

The Nile River Records Revisited: How good were Joseph's predictions?

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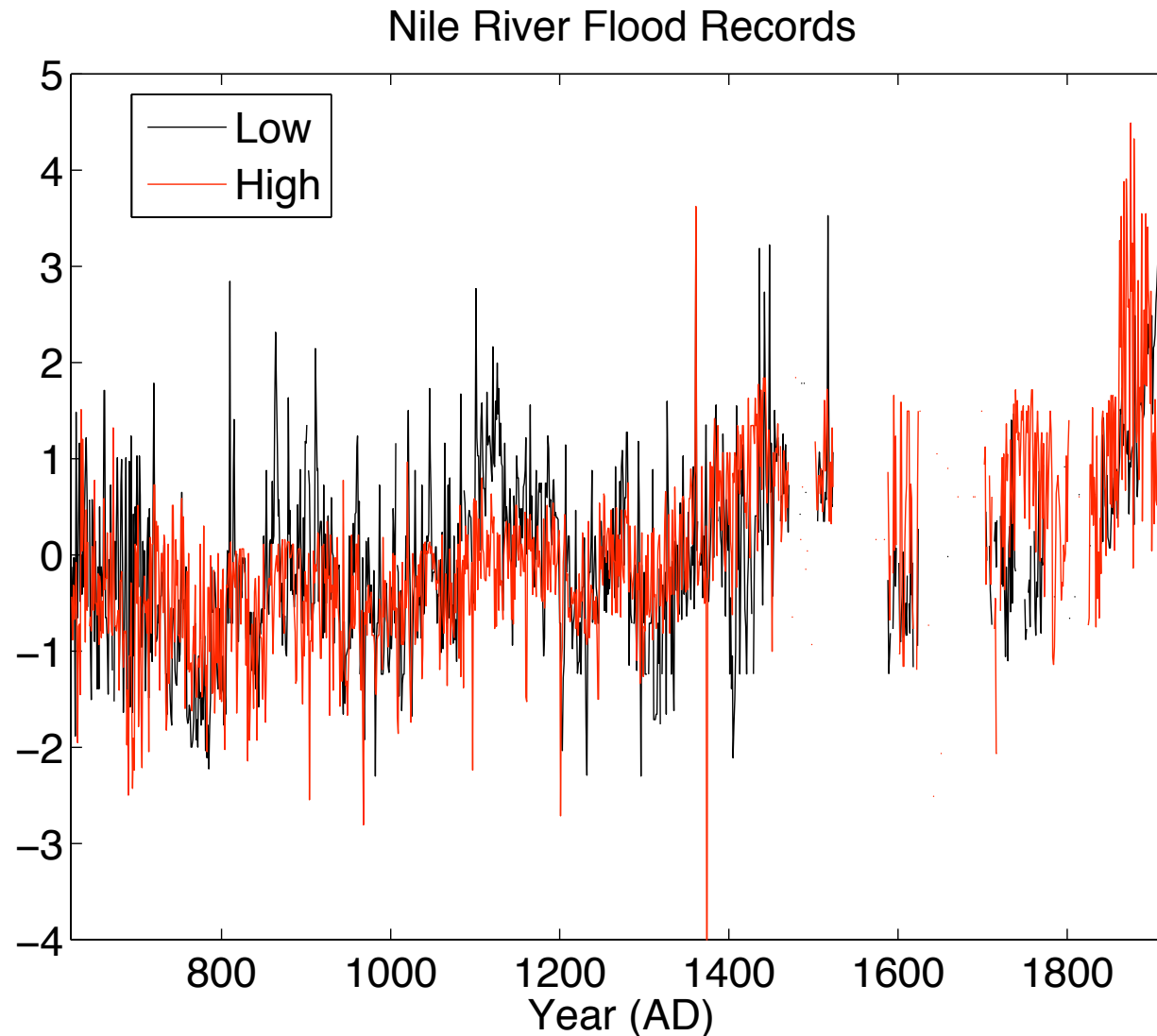
Why are there data missing?



Hard work

◦ Byzantine-period mosaic from **Zippori**, the capital of **Galilee** (1st century B.C. to 4th century A.D.); photo by **Yigal Feliks**, with *permission from the Israel Nature and Parks Protection Authority*)

Historical records are full of “gaps”....



- Annual maxima and minima of the water level at the nilometer on Rodah Island, Cairo.

Motivation

- Significant association between the rainfall in the catchment area of the Nile tributaries, the Indian monsoon, and ENSO [Walker, 1910; Quinn, 1992].
- A recent weakening of the close relationship between ENSO and the Indian monsoon [Kumar *et al.*, 1999], however, might foreshadow a similar weakening of the East-Africa–ENSO correlation.
- North Atlantic influences over North Africa and the Middle East have been detected in several geologic [Felis *et al.*, 2004] and historical [Mann, 2002] records, and may extend all the way into the Nile River's source area, further to the south.

To ascertain whether this is so, we apply advanced methods for filling the gaps in the records and for their spectral analysis, with appropriate statistical confidence tests.

Singular Spectrum Analysis (SSA)

Spatial EOFs

$$\phi(\underline{x}, t) = \sum a_k(t) e_k(\underline{x})$$

PC EOF

x - space

SSA

$$X(t + \underline{s}) = \sum a_k(t) e_k(\underline{s})$$

s - lag

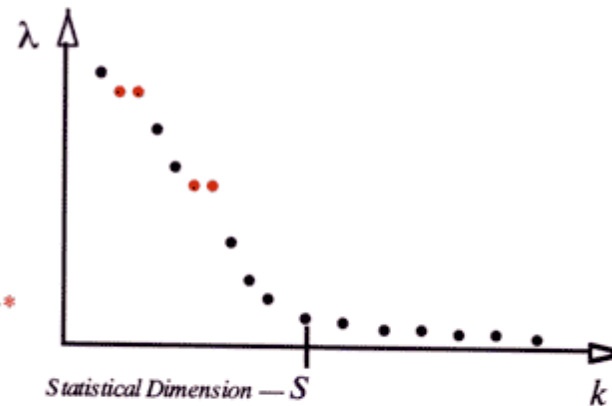
$$C_\phi(\underline{x}, \underline{y}) = E\phi(\underline{x}, \omega)\phi(\underline{y}, \omega) \quad C_X(\underline{s}) = EX(\cdot, \omega)X(\underline{s}, \omega)$$

$$\cong \frac{1}{T} \int_0^T \phi(\underline{x}, t)\phi(\underline{y}, t) dt \quad \cong \frac{1}{T} \int_0^T X(t)X(t + \underline{s}) dt$$

$$C_\phi e_k(\underline{x}) = \lambda_k e_k(\underline{x})$$

$$C_X e_k(\underline{s}) = \lambda_k e_k(\underline{s})$$

Pairs \Rightarrow oscillations
(nonlinear) sine + cosine pair*



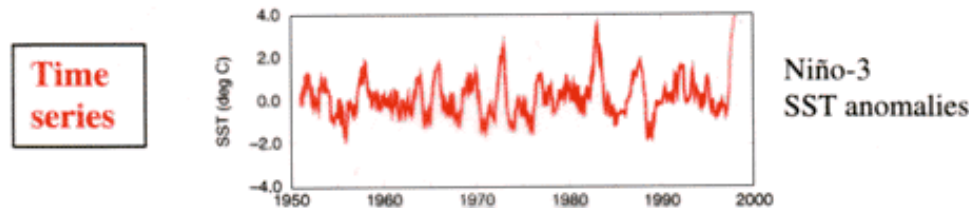
Colebrook (1978), Weare and Nasstrom (1982), Broomhead and King (1986: BK),
Fraedrich (1986)

* Vautard and Ghil (1989: VG), *Physica*, 35D, 395–424

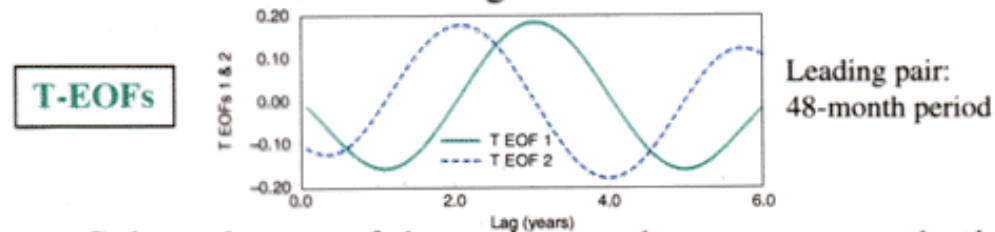
BK+VG: Analogy between Mañe-Takens embedding & Wiener-Khinchin theorem

Singular Spectrum Analysis

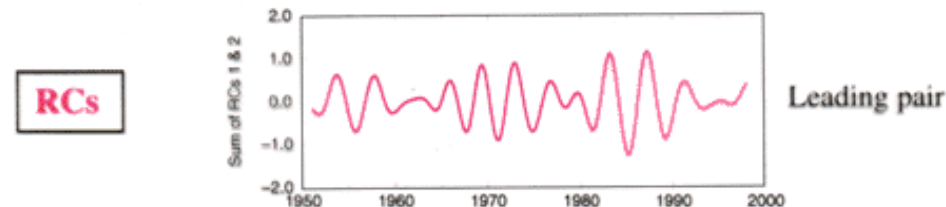
SSA decomposes geophysical time series:



into Temporal EOFs (T-EOFs) and
Temporal Principal Components (T-PCs),
based on the series' lag-covariance matrix:



Selected parts of the series can be reconstructed, via
Reconstructed Components (RCs):

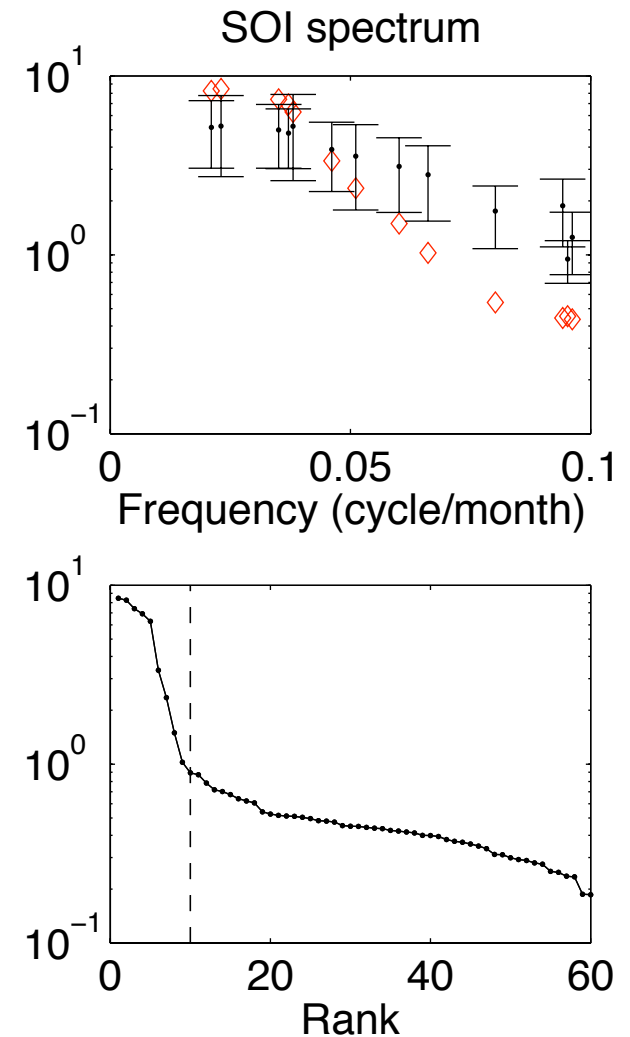
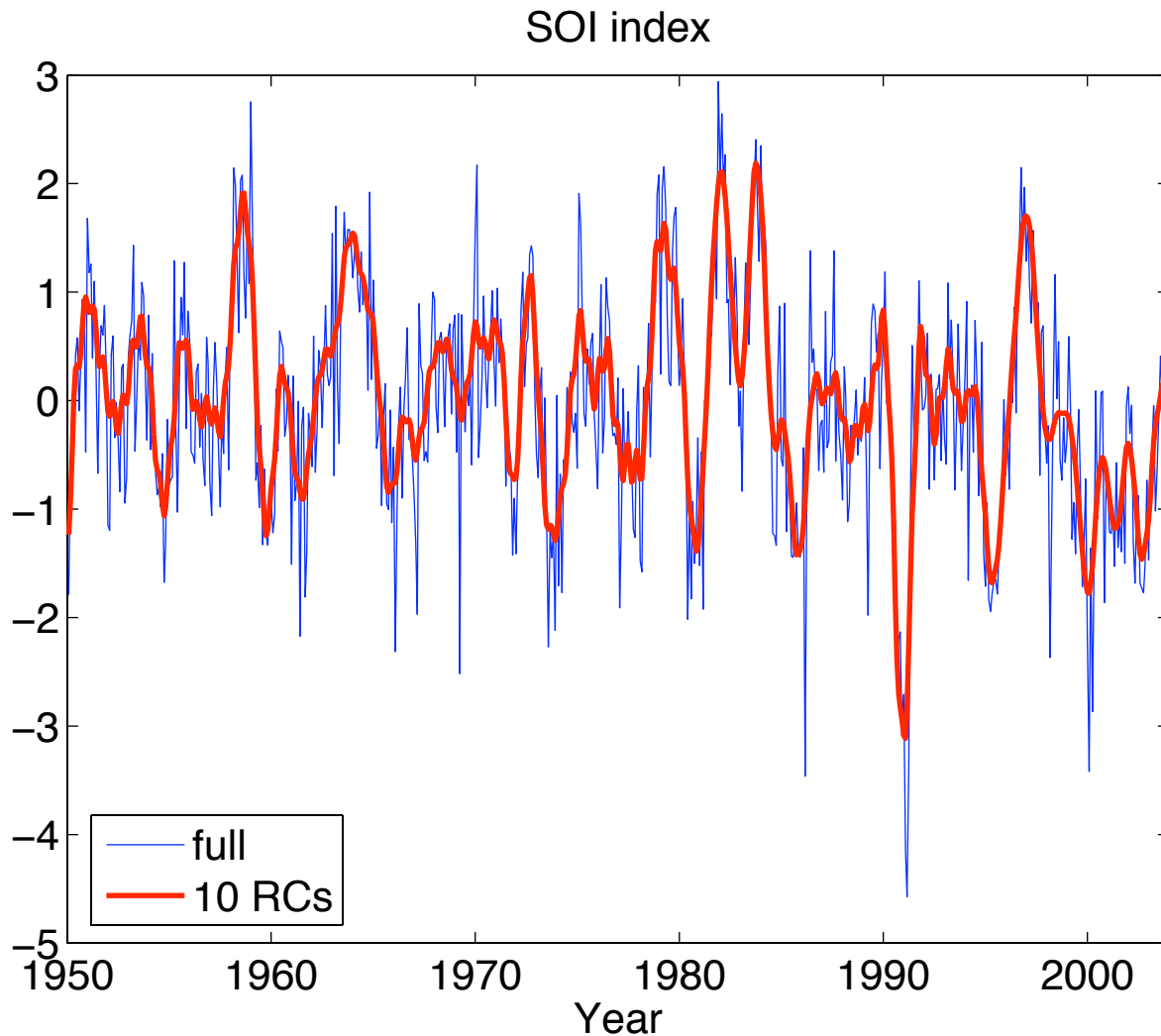


- SSA is good at isolating oscillatory behavior via paired eigen-elements.
- SSA tends to lump signals that are longer-term than the window into one or two trend components.

Selected References

Vautard & Ghil, 1989, *Physica D*; Dettinger *et al.*, 1995, *Eos, Trans. AGU*.

SSA (& M-SSA), continued...



- Break in slope of SSA spectrum marks “**noise**” EOFs
- Formal Monte-Carlo test (*Allen and Smyth 1994*) identifies 4-yr and 2-yr ENSO oscillatory modes
- Size of window $M = 60$ is enough to “resolve” these modes in a monthly SOI time series

What to do about gaps?

- Most of the advanced *filling-in* methods are different flavors of **Optimal Interpolation (OI)**: Reynolds & Smith, 1994; Kaplan, 1998).

Drawbacks: they either (i) require error statistics to be specified *a priori*; or (ii) derive it **only** from the interval of dense data coverage.

EOF Reconstruction (Beckers & Rixen, 2003): (i) iteratively compute **spatial-covariance** matrix using **all the data**; (ii) determine via cross-validation “**signal**” EOFs and use them to fill in the missing data. Accuracy is similar to or better than **OI** (*Alvera-Azcarate et al.*, 2004).

Drawbacks: uses **only** spatial correlations ==> cannot be applied to very **gappy** data.

We propose to fill in gaps by applying iterative SSA (or M-SSA):

Utilize **both the spatial and temporal correlations** of the data set ==> can be used for **highly gappy data sets**; simple and easy to implement!

SSA (M-SSA) Gap Filling

Main idea: utilize **both spatial and temporal correlations** to iteratively compute self-consistent lag-covariance matrix (M-SSA with $M = 1$ is the same as the *EOF reconstruction method* of *Beckers & Rixen, 2003*)

Goal: keep the “**signal**” and truncate “**noise**” — usually a few leading EOFs correspond to the dominant oscillatory modes, while the rest is noise.

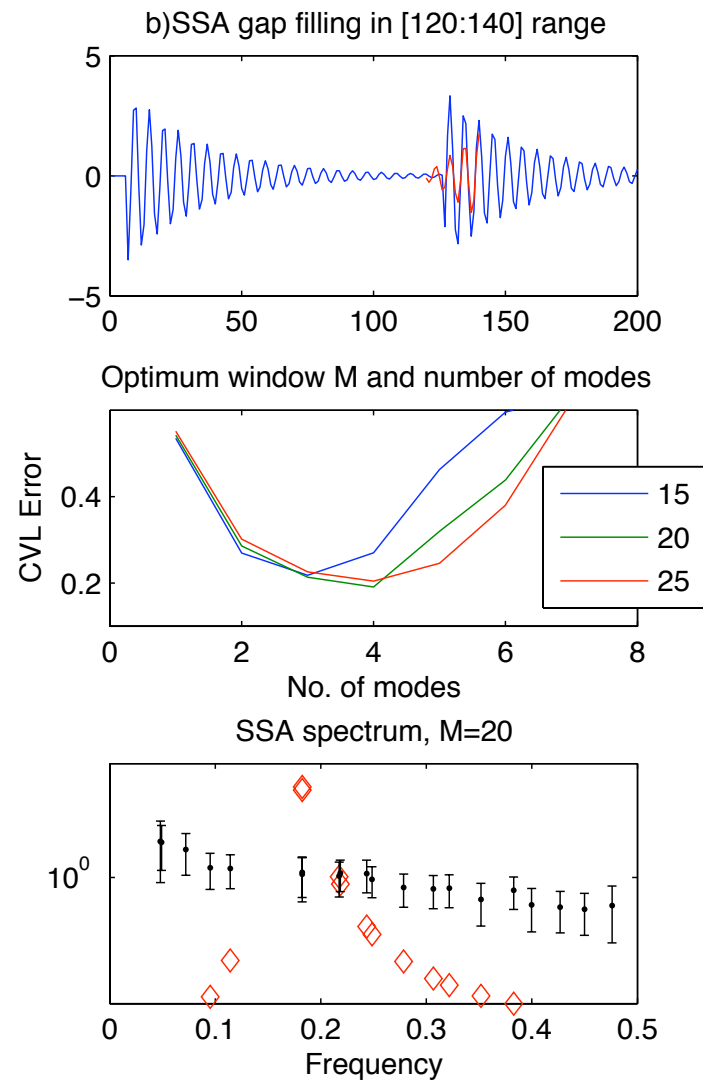
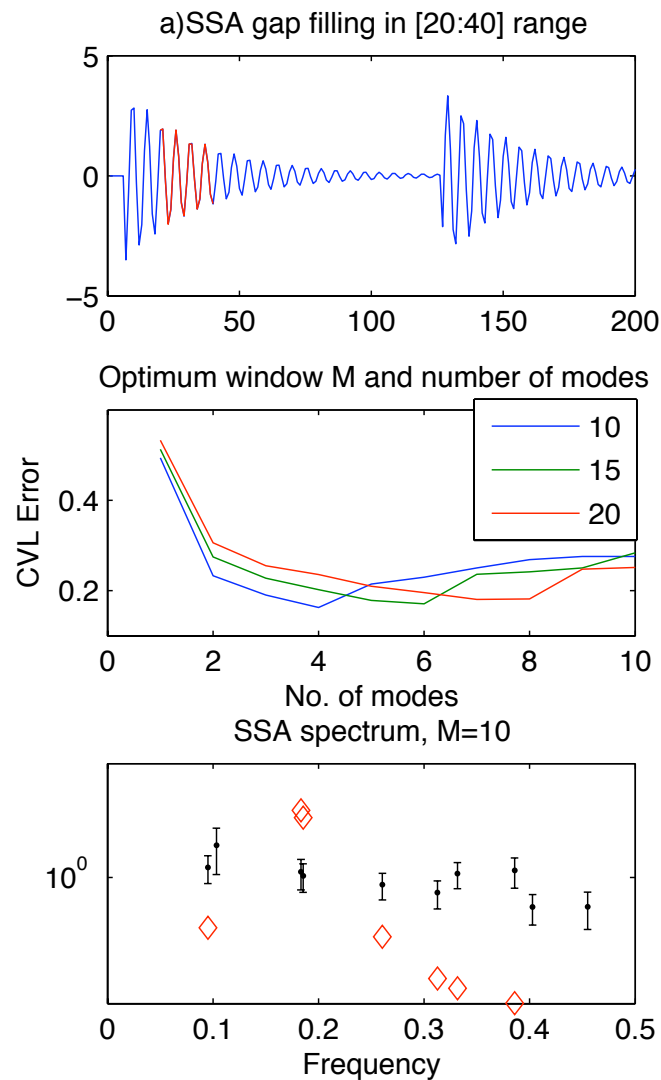
(1) for a given window width M : center the original data by computing the unbiased value of the mean and set the missing-data values to zero.

(2) start iteration with the first EOF, and replace the missing points with the reconstructed component (RC) of that EOF; repeat the SSA algorithm on the new time series, until convergence is achieved.

(3) repeat steps (1) and (2) with two leading EOFs, and so on.

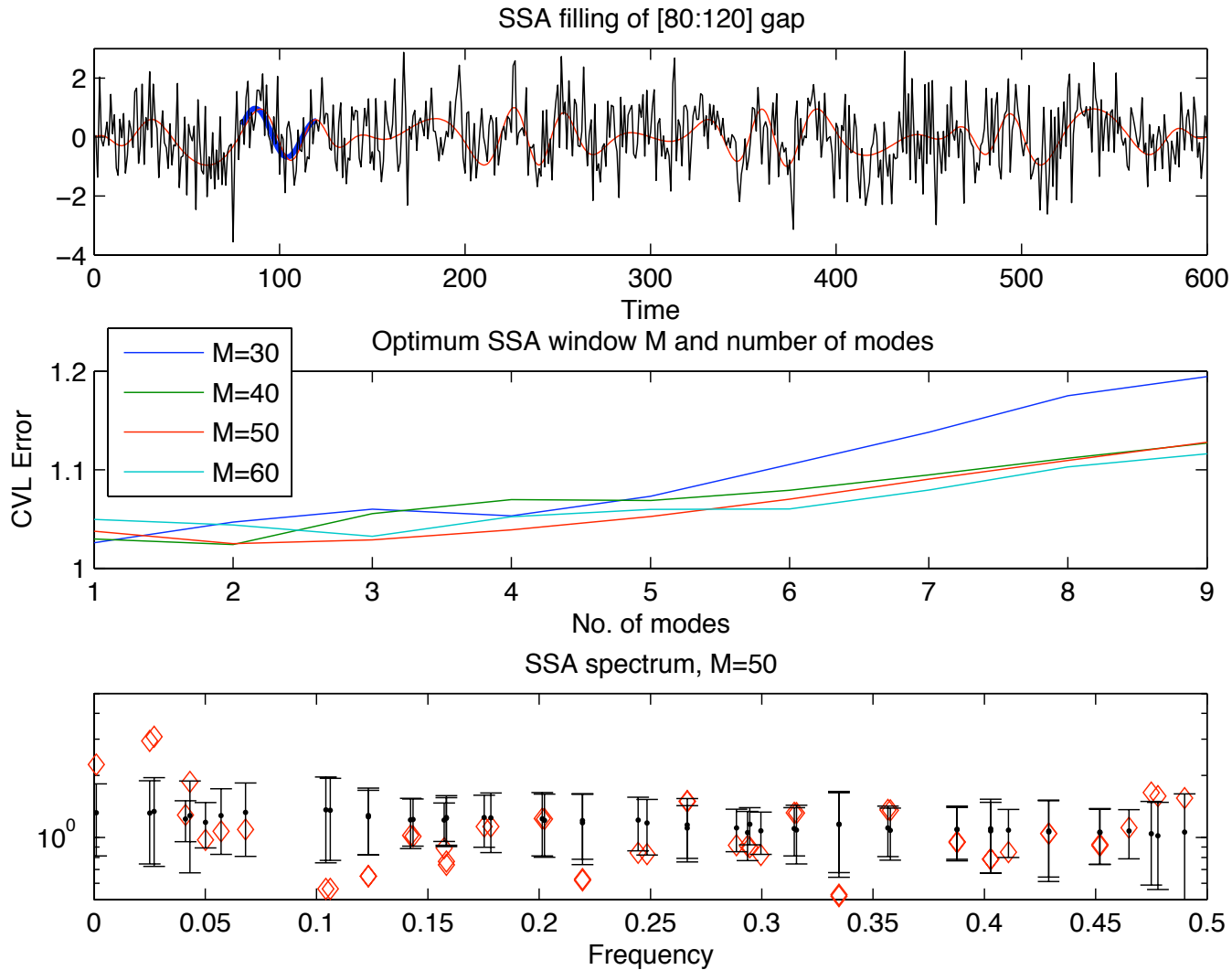
(4) **apply cross-validation** to optimize the *window width* M and *number* of dominant SSA (M-SSA) modes to fill the gaps: a portion of available data (selected at random) is flagged as missing and RMS error in reconstruction is computed.

Synthetic I: Gaps in Amplitude-Modulated Oscillatory Signal (with no noise)



- Very good gap filling for smooth modulation; OK for sudden modulation.

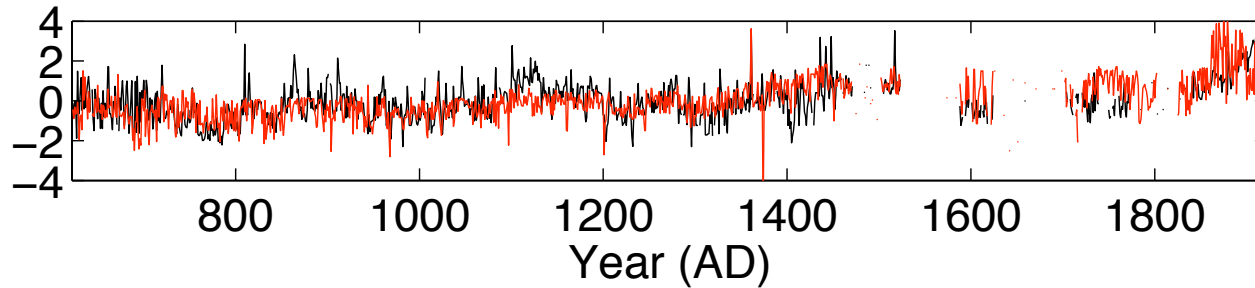
Synthetic II: Gaps in Oscillatory Signal + Noise



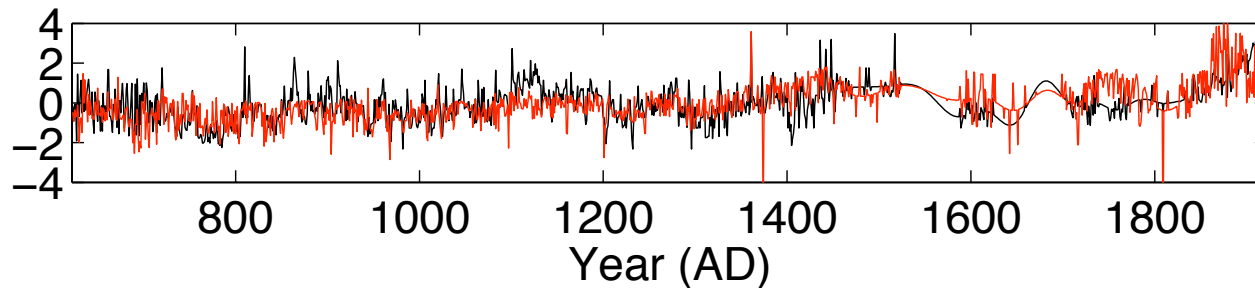
$$x(t) = \sin\left(\frac{2\pi}{300}t\right) * \cos\left(\frac{2\pi}{40}t + \frac{\pi}{2}\sin\frac{2\pi}{120}t\right)$$

Nile River Records

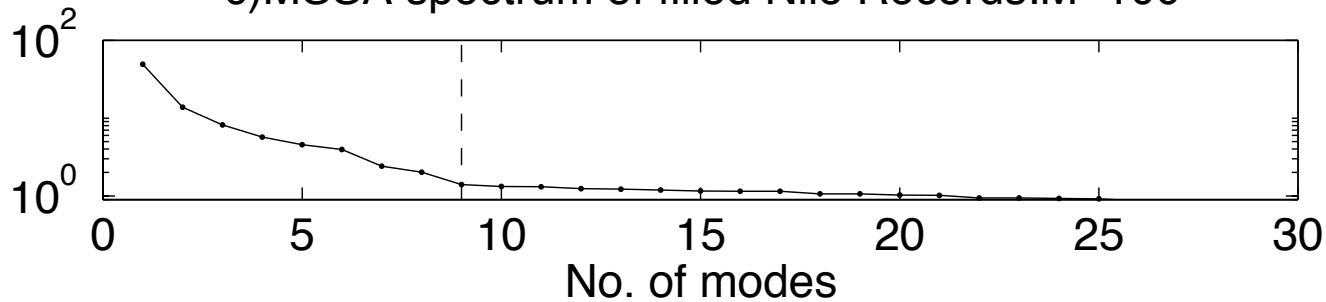
a) Original records



b) MSSA filled in



c) MSSA spectrum of filled Nile Records: $M=100$



○ High level

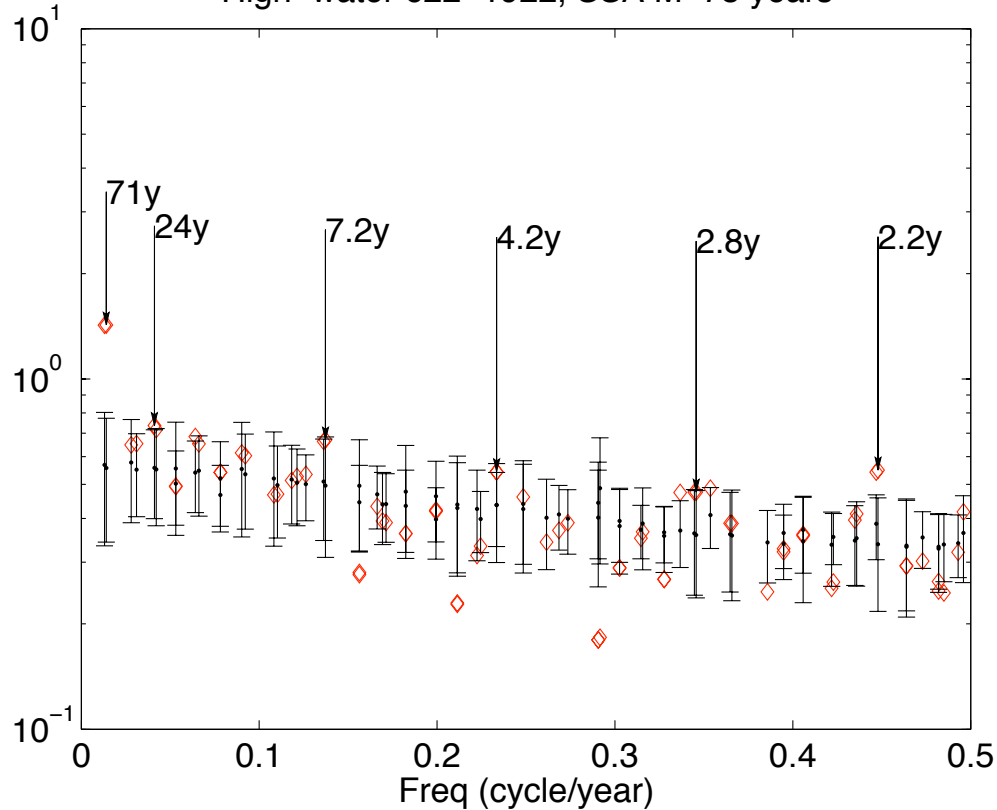


○ Low level

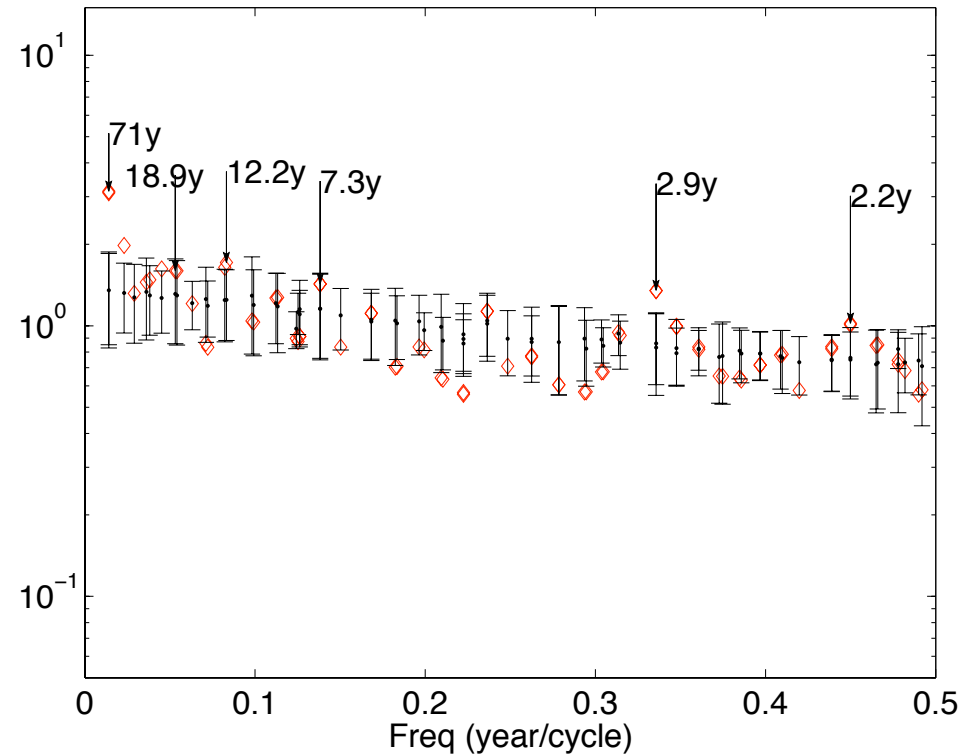


MC-SSA of Filled-in Records

High-water 622–1922, SSA M=75 years



High-Low Water Difference, 622–1922, SSA M=75 years



SSA results for the extended Nile River records;
arrows mark highly significant peaks (at 95%), in both SSA and MTM.

Table 1a: Significant oscillatory modes in short records (A.D. 622–1470)

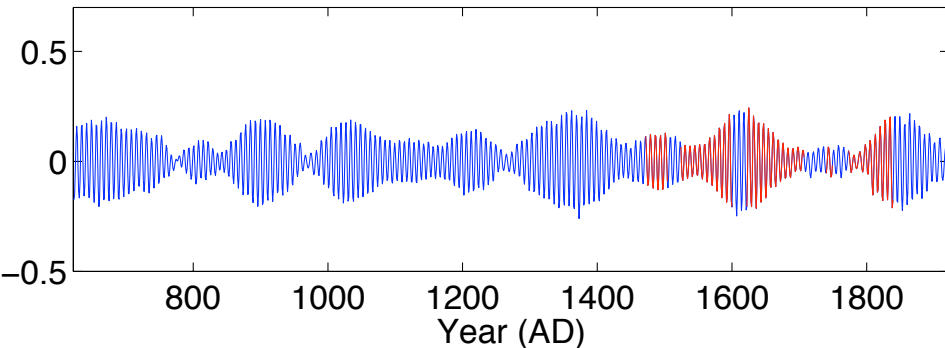
Periods	Low	High	High-Low
40–100yr	64 (9.3%)	64 (6.9%)	64 (6.6%)
20–40yr		[32]	
10–20yr	12.2 (5.1%), 18.0 (6.7%)		12.2 (4.7%), 18.3 (5.0%)
5–10yr	6.2 (4.3%)	7.2 (4.4%)	7.3 (4.4%)
0–5yr	3.0 (2.9%), 2.2 (2.3%)	3.6 (3.6%), 2.9 (3.4%), 2.3 (3.1%)	2.9 (4.2%),

Table 1b: Significant oscillatory modes in extended records (A.D. 622–1922)

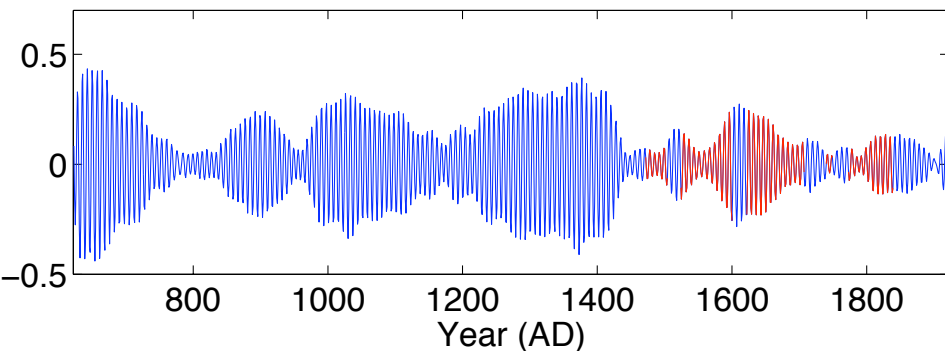
Periods	Low	High	High-Low
40–100yr	64 (13%)	85 (8.6%)	64 (8.2%)
20–40yr		23.2 (4.3%)	
10–20yr	[12], 19.7 (5.9%)		12.2 (4.3%), 18.3 (4.2%)
5–10yr	[6.2]	7.3 (4.0%)	7.3 (4.1%)
0–5yr	3.0 (4%), 2.2 (3.3%)	4.2 (3.3%), 2.9 (3.3%), 2.2 (2.9%)	[4.2], 2.9 (3.6%), 2.2 (2.6%)

Significant Oscillatory Modes

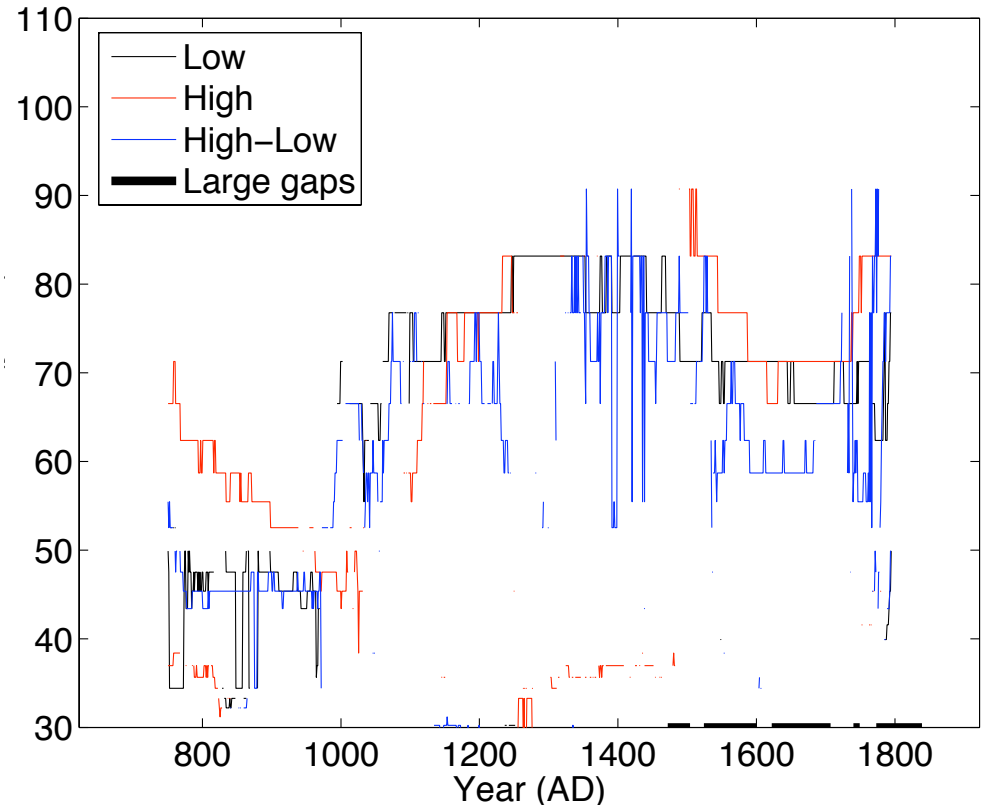
a) 7.2yr cycle in high water



b) 7.2yr cycle in high-low



- SSA reconstruction of the 7.2-yr mode in the extended Nile River records: (a) high-water, and (b) difference. Normalized amplitude; reconstruction in the large gaps in red.



Instantaneous frequencies of the oscillatory pairs in the low-frequency range (40–100 yr).

The plots are based on multi-scale SSA [Yiou *et al.*, 2000]; local SSA performed in each window of width $W=3M$, with $M=85$ yr.

Summary

- **SSA (M-SSA)** can be used for filling **gaps in geophysical data sets**, by using **dominant spatio-temporal modes** of the data.
- The **7–8-yr period in Nile River records** equals that of a **North Atlantic spectral peak** [Ghil & Vautard, 1991; Moron *et al.*, 1998; Wunsch, 1999].
- This peak may be due to **intrinsic ocean variability** [Speich *et al.*, 1995; Dijkstra & Ghil, 2005; Simonnet *et al.*, 2005].
- Our results suggest that the **climate of East Africa** has been subject to influences from the **North Atlantic**, besides those already documented from the **Tropical Pacific**.

Kondrashov, Feliks & M. Ghil (2005): Oscillatory modes of extended Nile River records (A.D. 622–1922), *Geophys. Res. Lett.*, in press.

Free SSA-MTM Toolkit at <http://www.atmos.ucla.edu/tcd/ssa>

How good were Joseph's predictions?



Pretty good!