Inverse Climate Modelling

Walter Acevedo Valencia

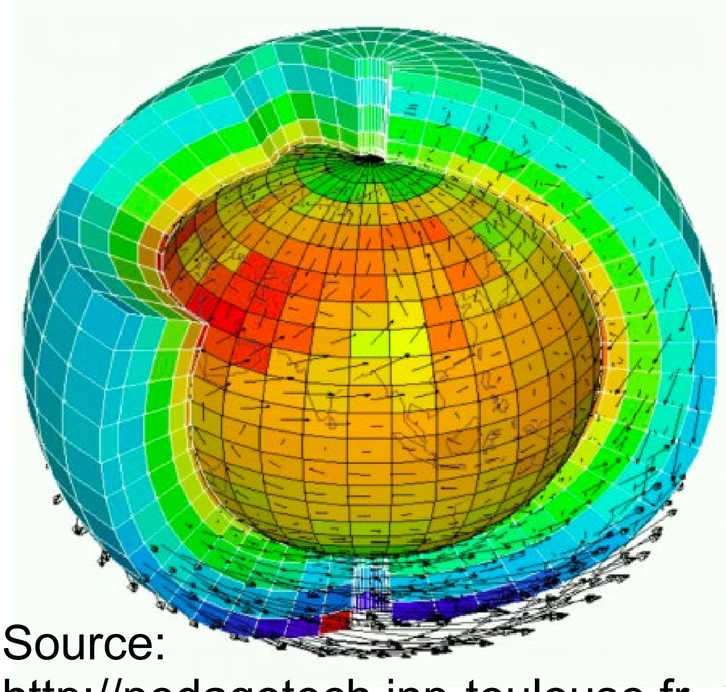
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Scientific study approaches

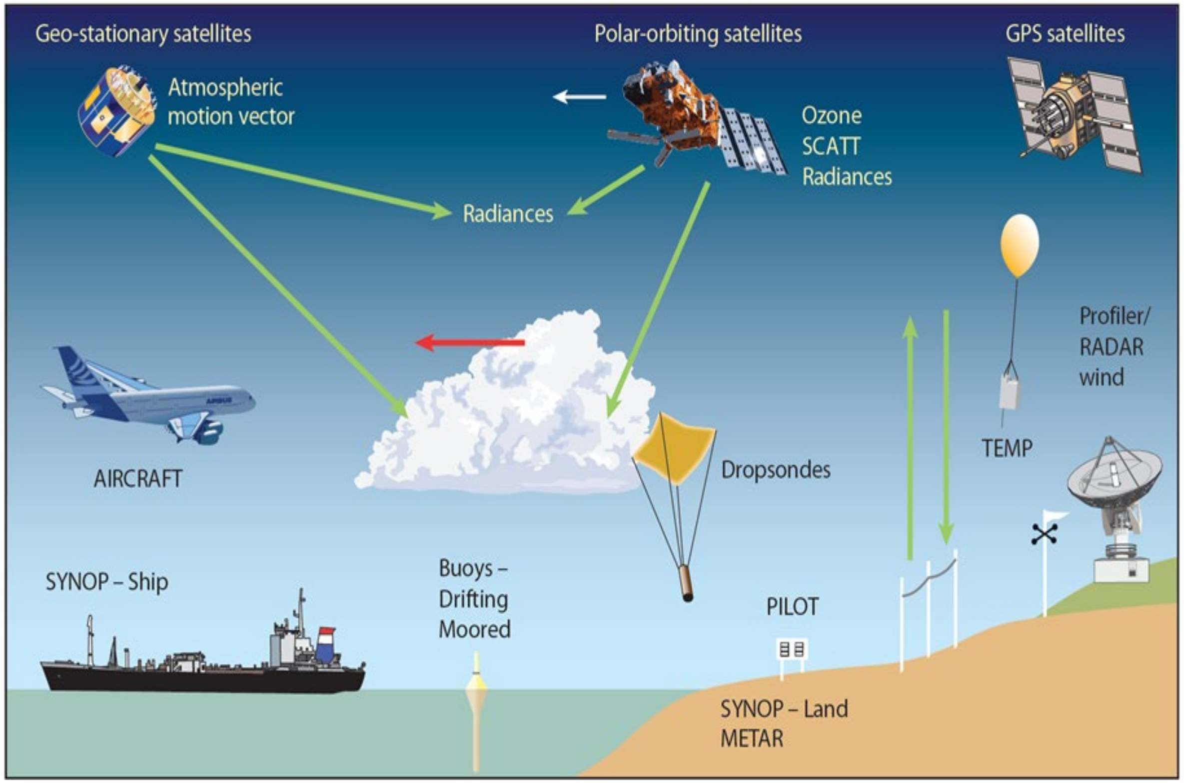
Forward Problem

Model space

Data space



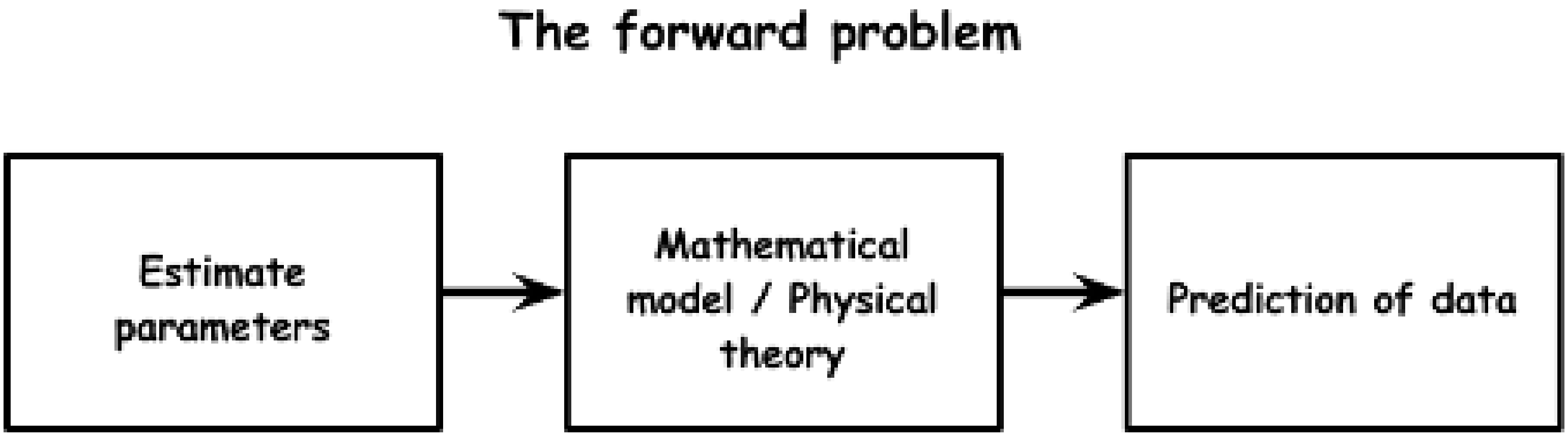
Source: http://pedagotech.inp-toulouse.fr



Source:http://www.ecmwf.int/en/research

Inverse Problem

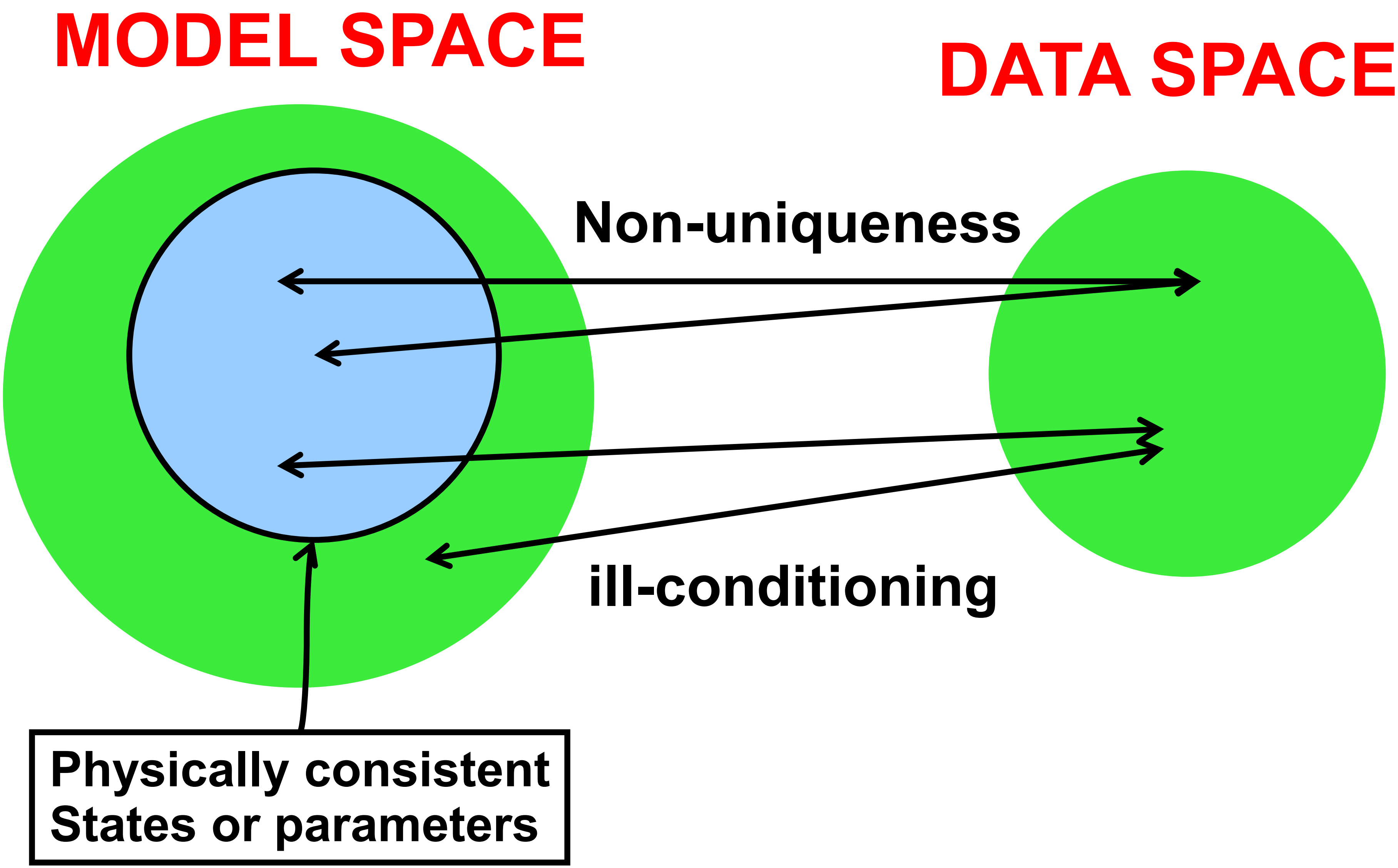
Scientific study approaches



Outline

- Introduction
- Inverse Problem
- Model optimization
- State estimation
  - Weather forecasting
  - Reanalysis
  - Paleo-Reanalysis

Inverse modeling challenges



Bayes Theorem

Likelihood
Probability of collecting this data when our hypothesis is true

Bill Howe, UW

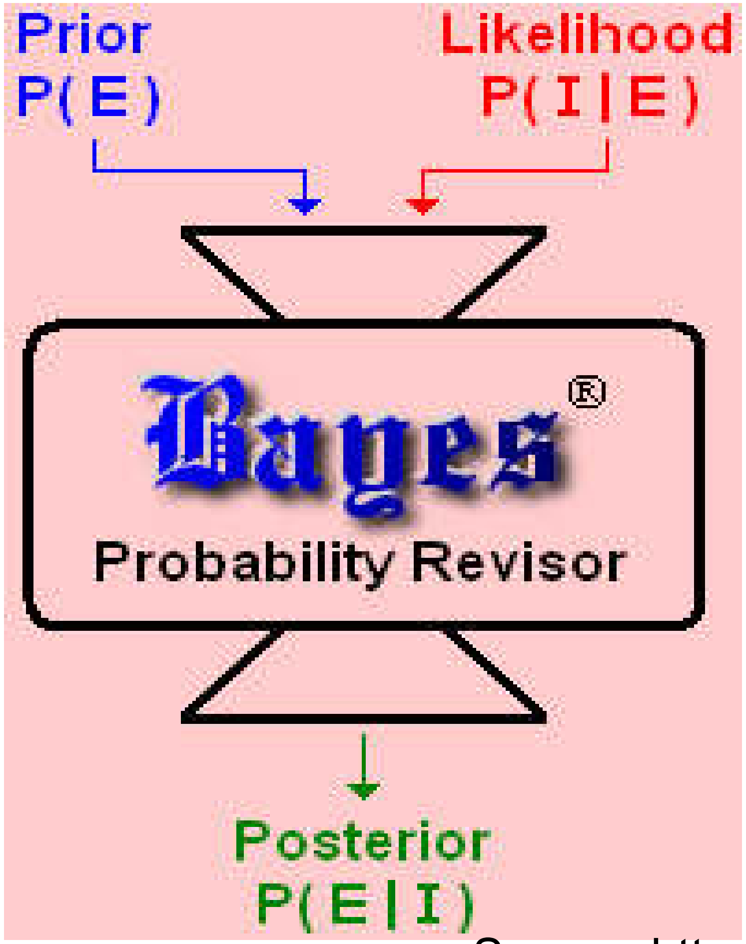
Prior
The probability of the hypothesis being true before collecting data

$$P(H|D) = \frac{P(D|H)\,P(H)}{P(D)}$$

Posterior
The probability of our hypothesis being true given the data collected

Marginal
What is the probability of collecting this data under all possible hypotheses?

Bayes Theorem



See DART tutorial section 1

Source: http://decmod.diegoazeta.org

Main atmospheric Inverse Problem

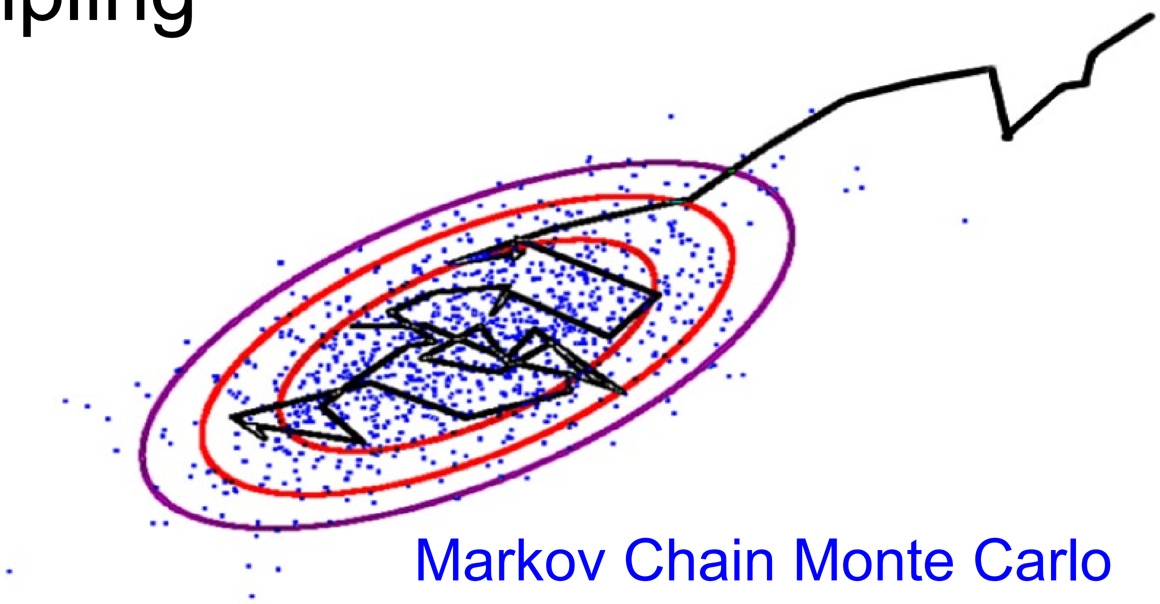
APPLICATION	MODEL SPACE	DATA SPACE
DATA ASSIMILATION	Model State	Current Observations
MODEL TUNING	Model Parameters	Observational Climatology

Model Optimization

Model Optimization

Strategies to sample the parameter Space

- Regular grid
- Random Sampling
- Importance Sampling



Markov Chain Monte Carlo

Tuning a Tree-ring Growth Model

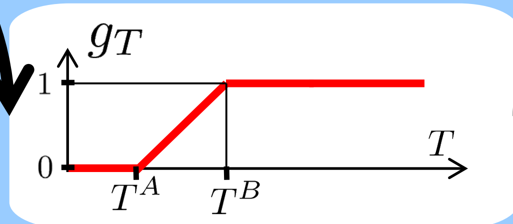
VS-Lite Scheme

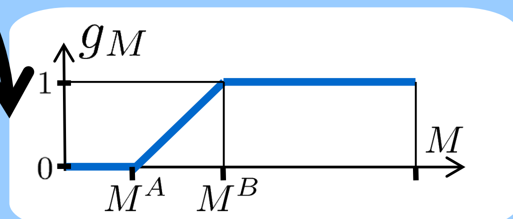
Surface Temperature

Soil Moisture

Sunlight

Response functions





I : Solar Irradiation

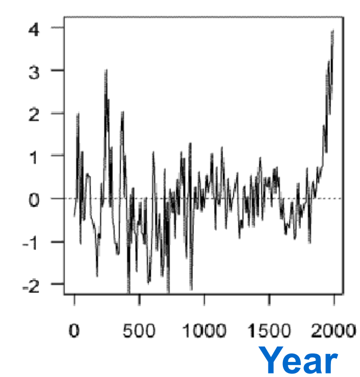
Limiting factors principle

$$g = \min(g_T, g_M)$$

Tree-ring Width

$$TRW_n = \int_{t_n - \tau_{ta}}^{t_n} g(t) \cdot I(t)\ dt$$

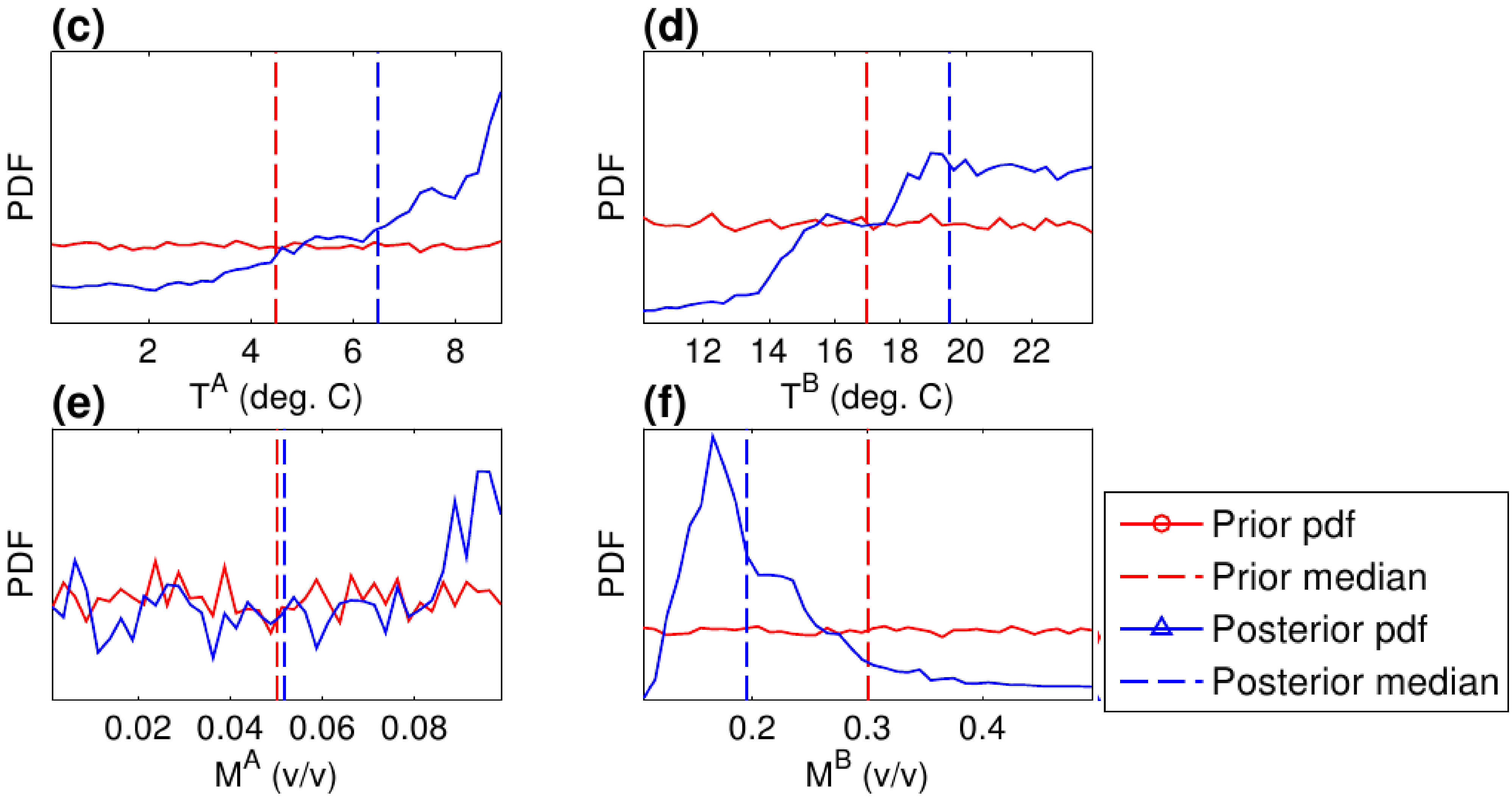
Standardization



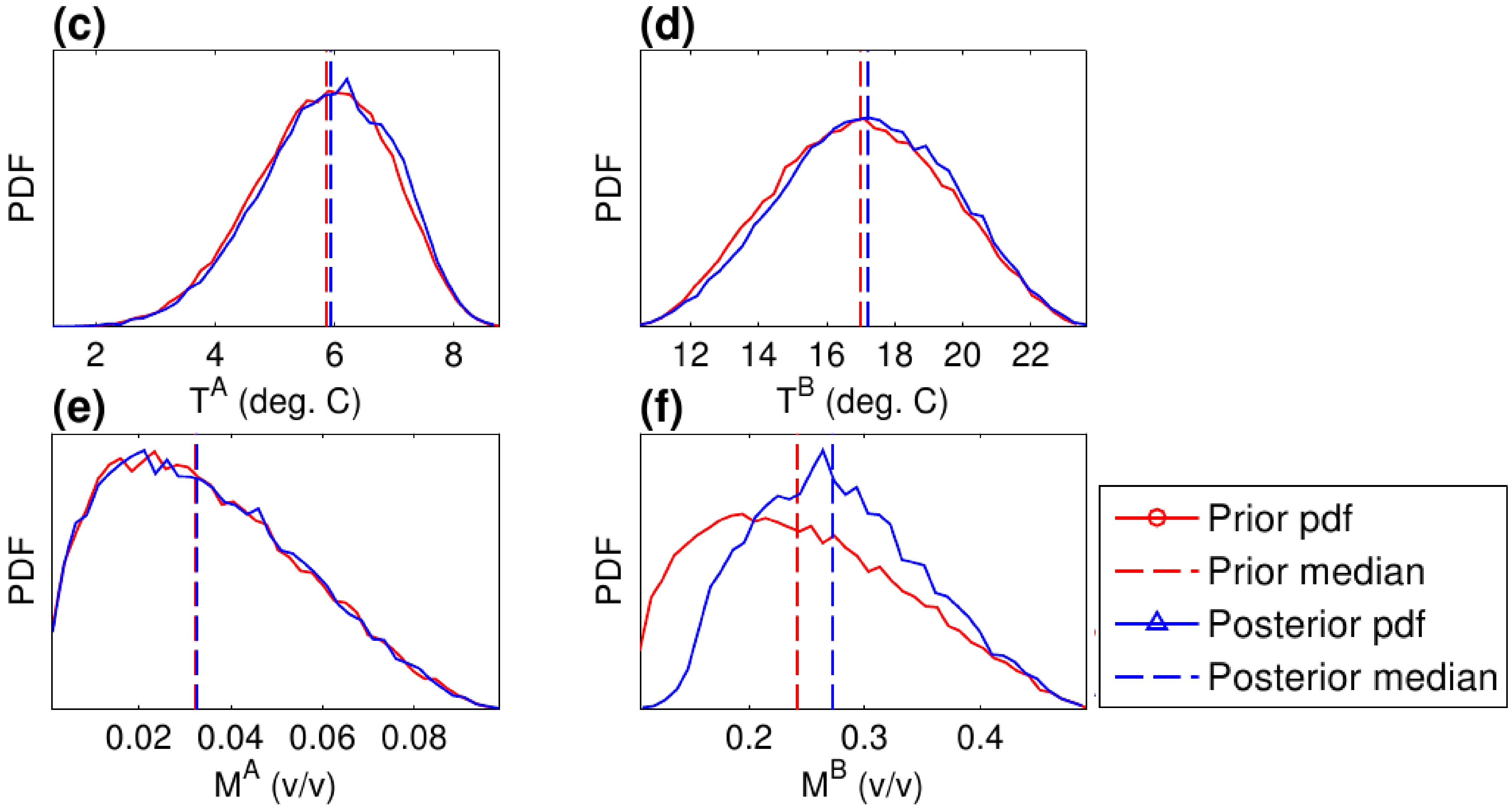
Simulated Tree-ring-width Chronology

Ring-

Model tuning with non-informative prior



Model tuning with informative prior



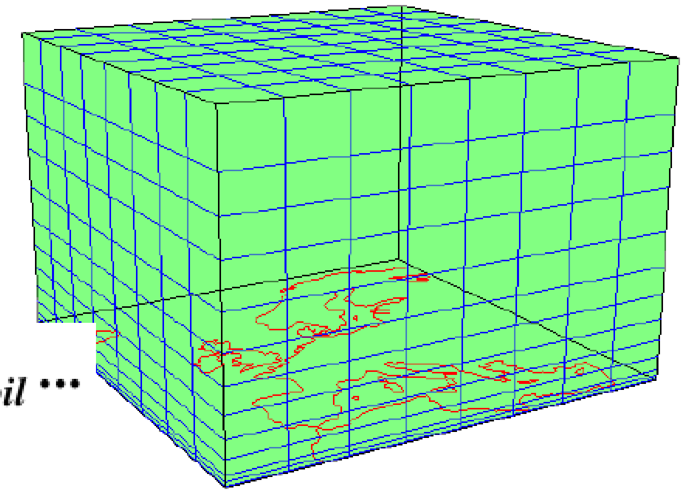
State Estimation

Atmosphere state estimation problem

Equations

Navier–Stokes equations on a rotating sphere with energy sources (radiation, latent heat).

Typical Regional model grid



Typical Model variables

$u, v, T, q, p_s \quad q_{sfc}, T_{sfc}, w_{snow}, T_{snow}, w_{soil}, T_{soil} \ldots$

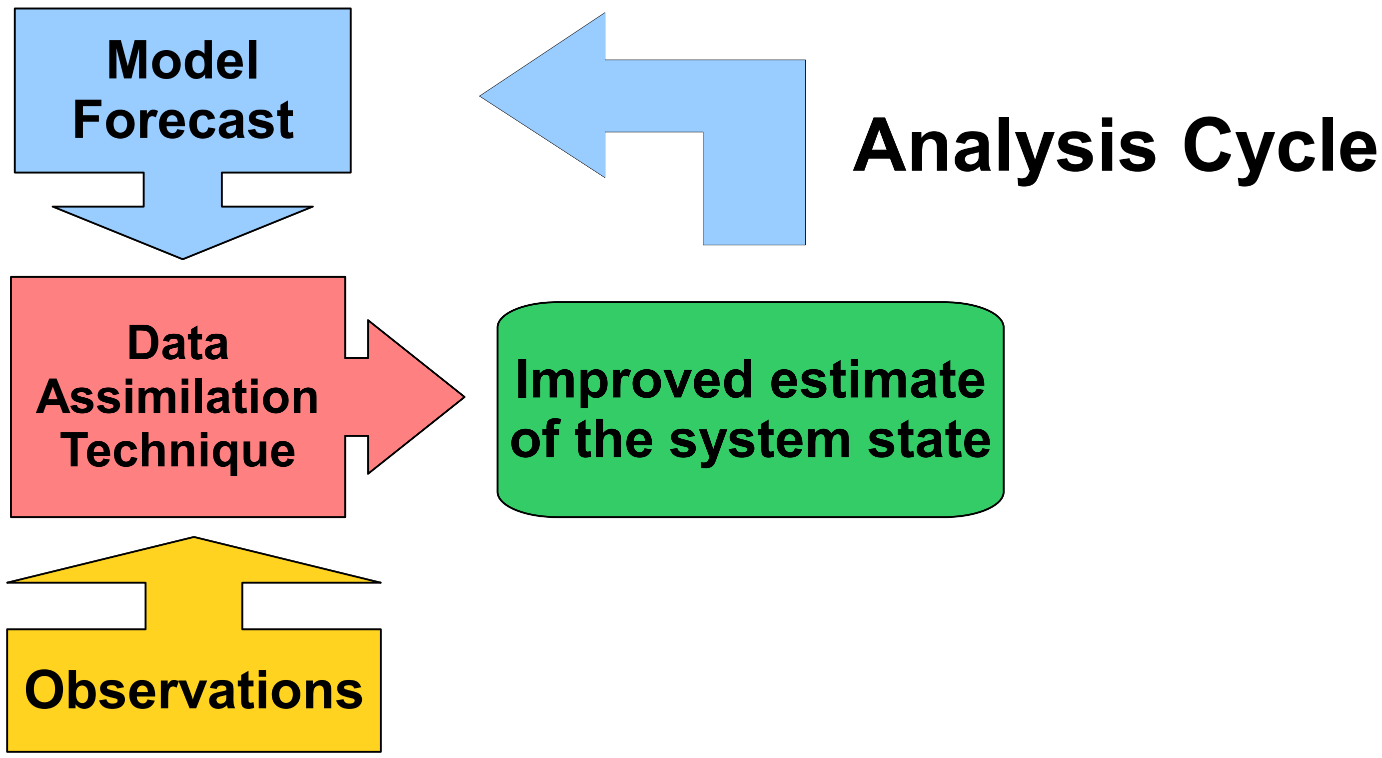
Facts:

- Both predictions and measurements are uncertain
- Models are high-dimensional (# degrees of freedom ~ 10^7)
- Obs. are irregularly distributed and sparse (Obs # ~ 10^4)

Based only on observations the atmospheric state estim

Atmosphere state estimation problem

Solution: Use a first guess or background field
(e.g. climatology or previous short-range forecast)



Data Assimilation Rationale

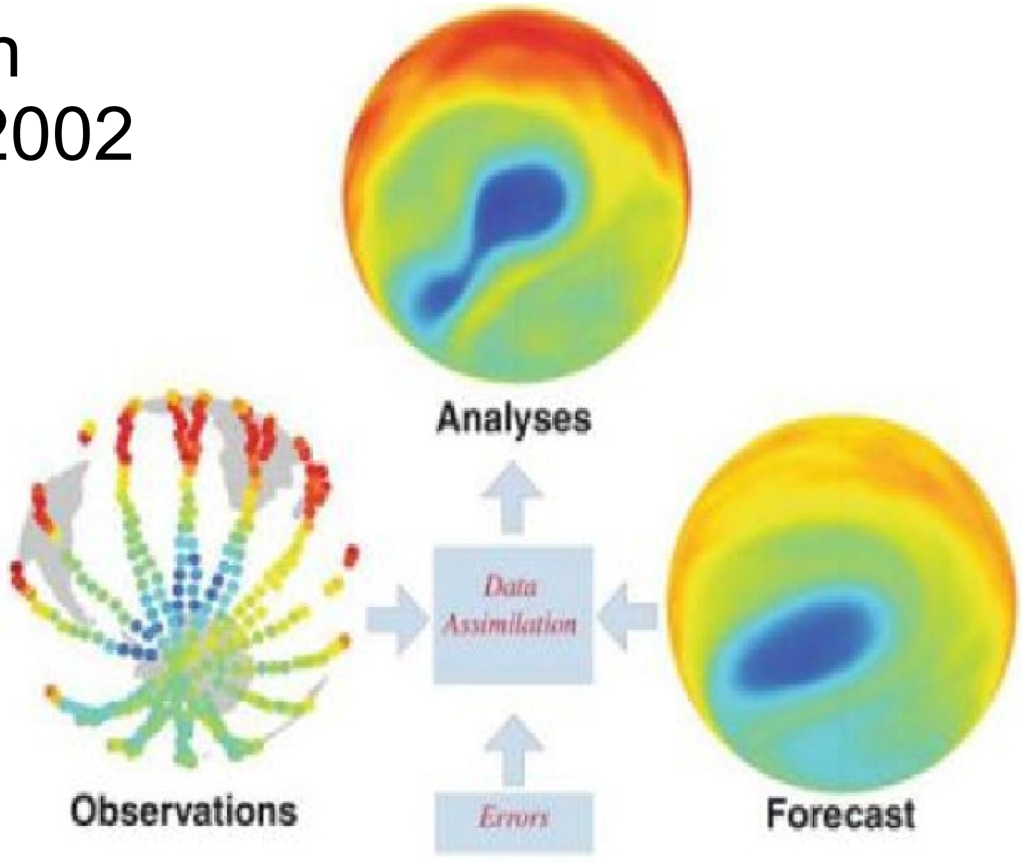
- Merge instrumental data and model output via an analysis cycle, so as to provide a complete estimate of the state of the system.
- As time goes by, observational information accumulates and propagates to unobserved variables and geographical areas of the model.

Main applications:

- Meteorological Forecasting
- Process-based Climate Reconstructions “Reanalyses”

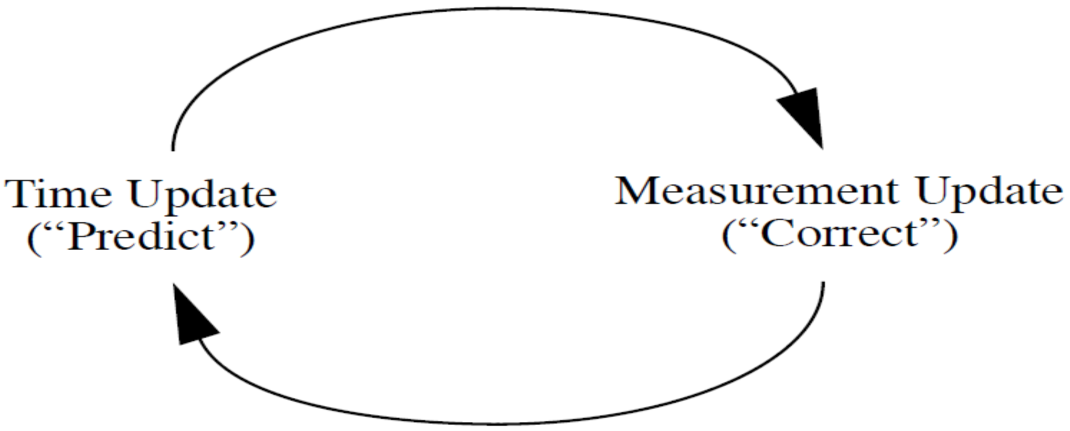
Data Assimilation Rationale

Nice example:
Ozone Concentration
at 10 hPa on 23.09.2002
(Lahoz 2010)

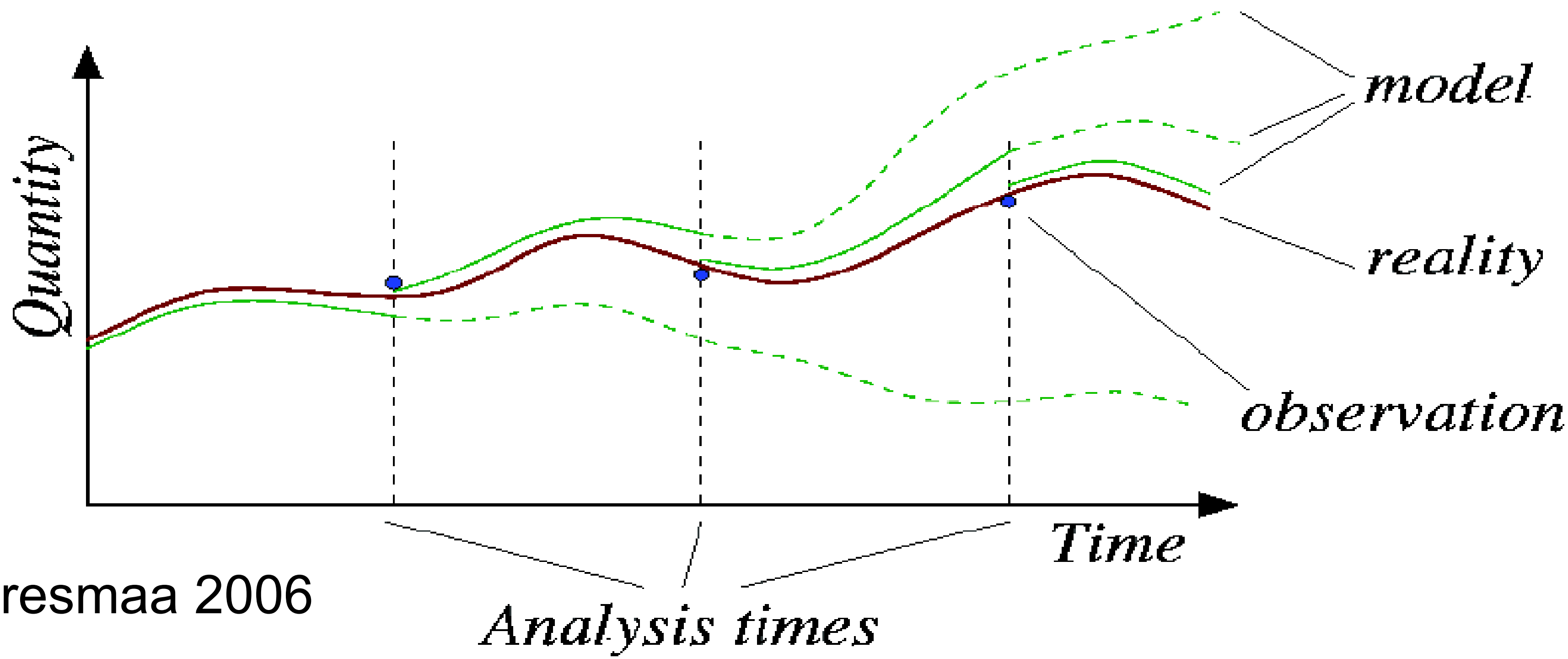


Weather Forecasting

Analysis cycle



Without observational input the forecast drifts away from the actual state of the system.



Eresmaa 2006

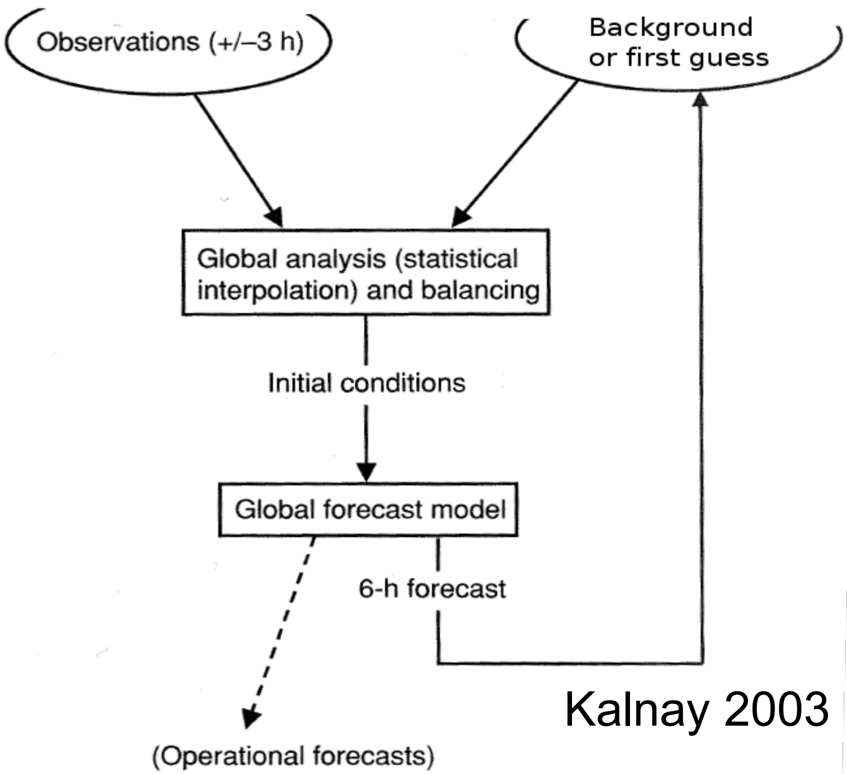
Non-linearity and predictability

Lorentz model

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \sigma(y - x),$$
$$\frac{\mathrm{d}y}{\mathrm{d}t} = x(\rho - z) - y,$$
$$\frac{\mathrm{d}z}{\mathrm{d}t} = xy - \beta z.$$

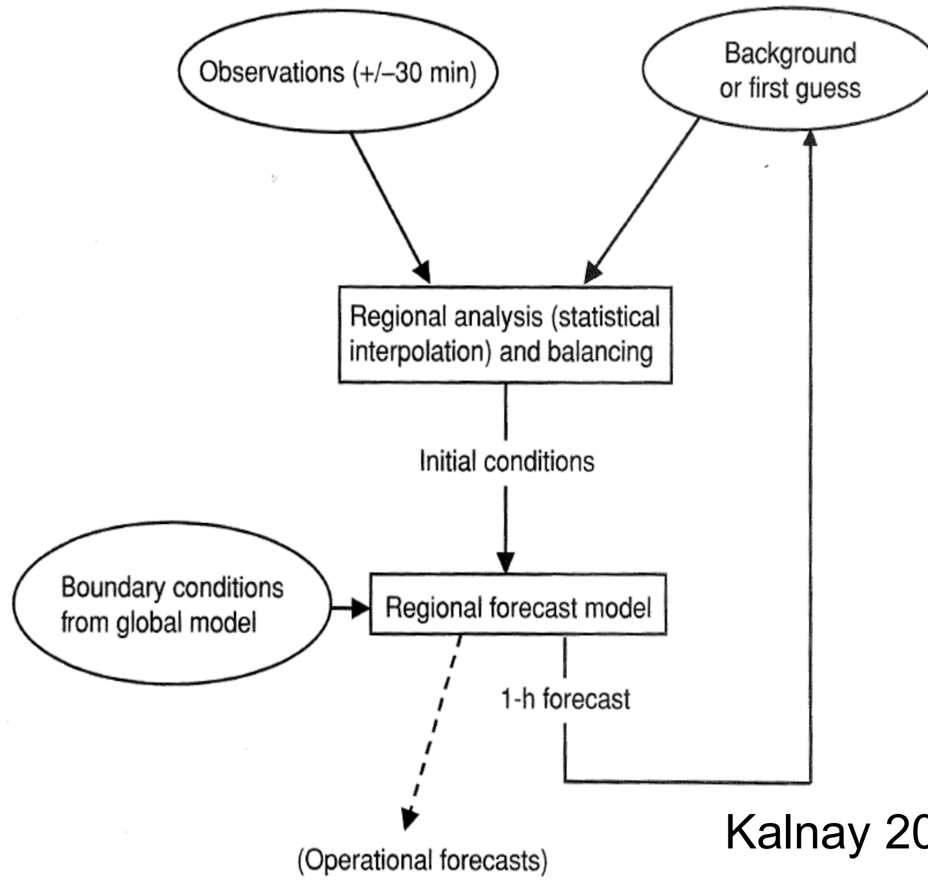
Attractor for $\sigma = 10$, $\beta = 8/3$ and $\rho = 28$.

Typical Operational Analysis cycles



Kalnay 2003

Typical Global Analysis Cycle



Kalnay 2003

Typical Regional Analysis Cycle

Main types of DA techniques

- **Empirical Schemes**: Interpolation, SCM and nudging

Affordable and direct but hardly consider uncertainties.

- **Sequential methods**: OI and Ensemble Kalman Filters

Handle well uncertainties but are expensive and complex

- **Variational strategies**: 3D-Var, 4D-Var and PSAS

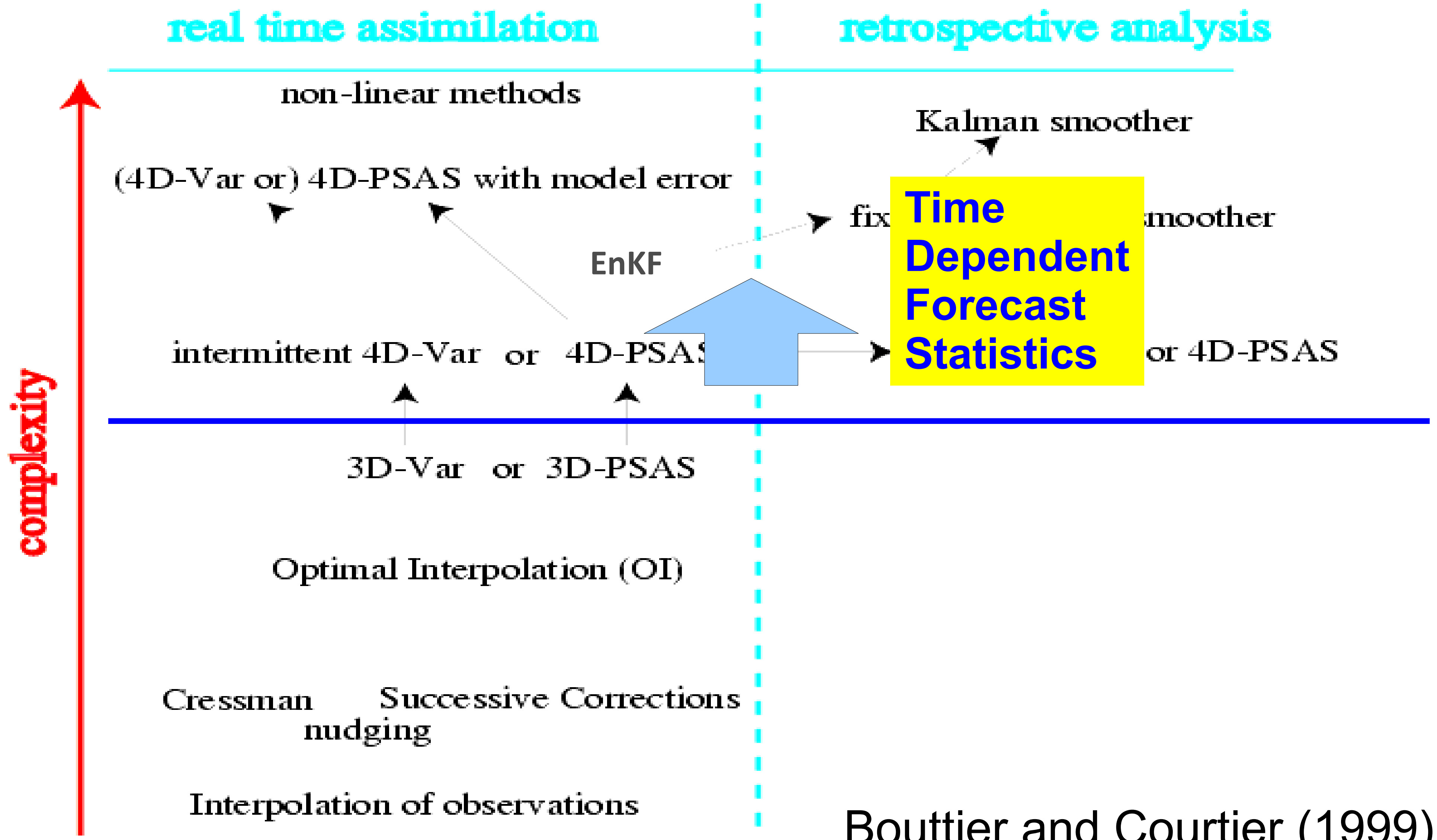
Similar conditions as Seq. Methotds but

Tangent linear model is **HARD** to implement

- **Hybrid techniques**
- Try to take the best of each approach. Quite complex

Flow dependent background errors are always desirable but make everything much more complex and expensive

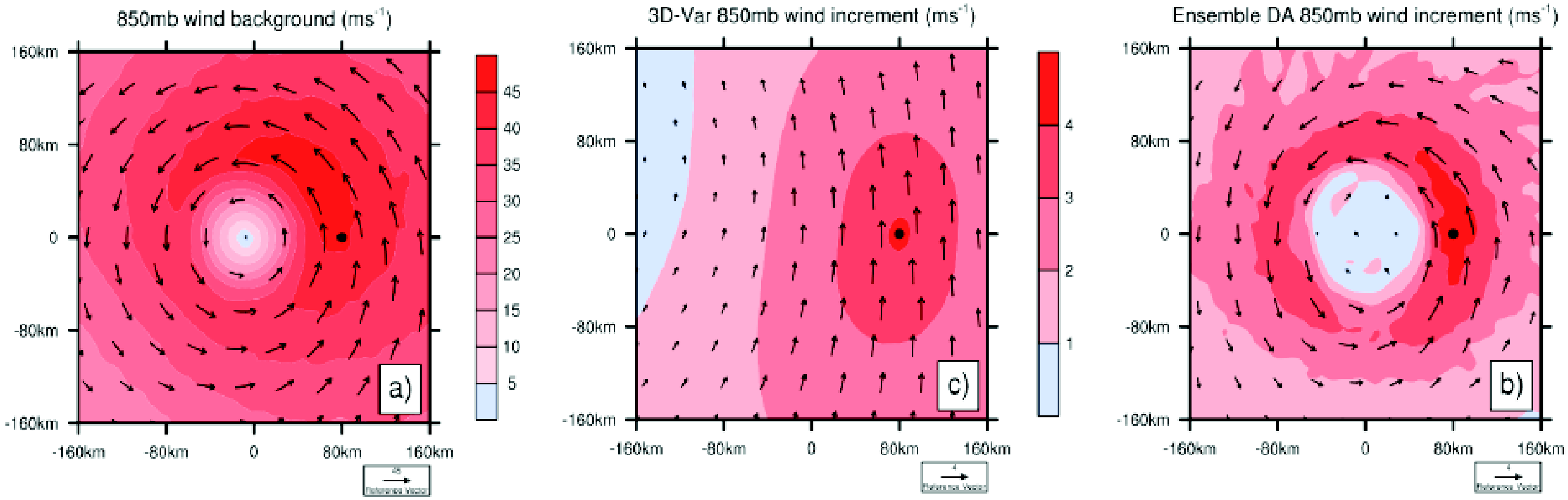
A summarized history of data assimilation



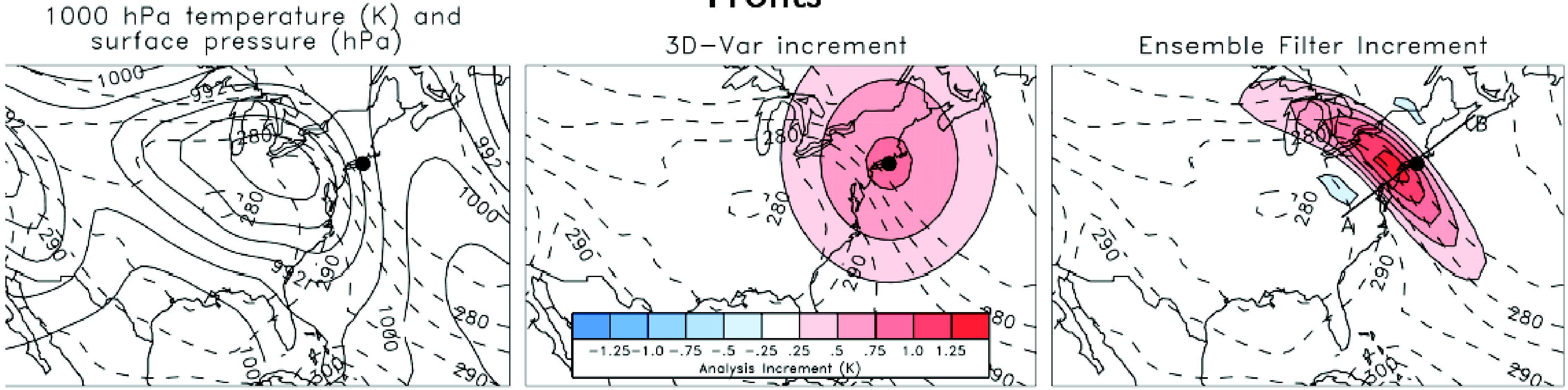
Bouttier and Courtier (1999)

Benefits of time-dependent forecast stats

Hurricanes

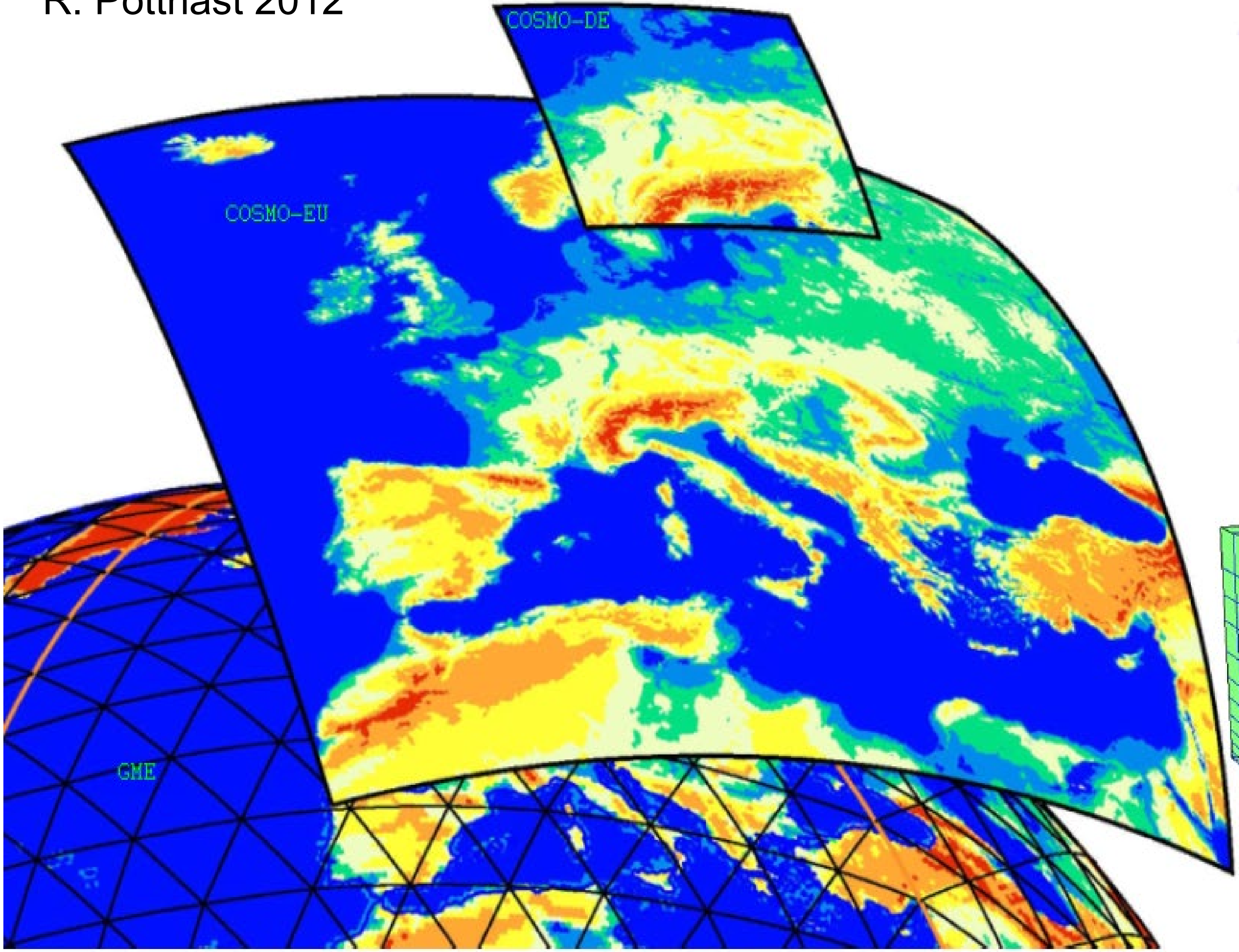


Fronts

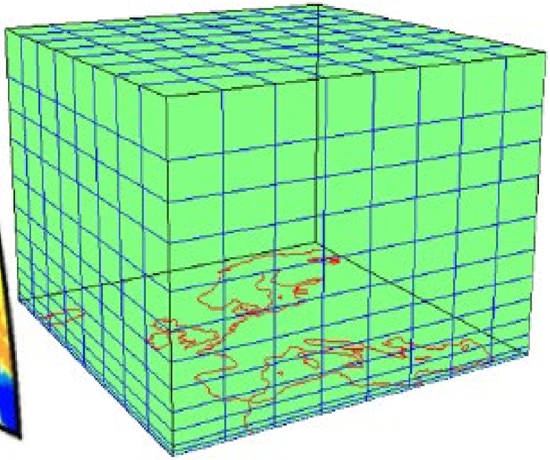


DWD Numerical Weather Prediction system

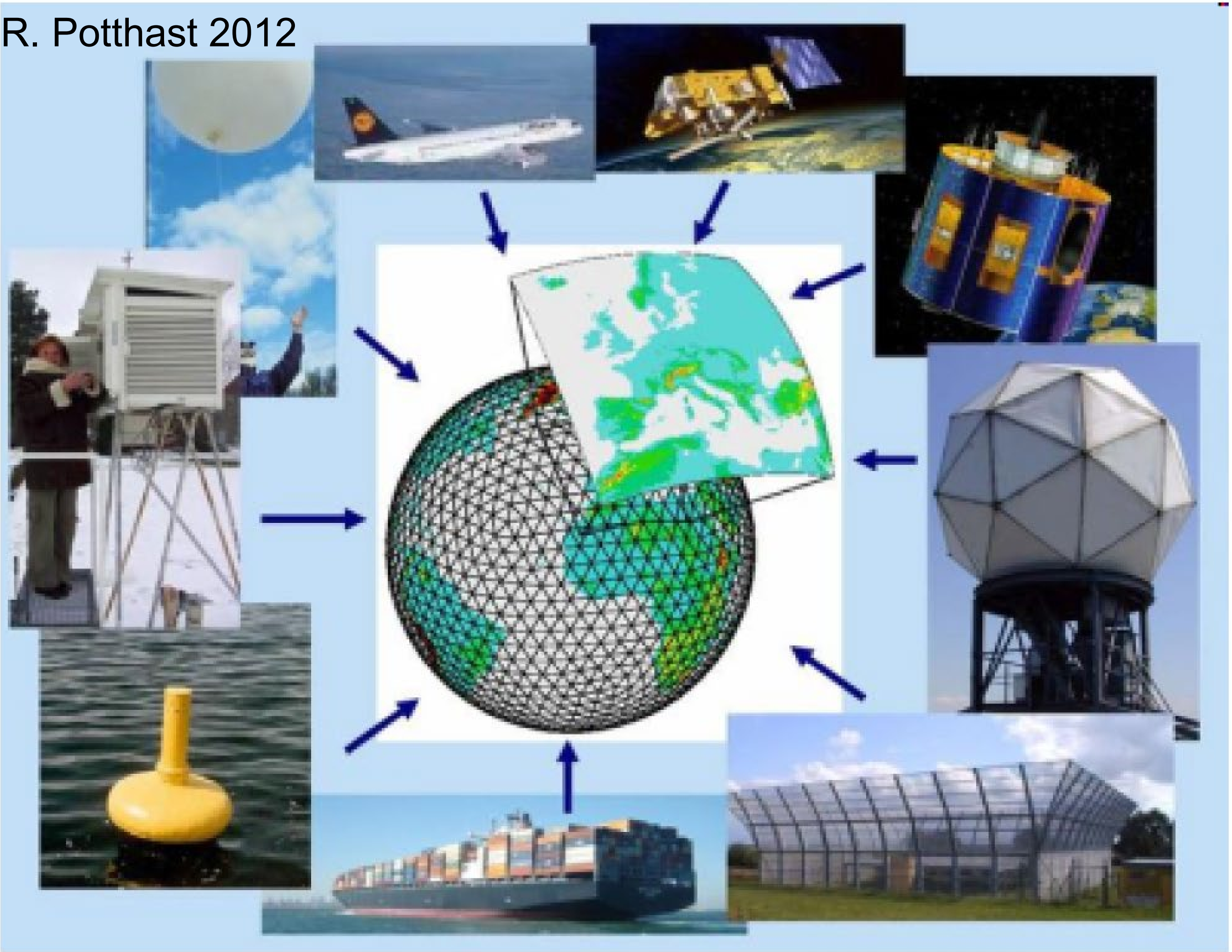
R. Potthast 2012



- GME/ICON
  Resolution 20km
- COSMO-EU
  Resolution 7km
- COSMO-DE
  Resolution 2.8km



DWD observation sources



Synop, TEMP, Radiosondes, Buoys, Airplanes, Radar, Wind Profiler, Scatterometer, Radiances, GPS/GNSS, Ceilometer, Lidar

Models and assimilation systems at DWD

Present :

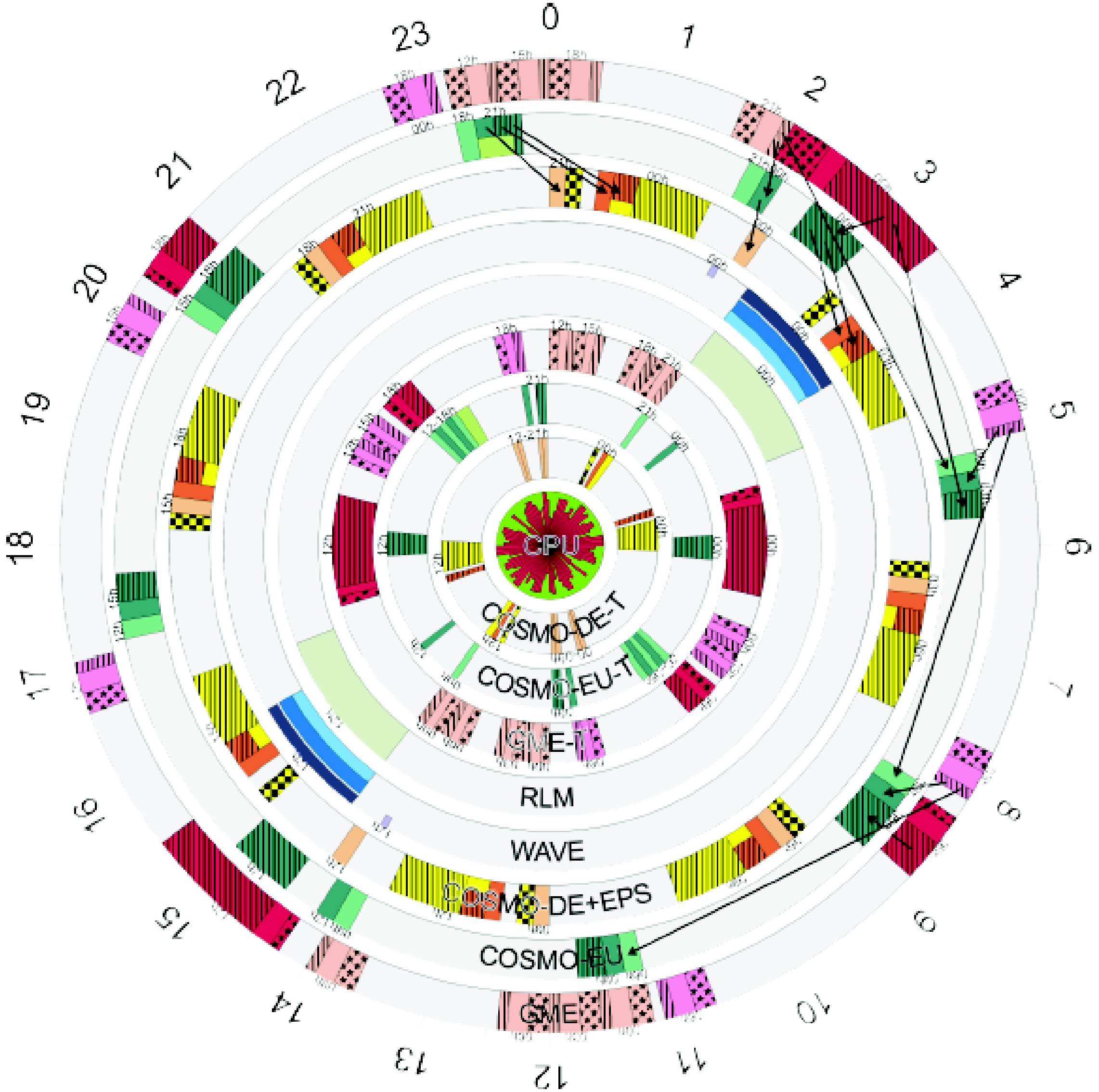
GME	global	30 km	3D-Var–PSAS
COSMO-EU	regional	7 km	Nudging
COSMO-DE	regional	2.8 km	Nudging, Latent Heat Nudging

Future :

ICON	global, regional refinements		Hybrid 3D-Var/EnKF
COSMO-DE	regional	convective scale	LETKF

A. Rhodin 2012

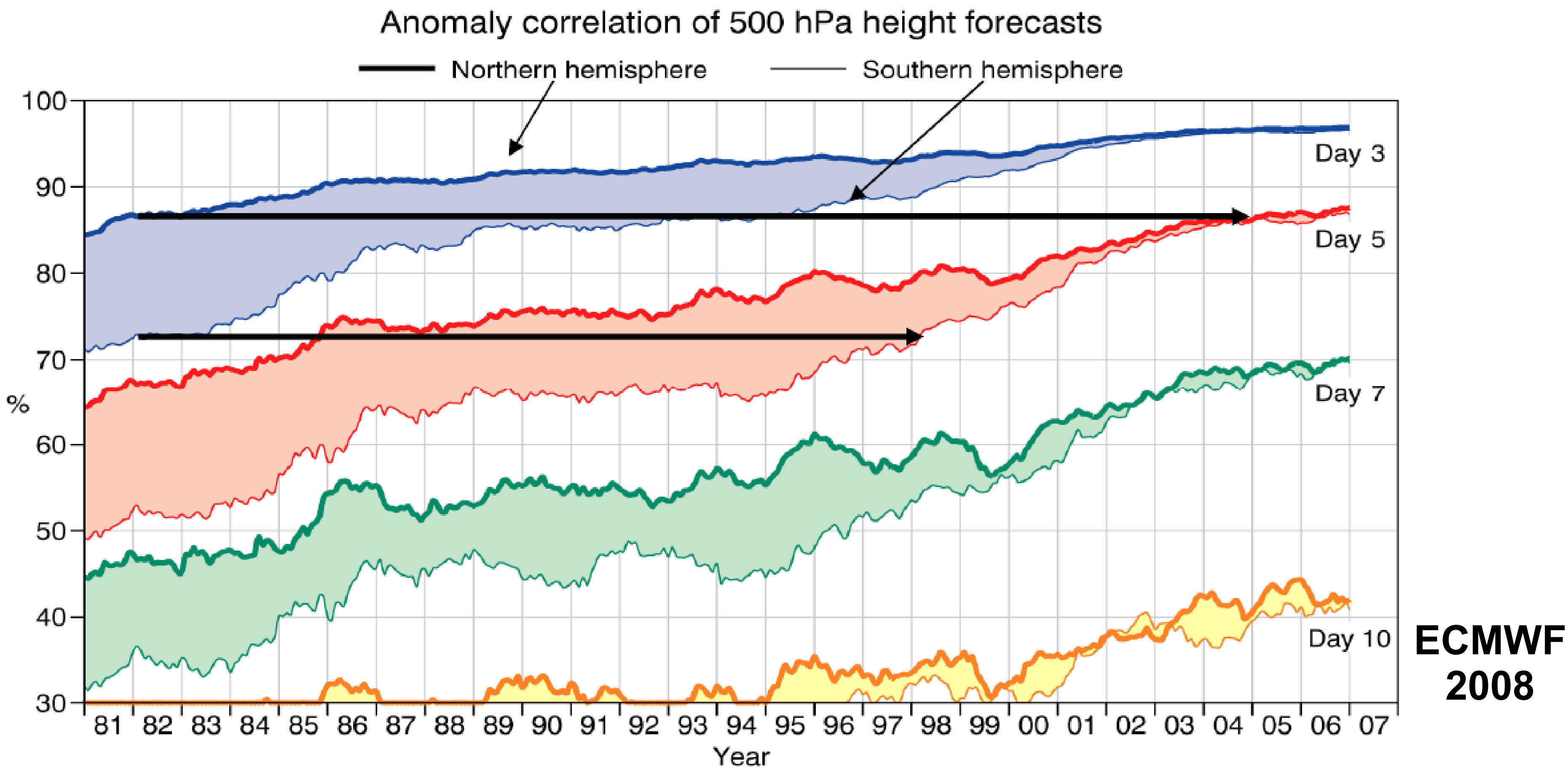
DWD operational cycle



Operational timetable of the DWD model suite with dataflow

	GME, COSMO: Analysis / Nudging
	GME Analysis: serial part
	GME, COSMO: Forecast
	COSMO-DE-EPS: Interpolation
	WAVE (GSM, LSM, MSM)
	COSMO-EU: Surface moisture analysis
	Main run
	Pre-Assimilation
	Assimilation
00..23	real time [UTC]
00h, 03h, ..	model time [UTC]
T	Testsuite

Forecast skill at ECMWF since 1981



- 5 day NH forecast is now better than 3 day forecast in 1981
- SH Forecasts are now nearly as good as NH ones

Reanalysis

Reanalysis Idea

Motivation:

Historical weather analyzes carry plenty of information of the atmospheric state, thus they might be valuable for climate monitoring

but

frequent operational updates introduce inconsistency

Solution:

Reanalyze historical observations using a “frozen” data assimilation scheme and model

Reanalysis Assets

- Provide global data sets with consistent spatial and temporal resolutions
- BIG amounts of obs. (~ 10^6) assimilated
- Incorporates more obs. than forecasting system
- All model variables available.
- Data sets are very user friendly.

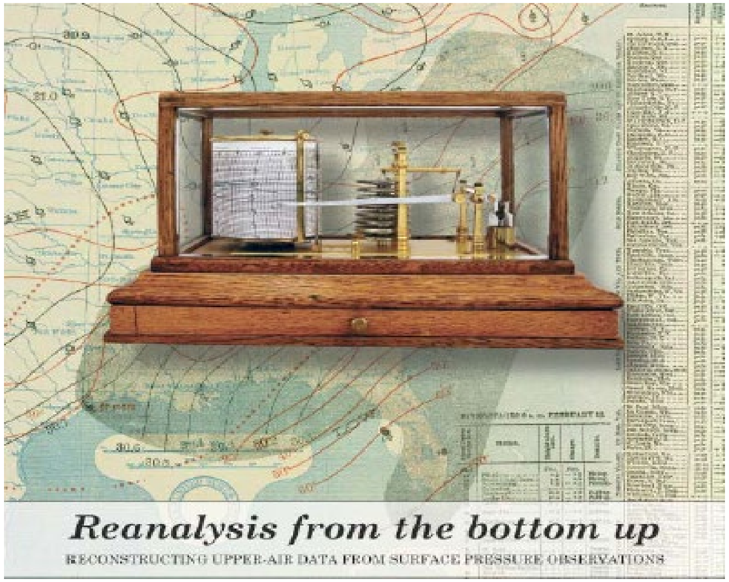
Reanalysis Caveats

- Changing amount and quality of observations introduces spurious variability and trends
  - Faster radiosonde sensors show (if uncorrected) a false atmosphere drying trend
  - Satellite introduction changed the whole picture
- Observational constraints strongly very depending on variable, location and time
  - Precipitation (depending in the reanalysis) and Evapo-transpiration not directly constrained
  - Moisture is known not to be conserved
- **Reanalyzes should not be equated to reality!!**

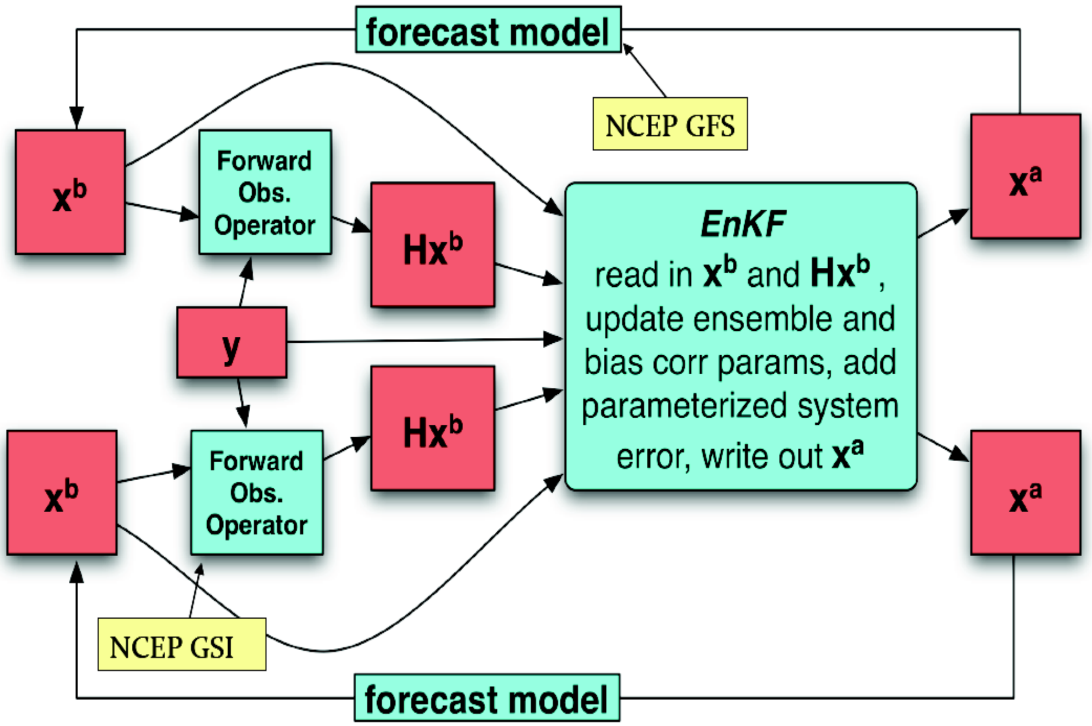
Go to Reanalyses table

20^{th} Century Reanalysis (Compo et al 2011)

High-quality tropospheric reanalyses for the last 100 years u



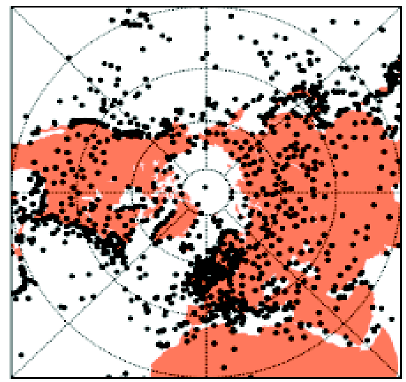
Double EnKF Scheme



Some validation results

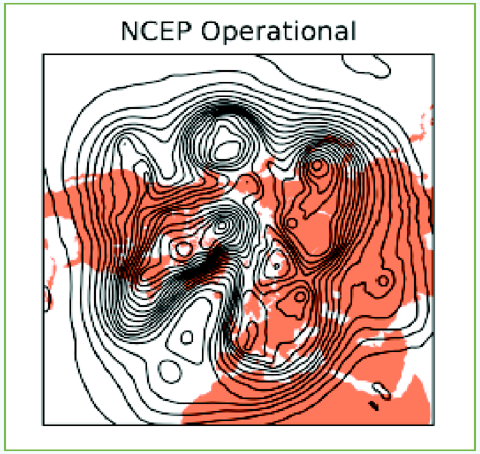
Example : 500-hPa Height Analyses Assimilating Only p_s obs

Whitaker et al 2009: June MWR

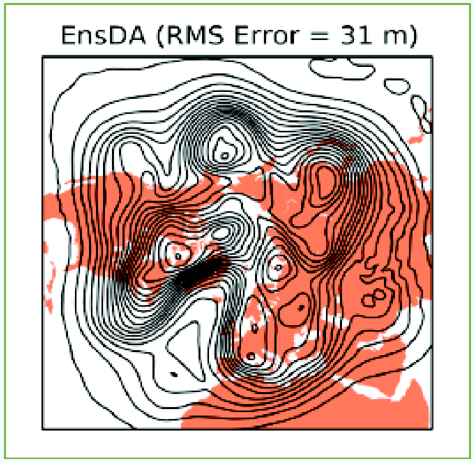


Black dots show 300+ surface pressure observation locations (similar to 1930's network)

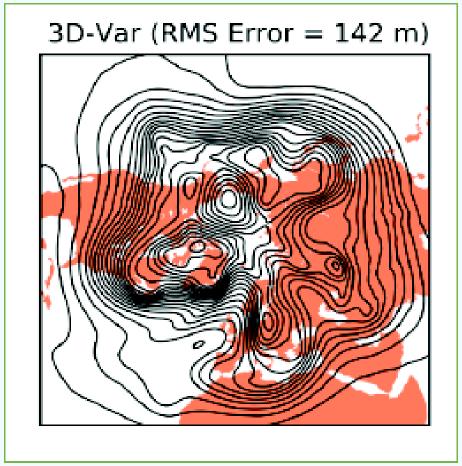
Full NCEP operational analysis (3D-Var)
1000000+ obs



EnKF
only 300+surface pressure obs

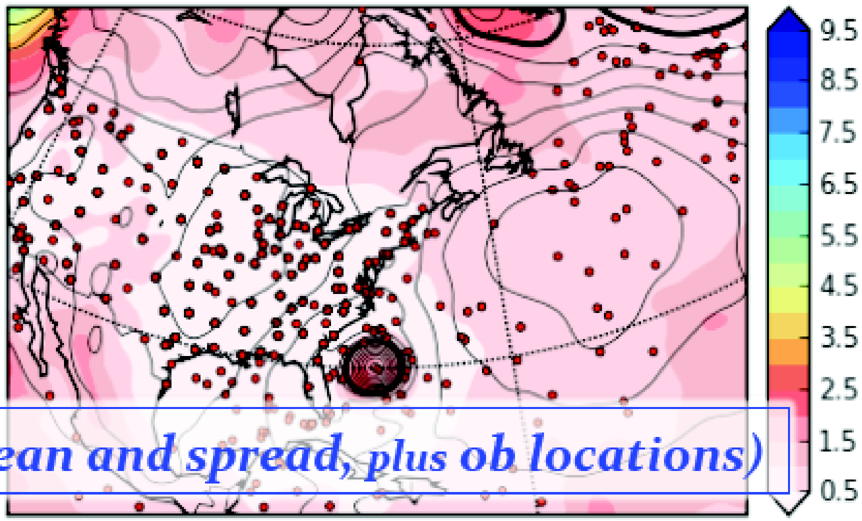


ECMWF 3D-Var
only 300+surface pressure obs

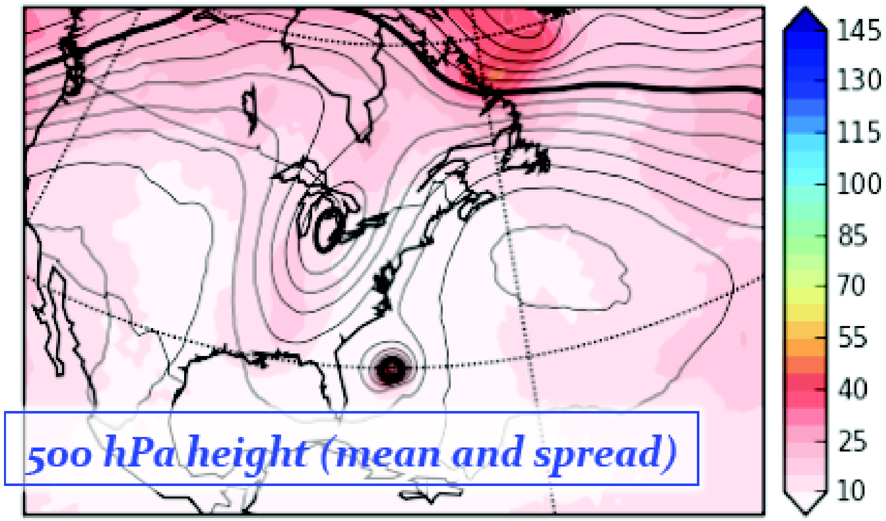


Some validation results

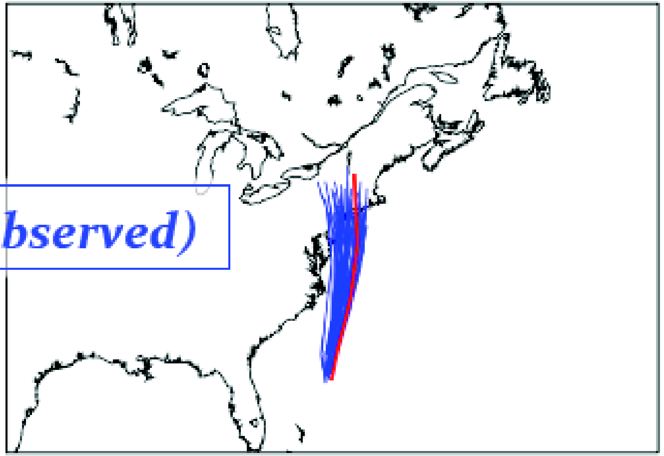
Reanalysis of the 1938 New England Hurricane using only p_s obs



MSLP (mean and spread, plus ob locations)



500 hPa height (mean and spread)



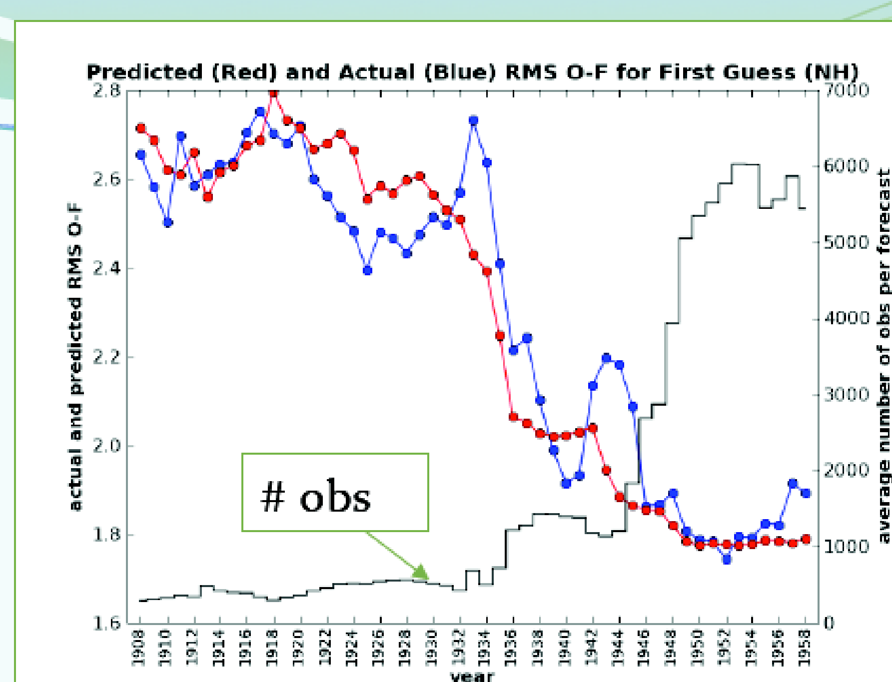
24-h track forecasts (red observed)

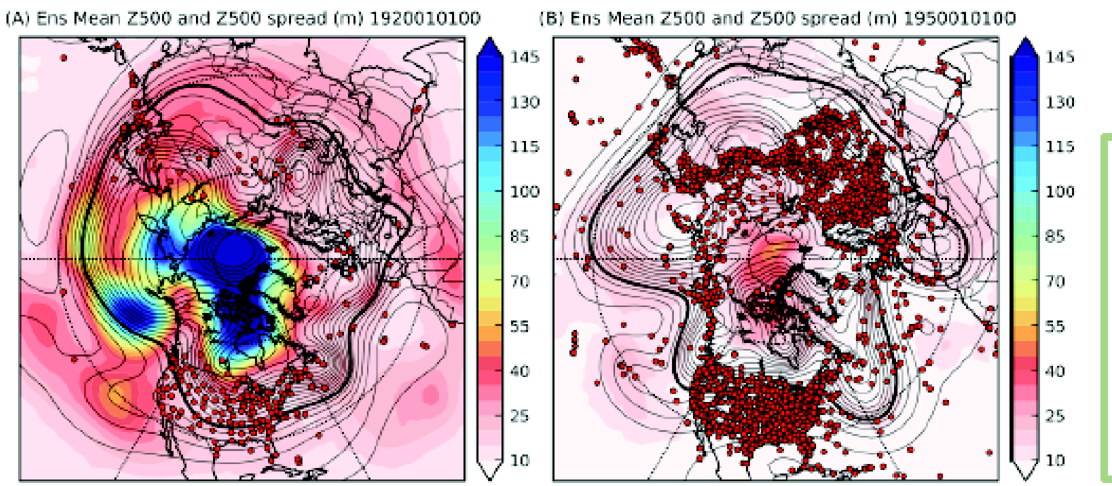
21 Sept. 1938

20th CR Features

Estimating Space and Time-Varying Uncertainty in Reanalyses

(20th Century Reanalysis Project, led by Gil Compo)





EnKF accurately captures changing uncertainty as observing network changes.

References

- http://reanalyses.org/
- ClimateDataGuide https://climatedataguide.ucar.edu/climate-data/atmospheric-reanalysis-overview-comparison-tables
- RealClimate http://www.realclimate.org/index.php/archives/2011/07/reanalyses-r-us/

Thanks for your attention!

Vielen Dank für Ihre Aufmerksamkeit!

Muchas Gracias!

Spasibo boshóe