Validation Report for "Precipitating Clouds" (PC-PGE04 v1.4)

SAF/NWC/CDOP/SMHI/VR/01, Issue 1 Rev. 4

19 November 2007

Applicable to SAFNWC/MSG version 2008

Prepared by SMHI

REPORT SIGNATURE TABLE

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DOCUMENT CHANGE RECORD

Version	Date	Pages	CHANGE(S)
0.0	19 November 2007		Original internal version on prototyping results
1.0	*24 October 2006*		Updated to match v2.0 of PGE04, shortened for better clarity for the user.
1.0	*31 January 2007*		Implemented modifications after ORR-2, OBJ1_SCI_Rep_PGE04 Rid numbers:67, 69,70,72 73, 74,75,76,77,78
1.0	*28 February 2007*		Changed PGE04 preliminary version2.0 to v1.3 in accordance with SG-11 decision
1.4	*19 November 2007*		Document content identical with SAF-NWC-IOP-SMHI-MSG-SCI-RP-04 v1.0 For release of MSG package 2007 No scientific updates, adapted document name and references to CDOP naming convention

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1. INTRODUCTION

1.1 PURPOSE

This document describes scientific prototyping and validation for the MSG Precipitating Clouds (PC) product for a one year period (2004) as has been performed in preparation for v2.0 of the software. The precipitating clouds product supplies estimates of precipitation likelihood to support Nowcasting applications.

1.2 SCOPE OF THE DOCUMENT

This document summarises prototyping and verification results directly applicable to version 2.0 of PGE04. Main new feature in this version is the introduction of cloud type dependent tuning of an algorithm developed on a one year dataset of French gauge data (2004) and verified on Hungarian gauge data for 2004. For reference, results from prototyping work for a cloud type independent tuning of the same algorithm (same coefficients used in calculating the precipitation index PI which is matched to precipitation likelihood) are supplied as well, even if auxiliary files for this version of cloud type independent tuning are not supplied with version 2.0.

The PC algorithm supplied with version 1.2 of PGE04 software, which was developed using the current weather code in synop observations over Europe and northern Afrika and verified against gauge observations, can still be configured to be used with the 2.0 softwarepackage when not specifying cloud type dependence. Therefore a summary of validation results for this algorithm supplied previously in [RD2] is given as well.

1.3 DEFINITIONS, ACRONYMS AND ABBREVIATIONS

AMSU	ATOVS Microwave Sounding Unit
AVHRR	Advanced Very High Resolution Radiometer (onboard NOAA and EPS satellites)
BRDC	BALTRAD Radar Data Centre
CT	Cloud type
MSG	Meteosat Second Generation
NWCSAF	Satellite Application Facility for NowCasting and Very Short Range Forecasting
PI	Precipitation Index
PGE	Product Generating Element
PC	Precipitating Cloud
SEVIRI	Imager onboard MSG
SMHI	Swedish Meteorological and Hydrological Institute

1.4 REFERENCES

1.4.1 Applicable Documents

Reference	Title	Code	Vers	Date
[AD 1]	Scientific User manual for MSG PGE04	SAF/NWC/CDOP/SMHI-MSG/SCI/SUM/04	1.4	2008 TBD
[AD 2]	Software Users Manual (SW/SUM) and the Software Users Manual for the Task Manager of the SAFNWC/MSG	SAF/NWC/CDOP/INM/SW/SUM/2	2.1	2008 TBD
[AD 3]	Interface Control Document for the External and Internal Interfaces of the SAFNWC/MSG	SAF/NWC/CDOP/INM/SW/ICD/1	2.1	2008 TBD
[AD 4]	SAFNWC/MSG Output Product Format Definition	SAF/NWC/CDOP/INM/SW/ICD/3	2.1	2008 TBD
[AD 5]	Architectural Design Document for the SAFNWC	SAF/NWC/CDOP/INM/SW/AD/1	2.1	2008 TBD

Table 1: List of Applicable Documents

1.4.2 Reference Documents

Reference	Title	Code	Vers	Date
[RD 1]	Scientific report on checking and tuning for MSG PGE04	SAF/NWC/IOP/SMHI/MSG/SCI/RP/02, Issue 1, Rev. 2	1.3	
[RD 2]	Scientific report on checking MSG PGE04 version 1.2	SAF/NWC/IOP/SMHI/MSG/SCI/RP/03 , Issue 1	1.0	

Table 2: List of Referenced Documents

1.5 SOFTWARE VERSION IDENTIFICATION

This document is compliant with version 2008 of the SAFNWC software package.

2 TUNING EVALUATION CLOUD TYPE DEPENDENT TUNING

The mapping of the likelihood thresholds is evaluated for the different cloud type groups, CT 9-10 (medium level clouds), CT 11-14 (high and very high opaque clouds), CT 17 (high semi-transparent thick clouds) and CT 18 (high semi-transparent above lower clouds). These are the cloud types expected to provide precipitation; all others cloudtypes are not considered to be precipitating.

2.1 LIKELIHOOD THRESHOLDS

When investigating how different cloud types match the observed likelihood of precipitation, it becomes apparent that the overall fit of likelihood estimate to observed precipitation frequency can be improved by cloud type dependent tuning. The algorithm to estimate likelihood has been calibrated on French gauge data without taking into account different cloud types and has been validated on Hungarian gauge data and thus providing an independent validation.

The threshold seems to have been well represented. The amount of derived rain cases correspond to the observed amount. The day algorithm looks good and also the night algorithm for low likelihood thresholds.

The rain cases of the PC product are now studied for different cloud type groups:

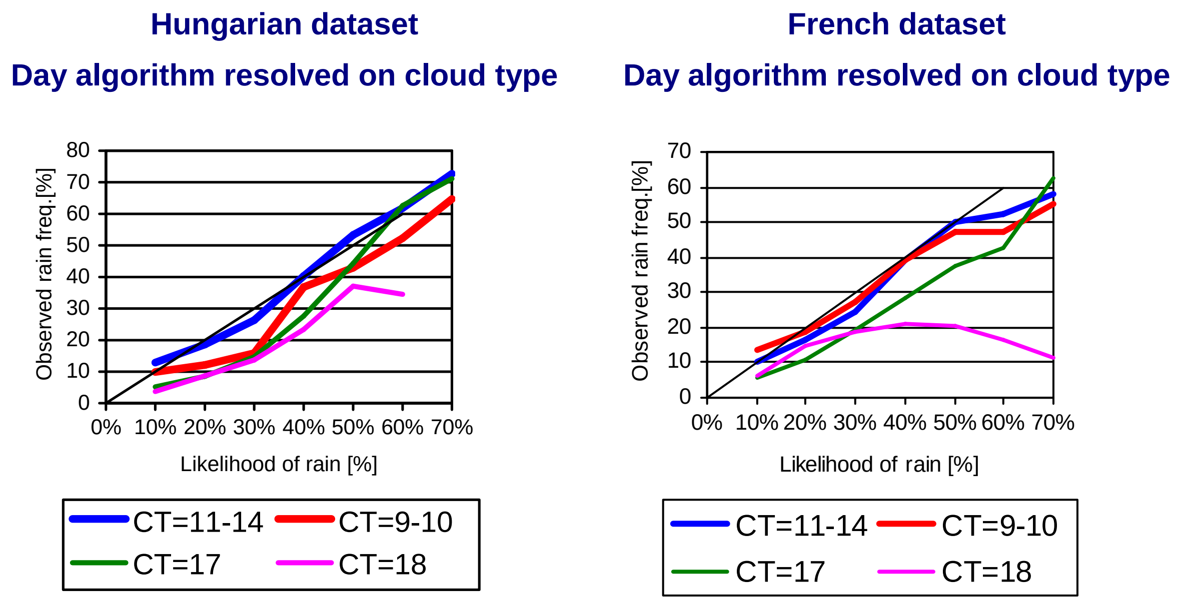


Figure 1 Likelihood of rain versus observed rain frequency resolved on cloud type. Day algorithm tuned on French data without tuning to specific cloud classes. This algorithm was used for prototyping, but is not part of v2.0 delivery:.

This study shows that for the high opaque clouds (CT 11-14) the mapping of the precipitation index gives likelihood very close to the actual observed quantity. For other cloud types the likelihood is overestimated.

The differences for the cloud types are even more obvious for the night algorithm:

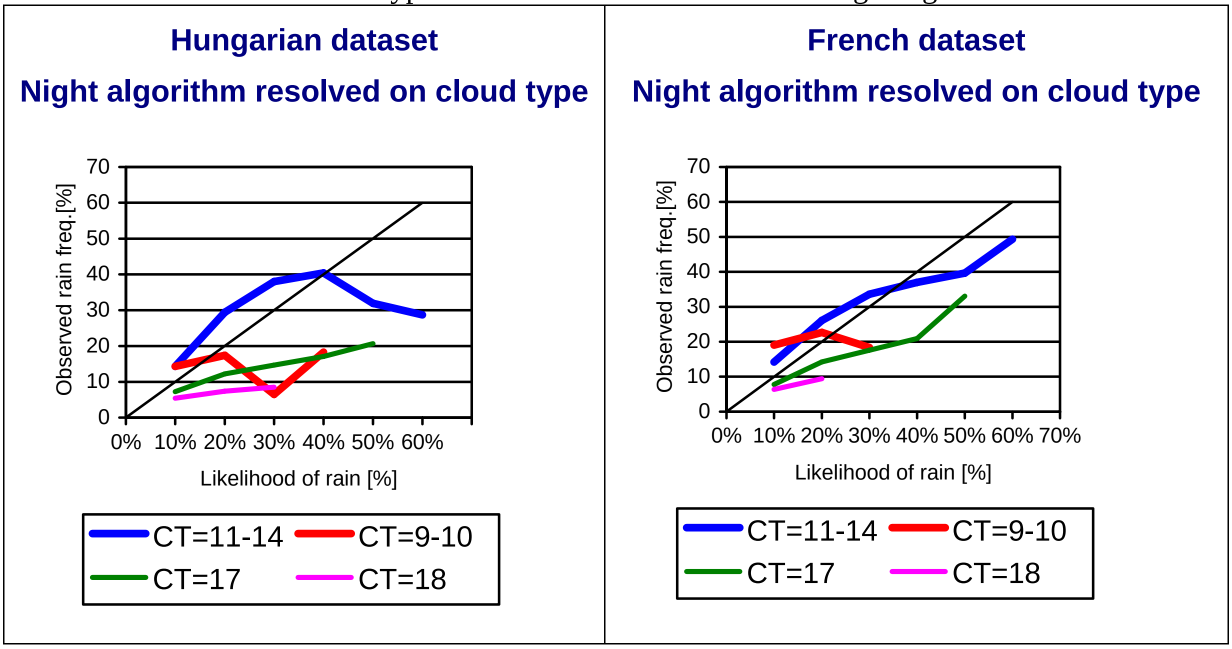


Figure 2 Likelihood of rain versus observed rain frequency resolved on cloud type for night algorithm

For the night algorithm high rain is underestimated for high and very high clouds in the range of 20%- 30% (40% when comparing to Hungarian data). In the same intensity interval rain is overestimated for cirrusclasses and partly even for medium high clouds. For the night algorithm the result looks good overall, but are there differences for different cloud types. This shows the importance of handling the cloud classes separately.

2.2 Cloud type dependent tuning- day algorithm

The constants of the equation for calculating the precipitation index are not re-tuned. Only the likelihood threshold mapping is changed and every group of cloud gets its own mapping. The mapping is tuned on French gauge dataset like the earlier tuning and therefore the new thresholds corresponds well to the French gauge dataset but not as well to the Hungarian dataset.

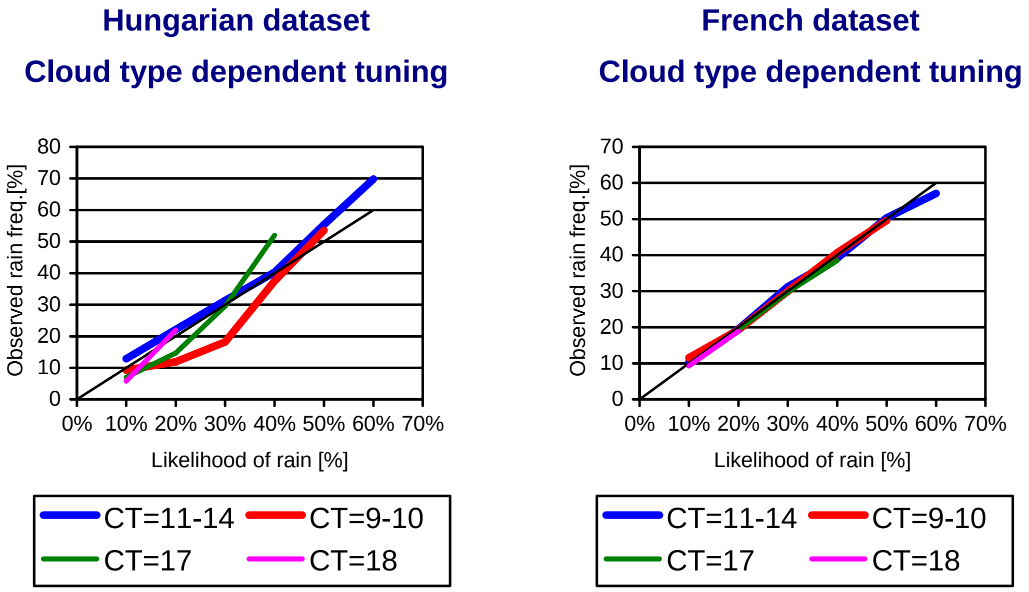


Figure 3: Likelihood of rain versus observed rain frequency. Cloud type dependent tuning on French gauge data for day algorithm.

2.3 Cloud type dependent tuning- night algorithm

The tuning of the likelihood mapping of the night algorithm is a more delicate problem because of the small amount of co-locations- especially for the high semi-transparent clouds above lower clouds (CT 18).

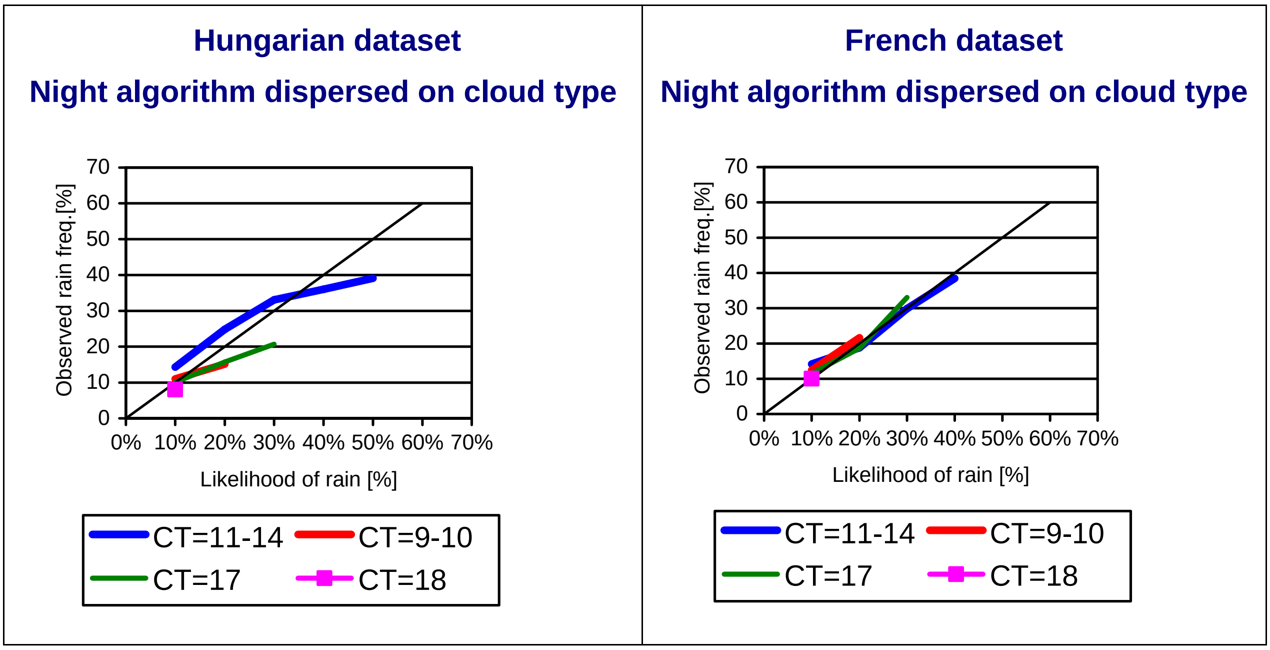


Figure 4 Likelihood of rain versus observed rain frequency. Cloud type dependent tuning on French gauge data.

3 VALIDATION RESULT OF CT DEPENDENT TUNING

3.1 SCORES

To summarize the information content of contingency tables, a number of scores have been calculated as defined below:

	Satellite rain	Satellite no rain
Reference rain	**Hits**	**Misses**
Reference no rain	**False alarms**	**Correct negatives**

Table 3 : Score definition

Probability of detection: POD=hits / (hits+misses)

False alarm rate: FAR=false alarms / (false alarms+hits)

Probability of false detection: POFD=false alarms / (correct negatives + false alarms)

Hansen Kuiper descriminant: HK=POD-POFD

Bias score (0 to infinity, 1 = unbiased):

Bias=(hits+false alarms) / (hits + misses)

Accuracy (=percent correct/100.):

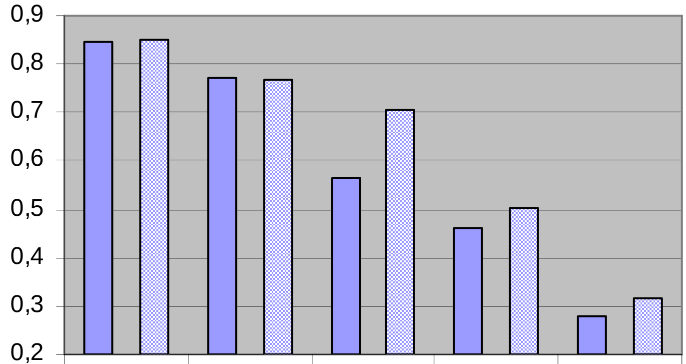
ACC=(hits + correct negatives) / (total)

3.2 VALIDATION AGAINST HUNGARIAN DATA

The Hungarian dataset represents an independent reference source for the algorithm tuned on French data. For the whole year 238095 co-locations were found and scores are derived for the whole year of 2004.

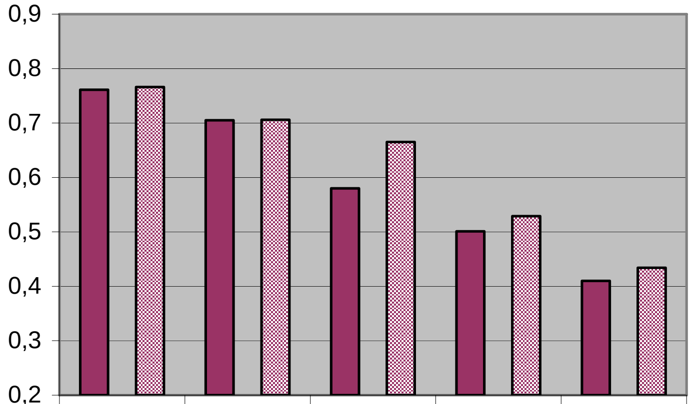
The results for the two cases of cloud type dependent tuning are compared to the earlier validation results. For all cases the PI calculation is tuned on French gauge data, but the tuning of the likelihood mapping differs. In the CT non dependent case the mapping is the same for all cloud types and tuned on French gauge data. In the CT tuning on France case the mapping is tuned on French gauge data and differs between the cloud types.

Tuning on CT versus non CT dependent tuning
POD- probability of detection



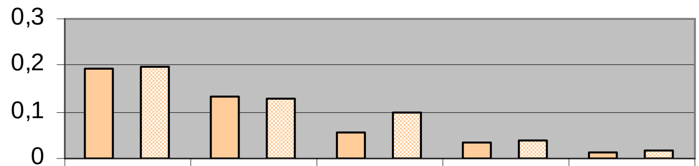
	10%	20%	30%	40%	50%
Tuning on France	0,848	0,771	0,566	0,462	0,279
Non CT dependent tuning	0,852	0,767	0,704	0,503	0,315

Tuning on CT versus non CT dependent tuning
FAR- false alarm ratio



	10%	20%	30%	40%	50%
Tuning on France	0,761	0,705	0,58	0,501	0,41
Non CT dependent tuning	0,766	0,706	0,665	0,529	0,434

Tuning on CT versus non CT dependent tuning
POFD- probability of false detection



	10%	20%	30%	40%	50%
Tuning on France	0,191	0,131	0,055	0,033	0,014
Non CT dependent tuning	0,197	0,13	0,099	0,04	0,017

Figure 5 Validation against Hungarian data: POD, FAR and POFD result for day algorithm. Cloud type dependent versus non dependent map tuning

The differences are small. For 20% threshold (that is recommended in earlier versions) POD-score increases slightly while FAR and POFD is the same for the French CT tuning.

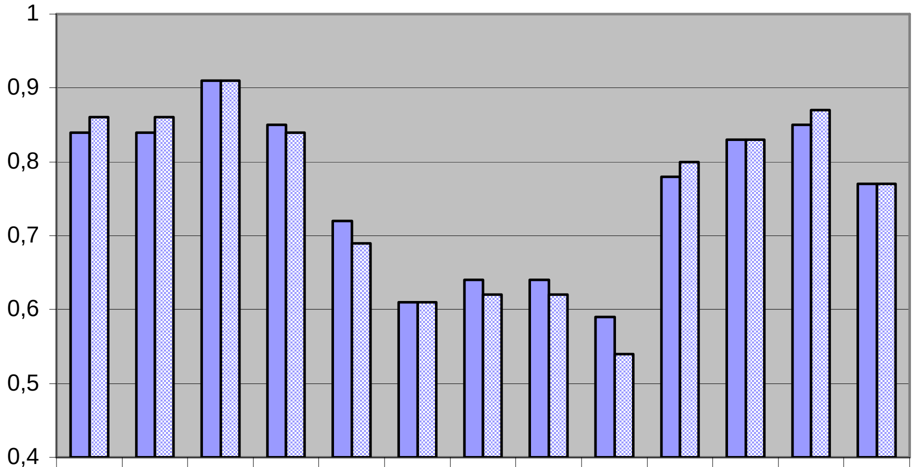
On the other hand: for 30% threshold and for both CT tuning algorithms FAR decreases when using the cloud type dependent tuning, but not as much as the POD score. Since POFD decreases even more, it is hard to say anything about if this is a deterioration or an improvement.

Overall only a very slight improvement by applying cloud type dependent tuning can be observed. Results more stratified for different situations (month, Cloud type etc) are presented below.

3.2.1.1 Validation result on separate months

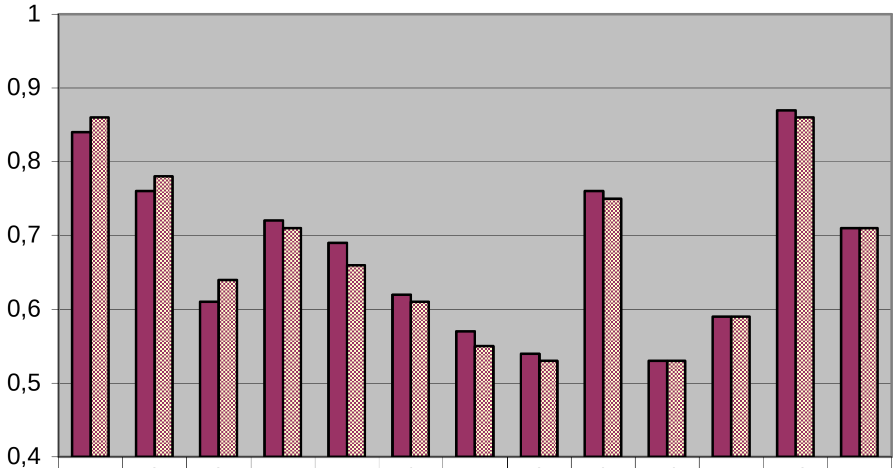
Diagrams with scores monthly separated shows that there is a break even for the scores, better POD gives worse FAR and POFD.

POD distributed on months
Tuning on CT versus non CT dependent tuning

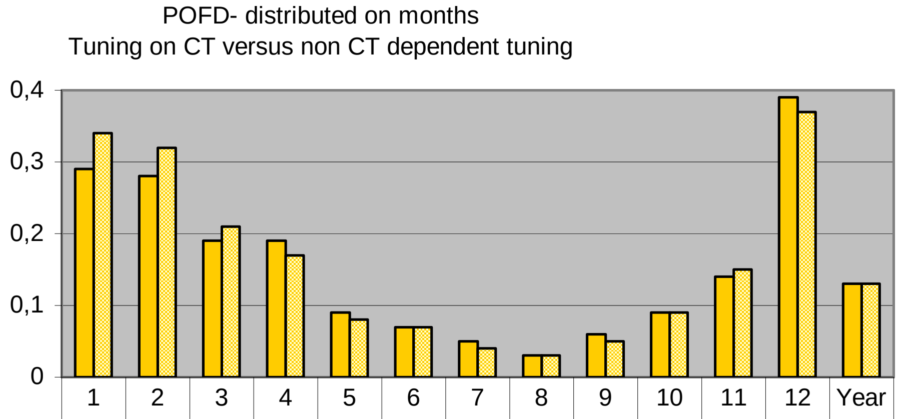


	1	2	3	4	5	6	7	8	9	10	11	12	Year
Tuning on France	0,84	0,84	0,91	0,85	0,72	0,61	0,64	0,64	0,59	0,78	0,83	0,85	0,77
Non CT dependent tuning	0,86	0,86	0,91	0,84	0,69	0,61	0,62	0,62	0,54	0,8	0,83	0,87	0,77

FAR- distributed on months
Tuning on CT versus non CT dependent tuning



	1	2	3	4	5	6	7	8	9	10	11	12	Year
Tuning on France	0,84	0,76	0,61	0,72	0,69	0,62	0,57	0,54	0,76	0,53	0,59	0,87	0,71
Non CT dependent tuning	0,86	0,78	0,64	0,71	0,66	0,61	0,55	0,53	0,75	0,53	0,59	0,86	0,71



	1	2	3	4	5	6	7	8	9	10	11	12	Year
Tuning on France	0,29	0,28	0,19	0,19	0,09	0,07	0,05	0,03	0,06	0,09	0,14	0,39	0,13
Non CT dependent tuning	0,34	0,32	0,21	0,17	0,08	0,07	0,04	0,03	0,05	0,09	0,15	0,37	0,13

Figure 6 *Validation against Hungarian data: POD, FAR and POFD result for day algorithm distributed on months. Cloud type dependent tuning versus non dependent tuning.(Threshold 20%)*

These diagrams shows that POD is generally higher (good!) in the summer, at the cost of FAR (and POFD) which is also higher (bad!). For the winter months the contrary is true.

This may be an effect of that the dominating cloud types are different in winter and summer, and the tuning adjustment affects the cloud classes different much. However, there is no extreme monthly variance and over the year difference average out.

3.2.1.1 Validation result on separate cloud types

It is of interest to study the result of each cloud type for the CT dependent tuning. This validation is for the day algorithm against Hungarian data. Note that probabilities of false detection are much higher, since only statistics within the respective and possibly precipitating cloud type are presented.

CT 9-10:

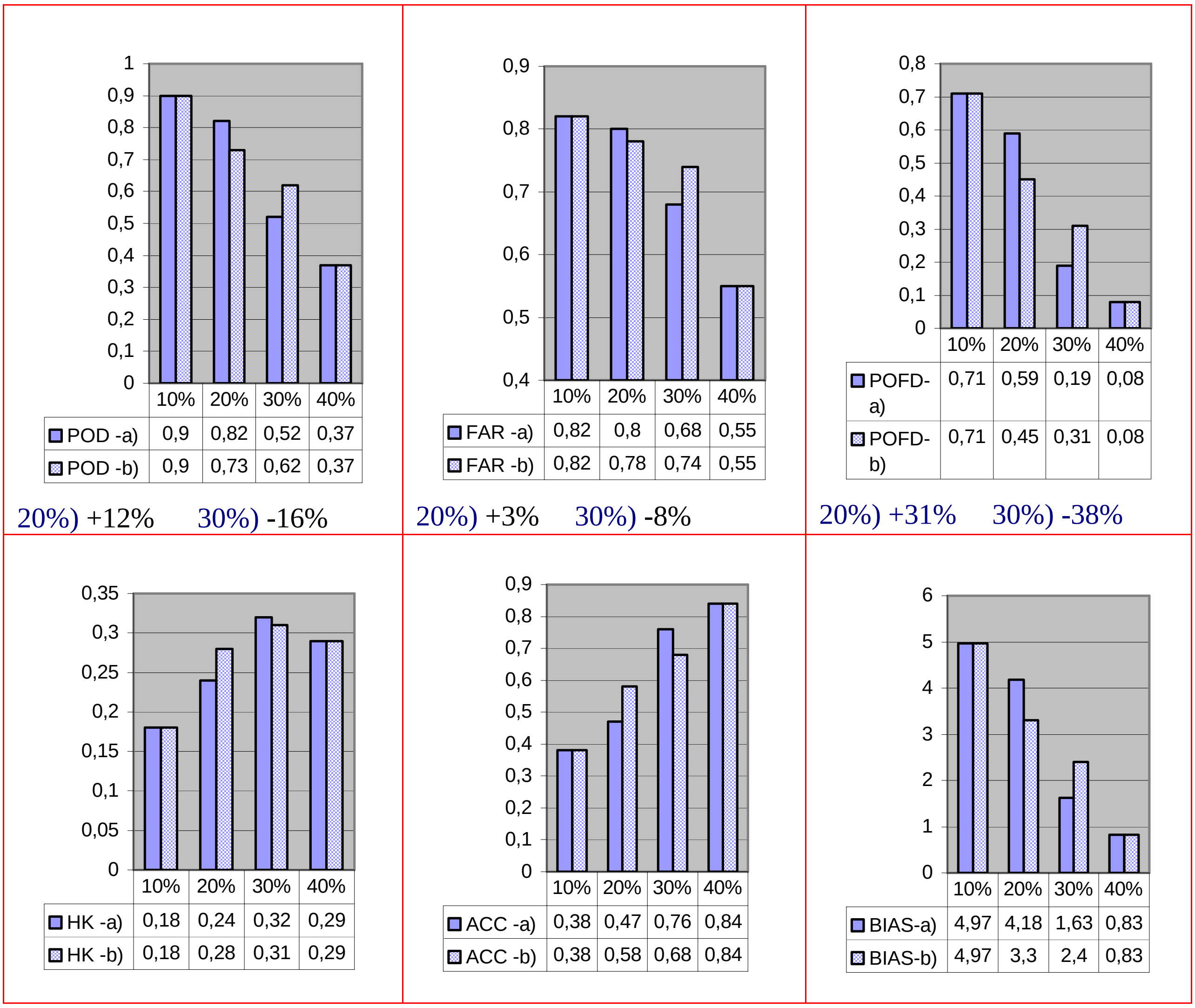


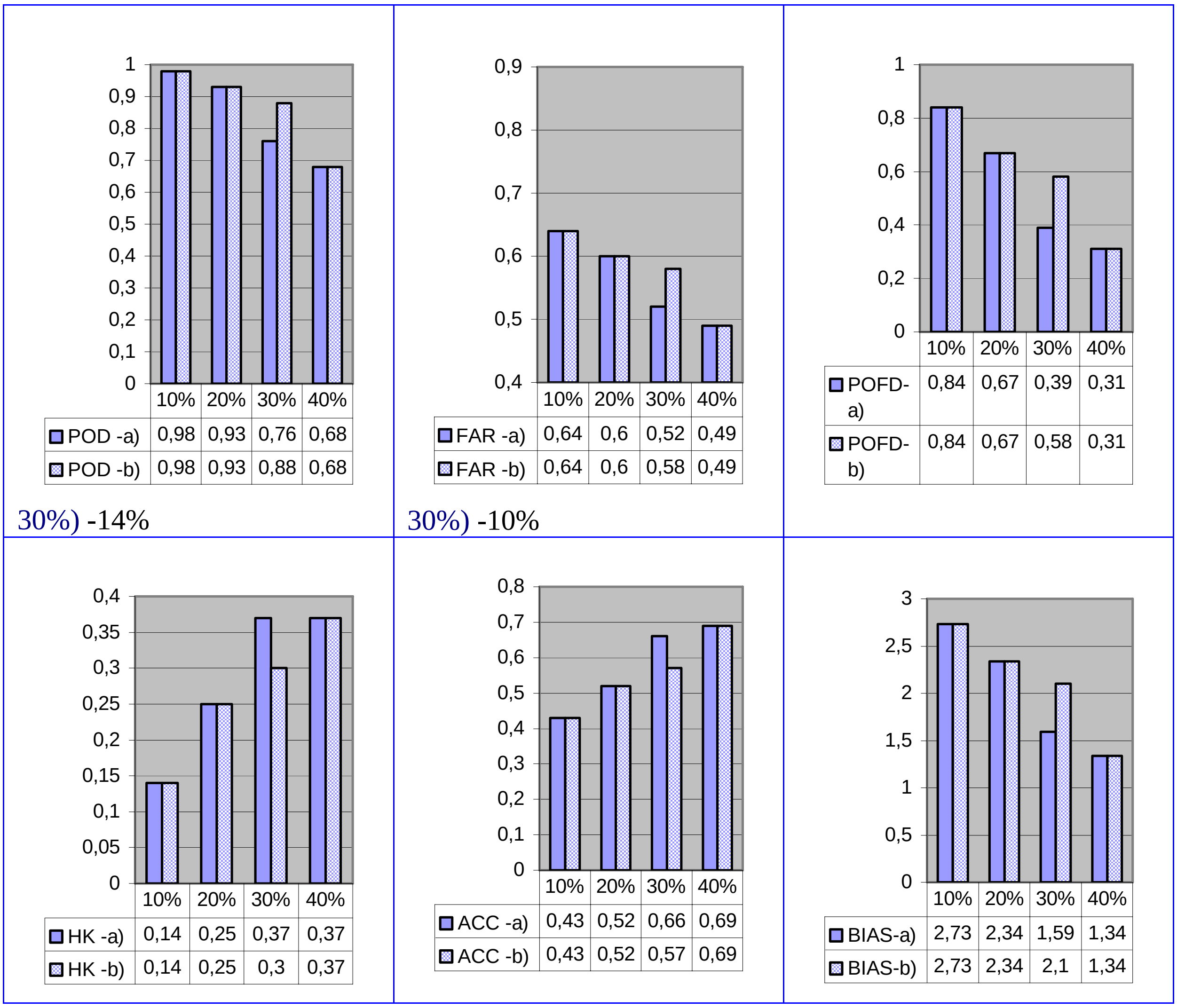
Figure 7 Cloud type dependent tuning versus non dependent tuning. Only CT 9-10.

a) CT dependent tuning *b)CT non dependent tuning, reference*

The result for 30% threshold looks really better for the cloud type dependent tuning, for all scores but POD- probability of detection- that one is low with only 50%of precip detected at this level when a hardclustering with this threshold is performed!

The 20% might still be more adequate as a hardclustering threshold for precipitation ensuring 82% detection of precipitating medium level clouds.

CT 11-14:



	10%	20%	30%	40%
POD -a)	0,98	0,93	0,76	0,68
POD -b)	0,98	0,93	0,88	0,68

	10%	20%	30%	40%
FAR -a)	0,64	0,6	0,52	0,49
FAR -b)	0,64	0,6	0,58	0,49

	10%	20%	30%	40%
POFD-a)	0,84	0,67	0,39	0,31
POFD-b)	0,84	0,67	0,58	0,31

30%) -14%

30%) -10%

	10%	20%	30%	40%
HK -a)	0,14	0,25	0,37	0,37
HK -b)	0,14	0,25	0,3	0,37

	10%	20%	30%	40%
ACC -a)	0,43	0,52	0,66	0,69
ACC -b)	0,43	0,52	0,57	0,69

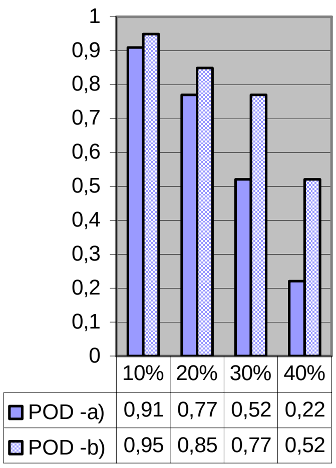
	10%	20%	30%	40%
BIAS-a)	2,73	2,34	1,59	1,34
BIAS-b)	2,73	2,34	2,1	1,34

Figure 8 Cloud type dependent tuning versus non dependent tuning. Only CT 11-14.

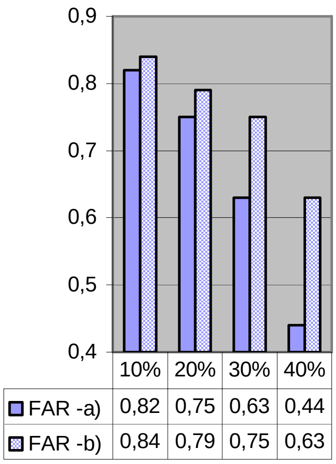
a) CT dependent tuning *b) CT non dependent tuning, reference*

Only the 30% threshold seems to have been affected. The POD has decreased, but all other scores are improved marked. With some hesitation the CT dependent tuning improves the result for threshold 30%.

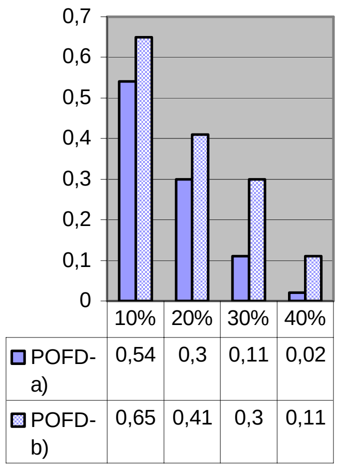
CT 17:



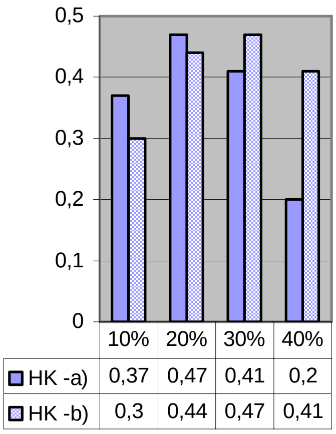
20%) -9% 30%) -32%

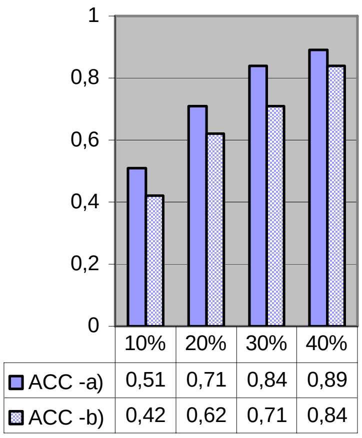


20%) -5% 30%) -16%



20%) -27% 30%) -63%





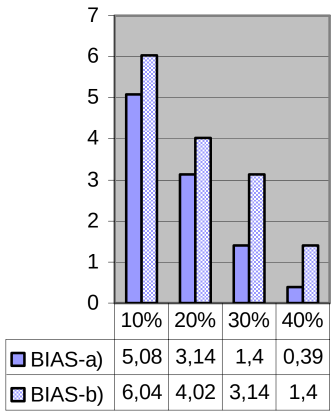


Figure 9 Cloud type dependent tuning versus non dependent tuning. Only CT 17.

a) CT dependent tuning *b)CT non dependent tuning, reference*

For CT 17, note the low POFD- probability of false detection. With the CT dependent tuning it decreases even more. POD also decreases, but at least for 20% threshold the validation scores seems slightly better.

CT 18:

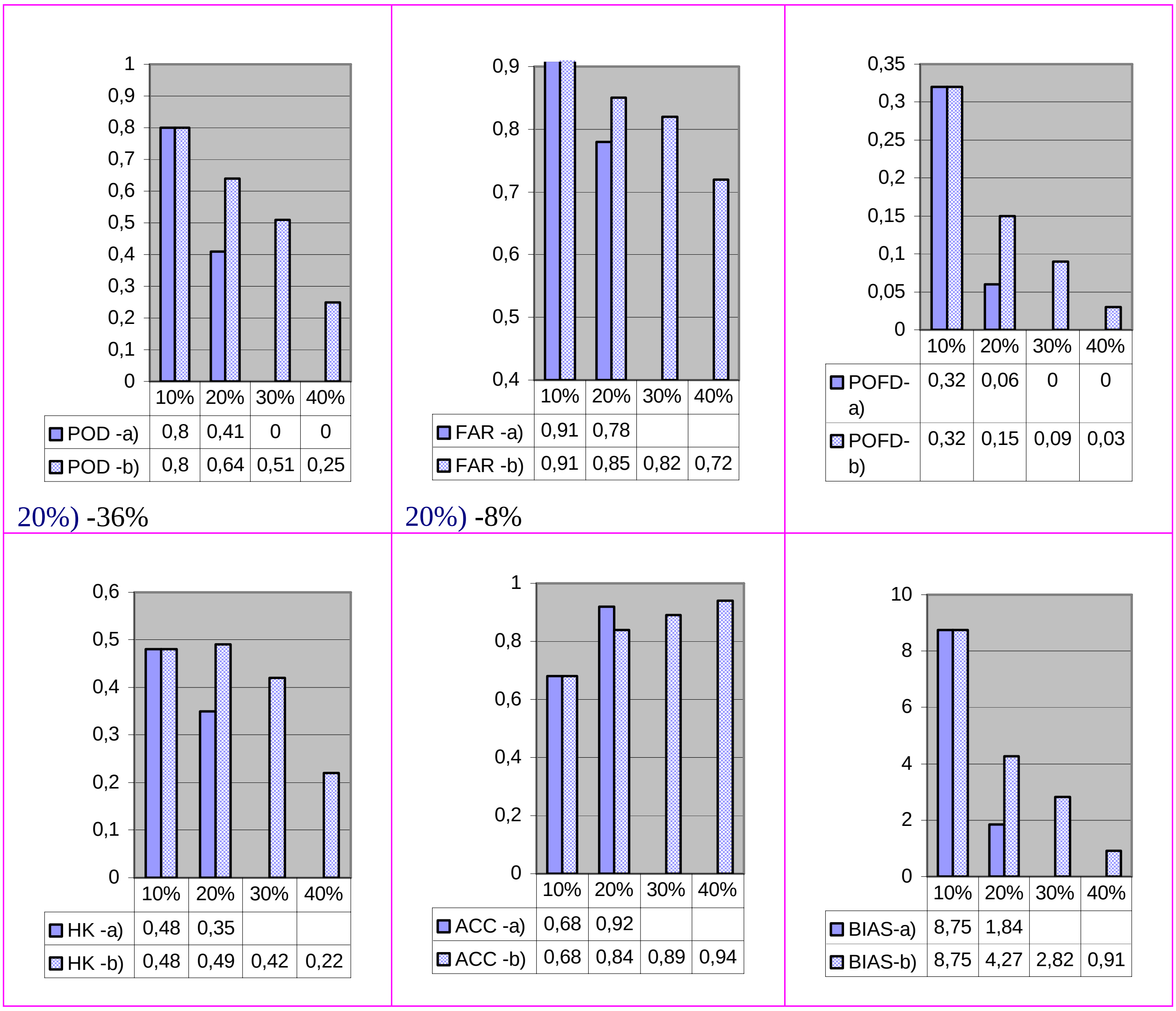


Figure 10 Cloud type dependent tuning versus non dependent tuning. Only CT 18.

a) CT dependent tuning *b) CT non dependent tuning, reference*

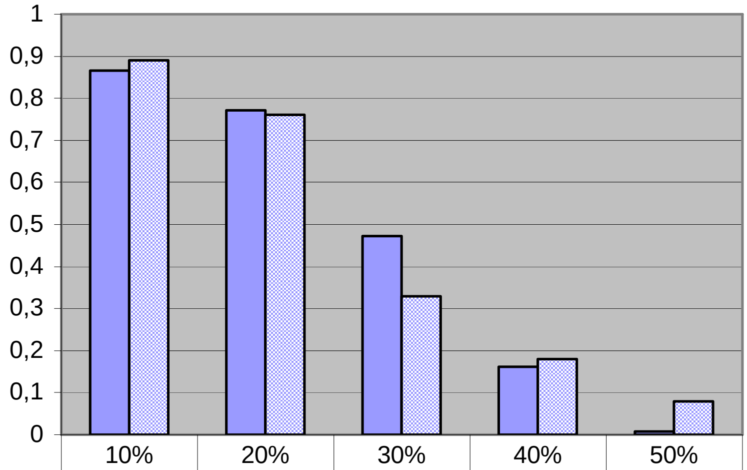
For CT 18 the scores are really bad, and it do not get any better by an own particular tuning.

Remarkable is the bad result for CT 18 and also for CT 17 and the fact that the overall result is not improved by cloud type dependent tuning. Generally the last three scores present better values, HK and the ACC scores increases in most cases and BIAS decreases with CT dependent tuning. Note also the high BIAS score that indicates that cloud type 9-10 is still overestimated. (A Bias score between 0 and 1 would indicate that the amount of precipitation is underestimated; a score greater than 1 indicates an overestimate of precipitation). This hold also for CT 17 and 18 (low thresholds).

3.2.2 Night algorithm

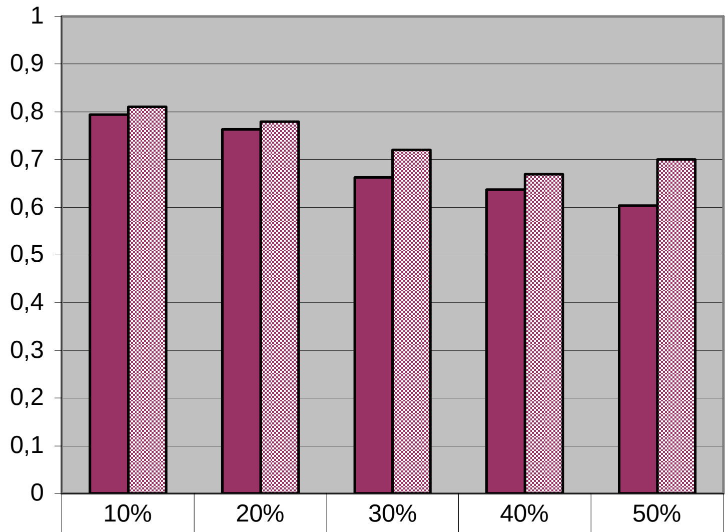
The differences are small also for the night algorithm. But the tendency is that the cloud type dependent tuning shows a little bit better result. For both 20 and 30% threshold (recommended in earlier versions) POD-score is higher and FAR-score is lower. Also POFD is lower for 20%.

Tuning on CT versus non CT dependent tuning
POD- probability of detection

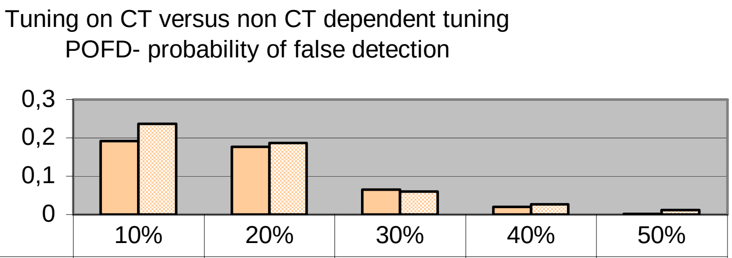


	10%	20%	30%	40%	50%
Tuning on France	0,866	0,771	0,472	0,162	0,007
Non CT dependent tuning	0,89	0,76	0,33	0,18	0,08

Tuning on CT versus non CT dependent tuning
FAR- false alarm ratio



	10%	20%	30%	40%	50%
Tuning on France	0,794	0,764	0,662	0,637	0,604
Non CT dependent tuning	0,81	0,78	0,72	0,67	0,7

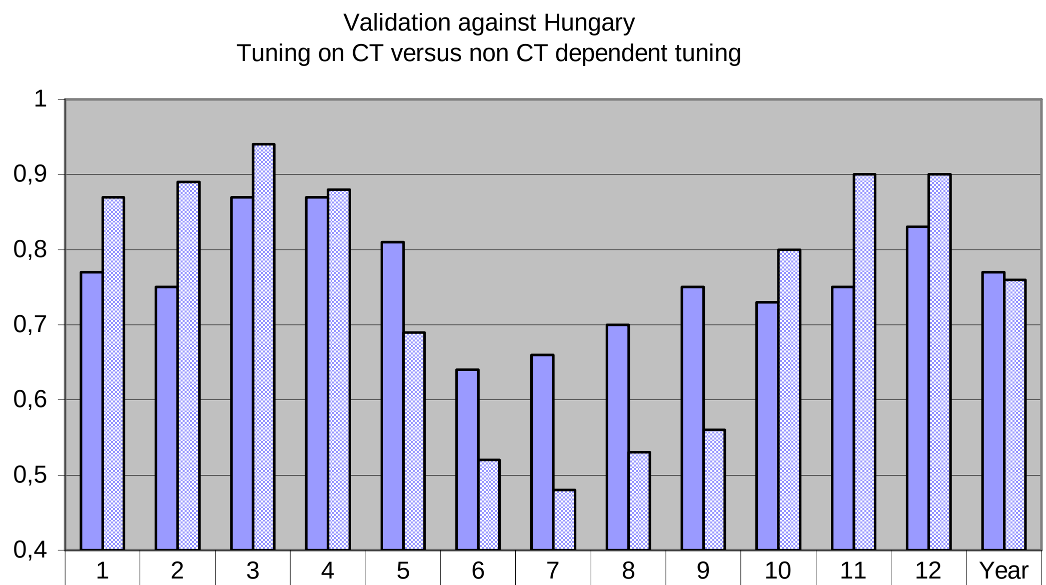


	10%	20%	30%	40%	50%
Tuning on France	0,191	0,177	0,065	0,02	0,001
Non CT dependent tuning	0,237	0,187	0,06	0,027	0,012

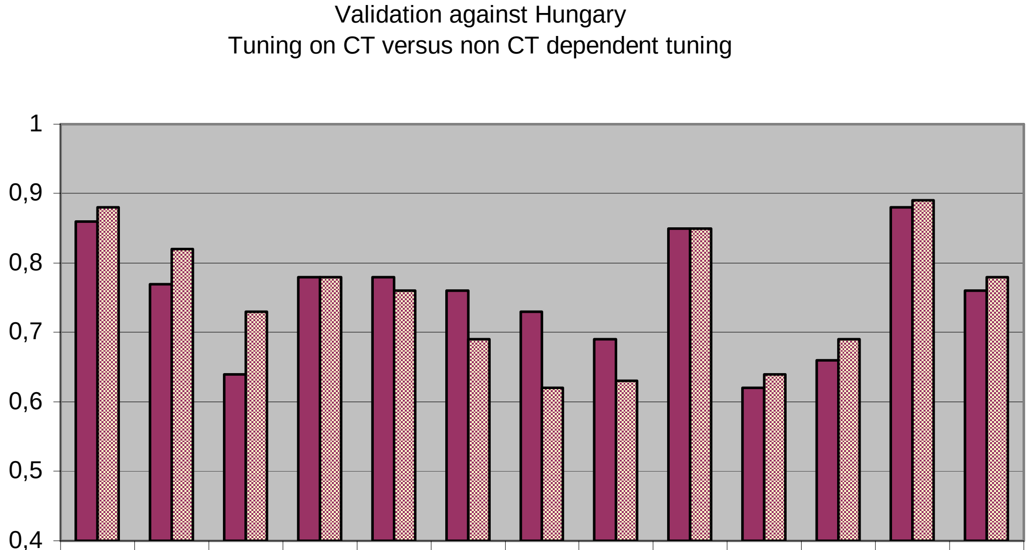
Figure 11 Validation against Hungary: POD, FAR and POFD result for night algorithm. Cloud type dependent versus non dependent map tuning:

3.2.2.1 Validation result on separate months

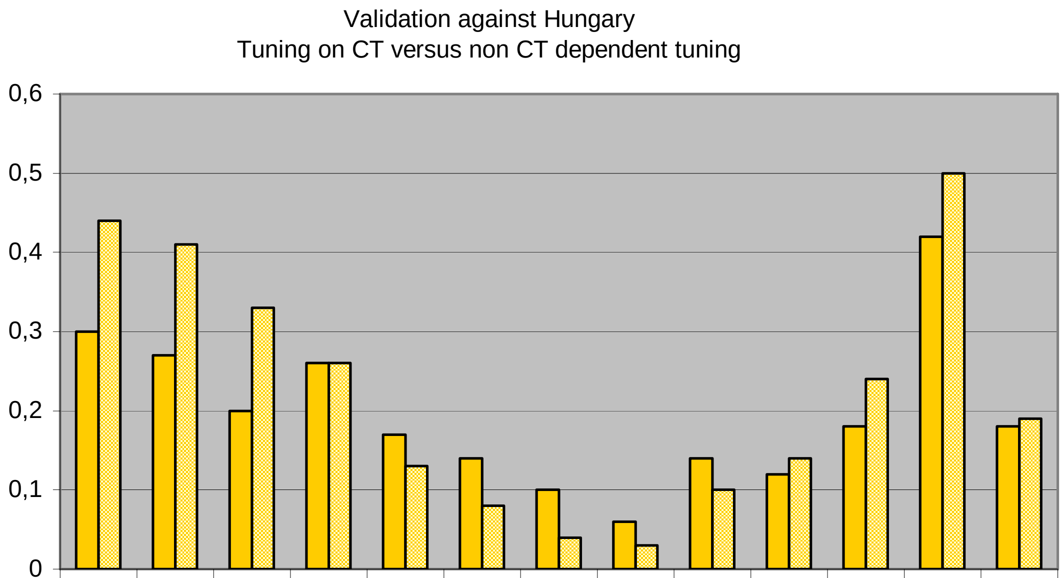
For the day algorithm there was a break even for the scores, better POD gives worse FAR and POFD. The result looks similar for the night algorithm, but for the summer months (May-September) the increase of POD is bigger than the increase of FAR. For example July POD increases with 37% but FAR only increases with 18%. The improvement of the CT dependent tuning is nevertheless not unambiguous; the POFD increases even more for all of the summer months but POFD is relatively low anyway. For the night algorithm there is a clear tendency that the strong seasonal cycle in algorithm performance is reduced which is positive.



	1	2	3	4	5	6	7	8	9	10	11	12	Year
POD -a)	0,77	0,75	0,87	0,87	0,81	0,64	0,66	0,7	0,75	0,73	0,75	0,83	0,77
POD -b)	0,87	0,89	0,94	0,88	0,69	0,52	0,48	0,53	0,56	0,8	0,9	0,9	0,76



	1	2	3	4	5	6	7	8	9	10	11	12	Year
FAR -a)	0,86	0,77	0,64	0,78	0,78	0,76	0,73	0,69	0,85	0,62	0,66	0,88	0,76
FAR -b)	0,88	0,82	0,73	0,78	0,76	0,69	0,62	0,63	0,85	0,64	0,69	0,89	0,78



	1	2	3	4	5	6	7	8	9	10	11	12	Year
POFD -a)	0,3	0,27	0,2	0,26	0,17	0,14	0,1	0,06	0,14	0,12	0,18	0,42	0,18
PODF -b)	0,44	0,41	0,33	0,26	0,13	0,08	0,04	0,03	0,1	0,14	0,24	0,5	0,19

Figure 12 Validation against Hungarian data: POD, FAR and POFD result for night algorithm distributed on months. Cloud type dependent tuning versus non dependent tuning.

(Threshold 20%)

3.2.2.2 Validation result on separate cloud types

This is the validation result of the CT dependent tuned night algorithm, against Hungarian data, for each cloud type.

CT 9-10:

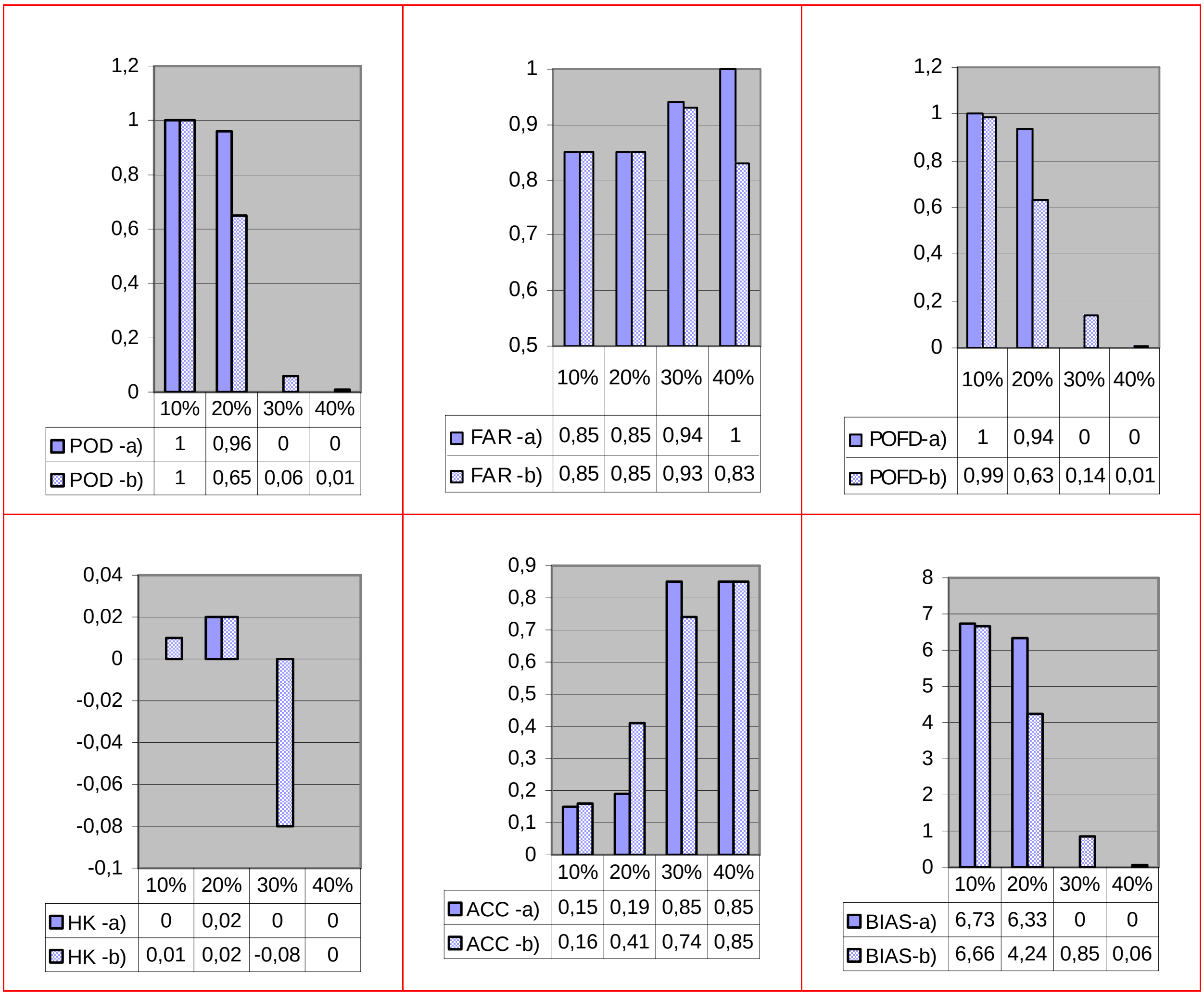


Figure 13 Cloud type dependent tuning versus non dependent tuning. Only CT 9-10.

a) CT dependent tuning *b) CT non dependent tuning, reference*

The scores for POD 20% threshold is considerably better with the CT dependent tuning, but also the POFD increases the same proportion. Actually it seems like almost all co-locations is classed as rain. The FAR, however, shows that 85% are false alarms of the co-locations classed as rain. The BIAS also shows a large overestimation, and larger for the CT dependent tuning.

The scores are bad and get no better with the CT dependent tuning.

CT 11-14:

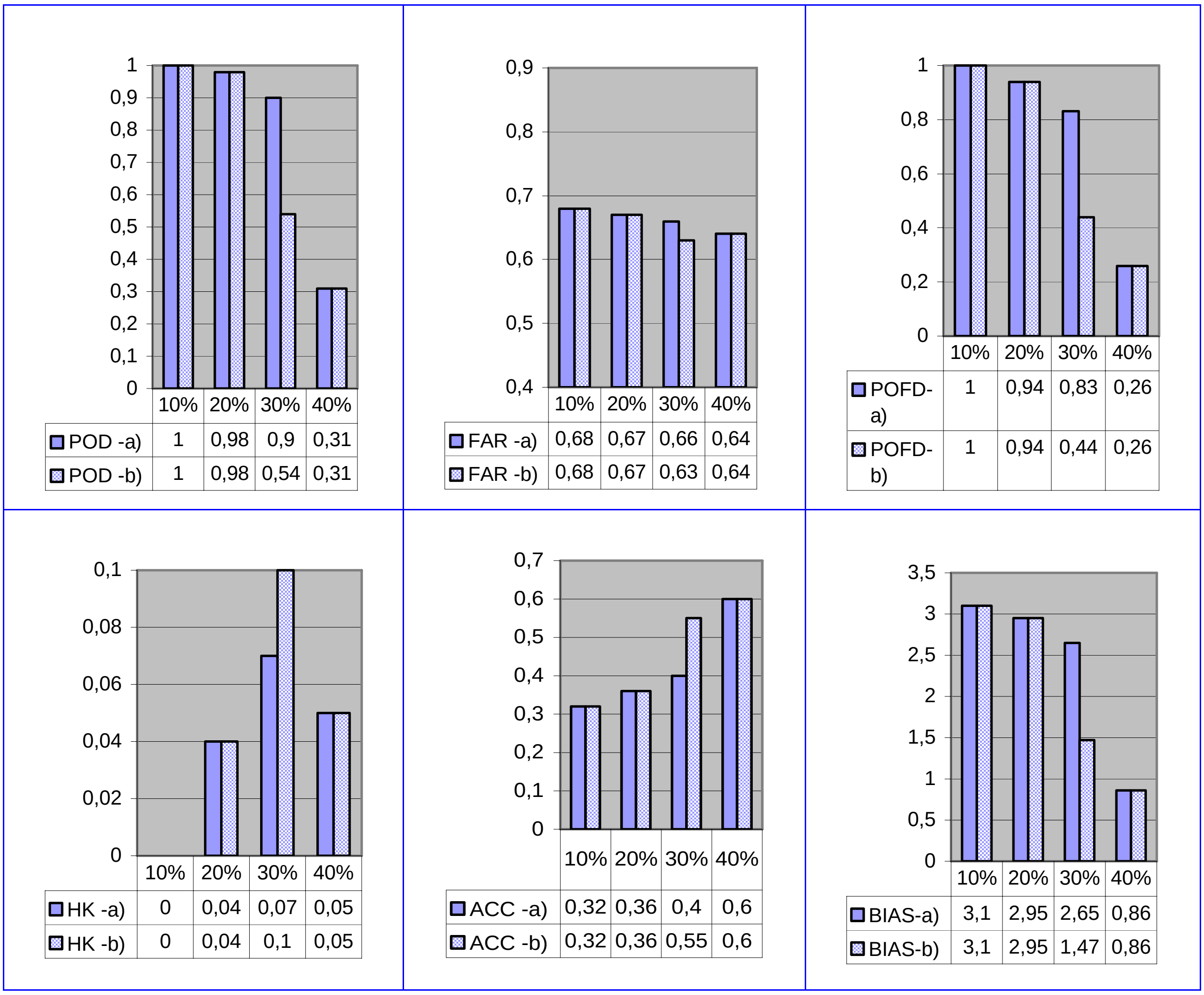


Figure 14 Cloud type dependent tuning versus non dependent tuning. Only CT 11-14.

a) CT dependent tuning *b) CT non dependent tuning, reference*

For CT 11-14 the only threshold case affected is 30%. Here the same discussion as for CT 9-10 20% can be used. The CT dependent tuning does only increase the overestimation. Anyway, the scores for CT 11-14 are overall pretty good.

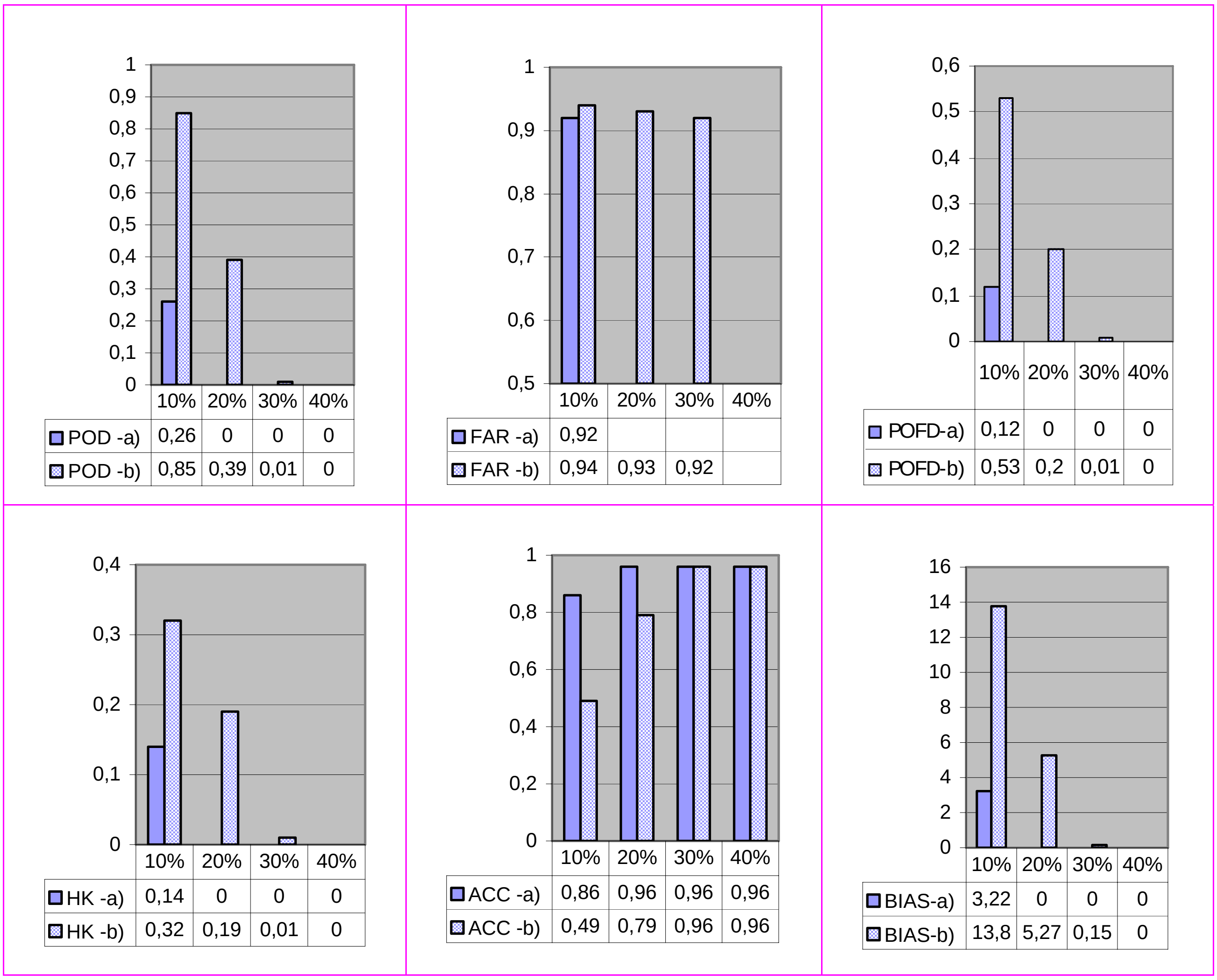
CT 17:

Figure 15 Cloud type dependent tuning versus non dependent tuning. Only CT 17.

a) CT dependent tuning *b) CT non dependent tuning, reference*

For both 20 and 30% threshold- the cases of interest and that are most affected- the discussion is the opposite. The CT dependent tuning reduces the overestimation a great deal, but still the rain is overestimated. The POD gets that low, that the tuning cannot be called an improvement.

CT 18:



	10%	20%	30%	40%
POD -a)	0,26	0	0	0
POD -b)	0,85	0,39	0,01	0

	10%	20%	30%	40%
FAR -a)	0,92			
FAR -b)	0,94	0,93	0,92	

	10%	20%	30%	40%
POFD-a)	0,12	0	0	0
POFD-b)	0,53	0,2	0,01	0

	10%	20%	30%	40%
HK -a)	0,14	0	0	0
HK -b)	0,32	0,19	0,01	0

	10%	20%	30%	40%
ACC -a)	0,86	0,96	0,96	0,96
ACC -b)	0,49	0,79	0,96	0,96

	10%	20%	30%	40%
BIAS-a)	3,22	0	0	0
BIAS-b)	13,8	5,27	0,15	0

Figure 16 Cloud type dependent tuning versus non dependent tuning. Only CT 18.

a)CT dependent tuning *b)CT non dependent tuning, reference*

Also for CT 18 the overestimation is reduced, but it can only be registered for threshold 10%, probably because of the low amount of rain co-locations.

The cloud type dependent tuning may be better, but the night algorithm is that poor that it is hard to establish.

3.2.3 Day versus night- all indices

A complete comparison, with whole dataset, for the day algorithm versus the night algorithm also shows that the differences are small. For the night algorithm there is a small improvement with the cloud type dependent tuning, but the scores result is poor anyway.

All indeces:

Year 2004 (238095)	Day CT tuned (v2.0 default)	Day Non CT tuned (reference only)	Night CT tuned (v2.0 default)	Night Non CT tuned (Reference only)	Day synop tuned (v2.0 option)	Night synop tuned (v2.0 option)
10% threshold						
POD	0.85	0.85	0.87	0.89	0.80	0.90
FAR	0.76	0.77	0.79	0.81	0.80	0.83
POFD	0.19	0.19	0.24	0.27	0.23	0.30
HK	0.66	0.65	0.63	0.62	0.57	0.60
Bias	3.54	3.64	4.21	4.70	4.05	5.20
ACC	0.81	0.81	0.77	0.74	0.77	0.71
20% threshold						
POD	0.77	0.77	0.77	0.76	0.57	0.75
FAR	0.71	0.71	0.76	0.78	0.72	0.77
POFD	0.13	0.13	0.18	0.19	0.11	0.18
HK	0.64	0.64	0.59	0.57	0.46	0.57
Bias	2.61	2.61	3.27	3.40	2.06	3.29
ACC	0.86	0.86	0.82	0.81	0.87	0.82
30% threshold						
POD	0.57	0.70	0.47	0.33	0.42	0.33
FAR	0.58	0.67	0.66	0.72	0.64	0.71
POFD	0.06	0.10	0.07	0.06	0.05	0.06
HK	0.51	0.60	0.41	0.27	0.36	0.27
Bias	1.35	2.10	1.39	1.17	1.15	1.11
ACC	0.92	0.89	0.90	0.90	0.91	0.90

Table 4 : CT dependent tuning versus non CT dependent tuning. On the left synop based CT independetnt tuning as supplied with v1.2 and optionally configurable in v2.0. All indices at different thresholds. Validation against Hungarian dataset over the whole year.

3.3 CONCLUSIONS

- The cloud type dependent tuning (based on French gauge data) gives slightly better results than the cloud type independent tuning on the same dataset, but the differences are small. Only the cloud type dependent version of tuning is supplied with version 2.0.

- The night algorithm is somewhat more improved than the day algorithm by cloud type dependent tuning, especially with regard to a more even performance over the year. Poor performance in summer is improved considerably. In case studies even some strange behaviour with precipitation likelihood of Cirrus clouds in winter could be avoided by cloud type dependend tuning. On the other hand the tuning will lead to miss more really precipitating clouds characterized as thick cirrus in winter.
- In winter months the probability of false detection is reduced by using cloud type dependent tuning.
- There are big differences between the cloud types. The cloud type dependent tuning seems to improve results for some cloud types, for others not.
- The work with separating cloud types has also shown that:
  - Cloud type class 9-10 is overestimated at 20 percent detection level especially at night time
  - Cloud type class 17 and 18 give bad results overall, but large biases at 20%detection level could be reduced significantly by introducing cloud type dependend tuning.
  - Cloud type class 11-14 seems to be the easiest to handle

- **The default configuration for version 2.0 (cloud type dependent gauge tuned) is clearly superior to the optional configuration for synop tuned dataset during day time (active in v1.2). Night time performance is slightly improved with version 2.0 over version 1.2.**
- Day and night algorithms still exhibit different characteristics in v2.0, but differences are less than in version 1.2.
- At the 20% detection threshold day and night algorithms perform almost equally well, whereas the day algorithm clearly exhibits more skill at the 30% threshold than the night algorithm.