



**Extracting Environmental and Climate Signals in Coastal
Ecosystem Data with Two-Stage Multivariate Dynamic Linear
Models**

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JSM
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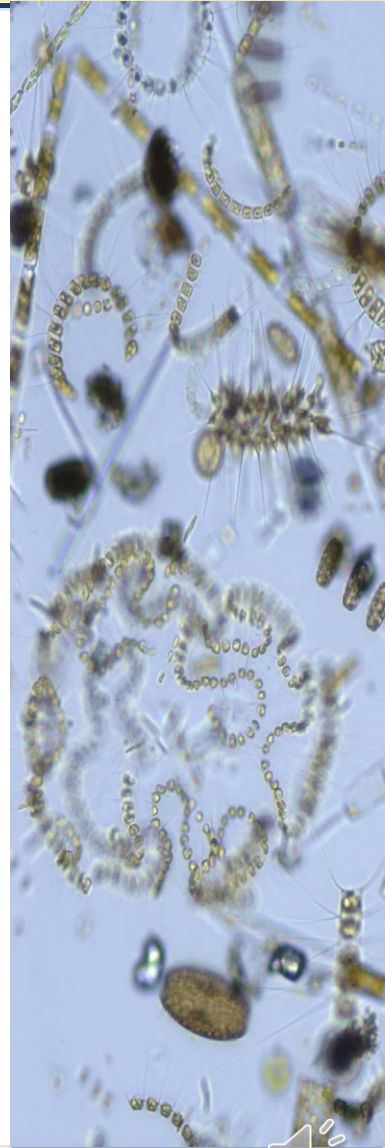
Why Phytoplankton?

What are phytoplankton?

- Microscopic marine algae

Why study phytoplankton?

- Production of 49-60 Gt C yr⁻¹ (Carr et al. 2006)
- Drive global biogeochemical cycling (e.g. carbon; Falkowski 1994)
- Form the basis of production in marine food webs (Steinberg and Landry 2017)



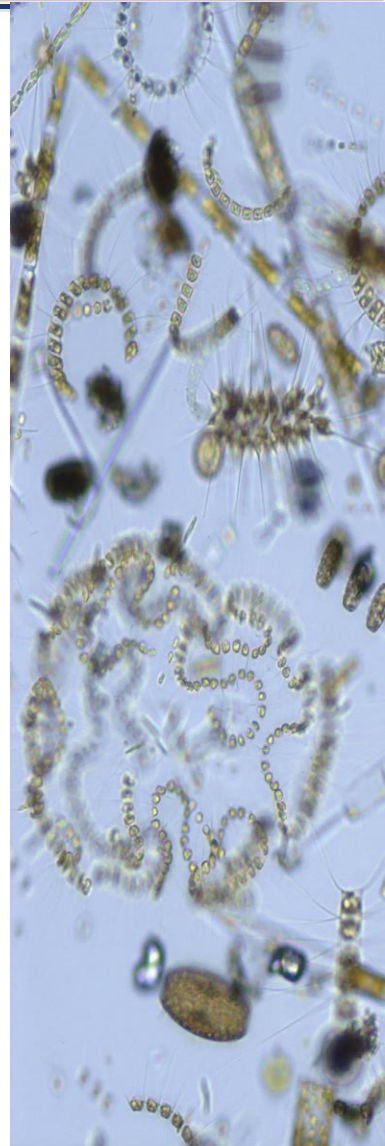
Why is phytoplankton size important?

Phytoplankton size affects:

- Metabolic rate (López-Urrutia et al. 2011)
- Algae bloom formation (Irigoien et al. 2005)
- Food chain length (Sprules and Munawar 1986)

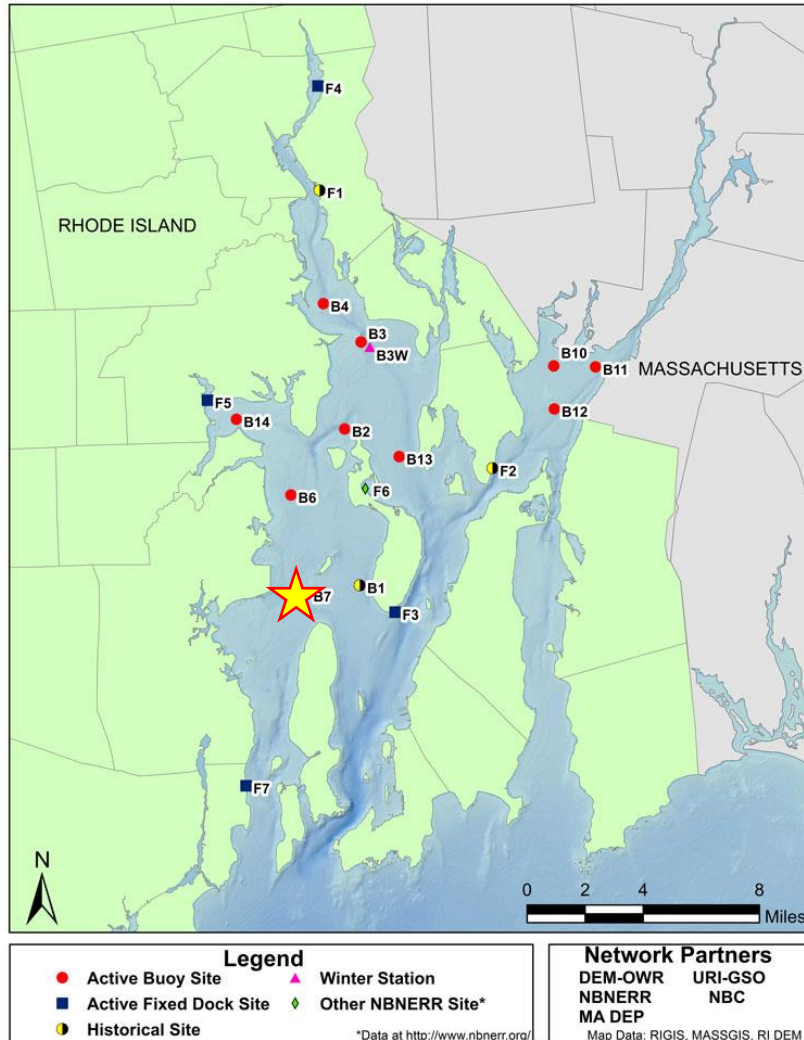
Phytoplankton size affected by:

- Cell size scales inversely with temperature (Atkinson et al. 2003)
- Cell size directly imposes a physical constraint on the potential rate of nutrient supply (e.g. Mei et al. 2009)

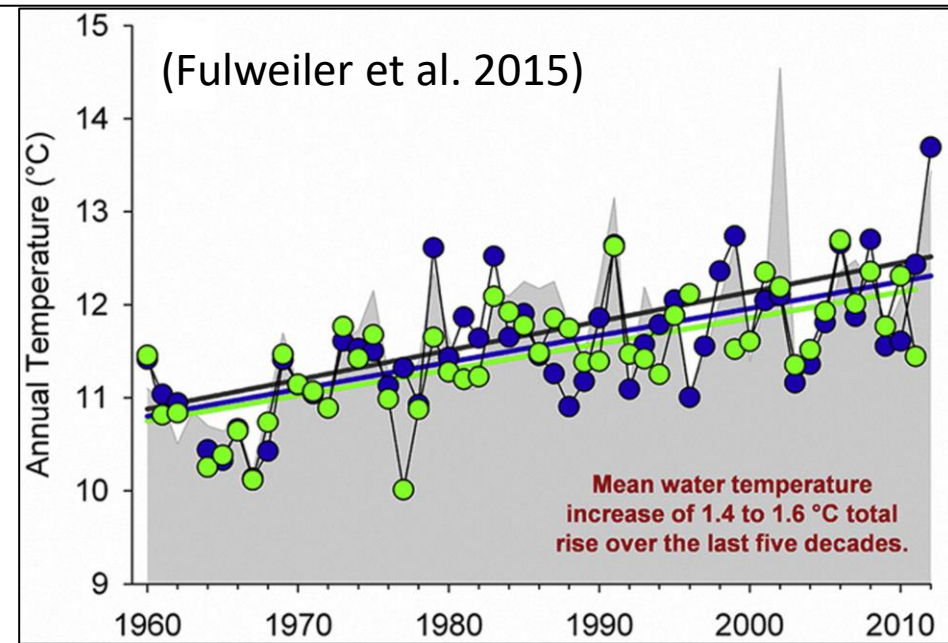


Could ecosystem changes be changing cell size locally?

Narragansett Bay Fixed-Site Water Quality Monitoring Network Locations



- In Narragansett Bay, Rhode Island, USA:
- **Temperature** has shown an increase of 1.4-1.6°C by a linear regression of mean annual levels (Fulweiler et al. 2015)
 - **Nitrogen** pollution in wastewater was required by RI Department of Environmental Management to be cut 50% from 2005 to 2012 (RI DEM 2005)

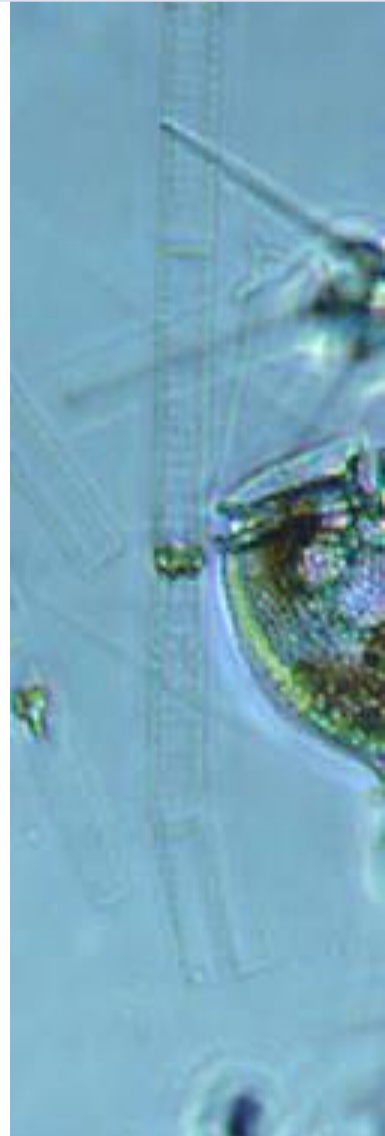


<http://www.dem.ri.gov/programs/emergencyresponse/bart/stations.php>

Research Objective

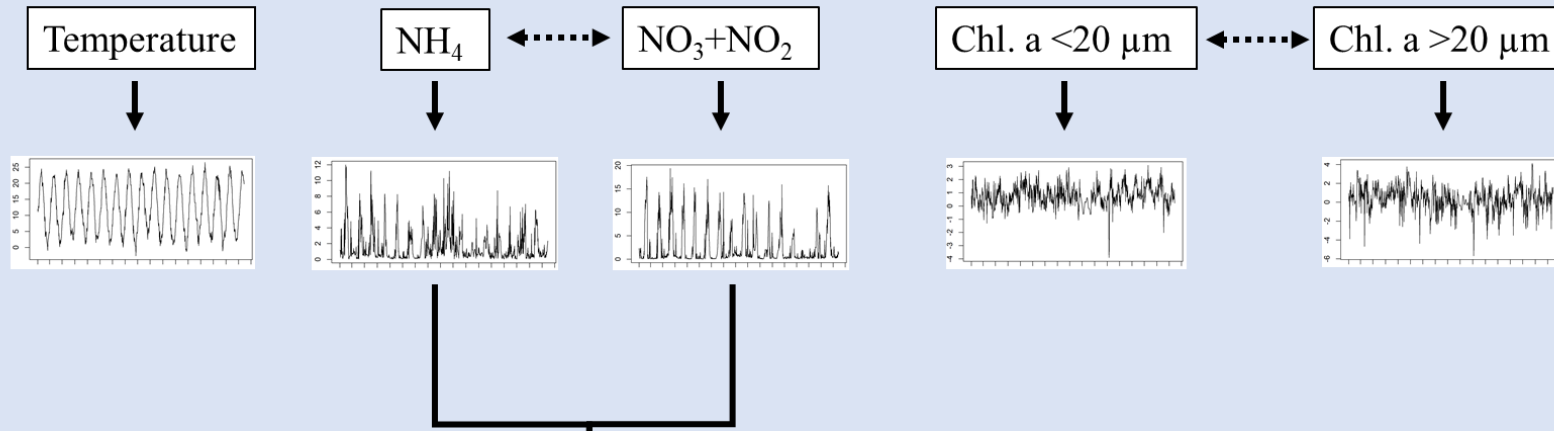
Use Bayesian Dynamic Linear Models to:

1. Characterize long-term changes in Narragansett Bay (2003-2019):
 - Temperature
 - DIN (Dissolved inorganic nitrogen)
 - Size Fractionated Chlorophyll
($< 20\mu\text{m}$, $>20\mu\text{m}$, proxy for phytoplankton biomass)
2. Impute missing data
3. Test the influence of DIN on phytoplankton size structure through dynamic linear regression

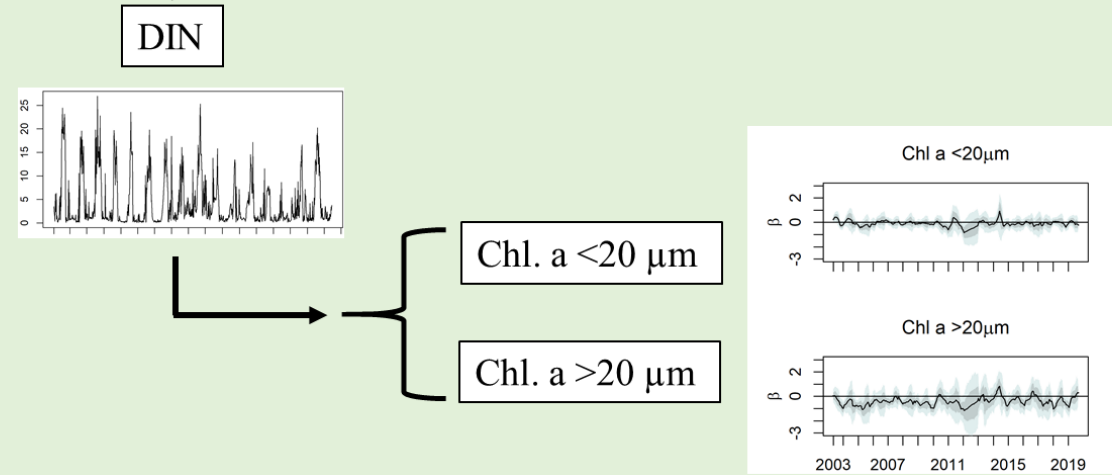


Outline

Stage 1 Models



Stage 2 Model



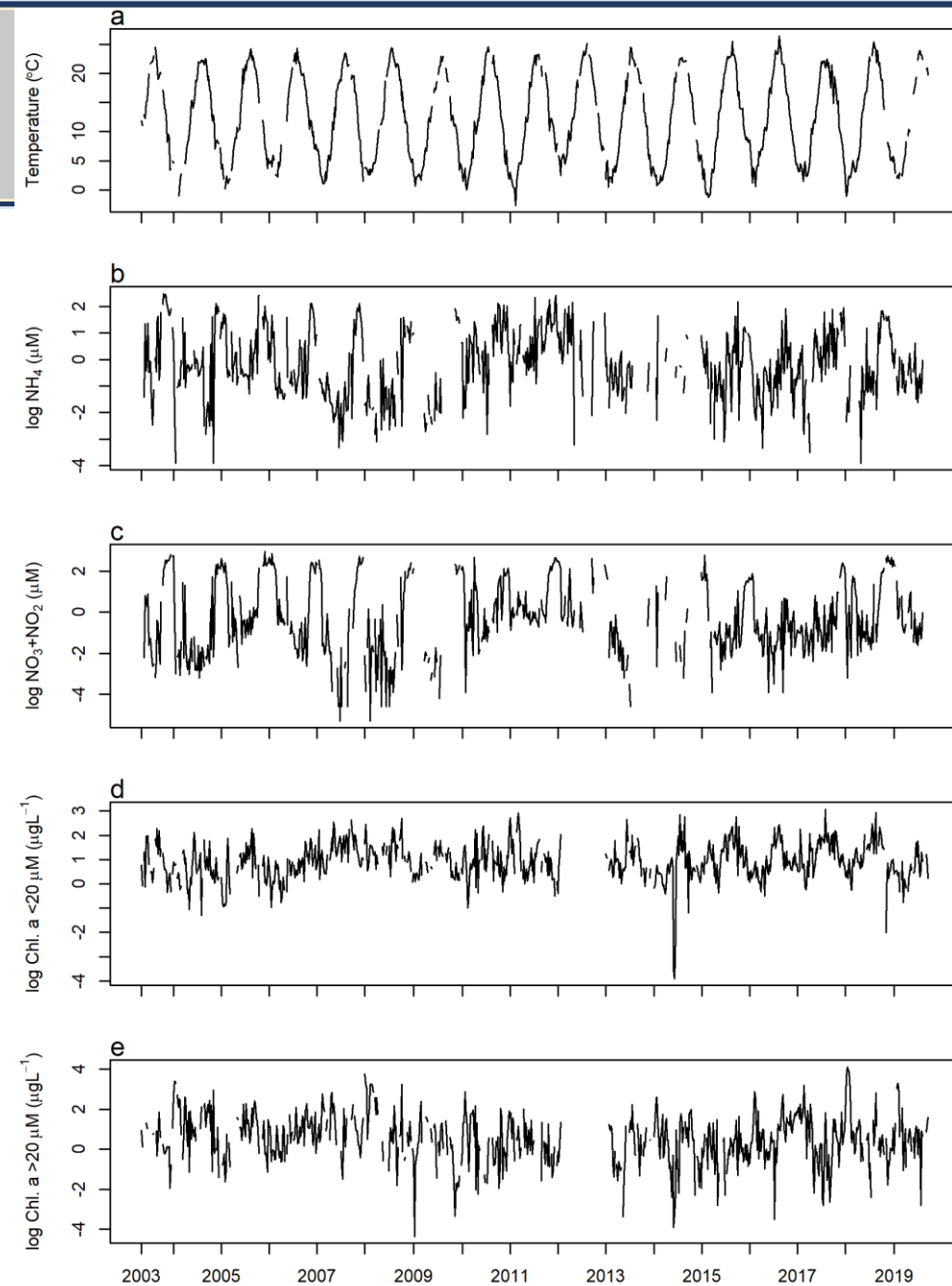
Purpose

- Missing data imputation
- Exploration
- Inference:
 - Long-term change
 - Seasonal change

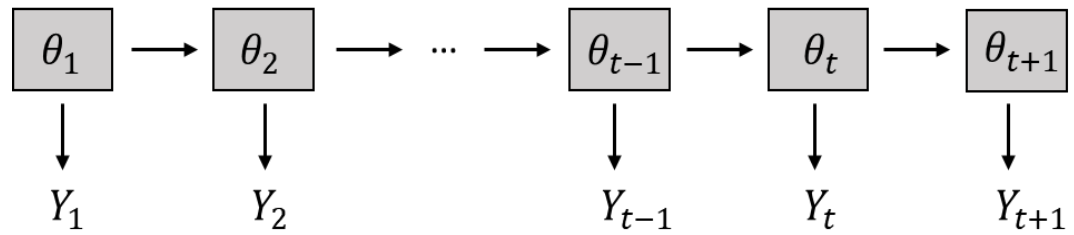
- Describe the relationship of DIN and size structure

Data Description

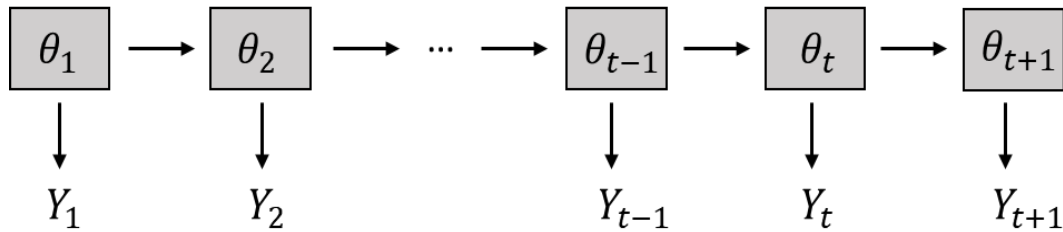
- Narragansett Bay Long-term Plankton Time Series
 - Source: <https://web.uri.edu/gso/research/plankton/>
- Time-period:
 - April 29, 2003- September 17, 2019
 - Weekly resolution
- Variables:
 - water temperature ($^{\circ}\text{C}$)
 - NH_4
 - NO_3+NO_2 (μm)
 - Chlorophyll a $< 20 \mu\text{m}$ ($\mu\text{g L}^{-1}$)
 - Chlorophyll a $> 20 \mu\text{m}$ ($\mu\text{g L}^{-1}$)
- Missingness:
 - MCAR
 - Missingness lengths 1-48 observations



Dynamic Linear Models



Dynamic Linear Models



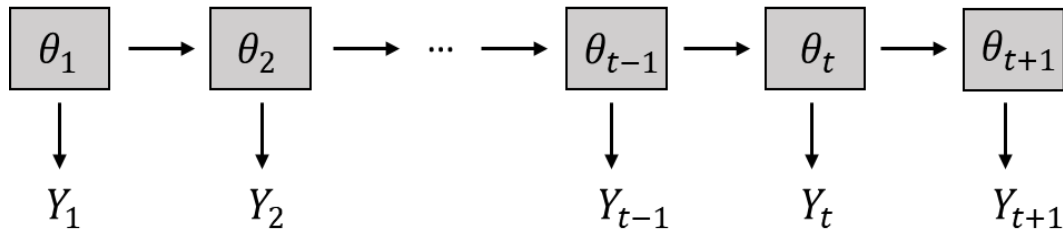
$$Y_t = \mathbf{F}_t \boldsymbol{\theta}_t + v_t, \quad v_t \sim N(0, \mathbf{V}) \quad \left. \begin{array}{l} \text{Observation equation} \\ \text{State equation} \end{array} \right\}$$

$$\boldsymbol{\theta}_t = \mathbf{G}_t \boldsymbol{\theta}_{t-1} + w_t, \quad w_t \sim N(0, \mathbf{W})$$

$$\left. \begin{array}{l} \boldsymbol{\theta}_0 \sim N(\mathbf{m}_0, \mathbf{C}_0) \\ \mathbf{V} \sim IG(a_v, b_v) \\ \mathbf{W} \sim IW(a_w, b_w) \end{array} \right\} \text{ Priors}$$

Variable	Definition
Y_t	Datum/Data
F_t	Observational matrix
G_t	Evolutional Matrix
θ_t	Unobserved state
V_t	Observational variance/covariance
W_t	Evolutional variance/covariance

Dynamic Linear Models



$$\begin{aligned}
 Y_t &= \mathbf{F}_t \boldsymbol{\theta}_t + v_t, & v_t &\sim N(0, \mathbf{V}) \\
 \boldsymbol{\theta}_t &= \mathbf{G}_t \boldsymbol{\theta}_{t-1} + w_t, & w_t &\sim N(0, \mathbf{W})
 \end{aligned}$$

Observation equation
State equation

$$\begin{aligned}
 \boldsymbol{\theta}_0 &\sim N(\mathbf{m}_0, \mathbf{C}_0) \\
 \mathbf{V} &\sim IG(a_v, b_v) \\
 \mathbf{W} &\sim IW(a_w, b_w)
 \end{aligned}$$

Priors

Variable	Definition
Y_t	Datum/Data
F_t	Observational matrix
G_t	Evolutional Matrix
θ_t	Unobserved state
V_t	Observational variance/covariance
W_t	Evolutional variance/covariance

Why?

- Flexible structure
- Components are additive
 - long-term trend, season, regression components separately
- Any parameter and component can time vary
 - Important when we are hypothesizing changing ecosystem function
- Interpolation via inference
- Quantify uncertainty in missingness and states

Stage 1: Models, Environment

Stage	Model	Response Variable(s)	θ Components	V Specification	W Specification
1	1	Temperature	Dynamic, Intercept (μ)	Static, IG prior	Static, IW prior
			Dynamic, Season (S_i), $i=1$		
	2	log NH ₄ , log NO ₃ + NO ₂	Dynamic, Intercept (μ)	Static, IW prior	Static, IW prior
			Dynamic, Season (S_i), $i=1, \dots, 6$		
	3	log Chl. <20, log Chl. >20	Dynamic, Intercept (μ)	Static, IW prior	Static, IW prior
			Dynamic, Season (S_i), $i=1, \dots, 6$		

Outline

Stage 1

$$\begin{cases} \mathbf{Y}_t^Q = F_t^Q \boldsymbol{\theta}_t^Q + v_t^Q, & v_t^Q \sim \mathcal{N}_r(\mathbf{0}, \mathbf{V}_t^Q) \\ \boldsymbol{\theta}_t^Q = \mathbf{G}_t^Q \boldsymbol{\theta}_{t-1}^Q + w_t^Q, & w_t^Q \sim \mathcal{N}_n(\mathbf{0}, \mathbf{W}_t^Q) \end{cases} \quad (2)$$

Stage 2

$$\begin{cases} \mathbf{Y}_t^Z = F_t^Z \boldsymbol{\theta}_t^Z + v_t^Z, & v_t^Z \sim \mathcal{N}_z(\mathbf{0}, \mathbf{V}_t^Z) \\ \boldsymbol{\theta}_t^Z = \mathbf{G}_t^Z \boldsymbol{\theta}_{t-1}^Z + w_t^Z, & w_t^Z \sim \mathcal{N}_{rw}(\mathbf{0}, \mathbf{W}_t^Z \otimes \mathbf{V}_t^Z) \\ F_{X,t}^Z \sim P(g((\Psi_{Stage1}^X))) \end{cases} \quad (3)$$

$$\Psi_0 \sim \prod_{k=1}^K P(\Psi_{0,k})$$

$$\Psi_0 = \{\theta_0^Z, \theta_0^Q, V_0^Z, V_0^Q, W_0^Z, W_0^Q\}$$

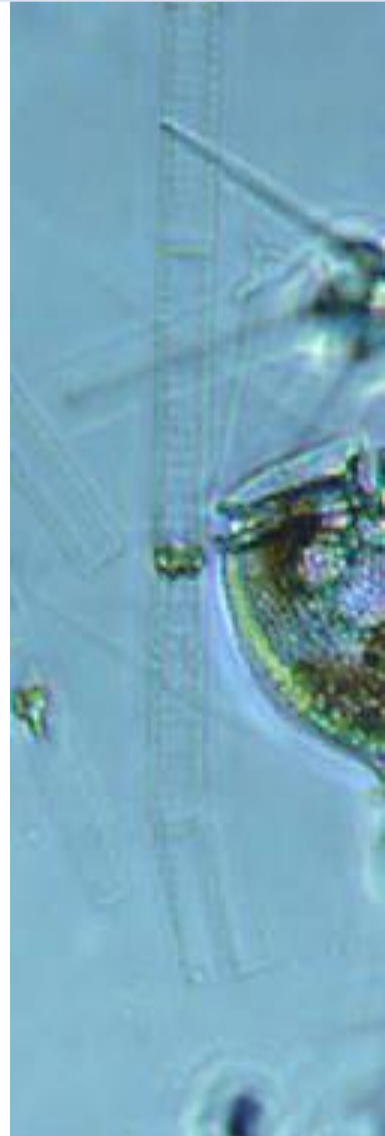
Stage 1: Models, Environment

Inference and Sampling:

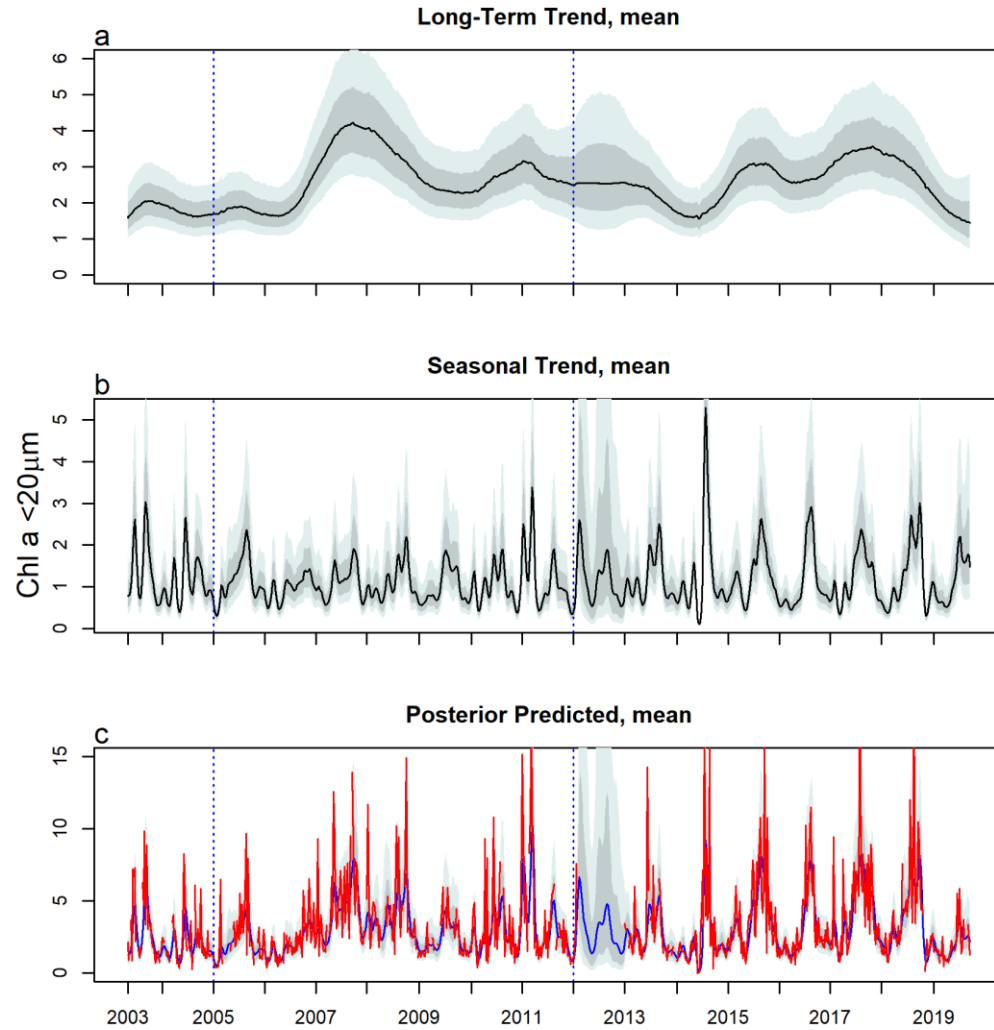
- Non-conjugate (no closed form of posterior distribution)
- Markov Chain Monte Carlo (MCMC) Simulation of Posteriors

- Gibbs Sample each conditional posterior distribution

- $\theta_{1:T} | Y_{1:T}, V, W$ Kalman Filtering and Smoothing
- $V | Y_{1:T}, W, \theta_{1:T}$ \sim Inverse – Gamma ($\nu_0 + T, S_0 + RSS_y$)
- $W | Y_{1:T}, V, \theta_{1:T}$ \sim Inverse – Wishart ($\nu_0 + T, S_0 + RSS_\theta$)



Decomposing seasonal and long-term trends



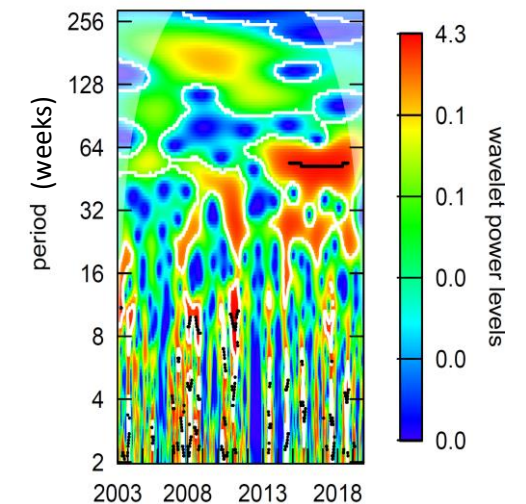
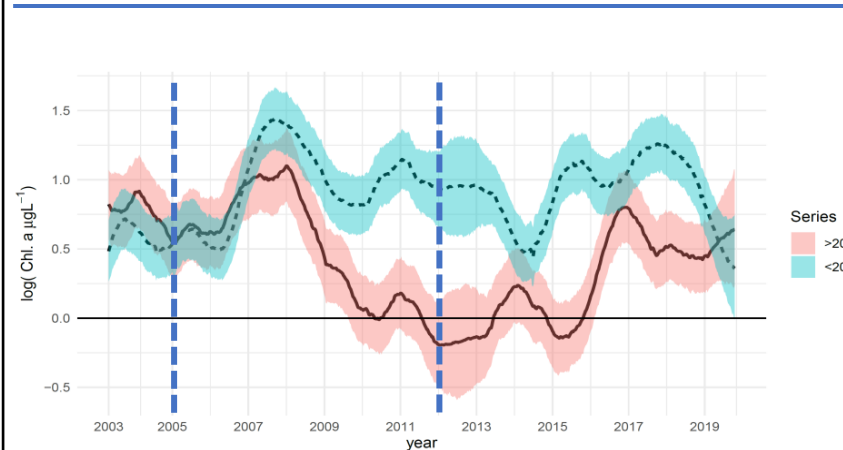
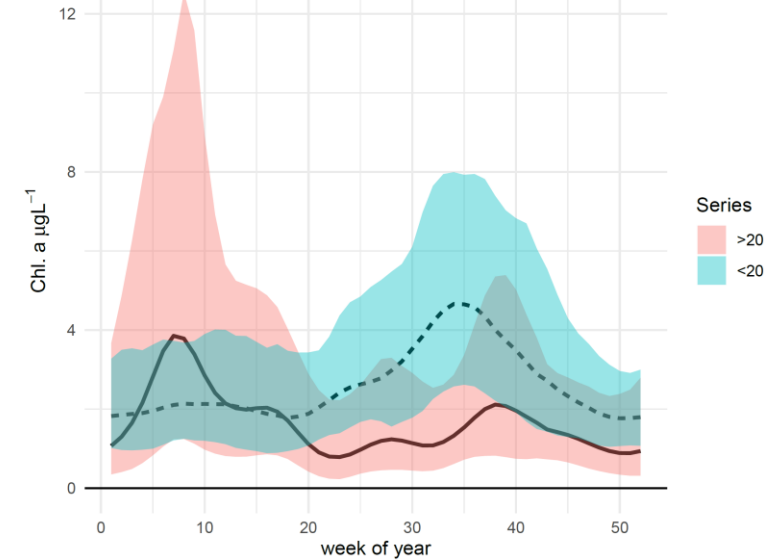
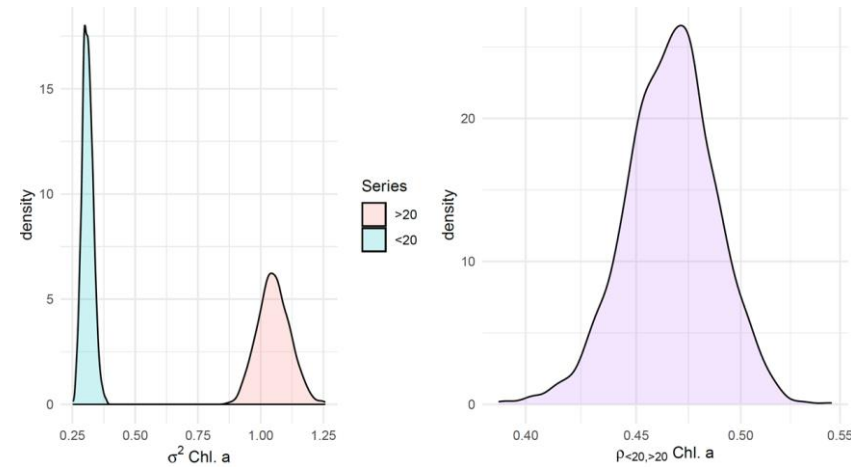
Stage 1: Models, Environment

Chl. a < 20 μm

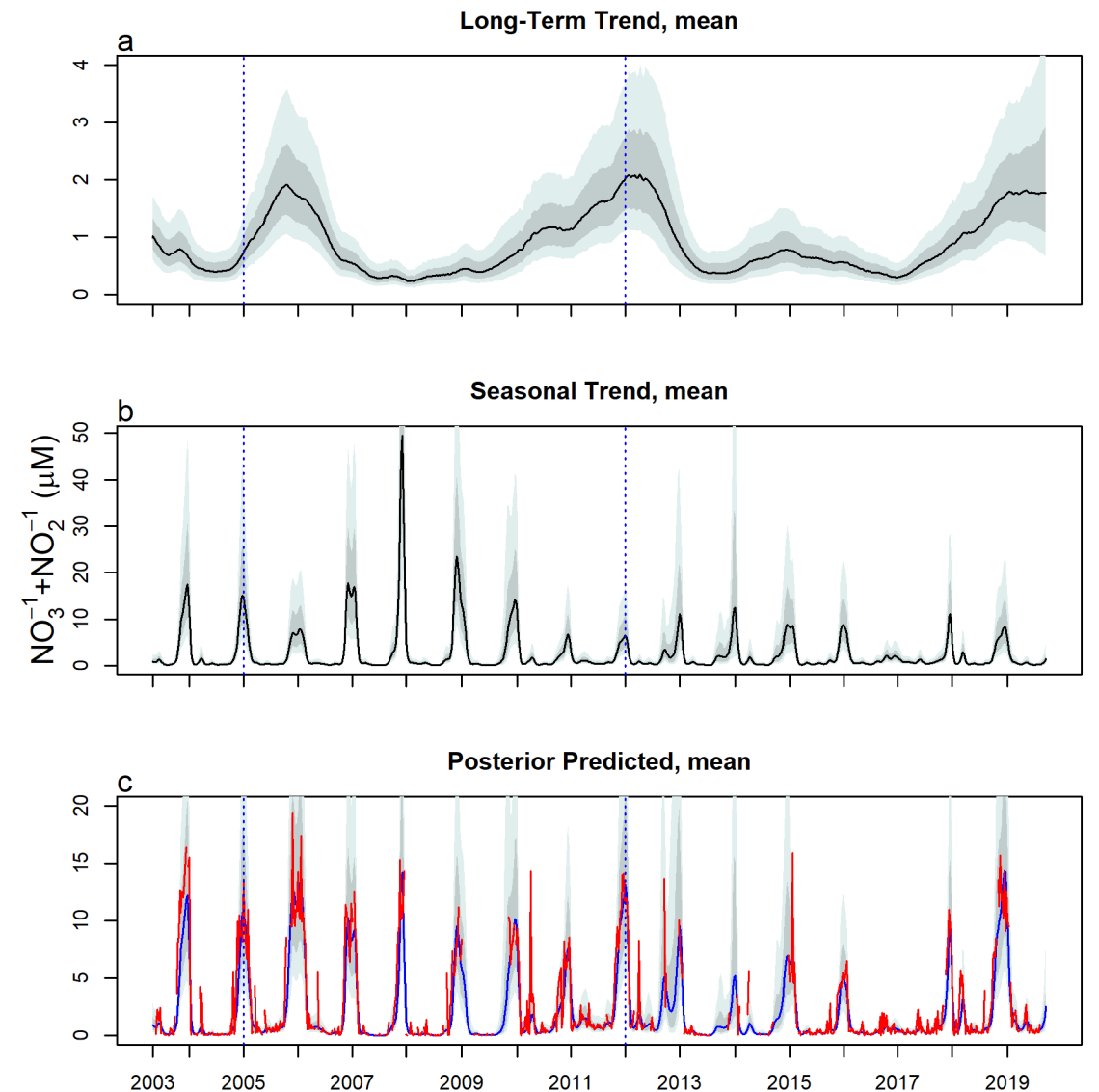
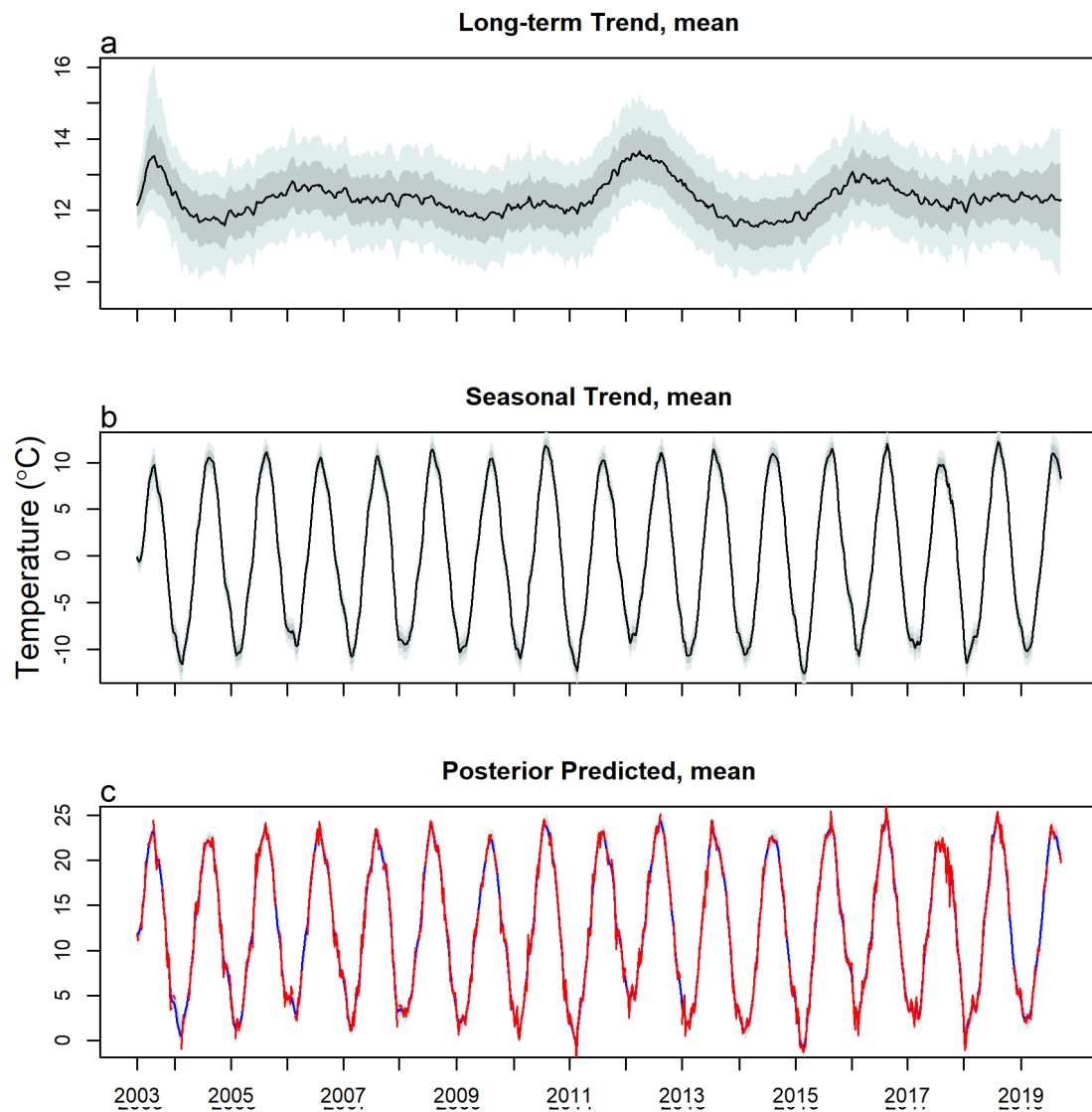
- Less variable
- Seasonal peak in autumn
- Increase in mean levels
- Intensifying seasonality

Chl. a > 20 μm

- More variable
- Seasonal peak in spring
- Decrease in mean levels
- Seasonal intensity inversely correlated with mean levels



Temperature & Nitrogen Species



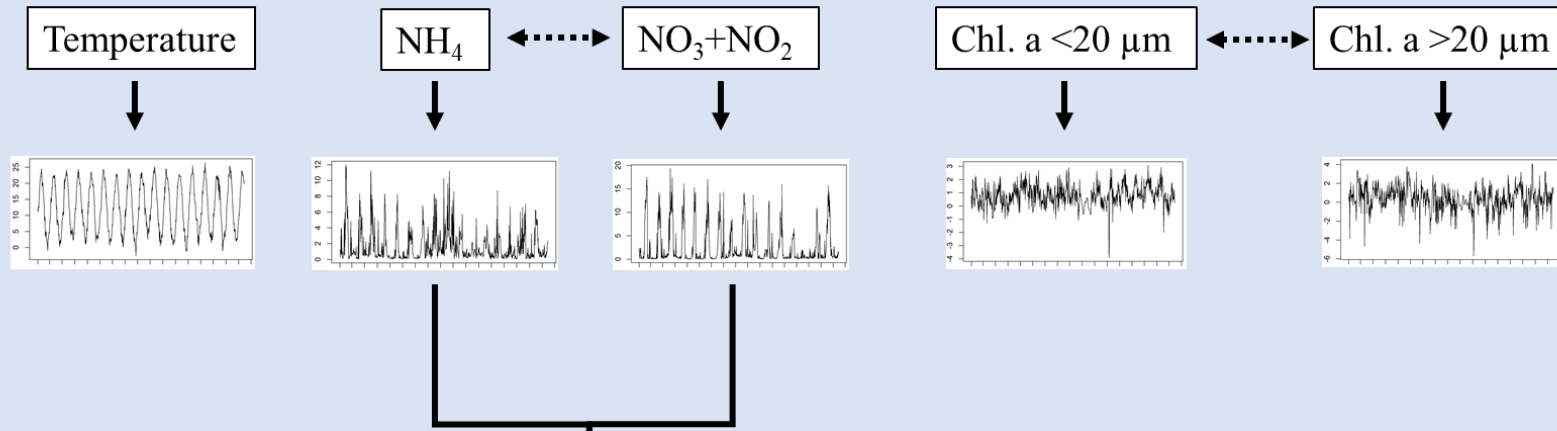
Stage 2 Model: Multivariate Dynamic Linear Regression

Stage 2 Model: Regression

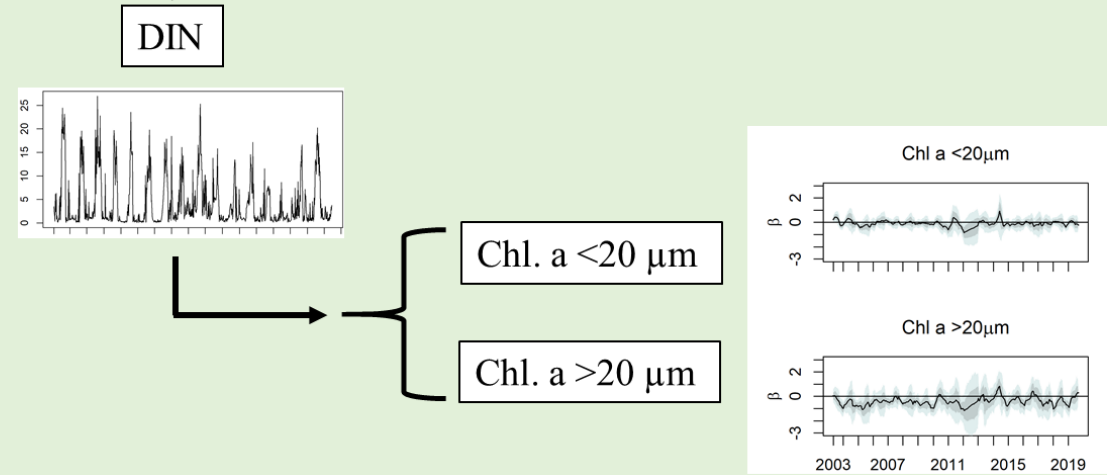
Stage	Model	Response Variable(s)	θ Components	V Specification	W Specification
2	4	log Chl. <20, log Chl. >20	Dynamic, Intercept (μ)	Static, IW prior	Dynamic, Fixed Discount Factor
			Dynamic, Regression on DIN		
			Static, Season (S_i), $i=1$		

Outline

Stage 1 Models



Stage 2 Model

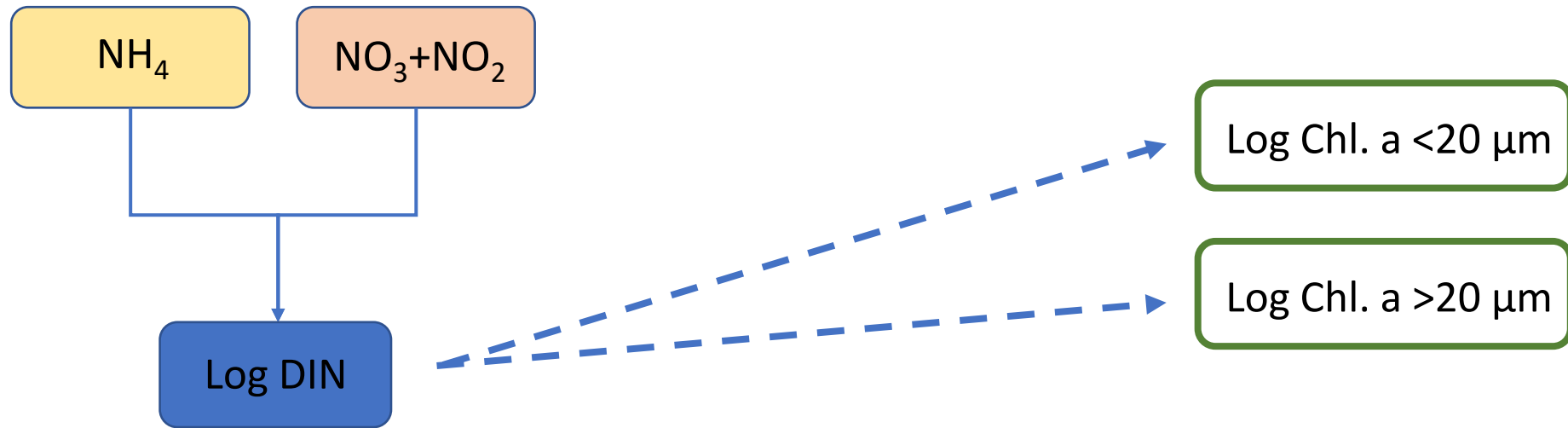


Purpose

- Missing data imputation
- Exploration
- Inference:
 - Long-term change
 - Seasonal change

- Describe the relationship of DIN and size structure

DIN as a regressor



$$\log \text{DIN} = \log(\exp(F_{1:T}\theta_{\text{NH}_4,1:T}) + \exp(F_{1:T}\theta_{\text{NO}_3,2,1:T}))$$

$$\theta_{\text{NH}_4,1:T} | Y_{1:T} \sim \int P(\theta_{\text{NH}_4,1:T} | Y_{1:T}, \cdot) P(\cdot | Y_{1:T}) d\cdot$$

$$\theta_{\text{NO}_3,2,1:T} | Y_{1:T} \sim \int P(\theta_{\text{NO}_3,2,1:T} | Y_{1:T}, \cdot) P(\cdot | Y_{1:T}) d\cdot$$

$$\int \underbrace{p(\Phi | \text{DIN}, \cdot)}_{\text{sample}} \underbrace{p(\text{DIN})}_{\text{sample}} d\text{DIN} = p(\Phi | \cdot)$$

MCMC

The diagram shows the integral equation above. Below the integrand, two brackets labeled 'sample' are positioned under $p(\Phi | \text{DIN}, \cdot)$ and $p(\text{DIN})$ respectively. A blue arrow points from the integral to the right-hand side of the equation. Below the 'sample' labels, a curved blue arrow labeled 'MCMC' indicates the sampling process.

Stage 2 Model: Regression

Inference:

- Non-conjugate (no closed form of posterior distribution)
- Markov Chain Monte Carlo (MCMC) Simulation of Posteriors
- Fixed δ levels, run in parallel in separate models

- Sample each posterior distribution

➤ $DIN_{1:T} | \cdot$

From Stage 1 Model

➤ $\theta_{1:T} | Y_{1:T}, V, W_t$

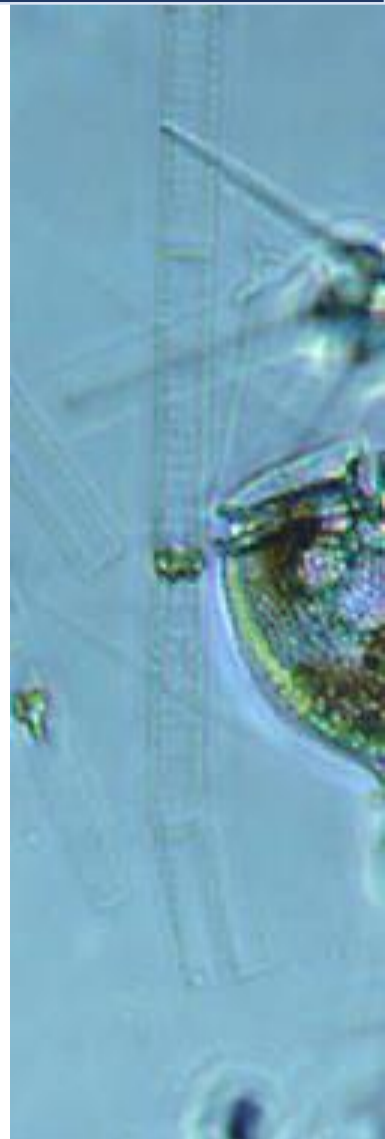
Kalman Filtering and Smoothing

➤ W_t

Discount Specification

➤ $V | Y_{1:T}, W_t$

$\sim \text{Inverse - Wishart} (\nu_0 + T, S_0 + RSS_\theta)$



Stage 2 Model: Dynamic Regression

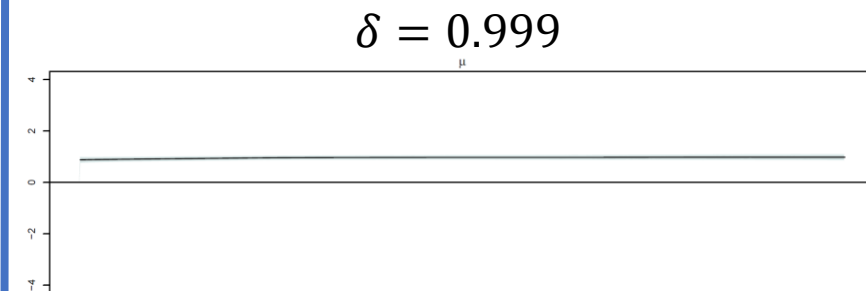
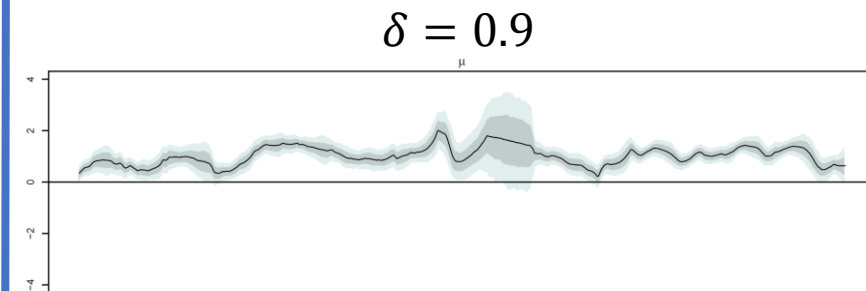
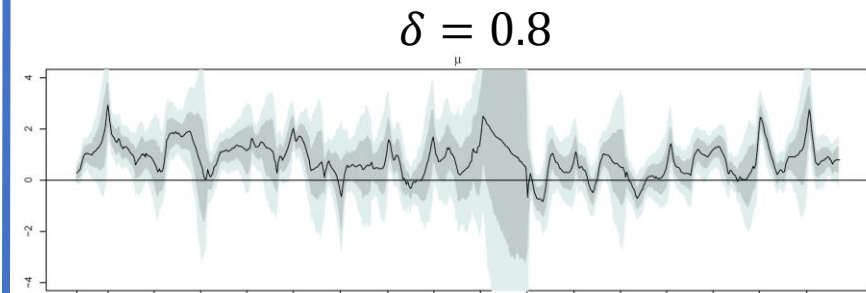
Evolutional Covariance specification:

$$W_t = \frac{1 - \delta_i}{\delta_i} P_{i,t},$$
$$P_{i,t} = G_t C_{t-1} G_t'$$

- Discount factor δ_i , describes the loss of information between time-steps
 - $\delta_i = 1$ is equivalent to a static model (no evolutionary change in the states)
 - Commonly specified between 0.85 and 0.999
- Practical discounting constrains information loss to a linear rather than exponential rate during longer period missingness

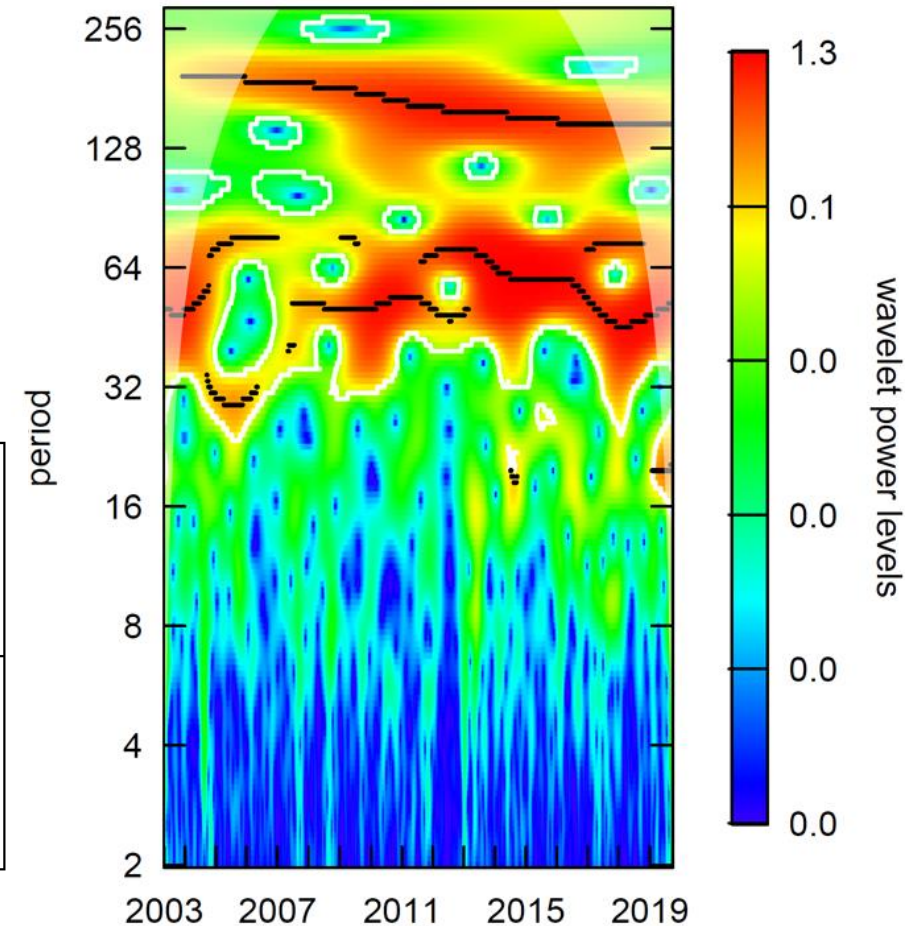
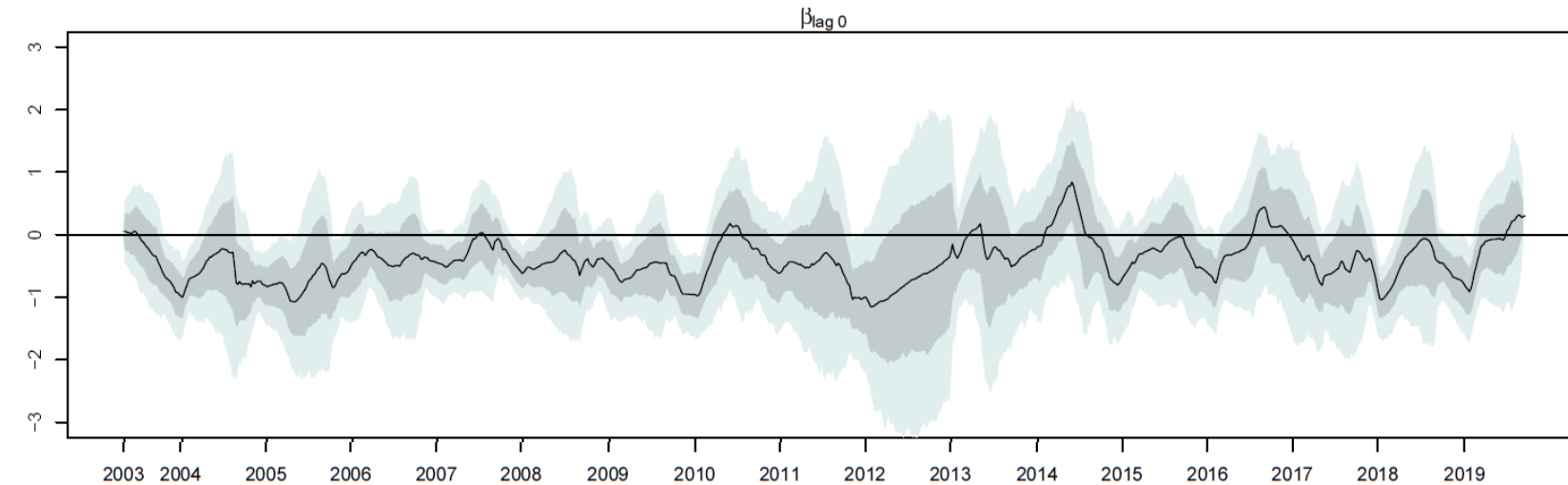
$$R_t(k) = \frac{G^k C_t G'^k}{\delta^k}$$

if $k > 1$, $R_t = G^{k-1} C_{t+1} G'^{k-1}$



Chl. a > 20 μm

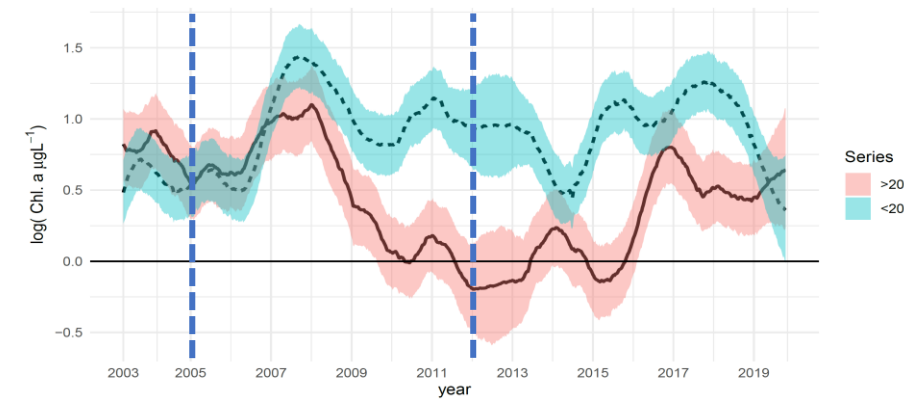
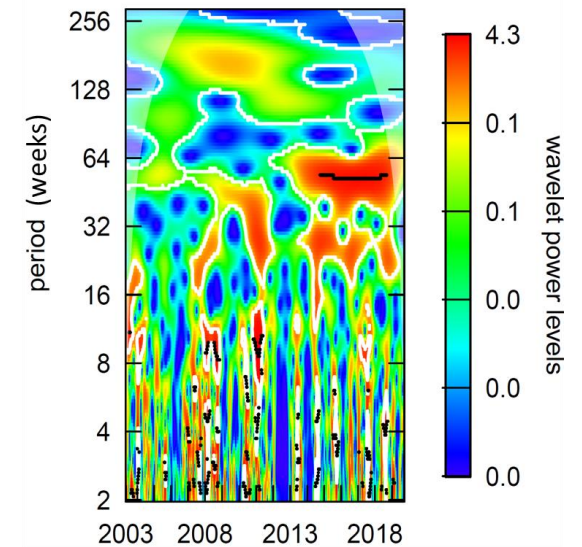
- DIN significantly associated with Chl. a > 20
- Chl. a > 20 μm negatively associated with DIN, suggesting that DIN is shaped by the Chl. a > 20 μm community, but not <20 μm
- No long-term-prediction of decline by ambient DIN



Conclusions

Biotic Change

- Narragansett Bay has switched from being dominated by organisms $>20\ \mu\text{m}$ to those $<20\ \mu\text{m}$
- Seasonal variation has amplified in phytoplankton $<20\ \mu\text{m}$
- The seasonally significant associations between large phytoplankton and DIN suggest large phytoplankton drive bay dynamics during winter periods

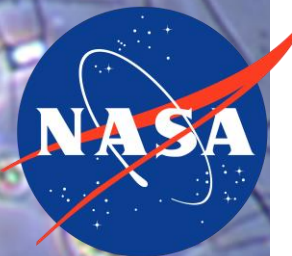


Conclusions

- The multi-stage DLM provides a convenient structure for multivariate time-series analysis
- Useful when :
 - Modeling may have multiple goals such as describing long-term patterns and regression on these features
 - Missing data or posterior parameters of time series may be useful in other models
- Advantage over a joint model due to simplicity, and computational savings during model development :
 - Posteriors of model stages can be saved and sampled, and thereby do not need to be re-estimated if later stages need to be adjusted

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 - NASA STEM -NNX15AI06H



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