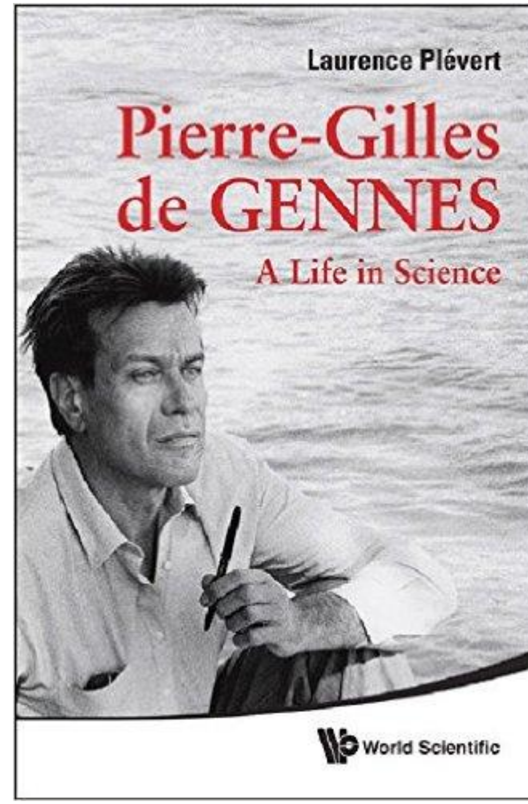
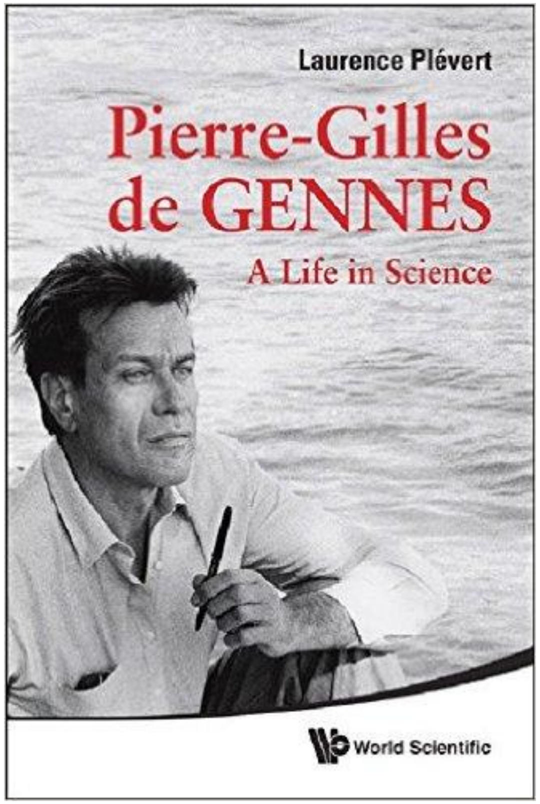
Part III

Пьер Жиль де Жен (фр. *Pierre-Gilles de Gennes*; 24 октября 1932, Париж — 18 мая 2007, Орсе) — французский физик, лауреат Нобелевской премии по физике в 1991году «за обнаружение того, что методы, развитые для изучения явлений упорядоченности в простых системах, могут быть обобщены на жидкие кристаллы и полимеры». Де Жен известен прежде всего тем, что открыл структуру, положившую начало производству ЖК-дисплеев. За множество фундаментальных открытий многие научные круги называют де Жена «Ньютоном нашего времени».



Пьер Жиль де Жен (фр. *Pierre-Gilles de Gennes*; 24 октября 1932, Париж —

“The easiest thing in physics is the mathematics, the difficult bit is what it means”



дисплеев. За множество фундаментальных открытий многие научные круги называют де Жена «Ньютоном нашего времени».

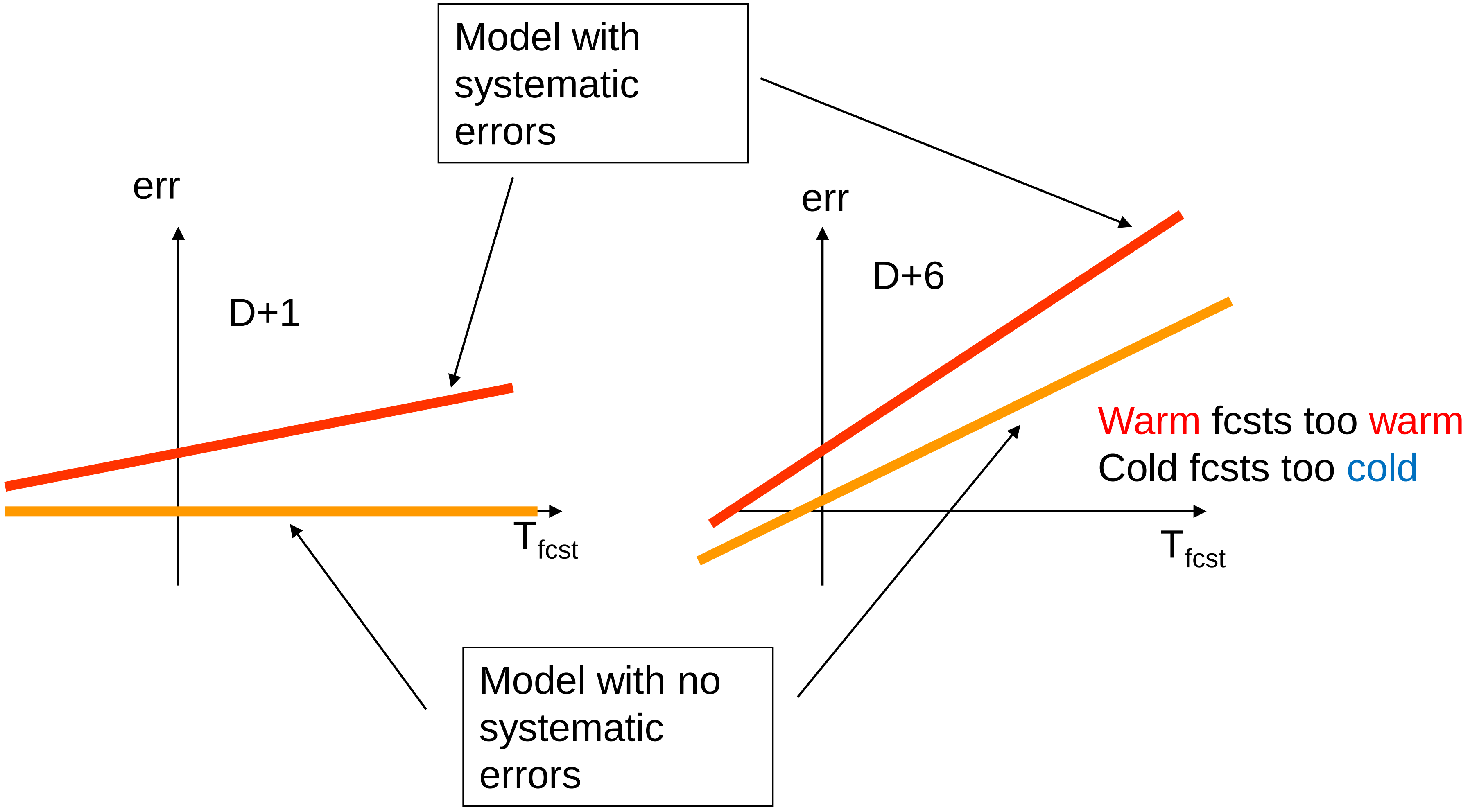
Mean errors are not the only "systematic" errors

a) A mean error which is much smaller than the variance does not point to any "systematic" error
b) In the opposite case we are dealing with a plain bias. But that is not the only type of "systematic" error
c) Errors are systematic if they can be described/explained by a (linear) equation

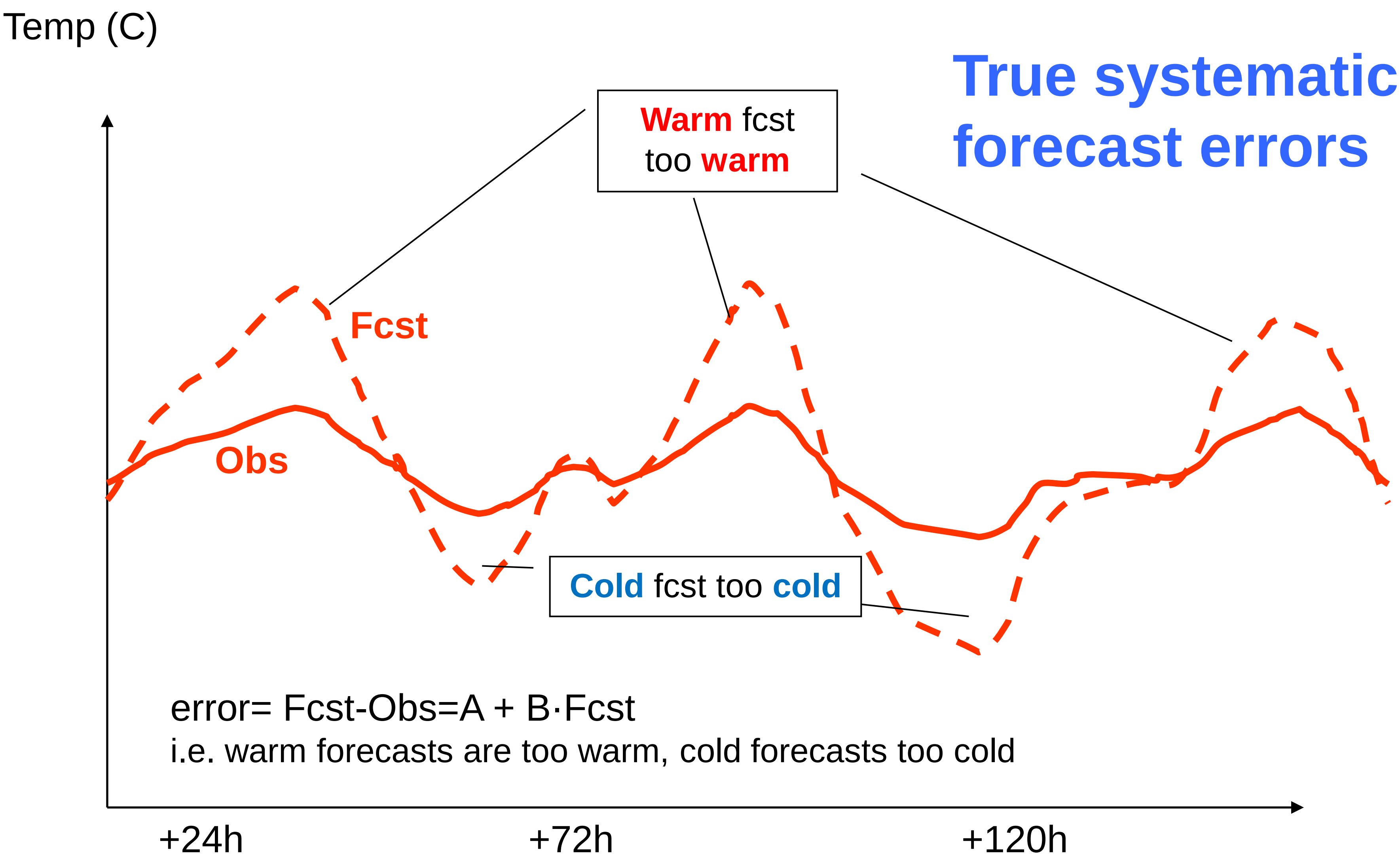
False systematic errors

Non-systematic errors that look like systematic

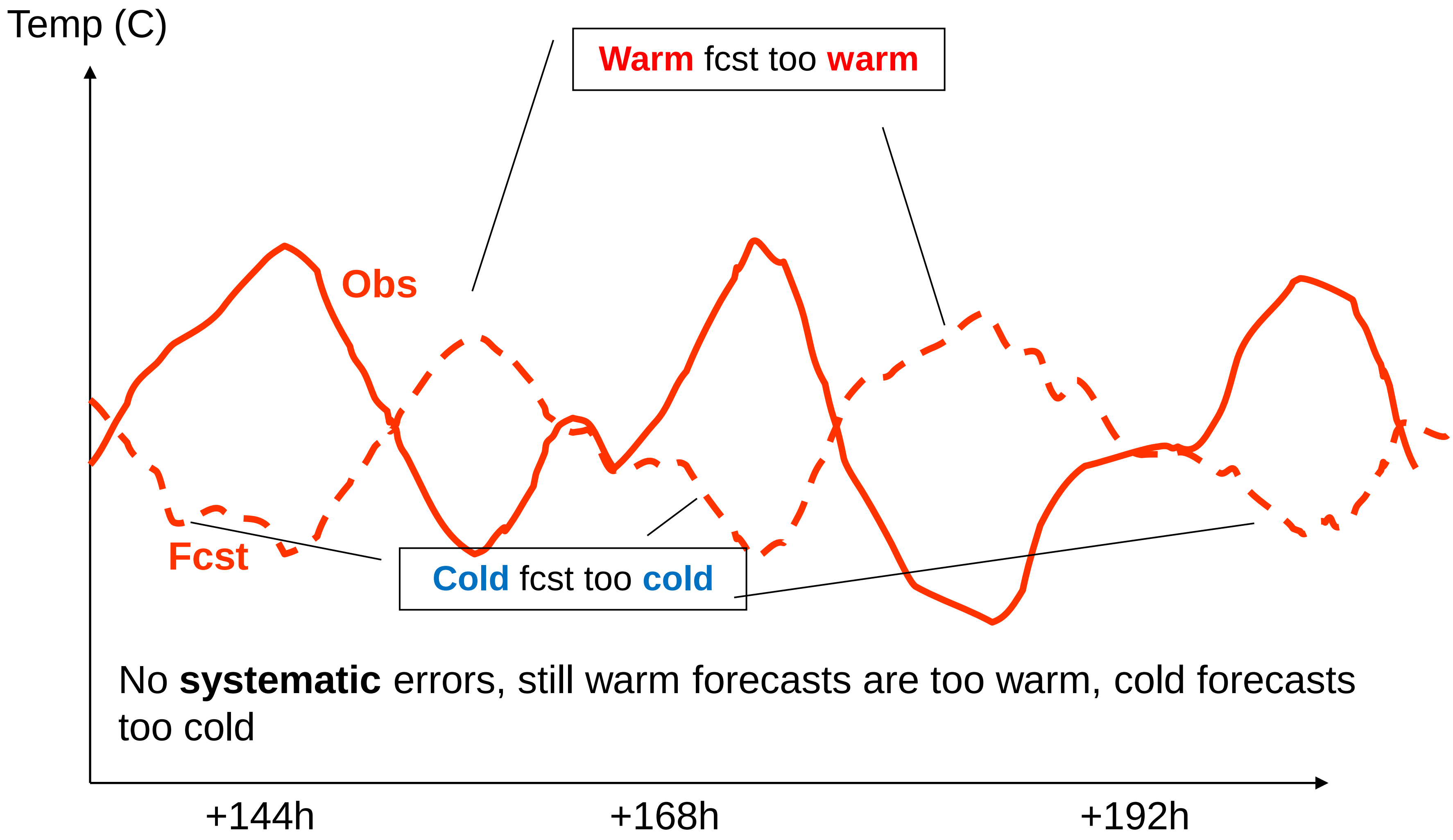
A model with no systematic errors (orange) will, with increasing lead time, appear to show a false drift towards increasing systematic errors



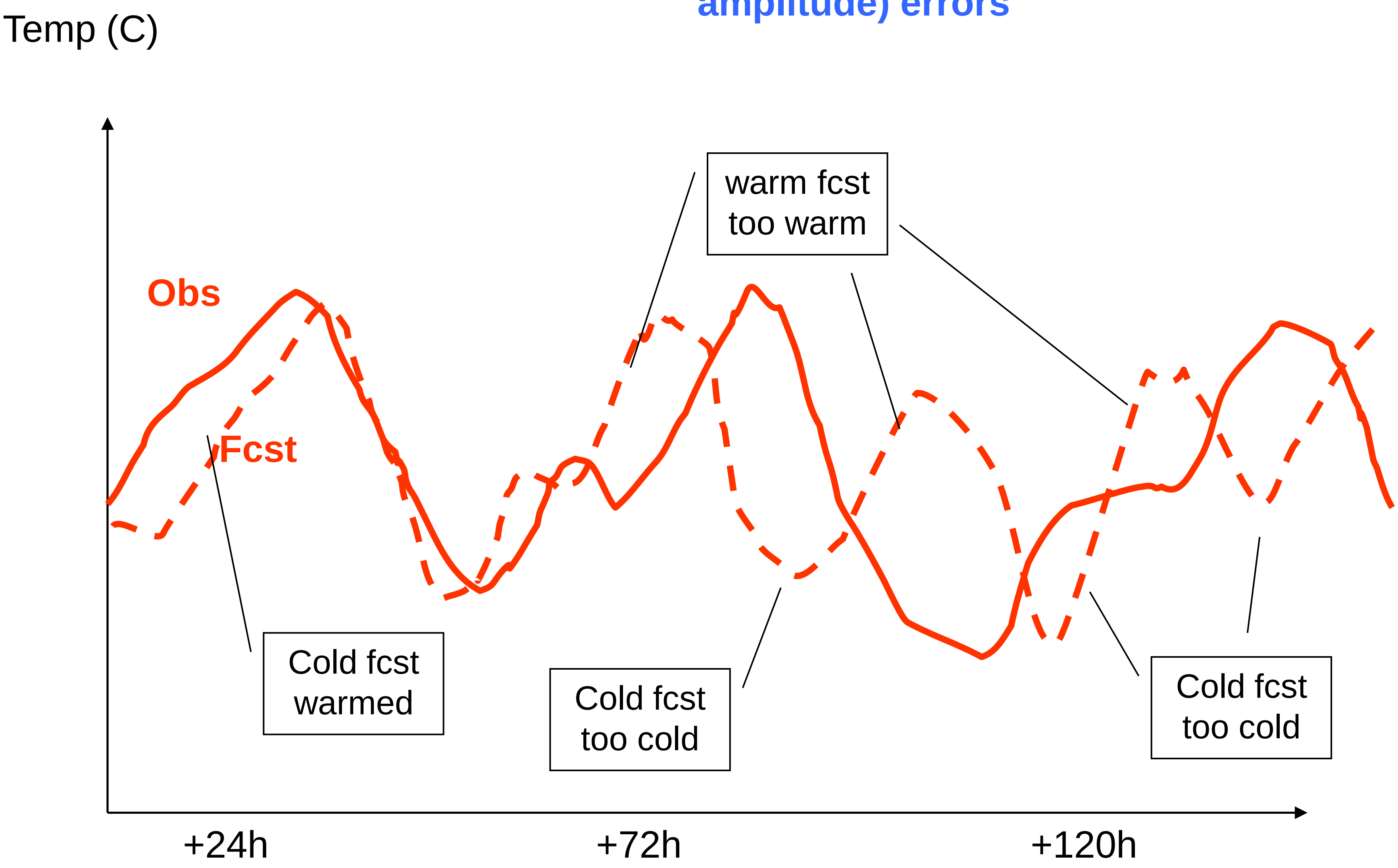
True systematic forecast errors



True non-systematic forecast errors (severe phase speed errors)



Typical medium range forecast (phase and amplitude) errors



What looks good can be bad – what looks bad can be good

On the interpretation of verification statistics

Decomposition of the RMSE

The complete formula for RMSE

The full mathematical expression for the RMS error (E_j) of a **j**-day forecast issued on day **i** verified over **N** gridpoints over a period of **T** days

$$E_j = \sqrt{\frac{1}{T}\frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T}(f_{i,j} - a_{i+j})^2}$$

But the “Double Penalty Effect” is a manifestation of a more fundamental effect which can be understood through the trivial equation:

$$(a+b)^2 = a^2 + b^2 + 2ab$$

From the RMSE to the MSE

We make things easier for us by considering the ***square*** of the RMSE

$$E_j^2 = \frac{1}{T}\frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T}(f_{i,j} - a_{i+j})^2$$

Simplifying the notations

$$E_j^2 = \frac{1}{T}\frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T}(f_{i,j} - a_{i+j})^2$$

The notation is further simplified by replacing the Σs with an overbar symbolising all temporal and spatial averages. We also skip all the indices.

$$E^2 = \overline{(f - a)^2}$$

Decomposing the MSE around climate

Decomposing the RMSE

$$E^2 = \overline{(f-a)^2}$$

Introduce **c** as the climate value of the verifying day

$$E^2 = \overline{(f-c+c-a)^2}$$

Reposition **c** to form **f-c** and **a-c**

$$E^2 = \overline{((f-c)-(a-c))^2}$$

Apply **$(a+b)^2=a^2+b^2+2ab$**

$$E^2 = \overline{(f-c)^2} + \overline{(a-c)^2} - 2\overline{(f-c)(a-c)}$$

Each of these three terms has its own story to tell

What looks bad might be good…

The *improvement* of the model, as a simulation of the atmospheric system, may therefore appear as *deterioration* of the quality of the model!

An increase in forecast variability increases $\mathbf{A_f}^2$

...compensates the decrease of the RMSE due to improved forecasts

$$E^2 = \overline{(f-c)^2} + \overline{(a-c)^2} - 2\overline{(f-c)(a-c)}$$

...to the level of the observed variability $\mathbf{A_a}^2$

The Error Saturation Level

The atmosphere's variability

When **f=c** the first and last terms disappear

$$E^2 = \overline{(f-c)^2} + \overline{(a-c)^2} - 2\overline{(f-c)(a-c)}$$

$$E^2 \rightarrow \overline{(a-c)^2}$$

$$E^2 \rightarrow A_a^2$$

We take the square root….

$$E \rightarrow A_a$$

Which is the error level for a purely climatological statement

The RMS error saturation level

When the forecasts start to lose skill and the RMSE start to approach high error levels the last term disappears

$$E^2 = \overline{(f-c)^2} + \overline{(a-c)^2} - 2\overline{(f-c)(a-c)}$$

$$E^2 \rightarrow A_f^2 + A_a^2$$

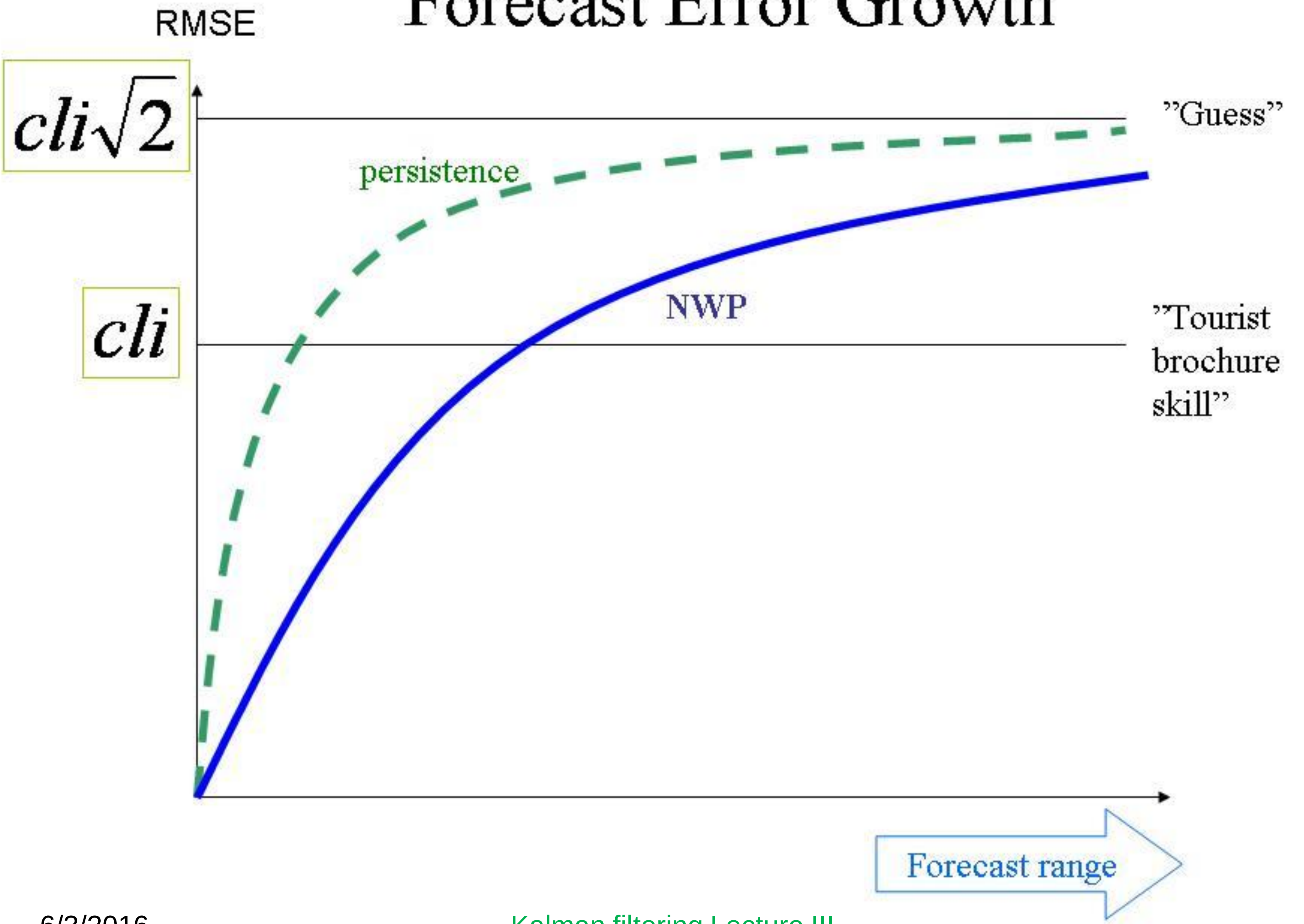
$$E^2 \rightarrow 2A_a^2$$

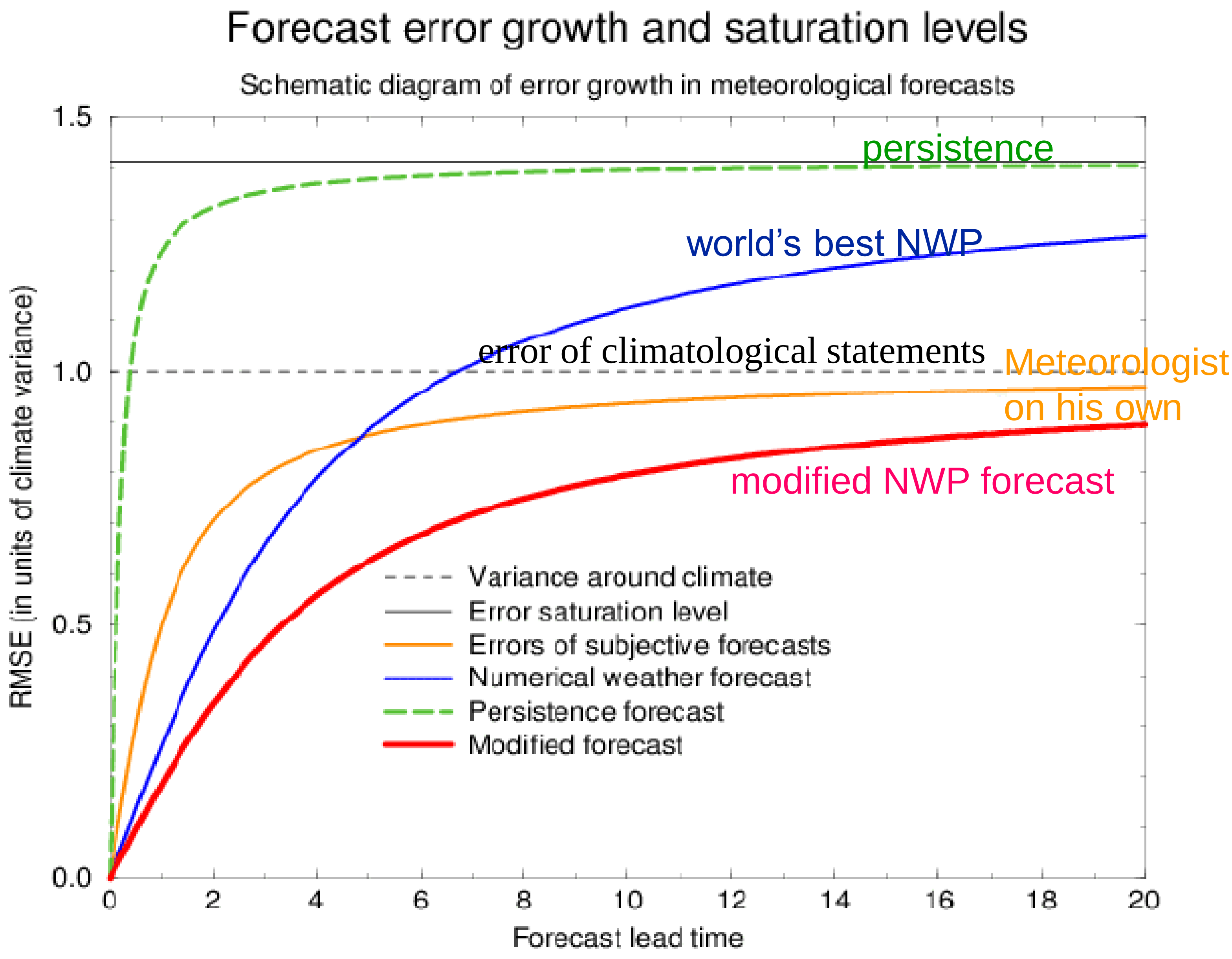
$$E \rightarrow A_a\sqrt{2}$$

Which is the uppermost error level for a realistic NWP model, 41% above the error level of a purely climatological statement

It is also called *The Error Saturation Level (ESL)*

Forecast Error Growth

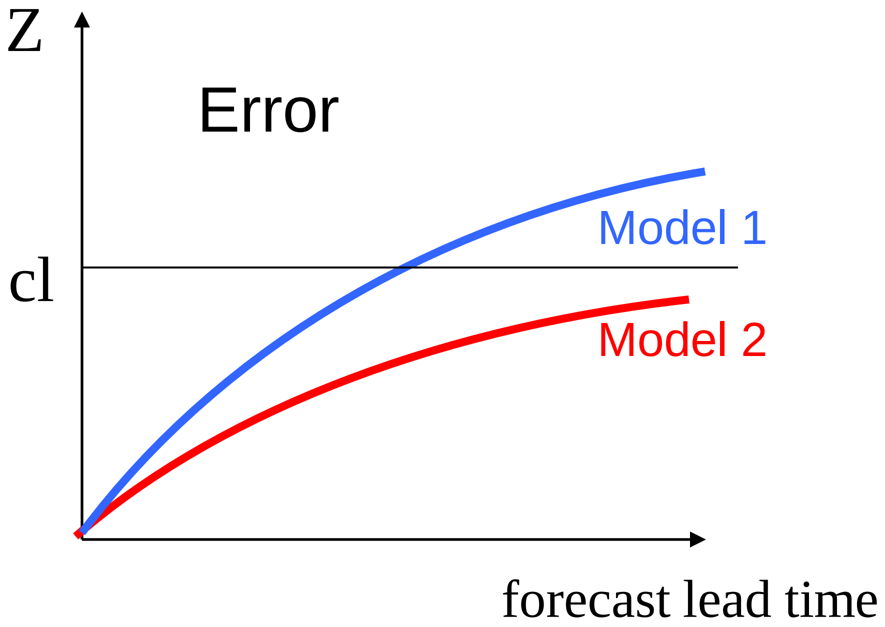


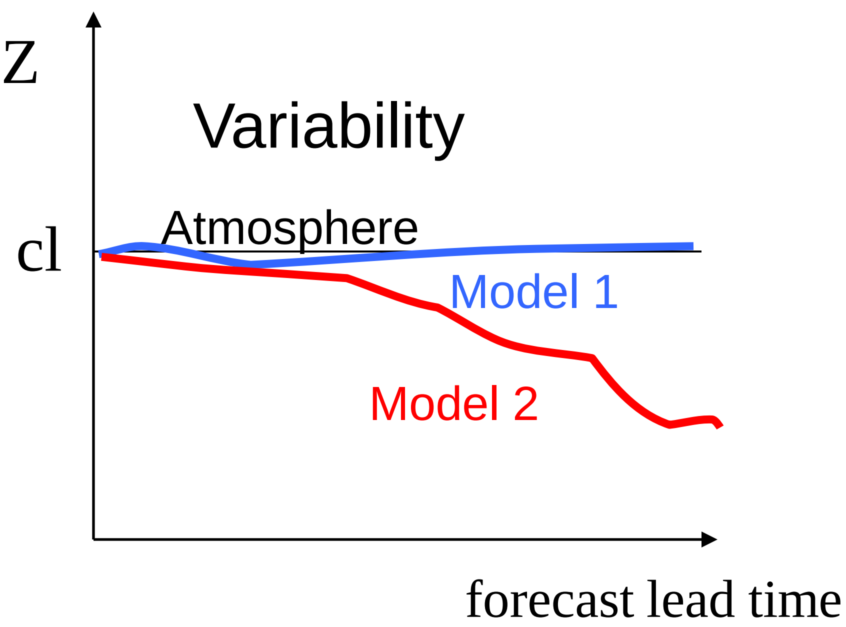

Forecast error growth and saturation levels
Schematic diagram of error growth in meteorological forecasts
persistence
world's best NWP
error of climatological statements
Meteorologist
on his own
modified NWP forecast
Variance around climate
Error saturation level
Errors of subjective forecasts
Numerical weather forecast
Persistence forecast
Modified forecast
RMSE (in units of climate variance)
Forecast lead time
1.5
1.0
0.5
0.0
0
2
4
6
8
10
12
14
16
18
20

The use of the decomposition of the RMSE

$$E^2 = \overline{(f-a)^2} = \overline{(f-c)^2} + \overline{(a-c)^2} - \overline{2(f-c)(a-c)}$$

model variab. atm. variab. "skill"



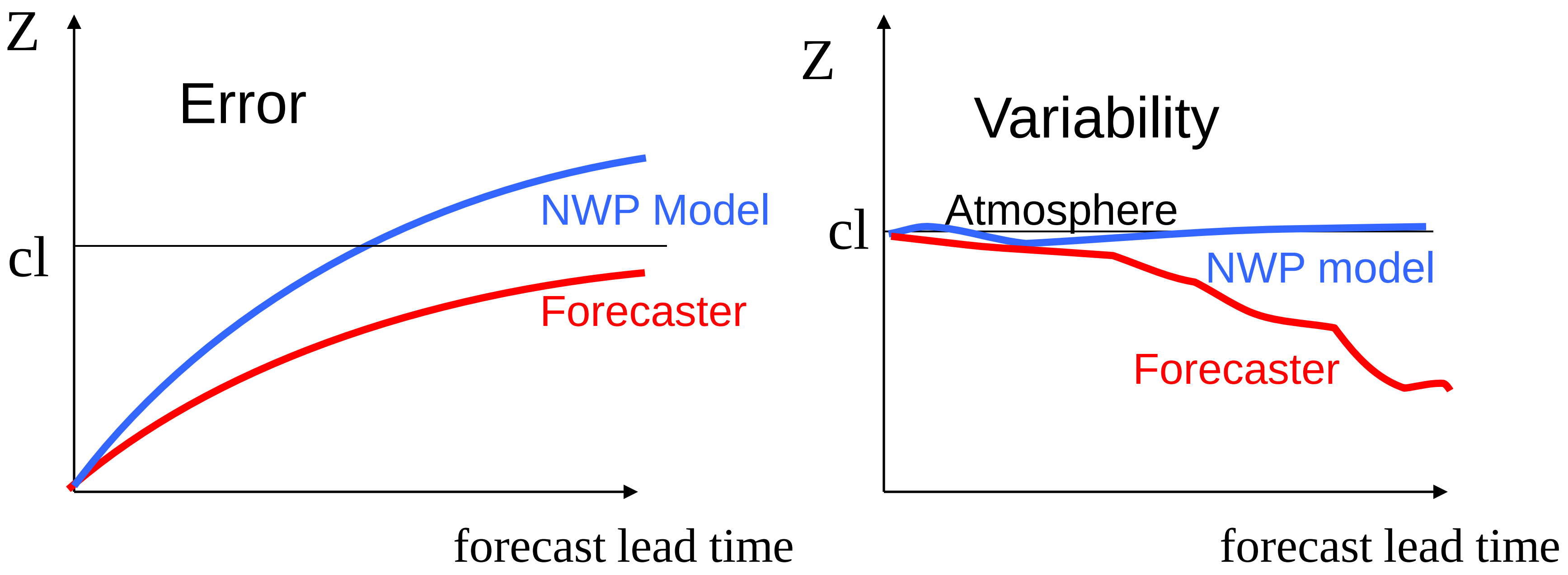


The decrease in variability of Model 2 (bad) gave low (good) RMSE verifications

But the same does not apply to a forecaster

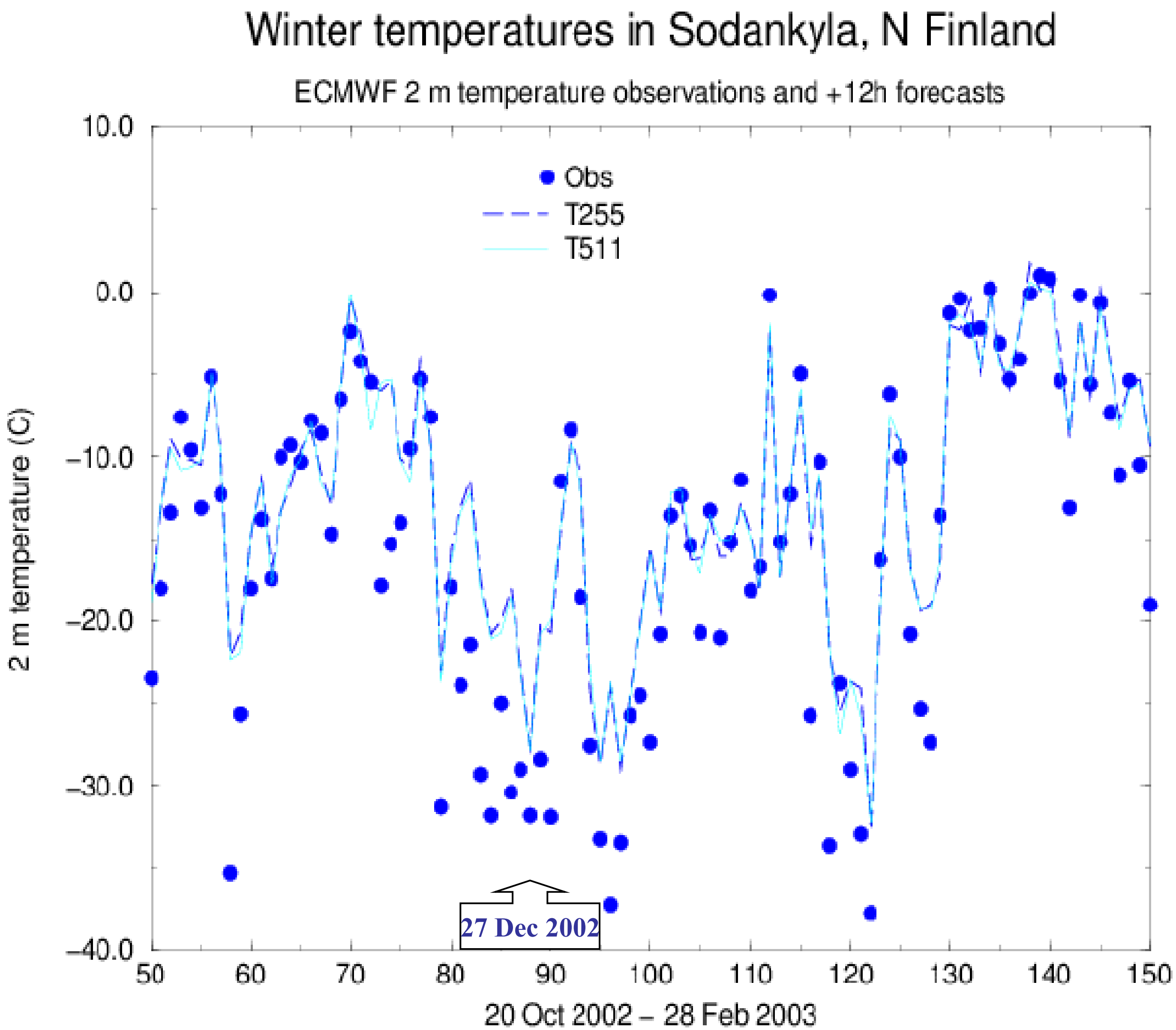
$$E^2 = \overline{(f-a)^2} = \overline{(f-c)^2} + \overline{(a-c)^2} - \overline{2(f-c)(a-c)}$$

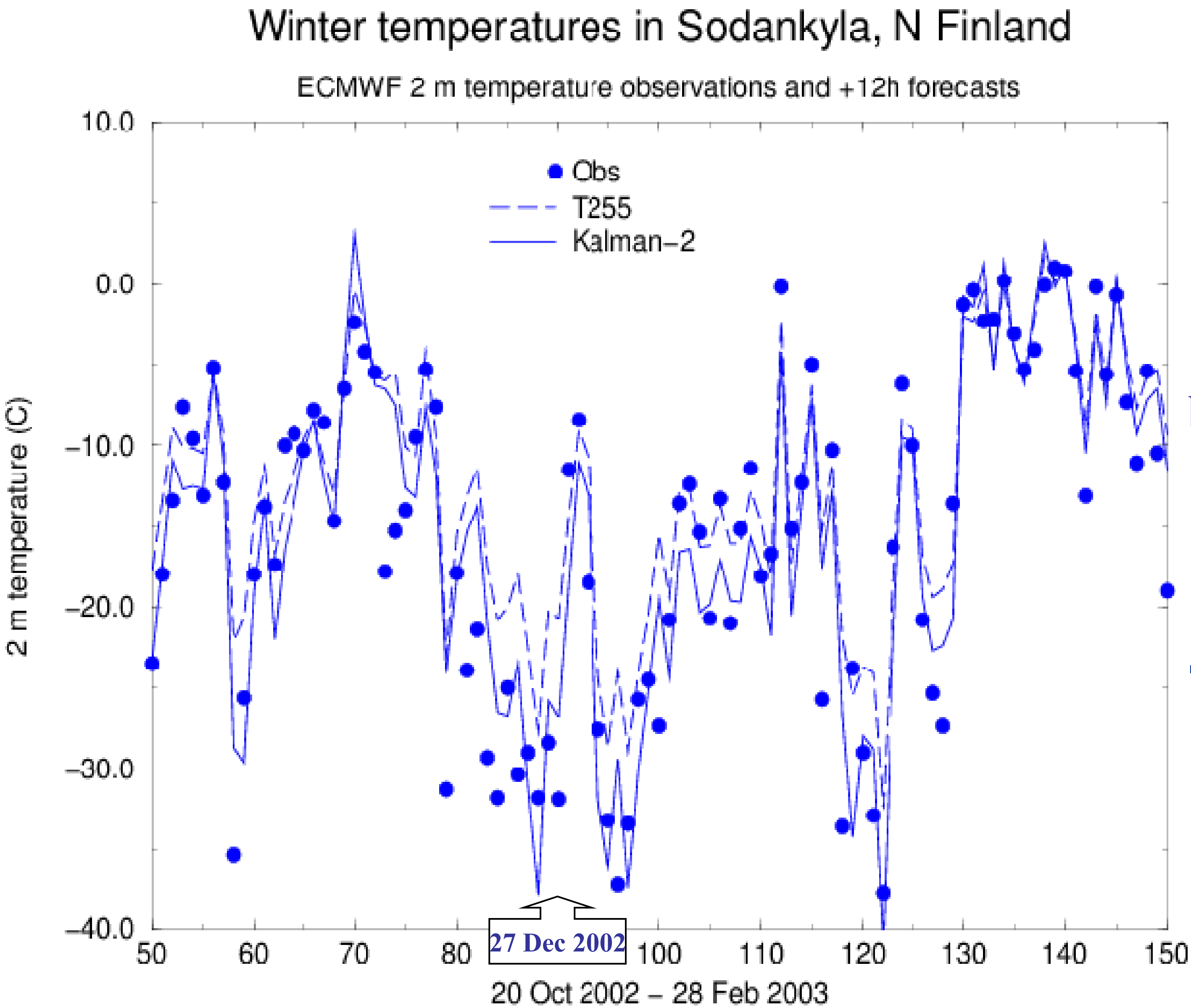
Forecast variab. Atm. variab. "skill"



The decrease in variability of the good forecaster gave low (good) RMSE verifications

What’s the point of compensating for under variability if it does not improve the forecasts sufficiently?

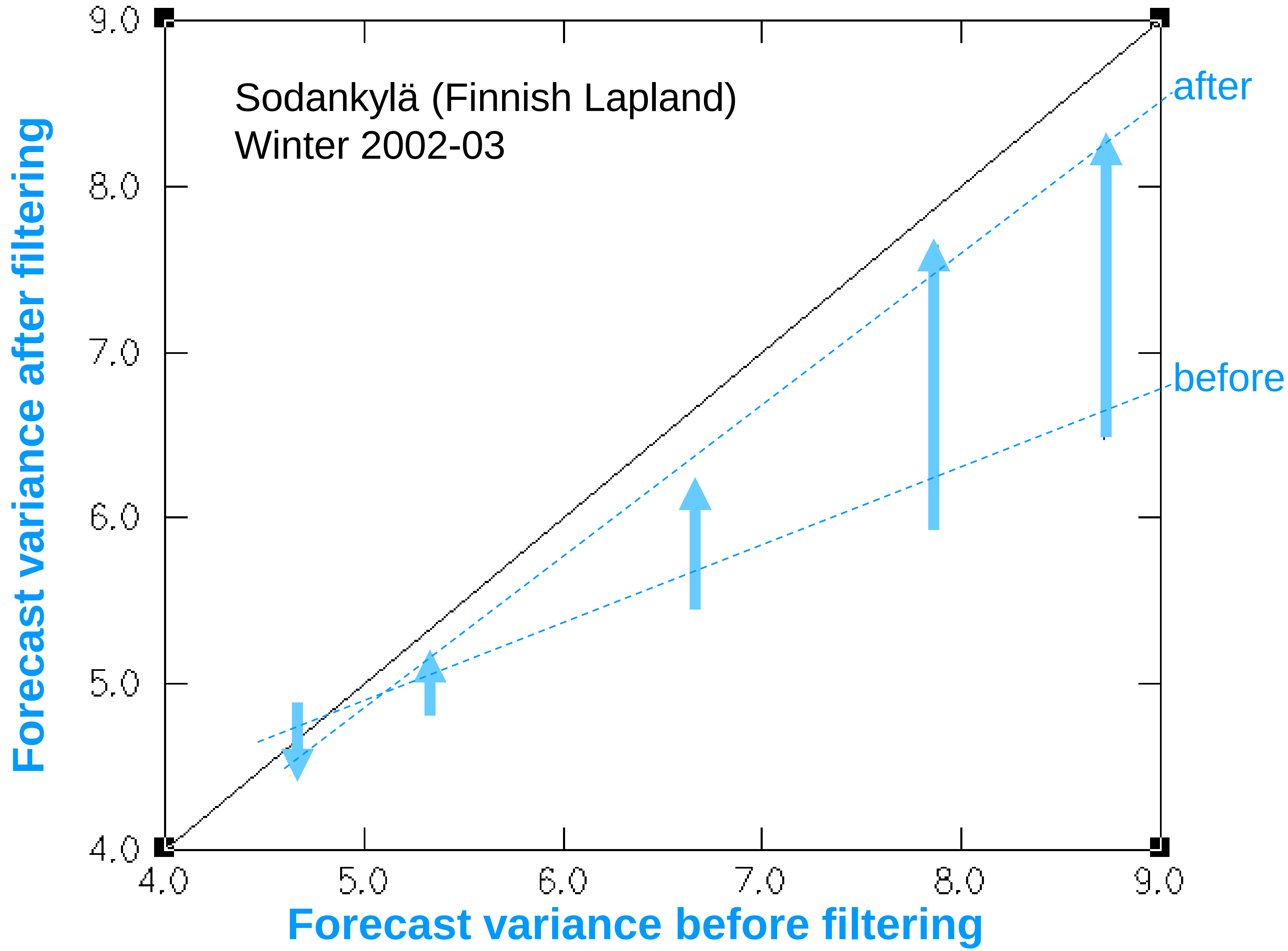

Winter temperatures in Sodankyla, N Finland
ECMWF 2 m temperature observations and +12h forecasts
Obs
T255
T511
2 m temperature (C)
10.0
0.0
−10.0
−20.0
−30.0
−40.0
50
60
70
80
90
100
110
120
130
140
150
20 Oct 2002 – 28 Feb 2003
27 Dec 2002



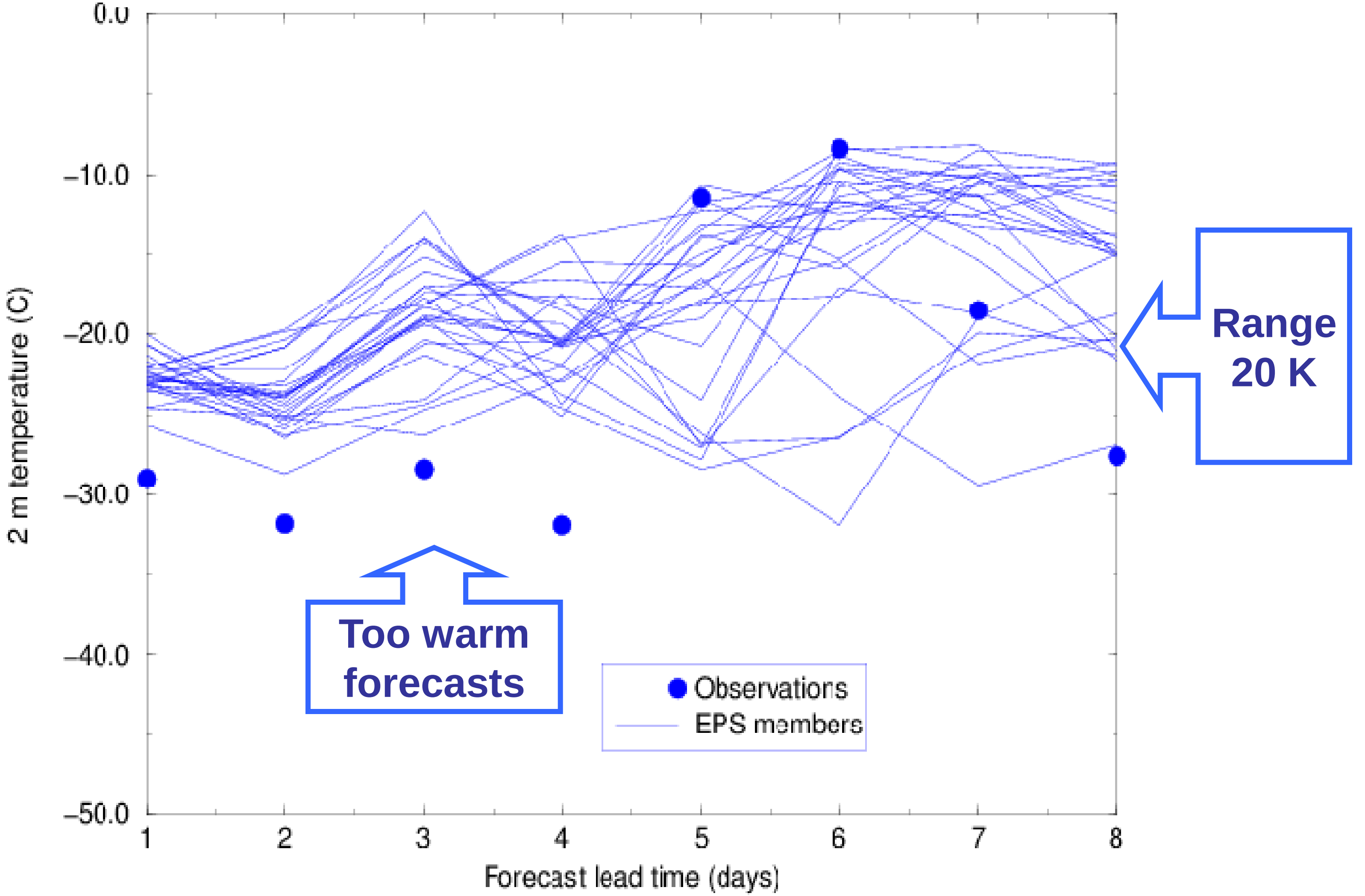
The mean error (ME) decreased by 1-2 K but the RMSE only by 0.5 K

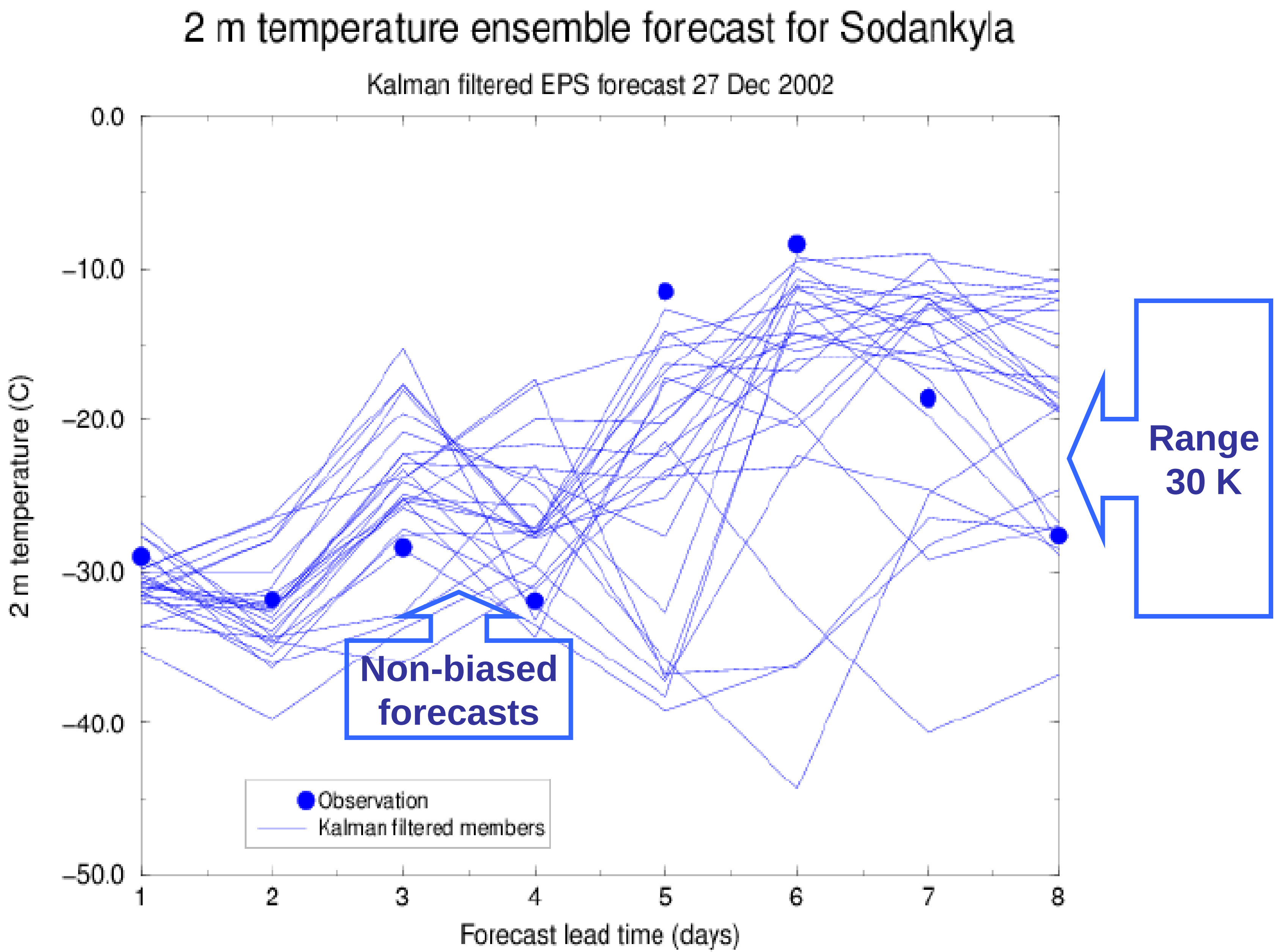
The solution lies in the ensemble approach...

The Kalman 2 filter improvement of forecast variance



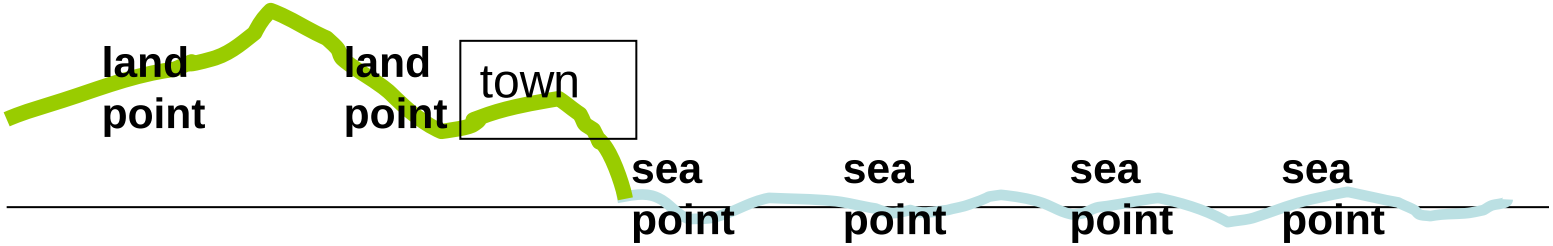
The T255 (and T511) have problems with temperatures below -25 C



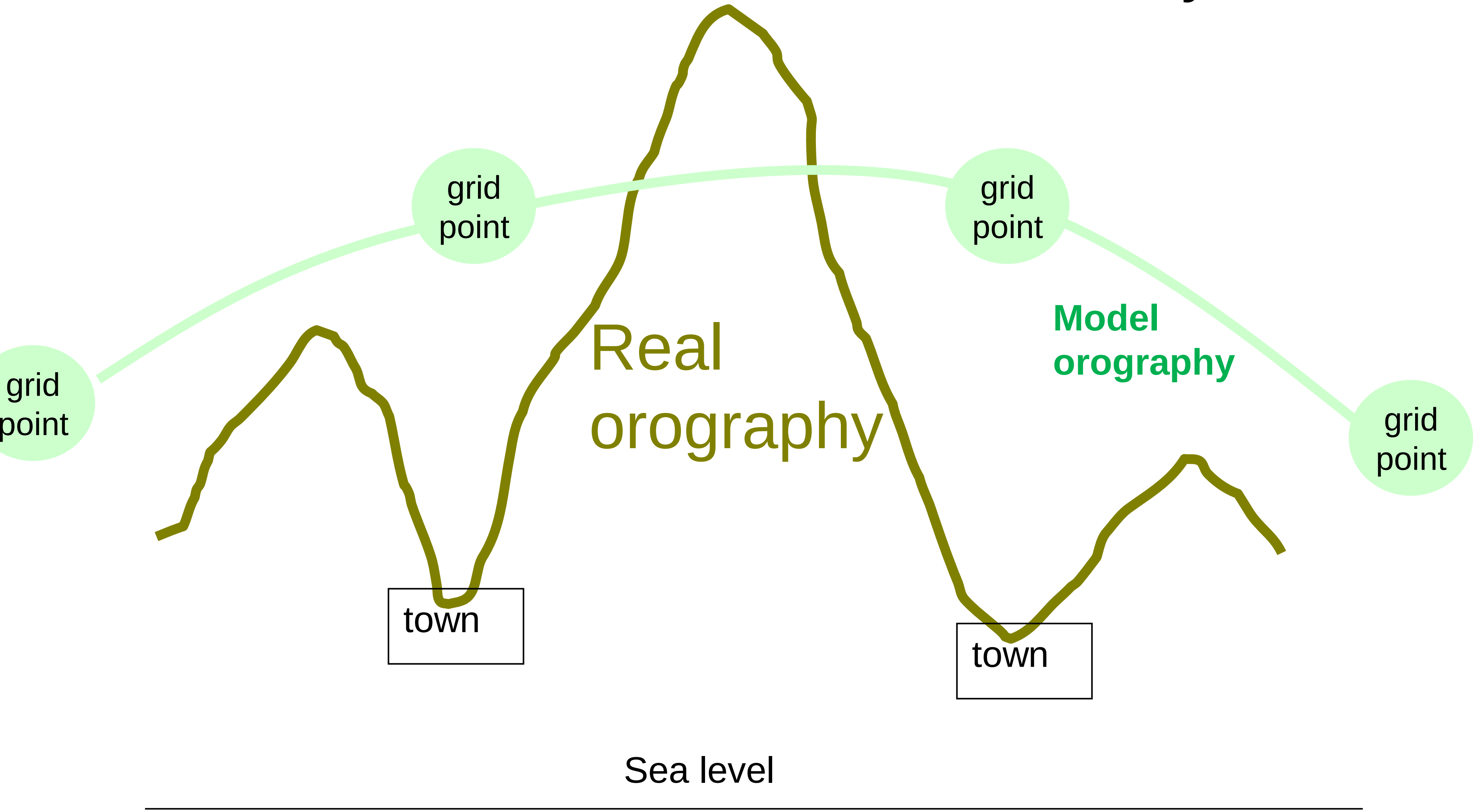


2 m temperature ensemble forecast for Sodankyla
Kalman filtered EPS forecast 27 Dec 2002
0.0
−10.0
−20.0
−30.0
−40.0
−50.0
2 m temperature (C)
1
2
3
4
5
6
7
8
Forecast lead time (days)
Observation
Kalman filtered members
Non-biased forecasts
Range 30 K

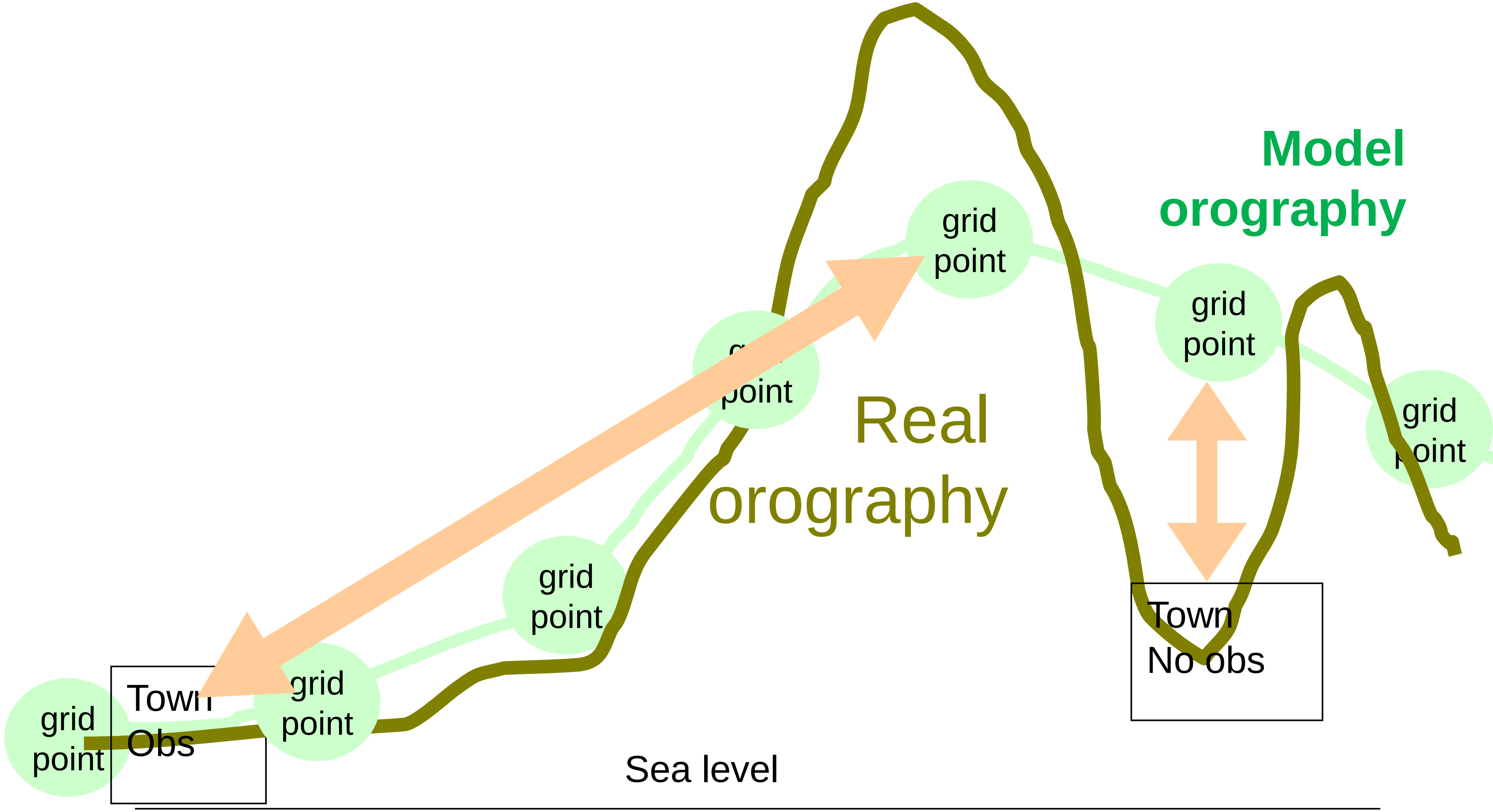
The issue so far has been the relation between observations and grid points at about the same height



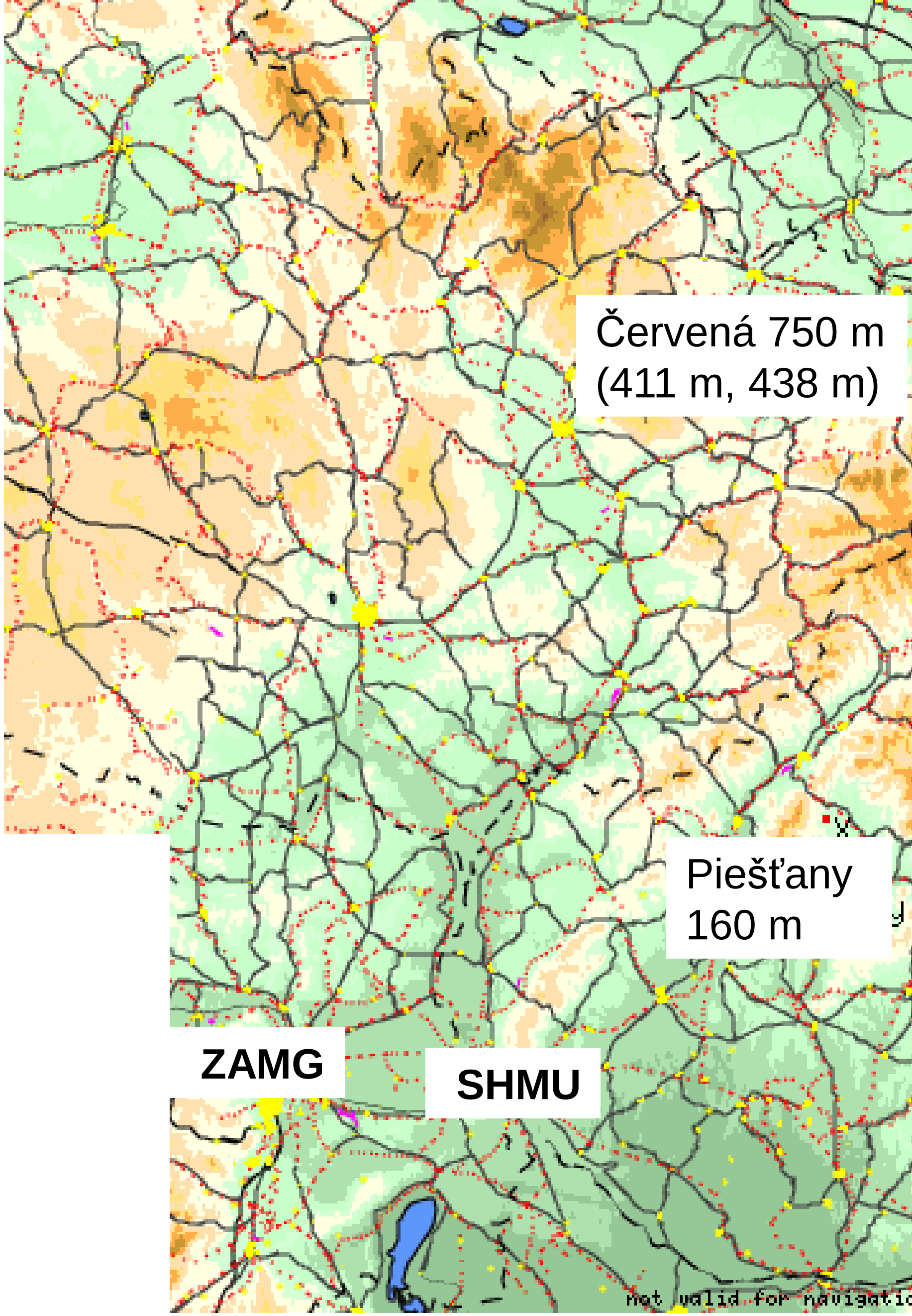
A more difficult problem is to adjust model level data to stations in valleys



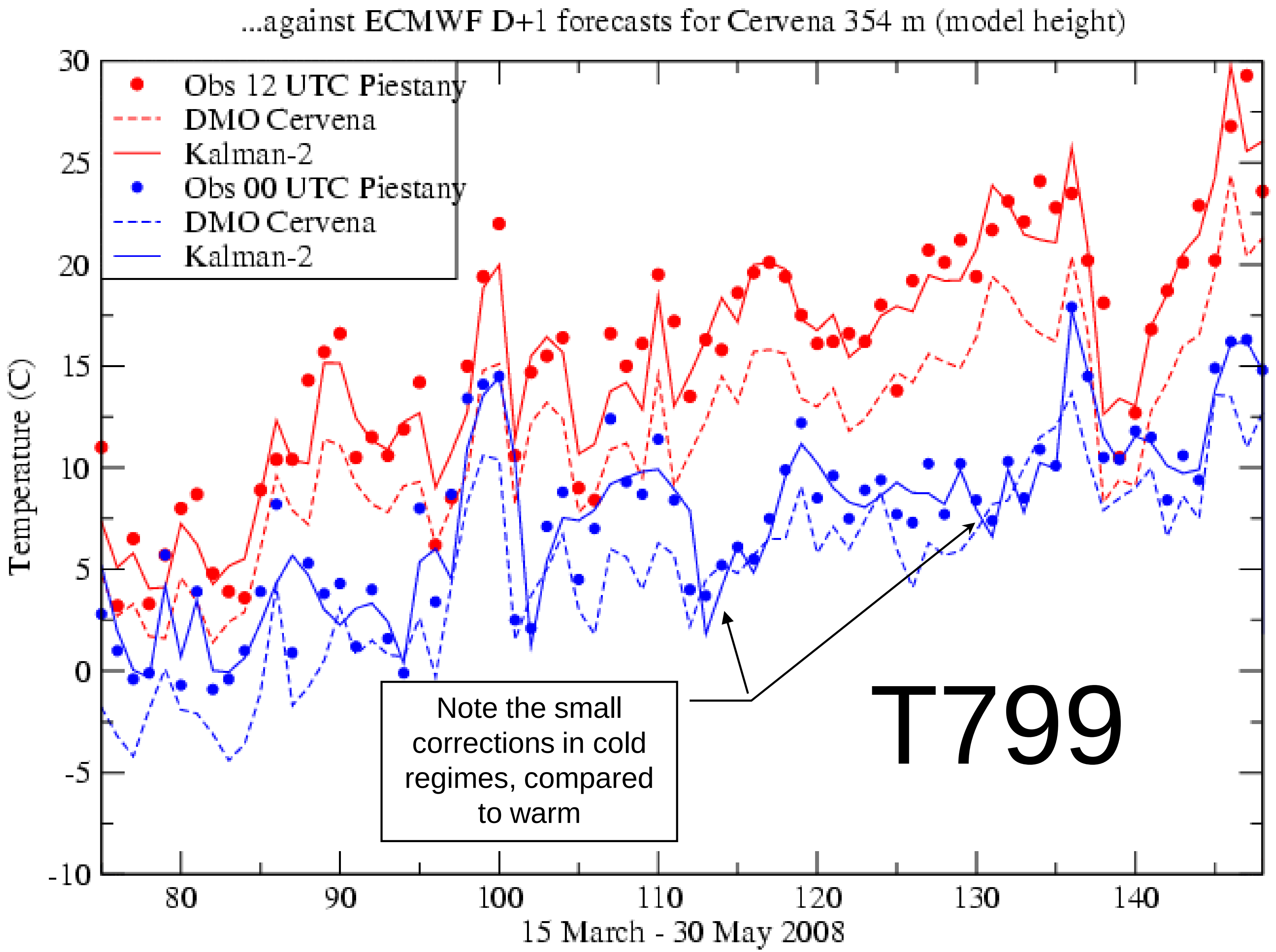
For practical reason my comparison between high altitude grid point data low altitude observations also involved great horizontal differences

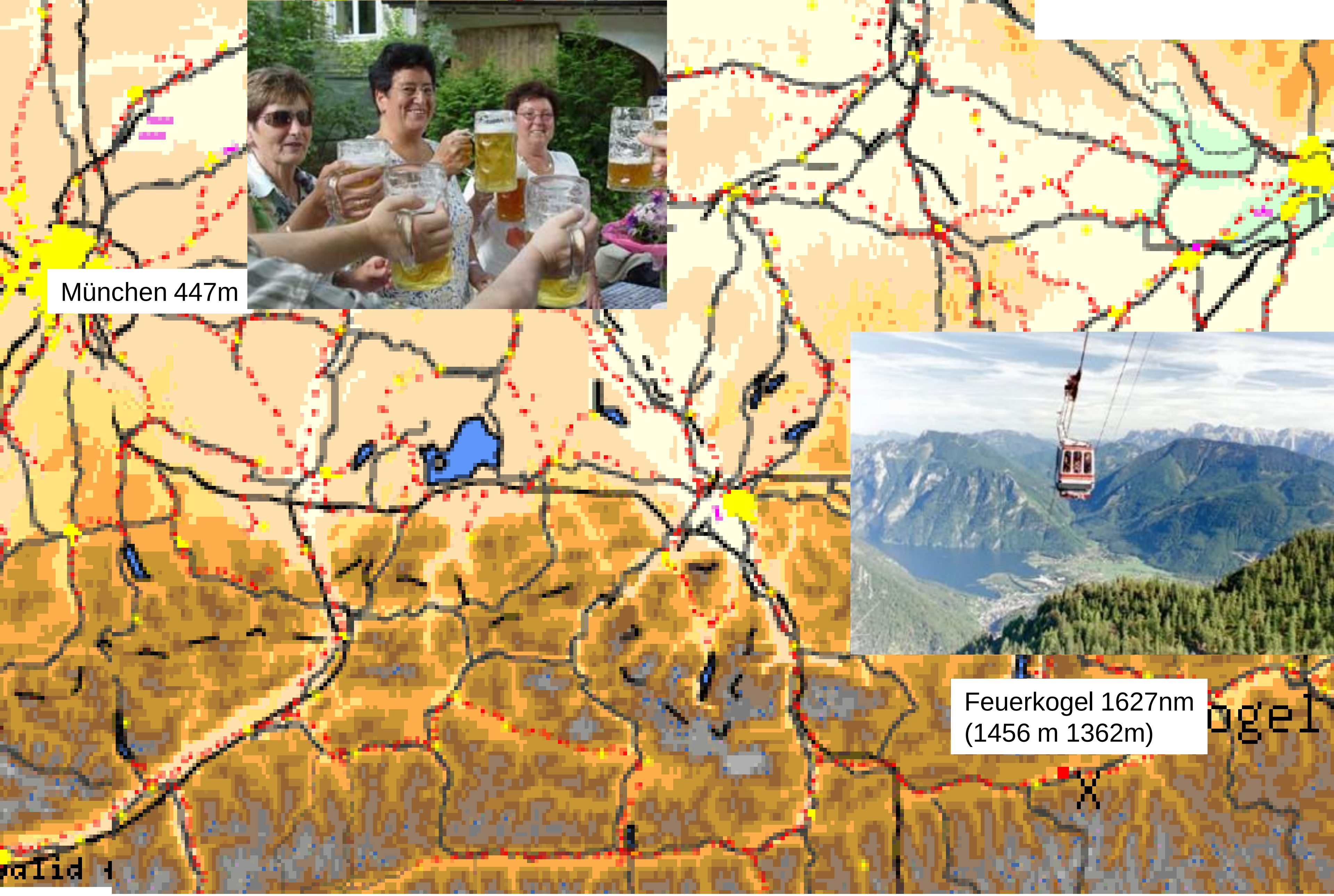


Comparison between high altitude grid points and low altitude observations, which for practical reasons also happened to be situated at some considerable distance

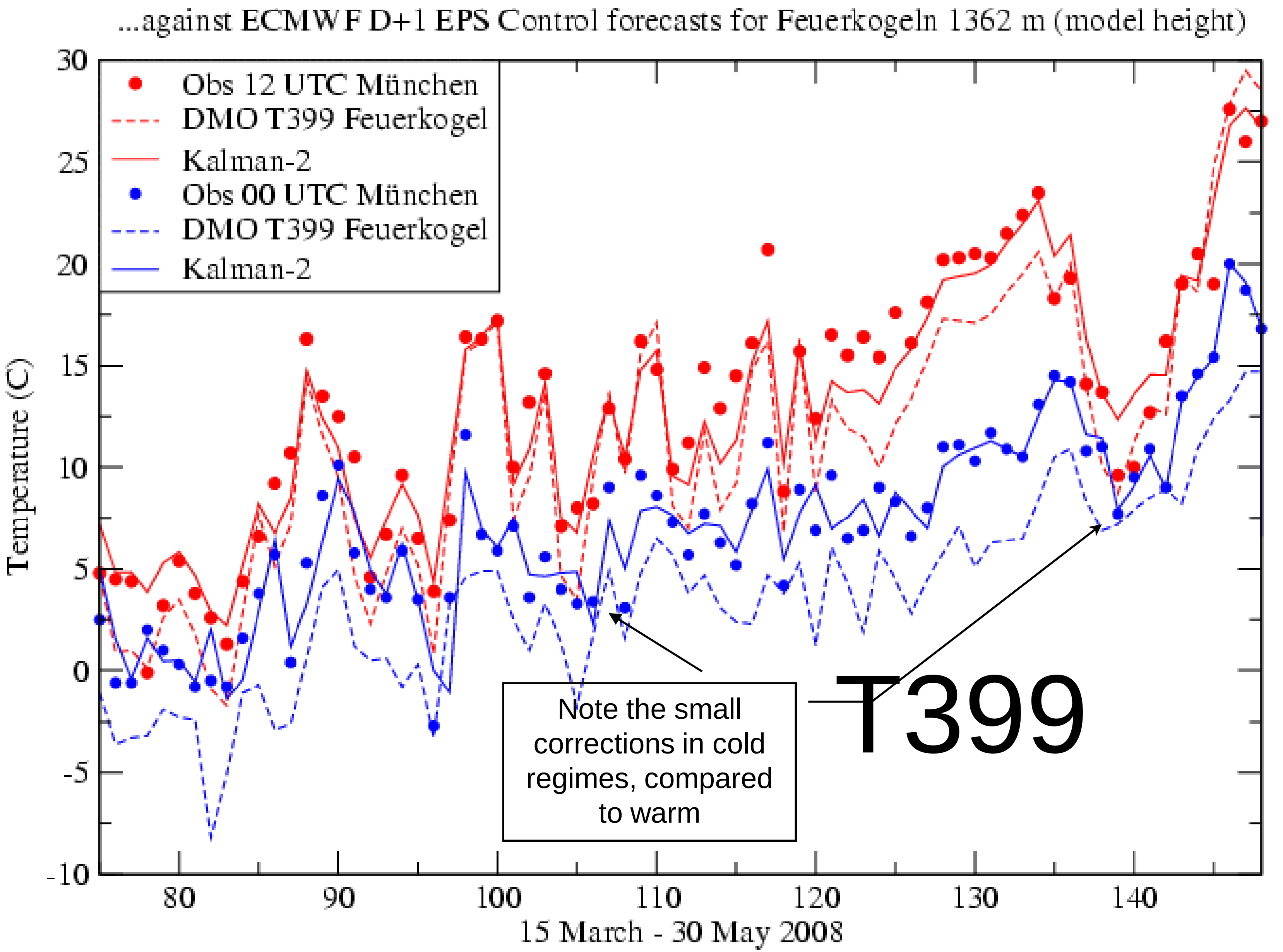

Červená 750 m
(411 m, 438 m)
Piešťany
160 m
ZAMG
SHMU
not valid for navigation

Kalmanfiltering ECMWF D+1 forecasts for Piestany (160 m)



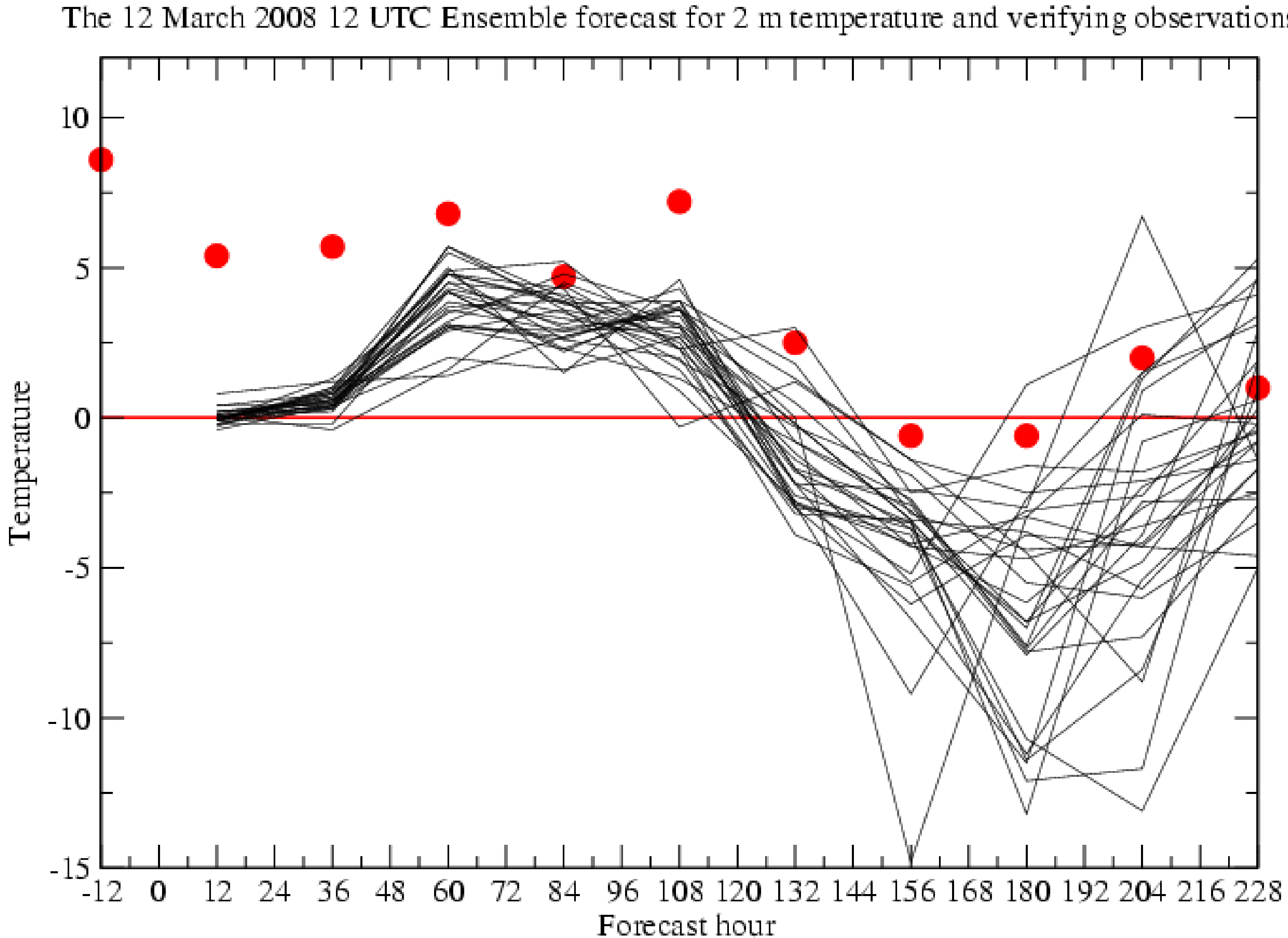

München 447m
Feuerkogel 1627nm
(1456 m 1362m)

Kalmanfiltering ECMWF D+1 forecasts for München (447 m)

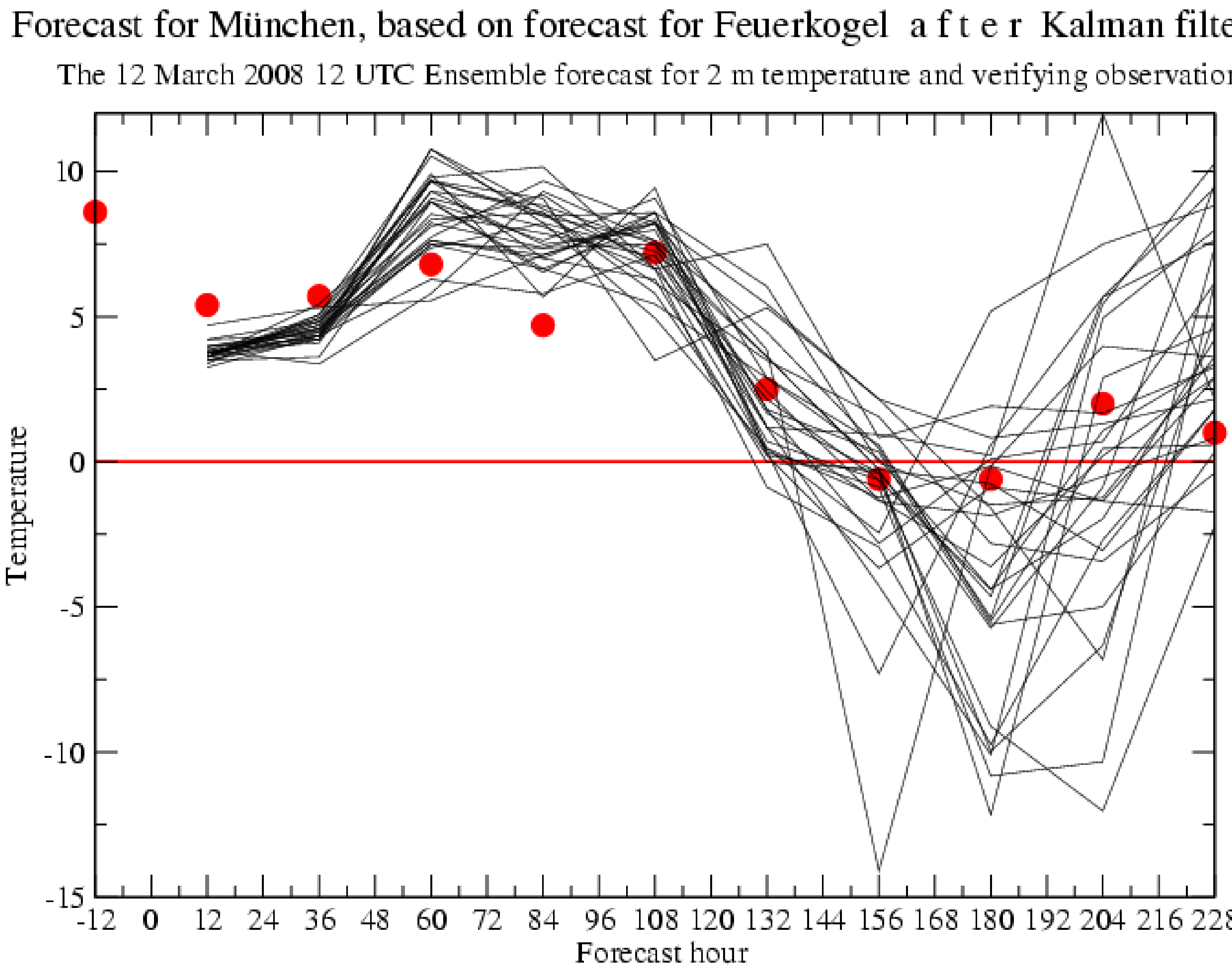


. . . or the Central European mountain sites:

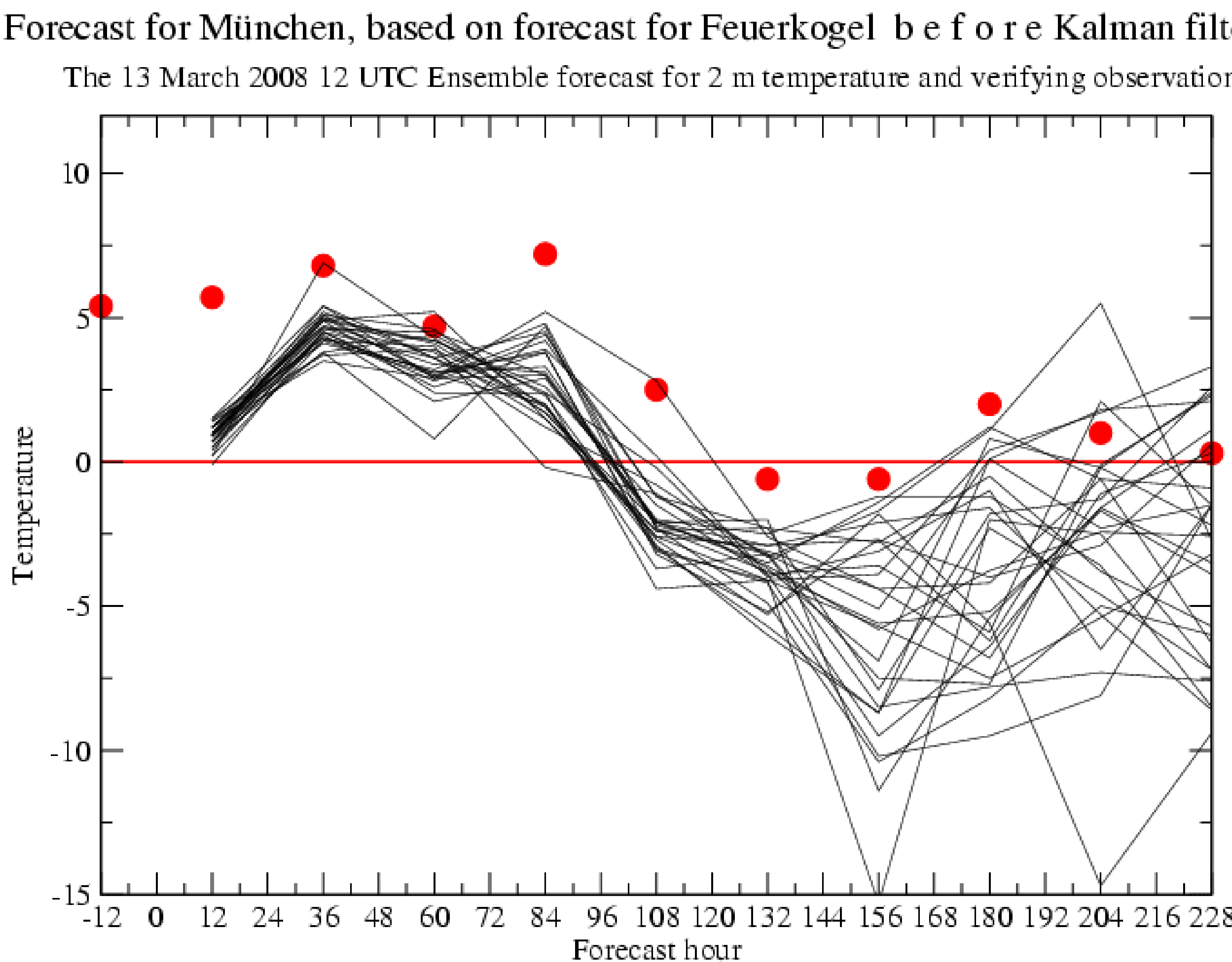
Forecast for München, based on forecast for Feuerkogel b e f o r e Kalman filtering



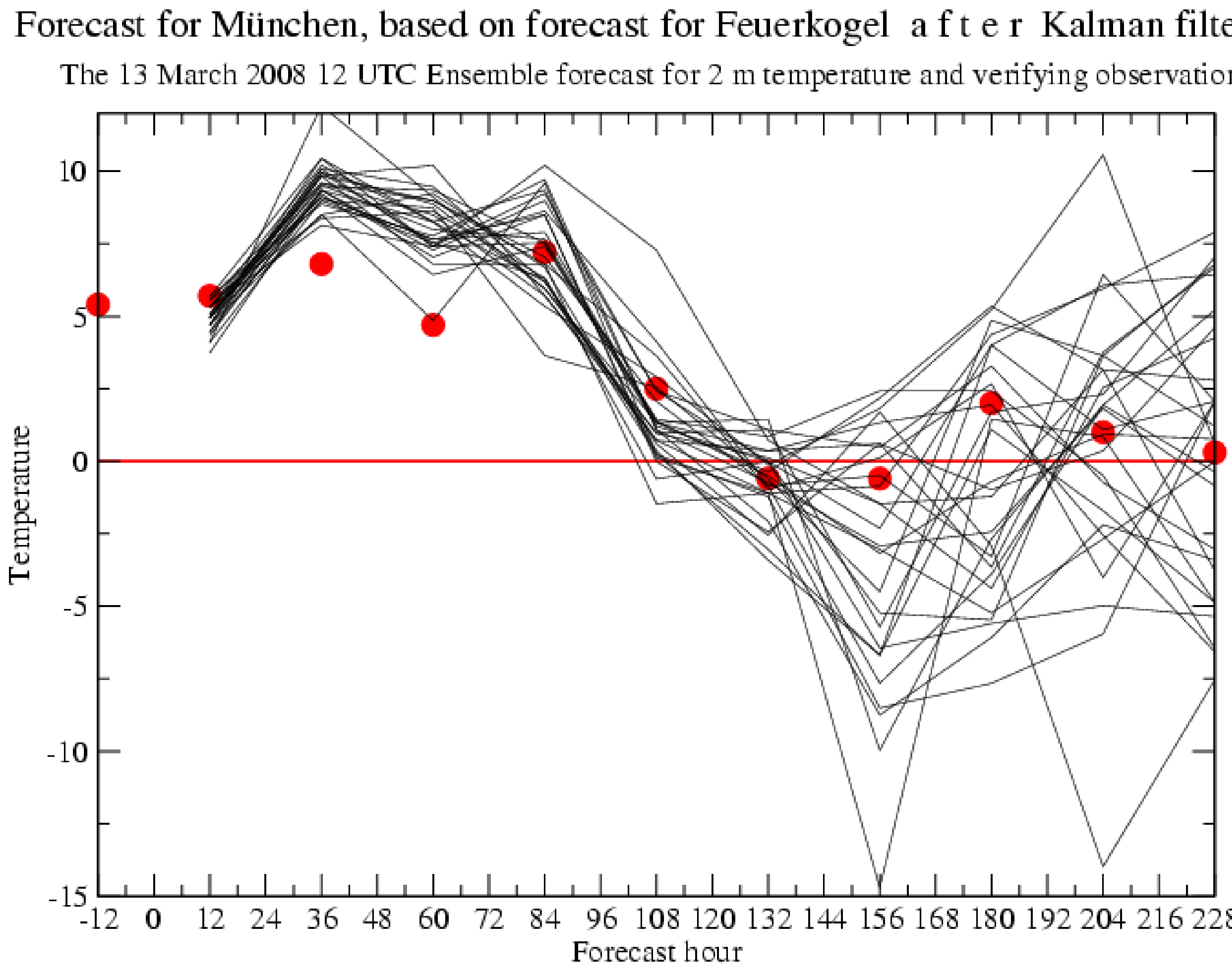
Range before filtering 21 K



Range after filtering 27 K

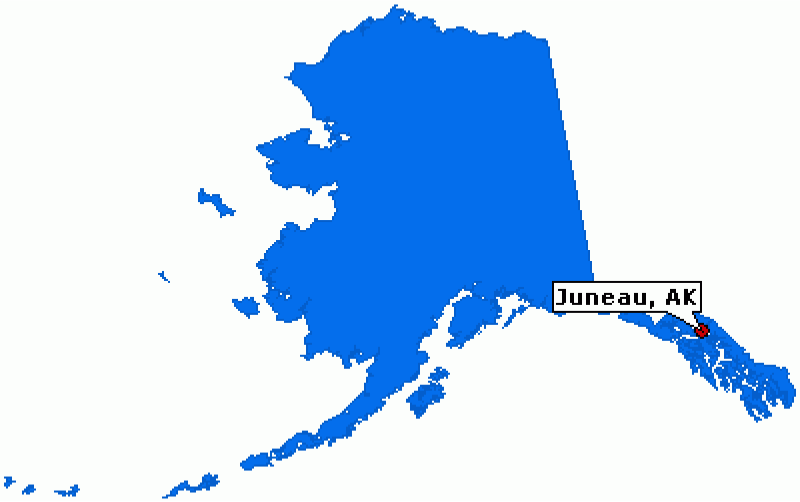


Range before filtering 20 K



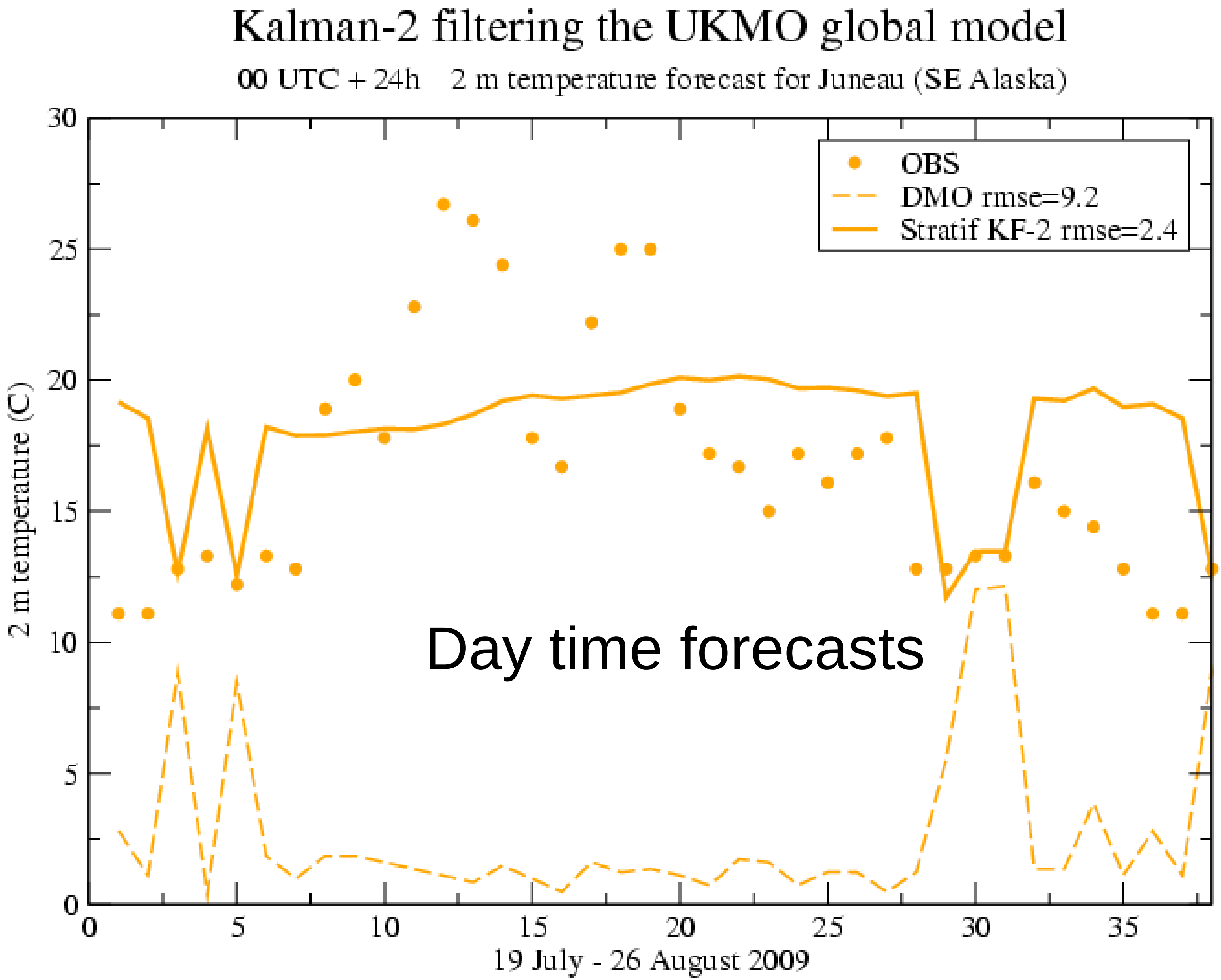
Range after filtering 26 K

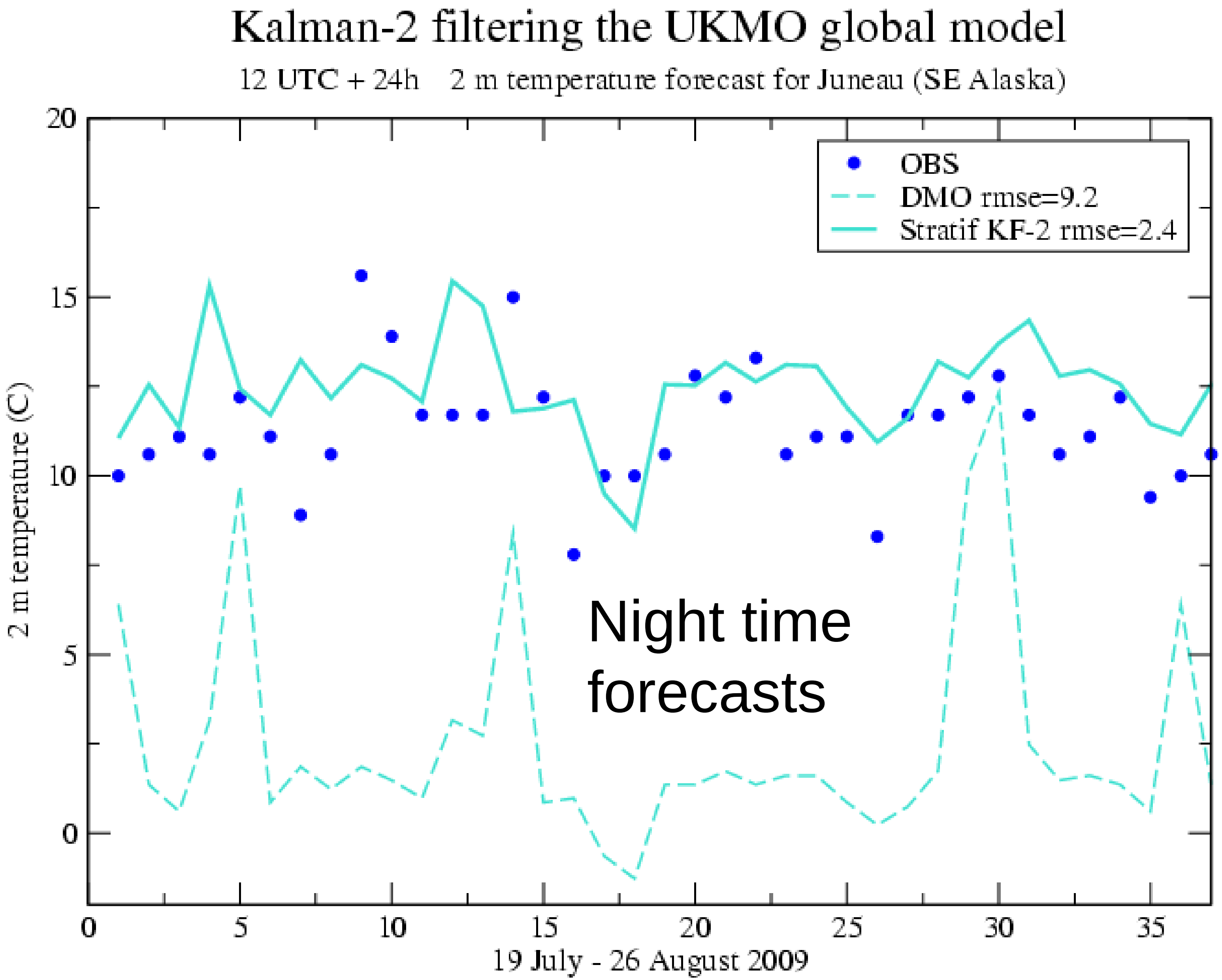
Two Kalman filters operating in parallel
The case of Juneau in Alaska



Wind from NE gave NWP ≈ 2ºC
Wind from SE gave NWP ≈ 10ºC

One filter only worked for NWP 0-5ºC, the other one only for 5-15ºC


Kalman-2 filtering the UKMO global model
00 UTC + 24h 2 m temperature forecast for Juneau (SE Alaska)
OBS
DMO rmse=9.2
Stratif KF-2 rmse=2.4
Day time forecasts
2 m temperature (C)
19 July - 26 August 2009
0
5
10
15
20
25
30
35

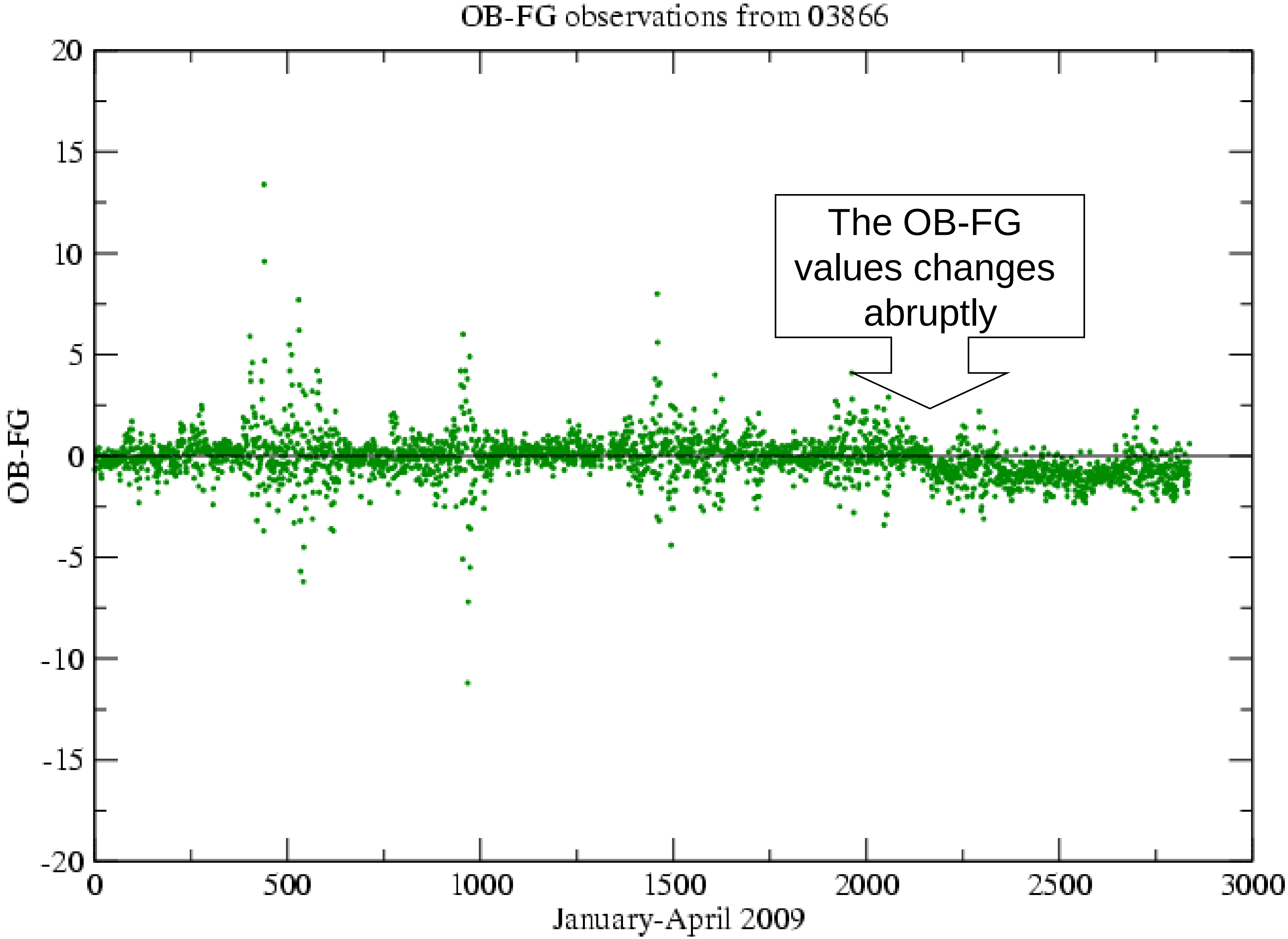

Kalman-2 filtering the UKMO global model
12 UTC + 24h 2 m temperature forecast for Juneau (SE Alaska)
OBS
DMO rmse=9.2
Stratif KF-2 rmse=2.4
2 m temperature (C)
19 July - 26 August 2009
0
5
10
15
20
25
30
35
Night time forecasts

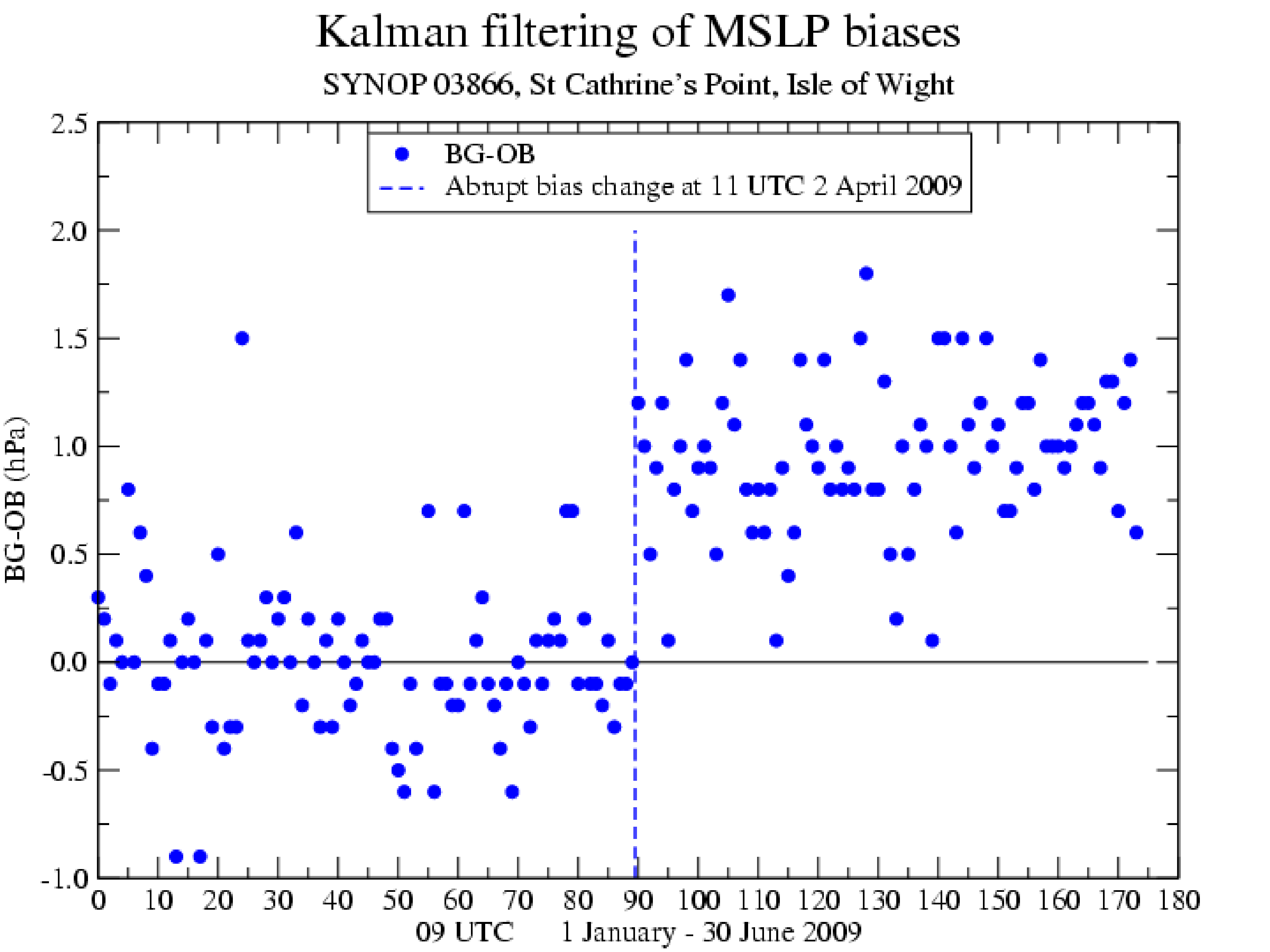
The reason for the bad forecasts for Juneau in Alaska?

The model had kept ice in the region
From the last Ice Age?

Other simple applications of Kalman filtering

Kalman-1 filtering of biased platforms

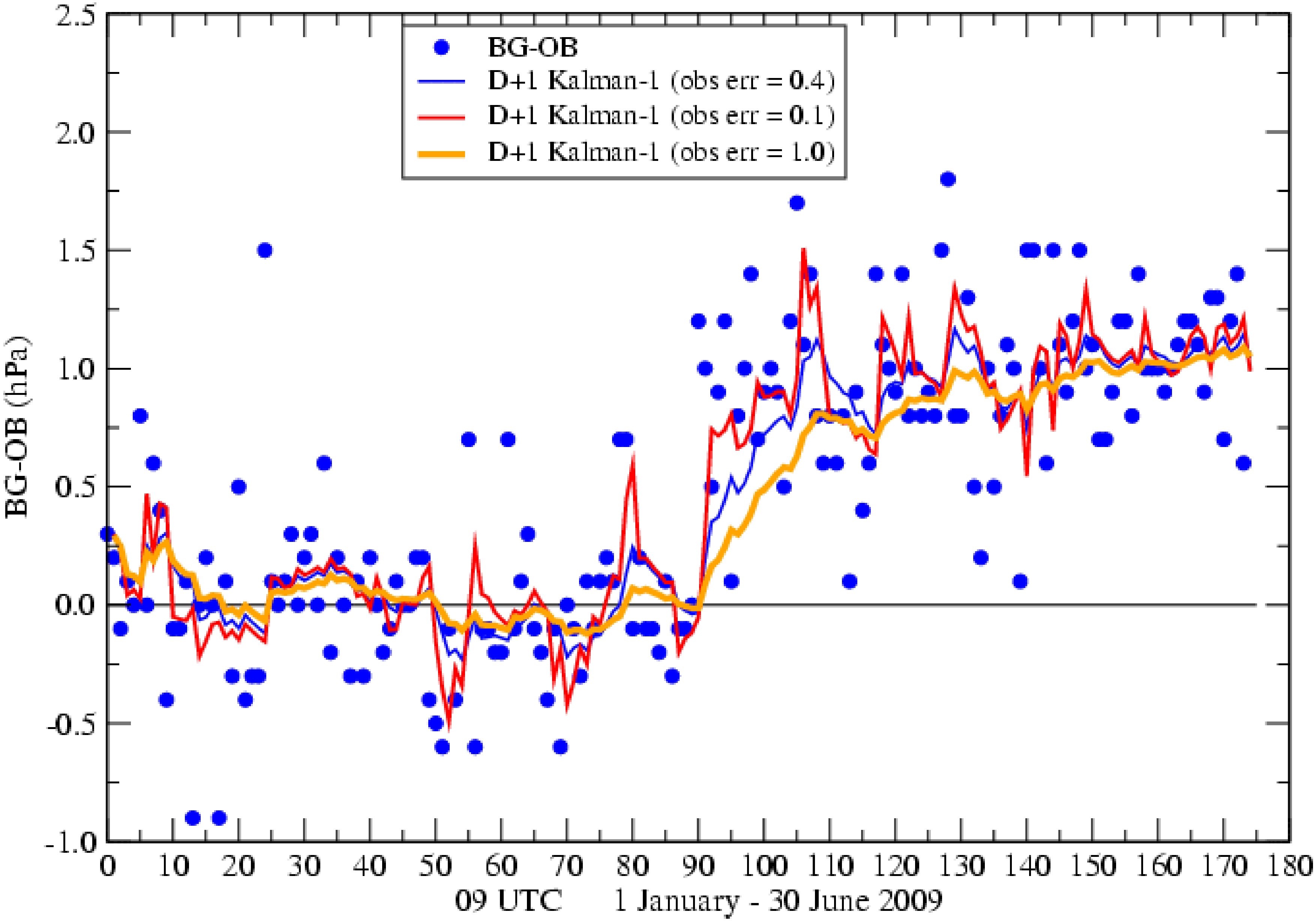




Kalman filtering of MSLP biases
SYNOP 03866, St Cathrine's Point, Isle of Wight
BG-OB
Abrupt bias change at 11 UTC 2 April 2009
BG-OB (hPa)
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
09 UTC 1 January - 30 June 2009

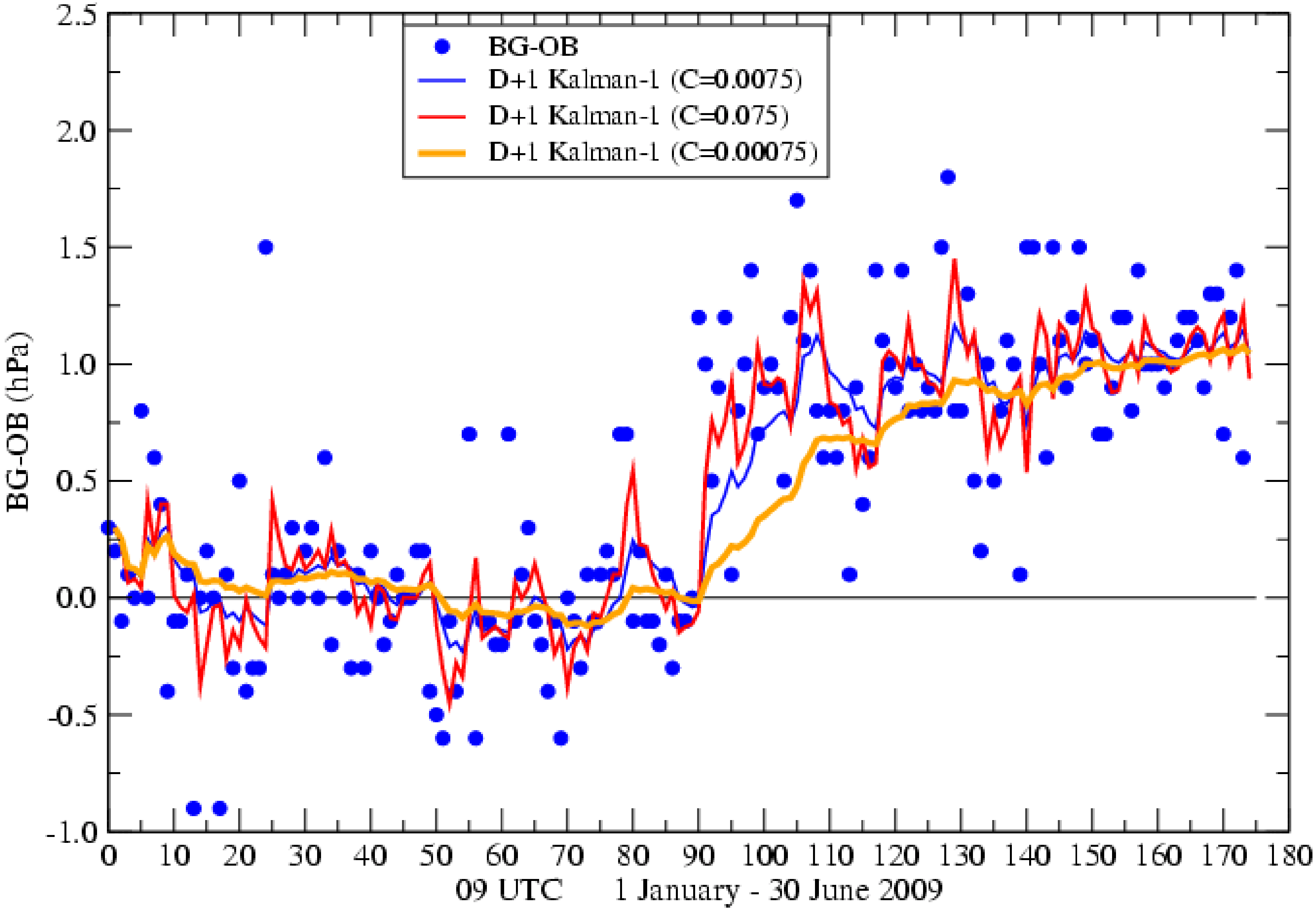
Kalman filtering of MSLP biases

SYNOP 03866, St Cathrine's Point, Isle of Wight (C=0.0075)



Kalman filtering of MSLP biases

SYNOP 03866, St Cathrine's Point, Isle of Wight (obs err=0.4)



Can we extract probabilities, or at least error bars, from the Kalman filtered output?

The "Kalman gain"

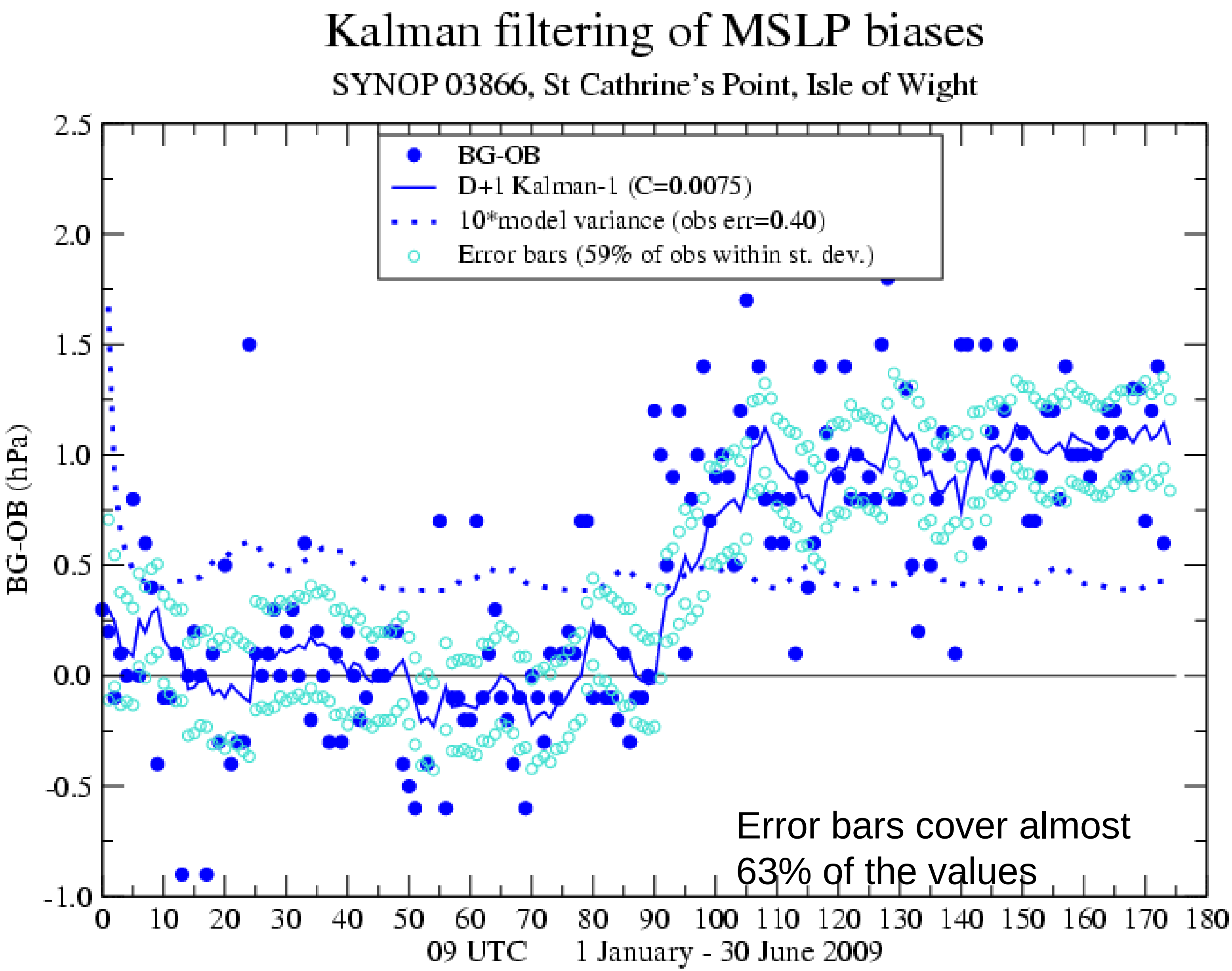
$$\mathbf{k}_t = \frac{\mathbf{P}_{t/t-1}\mathbf{f}_t}{r_t + \mathbf{f}_t^T \mathbf{P}_{t/t-1}\mathbf{f}_t}$$

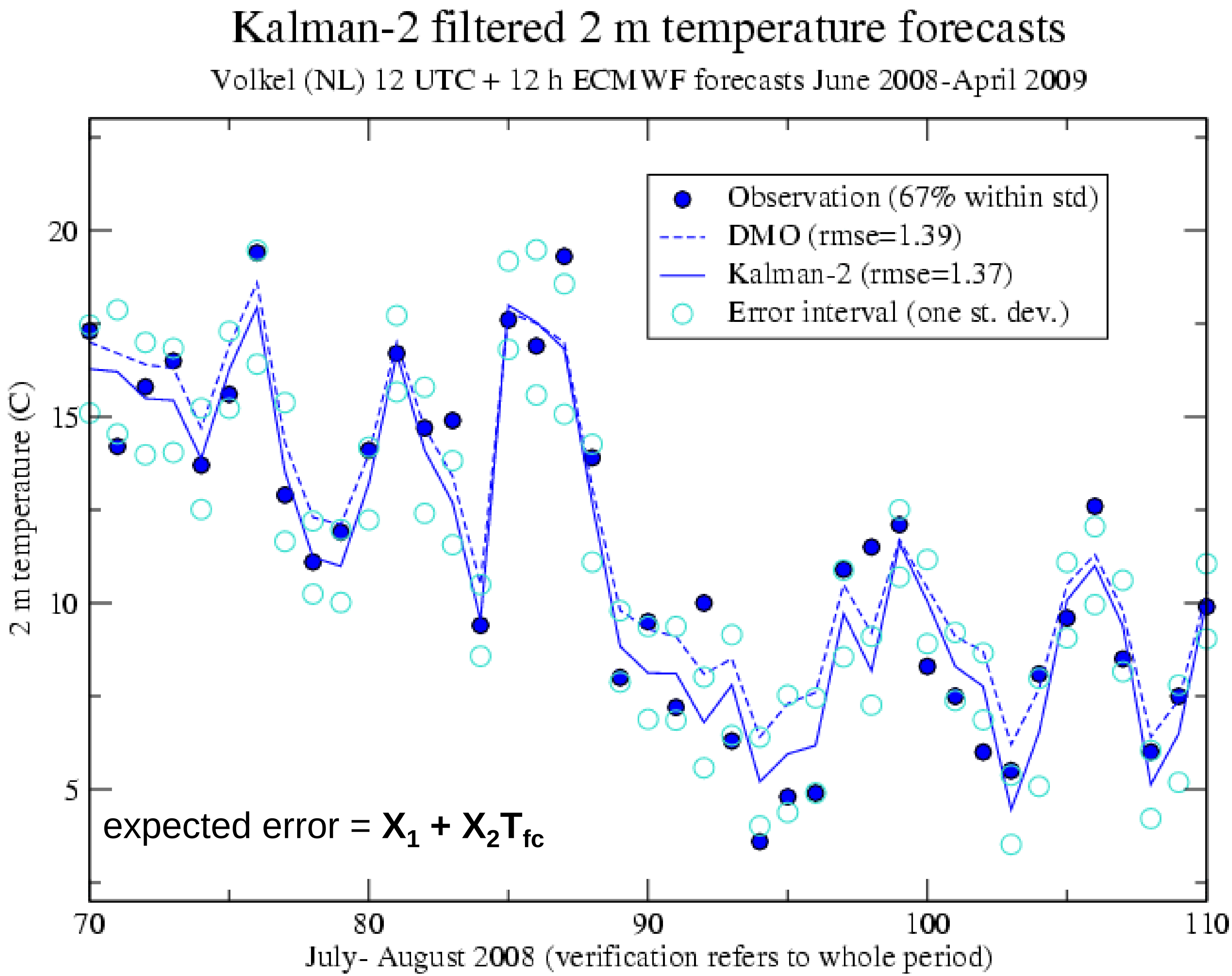
..where the nominator is the sum of the observation and model uncertainties and the updated model uncertainty is:

$$\mathbf{P}_{t/t} = (\mathbf{I} - \mathbf{k}_t)\mathbf{P}_{t/t-1}(\mathbf{I} - \mathbf{k}_t)^T + \mathbf{k}_t r_t \mathbf{k}_t^T$$

…which means that

$$(\text{total error})^2 = \mathbf{f}_t^T \mathbf{P}_{t/t}\mathbf{f}_t$$

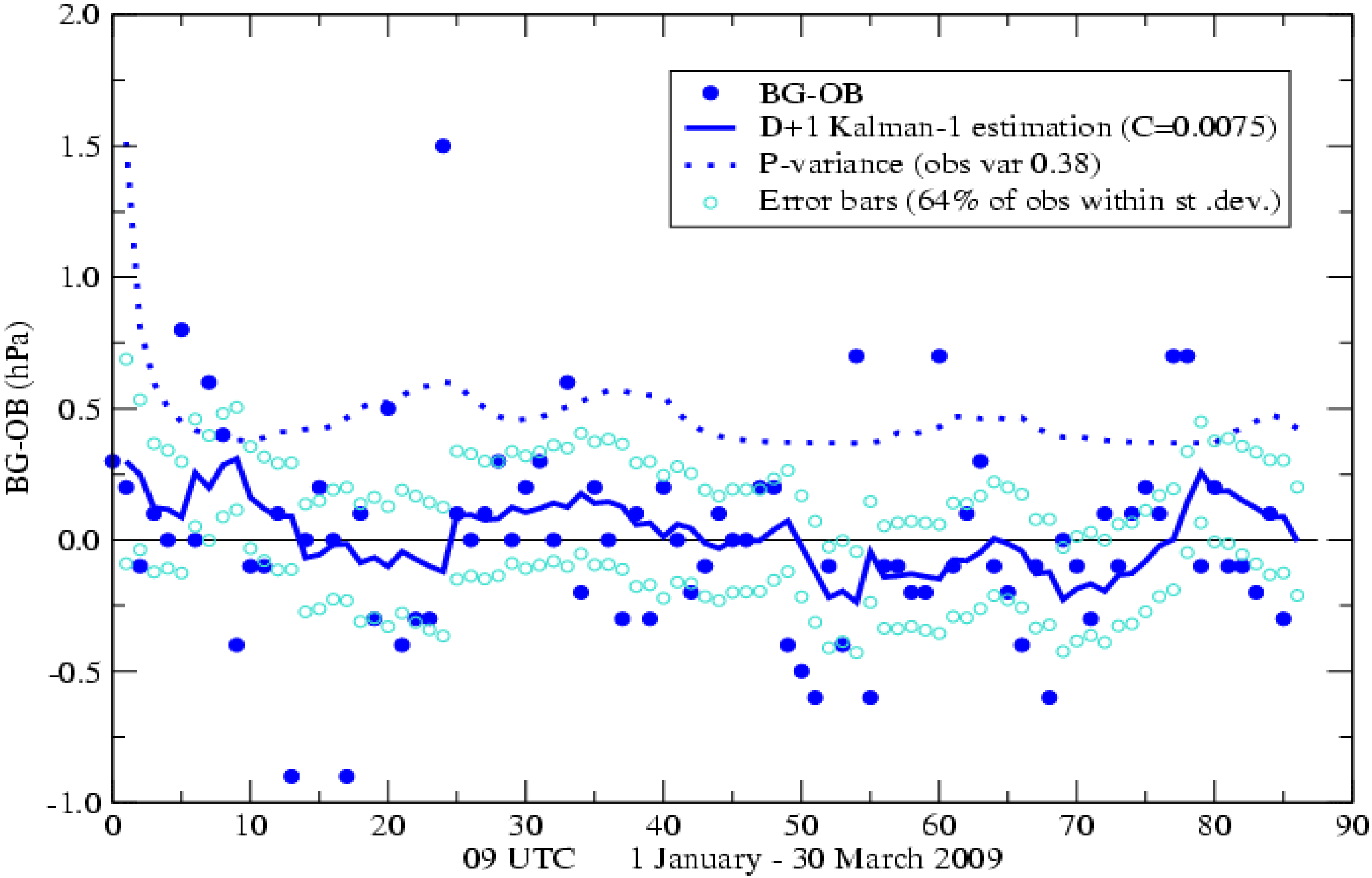

Kalman filtering of MSLP biases
SYNOP 03866, St Cathrine's Point, Isle of Wight
BG-OB
D+1 Kalman-1 (C=0.0075)
10*model variance (obs err=0.40)
Error bars (59% of obs within st. dev.)
BG-OB (hPa)
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
09 UTC
1 January - 30 June 2009
Error bars cover almost
63% of the values



Kalman-2 filtered 2 m temperature forecasts
Volkel (NL) 12 UTC + 12 h ECMWF forecasts June 2008-April 2009
Observation (67% within std)
DMO (rmse=1.39)
Kalman-2 (rmse=1.37)
Error interval (one st. dev.)
2 m temperature (C)
20
15
10
5
70
80
90
100
110
July- August 2008 (verification refers to whole period)
expected error = $X_1 + X_2T_{fc}$

Kalman filtering of MSLP biases

SYNOP 03866, St Cathrine's Point, Isle of Wight



END