

Data analysis methods in weather and climate research

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9. Introduction to time series analysis & modelling

- Basic concepts
- Trend, periodic, and irregular components
- Filtering and smoothing
- Serial correlation
- Autoregressive time series models

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1

9. Introductory reading on time series

- www.met.rdg.ac.uk/cag stats@reading
- C. Chatfield, *The Analysis of Time-series: An Introduction*, CRC press, 6th edition 2003.
- P.J. Brockwell and R.A. Davis, *Introduction to Time Series and Forecasting*, Springer Verlag, 1996.
- P. Bloomfield, *Fourier Analysis of Time Series: An Introduction* (Wiley Series in Probability & Statistics), 2000.

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2

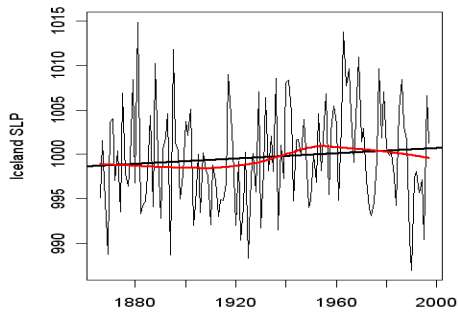
9. Some basic concepts

- Discrete time series = sequence of values $x_1, x_2, x_3, \dots, x_n$ recorded at discrete times $t_1, t_2, t_3, \dots, t_n$
- usually regular $t_n = n\Delta$
- Aims: to monitor, forecast, and control systems
- Approaches: Time domain or frequency domain*
- Exploratory data analysis EDA (descriptive)
→ time series modelling (inferential)

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3

9. Long-term time trend T



```
> abline(lsfit(x,y),lwd=3,col=1)
> lines(lowess(x,y),lwd=3,col=2)
```

9. Filtering and smoothing

Lanczos filter with span k:

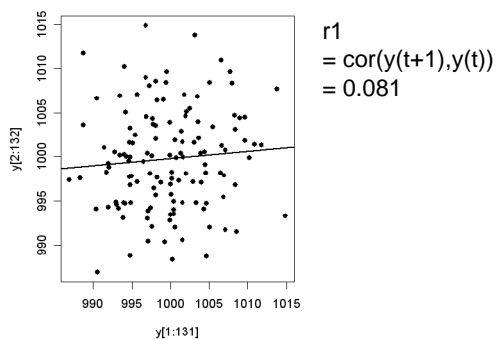
$$y'_t = \sum_{lag=-k}^{lag=+k} w_{lag} y_{t+lag}$$

- Low-pass (smoothing) e.g. MA(.), binomial,...
- High pass: $y - y'$
- Band-pass: $y'' - y'$

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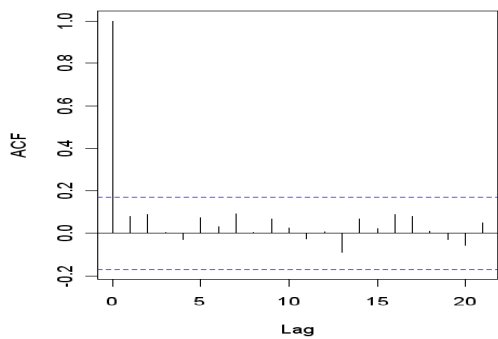
8

9. Serial correlation: SLP(t+1) versus SLP(t)



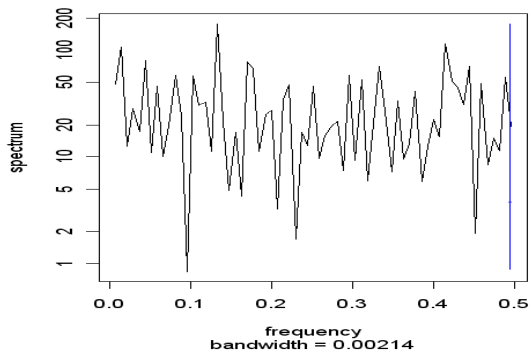
```
> plot(y[1:131],y[2:132],pch=16)
> abline(lsfit(y[1:131],y[2:132]),lwd=2)
```

9. Autocorrelation function for Iceland



10

9. Unsmoothed power spectrum: periodogram



> spectrum(y)

9. Autoregressive and Moving Average models

AR(1) - Autoregressive order 1 time series model:

$$y_{t+1} = \beta y_t + \varepsilon_t$$

AR(3) time series model:

$$y_{t+1} = \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \varepsilon_t$$

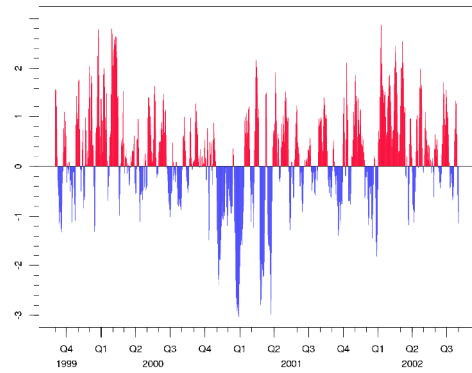
MA(2) time series model:

$$y_{t+1} = \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2}$$

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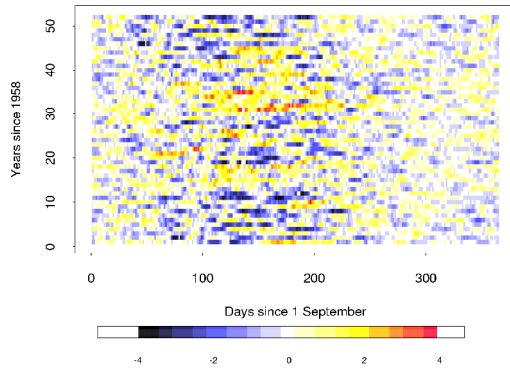
12

9. Daily NAO index from Sep 1999 - 2002

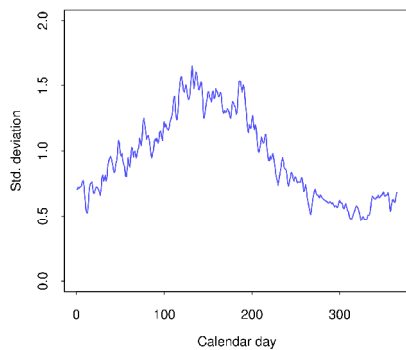


13

9. Persistence in the daily NAO index

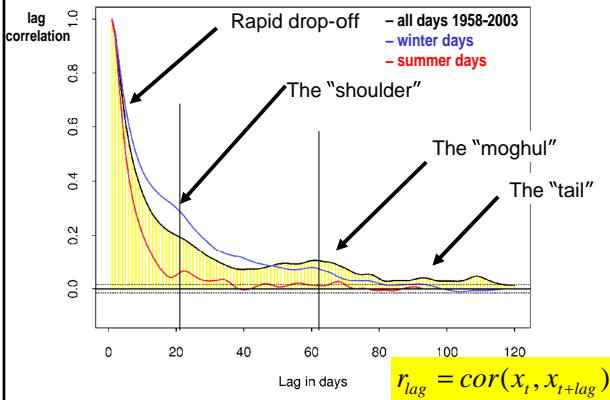


9. Varying variance (heteroskedasticity)

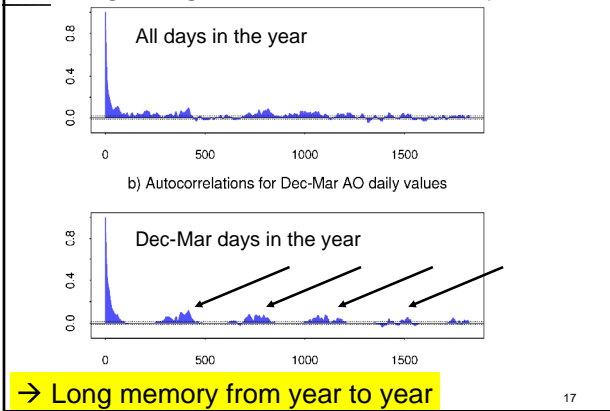


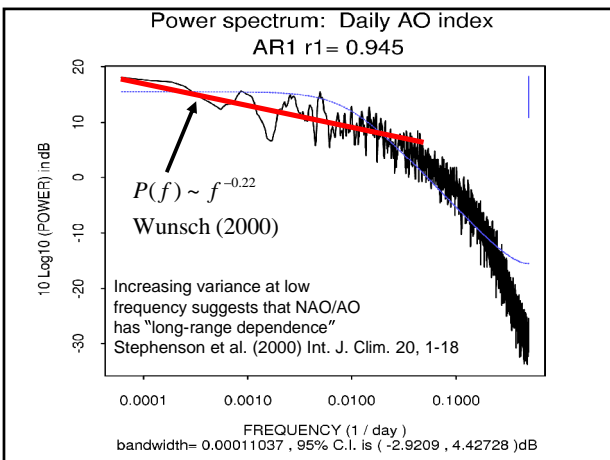
→ Almost 10 times the variance in winter than in summer

9. Daily NAO autocorrelation 1958-2003



9. Long-range correlation in daily NAO





9. Causality analysis in macro-economics



Granger Causality

If the past history of one variable, X, gives extra predictive information for another variable, Y, then X "Granger causes" Y

"Testing for causality and feedback," *Econometrica*, 37, 1969, 424-438.

Clive W.J. Granger receiving a Nobel Prize for econometric time series analysis from His Majesty the King of Sweden at the Stockholm Concert Hall. 10 December 2003

<http://www.nobel.se/economics/laureates/2003/>

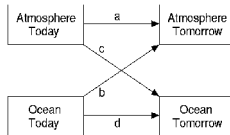
22

9. Granger causality testing

- Fit a Vector AutoRegressive VAR(p) time series model to the data:

$$N_t = \sum_{i=1}^p a_i N_{t-i} + \sum_{i=1}^p b_i S_{t-i} + \varepsilon_t$$

$$S_t = \sum_{i=1}^p c_i N_{t-i} + \sum_{i=1}^p d_i S_{t-i} + \eta_t$$



- Determine the best order p by minimising the Schwarz criterion
- Significance test for b=0 by comparing the log-likelihood ratio

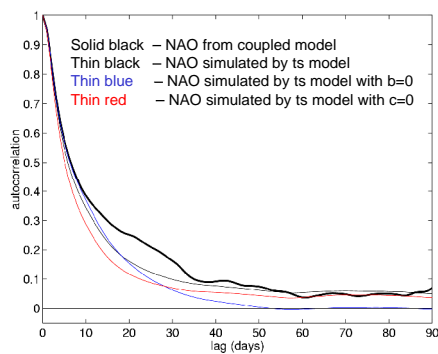
$$L = N(\log|\Omega_{b=0}| - \log|\Omega|)$$

to the chi-squared distribution with p degrees of freedom

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23

9. Autocorrelation of simulated NAO

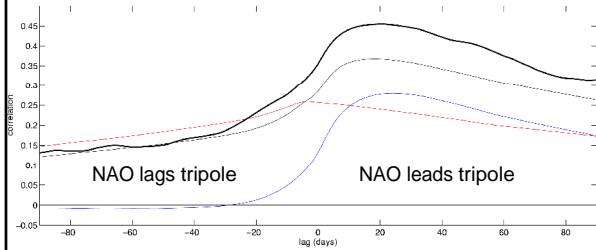


Need o→a interaction to get long tail in NAO

24

9. Cross-correlation of NAO and tripole

Solid black – NAO from coupled model
 Thin black – NAO simulated by ts model
 Thin blue – NAO simulated by ts model with $b=0$
 Thin red – NAO simulated by ts model with $c=0$



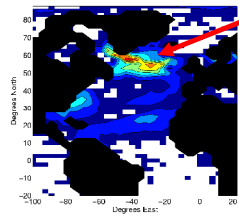
Need $a \rightarrow o$ interaction to get cross-correlations

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25

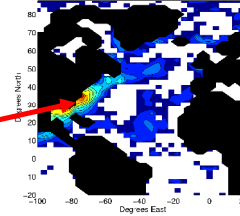
9. Causality for NAO and local SSTs?

NAO \rightarrow local SST causality



NAO causal effect on N. Atlantic SSTs (as found by Bjerknes)

local SST \rightarrow NAO causality



Interesting causal effect of Gulf stream SSTs on NAO

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26

9. Summary

- Time series can have fascinatingly rich serial structure
- EDA exists for exploring the different time series components: trend+periodic+irregular
- Regression models can be used to MODEL the process that generated the time series and hence provide insight.
- Lots of good books on time series analysis that are worth reading: Chatfield, Brockwell and Davis, Bloomfield, Priestley, ...

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27

Probability Problem Solution

Two types of simple event: G=girl B=boy

Event space: GG GB BG BB

$P(\text{GG} | (\text{GB or BG or GG}))$

$= P(\text{GG}) / P(\text{GB or BG or GG})$

$= 0.25/3 * 0.25 = 1/3$

Three types of simple event: B=boy R=girl rare name C=girl not rare name

$P(B)=1/2$ $P(R)=p/2$ $p(C)=(1-p)/2$

Event space: RR RC RB CC CR CB BR BC BB

$P(\text{RR or RC or CR} | (\text{RR or RC or CR or RB or BR}))$

$= (2-p)/(4-p)$ (but note that there are many girl's names so p is often small!)
