

# A Bayesian Approach to OC4

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# 1 Introduction

## 1.1 Background

- Necessity for estimating chlorophyll
- State of current chlorophyll algorithms
- Basic empirical form

$$\log_{10}(\text{chlor}_a) = a_0 + \sum_{i=1}^j a_i \log_{10} \left( \frac{\max(Rrs(\lambda_{blue}))}{Rrs(\lambda_{green})} \right) \quad (1)$$

- Problems with current algorithms:
  - collinearity of inputs
  - poor performance in coastal
  - maximum likelihood estimation approach  $\rightarrow$  increased odds of overfitting (lack of in-situ data availability compared to satellite data makes it worse)

## 1.2 Proposed framework

### 1.2.1 Basis reduction via PCA

- PCA of Rrs to reduce overlap of information between predictor variables

### 1.2.2 Bayesian framework for chlorophyll estimation from remote sensing data

- transparent construction of models with explicit formulation of assumptions,
- assumptions/background information codified as priors,
- feasibility of priors verifiable before data collection via prior predictive checks
- built-in structure for selecting relevant features,
- posterior distribution as rich information structure from which to estimate parameter uncertainty as well as output prediction uncertainty,
- predictive ability of model assessed via posterior predictive checks
- multiple models encouraged by bayesian workflow,
- evaluation/comparison between models using both information about model complexity and posterior distribution (WAIC),

### 1.2.3 Reproducibility

- iterative process of bayesian framework relies on reproducibility for progress
- code available via github
- data available via osf

## **2 Methods**

### **2.1 Model Development**

#### **2.1.1 Bayesian Linear Regression**

- Order 1 regression for interpretable coefficients
- no interaction terms
- regularized horseshoe prior for feature selection

#### **2.1.2 Bayesian Linear Regression with Interaction Terms**

- generation of 1st order interaction terms
- allowing for both strong and weak heredity

#### **2.1.3 Bayesian Neural Network**

- Specific hierarchical structure for ARD
- HL1 4 NN with elu activation

#### **2.1.4 Bayesian OC4 version as Baseline**

### **2.2 Prior Predictive Checks**

### **2.3 Data Acquisition/Exploration/Transformation**

### **2.4 Model Fitting**

### **2.5 Marginal Posterior of Coefficients $\rightarrow$ Feature Relevance Determination**

### **2.6 Posterior Predictive Checks**

### **2.7 Model Comparison Through Posterior Predictive Checks**

## **3 Results**