

sSHAI Non-linear Retrieval of atmospheric vertical profiles from MTG-IRS data

1. Introduction

During the past 30 years EUMETSAT has been providing critical information to contribute to operational nowcasting and climate monitoring. In the future, EUMETSAT will add to its satellite fleet the Meteosat Third Generation (MTG), which will provide an evolution of the imaging service. The satellite series will comprise: four Imaging Satellites (MTG-I) and two Sounding Satellites (MTG-S).

MTG-S, includes an interferometer, the Infrared Sounder (IRS) which is based on an imaging interferometer with a very high spectral resolution, commonly known as hyperspectral infrared sounders.

In this work, the IASI (Infrared Atmospheric Sounding Interferometer) hyperspectral sonder, on board MetOp satellite series, has been used as a proxy of MTG-IRS.



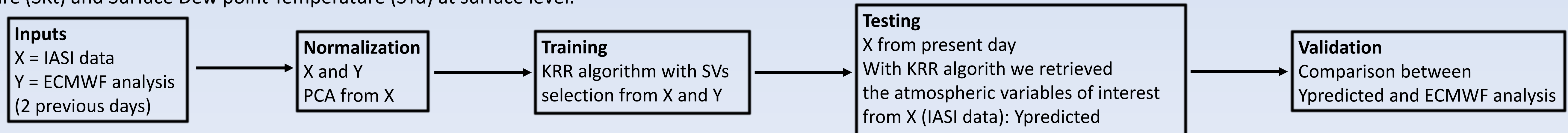
2. Methodology

The main objective of this work, is to characterize the new MTG-IRS capabilities in providing information on atmospheric temperature and humidity profiles. To achieve this goal, we have developed a method based on Machine Learning/Artificial Intelligence techniques for IASI-MetOp (as a proxy MTG-IRS) to estimate atmospheric vertical profiles. The method developed in this work is a Kernel Ridge Regression (KRR) model, that allow us to select an amount of Support Vectors (SVs) to minimize the training dataset with the aim to design an operational non-linear regression. The KRR model used in this work to retrieve atmospheric vertical profiles from IASI data is based on a Radial Basis Function kernel, i.e. a Gaussian Kernel defined as: $K = \frac{-|X_{test} - X_{train}|^2}{2\sigma^2}$

Where X_{test} is the new atmospheric state vector from IASI data used to test the KRR model (on July 15th 2015 between 9:45Z and 11:27Z). X_{train} are the atmospheric state vectors from IASI data used to train the KRR model (from July 13th and 14th, 2015). And finally, σ is defined like the kernel distance. It is important to note that the SVs selection method is based on kernel distance, since kernel distance is linked with the information that new data is introduced to the KRR model.

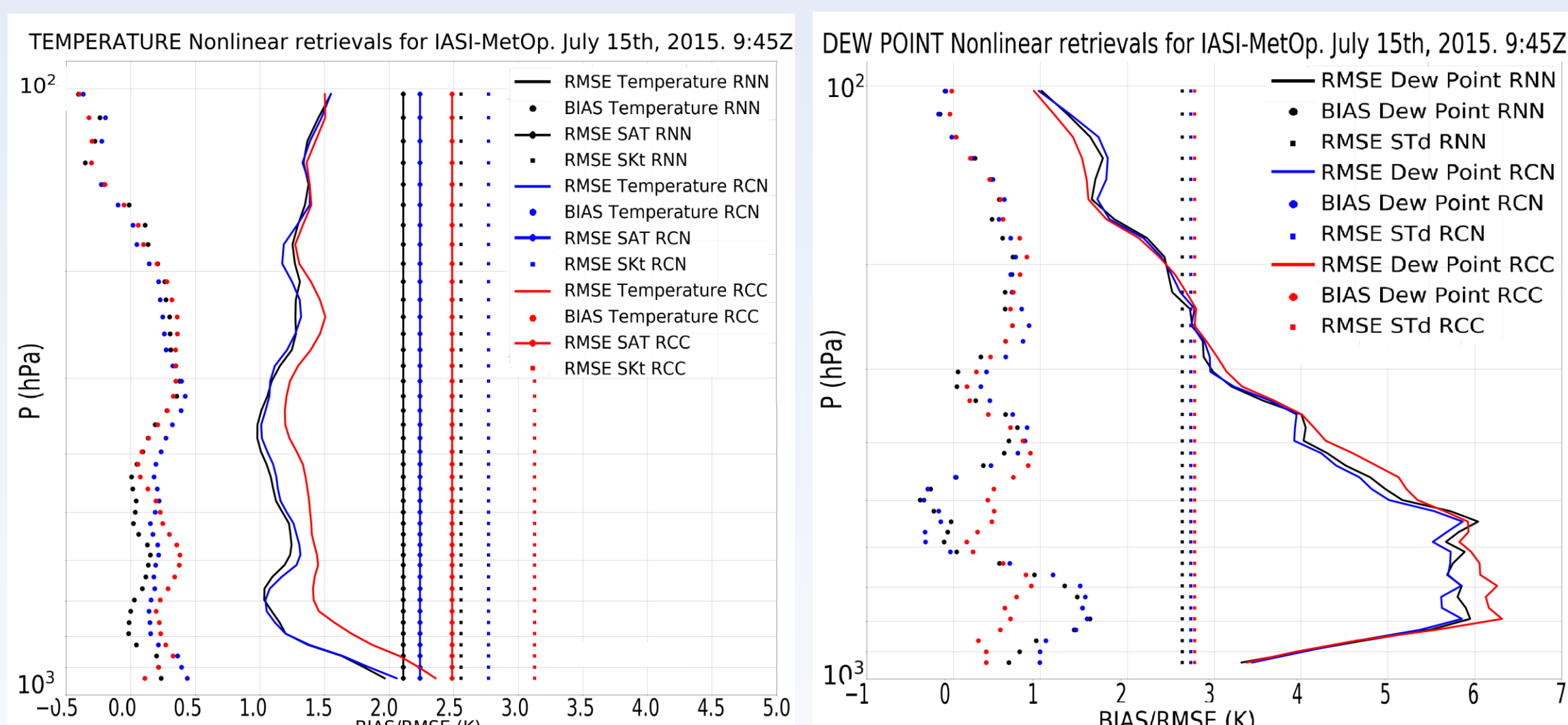
This selection of SVs allows us to select a limited amount of data, minimizing the high computational cost of the processing techniques required for the retrieval of atmospheric variables from the IASI data (Radiances, Vertical Solar/Satellite Zenith Angle, latitude and Surface pressure of each pixel). The input dependent variables are built with ECMWF analysis consisting of: Temperature and water vapour profiles at 90 pressure levels, Surface Air Temperature (SAT), Skin Temperature (SKT) and Surface Dew point Temperature (STD) at surface level. This is therefore a case of "multivariate regression". Thus, by discarding a number of IASI, and selecting the most informative ones for the atmospheric variables of interest, we have managed to reduce the input dimensions. We then applied a principal component analysis to reduce the dimensionality of the input dataset, selecting the SVs by the information they provide to the KRR model and avoiding redundancies in the information provided by the SVs.

The atmospheric variable of interest retrieved from IASI data are: Temperature (T) and Dew Point Temperature (Td) vertical profiles at 90 pressure levels, Surface Air Temperature (SAT) at 2m from the surface, Skin Temperature (SKT) and Surface Dew point Temperature (STD) at surface level.



3. Results

First, the results obtained from the statistical comparison between the atmospheric variables of interest retrieved from IASI data using the KRR model on July 15th between 9:45Z and 11:27Z and ECMWF analysis at 12Z are shown:



Graphic 1 – Comparison between IASI non-linear retrievals retrieved between 9:45Z and 11:27Z, and ECMWF analysis at 12Z on July 15th, 2015. RMSE (solid line) and BIAS (dash) obtained for Temperature profiles, SAT and SKT (left) and for water vapour profiles and STD (right).

RMSE y BIAS between ECMWF analysis and RNN

	T (K)	Td (K)	SAT (K)	SKT (K)	STD (K)
RMSE	1.24	3.87	2.11	2.56	2.63
BIAS	0.09	0.47	-	-	-

RMSE y BIAS between ECMWF analysis and RCN

	T (K)	Td (K)	SAT (K)	SKT (K)	STD (K)
RMSE	1.26	3.83	2.24	2.77	2.73
BIAS	0.16	0.55	-	-	-

RMSE y BIAS between ECMWF analysis and RCC

	T (K)	Td (K)	SAT (K)	SKT (K)	STD (K)
RMSE	1.46	3.96	2.49	3.13	2.78
BIAS	0.17	0.49	-	-	-

IASI nonlinear retrievals show a high quality to study the atmosphere characteristics in scenes with a cloud fraction up to until 80%, allowing to obtain information about atmospheric episodes even in cloudy skies conditions.

The day (15/07/2015) and the area (Iberian Peninsula) have been selected for their characteristics. Since, over Spain, this day was a suitable day for hyperspectral sounders with clear skies in the morning and a convective situation of interest in the afternoon, with convection developing and atmospheric instability in several points of the Iberian Peninsula.

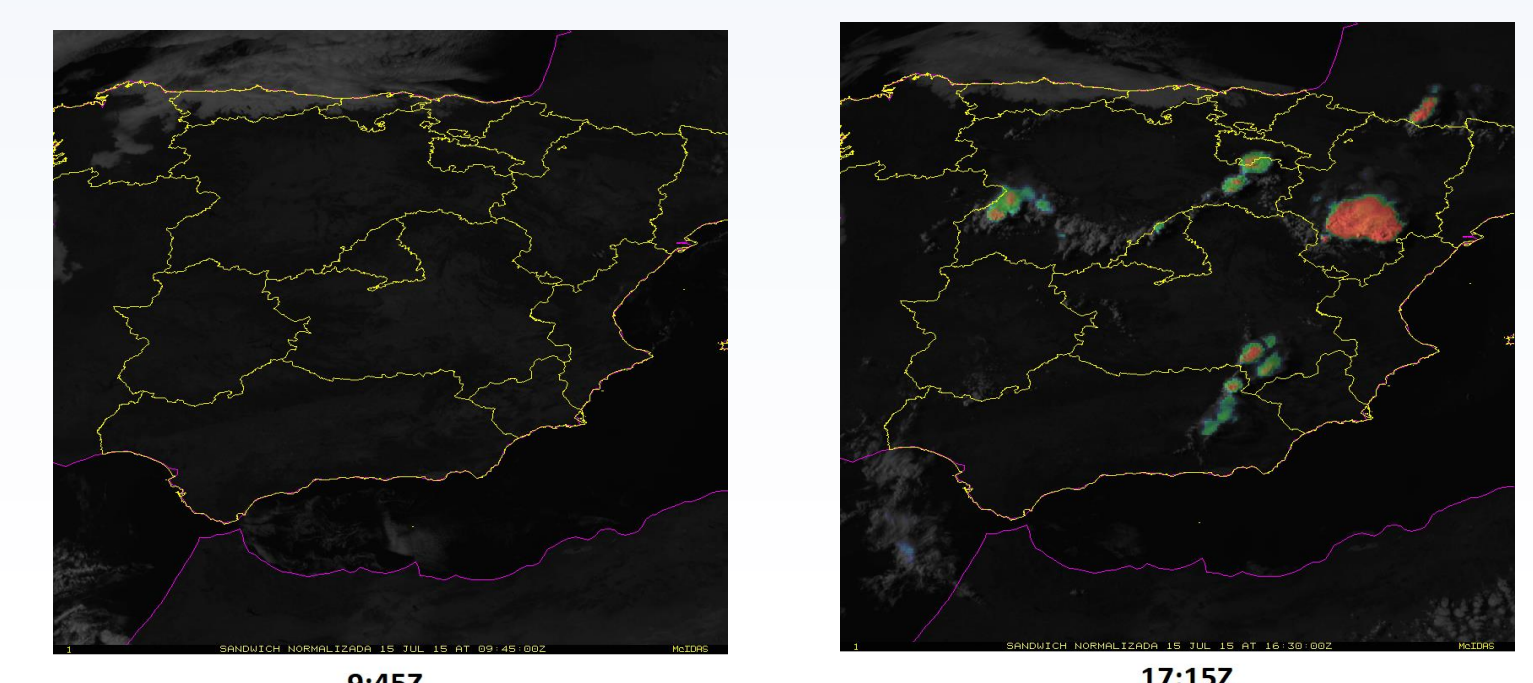
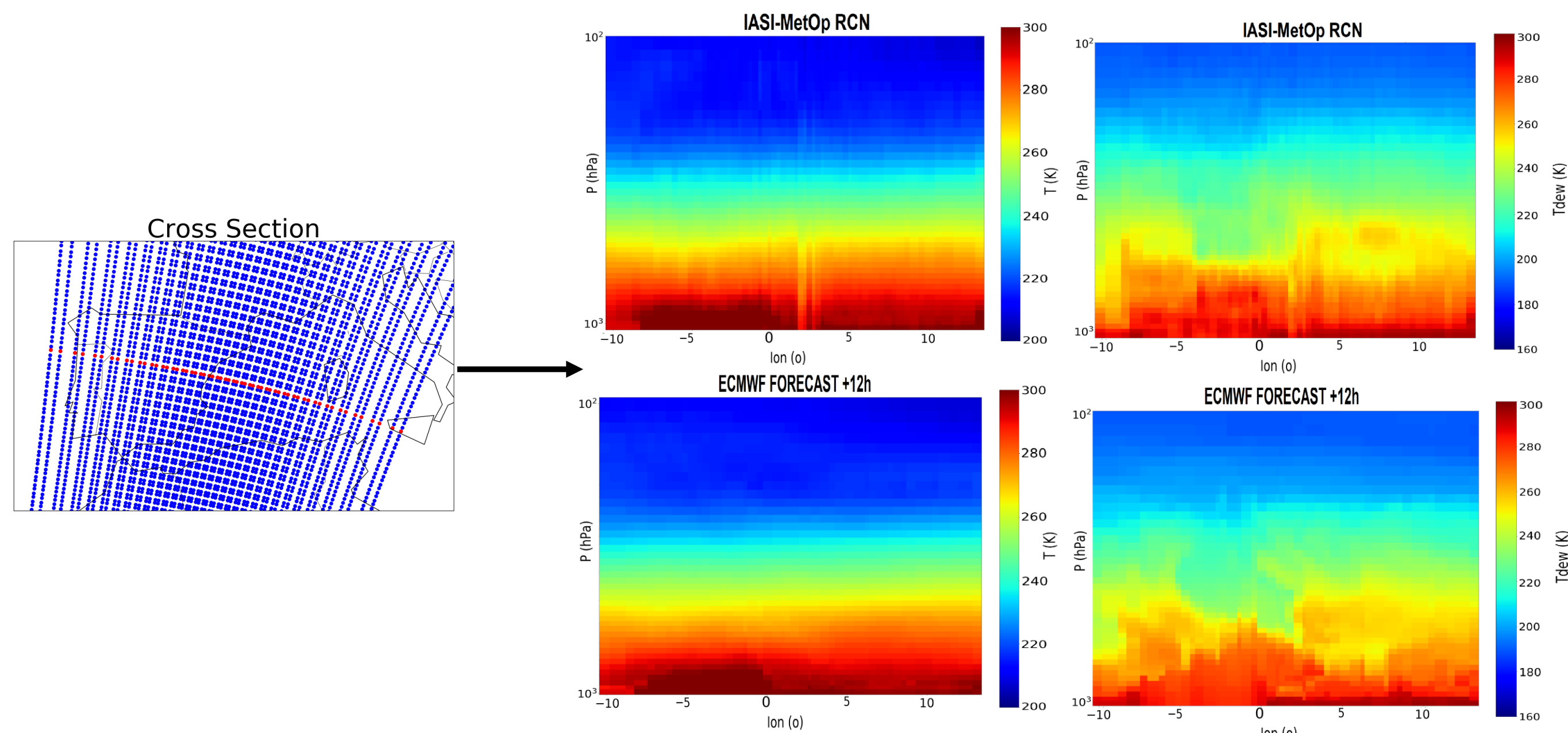


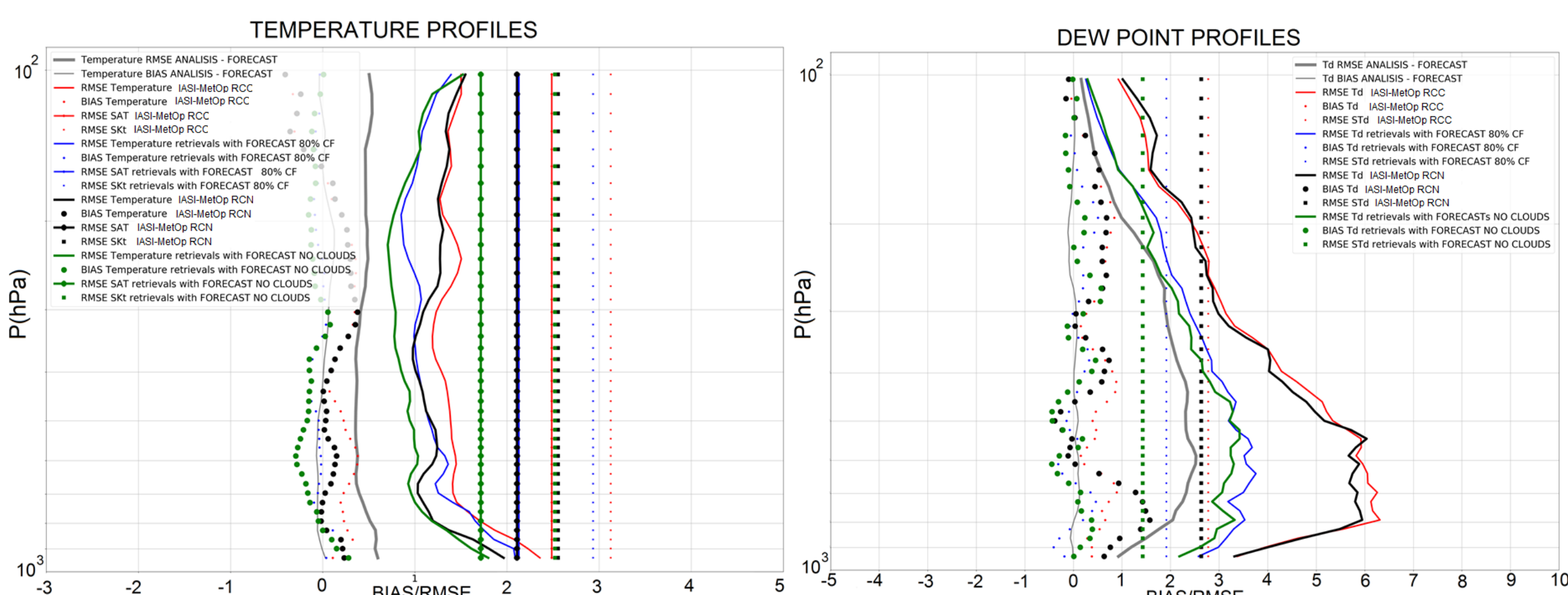
Figure 1 – Meteosat RGB Images on 15/07/2015. On the left side shown the image at 9:45Z. On the right side it is shown the image at 17:15Z.

The following figure shows the vertical profiles of T (K) and Td (K) retrieved for RCN (IASI retrievals trained with all scenes with a cloud fraction until up to 80% and tested with no cloud scenes), RCC (IASI retrievals trained and tested with all scenes with a cloud fraction until up to 80%) and ECMWF forecast 00+12h on 15/07/2015. For comparison between these datasets we show the vertical profiles of temperature and water vapour in the cross section over the convective storm in Aragon (40.73°N, 0.9°W):



3.1 IAS Nonlinear Retrievals with ECMWF forecast as input

The KRR model is a powerful tool to obtain IASI nonlinear retrievals with a high potential to analyze the atmospheric instability and convective situations. The retrievals obtained also using ECMWF forecast 00+12 as input to the KRR model to retrieve the atmospheric variables of interest are shown below:



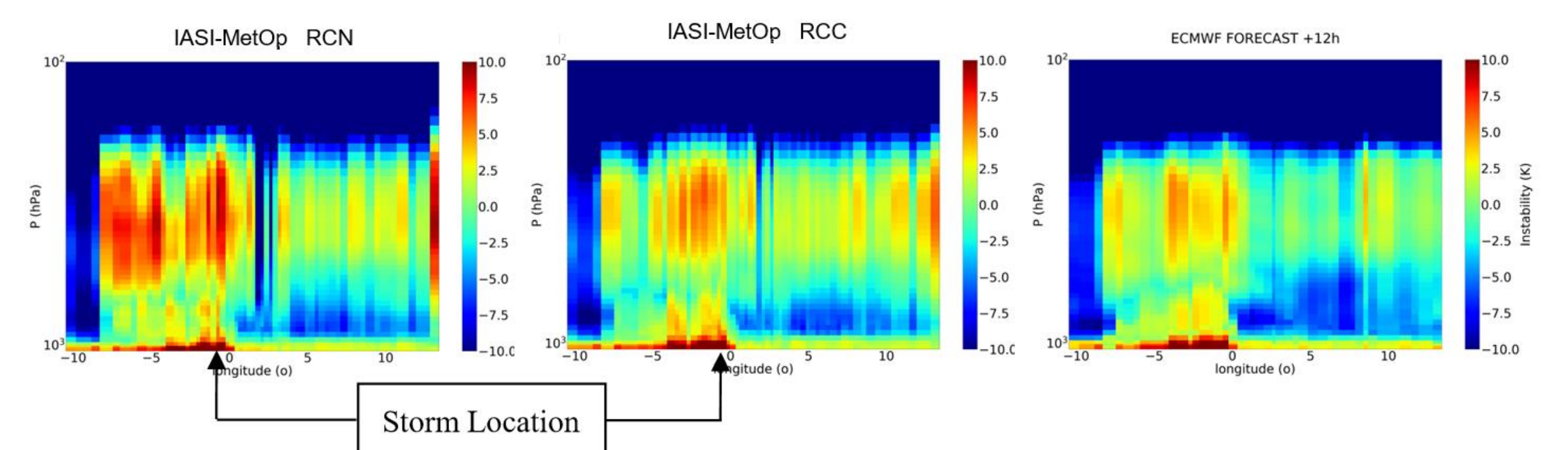
Graphic 2 – Comparison between IASI non-linear retrievals (with and without ECMWF forecast 00+12h as input) retrieved between 9:45Z and 11:27Z, and ECMWF analysis at 12Z on July 15th, 2015. RMSE (solid line) and BIAS (dash) obtained for Temperature profiles, SAT and SKT (left) and for water vapour profiles and STD (right).

4. Conclusions

The results of the application of the KRR model to the IASI-MetOp data (as a proxy for MTG-IRS) indicate a high improvement of the meteorological analyses for the analysed weather scenarios. If we analyse these improvements in detail they should have a direct positive influence on the accuracy of the forecasts, providing the NWCSAF with high quality non-linear retrievals of IASI, which form a powerful tool for analysing and monitoring the atmospheric state in all situations around the globe.

To study this situation in more detail, we have plotted the instability cross section for the selected longitudes. Where we have considered the instability as the difference between temperature profile of each dataset and its ascending adiabatic line:

$$\text{Instability} = T_{\text{ascending adiab}} - T_{\text{profile}}$$



3.2 NWC SAF sSHAI examples: CAPEs results

One of the most widely used convective parameters in operational forecasting is the CAPE (Convective Available Potential Energy). The following figures show the results of the CAPE calculated for the day of interest using the IASI non-linear retrievals adding as input the ECMWF forecasts, as well as the instability maps obtained for the IASI non-linear retrievals with forecast:

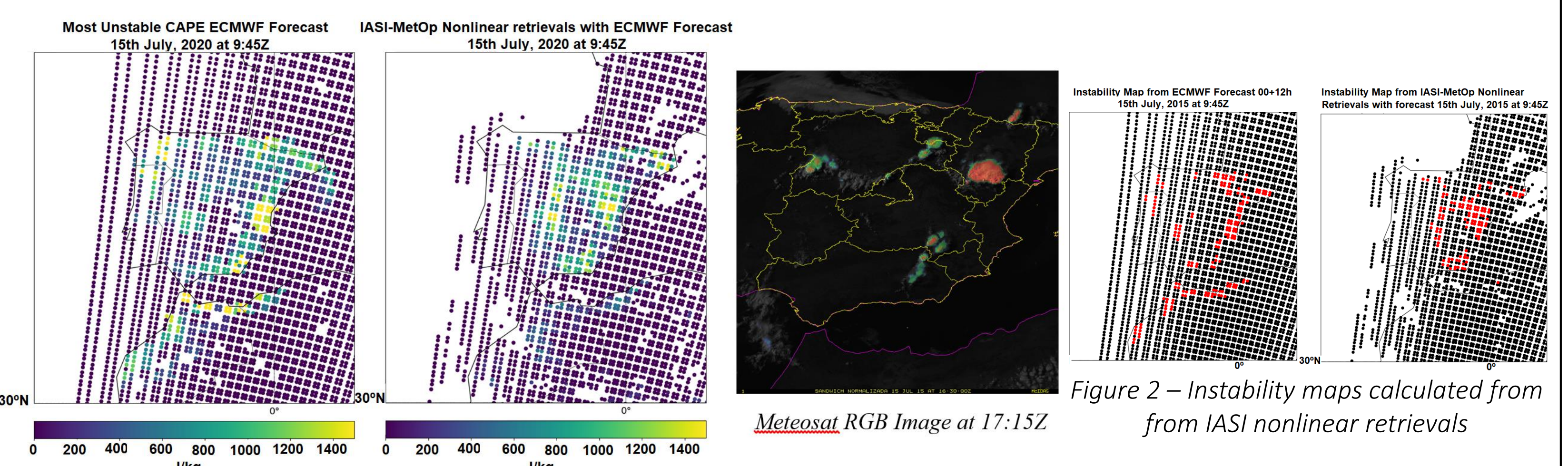


Figure 2 – Instability maps calculated from IASI nonlinear retrievals

5. References

- Camps-Valls, G., Gómez-Chova, L., Calpe, J., Soria, E., Martín, J.D., Alonso, L., Moreno, J., 2004. Robust support vector method for hyperspectral data classification and knowledge discovery. *IEEE Trans. Geosc. Rem. Sens.* 42 (7), 1530–1542.
- Camps-Valls, G., Bruzzone, L., 2005. Kernel-based methods for hyperspectral image classification. *IEEE Trans. Geosc. Rem. Sens.* 43 (6), 1351–1362.
- Camps-Valls, G., Bruzzone, L., 2009. Kernel Methods for Remote Sensing Data Analysis. *IEEE Transactions on Geoscience and Remote Sensing* 47 (3), 862–873.
- Camps-Valls, G., Muñoz, J., Gómez-Chova, L., Guanter, L., Calbet, X., 2012. Nonlinear statistical retrieval of atmospheric profiles from metop-IASI and MTG-IRS infrared sounding data. *IEEE Trans. Geosci. Rem. Sens.* 50 (5), 1759–1769.