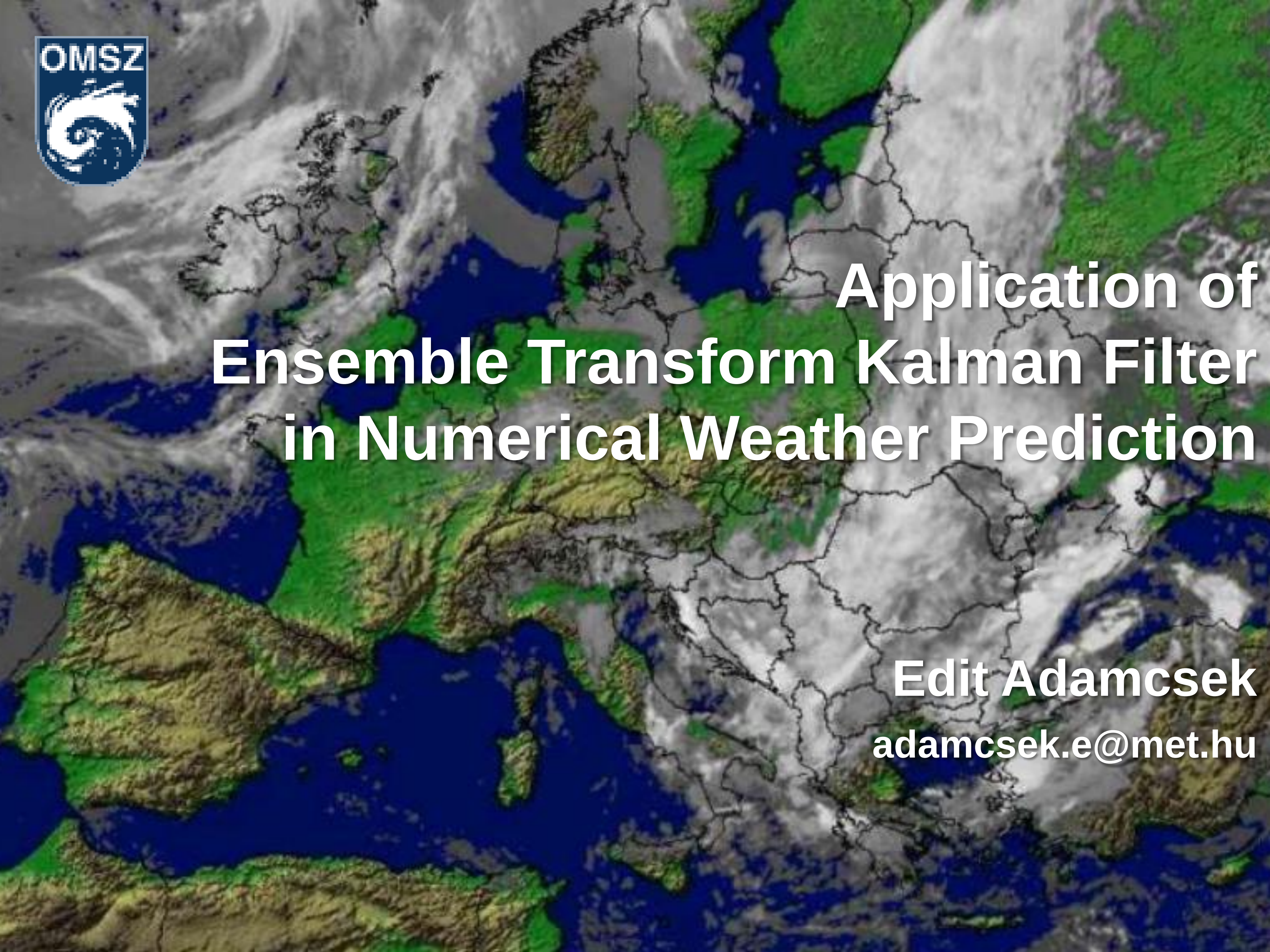

Application of Ensemble Transform Kalman Filter in Numerical Weather Prediction

Edit Adamcsek

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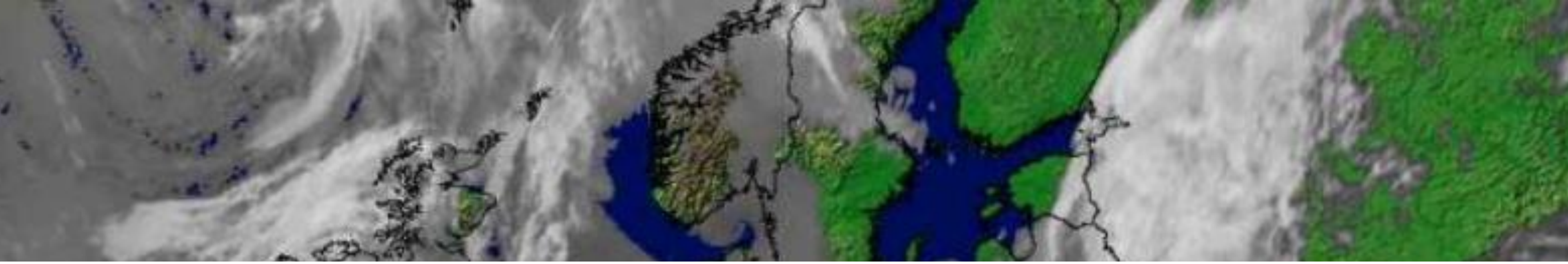


Numerical Weather Prediction

Numerical Weather Prediction

- Aim: give an estimation of the future state of the atmosphere, i.e. give a weather forecast.
- How? Numerically solve the hydro-thermodynamic equations, which describe the atmospheric flow.
- This is a system of non-linear Partial Differential Equations.

$$\frac{d\bar{v}}{dt} = -\frac{1}{\varrho}\nabla p + \bar{g} - 2\bar{\Omega} \times \bar{v}$$

$$\frac{d\varrho}{dt} = -\varrho \cdot div\bar{v}$$

$$\frac{dQ}{dt} = c_p\frac{dT}{dt} - \alpha\frac{dp}{dt}$$

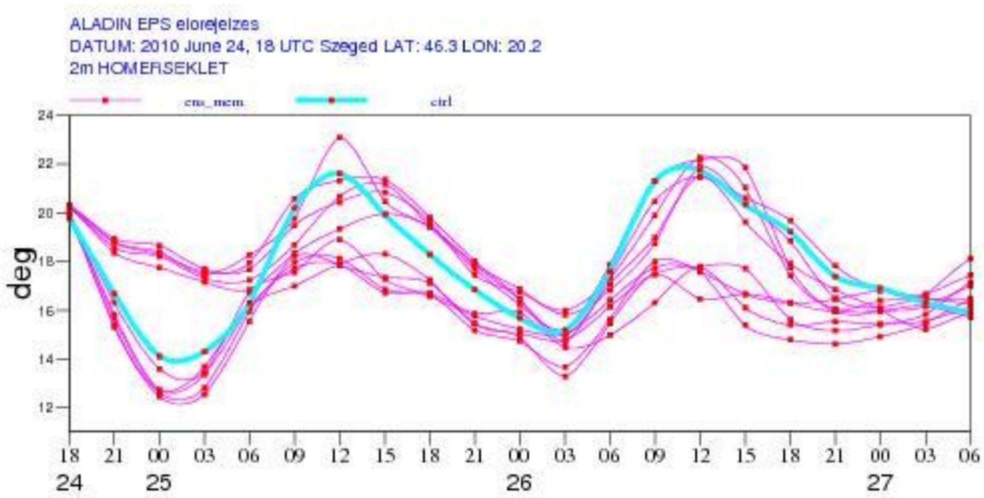
$$\frac{dq}{dt} = -\frac{1}{\varrho}M$$

$$p = \varrho RT$$

$\bar{v}$: wind
ϱ: density
T: temperature
p: pressure
q: humidity

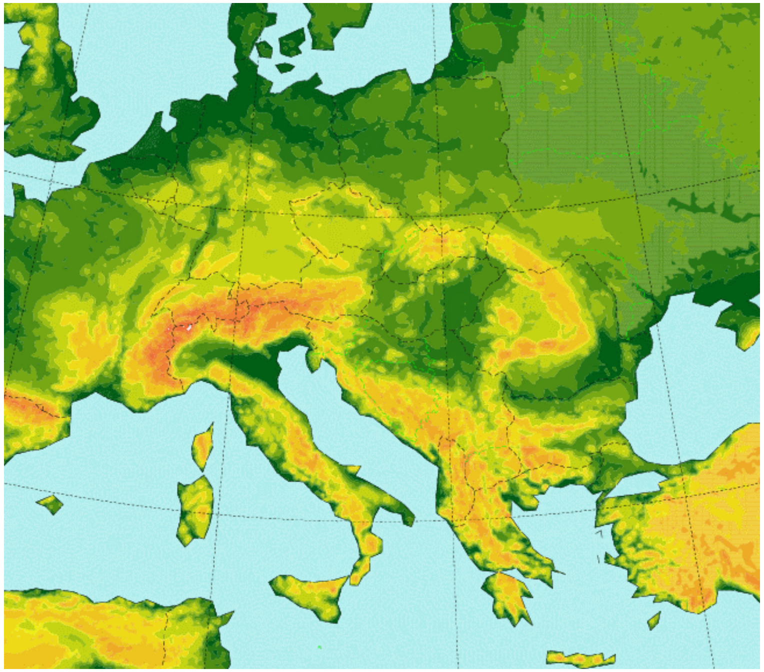
Data Assimilation

- The model needs initial- and lateral boundary conditions.
- The models are extremely sensitive to changes in the initial condition, so their precise estimation is crucial in NWP.
- Data Assimilation is the method to create the best possible estimate of the atmospheric state at the initial time, i.e. the analysis.



Operational ALADIN / HU

- ALADIN NWP model (cycle 33)
- LAM domain over Central Europe
- 8 km horizontal resolution, 49 vertical levels
- LBC from the IFS model (ECMWF)
- IC: local data assimilation
- analysis 6 hourly



Data Assimilation

- Analysis: the best possible estimate of the state vector.
- Two kind of information are used:
  - observations and
  - background information (a forecast from a previous analysis)
- The analysis is obtainded by the minimization of the cost function:

$$E\left|x_t - x_a\right|^2 \rightarrow \min$$

Data Assimilation

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- The analysis is obtainded by the minimization of the cost function:

$$J(x) = \frac{1}{2}(x_f - x)P_f^{-1}(x_f - x)^T + \frac{1}{2}(y - \mathrm{H}(x))R^{-1}(y - \mathrm{H}(x))^T$$

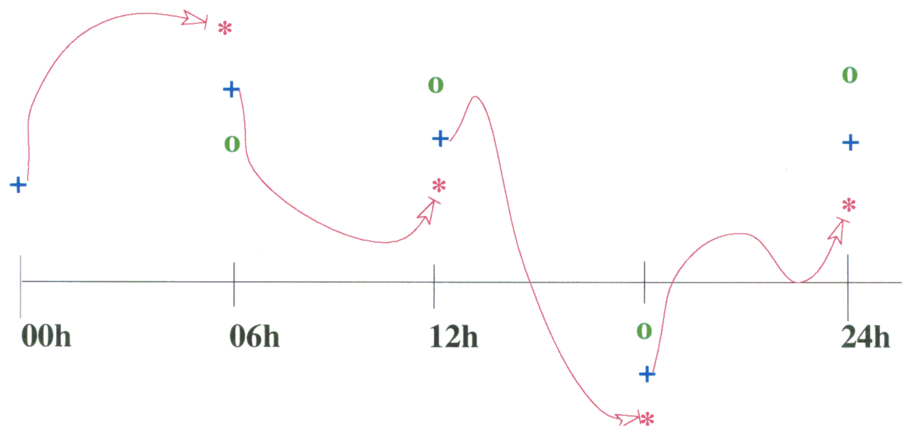
$$x_a = \arg\min J(x)$$

distance from the background weighted by the reliability of the forecast

distance from the observation weighted by the reliability of the observation

$x_t, x_a, x_f \in \mathbb{R}^n$ model space
(true state, analysis, forecast)
Observations: $y \in \mathbb{R}^p$
Observation space $\subset \mathbb{R}^p (p \approx 10^5)$
Observation operator $\mathrm{H}: \mathbb{R}^n \rightarrow \mathbb{R}^p$
P_f: forecast error covariance matrix
R: observation error covariance matrix

Data Assimilation



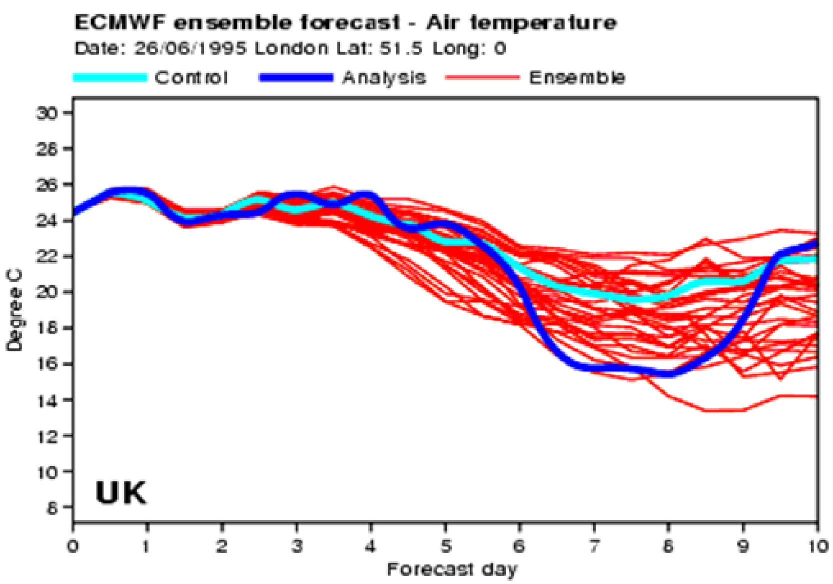
background + new observation → analysis

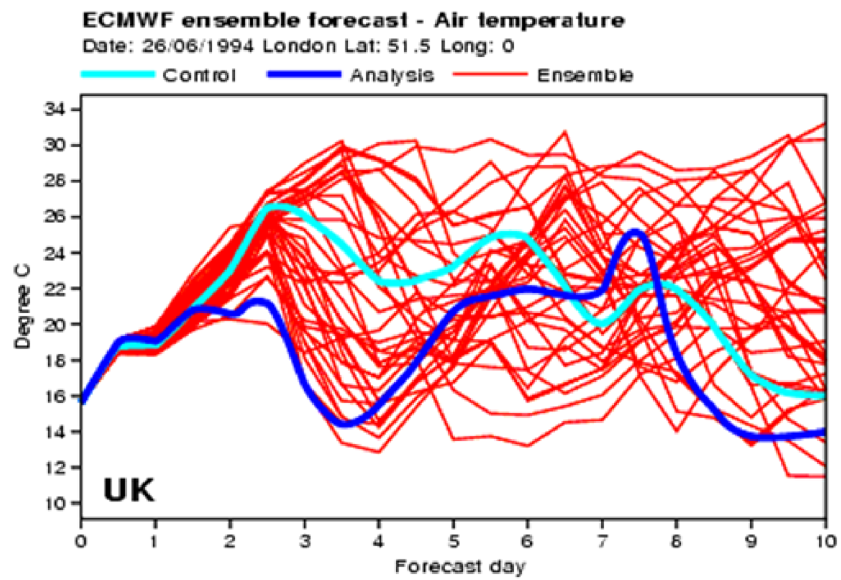
$$x_f(k+1) = \mathrm{M}x_a(k)$$

$$J(x) = \frac{1}{2}(x_f - x)P_f^{-1}(x_f - x)^T + \frac{1}{2}(y - \mathrm{H}(x))R^{-1}(y - \mathrm{H}(x))^T$$
$$x_a = \arg\min J(x)$$

Forecast error statistics are time-invariant in the model.

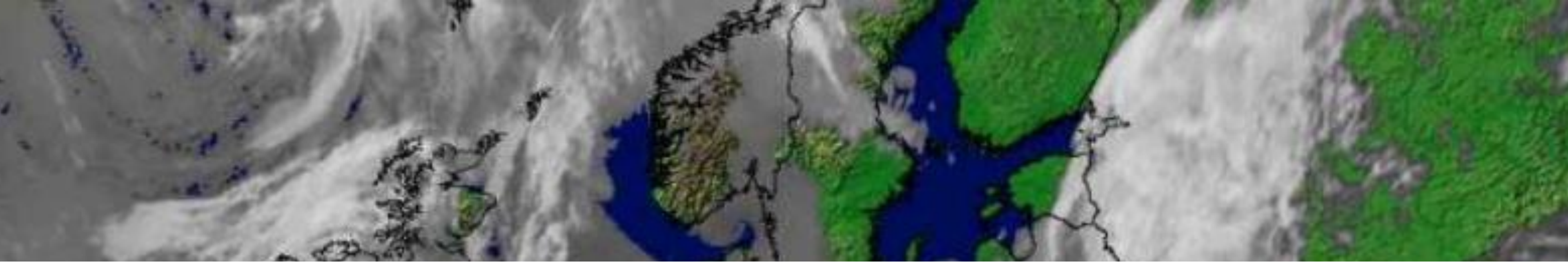
Forecast error





Ensemble forecast
London
1 year difference: 26/06/1995 and 26/06/1994

Aim of the research: flow-dependent computation of the forecast error covariance matrix.



Ensemble Transform Kalman Filter

Kalman Filter

Time evolution of forecast error:

$$P_f(k+1) = MP_a(k)M^T + Q$$

M linear model

P_a analysis error

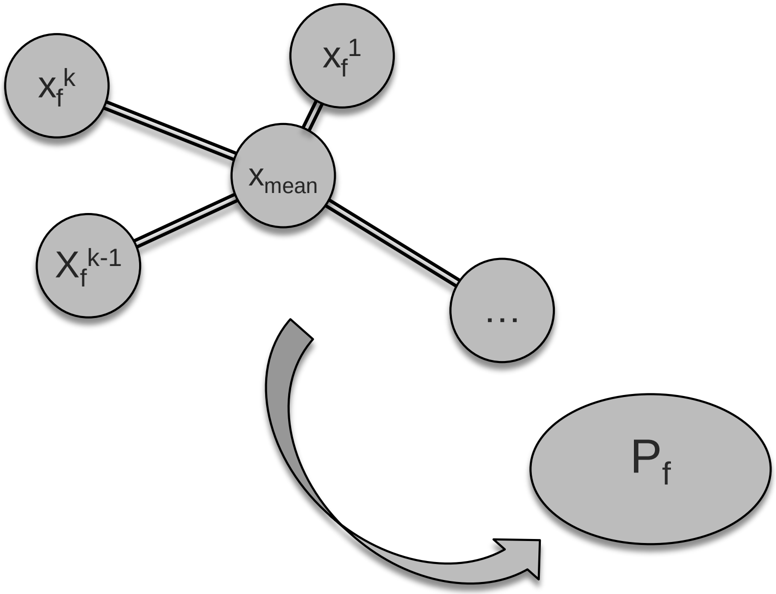
Q model error

Kálmán Rudolf Emil
(1930-   )

Ensemble Transform KF

The forecast error (P_f) is represented by the forecast ensemble.

Forecast ensemble



Ensemble Transform KF

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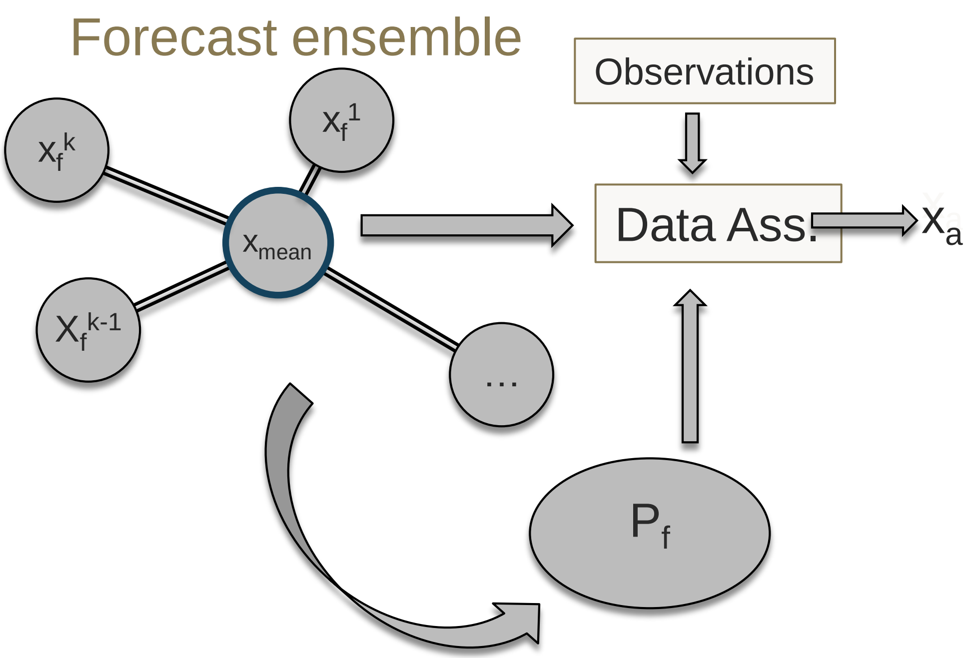
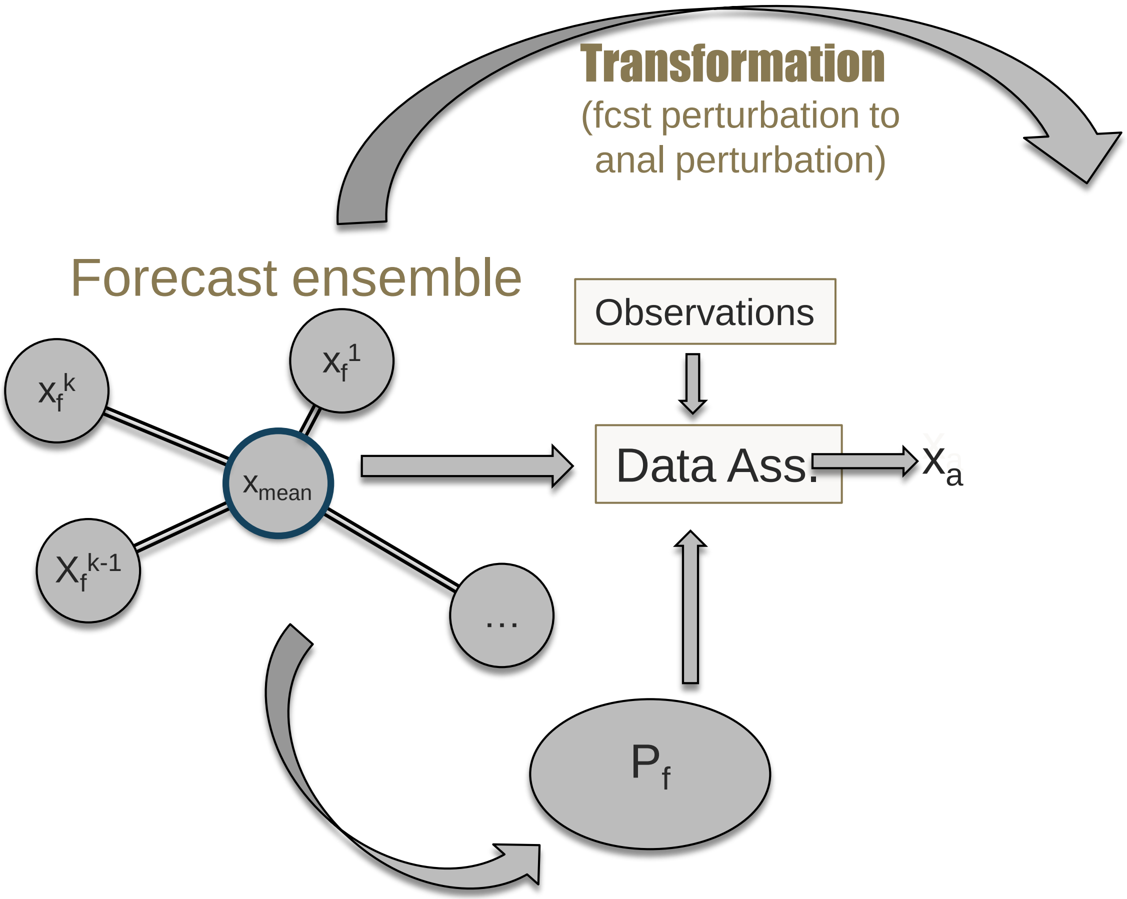
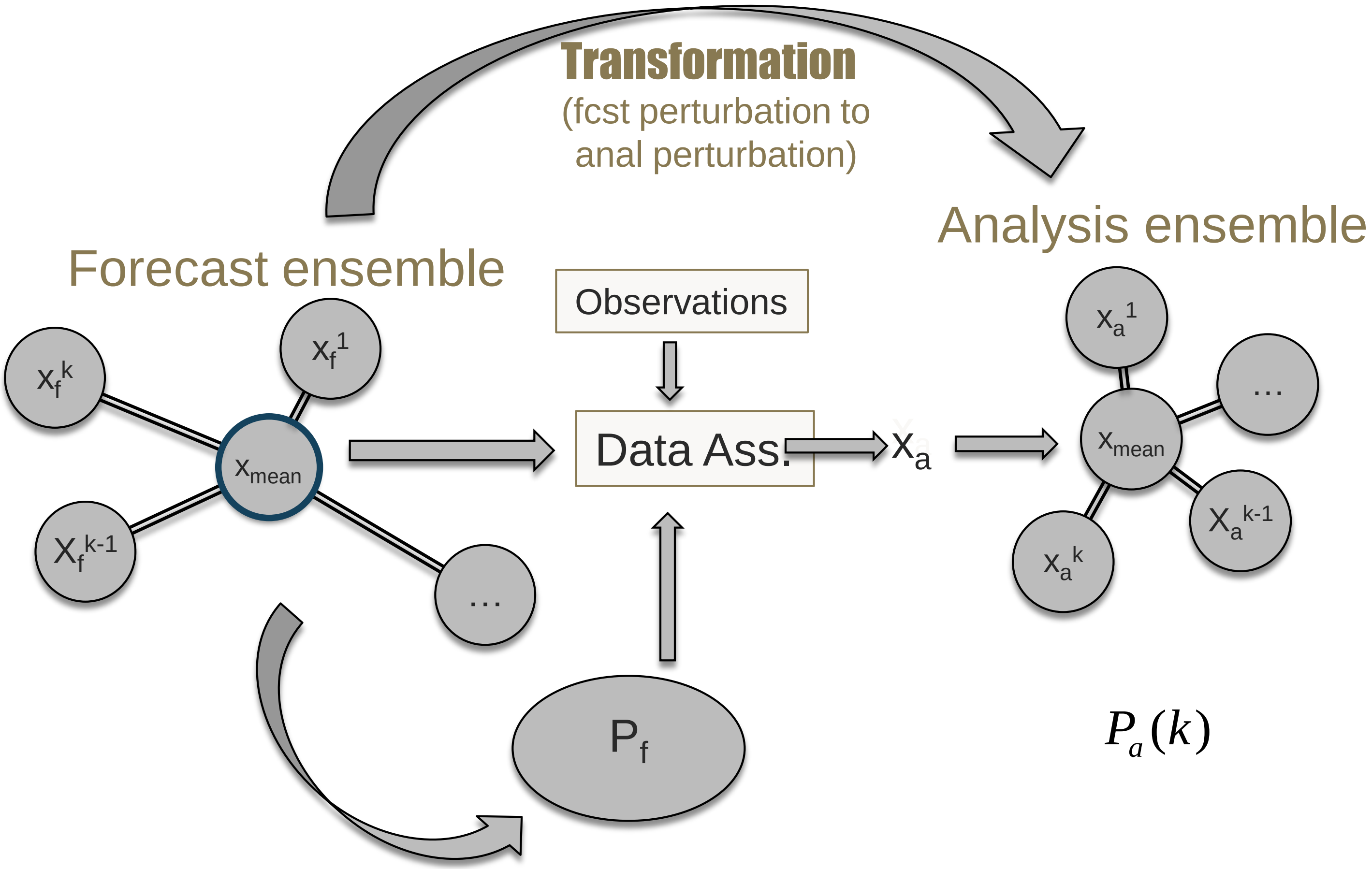


Ensemble Transform KF

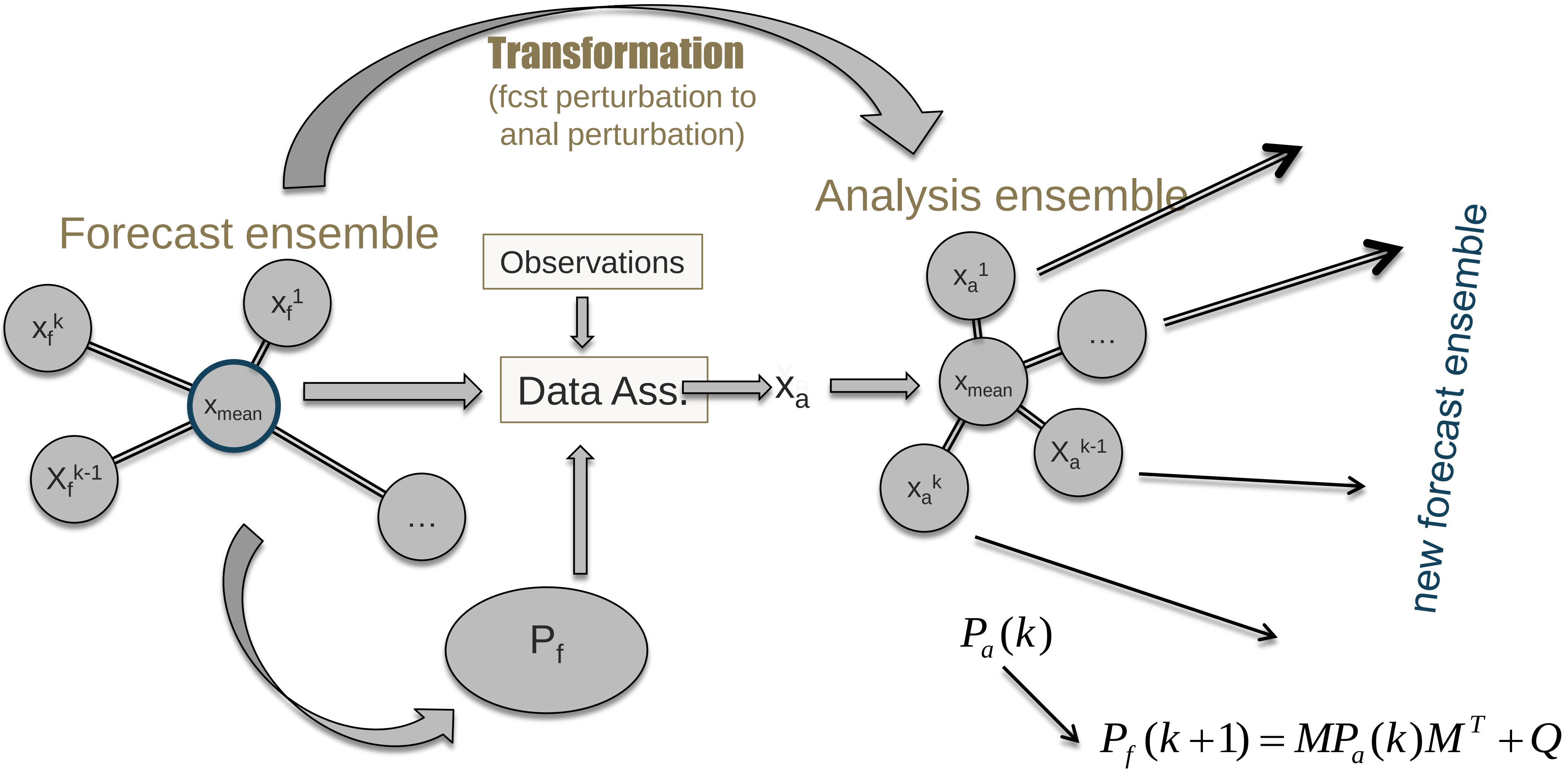


Ensemble Transform KF



The analysis error will be represented by the analysis ensemble.

Ensemble Transform KF



The new P_f will be represented by the new forecat ensemble.