Constraining simulated atmospheric states by sparse empirical information

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Content

Motivation for data assimilation on climate timescales

Data assimilation in meteorology and for 20th century reanalyses

Data assimilation for reconstructing the climate of the last millennium

- choosing from ensemble members (Hugues Goosse et al.)

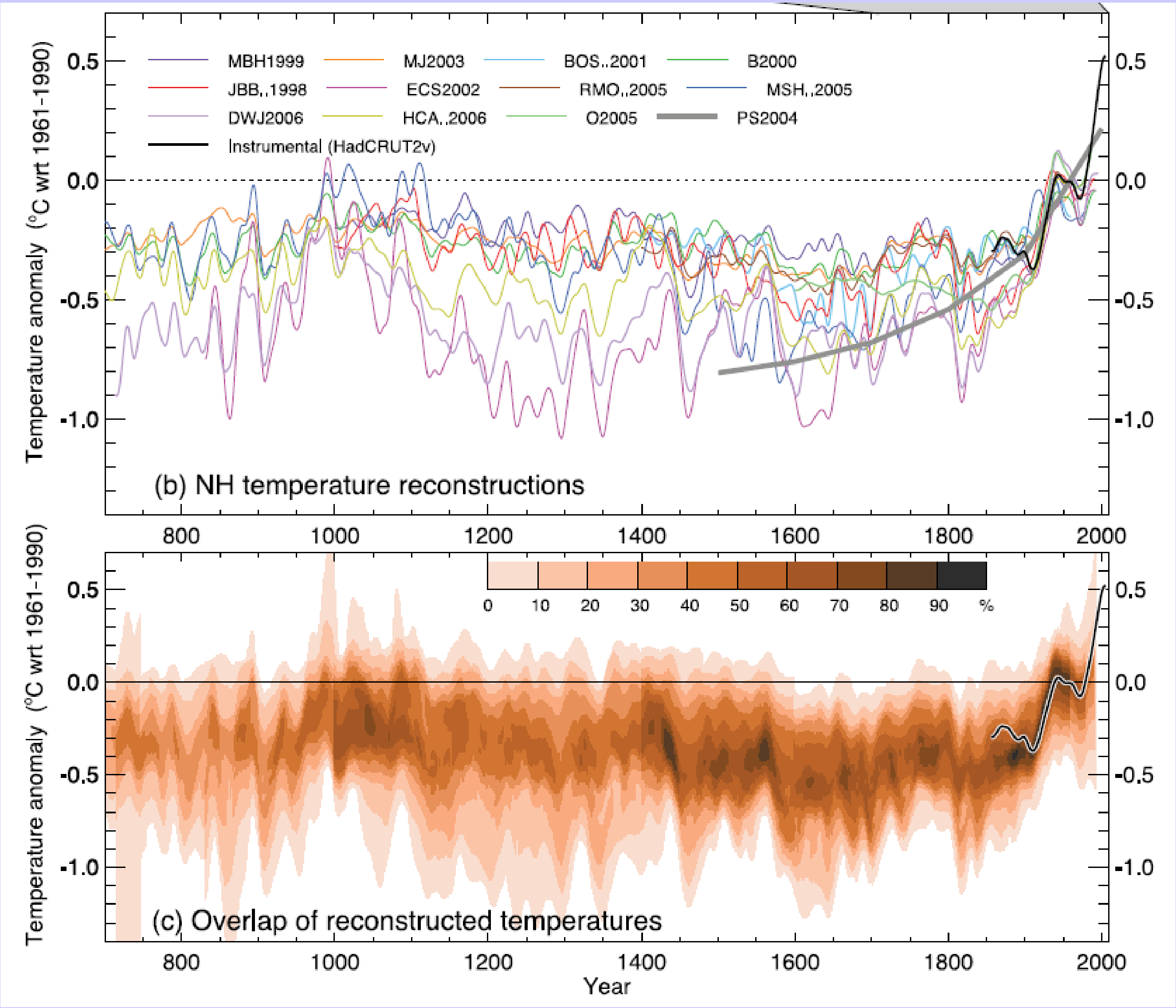
- prescribing large-scale circulation with Forcing Singular Vectors (Gerard van der Schrier et al.)

- prescribing large-scale circulation with Pattern Nudging (Martin Widmann et al.)

Challenges (version 1)

Motivation for DA for the climate of the last millennium

Proxy-based estimates of climate variability still contain considerable uncertainties



Issues:

seasonal representativity

influence of methods

stationarity of statistical relationships used to estimate large-scale climate from sparse proxies

incomplete error estimates

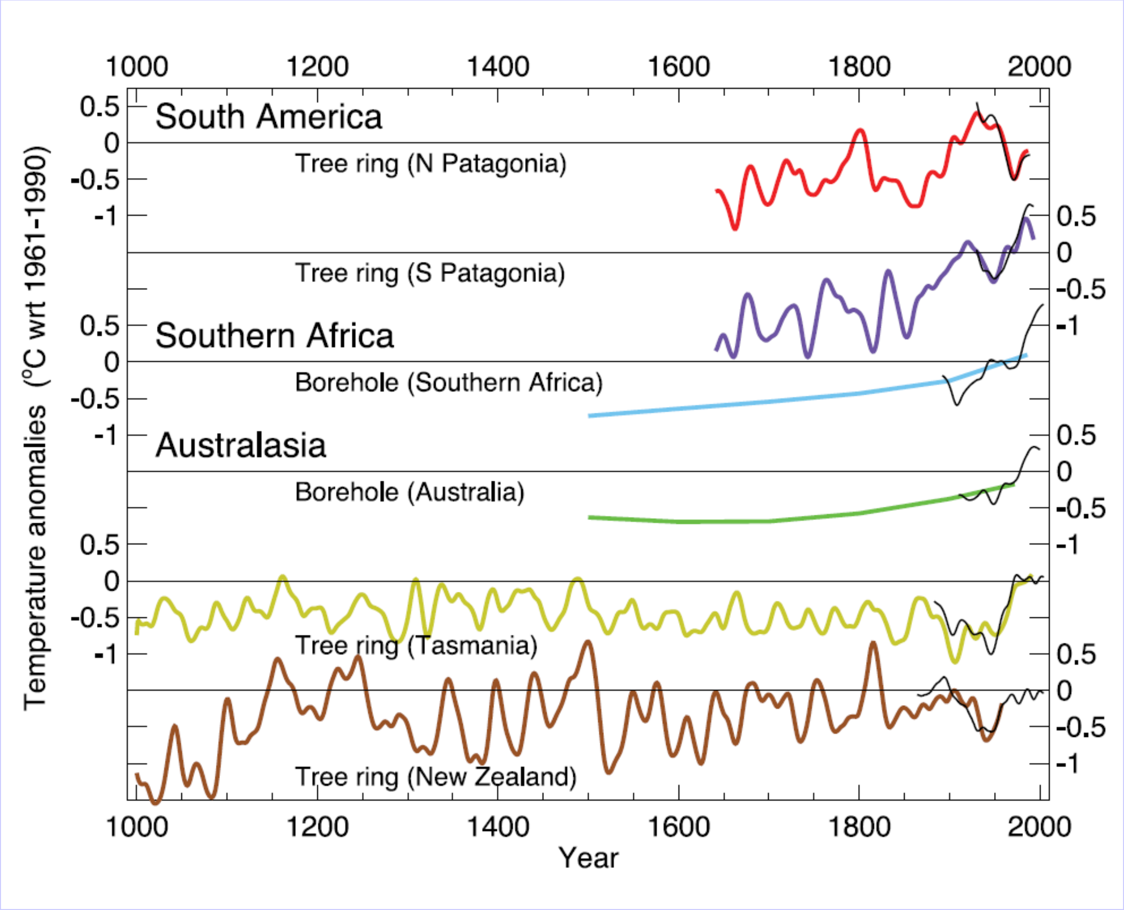
(IPCC AR4, chap 6)

Motivation for DA for the climate of the last millennium

- some, but not all proxy-based reconstructions provide spatial fields

- uncertianties on regional scales may be even larger

- large areas for which nothing is know, for instance in the SH



(IPCC AR4, chap 6)

Motivation for DA for the climate of the last millennium

Estimates for past climate can also be obtained from simulations

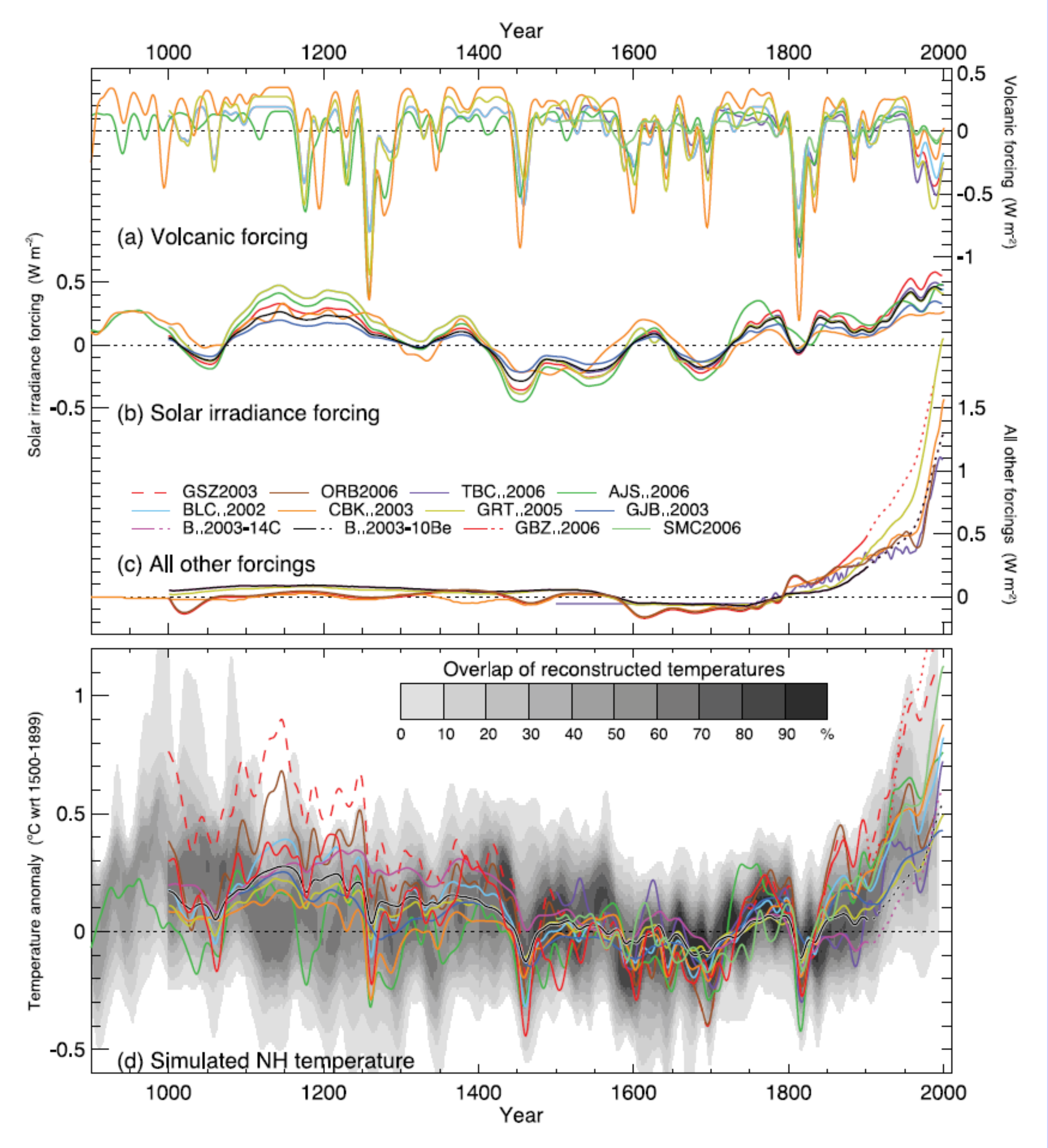
- process understanding

- spatially complete

- independent estimate that can be checked for consistency with proxies (on large- or regional scale)

There are only a few attempts until now to combine paleosimulations and observations through data assimilation.

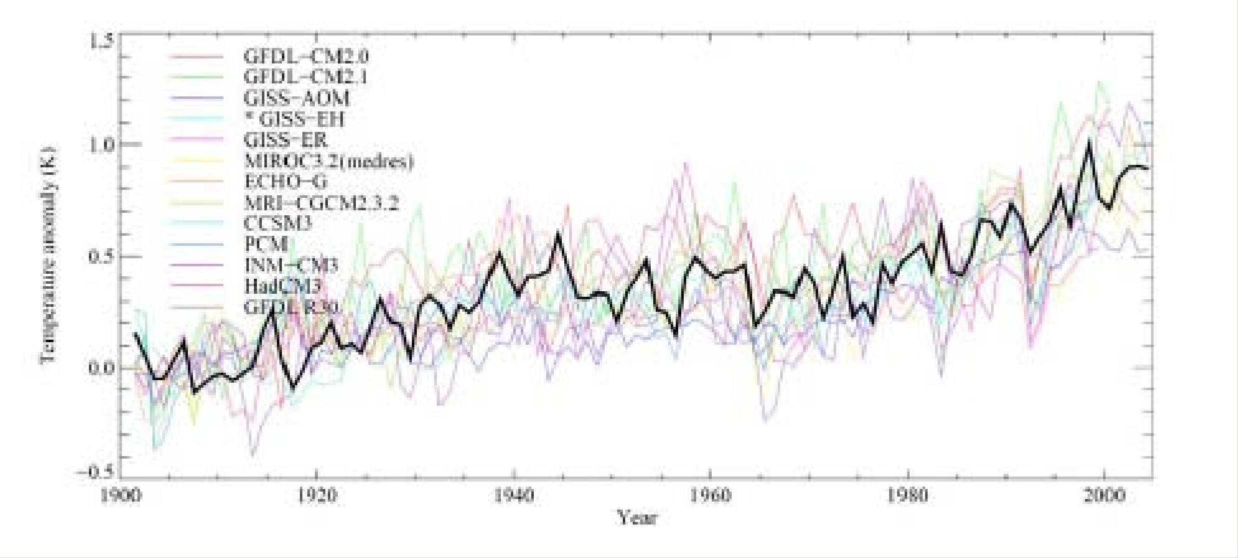
Sophisticated data assimilation methods are used in meteorology and oceanography.



(IPCC AR4, chap 6)

Motivation for DA for the climate of the last millennium

Global mean temperature in transient GCM simulations



Interannual to decadal temperature variations have a large chaotic (non-forced) component and thus agreement of simulations and observations is very unlikely.

Aims of data assimilation (state estimation):

- capture random, non-forced variability in a simulation

- provide information for variables (types and locations) for which no empirical estimates exist

- provide error estimates

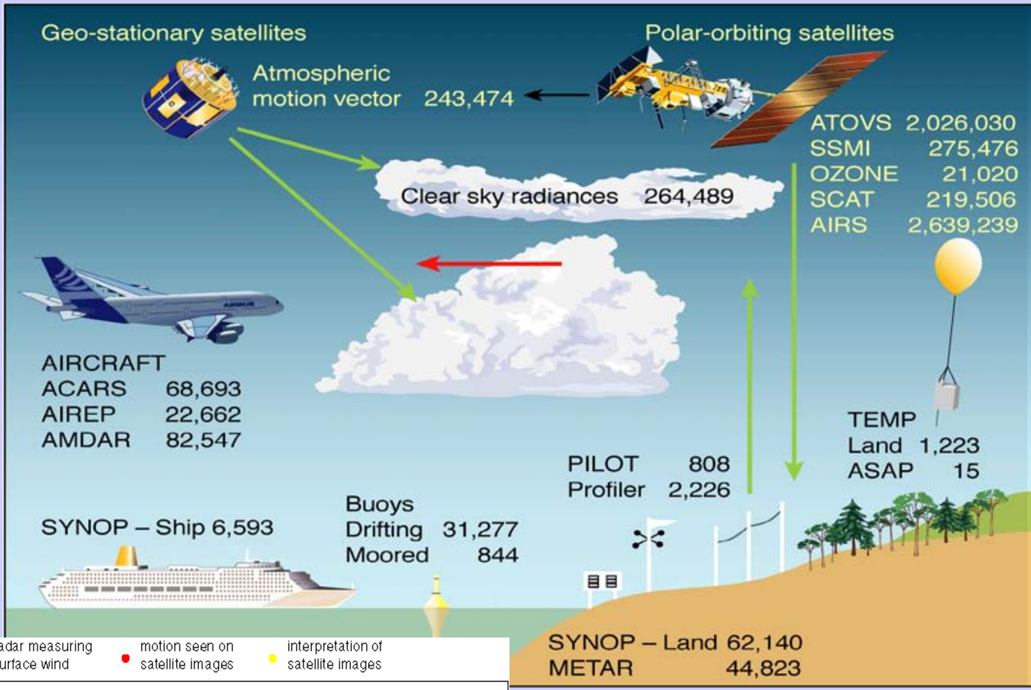
DA in weather forecasting and for atmospheric reanalyses

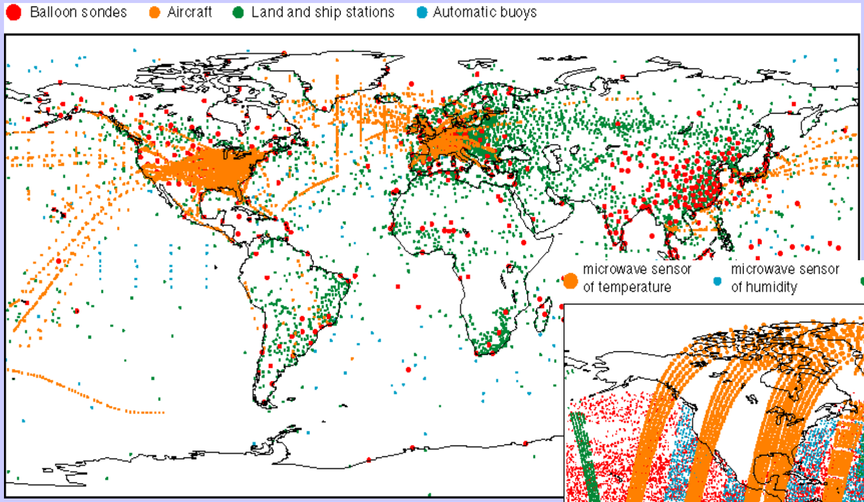
DA used to

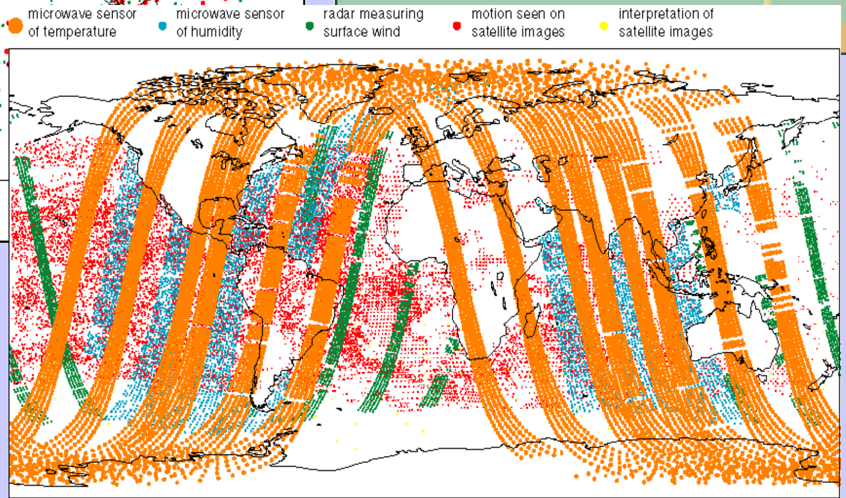
- **define the initial conditions for weather forecast**

- **reconstruct atmospheric states for second half of 20th century (NCEP and ERA40 reanalyses)**

Observations assimilated at ECMWF over 24 hours on 13 Feb. 2006





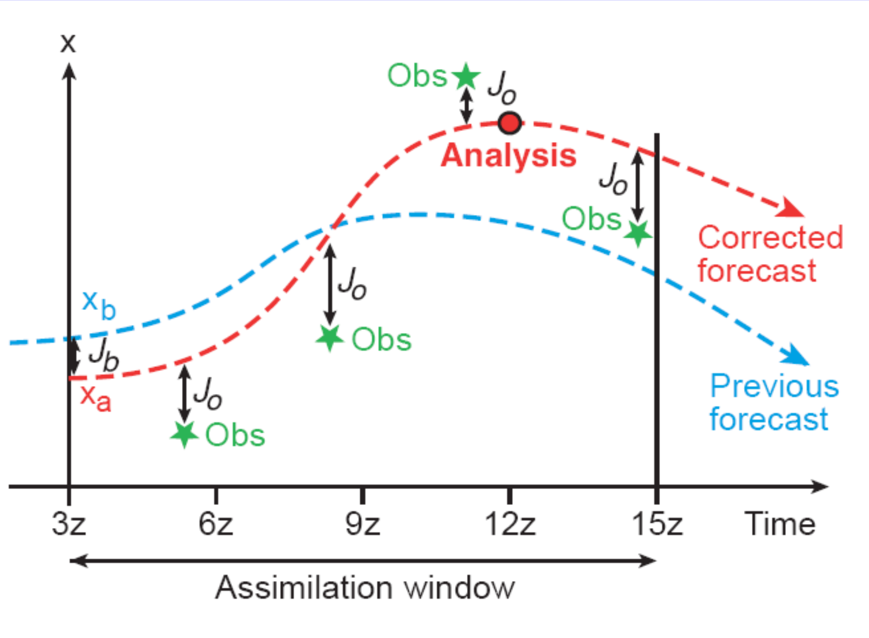


(courtesy ECMWF)

Variational DA in meteorology

The optimal analysis x^a is defined by the nonlinear least squares problem

$$\min \; J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x}^b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b) + \frac{1}{2}\sum_{i=0}^{n}(H_i[\mathbf{x}_i] - \mathbf{y}_i^o)^T \mathbf{R}_i^{-1}(H_i[\mathbf{x}_i] - \mathbf{y}_i^o)$$



subject to

$$\mathbf{x}_i = S(t_i, t_0, \mathbf{x}^a)$$

(true states follow model equations S)

- $\mathbf{x}_b$ - Background state (simulation)
- $\mathbf{y}_i$ - Observations
- H_i - Observation operator (or forward model, can be non-linear)
- $\mathbf{B}$ - Background error covariance matrix
- $\mathbf{R}_i$ - Observation error covariance matrix

Solved using adjoints, needs good linear approximation of dynamical system

Sequential data assimilation and Kalman Filter

If we base the analysis x_k^a at time k only on observations at time k and on background fields x_k^b at this time the analysis solves

$$\min \; J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}_k^b)^T \mathbf{B}_k^{-1}(\mathbf{x}-\mathbf{x}_k^b)$$
$$+\frac{1}{2}(H_k[\mathbf{x}]-\mathbf{y}_k^o)^T \mathbf{R}_k^{-1}(H_k[\mathbf{x}]-\mathbf{y}_k^o)$$

Approximate solution (exact for linear system) is given by

$$\mathbf{x}_k^a = \mathbf{x}_k^b + \mathbf{B}_k \mathbf{H}_k^T (\mathbf{H}_k \mathbf{B}_k \mathbf{H}_k^T + \mathbf{R}_k)^{-1} (\mathbf{y}_k^o - H_k \mathbf{x}_k^b)$$

(analysis = forecast + weight * (observation – observation estimated from forecast)

where $$\mathbf{H}_k = \frac{\partial H_k}{\partial x}$$ **is the linearised observation operator**

(following Swinbank et al. 2002)

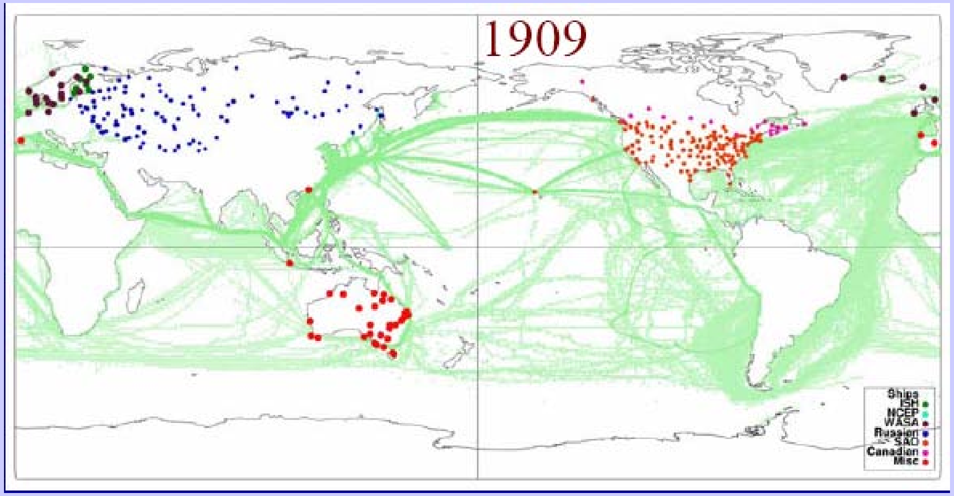
The 20th century reanalysis project

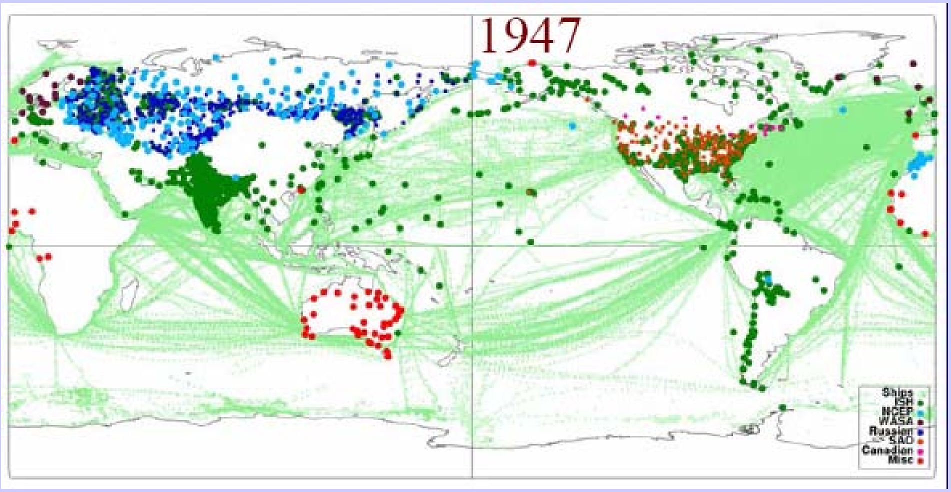
An international collaborative project led by NOAA
(Gil Compo, Jeff Whitaker, Prashant Shardeshmuk)

Tropospheric reanalyses for last 100 years using only surface observations

Shown to work with 4D-Var and Ensemble Kalman Filter, but not with 3D-Var
(as used in NCEP/NCAR and ERA40 reanalyses)

locations of surface and sea level pressure observations





(courtesy G. Compo)

Ensemble Kalman Filter Algorithm

Analysis x^a is a weighted average of the first guess x^b and observation y^o

$$\mathbf{x}^a = \mathbf{x}^b + K(\mathbf{y}^o - H\ \mathbf{x}^b)$$

Algorithm uses an ensemble to produce the weight K that varies with the atmospheric flow and the observation network

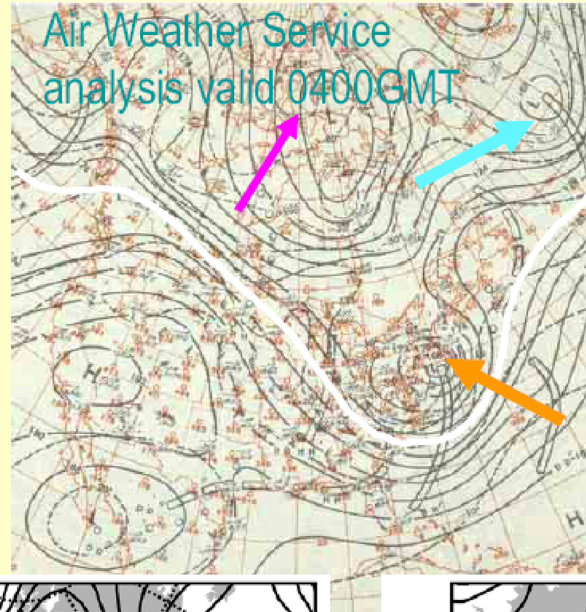
y^o is only surface pressure,
Hx^b is guess surface pressure
x is pressure, air temperature, winds, humidity, etc. at all levels and gridpoints.

Using 56 member ensemble

HadISST monthly boundary conditions (Rayner et al. 2003)
Version 1 (1908-1958): T62, 28 level NCEP CFS03 atmospheric model
Version 2 (1871-2008): T62, 28 level NCEP GFS08ex model
- time-varying CO_2, solar and volcanic radiative forcing

Analyses of 500 hPa Geopotential Height 27 December 1947

Using only surface pressure observations, Ensemble Filter analysis compares well with analyses using upper-air observations.

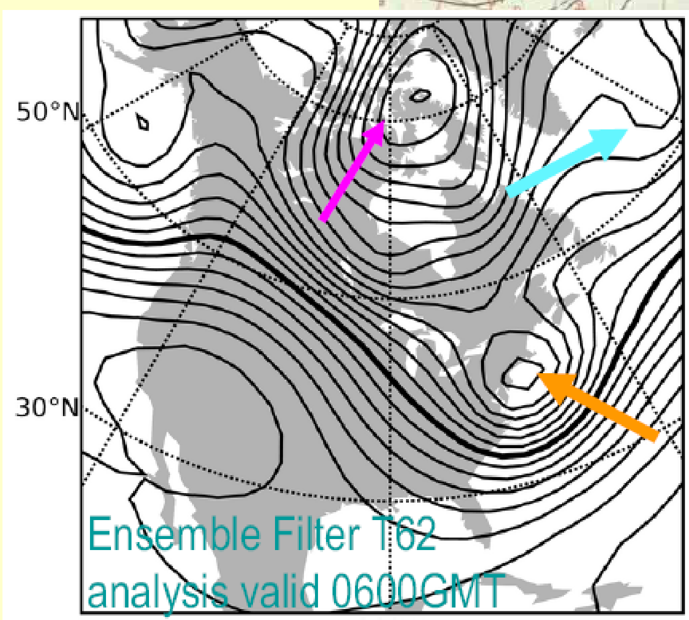


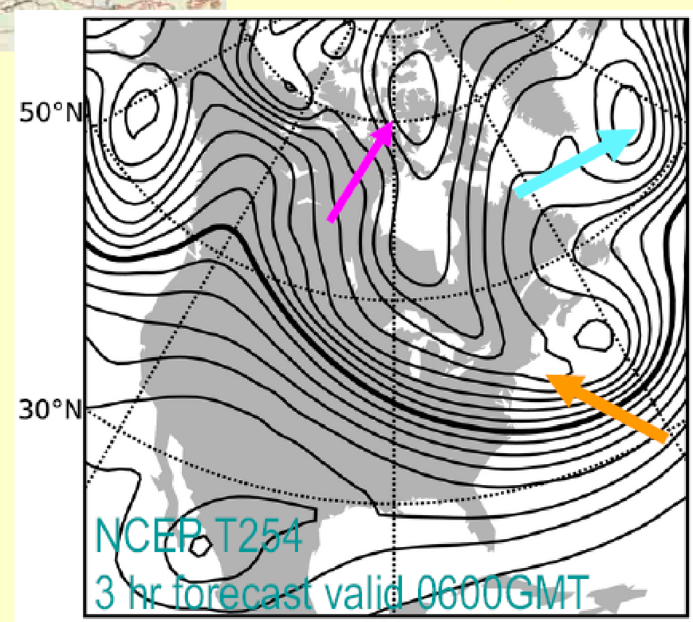
Severe snowstorm case in New York City, USA.

Using all available surface <u>and</u> upper-air obs

5500 m (18000 ft) contour is thickened

Using <u>only</u> surface pressure obs



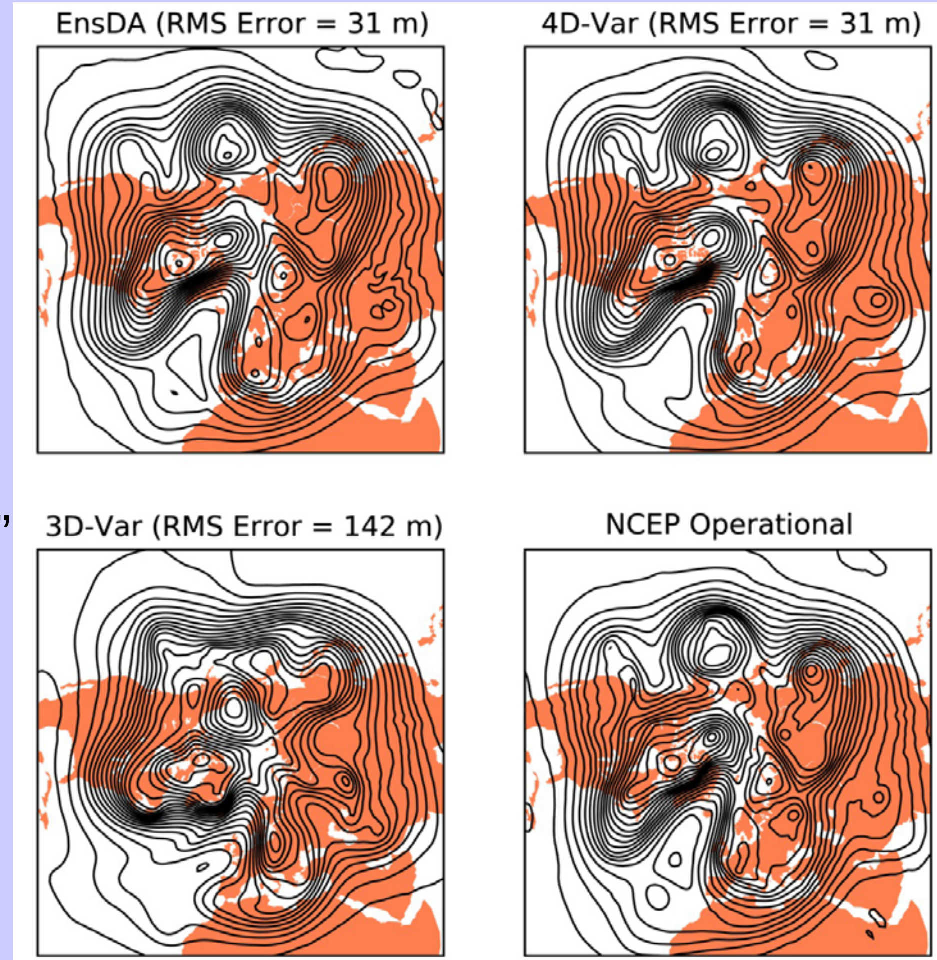


(courtesy G. Compo) (Compo, Whitaker, Sardeshmukh, 2007)

(Kocin and Uccellini, 2004)

500 hPA Height Analyses for 20 Feb 2005 12Z

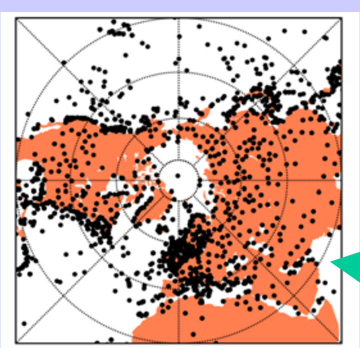
Ensemble Filter
(~3800 surface pressure obs)
RMS = 31 m



ECMWF “Surface” 4D-Var
(~3800 surface pressure obs)
RMS = 31 m

ECWMF “Surface” 3D-Var
(~3800 surface pressure obs)
RMS = 142 m

Full NCEP Operational
(>1,000,000 obs)



Surface pressure network reduced to ~1930’s

Whitaker, Compo, Thepaut (2009)

Motivation for data assimilation (state estimation) in paleoclimatology

Assimilation could substantially improve paleo simulations

- account for internally generated, random variability

whose temporal evolution can not be simulated in forced simulations

or whose statistical properties are unrealistically simulated

- account for unrealistic and/or incomplete forcings

- account for unrealistic responses to forcings

and through the combination of empirical data and simulations/physics lead to better estimates for past climate states (needs to be shown through validation).

Data assimilation for the climate of the last millennium

Challenge because empirical estimates constrain only

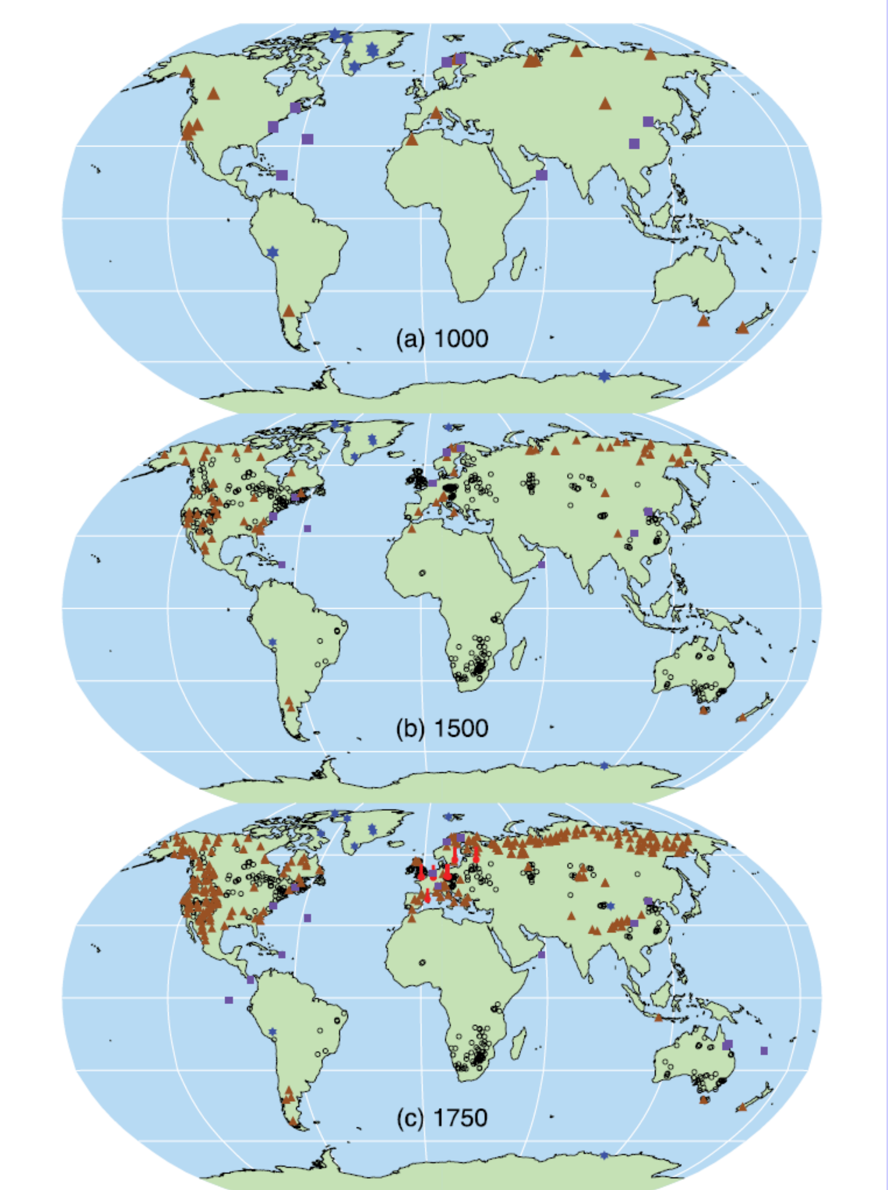
- a few locations or large-scale patterns (i.e. a low-dimensional subspace)
- seasonal and longer variability

Using standard assimilation methods is not straightforward, because

- methods need to be efficient enough for long simulations
- model and proxy errors unknown
- technical/mathematical problems with observations integrated over long periods (e.g. linearisations and adjoints)

Few attempts have been undertaken

Proxy sites back to 1000/1500/1750 AD



Data assimilation for the climate of the last millennium

Approach 1

Use EMIC ensemble simulations and chose ensemble members consistent with proxy evidence for temperature

(H. Goosse, M. Mann, H. Renssen and A. Timmermann)

Approach 2

Prescribe atmospheric circulation with target states based on proxy evidence or idealized states

- use EMIC and forcing singular vectors

(G. van der Schrier, J. Barkmeijer)

- use GCM and pattern nudging

(M. Widmann, H. von Storch, R. Schnur, I. Kichner, T. Kleinen)

(Widmann, Goosse, van der Schrier, Schnur and Barkmeijer, 2010, Climate of the Past, in press)

Data assimilation for the climate of the last millennium

Both approaches attempt to bring certain aspects of
a simulation in agreement with either proxy-based evidence
or idealized situations.

They thus

- do not formally attempt to provide optimal state estimates
  based on taking into account model and observation error,

- are not formulated within the standard framework of
  classical data assimilation.

Using paleoclimate proxy-data to select the best realisation in an ensemble

Simulation of the climate of the last 1000 years : selecting among a relatively large ensemble of simulations the one that is the closest to the observed climate.

The experiment selected is the one that minimise a cost function CF for a particular period :

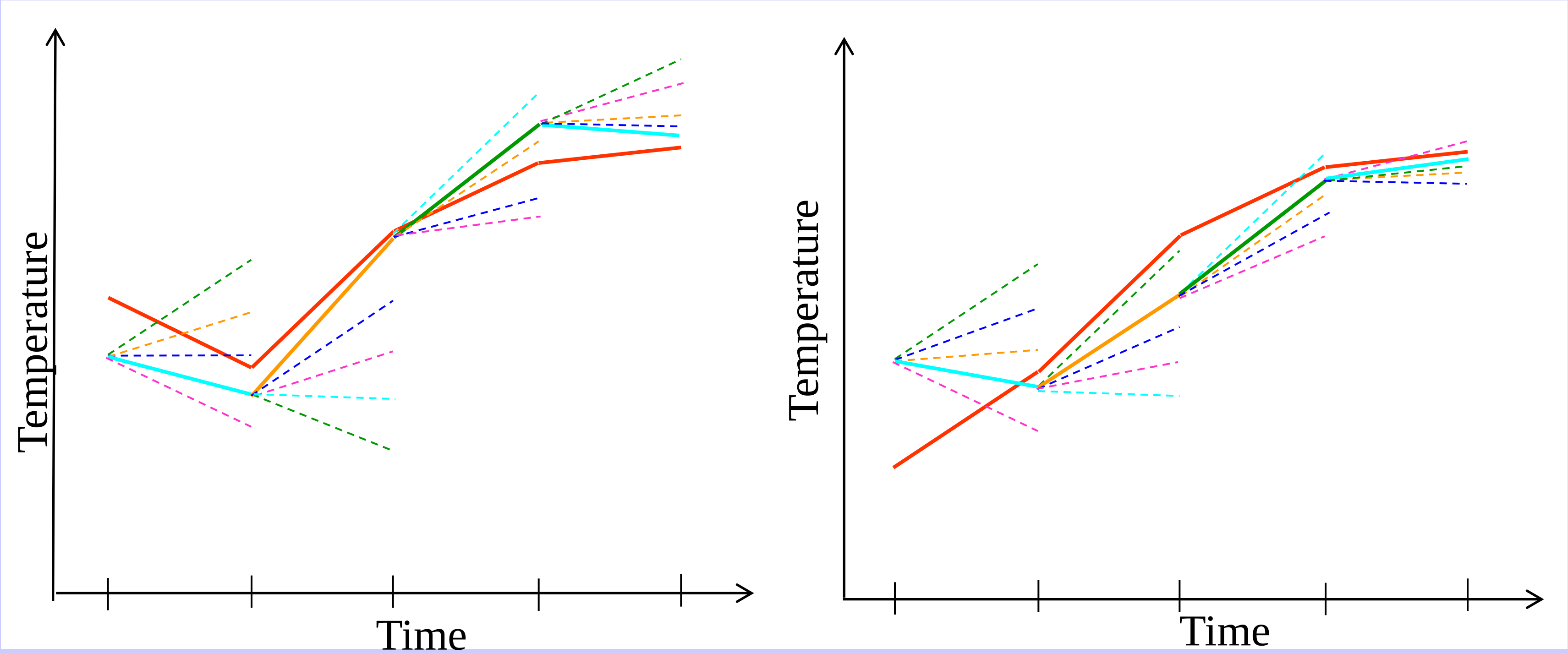
$$CF(t) = \sqrt{\sum_{i=1}^{n} w_i \left(F_{obs}(t) - F_{\mathrm{mod}}(t)\right)^2}$$

Where n is the number of reconstructions used in the model/data comparison. F_{obs} is the reconstruction of a variable F, while F_{mod} is the simulated value of the corresponding variable. w_i is a weight factor.

Goosse et al. 2006

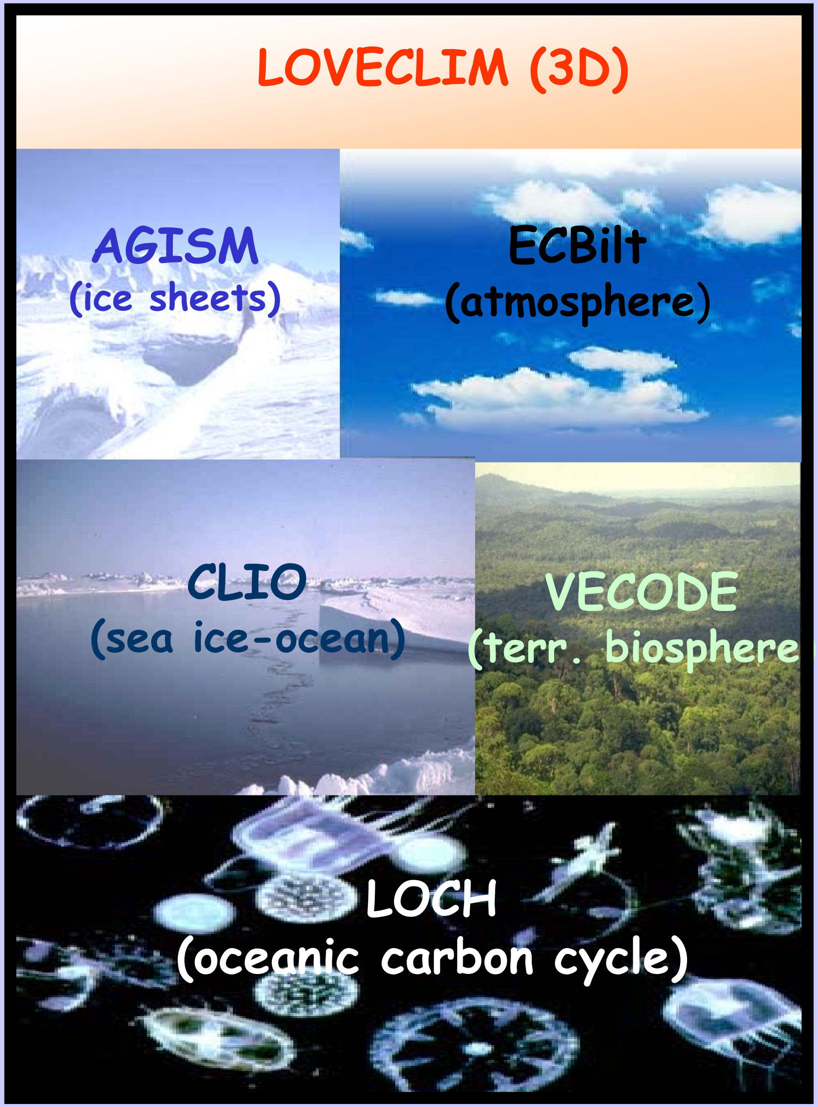
Using paleoclimate proxy-data to select the best realisation in an ensemble

Example using 5 ensemble members and two constraints (observations, in red). The best member selected is displayed in bold while the other ones are dashed



Goosse et al. 2006

Description of LOVECLIM



ECBilt (Opsteegh et al., 1998)
Quasi-geostrophic atmospheric model (prescribed cloudiness; T21, L3).

CLIO (Goosse and Fichefet, 1999)
Ocean general circulation model coupled to a thermodynamic-dynamic sea ice model (3 x 3, L20).

VECODE (Brovkin et al., 2002)
Reduced-form model of the vegetation dynamics and of the terrestrial carbon cycle (same resolution as ECBilt).

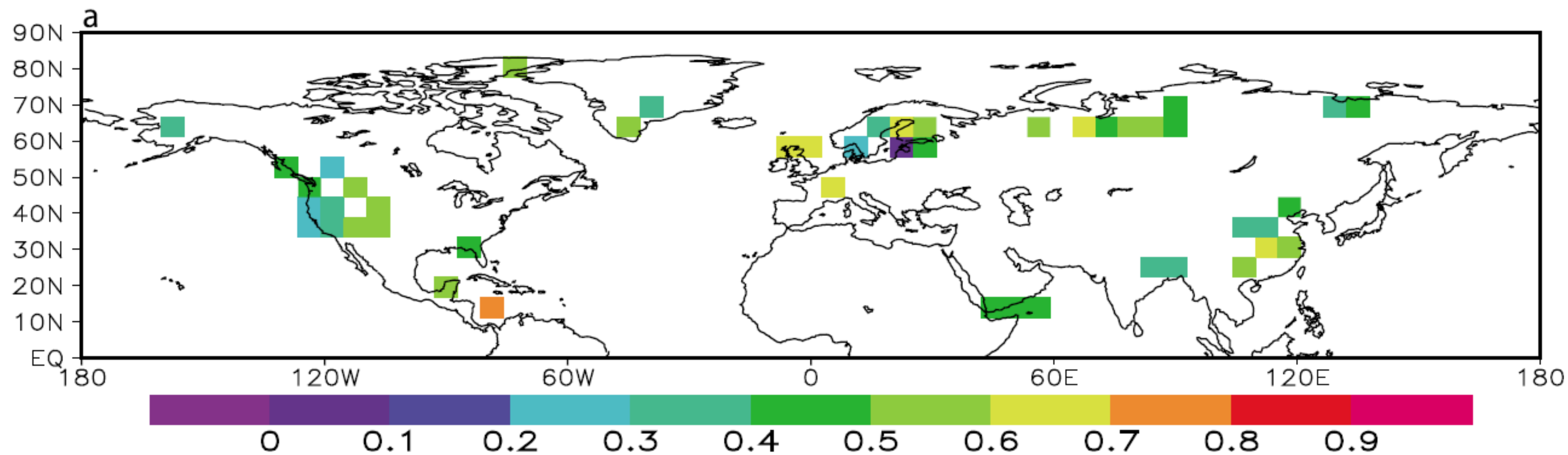
LOCH (Mouchet and François, 1996)
Comprehensive oceanic carbon cycle model (same resolution as CLIO).

AGISM (Huybrechts, 2002)
Thermomechanical model of the ice sheet flow + visco-elastic bedrock model + model of the mass balance at the ice-atmosphere and ice-ocean interfaces (10 km x 10 km, L31).

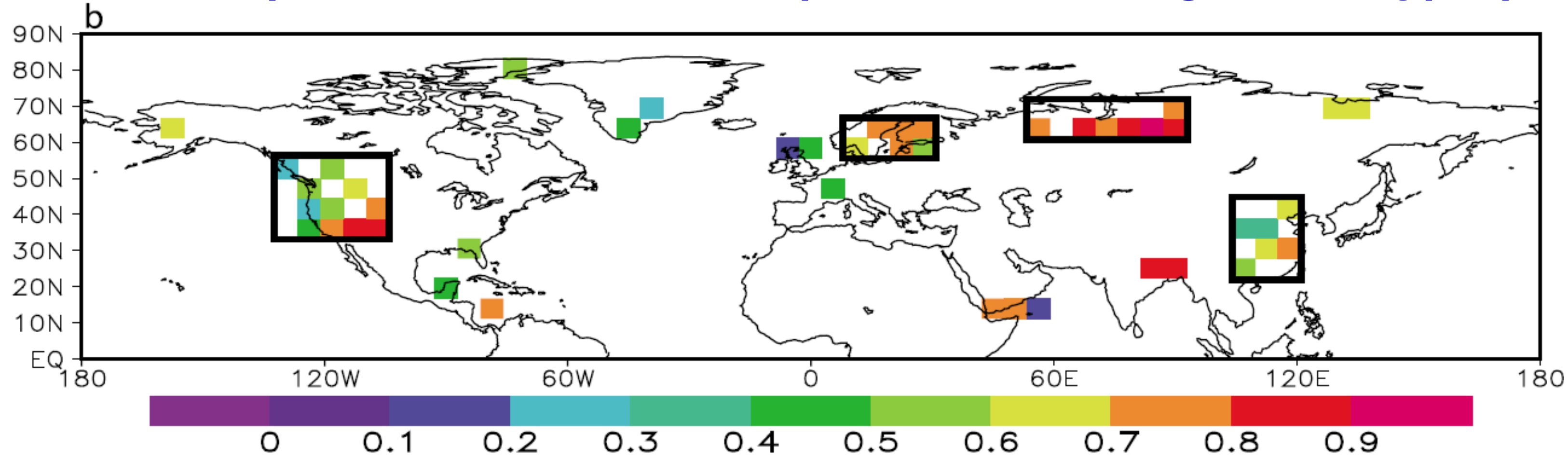
(courtesy H. Goosse)

Reconstructing temperature using 56 proxy records, 96 ensemble members and 11 combinations of cost function and model parameters (types)

Correlation proxies with HadCRUT3 (decadal filter)



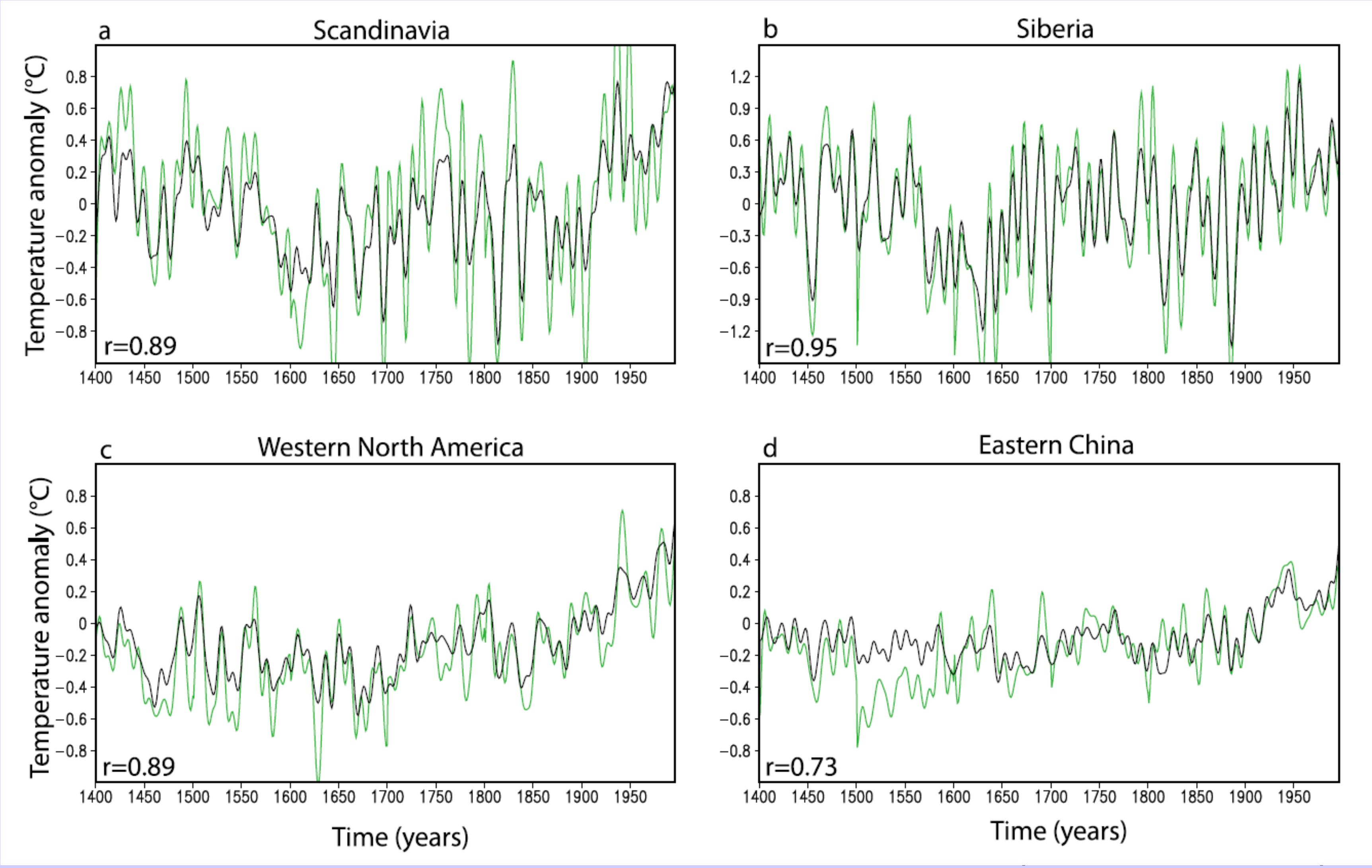
Correlation proxies with simulation (1400-1995, averaged over types)



(Goosse et al., 2010)

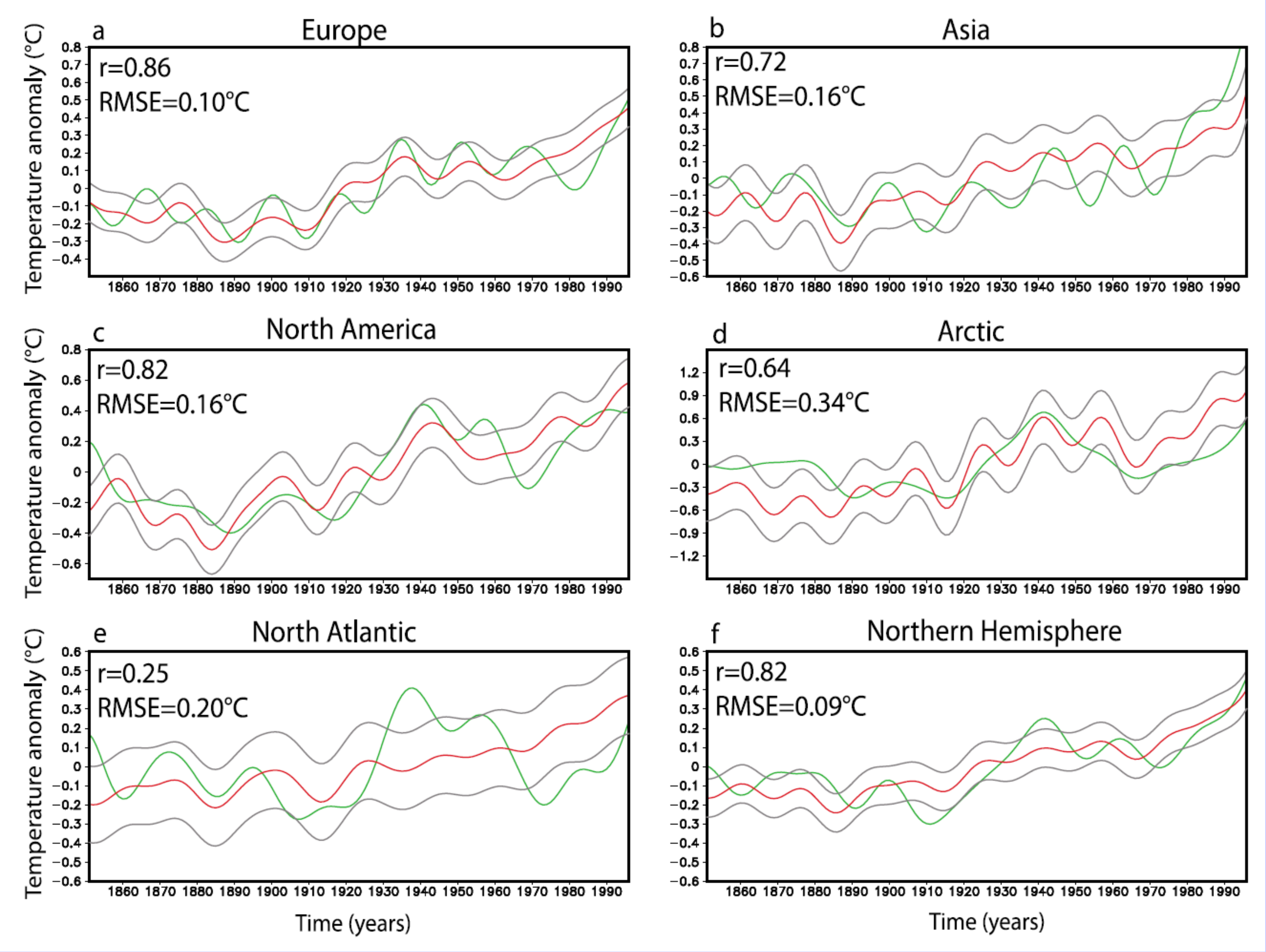
Reconstructing temperature using 56 proxy records, 96 ensemble members and 11 types

Simulated and proxy-based temperatures



Reconstructing temperature using 56 proxy records, 96 ensemble members and 11 types

HadCRUT3 and simulated temperatures



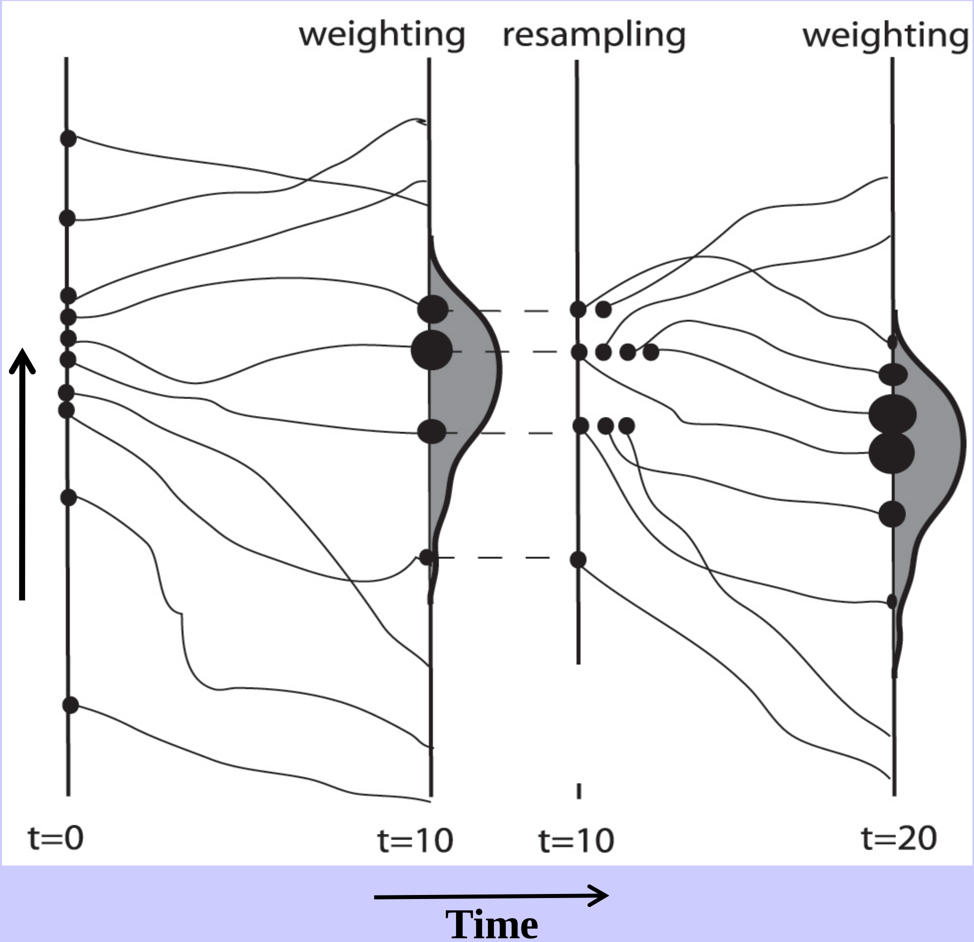
(Goosse et al., 2010)

Extension of ensemble member selection to particle filter

Keep more than one ensemble member.

Number of similar members in next step proportional to weight.

The weight is proportional to the likelihood of the model state, knowing the observations. derived from comparing simulation with observations.

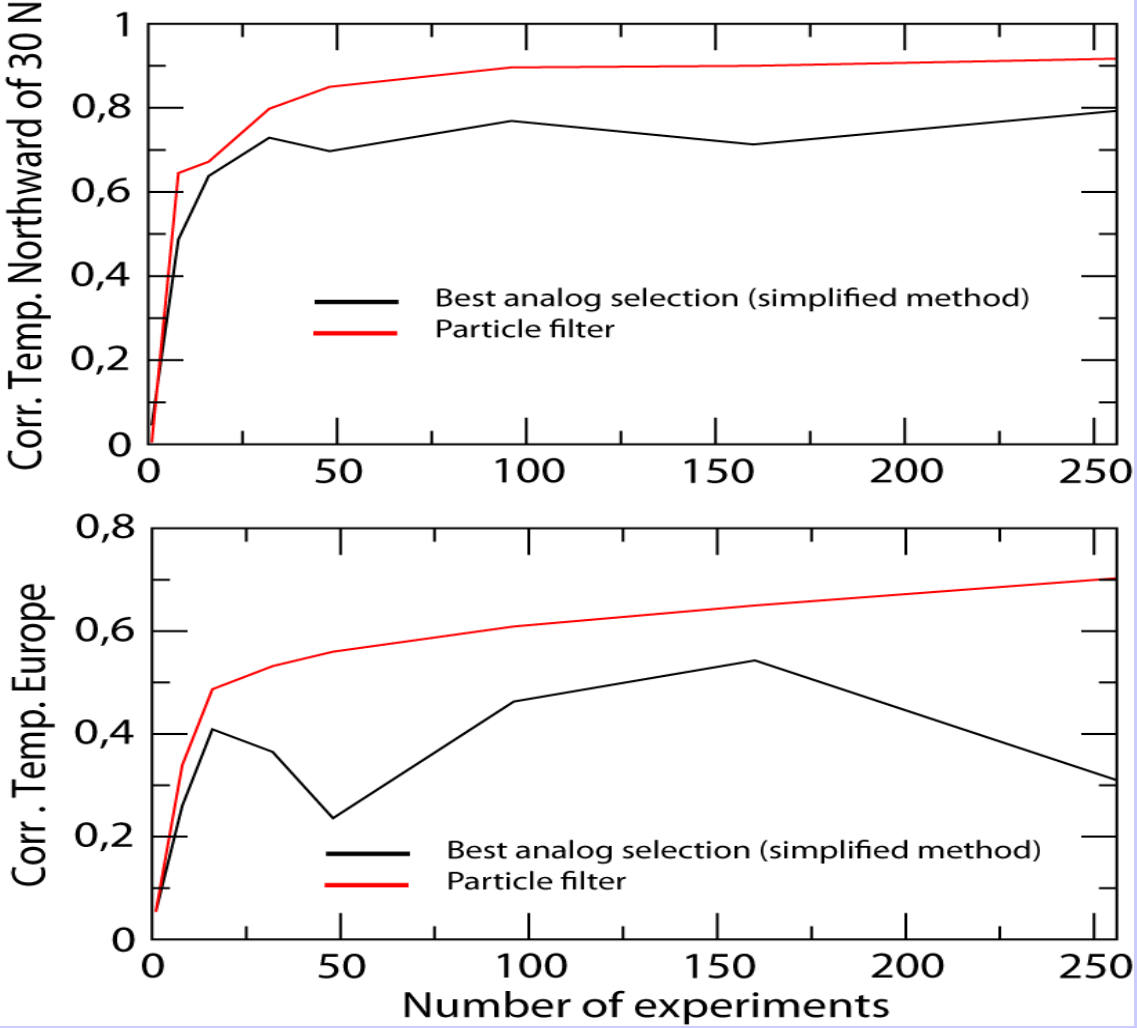


(courtesy H. Goosse)

Skill as a function of ensemble members

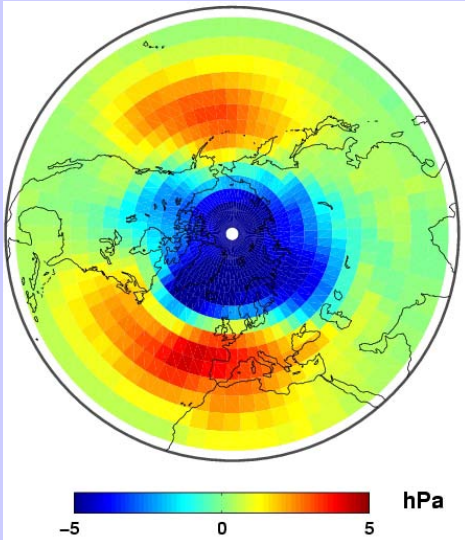
Determined from twin experiments (pseudo reality, lower complexity).

Levels off after about 30 members.



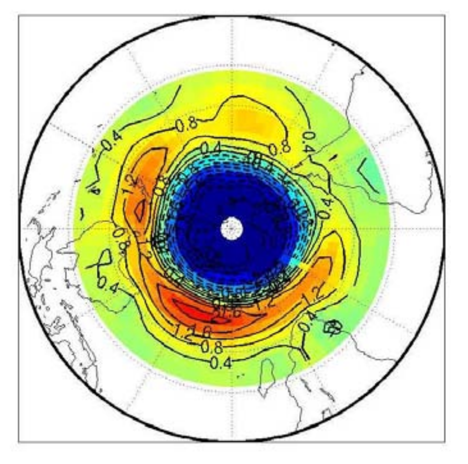
(courtesy H. Goosse)

Assimilation of large-scale circulation states



General comments

- large-scale circulation has a strong internally generated random component
- forced component difficult to simulate
- circulation influences regional temperatures



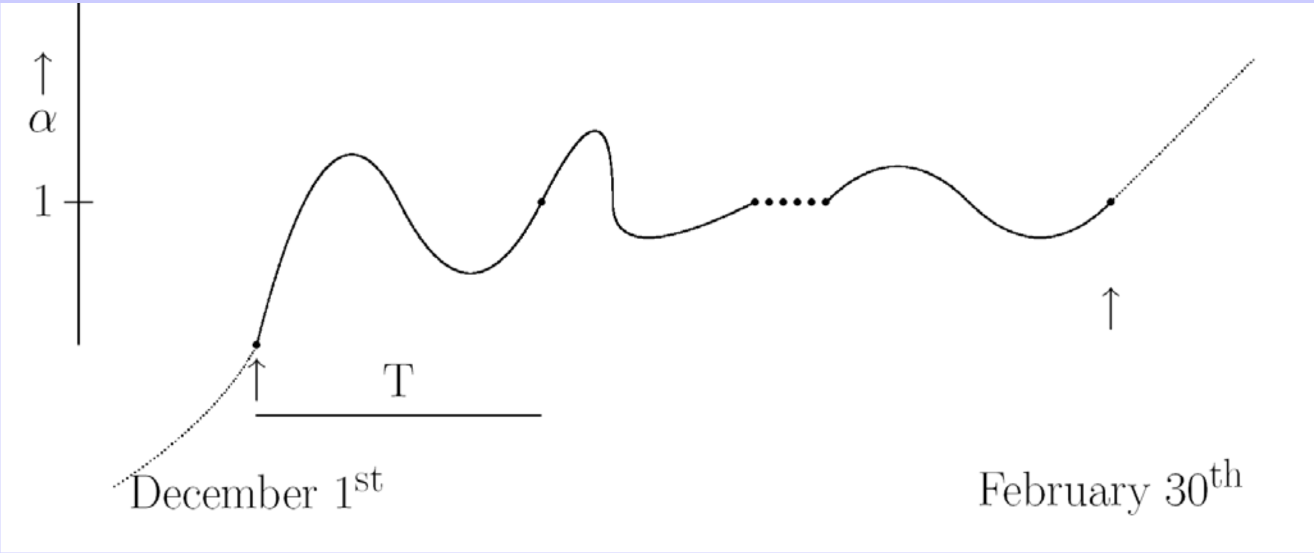
Approach

rely on model to estimate hemispheric temperature response to forcings and on empirical estimates to constrain aspects of the large-scale circulation

estimated large-scale circulation are based on statistical upscaling and stability assumptions

Forcing singular vectors (van der Schrier and Barkmeijer)

Aim: keep circulation anomaly close to target pattern



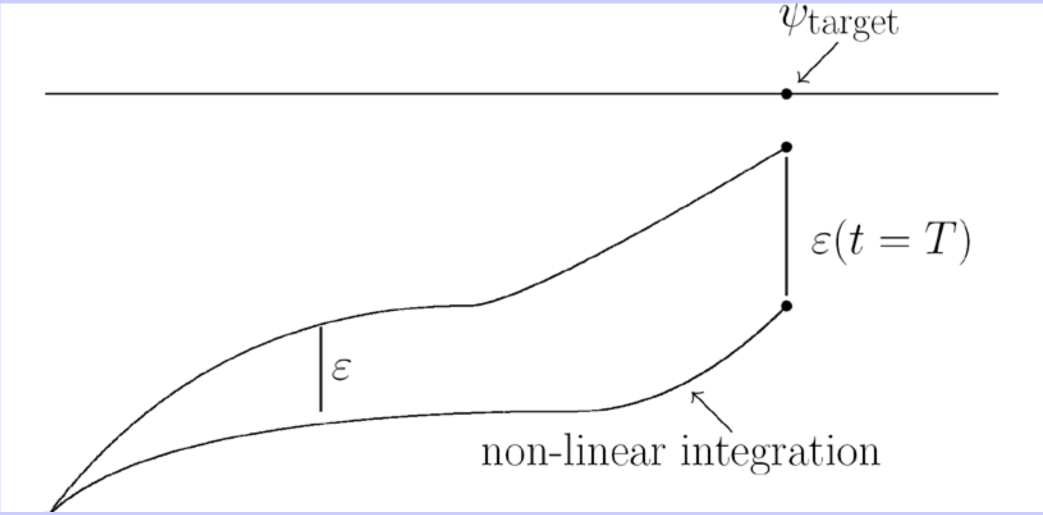
reconstructed state $$\psi_{\text{past}} = \psi_{\text{clim}} + \psi_{\text{target}}$$

simulated state $$\psi = \psi_{\text{clim}} + \alpha\psi_{\text{target}} + \sum_{n=2} \alpha_n \psi_n$$

Forcing singular vectors

- add extra forcing such that target state is reached

- used with ECBILT-CLIO



$$\frac{\mathrm{d}\varepsilon}{\mathrm{d}t} = \mathbf{L}\varepsilon + \mathbf{f}$$

change = linearized model + perturbation

difference between original and perturbed simulation

$$\varepsilon(T) = \mathcal{M}\mathbf{f} \text{ with } \mathcal{M} = \int_0^T \mathbf{M}(s, T)ds$$

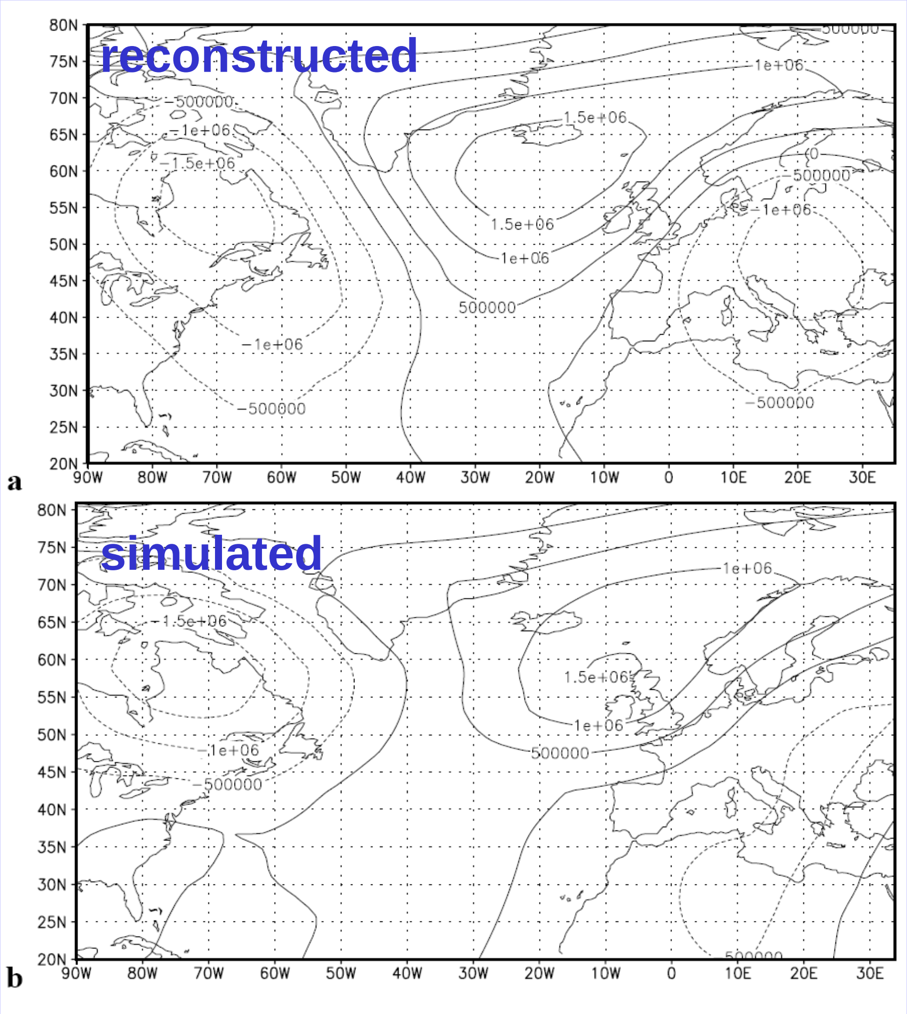
chose forcing such that target state is reached, minimize:

$$J(\mathbf{f}) = |P\left(\mathcal{M}\mathbf{f} - (1-\alpha)\psi_{\text{target}}\right)|$$

(van der Schrier and Barkmeijer 2005)

Forcing singular vectors

Winter streamfunction anomaly 1790-1820



- good (but not perfect) agreement in this case

- if the target pattern is not within the set of patterns produced by the model, the target state is not well approximated

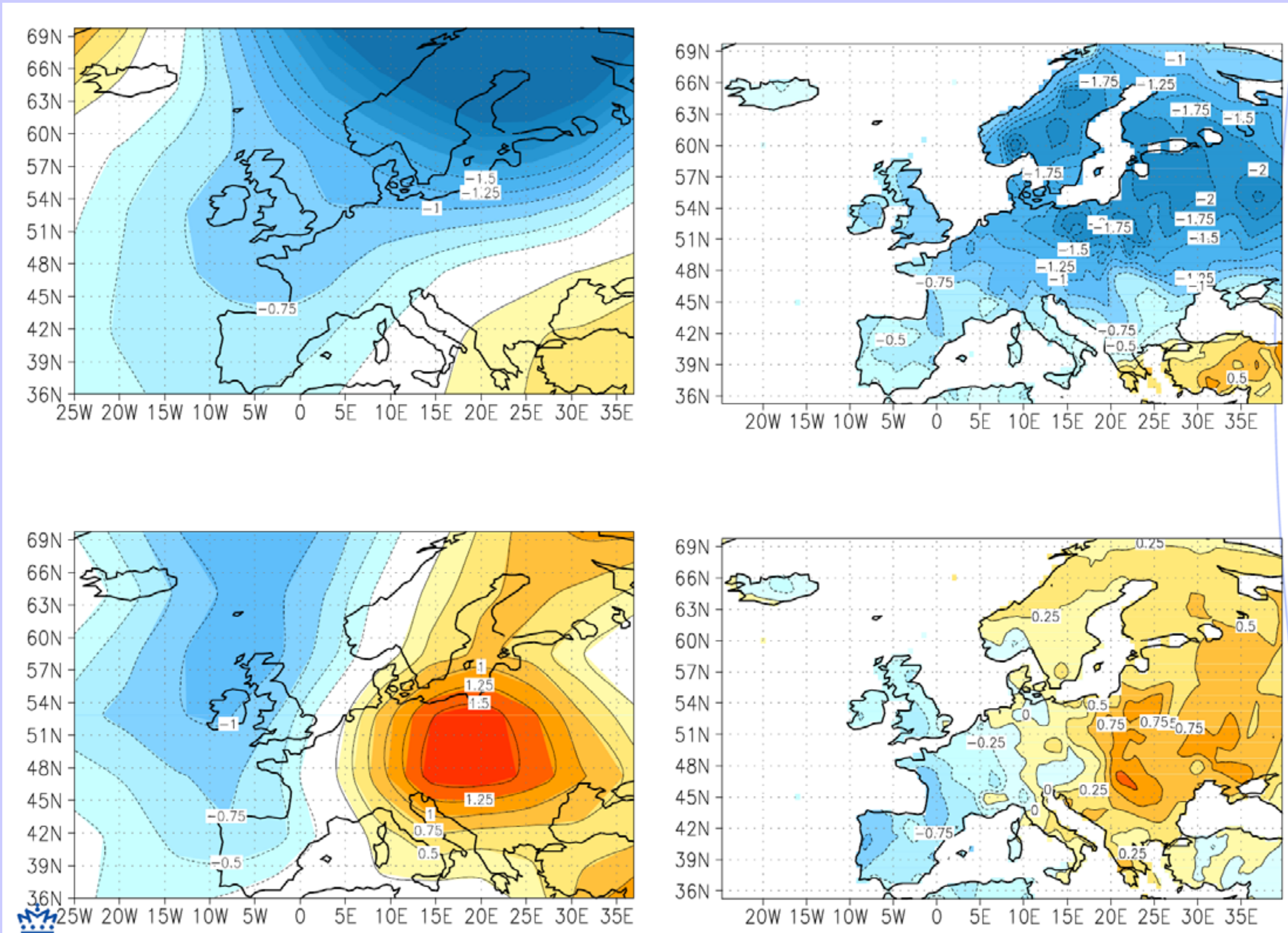
(Van der Schrier and Barkmeijer, 2005, 2007)

Simulated and reconstructed temperature anomaly using circulation forcing singular vectors

simulation **reconstruction**

DJF

JJA



Pattern Nudging

- push simulated amplitude of given pattern towards prescribed values without directly affecting orthogonal or suppressing variability

- no adjoints or ensembles needed

- simulation of the response of small scales, synoptic-scale variability, and non-nudged variables

field expansion

$$\Psi(x,t) = \overline{\Psi}(x) + \alpha_T(t)\Phi_T(x) + \sum_{i=2}^{\infty} \alpha_i(t)\Phi_i(x)$$

$$\alpha_{mod}(t) = \frac{(\Delta\Psi(x,t), \Phi_T(x))}{(\Phi_T(x), \Phi_T(x))}$$

$$\Delta\Psi(x,t) = \Psi_{mod}(x,t) - \overline{\Psi}(x)$$

additional nudging term

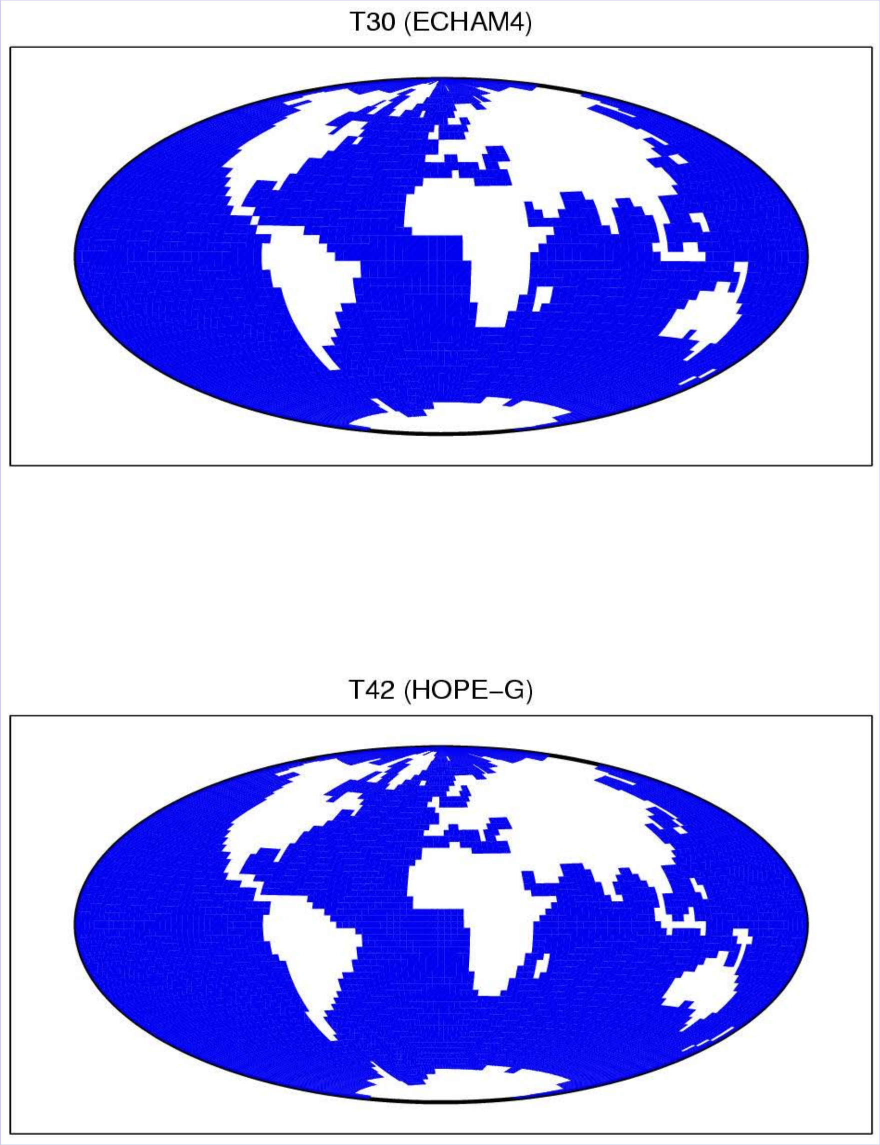
$$R = G\ (\alpha_T - \alpha_{mod}(t))\,\Phi_T(x)$$

ECHO-G

ECHAM4 coupled with HOPE-G

ECHAM4
- 19 atmospheric levels
- T30, approx. 3.8 x 3.8 degrees

HOPE-G
- 20 ocean levels
- approx. 2.8 x 2.8 degrees
- dynamic-thermodynamic sea-ice



Model is flux corrected, with prescribed vegetation and land ice.

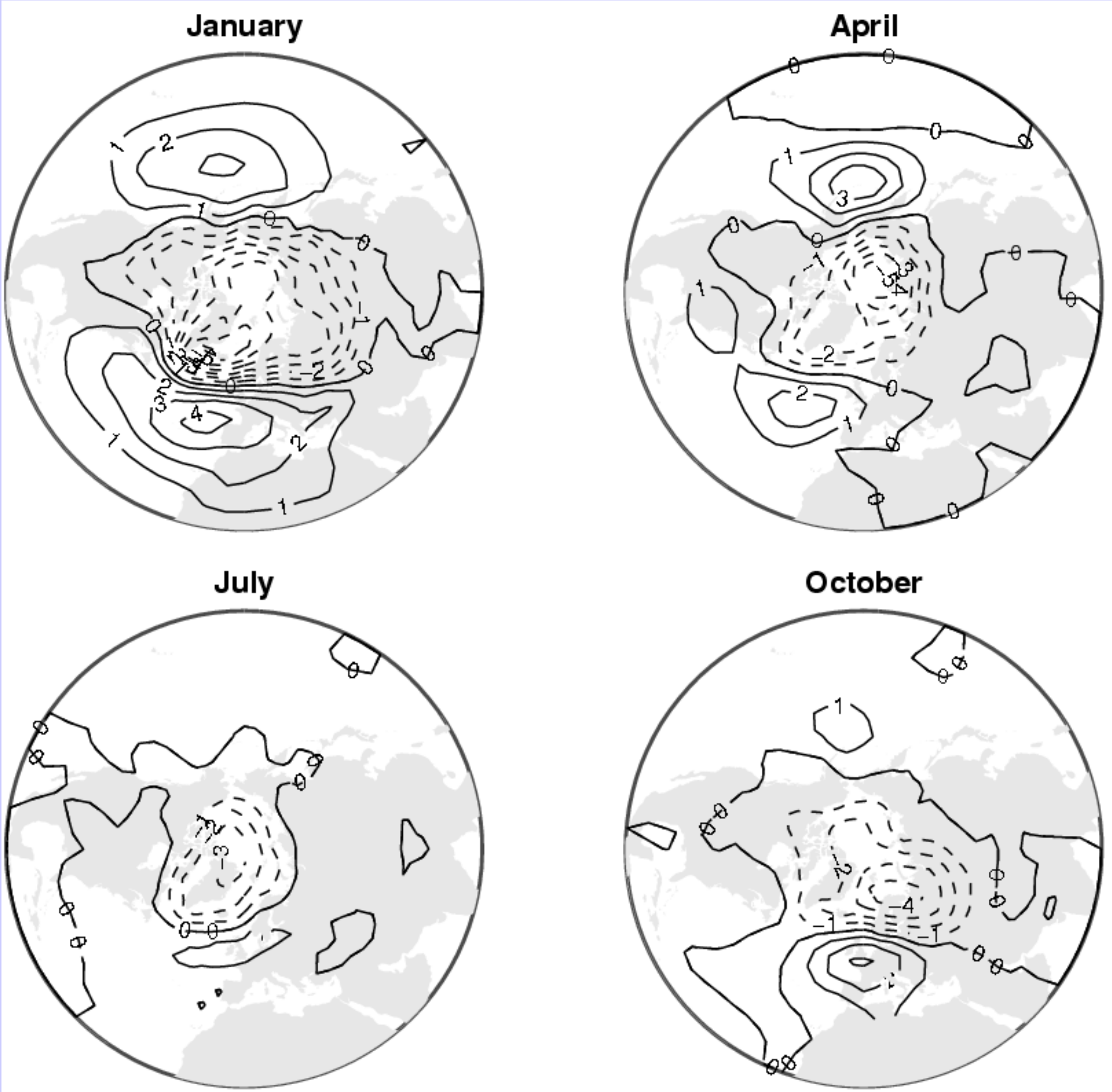
Simulation speed of ~500 years/month on NEC SX6 8 processors.

Pattern nudging test runs: definition of target pattern

EOF1 of monthly NH SLP from NCEP reanalysis

we assume that the amplitude of these patterns can be estimated from proxies

(Widmann et al., 2010)



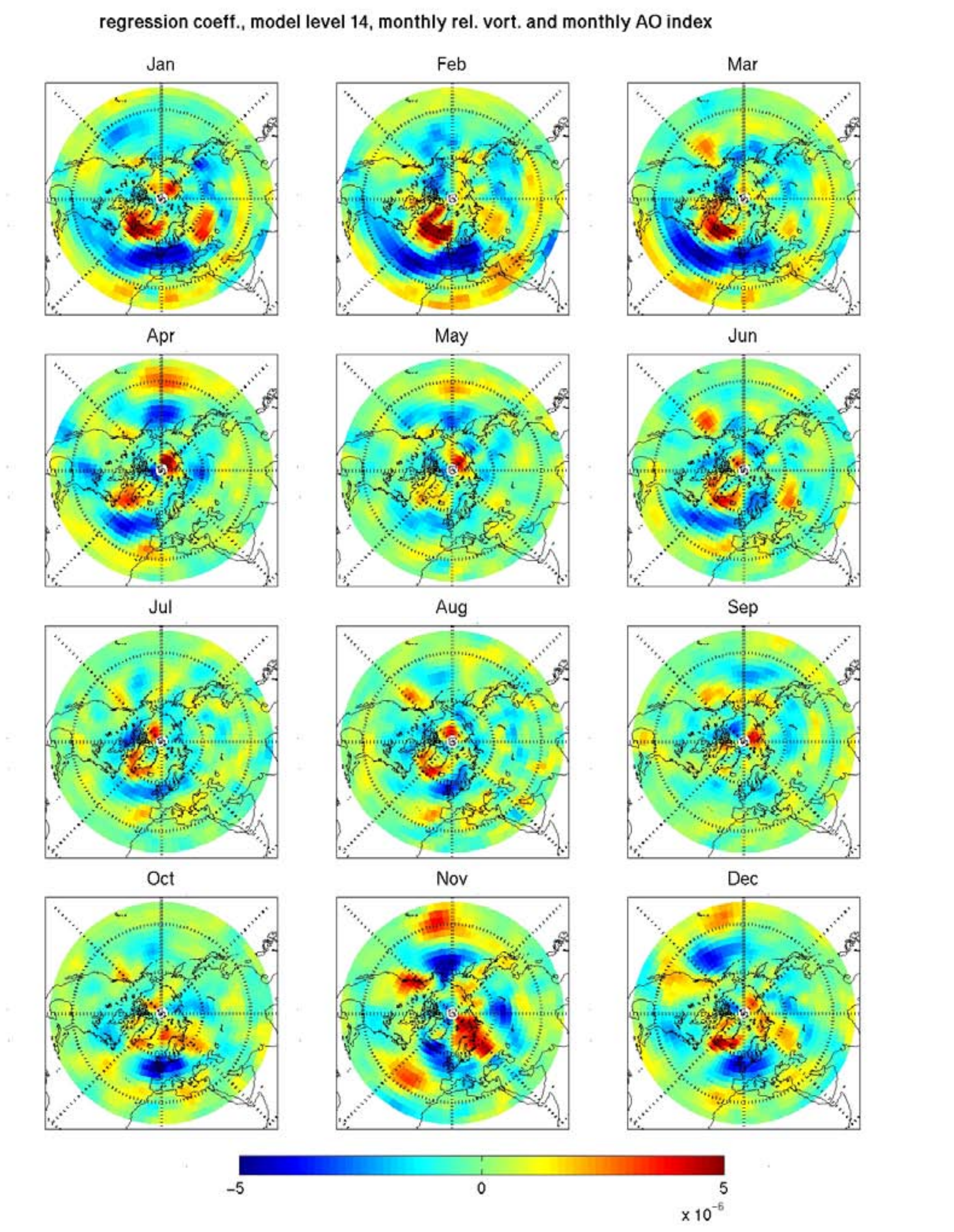
Definition of target pattern

regression of monthly
relative vorticity on
model level 14 (850 hPa)
on SLP PC1 based on NCEP

these are the target patterns

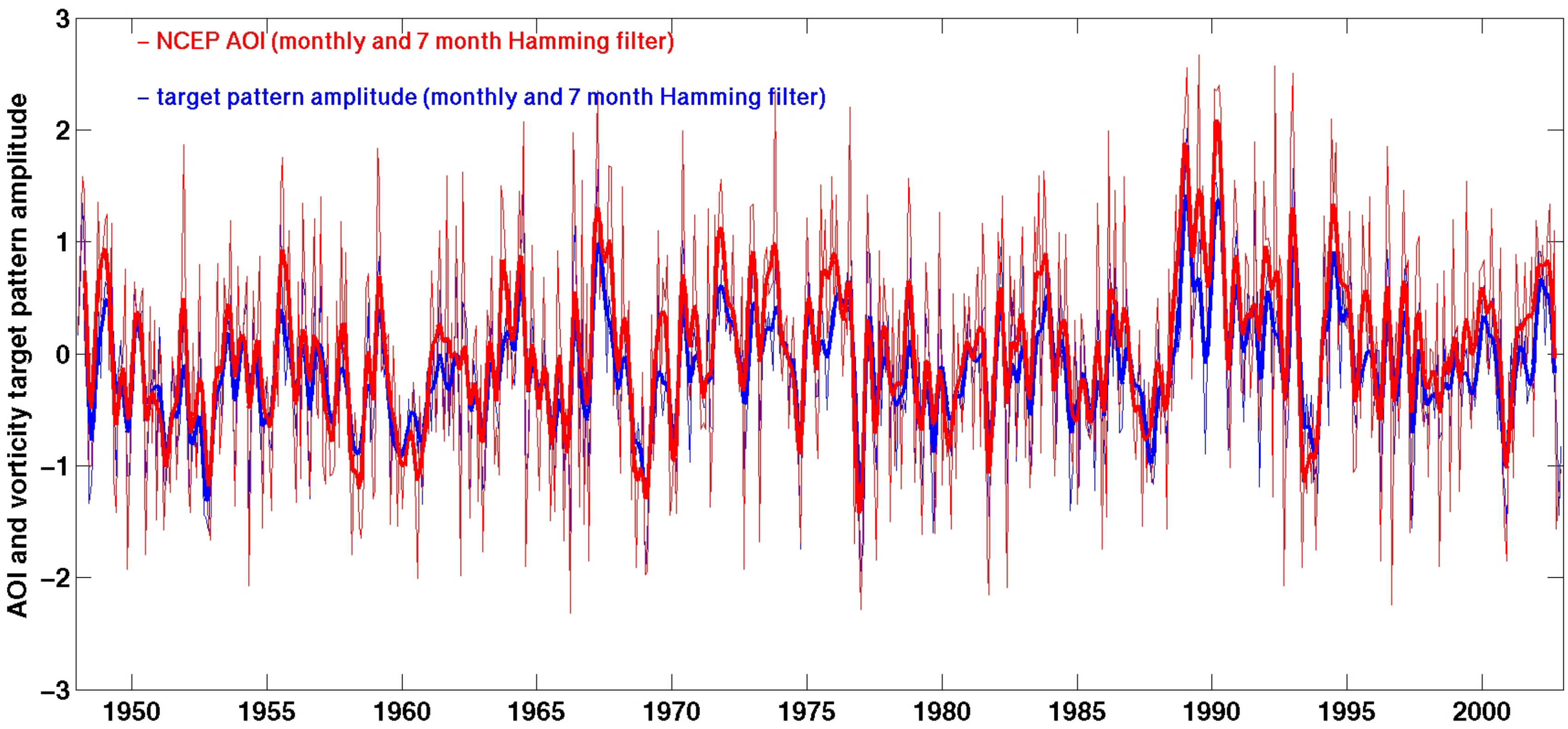
we nudge levels 3-10
950 hPa – 500 hPa

we don‘t want to estimate
this from proxies



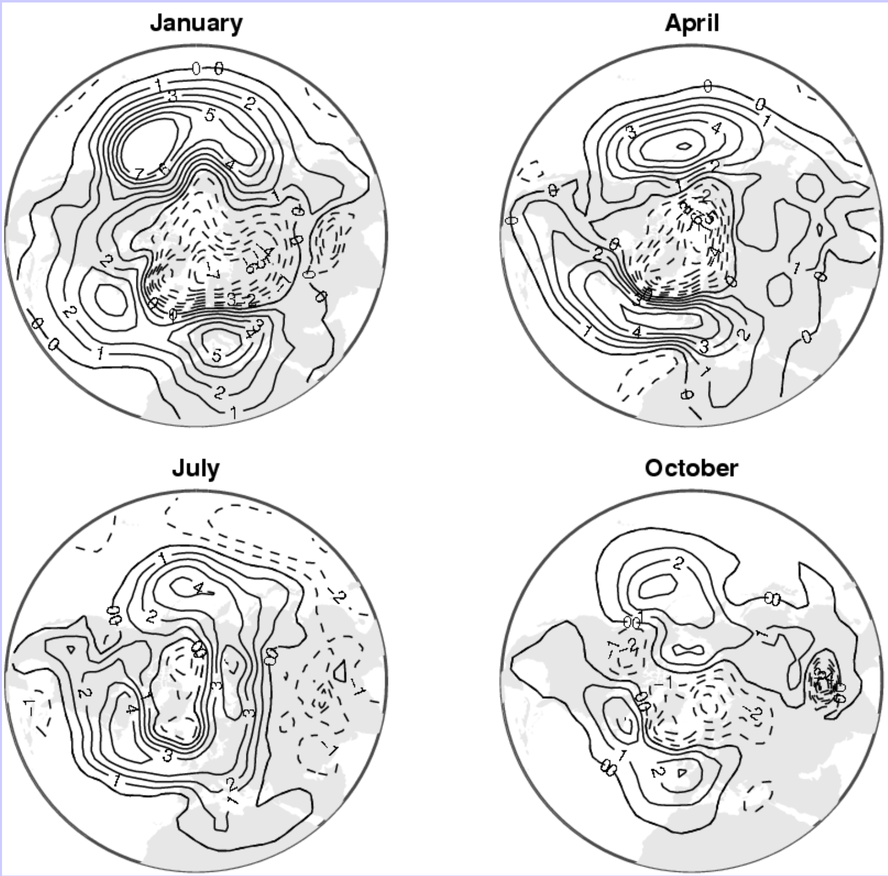
Pattern nudging towards the monthly NCEP AO Index

t_relax = 24 h

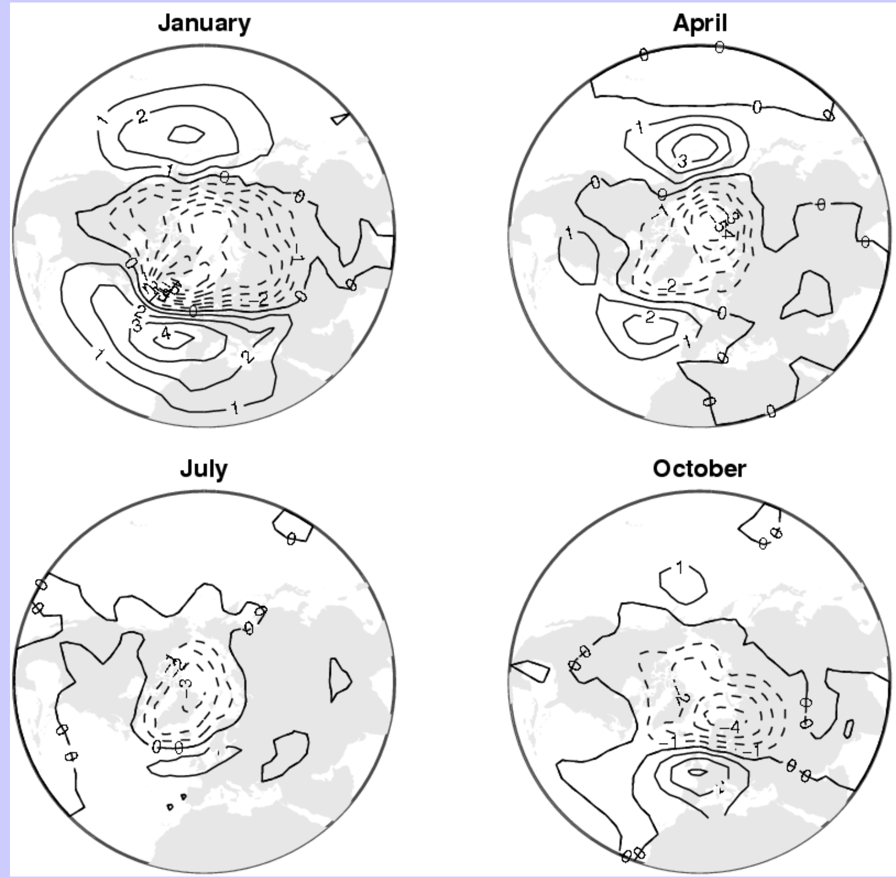


SLP response and EOF1

response (target AOI = 2)



SLP EOF1 (AOI = 1)

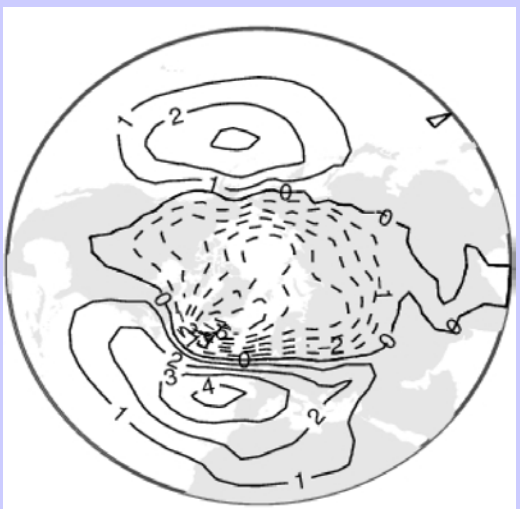


potential reasons for differences:
vorticity nudging is not perfect, EOF not situation,
sampling, model bias

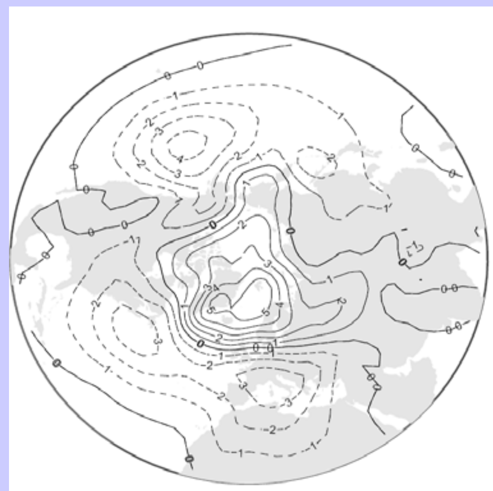
SLP and temperature response

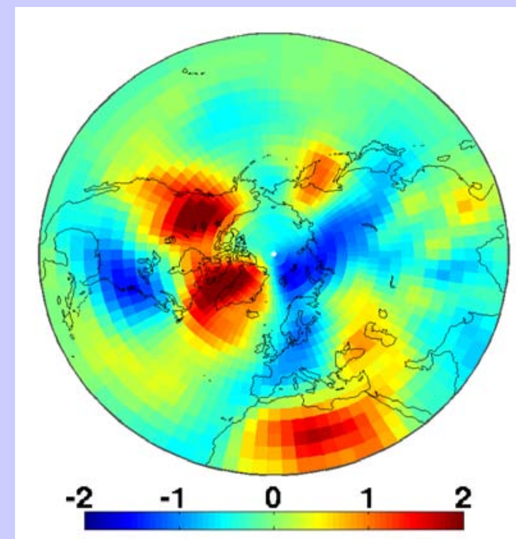
Nudging towards negative NAM index

Winter SLP EOF1



Simulated SLP and temp. anomaly (NAM index -2)



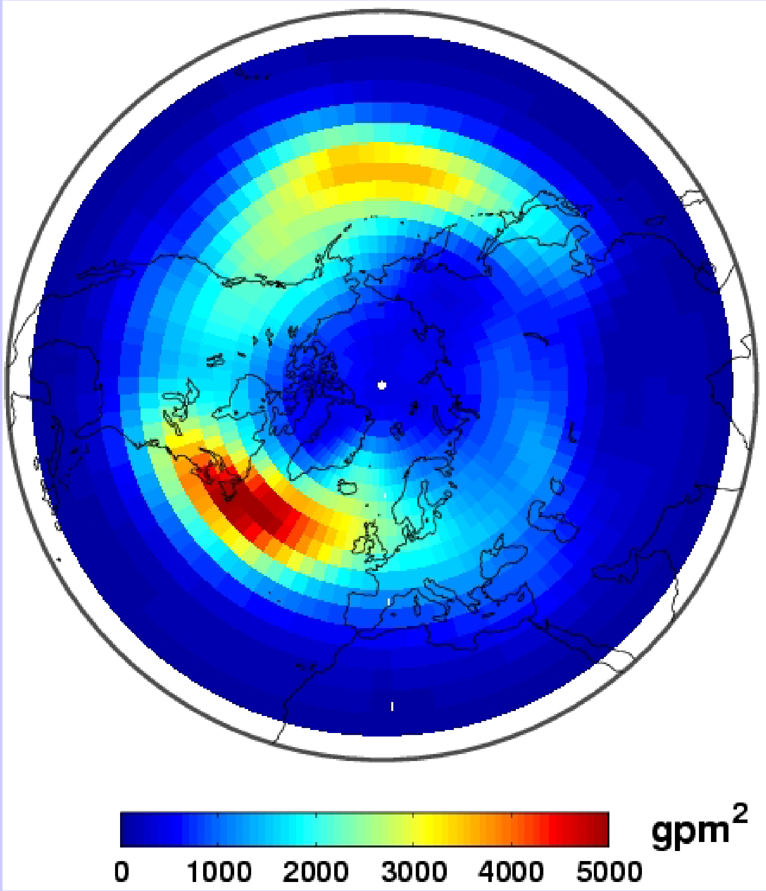


(Widmann et al., 2010)

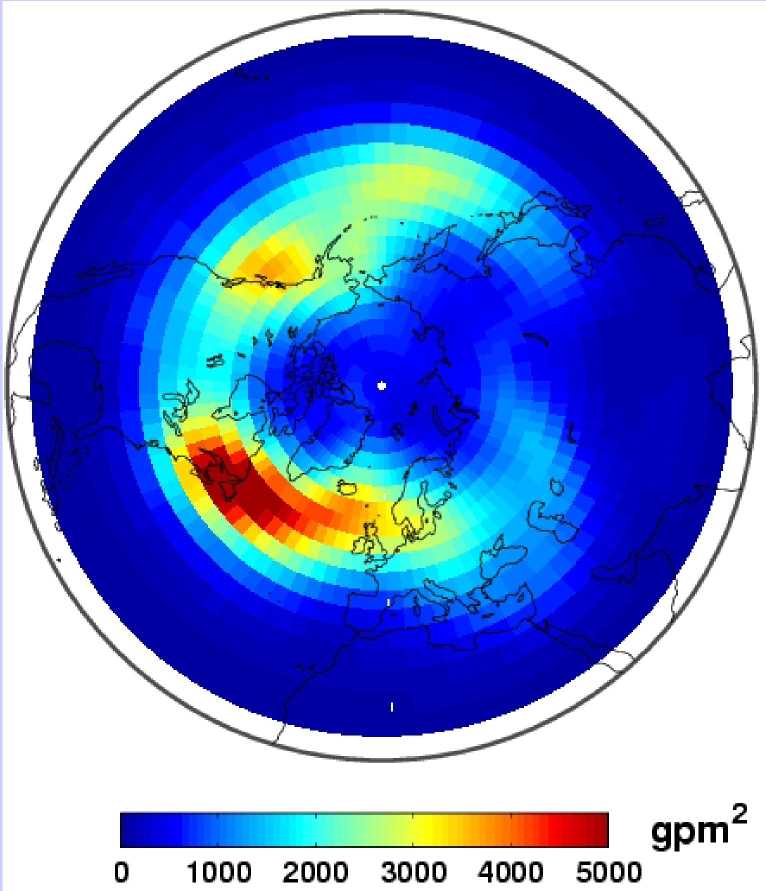
Stormtracks (DJF) with and without nudging

7y, t_relax = 12 h, mean TEC = 1.8
variance of 2.5d-6d bandpass filtered Z500

no nudging



with nudging



Summary for the 3 methods presented

Methods for assimilation of palaeodata exist for EMICs and GCMs, results are encouraging.

They are simpler and less mathematically rigorous than standard DA methods and do neither provide optimal state estimates nor uncertainties.

Forcing Singular Vectors and Pattern Nudging deal with time-averaged empirical information in an unclean way.

Ensemble Member Selection and particle filter are closest to the standard framework.

Unrealistic model mean and variability causes problems.

No systematic method intercomparison yet.

Challenges and questions (version 1)

Can EnKF be adapted to assimilate time-averaged information?
(talk by Greg Hakim)

Is EnKF or particle filter preferable for assimilation of time-averaged information (non-linear dynamical system)?

Is particle filter feasible with full-complexity GCMs?

How well is the observation operator known and how stable is it in time?

Is DA based on forward modelling always preferable to assimilating information from upscaling/inverse modelling?