CANARI “summer problem”

Description of problem

During summer 2010, verification results showed bad behavior of the production from assimilation system (ASSIM) when compared with the operational setup production (OPER) (details about assimilation and operational setup can be found in Appendix). The problem was with a 2 meter temperature (T2m) and relative humidity (RH2m) BIAS results. With start of the “summer” period in June, positive T2m BIAS for ASSIM was notices in the morning hours and for the same time OPER had almost no T2m BIAS. However, in the afternoon hours ASSIM had a smaller negative T2m BIAS than OPER. BIAS of ASSIM relative humidity at 2m was more or less neutral in June. As the summer progressed, ASSIM grow bigger T2m BIAS than OPER in July and August especially for the afternoon hours, while for RH2m, ASSIM had bigger positive BIAS than OPER in the afternoon hours and smaller negative BIAS in the morning hours (Figure 1).

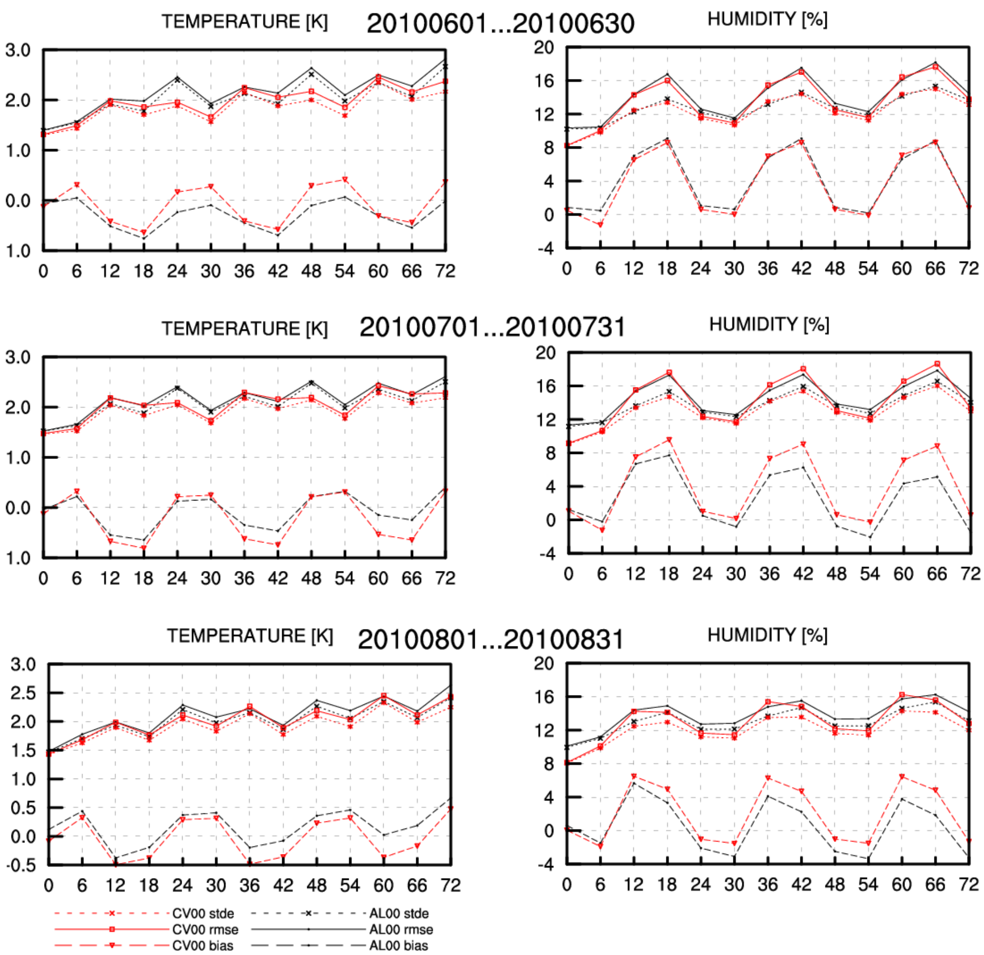

Figure 1: VERAL scores for production from ASSIM (red) and OPER (black) for period June-August. Scores are computed every six hours and averaged over all SYNOP and TEMP stations in the ALADIN domain. Results show BIAS, root mean square error (RMSE) and standard deviation (STD) against forecast hour. BIAS-dashed lines, RMSE-full line, STD-dotted line.

This BIAS problem was investigated for a period of February 2010 until May 2011. Monthly verification was preformed for the selected period and the results showed that compared to OPER for months from February till May (2010) or January till April (2011), T2m and RH2m scores are better for ASSIM (both bias and RMSE), for June till August (2010) or in May (2011) T2m and RH2m (in afternoon hours) scores are worse for ASSIM (in BIAS and sometimes RMSE) while for the other parts of year scores are rather neutral for T2m BIAS and a bit better for BIAS of ASSIM RH2m. It seems that there is seasonal evolution of T2m and RH2m scores, in “spring” and “winter” ASSIM BIAS is smaller, in “summer” ASSIM T2m BIAS is bigger, while for “autumn” results are rather neutral or mixed compared to OPER.

Another thing can be noticed for T2m BIAS scores for June-August (Figure 1) and May 2011 (not shown). It seem that there is slope of BIAS curve in a way that afternoon bias is reduced with forecast range and it can be noticed both in ASSIM and OPER. For morning hours this BIAS slope is a bit smaller. Also in this months daily amplitude of T2m is bigger for OPER.

What are the reasons for such behavior? As the problem arose in “summer” period, one of the possible reasons could be a bad initialization of the soil moisture. During a “summer” period there is strong solar forcing which increases surface sensible and latent heat fluxes and there soil moisture plays important role. To test this the experiment where SURFACE ANALYSIS in assimilation cycle was replaced by simply copying land surface fields form ARPEGE analysis was performed. This was done for June 2010. When production from such cycle is performed and compared with OPER, verification results were very similar (Figure 2). From this simple experiment it can be noticed that most probably bad soil initialization is responsible for bad verification scores in summer period.

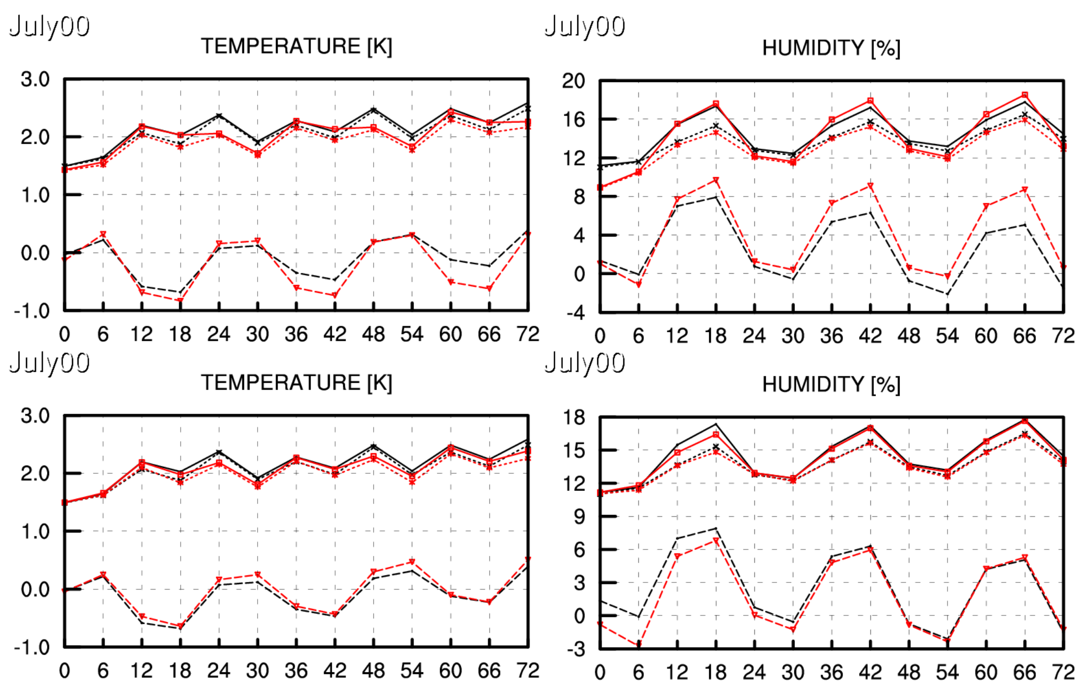

Figure 2: VERAL scores for production from ASSIM (red) and OPER (black) for period June-August 2010. Scores are computed every six hours and averaged over all SYNOP and TEMP stations in the ALADIN domain. Results show BIAS, root mean square error (RMSE) and standard deviation (STD) against forecast hour. BIAS-dashed lines, RMSE-full line, STD-dotted line.

SWI evolution

SWI provides fractional value between wilting point and field capacity and it is defined as:

$$SWI = \frac{W_p - W_{wilt}}{W_{fc} - W_{wilt}}$$

where W_{fc} represents field capacity, W_{wilt} is wilting point and W_p is total layer reservoir. Evolution of SWI in assimilation cycle and in operational configuration is shown on Figure 3. In operational setup, updated water content comes from ARPEGE analysis interpolated to ALADIN HR grid, while in assimilation cycle CANARI analysis is performed in order to update surface fields. As it can be seen SWI for analysis and background is quite similar all the time, while it can be much different when comparing analysis or background with OPER.

During April mean SWI of analysis is much lower than mean SWI of OPER. This is beneficial for verification scores of T2m and RH2m where both RMSE and BIAS have much lower values for ASSIM than for OPER. As time progresses mean SWI of analysis is growing until mid of May where it settles at values around 0.6. At same time SWI of oper is decreasing and at beginning of May mean SWI of oper has values similar to analysis. After mid May SWI for both analysis and oper starts to decrease but this decrees is more pronounced for oper. After that SWI of oper stays below SWI of analysis during whole period shown. This smaller mean SWI is beneficial for OPER verification scores in June and July. At the same figure mean domain SWI increments at 00 and 12 UTC are shown. Increments for 06 and 18 UTC are not shown because in our assimilation setup guess and analysis (after DFI) for those times are not stored. Also at some dates analysis was not available so increments were not plotted. Looking at whole period it can be noticed that there is clear separation between increments at 00 and 12 UTC, where positive increments are at 00 UTC and negative increments are at 12 UTC. This is not so apparent for April but as “summer” time begins this behavior gets more pronounced. In June and July increments at 00UTC tend to get higher values than i April or May. This separation of increments is result of known model bias, cold bias at afternoon hours and warm bias at night time hours.

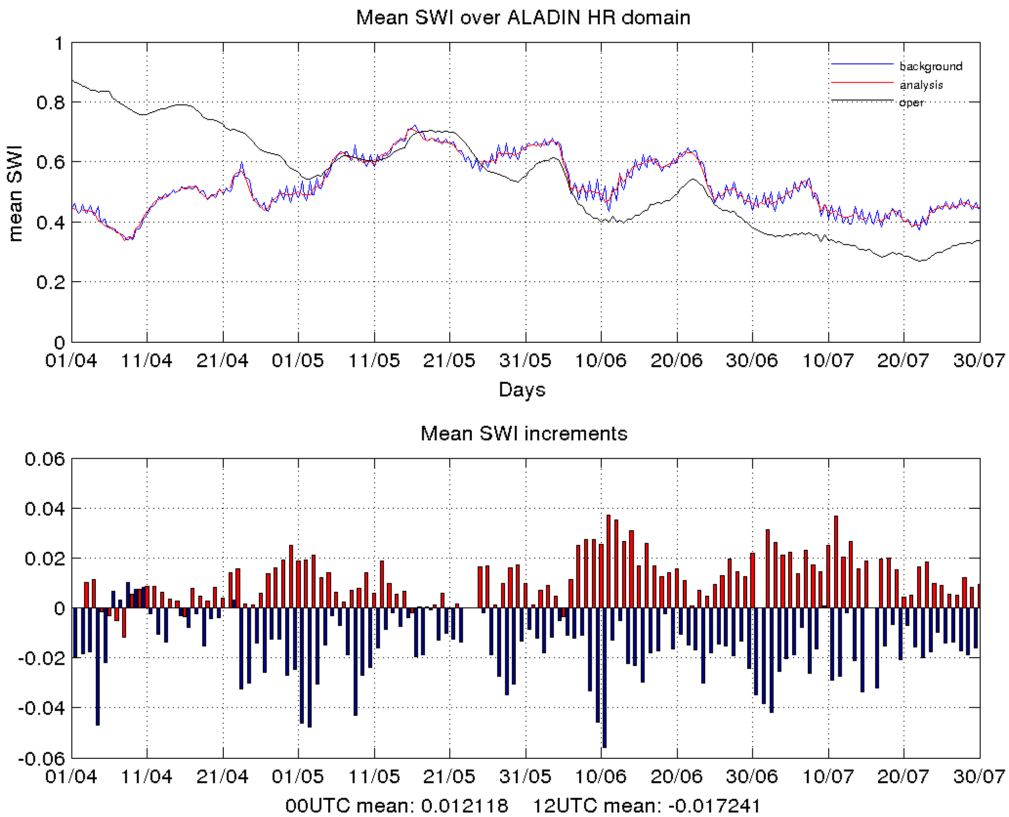

Figure 3: Top row: Evolution of mean domain SWI over land from April 2010 until July 2010 for background (6 hour forecast from assimilation cycle), analysis (after CANARI and 3dVar analysis), oper (ARPEGE analysis interpolated to ALADIN HZ grid). Values are shown every 6 hours for background (blue) and every 12 hours for oper (black) and analysis (red). Bottom row: Mean SWI incremenst at 00UTC (red) an at 12UTC(black).

In 2011. similar pattern can be noticed (Figure 4). Again oper has much higher values (almost at field capacity) of SWI at March, and as “summer” time starts values of mean SWI for oper are decreeing while for analysis are increasing. Result is that at the end of May oper has smaller values of mean SWI than analysis.

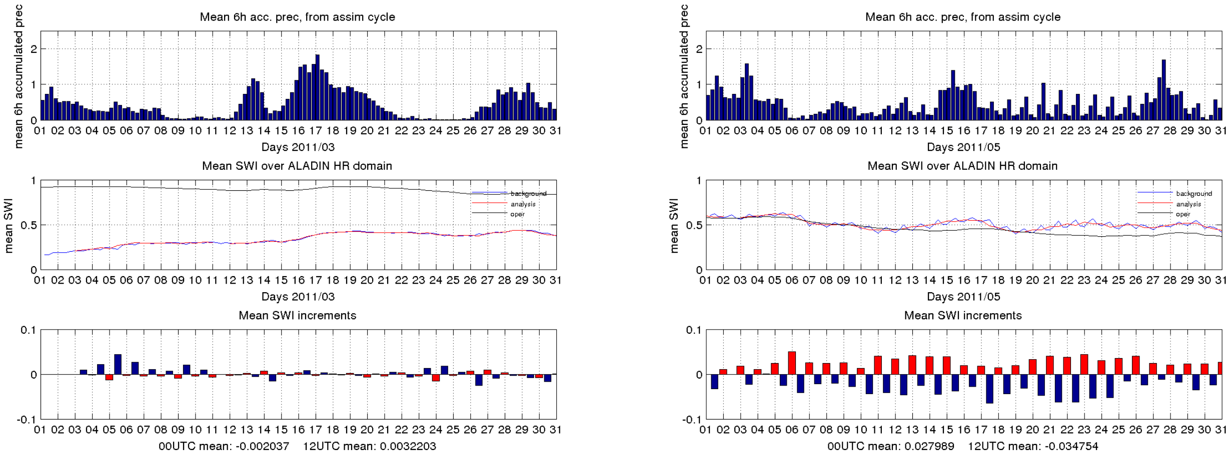

Figure 4: First row: Mean domain 6h accumulated precipitation over land taken from 6h forecast inside assimilation cycle. Second row: Mean domain SWI over land. Third row: Mean domain SWI increments over land. Left are plots for March 2011 and right plots for May 2011.

CANARI tuning of error statistics

Tuning of error statistics was performed using observation minus guess (O-G) departures of 6h forecast in assimilation cycle. Departures were calculated for ~1 year of data (01.12.2010.-06.12.2011.).
In CANARI OI for analysis of 2m temperature and relative humidity background correlations are modeled on following way:

$$cov(x_i^G, x_j^G) = \sigma_{x_i}^G \cdot \sigma_{x_i}^G * cor(x_i^G, x_j^G) = \sigma_{x_i}^G \cdot \sigma_{x_i}^G * corj(x_i^G, x_j^G) \cdot corv(x_i^G, x_j^G) = \sigma_{x_i}^G \cdot \sigma_{x_i}^G \cdot f(r) \cdot g(z) \quad (1)$$

where $f(r) = e^{\frac{-1}{2}\cdot(\frac{r}{d})}$ (2) and $g(z) = 1$ (3). Purpose of this study is to evaluate (2).

Using O-G following calculation can be done using several assumptions:

- guess and observation are unbiased $\overline{x_i^G - x_i^T} = \overline{x_i^O - x_i^T} = 0$
- observation errors are non correlated $\overline{(x_i^O - x_i^T)(x_j^O - x_j^T)}$
- observation errors and model errors are non correlated $\overline{(x_i^G - x_i^T)\cdot(x_j^O - x_j^T)} = 0$

$$\overline{(x_i^G - x_i^O)\cdot(x_j^G - x_j^O)} = \overline{(x_i^G - x_i^T + x_i^T - x_i^O)\cdot(x_j^G - x_j^T + x_j^T - x_j^O)} =$$
$$= \overline{(x_i^G - x_i^T)\cdot(x_j^G - x_j^T) + (x_i^G - x_i^T)\cdot(x_j^T - x_j^O) + (x_i^T - x_i^O)\cdot(x_j^G - x_j^T) + (x_i^T - x_i^O)\cdot(x_j^T - x_j^O)} =$$
$$= cov(x_i^G, x_j^G) = \sigma_i^G \cdot \sigma_j^G \cdot \rho_{ij}^G$$

If we suppose that $\sigma_i^G = \sigma_j^G = \sigma^G$ than we can write:

$$\overline{(x_i^G - x_i^O)\cdot(x_j^G - x_j^O)} = (\sigma^G)^2 \cdot \rho_{ij}^G \quad (4).$$

According to this observation minus guess (O-G) are computed for all SYNOP stations in ALADIN-HR domain, and they can be used to calculate $\sigma^G \cdot \rho_{ij}^G$. Comparing (1) and (2) one can see that in order to evaluate how *f(r)* should look like, result from (4) should be divided by $(\sigma^G)^2$. In theoretical assumption and with *f(r)* given as (2) one can expect that background covariances would decrease with mutual station distance and therefore $(\sigma^G)^2$ for dividing in empirical calculation could be approximated with covariance of first class (e.g. smallest mutual distance between stations) or a bit higher. But in empirical calculation results show that covariance of stations having greater mutual distance can be higher than covariance of stations having mutual smaller distance. Fortunately, this was case only for few datasets. Nevertheless, in order to scale covariances approach where $(\sigma^G)^2$ was maximum covariance for given dataset was chosen.

a) First approach

On Figure 1 and Figure 2 background covariances calculated from O-G statistics are shown. Statistic were calculated for every season (winter, spring, summer and autumn) and for every analysis time (00, 06, 12, 18 UTC). Some theoretical functions with slightly changed parameters in (2) are shown.

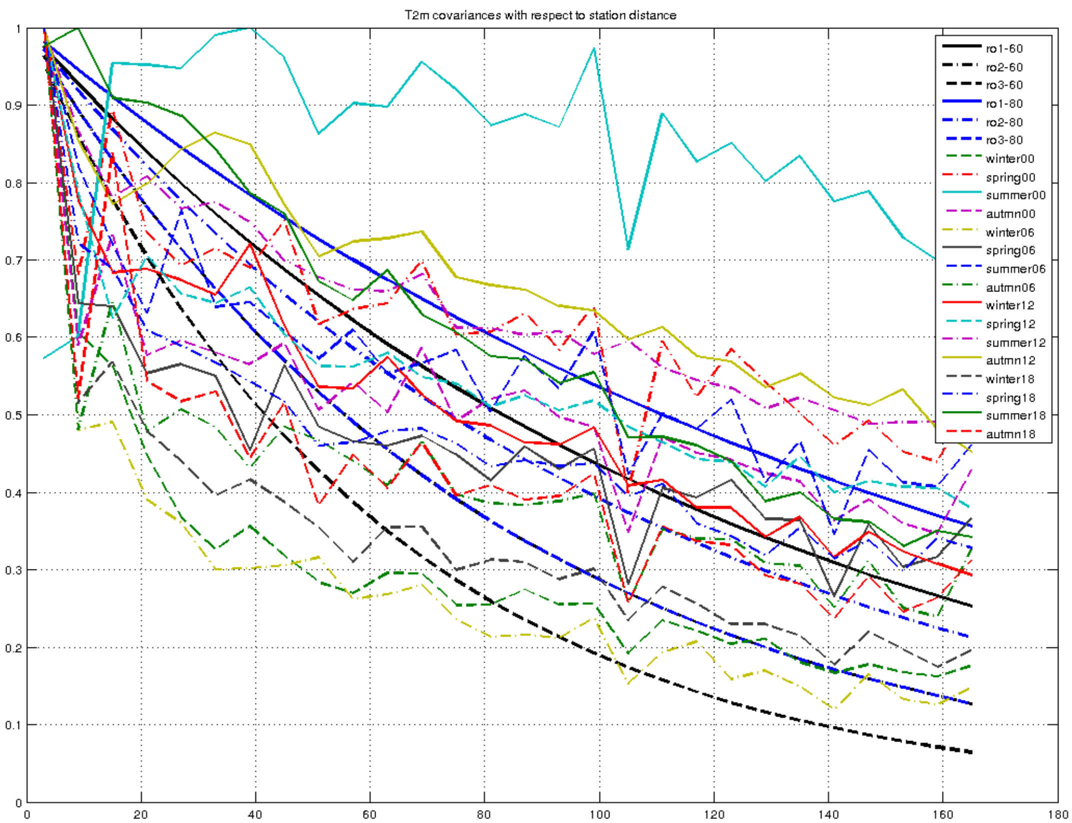

Figure 5: T2m covariances with respect to station distance and for different seasons and analysis time. With ro different theoretical functions are denoted.*

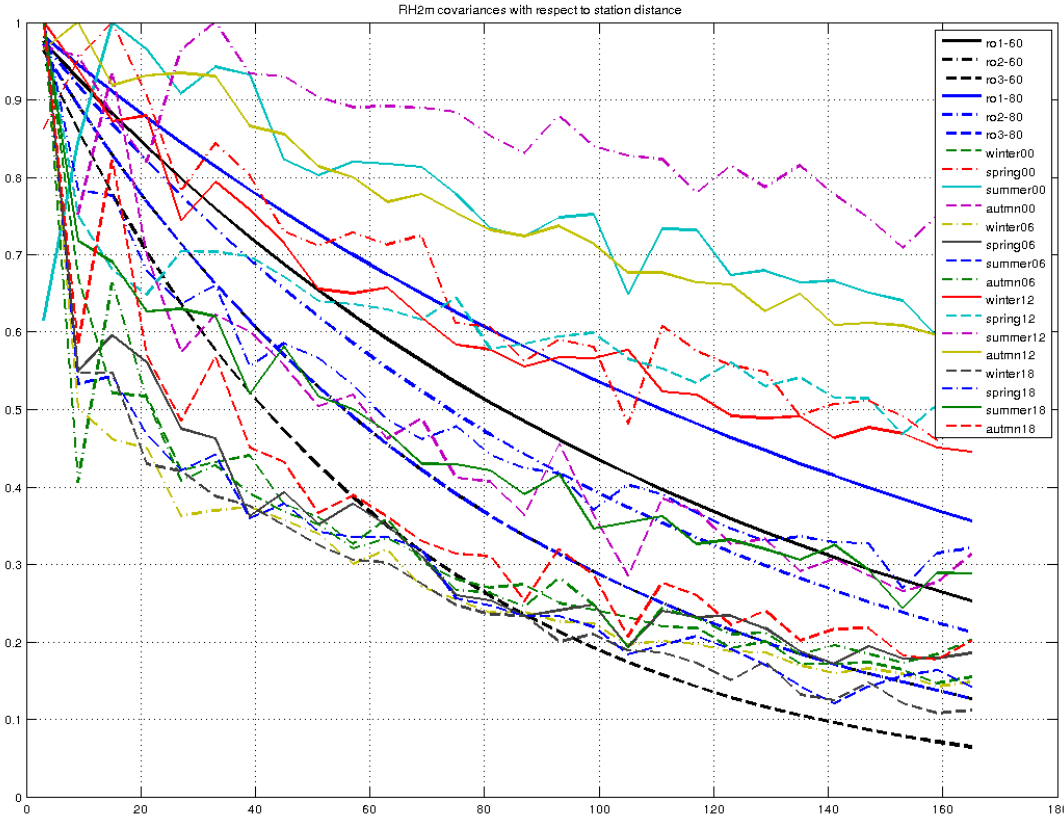

Figure 6: RH2m covariances with respect to station distance and for different seasons and analysis time. With ro different theoretical functions are denoted.*

RH2m				**T2m**		
ro3-60	ro2-80	ro1-80	ro1-150	ro3-80	ro1-60	ro1-80
winter00	spring18	spring00	summer00	winter00	autmn00	autmn12
winter06	summer18	spring12	summer12	winter06	autmn06	summer12
winter18	autmn00	winter12	autmn12	winter18	autmn18	summer18
spring06					winter12	spring00
autmn06					spring18	spring12
summer06					spring06	summer06
autmn18					summer06	

Table 1: Results from different datasets are subjectively grouped in accordance to best fit on some theoretical correlation function.

Functions used:

$$ro1 = e^{(-0.5 * r/d)}$$
$$ro2 = e^{(-0.75 * r/d)}$$
$$ro3 = e^{(-r/d)}$$

Horizontal lengthscale (d) varied between 60km, 80km and 150 km.

In Table 1 results from different datasets are subjectively grouped in accordance to best fit on some theoretical correlation function. According to this table some compromising solution would look like:

- 00: ro1 with d=80km
- 06: ro3 with d=60km
- 12: ro1 with d=80km or bigger d
- 18: ro1 with d=80km

If one would look by seasons:

- spring: 00 – ro1-80
06 – ro3-60 or ro1-60
12 – ro1-60 or ro1-80
18 – ro2-80 or ro1-60 (similar)
- summer: 00 – ro1-80 or bigger d
06 – ro1-60 or ro3-60
12 – ro1-80 or bigger d
18 – ro1-80 or ro2-80
- autumn: 00 – ro1-60
06 – ro1-60 or ro3-60
12 – ro1-80 or bigger d
18 – ro1-60 or ro3-80
- winter: 00 – ro3-60
06 – ro3-60
12 – ro1-60 or ro1-80
18 – ro3-60

Finally all above results are summarized in following table:

ro1-80	Winter				Spring				Summer				Autumn			
r01-60	00	06	12	18	00	06	12	18	00	06	12	18	00	06	12	18
r03-60																

Table 2: Summary.

b) Second approach

In second approach, covariances are not normalized with variance of guess (Figure 7 and Figure 8). Fit with theoretical function was done by changing background variance and horizontal length-scale (d).

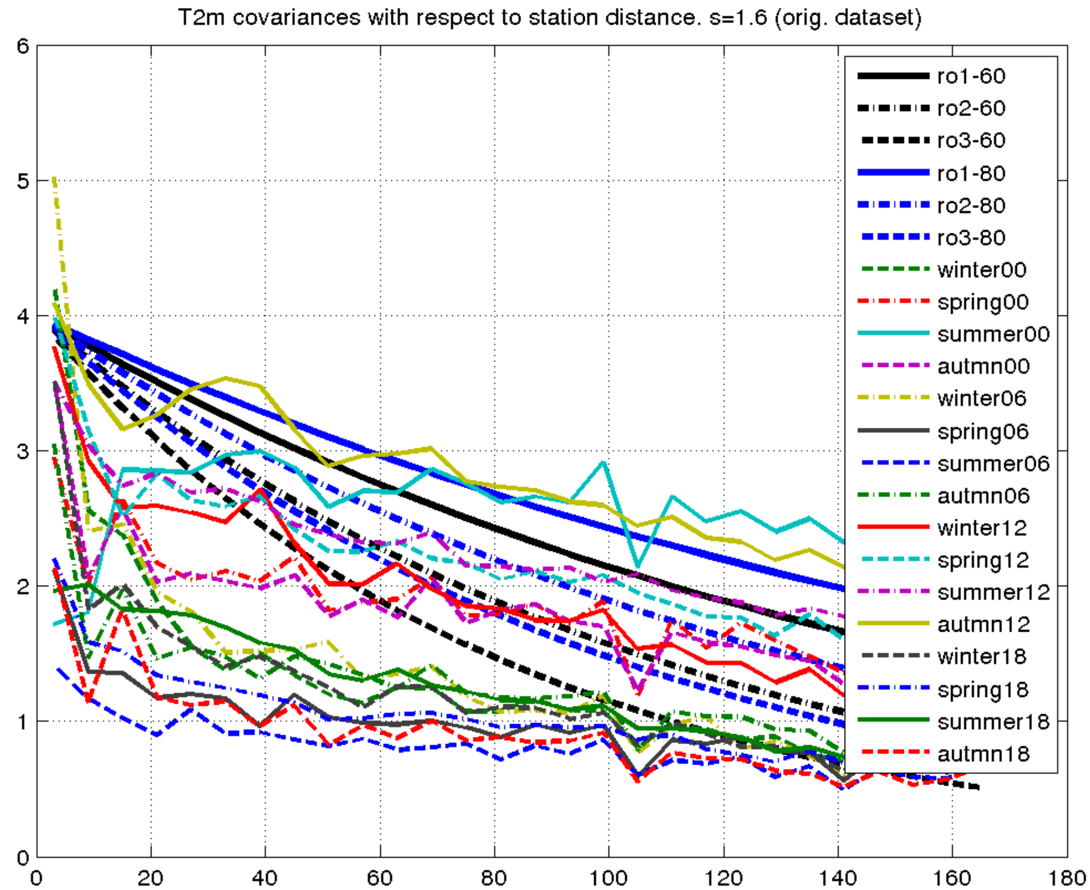

Figure 7: T2m covariances with respect to station distance and for different seasons and analysis time. With ro different theoretical functions are denoted.*

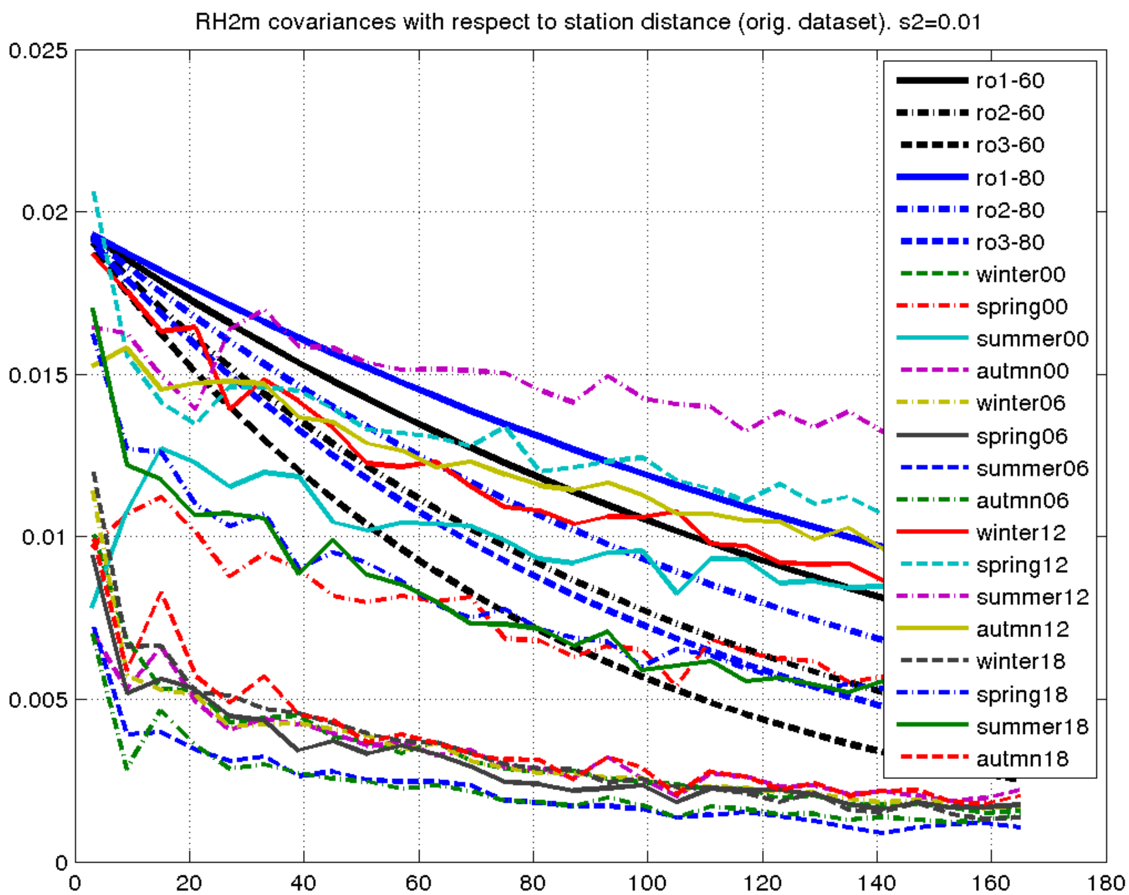

Figure 8: RH2m covariances with respect to station distance and for different seasons and analysis time.

Time	**00**		**12**		**06 and 18**	
Variable	T2m	RH2m	T2m	RH2m	T2m	RH2m
D [km]	90	90	120	120	60	60
Standard deviation	1.7	0.1	1.8	0.135	1.6	0.09

Table 3: Summary for second approach.

c) Third approach

Before calculating covariances mean difference (in given period) between model forecast and observation for every station separately was removed.
This is still not done.

Tests

1) In first test few parameters in CANARI namelist will be changed:
   1. horizontal length scale (REF_A_H2, REF_A_T2) according to Table 3
   2. standard deviation (REF_S_H2, REF_S_T2) according to Table 3
   3. maximum distance for horizontal selection (QDSTRA) was changed from original settings of 1000km to 150km
   4. maximum number of observations per quadrant (NMXGQA) was reduced from 50 to 7
   5. smoothing radius (RA_SM_WP) was changed from 5km to 8km

Reasons for changing 3. is that on this way we avoid influence of costal stations on model grid-points inland. Similar reason is for changing parameter 4.. Smoothing radius was changed to be the same as horizontal model grid spacing.

Testing period will be May 2011, where first 20 day will be used as worm up period for cycling and last 10 days will be used for production and verification.

Appendix - Description of assimilation setup and operational setup

Description of tags used in text:

- background - 6 hour forecast from assimilation cycle
- analysis - initial file for production from assimilation cycle, thus after CANARI, 3DVar and DFI
- oper - initial file for production from assimilation cycle obtained by interpolating ARPEGE to ALADIN grid and after DFI
- ASSIM - production from assimilation cycle
- OPER - production from operational setup

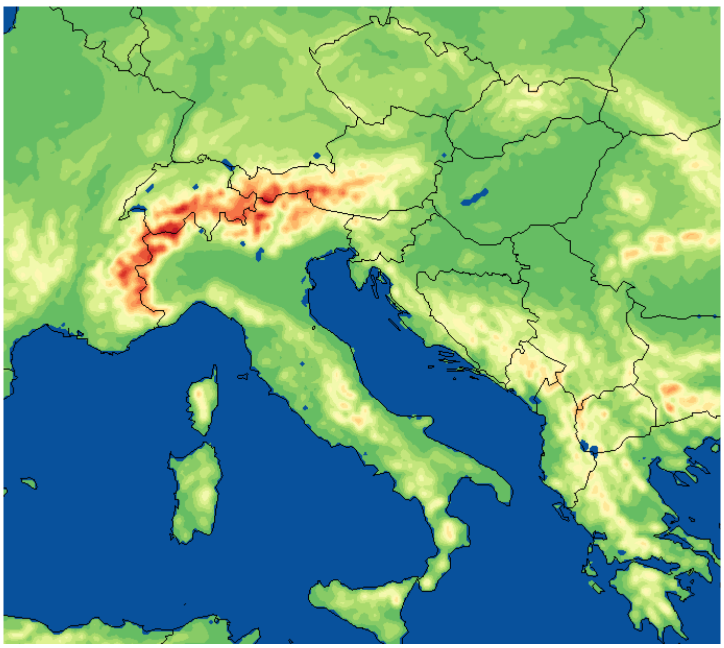

Figure 9: ALADIN HR domain.

Operational ALADIN HR domain is shown at Figure 7. Some details on ALADIN HR:

- horizontal resolution 8x8 km
- 37 vertical levels
- LBC: global model ARPEGE, coupling frequency 3 hours
- 229x205 (240x216) grid points
- AL32T3: ALARO0-3MT, old radiation scheme, DFI
- 72 hours forecast, 1-3 hourly output

Assimilation setup is shown at Figure [fig:Scheme-of-assimilation]. The assimilation cycle consists of several steps. In the first step (BLENDSUR), a 6 h forecast from a previous assimilation cycle is taken, and the sea surface temperature SST is replaced with the SST coming from the long cut off analysis of the ARPÉGE model (the ARPÉGE model is run later, whereas in the assimilation, all available data are used). This is done because SST is not locally assimilated. In the second step, surface analysis is performed, during which temperature and relative humidity at 2 m are used for updating land surface variables. In next step, the upper airfields are analyzed, and the output is used for initiating the 6 hour forecast at the end of the assimilation cycle. The assimilation cycle is run with a time delay sufficient to enable the use of the ARPÉGE long cut off coupling files as the boundary conditions for the short range (6 h) forecast. Because the timing of assimilation cycle and production is quasi-operational, long cut off ARPÉGE files and long cut off data is not available for production from the assimilation cycle; thus, short cut off ARPÉGE files and data are used. Steps in production are the same as in the cycle; the only difference is that, at the end, the 72 h forecast is done. A digital filter initialization (DFI) is used for both the cycle and production before the integration of the model.