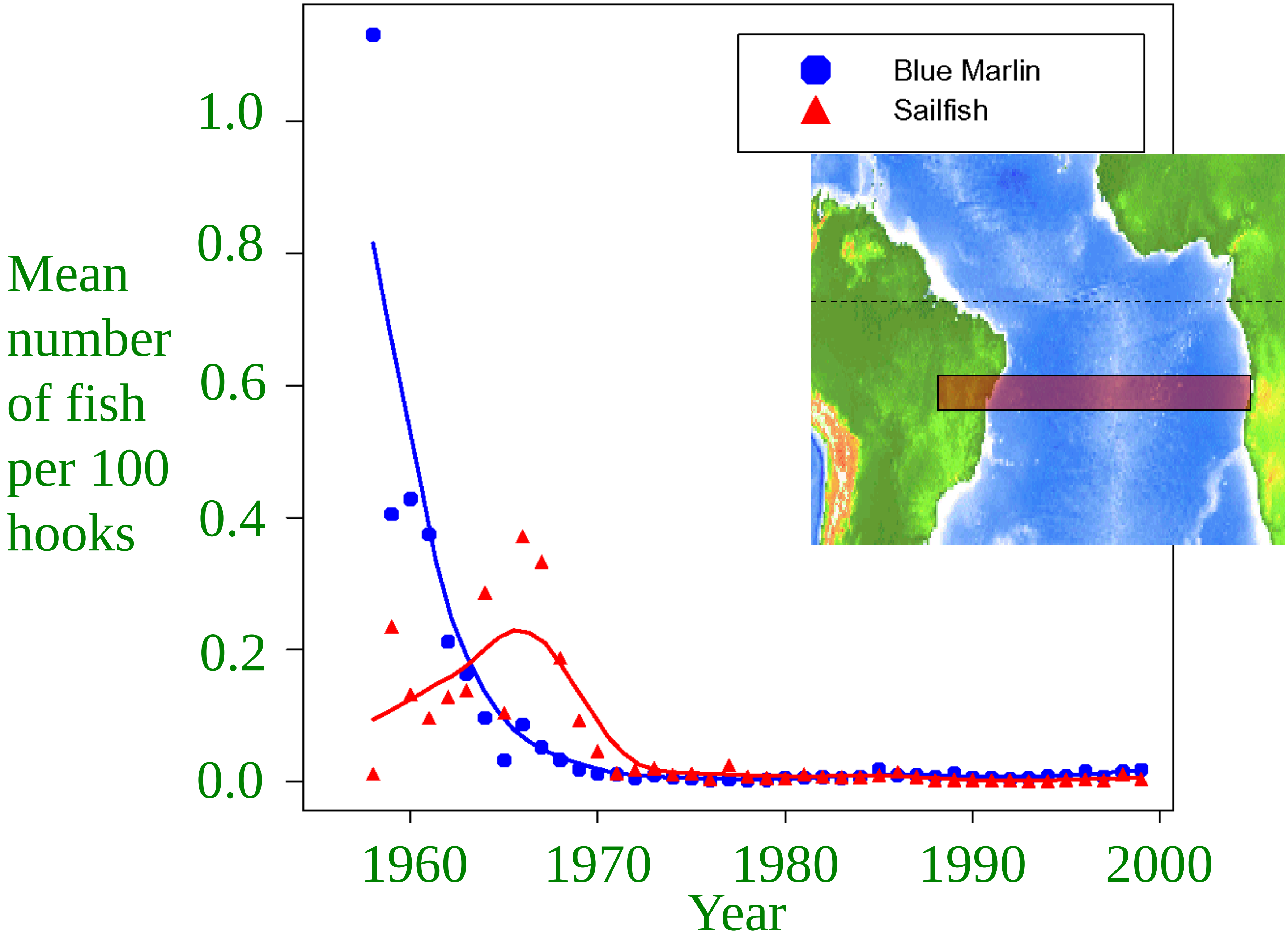
Blue marlin (*Makaira nigricans)*

Sailfish (*Istiophorus albicans)*

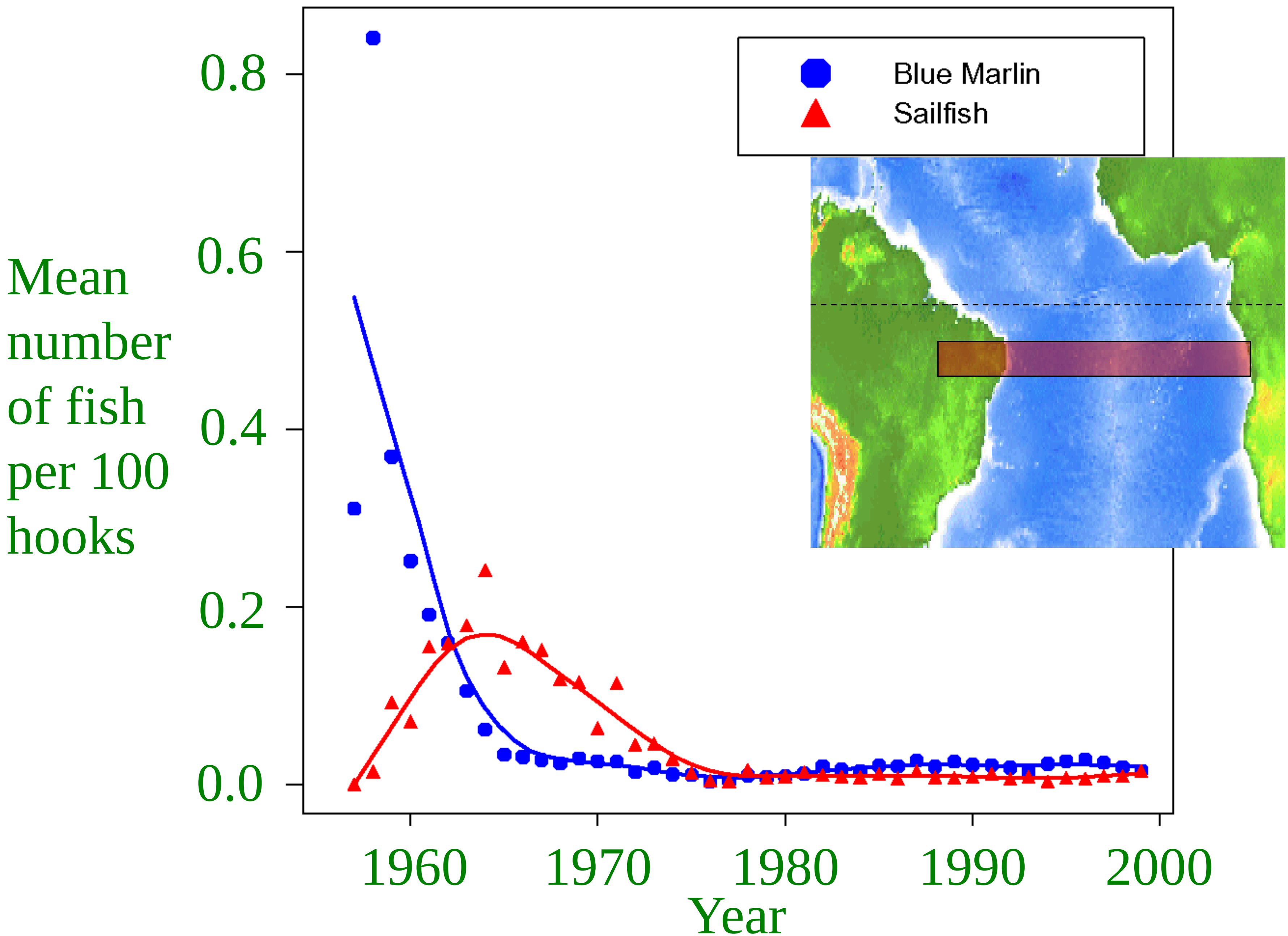


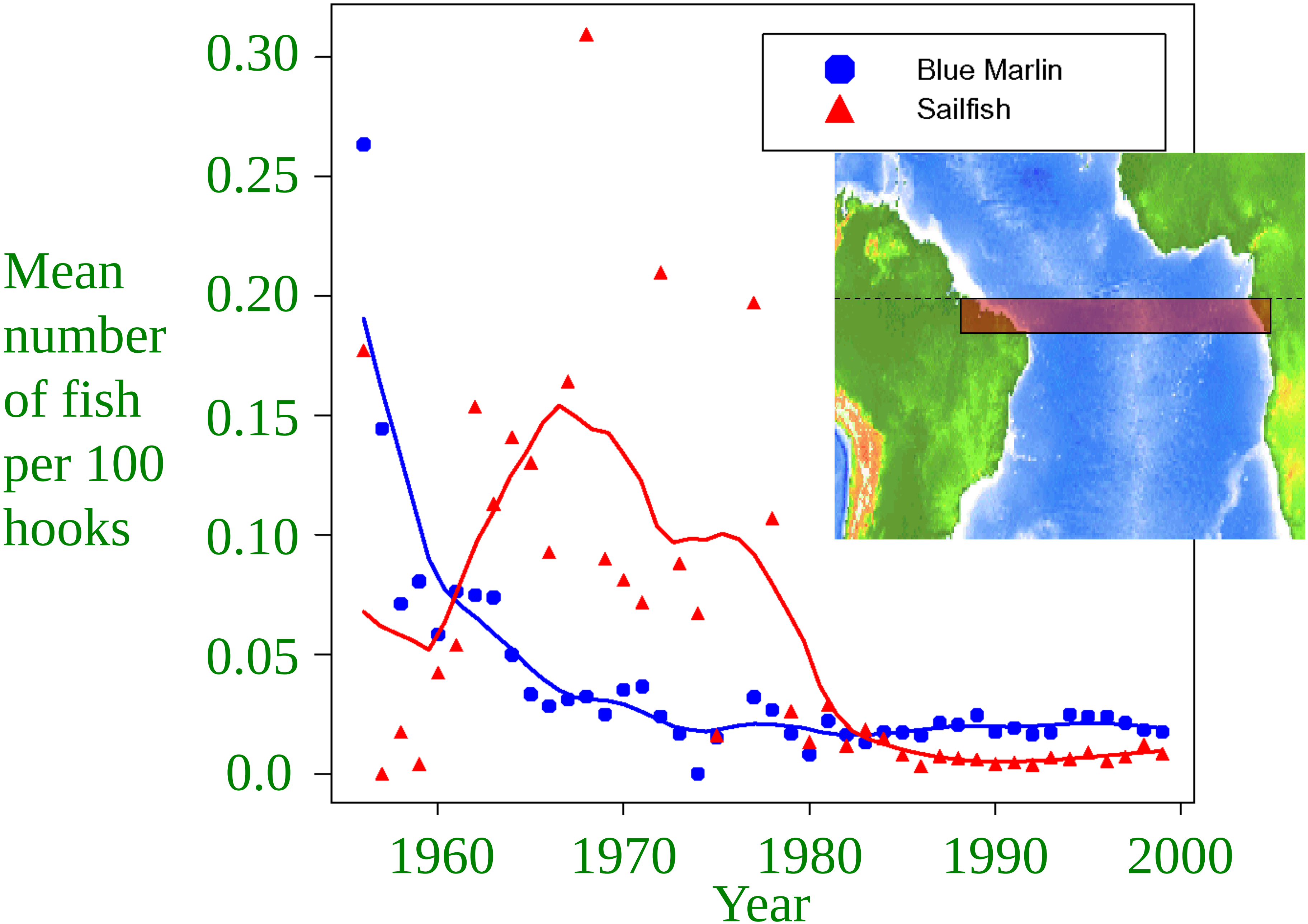
Blue Marlin
Sailfish
Mean number of fish per 100 hooks
1.5
1.0
0.5
0.0
1960
1970
1980
1990
2000
Year

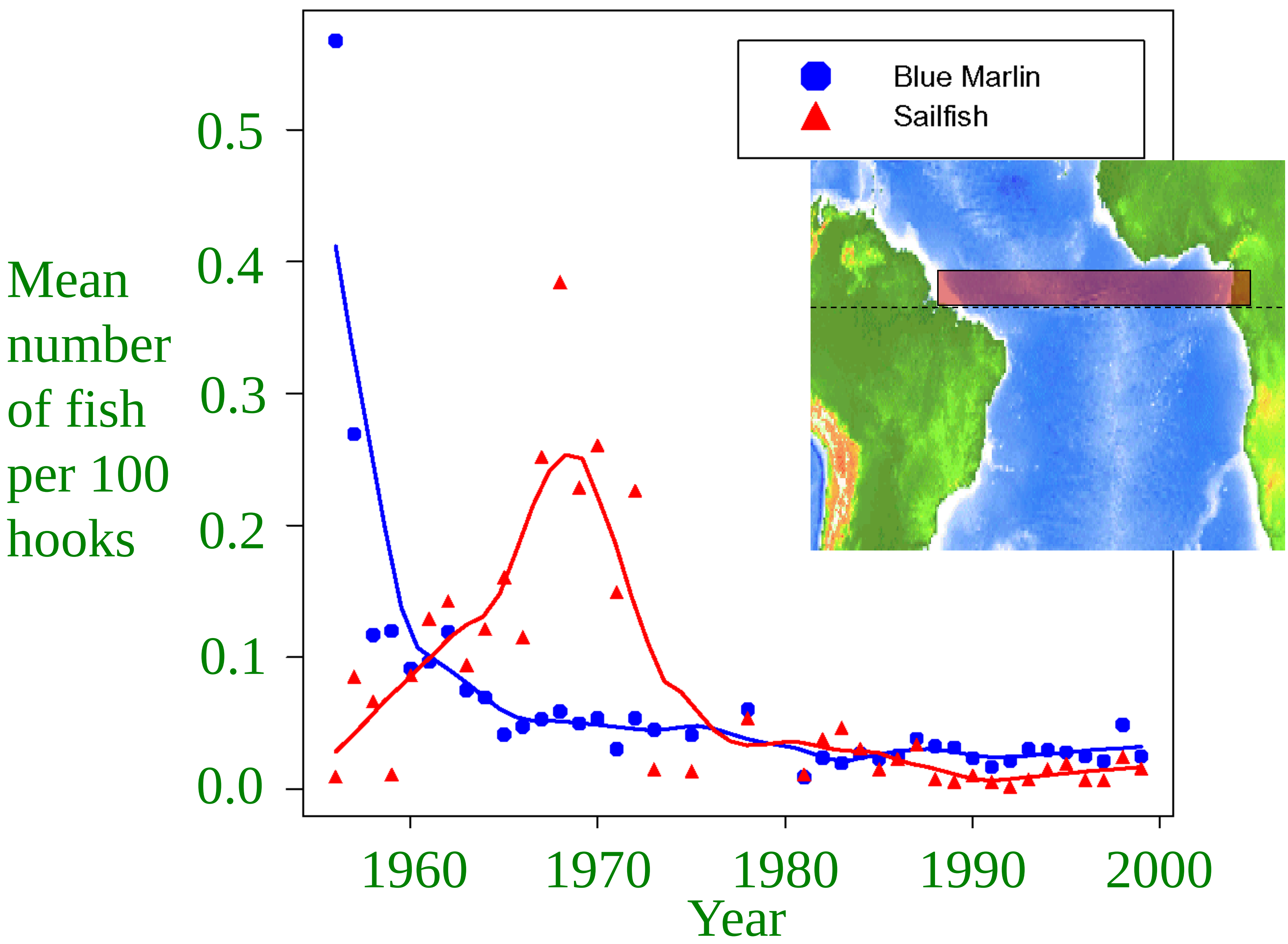

Mean number of fish per 100 hooks
1.0
0.8
0.6
0.4
0.2
0.0
Blue Marlin
Sailfish
1960
1970
1980
1990
2000
Year



Mean number of fish per 100 hooks
1.0
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish


Mean number of fish per 100 hooks
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish


Mean number of fish per 100 hooks
0.30
0.25
0.20
0.15
0.10
0.05
0.0
Blue Marlin
Sailfish
1960
1970
1980
1990
2000
Year


Blue Marlin
Sailfish
Mean number of fish per 100 hooks
0.5
0.4
0.3
0.2
0.1
0.0
1960
1970
1980
1990
2000
Year

Critical Modeling Tools

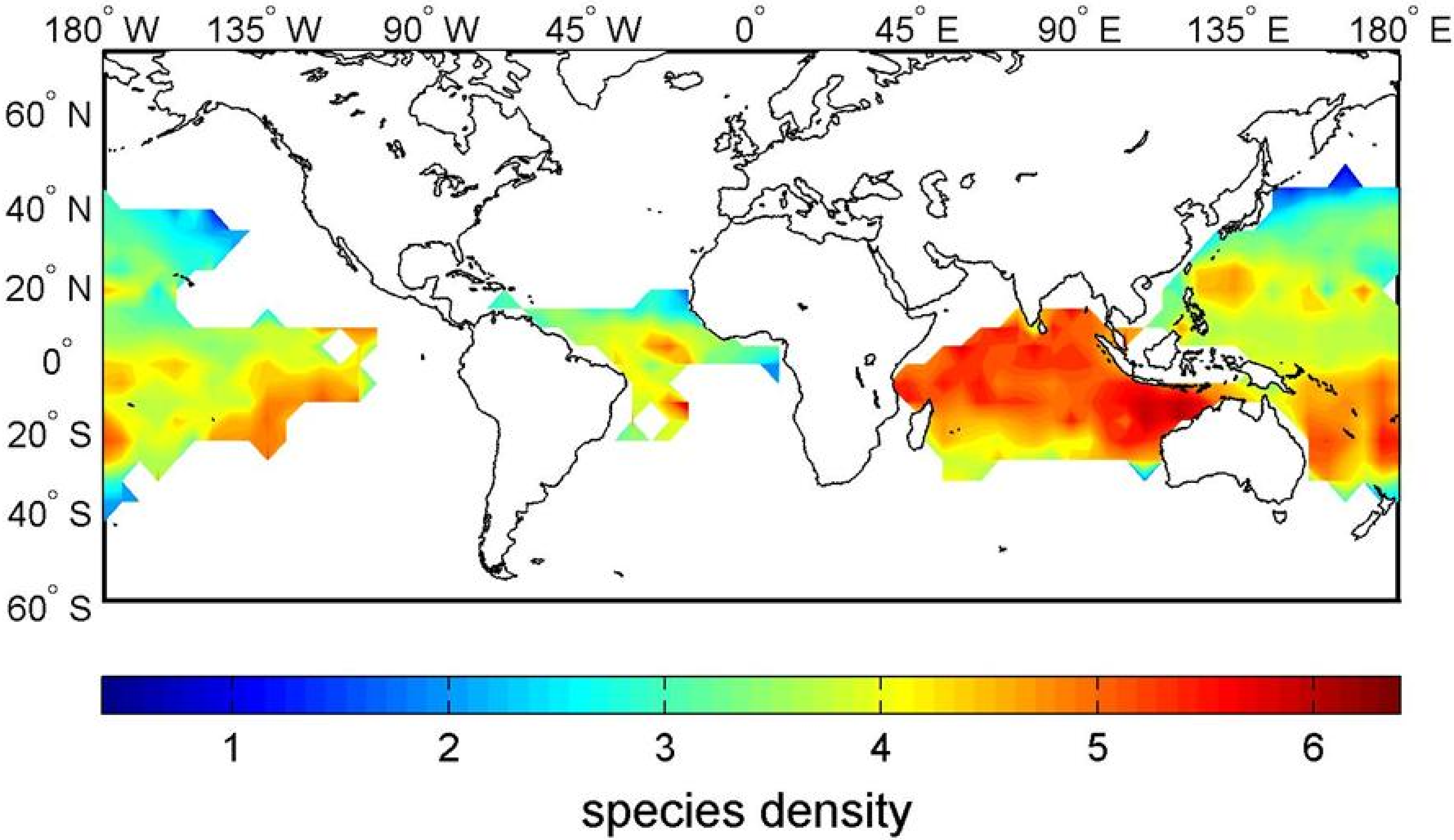
- Hierarchical Bayes State-Space Models

Loss of species density per decade

- Displayed is the number of tuna and billfish species that are found on a standard longline with 1000 hooks
- The time series runs from 1952-1999
- It shows how large hotspots are disappearing over time and how few concentrations of diversity remain today

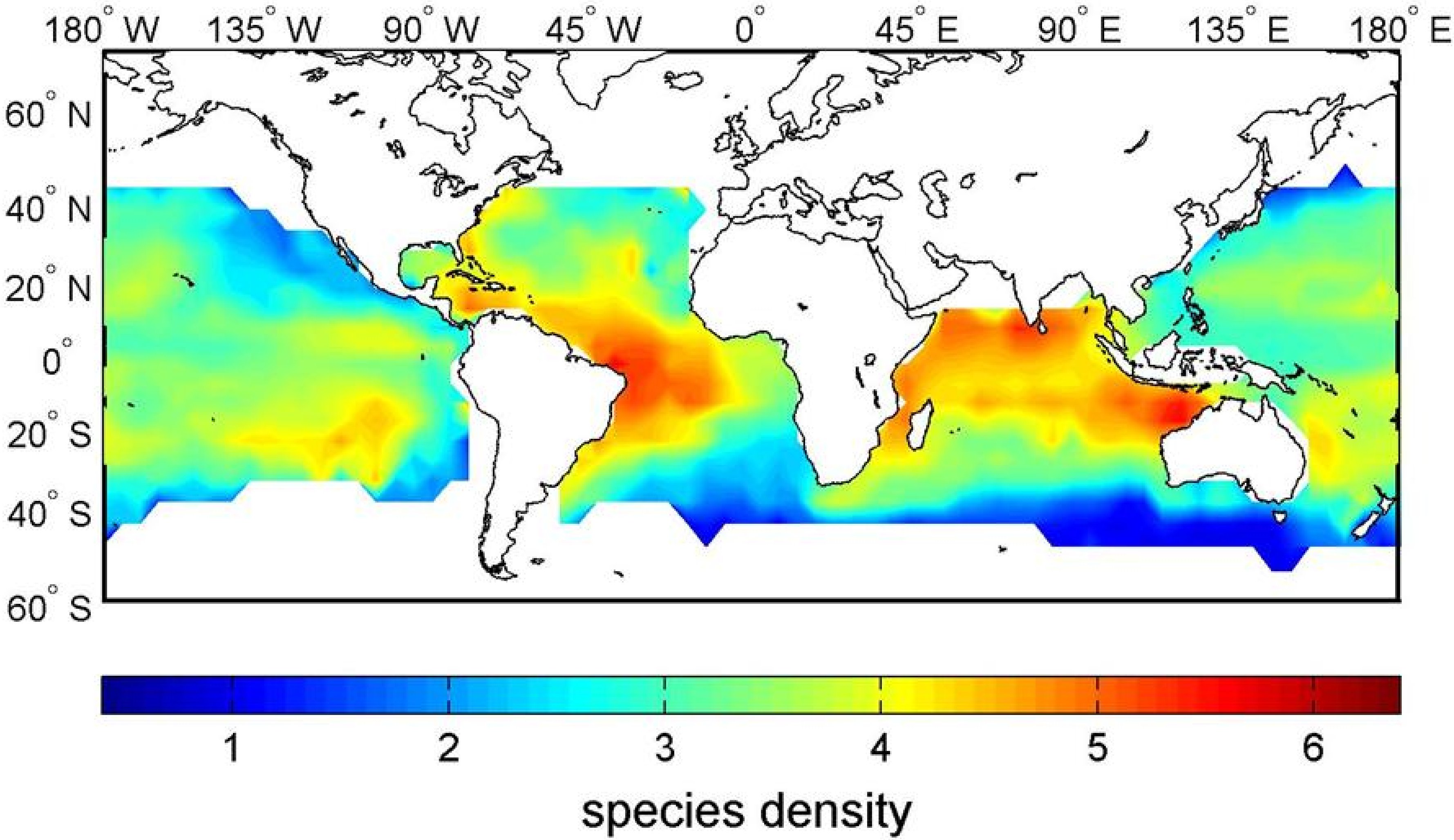
After data from: Worm B, Sandow M, Oschlies A, Lotze HK, Myers RA (2005) Global patterns of predator diversity in the open oceans. **Science** Aug. 2005.

1950s



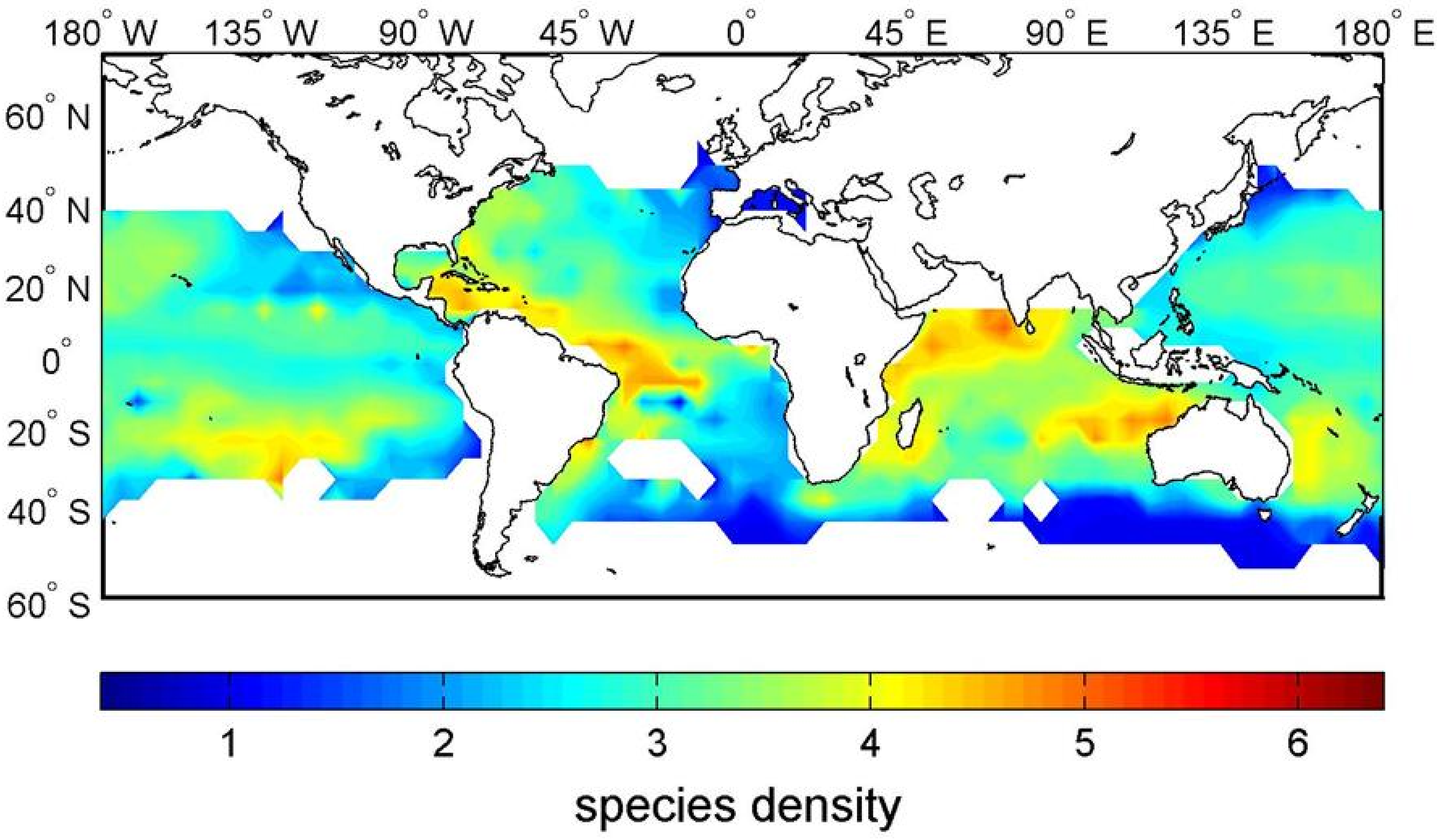
Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-1369

1960s



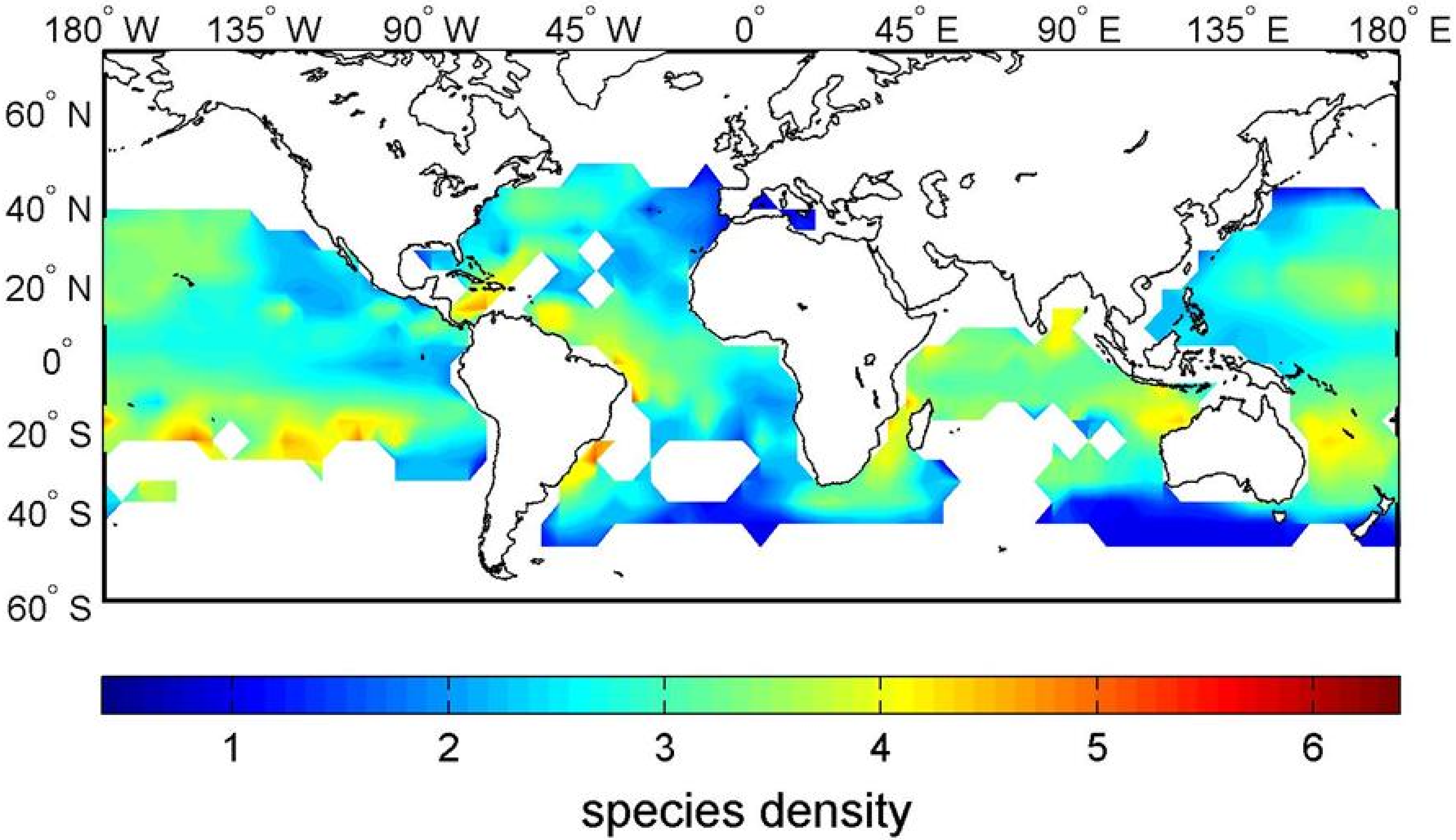
Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-136

1970s



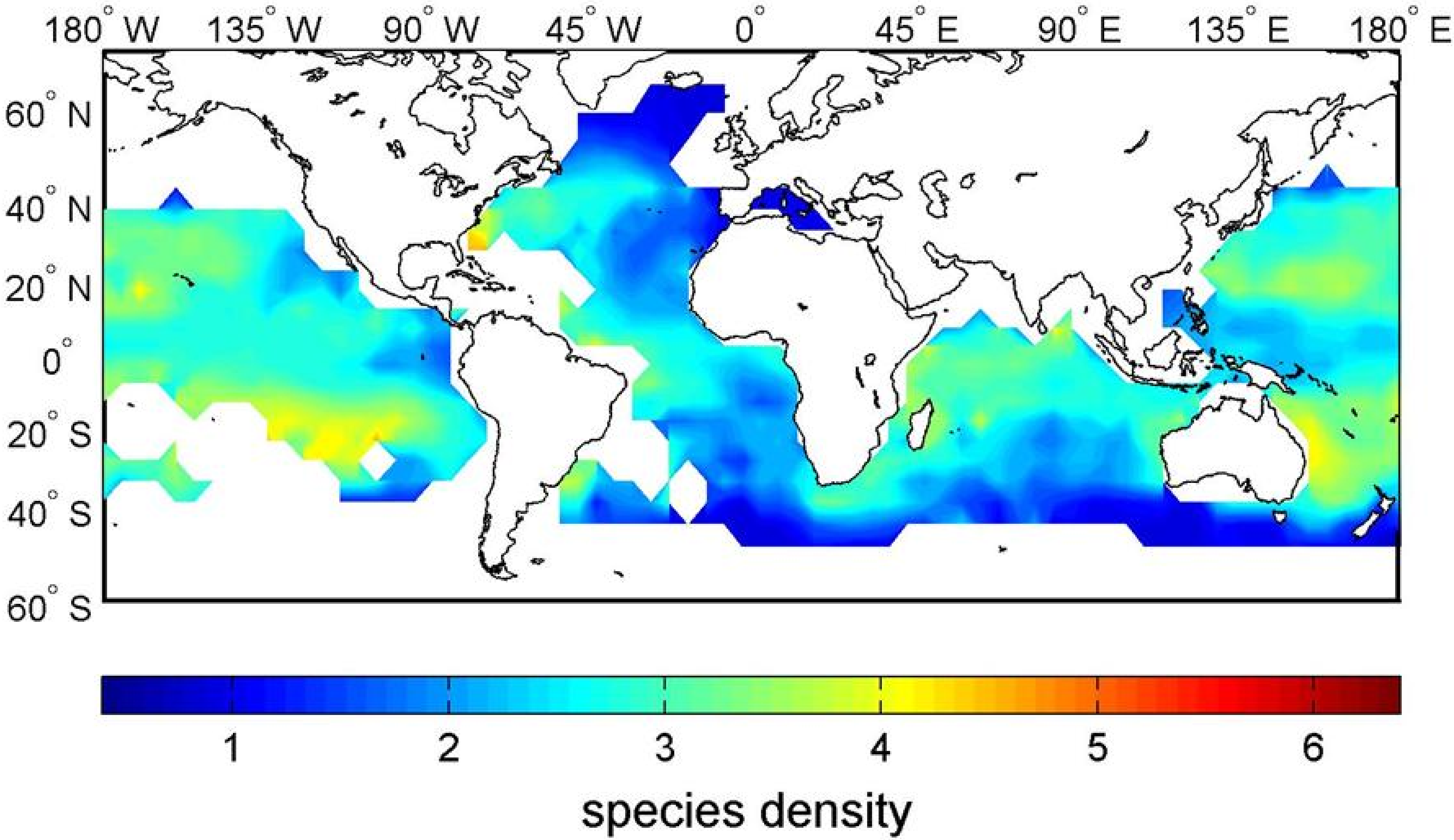
Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-136

1980s



Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-13

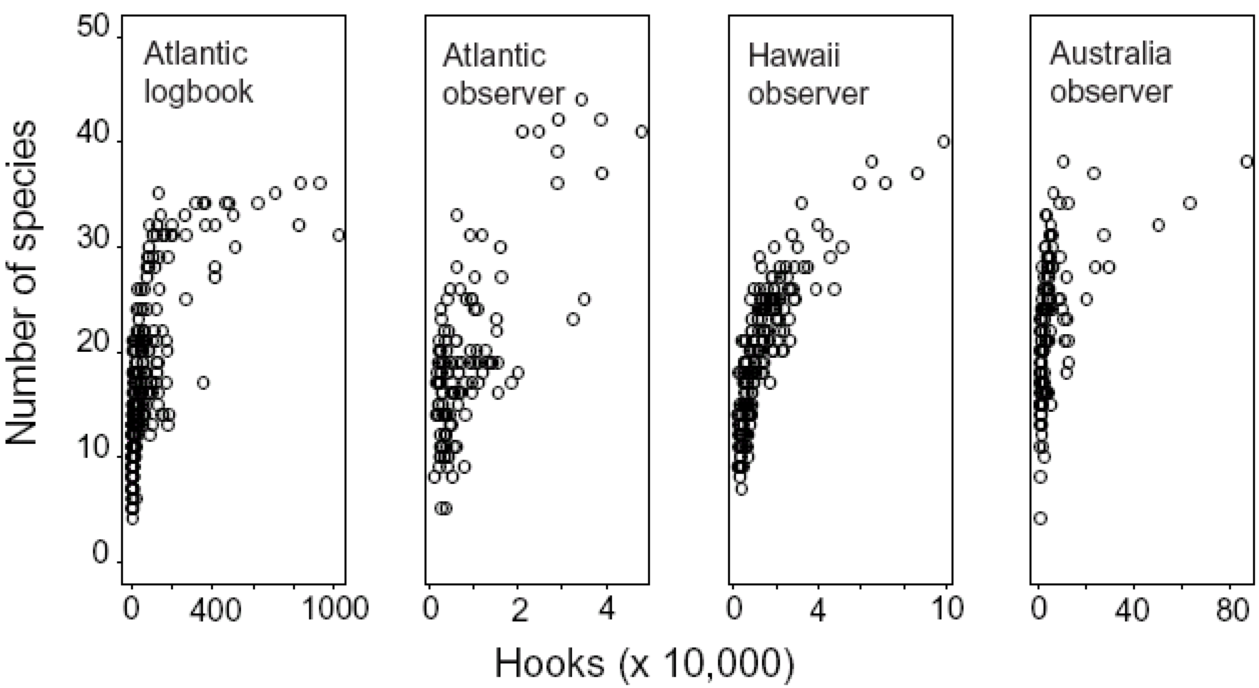
1990s

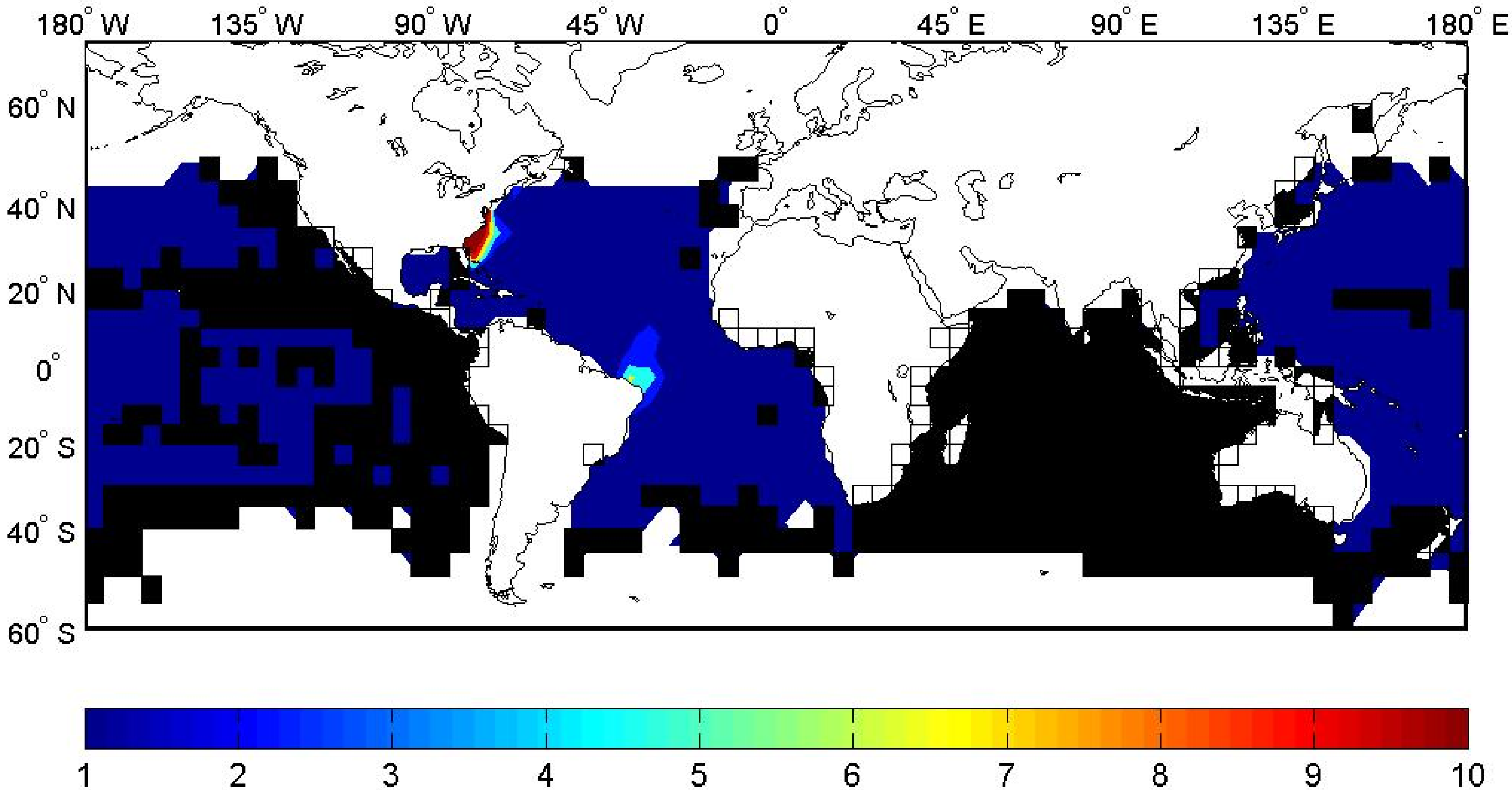


Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-136

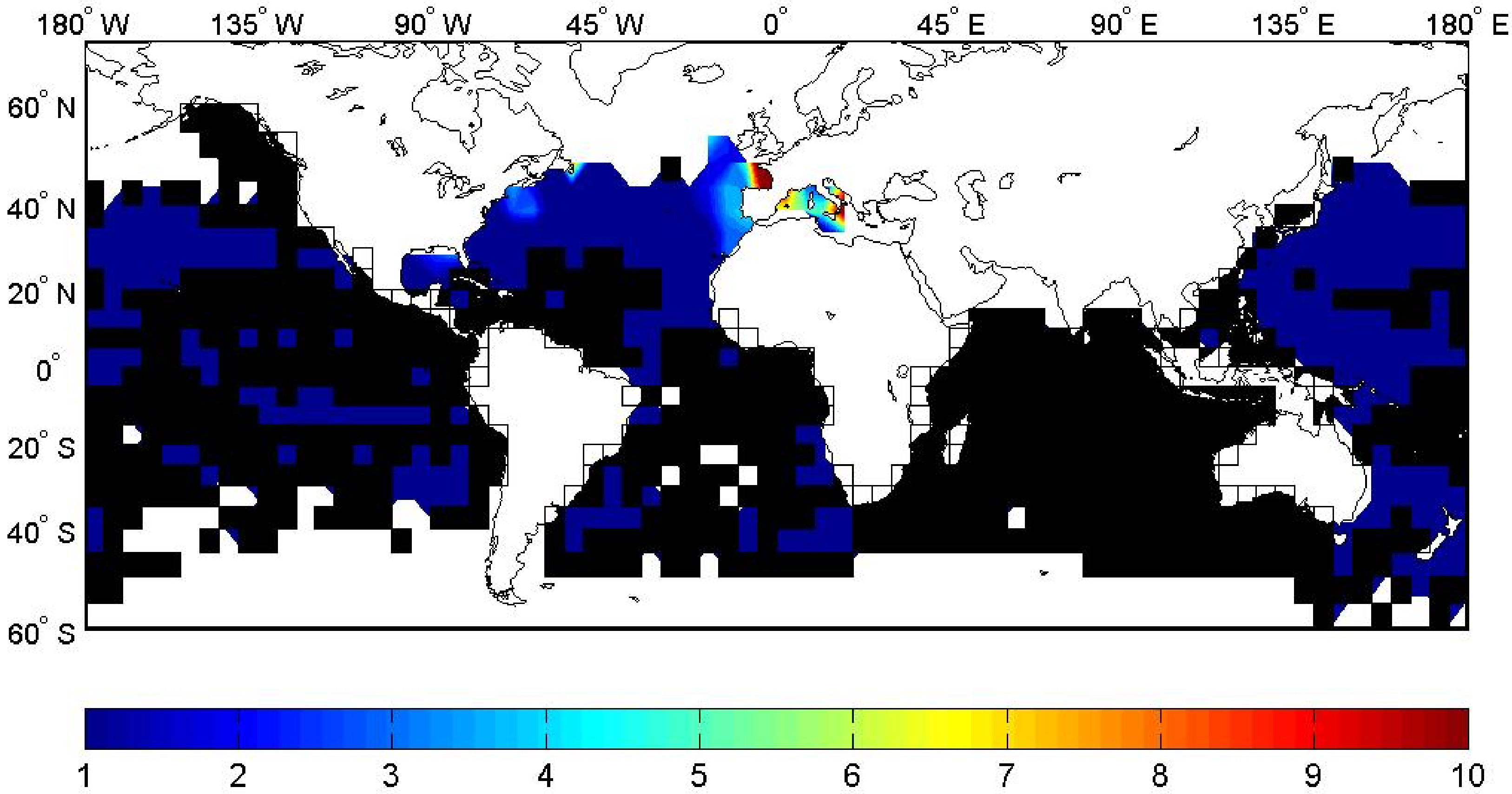
Critical Modeling Tools: Rarefaction diversity

- Compare diversity between cells with different sample size
- Species richness: Expected number of species per 50 individuals
- Species density: expected number of species per 1000 hooks

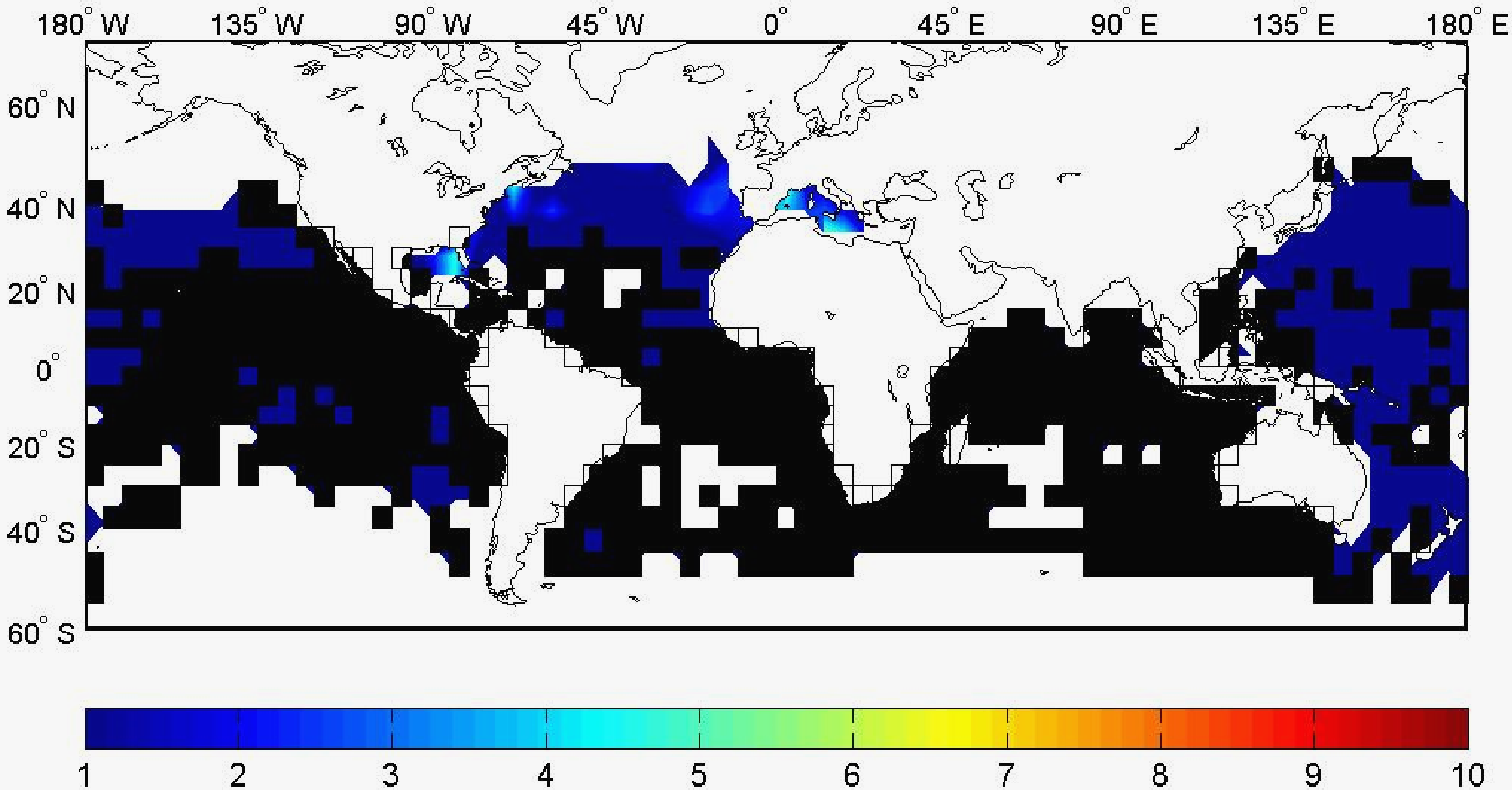




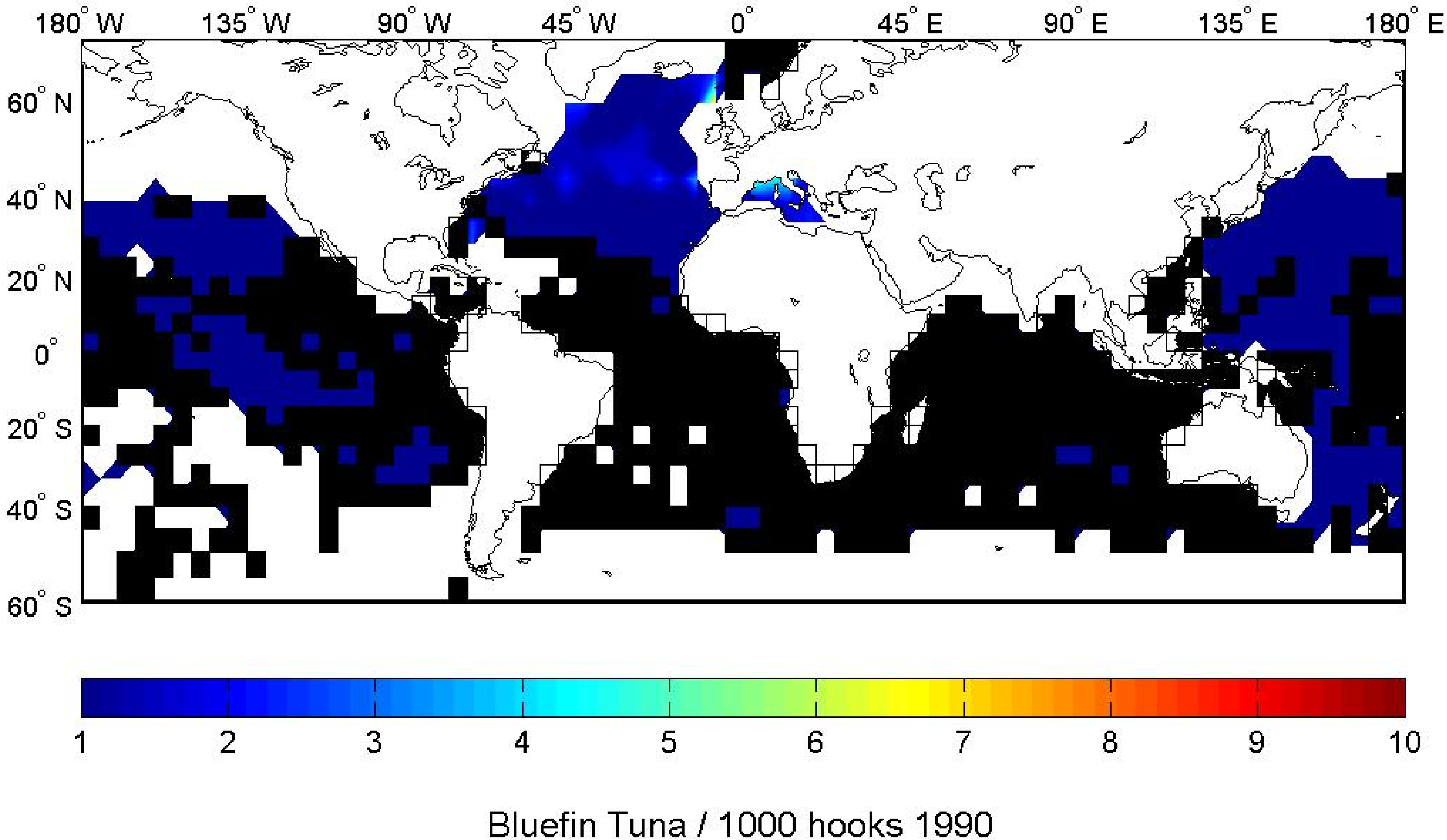
Bluefin Tuna / 1000 hooks 1960



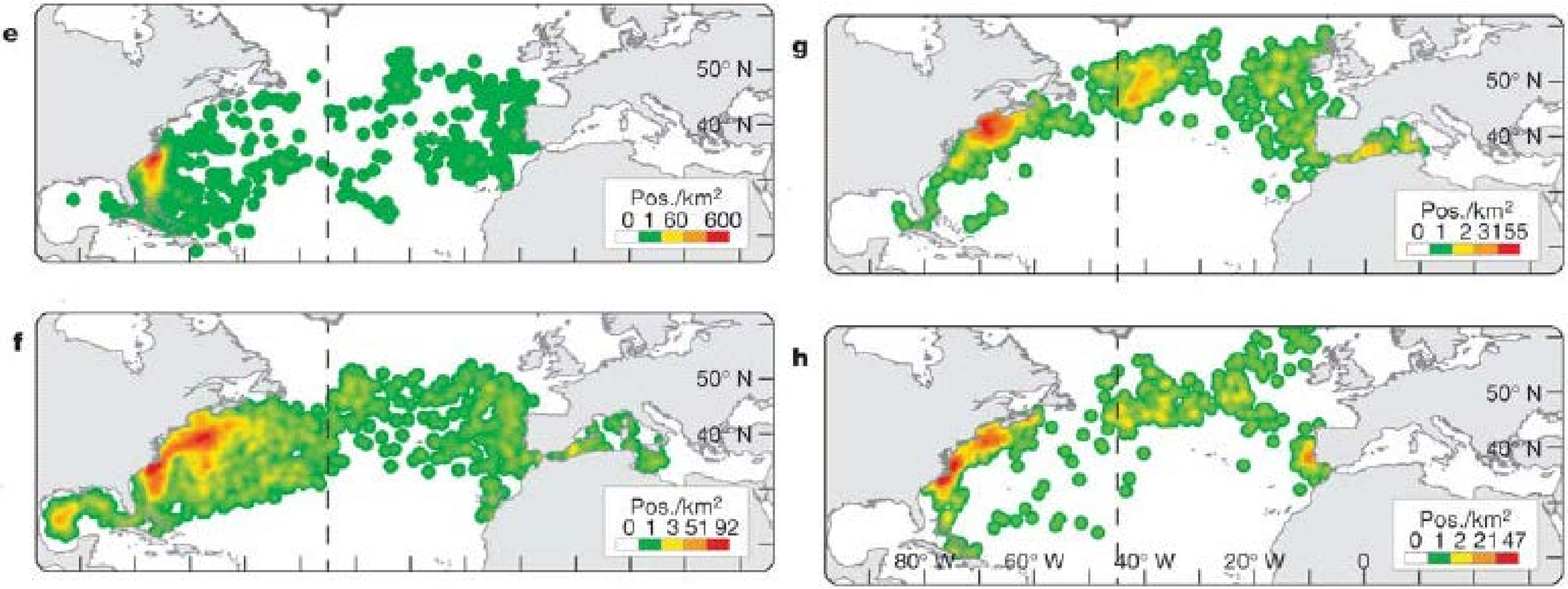
Bluefin Tuna / 1000 hooks 1970



Bluefin Tuna / 1000 hooks 1980


180° W
135° W
90° W
45° W
0°
45° E
90° E
135° E
180° E
60° N
40° N
20° N
0°
20° S
40° S
60° S
1
2
3
4
5
6
7
8
9
10
Bluefin Tuna / 1000 hooks 1990

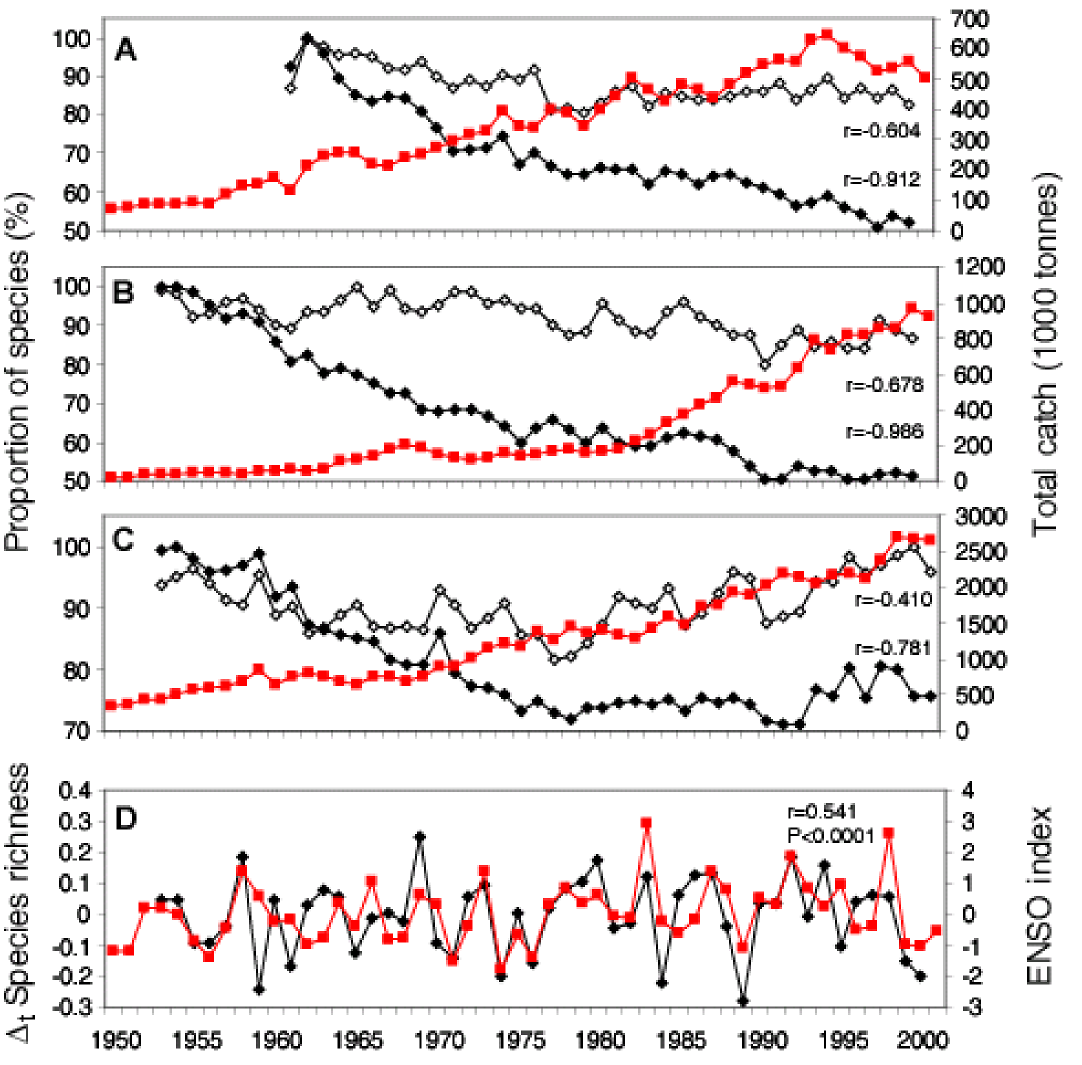
Tagging also shows bluefin restricted to N Atlantic



Source: Block et al. 2005. Nature 434: 1121-1127

Global decline in ocean predator diversity

- Increasing catches
- Decreasing diversity
- Long-term decline linked to fishing
- Yearly variability linked to climatic changes

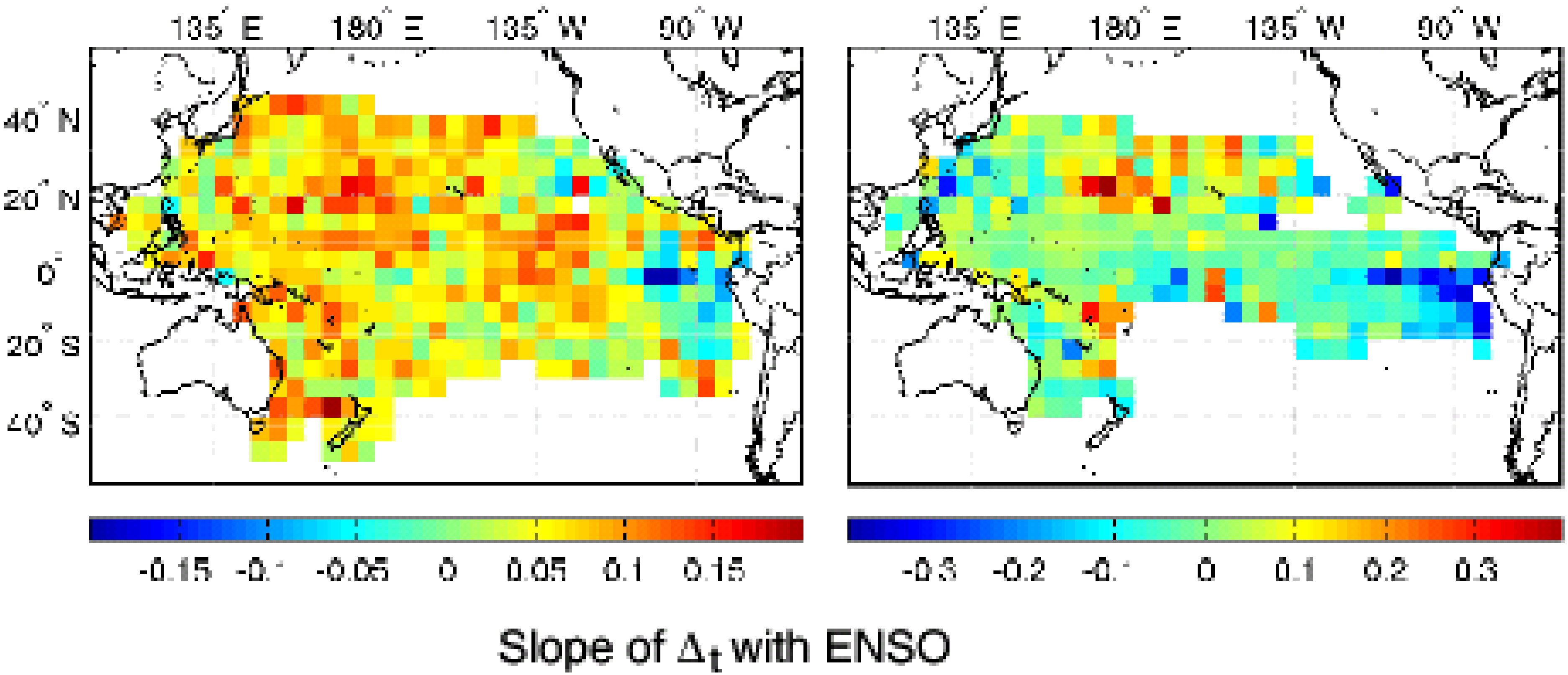


Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-1369

ENSO affects diversity across entire Pacific

Species richness

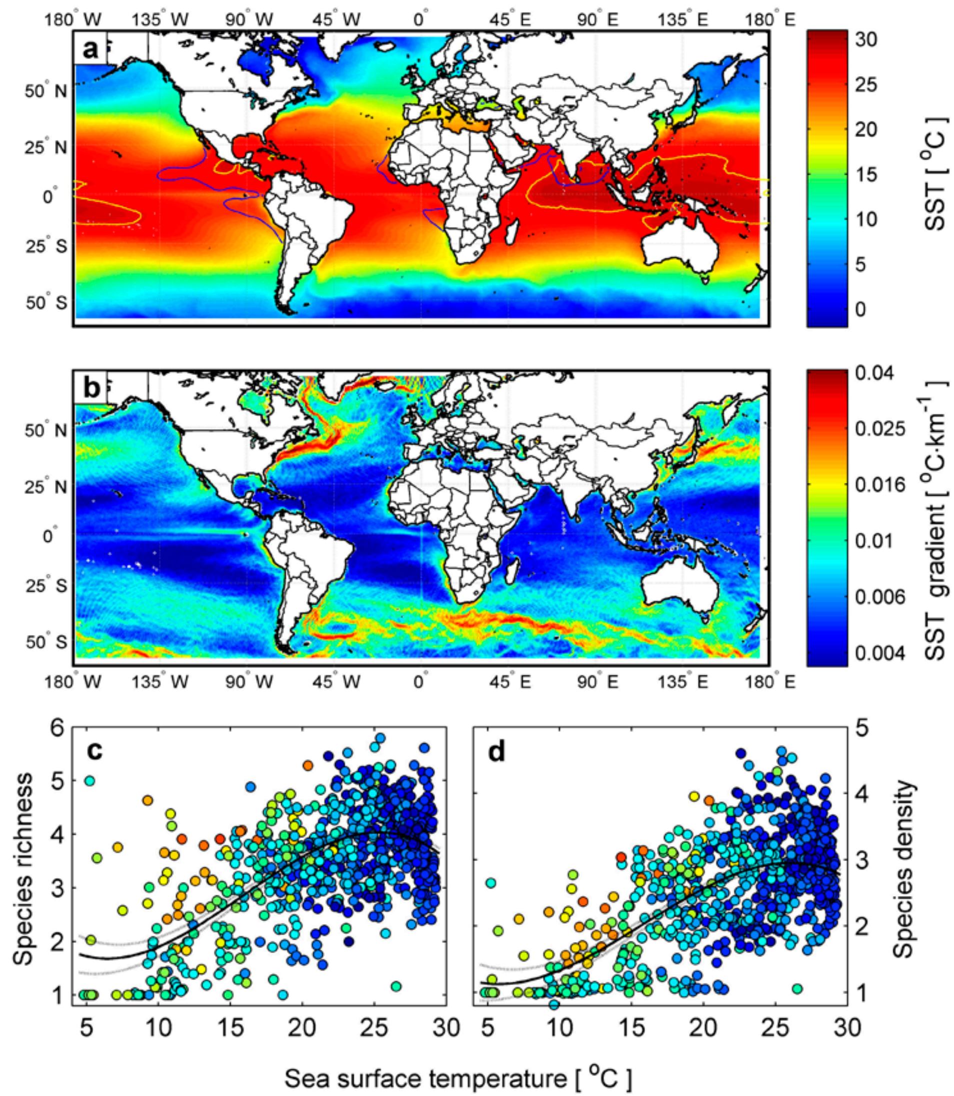
Blue marlin catch rates



Source: Worm, Sandow, Oschlies, Lotze, Myers 2005. Science 309:1365-1369

Understand oceanographic drivers of diversity

Patterns of diversity were explained by
- Mean temperature
- Fronts and eddies
- Oxygen



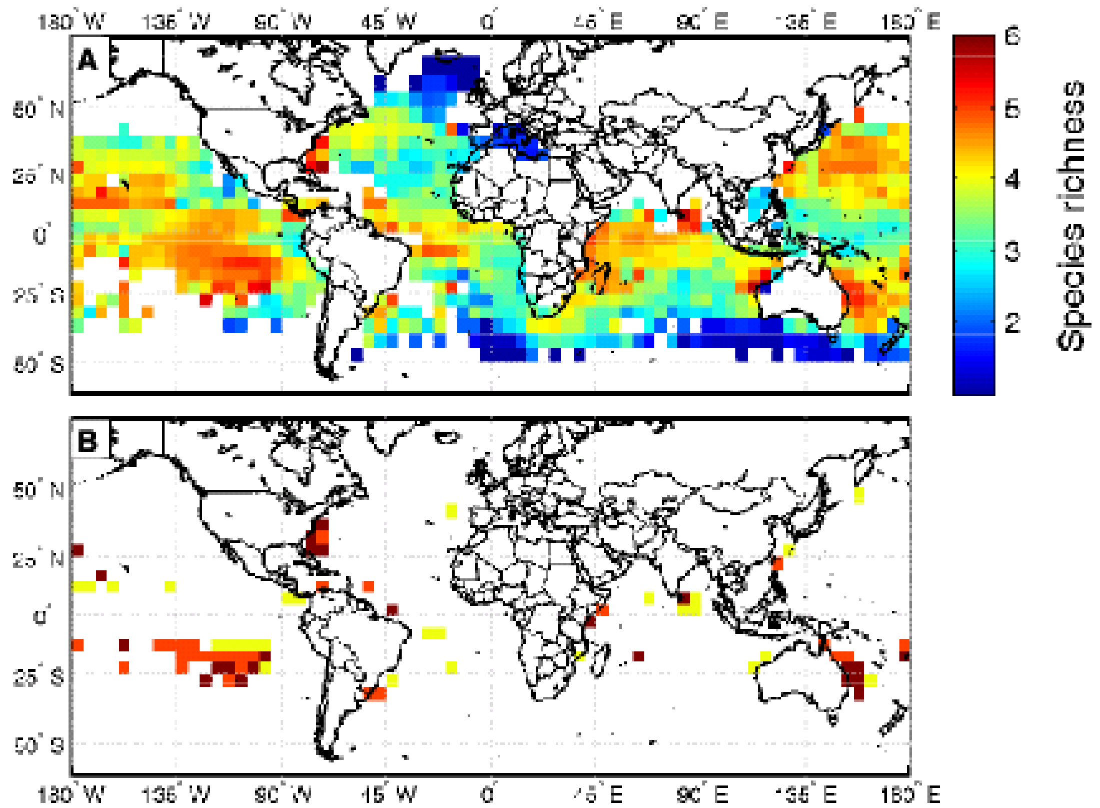
Source: Worm et al. 2005. Science 309:1365-1369

Critical Modeling Methods

- Spatial regression with anisotropic spatially correlated errors
- We used SAS Proc MIXED (and the generalized linear model additions) which are very fast, and easy to use.

Use remaining hotspots for global conservation

- Consistent patterr of species richnes and density
- Five major hotspo
  - U.S. east coast
  - Hawaiian chain
  - Southeast Pacific
  - Australian east co
  - Sri Lanka



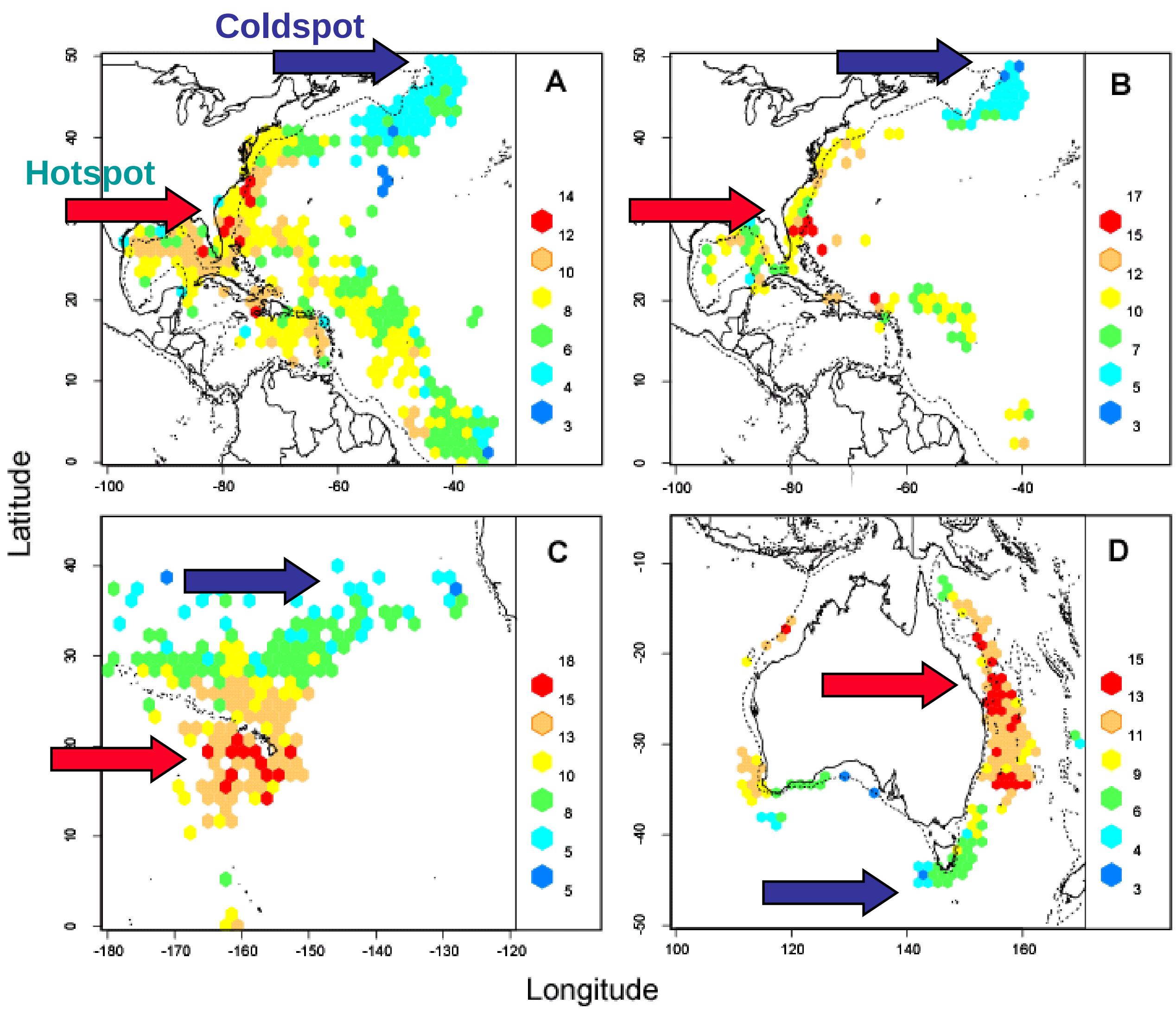
Source: Worm et al. 2005. Science 309:1365-1369

Protect diversity hotspots in national waters

- Special places where many species aggregate

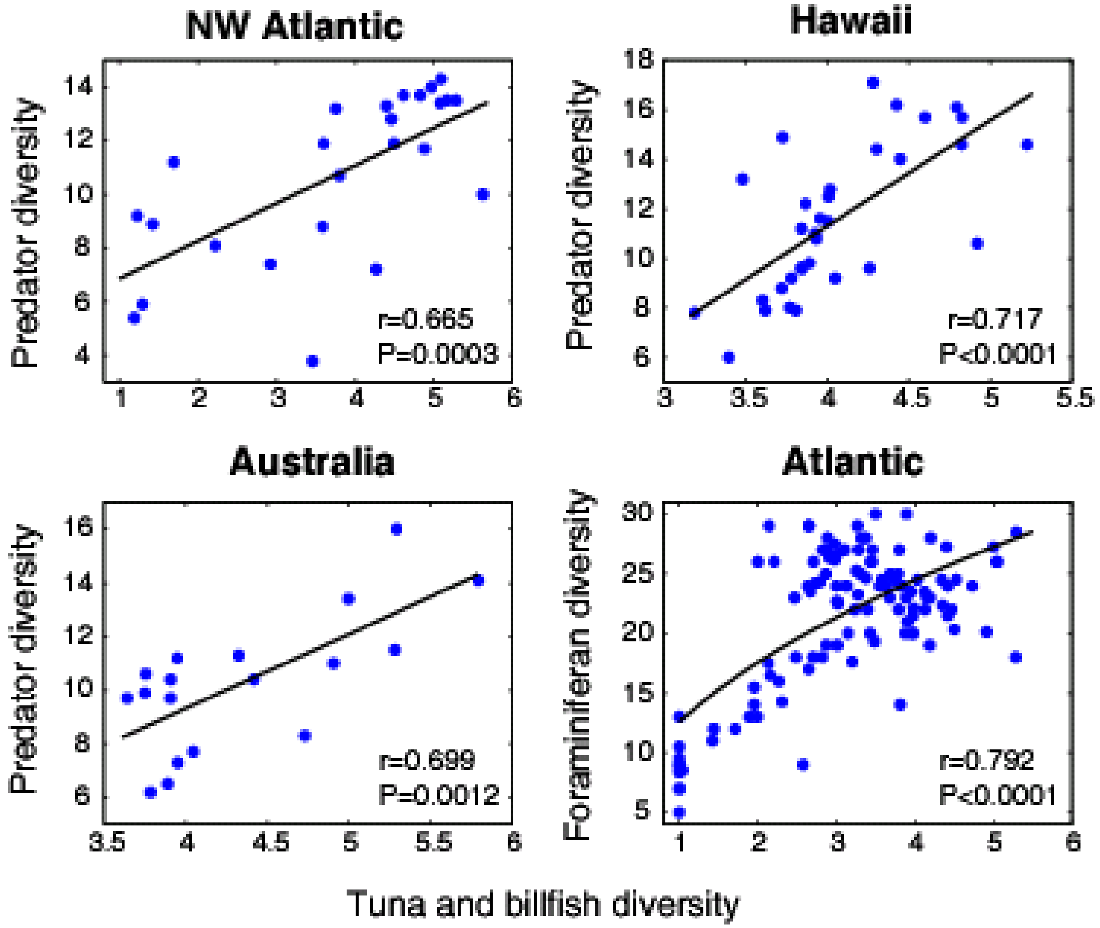
- Key habitats

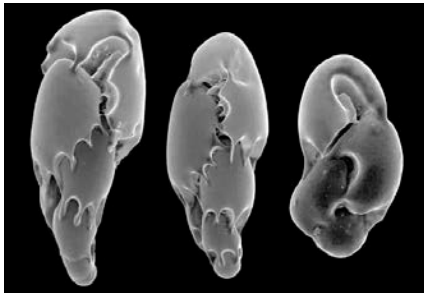
- Food supply



Worm Lotze Myers 2003. PNAS 100:9884-9888

Validate hotspots across species groups

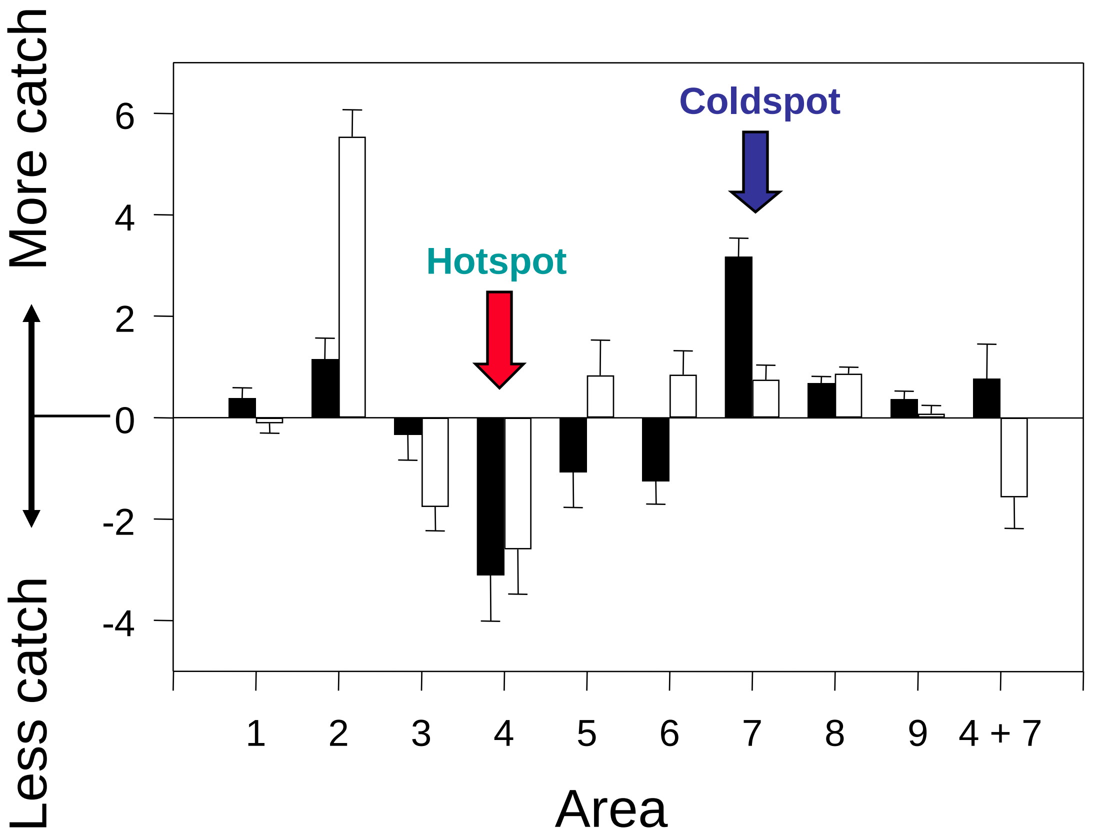




Source: Worm et al. 2005.
Science: 309:1365-1369

Simulating area closures

- Hotspot closure reduces catch of threatened species
- Displacement issues must be considered
- Fishing effort needs to be reduced as well



Worm Lotze Myers. 2003.
PNAS 100:9884-9888

Critical Modeling Method

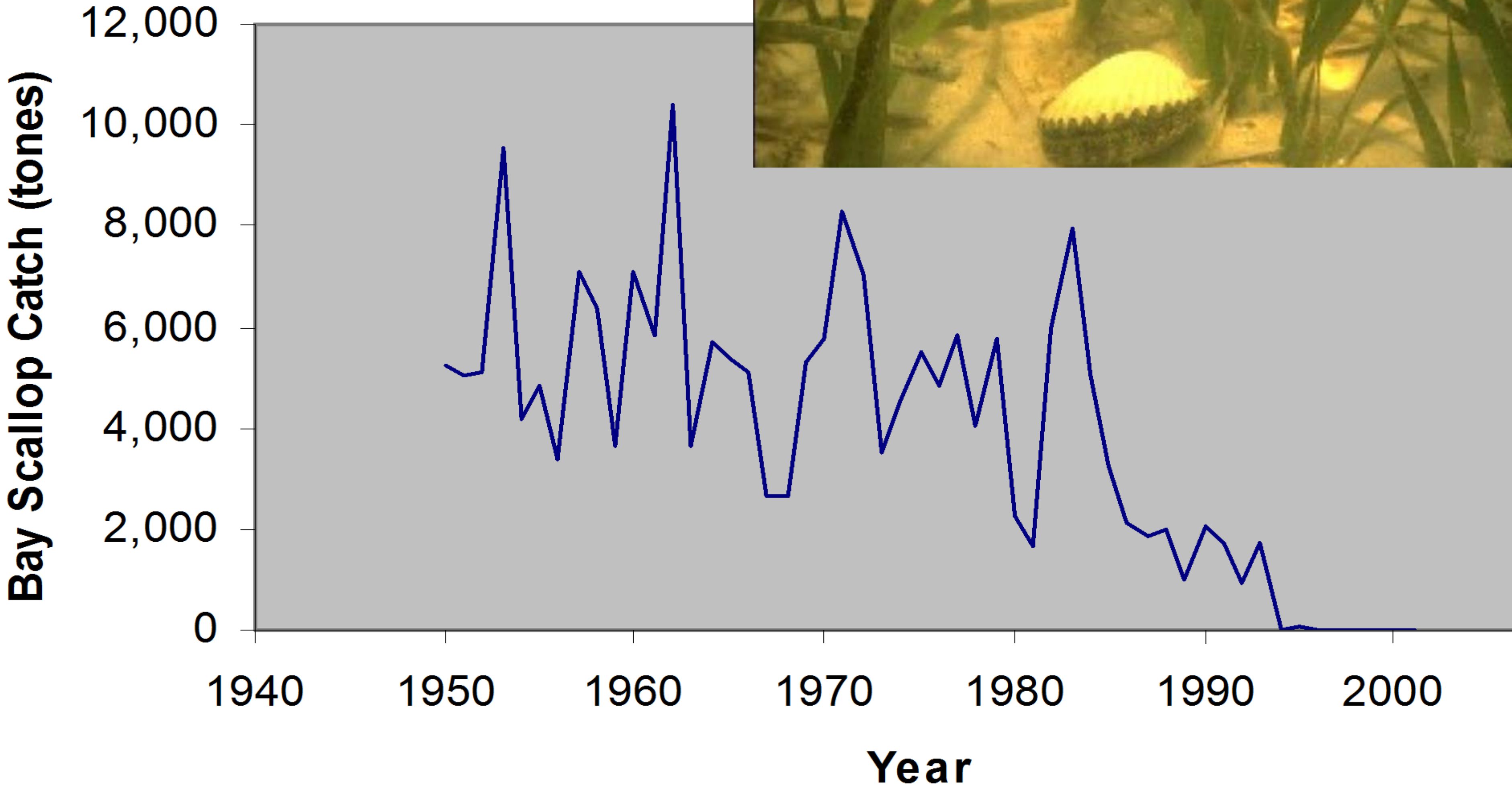
- Simulation methods

The First Collective Act of Humanity was to save the great whales –

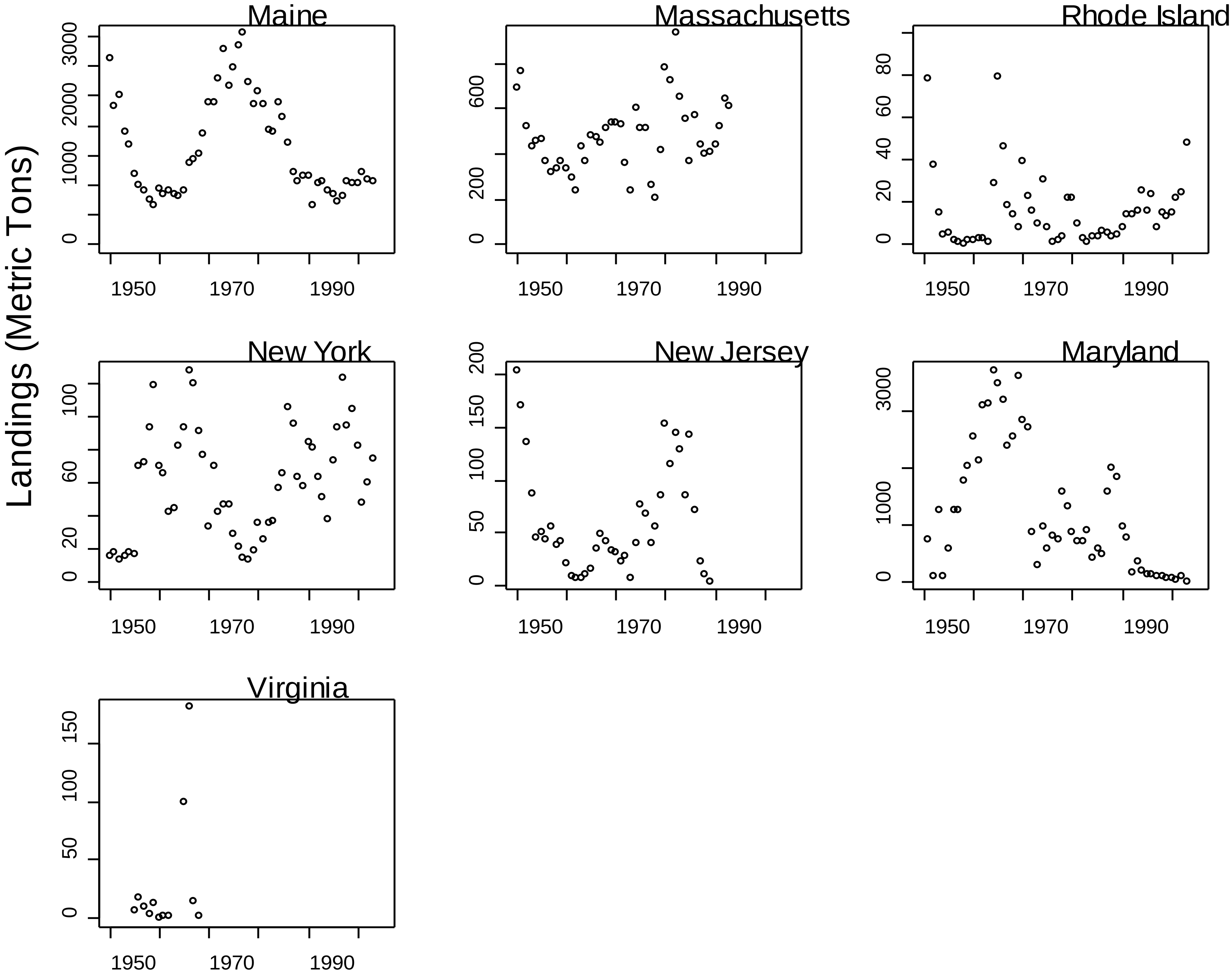
despite massive denial

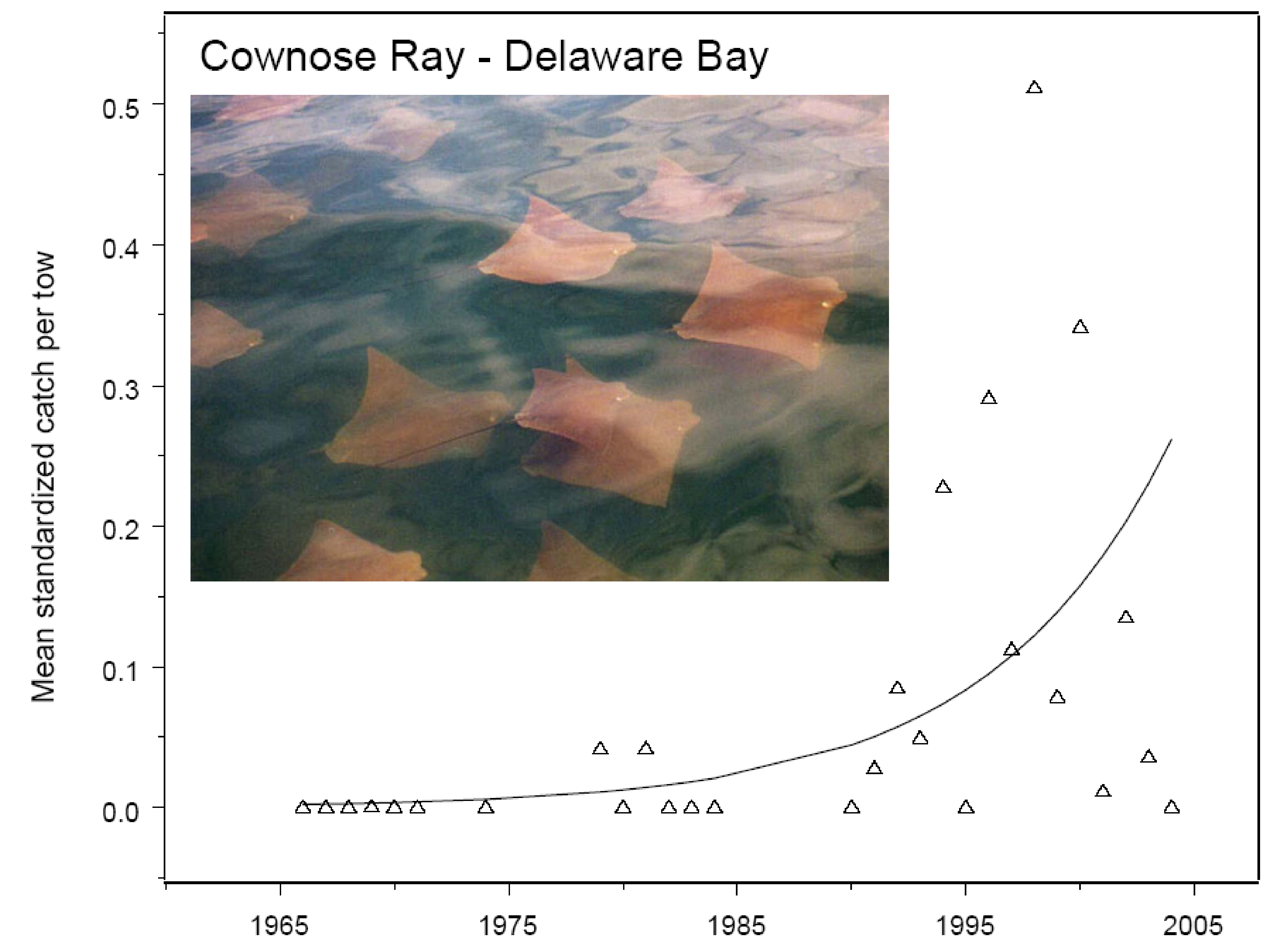
– we can do
the same for the remaining virgin areas of the oceans and for the great sharks.

USA Bay Scallops Landings

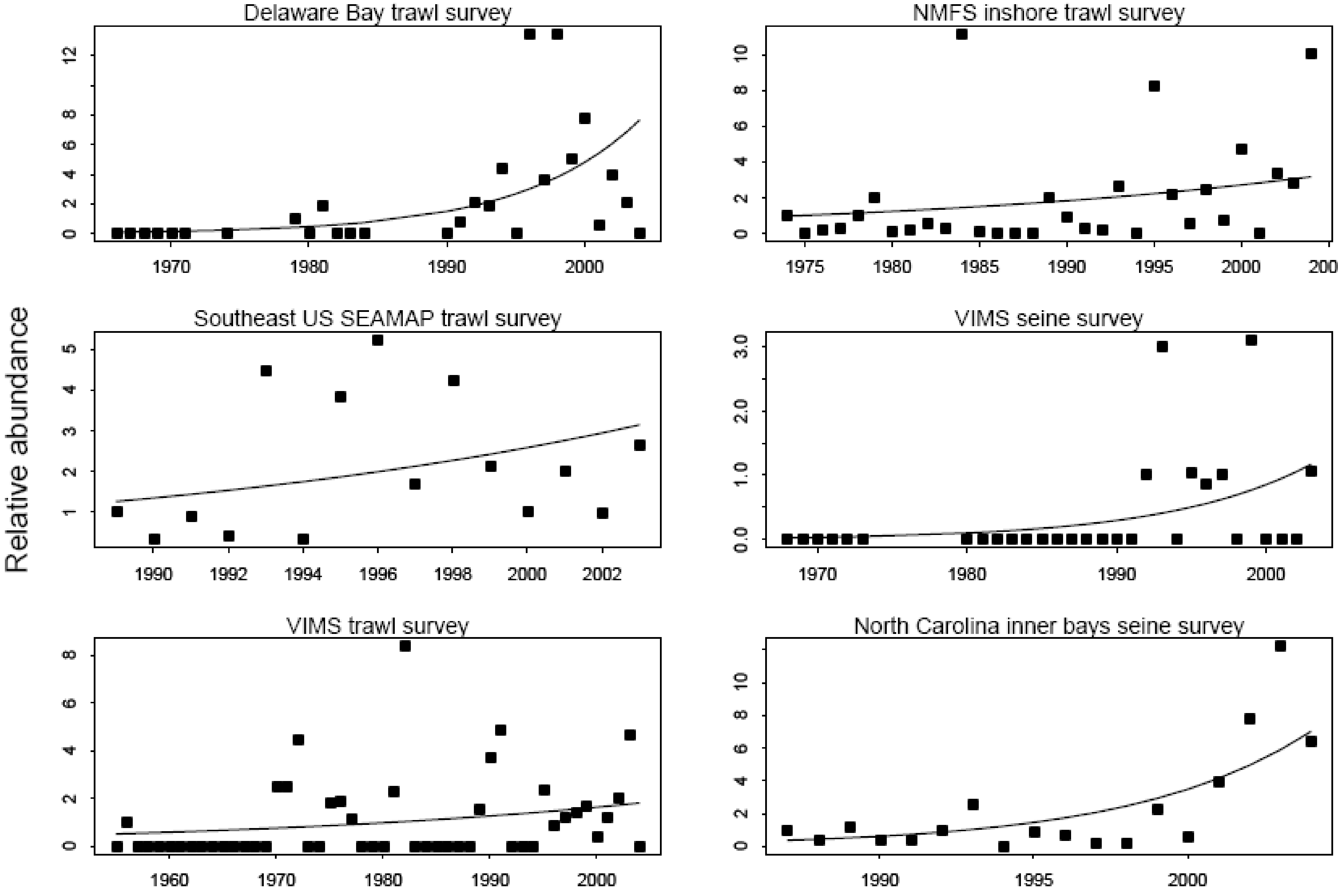


Loss of softshell clams south of Long Island



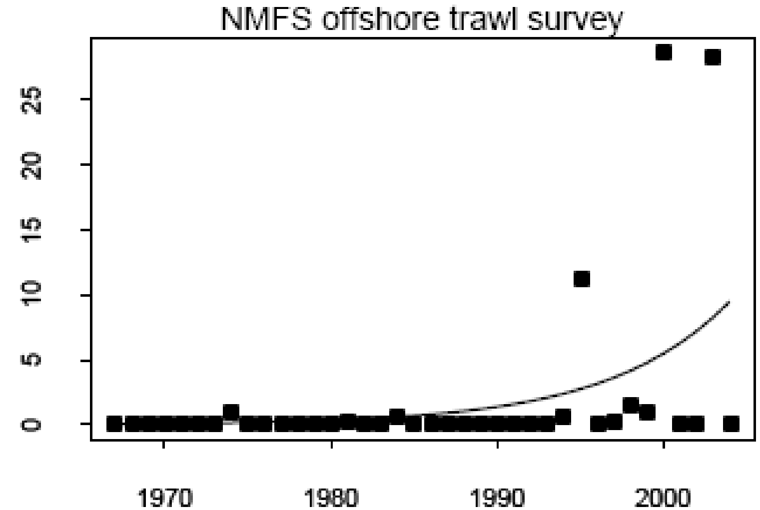

Cowenose Ray - Delaware Bay
Mean standardized catch per tow
0.5
0.4
0.3
0.2
0.1
0.0
1965
1975
1985
1995
2005

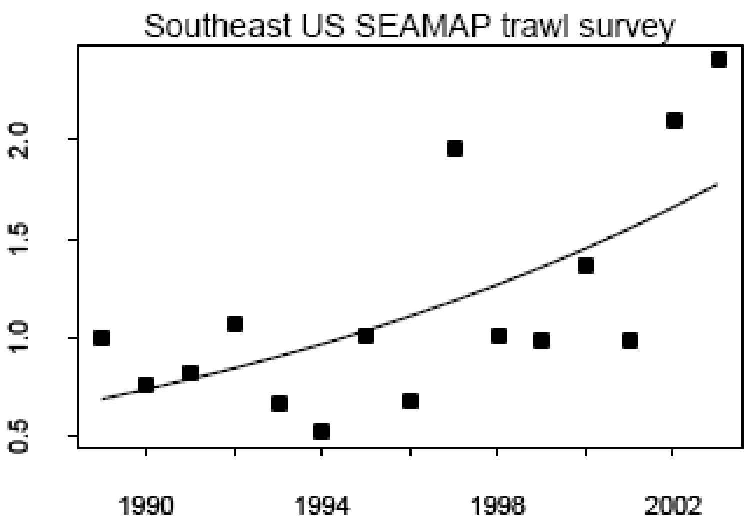
Meta-analysis of cownose ray trends

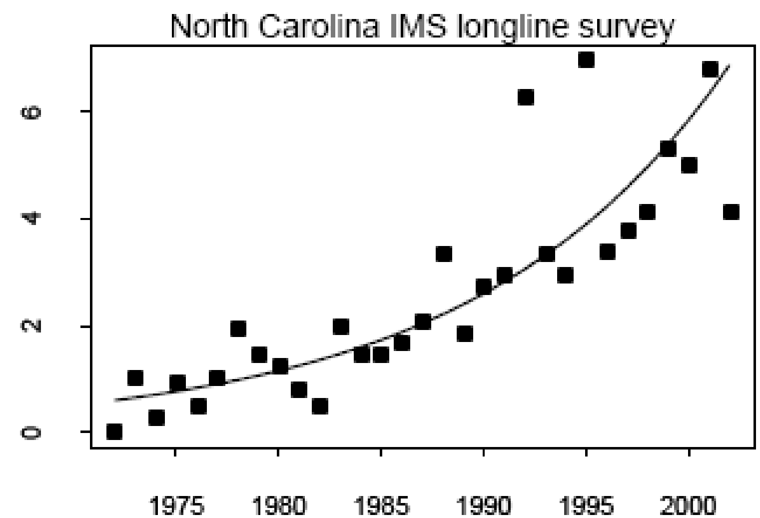


Increase in small sharks: sharpnose shark

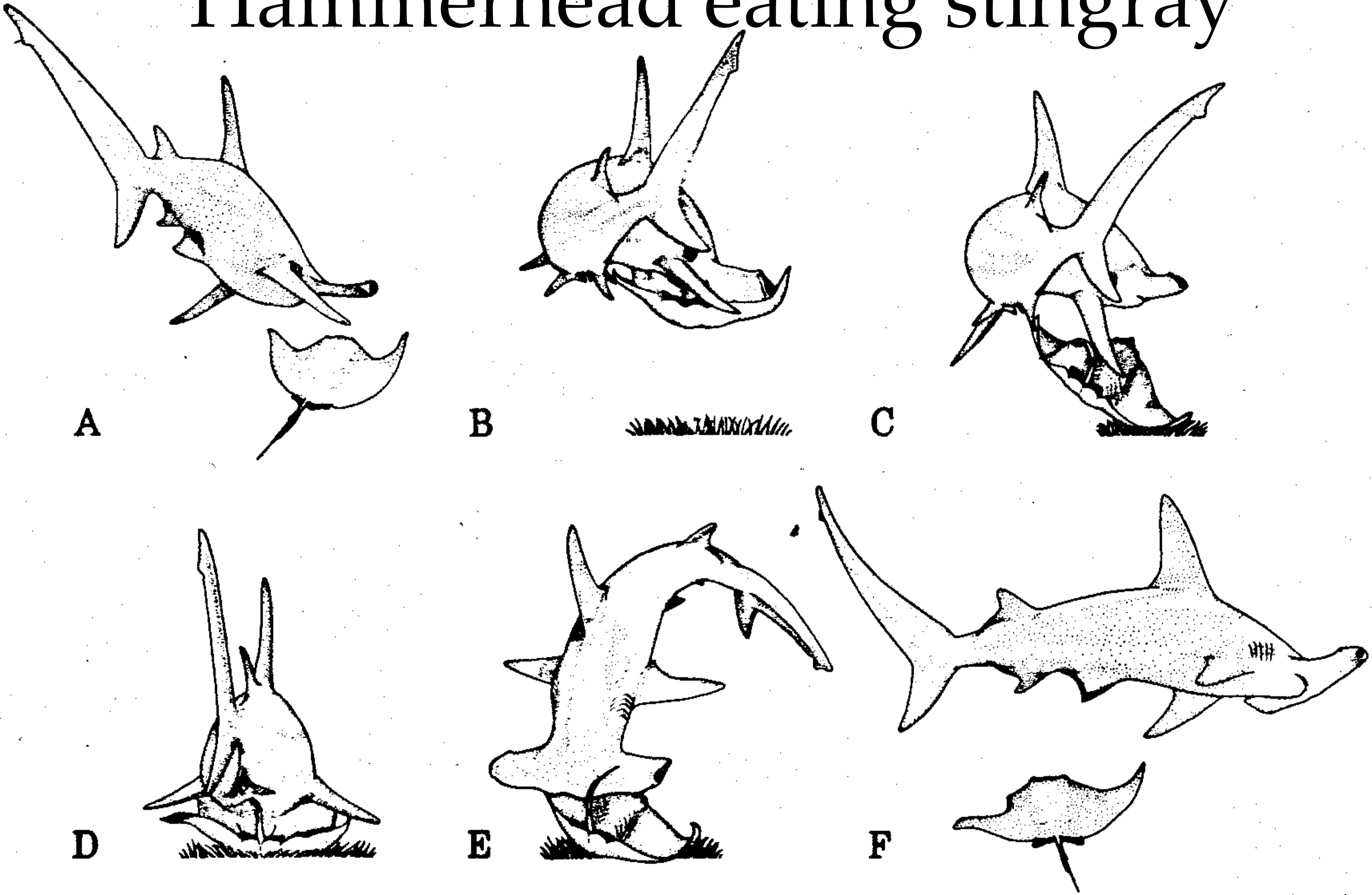
Relative abundance







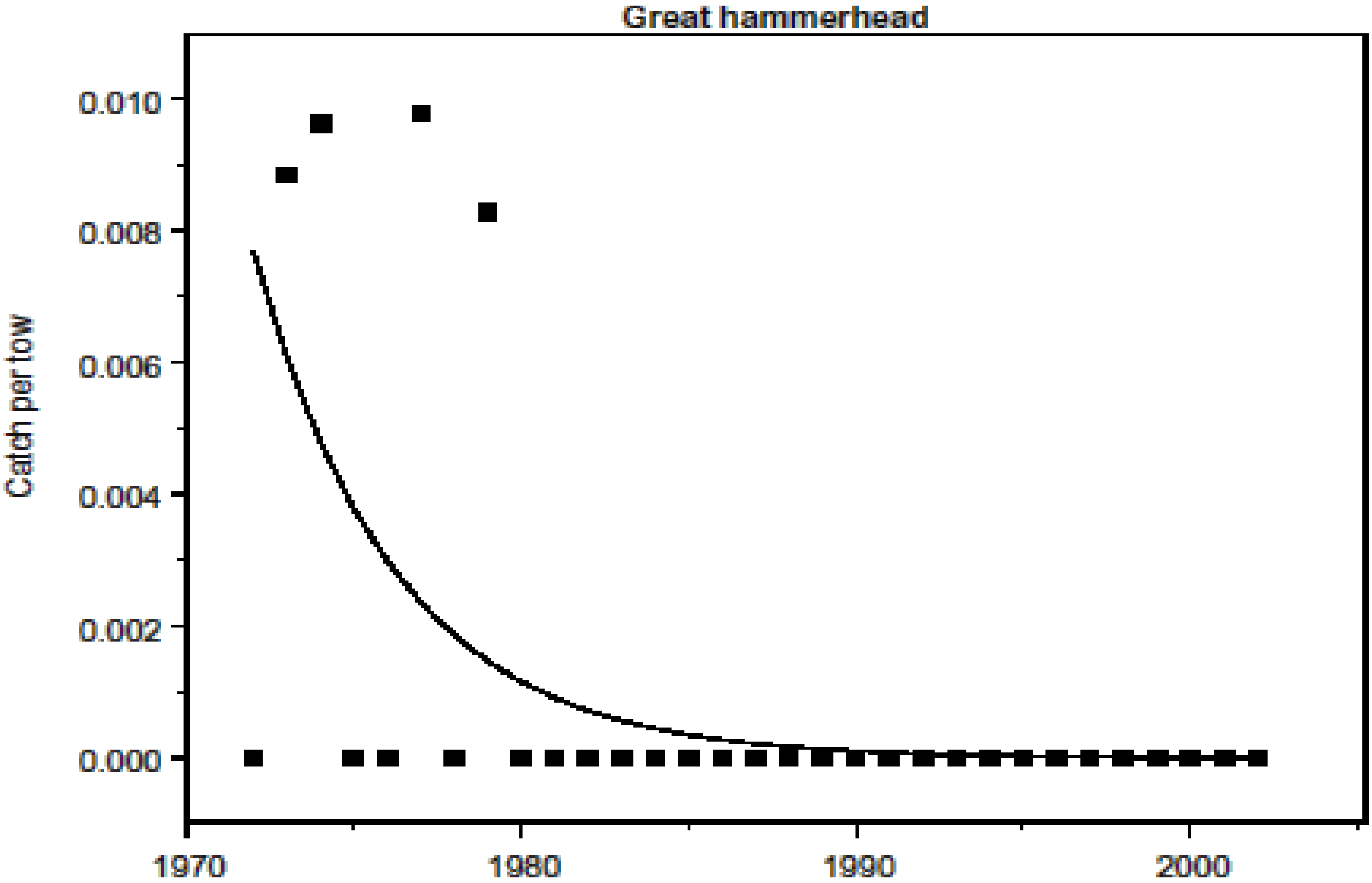
Hammerhead eating stingray



Strong, W.R. Jr; Snelson, F.F. Jr; Gruber, S.H. Copeia 1990, 836-839

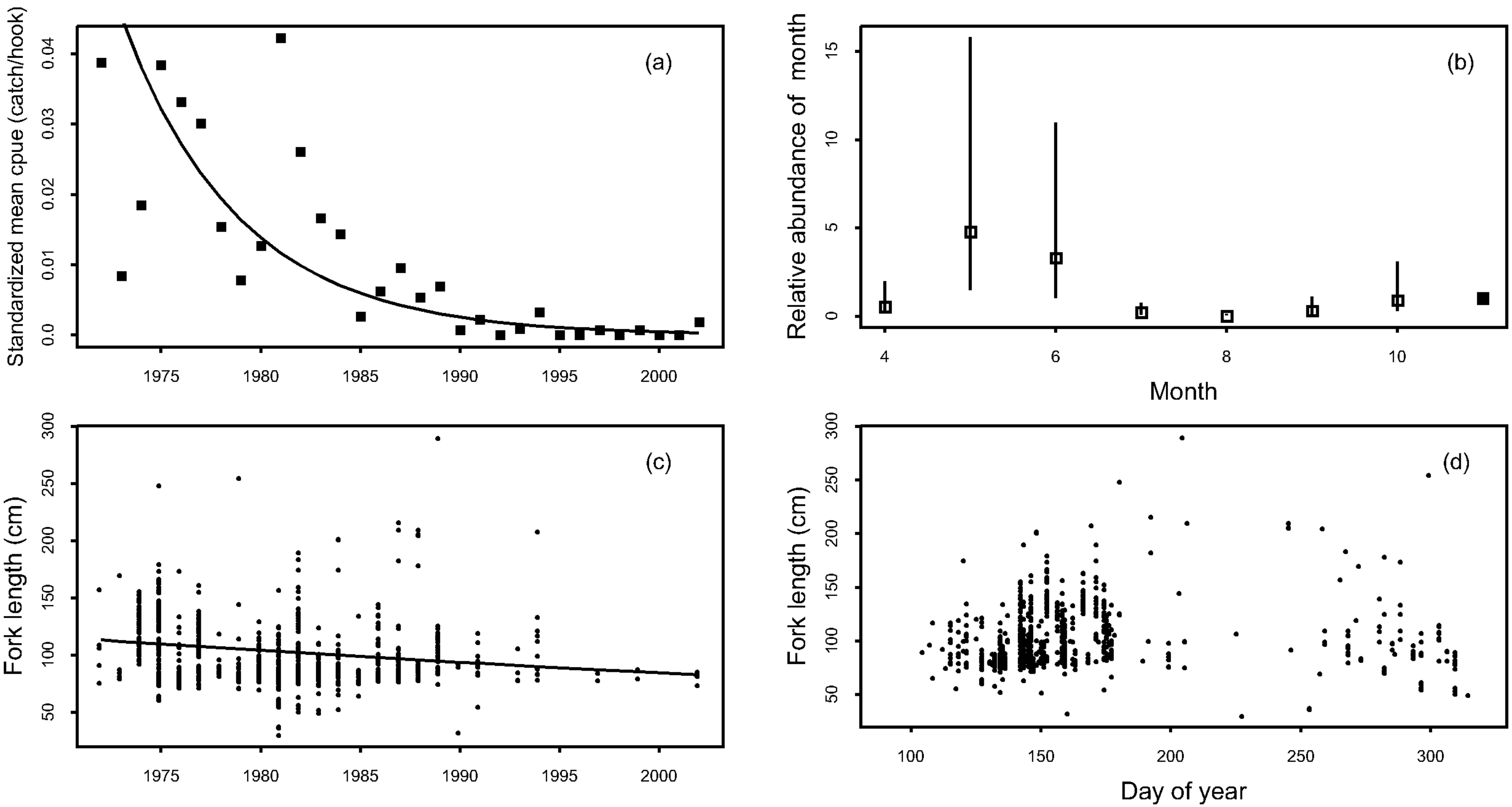

GREAT HAMMERHEAD SHARK PREDATION UPON
SPOTTED EAGLE RAY
Photo by Demian Chapman
D. D. Chapman and S. H. Gruber, 2002 Bull. of Mar. Sci. 70: 947–952

Loss of hammerheads from surveys



Shepherd and Myers, 2005, Ecology Letters

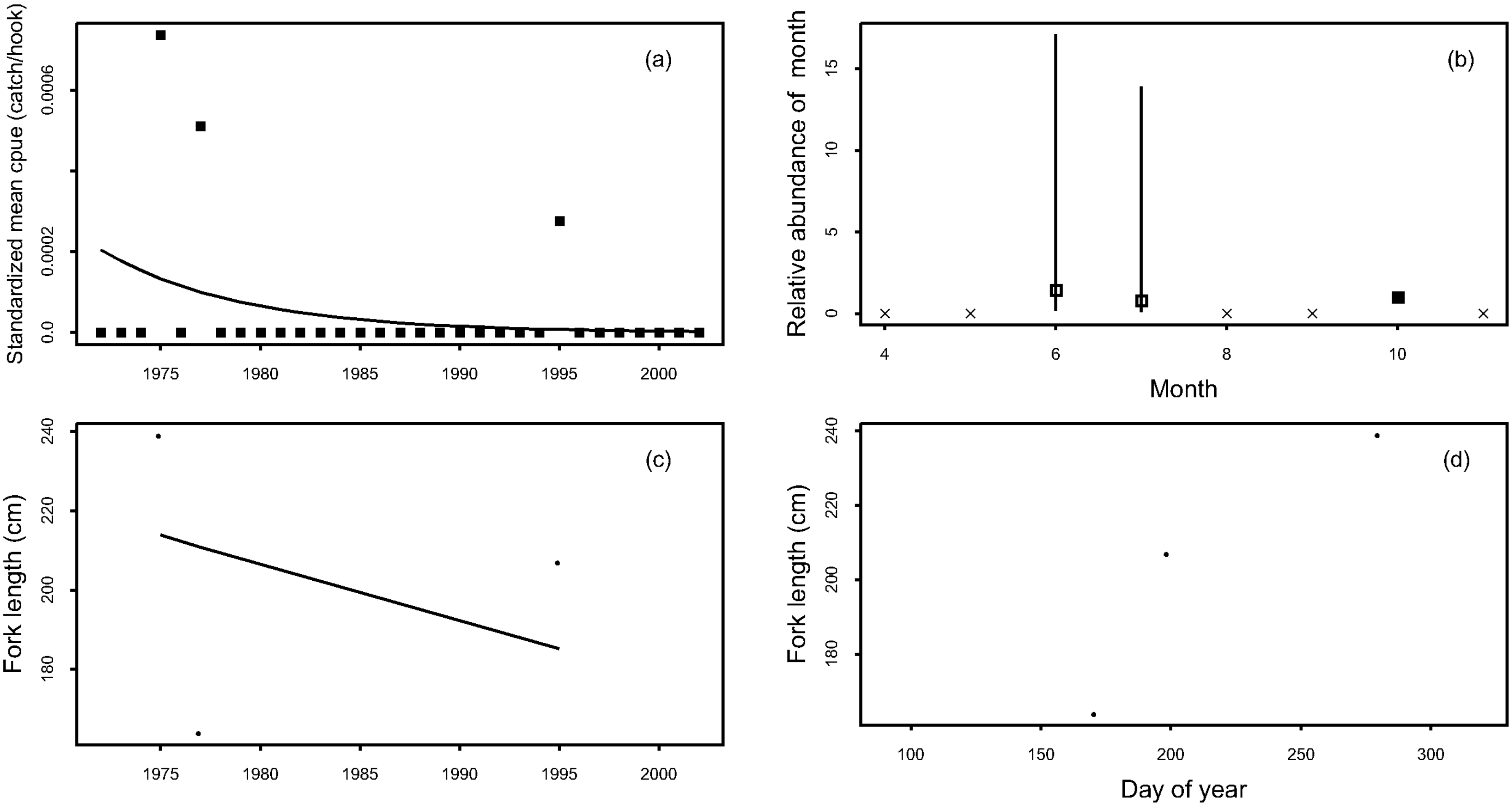
Dusky shark



Generalized linear model results

	Estimate	StdErr	p	k/scale
Abundance	-0.169	0.0171	5.67e-23	4.28
Length	-0.0105	1.4e-3	8.85e-14	18.8

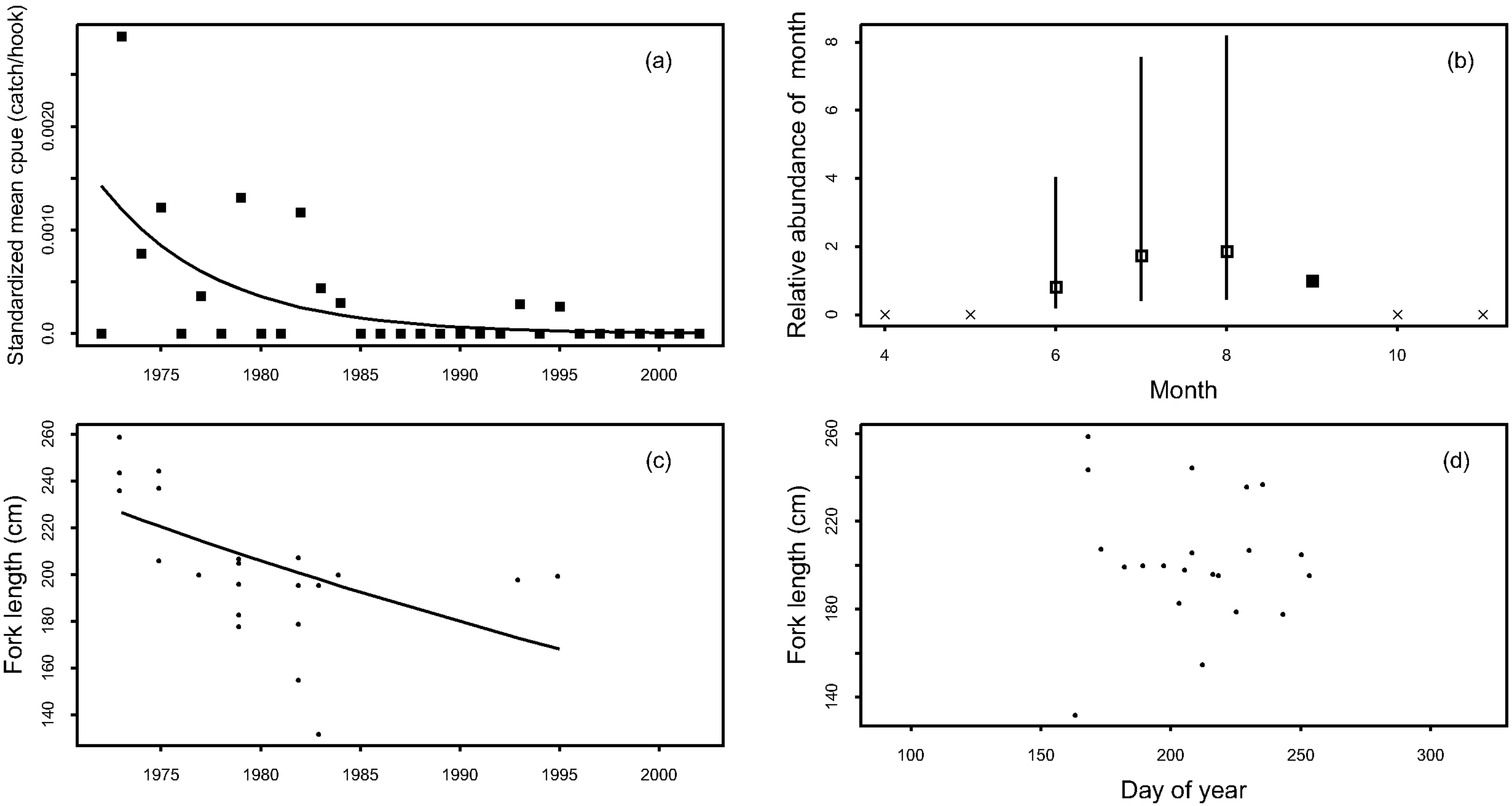
Great hammerhead



Generalized linear model results

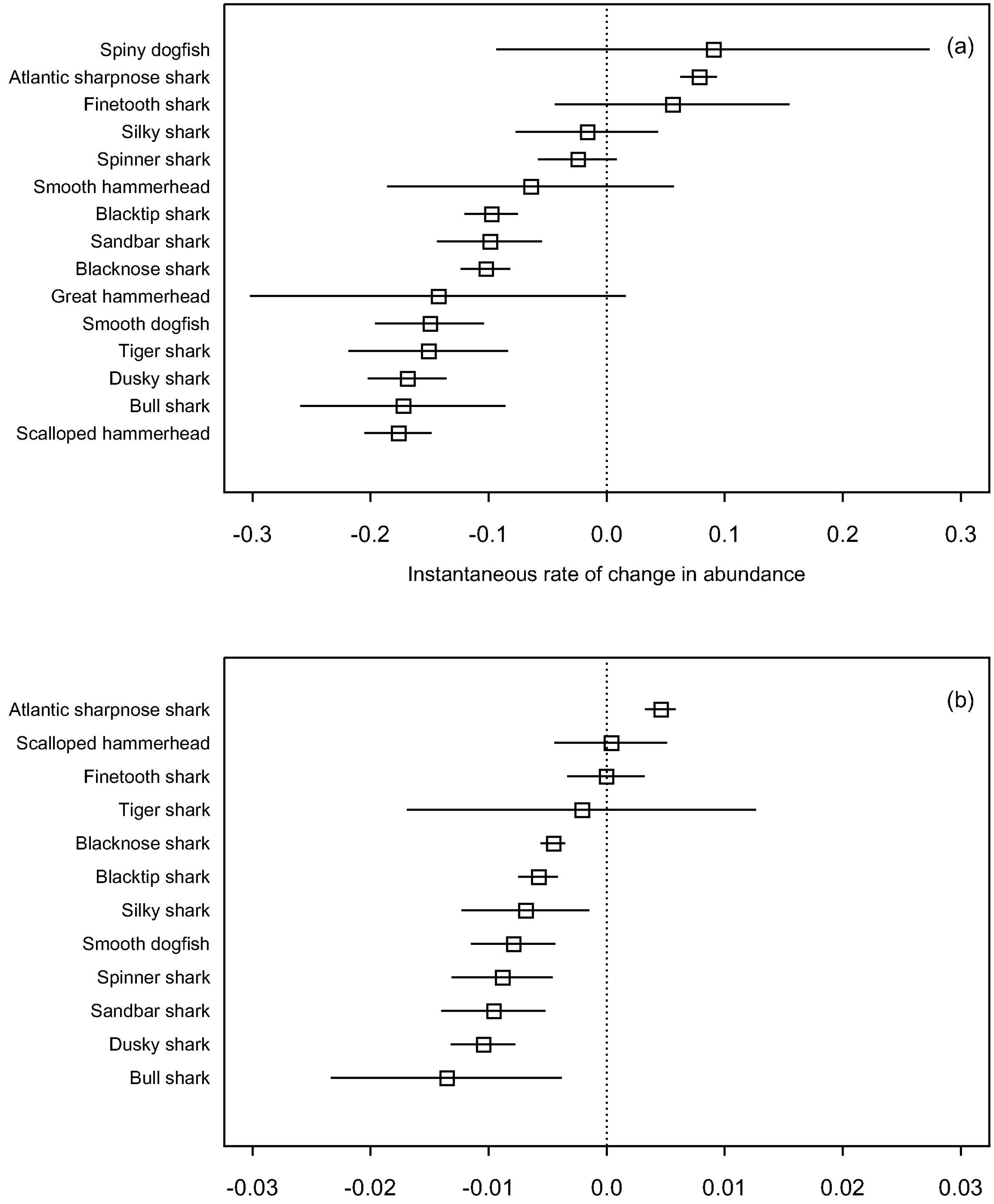
	Estimate	StdErr	p	k/scale
Abundance	-0.143	0.0812	0.079	1.96
Length	-7.19e-3	0.0707	0.919	1

Bull shark

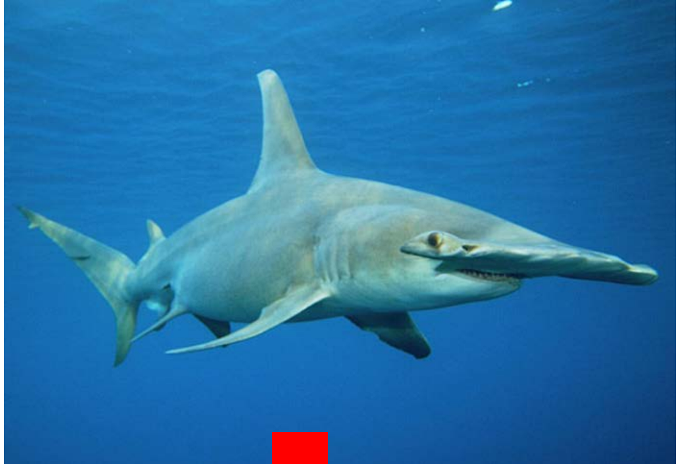


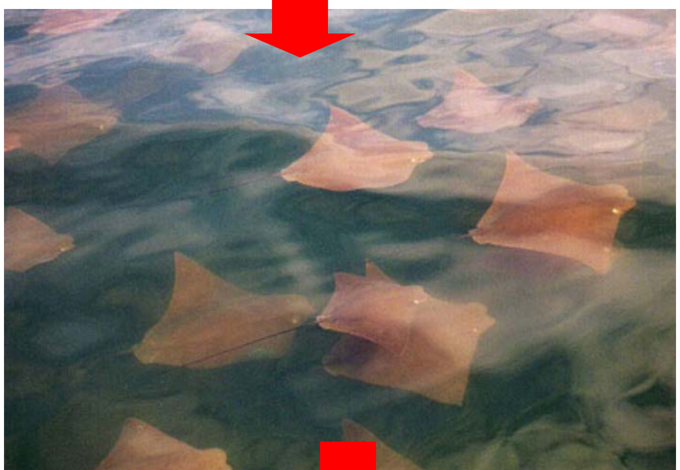
Generalized linear model results

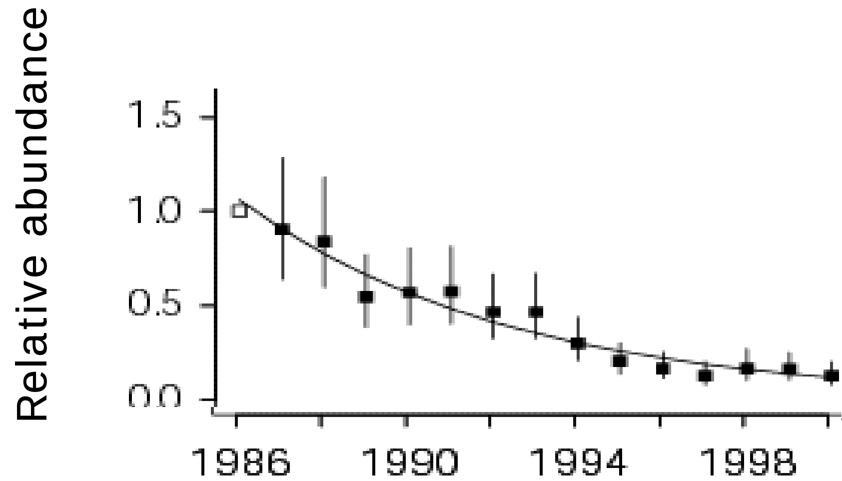
	Estimate	StdErr	p	k/scale
Abundance	-0.172	0.0443	9.99e-5	4.28
Length	-0.0136	5.e-3	6.69e-3	63.2

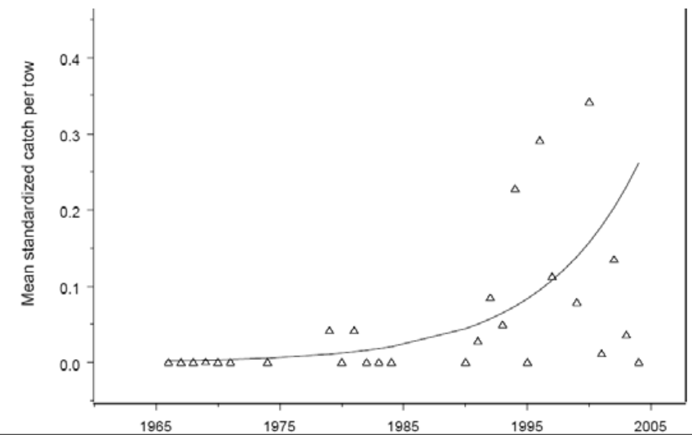


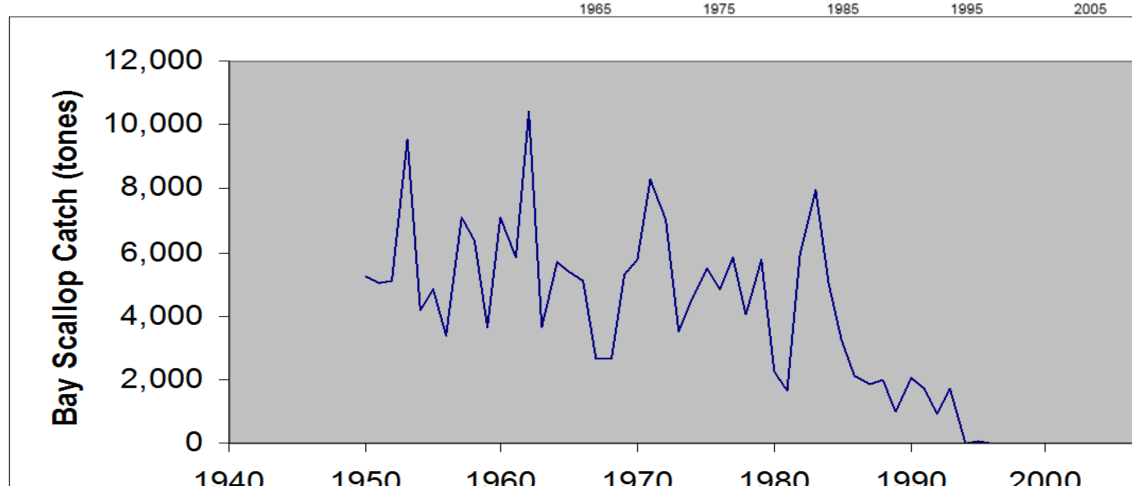
(a)
Spiny dogfish
Atlantic sharpnose shark
Finetooth shark
Silky shark
Spinner shark
Smooth hammerhead
Blacktip shark
Sandbar shark
Blacknose shark
Great hammerhead
Smooth dogfish
Tiger shark
Dusky shark
Bull shark
Scalloped hammerhead
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
Instantaneous rate of change in abundance
(b)
Atlantic sharpnose shark
Scalloped hammerhead
Finetooth shark
Tiger shark
Blacknose shark
Blacktip shark
Silky shark
Smooth dogfish
Spinner shark
Sandbar shark
Dusky shark
Bull shark
-0.03
-0.02
-0.01
0.0
0.01
0.02
0.03

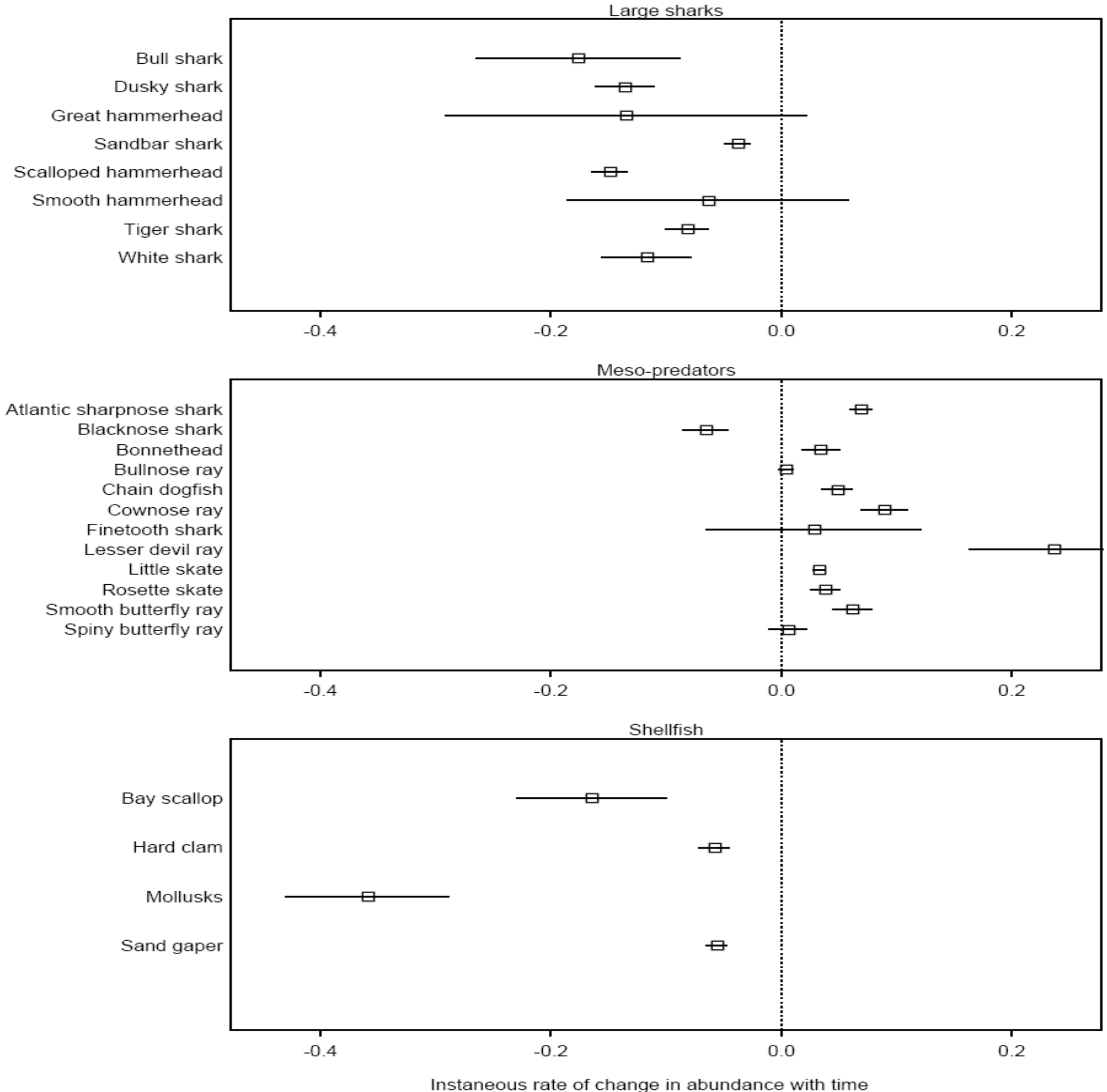




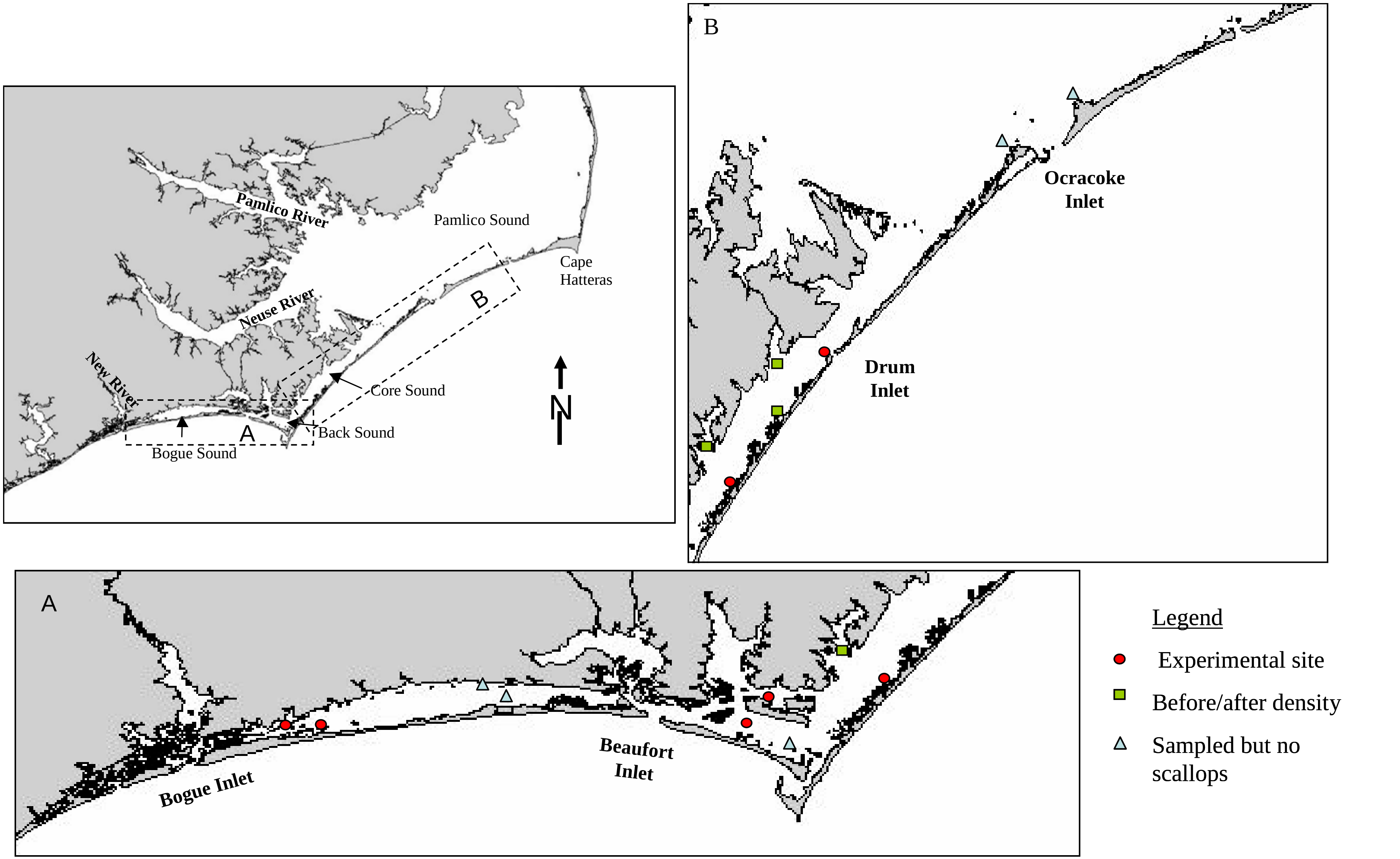

Relative abundance
1.5
1.0
0.5
0.0
1986
1990
1994
1998


Mean standardized catch per tow
0.4
0.3
0.2
0.1
0.0
1965
1975
1985
1995
2005

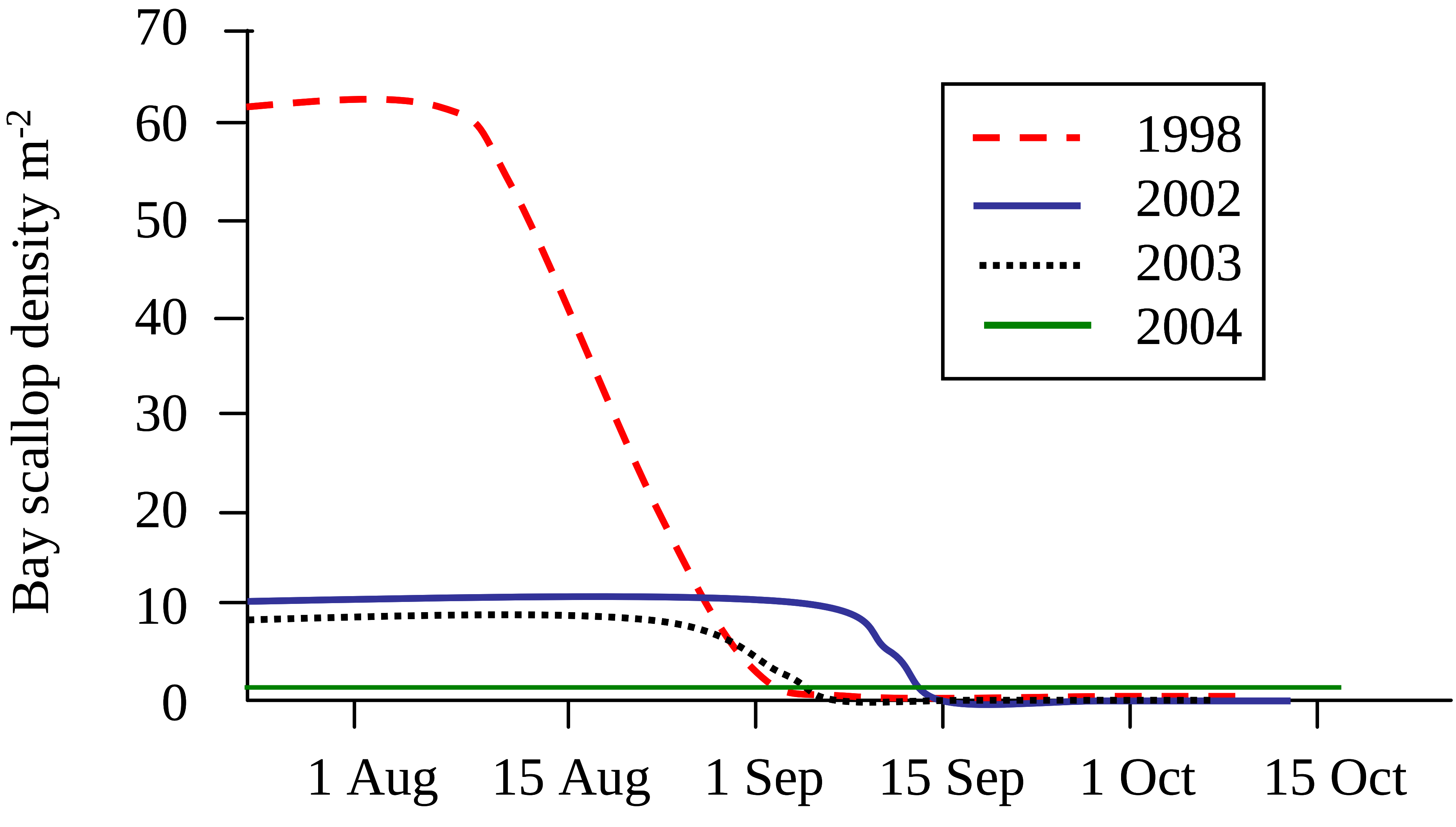

Bay Scallop Catch (tones)
12,000
10,000
8,000
6,000
4,000
2,000
0
1940
1950
1960
1970
1980
1990
2000


Large sharks
Bull shark
Dusky shark
Great hammerhead
Sandbar shark
Scalloped hammerhead
Smooth hammerhead
Tiger shark
White shark
-0.4
-0.2
0.0
0.2
Meso-predators
Atlantic sharpnose shark
Blacknose shark
Bonnethead
Bullnose ray
Chain dogfish
Cownose ray
Finetooth shark
Lesser devil ray
Little skate
Rosette skate
Smooth butterfly ray
Spiny butterfly ray
-0.4
-0.2
0.0
0.2
Shellfish
Bay scallop
Hard clam
Mollusks
Sand gaper
-0.4
-0.2
0.0
0.2
Instaneous rate of change in abundance with time

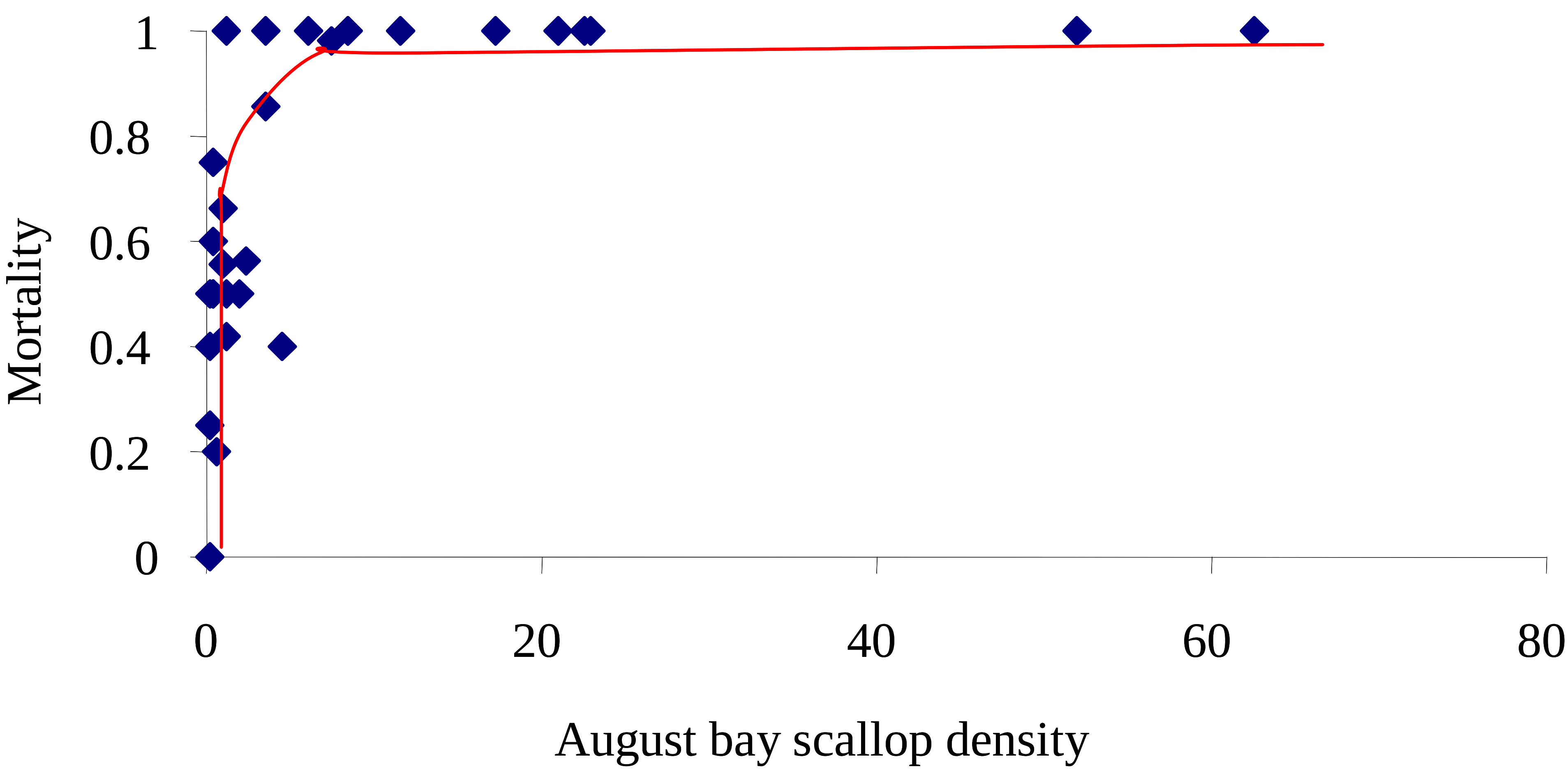
Experimental Results of Pete Peterson and Sean Powers in North Carolina



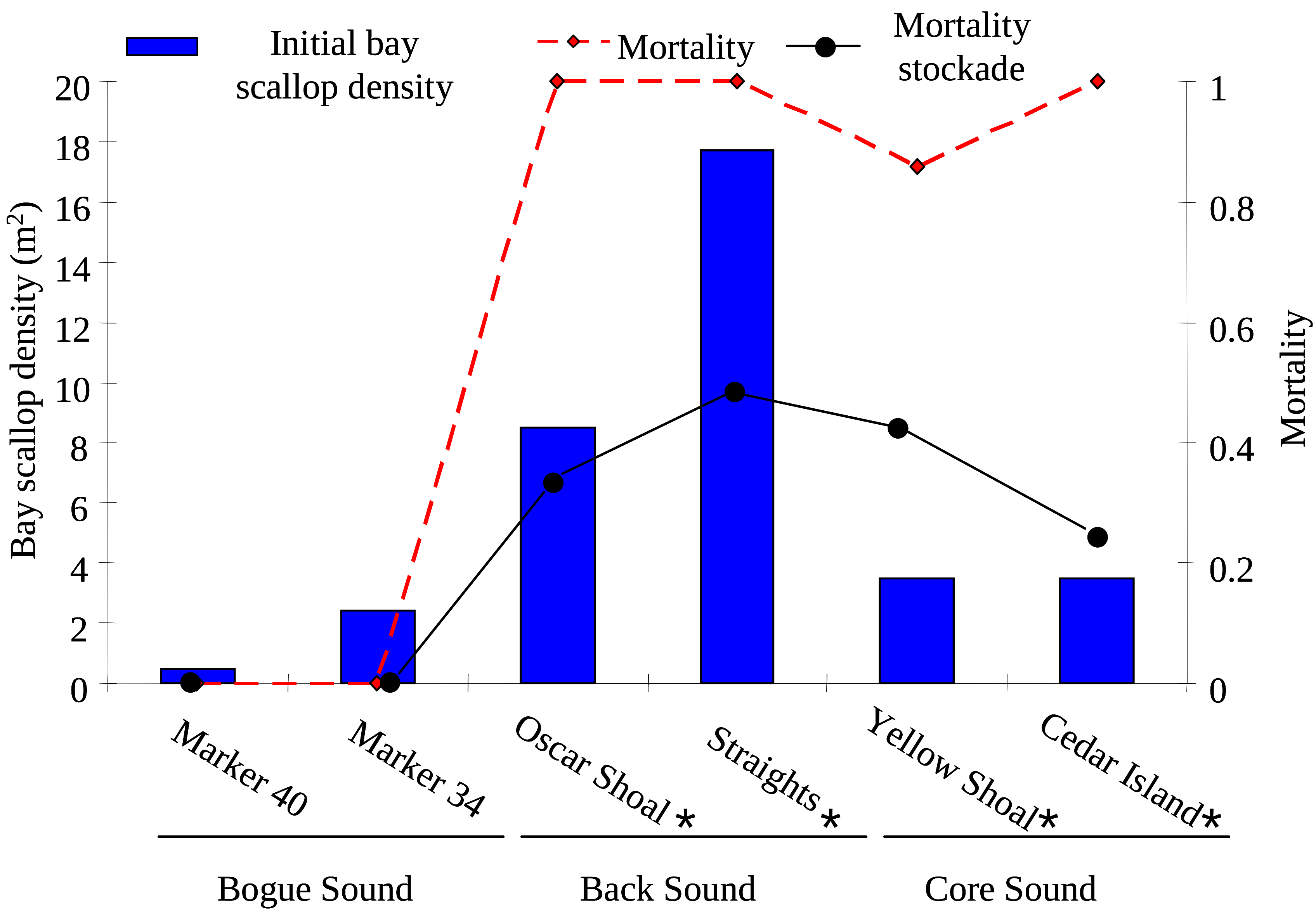
Loss of Bay Scallops with Cownose Ray Fall Migration

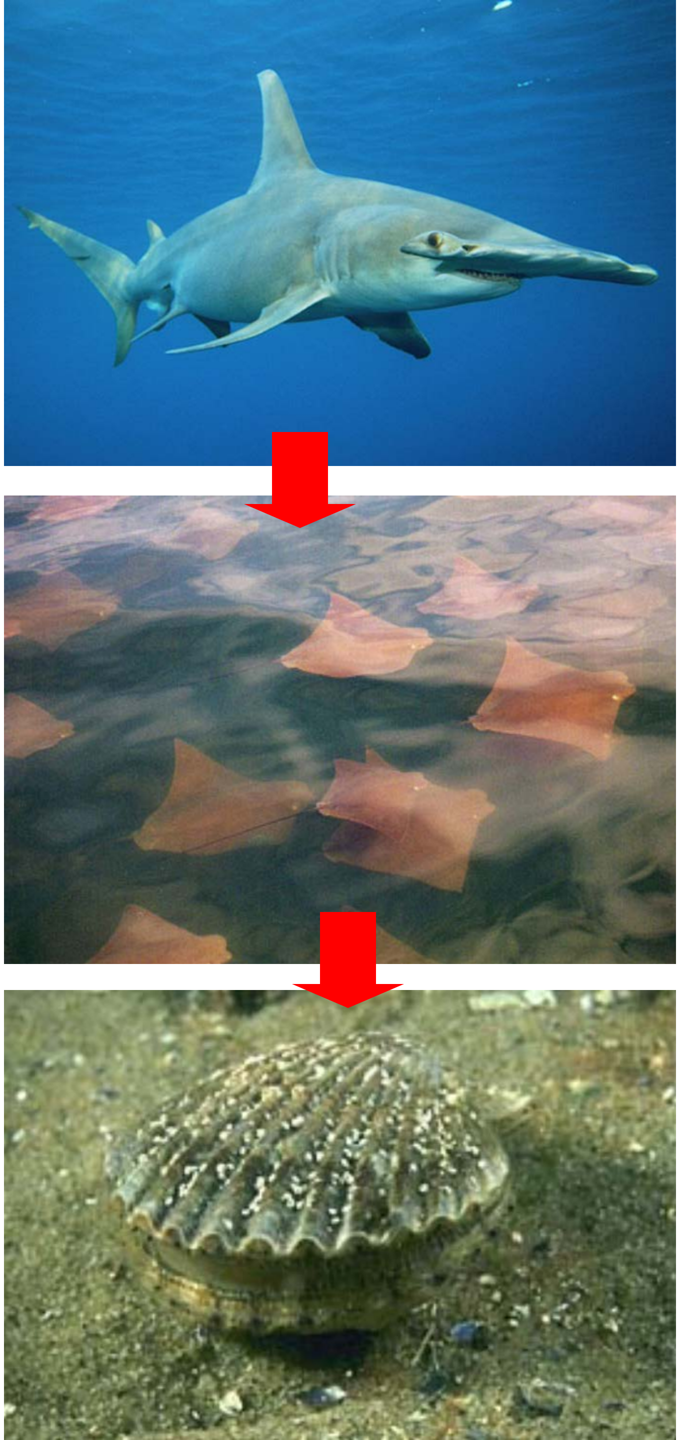


Mortality of almost 100% during fall migration of cownose rays



Excluding cownose rays allow the survival of bay scallops.





Trophic Cascades: Consequences of the loss of top predators may be greater than we think

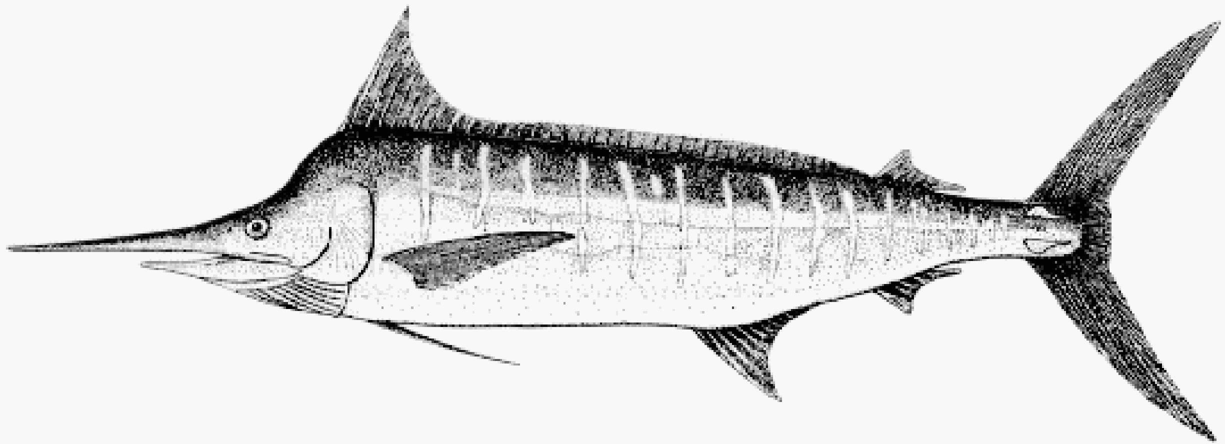
The First Collective Act of Humanity was to save the great whales –

despite massive denial

– we can do
the same for the remaining virgin areas of the oceans and for the great sharks.

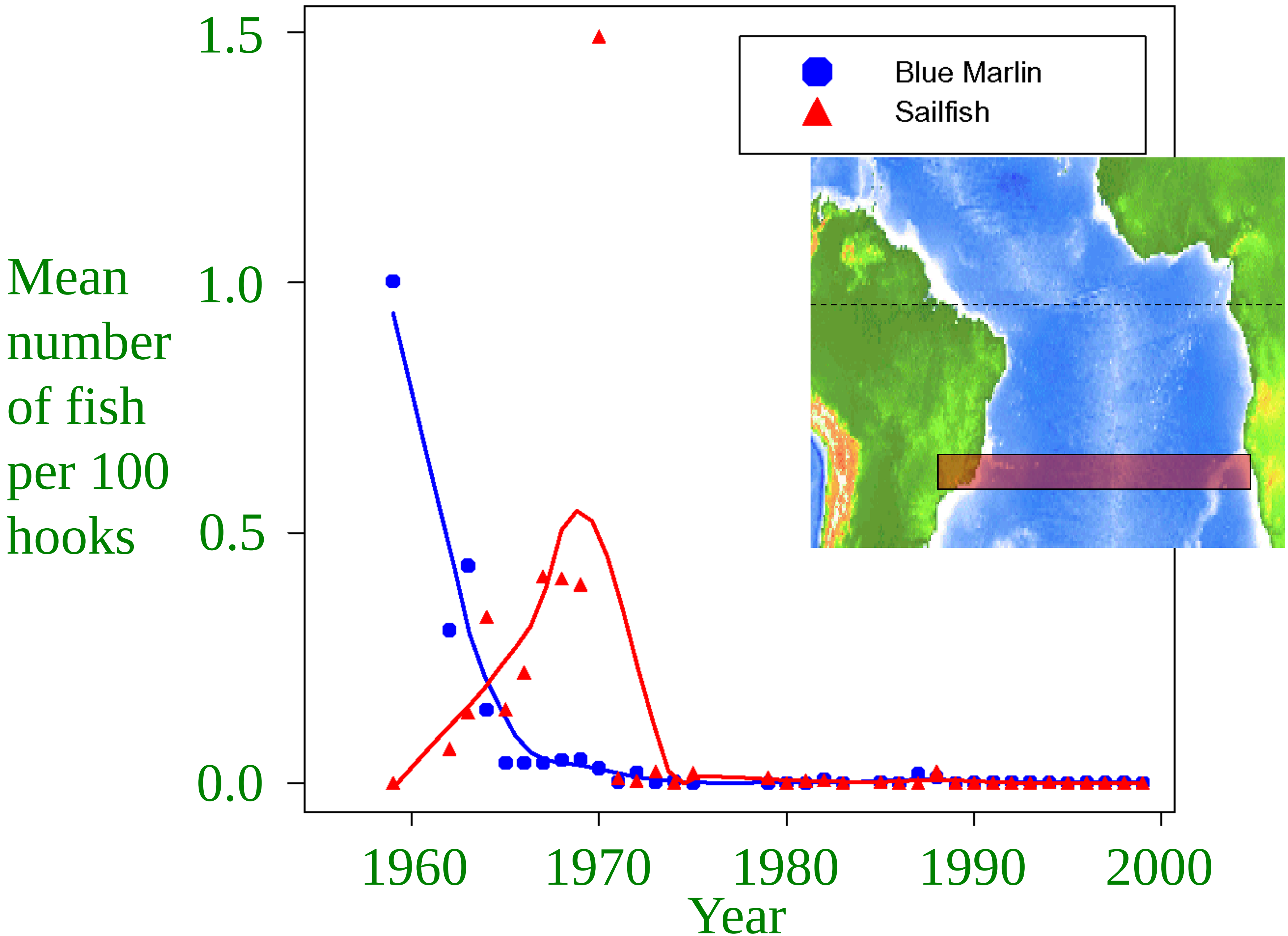
Past use of State-Space Models for Movement

- Models by David Brillinger in 1998 showed migration across oceans using a directional random walk on a sphere.
- John Sibert used “almost linear” Kalman filter models to improve popup tags locations (see U. of Hawaii website)
- Morales, Haydon, Friar, Holsinger, Fryxell (Ecology 2004) used hidden Markov models

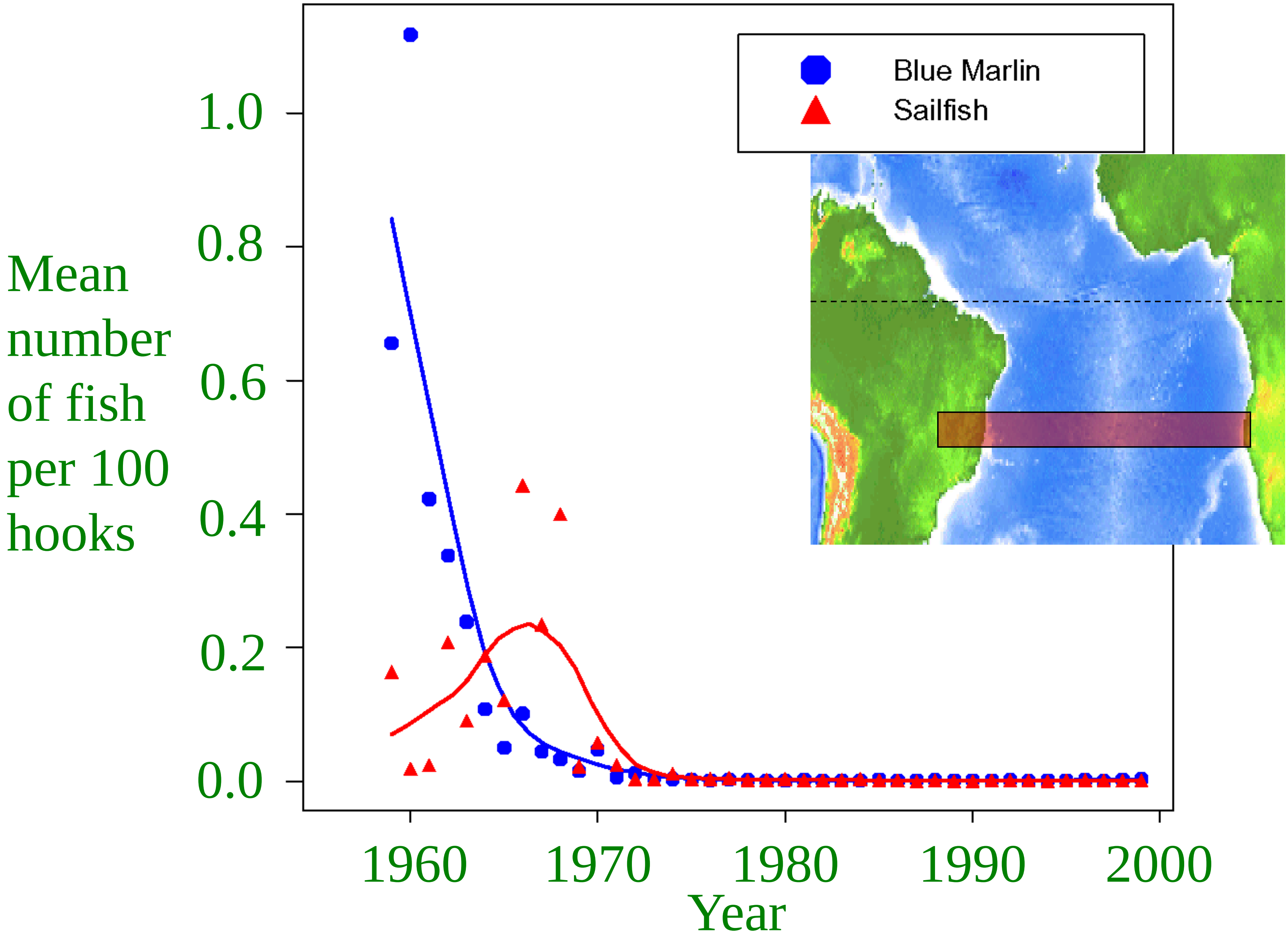


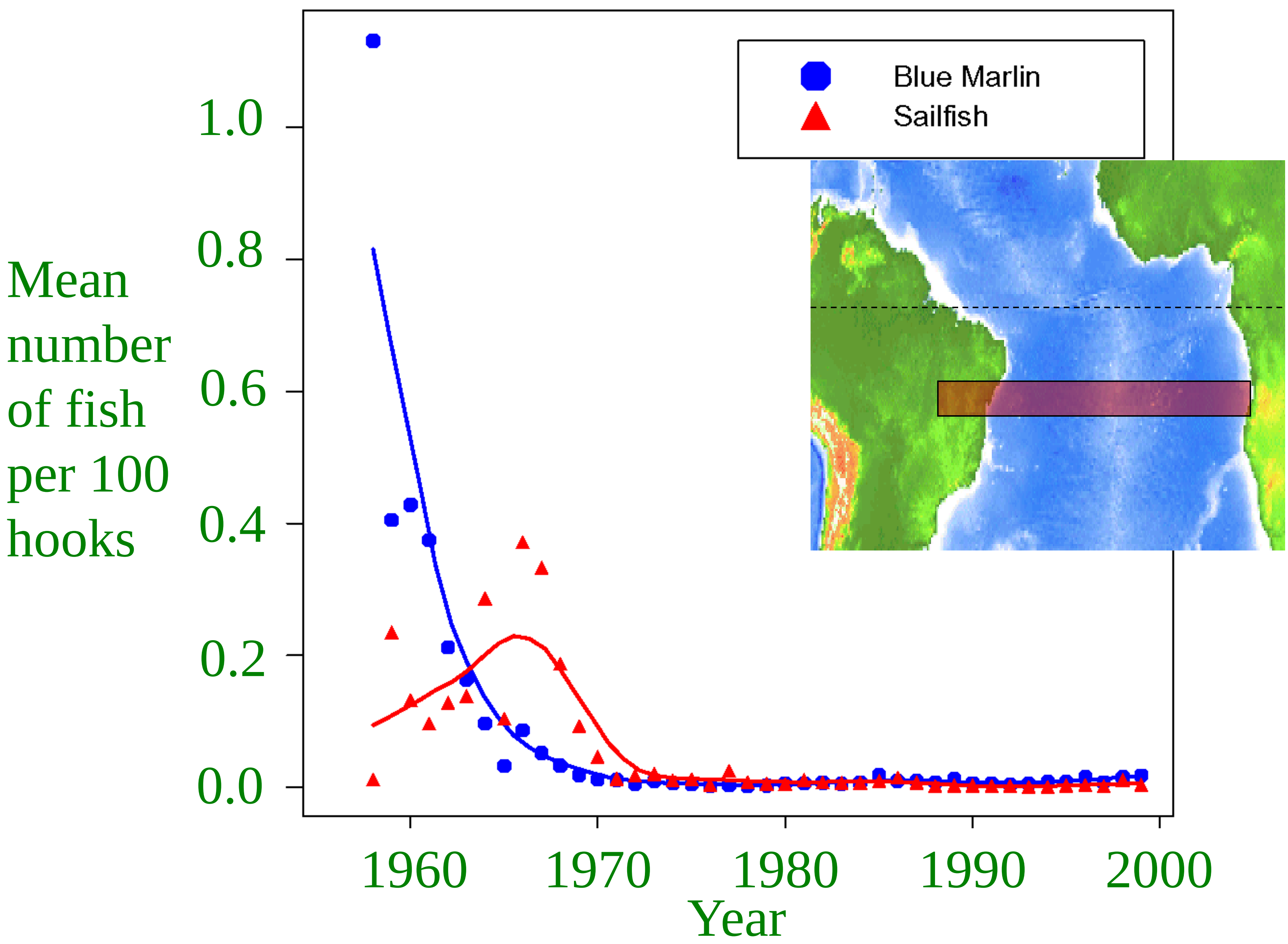
Blue marlin (*Makaira nigricans)*

Sailfish (*Istiophorus albicans)*

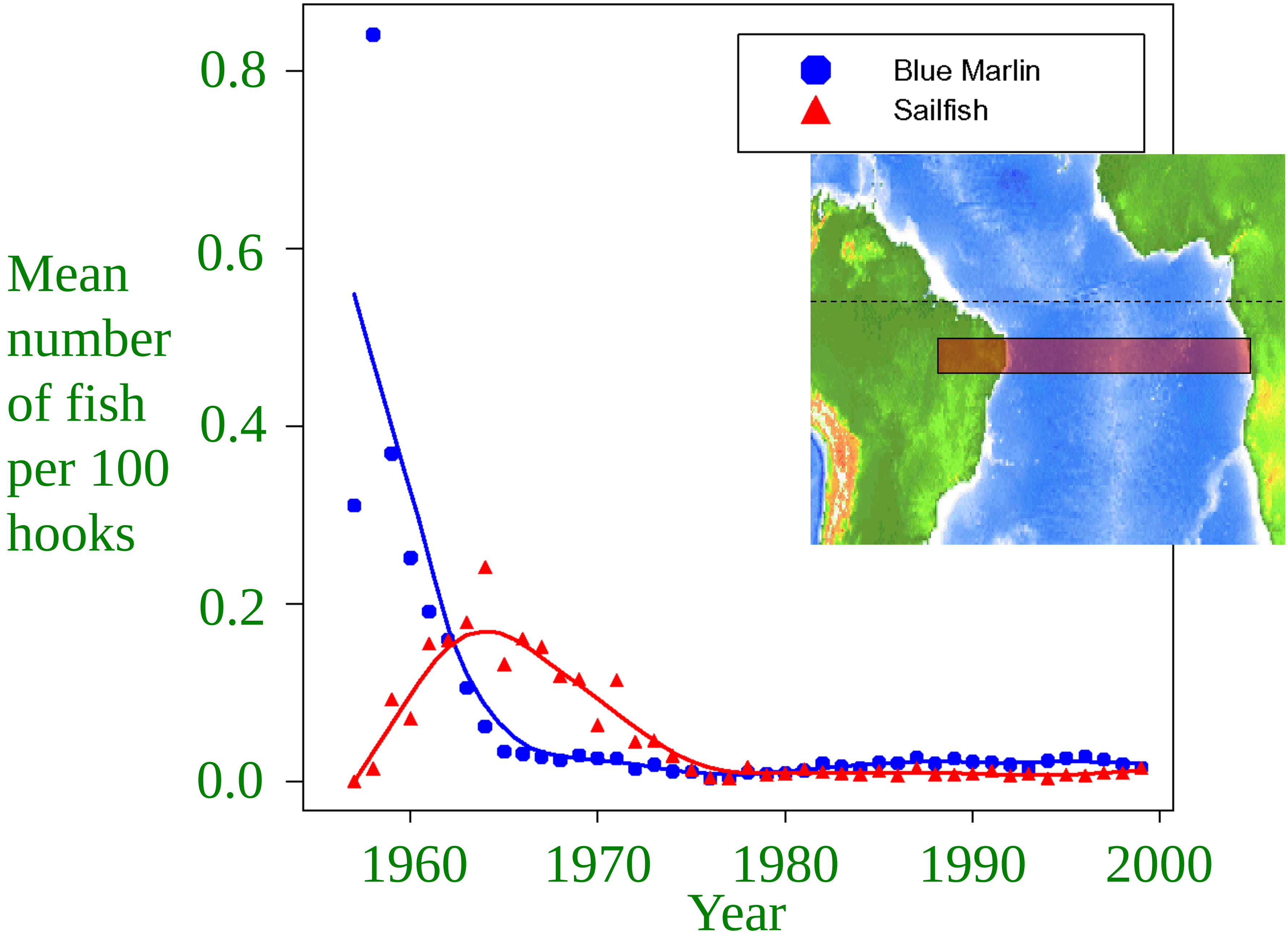


Blue Marlin
Sailfish
Mean number of fish per 100 hooks
1.5
1.0
0.5
0.0
1960
1970
1980
1990
2000
Year

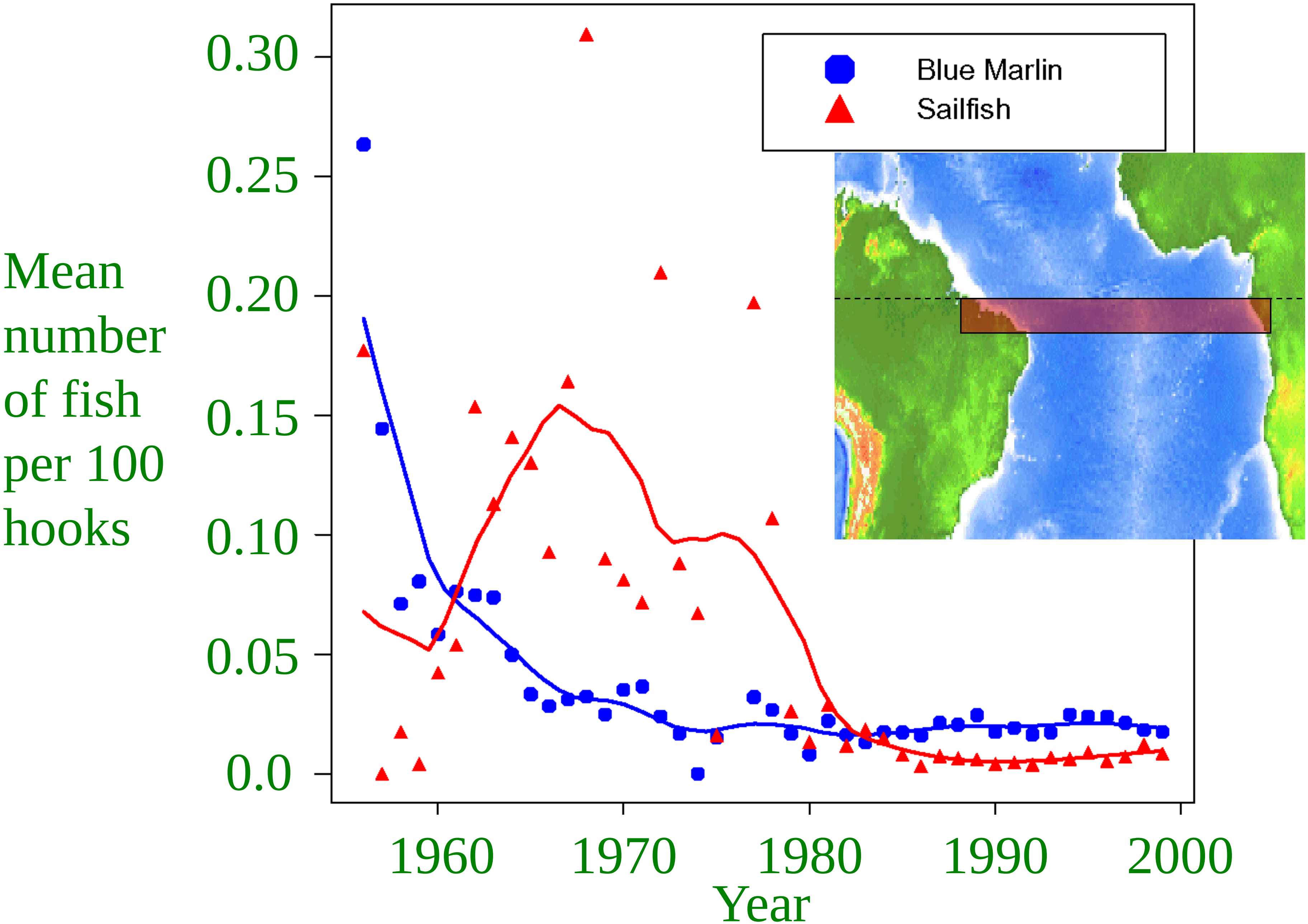

Mean number of fish per 100 hooks
1.0
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish

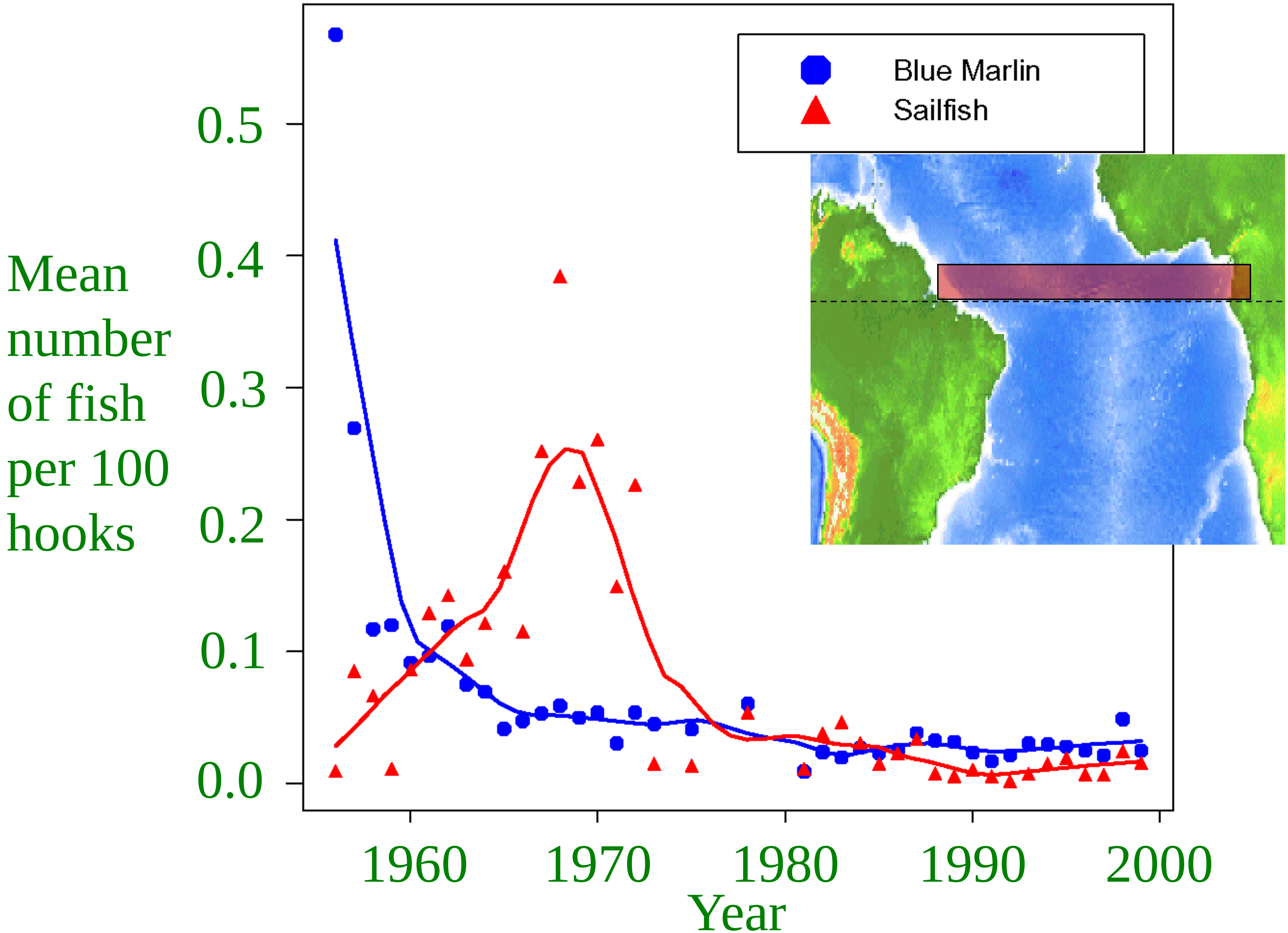


Mean number of fish per 100 hooks
1.0
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish



Mean number of fish per 100 hooks
0.8
0.6
0.4
0.2
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish

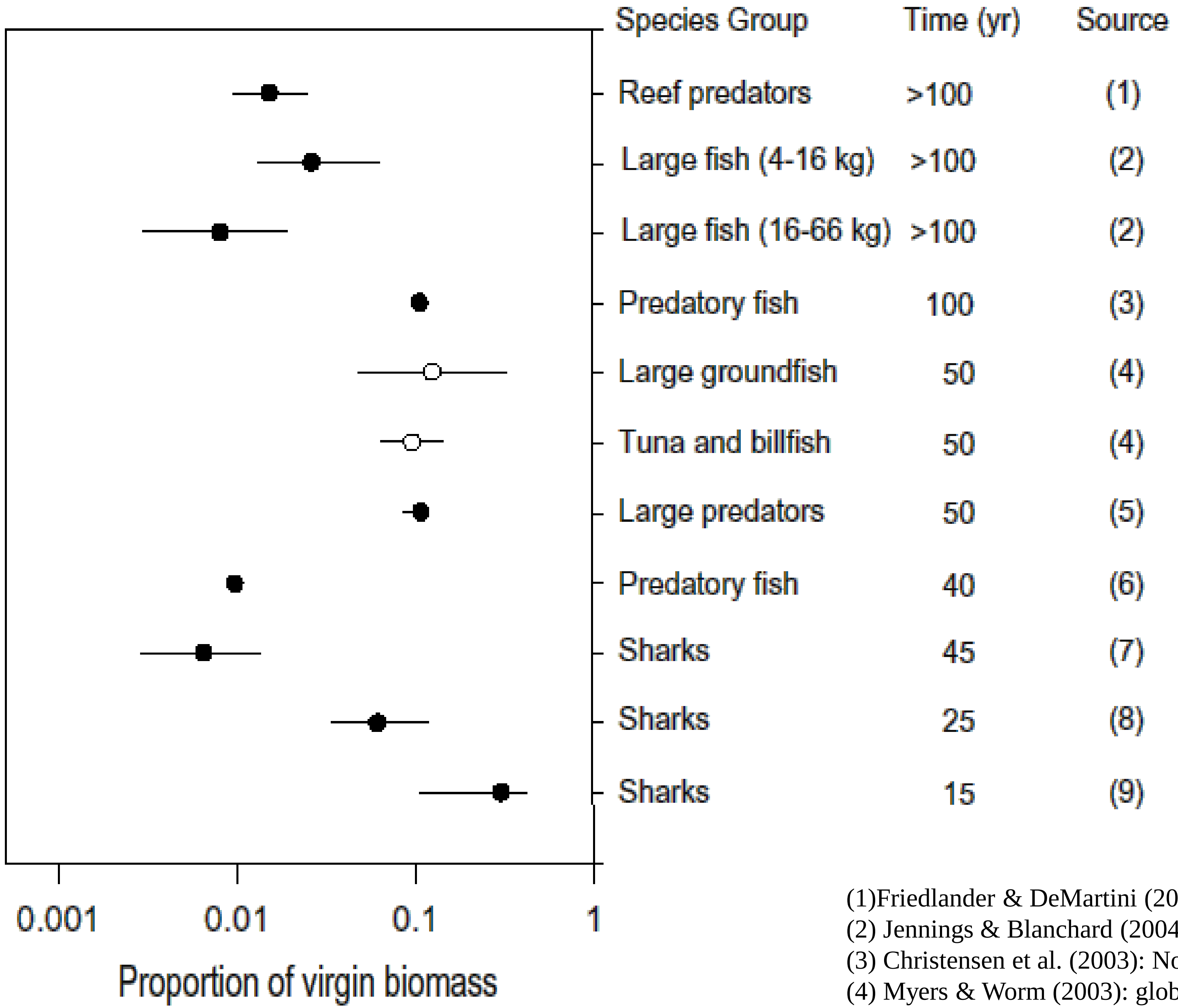

Mean number of fish per 100 hooks
0.30
0.25
0.20
0.15
0.10
0.05
0.0
1960
1970
1980
1990
2000
Year
Blue Marlin
Sailfish



Blue Marlin
Sailfish
Mean number of fish per 100 hooks
0.0
0.1
0.2
0.3
0.4
0.5
1960
1970
1980
1990
2000
Year

Not only have large predators declined by at least a fact
10, but mesopredators have often increased by at least a
factor of 10.

FMAP (Future of Marine Animal Populations)
part of the Sloan Census of Life http://www.fmap.ca
Pew Global Sharks Assessment http://www.globalsharks.ca



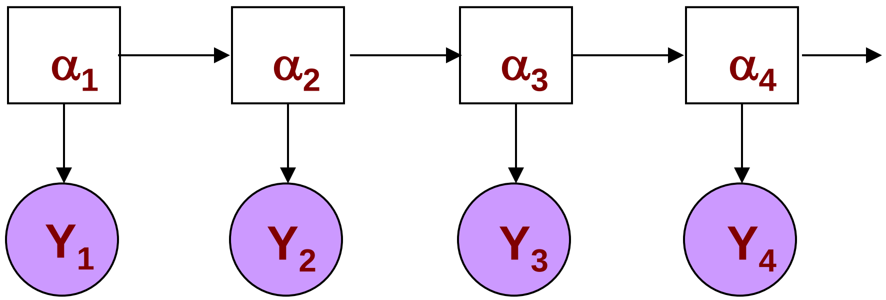
(1)Friedlander & DeMartini (2002): Hawaiian reefs;
(2) Jennings & Blanchard (2004): North Sea;
(3) Christensen et al. (2003): North Atlantic;
(4) Myers & Worm (2003): global;
(5) Ward & Myers (2003): North Pacific;
(6) Tang et al. (2003): Bohai Sea;
(7) Baum & Myers (2004): Gulf of Mexico;
(8) Vacchi et al. (2000): Mediterranean Sea;
(9) Baum et al. (2003): Northwest Atlantic.

Source: Myers and Worm 2005.
Proc. R. Soc. Lond. B (2005)

Not only have large predators declined by at least a fact
10, but mesopredators have often increased by at least a
factor of 10.

FMAP (Future of Marine Animal Populations)
part of the Sloan Census of Life http://www.fmap.ca
Pew Global Sharks Assessment http://www.globalsharks.ca

Special Case of State-Space Models: Hidden Markov Model



- one **discrete** hidden node and one discrete or continuous observed node per time slice.
- α: hidden variables
- Y: observations
- Structures and parameters remain same over time
- Three parameters in a HMM:
  - The initial state distribution $P(\alpha_1)$
  - The transition model $P(\alpha_t \mid \alpha_{t-1})$
  - The observation model $P(Y_t \mid \alpha_t)$

State Space Models

Maximize likelihood
to estimate model parameters
γ

Use Markov Chain
Monte Carlo methods
in WinBugs

Error function

$$y_t = h\,(\alpha_t\,,\,\varepsilon_t)$$

observed location

true location

$$\alpha_t = f\,(\alpha_{t\text{-}1},\ \eta_t\,;\,\gamma)$$

movement function

parameters

State-Space Models

Process model
true location $\alpha_{t+1} = f$(true location α_t, parameters, process variability)

Observation model
observed location $\mathbf{y}_t = h$(true location α_t, observation error)

State-Space Models

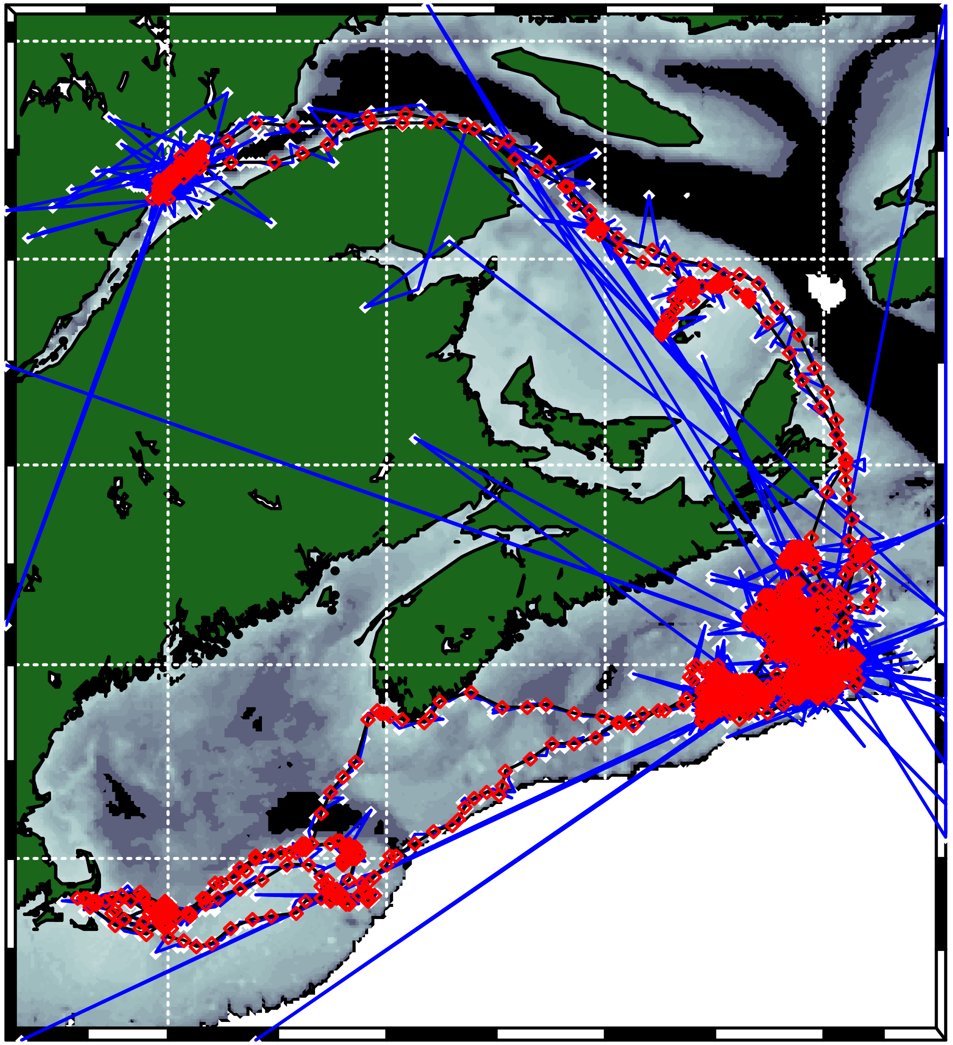
Process model

true location $\alpha_{t+1} = f$(true location α_t, parameters, process variability)

Observation model

observed location $\mathbf{y}_t = h$(true location α_t, observation error)

Location Estimates



This represents a different way of thinking

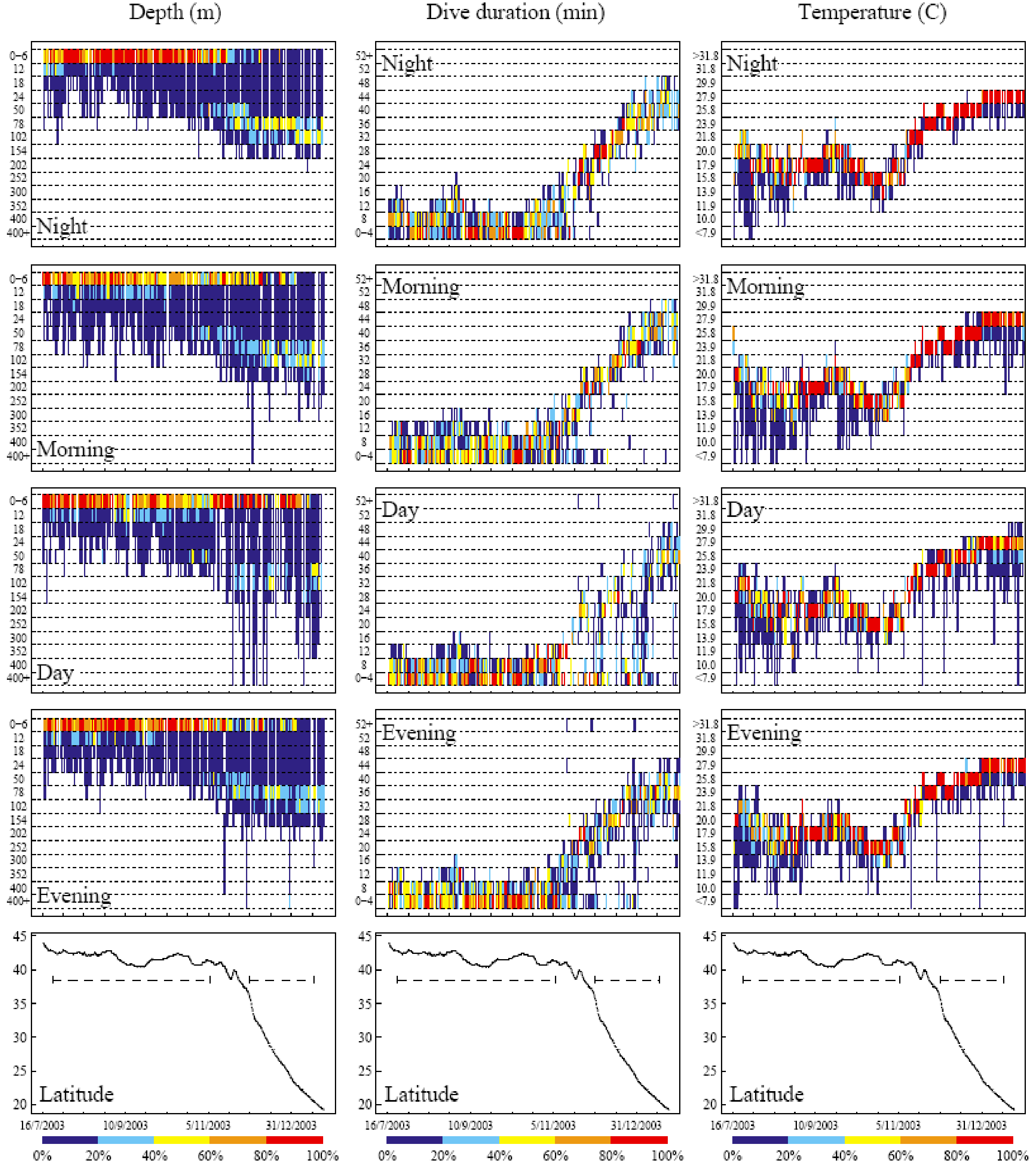
How are animals different from particles?

- They have free will
- They have “inertia”, they tend to keep going the same direction.
- They have different behaviours

Why State Space Models

- This is simply one of the key “right ways” to think about many key modern problems:
- Engineers, economists, oceanographers, and speech recognition scientists, use modifications of this idea;
- If you want to shoot down a missile, you use a state space model.

When migrating leatherbacks spend more time close to the surface during the day.



From James, Ottensmeyer, and Myers (in review)

Economometrics:

How our analysis differs:

- We use a large amount of prior information on the accuracy of locations, i.e. they are described by “heavy tailed” distributions.
- We model the performance of each transmitter, because there are very clear differences among transmitters.
- We use the first state-space model of switching for movement implemented for an ecological problem.
- First meta-analytic approach which combines information from different tracts using a hierarchical random-effects meta-analytic approach.

Making Switching Models Work

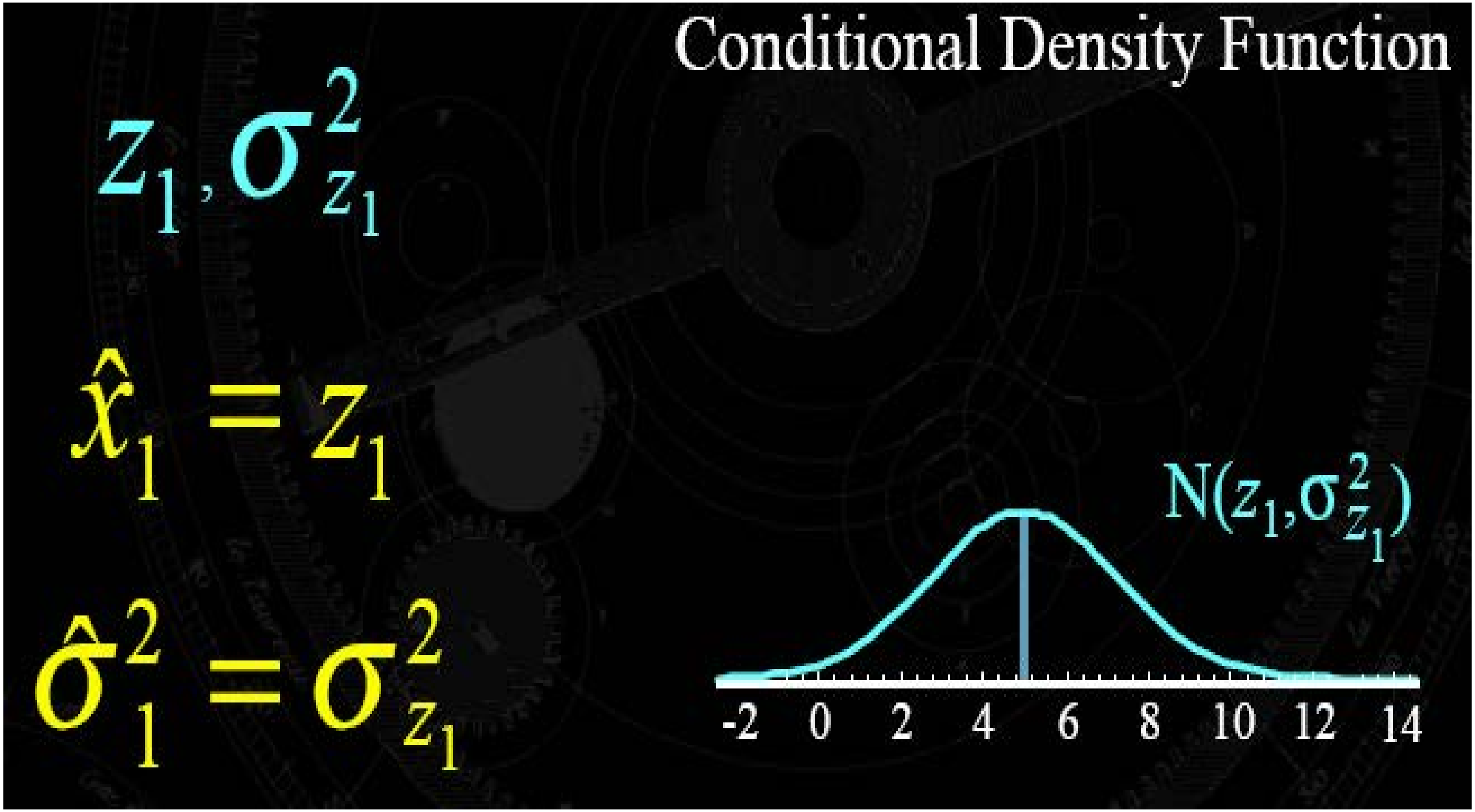
- Meta-analysis greatly improves the estimates because relative few transitions are observed for each track.

- In the Bayesian approach, both the parameters ?? and the values of the states (α_1, α_2, ...,α_T) are viewed as random variables.

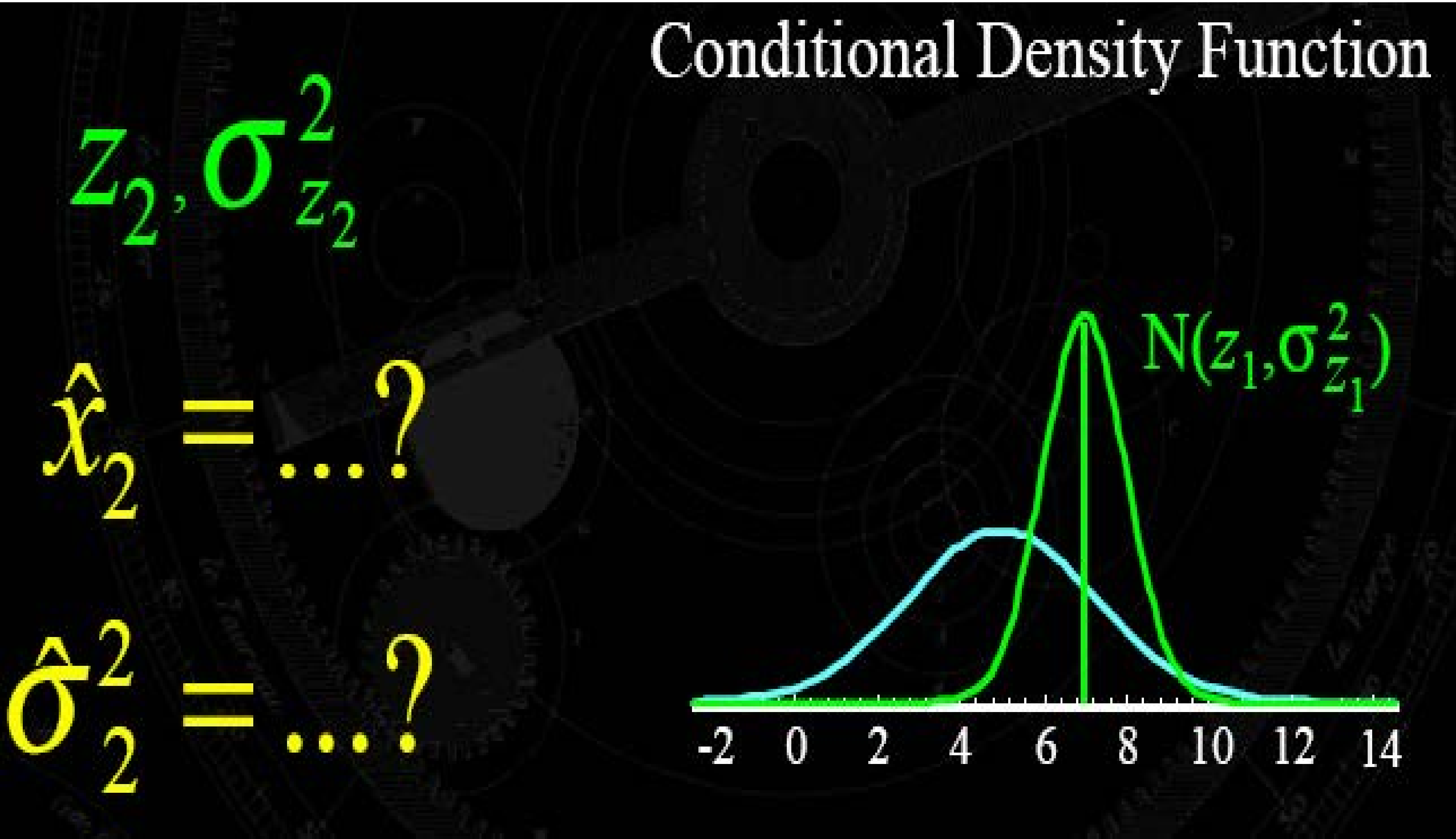
What is Kalman Filtering Used For?

- **What is it used for?**
- **Tracking missiles**
- **Tracking heads/hands/drumsticks**
- **Extracting lip motion from video**
- **Lots of computer vision applications**
- **Economics**
- **Navigation**

First Measurement



Second Measurement



Combine Estimates

$$\hat{x}_2 = \hat{x}_1 + K_2\left(z_2 - \hat{x}_1\right)$$

$$K_2 = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_{z_2}^2}$$

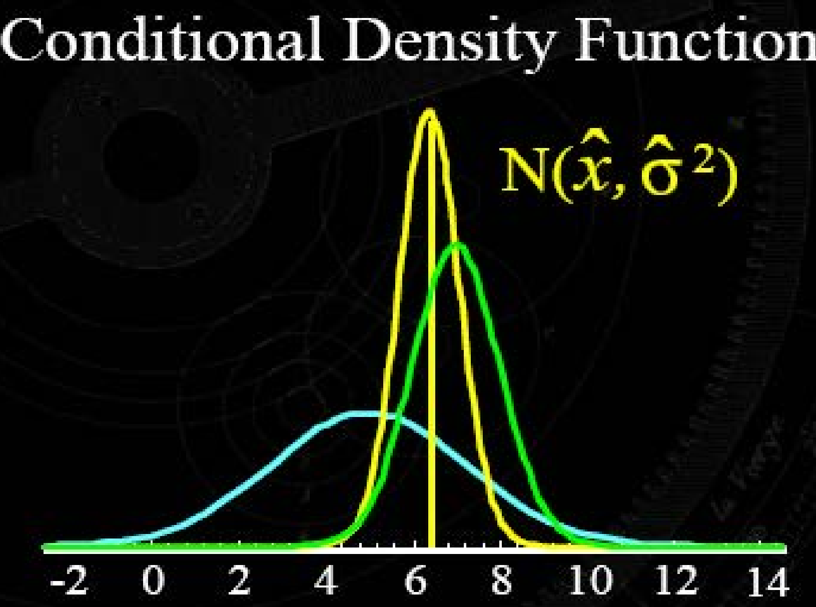
Combine variances

$$\frac{1}{\sigma_2^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_{z_2}^2}$$

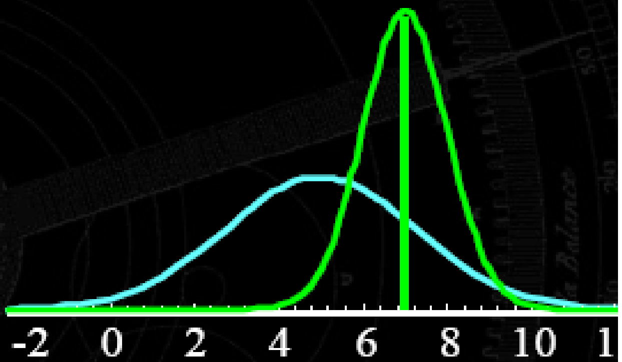
Combined Estimates

$$\hat{x} = \hat{x}_2$$

$$\hat{\sigma}^2 = \sigma_2^2$$



But suppose we’re moving



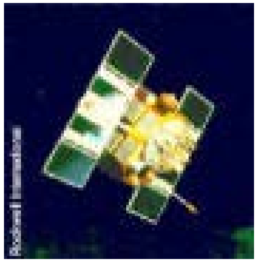
- Not *all* the difference is error
- Some may be motion
- KF can include a motion model
- Estimate velocity and position

Switching Models

- Does not work well on one animal
- Works well if animals have the same switching parameters (this is the same as a fixed effect meta-analysis).
- We would like to have a hier. model, where parameters are random variables.

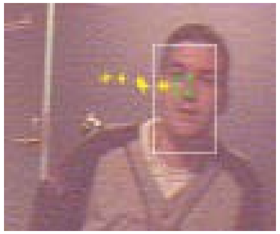
Applications

GPS



Satellite orbit computation

Active noise control



Tracking

Examples - Target tracking

The state process consists of the position, velocity, and acceleration coördinates (9 dimensions in all) of a ballistic or steered target (i.e rocket or missle); randomness in the state process may come from interactions with the atmosphere, or from evasive maneuvers. Observations consist of data from radar and infrared sensors, and prior knowledge of the initial location of the target; observation noise comes from background noise sources such as clutter, or internal thermal noise in the sensor.

Examples: **Weather and Ocean Prediction**

Nonlinear filtering theory allows new data to be assimilated into the differential equations which drive a numerical model of the ocean and/or atmosphere.

Examples

- **Asset Pricing - Each component of the state is the value of some asset or derivative, or else an underlying interest rate; the observations consist of data on specific sale prices of related assets at a sequence of times.**

Different short behavors

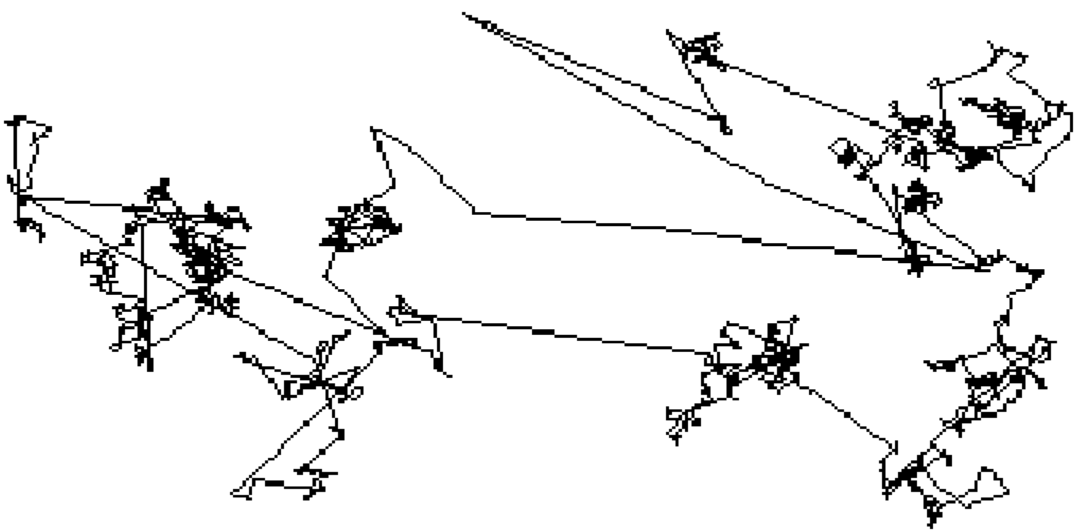
Why state-space models?

- Only method that models time series structure with missing values.
- Models estimation error.
- Models non Gaussian errors.
- Models nonlinear relationships.

Further advantages

- Switching models

What about Levy flights?
Heuristic, but not mechanistic.



State space models

- State variables
- parameters
- forcing functions
- rules of change
- the state variables in the future depend upon the current state, the parameters (constants), any external perturbations (the forcing functions), and the rules of change

State variables

- The complete description of the current state of the system -- complete enough that you can “rebuild” the system with this amount of information
- examples - the number of animals in the population - the age structure of a population, the presence or absence of species in a community matrix ….

Parameters

- Do not change over time and are the constants that describe the rates or limits
- intrinsic rates of growth, carrying capacity, survival rates, fecundity rates etc.

Forcing functions

- Natural or anthropogenic factors that affect the state
- weather impacts on survival or reproduction
- harvesting
- These are “external” to the model -- that is we don’t attempt to describe the dynamics of these factors

Rules of change

- The equations that describe how the state variables change over time in relation to the current values of the state, the parameters, the the forcing functions.
- $S_{t+1} = f(S_t, p, u_t)$

A simple state space model Logistic growth

- Numbers next year are number this year + net production, minus removals
- $N_{t+1}=N_t + rN_t(1-N_t/k)-C_t$
- N is the population size
- r is the intrinsic rate of increase
- k is the carrying capacity
- C is the catch

Quiz #1

- Take a piece of paper
- From this logistic growth model
- 1 - what are the state variable(s)
- 2 - what are the parameter(s)
- 3 - what are the forcing function(s)
- 4 - what are the rules of change

The answer

- The state variable is the population size
- The parameters are the intrinsic rate of increase r, and the carrying capacity k
- The forcing function is the catch
- The rules of change is the equation

Components of rules of change

- Logical relationships
  - statements that are true by definition
  - numbers next year = numbers this year + births - deaths + immigration - emigration
  - also known as tautologies
- Functional relationships
  - specify the relationship between a rate and a state variable or something related to a state variable (survival as a function of density)

For logistic growth model

- A logical relationship
  - number alive next year is number alive this year plus net production minus catch
- The functional relationship
  - net production = $rN_t(1-N_t/k)$

- **STATE PROCESS**
- The primary object of study is a Markov process, X, whose probability law is known, but which **cannot be observed directly**. It serves as a model for the **true state** of the system under study; hence X is called the **state process**. The simulation below shows a real-valued process; in practice X may be high-dimensional, with values in a manifold or metric space.

- **OBSERVATIONS**
- At certain times t[1],t[2],… (perhaps continuously), some function of the state, corrupted by noise, is observed. For example, observations might be of the form
- Yt[n]=h[Xt[n],Vt[n]]
- where h is a continuous function, and Vt[1],Vt[2],… are independent random variables, independent of X.

Structural Equation Modelling (SEM)

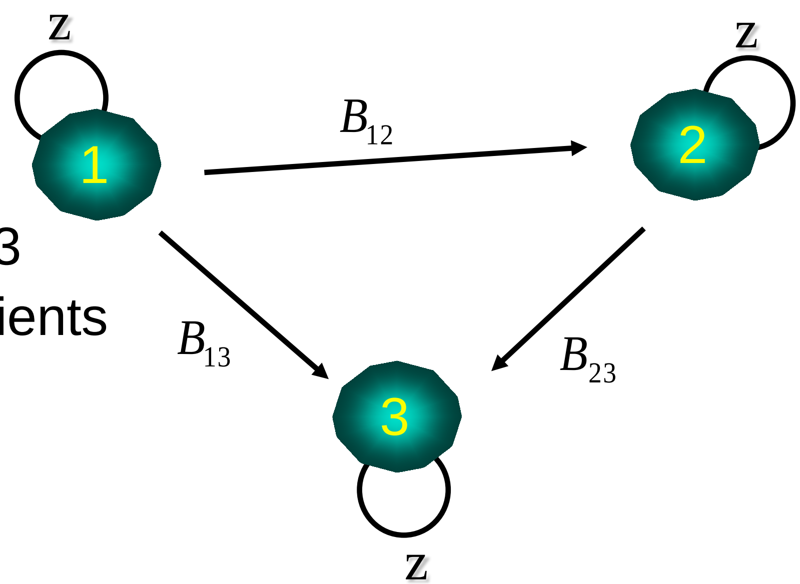
Minimise the difference between the observed (S) and implied (Σ) covariances by adjusting the path coefficients (B)

The implied covariance structure:

$$x = x.B + z$$
$$x = z.(I - B)^{-1}$$

x : matrix of time-series of Regions 1-3

B: matrix of unidirectional path coefficients



Variance-covariance structure:

$$x^T . x = \Sigma = (I-B)^{-T}. C.(I-B)^{-1}$$
$$\text{where } C = z^T z$$

$x^T.x$ is the implied variance covariance structure Σ

C contains the residual variances (u,v,w) and covariances

The free parameters are estimated by minimising a [maximum likelihood]

Modeling Sequential Data

- Sequential data arises in many areas of science & engineering
- Types of data sources:
  - Time series, generated by a dynamical system
  - Sequence generated by one-dimensional spatial process
- On- line analysis vs. Off-line analysis

Classical Solutions

- Classic approaches to time-series prediction
  - Linear models: ARIMA(auto-regressive integrated moving average), ARMAX(autoregressive moving average exogenous variables model)
  - Nonlinear models: neural networks, decision trees
- Problems with classic approaches
  - prediction of the future is based on only a finite window
  - it’s difficult to incorporate prior knowledge
  - difficulties with multi-dimensional inputs and/or outputs

State-Space Models

- Assumptions:
  - There is some underlying hidden state of the world **(query)** that generates the observations **(evidence)**, and evolves in time, possibly as a function of our inputs
  - Models are first-order Markov, i.e.,

$$P(X_t | X_{1:t-1}) = P(X_t \mid X_{t-1})$$

  - observations are conditional first-order Markov

$$P(Y_t \mid X_t, Y_{t-1}) = P(Y_t \mid X_t)$$

  - Time-invariant or homogeneous

- The goal: computing of the belief state:

  The belief on the hidden state of the world given the observations up to the current time $y_{1:t}$ and inputs $u_{1:t}$ to the system, **$P(X \mid yS_{1:t}, u_{1:t})$**

- State-space model must define a prior $P(X_1)$, a state-transition function, $P(X_t \mid X_{t-1})$, and an observation function, $P(Y_t \mid X_t)$

SSM: Representation

Hidden Markov Models (HMMs):

X_t is a discrete random variables

Kalman Filter Models (KFMs):

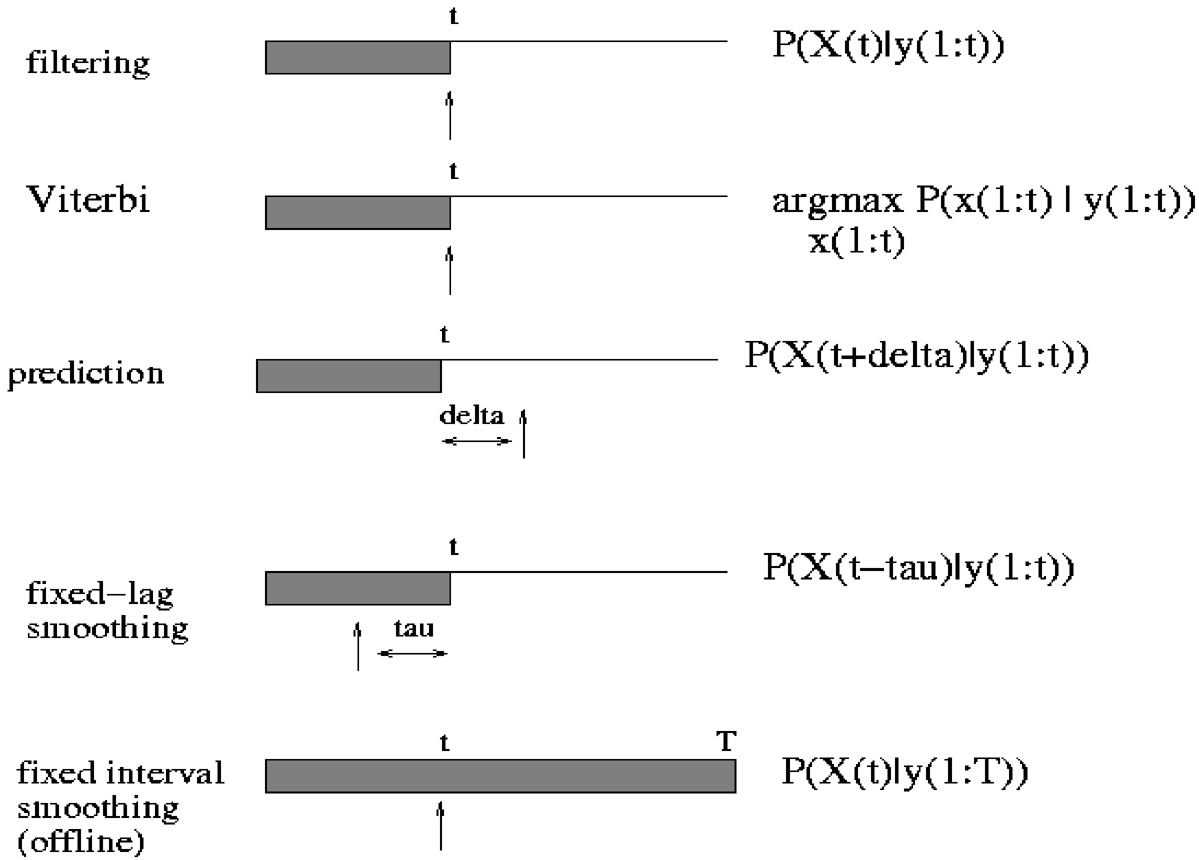
X_t is a vector of continuous random variables

Dynamic Bayesian Networks (DBNs):

more general and expressive language for representing state-space models

SSM: Inference

- A state-space model defines how X_t generates Y_t and $X_{t.}$
- The goal of inference is to infer the hidden states (query) $X_{1:t}$ given the observations (evidence) $Y_{1:t}$.



SSM: Inference (cont.)

- Inference tasks:
  - Filtering (monitoring): recursively estimate the belief state using Bayes' rule
    - prediction: computing $P(X_t \mid y_{1:t-1})$
    - updating: computing $P(X_t \mid y_{1:t})$
    - throw away the old belief state once we have computed the prediction ("rollup")
  - Smoothing: estimate the state of the past, given all the evidence up to the current time
    - Fixed-lag smoothing (hindsight): computing $P(X_{t-l} \mid y_{1:t})$ where $l > 0$ is the lag
    - Fixed-interval smoothing (offline): computing $P(X_t \mid y_{1:T})$ for all $1 \le t \le T$
  - Prediction: predict the future
    - Lookahead: computing $P(X_{t+h} \mid y_{1:t})$ where $h > 0$ is how far we want to look ahead
  - Viterbi decoding: compute the most likely sequence of hidden states given the data
    - MPE (abduction): $x^*_{1:t} = \text{argmax } P(x_{1:t} \mid y_{1:t})$

SSM: Learning

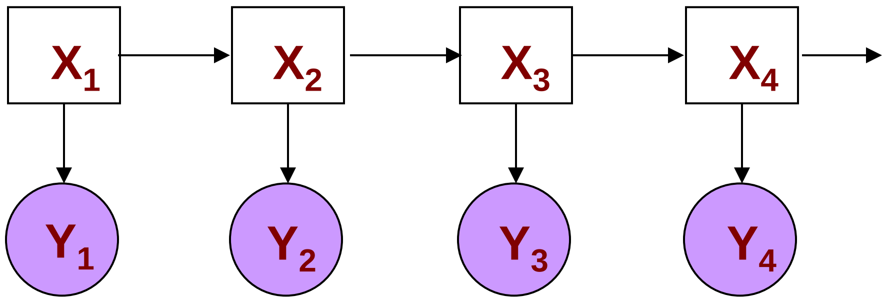
- Parameters learning (system identification) means estimating from data these parameters that are used to define the transition model $P(X_t \mid X_{t-1})$, the observation model $P(Y_t \mid X_t)$ & the prior $P(X_1)$
- The usual criterion is maximum-likelihood(ML)
- The goal of parameter learning is to compute
  - $\theta^*_{ML} = \arg\max_\theta P(Y \mid \theta) = \arg\max_\theta \log P(Y \mid \theta)$, where

$$\log P(Y \mid \theta) = \log \prod_{m=1}^{N_{train}} P(y_{1:T}^m \mid \theta) = \sum_{m=1}^{N_{train}} \log P(y_{1:T}^m \mid \theta)$$

  - Or $\theta^*_{MAP} = \arg\max_\theta \log P(Y \mid \theta) + \log P(\theta)$ if we include a prior on the parameters
  - Two standard approaches: gradient ascent and EM(Expectation Maximization)

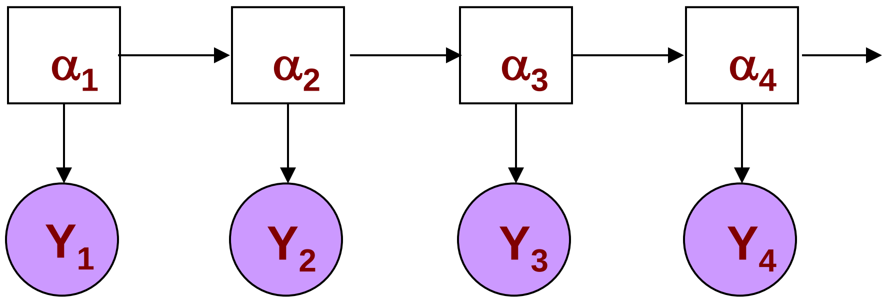
- Problem: Hidden variables complicate finding of the globally optimal parameters
- Structure learning: more ambitious

HMM: Hidden Markov Model



- one discrete hidden node and one discrete or continuous observed node per time slice.
- X: hidden variables
- Y: observations
- Structures and parameters remain same over time
- Three parameters in a HMM:
  - The initial state distribution $P(X_1)$
  - The transition model $P(X_t \mid X_{t-1})$
  - The observation model $P(Y_t \mid X_t)$

HMM: Hidden Markov Model



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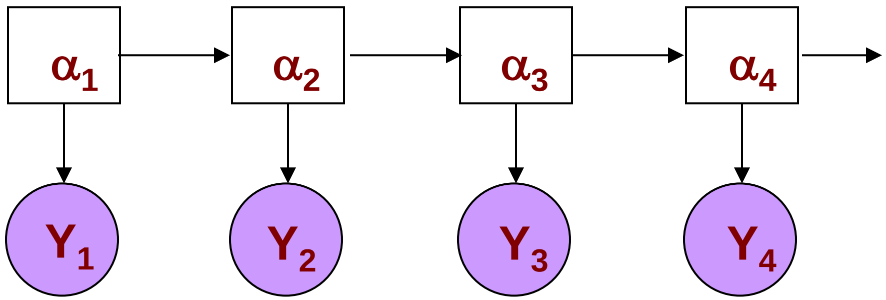
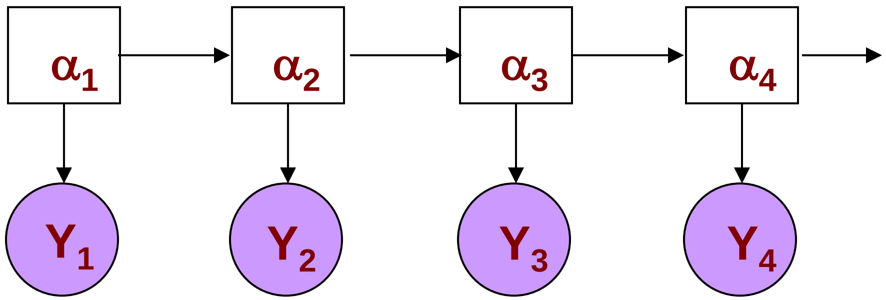
- Structures and parameters remain same over time
- Three parameters in a HMM:
  - The initial state distribution $P(X_1)$
  - The transition model $P(X_t \mid X_{t-1})$
  - The observation model $P(Y_t \mid X_t)$
- HMM is the simplest DBN
  - a discrete state variable with arbitrary dynamics and arbitrary measurements

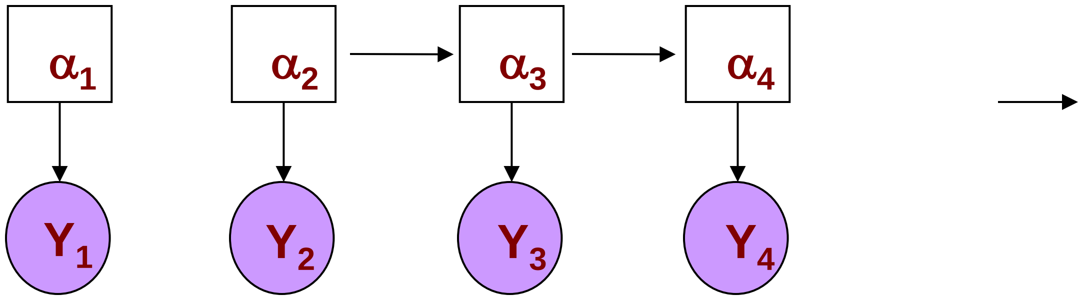
Special Case of State-space Models: Hidden Markov Model



- one **discrete** hidden node and one discrete or continuous observed node per time slice.
- α: hidden variables
- Y: observations
- Structures and parameters remain same over time
- Three parameters in a HMM:
  - The initial state distribution $P(\alpha_1)$
  - The transition model $P(\alpha_t \mid \alpha_{t-1})$
  - The observation model $P(Y_t \mid \alpha_t)$

HMM: Hidden Markov Model





KFM: Kalman Filter Model

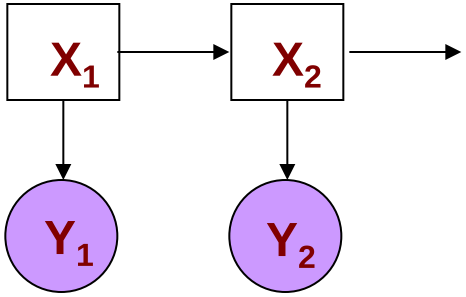
- KFM has the same topology as an HMM
- all the nodes are assumed to have linear-Gaussian distributions

x(t+1) = A*x(t) + v(t),

v ~ N(0, Q) : process noise, x(0) ~ N(X(0), V(0))

y(t) = C*x(t) + w(t),

w ~ N(0, R) : measurement noise



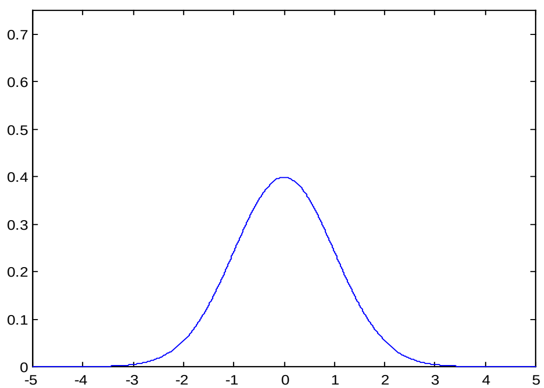
- Also known as Linear Dynamic Systems (LDSs)
  - a partially observed stochastic process
  - with linear dynamics and linear observations: f(a + b) = f(a) + f(b)
  - both subject to Gaussian noise
- KFM is the simplest continuous DBN
  - a continuous state variable with linear-Gaussian dynamics and measurements

All Roads Lead From Gauss 1809

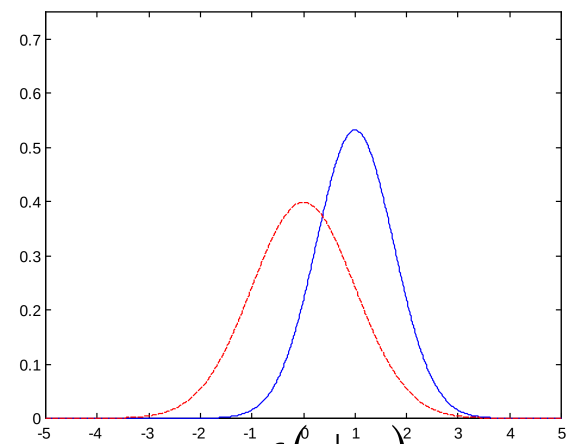
- “ … since all our measurements and observations are nothing more
- than approximations to the truth, the same must be true of all
- calculations resting upon them, and the highest aim of all
- computations made concerning concrete phenomenon must be to
- approximate, as nearly as practicable, to the truth. But this can be
- accomplished in no other way than by suitable combination of more
- observations than the number absolutely requisite for the determination of
- the unknown quantities. This problem can only be properly undertaken
- when an approximate knowledge of the orbit has been already attained,
- which is afterwards to be corrected so as to satisfy all the observations
- in the most accurate manner possible.”
-
- \- From Theory of the Motion of the Heavenly Bodies Moving about the Sun in Conic Sections, Gauss, 1809
-

What does a Kalman filter do ?

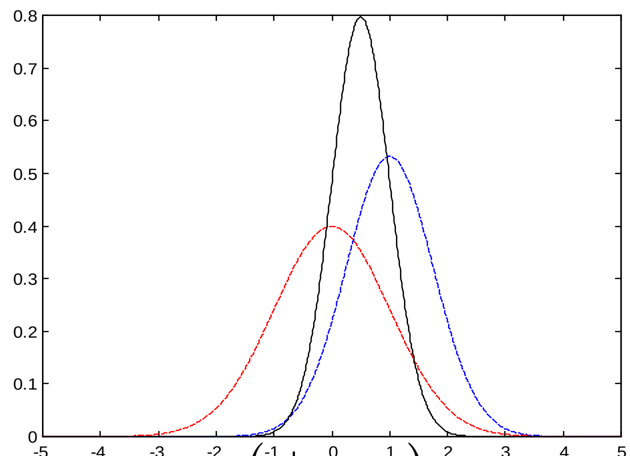
- The Kalman filter propagates the conditional density in time.



$$f\left(y \middle| x_1\right)$$



$$f\left(y \middle| x_2\right)$$



$$f\left(y \middle| x_1, x_2\right)$$

How does it do it ?

- The Kalman filter iterates between two steps
  - Time Update (Predict)
    - Project current state and covariance forward to the next time step, that is, compute the next a priori estimates.
  - Measurement Update (Correct)
    - Update the a priori quantities using noisy measurements, that is, compute the a posteriori estimates.

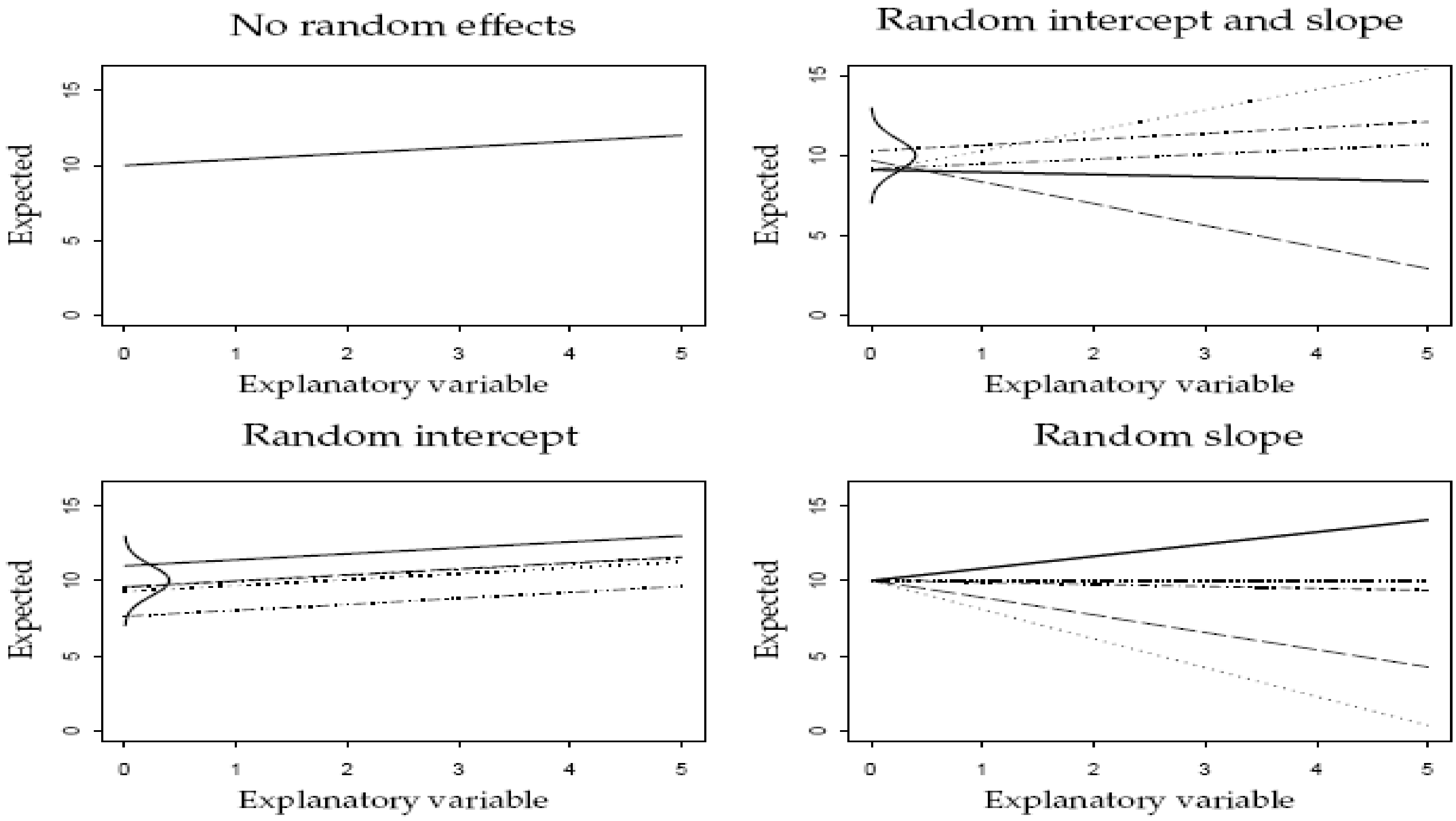
$$\hat{y}_k = \hat{y}_k^- + K_k\left(x_k - M_k \hat{x}_k^-\right)$$

- Choose K_k to minimize error covariance

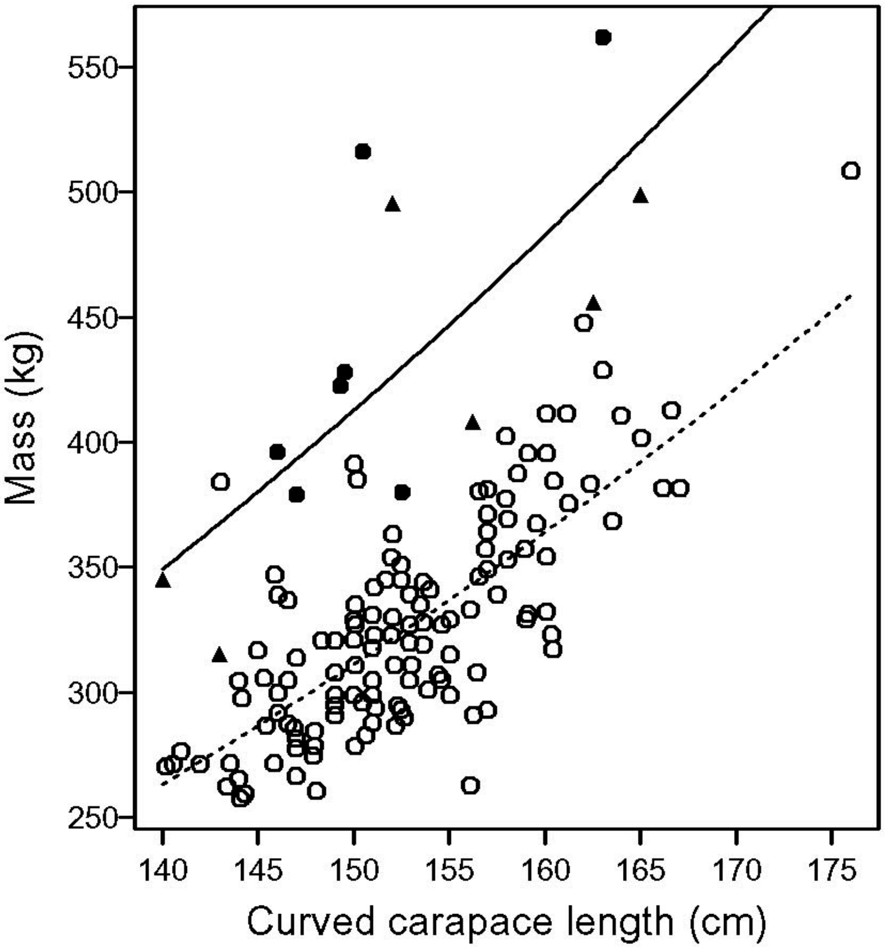
You can ask questions and think about questions you can not otherwise.

- Circle of confusion
- Turtle speed at night
- Are there modes, or “behavioural states” in their behaviour.

Random Effect Model



Weights in Canadian waters



Turtles are 33% heavier in Canadian coastal areas versus on the nesting beach

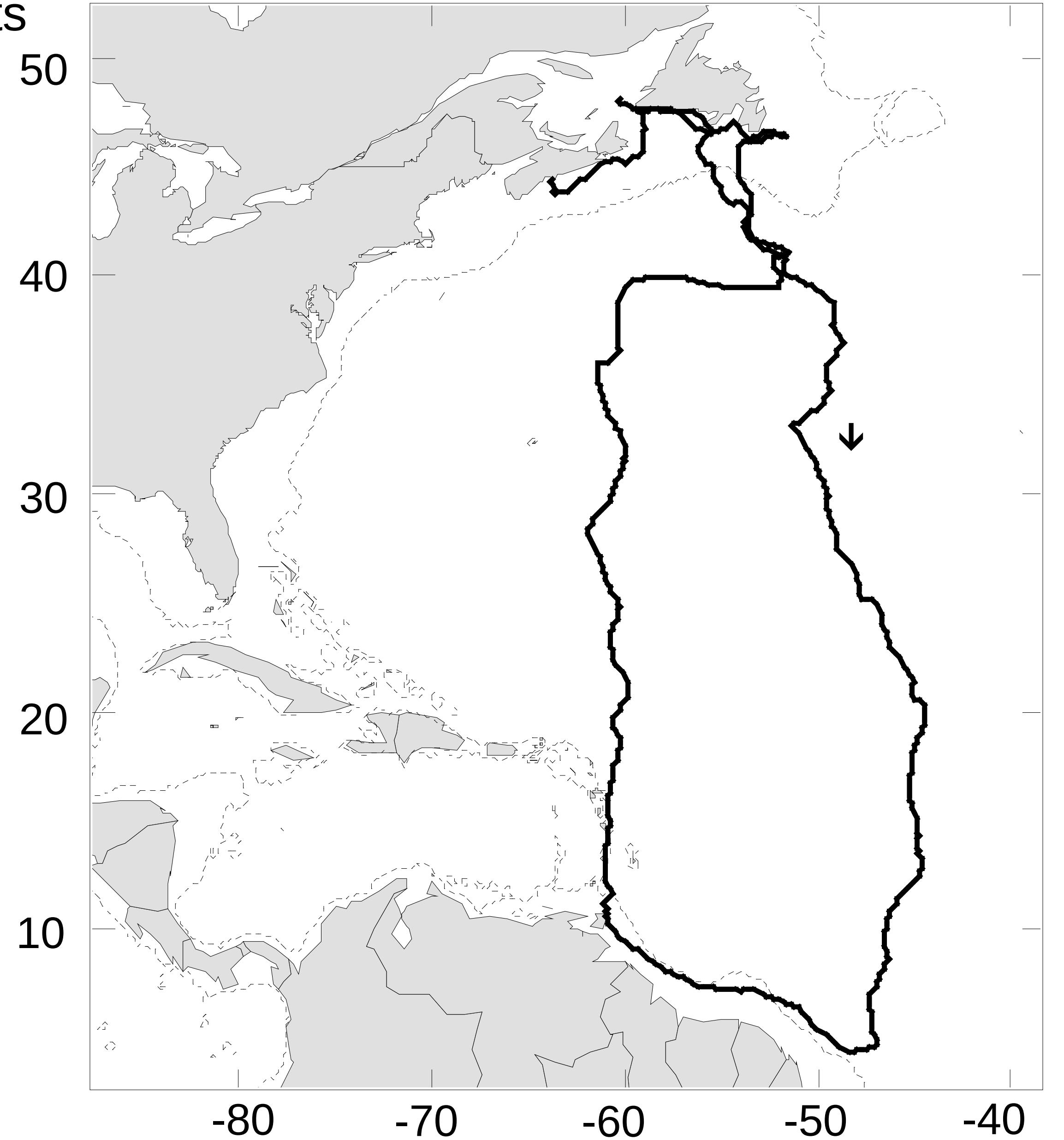
Nesting female morphometrics: St. Croix, U.S.V.I.
Boulon et al. 1996. Chelonian Conserv, Biol. 2:141-147.
Lines fit by constant slope analysis of covariance after log transformation.

Male leatherback movements

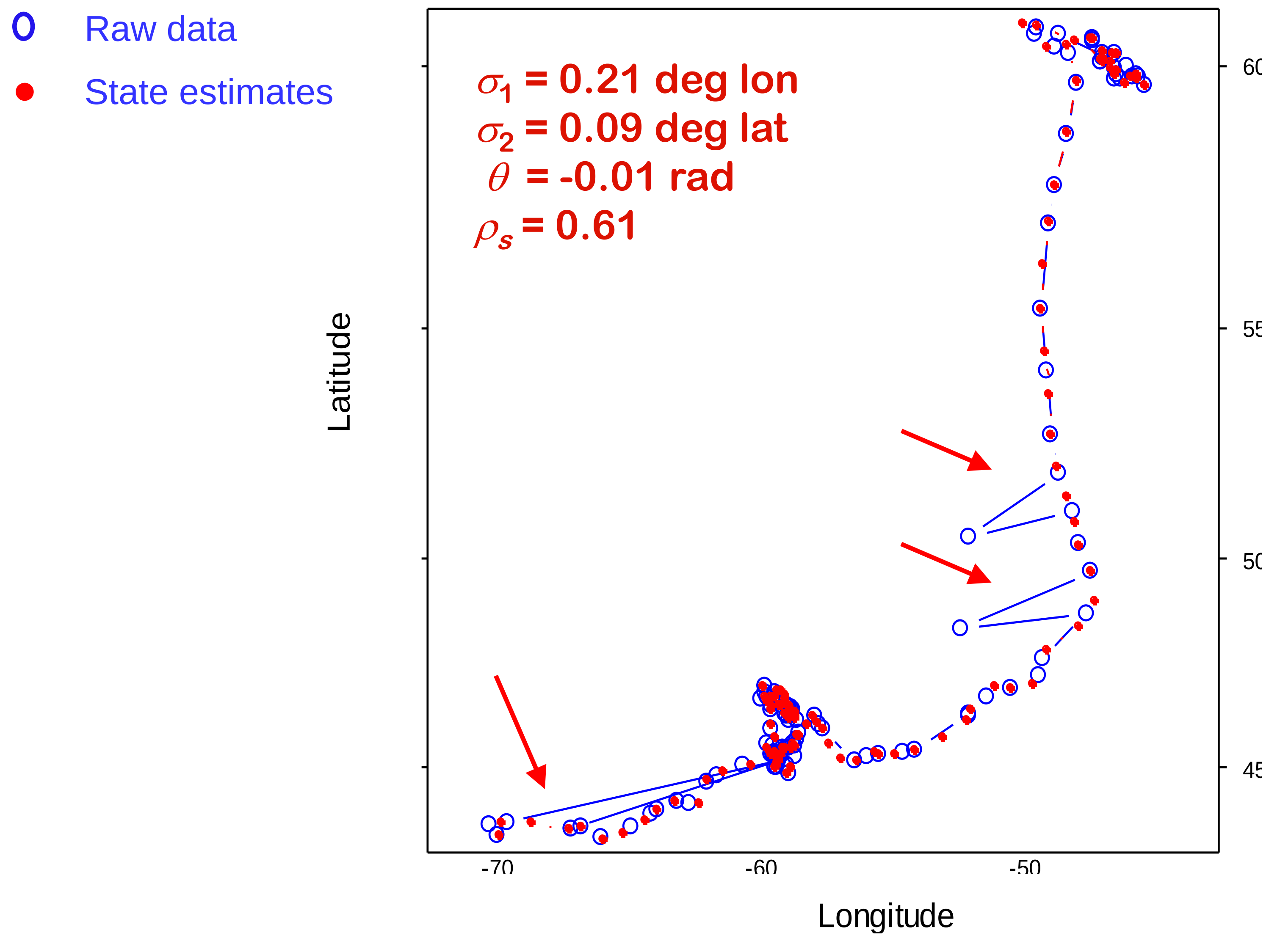
- not previously described

- annual migratory cycle that includes movement between temperate foraging areas and tropical breeding areas

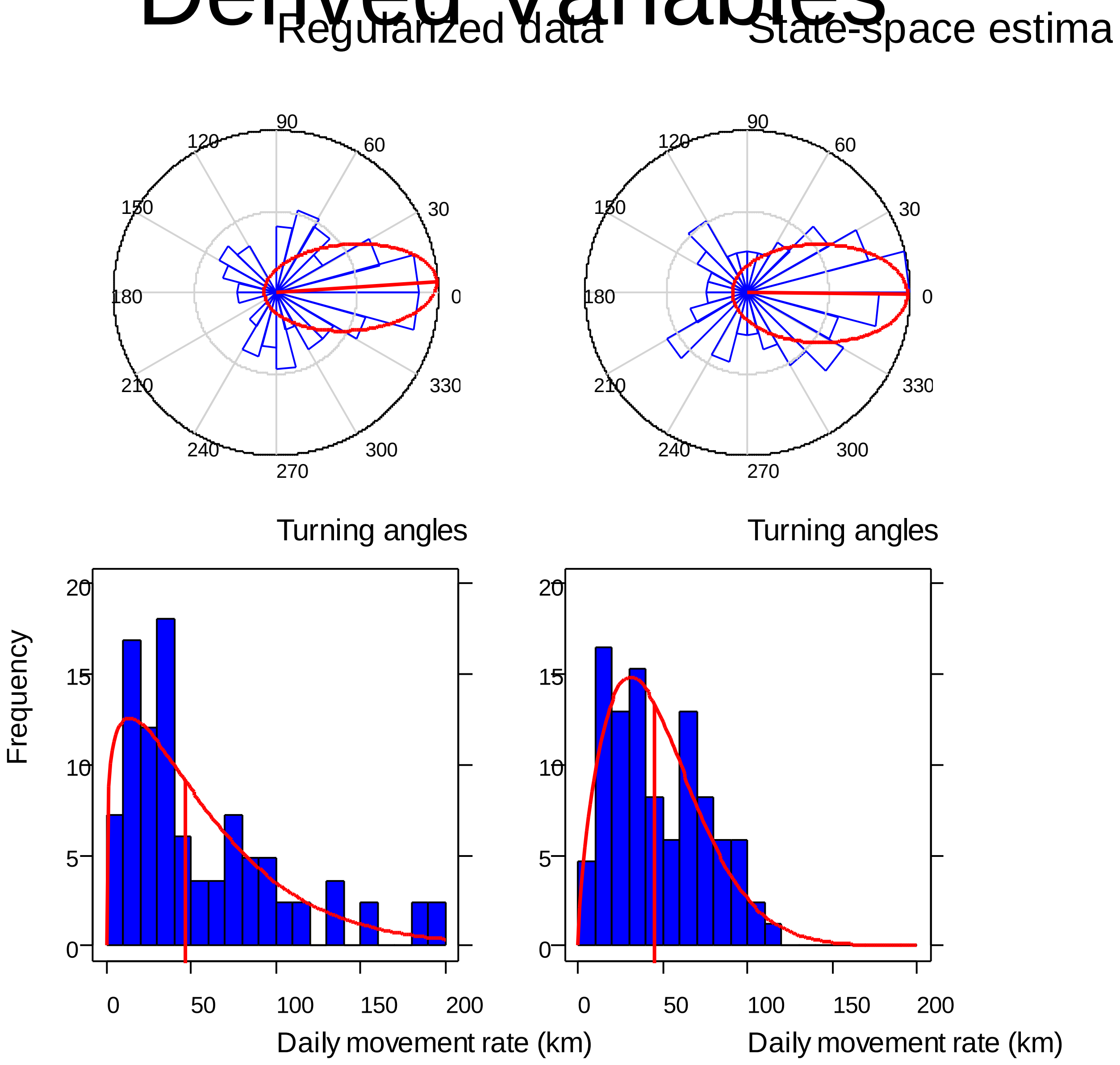
James, Eckert and Myers
Marine Biology (*in press*)

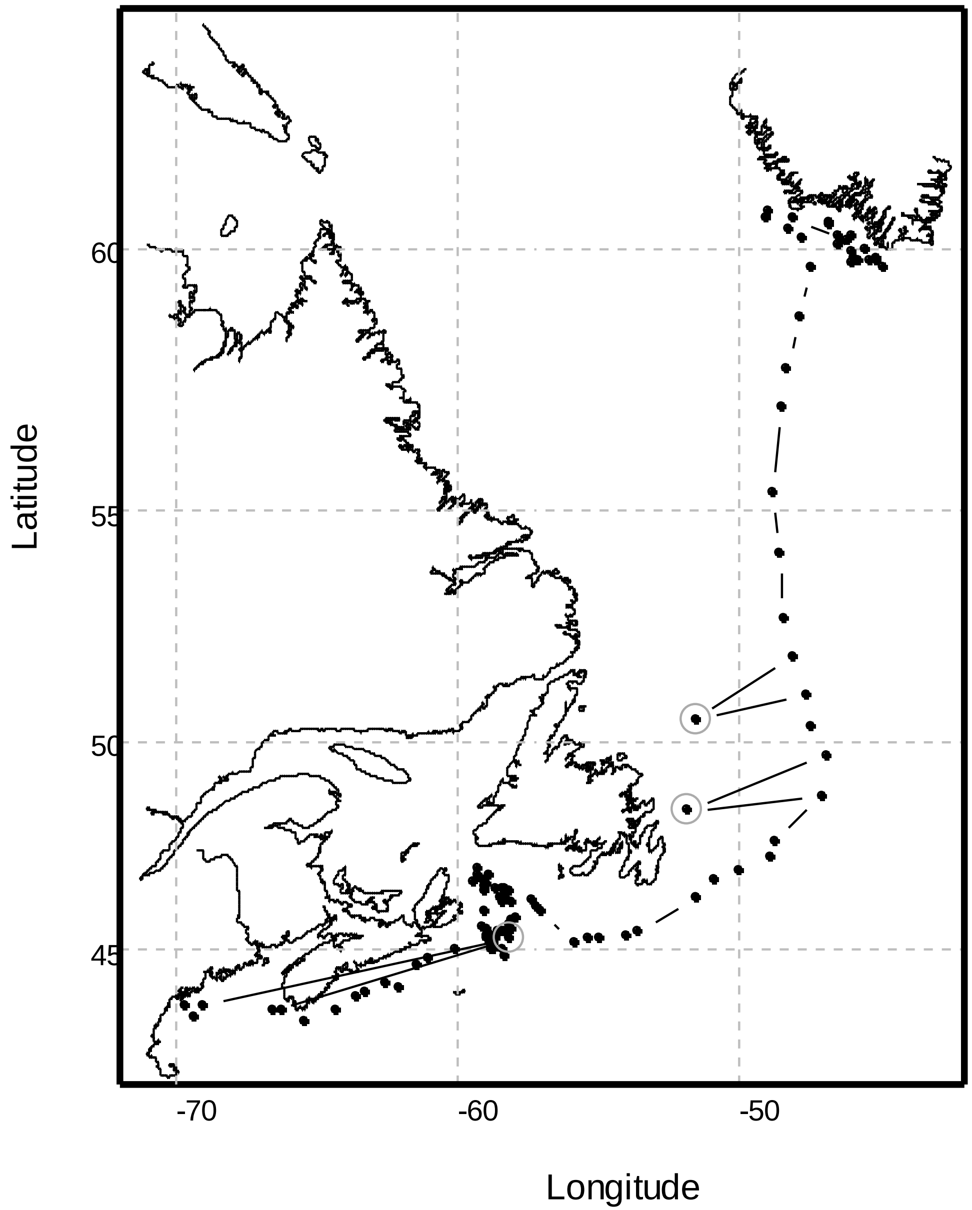


Filtered Data



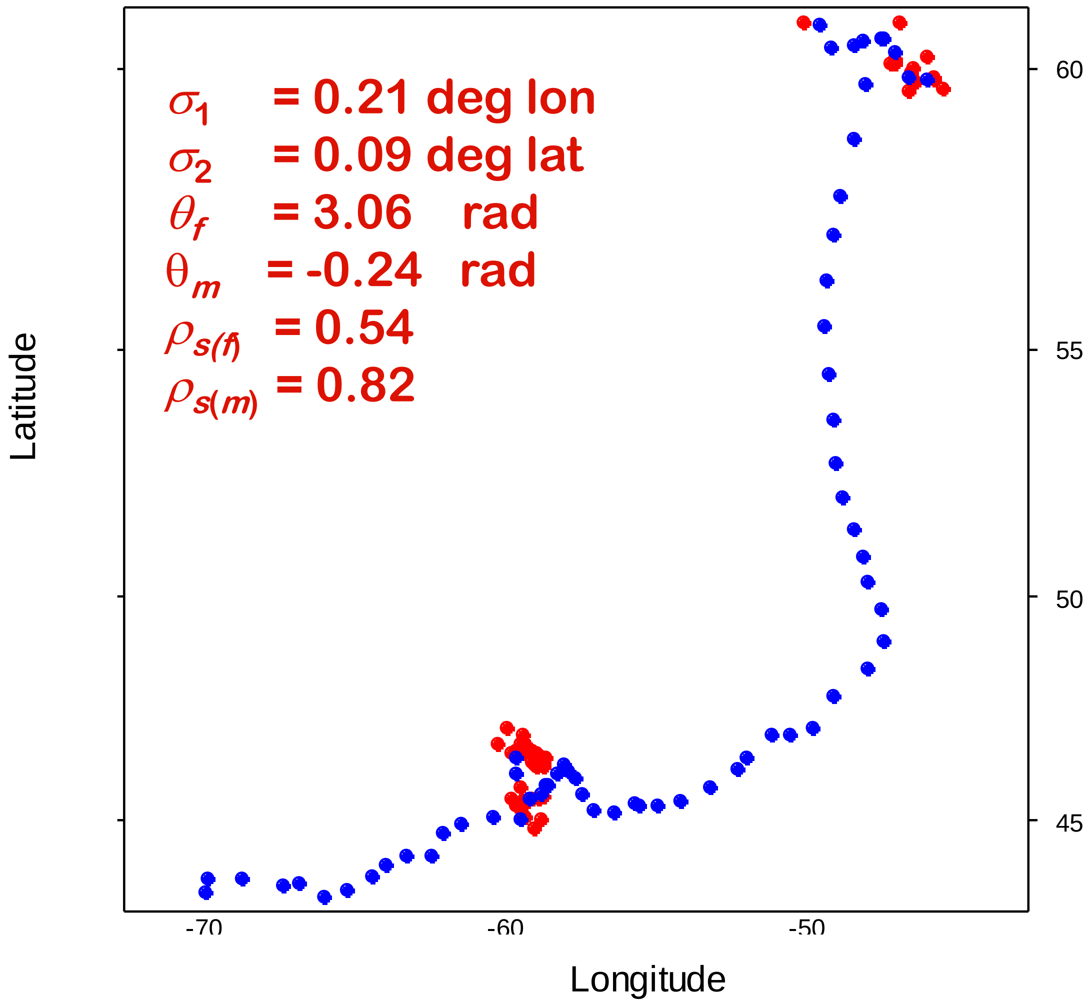
Derived Variables

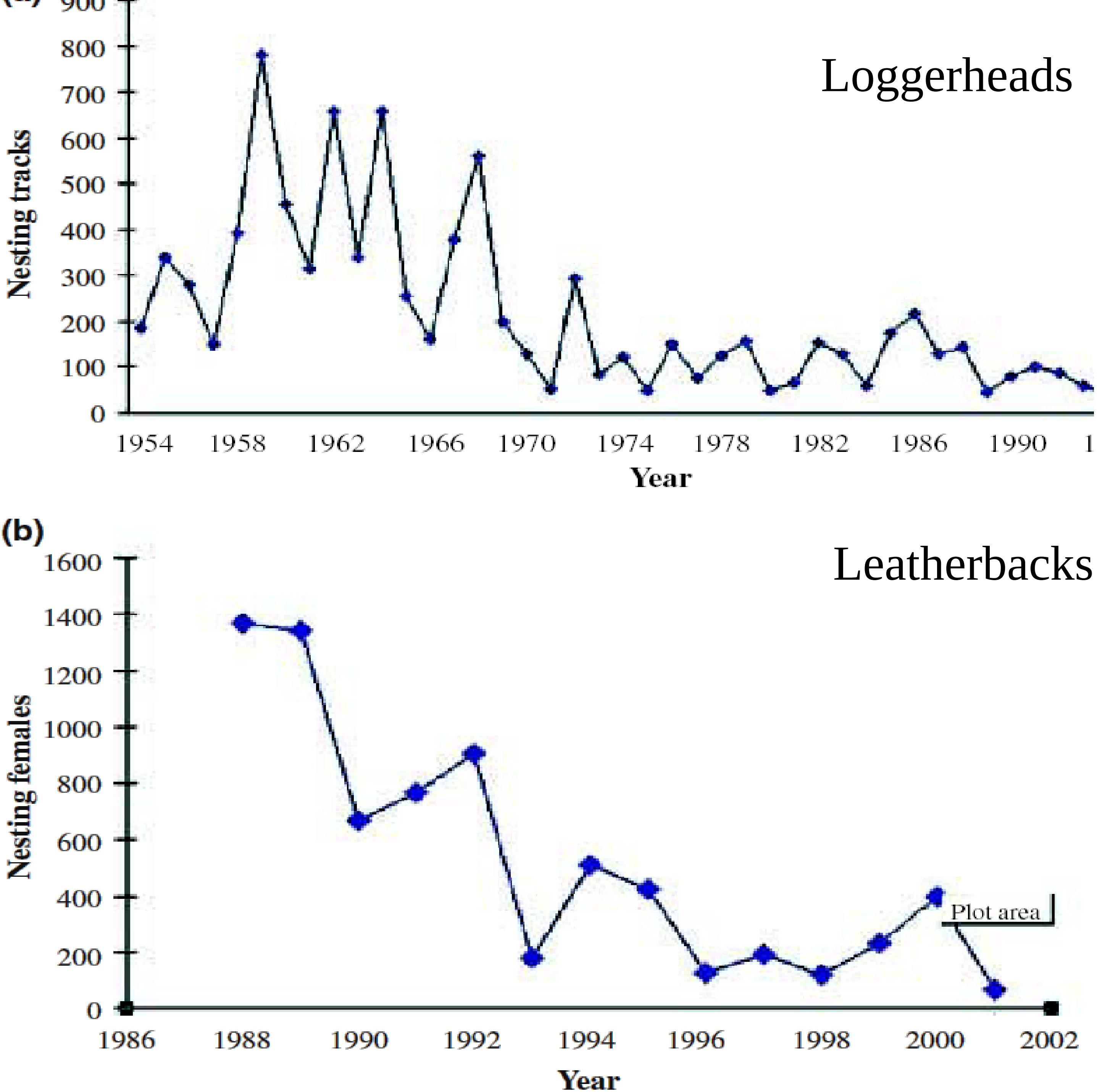



Latitude
60
55
50
45
-70
-60
-50
Longitude

A Switching SSM

Switching model, estimates switches b/w 2 behavioural states

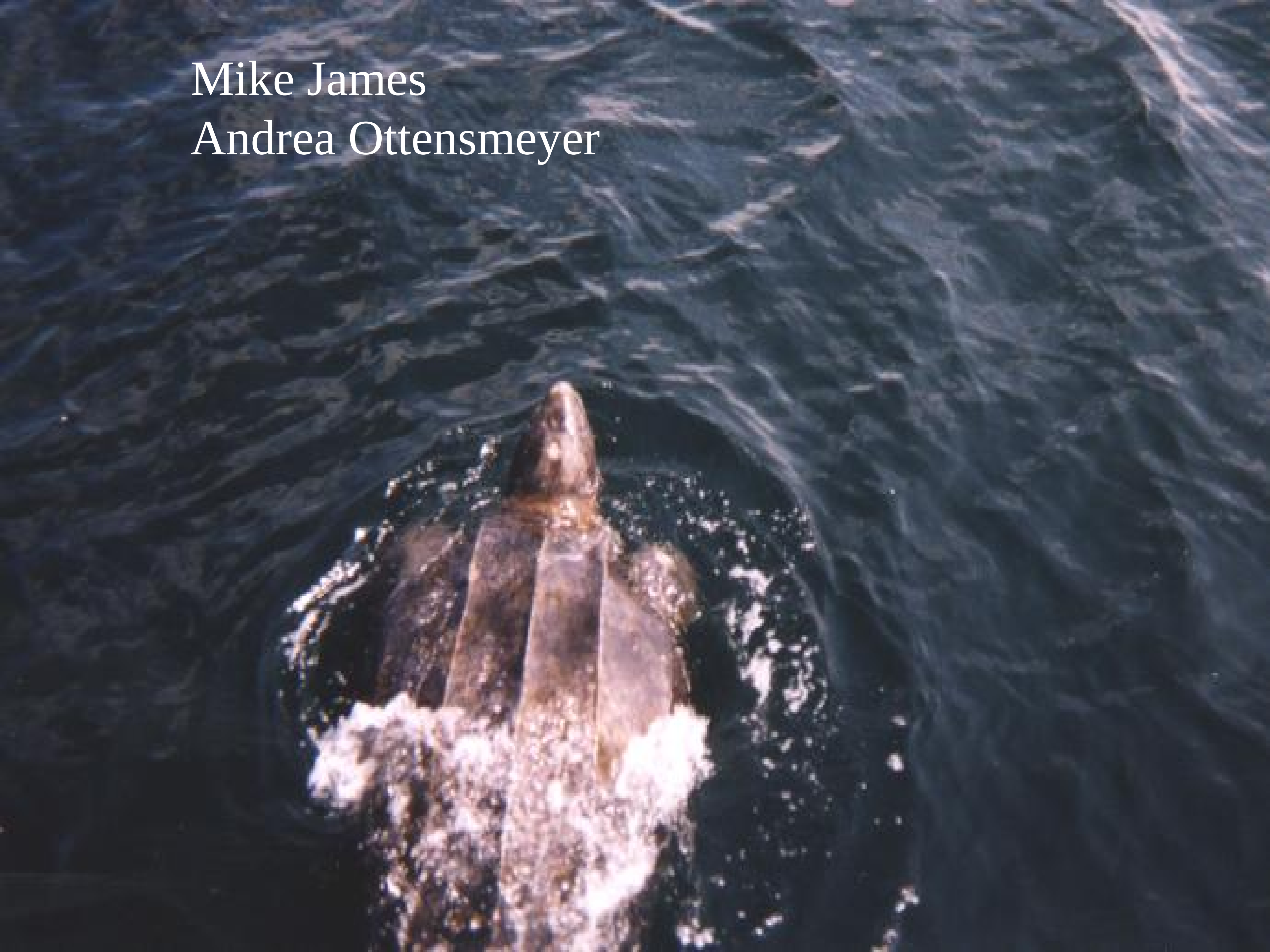




Lewison et al. 2004
Ecology Letters

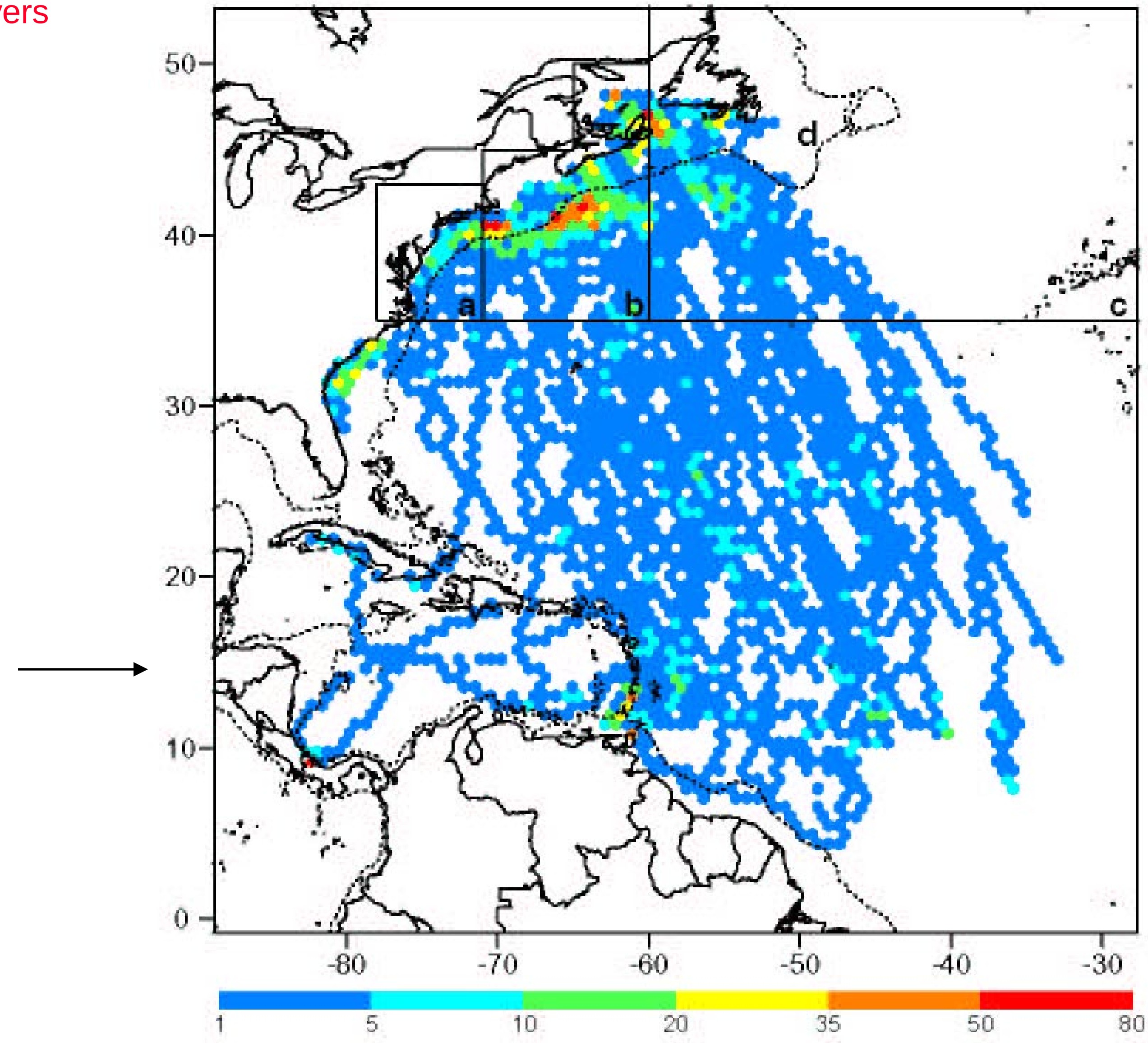
Photo by Matthew Godfrey

Swordfishing fleet at anchor, Neils Harbour, Cape Breton. 13.

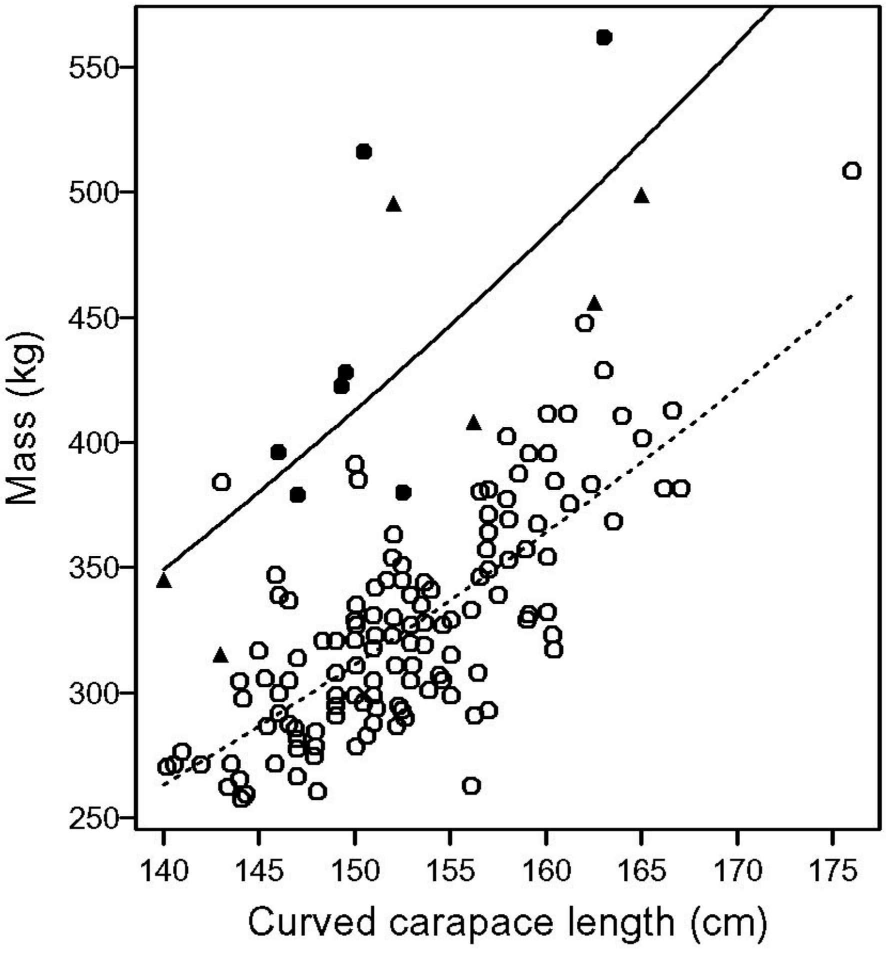

Mike James
Andrea Ottensmeyer

Identification of high-use areas and threats to leatherback sea turtles in northern waters

James, Ottensmeyer and Myers
Ecology Letters (2005)



Weights in Canadian waters



Turtles are
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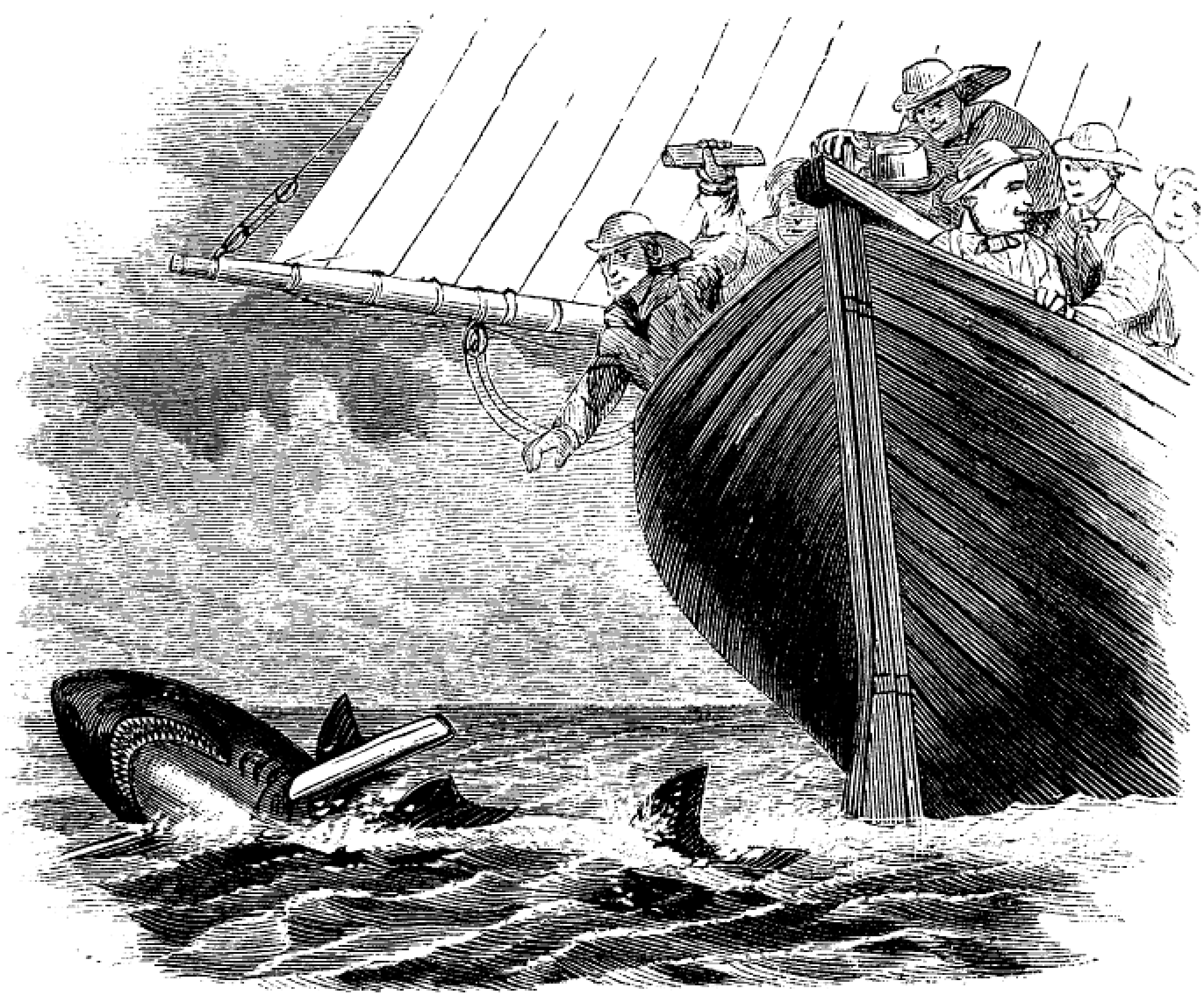
Lines fit by constant slope analysis of covariance after log transformation.

tience as some line got fouled in the rapid hauling, or an obstreperous fellow in the depths below made off with the best part of a valuable line. To an unsophisticated observer our crew,

Fish, like women, are a very uncertain institution, and their tastes are equally unaccountable. When you least expect it, off they sail and leave you in the lurch when the prize is almost within your grasp; at least such has proved my sailor's experience with them. Thus it was that, while we were merrily hauling up the denizens of Whale Deep, the supply suddenly gave out—either our bait had cloyed on their palates, or, what is quite as likely, they began to smell a submarine rat, and regarded the sudden upward movement of their companions with well-grounded suspicion. As if by simultaneous agreement they suddenly ceased to bite, and after wooing them in vain for a couple of days, we resolved to weigh and head for the northward.

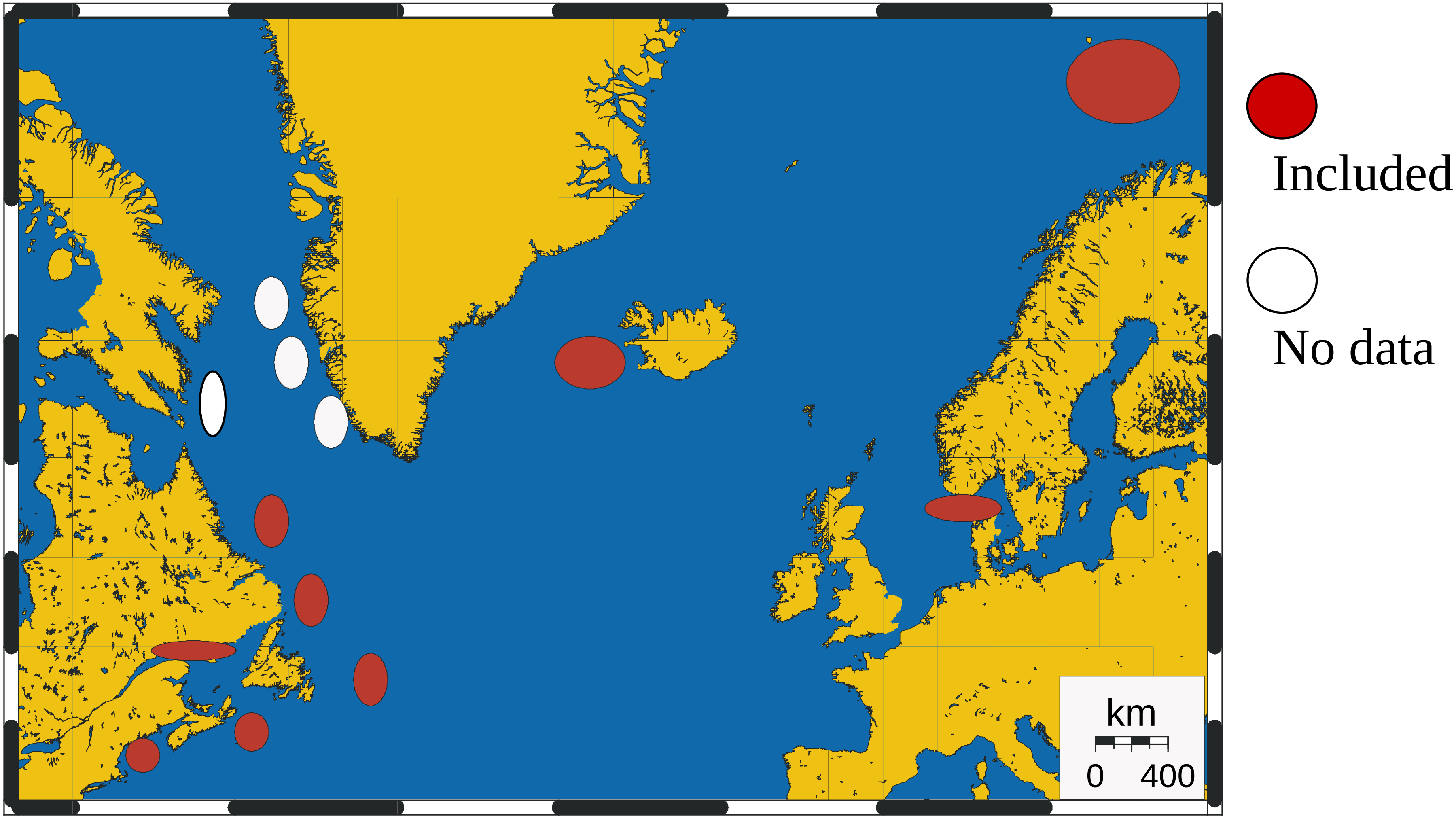


GAFFING A SHARK.

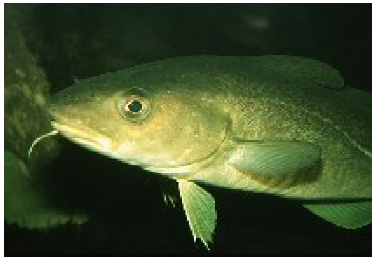
Questions?

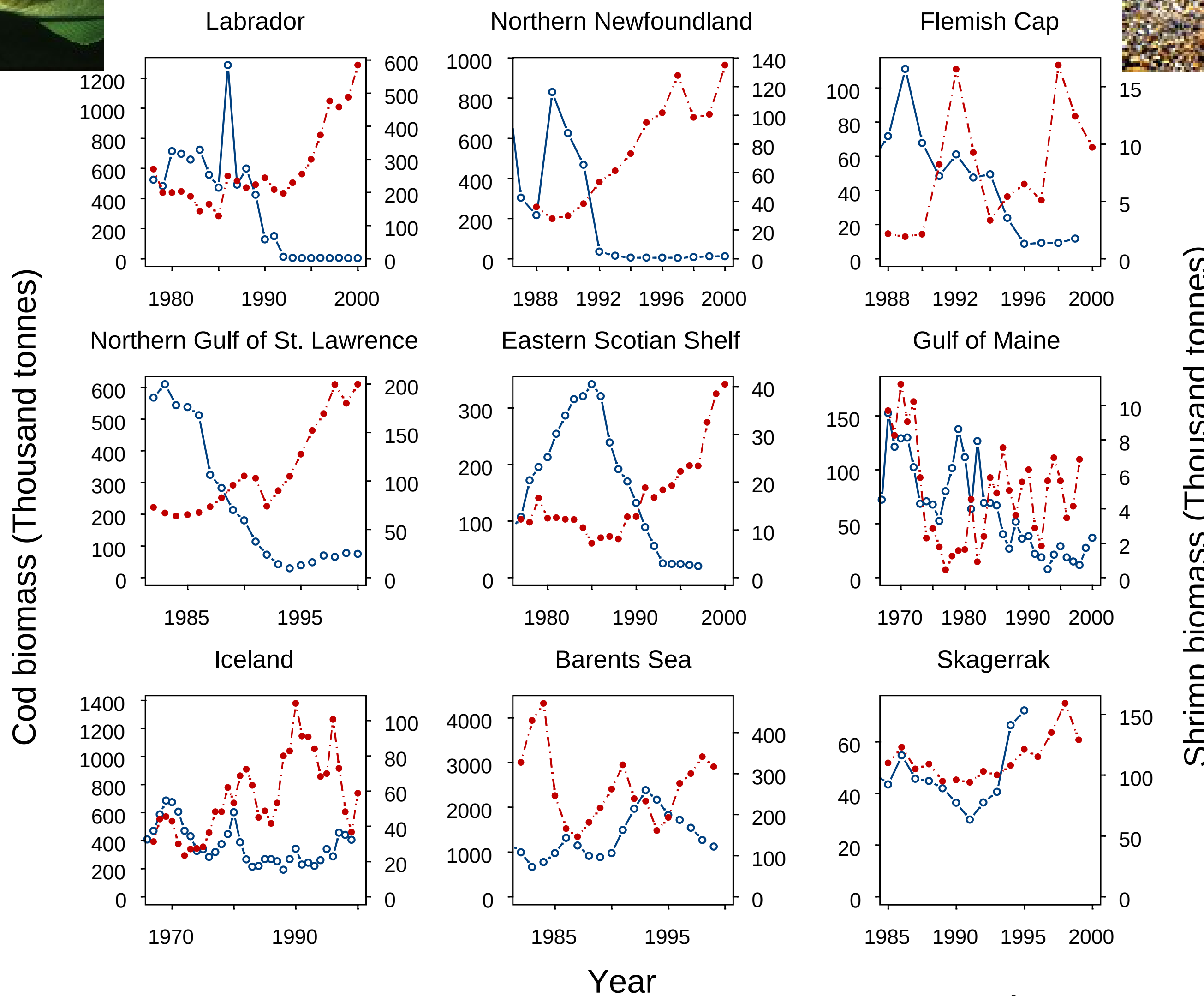
- What are the fundamental changes in a community that occur after the apex predators are removed?
- Have lower trophic levels responded?
- How can we carry our a meta-analysis in different communities that may not be independent?

Major shrimp stocks in the North Atlantic



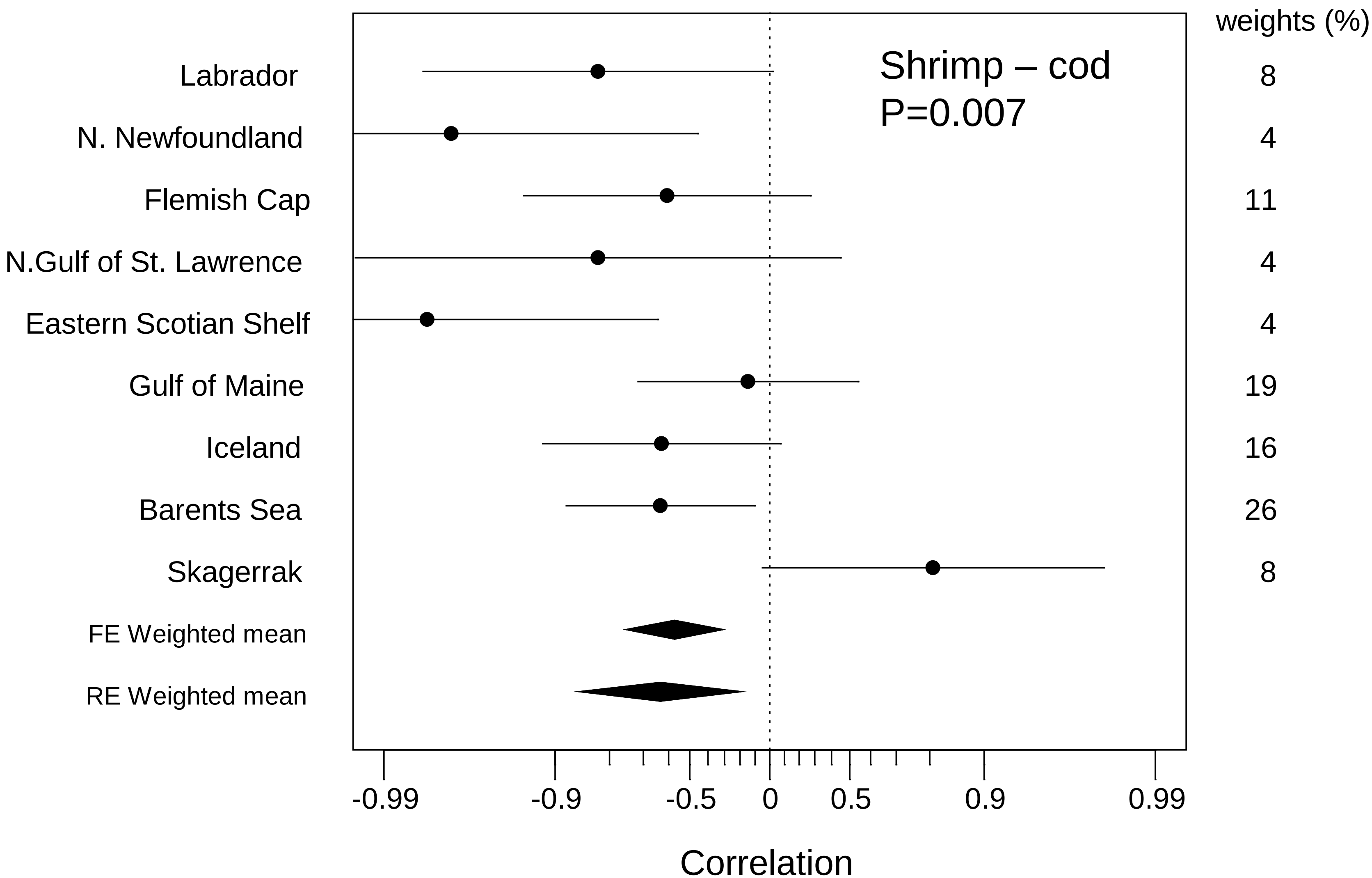
Cod and shrimp biomass in the North Atlantic: time series



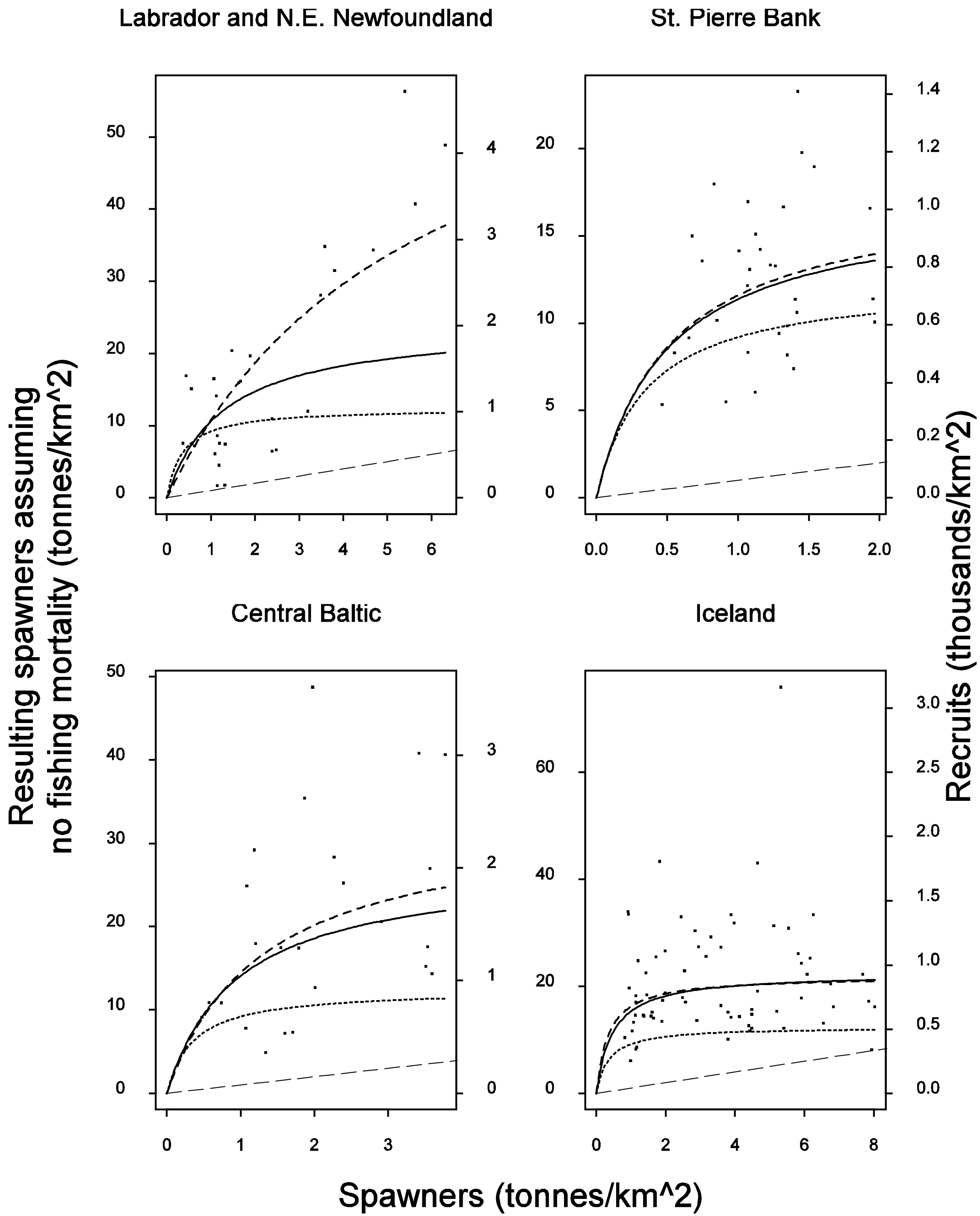


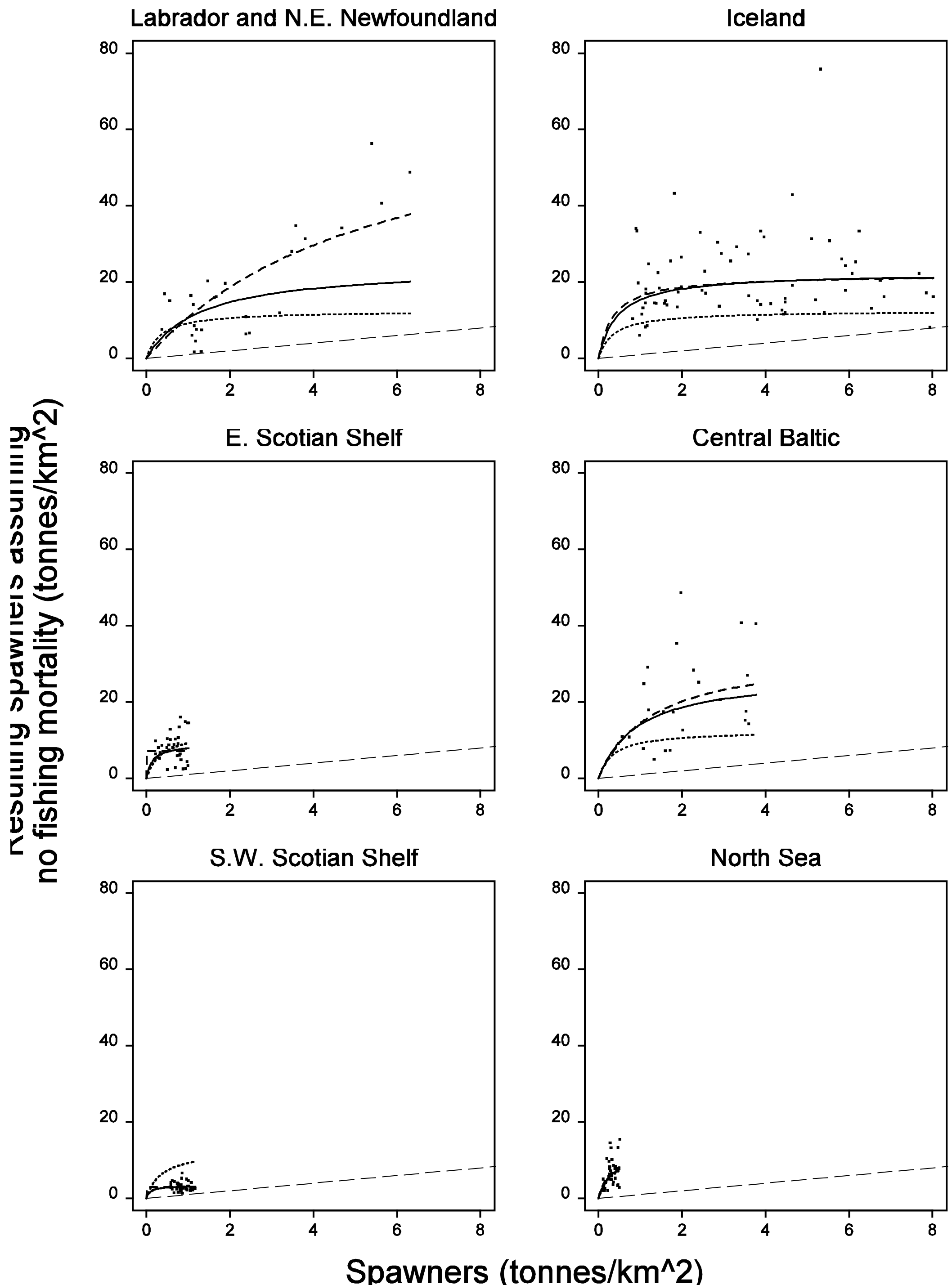
Worm and Myers, Ecology 2003

Step 2: Random-effects meta-analysis

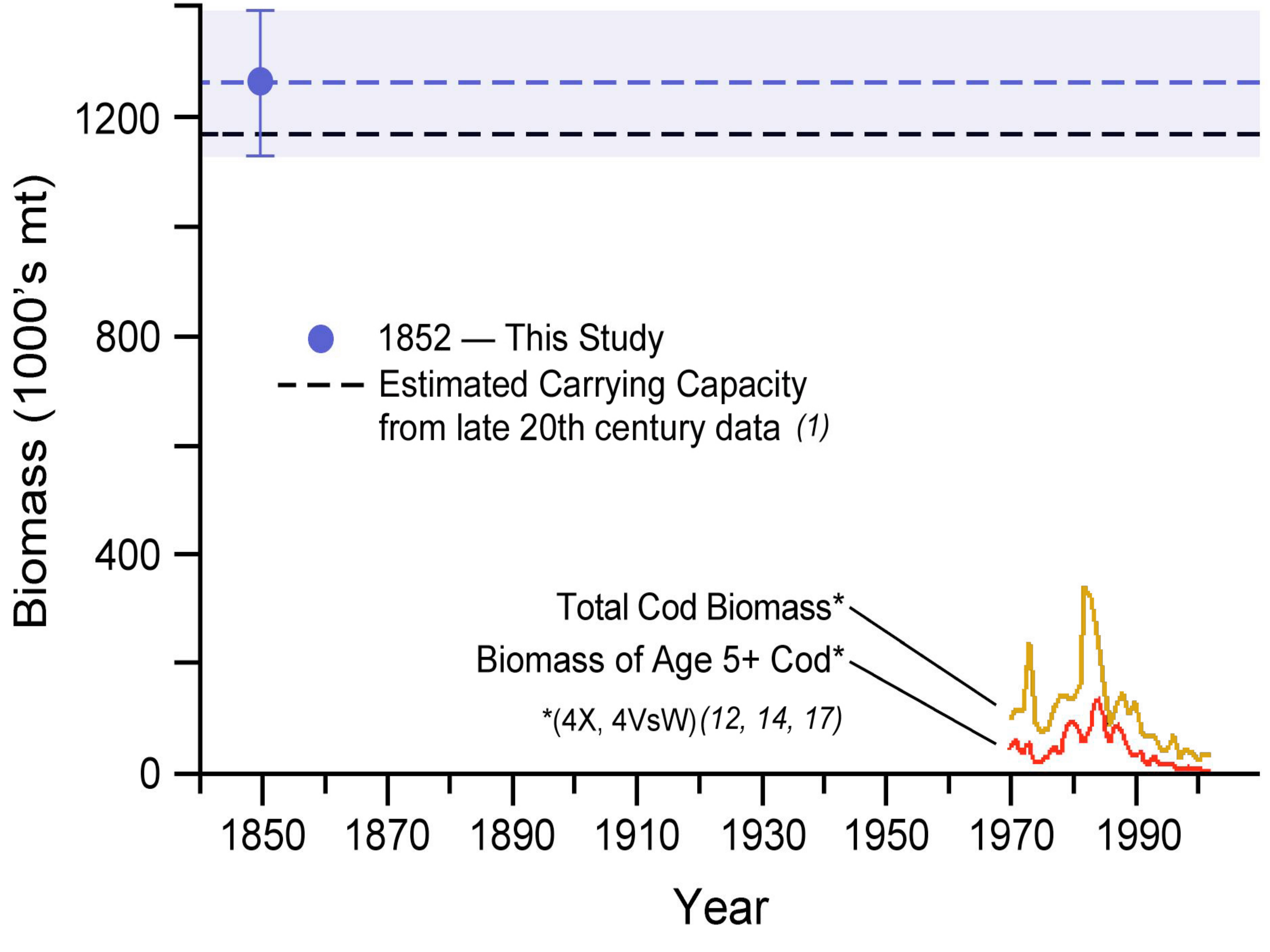



788
757
525
650
620
770

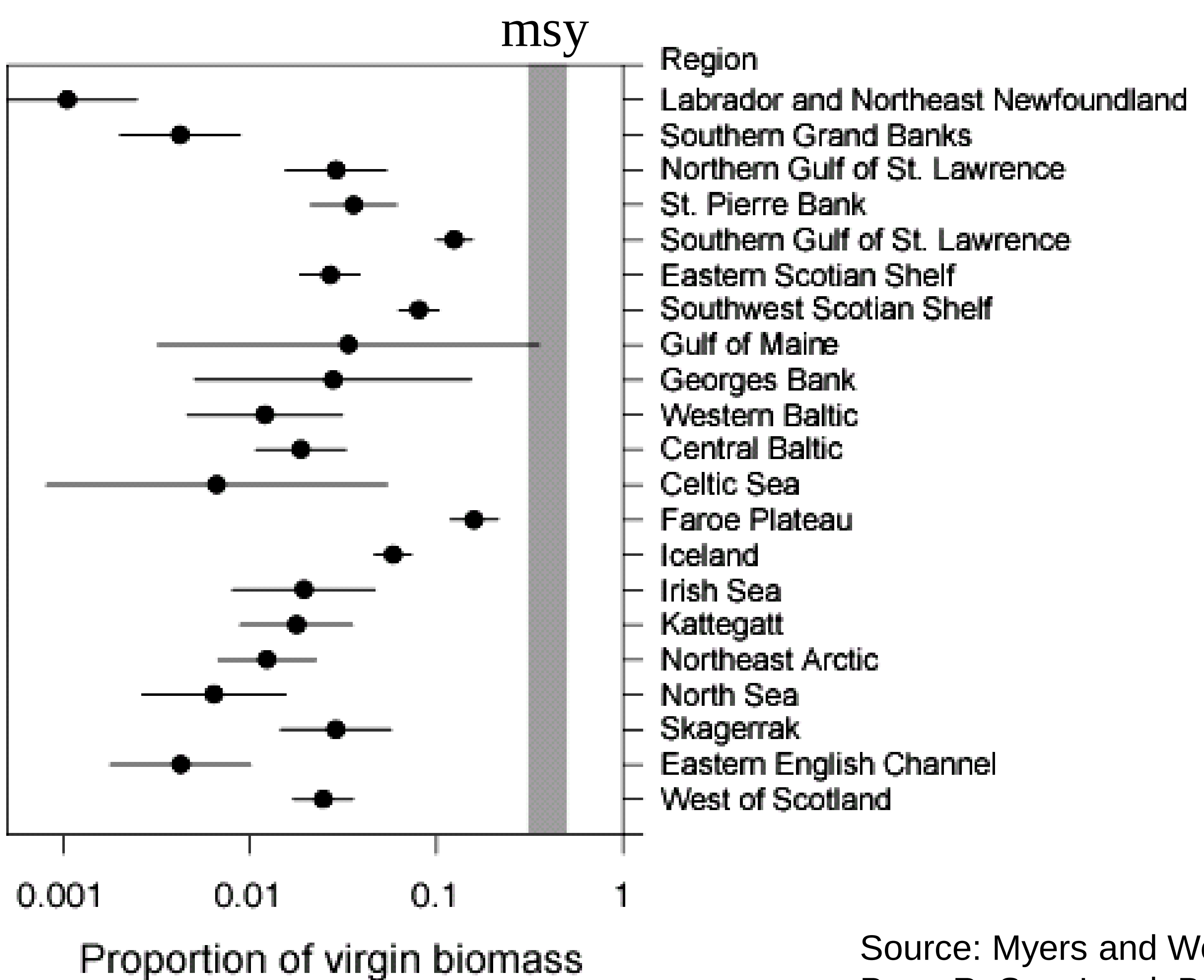

Labrador and N.E. Newfoundland
St. Pierre Bank
Central Baltic
Iceland
Resulting spawners assuming
no fishing mortality (tonnes/km^2)
Recruits (thousands/km^2)
Spawners (tonnes/km^2)



Labrador and N.E. Newfoundland
Iceland
E. Scotian Shelf
Central Baltic
S.W. Scotian Shelf
North Sea
Resulting spawners assuming no fishing mortality (tonnes/km^2)
Spawners (tonnes/km^2)

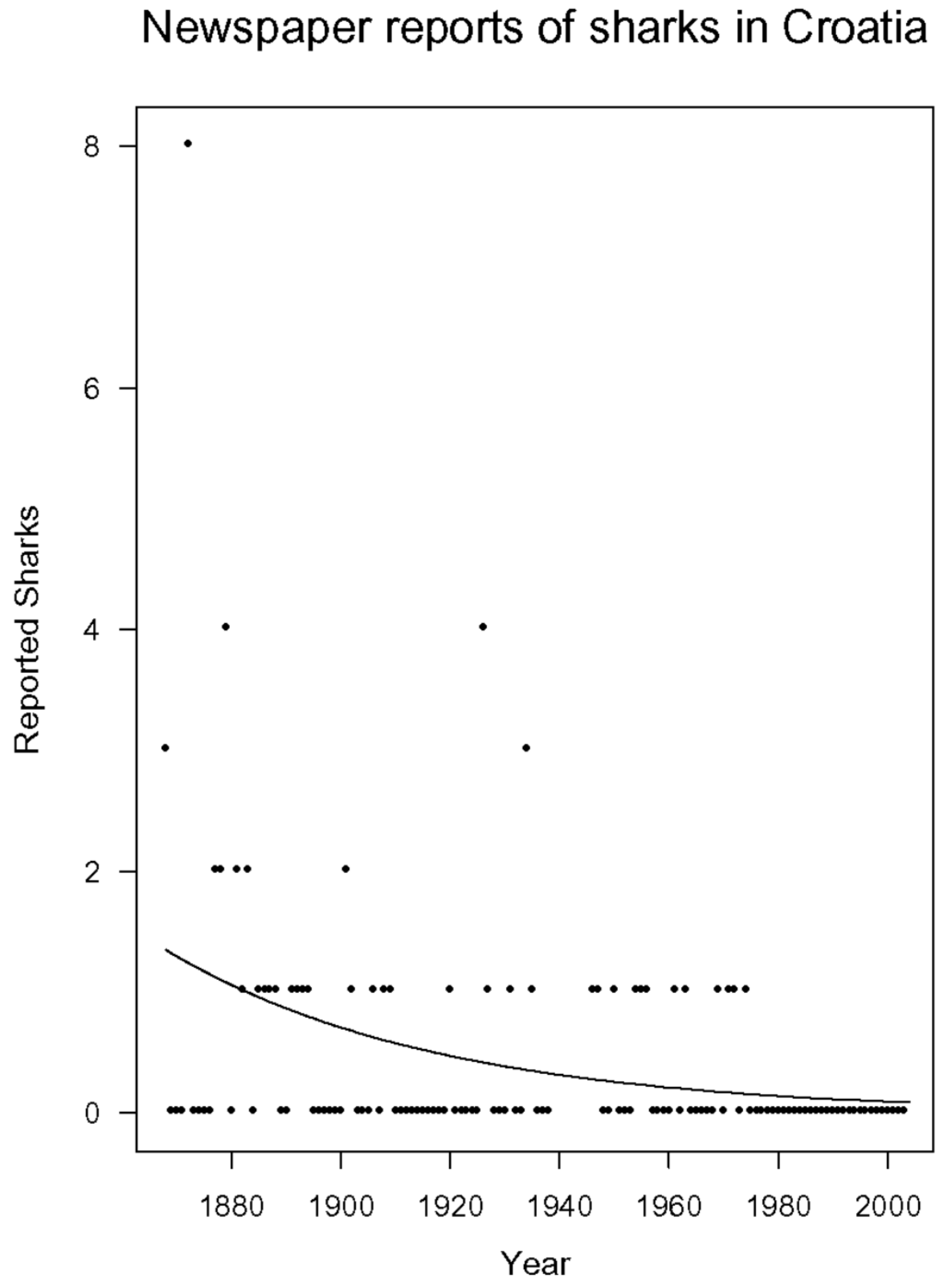

1200
800
400
0
Biomass (1000's mt)
1852 — This Study
Estimated Carrying Capacity
from late 20th century data (1)
Total Cod Biomass*
Biomass of Age 5+ Cod*
*(4X, 4VsW) (12, 14, 17)
1850
1870
1890
1910
1930
1950
1970
1990
Year

There is much less than 10% of cod left -



Source: Myers and Worm 2005.
Proc. R. Soc. Lond. B

Fitting a simple model to crazy data can yield reliable, and very powerful conclusions



With training, “experts” can ignore the most obvious of data:

1872 - Man's head and leg and dolphin in stomach

1872 – 8 Great White Sharks reported caught

1888 - Woman's body and lamb in stomach

1894 - Preserved at Zagreb Nat. Hist. Mus.

1926 - Woman's shoes, laundry in stomach

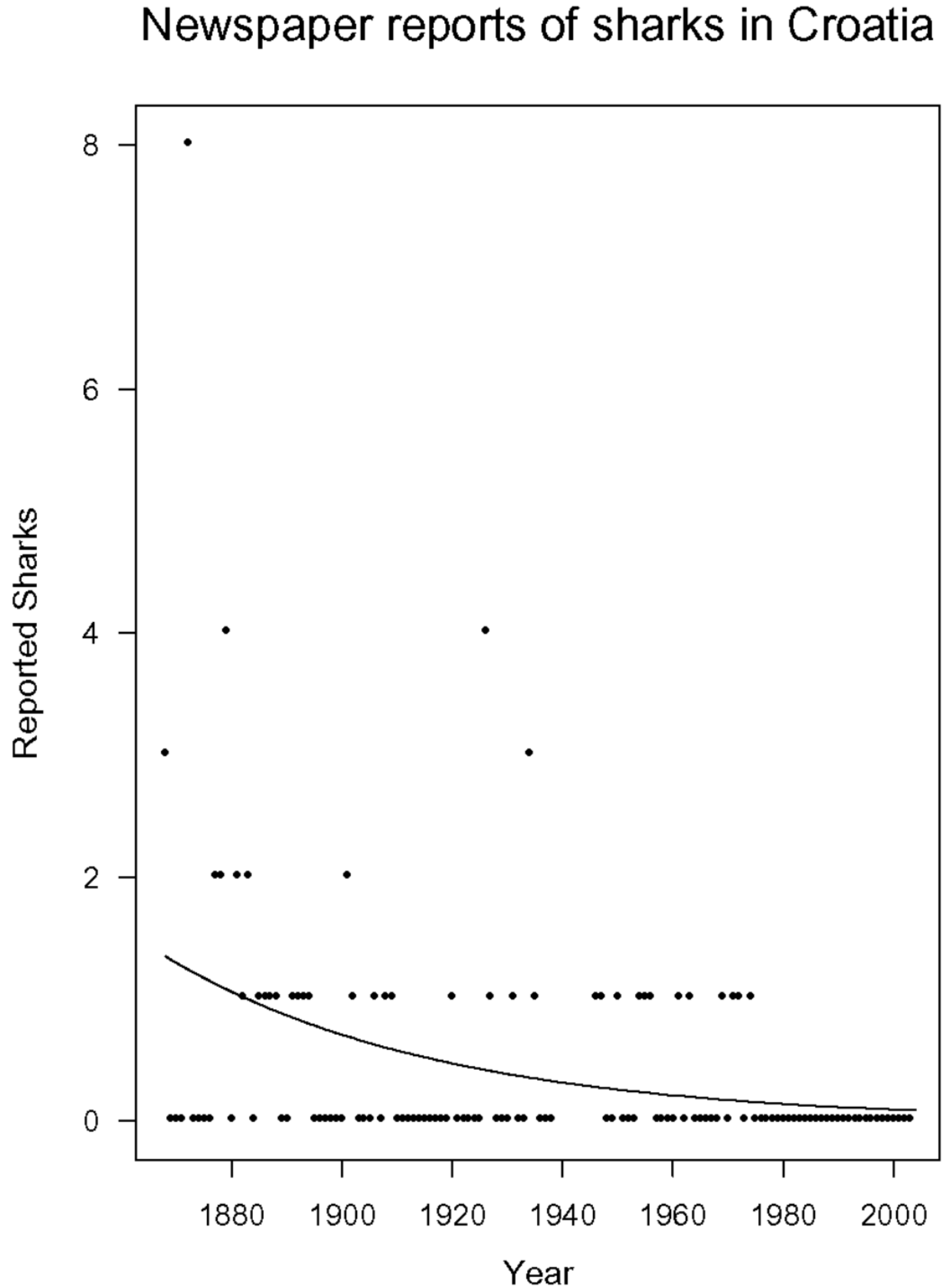
1946 - Pig of 10 kg in stomach

1950 - Encounter during eating a dead calf

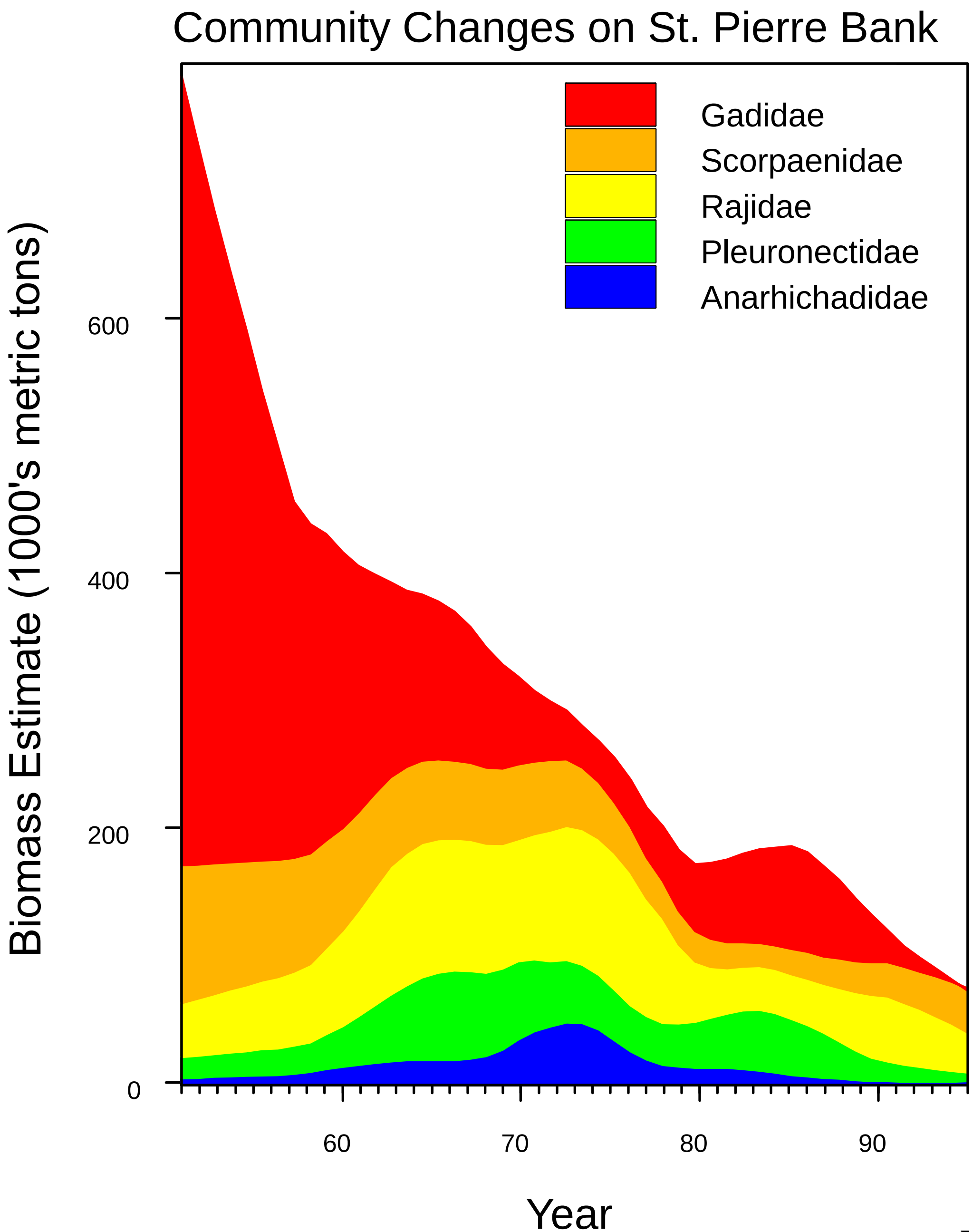
1954 - Attack on boat

1975+ -No sightings.

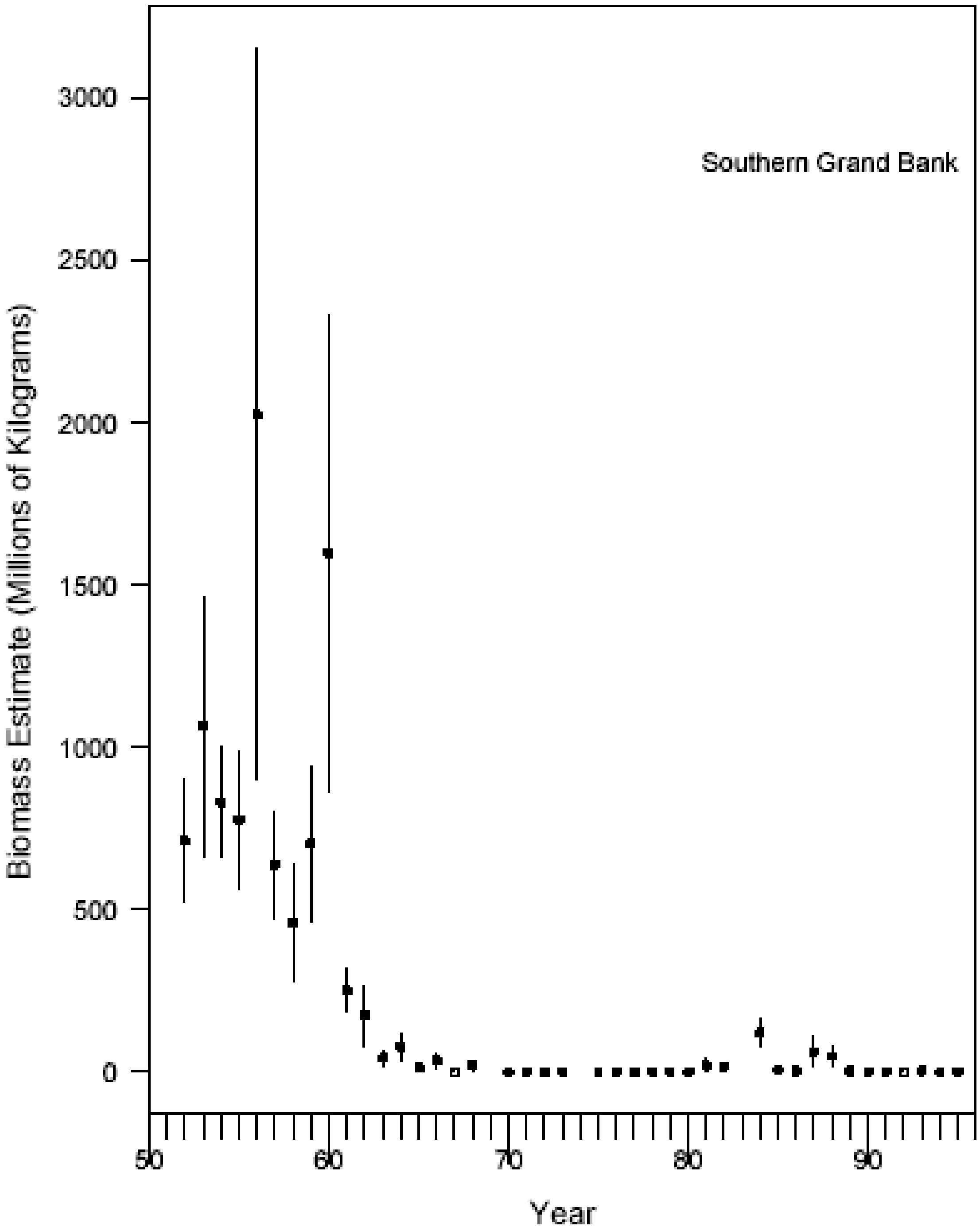
Soldo and Jardas, Periodicum Bologorum, 2002



Newspaper reports of sharks in Croatia
Reported Sharks
0
2
4
6
8
Year
1880
1900
1920
1940
1960
1980
2000

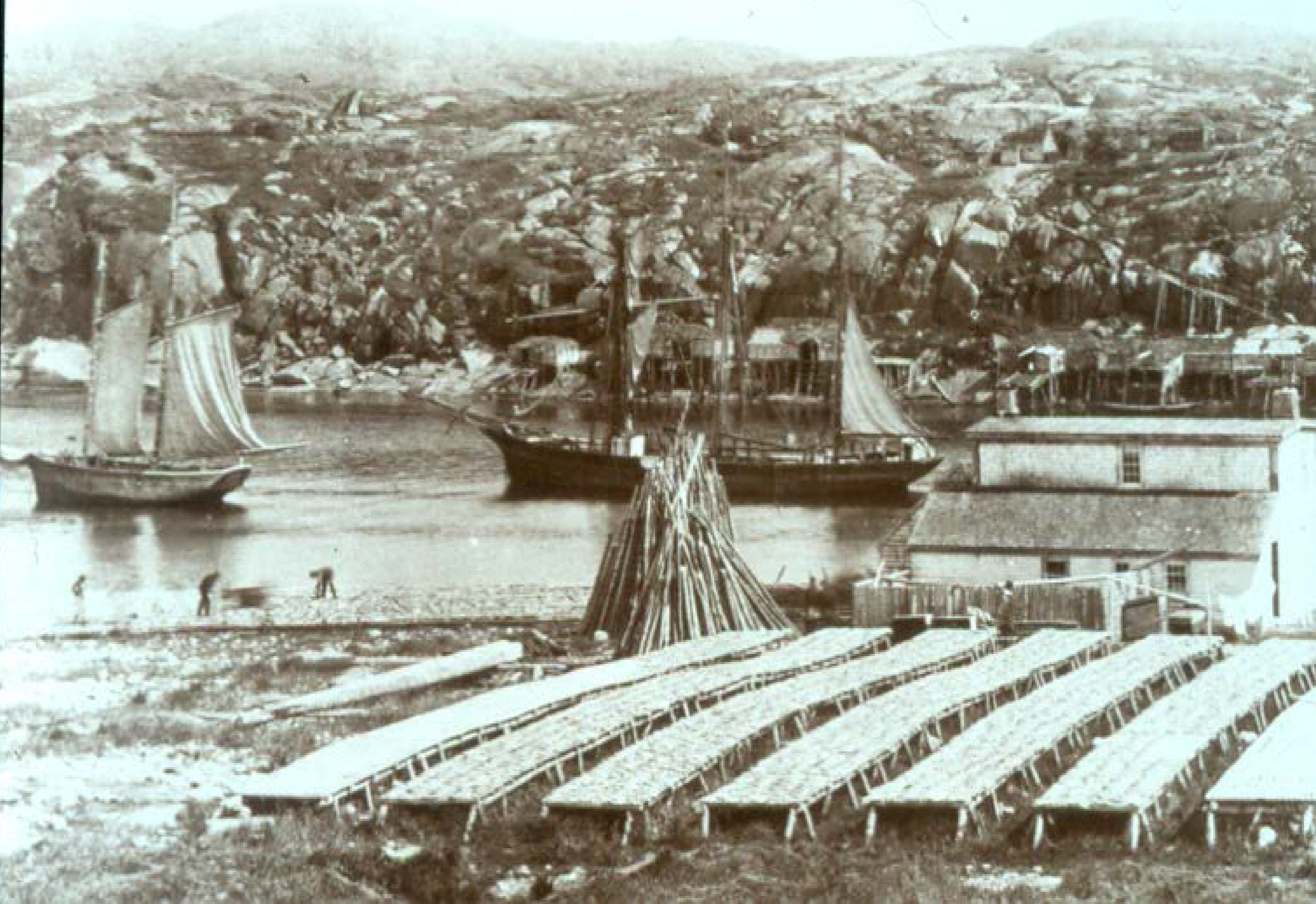


Myers and Worm 2003 Nature



Loss of haddock on the Grand Banks – data from research surveys

Spatial Loss of Cod History



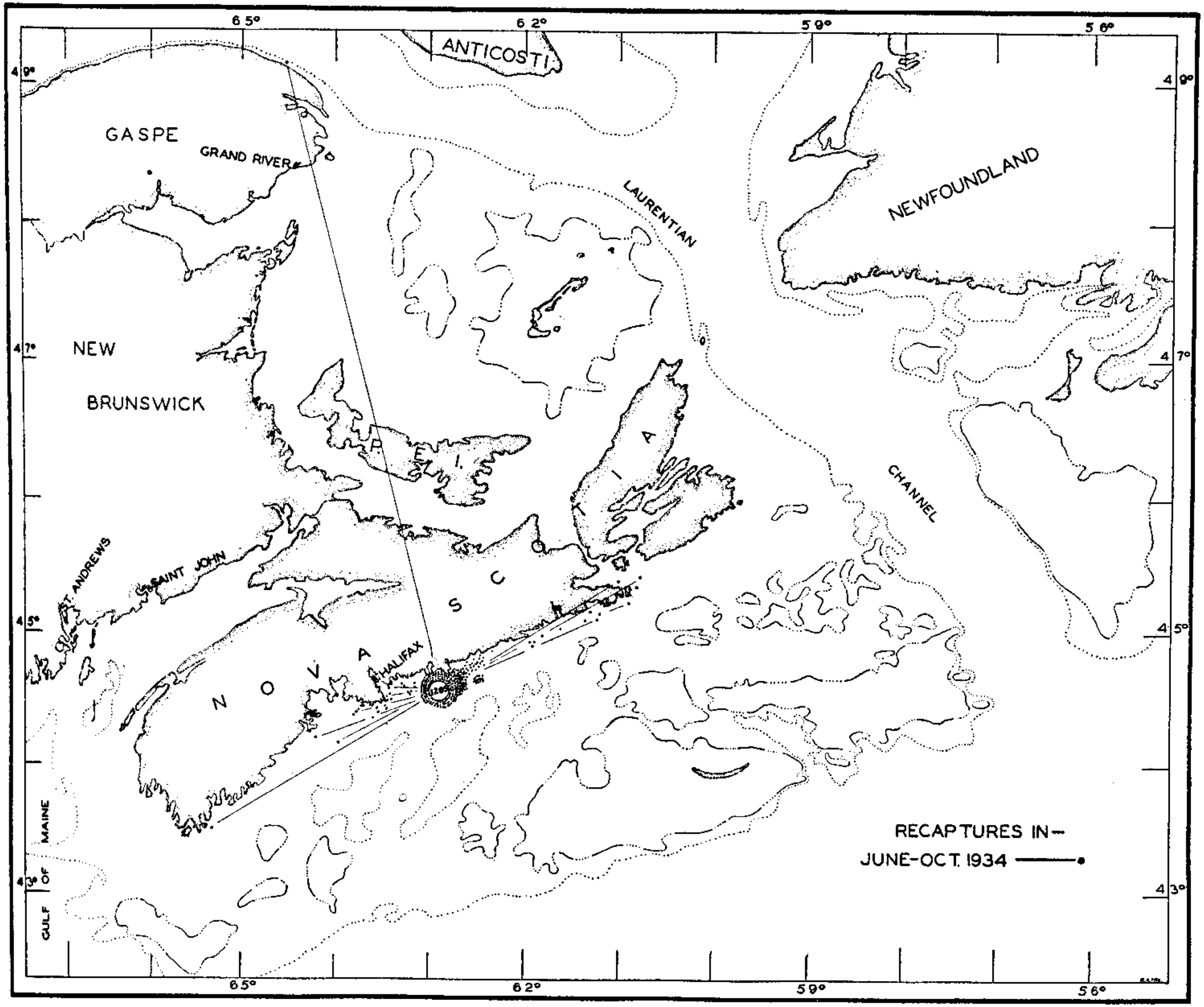


FIG. 21.—Recaptures to October, 1934, of cod tagged in the Jeddore Rock to Egg Island area, N.S., in May, 1934.

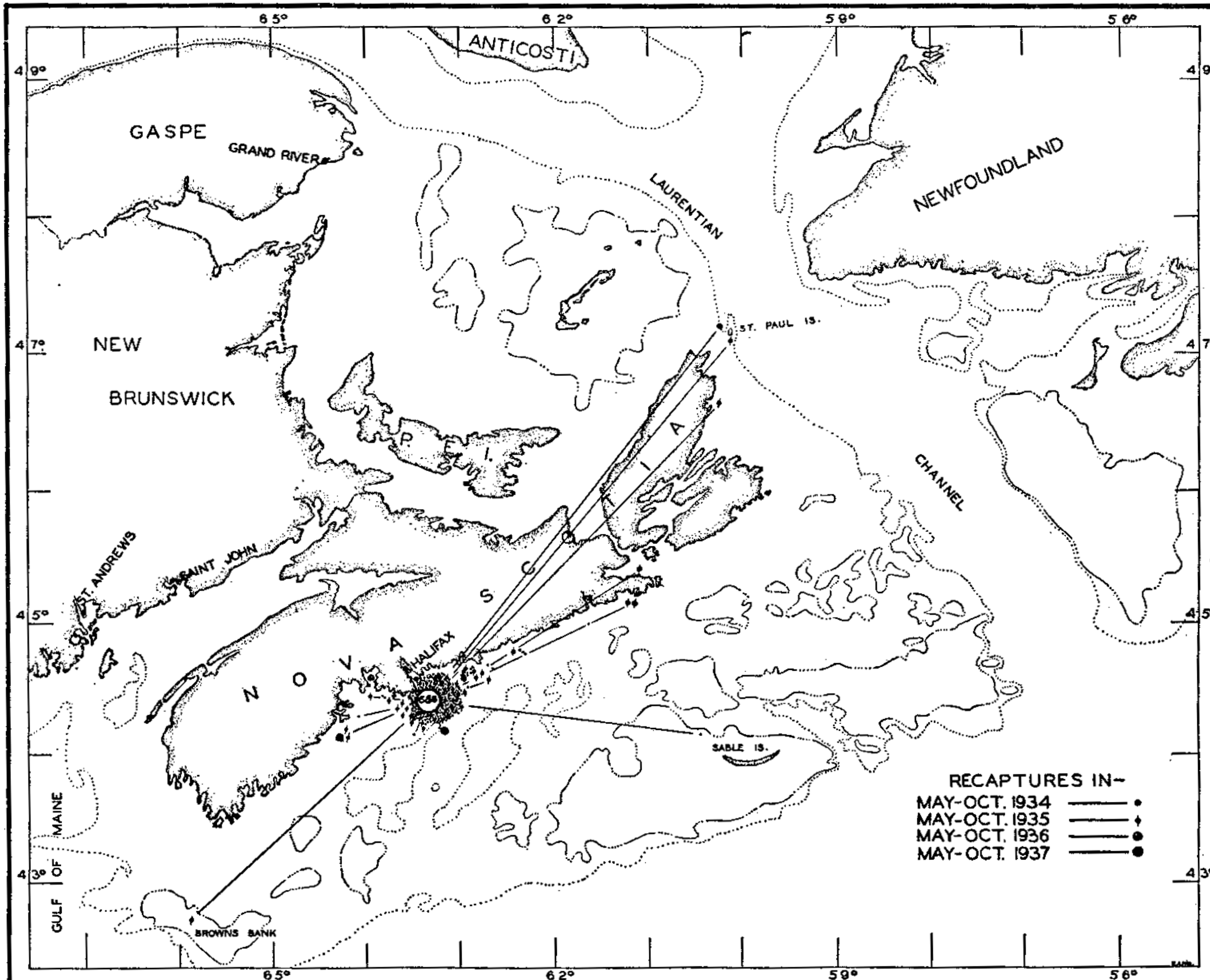


FIG. 18.—Recaptures in May to October, 1934, 1935, 1936 and 1937, of cod tagged near Halifax in June, 1934.

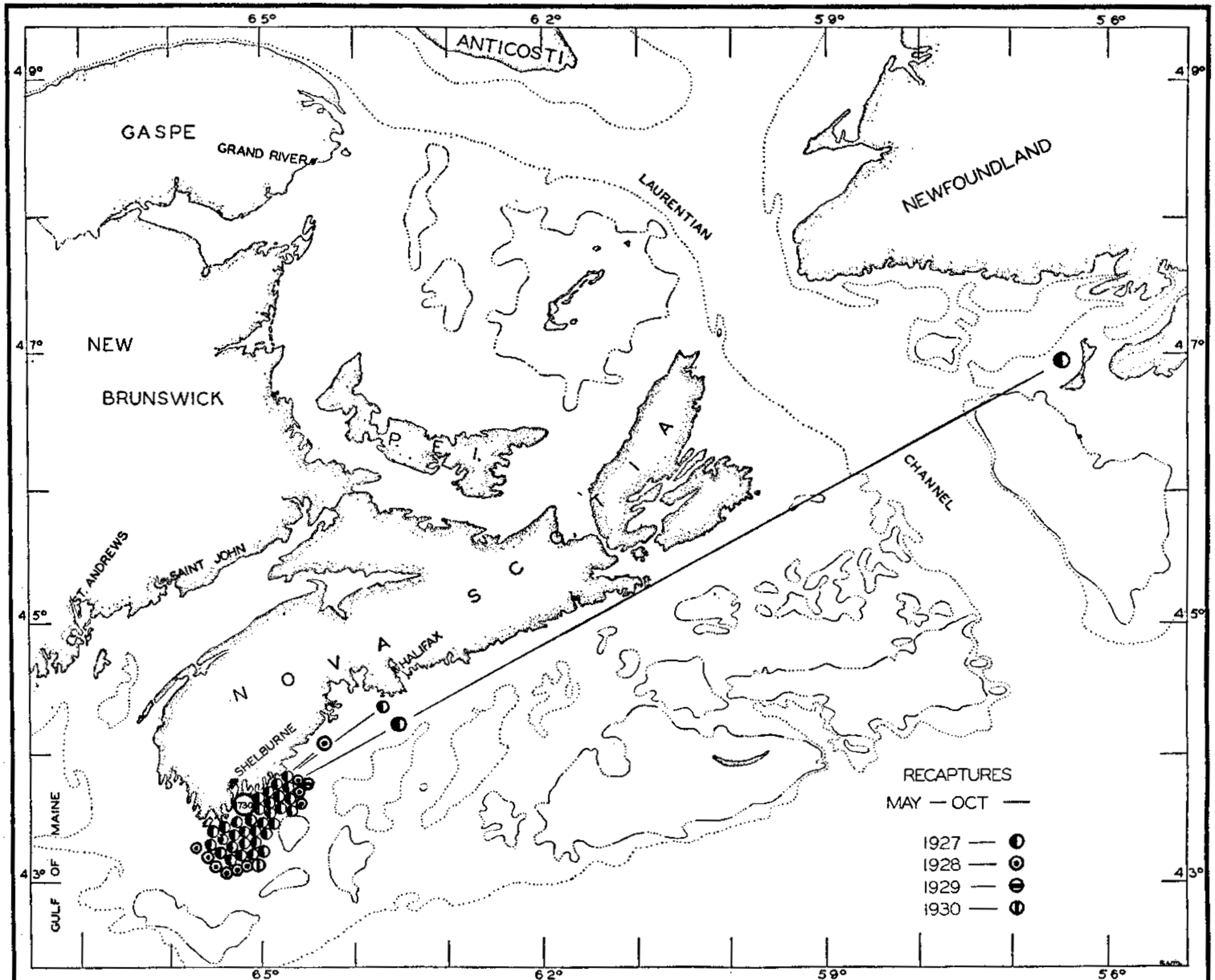
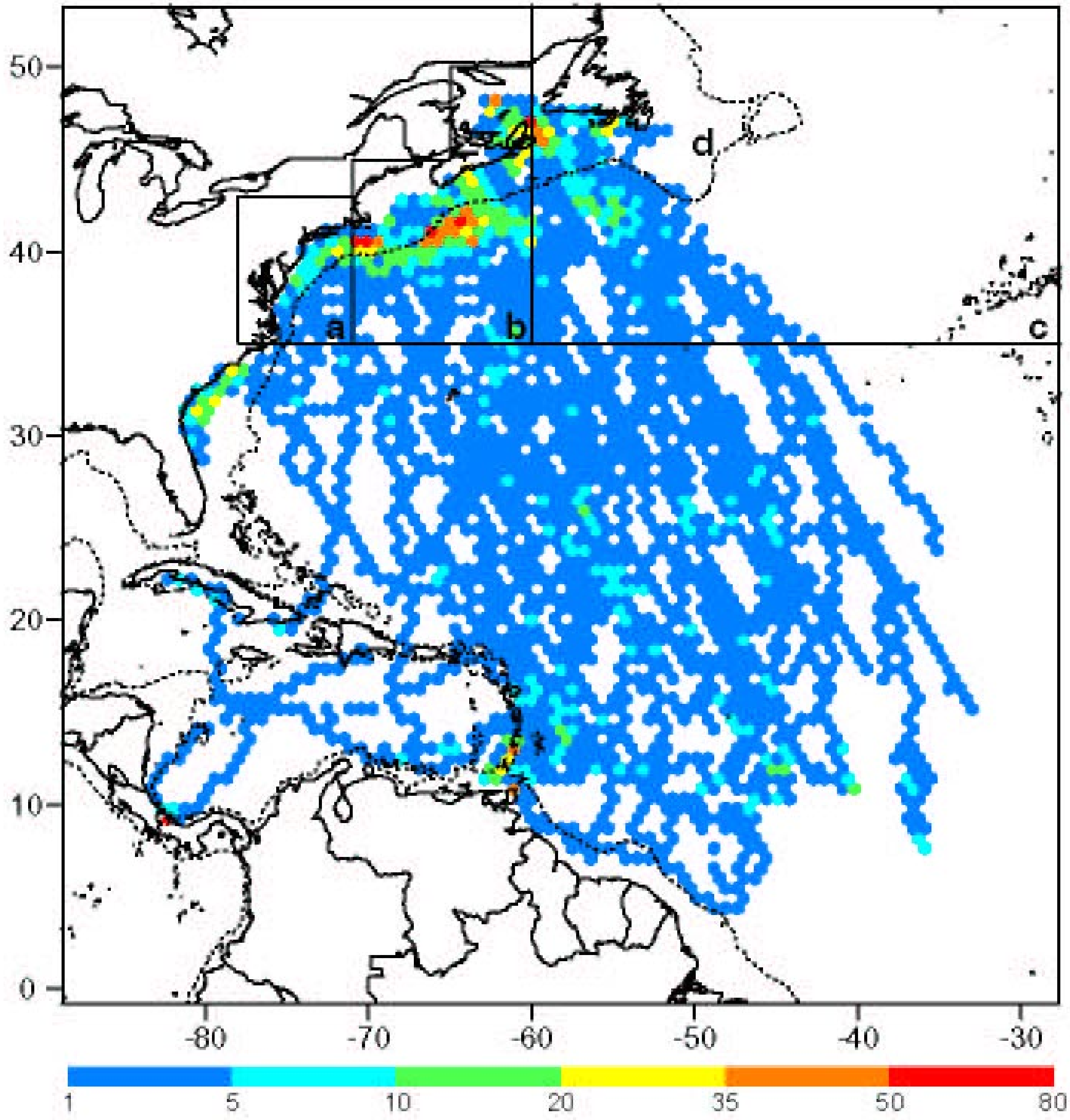


FIG. 15.—Recaptures during "summers" of 1927, 1928, 1929 and 1930 of cod tagged off Shelburne, N.S., during September and the first day of October, 1926.

Identification of high-use areas and threats to leatherback sea turtles in northern waters

James, Ottensmeyer and Myers
Ecology Letters (2005)




Global changes in species diversity
joint work with Boris Worm
Dalhousie University