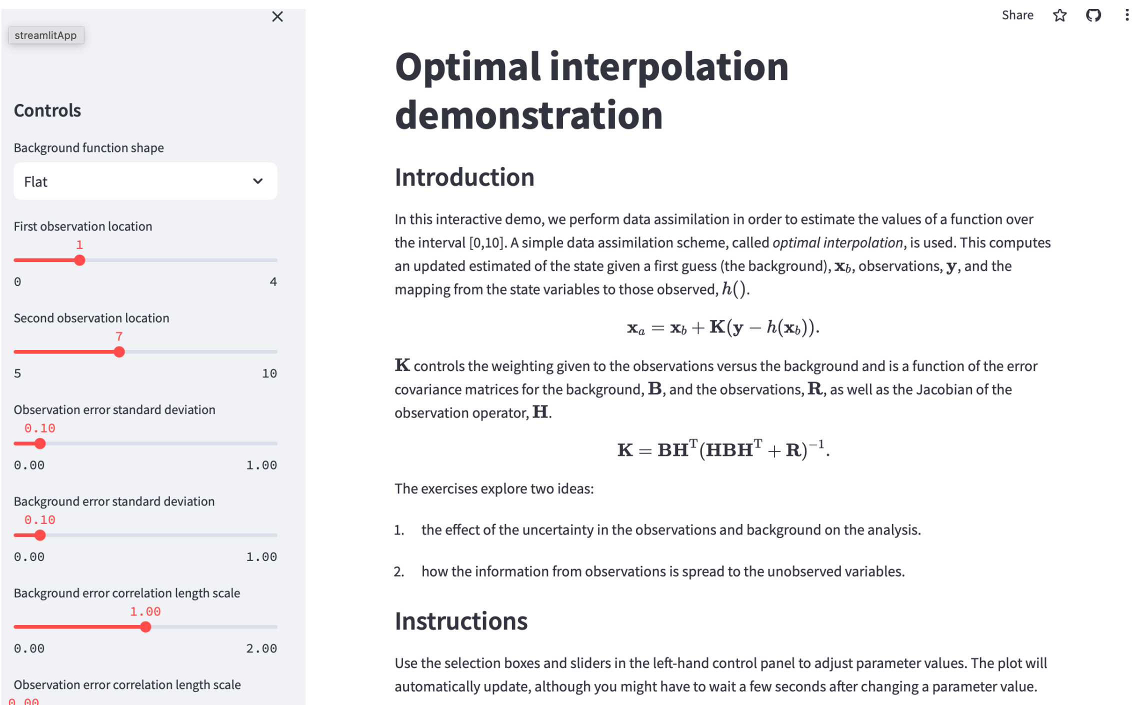
DA ingredients practical

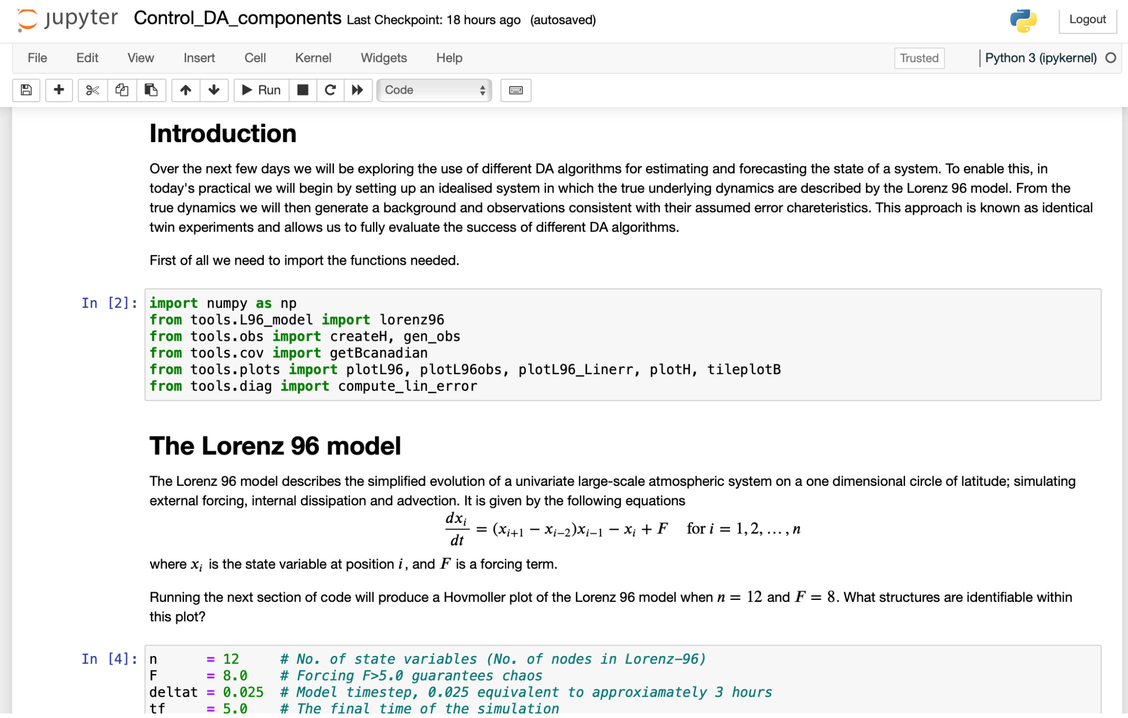
Instructions

All code and links can be found on the Github repository.

In part 1 of the practical, we will use streamlit to look at the role of the error covariances in a simple 1D system.

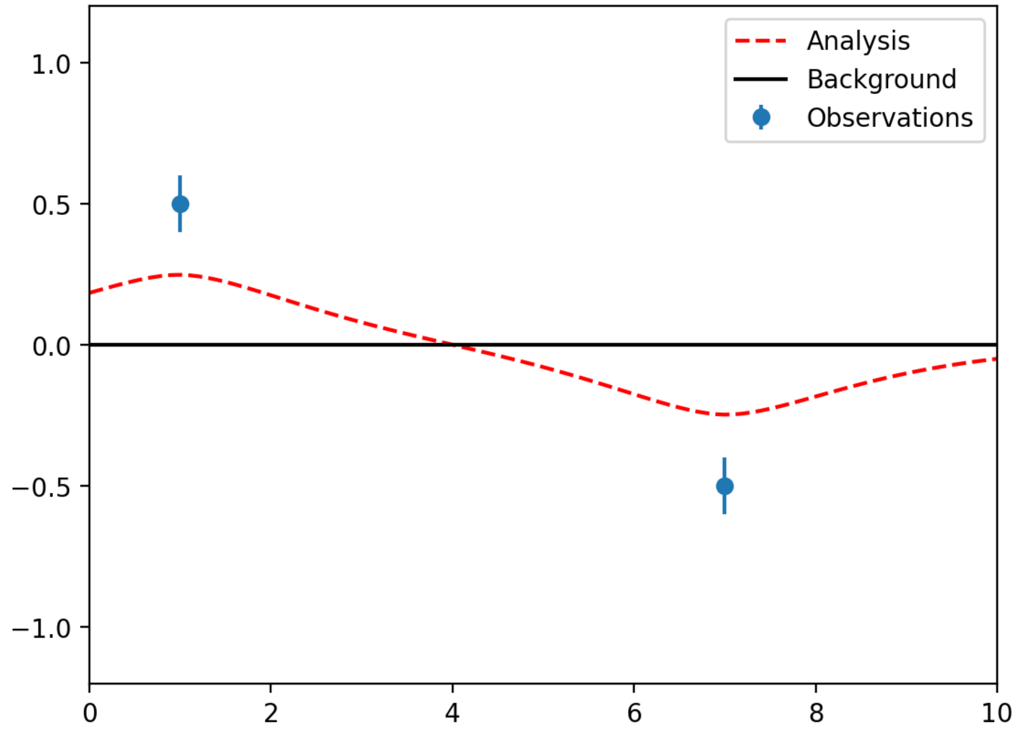
In part 2 we will use Jupyter notebooks to look at the DA ingredients needed to assimilate data into the toy Lorenz 96 model.





Streamlit: Optimal interpolation demonstration

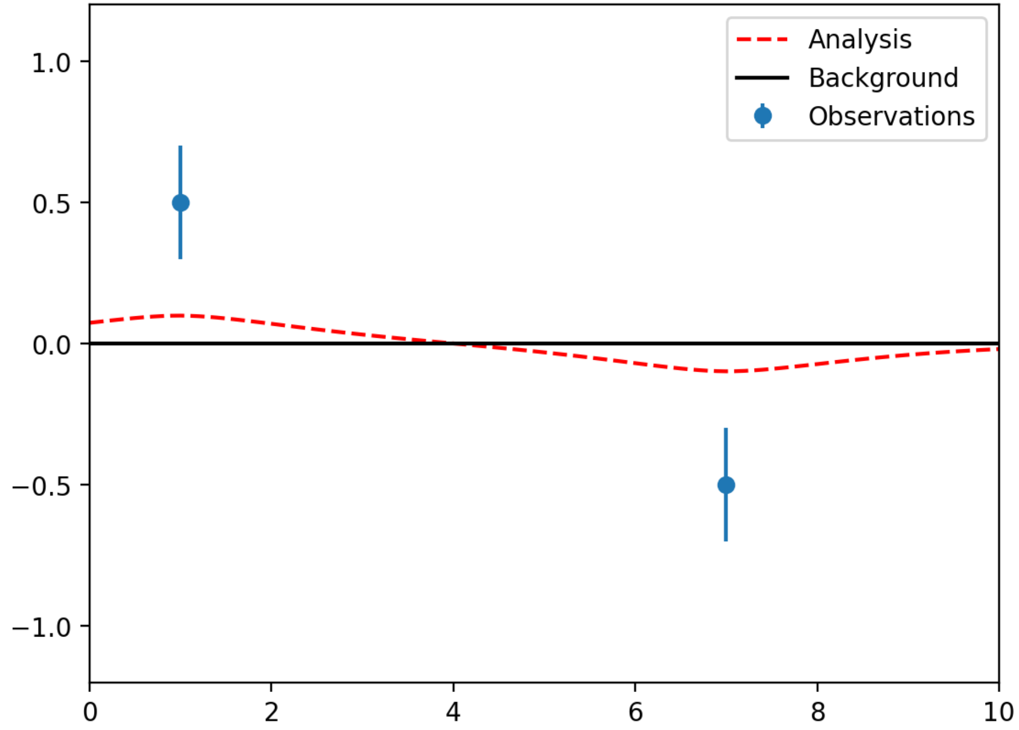
The effect of the uncertainty in the observations and background on the analysis



Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1

Streamlit: Optimal interpolation demonstration

The effect of the uncertainty in the observations and background on the analysis

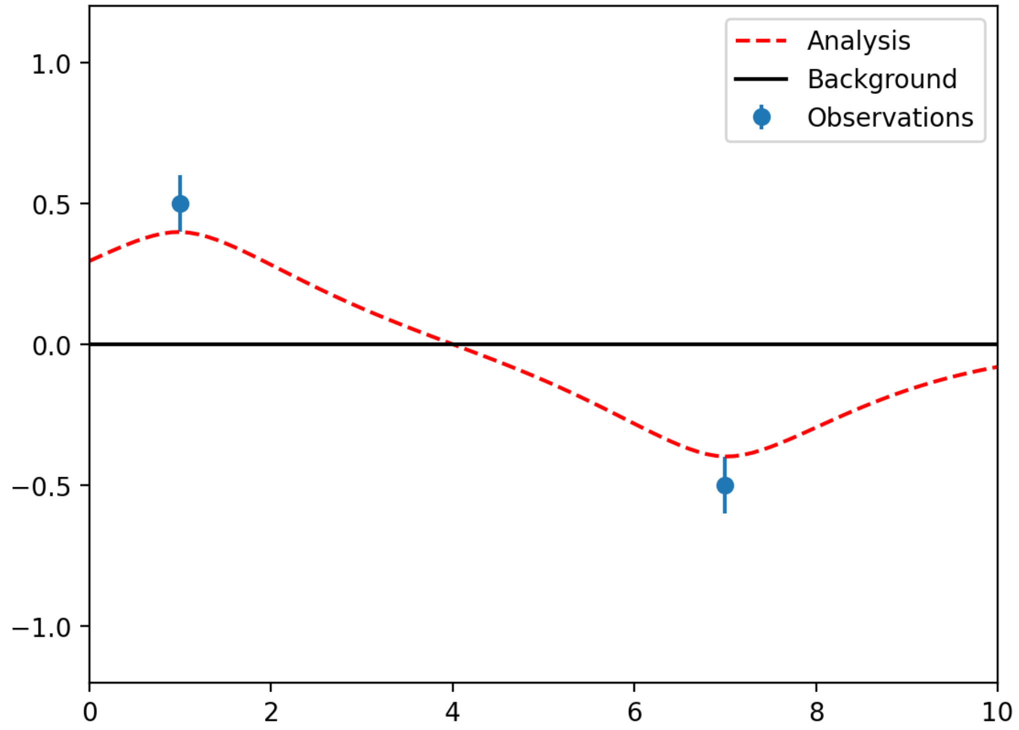


Parameters:
Observation error standard deviation 0.2
Background error standard deviation 0.1

Increasing the observation error standard deviation reduces the analysis fit to the observations

Streamlit: Optimal interpolation demonstration

The effect of the uncertainty in the observations and background on the analysis

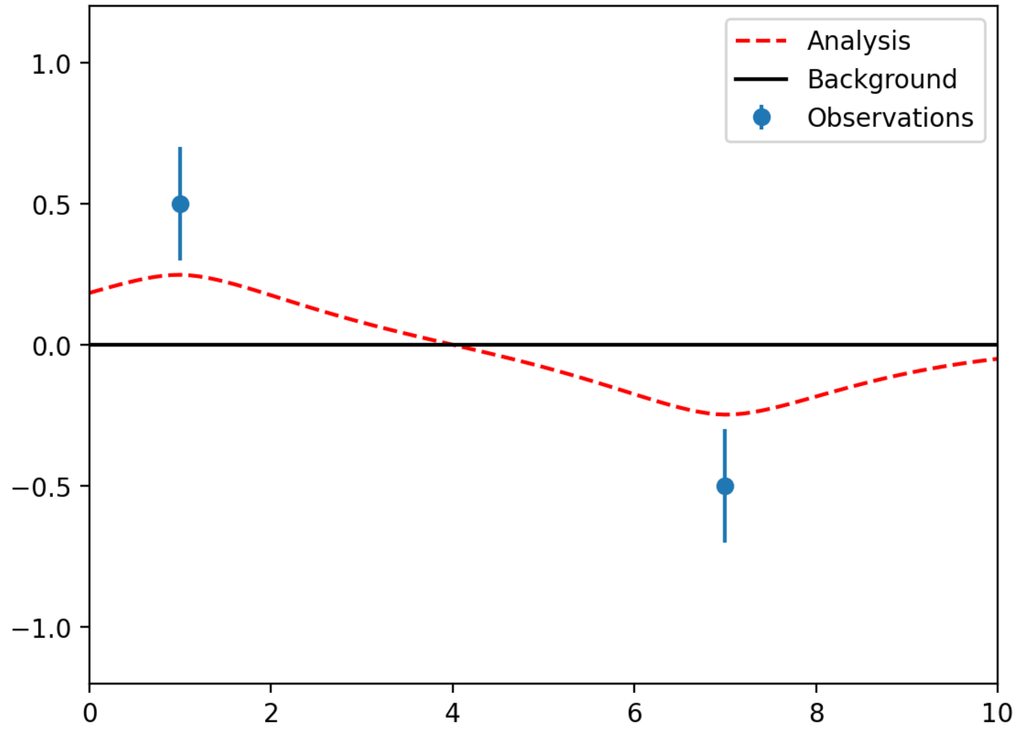


Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.2

Increasing the background error standard deviation increases the analysis fit to the observations

Streamlit: Optimal interpolation demonstration

The effect of the uncertainty in the observations and background on the analysis

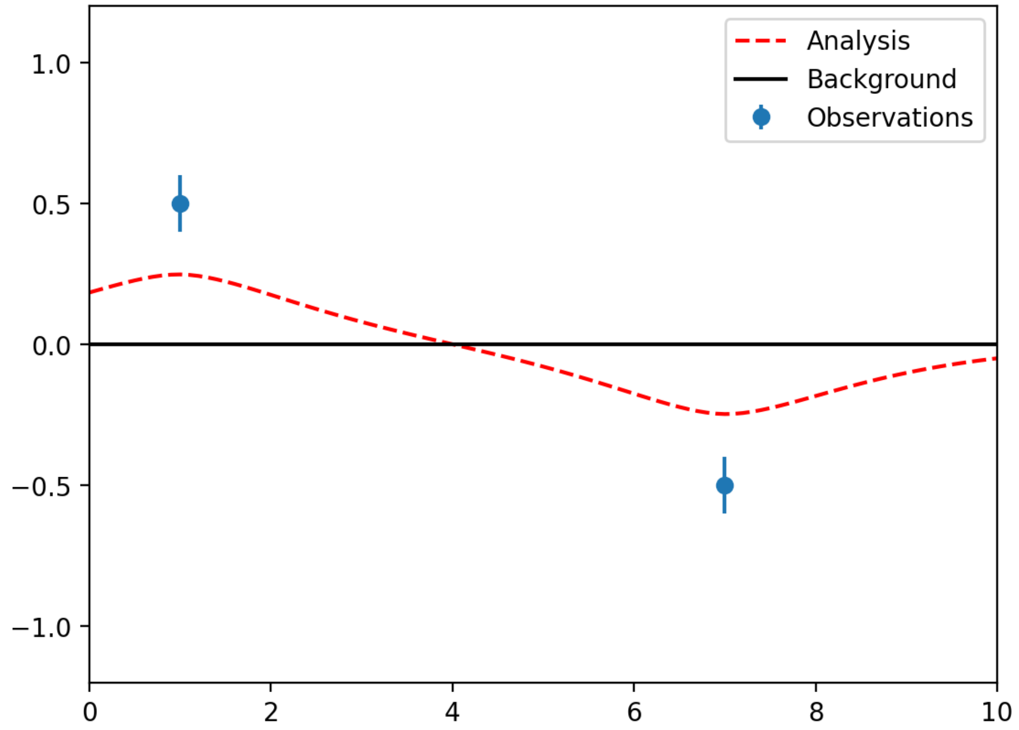


Parameters:
Observation error standard deviation 0.2
Background error standard deviation 0.2

It is the ratio of the observation to background error standard deviation that is important

Streamlit: Optimal interpolation demonstration

The effect of the uncertainty in the observations and background on the analysis

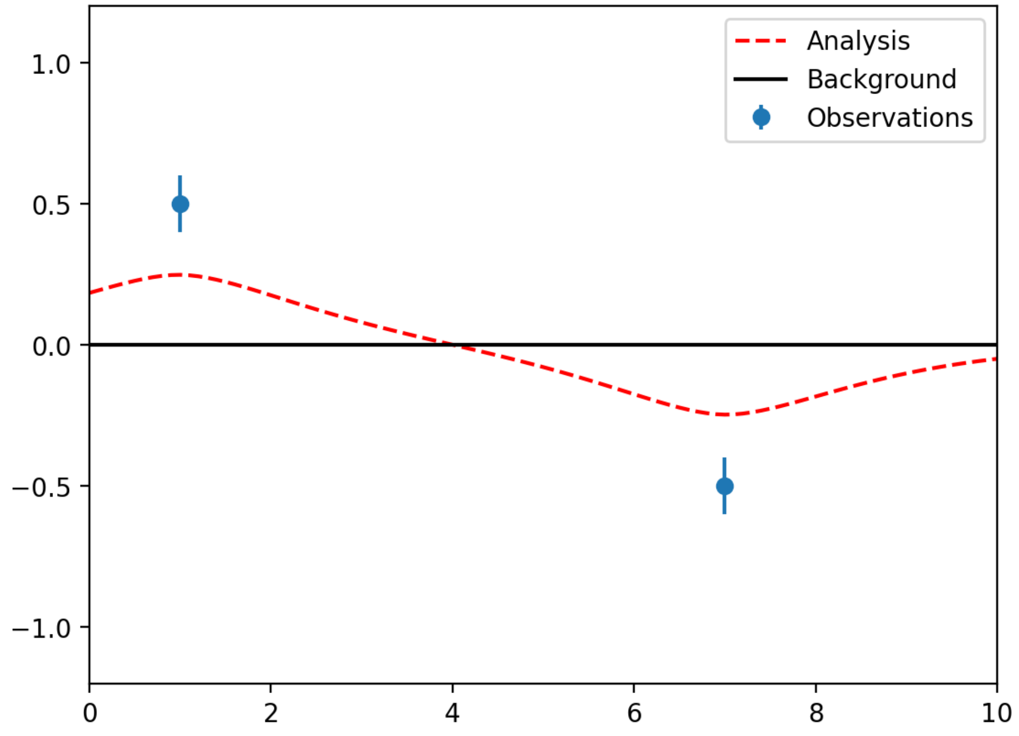


Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1

It is the ratio of the observation to background error standard deviation that is important

Streamlit: Optimal interpolation demonstration

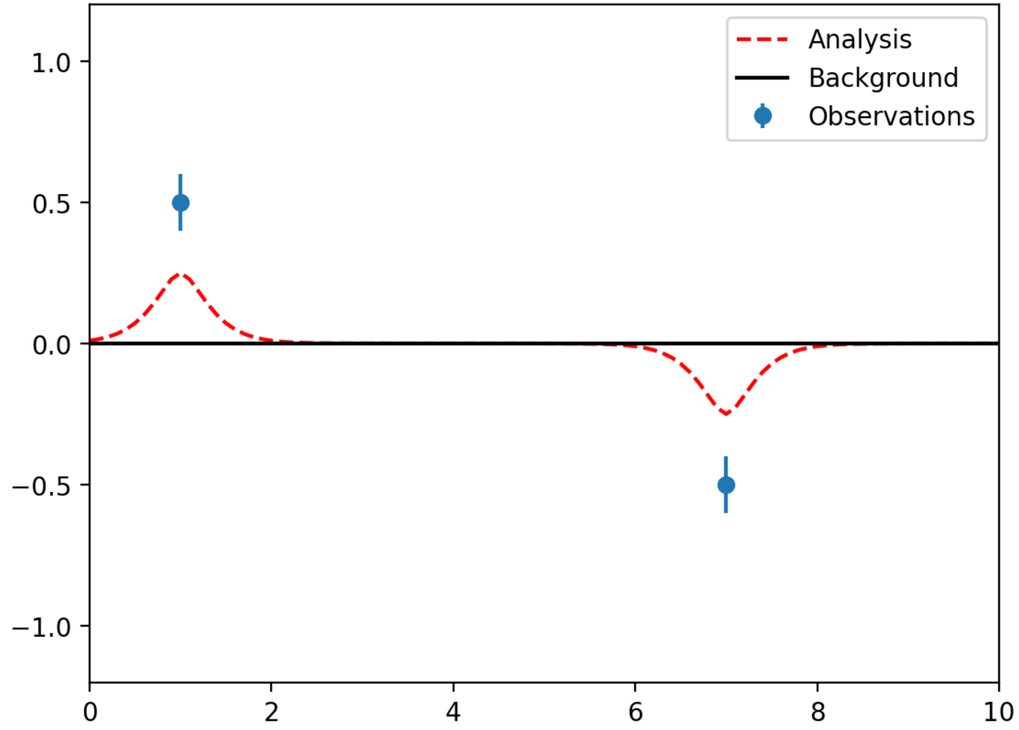
How the information from observations is spread to the unobserved variables: the role of the background error correlations



Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 1
Observation error correlation length scale 0

Streamlit: Optimal interpolation demonstration

How the information from observations is spread to the unobserved variables: the role of the background error correlations

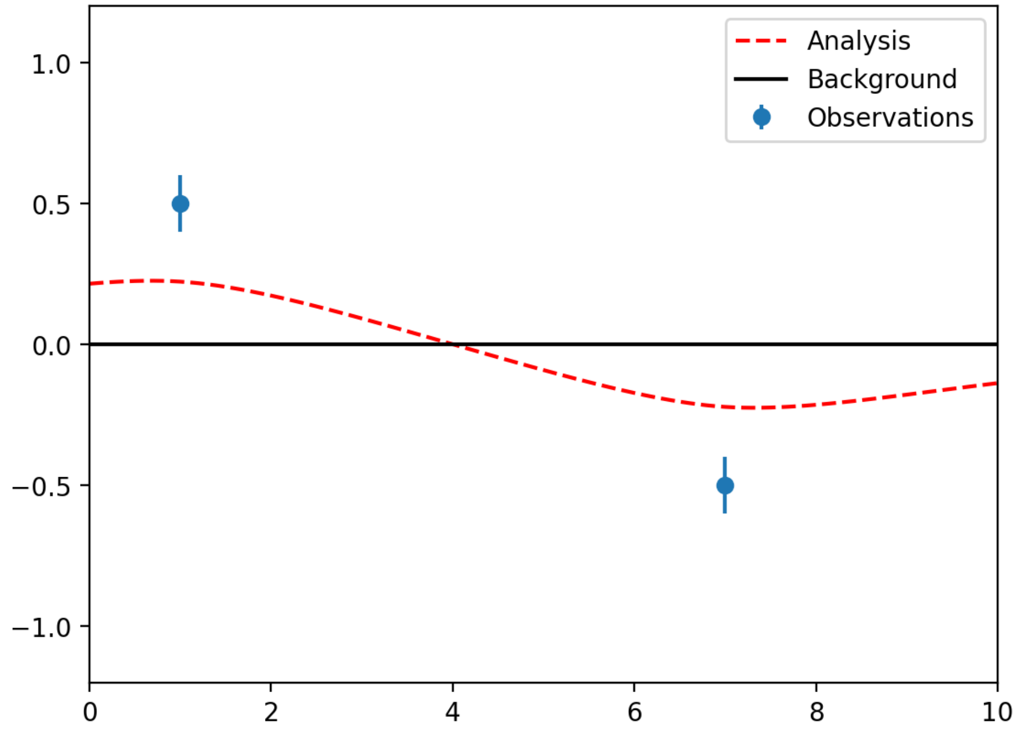


Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 0.2
Observation error correlation length scale 0

decreasing the background error correlation length scale reduces the spread of information from the observations.

Streamlit: Optimal interpolation demonstration

How the information from observations is spread to the unobserved variables: the role of the background error correlations

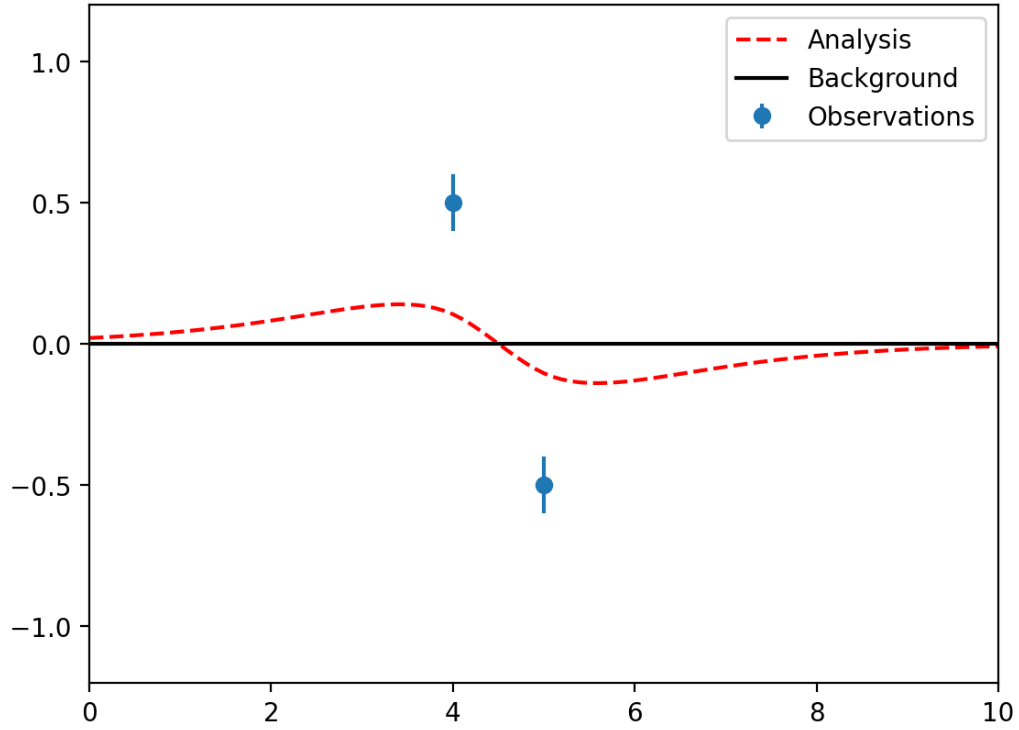


Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 2
Observation error correlation length scale 0

Increasing the background error correlation length scale increases the spread of information from the observations.

Streamlit: Optimal interpolation demonstration

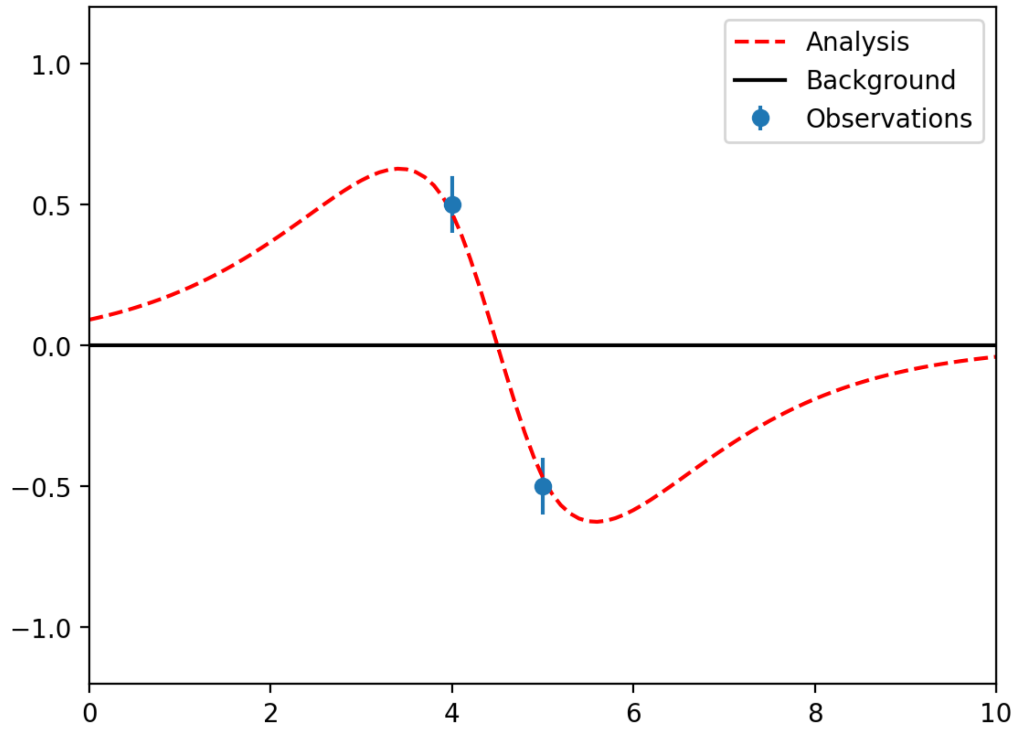
How the information from observations is spread to the unobserved variables: the role of the observation error correlations



Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 1
Observation error correlation length scale 0

Streamlit: Optimal interpolation demonstration

How the information from observations is spread to the unobserved variables: the role of the observation error correlations



Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 1
Observation error correlation length scale 5

Increasing the observation error correlation length scale allows the observations to provide more information about gradients.

Streamlit: Optimal interpolation demonstration

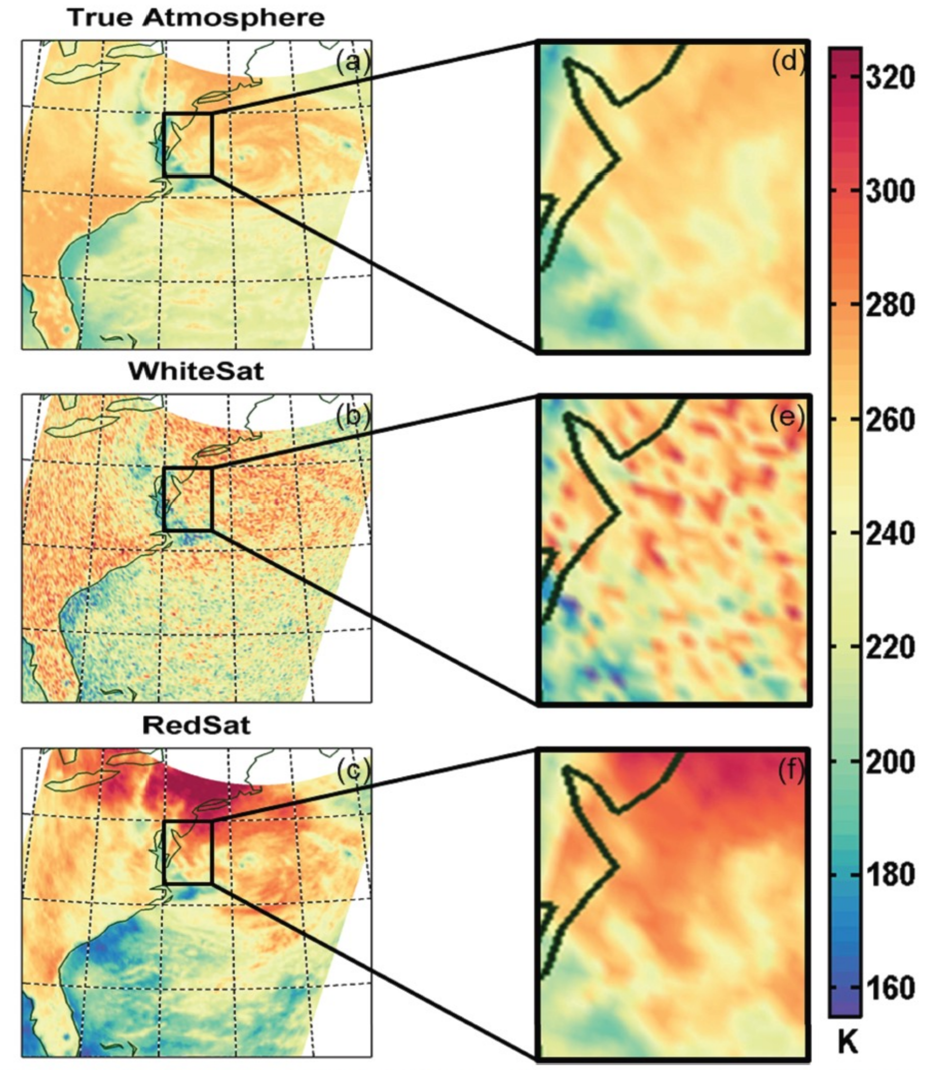
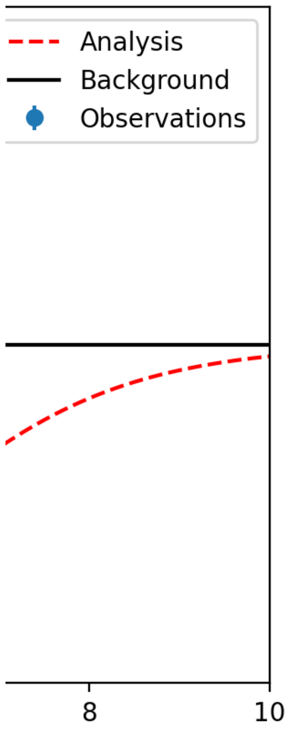


Figure 1. (a) A microwave satellite image of Hurricane *Sandy* on 24 October 2012, which is treated as truth. (b) Panel (a) plus white (uncorrelated) noise; (c) panel (a) plus red (spatially correlated) noise. (d)–(f) Detail views of (a)–(c), respectively. The colour scale for all panels is brightness temperature in Kelvin. This figure is for illustrative purposes.

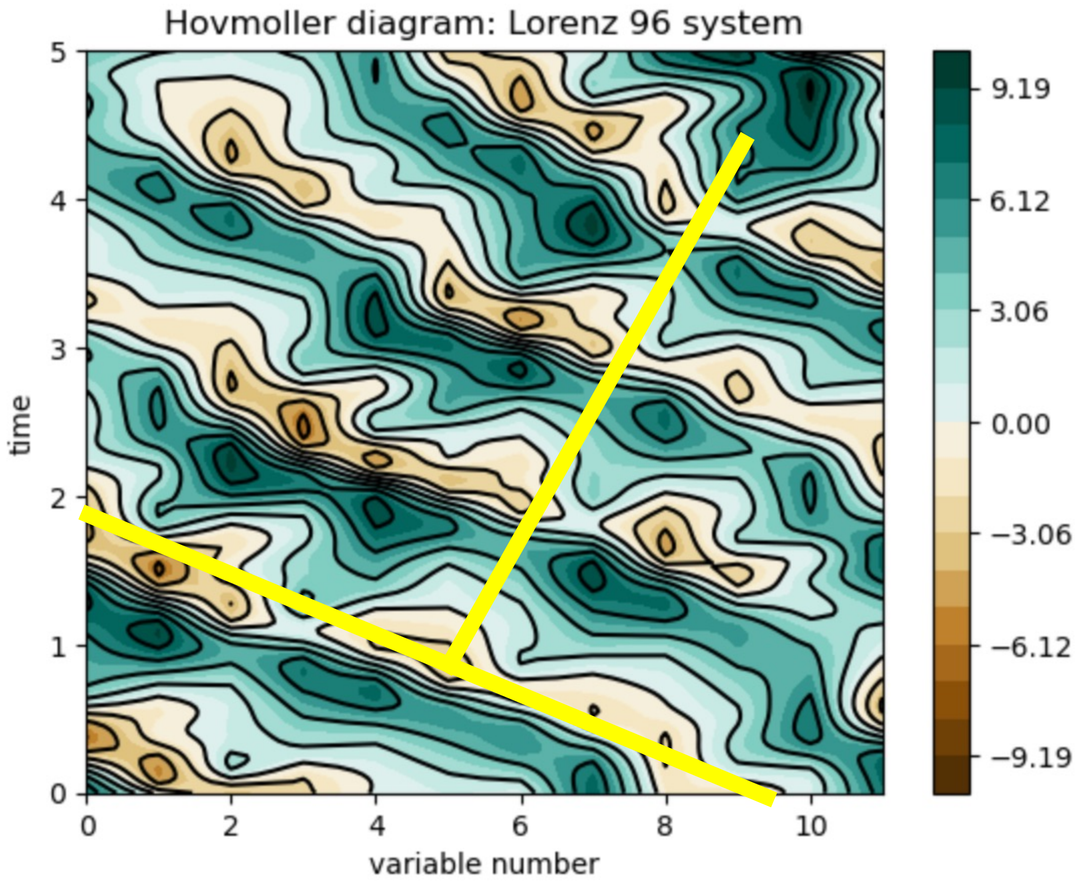
observations is spread to the unobserved
›servation error correlations

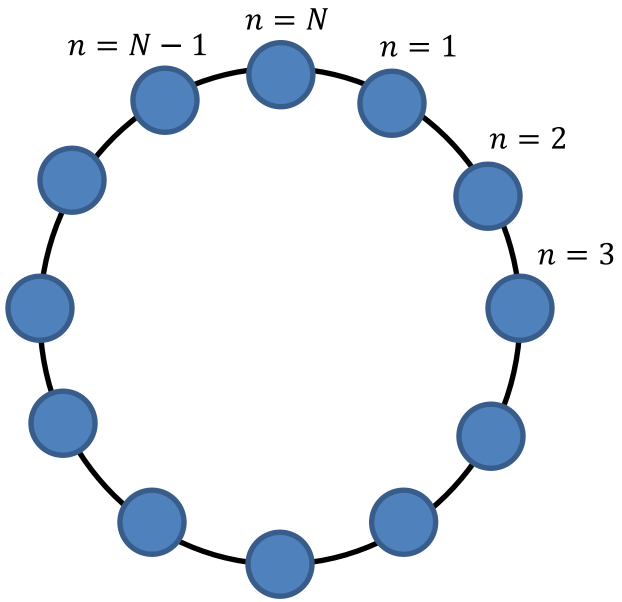


Parameters:
Observation error standard deviation 0.1
Background error standard deviation 0.1
Background error correlation length scale 1
Observation error correlation length scale 5

Increasing the observation error correlation length scale allows the observations to provide more information about gradients.

Lorenz 96 model

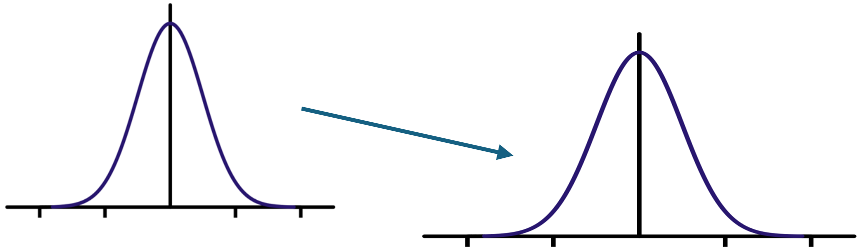




$$\frac{dx_i}{dt} = \underbrace{(x_{i+1} - x_{i-2})x_{i-1}}_{\text{advection}} \underbrace{- x_i}_{\text{dispersion}} + \underbrace{F}_{\text{External forcing}} \quad \text{for } i = 1, 2, \ldots, n$$

F=8 is the chaotic regime.
Hovmoller plot demonstrates the presence of 'waves' with positive phase speed and negative group speed. Spatially coherent waves move left at a speed of 4 grid points per time unit

Lorenz 96 model – error in linear assumption

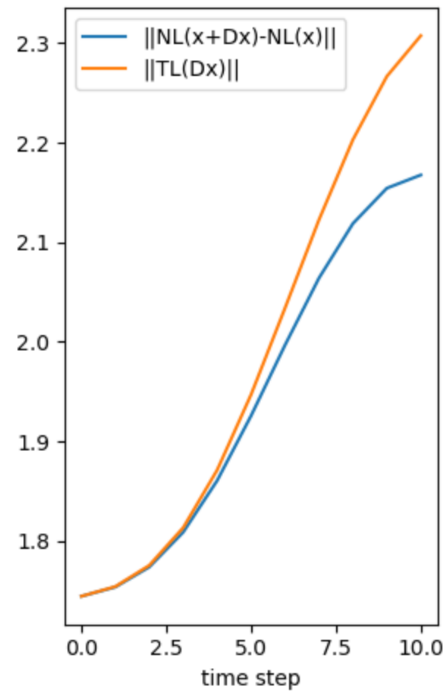


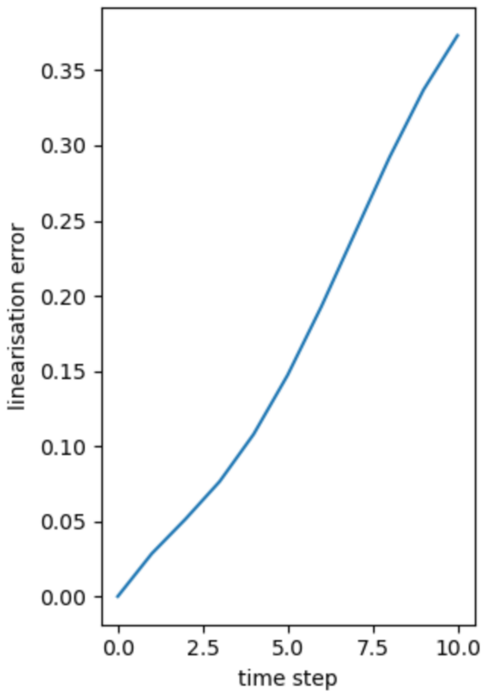
Many DA algorithms assume that the propagating model is near linear.

This is related to the Gaussian assumption.

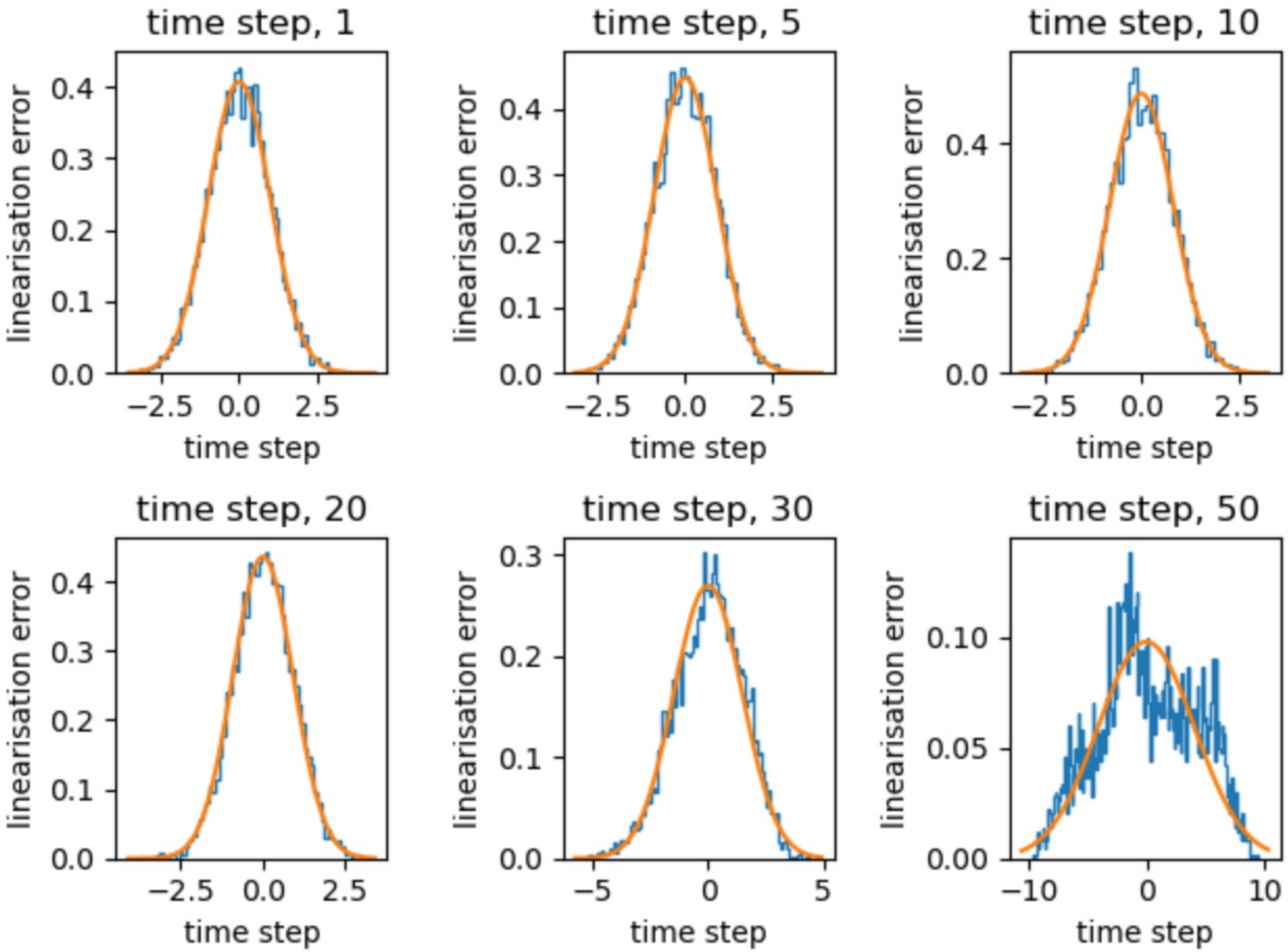
The linearization error can be quantified as

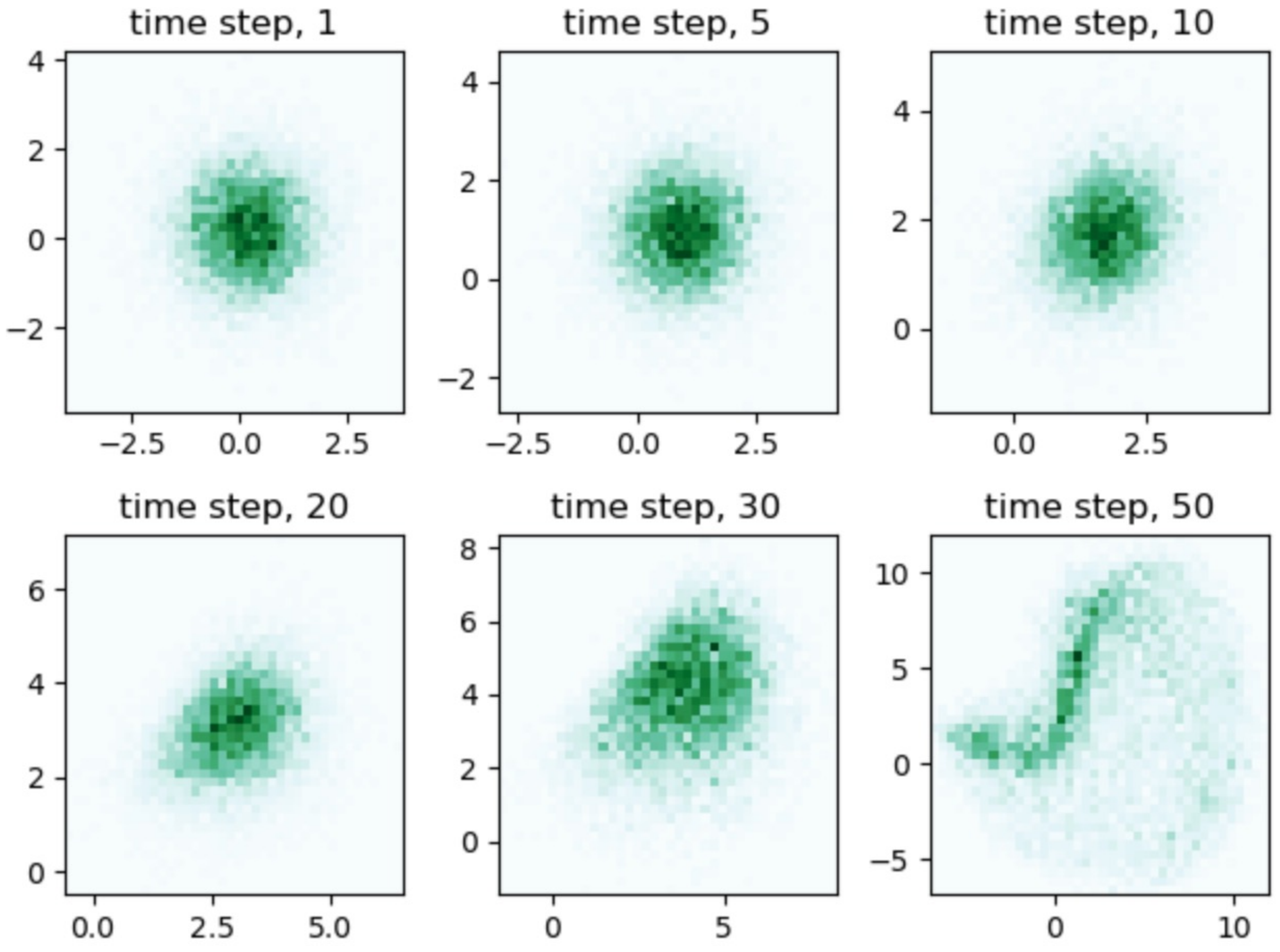
$$linerror(t) = ||NL(\mathbf{x}+\Delta\mathbf{x},t) - NL(\mathbf{x},t) - TL\Delta\mathbf{x},t||$$





The linearization depends on the magnitude of the perturbation, Δx, and the length of the simulation.
The size of the perturbation is related to the size of the corrections we want to make during the DA process.
The linearization error should be used to guide how frequently the assimilation should be performed.


time step, 1
time step, 5
time step, 10
time step, 20
time step, 30
time step, 50
linearisation error
time step

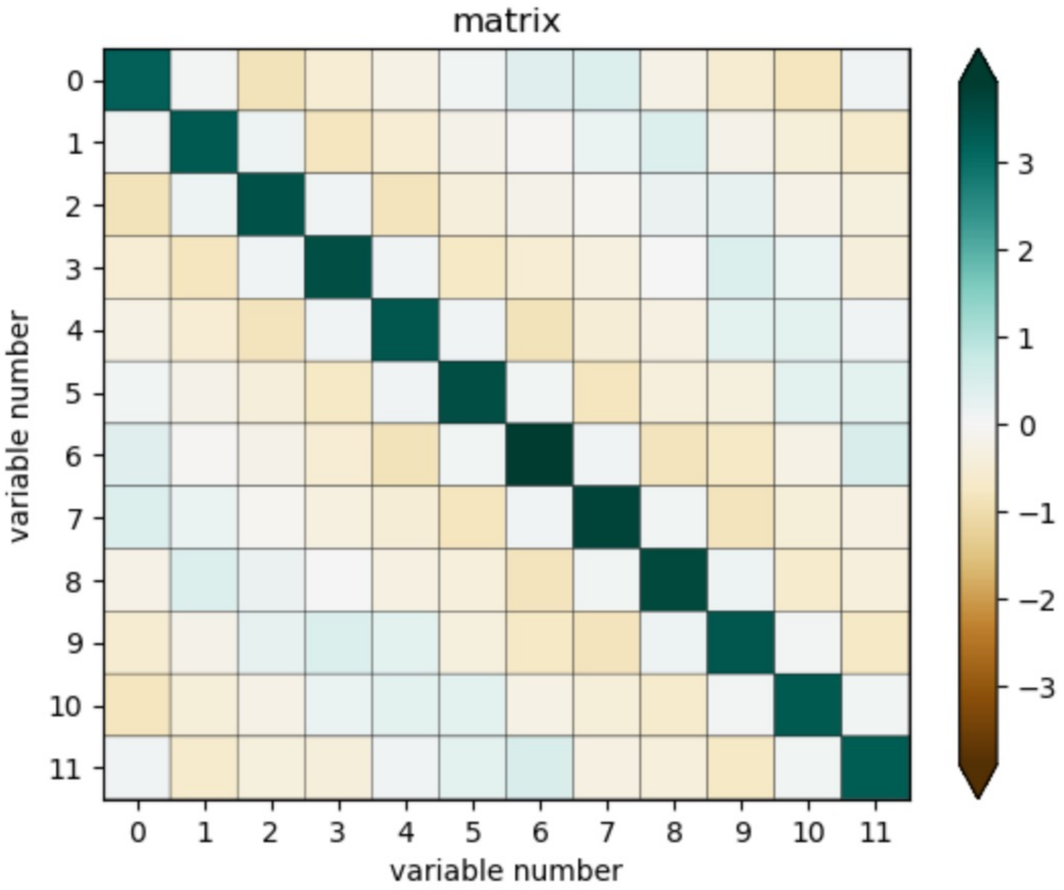


time step, 1
time step, 5
time step, 10
time step, 20
time step, 30
time step, 50

Lorenz 96 – B matrix

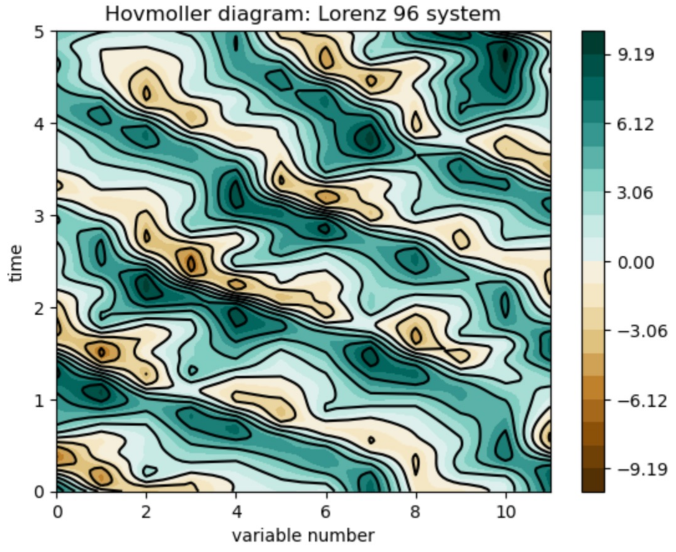
We generate an approximate B matrix using the Canadian Quick method

$$\epsilon = (\mathbf{x}(t+T) - \mathbf{x}(t))/\sqrt(2)),$$



Sample size =10000

The structure in the B matrix can be compared back to the Hovmoller plot.



Lorenz 96 – B matrix

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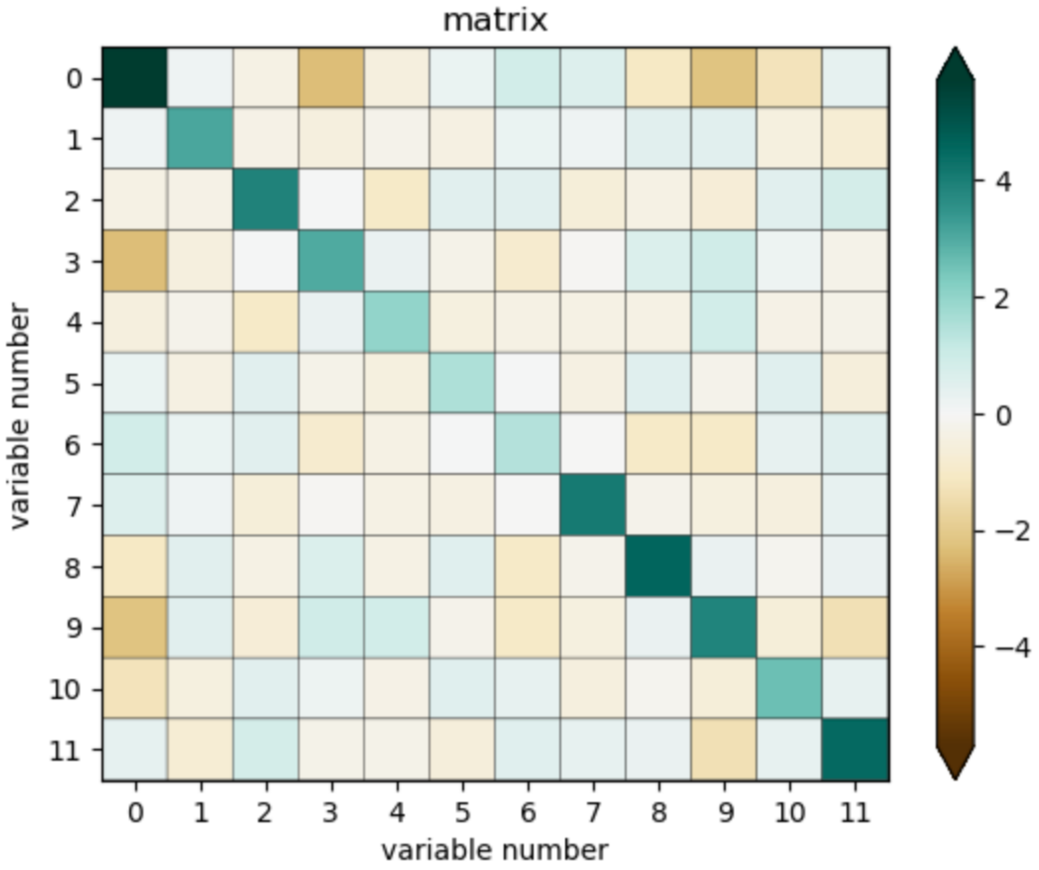
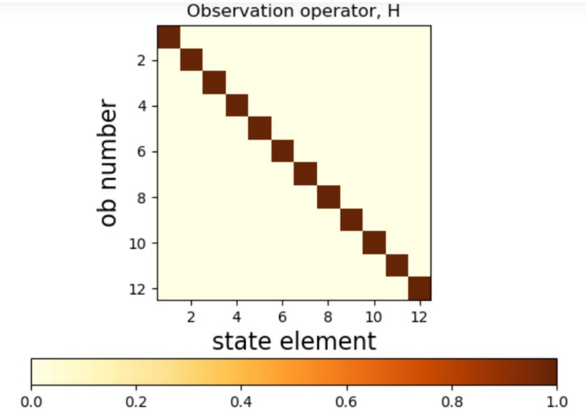
$$\epsilon = (\mathbf{x}(t+T) - \mathbf{x}(t))/\sqrt{(2)}),$$

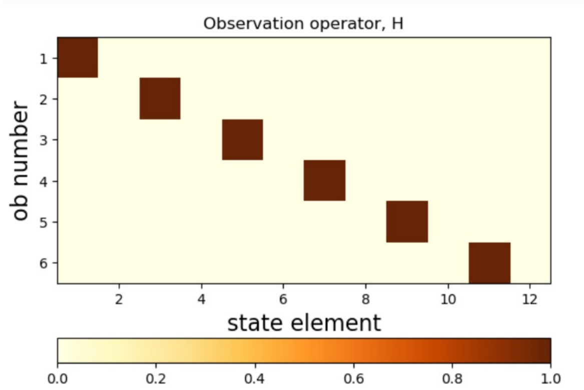


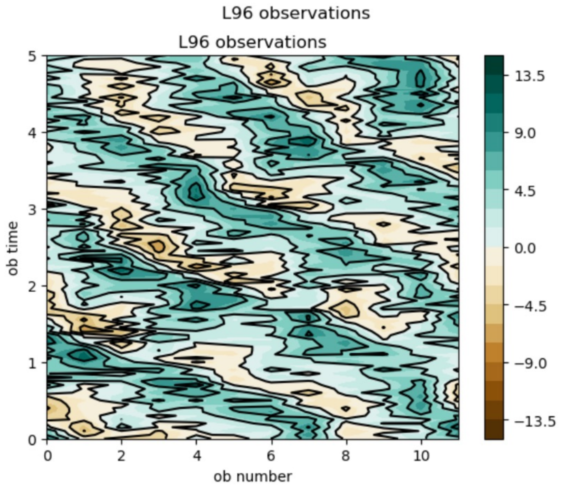
Reducing the sample size to 200 results in noisy unphysical correlations that will affect how the information in the observations is used.

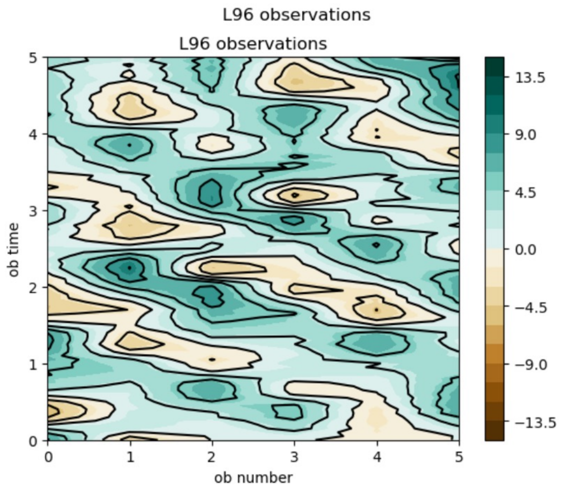
Lorenz 96 – generating observations

We generate observations consistent with the observation error standard deviations and observation operator









Which is better observing every grid point with a large error standard deviation or observing every other grid point with a small error standard deviation?

We can explore this question in the practicals other the rest of the week.