# Using principal component analysis in empirical-statistical downscaling to emphasise synoptic scales

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### What is PCA?

A way of organising the data according to information contents

Similar to

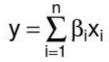
Eigenvalues

Empirical Orthogonal Functions (EOFs)

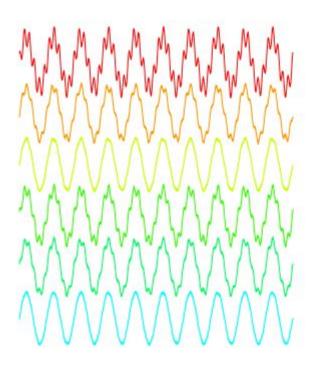
Fourier series

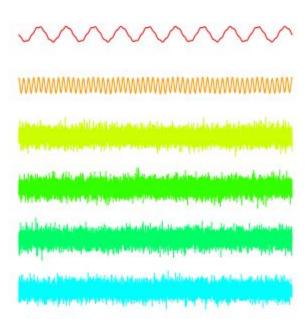


# What is PCA?



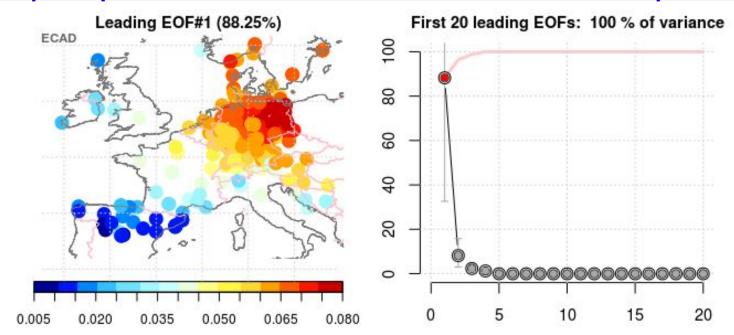




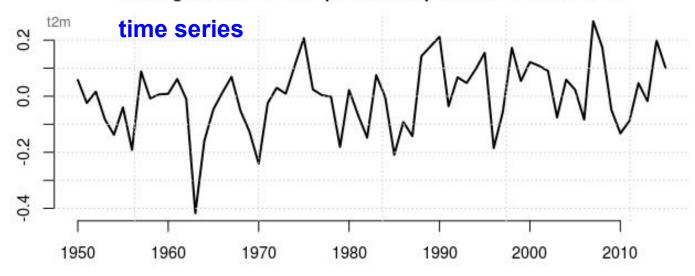


Original data

Principal components (PCs)



Leading PC#1 of Mean temperature - Explained variance = 88.25%



# Why principal component analysis (PCA)?

Redundant information

Signal enhancement: emphasis large scales

Covariance preservation

Computation time

Orthogonality



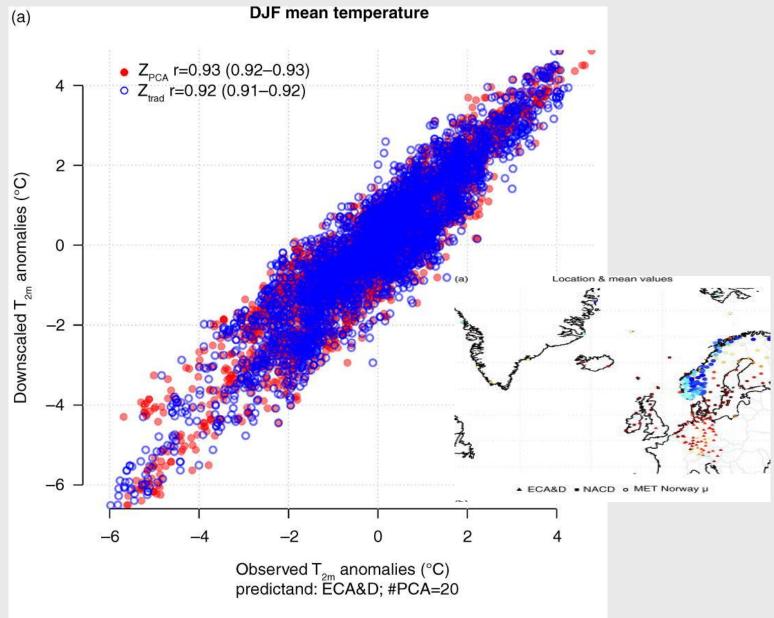
# **Computation speed**

- Apply multiple regression to single principal components.
- Fast: 4 leading modes rather than ~400 stations
  - especially for large ensembles

# **Computation speed**

- Apply multiple regression to single principal components.
- Fast: 4 leading modes rather than ~400 stations
  - especially for large ensembles
- Works for station groups and gridded data

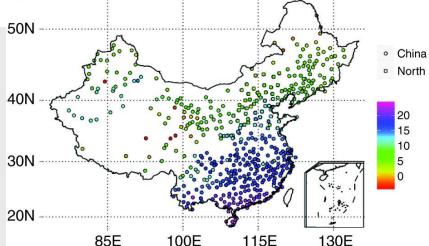
# Signal: Restructure data with information first



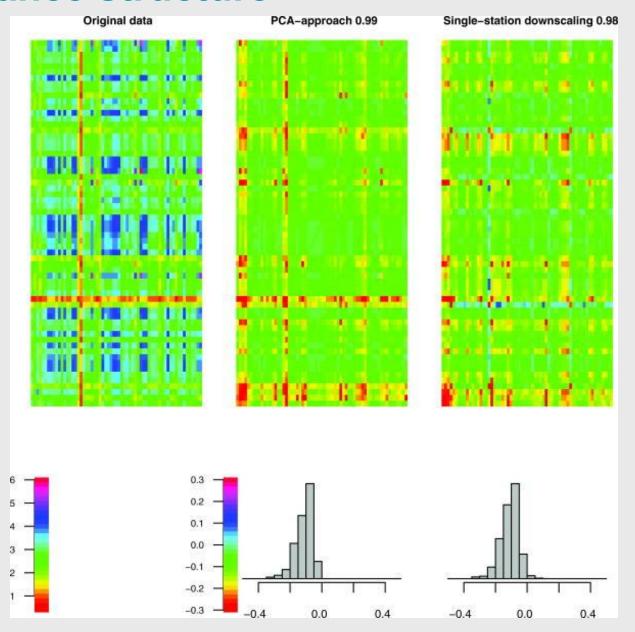
#### Signal: Sensitivity to the choice of large-scale domain

Area (km <sup>2</sup> )	27 800 000	31 800 000	35 800 000	34 400 000	39 300 000	44 200 000
DJF						
PCA	0.87	0.86	0.87	0.87	0.86	0.86
trad.	0.83	0.82	0.82	0.84	0.83	0.82
JJA						
PCA	0.71	0.69	0.72	0.73	0.70	0.70
trad.	0.70	0.71	0.70	0.68	0.65	0.64
NPCA	20	20	20	20	20	20
Domain						
W(°E)	70.00	65.00	60.00	70.00	65.00	60.00
E(°E)	140.00	145.00	150.00	140.00	145.00	150.00
S(°N)	15.00	15.00	15.00	10.00	10.00	10.00
N (°N)	55.00	55.00	55.00	60.00	60.00	60.00
NPCA	20	20	20	20	20	20

The entries are correlation scores from the cross-validation. The predictor was the NCEP/NCAR reanalysis and predictands included 499 stations with complete time series over the period 1961–2012. The highest score in each of the comparisons is shown in bold.



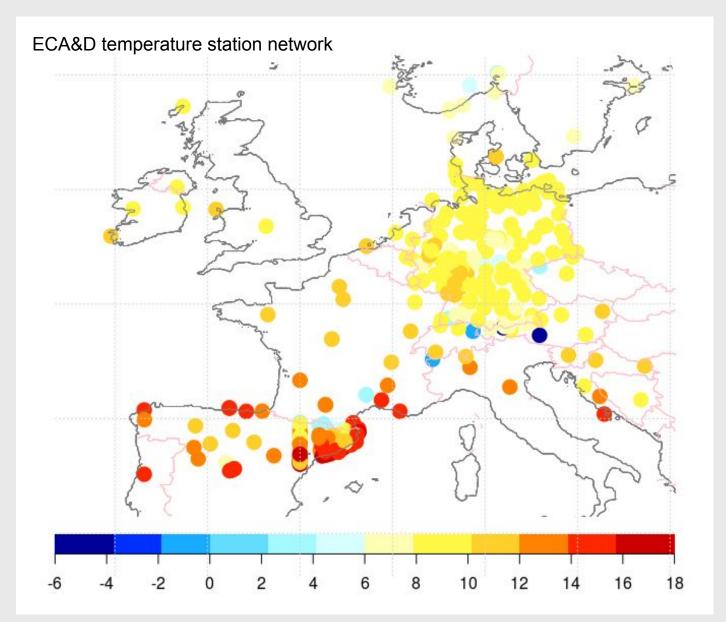
### **Covariance structure**



# Requirements for PCA-based downscaling

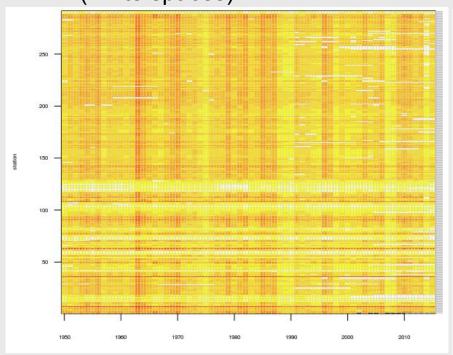
- No missing data
- Suitable distribution
- Not too spatially spread

### 'pcafill' (esd R-package)

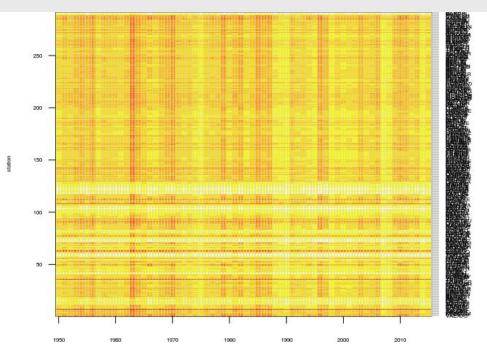


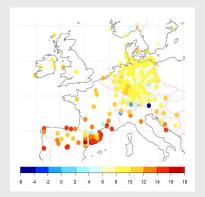
### 'pcafill' (esd R-package)

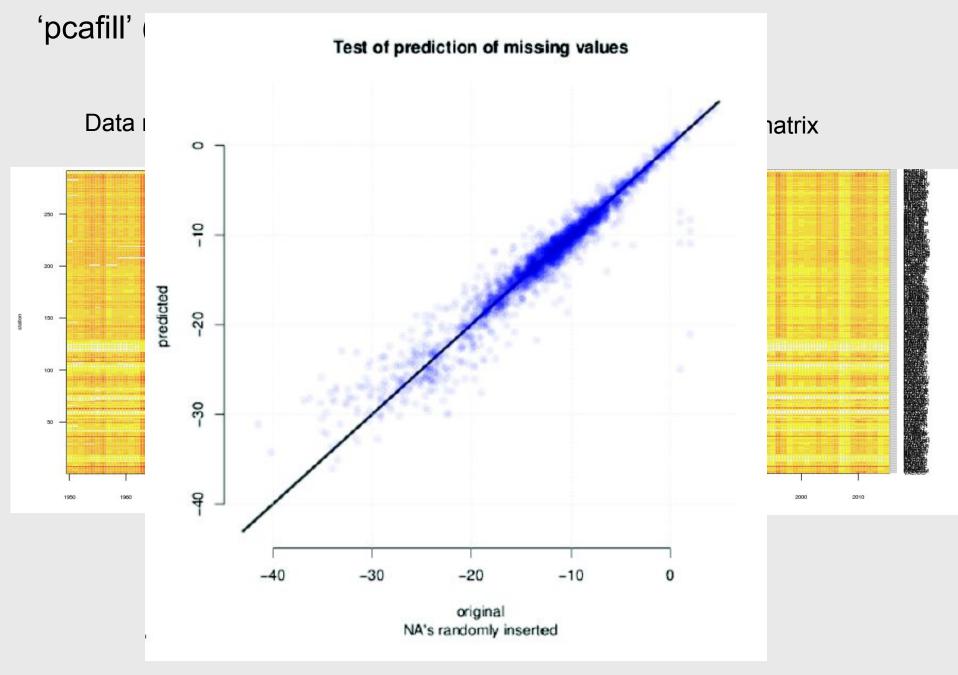
# Data matrix with missing data (white spaces)



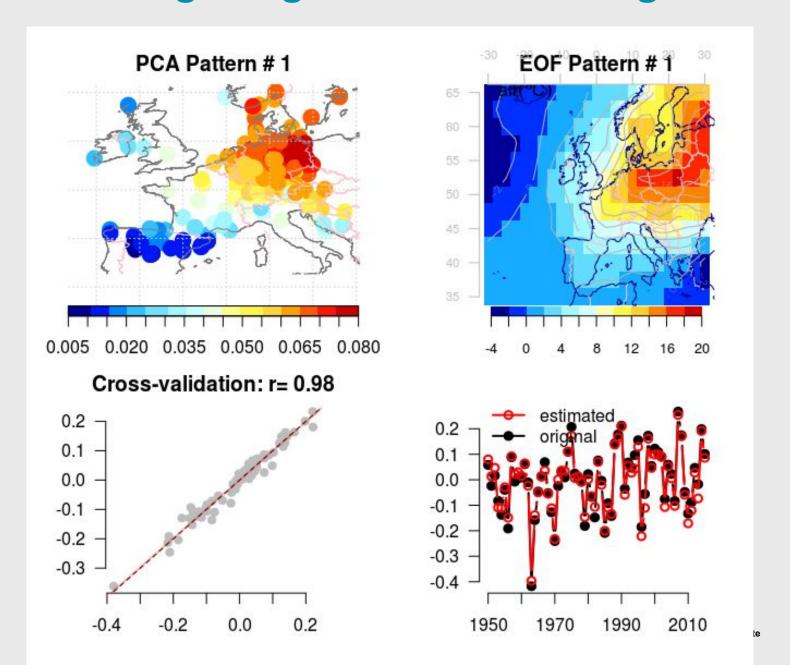
#### Complete data matrix



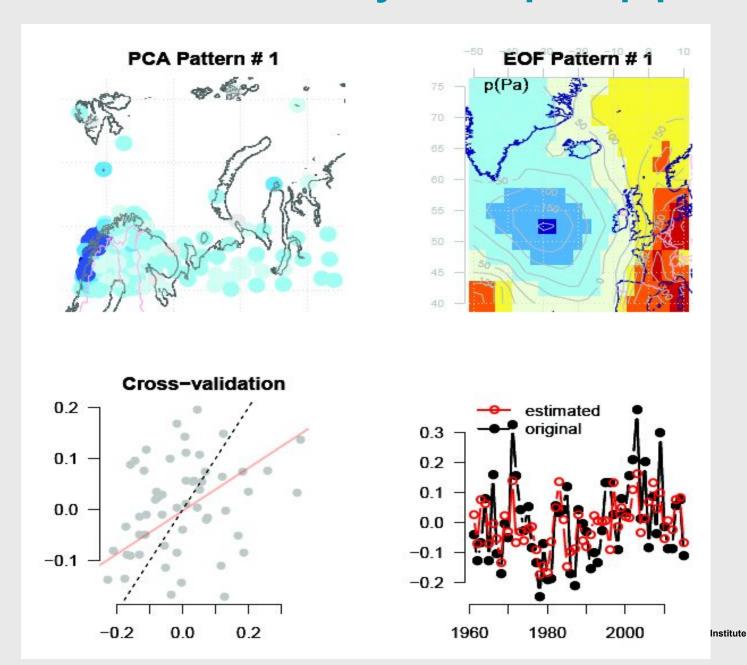




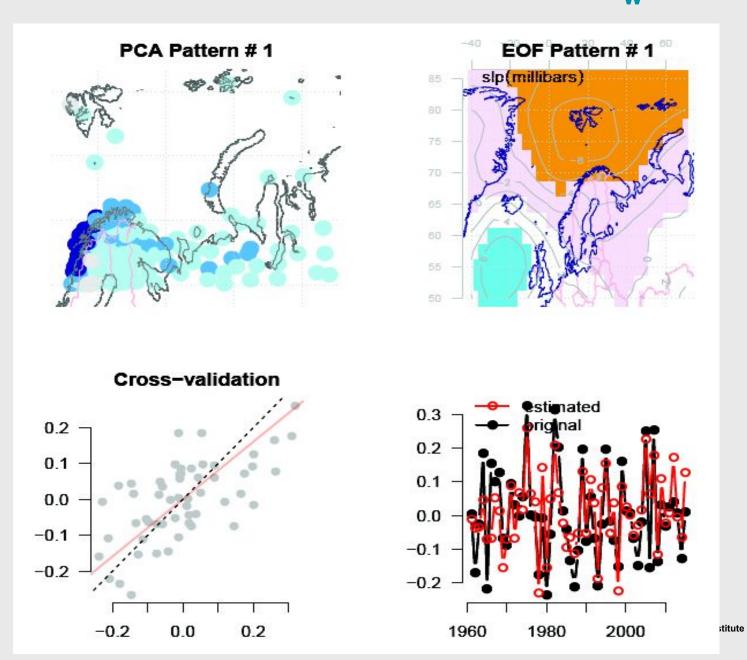
## Downscaling: diagnostics for leading PCA



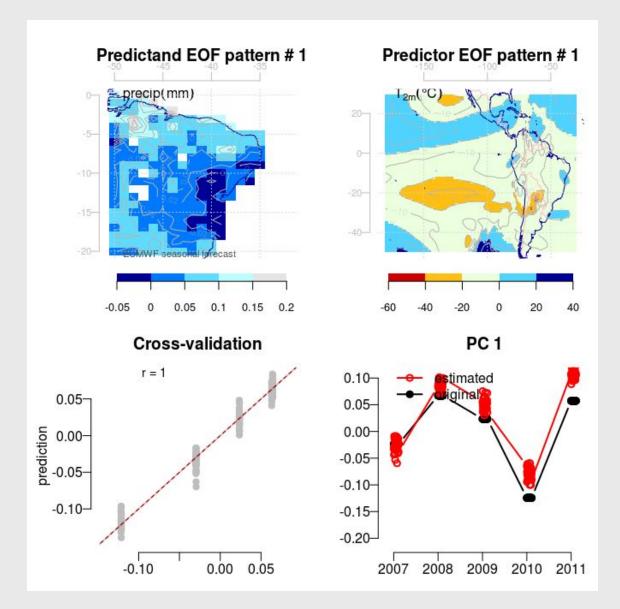
# "Warm season" wet-day mean precip µ



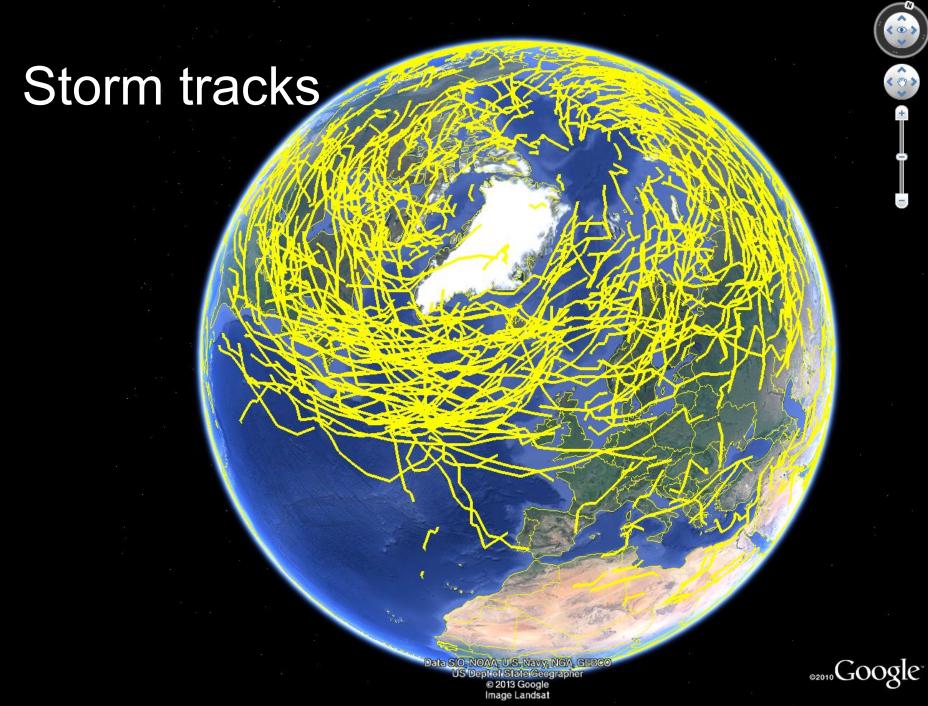
# "Warm season" wet-day frequency f<sub>w</sub>



# Model output statistics (MOS) in seasonal prediction ensemble



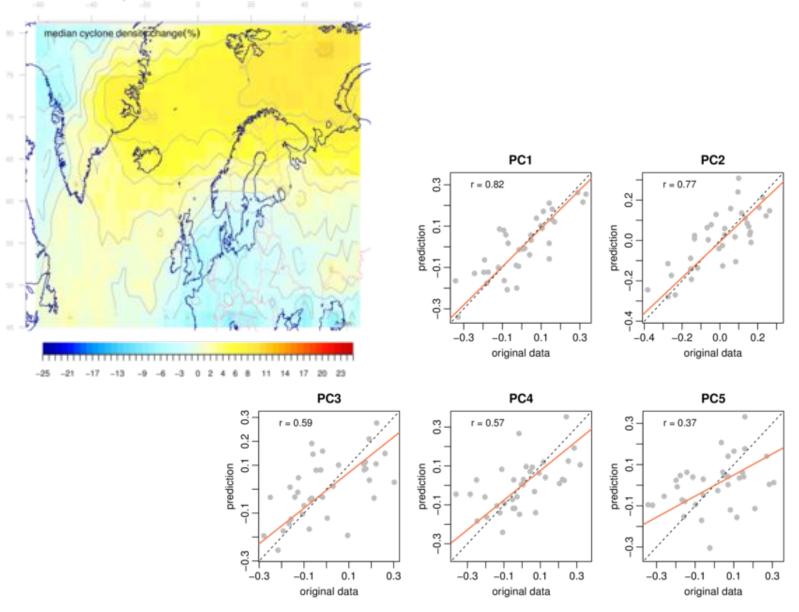






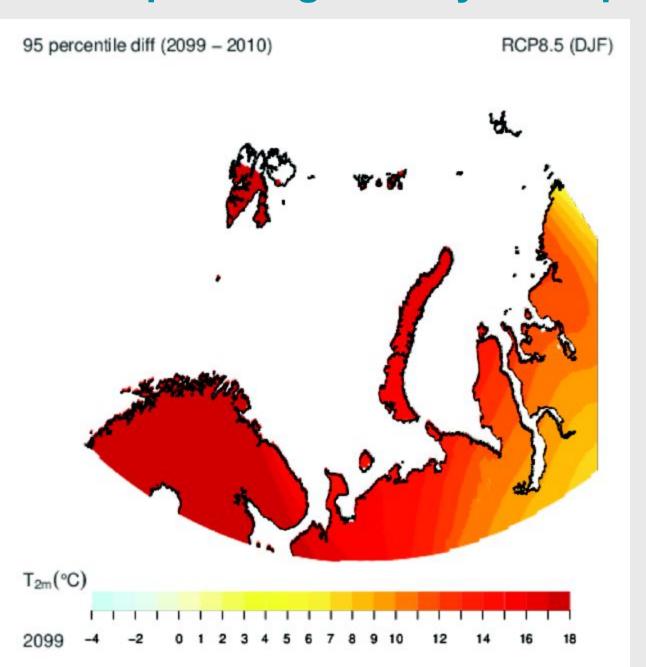
# "Warm season" wet-day mean precip µ

rcp85, 1981-2010 to 2071-2100



# Easier post-processing

# PCA quick to grid: only a few patterns



# LatticeKrig Covariate: z



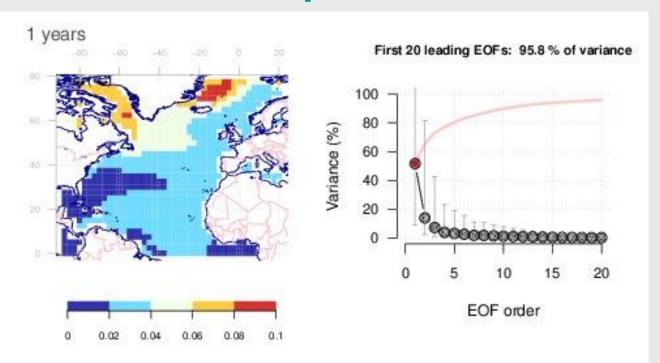
# Thank you for your attention!

Tellus A 2015, 67, 28326, http://dx.doi.org/10.3402/tellusa.v67.28326

Benestad, Rasmus; Parding, Kajsa; Isaksen, Ketil, Mezghani, Abdelkader "Climate change and projections for the Barents region: what is expected to change and what will stay the same?", ERL-102170.R2 (accepted)

https://github.com/metno/esd\_Rmarkdown/tree/master/CORDEX

# MOS in decadal prediction ensemble



Leading PC#1 of Monthly Mean Air Temperature at sigma level 0.995 - Explained variance = 51.71%

