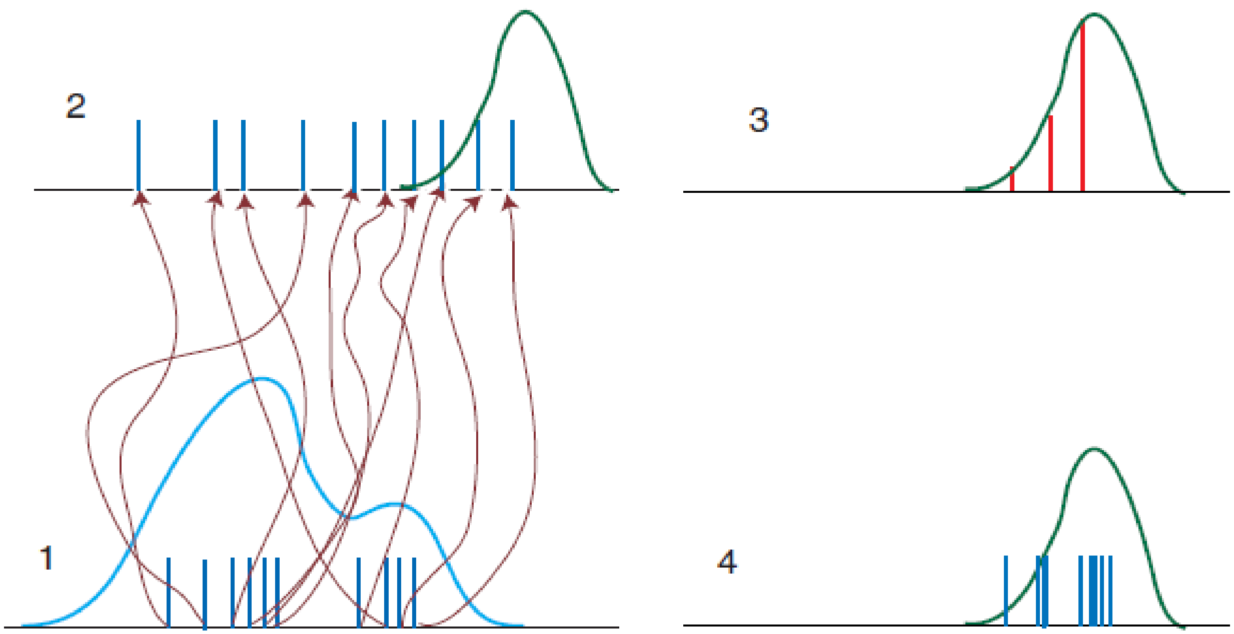
Hans-Ertel-Zentrum für Wetterforschung
Deutscher Wetterdienst
DWD

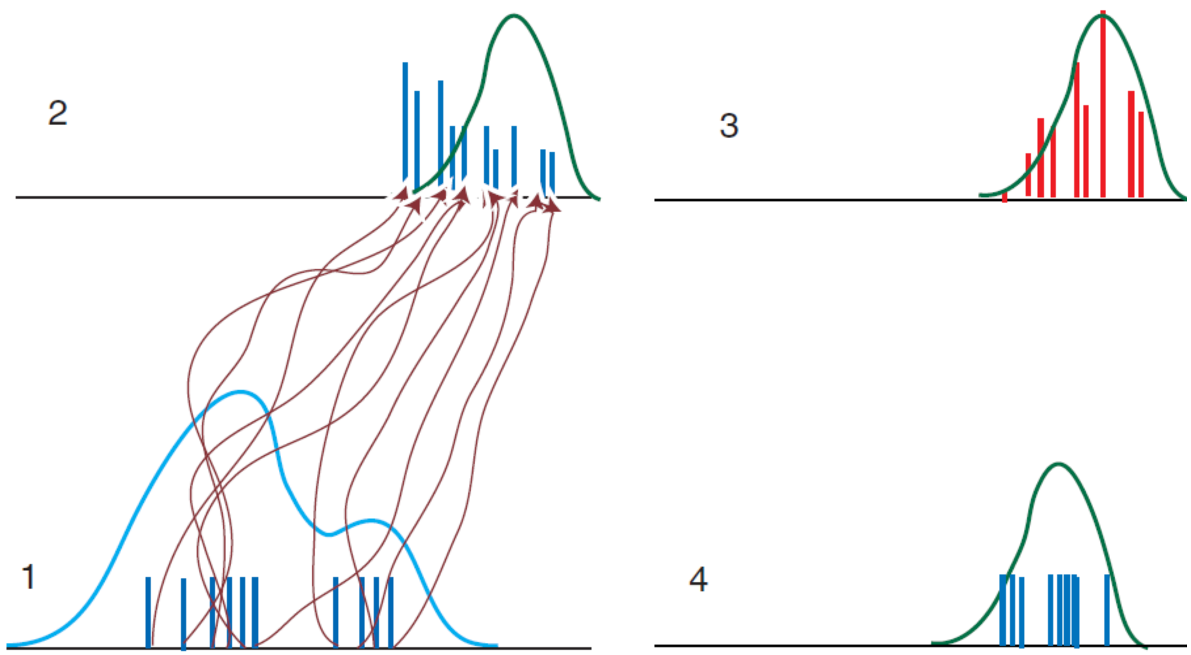
Nonlinear Data Assimilation methods

General goal of the PhD: (Try to) improve existing data assimilation methods for very nonlinear, non-Gaussian problems

Current work: Implement a simplified version of the New Particle Filter (P.v.Leeuwen, 2010) , based on the Standard Particle Filter (Craig and Wuersch, 2011)

1. Remember the Standard PF vs New PF:


2
3
1
4



2
3
1
4

What is a simplified version of the New Particle Filter?

2. Algorithm:

- Step 1: Generate a new ensemble of particles according to

$$\psi^n = f(\psi^{n-1}) + \widehat{\beta}^n + K(d^n - H\psi^{n-1}),$$

where K is a matrix, $\widehat{\beta}^n \sim N(0, \widehat{Q})$ and with state distribution

$$p(\psi^n) = \frac{1}{N} \sum_{i=1}^{N} \delta(\psi^n - \psi_i^n)$$

- Step 2: Combine model and observations (analysis)

$$q(\psi^n|\psi^{n-1}, d^n) \sim N(K(d^n - H\psi^{n-1}), \widehat{Q})$$

- Step 3: Find new weights: For any function $f(\psi)$,

$$E(f(\psi^n)|d^n) = \int f(\psi^n) \frac{p(\psi^n|d^n)}{q(\psi^n|\psi_i^{n-1}, d^n)} q(\psi^n|\psi_i^{n-1}, d^n) d\psi$$
$$= \int A_i(\psi^n) dq(\psi^n),$$

where

$$A_i(\psi^n) = \frac{1}{Np(d^n)} \sum_{i=1}^{N} f(\psi^n) \frac{p(d^n|\psi^n)p(\psi^n|\psi_i^{n-1})}{q(\psi^n|\psi_i^{n-1}, d^n)}$$

with the result:

$$\Rightarrow E(f(\psi^n)|d^n) \approx \sum_{i=1}^{N} w_i f(\psi_i^n),$$

where

$$w_i = \frac{1}{A}\frac{p(d^n|\psi_i^n)p(\psi_i^n|\psi_i^{n-1})}{q(\psi_i^n|\psi_i^{n-1}, d^n)}$$

- Step 4: Resample (step 4)

3. Perspectives

-Testbed models for the New Particle Filter:
Lorenz96 model, stochastic cloud model,...?

-How does the distance between 2 observations influence the weights?
-How many particles are necessary to get "good" results? -How does the number of observations influence the results?

-Nudging Term:
-What makes the Nudging term effective (number of timesteps,..)?
-How strong or weak should the Nudging term be?

-Outlook: develop a measure for the effectiveness of the Nudging term?