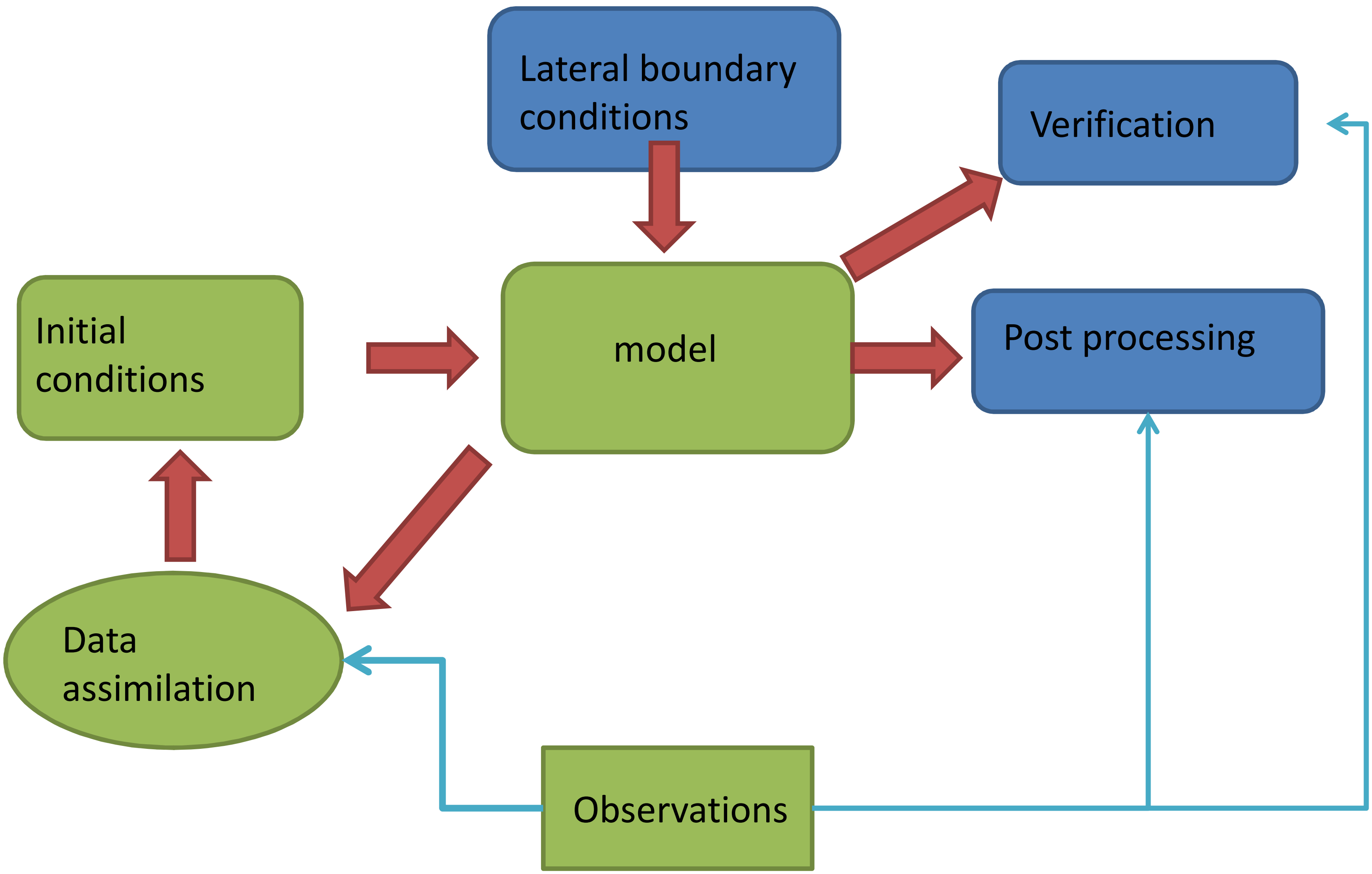
Data assimilation

T-NOTE – Buenos Aires, 5-16 August 2013 – Juan Ruiz and Celeste Saulo

A forecasting system based on numerical weather prediction models

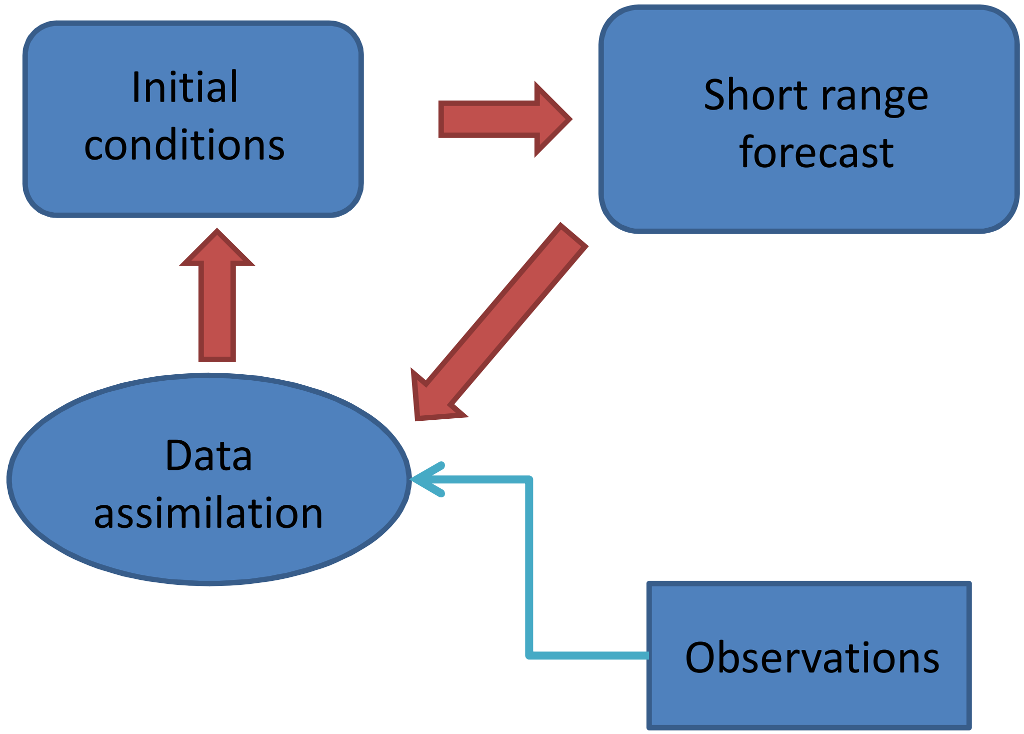


Data assimilation

A method to combine observations and forecasts in order to obtain an optimal estimation of the state of a system (i.e. the atmosphere).

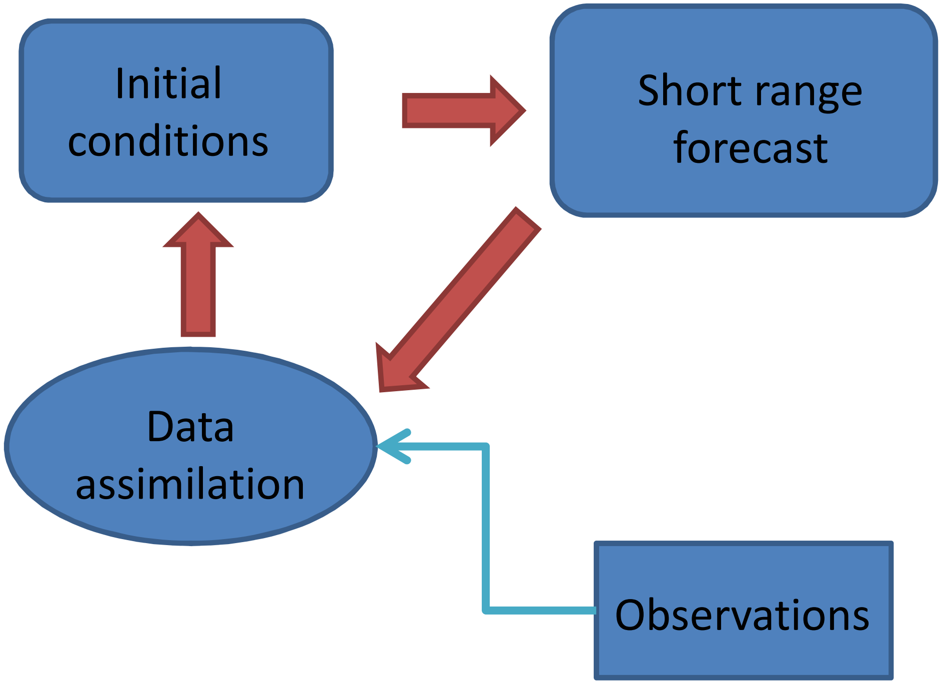
This estimation should be as consistent as possible with model dynamics (i.e. balance in large scale data assimilation)

The data assimilation cycle



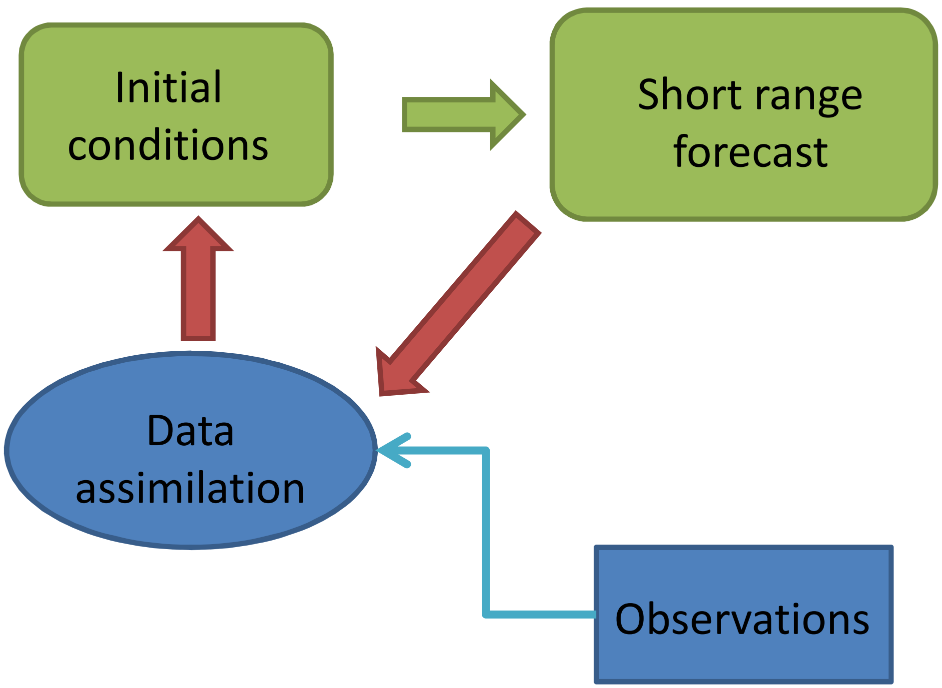
Observations are used to correct the short range forecast so it can be used to initialize the next forecast.

Why do we use a short range forecast?



- As long as the forecast came from a good model it should provide a good "first guess" of the state of the atmosphere (at least most of the time)
- The forecast keeps the information from the observations that has been previously assimilated
- The forecast dynamically "transport" the information provided by the observations (sometimes from areas with a lot of data to areas with almost no data)
- Forecasted fields are dynamically, physically and numerically consistent with the model equations
- Helps with the quality control of the observations

Step one: Generate a short range forecast

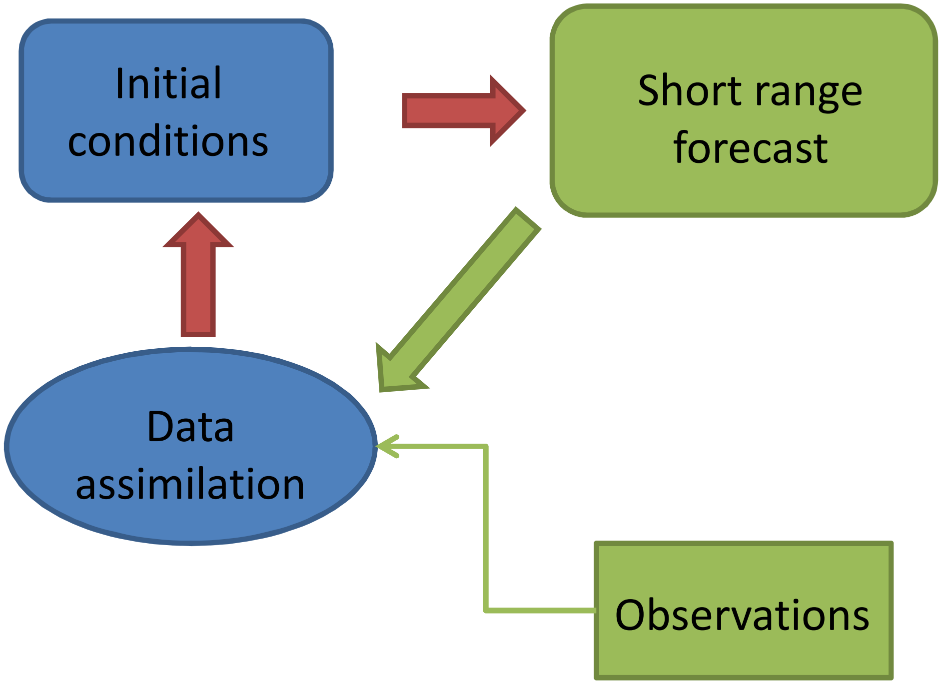


This step is not different from running a forecast.

Start from the previous step analysis and run the model until you reach the time of the next assimilation cycle (usually run it a little longer to incorporate more observations)

The assimilation frequency depends on the scale of interest. At smaller scales forecast error grows faster so in order to keep short range forecast "good" we have to correct them more frequently. At synoptic timescales, the typical time would be ~6 hs, while for nowcasting we should consider doing it more often (~15 minutes and 1 hour)

Step two: Compare the short range forecast and the observations

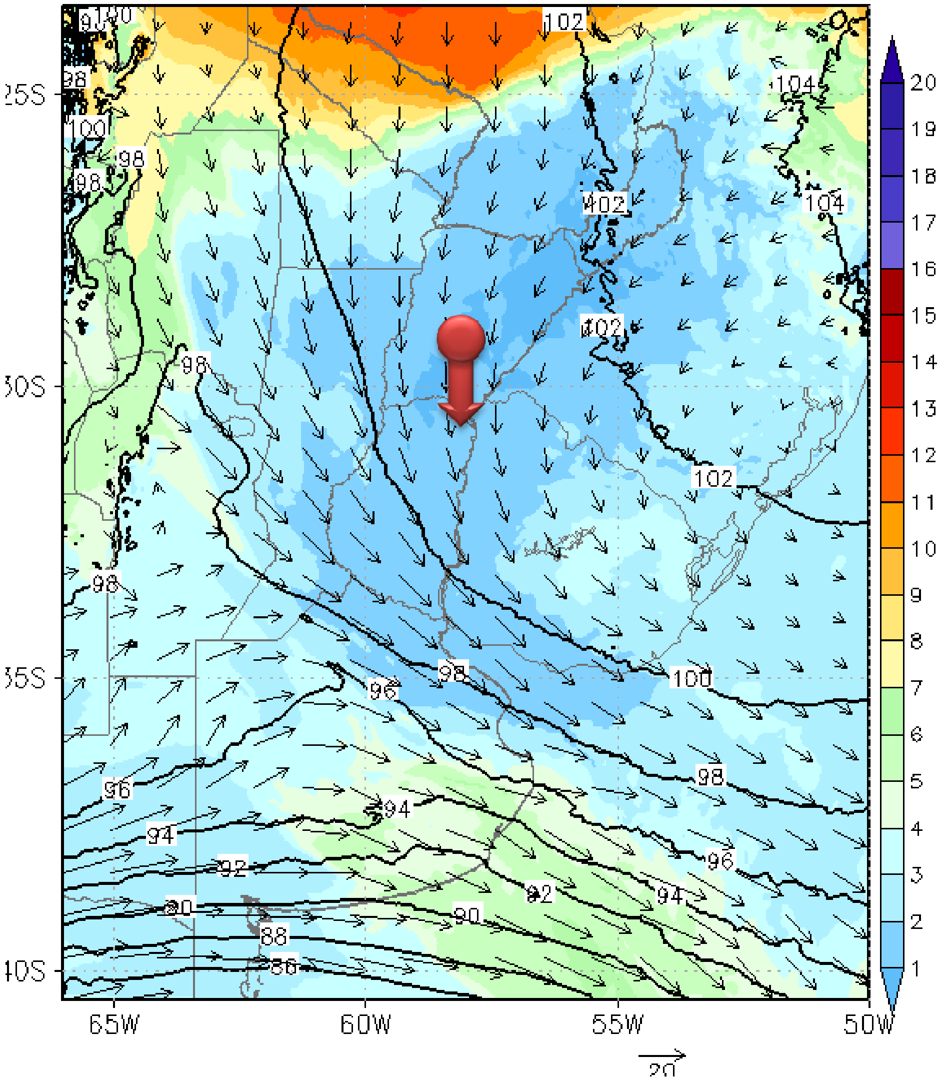


The difference between the forecast and the observations is called the innovation.

•Model output is interpolated to the observation's position. Observed quantities are derived from model variables (i.e. satellite radiance is derived from temperature and moisture fields)

•Quality control based on forecast-observations comparison. Discard observations that respond to features that cannot be resolved by the model.

Example: 900 hPa wind, geopotential and moisture short range forecast



•Observation (red dot). Wind from the north at 12 m/s.

•Interpolate model forecast to observation location and compare model forecast with observation (interpolation can be in space and time)

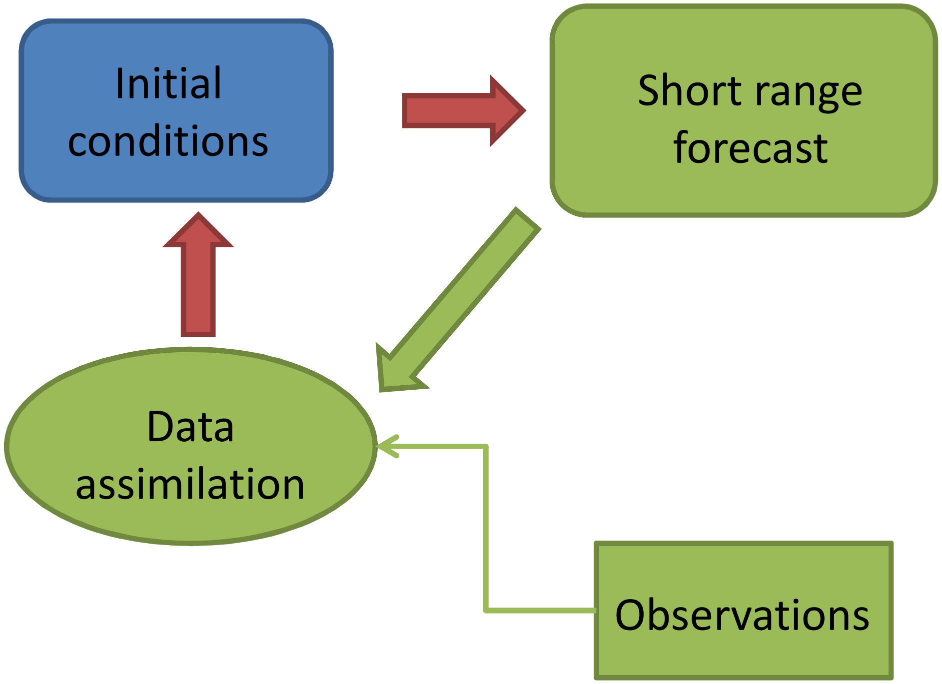
•Observation has a northerly wind 2 m/s stronger than the forecast.

•Quality control says that observation is good because both the forecast and the observations have winds from the same direction and at a similar speed.

•This has to be done with all available observations…

How can we correct the forecast using the information provided by the observation?
Is the observation the truth? Is the forecast the truth? How far are the forecast and the observation from the truth?

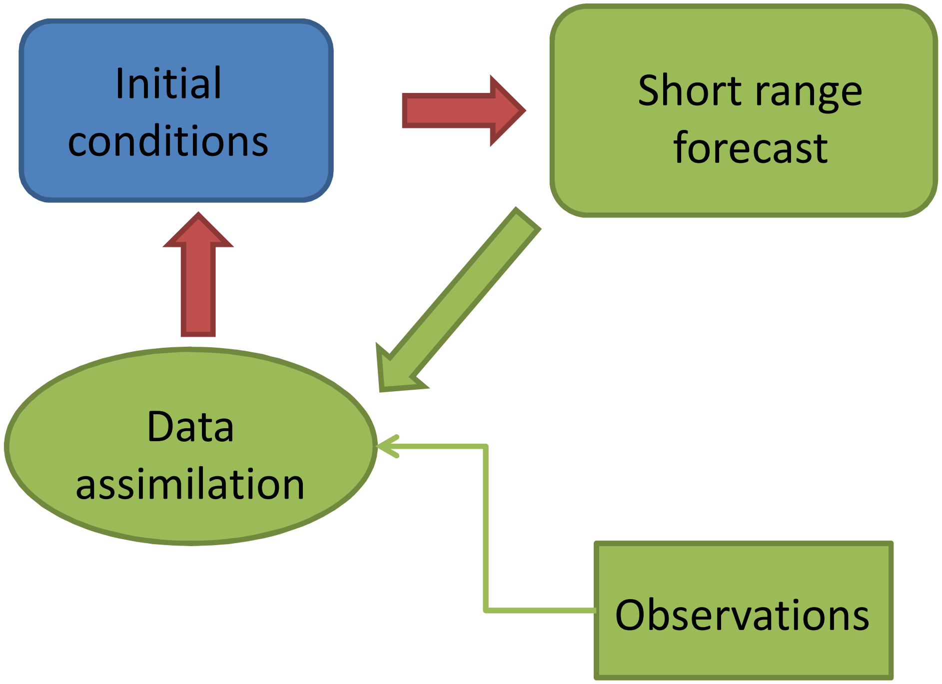
Step three: Objective analysis procedure (how to actually combine forecasts and observations)



In this step short range forecasts and observations are combined with each other.

Information provided by each source is weighted according to their error

Error sources



Errors in the forecast:

- Due to errors in the previous initial condition
- Model error

Error in the observations:

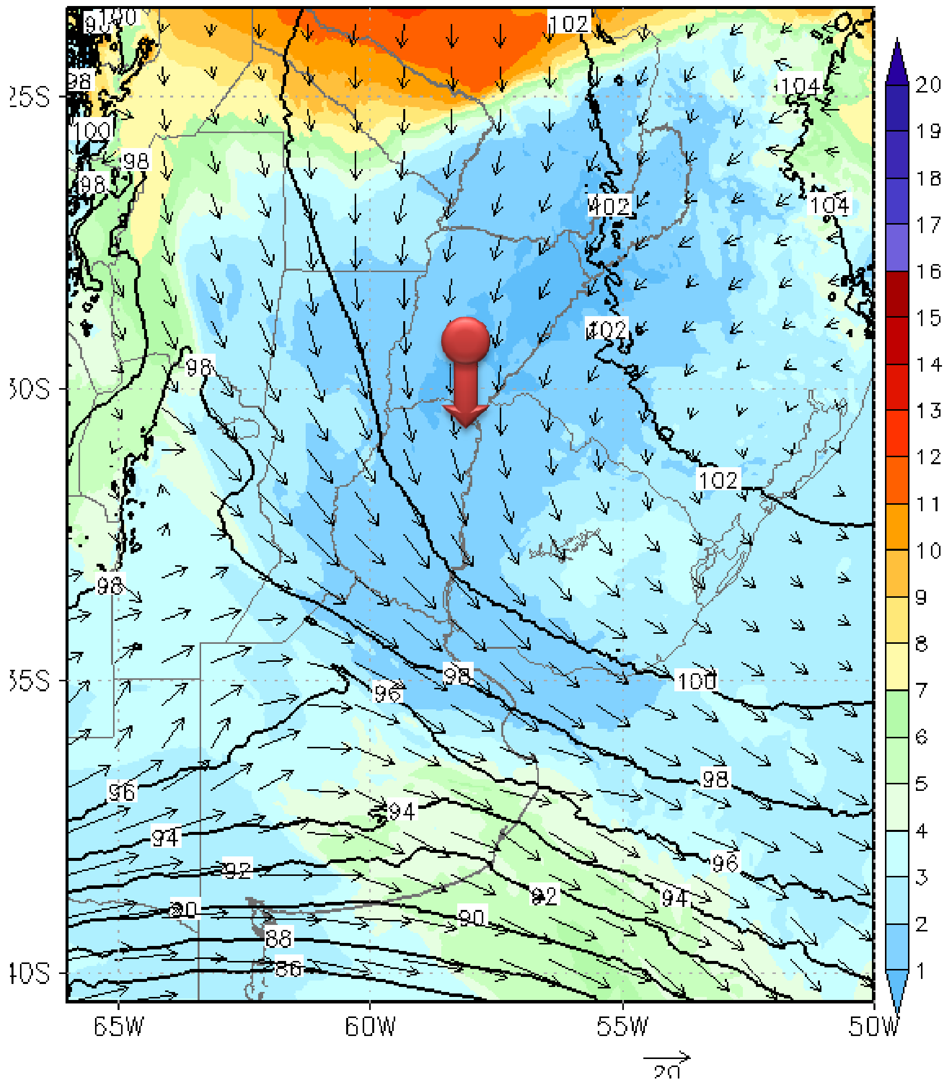
- Instrument error
- Location error

Combination errors:

- Interpolation errors
- Error in variable transformation (i.e. from model temperature to radiance)
- Representativeness errors (scales not resolved by the model, but present in the observations)

Data assimilation requires some knowledge about forecast errors and observation errors

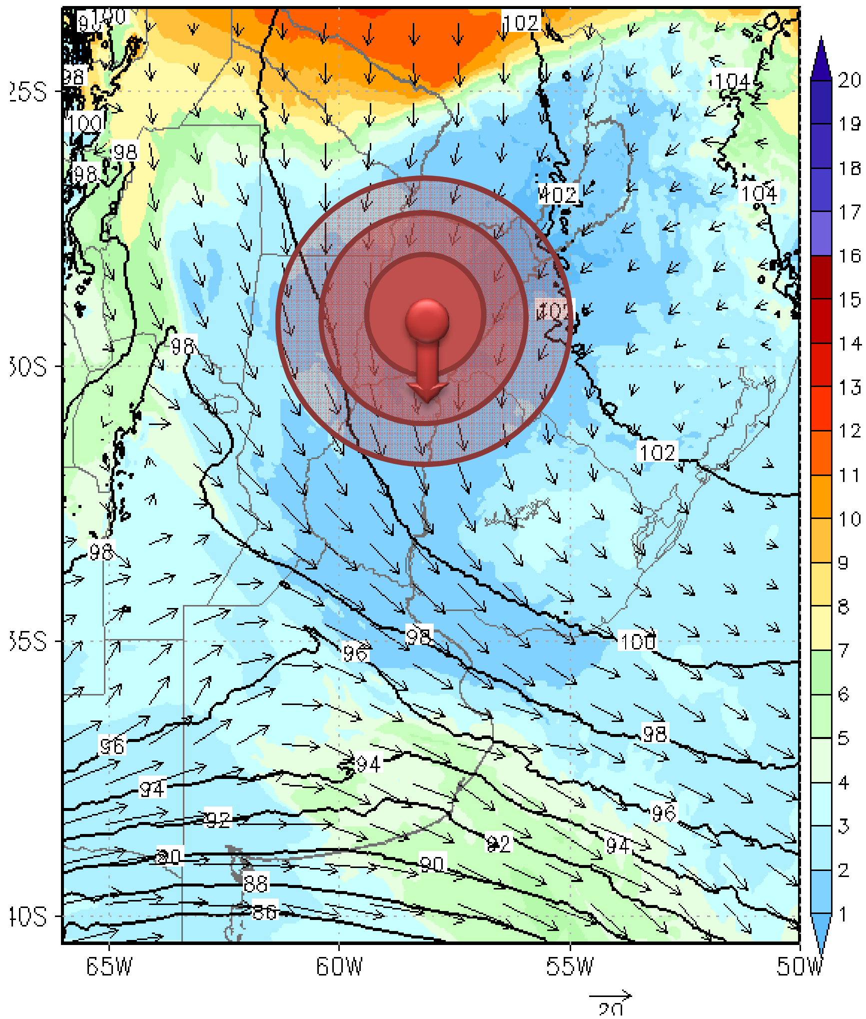
Both are difficult to estimate!!



- If the observation error is small compared to the forecast error then data assimilation will introduce a bigger correction to the forecast
- If the observation error is bigger, then the correction will be smaller (we will trust the forecast more)
- So far we have a comparison between forecast and observation at the observation's location
- How can we correct the forecast at nearby grid points?
- Can we correct variables other than wind?

Data assimilation requires some knowledge about forecast errors and observation errors

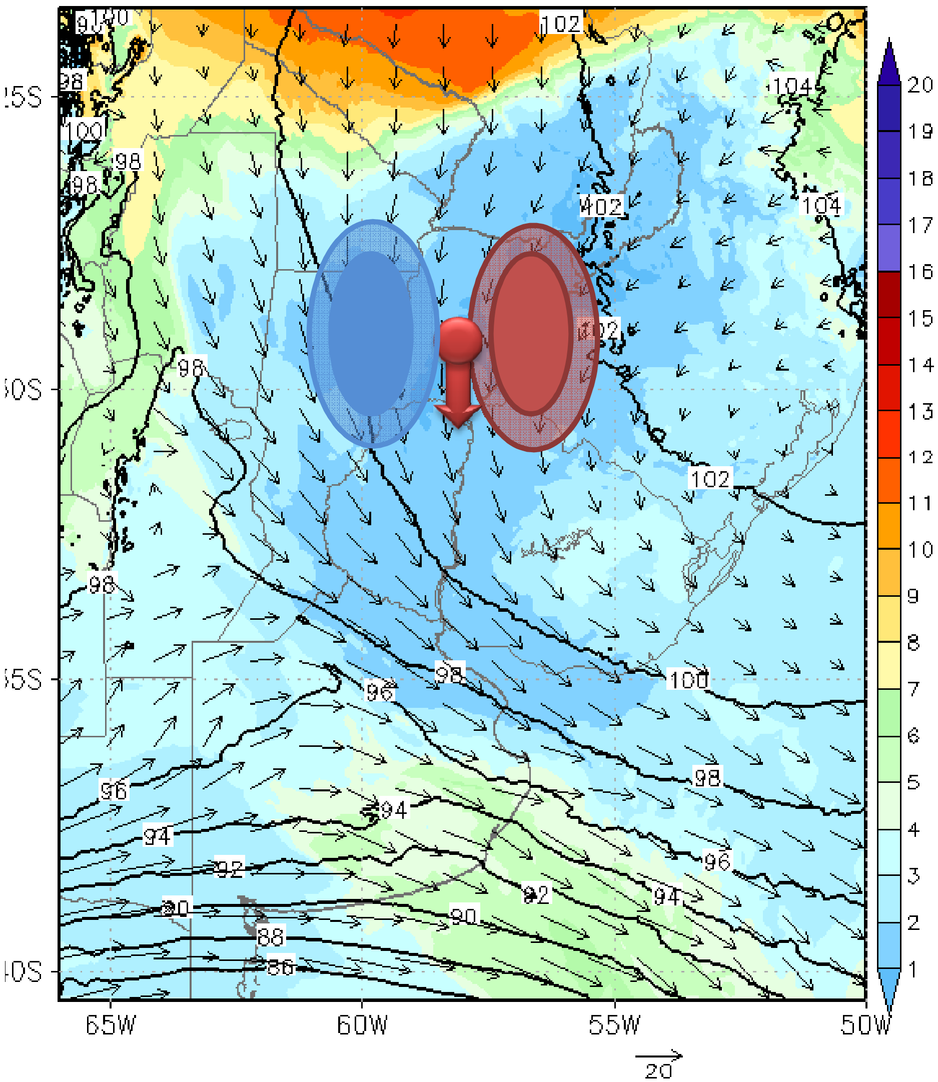
We need to know the relationship between errors in different model variables
Are errors at different grid points related to each other?



- Errors at grid points that are close to each other are usually highly correlated
- We can use this information to “spread” the correction introduced by the observation in the horizontal and vertical directions
- In this example the observation suggests introducing an increase in wind speed. This increase is applied to all the grid points that are close to the observation
- How far should we “spread” the information provided by the observation? It depends on the observation type and the scales resolved by the model

Data assimilation requires some knowledge about forecast errors and observation errors

What about other model variables. Can we correct geopotential field using wind observations?

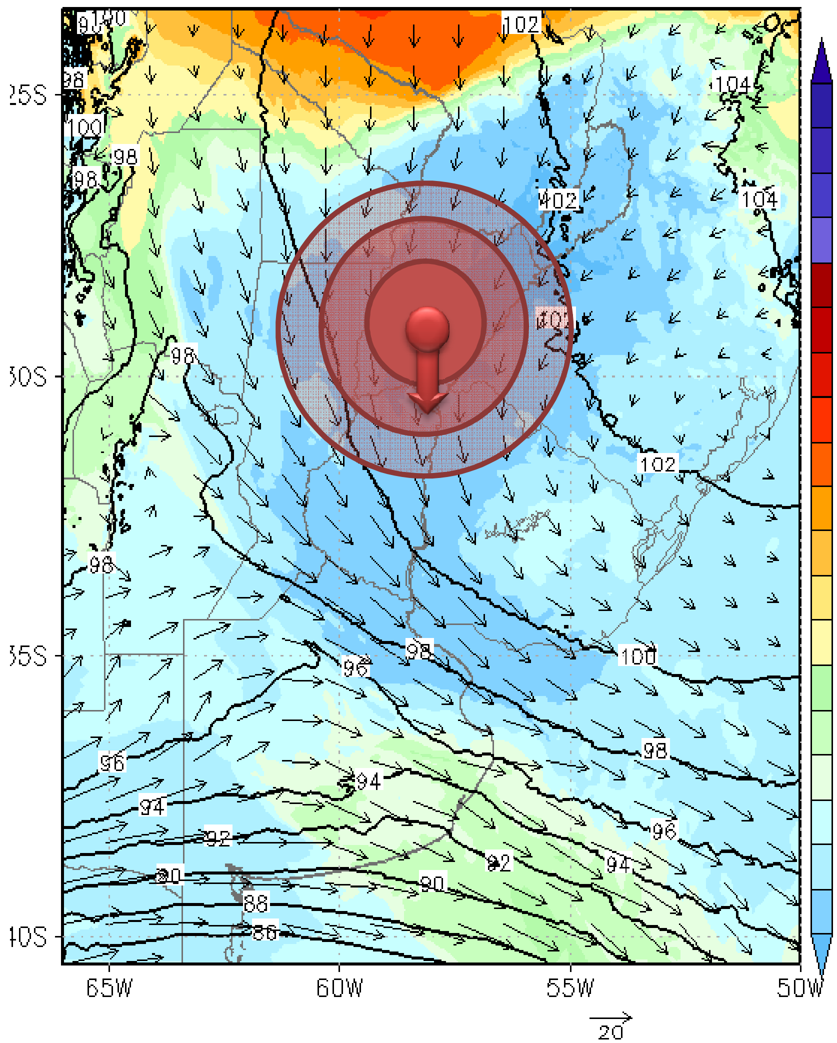


What can we say about the moisture field?

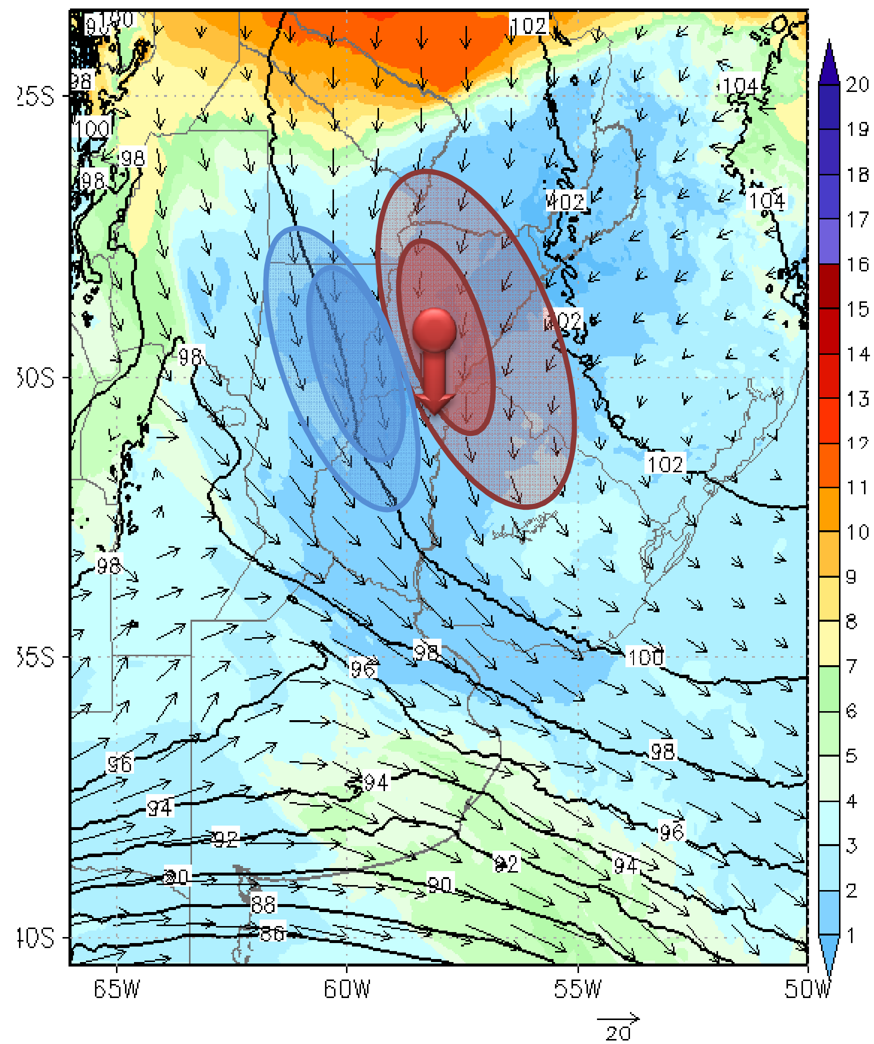
- Error relationships between model variables also include error relationship among different variables. (i.e. geostrophic balance)
- The wind observation in this case provides also information about how to correct geopotential height so that the correction is approximately in geostrophic balance.
- This relationships among variables depends on location (i.e. tropics vs mid latitudes) and scale (synoptic vs convective scales).
- In this case we are introducing a large scale correction at mid latitudes. To keep geostrophic balance we have to increase geopotential heights to the east and reduce it to the west.

State dependent corrections

The shape of optimal corrections may be state dependent. Also the relationship among errors in different variables might depend on the flow state.

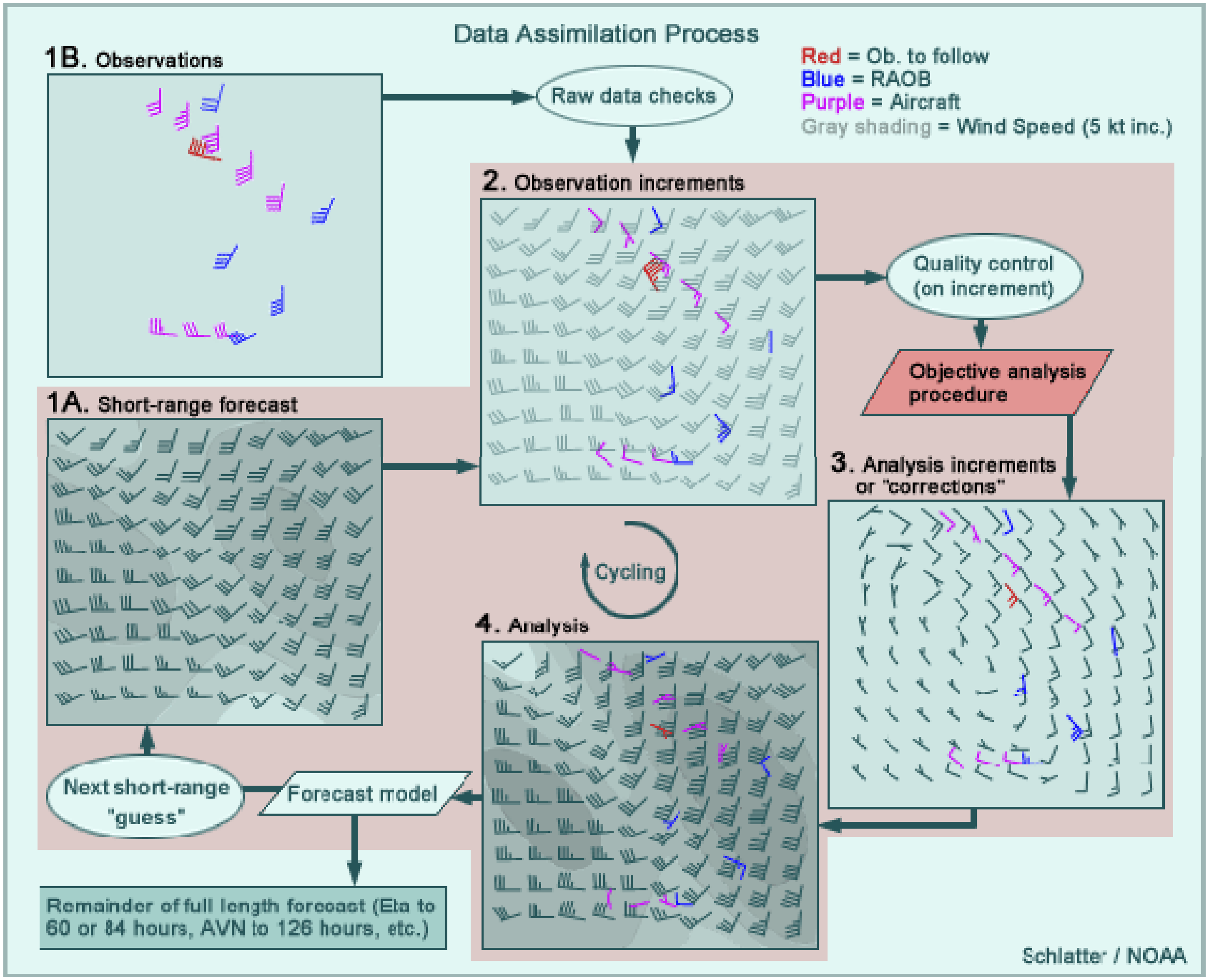


Fixed



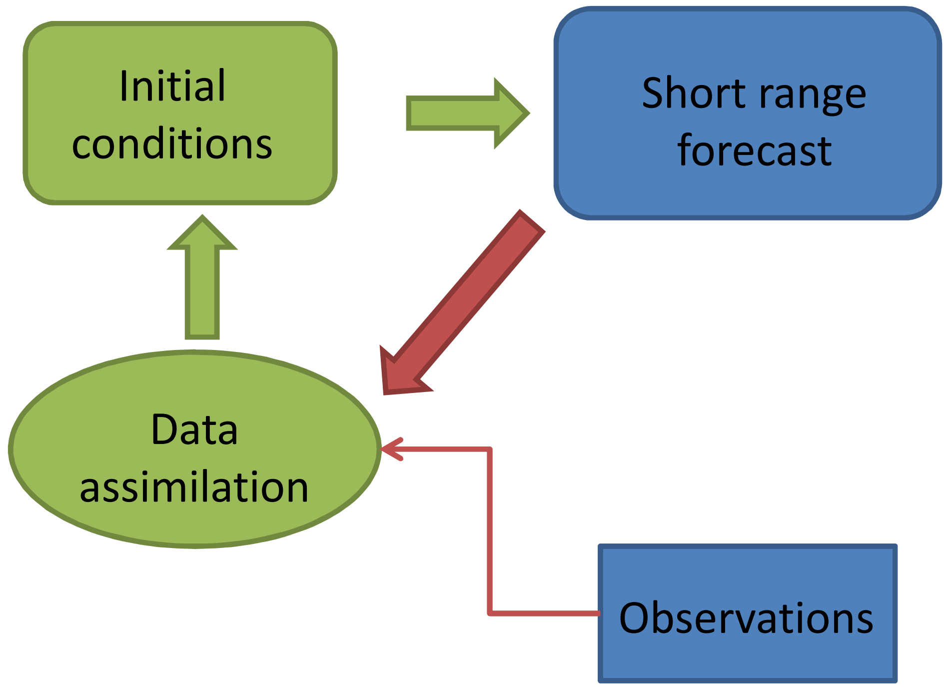
State dependent

Summary and example with several observations



Comet Program.

Step four: Apply the correction and generate the initial condition for the next cycle



Add the correction to the short range forecast to obtain the analysis

Repeat steps one to four again for the next assimilation cycle

3DVAR:
Defines the analysis as the state (x) at time t that produce the minimum of the following cost function:

$$J(\mathbf{x}) = \frac{1}{2}\left(\mathbf{x}_b - \mathbf{x}\right)^{\mathrm{T}} \left(\mathbf{P}_b\right)^{-1} \left(\mathbf{x}_b - \mathbf{x}\right) + \frac{1}{2}\left(\mathbf{y} - \mathcal{H}(\mathbf{x})\right)^{\mathrm{T}} \mathbf{R}^{-1} \left(\mathbf{y} - \mathcal{H}(\mathbf{x})\right)$$

Distance to short range forecast　　　　Distance to observations

Pb is the forecast error covariance matrix (has information about covariance between errors at different grid points or between different variables.

R is the observation error covariance matrix (has the information about the errors in the observations and also includes representativity errors)

H is a function that transforms the model variables into the observed variables (interpolation, variable transformation)

The analysis is found using highly efficient minimization techniques

4DVAR:

Defines the analysis as the state (x) at time t-1 that produce the minimum of the following cost function:

$$
\begin{aligned}
J(\mathbf{x}) \quad = \quad & \frac{1}{2}(\mathbf{x}_b - \mathbf{x})^{\mathrm{T}} (\mathbf{P}_b)^{-1} (\mathbf{x}_b - \mathbf{x}) \\
& + \frac{1}{2} \sum_{k=0}^{K} (\mathbf{y}_k - \mathcal{G}_k(\mathbf{x}))^{\mathrm{T}} \mathbf{R}_k^{-1} (\mathbf{y}_k - \mathcal{G}_k(\mathbf{x}))
\end{aligned}
$$

Observations are compared with forecast within a time window

The analysis (the minimum of the cost function) is computed at the beginning of the time window.

4DVAR finds the initial conditions that produce a model trajectory that best fits the observations within the time window.

Gk transforms the state x at the beginning of the time window to the observations at different times (the model is used here to evolve the initial condition up to the time of the observations)

Minimization is more difficult in 4DVAR because efficient minimization algorithms requires the adjoint of the model equations