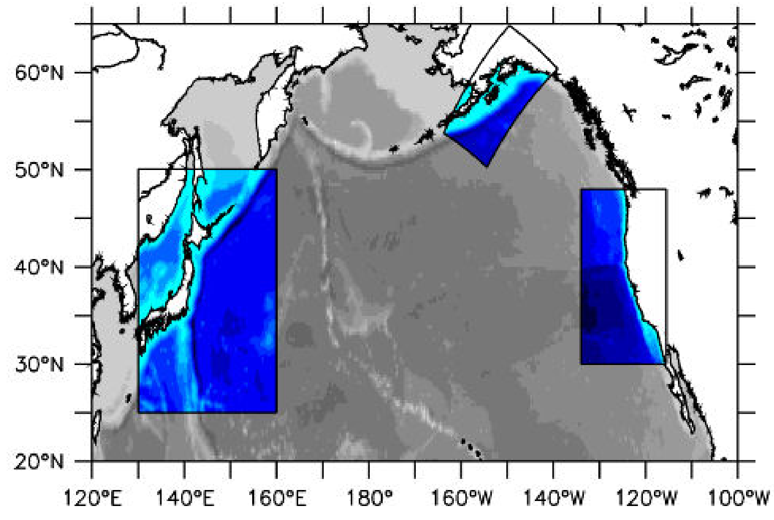
Bayesian Approach to Estimating Ecosystem Model Uncertainties and Climate Change Impacts in the North Pacific Ocean

Ralph F. Milliff and Jeremiah Brown, NWRA, CoRA Div.

Andrew M. Moore and Jerome Fiechter, UC Santa Cruz

Thomas M. Powell, UC Berkeley

Christopher K. Wikle, U. Missouri, **Mevin Hooten**, Utah State



Motivation

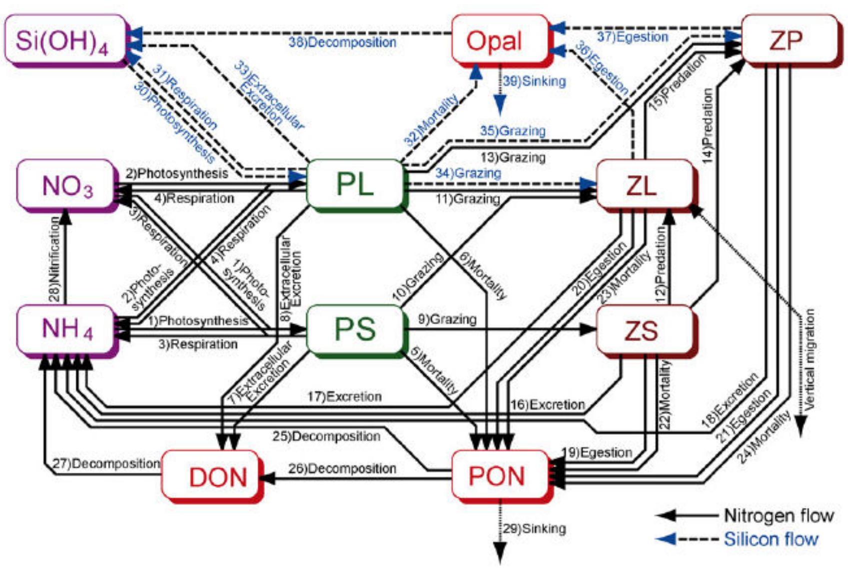
• Parameterization of lower tropic level ecosystem models carry substantial amount of uncertainty.

• Traditional (NPZD-type) lower trophic level ecosystem models do not account for parameterization uncertainty.

• Recent advances in “physical-statistical” modeling suggest that relatively simple hierarchical models with random parameterization can adapt to realistic settings given data (e.g., Berliner, 2003; Wikle, 2003).

Traditional (NPZD-type) Ecosystem Models

- Nutrients – Phytoplankton – Zooplankton – Detritus
- Parameters ~ Components^2
  - NPZD (Powell et al., 2006): 4 components, 17 parameters
  - NEMURO (Kishi et al., 2007): 11components, 83 parameters



NPZD Lower Trophic Ecosystem Model

Nitrate: $$\frac{\partial N}{\partial t} = \delta D + \gamma_n GZ - UP$$

Phytoplankton: $$\frac{\partial P}{\partial t} = UP - GZ - \sigma_d P$$

Zooplankton: $$\frac{\partial Z}{\partial t} = (1-\gamma_n)GZ - \zeta_d Z$$

Detritus: $$\frac{\partial D}{\partial t} = \sigma_d P + \zeta_d Z - \delta D + w_d \frac{\partial D}{\partial z}$$

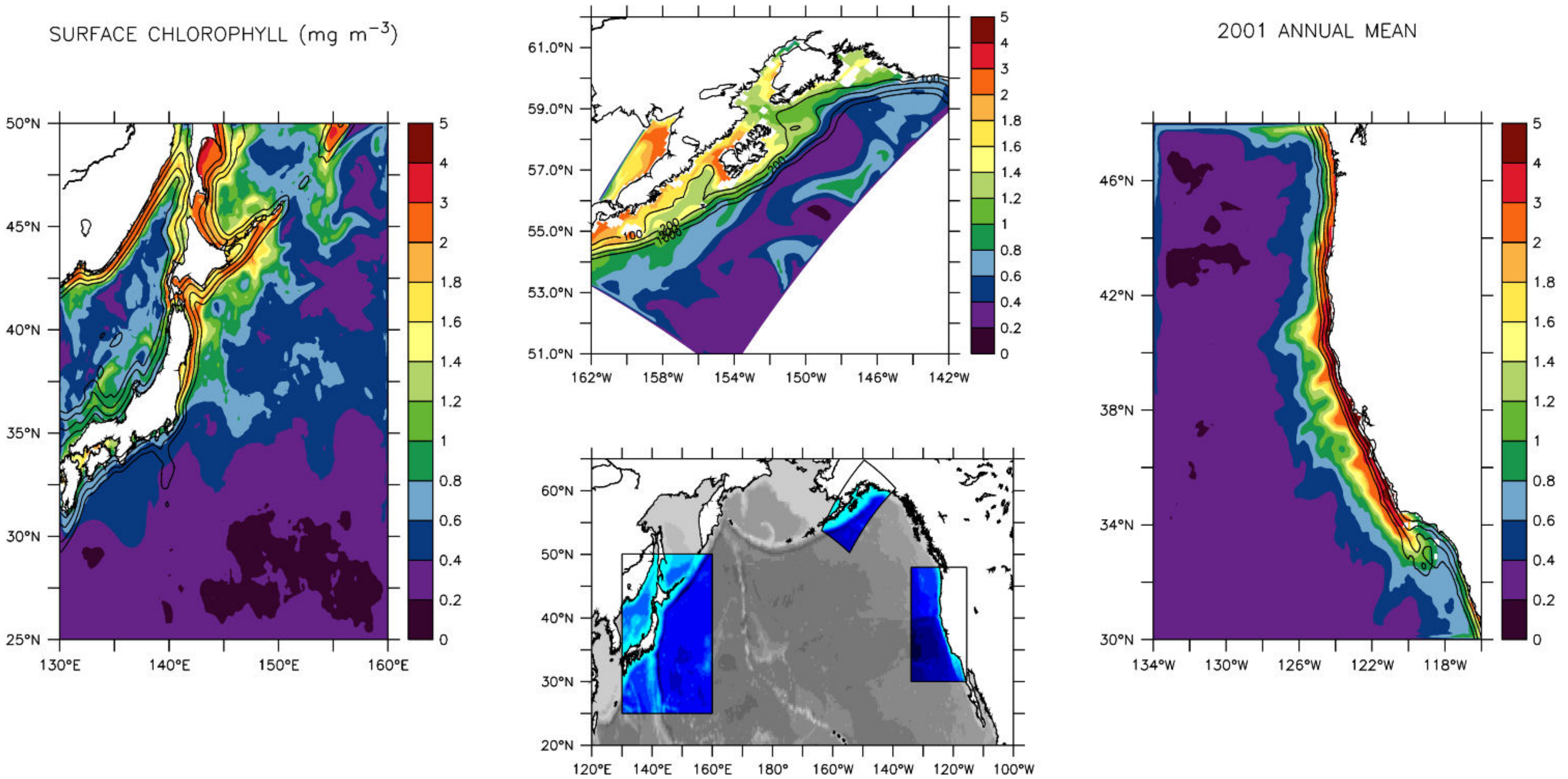
Light availability at depth (negative z): $$I = I_0 \exp\left(k_z z + k_p \int_z^0 P(z')dz'\right)$$

Nitrate-limited phytop. growth rate: $$U_N = \frac{V_m N}{N + k_N} \frac{\alpha I}{\sqrt{V_m^2 + \alpha^2 I^2}}$$

Zooplankton growth rate: $$G = R_m\left(1 - e^{-\Lambda P}\right)$$

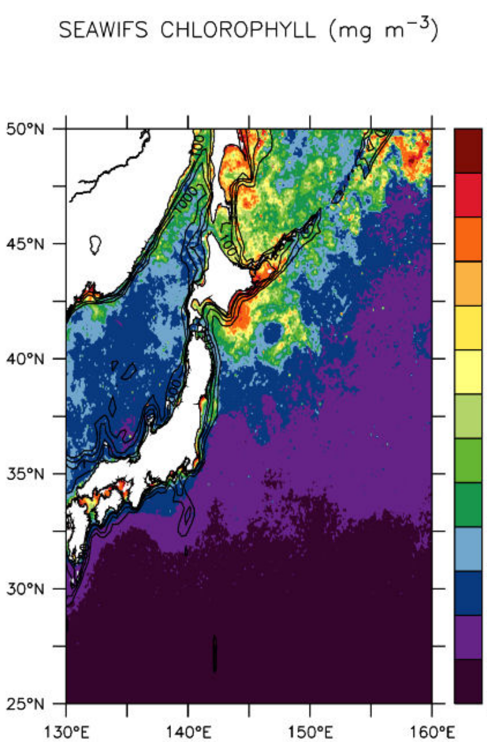
Traditional (NPZD-type) Ecosystem Models

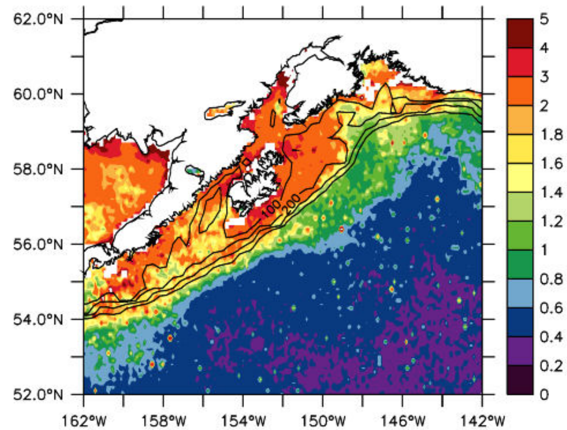
- ROMS + NEMURO + Iron Limitation
  - Western Pacific, Coastal Gulf of Alaska, California Current

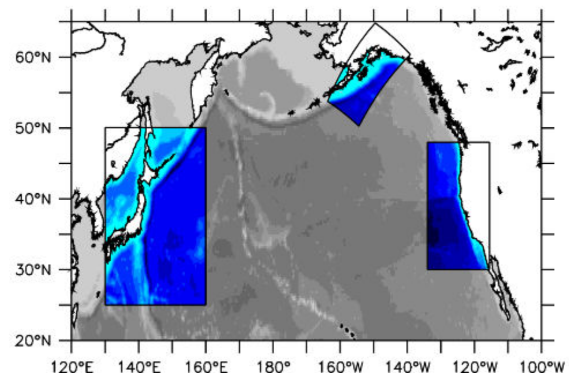


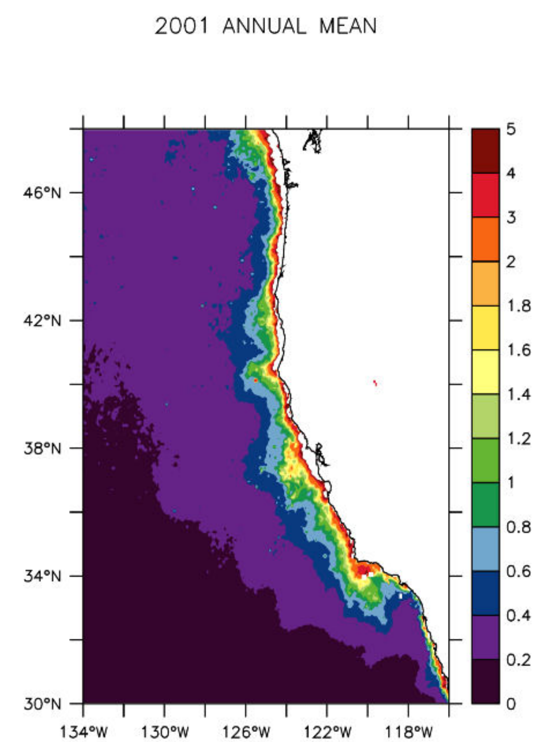
Traditional (NPZD-type) Ecosystem Models

- SeaWiFS
  - Western Pacific, Coastal Gulf of Alaska, California Current





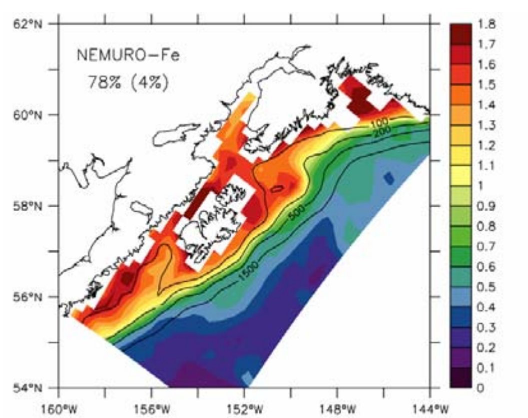




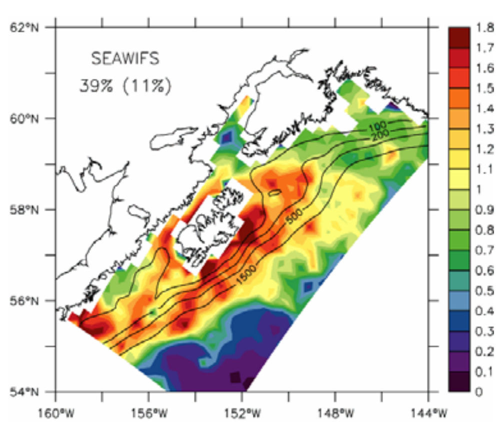
Traditional (NPZD-type) Ecosystem Models

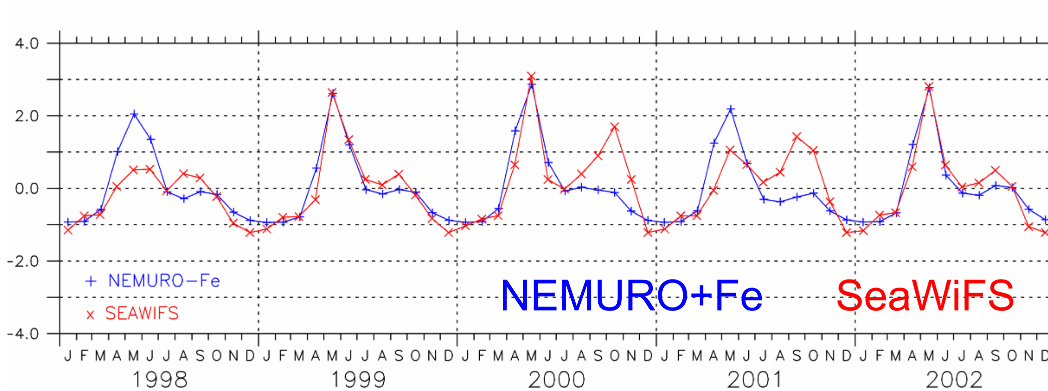
- Interannual spring bloom variability in CGOA (1998-2002)
  - Enhanced winter Ekman pumping leads to higher spring chlorophyll

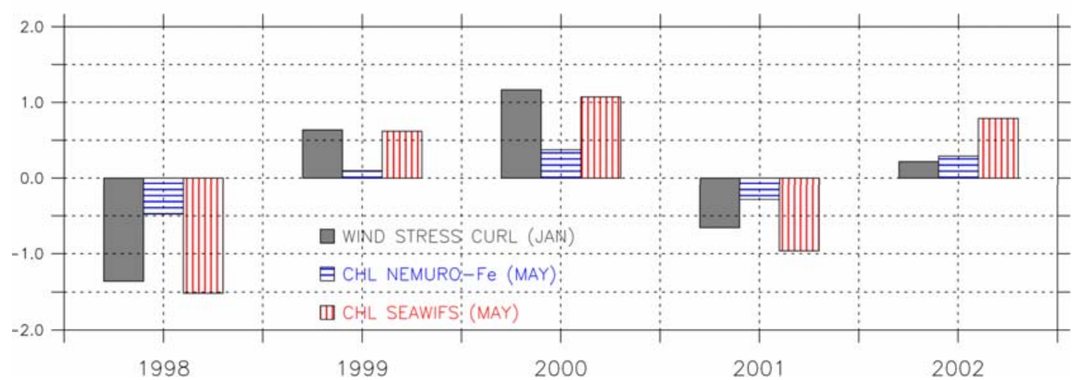
NEMURO+Fe



SeaWiFS



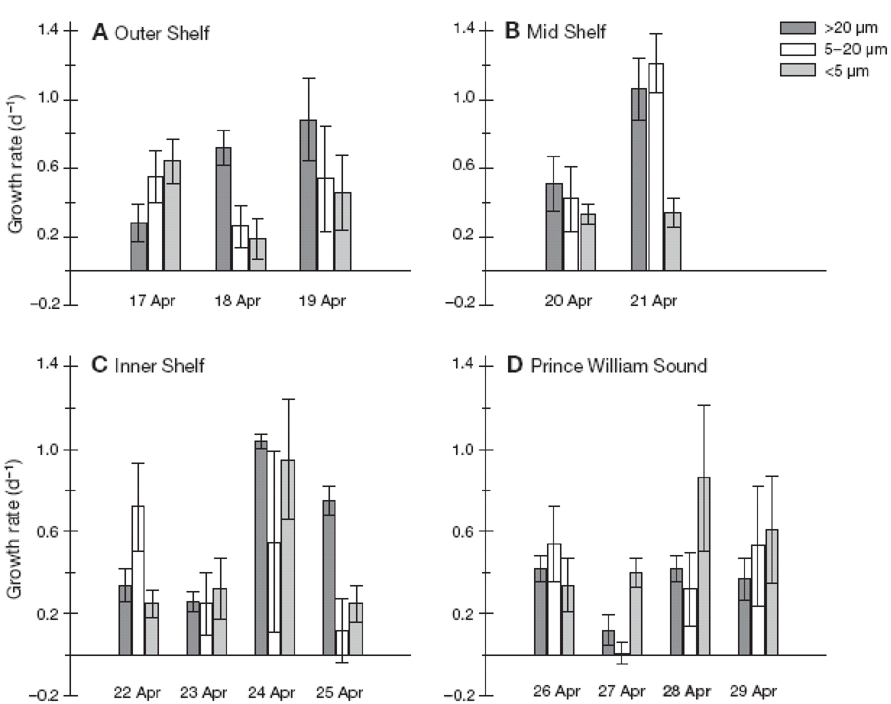


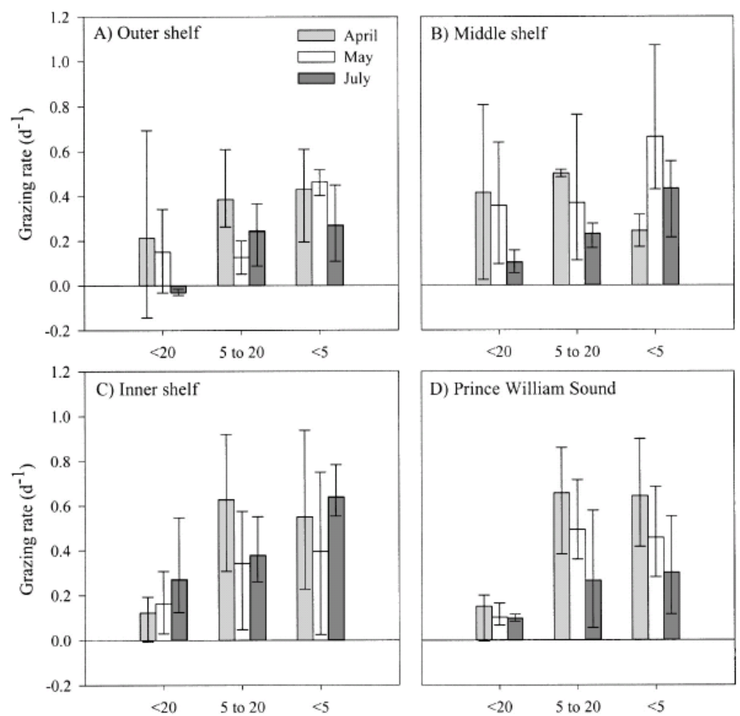


Fiechter and Moore, 2009

Traditional (NPZD-type) Ecosystem Models

- NPZD, NEMURO parameterization in CGOA
  - In situ P growth rates and Z grazing rates (Strom et al., 2006, 2007)
  - Spatial and temporal variability, uncertainty (error bars)





Parameter Variability and Uncertainty

• In traditional lower trophic level ecosystem models, uncertainty can be addressed by generating ensemble of runs with different parameter values.

• In "physical-statistical" approach, Bayesian hierarchical models (BHM) can provide posterior distributions and uncertainty estimates for ecosystem model parameters.

So… What is a BHM?

Bayesian Hierarchical Models (BHM)

Bayes theorem: $[\,\mathbf{X}, \theta_{\mathrm{d}}, \theta_{\mathrm{p}} \,|\, \mathbf{Y}\,] \propto [\,\mathbf{Y} \,|\, \mathbf{X}, \theta_{\mathrm{d}}\,][\,\mathbf{X} \,|\, \theta_{\mathrm{p}}\,][\,\theta_{\mathrm{d}}\,][\,\theta_{\mathrm{p}}\,]$

$[\,\mathbf{X}, \theta_{\mathrm{d}}, \theta_{\mathrm{p}} \,|\, \mathbf{Y}\,]$

Posterior Distribution (“Posterior Mean”)

- spread quantifies uncertainty (MCMC distributions)

$[\,\mathbf{Y} \,|\, \mathbf{X}, \theta_{\mathrm{d}}\,]$

Data Stage Distribution (“Likelihood”)

- e.g., satellite observations, in situ measurements

$[\,\mathbf{X} \,|\, \theta_{\mathrm{p}}\,]$

Process Model Stage Distribution (“Prior”)

- NPZD, NEMURO + Error Models

$[\,\theta_{\mathrm{d}}\,][\,\theta_{\mathrm{p}}\,]$

Parameter Distributions

- fixed vs. random parameters

Bayesian Hierarchical Models (BHM)

Bayes theorem: $[\mathbf{X}, \theta_d, \theta_p \mid \mathbf{Y}] \propto [\mathbf{Y} \mid \mathbf{X}, \theta_d][\mathbf{X} \mid \theta_p][\theta_d][\theta_p]$

DATA STAGE

$[\mathbf{Y} \mid \mathbf{X}, \theta_d]$

$[\theta_d]$

Probability distribution of observations Y (e.g., SeaWiFS) given the true process X (e.g., chlorophyll concentration)

True process is not known, but expected measurement distribution can be characterized from measurements error models

Parameters: interpolation operator, distribution variance, etc.

PROCESS STAGE

$[\mathbf{X} \mid \theta_p]$

$[\theta_p]$

Model approximation of true process X, converted from continuous to stochastic formulation:

$X(t) = F(X(t-1), \theta_p) + \varepsilon_X(t)$

where F might represent advection, diffusion, biological source/sink terms, etc.

Parameters: vertical mixing coefficient, growth rates, etc.

BHM: A Different Perspective…

“ As we know, there are known knowns.

These are things we know we know.

We also know there are known unknowns, that is to say

We know there are some things we do not know.

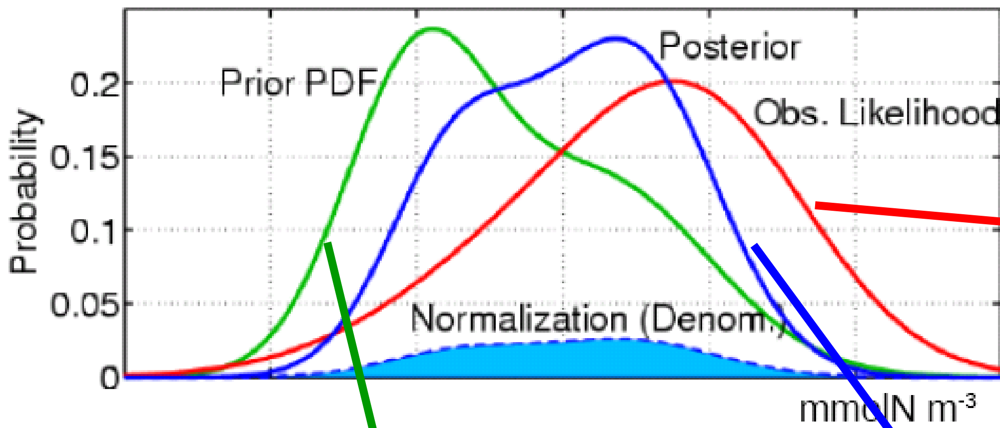
But there are also unknown unknowns,

The ones we don't know we don't know. “

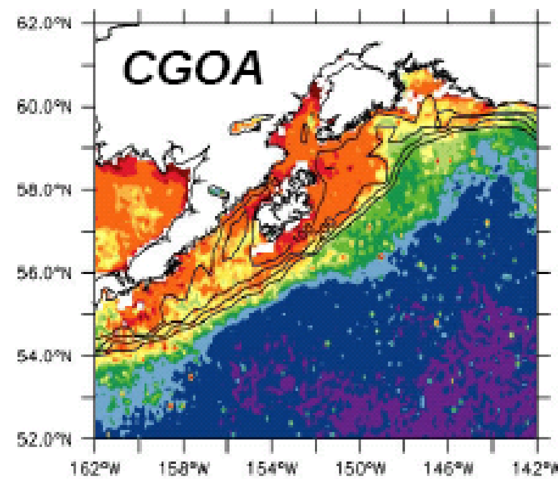
- Donald Rumsfeld, former U.S. Defense Secretary on

Bayesian Hierarchical Models, 12 Feb. 2002

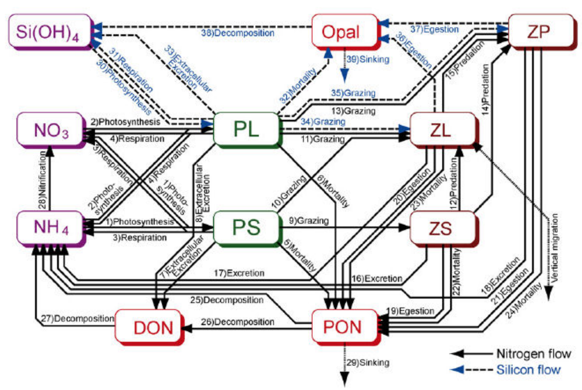
Bayesian Hierarchical Models (BHM)



SeaWiFs

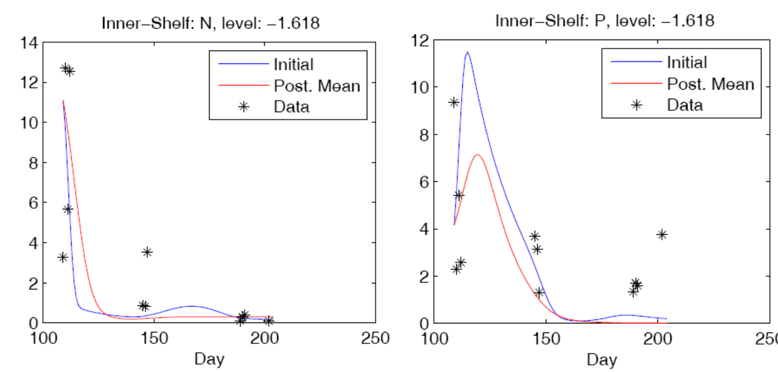


NEMURO



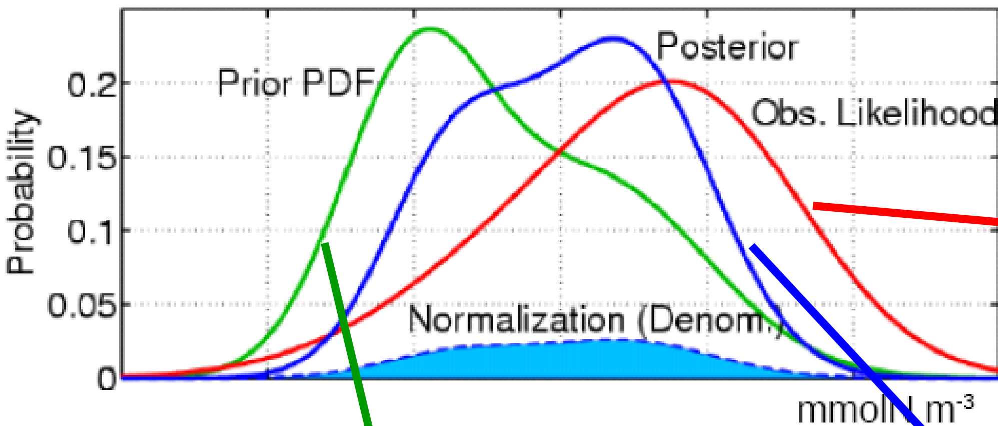
$$X(t) = F(X(t-1), \theta_p) + \varepsilon_X(t)$$

Posterior Means



Surface N, P (inner shelf)

BHM Example – CGOA NPZD+Fe, In Situ Observations



GLOBEC in situ Observations

NO3, Chlorophyll

Seward Line

April, May, and July

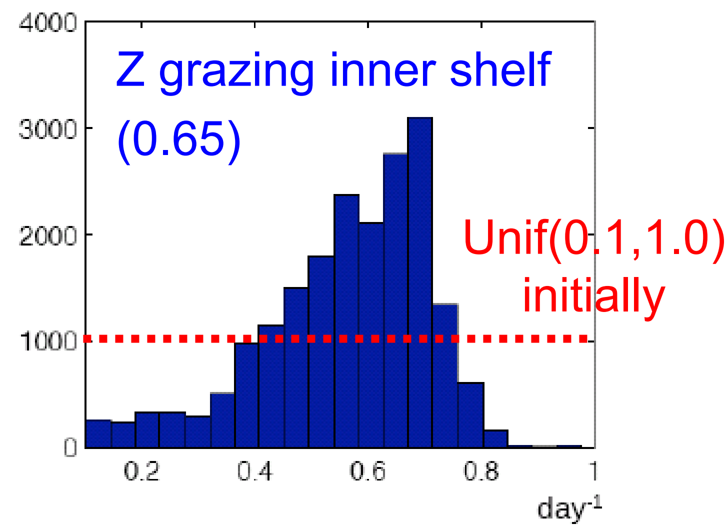
1-D NPZD + Iron

No physical processes

Short wave radiation

Single locations in CGOA
(inner, mid, and outer shelf)

Posterior Distributions



BHM Example – CGOA NPZD+Fe, In Situ Observations

- BHM: Markov Chain Monte Carlo with Metropolis-Hastings updates (3-month run (Apr-Jun); 20,000 samples for posterior distributions)

- Fixed NPZD Parameters

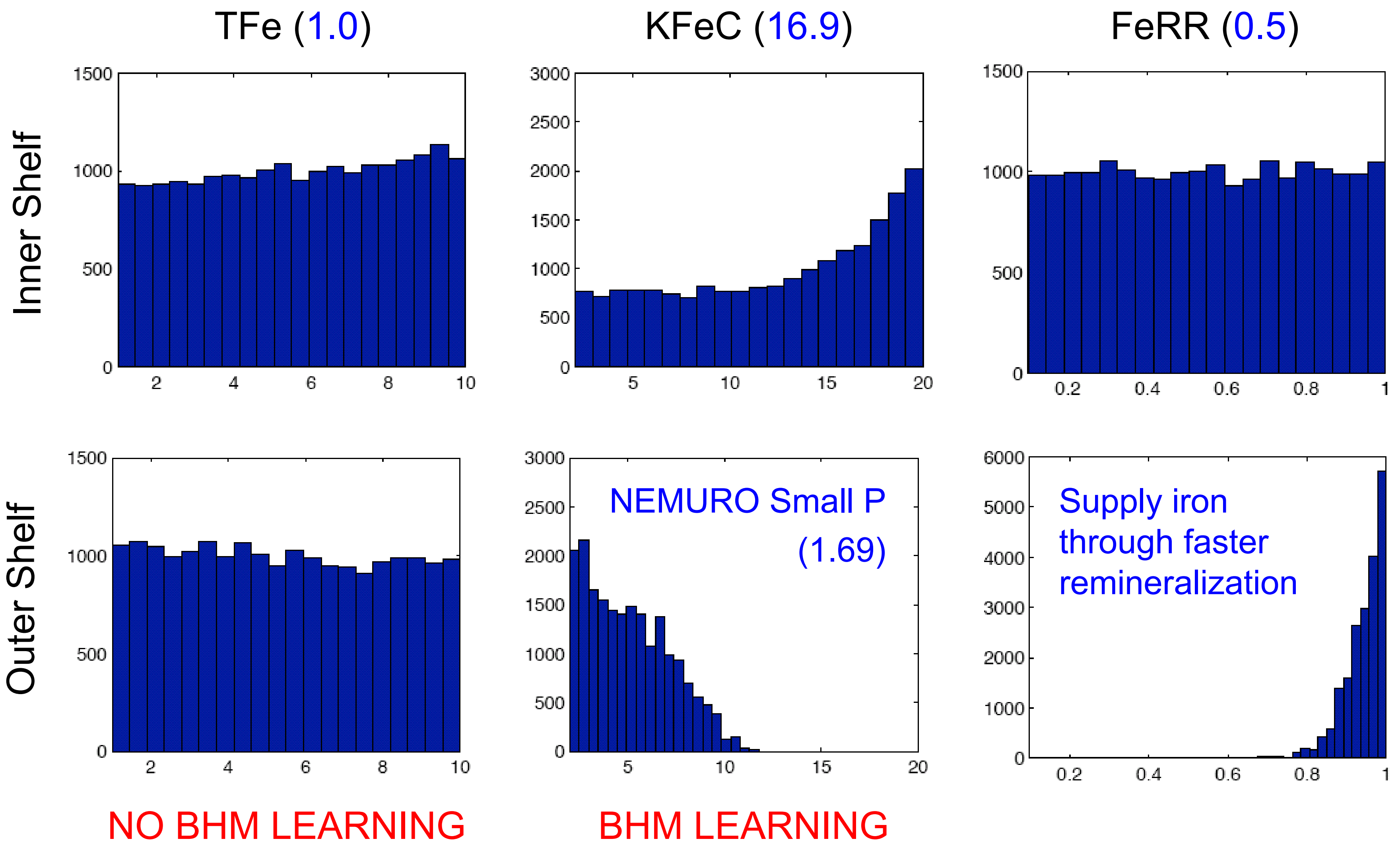
```
PARfrac = 0.43;%fraction of sw-radiation that is photosynth. avail
AttPhy = 0.04; %Self-Shading Coefficient
PhyIS = 0.02; %Initial Slope of P-I Curve
PhyMRN = 0; %sigmaN
Ivlev = 0.84; %Ivlev Constant
ZooEED = 0; %gammaD
ZooEEN = 0.3; %Zooplankton Excretion Efficiency
ZooMRN = 0; %zetaN
wPhy = 0; %wP
A_Fe = 0.6; %Empirical Power
B_Fe = 64; %Empirical Coefficient
```

- Random NPZD Parameters with Prior Distributions

```
AttSW = 0.067; %Light Attenuation (Extinction) Coefficient          AttSW ~ Unif(0.04,0.4)
Vm_NO3 = 1; %Phytoplankton Nitrate Uptake Rate                      Vm_NO3 ~ Unif(0.2,2.0)
PhyMRD = 0.1; %Phytoplankton Senescence (Mortality) Rate            PhyMRD ~ Unif(0.02,0.2)
ZooGR = 0.65; %Zooplankton Grazing Rate                             ZooGR ~ Unif(0.1,1.0)
ZooMRD = 0.145; %Zooplankton Mortality Rate                         ZooMRD ~ Unif(0.02,0.2)
DetRR = 1; %Detritis Remineralization Rate                          DetRR ~ Unif(0.1,1.0)
wDet = 8; %Detritis Sinking Rate                                    wDet ~ Unif(0,50)
T_Fe = 1; %Iron Uptake Time Scale                                   T_Fe ~ Unif(1,10)
FeRR = 0.5; %Iron Remineralization Fraction                         FeRR ~ Unif(0.1,1.0)
K_NO3 = 1; %Phytoplankton Half-Saturation Constant for Nitrate      K_NO3 ~ Unif(0.3,3.0)
K_FeC = 16.9; %Phytoplankton Half-Saturation Constant for Iron      K_FeC ~ Unif(2,20)
```

BHM Example – CGOA NPZD+Fe, In Situ Observations

- Posterior distributions for phytoplankton iron parameters



Summary

- Test sensitivity to data availability by using more complicated models (e.g., NEMURO) as data stage.

- Augment in situ data with satellite (e.g., SeaWiFS) observations (chlorophyll mismatch problems).

- More realistic error distributions; dependence structure in parameters; fixed vs. random parameters.

- Working towards full 4-D relocatable implementation (WPAC, CGOA, and CCS).