Adaptive Implementation Modeling and Monitoring for TMDL Refinement

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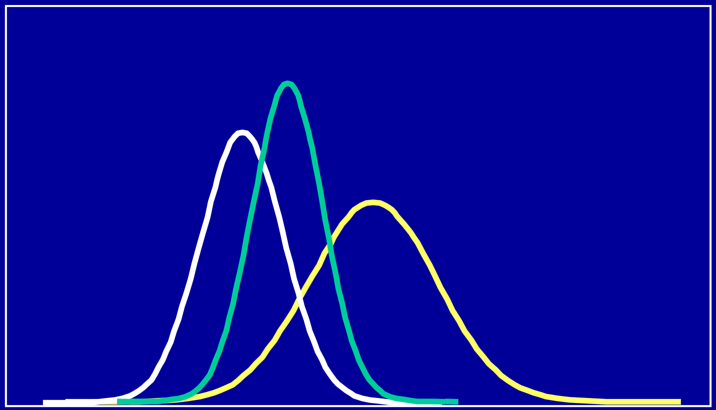
November 3, 2005

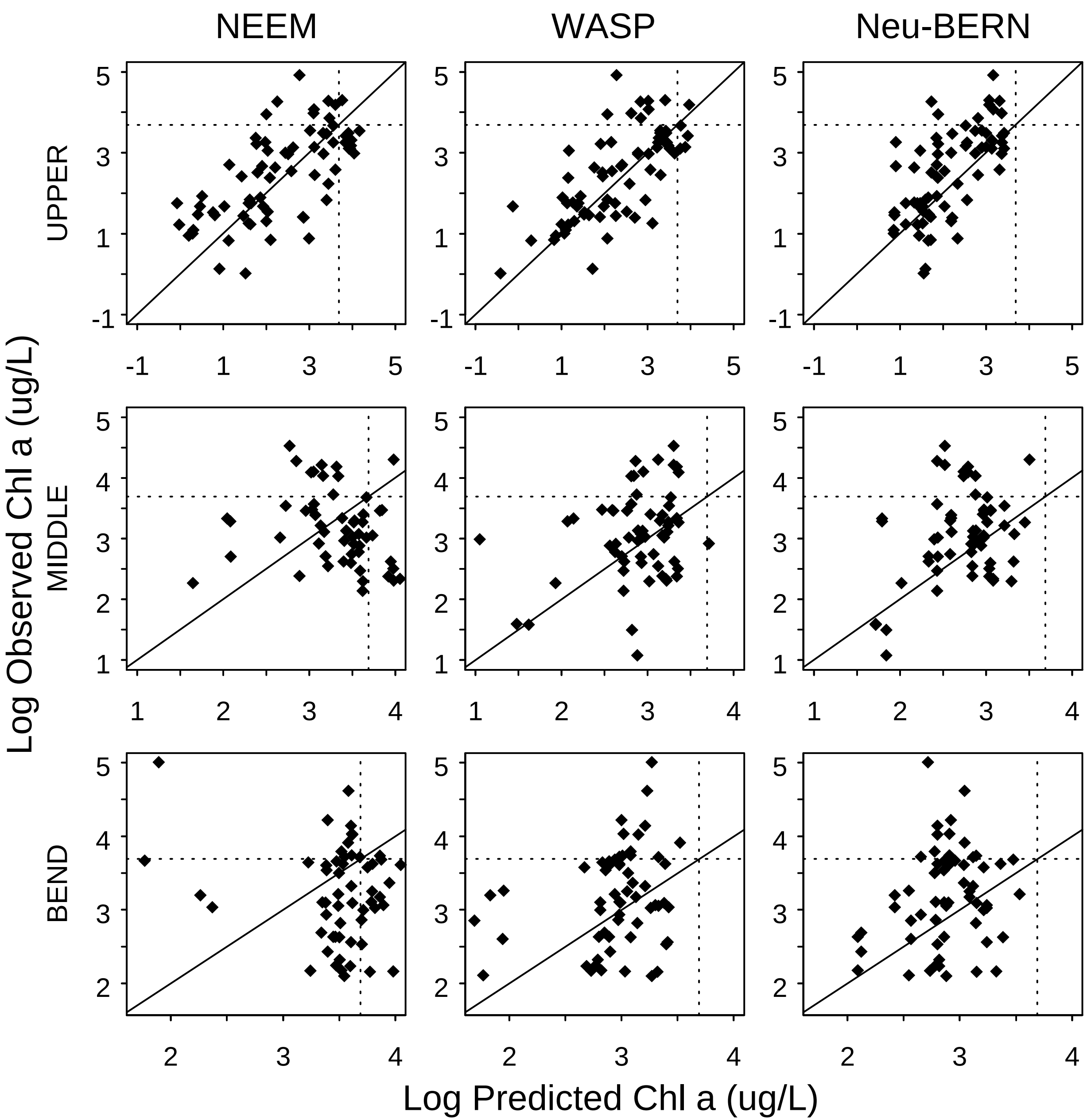


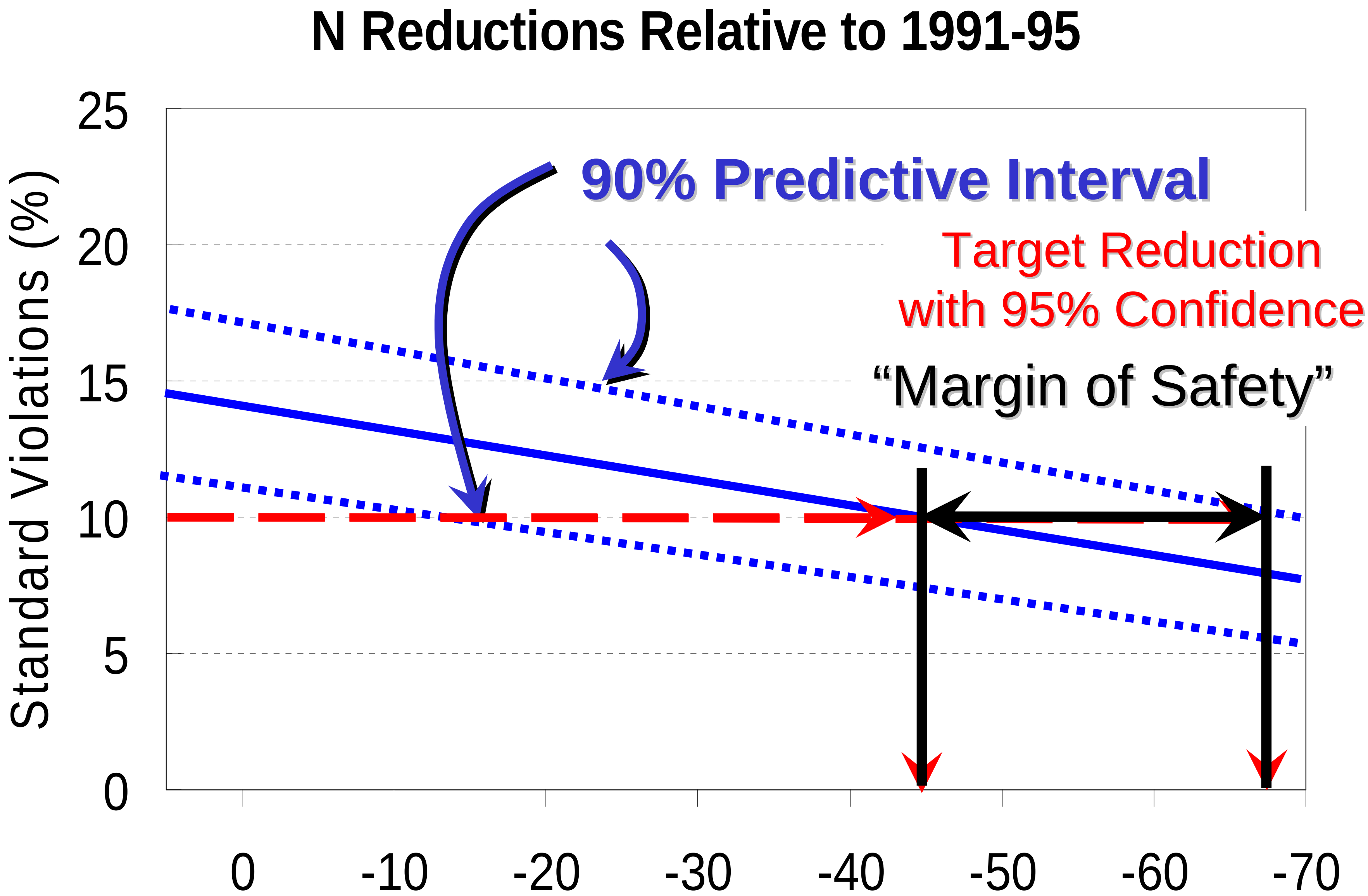
This research is funded by
U.S. EPA - Science To Achieve Results (STAR) Program
Grant # R830883

Project Objectives

- Develop an adaptive implementation modeling and monitoring strategy (AIMMS) for TMDL improvement.

- Apply and evaluate AIMMS on the Neuse Estuary TMDL in North Carolina.


NEEM
WASP
Neu-BERN
UPPER
MIDDLE
BEND
Log Observed Chl a (ug/L)
Log Predicted Chl a (ug/L)


N Reductions Relative to 1991-95
90% Predictive Interval
Target Reduction
with 95% Confidence
"Margin of Safety"
Standard Violations (%)
25
20
15
10
5
0
0
-10
-20
-30
-40
-50
-60
-70

We need predictions to guide TMDL decision making, so what should we do?

Adaptive Implementation

We can “learn while doing;” that is, we can observe how the real system (the actual waterbody) responds, and then use that information to augment and improve the prediction for the modeled system.

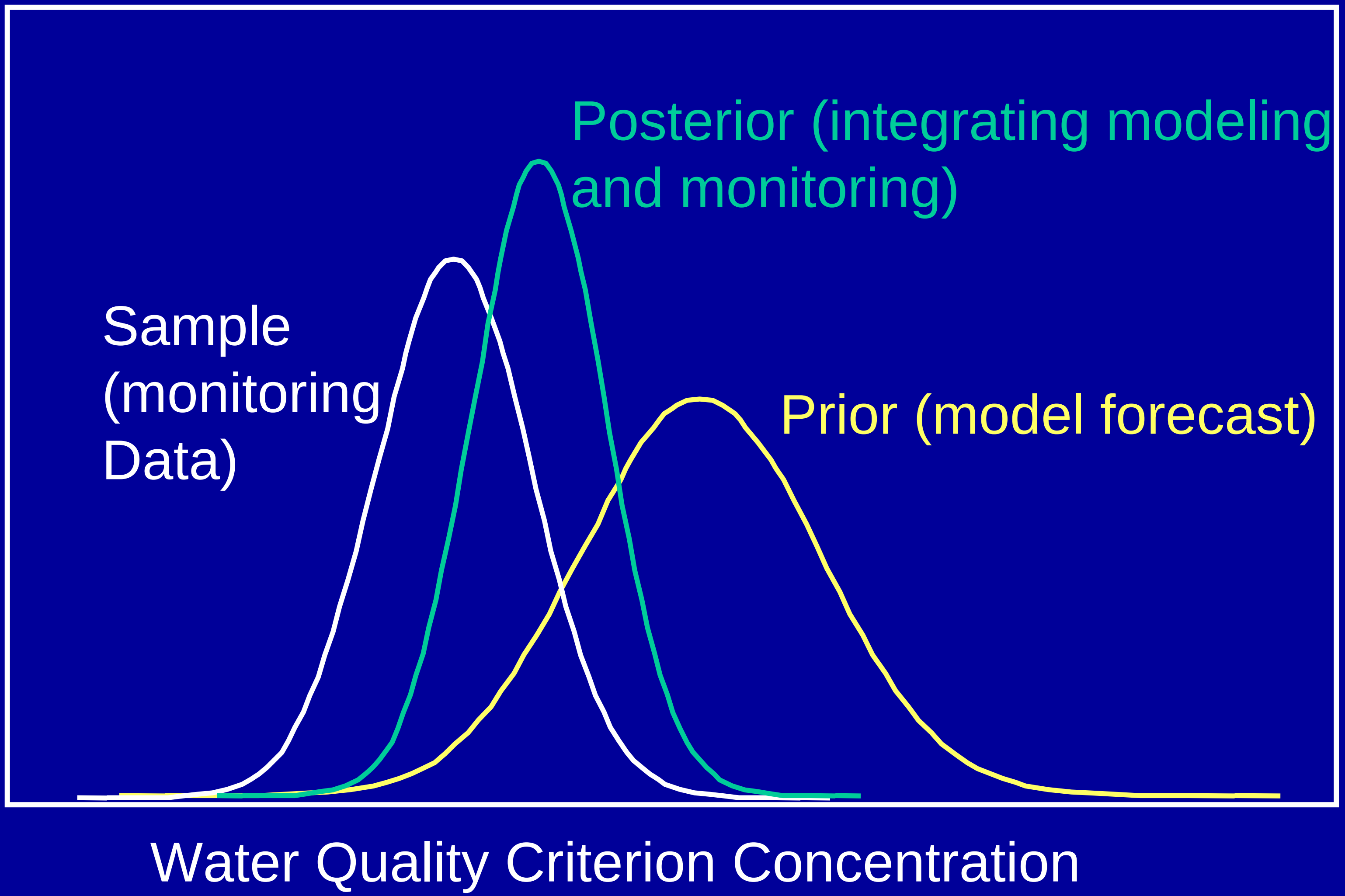
How might we conduct adaptive implementation?

• ***Step 1:*** **To define the allowable pollutant load (the TMDL), a water quality model is applied; the forecast from this model provides the initial estimate of how the waterbody will respond to the pollutant load reductions required in the TMDL.**

• ***Step 2:*** **After the TMDL is implemented (i.e., nonpoint & point source pollution controls in place), a *properly-designed* monitoring & research program is established; this program can be focused on assessment of particular pollutant controls and/or on overall waterbody compliance with standards.**

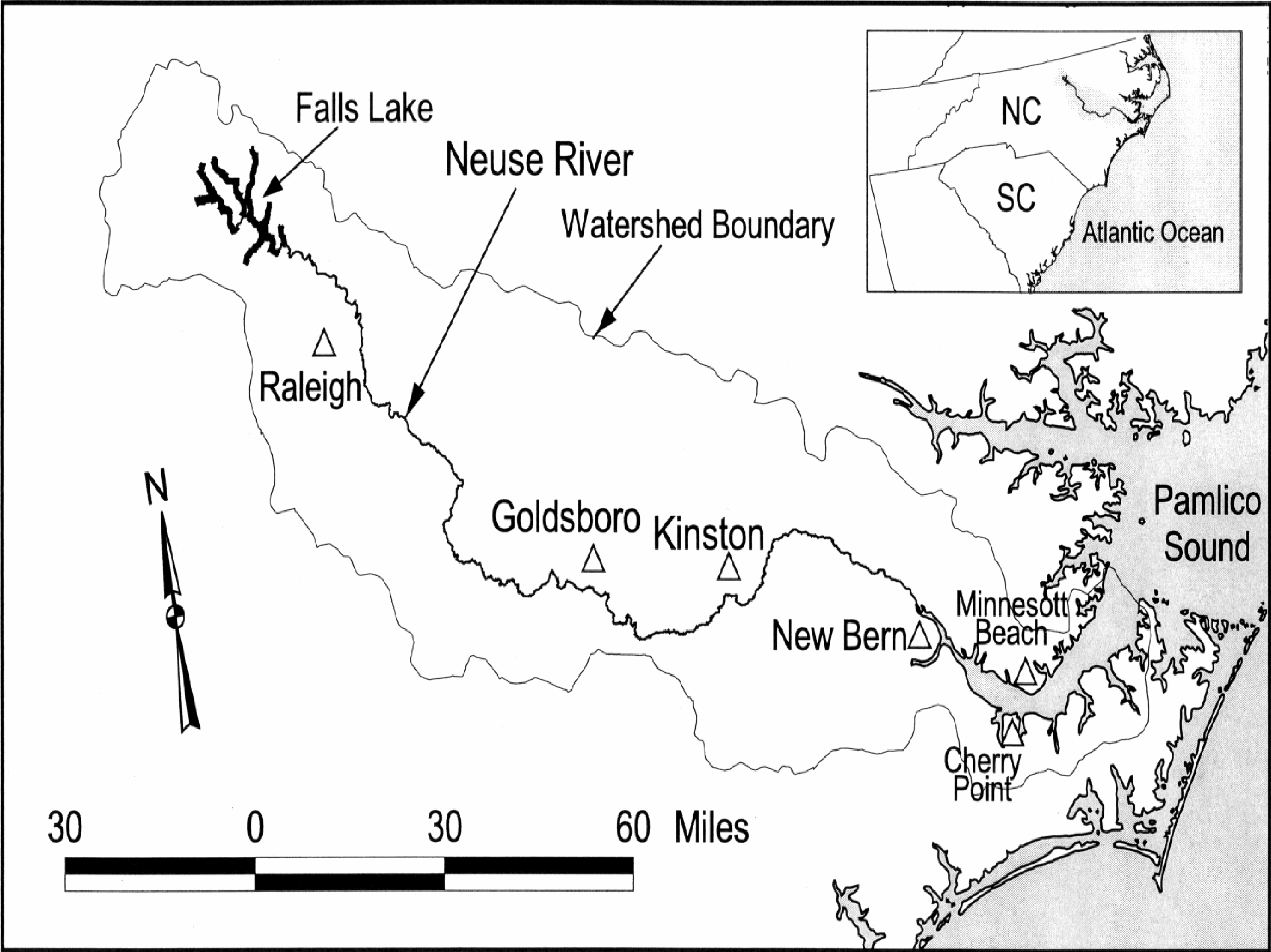
• ***Step 3:*** **The pre-implementation model forecast (from step 1) is combined with the post-implementation monitoring (from step 2); this provides the best overall estimate of TMDL success and provides the basis for any necessary revisions to the TMDL.**

Adaptive Implementation: Bayesian Analysis



Example: TN in Neuse Estuary

- Prior distribution of log TN concentration assessed from the Bayesian SPARROW model
- TN monitoring data collected from 1992 – 2000
- The log TN distribution is updated using one year’s data at a time to illustrate sequential updating.



Falls Lake
Neuse River
Watershed Boundary
NC
SC
Atlantic Ocean
Raleigh
Goldsboro
Kinston
New Bern
Minnesott Beach
Cherry Point
Pamlico Sound
N
30
0
30
60
Miles

Neuse SPARROW Model

$$\text{TN Load}_i = \sum_{j \in J(i)} \sum_{n=1}^{N} \beta_n S_{n,j} \exp(-\alpha' Z_j) H^r_{i,j} H^s_{i,j} \; \varepsilon_i$$

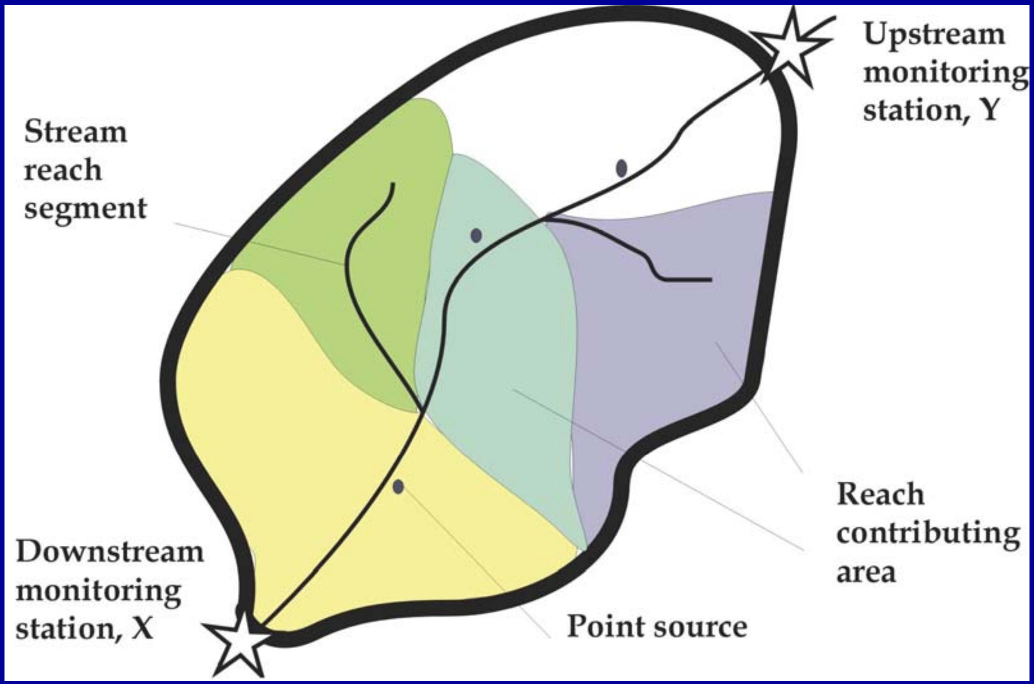
Stream Load at reach i

Sources

Land-to-water transport

Aquatic transport

Error



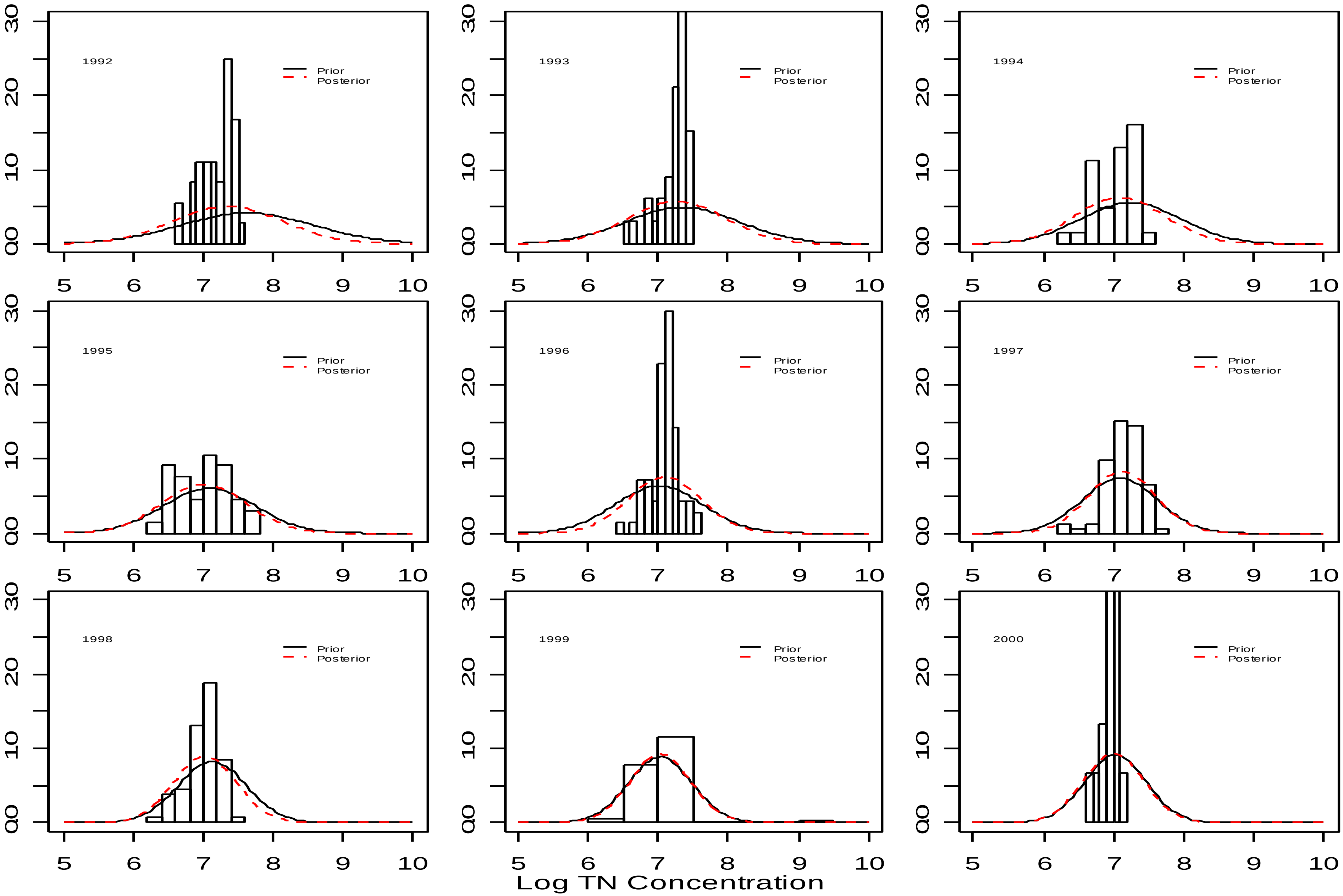
n = number of sources
j = reaches in the set J(I)

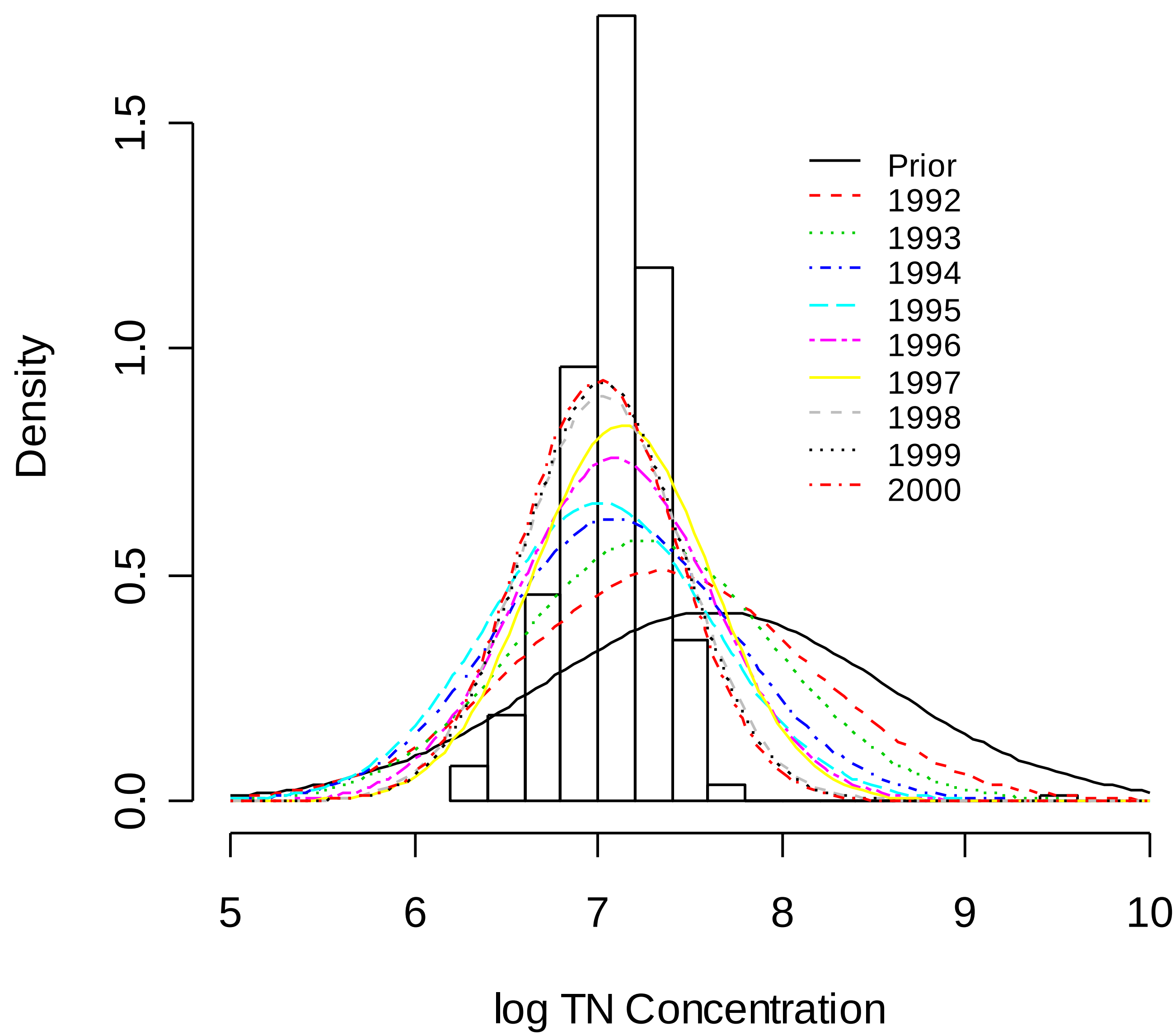
Neuse Estuary: Prior Parameters

Using the Bayesian SPARROW model to create the prior distribution, we generated 10,000 pairs of samples of the mean and variance for log TN.

Sequential Updating

- Repeated use of the Bayes theorem
- Current posterior becomes prior when new data are available.


1992
1993
1994
1995
1996
1997
1998
1999
2000
Prior
Posterior
Log TN Concentration

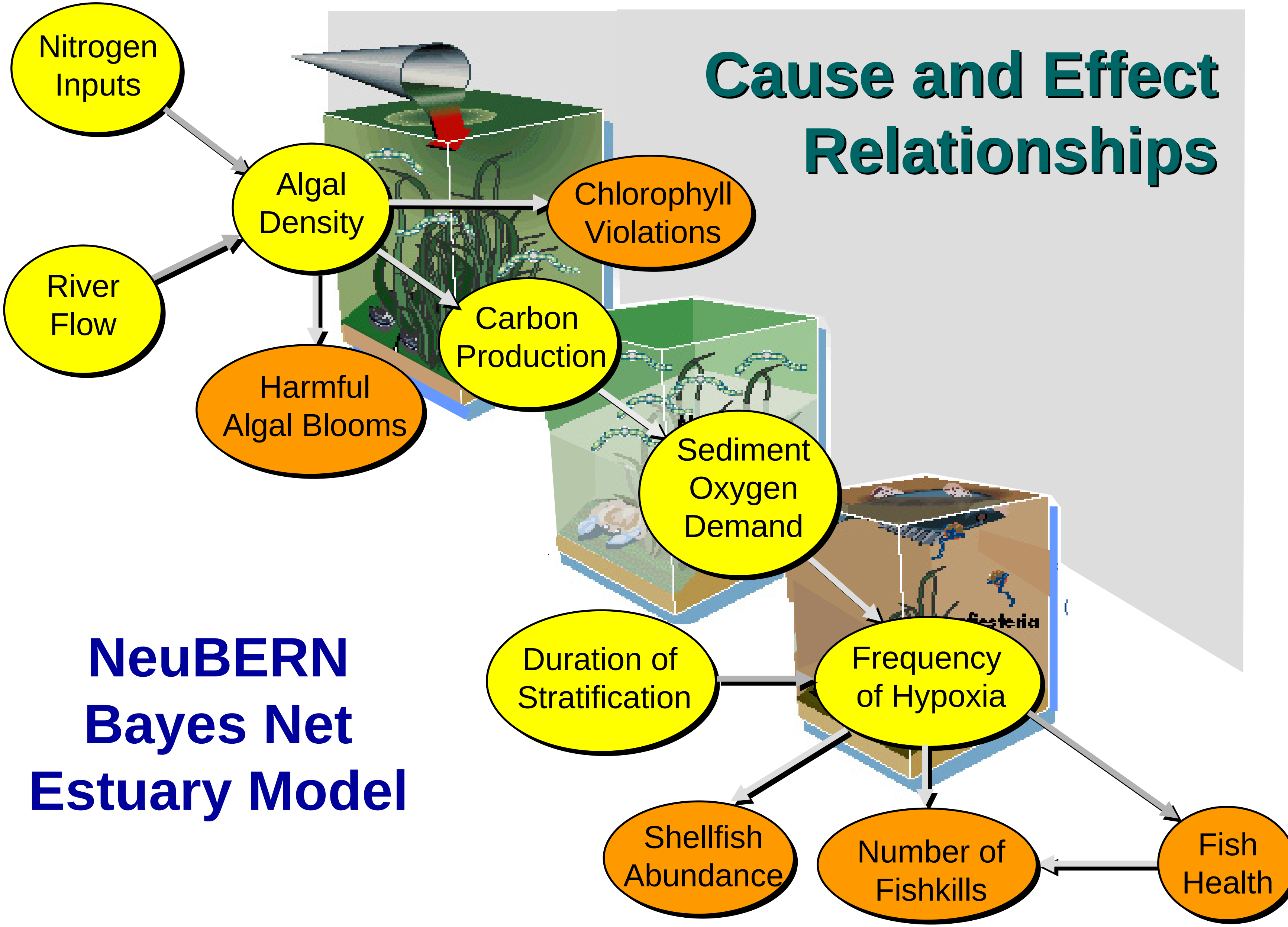

Density
0.0
0.5
1.0
1.5
5
6
7
8
9
10
log TN Concentration
Prior
1992
1993
1994
1995
1996
1997
1998
1999
2000

Example: Chl a in Neuse Estuary

The Chlorophyll model in NeuBERN:

$$\log(chla) = \begin{cases} \beta_1 + \log(\theta)(T-20) + \beta_2(15.7 - Log(Flow)) + \beta_4 e^{TN}, & \\ & Log(Flow) \le 15.7 \\ \beta_1 + \log(\theta)(T-20) + \beta_3(Log(Flow) - 15.7) + \beta_4 e^{TN}, & \\ & Log(Flow) > 15.7 \end{cases}$$

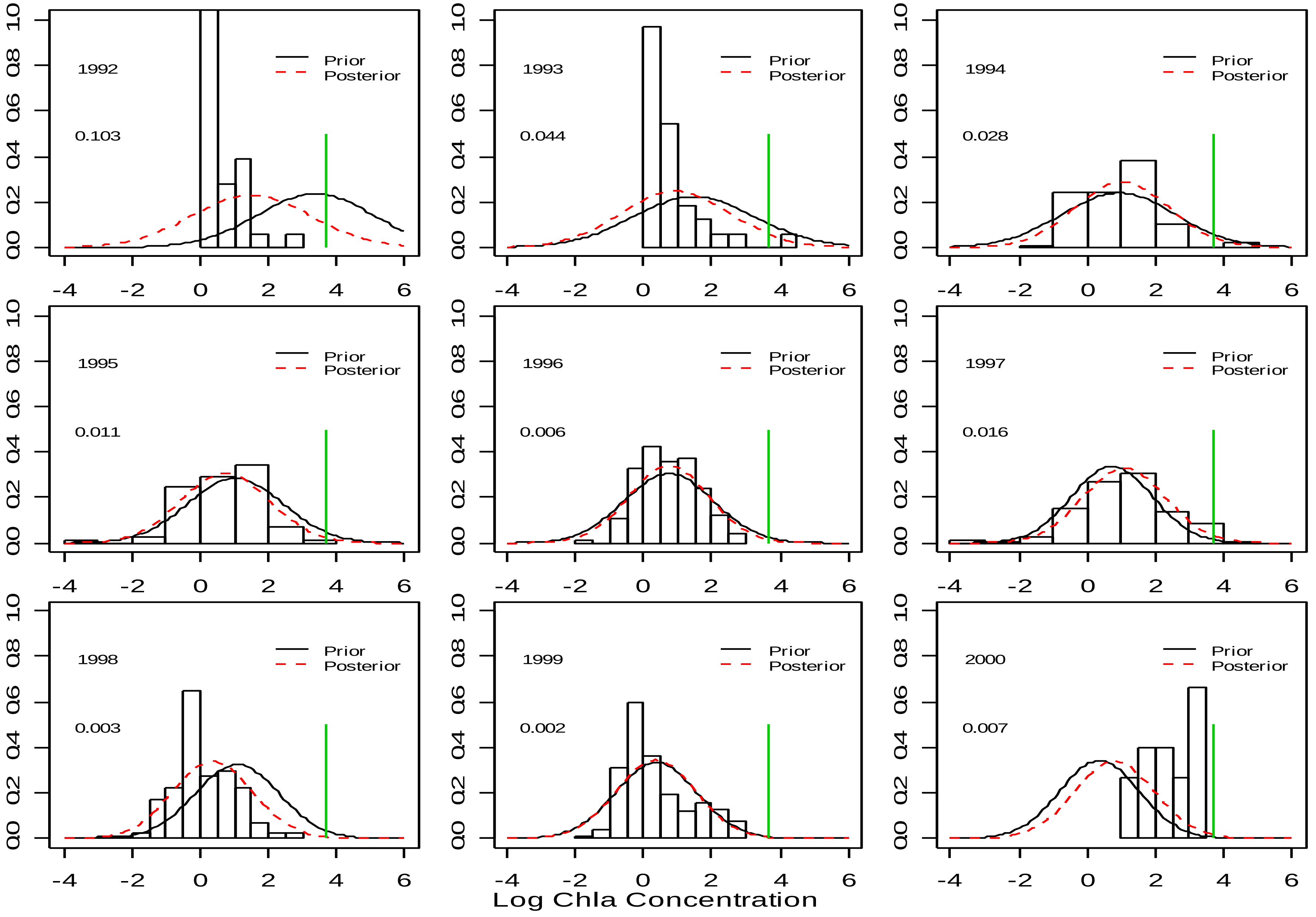
Cause and Effect Relationships

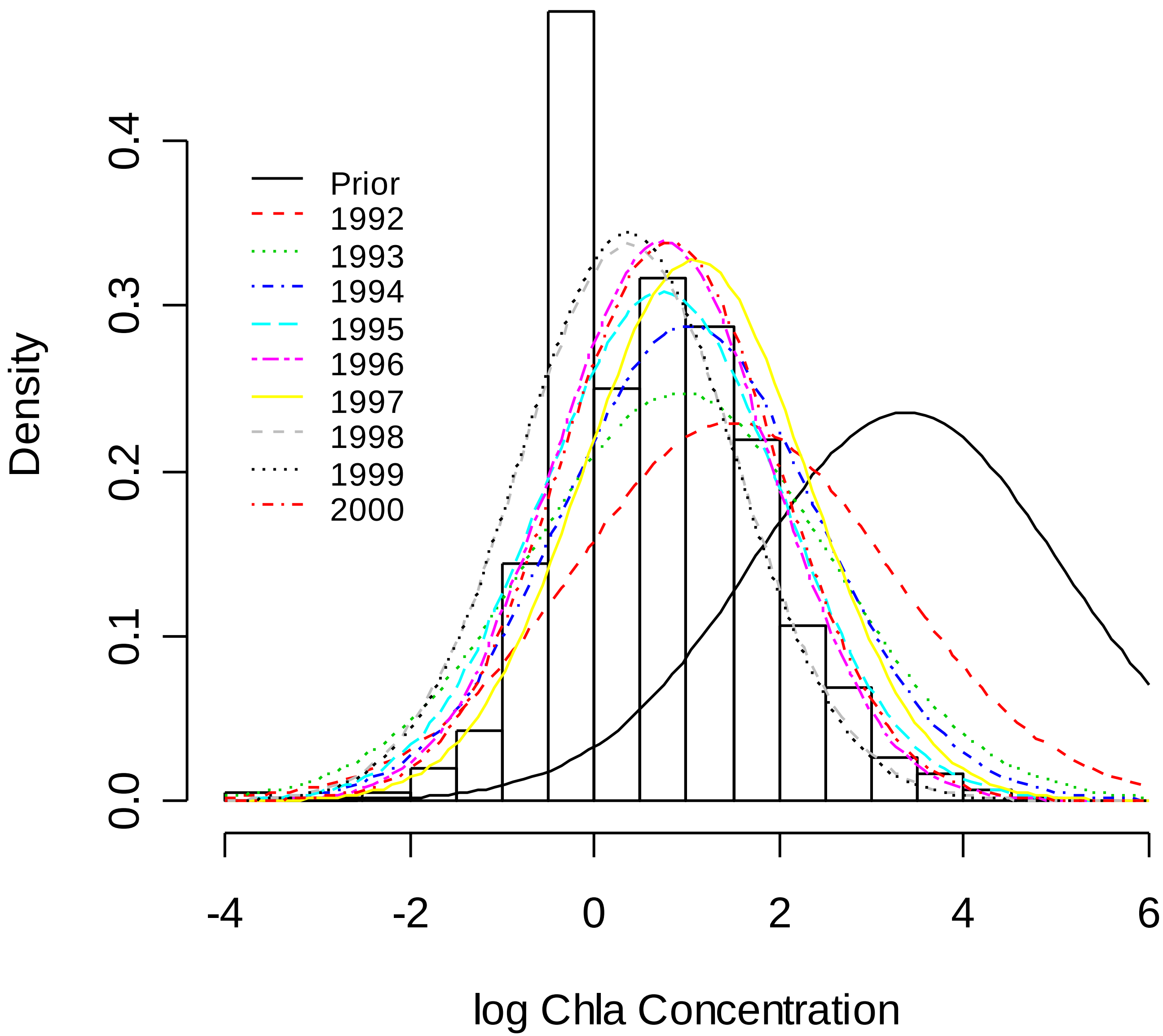


NeuBERN Bayes Net Estuary Model

Prior Information

- TN: random samples from Bayesian SPARROW
- β's: original NeuBERN regression analysis
- Model error: original regression analysis
- Monte Carlo simulation: random samples of log(*chla*)
- Assume log(*chla*) ~ N(μ, σ^2)


1992
0.103
1993
0.044
1994
0.028
1995
0.011
1996
0.006
1997
0.016
1998
0.003
1999
0.002
2000
0.007
Prior
Posterior
Log Chla Concentration


Density
0.0
0.1
0.2
0.3
0.4
Prior
1992
1993
1994
1995
1996
1997
1998
1999
2000
-4
-2
0
2
4
6
log Chla Concentration

Example: Chla Model Updating

- Using yearly data to update model parameters

$$\log(chla) = \begin{cases} \beta_1 + \log(\theta)(T-20) + \beta_2(Ch - Log(Flow)) + \beta_4 e^{TN}, \\ \hfill Log(Flow) \le Ch \\ \beta_1 + \log(\theta)(T-20) + \beta_3(Log(Flow) - Ch) + \beta_4 e^{TN}, \\ \hfill Log(Flow) > Ch \end{cases}$$

Example: Chla Model Updating

- Probabilistic expression:

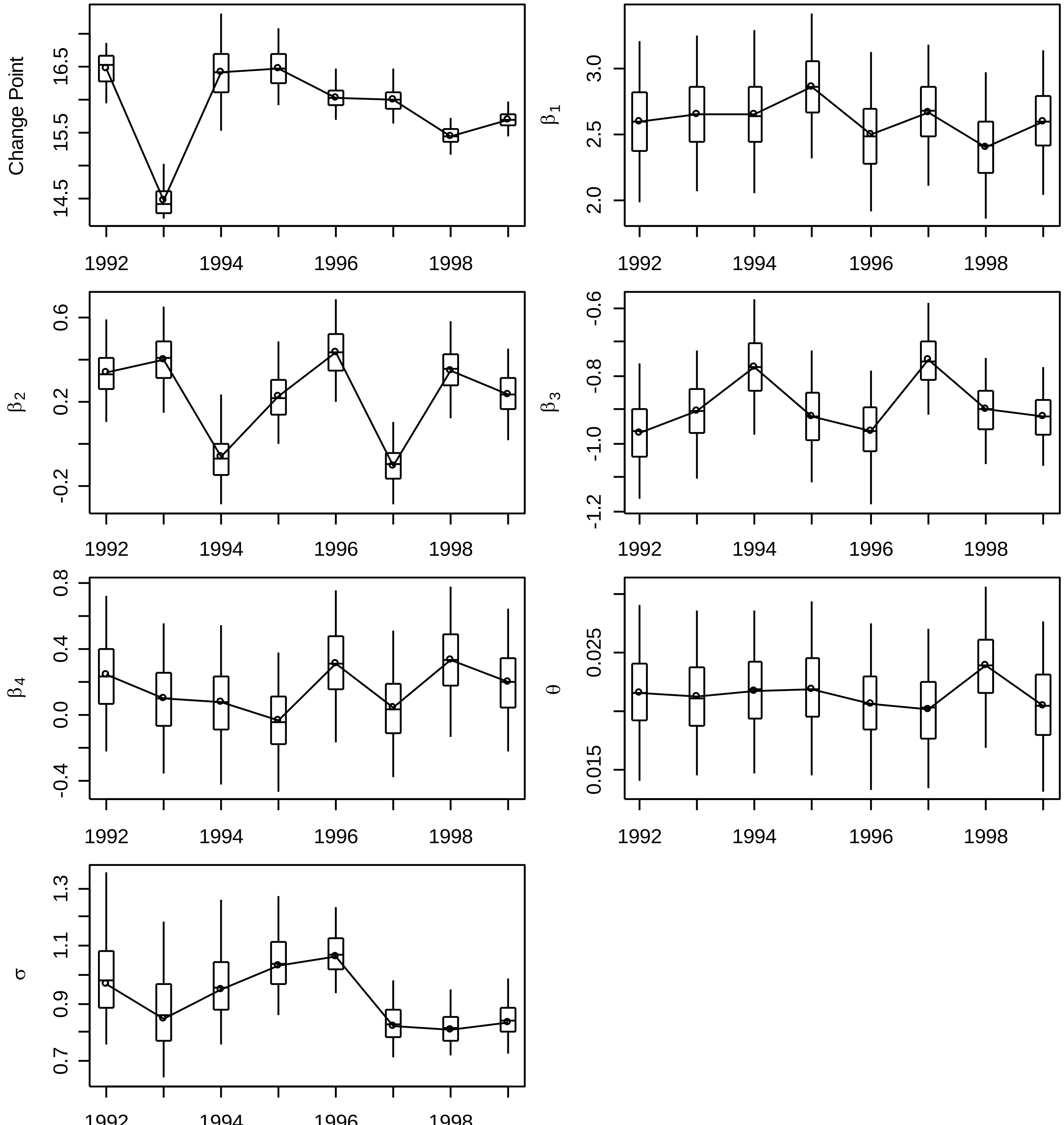
$$\log(Chla) \sim N(\mu, \sigma^2)$$

Where: $$\mu = f(\beta, \theta, Ch, T, TN)$$

Same general setting under Bayes Theorem, but with a large number of parameters

Example: Chla Model Updating

- No conjugate family of priors
- No analytical solutions for posteriors
- Numerical solution using Markov chain Monte Carlo simulation



Change Point
16.5
15.5
14.5
1992
1994
1996
1998
β_1
3.0
2.5
2.0
β_2
0.6
0.2
-0.2
β_3
-0.6
-0.8
-1.0
-1.2
β_4
0.8
0.4
0.0
-0.4
θ
0.025
0.015
σ
1.3
1.1
0.9
0.7

Post (TMDL) Implementation Questions

- **Has compliance with the water quality standard been achieved?**

- **If compliance has not been achieved, what pollutant reduction actions did not respond as predicted?**

Tasks Completed or Underway

- NeuBERN and SPARROW models have been linked within a Bayesian framework (WinBUGS)
- NeuBERN is being re-specified to add more mechanism.
- SPARROW has been re-calibrated to address spatial correlation and improve parameter estimators. Ultimately, it will be further revised to allow for subwatershed-specific parameters.

Issues to Address in Year 3

- Use the CUAHSI “digital watershed” to efficiently link SPARROW and NeuBERN
- Represent land use (pollutant load) change in SPARROW
- Characterize prior probabilities for SPARROW parameters
- Design monitoring program (sensitivity analysis)
- Assess role of stakeholders

Expected Outcomes

- Re-assessment of the Neuse nitrogen TMDL for NC Division of Water Quality

- Development of guidelines and procedures for adaptive implementation of TMDLs

- Determination of effective roles for stakeholders