

# Estimating continuous measures of ecological resilience from palaeoecological time series

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Gavin L. Simpson · Stefano Mezzini  
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# Acknowledgements



Slides: [bit.ly/inquaresilience](https://bit.ly/inquaresilience)

Data: Lake 227 pigments, Peter Leavitt (Regina)

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# Resilience

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# Alternative stable states – Marten Scheffer

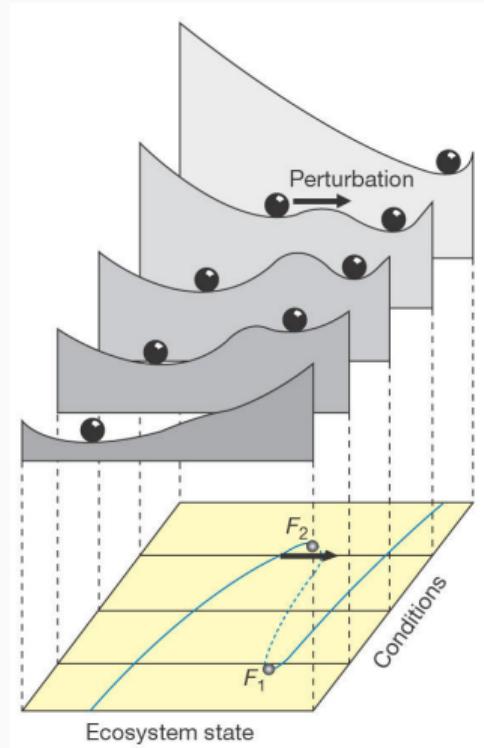
Under range of conditions multiple ecosystem states may exist

Stability landscapes depict equilibria and basins of attraction

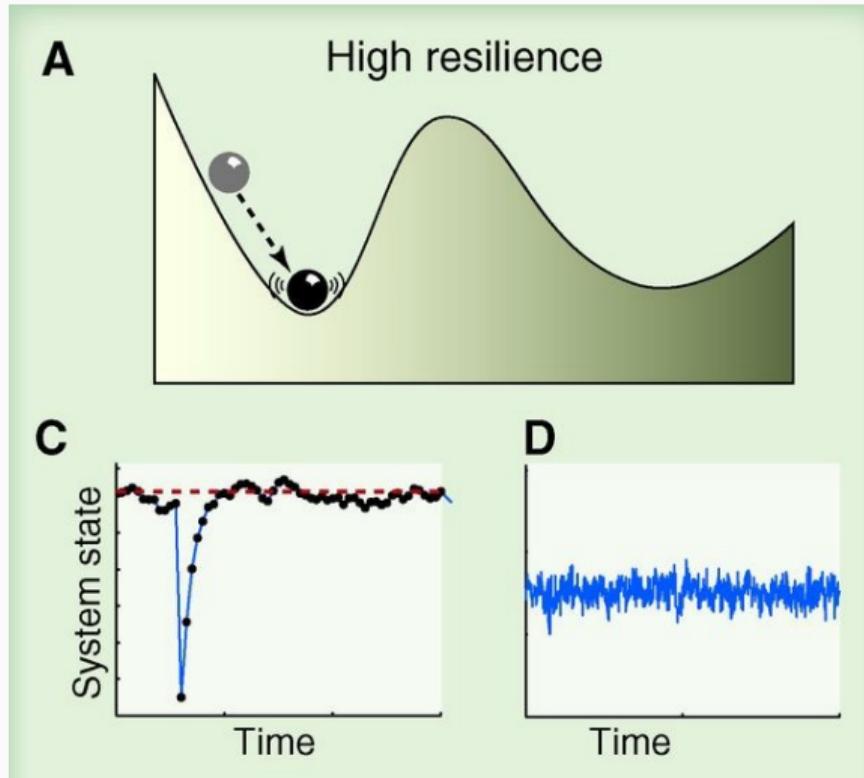
Valleys are stable states

External conditions alter the stability landscape

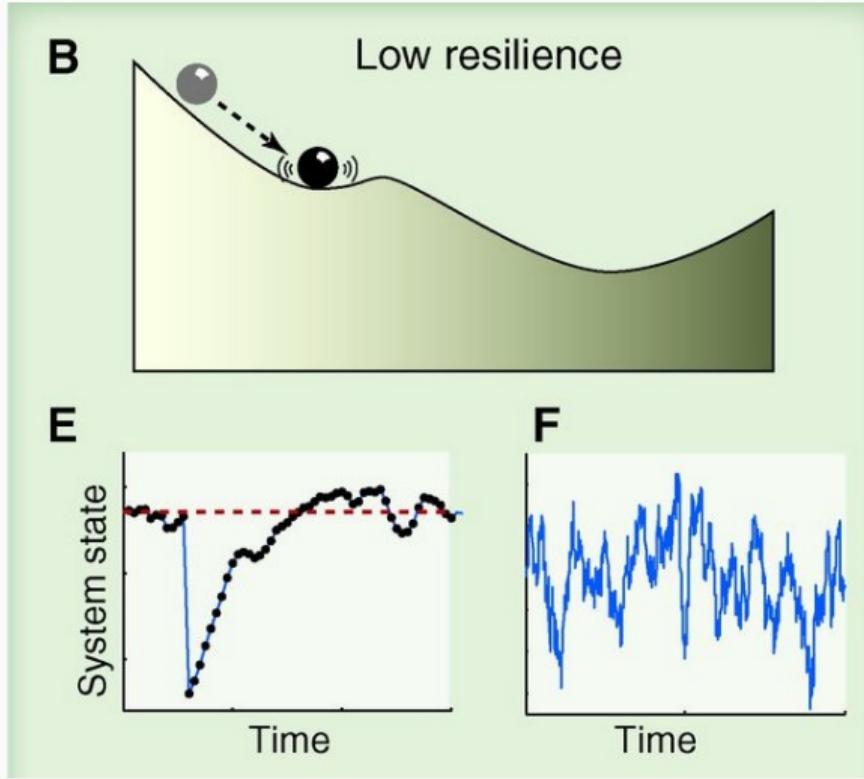
Disturbances can kick a system between states



# Early warnings & Resilience to change



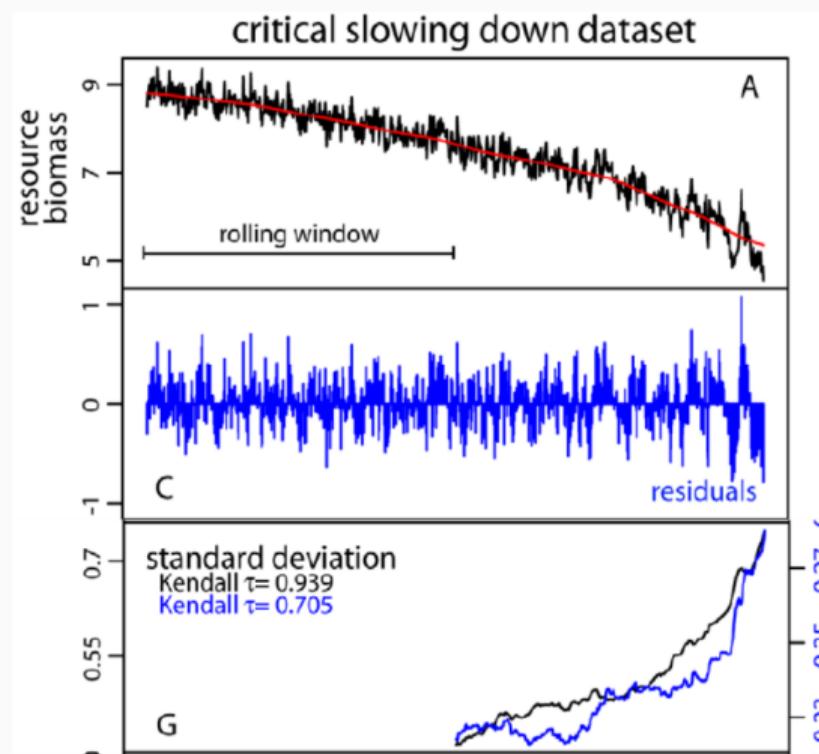
# Early warnings & Resilience to change



## Modelling variance

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## Estimating resilience using moving windows – probably shouldn't



Source: modified from Dakos et al *PLOS One* (2012)

# Problems

Ad hoc

- What window width?
- How to detrend (method, complexity of trend, ...)

Ideally regularly spaced data

- What to do about gaps, missing data?

Statistic testing hard

- Kendall's  $\tau$  assumes independence
- Surrogate time series assumes regular sampling, sensitive to choice of ARMA

Results in incomplete time series

## Distributional models

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# MODEL



## Linear models

$$y = \beta_0 + \beta_1 \text{time} + \varepsilon$$



**WIGGLY**  
**-THINGS-**

## Generalized additive models (GAMs)

$$y = \beta_0 + f(\text{time}) + \varepsilon$$

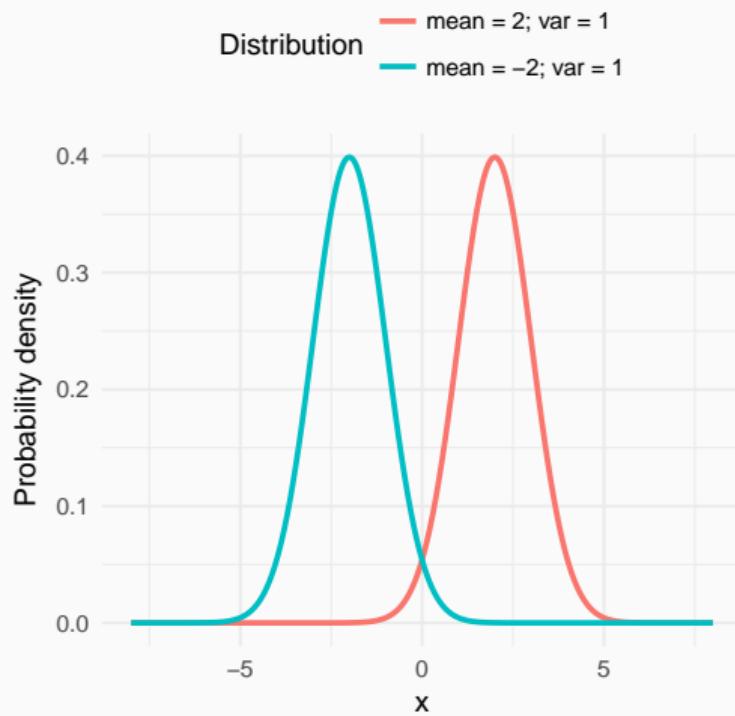
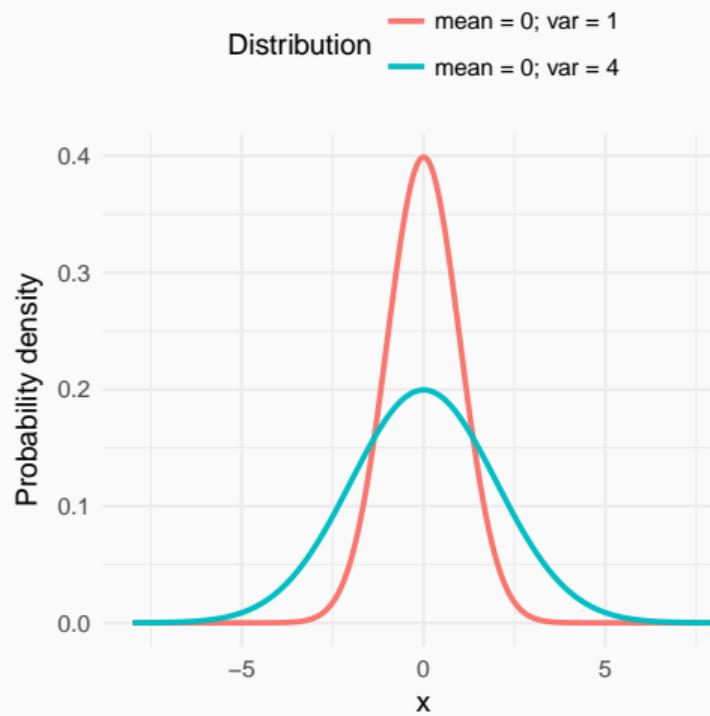
$f$  is a smooth function

Learn about the shape of  $f$  from the data

Penalty on wigginess to avoid overfitting

# Gaussian distribution – defined by 2 parameters

- mean –  $\mu$  and variance –  $\sigma^2$



## Distributional models – model all of the things

Allows, for certain suitable distributions, the ability to model one or more of the mean, variance, skewness, and kurtosis.

$$y_i \sim \mathcal{N}(\mu = \eta_{1,i}, \sigma^2 = \eta_{2,i})$$

- GAMLSS models of Rigby and Stasinopoulos (2005)
- Vector GAM (VGAM) models of Yee (e.g. Yee and Mackenzie (2002))
- General smooth models of Wood/mgcv

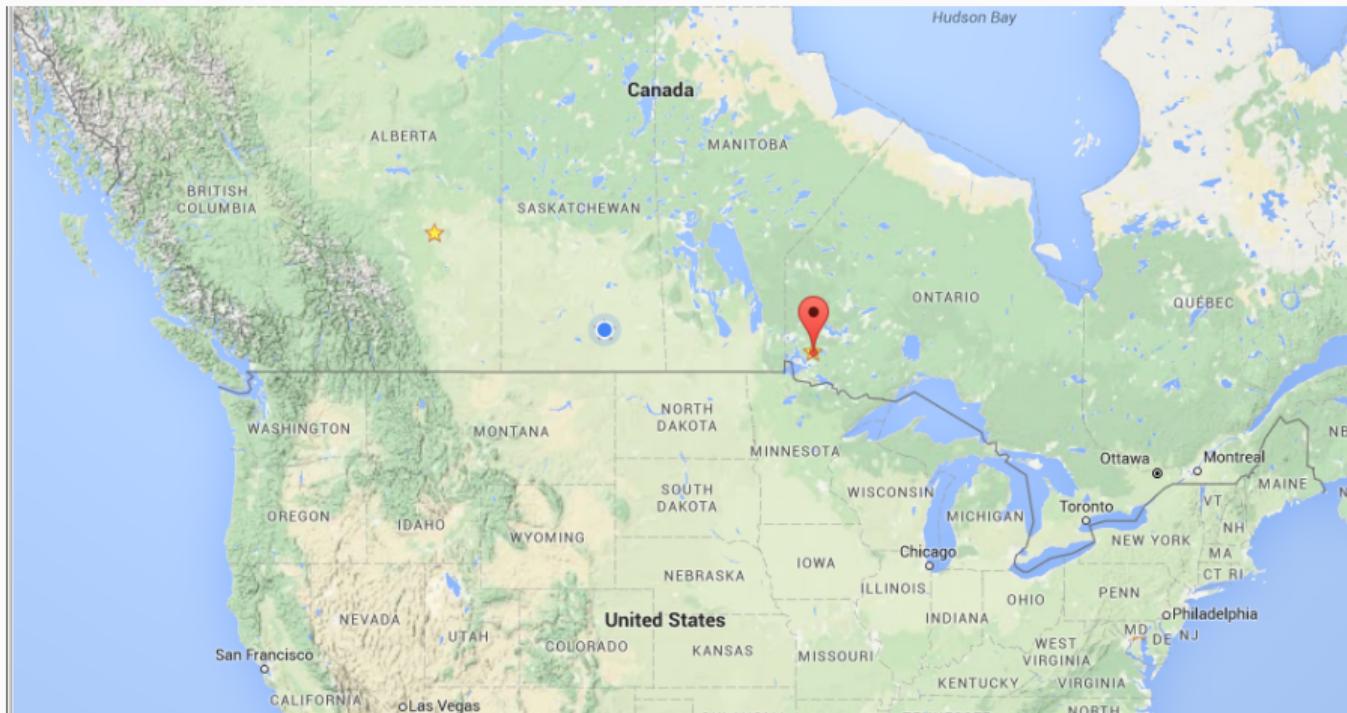
E.g.:  $y_i$  are Gaussian with mean  $\mu_i$  and variance  $\sigma_i^2$ , each of which are modelled via a linear predictor  $\eta$  of smooth functions of covariates  $x_j$  and  $z_j$

# Lake 227

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# Lake 227

Experimental Lakes Area, NW Ontario, Canada — Dilute headwater lake (5 ha, 10 m deep)



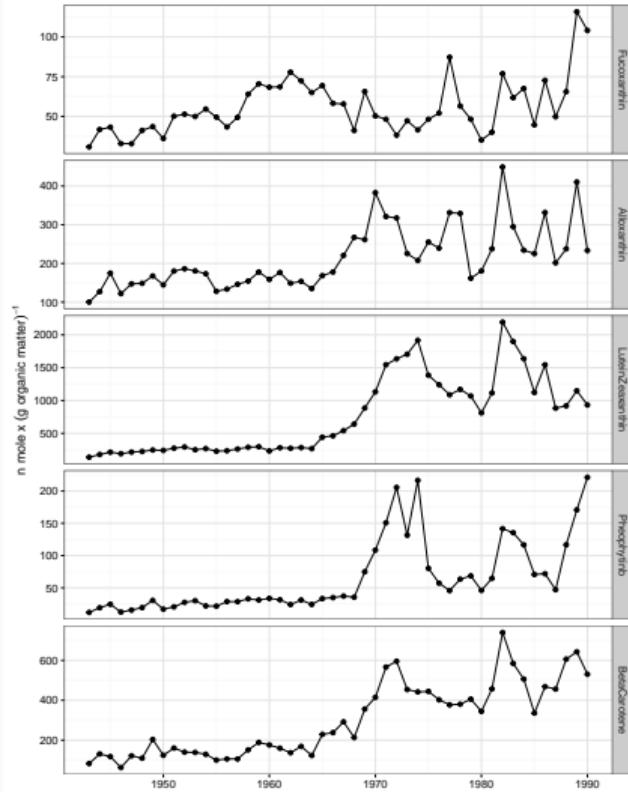
# Lake 227

Experimental Lakes Area, NW Ontario, Canada — Dilute headwater lake (5 ha, 10 m deep)



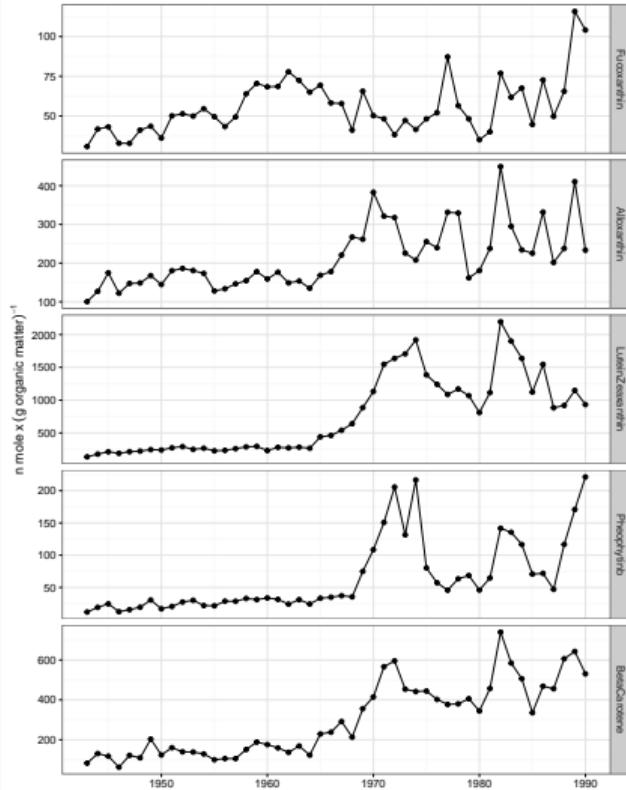
# Lake 227 sedimentary pigments

- Experimentally manipulated
  - 1969– :~10x increase in P load
  - 1969–74: N added in 14:1 ratio
  - 1975–82: N load reduced to 5:1
- Annual sediment samples 1943–1990
- Analysed for fossil pigments
  - *Fucoxanthin*; diatoms, chrysophytes
  - *Alloxanthin*; cryptophytes
  - *Lutein-zeaxanthin*; cyano, chlorophytes
  - *Pheophytin b*; chlorophytes
  - $\beta$  *carotene*; total algae
- Cottingham, Rusak, and Leavitt (2000)

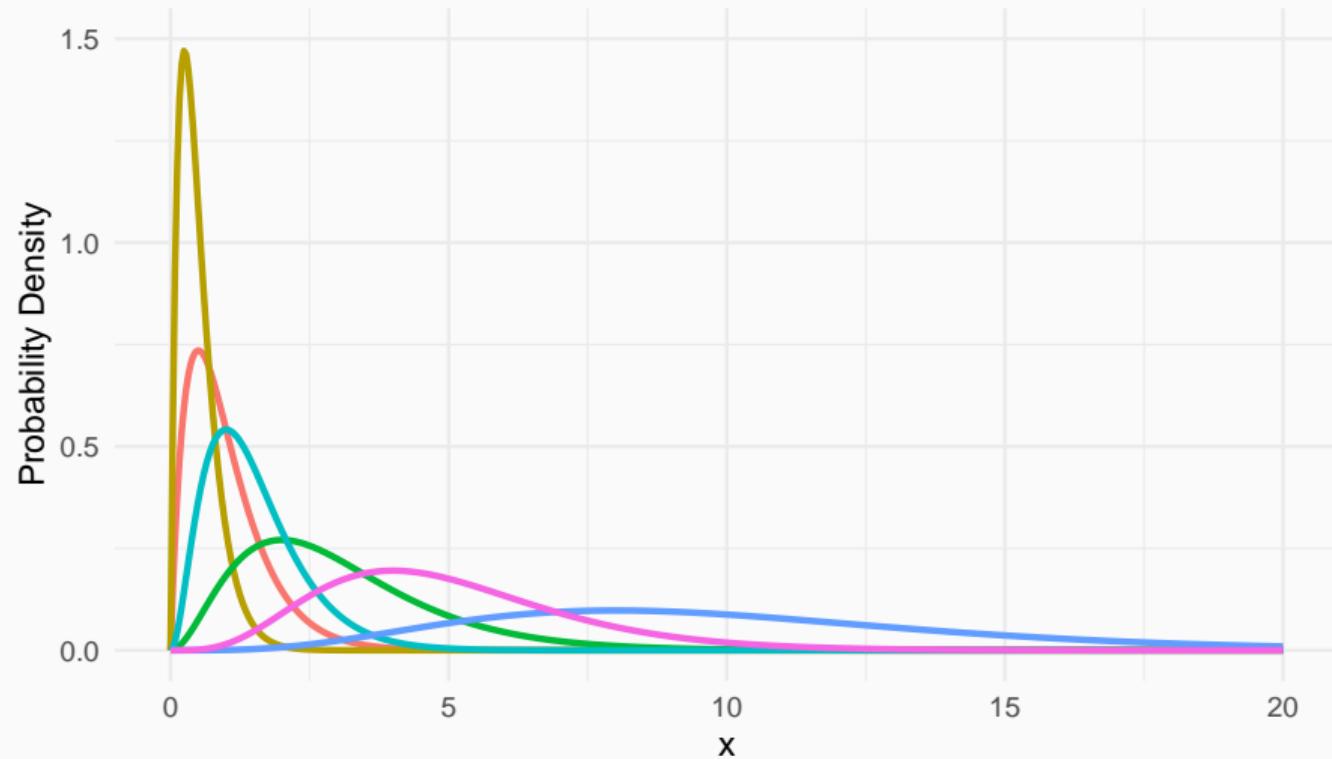


# Pigment data

- Pigment data are strictly positive
  - Any value  $x_i < c$  is censored
  - Aphanizophyll
- Treating these as Gaussian seems wrong
  - $\log(x_i)$  causes problems
- Use a different distribution
  - the gamma distribution



# The Gamma distribution



# Lake 227 sedimentary pigments

Fitted gamma distributional model using **brms** and Stan

$$y_t \sim \mathcal{G}(\mu = \eta_{1,t}, \alpha = \eta_{2,t})$$

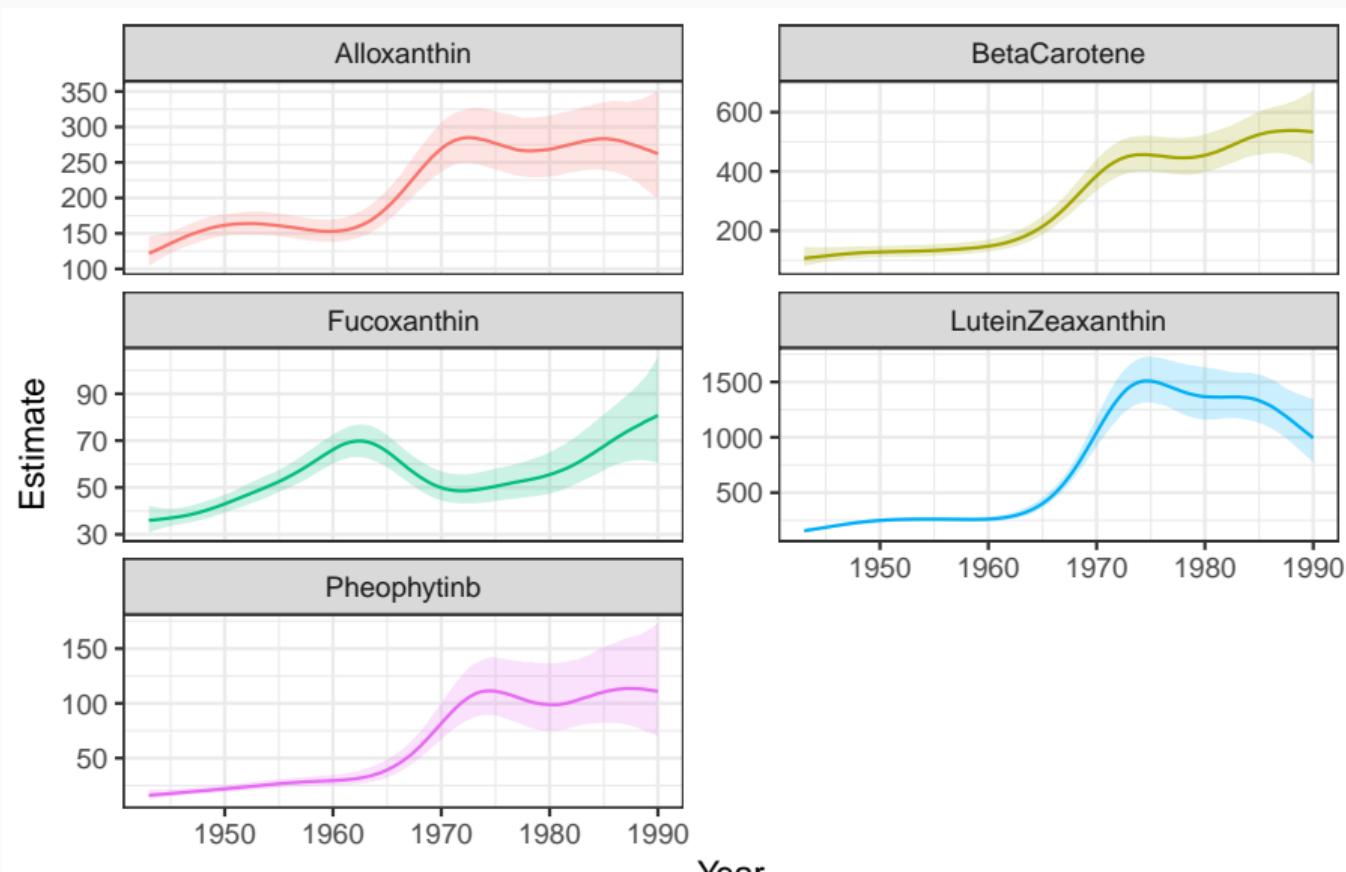
$$\eta_{1,t} = \exp(f_{1,\text{pigment}}(\text{Year}_t))$$

$$\eta_{2,t} = \exp(f_{2,\text{pigment}}(\text{Year}_t))$$

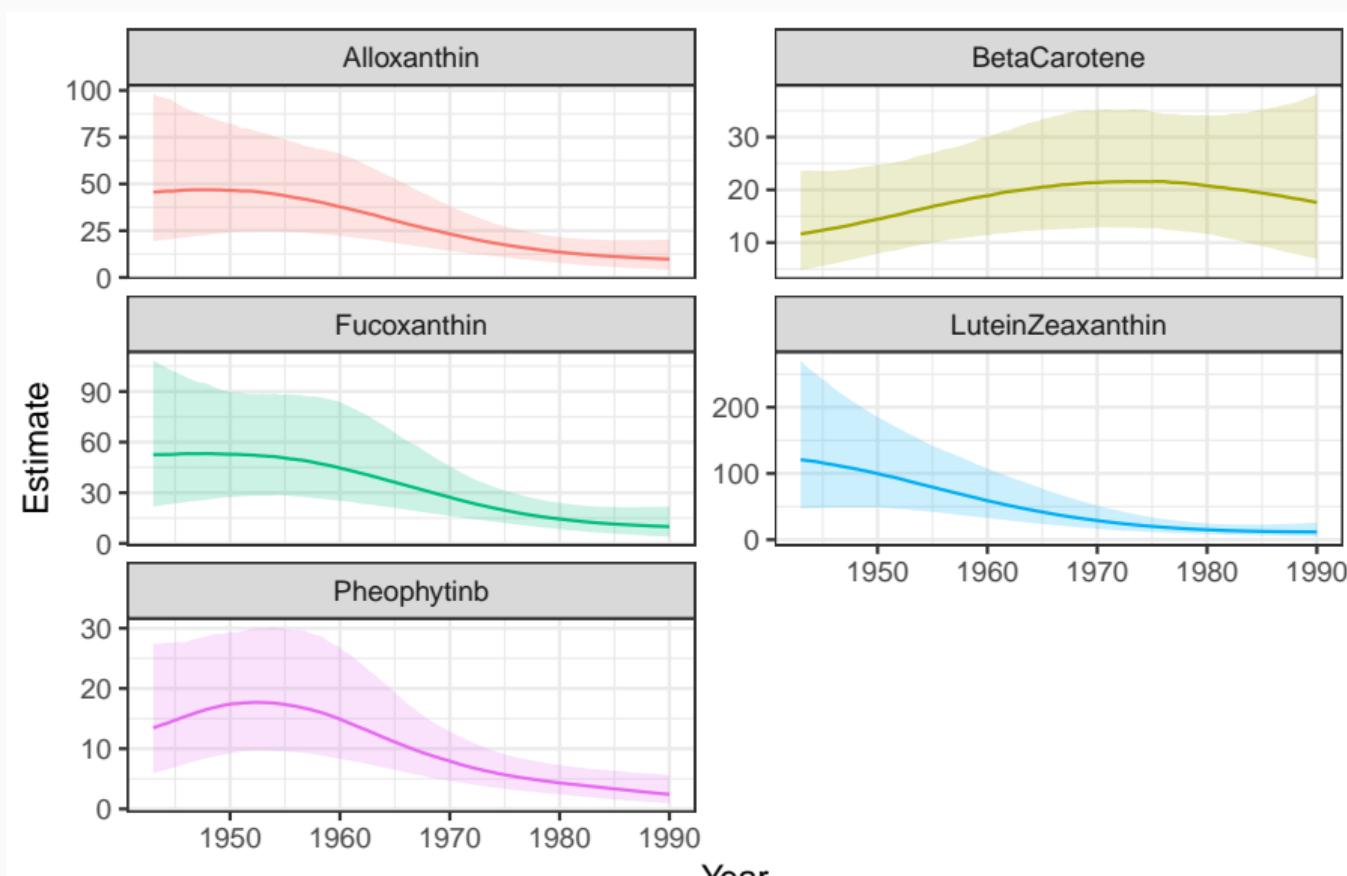
Mean ( $\mu$ ) & shape ( $\alpha$ ) each modelled with:

- “Random effect” spline (spline-factor interaction `bs = "fs"`)
- Fully Bayesian
- In this example no censoring

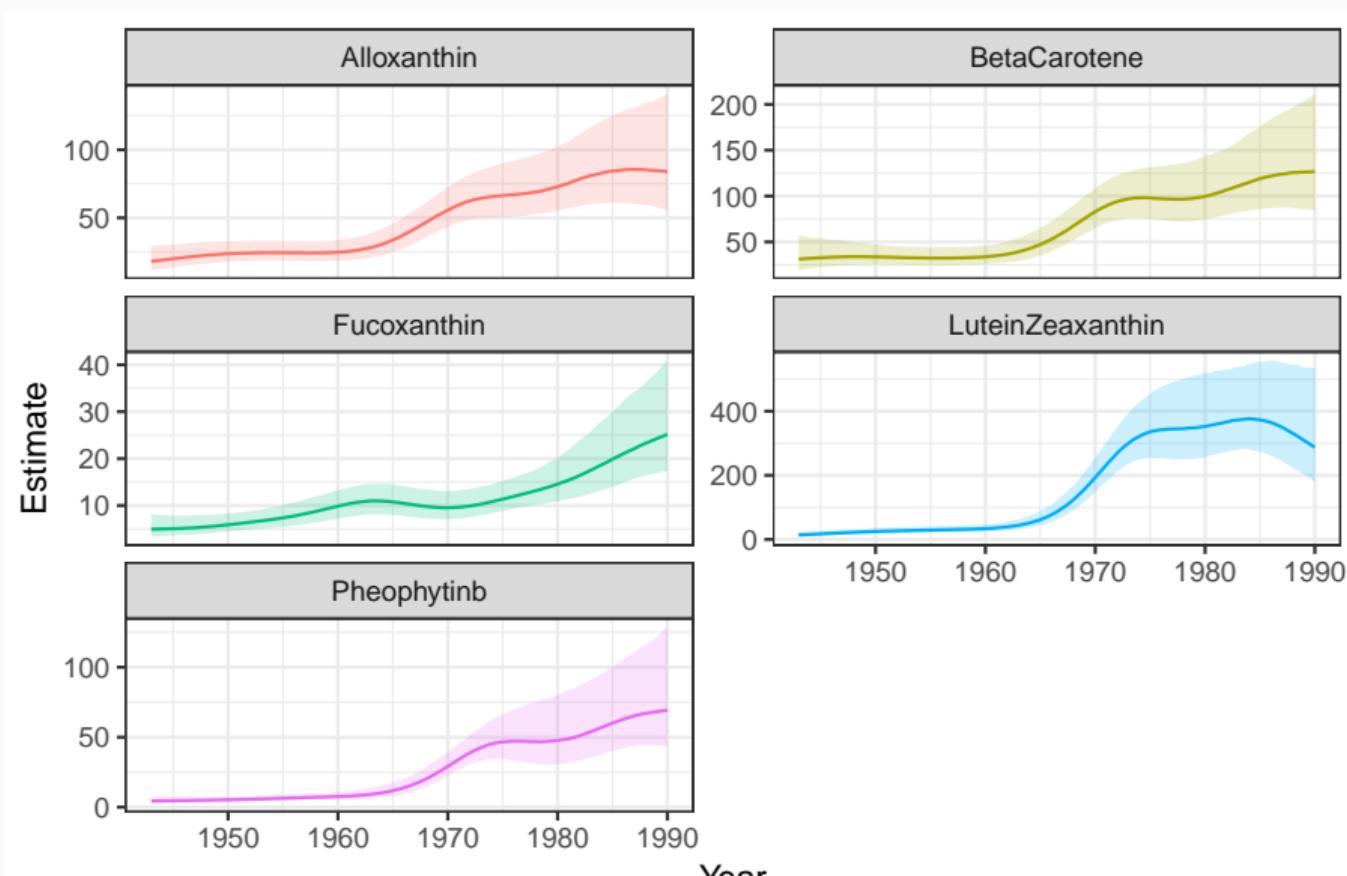
# Lake 227 sedimentary pigments – fitted mean functions



# Lake 227 sedimentary pigments – fitted shape functions



# Lake 227 sedimentary pigments – fitted variance functions



## Summary

Ecosystems are under threat from a range of natural and anthropogenic factors

Research over the past 40–50 years suggests that ecosystems respond in a myriad complex ways

GAMs have proven useful for testing some of these ideas with long time series & palaeo data

GAMs can estimate trends in variance in difficult data without very complex models or *ad hoc* solutions

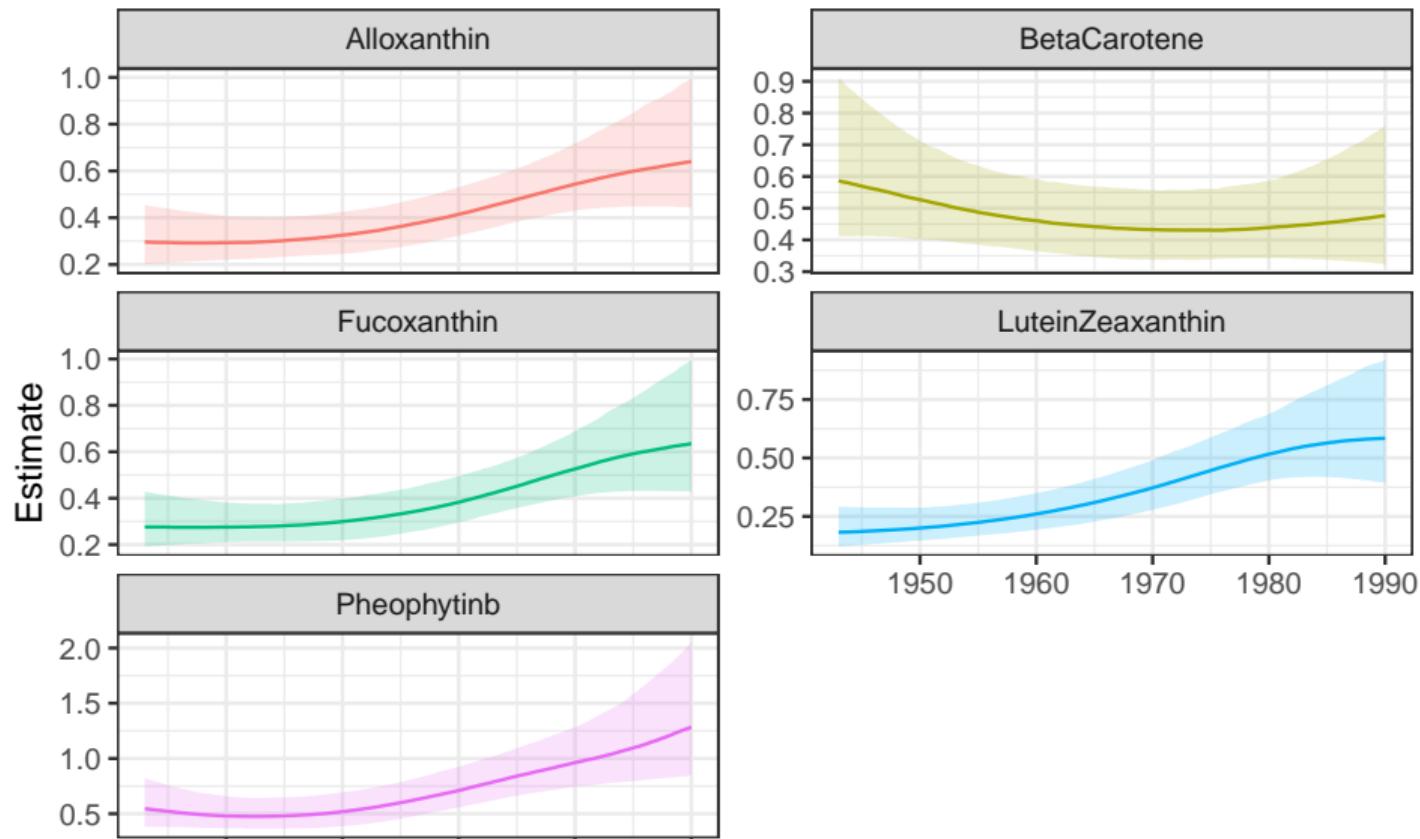
## What's next...?

GAM-based models for other Early Warning Signals / Resilience indicators?

- Autocorrelation
- Skewness & kurtosis

Other distributional models & recently-developed quantile GAM approaches might work

# Lake 227 sedimentary pigments – estimated skewness functions



## Extra examples / slides

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## Baldeggeree

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# Baldegggersee

- Nutrient rich, hardwater lake, located on the central Swiss Plateau
- Developed anoxic bottom waters in 1885
- Intensive farming & agriculture in catchment
- Artificial oxygenation & circulation as remediation from 1982
- Cored in 1993 • 91 samples • 75 diatom taxa
- Source: Lotter (1998) *The Holocene* 8(4), 395–405



Source: © Andy Lotter

# Baldeggersee

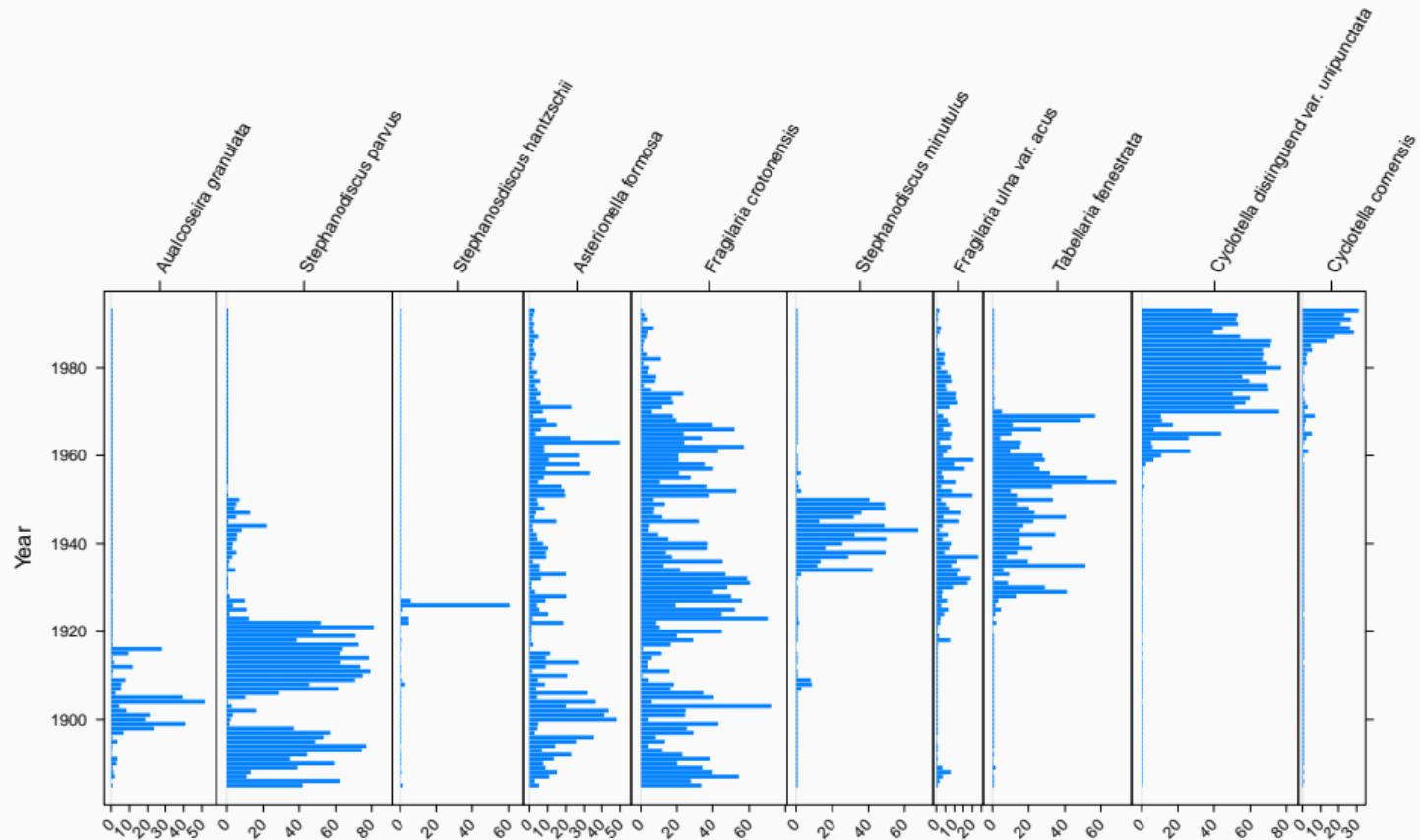
- Iconic example of a **critical transition**
- Deep lakes can exhibit bistable conditions
  - Nutrients increase phytoplankton
  - Decomposition can increase anoxia
  - Stimulates P release from sediments
- Marl lake
- **Flickering** (?)

Are early warning signals (increased variance) present?



Source: © Andy Lotter

# Baldeggersee – Stratigraphy



Long gradients of temporal change in diatom abundances & composition

PCA not a good decomposition of the data — temporal trend spread over multiple PCs

**Principal Curves** are one non-linear approach related to PCA

Fits a non-linear curve that passes through the data minimising the orthogonal distance between samples & the curve, subject to some constraints

# Baldeggersee – Stochastic Volatility Model

Stochastic Volatility – an econometric time series model of variance or *volatility*

In a SV model, each observation  $y_t$  assumed to have its own variance  $e^{h_t}$  &  $h_t$  assumed to follow an AR(1) process

$$y_t|h_t \sim \mathcal{N}(0, \exp h_t) \quad (1)$$

$$h_t|h_{t-1}, \mu, \phi, \sigma_\eta \sim \mathcal{N}(\mu + \phi(h_{t-1} - \mu), \sigma_\eta^2) \quad (2)$$

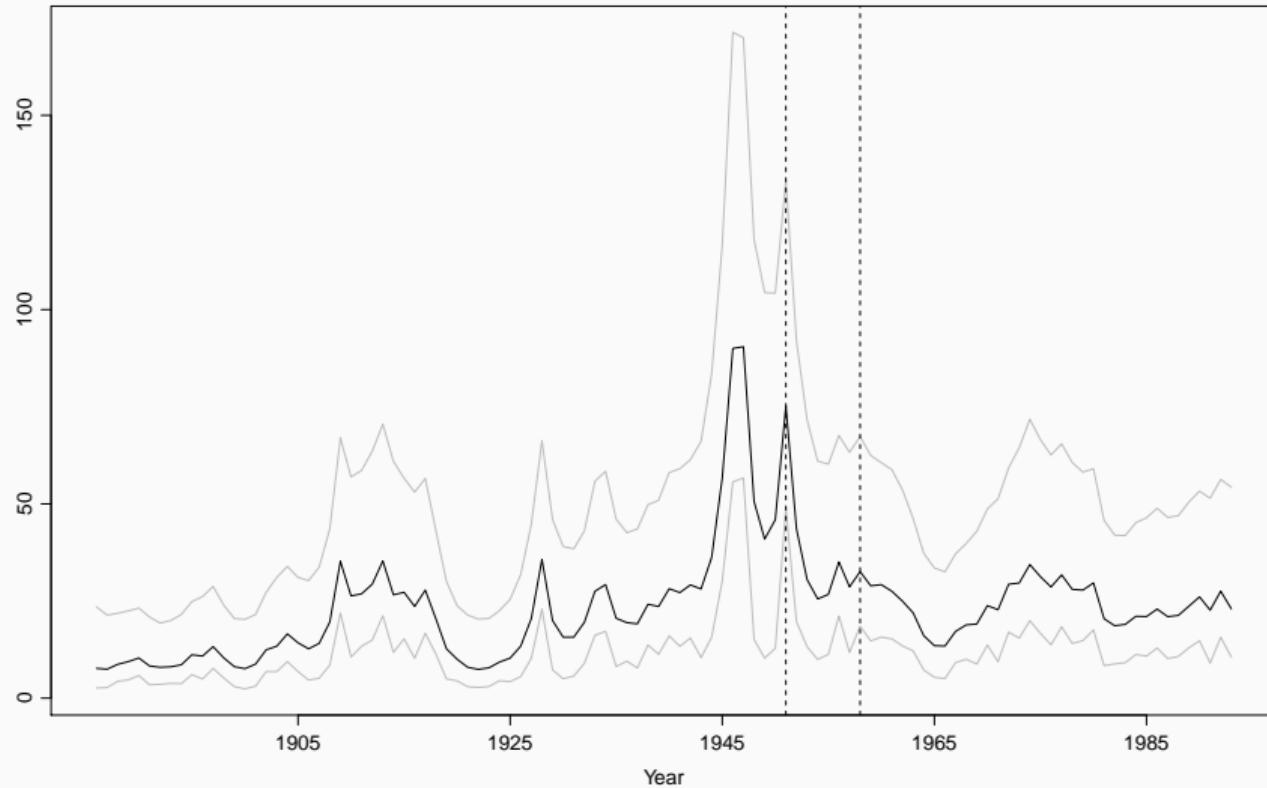
$$h_0|\mu, \phi, \sigma_\eta \sim \mathcal{N}(\mu, \sigma_\eta^2/(1 - \phi^2)) \quad (3)$$

$\mu, \phi, \sigma_\eta^2$  are the *level*, *persistence*, & *volatility* of the log-variance

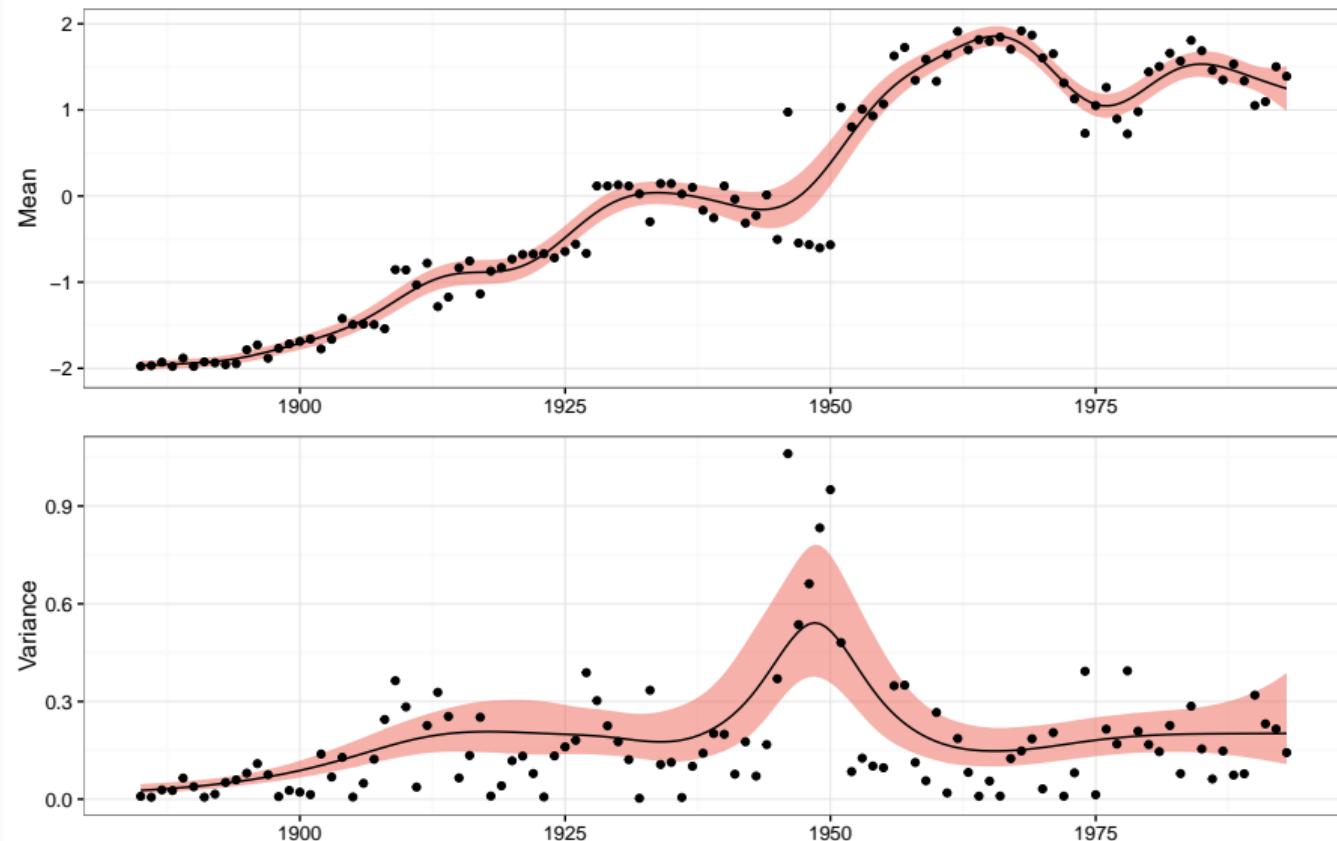
$h$  is *unobserved* and modelled as a latent process

Fitted using **stochvol** R Package (Gregor Kastner)

# Baldeggersee – Stochastic Volatility Model



# Baldeggersee – GAM Location and Scale fits

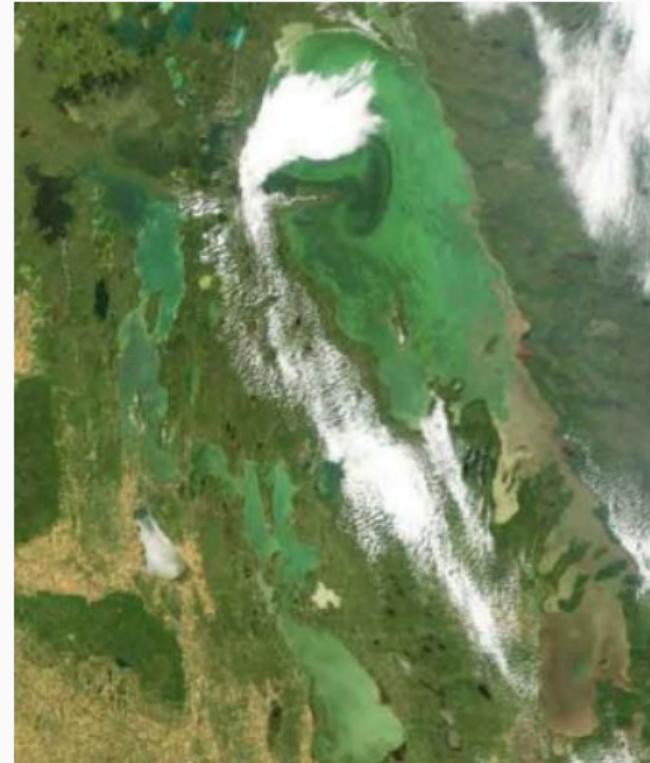


## Lake Winnipeg

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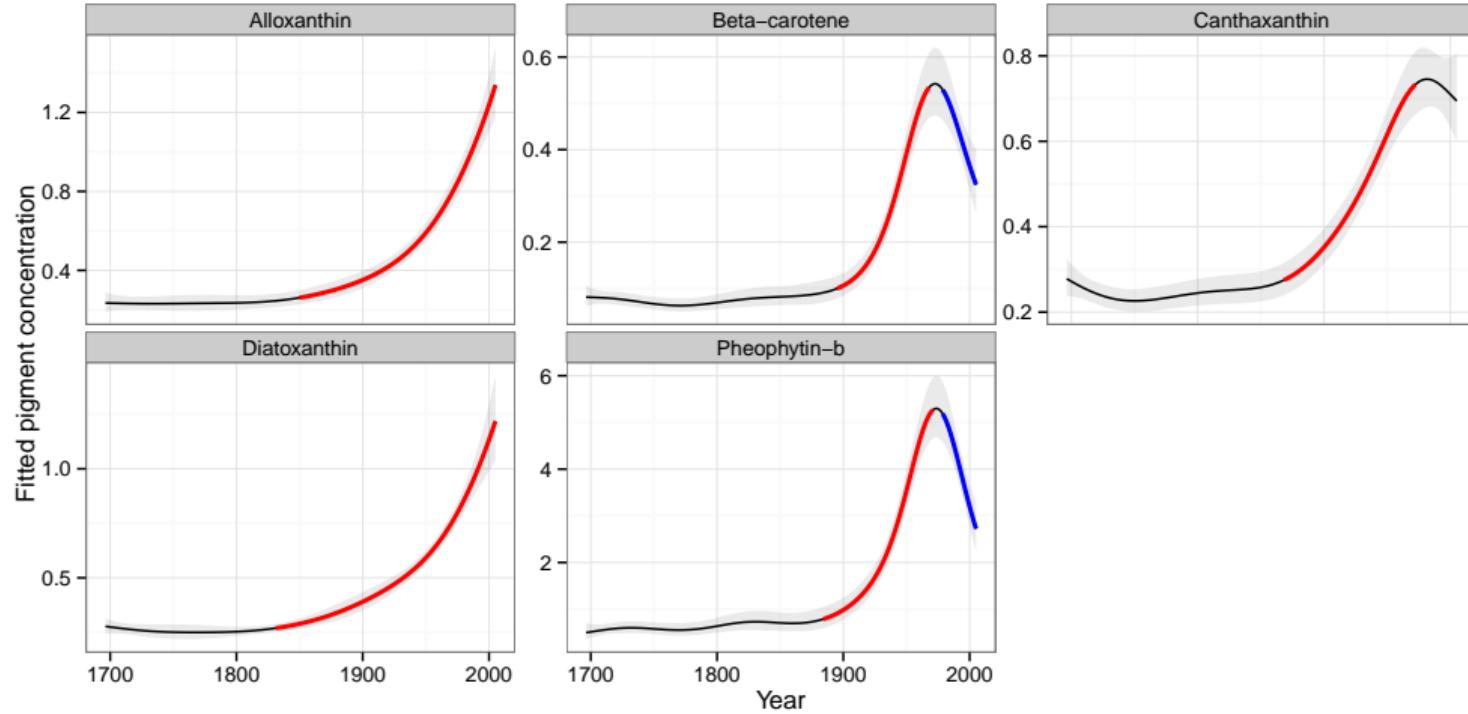
# Has Lake Winnipeg suffered a catastrophic regime shift?

- Large, shallow, polymictic, lake
- Eutrophic
- Algal blooms
- Regime shift / critical transition?
- Increased destabilization with increased N & P?



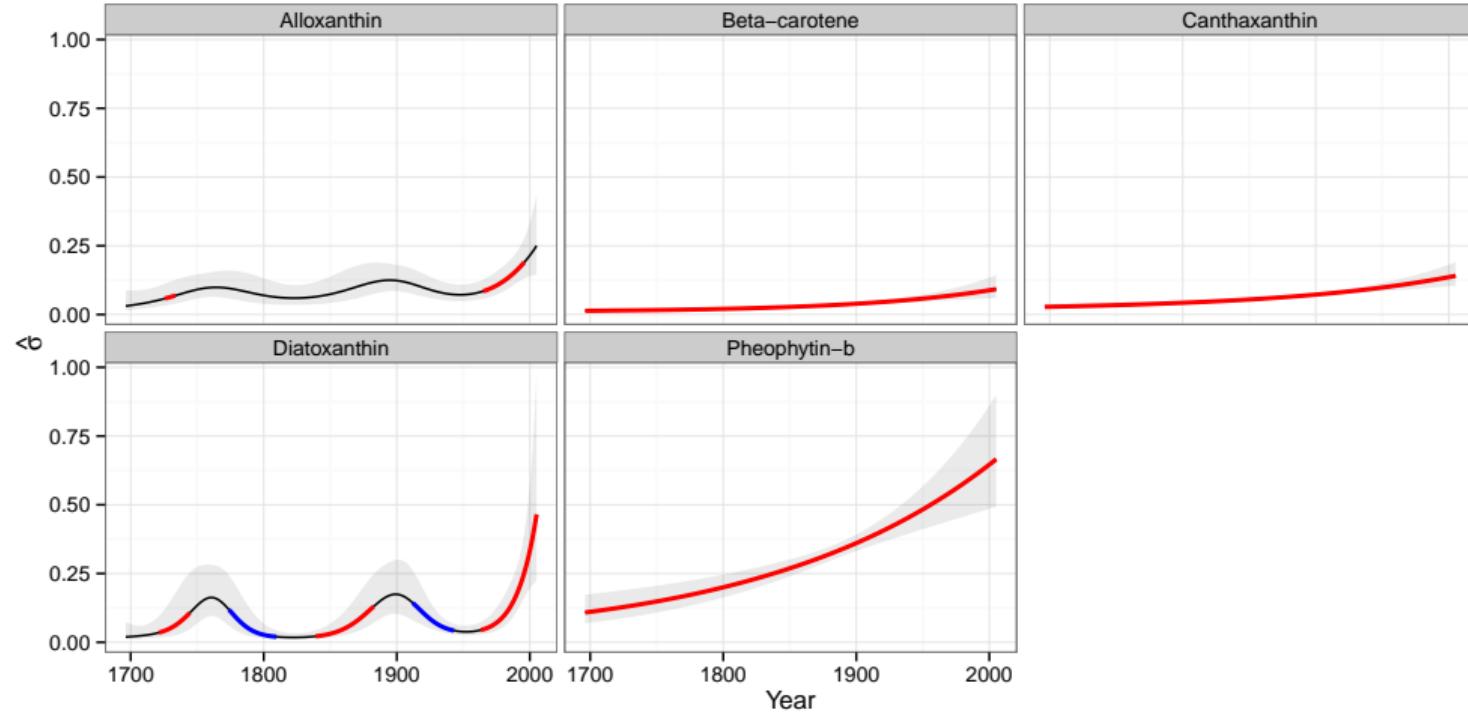
Source: Public domain

# Has Lake Winnipeg suffered a catastrophic regime shift?



Source: Bunting et al *Limnology & Oceanography* 2016

# Has Lake Winnipeg suffered a catastrophic regime shift?



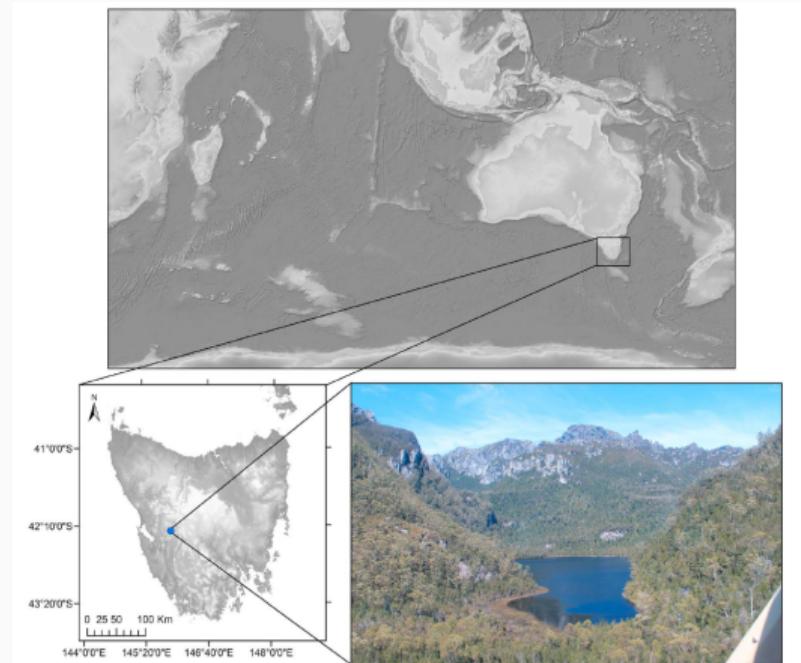
Source: Bunting et al *Limnology & Oceanography* 2016

## Lake Vera, Tasmania

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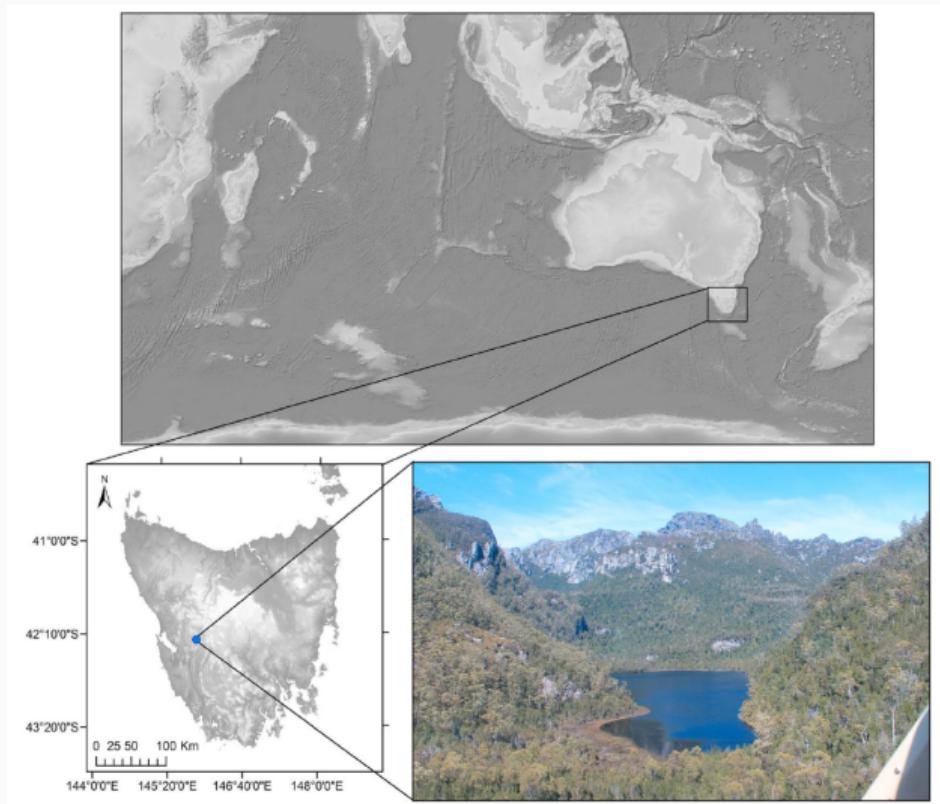
# Lake Vera

- Small, moraine-bound lake
- Deep (48 m)
- Oligotrophic, acidic
- Fire is major driver of terrestrial change
- What affect on the lake?



Source: Beck et al *JGR: Biogeoscience* 2018

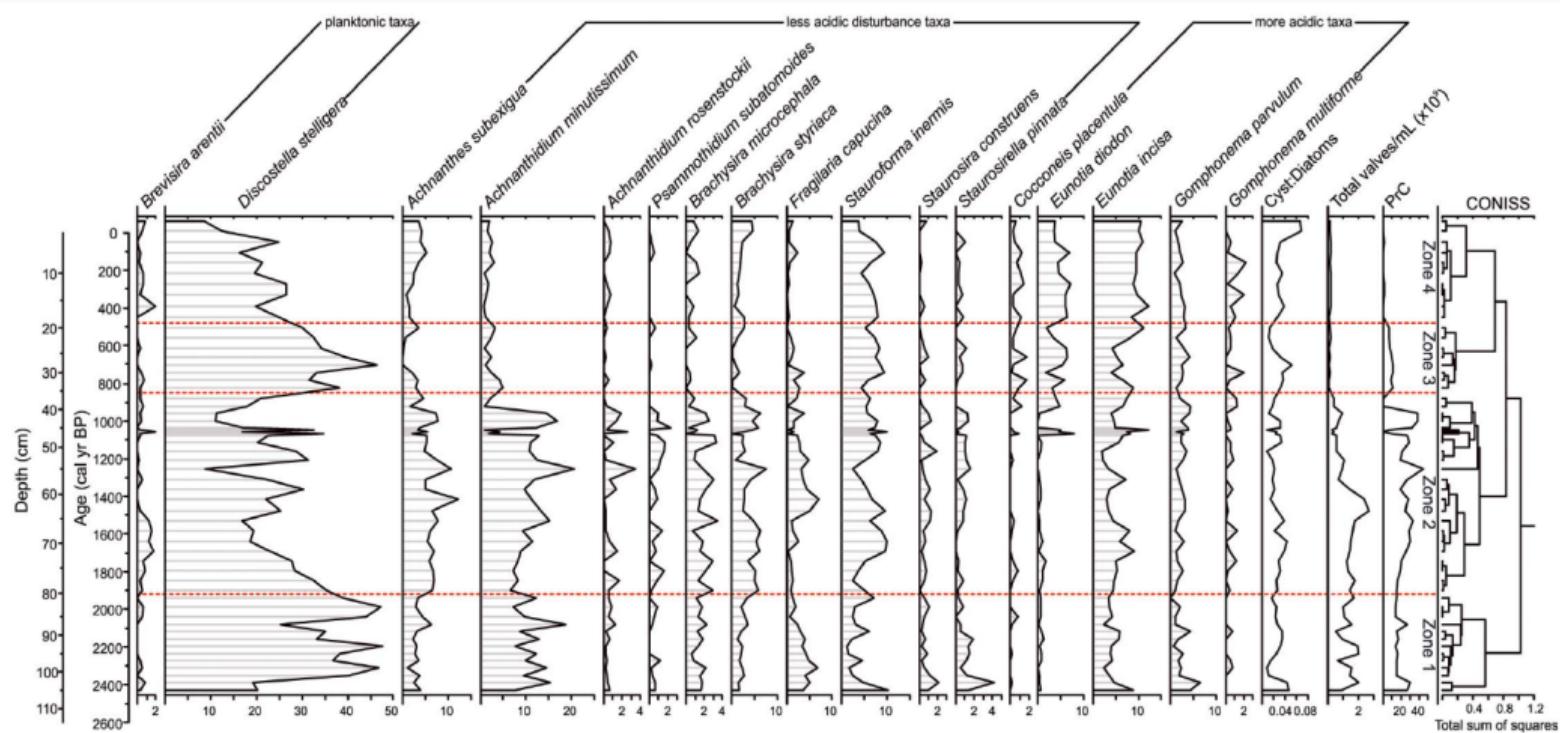
# Lake Vera



# Lake Vera

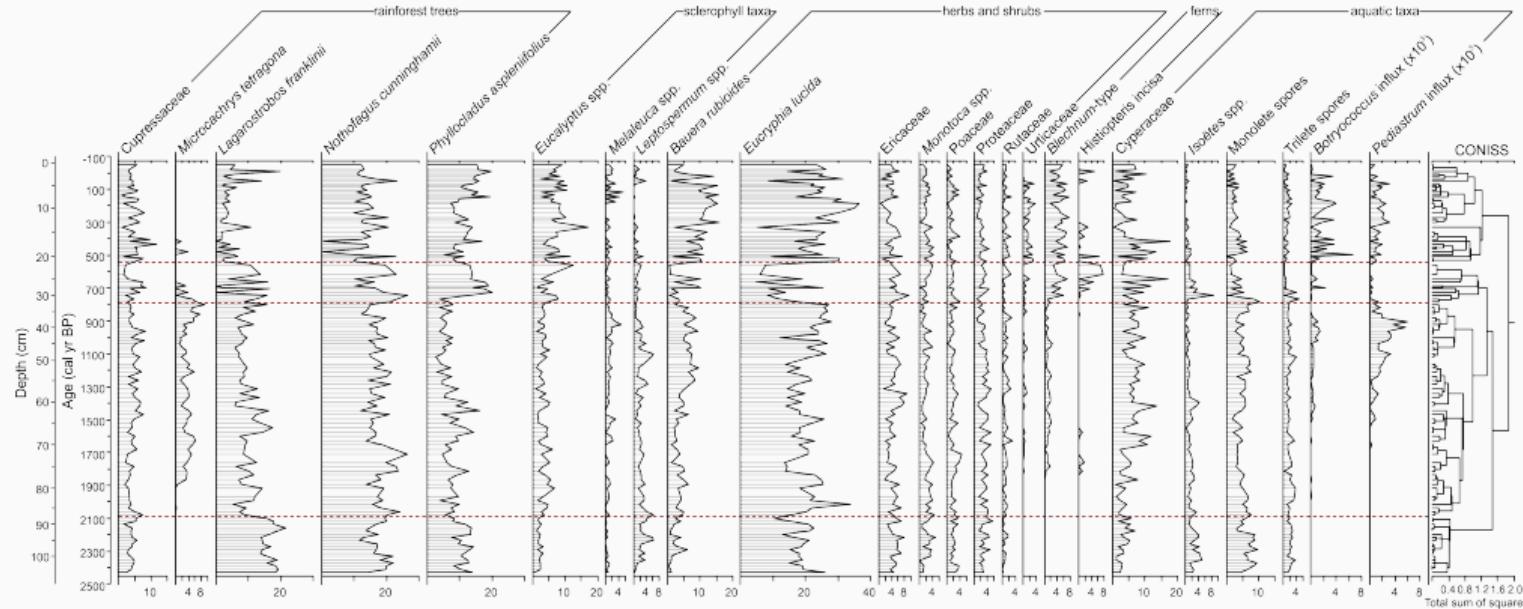


# Lake Vera



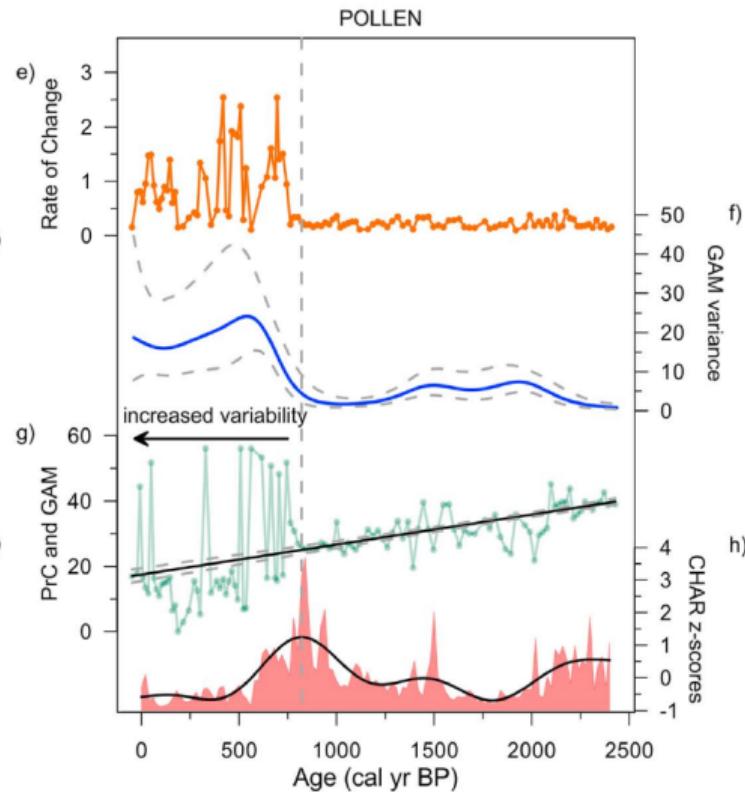
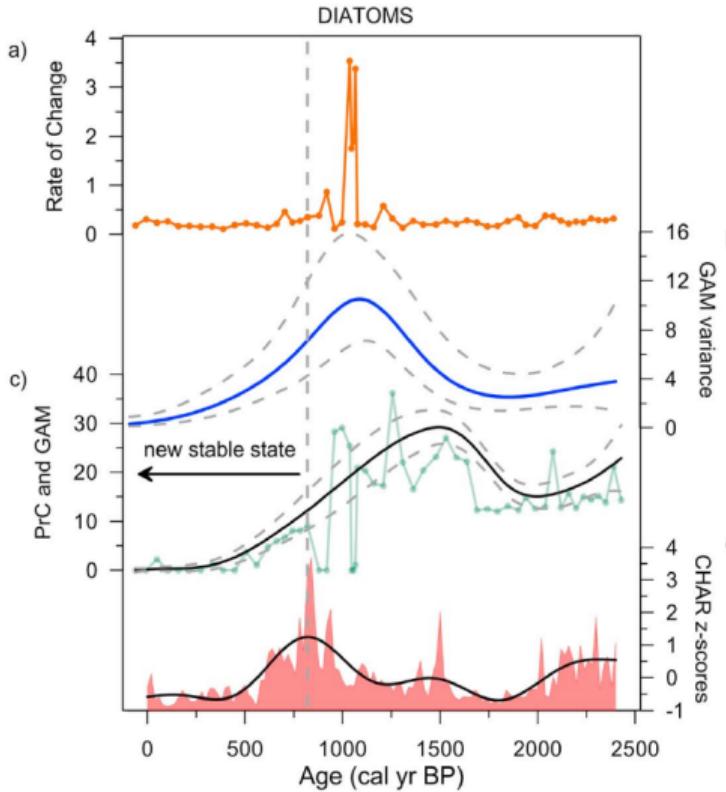
Source: Beck et al J Geophysical Research: Biogeoscience 2018

# Lake Vera



Source: Beck et al J Geophysical Research: Biogeoscience 2018

# Lake Vera



## References i

- Cottingham, K L, J A Rusak, and P R Leavitt. 2000. "Increased Ecosystem Variability and Reduced Predictability Following Fertilisation: Evidence from Palaeolimnology." *Ecology Letters* 3 (4): 340–48. <https://doi.org/10.1046/j.1461-0248.2000.00158.x>.
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- Yee, Thomas W, and Monique Mackenzie. 2002. "Vector Generalized Additive Models in Plant Ecology." *Ecol. Modell.* 157 (2-3): 141–56.