Current status of the NWCSAF/MSG Clear Air Products

28th November, 2007

Miguel A. Martínez

INM (SPAIN)

Overview

- Framework
- Algorithms description
- Training dataset
- Neural Networks
- Corrections
- Proposal for algorithms modification
  - Splitting of the middle layer: case study

FRAMEWORK: NWCSAF

FRAMEWORK: NWCSAF

EUMETSAT Satellite Application Facilities for Nowcasting and Very Short Range Forecasting (NWCSAF)

- Near Real Time (NRT)
- Full resolution (3km x 3km at Nadir)
- Frequency to be selected by the user (default every repeat cycle)
- Region to be selected by the user

SAFNWC Products

No.	Product Name (Acronym)	Characteristics	Institute
1	**Cloud Mask and Cloud Amount** (CMa)	ICloud products	MF
2	Cloud Type (CT)	Cloud products	MF
3	Cloud Top Temperature/ Height (CTTH)	Cloud product	MF
4	Precipitating Clouds (PC)	Precipitation product	SMHI
5	Convective Rainfall Rate (CRR)	Precipitation product	INM
6	Total Precipitable Water (TPW)	Air mass product	INM
7	**Layer Precipitable Water** (LPW)	Air mass product	INM
8	**Stability Analysis Imagery (SAI)**	Air mass product	INM
9	High resolution Wind from HRVIS (HRW)	Wind product	INM
10	Automatic Satellite Image Interpretation (ASII)	Thunderstorm product	ZAMG
11	Rapidly Developing Thunderstorm (RDT)	Conceptual Models product	MF
12	**Air Mass Analysis** (AMA)	Air mass products	ZAMG

Air Mass Products: TPW, LPW, SAI and AMA.

Retrieved air clear parameters (delivery 2008)

TPW is the amount of liquid water, in mm, if all the atmospheric water vapour in the column was condensed.

LPW provides information on the water vapor contained in a vertical column of unit cross-section area in three layers in the troposphere:

- Boundary Layer (BL): 1013hPa-840 hPa
- Middle Layer (ML): 840hPa-437hPa
- High Layer (HL): <437hPa

SAI provides estimations of the atmospheric stability in cloud-free areas. Among all the potential indexes, the Lifted Index (LI) has been implemented and coded.

LI = T (500-hPa environment) − T (500-hPa parcel) (in °C)

SAFNWC TPW, LPW and SAI algorithms (Overview)

- The quantitative estimation about humidity vertical distribution and stability indices using satellite data is based upon two ways:
  - Physical retrieval, based on an inversion scheme.
  - The use of previously determined statistical relationships between observed (or synthetic) radiances and the corresponding atmospheric parameters a statistical retrieval. This way is a computationally efficient method for determining precipitable water parameter and stability indices from satellite IR measurements.

- A statistical retrieval scheme, based on neural network is the baseline of PGE06 (Total Precipitable Water) PGE07 (Layer Precipitable Water) and PGE08 (Stability Analysis Imagery) SAFNWC products.

- Synthetic radiances have been used to train the algorithm, since the differences between synthetic and measured clear-sky radiances are mitigated with a radiance bias correction.

- These products are obtained by default at pixel resolution but it is possible to select 3x3 or 5x5 pixel arrays where the radiances for clear air are smoothed (reduce radiometric noise…)

- The infrared radiances depend on satellite zenith angle, so a zenith neural network has been trained to take into account this dependence.

Algorithm (COMMON PART)

INPUTS

- 7 SEVIRI IR radiances (6.2,7.3,8.7,9.7,10.8,12,13.4 μm)
- Cloud Mask (SAFNWC- PGE01)
- Satellite Zenith angle
- Topographic altitude (only land)

PRE-PROCESSING

- Clear pixel identification (CMa)
- Smoothing of SEVIRI radiances (optional)
- Local radiance-bias correction
- Normalization of SEVIRI radiances (max-min)
- Zenith angle correcting of SEVIRI radiances to 45 degrees.

Including in the delivery 2008. The most significant improvements are over Centre Europe

Algorithm (SPECIFIC PART)

PROCESSING

- ❖ Land sea mask
- ❖ A Neural Network run for each different parameter (one for sea and another for land pixels)

Including in the delivery 2008

POST-PROCESSING

- ❖ Denormalization of the parameters
- ❖ Local parameter bias adjustment (optional)
- ❖ Smoothing of each parameter (optional)
- ❖ Conversion to grey levels
- ❖ Writing of HDF-5 files

A quantification error is included in this step
TPW=0,58mm(70/119) BL=0,29mm (35/119)
ML=0,38mm(45/119) HL=0,07mm(8/119)
LI = 0.34ºC (40/120)

OUTPUTS

PGE06: TPW

PGE07: LPW_BL, LPW_ML, LPW_HL

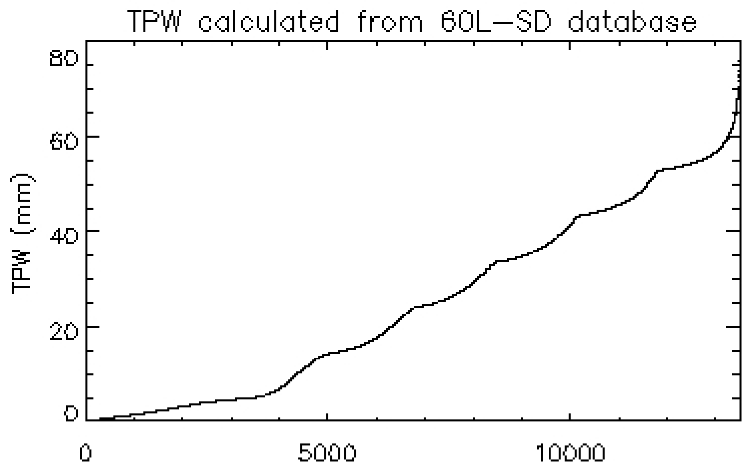
PGE08: SAI_LI

Training dataset

- The main problem concerning the neural networks is to have a good training dataset covering a wide range.

PW training dataset: 60L-SD+RTTOV7

- The 60L-SD is a sampled database that summarizes the characteristics of diverse profile data set from the ERA-40. The 60L-SD database contains the same number of samples from seven subgroups differing by the total precipitable water vapor content of the profiles.



- It is a suitable database to implement the TPW and LPW algorithm

✓ Note: This dataset and the RTTOV are provided by the NWPSAF

SAI training dataset (“SSDB+60L-SD”+RTTOV7)

- The number of unstable cases that the 60L-SD profiles contain is small and most of them have low instability.
- We found that the SAI neural networks trained with this database classified too much, probably because all the ranks did not have an equivalent weight in the training set.
- A new special database well-suited to represent the different stability cases (SSDB) was built using as support the ECMWF analyses from November 2002 to October 2003.
- The SSDB was mixed with the 60L-SD to build the new special training dataset for stability parameters (SSDB+60L-SD). In order to build the new training dataset for SAI sea and land neural networks, all profiles of the SSDB+60L-SD database were used as inputs to the RTTOV-7.

Modification in the Training Datasets

- For training the zenith angle correction NN, an extended 60L-SD dataset has been created. This dataset has been created varying the zenith angle every 5 degrees from 0º to 70º for each 60L_SD profile. That is equivalent to applying 15 times the RTTOV-7 to every profile assigning a different zenith angle at each time.

- In order to better handle the problems of the surface temperature (Tsfc), the surface temperatures of the datasets (SSDB and 60L-SD) have been modified by adding or subtracting between minus 5º and plus 5º every degree. This way, the SEVIRI synthetic radiances used in the training have been obtained using profiles with perturbed Tsfc.

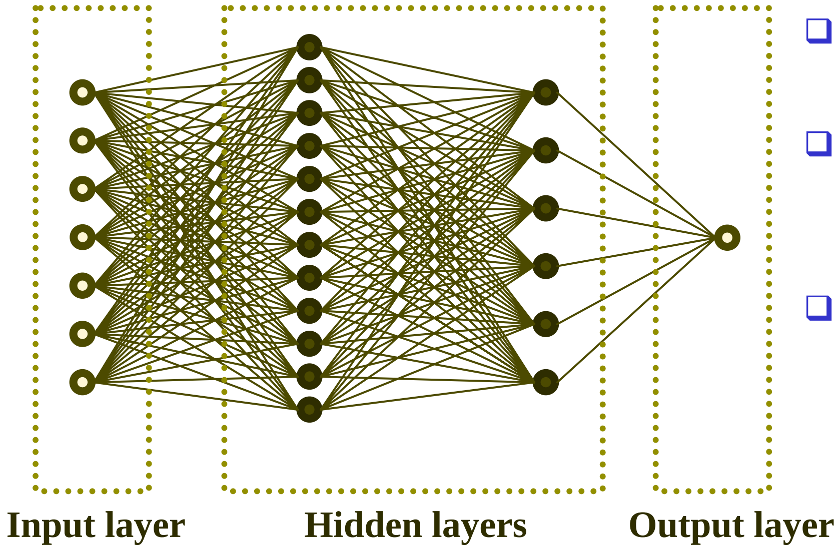
Neural Networks

- Statistical relations between the radiances and the meteorological parameters are gained from a neural network. The neural network allows to take into account non-linear relationships between a number of input values – the predictors- and one output value – the clear air parameter.

Multilayer Perceptrons

- Multilayer Perceptrons (MLPs) have been used to determine the relationships between SEVIRI IR synthetic radiances and the corresponding atmospheric parameters (PW parameters and LI index).

- The MLP is made up of neurones (nodes) arranged as input, output and hidden layers connected by weighted links, and it estimates a mapping function from one vector space X (inputs) to another Y (outputs).



- The number of neurones in the input layer is determined by the dimensionality of X.
- The number of neurones in the output layer is determined by the dimensionality of Y.
- The number of nodes in the hidden layer(s) is determined by the researcher.

Back Propagation Algorithm

- The derivates of the error with respect to the weights can be used to find the weight values which minimize the error function, by using gradient descent (or other powerful optimization methods).

- The algorithm for evaluating the derivatives of the error function is known as back-propagation since, it corresponds to a propagation of the errors backwards through the network.

- The term "back propagation" is used in the literature with a variety of meanings. Here, the term is used to describe the training of a multilayer perceptron using gradient descent applied to a sum of squared error functions.

- A back propagation algorithm (supervised learning algorithm) has been employed to derive the relationships between SEVIRI IR synthetic radiances and the corresponding atmospheric parameters (precipitable water parameters and stability index), thus requiring a desired response to be trained.

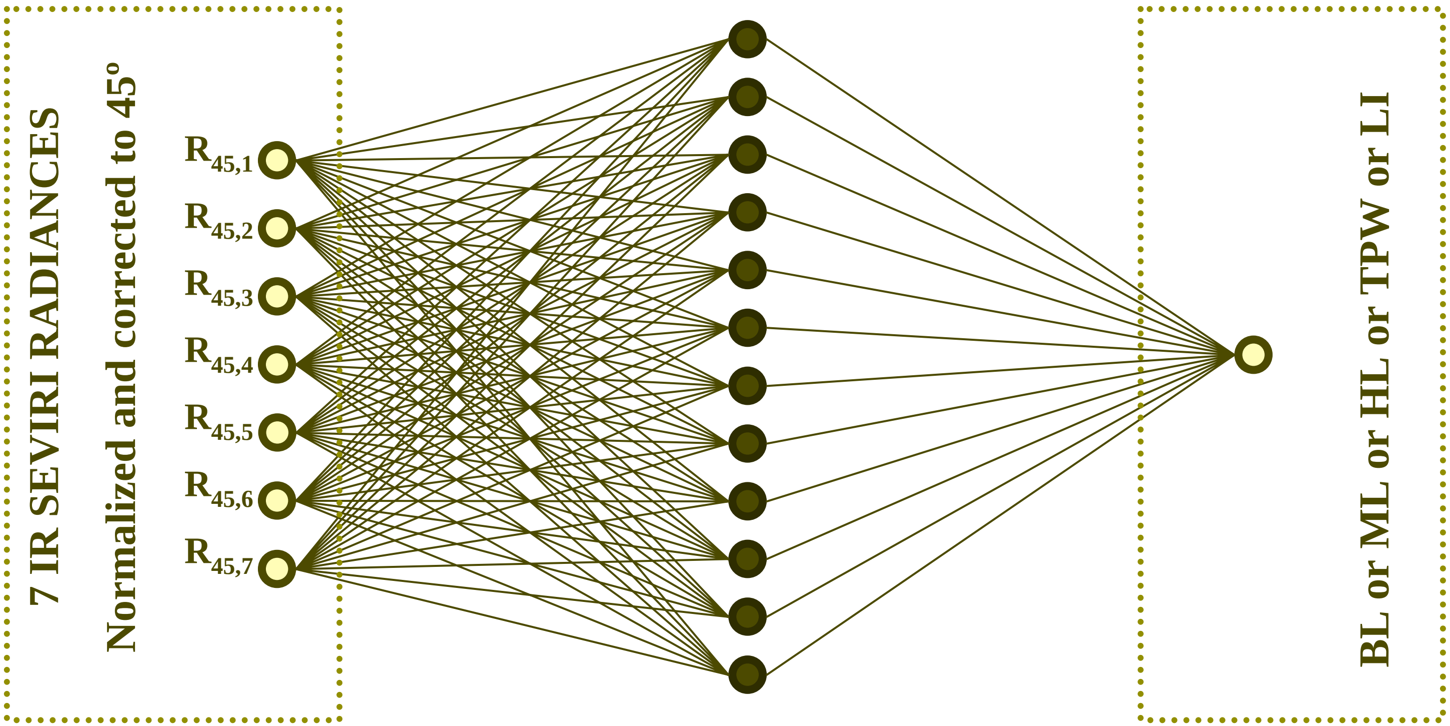
How the Topology of each NN is selected?

- To investigate the configuration which gave the minimum root mean square error (RMSE) and fastest convergence, different topologies of MLP-NNs were evaluated using the Stuttgart Neural Network Simulator (SNNS) modifying the number of hidden layers and the neurones that each hidden layer contains.

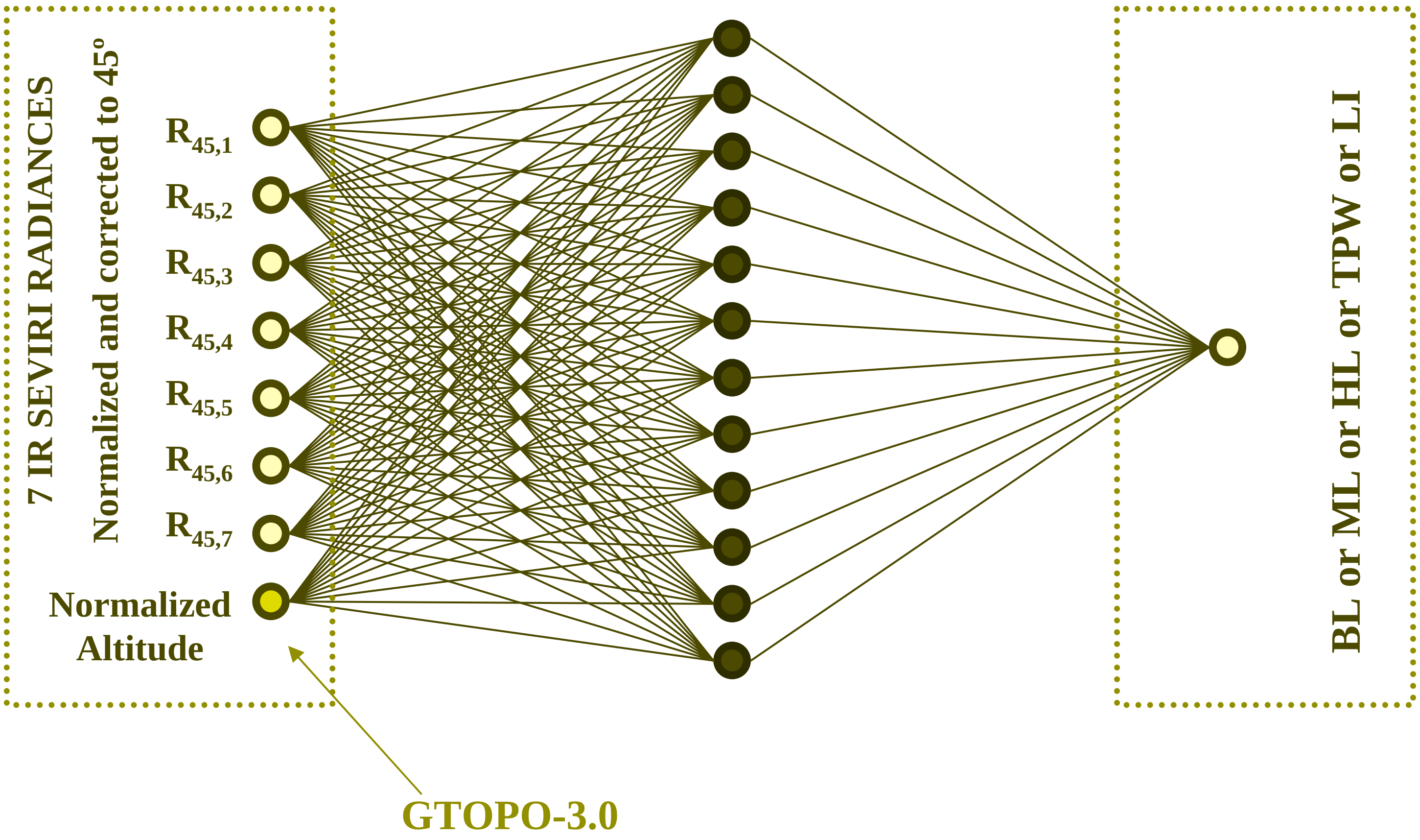
- From this, the finally selected neural networks have only one hidden layer that contains
  - 12 neurons for land and sea neural networks for each parameter.
  - 16 neurons for zenith angle neural network.

✓ Note: The NNs are written in SNNS format (ASCII files); therefore the weights of the NNs included in SAFNWC software package can be displayed with the SNNS software package (http://www-ra.informatik.uni-tuebingen.de/SNNS/).

Topology of the Sea Neural Networks 7:12:1



Topology of the Land Neural Networks
8:12:1

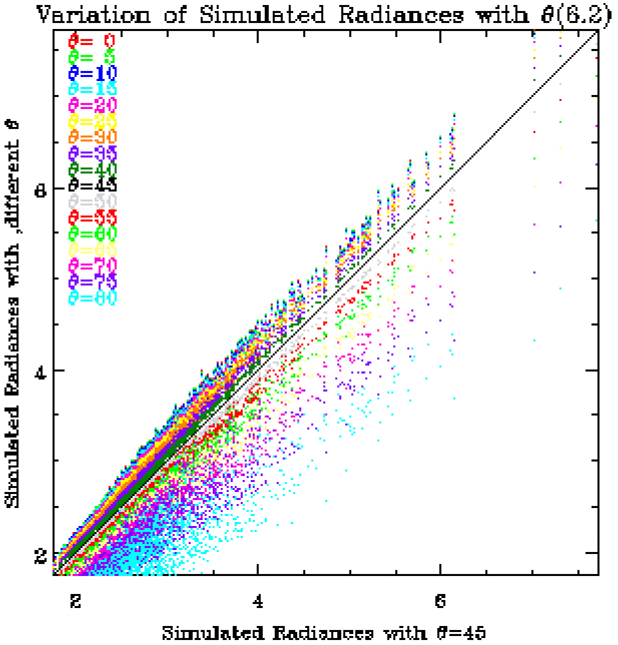


Necessity of the Zenith Correction

- MSG IR synthetic radiances have been calculated considering different satellite zenith angles [0º-80º] for each profile

- Scatter plots of radiances for different satellite zenith angle versus radiances at 45º are shown.

- All IR radiances are sensible to the satellite zenith angle. The scatter is significant.



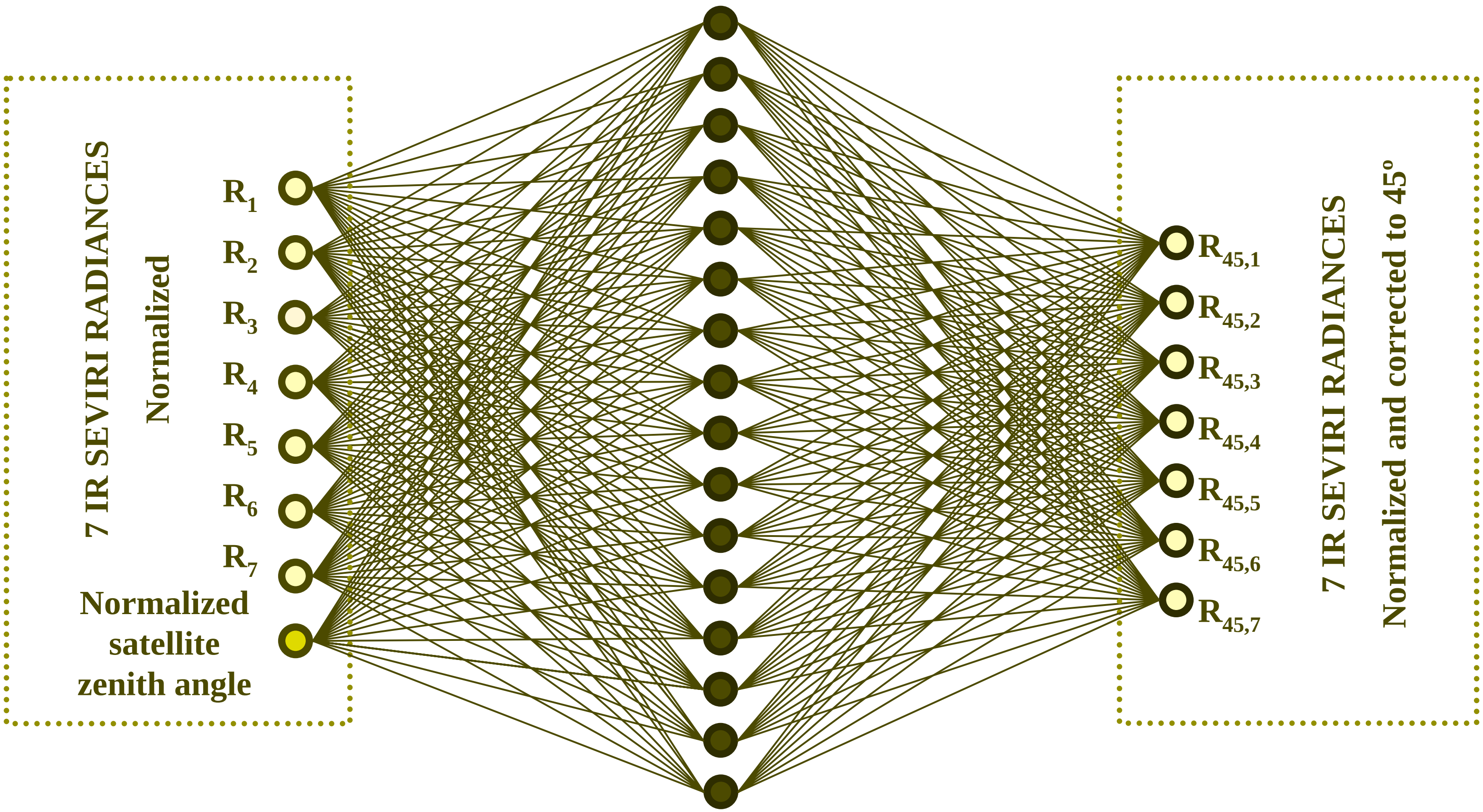
Approaches to Correct the Zenith Satellite Angle

- There are two commonly used approaches to correct the zenith angle in clear air products:

  - The algorithms are determined for n different satellite angles using simulations with a radiative transfer model and regression analysis. A linear interpolation method is used to determine the coefficients for the rest of zenith angles.

  - The other approach is to introduce a new term to the algorithms to account for this effect. Additive correction expressions in (sec (θ)-1) have been looked for.

Topology of the Zenith Angle Neural Networks 8:16:7



Example of a Zenith Correction Pattern File

```
No. of patterns     :        17332
No. of input units  :            8
No. of output units :            7
```

0.7907567	0.7160961	0.7071148	0.7956898	0.6930246	0.4751507	0.2495250	0.0000000	0.7563310	0.7083275	0.6995699	0.7991489	0.6916119	0.4394257	0.1752120
0.8166161	0.7261187	0.7128817	0.8048336	0.7051659	0.6428032	0.4420553	0.0000000	0.7930525	0.7251341	0.7094949	0.8100215	0.7074850	0.6239852	0.3678324
0.7060142	0.6065832	0.5841258	0.5705551	0.5610220	0.5352017	0.3288417	0.0000000	0.6891828	0.6183451	0.5922525	0.5499358	0.5689563	0.5123047	0.2546931
0.7496131	0.6734947	0.6645848	0.7642633	0.6466842	0.4153737	0.2033109	0.0000000	0.7117287	0.6633698	0.6558698	0.7676204	0.6448056	0.3775671	0.1318396
0.5701499	0.4638579	0.4406655	0.4676538	0.4108894	0.3630220	0.1997364	0.0000000	0.5524999	0.4761469	0.4498593	0.4546372	0.4184612	0.3364750	0.1302942
0.7412623	0.6558989	0.6515809	0.7586803	0.6450190	0.5339679	0.3803057	0.0000000	0.7057841	0.6367851	0.6315884	0.7517893	0.6359177	0.5171437	0.3074786
0.6602945	0.5679659	0.5428586	0.5541962	0.5143607	0.4690206	0.2699492	0.0000000	0.6457495	0.5850155	0.5552620	0.5446729	0.5237247	0.4407396	0.1982357
0.3025077	0.3409622	0.3220259	0.2997475	0.2678865	0.1998667	0.1310406	1.0000000	0.3845708	0.3658500	0.3399428	0.3940674	0.3045387	0.2811553	0.1752396

.....

Input variables

Normalized IR13.4, IR12.0 , IR10.8, IR9.7, IR8.7, WV7.3, WV6.2µm & Normalized zenith satellite angle

Output variables

Normalized IR13.4, IR12.0 , IR10.8, IR9.7, IR8.7, WV7.3, WV6.2µm for satellite zenith angle = 45º

Bias Correction

- Synthetic radiances have been used to train the algorithm, since the differences between synthetic and measured clear-sky radiances are mitigated with a radiance bias correction.

Local Radiance Bias Correction

- ECMWF GRIB files with the analyses profiles have been downloaded from MARS/ECMWF:
  - Grid step of 0.5º
  - Period: Jul-04 to Jun-05
  - Region defined by the corners (70ºN, 40ºW) and (28ºN, 40ºE)
- SEVIRI synthetic radiances = analysis profiles + RTTOV-7.
- The maximum of IR10.8 radiances is searched at every ECMWF 0.5º grid point and the radiances are selected (sea/land)
- A dataset with observed and synthetic radiances is obtained every ECMWF 0.5º grid point
- A robust regression is applied in 5x5 window → the scale and offset between observed and synthetic radiances are calculated.
- The scale and offset values were bi-lineally interpolated to the SEVIRI MSG-N points over sea and non-desert land for each IR channel.

Parameter Local Adjustment

- Part of the spatial variability of the version 1.3 is associated with the spatial variability of the bias between observed and synthetic radiances (corrected by local radiance bias) and the rest is due to the algorithm which does not present the same performances in all places. This tuning step has been coded in order to locally improve the quality of the algorithm in all MSG-N area.

Filling up the Local Matrices

- Over sea and non-desert land pixels:
  - The local bias radiance correction and the local bias parameter adjustment have been filled up with the scale and offset values bi-lineally interpolated to the SEVIRI MSG-N points

- In desert pixels and pixels out of MSG_N region:
  - the local bias radiance matrices have been filled up with the offset and scale obtained with a global bias correction obtained only over sea pixels.
  - The local bias parameter matrices have been filled up with offset equal to 0 and scale equal to 1.

Global Correction

- This step allows to consider the differences in the radiance calibrations as a global correction

Global Correction

- Adaptation of the software to SEVIRI on board Meteosat 9, 10, 11 by only changing the global scale and offset coefficients in the configuration file.
  (It takes into account the global radiance bias between SEVIRI on board MSG-8 and SEVIRI on board the other MSG satellites).

- 2008 SEVIRI radiance change: Effective blackbody radiance rather than spectral blackbody radiance.

Proposal for Algorithm Modification

- Changing the outputs:
  - from counts to millimetres
  - from count to ºC

To avoid the quantification error

TPW=0,58mm(70/119) BL=0,29mm (35/119)

ML=0,38mm(45/119) HL=0,07mm(8/119)

LI = 0,34ºC (40/120)

- Modifying the training dataset using RTTOV-9
- Emissivity.
- Including other instability index without boundary layer influence:
  - Showalter stability index.
  - K-index.
- Splitting of ML around 700 hPa

New sub-layers

- Splitting the Middle Layer of LPW NWCSAF/MSG satellite product in order to improve the monitoring of pre-convective environments.

PGE07_LPW: Splitting of ML around 700 hPa

LPW Parameter	Bottom level	Top level
BL	SFC	840 hPa
ML	840 hPa	437 hPa
HL	437 hPa	0 hPa

SPLITTING OF THE MIDDLE LAYER

LPW_M1

(840-703)

LPW_M2

(703-437)

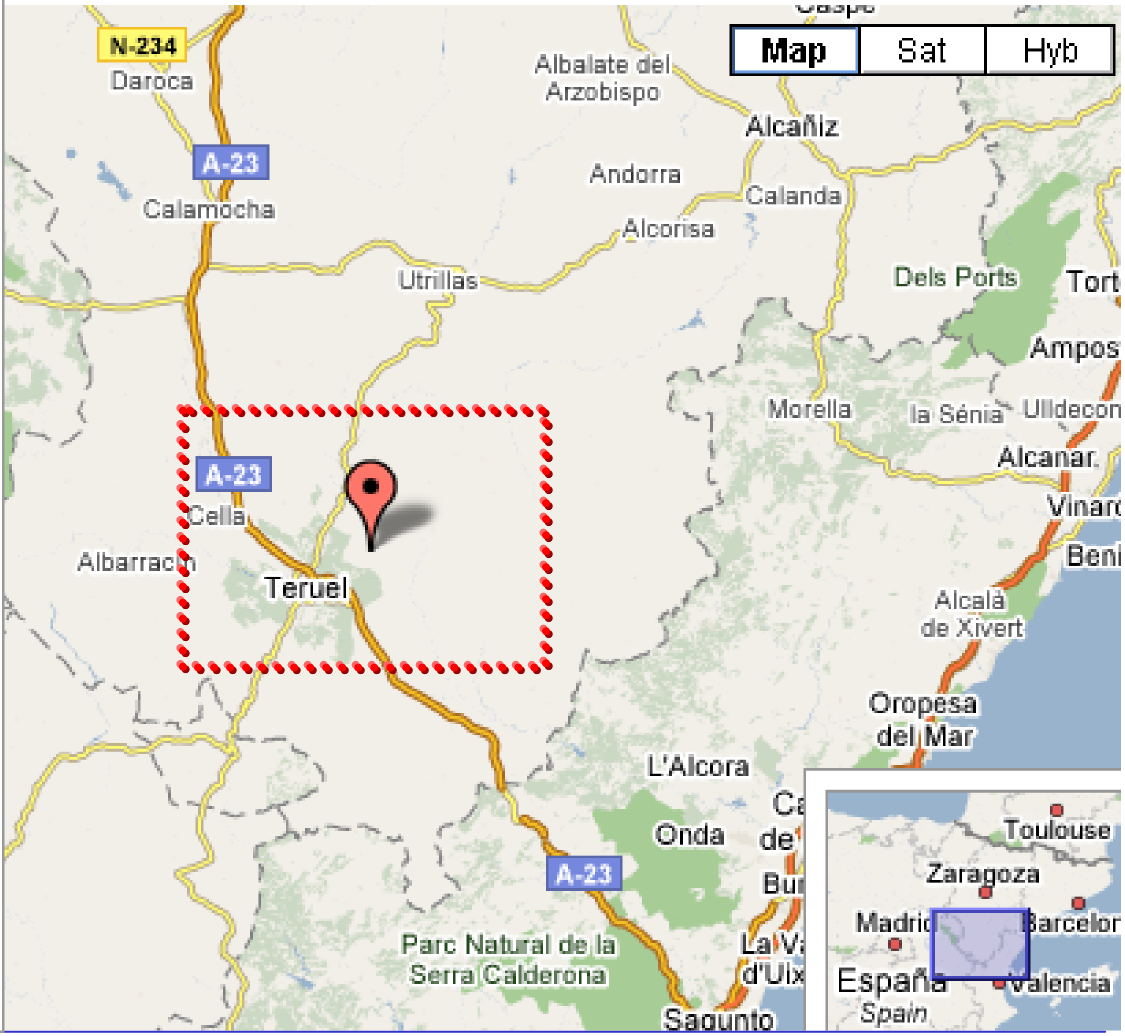
RTTOV levels

Study Case: Severe weather event (28-8-04)

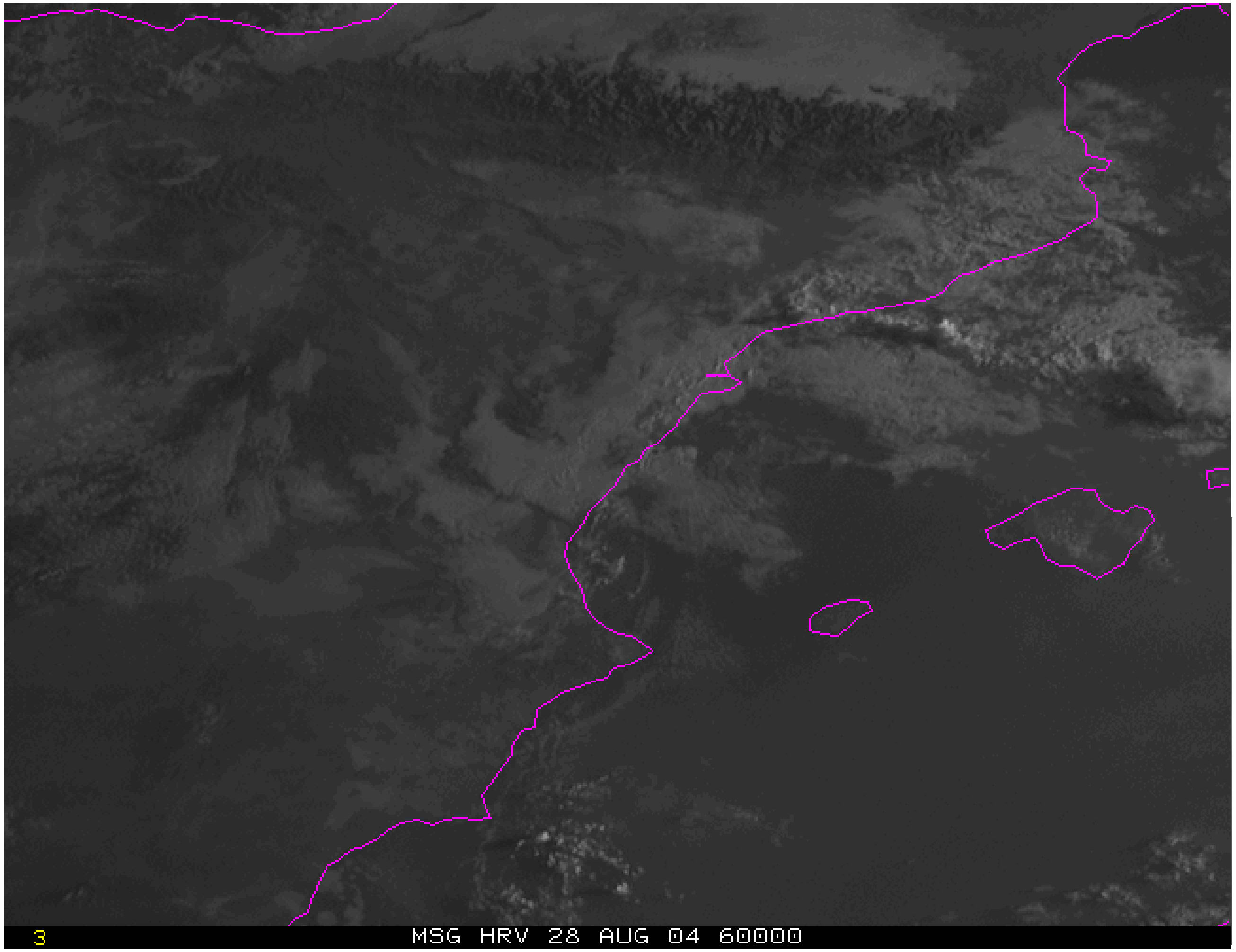
A thunderstorm over Teruel produced intense precipitation and hail.

While the thunderstorm was moving towards SSE a tornado (~ F2) developed between 17:00Z and 17:20Z.

Antonio Conesa (INM) analysed the event and found a tornado track of 400-700 m width along 8km.



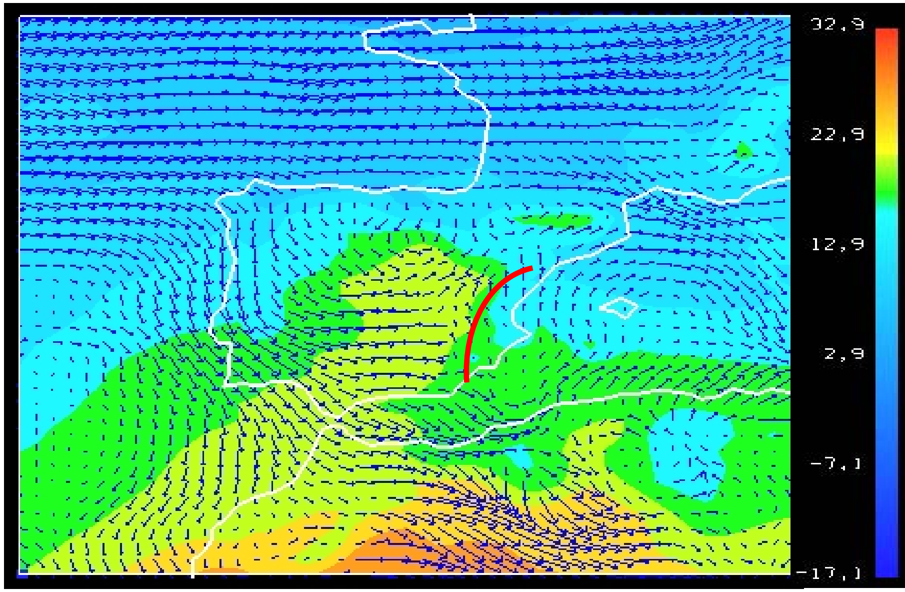
MSG High Resolution Visible Image

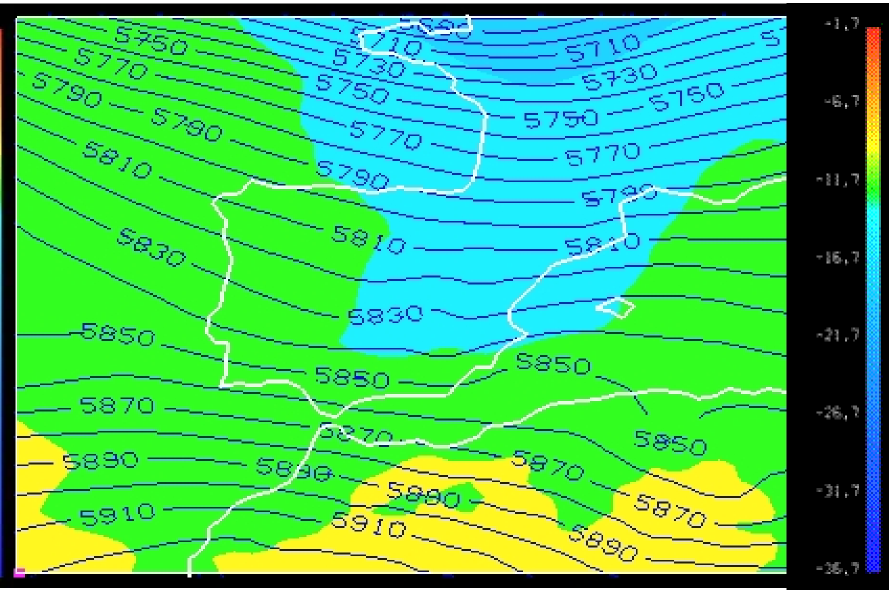


Study Case: Synoptic Framework (ECMWF)

850hPa temperature and wind

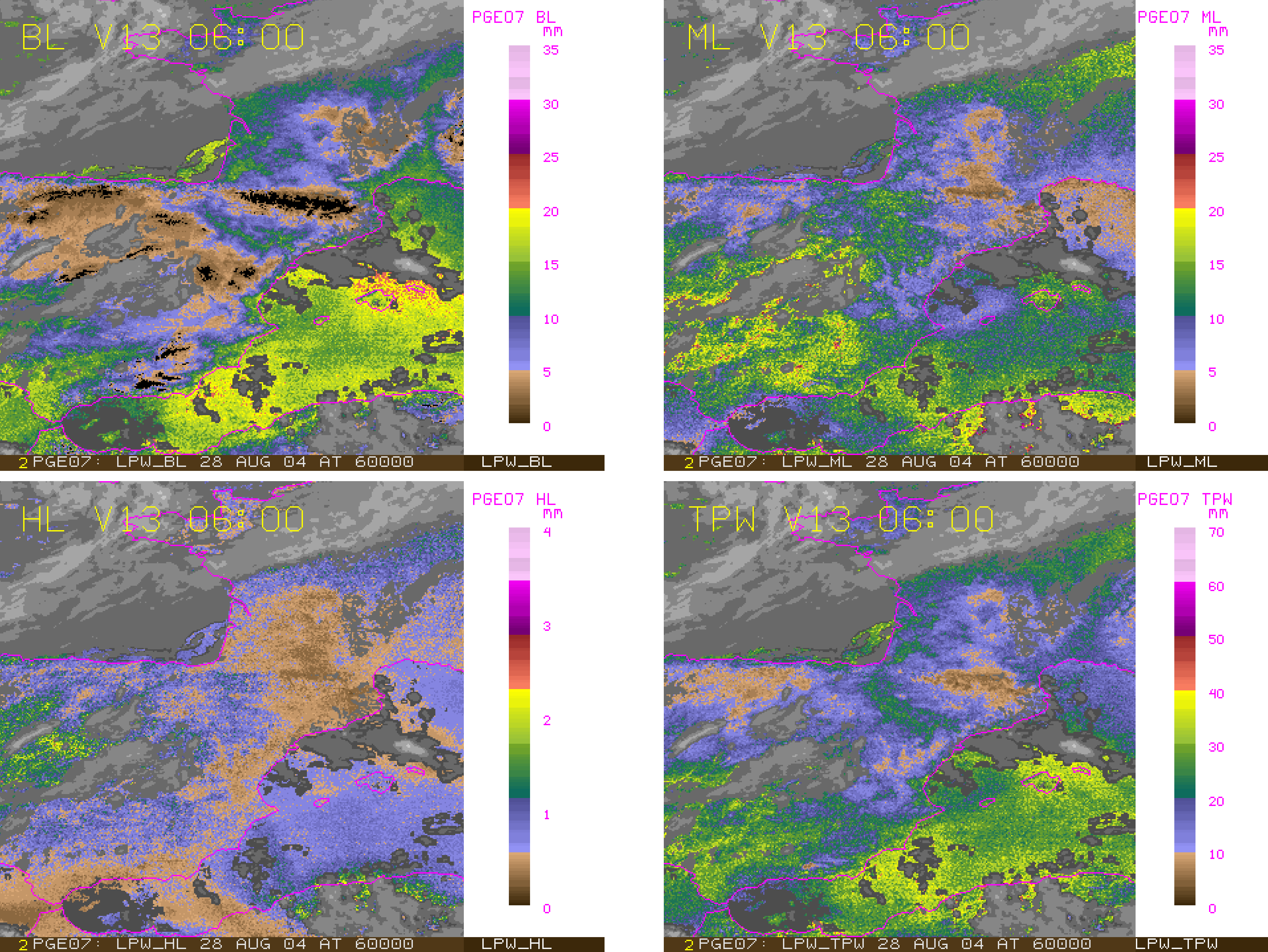
500hPa temperature and Z



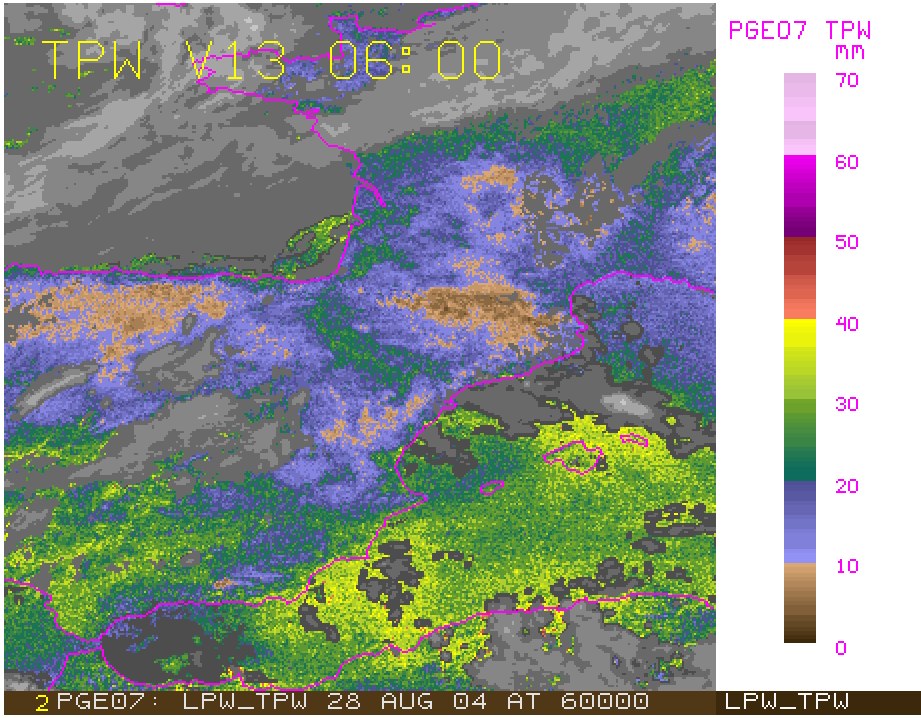


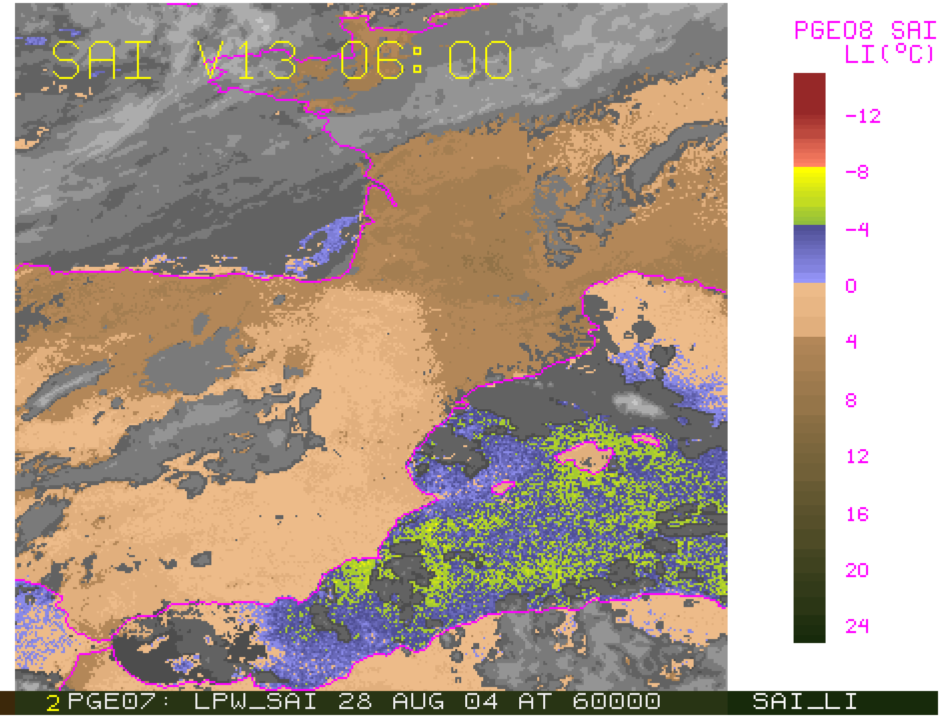
- **Convergence at low levels (surface, 850 hPa)**
- **Cooling at 500hPa.**

ECMWF H+3 PAS=12Z


BL V13 06:00
PGE07 BL
mm
35
30
25
20
15
10
5
0
2 PGE07: LPW_BL 28 AUG 04 AT 60000
LPW_BL
ML V13 06:00
PGE07 ML
mm
35
30
25
20
15
10
5
0
2 PGE07: LPW_ML 28 AUG 04 AT 60000
LPW_ML
HL V13 06:00
PGE07 HL
mm
4
3
2
1
0
2 PGE07: LPW_HL 28 AUG 04 AT 60000
LPW_HL
TPW V13 06:00
PGE07 TPW
mm
70
60
50
40
30
20
10
0
2 PGE07: LPW_TPW 28 AUG 04 AT 60000
LPW_TPW

Total Precipitable Water and Lifted Index evolution

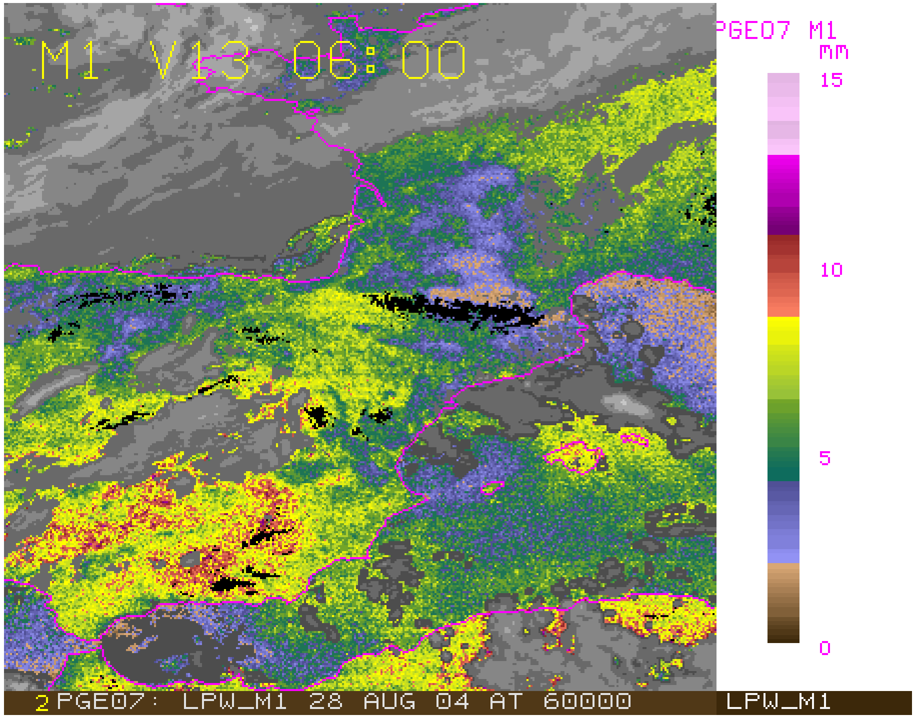


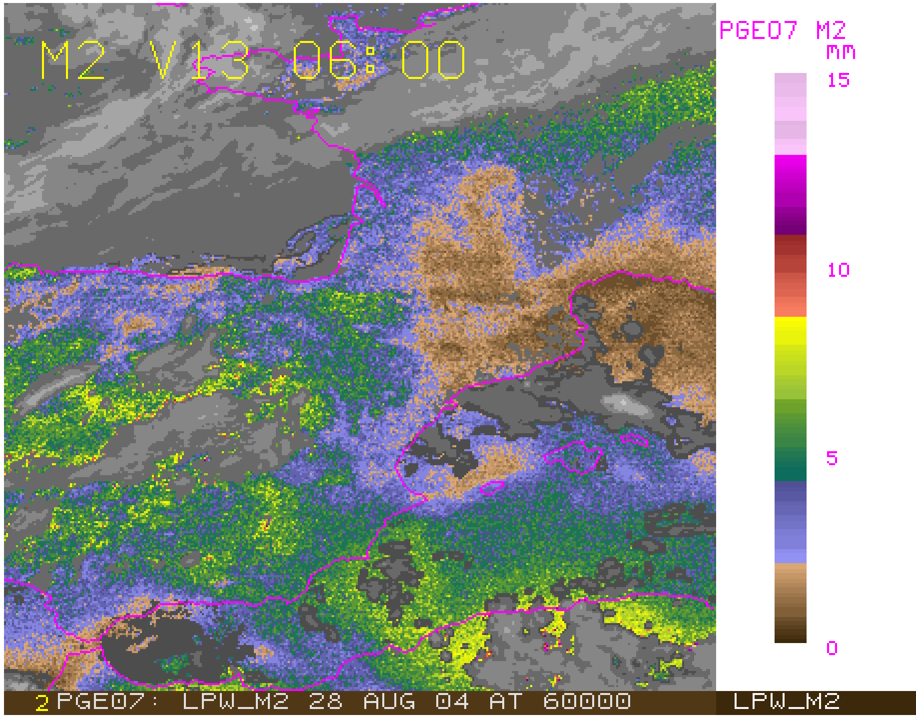


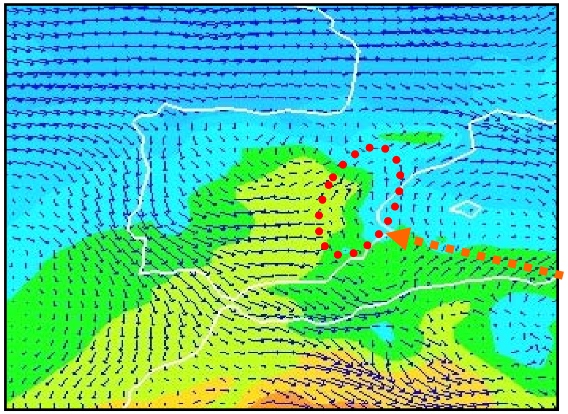
- TPW increases around the convective region.
- Lifted Index decreases (gain of air instability)

New Layers Evolution

M1 (840-700 HPa) — **M2 (700-437 HPa)**







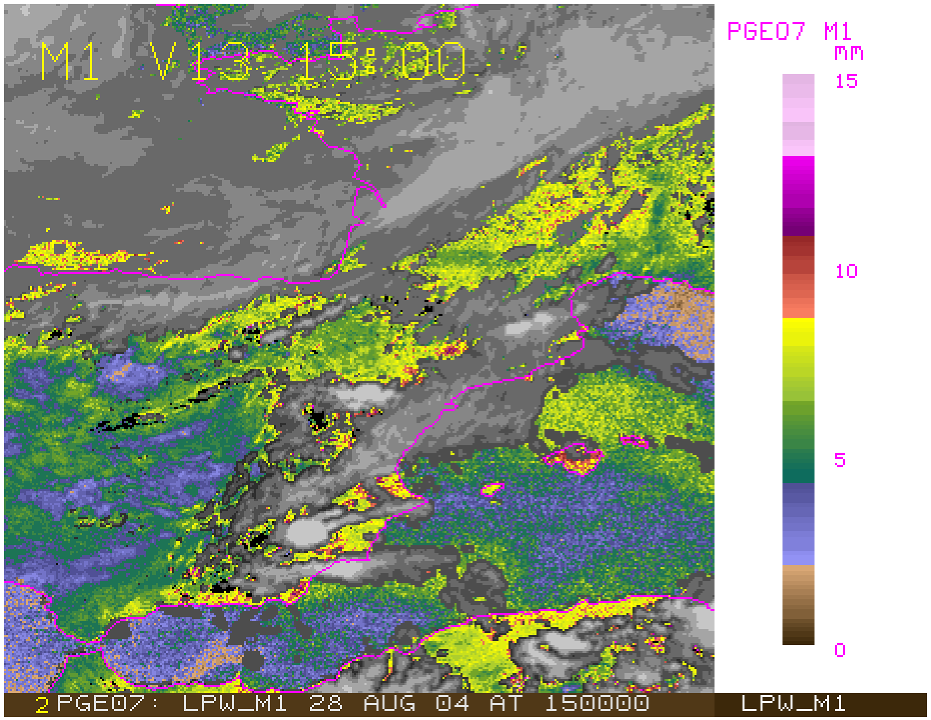
ECMWF H+3 PAS=12Z

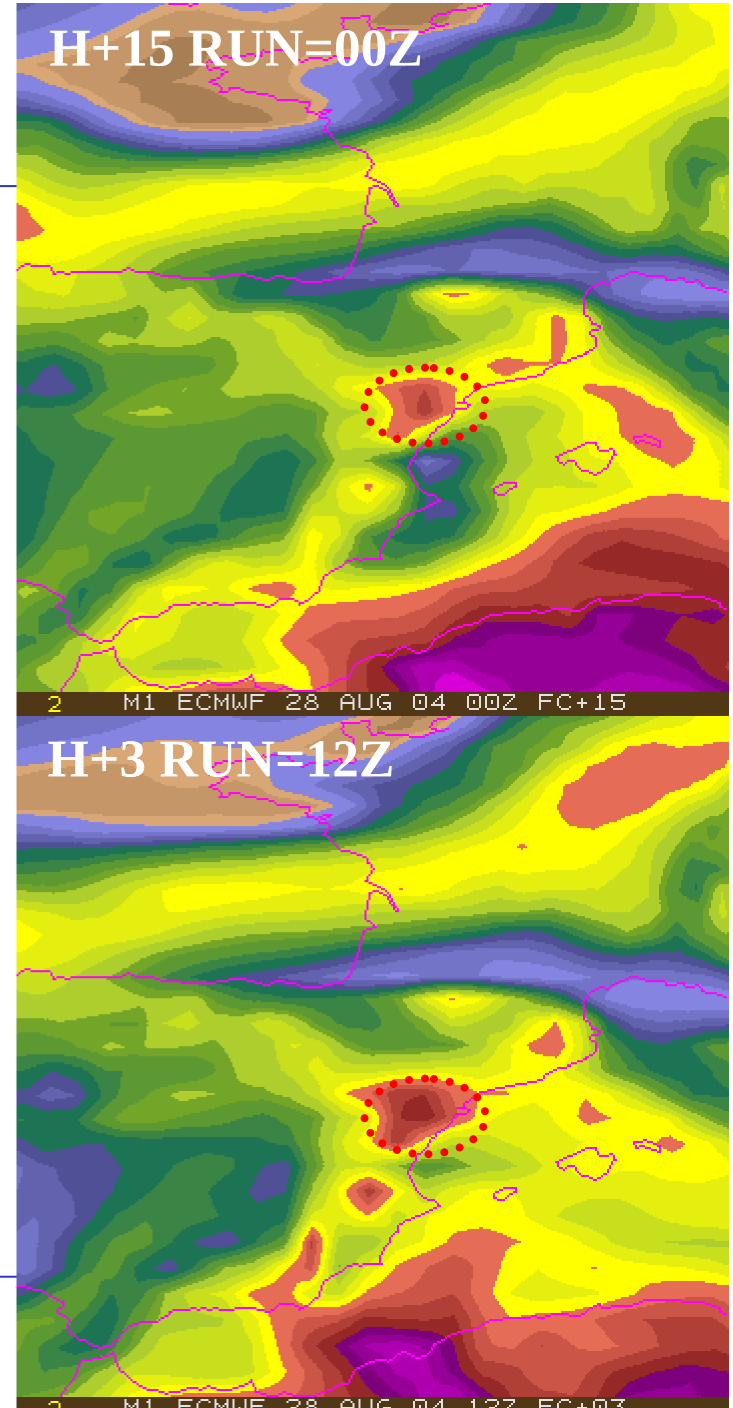
Increase of precipitable water content at each new sub-layer (higher in M1)

↕

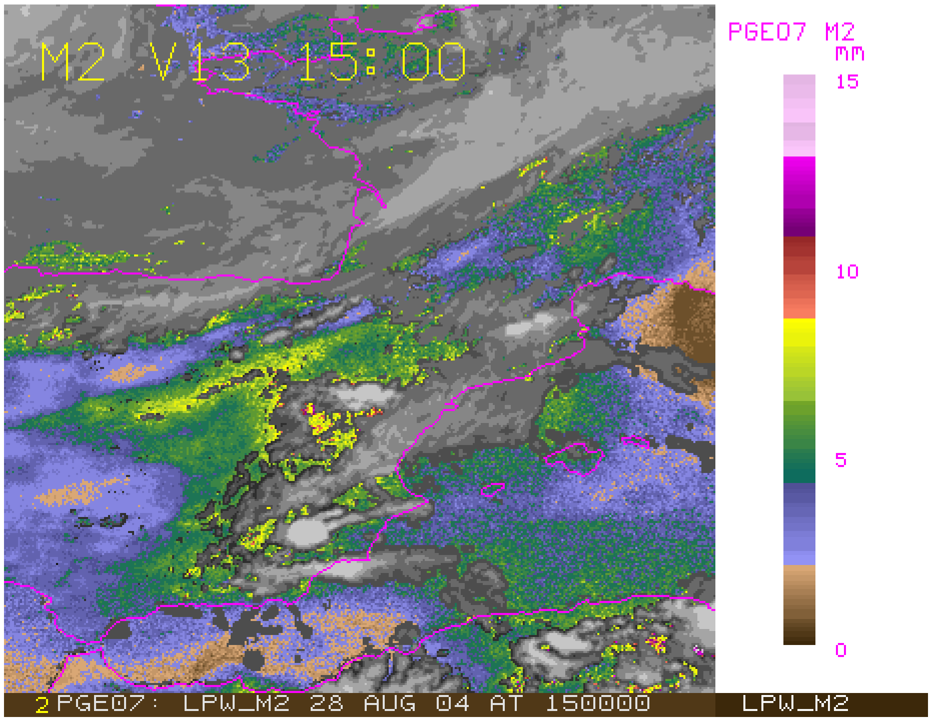
Humidity convergence at low levels (850hPa)

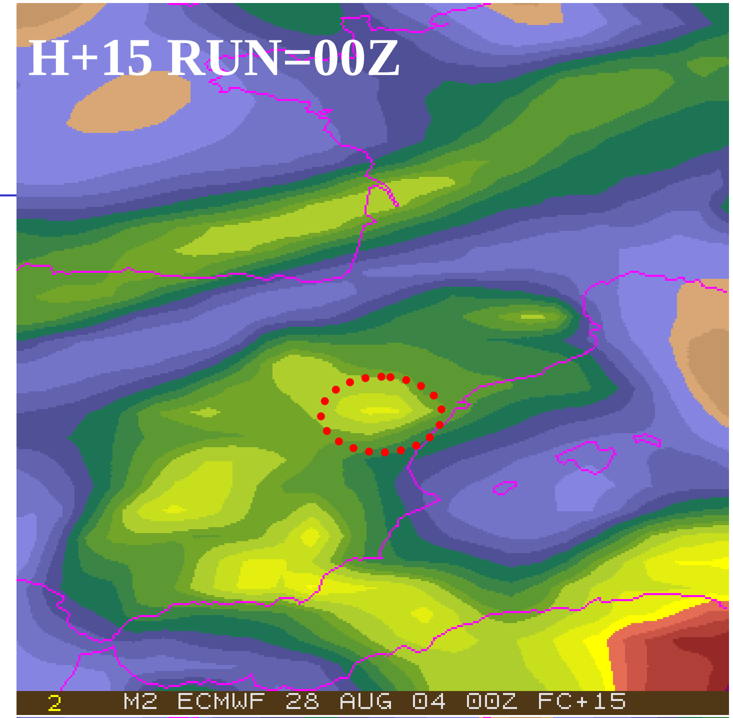
M1 ECMWF comparison

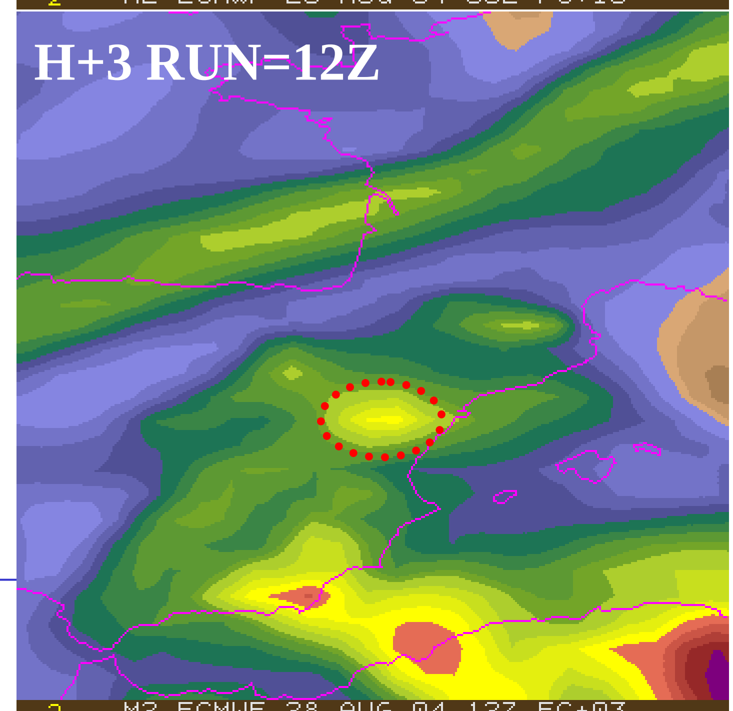


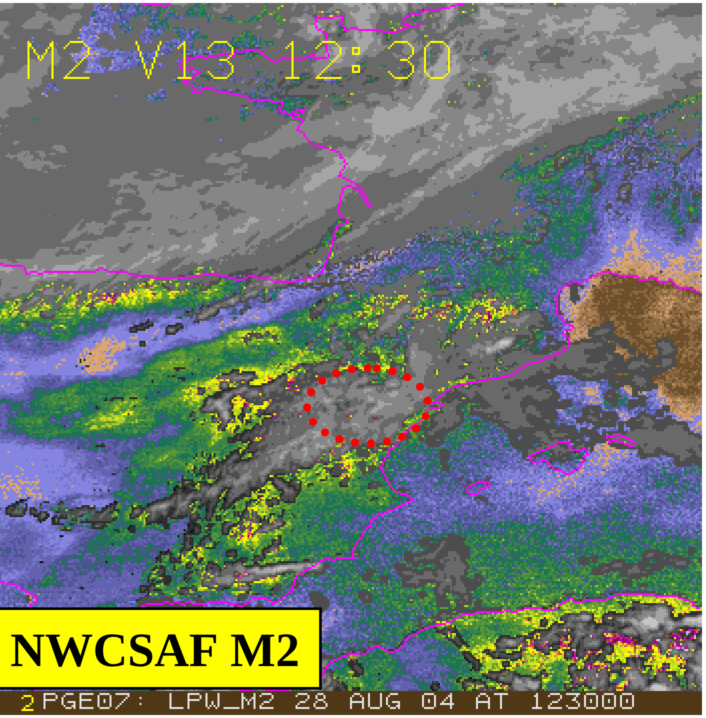


M2 ECMWF comparison

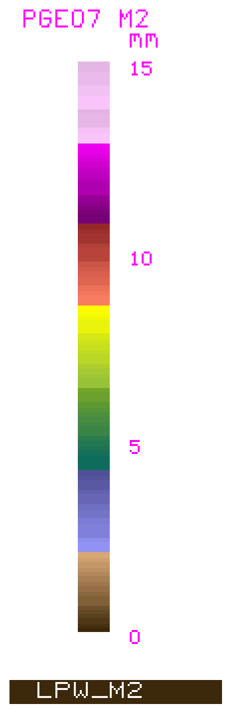


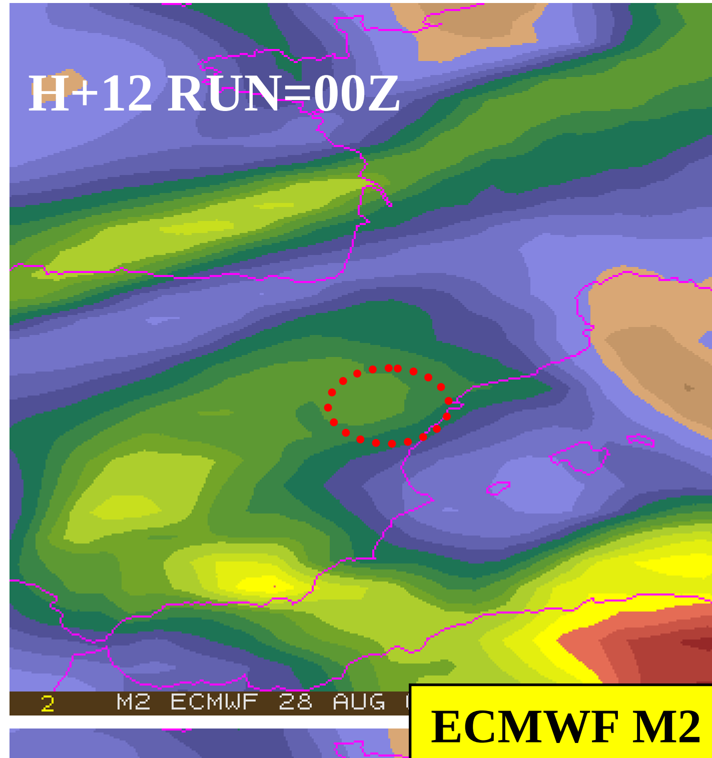


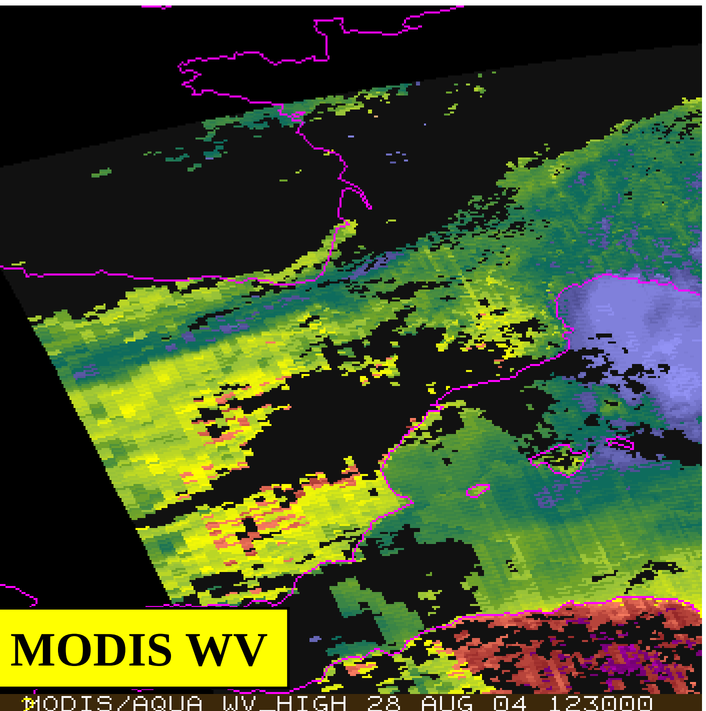




M2 vs ECMWF & MODIS

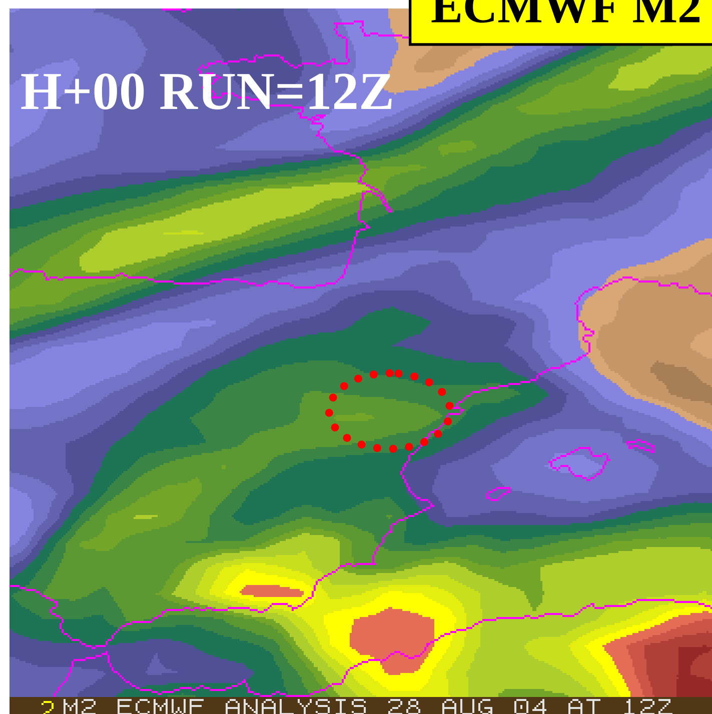






SAFNWC M2 AND ECMWF M2 700-437hPa

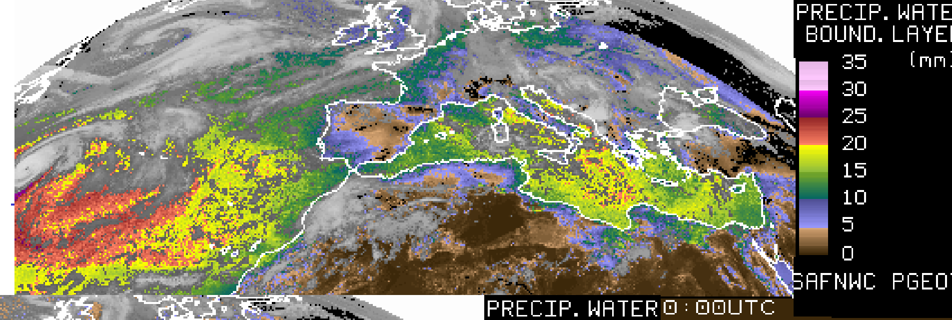
MODIS WV_HIGH 700-300hPa

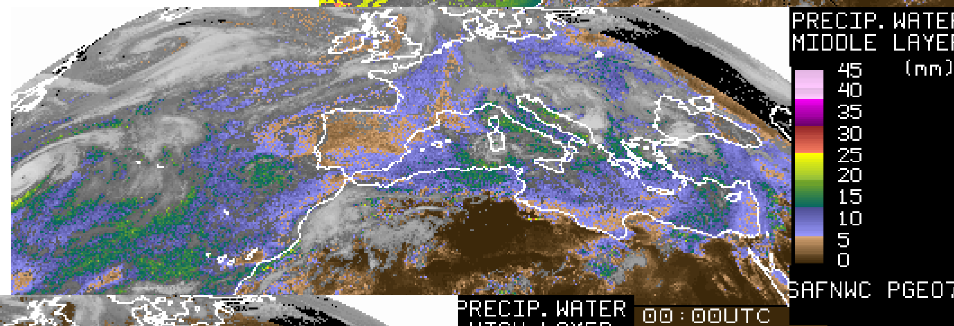


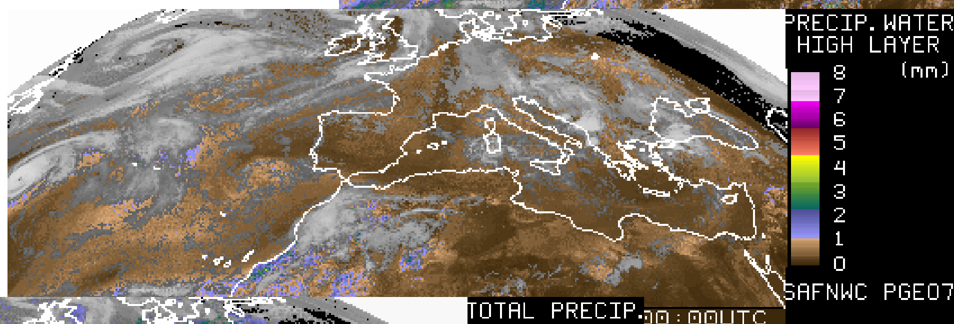
SUMMARY (New sub-layers)

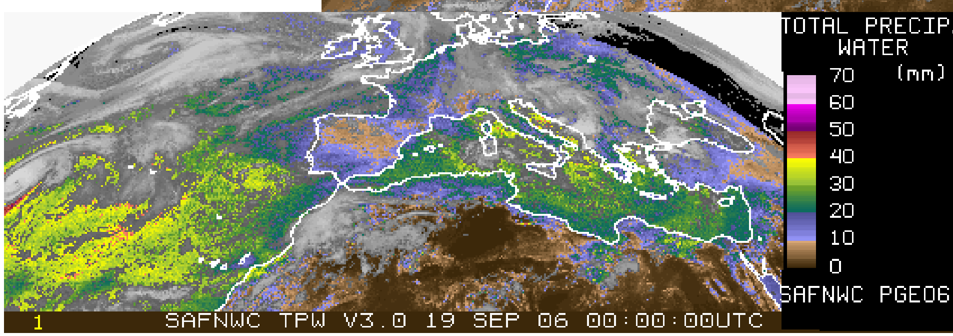
- Humidity advections are clearly appreciated on the image loops thanks to the SEVIRI temporal resolution (15min).
- The new sub-layer parameters help to monitoring pre-convective episodes.
- Both parameters retrieved from IR SEVIRI channels give information consistent with the analysis. The middle levels spatial distribution of moisture is in better agreement with the 12+3H forecast (ECMWF) than with the 00+15H.
- MODIS WV_HIGH (700-300hPa) spatial patterns are consistent with the M2 (700-437hPa) spatial patterns.

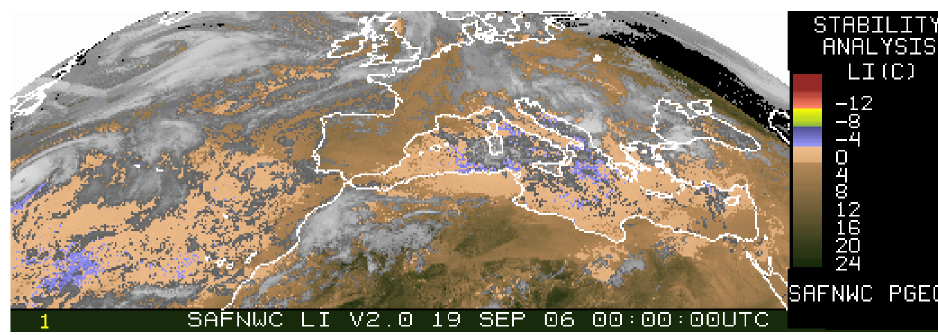
Thanks for your attention











OTHERS SLIDES

USED DATASET

To implement the algorithms

Training dataset

60L-SD
(extracted from 40-ERA)

SSDB
(extracted from ECMWF analyses Nov-02 to Oct-03)

Local bias radiances & local adjustment of each parameter
(ECMWF analyses profiles Jul-04 to Jun-05)

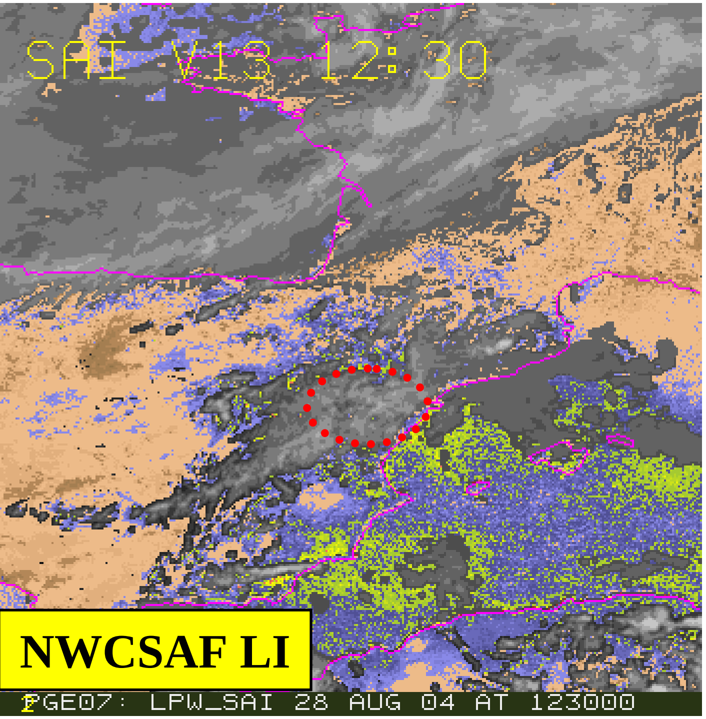
To validate the algorithms

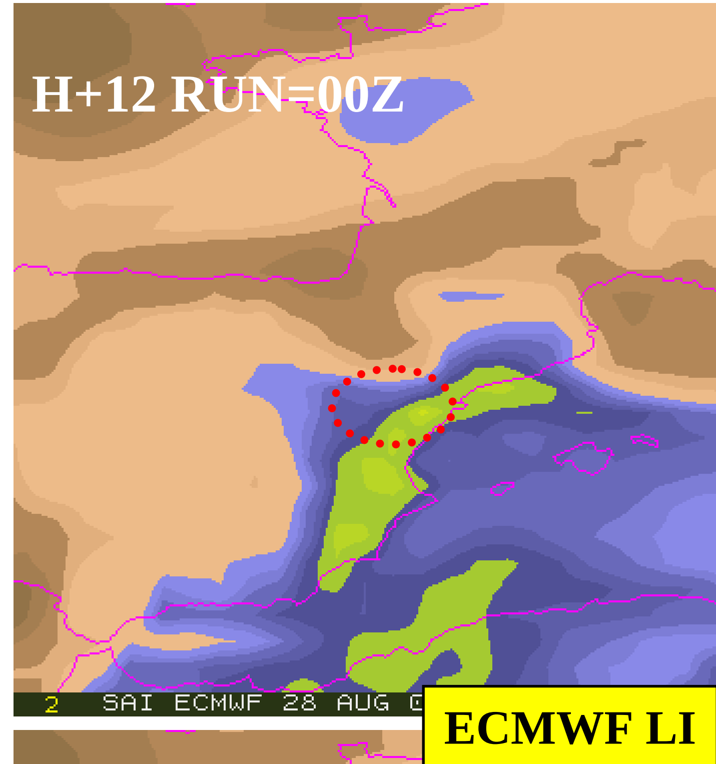
ECMWF analysis profiles
(MSG-N, Jul-05 to Jun-06)

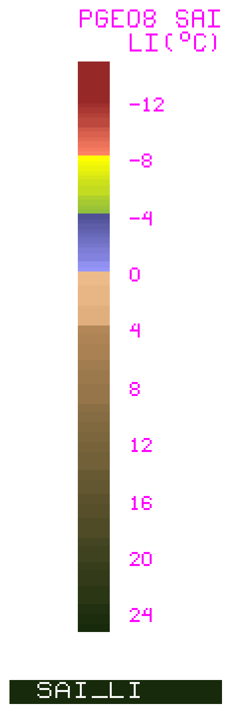
RAOB stations
(MSG-N, Jul-05 to Dec-06)

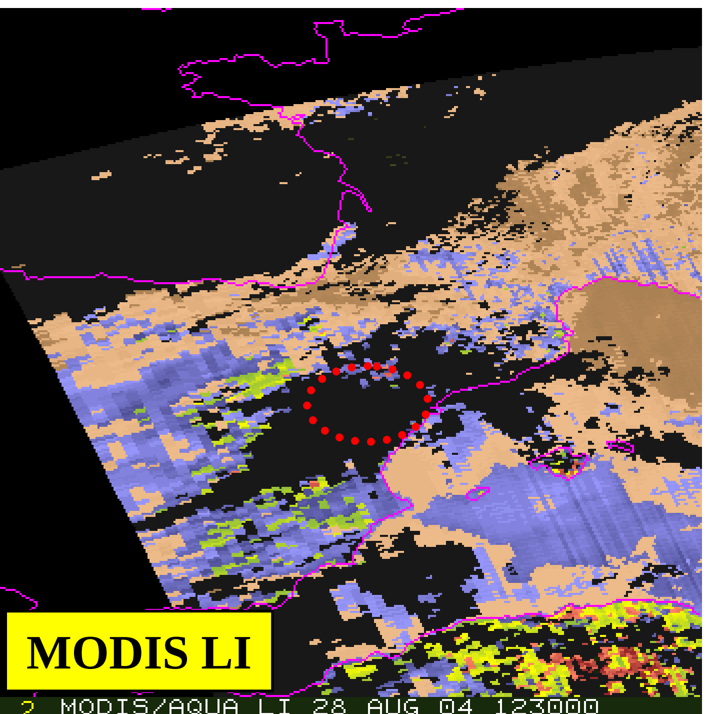
GPS IWV for two centers: GFZ and METO
(May-05 to Apr-06)

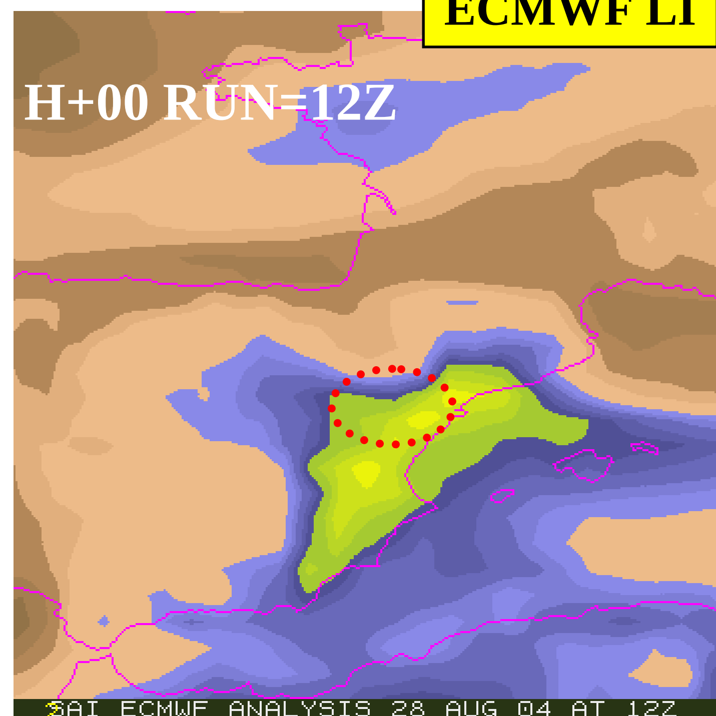
LI vs ECMWF & MODIS



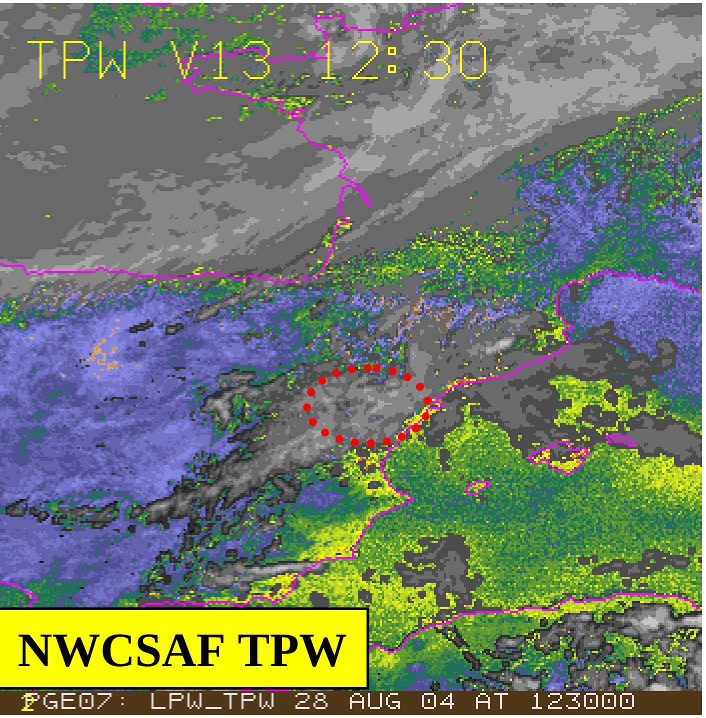


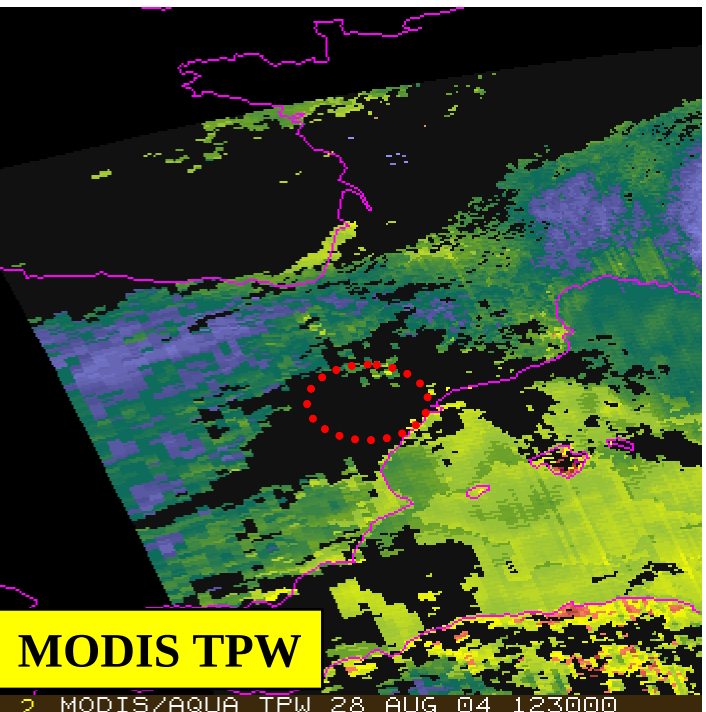


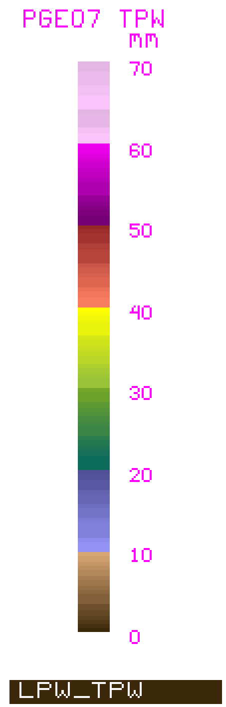


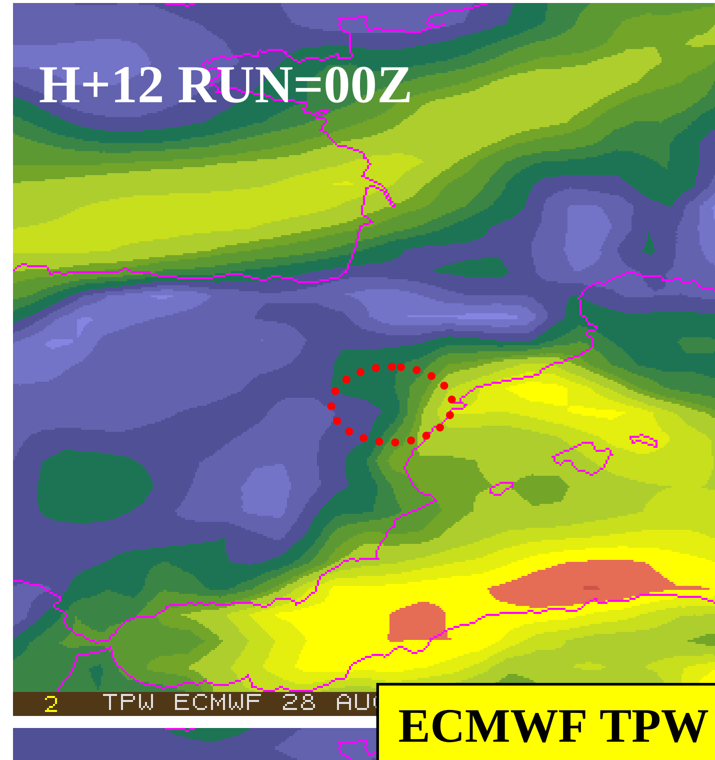


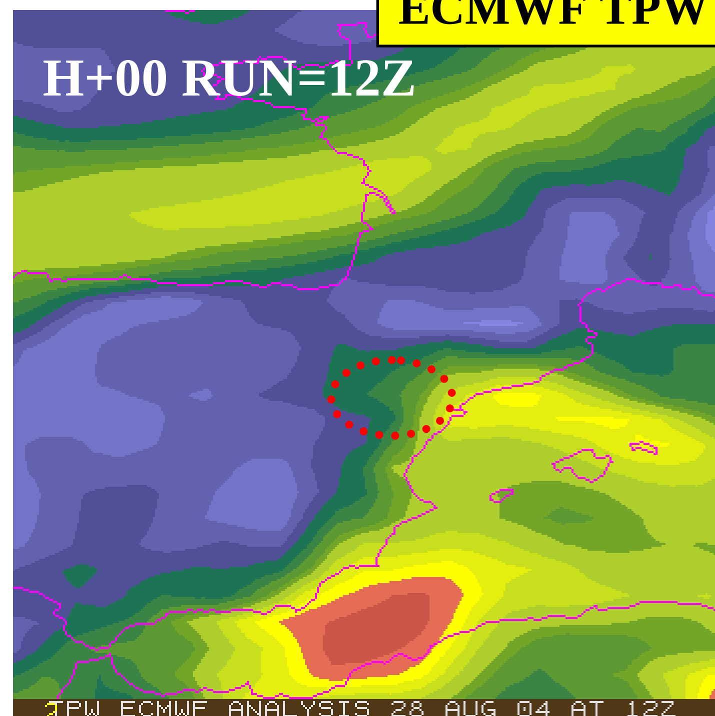
TPW vs ECMWF & MODIS





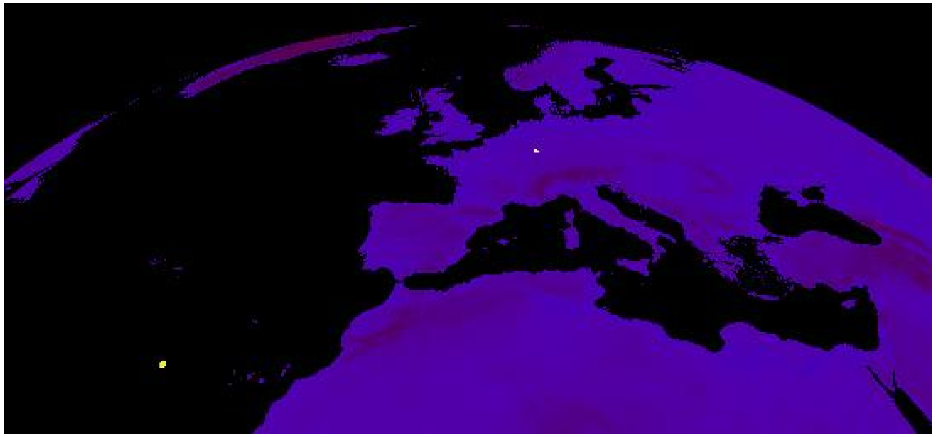






Points used to check the local bias correction

- Reference points in yellow.
  - Sea point
    (24.0ºW, 29.5ºN)
  - Central Europe point
    (7.0ºE, 49.5ºN)



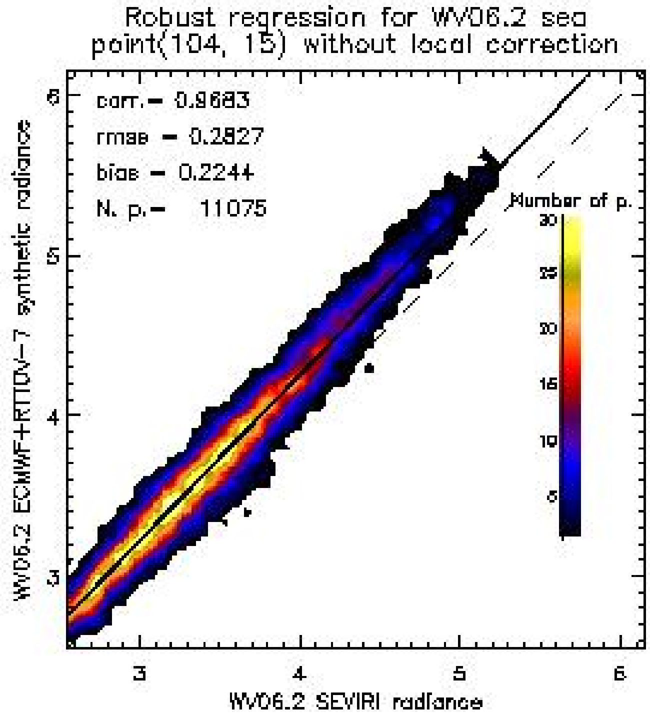
It can be observed (next slides):

Water vapour channels (with less surface influence) present similar adjustments in both points (sea and land)

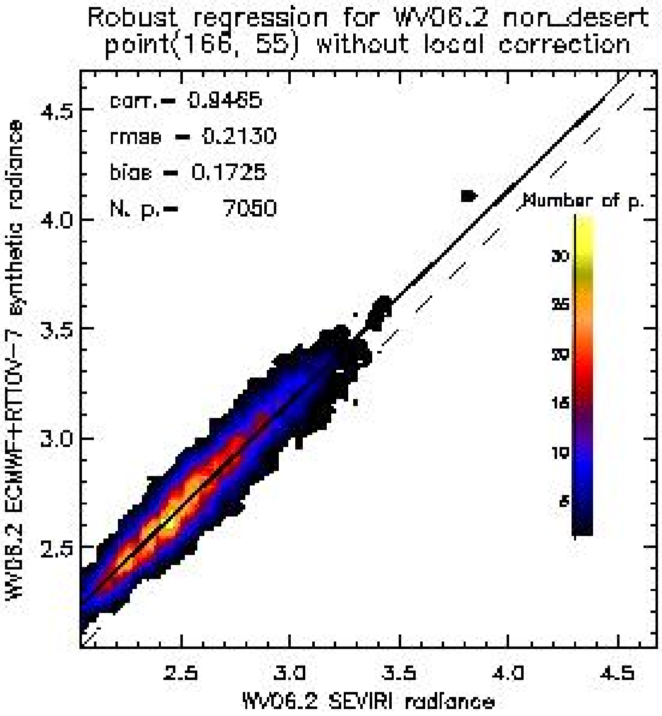
Window channels are more spread out in the land pixel (over Central Europe) than in the sea pixel.

WV6.2 channel

SEA



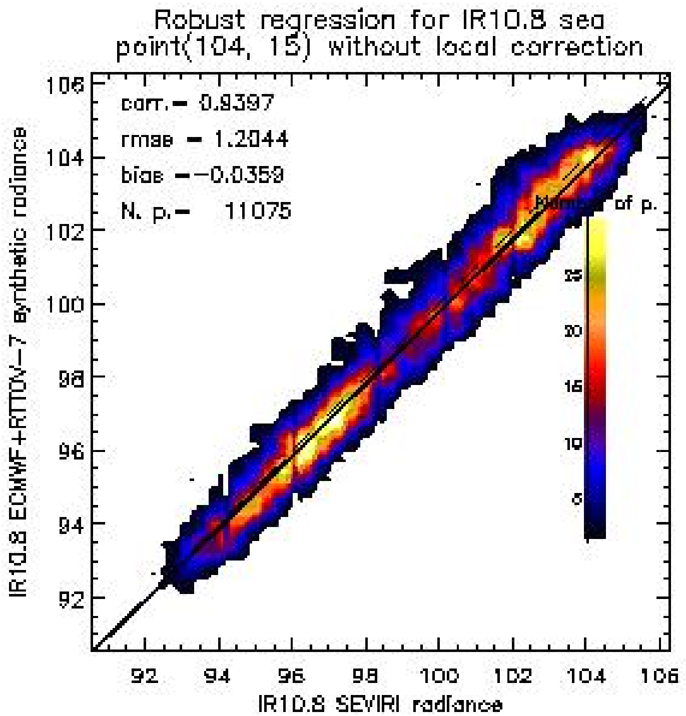
LAND

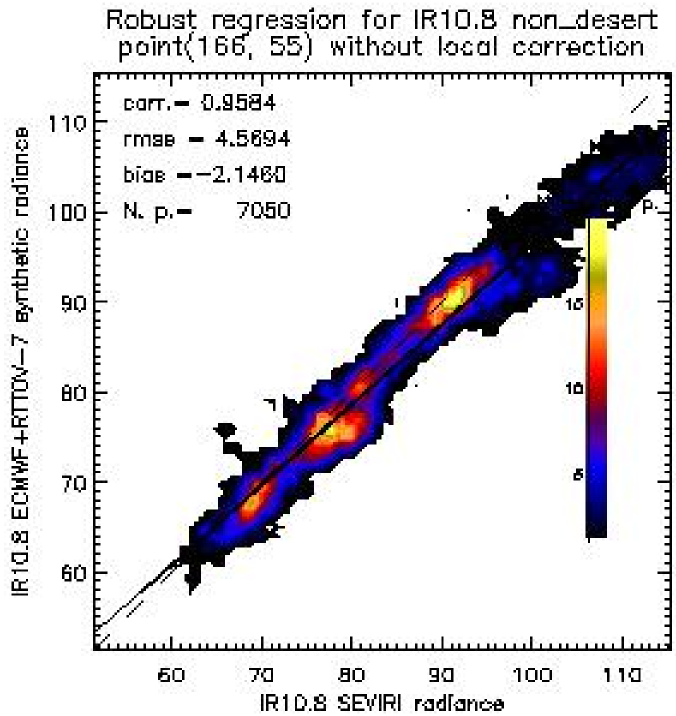


Both points (sea and land) present similar adjustments

IR10.8 channel

SEA **LAND**





Windows channels are more spread out in the land pixel (over Central Europe) than in the sea pixel.