Analysis of severe convection situations in Africa and Europe with the new NWC SAF sounder Satellite Humidity And Instability (sSHAI) product derived from IASI as a proxy for MTG-IRS data

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1. INTRODUCTION

In this work, a Machine Learning/Artificial Intelligence algorithm is presented for IASI-MetOp (as a proxy for MTG-IRS) to characterize its capabilities in providing information of the atmospheric temperature, humidity and instability profiles. However, the hyperspectral infrared sounders on board satellites have significant limitations in deriving high-quality atmospheric profiles. This is because retrievals lose accuracy in the lower layers of the atmosphere, where it is most critical for instability indices (e.g. CAPE). In this work, a solution is provided by adding ground-based data to complement the Infrared Sounder profiles. The aim is to provide a real-time operational non-linear regression method, the **NWC SAF sSHAI product,** to help forecasters monitor and analyze the atmosphere and the possible occurrence of severe phenomena such as severe convection.

2. METHODOLOGY

sSHAI product: Provide atmospheric vertical profile retrievals (temperature and humidity) (based on Machine Learning) and derived stability indices.

The ML model used in this work is a Kernel Ridge Regression (KRR) model based on a Radial Basis Function kernel, that is a Gaussian Kernel defined as: $K = \exp(\frac{-|X_{test}-X_{train}|^2}{2\sigma^2})$

The data inputs (X) are built with IASI data: Radiances, Vertical Solar/Satellite Zenith Angle, Latitude and Surface Pressure from each pixel.

While, the training dependent variable (Y) are built with ECMWF analysis: Temperature (T) and Water Vapour (Td) profiles at 90 pressure levels, Surface Air Temperature (SAT), Skin Temperature (SKT) and Surface Dew point Temperature (STd).

The retrieved **atmospheric variables** are: **T and Td** vertical profiles at 90 pressure levels, **SAT** and **STd** at 2m from the surface and **SKT** at surface level.

TRAINING DATA
- X = IASI data
- Y = ECMWF analysis

(data from 2 previous days)

→ **NORMALIZATION**
- X and Y
- PCA from X

(data from 2 days before)

→ **TRAINING**
- KRR algorithm with SVs selection from X and Y

→ **TESTING**
- Retrievals of atmospheric variables from IASI data

→ **VALIDATION**
- Comparison with ECMWF analysis

3. NWC SAF sSHAI RESULTS

To test IASI machine learning retrievals, **several characteristic cases** have been selected. These **days** were **suitable days for hyperspectral sounders** with **clear skies in the morning** and some of them with **stationary synoptic conditions** throughout the day. **Convection** was triggered **in the afternoon**. **Two** classes of **retrievals** have been tested using IASI-MetOp data **in scenes with a cloud fraction** up to **until 80%**: 1) **Retrievals** using just **IASI data** as input and 2) **Retrievals** using **IASI data and ECMWF forecast** as input.

3.1 Case 1: 15 July 2015 over Spain

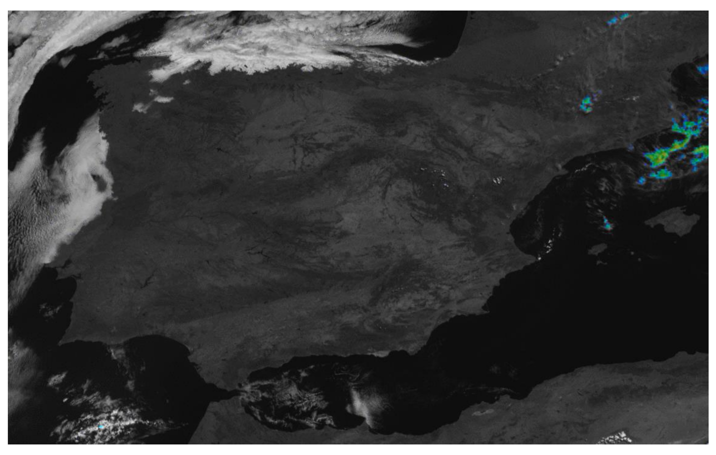


Figure 2 – Meteosat RGB Image on 15/07/2015 at 9:30Z

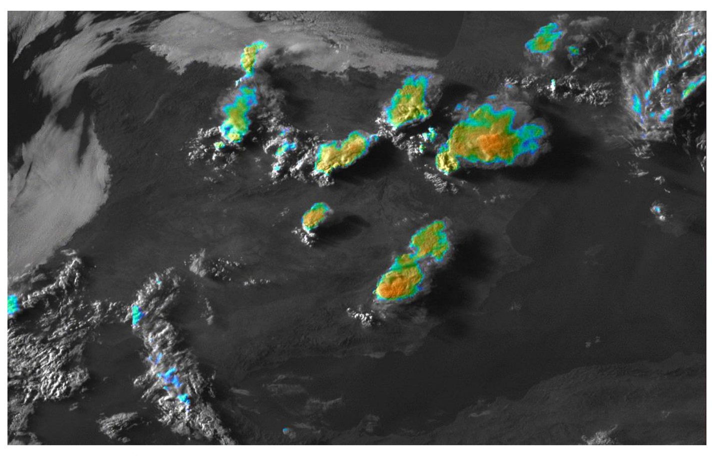


Figure 3 – Meteosat RGB Image on 15/07/2015 at 17:30Z

Retrievals lose accuracy in the lower layers of the atmosphere, where it is most critical for instability indices (e.g. CAPE). In this test, we have added humidity ground-based data to complement the Infrared Sounder profiles.

3.1.2 Improving ECMWF forecast and IASI retrievals

Surface Station WV averaged over previous 6 hours →Transformed into a surface field by Kriging.

Surface parameters from IASI retrievals or ECMWF forecasts are substituted by this surface field from Surface Stations Kriging.

In this work we validate this by locating the afternoon triggered convection.

3.1.1 Comparison between ECMWF forecast & IASI retrievals vs Surface Stations

In AEMET, Surface Station Water Vapour (WV) data consists of the average of only the ninth minute every ten minutes → Cannot do proper averages of an stochastic variable

We average several previous hours of WV measurements to achieve an average similar to IASI or ECMWF resolution.

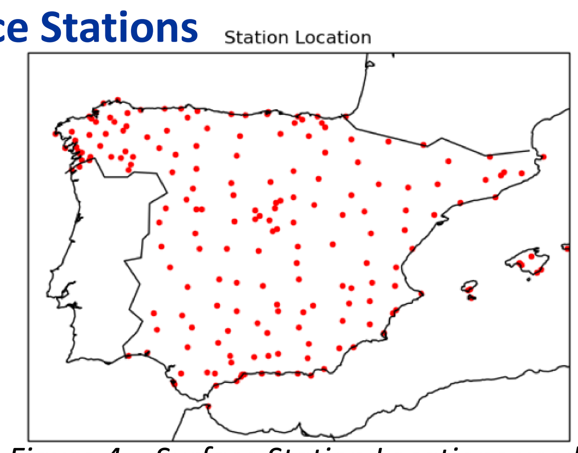


Figure 4 – Surface Station Locations used

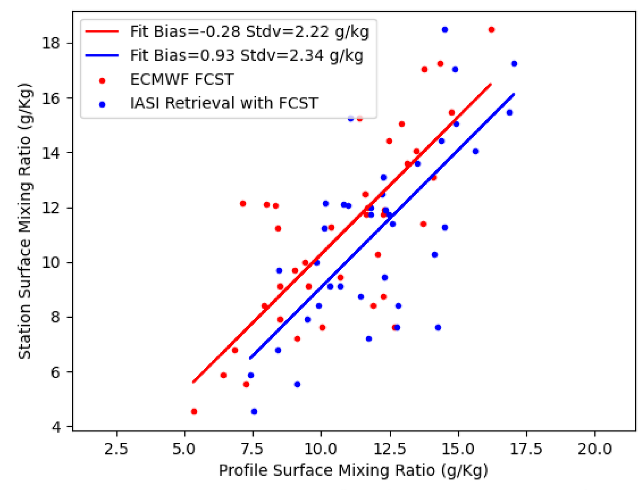


Figure 5 – WV ECMWF fct & IASI retrievals vs surface stations data (before)

- Best result obtained with 6h average, equivalent between 3 to 35 km → Similar to IASI FOV extension or ECMWF resolution.
- Does NOT work for Temperature due to its daily cycle

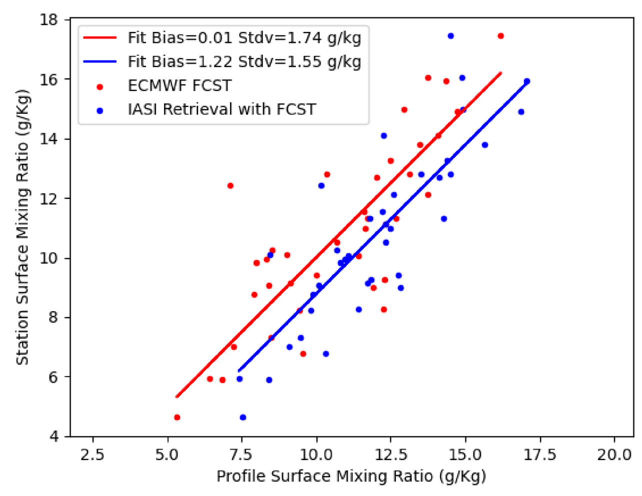
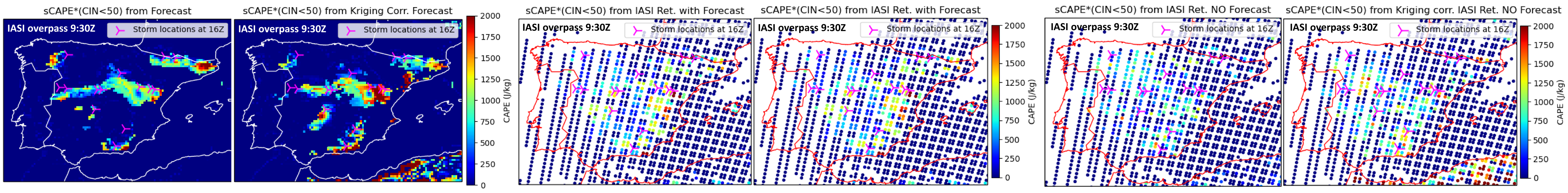


Figure 6 –WV ECMWF fct & IASI retrievals vs surface stations data (after)

The dispersion without time averaged of surface station data is quite high

→ The dispersion averaging surface station data decreases significantly



High agreement between CAPE maps calculated and the location **where convective storms were triggered in the afternoon due to summer solar radiation.**

3.2 Case 2: 5 June 2024 over Hungary

During 5 June 2024 **several storms** hit **Hungary** due to atmospheric **instability developed during mid-day.**

In Hungary, Surface Station WV data consists of the average of the previous ten minutes every ten minutes → Better proper averages of an stochastic variable than in Spain.

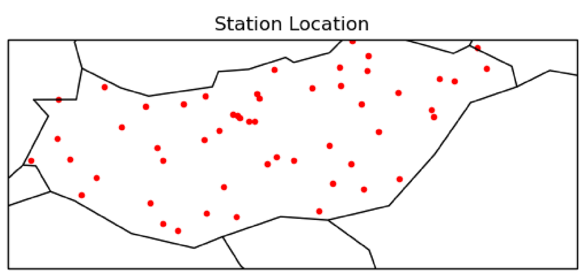
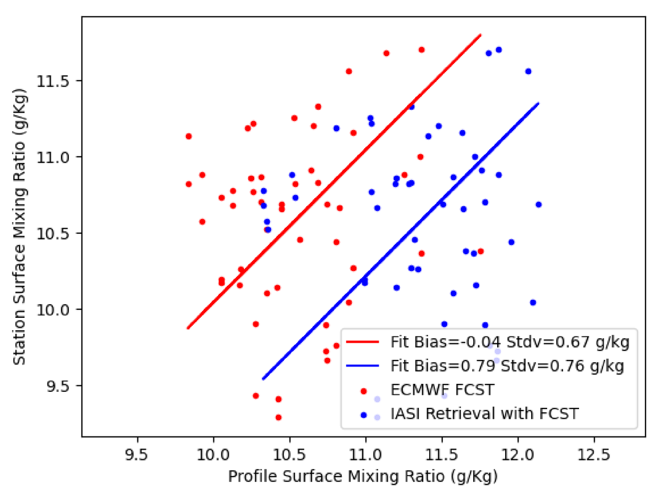
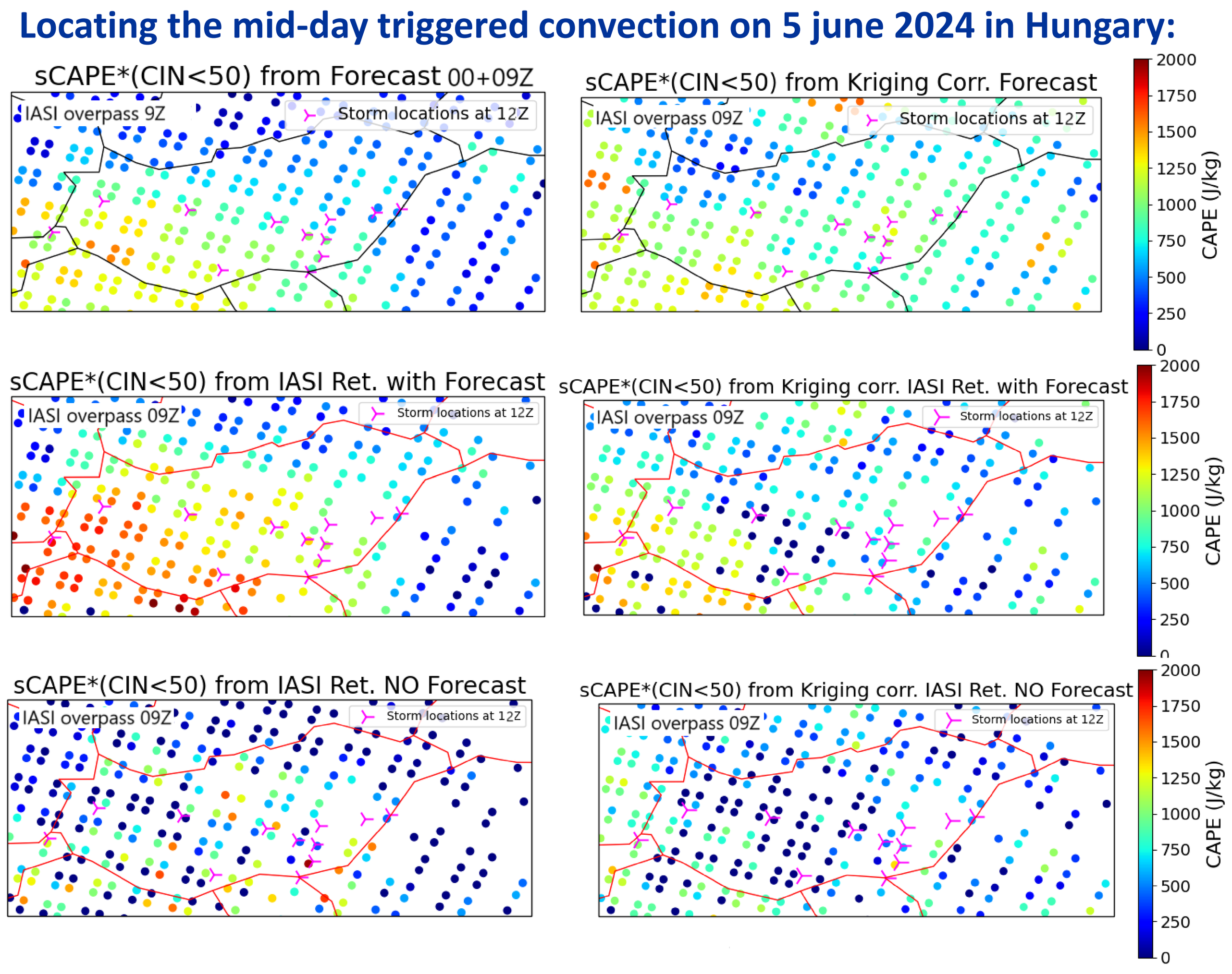


Figure 7 –Surface stations used in Hungary

Averaged several hours of WV measurements to achieve a similar resolution to IASI or ECMWF. Very low Bias and Std Deviation between ECMWF forecast and IASI retrievals vs surface stations.



Locating the mid-day triggered convection on 5 june 2024 in Hungary:



By using kriging, high CAPE values are localized better. In this case the high CAPE values are not perfectly coincident with the storms locations, possibly due to the variable dynamic situation and the 5h time mismatch between IASI overpass and the storms.

3.3 Events in Africa

No Surface data available in Africa. The **Surface CAPE** maps calculated with ECMWF forecast and IASI retrievals for two convective events in Nigeria and South Africa are shown.

3.3.1 Case 3: 18 January 2022 over South Africa

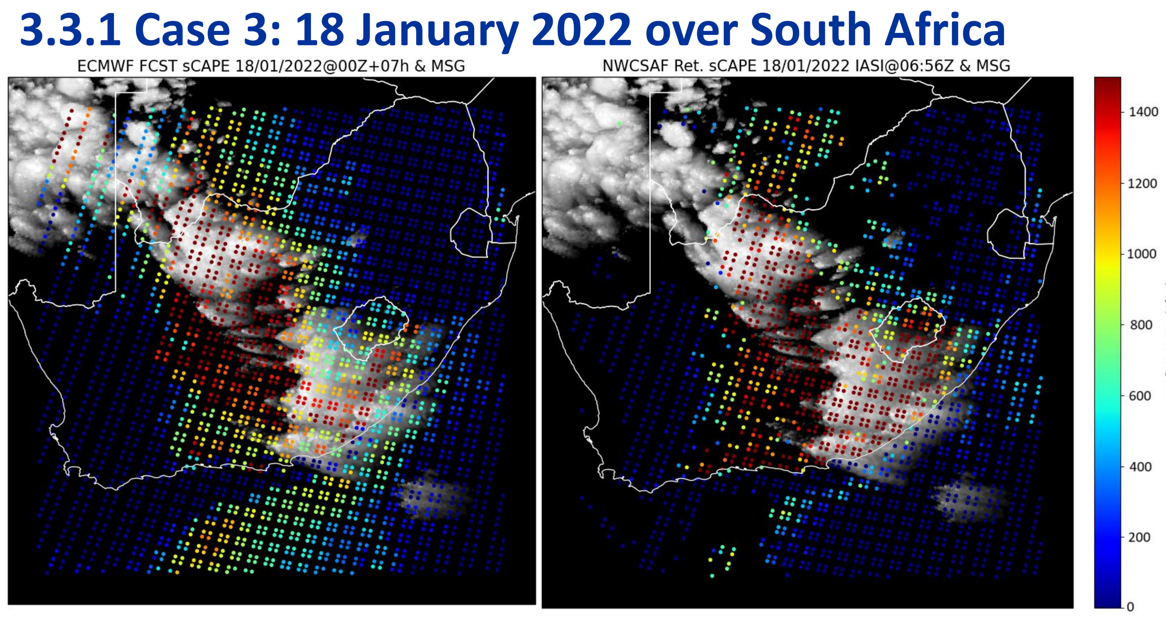


Figure 8 – Surface Cape at 07:00 UTC from ECMWF MSG 10.8 μm BT from 9:00 to 24:00

Figure 9 – Surface Cape at 06:56 UTC from IASI retrieval MSG 10.8 μm BT from 9:00 to 24:00

The instability areas, where **convection** later develops, is located by IASI retrievals with a great accuracy.

3.3.2 Case 4: 11 October 2022 over Nigeria

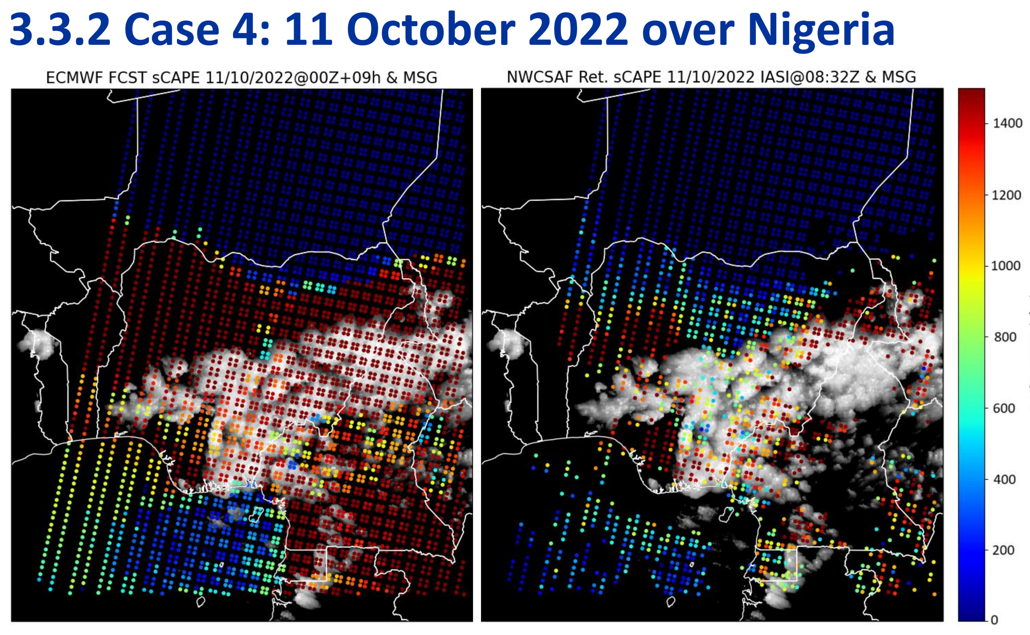


Figure 10 – Surface Cape at 09:00 UTC from ECMWF-MSG 10.8 μm BT from 9:00 to 24:00

Figure 1 – Surface Cape at 08:32 UTC from IASI retrieval MSG 10.8 μm BT from 9:00 to 24:00

Surface CAPE from **IASI ret. localizes better than ECMWF fcst** the instability areas, where **convection** later develops.

4. CONCLUSIONS

The results of the application of the Machine Learning 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. Complementing IASI hyperspectral retrievals with ground-based data seems to provide a powerful nowcasting tool for forecasters. A closer time monitoring will be available in the future with MTG-IRS data.

5. REFERENCES

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