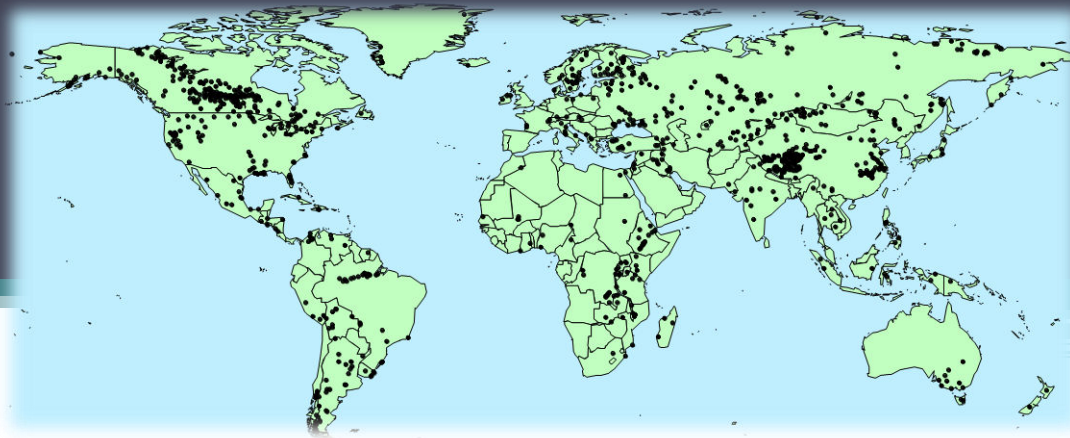


# Globolakes : Global coherence of lake water quality

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**Globolakes**

Global Observatory of Lake Responses to Environmental Change



**PML**

Plymouth Marine Laboratory

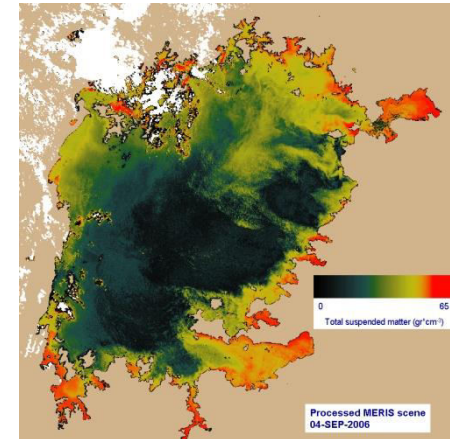


**UNIVERSITY OF STIRLING**



# Globolakes ([www.globolakes.ac.uk](http://www.globolakes.ac.uk))

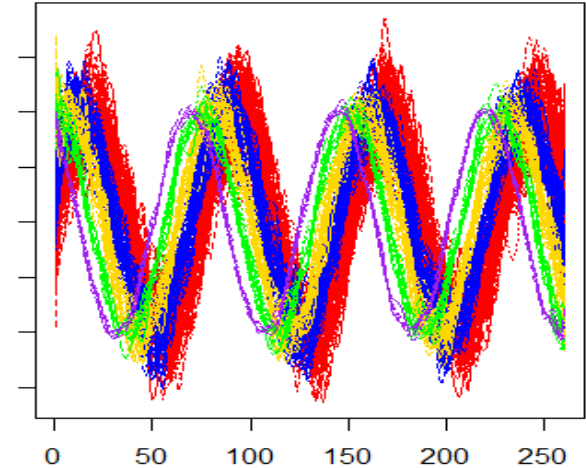
- **Globolakes** is a 5 year consortium project involving 6 UK research groups
- Our goal is to investigate the state of 1000 lakes and their response to climatic and other environmental drivers of change at a global scale using a 20 year archive of satellite based observations.
- One of our key aims is to identify patterns of temporal coherence for individual remotely sensed lake characteristics and the spatial extent of coherence for 1000 lakes.





# Coherence

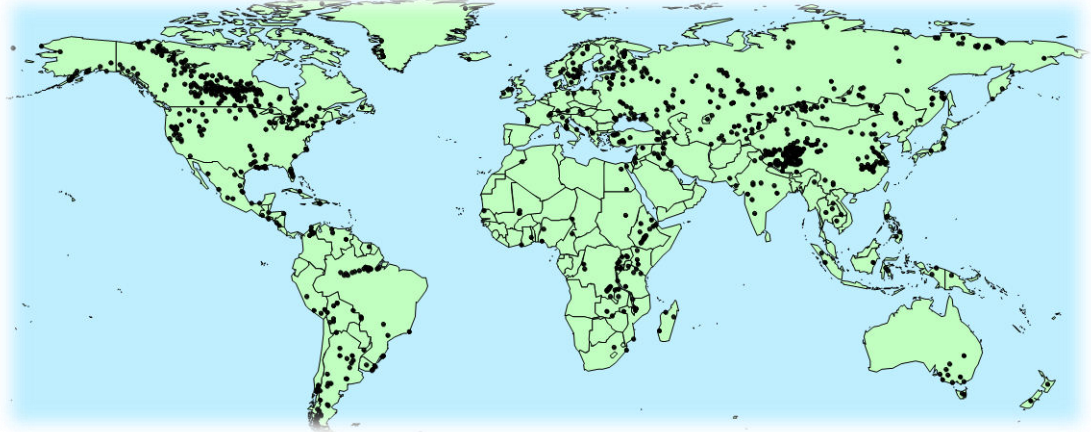
- Identifying both long-term change and phenological/seasonal changes is of great ecological importance.
- The synchrony between major fluctuations in a set of time series is often described as **temporal coherence**.
- Aim: group time series into a suitable number of clusters where two time series belong to the same cluster if they are coherent with each other.
- Focus on comparing a large number of time series and obtain groupings based on common features across time.
- A **functional data analysis** approach has been taken





# ARCLake data

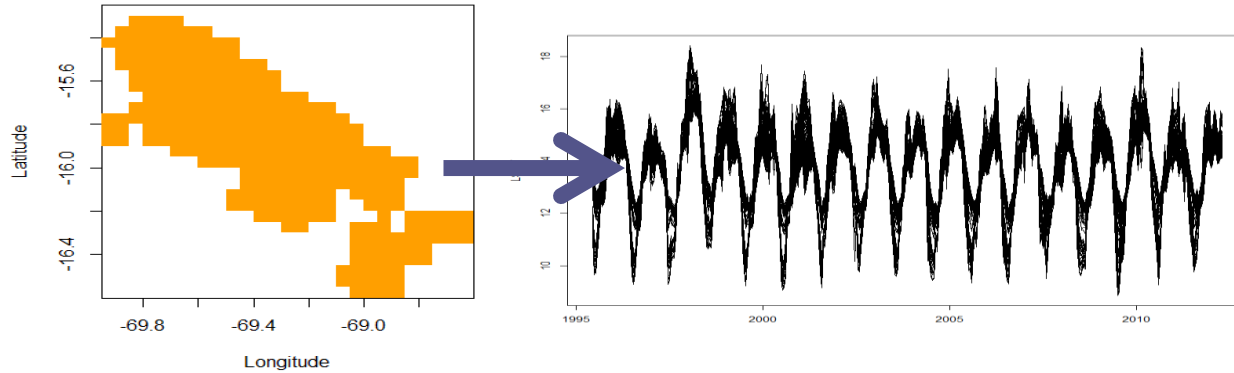
- Average lake surface water temperature data (processed using images from AATSR satellite)
- For global coherence, lake mean time series are considered
- Twice monthly observations covering an 18 year time period between 1995 and 2012
- Data on 700 lakes across entire time period
- Investigate clusters based on trend and seasonality together



ARClakes/GloboLakes Lakes Locations

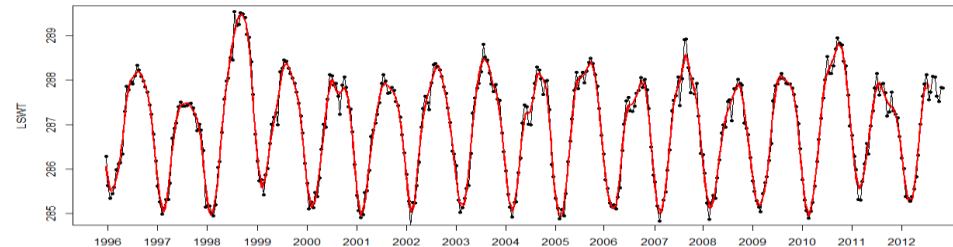


# Functional Data Analysis



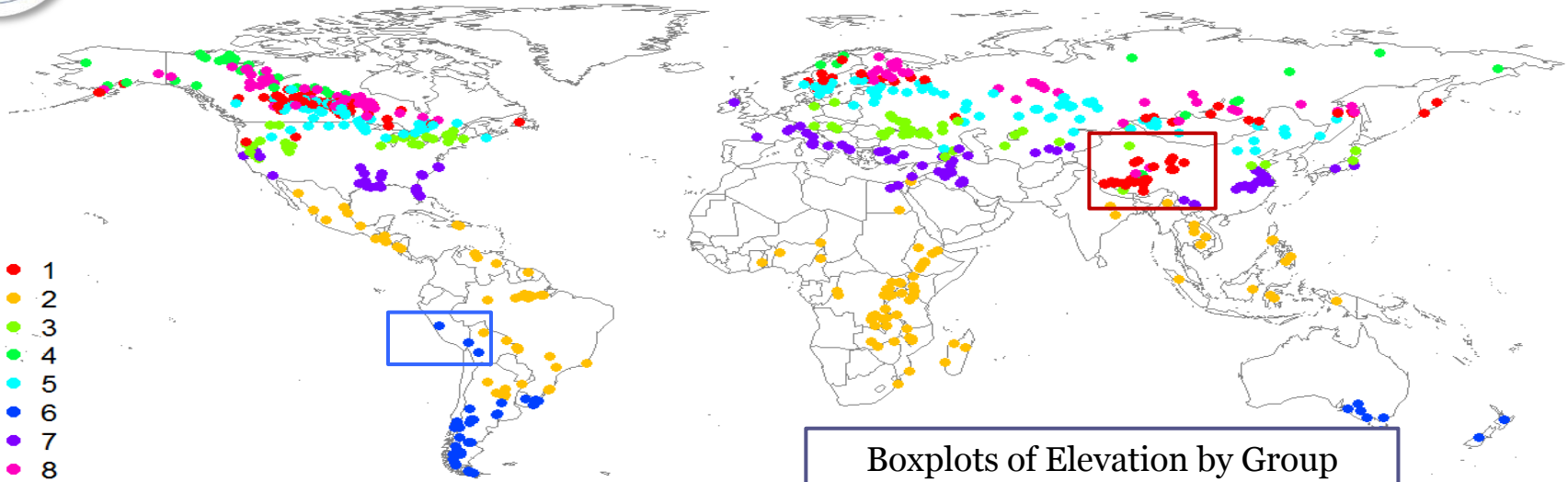
- Each time series corresponds to a pixel
- Compute mean curves
- Each time series can be smoothed – keep key features but remove local variability

- Smooth curves fitted to each lake means using a b-spline basis
- Model based clustering applied to the b-spline coefficients which define the smooth curves
- Results are data driven

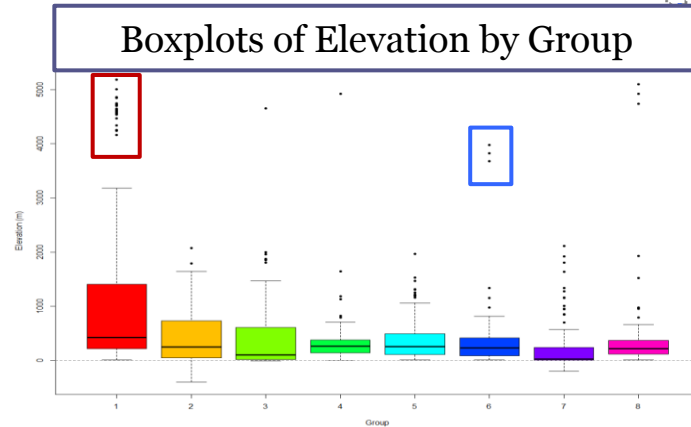




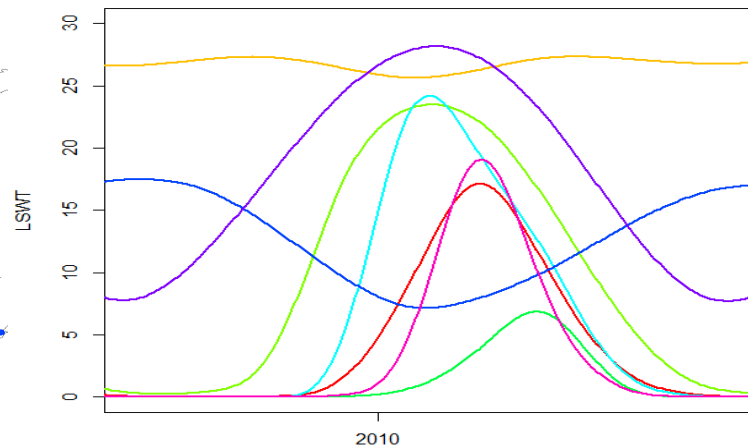
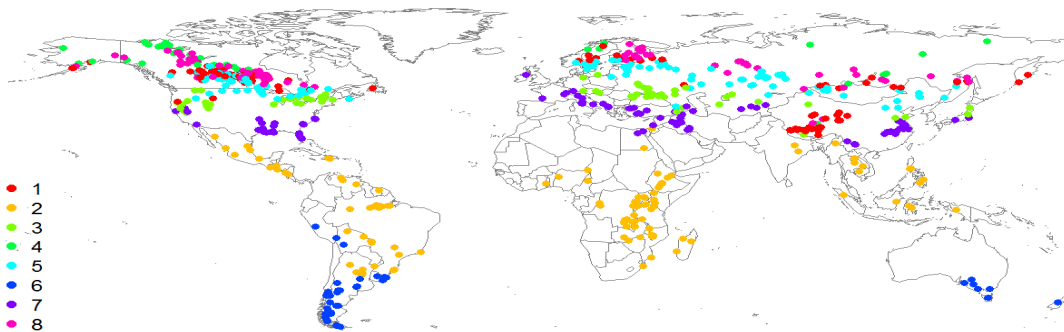
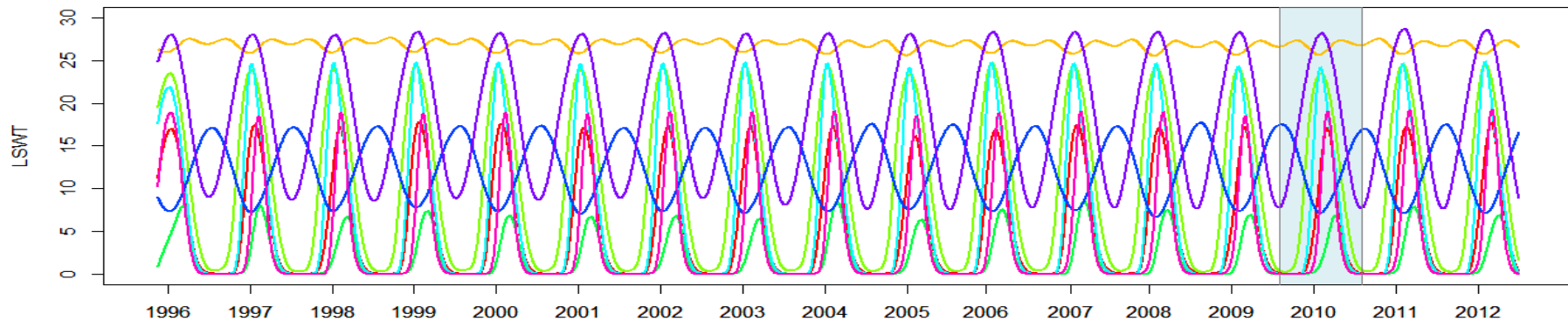
# Results: Global Coherence



- 8 clusters identified as statistically optimal
- Map shows distribution of clusters
- Only temperature data underpins the formation of the clusters



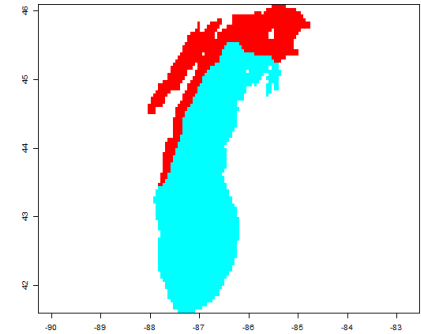
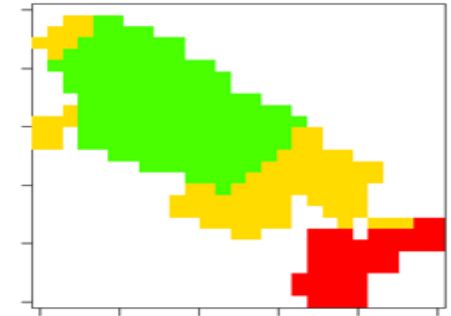
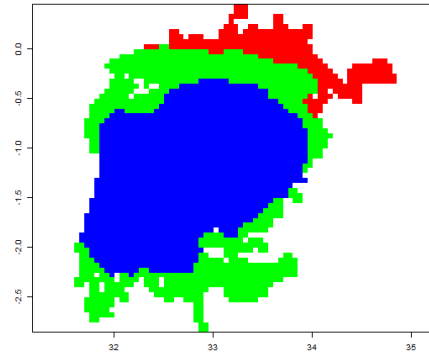
# Results: Global Coherence





# Within Lake Coherence

- Investigate the similarities of different areas within lakes
- Large lakes may have several basins/areas within them that have different characteristics in terms of the trends, seasonal patterns and levels of determinands present
- How do we identify these different areas?
- We have taken a two stage approach;
  - Functional Principal Component Analysis (FPCA)
- Use FPCA to find dominant modes of variation in the data (known as principal components or PCs)
- Keep a small number of these PCs in order to approximate the original data

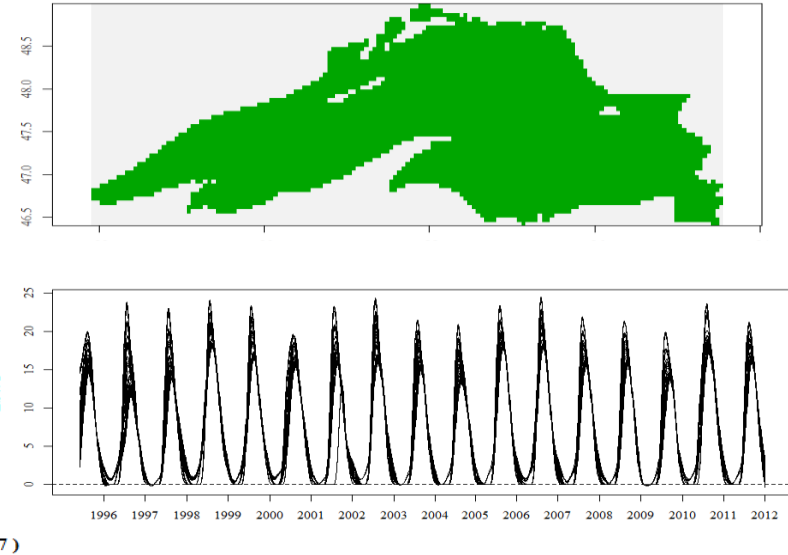




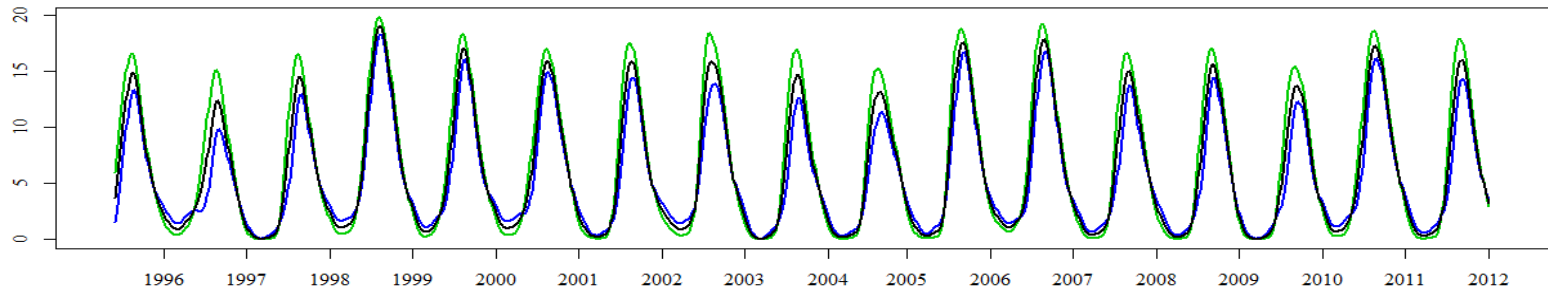


# Within Lake Coherence: Example

- Example: Lake Superior - 4094 pixels
- Smooth the time series for each pixel – 4094 smooth curves
- First two FPC scores explain 86% of the variability in the curves



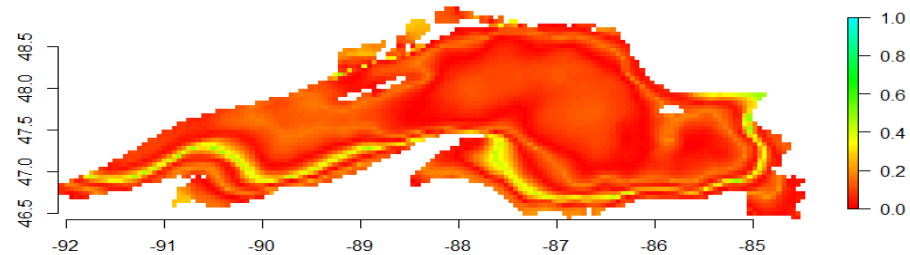
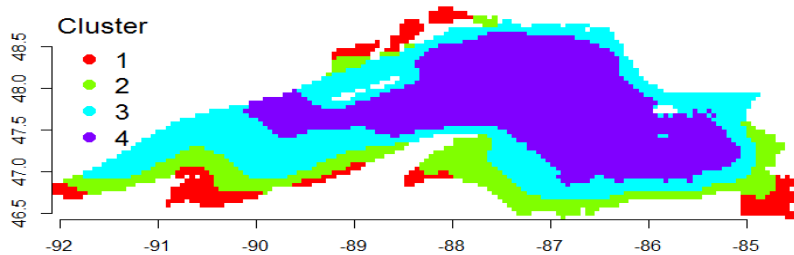
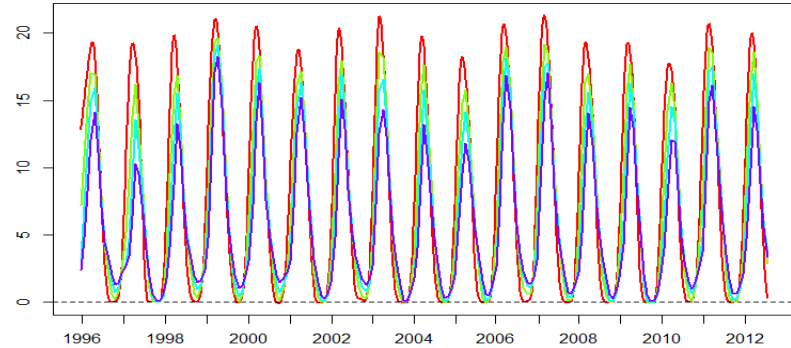
PC function  
(Percentage of variability 77)





# Within Lake Coherence: Example

- 4 clusters identified as statistically optimal
- Clear distinctions between the mean functions corresponding to these four groups
- Key discrepancy is amplitude of the seasonal patterns each year.





# Summary

- Our approach enables clusters of curves to be identified which are coherent in terms of temporal dynamics.
- Functional data analysis reduces dimensionality while retaining important information
- The methods are very computationally efficient (run on standard desktop)
- Model based clustering can be used to identify statistically optimal (data driven) number of clusters
- Uncertainty in cluster classification is also obtained

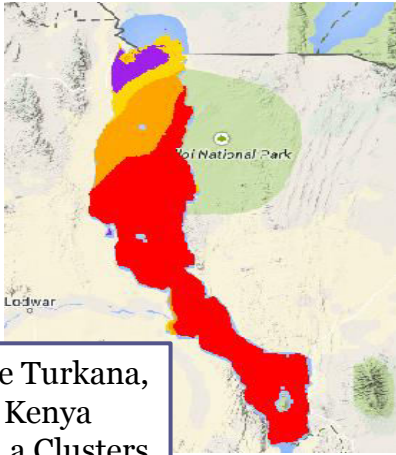




# Next Steps

Analysis of lake mean curves gives us an overview of global coherence

Within lake clustering captures smaller scale detail - our ultimate goal is to incorporate within lake clustering results into global coherence

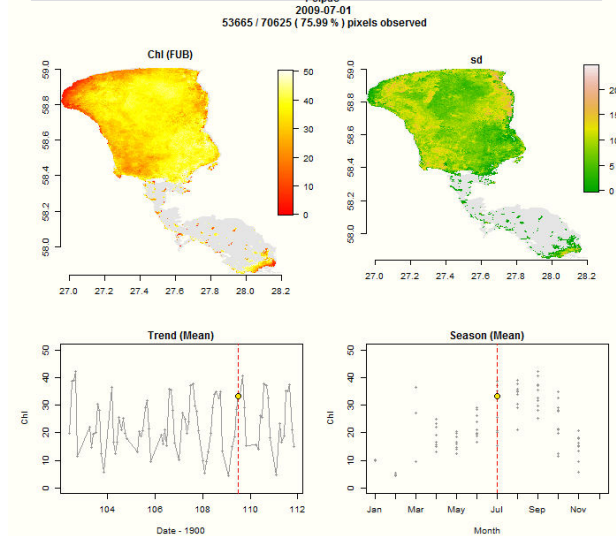


Lake Turkana, Kenya  
Chl a Clusters

We will also explore more variables such as chlorophyll and coloured dissolved organic matter at a much finer resolution.

Missing data through time and in space present new statistical challenges

## Chlorophyll at Lake Peipsi, Estonia Monthly obs, 2002-2012 (Data from DIVERSITY II project)





# References

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GloboLakes consortium  
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