

On the Statistical Significance of Climate Trends

Christian Franzke

British Antarctic Survey, Cambridge, UK



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

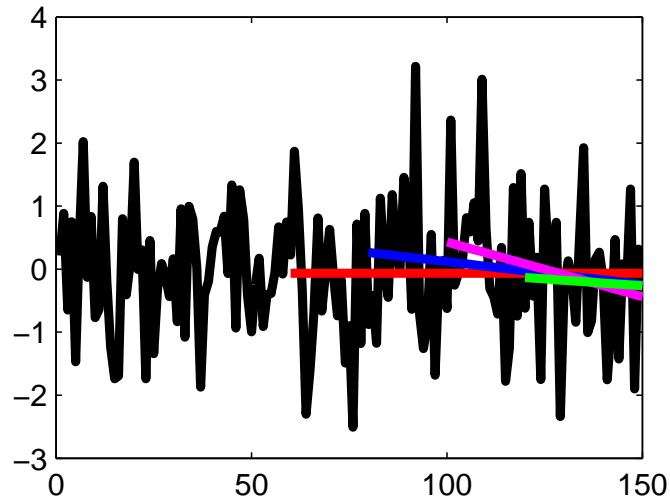
Motivation

- An important problem in climate science is the identification of statistically significant trends
- **Problem:** Even simple noise processes can exhibit 'trends' over finite periods of time
- Trends are not necessarily linear and also have to be distinguished from internal climate variability
- A recently developed time series analysis technique is Empirical Mode Decomposition (EMD). This method can analyse nonlinear and non-stationary time series and is able to detect non-linear trends
- We apply this method to Antarctic station temperature time series

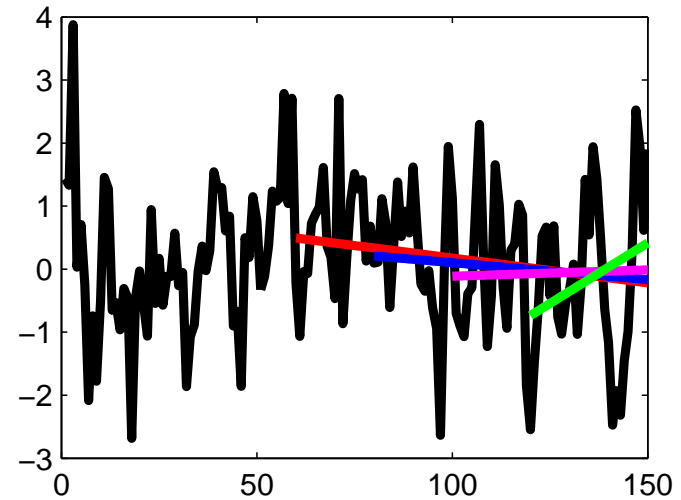


Are there trends in noise?

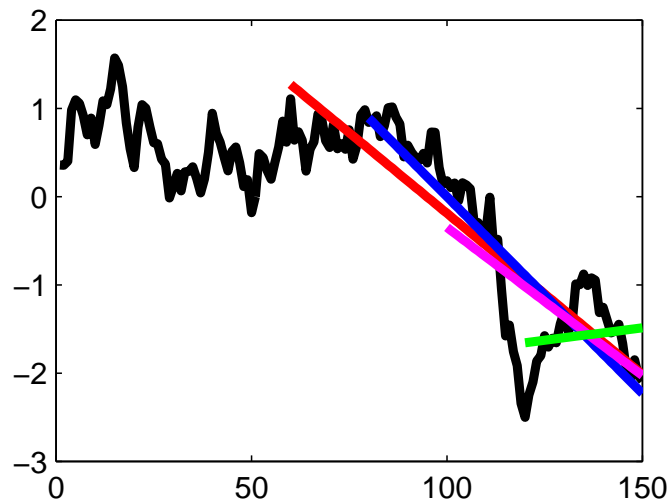
White Noise



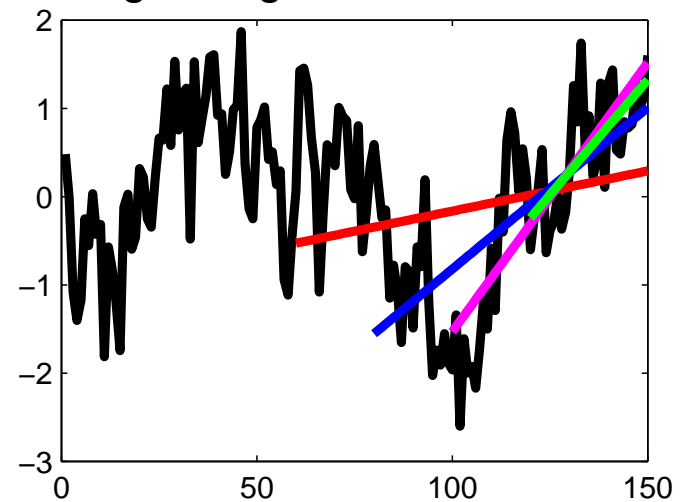
Short-Range Correlated Noise



Random Walk



Long-Range Correlated Noise



How to model the background climate variability

- Most used model for background climate variability is an **Autoregressive Process of First Order AR(1)**. This is a short-range dependent process with exponential decay of autocorrelation.
- There is increasing evidence for long-range dependence in surface temperatures (e.g. Koscielny-Bunde et al. 1998; Huybers and Curry 2006; Vyushin and Kushner 2009).
- The paradigmatic model for long-range dependence is a FARIMA(0,d,0) (Hosking 1981; Stoev and Taqqu 2004).
- For both processes we only need to estimate 2 parameters from the data.



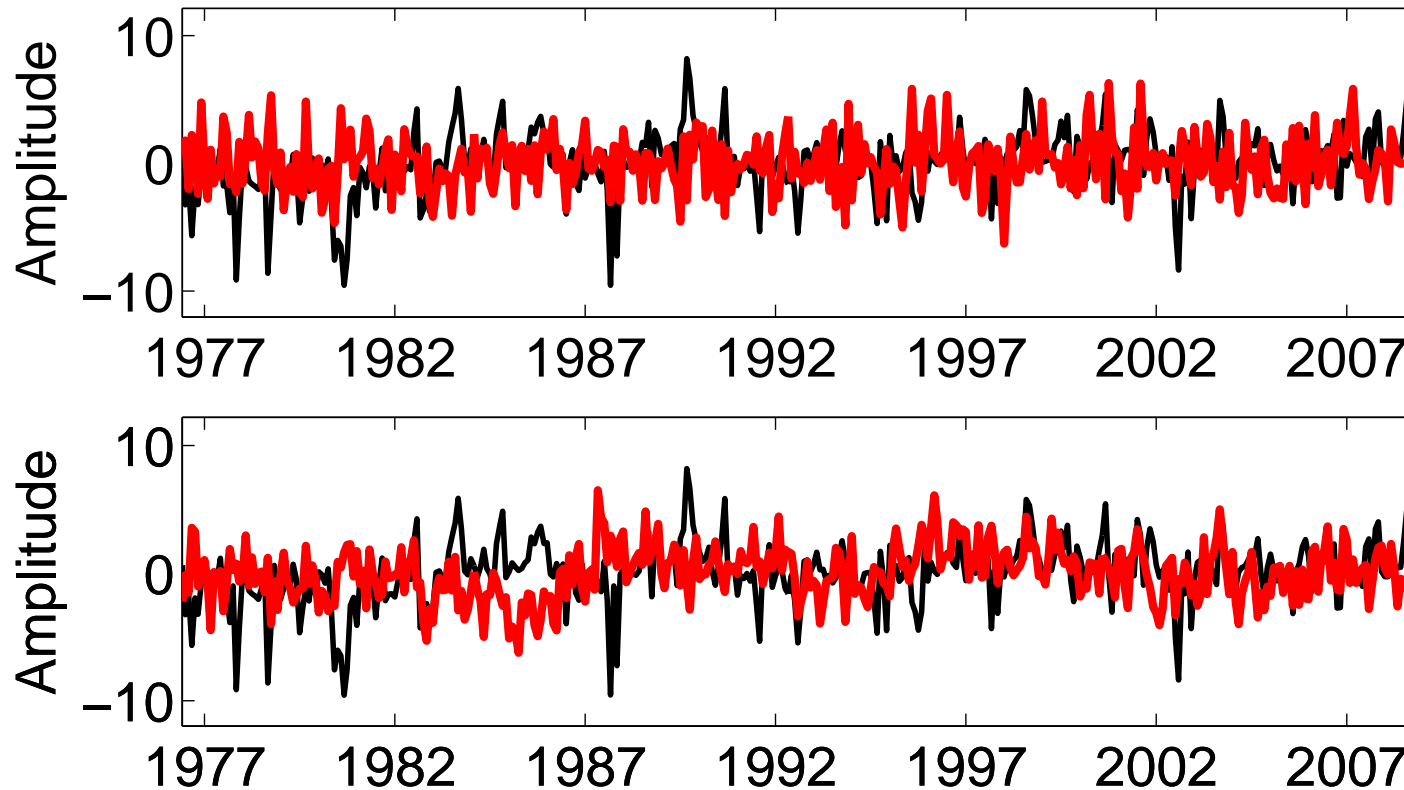
'Physical' models with long-range dependence

- Critical Phenomena (Ising model)
- Aggregation of short-range dependence models (different climate components have different intrinsic time scales)



Climate Variability

Can the observed variability be represented by a simple stochastic process?



Sequence of a monthly temperature time series (deviations from climatological mean) at Rothera (black line) and sequence of the corresponding AR(1) (top) and FARIMA(0,1,0) (bottom) process (red line).



Statistical Significance Test

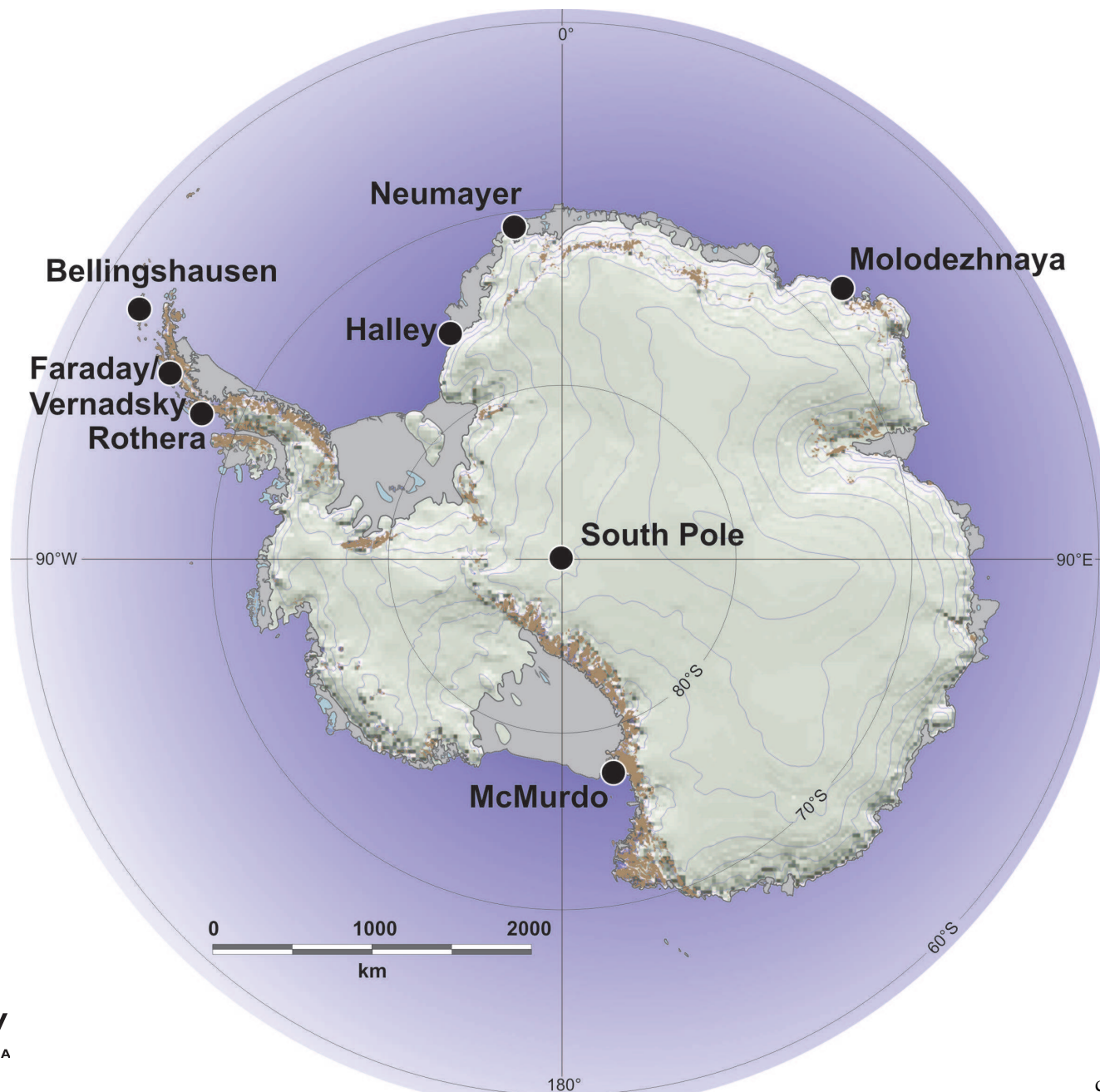
Main topic of this talk:

Does the model for the background variability (short- or long-range dependence) make a difference in practical applications?

Here testing for statistically significant trends in Antarctic temperatures.



Antarctic Stations



Antarctic Stations

Station	Time period
Bellingshausen	01.03.1968-30.09.2008
Faraday-Vernadsky	01.01.1951-28.02.2007
Halley	01.01.1957-30.09.2008
McMurdo	01.04.1956-28.02.2007
Molodezhnaya	01.03.1963-30.06.1999
Neumayer	01.02.1981-28.02.2007
Rothera	01.04.1976-30.09.2008
South Pole	01.02.1957-30.11.2000



Empirical Mode Decomposition

The Empirical Mode Decomposition (Huang et al. 1998, Huang and Wu 2008) is an algorithm to decompose a time series into a finite number of Intrinsic Mode Functions (IMF)

$$x(t) = \sum_{j=1}^M \psi_j(t) + R(t) \quad (1)$$

where the IMF ψ_j can be written in polar coordinates

$$\psi_j(t) = r_j(t) \sin(\theta_j(t)) \quad (2)$$

where r_j is the j -th amplitude, θ_j the j -th instantaneous frequency and R the residual. Both, the amplitude and frequency are time-dependent. As (2) shows, an IMF is different from Fourier modes where both r_j and θ_j are time independent.



Empirical Mode Decomposition

An IMF is defined by the following two properties (Huang et al. 1998)

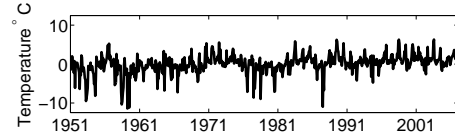
- Each IMF ψ_j has exactly one zero-crossing between two consecutive local extrema.
- The local mean of each IMF ψ_j is zero

The residual $R(t)$ will be interpreted as a trend in this study.

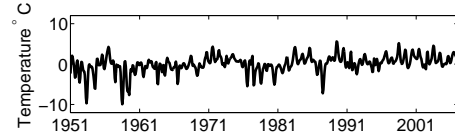


IMF

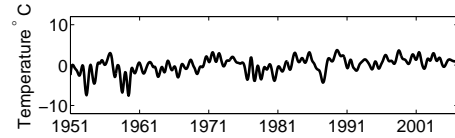
Faraday (annual cycle subtracted)



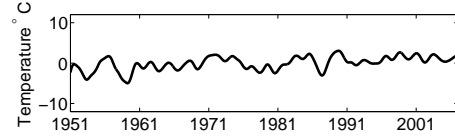
IMF-1 subtracted



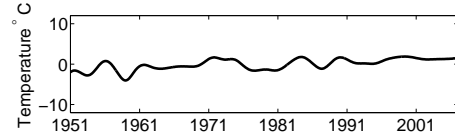
IMF-2 subtracted



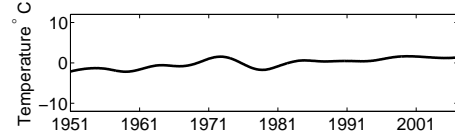
IMF-3 subtracted



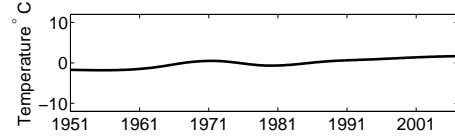
IMF-4 subtracted



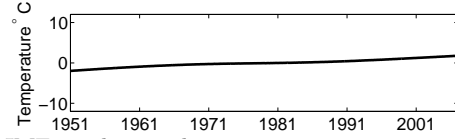
IMF-5 subtracted



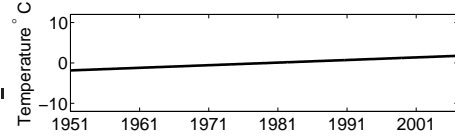
IMF-6 subtracted



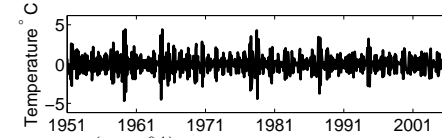
IMF-7 subtracted



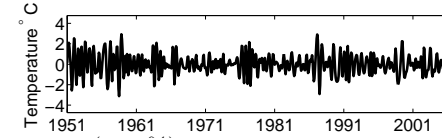
IMF-8 subtracted



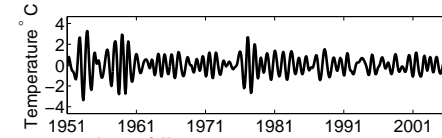
IMF-1 (34.1%)



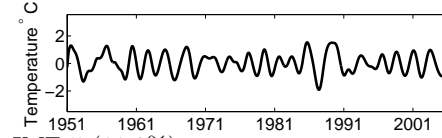
IMF-2 (16.8%)



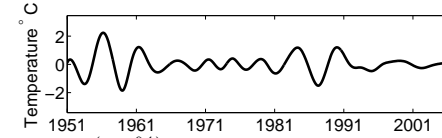
IMF-3 (17.9%)



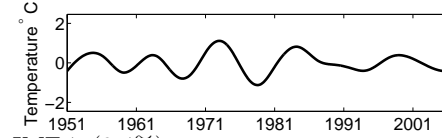
IMF-4 (10.1%)



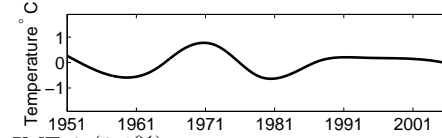
IMF-5 (11.9%)



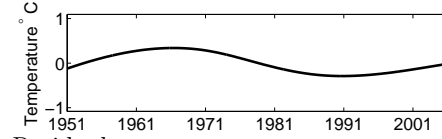
IMF-6 (6.9%)



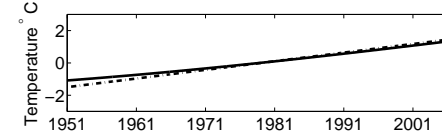
IMF-7 (3.4%)



IMF-8 (0.1%)



Residual

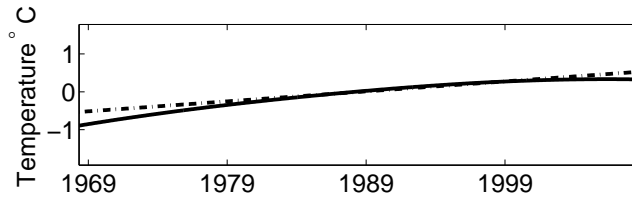


British Antarctic Survey

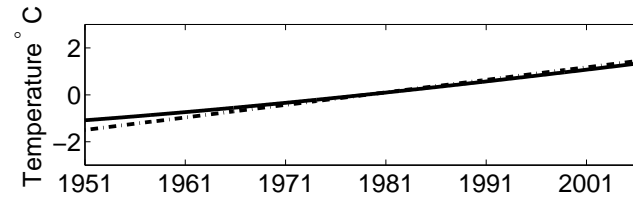
NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Trends

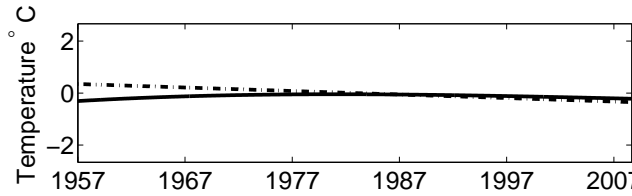
a) Bellingshausen



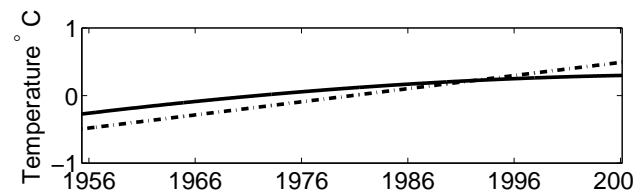
b) Faraday-Vernadsky



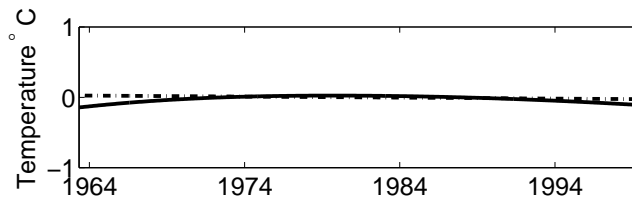
c) Halley



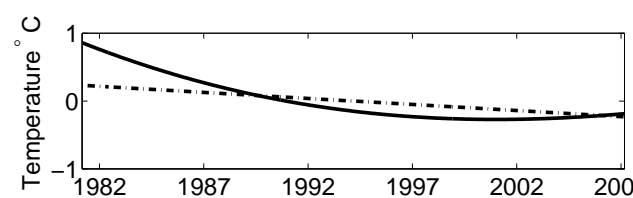
d) McMurdo



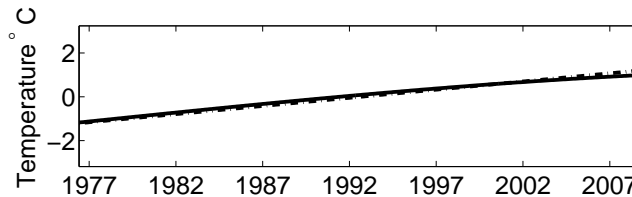
e) Molodezhnaya



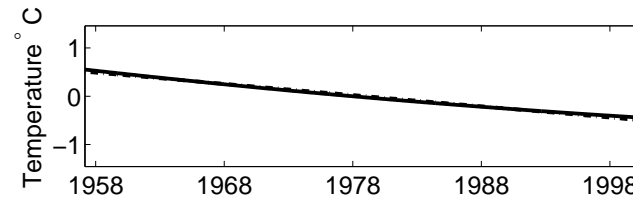
f) Neumayer



g) Rothera



h) South Pole



Surface temperature trends in $^{\circ}\text{C}$ from monthly mean data at selected Antarctic stations (annual cycle removed). Solid line: EMD trends, Dashed line: linear least-squares fit.



Estimation of long-range dependence

A series with long-range dependence has a spectral density proportional to $|\lambda|^{1-2d}$ close to the origin. Since $\hat{S}(\lambda)$ is an estimator of the spectral density, a regression of the logarithm of the periodogram versus the logarithm of the frequency λ should give a coefficient of $1 - 2d$. Thus having calculated the spectral density estimate $\hat{S}(\lambda)$, semiparametric estimators search to find a power law fit of the form

$$f(\lambda; b, d) = b |\lambda|^{1-2d} \quad (3)$$

where b is the scaling factor, a positive and finite rational. The long-range dependency parameter d is inferred by the Geweke Porter-Hudak semi-parametric estimator (Geweke and Porter-Hudak 1983; Hurvich and Deo 1999).



EMD Trends

Coefficients of the AR(1) parameters α and σ and the long-range dependence parameter d and with the corresponding 5% confidence bounds.

Station	α	σ (AR(1))	d
Bellingshausen	0.62 ± 0.013	2.77 ± 0.03	0.28 ± 0.038
Faraday-Vernadsky	0.74 ± 0.009	3.06 ± 0.04	0.28 ± 0.038
Halley	0.73 ± 0.009	4.17 ± 0.06	0.11 ± 0.048
McMurdo	0.79 ± 0.008	3.09 ± 0.05	0.12 ± 0.051
Molodezhnaya	0.58 ± 0.014	3.82 ± 0.04	0.17 ± 0.028
Neumayer	0.60 ± 0.016	5.04 ± 0.07	0.08 ± 0.056
Rothera	0.77 ± 0.011	2.99 ± 0.06	0.26 ± 0.049
South Pole	0.77 ± 0.010	3.73 ± 0.06	0.12 ± 0.053



Monte Carlo Experiments

- Generate ensembles of 1000 AR(1) and FARIMA(0,d,0) member with accounting for parameter uncertainty
- Estimate EMD trends from ensemble members
- If observed EMD lies outside 95% percentile then I claim that observed EMD trend is significant against the respective null model



EMD Trends

The EMD trends are tested against 2 different null models: AR(1) and FARIMA(0,d,0); see text for explanation. EMD trends significant at the 5% level are indicated by a X.

Station	AR(1)	FARIMA(0,d,0)
Bellingshausen	X	
Faraday-Vernadsky	X	X
Halley		
McMurdo		
Molodezhnaya		
Neumayer		
Rothera	X	
South Pole		



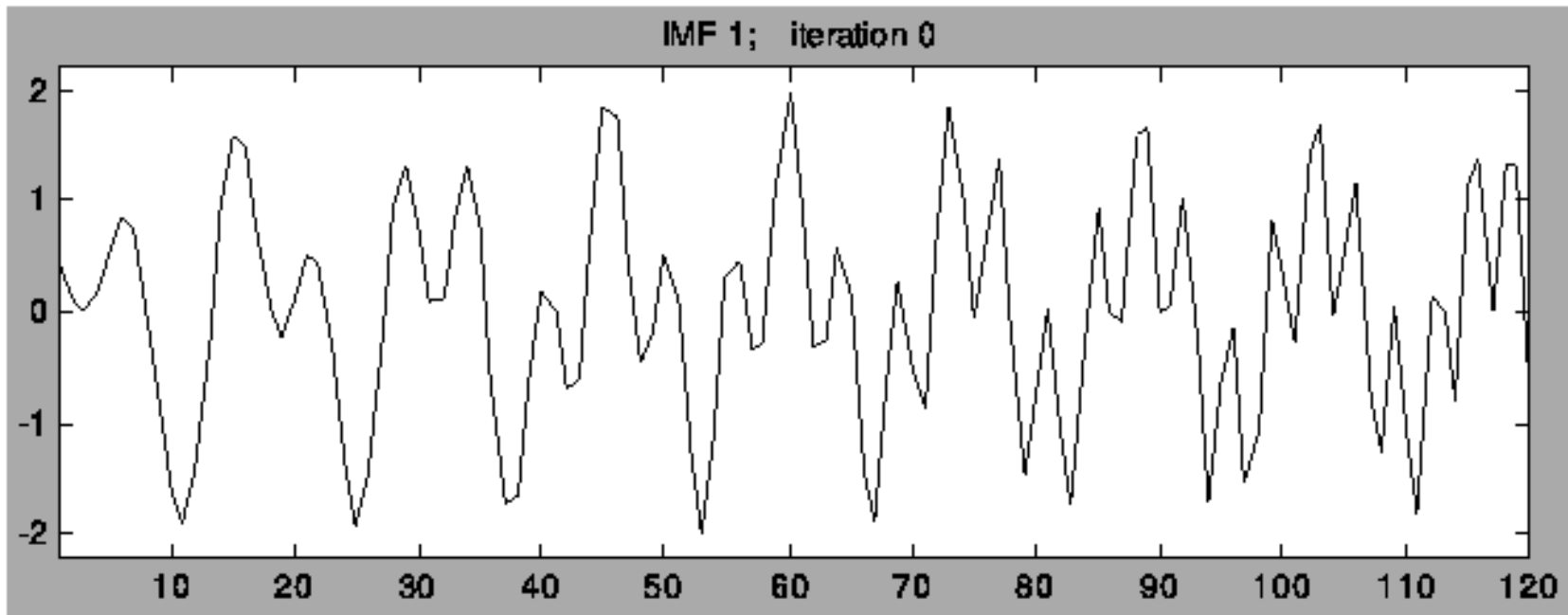
Summary

- The choice of a long-range, rather than a short-range, dependent null model negates the significance of temperature trends at 2 out of 3 stations in Antarctica.
- All trends and mode functions should be tested against various null models (e.g. short- and long-range dependent)
- These results emphasize the need to better investigate the correlation structure of climatic time series.

Franzke: Long-Range Dependence and Climate Noise Characteristics of Antarctic Temperature Data. *J. Climate*, accepted, 2010.



EMD Iteration



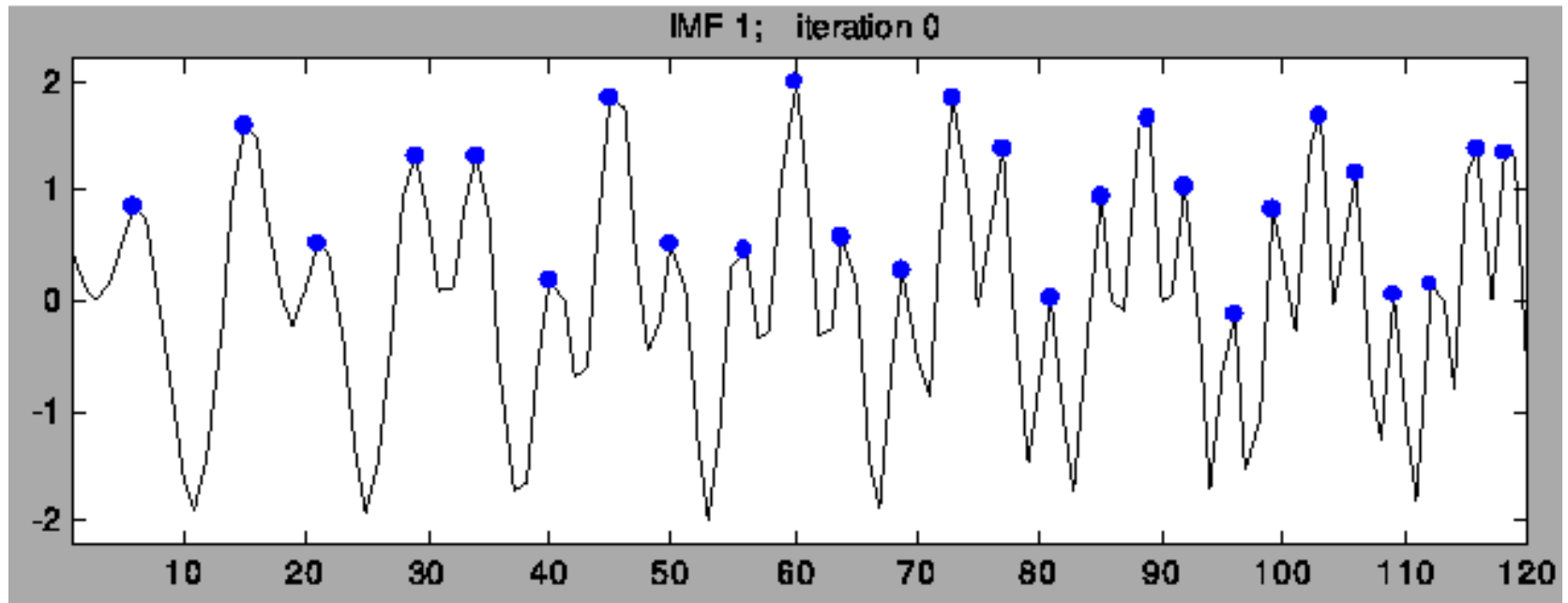
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



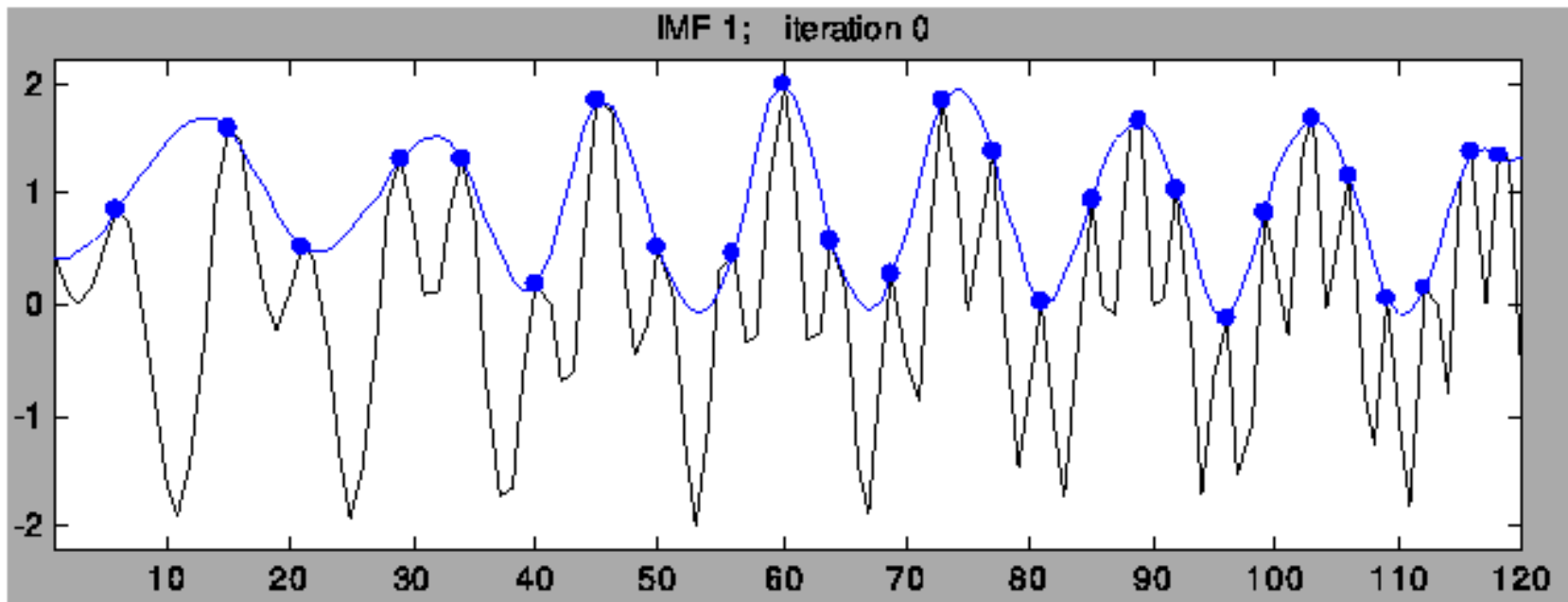
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



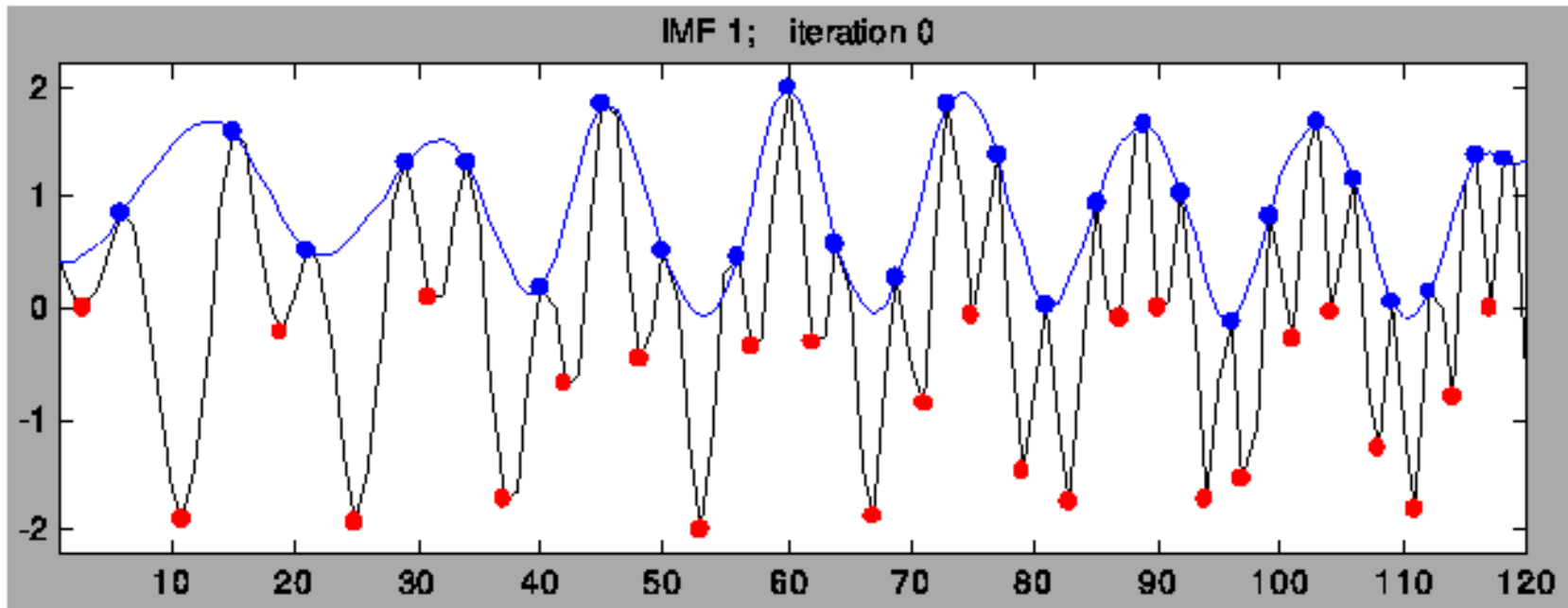
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



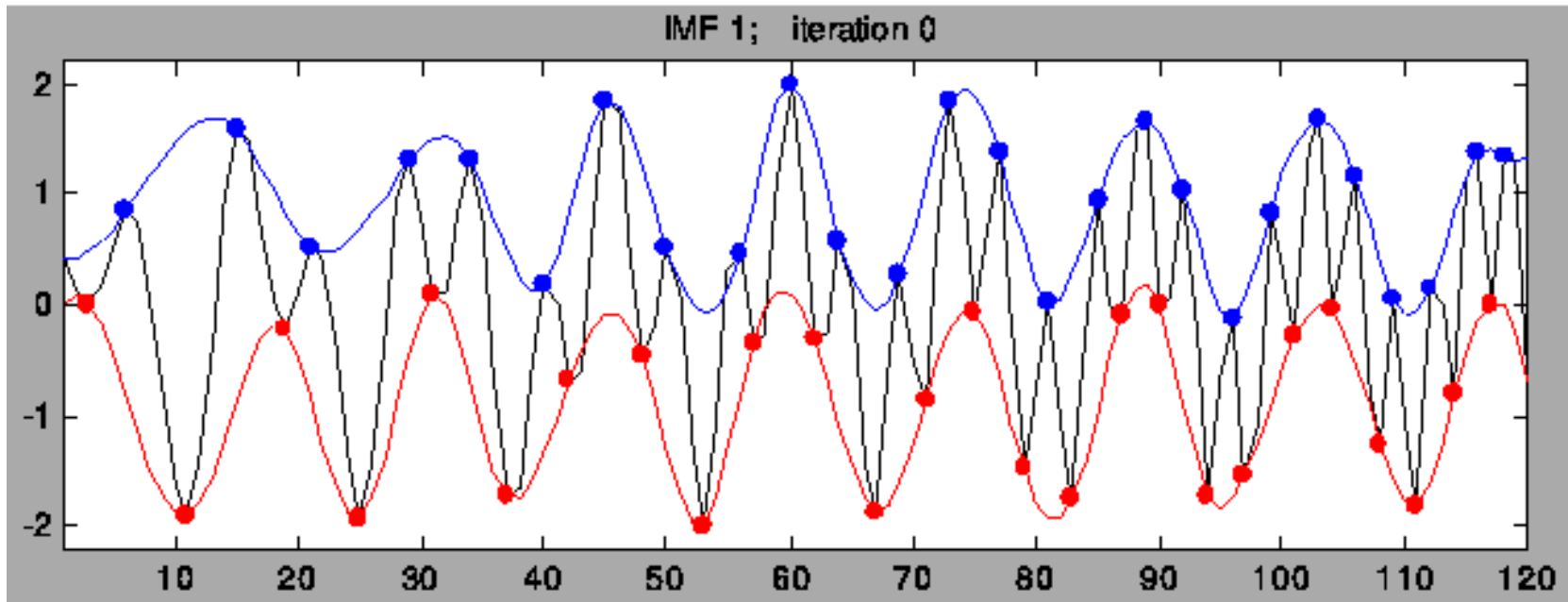
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



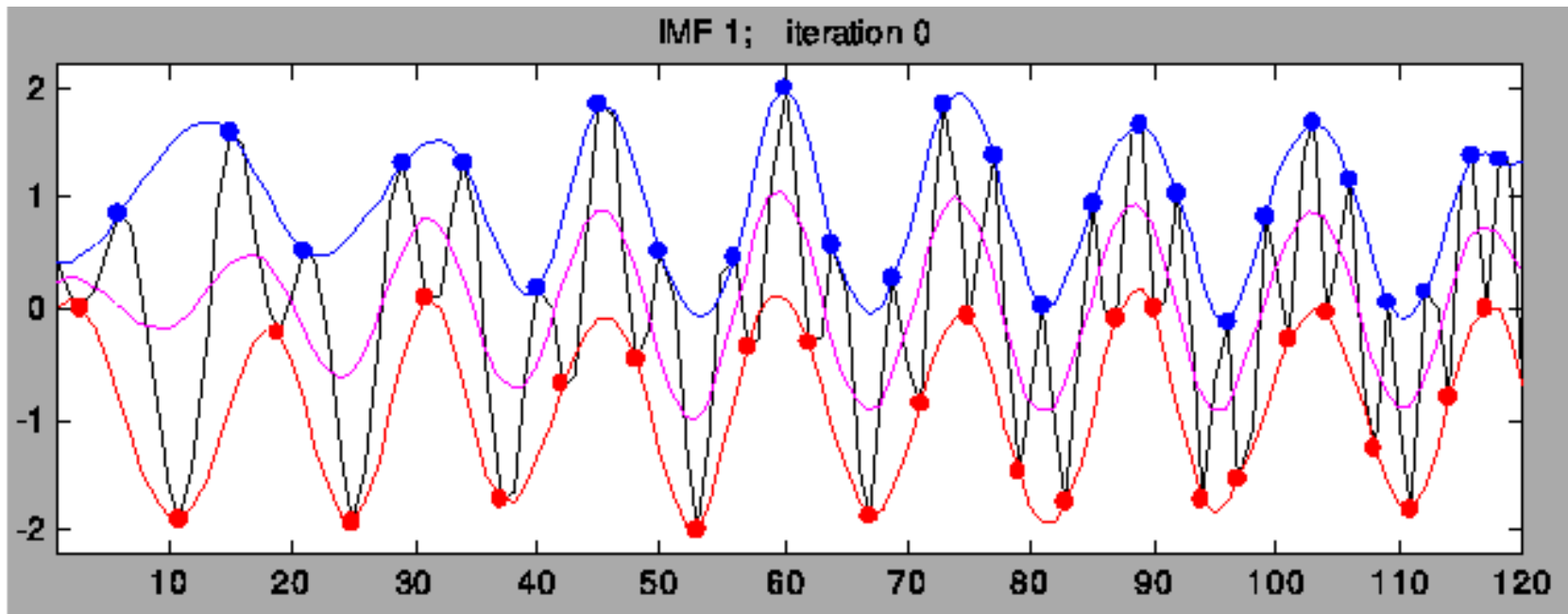
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



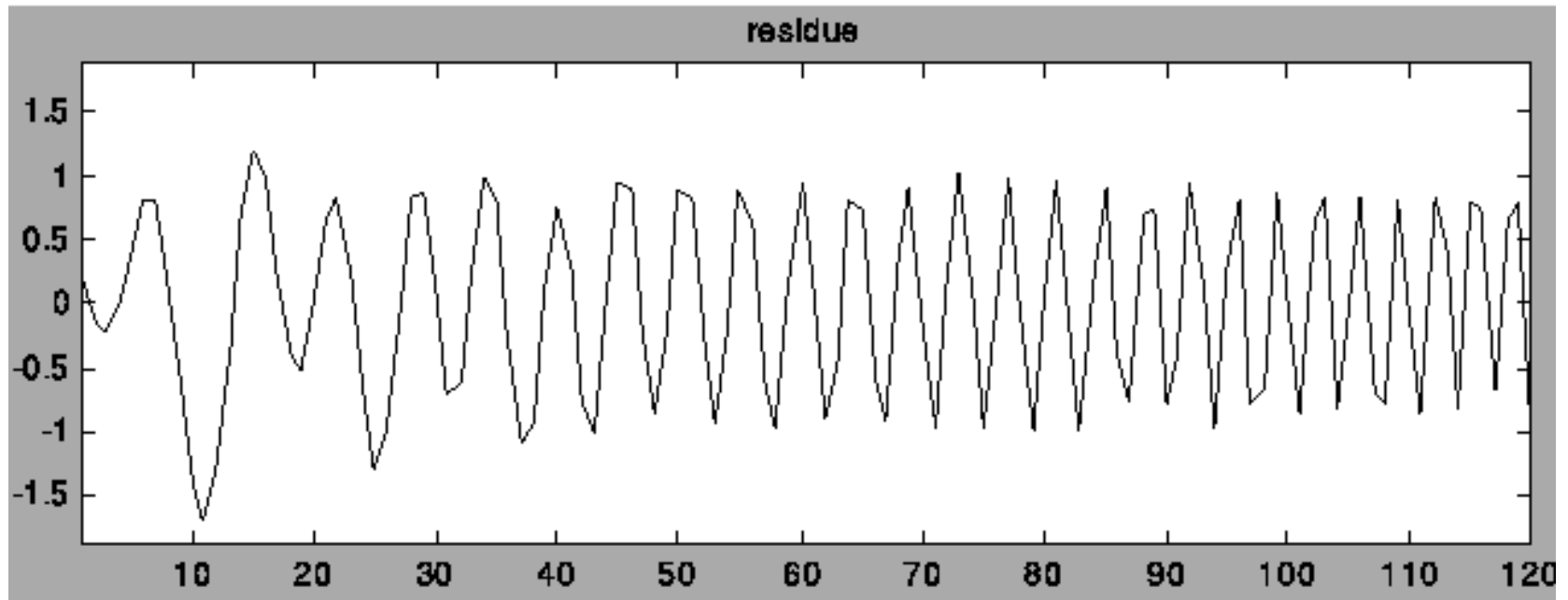
Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL

EMD Iteration



Source: P. Flandrin



**British
Antarctic Survey**

NATURAL ENVIRONMENT RESEARCH COUNCIL