

US EPA ARCHIVE DOCUMENT

STAR Progress Review Workshop  
Old Town Alexandria, VA  
June 16-18, 2004

## Bayesian Methods for Regional Eutrophication Models

E. Conrad Lamont III  
Dept. of Environmental Studies  
Louisiana State University  
and  
Craig A. Stow  
Department of Environmental Health Sciences  
University of South Carolina

## Overview

- Goals and Objectives
- Approach
- Preliminary Findings
- Significance
- Next Steps

## Goals and Objectives

- Use modern classification and regression trees and hierarchical Bayesian techniques to link multiple environmental stressors to biological responses and quantify uncertainty in model predictions and parameters.

## Guidance for TMDL model selection (NRC 2001)

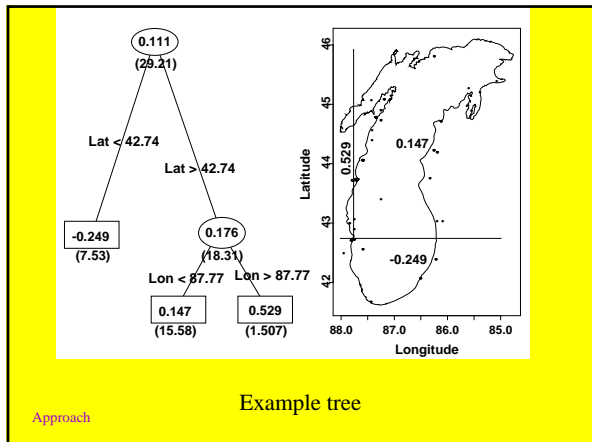
- report prediction uncertainty
- be consistent with the amount of data available
- flexible enough to permit updates and improvements

## Approach

Approach

## Tree based methods

- are a flexible approach useful for variable subset selection
- when the analyst suspects global non-linearity
- and cannot (or does not want to) specify the functional form of possible interactions *a priori*.



Approach

### Methods

- Classification And Regression Trees (CART),
- it's Bayesian analogue, BCART
- a recently developed enhancement to the BCART procedure, which includes BCART as a model subclass, known as Bayesian Treed (BTREED) models, and
- Bayesian Hierarchical Models

Approach

### BCART and BTREED Models

- Will be used with the EPA Nutrient Criteria Database to identify and estimate regional eutrophication stressor – response models for EPA STAR funded research.
- ✓ Lamon and Stow, 2004, Water Research, 38(11): 2764-2774.

Approach

### Bayesian Treed models

- Bayesian Hierarchical model to:
  - Select subsets on  $X \rightarrow X_s$
  - Fit linear models to these subsets  $X_s$
- Tree structured models
  - “ANOVA in Reverse”
- “Leaves” contain linear models, not just a mean (like in CART models)

Approach

### Bayesian Treed model specification

$y|x$ , with  $x = (x_1, x_2, \dots, x_p)$ ,  
 where  $p$  = number of predictor variables.

**two components of model**

1. tree  $T$  with  $b$  bottom nodes,
2. parameter vector  $\theta = (\theta_1, \theta_2, \dots, \theta_b)$ ,

where  $\theta_i$  is associated with the  $i$ th bottom node. If  $x$  is in the  $i$ th node, then  $y|x = f(y|\theta_i)$ , where  $f$  is a parametric family indexed by  $\theta_i$ .

Approach

### Bayesian Treed model specification (cont.)

Tree is fully specified by  $(\theta, T)$   
 need a prior,  
 $p(\theta, T)$ .

Because  $\theta$  indexes a parametric model for each  $T$ , we can use Bayes theorem such that  
 $p(\theta, T) = p(\theta | T)p(T)$ .

So, specify prior in two stages:

- 1 – on the tree space,  $p(T)$ , and
- 2 – on the distribution of  $Y$  at the bottom nodes, conditional on  $T, p(\theta | T)$ .

Approach

### Bayesian Treed model search

- MCMC used to stochastically search for high posterior probability trees  $T$ .
- Metropolis –Hastings algorithm simulates a Markov chain with limiting distribution  $p(T|Y,X)$
- Chipman, George and McCulloch, 2000, JASA.  
<http://gsbwww.uchicago.edu/fac/robert.mcculloch/research/papers/index.html>

Approach

### Data

- Response variables may be
  - either continuous (such as biological indices of abundance) or
  - discrete (such as designated use attainment classes).

EPA NES example: response variable is lake-wide, summer average  $\log_{10}$  Chlorophyll  $a$  concentration.

Approach

### Data

Predictor variables in tree based methods may also be continuous or discrete, and may include : source agency, basin, sub-watersheds, states, EPA regions, latitude and longitude, and many continuous predictors related to water chemistry, water use, discharges or pollutant loading.

Approach

### Data

For the EPA NES example, Latitude and Longitude were used in the tree portion, and

$$\log_{10} Q_{in}, \quad \log_{10} Z \quad \log_{10} \tau_w$$

$$\text{In-lake } \log_{10} \text{ TP} \quad \text{In-lake } \log_{10} \text{ TN}$$

For the linear model within each bottom node (leaf)

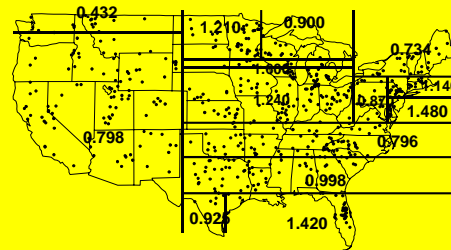


### Preliminary Findings

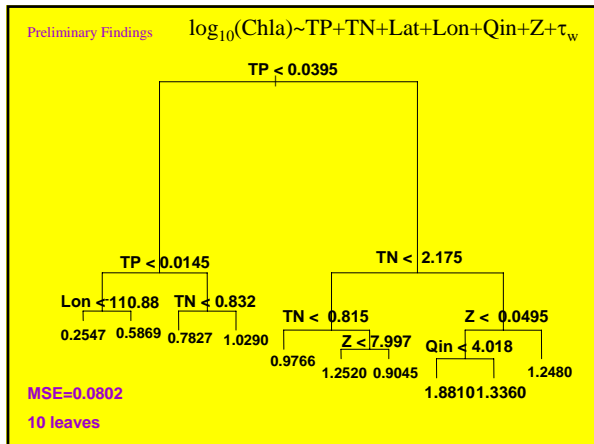
Lamon, E.C., and C.A. Stow, 2004.  
 Bayesian Methods for regional-scale eutrophication models,  
Water Research, 38(11): 2764-2774.

Preliminary Findings

$$\log_{10}(\text{Chl}a) \sim \text{latitude} + \text{longitude}$$



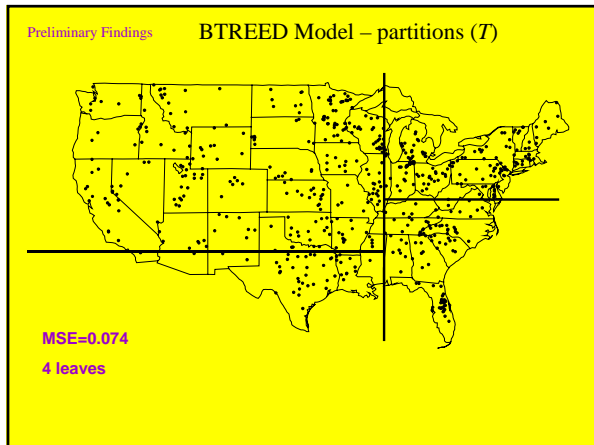
MSE=0.1092  
 14 leaves



Preliminary Findings

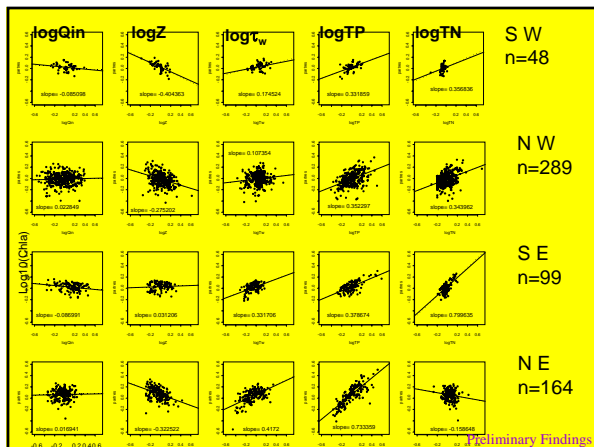
## Results

- Bayesian Treed Model



Region	Int.	$\log_{10}Q_m$	$\log_{10}Z$	$\log_{10}\tau_w$	In-lake $\log_{10}TP$	In-lake $\log_{10}TN$	MSE	n
SW	0.02166	-0.0851	-0.4044	0.1745	0.3319	0.3568	0.027	48
	0.0210 (0.0209)	-0.0691 (0.0927)	<b>-0.4390</b> (0.1426)	0.2107 (0.1534)	<b>0.3280</b> (0.1036)	<b>0.4012</b> (0.1957)		
NW	-0.0116	0.0228	-0.2752	0.1074	0.3523	0.3440	0.095	289
	-0.0117 (0.0068)	0.0241 (0.0478)	<b>-0.2763</b> (0.0647)	0.1091 (0.0678)	<b>0.3528</b> (0.0553)	<b>0.3449</b> (0.0715)		
SE	0.0290	-0.0870	0.0312	0.3317	0.3787	0.7996	0.037	99
	<b>0.0299</b> (0.0090)	-0.0845 (0.0526)	0.0385* (0.0734)	<b>0.3325</b> (0.0862)	<b>0.3683</b> (0.0772)	<b>0.8456</b> (0.1514)		
NE	0.0642	0.0169	-0.3225	0.4172	0.7334	-0.1586	0.073	164
	<b>0.0653</b> (0.0111)	0.0222 (0.0734)	<b>-0.3306</b> (0.0997)	<b>0.4275</b> (0.0854)	<b>0.7398</b> (0.0653)	-0.1665 (0.1048)		
<b>total</b>							<b>0.074</b>	<b>600</b>

Preliminary Findings



## Next Steps

## Next Steps

- More predictor variables
- Apply these methods to the Nutrient Criteria Database
- Use resultant tree structures to identify important hierarchical structure
- Explore these structures with other Hierarchical Bayesian methods
- Non-linear specification? Spline basis functions in leaf model or inclusion of all predictors in tree
- Tools

## Thanks!



- EPA STAR program for funding.
- Hugh Chipman, Univ. of Waterloo and Robert McColloch, University of Chicago for BCART/BTREED computer code.