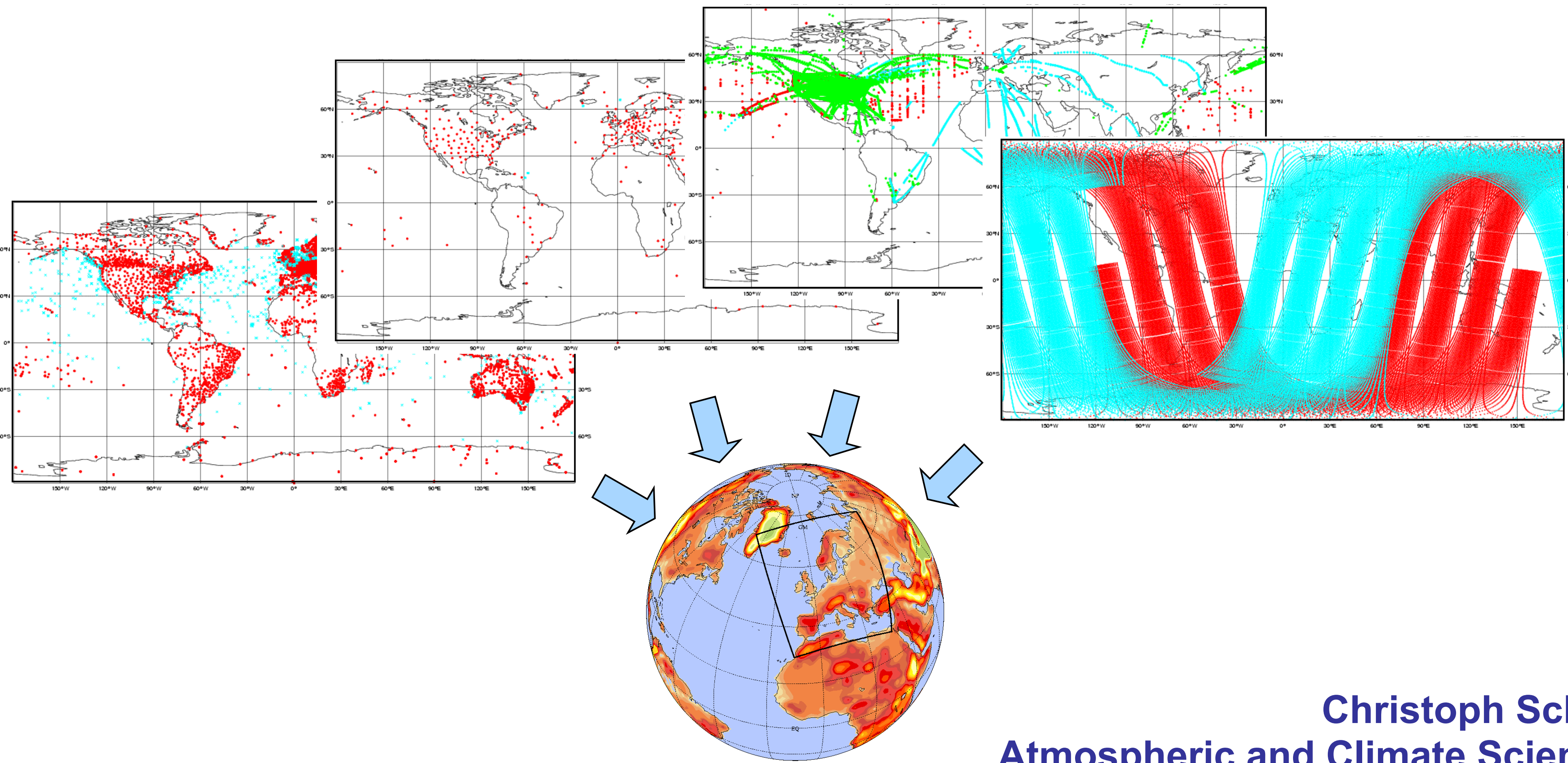
Atmospheric Data Assimilation



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Lecture Notes "Numerical Modelling of Weather and Climate"

May 2015

Outline

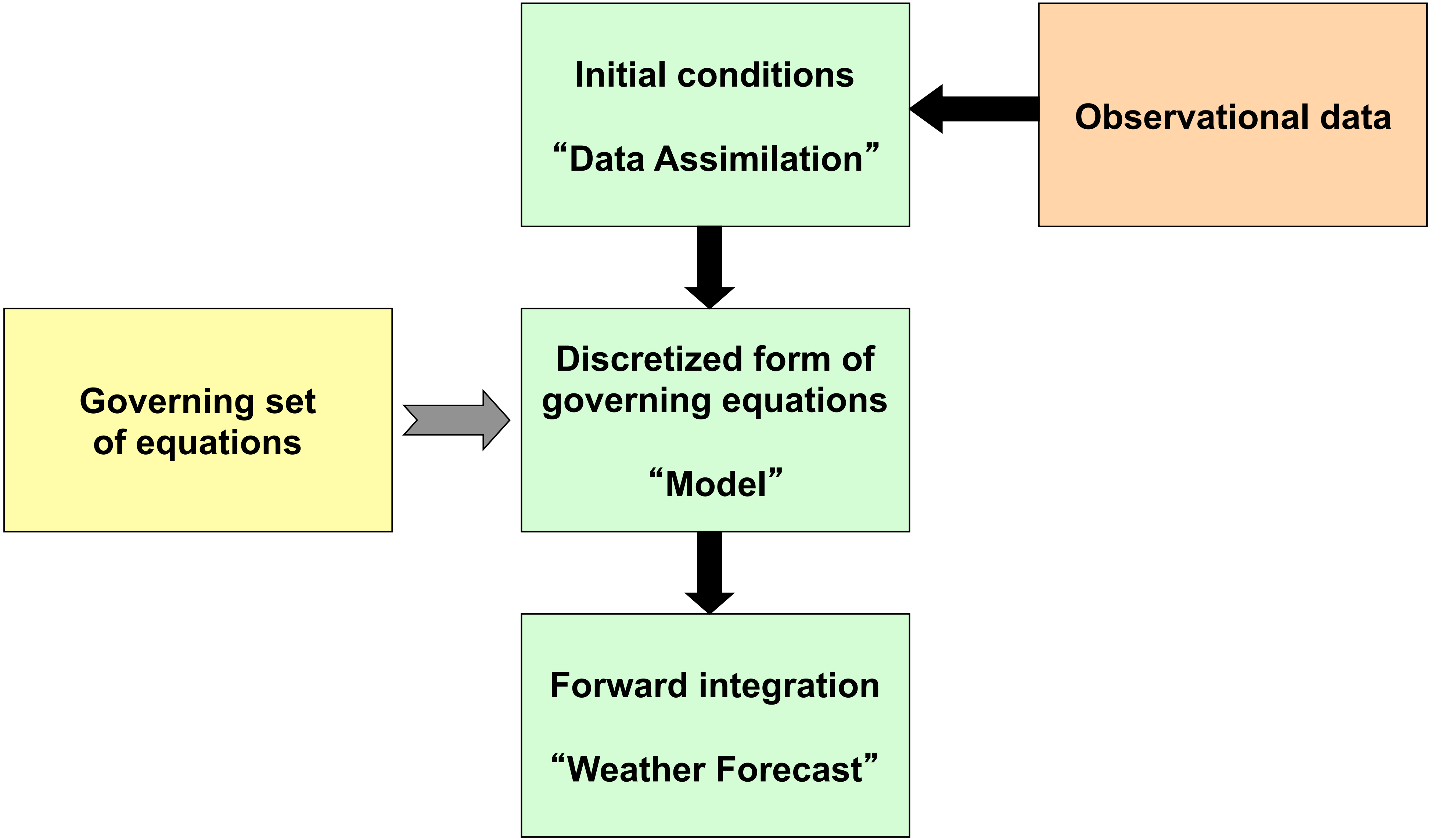
Global observing and data assimilation systems

Data assimilation methods

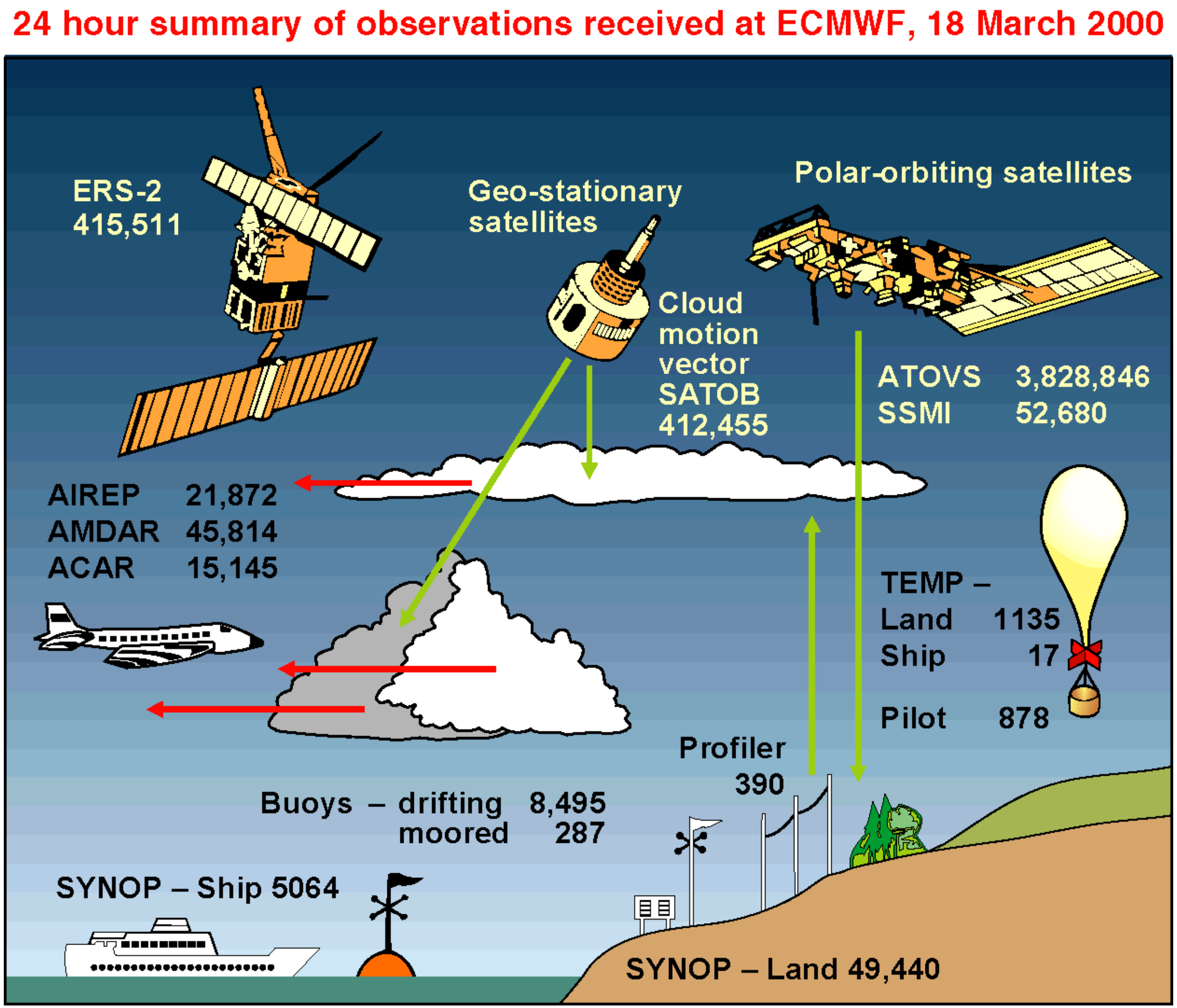
Use and impact of satellite data

Reanalyses and climate data sets

Steps in a deterministic weather forecast

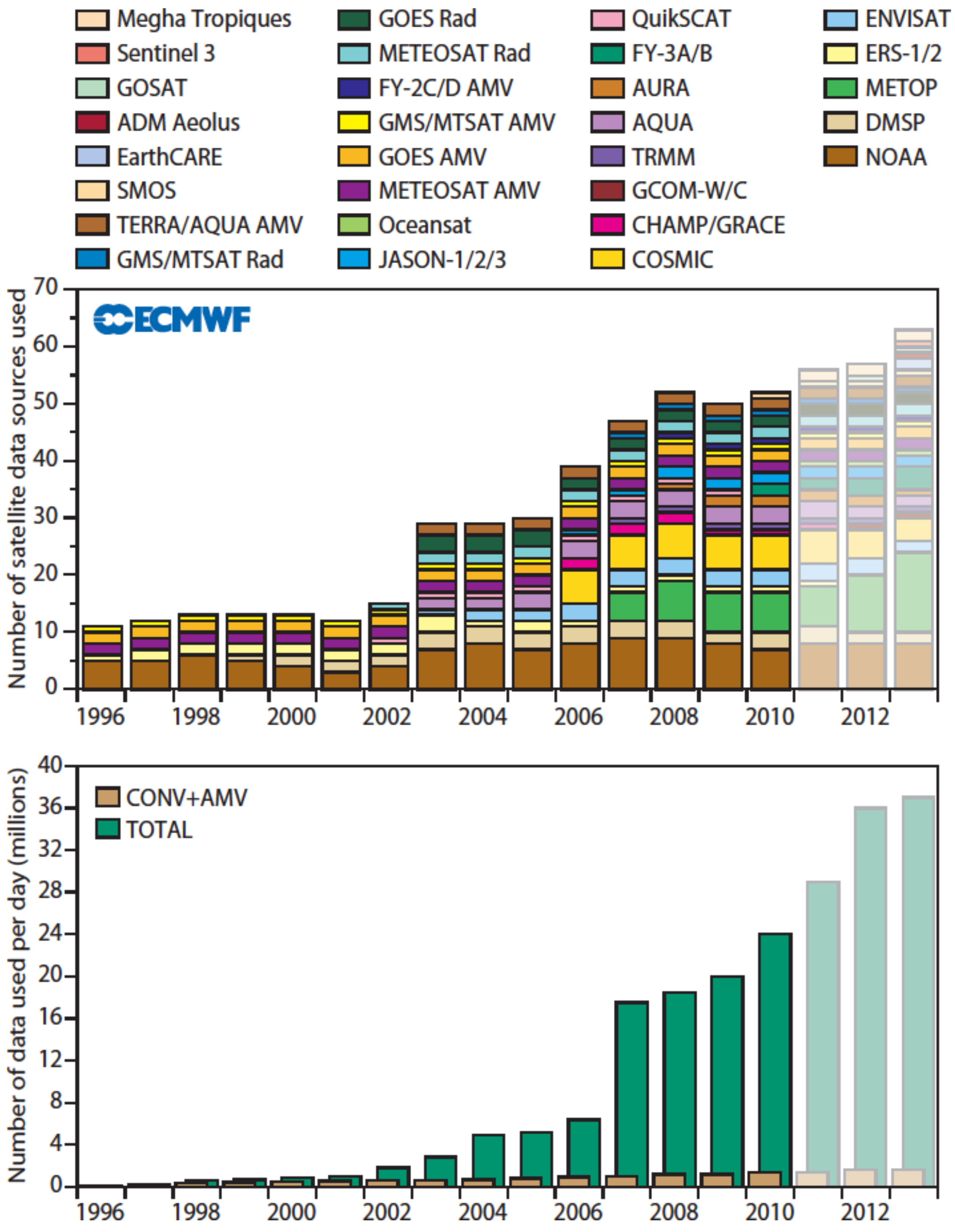


Summary of observational data



(ECMWF 2001)

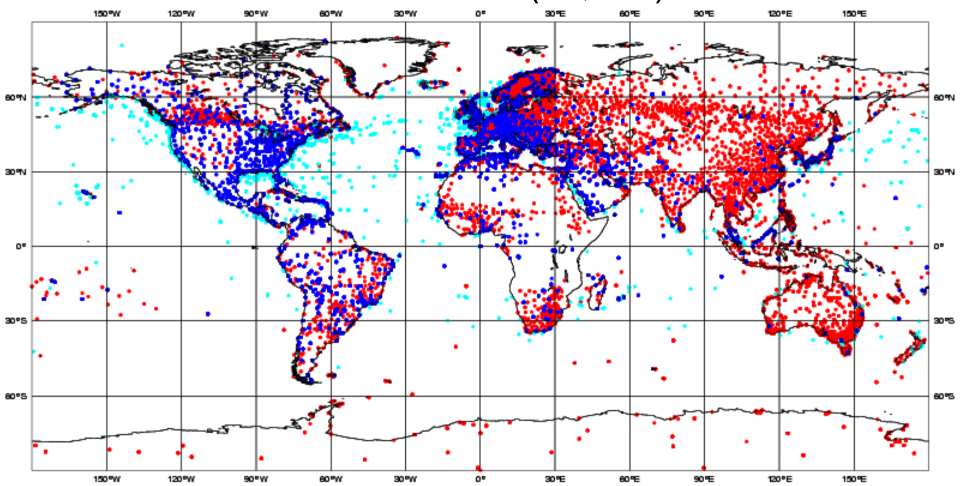
Satellite Data



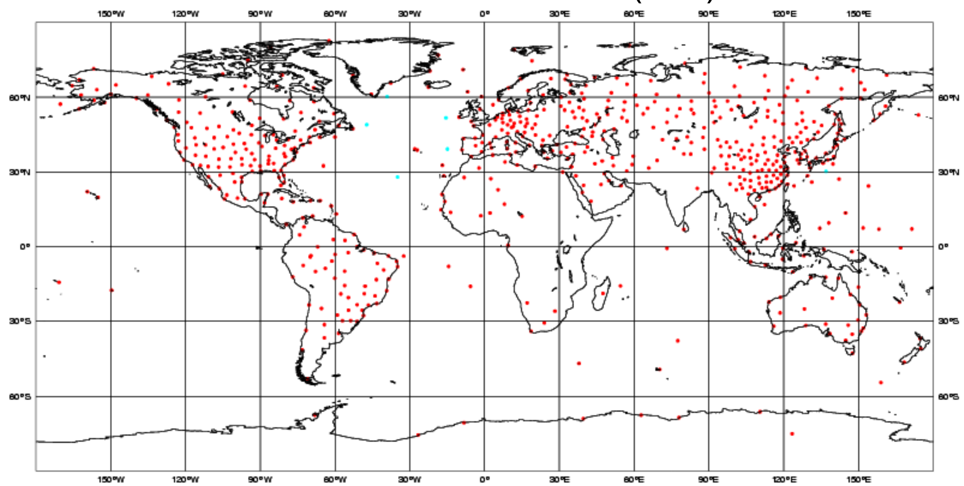
(ECMWF, 2011)

Global observing system: in-situ data

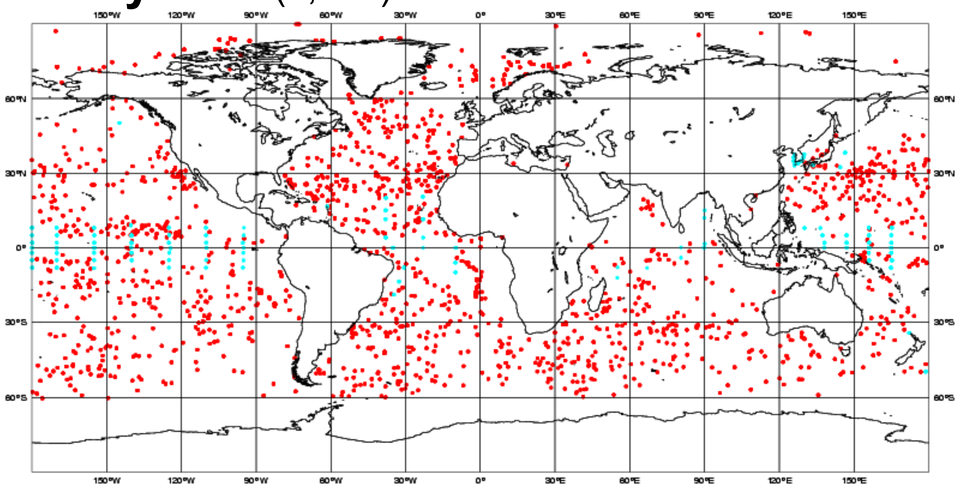
Surface observations (33,904)



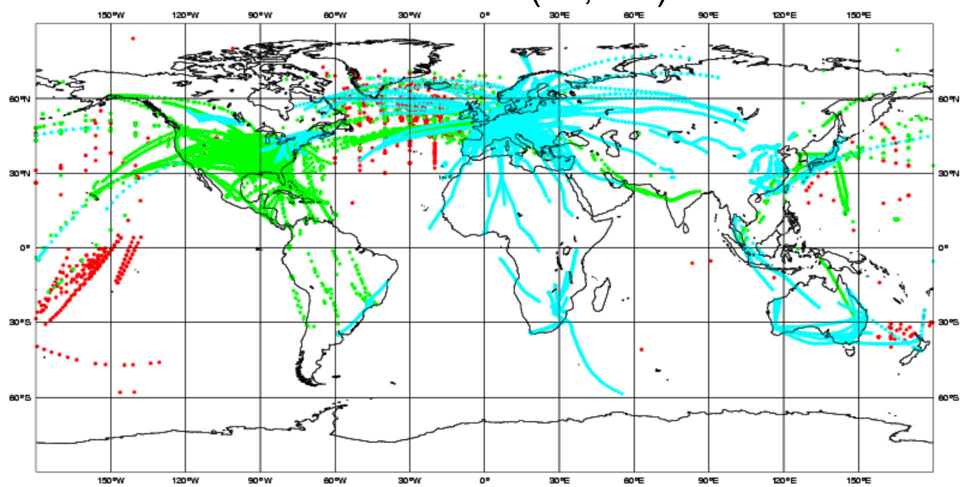
Radiosonde observations (641)



Buoy data (9,625)



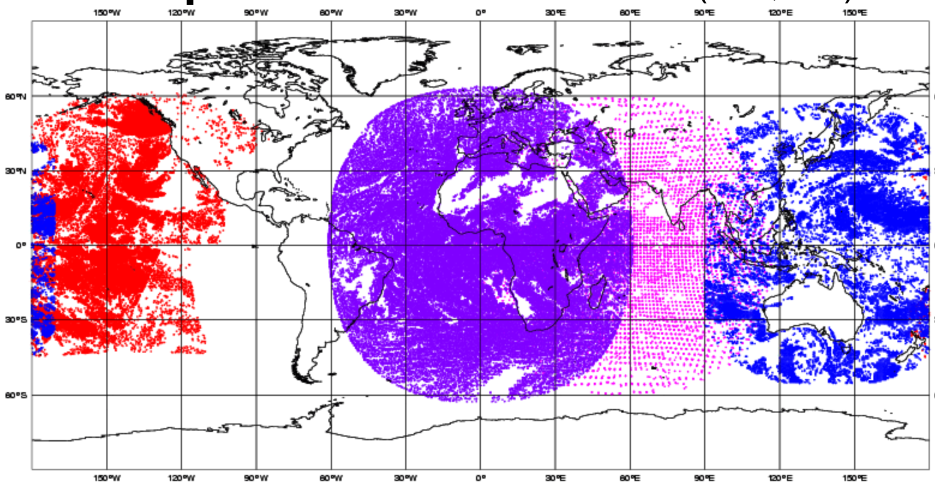
Aircraft observations (46,037)



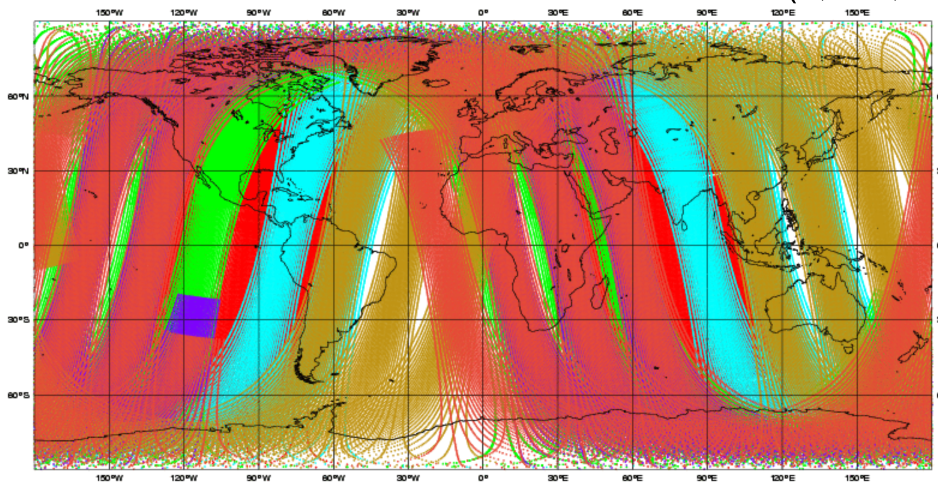
Data received at ECMWF on May 3, 2010, 9–15 UTC (in brackets: number of obs)

Global observing system: remote-sensing data

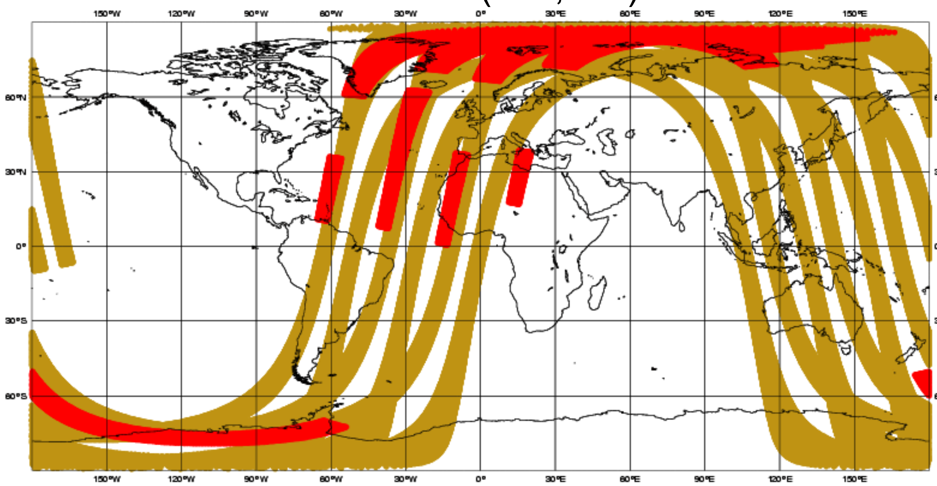
Atmospheric motion vectors (351,655)



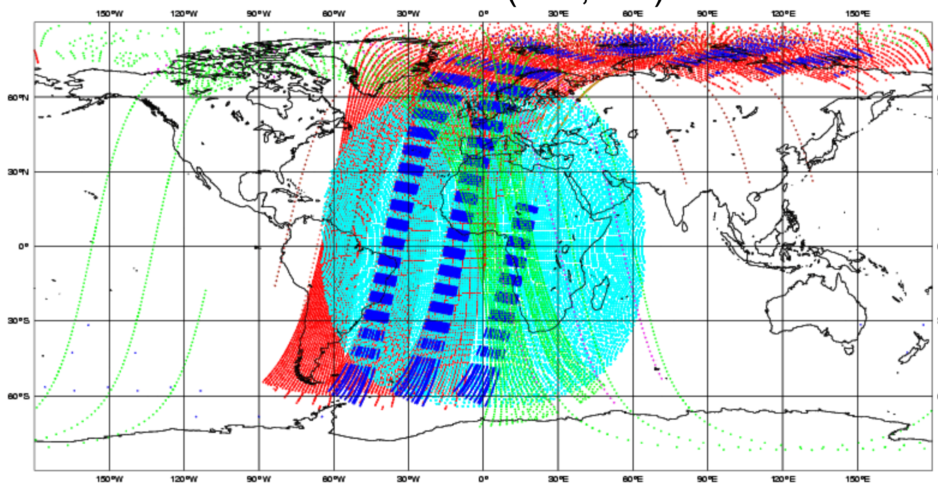
Microwave and infrared sounder (1,343,053)



Scatterometer data (485,359)



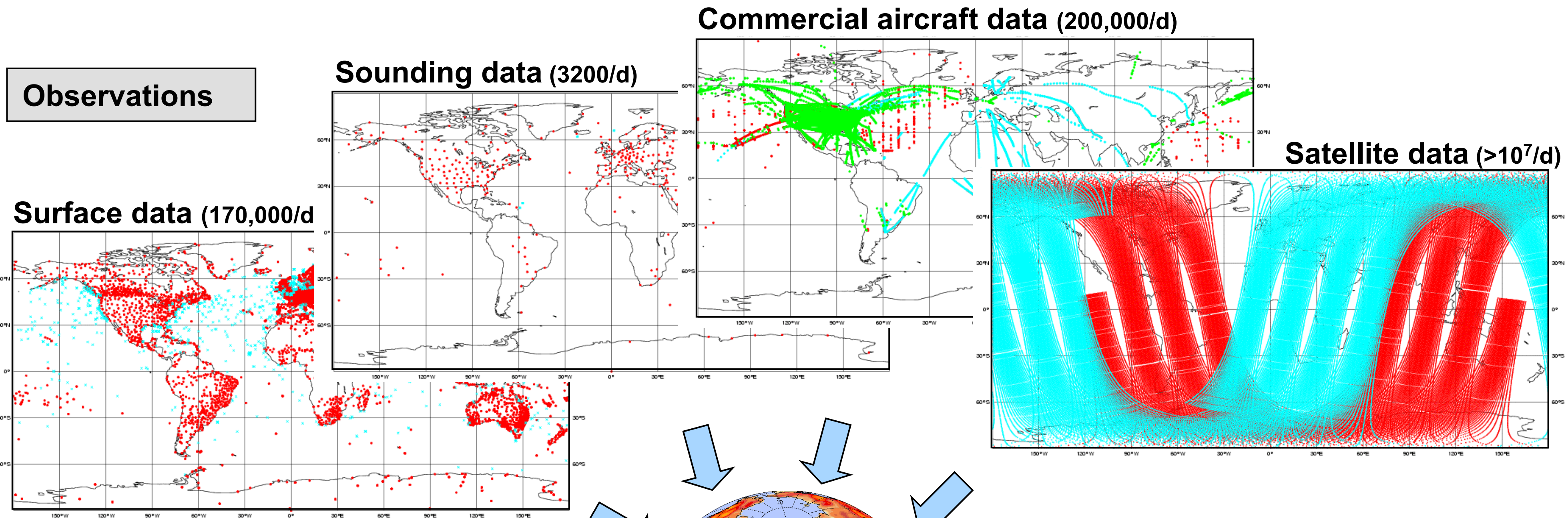
Ozone observations (101,945)

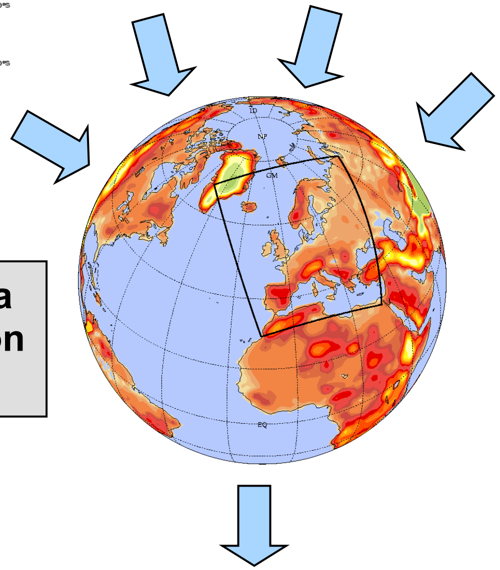


Data received at ECMWF on May 3, 2010, 9–15 UTC (in brackets: number of obs)

Global atmospheric data assimilation

Observations





Global data assimilation system

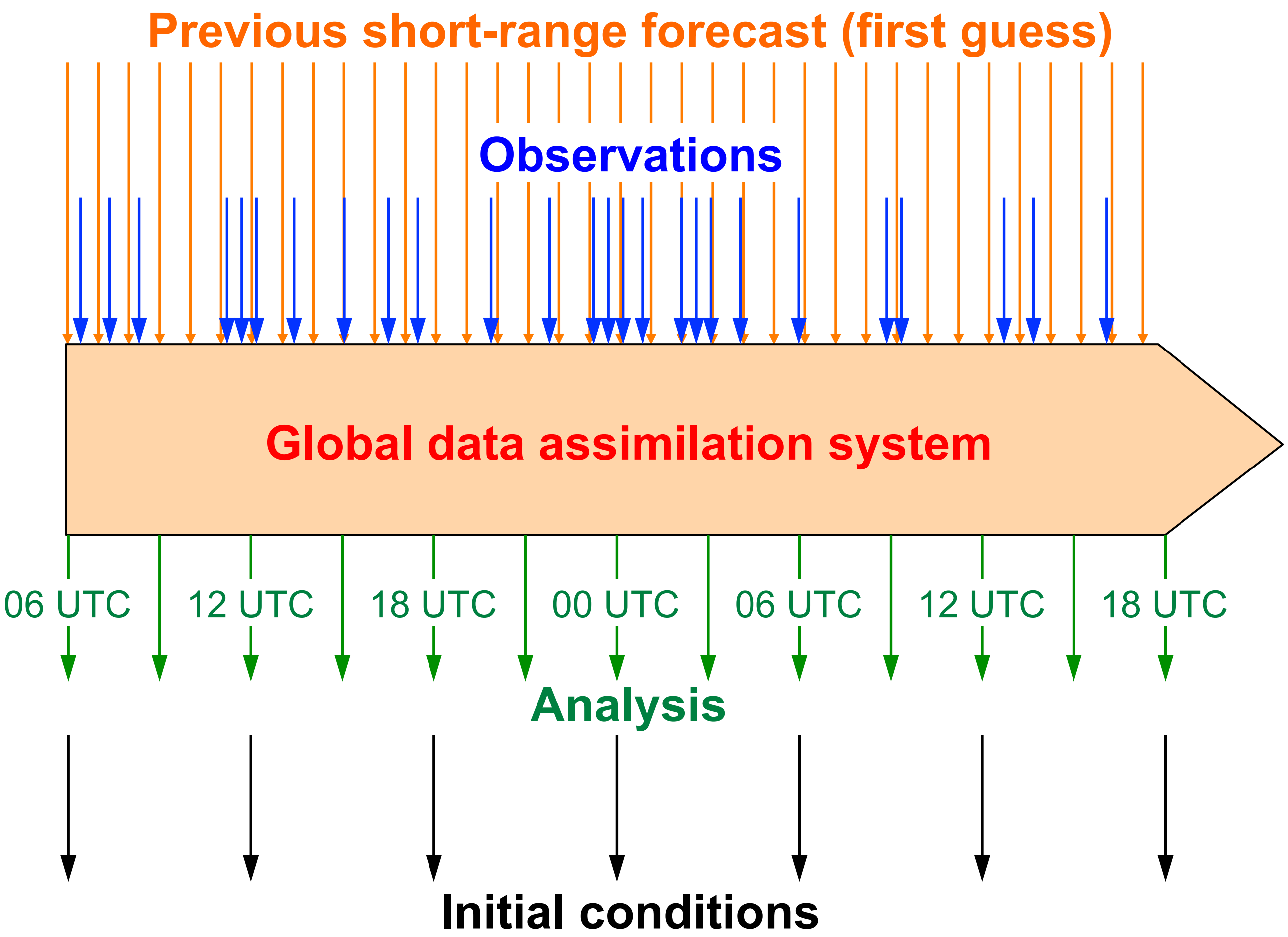
Internally consistent global atmospheric data set on a computational mesh

Numerical weather prediction:
- **ECMWF operational analysis**

Reanalysis:
- **ERA-interim (1989-today)**
- **ERA-40 (1958-2001)**

(ECMWF)

Global data assimilation



Assimilation: An analysis technique in which the observed information is accumulated into the model.

Analysis: spatially and temporally coherent data set on a grid, based on observations as far as feasible

Global data assimilation systems ingest a wide range of data from various instruments and observation times. They run a general circulation model (GCM) in hindcast mode. The resulting analysis is a spatially and temporally coherent description of the actual state of the atmosphere. In data sparse regions, where few observations are available, these systems in essence provide a mixture between a short-range (e.g. 6 h) forecast and the available observations.

Outline

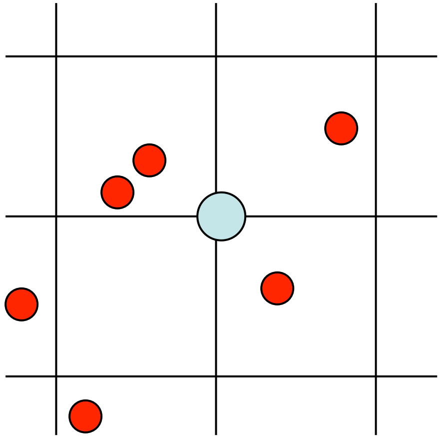
Global observing and data assimilation systems

Data assimilation methods

Use and impact of satellite data

Reanalyses and climate data sets

Optimal Interpolation (OI)



- Observations $(z_i^{obs},\ z_i^{fg})$
- Gridpoint $(z,\ z^{fg})$

Here z^{fg} refers to the first guess (or background), which is derived from a previous short-range forecast.

Assumption 1: The analysis is defined as a weighted mean over neighboring observations:

$$z = z^{fg} + \sum_{i=1}^{m} A_i \left(z_i^{obs} - z_i^{fg} \right)$$

Here z_i^{fg} is the interpolation of z^{fg} to the location of the observation.

Assumption 2: The weights A_i are chosen such, that the mean error over many cases is minimized (in the least square sense). To this end, the following functional must be minimized

$$J = \frac{1}{2} \left\langle \left(z^t - z \right)^2 \right\rangle$$

where z^t denotes the true value at the grid point, and where the outer brackets denote the mean over some time period.

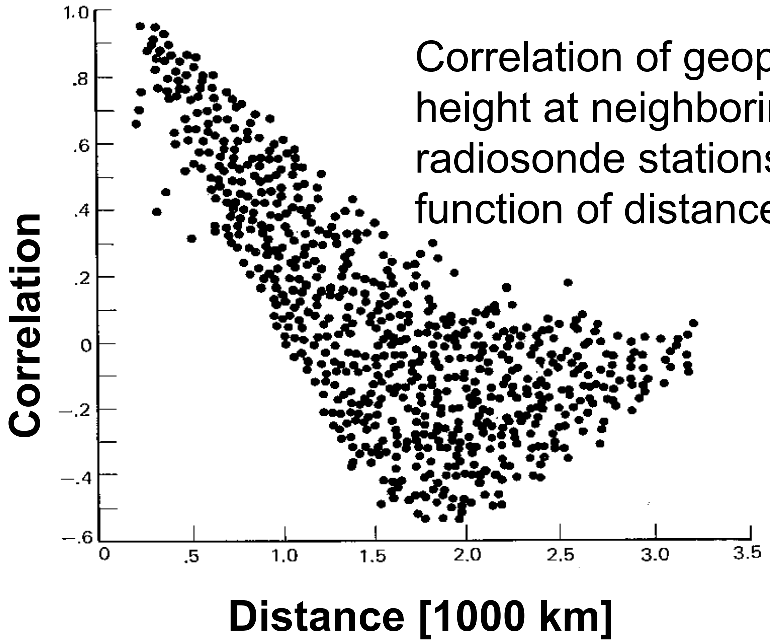
How to choose the weights in OI

(1) Statistics of observations:

To estimate the “analysis error”, one assumes that the respective covariances, i.e.

$$B_i = \left\langle \left(z^t - z^{fg} \right) \left(z_i^{obs} - z_i^{fg} \right) \right\rangle$$

depend upon the distance between observations only.



Correlation of geopotential height at neighboring radiosonde stations as a function of distance.

(2) Past performance of the OI system:

To assess the first-guess error covariance between neighboring observations, i.e.

$$C_{li} = \left\langle \left(z_l^{obs} - z_l^{fg} \right) \left(z_i^{obs} - z_i^{fg} \right) \right\rangle$$

one uses information from the past performance of the assimilation system

Combining these two types of information, allows to objectively choose the optimal weights A_i for the analysis.

The procedure is intricate and involves the past performance of an older OI data assimilation system, and the solution of a linear set of equations.

3D variational data assimilation

Model state:	model vector $\mathbf{x}$ ($n \approx 10^7$ to 10^9 degrees of freedom)
"First Guess":	short-range forecast $\mathbf{x}^{fg}$
Observations:	vector $\mathbf{y}$ ($m \approx 10^4$ to 10^7 observations / time window)
Observations operator $\mathbf{H}$:	simulated observations: $\mathbf{y}^{sim} = \mathbf{H}(\mathbf{x}^{fg})$

Minimization of penalty funktion $J(\mathbf{x})$

$$J(\mathbf{x}) = \underbrace{\frac{1}{2}\sum_{p=1}^{n}\frac{\left(x_p - x_p^{fg}\right)^2}{F_p^{fg}}}_{\text{Minimizes distance between fg and analysis}} + \underbrace{\frac{1}{2}\sum_{q=1}^{m}\frac{\left(H_q(\mathbf{x}) - y_q\right)^2}{F_q^{obs} + F_q^{H}}}_{\text{Minimizes distance between OBS and analysis}}$$

where

F^{obs} mean error of observations

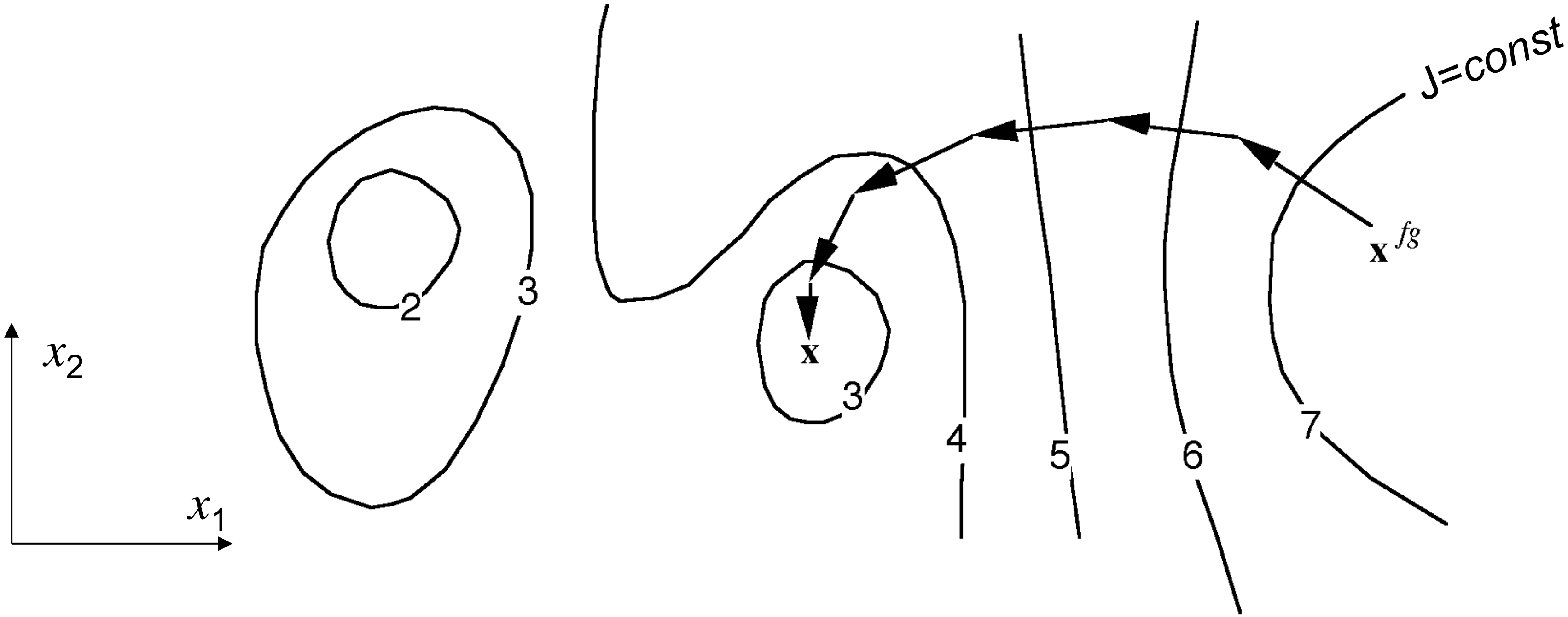
F^{H} mean error of observations operator

F^{fg} mean error of first guess

Statistical estimates are derived from past forecast performance

Minimization in variational assimilation

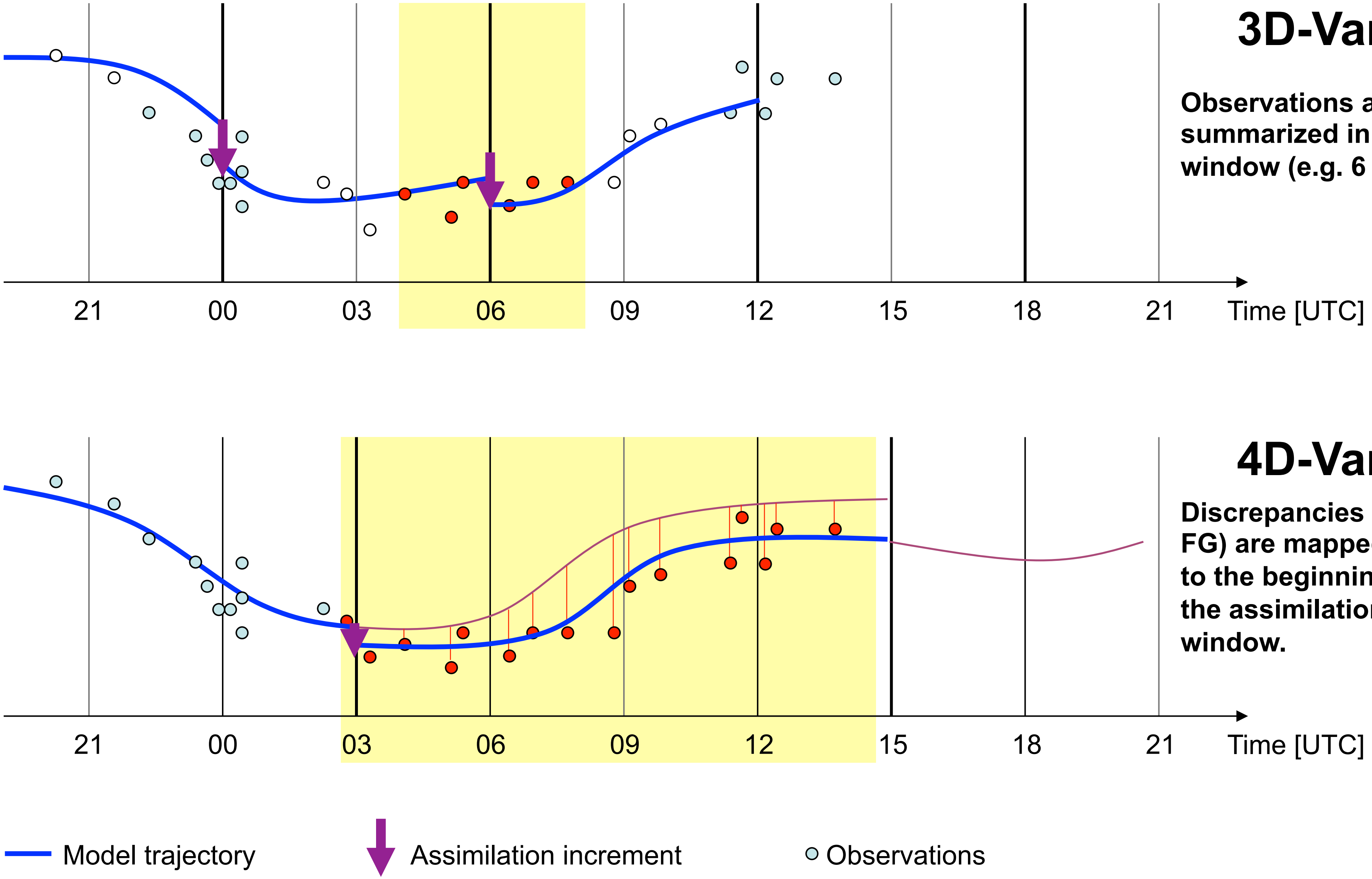
Minimization of penalty funktion $J(\mathbf{x})$ starting at first guess $\mathbf{x}^{fg}$



Minimization of J requires computation of gradient

$$[\nabla J(\mathbf{x})]_p = \frac{x_p - x_p^{fg}}{F_p^{fg}} + \sum_{q=1}^{m} \frac{H_q(\mathbf{x}) - y_q}{F_q^{obs} + F_q^H} \frac{\partial H_q(\mathbf{x})}{\partial x_p}$$

3D versus 4D Assimilation



3D-Var

Observations are summarized in a time window (e.g. 6 h)

4D-Var

Discrepancies (OBS-FG) are mapped back to the beginning of the assimilation window.

3D versus 4D Assimilation

3D-Var

$$J(\mathbf{x}) = \frac{1}{2}\sum_{p=1}^{n}\frac{\left(x_p - x_p^{fg}\right)^2}{F_p^{fg}} + \frac{1}{2}\sum_{q=1}^{m}\frac{\left(H_q(\mathbf{x}) - y_q\right)^2}{F_q^{obs} + F_q^{H}}$$

Observations are summarized in a time window (e.g. 6 h)

The sum p runs over all degrees of freedom of the model.

The sum q runs over all observations available.

4D-Var

$$J(\mathbf{x}^o) = \frac{1}{2}\sum_{i=0}^{T}\sum_{p=1}^{n}\frac{\left(x_p^i - x_p^{fg,i}\right)^2}{F_p^{fg}} + \frac{1}{2}\sum_{i=0}^{T}\sum_{q=1}^{m_i}\frac{\left(H_{i,q}\left(\mathbf{x}^i\right) - y_q^i\right)^2}{F_q^{obs,i} + F_q^{H,i}}$$

Discrepancies (OBS-FG) are mapped back to the beginning of the assimilation window.

The sum i runs over all time windows (with a length of e.g. 1h), where $\mathbf{x}^o$ and $\mathbf{x}^i$ denote the model state at $t=t^o$ and $t=t^i$, respectively.

The minimization in 4D-Var involves the tangent linear approximation.

Tangent linear approximation in 4D-Var

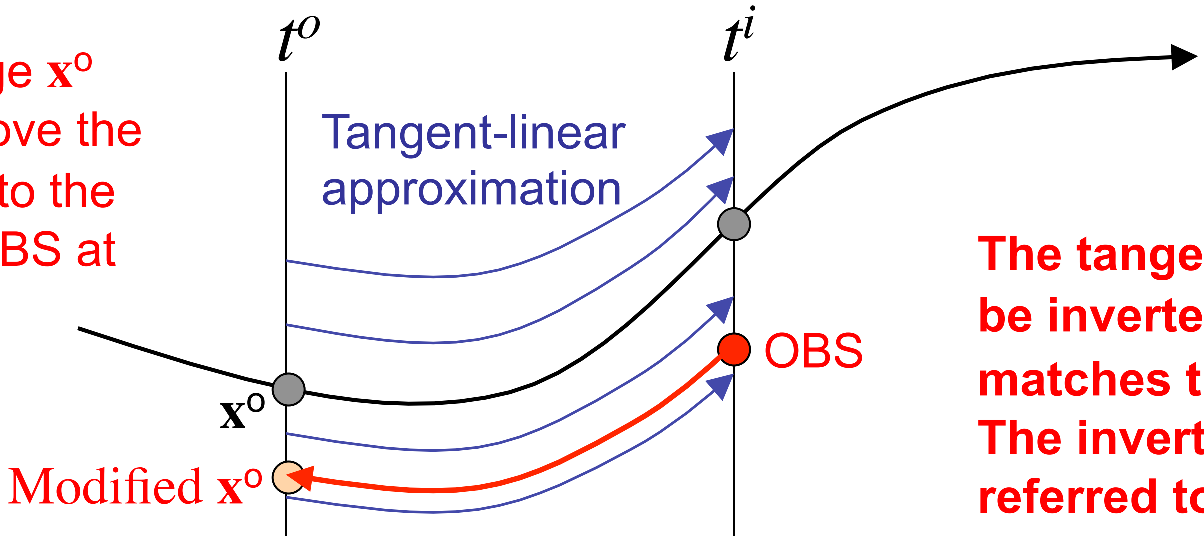
Minimization of $J(\mathbf{x}^o)$ requires terms of the form

$$\left(\mathbf{A}^i\right)_{p,l} = \frac{\partial x_p^i}{\partial x_l^o}$$

Thus, we need to know how the model state $\mathbf{x}^i$ depends upon $\mathbf{x}^o$.

For simplification, one makes the **tangent-linear approximation**, which refers to the linearization around a particular non-linear model trajectory:

How to change $\mathbf{x}^o$ such as to move the endpoint $\mathbf{x}^i$ into the direction of OBS at time t^i?



The tangent-linear model can be inverted to find $\mathbf{x}^o$ that matches the state $\mathbf{x}^i$ at time t^i. The inverted model is referred to as adjoint model.

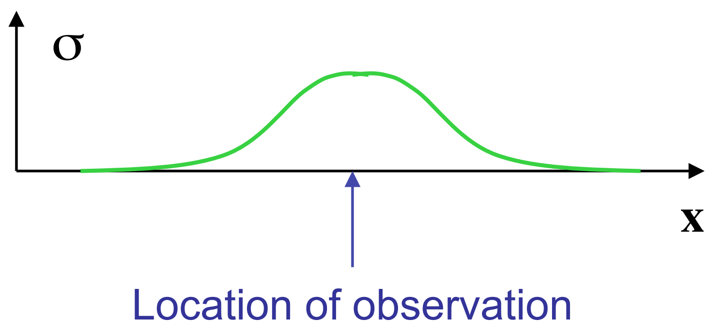
Nudging

$$\overbrace{\frac{\partial \chi}{\partial t} = \text{physical terms}}^{\text{“governing equations”}} + \underbrace{\sum_i \varepsilon_i \;\; \sigma_i(\mathbf{x}-\mathbf{x}_i, t-t_i)\,\left(\chi_i^{obs} - \chi(\mathbf{x}_i, t_i)\right)}_{\text{Nudging terms}}$$

where

ε_i = weight of observation i

σ_i = weight in space and time



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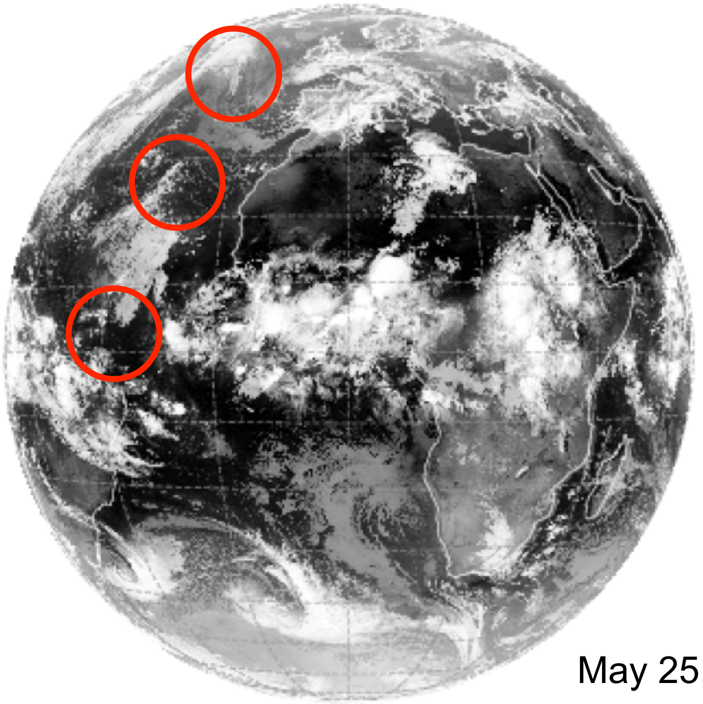
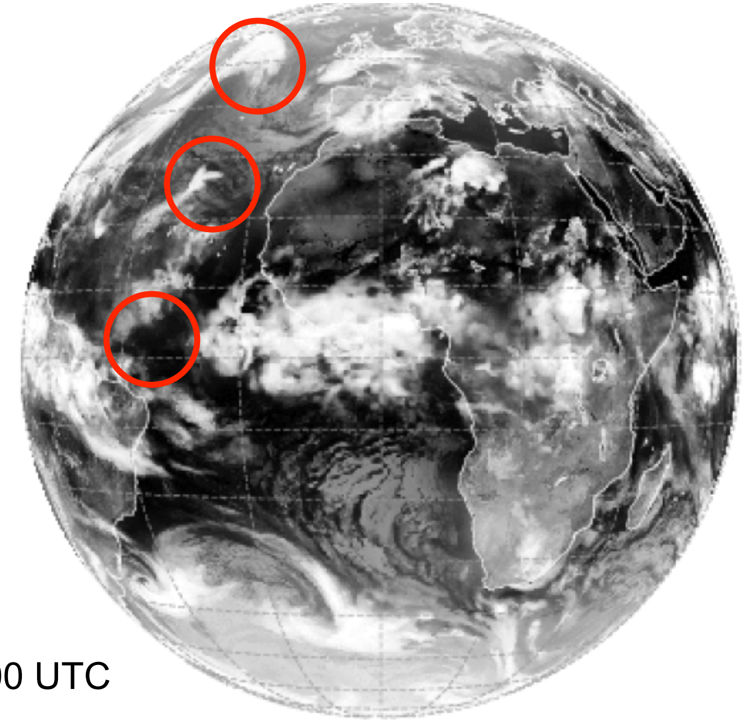
Why so difficult to use?

Real satellite picture (Meteosat 9, IR IR10.8)



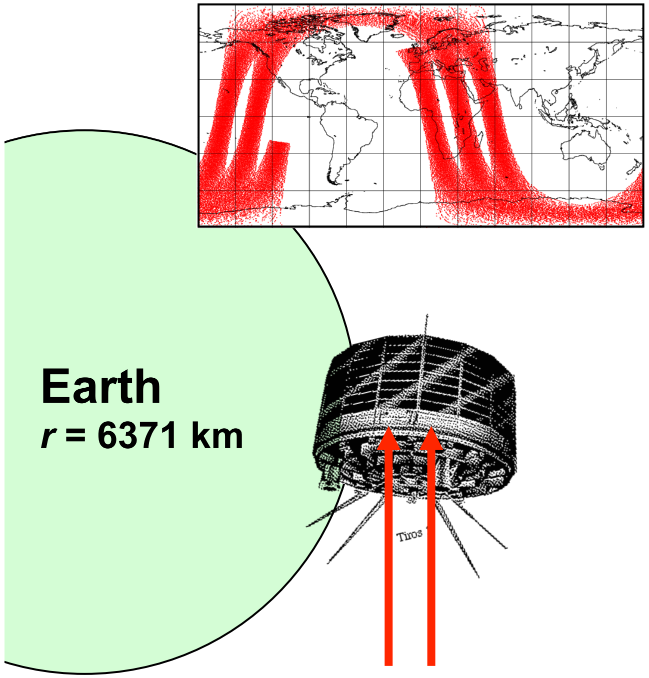
Synthetic satellite picture from assimilation system (ECMWF)



May 25, 2008, 00 UTC

- **Comparison shows differences in radiative transfer at top of the atmosphere (which is affected by profiles of cloud, temperature, humidity and underlying surface).**
- **How should this be converted into primary variables of the assimilation system (including wind and pressure data)**

Satellite orbits



Polar orbit
d = 700-1700 km
T = 1.5-2 h

Inclination of orbit to equator may be selected to map most of the planet in sun-synchronous orbits.

Examples:
NOAA-19, MetOp, Terra, Aqua, …

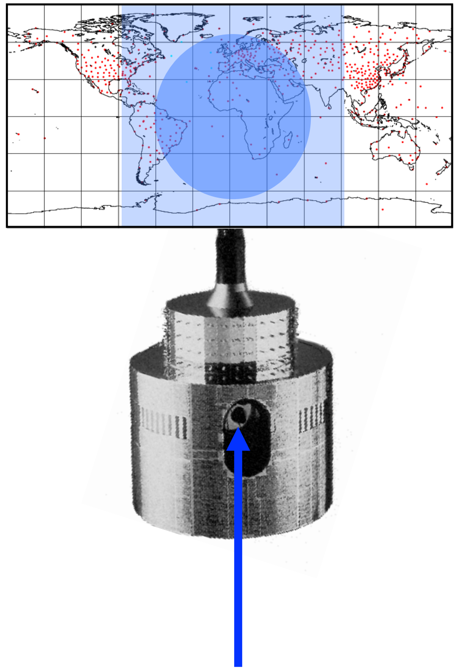
Orbital period

$$T = 2\pi\sqrt{\frac{a^3}{\Gamma M}}$$

a = semi-major axes
Γ = gravitational constant
M = Earth's mass

$$T \approx 1.406\mathrm{h}\sqrt{\left(\frac{r+d}{r}\right)^3}$$

r = Earth's radius
d = distance from Earth



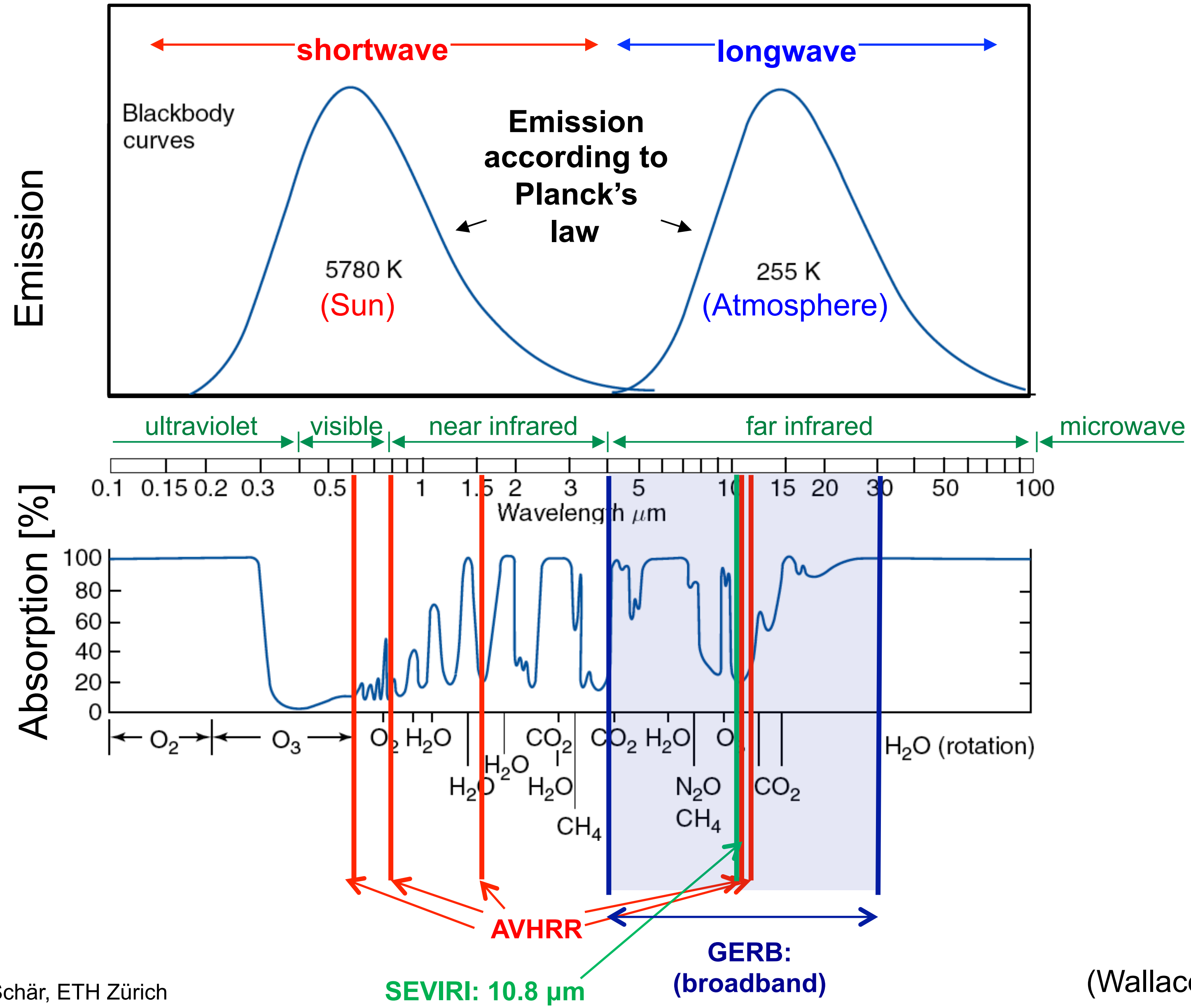
Geostationary orbit
d = 35,786 km
T = 23.93 h
(1 sidereal day)

Satellite is fixed above equator, view covers half of planet.

Examples:
Meteosat-9,
GOES-11, GOMS, …

Further info: http://en.wikipedia.org/wiki/List_of_Earth_observation_satellites

Satellite Sensors



Examples of instruments

AVHRR / HIRS
- large number of channels
- on NOAA (polar orbiting)

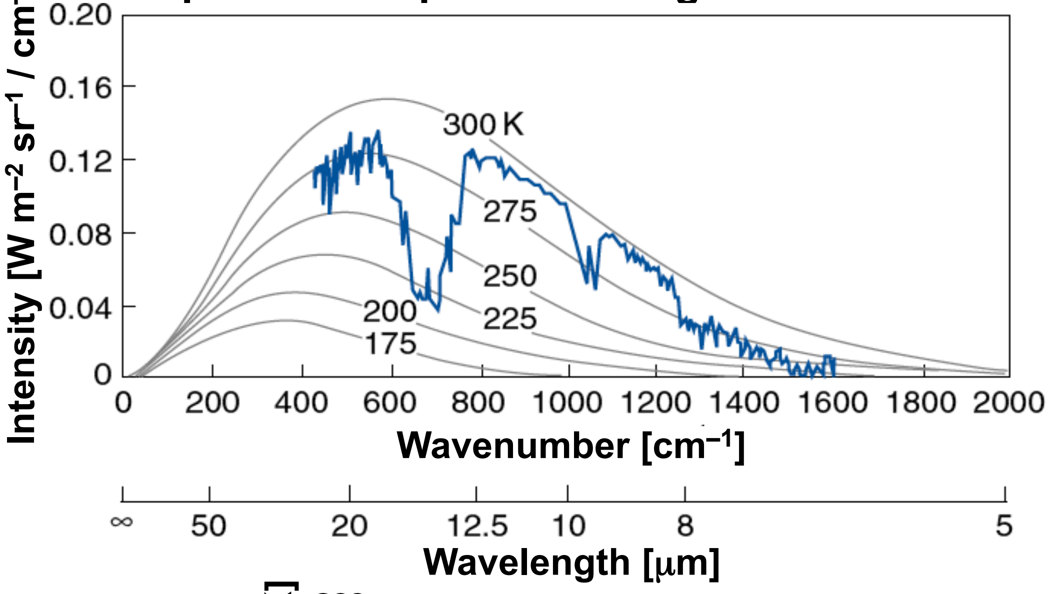
SEVIRI 10.8 μm channel
- temporal resolution 15'
- on Meteosat MSG

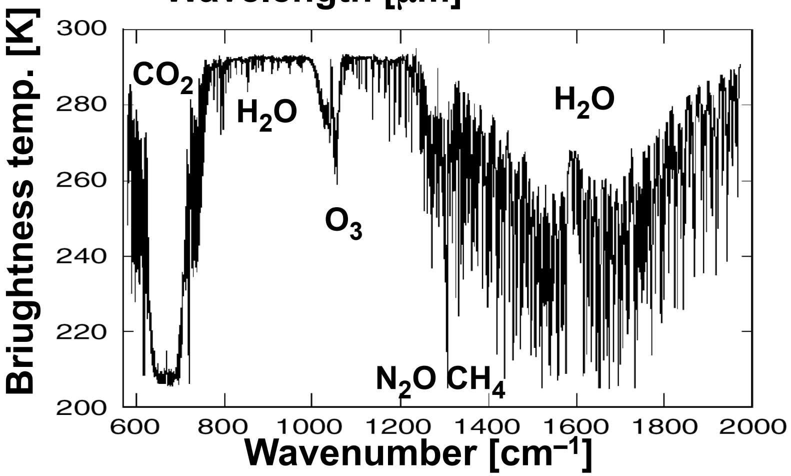
GERB
- broadband far infrared
- on Meteosat MSG

(Wallace and Hobbs, 2006; Michael Keller)

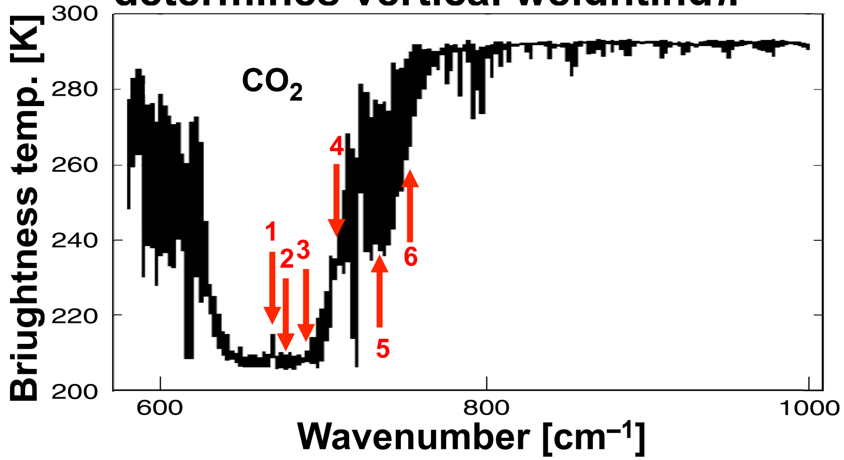
Vertical information in atmospheric radiances

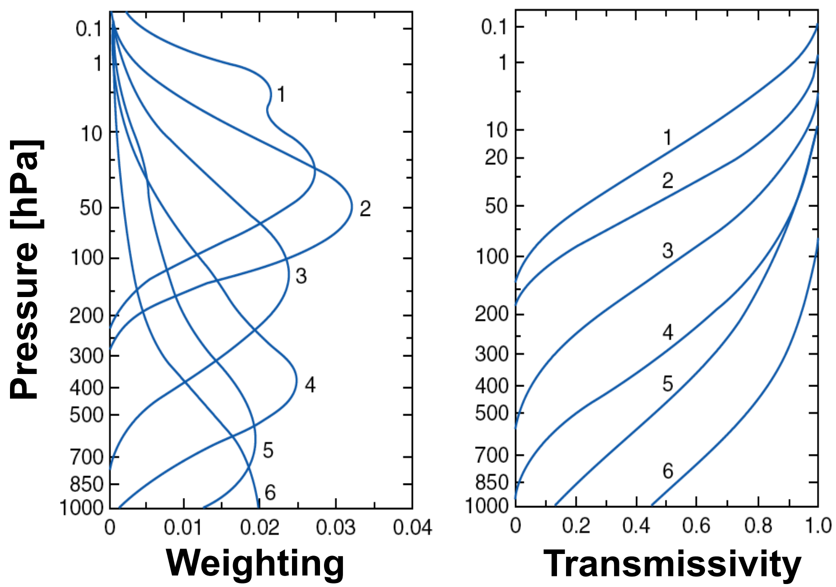
Radiances at TOA depend on surface emission plus atmospheric absorption / emission. Gaseous effects has strong dependence upon wavelength.





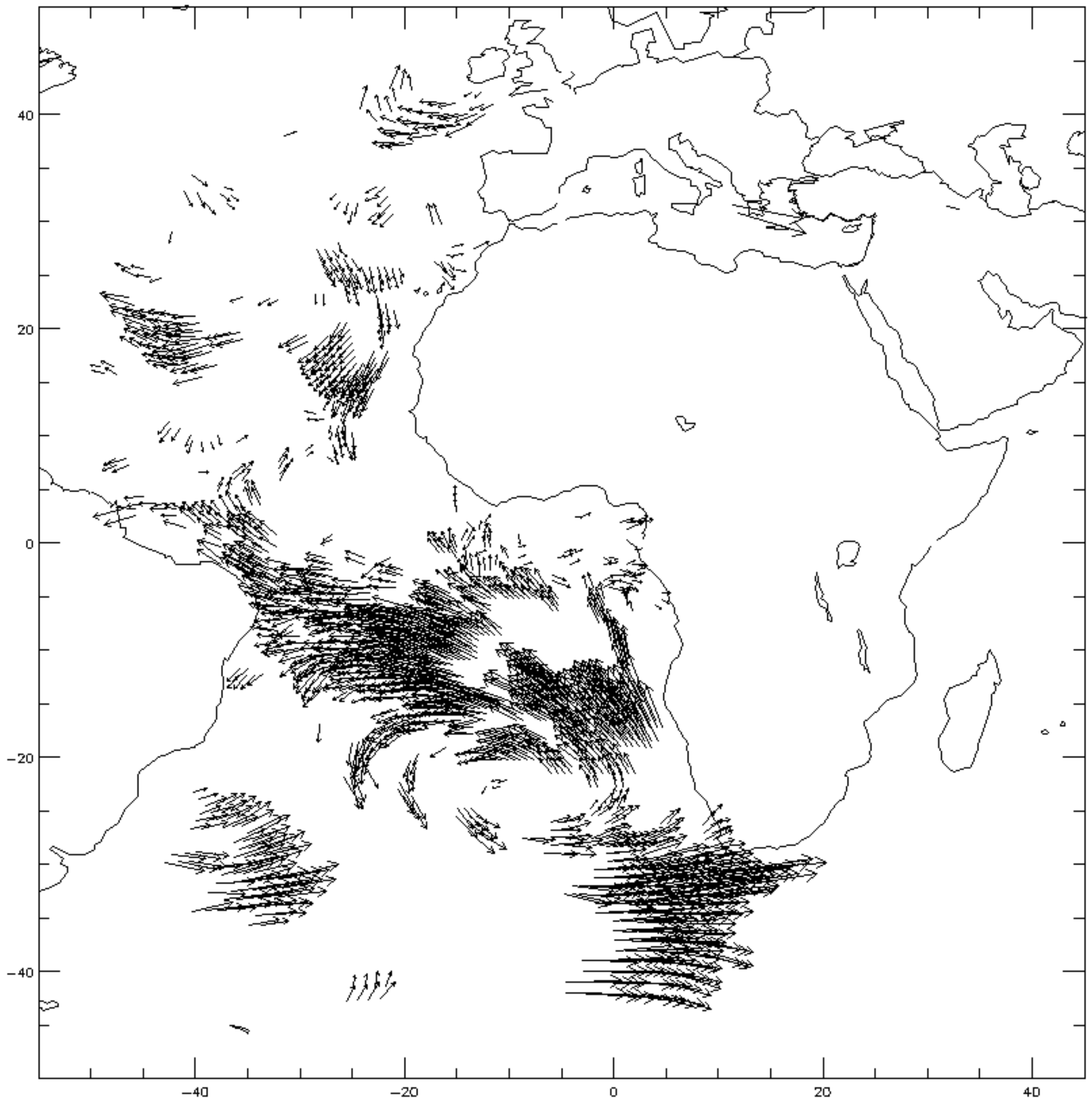
Different infrared channels can be combined to gain information about vertical structure (wave length determines vertical weighting).





(Wallace and Hobbs 2006)

Atmospheric motion vectors (AMVs)



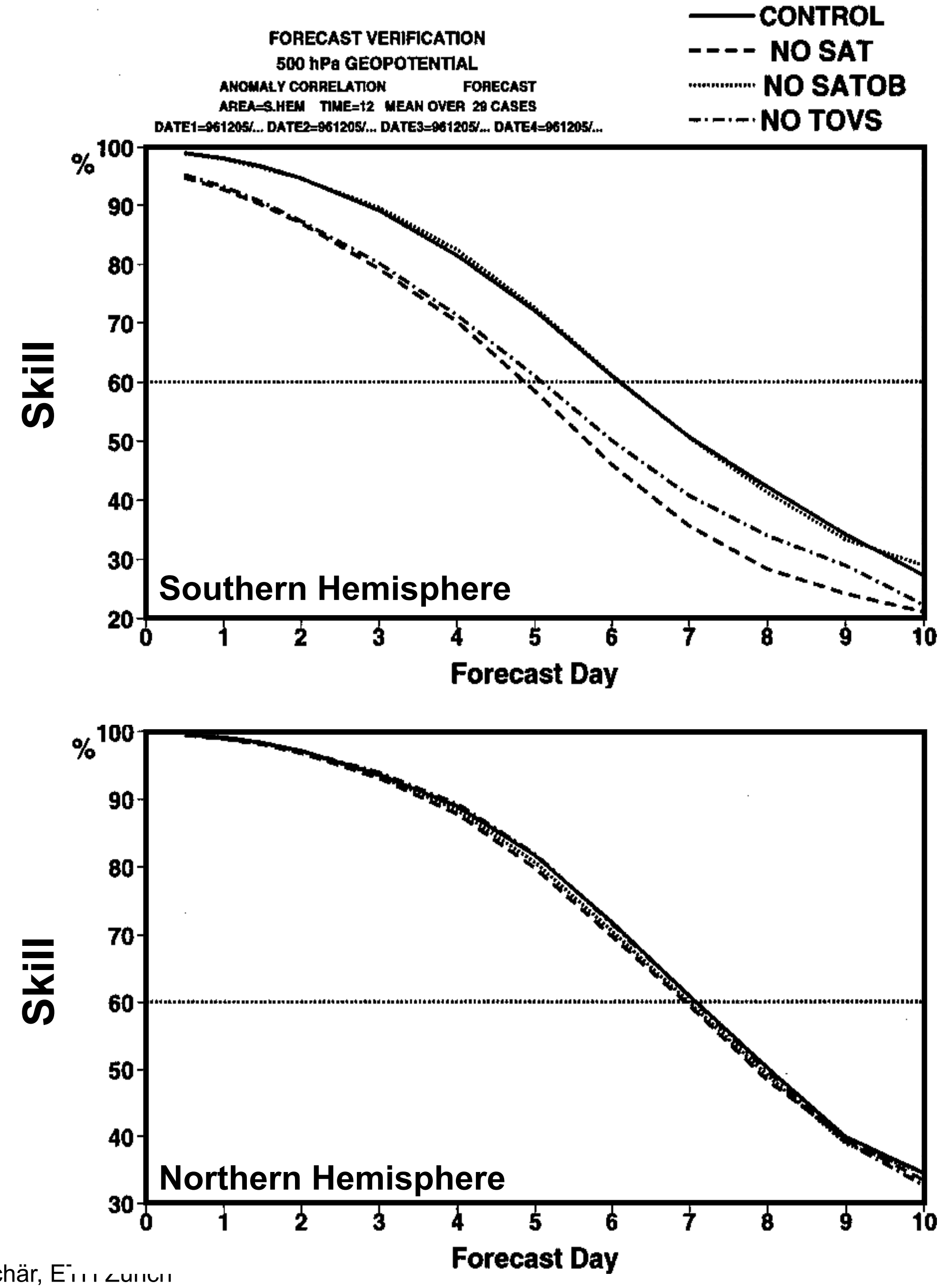
Example of high-resolution AMVs (EUMETSAT)

AMVs are generated by applying a correlation algorithm to sequences of three images, based on visible, infrared or water-vapor satellite data.

By tracking the movement of cloud fields (or humidity structures), winds can be extracted. The height can be estimated from the infrared temperature.

Most AMVs are based on geostationary satellite products.

Impact on forecast



Until about 15 years ago, satellite data did only marginally contribute to the quality of weather forecasts on the northern hemisphere (if at all).

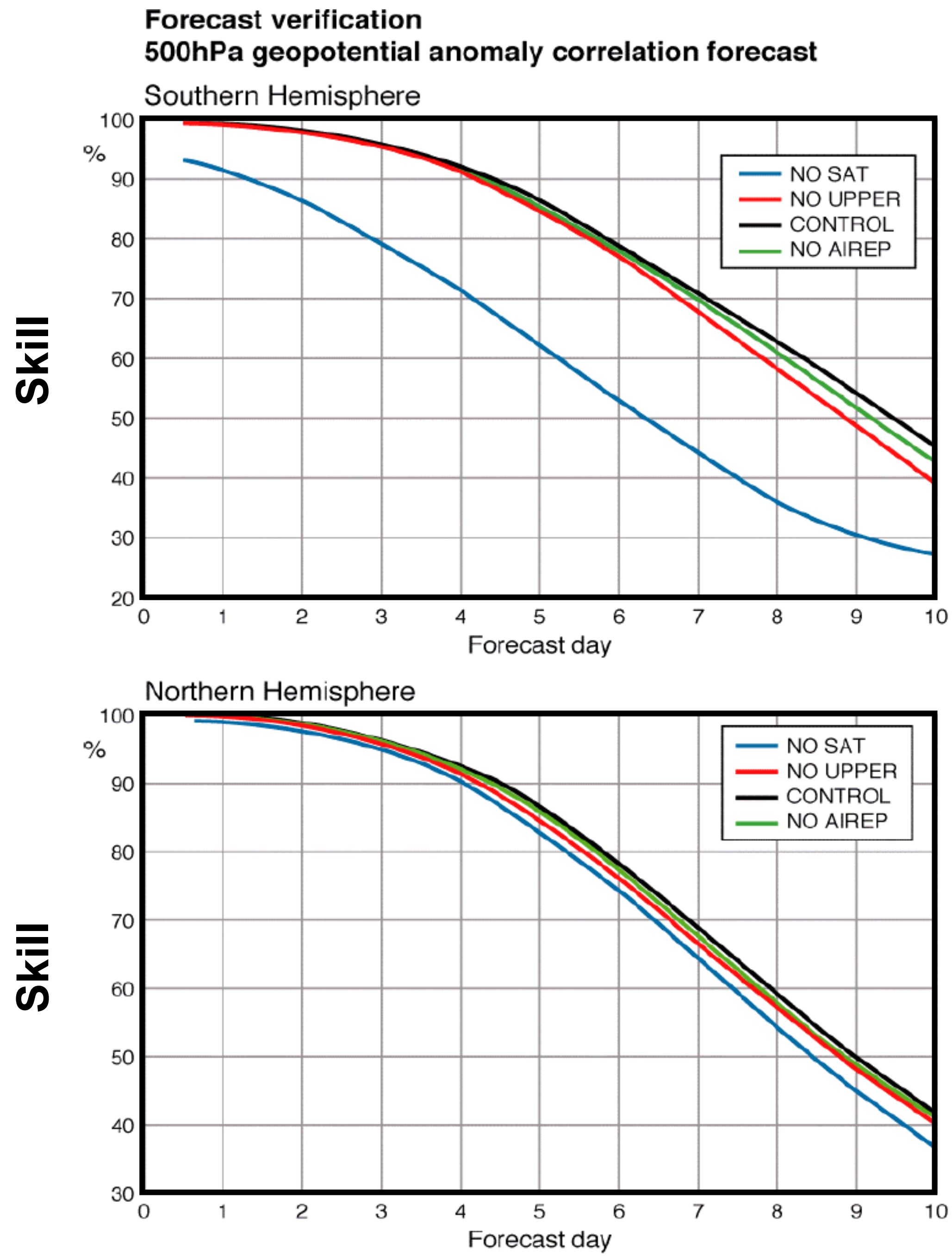
This statement is based on an objective evaluation exploiting the associated medium-range forecast skill (here the anomaly correlation skill score of the 500 hPa height field) as a function of lead time.

The different versions of the combined assimilation/forecast system use different data sets in the assimilation.

The limited success of satellite data was mostly due to the inability to properly assimilate satellite data, and not due to the quality of the data itself.

ECMWF 1997, SAC26(97)4b

Impact on forecast



Successful assimilation of satellite data became feasible in the late 1990ies after introduction of 3D-Var.

As satellite data involves radiances (rather than primary model variables), variational data assimilation systems have systematic advantages.

The differences between northern and southern hemisphere are due to vastly different coverage with conventional data.

The importance of satellite data is still rapidly improving today. The focus is shifting towards the assimilation of the hydrological cycle.

ECMWF 2003, SAC03

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Reanalyses

Reanalysis refers to the objective analysis over an extended periods. Typically they

- cover many decades,
- use a homogeneous numerical model and a homogeneous data assimilation system,
- use most of the data available for the respective periods,
- generally rely on a non-homogeneous data stream.

The most popular reanalyses are:

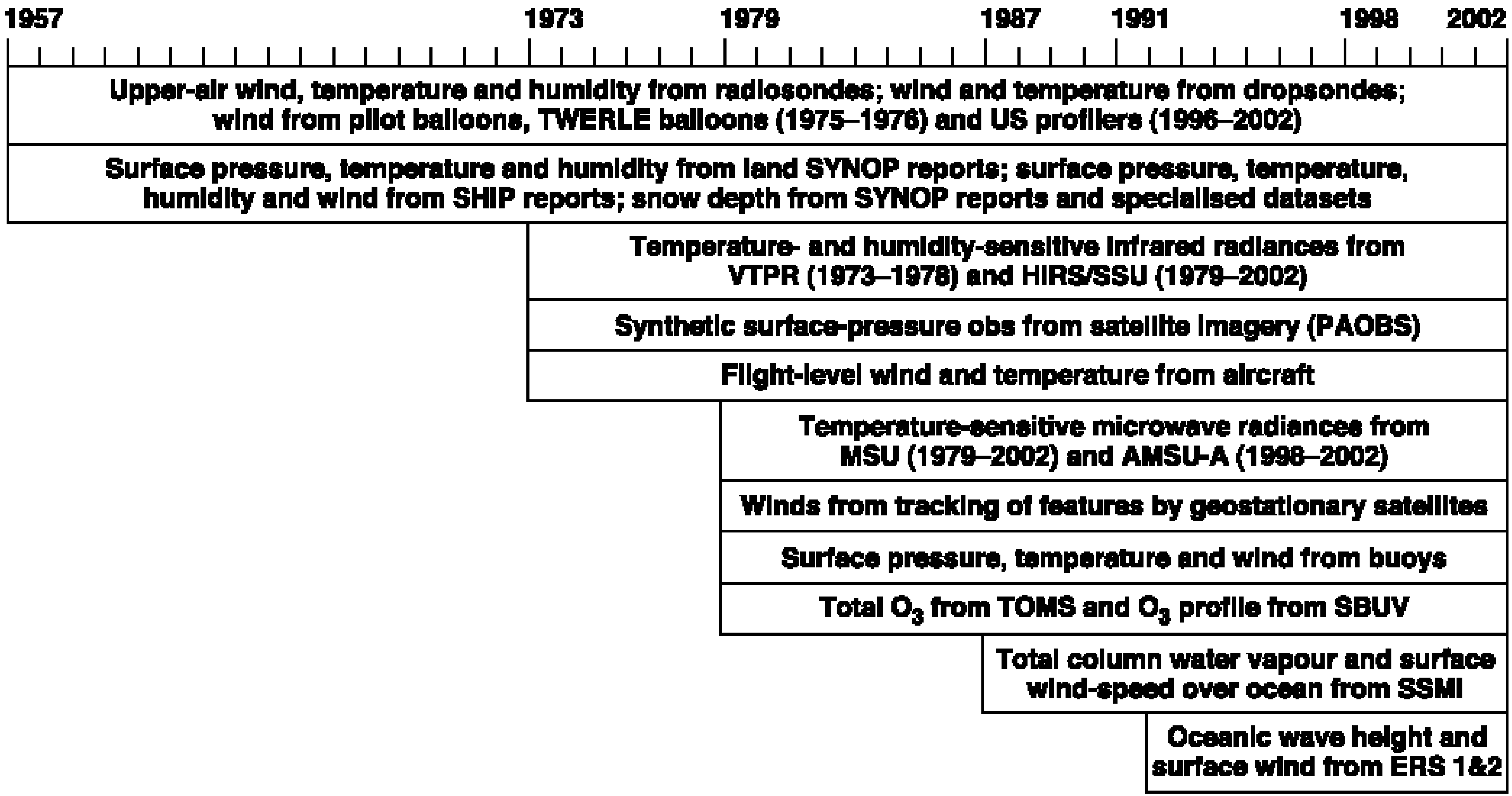
ERA-40 Reanalysis (1958-2002):
see http://www.ecmwf.int/research/era/
Intermediate-resolution: 60 levels, T_L159 (≈100 km), 3D-Var

ERA Interim Reanalysis (1979-present):
see http://www.ecmwf.int/research/era/
High-resolution, real-time: 60 levels, T_L255 (≈70 km), 4D-Var

NCEP / NCAR Reanalysis (1948-present):
see http://www.cdc.noaa.gov/cdc/reanalysis/
Low-resolution, long-term reanalysis: 28 levels, T62 (≈220 km), OI

20th Century Reanalysis Project (1871-2010):
see http://www.esrl.noaa.gov/psd/data/20thC_Rean/
Low-resolution, long-term reanalysis: 28 levels, T62 (≈220 km), Ensemble Kalman Filter (using surface pressure data only)

Data in ERA-40



Data coverage in ERA-40

Radiosonde-coverage

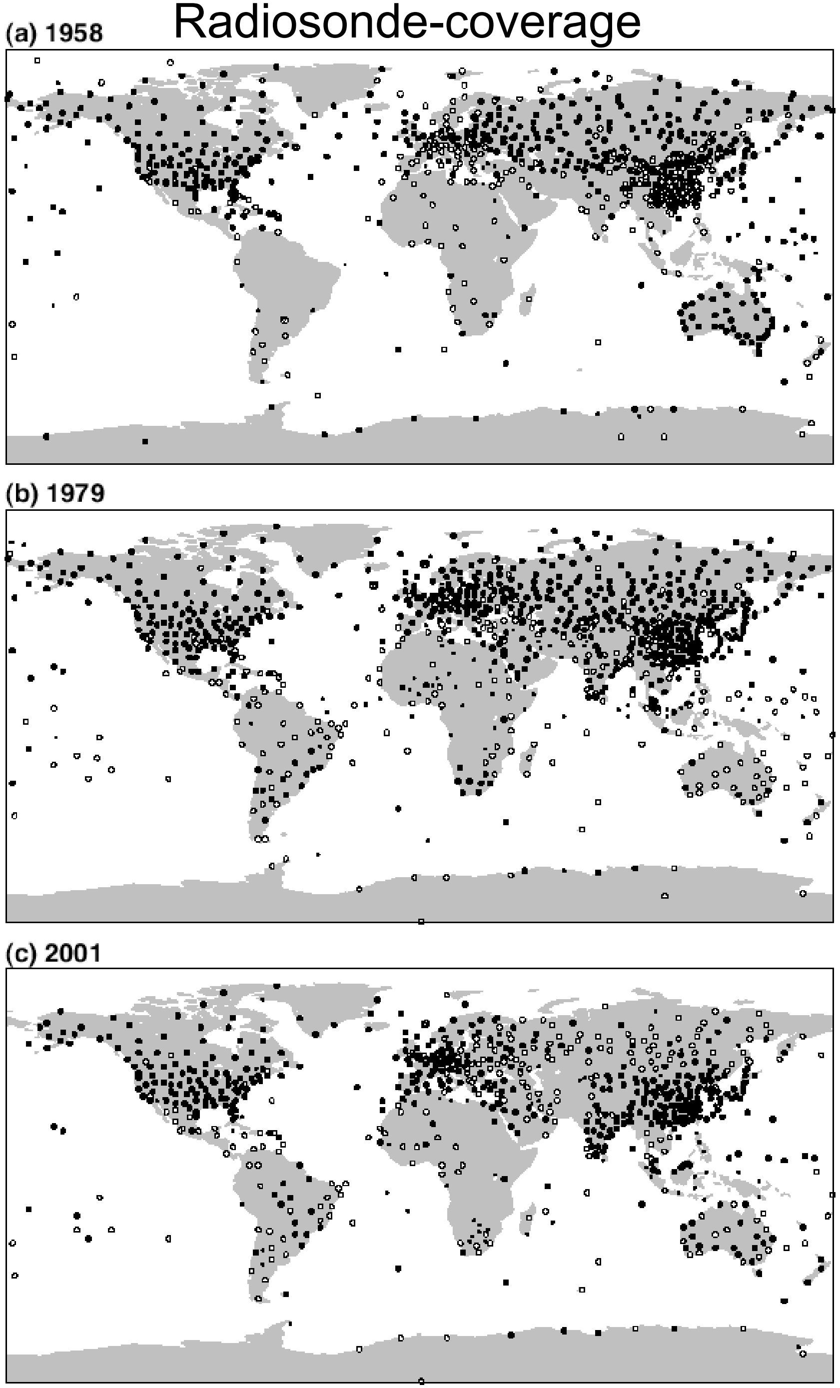
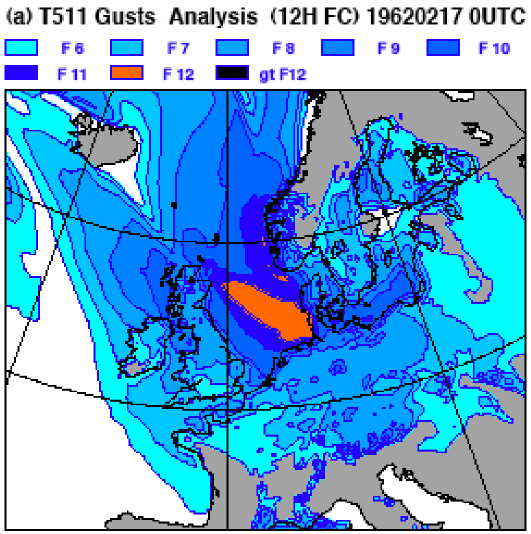


TABLE 1. AVERAGE DAILY COUNTS OF VARIOUS TYPES OF OBSERVATION SUPPLIED TO THE ERA-40 DATA ASSIMILATION, FOR FIVE SELECTED PERIODS

Observation type	1958–66	1967–72	1973–78	1979–90	1991–2001
SYNOP/SHIP	15 313	26 615	28 187	33 902	37 049
Radiosondes	1 821	2 605	3 341	2 274	1 456
Pilot balloons	679	164	1 721	606	676
Aircraft	58	79	1 544	4 085	26 341
Buoys	0	1	69	1 462	3 991
Satellite radiances	0	6	35 069	131 209	181 214
Satellite winds	0	0	61	6 598	45 671
Scatterometer	0	0	0	0	7 575
PAOBs	0	14	1 031	297	277

(Uppala et al. 2005, QJRMS)

Example of a reanalyzed historic event



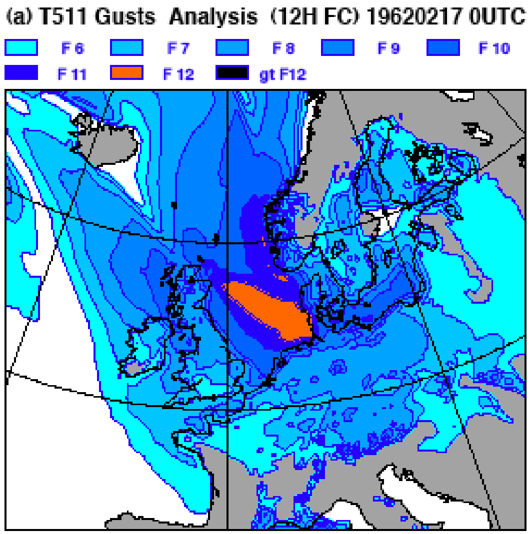
Reanalyses address past events with today's tools. The example relates to the reanalysis (top left) and re-foreasts of the storm of February 17, 1962. This devastating storm created a storm surge that flooded the town of Hamburg and killed 340 people.

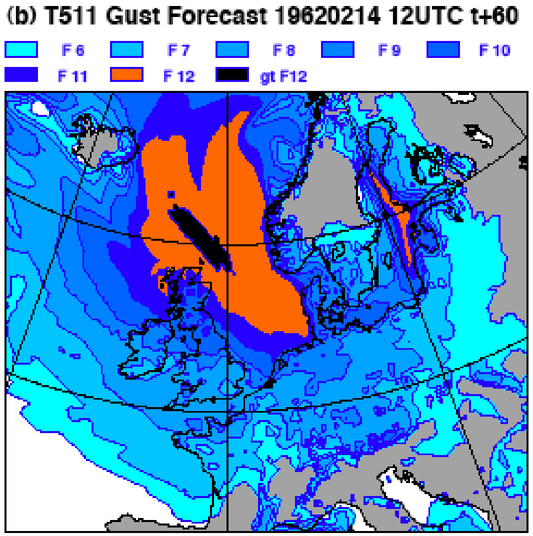
The plotted field is the 10m wind gust in the Beaufort scale. The Beaufort scale is an empirical damage-oriented scale defined by

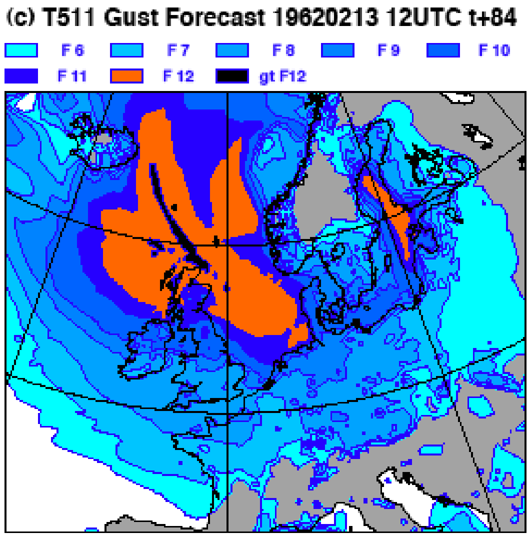
Velocity = 0.836 $B^{3/2}$ m/s.

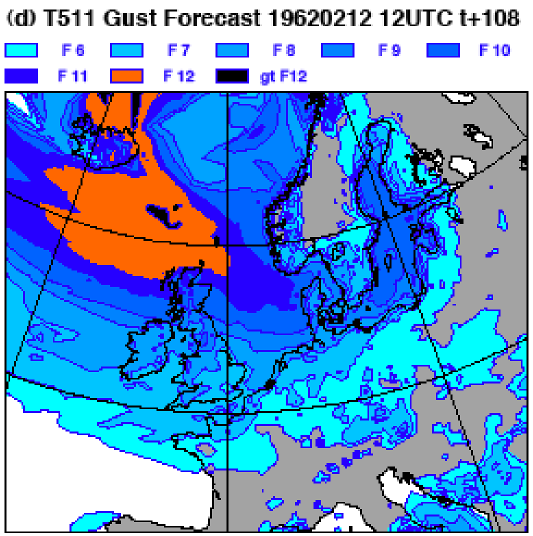
(Jung et al. 2003, ECMWF TM)

Example of a reanalyzed historic event









Reanalyses address past events with today's tools. The example relates to the reanalysis (top left) and re-foreasts of the storm of February 17, 1962. This devastating storm created a storm surge that flooded the town of Hamburg and killed 340 people.

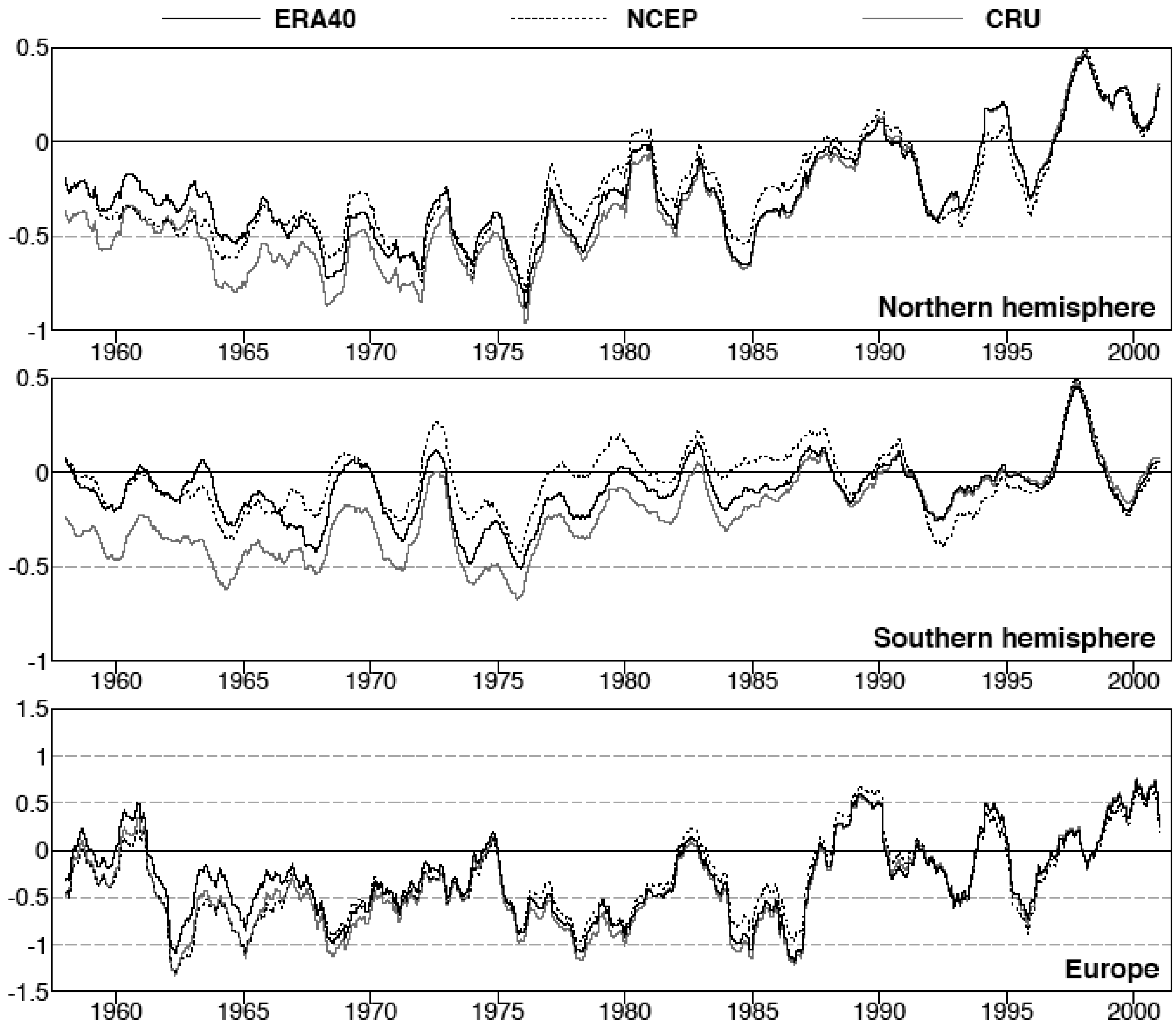
With todays forecasting capability a resonable forecast was feasible with a lead of about 3-4 days.

The plotted field is the 10m wind gust in the Beaufort scale. The Beaufort scale is an empirical damage-oriented scale defined by

Velocity = 0.836 $B^{3/2}$ m/s.

(Jung et al. 2003, ECMWF TM)

2m-Temperature



Reanalyses are also used to study interannual and interdecadal climate variations.

In terms of standard fields (such as T2m), the quality of these analysis cannot compete with traditional analysis, but the strength of the assimilation is in the consistent four-dimensional coverage of many variables.

(Simmons et al. 2006, JGR)

Summary

- Data assimilation has become a key element of numerical weather prediction. For the forecast skill, the quality of data assimilation is as important as that of the forecasting model.
- In terms of computing requirements and complexity, data assimilation is about as costly as the forecast run.
- Use of modern data assimilation systems has allowed exploiting satellite data. This is particularly important on the southern hemisphere (where only little conventional data is available).
- Reanalyses may provide high-resolution (in space and time) information about past weather events. Quality of reanalysis in terms of climate trends is not yet fully convincing.