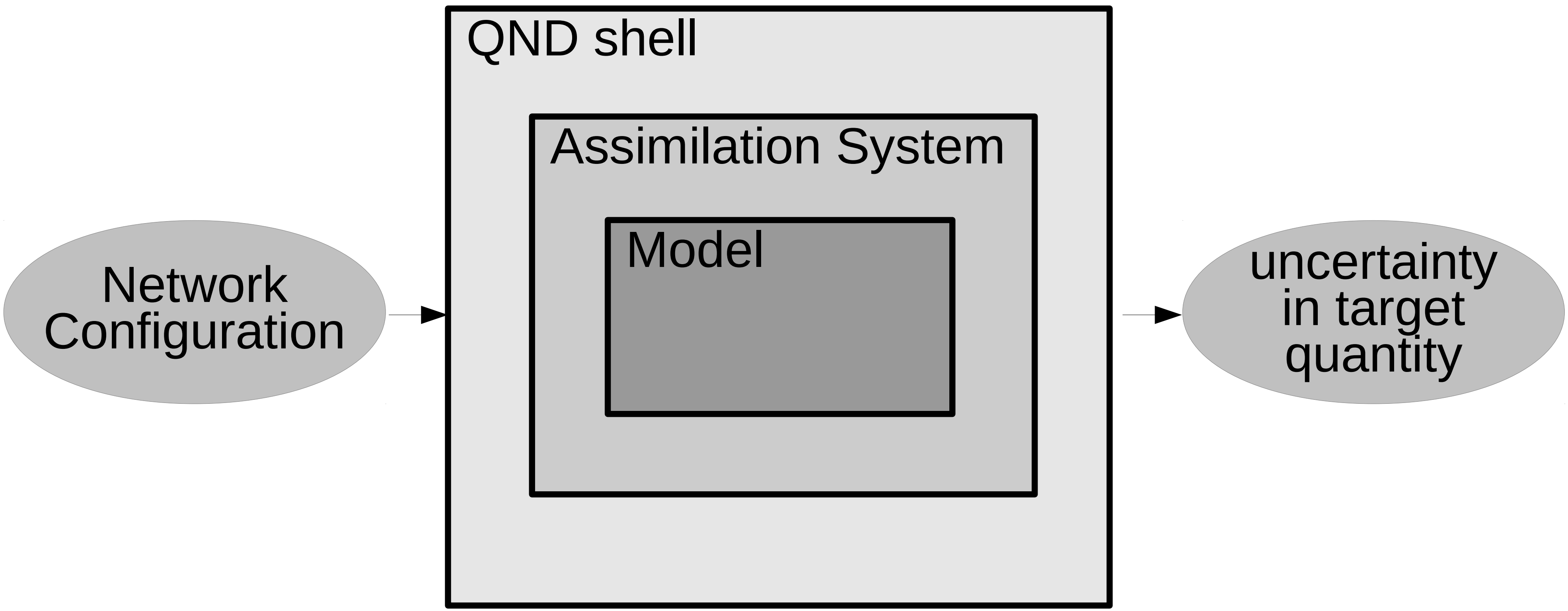
Quantitative Design of Observational Networks for the Arctic

Thomas Kaminski and Frank Kauker

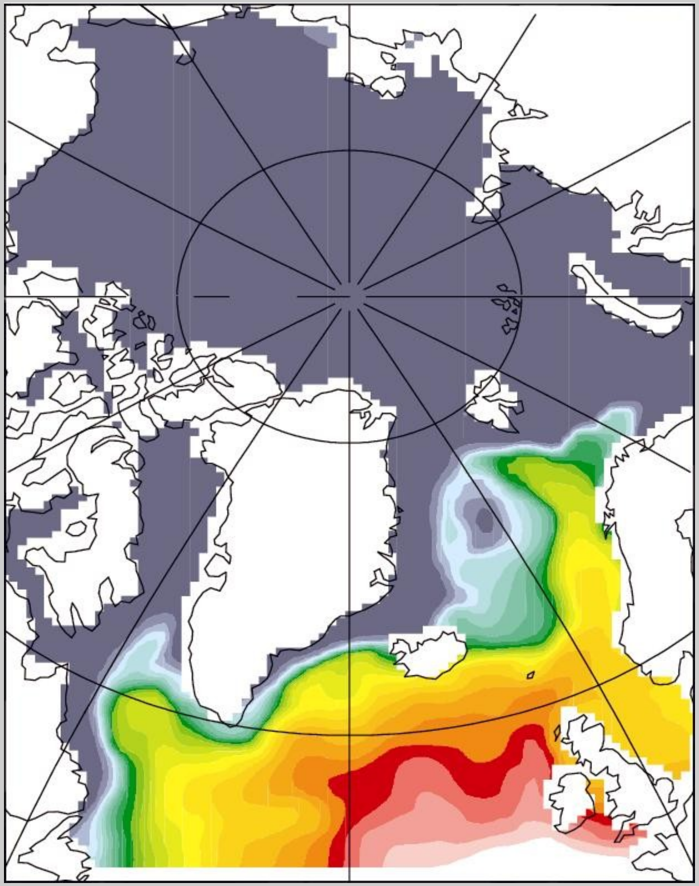
Sea Ice Workshop - Airborne-based observations of sea ice thickness and snow depth, GSFC, January 2013

Quantitative Network Design



Modelling: NAOSIM

- Sea Ice/Ocean model
- Time step: 1/2 hour
- 0.5 x 0.5 degree hor. res., rotated
- 20 vertical layers
- Model domain: north of about 50°N
- Forcing: daily NCEP reanalysis (but also: JRA25, ERAinterim)



Kauker et al. (2005)

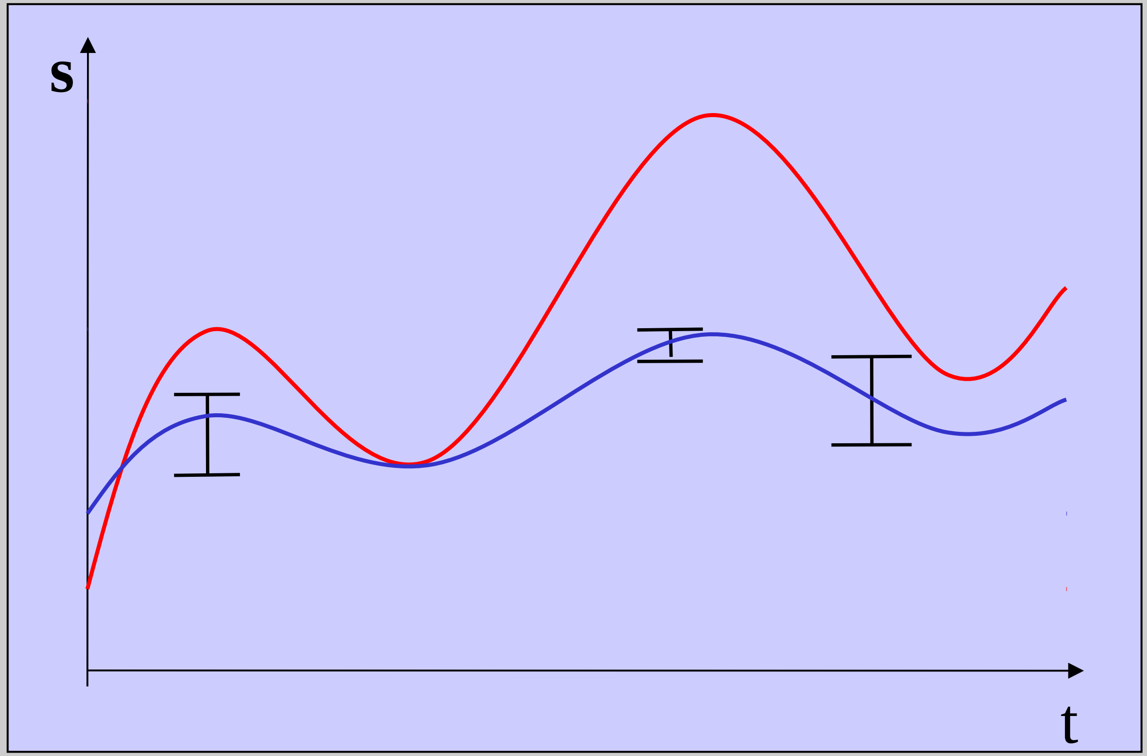
Variational Data Assimilation

Notation:
s : state vector
(ocean: u', v', s, tpot, Φ; ice: h , a, hsn)
t : time
d : vector of observations
σ : vector observational uncertainties

Principle:
•define vector of control variables **x**, e.g.,

- forcing/boundary conditions (**f**)
- Initial state (s0)
- internal model parameters (**p**)

•define quality of fit by cost function:
•minimise J(**x**) by variation of **x**



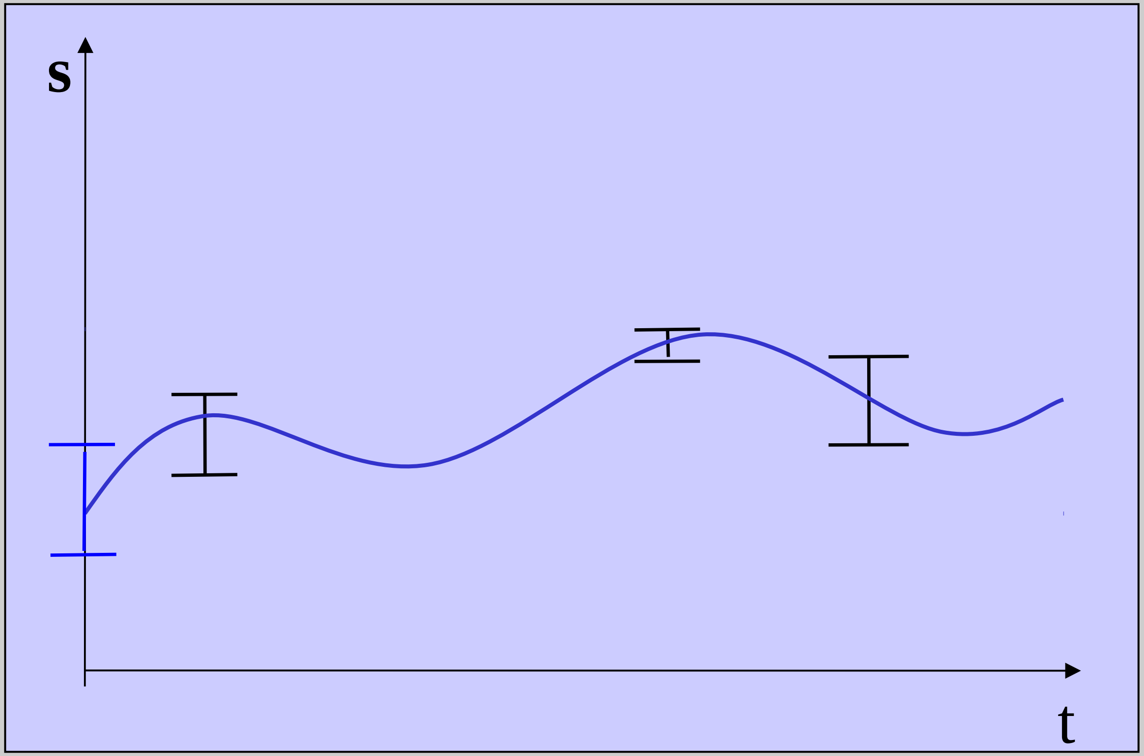
$$J(x) = \frac{1}{2}((M(x) - d)^T C_d{}^{-1}(M(x) - d) + (x - p)^T C_p{}^{-1}(x - p))$$

uncertainty for obs. term

uncertainty for prior term

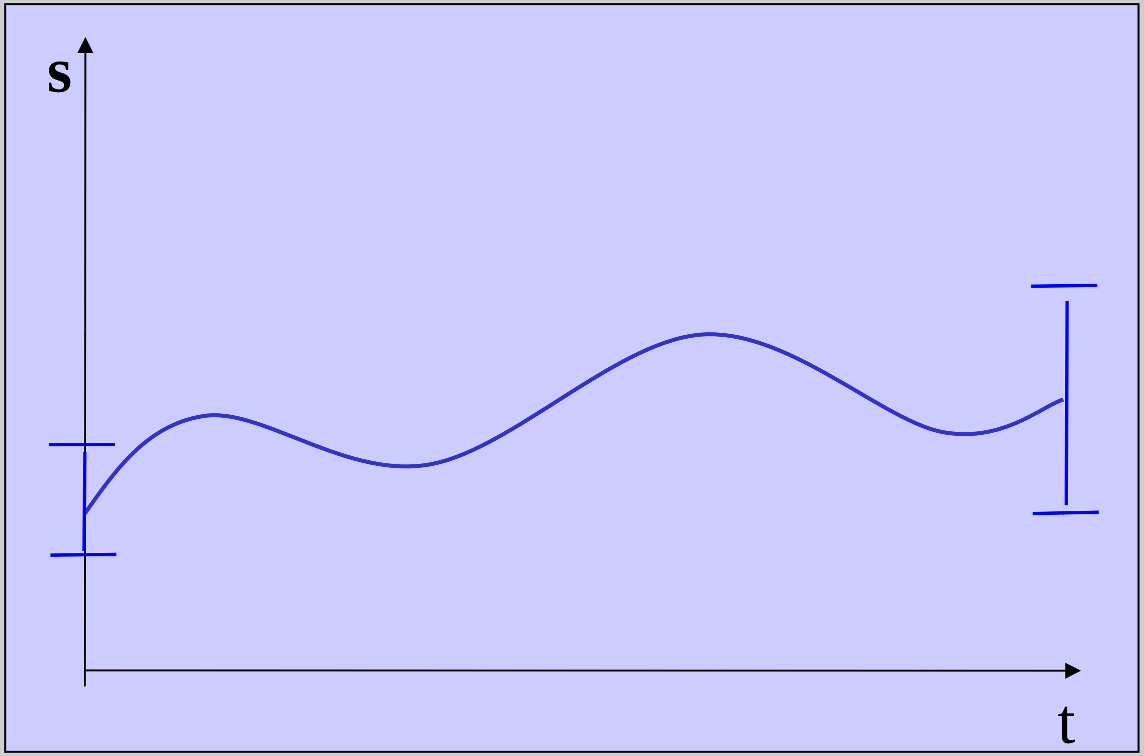
Quantitative Network Design

**Which Error bar in x
is consistent
with the error bars in data?**



Quantitative Network Design

And how does this error bar in x project onto error bars for target quantities of interest?



Uncertainty for target in 2 steps

x: Parameters
x_{pr}: Priors
C_{pr}: Uncertainties
$M(x)$: Model
d: Observations
C_d: Their uncertainties
σ_{d_i}: Uncorrelated!
$J(x)$: Cost function
$\frac{d^2 J(x)}{dx^2}$: Hessian
x_{po}: Posterior parameters
C_{po}: Posterior uncertainties
$y(x)$: Target quantity
σ_y: Its uncertainty

$$J(x) = \frac{1}{2}(x - x_{pr})^T {C_{pr}}^{-1} (x - x_{pr}) + \frac{1}{2} \sum_{i=1,nd} \left(\frac{M_i(x) - d_i}{\sigma_{d_i}} \right)^2$$

$$\frac{d^2 J(x)}{dx^2} = {C_{pr}}^{-1} + \sum_{i=1,nd} \frac{1}{\sigma_{d_i}^2} \frac{d^2}{dx^2} (M_i(x) - d_i)^2$$

uncertainty in model and obs

- Hessian independent of x for linear model
- For synthetic data use $d = M(x)$.
- Decomposes nicely, can precompute model contribution

$$C_{po} \approx \frac{d^2 J(x_{po})}{dx^2}^{-1}$$

$$\sigma_y \approx \frac{dy(x_{po})}{dx} C_{po} \frac{dy(x_{po})}{dx}^T \approx \frac{dy(x_{po})}{dx} \frac{d^2 J(x_{po})}{dx^2}^{-1} \frac{dy(x_{po})}{dx}^T$$

For details on methodology see
Kaminski and Rayner, 2008
Kaminski et al., 2012a,b

Simple Test

Model Setup:

- coarse 2 degree resolution
- simulation starting on Jan 1, 2007
- simulation period: 1 month

Simple Test

Control Variables:

- initial temperature ocean
- 2-meter atmospheric temperature
- surface wind stress, x direction
- kappa_m (constant in ocean model)
- kappa_h (constant in ocean model)
- pstar (constant in ice model)
- h0 (constant in ice model)

Example

Available Target Quantities:

•Ekin: average ocean Kinetic Energy

•T_mean: mean ocean temperature

•S_mean: mean ocean salinity

•V : integrated ice volume

•A : integrated ice area

Averages computed over January 2007

Simple Test

Available Data Streams:

- a: ice concentration
- h: ice thickness
- hsn: snow thickness

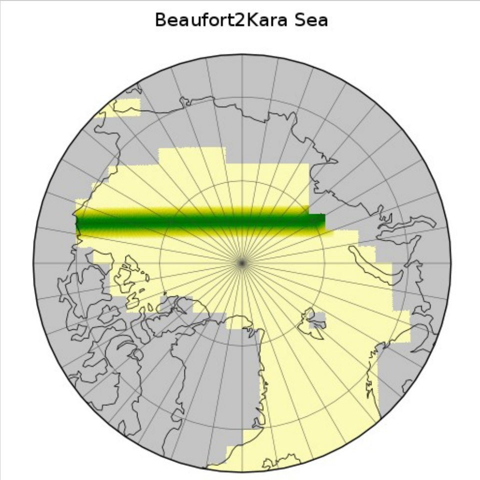
All data streams available

- over each model grid cell
- for each day in January
- with variable data uncertainty

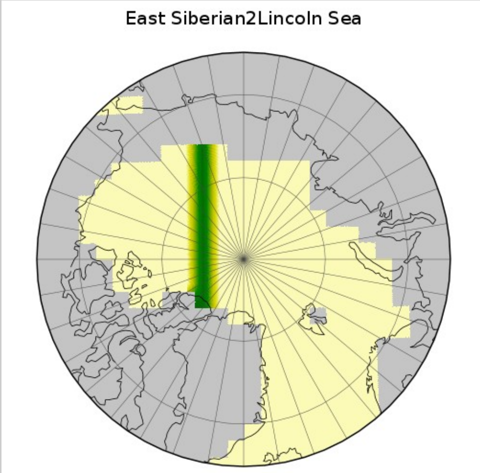
Simple Test

Aircraft Sections:

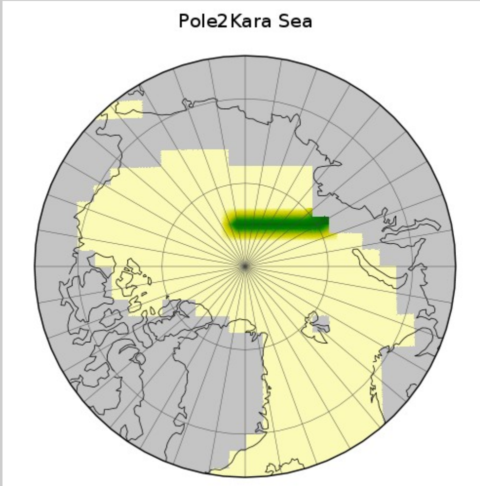
Beaufort - Kara



East Siberian - Lincoln Sea



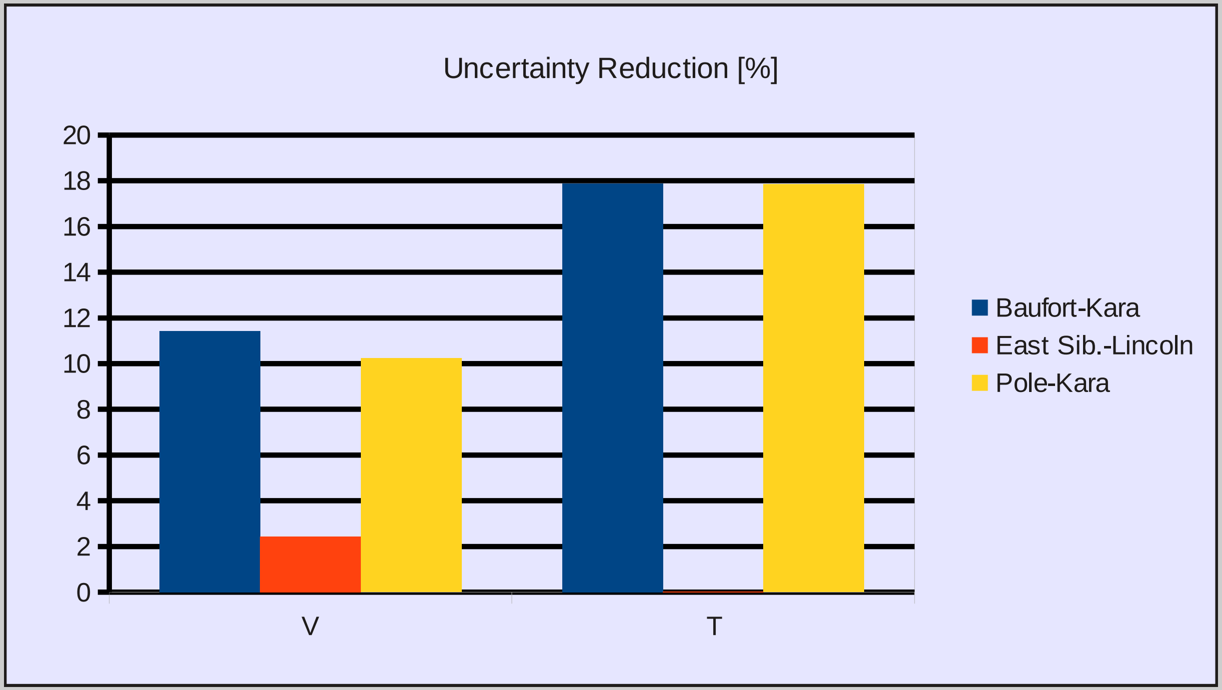
Pole - Kara Sea



All sections observe

- On January 15
- Ice thickness of entire 2x2 deg. grid cells with sigma of 30 cm
- Snow thickness of entire 2x2 deg. grid cells with sigma of 30 cm

Uncertainty Reduction



Discussion

• Simple test provides only rough assessment in coarse model with short control vector

• Technique is powerful, can also do

– remotely sensed observations (see ACCESS newsletter #4)

– hydrographic observations

– can help to assess the complementary of observational data streams (Kaminski et al., 2012a)

– can be used to assess the benefit of a planned space mission (Mission Benefit Analyis, see Kaminski et al., 2012b)

– can assist the design of an in situ observing strategy