# Can we trust observational data and models of the state of the Baltic Sea?

Anders Grimvall

Division of Statistics, Department of Computer and Information Science Linköping University, SE-58183 Linköping, Sweden

E-mail: anders.grimvall@liu.se

**Some examples of low data quality** 

□ A model of acidification of the Baltic Sea

- Observational pH and alkalinity data from the Baltic Proper
- General comments on tools for change-point detection and trend assessment

Trend curve for temperature-normalized concentrations of phosphorus along with measured concentrations at different depths (0.5 – 70 m) at Dagskärsgrundet in Lake Vänern





# Trend surface for normalized concentrations of total phosphorus in riverine input to the Gulf of Bothnia

Normalization with respect to discharge and transport of particulate matter





Trend curves for the arithmetic mean of normalized concentrations of phosphorus in riverine input to the Kattegat/Skagerrak and the Gulf of Bothnia

Normalization with respect to discharge and transport of particulate matter









Trend surface for flow-normalized concentrations of total nitrogen in riverine input to the Kattegat and Skagerrak

(Tot-N concentrations determined by persulphate digestion)





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Trend surface for flow-normalized concentrations of total nitrogen in riverine input to the Kattegat and Skagerrak

(Tot-N concentrations determined as the sum of nitrite/nitrate nitrogen and Kieldahl nitrogen)





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Trend curves for the arithmetic mean of flow-normalized concentrations of total nitrogen in rivers discharging into the Kattegat and Skagerrak

Tot-N (ps) = total nitrogen determined by persulphate digestion Tot-N (Kj) = sum of nitrite/nitrate nitrogen and Kjeldahl nitrogen







### Acidification of the Baltic Sea

- Increased CO<sub>2</sub> levels in the atmosphere can lower the pH of weakly buffered waters
- It has been stated that the pH of sea water has decreased 0.1 units during the past century
- ❑ The effect of increasing CO<sub>2</sub> levels can be modified by changes in the input of nutrients to the Baltic Sea

# Modelled pH in the Baltic Proper 1960-2006, surface water (0-10 m)



Anders Omstedt, GU

### Modelled pH in the Baltic Proper 1960-2006, surface water, winter data (Jan-Mar)







# Mann-Kendall tests of trends in modelled pH in the Baltic Proper

#### 1960-2006

### 1990-2006

	MK	p-value	Significance	Slope					0		
Month	statistic	(twosided)	code	(change/yr)	Median	Month	MK	p-value	Significance	Slope	Madian
1	-698	0.0000		-0.0018	7.992	Month	statistic	(twosided)	code	(change/yr)	
2	-646	0.0000		-0.0015	7.98	1	-28	0.24/1		-0.0011	7.964
3	_337	0 0020		-0 0011	7 955	2	-45	0.0631		-0.0010	7.96
4	470	0.0020		0.0000	7.047	3	-15	0.5356		-0.0007	7.948
4	-178	0.1026		-0.0006	1.941	4	-38	0.1169		-0.0023	7.941
5	18	0.8689		0.0001	8.282	5	-37	0.1272		-0.0048	8.306
6	-293	0.0072		-0.0012	8.2545	6	-38	0 1175		-0 0030	8 241
7	-277	0.0111	-	-0.0016	8.233	7		0.03/3		0.0002	8 233
8	-395	0.0003		-0.0018	8,173			0.000		0.0002	0.200
	464	0,0000		0.0014	0.453	8	-28	0.2487		-0.0017	8.140
9	-404	0.0000		-0.0014	8.153	9	-25	0.3027		-0.0011	8.1335
10	-458	0.0000		-0.0013	8.106	10	3	0.9016		0.0001	8.092
11	-448	0.0000		-0.0014	8.037	11	-24	0.3228		-0.0012	8.015
12	-560	0.0000		-0.0013	8.002	12	-33	0.1737		-0.0013	7.985

# Comparison of model outputs and observational data 1963-2006



# Mann-Kendall tests of trends in observed pH levels at BY15 in the Baltic Proper

#### 1963-2009

### 1990-2009

		p-value	Significance	Slope	
Institute	Month	(twosided)	code	(change/yr)	Median
SMHI	1	0.6345		-0.0006	8.07
SMHI	2	0.5383		-0.0021	8.07
SMHI	3	0.5439		-0.0012	8.1
SMHI	4	0.0384	+	0.0050	8.23
SMHI	5	0.4911		0.0012	8.43
SMHI	6	0.2230		-0.0029	8.4
SMHI	7	0.0102	-	-0.0200	8.225
SMHI	8	0.7817		-0.0007	8.16
SMHI	9	0.6153		-0.0010	8.23
SMHI	10	0.5892		-0.0011	8.19
SMHI	11	0.8003		0.0000	8.13
SMHI	12	0.8561		0.0000	8.07
SMHI	All cate	0.6060		-0.0003	8.17

		p-value	Significance	Slope	
Institute	Month	(twosided)	code	(change/yr)	Median
SMHI	1	0.9601		0.0000	8.07
SMHI	2	0.7845		0.0000	8.065
SMHI	3	0.1489		0.0036	8.1
SMHI	4	0.4155		0.0050	8.265
SMHI	5	0.8046		-0.0017	8.44
SMHI	6	0.2943		-0.0086	8.35
SMHI	7	0.0102	-	-0.0200	8.225
SMHI	8	0.7720		-0.0008	8.13
SMHI	9	0.3272		-0.0062	8.225
SMHI	10	0.3889		-0.0036	8.19
SMHI	11	0.5536		0.0010	8.12
SMHI	12	0.7578		-0.0008	8.07
SMHI	All cate	0.4165		-0.0011	8.15

# Comparison of observational and modelled pH data – BY15 and the Baltic Proper



# Visual inspection of observational data



# Major achievements in visual data analysis

- Interactive linked diagrams (Becker & Cleveland, 1987; www.Ggobi.org)
- Motion charts (Rosling; <u>www.gapminder.org</u>; Google gadget; VB-macros for Excel)

Statistical tools for assessing the quality of environmental data

**Trend surface methodologies** 

**Change-point detection** 

Detection of abrupt changes in the presence of smooth trends

Assessing time series of data one by one for the presence of abrupt level shifts



# Assessing multiple time series of data for the presence of synchronous smooth changes



# Assessing multiple time series of data for the presence of smooth changes and break points



A general semiparametric model for smoothing a vector of time series with similar trends and synchronous change-points

Let  $y_{tj}$  be the observed value in the *j*th series at time *t* 





Impose constraints on the variability of the intercepts by penalizing nonlinear variation in these coefficients



### **Computational aspects**

Use a back-fitting algorithm that alternates between

- i. Estimation of a smooth trend surface in the presence of a given set of change-points
- ii. Detection and estimation of level shifts in the presence of a given smooth response surface
- Estimate the smooth trend using a roughness penalty technique allowing smoothing over time and across series
- Estimate level shifts by first using a tree algorithm to identify candidate change-points and then using dynamic programming for the final detection and estimation of level shifts

# Two-stage search for change-points

Identification of candidate change-points using a tree algorithm

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10
Series1		R1			R7 <b>R8</b>		8	R13		
Series2		IX1						D14		D45
Series3	R2 R3			R9				K14		K I D
Series4										
Series5										
Series6	R4	R	5		<b>R10</b>		R11		-	
Series7		1.000					R16			
Series8										
Series9	De		R12							
Series10	RO									

**Final estimation** of change-points (identification of a relevant subset of the candidate changepoints)

	Year1	Year2	Year3	Year4	Year5	Year6	Year7	Year8	Year9	Year10
Series1										
Series2										
Series3						100				
Series4					R	2				
Series5		<b>D</b> 4								
Series6		<b>N</b> I								
Series7									R3	
Series8										
Series9										
Series10										

Dynamic programming for optimal segmentation of a univariate time series





**Determine** c(1,t,k) recursively for  $1 \le t \le T$  and  $1 \le k \le K$ 

# **Optimal segmentation of a multivariate time series into** *K* **blocks**

#### Basic equation for dynamic programming



**Determine** C(1,m,K) recursively for  $1 \le m \le M$  and  $1 \le K \le K_{max}$ 

# Inputs and outputs of our integrated algorithm





Noise

# **Concluding remarks**

Interactive visualization techniques provide new indispensable tools for data analysis

Semiparametric smoothing techniques can provide a useful basis for the analysis of multiple time series of environmental data

Analysis of large datasets requires efficient algorithms