Challenges in Data Assimilation for Numerical Weather Prediction

Melina Freitag

Department of Mathematical Sciences
University of Bath

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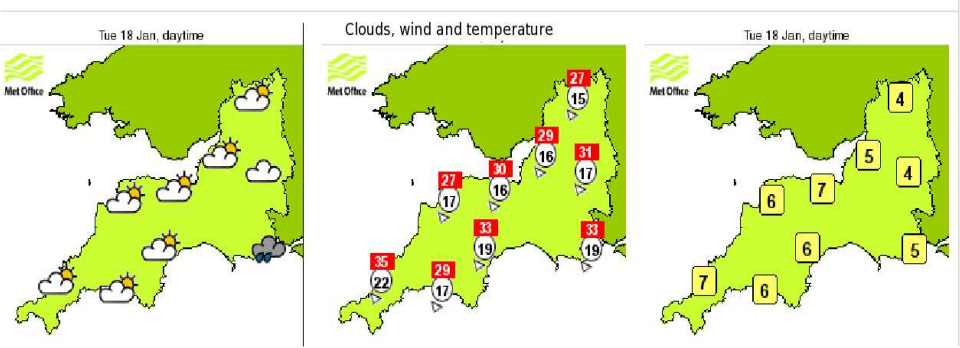
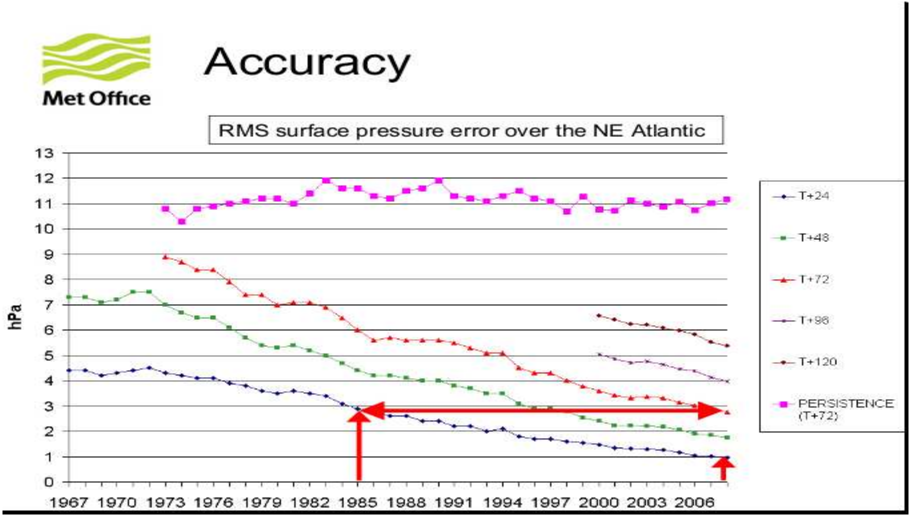
The MetOffice weather forecast for today (18/01/2011)

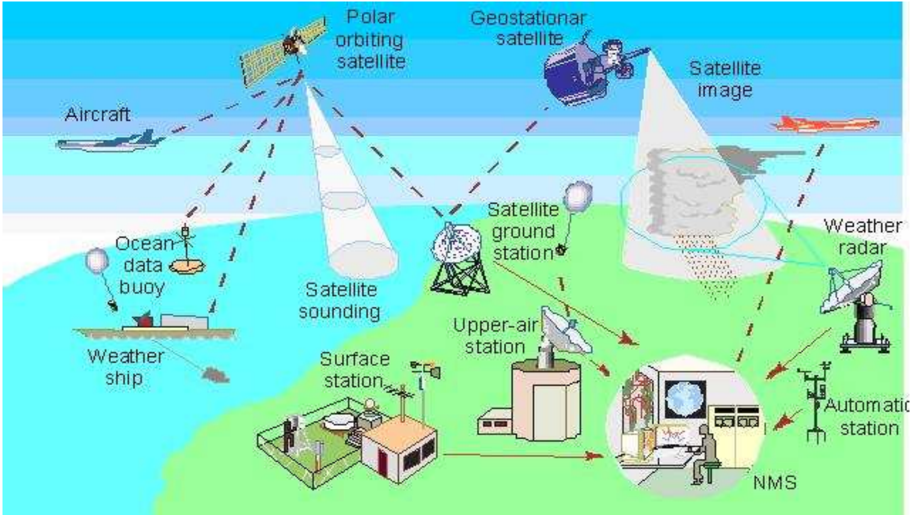


Forecast Bath: White Cloud, Temperature 0° - 4° Celsius, Wind 17 mph.

The UK MetOffice forecast over the last 40 years



Observation network



Global model

Introduce a 3D grid covering the atmosphere:

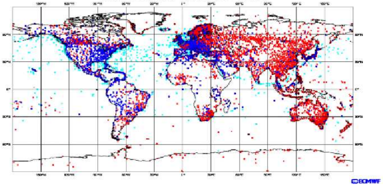
Global model

Introduce a 3D grid covering the atmosphere:

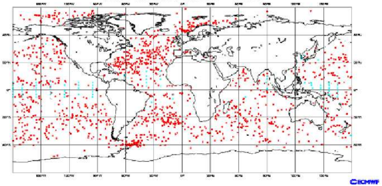
- In each of the $432 \times 320 \times 50$ grid points we have 7 variables (pressure, humidity, temperature, wind speed).
- Size of the state vector $\mathbf{x}$: $432 \times 320 \times 50 \times 7 \approx 10^7$.

Observations

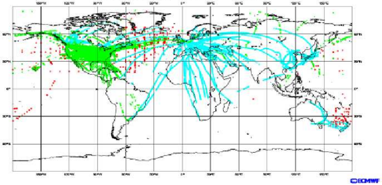
ECMWF Data Coverage (All obs DA) - SYNOP/SHIP
21/APR/2008; 00 UTC
Total number of obs = 28683



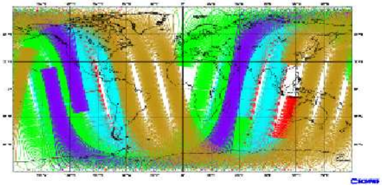
ECMWF Data Coverage (All obs DA) - BUOY
21/APR/2008; 00 UTC
Total number of obs = 7438



ECMWF Data Coverage (All obs DA) - AIRCRAFT
21/APR/2008; 00 UTC
Total number of obs = 51809



ECMWF Data Coverage (All obs DA) - ATOVS
21/APR/2008; 00 UTC
Total number of obs = 341239



Observations and state vector

- We put all the observations into a vector $\mathbf{y}$ (size $\approx 10^5 - 10^6$).
- Size of the state vector $\mathbf{x}$: $432 \times 320 \times 50 \times 7 \approx 10^7$.
- $\mathbf{y} = H(\mathbf{x})$ maps from state space into observation space.
- Problem is under-determined and the observations are very irregular.

Wanted: estimate $\mathbf{x}_i$ (time i) for the true atmospheric state

Observations $\mathbf{y}_i$

Satellites, ships and buoys, surface stations, aeroplanes

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Model

model for the atmosphere

$$\mathbf{x}_{i+1} = M(\mathbf{x}_i)$$

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A priori information $\mathbf{x}_i^B$

Background state (previous forecast)

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Assimilation algorithms

- find an (approximate) state of the atmosphere $\mathbf{x}_i$ at time i
- forecast future states of the atmosphere

Wanted: estimate $\mathbf{x}_i$ (time i) for the true atmospheric state

Model has errors!

model for the atmosphere

$$\mathbf{x}_{i+1} = M(\mathbf{x}_i)$$

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Satellites, ships and buoys, surface stations, aeroplanes

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Schematics of Data Assimilation (in 1D)

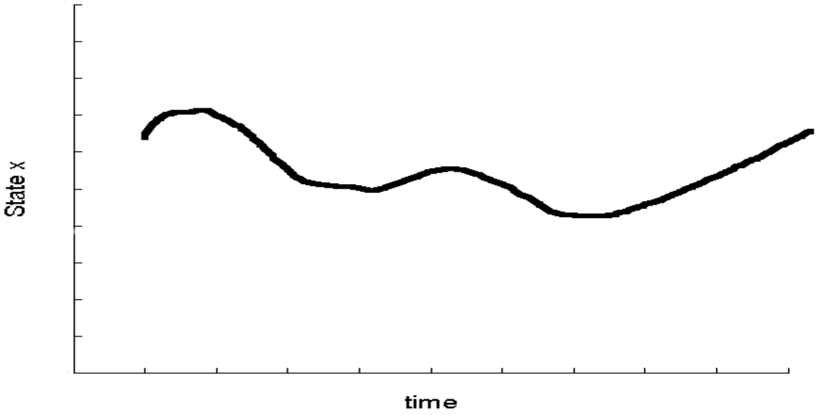

Figure: Previous forecast $\mathbf{x}^B$

Schematics of Data Assimilation (in 1D)

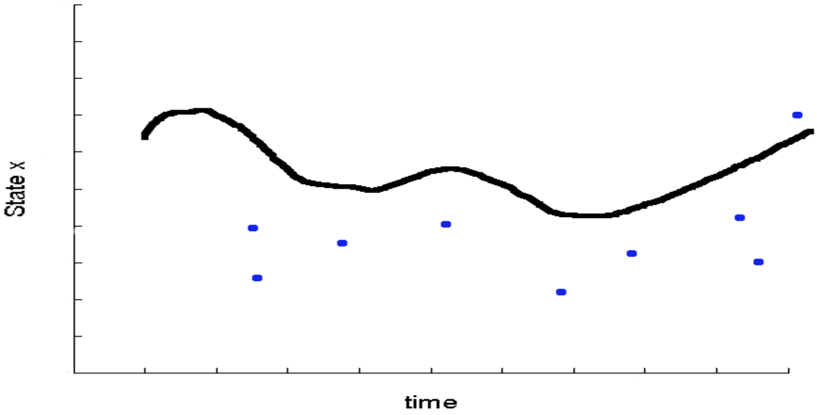

Figure: Observations $\mathbf{y}$

Schematics of Data Assimilation (in 1D)

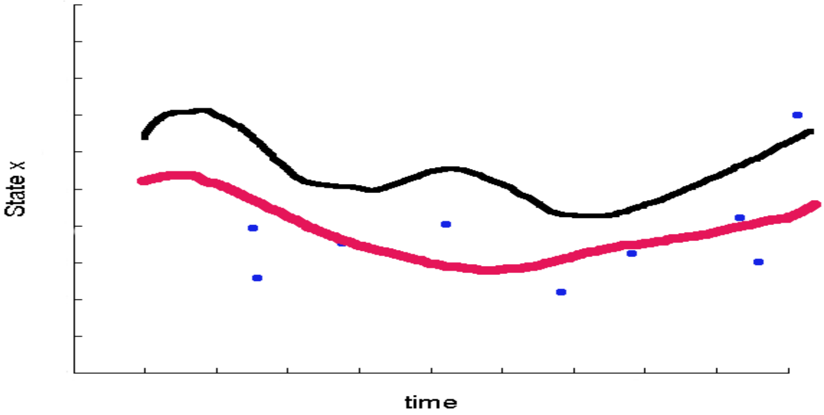

Figure: Analysis $\mathbf{x}^A$ (consistent with observations and model dynamics)

Four-dimensional variational assimilation (4DVar)

Minimise the cost function

$$J(\mathbf{x}_0) = (\mathbf{x}_0 - \mathbf{x}_0^B)^T \mathbf{B}^{-1} (\mathbf{x}_0 - \mathbf{x}_0^B) + \sum_{i=0}^{n} (\mathbf{y}_i - H(\mathbf{x}_i))^T \mathbf{R}_i^{-1} (\mathbf{y}_i - H(\mathbf{x}_i))$$

subject to model dynamics $\mathbf{x}_i = M_{0\to i}\mathbf{x}_0$.

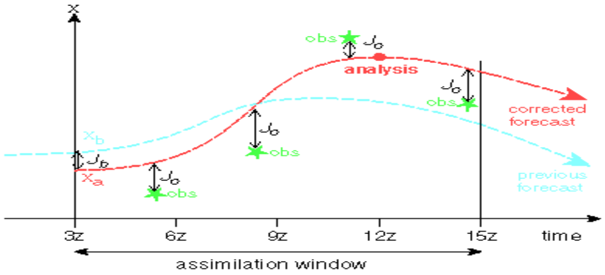

Figure: Copyright:ECMWF

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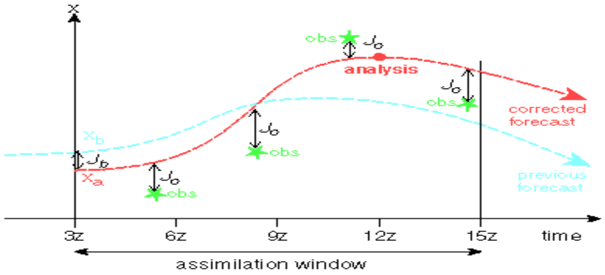

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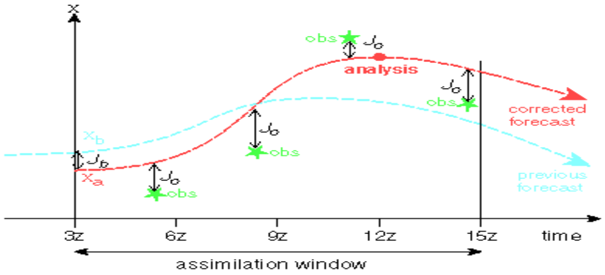

Figure: Copyright:ECMWF

Inverse Problems

Data Assimilation belongs to the class of Inverse Problems

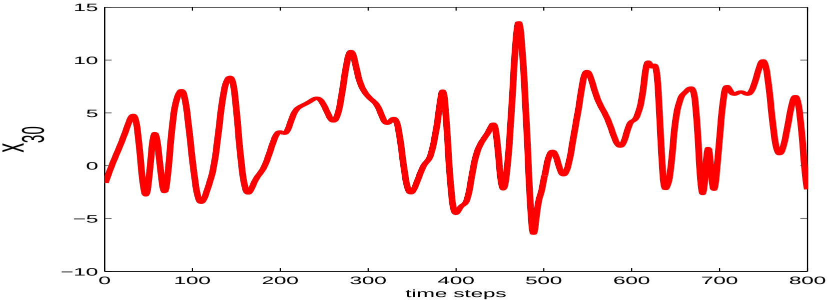

Figure: Solution to a "chaotic" problem

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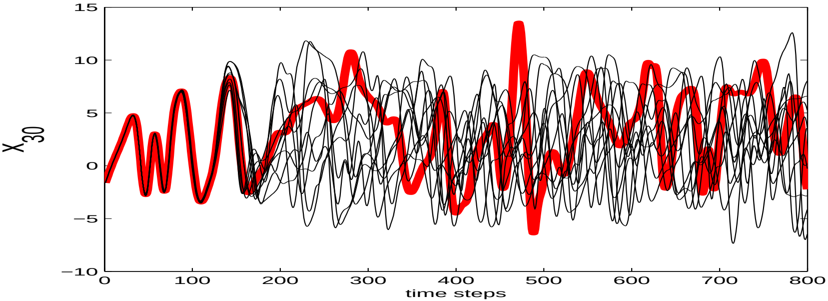
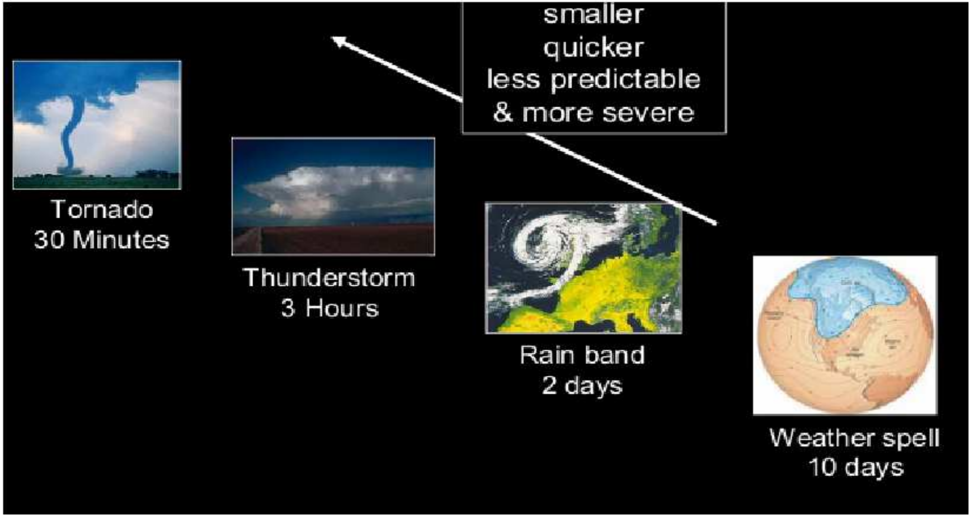


Figure: Solution to a "chaotic" problem

Resolution


smaller
quicker
less predictable
& more severe
Tornado
30 Minutes
Thunderstorm
3 Hours
Rain band
2 days
Weather spell
10 days

Challenges in Data Assimilation

- forecast needs to be improved at smaller "spacial scales" and "time scales" in order to forecast severe weather events
- increasing the model resolution leads to computational challenges - efficient implementations of Data Assimilation algorithms
- several components of the Data Assimilation process need to be improved
  - model error
  - estimating the correct covariance matrices
  - using better algorithms in order to forecast sharp fronts