Precipitation verification in Italy: Long term trends

Elena Oberto
Naima Vela
Maria Stefania Tesini
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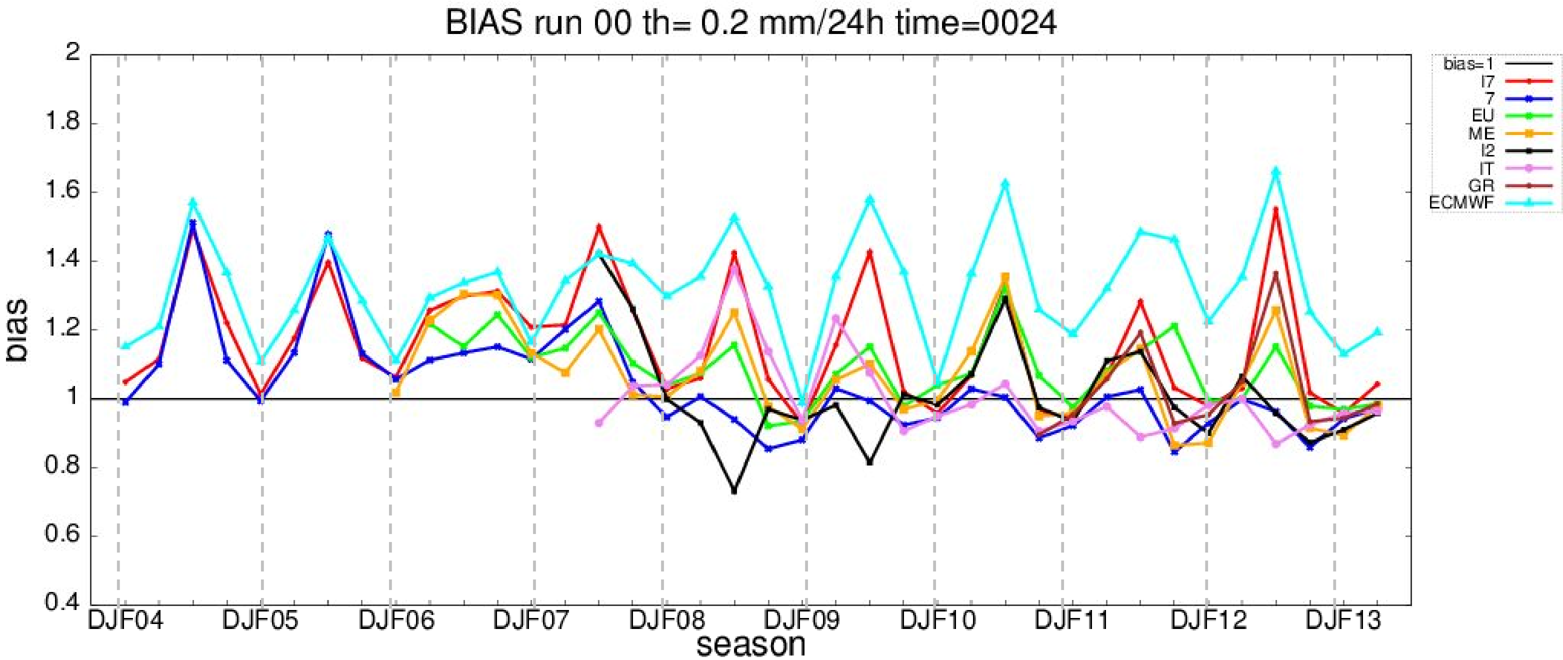
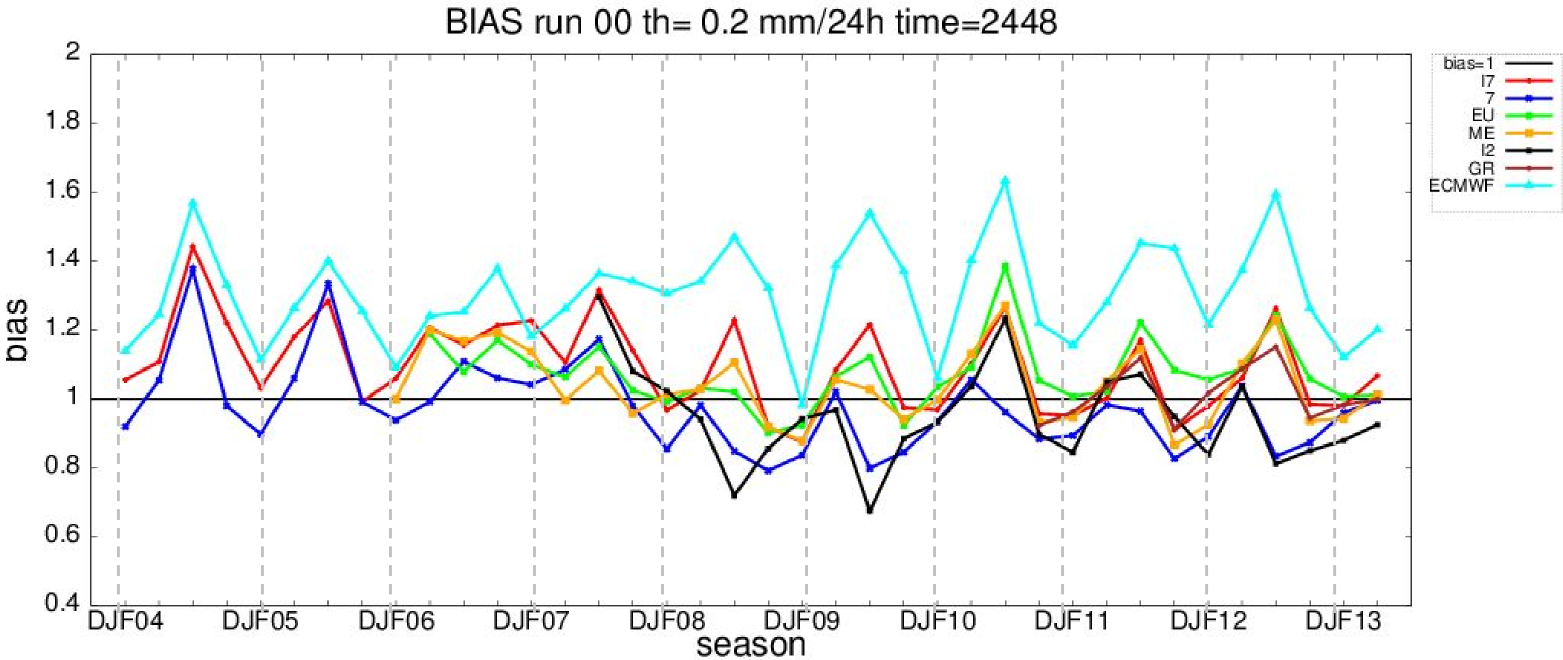
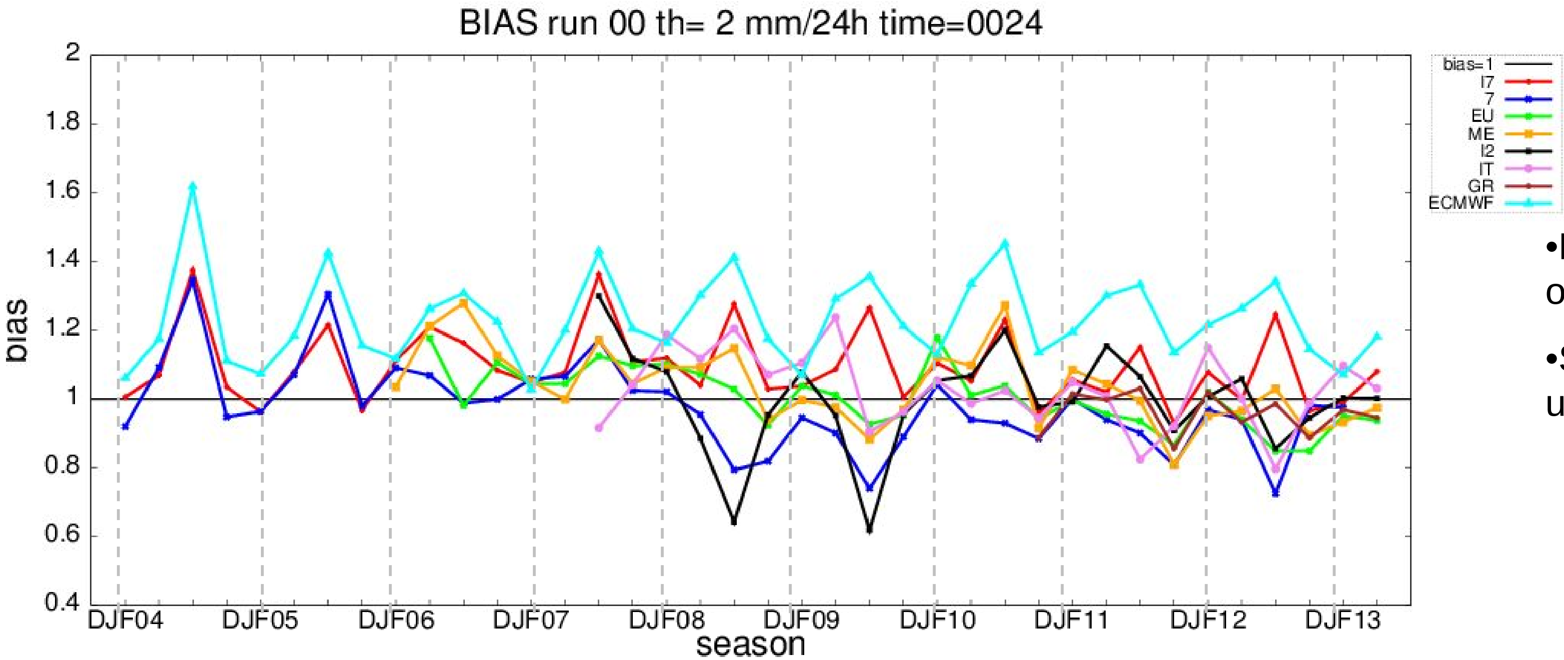
Cosmo General Meeting 2013 – Sibiu (Romania)

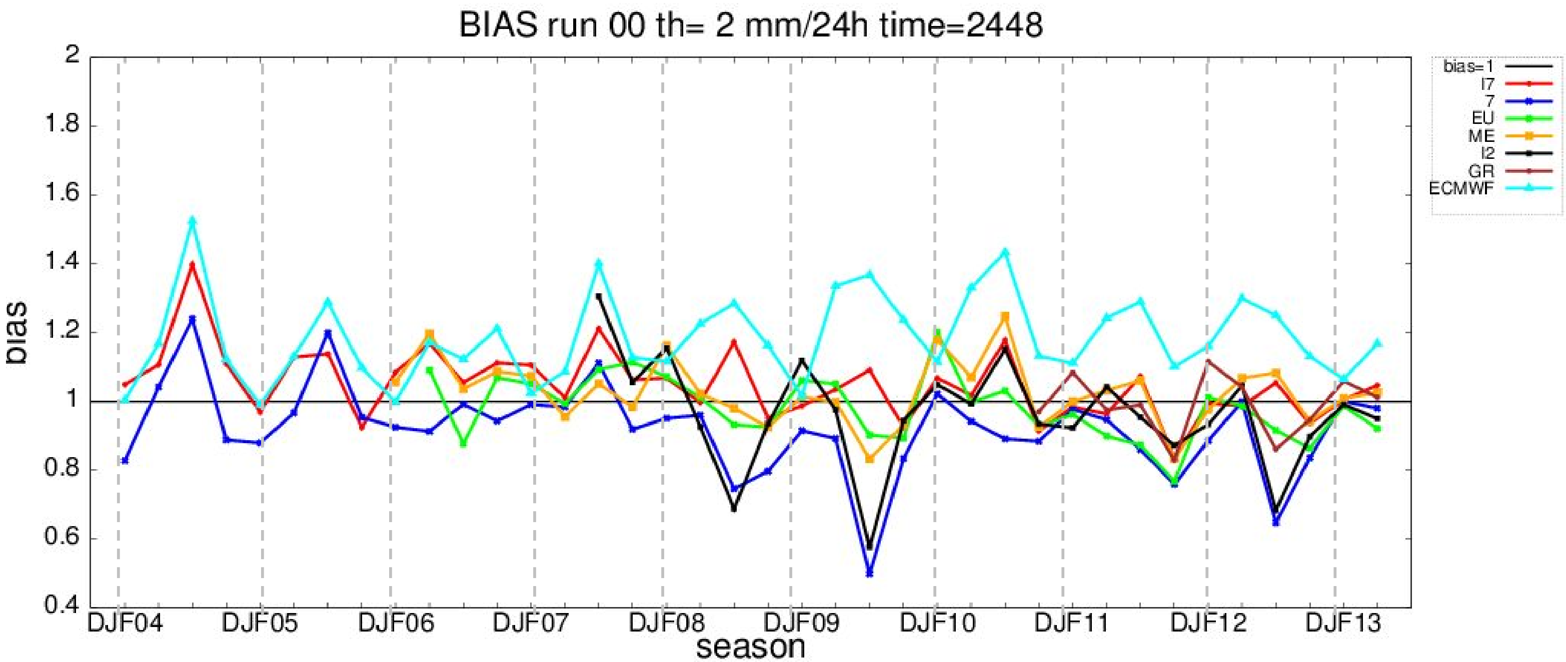


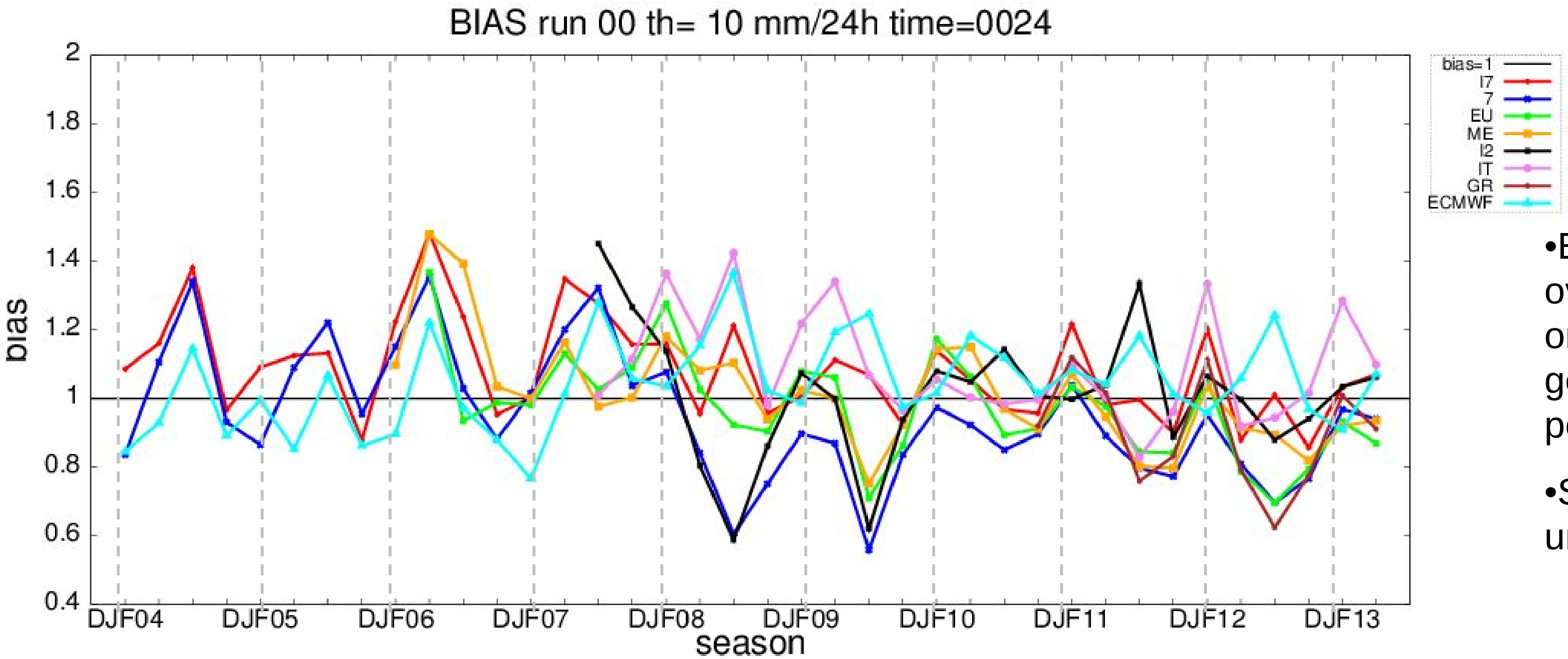
- Ecmwf overestimation
- Summer overestimation



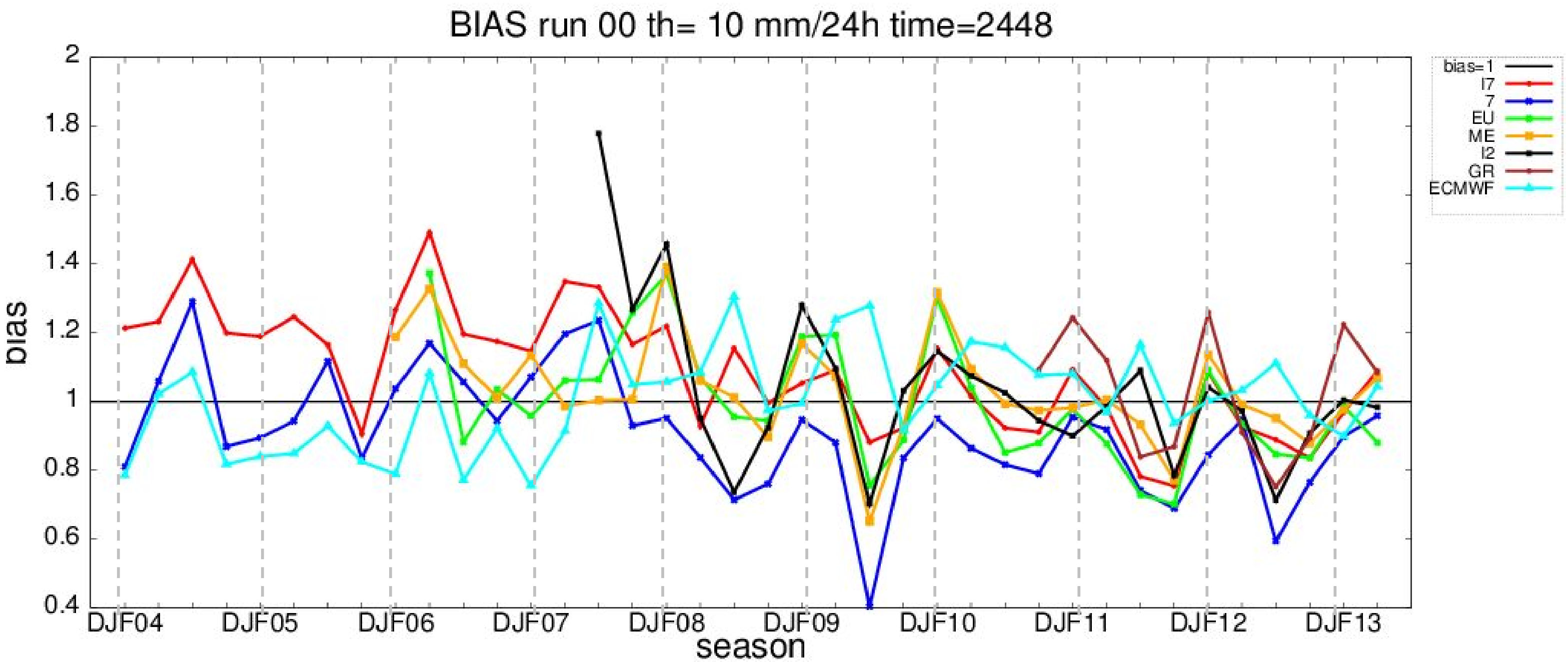


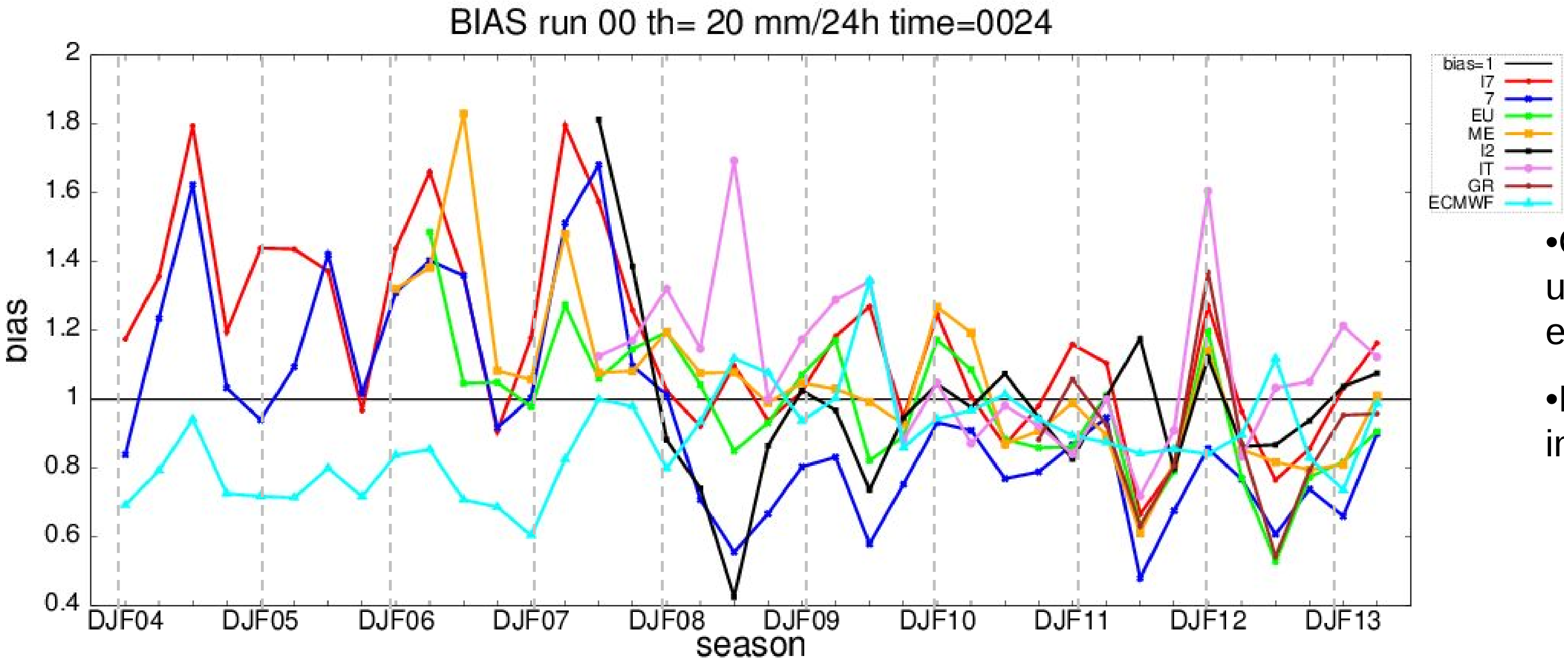
- Ecmwf overestimation
- Summer underestimation



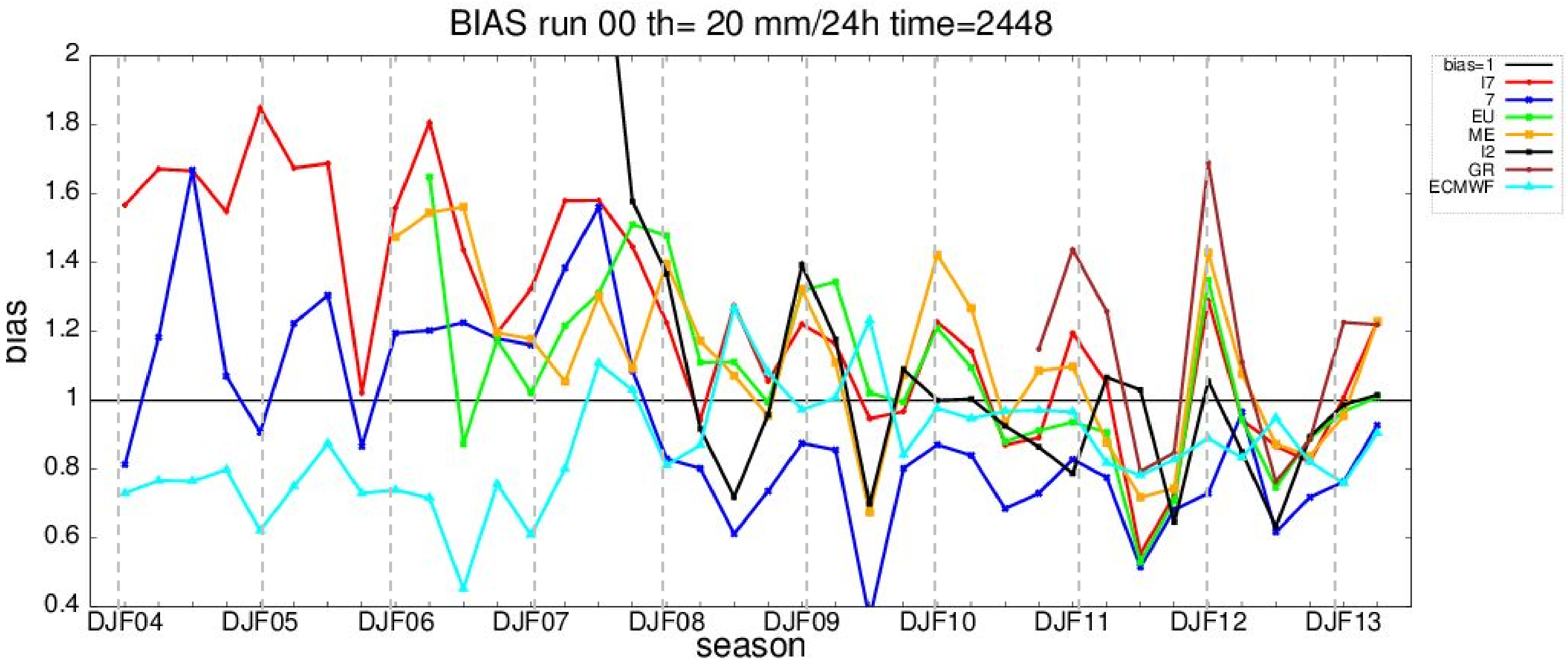


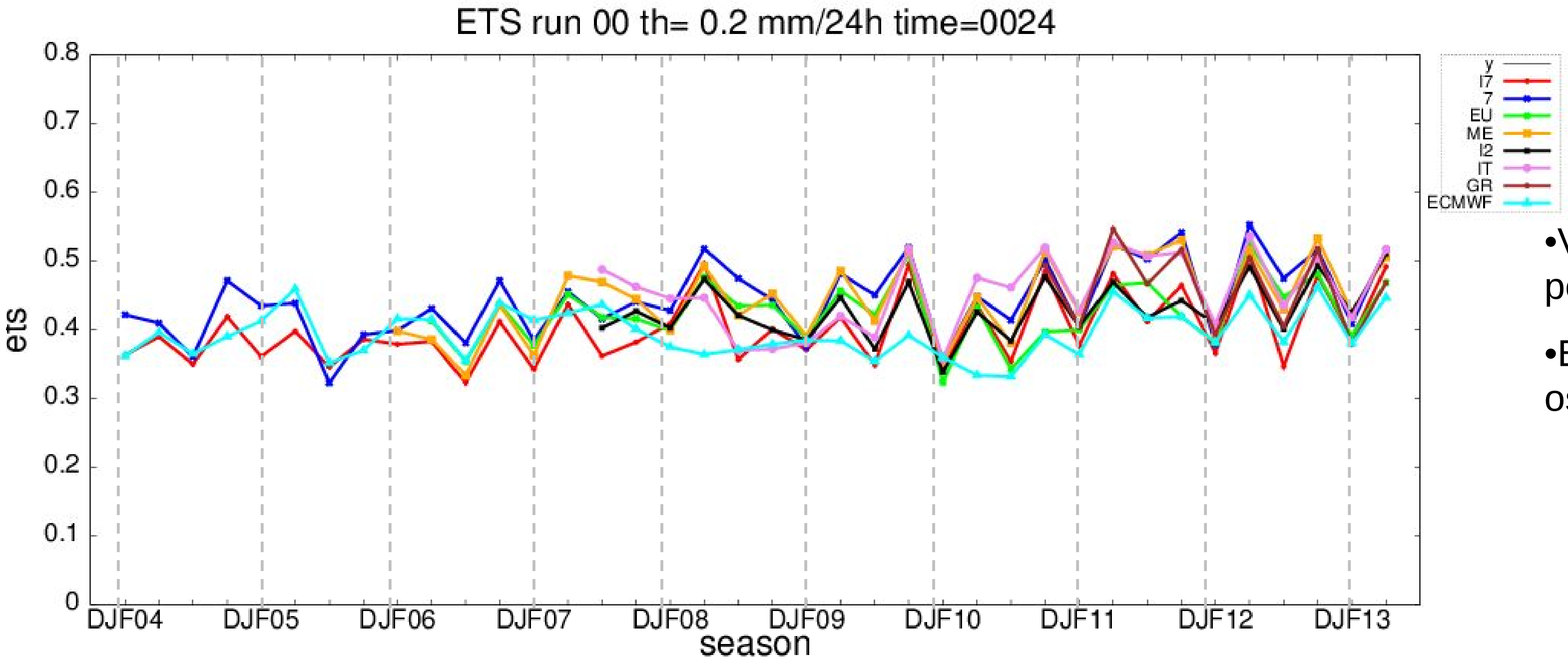
- Ecmwf overestimation only in summer, good performance
- Summer underestimation

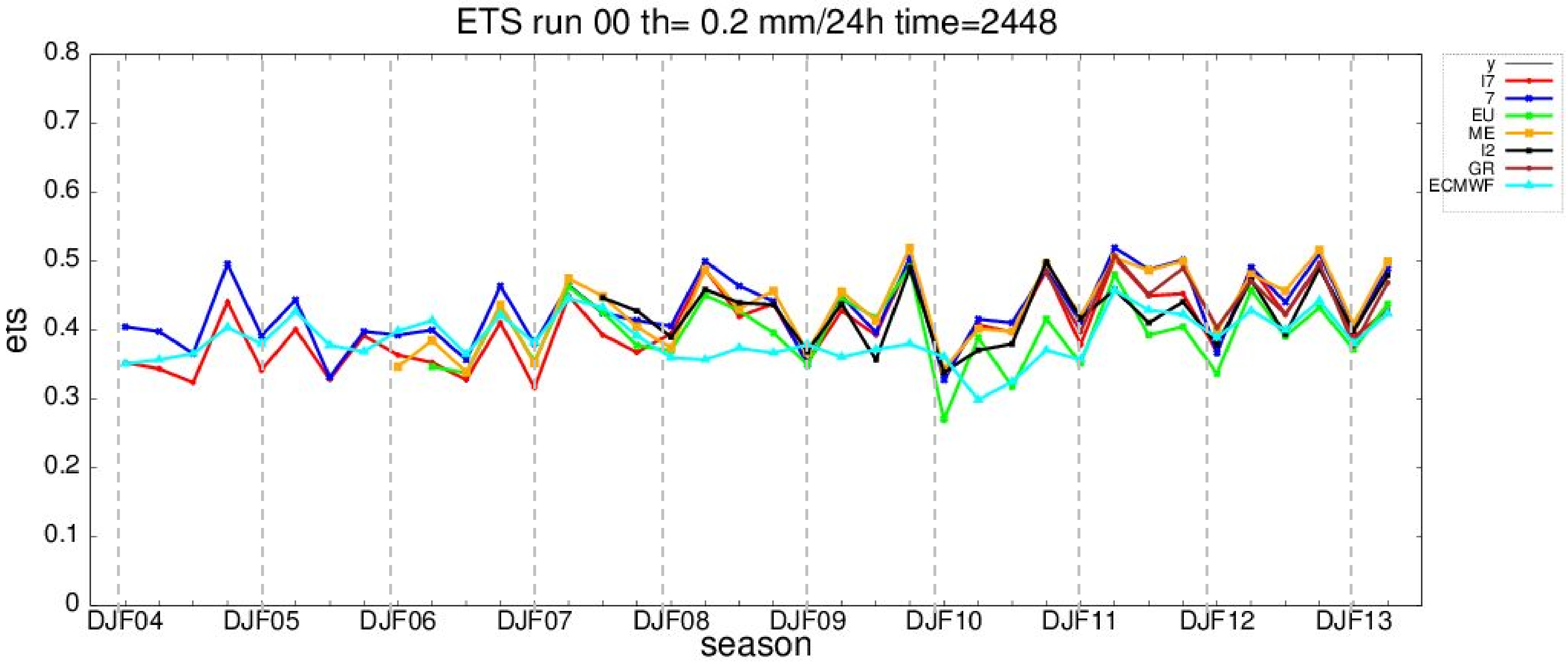




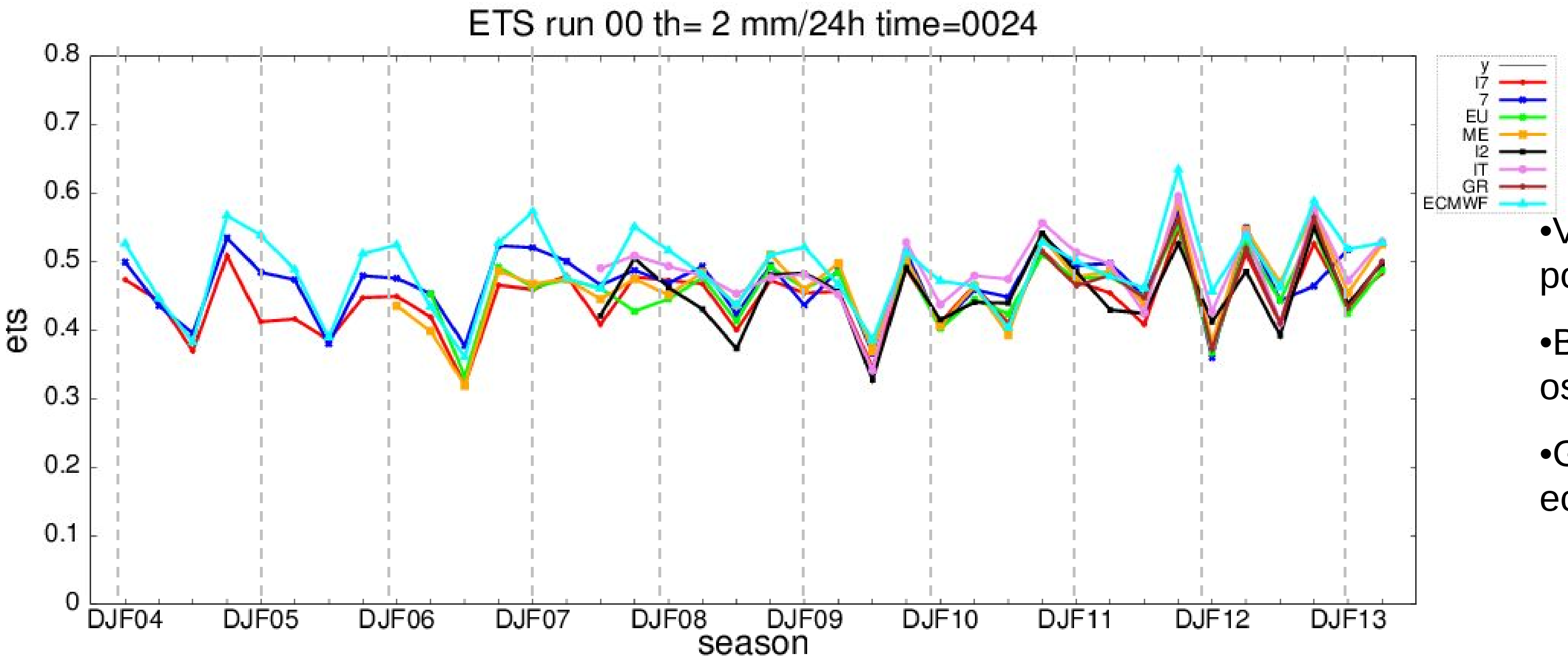
- General underestimation, especially 7, EU
- Big prec. Peak in summer’12



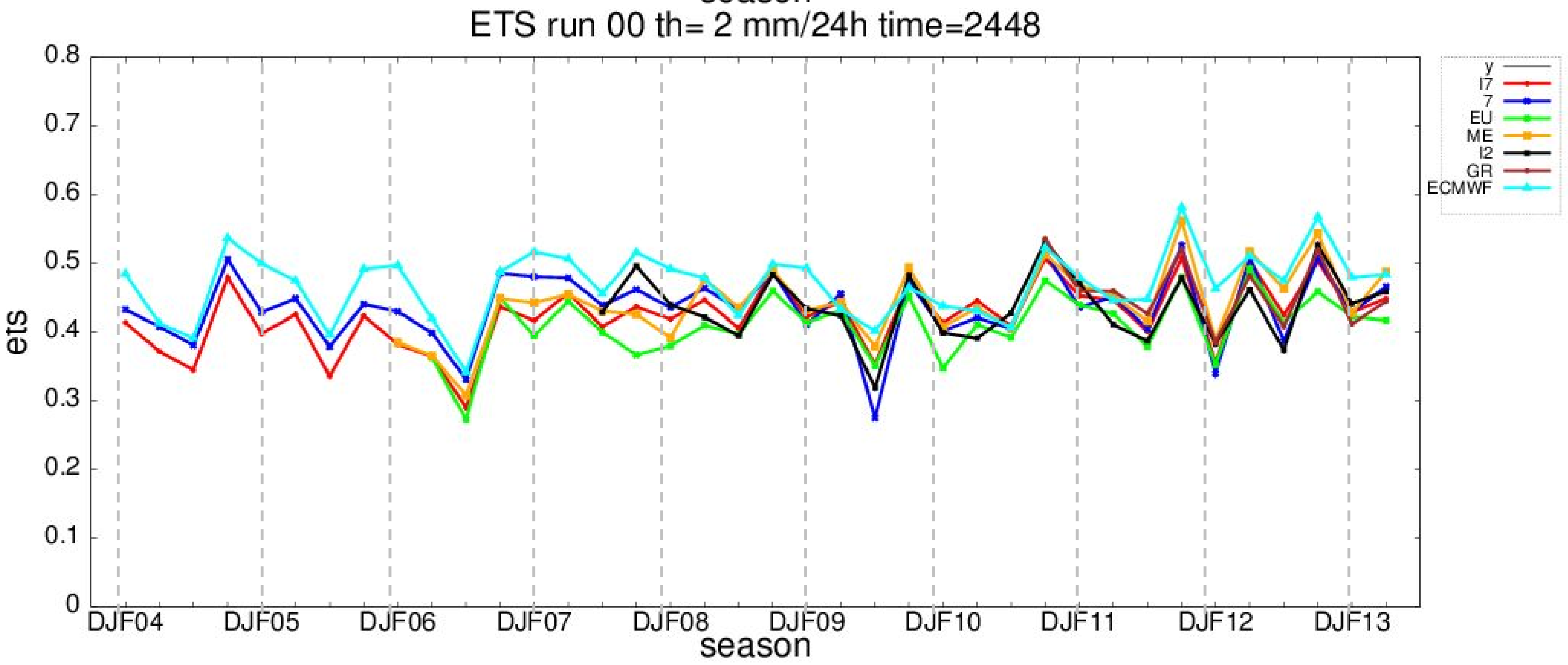


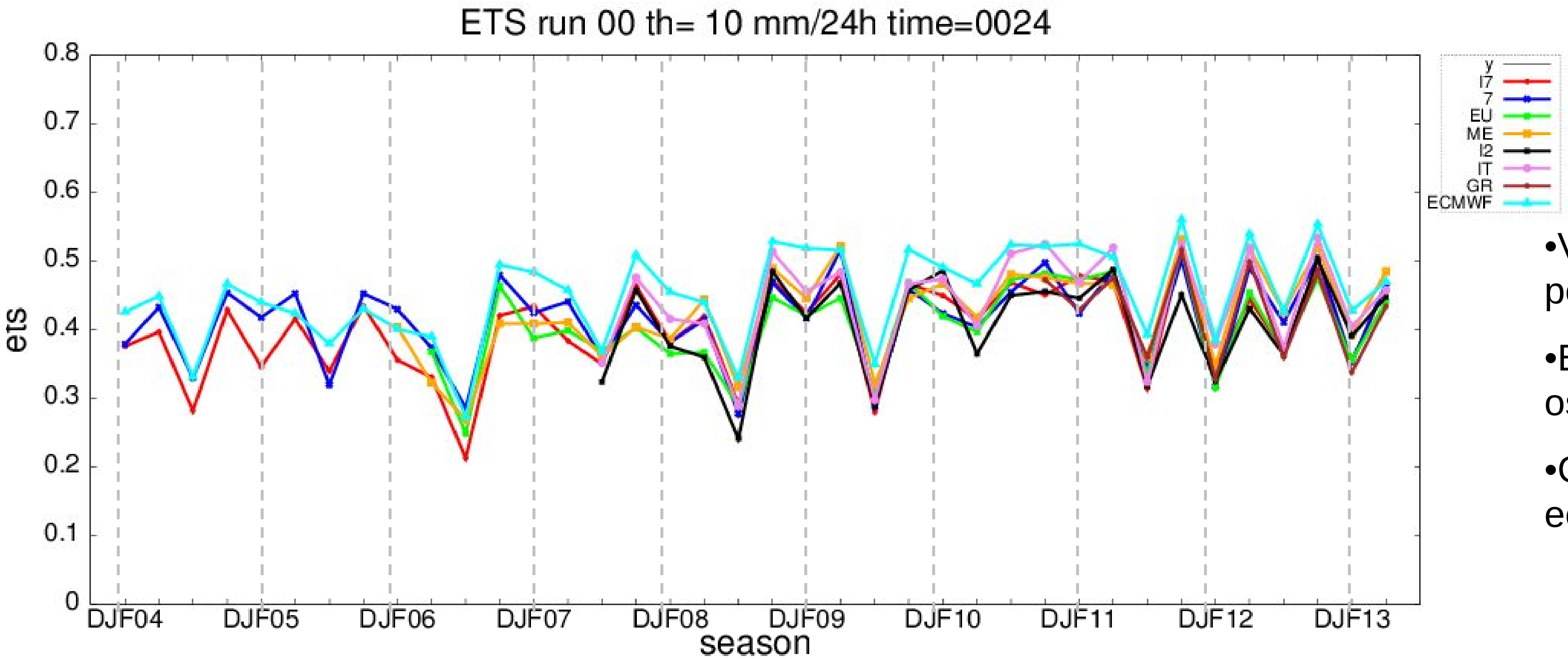


- Very slightly positive trend
- Big seasonal oscillation



- •Very slightly positive trend
- •Big seasonal oscillation
- •Good ets for ecmwf





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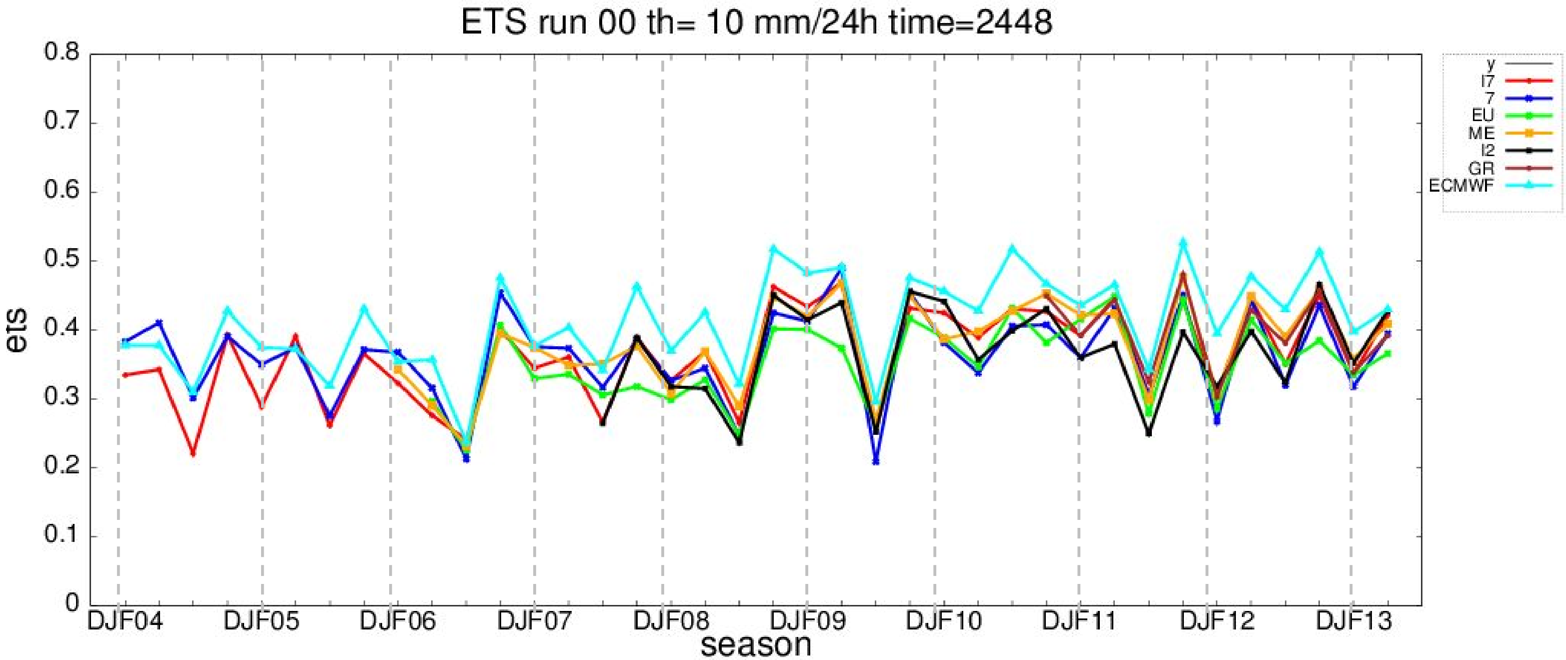

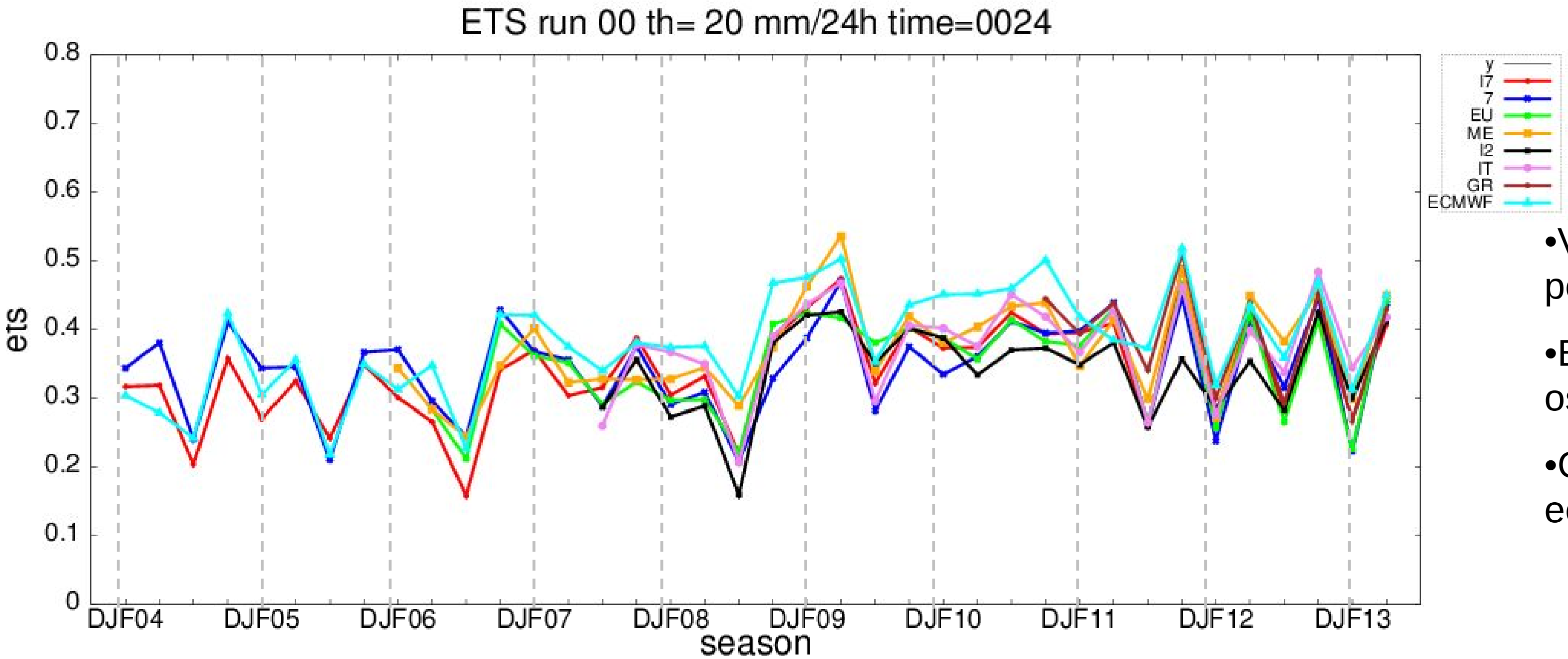

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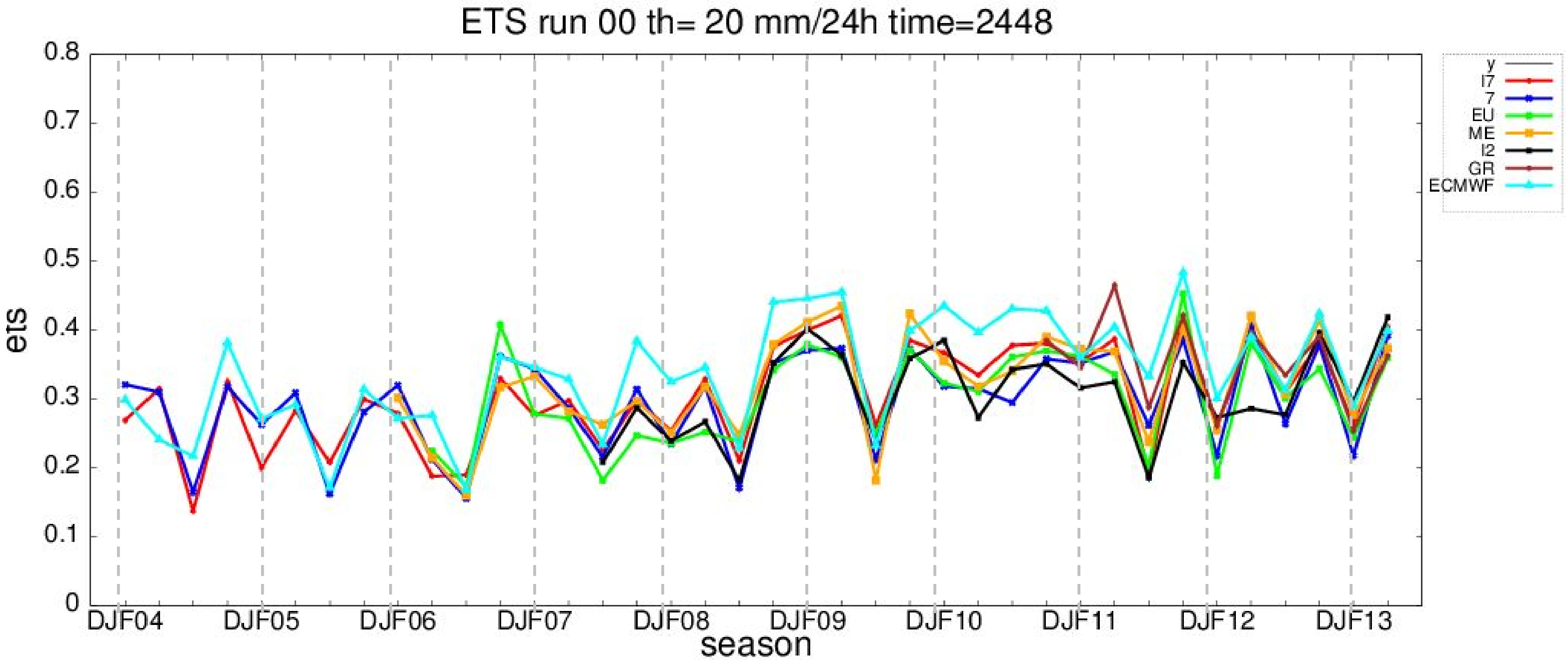
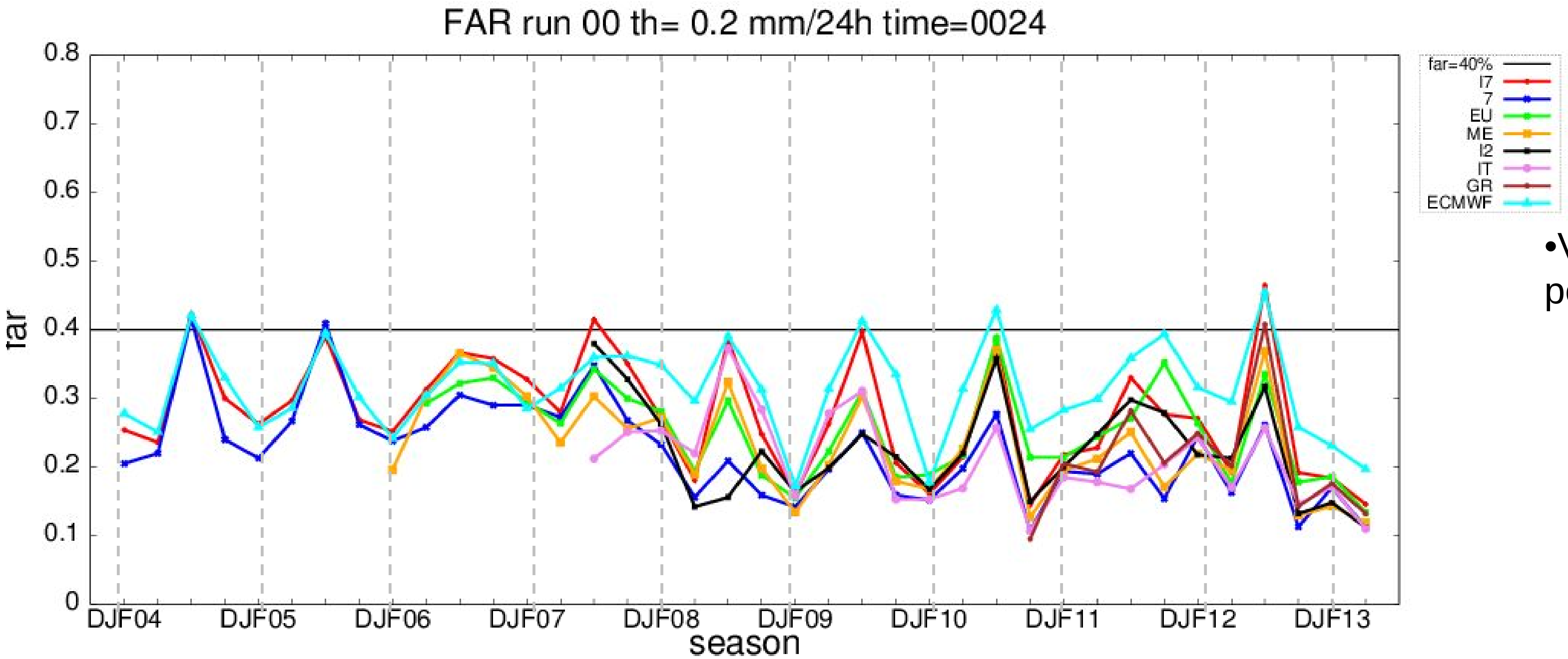
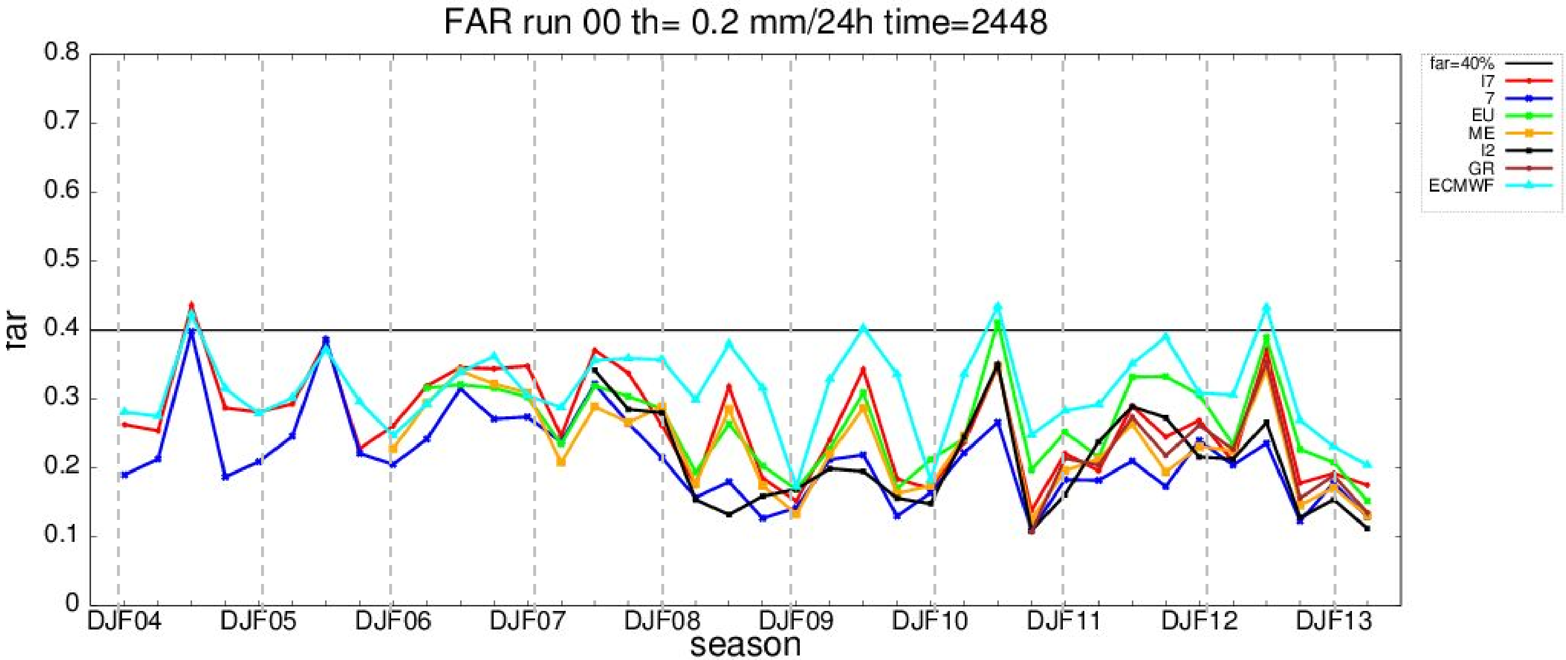
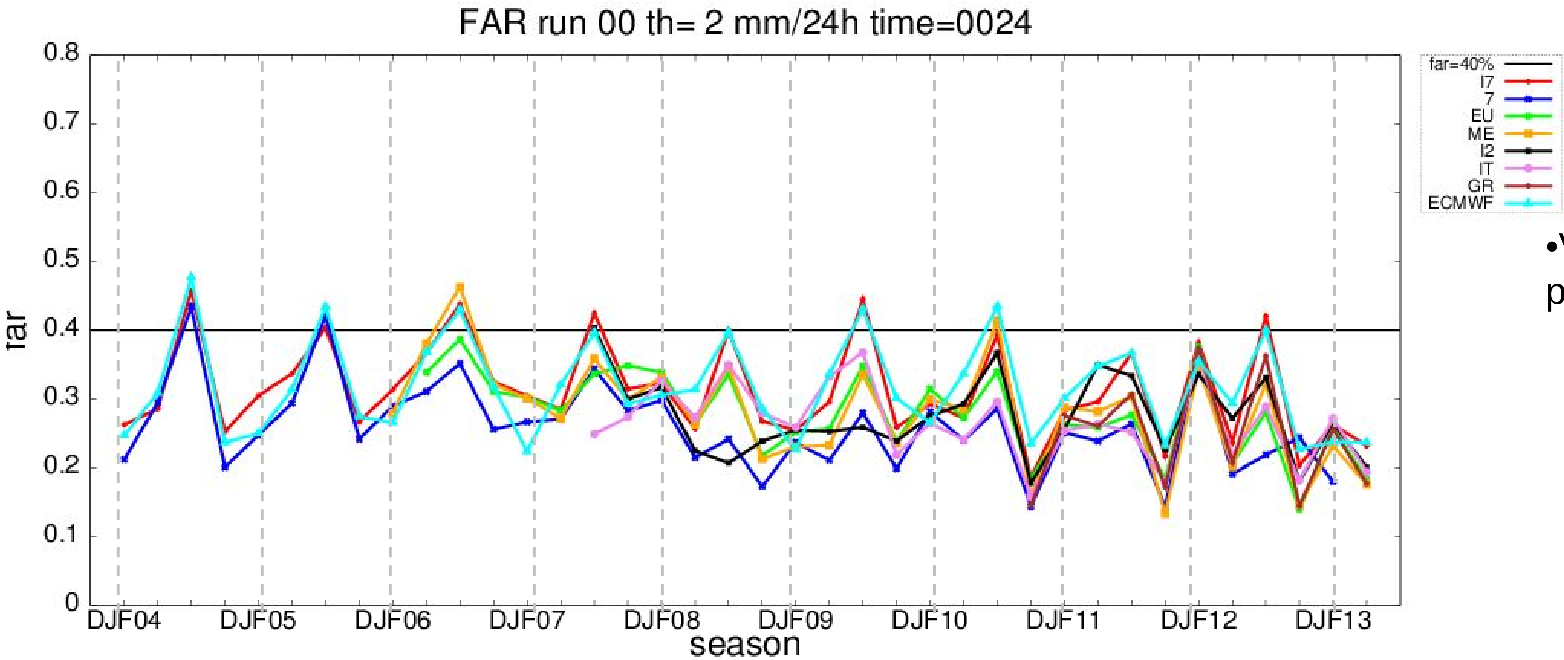


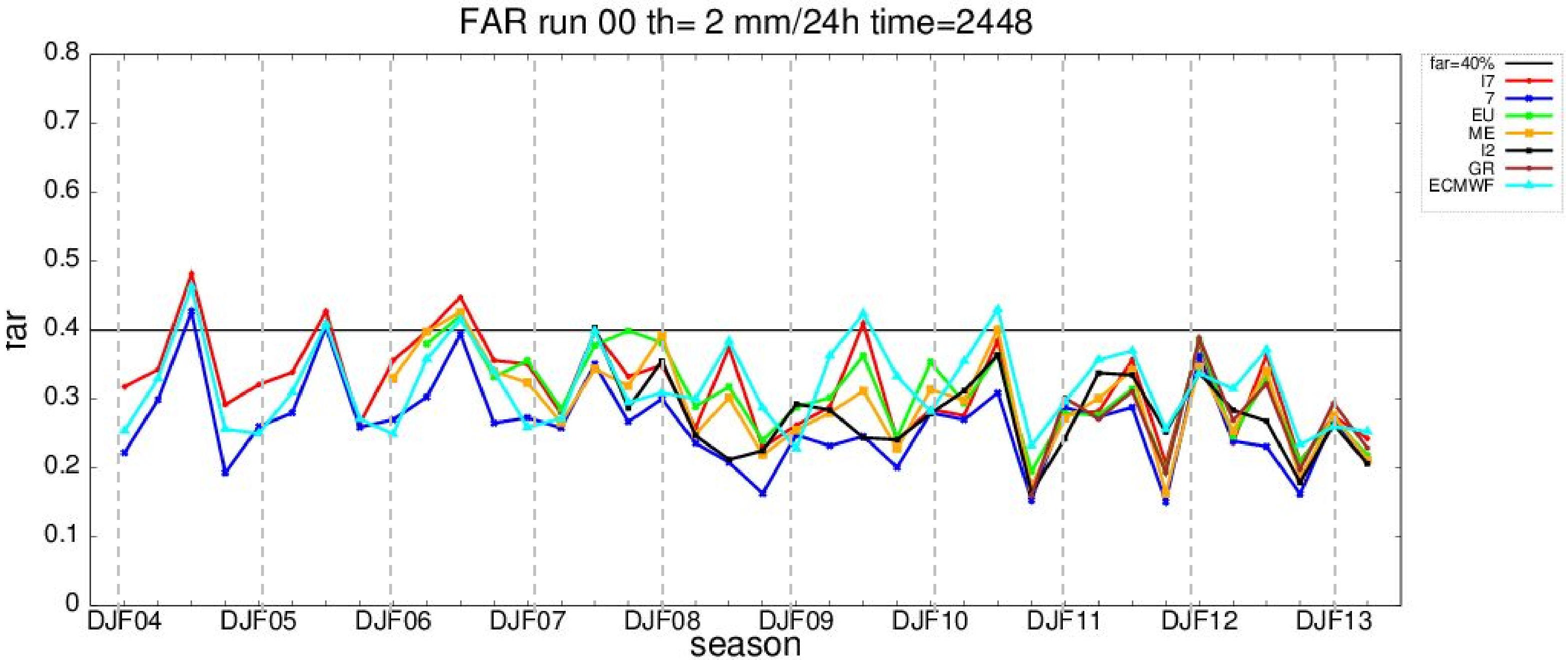


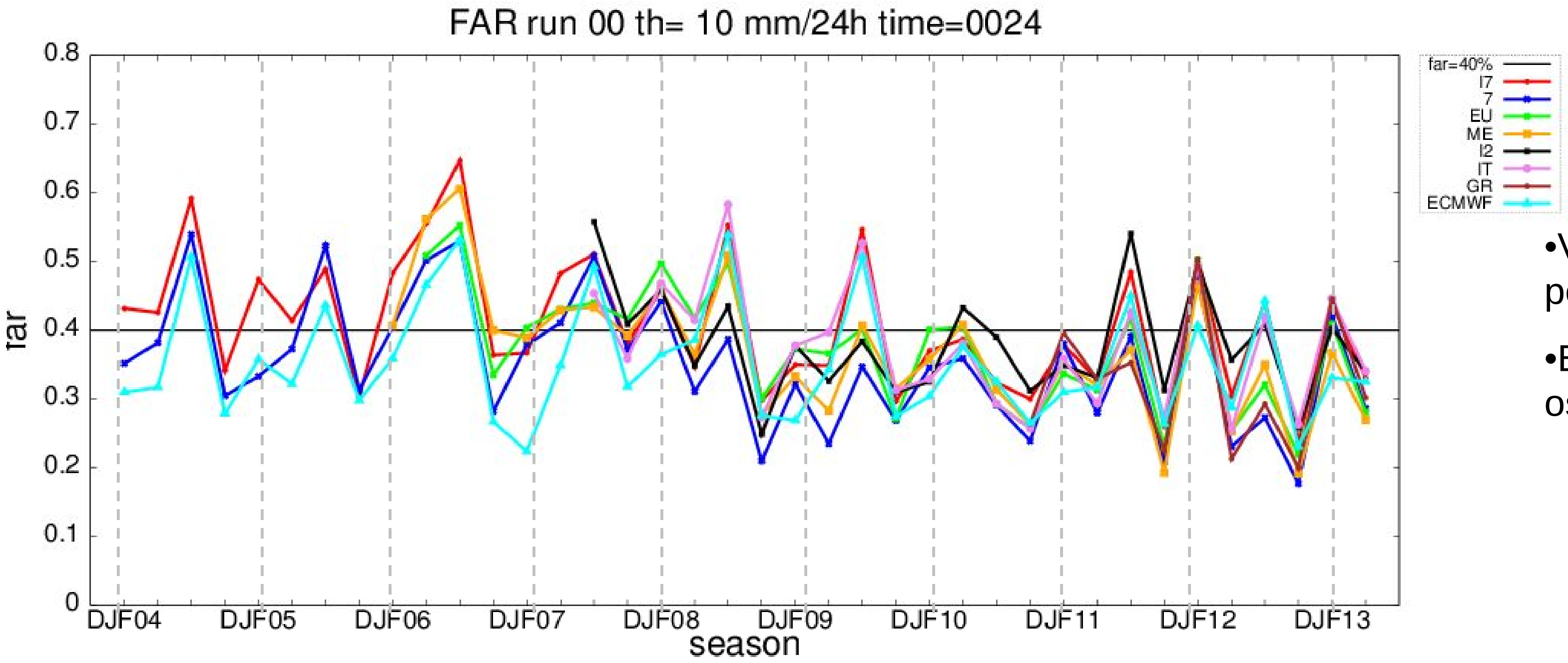
•Very slightly positive trend



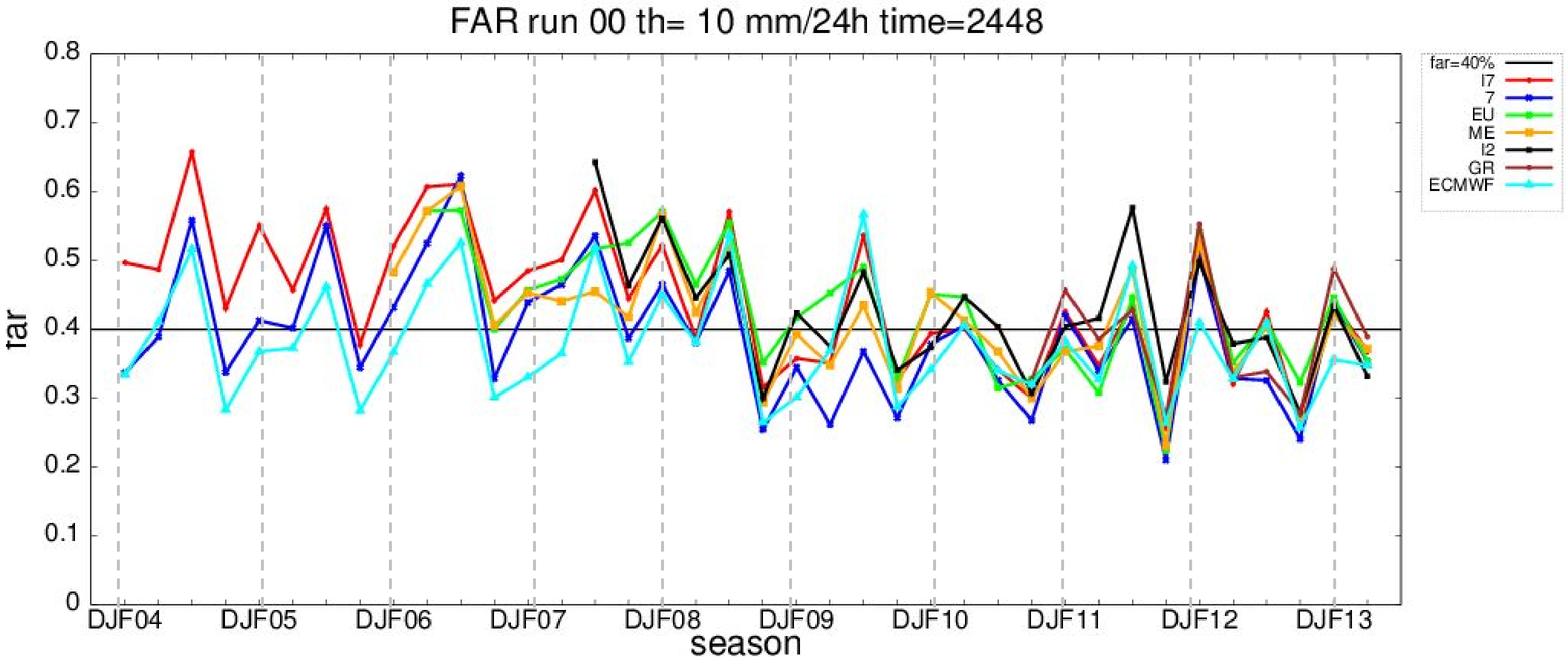


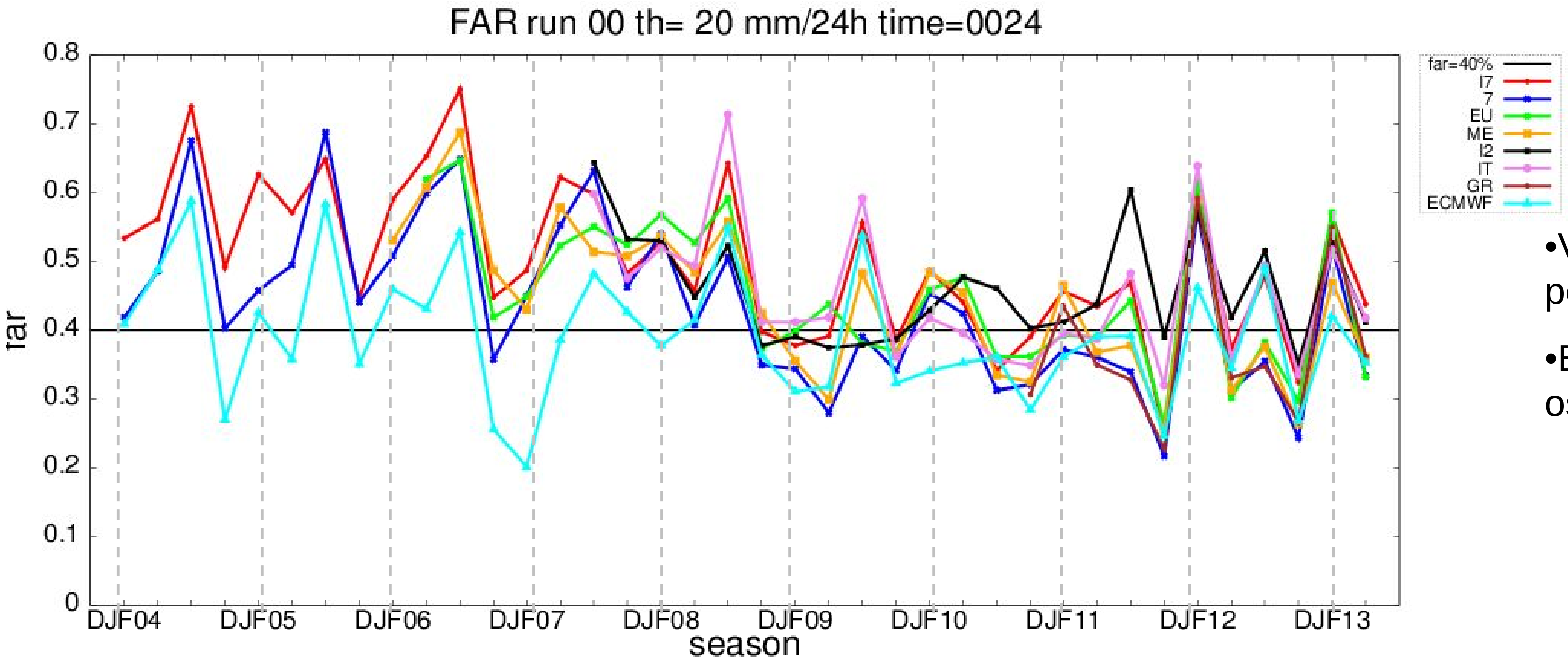
• Very slightly positive trend





- Very slightly positive trend
- Big seasonal oscillation





- Very slightly positive trend
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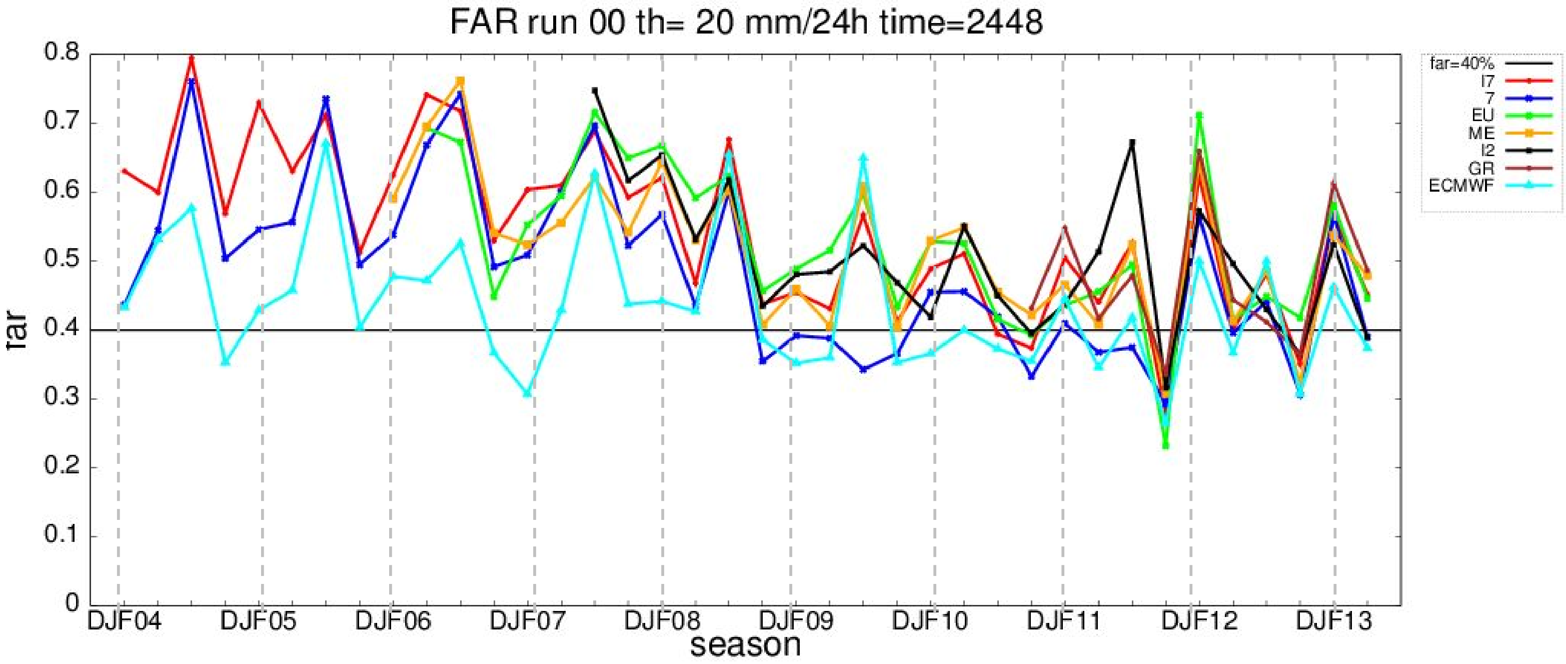
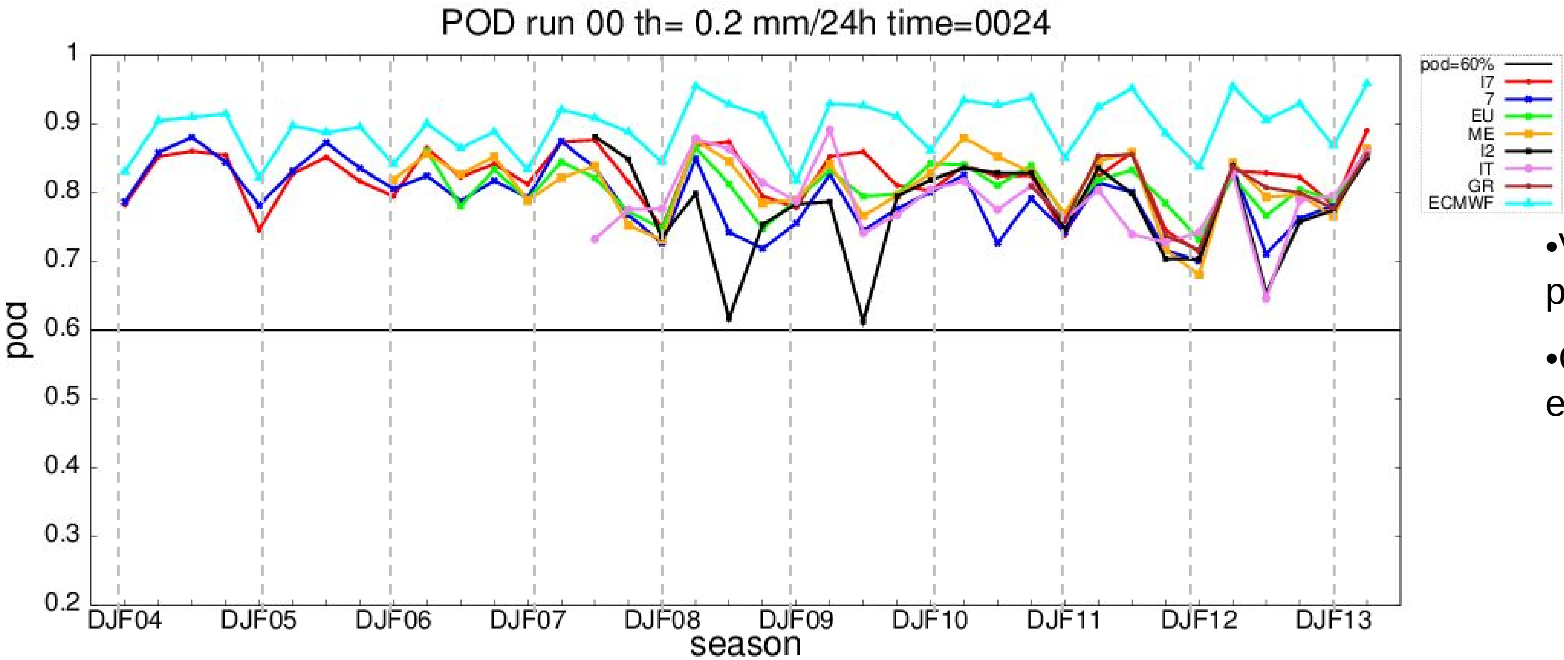
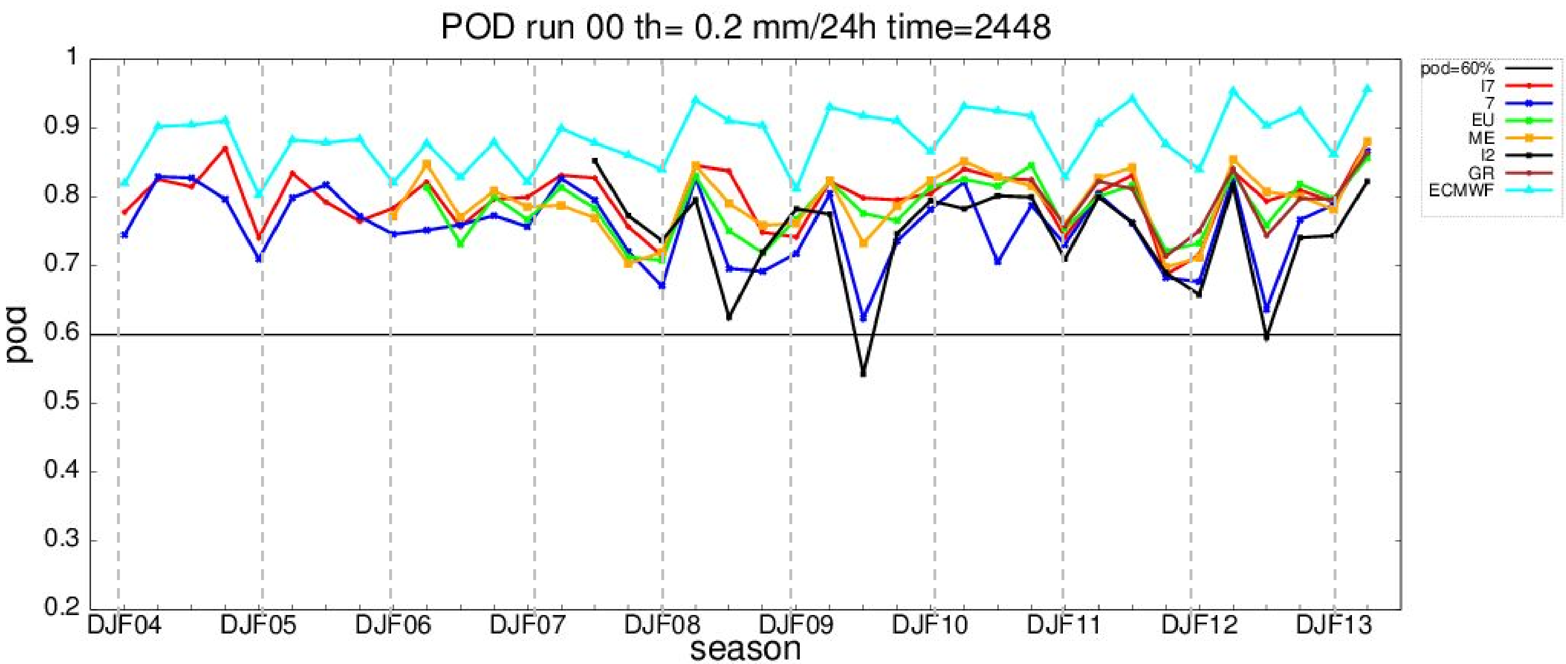
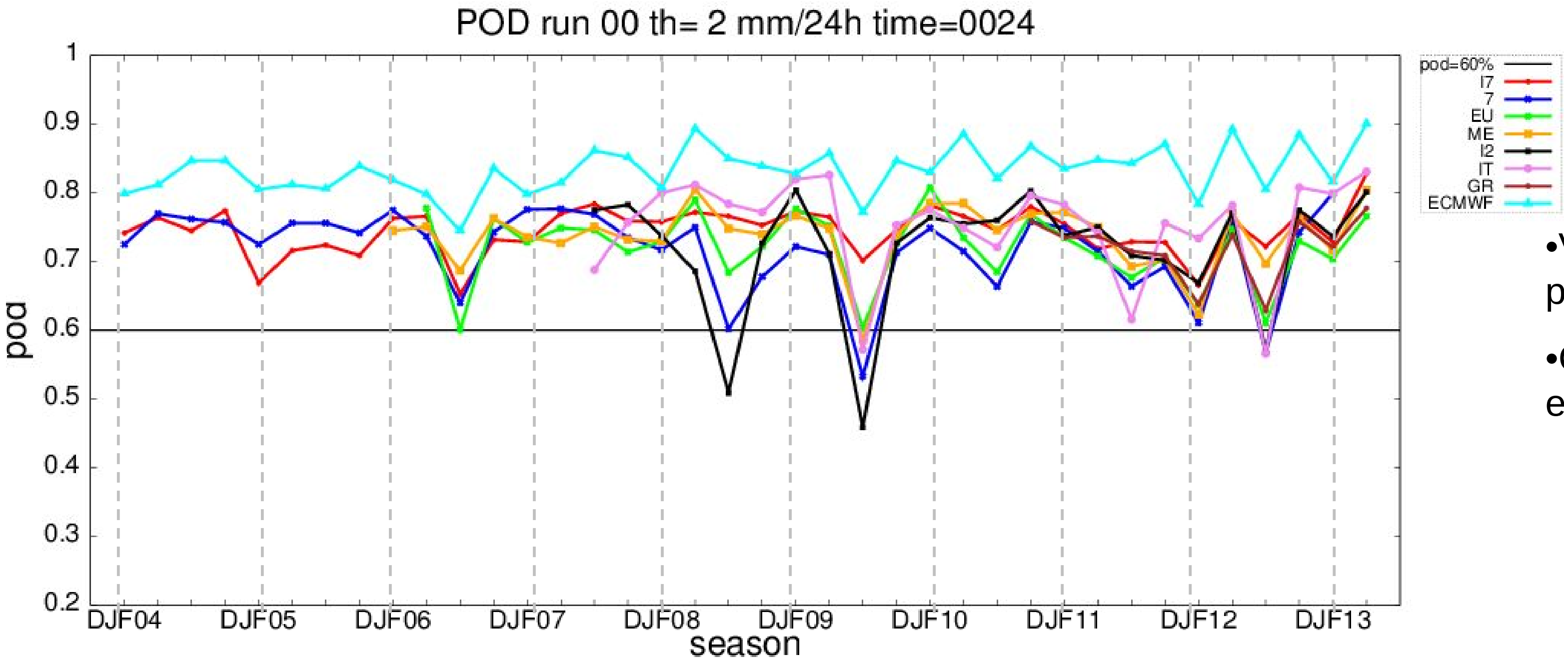




- Very slightly positive trend
- Good pod for ecmwf





- Very slightly positive trend
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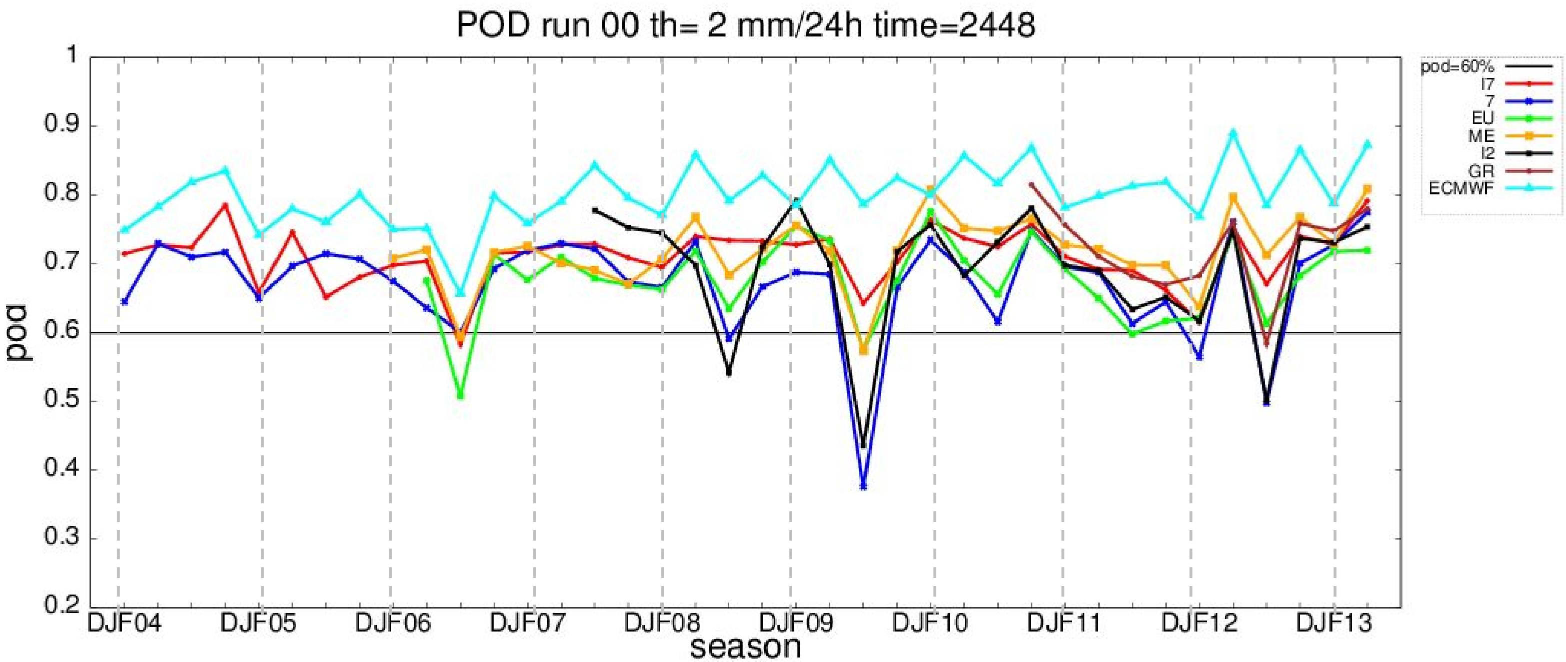
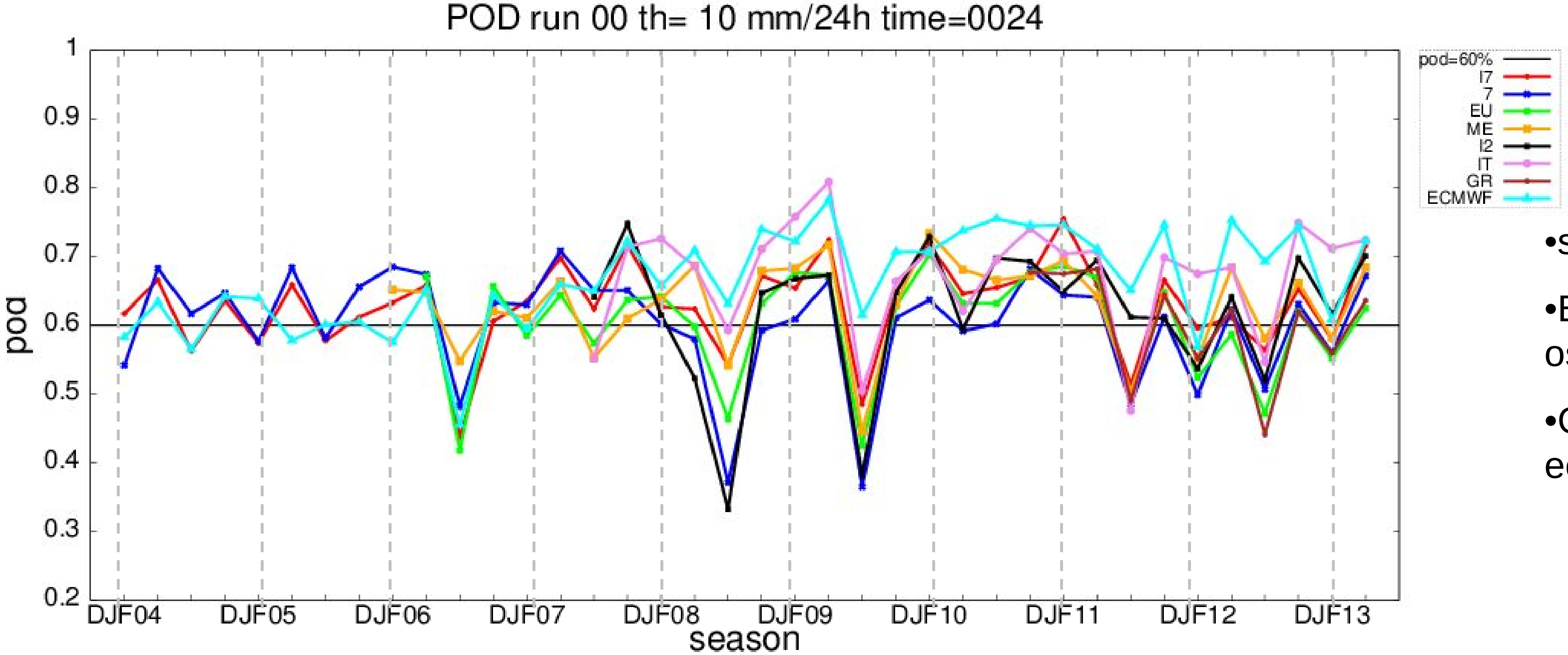
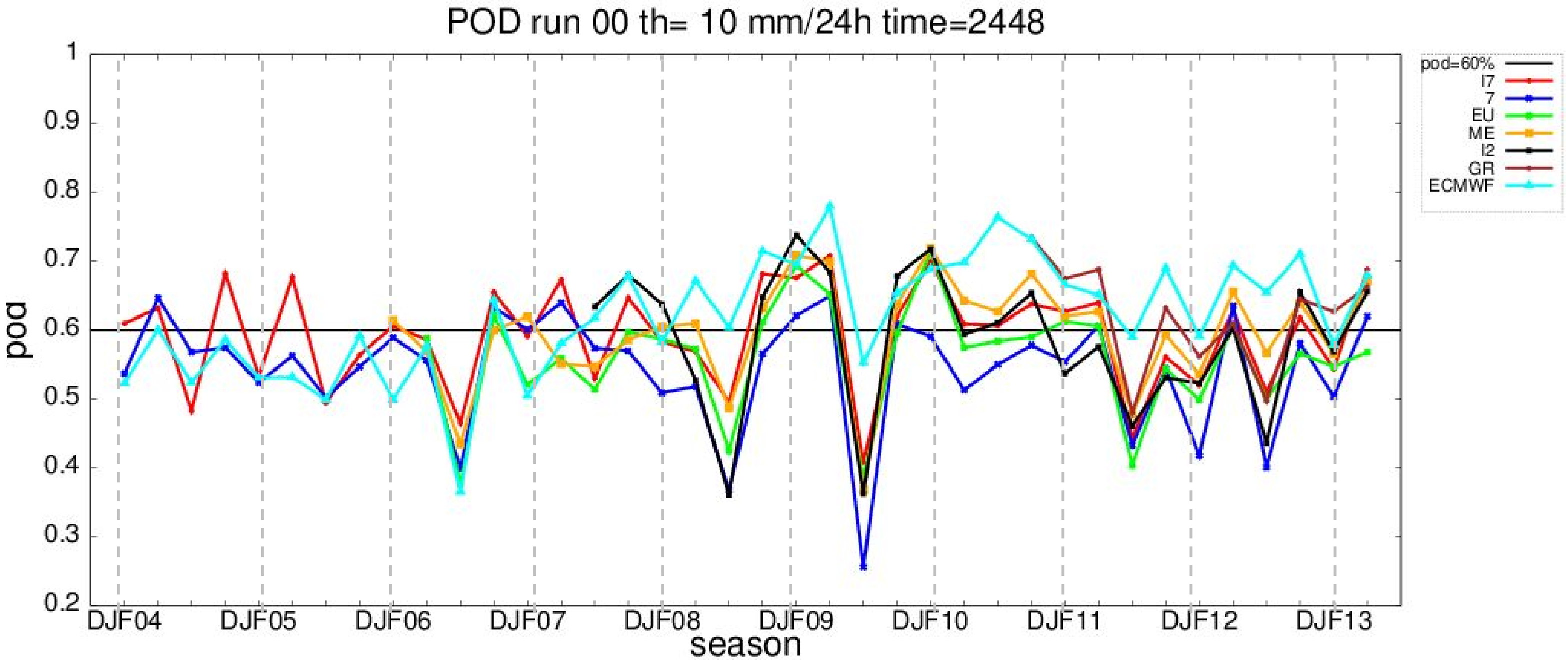
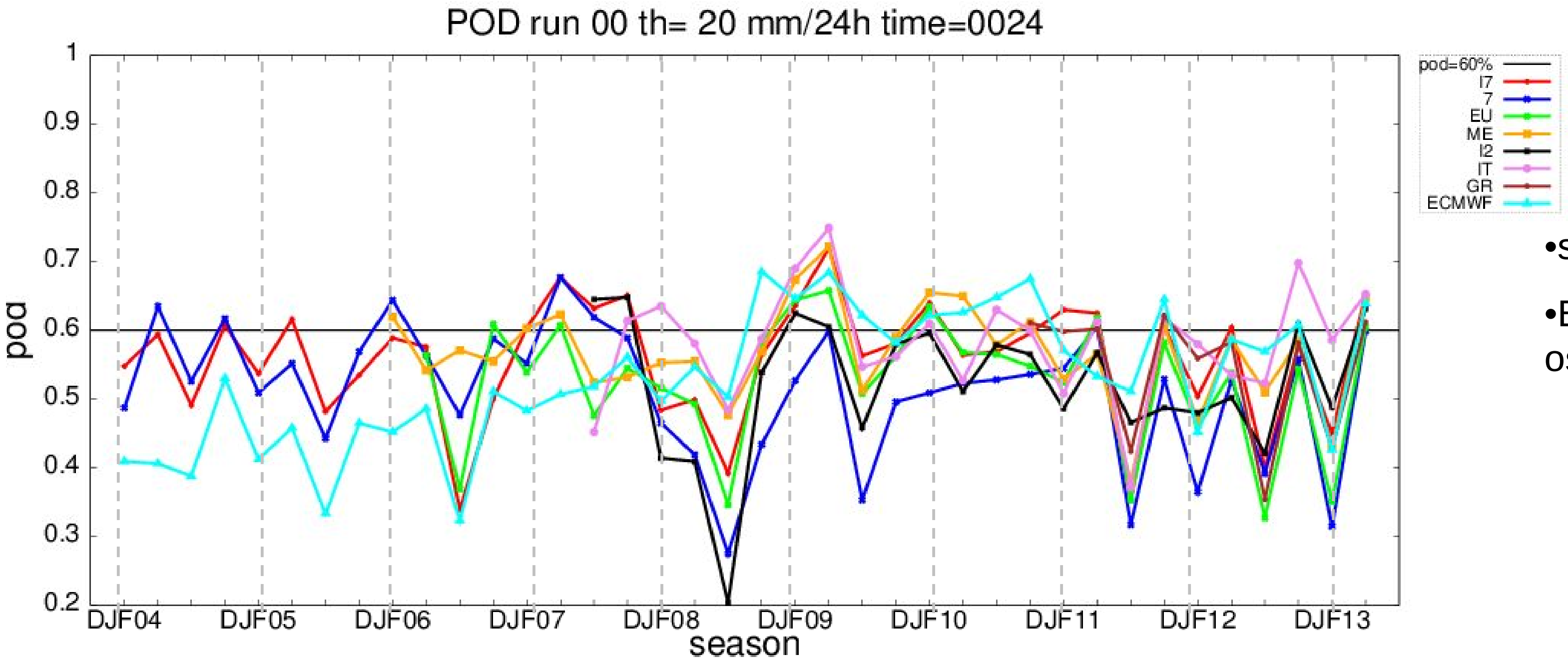


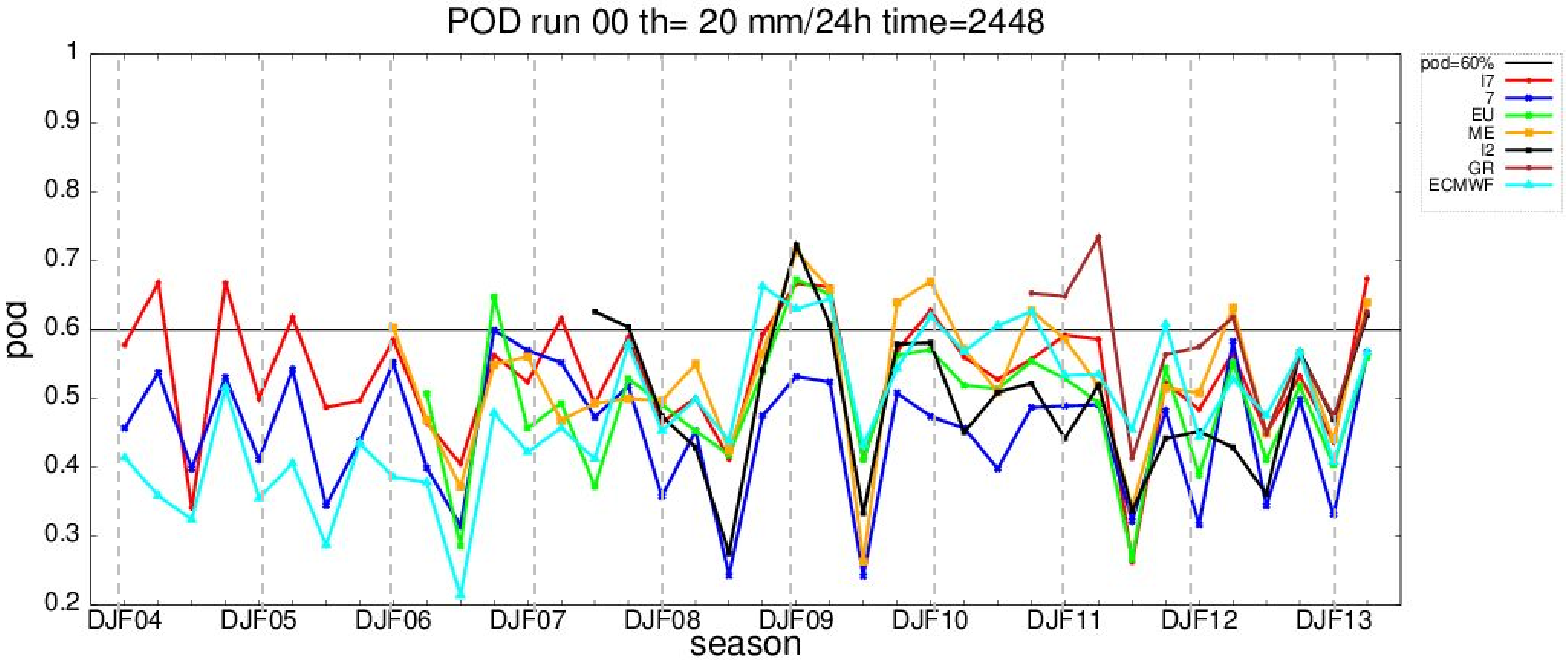


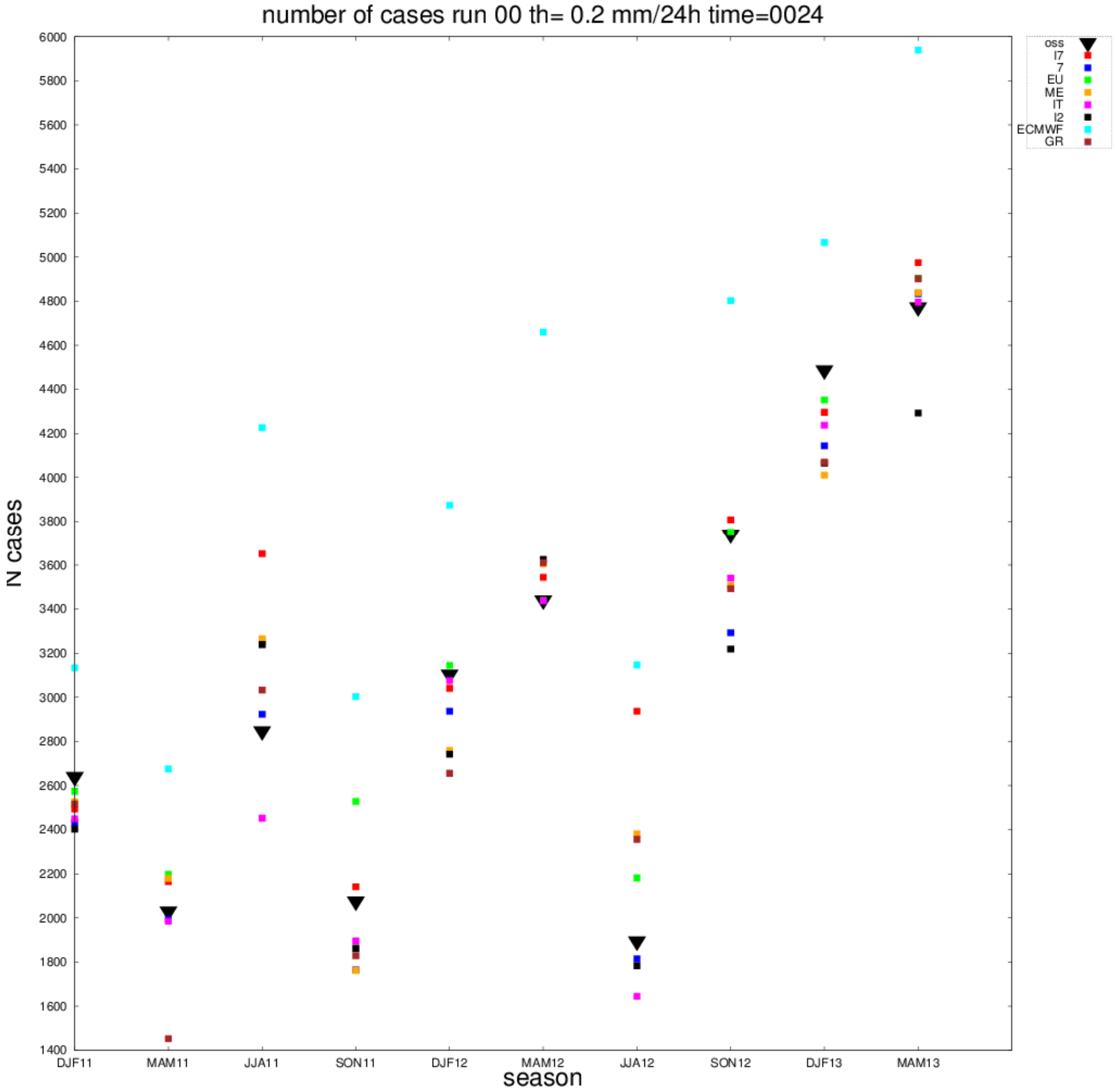
- stationary trend
- Big seasonal oscillation
- Good pod for ecmwf



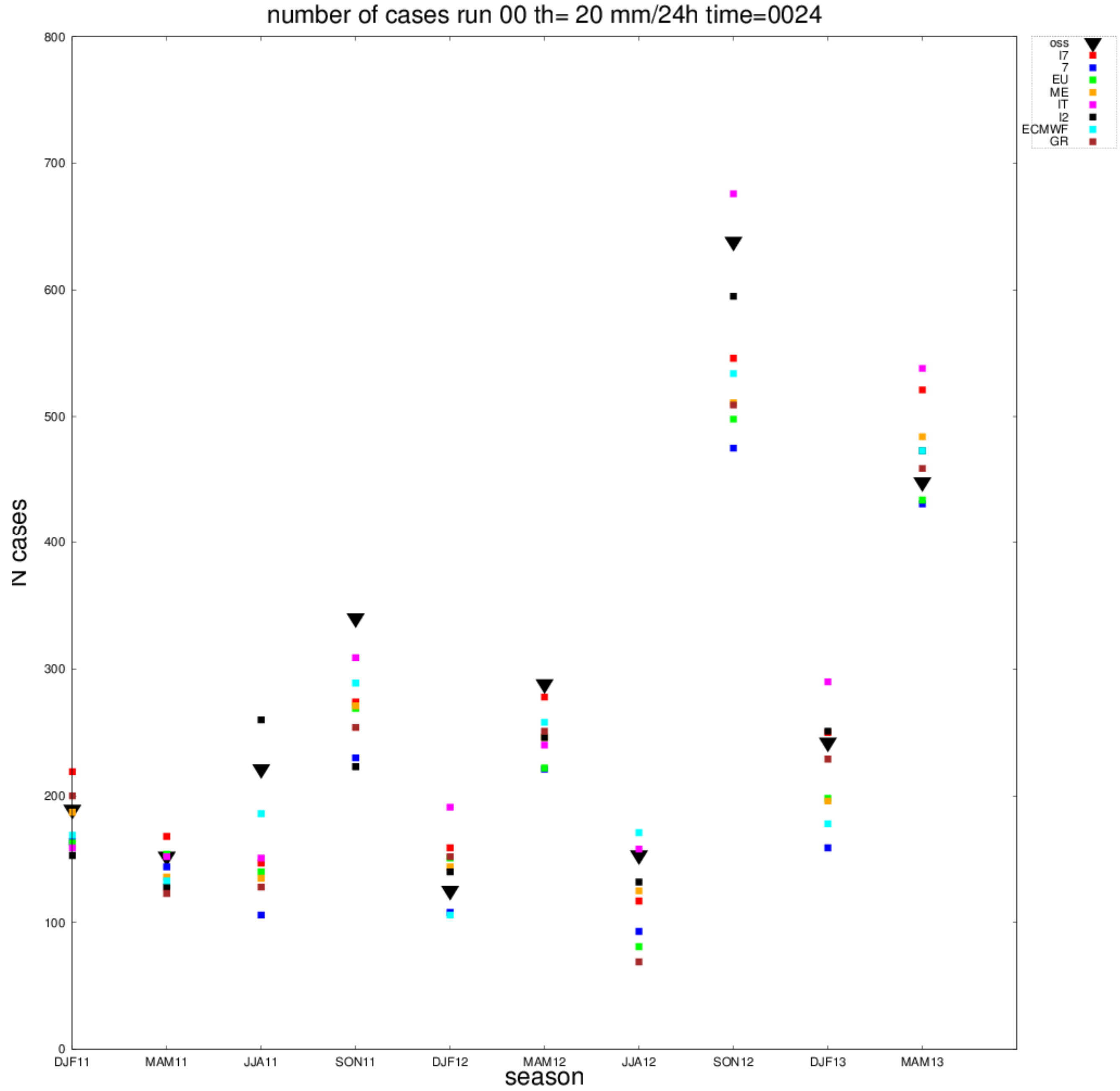


- stationary trend
- Big seasonal oscillation



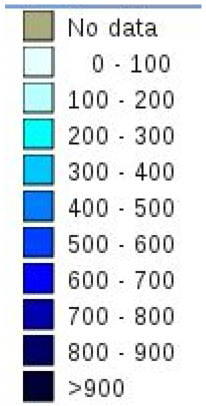


number of cases run 00 th= 0.2 mm/24h time=0024
N cases
season
6000
5800
5600
5400
5200
5000
4800
4600
4400
4200
4000
3800
3600
3400
3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
DJF11
MAM11
JJA11
SON11
DJF12
MAM12
JJA12
SON12
DJF13
MAM13
oss
I7
7
EU
ME
IT
I2
ECMWF
GR


number of cases run 00 th= 20 mm/24h time=0024
N cases
season
0
100
200
300
400
500
600
700
800
DJF11
MAM11
JJA11
SON11
DJF12
MAM12
JJA12
SON12
DJF13
MAM13
oss
I7
7
EU
ME
IT
I2
ECMWF
GR

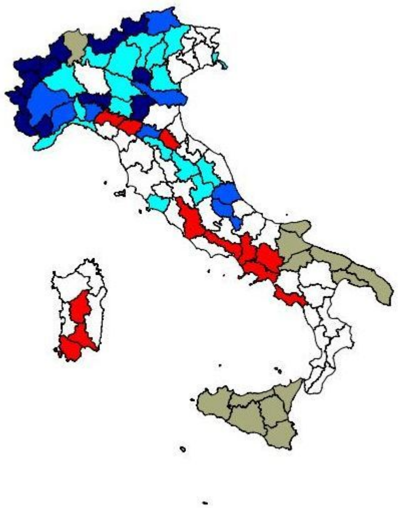
Cumulated obs. Prec.

Cumulated seasonal precipitation (mm)

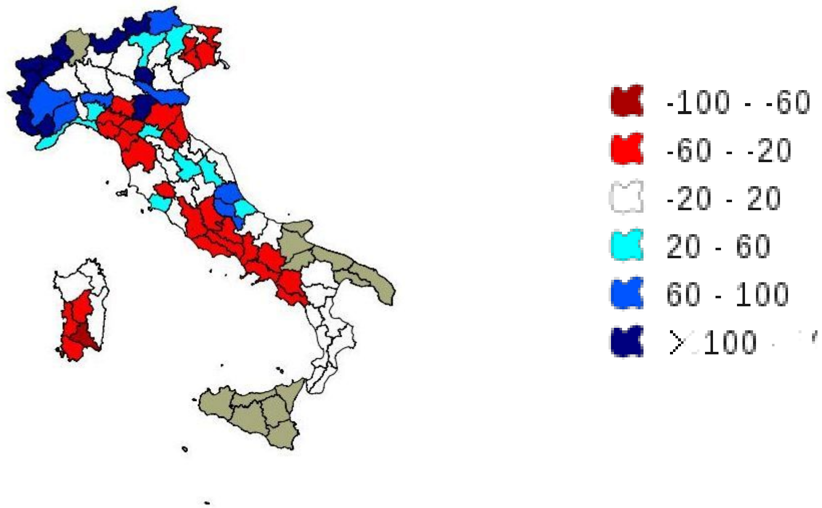


Long trend relative errors WINTER'12

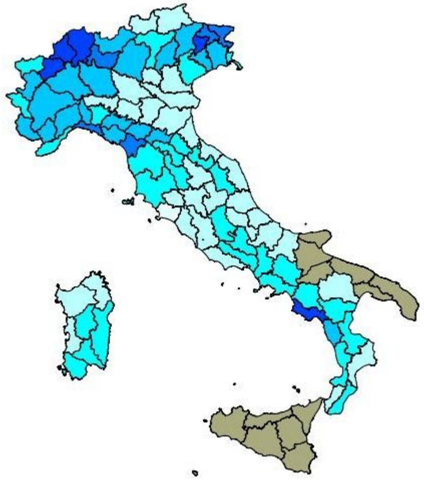
Cosmo-I7



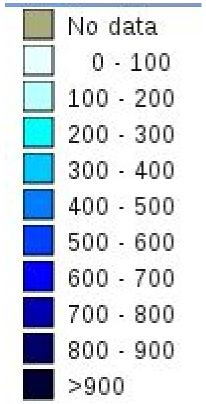
Cosmo-ME



Cumulated obs. Prec.

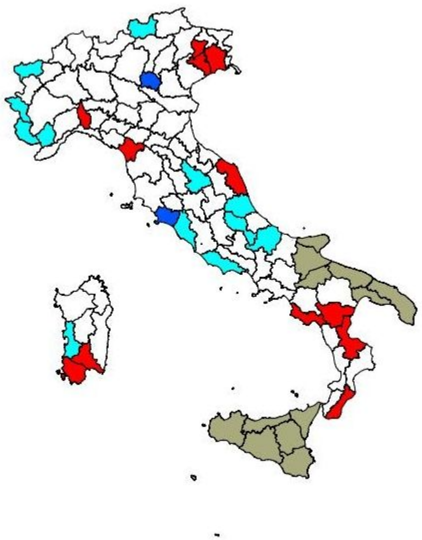


Cumulated seasonal precipitation (mm)

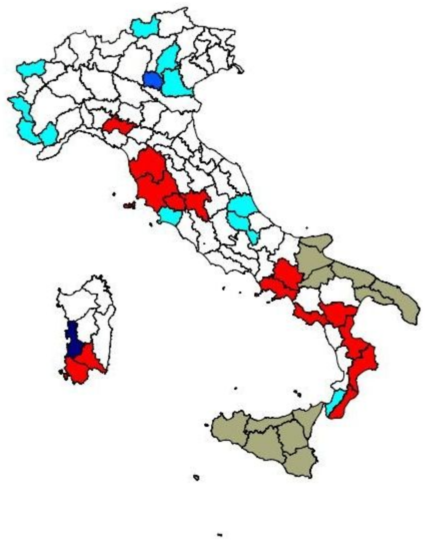


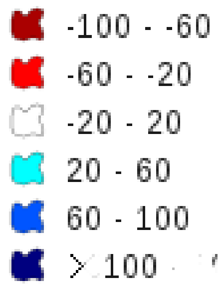
Long trend relative errors SPRING'12

Cosmo-I7



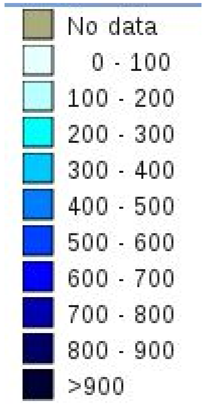
Cosmo-ME





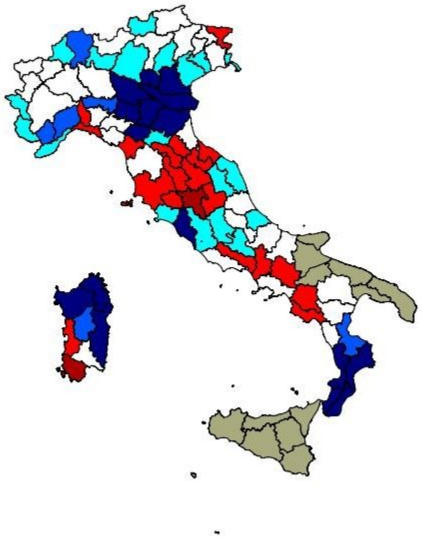
Cumulated
obs. Prec.

Cumulated seasonal
precipitation (mm)

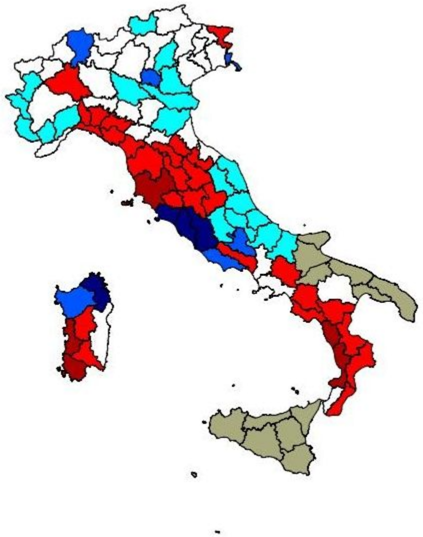


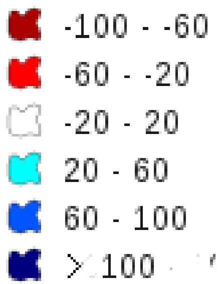
Long trend relative errors SUMMER ‘12

Cosmo-I7

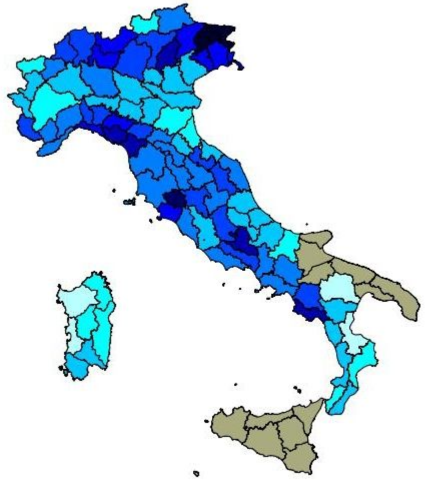


Cosmo-ME

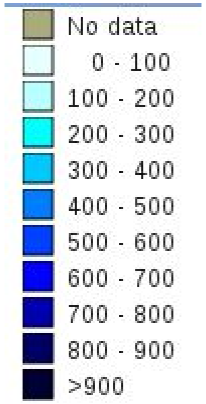




Cumulated obs. Prec.

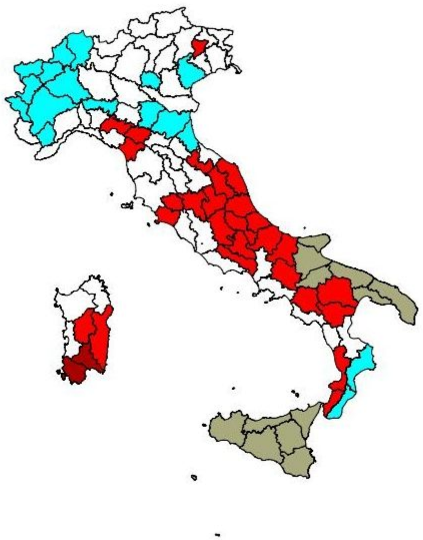


Cumulated seasonal precipitation (mm)

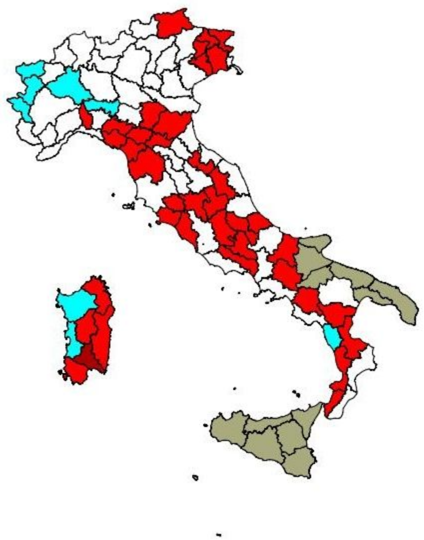


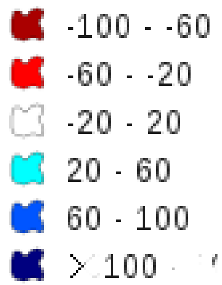
Long trend relative errors FALL ‘12

Cosmo-I7

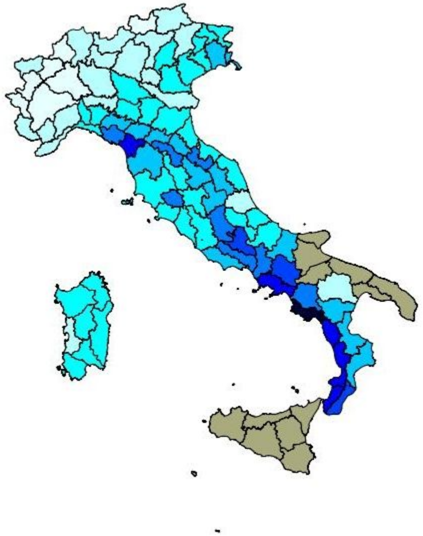


Cosmo-ME





Cumulated obs. Prec.

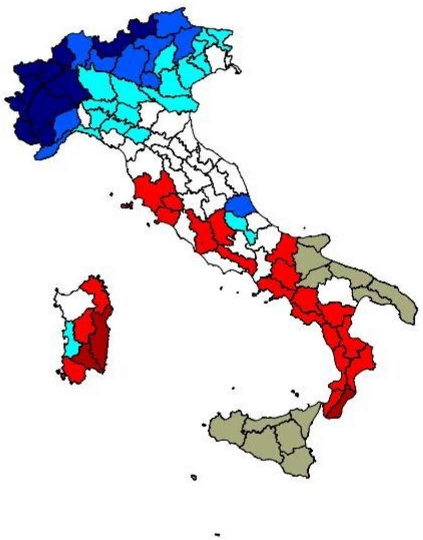


Cumulated seasonal precipitation (mm)

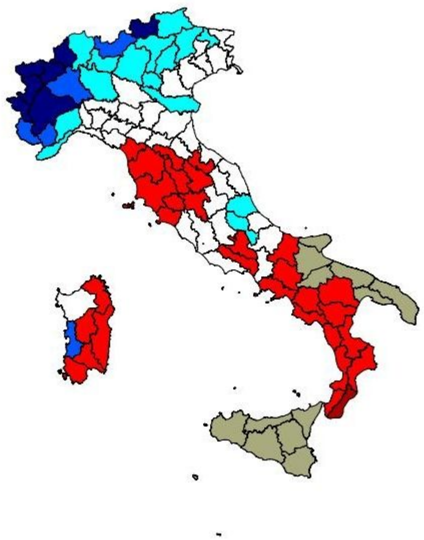
No data	
0 - 100	
100 - 200	
200 - 300	
300 - 400	
400 - 500	
500 - 600	
600 - 700	
700 - 800	
800 - 900	
>900	

Long trend relative errors WINTER'13

Cosmo-I7

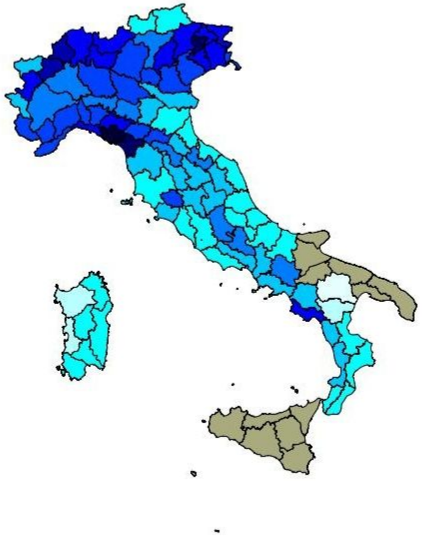


Cosmo-ME



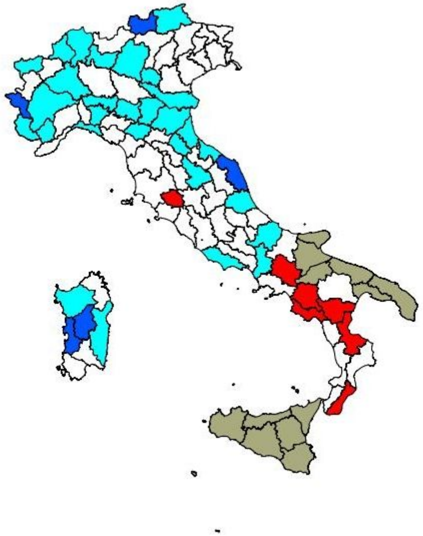
-100 - -60
-60 - -20
-20 - 20
20 - 60
60 - 100
> 100

Cumulated
obs. Prec.

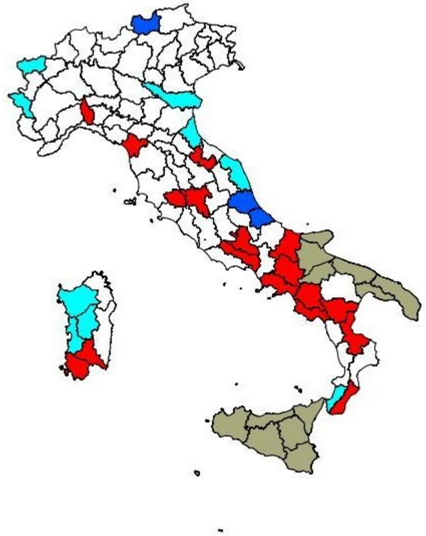


Long trend relative errors SPRING'13

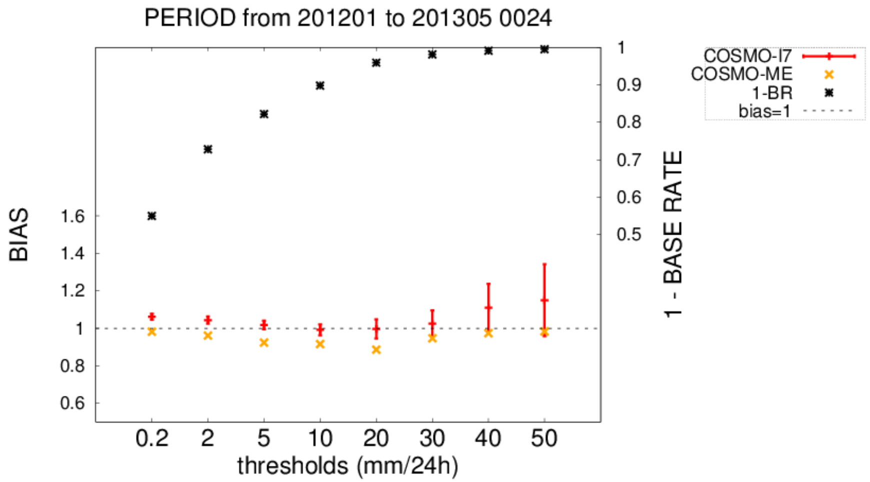
Cosmo-I7

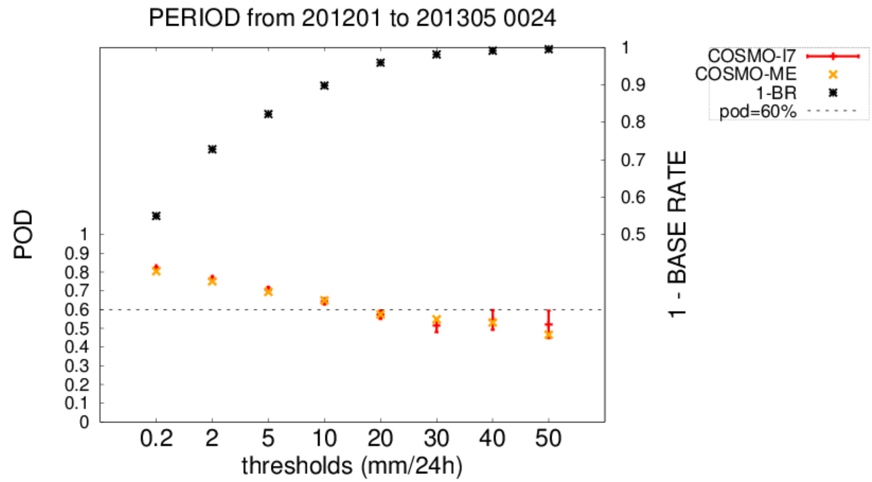


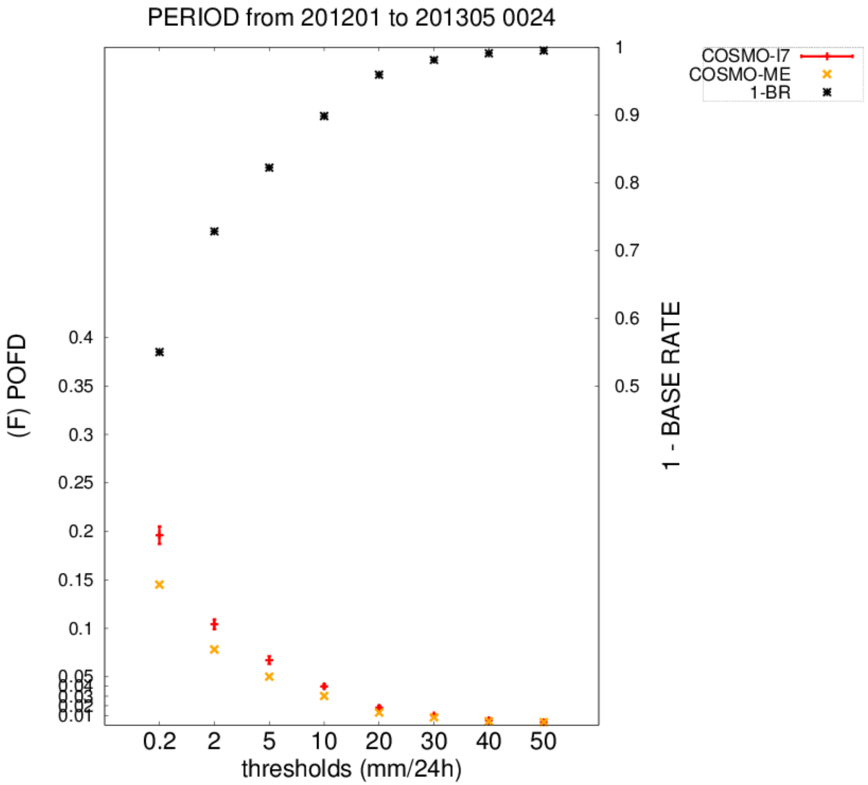
Cosmo-ME

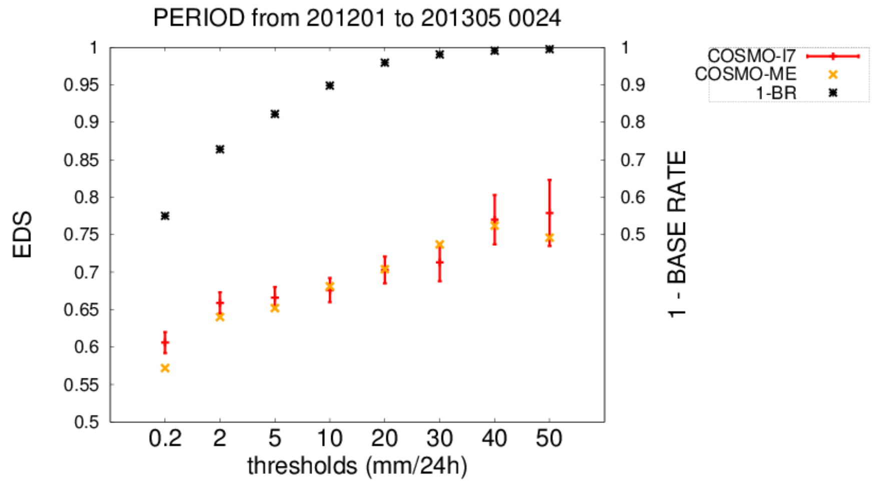


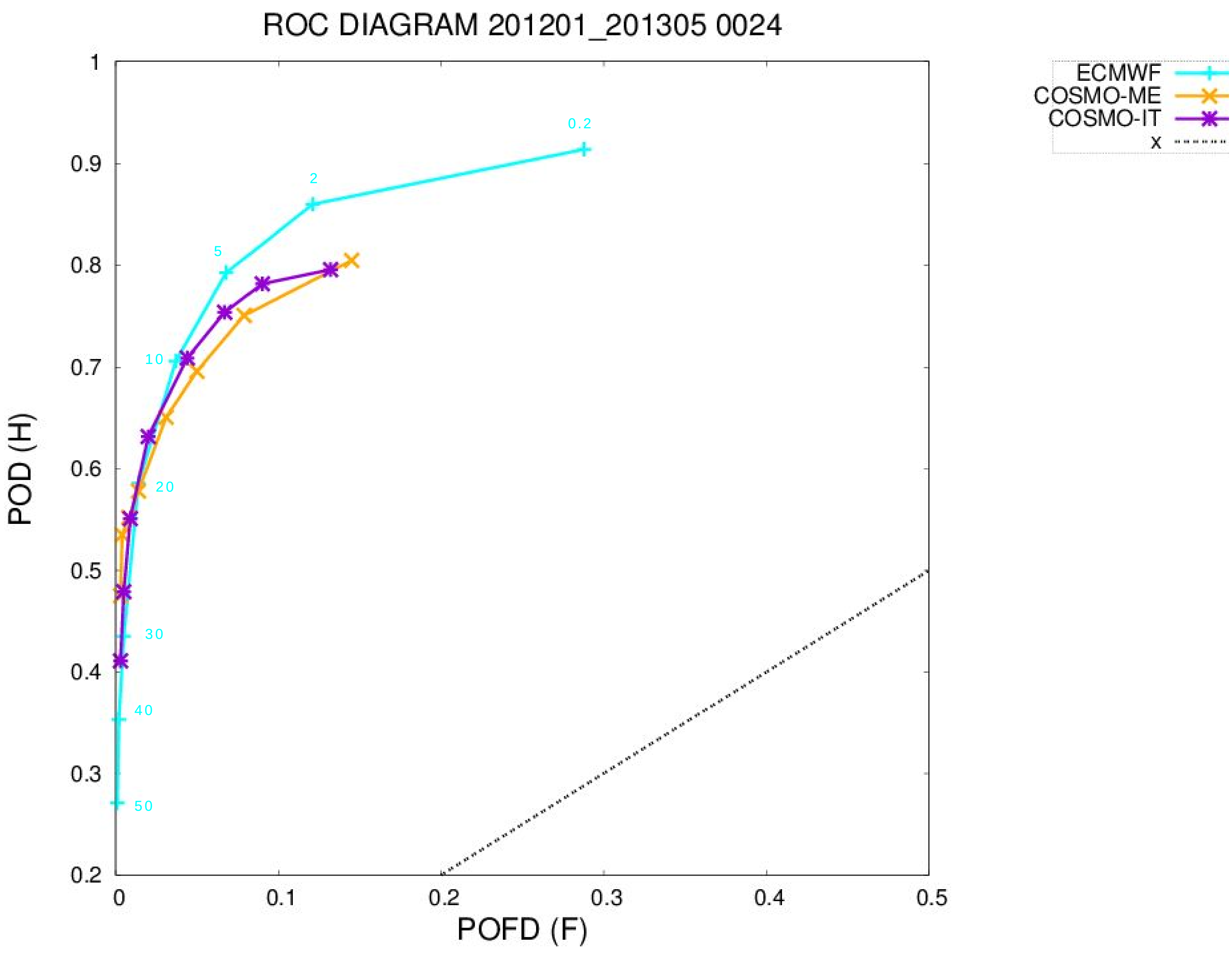
Intercomparison COSMO-ME/COSMO-I7, FIRST 24H



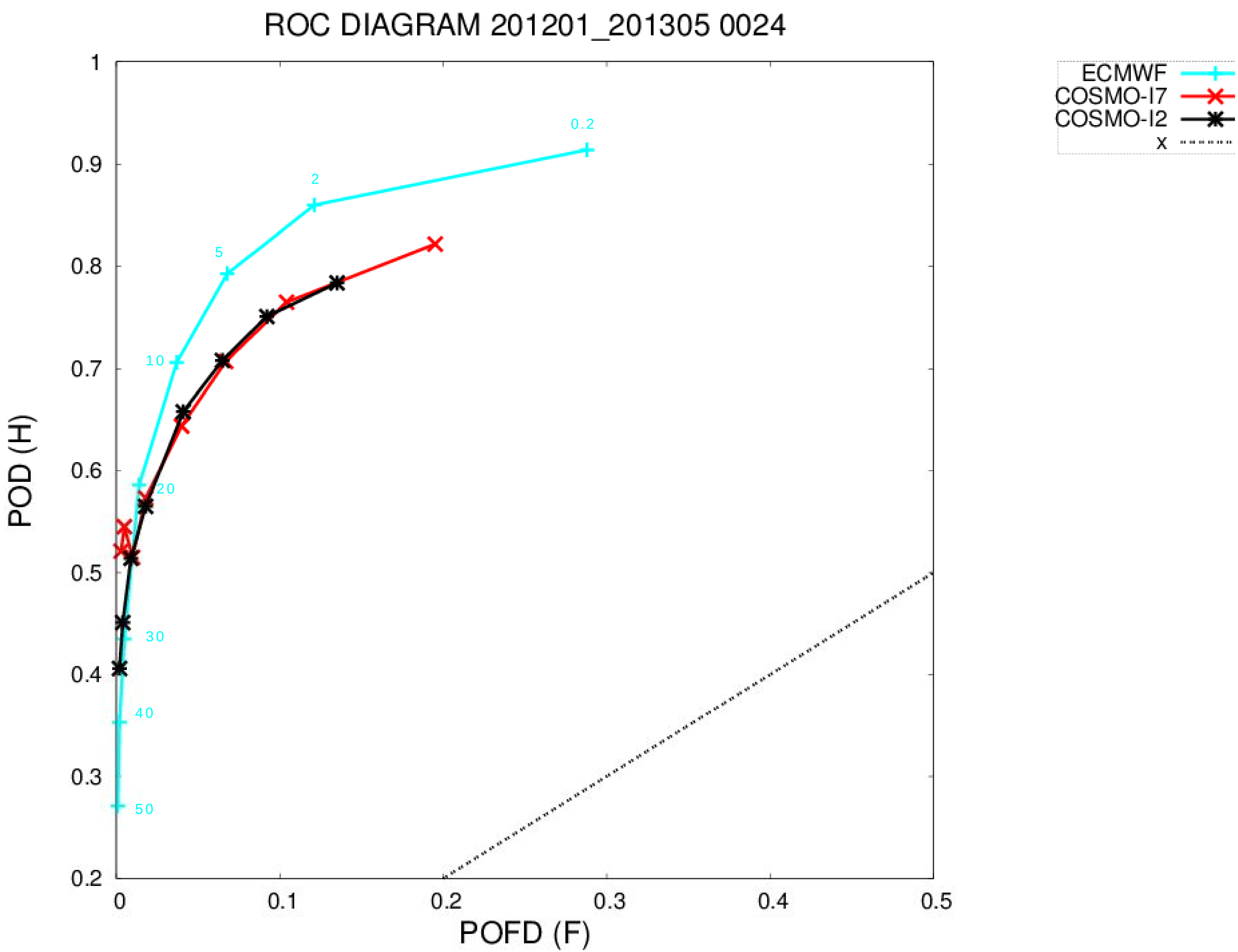






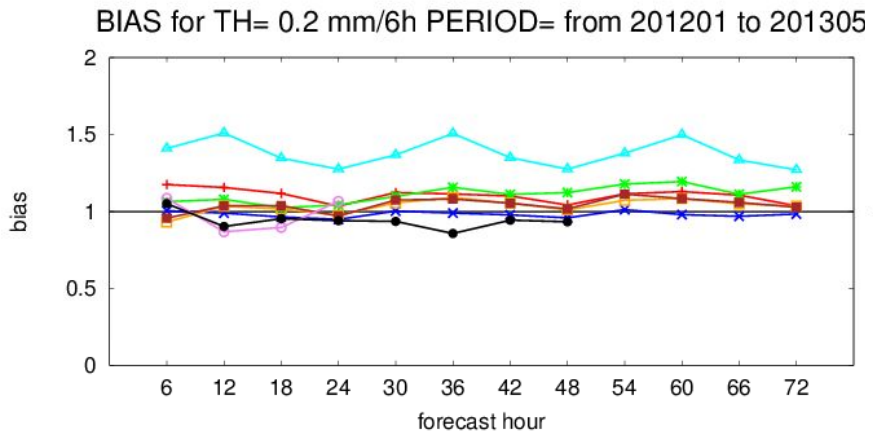


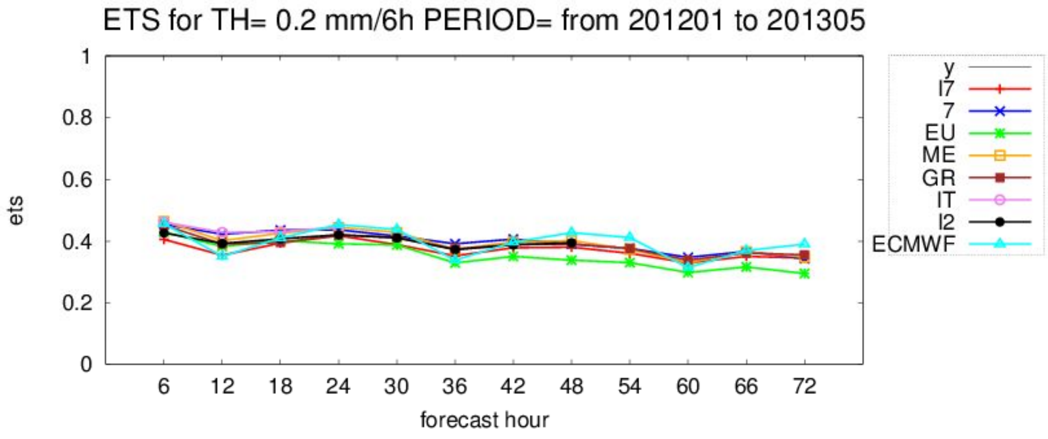
ROC DIAGRAM 201201_201305 0024
ECMWF
COSMO-ME
COSMO-IT
x
0.2
2
5
10
20
30
40
50
POD (H)
POFD (F)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
0.1
0.2
0.3
0.4
0.5

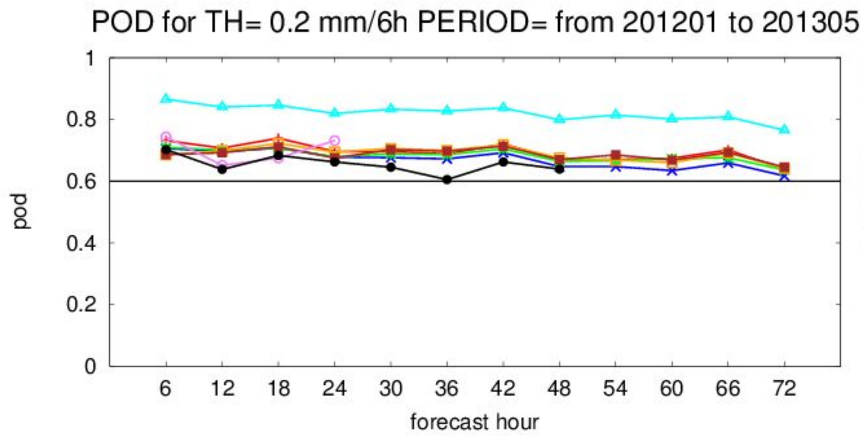


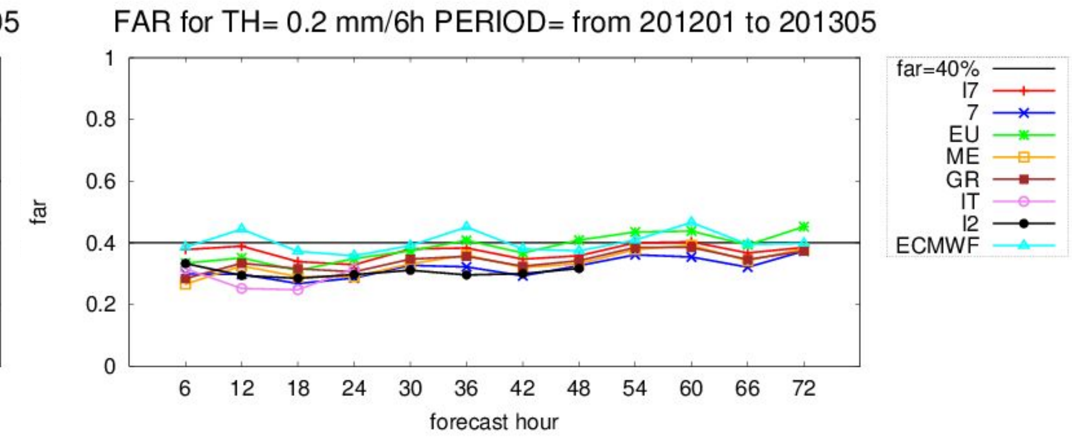
ROC DIAGRAM 201201_201305 0024
ECMWF
COSMO-I7
COSMO-I2
x
0.2
2
5
10
20
30
40
50
POD (H)
POFD (F)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
0.1
0.2
0.3
0.4
0.5

6h cumulated precipitation average over areas: 201201-201305

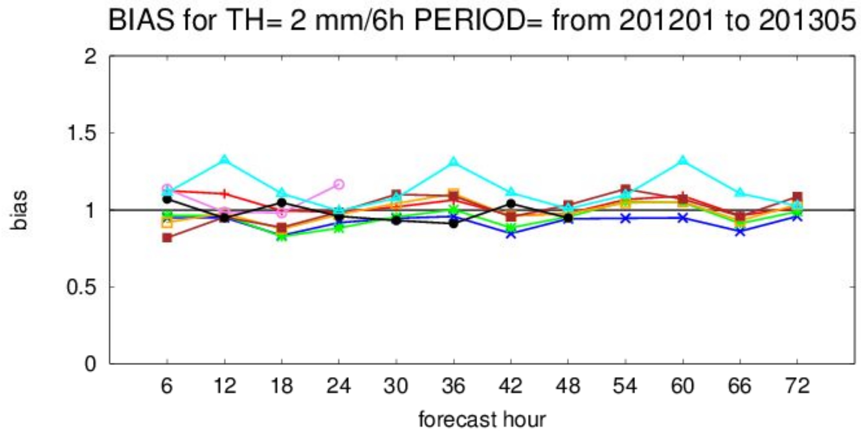


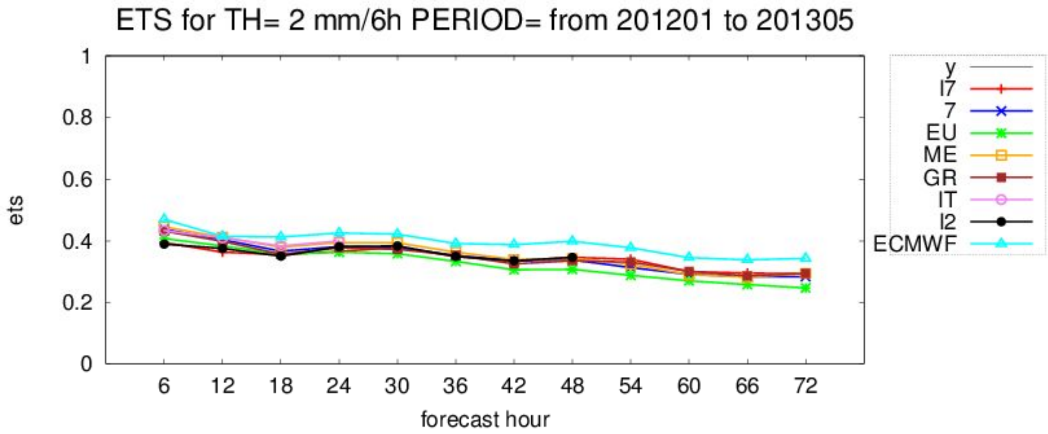


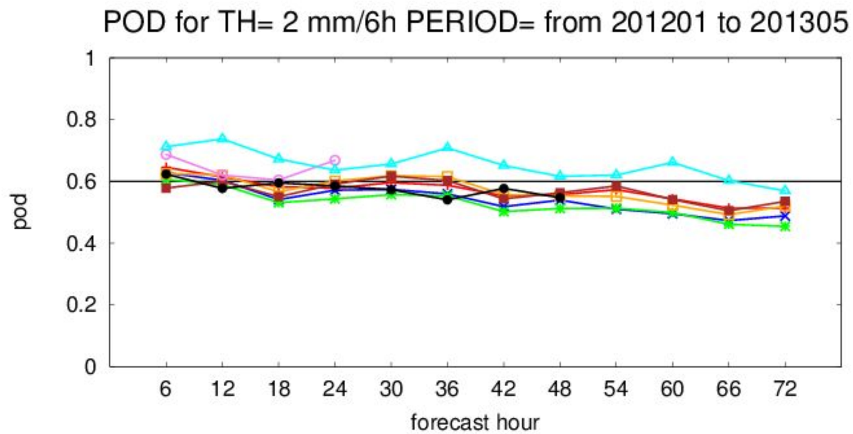


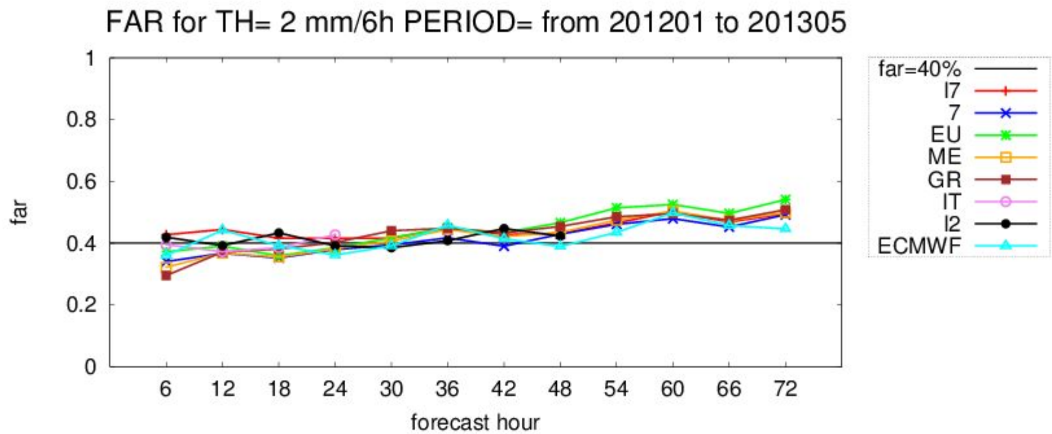


6h cumulated precipitation average over areas: 201201-201305

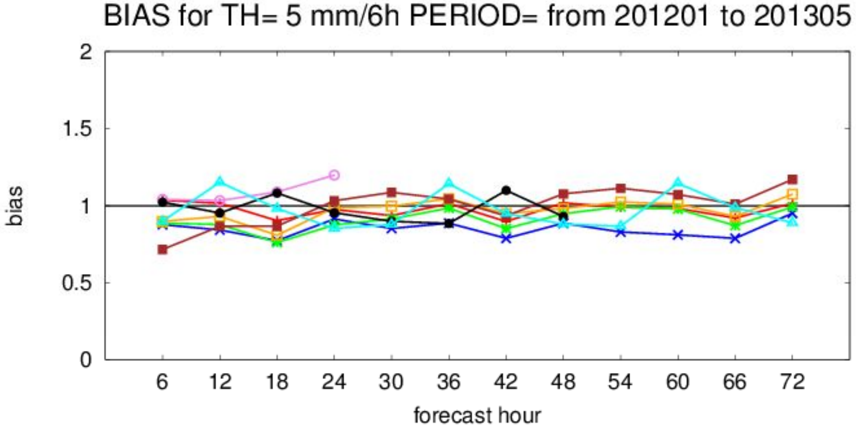


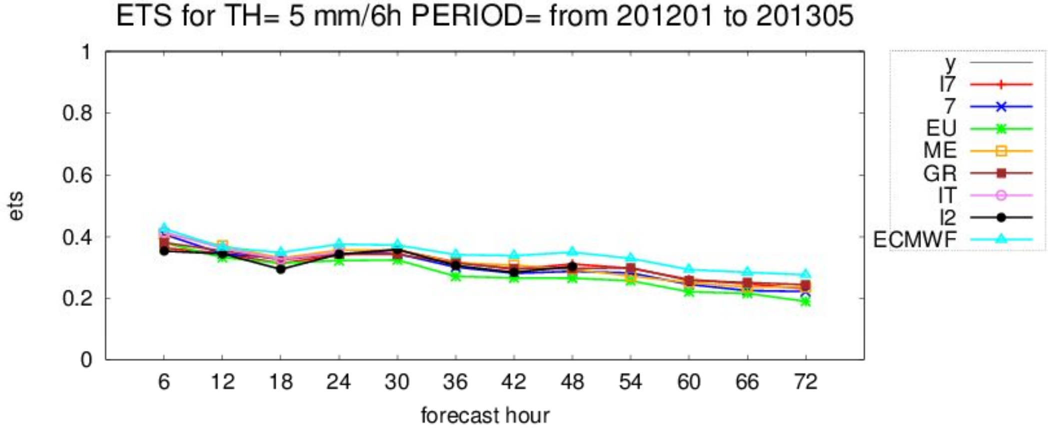


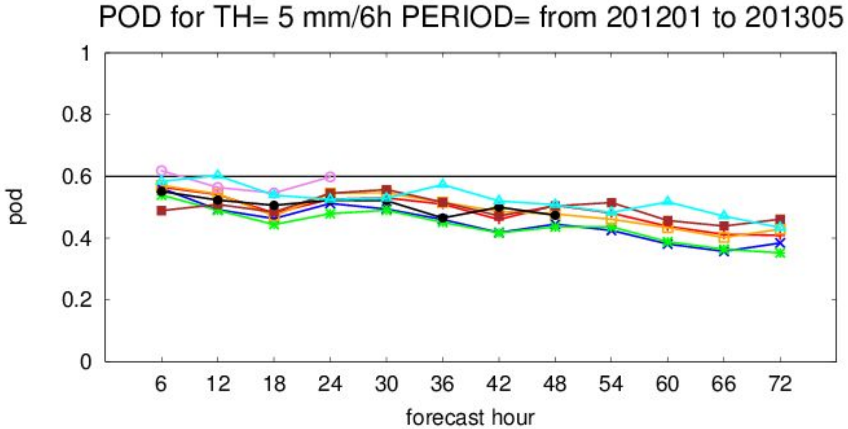


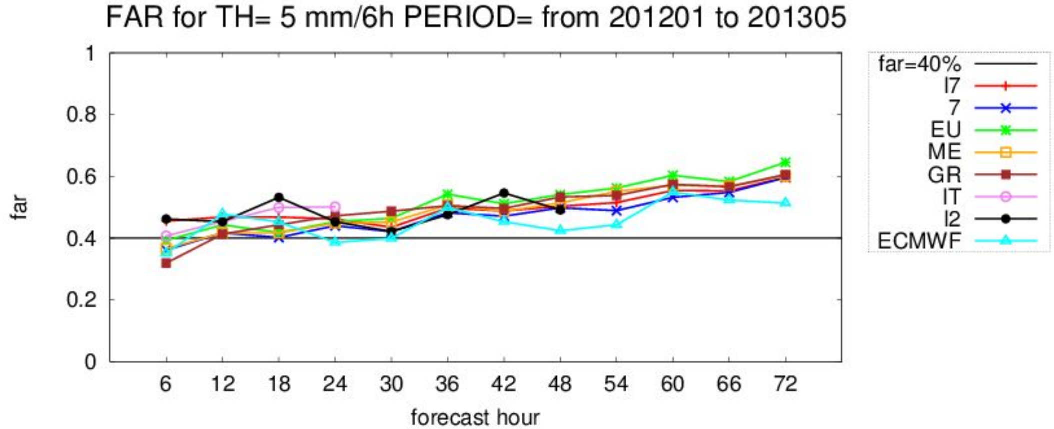


6h cumulated precipitation average over areas: 201201-201305

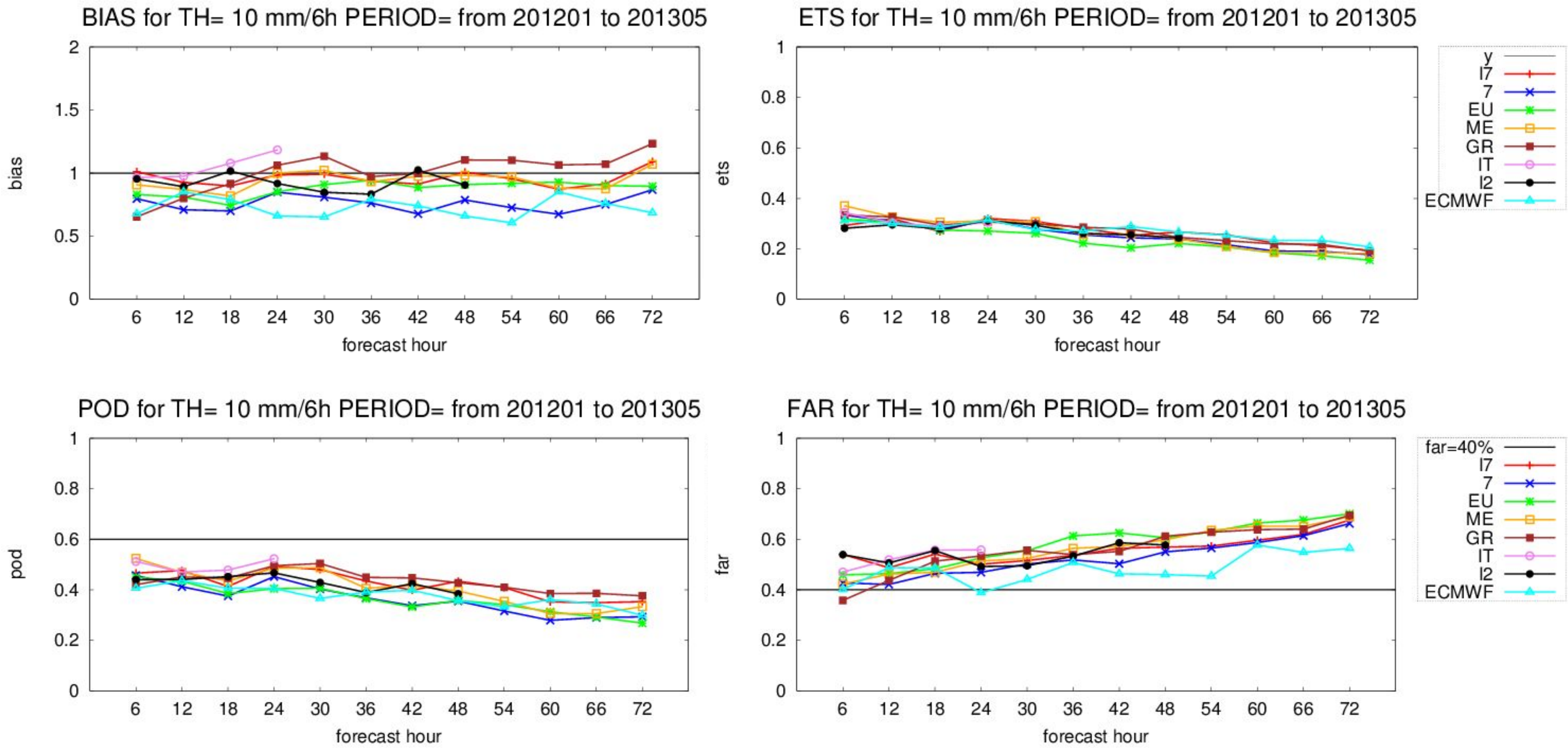




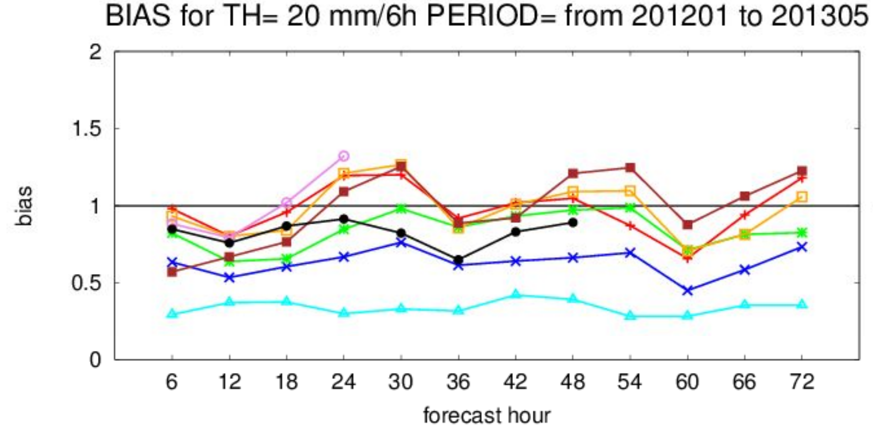


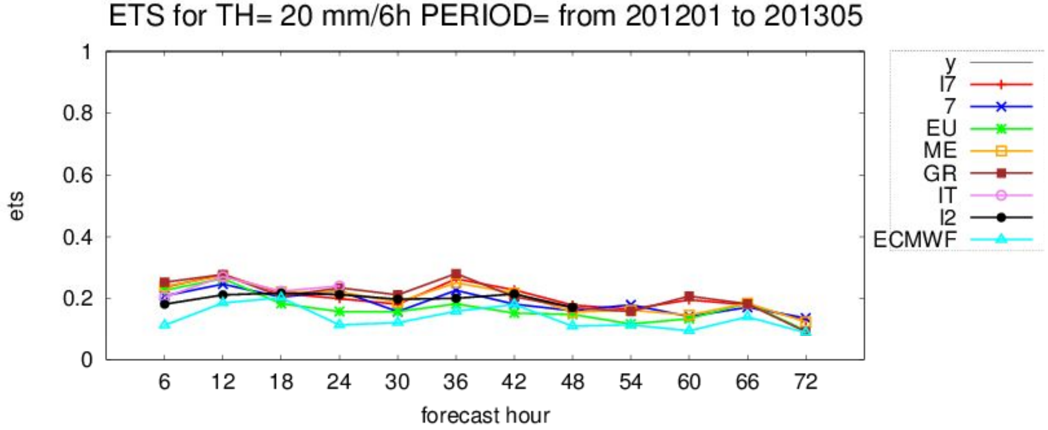


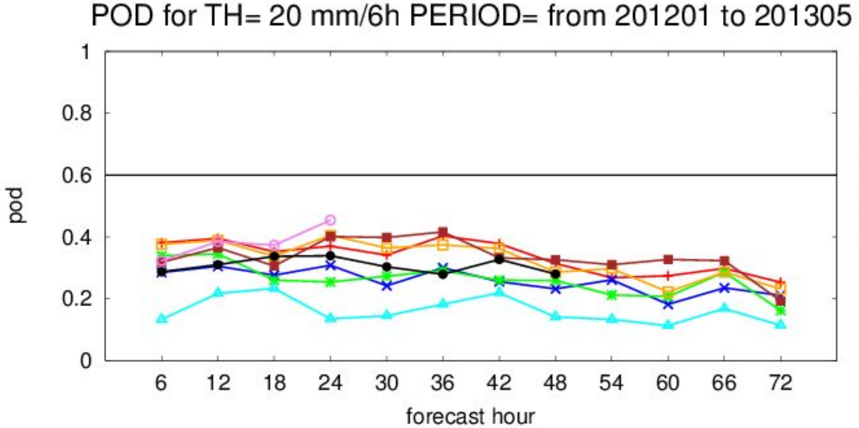
6h cumulated precipitation average over areas: 201201-201305

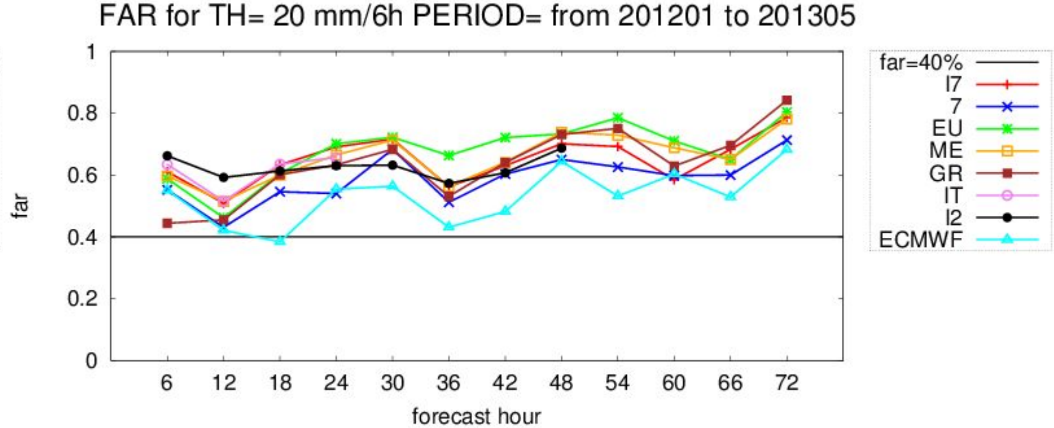


6h cumulated precipitation average over areas: 201201-201305

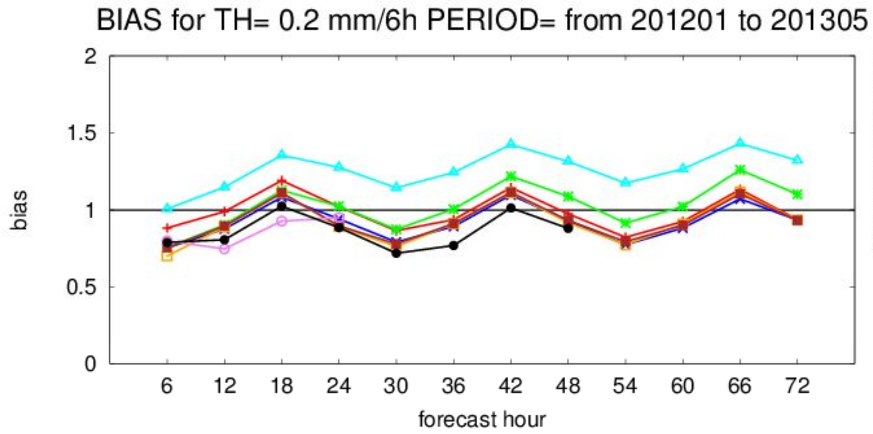


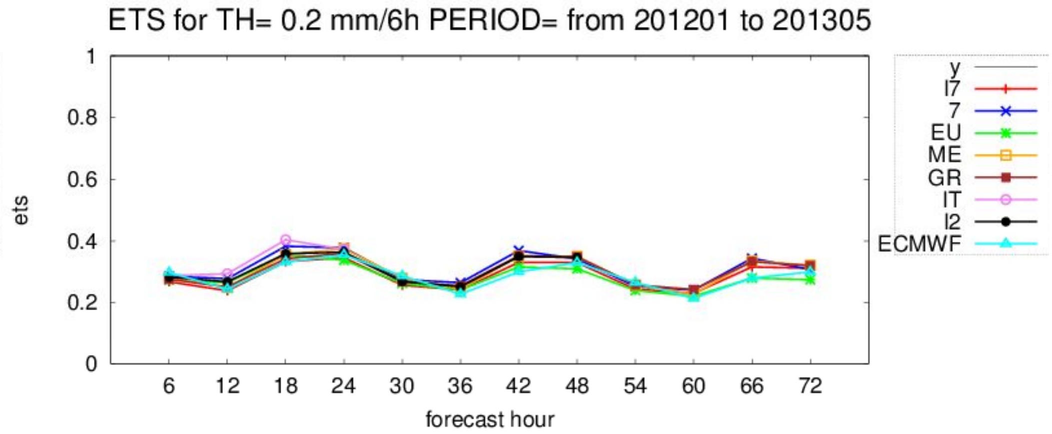


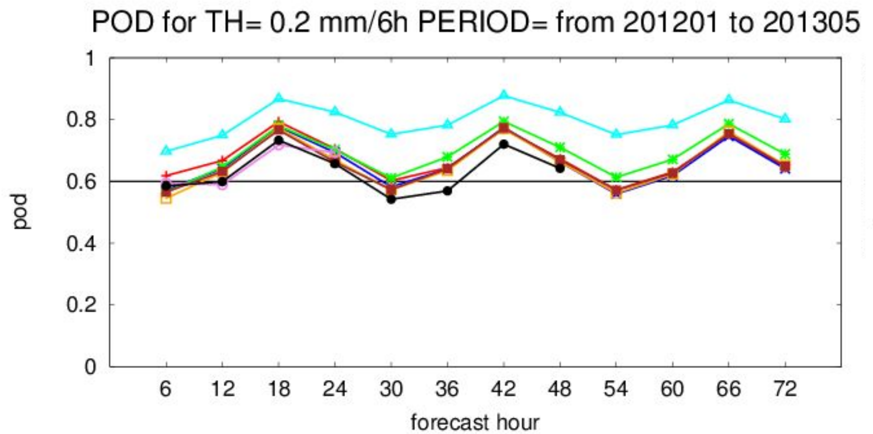


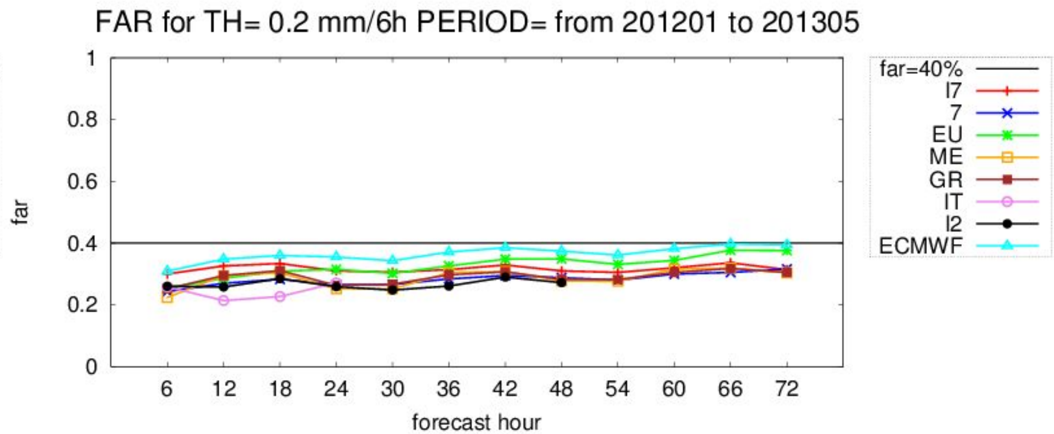


6h cumulated precipitation maximum over areas: 201201-201305

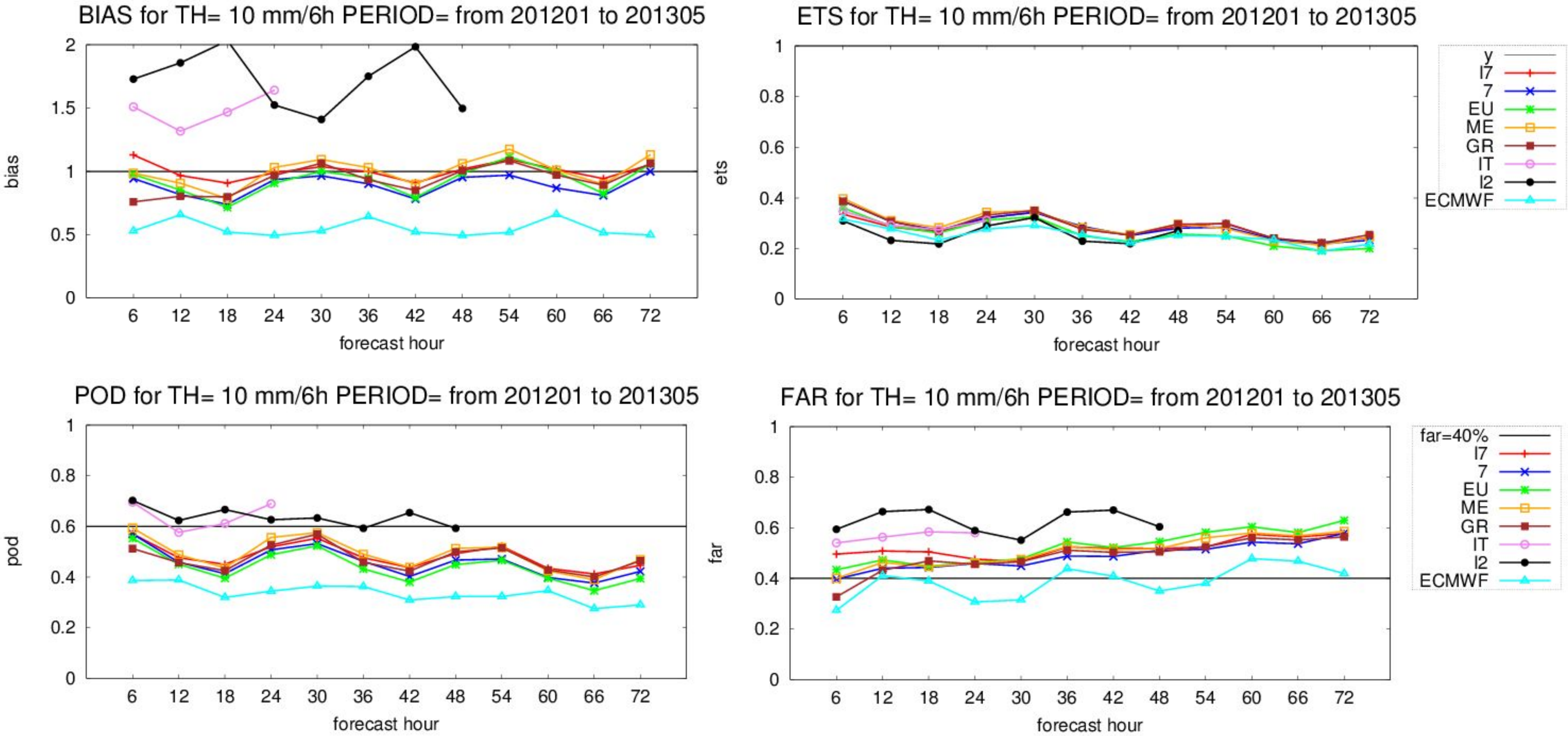




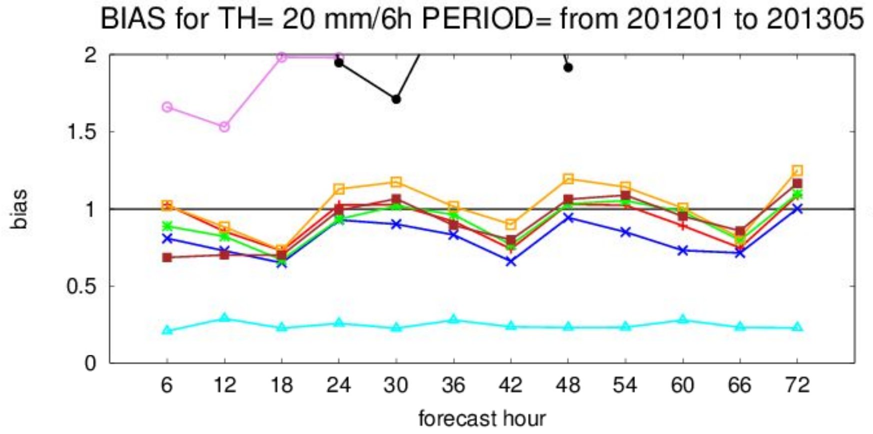


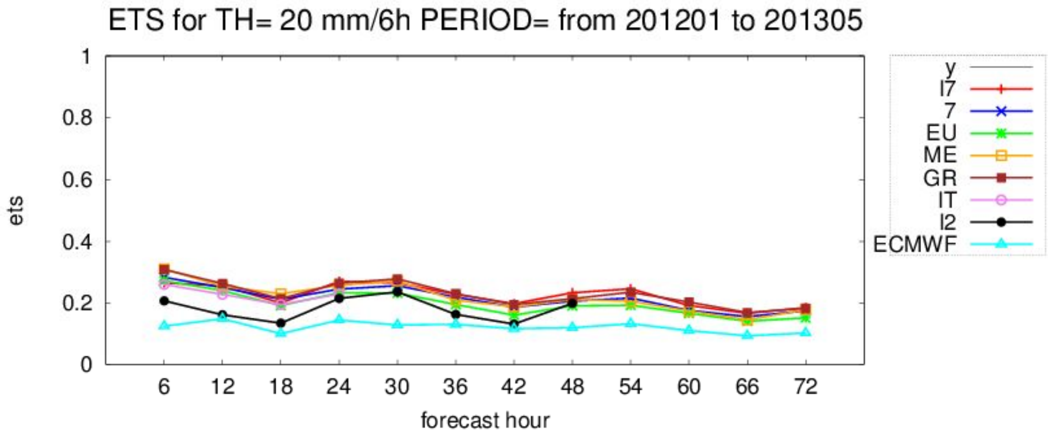


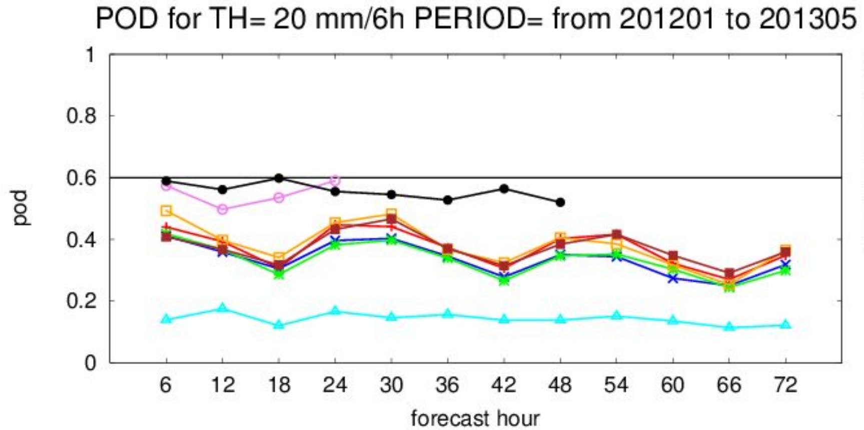
6h cumulated precipitation maximum over areas: 201201-201305

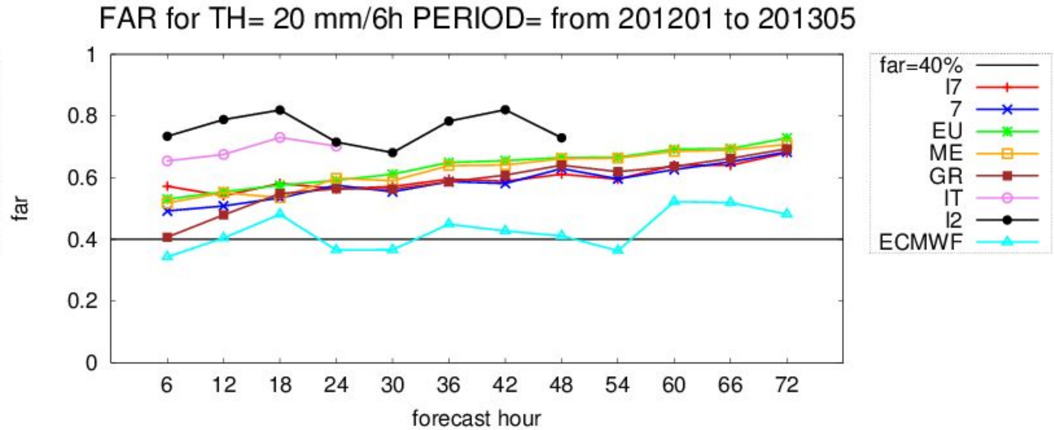


6h cumulated precipitation maximum over areas: 201201-201305









extreme dependency score → investigate the performance of an NWP model for rare events

Stephenson et al. Introduce the extreme dependency score (EDS) as a good alternative to standard scores for verification of rare events.

	Event observed yes	Event observed no	Total
Forecast yes	A	b	$a + b$
Forecast no	c	d	$c + d$
Total	$a + c$	$b + d$	$n = a + b + c + d$

frequency bias index	*FBI = (a + b)/(a + c)*	[0,∞] best 1	The frequency bias index indicates whether the forecasting system under or over-forecasts the number of events.
hit rate (POD)	*H = a/(a + c)*	[0,1] best 1	The hit rate represents the probability that the event is forecast when it occurs
false alarm rate (POFD)	*F = b/(b + d)*	[0,1] best 0	The false alarm rate represents the probability of forecasting the event when it did not occur. % not events obs. Not correctly forecasted. fraction of the observed "no" events were incorrectly forecast as "yes“.
true skill score	*T SS = H −F*	[-1,1] best 1	The true skill score gives information on how the forecasting system distinguishes between occurrences and not occurrences.
base rate	*BR = (a + c)/n*	[0,1]	The base rate represents the probability that the event occurs. By definition, 1-BR plotted versus increasing thresholds represents the probability that precipitation amount does not exceed a certain threshold.
extreme dependency score	*EDS= 2[ln((a+c)/n)/ln(a/n)] -1*	[-1,1] best 1	What is the association between forecast and observed rare events? Converges to 2η-1 as event frequency approaches 0, where η is a parameter describing how fast the hit rate converges to zero for rarer events. EDS is independent of bias, so should be presented together with the frequency bias

- To get clear information about how the forecasting system detects the extreme events, it would be fair if the EDS is compared for events having the same base rate. One has to investigate if better value of the EDS are related to an improvement in the quality of the forecasting system or if they are due to the event variability over the years.
- The equation defining the EDS uses the left hand side of a contingency table and the total number of cases (sample size). This results in an increased freedom for false alarms and correct negatives, which can freely vary with the only restriction that their sum has to be constant. Therefore, it is paramount to use the EDS in combination with other scores that include the right hand side of the contingency table, as the F and/or the FBI to show that improvements are not due to an increase of false alarms. (Ghelli&Primo,2009)

The affect of the base rate on the extreme dependency score (Ghelli&Primo,2009)

The Extreme Dependency Score (EDS) has been introduced as an alternative measure to verify the performance of numerical weather prediction models for rare events, taking advantage of the non-vanishing property of the score when the event probability tends to zero.
This score varies from 1 (best value) to −1 (worst value).

The EDS is written as a function of BR:

EDS =[ln(BR) − ln(HR)]/[ln(BR) + ln(HR)]

Equation presents the EDS as a function of the base rate and the hit rate. when HR = 1, the EDS = 1 and when BR = 1, the EDS = −1.
On the other hand, when the base rate is equal to one, the event happens all the time and so the EDS is not an appropriate score since it is focused on verification of extreme events (low probability of occurrence). Therefore, if different data samples need to be compared, it is imperative to have similar base rate.

- Thus, even if there are no misses and the EDS value is maximum, the forecasting system might have a high number of false alarms. Therefore, an EDS = 1 does not imply a skilful system. If values of the EDS for different periods need to be compared, then the base rate must be constant in time to avoid changes in the EDS to be just a reflection of changes in the BR.
- If the base rate is constant, an increase of the EDS implies a better probability of detection (hit rate), i.e. a more skilful system. If only the hit rate is constant, then an increase of the EDS is only due to a higher event probability. If neither the base rate nor the hit rate is constant, then the improvement of the EDS could be due to any of the previous reasons.

The extreme dependency score: a non-vanishing measure for forecasts of rare events (Stephenson et al.)

⬇

EDS takes the value of 1 for perfect forecasts and 0 for random forecasts, and is greater than zero for forecasts that have hit rates that converge slower than those of random forecasts

EDS has demonstrated here that there is dependency between the forecasts and the observations for more rare events, which is masked by the traditional skill scores that converge to zero as the base rate vanishes. EDS does not explicitly depend on the bias in the system for vanishing base rate and so is less prone to improvement by hedging the forecasts. EDS has the disadvantage that it is based only on the numbers of hits and misses, and so ignores information about false alarms and correct rejections. Therefore, EDS is non-informative about forecast bias, and a forecasting system with a good EDS could be very biased. Therefore, one should present EDS together with the frequency bias as a function of threshold in order to provide a complete summary of forecast performance.