

## Statistics of the aquatic environment. What is on the horizon?

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Scottish Freshwater Group, Nov 2014

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Insutat.



# The changing data world?

 Emerging sensor technology is able to deliver enhanced dynamic detail of environmental systems at unprecedented scale and "will revolutionise our understanding of the environment by providing observations at .....expanding observational scales that will enable a deeper and broader understanding of environmental variability and change ... improving public awareness, enabling better informed public policies and addressing the intrinsic interdependence of human society and the natural environment." (NSF, 2004).



#### The state of the environment

#### Four questions:

- What is changing?
- What are the changes?
- What is driving the changes?
- How certain are we?



The changing nature of how we report the "state"





# What new future challenges?

#### Data

- multi-pollutant concentration data from monitoring networks
- Many covariates: meteorological, land morphology, etc.
- -Different data streams

#### **People and Society**

- Ecosystems (services and values)networks
- Social and economic factors
- Policy
- Sustainability





Making sense of the environment- partial pressure of carbon dioxide



Susan Waldron, carbon dioxide monitoring in freshwater catchments





#### patterns of interest



epCO<sub>2</sub>, flow, temperature, conductivity and pH over 3 years



## What are the questions?

- How is epCO<sub>2</sub> (or the measurand) changing?
- What are the drivers of change?
- What are the temporal and spatial scales of change?
- Events, anomalies, unusual conditions
- We begin by visualisation, and then follow with models to allow us to make inferences, predictions etc



# visualising the components (in time)



![](_page_7_Figure_3.jpeg)

Complex and transient relationships

![](_page_7_Figure_5.jpeg)

![](_page_7_Figure_6.jpeg)

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## Making sense of the environment- the future

![](_page_8_Figure_2.jpeg)

- •15 minute data, 1 hydrological year
- •The highest variability is in the 8 hour signal. This reflects changes in photosynthetic / respiratory dominance, changing seasonally.
- •The smoothed component relates to variations of 21+ days and higher- approx monthly?
- more variation during summer than winter reflecting differences in CO<sub>2</sub> input versus consumption.

![](_page_9_Picture_0.jpeg)

### Optimising samplingfunctional data analysis

- 104 sites
- 30 distinct groupings
- 2 8 lochs in each group
  Focus on a subset of data;
- 7 groups
- 24 lochs
- **Alkalinity,** TON, Nitrate, Phosphorus Chlorophyll<sub>a</sub>

Our goal: to use observed chemistry data to investigate different groups

Ruth Haggarty, PhD and SEPA, Haggarty et al, 2012

![](_page_9_Figure_10.jpeg)

![](_page_10_Picture_0.jpeg)

#### **Comparing Sites**

Inconsistency in the quantity of data and time period covered

-matching by date or season inefficient

-More informative to compare trends and seasonal patterns in the lochs using smooth curves

•Functional data analysis

![](_page_10_Figure_6.jpeg)

#### Det Codes: 200200

![](_page_11_Picture_0.jpeg)

**Functional Data Analysis** 

- Compare seasonal patterns/trends in the data rather than observed values
- Overcomes some of the problems involved with matching dates
  - Time series of data collected on each individual – each loch
  - These are measurements of a continuous function taken at a finite number of time points
  - Any observed trajectory can be viewed as a noisy measurement of an unobservable curve
  - Fit a smooth curve to the points from each loch and cluster these curves

![](_page_11_Figure_8.jpeg)

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### Functional Data

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**Functional clustering** 

Identification of clusters of common signals by FDA

![](_page_13_Figure_3.jpeg)

Cluster mean curves

#### Haggarty et. al (2012), Environmetrics

![](_page_13_Picture_6.jpeg)

![](_page_14_Picture_0.jpeg)

#### **River networks**

Spatial models for stream networks have recently been developed that include a spatial covariance structure based on stream distance rather than Euclidean distance (ver Hoef et al, (2006, 2010)).

The user can specify if monitoring sites are 'flow connected' (A and C or B and C) or 'flow unconnected' (A and B).

![](_page_14_Figure_4.jpeg)

Flexible regression models over river networks, O'Donnell, Rushworth, Bowman, Scott and Hallard (2014)

![](_page_15_Picture_0.jpeg)

#### Spatial patterns of change- at river basin scale

![](_page_15_Figure_2.jpeg)

the circles represent the stations on the network, clearly not spatially representative

Joint work with David O'Donnell, Mark Hallard (SEPA), Adrian Bowman, Alastair Rushworth

![](_page_16_Picture_0.jpeg)

#### Functional data analysis

The time series of data from each sensor can be regarded as a curve, the curve then becomes the "*data point*".

The statistical model is then based on the curves or functions which are assumed to be smooth. We can decompose the function to include trend, seasonal pattern, and relationships with other covariates.

FDA is very powerful and there are functional equivalents of many standard statistical techniques. We have been using such techniques to look at coherent spatial clusters.

![](_page_16_Picture_5.jpeg)

![](_page_17_Picture_0.jpeg)

### **TOC** in Scottish rivers

- Functional clustering methodology has been applied to Total Organic Carbon (TOC) data from several hundreds of monitoring locations across rivers in Scotland over 44 months, covering the period January 2007 - August 2010.
- Each of the 333 river time series are first standardised, individually, to have zero mean and unit variance.
- Number of clusters and cluster membership are then estimated, and plotted spatially.

Water @ Glasgow

![](_page_17_Picture_6.jpeg)

Stephen Reid, MSc, Francesco Finazzi, U of Bergamo, SEPA

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#### TOC in Scottish rivers

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#### Water @ Glasgow

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Globolakes

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set up to investigate the state of lakes using satellite data for 20 years of lake temperature, suspended matter, chlorophyll to:

> Detect spatial and temporal trends and attribute causes of change Forecast lake sensitivity to environmental change

With Claire Miller and Ruth Haggarty, Globolakes consortium

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#### **Pixels to Time Series**

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NATURAL ENVIRONMENT RESEARCH COUNCIL DUNDEE

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![](_page_21_Picture_1.jpeg)

On a global scale

- Clustering approaches are applied to the LSWT time series of the ARC-Lake data set (www.geos.ed.ac.uk/arclake) in order to cluster the lakes into homogeneous groups with respect to their temporal coherence
- 5 years of weekly mean values were used in the analysis (2006-2010) for 261 lakes.
- functional clustering identified 11 clusters as optimal.

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#### Cluster curves

Each approach provides a different clustering result, however, the temporal patterns they identify are similar. Results for two clusters are shown.

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![](_page_22_Figure_4.jpeg)

GloboLake

![](_page_22_Figure_5.jpeg)

![](_page_22_Figure_6.jpeg)

![](_page_22_Figure_7.jpeg)

University of

Reading

![](_page_22_Picture_8.jpeg)

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Finazzi et al, 2014

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## Spatial cluster structure

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### challenges

- Data characteristics- quantity and quality, missingness
- Non stationary, complex nature of the relationships
- For networks of sensors- building fast and efficient spatiotemporal models, functional data analysis provides part of that solution
- Aspects of scale and aggregation
- uncertainty evaluation and visualisation multi-disciplinarity

Water @ Glasgow

![](_page_24_Picture_8.jpeg)

![](_page_25_Picture_0.jpeg)

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- Finazzi, F., Haggarty, R., Miller, C., Scott, M., Fasso, A. A comparison of clustering approaches for the study of the temporal coherence of multiple time series, *Stochastic Environment Research and Risk Assessment*.
- Miller C, Magdalina A, Willows R, Bowman A, Scott E M, Lee D, Burgess C, Pope L, Pannullo F, Haggarty R (2014). Spatiotemporal statistical modelling of long term change in river nutrient concentrations in England and Wales. *Sci Tot Env, 466-467.*