

EOF analysis

Examples

- EOF analysis determines a set of orthogonal functions that characterizes the covariability of time series for a set of grid points. So instead of X grid points each with N values in time we have X EOF patterns each with N values in time.
- Analogous to Fourier Transform, but more useful than FT if the time series has “jumps” in it

How are the EOFs chosen?

- EOF 1: It is the index time series that produces regression/correlation maps with the overall strongest amplitudes.
- EOF 2: It is the index time series that produces regression/correlation maps with the overall strongest amplitudes AFTER the variability associated with EOF 1 is subtracted out of the data. And so on for EOF 3, 4 etc.

Why is this useful?

- Going back to the Fourier analysis analogy, the data are more compactly characterized by EOFs. Large-scale variability will be in the low-order EOFs and the higher-order EOFs will have low-amplitude spatially-incoherent “noise”.

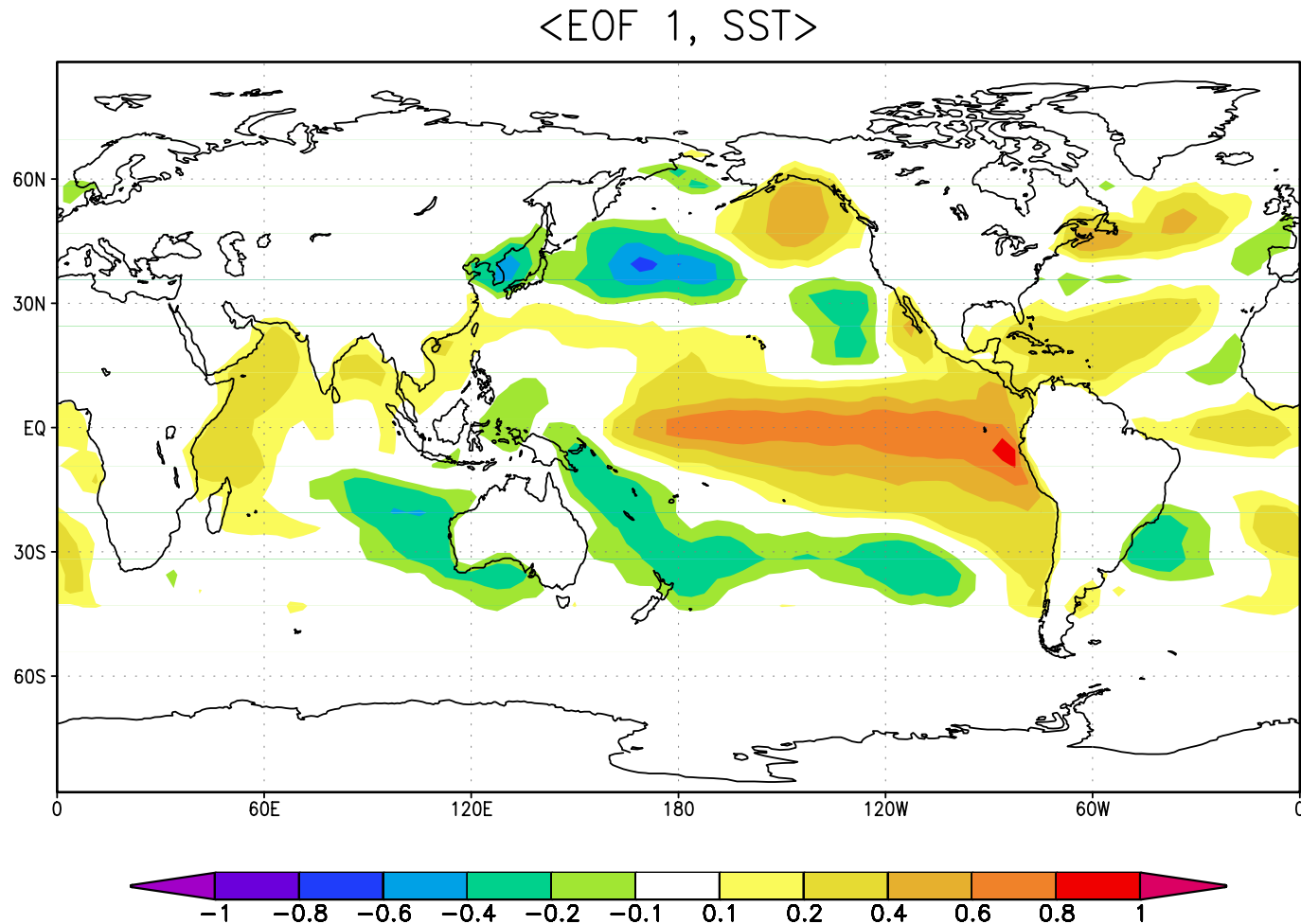
Advantages of EOF analysis

- Produces the index time series which explains the greatest amount of variability (i.e., amplitude of regression map)
- Convenient method for characterizing dominant spatial pattern of variability
- Compact representation of data
- EOF patterns and time series are linearly independent

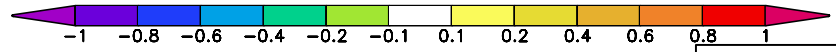
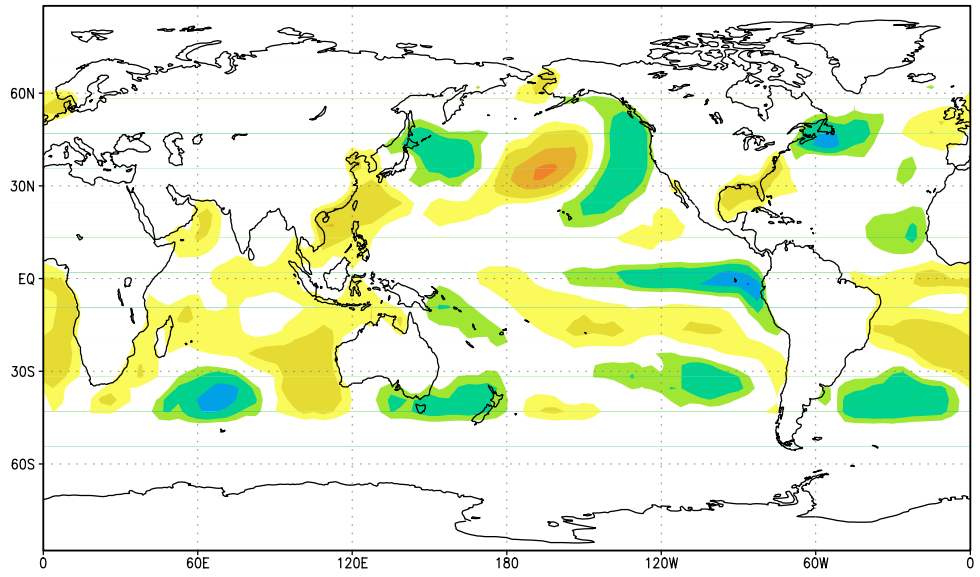
Disadvantages of EOF analysis

- Can be sensitive to choice of spatial domain and time period
- Features can be mixed between EOFs if their eigenvalues are similar and the degrees of freedom in the time series are too small.
- No guarantee the EOF pattern has physical meaning (i.e., EOF analysis can create patterns from “noise”)

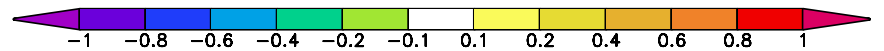
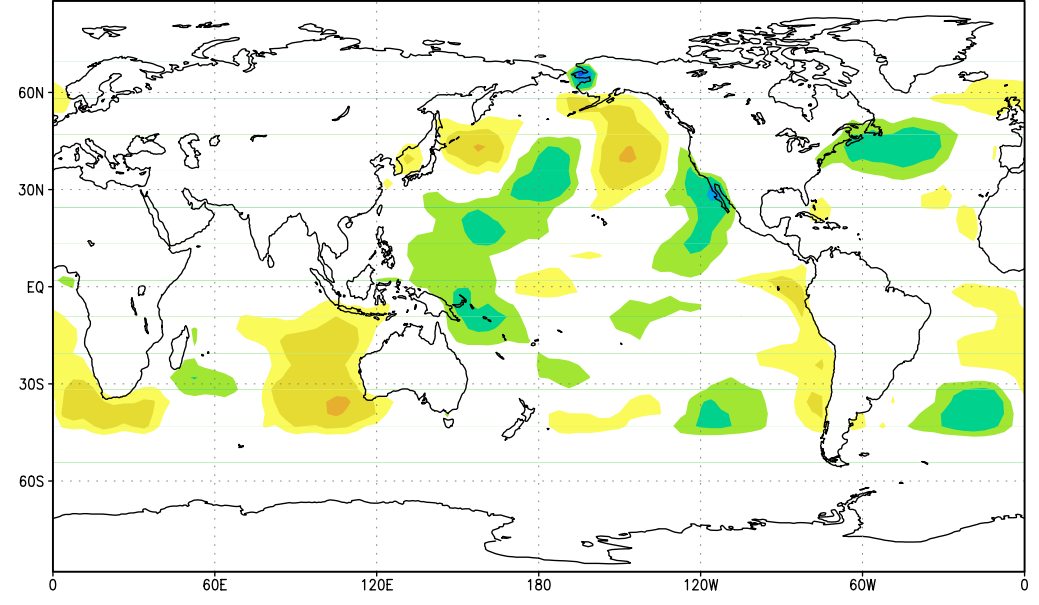
Examples of detrended global EOFs in summer calculated over 1980-1999



<EOF 2, SST>



<EOF 3, SST>

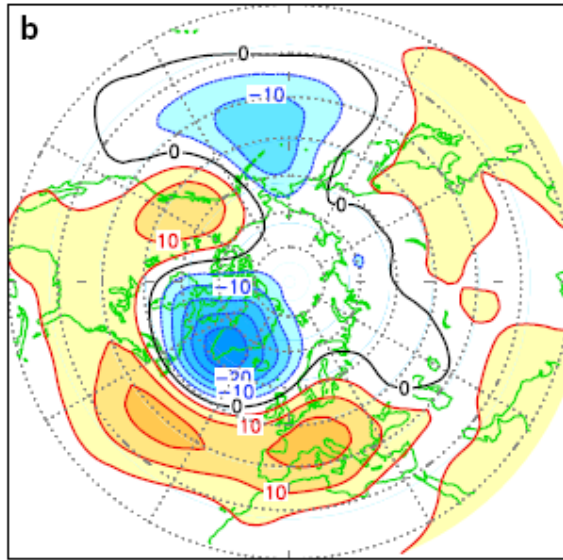


GrADS: COLA/IGES

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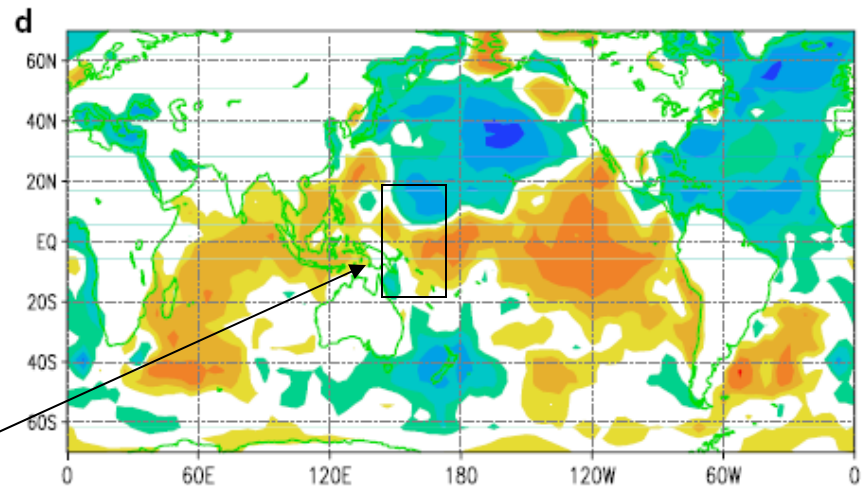
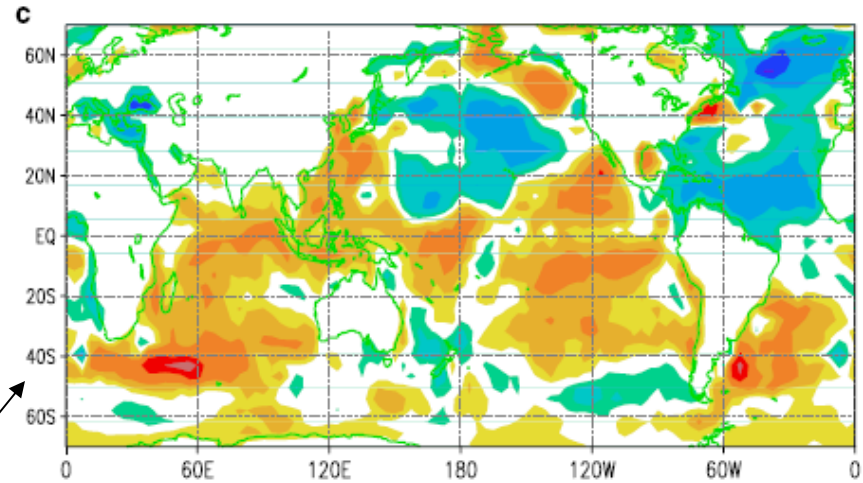
| | | | | | | |
|-------|----------|-------|--------|--------|--------|--------|
| PC 1 | St.Dev.: | 0.267 | ExpVar | 44.29% | CumVar | 44.29% |
| PC 2 | St.Dev.: | 0.138 | ExpVar | 11.92% | CumVar | 56.21% |
| PC 3 | St.Dev.: | 0.104 | ExpVar | 6.75% | CumVar | 62.96% |
| PC 4 | St.Dev.: | 0.098 | ExpVar | 5.98% | CumVar | 68.95% |
| PC 5 | St.Dev.: | 0.086 | ExpVar | 4.64% | CumVar | 73.59% |
| PC 6 | St.Dev.: | 0.082 | ExpVar | 4.22% | CumVar | 77.81% |
| PC 7 | St.Dev.: | 0.073 | ExpVar | 3.29% | CumVar | 81.10% |
| PC 8 | St.Dev.: | 0.066 | ExpVar | 2.75% | CumVar | 83.84% |
| PC 9 | St.Dev.: | 0.060 | ExpVar | 2.25% | CumVar | 86.09% |
| PC 10 | St.Dev.: | 0.056 | ExpVar | 1.94% | CumVar | 88.02% |

another example NAO related from Kucharski, Molteni and Bracco, 2006

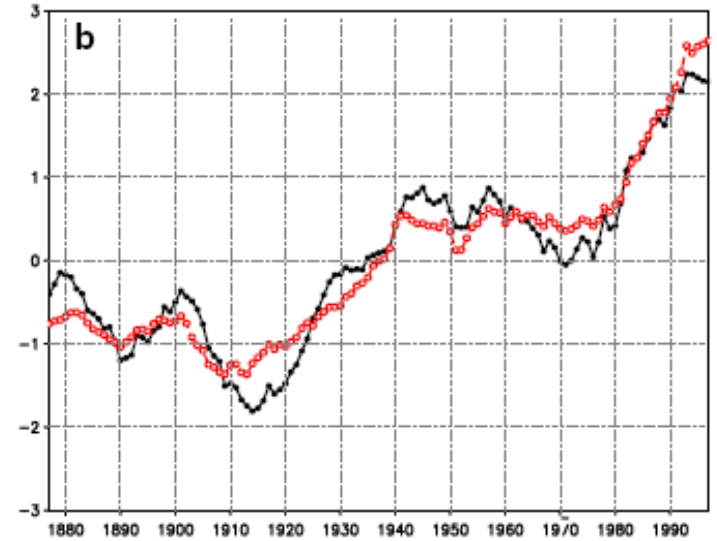
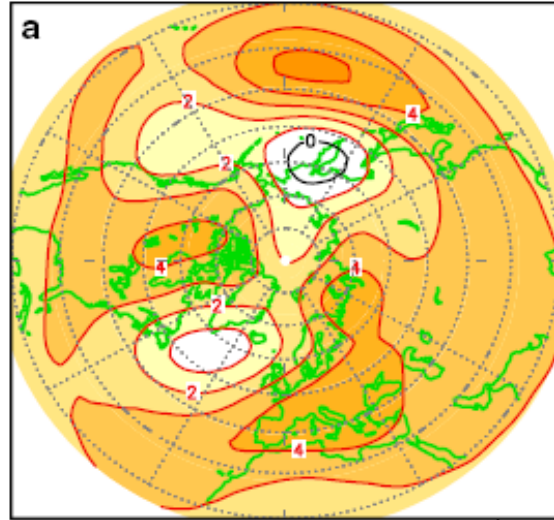


regression of 500 hPa height and
SST onto the NAO index

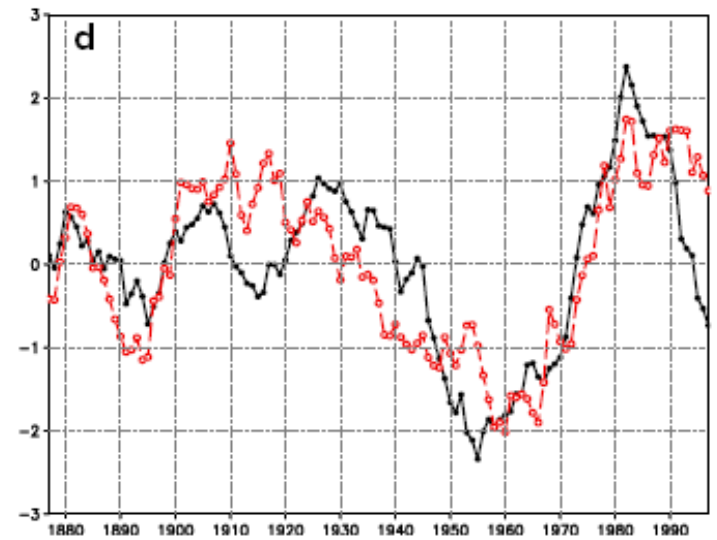
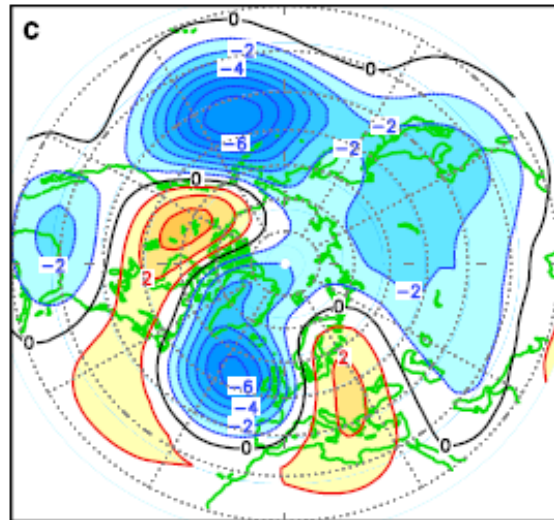
and regression of SST onto WTP
index defined as difference in SST
averaged over 140E to 170W
and 20S to 20N.



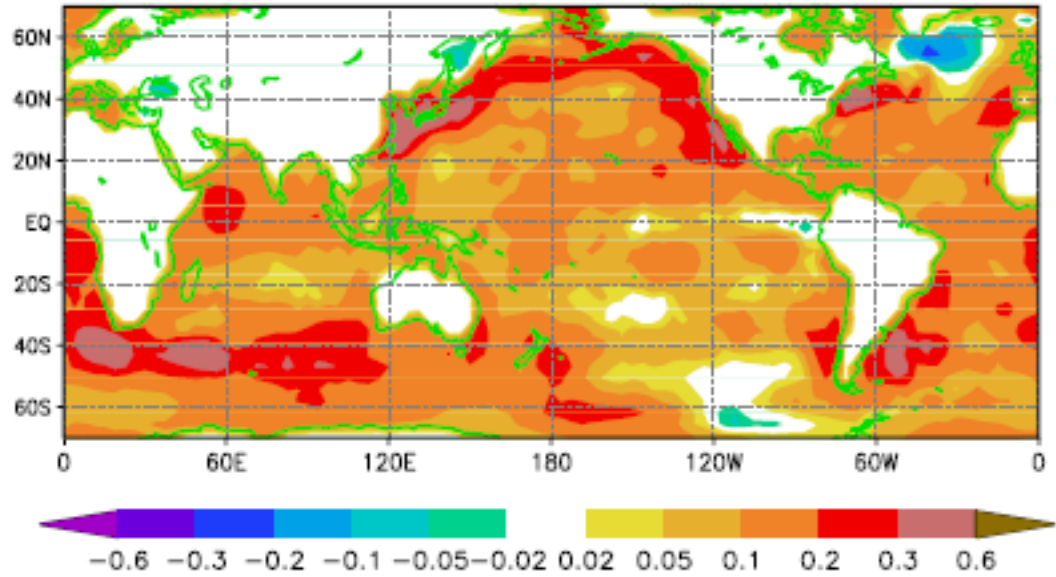
EOF1 of the 500 hPa height from globally SST forced experiments and principal component (PC) associated with EOF1 and globally averaged SST (red)



EOF2 of the 500 hPa height from EXP1 and PC associated with EOF2 and WTP SST gradient index (red)



Regression of SST onto PC1 (in K)



regression of SST onto PC2 (in K)

